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Statistical Downscaling:

A CMIP5 Perspective (open issues/problems)

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CSIC

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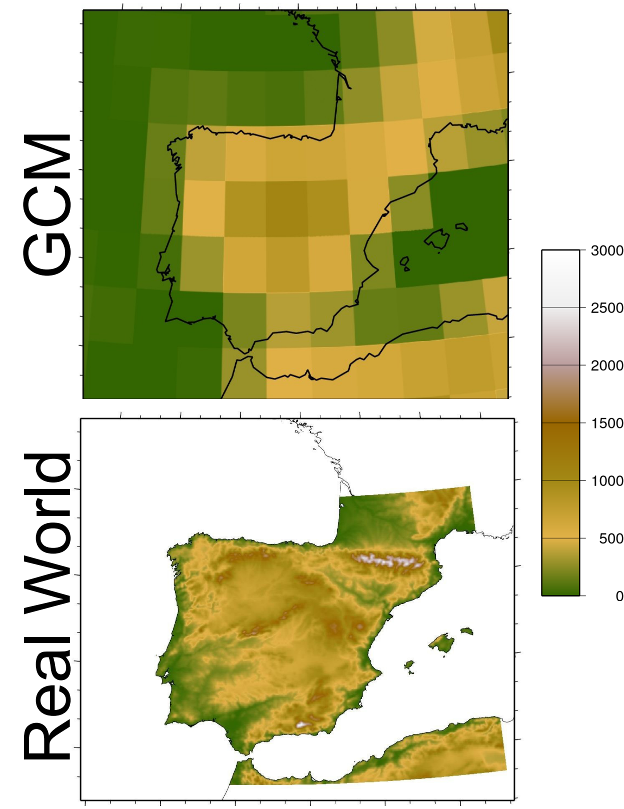
Instituto de Física de Cantabria



Workshop IS-ENES. Statistical downscaling of climate scenarios for the impact communities. A CMIP5 Perspective, Paris 16-17 October 2012

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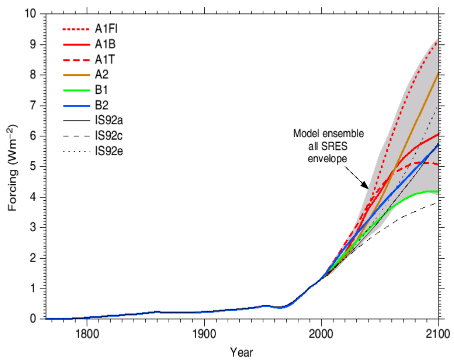
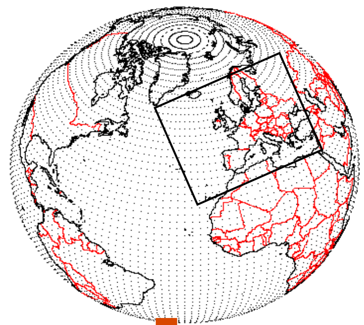
  - Key past projects: ENSEMBLES.
  - Statistical vs. Dynamical downscaling.
- Perfect Prognosis Approach:
  - Selecting the predictors (reanalisys-GCM consitency).
  - Robustness in non-stationary conditions.
- MOS-like downscaling:
  - MOS based on analogs for RCMs.
- Conclusions

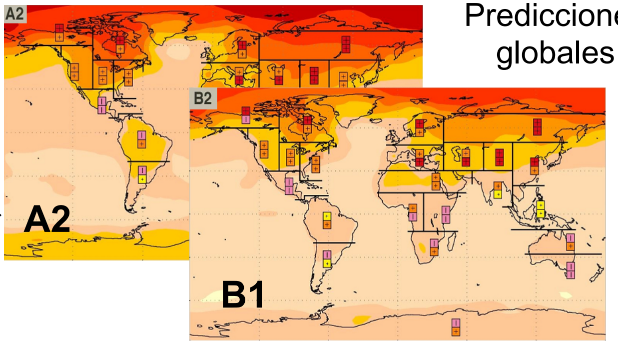
Downscaling: Dynamical (RCMs) and Statistical Approaches

Escenarios de emisión

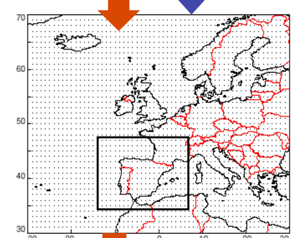




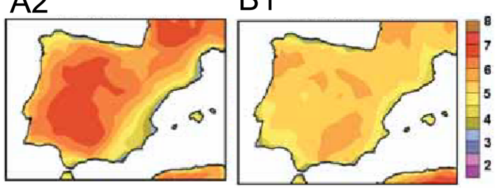
Predicciones globales



RCM



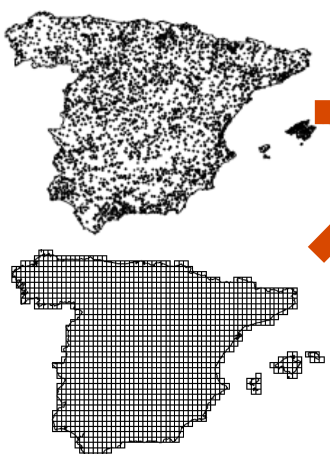
A2 B1



Downscaling Dinámico:
basado en Modelos Regionales del Clima (RCMs)

SDM

Registros históricos



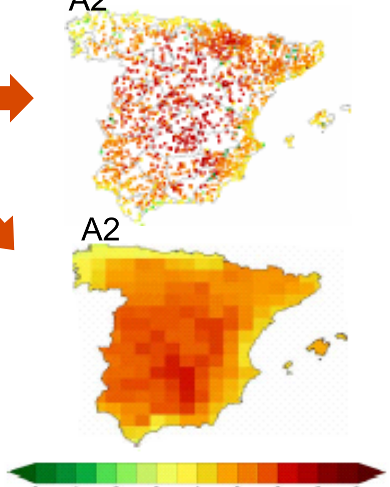
Rejilla interpolada (**20 km**)

$$\mathbf{Y} = f\,(\mathbf{X};\theta)$$

Los parámetros de los modelos son ajustados con los datos observados y simulados en clima presente.

A2

A2



Downscaling Estadístico:
basado en métodos estadísticos que relacionan las ocurrencias locales con las simulaciones globales.

Santander Meteorology Group

A multidisciplinary approach for weather & climate

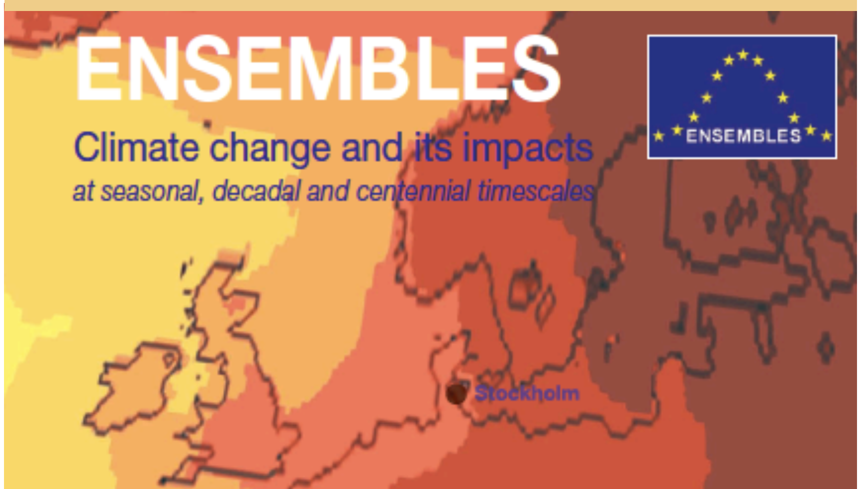
EU-funded Project (2004-2009)

http://ensembles-eu.metoffice.com

ENSEMBLES Project (2004-2009)

Develop an ensemble prediction system for climate change and linking the outputs to a range of applications.

- **Statistical Downscaling (SD) methods/tools.**
- **RCM simulations.**
- **Gridded observations: E-OBS**



The statistical downscaling portal is a free tool for user-friendly downscaling.

http://www.meteo.unican.es/ensembles

Downscaling Portal

https://www.meteo.unican.es/downscaling/ensembles

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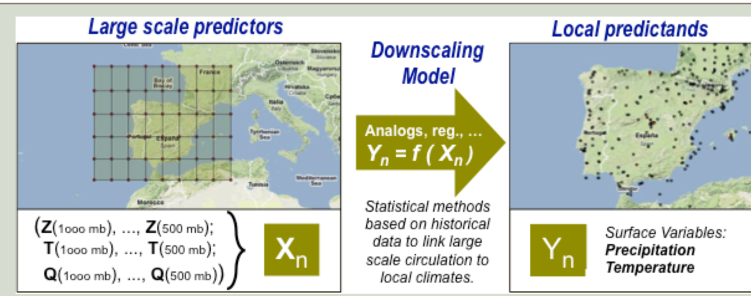
Downscaling Portal
Santander MetGroup

ENSEMBLES Downscaling Portal (version 2)

One of the goals of the ENSEMBLES project is maximizing the exploitation of the results by linking the outputs of the ensemble prediction system (multi-model climate change global simulations) to a range of applications, including agriculture, health, food security, energy, water resources, and insurance, which use high resolution climate inputs to feed their models. The **downscaling portal** allows end-users to calibrate/downscale the coarse model outputs in the region of interest using historical observed records. The portal includes public observation datasets (e.g. GSOD) and allows uploading new historical data (including private datasets, not available for other users).

This Statistical Downscaling portal provides **user-friendly web access** to different statistical downscaling techniques and works transparently with the observations, reanalysis and global climate simulations (see the common list of variables available for all models in the portal), obtaining the resulting **outputs in simple formats (e.g., text files).**



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., and Manzanas, R. (2011) User Guide of the ENSEMBLES Downscaling

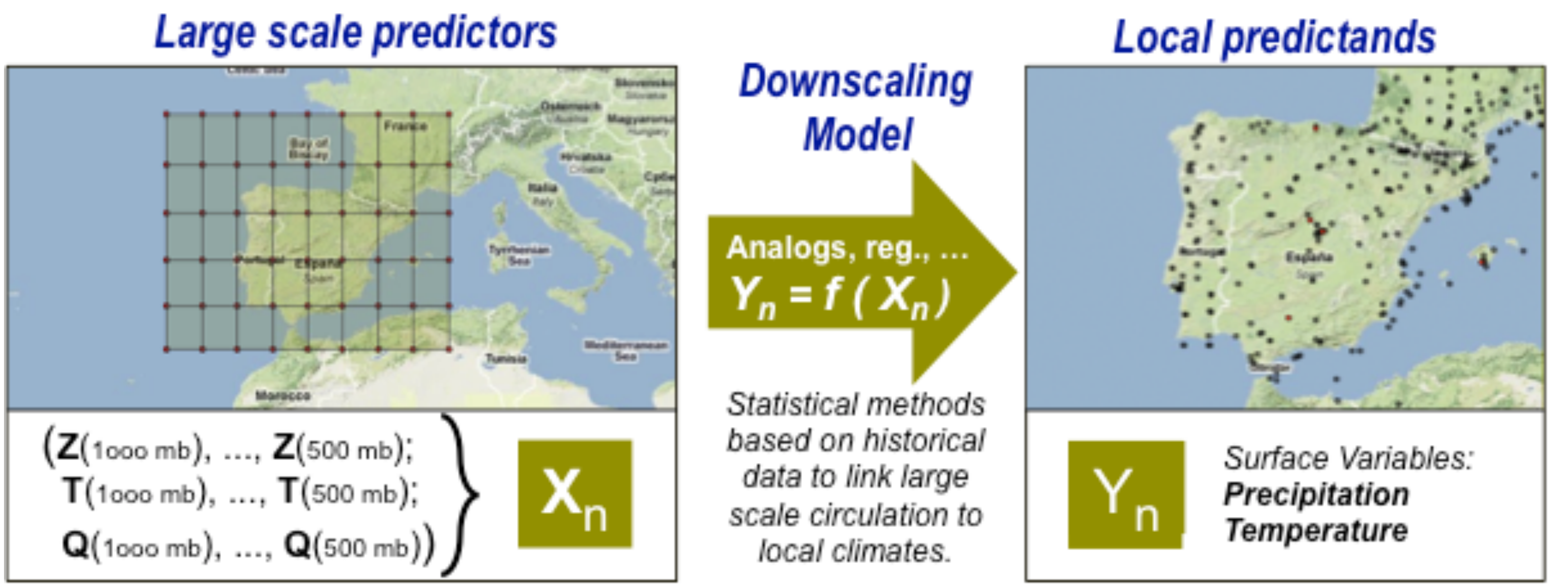
Two main methodologies: **algorithmic** and **transfer functions** (from the ENSEMBLES downscaling portal).

