http://www.meteo.unican.es

Perfect Prog(nosis)

Statistical Downscaling Methods

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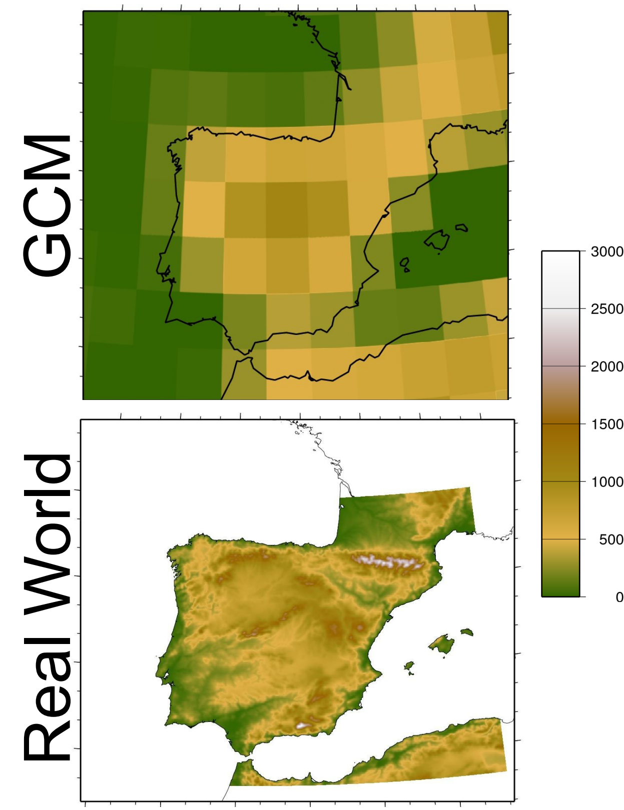
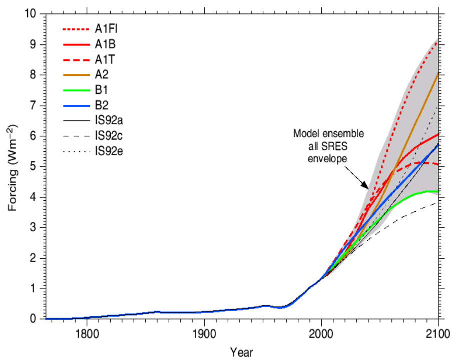
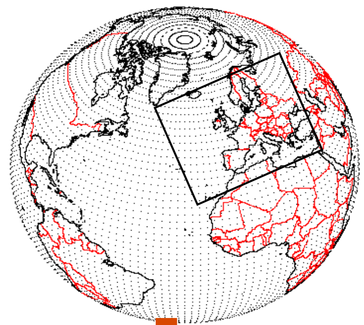


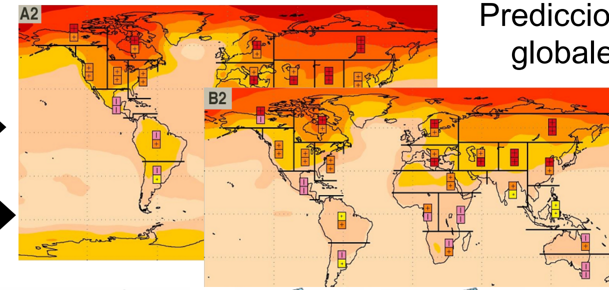
First VALUE training school: "Introduction to Dynamical and Statistical Downscaling".
Santander 6-15 November 2012

Statistical Downscaling

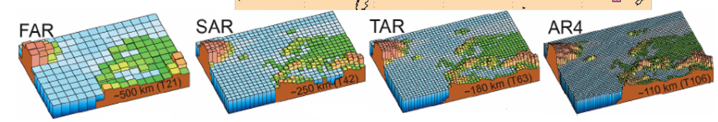
Escenarios de emisión



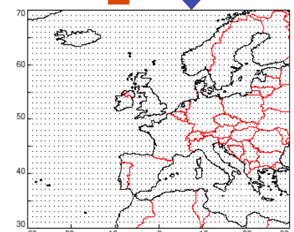




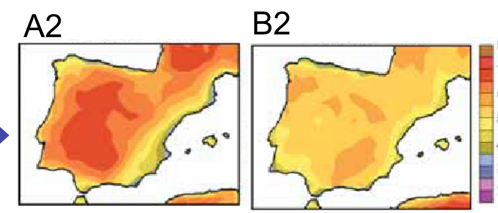
Predicciones globales



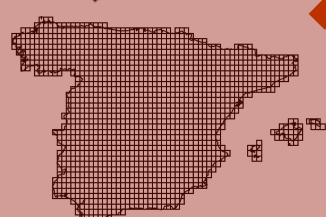
RCM



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



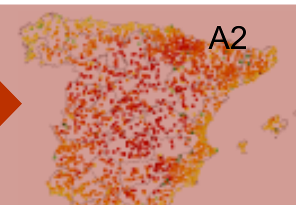
Registros históricos

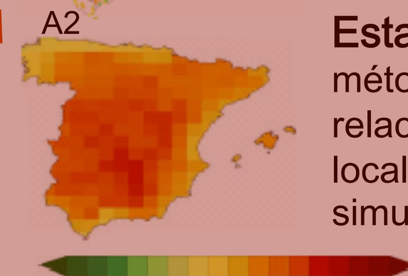


Rejilla interpolada (**20 km**)

$$Y = f\,(X;\theta)$$

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





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

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

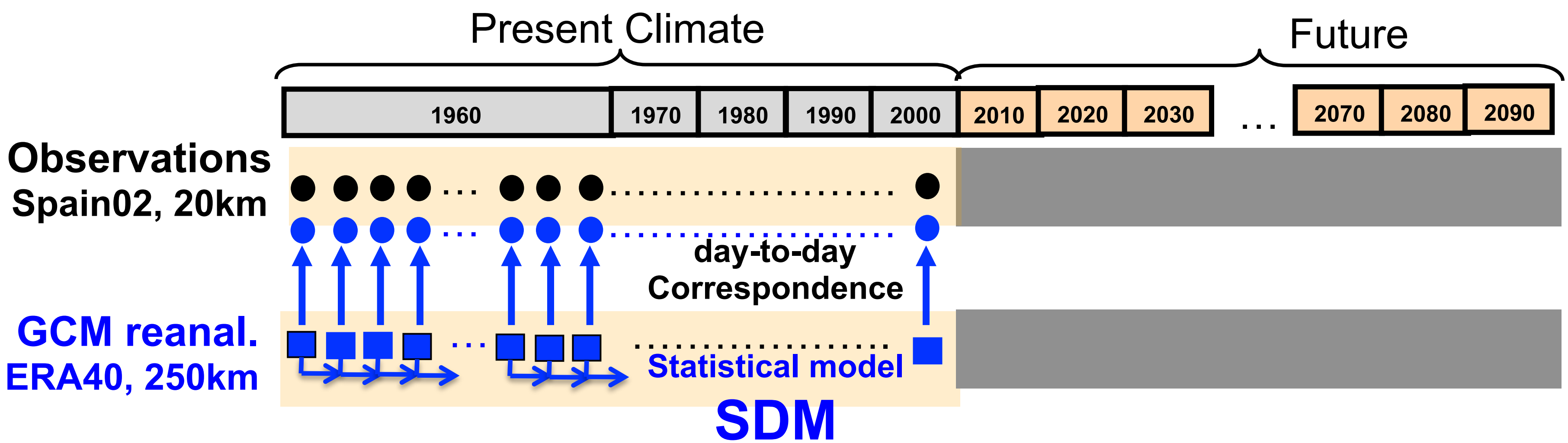
RCMs provide a **large number of physically consistent variables**.

However, they exhibit **large biases which need to be calibrated** for impact studies. This callibration process **assumes stationarity**.

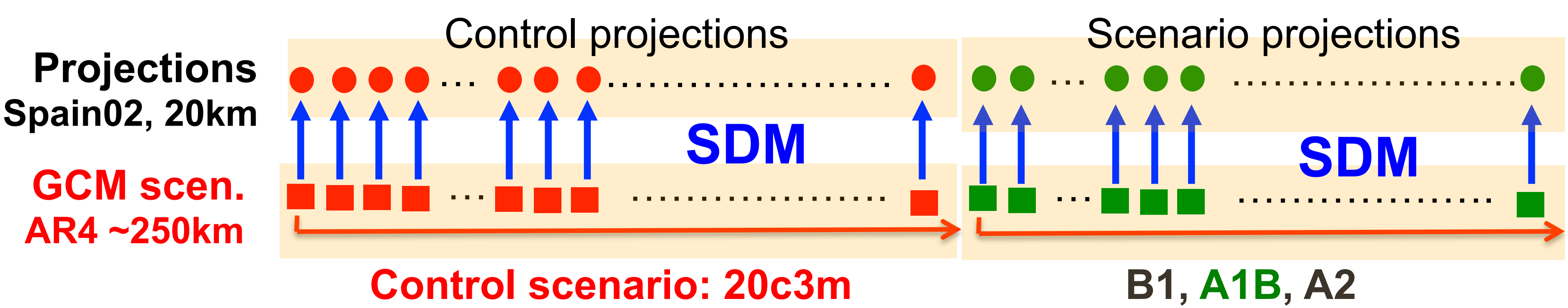
SDM require historical records of the variables under study.

SDM has some theoretical limitations: non-stationarity?

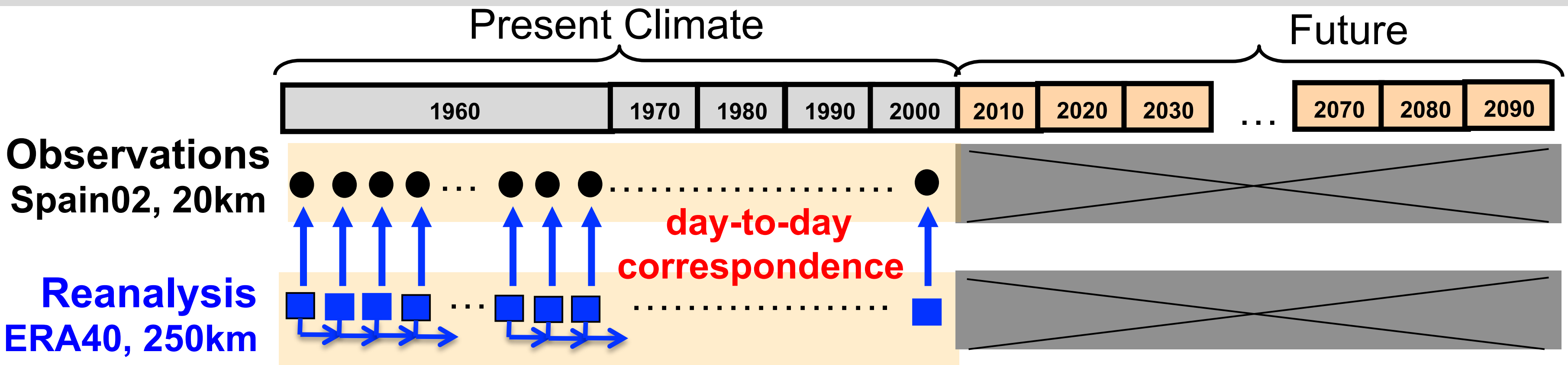
Statistical Downscaling: Perfect Prog.



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



On the use of Reanalysis data



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

On the use of Reanalysis data

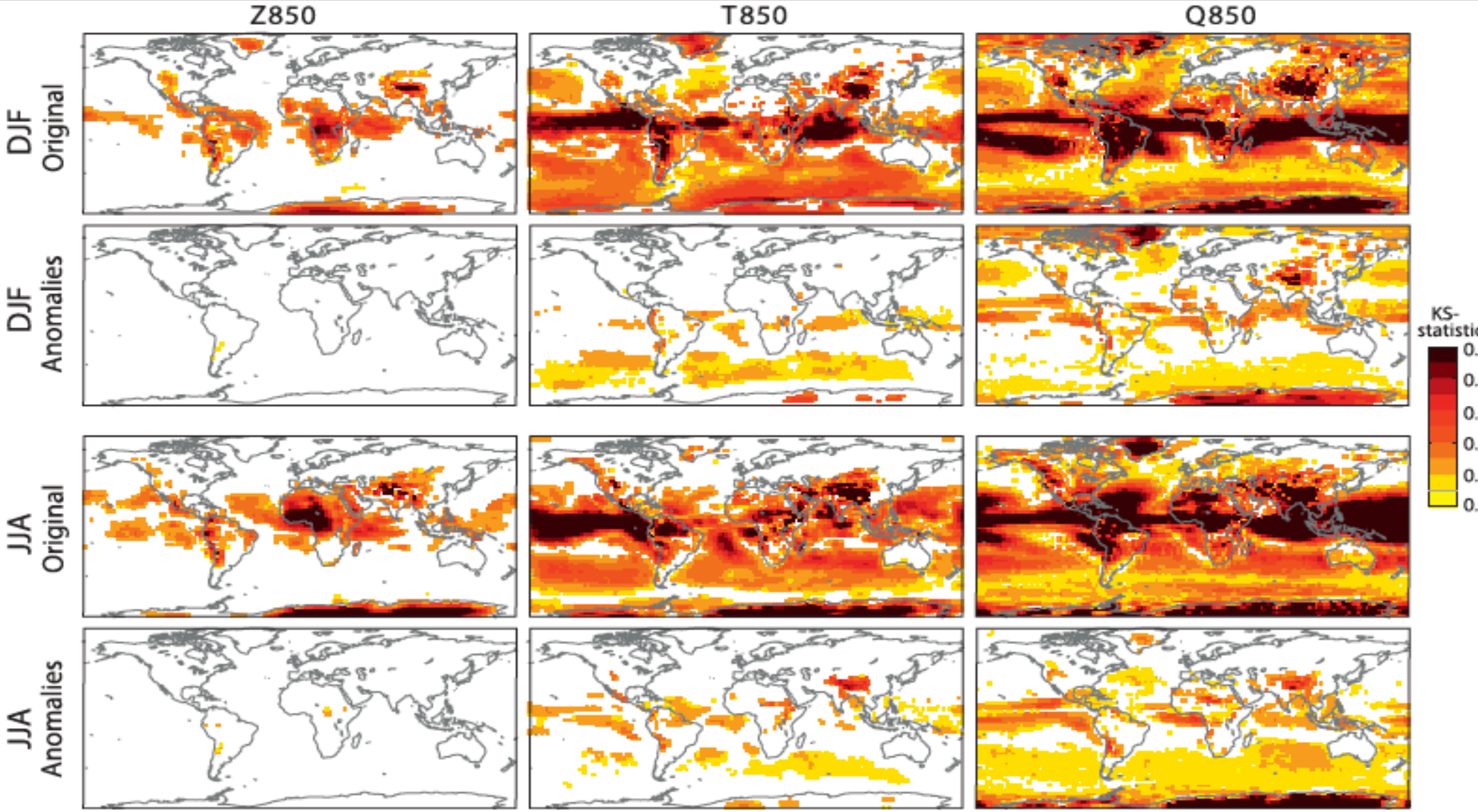


FIG. 3. Maps of distributional similarity for the daily time series of ERA-40 and NCEP–NCAR Z, T, and Q at (top) 500 and (bottom) 850 hPa, as revealed by the KS statistic. Color darkening from yellow to black indicates increasing dissimilarity. If the H_0 values of equal distributions cannot be rejected 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.

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 **conditioned on WTs**	Simple Easy to interpret Nonlinear	Linear assumption Selection of predictors
Neural networks	Nonlinear	Local minima Selection of predictors

Santander Meteorology Group

A multidisciplinary approach for weather & climate

EU-funded Project (2004-2009)

http://ensembles-eu.metoffice.com

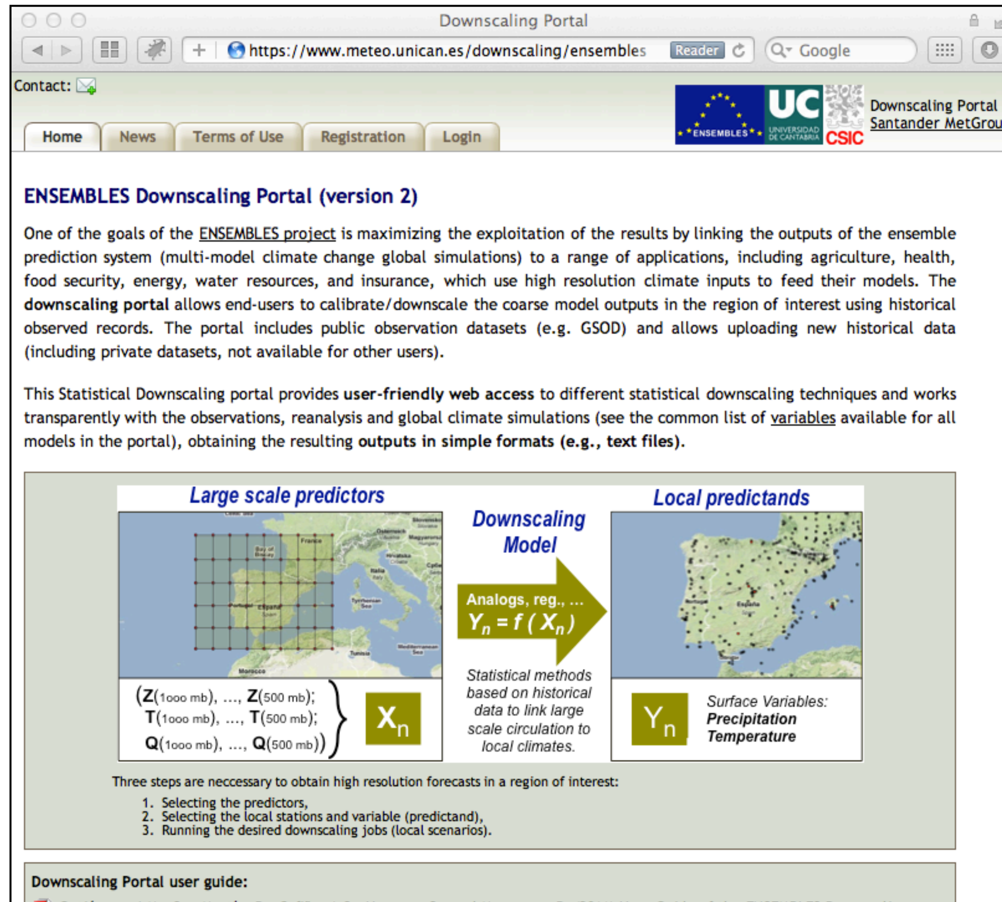
ENSEMBLES Project (2004-2009)

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

General classes of downscaling

Local climate = f (larger scale predictors) + locally forced variance

Dynamical
Two approaches

- RCM
- Hi-res GCM

Empirical-statistical
Three main classes

- **Weather Generators**
  - Trained on long term time series and atmospheric re-analysis data
  - Conditioned by GCM parameters to capture low frequency variance
- **Transfer Functions**
  - Trained on time series that spans range of variability, and atmospheric re-analysis data
  - Residual local scale variance added stochastically
- **Index / analogues**
  - Requires long term data sets and uses weather typing or historical analogues

Perturbed observed

Source:
Bruce Hewitson

Climate System Analysis Group
University of Cape Town
www.csag.uct.ac.za

Home | VALUE: COST Action ES1102 (2012-2015)

D2: Inventory of downscaling methods, validation studies and gaps of knowledge

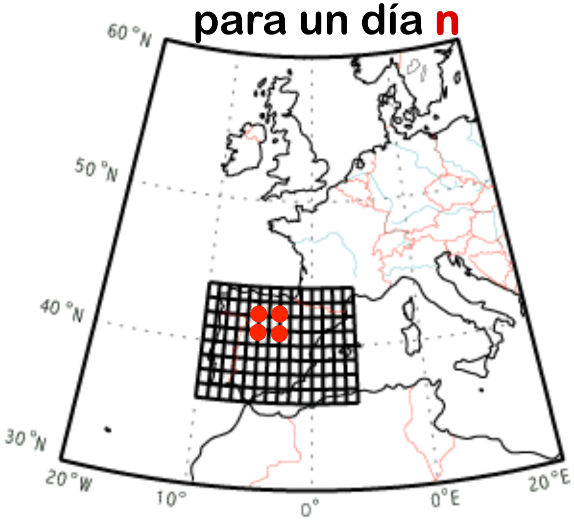
Type: Report

Working groups: WG1: Synthesis,WG3: Downscaling,WG4: Extremes,WG5: Sub-daily
Deadline: 2012-12-31

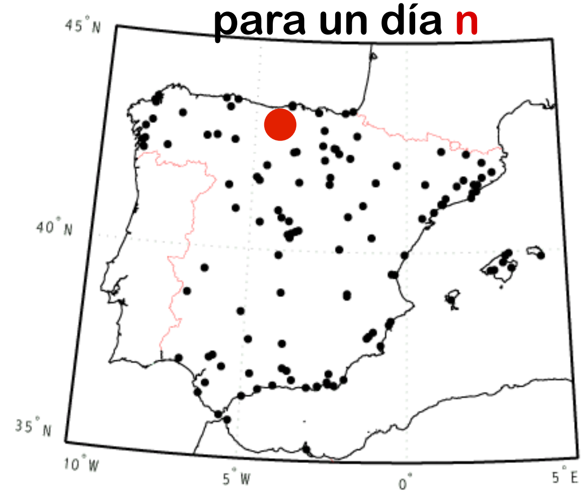
The inventory of downscaling methods will encompass the range of state-of-the-art RCMs with a focus on European models, but include also non-European models; traditional PP statistical downscaling methods such as linear and non-linear regression (e.g., artificial neural networks), weather typing and analogue methods; MOS methods such as variants of the direct method (including scaling) and quantile mapping methods. Additionally, the inventory will search for new methods based on stochastic models and downscaling of full PDFs, and methods for downscaling daily time series to sub-daily time series. The inventory will group the methods according to the downscaling approach as well as to its applicability (e.g., number of downscaled variables, local vs. spatially distributed, time scales provided). As this inventory is concerned with methods for different purposes, it will be carried out by WG3-5, coordinated by WG1. WG3 is responsible for temporal and spatial variability, WG4 for extremes, and WG5 for sub-daily scales.

