

# Statistical downscaling and bias correction

Christian Pagé

[christian.page@cerfacs.fr](mailto:christian.page@cerfacs.fr)

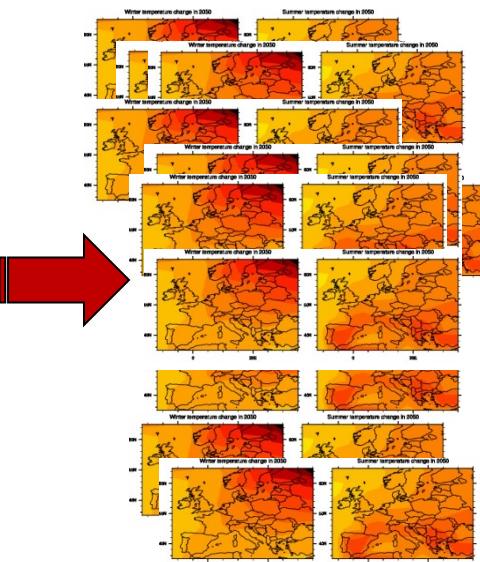
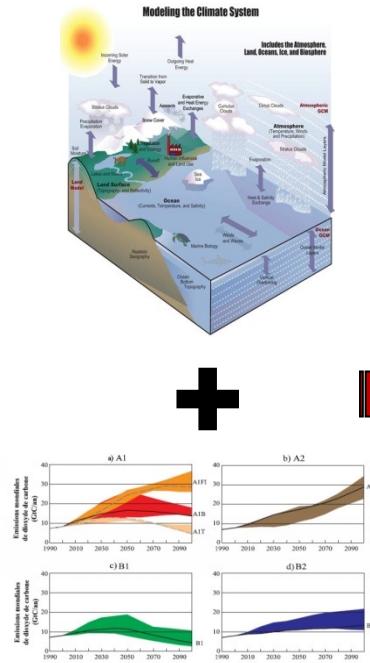
IS-ENES3 Central&Eastern Europe Autumn School  
From Climate Projections to Climate impacts via Regional Downscaling  
Prague, 28 November-2 December 2022

# Structure

- General principles
- Methods
  - Simples
  - Dynamical: Bias correction
  - Statistical
    - General
    - Analogs
    - Weather Types
    - Validation
    - Uncertainties
  - Limitations
- Conclusions

# Climate Projections

### Several climate models: *uncertainties*



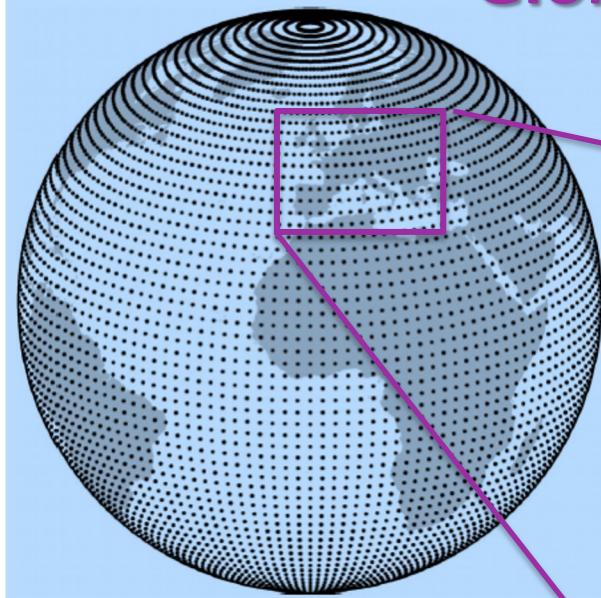
## Greenhouse Gas Scenarios *More uncertainties*

# **Only a few very large centres**

## **Very high computational costs**

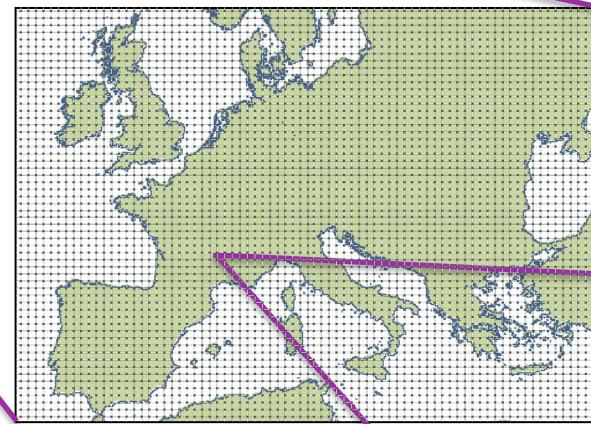
# Downscaling: a required step

Global



Resolution:  
 $\approx 100 \text{ km}$

Regional

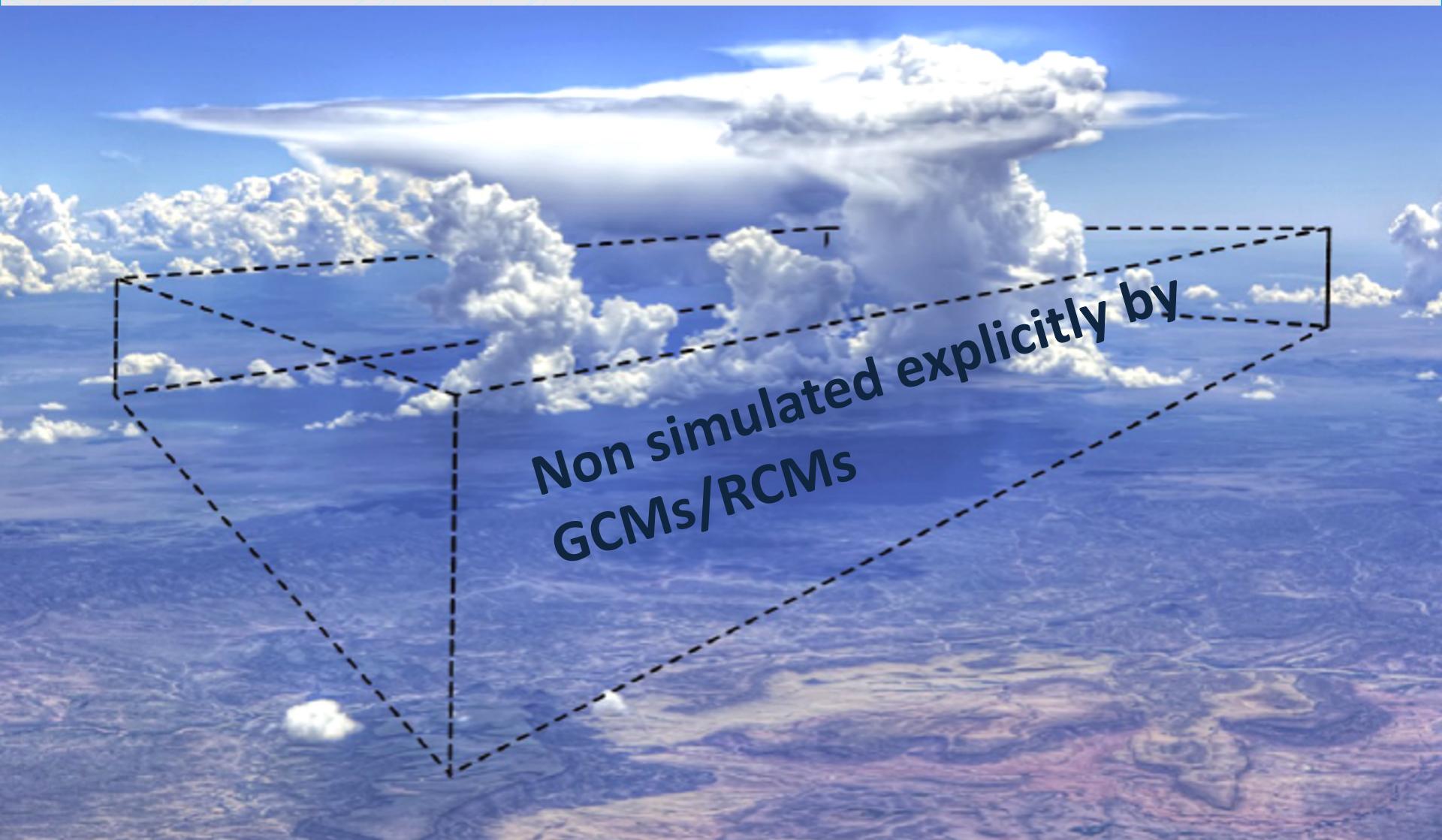


Resolution:  
 $\approx 10 \text{ km}$

Local

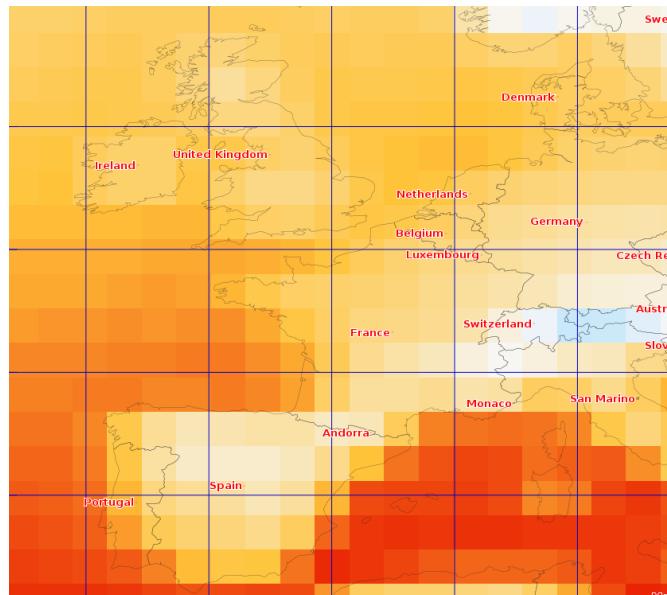


# Downscaling and Bias Correction: a required step



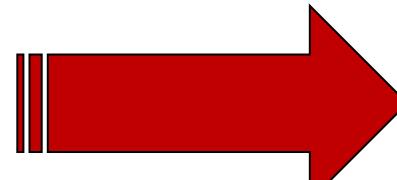
# Downscaling: a required step

Typical spatial resolution  
of a global climate model  
CMIP6

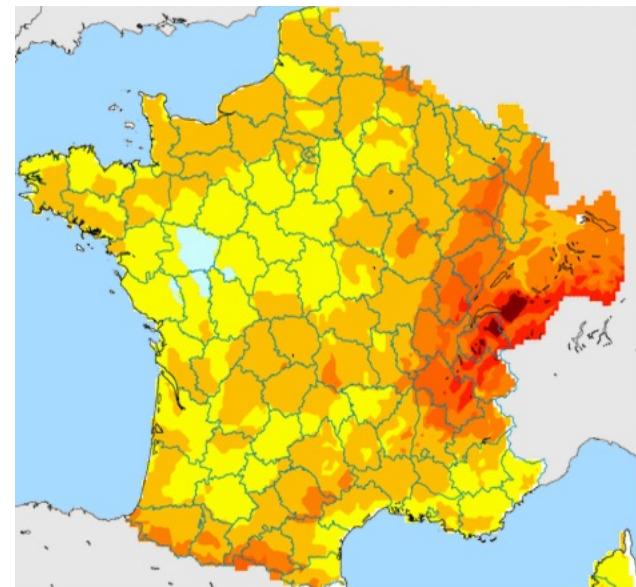


$\approx 125 \text{ km}$

Needed spatial resolution  
for impact modeling and  
studies

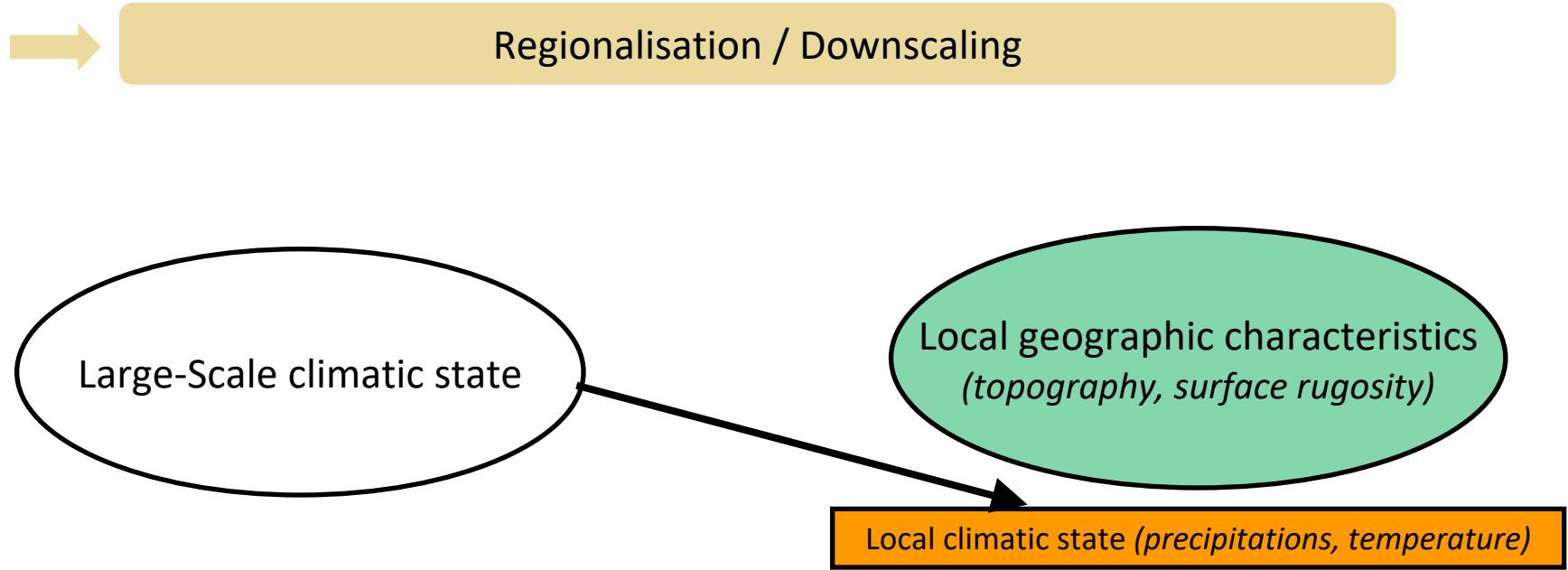


Downscaling



8 km

# Downscaling: a required step



## Statistical

Build a statistical model using relationships between local and large-scale climate variables