	Advantages	**Shorcomings**
Analogs (k-NN)	Nonlinear Spatial consistency	Algorithmic. No model. Difficult to interpret
Weather Typing (k-means, SOM)	Nonlinear Easy to interpret Spatial consistency	Algorithmic. No model. Loss of variance
Regression: Linear, GLMs	Simple Easy to interpret	Linear assumption Selection of predictors
Regression conditioned on Weather Types	Nonlinear Easy to interpret Spatial consistency	Loss of variance Problem with borders

ENSEMBLES

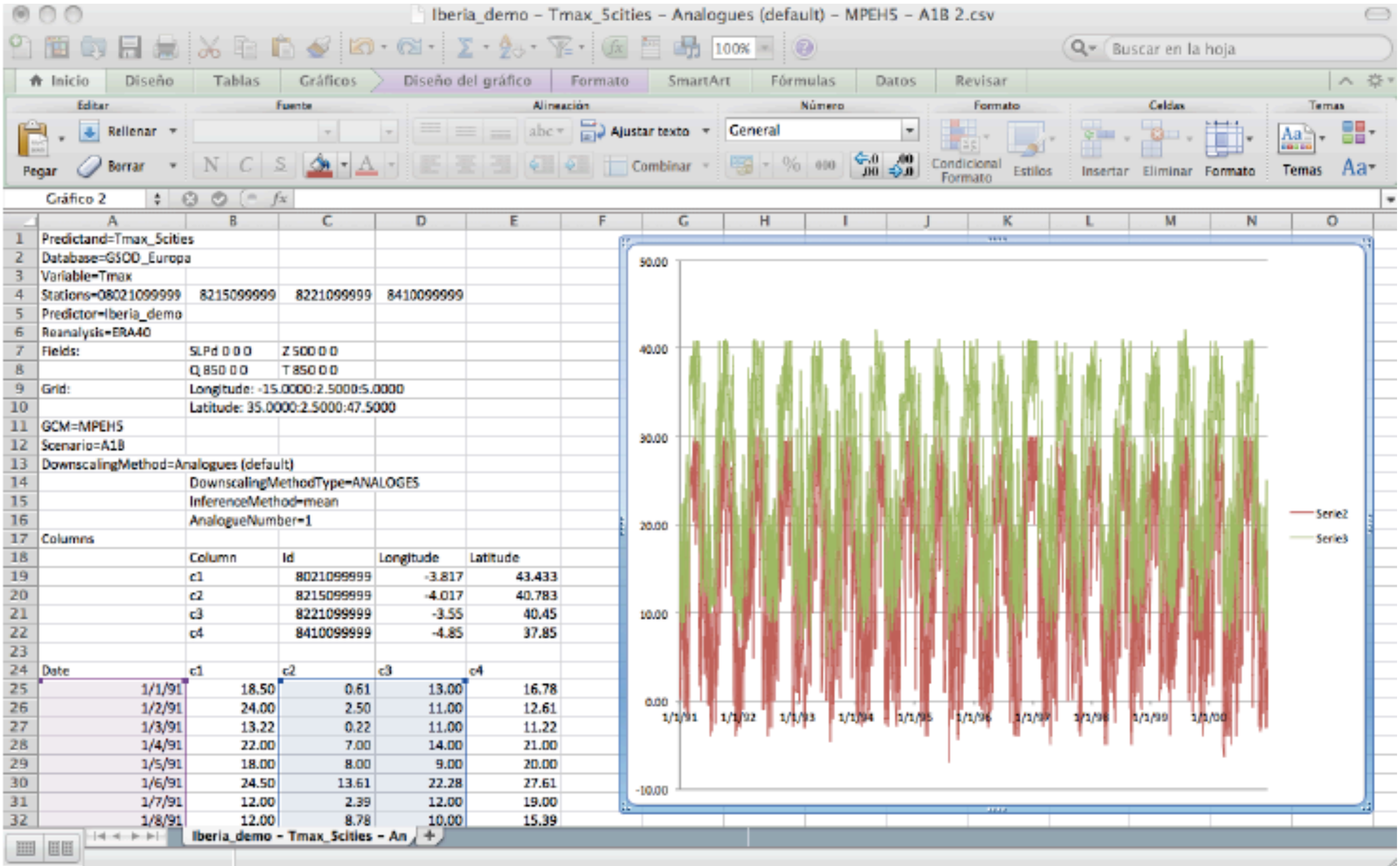
The ENSEMBLES downscaling portal allows to friendly perform statistical downscaling based on the following elements:

- **Predictors** (large scale reanalysis & GCM fields),
- **Predictands** (local variables of interest),
- **Statistical** downscaling methods.



http://www.meteo.unican.es/downscaling

Downs. Portal: Friendly Output



	A	B	C	D	E
1	Predictand=Tmax_5cities				
2	Database=GSOD_Europa				
3	Variable=Tmax				
4	Stations=08021099999	8215099999	8221099999	8410099999	
5	Predictor=Iberia_demo				
6	Reanalysis=ERA40				
7	Fields:	SLPd 0 0 0	Z 500 0 0		
8		Q 850 0 0	T 850 0 0		
9	Grid:	Longitude: -15.0000:2.5000:5.0000			
10		Latitude: 35.0000:2.5000:47.5000			
11	GCM=MPEH5				
12	Scenario=A1B				
13	DownscalingMethod=Analogues (default)				
14		DownscalingMethodType=ANALOGUES			
15		InferenceMethod=mean			
16		AnalogueNumber=1			
17	Columns				
18		Column	Id	Longitude	Latitude
19		c1	8021099999	-3.817	43.433
20		c2	8215099999	-4.017	40.783
21		c3	8221099999	-3.55	40.45
22		c4	8410099999	-4.85	37.85
23					
24	Date	c1	c2	c3	c4
25	1/1/91	18.50	0.61	13.00	16.78
26	1/2/91	24.00	2.50	11.00	12.61
27	1/3/91	13.22	0.22	11.00	11.22
28	1/4/91	22.00	7.00	14.00	21.00
29	1/5/91	18.00	8.00	9.00	20.00
30	1/6/91	24.50	13.61	22.28	27.61
31	1/7/91	12.00	2.39	12.00	19.00
32	1/8/91	12.00	8.78	10.00	15.39

EU-funded Project (2004-2009)

http://ensemblesrt3.dmi.dk

Dynamical downscaling:
Fifteen institutes ran their RCMs at 25km spatial resolution, with boundary conditions from five different GCMs, all using the A1B emissions scenario, creating a GCM/RCM matrix filled with 25 runs.

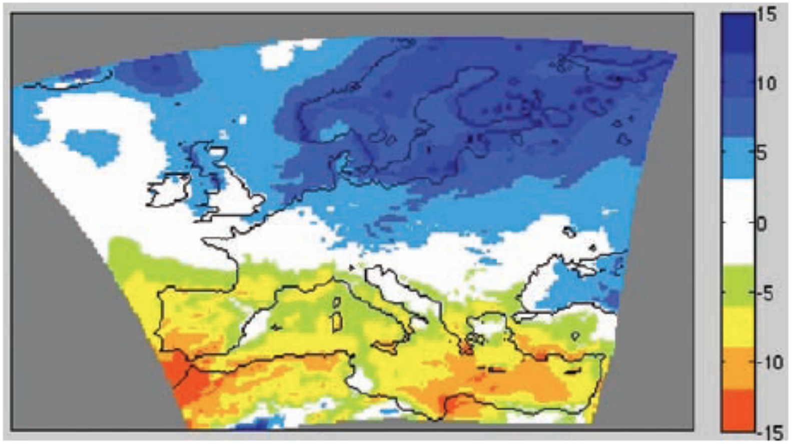


Figure 6.5: Climate-change signal (2021–2050 relative to 1961–1990) for annual precipitation total (%) for the multi-model mean of the ENSEMBLES RCMs.

Table 1. Summary of the RCM Simulations Nested in ERA40 Data Produced for the ENSEMBLES Project[a]

Acronym	Institution	Model	Reference
CNRM	Centre National de Recherches Meteorologiques	ALADIN-Climat	*Radu et al.* [2008]
DMI	Danish Meteorological Institute	HIRHAM	*Christensen et al.* [2008b]
ETHZ[b]	Swiss Institute of Technology	CLM	*Jaeger et al.* [2008]
KNMI[b]	Koninklijk Nederlands Meteorologisch Instituut	RACMO	*Van Meijgaard et al.* [2008]
HC[b]	Hadley Center/UK MetOffice	HadRM3 Q0	*Collins et al.* [2006]
ICTP	Abdus Salam International Centre for Theoretical Physics	RegCM3	*Pal et al.* [2007]
METNO	The Norwegian Meteorological Institute	HIRHAM	*Haugen and Haakensatd* [2005]
MPI[b]	Max Planck Institute for Meteorology	M-REMO	*Jacob* [2001]
SMHI	Swedish Meteorological and Hydrological Institute	RCA	*Kjellström et al.* [2005]
UCLM[b]	Universidad de Castilla la Mancha	PROMES	*Sanchez et al.* [2004]

[a]The columns are the acronym used in the paper, the institution running the simulation, the model used and a reference publication.
[b]The best performing models in this region according to *Herrera et al.* [2010].

Dynamical vs. Statistical Downscaling

Variables	Description	Units
tas	2-meter temperature	K
tasmax	Daily maximum 2-m temperature	K
tasmin	Daily minimum 2-m temperature	K
uas	10-meter U-wind	m/s
vas	10-meter V-wind	m/s
wss	10-meter wind speed	m/s
huss	2-meter specific humidity	Kg/kg
hurs	2-meter relative humidity	%
tdps	2-meter dew point temperature	K
psl	Mean sea level pressure	Pa
pr	Precipitation	Mm
prc	Convective precipitation	Mm
prls	Large-scale precipitation	Mm
evspsbl	Evaporation	Mm
evspsblpot	Potential Evapotranspiration	Mm
rss	Net SW surface radiation	W/m^2
rls	Net LW surface radiation	W/m^2
rst	Top net SW	W/m^2
rsds	Downward SW surface radiation	W/m^2
rlds	Downward LW surface radiation	W/m^2
rsdt	Top downward SW radiation	W/m^2

RCMs provide a **large number of physically consistent variables**. However, they should be calibrated for impact studies **(assumes stationarity)**.

SDM require historical records of the variables under study. Some impact communities do have this information.

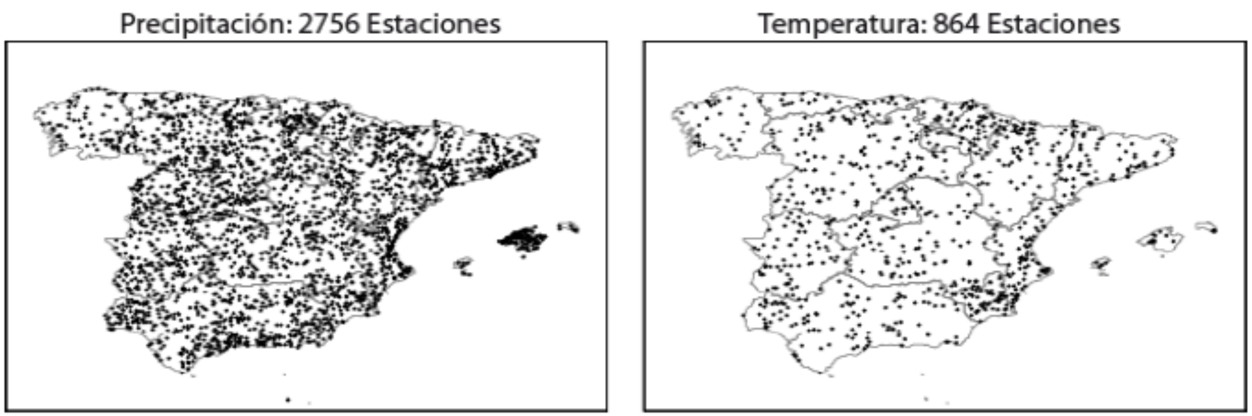
Freely-available observations in Iberia (Spain02)

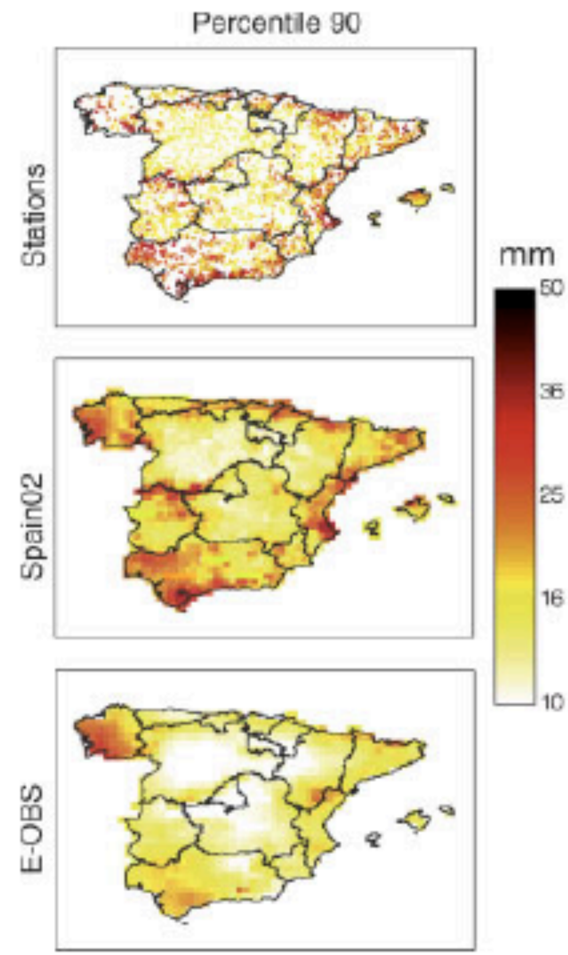
INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. (2010)
Published online in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/joc.2256

RMetS
Royal Meteorological Society

Development and analysis of a 50-year high-resolution daily gridded precipitation dataset over Spain (Spain02)

S. Herrera,[a]* J. M. Gutiérrez,[a] R. Ancell,[b] M. R. Pons,[b] M. D. Frías[c] and J. Fernández[c]
[a] *Instituto de Física de Cantabria, CSIC-University of Cantabria, Avenida de los Castros s/n, Santander, Spain*
[b] *Agencia Estatal de Meteorología (AEMET), Santander, Spain*
[c] *Department of Applied Mathematics and Computer Science, Universidad de Cantabria, Santander, Spain*





Precipitation, min. and max. temperatures

Freely available at:
http://www.meteo.unican.es/datasets/spain02

Variables	Description	Units
tas	2-meter temperature	K
tasmax	Daily maximum 2-m temperature	K
tasmin	Daily minimum 2-m temperature	K
uas	10-meter U-wind	m/s
vas	10-meter V-wind	m/s
wss	10-meter wind speed	m/s
huss	2-meter specific humidity	Kg/kg
hurs	2-meter relative humidity	%
tdps	2-meter dew point temperature	K
psl	Mean sea level pressure	Pa
pr	Precipitation	Mm
prc	Convective precipitation	Mm
prls	Large-scale precipitation	Mm
evspsbl	Evaporation	Mm
evspsblpot	Potential Evapotranspiration	Mm
rss	Net SW surface radiation	W/m^2
rls	Net LW surface radiation	W/m^2
rst	Top net SW	W/m^2
rsds	Downward SW surface radiation	W/m^2
rlds	Downward LW surface radiation	W/m^2
rsdt	Top downward SW radiation	W/m^2

RCMs provide a **large number of physically consistent variables**. However, they should be calibrated for impact studies **(assumes stationarity)**.

SDM require historical records of the variables under study. Some impact communities do have this information.

SDM has some theoretical limitations: non-stationarity?