1. Transfer Functions

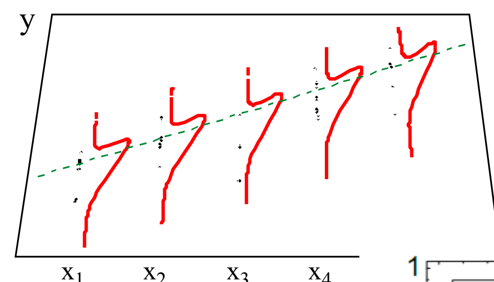
Rejilla de patrones atmosféricos para un día n



Predictandos: *precip*., etc. para un día n



$$(\mathbf{T}(1000\text{ mb}),\ldots,\mathbf{T}(500\text{ mb});\ \mathbf{Z}(1000\text{ mb}),\ldots,\mathbf{Z}(500\text{ mb});\ \ldots\ldots;\ \mathbf{H}(1000\text{ mb}),\ldots,\mathbf{H}(500\text{ mb})) = \mathbf{X}_n$$



Y_n

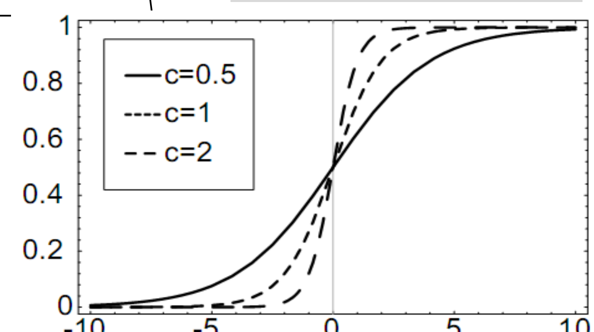
Linear regression:

$$\hat{Y}_n = a\,X_n + b$$

Logistic regression

Probabilistic prediction

$$\hat{Y}_n = F(a\,X_n + b)$$



Redundancy: EOFs

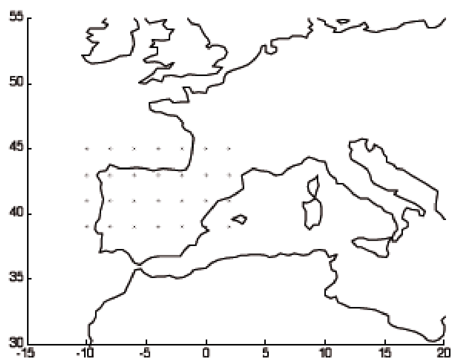


Figura 3. Área de estudio y rejilla utilizada para definir los predictores de los métodos de downscaling estadístico.

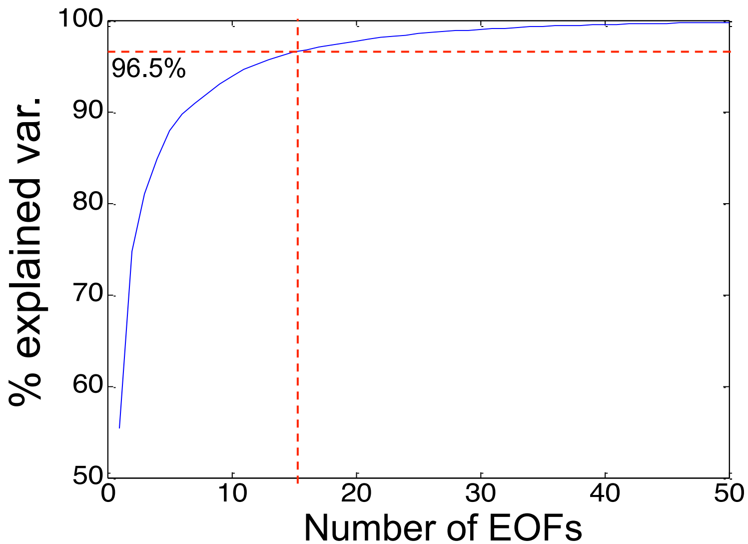
Variable	Nivel	Hora
Geopotencial	500	0 UTC
Geopotencial	1000	0 UTC
Temperatura	500	0 UTC
Temperatura	850	0 UTC
Humedad Relativa	850	0 UTC

140 parameters (5 variables, 28 gridboxes), n=16434

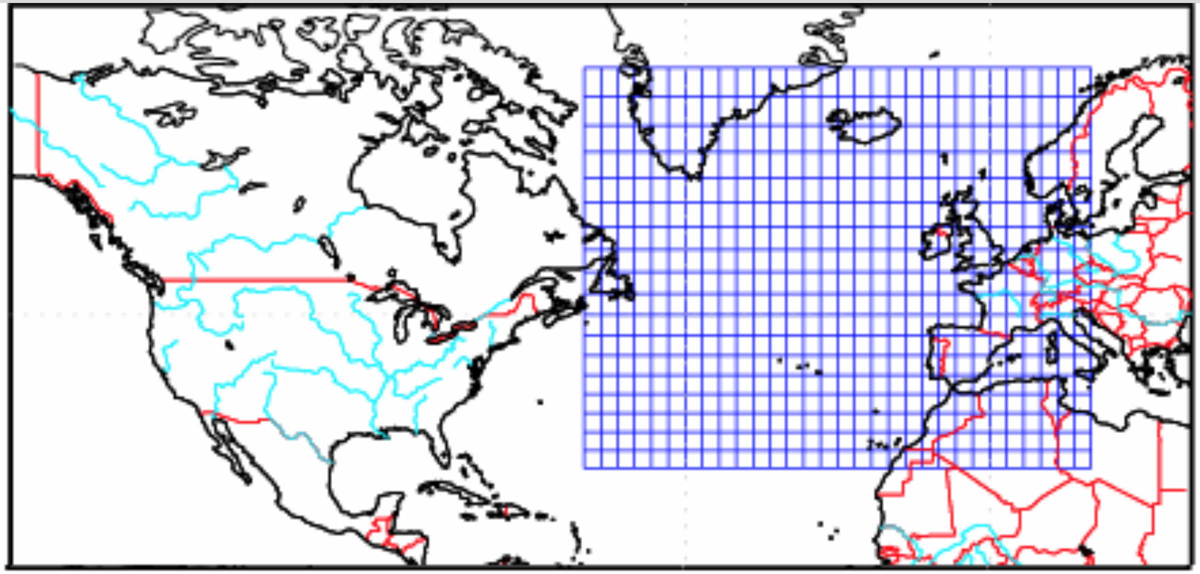
Redundancy (correlation):

- Principal Components

- Nearest grid-boxes

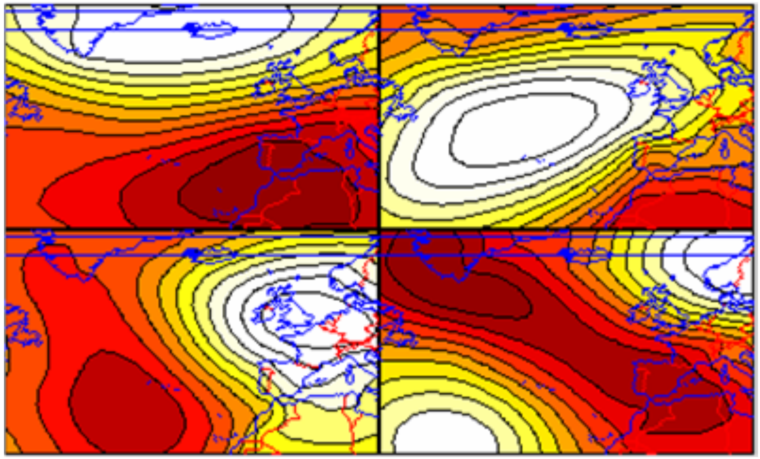


Redundancy: EOF & CPs

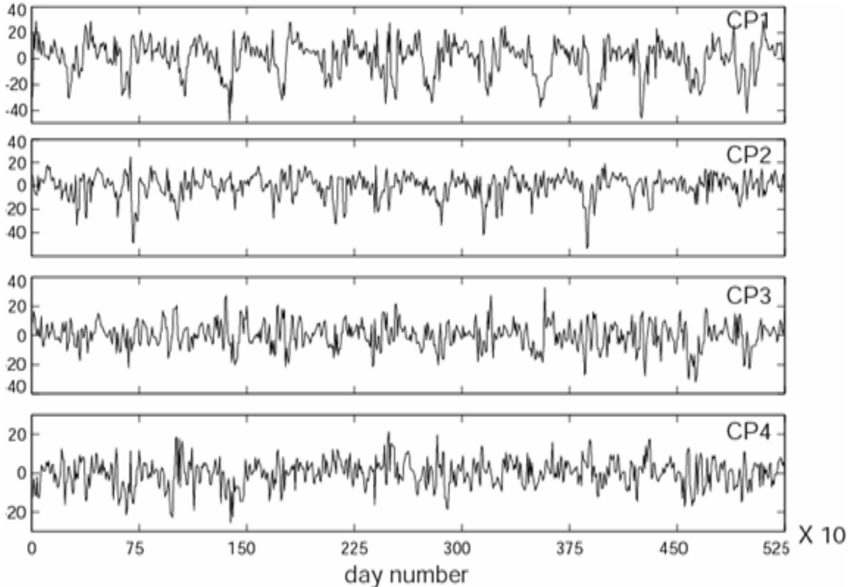


	AN
EOF_1	32.91
EOF_2	19.14
EOF_3	14.40
EOF_4	8.86
$Acumulado$	75.31

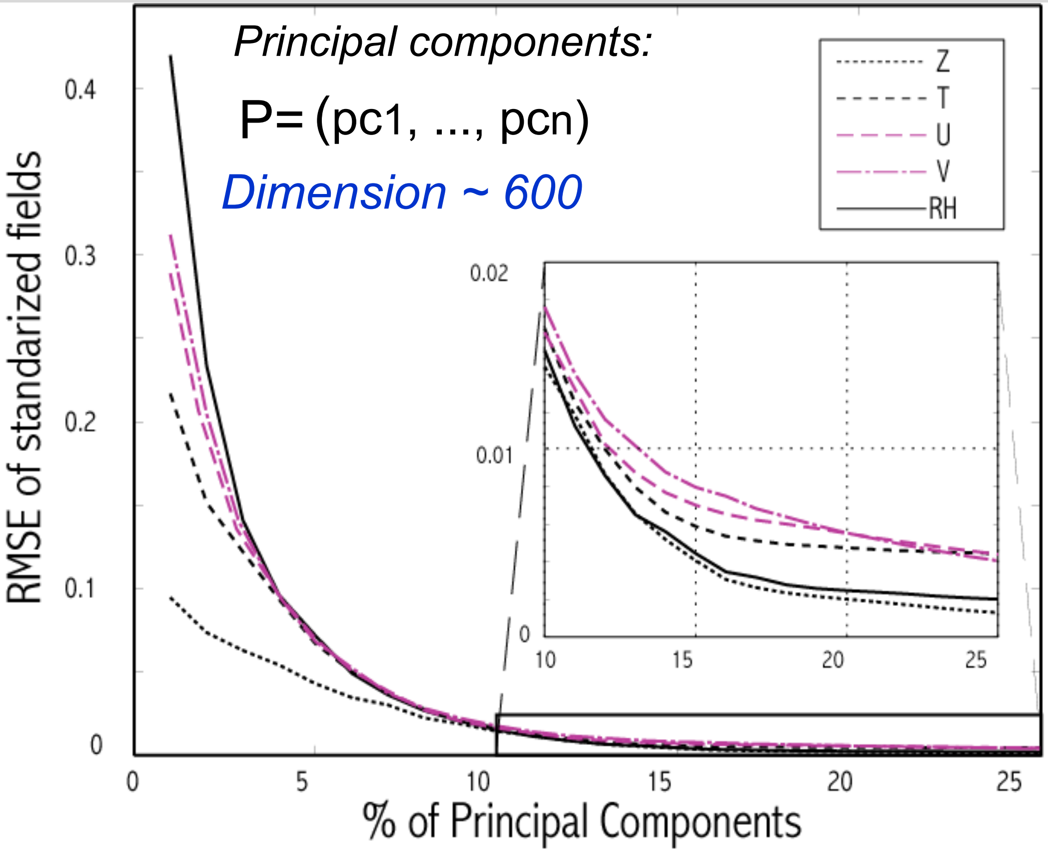
EOF 1 EOF 2



EOF 3 EOF 4



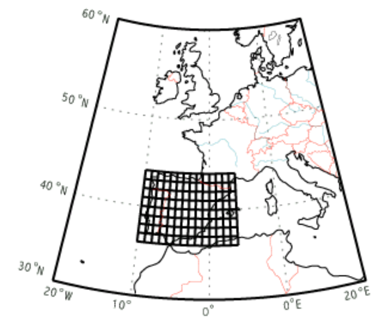
EOFs of Combined Fields



In the numerical output for Spain we can reduce *the dimension from over 6000 to only 600,* spanning the maximum variance, of the spatial gridded fields

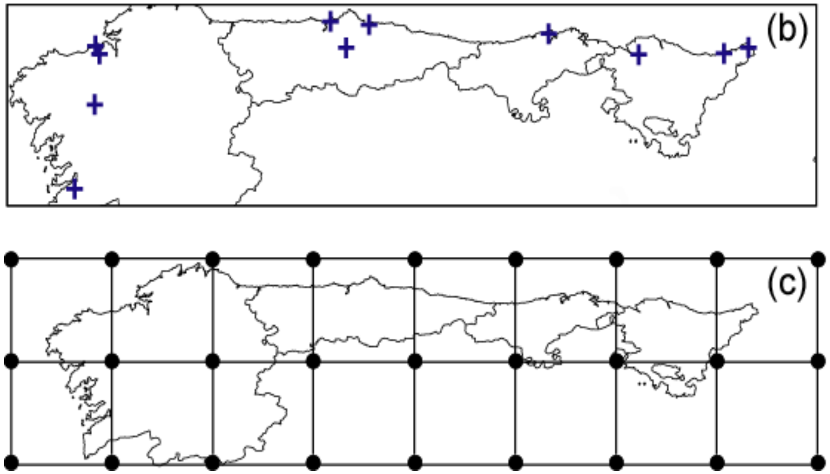
(T(1ooo mb),..., T(500 mb); Z(1ooo mb),..., Z(500 mb), ..., H(1ooo mb),..., H(500 mb))

Dimension > 6000



With only the 10% of Principal Components we can reconstruct the original standarized fields generating minor RMSE of 0.02

An illustrative example



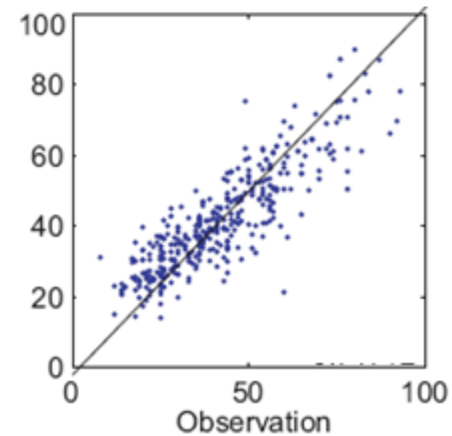
Wind Speed ➔ [0,∞)

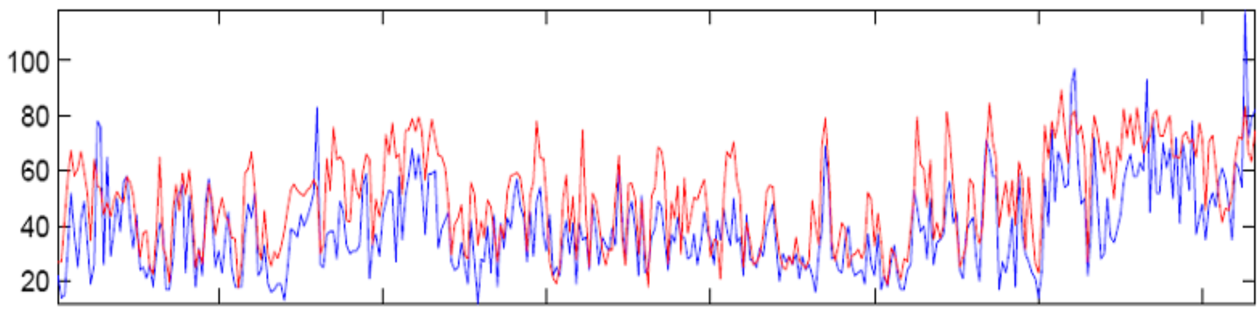
P(Wind Speed > 50km/h) ➔ [0,1]

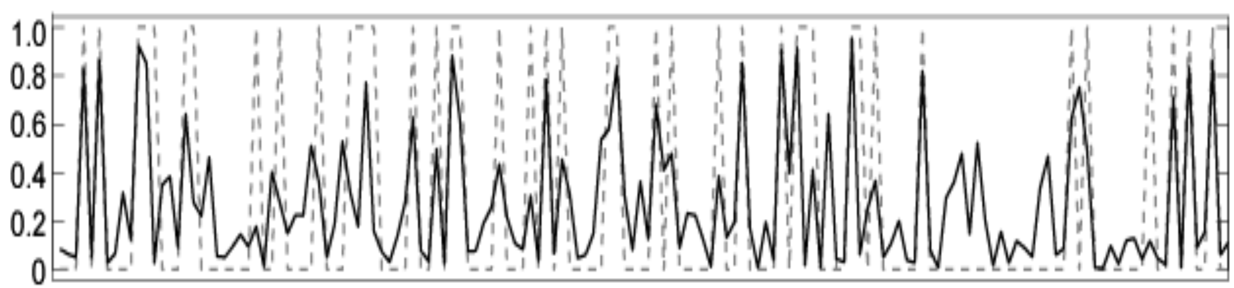
Observations from **1977- 2002.**

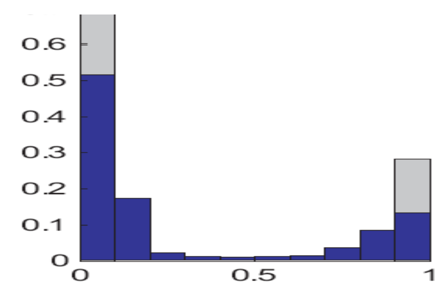
ERA40 over 27 grid points for the same period

**(60% for trainning
40% for validation)**







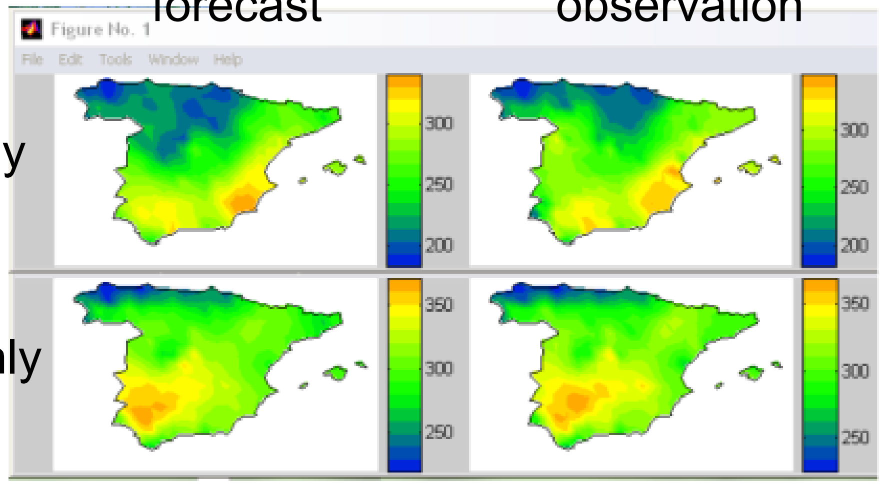


Limitations

forecast observation

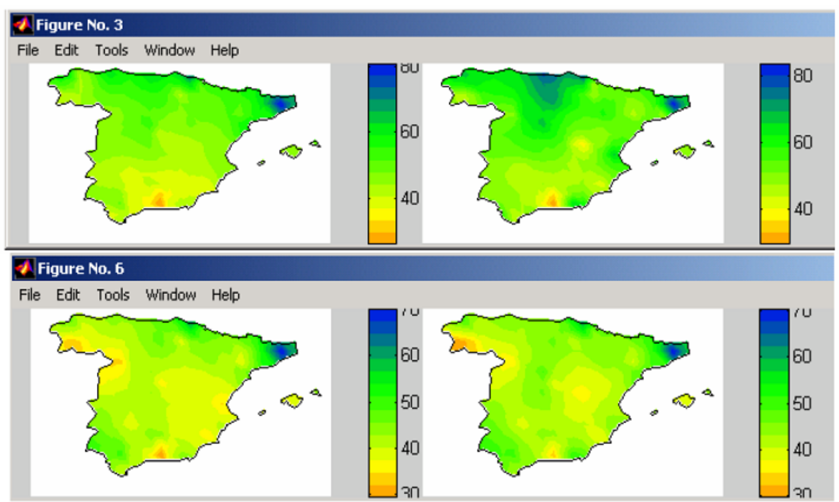
daily

monthly

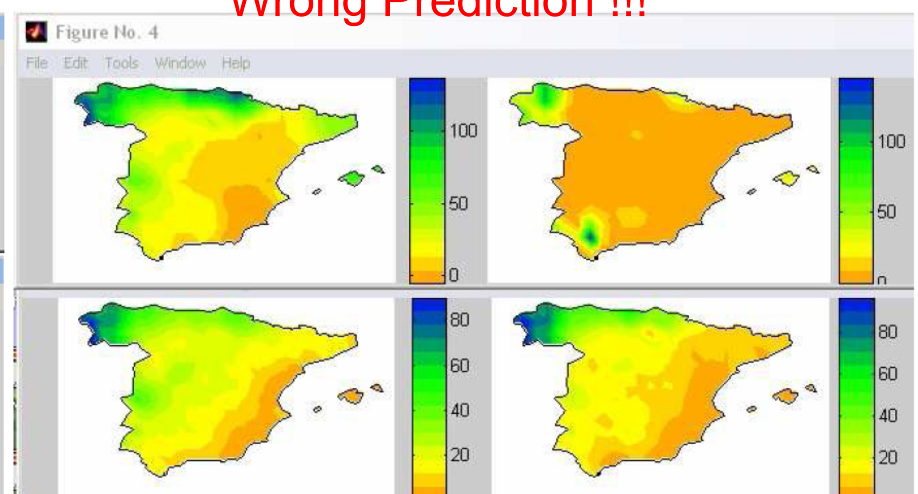


Temperature

Wrong Prediction !!!