## Dynamical

Resolve explicitly the physical equations of the regional climate system



# Simple Statistical Downscaling Method



## Anomaly Method (Delta Method)

- Time Series of observations
- Deltas (anomalies) of climate models

## Principles

- Reproduce a time series of observations in the future by repeating the time series
- Apply a tendency from a climate model simulation



# Simple Statistical Downscaling Method



## Advantages

- Easy to interpret
- Reproduce the correct inter-daily and inter-annual variabilities
- No systematic bias

## Limitations

- Does not reproduce the possible changes of future climate variabilities
- Decadal cycles are reproduced exactly like in the past
- Raises artificially the frequency of occurrence of extreme events that have a long return period

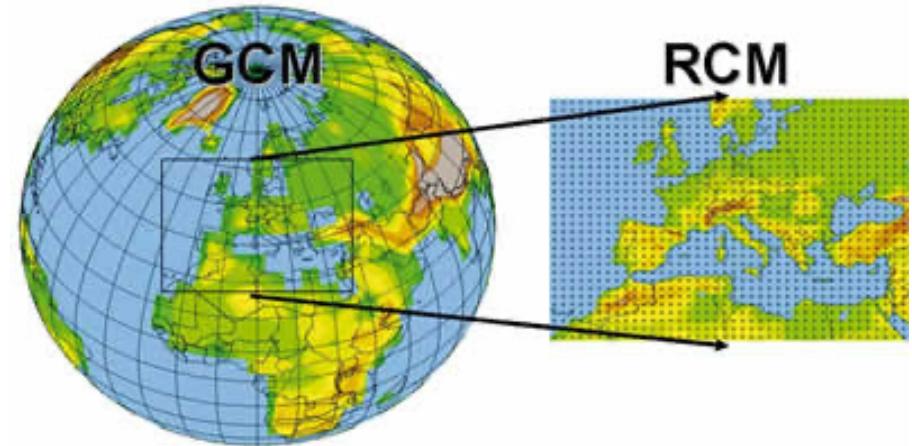
# Dynamical Methods with Bias Correction

Based on

- Higher Spatial resolution numerical models (10 — 50 km)

How to deal with the computational costs ?

- Variable grid projection
- Limited Area Model
- Limited number of simulations



Hidden Hypothesis

- Statistical relationships of physical parameterisations will be identical in the future climate

# Dynamical Methods

Still biases...?

- Spatial resolution: still not fine enough
- Vertical Interpolation
- Simplified representation of surface interactions
- Simplified Microphysics



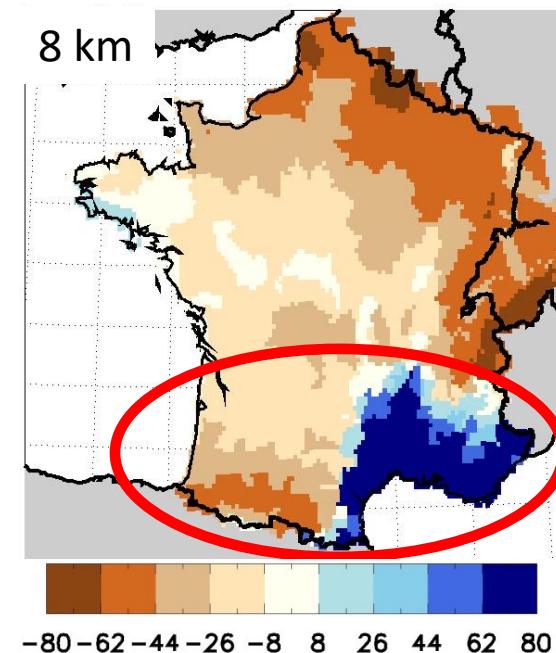
Bias correction is needed

- In Weather Forecasting it is called Model Output Statistics (MOS): same exact idea

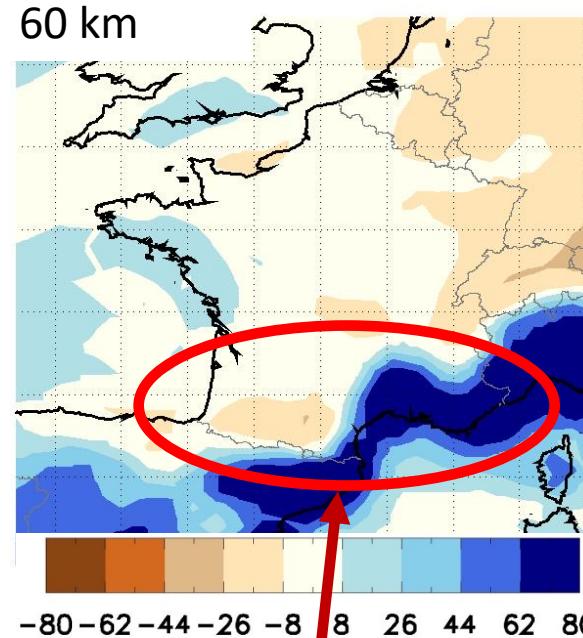
# Bias Correction

High spatial resolution numerical model embedded in a global climate model

## Precipitations Anomalies (%)

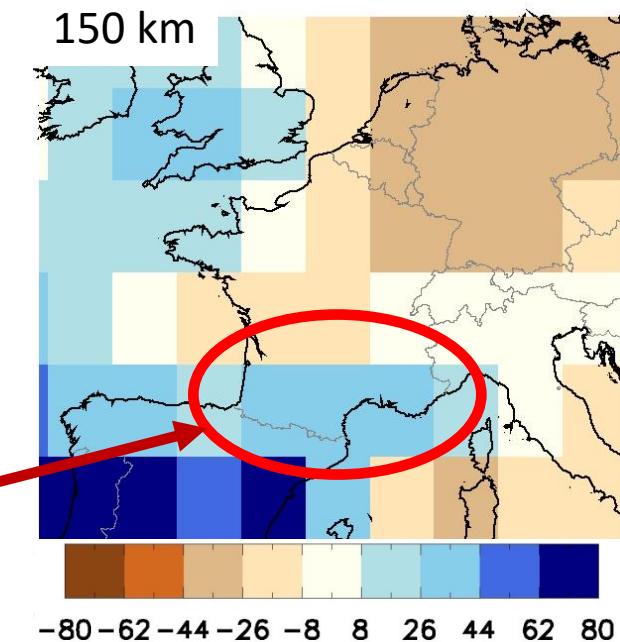


## Regional Climate Model



Biases partly corrected

Observations



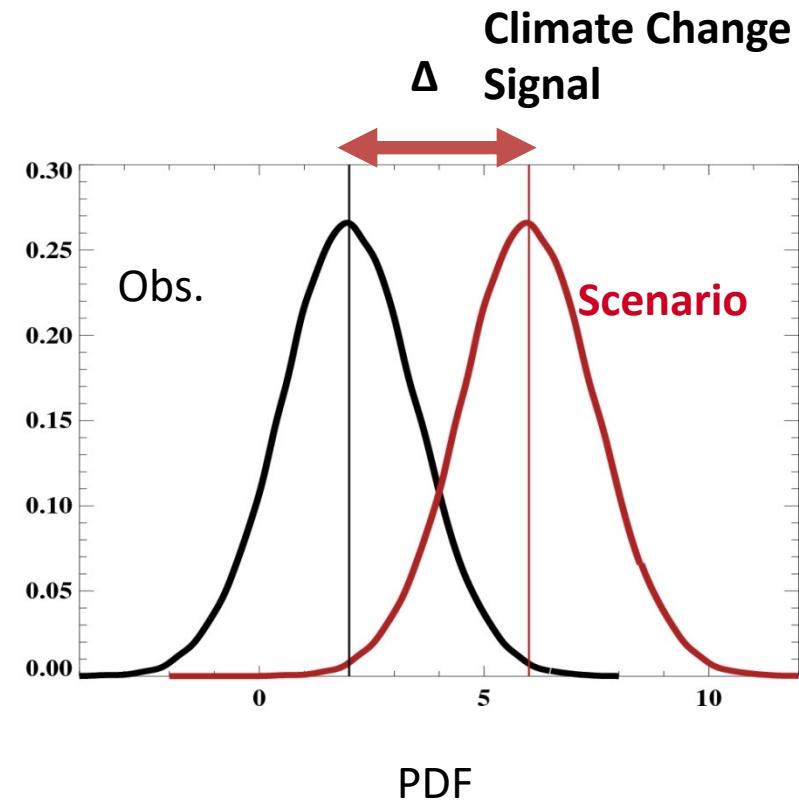
Global Climate Model

# Bias Correction

High spatial resolution numerical model embedded in a global climate model

## Bias Correction

=> Quantile-Quantile  
(Déqué, 2007)

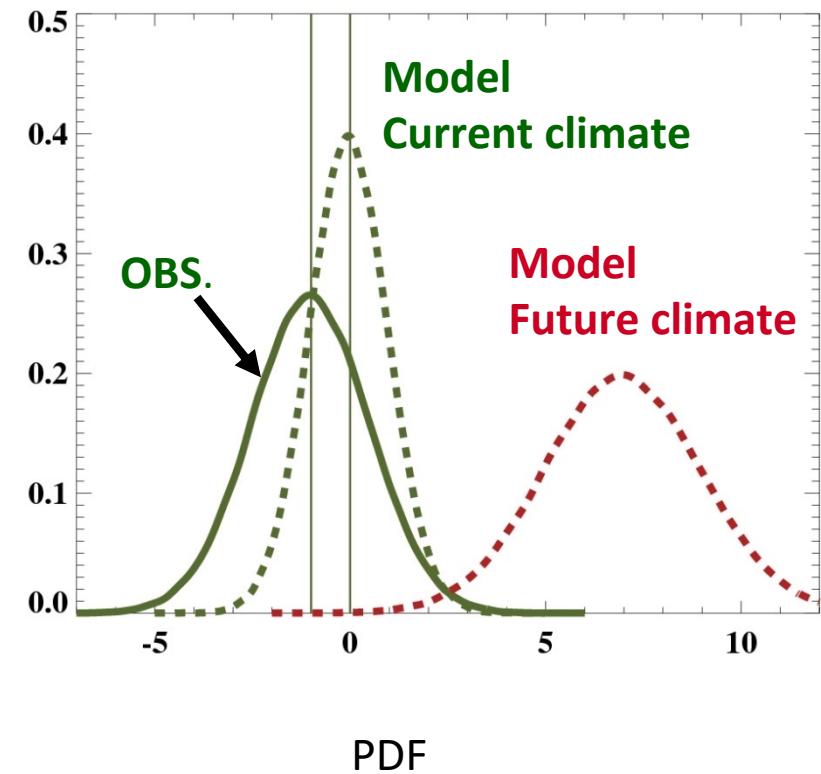


# Bias Correction

High spatial resolution numerical model embedded in a global climate model

## Bias Correction

=> Quantile-Quantile  
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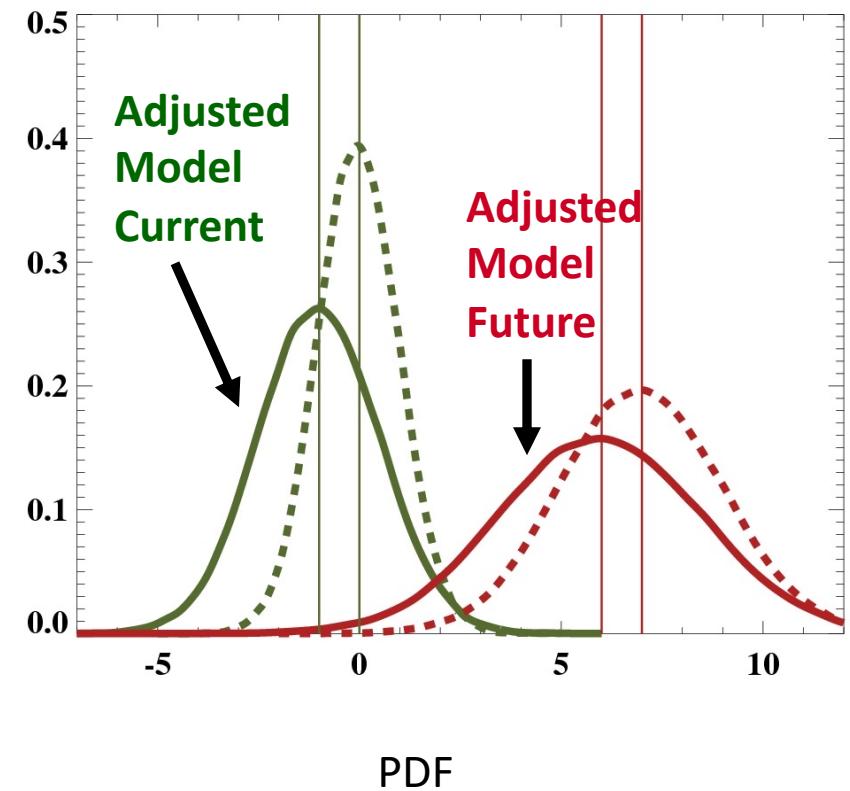


