Statistical downscaling model

Carlo Cacciamani

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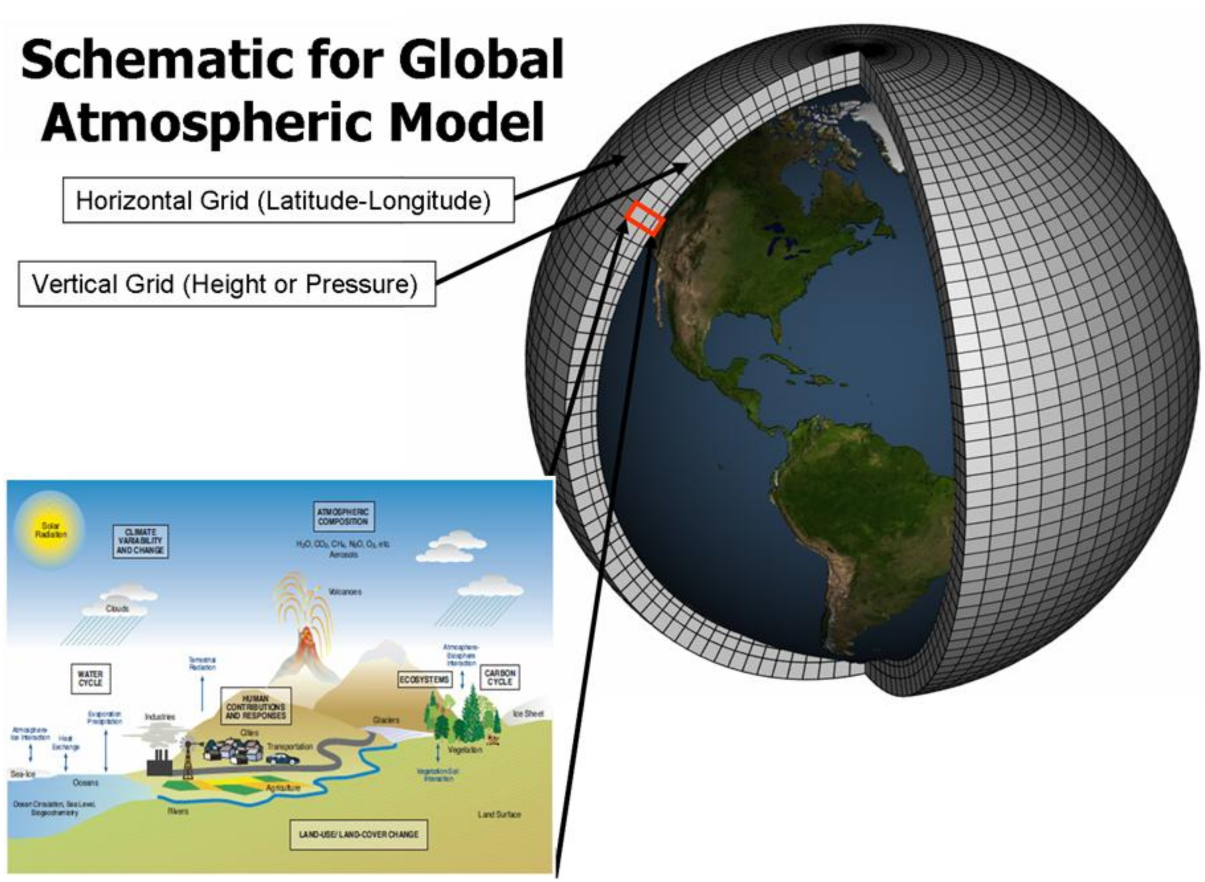
AOGCM: status of the art

Coupled AOGCMs are the modelling tools traditionally used for generating projections of climatic changes due to anthropogenic forcings.



AOGCM: status of the art

Coarse resolution AOGCMs (100-200 Km) simulate atmospheric general circulation features well in general. At the regional scale the models display area-average biases that are highly variable from region-to-region and among models, with sub-continental area-averaged seasonal temperature biases.

A correction is needed to apply these AOGCM outputs

AOGCM: status of the art

Furthermore, regional climate is often affected by forcings and circulations that occur at the sub-AOGCM horizontal grid scale (e.g., Giorgi and Mearns, 1991). Consequently, AOGCMs cannot explicitly capture the fine-scale structure that characterises climatic variables in many regions of the world and that is needed for impact assessment studies

The ‘Mismatch’ of Scale Issue

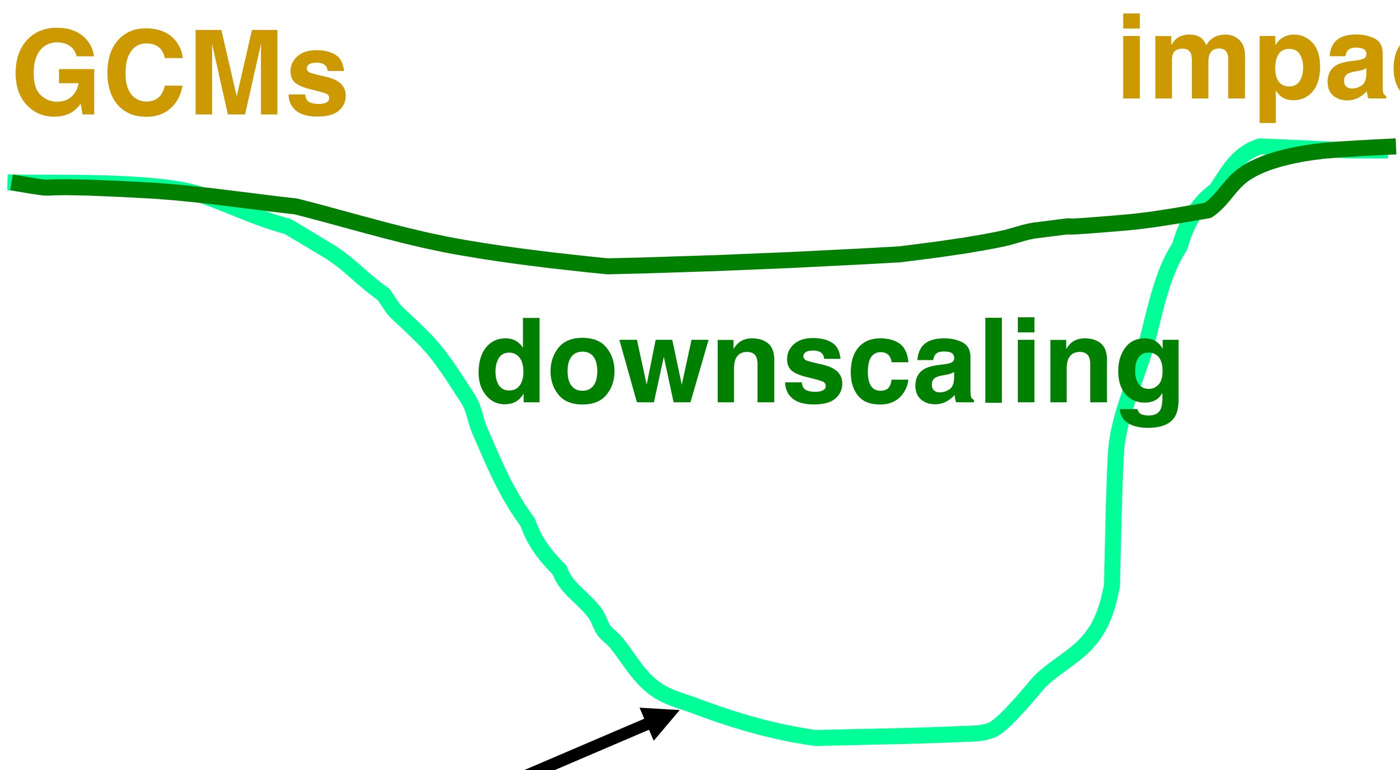
- Most GCMs neither incorporate nor provide information on scales smaller than a few hundred kilometers. The effective size or scale of the ecosystem on which climatic impacts actually occur is usually much smaller than this. We are therefore faced with the problem of estimating climate changes on a local scale from the essentially large-scale results of a GCM.”

- “One major problem faced in applying GCM projections to regional impact assessments is the coarse spatial scale of the estimates.”

- „downscaling techniques are commonly used to address the scale mismatch between coarse resolution GCMs … and the local catchment scales required for … hydrologic modeling“

Downscaling

- Bridge mismatch of spatial scale between the scale of global climate models and the resolution needed for impacts assessment



End user needs

Depending on the actual application, the end user needs a reliable representation of

- event intensities
- temporal variability and time scales
- spatial coherence and event size
- physical consistency

In many cases, these are required for climate change scenarios.

Maraun et al., Rev. Geophys., 2010

RCMs and SD

- RCMs and SD improve the spatial detail of simulated climate compared to General Circulation Models (GCMs). RCMs driven by observed boundary conditions show area-averaged temperature biases generally within 2ºC and precipitation biases within 30%-50% of observations. Statistical downscaling demonstrates similar performance, although greatly depending on the methodological implementation and application.

DOWNSCALING – approaches

- dynamical (regional climate models)
- statistical
  - “in a narrow sense”
  - stochastic models – weather generators etc.

Statistical downscaling vs RCMs

- comparable performance
- + of statistical downscaling:
  - computationally simple
  - provides local information
- + of RCMs:
  - physical consistency among variables

Statistical downscaling vs RCMs

- not competing, but complementary techniques
- both have caveats that are frequently
  - not admitted
  - not reconciled

statist. downscaling: **HISTORY**

- beginnings: 1950’s
- weather prediction
- NWP in similar state to present climate modelling – unable to provide regional / local details
- ‘specification’ of sfc. weather from large-scale circulation
- pioneering work by W.H. Klein

statist. downscaling: **HISTORY**

- 1st climate application: Kim et al. (1984)
- ‘climate inversion’
- since ~1990 a boom ← need for a local climate change information

statist. downscaling: BASICS

- statistical relationships
  - large scale / free atmosphere variables

    x

  - regional / local scale surface variables
- identified in real world (observed data)
- applied to model world (control + perturbed GCM simulations)

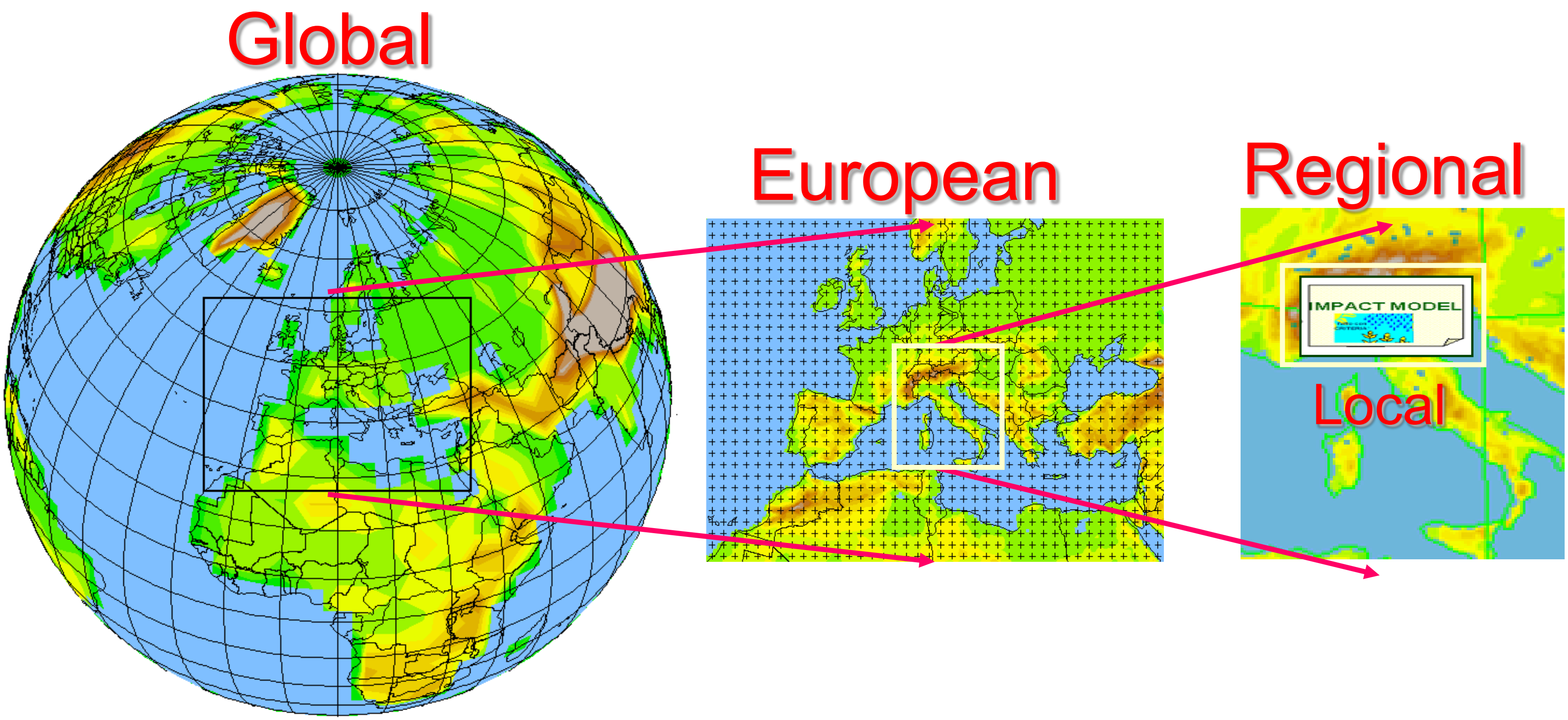
statist. downscaling: **ASSUMPTIONS**

- SD makes sense if local climate variable (predictand) is simulated incorrectly by a GCM
- There is a strong correlation between local climate and large scale parameter (predictand/predictor relationship)
- AOGCMs simulate well large scale parameter (predictors)

statist. downscaling: **ASSUMPTIONS**

- predictor simulated successfully by GCM
- predictor explains large enough portion of predictand's variance
- predictor x predictand relationship is constant in time
- predictor x predictand relationship holds in future climate

