RCM Multi-physics ensembles and parameterization sensitivity

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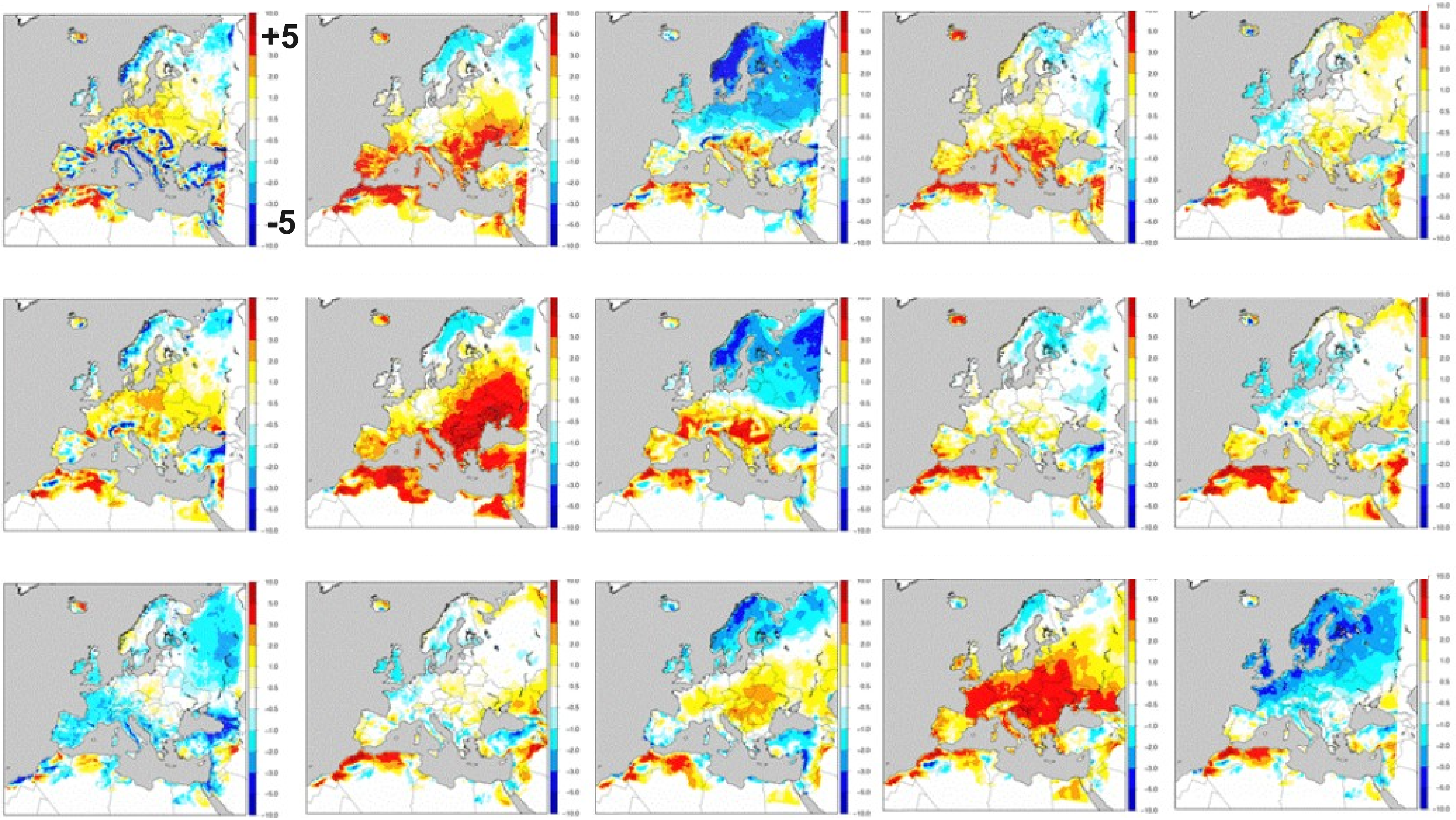
Outline

- Multi-physics ensembles
- Ensemble design
- Best parameterization set
- Most influential parameterized process
- Relative importance of physical schemes under CC conditions
- Observational uncertainty
- Beyond precipitation and temperature
- Right result for the wrong reason

Multi-model vs. multi-physics



Bias of the 90th percentile of summer (JJA) temperature

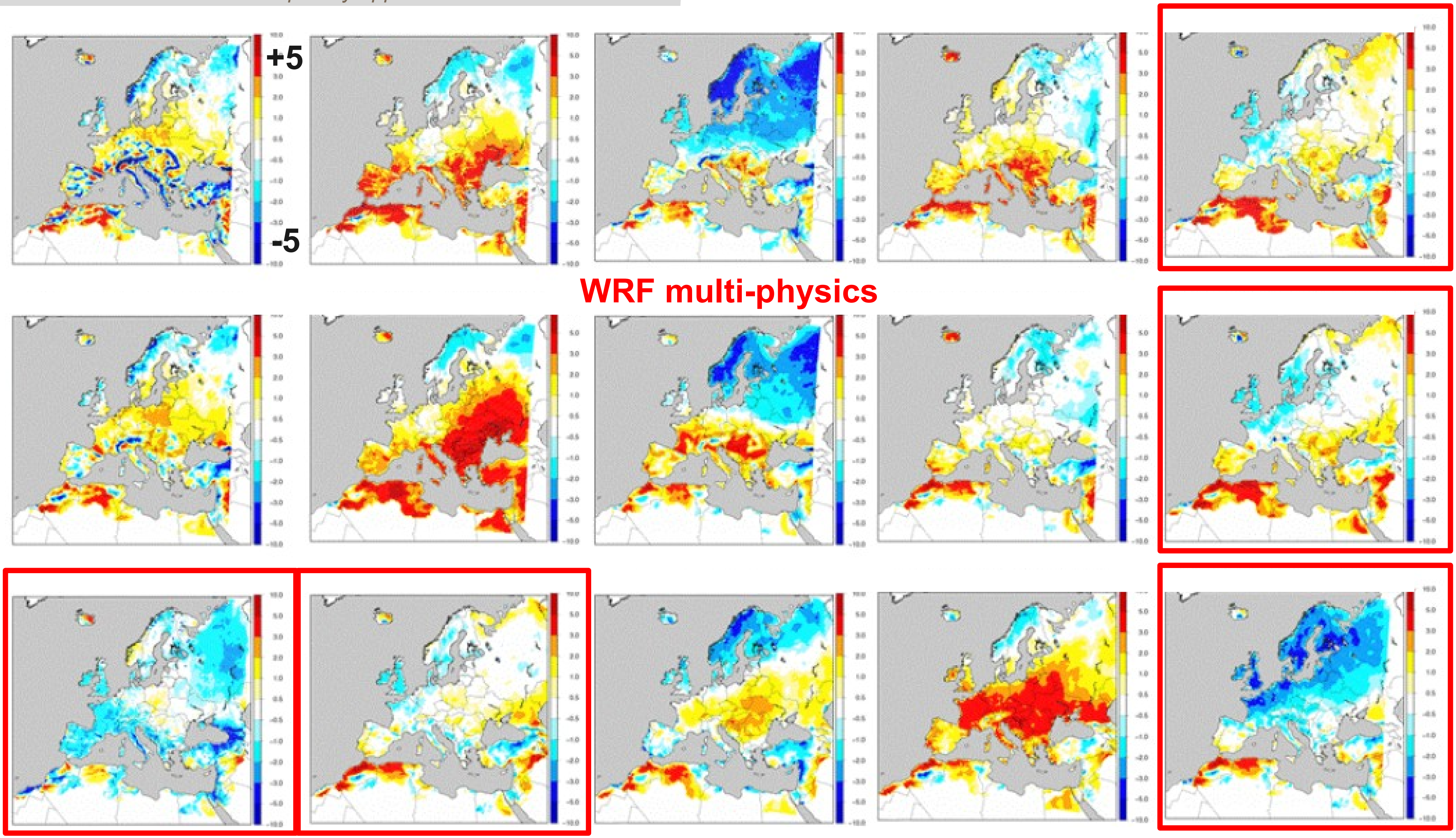
Source: Vautard et al. (2012)
Submitted to Clim. Dyn.

http://www.meteo.unican.es

Santander Meteorology Group

A multidisciplinary approach for weather & climate

Multi-model vs. multi-physics



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SPREADS ARE AS LARGE AS IN MULTI-MODEL ENSEMBLES!

	ΔTmean DJF	ΔTmean JJA	ΔTsdev DJF	ΔTsdev JJA
ES	2.23	1.23	0.12	0.26
MS	2.50	3.25	0.15	0.36

(Units: K)

	ΔPmean DJF	ΔPmean JJA	ΔPsdev DJF	ΔPsdev JJA
ES	8.8	15.6	7.8	1.3
MS	31.8	31.8	16.5	2.4

(Units: mm/month)

(Δ = bias; MS from *Jacob et al., 2007*)

Jerez, 2011 (PhD Th.)

Multi-model vs. multi-physics

- Multi-model ensembles are usually ensembles of opportunity, while multi-physics ensembles can be “designed” to identify problems and improve RCM parameterizations.
- RCM-to-RCM differences are too many (dynamics, numerics, parameters AND parameterizations) to identify the cause of the differences found. Different RCMs are treated as equally valid models.
- The multi-model ensemble can be used to characterize uncertainty, but can hardly be used to improve RCMs.

Multi-model vs. **multi-physics**

- When you have an RCM with multiple parameterizations built-in for the same sub-grid physical process:
  - You don't know anymore which one to use, but …
  - … you can use a multi-physics ensemble to
    - Select the best for your region → No
    - Reject the worst for your region → Sometimes
    - Characterize the uncertainty introduced by a given parameterized process → Yes
    - Find out which parameterized process is (or is not) introducing those biases in your results. → Yes
    - Quantify the role of physical parameterizations in the RCM-uncertainty → Yes
    - …

Ensemble design

- **Full factorial**
  - Computationally very (VERY) expensive
  - Allows assessment of physics interactions
- **One change at a time**
  - Computationally cheaper
  - Allows assessment of the impact of individual changes
  - Interactions cannot be fully explored
  - **With a reference configuration**
    - Requires to find a good reference configuration
  - **Without a reference configuration**
    - Allows more comparisons with the same number of simulations
    - Interactions can hardly be explored
- **Multiple "levels" of changes**
  - Allows the study of selected interactions
- **Ensemble of opportunity**
  - Potential of multi-physics is lost
  - Only usable to assess overall uncertainties related to parameterizations

Full factorial

Sim.	PBL	CML	MIC
1	Eta	GR	SI
2	MRF	GR	SI
3	Eta	KF	SI
4	MRF	KF	SI
5	Eta	GR	MP
6	MRF	GR	MP
7	Eta	KF	MP
8	MRF	KF	MP

Jerez et al., 2012a

2x2x2=8

Ensemble member	Planetary boundary layer physics/surface layer physics	Cumulus physics	Micro-physics	Shortwave/longwave radiation physics
1	YSU/MM5 similarity	KF	WSM 3 class	Dudhia/RRTM
2	YSU/MM5 similarity	KF	WSM 3 class	CAM/CAM
3	YSU/MM5 similarity	KF	WSM 3 class	RRTMG/RRTMG
4	YSU/MM5 similarity	KF	WSM 5 class	Dudhia/RRTM
5	YSU/MM5 similarity	KF	WSM 5 class	CAM/CAM
6	YSU/MM5 similarity	KF	WSM 5 class	RRTMG/RRTMG
7	YSU/MM5 similarity	KF	WDM 5 class	Dudhia/RRTM
8	YSU/MM5 similarity	KF	WDM 5 class	CAM/CAM
9	YSU/MM5 similarity	KF	WDM 5 class	RRTMG/RRTMG
10	YSU/MM5 similarity	BMJ	WSM 3 class	Dudhia/RRTM
11	YSU/MM5 similarity	BMJ	WSM 3 class	CAM/CAM
12	YSU/MM5 similarity	BMJ	WSM 3 class	RRTMG/RRTMG
13	YSU/MM5 similarity	BMJ	WSM 5 class	Dudhia/RRTM
14	YSU/MM5 similarity	BMJ	WSM 5 class	CAM/CAM
15	YSU/MM5 similarity	BMJ	WSM 5 class	RRTMG/RRTMG
16	YSU/MM5 similarity	BMJ	WDM 5 class	Dudhia/RRTM
17	YSU/MM5 similarity	BMJ	WDM 5 class	CAM/CAM
18	YSU/MM5 similarity	BMJ	WDM 5 class	RRTMG/RRTMG
19	MYJ/Eta similarity	KF	WSM 3 class	Dudhia/RRTM
20	MYJ/Eta similarity	KF	WSM 3 class	CAM/CAM
21	MYJ/Eta similarity	KF	WSM 3 class	RRTMG/RRTMG
22	MYJ/Eta similarity	KF	WSM 5 class	Dudhia/RRTM
	similarity	KF	WSM 5 class	CAM/CAM
	similarity	KF	WSM 5 class	RRTMG/RRTMG
	similarity	KF	WDM 5 class	Dudhia/RRTM
	similarity	KF	WDM 5 class	CAM/CAM
	similarity	KF	WDM 5 class	RRTMG/RRTMG
	similarity	BMJ	WSM 3 class	Dudhia/RRTM
	similarity	BMJ	WSM 3 class	CAM/CAM
	similarity	BMJ	WSM 3 class	RRTMG/RRTMG
	similarity	BMJ	WSM 5 class	Dudhia/RRTM
	similarity	BMJ	WSM 5 class	CAM/CAM
	similarity	BMJ	WSM 5 class	RRTMG/RRTMG
	similarity	BMJ	WDM 5 class	Dudhia/RRTM
	similarity	BMJ	WDM 5 class	CAM/CAM
	similarity	BMJ	WDM 5 class	RRTMG/RRTMG

Experiment ID	Microphysics	Cumulus	PBL	Radiation
4322	simple ice	Grell	Blackadar	cloud
4324	simple ice	Grell	Blackadar	RRTM
4352	simple ice	Grell	MRF	cloud
4354	simple ice	Grell	MRF	RRTM
4622	simple ice	Kain-Fritsch	Blackadar	cloud
4624	simple ice	Kain-Fritsch	Blackadar	RRTM
4652	simple ice	Kain-Fritsch	MRF	cloud
4654	simple ice	Kain-Fritsch	MRF	RRTM
5322	mixed phase	Grell	Blackadar	cloud
5324	mixed phase	Grell	Blackadar	RRTM
5352	mixed phase	Grell	MRF	cloud
5354	mixed phase	Grell	MRF	RRTM
5622	mixed phase	Kain-Fritsch	Blackadar	cloud
5624	mixed phase	Kain-Fritsch	Blackadar	RRTM
5652	mixed phase	Kain-Fritsch	MRF	cloud
5654	mixed phase	Kain-Fritsch	MRF	RRTM

Fernández et al, 2007

2x2x2x2=16

2x2x3x3=36

Evans et al., 2011

one change at a time

	CU			BL		MP		LS			HIDR	
	KF	BM	GD	YS	PX	W5	W3	MN	AN	AR	NH	HR
Ref. → CTRL	O			O		O		O			O	
CUBM	O			O		O		O			O	
CUGD	O			O		O		O			O	
BLAC	O			O		O		O			O	
MP3C	O			O		O		O			O	
LSAN	O			O		O		O			O	
LSAR	O			O		O		O			O	
HIDR	O			O		O		O			O	
	Kain-Fritsch	Betts-Miller-Janjic	Grell-Devenyi	Yonsei University	Assymetric Convective Model 2 (Pleim)	WSM Single moment 5-class	WSM 3-class simple ice scheme	Noah Land Surface model (MODIS)	Noah Land Surface model (AVHRR)	RUC Land Surface model (AVHRR)	No hydrostatic	Hydrostatic

8 ensemble members testing CU, PBL, MP, LSM and hydrostatic option

WRF 3.3.1 over Africa CORDEX domain 2002-2006

Casanueva et al., 2012

one change at a time / no ref.

MM5

Name of the experiment	Cumulus scheme	Model v	PBL	Grid nudg
GR/ETA	Grell	3.6	ETA	No
KF/ETA	Kain Fritsch	3.6	ETA	No
BM/MRF	Best-Miller	3.6	MRF	No
GR/MRF	Grell	3.6	MRF	No
KF2/MRF	Kain Fritsch 2	3.6	MRF	No
KF/MRF	Kain Fritsch	3.6	MRF	No
KF/MRF/VER	Kain Fritsch	3.7	MRF	No
KF/MRF/VER/NUD	Kain Fritsch	3.7	MRF	Yes
GR/MRF/VER/NUD	Grell	3.7	MRF	Yes

9 ensemble members testing CU, PBL, Model version (change in physics call order) and nudging

Solman & Pessacg, 2012

Multiple "levels"

MM5 3.7.4

Expt	Physical parameterization settings
RE	KF, Reisner 1, RRTM, Eta PBL, NOAH LSM, shallow convection, vertical levels = 30, SST and feedback off, pressure at model top = 100 mb
HD	Zängl *z* diffusion
CU1	BM
CU2	GR (no shallow convection)
SS	MRF PBL
MP	Reisner 2
VE1	Vertical levels = 40
VE2	Vertical levels = 20
FB	Feedback on
L2A	Reisner 2, MRF PBL
L3A	Reisner 2, MRF PBL, feedback on
L3B	Reisner 2, MRF PBL, feedback on, vertical levels = 40
L3C	Reisner 2, MRF PBL, feedback on, vertical levels = 20

WRF 2.2.1

Expt	Physical parameterization settings
RE	GD, Ferrier, Goddard, RRTM, MOJ, NOAH, MYJ, vertical levels = 30, SST and feedback on, pressure at model top = 50 mb
PT	Pressure at model top = 100 mb
CU1	KF
CU2	BMJ
MP	WSM6
DA	Model filter: damping on
SW1	Dudhia
SW2	GFDL
SS	MOS, YSU
VE	Vertical levels = 20
L2A	BMJ, WSM6
L2B	KF, MOS, YSU
L2C	KF, Dudhia
L3A	KF, MOS, YSU, Dudhia
L3B	KF, MOS, YSU, Dudhia, WSM6
L3C	KF, MOS, YSU, Dudhia, Thompson

Ref.

Level 1

Level 2

Level 3

Level-n changes "n" options w.r.t. the reference configuration

<u>29 ensemble members</u> testing CU, MP, PBL, ToA, no. vertical levels, diffusion, damping and feedback

Awan et al., 2011

Question

Are model-to-model differences
larger than
physics-to-physics differences
within a single model?

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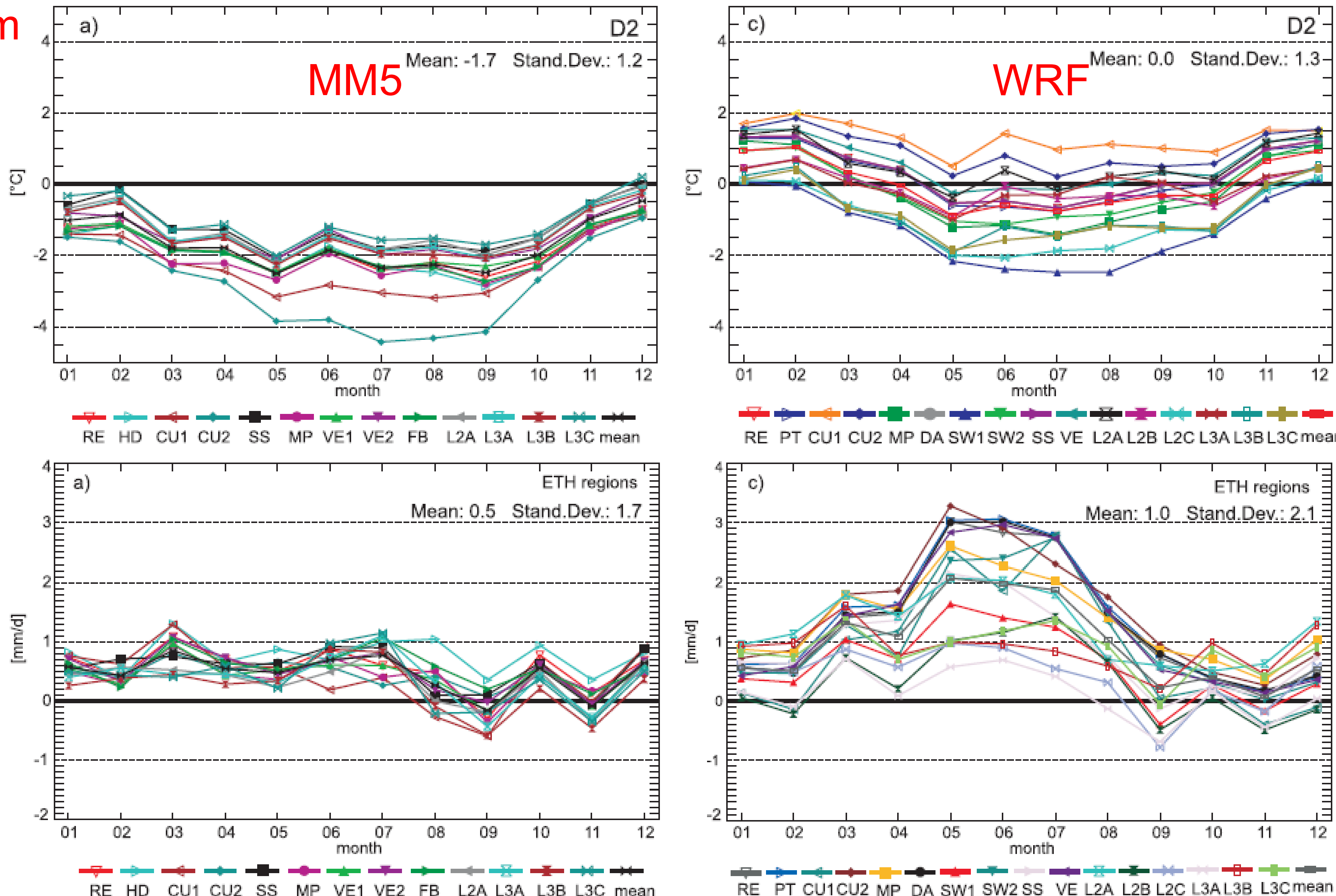
Jerez, 2011 (PhD Th.)

Monthly biases (area avg.)

T2m

P



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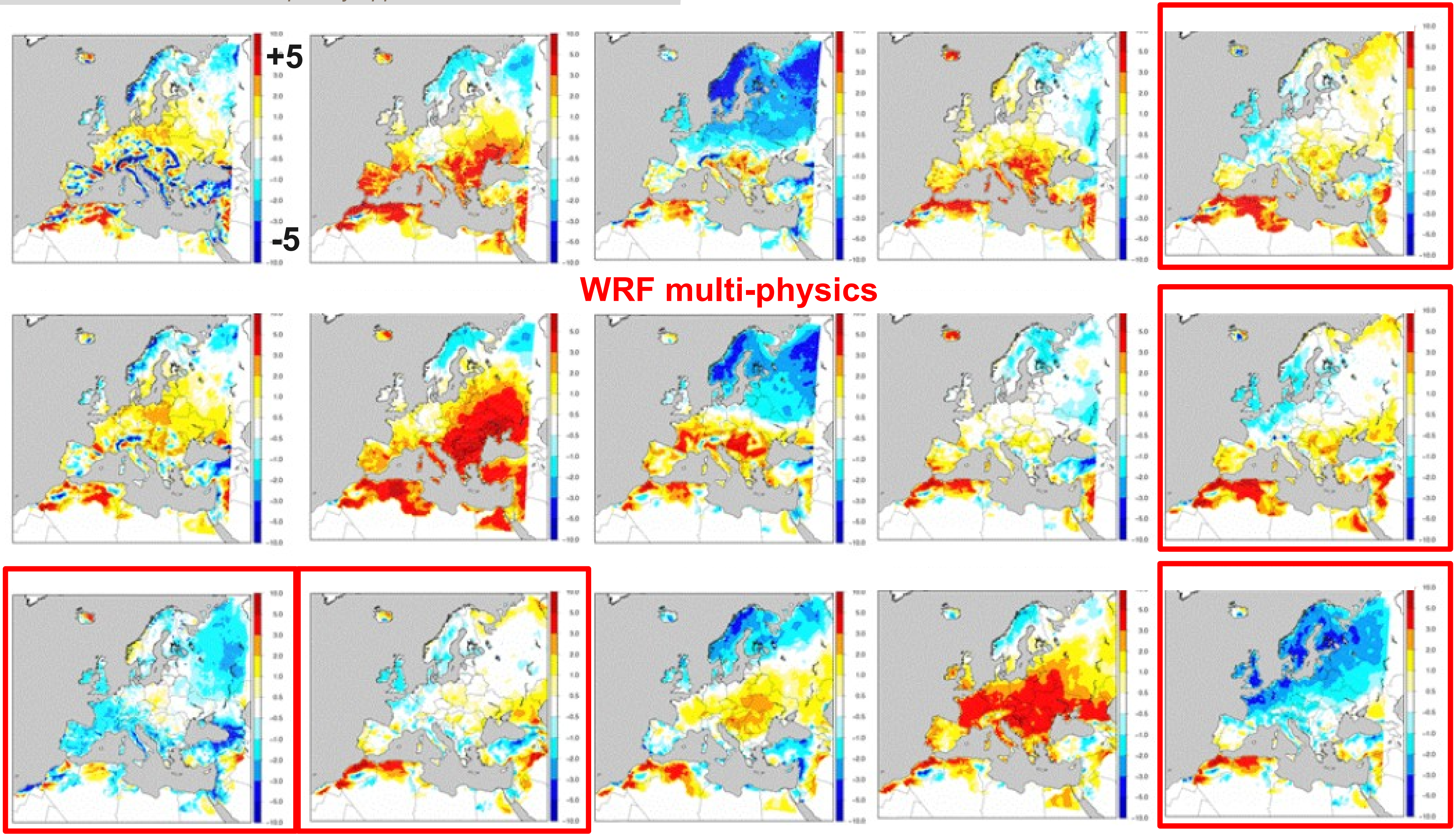