# Bias Correction

High spatial resolution numerical model embedded in a global climate model

## Bias Correction

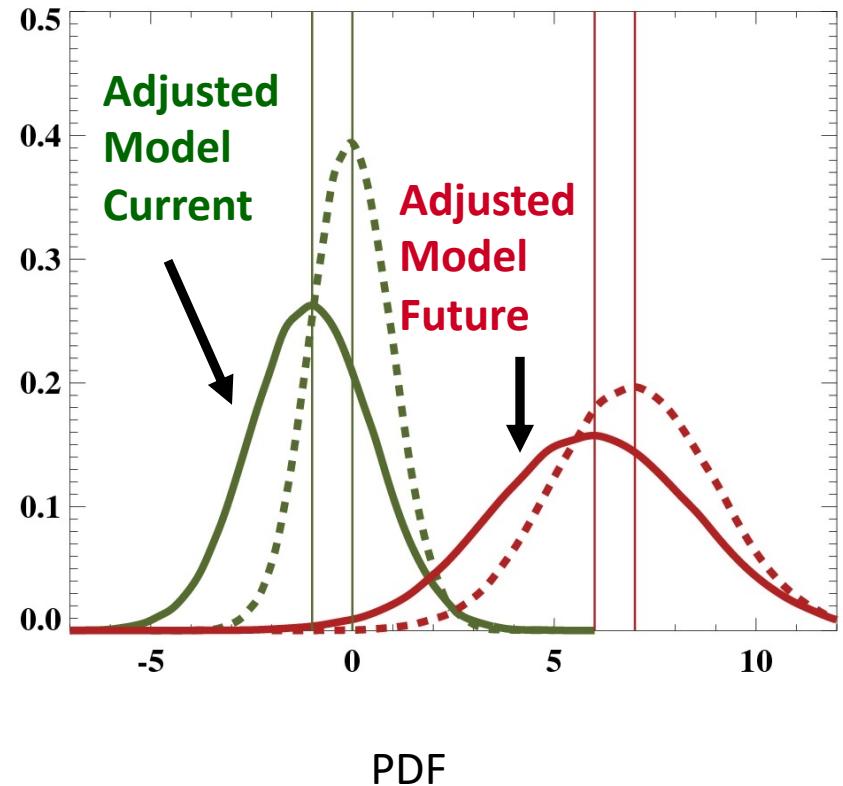
=> Quantile-Quantile  
(Déqué, 2007)



# Bias Correction

## Bias correction: limitations?

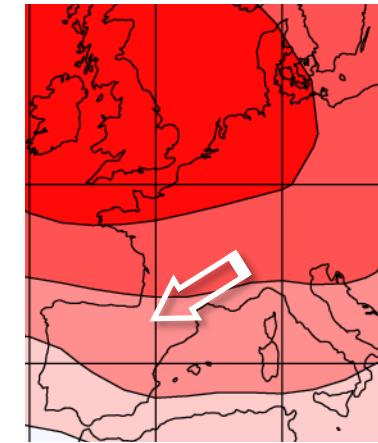
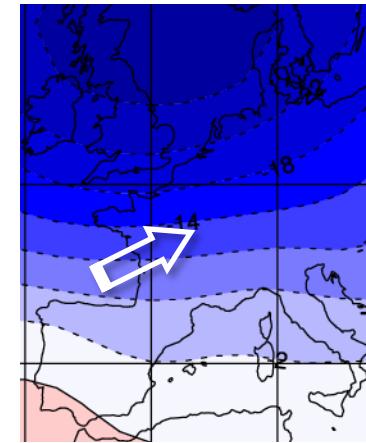
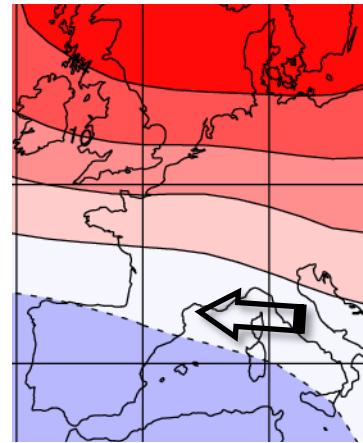
- Covariances between variables are not taken into account
- Extremes: extrapolations needed if all values did not happen in the past
- Statistical relationships of the biases between observations and model variables do not change in the future



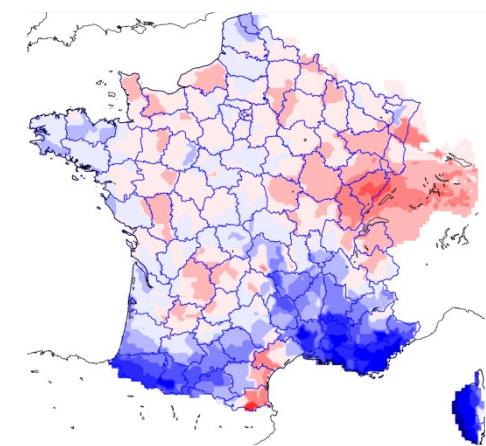
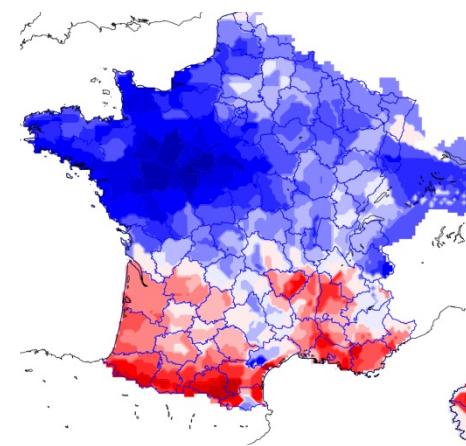
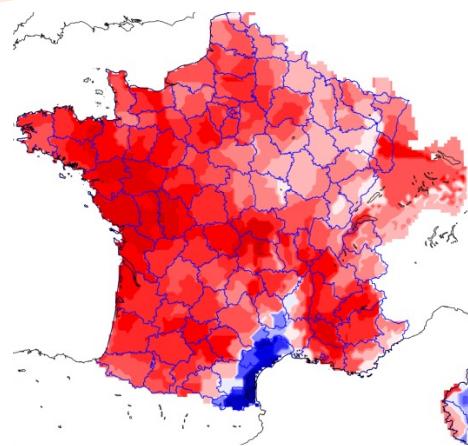
# Statistical Methods

Examples of winter weather types and precipitation anomalies

Mean Sea-Level Pressure Anomalies



Physical  
Relationships



Precipitation Anomalies

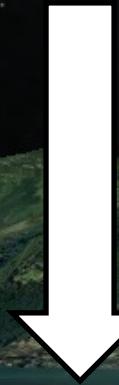
IS-ENES3 has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 824084



# Statistical Methods

Predictor(s):

SLP, Z, T,  
H, V, ...



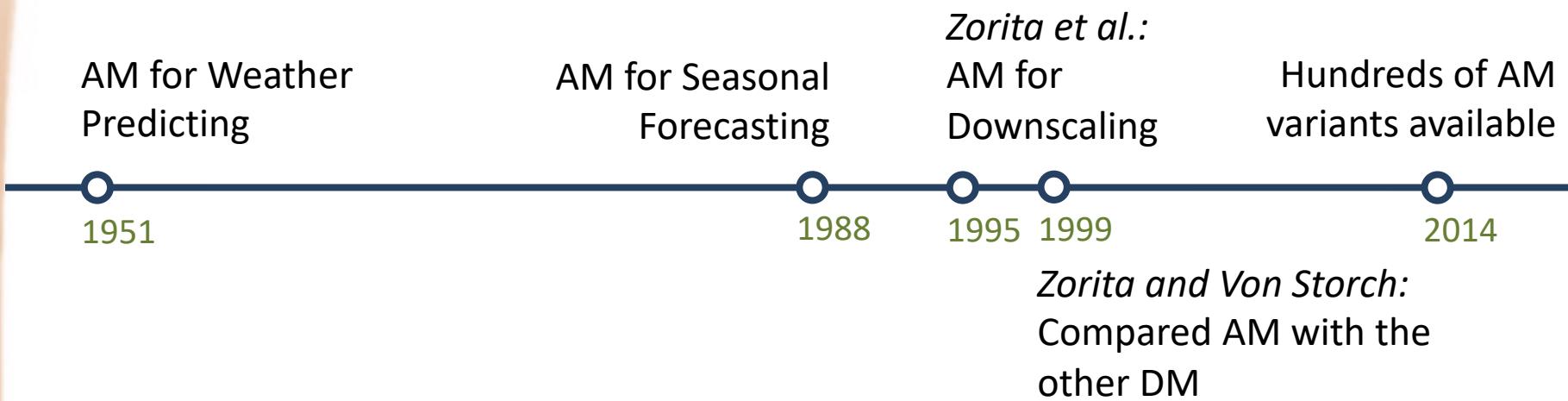
Large-Scale  
Variables (grid)

Predictant(s):

P, T<sub>2m</sub> (max/min),  
R, ...

Local Climate

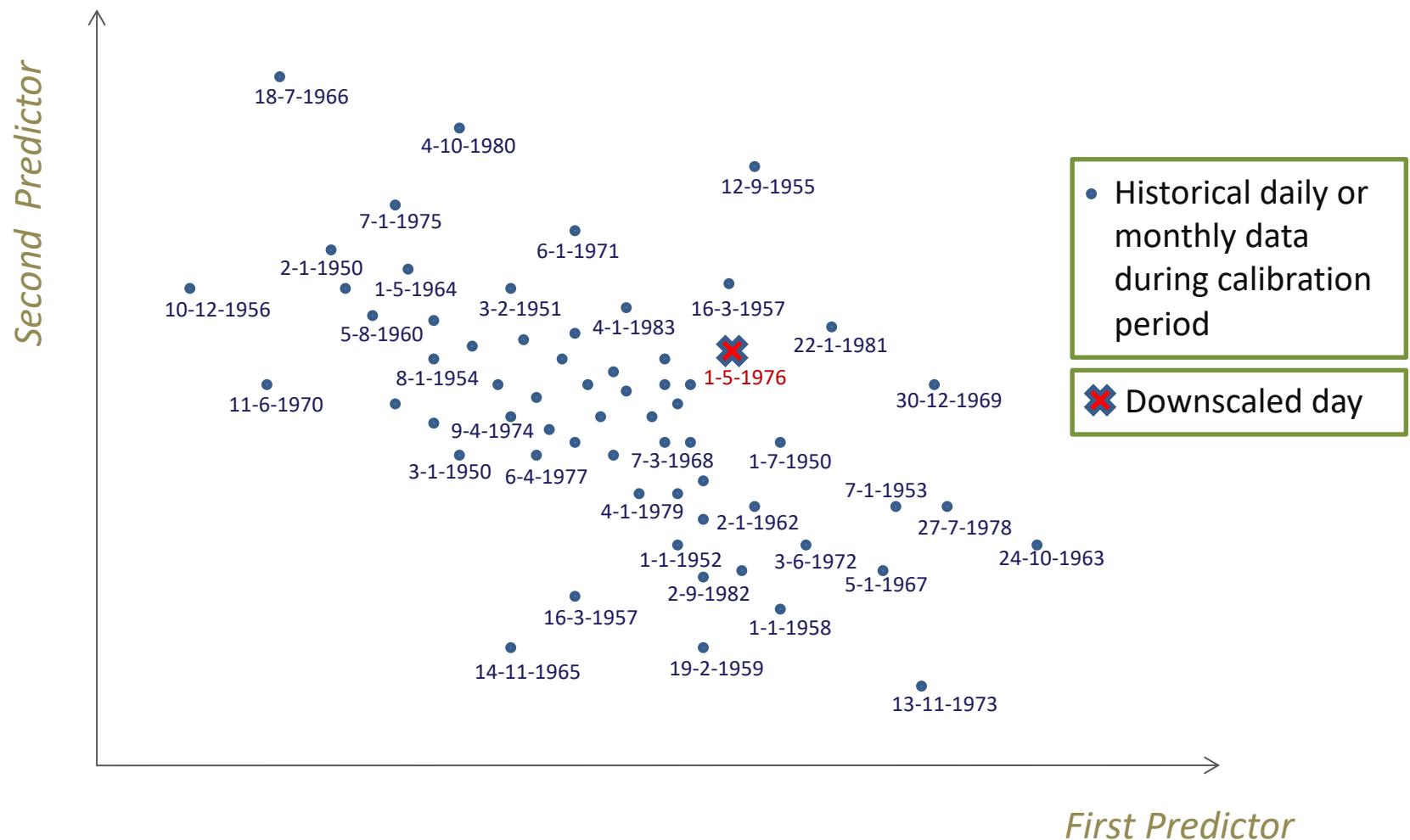
# A brief history of the Analogue Method (AM)



