Exploring the concept of assigning relative weights to regional climate models: Experiences from the ENSEMBLES project

Acknowledgements to ENSEMBLES RT3 Partners (ICTP,CNRM,CUNI,DMI,HC,KNMI,MPI,SMHI,UCLM)

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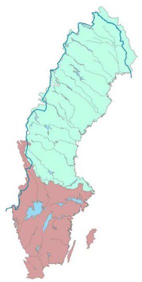
Presentation at the Workshop on Uncertainties of scenario simulations, SMHI

14 October 2010

Why model weighting?

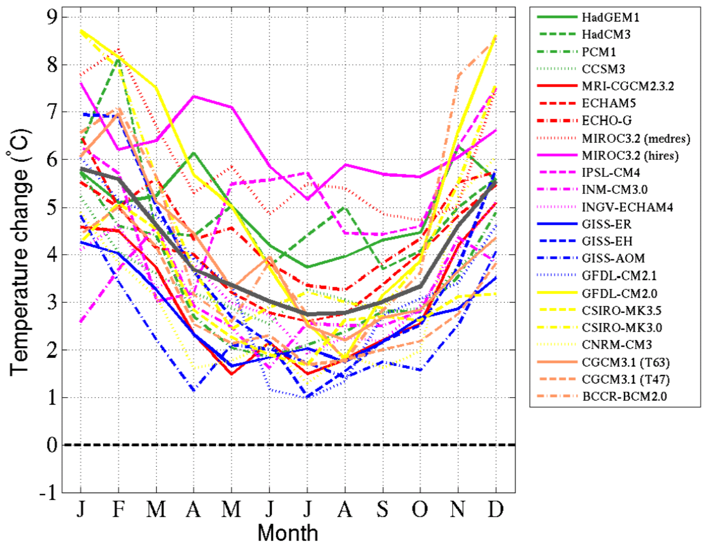
- Multi-model ensemble predictions/projections can be characterized by a large uncertainty due to the inter-model spread



Climate change in Northern Sweden

Comparing 2071-2100 vs 1961-1990

All models run under SRES A1B



- Different models within the ensemble might have different levels of performance in climate simulation/prediction

- By weighting the models based on their “performance” it might be possible to reduce the uncertainty and increase the reliability of the prediction/projection

The ENSEMBLES GCM-RCM Matrix

ENSEMBLES SMHI

Global climate models (GCMs)

Regional climate models (RCMs)

Global model / Regional inst.	METO-HC Standard	METO-HC Low sens.	METO-HC Hi sens.	MPIMET Standard	MPIMET Ens.m. 1	MPIMET Ens.m. 2	IPSL	CNRM	NERSC	MIROC	CGCM3	Total number
METO-HC	2100	2100*	2100*	2100 (late 2010)								4
MPIMET				2100			2050*					2
CNRM								2100				1
DMI				2100*				2100	2100* (04/2010)			3
ETH	2100											1
KNMI				2100* 2100	2100*	2100*				2100*		1+4
ICTP				2100								1
SMHI		2100*		2100* 2100*					2100			3+1
UCLM	2050											1
C4I			2100*		2050 (A2)*							2
GKSS							2050*					1
METNO	2050*								2050*			1
CHMI								2050* (12/2009)				1
OURANOS**											2050*	1
VMGO**	2050*											1
Total (1951-2050)	5	2	2	7+2	0+1	0+1	2	3	3	0+1	1	25+5

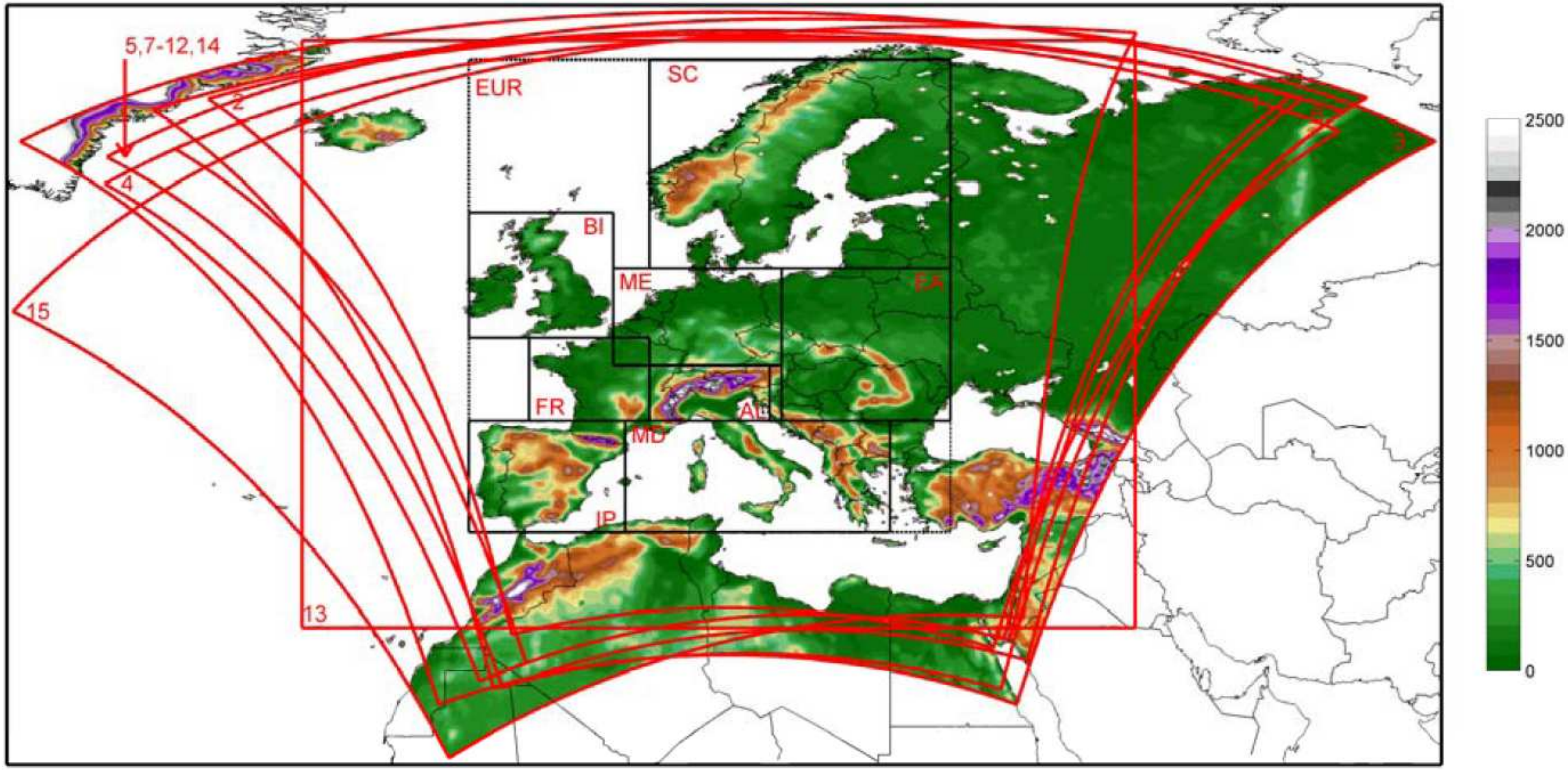
Red: Online now; *: non-contractual runs; **:affiliated partners without obligations; underscore: 50km resolution; (in parantheses): Expected date. For partner acronym explanations, see the participant list. **NOTE** that all partners also did an ERA-40 driven analysis 1951(1961)-2000