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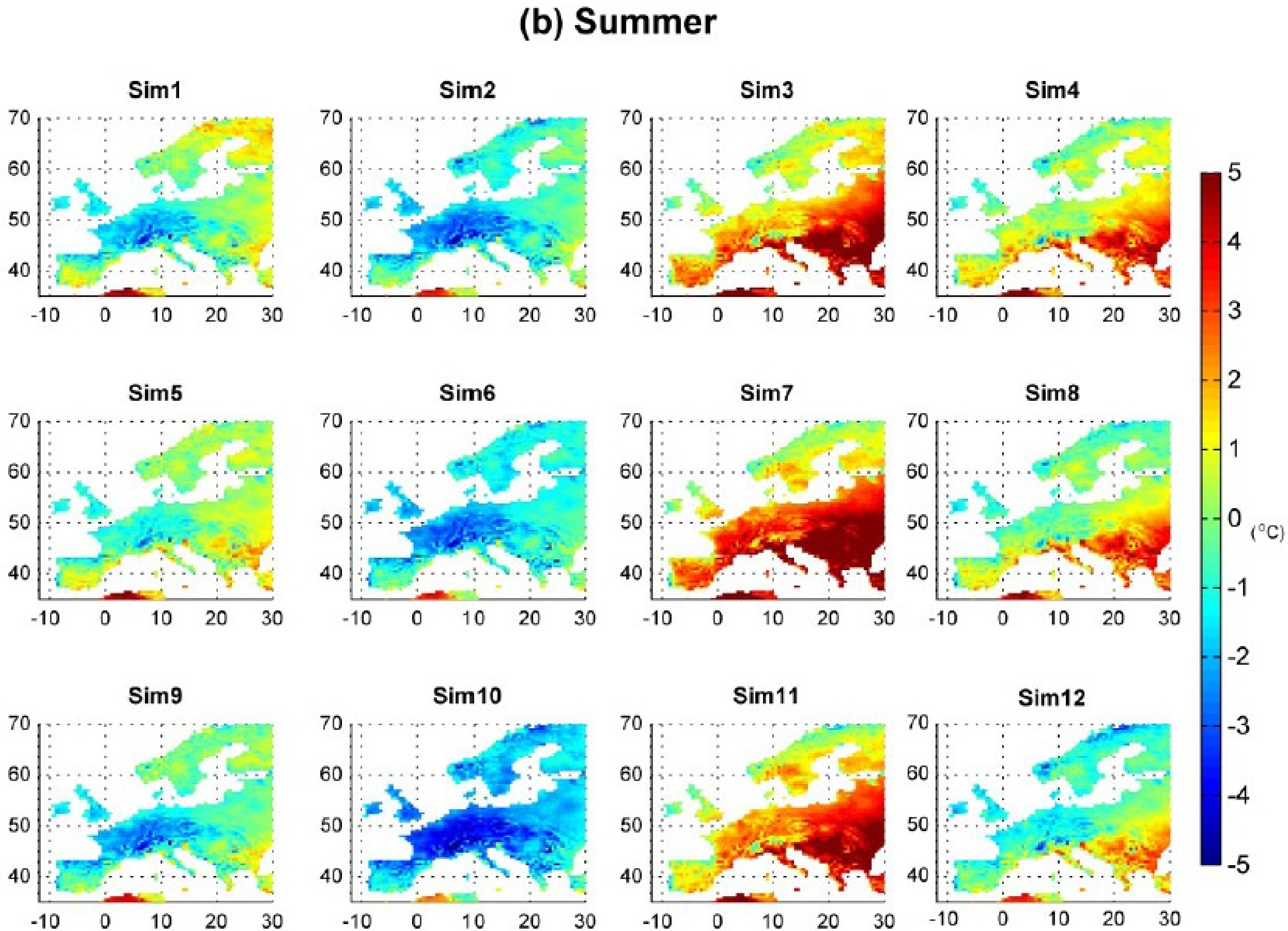


WRF
1990-1995

NOAH LSM
(used in all Euro-CORDEX runs)

RUC LSM

Mooney et al, 2012

Question

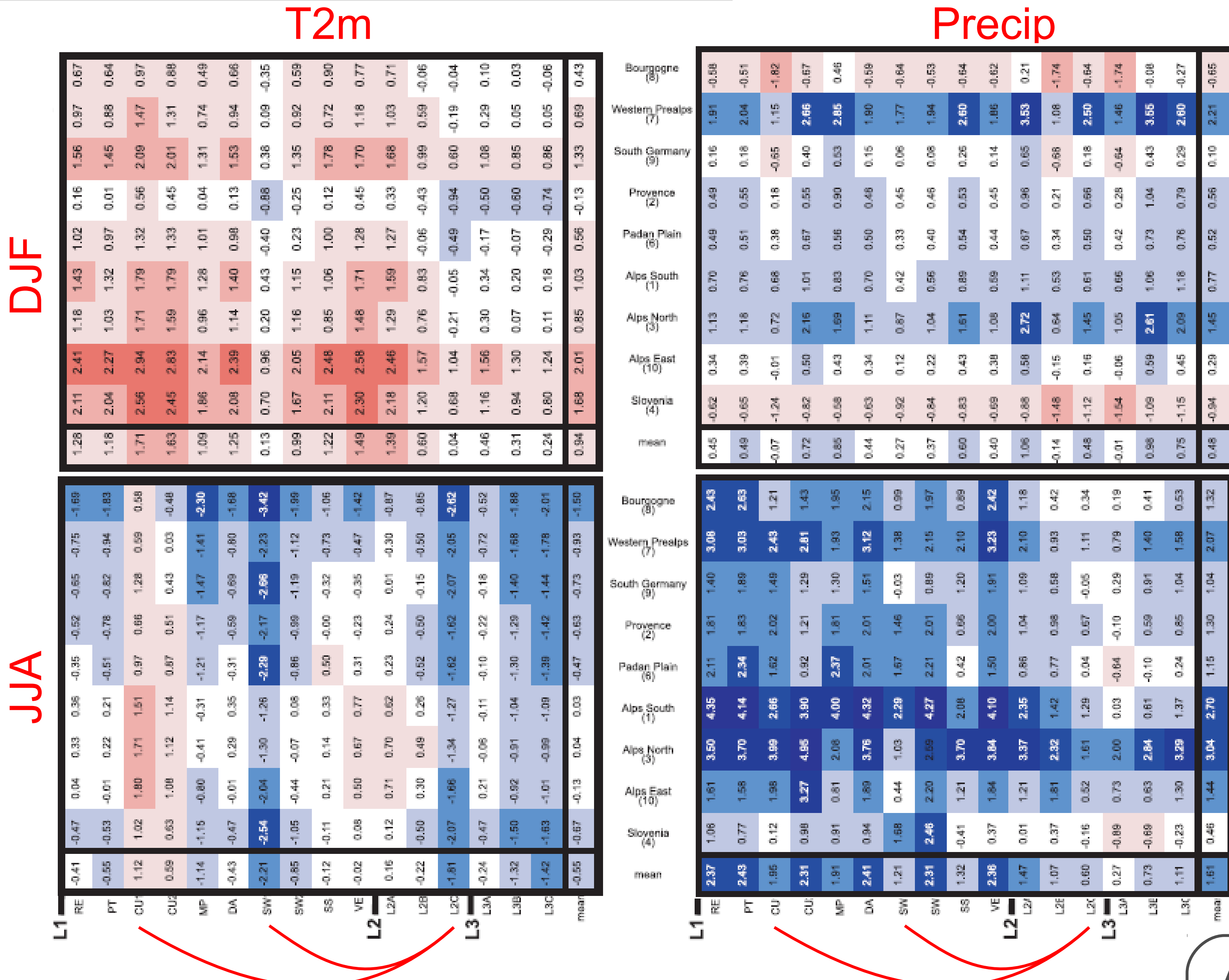
Are model-to-model differences
larger than
physics-to-physics differences
within a single model?

Probably yes, but not by orders of magnitude.
Physical parameterization uncertainty accounts
for a large part of the RCM uncertainty.

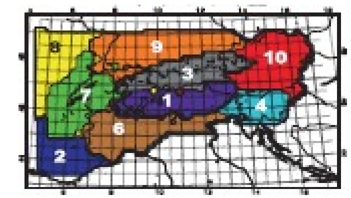
Question

Do the different parameterizations interact linearly?

Seasonal biases per region



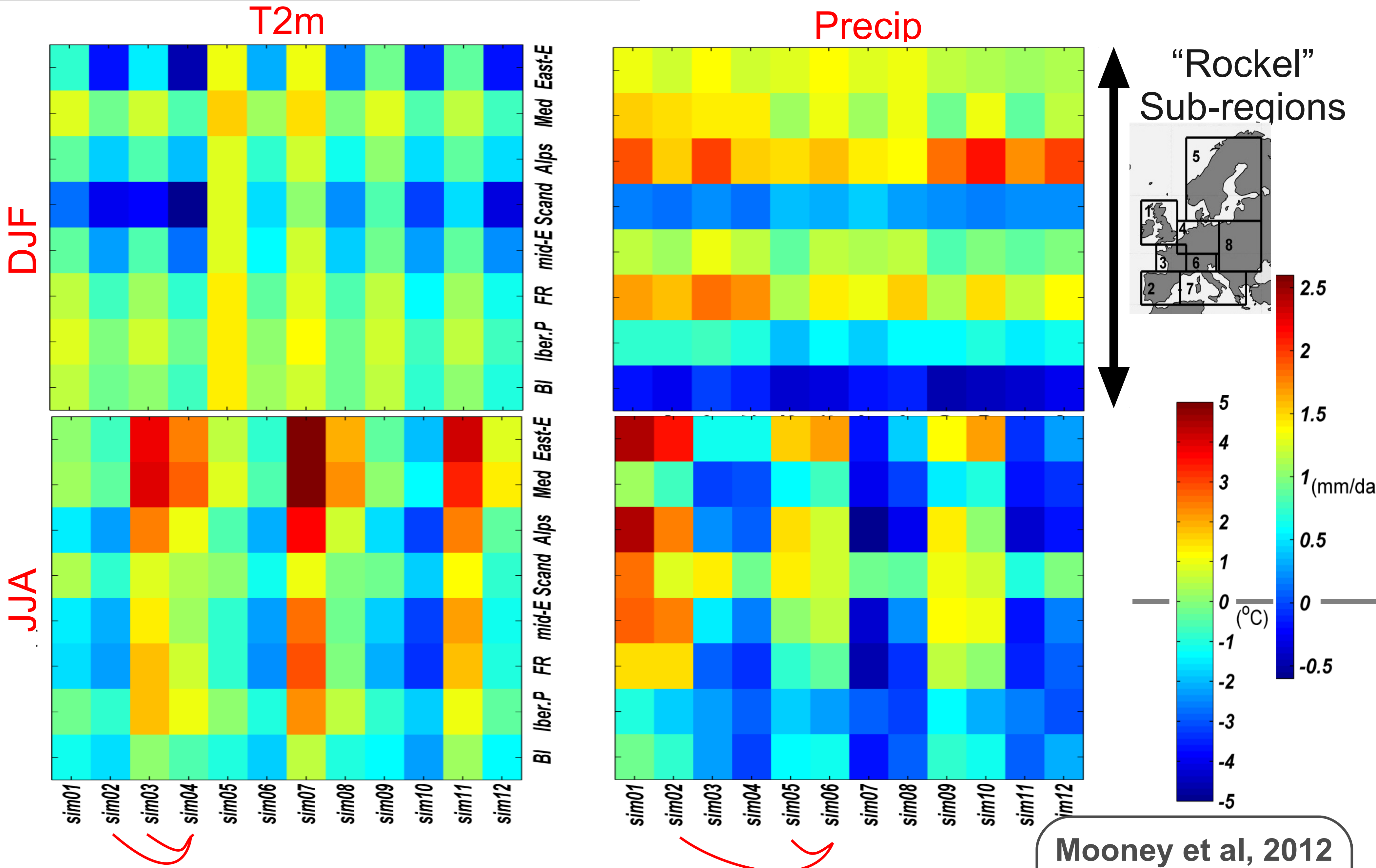
Sub-regions in the Alps



No, they don't

Awan et al., 2011

Seasonal biases per region

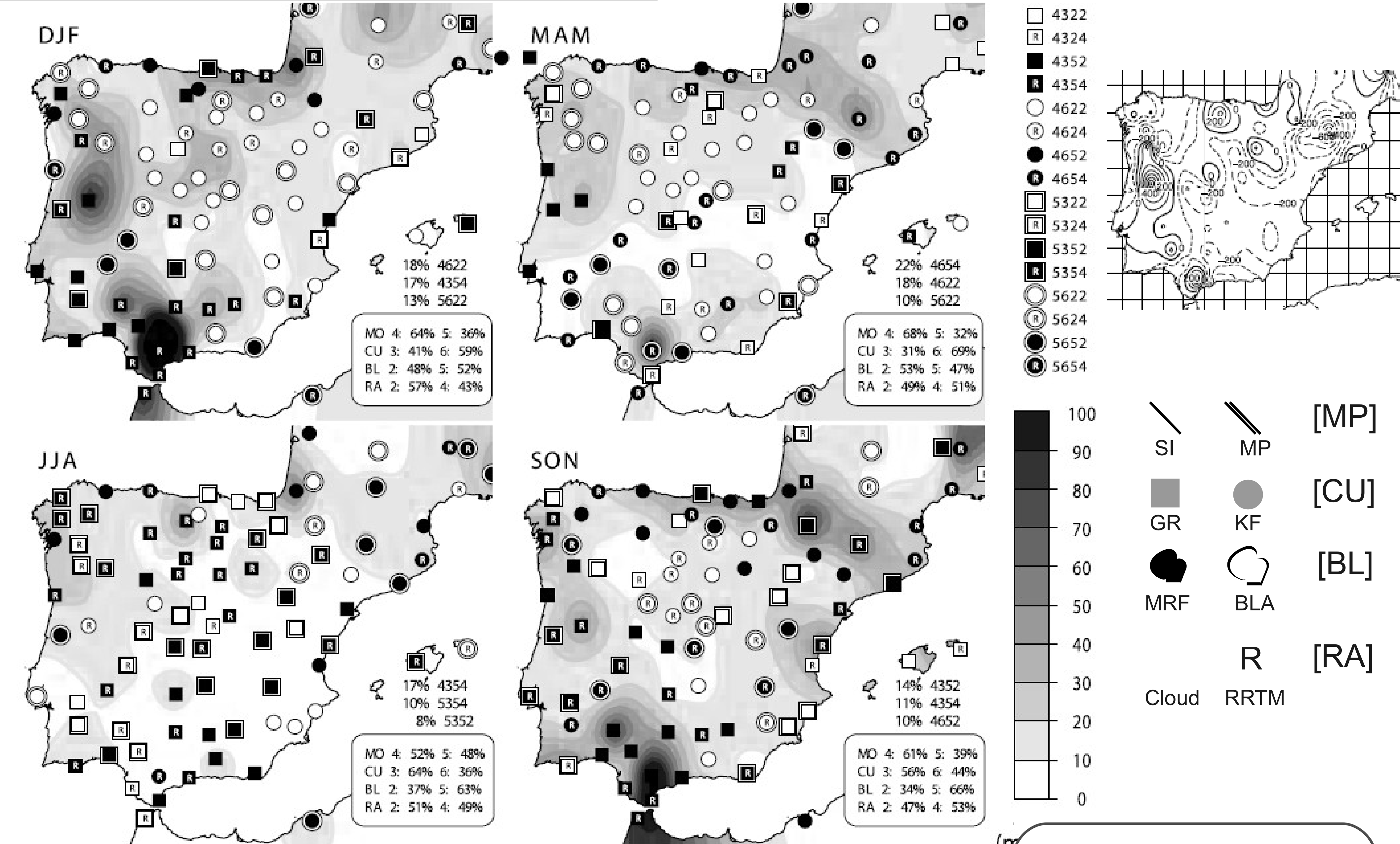


Mooney et al, 2012

Question

Does the “best” parameterization combination exist?

Best parameterization set



Fernández et al, 2007

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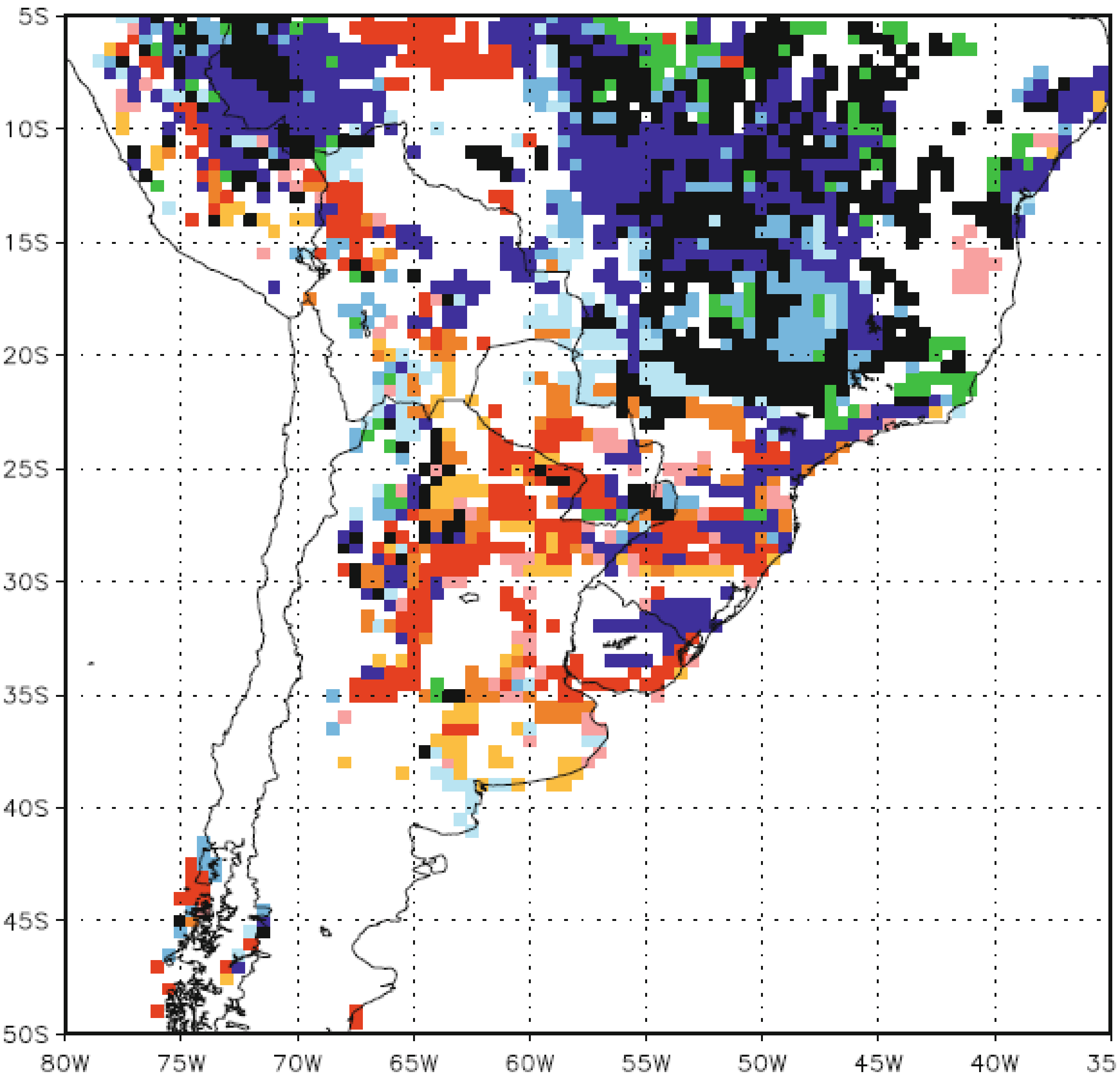

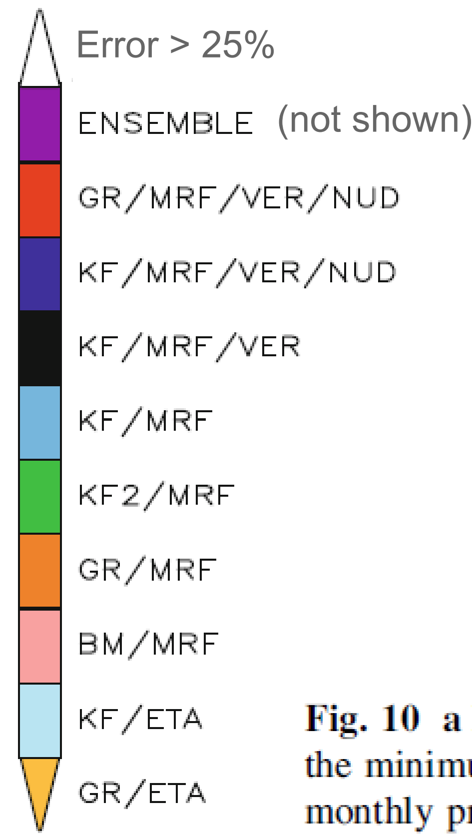

Fig. 10 **a** Experiment depicting the minimum relative error of monthly precipitation for November and December, only if the relative error was less than 25% compared with CRU, considering the experiments listed in Table 1. **b** Same as **a** but including the ensemble of experiments

Solman & Pessacg, 2012

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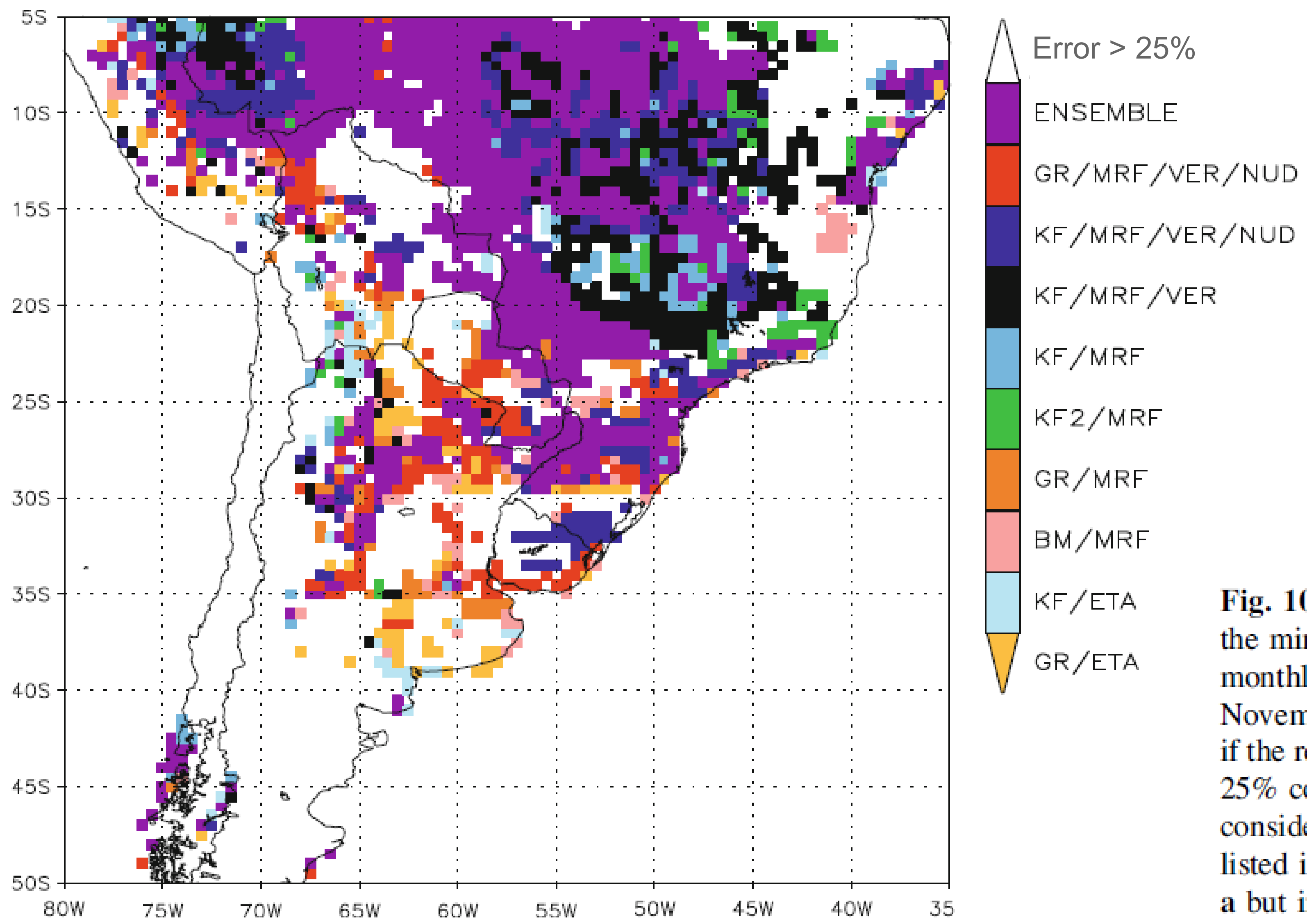

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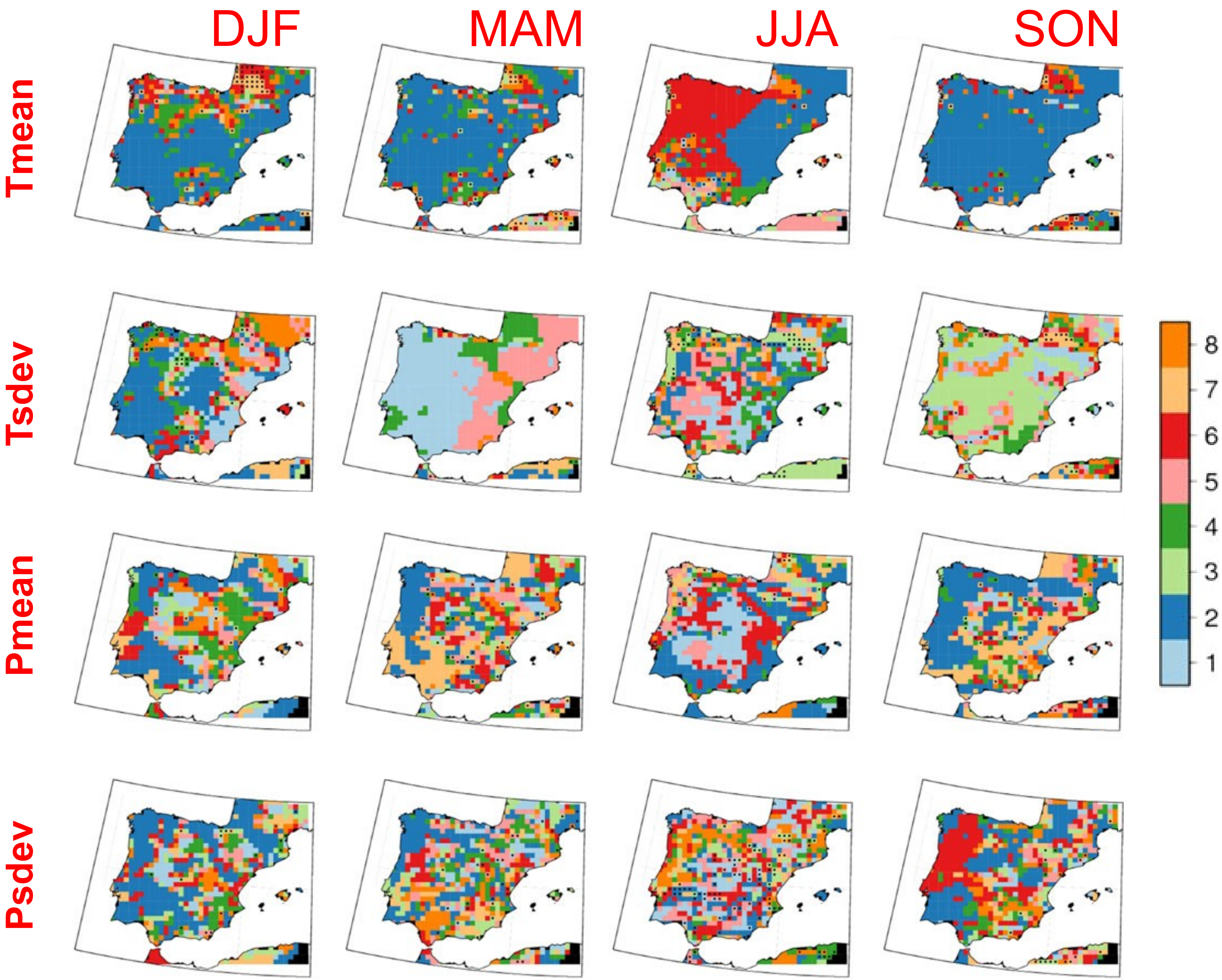