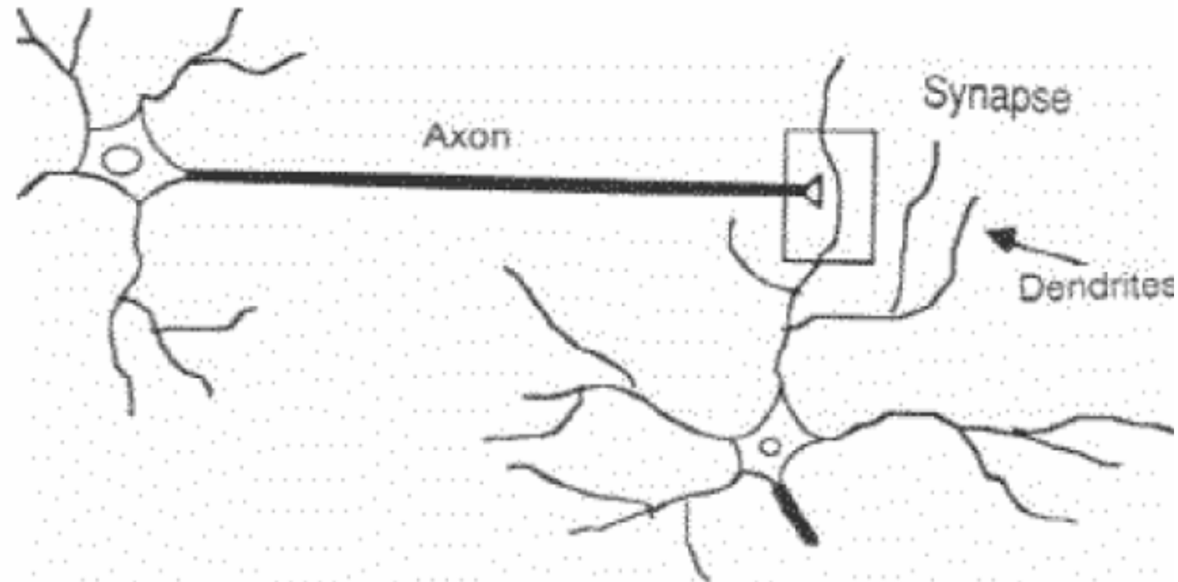
Rx



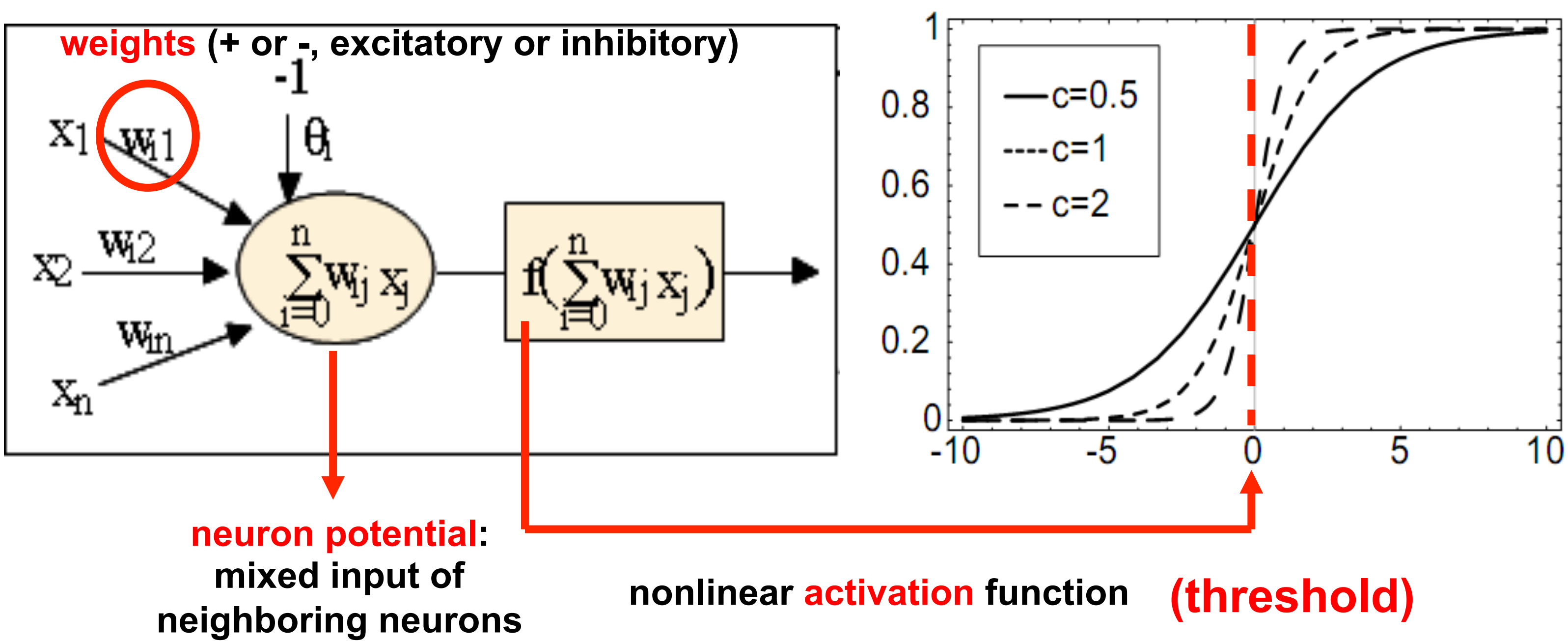
Precip

Artificial Neural Networks are inspired in the structure and functioning of the **brain**, which is a collection of **interconnected neurons** (the simplest computing elements performing information processing):

- ✓Each neuron consists of a cell body, that contains a cell **nucleus**.
- ✓There are number of fibers, called **dendrites**, and a single long fiber called **axon** branching out from the cell body.
- ✓The axon connects one neuron to others (through the dendrites).
- ✓The connecting junction is called **synapse**.

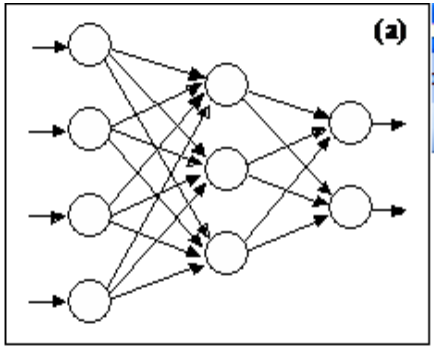


- The synapses releases chemical transmitter substances.
- The chemical substances enter the dendrite, raising or lowering the electrical potential of the cell body.
- When the potential **reaches a threshold**, an electric pulse or action potential is sent down to the axon affecting other neurons. *(Therefore, there is a nonlinear activation).*
- Excitatory and inhibitory synapses.



Supervised Problems. Input-Output pairs are provided:
(x1,y1), (x2,y2), ..., (xn,yn) and the network learns y = f(x).

Multilayer Networks or Feedforward Nets.
Several layers connected (input+hidden+output)



Pattern Recognition
- OCR
- Natural Language Proc

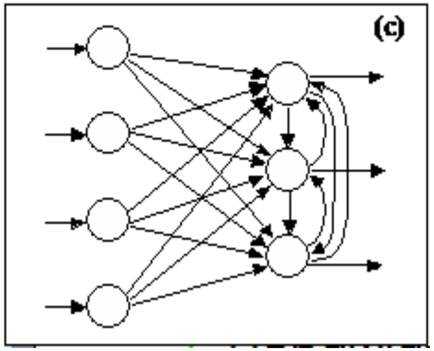
Interpolation and fitting

Prediction: Input => Output

Unsupervised Problems. Only input data is provided:
x1, x2, ..., xn and the network self-organizes it to provide an output.

Less intuitive.
e.g. SOM

Competitive Networks
Multilayer networks with lateral connections (competitive) in the last layer.

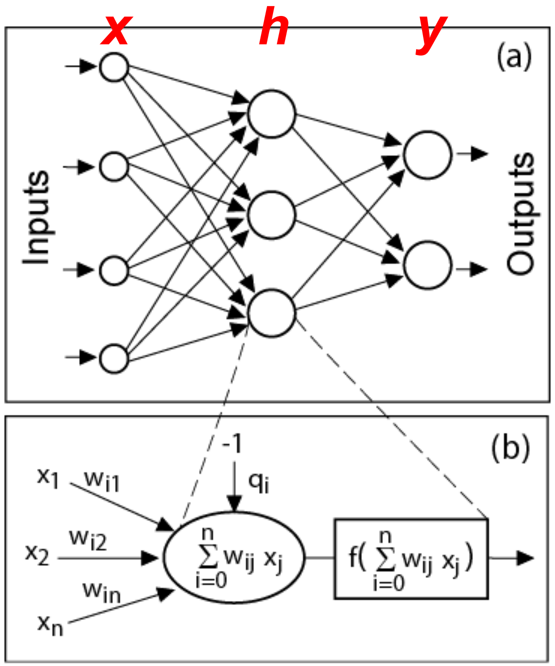


Classification

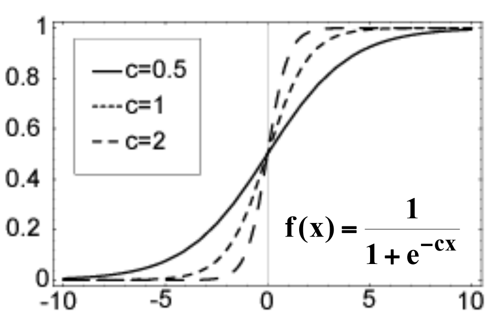
Topologic reconstruction

Feature extraction.

Neural Networks



The neural activity (output) is given by a nonlinear function.



$$y_j = f(\sum_i \beta_{ji} \underbrace{f(\sum_k \alpha_{ik} x_{kp})}_{h_i})$$

Inputs $\{x_{1p}, \dots, x_{mp}\}$

Outputs $\{y_{1p}, \dots, y_{np}\}$

$$\begin{aligned} E(\alpha, \beta) &= \frac{1}{2} \sum_{j,p} (y_{jp} - f(\sum_i \beta_{ji} f(\sum_k \alpha_{ik} x_{kp})))^2 \\ &= \sum \|\mathbf{y}_p - f(\beta^T f(\alpha^T \mathbf{x}_p))\| \end{aligned}$$

Gradient descent $\Delta\beta_{ik} = -\eta \frac{\partial E}{\partial \beta_{ik}}; \ \Delta\alpha_{kj} = -\eta \frac{\partial E}{\partial \alpha_{kj}},$

1. Init the neural weight with random values

2. Select the input and output data and train it

3. Compute the error associate with the output

$$\delta_{jp} = (y_{jp} - \hat{y}_{jp}) f'(\beta_j^T \hat{\mathbf{h}}_p)$$

4. Compute the error associate with the hidden neurons

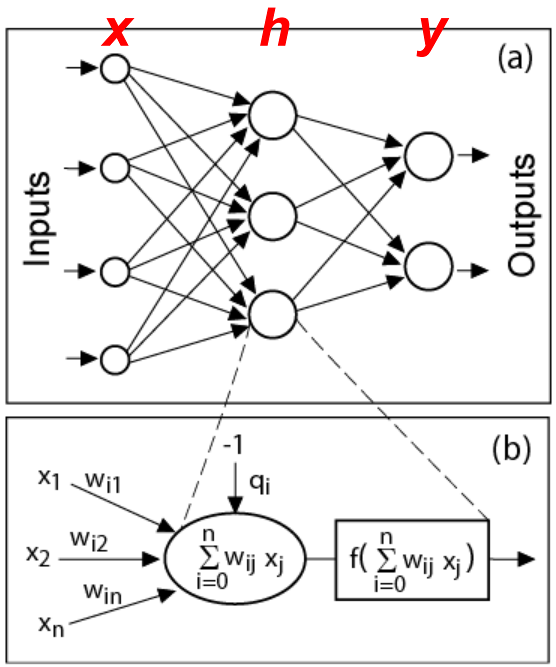
$$\psi_{jp} = \sum_k \delta_{jp} \beta_{jk} f'(\alpha_k^T \mathbf{x}_p)$$

5. Compute

$$\Delta\beta_{jk} = \eta \hat{h}_k \delta_{jp}, \ \Delta\alpha_{ki} = \eta \sum_j x_{ip} \delta_{jp} \psi_{jp},$$

and update the neural weight according to these values

Extreme Lear. Machines (ELMs)



$$y_j = f\Big(\sum_i \beta_{ji} f\Big(\sum_k \alpha_{ik} x_{kp}\Big)\Big)$$

The input-to-hidden weights are randomly initilialized. The corresponding optmization problem is a linear one (using Moore-Penrose generalized inverse).

Int. J. Mach. Learn. & Cyber. (2011) 2:107–122
DOI 10.1007/s13042-011-0019-y

ORIGINAL ARTICLE

Extreme learning machines: a survey

Guang-Bin Huang · Dian Hui Wang · Yuan Lan

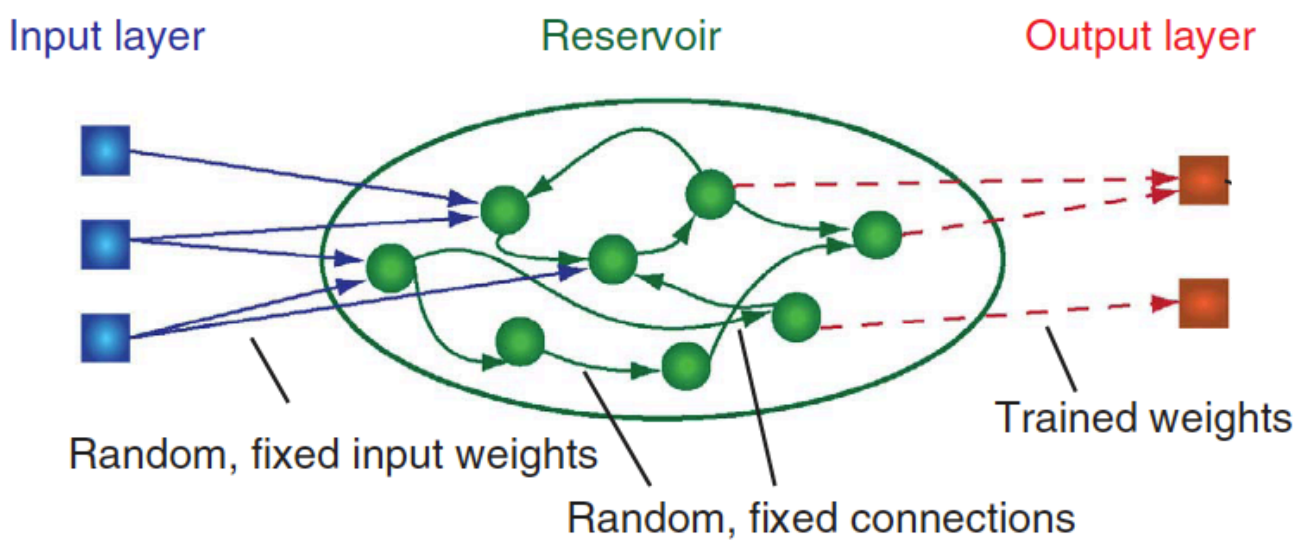
```
IWeight=rand(HNeurons,INeurons)*2-1;
BiasofHNeurons=rand(HNeurons,1);
tempH=InputWeight*P;
BiasMatrix=BiasofHNeurons(:,ind);
tempH=tempH+BiasMatrix;
H = 1 ./ (1 + exp(-tempH));

OutputWeight=pinv(H') * T';
```

RC models (e.g. Echo State Networks, ESN) are supervised (input-output) machine learning tools which are built in two steps:

Building the reservoir (high-dimensional recurrent nonlinear network) and mapping the input to the reservoir

Fitting the output to the reservoir using a simple linear model.

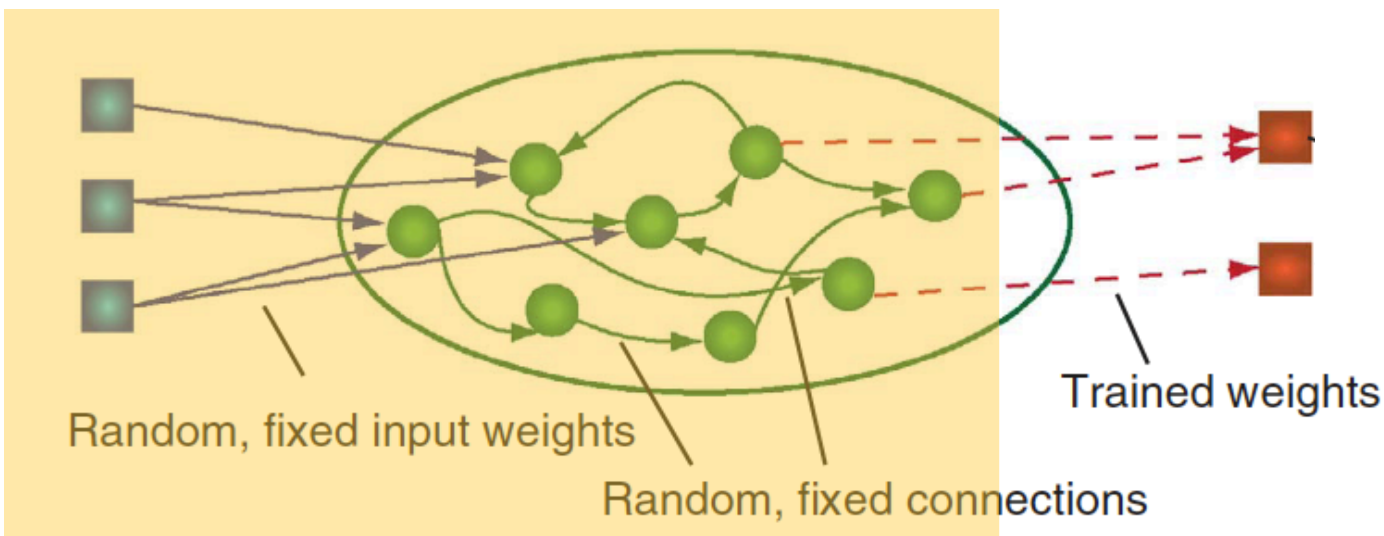


¡Only the output connections are trained !!

So the final optimization can be easily solved

However, there are several problems preventing RC to become widely adopted for machine learning problems.

- **The input- and reservoir-weights (including network connectivity) are randomly chosen**. Thus, **performance relies on <u>trial and error</u>** (testing different model realizations).



- **Some properties of the reservoir are poorly understood**; i.e. It is used as a **<u>black-box technique</u>**.

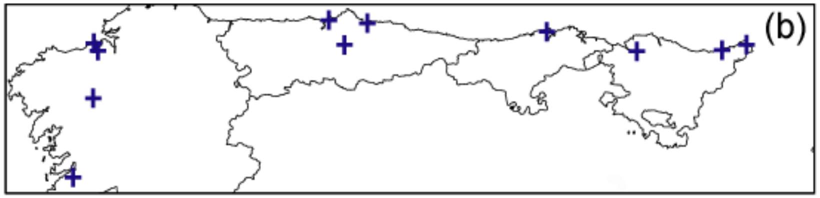
Regression vs. Neural Nets.