Climate regionalization (or downscaling): from global scale to local scale



statist. downscaling: **PREDICTANDS**

- commonly downscaled variables:
  temperature, precipitation amount
- others:
  cloudiness, sunshine duration, cloud ceiling height, humidity variables, sea level, snow cover, wind speed & direction, precipitation probability, extreme values & various distributional characteristics,…

statist. downscaling: **PREDICTANDS**

- spatial resolution
  - station (site-specific)
  - well defined area (river basin)
  - gridbox (of various size)
    - more successful (← reduced variability by spatial averaging)
    - ‘incomplete’ downscaling

statist. downscaling: **TIME SCALES**

- daily → monthly → seasonal
- subdaily (hourly) – limited by data availability

statist. downscaling: **PREDICTORS**

- 3 basic approaches – may be combined
  - multiple variables at multiple levels at closest / a few close gridpoint(s)
  - same variable as predictand on a large-scale grid
  - one (a few) large-scale upper-air field(s)

statist. downscaling: **PREDICTORS**

- different predictands require different predictors
- frequently – preprocessing by PCA

statist. downscaling: **USE OF CLASSIFICATIONS**

- mean values attributed to each type
  - only works for circulation-induced changes
- frequency of types as a predictor for monthly / seasonal values
- stratification of data; downscaling performed in each type separately
  - improvement due to stratification not quantified yet ➔ invitation to almost closing presentation (Friday before noon)

statist. downscaling: **METHODS**

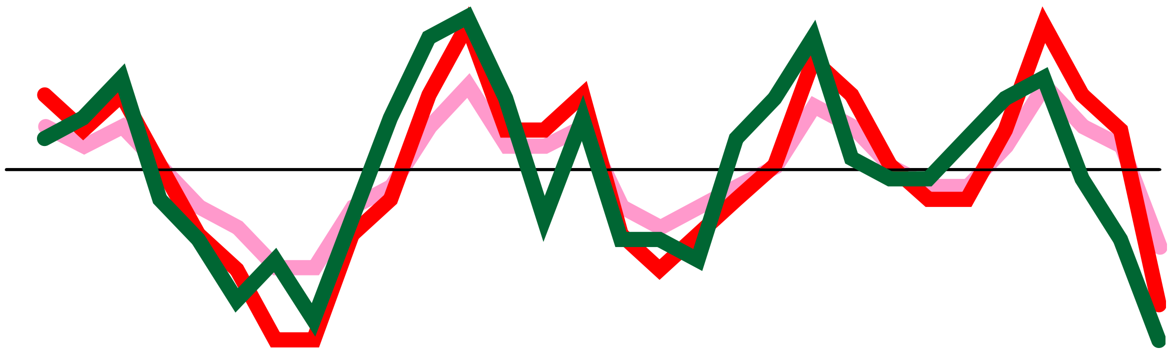
- linear – in large majority of studies
  - regression
  - canonical correlation / covariance (SVD) analysis
- nonlinear
  - esp. neural networks
  - are nonlinear methods superior? – not confirmed yet ➔ invitation to almost closing presentation (Friday before noon)

statist. downscaling:
REPRODUCTION of VARIANCE

- underestimated variance in downscaled data
- two ways of reproduction of variance
  - inflation (enhancement of anomalies by a constant factor)
    - physically questionable ← all forcing comes from large-scales
  - adding noise
    - white noise
    - regression residuals
    - noise with pre-specified statistical characteristics

statist. downscaling:

REPRODUCTION of VARIANCE



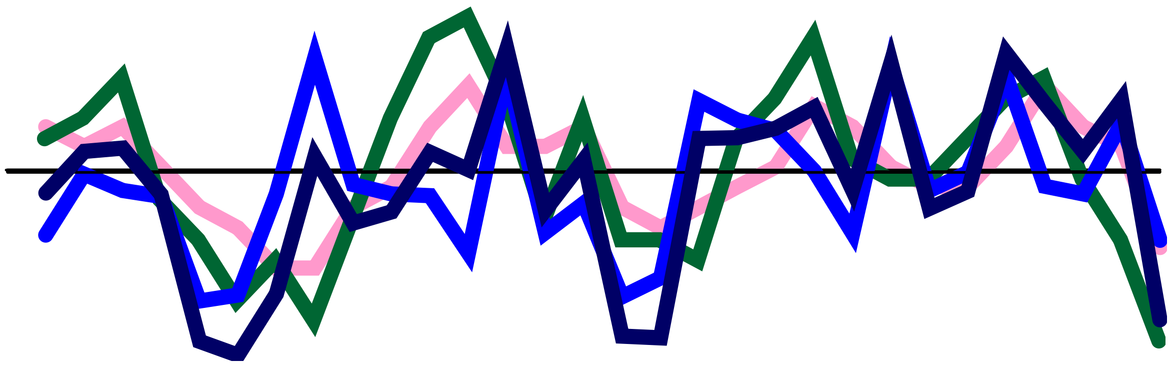
observed

downscaled: stddev = 58% obs

downscaled inflated

statist. downscaling:

REPRODUCTION of VARIANCE



observed

downscaled: stddev = 58% obs

white noise

downscaled with added white noise

statist. downscaling:

REPRODUCTION of VARIANCE

	obs	down	infl	added white n.
correlation with OBS	1.000	0.826	0.826	0.598
autocorrel.	0.587	0.619	0.619	0.305

statist. downscaling: **VALIDATION**

- majority of studies: only fit to observed data
  - rmse, correlation
- mean, std.deviation – easy to reproduce by definition (in most cases) – unnecessary to validate

statist. downscaling: **VALIDATION**

- seldom, but potentially important in various applications
  - higher-order statistical moments, extreme values, distribution tails
  - time structure
  - spatial structure
  - intervariable relationships
  - trends / contrasting climatic states

statist. downscaling: **EXAMPLE**

- 39 European stations
- DJF
- 1982/83 – 1989/90
- daily mean temperature
- cross-validation

SD: **EXAMPLE - rmse**

No. of PCs	Rmse stepwise regression
3	4.00
5	3.84
7	3.69
9	3.55
11	3.53
15	3.52
Pointwise	2.88

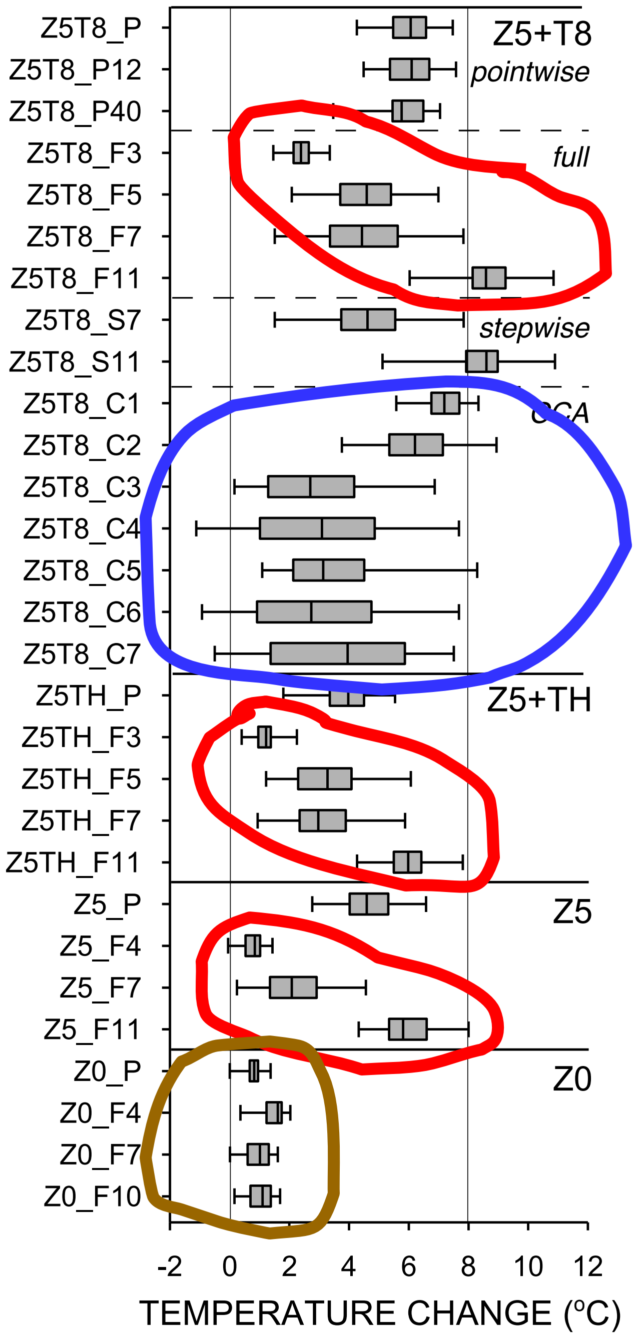
areal mean rmse in deg. C

regression of PCs

regression of gridpoints

statist. downscaling: **SCENARIO CONSTRUCTION**

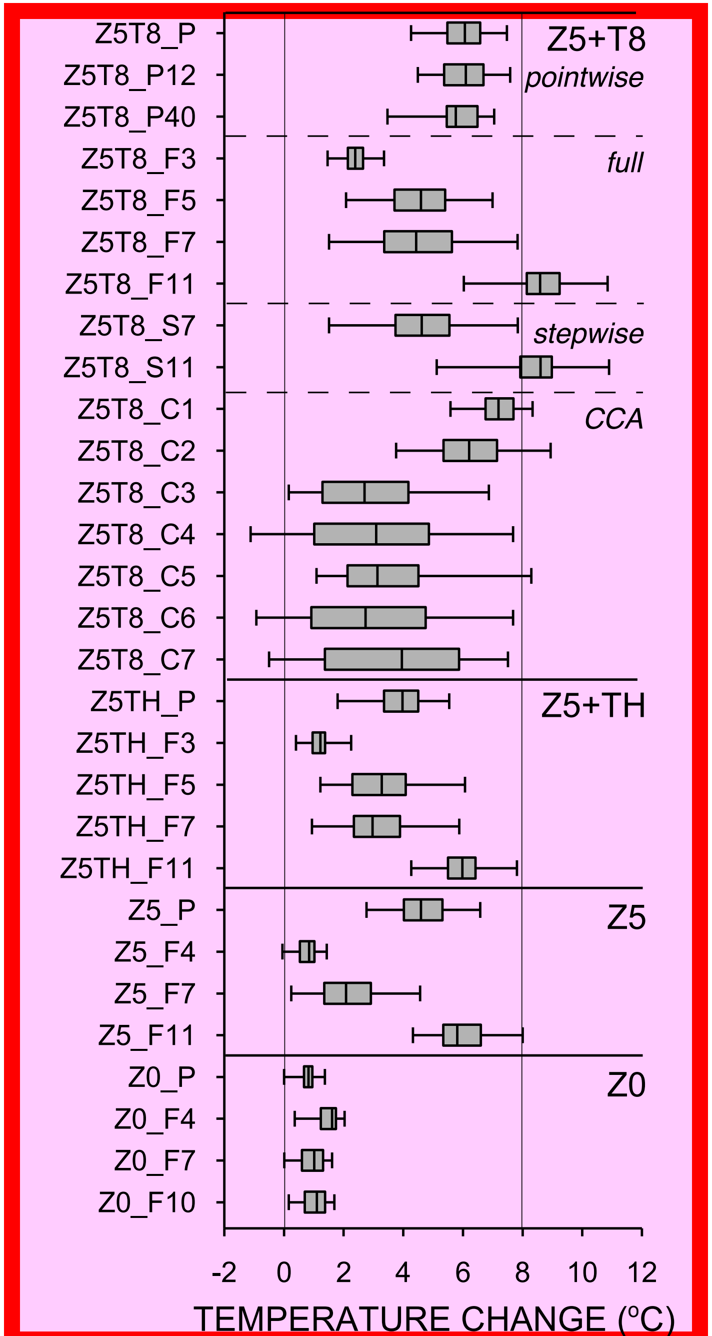
- observed relationships applied to perturbed GCM runs
- problem: extremely high sensitivity to
  - method
  - predictors
  - parameters (no. of PCs, canonical pairs,…)



dT increases with increasing number of PCs

dT changes with changing number of canonical pairs

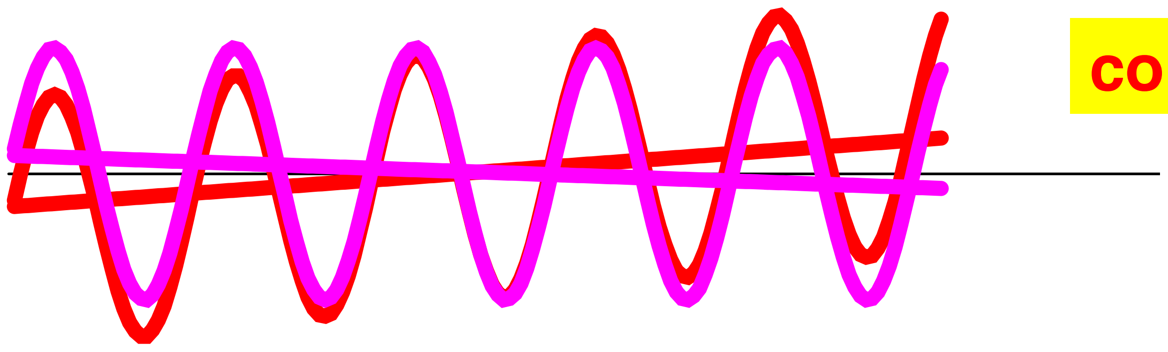
1000 hPa heights as only predictor lead to negligibly low dT



- all models are good in terms of rmse
- mean temperature change varies from +0.5 to +8.5 deg. C
- **so which model to prefer???**

WHICH MODEL?