<u>Depends on:</u>
sub-region,
season,
variable...
… and statistic

Jerez et al., 2012a

Question

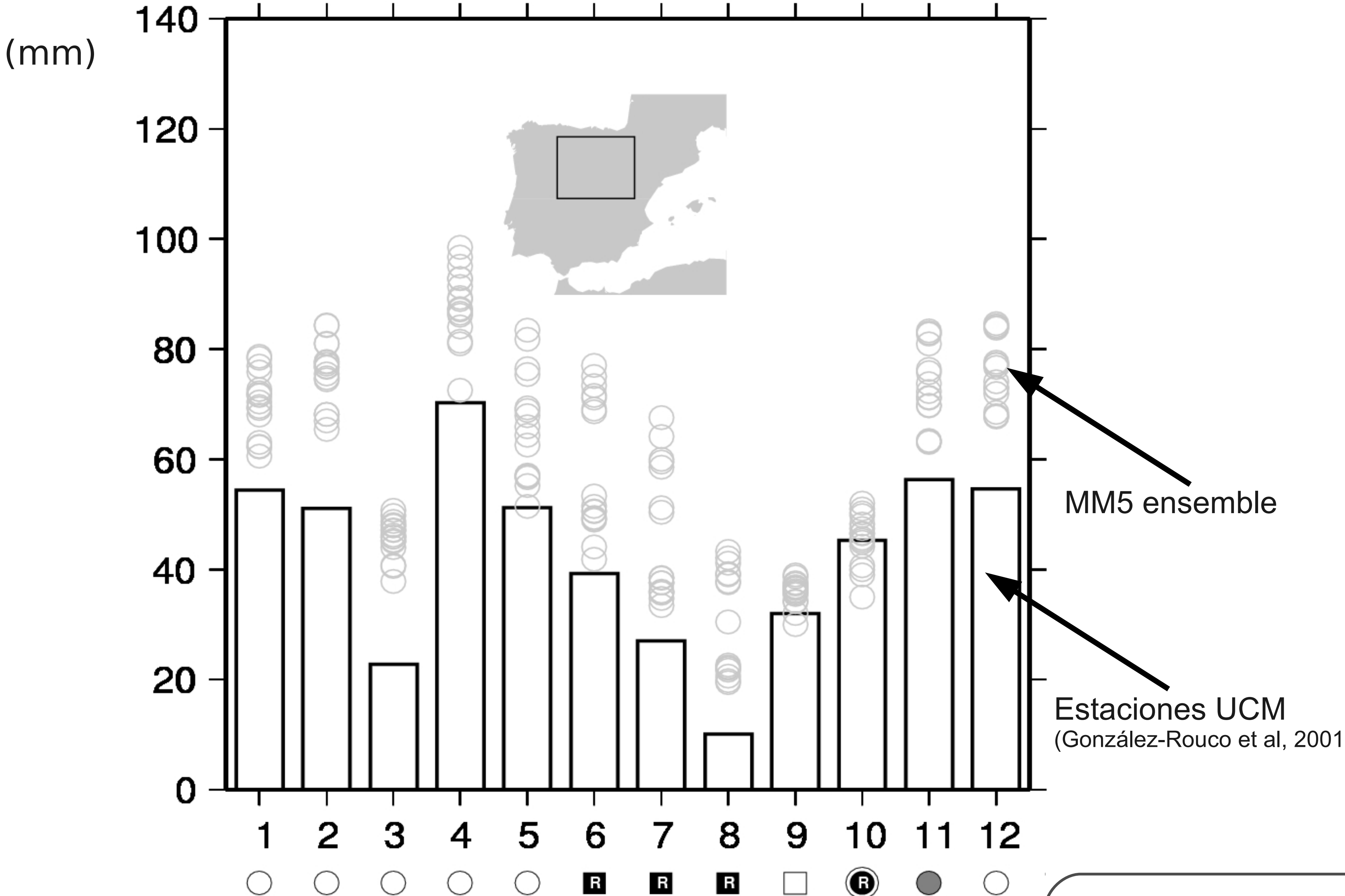
Does the “best” parameterization combination exist?

NO

Can we, at least, identify the parameterized processes which have a larger impact on the results?

(in this way we can try to maximize the spread to catch the observations with a minimal set of simulations)

Most influential param'd process



Fernández et al, 2007

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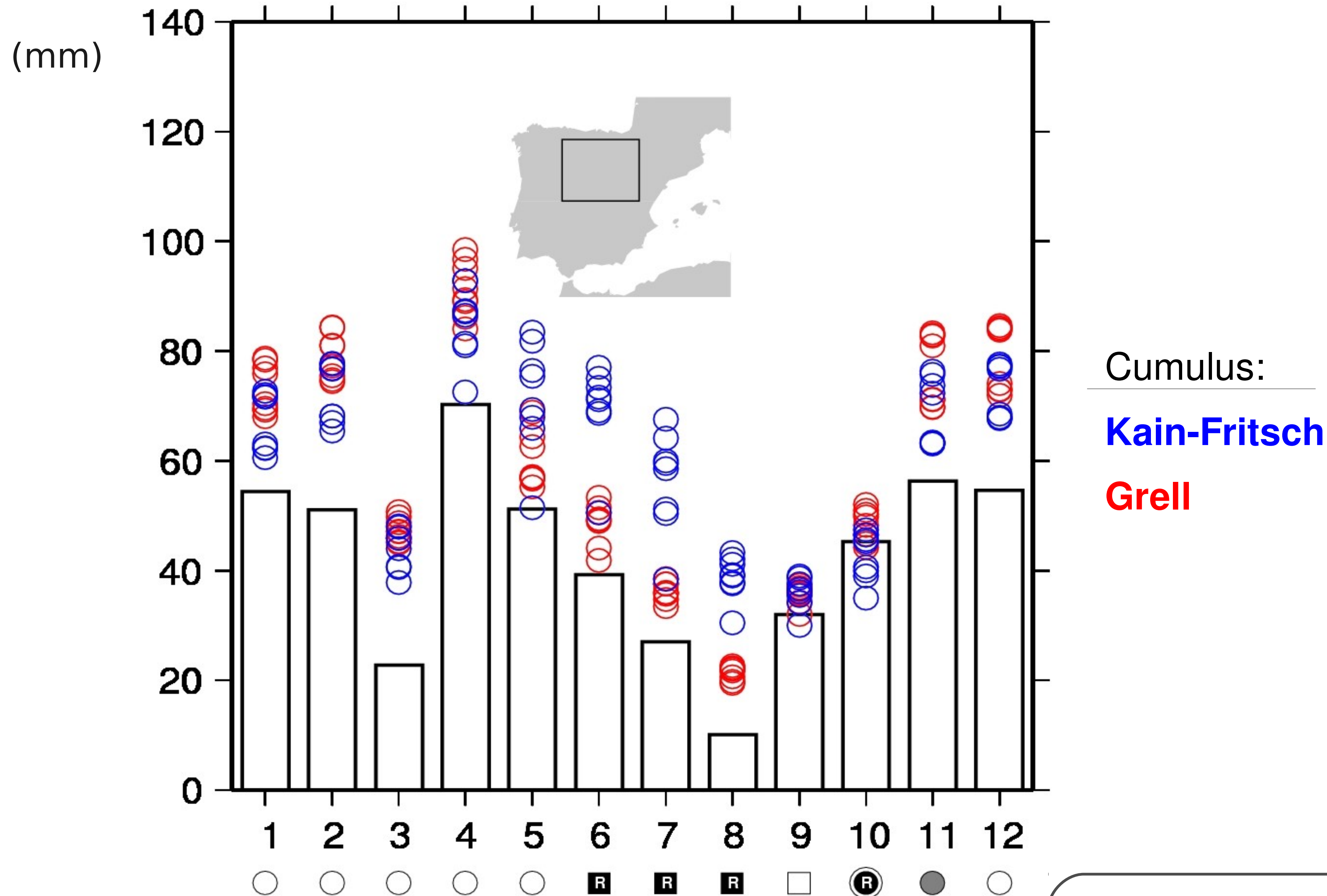

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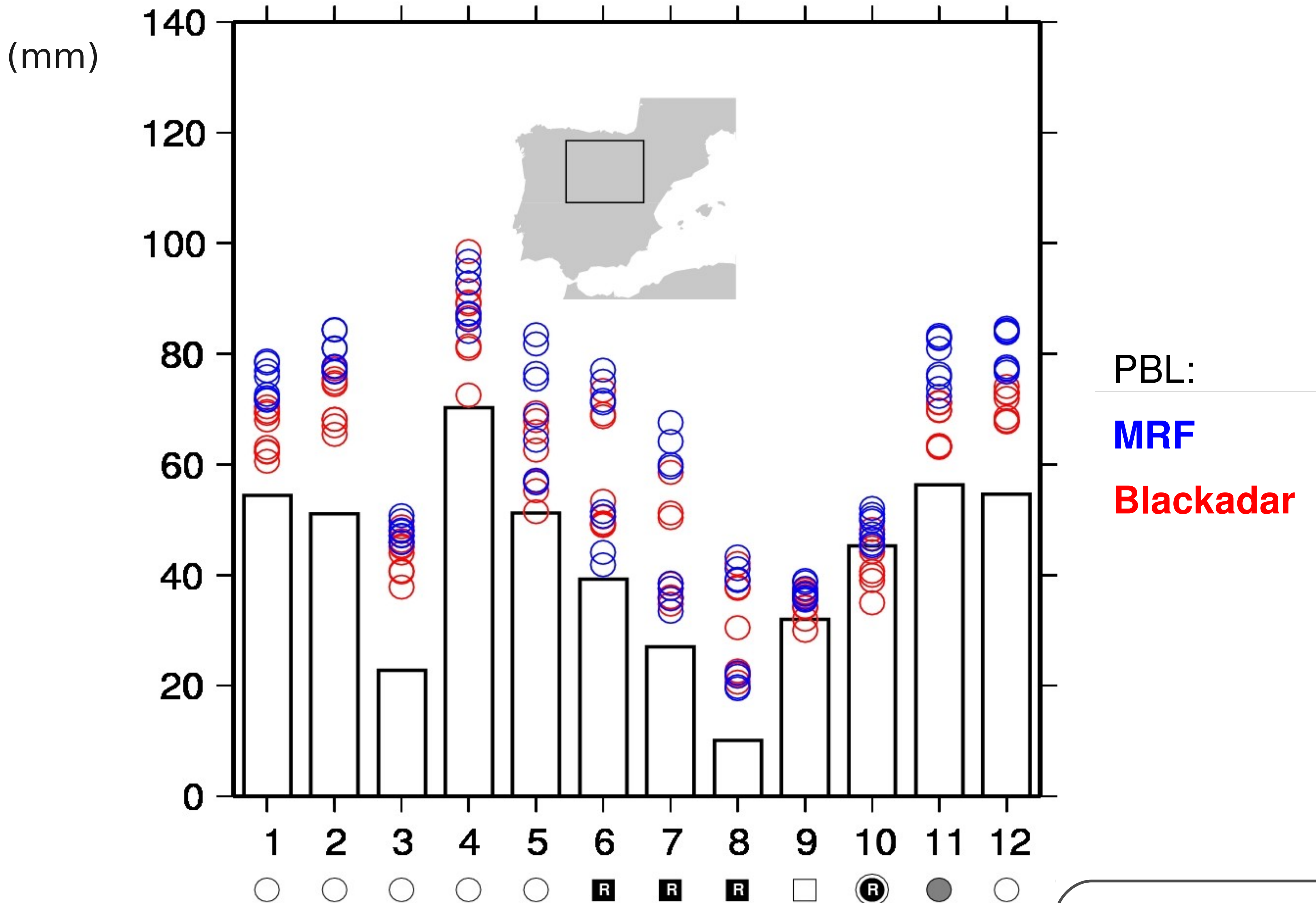

Fernández et al, 2007

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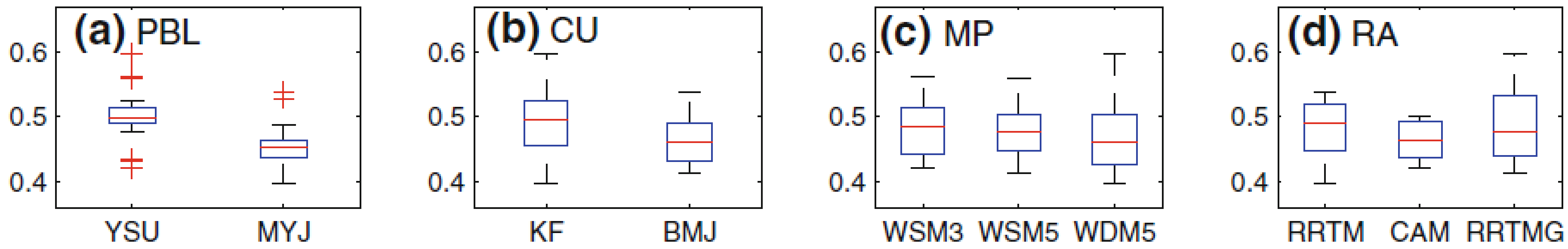
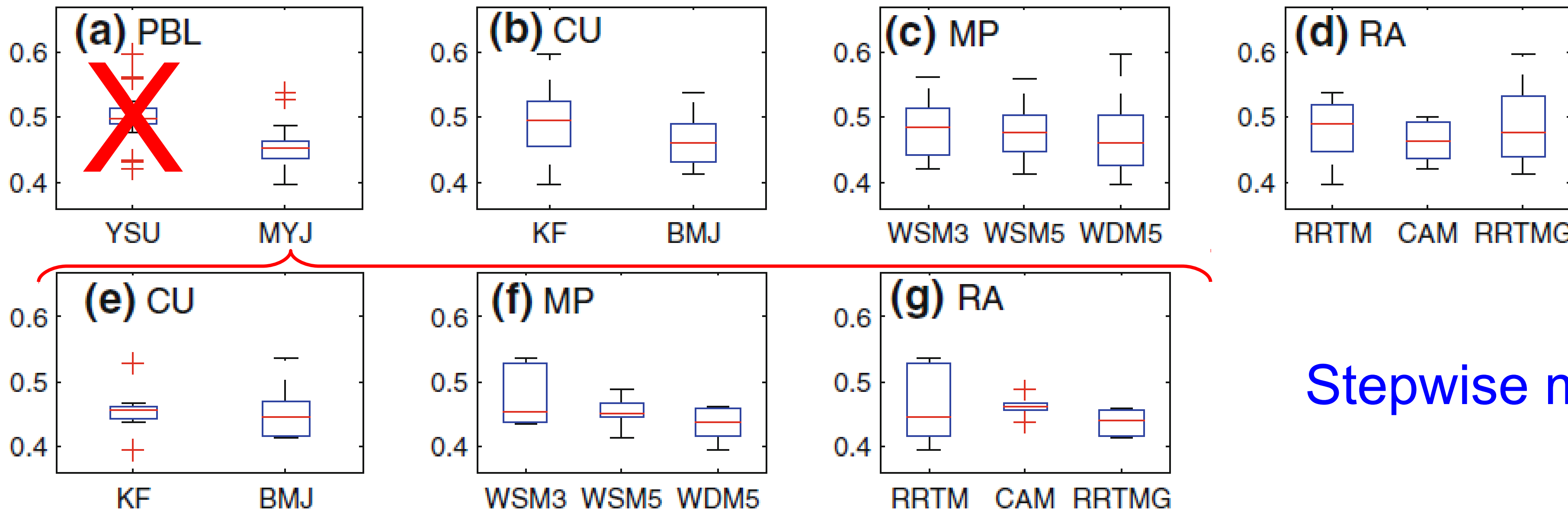


Stepwise method

- “Sub-ensembles” considering separately each option for a given parameterized process
- Non-overlaping IQR as a guide to “robustly” reject options

Evans et al., 2011

Most influential param'd process



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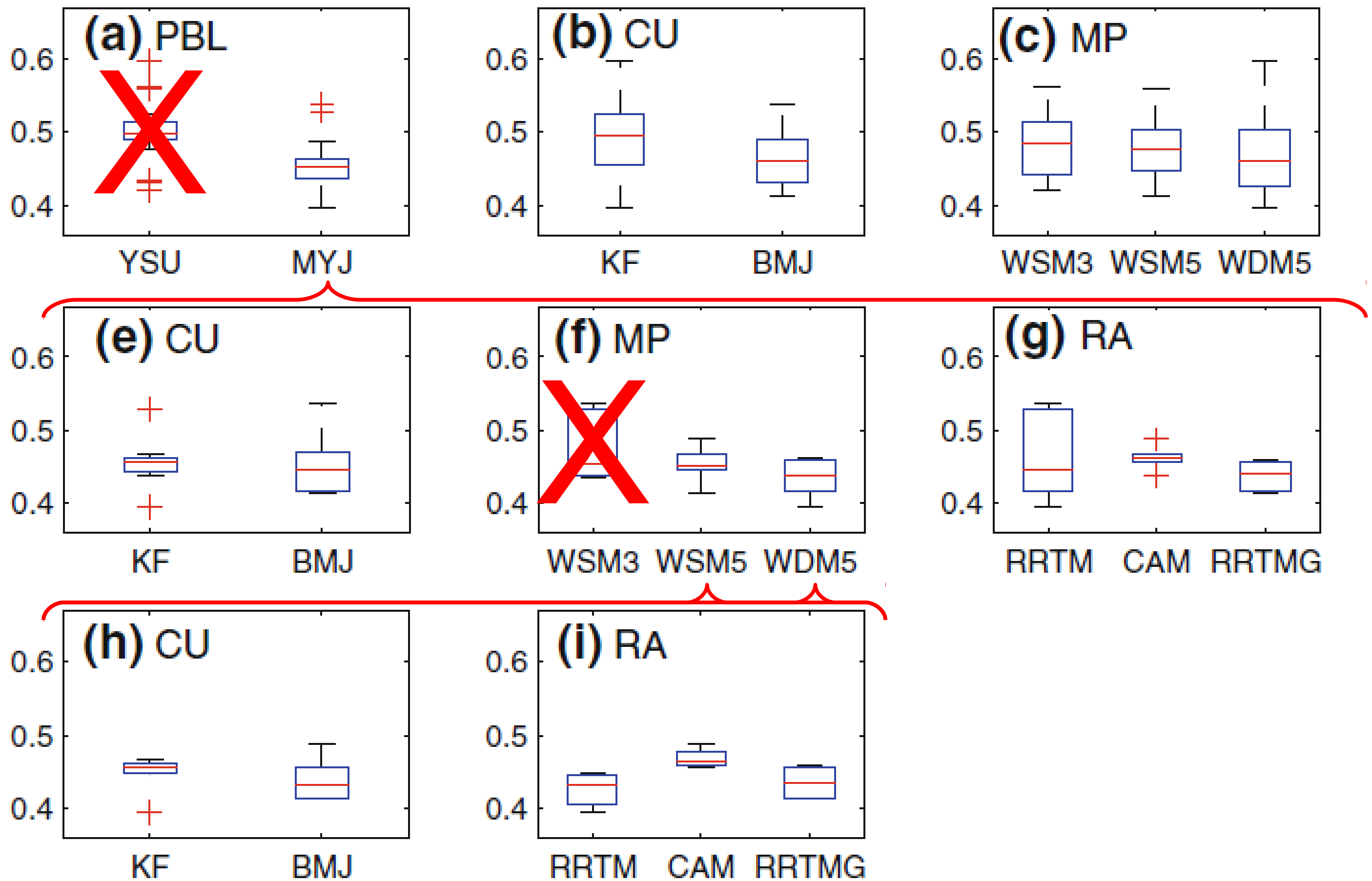

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Evans et al., 2011

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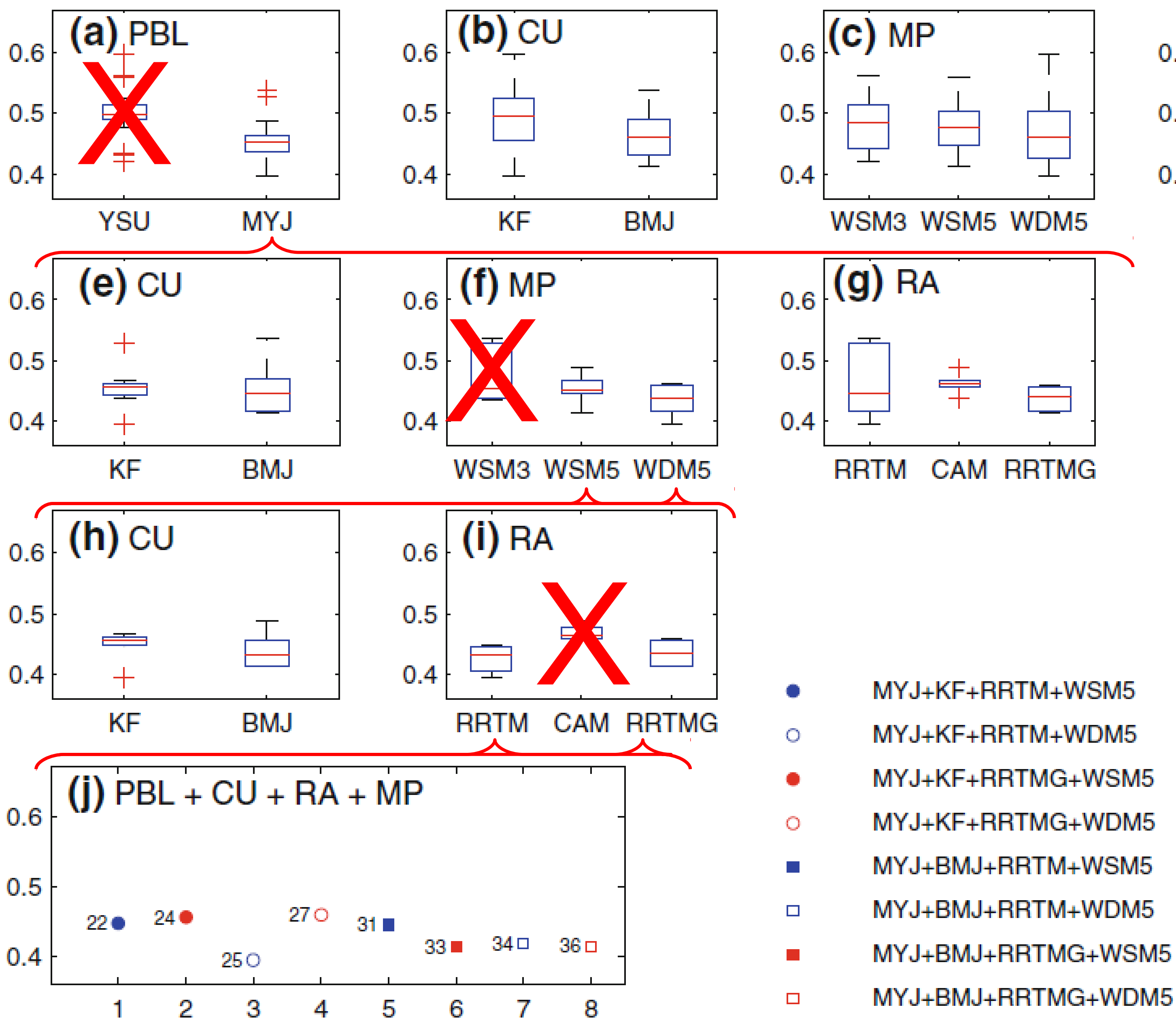

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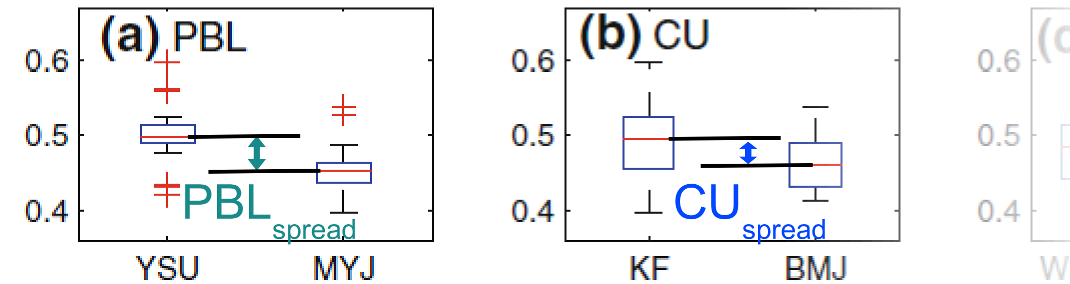
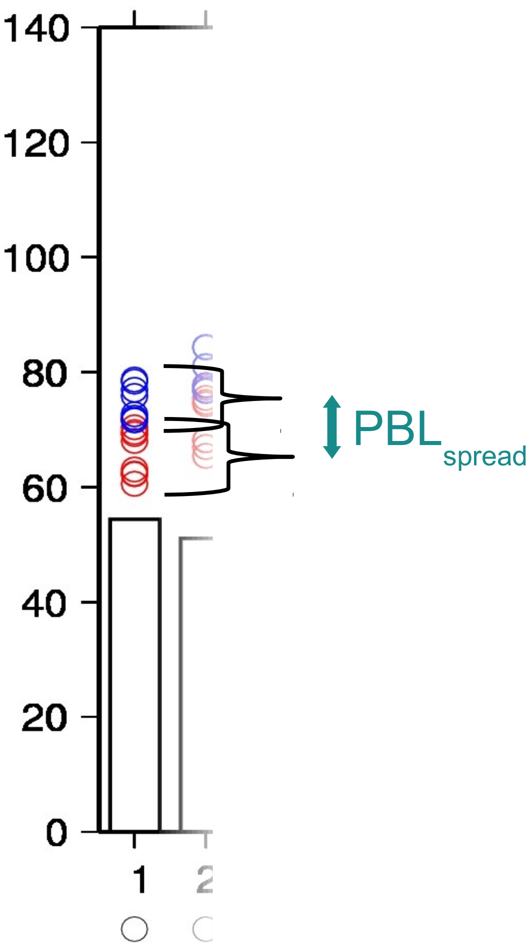




Jerez et al. (2012a) quantify the most influential parameterized process by defining:

Mean Ensemble Spread (MES):

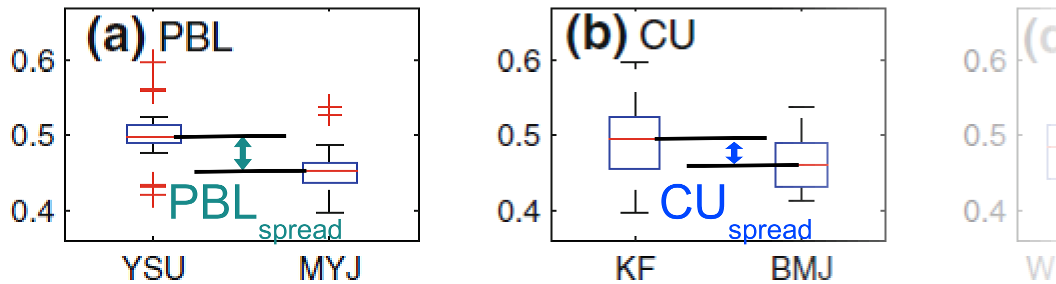
$$\mathrm{MES} = \sum \mathrm{PROC}_{spread}$$

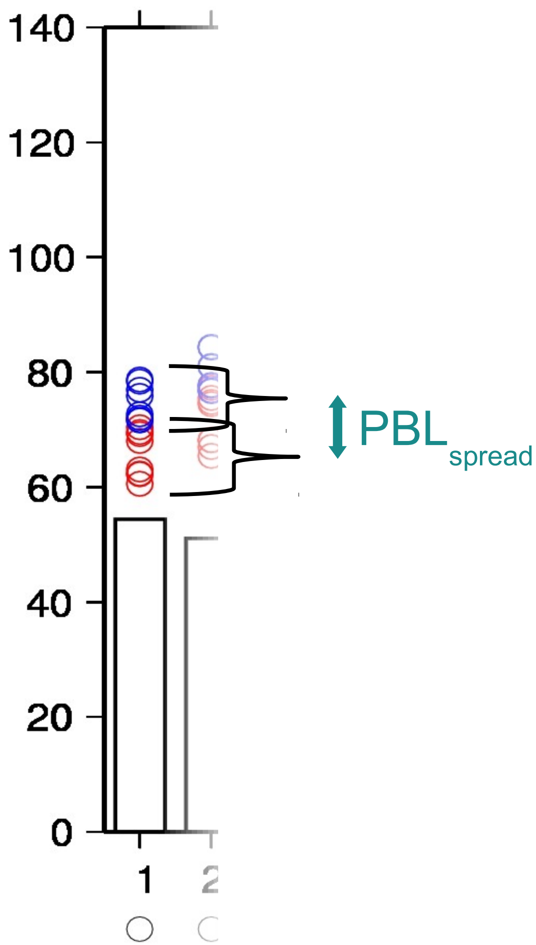
Where the PROC_{spread} is the difference between two sub-ensemble means (of a given metric).