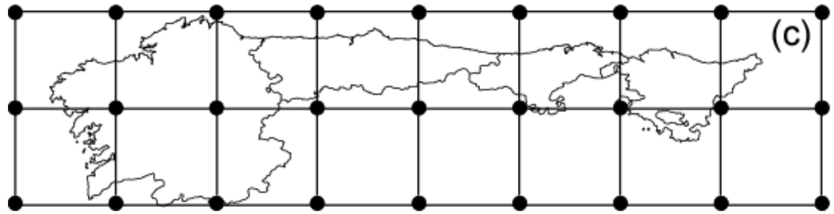
Wind Speed → [0,∞)

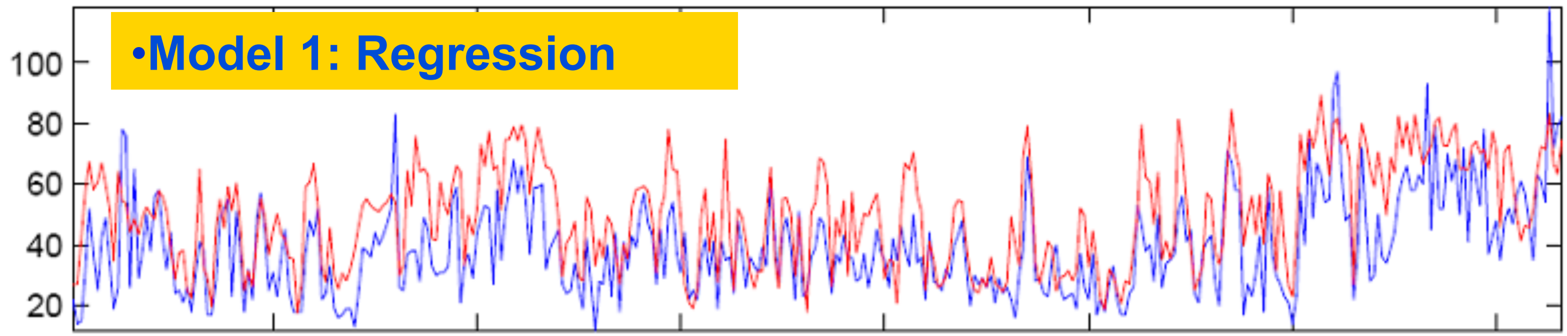
Observations from 1977- 2002.

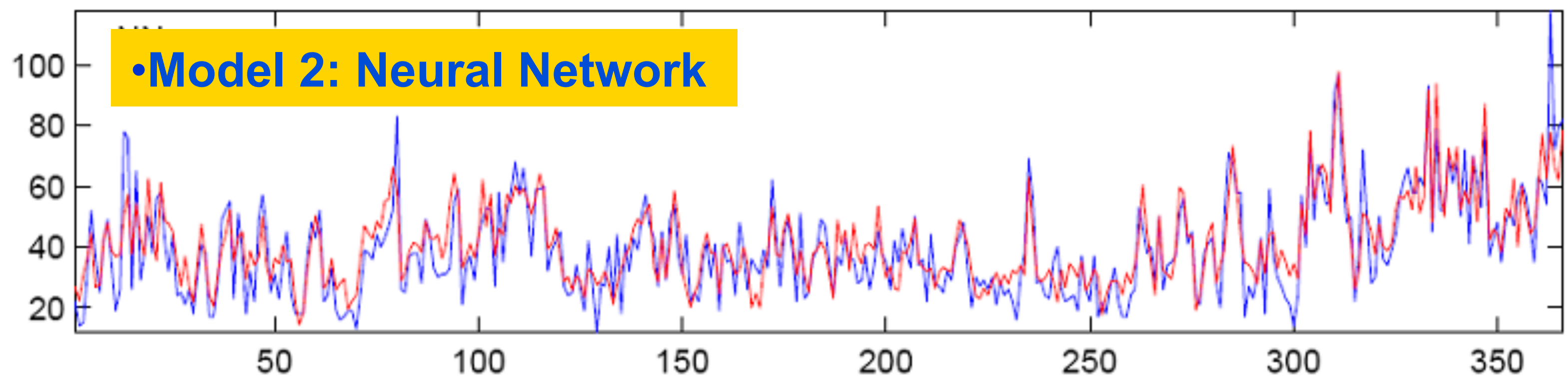
ERA40 over 27 grid points for the same period

60% for trainning and
40% for validation

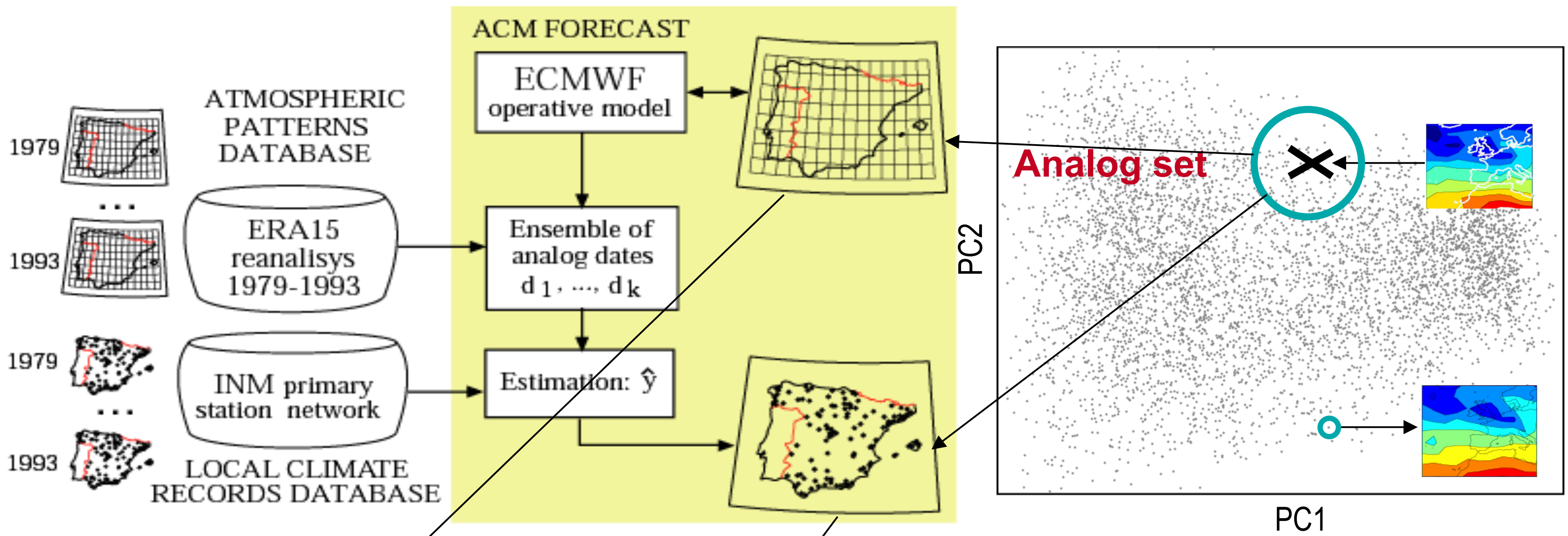


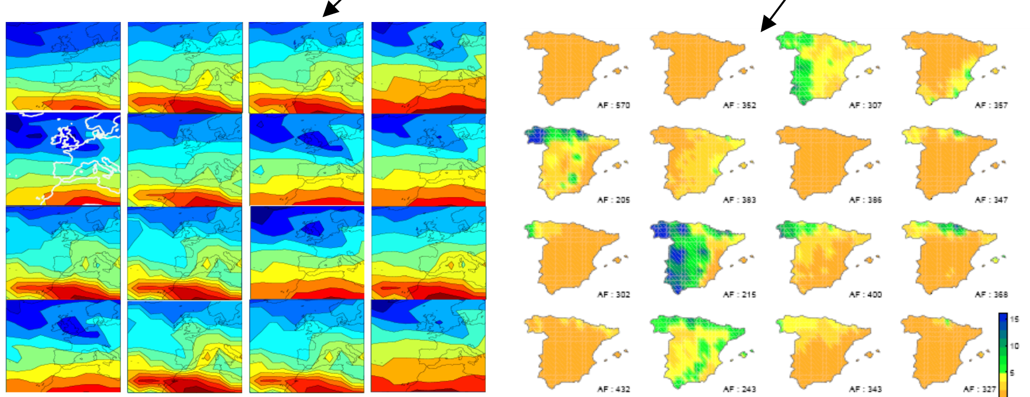






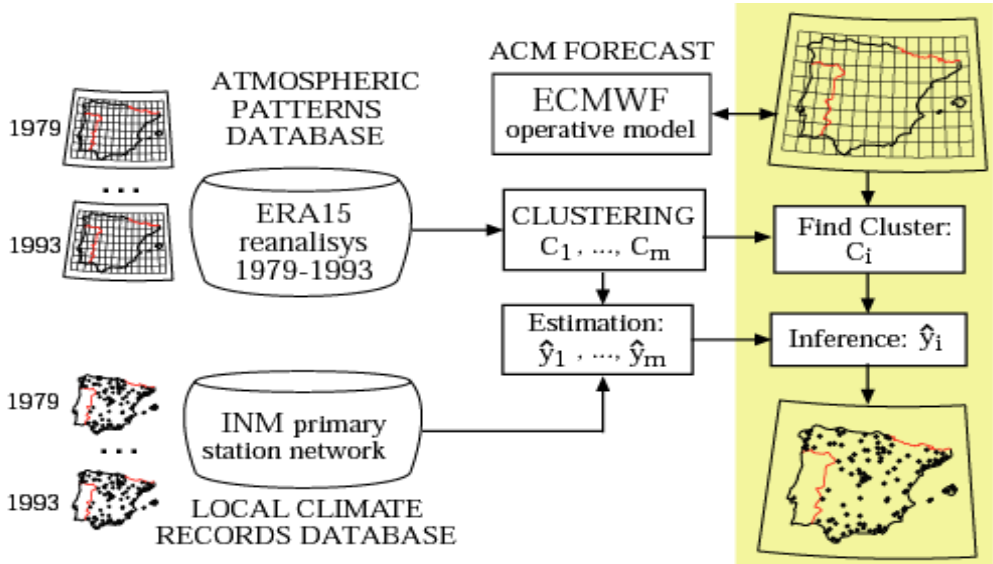
The method of analogs (k-nearest neighbors) is one of the most popular techniques in statistical downscaling, introduced by E. Lorenz (1969).



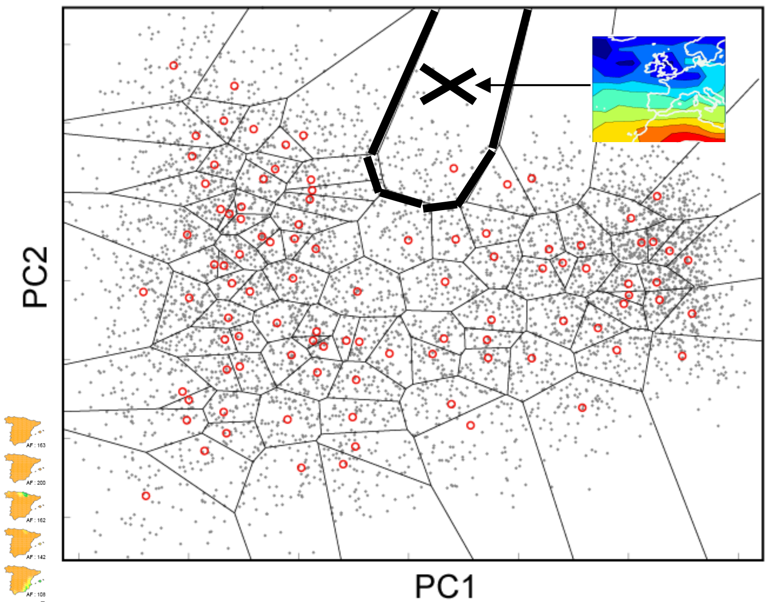


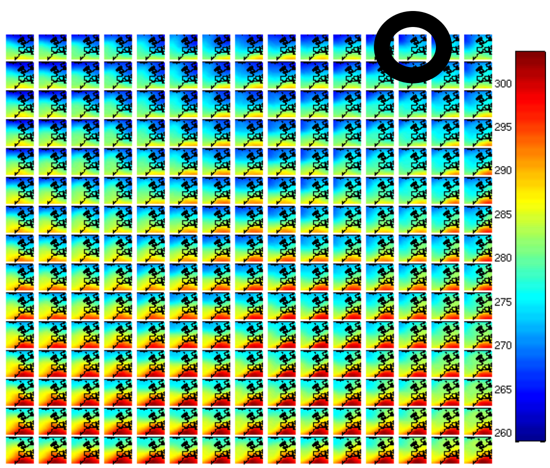
- Mean
- Median
- Frequency

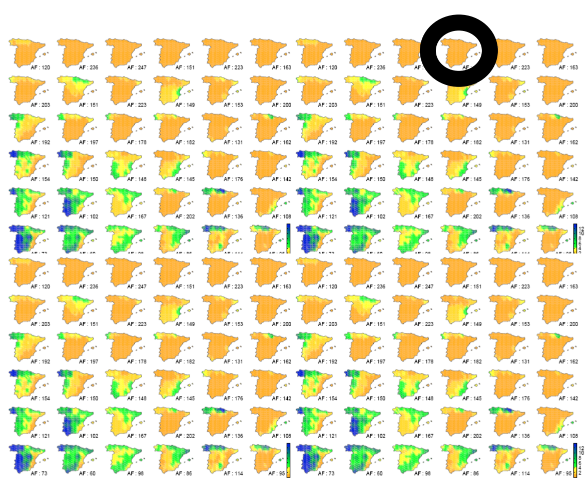
Weather Typing (WT)



Based on partitioning the atmospheric space (using the reanalysis data) in a predefined number of groups.



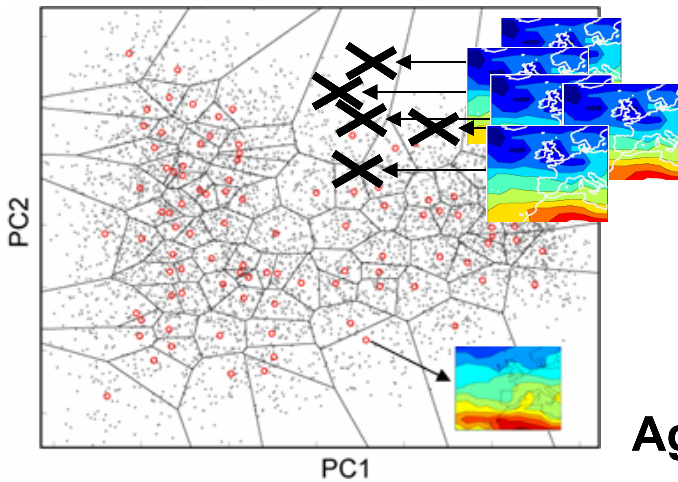




Given a new pattern (**X**), the group is obtained Ck. Then, the forecast is P(y>u|Ck).

$$P_{forecast}(precip > u) = \Sigma_{Ck}\, P(precip > u \mid Ck)\, P_{forecast}(Ck)$$

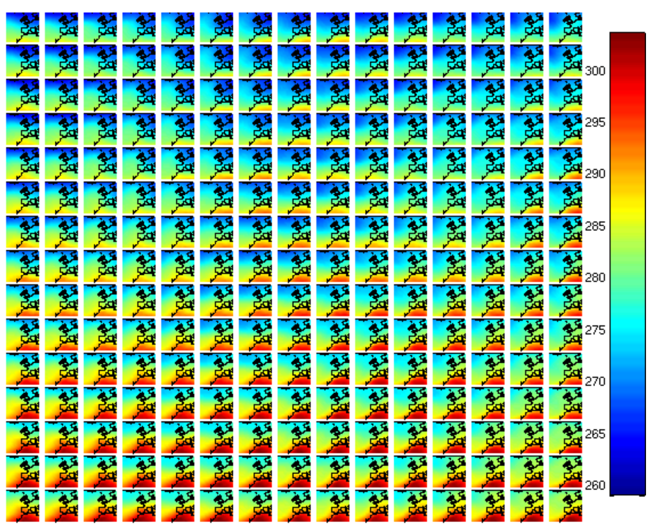
The application to an EPS requires applying the method to each of the ensemble members:

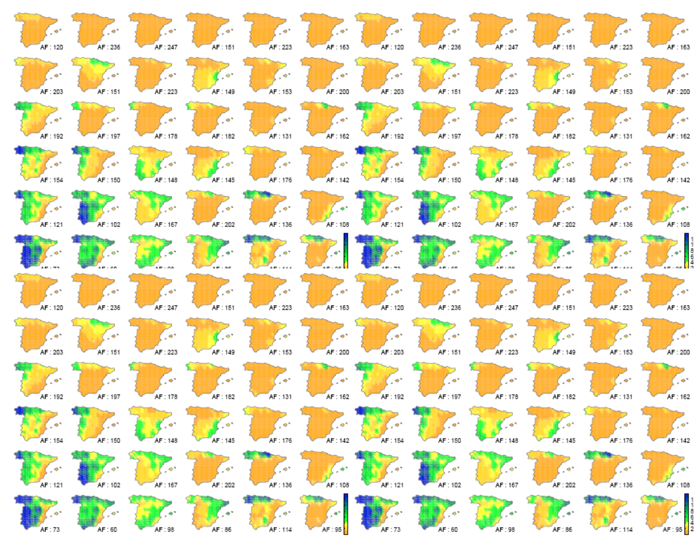


→ x1
→ x2
→ x3
→ x4
→ x5
…

Prob(x)
Mean(x)

Aggregation of results





- $X_1,\ldots, X_N$ are data points or vectors or observations
- Each observation will be assigned to one and only one cluster
- $C(i)$ denotes cluster number for the i^{th} observation
- Dissimilarity measure: Euclidean distance metric
- ***K*-means minimizes within-cluster distances**:

$$W(C) = \frac{1}{2}\sum_{k=1}^{K}\sum_{C(i)=k}\sum_{C(j)=k}\left\|x_i - x_j\right\|^2 = \sum_{k=1}^{K} N_k \sum_{C(i)=k}\left\|x_i - m_k\right\|^2$$

where

m_k is the mean vector of the k^{th} cluster

N_k is the number of observations in k^{th} cluster

- For a given assignment C, compute the cluster means m_k:

$$m_k = \frac{\sum_{i:C(i)=k} x_i}{N_k},\ k = 1, \ldots, K.$$

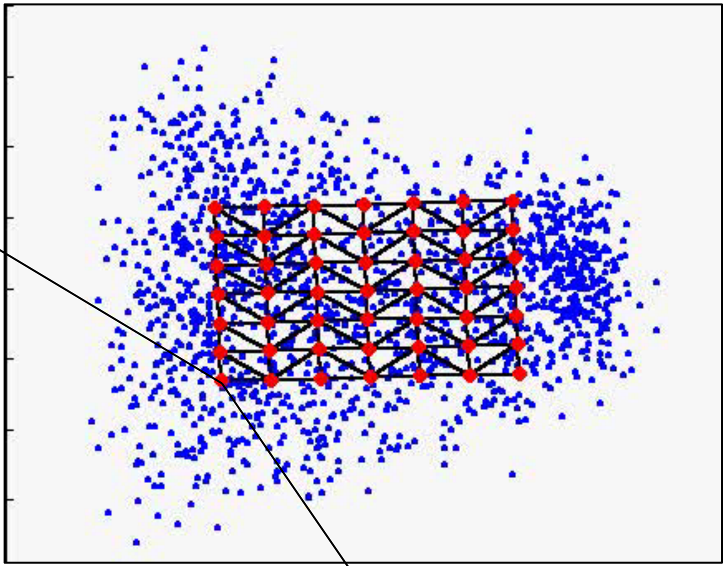
- For a current set of cluster means, assign each observation as:

$$C(i) = \arg\min_{1 \le k \le K} \|x_i - m_k\|^2,\ i = 1, \ldots, N$$

- Iterate above two steps until convergence

The SOM is made with an arbitrary number of centers/prototypes arranged in a 2D grid.

SOM 7 x 7



Each prototype $\mathbf{w}_i=(w_{i1}, \ldots, w_{in})$
n is the dimension of the original space.