- one clear fact: degree of fit with observed data (whatever measure is used) cannot be the only criterion!!!



corr = 0.95

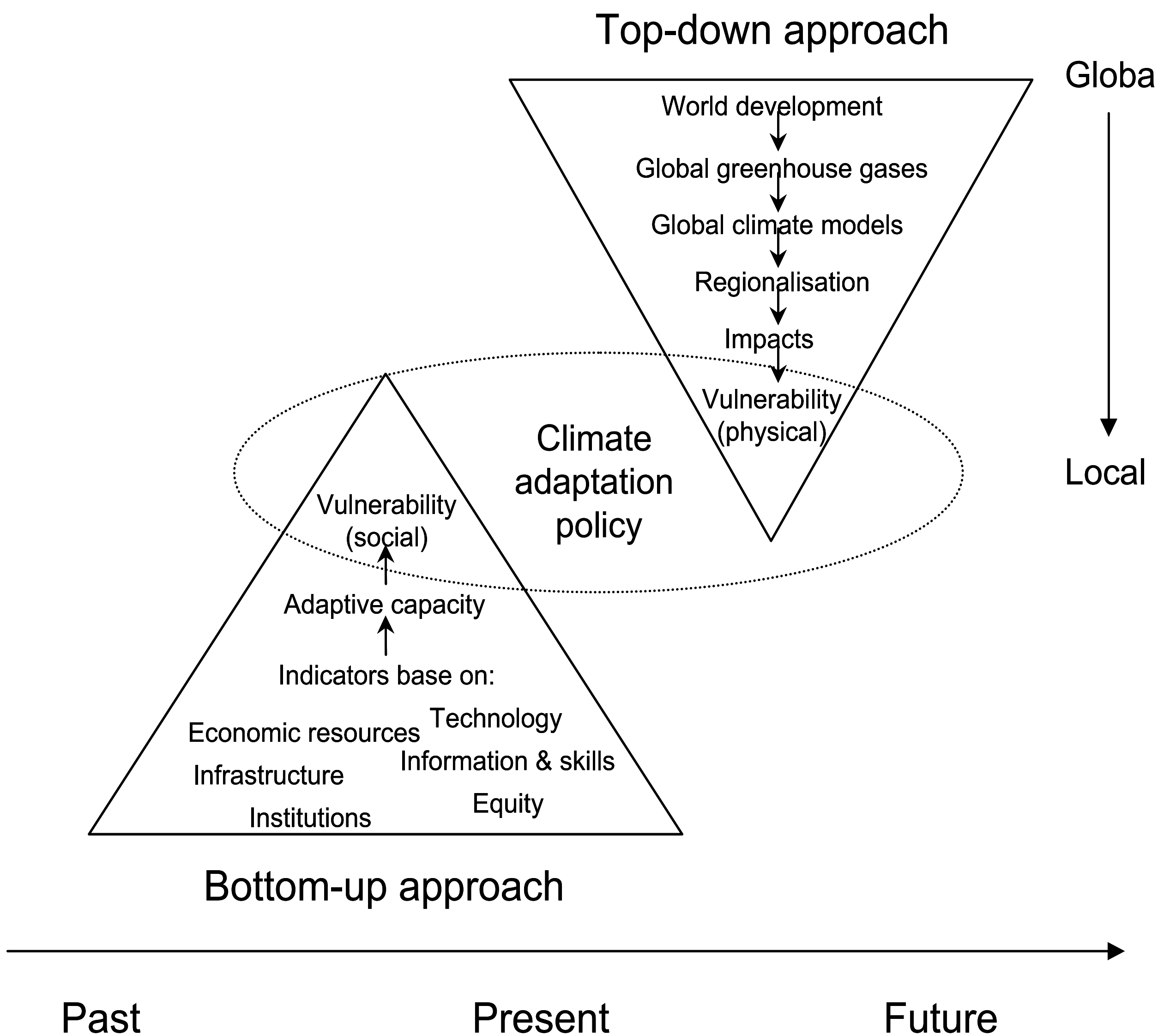
PRINCIPAL PROBLEM of statistical downscaling

- Models are fitted to variability on time scales much shorter than on which climatic change proceeds

PRINCIPAL PROBLEM of statistical downscaling

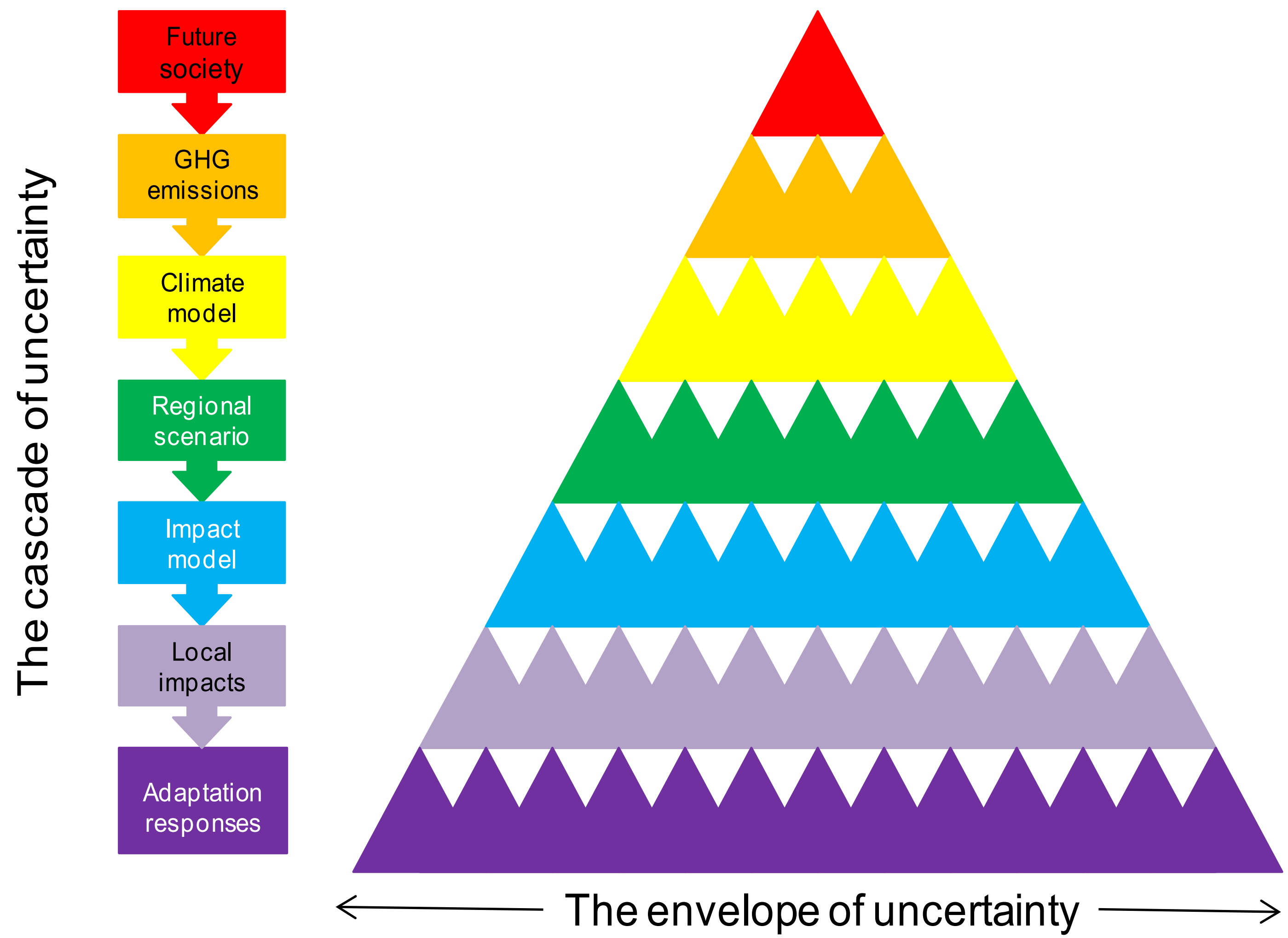
- possible REMEDY:
  - validate trends (but recent and future trends may result from different mechanisms!)
  - check ability to simulate contrasting climatic states (cold / warm; dry / wet years) (similar objection)
  - verify consistency with driving GCM (but GCM may be wrong!)

AOGCM→SD→Impact Study→Adaptation Policy



From: Dessai, S., and M. Hulme (2004), Does climate adaptation policy need probabilities?, *Climate Policy*, 4(2), 107-128.

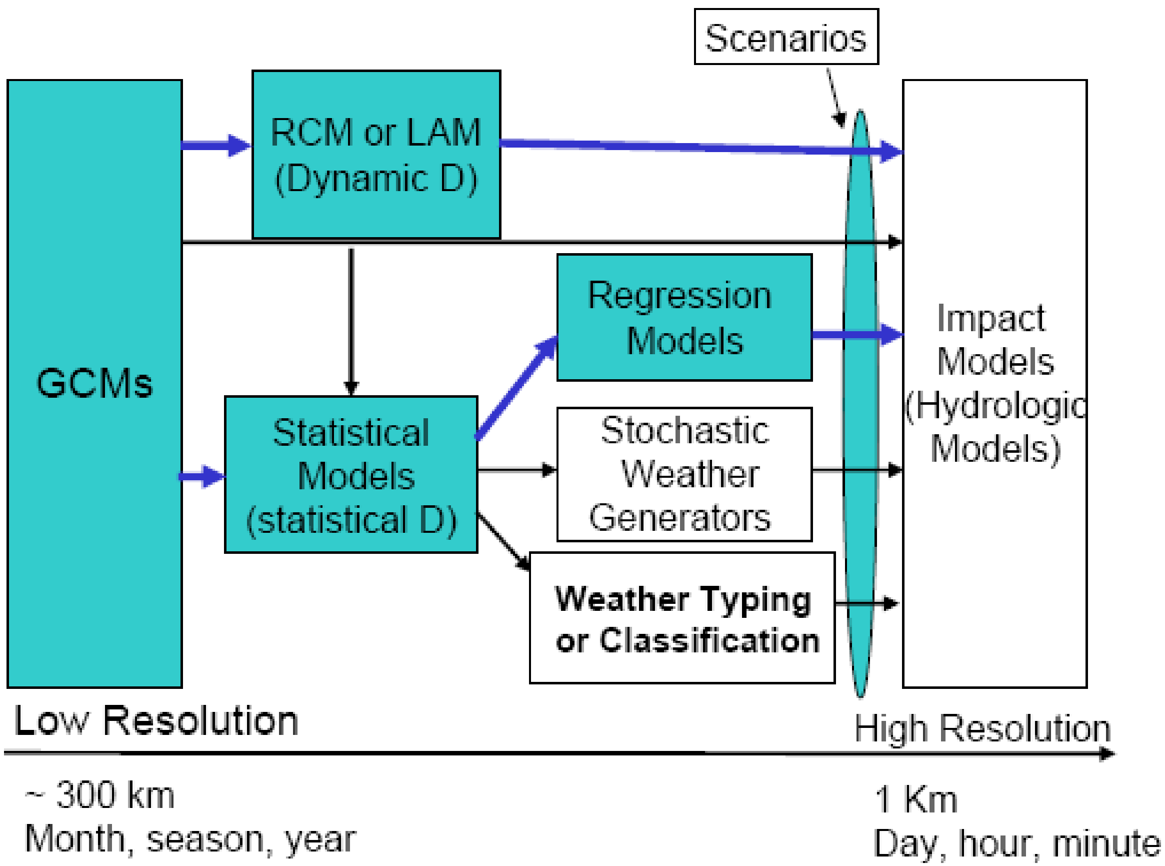
Warning !! We we have a chain of uncertainty to take into account...

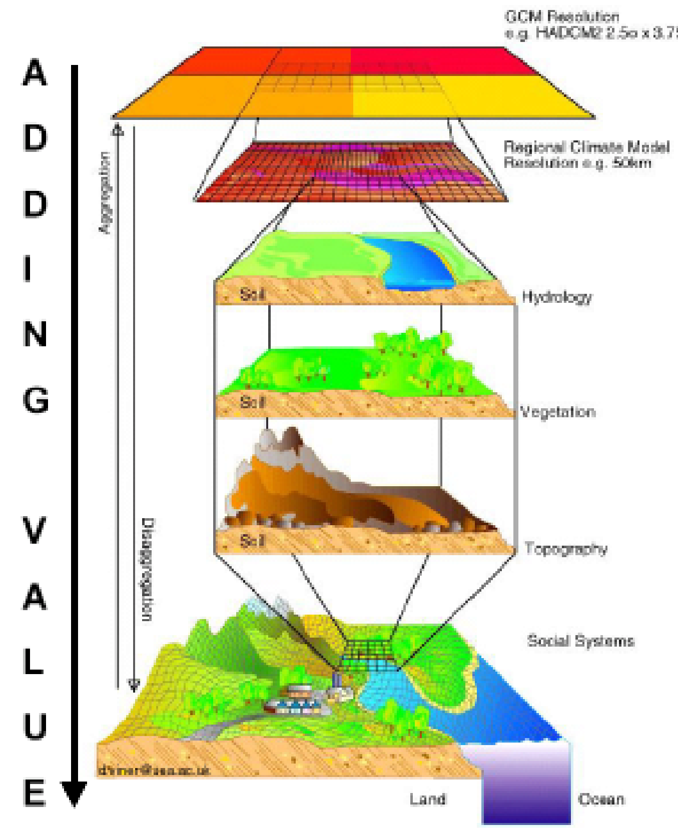


Downscaling methods:

⇒ Dynamical downscaling:
extracting local-scale information by developing and using regional climate models (RCMs) with the coarse GCM data used as boundary conditions.

⇒ **Statistical downscaling**:
« Parameterization » of local scale information (*Predictand*) from larger scale *Predictors*

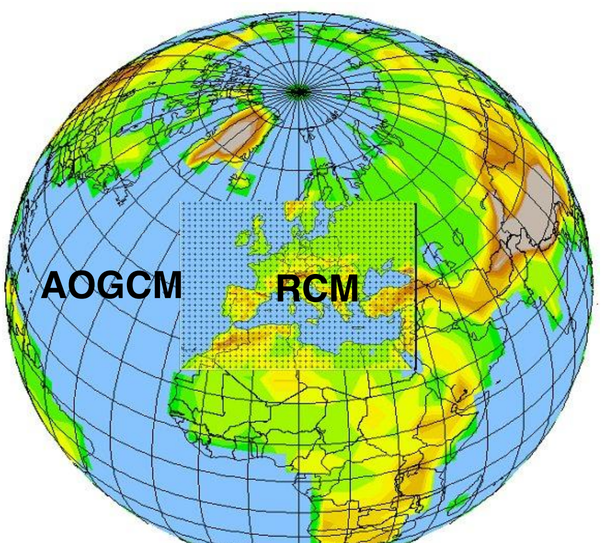




RCM and SD

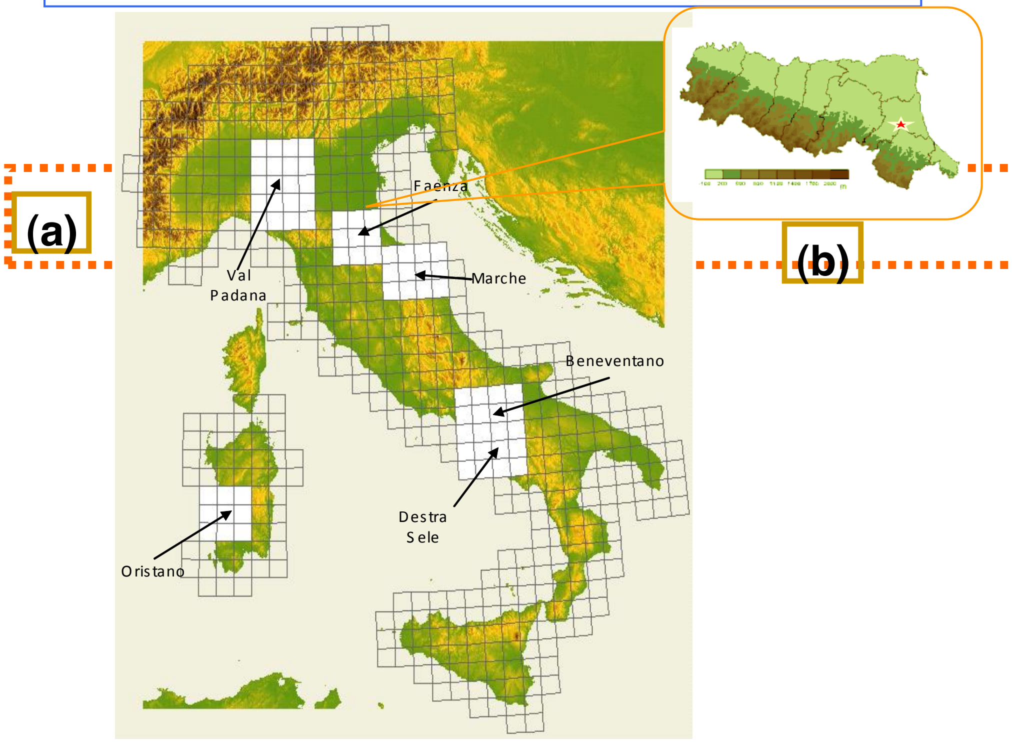
RCMs – High resolution numerical models nested in AOGCM (Dynamic *Downscaling*)

resolution 50 - 25 Km



Statistical Downscaling - SD

resolution: grid – point (**a**), station (**b**)



SD vs RCMs: " advantage " and " disadvantage "

Advantage

- get information at station level;
- used to derive variables not available from RCMs/GCM (frequency of extreme events);
- SD are computationally inexpensive.