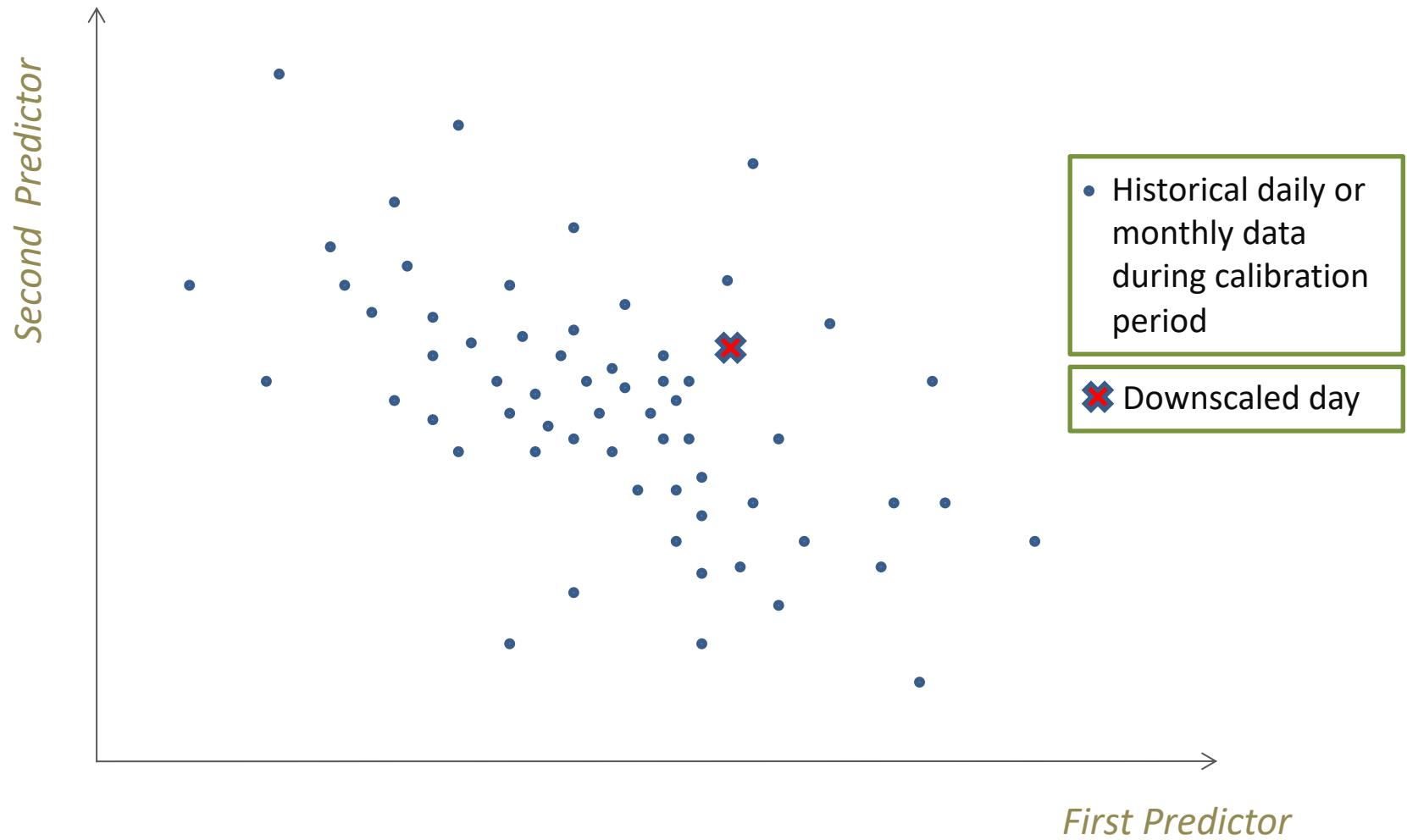
# Advantages of the AM

1. *Non-parametric*
2. *Non-linear*
3. *Do not underestimate the variance*
4. *Spatially Coherent*
5. *Easy to implement*
6. *Low computational cost*