The training is made in cycles **(t=1,…,n)**:

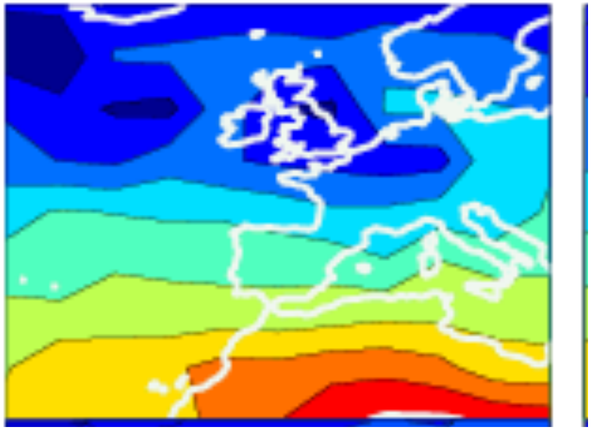
1) Compute the winner prototype (closest) $\mathbf{w}_{i(t)}$ for each pattern v_k :

$$\| v_k - w_{i(t)} \| = \min_i \{ \| v_k - w_i \|, i=1,\ldots,m \}.$$

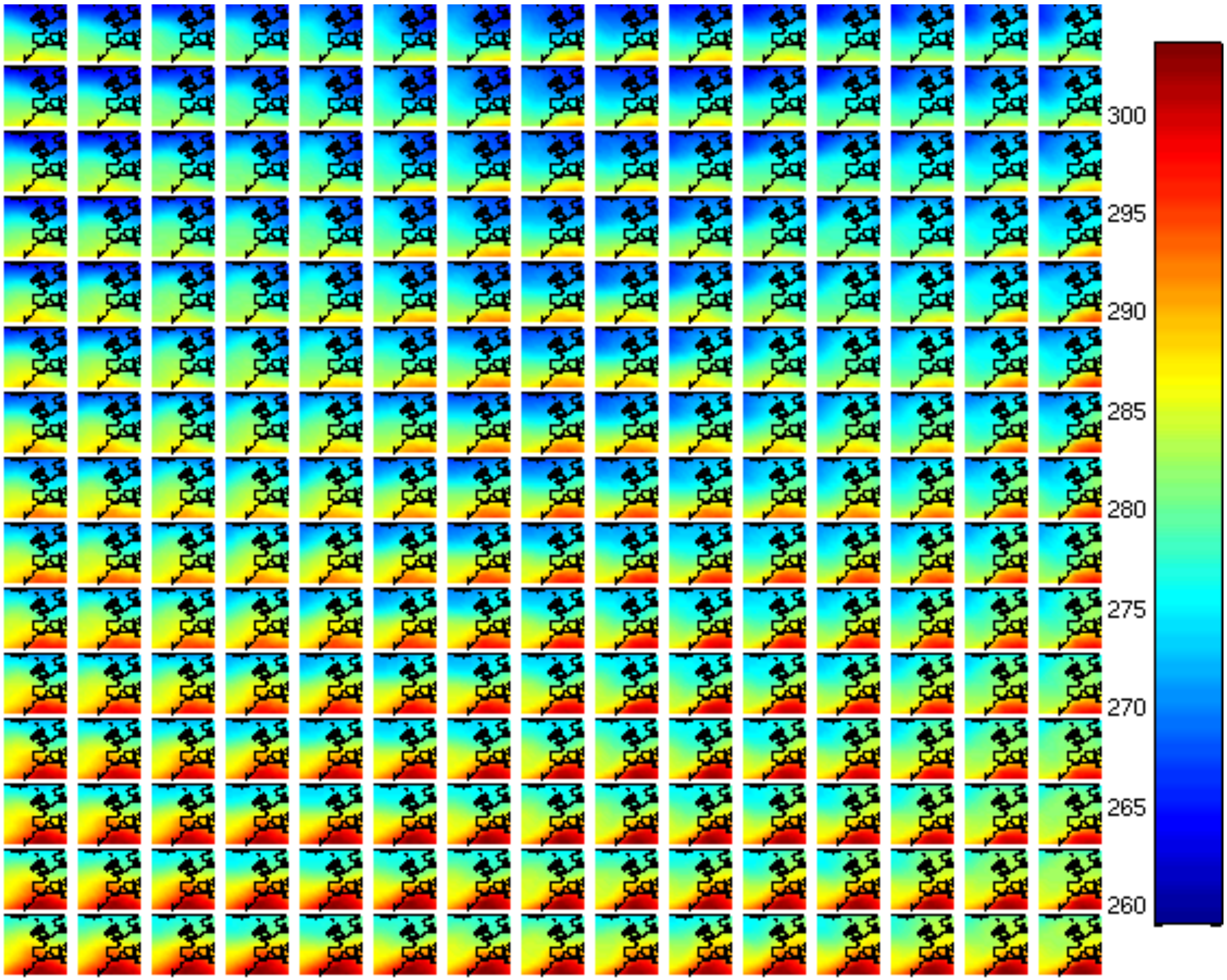
2) The winner prototype and the neighbors are moved towards the data point:

$$w_i(t+1)=w_i(t)+a(t)\,\mathbf{v}_k\, h(\|w_i(t) - w_{i(k)}(t)\|),$$

a(t) learning rate **(linear decreasing);**
h(x) neighborhood kernel **(linear decreasing of the variance)**



Oja E. And Kaski S., 1999: Kohonen Maps. Amsterdam, Elsevier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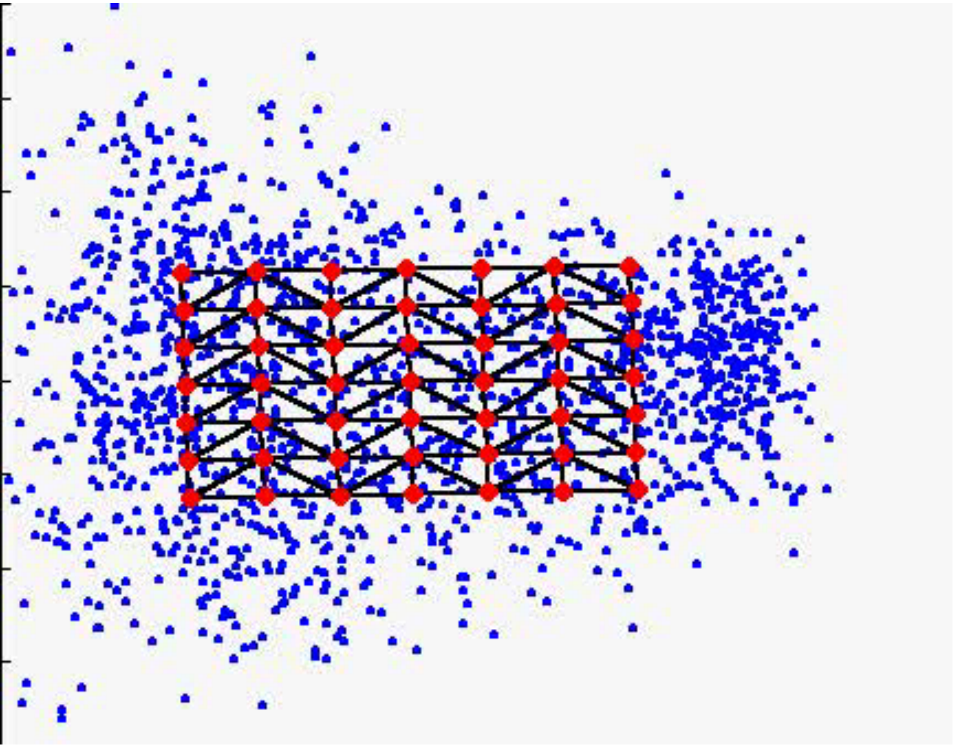
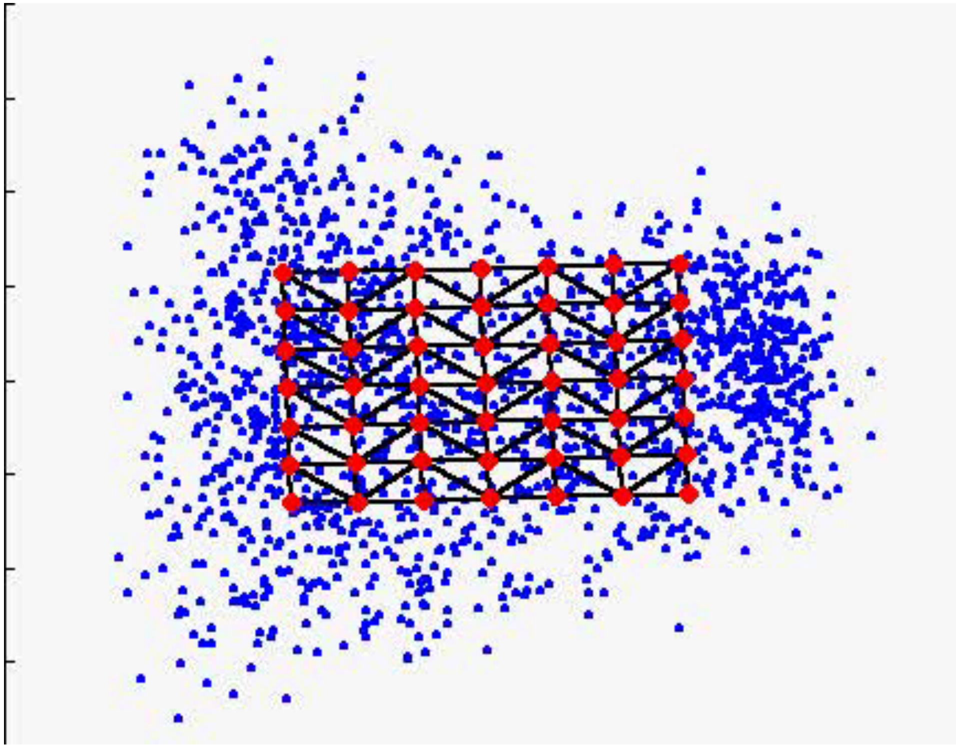
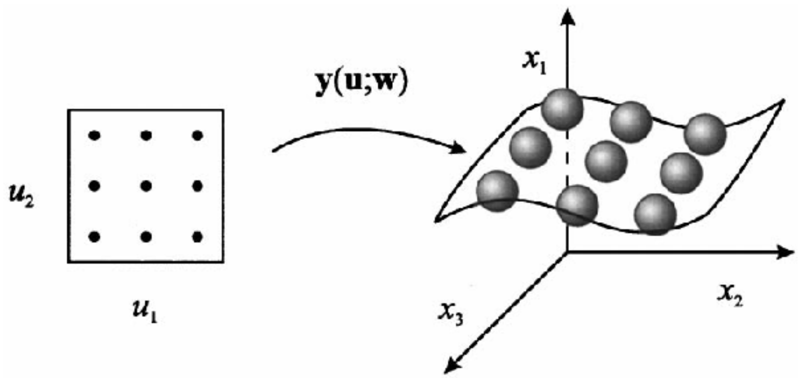




GTMs

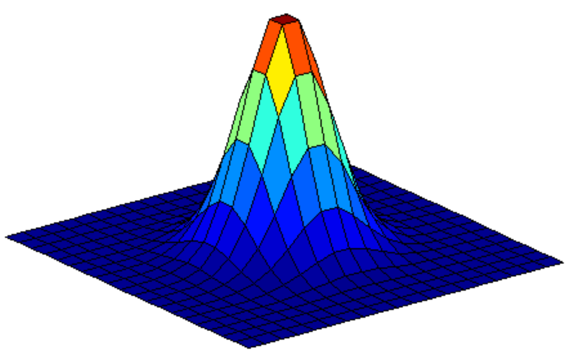
The Generative Topographic Maps (GTM) was introduced as a probabilistic re-formulation of the self-organizing maps (SOM)

The GTM define a non-linear transformation from a latent space **u** to the data space given by a linear combination of a set of non-linear basis functions



$$y = W\phi(u),$$

And now a point in the real space **x** has a probabilistic distribution over the latent space (centers).



With this formulation the border problem overcome and can also provide a predictability measure for deterministic forecast.

Domain selection

Clustering Methods for Statistical Downscaling in Short-Range Weather Forecasts

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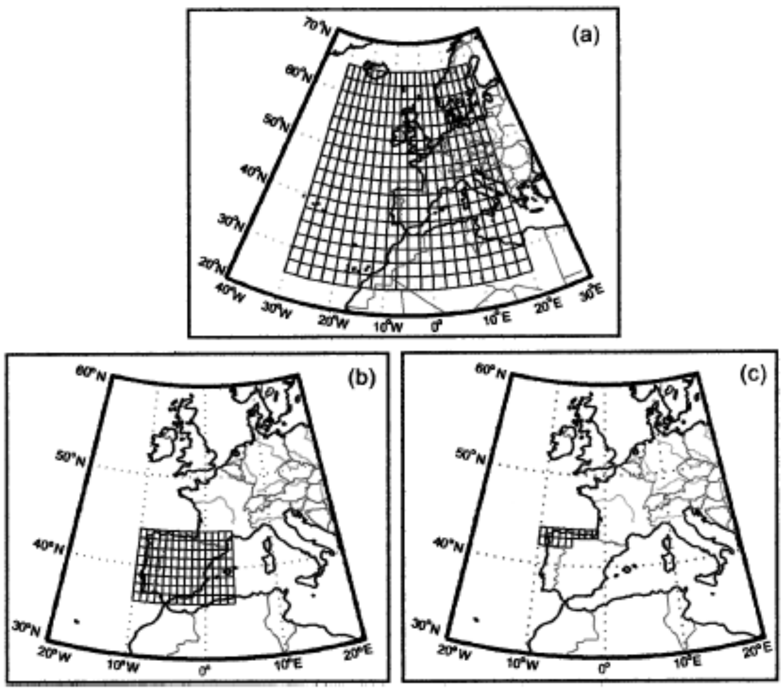


FIG. 2. Maps of the model grid domains used in this study: (a) large-scale macro-β grid considered for model 1, (b) meso-α grid covering the peninsula for model 2, and (c) meso-β model 3 grid for the northern basin. (Twelve different grids were considered, one for each basin of the Iberian Peninsula. For the sake of clarity only the north basin is shown.)

$$\mathbf{x}_{12} = (T_{12}^{1000}, \ldots, T_{12}^{300}, H_{12}^{1000}, \ldots, H_{12}^{300}, \ldots, V_{12}^{1000}, \ldots, V_{12}^{300}).$$

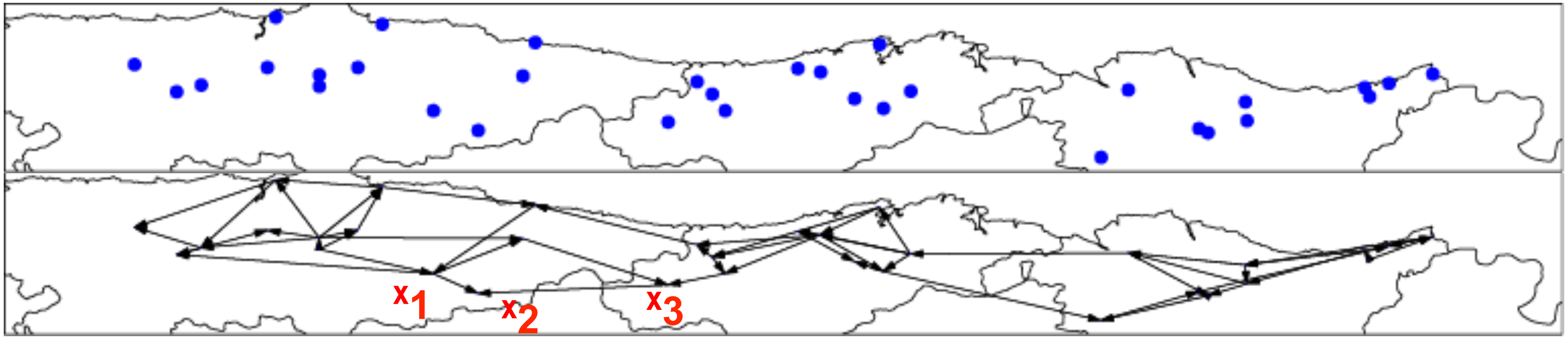
$$\mathbf{x} = (\mathbf{x}_{06}, \mathbf{x}_{30}).$$

$$\mathbf{x} = (\mathbf{x}_{06}, \mathbf{x}_{12}, \mathbf{x}_{18}, \mathbf{x}_{24}, \mathbf{x}_{30}).$$

Annual spatial averaged RSA for precipitation

Forecast	Method	>0.1 mm		
		1	2	3
D + 1	Analog	0.647	0.750	<u>0.791</u>
	Cluster	0.538	0.682	<u>0.744</u>
	WCluster	0.597	0.733	<u>0.783</u>
D + 2	Analog	0.633	0.737	<u>0.771</u>
	Cluster	0.523	0.669	<u>0.716</u>
	WCluster	0.588	0.711	<u>0.763</u>
D + 3	Analog	0.572	0.693	<u>0.734</u>
	Cluster	0.449	0.640	<u>0.678</u>
	WCluster	0.542	0.680	<u>0.726</u>

Spatial dependency is very important in Meteorology



The graph allows to define the JPD **P(x1,...,xn)** in a local factorized form, which allows us to make inference:
P(x | evidence).

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P_i(x_i | \pi_i)$$

P(x1=0)=0.45
P(x1=0 | x2=0)=0.89

x_1 and x_3 are dependent

P(x1=0 | x2=0, x3=0)=0.89

but they conditionally independent given x_2.

The graph factorizes the JPD, including only the dependencies of the graph.

$$P(x_1,\ldots,x_n)=\prod_{i=1}^{n}P_i(x_i|\pi_i)$$

π_i is the set of variables directly connected to x_i

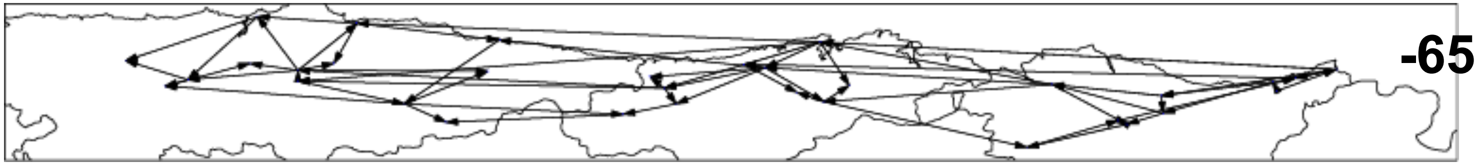
hence, dramatically reducing the number of parameters.

Given a data base with N samples, the graph can be inferred using automatic algorithms (NP-hard).

Search and score strategies *using the* ***Minimum Description Length*** *(MDL) as a quality score metric:*

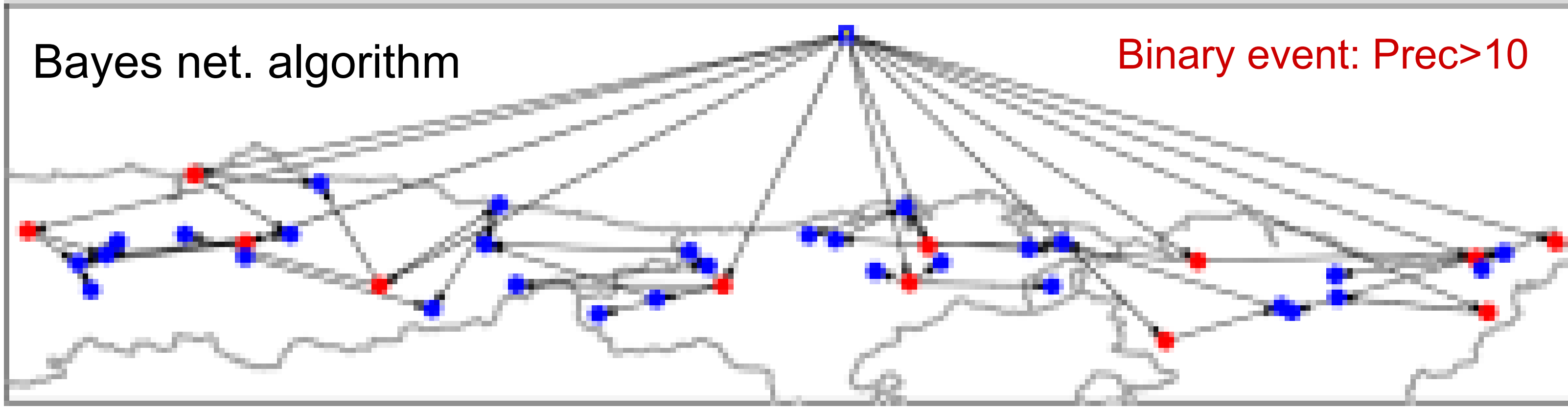
$$DL(\theta)=-\sum_{i=1}^{k}\log\pi(\theta_i)+\frac{k\,logn}{2}+\frac{n}{2}\log\left(\frac{1}{n}\sum_{j=1}^{n}e_j(\theta)^2\right)$$