Methodological approach

- Develop weights based on different metrics of model performance in reproducing present day climate characteristics, with emphasis on the “added value” obtained from RCMs
- Six metrics were identified (based on ERA40-driven runs)
  - F1: Large scale circulation and weather regimes (CNRM)
  - F2: Temperature and precipitation meso-scale signal (ICTP)
  - F3: PDFs of daily precipitation and temperature (DMI, UCLM,SHMI)
  - F4: Temperature and precipitation extremes (KNMI; HC)
  - F5: Temperature trends (MPI)
  - F6: Temperature and precipitation annual cycle (CUNI)
- Weights have been calculated for single seasons and regions and then averaged to yield one final number per model

Christensen et al., Clim. Res. accepted for publication

The RCM ensemble



- 15 RCMs at 25km, lateral boundary conditions from ERA40
- Analysis period 1961-2000
- Common minimum domain, all data regridded to a common 25 km lat-lon grid
- Observations on monthly {CRU 0.16 degree (Mitchell et al. 2003)} and daily {EOBS 0.25 degree (Haylock et al. 2008)}

Christensen et al., Clim. Res. accepted for publication

F1: Large scale circulation and weather regimes

SMHI

- Mean behavior
  - Frequency of occurrence, W(1,1,2)
  - Spatial composite, W(1,1,1)
  - Duration, W(1,1,3)
- Interannual variability
  - Variance of the frequency of occurrence, W(1,2,1)
  - Temporal correlation, w(1,2,2)
- Daily behavior
  - Total number of days per season, W(1,3,1)

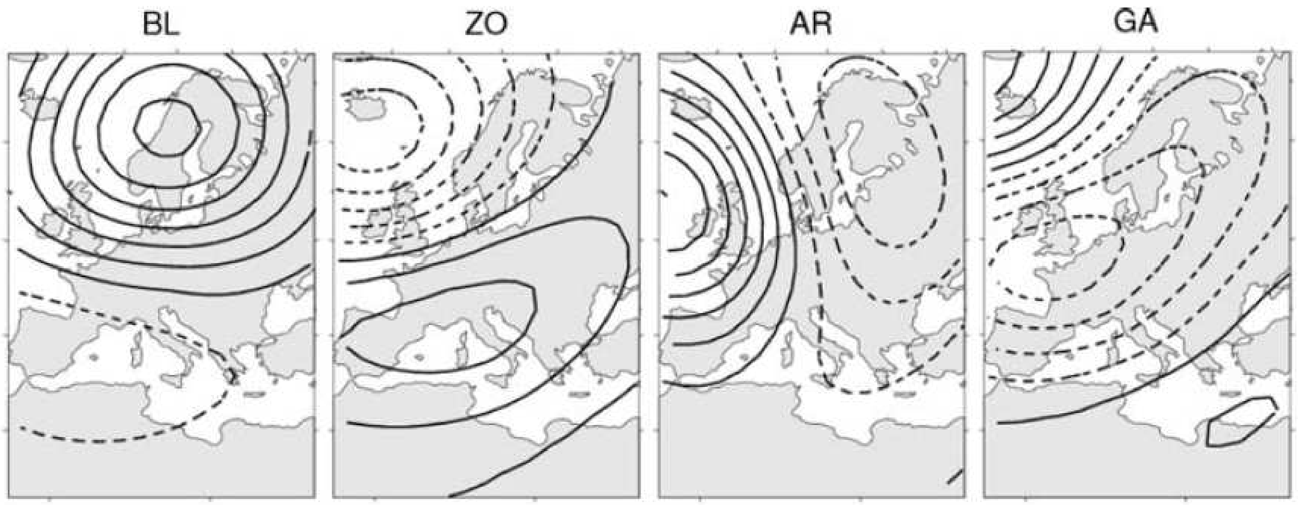
$$w_1^{i,s} = w_{111}^{\alpha_{111}} * w_{112}^{\alpha_{112}} * w_{113}^{\alpha_{113}} * w_{121}^{\alpha_{121}} * w_{122}^{\alpha_{122}} * w_{131}^{\alpha_{131}}$$

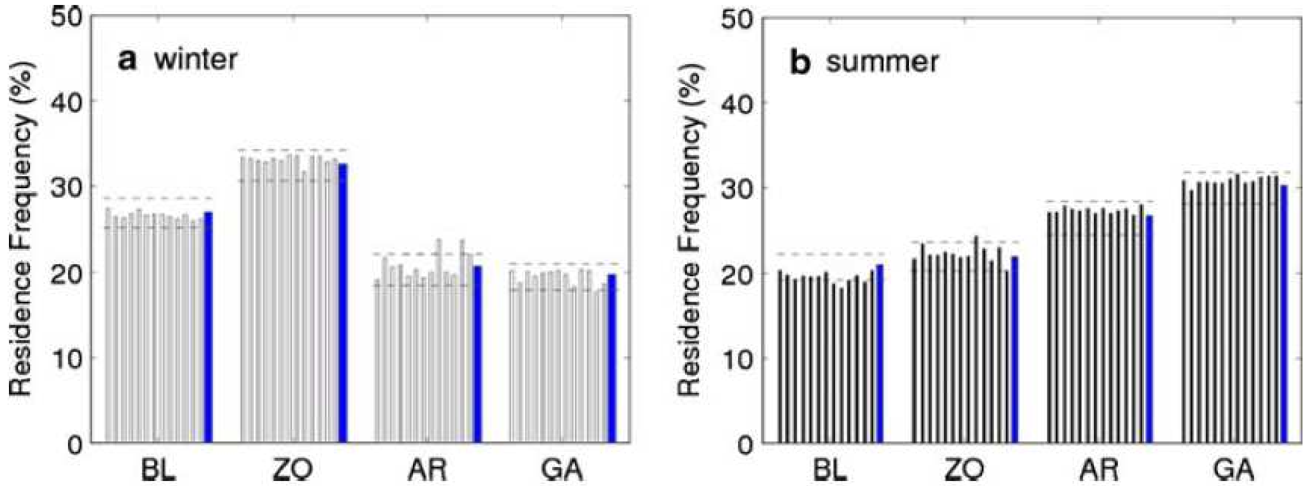
$$\tilde{w}_1^{i,s} = \frac{w_1^{i,s}}{\sum_i w_1^{i,s}}$$

Samuel Somot (CNRM)

Weather regimes

- Daily Z500 data
- Clustering by PCA
- 4 regimes:
  Blocking
  Zonal
  Atlantic Ridge
  Greenland anticyclone





