Downscaling climate information

Jesús Fernández

Jesus.Fernandez@unican.es

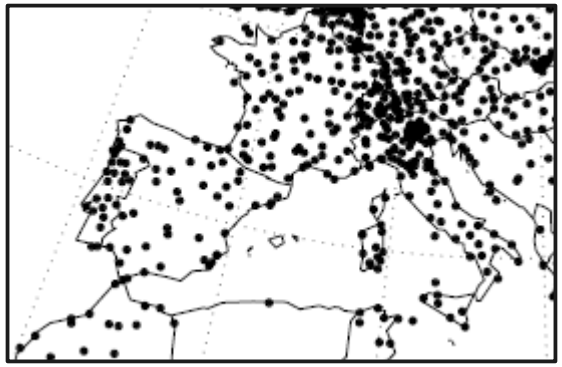
Meteorology Group
Universidad de Cantabria
Dept. Matemática Aplicada y CC Comp.

Downscaling climate information

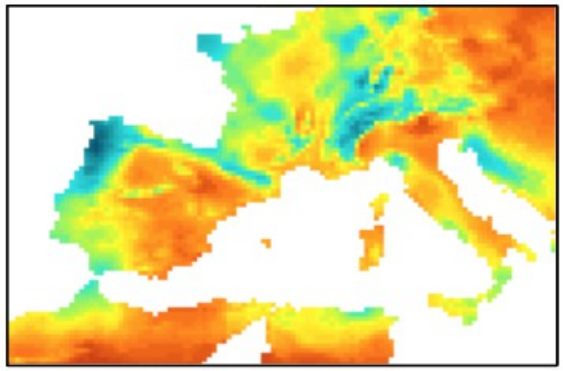
- Downscaling: why?
- Approaches: dynamical vs statistical DS
- Uncertainties
- DS initiatives / data sources
  - CORDEX, VALUE, Escenarios-PNACC 2012

Observations & models

"real" World

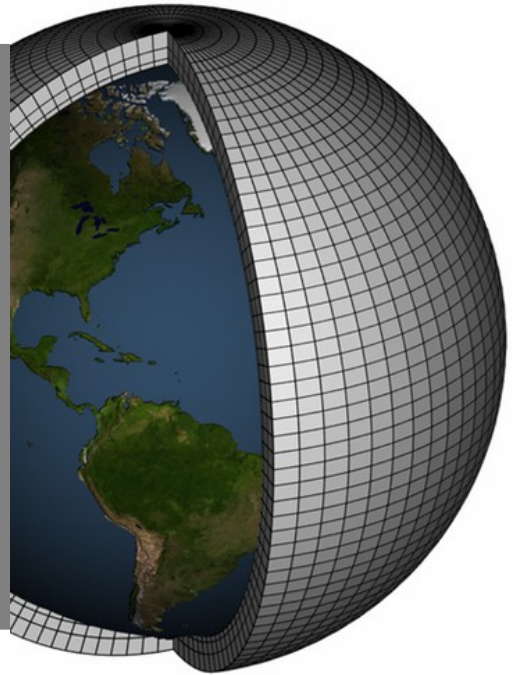


Point observations

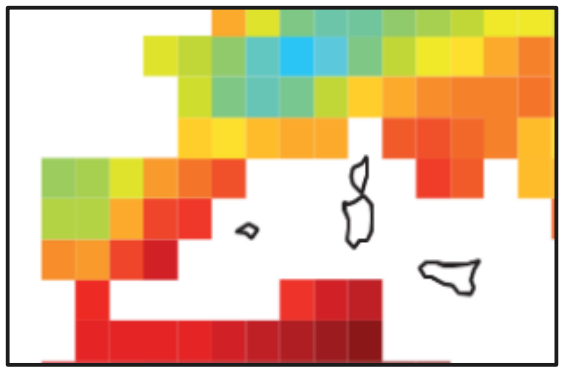


→ Gridded obs-based products

Model World



Average grid-cell values



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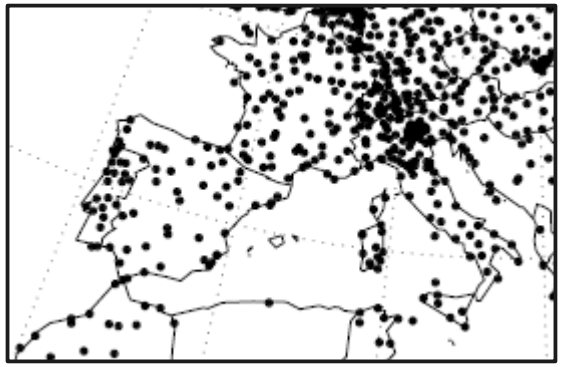
Observations & models

"real" World



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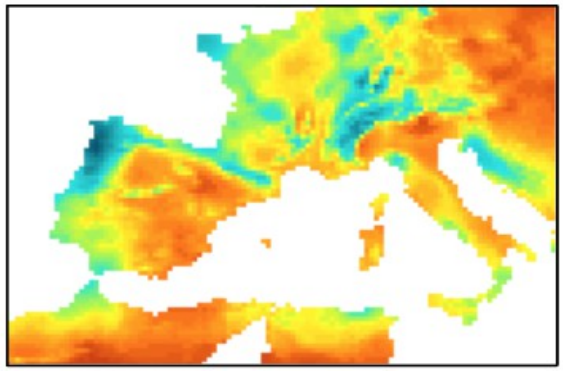

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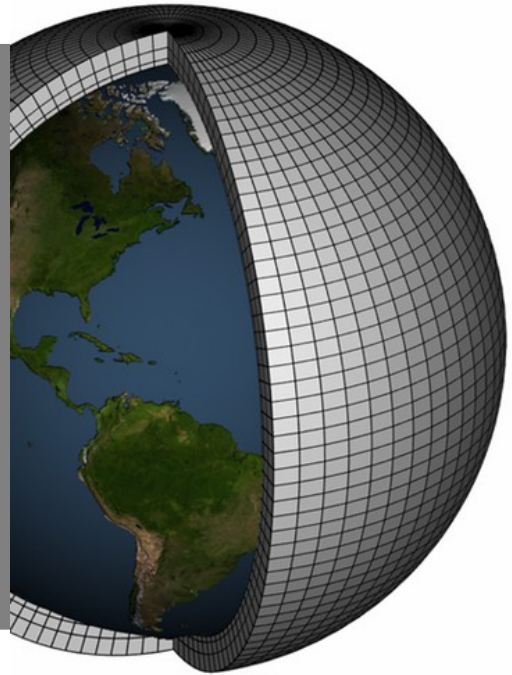
Downscaling

Model World



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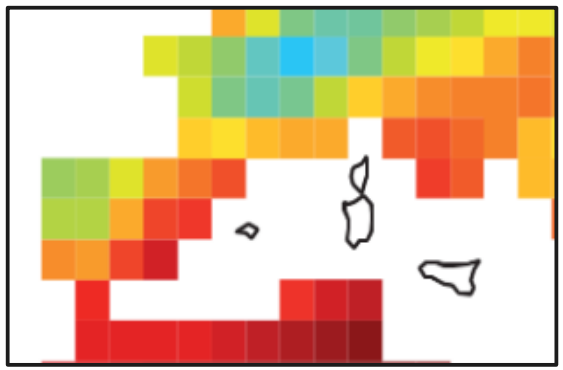
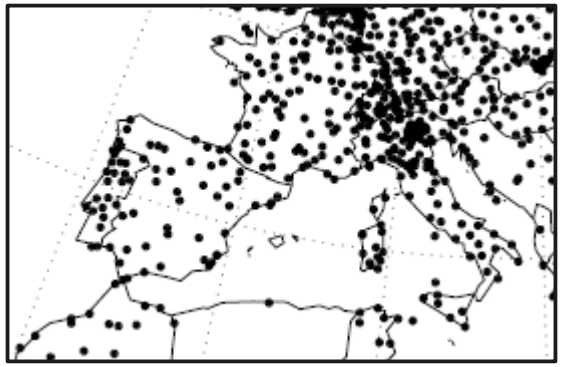


Observations & models

"real" World



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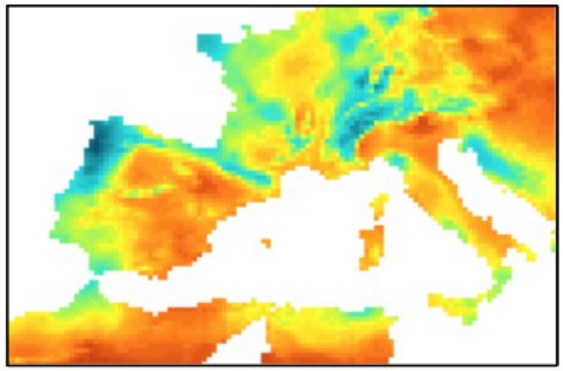

→ Gridded obs-based products

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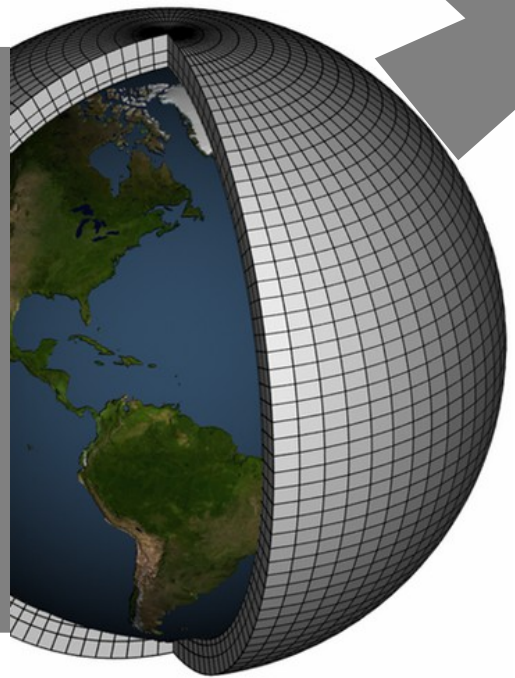
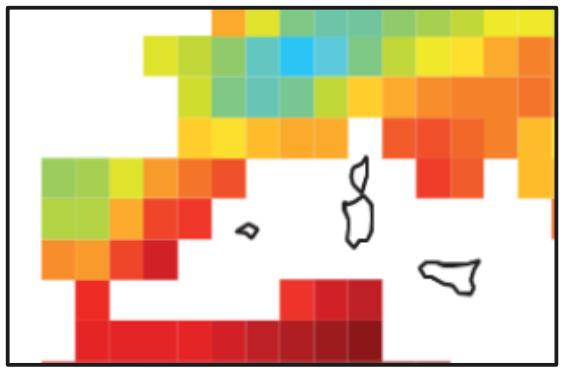
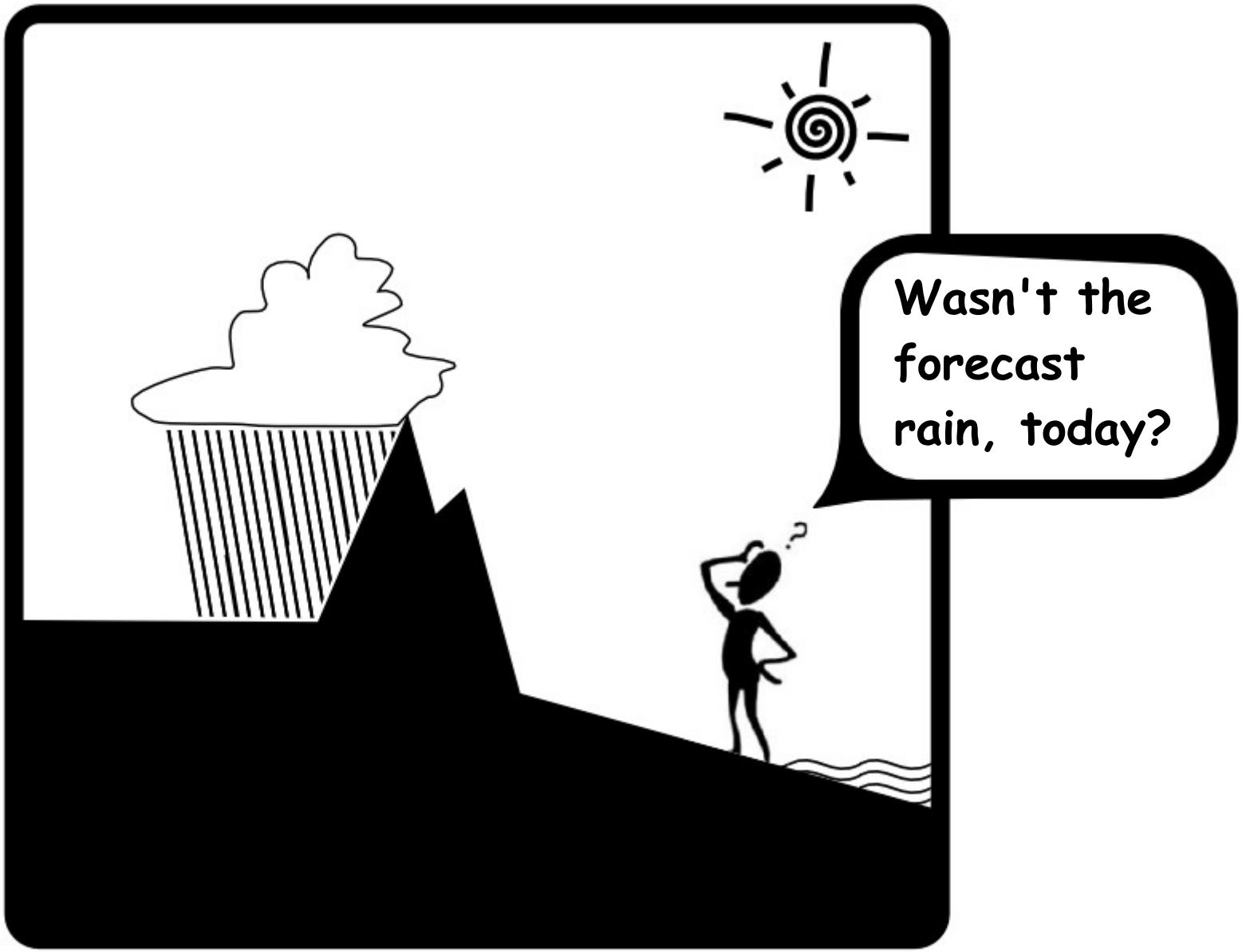


(Re)Analysis

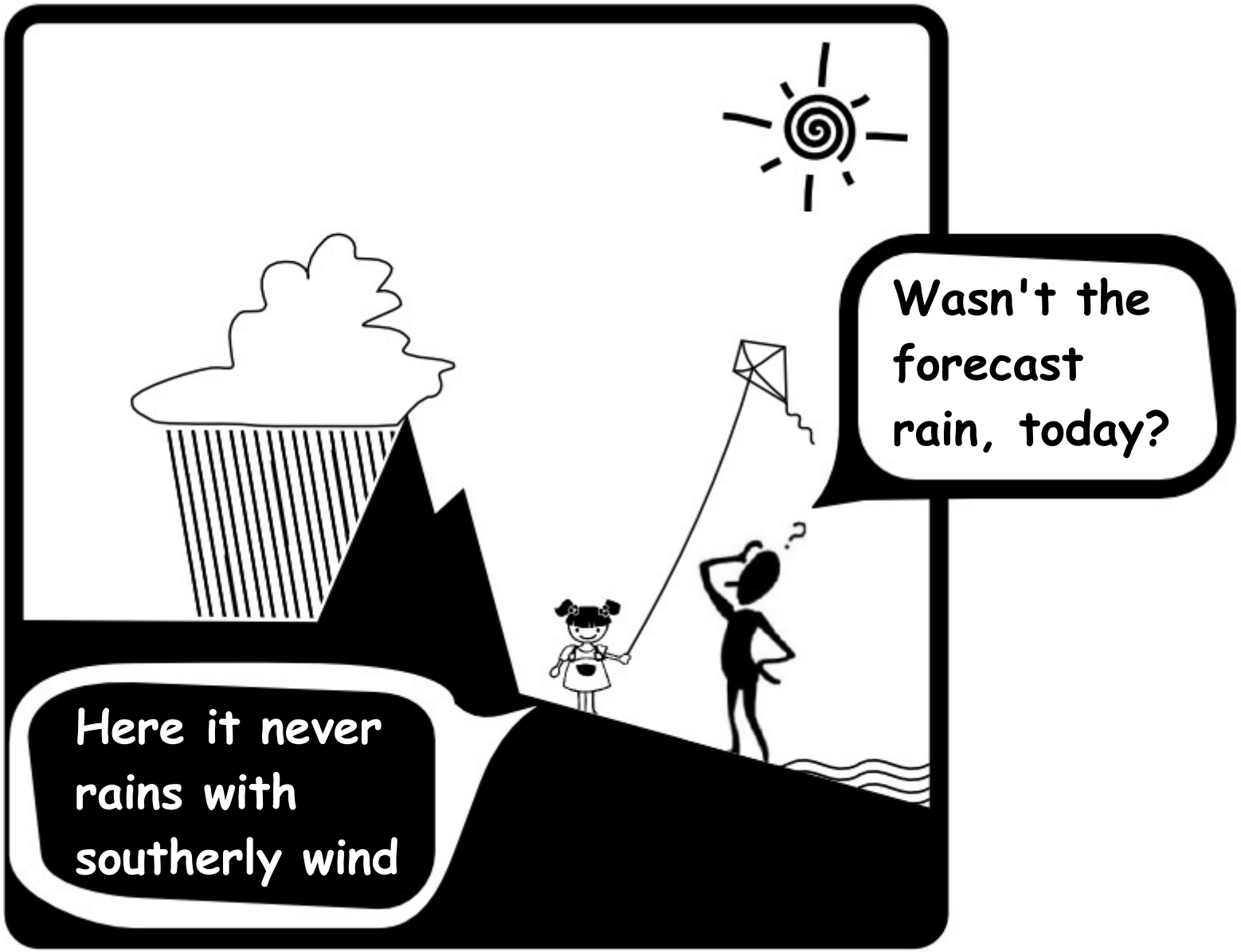
Average grid-cell values



Life in a model grid cell



Statistical downscaling



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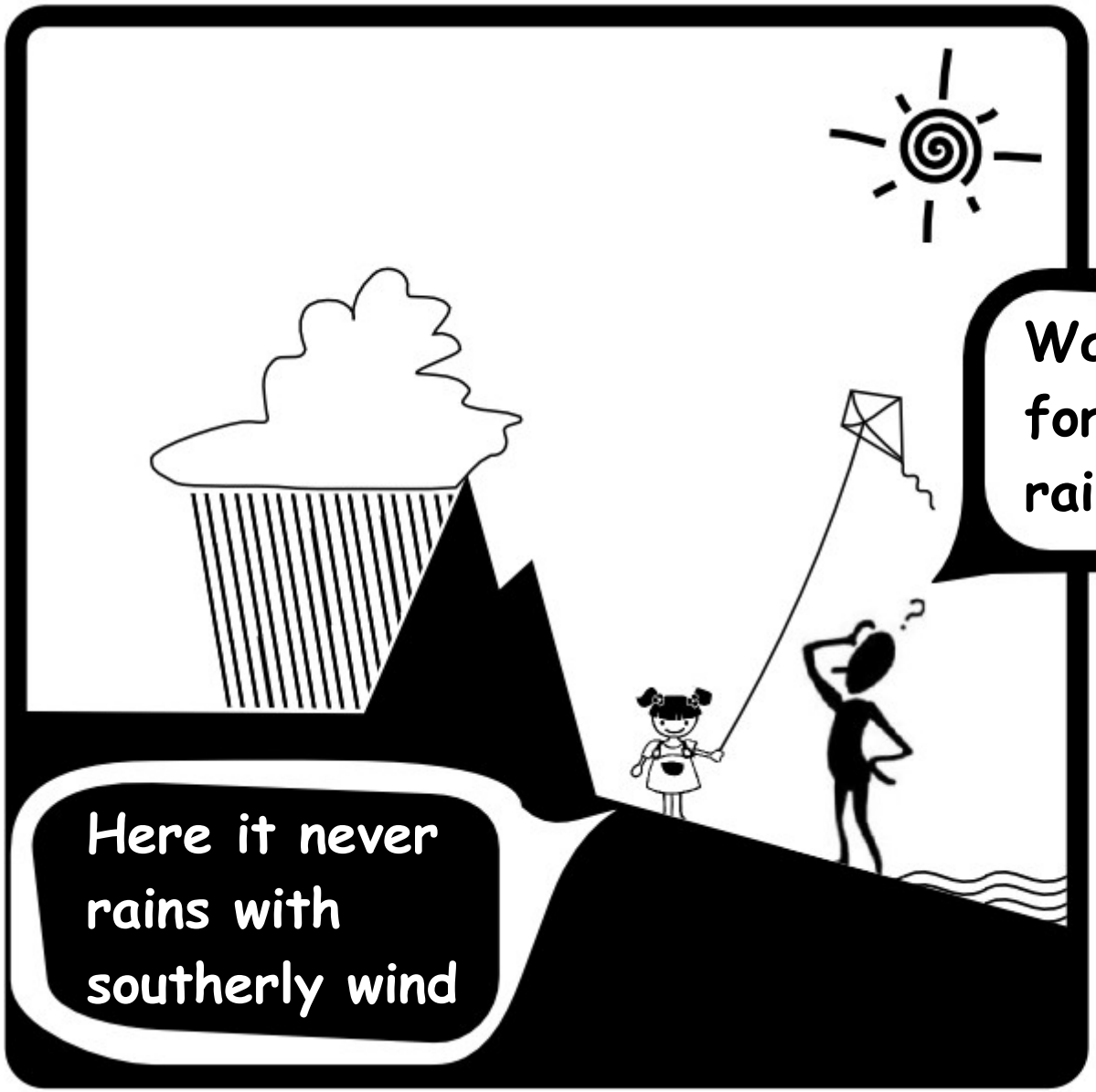
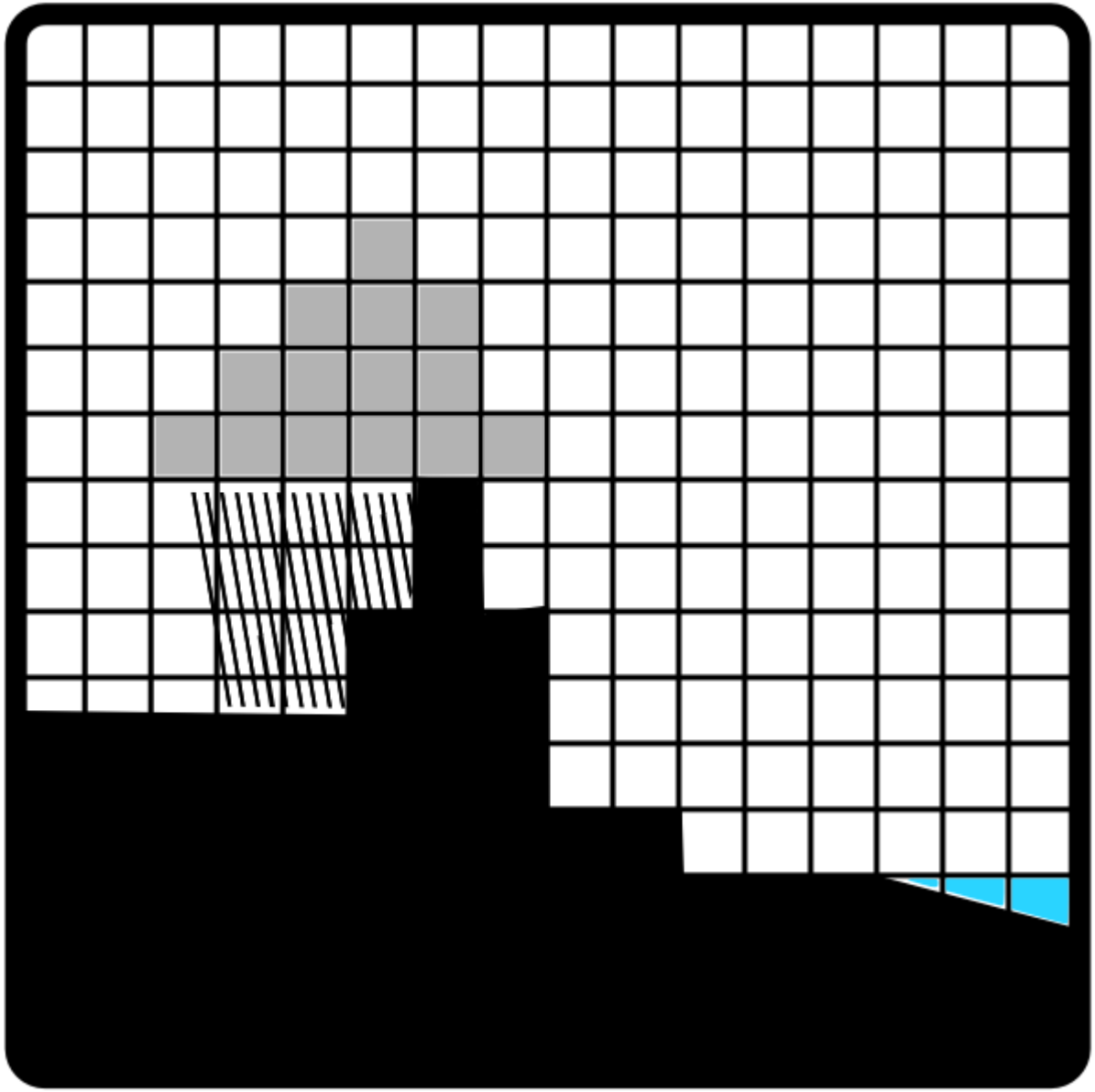


Obs. Model

$$Y = f(X; c)$$

Local forecast

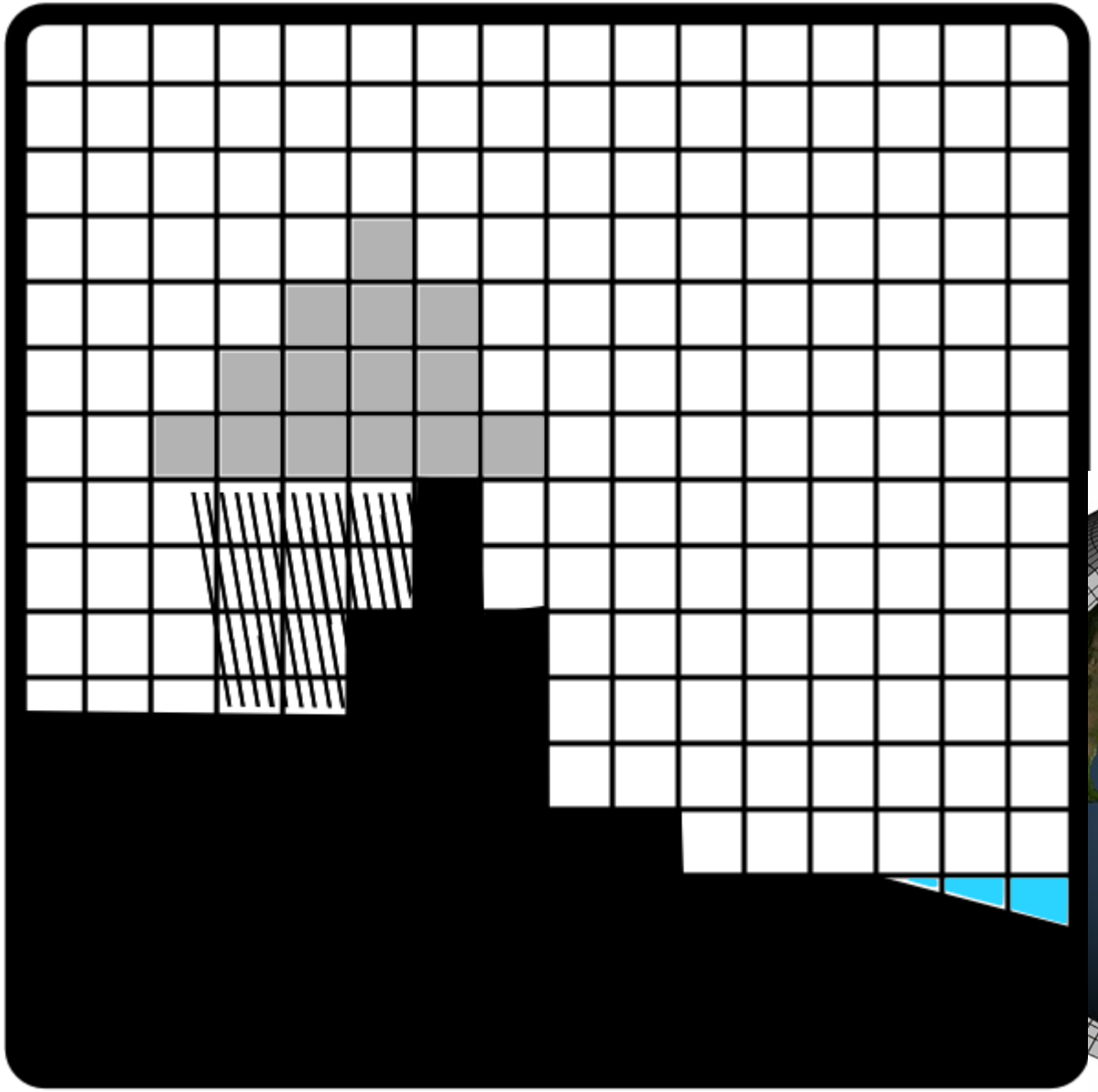
Dynamical downscaling



In this example, computing time would increase by a factor ~15000

1h → 2 years

Dynamical downscaling



In this example, computing time would increase by a factor ~15000

1h → 2 years

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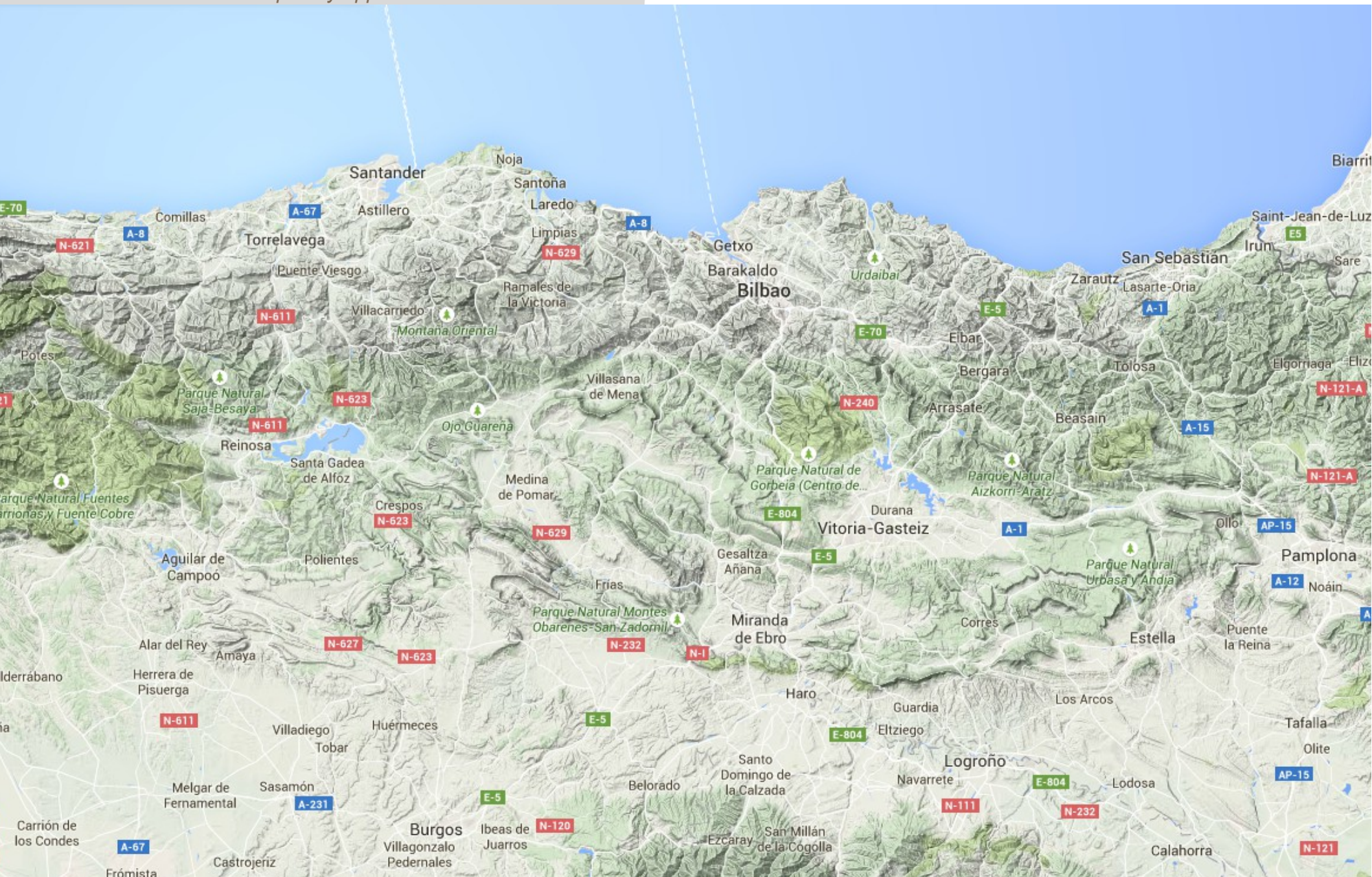
How big are model grid cells?