Geography Compass 5/6 (2011): 275–300, 10.1111/j.1749-8198.2011.00425.x

Climate Scenario Development and Applications for Local/Regional Climate Change Impact Assessments: An Overview for the Non-Climate Scientist

Part I: Scenario Development Using Downscaling Methods

Julie A. Winkler[1]*, Galina S. Guentchev[2], Perdinan[1], Pang-Ning Tan[3], Sharon Zhong[1], Malgorzata Liszewska[4], Zubin Abraham[3], Tadeusz Niedźwiedź[5] and Zbigniew Ustrnul[6]
[1]*Department of Geography, Michigan State University*
[2]*UCAR CLIVAR Postdocs Applying Climate Expertise (PACE) Program*
[3]*Department of Computer Science and Engineering, Michigan State University*
[4]*Interdisciplinary Centre for Mathematical and Computational Modelling, University of Warsaw*
[5]*Department of Climatology, University of Silesia*
[6]*Department of Climatology, Jagiellonian University*

Part II: Considerations When Using Climate Change Scenarios

Julie A. Winkler[1]*, Galina S. Guentchev[2], Malgorzata Liszewska[3], Perdinan[1] and Pang-Ning Tan[4]
[1]*Department of Geography, Michigan State University*
[2]*UCAR CLIVAR Postdocs Applying Climate Expertise (PACE) Program*
[3]*Interdisciplinary Centre for Mathematical and Computational Modelling, University of Warsaw*
[4]*Department of Computer Science and Engineering, Michigan State University*

Follow-on projects: VALUE, CORDEX, etc.

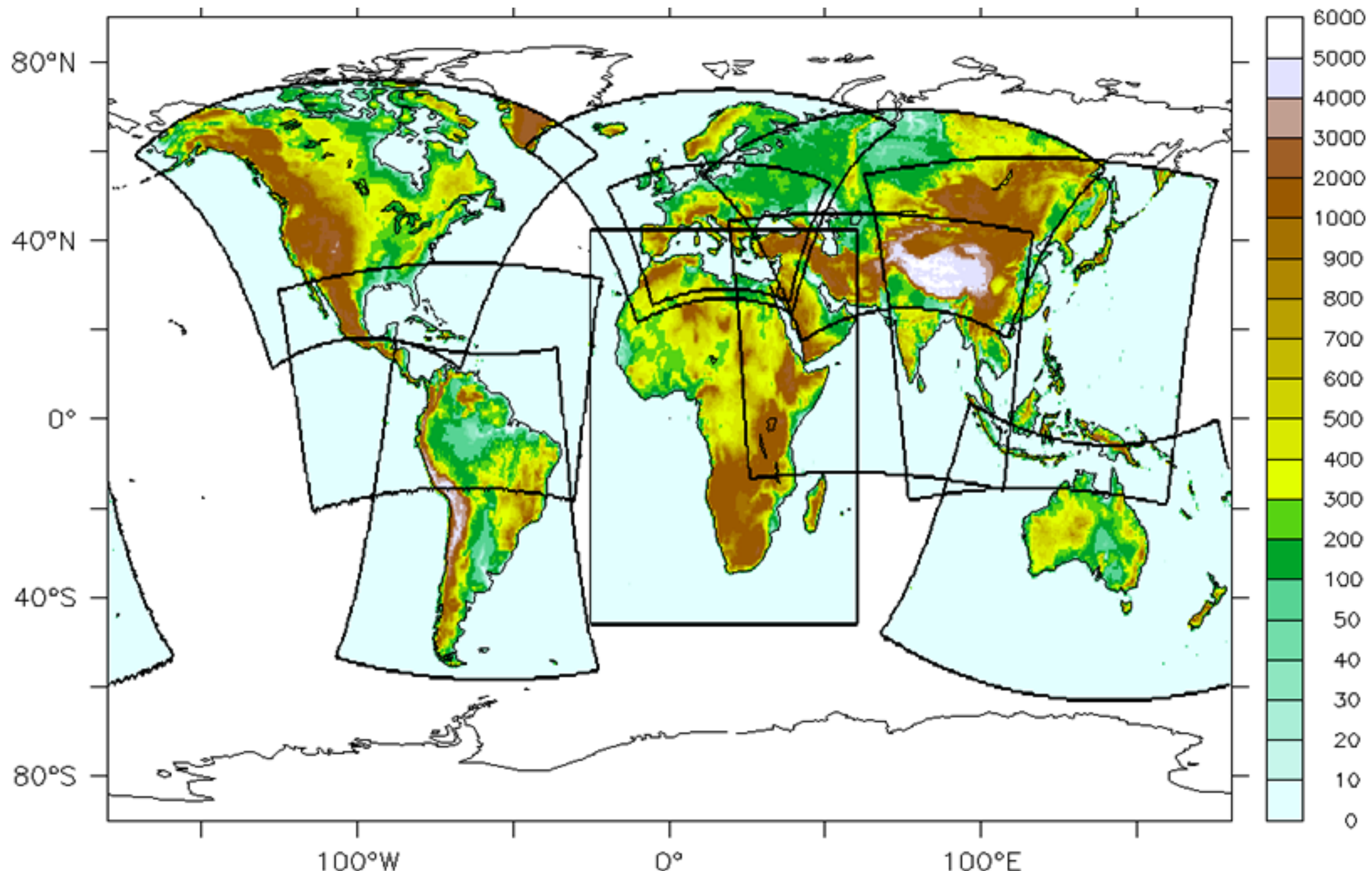
cost
EUROPEAN COOPERATION
IN SCIENCE AND TECHNOLOGY

The main objective is to establish a network to systematically validate and improve downscaling methods for climate change research.

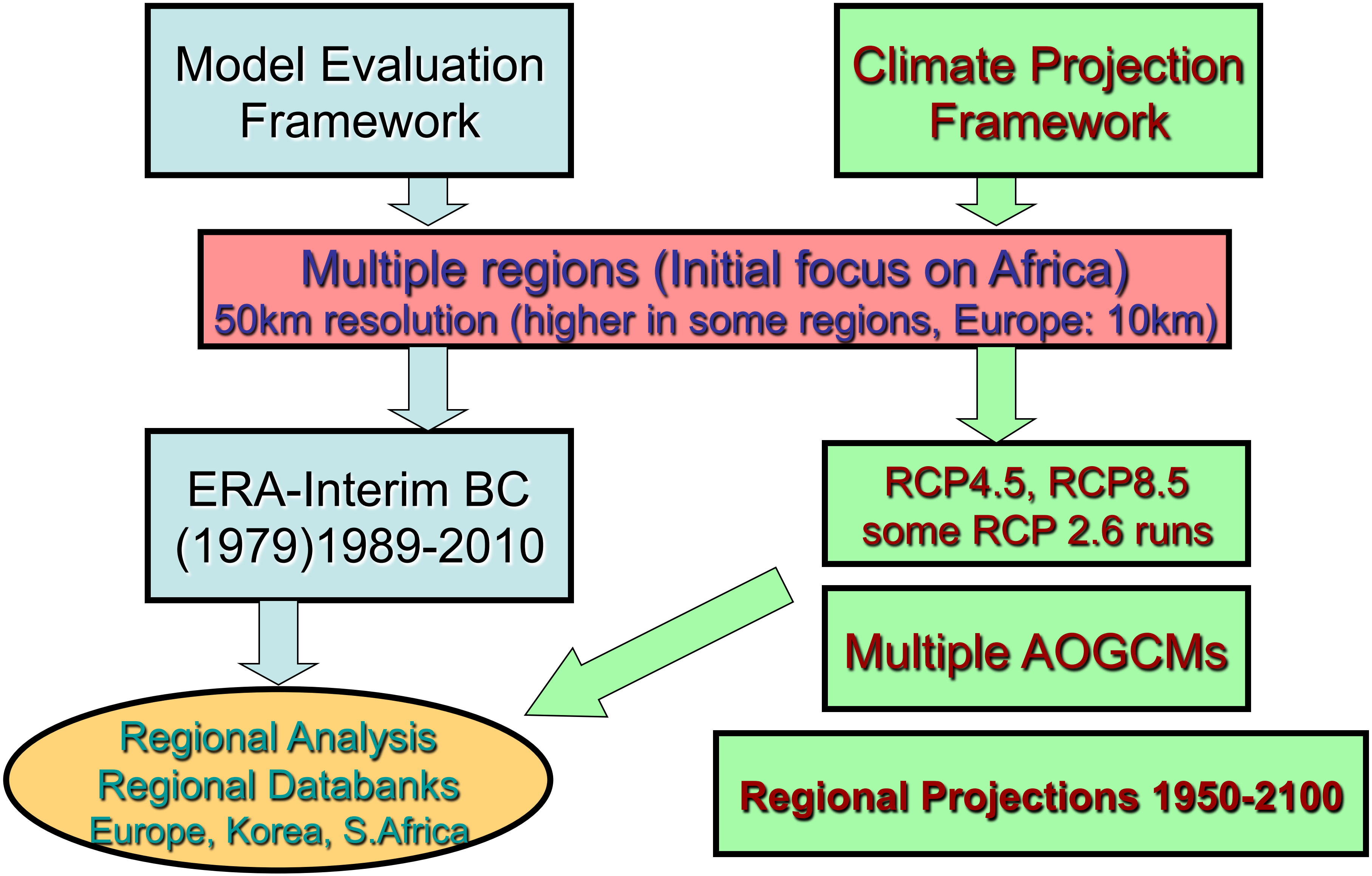
Follow-on projects: VALUE, CORDEX, etc.

WCRP CORDEX

- 12 domains with a resolution of 0.44º.
- Initial Focus on Africa.
- High resolution (~0.11°) for Europe.



CORDEX: Experiment Design



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  - **Robustness in non-stationary conditions.**
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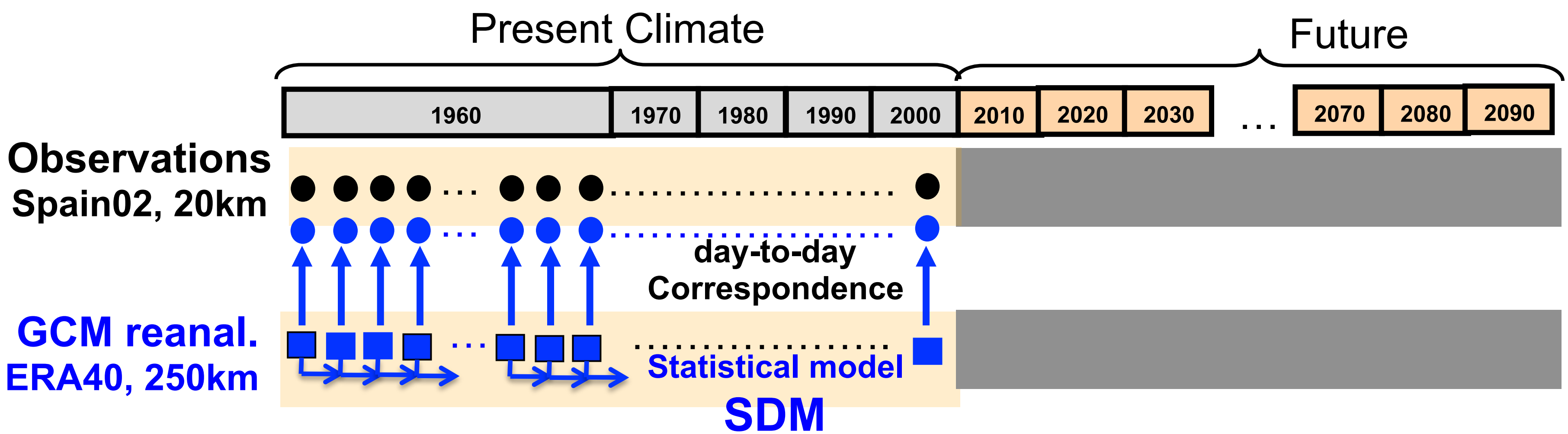
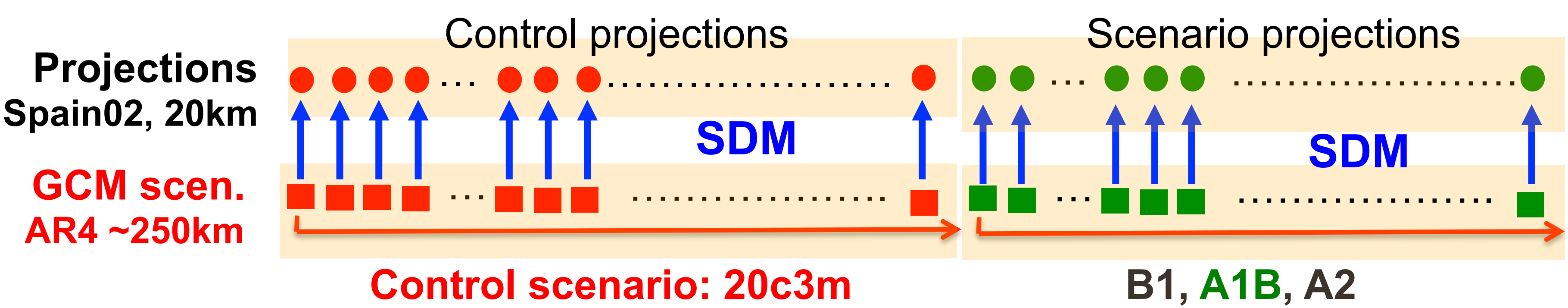
  - MOS based on analogs for RCMs.
- Conclusions

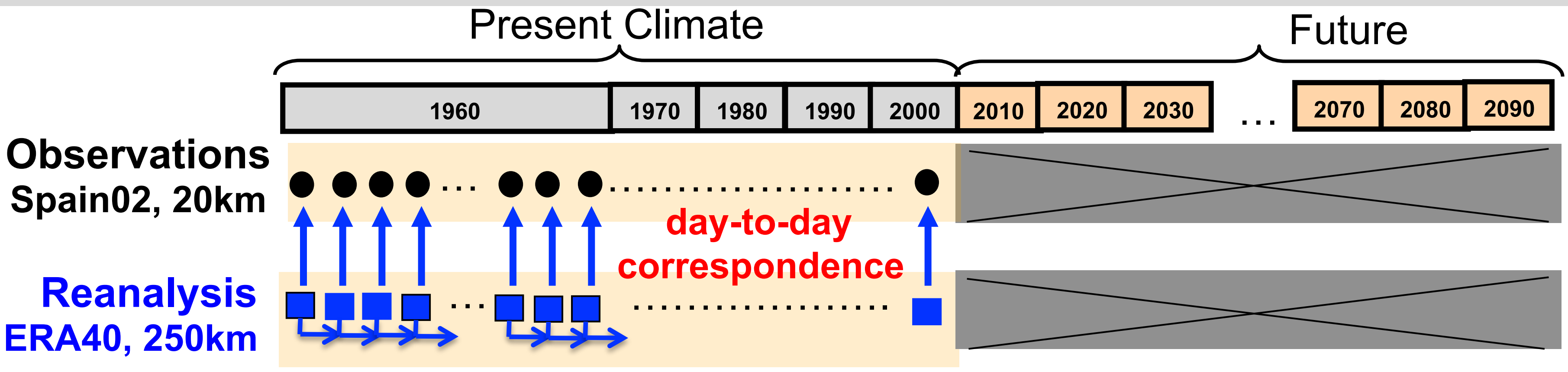
Statistical Downscaling (Perfect Prog.)