Sanchez-Gomez et al., Clim. Dyn., 2008

F2: Temperature and precipitation mesoscale signal

- First run a smoother on the original fields to identify a large scale signal
- Define the mesoscale signal as the difference between the original fields and the large scale fields
- Define the 5 functions:

$$g_1 = R(p)^n \qquad g_2 = R(T)^n \qquad g_3 = \sigma(t)^{p}{}_{CRU} \Big/ RMSE(p)$$

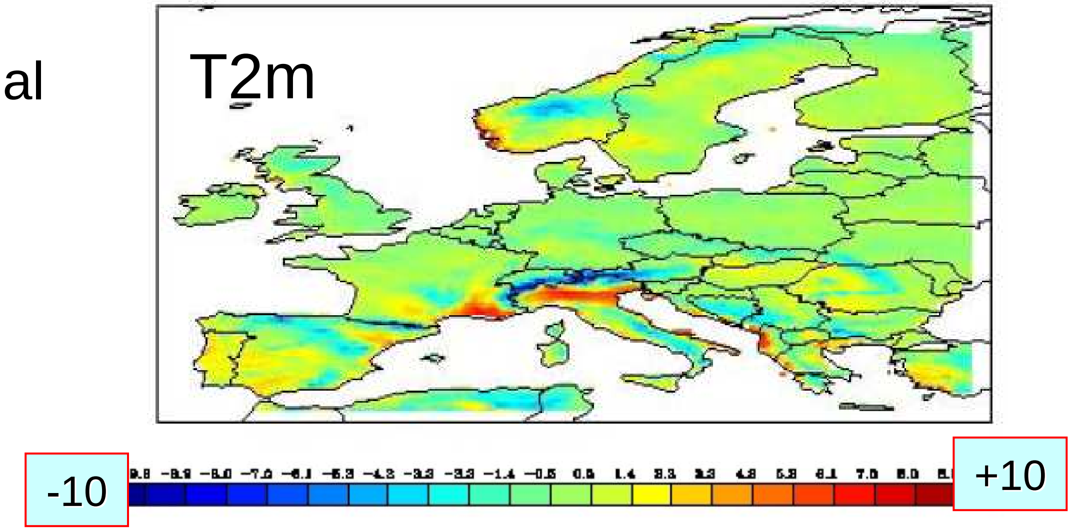
$$g_4 = \sigma(t)^{T}{}_{CRU} \Big/ RMSE(T) \qquad g_5 = \left[L - \left(\left| R_{pT}{}^{CRU} - R_{pT}{}^{mod} \right| \Big/ 2 \right) \right]$$

The weight is given by

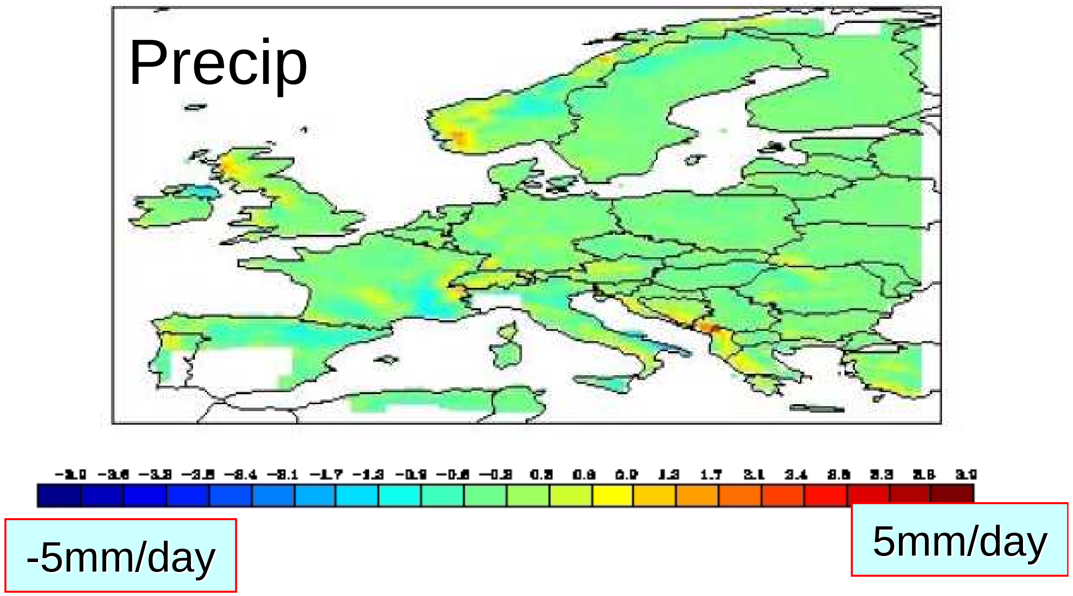
$$w_i = g_1 * g_2 * g_3 * g_4 * g_5$$

What is the mesoscale signal?

- Calculate 9x9 gridpoint spatial mean to get ”large-scale” signal.
- Subtract the ”large-scale” signal from the total field to get the ”mesoscale” signal



- Particularly orographic features stands out. But also some coastal areas and large lakes



Coppola et al., Clim. Res. Accepted for publication

F3: PDFs of daily and monthly temperature and precipitation

The skill score metric for daily data

Cumulative minimum of two distributions.