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Short range forecasts

15 km (~Operational ECMWF forecast)

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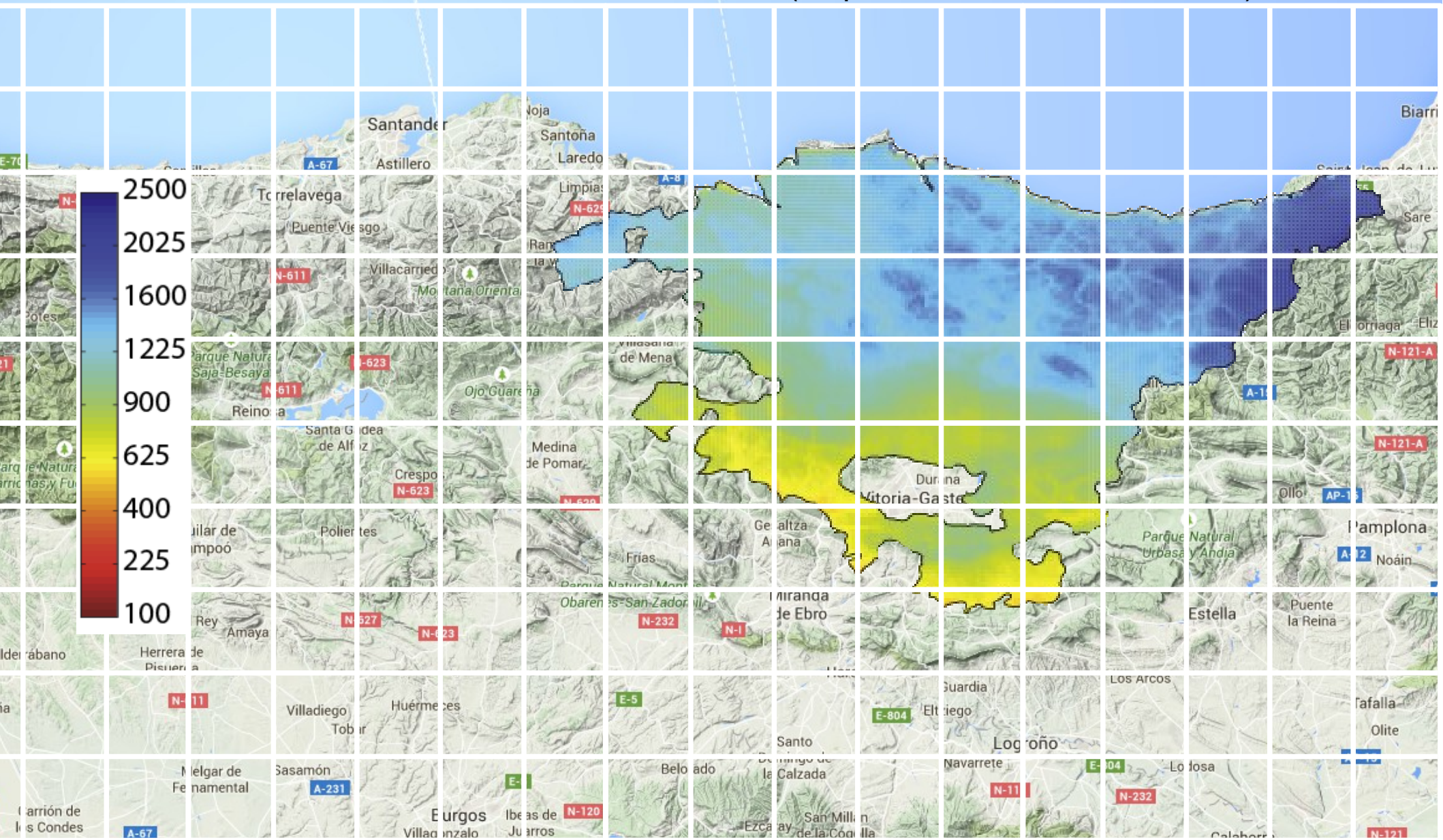

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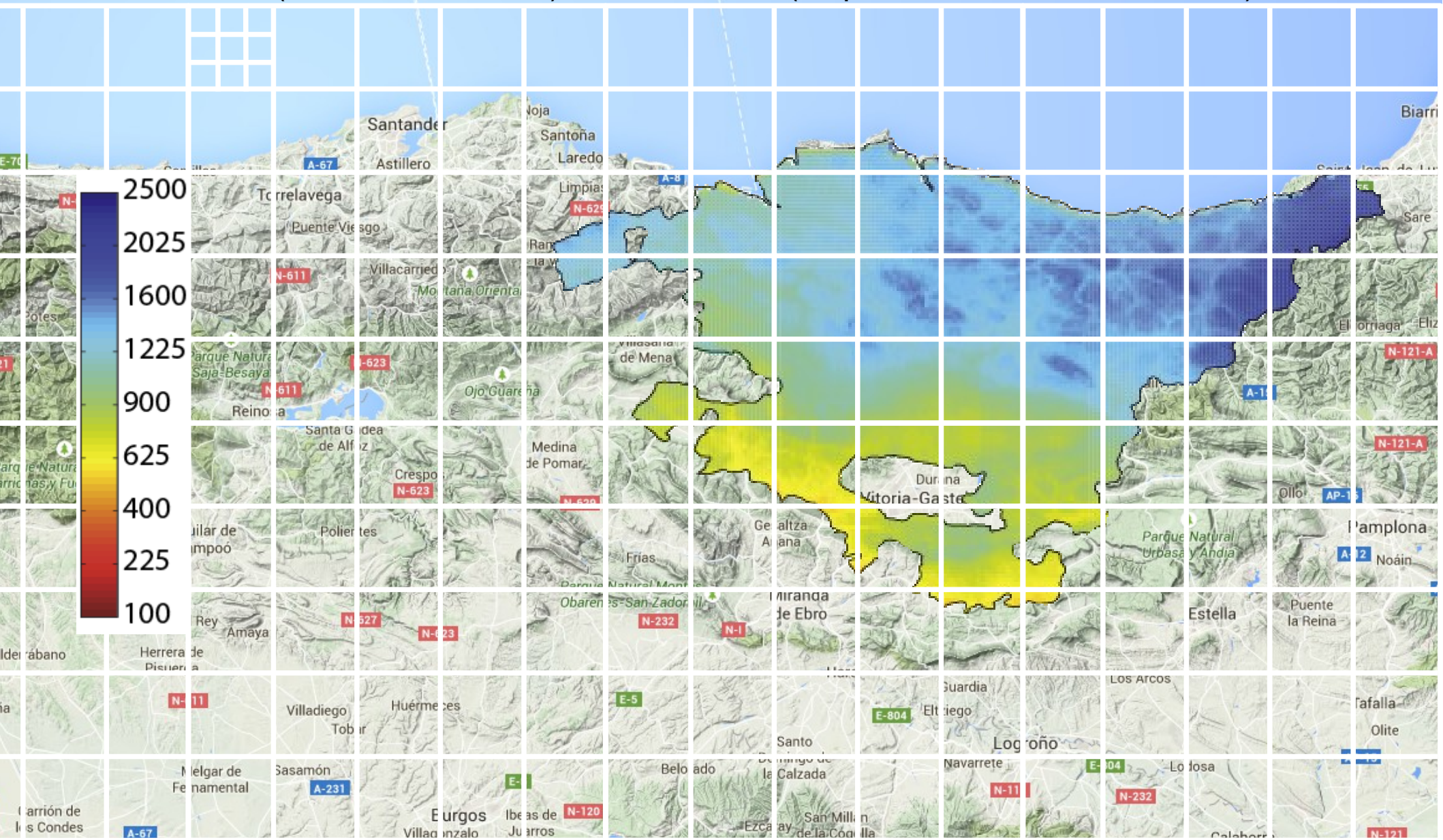
Short range forecasts

5 km (~AEMET HIRLAM)

15 km (~Operational ECMWF forecast)



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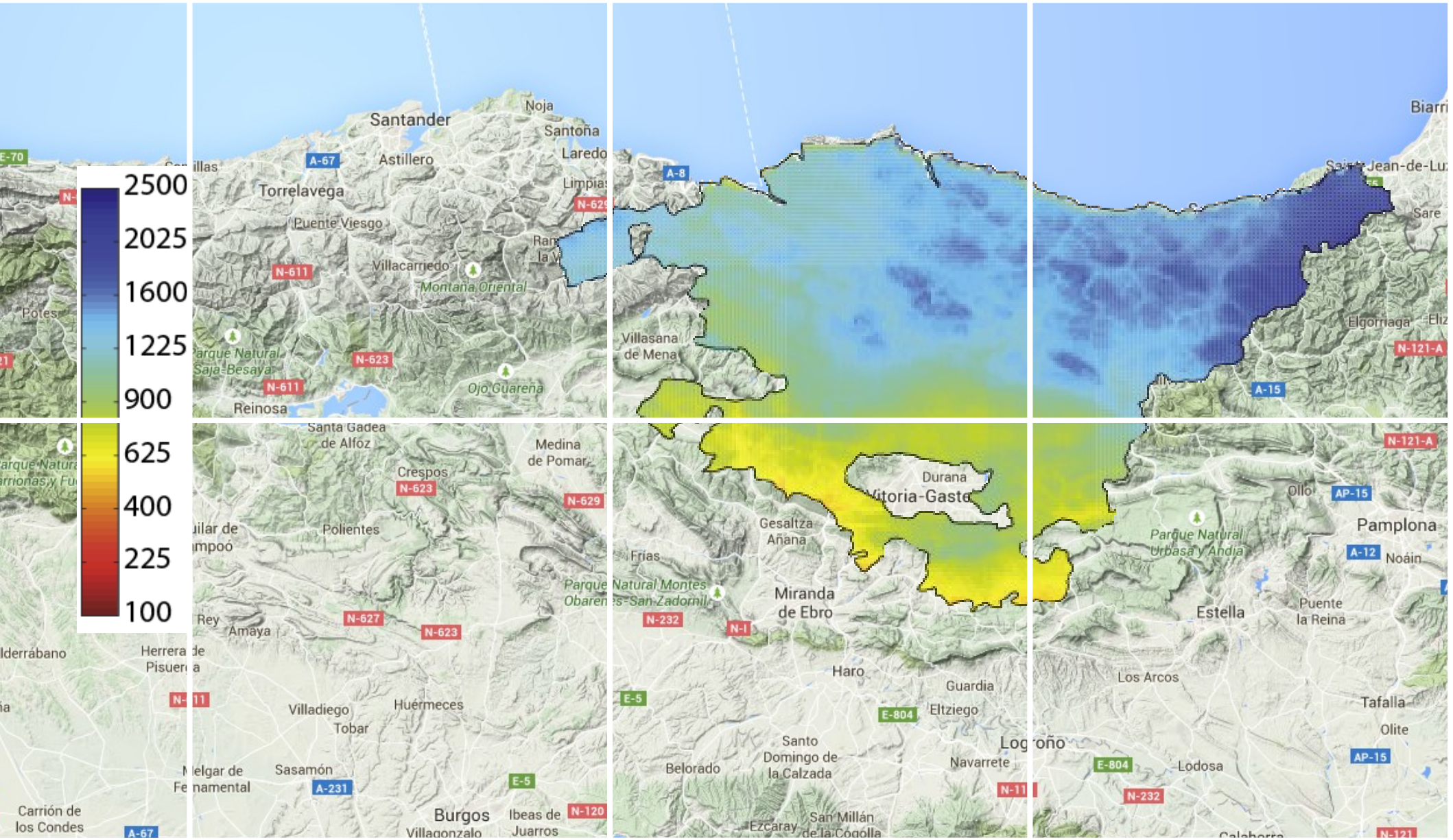
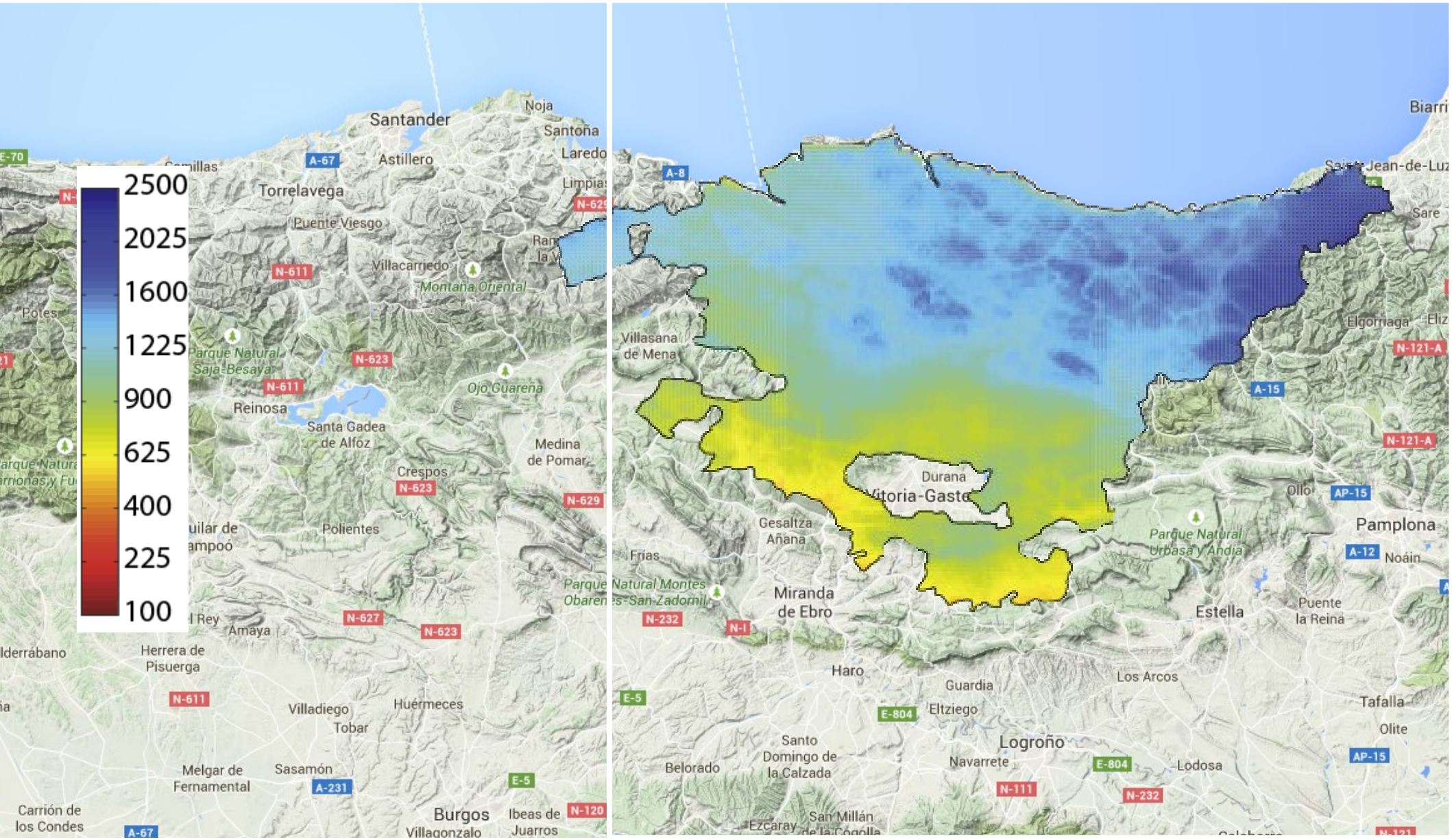
Reanalyses/Seasonal forecasts

75 km (~ERA-Interim / System4)



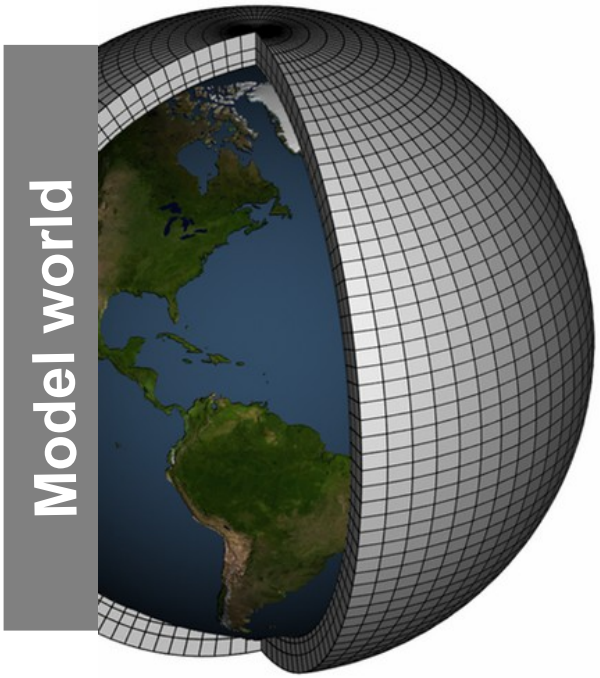
Climate change projections

150 km (AR4 → AR5 GCMs)



Downscaling

- *Downscaling* techniques try to adapt the coarse global model output to the local features of a given region.



Downscaling

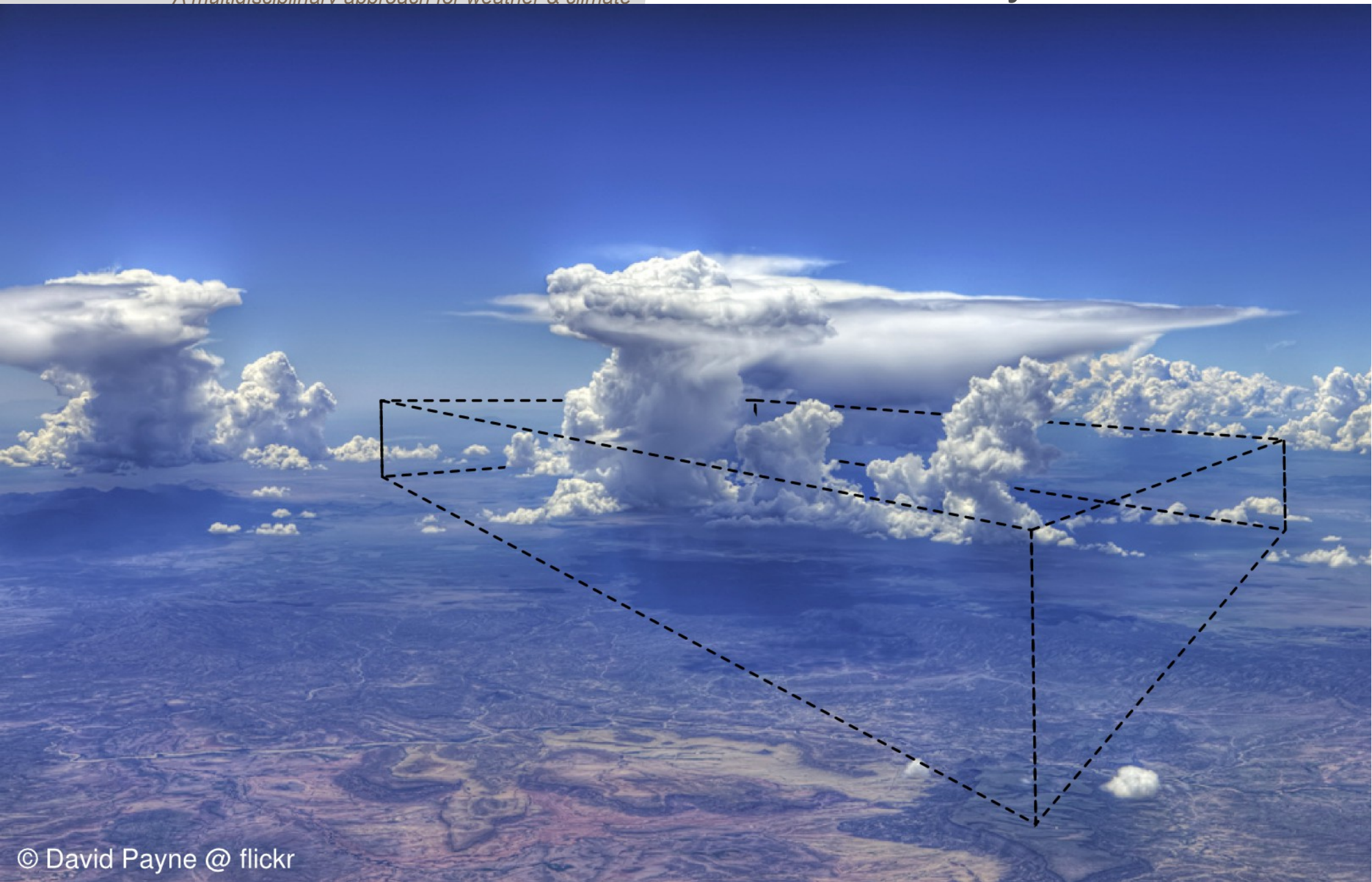
- *Downscaling* techniques try to adapt the coarse global model output to the local features of a given region.

- This can be achieved through dynamical techniques, which solve numerically the governing equations of the atmosphere on a finer grid,

$$
\begin{aligned}
\frac{d\vec{v}}{dt} &= -\frac{1}{\rho}\vec{\nabla}p - \vec{\nabla}\phi + \vec{F} - 2\vec{\Omega}\times\vec{v} \\
\frac{\partial\rho}{\partial t} &= -\vec{\nabla}\cdot(\rho\vec{v}) \\
p &= \rho RT \\
Q &= C_p\frac{dT}{dt} - \frac{1}{\rho}\frac{dp}{dt} \\
\frac{\partial\rho q}{\partial t} &= -\vec{\nabla}\cdot(\rho q\vec{v}) + \rho(E-C)
\end{aligned}
$$

The most common are **nested RCMs**

Not seen by a GCM / RCM



© David Payne @ flickr

Physical parameterizacions

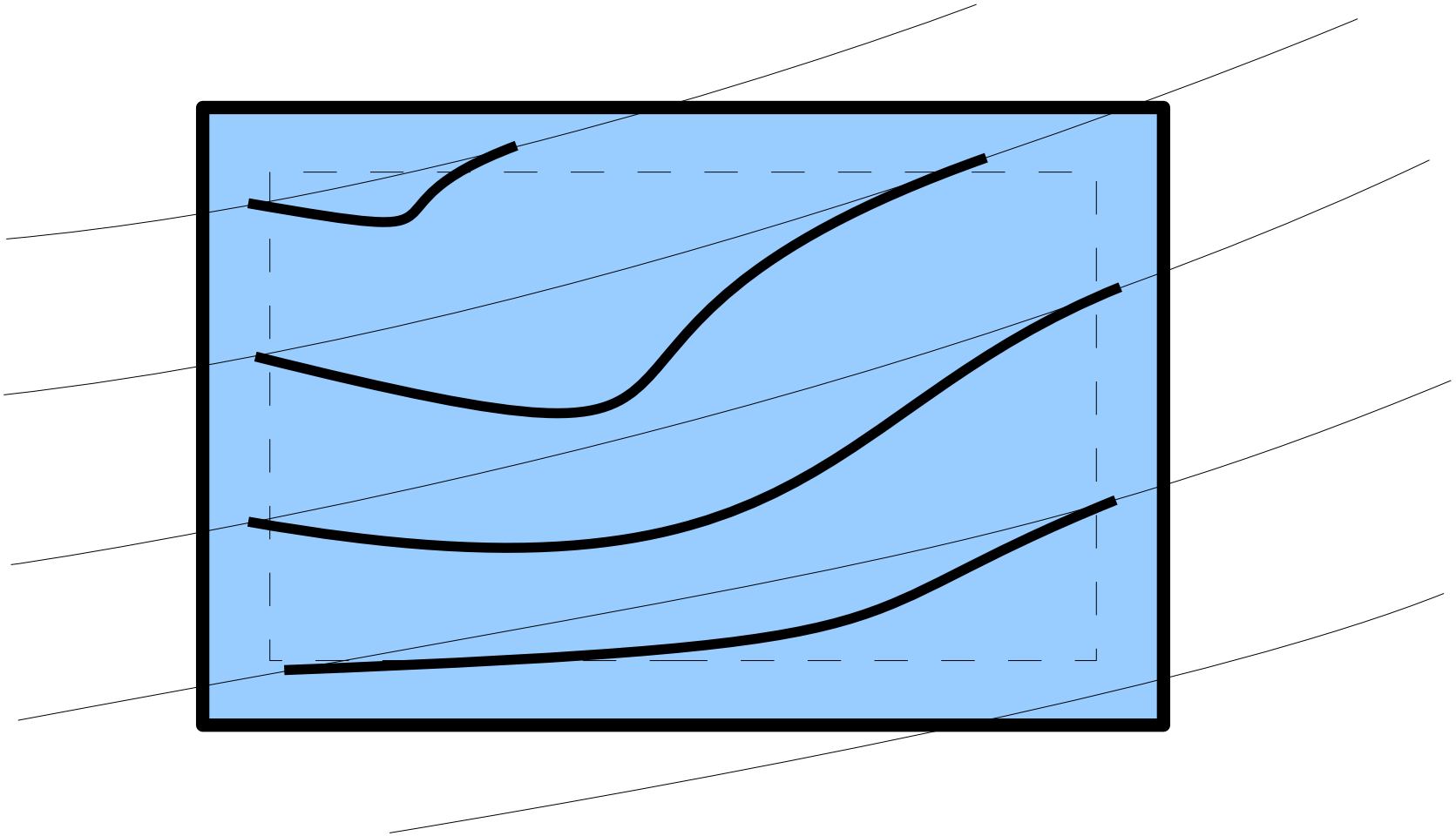
A parameterization is a **statistical** representation of the **net effect** of processes occurring on **spatial scales smaller than the grid** spacing of a dynamical model (GCM, RCM, CRM, LES, …) **on mean variables** at each grid cell.

Parameterizations are based on the **physics** of the processes, plus **simplifying (closure) assumptions** to relate unknown variables to prognostic (mean) model variables.

Parameters are obtained from:

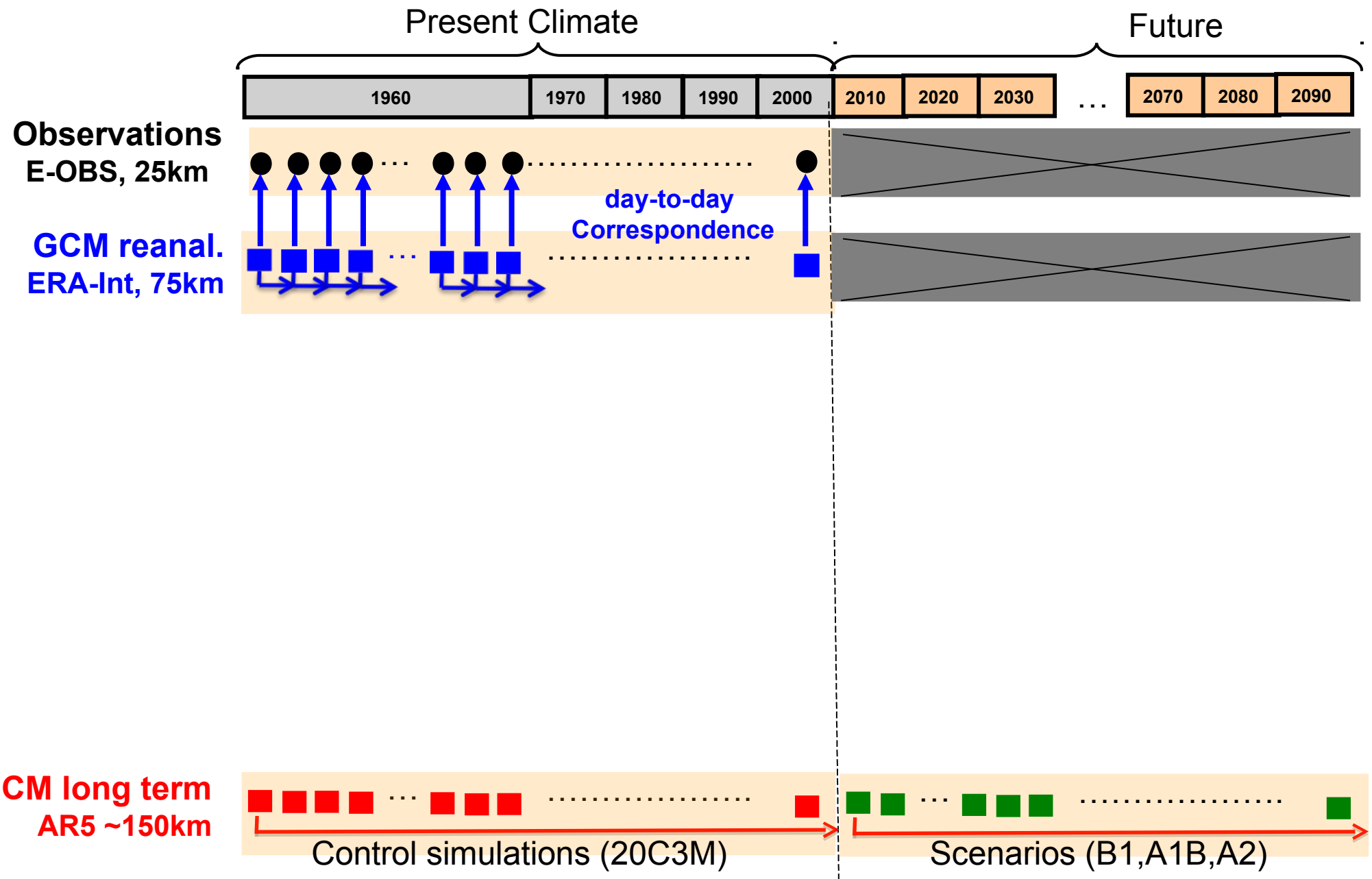
- Theory (e.g. known physical constants)
- Field campaigns
- Higher resolution models (CRM, LES)

RCM domain



Nested RCMs require **boundary conditions**
(values meteorological variables at the borders of the domain)
provided by reanalysis or GCM data.

Dynamical downscaling (Climate change)



Dynamical downscaling (Climate change)

Present Climate

Future

1960 1970 1980 1990 2000 2010 2020 2030 … 2070 2080 2090

Observations
E-OBS, 25km

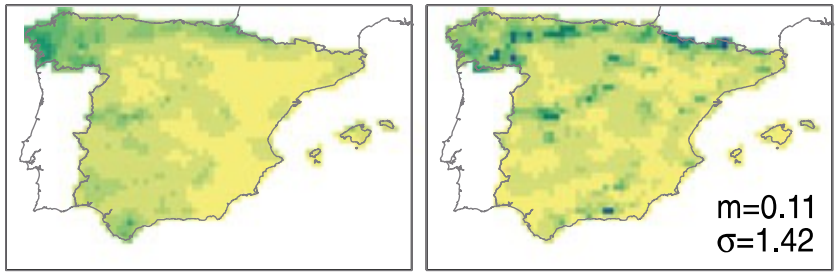
GCM reanal.
ERA-Int, 75km

RCMs
EURO-CDX 12km

day-to-day Correspondence

RCM VALIDATION OPTIMAL CONDITIONS

(a) Spain02 (b) DMI-ERA40



GCM long term
AR5 ~150km

Control simulations (20C3M)

Scenarios (B1,A1B,A2)

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Dynamical downscaling (Climate change)

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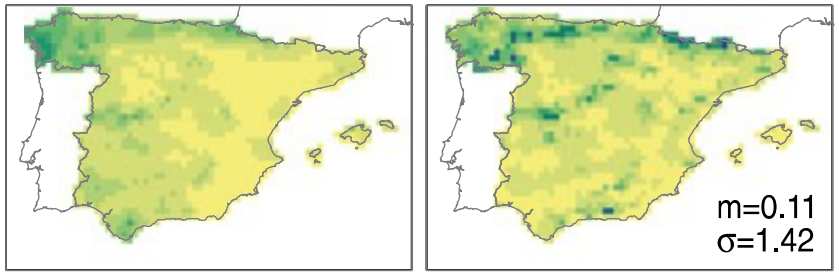

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EURO-CDX 12km

VALIDATION RCM-GCM

RCM VALIDATION OPTIMAL CONDITIONS

(a) Spain02

(b) DMI-ERA40

m=0.11
σ=1.42

(g) DMI-ARPEGE

m=-0.03
σ=1.18

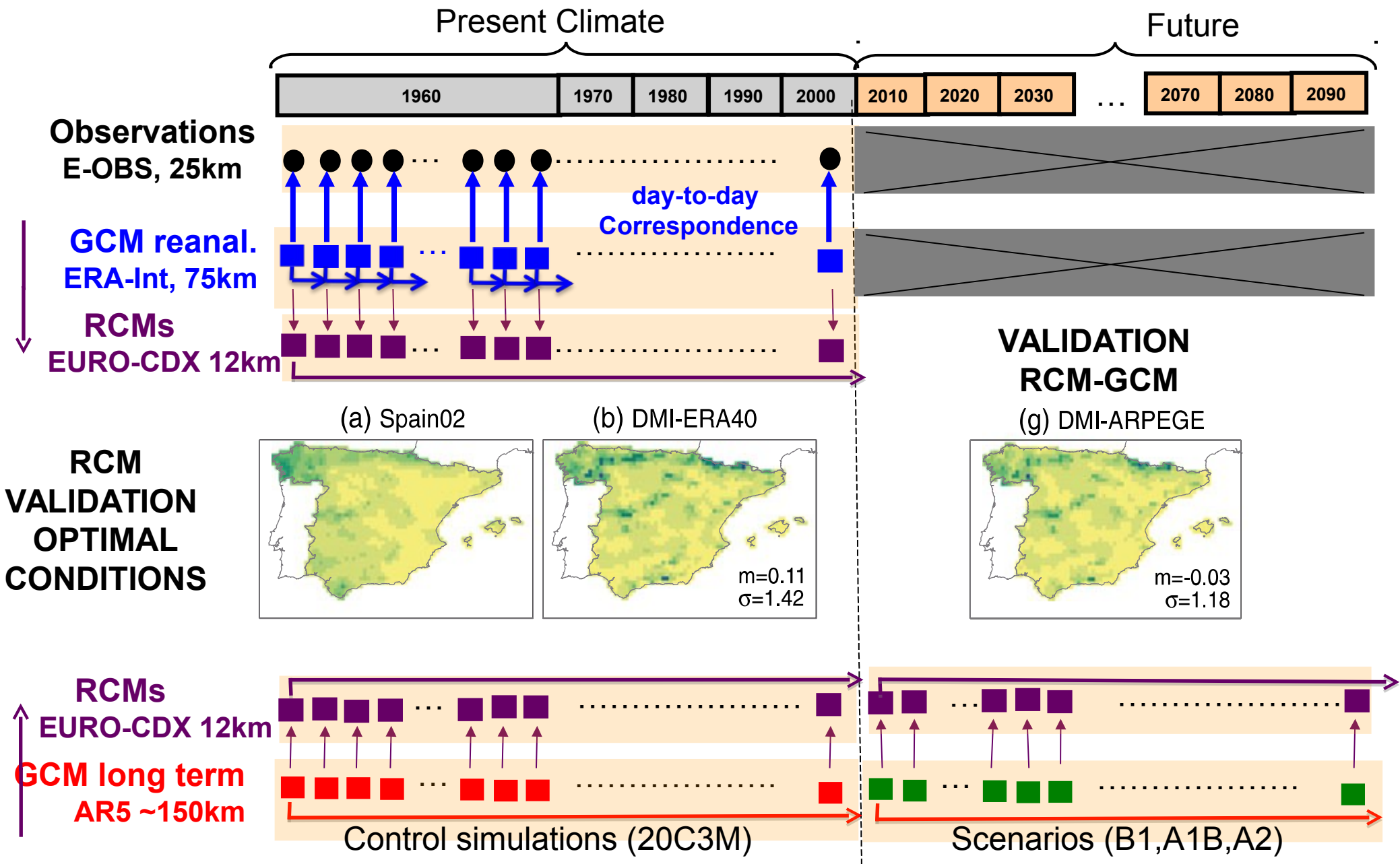
RCMs
EURO-CDX 12km

GCM long term
AR5 ~150km

Control simulations (20C3M)

Scenarios (B1,A1B,A2)

Dynamical downscaling (Climate change)



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Dynamical downscaling (Climate change)

Present Climate

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EURO-CDX 12km

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PROJECTION DELTA-METHOD

RCM VALIDATION OPTIMAL CONDITIONS

(a) Spain02

(b) DMI-ERA40

m=0.11
σ=1.42

r=0.72
m=-2.74

60%
40%
20%
0%
-20%
-40%
-60%

RCMs
EURO-CDX 12km

GCM long term
AR5 ~150km

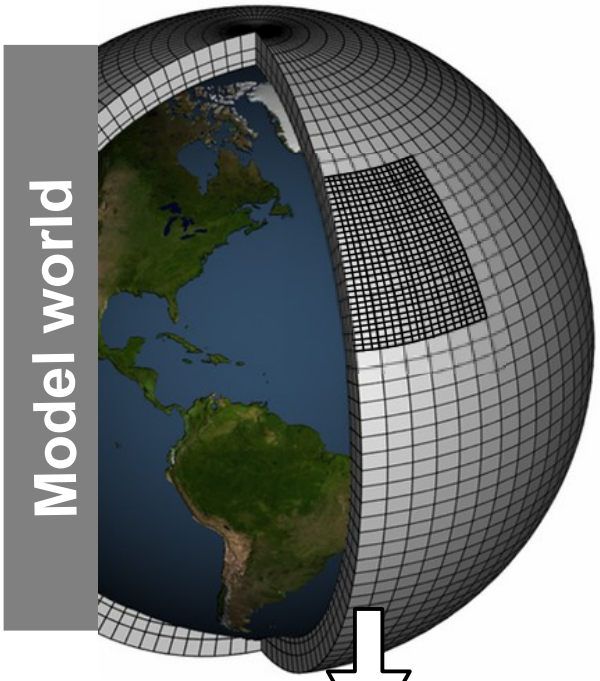
Control simulations (20C3M)

Scenarios (B1,A1B,A2)

Downscaling

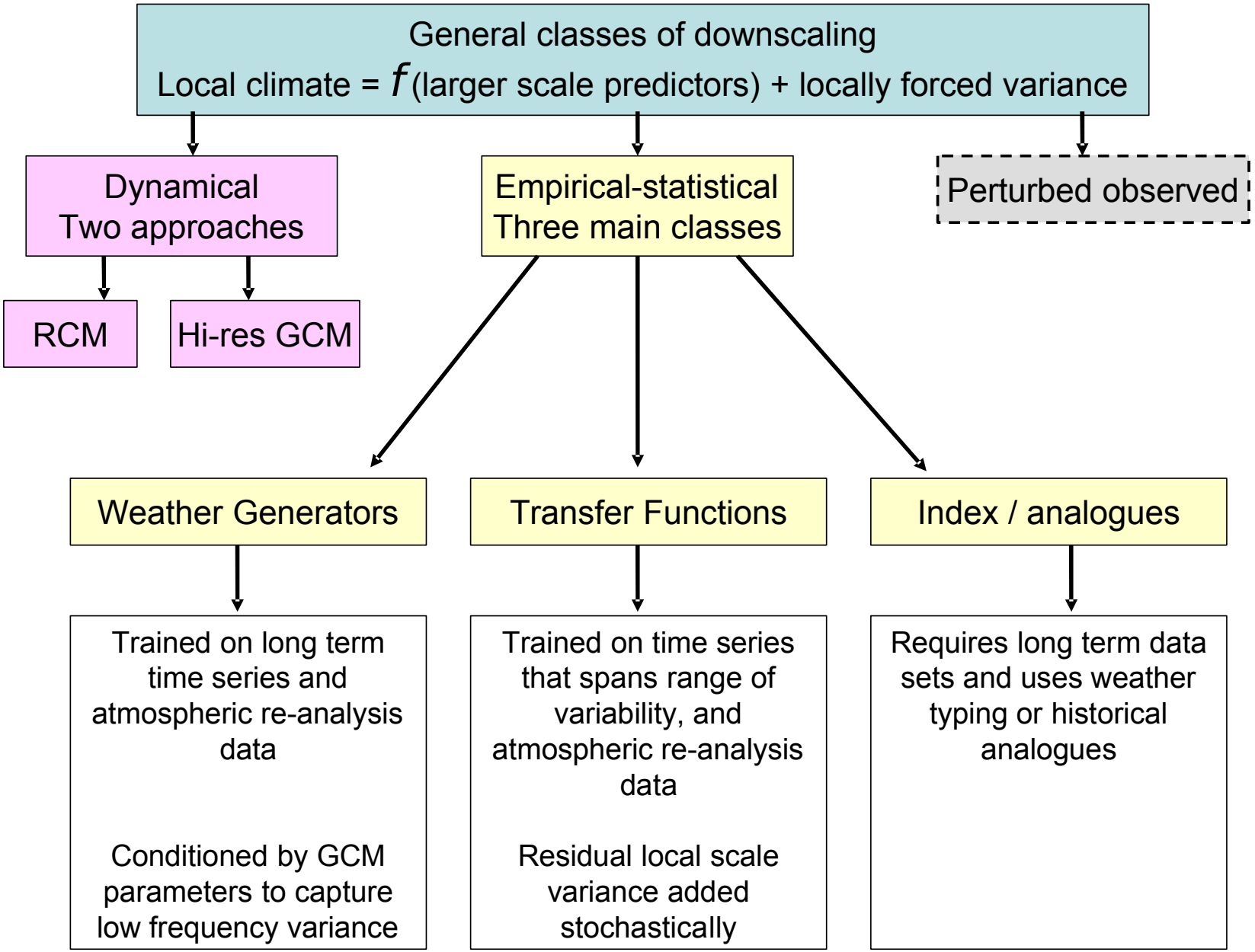
- *Downscaling* techniques try to adapt the coarse global model output to the local features of a given region.