Disadvantage

- SD need long and homogeneous observational time series for fitting and validating the statistical relationship.

SD methods

2 basic approach: linear and non-linear models.

Linear models:

- **simple/multiple regressions (Johansson and Chen, 2003; Hanssen-Bauer *et al*., 2003; Matulla *et al*., 2003; Huth,2004);**
- **canonical correlation analysis (CCA) (von Storch *et al*., 1993; Busuioc *et al*., 2008; Huth, 2004;**
- **singular-value decompositions (e.g. Huth, 2002; Widmann *et al*., 2003).**

Nonlinear models

- **weather classification/analogue method (Zorita and von Storch, 1999; Palutikof *et al*.,2002);**
- **neural networks/self-organizing maps (e.g. Trigo and Palutikof, 2001; Cavazos *et al*., 2002;**
- **weather generators/stochastic models (Palutikof *et al*., 2002; Busuioc and von Storch, 2003; Katz *et al*., 2003;.**

The basic idea

Mapping between a large (or larger) scale predictor X and the expected value of a local-scale predictand Y:

$$E(Y|X) = f(X, \beta)$$

β: vector of unknown parameters

Variability not explained by X can be modelled as noise η.

Observed X for calibration $\Rightarrow$ Perfect Prog (PP);
Modelled X for calibration $\Rightarrow$ Model Output Statistics (MOS).

Predictor Choice

Predictors are required to be

- informative
- stationary relationship with predictand
- capturing long term variability
- well represented by GCMs

Predictors need to capture

- atmospheric circulation (pressure fields, airflow indices, weather types)
- temperature
- moisture

Predictors are often transformed, e.g., by PCA, “physical” transformations or cluster analysis.

Charles et al., Clim. Res., 1999; Wilby et al., J. Hydrol., 1998; Wilby & Wigley, Int. J. Climatol., 2000; Maraun et al., Rev. Geophys., 2010

Linear Model

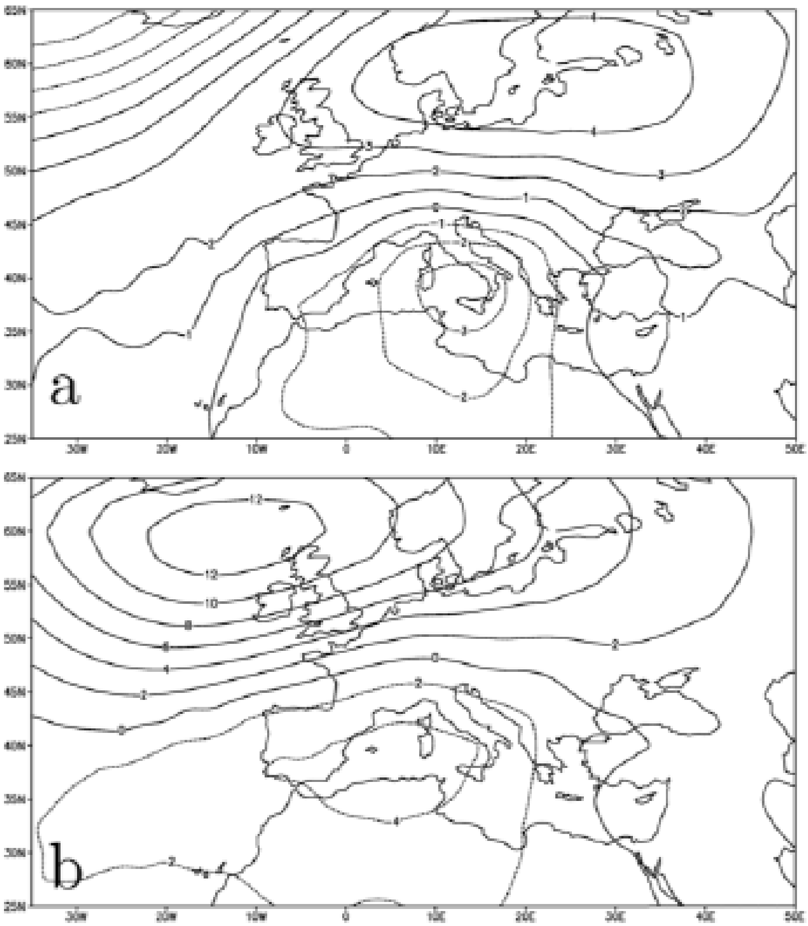
$$E(y_i) = \mu_i = \beta_0 + \sum_{k=1}^{K} \beta_k x_{i,k}$$

unexplained variability is modelled (here: added) by Gaussian noise;
x predictors, y predictands, K number of predictors.

Weather Types

$$\mu = \mu(x_k)$$

x_k categorical weather type,
$k = 1..K$, $K \ll N$
$\mu(x_k)$ mean rainfall



SLP patterns associated with extreme winter precipitation in the western Mediterranean;

Toreti et al., NHESS, 2010

Further Methods

Nonlinear Regression

- e.g., artificial neural networks (ANNs)

Analogue Method

- weather typing with N weather types

$$y_i = y(\text{analog}(x_i))$$

x_i weather situation at day i;
y_i downscaled precipitation at day i;
$y(\text{analog}(x_i))$ precipitation at analogue.

Work done at ARPA-SIMC

A) SD at ARPA-SIMC;

B) Statistical Downscaling Model (SDM) and data used:
- Calibration ;
- Validation (SDM skill);
- Evaluation of Uncertanties of SDM

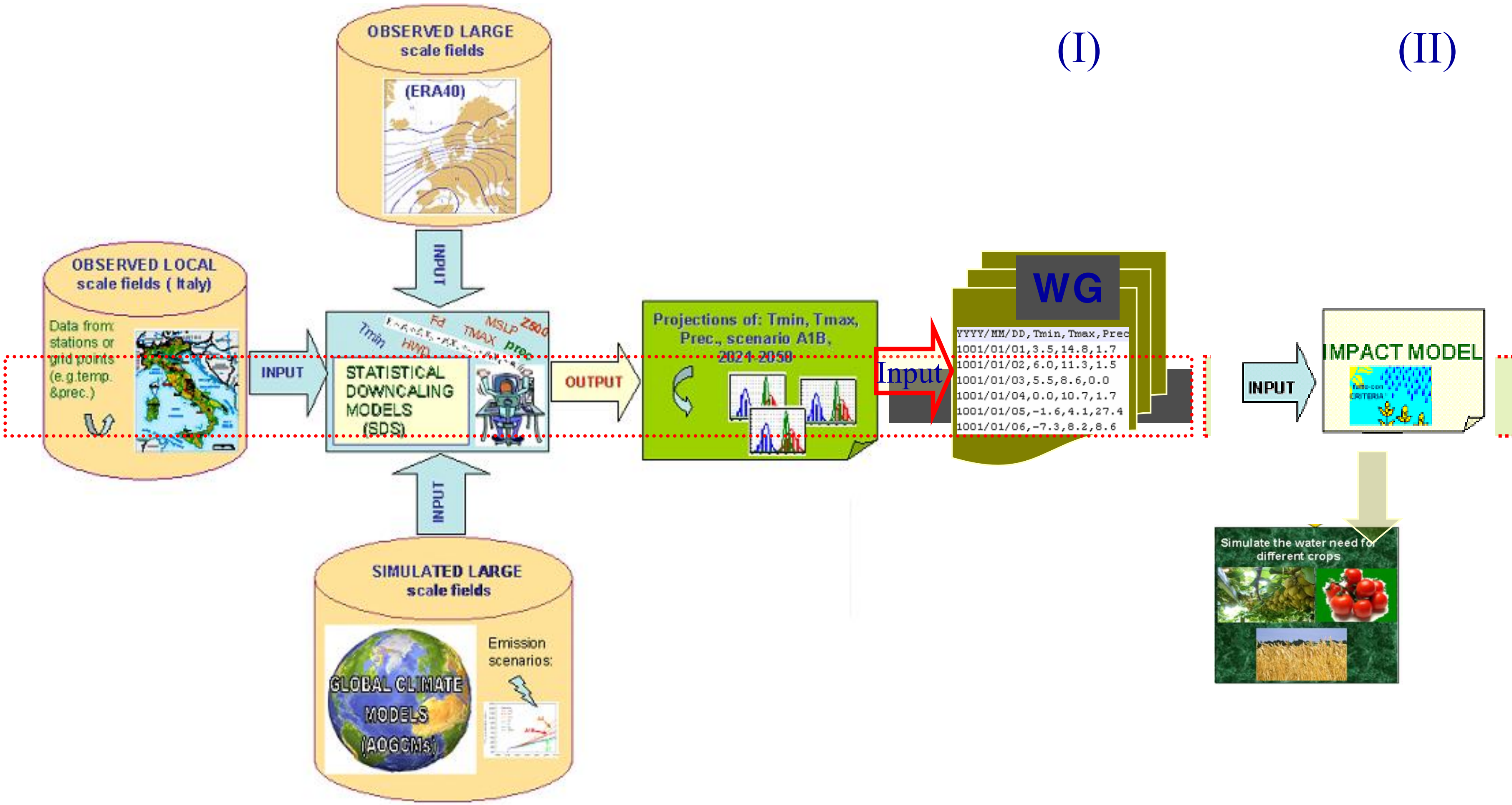
C) Climate Change of TMIN, TMAX and PRECIP over selected areas in Italy (Agroscenari results)
- Present climate;
- Climate change scenario for 2021-2050; ES: A1B

SD at ARPA-SIMC

At ARPA-SIMC we developed a SD technique since 2002 within:

- Stardex project - EU-fp5 http://www.cru.uea.ac.uk/projects/stardex/
- Ensembles project - EU fp6- http://www.ensembles-eu.org/
- CIRCE - EU- fp6 - http://www.cmcc.it/it/projects/circe-climate-change-and-impact-research-the-mediterranean-environment
- Agroscenari http://www.agroscenari.it/ - an Italian project funded by MiPaf finalyzed to study the impact of climate change and propose adaptation action in Agriculture

The SD scheme



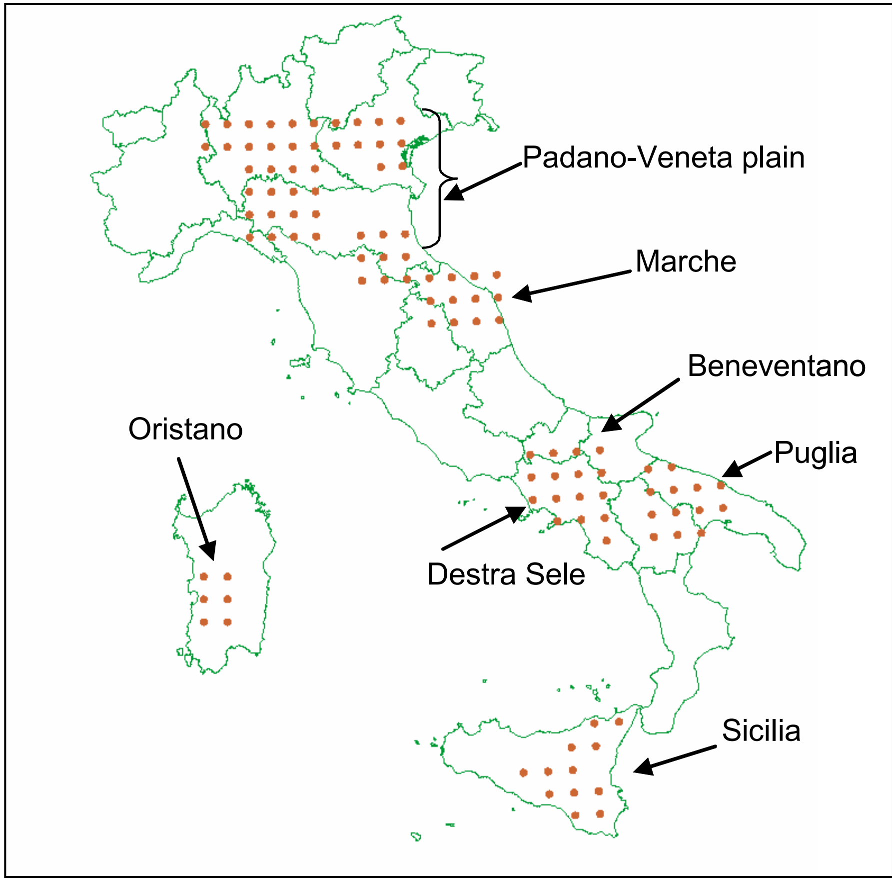
Activity performed

- Climate Change (CC) scenarios of seasonal Tmin, Tmax and Precipitation over different Italian areas, period 2021-2050 against 1961-1990 are assessed.
- Relevant impacts of CC on local agricultural practises are present in these areas (Padano-Veneta plain, Marche, Beneventano, Destra Sele, Oristano, Puglia and Sicilia).
- A SD technique is applied to ENSEMBLES global climate simulations (STREAM1), scenario A1B. The SD consists of a Multivariate Regression (MR) based on Canonical Correlation Analysis (CCAReg) constructed using large scale fields (predictors) derived from ERA40 ECMWF Reanalysis and seasonal Tmin, Tmax and Precipitation (predictands), derived from observed daily gridded data (resolution around 35km) belonging to CRA-CMA
- The observed period used to set-up the statistical downscaling scheme is 1958-2002. Once the most skilfull statistical downscaling scheme has been selected for each season and variables using ERA40, this is then applied to the predictors derived from the ENSEMBLES models experiments, A1B scenario, in order to construct climate change scenario at each grid point over 2021-2050 period

… Data-set (I)

Local Scale (Predictand)

- Tmin, Tmax,
- prec – daily data;
- Period: 1958-2002;
- Source: UCEA (CRA-MiPaf, 35Km grid spacing



(Agroscenari project)

… Data-set (II)

Large Scale (Predictor)

WINDOW: 90°W-90°E and 0°-90°N
Period: mid-1957 (September) to mid-2002 (August).

GCM simulations: ENSEMBLES model fields , archived in the Climate and Environmental Retrieval and Archive (CERA data base) of the World Data Center System for Climate (WDC) http://ensembles.wdc-climate.de.

STREAM1 simulations, (http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php.

Emission scenario: A1B

Control run: referred to 1961-1990, extracted from the historical simulation 1860-2000,

Scenario: referred to the periods: 2021-2050 and 2070-2099. Simulations produced by the following modelling groups have been analysed: INGV, NERSC, FUB, IPSL, METOHC (2 runs), MPIMET+DMI.