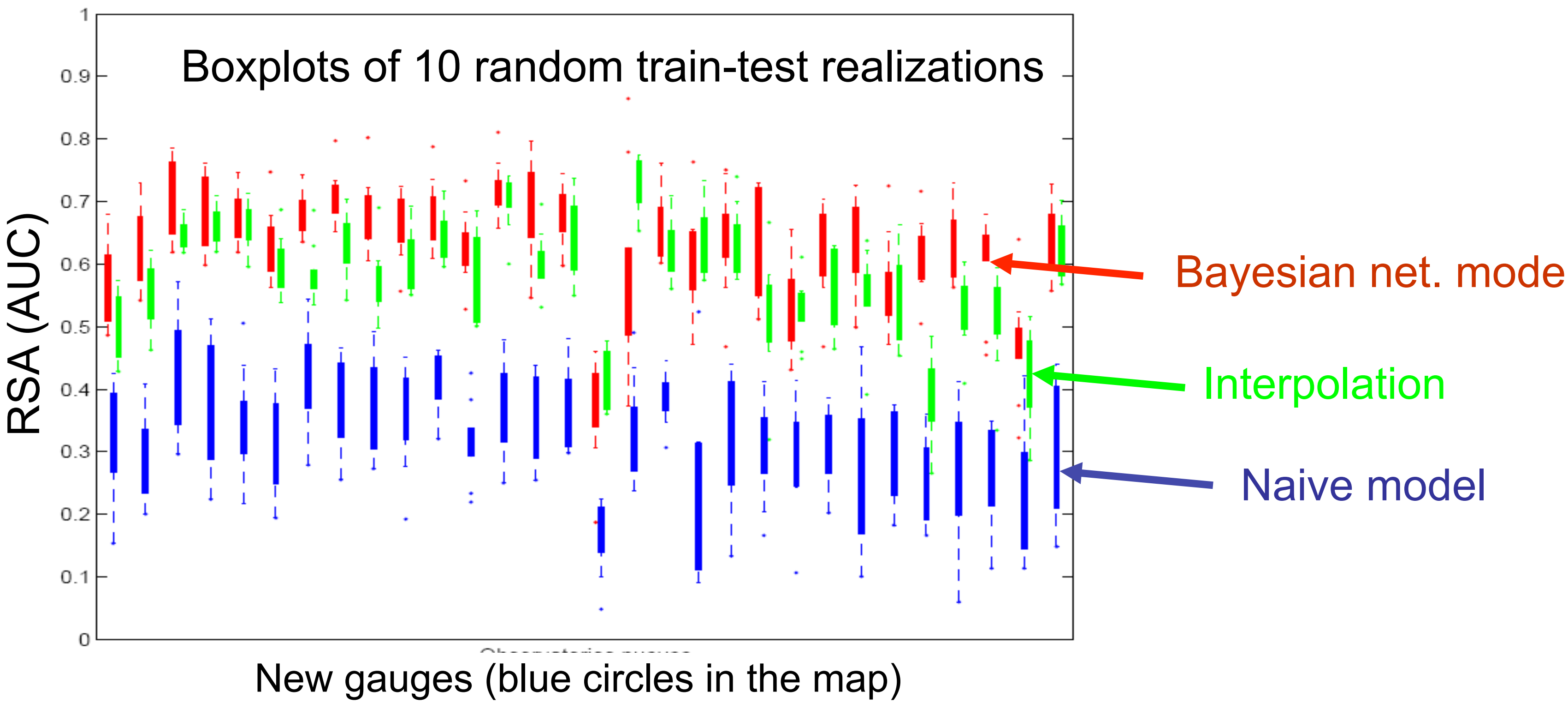
-67186



-65100

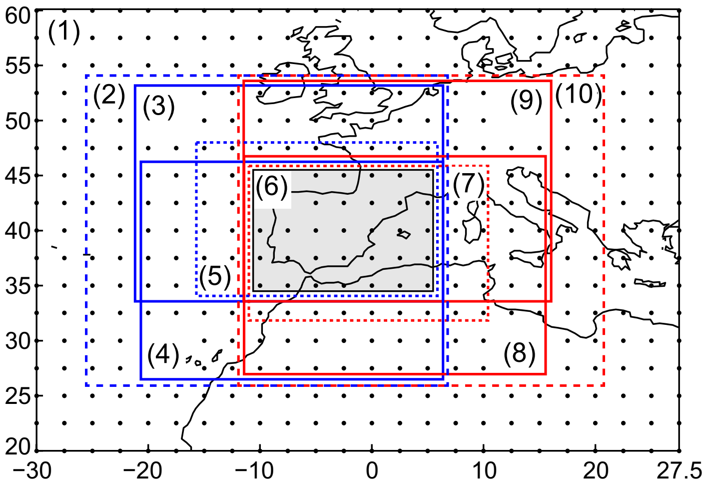
Bayesian Networks. Downscaling





An example in Spain: PNACC-2012

Geographical domains



Consistent Predictors

Code	*Predictor variables*
P1*	SLPd, T850, Q850, U500, V500
P2*	SLPd, T850, Q850, Z500
P3*	SLPd, T850, Q850
P4*	SLPd, T850
P5	SLPd, T2d
P6*	T850
P7	T2d
P8	Tmax
P9	Tmin

SD 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)

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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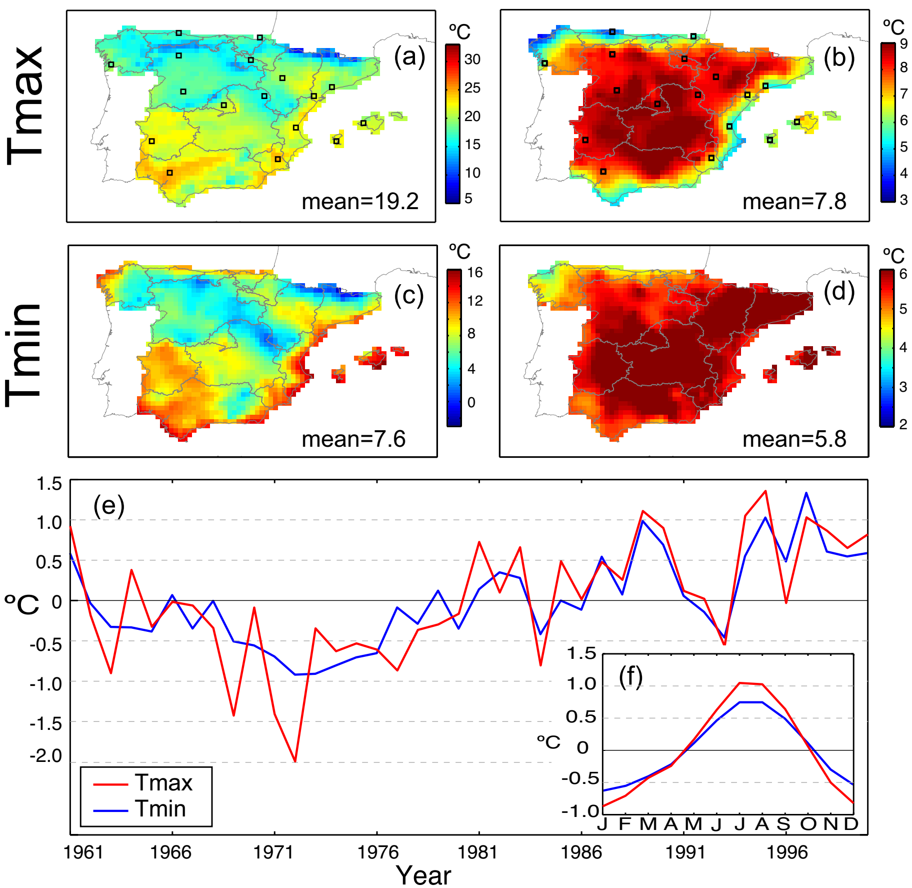
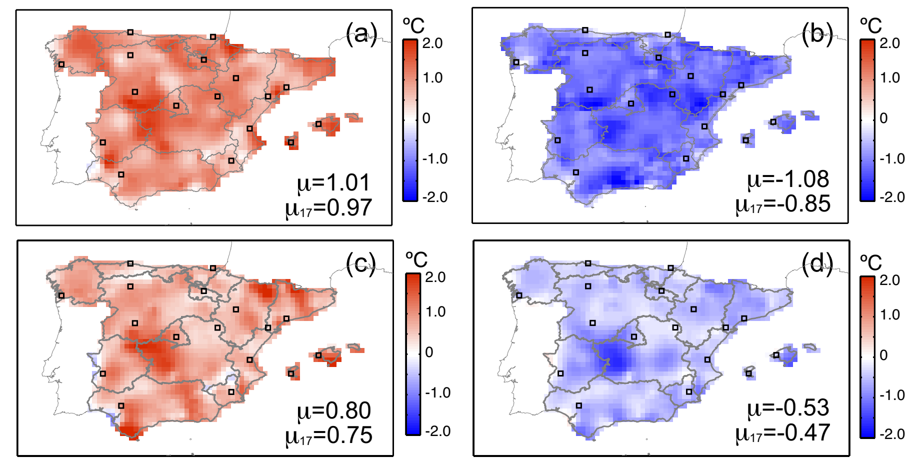
Cross-validation meethodology

A **k-fold cross-validation** (5-fold) approach (1961-2000).

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

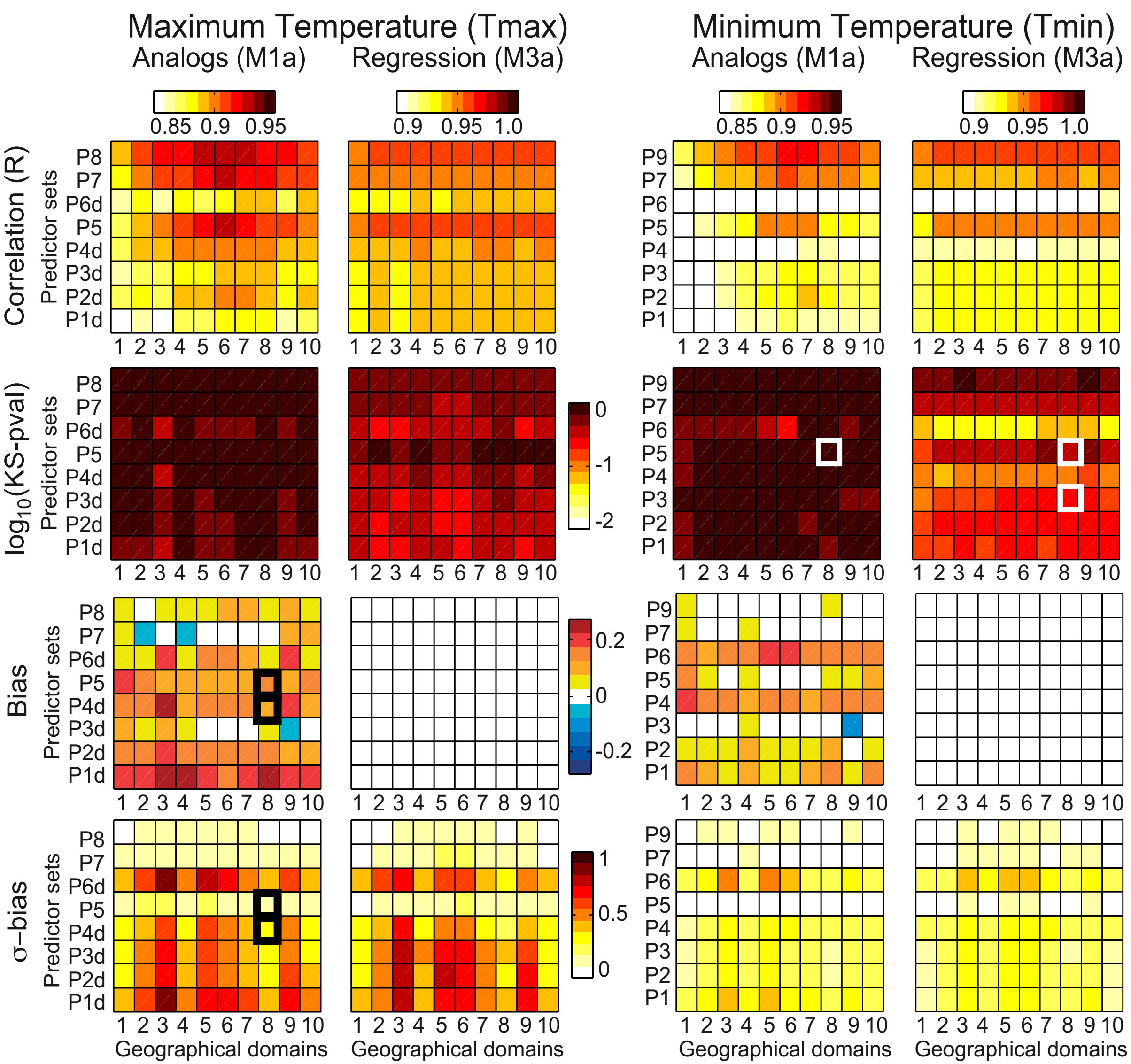
1960 **1961** 1962 1963 1964 **1965** **1966** … **1996** **1997** 1998 1999 2000

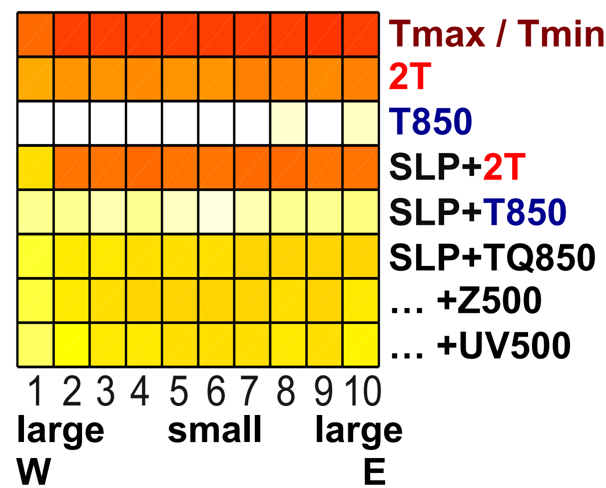


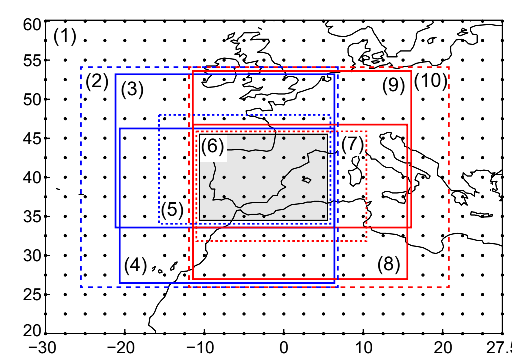


To test the robustness of the SD methods we also consider the eight **warmer**/**colder** years.

Callibration and Selection of SD Methods

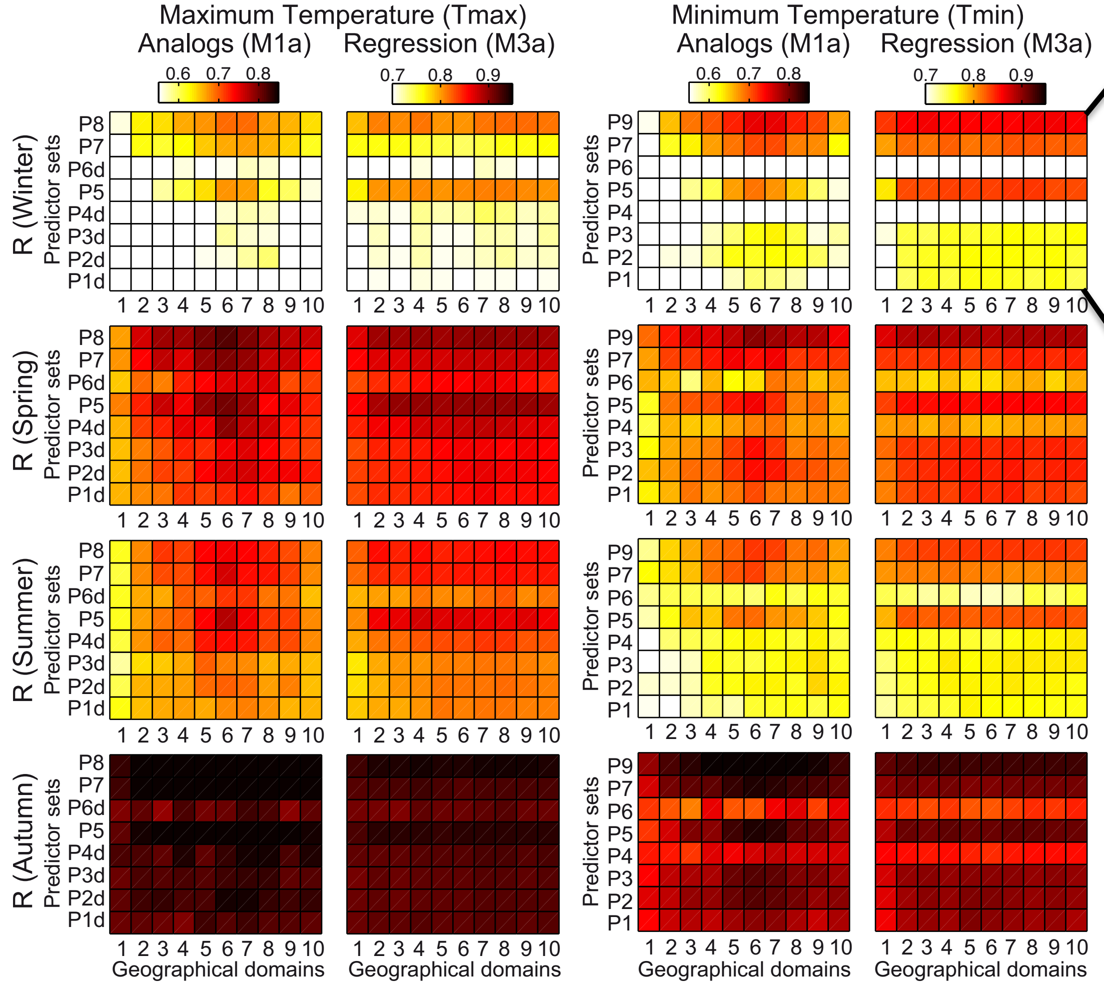






Correlation

$$RMSE = \sqrt{\sigma_p^2 + \sigma_o^2 - 2r\sigma_p\sigma_o + b^2} \text{ (Murphy 1988)}$$



Tmax / Tmin
2T
T850
SLP+2T
SLP+T850
SLP+TQ850
… +Z500
… +UV500

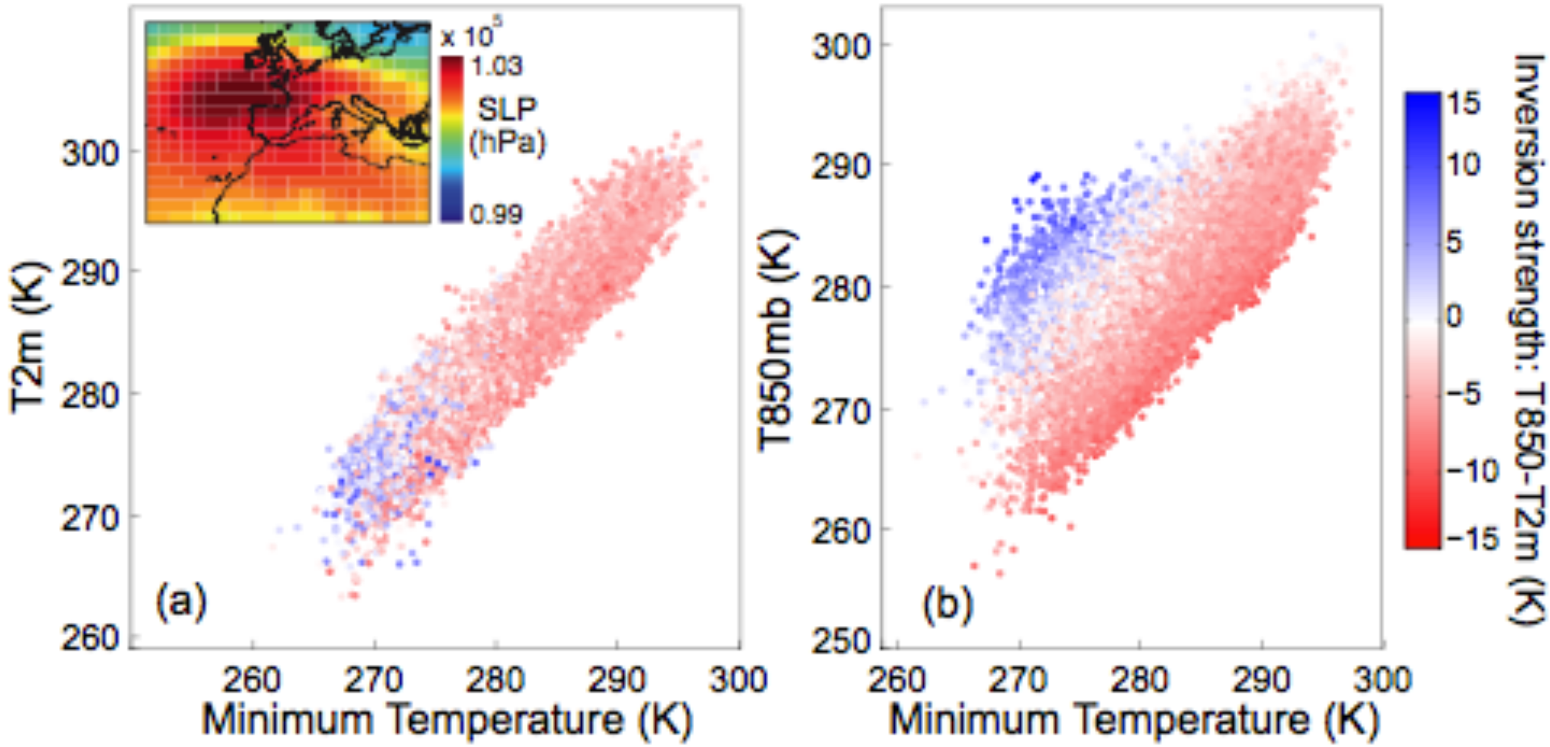


FIG. 5. Analysis of the effect of temperature inversion on the relationship of minimum temperature observations (x-axis) vs. two predictors: (a) T2m and (b) T850. Colors indicate inversion strength, defined as the temperature difference between T850 and T2m. The values correspond to an illustrative gridbox labelled as (A) in Fig. 2a. The inset in panel a shows a typical situation of temperature inversion, obtained as the weather type with higher inversion frequency out of a set of 25 weather types obtained applying the *k*-means algorithm to SLP.