- **PROBLEM 1: Choosing consistent predictors:**
- **PROBLEM 2: Stationarity/robustness: SDM SDM**



Perfect Prog. Choosing a Reanalysis



Atmospheric Reanalyses Comparison Table

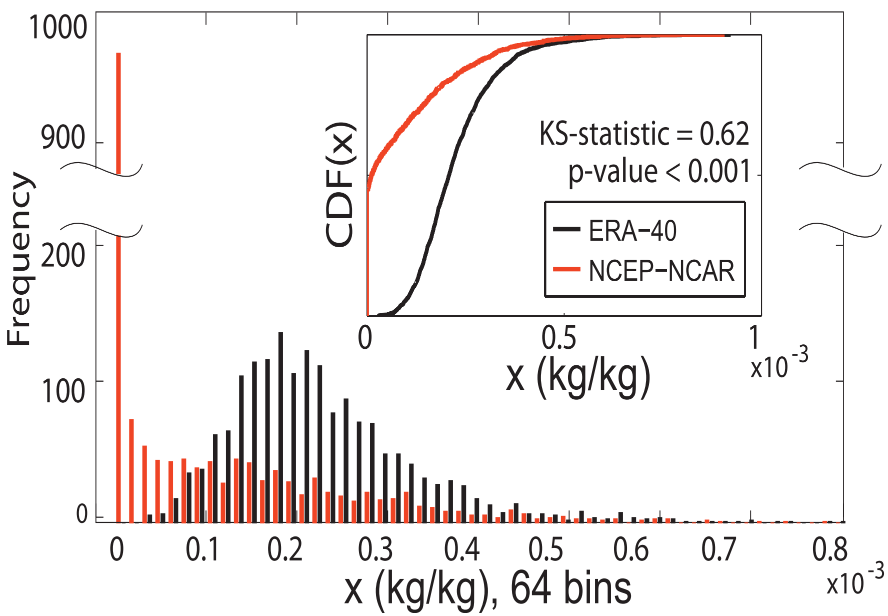
Name	Source	Time Range	Assimilation	Model Resolution	Model Output Resolution	Publicly Available Dataset Resolution
Arctic System Reanalysis (ASR)	Polar Met Group	2000-2010	WRF-Var	10-20km	10-30km	10-30km
ECMWF Interim Reanalysis (ERA Interim)	ECMWF	1989-present	4D-VAR	T255L60	125 km	1.5x1.5 / 0.7x0.7
ECMWF 40 year Reanalysis (ERA-40)	ECMWF	1958-2001	3D-VAR	T159L60	80 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

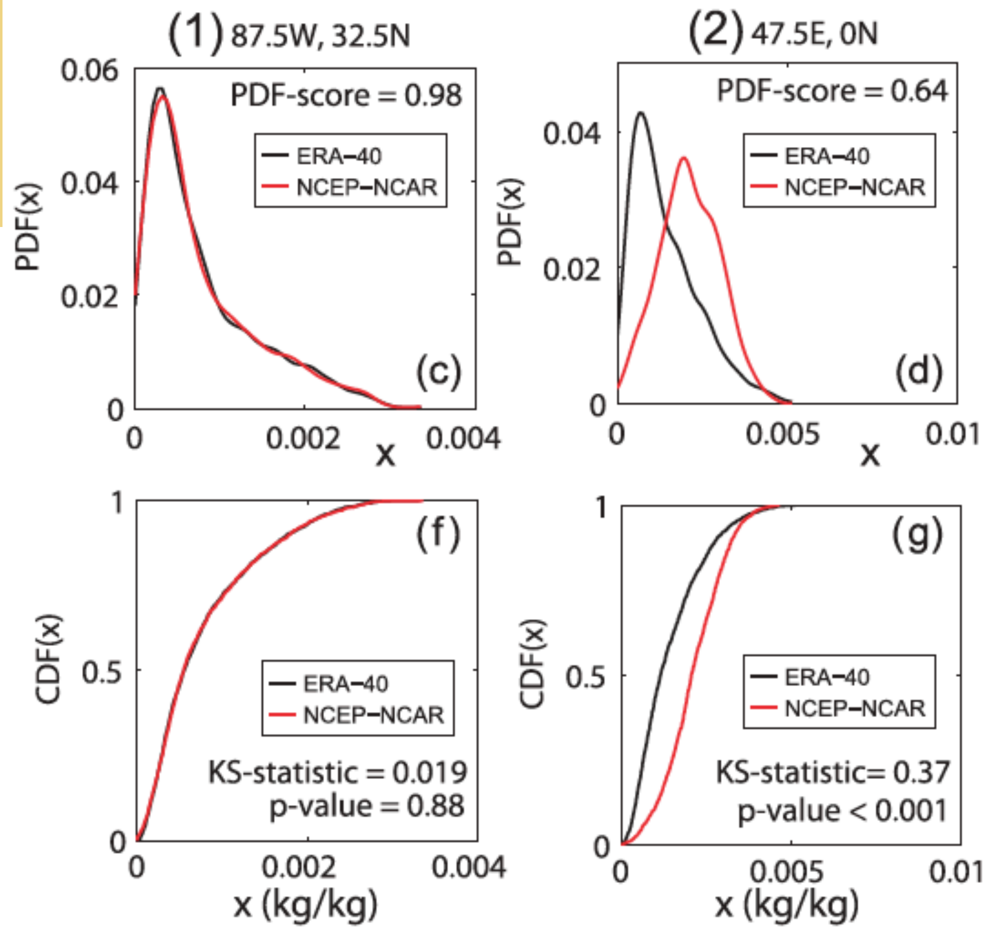
Comparing Reanalysis Data

Comparing the distributional similarity (at a daily grid-box basis) between ERA40 and NCEP for typical predictors using both the classical Kolmogorov-Smirnov (KS) test and the more recent PDF-score.

$$\text{PDF-score} = \sum_{i=1}^{N} \min\{f(m_i), g(m_i)\}.$$

$$\text{KS-statistic} = \max_{i=1}^{2n} |F(z_i) - G(z_i)|,$$





KS-test was found to be more appropriate. They both provide similar results.

Comparing Reanalysis Data

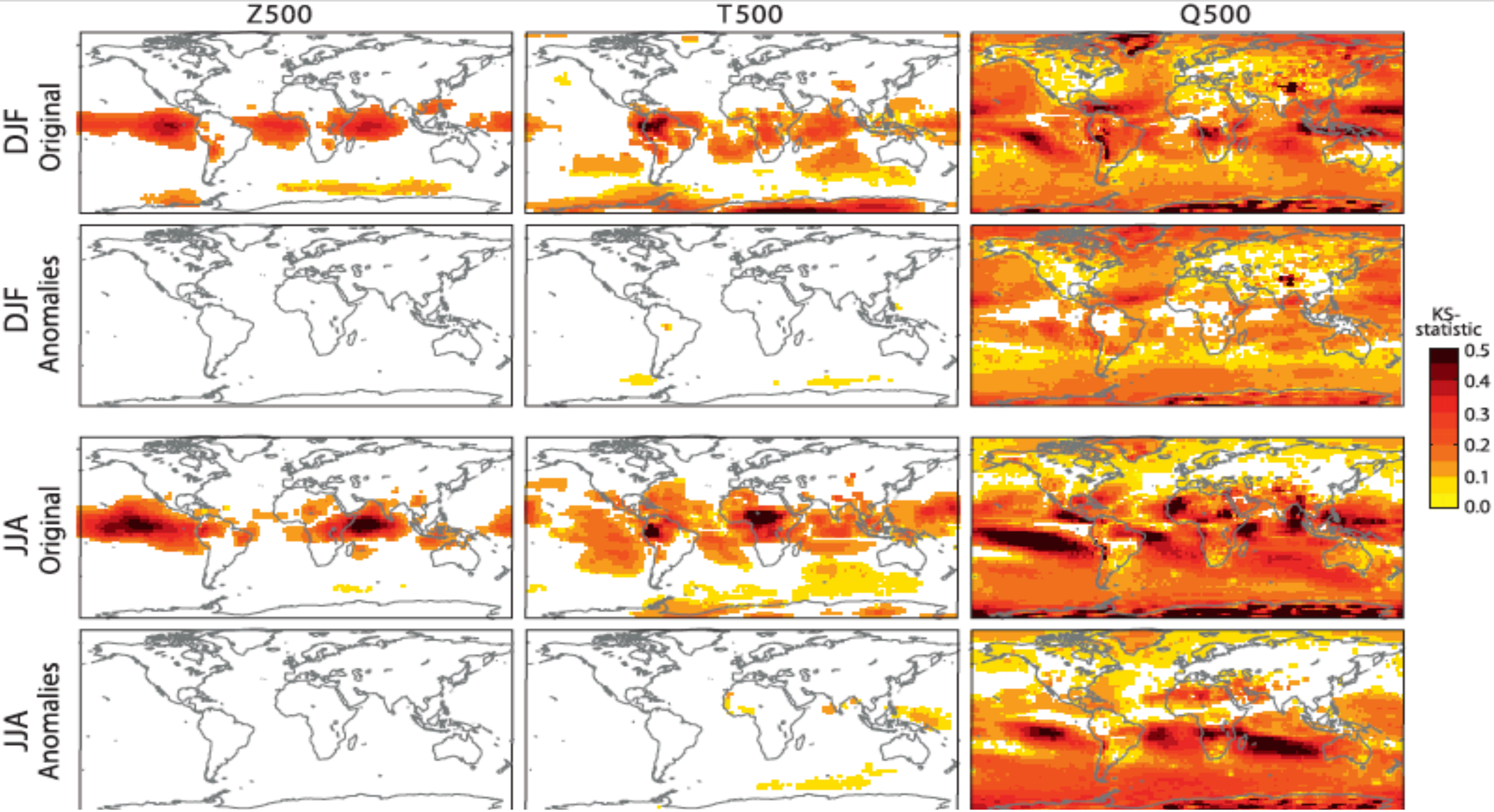
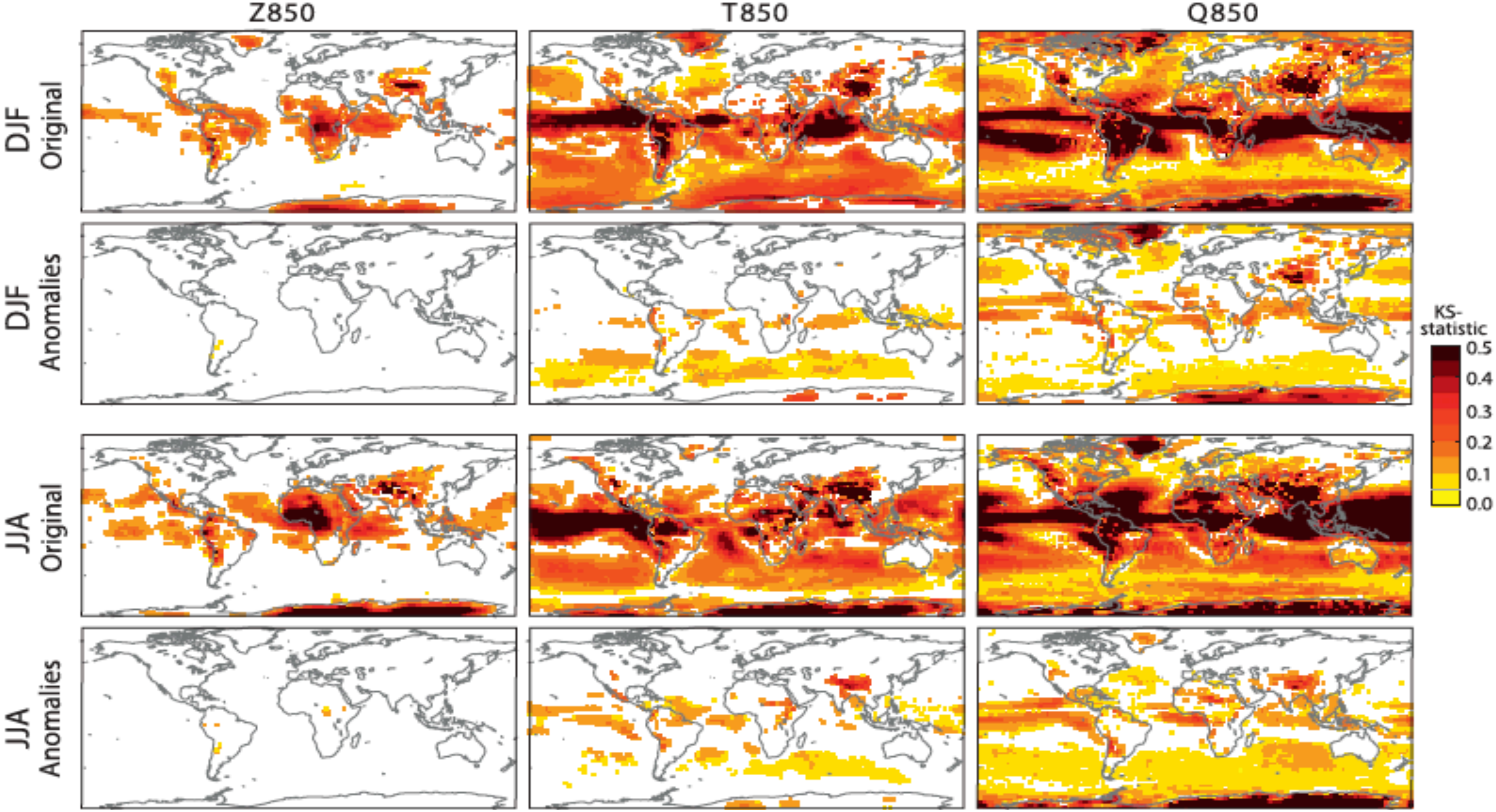


FIG. 3. Maps of distributional similarity for the daily time series of ERA-40 and NCEP–NCAR *Z*, *T*, and *Q* at (top) 500 and (bottom) 850 hPa, as revealed by the KS statistic. Color darkening from yellow to black indicates increasing dissimilarity. If the H_0 values of equal distributions cannot be rejected at a test level of 5%, the grid box is whitened and the distributional similarity is assumed to be optimal. Results are presented for both the original and anomaly data.