- Temperature 850hPa (T850)
- Mean sea level pressure(MSLP)
- Geop. height 500hPa (Z500)

Source:

- **ERA40** (re-analysis) 1958-2002 (http://www.ecmwf.int/products/)
- **AOGCMs :**

1. ***Ensembles*** (http://ensembles.wdc-climate.de)
2. ***Circe*** (http://www.circeproject.eu/)

Rationale the SD scheme I

SDs skill depends on predictors (type, domain, filtering of data) as well as on the predictands (quality of input data, filtering of data).

The skill analysis is done most commonly through “cross-validation” or “calibration-validation” with observed data.

The second method has been used in the present paper, namely calibration-validation. In order to do this the whole interval was divided into two homogeneous (including positive and negative anomalies) sub-intervals: 1958-1978 together with 1996-2002, and 1979-1995 which alternatively considered as fitting and validation.

Then, the most skilful model has been retained in order to construct climate change projections at station level. The skill of the downscaling model is quantified at grid point level in terms of Spearman rank-correlation coefficient, BIAS, root-mean square-error (RMSE).

Rationale the SD scheme II

Need to choice the BEST predictors and a strong, stable and physically meaningful predictor-predictand relationships (ERA40 reanalysis);

How to do that ?

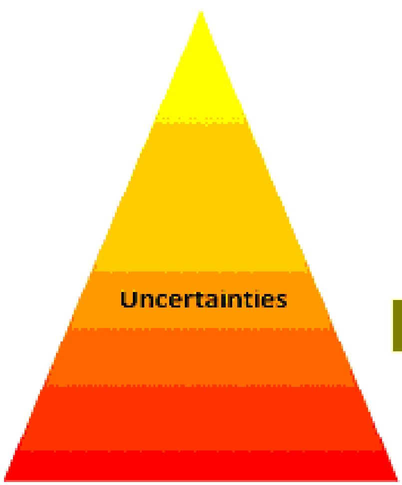
Testing different domains and predictors

Testing different number of EOFs in CCA

Construction of the SDMs on different period (i.e.inverse the period of validation/calibration; cross validation & jacknife tech.etc...)

....

Uncertainty: how to manage it ?



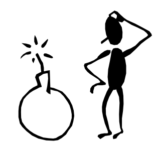
a) GLOBAL EMISSION SCENARIO

b) GENERAL CIRCULATION MODELS

c) STATISTICAL DOWNSCALING MODELS

d) IMPACT MODELS

solutions?



Use of many models

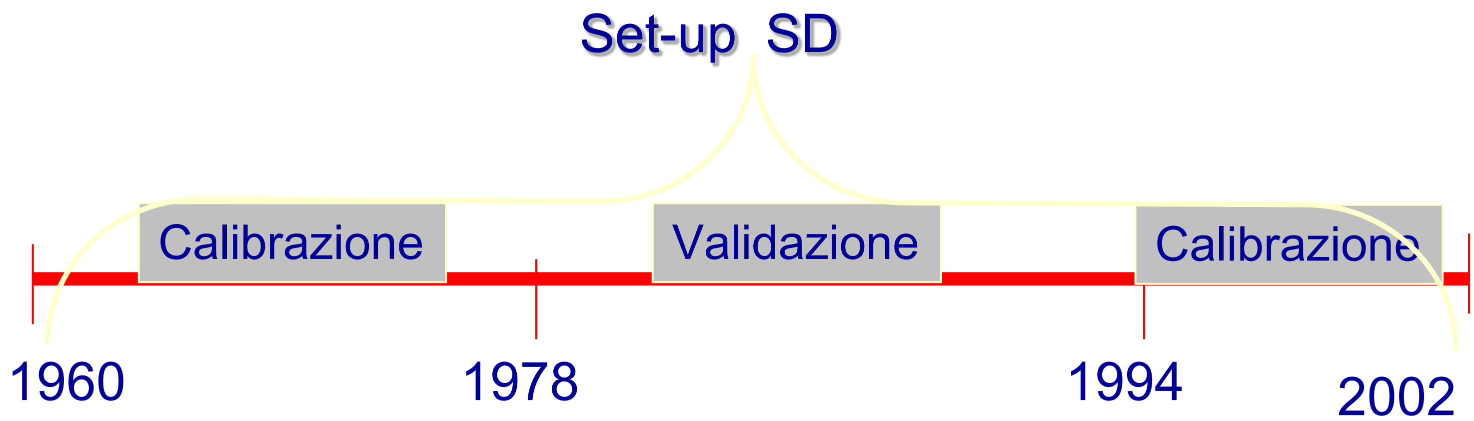
EM and PDF

Predictors – Circulation indices deduced by ERA40 and AOGCMs – Uncertainty due to different AOGCM

Ensembles project – (STREAM 1)	INSTITUTIONS	Resolution	AGCM	OGCM
FUB-EGMAM	Freie Universitaet Berlin(Germany)	3.75°×3.75°	ECHAM4 (T30L39)	HOPE-G (T42 with equatorial refinement, L20)
METO-HC (HADGEM1)	Met Office's Hadley Centre (UK)	1.875°×1.875°	HadGAM1(includes land and river routing components)	HadGOM1(includes sea ice components)
IPSL-CM4	Inst.Pierre Somon Laplace (France)	3.75°×3.75°	LMDZ (96x72x19)	OPA8.2
ECHAM5 MPI OM	Max-Planck Institute(Germany)	1.875°×1.875°	ECHAM5.2.02 (T63L31)	MPI-OM Vers. 1.0 (GR1.5L40)
INGV-SINTEX-G	INGV-Italy	1.125°×1.125°	ECHAM4 (T106L19)	OPA 8.2

CIRCE model	Componente atmosferica		Componente globale oceanica		Mar Mediterraneo	
	modello	risoluzione	modello	risoluzione	modello	risoluzione
CMCC – Med (INGV)	ECHAM	T159 (~ 80km) 31 livelli verticali	OPA8.2	~ 2°x2° con affinamento all'equatore 31 livelli verticali	MFS	1/16° (~ 7Km) 71 livelli verticali

➤ Emission Scenario: A1B

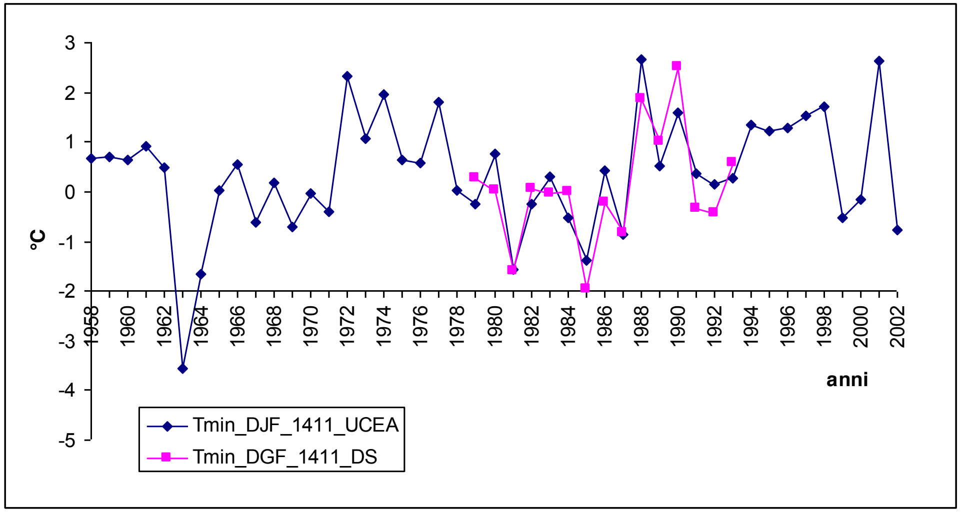


skill - SDs

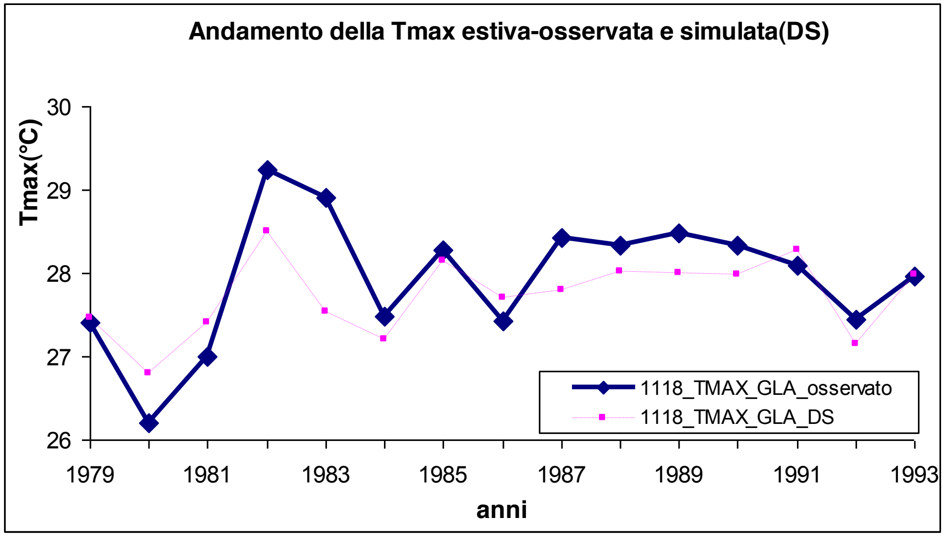
- correlation coefficient (Spearman coefficient)- R_s;
- BIAS= $\langle index_{model} \rangle_{verification} - \langle index_{obs} \rangle_{verification}$
- RMSE= $\sqrt{\frac{1}{N} \sum_{i \in verification period} \left[index_{model}(i) - index_{obs}(i) - BIAS \right]^2}$

… skill SDM (fase di validazione)…

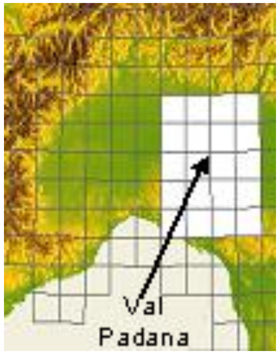
Confronto tra il valore osservato e output SDM-
punto di griglia 1411 (Val Padana)



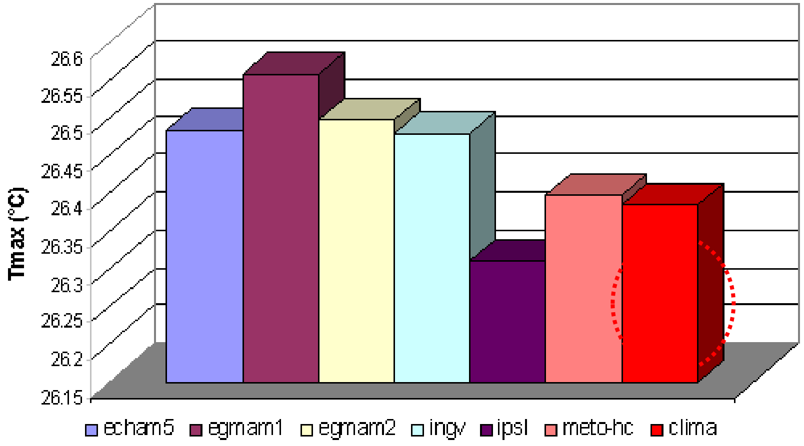
Confronto tra il valore osservato e output SDM-
punto di griglia 1118 (Oristano)



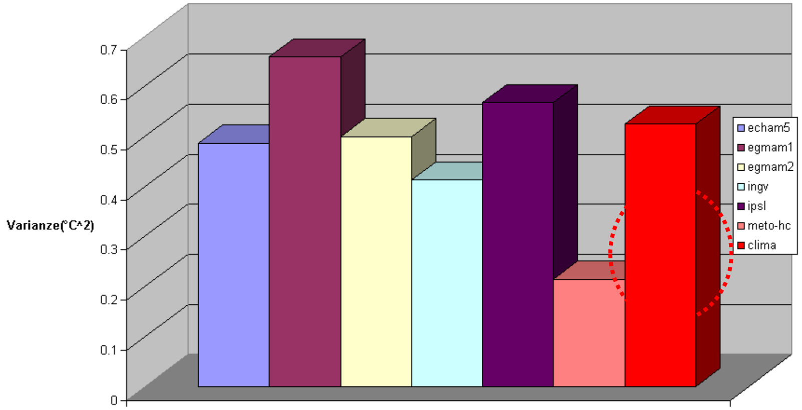
Comparison obs-mod Tmax summer Po Valley (average over all grid points)



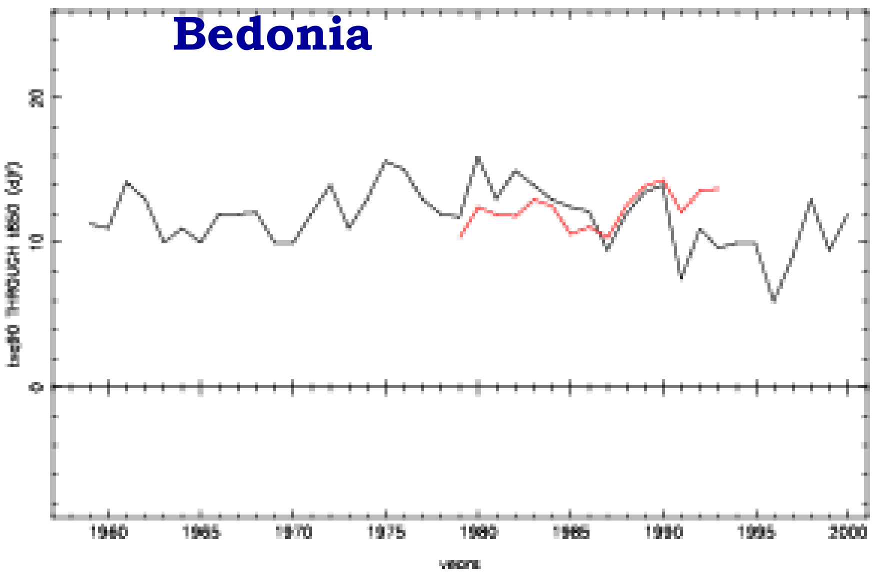
Mean (1961-1990)