This formulation requires (1) a full factorial design and (2) two options per scheme.

Jerez et al., 2012a

Most influential param'd process





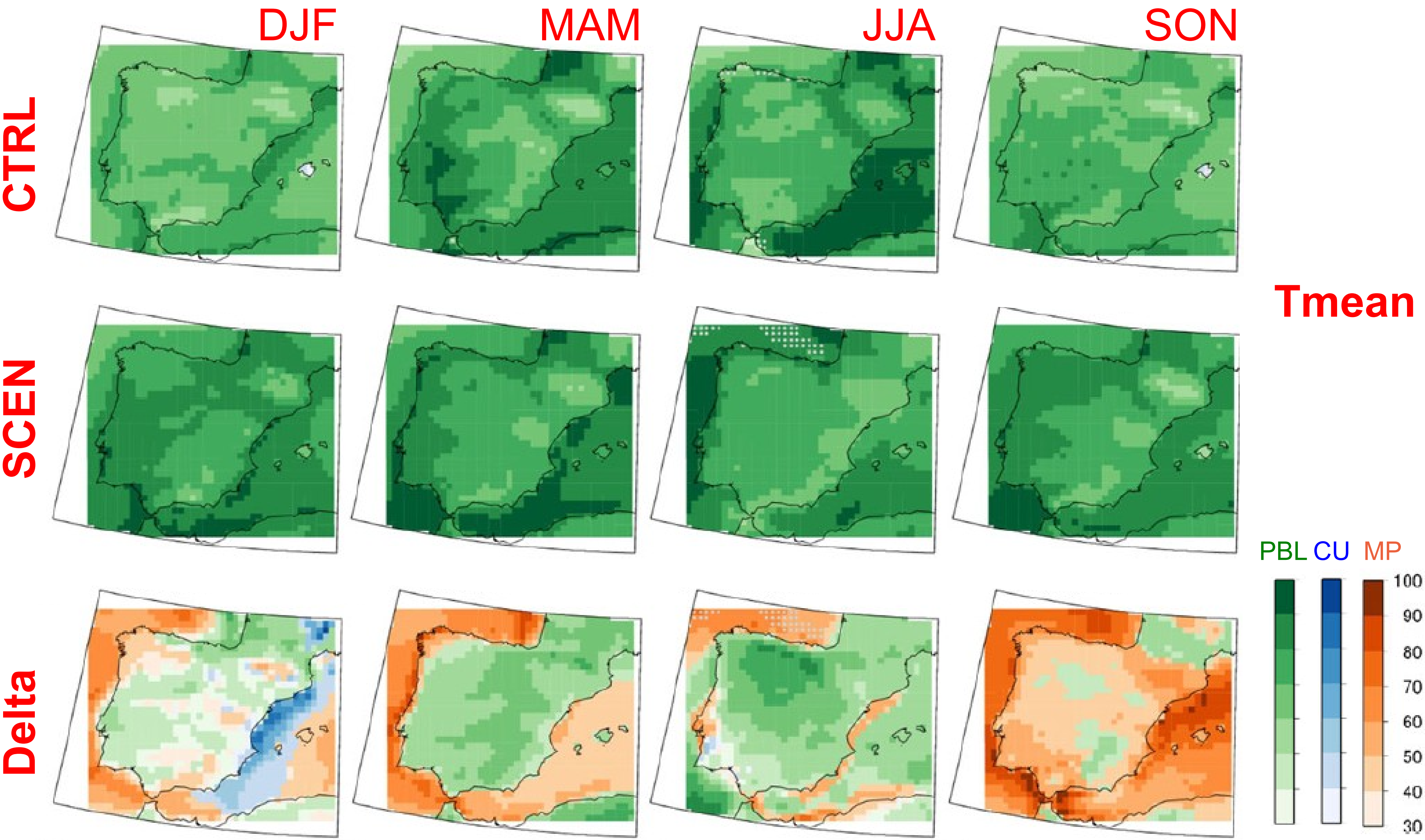
This approach can be used to define the relative contribution of each process to the MES. E.g. for the PBL:

$$\frac{\mathrm{PBL}_{spread}}{\mathrm{MES}} \times 100$$

provides the contribution (in %) of the PBL scheme to the ensemble spread.

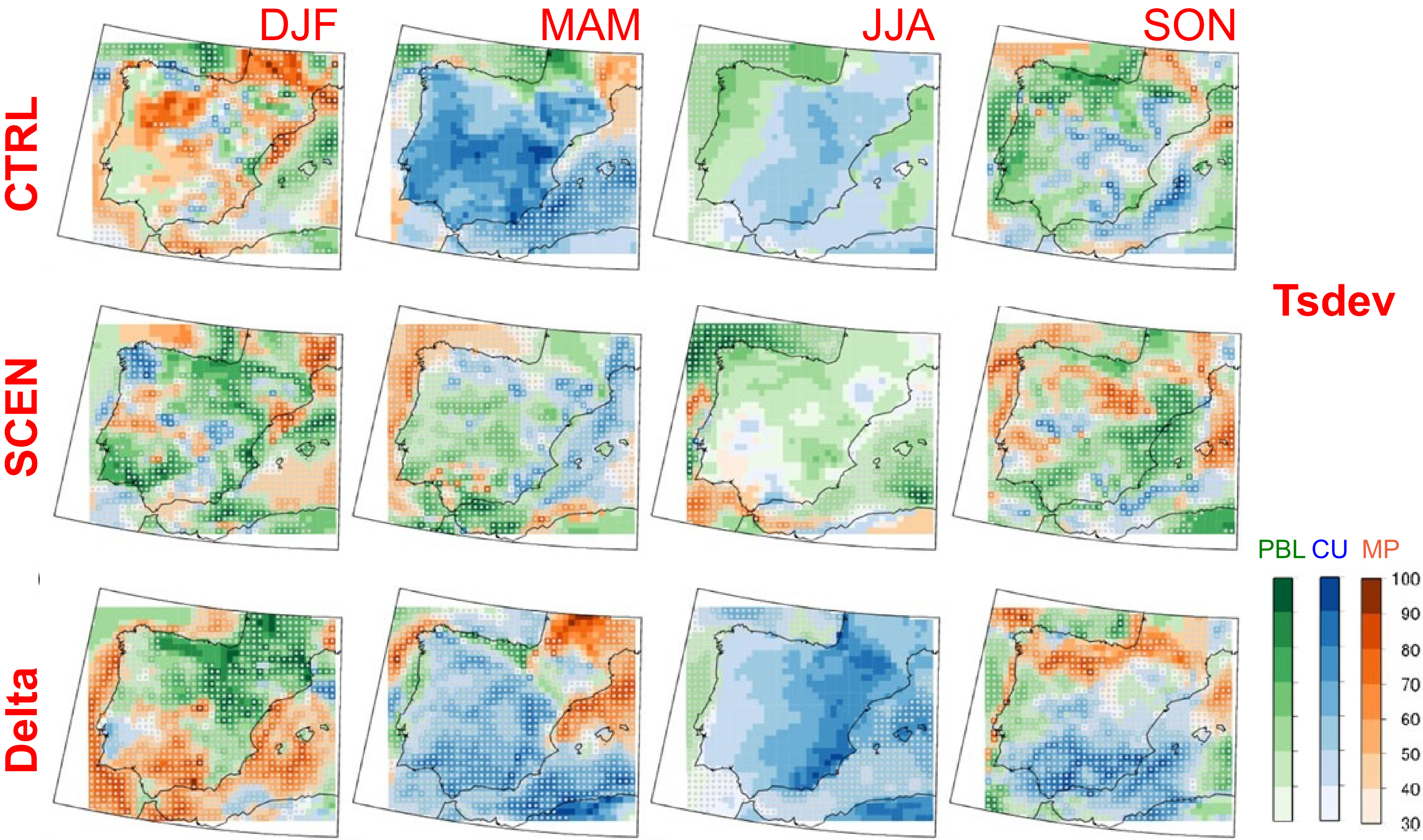
Jerez et al., 2012a

Most influential param'd process



Jerez et al., 2012b

Most influential param'd process



Jerez et al., 2012b

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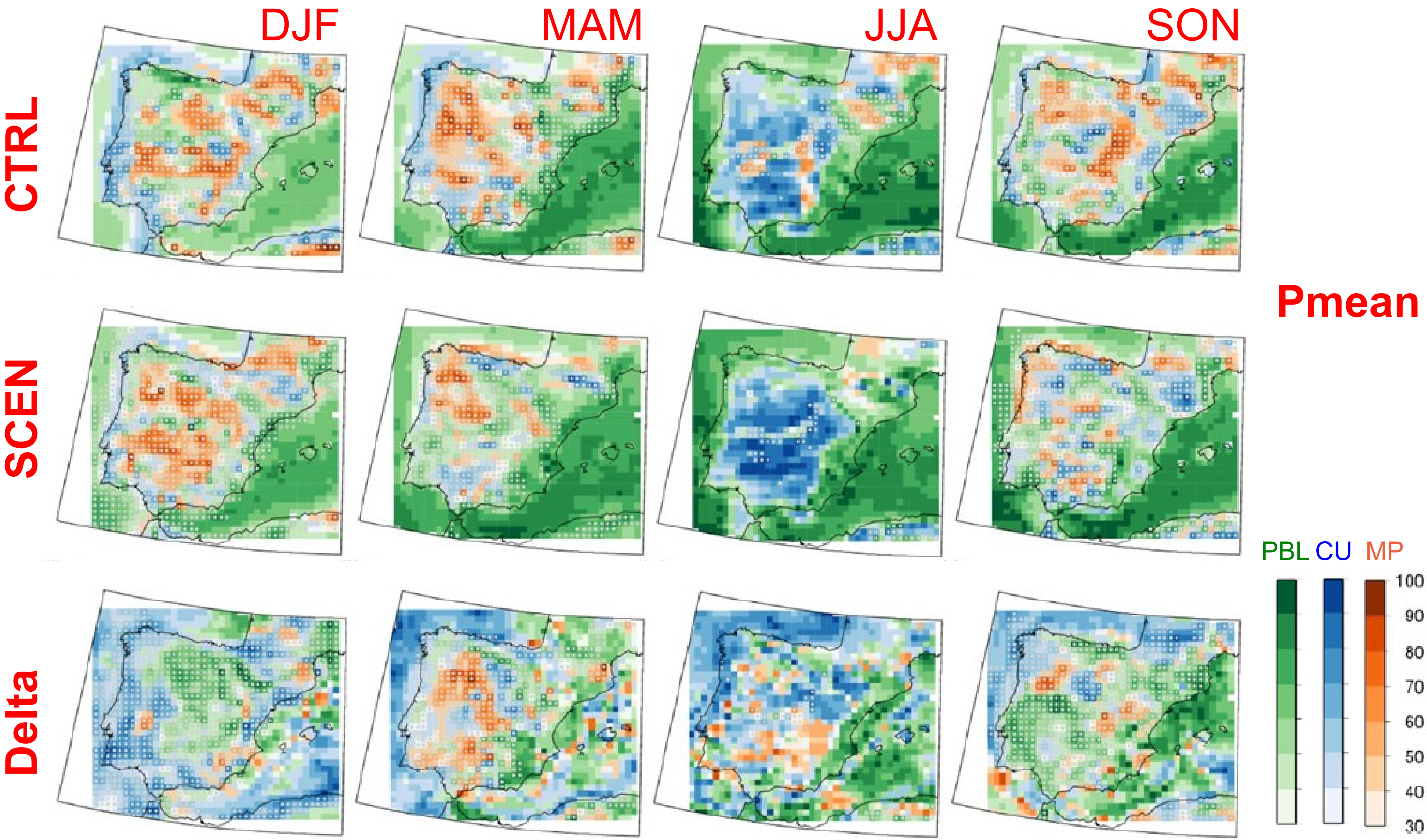

Jerez et al., 2012b

Question

Can we, at least, identify the parameterized processes which have a larger impact on the results?

We can, but they still depend on variable, statistic, … and those relevant under present conditions do not necessarily maximize the spread of the future scenarios.

Question

If a model configuration is warmer/wetter than another under present conditions, does this still hold under future conditions?

(i.e. can we reliably use the delta method to remove present climate biases?)

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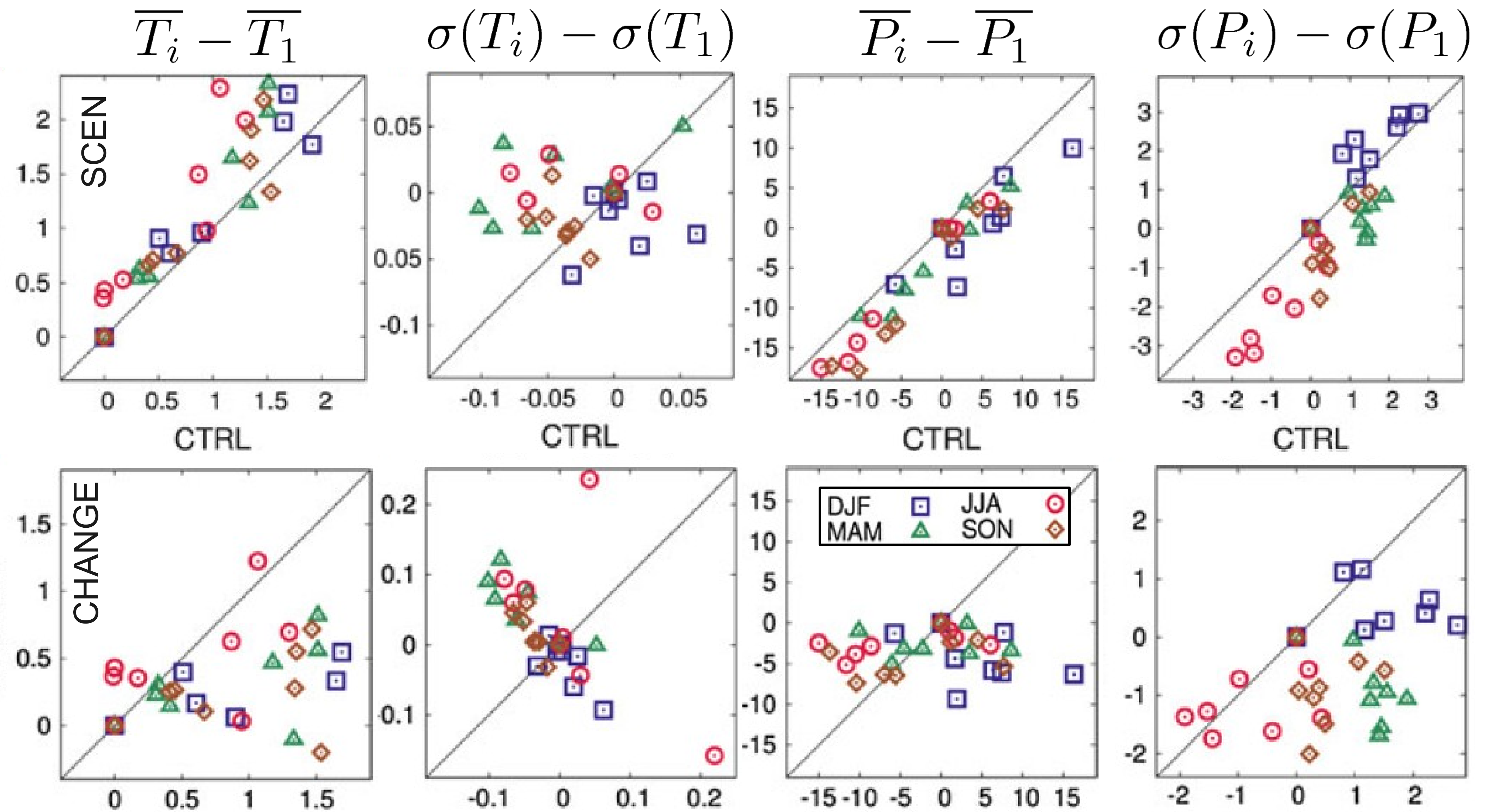
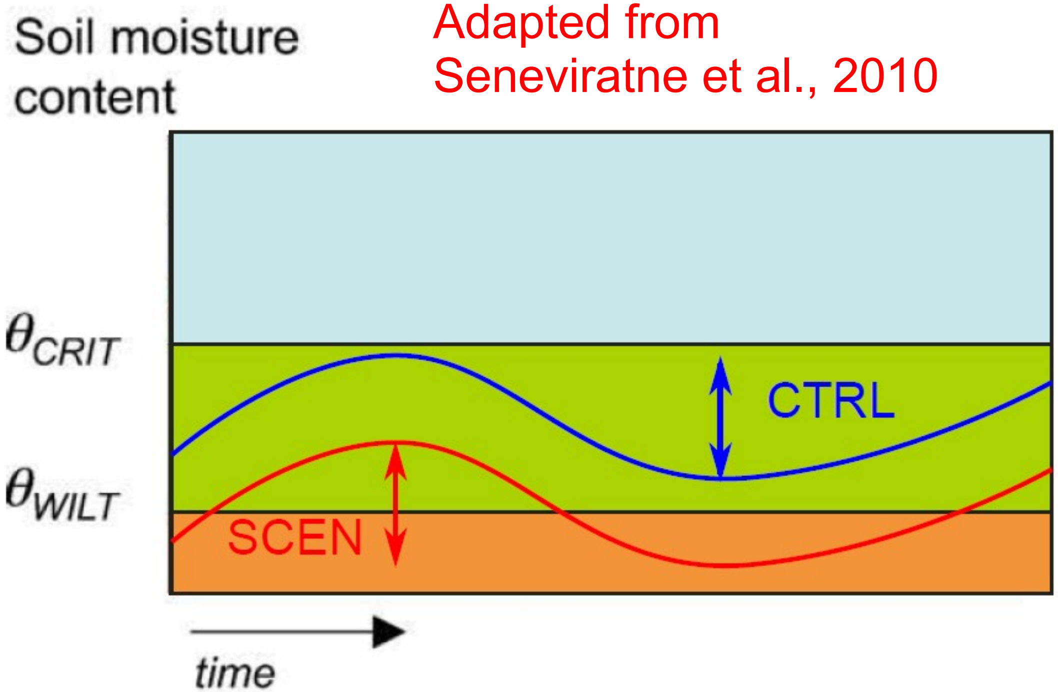
Relative statistics in a MP ens.

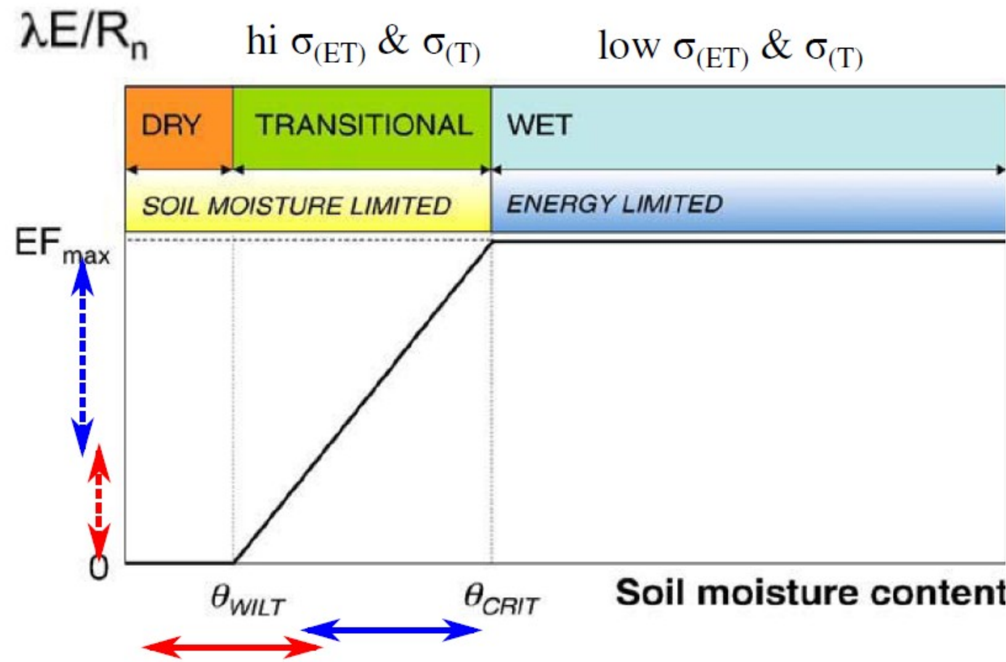


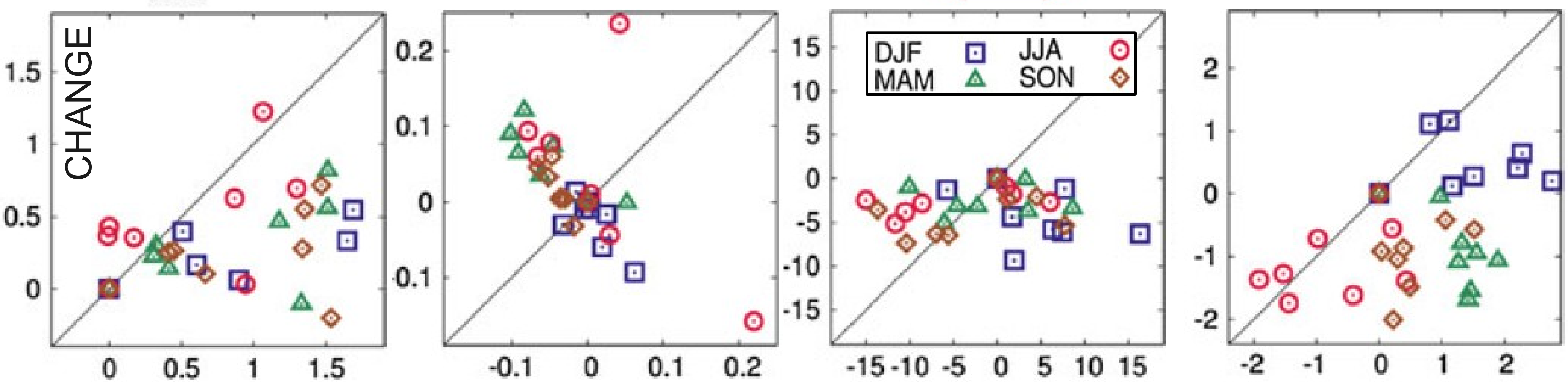
Jerez et al., 2012b

Relative statistics in a MP ens.

Adapted from Seneviratne et al., 2010







Jerez et al., 2012b

Question

If a model configuration is warmer/wetter than another under present conditions, does this still hold under future conditions?

Mostly, yes. But there are also non-linearities / threshold processes which can alter this relative behaviour.

Outline

- Multi-physics ensembles
- Ensemble design
- Best parameterization set
- Most influential parameterized process
- Relative importante of physical schemes under CC conditions
- Observational uncertainty
- Beyond precipitation and temperature
- Right result for the wrong reason

Observational uncertainty

Manage with much care global gridded observational products...