$$S_{\text{score}} = \sum_{1}^{n} \text{minimum}(Z_m, Z_o),$$

Takes a value between 0 and 1

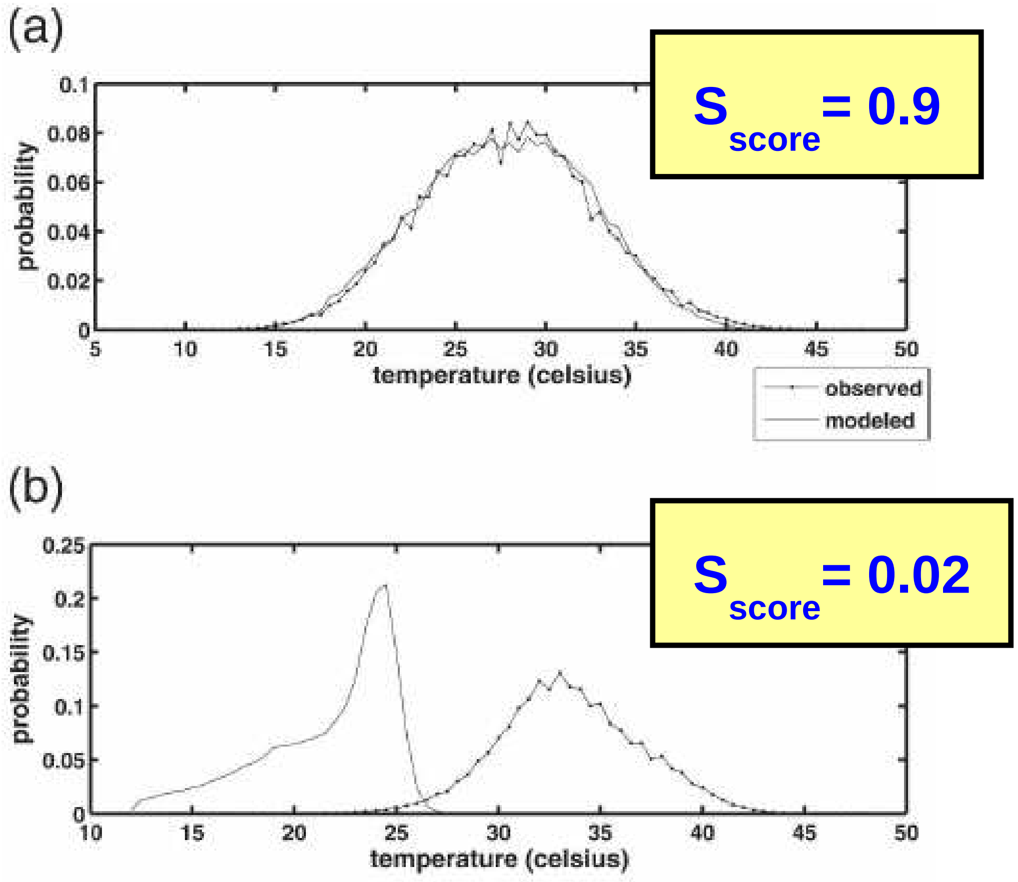
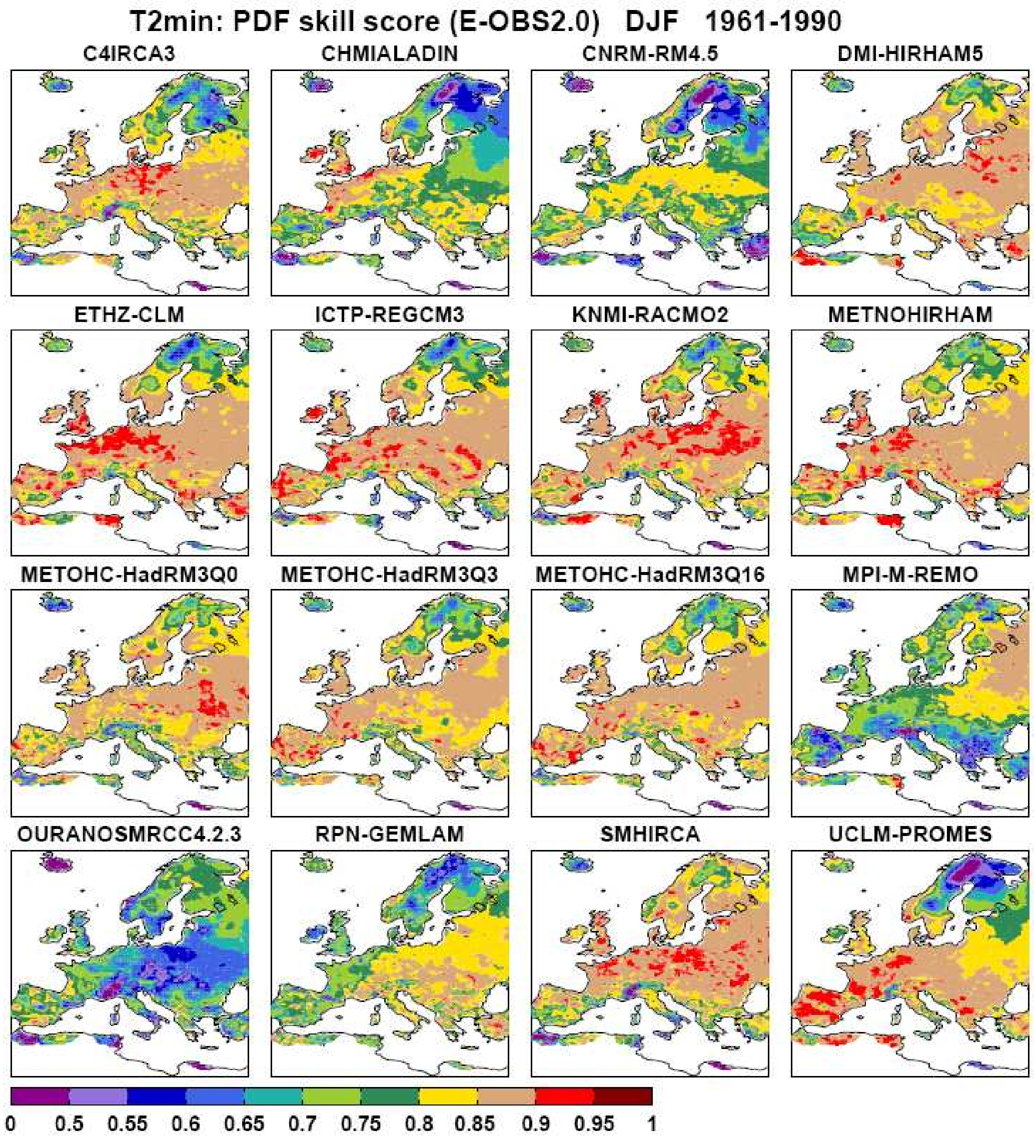


FIG. 3. Diagrams of modeled vs observed PDF illustrating the total skill score in (a) a near-perfect skill score test (0.9) and (b) a very poor skill score (0.02).

Perkins et al., *J. Clim., 20,* 2007

Skill scores based on daily data for winter T_{min}



Kjellström et al., Clim. Res. Accepted for publication

An alternative skill score metric for comparing CDFs

$$f_{1j} = 1 - \left(\frac{|A_{RCM_j} - A_{CRU}|}{2 \cdot A_{CRU}} \right)^{0.5}$$

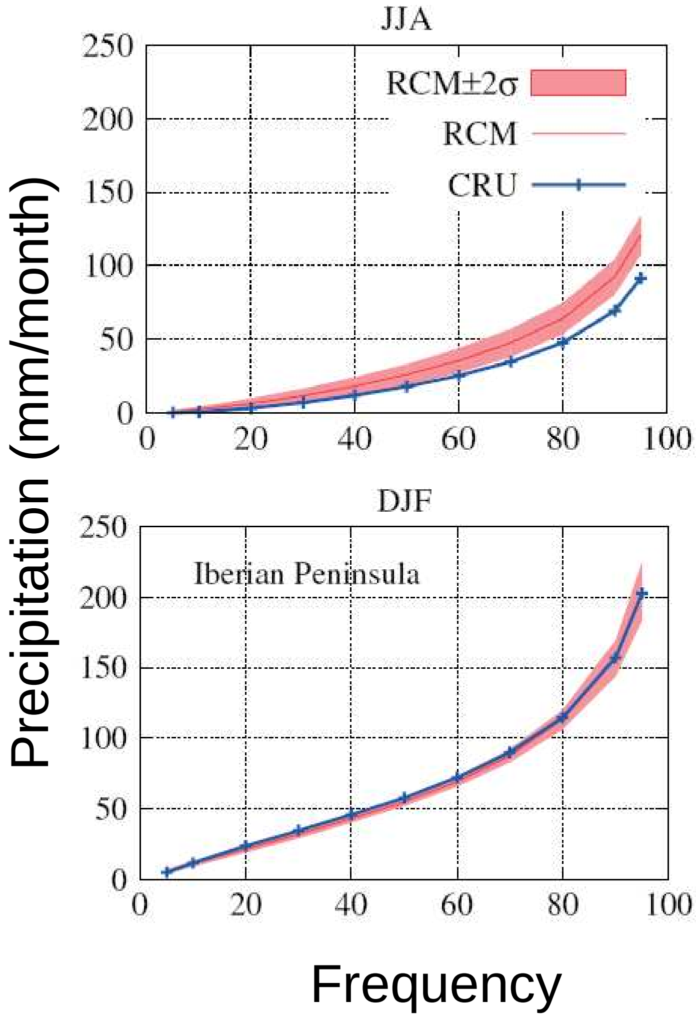
$$f_{2j} = 1 - \left(\frac{|A^{+}_{RCM_j} - A^{+}_{CRU}|}{2 \cdot A^{+}_{CRU}} \right)^{0.5}$$