Comparing Reanalysis Data



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GCMs in CMIP3 (IPCC-AR4)

THE WCRP CMIP3 MULTIMODEL DATASET

A New Era in Climate Change Research

BY GERALD A. MEEHL, CURT COVEY, THOMAS DELWORTH, MOJIB LATIF, BRYANT MCAVANEY, JOHN F. B. MITCHELL, RONALD J. STOUFFER, AND KARL E. TAYLOR

SEPTEMBER 2007 BAMS | 1383
AMERICAN METEOROLOGICAL SOCIETY
DOI:10.1175/BAMS-88-9-1383

Performance metrics for climate models

P. J. Gleckler,[1] K. E. Taylor,[1] and C. Doutriaux[1]

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 113

Table 1. Model Identification, Originating Group, and Atmospheric Resolution

IPCC I.D.	Center and Location	Atmosphere Resolution
BCCR-BCM2.0	Bjerknes Centre for Climate Research (Norway)	T63 L31
CGCM3.1(T47) CGCM3.1(T63)	Canadian Centre for Climate Modelling and Analysis (Canada)	T47 L31 T63 L31
CSIRO-Mk3.0	CSIRO Atmospheric Research (Australia)	T63 L18
CNRM-CM3	Météo-France, Centre National de Recherches Météorologiques (France)	T42 L45
ECHO-G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group (Germany and Korea)	T30 L19
GFDL-CM2.0 GFDL-CM2.1	US Dept. of Commerce, NOAA Geophysical Fluid Dynamics Laboratory (USA)	N45 L24 N45 L24
GISS-AOM GISS-EH GISS-ER	NASA/Goddard Institute for Space Studies (USA)	90 × 60 L12 72 × 46 L17 72 × 46 L17
FGOALS-g1.0	LASG/Institute of Atmospheric Physics (China)	128 × 60 L26
INM-CM3.0	Institute for Numerical Mathematics (Russia)	72 × 45 L21
IPSL-CM4	Institut Pierre Simon Laplace (France)	96 × 72 L19
MIROC3.2(medres) MIROC3.2(hires)	Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC) (Japan)	T42 L20 T106 L56
MRI-CGCM2.3.2	Meteorological Research Institute (Japan)	T42 L30
ECHAM5/MPI-OM	Max Planck Institute for Meteorology (Germany)	T63 L32
CCSM3 PCM	National Center for Atmospheric Research (USA)	T85 L26 T42 L18
UKMO-HadCM3 UKMO-HadGEM1	Hadley Centre for Climate Prediction and Research, Met Office (UK)	96 × 72 L19 N96 L38

Perfect Prog. Consistent Predictors

Typical downscaling predictors:

Vol. 48: 145–161, 2011
doi: 10.3354/cr00995

CLIMATE RESEARCH
Clim Res

Published August 30

Contribution to CR Special 27 'Climate change in the NW Iberian Peninsula'

OPEN ACCESS

Validation of the ENSEMBLES global climate models over southwestern Europe using probability density functions, from a downscaling perspective

S. Brands*, S. Herrera, D. San-Martín, J. M. Gutiérrez

Instituto de Física de Cantabria (CSIC – Universidad de Cantabria), 39005 Santander, Spain

MSLP
2T

U,V
Z
T
Q, R
500,850mb

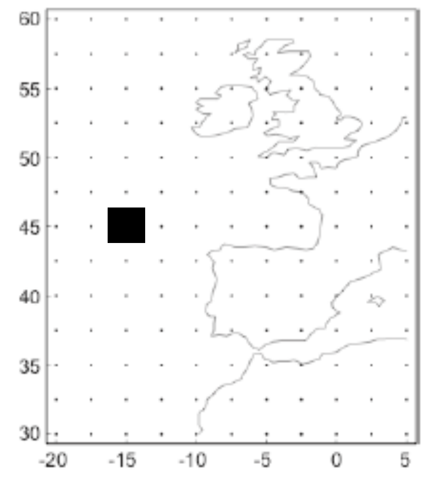

Table 2. Overview of the global climate models (GCMs) used in the present study, taken from the 2 streams of the ENSEMBLES project. Stream 1: model versions from the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC-AR4); Stream 2: new versions developed within the ENSEMBLES project

GCM name	Acronym	Stream	Institution	Source
BCCR-BCM2	BCM2	1	Bjerknes Centre for Climate Research, Norway	Drange (2006)
CNRM-CM3	CNCM3	1	Centre National de Recherches Météorologiques, France	Royer (2006)
ECHO-G	EGMAM	1	Freie Universität Berlin, Germany	Niehörster (2008)
IPSL-CM4	IPCM4	1	Institut Pierre Simon Laplace, France	Dufresne (2007)
METO-HC-HadGEM	HADGEM	1	Met Office Hadley Centre, UK	Johns (2008)
MPI-ECHAM5	MPEH5	1	Max Planck Institute for Meteorology, Germany	Roeckner (2007)
CNRM-CM33	CNCM33	2	Centre National de Recherches Météorologiques, France	Royer (2008)
ECHO-G2	EGMAM2	2	Freie Universität Berlin, Germany	Huebener & Koerper (2008)
IPSL-CM4v2	IPCM4V2	2	Institut Pierre Simon Laplace, France	Dufresne (2009)
METO-HC-HadCM3C	HADCM3C	2	Met Office Hadley Centre, UK	Johns (2009a)
METO-HC-HadGEM2	HADGEM2	2	Met Office Hadley Centre, UK	Johns (2009b)
MPI-ECHAM5C	MPEH5C	2	Max Planck Institute for Meteorology, Germany	Roeckner (2008)

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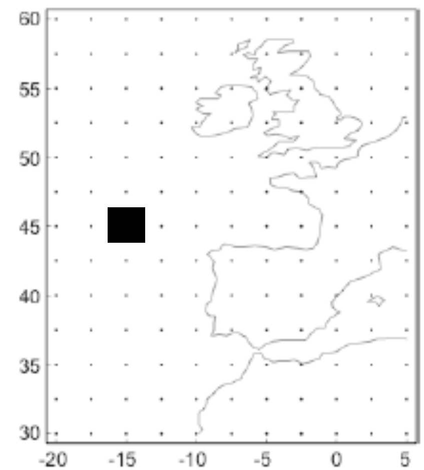
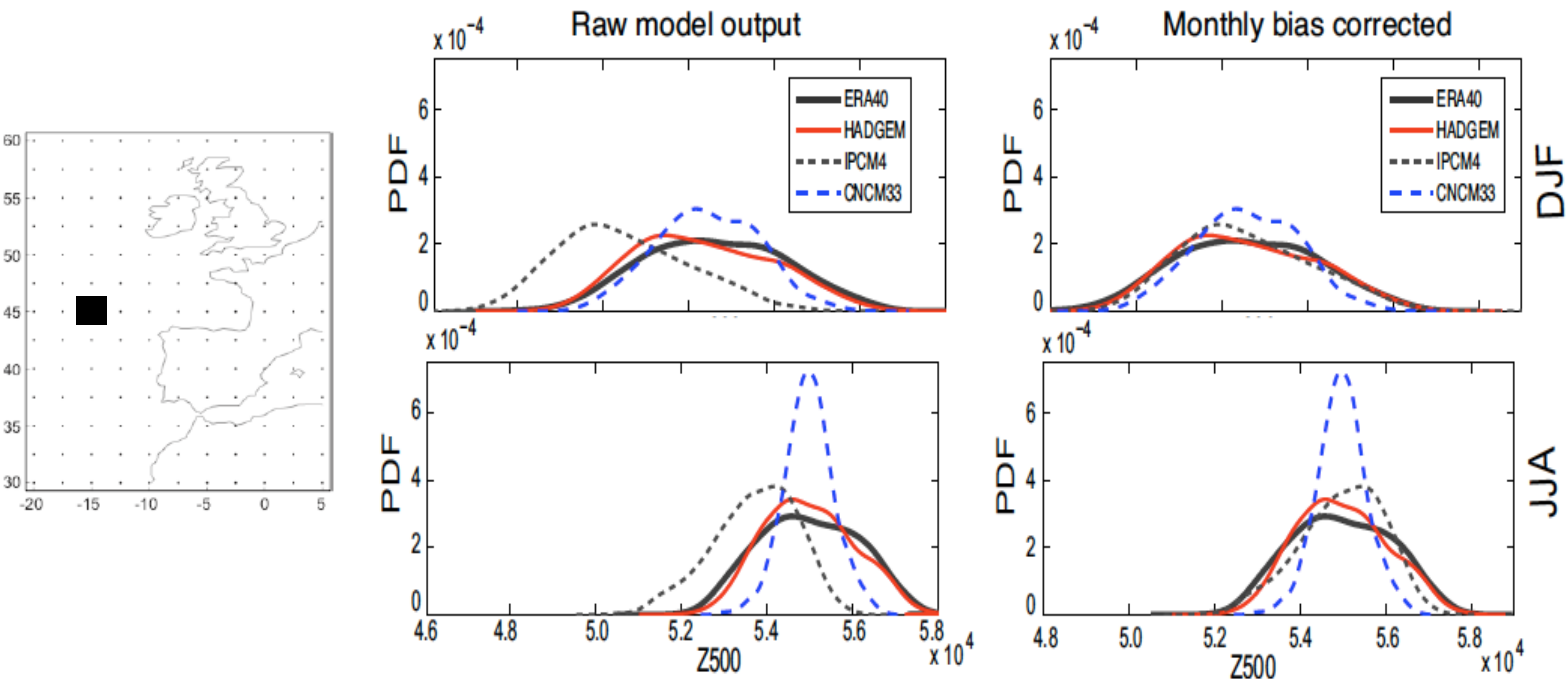


Table 3. List of variables (by pressure level in hPa) available for the 12 models. See Tables 1 & 2 for abbreviations. x: available

Model	Variable																			
	T			Q			R			Z			U				V			MSLP
	850	700	500	850	700	500	850	700	500	850	700	500	1000	850	700	500	850	700	500	sea level
MPEH5	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
MPEH5C	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
HADGEM	x		x				x	x	x	x	x	x		x			x		x	
HADGEM2	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x
HADCM3C	x	x	x				x	x	x	x	x	x	x	x	x	x		x	x	x
CNCM3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
CNCM33	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
BCM2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
EGMAM	x	x	x	x	x	x				x	x	x	x	x	x	x	x	x	x	x
EGMAM2	x	x	x	x	x	x				x	x	x	x	x	x	x	x	x	x	x
IPCM4	x	x	x	x	x	x				x	x	x		x	x	x	x	x	x	x
IPCM4V2	x	x	x	x	x	x				x	x	x		x	x	x	x	x	x	x

Assessing GCM Data

Since the SD methods are trained with reanalysis data and later applied to GCM data, the predictors should at least satisfy that they have “similar” distributions for both reanalysis and GCMs.



- Tests for distributions (e.g. **KS-test**) or similarity scores (**PDF-score**).

Typical downscaling predictors:

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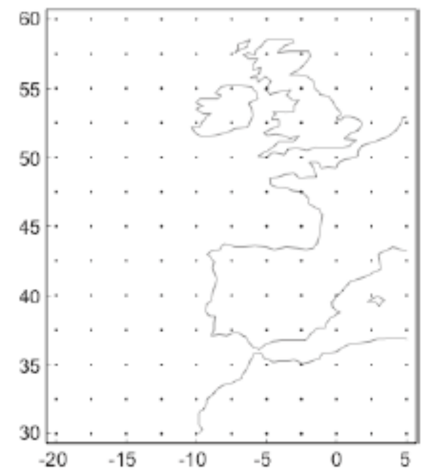
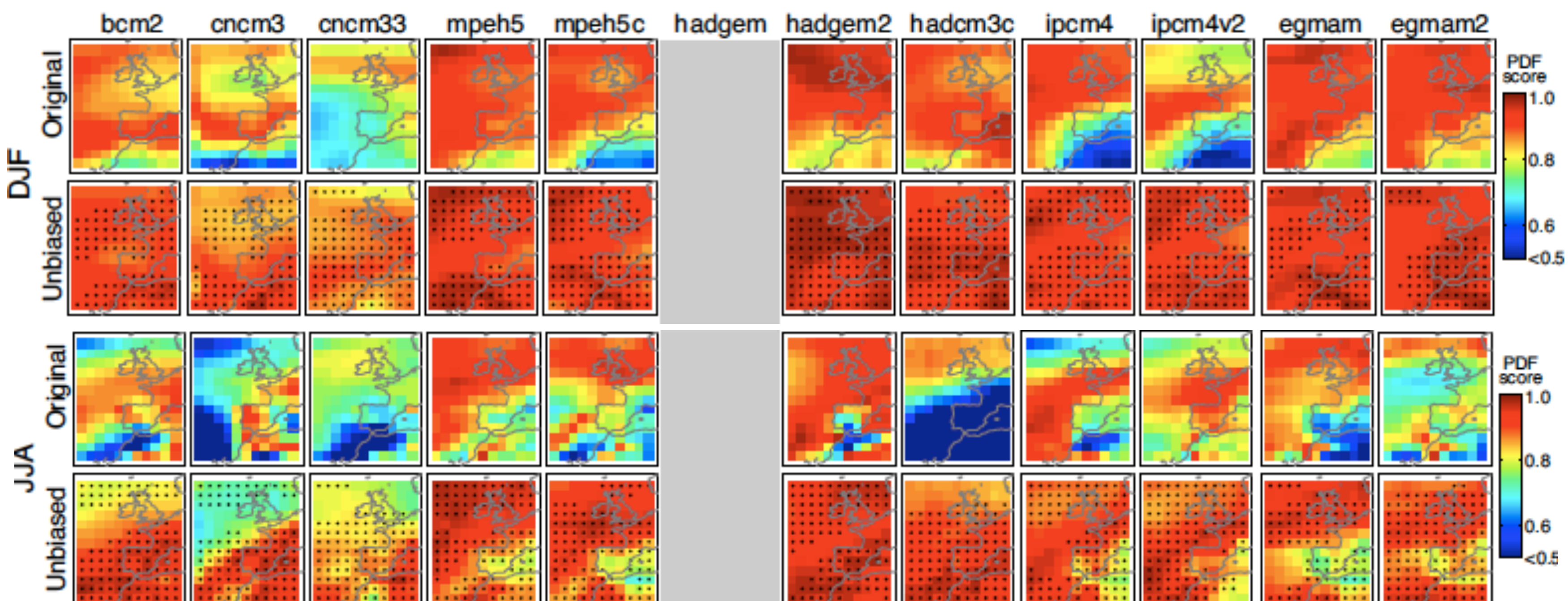
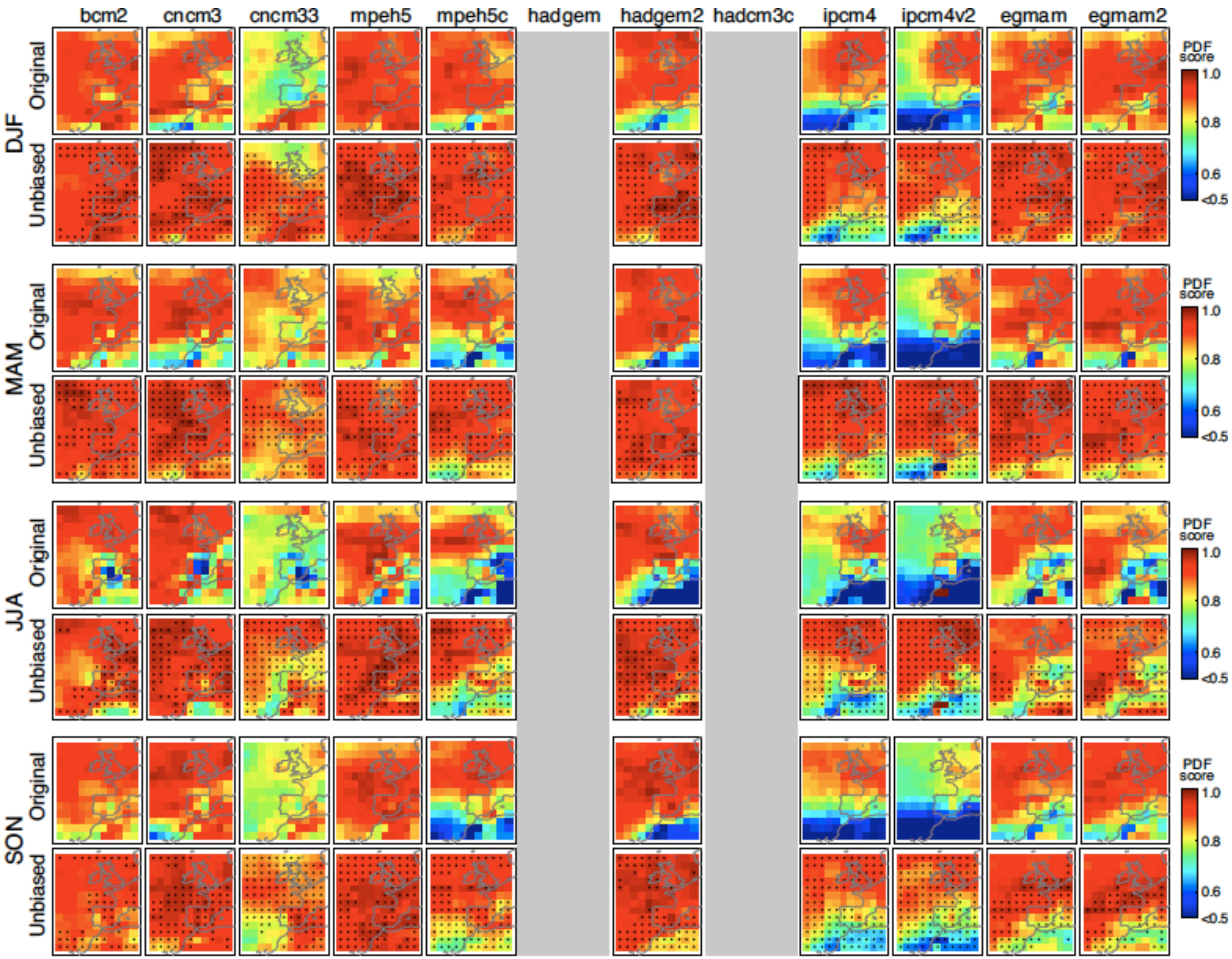




Assessing GCM Data (Q)



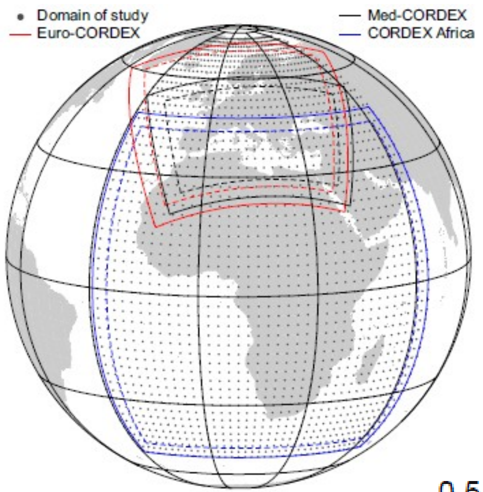
CMIP5 Earth System Models considered in this study

Model	Hor. Resolution	Reference
CanESM2	$2.8 * 2.8°$	Chylek et al (2011)
CNRM-CM5	$1.4 * 1.4°$	Voldoire et al (2011)
HadGEM2-ES	$1.875 * 1.25°$	Collins et al (2011)
IPSL-CM5-MR	$1.5 * 1.27°$	Dufresne et al (submitted)
MIROC-ESM	$2.8 * 2.8°$	Watanabe et al (2011)
MPI-ESM-LR	$1.8 * 1.8°$	Raddatz et al (2007); Jungclaus et al (2010)
NorESM1-M	$1.5 * 1.9°$	Kirkevag et al (2008); Seland et al (2008)

Table 2 Variables considered in this study.

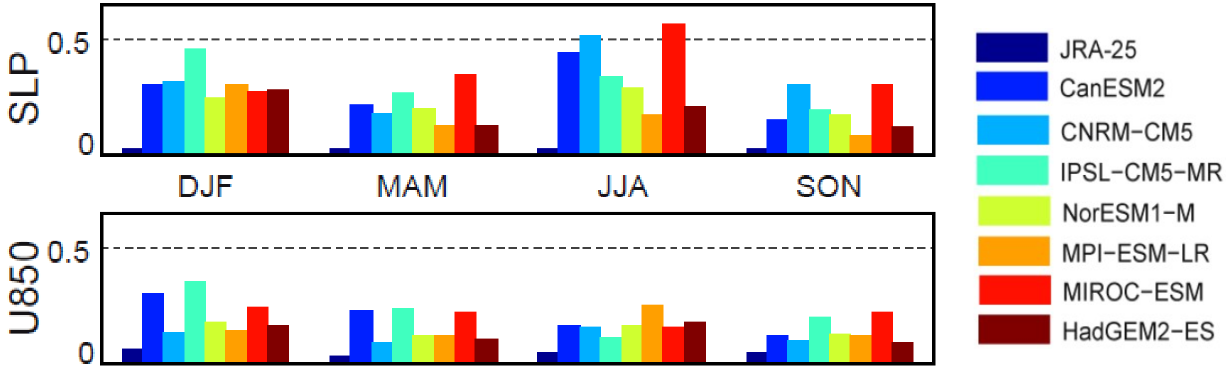
Code	Name	Height	Unit
Z	Geopotential	500hPa	$m^2 s^{-2}$
T	Temperature	2m, 850hPa	K
Q	Specific humidity	850hPa	$kg\, kg^{-1}$
U	U-wind	850hPa	$m\, s^{-1}$
V	V-wind	850hPa	$m\, s^{-1}$
SLP	Sea-level pressure	mean sea-level	Pa

CMIP5 ESM Comparison for downscaling purposes



Testing large-scale fields (SLP, Z, Q, ...) to be used by:

- **Statistical downscaling**
  Checking unbiased fields
- **Regional Climate Models**
  Assesing the performace of 3D variables at the boundaries of the CORDEX simulation domains (for Europe, Mediterranean and Africa)



Might help in the decision of which GCMs to downscale within EuroCORDEX

Brands et al (2012) **"How well do CMIP5 Earth System Models simulate present climate conditions? A performance comparison for the downscaling community"**
Submitted to Climate Dynamics (draft available at: www.meteo.unican.es)

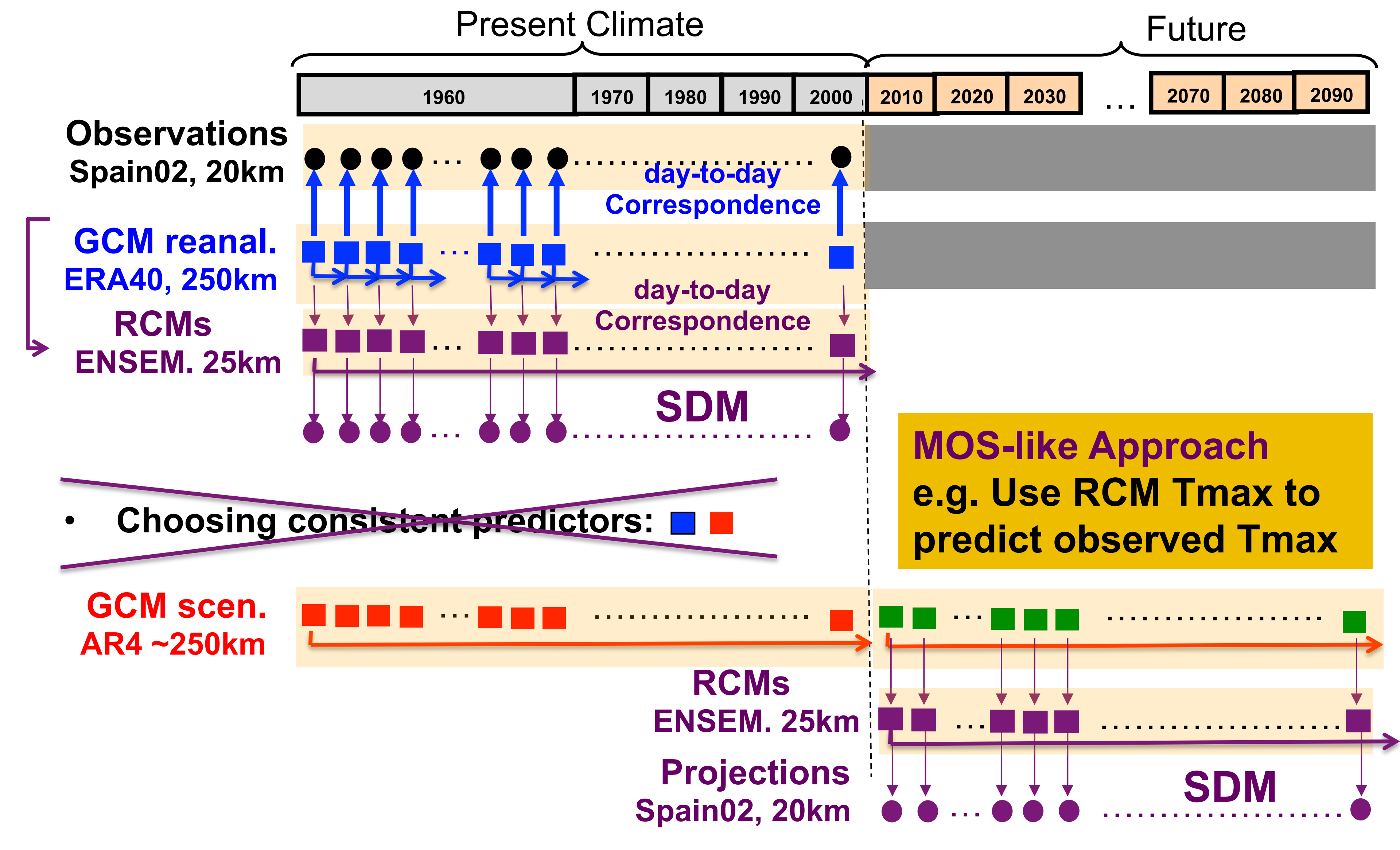
Contents

- Introduction
  - Key past projects: ENSEMBLES.
  - Statistical vs. Dynamical downscaling.
- Perfect Prognosis Approach:
  - Selecting the predictors (reanalisys-GCM consitency).
  - Robustness in non-stationary conditions.
- **MOS-like downscaling:**
  - **MOS based on analogs for RCMs.**
- Conclusions

Santander Meteorology Group

A multidisciplinary approach for weather & climate

Statistical Downscaling (MOS Approach)



- ~~Choosing consistent predictors:~~

MOS-like Approach
e.g. Use RCM Tmax to predict observed Tmax

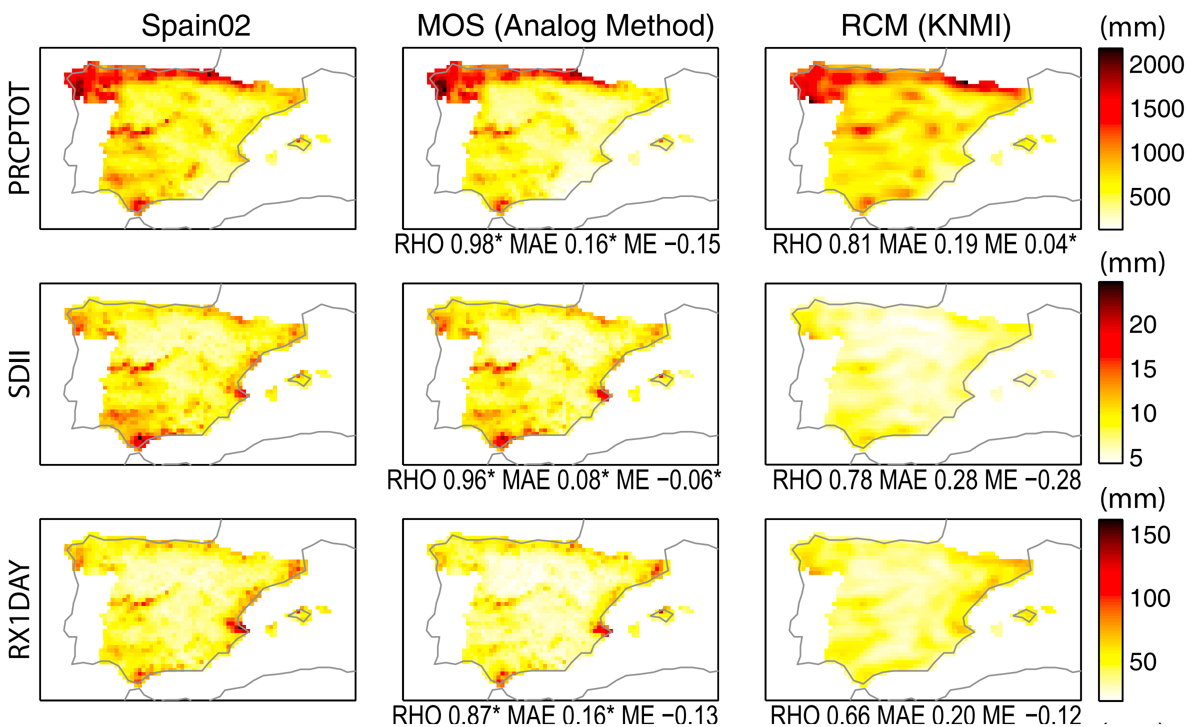
Statistical Downscaling from RCMs (MOS Approach)