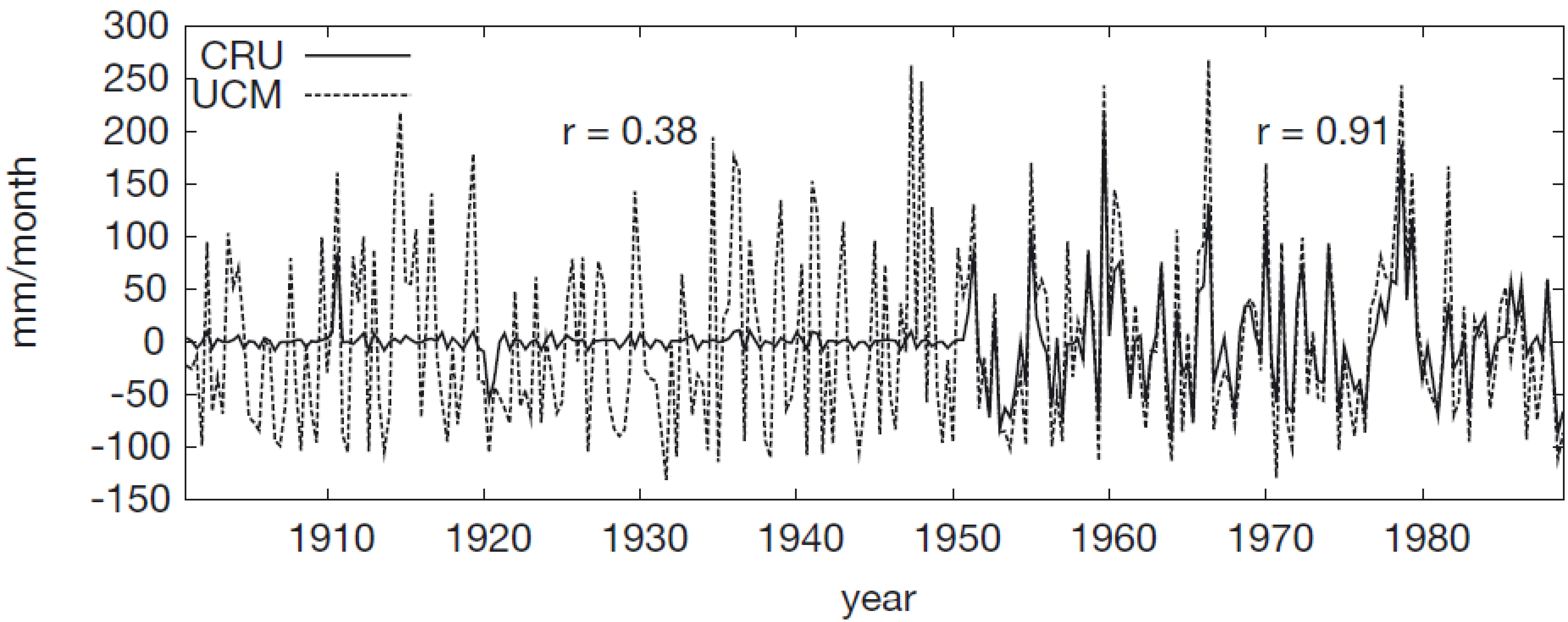
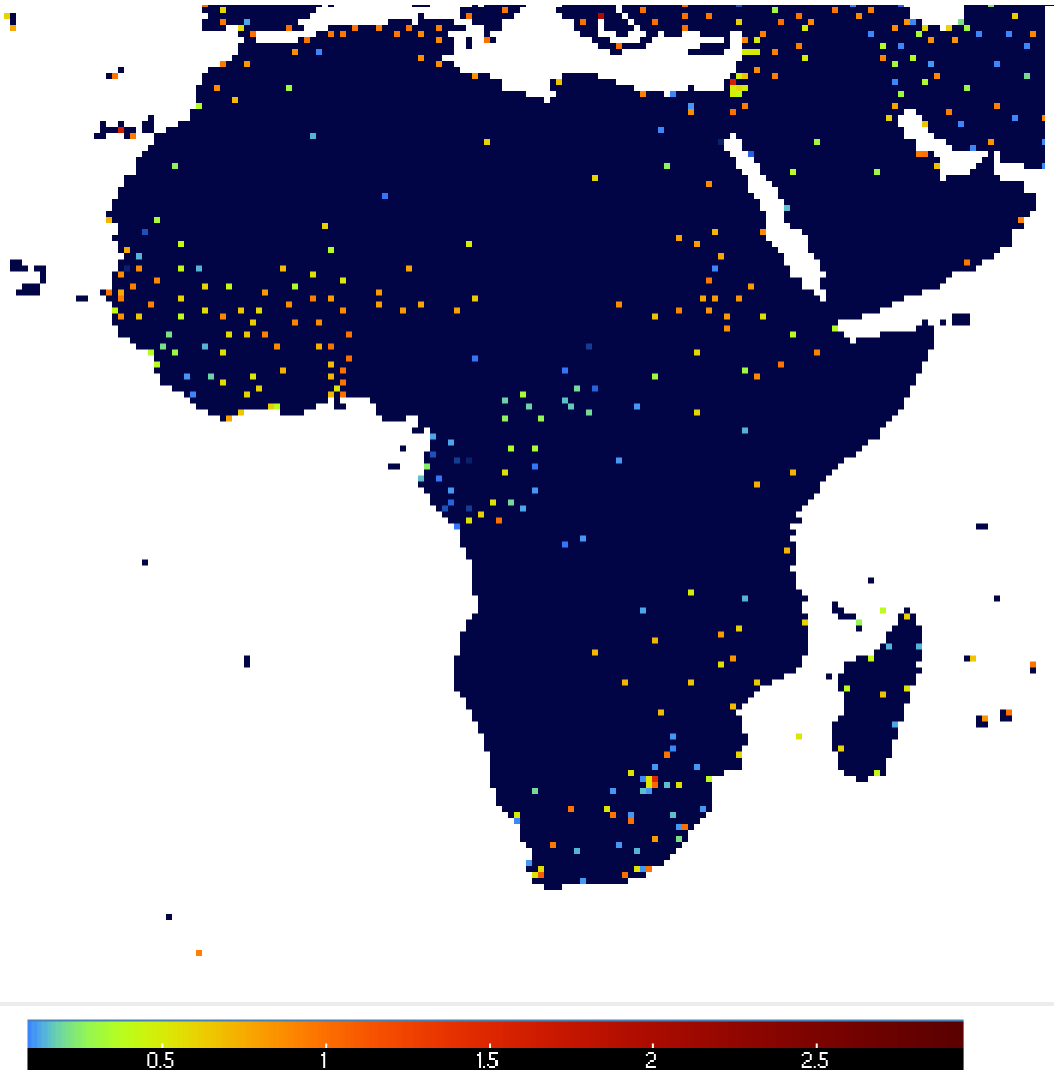
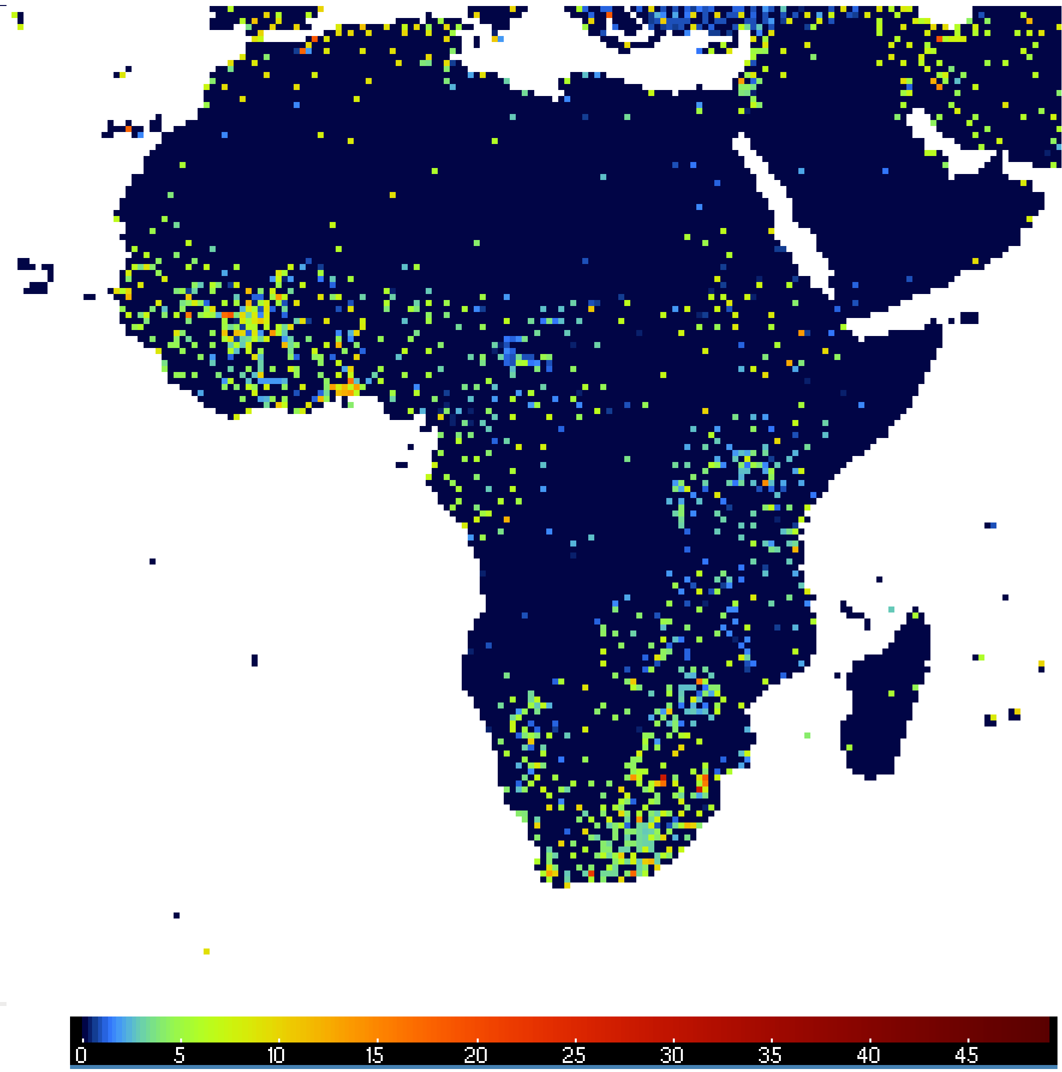


Fig. 2. Deseasonalized monthly precipitation anomaly according to the CRU (grid point 43°15′N, 7°15′W) and UCM (Lugo station, 43°15′N, 7°28′W) data sets; r: correlation between both series up to, and after 1950

Fernández & Sáenz, 2003

CRU



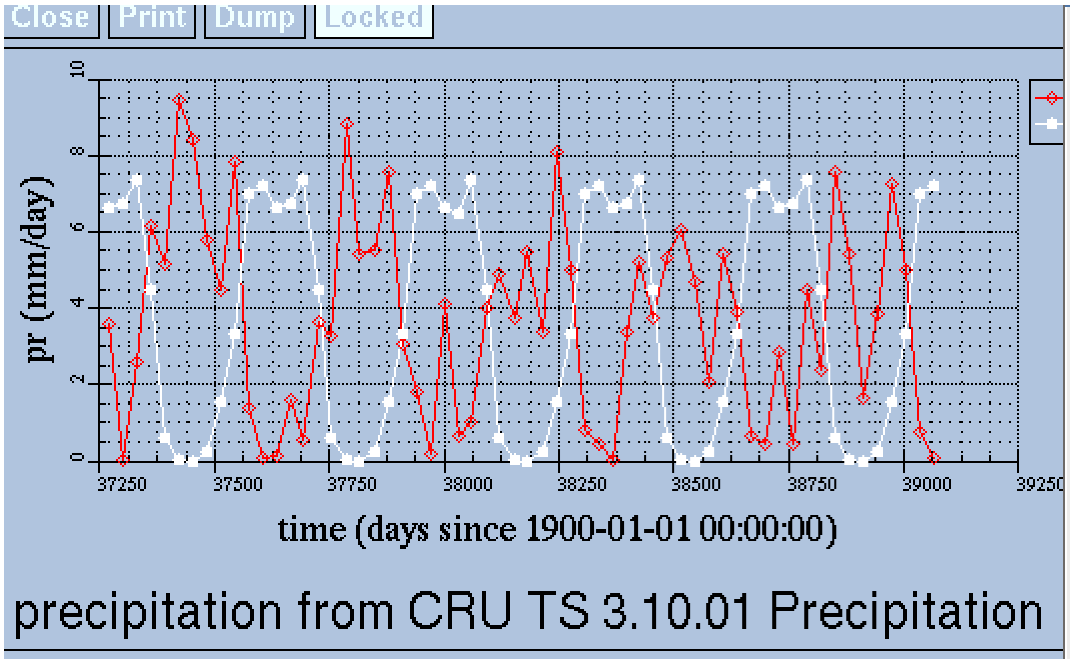


temperature

precipitation

Number of stations per grid box averaged in time 1989-2008

CRU


Close
Print
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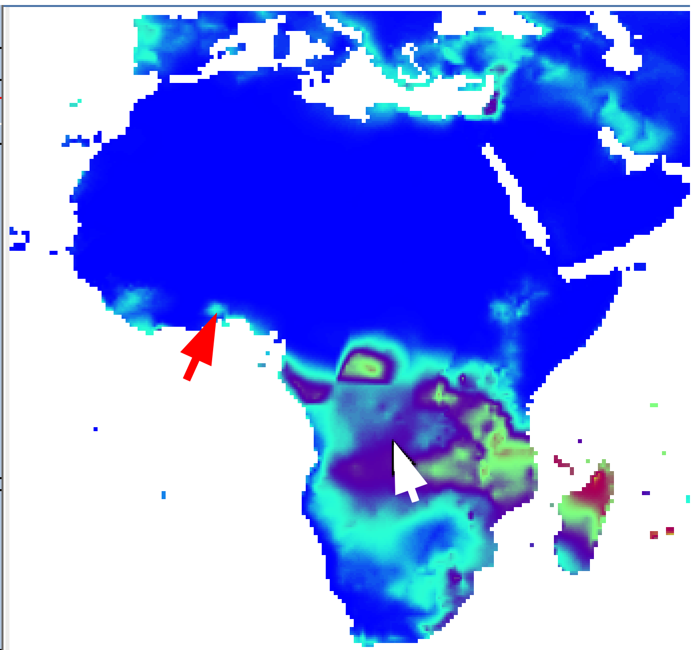
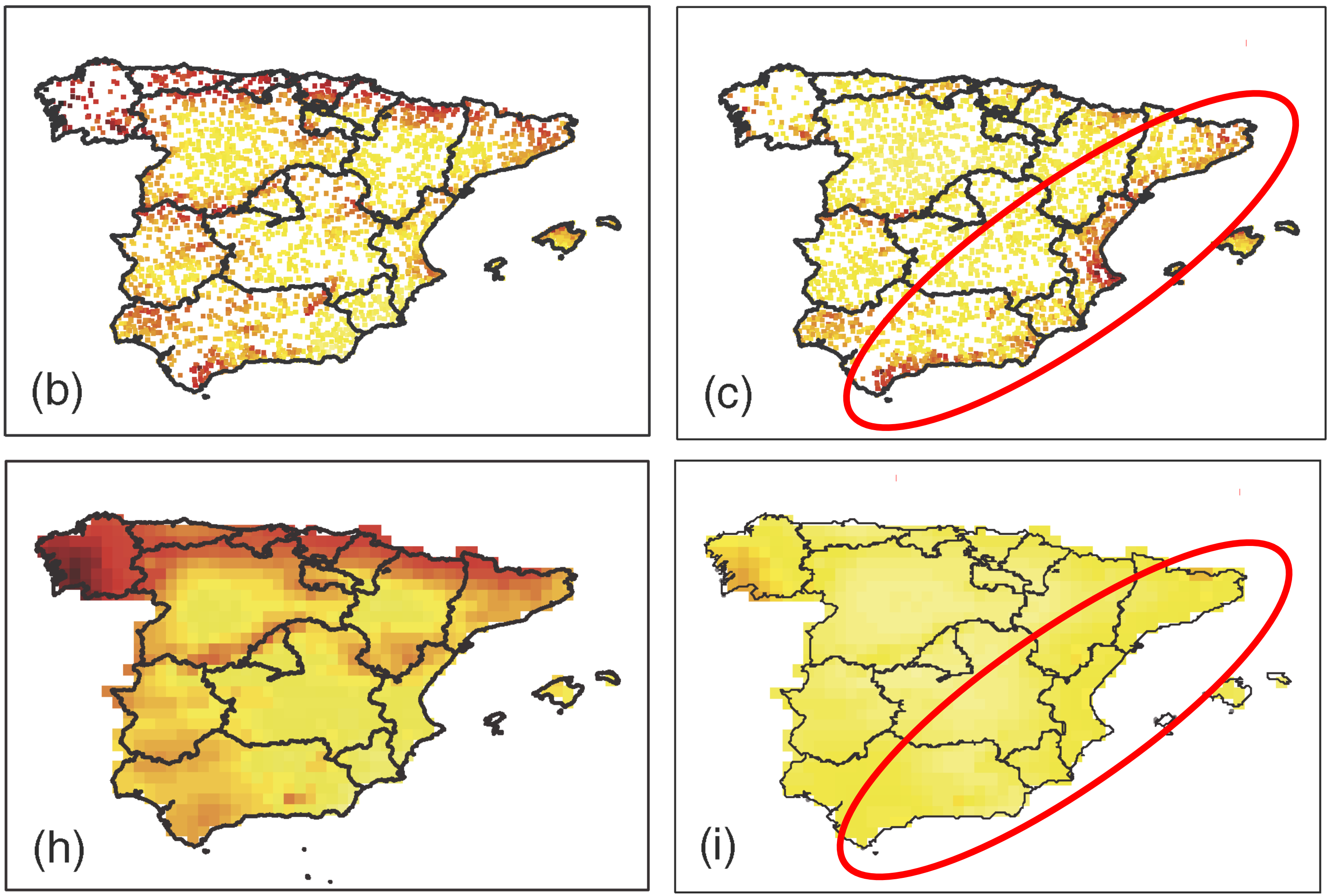
pr (mm/day)
0
2
4
6
8
10
37250
37500
37750
38000
38250
38500
38750
39000
39250
time (days since 1900-01-01 00:00:00)
precipitation from CRU TS 3.10.01 Precipitation



Observational uncertainty

Rainfall Amount
(yearly accumulated)

Rainfall Variability
(σ for Precip>0.1mm)

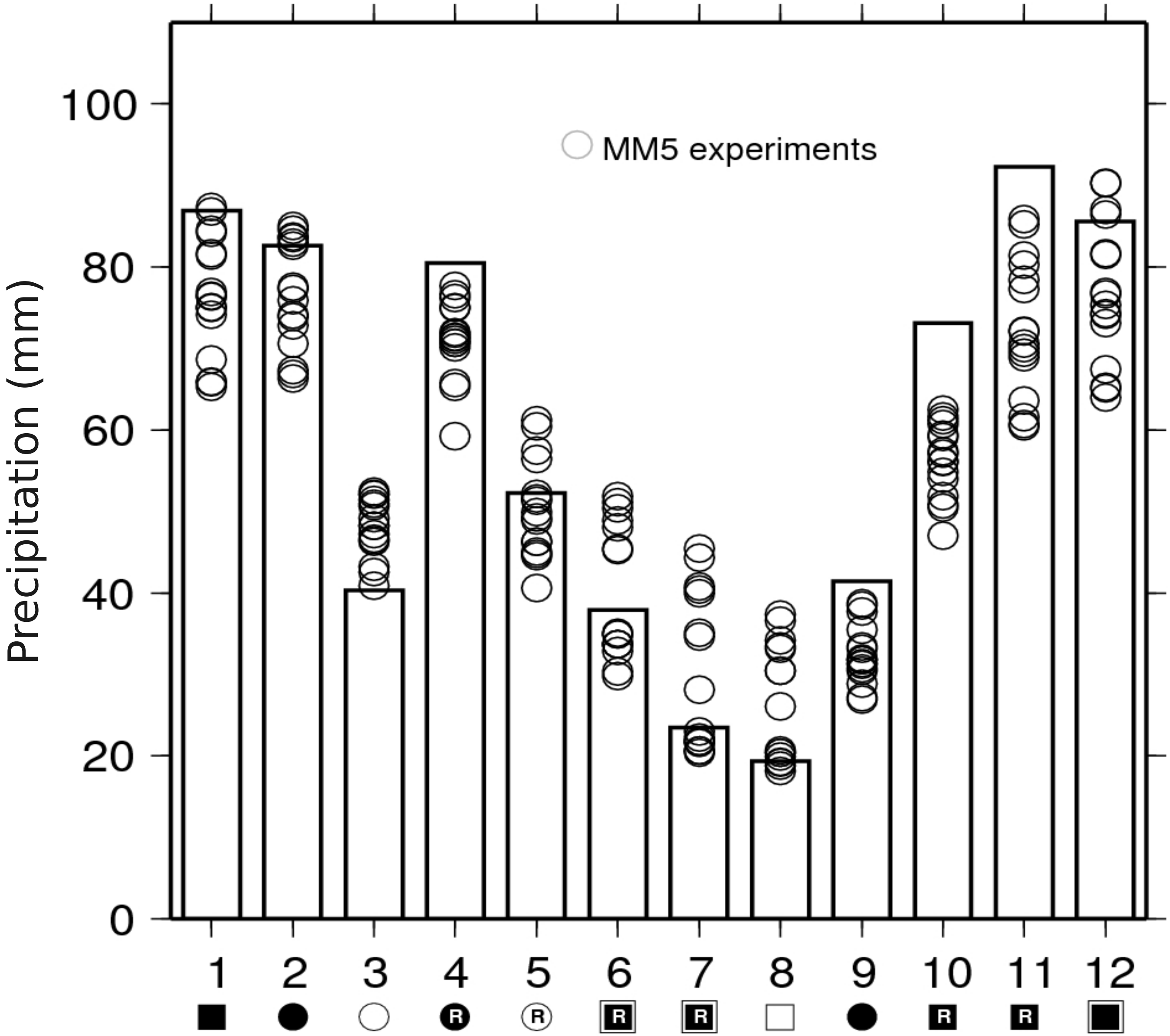


… or even continental-scale products.