$$f_{3j} = 1 - \left(\frac{|A^{-}_{RCM_j} - A^{-}_{CRU}|}{2 \cdot A^{-}_{CRU}} \right)^{0.5}$$

$$f_{4j} = 1 - \left(\frac{|\overline{P_{RCM_j}} - \overline{P_{CRU}}|}{2 \cdot \overline{P_{CRU}}} \right)^{0.5}$$

$$f_{5j} = 1 - \left(\frac{|\sigma_{RCM_j} - \sigma_{CRU}|}{2 \cdot \sigma_{CRU}} \right)^{0.5}$$

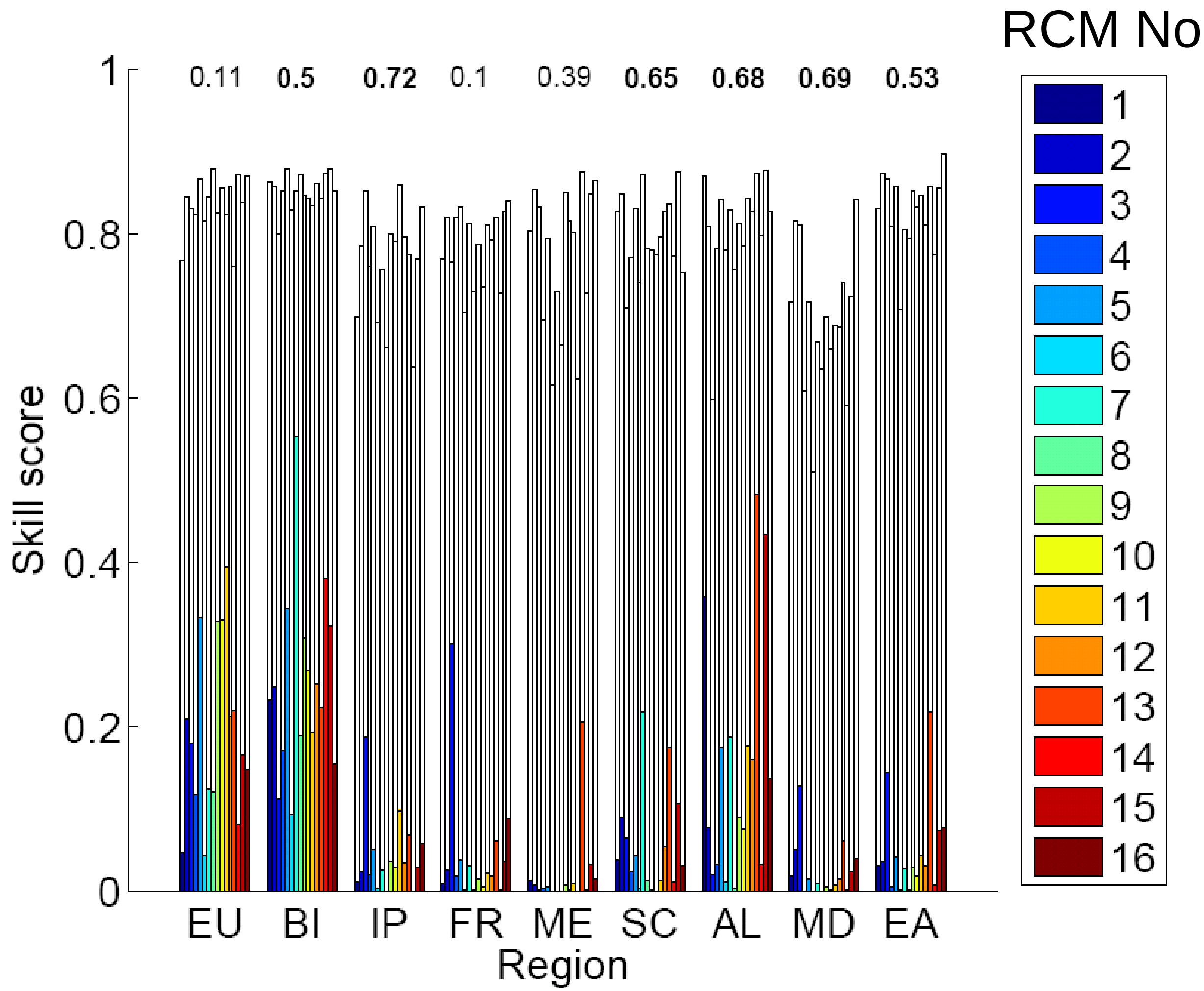
$$W_j = f_{1j} \cdot f_{2j} \cdot f_{3j} \cdot f_{4j} \cdot f_{5j}$$



Sanchez et al., ASL, 2009

Comparing two different metrics for calculating skill scores

- Perkins (cumulative minimum) – unfilled bars
- Sanchez (5 aspects of CDF match) – colored bars
- Absolute numbers are very different
- Ordering of RCMs differ



Kjellström et al., Clim. Res. accepted for publication

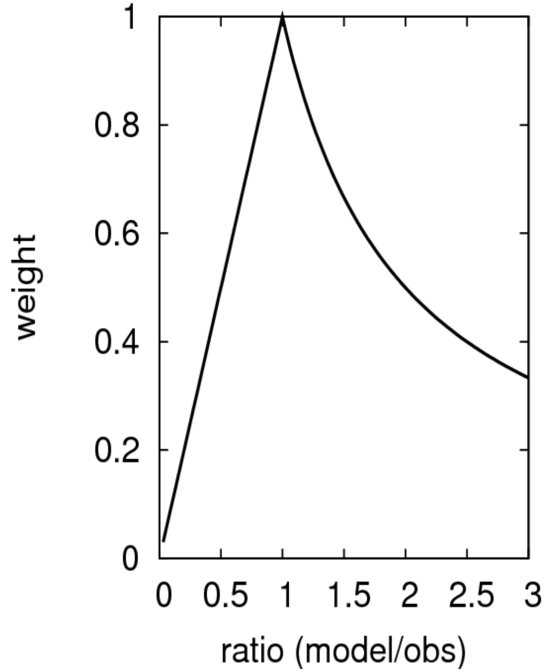
F4: Temperature and precipitation extremes