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 116, D18109, doi:10.1029/2011JD016166, 2011

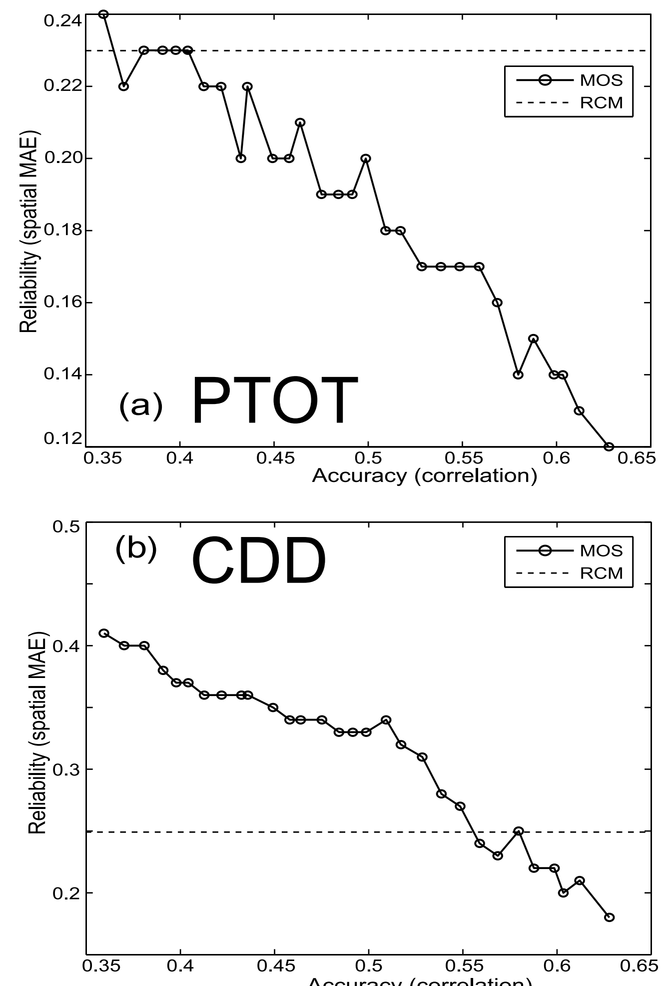
Testing MOS precipitation downscaling for ENSEMBLES regional climate models over Spain

M. Turco,[1] P. Quintana-Seguí,[2] M. C. Llasat,[1] S. Herrera,[3] and J. M. Gutiérrez[3]

Received 27 April 2011; revised 16 June 2011; accepted 24 June 2011; published 23 September 2011.



Do ERA40-driven RCMs show day-to-day correspondence with observations?



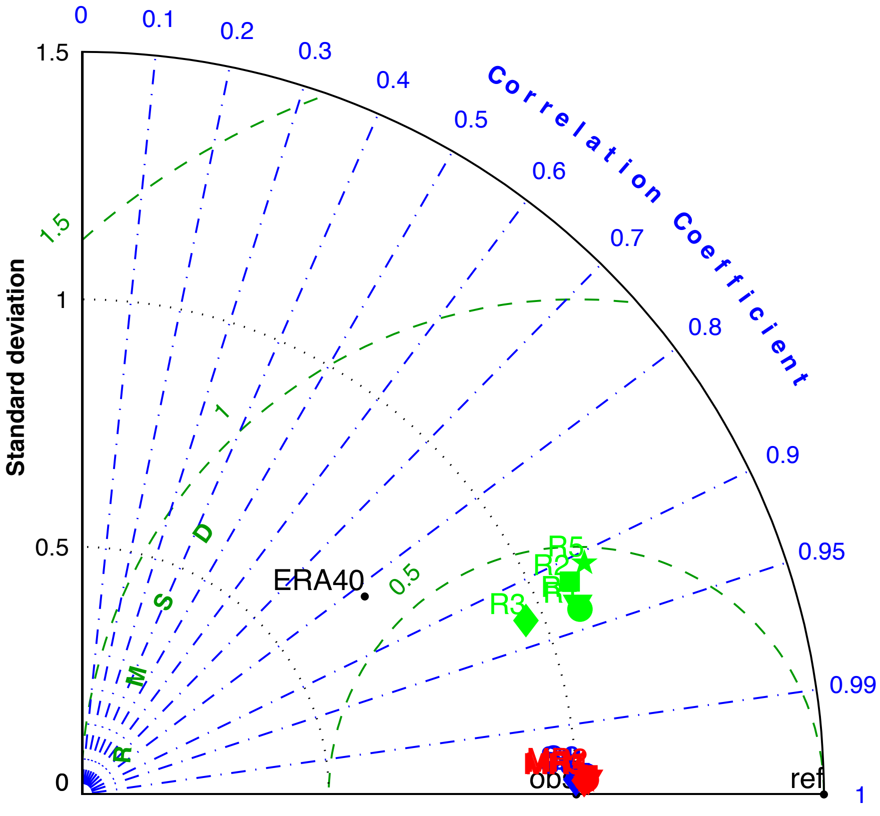
The method achieves temporal and spatial "calibration" while preserving the accuracy.

Comparing the Different Approaches

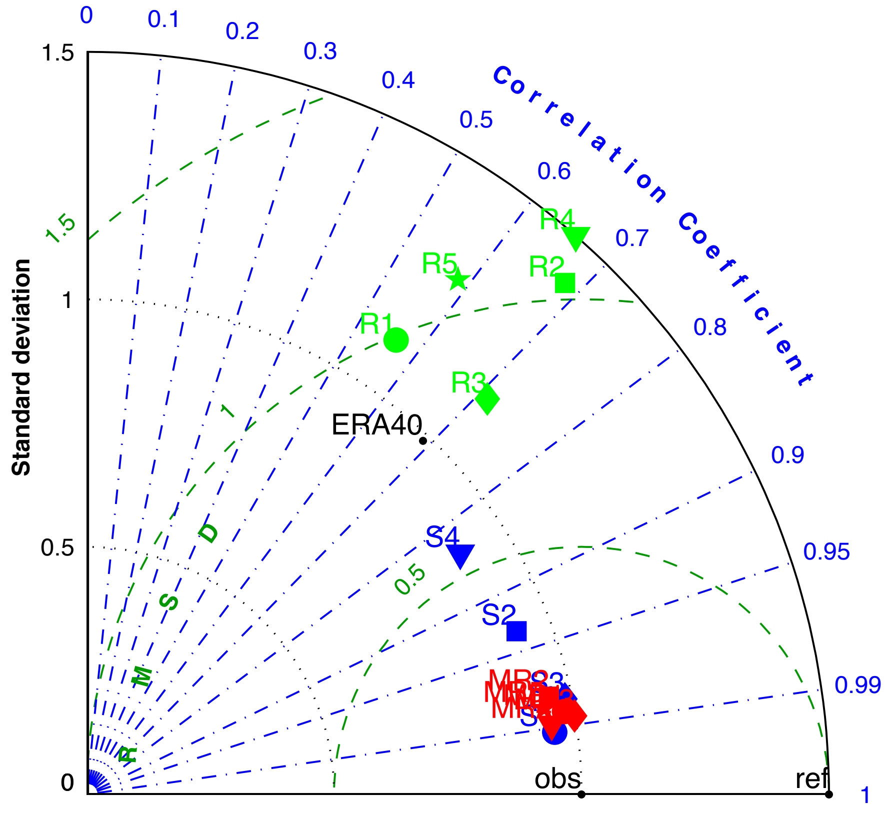
ERA40 RCMs SDMs MOS-RCMs

S1. Analog

Spatial mean



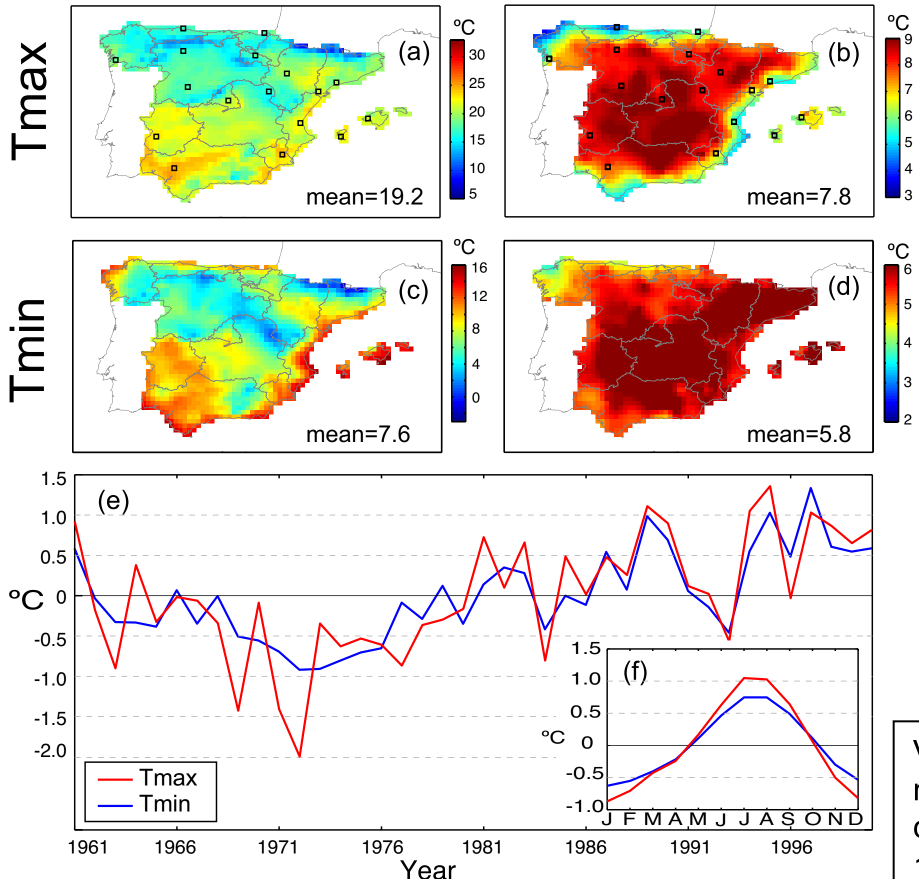
Spatial standard deviation

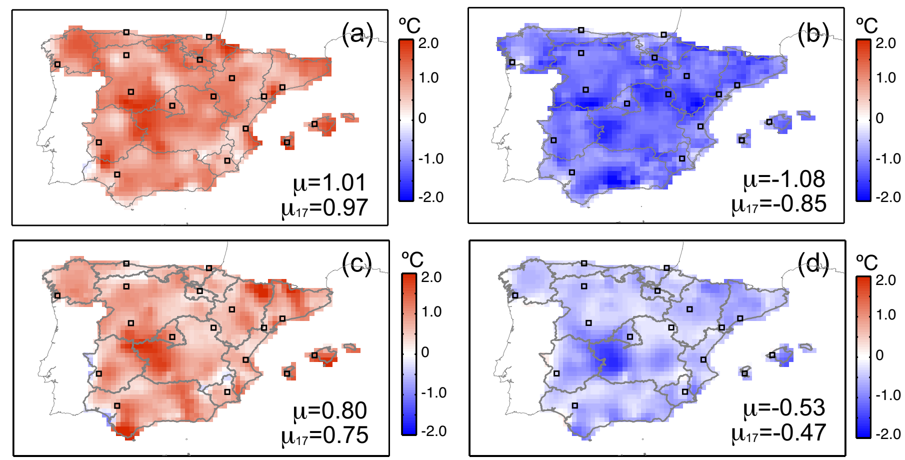


Statistical Downscaling: Testing Non-Stationarity

A k-fold cross-validation (5-fold) approach has been applied using the 1961-200 period:

- *5 independent test samples with 8 years each (32 for train).*





To test the robustness of the SD methods we also consider the eight **warmer**/**colder** years.

Vrac, M., M. L. Stein, K. Hayhoe, and X.-Z. Liang (2007), A general method for validating statistical downscaling methods under future climate change, *Geophys. Res. Lett.*, *34*, L18701, doi: 10.1029/2007GL030295.