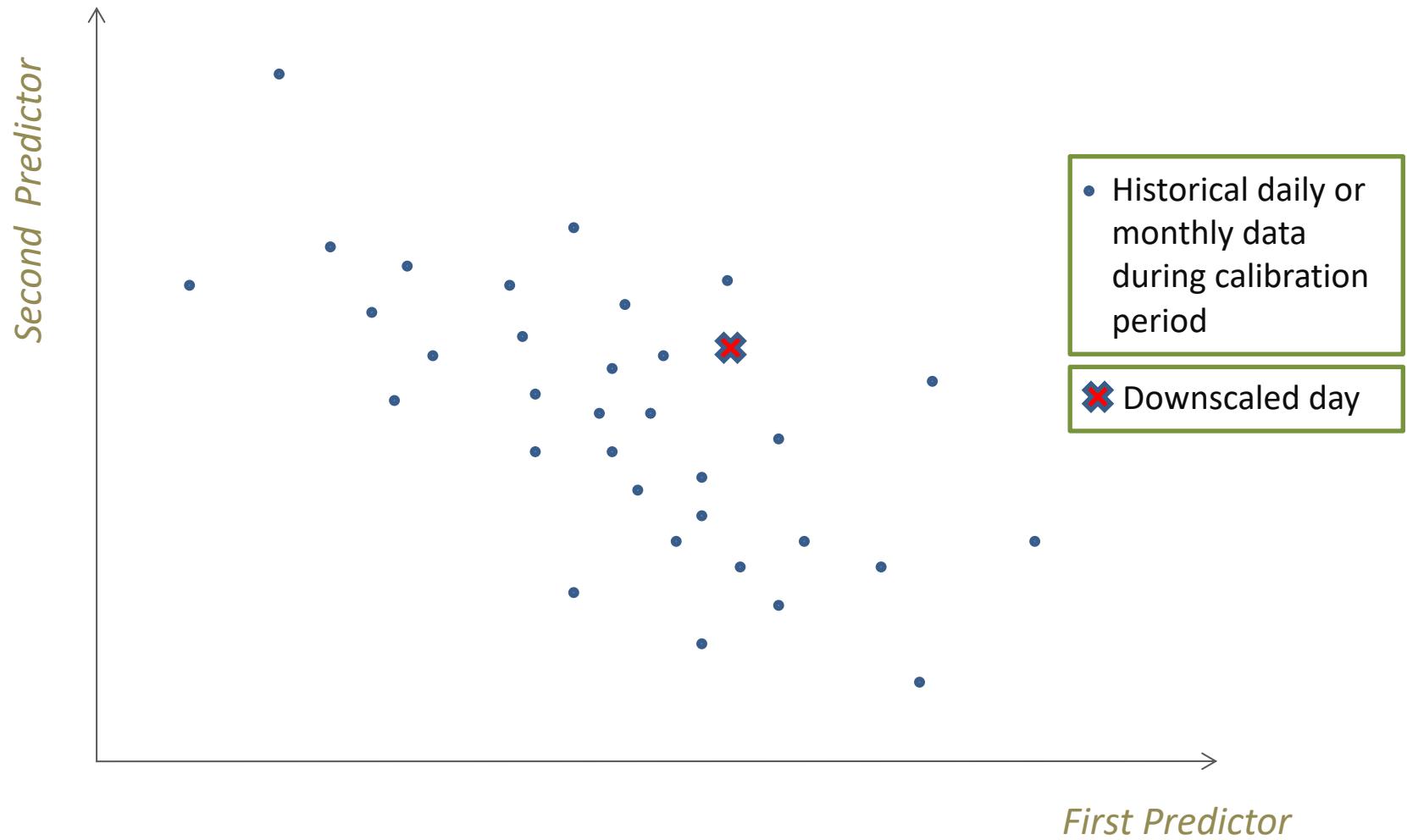
# How the AM works



# Search Radius

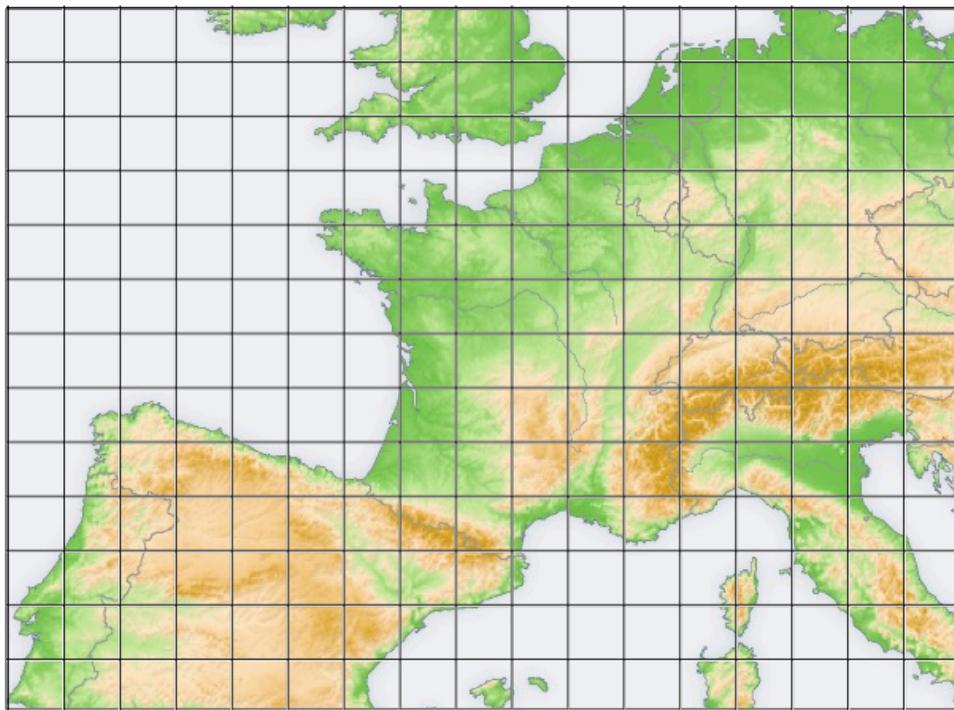


# Search Radius



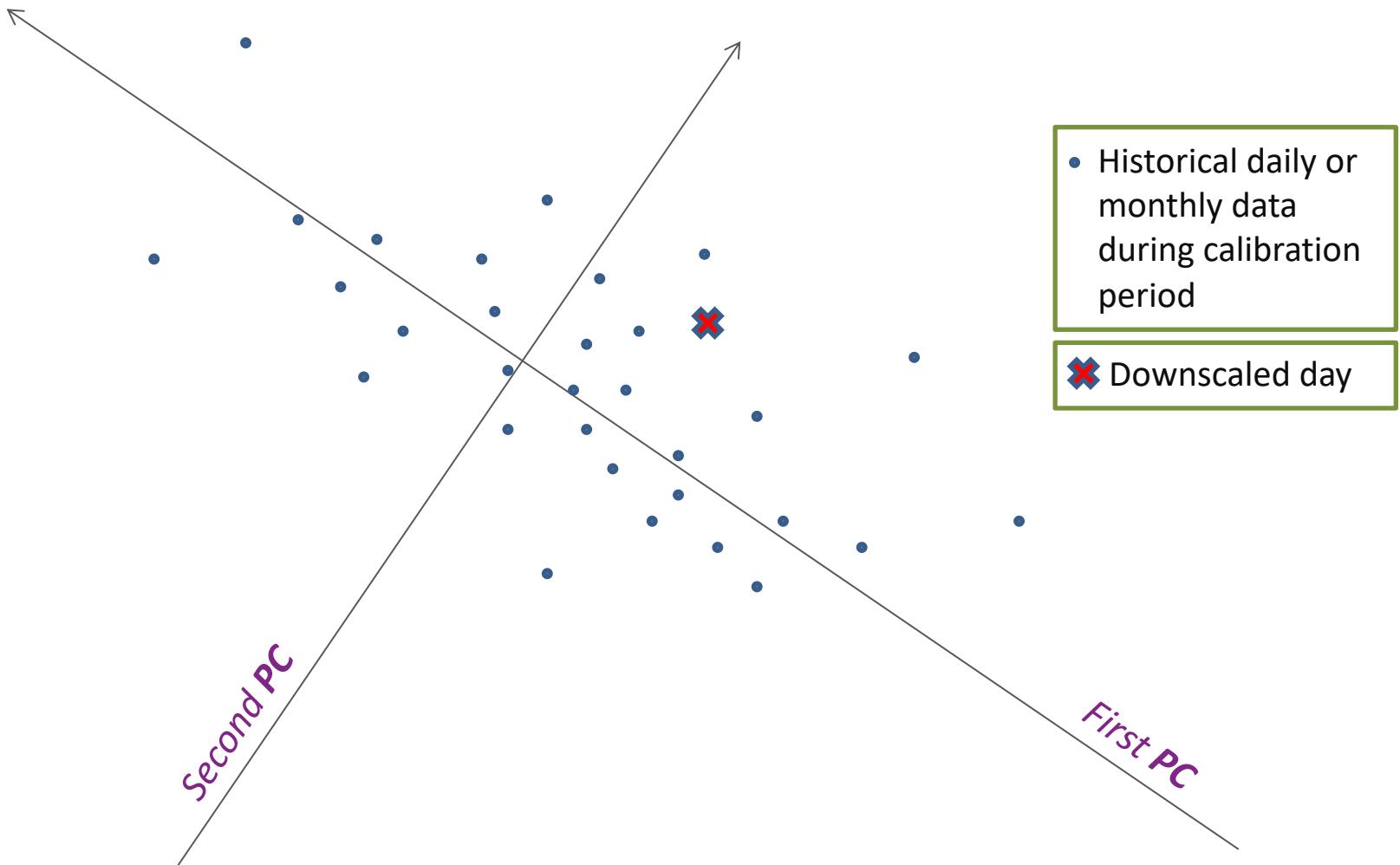
# How the AM works

Typical Domain Size of a Predictor Field

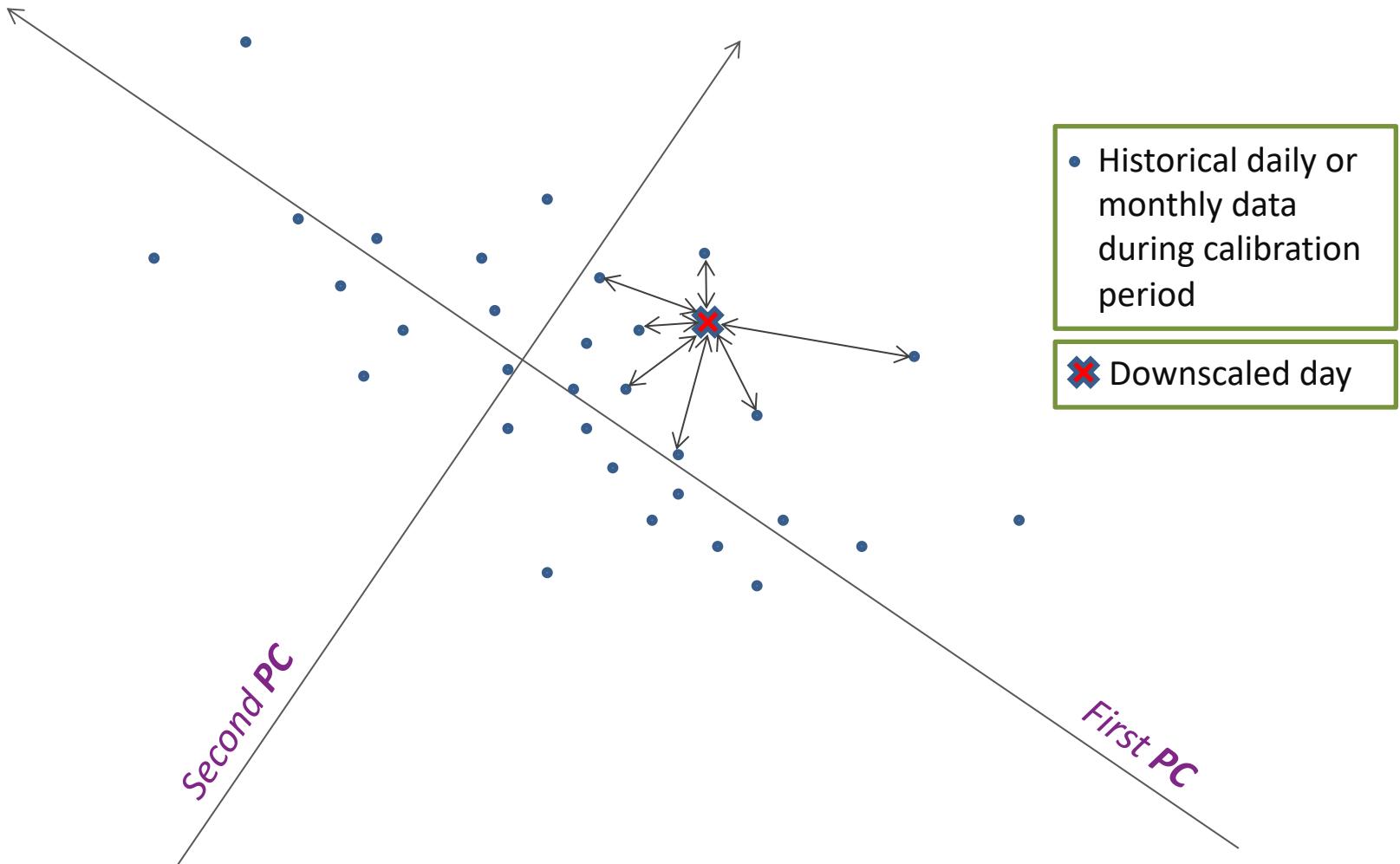


**PCA**

# How the AM works



# Similarity Measure



# Similarity Measure

- (Weighted) Euclidean distance:
- Sum of the absolute values of each component of  $\mathbf{z}$ :
- Cosine of the angle between  $\mathbf{x}$  and  $\mathbf{y}$ :
- Mahalanobis distance:
- Pattern correlation:
- Teweles-Wobus score:
- Minimize the sequence of days instead:

$$d(\vec{x}, \vec{y}) = \sqrt{\sum_{i=1}^n w_i z_i^2}$$

$$d(\vec{x}, \vec{y}) = \sum_{i=1}^n |z_i|$$

$$d(\vec{x}, \vec{y}) = \cos \theta_{\vec{x}, \vec{y}}$$

$$d(\vec{x}, \vec{y}) = -\sum_{i=1}^n \frac{x_i y_i}{\sqrt{\lambda_i}}$$

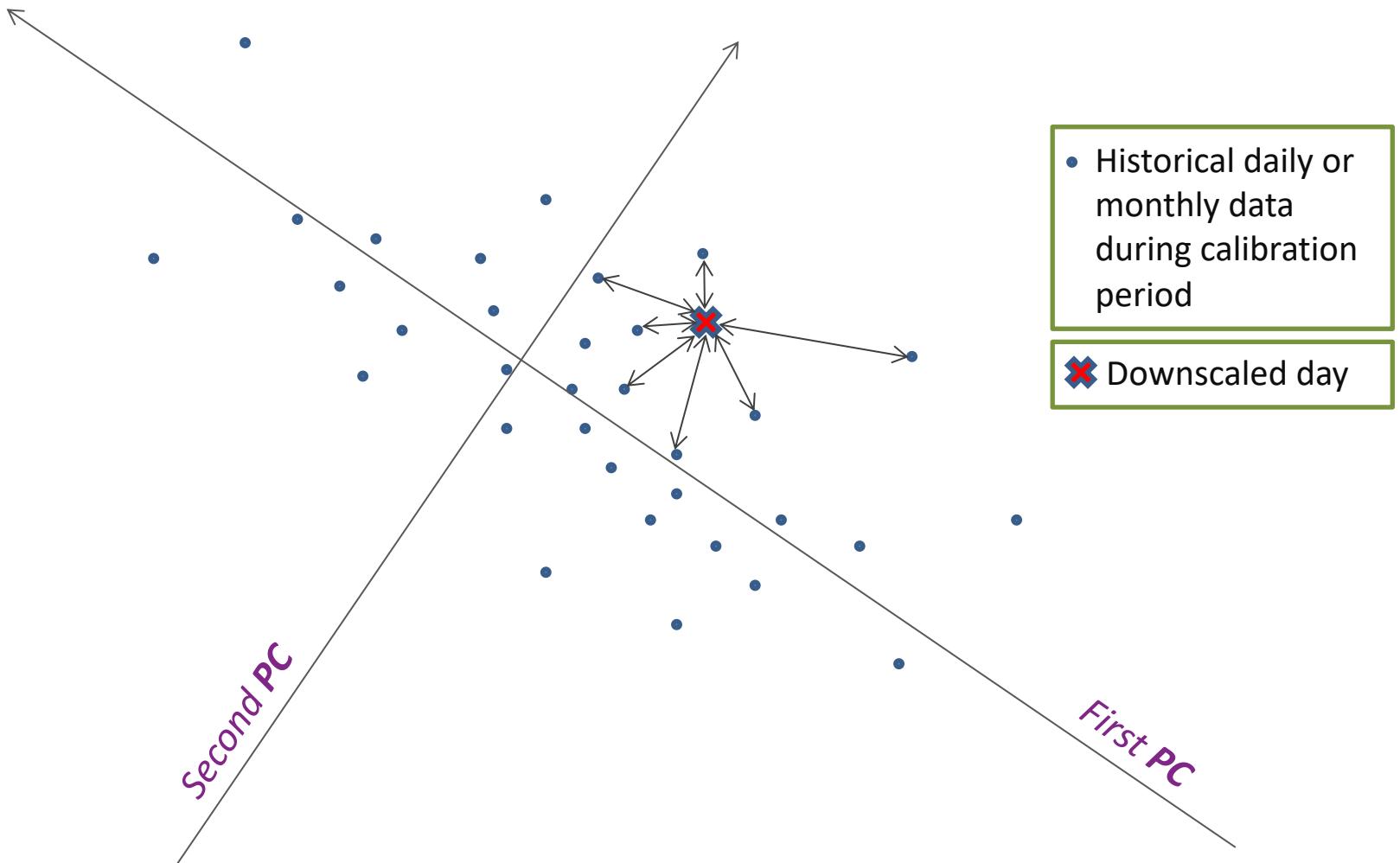
$$d(\vec{x}, \vec{y}) = r_{(P_1, P_2)}$$

$$d(\vec{x}, \vec{y}) \approx \nabla P_1 - \nabla P_2$$

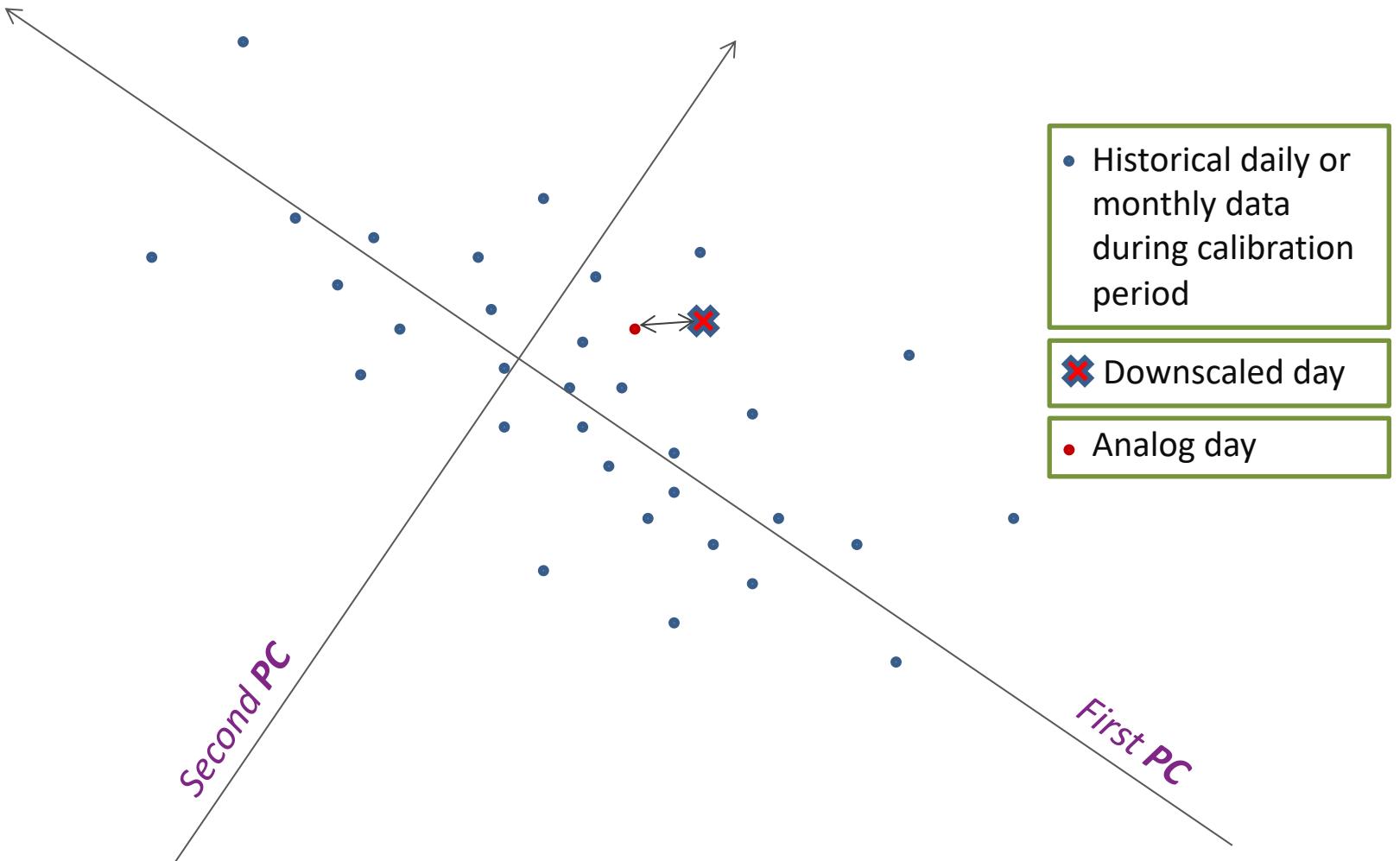
$$d(\vec{x}, \vec{y}) = \sum_{t=0}^T w_t d(\vec{x}(t), \vec{y}(t))$$

$\mathbf{x}$  and  $\mathbf{y}$  are two vectors whose components are the values of the  $n$  Principal Components for the 1st and 2nd day, respectively, and:  $\mathbf{z} = \mathbf{x} - \mathbf{y}$