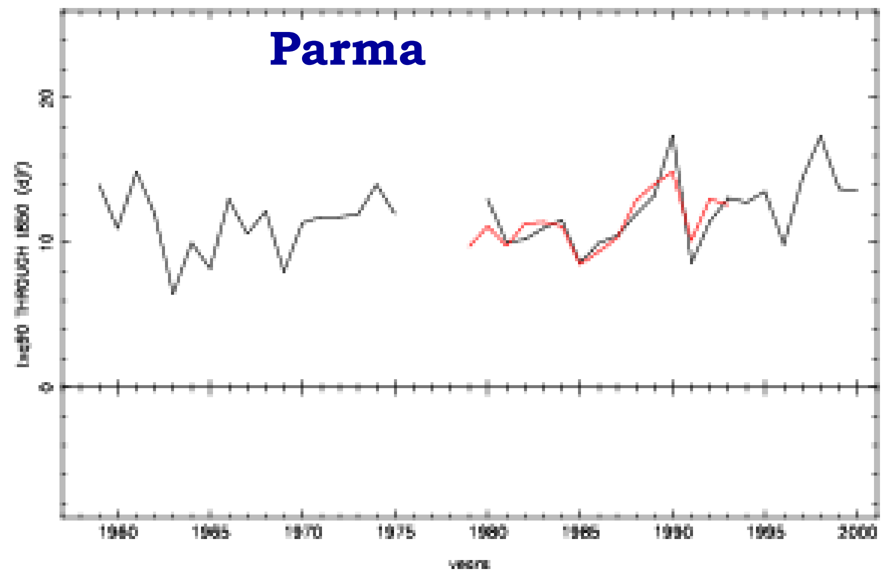


Variance (1961-1990)



Nota: Good reproduction of mean values, under and over reproduction of variance


Bedonia
0
10
20
1960
1965
1970
1975
1980
1985
1990
1995
2000
years


Parma
0
10
20
1960
1965
1970
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1980
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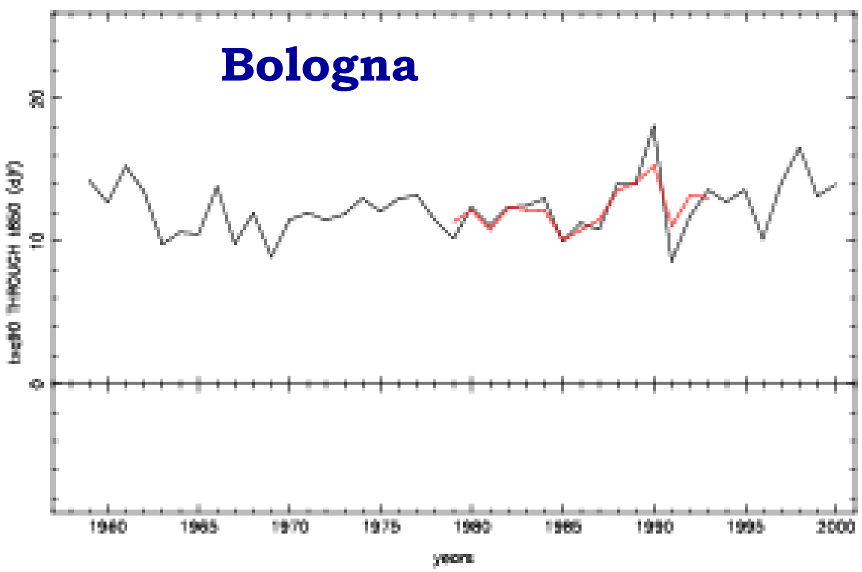
2000
years


Bologna
0
10
20
1960
1965
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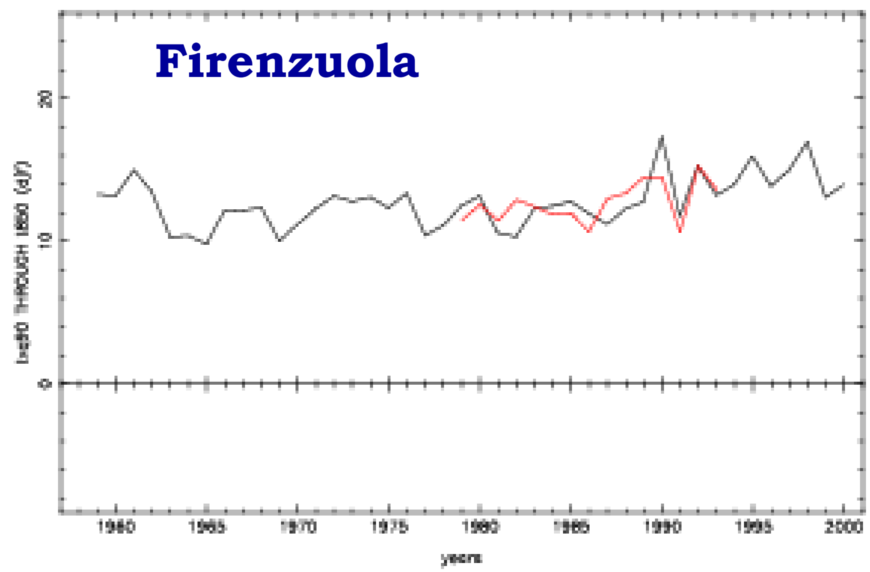
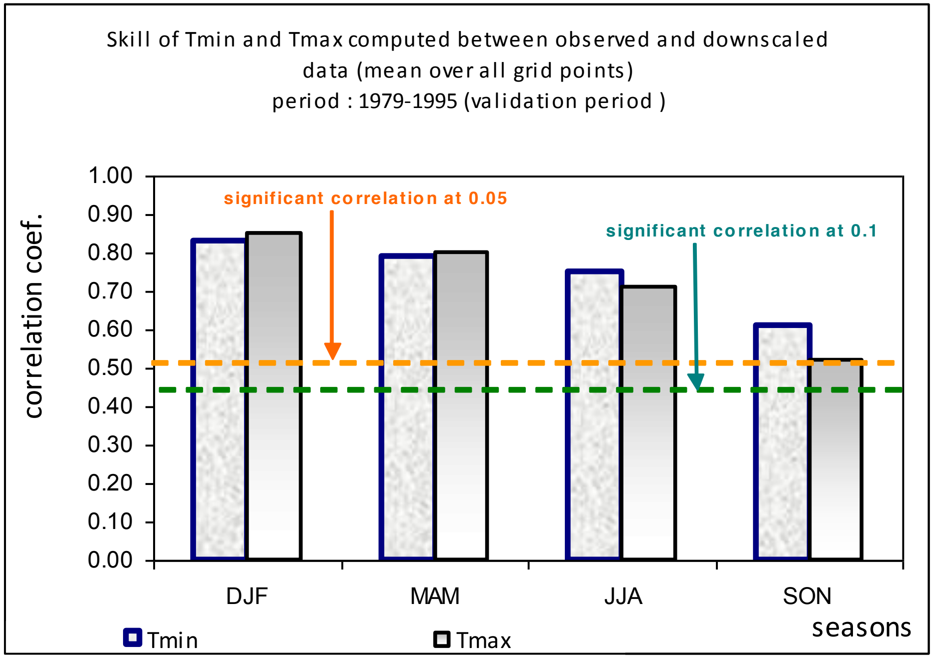
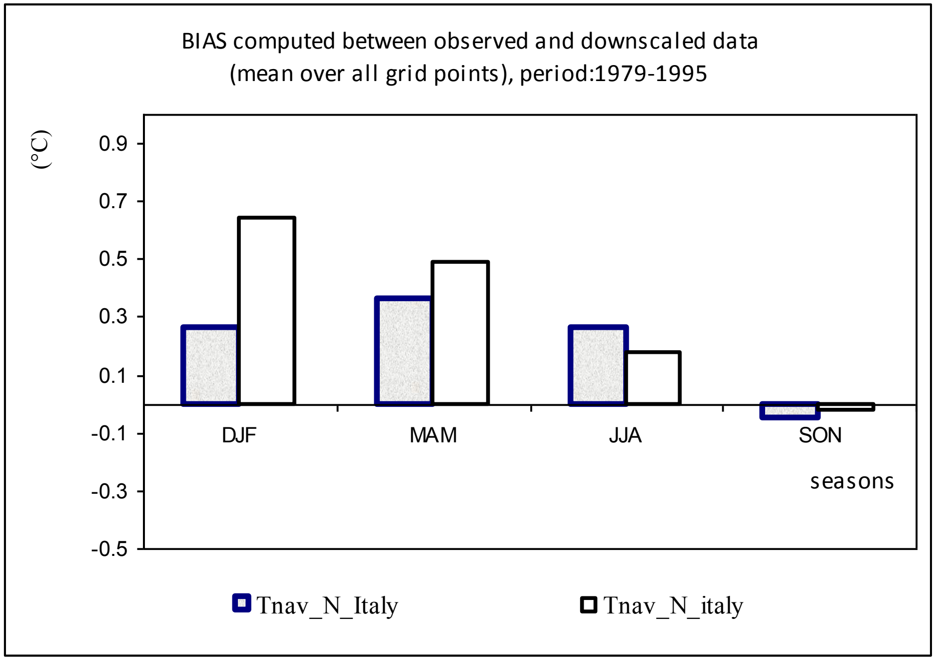
years


Firenzuola
0
10
20
1960
1965
1970
1975
1980
1985
1990
1995
2000
years

Selection of predictors and results from validation





Best predictors selected taking into account different indices of performance: BIAS, RMSE and rank correlation as indices of performance.

T850 is the best predictor for minimum and maximum temperature,
MSLP is in generally the best predictor for cumulated precipitation.

Good performances obtained for both minimum and maximum temperatures during all seasons. Regarding precipitation good performances are obtained during winter and autumn seasons, while during spring and summer the performance is smaller.

Scenario results

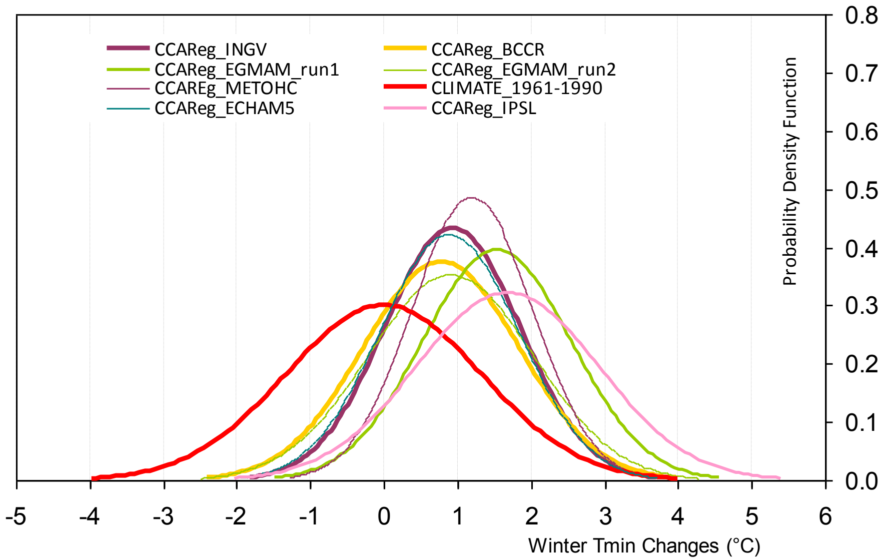
The SD technique have been then applied to the predictors simulated by the GCMs to construct future projections at local scale.

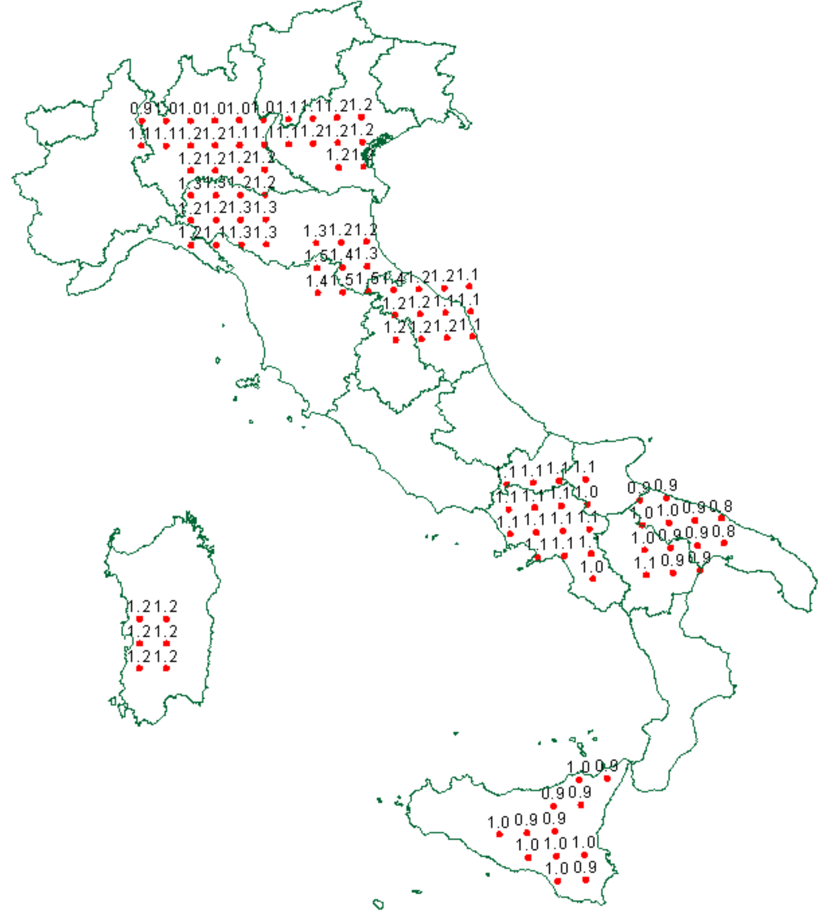
Results presented also as Probability Density Function (PDF) or maps of changes, constructed for each model or for the Ensemble Mean (EM). In this way an information concerning uncertainty is available

Temperature (min & max): Possible increase over all analysed areas, in all seasons, during the period 2021-2050 with respect to 1961-1990.