This is an early version of E-OBS

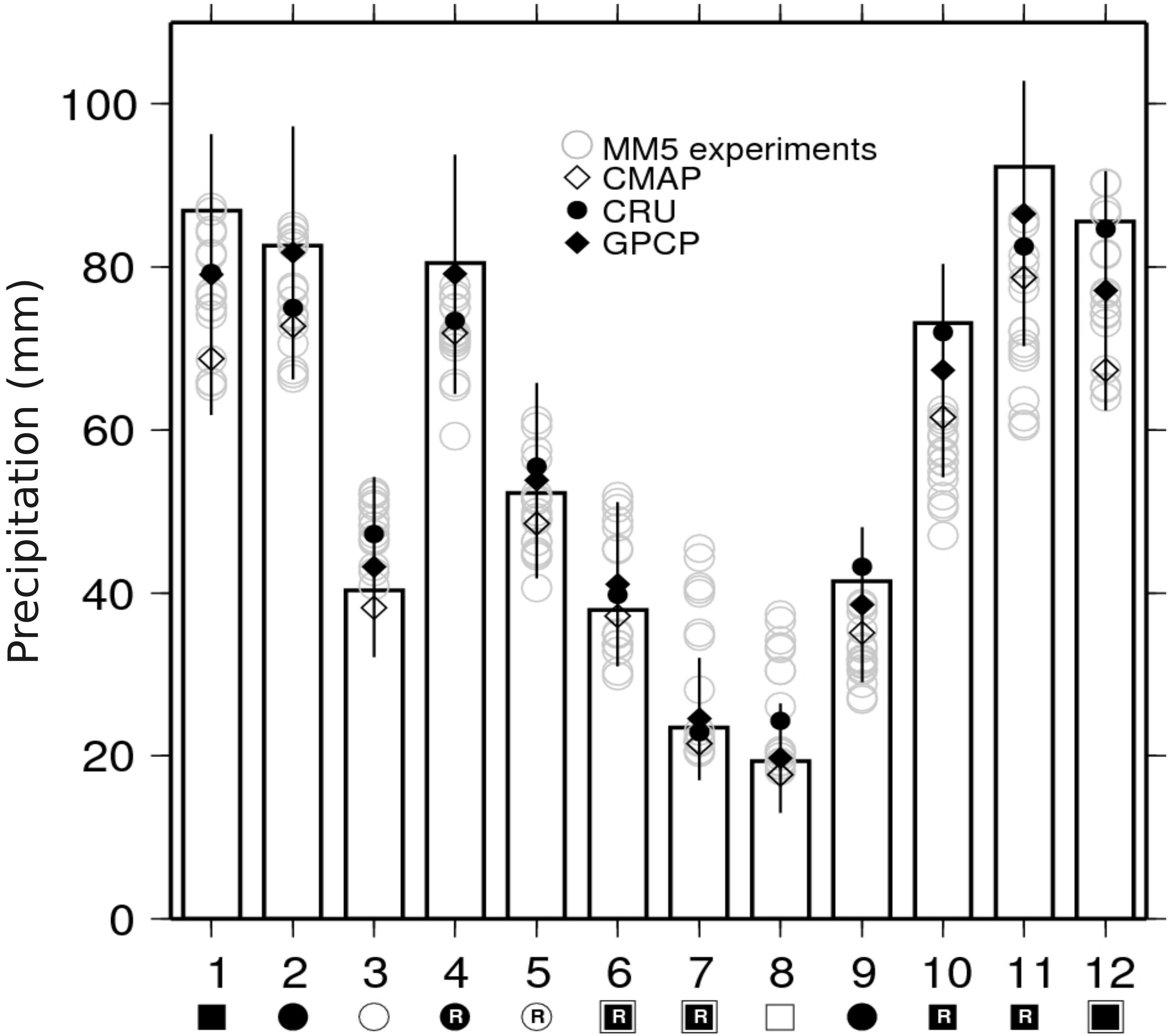
Herrera et al., 2012

Observational uncertainty



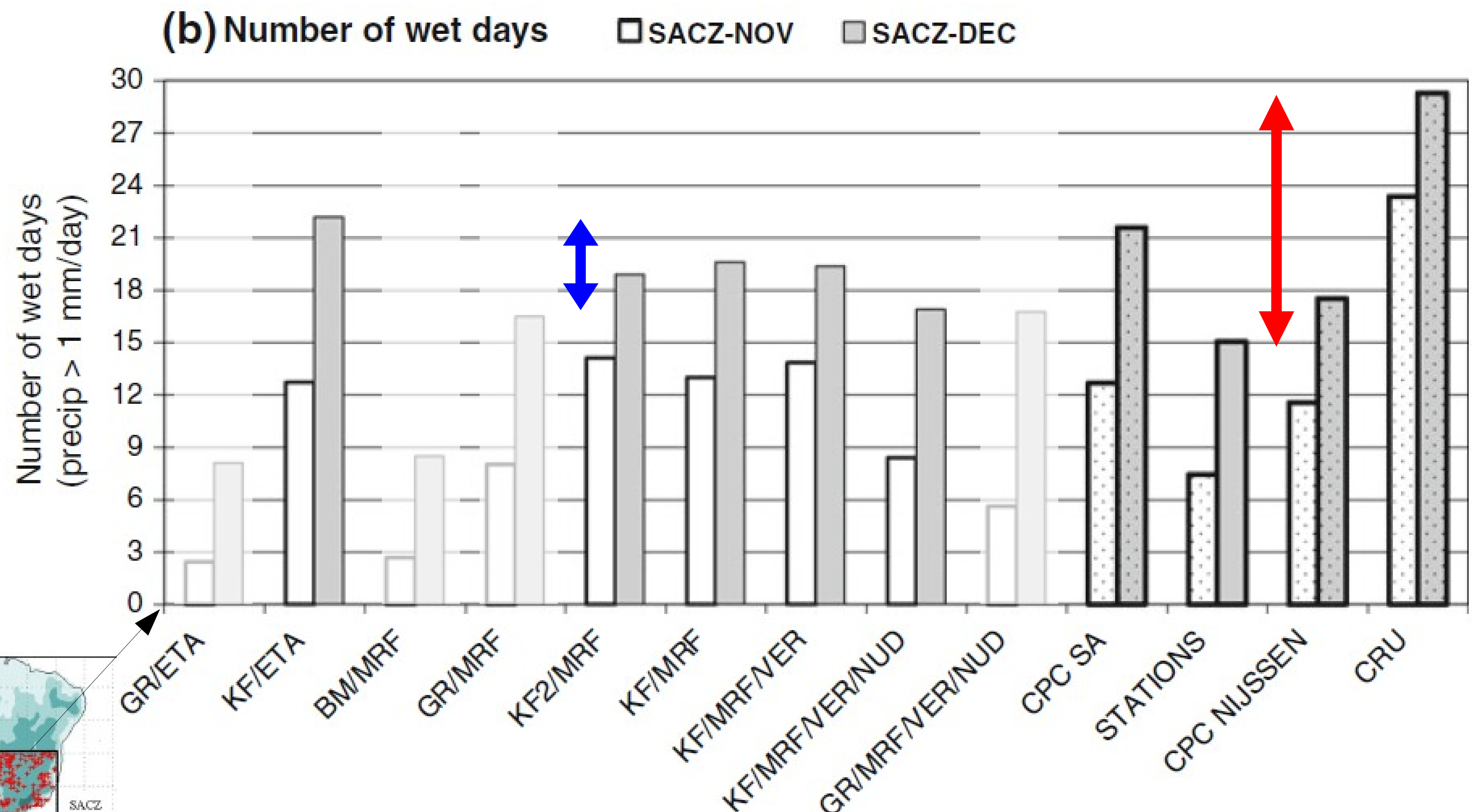
Fernández et al, 2007

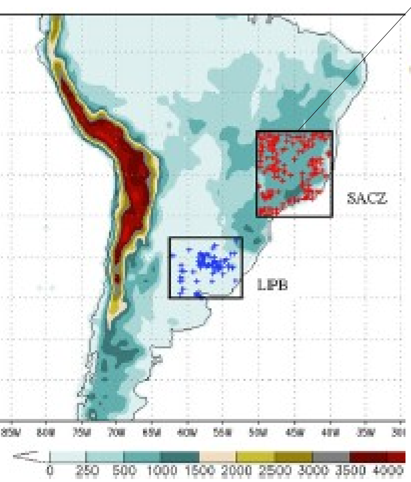
Observational uncertainty



Fernández et al, 2007

Observational uncertainty





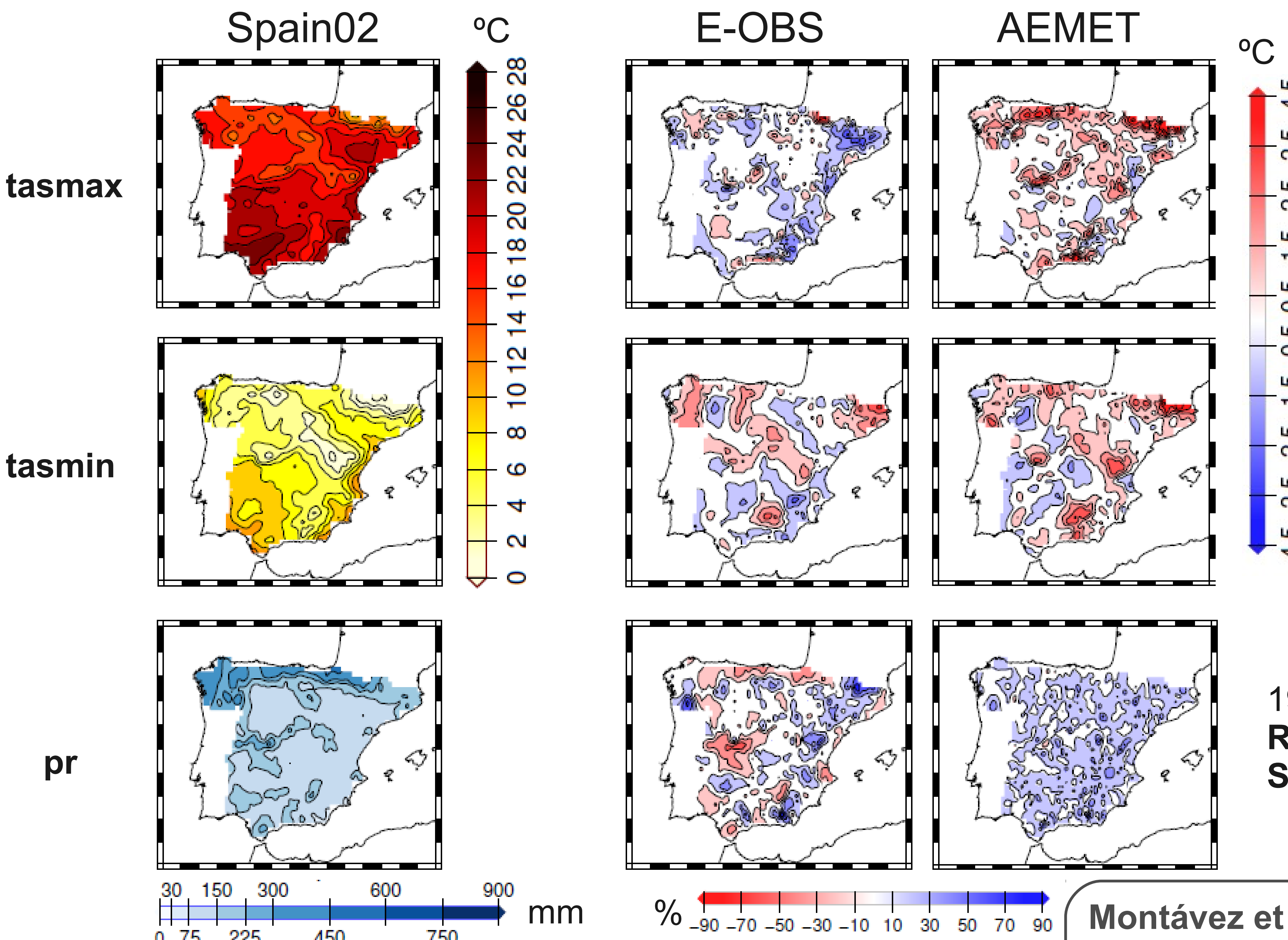
MM5 Kain-Fritsch

← Observations →

seems to be the best, but...
… which one?

Solman & Pessacg, 2012

Observational uncertainty

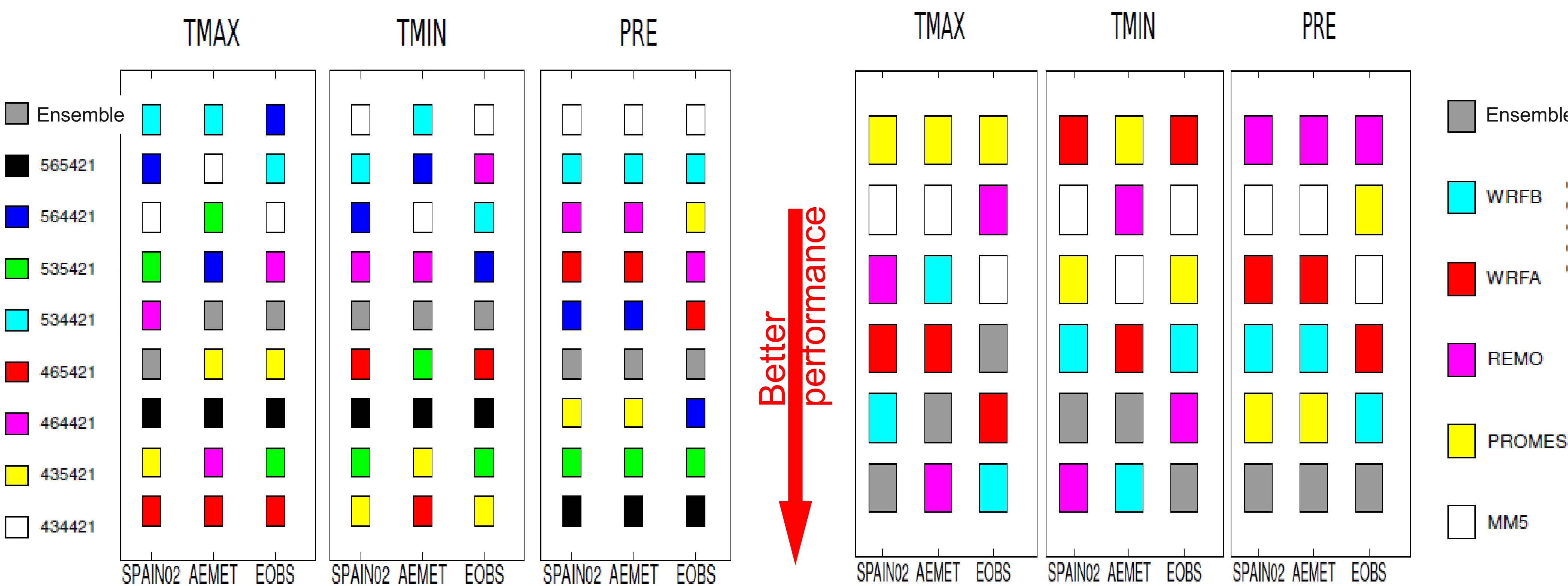


1950-2008
Res: ~0.2º
Seas: MAM

Montávez et al., 2012

Ranking by diff. observations

Multi-physics (MM5, Jerez et al) | Multi-model (ESCENA)



Ranked by the spatial correlation
of the seasonal (MAM) climatology (MM5: 1970-2000, ESCENA: 1998-2008)

Montávez et al., 2012

Why precip. and temperature?

- Why are we evaluating P and T all the time?

  Well... two main reasons:

  - Human beings are sensitive to them.
  - To evaluate climate statistics at regional scale we need long records in many places. P & T are the two variables best meeting these requirements.

- For better physical insight and understanting of the biases found we need to look at other variables, other statistics, sub-daily data, …

  But these are only available for short time periods and/or selected locations. The conclusions drawn cannot be extrapolated to climate or to other region.

- García-Díez et al (2012) try to mix both approaches in a single study.

García-Díez et al., 2012

Temperature biases

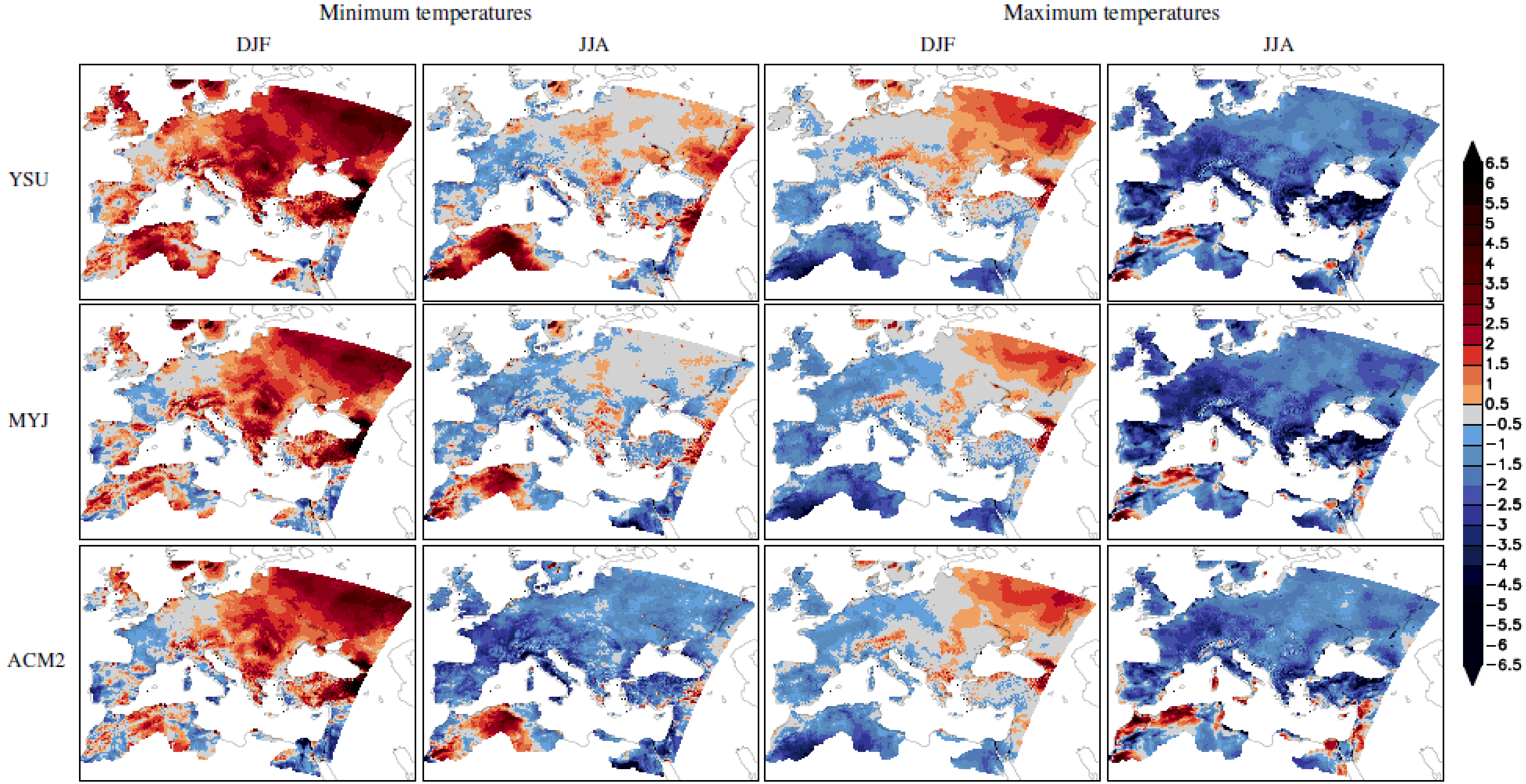
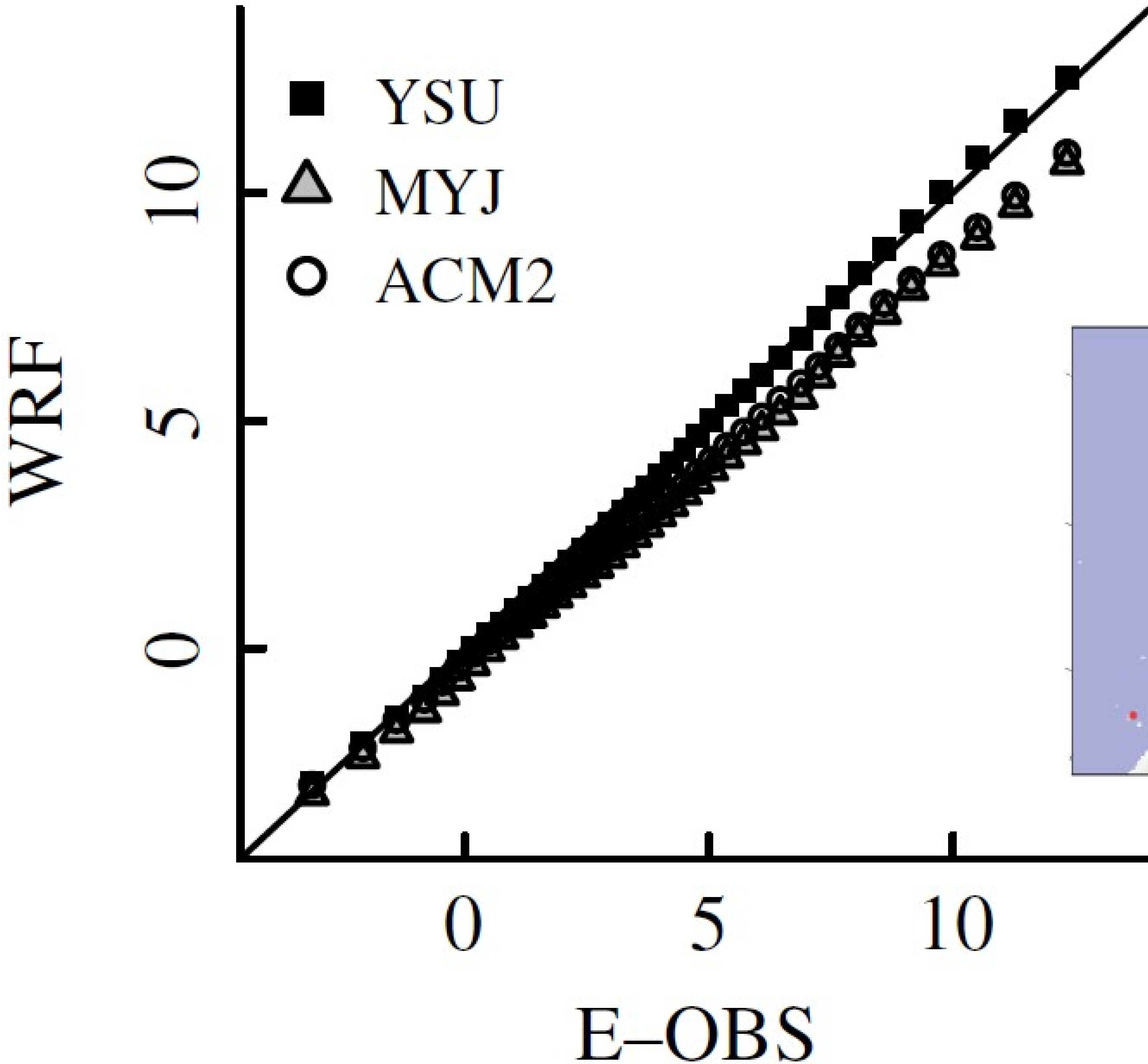


Figure 3. Minimum and maximum temperature bias of WRF compared with E-OBS. Rows are the three PBL schemes used, and columns the seasons, excluded MAM and SON.

1-yr simulations covering a full annual cycle (interannual variability may still be an issue!) in "re-forecast" mode.