Bias

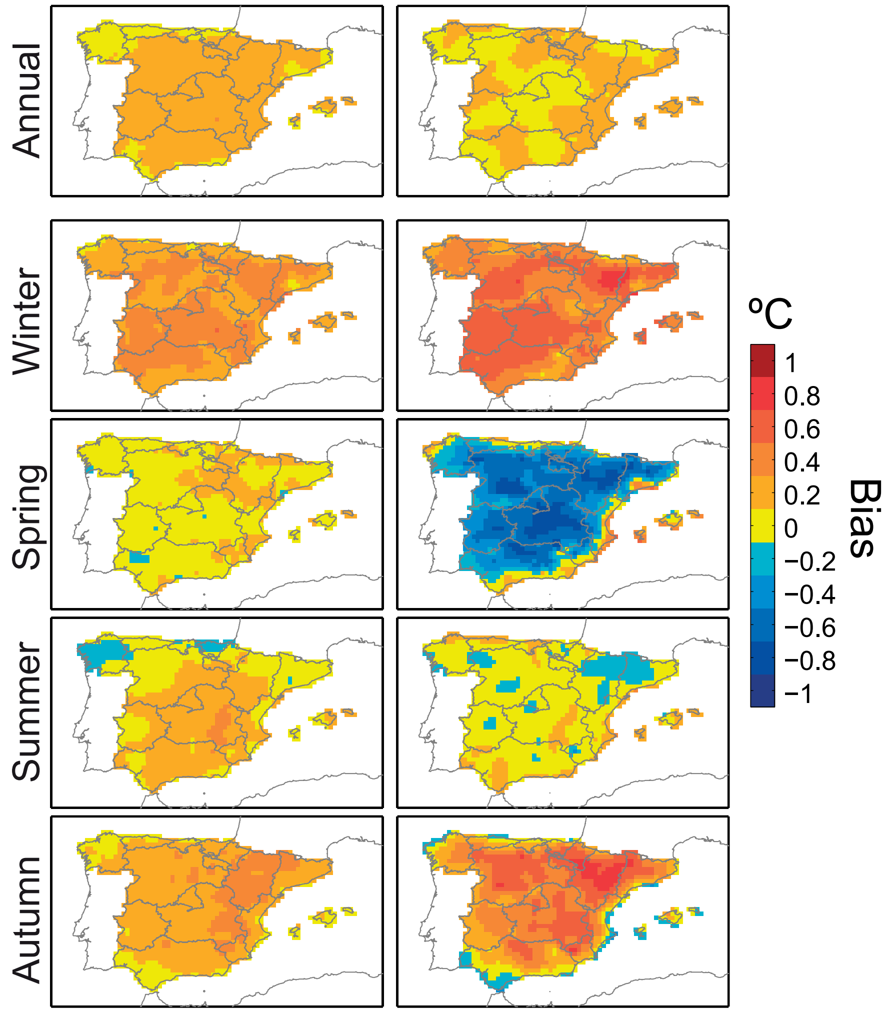
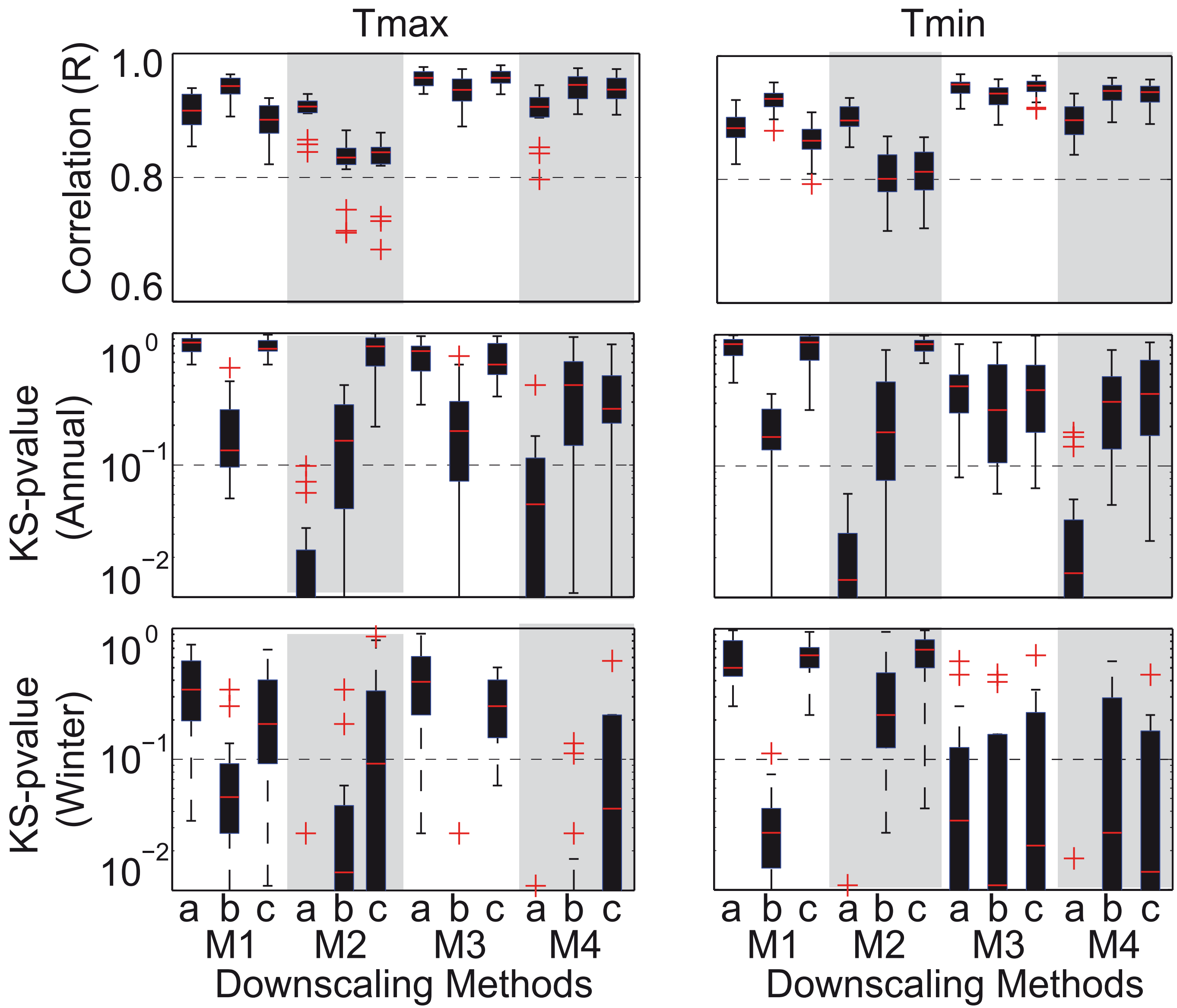
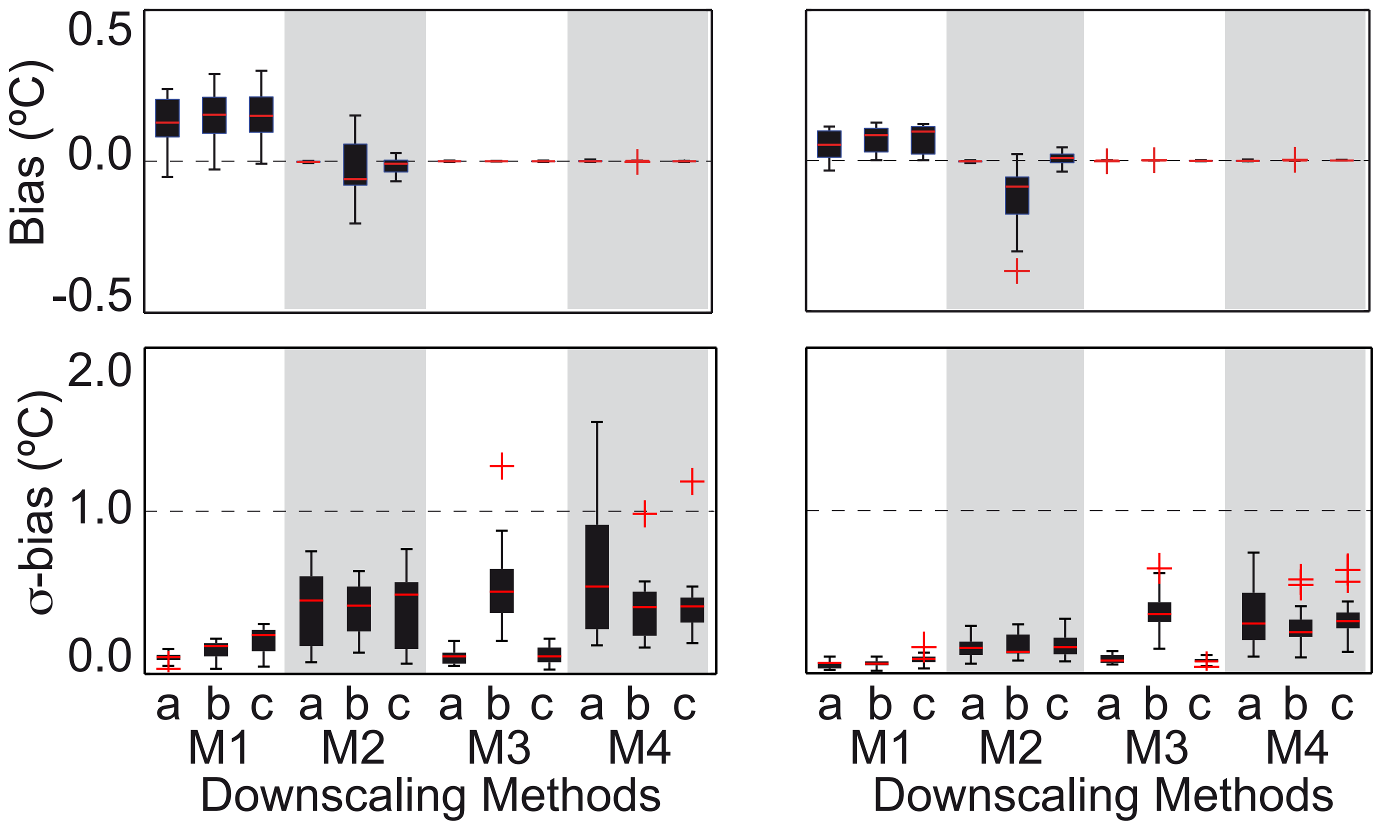


FIG. 8. Annual (first row) and seasonal (in rows) biases for the same downscaling method (analogs, $M1a$) and geographical region ($Z8$), but with two different predictor sets: $P5$ (left) and $P4d$ (right).

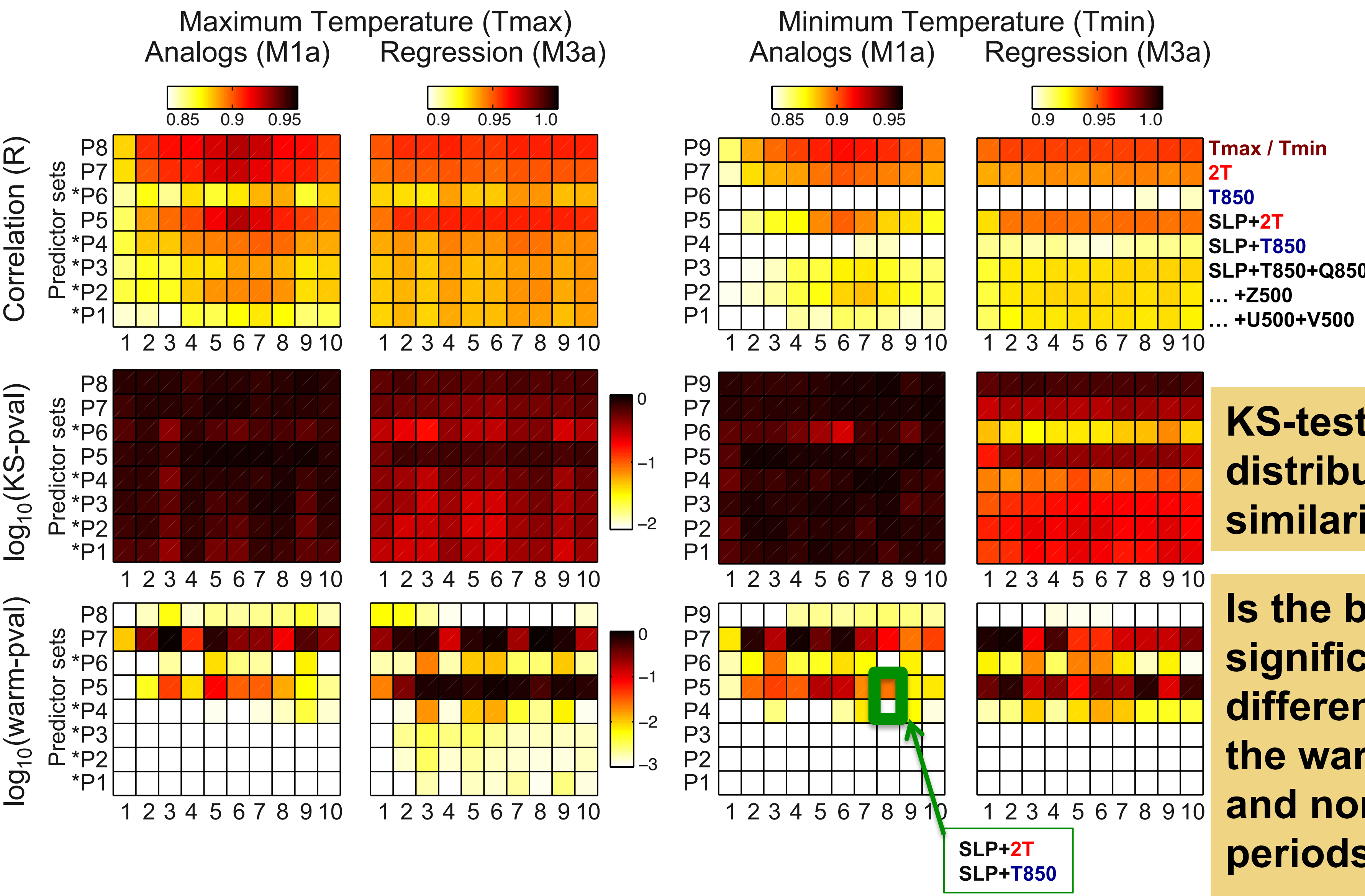
Callibration and Selection of SD Methods



Callibration and Selection of SD Methods



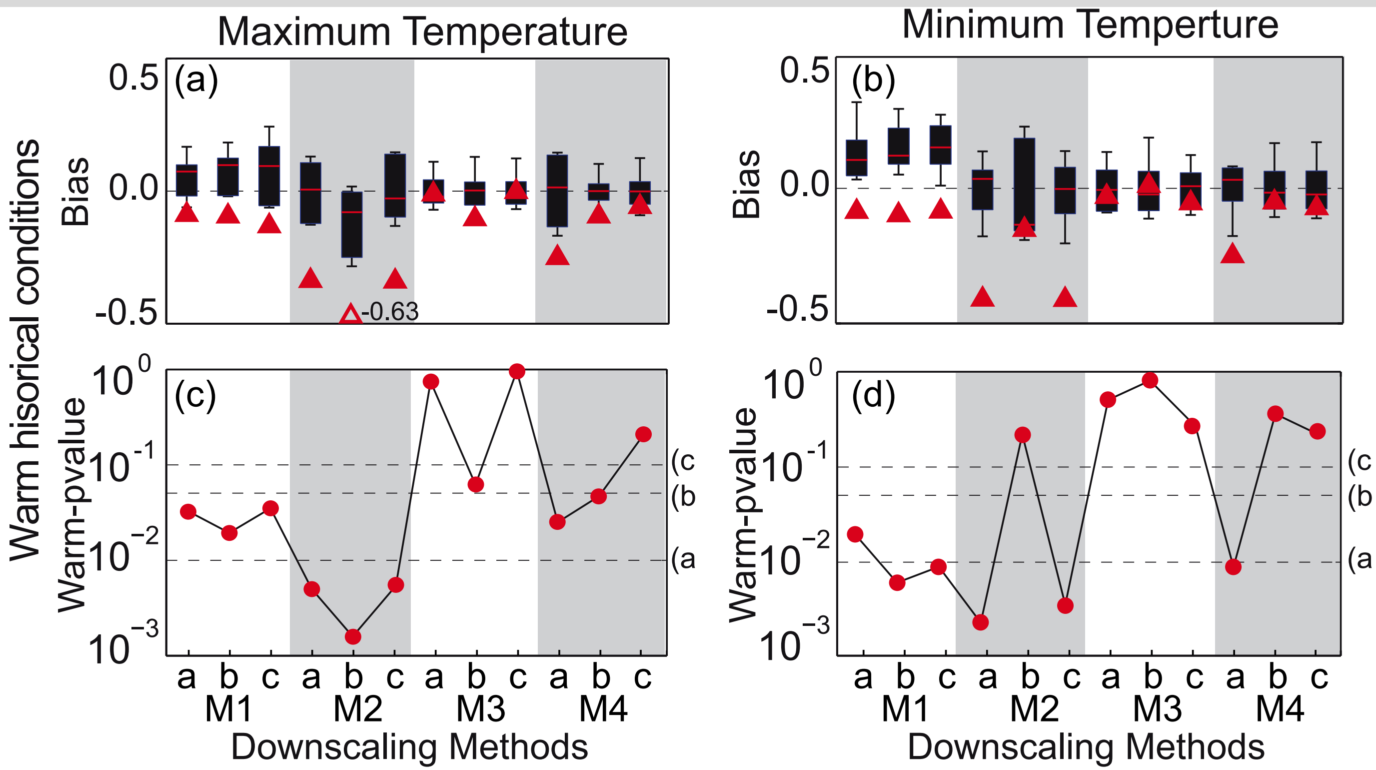
Callibration and Selection of SD Methods



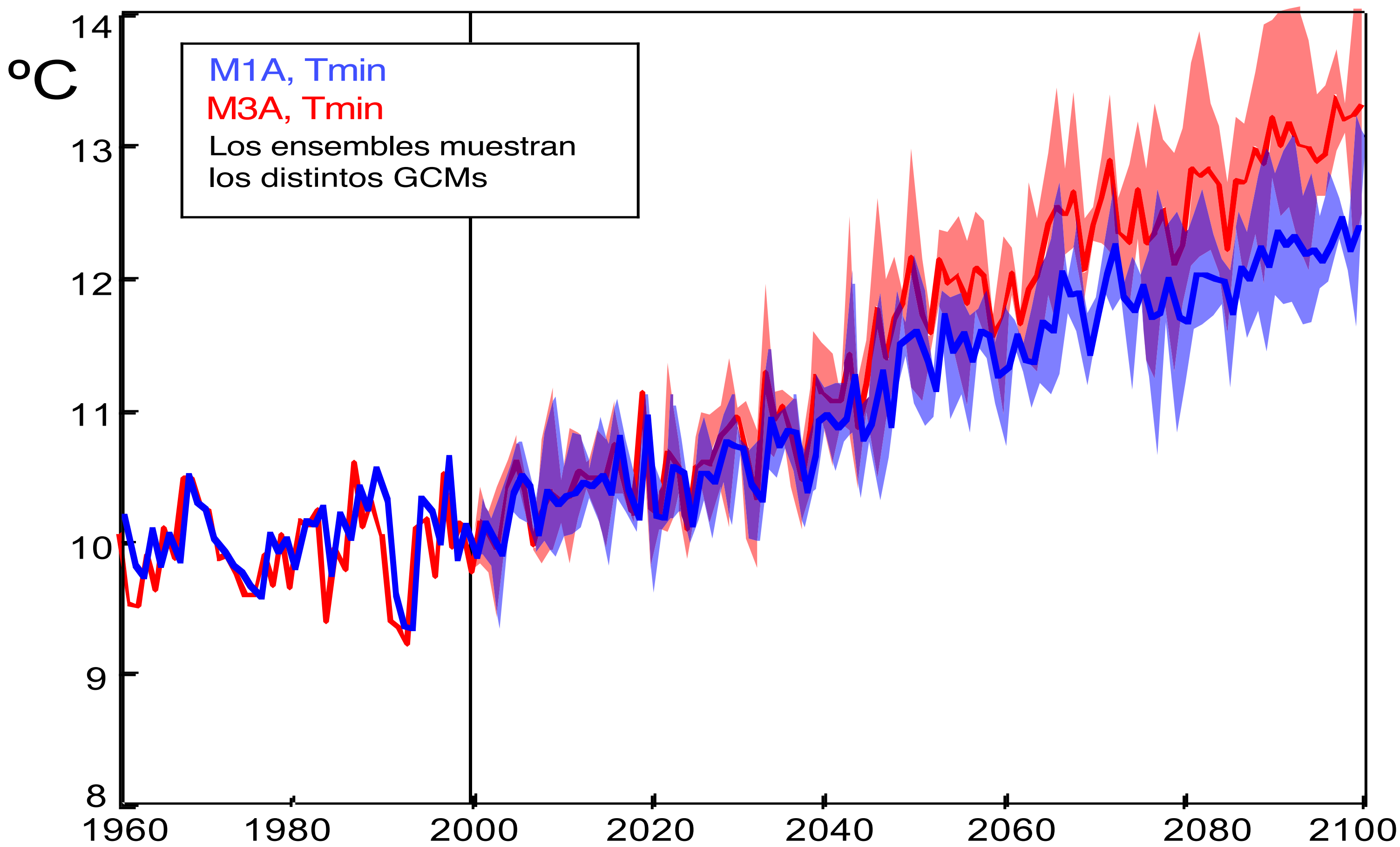
KS-test for distribution similarity.

