COMPARING DYNAMICAL, STOCHASTIC AND COMBINED DOWNSCALING APPROACHES. LESSONS FROM A CASE STUDY IN THE MEDITERRANEAN REGION

N. Guyennon (1), E. Romano (1), F. Salerno (2), S. Calmanti (3), E. Bruno (4), I. Portoghese (4), A.B. Petrangeli (1), G. Tartari (2), and D. Copetti (2)

(1) National Research Council, Water Research Institute, Roma, Italy; (2) National Research Council, Water Research Institute, UOS Bari, Italy ; (3) ENEA, Energy and Environment Modeling Technical Unit, Roma, Italy; (4) National Research Council, Water Research Institute, UOS Brugherio, Italy

(a) Abstract

Many recent studies have compared the performance of downscaling methods, but the use of different spatial domains, predictor variables and assessment criteria makes direct comparison of relative performance difficult to achieve (Fowler et al., 2007). These studies are used to evaluate performances using mainly correlation coefficients, distance measures such as root mean squared error (*RMSE*), or explained variance (Fowler et al., 2007), although Busuioc et al. (2001) suggest that for climate change applications the more suitable downscaling model needs to be able to reproduce the low frequency variability.

We propose a methodology for evaluating the relative performances of a selected Global Circulation Model (*GCM)*, Dynamical Downscaling *(DD)*, Statistical Downscaling *(SD)* and their combination on the ground of their ability in :

- Reducing the meteorological bias between GCM and land data.
- improving the GCM ability in reproducing the observed climate and its non stationarity.
- improving the GCM ability in reproducing the observed trends and their spatial heterogeneity.

As concluded also by Diez et al. (2005) we found that using *DD* and *SD* methods in combination offers an improvement in terms of bias compared to the single method. Moreover, we found that the selected *DD* improves the representation of non-stationarity features which are not enough captured by the GCM. Finally, depending on the considered variable and associated typical heterogeneity scale, the selected *DD* and *SD* show limited but different contribution in improving the spatial heterogeneity of trends, while best results are obtained through their combinations.

(b) Methodology & Case study

The proposed methodological framework is applied to a meaningful case study located in Southern Italy, the Apulia region, in which the climate and landscape features, including the water exploitation policy, represent a serious threat for water resources availability in the near future. Monthly observations from 77 temperature stations and 111 rainfall gauge stations, covering the period 1950-2000 have been used as land control measurement network.