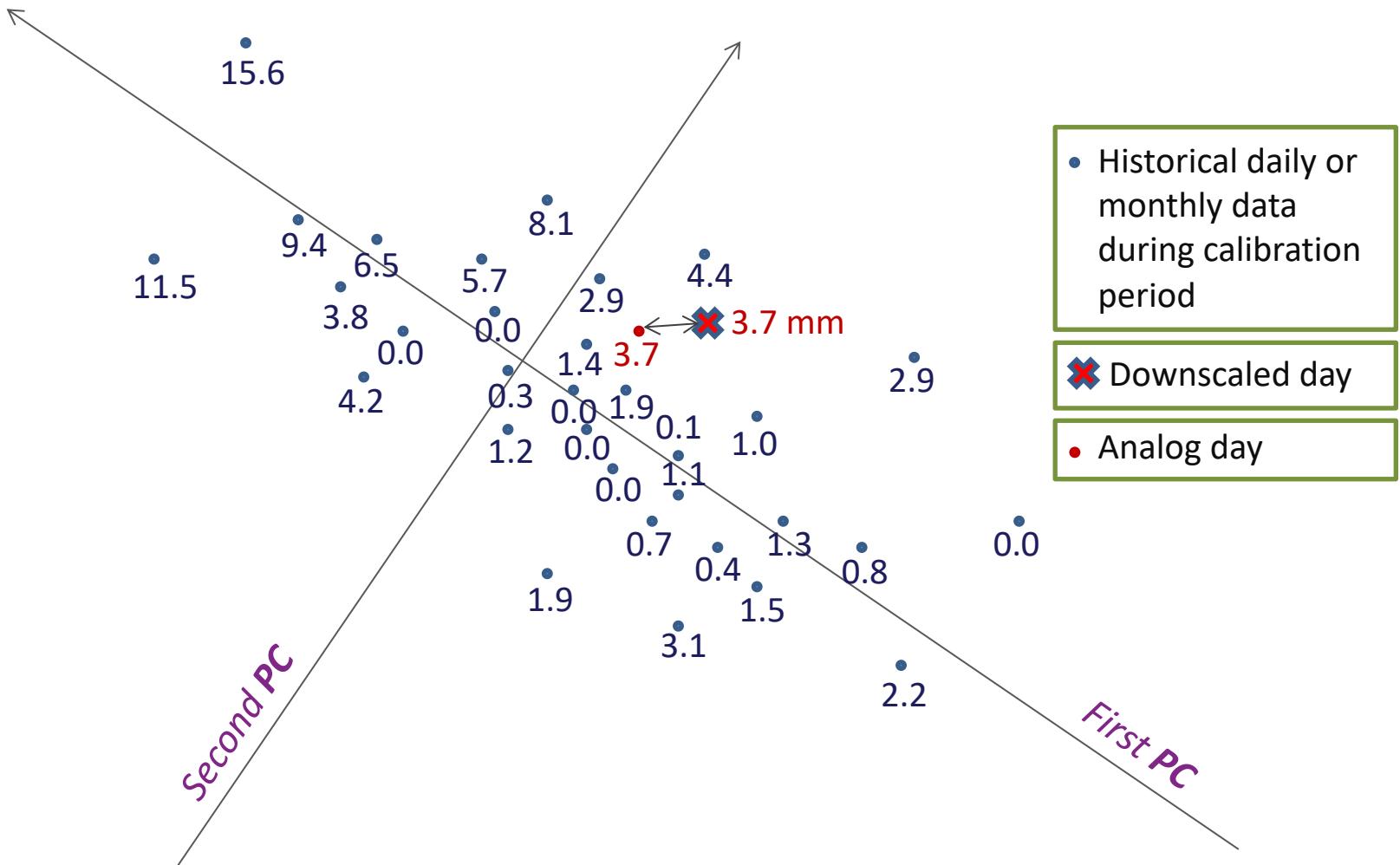
# Analog Day



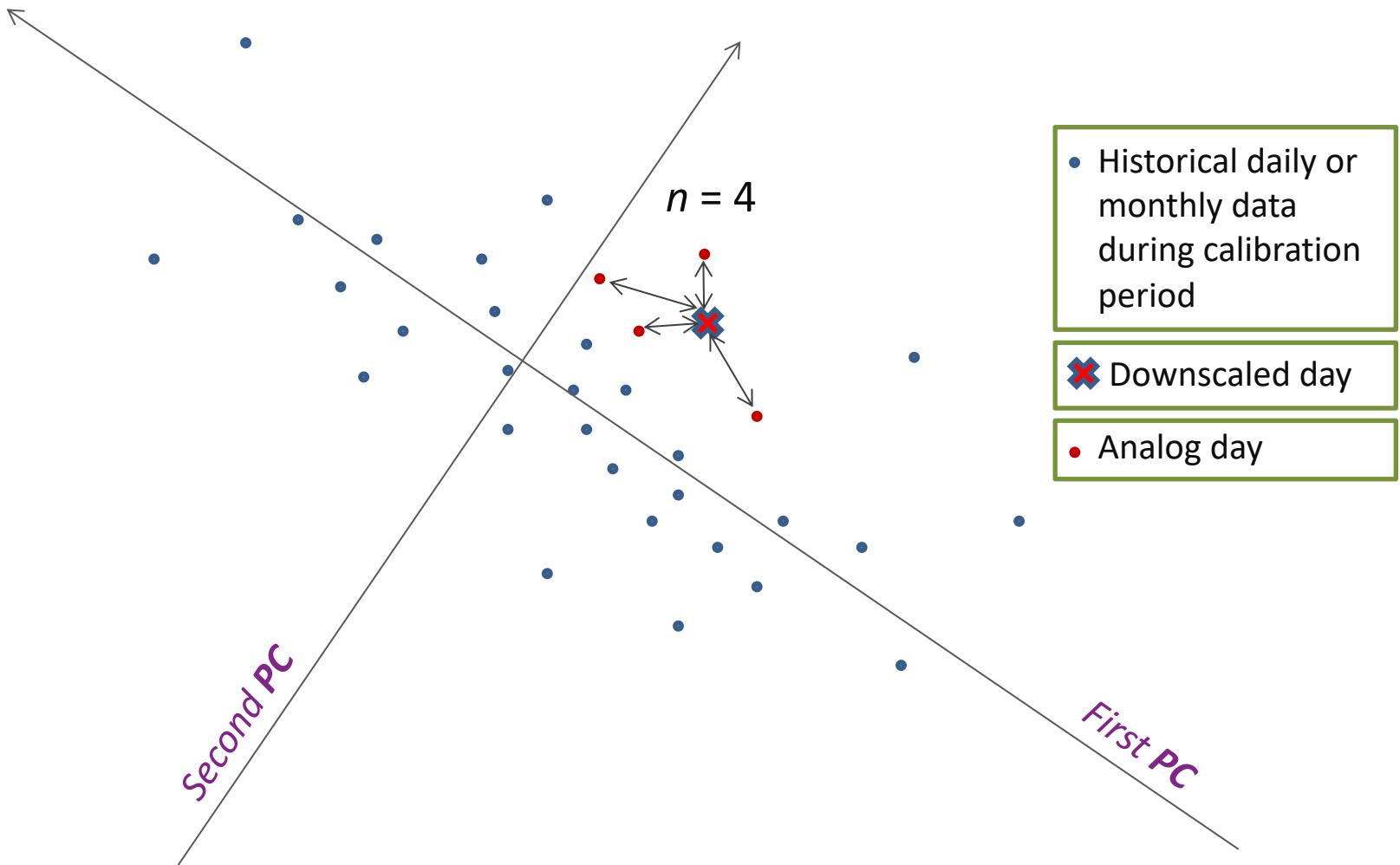
# Analog Day



# Analog Day

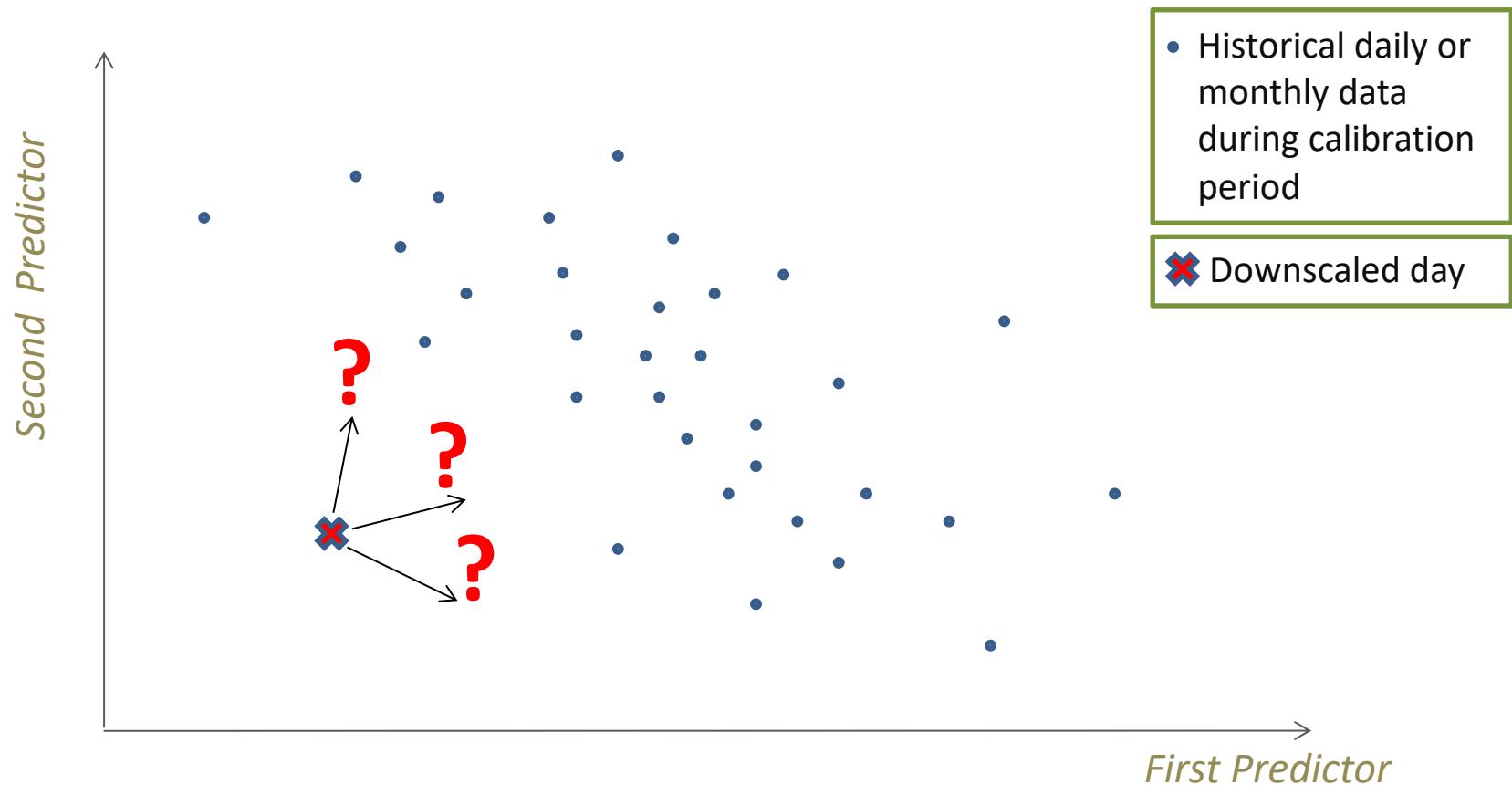


# Nearest Neighbour Resampling



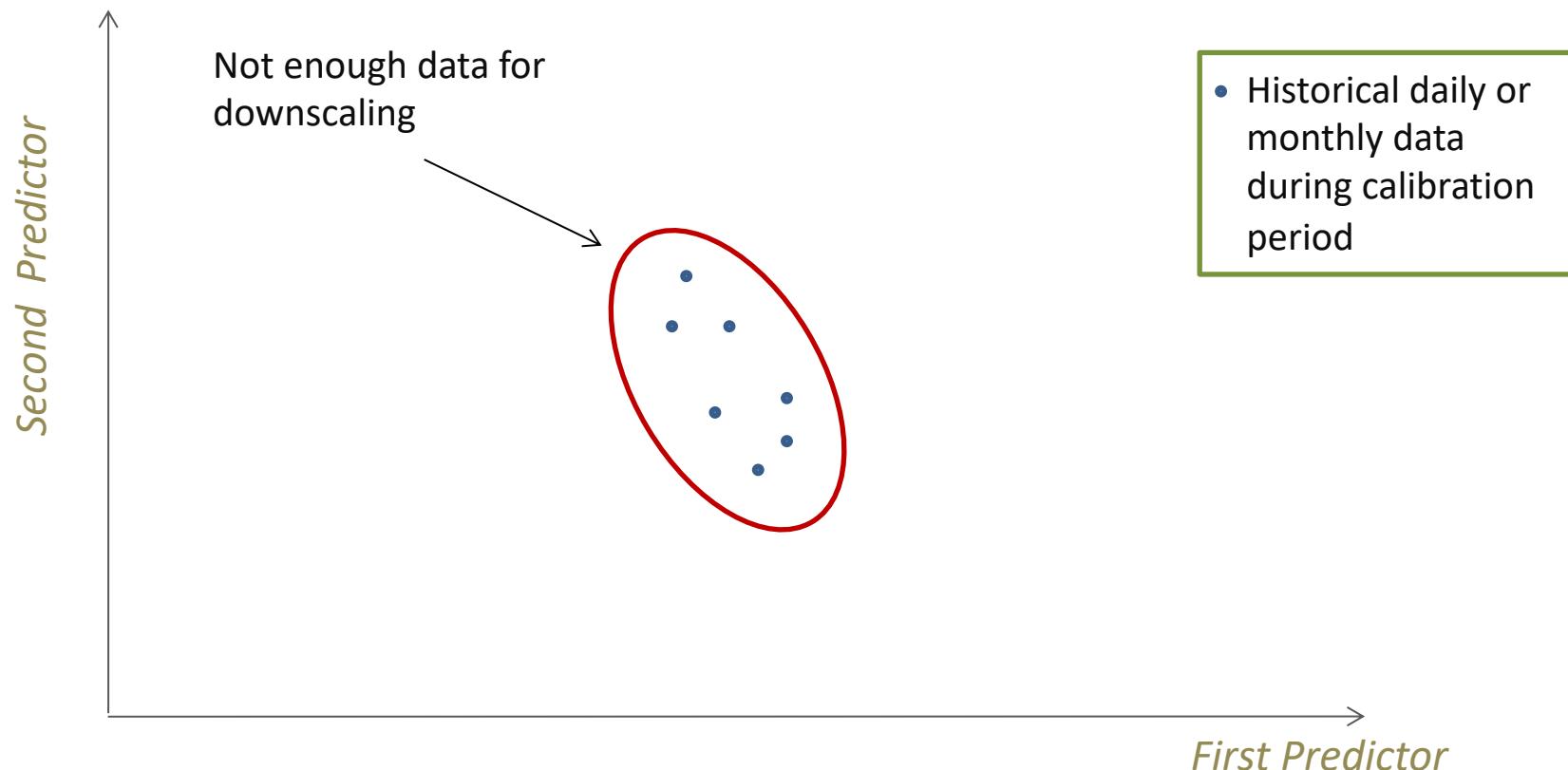
# Caveats of the AM

- It *cannot extrapolate values* outside the range of the observed data used in the calibration



# Caveats of the AM

- It needs *a large training sample* of observed data for calibration.