- This can be achieved through dynamical techniques, which solve numerically the governing equations of the atmosphere on a finer grid,
- or by statistical techniques, which seek empirical relationships between local and large-scale variables.



$$Y = f(X; c)$$

DS techniques



Source:
Bruce Hewitson
(CSAG)

Statistical downscaling approaches

Perfect Prognosis (PP)

Calibrated in the training phase using observational data for both the predictands and predictors (reanalysis). Since different GCMs are used in the training and downscaling phases, large-scale circulation variables well-resolved by the models are typically chosen as predictors in this approach. Variables directly influenced by model parameterizations and orography are not suitable predictors in this approach.

PP	Training	Downscaling
Large scale	Obs.	GCM
Local scale	Obs.	→

Typical predictors

ELSEVIER
Journal of Hydrology
Volume 225, Issues 1–2, 22 November 1999, Pages 67–91

A comparison of downscaled and raw GCM output: implications for climate change scenarios in the San Juan River basin, Colorado

R.L. Wilby[a, b], L.E. Hay[c], G.H. Leavesley[c]

Predictor variable	Abbrevation
Surface variables	
*Mean sea level pressure	mslp
Zonal velocity component	Us
Meridional velocity component	Vs
Strength of the resultant flow (hPa)	Fs
Vorticity (hPa)	Zs
Divergence (hPa)	Ds
2 m temperatures (°C)	T2m
Relative humidities (%)	RH
*Specific humidity (gm/kg)	SH
Upper-atmosphere variables (500 hPa)	
*500 hPa geopotential heights (m)	H
Zonal velocity component	Uu
Meridional velocity component	Vu
Strength of the resultant flow (hPa)	Fu
Vorticity (hPa)	Zu
Divergence (hPa)	Du

ELSEVIER
Available online at www.sciencedirect.com
ScienceDirect
Environmental Modelling & Software 23 (2008) 813–834
Environmental Modelling & Software
www.elsevier.com/locate/envsoft

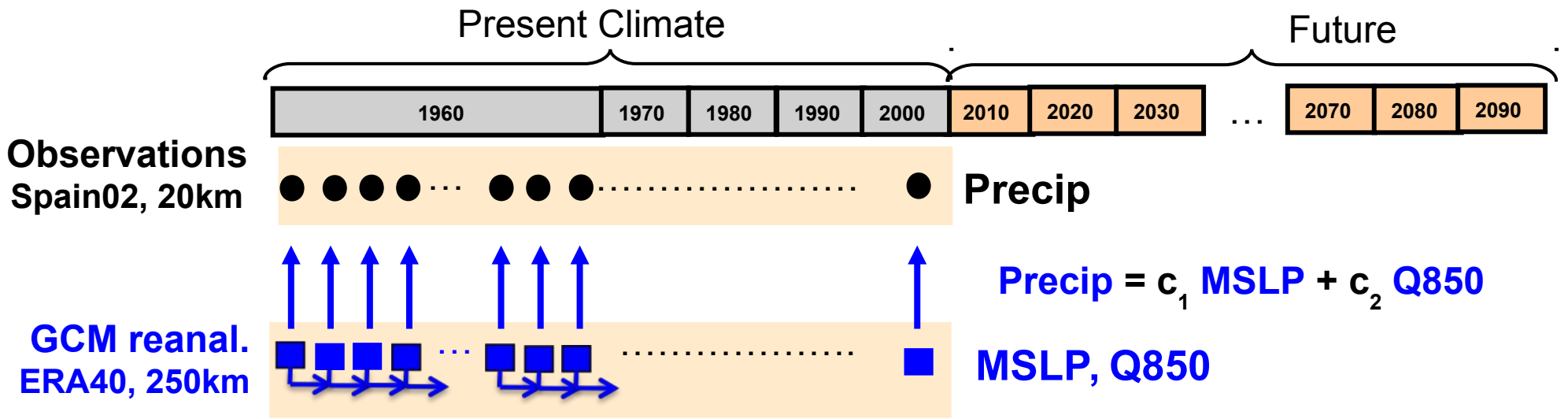
Automated regression-based statistical downscaling tool

Masoud Hessami [a,*], Philippe Gachon [b,c], Taha B.M.J. Ouarda [d], André St-Hilaire [d]

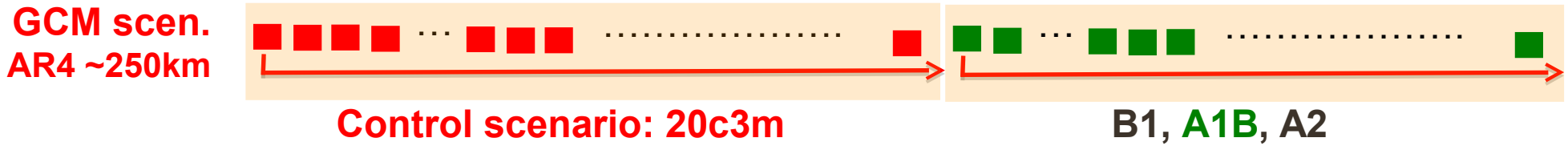
Table 1
NCEP predictor variables on CGCM1 grid

No.	Predictors	No.	Predictors
1	Mean sea level pressure	14	500 hPa divergence
2	Surface airflow strength	15	850 hPa airflow strength
3	Surface zonal velocity	16	850 hPa zonal velocity
4	Surface meridional velocity	17	850 hPa meridional velocity
5	Surface vorticity	18	850 hPa vorticity
6	Surface wind direction	19	850 hPa geopotential height
7	Surface divergence	20	850 hPa wind direction
8	500 hPa airflow strength	21	850 hPa divergence
9	500 hPa zonal velocity	22	Near surface relative humidity
10	500 hPa meridional velocity	23	Specific humidity at 500 hPa
11	500 hPa vorticity	24	Specific humidity at 850 hPa
12	500 hPa geopotential height	25	Near surface specific humidity
13	500 hPa wind direction	26	Mean temperature at 2 m

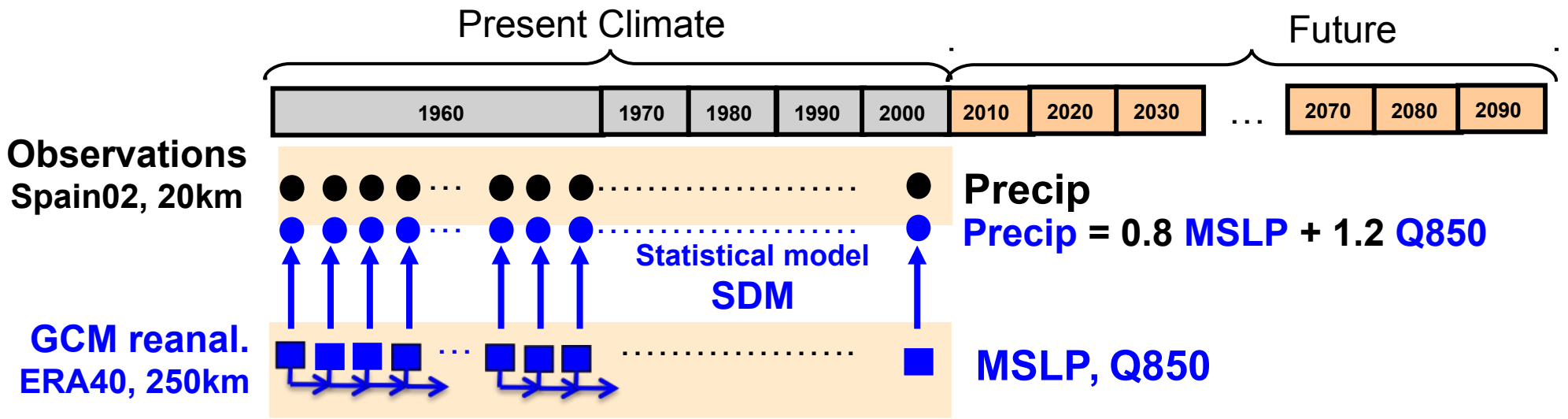
Statistical downscaling (Perfect Prog training)



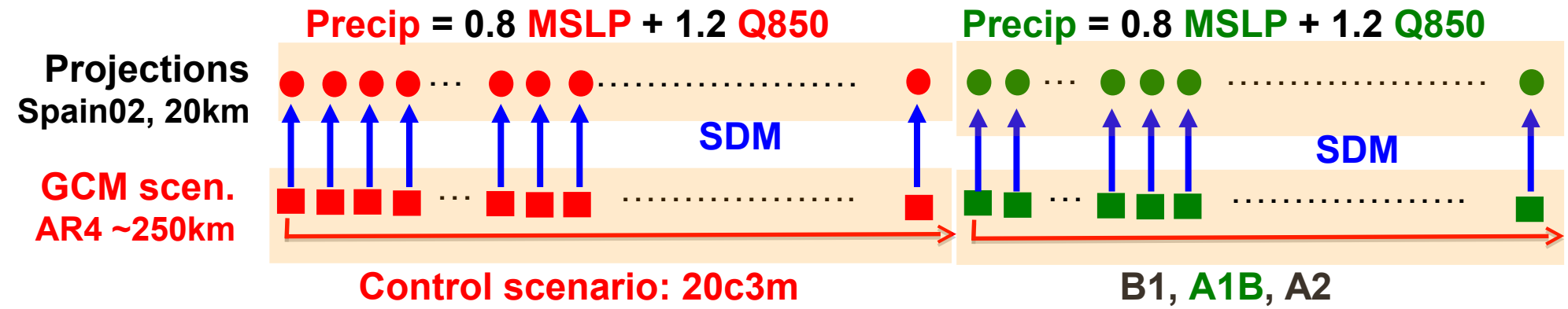
- **Assumption 1:** Reanalysis choice
- **Assumption 2:** Choosing consistent predictors:



Statistical downscaling (Perfect Prog application)



- **Assumption 1:** Reanalysis choice
- **Assumption 2:** Choosing consistent predictors:
- **Assumption 3:** Stationarity/robustness: SDM SDM



Statistical downscaling approaches

Model Output Statistics (MOS)

Predictors are taken from the global (or regional) model for both training and downscaling phases. They require the model output to have day-to-day correspondence with observations. These methods can work with the variable of interest as predictor. For instance, local precipitation can be derived from the direct model precipitation forecasts.

MOS	Training	Downscaling
Large scale	GCM	GCM
Local scale	Obs.	→

SDS: Classification

Appro. \ Tech.		Generative		non-Generative	
		Deterministic	Stochastic	Deterministic	Stochastic
PP	Eventwise	Regression, Neural Nets.	GLMs	Analogs, weather types	Analog resampling
	Distribution	Regression on PDF parameters			
MOS	Eventwise	Regression, Neural Nets.	GLMs	Analogs	Analog resampling
	Distribution	Bias correction, parametric q-q map	Nonhomogeneous HMM	q-q map	

Source: SPECS D52.1

Pros and cons

Statistical downscaling

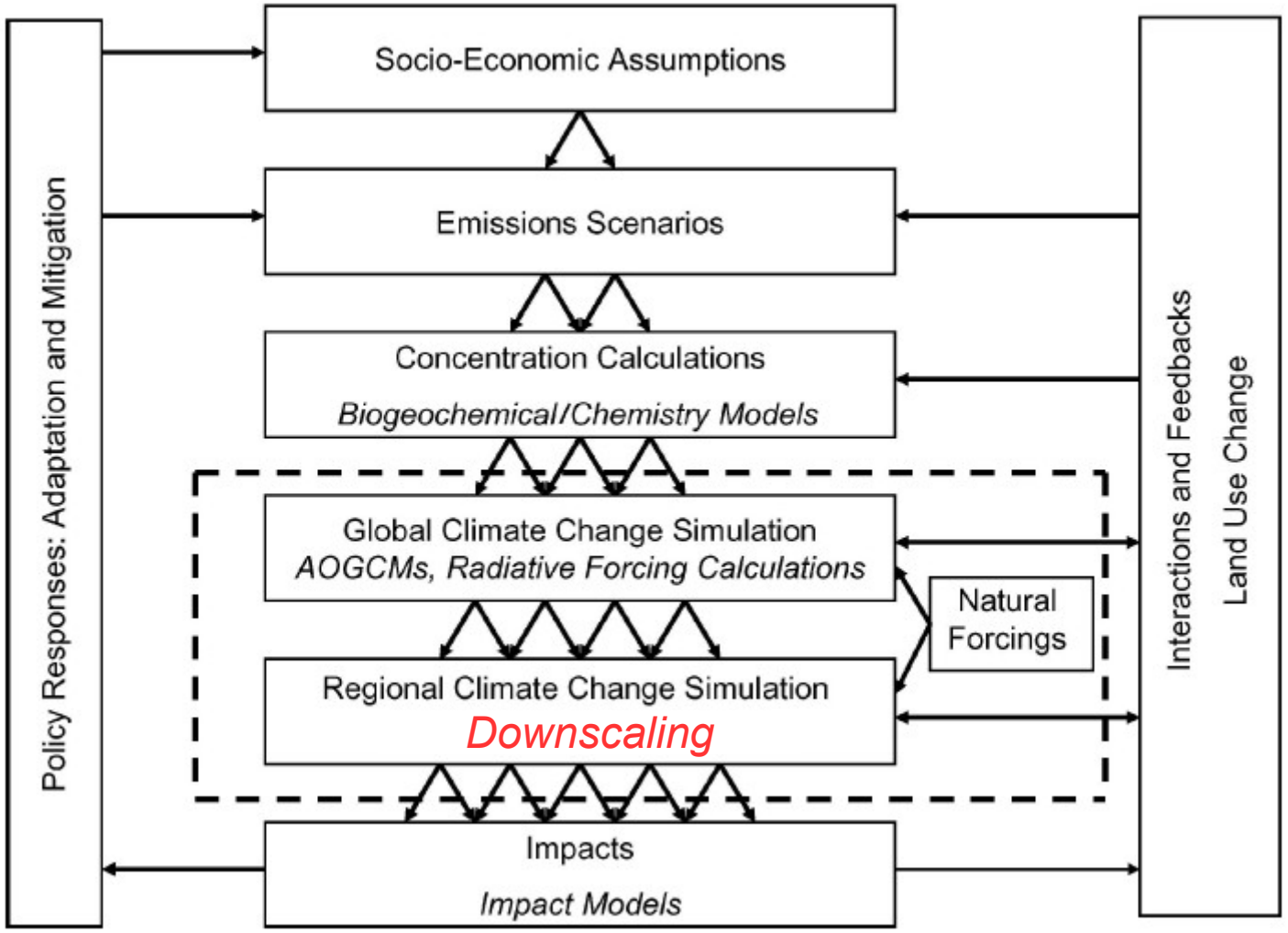
- ☹ Variables available as long as there are obs.
- ☹ Different variables probably do not keep physical or even spatial consistency
- ☹ Stationarity
- 😐 Variables keep the representativity of obs.
- ☺ Computationally cheap
- ☺ Biases are low
- ☺ Non-meteorological variables could be directly produced (e.g. impact indices) .

Pros and cons

Dynamical downscaling

- ☺ Plenty of variables, including 3D
- ☺ Subdaily data available
- ☺ Variables are physically consistent
- 😐 Variables represent areal averages
- ☹ Computationally expensive
- ☹ Biases are commonplace
- ☹ Stationarity?

Climate change uncertainties



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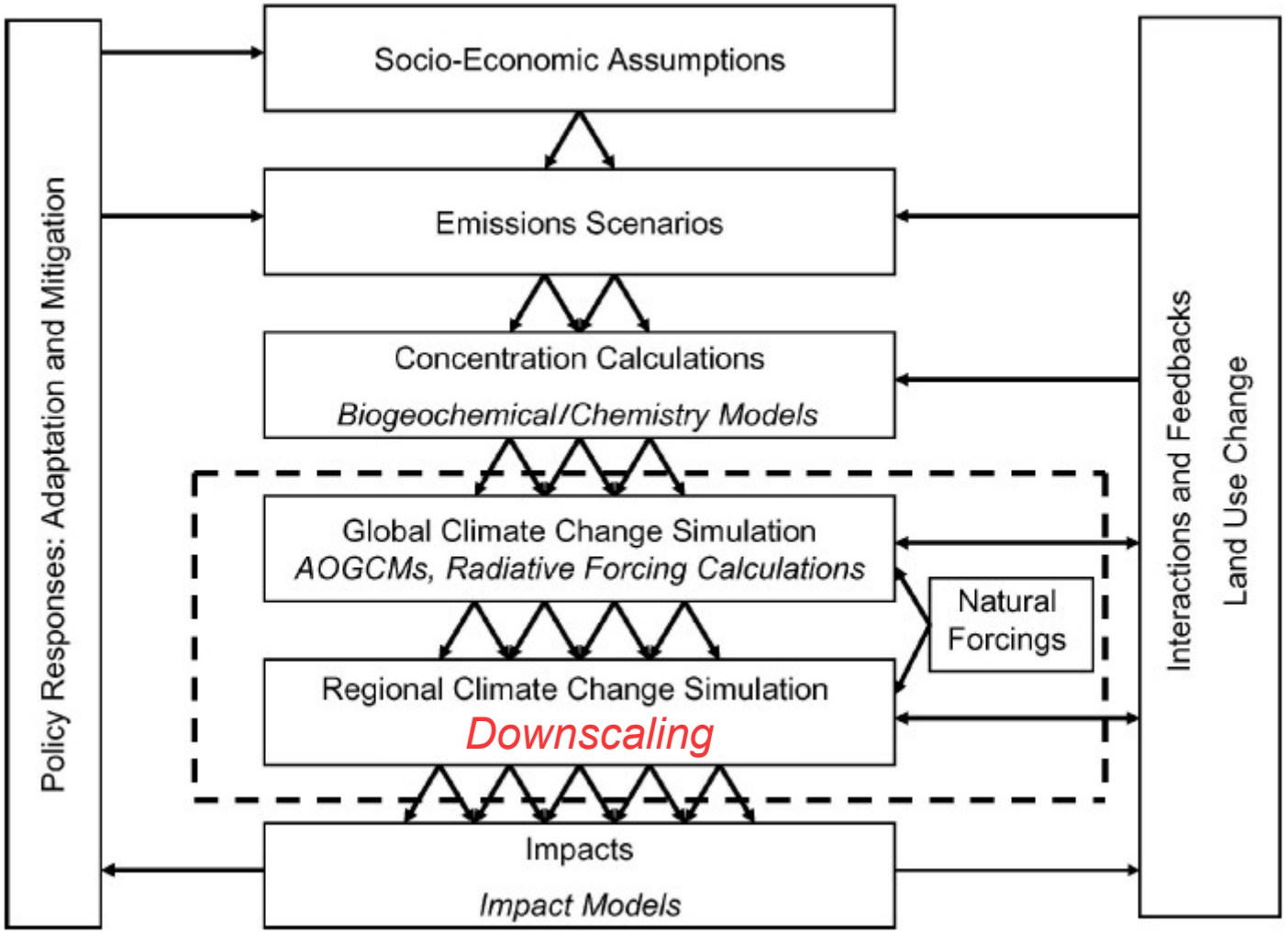
Giorgi (2005) “Climate change prediction” Climatic change 73:239-265

Climate change uncertainties



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Climate change uncertainties

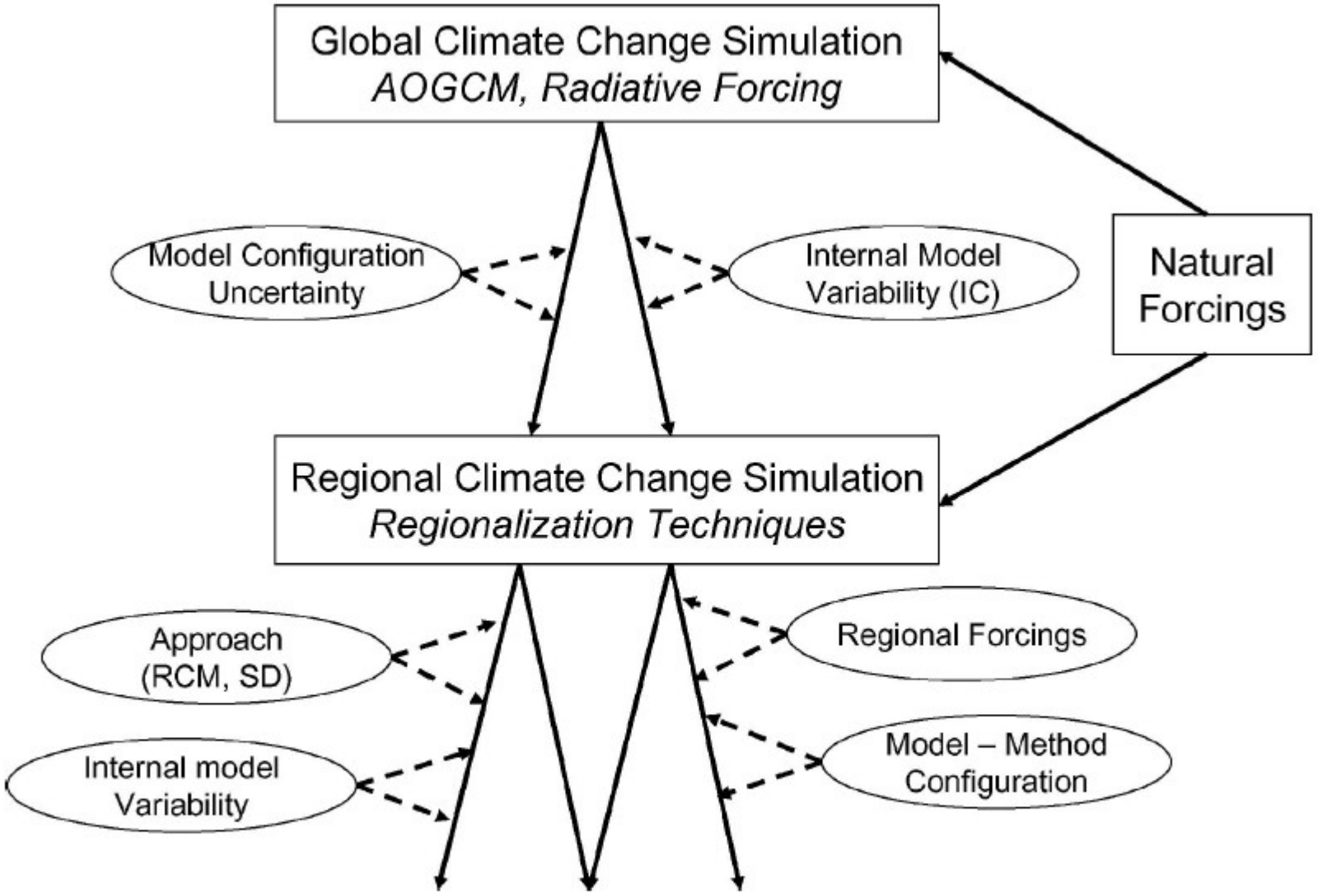


Figure 8. Climate simulation segment of the uncertainty cascade of Figure 7.

Giorgi (2005) "Climate change prediction" Climatic change 73:239-265

Generate a coordinated ensemble of high-resolution, historical/future regional climate projections for land-regions of the globe sampling; multiple GCM/RCP/RCM/ESDs methods. 1st phase based on CMIP5 historical-projection runs and/or ERA-int boundary data

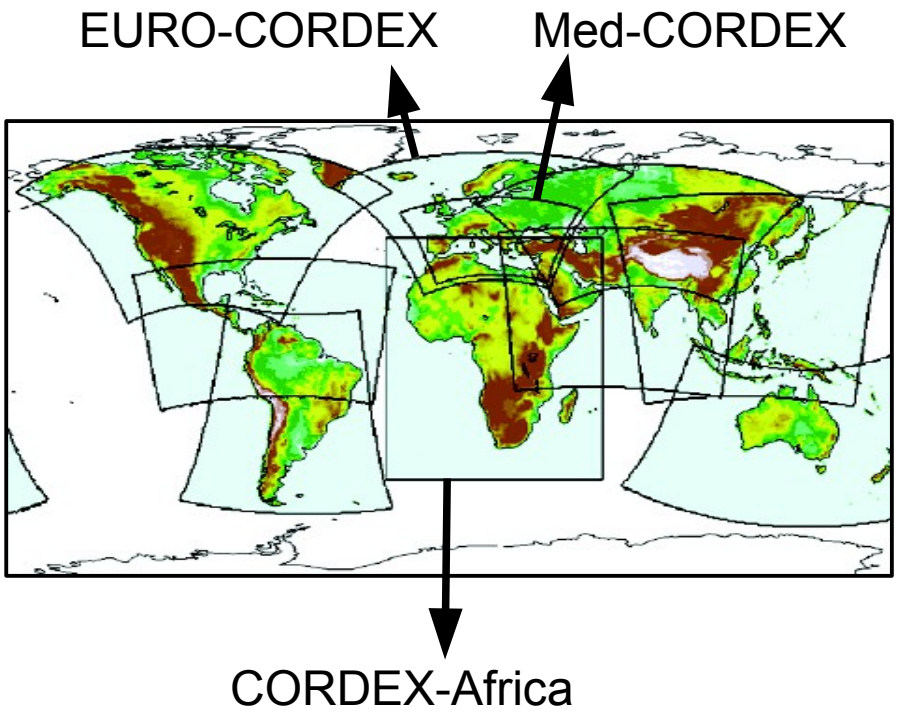
Make data accessible & useable in common format/file structure

Foster coordination between downscaling efforts & encourage local participation, in generating, analysing & communicating potential regional climate change and associated uncertainties & risks

Initial emphasis on African climate & IAV: START/WCRP sponsored 3 analysis/IAV workshops for an Africa-CORDEX team in 2011-12

Similar activities ongoing for South Asia, East Asia and South/Central America

CORDEX Phase I experiment design



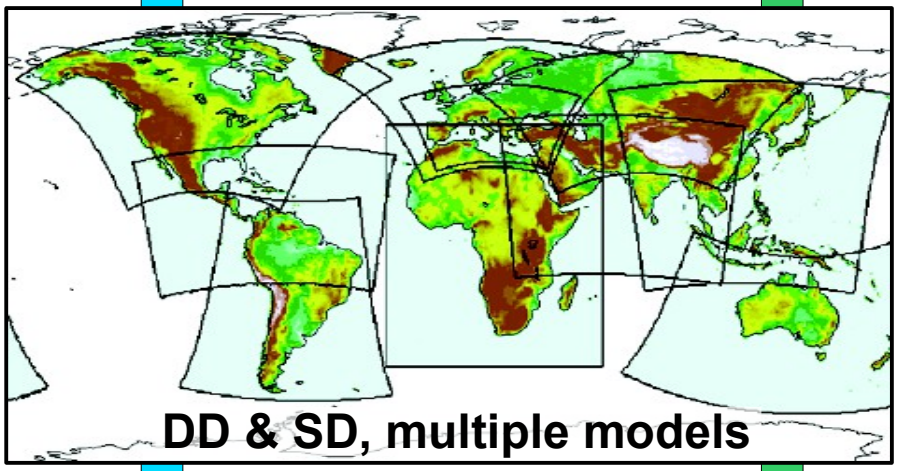
- Set of standard regions
- Common procedure/format

http://cordex.org

CORDEX Phase I experiment design

Model Evaluation Framework

Climate Projection Framework



ERA-Interim BC
1989-2008

RCP4.5, RCP8.5

Multiple AOGCMs

Projections
1951-2100

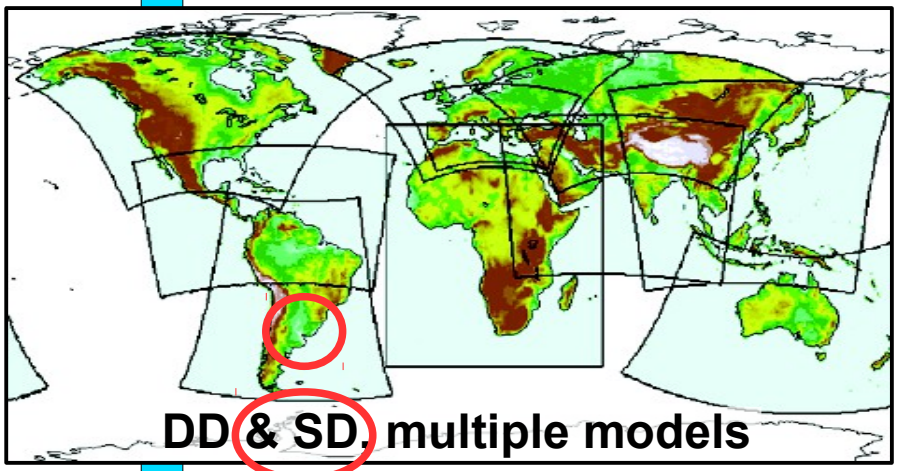
Regional analysis
Regional databanks

CORDEX Phase I experiment design

http://data.meteo.unican.es

CORDEX Phase I experiment design

Model Evaluation Framework



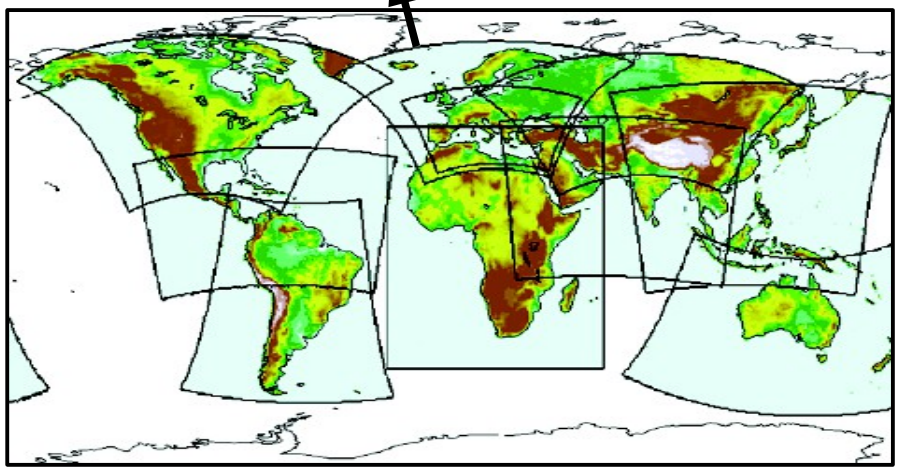
CORDEX ESD Experiment 1

ERA-Interim BC
1989-2008

Regional analysis
Regional databanks

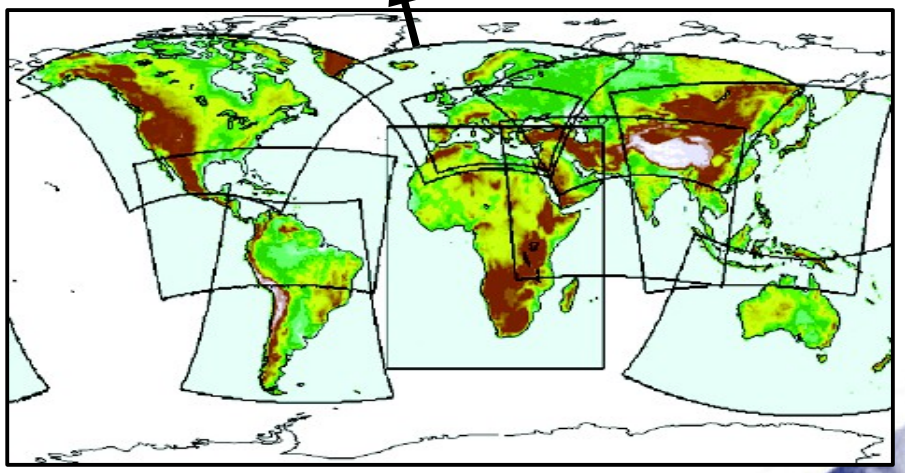
VALUE

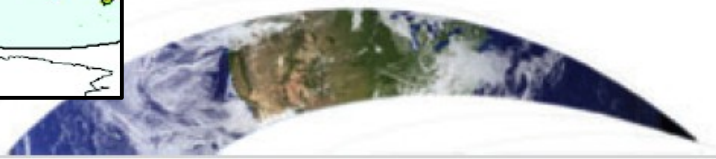
VALUE (~ EUROCORDEX ESD + RCM evaluation)



VALUE

VALUE (~ EUROCORDEX ESD + RCM evaluation)





Earth's Future

http://www.value-cost.eu

RESEARCH ARTICLE
10.1002/2014EF000259

VALUE: A framework to validate downscaling approaches for climate change studies

Key Points:
- VALUE has developed a framework to validate and compare downscaling methods
- The experiments comprise different observed and pseudo-reality reference data
- The framework is the basis for a comprehensive downscaling comparison study

Douglas Maraun[1], Martin Widmann[2], José M. Gutiérrez[3], Sven Kotlarski[4], Richard E. Chandler[5], Elke Hertig[6], Joanna Wibig[7], Radan Huth[8], and Renate A.I. Wilcke[9]

[1]GEOMAR Helmholtz Centre for Ocean Research Kiel, Kiel, Germany, [2]School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, UK, [3]Institute of Physics of Cantabria, IFCA, Santander, Spain, [4]Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland, [5]Department of Statistical Science, University College London, London, UK, [6]Institute of Geography, University of Augsburg, Augsburg, Germany, [7]Department of Meteorology and Climatology, University of Lodz, Lodz, Poland, [8]Department of Physical Geography and Geoecology, Faculty of Science, Charles University and Institute of Atmospheric Physics, Academy of Sciences of

Statistical Downscaling Portal

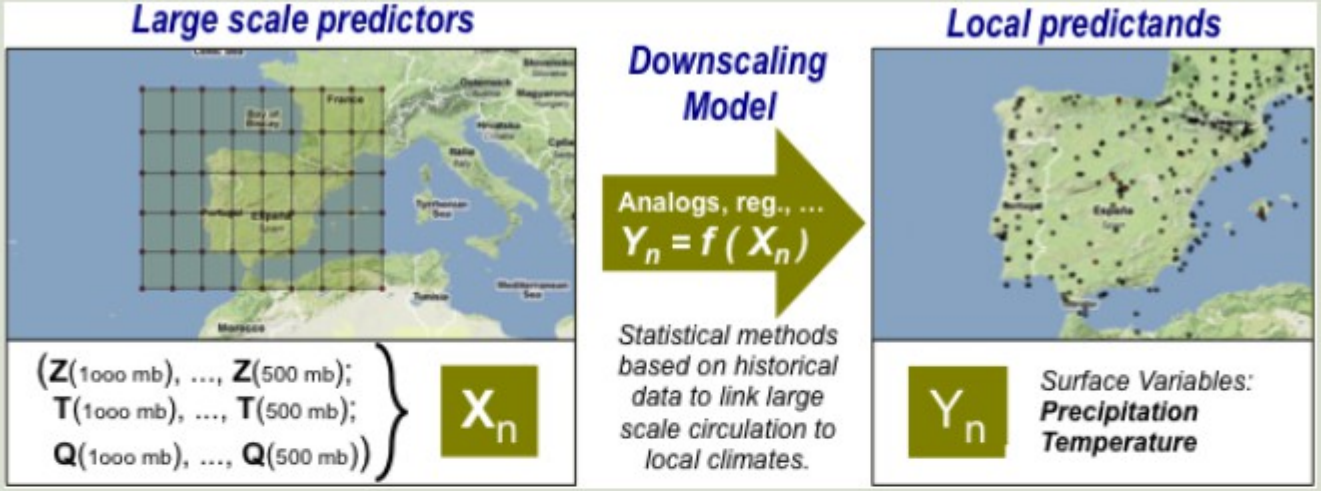
http://meteo.unican.es/downscaling

Contact:

Home | News | Terms of Use | Registration | Login

Downscaling Portal
Santander MetGroup

ENSEMBLES Downscaling Portal (version 2)



Three steps are neccessary to obtain high resolution forecasts in a region of interest:

1. Selecting the predictors,
2. Selecting the local stations and variable (predictand),
3. Running the desired downscaling jobs (local scenarios).