SMHI

- Biases in extreme percentiles for temperature and precipitation are first calculated (99., 99.9, 99.99, 99.999 %)
- Biases (B) are then turned into weights (W) using an asymmetric transfer function

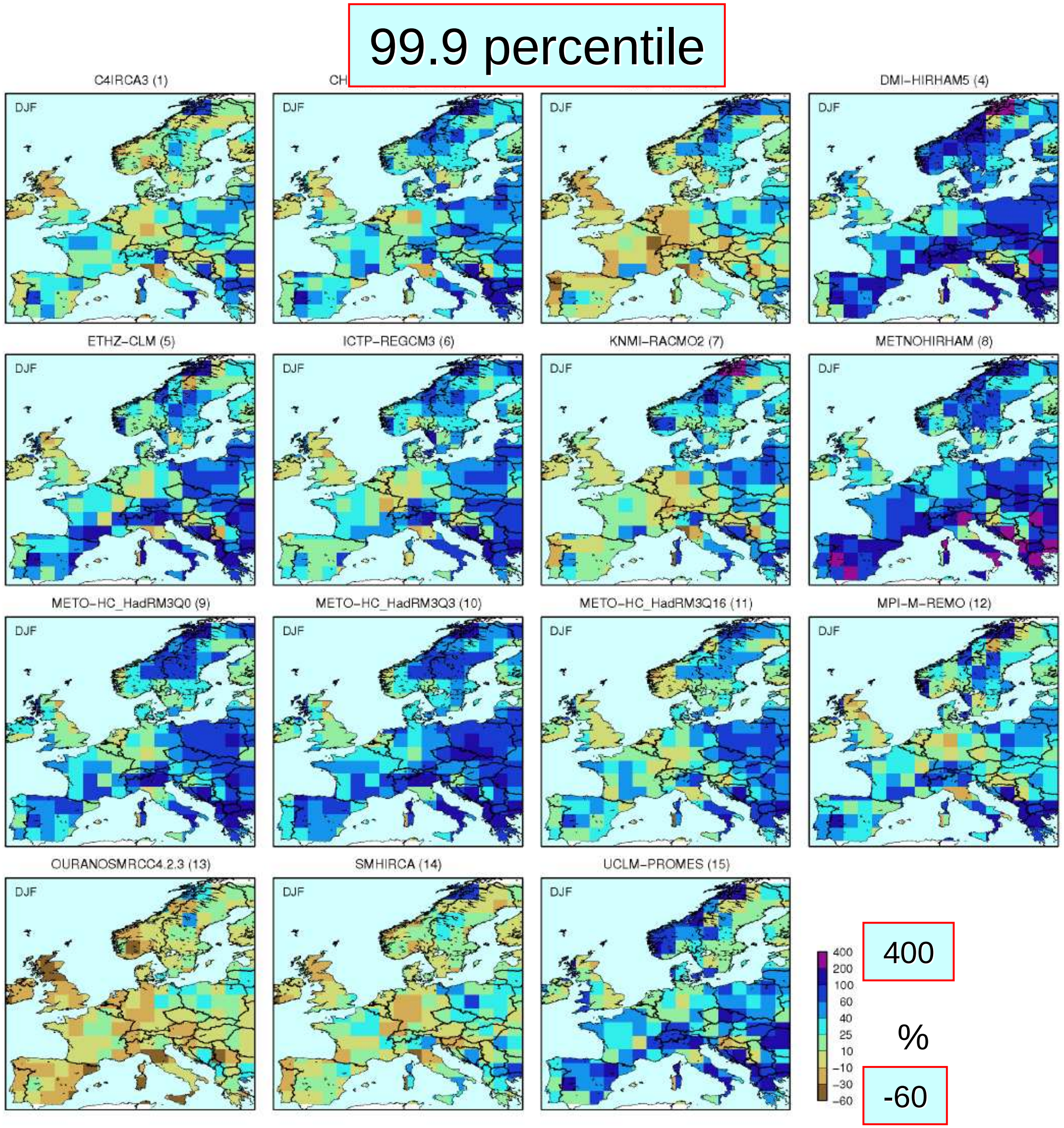
$$B = 100\left[\frac{P_{rcm}}{P_{obs}} - 1\right]$$

$$\begin{aligned} W &= 1 + B/100, & B < 0 \\ &= \frac{1}{1 + B/100}, & B > 0 \end{aligned}$$



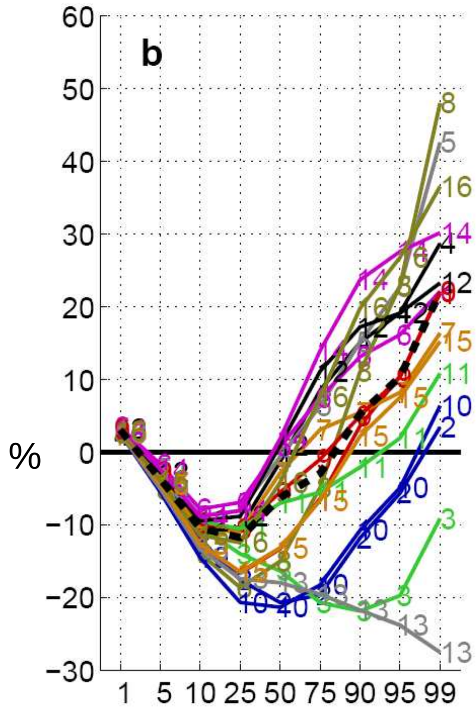
Lenderink., Clim. Res. accepted for publication

Biases in DJF extreme precipitation



Lenderink., Clim. Res. accepted for publication

- Wet biases compared to E-OBS in most but not all RCMs
- The spread between RCMs grow the further to the ”wet side” one looks