## Caveats of the AM

- It doesn't preserve the *spatial autocorrelation structure* of the observed variable or its observed temporal *frequency distribution* or its *persistence* (for daily precipitation).

Recently, a number of AMs that successfully deal with these issues have been presented:

- Ribalaygua et al. (2013): a two step Analogue/Regression method
- Benestad (2009): a two step Analogue/Quantile mapping method using the Extended EOFs instead of the classic EOFs.
- Hwang and Graham (2013): a two step Bias-correction/Stochastic AM
- Matulla et al. (2007): an AM applied to sequences of 2-3 days

# Suggested Readings

- *Introduction to the AM:*

Benestad et al. (2008) Empirical-Statistical Downscaling (Chapter 5). World Scientific Publishing Company.

- *Robustness Analysis:*

Gutierrez et al. (2013) Reassessing Statistical Downscaling Techniques for Their Robust Application under Climate Change Conditions. *J. Climate*, 26, 171-188. DOI: 10.1175/JCLI-D-11.00687.1

- *Similarity Measures:*

Matulla et al. (2007) Influence of similarity measures on the performance of the analog method for downscaling daily precipitation. *Clim. Dyn.* DOI: 10.1007/s00382-007-0277-2

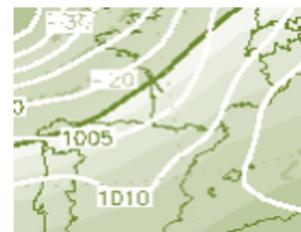
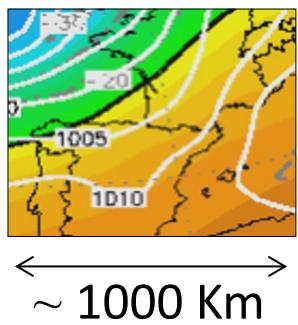
- *Two step Analogue/Regression method:*

Ribalaygua et al. (2013) Description and validation of a two step analogue/regression downscaling method. *Theor. Appl. Climatol.*, 114:253-269. DOI 10.1007/s00704-013-0836-x

# Weather Typing Method (WTM)

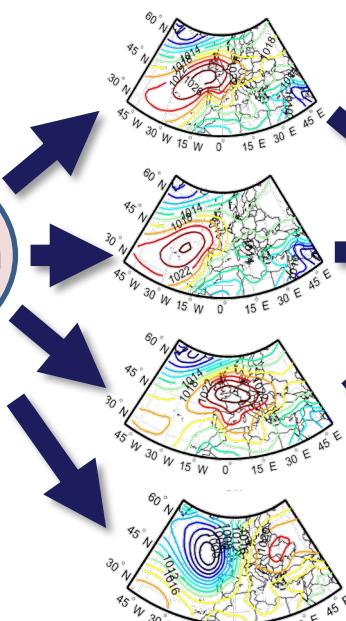
Composed by 2 steps:

Reanalysis  
SLP or Z Field



GCM output  
SLP or Z Field

4-43 Circulation or  
Weather Types (WTs)



Select  
Classification  
Scheme

Select  
Downscaling  
Method

Observed  
Local  
Predictand  
1950-2014

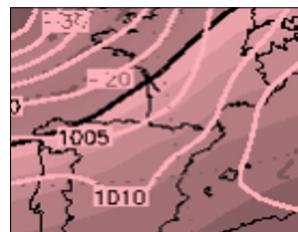
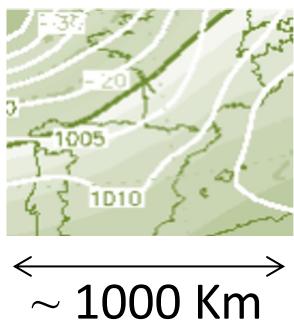
Relationships  
between WTs  
and the local  
predictand

Downscaled  
Local  
Predictand

# Weather Typing Method (WTM)

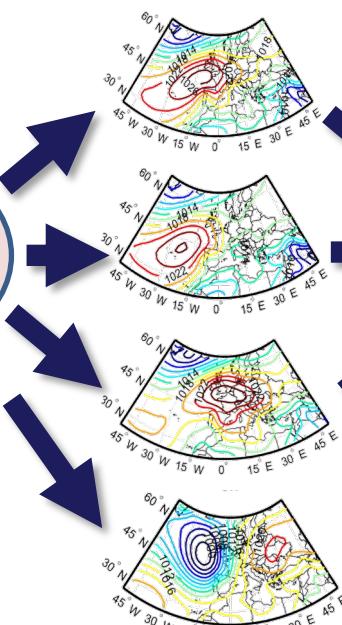
Composed by 2 steps:

Reanalysis  
SLP or Z Field



GCM output  
SLP or Z Field  
2050-2099

4-43 Circulation or  
Weather Types (WTs)



Select  
Classification  
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Select  
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Observed  
Local  
Predictand  
1950-2014

Relationships  
between WTs  
and the local  
predictand

Downscaled  
Local  
Predictand  
2050-2099

# Advantages of the WTM

1. *Greater understanding* of the problems involved
2. Weather Types useful for downscaling *Extreme Indices*
3. *Spatially coherent*
4. *Low computational cost*
5. It can be *non-linear*
6. It can avoid *underestimation of the variance*

# Statistical Downscaling Methods used with the WTM

- For Temperature: *Multiple Regression Models*
- For Daily Precipitation:
  - *Generalized Linear Models*
  - *Generalized Additive Models*
  - *Logistic (logit) Regression Model*
- *Weather Generators*
- *Analogue Method*
- *Canonical Correlation Analysis*

# A brief history of the Weather Type Classifications

COST733  
Catalogue:

72 WT  
classific.  
reported

*Hess and Brezowsky:*  
Grosswetterlagen  
WTs

1969 1972

Lamb:  
Lamb  
WTs

1977

Jenkinson and  
Collison:  
first automated  
Lamb  
classification.

1993

Jones *et al.*:  
assess the  
Lamb  
classification  
modified by  
Jenkinson and  
Collison

*Spellman:*  
Lamb classification  
for Spain

2000

Trigo and  
DaCamara:  
Lamb  
classification  
for Portugal

2007

James:  
Automated  
Grosswetterlagen  
classification

2010

# COST733 Catalogue

- 50 Classifications based on a *bottom-up approach*:

#	Abbreviation	Types	Parameters
<i>PCA (PCA based methods)</i>			
23	TPCA07	7	MSLP
24	TPCAC09	9	MSLP
25	TPCAC18	18	MSLP
26	TPCAC27	27	MSLP
27	TPCAV	6–12	MSLP
28	P27	27	Z500
29	P27C08	8	MSLP
30	P27C18	18	MSLP
31	P27C27	27	MSLP
32	PCAXTR	11–17	MSLP
33	PCAXTRC09	9–10	MSLP
34	PCAXTRC18	15–18	MSLP
<i>LDR (methods based on leader algorithm)</i>			
35	LUND	10	MSLP
36	LUNDC09	9	MSLP
37	LUNDC18	18	MSLP
38	LUNDC27	27	MSLP
39	ESLPC09	9	MSLP
40	ESLPC18	18	MSLP
41	ESLPC27	27	MSLP
42	EZ850C10	10	Z850
43	EZ850C20	20	Z850
44	EZ850C30	30	Z850
45	KHC09	9	MSLP
46	KHC18	18	MSLP
47	KHC27	27	MSLP

#	Abbreviation	Types	Parameters
<i>OPT (optimization methods)</i>			
48	CKMEANSC09	9	MSLP
49	CKMEANSC18	18	MSLP
50	CKMEANSC27	27	MSLP
51	PCACA	4–5	MSLP
52	PCACAC09	9	MSLP
53	PCACAC18	18	MSLP
54	PCACAC27	27	MSLP
55	PETISCO	25–38	MSLP, Z500
56	PETISCOC09	9	MSLP
57	PETISCOC18	18	MSLP
58	PETISCOC27	27	MSLP
59	PCAXTRKM	11–17	MSLP
60	PCAXTRKMC09	9–10	MSLP
61	PCAXTRKMC18	15–18	MSLP
62	SANDRA	18–23	MSLP
63	SANDRAC09	9	MSLP
64	SANDRAC18	18	MSLP
65	SANDRAC27	27	MSLP
66	SANDRAS	30	Z925, Z500
67	SANDRASC09	9	MSLP
68	SANDRASC18	18	MSLP
69	SANDRASC27	27	MSLP
70	NNW	9–30	Z500
71	NNWC09	9	MSLP
72	NNWC18	18	MSLP
73	NNWC27	27	MSLP

Table from Philipp et al. (2010)

# COST733 Catalogue

- 22 Classifications based on a *top-down approach*:

#	Abbreviation	Types	Parameters
<i>SUB (subjective methods)</i>			
1	HBGWL	29	not specified
2	HBGWT	10	not specified
3	OGWL	29	MSLP, Z500
4	OGWLSLP	29	MSLP
5	PECZELY	13	not specified
6	PERRET	40	not specified
7	ZAMG	43	not specified
<i>THR (threshold based methods)</i>			
8	GWT	18	MSLP
9	GWTC10	10	MSLP
10	GWTC18	18	MSLP
11	GWTC26	26	MSLP
12	LITADVE	9	MSLP
13	LITTC	27	MSLP
14	LITTC18	18	MSLP
15	LWT2	26	MSLP
16	LWT2C10	10	MSLP
17	LWT2C18	18	MSLP
18	WLKC09	9	U/V700
19	WLKC18	18	U/V700, Z925
20	WLKC28	28	U/V700, Z925/500
21	WLKC733	40	U/V700, Z925/500, PW
22	SCHUEPP	40	MSLP, Z500, U/VSFC/500

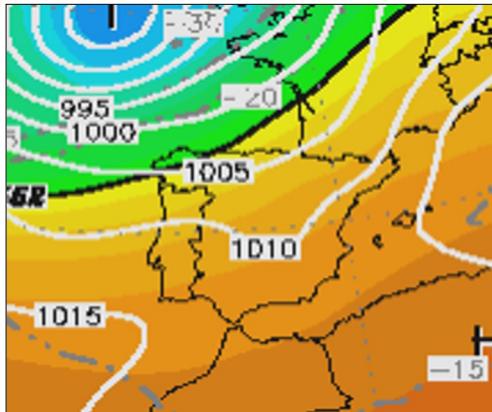
Grosswetterlagen  
WTs

Modified Lamb WTs

Table from Philipp et al. (2010)

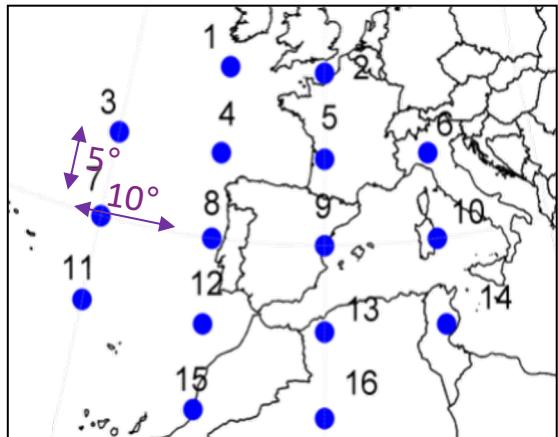
# Lamb classification modified by Jenkinson and Collison