Downscaling Methods

Code	*Specifications*
M1a	Nearest neighbour
M1b	Mean of 5 neighbours
M1c	One out of 15 neighbours, random selection
M2a	100 WTs (k-means), mean
M2b	100 WTs (k-means), random selection
M2c	100 WTs (k-means), simulation from adjusted gaussian parameters
M3a	*n* PCs (95% variance)
M3b	Local predictors in the nearest grid box
M3c	15 PCs + nearest grid box
M4a	D3c conditioned on 10 WTs (k-means)
M4b	D3b conditioned on 10 WTs (k-means)
M4c	D3b (T,Q) conditioned 10 WTs (SLP)

Journal of Climate 2012 ; e-View
doi: http://dx.doi.org/10.1175/JCLI-D-11-00687.1

Reassessing statistical downscaling techniques for their robust application under climate change conditions

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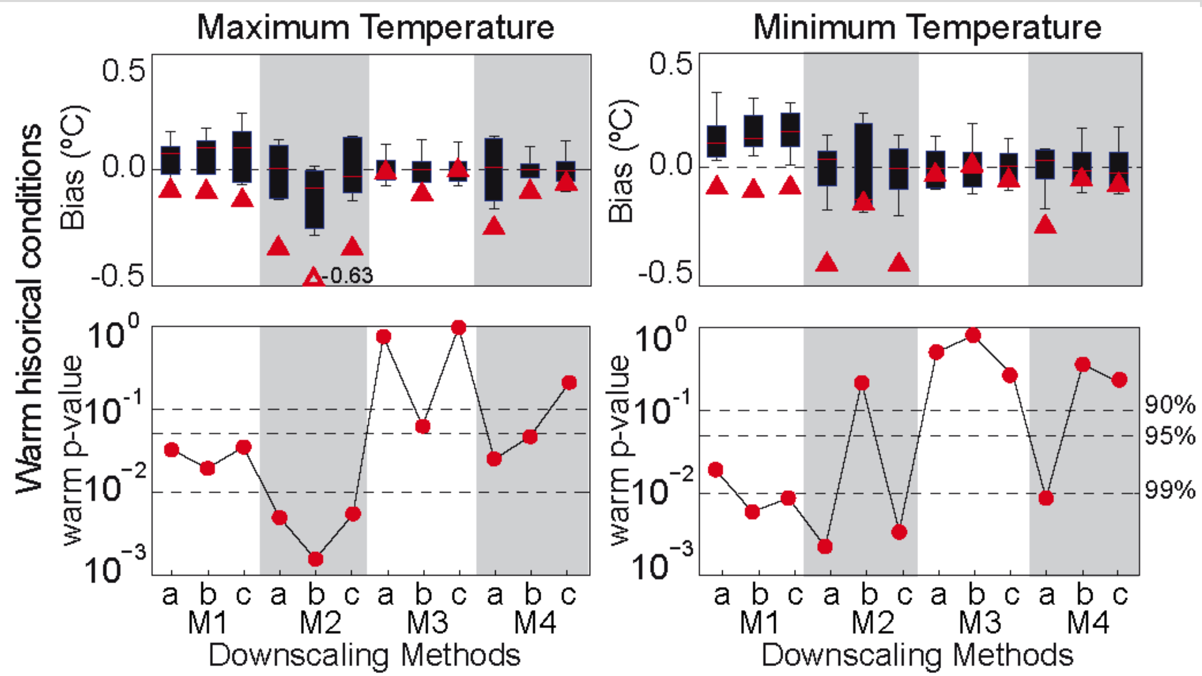
Statistical Downscaling: Testing Non-Stationarity

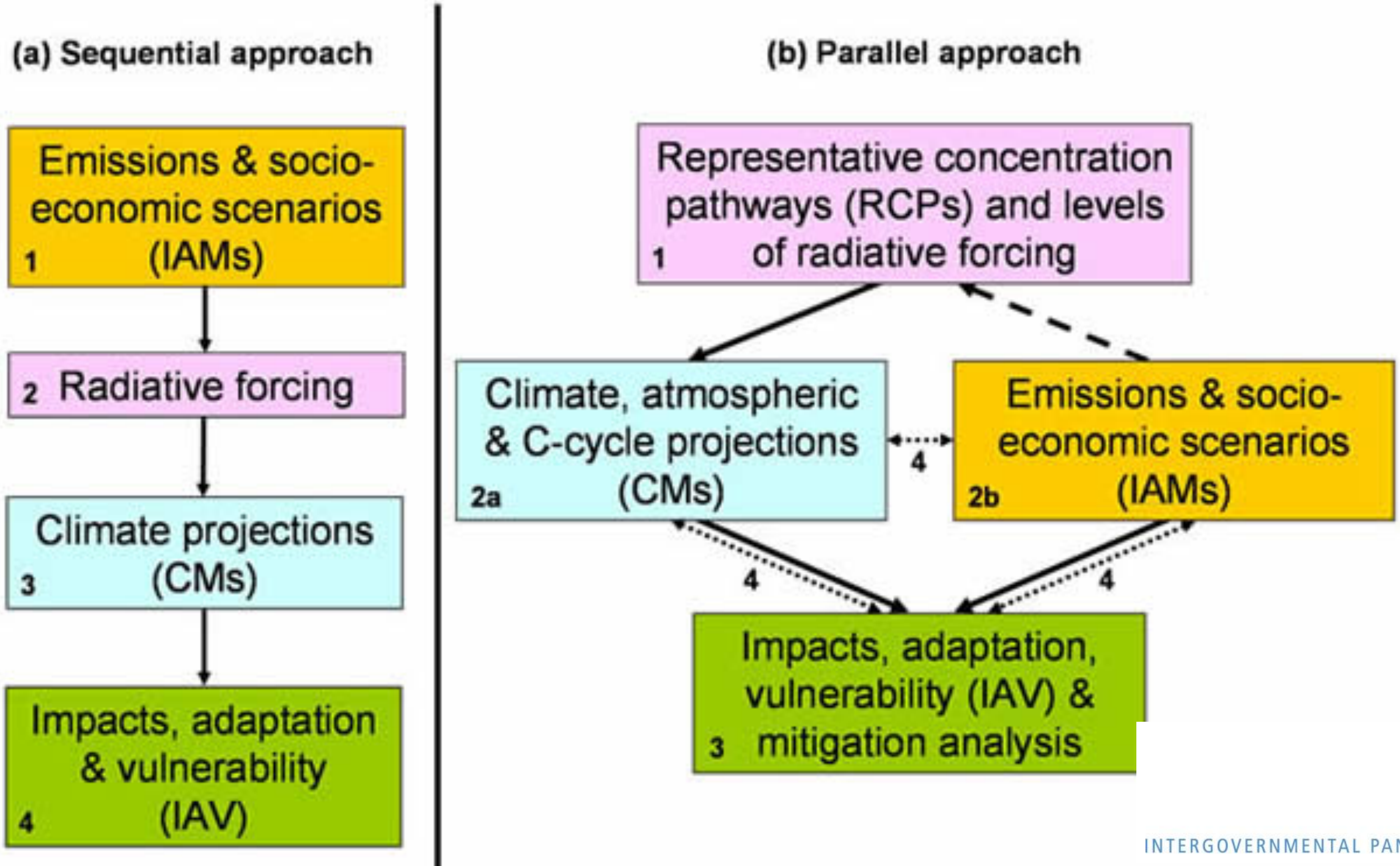


- The inability shown by non robust methods to capture the warming signal in present climate is translated to the late 21st

RCP Emission Scenarios (new for AR5)

The new scenarios take alternative futures in global greenhouse gas and aerosol concentrations as their starting point. These RCPs are used:

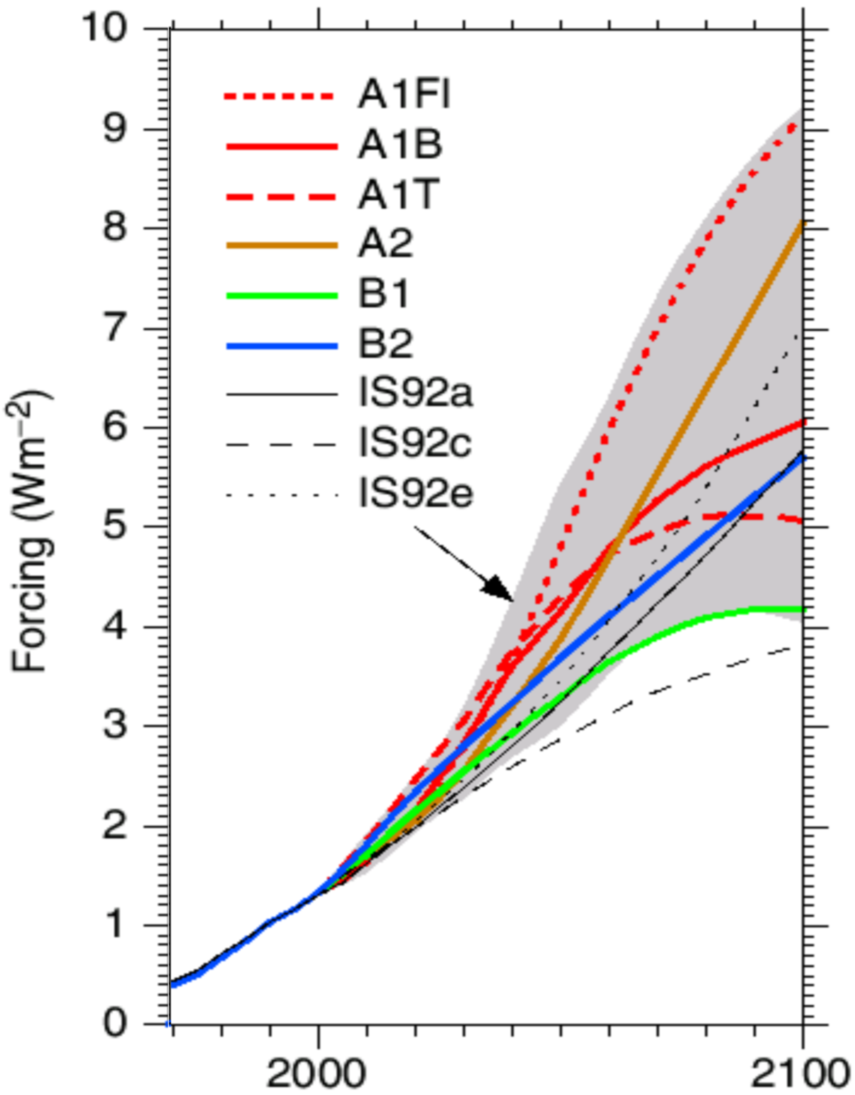
- by Earth System Models (ESMs): physical and biogeochemical resp.
- by Integrated Assessment Models (IAMs): socio-economic conditions

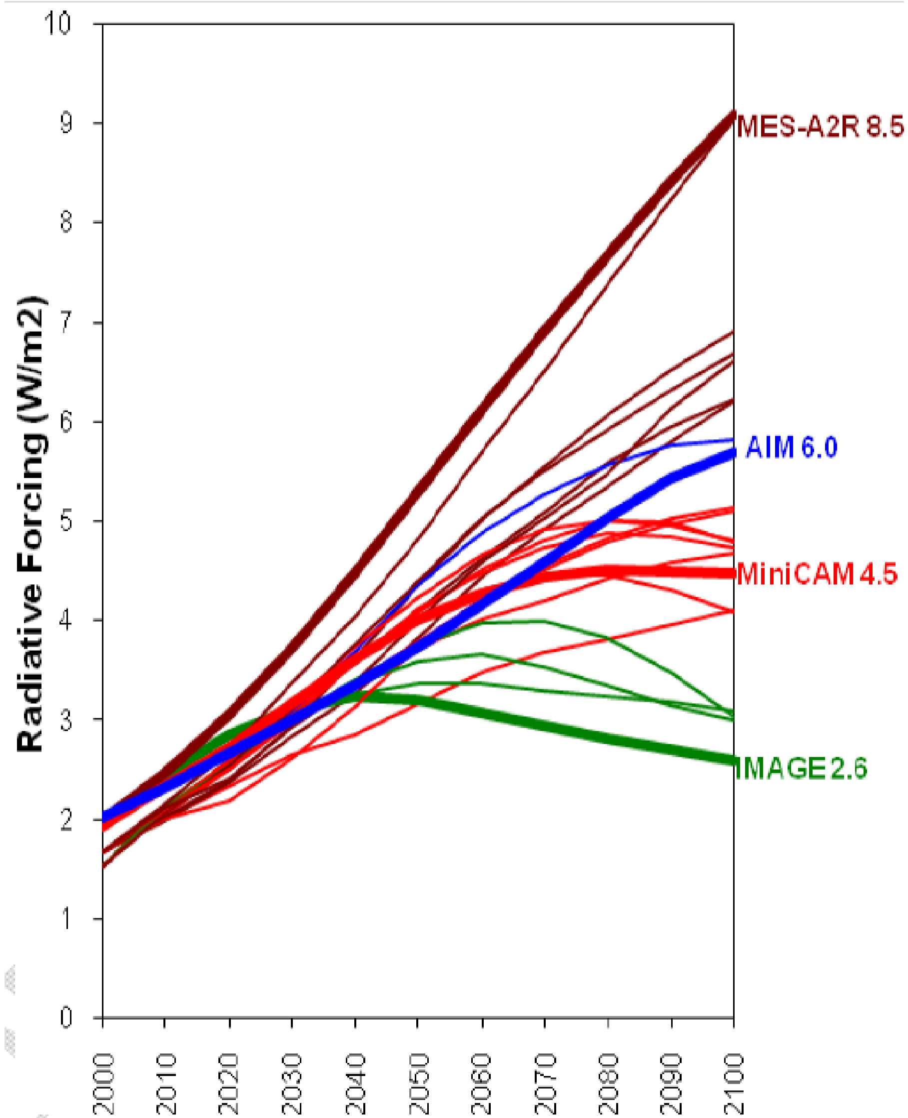


The four Representative Concentration Pathways (RCPs)

Name	Radiative forcing	Concentration	Pathway	Model providing RCP	Reference
RCP8.5	>8.5 W/m^2 in 2100	>1370 CO_2-eq in 2100	Rising	MESSAGE	Rao & Riahi (2006), Riahi et al. (2007)
RCP6.0	~6 W/m^2 at stabilisation after 2100	~850 CO_2-eq (at stabilisation after 2100)	Stabilisation without overshoot	AIM	Fujino et al. (2006), Hijioka et al. (2008)
RCP4.5	~4.5 W/m^2 at stabilisation after 2100	~650 CO_2-eq (at stabilisation after 2100)	Stabilisation without overshoot	MiniCAM	Smith & Wigley (2006), Clarke et al. (2007)
RCP3.0	Peak at ~3 W/m^2 before 2100 and then decline	Peak at ~490 CO_2-eq before 2100 and then decline	Peak and decline	IMAGE	van Vuuren et al. (2006, 2007)

SRES (AR4) vs. RCP (AR5) Emission Scenarios





Conclusions

GCMs: Distributional consistency between the reanalysis and the different GCMs varies from region to region for the different potential predictors. Bias correction of GCM output is necessary (not sufficient) for consistency. Note that this is not possible for RCMs (to keep physical consistency). Lack of data is still a problem in CMIP5.

RCMs: Provide many variables, but they need calibration.

Perfect prog. Some theoretical problems (e.g. stationarity) are being solved.

MOS techniques are a promising approach, since they solve some of above limitations.