Kjellström et al., Clim. Res. accepted for publication

F5: Temperature trends

- Linear temperature trends for the period 1961-2000 are calculated for observations and simulations

$$y_i = \alpha + \beta t_i + r_i$$

- The trends are then turned into skill scores (or weights) using the formula

$$S = 1 - \frac{|\beta - \beta_{REF}|}{\zeta + |\beta - \beta_{REF}|}$$

ζ Is a scaling parameter that determines the spread between the best/worst model

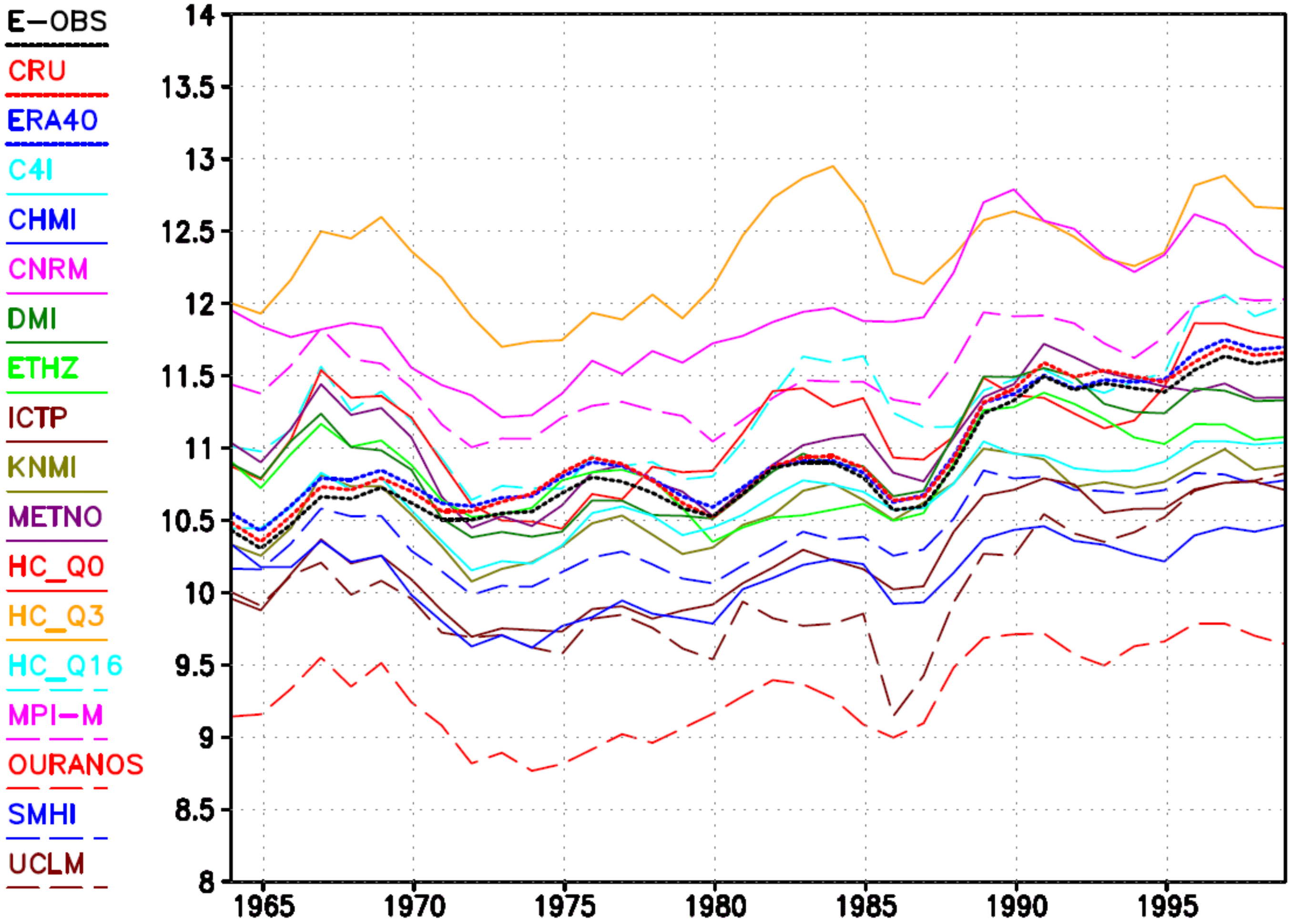
- Annual and seasonal values are combined using

$$S_{combined} = 0.5 * S_{Year} + 0.125 * (S_{DJF} + S_{JJA} + S_{MAM} + S_{SON})$$

Lorenz and Jacob, Clim. Res. submitted

What does the trends look like?

Annual mean temperature in "France"



Lorenz and Jacob, Clim. Res. submitted

F6: Temperature and precipitation annual cycle

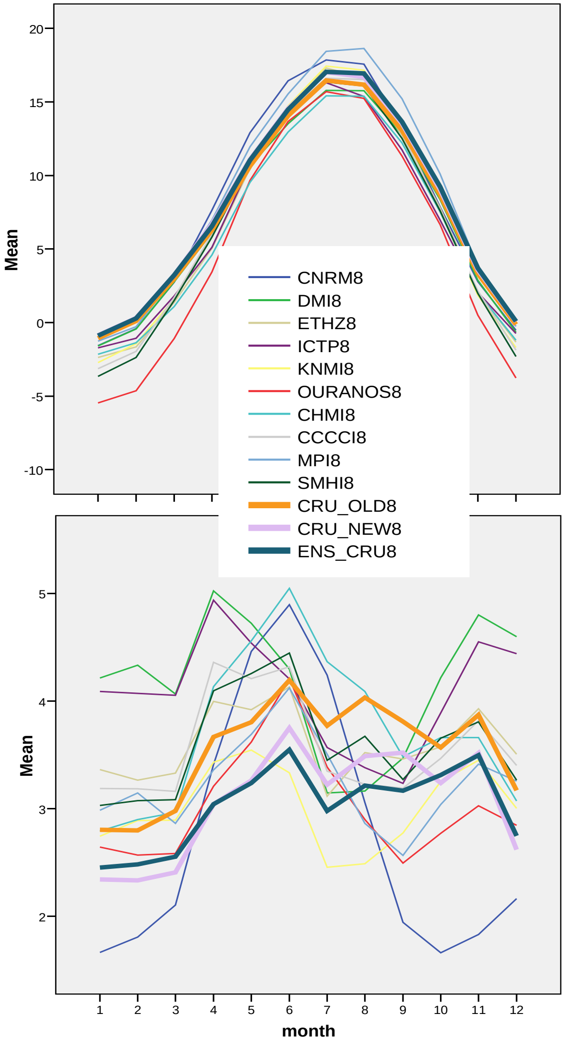
- The weight depends on the model skill in reproducing amplitude and phase of the annual cycle

$$S = \frac{4(1+R)}{\left(\sigma + \frac{1}{\sigma}\right)^2 (1+R_0)},$$

R=Correlation (Phase)

σ=Ratio simulated/observed STD (magnitude)

The Alpine region



Halenka et al., Clim. Res. submitted

How to combine this lot?