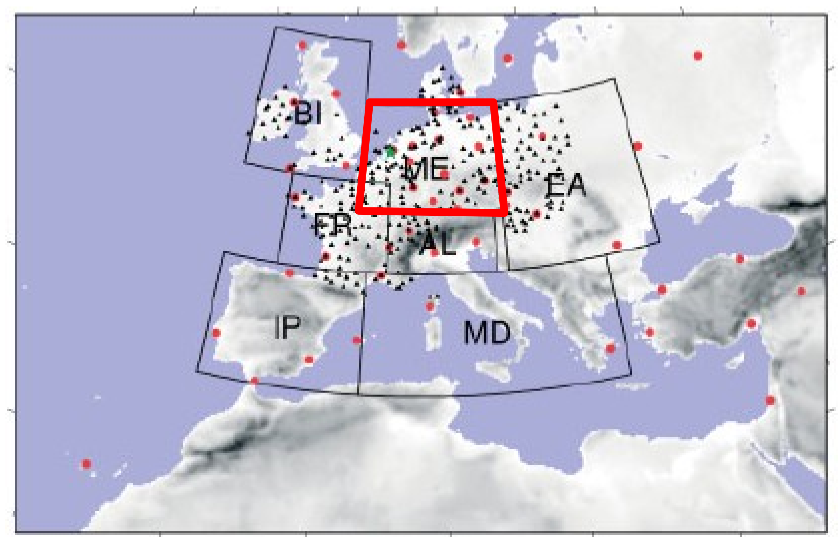
García-Díez et al., 2012

QQ-plot: beyond mean values



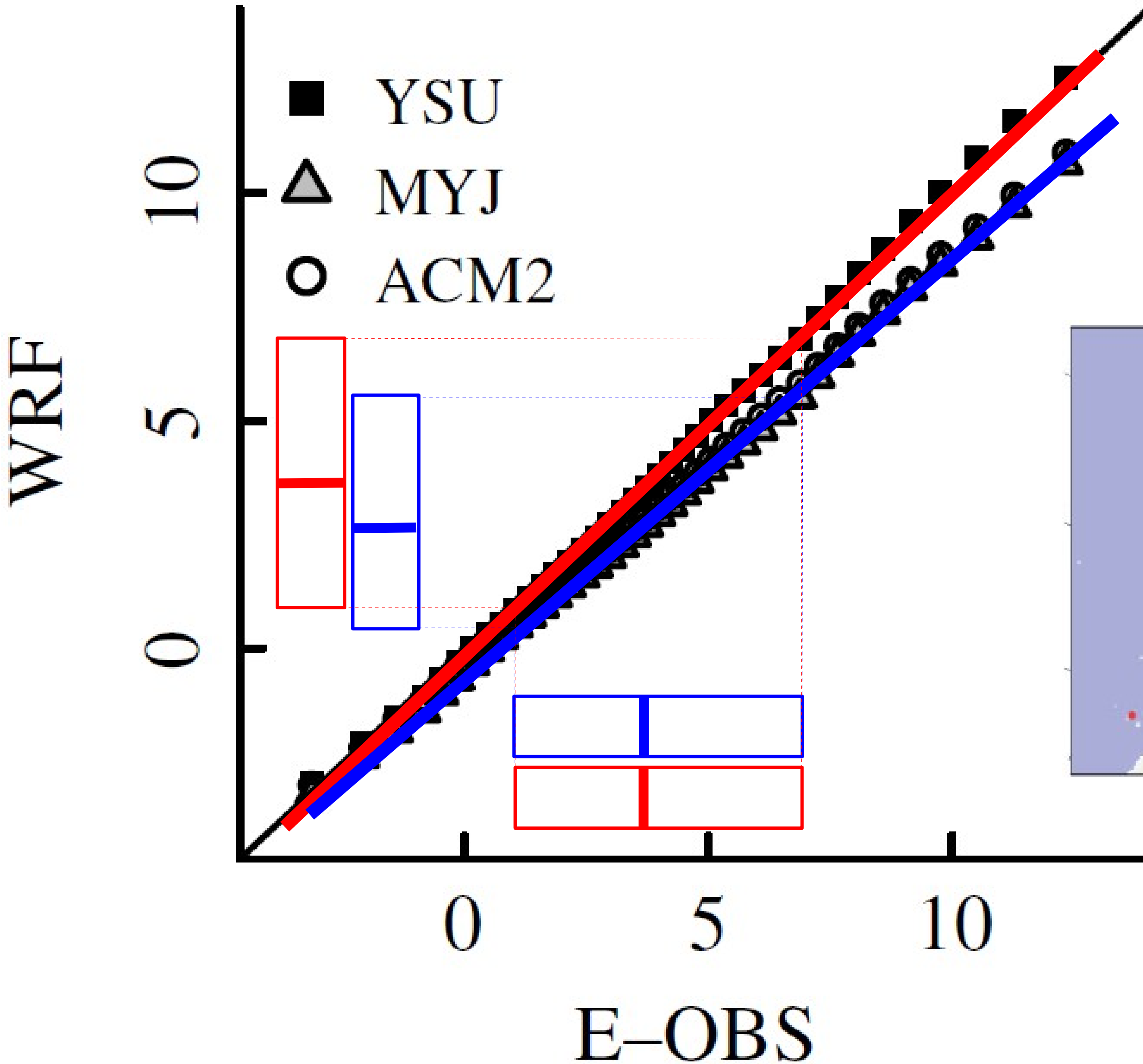
Example

DJF tasmax



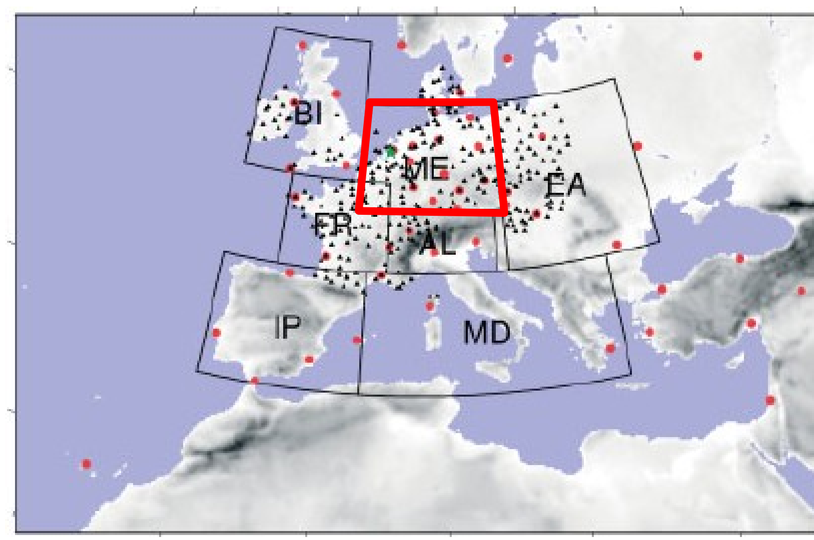
García-Díez et al., 2012

QQ-plot



Example

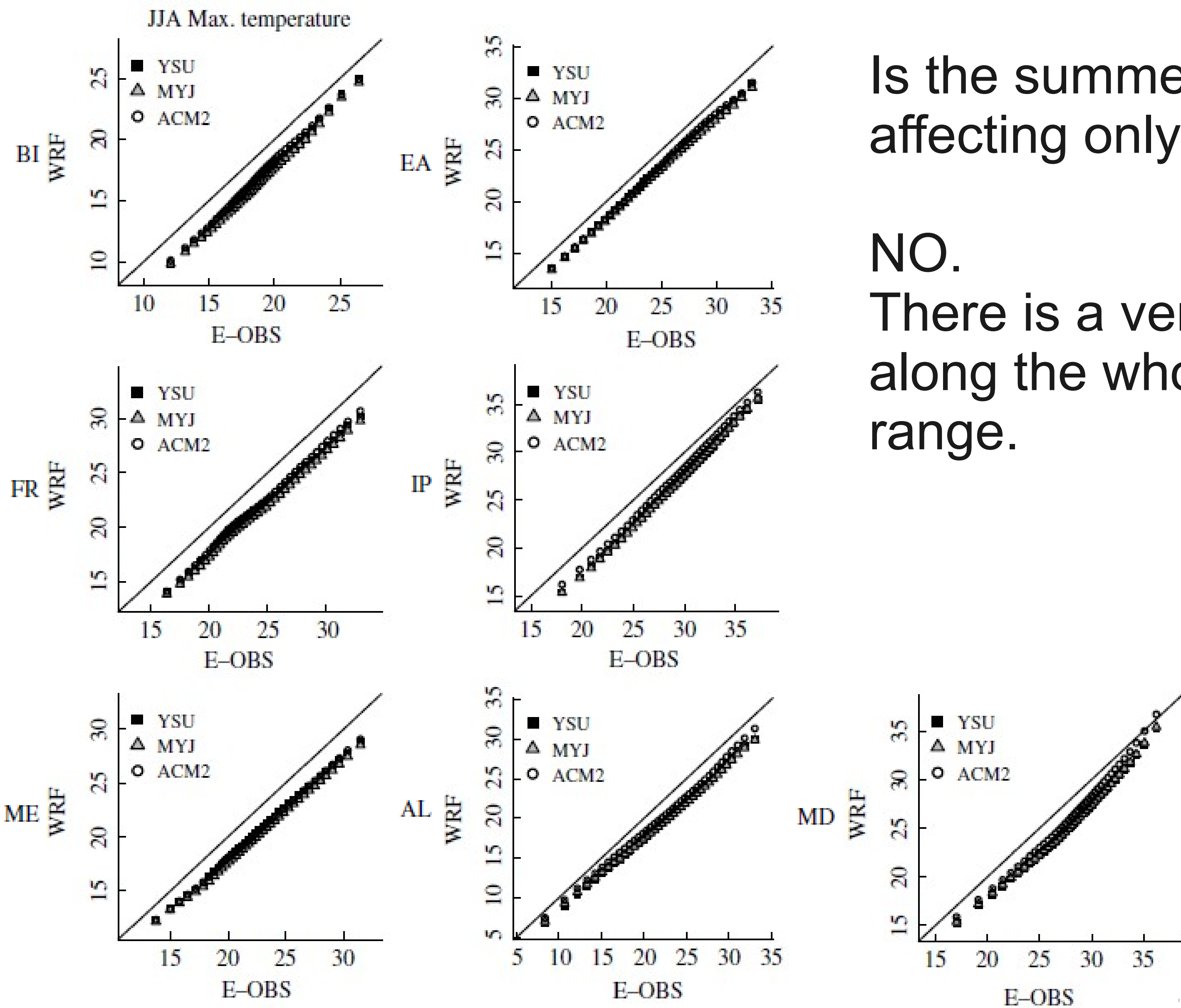
DJF tasmax



MYJ & ACM2 simulate a lower mean value and variability over ME

García-Díez et al., 2012

JJA tasmax

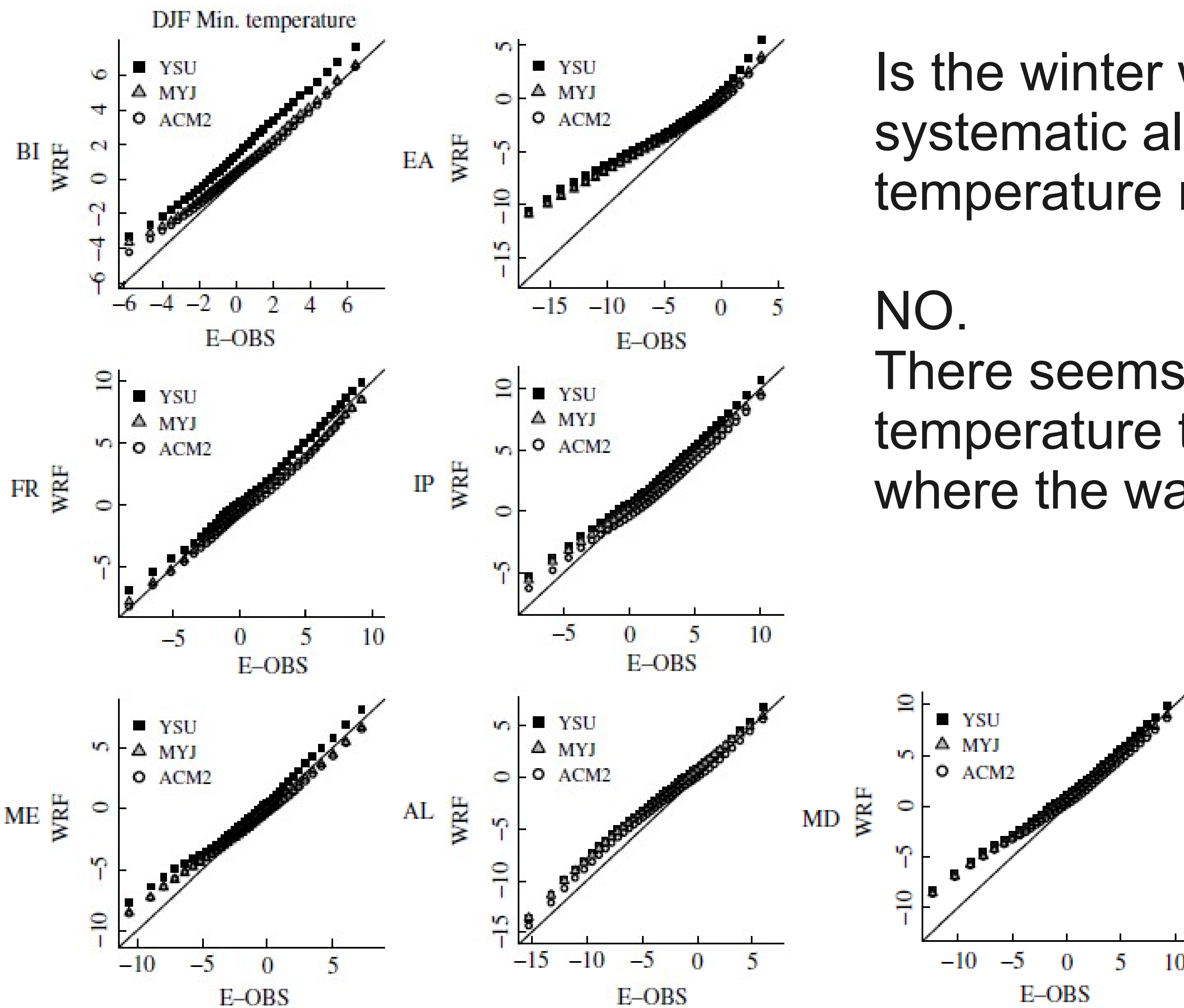


Is the summer cold bias affecting only the mean values?

NO.
There is a very systematic bias along the whole temperature range.

García-Díez et al., 2012

DJF tasmin

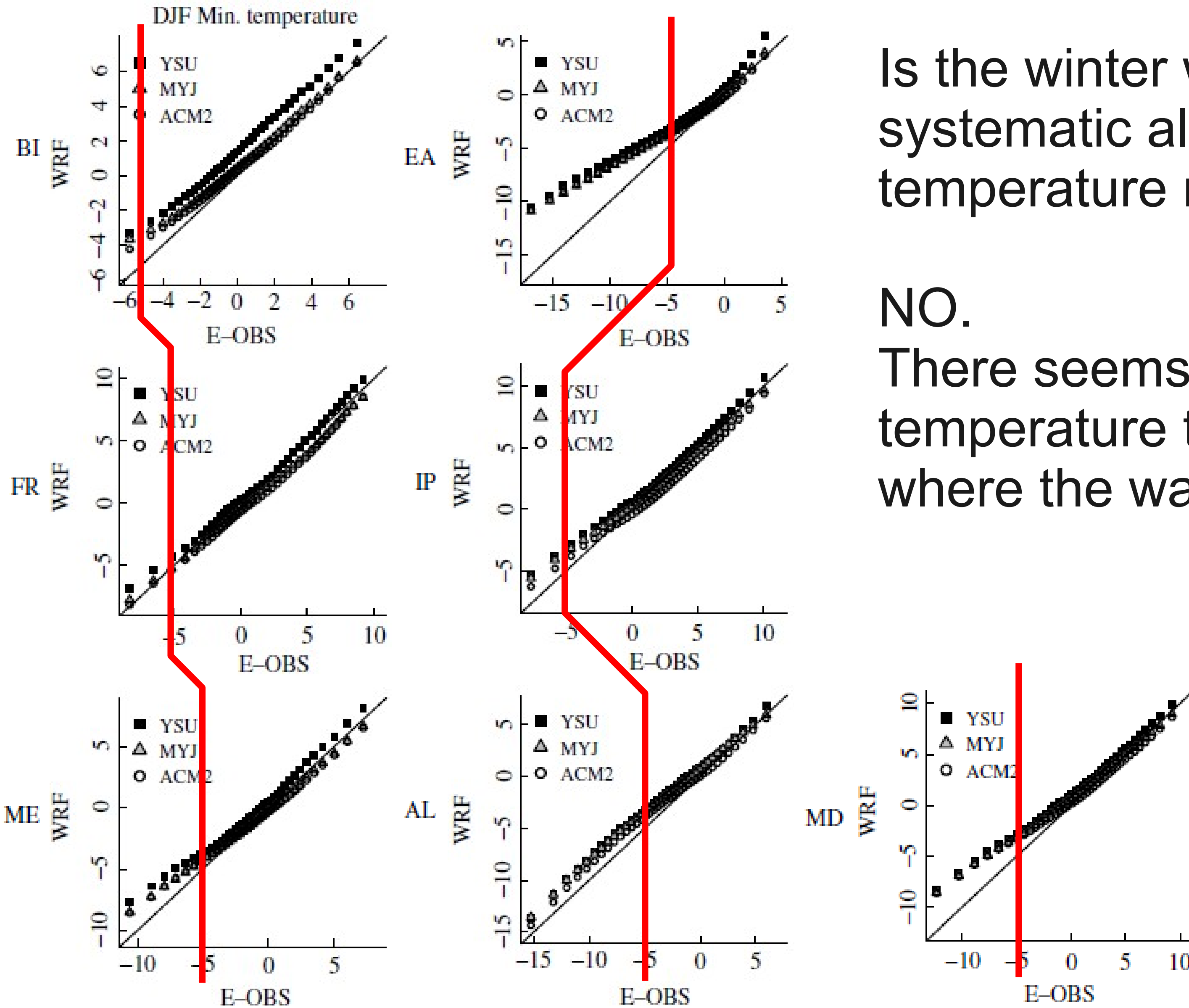


Is the winter warm bias also systematic along the whole temperature range?

NO.
There seems to be an absolute temperature threshold ~ -5ºC where the warm bias starts

García-Díez et al., 2012

DJF tasmin

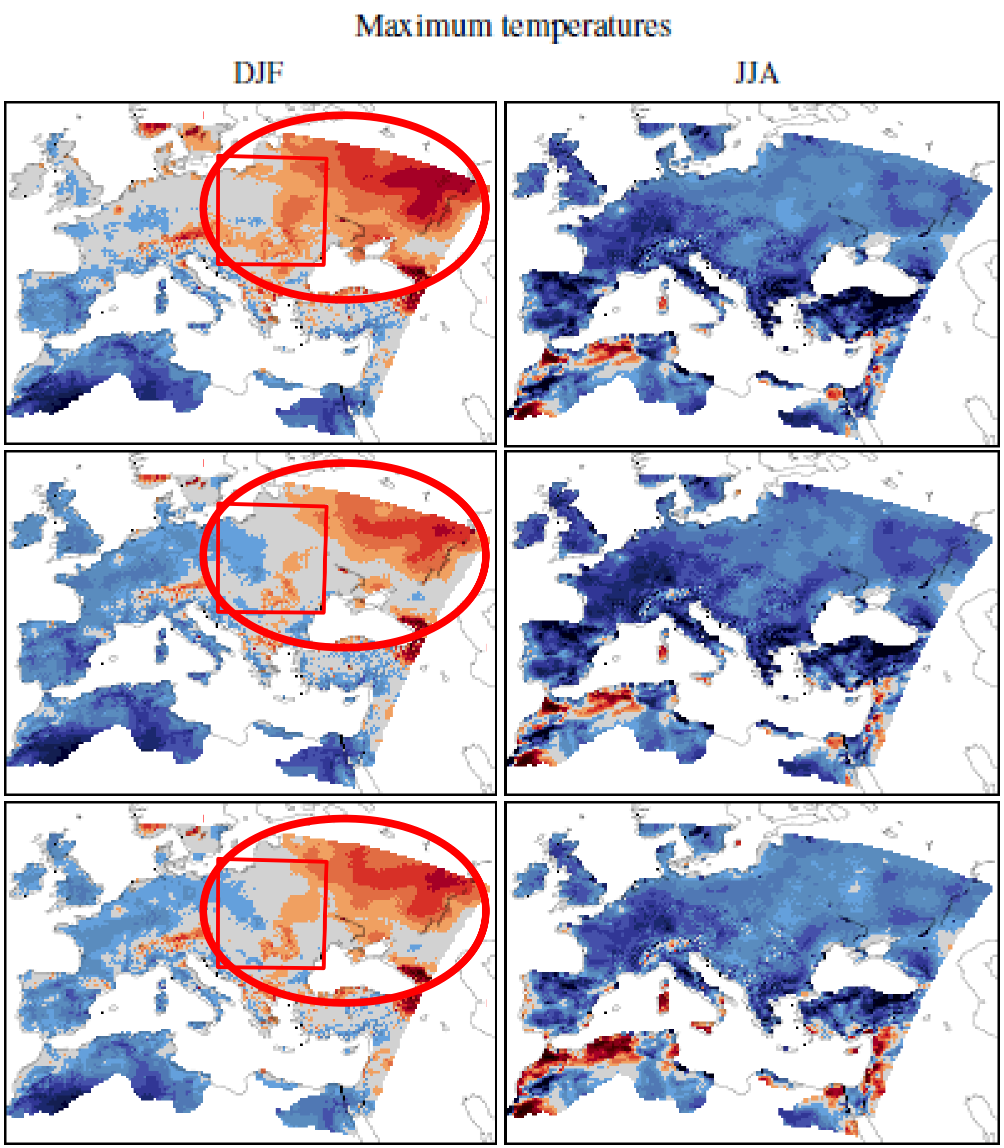


Is the winter warm bias also systematic along the whole temperature range?

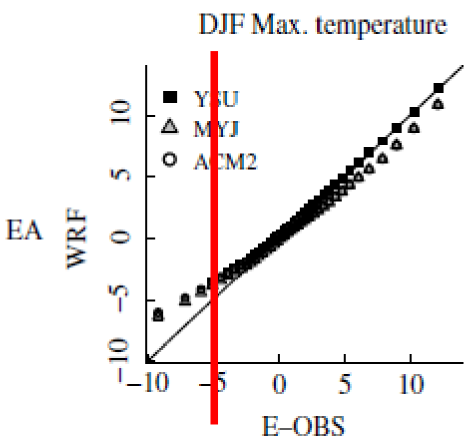
NO.
There seems to be an absolute temperature threshold ~ -5ºC where the warm bias starts

García-Díez et al., 2012

DJF tasmax



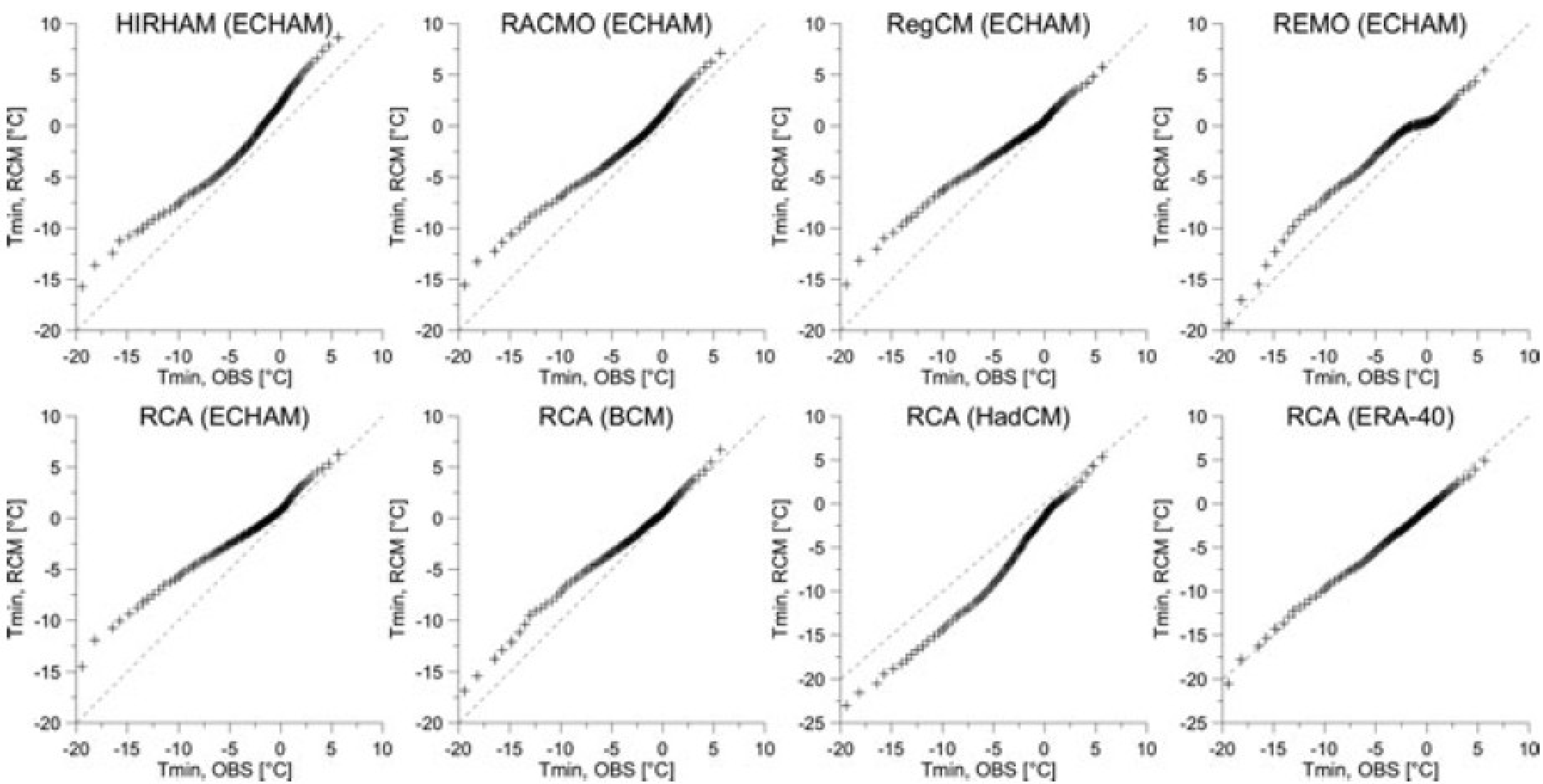
And this occurs also for maximum temperatures, where they happen to be below this threshold (in this domain, only over EA[stern Europe])



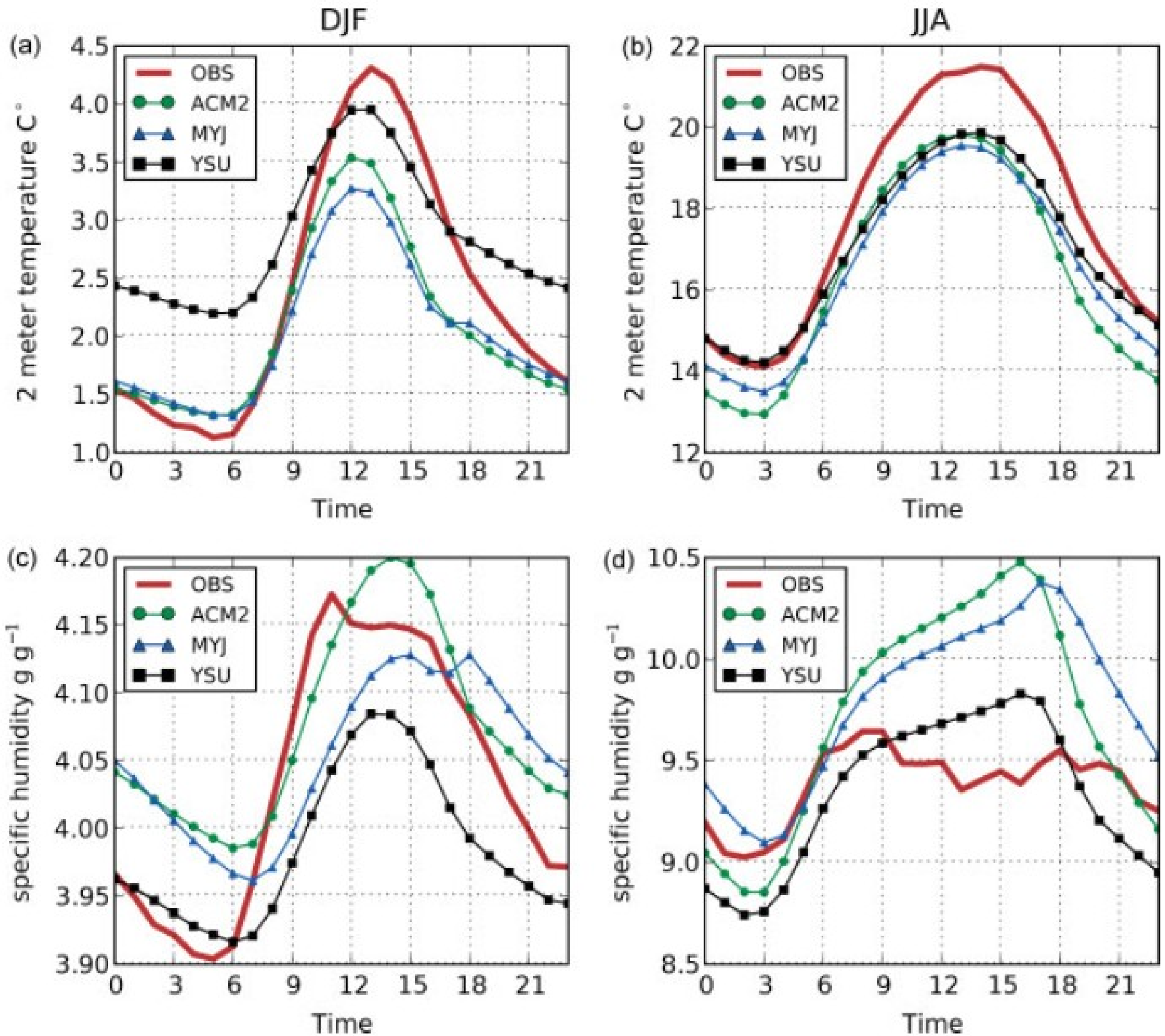
García-Díez et al., 2012

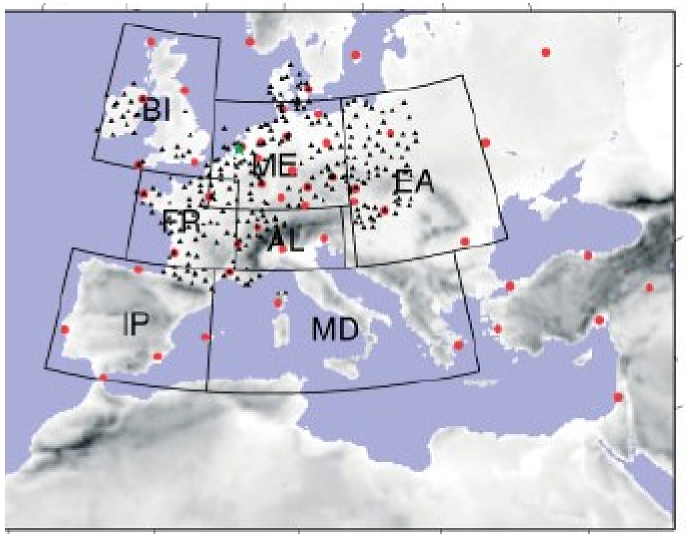
Common problem in RCMs

Qq-plots of ENSEMBLES RCMs in central Europe from Plavcova & Kysely (2011)