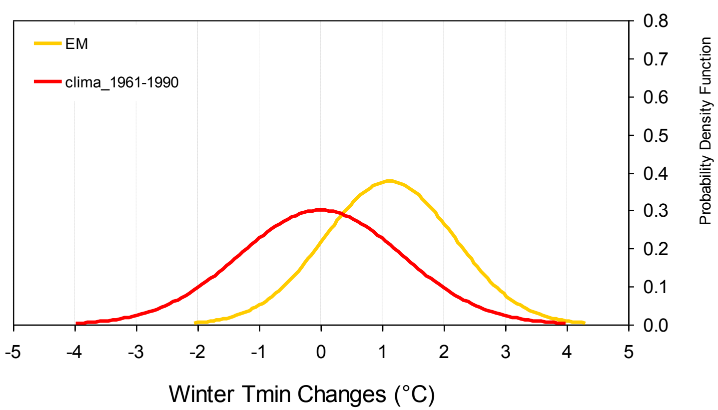
Scenario results

Scenario A1B (2021:2050 -1961:1990)





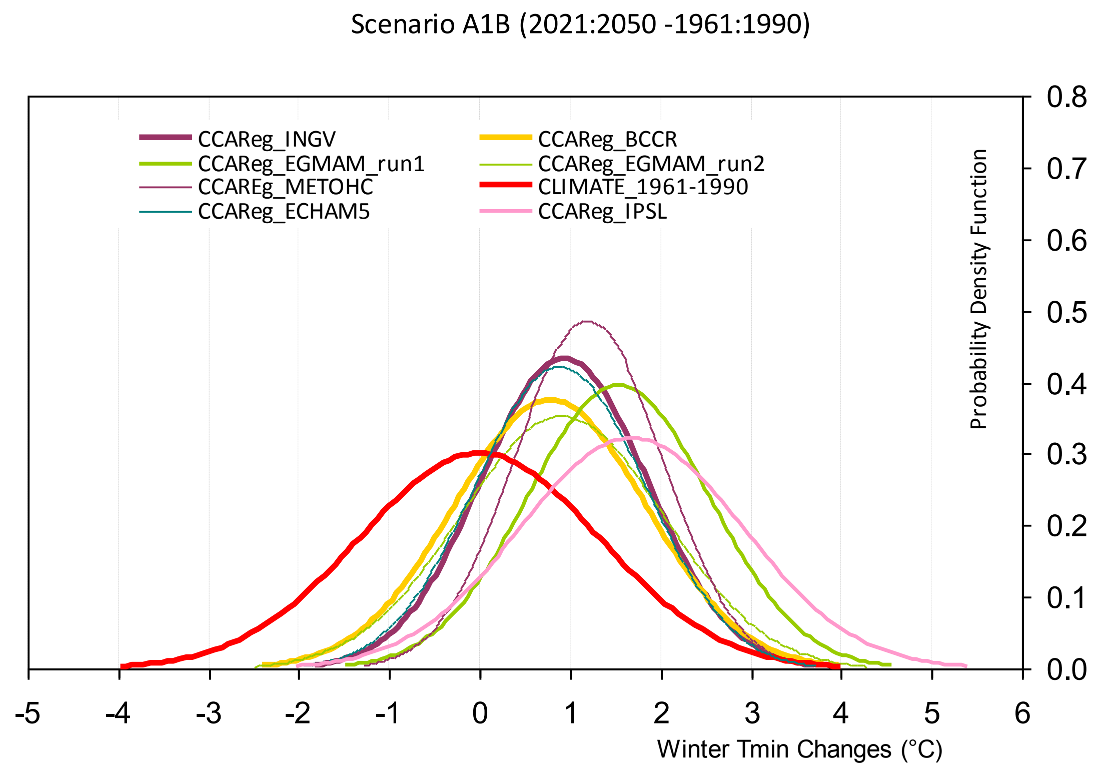
Scenario A1B (2021:2050-1961:1990)
Ensemble Mean



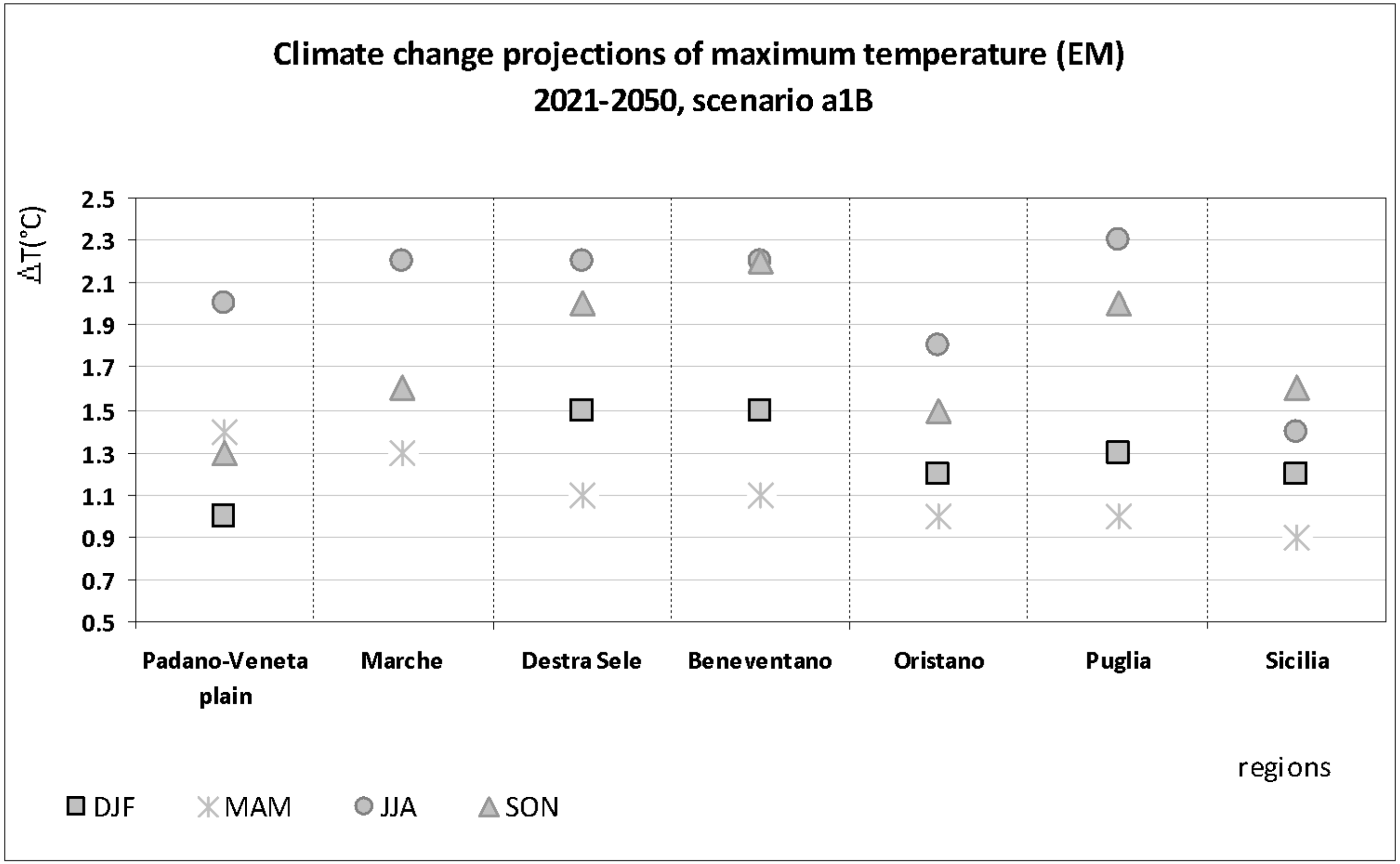
PDFs of changes Tmin (mean over all grid points, all GCMs and EnsMean) of winter Tmin changes. All models show an increase in winter minimum temperature over Italian areas from 0.8°C to 1.5 °C (CCAReg applied to ECHAM5, INGV, EGMAM run1 and IPSL models). Possible increase not only in the mean values but also in the tails of the distributions, both lower and upper, for the period 2021-2050 with respect to 1961-1990. For the other seasons, the projected changes in minimum temperature emphasise a warming more pronounced during summer season, with an icrease of 2°C with respect to 1961-1990 period.

Projected changes (mean over all areas) and standard deviation of winter Tmin obtained by the SDs applied to different AOGCMs: period 2021-2050, scenario A1B

	INGV	BCCR	EGMAM_ Run1	EGMAM_ Run2	ECHAM5	METO_HC	IPSL	EM
ΔT(°C)	0.9	0.8	1.5	0.9	0.9	1.2	1.7	1.1
St. dev.	0.9	1.1	1	1	0.9	0.8	1.2	1.1

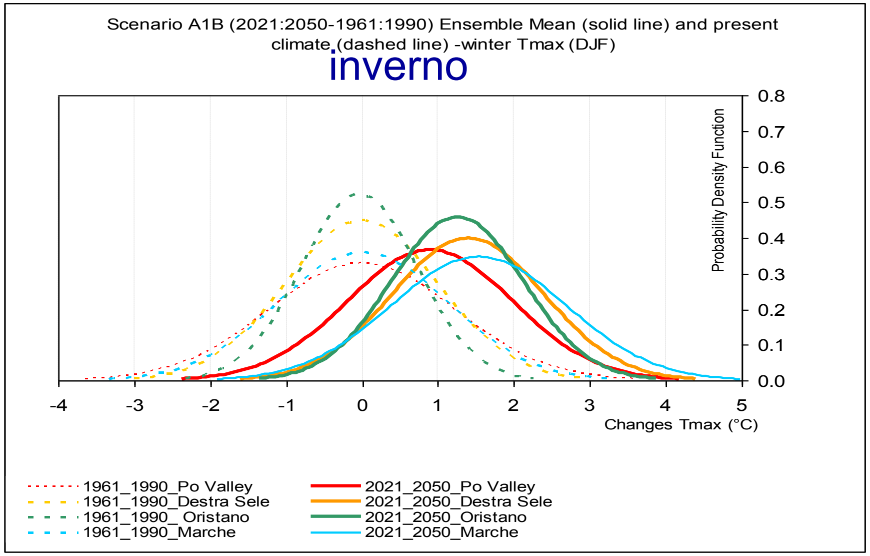


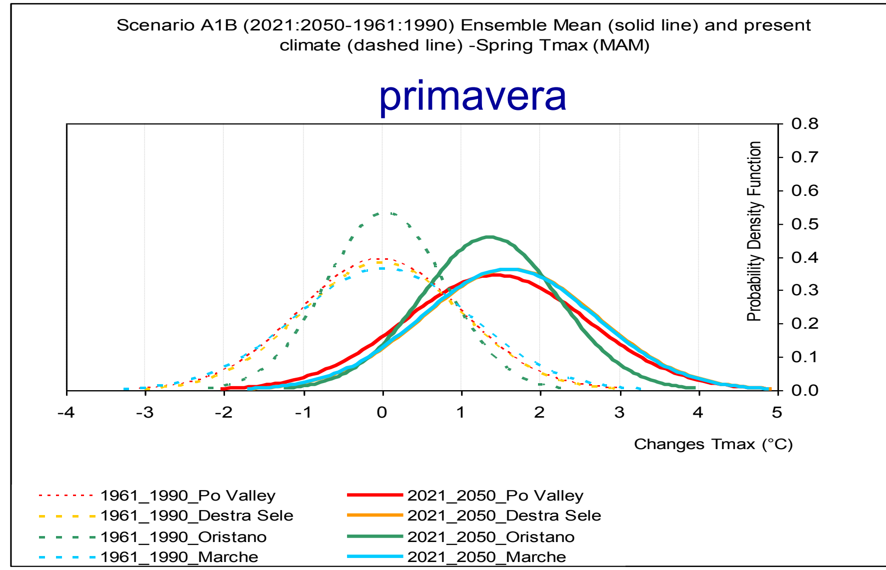
SD - Scenario results - Tmax

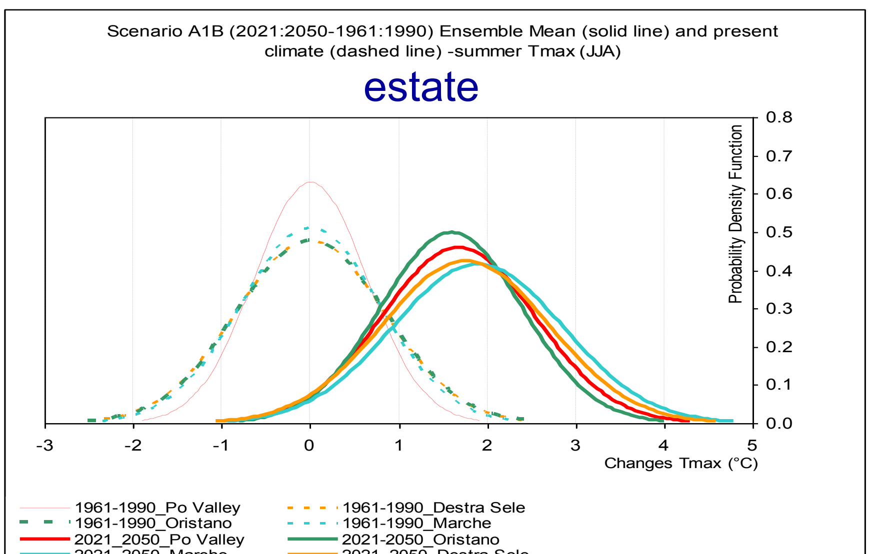


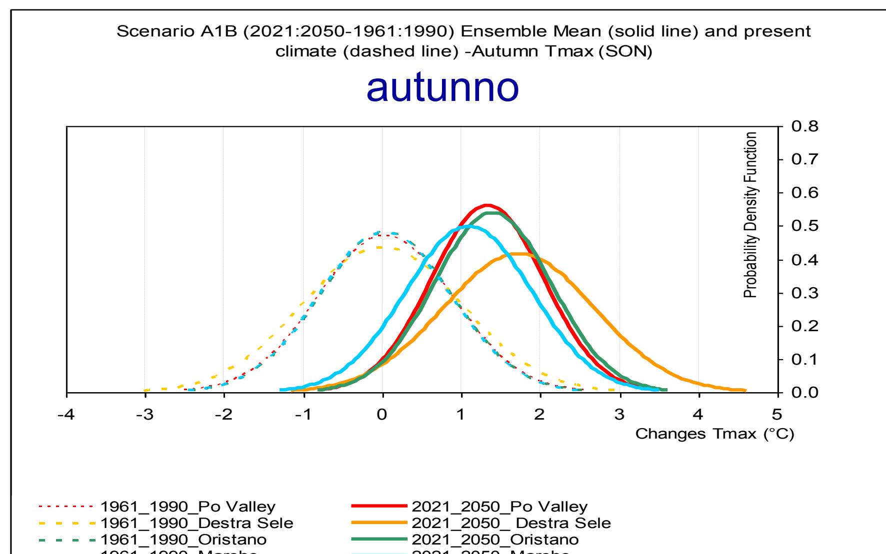
A similar signal of changes has been obtained for maximum temperature. The peak of changes is projected during summer (up to 2.3°C) followed be autumn (up to 2°C).