SMHI

- Six metrics were identified (based on ERA40-driven runs)
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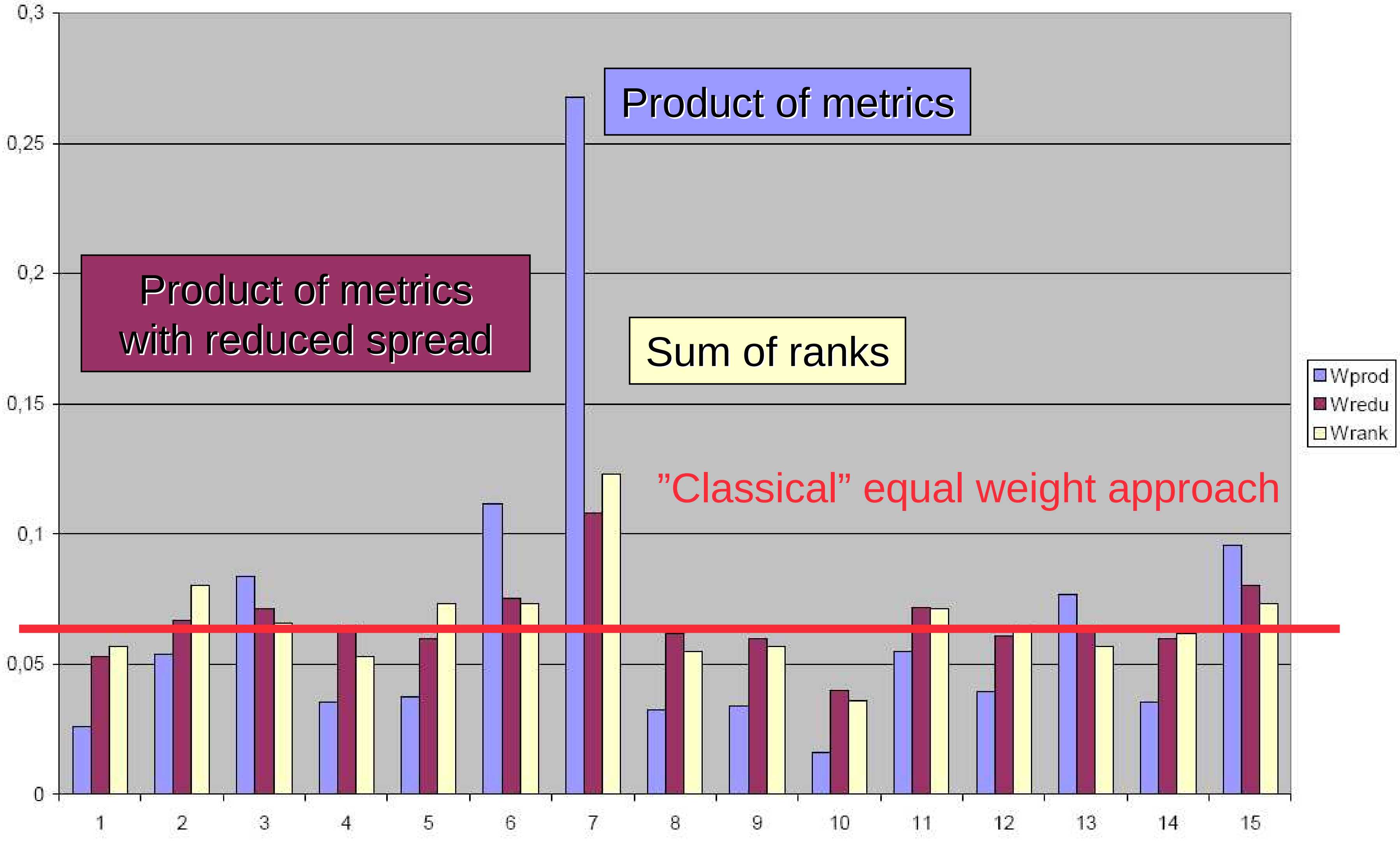
  - F5: Temperature trends (MPI)
  - F6: Temperature and precipitation annual cycle (CUNI)
- These were simply multiplied to yield the final weight $w_{RCM} = \prod_{i=1}^{6} f_i^{n_i}$
- A sensitivity study with a reduction in spread was performed (all single metric F1-F6 were allowed to be equally important)
- An alternative approach was to base the weight on ranking in the different metrics (F1-F6)

Final weights



Christensen et al., Clim. Res. accepted for publication

Final considerations and outstanding issues

- Skill scores differ between different RCMs for different regions, seasons and variables
- Multiplicative metrics implies that the overall weight can be dominated by one “outlier” metric. One may overcome this problem by
  - Combine the metrics in different ways (addition rather than multiplication)
  - Adopt different metrics for different variables
  - Weight differently each metric
  - Normalize the metric by the inter-model spread
- Large subjective component of the approach
- The derived weights are to be used for the whole ensemble as they are derived relative to each other
- May be necessary to calculate other weights for certain impact studies
- When run with LBCs from GCMs also the GCMs could/should be weighted

A number of papers describing this work will appear in a special issue in Climate Research in late 2010 or early 2011

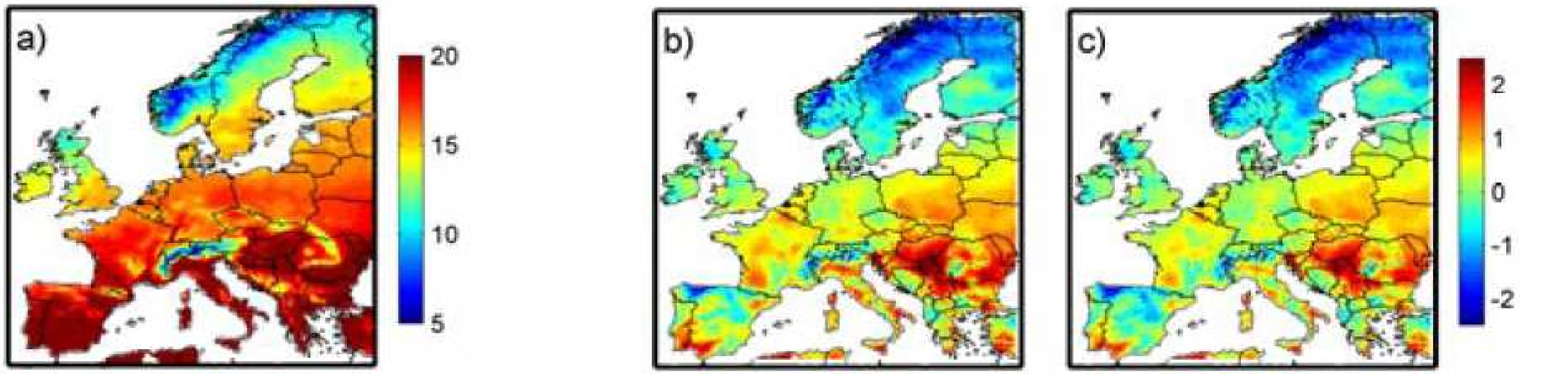
Does it matter?

Seasonal mean statistics

OBS
T (JJA)

Unweighted mean

Weighted mean



(MAE – mean absolute error, RMSE – root mean square error, Areal fraction where MAE decreases)

Variable	MAE	RMSE	Areal fraction
P (JJA)	0.292/0.286	0.565/0.543	**0.55**
P (DJF)	**0.372**/0.377	**0.455**/0.465	**0.53**
T_{2m} (JJA)	**0.740**/0.824	**0.928**/1.018	**0.74**
T_{2m} (DJF)	1.049/0.985	1.452/1.407	0.34
N_{tot} (JJA)	**10.60**/11.10	**12.87**/13.33	**0.63**
N_{tot} (DJF)	7.34/6.08	7.97/7.70	0.45

Bold face indicates improvements compared to unweighted means

Christensen et al., Clim. Res. accepted for publication