Downscaling Portal user guide:

Gutiérrez, J.M., San-Martín, D., Cofiño, A.S., Herrera, S., Manzanas, R., and Frías, M.D. (2012) User Guide of the ENSEMBLES Downscaling Portal. Version 3. Technical Note 2/2012. Santander Meteorology Group. Santander

References:

- Cofiño, A.S., San-Martín, and Gutiérrez, J.M. (2007) A web portal for regional projection of weather forecast using GRID

Developed by: predictia

Santander Meteorology Group. Downscaling Portal 2015.

Aims

- Dynamical downscaling of global historical and scenario simulations from AR4
  (plus ERA-Interim evaluation simulations)
- Coordination of Spanish regional modelling groups

Funding

- Strategic Action on Energy and Climate Change
  Ministerio de Agricultura, Alim. y Medio Ambiente

Partners

Coordination of Spanish regional modelling groups

- Univ. de Castilla-La Mancha (PROMES)
- Univ. de Murcia (MM5)
- Univ. de Cantabria (WRF)
- Univ. de Alcalá de Henares (REMO)

RCMs

PROMES

- *PROnóstico a MESoescala*, by UCLM

MM5

- Mesoscale Model version 5, by PSU/NCAR

WRF

- Weather Research & Forecasting Model, by NCAR
- 2 different PBL schemes: **WRF-A** and **WRF-B**

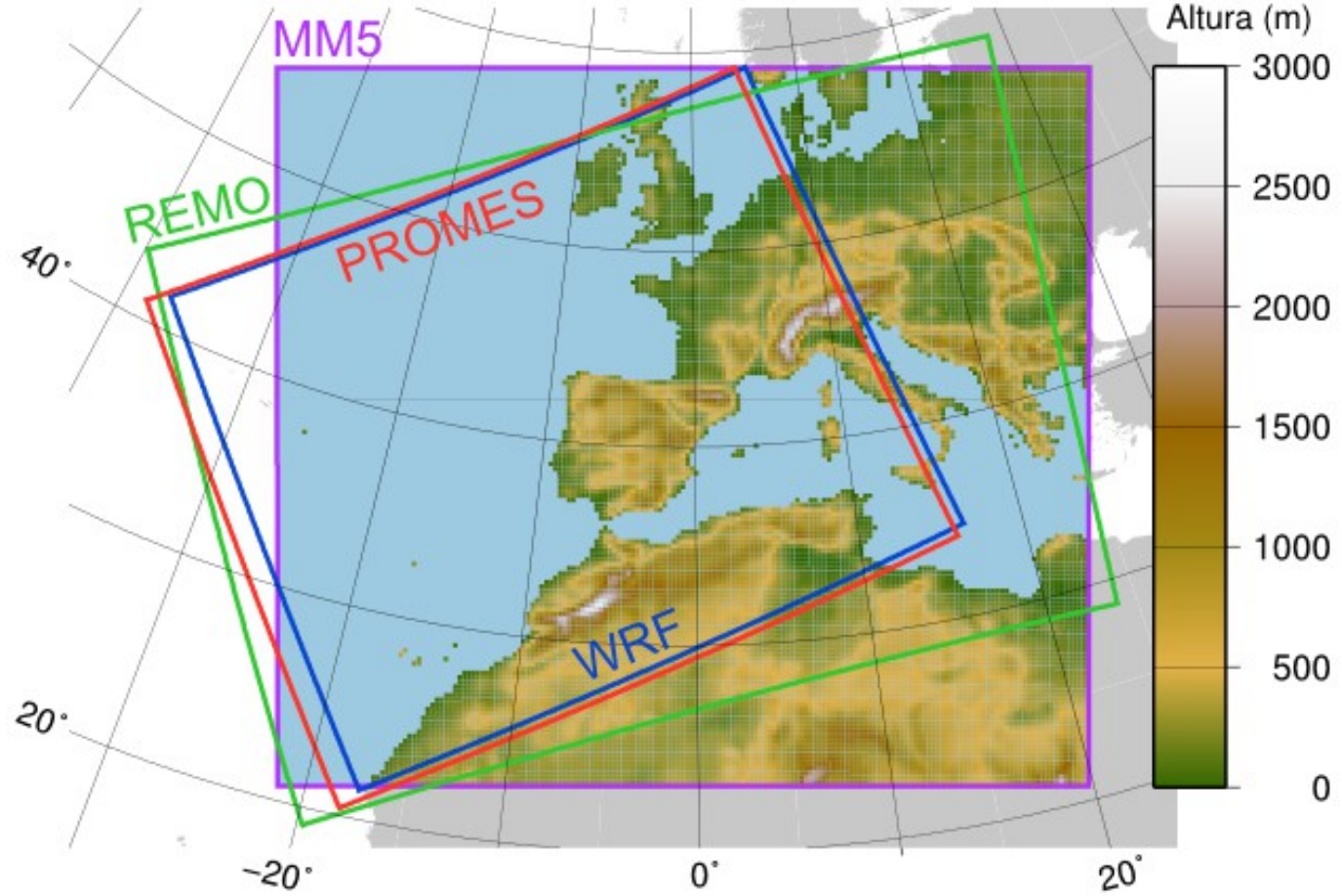
REMO

- REgional MOdel, by MPI-M

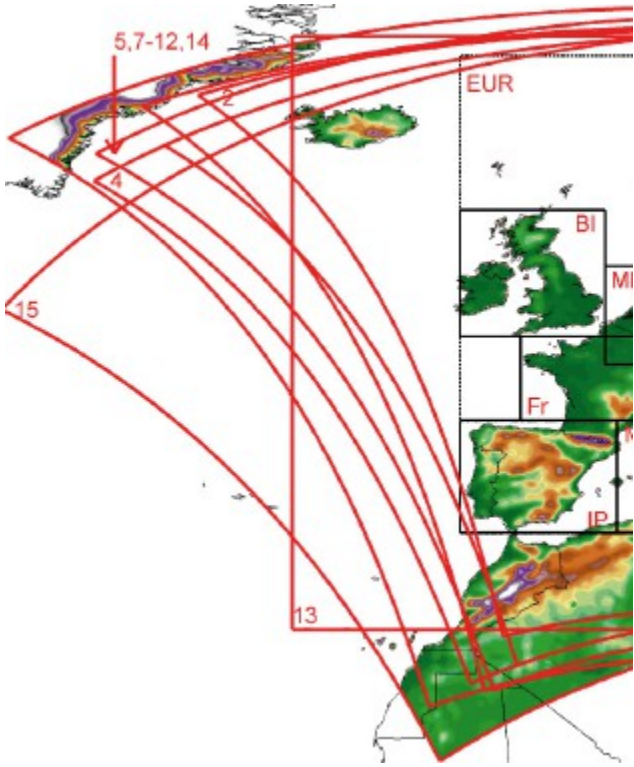
ESCENA simulation domains

PROMES / MM5 / WRF
Lambert Conic Conformal @ 25Km

REMO
Rotated lat-lon @ 0.22º



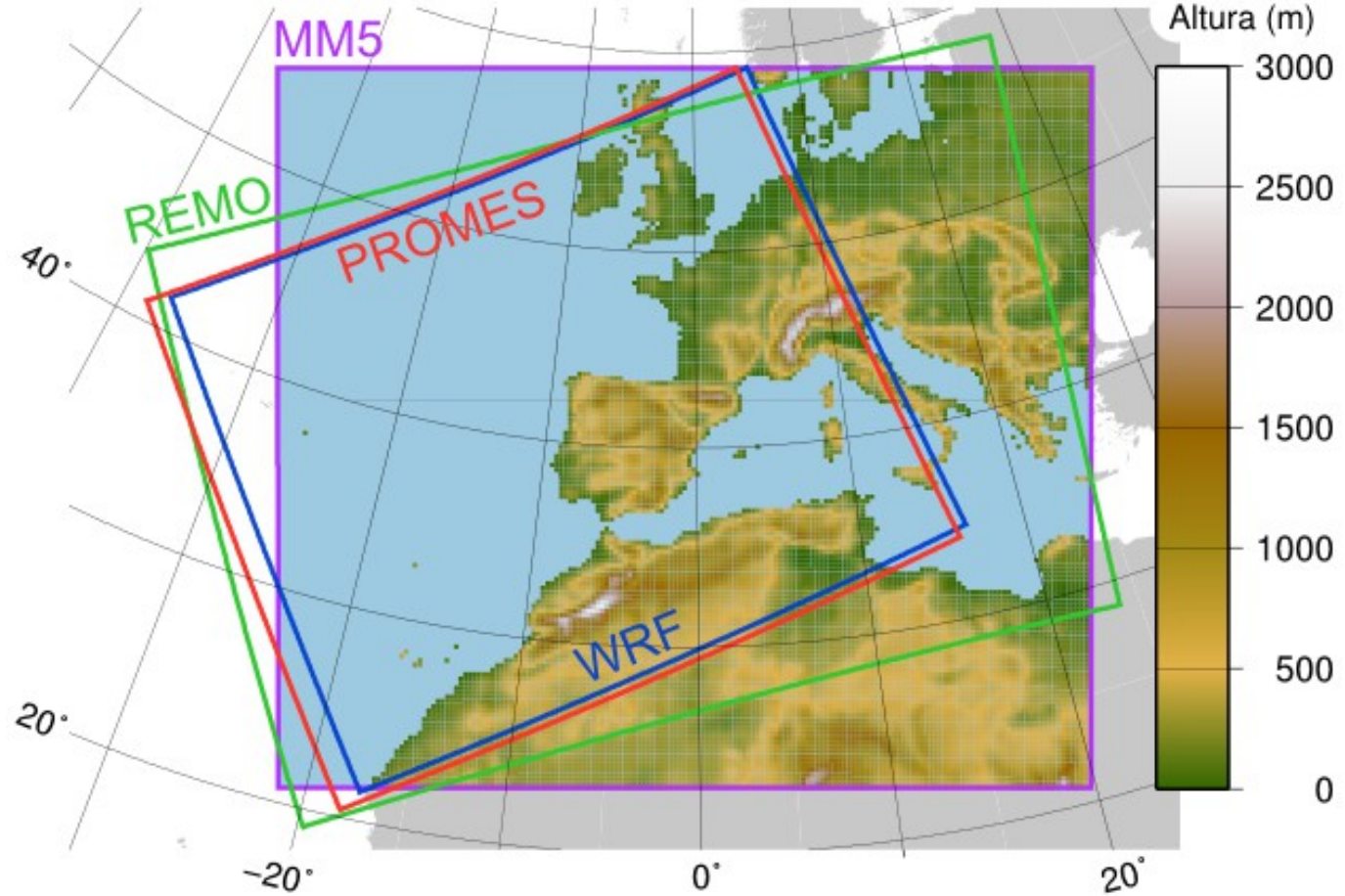
ENSEMBLES domains



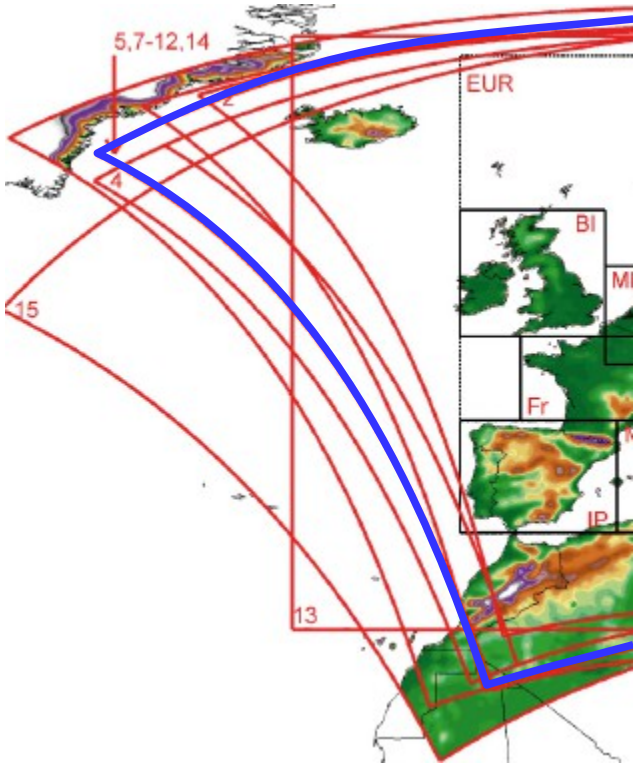
ESCENA simulation domains

PROMES / MM5 / WRF
Lambert Conic Conformal @ 25Km

REMO
Rotated lat-lon @ 0.22º



ENSEMBLES domains



EURO-CORDEX domain

Boundary forcing

Evaluation simulations

- ECMWF ERA-Interim Reanalysis
- Period: **1989-2008**

Historical + scenario simulations

- AR4 / CMIP3 GCMs
- 3 GCMs (ECHAM5, ARPEGE3, HadCM3)
- 2 param. perturbations (high / low temp. sensitivity)
- Historical GHG forcing (20C3M, **1951-2000**)
- Scenario GHG forcing (SRES A1B/A2/B1, **2001-2050**)

GCM/RCM matrix

		GCMs											
		ERAIN	EC5R2				ARPEG			HDQ03		HDQ16	
		Rean.	20C3M	A1B	A2	B1	20C3M	A1B	B1	20C3M	A1B	20C3M	A1B
RCMs	PROMES	X	X	X	X	X	X	X	X	X	X	X	X
	MM5	X	X	X	X	X	X	X	X	X	X	X	X
	REMO	X	X	X		X							
	WRF-A	X	X	X	X								
	WRF-B	X	X	X									

- The GCM/RCM matrix is not filled. However, …
- … 2 RCMs (PROMES, MM5) were nested to all GCMs and scenarios
- … 1 GCM forced by 1 scenario (ECHAM5-A1B) was downscaled by all RCMs
- This enables a number of sensitivity studies

Output data

variable	abreviatura	frec.	unidades
Variables 2D			
Temperatura del aire a 2m	tas	3h	K
Temperatura máx/mín del aire a 2m	tasmax / tasmin	d	K
Temperatura superficial máx/mín	tsmax / tsmin	d	K
Temperatura superficial del mar	sst	d0	K
Velocidad U/V del viento a 10 metros	uas / vas	3h	m s-1
Velocidad máx. del viento a 10 metros	wssmax	d	m s-1
Humedad específica a 2m	huss	3h	kg kg-1
Humedad relativa a 2m	hurs	3h	1
Humedad relativa máx/mín a 2m	hursmax / hursmin	d	1
Temperatura del punto de rocío a 2m	tdps	3h	K
Presión al nivel del mar	psl	3h	Pa
Presión en superficie	ps	3h	Pa
Precipitación	pr	d	kg m-2 s-1
Precipitación máxima en una hora	prhmax	d	kg m-2 s-1
Precipitación de gran escala	prls	d	kg m-2 s-1
Precipitación convectiva	prc	d	kg m-2 s-1
Agua precipitable	prw	d	kg m-2
Precipitación en forma de nieve	prsn	d	kg m-2 s-1
Evaporación	evspsbl	3h	kg m-2 s-1
Nubosidad total (fracción)	clt	d	1
Flujo de calor sensible/latente en superf.	hfss / hfls	3h	W m-2
Flujo de calor hacia el suelo	hfso	d	W m-2
Rad. onda corta/larga neta en superf.	rss / rls	d	W m-2
Rad. onda corta/larga incidente en superf .	rsds / rlds	d	W m-2
Rad. onda corta/larga neta en el tope atm.	rst / rlut	d	W m-2
Rad. onda corta incidente en el tope atm.	rsdt	d	W m-2
Humedad en los 10 primeros cm del suelo	mrsos	d	kg m-2
Humedad total del suelo	mrso	d0	kg m-2
Acumulación de nieve en superficie	snw	d0	kg m-2
Escorrentía superficial	mrros	d	kg m-2 s-1
Variables 3D (en niveles de presión)			
Altura geopotencial [A]	zg	6h	m
Humedad relativa [B]	hur	6h	1
Velocidad del viento U/V [C]	ua / va	12h	m/s
Temperatura [D]	ta	d0	K

- A large number of surface and upper-air variables are available.
- The frequency stored depends on the variable (mainly 3h and daily)
- 3-hourly variables are available for some simulations with MM5 and WRF.
  [Contact the groups directly]

Project website

http://proyectoescena.uclm.es

esTcena project

Aims

- Statistical downscaling of global historical and scenario simulations from AR4
  (plus ERA-Interim evaluation simulations)
- Coordination of Spanish SD groups

Funding

- Strategic Action on Energy and Climate Change
  Ministerio de Agricultura, Alim. y Medio Ambiente

https://meteo.unican.es/trac/estcena

GOBIERNO DE ESPAÑA
MINISTERIO DE AGRICULTURA, ALIMENTACIÓN Y MEDIO AMBIENTE
Ref: 200800050084078

Escenarios-PNACC 2012

Resultados de regionalización estadística

Aims

- Statistical downscaling of global historical and scenario simulations from AR4
  (plus ERA-Interim evaluation simulations)
- Coordination of Spanish SD groups

Catalog https://www.meteo.unican.es/thredds/catalog/PNACC2012/catalog.html

Dataset	Size	Last Modified
PNACC2012		--
Rejilla/		--
Puntuales/		--
Canarias/		--

THREDDS4.2 at Santander Meteorology Group
THREDDS Data Server [Version 4.2.10 - 20120413.1708] Documentation

Escenarios-PNACC 2012

http://www.aemet.es/es/serviciosclimaticos/cambio_climat/datos_mensuales

Thank you!

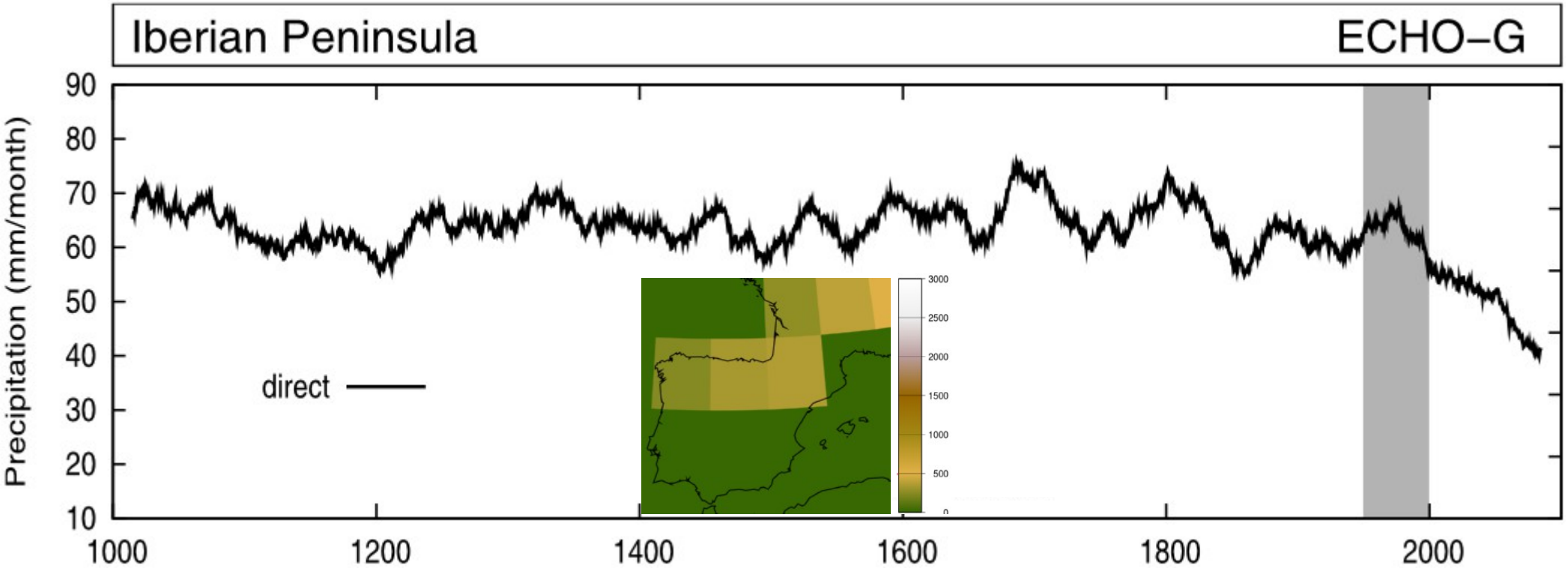
Jesus.Fernandez@unican.es

http://www.meteo.unican.es
@SantanderMeteo

UNIVERSIDAD DE CANTABRIA
METEOROLOGY GROUP

Additional material

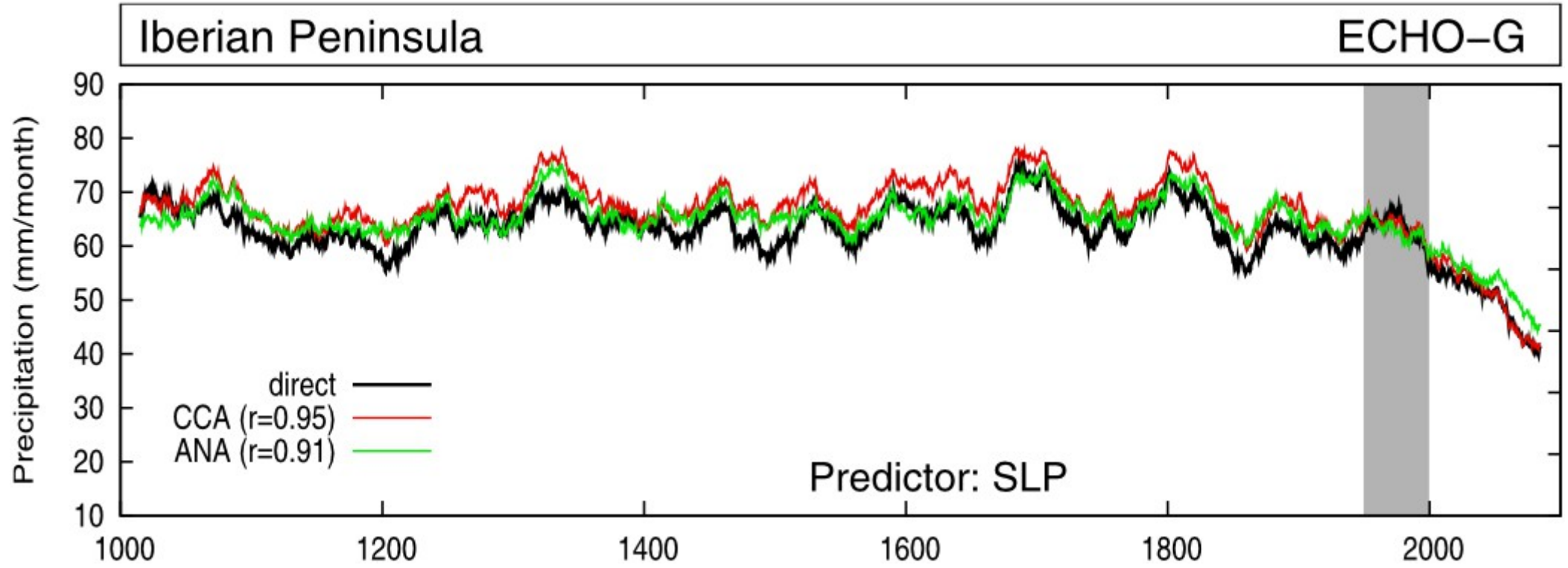
SD Stationarity



The stationarity problem refers to the lack of guarantee that the relationships established during the training of SD methods in the current climate will hold on a different (future) climate.

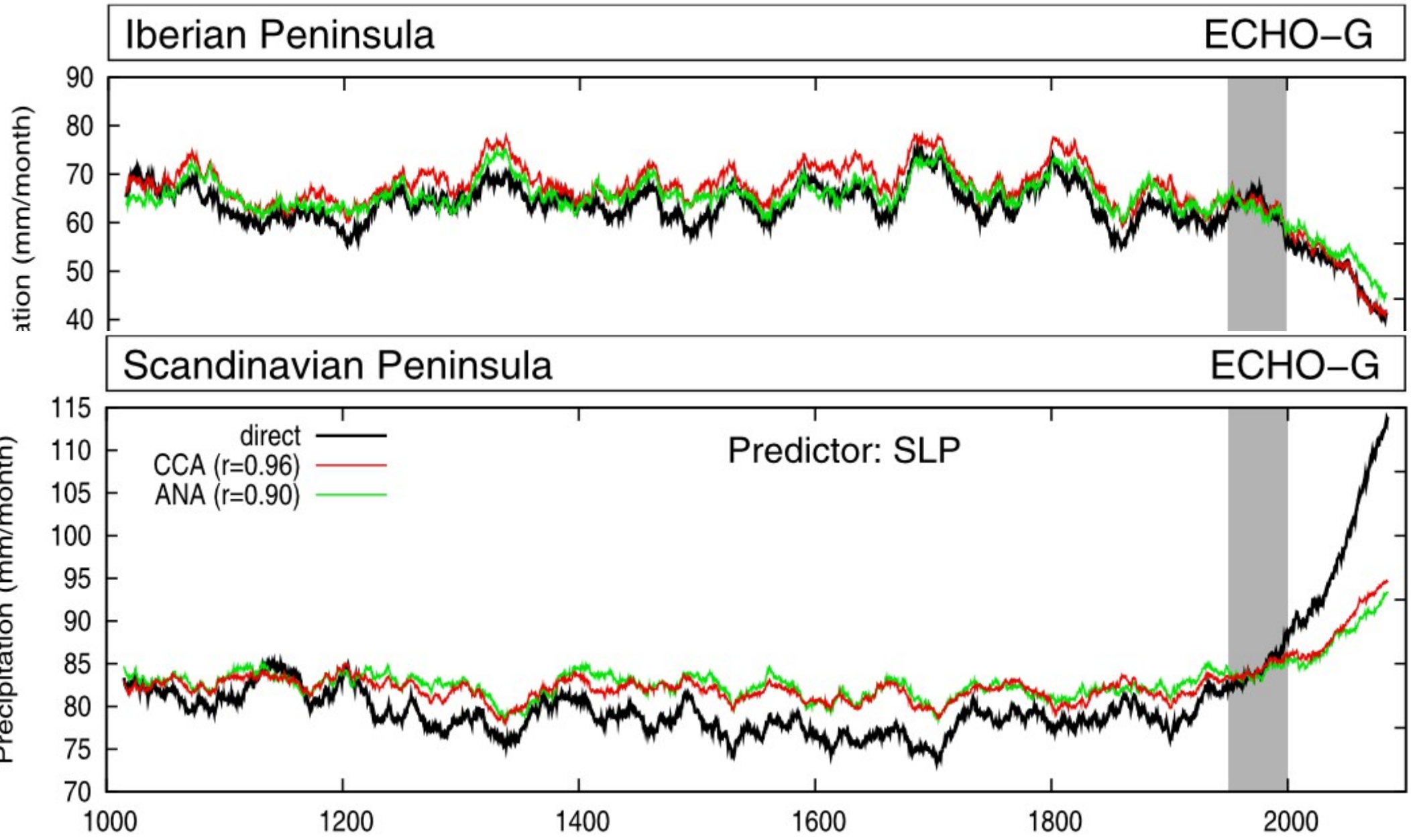
There are works raising plausibility arguments using the “model world” (a.k.a. pseudo-reality) as a surrogate of the climate system.

SD Stationarity



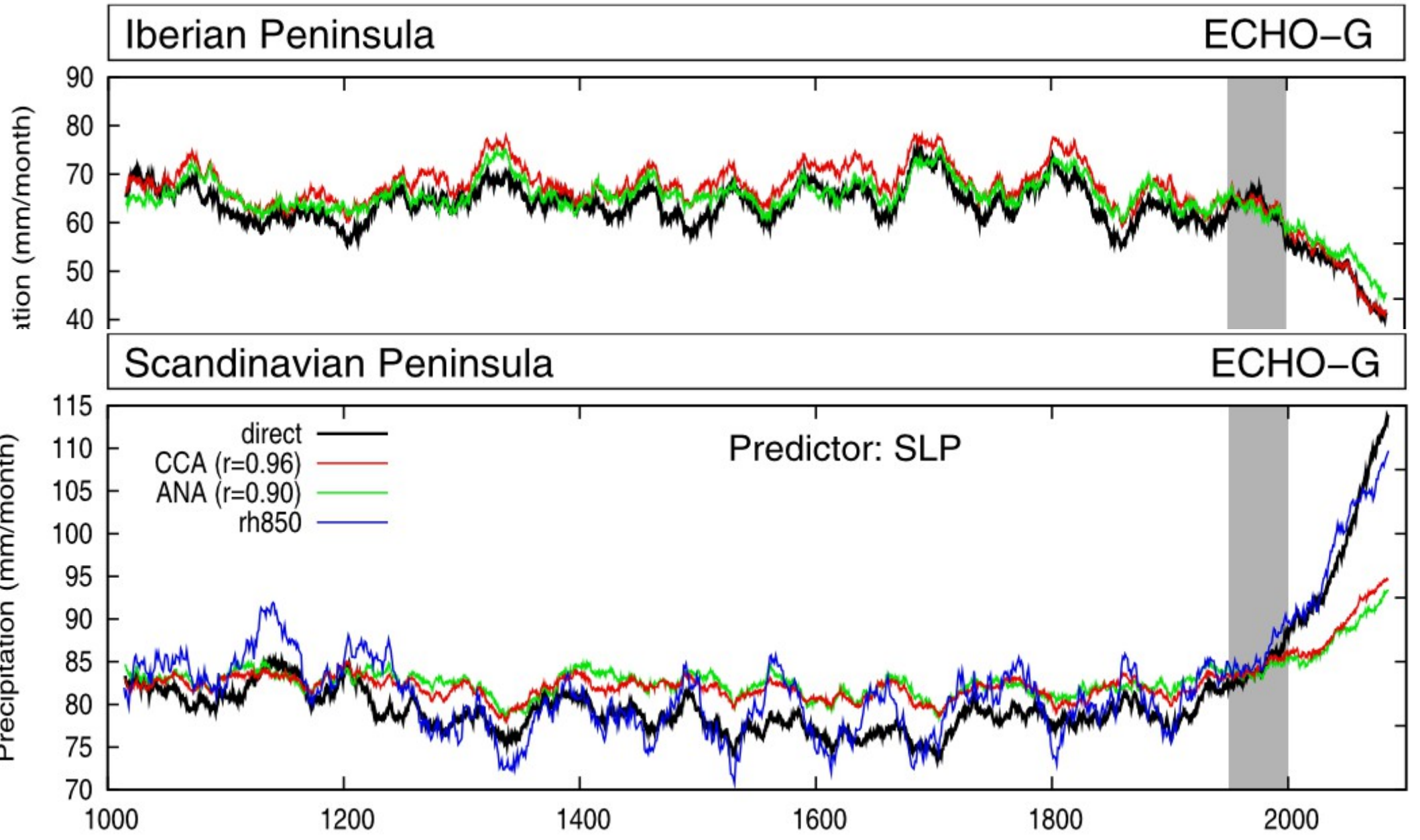
Frías et al. (2006) “Testing SD methods in simulated climates” Geoph Res Lett 33:L27453

SD Stationarity



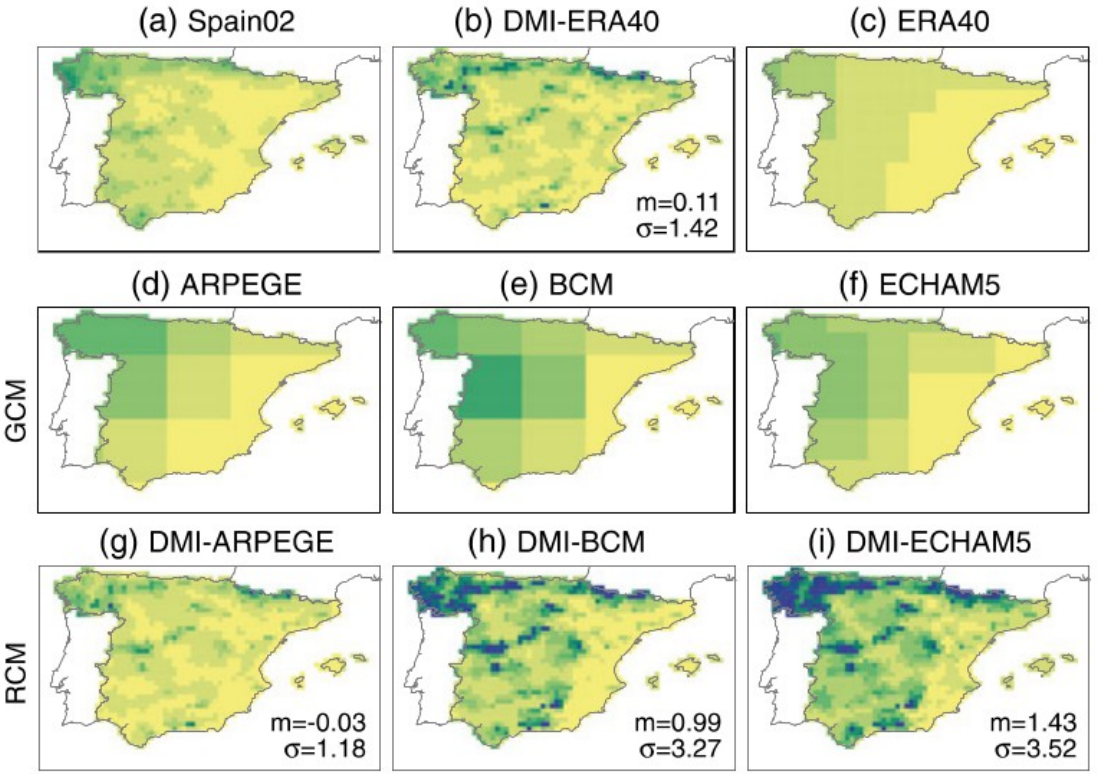
Frías et al. (2006) “Testing SD methods in simulated climates” Geoph Res Lett 33:L27453