Cambiamenti Tmax (°C) – Ensemble Mean 2021-2050 rispetto al 1961-1990, scenario A1B (un punto di griglia per ogni area)

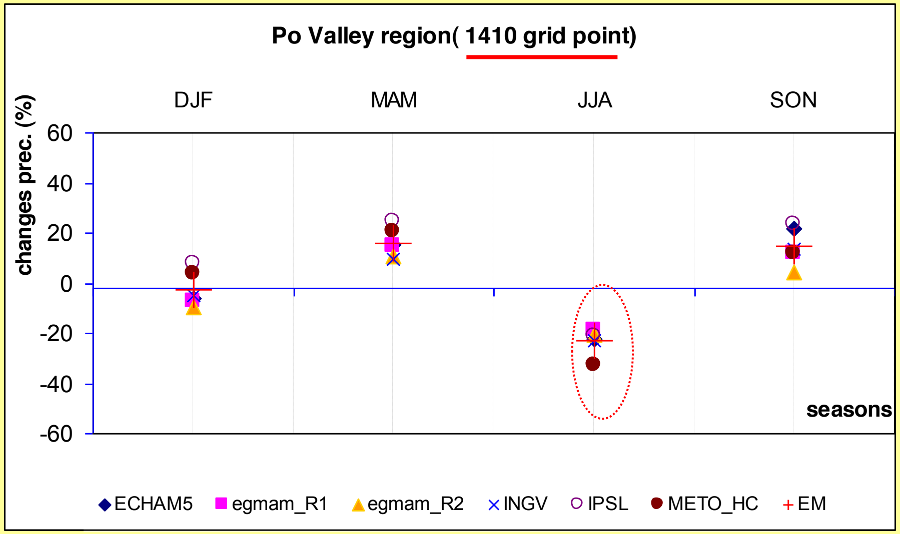


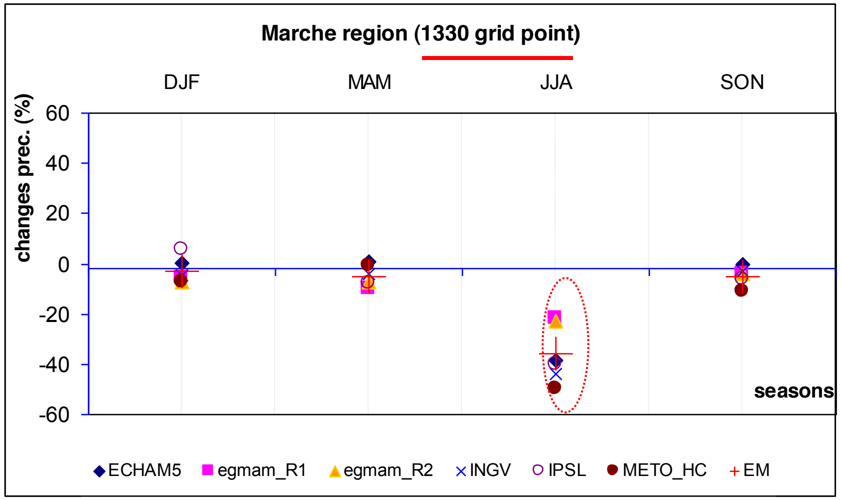


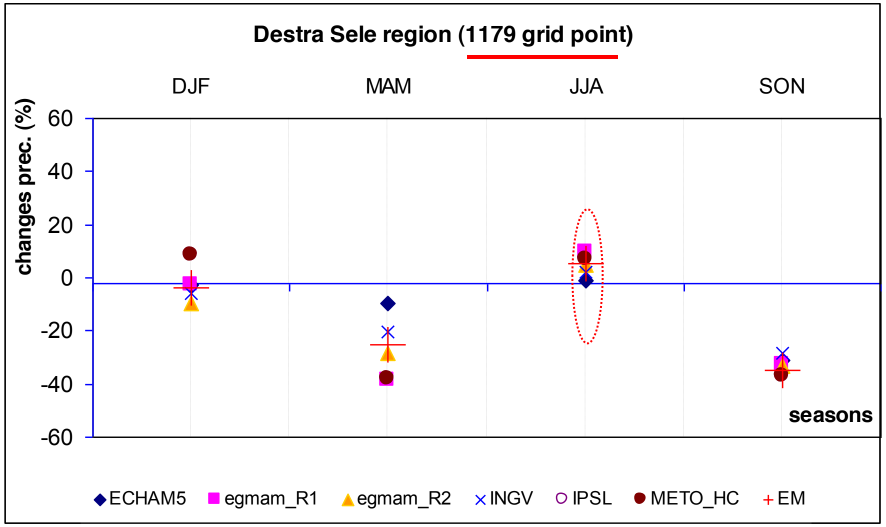


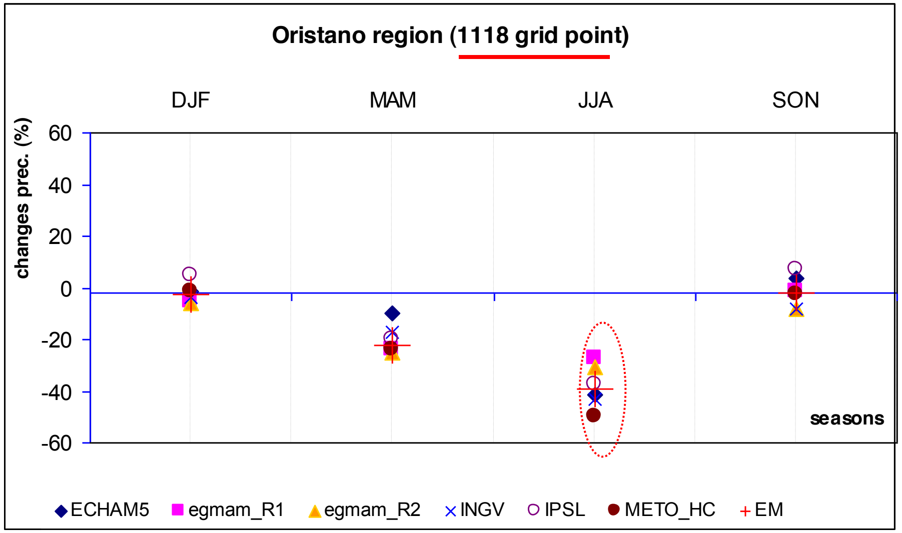


Scenari di cambiamento climatico – precipitazioni (%) 2021-2050 rispetto al 1961-1990, scenario A1B

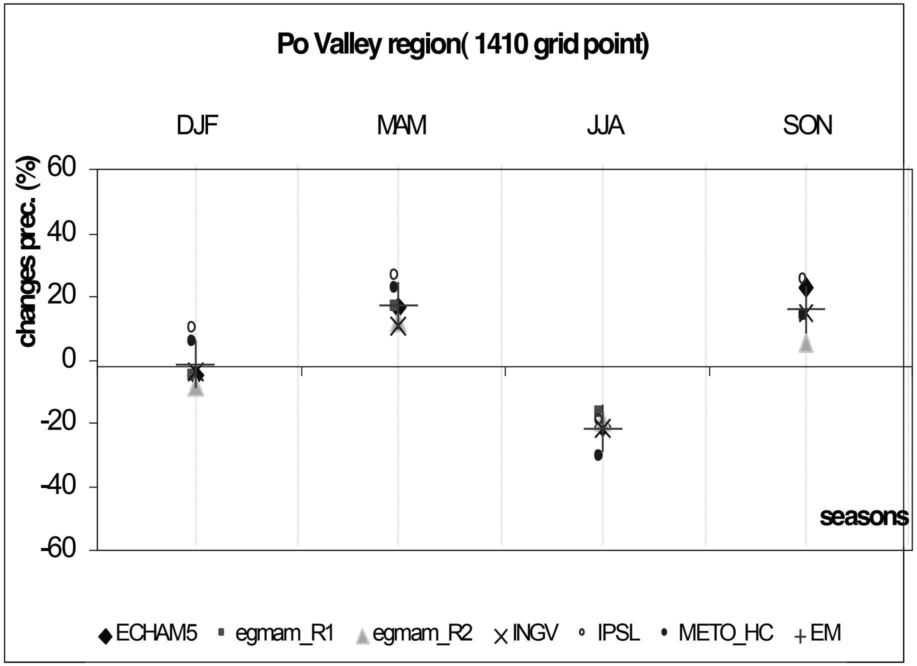


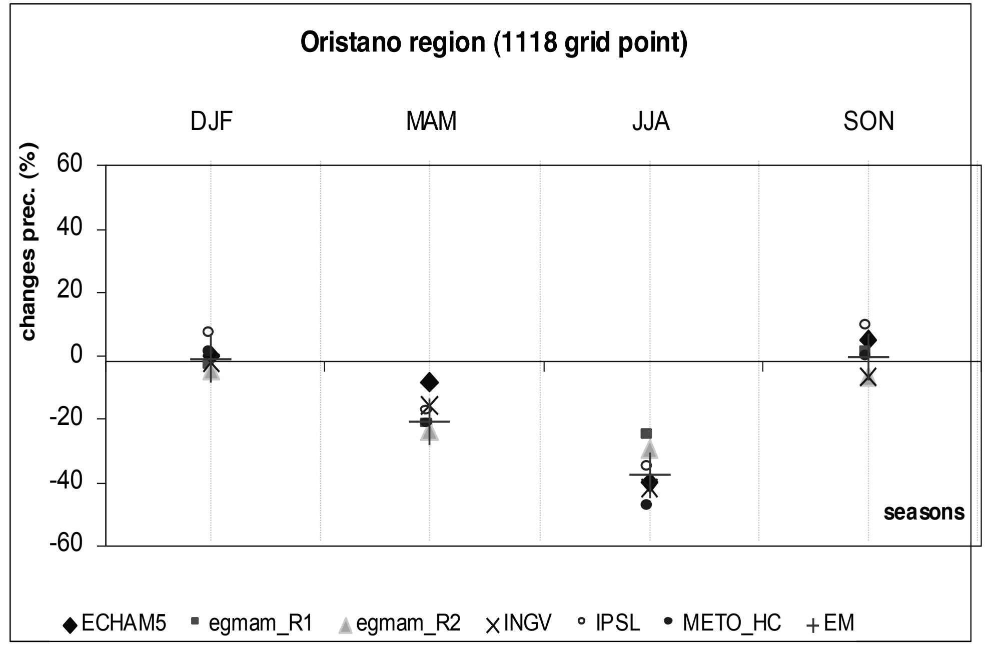






Scenario results - Precipitation

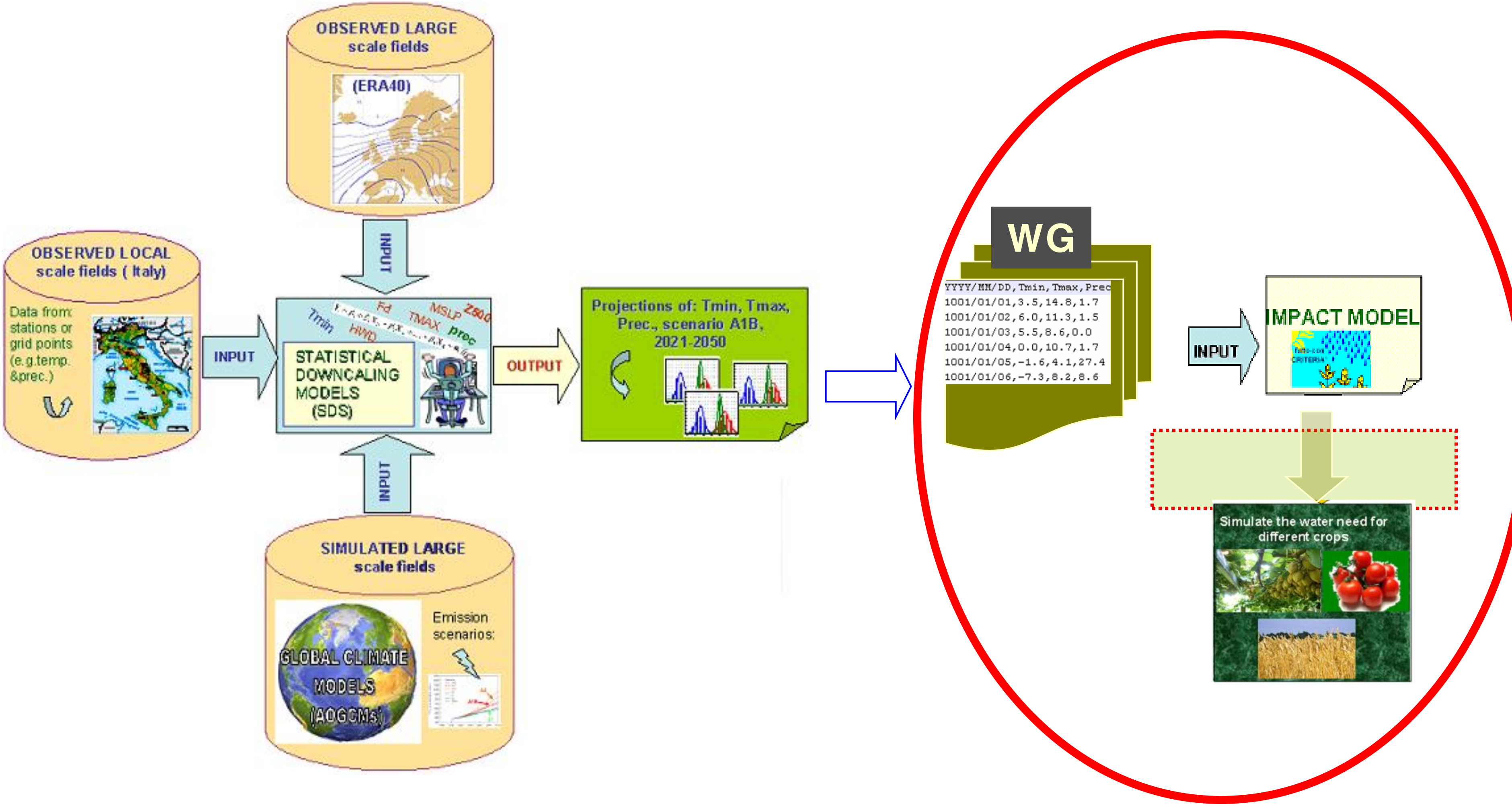




SD techn. show a pattern of changes more complex, different from season to season and over the areas. Future changes [(2021-2050)-(1961-1990)] of seasonal precipitation are expressed in % (with respect to 1960-1990), in one grid point that belongs to Po valley and to Oristano. Outputs obtained by applying the CCAReg to: ECAHM5, EGMAM runs, INGV, IPSL and METO_HC, and also the Ensemble Mean (EM).

A small decrease of precipitation in winter. During spring, only the grid point that belong to Po Valley shows a possible increase, around 15%-EM, while for the grid point that belong to Oristano area a possible decrease is projected. Summer is the season where the signal of changes goes in the same direction for all grid points: a possible decrease of amount of precipitation, more pronounced at Oristano region. As concerns autumn only the grid point from the Po Valley shows a possible increase

Application: Climate change impacts on water demand (tomato irrigation) over Po Valley



Talk of Giulia Villani – this afternoon

Conclusion

- Statistical downscaling scheme allows to construct climate projections at local scale for Tmin, Tmax and Prec. over different areas from the Italian peninsula.
- Uncertainty can be evaluated by using changing SD method and GCMs
- Results obtained can be used as input for impact studies in different sectors
- Concerning the scenario obtained: increases in Tmin and Tmax over the studied areas in all seasons, for the period 2021-2050 with respect to 1961-1990, A1B scenario;
- The Ensemble Mean computed using all simulations for each season, shows a change in the mean of the PDFs of minimum and maximum temperature, between 1.5- 2°C. The peak of changes is projected during summer for both, minimum and maximum temperature.
- A shift of the PDFs to warmer value is projected to occur for both Tmin and Tmax in all seasons. This shift is more pronounced in the upper tails and higher magnitude have been found during summer (up to 3°C with respect to present climate);
- A reduction of precipitation could be expected to occur during summer season, period 2021-2050, more pronounced in the areas situated in the central and southern part of Italian peninsula.

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Acknowledgments

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Thank you !