Mean Daily SLP Field



**Southerly Flow:**  $\mathbf{S} = 1.305 [0.25 (p_5 + 2p_9 + p_{13}) - 0.25 (p_4 + 2p_8 + p_{12})]$   
**Westerly Flow:**  $\mathbf{W} = [0.5 (p_{12} + p_{13}) - 0.5 (p_4 + p_5)]$   
**Total Flow:**  $\mathbf{F} = (\mathbf{S}^2 + \mathbf{W}^2)^{1/2}$       **Flow Direction:**  $\mathbf{D} = \text{arctg}(\mathbf{W}/\mathbf{S})$   
**Southerly Vorticity:**  $Z_S = 0.85 [0.25 (p_6 + 2p_{10} + p_{14}) - 0.25 (p_5 + 2p_9 + p_{13}) - 0.25 (p_4 + 2p_8 + p_{12}) + 0.25 (p_3 + 2p_7 + p_{11})]$   
**Westerly Vorticity:**  $Z_W = 1.12 [0.5 (p_{15} + p_{16}) - 0.5 (p_8 + p_9)] - 0.91 [0.5 (p_8 + p_9) - 0.5 (p_1 + p_2)]$   
**Total Vorticity:**  $Z = Z_S + Z_W$     ( $>0$ : Cyclonic ;  $<0$ : Anticyclonic)

Selection of  
16 grid points  
 $p_1, \dots, p_{16}$ :

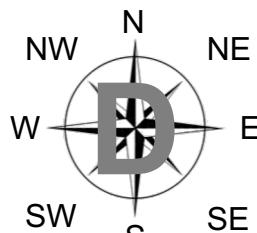


Extraction of 16  
SLP time series

Calculation of  
Geostrophical  
Indexes

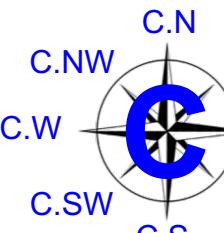
Selection of # WTs:

8 Directionals



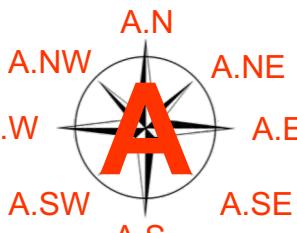
$|Z| < F$

9 Cyclonic

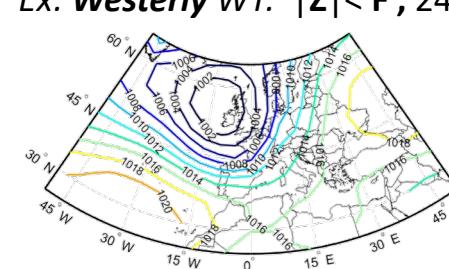


$|Z| > F, Z > 0$

9 Anticyclonic

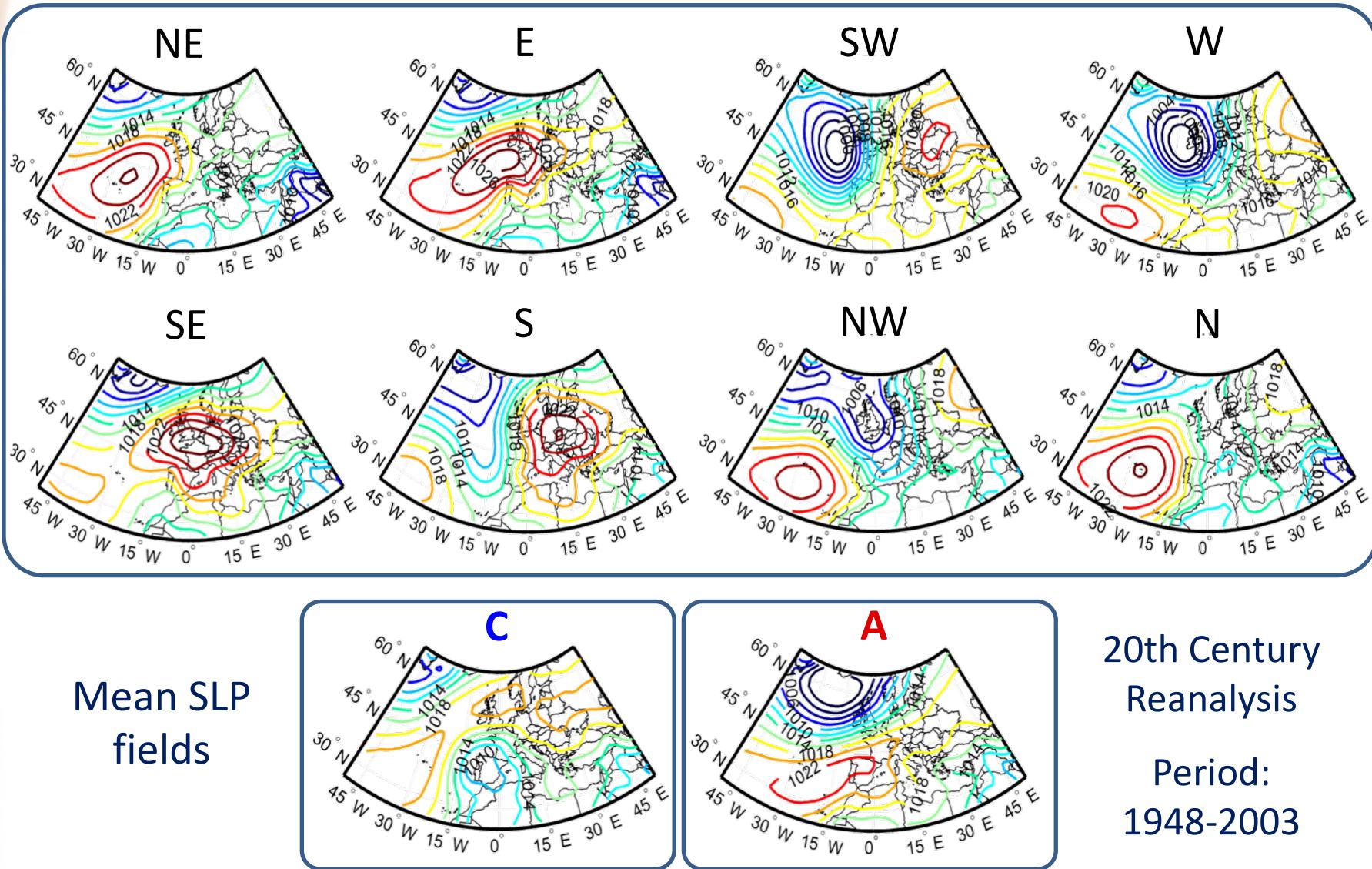


$|Z| > F, Z < 0$



Ex: **Westerly WT:**  $|Z| < F$ ,  $248^\circ < D < 292^\circ$   
**WTs Classification**

# Lamb classification modified by Jenkinson and Collison



## Caveats of the WTM

- Limit on the maximum number of Weather Types
  - Each WT must have a significant number of days of occurrence
- GCM pressure or geopotential predictors
  - They do not react sufficiently to climate change
- WTM often underestimate the temporal climate variability, especially the linear models.

# Caveats of both the AM and the WTM

- *Stationarity Hypothesis*
  - Relationships predictors/predictand are assumed to be constant in time
- *Convective structures* are still not well simulated
  - Limitations of GCMs: relies on parametrizations
- *Large-Scale Domain*
  - Must optimize the domain
  - Different predictors can also have different optimized domains

## Suggested Readings for the WTM:

- *Weather Types Catalogue:*

Philipp, A., Bartholy, J., Beck, C., Erpicum, M., et al. (2010) *Cost733cat—a database of weather and circulation type classifications*. Phys. Chem. Earth 35, 360–373. Doi:10.1016/j.pce.2009.12.010

- *Lamb Classification:*

Jones, P. D., Harpham, C., and Briffa, K. R. (2012) *Lamb weather types derived from reanalysis products*. International Journal of Climatology. Doi: 10.1002/joc.3498

- *SANDRA Classification:*

Lutz, K., Jacobbeit, J., Philipp, A., Seubert, S., Kunstmann, H. and Laux, P. (2012) *Comparison and evaluation of statistical downscaling techniques for station-based precipitation in the Middle East*. Int. J. Climatol., 32: 1579–1595. doi: 10.1002/joc.2381

- *A Classic:*

Goodess, C.M. and Palutikof, J.P. (1998) *Development of daily rainfall scenarios for southeast Spain using a circulation-type approach to downscaling*. Int.J.Climatol. 18,1051-1083.

# Statistical Downscaling: Recap

## Current Climate

Predictors:  
Obs/Reanalysis

*Model  
Calibration*

Statistical Relationships  
between Predictors and  
Predictants

Predictants:  
Obs/Reanalysis



## Future Climate

Predictors:  
GCMs

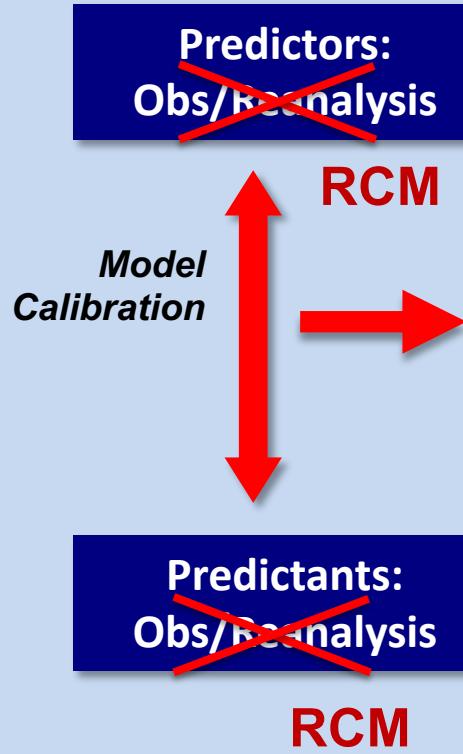
*Application*

*Downscaling*

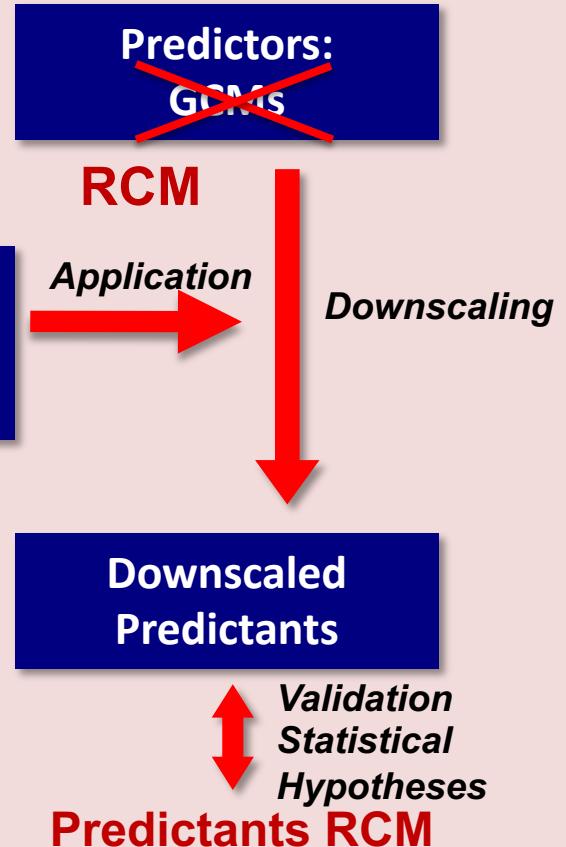
Downscaled  
Predictants

# Perfect Model Approach : validate the transferability

## Current Climate



## Future Climate



# Limitations and Advantages

## Statistical Downscaling

### Limits

- Uncertainties of the large-scale circulation
- Observations quality
- Limited by the number of observation locations
- Temperature tendencies are reproduced
- Most of methods are daily based
- New Extremes may not be reproduced
- Stationarity hypothesis

### Advantages

- Covariance of variables are kept
- Low cost to evaluate uncertainties
- Can also produce hourly data
- High or very high spatial resolution

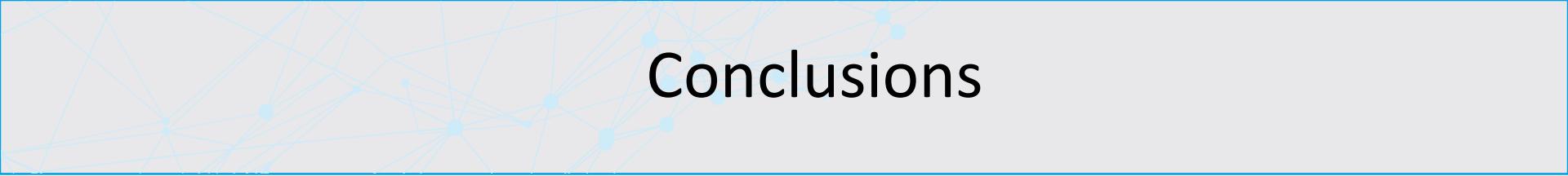
## Dynamical Downscaling/Bias Correction

### Limitations

- Bias correction is needed
  - Loss of covariances of variables (not always totally true)
- Limited by the number of observation locations
- Problems with some highly non-gaussian fields like precipitation
- Very high computational costs: limits uncertainties assessment and horizontal resolution

### Advantages

- More appropriate for extremes (but bias correction is not)
- Historical Cases simulation: days, events
- Stationarity hypothesis is less strong



# Conclusions

## ► **Summary of Statistical Downscaling and Bias Correction**

- ▶ Very fast to process, but sometimes complex to setup properly
  - ▶ Uncertainties Assessment
  - ▶ Multi-scenarios
- ▶ Multiple configurations
- ▶ Quality and performance dependent on the quality of the observations and reanalysis
- ▶ Can only provide values at the observation locations
- ▶ Need long time series of high-quality observations (25 years+)
- ▶ Bias correction is always required for impact modeling and studies at local and regional scale
- ▶ There exists a very large number of methods: not always easy to choose the best one(s)

Christian Pagé  
[christian.page@cerfacs.fr](mailto:christian.page@cerfacs.fr)

## Questions Time!