SD Stationarity



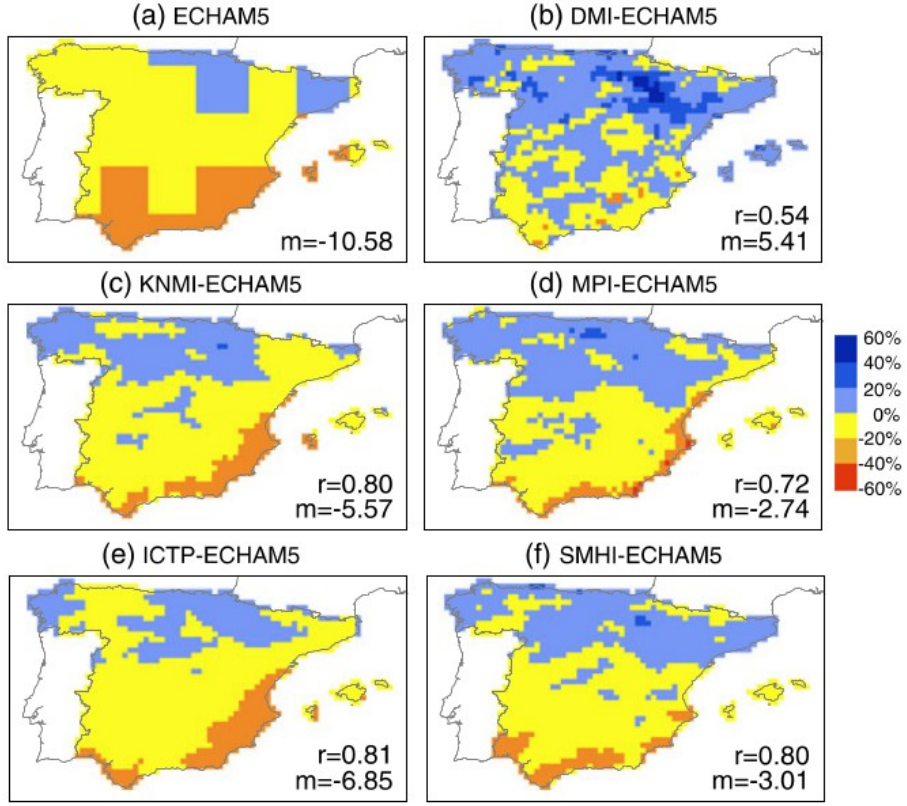
Frías et al. (2006) “Testing SD methods in simulated climates” Geoph Res Lett 33:L27453

GCM-RCM coupling



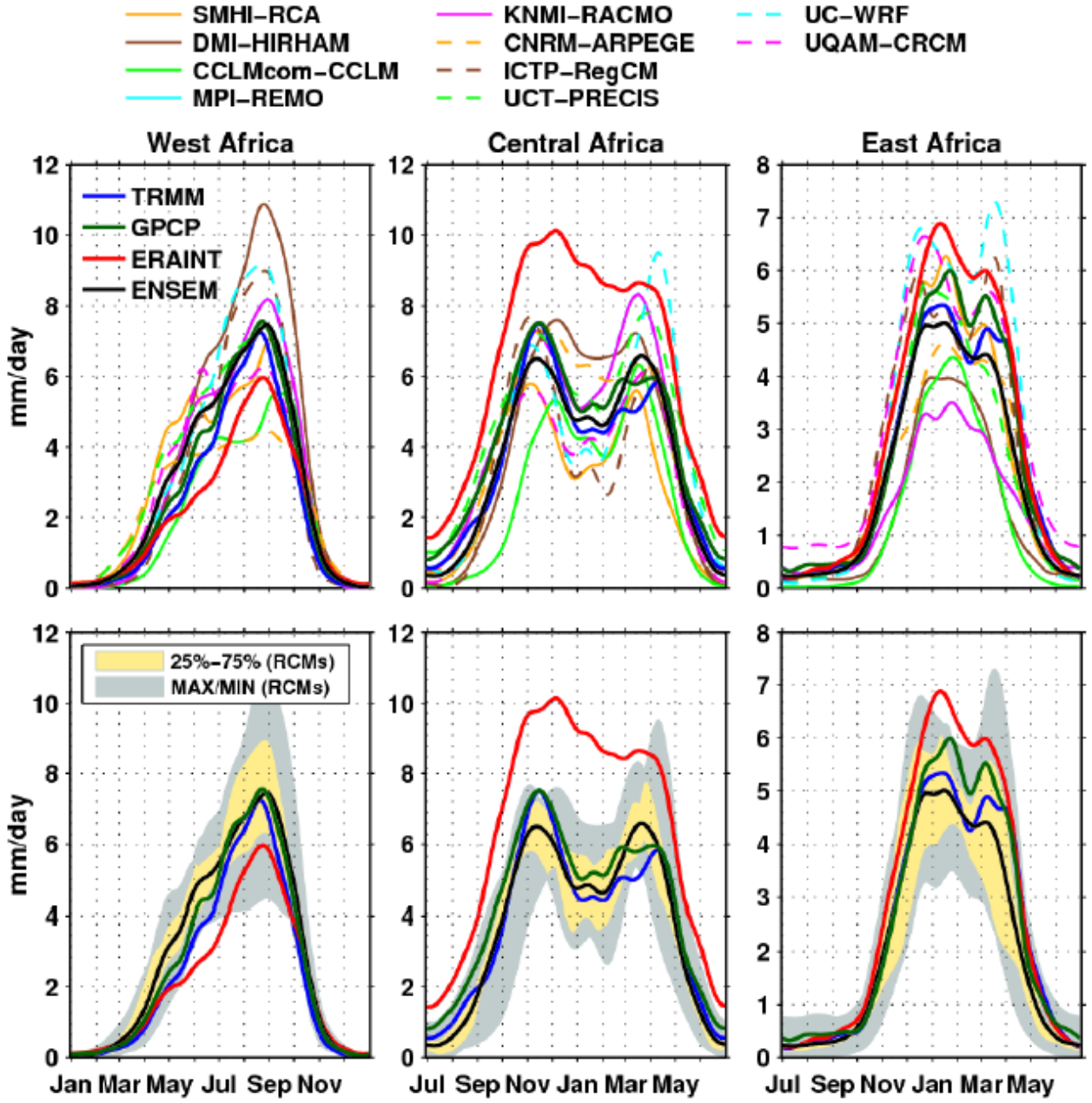
multi-GCM / single-RCM

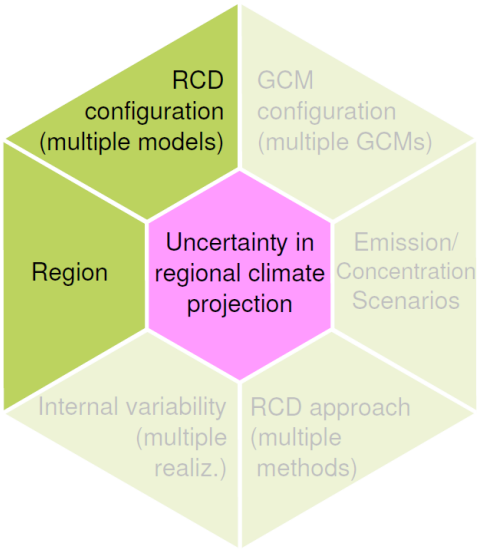
single-GCM / multi-RCM



Turco et al. (2013) “Large biases and inconsistent CC signals in ENSEMBLES …” CC 120:859

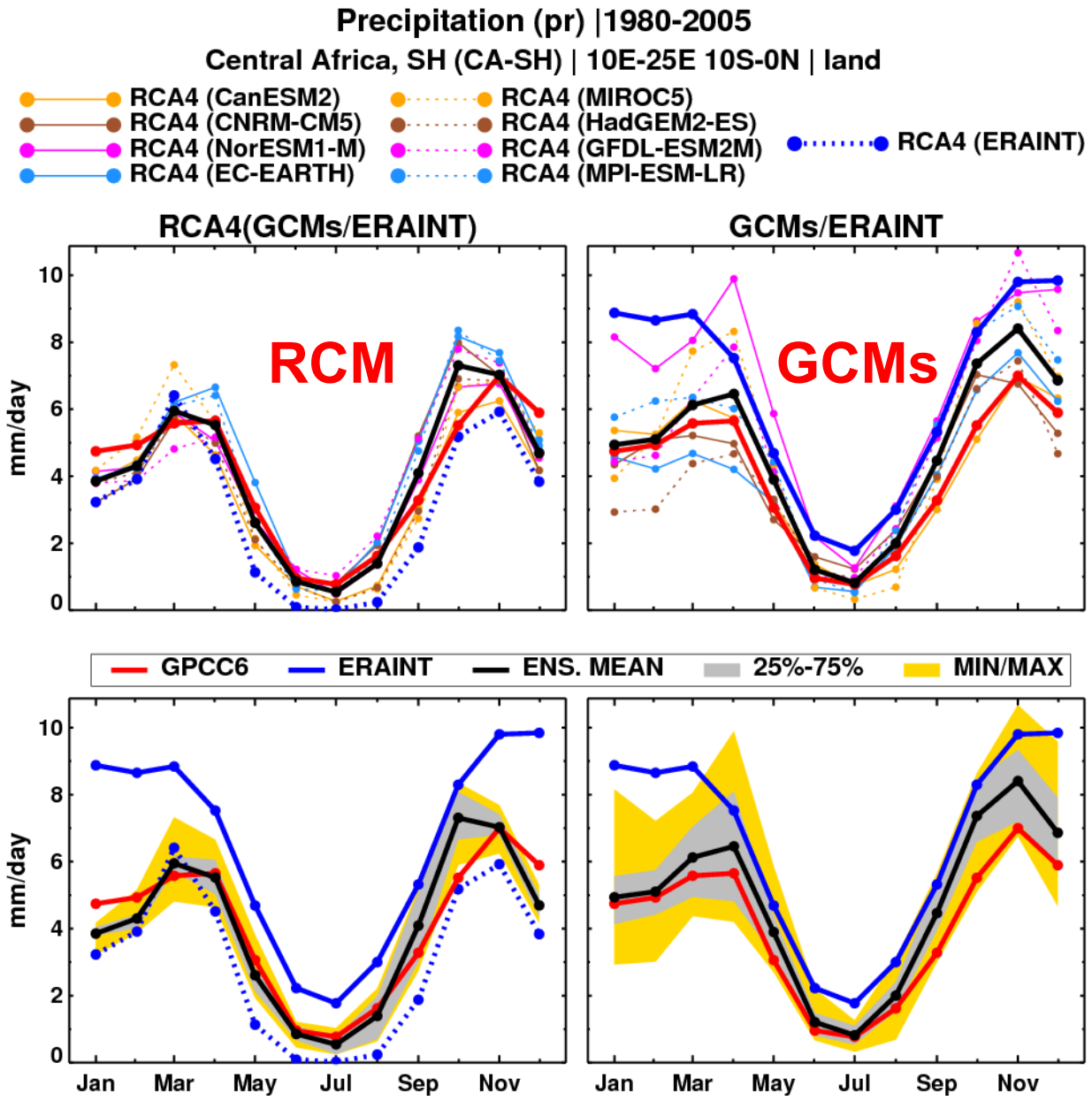
Added value

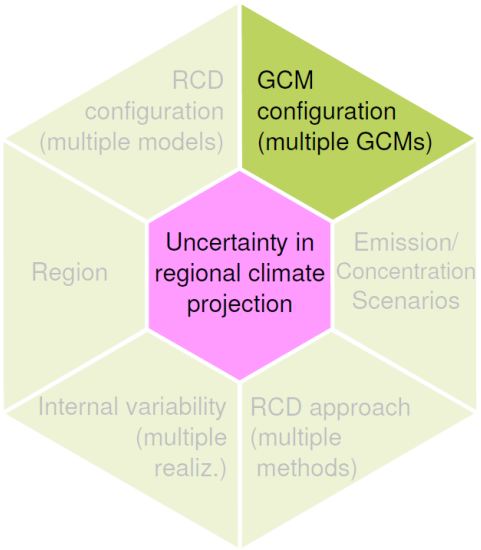




Source: Nikulin et al. (2012)
J. Clim. 25:6057-6078

Potential to narrow uncertainty

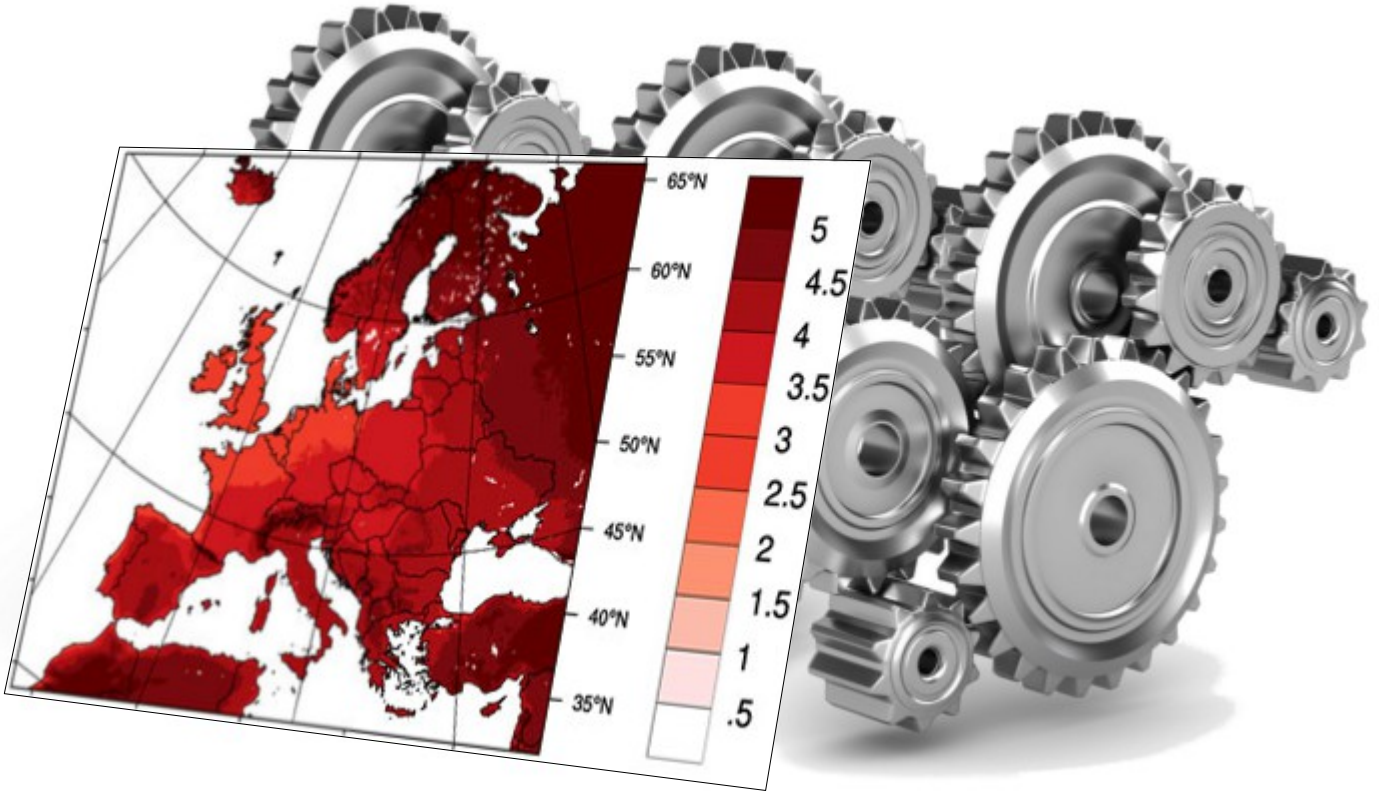




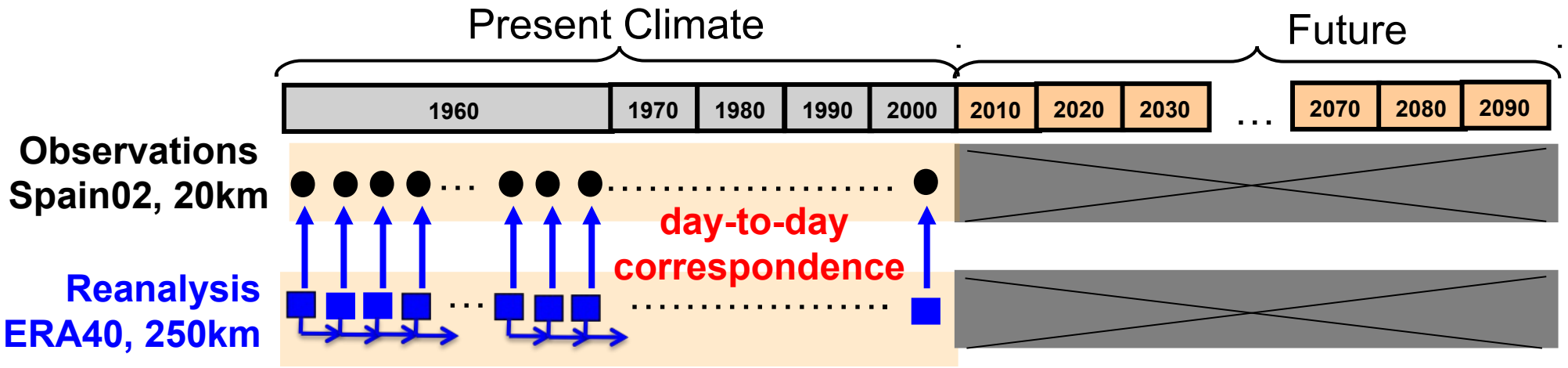
RCA4 nested into 8 ESMs

Source: SMHI

DS behind the scenes



Reanalysis choice



Atmospheric Reanalyses Comparison Table

Name	Source	Time Range	Assimilation	Model Resolution	Model Output Resolution	Publicly Available Dataset Resolution
Arctic System Reanalysis (ASR)	Polar Met Group	2000-2010	WRF-Var	10-20km	10-30km	10-30km
ECMWF Interim Reanalysis (ERA Interim)	ECMWF	1989-present	4D-VAR	T255L60	80 km	1.5x1.5 / 0.7x0.7
ECMWF 40 year Reanalysis (ERA-40)	ECMWF	1958-2001	3D-VAR	T159L60	125 km	2.5x2.5 / 1.125x1.125
Japanese Reanalysis (JRA-25)	Japan Meteorological Agency	1979-2004	3D-VAR	T106L40	1.125x1.125/2.5x2.5	1.125x1.125/2.5x2.5
NASA MERRA	NASA	1979-2010	3D-VAR	1/2x1/2 deg	1/2x1/2 deg	1/2x1/2 deg
NCEP Climate Forecast System Reanalysis (CFSR)	NCEP	1979-?	3D-VAR	T382 L64	.5x.5 and 2.5x2.5	.5x.5 and 2.5x2.5
NCEP/DOE Reanalysis AMIP-II (R2)	NCEP/DOE	1979-present	3D-VAR	T62 L28	2.5x2.5	2.5x2.5
NCEP/NCAR Reanalysis I (R1)	NCEP/NCAR	1948-present	3D-VAR	T62 L28	2.5x2.5 and 2x2 gaussian	2.5x2.5 and 2x2 gaussian
NCEP North American Regional Reanalysis (NARR)	NCEP	1979-present	RDAS	32km	32km	32km
NOAA-CIRES 20th Century Reanalysis (20CR)	NOAA/ESRL PSD	1871-2008	Ensemble Kalman Filter	T62 L28	2x2	2x2

Reanalysis & downscaling

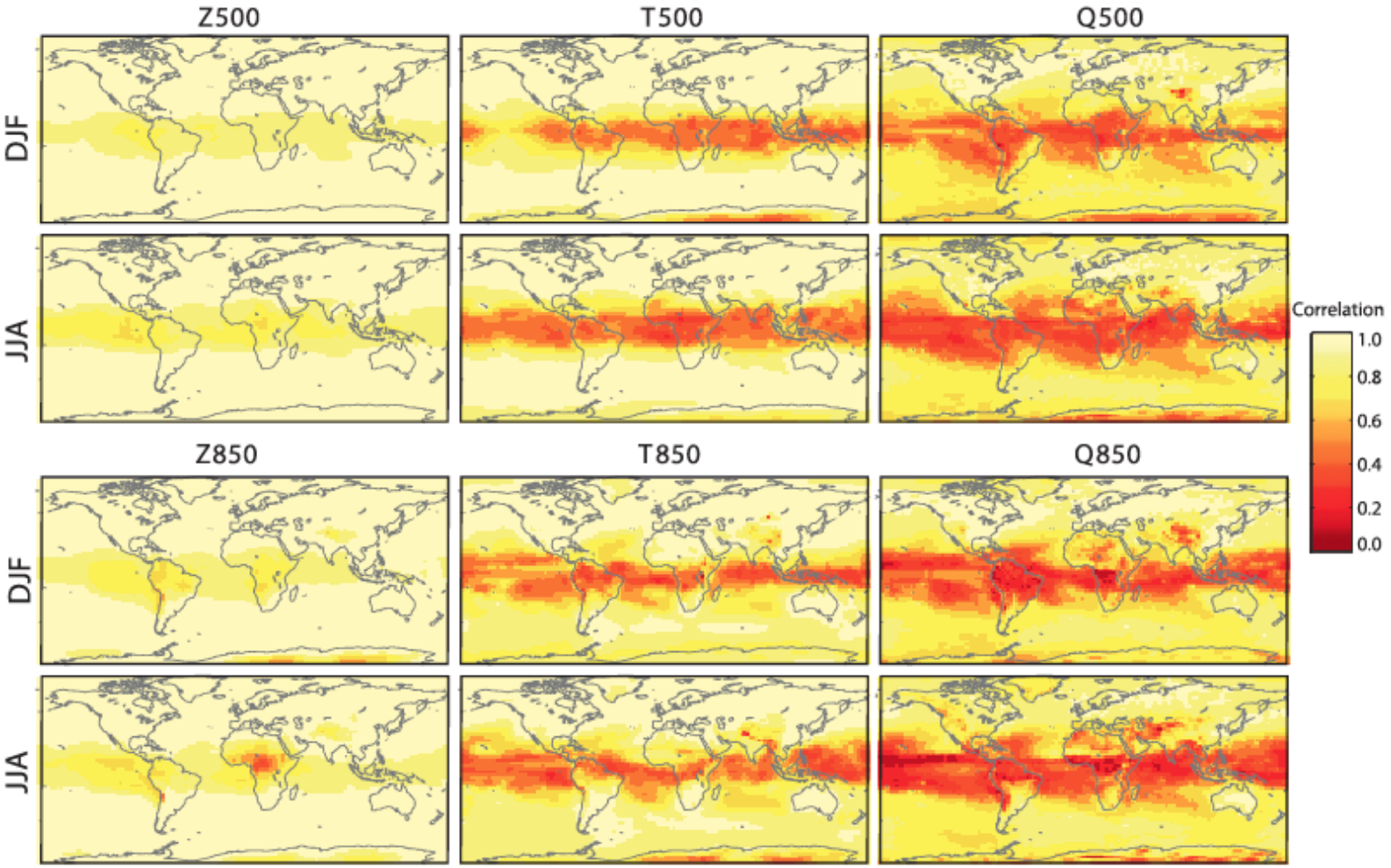
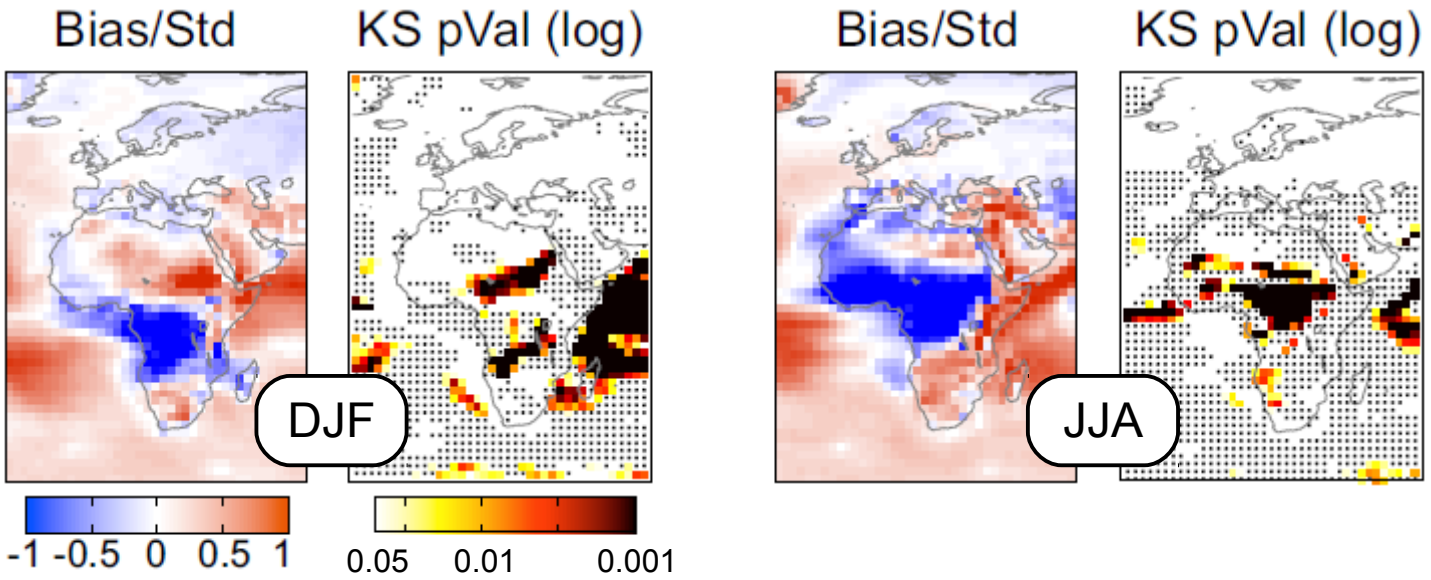


FIG. 5. Maps of consistency for the day-to-day sequence of the daily time series of ERA-40 and NCEP–NCAR Z, T, and Q at (top) 500 and (bottom) 850 hPa, as revealed by the Pearson correlation coefficient. Color darkening from yellow to black indicates increasing dissimilarity.

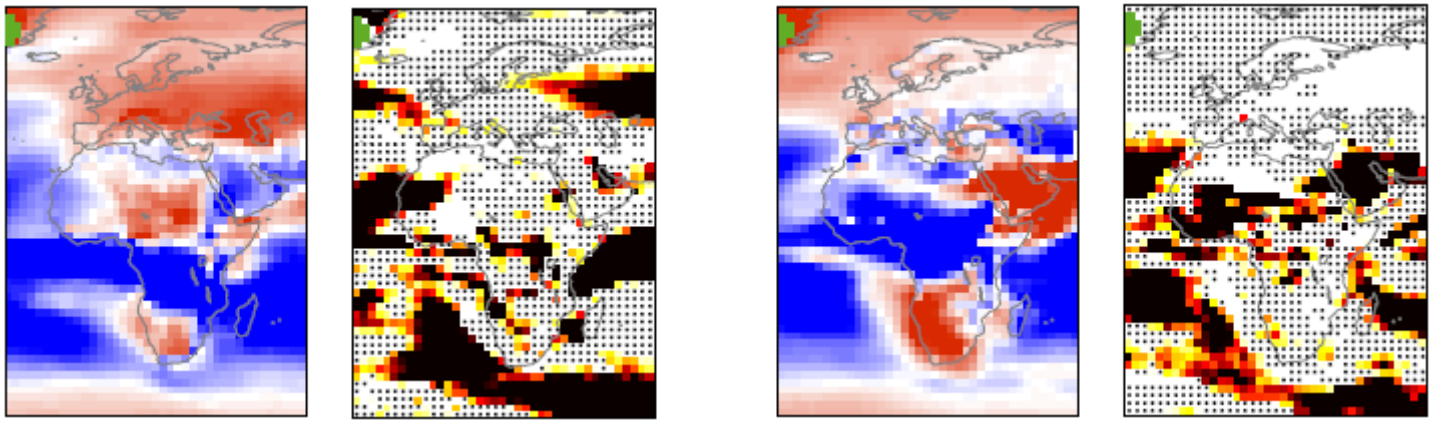
Brands et al. (2012) “On the use of reanalysis data for downscaling” J Clim 25:2517-2526

Q850: ESD implications



JRA25 *vs.* ERA-Interim

Reanalysis uncertainty compromises a basic assumption of the PP approach



MIROC-ESM *vs.* ERA-Interim

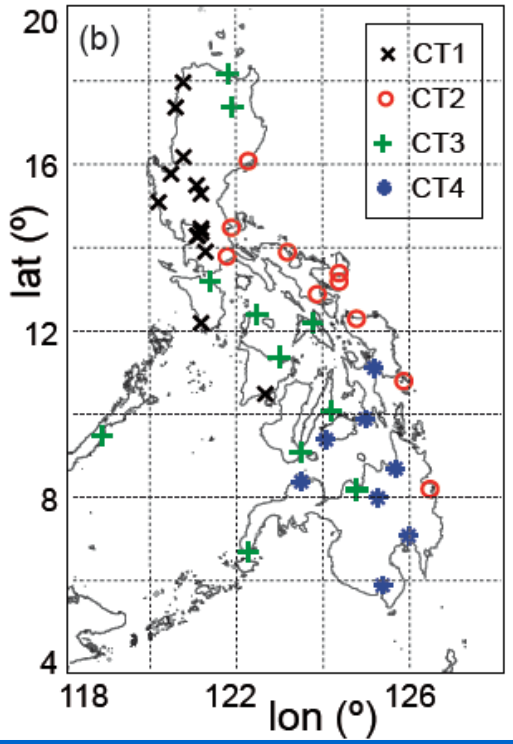
Unreliable GCM predictors

This is not a particular problem of this ESM and variable!
Check **Brands et al. (2013)** for many models/variables

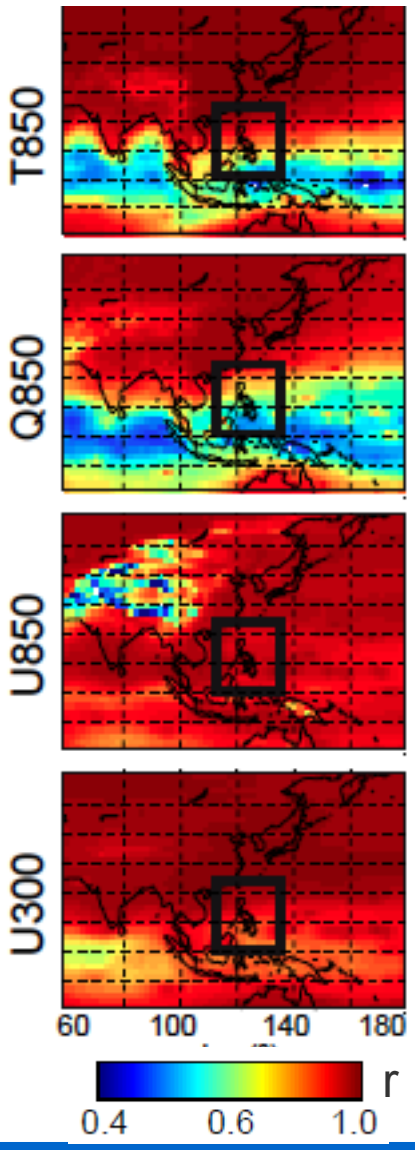
Reanalysis & downscaling

Perfect Prog downscaling of precipitation in the Philippines using *Generalized Linear Models (GLMs)*: logistic + gamma

(similar conclusions with analogs).