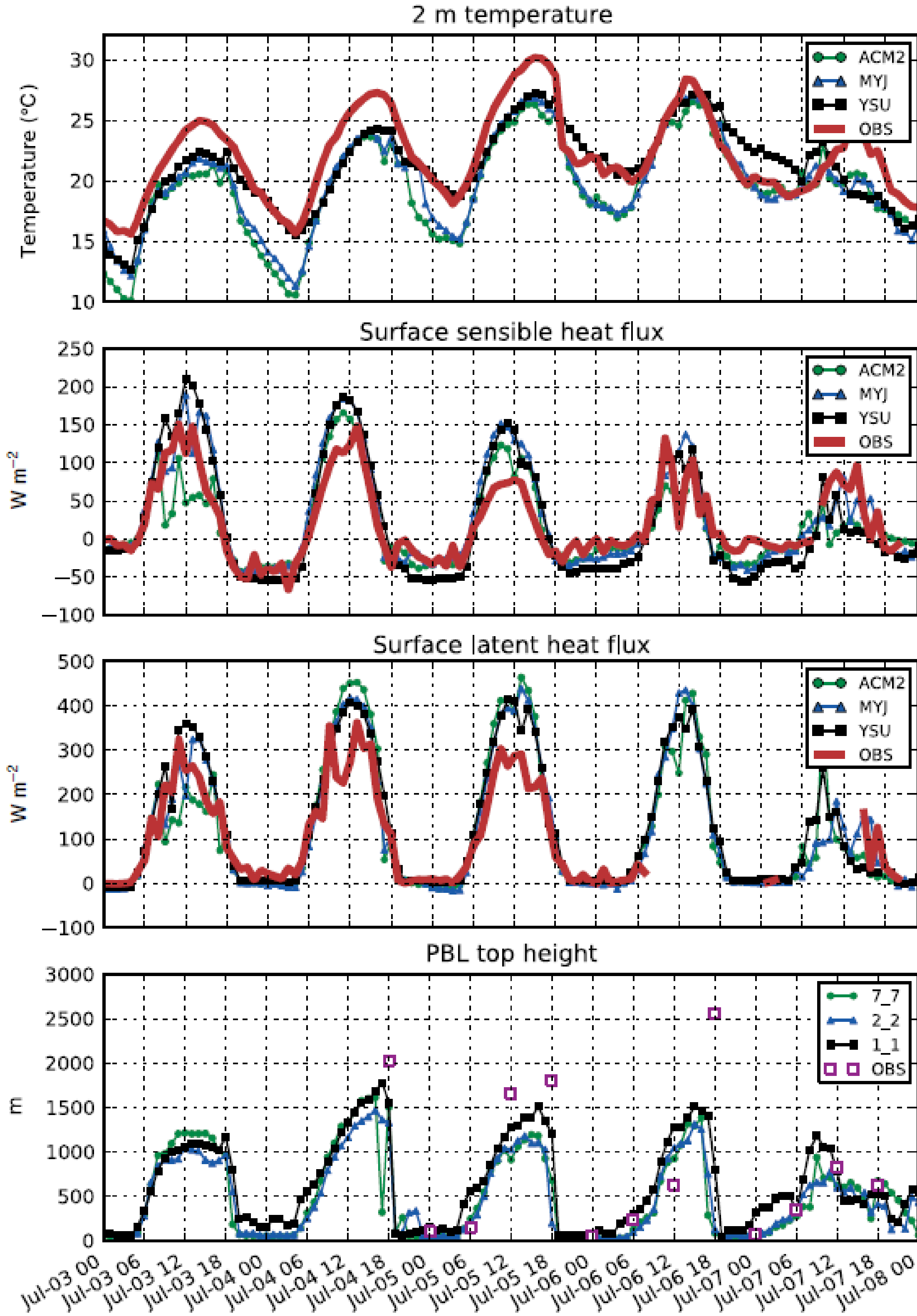
Beyond the daily time-scale





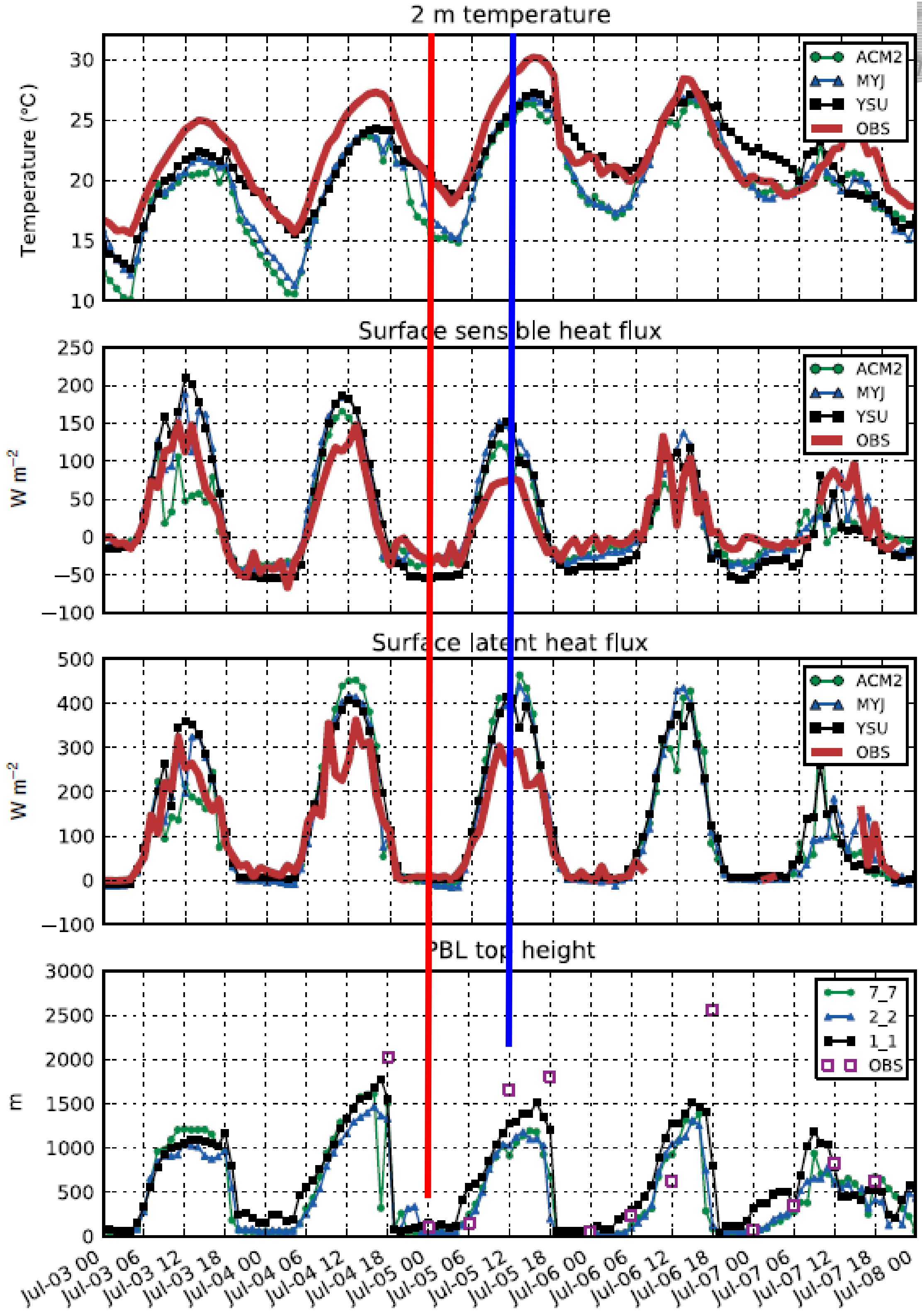
García-Díez et al., 2012

Beyond precip. & temp.



García-Díez et al., 2012

Beyond the surface



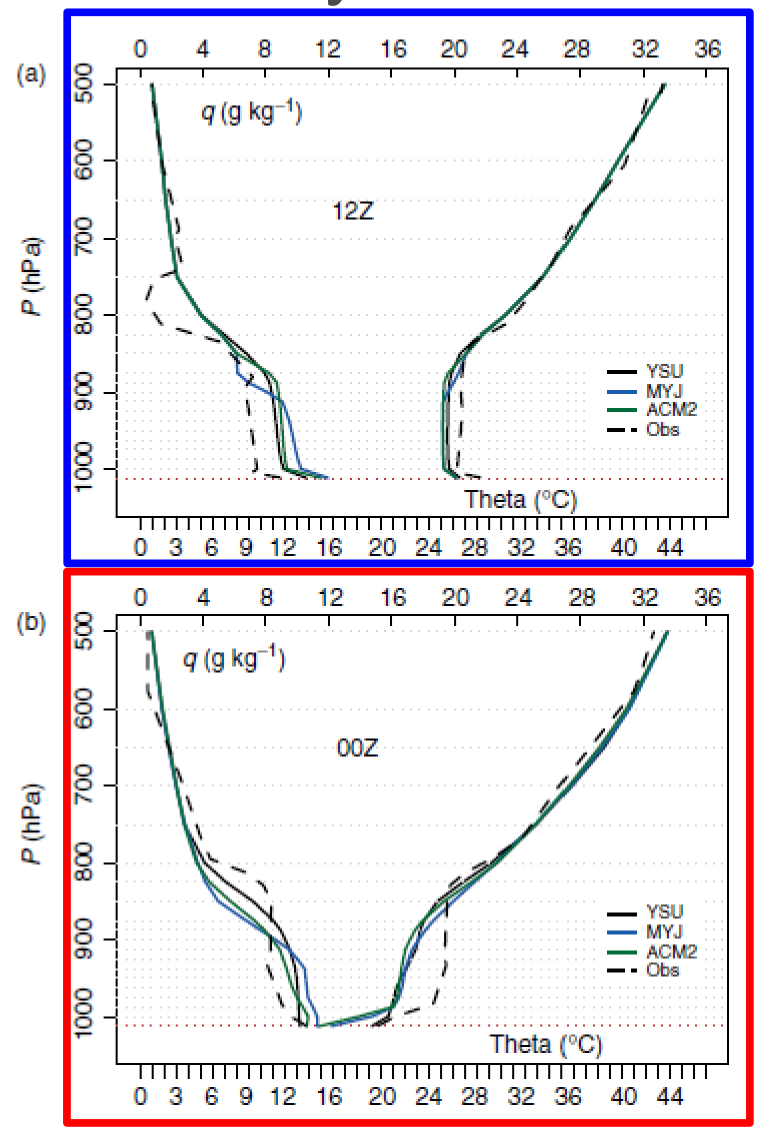
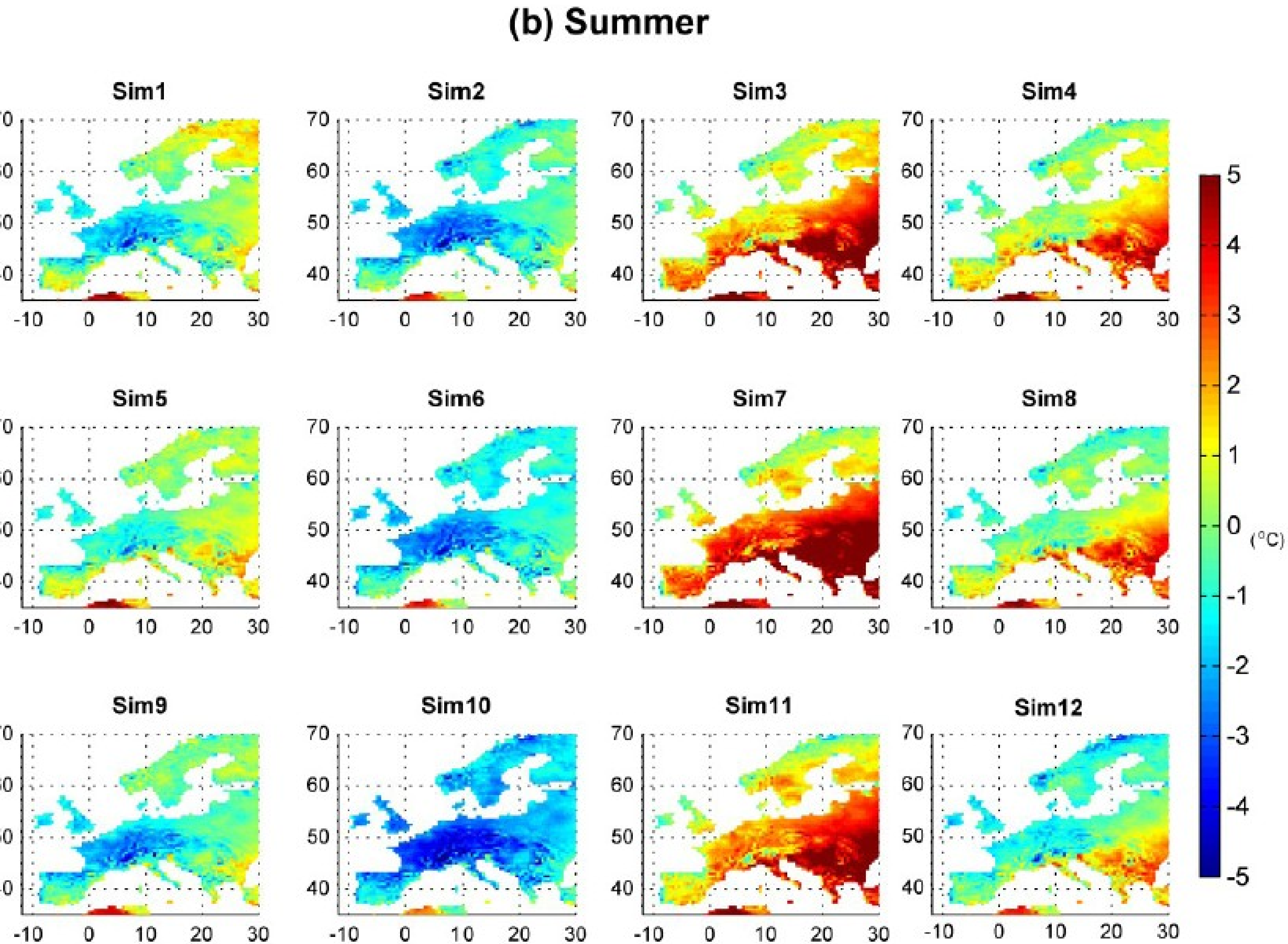


Figure 11. Simulated and observed potential temperature (lines on the right) and specific humidity (lines on the left) profiles in De Bilt, Netherlands, on 5 July 2001 at (a) 1200 UTC with Noah and (b) 0000 UTC with Noah.

García-Díez et al., 2012

NOAH vs. RUC LSM



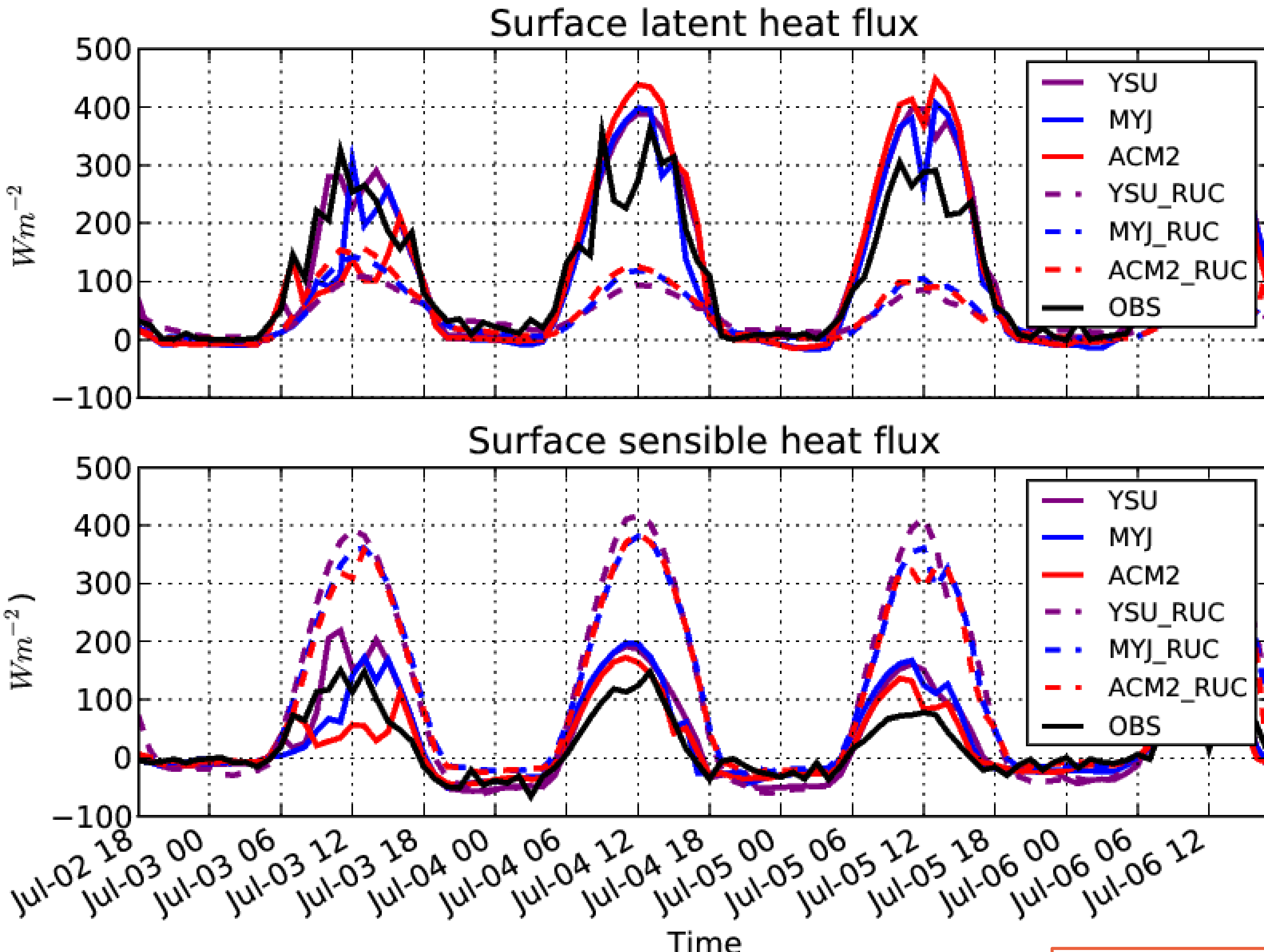
WRF
1990-1995

NOAH LSM
(used in all Euro-CORDEX runs)

RUC LSM

Mooney et al, 2012

Beyond precip. & temp.

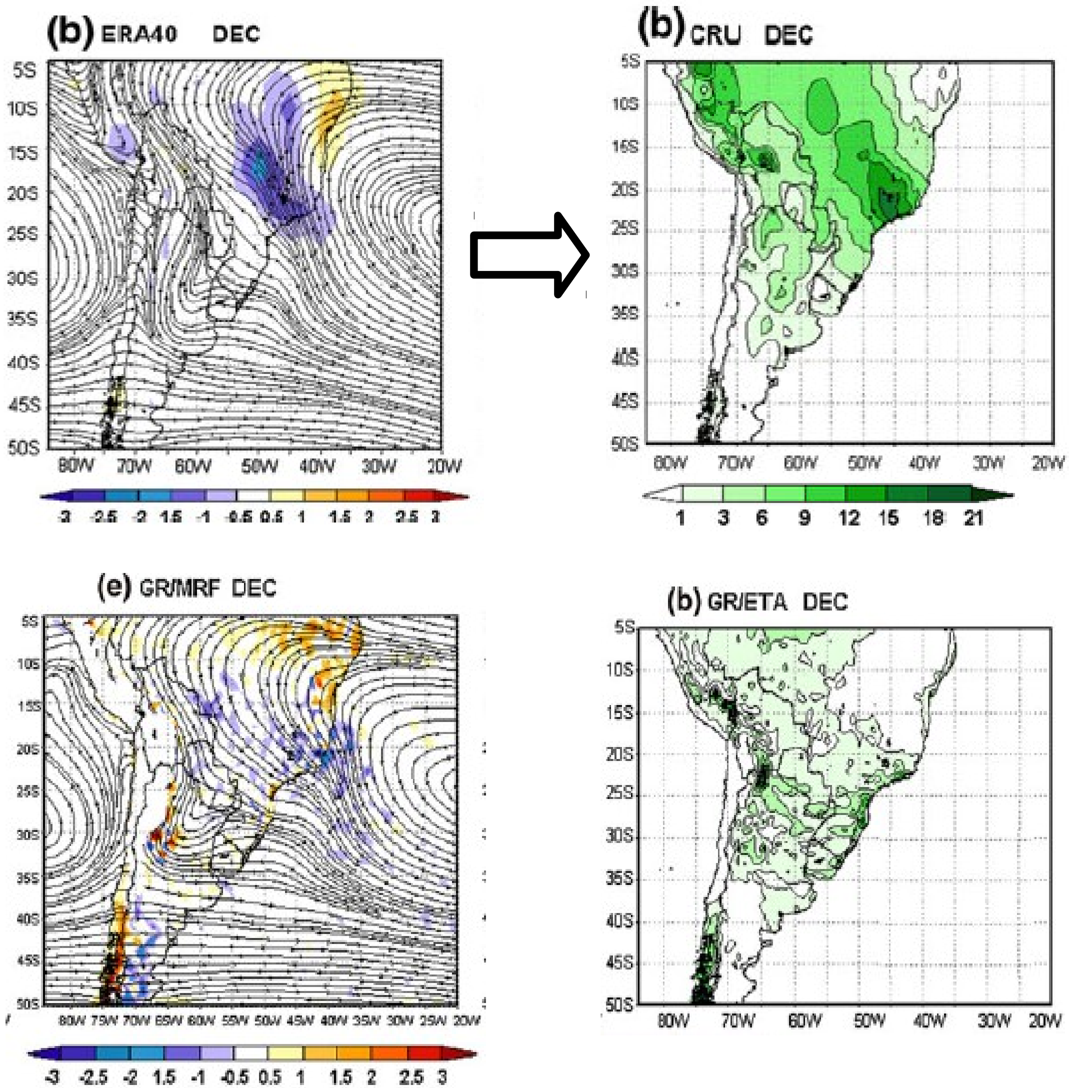


M. García-Díez

Right result / wrong mechanism

VIMT + div

precip



<u>Observations</u>

Precipitation driven by low level moisture convergence

<u>GR</u>

Worst performing (precip) cumulus scheme.

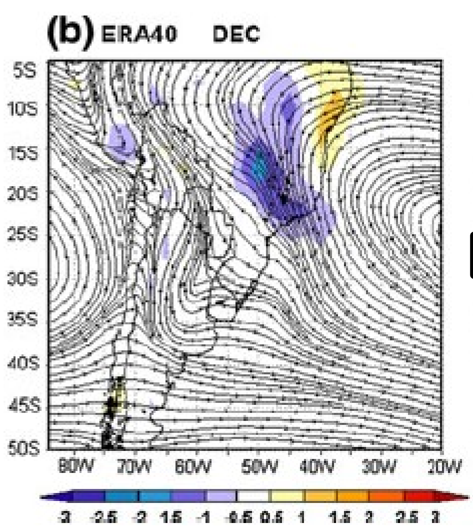
Reasonable moisture flow but not enough convergence.

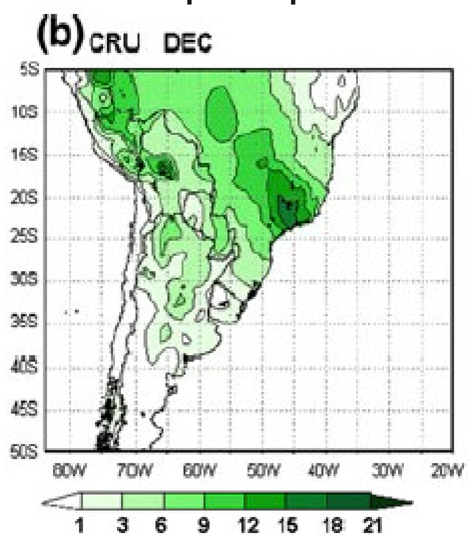
Solman & Pessacg, 2012

Right result / wrong mechanism

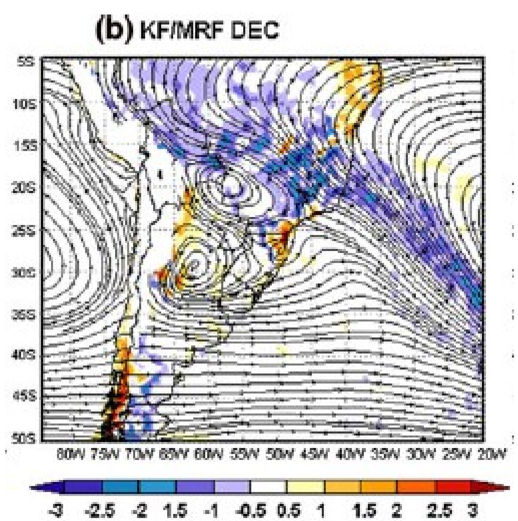
VIMT + div

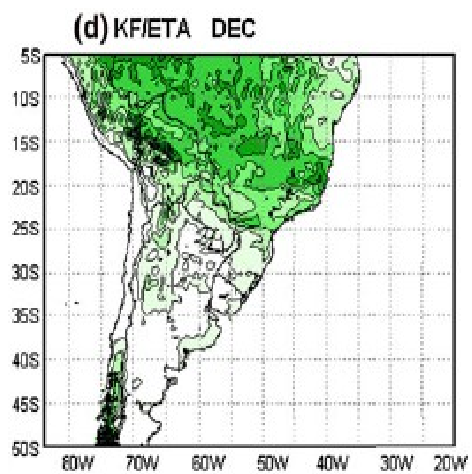
precip





<u>Observations</u>
Precipitation driven by low level moisture convergence





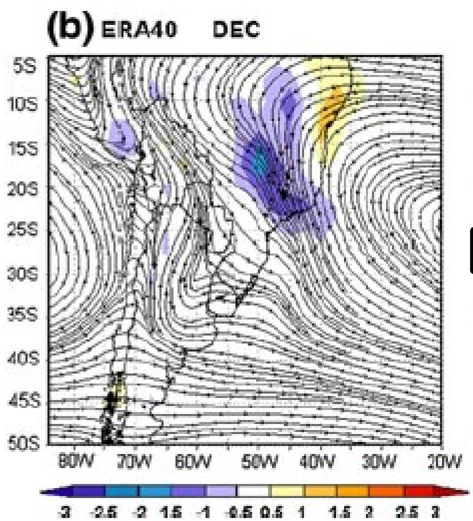
<u>KF</u>
Best performing (precip) cumulus scheme.
Wrong moisture flow.

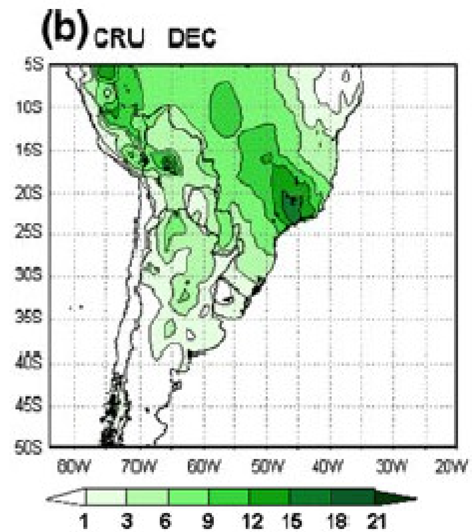
Solman & Pessacg, 2012

Right result / wrong mechanism

VIMT + div

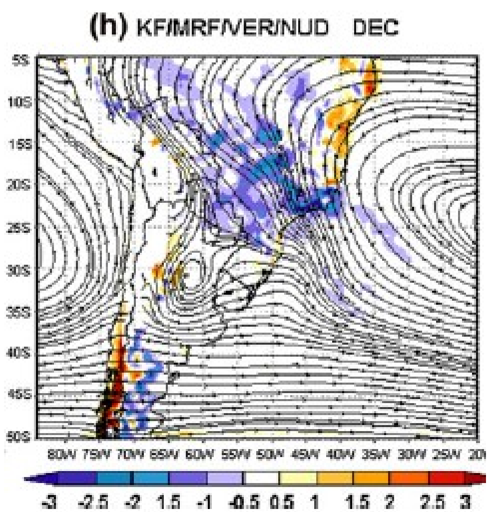
precip

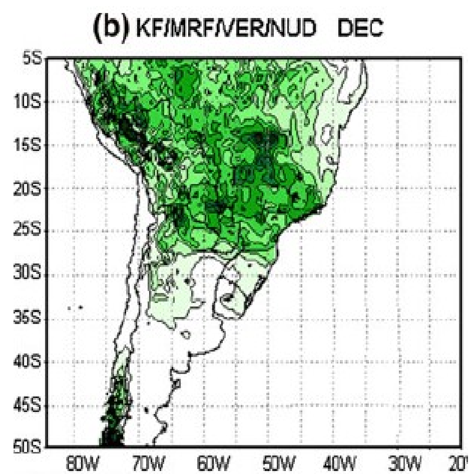




<u>Observations</u>

Precipitation driven by low level moisture convergence





<u>KF</u>

Best performing (precip) cumulus scheme.

Moisture flow greatly improved by grid nudging the wind over the PBL.

Solman & Pessacg, 2012

Summary

- Parameterization uncertainty accounts for a large fraction of RCM uncertainty
- The best parameterization set in a climate sense cannot be found (depends on … too many things)
- The most influential parameterized processes are also variable-dependent and their relative importance changes under CC conditions.
- Observational uncertainty is large. Model rankings make less sense
- Looking beyond mean precipitation and temperature can unveil error cancellation and right results for the wrong reason

Thank you!

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CORDEX WRF .ES
CGL2010-22158-C02-01
GOBIERNO DE ESPAÑA
MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

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