Is the bias significantly different in the warm and normal periods?

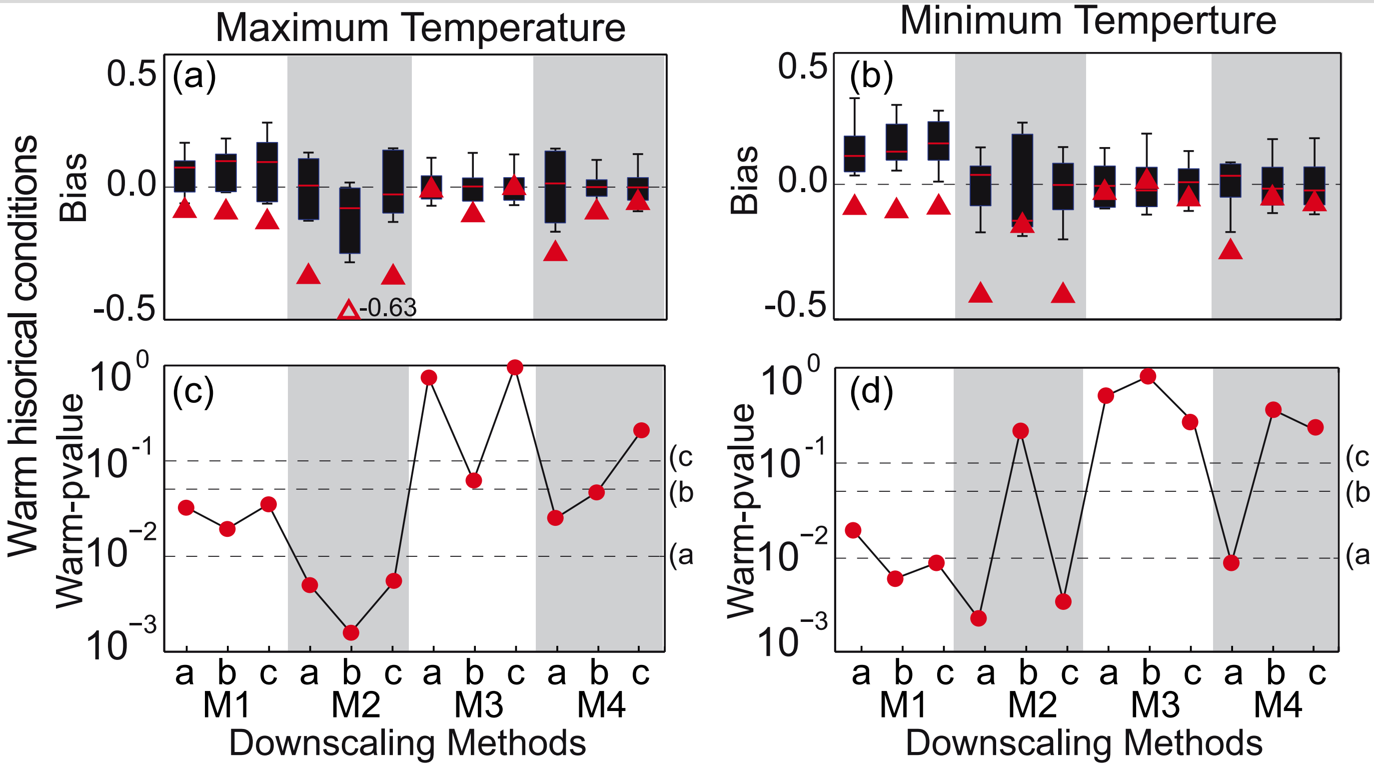
Callibration and Selection of SD Methods



The lack of robustness can lead to wrong future projections. In the example below the difference between two SD methods is much larger than inter-GCM variability.



Callibration and Selection of SD Methods



$$\bar{d} = \frac{1}{5}\sum_{k=1}^{5} d_k = \frac{1}{5}\sum_{k=1}^{5}(b_w - b_k)$$

$$t = \frac{\sqrt{5}\,\bar{d}}{\sqrt{var(d)}}; \qquad var(d) = \frac{1}{4}\sum_{k=1}^{5}(d_k - \bar{d})^2$$

t-distribution with 4 degrees of freedom

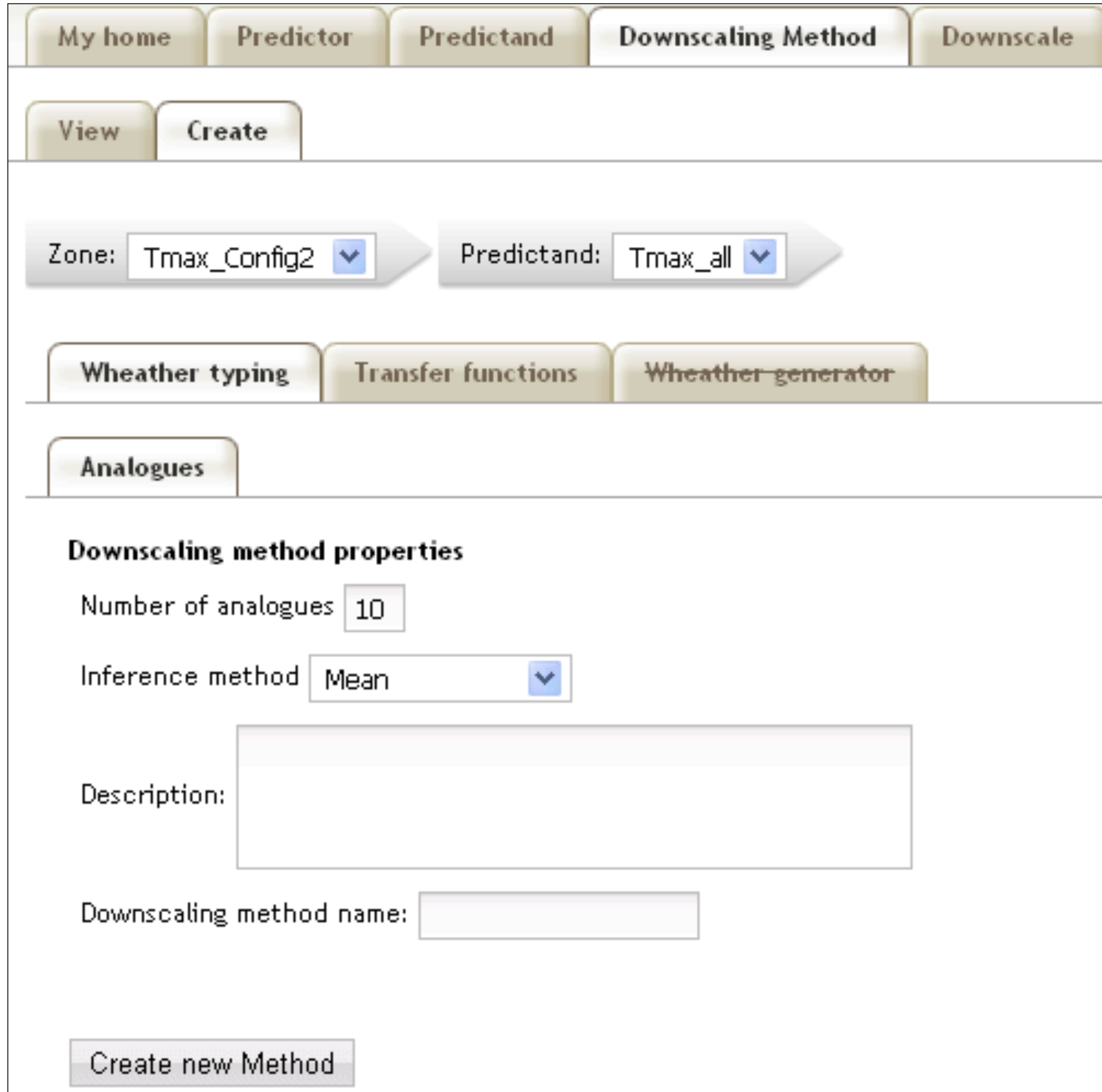
SD Portal: Downscaling Method

It also allows selecting a particular downscaling algorithm from the different families of methods:

- Analogs
- Regression
    - From CPs
    - From grid-points
- SOM weather types
- Weather generators

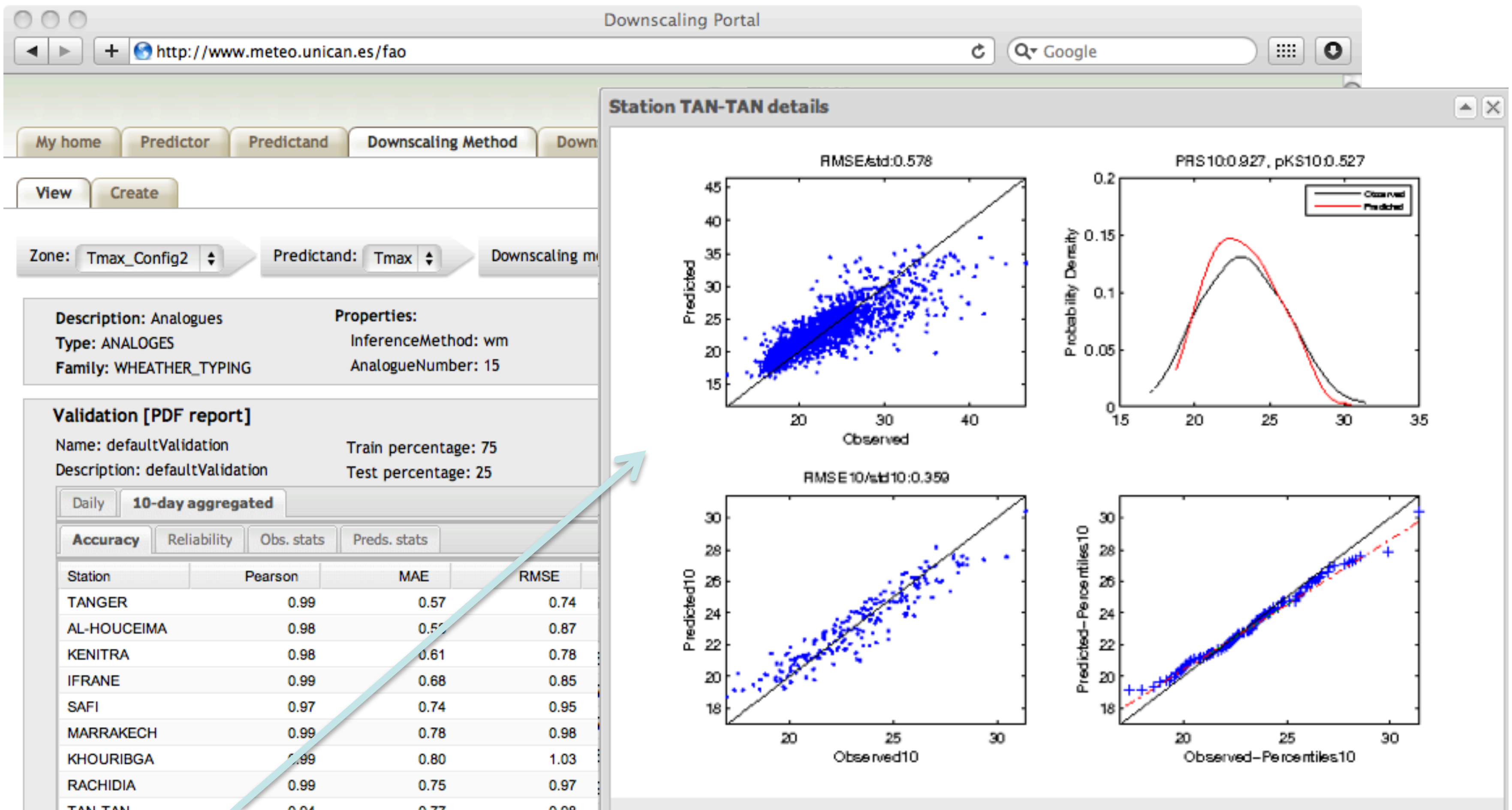
and defining a particular configuration:

- Number of analogs
- Numer of CPs.
- Etc.



SD Portal: Calibration & validation

Finally, it allows selecting a downscaling method (from the list of available ones, including regression, analogs, weather typing, etc.) and obtaining a cross-validation in present climate using renalysis data.



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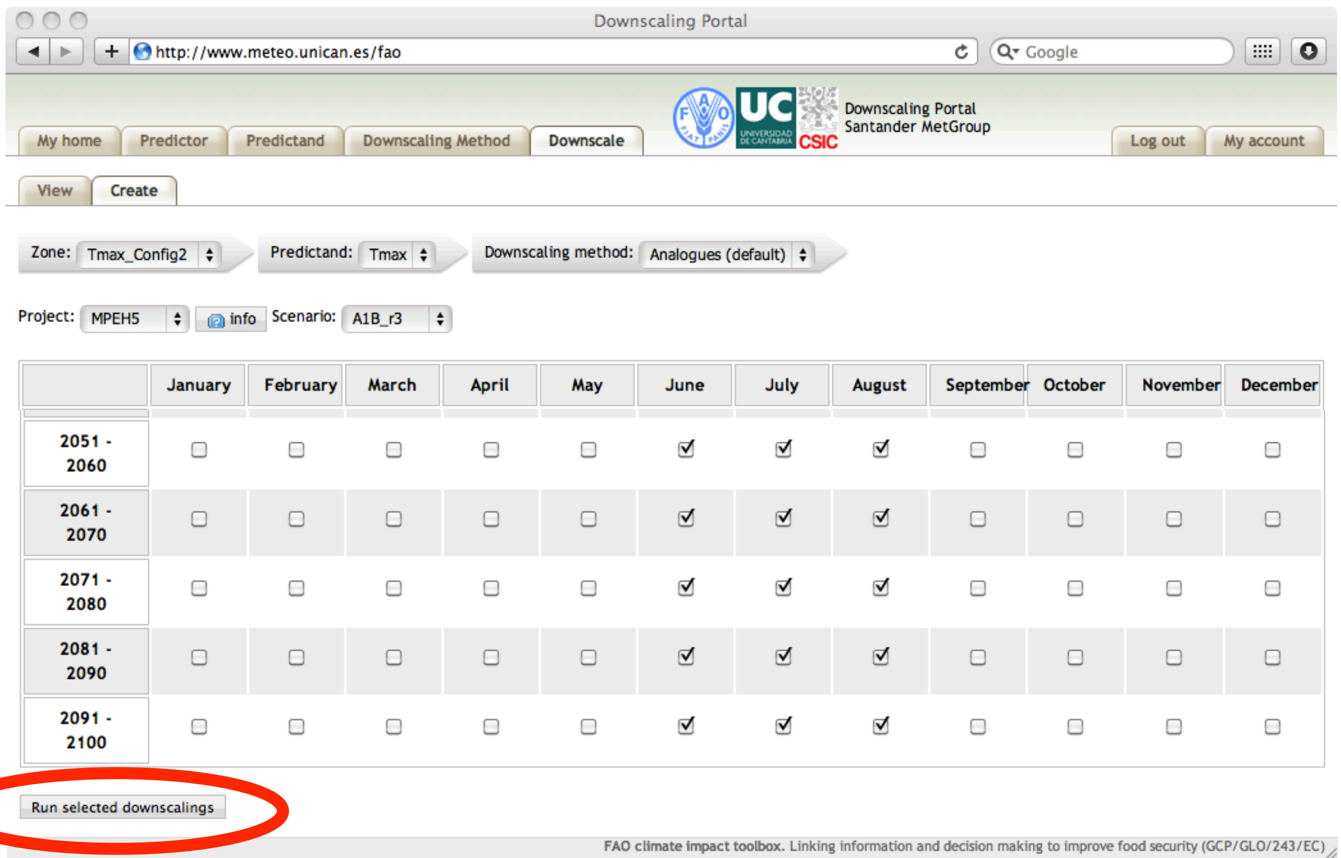
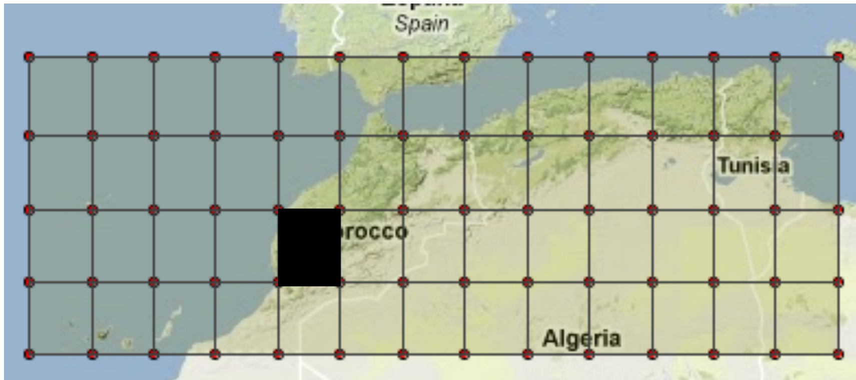
SD Portal: PRODUCTION

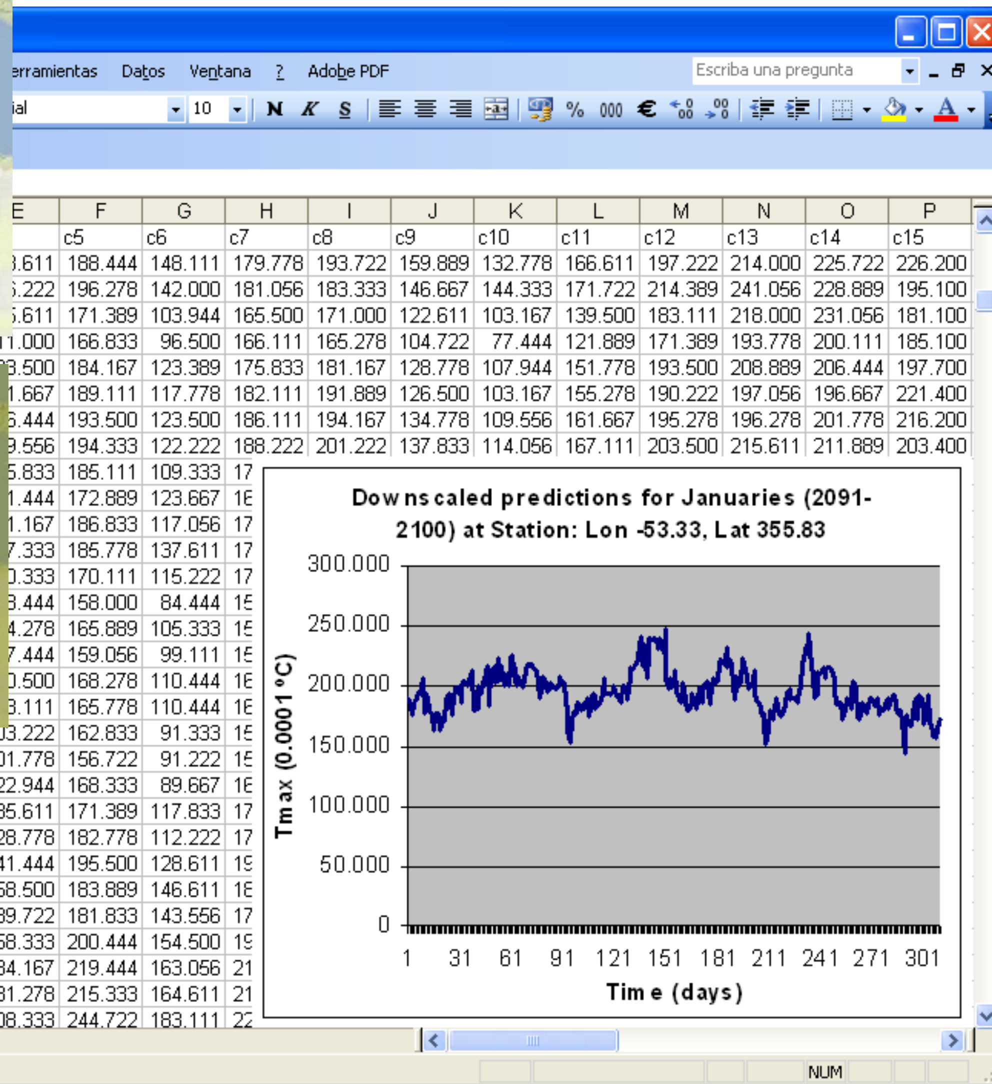
Once the method is defined and validated it can be used to downscale GCM models (e.g. ECHAM5) for future scenarios (e.g. A1B).
The resulting daily locally projected simulations can be downloaded as Excel (or ascii) files.



Downscaling summer JJA season.

SD Portal: Global vs. Local





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Portal de Downscaling