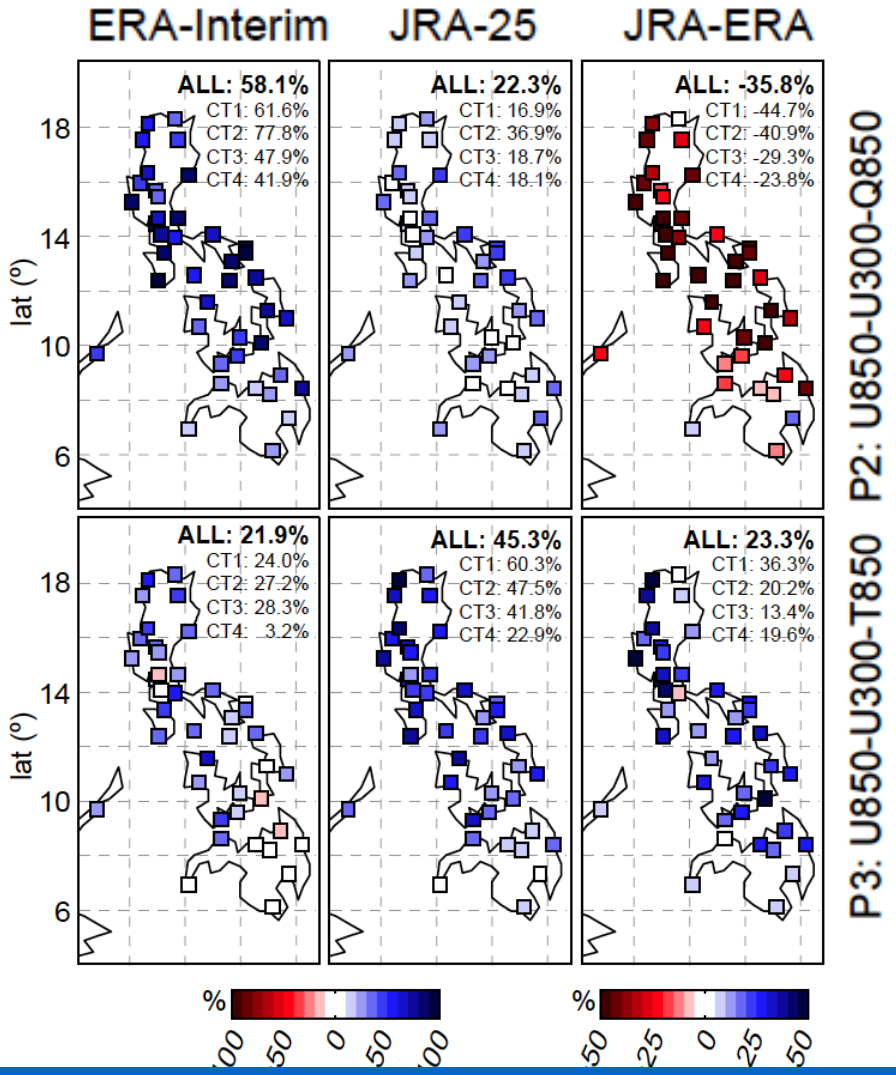


Predictors: JRA25 vs ERA-Interim

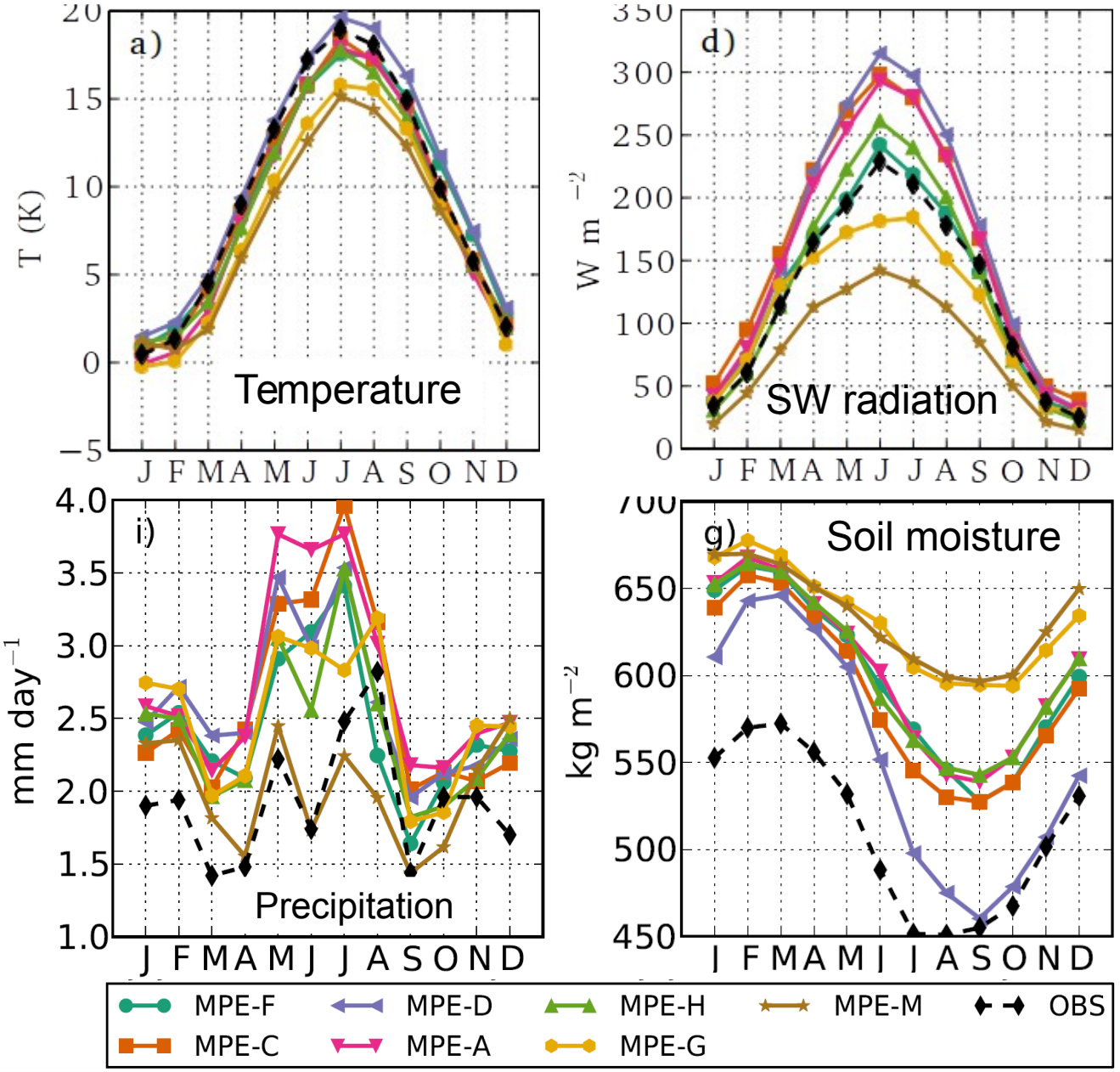


Projections: The differences are only due to the reanalysis

Δ(2071-2100)



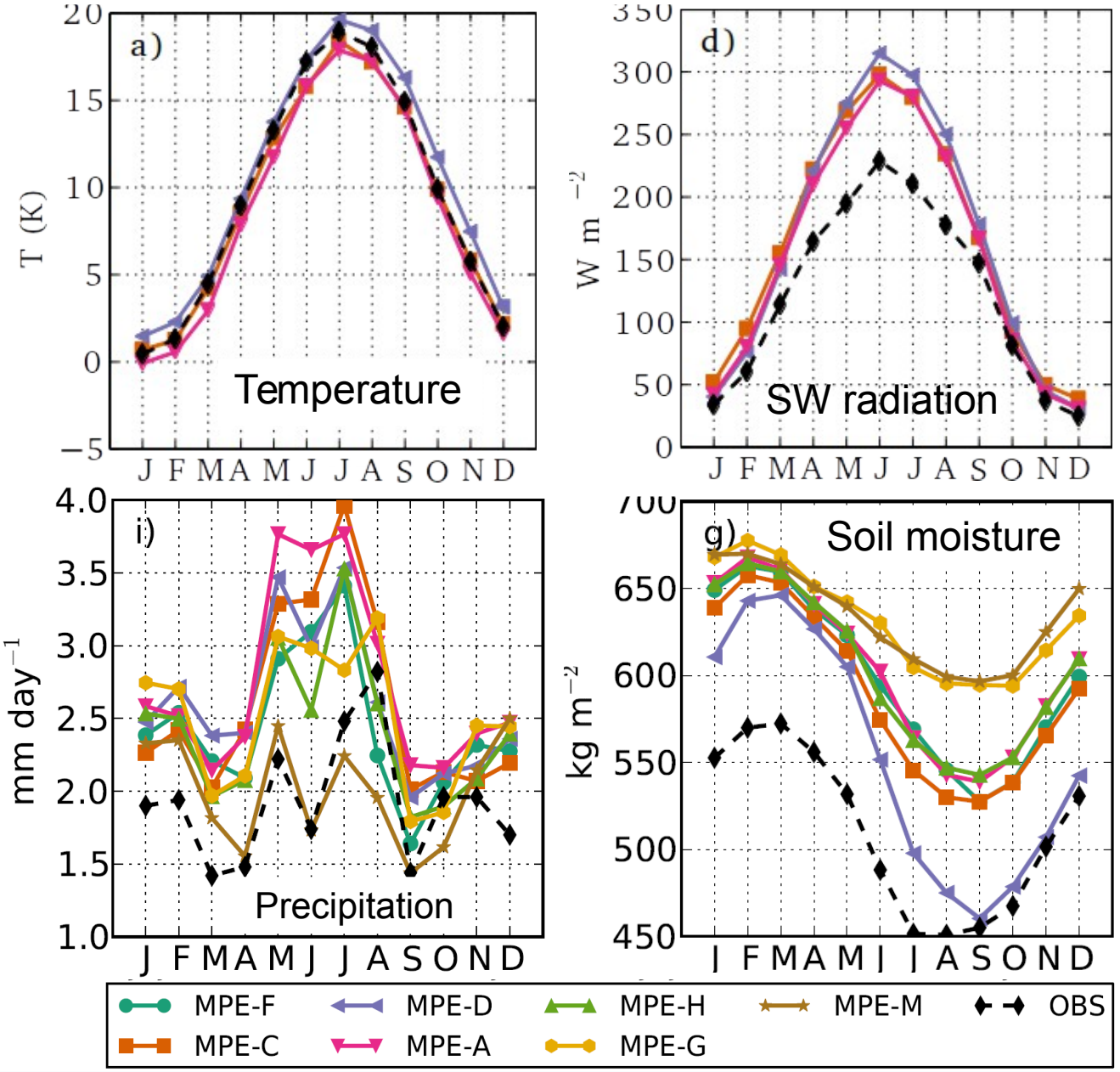
Multi-physics ens. E-CDX-WRF



- Huge spread
- Is M best for precip?
- Can D be trusted for autumn (SON) soil moisture?

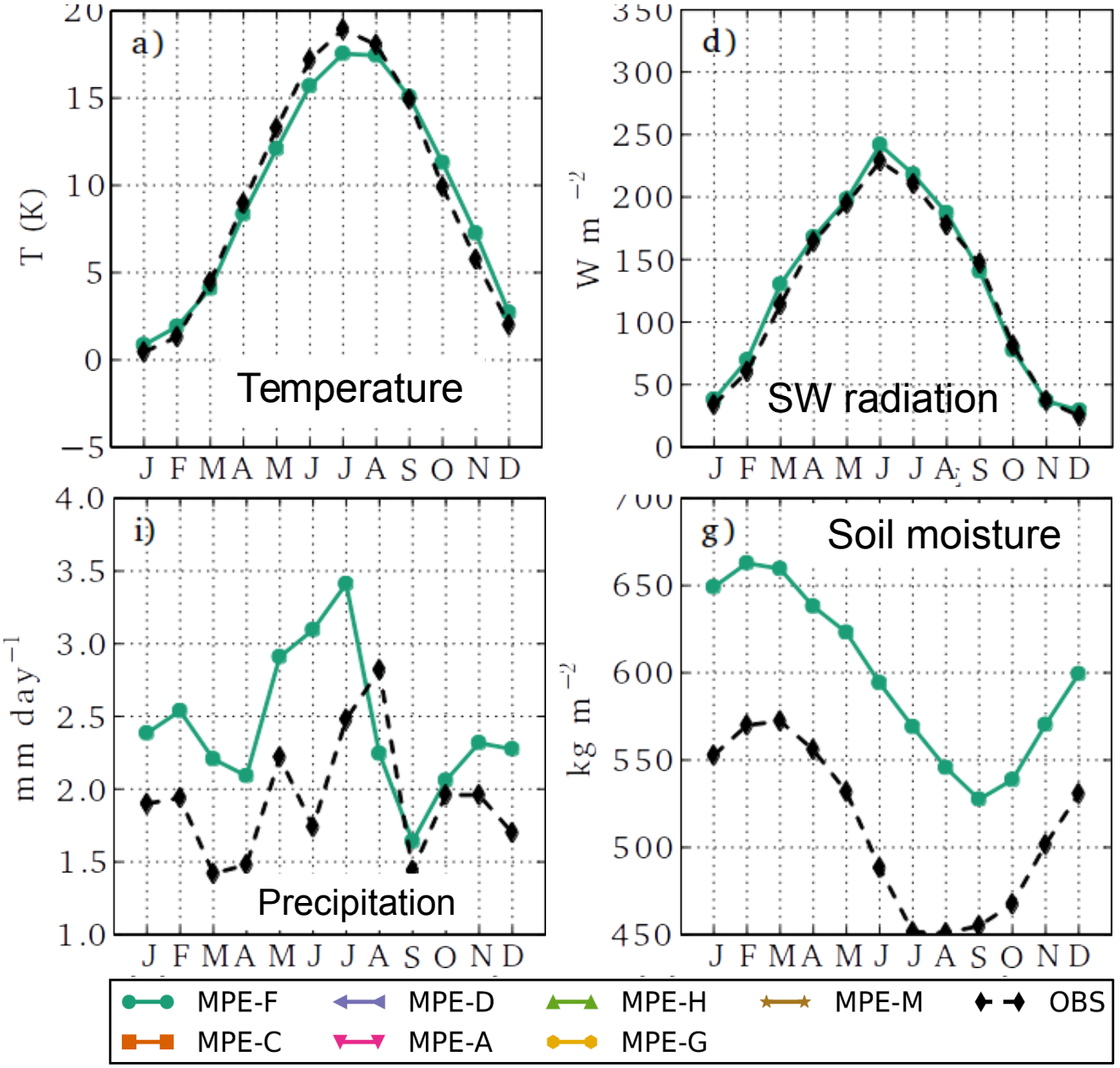
García-Díez et al. (2015) “An RCM multi-physics ensemble over Europe: multi-var” Clim Dyn

Multi-physics ens. E-CDX-WRF



- Watch out for error compensation!

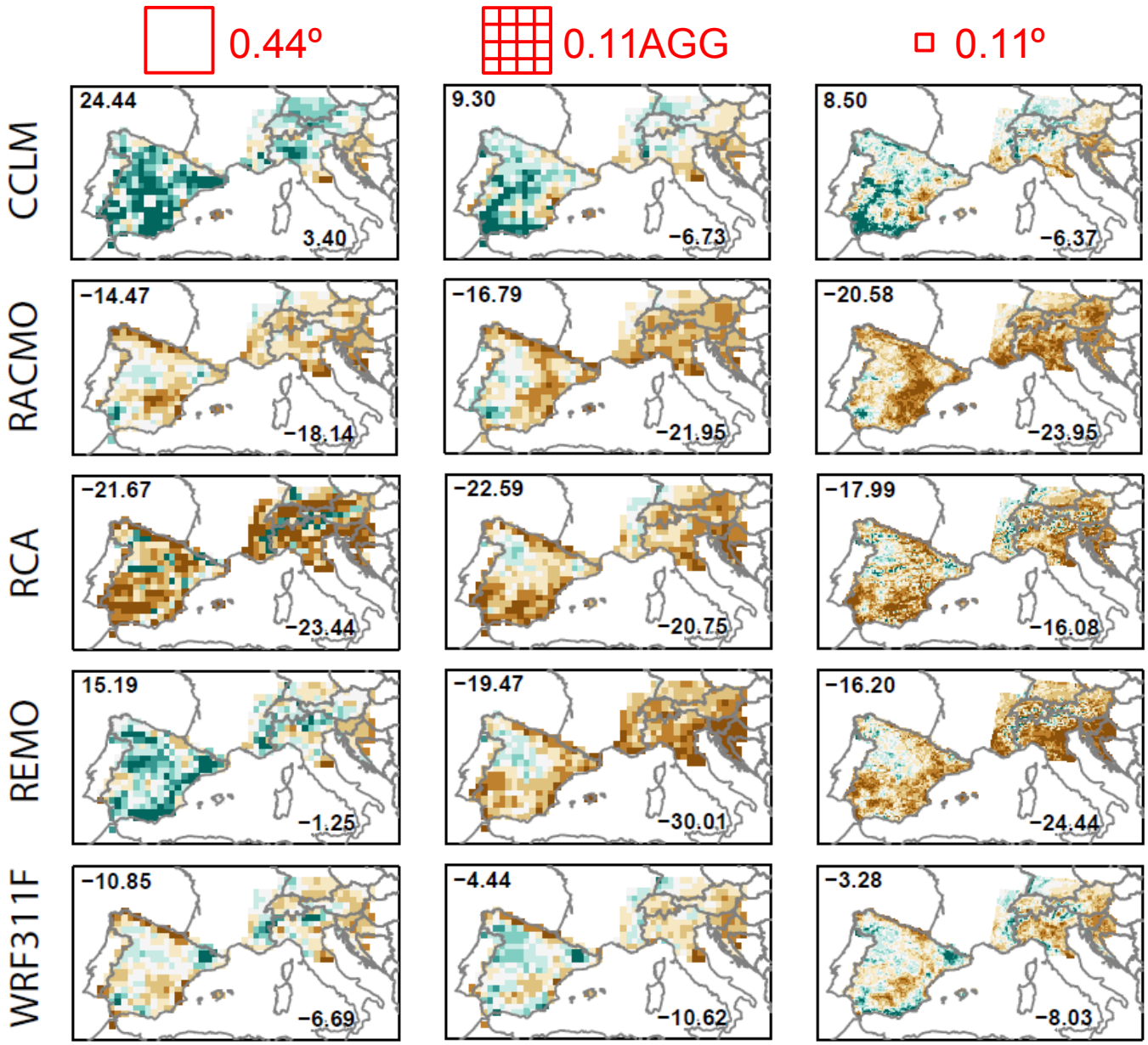
Multi-physics ens. E-CDX-WRF



- Is there a "best" model configuration?
- See also:
  Fernández et al (2007)
  Solman & Pessacg (2012)
  Jerez et al (2012)

García-Díez et al. (2015) "An RCM multi-physics ensemble over Europe: multi-var" Clim Dyn

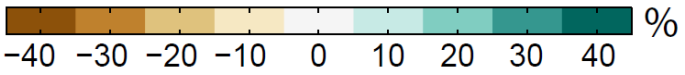
High resolution RCMs



Hi-res 0.11º Euro-CORDEX simulations took ~100x the computing power of the standard 0.44º CORDEX resolution.

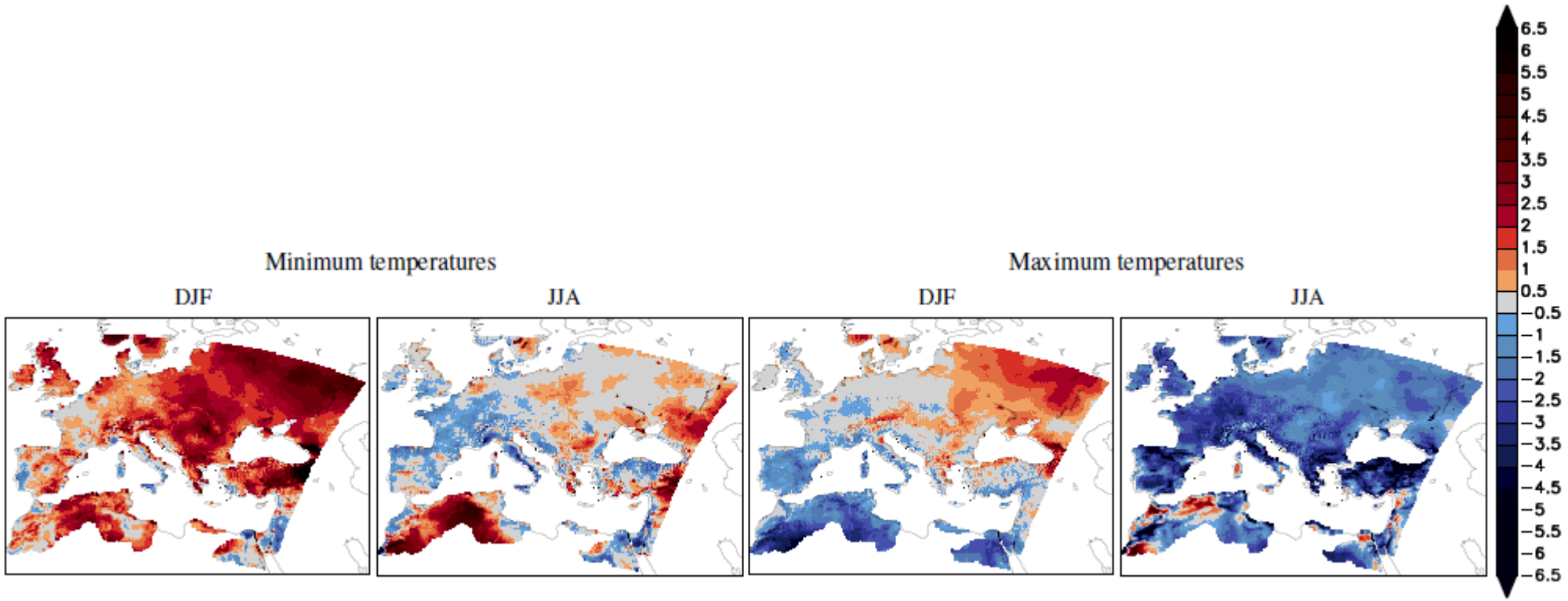
Where should we look for added value in hi-res simulations?

JJA SDII relative bias



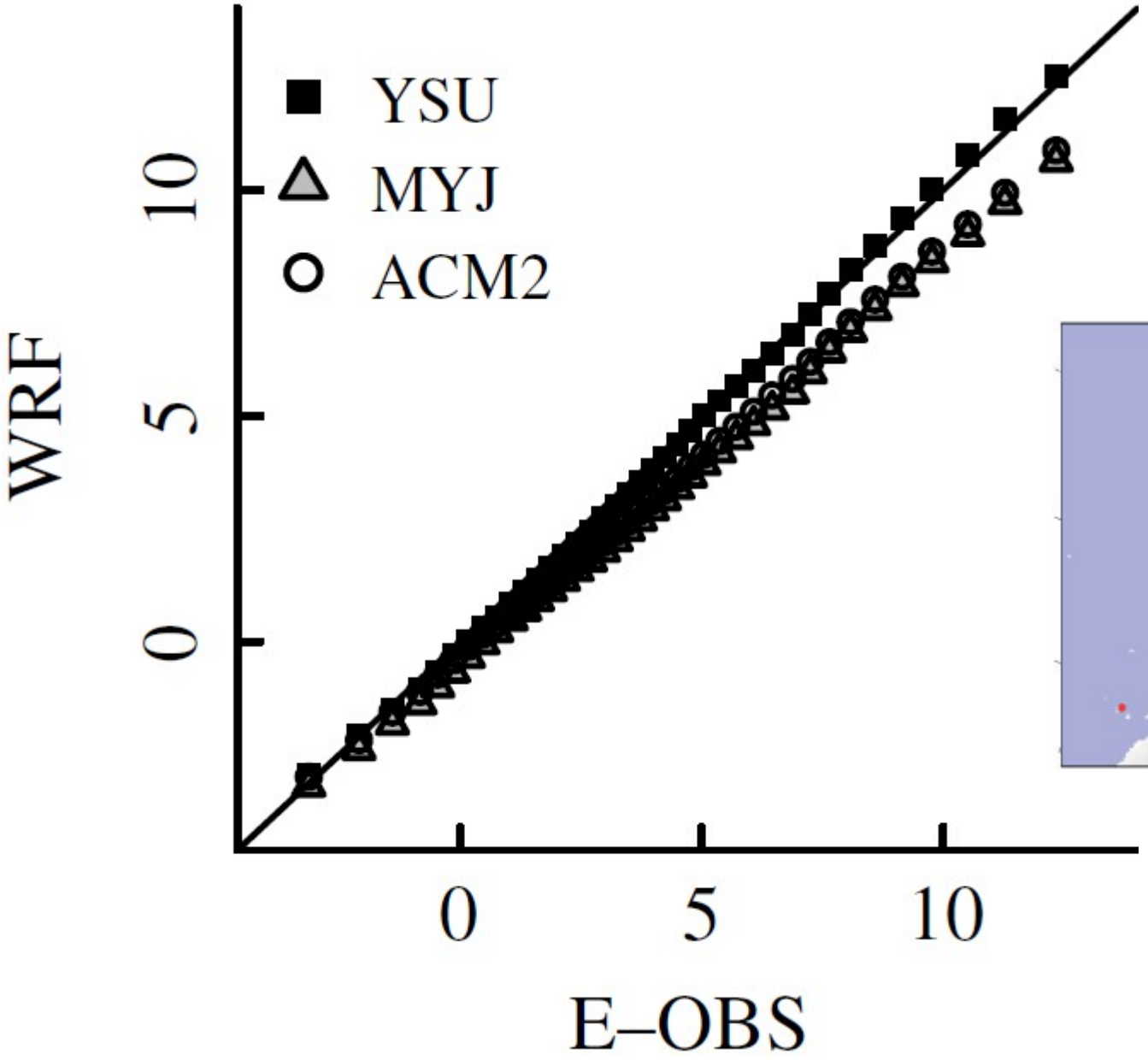
RCM biases

- Biases depend on location and season.
- They also depend on the time of the day (maximum/minimum temperature)



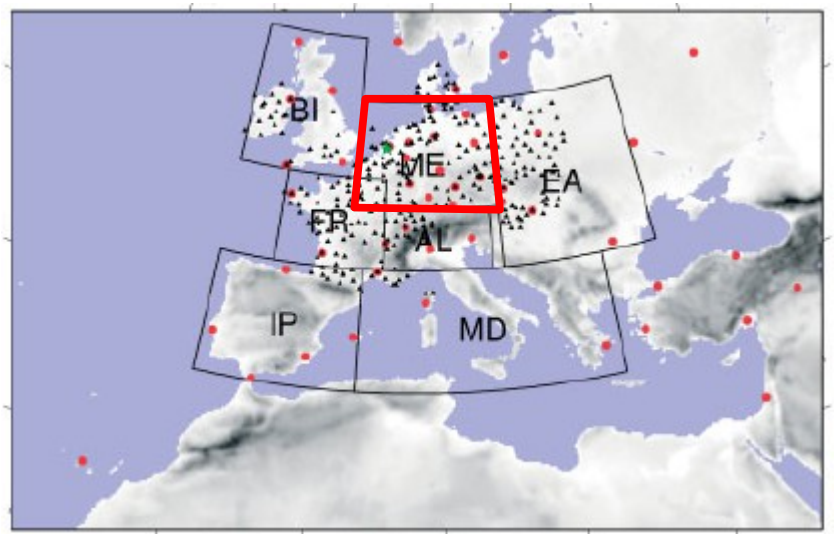
García-Díez et al., 2012

QQ-plot: beyond mean values



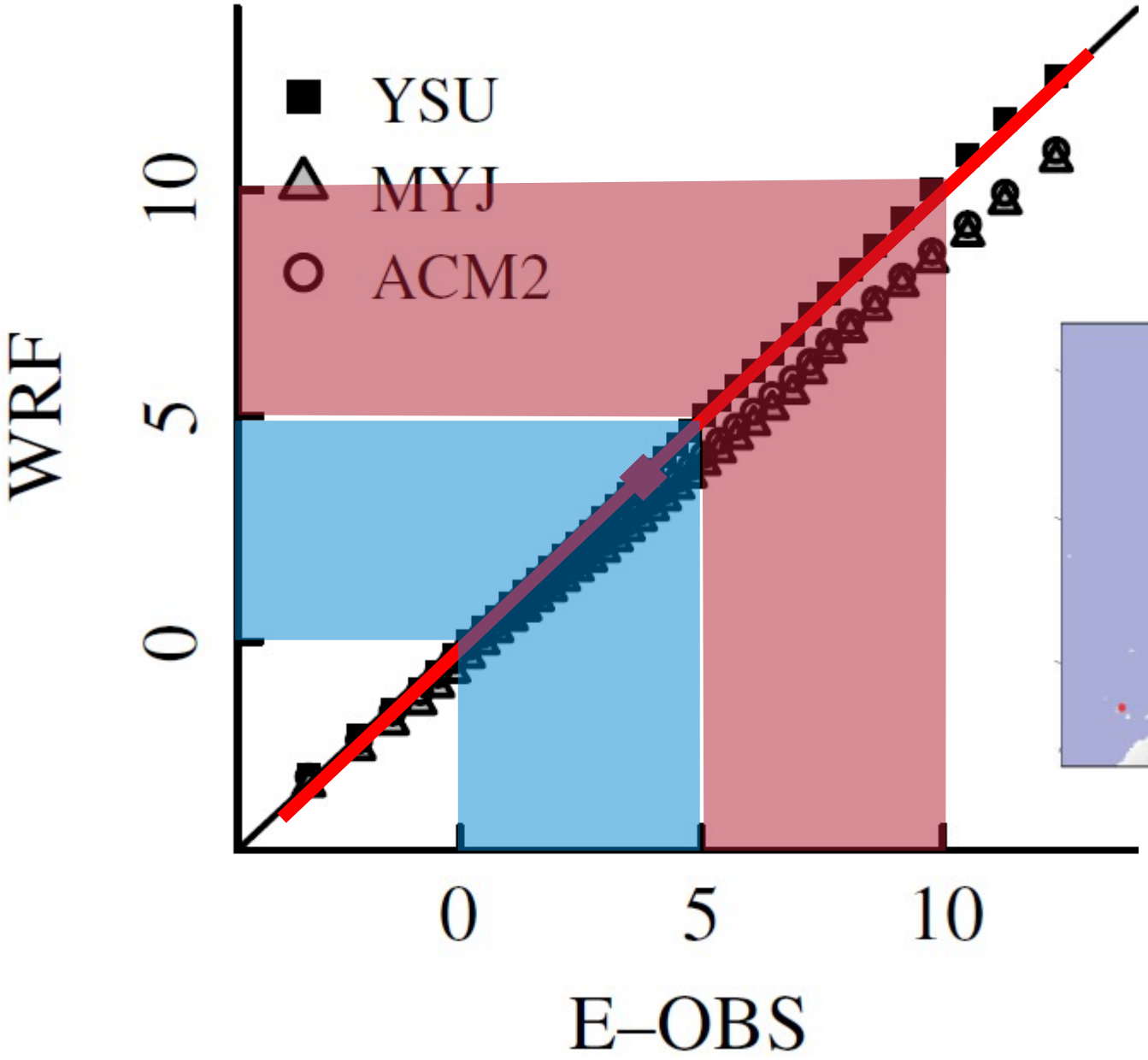
Example

DJF tasmax



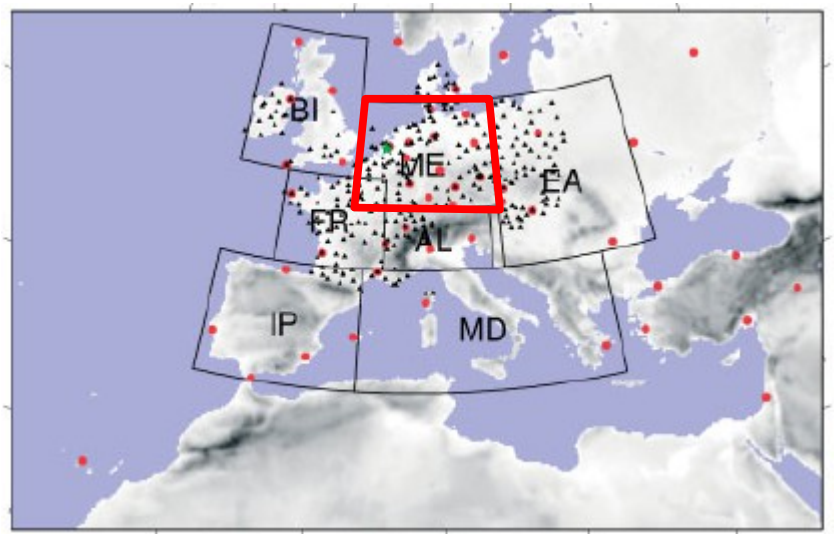
García-Díez et al., 2012

QQ-plot



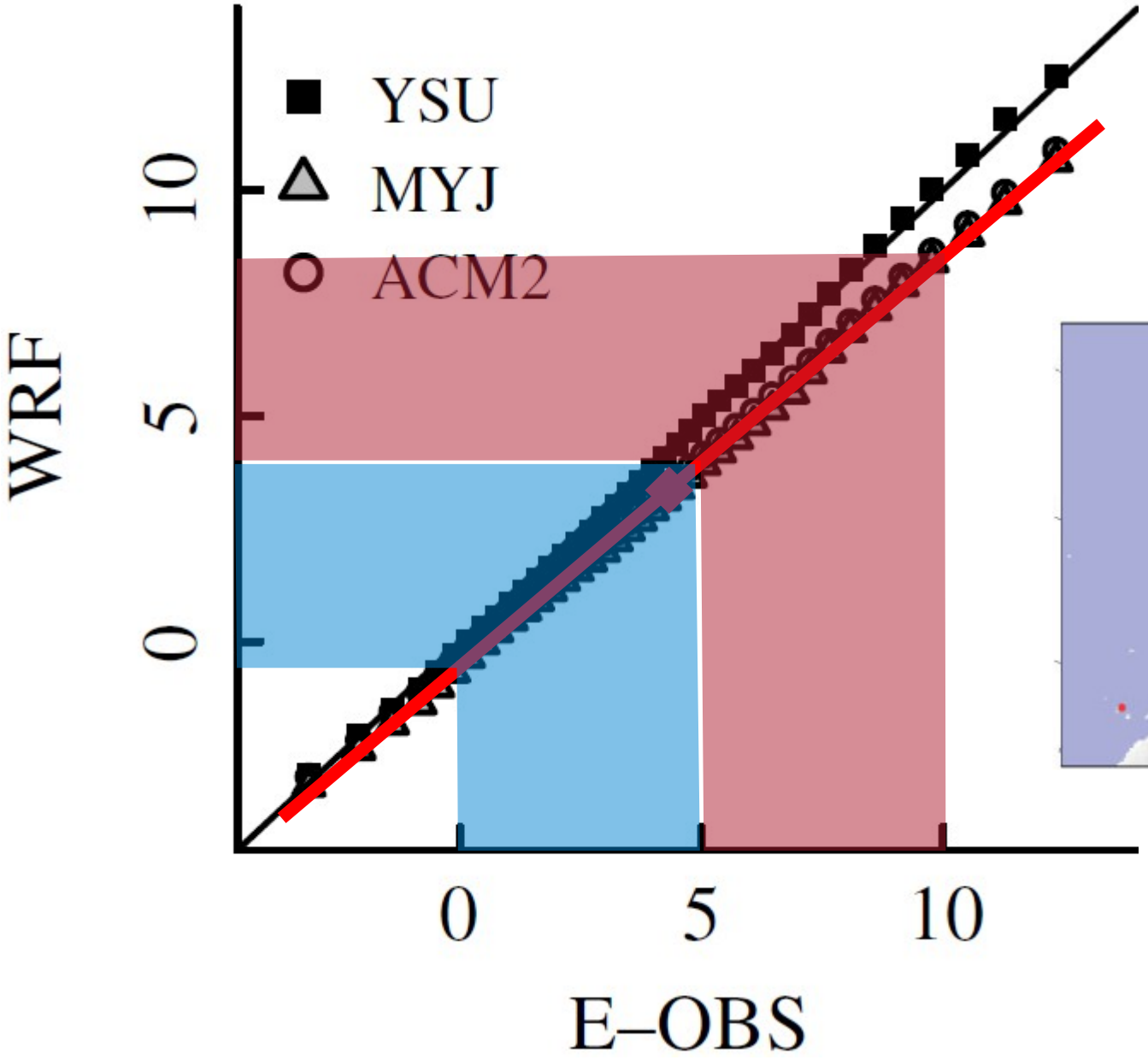
Example

DJF tasmax



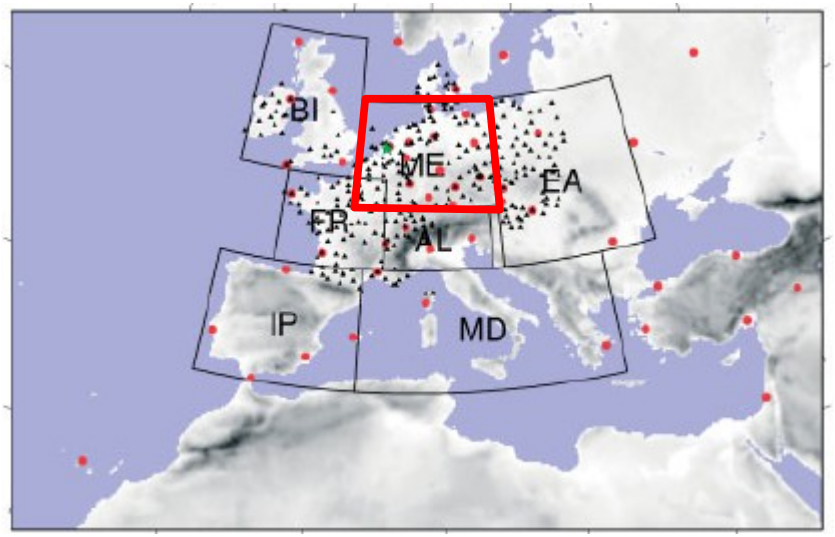
García-Díez et al., 2012

QQ-plot



Example

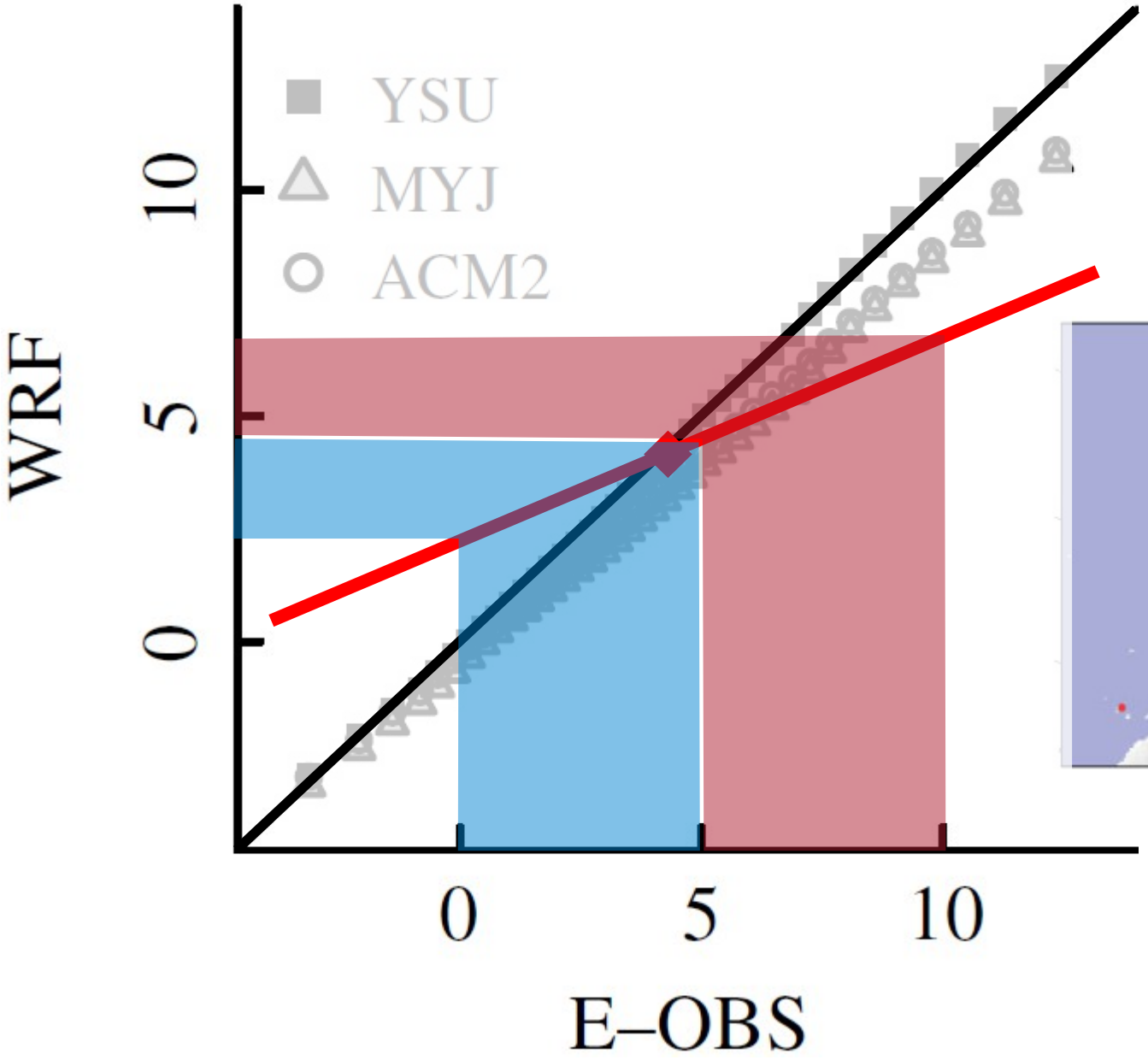
DJF tasmax



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

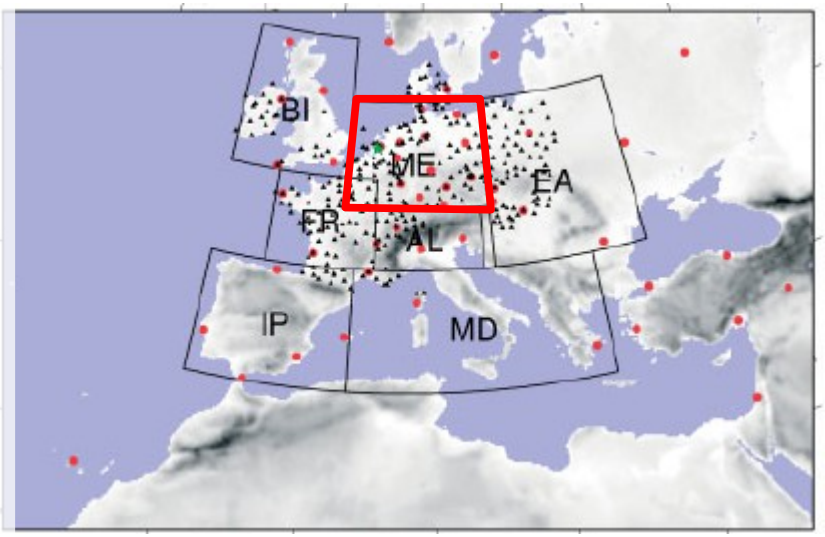
García-Díez et al., 2012

QQ-plot

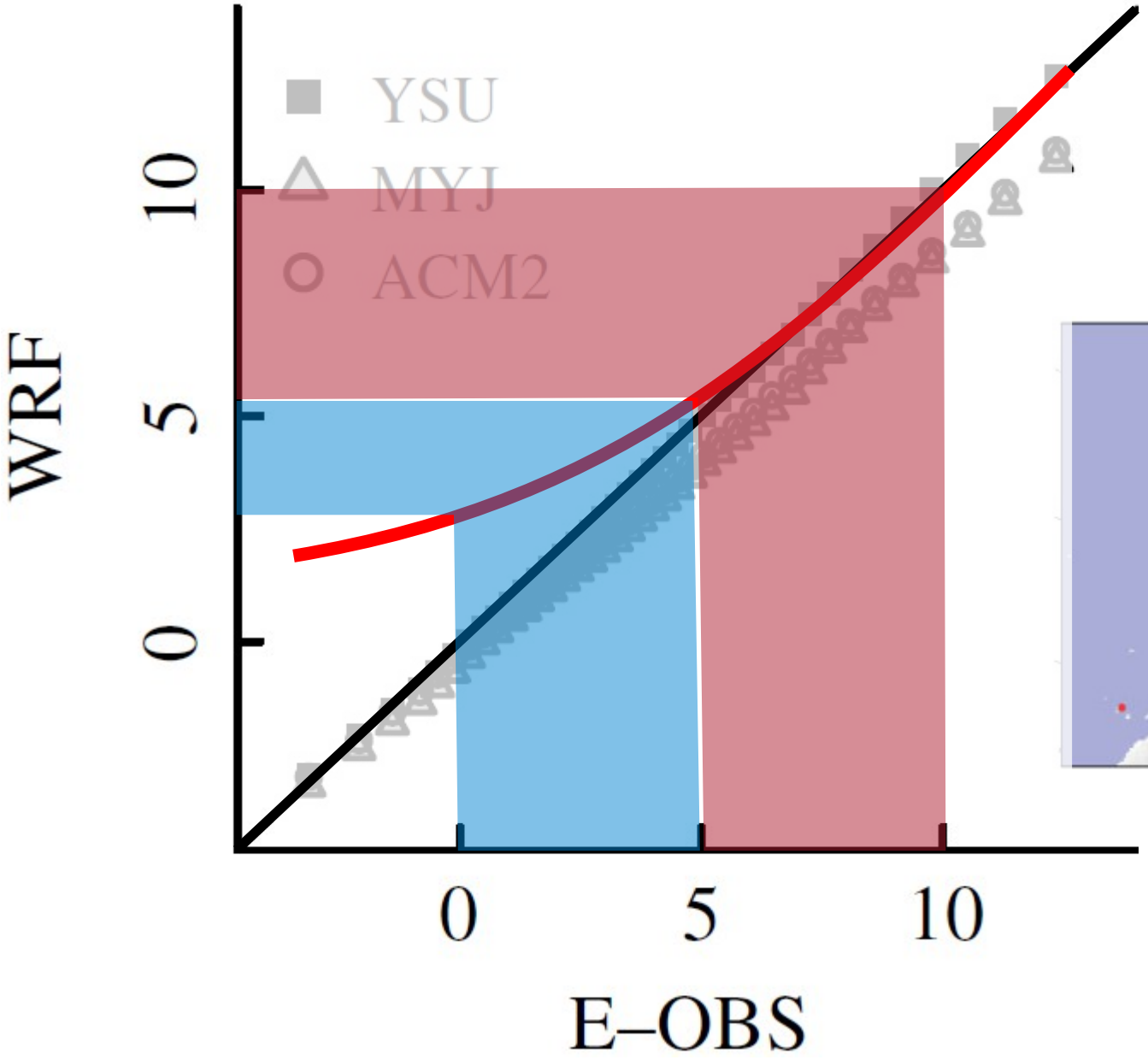


Example

DJF tasmax

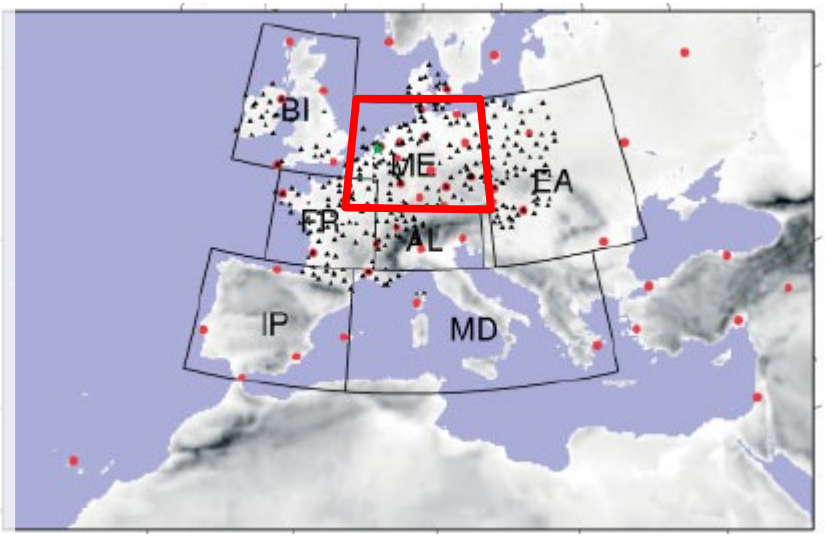


QQ-plot

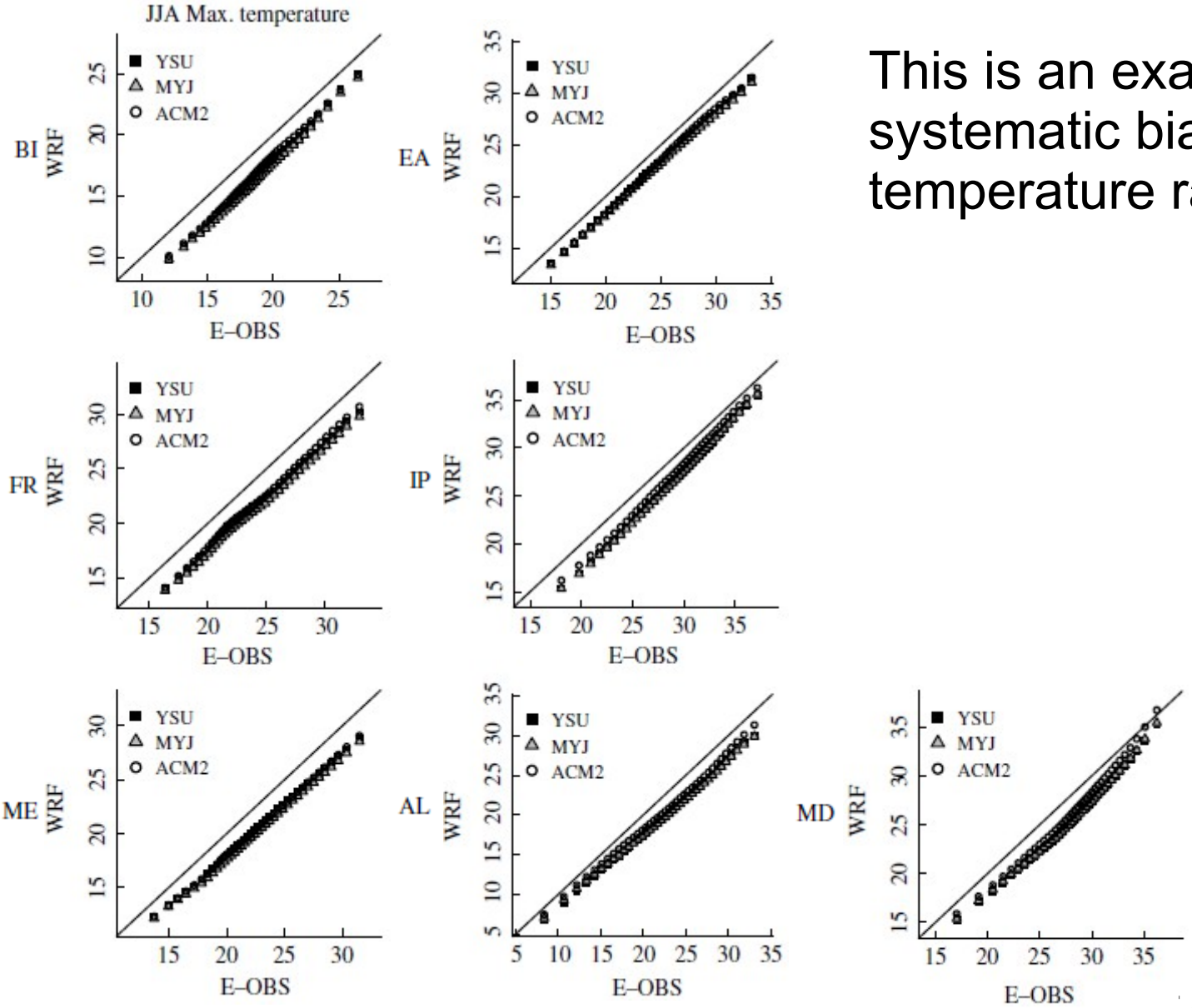


Example

DJF tasmax



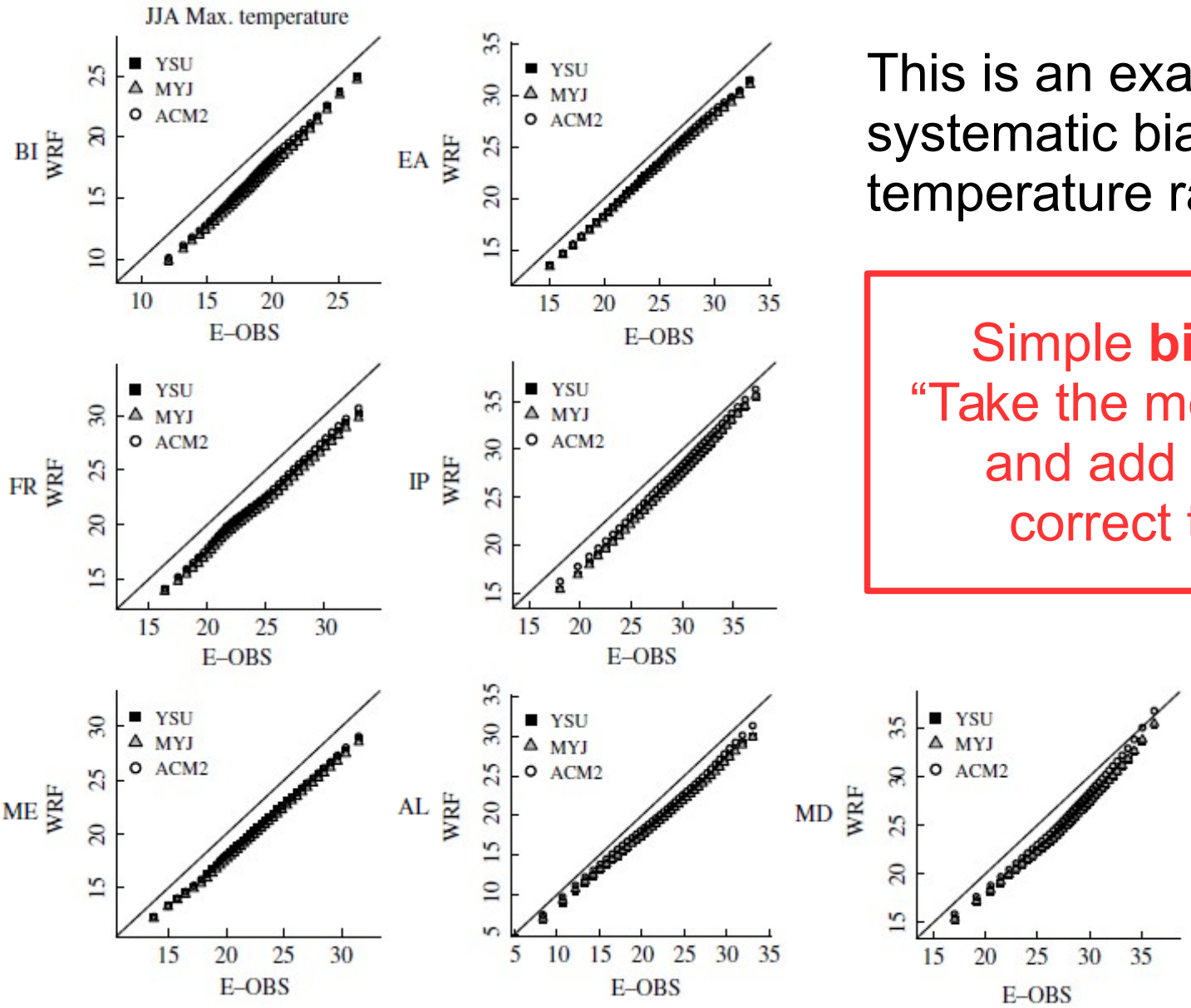
JJA tasmax



This is an example of a very systematic bias along the whole temperature range.

García-Díez et al., 2012

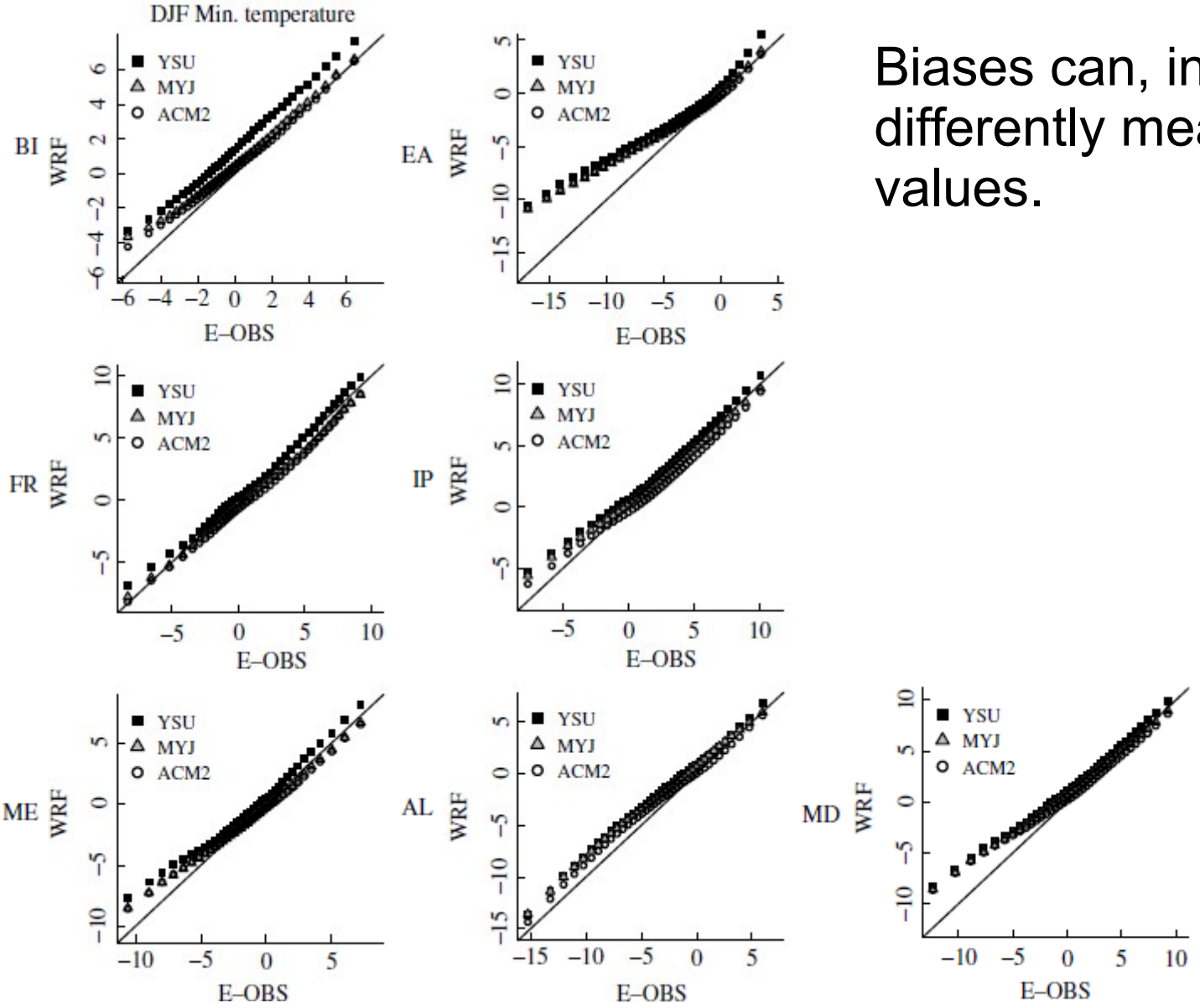
JJA tasmax



This is an example of a very systematic bias along the whole temperature range.

Simple **bias correction**
"Take the model temperature and add 2ºC to get the correct temperature"

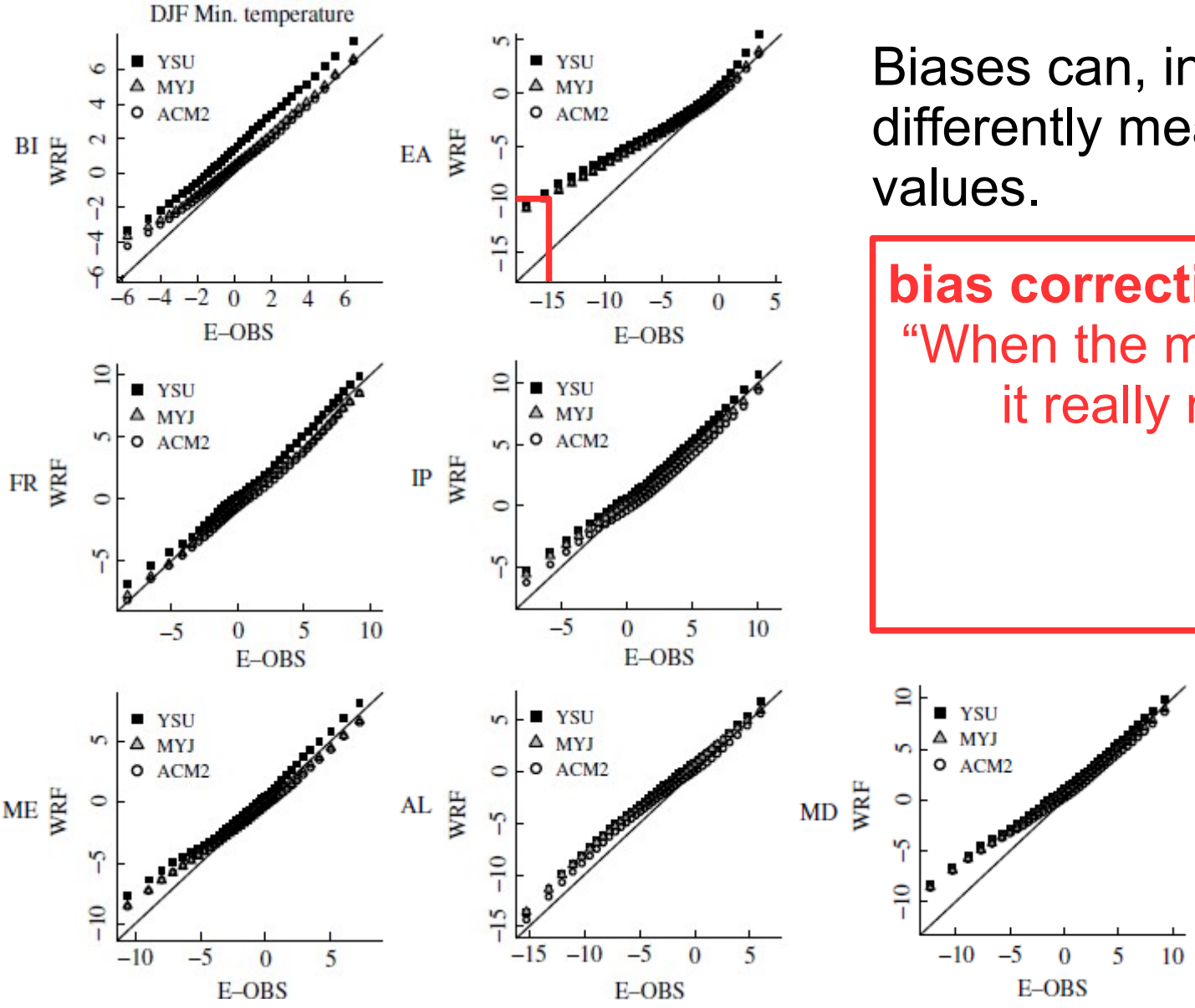
DJF tasmin



Biases can, in general, affect differently mean and extreme values.

García-Díez et al., 2012

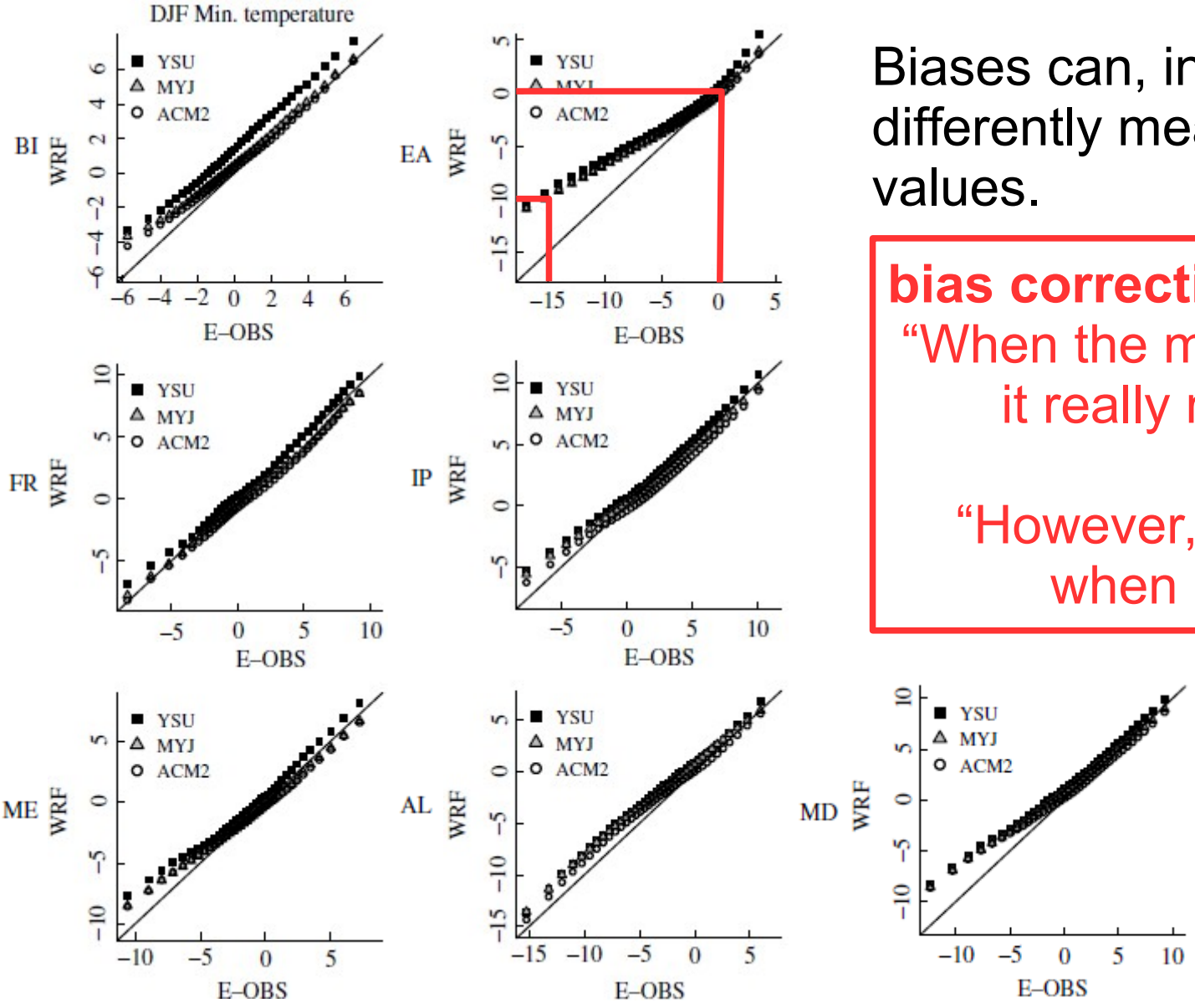
DJF tasmin



Biases can, in general, affect differently mean and extreme values.

bias correction (qq-mapping)
"When the model says -10ºC, it really means -15ºC"

DJF tasmin



Biases can, in general, affect differently mean and extreme values.

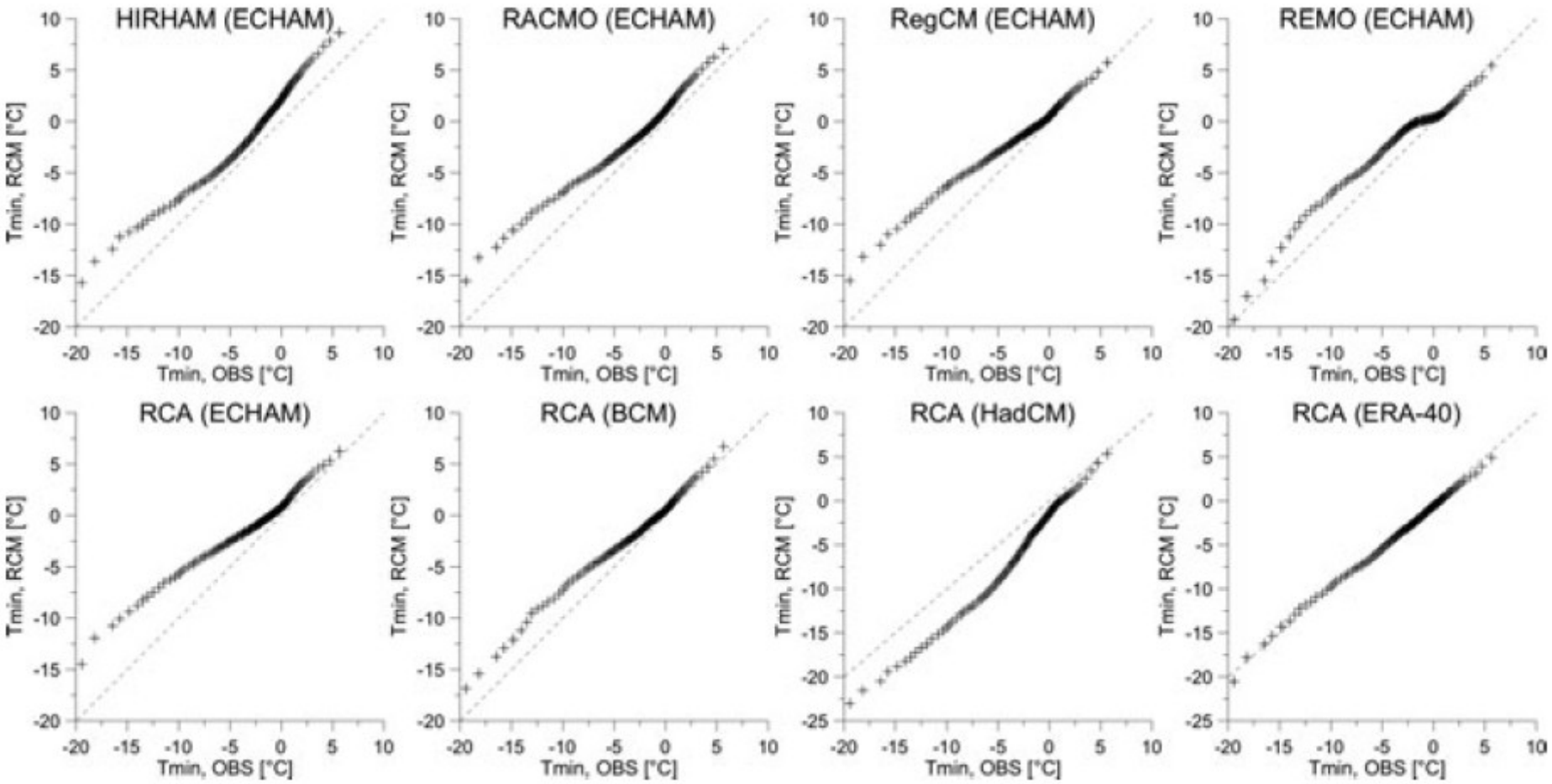
bias correction (qq-mapping)

"When the model says -10ºC, it really means -15ºC"

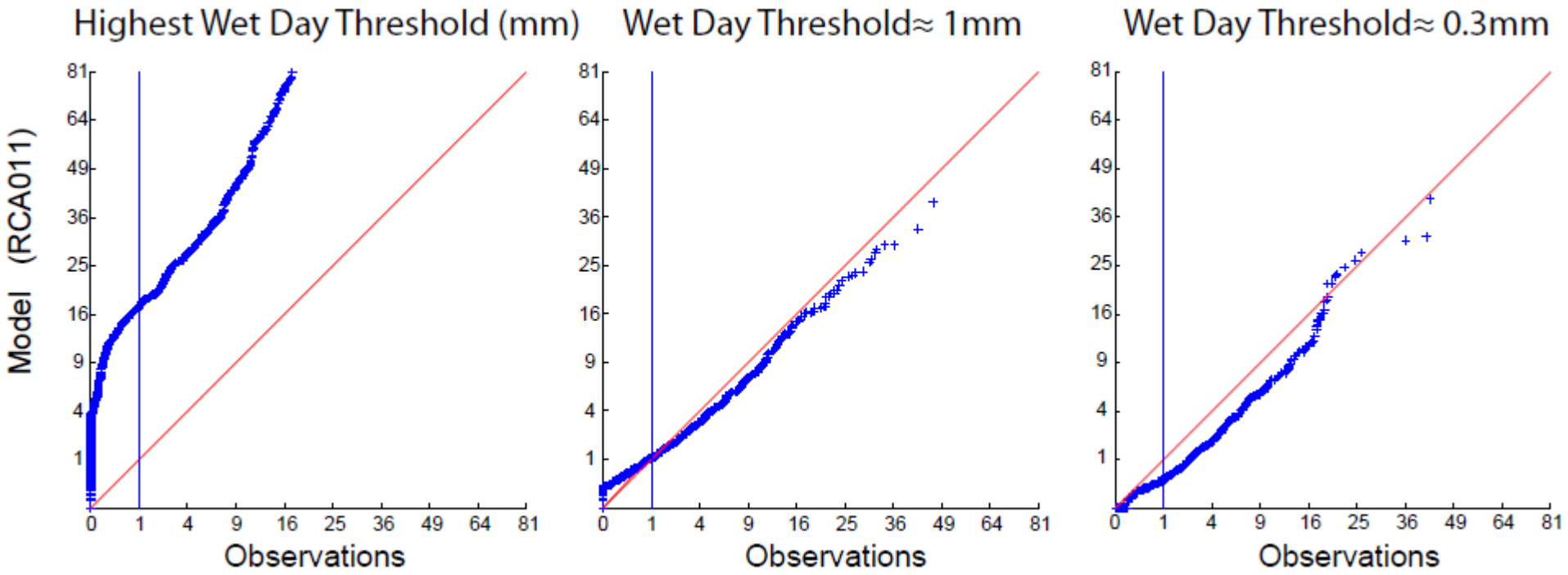
"However, you can trust it when it says 0ºC"

Common problem in RCMs

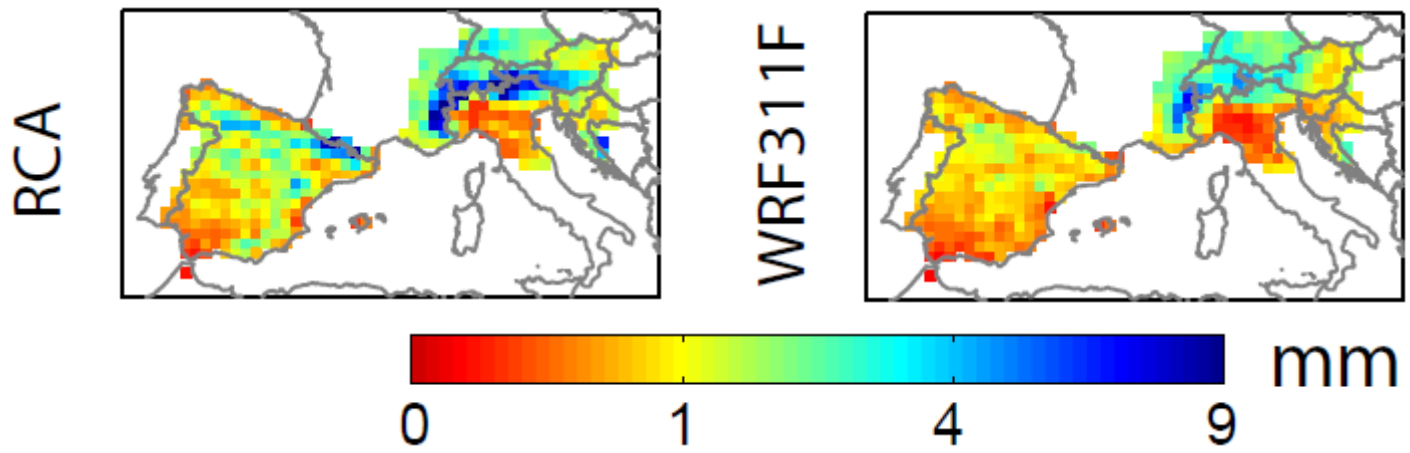
Qq-plots of ENSEMBLES RCMs in central Europe from Plavcova & Kysely (2011)



RCM pr biases



$$P^* = F_{RCM}^{-1}(F_{OBS}(1mm))$$

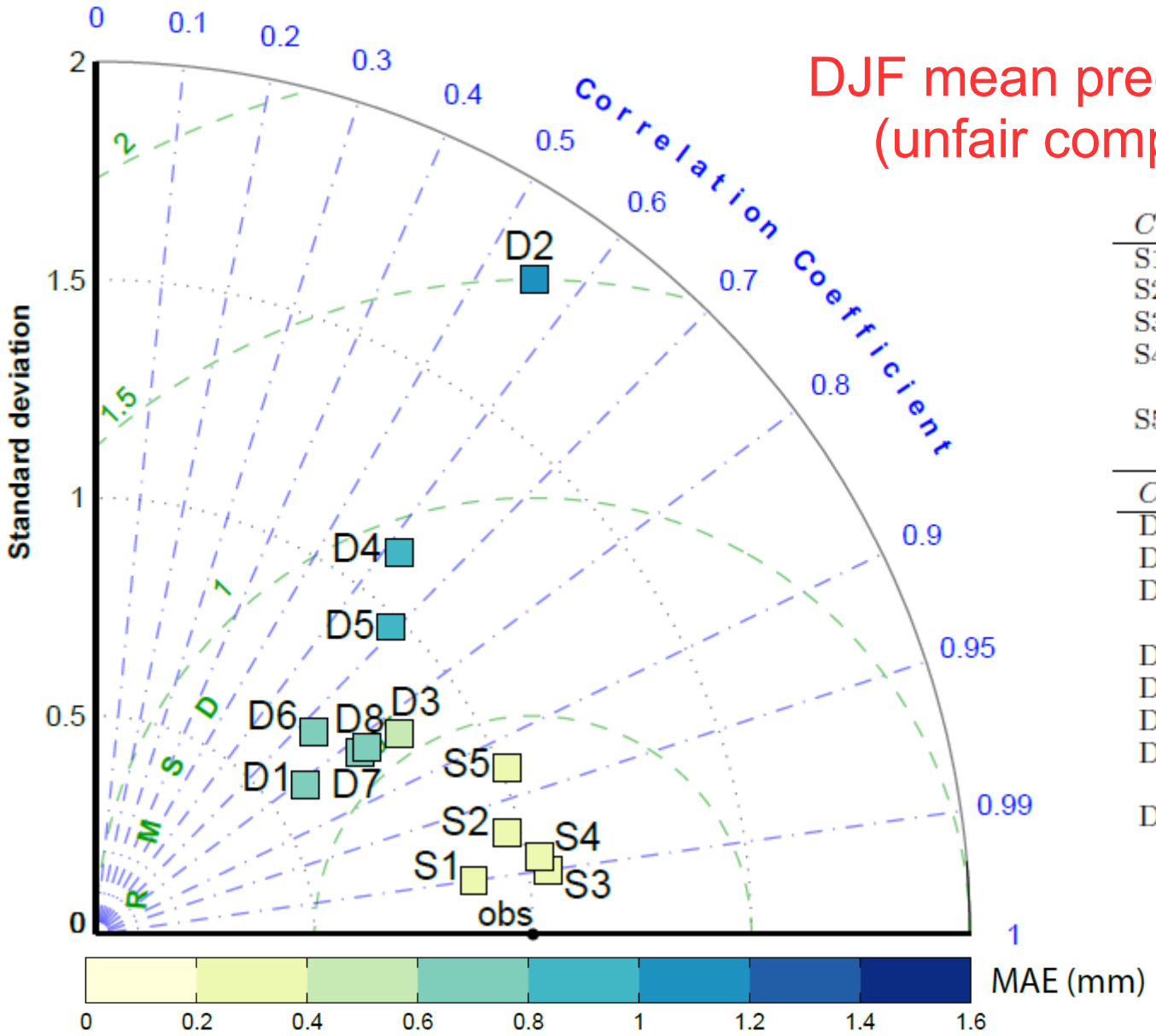


Comparison of DD and SD

- Statistical and dynamical downscaling are fundamentally different approaches
  - Observations enter the training process of SD
    - Low bias by construction
  - Observations also enter DD model tuning
    - The specific use of obs is essentially unknown
    - Cannot reduce biases in all variables
- Fairly evaluating the realism of DS products is a HARD task

RCMs vs SDMs

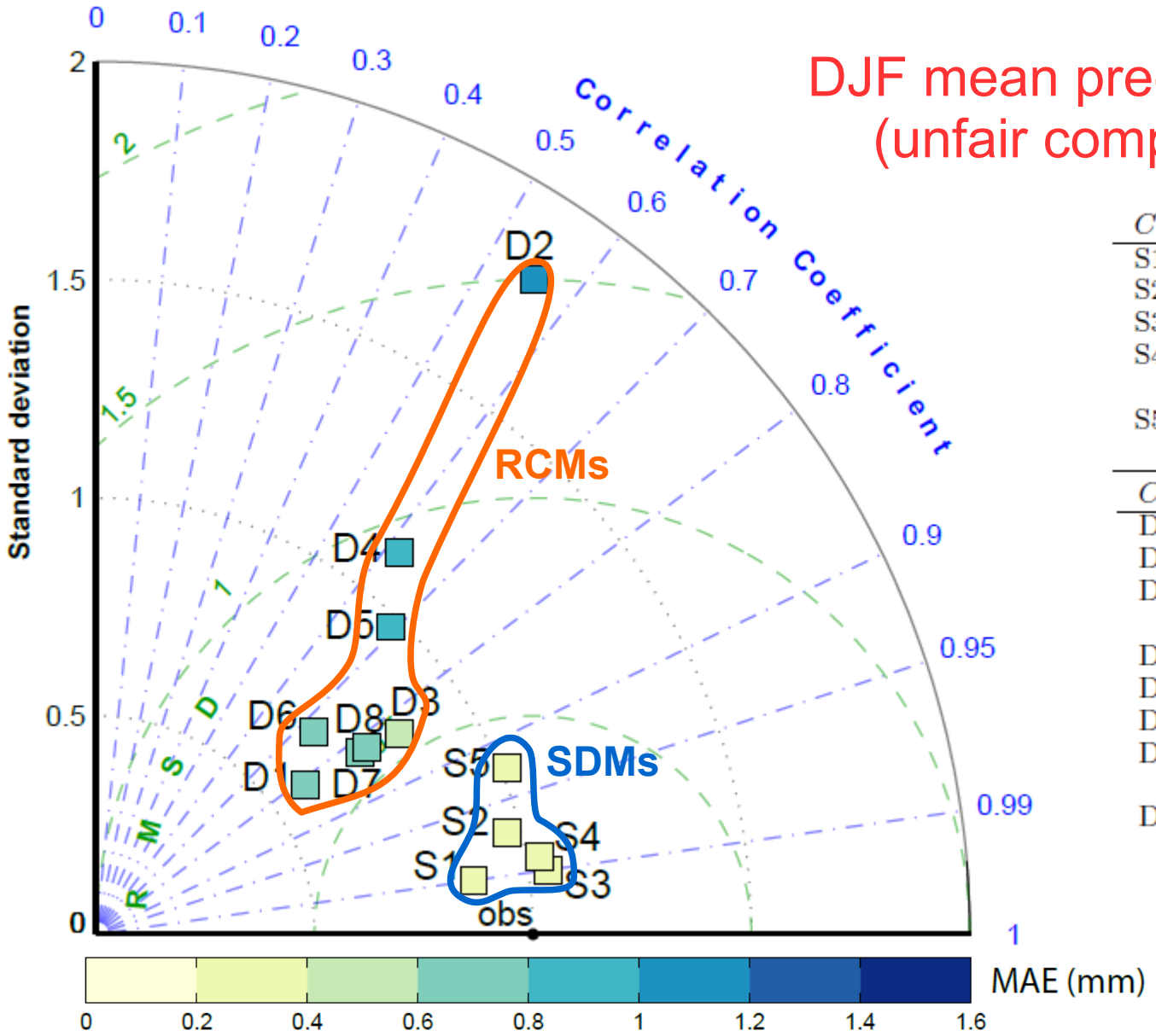
DJF mean precip pattern (unfair comparison)



Code	*CodeM14*	*Family*
S1	M1a	AN
S2	M2c	WT
S3	M4a	GLM
S4	M4c	GLM
S5	M5b	GLM-WT

Code	*RCM*
D1	CCLM
D2	HIRHAM
D3	RACMO
D4	RCA
D5	HadRM
D6	ALADIN
D7	WRF311F
D8	WRF331G

RCMs vs SDMs



DJF mean precip pattern
(unfair comparison)

Code	*CodeM14*	*Family*
S1	M1a	AN
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S3	M4a	GLM
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D1	CCLM
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D6	ALADIN
D7	WRF311F
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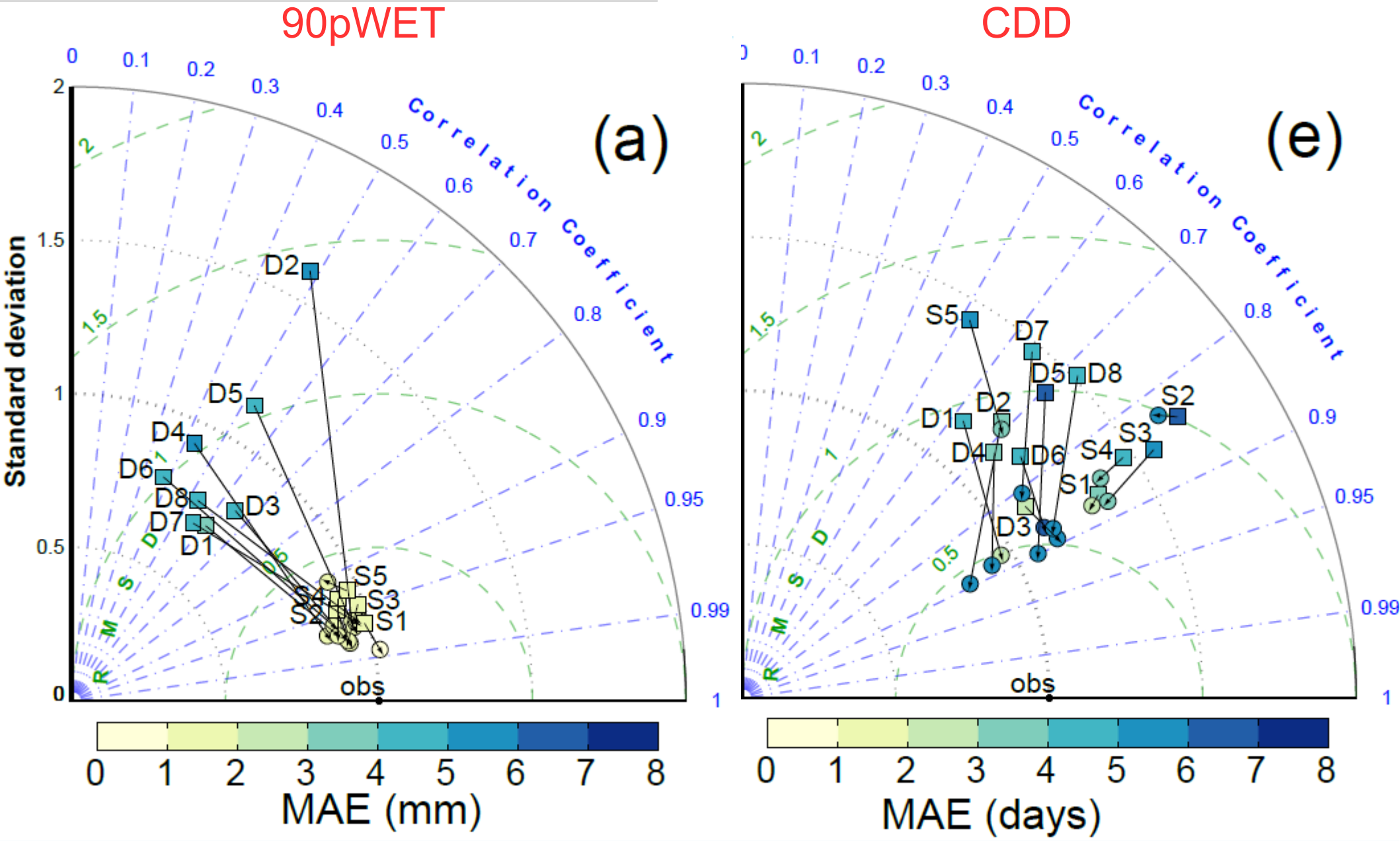
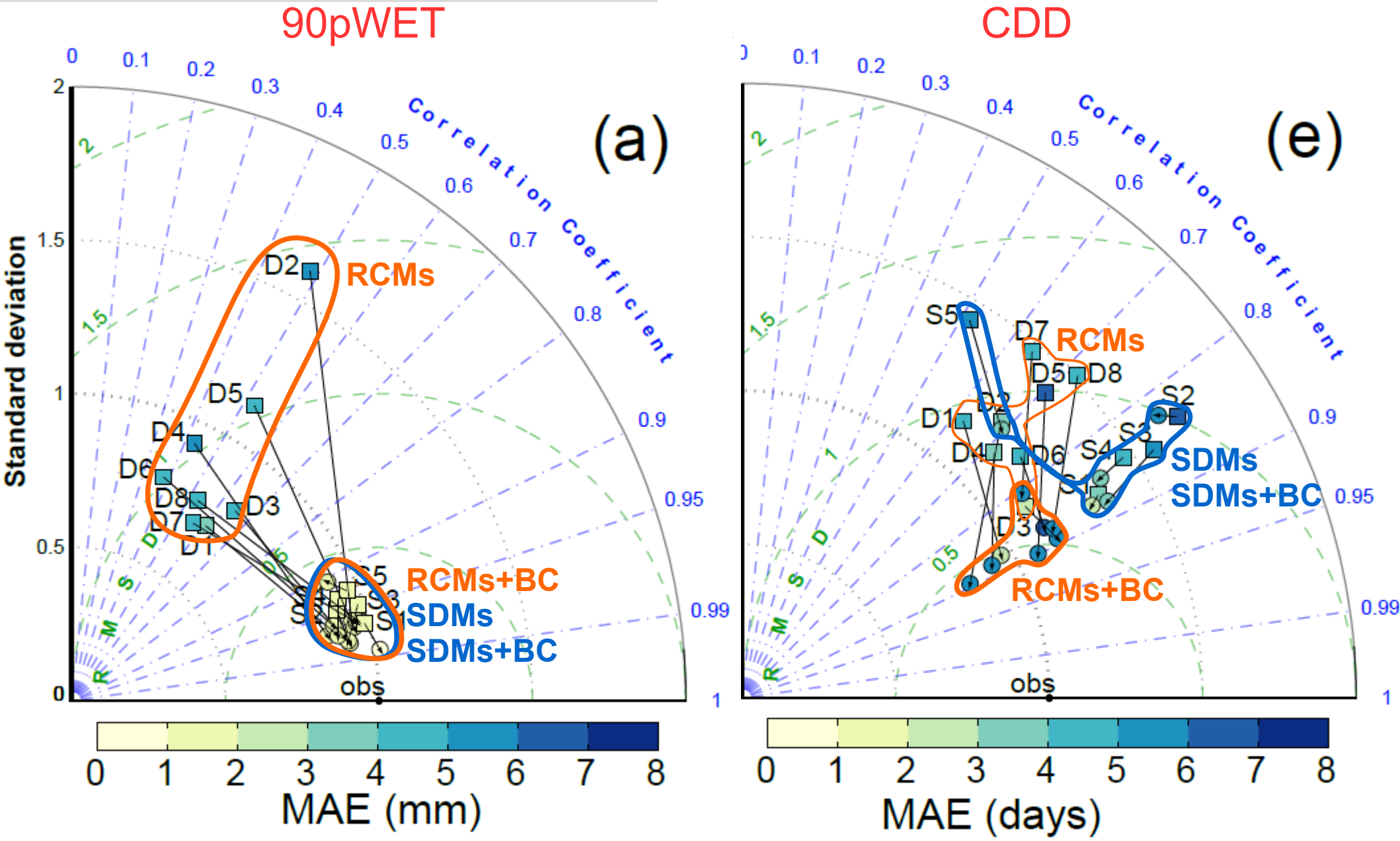
RCMs vs SDMs

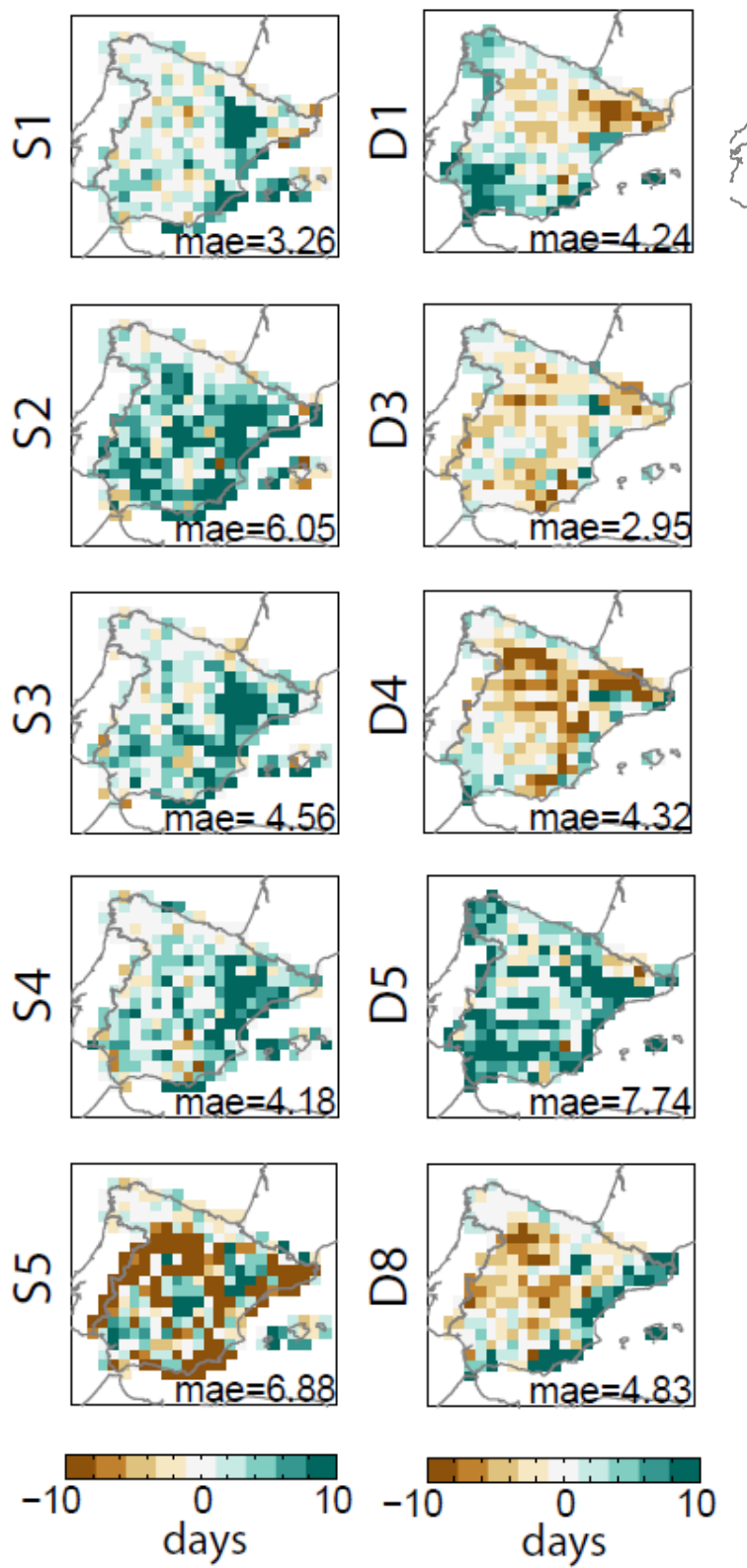

90pWET
CDD
(a)
(e)
Standard deviation
Correlation Coefficient
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0.95
0.99
1
0.5
1.5
2
D1
D2
D3
D4
D5
D6
D7
D8
S1
S2
S3
S4
S5
obs
R
M
S
D
0 1 2 3 4 5 6 7 8
MAE (mm)
MAE (days)

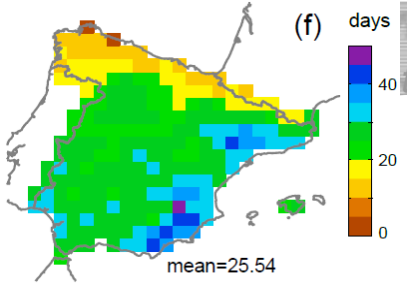
RCMs vs SDMs

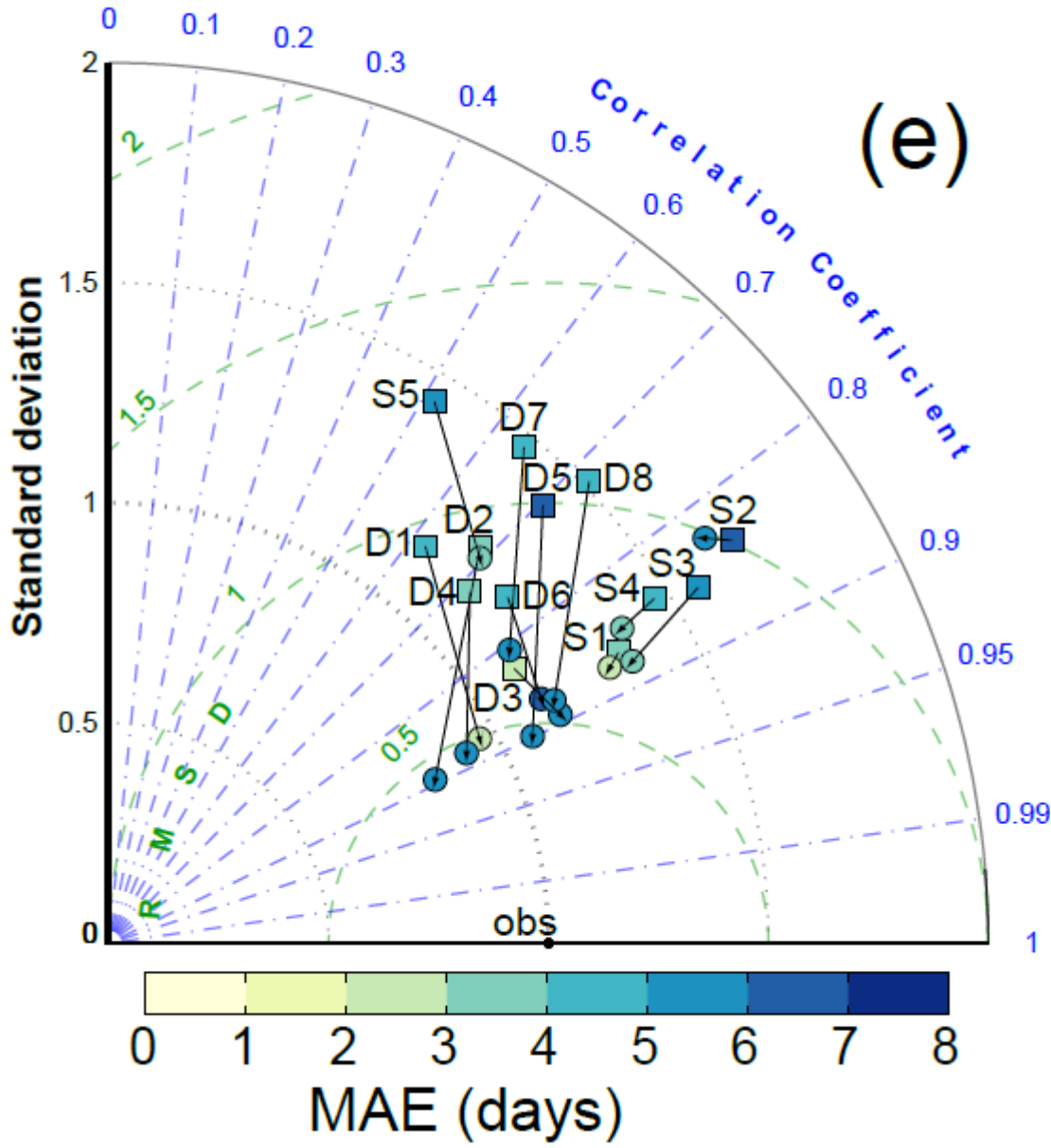

90pWET
CDD
(a)
(e)
Correlation Coefficient
Standard deviation
RCMs
SDMs
SDMs+BC
RCMs+BC
obs
MAE (mm)
MAE (days)

http://www.meteo.unican.es

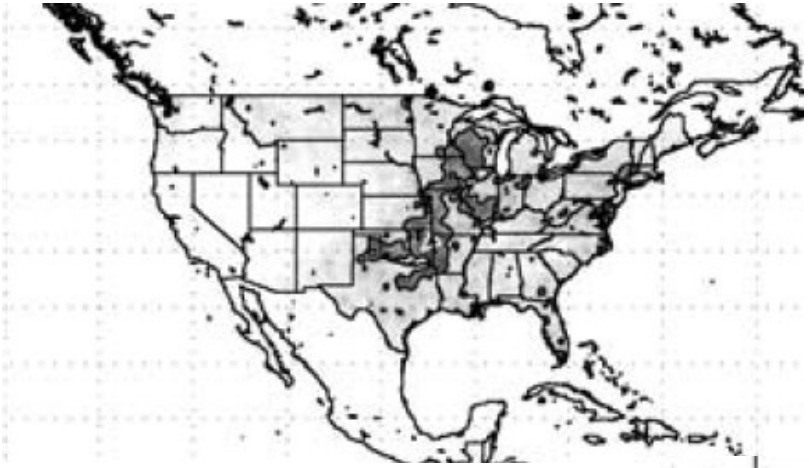
CDD



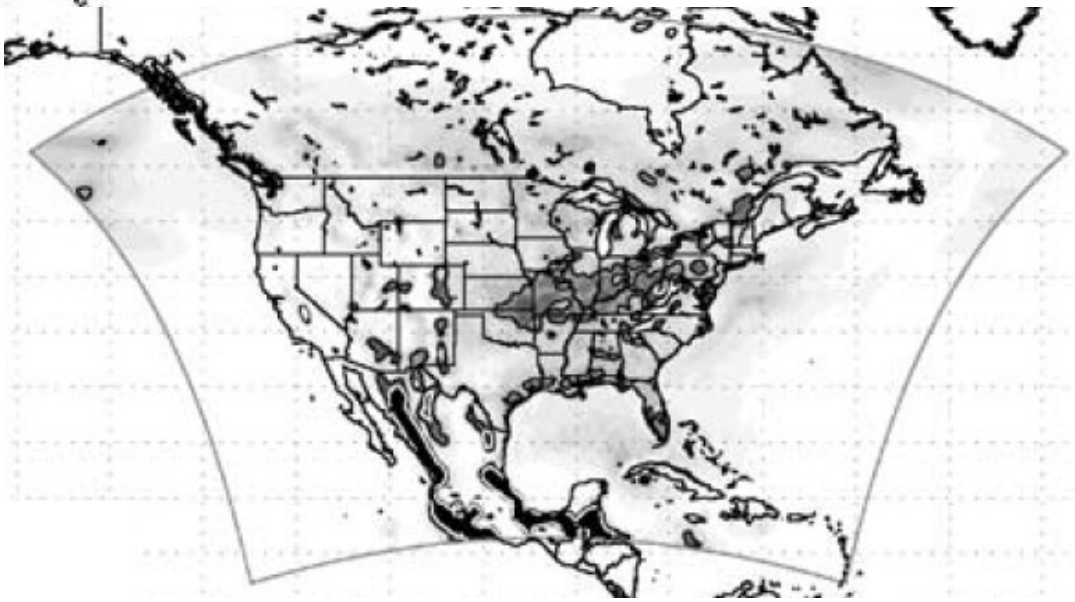




Sensibilidad (Posición del dominio)



Miguez-Macho et al. (2004)



Miguez-Macho et al. (2004) J Geoph Res 109D:13104 “Spectral nudging to eliminate the effects of domain position and geometry in RCM simulations”

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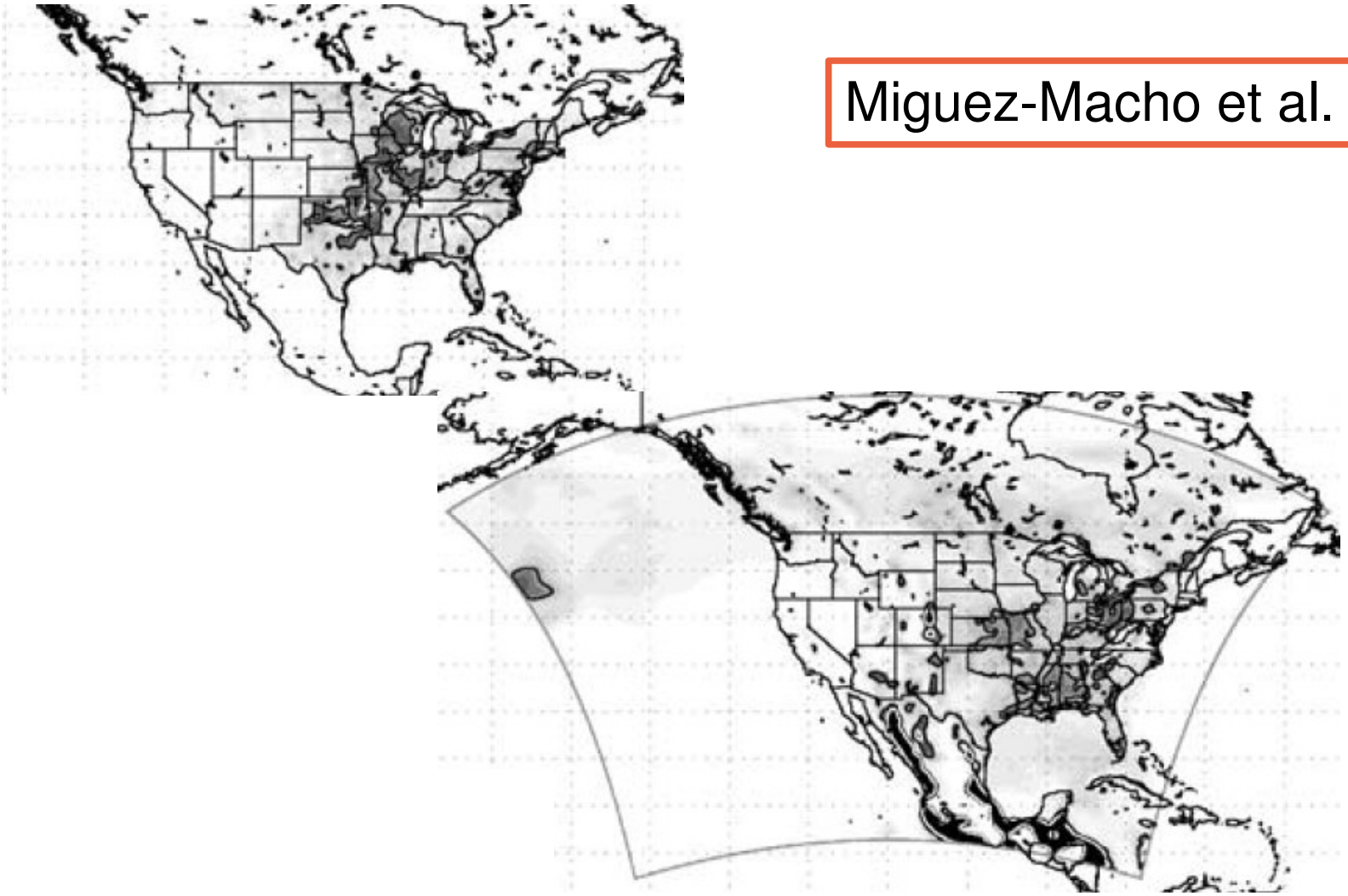

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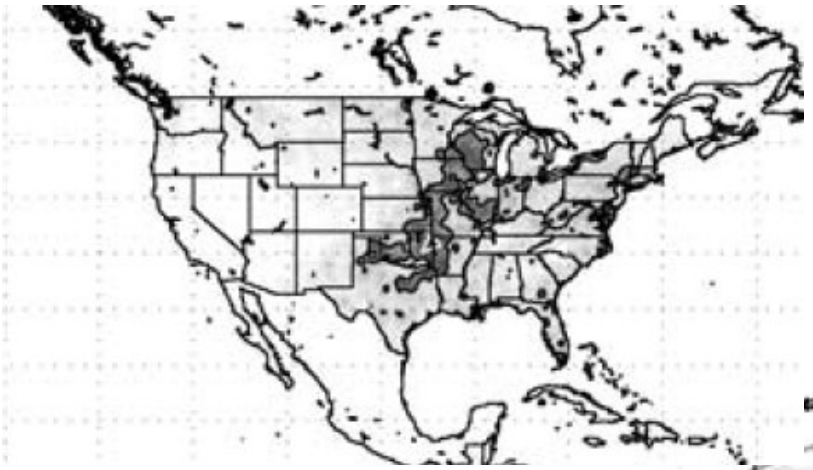

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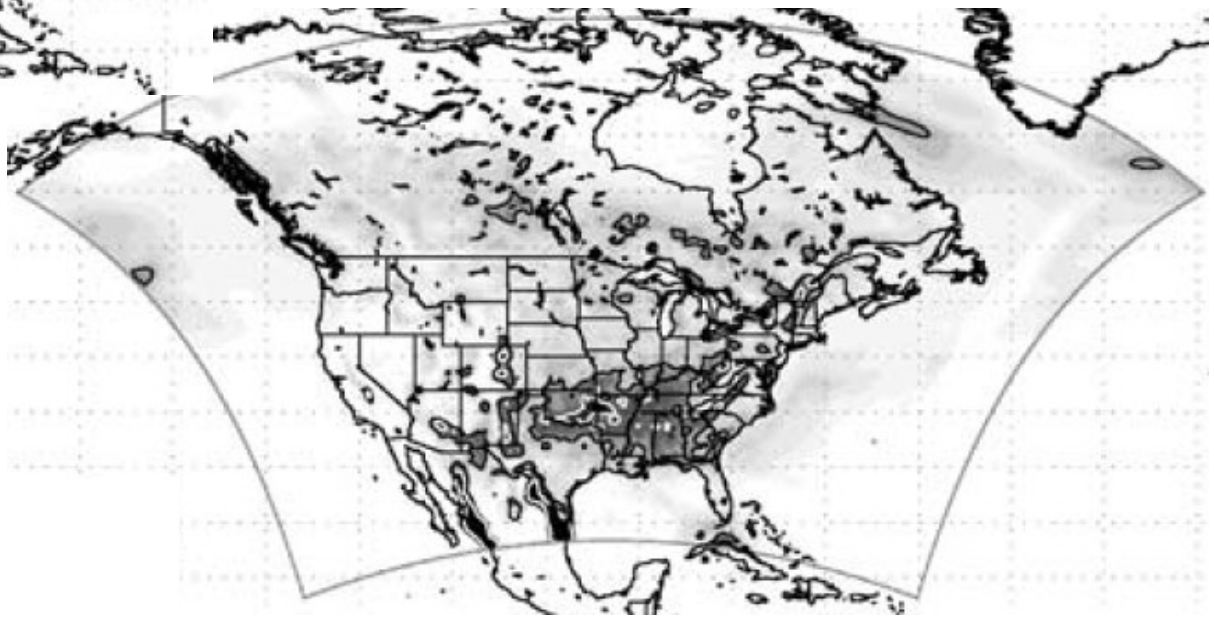

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