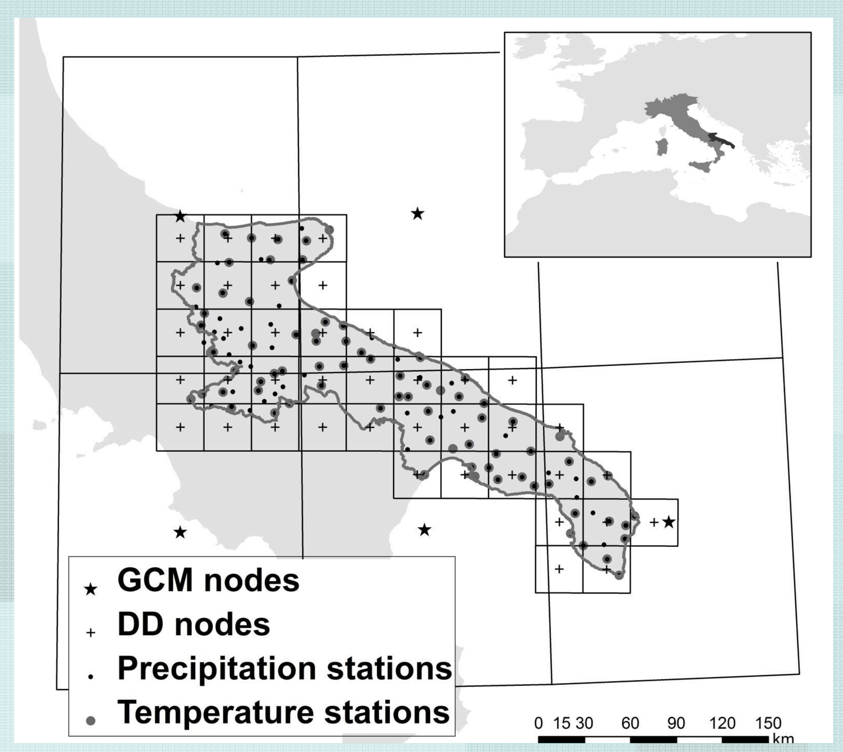

Fig.1 Case study.

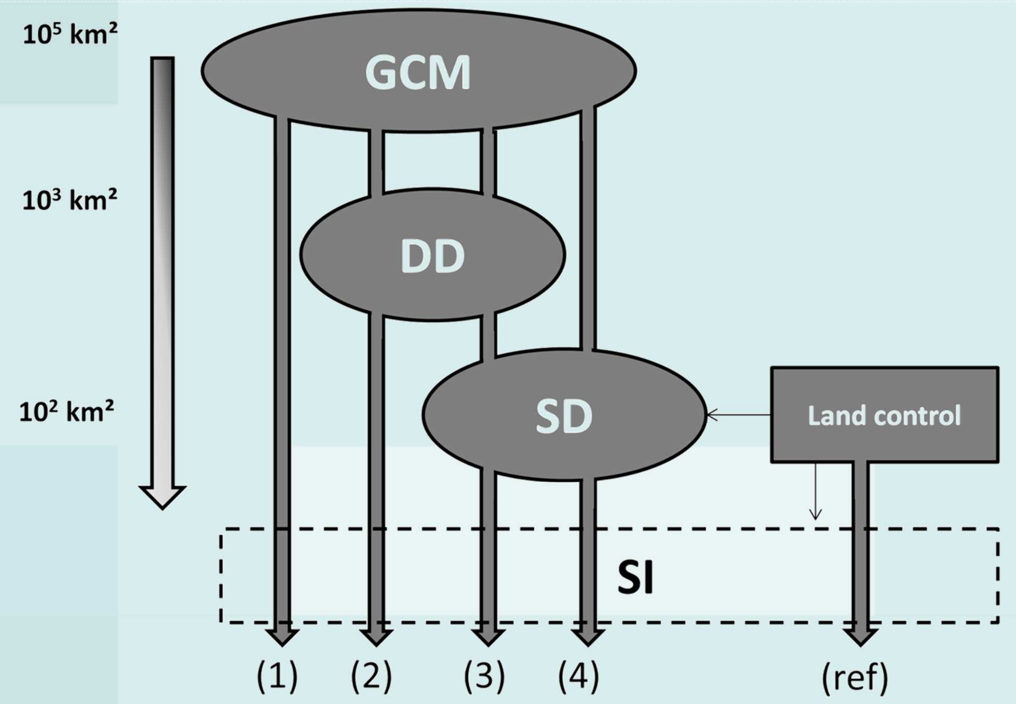

Fig.2 Methodological framework.

- Analyzed data: temperature and precipitation stations with less than 20% of missing data extract from the Apulia region database (mean density: one station each $2.76*10^2$ km² and $1.91*10^2$ km² respectively).
- Global circulation model grid from ECHAM5/MPI-OM (Roeckner et al. 2003) . (*GCM* resolution: $3.27*10^4$ km²).
- Dynamical downscaling grid from Protheus system (Artale et al. 2009). (*DD* resolution : $9.60*10^2$ km²).
- *SD* performed at sampling stations point scale using the quantile mapping method (Déqué, 2007) at monthly scale.
- Spatial homogenization done through a statistical interpolation (*SI*) (ordinary kriging) at $1*10^2$ km²

Four dataset processed from the *GCM* scenario and one from the observations (figure 2):

- elaboration (1) from the *SI* applied to *GCM* scenarios.
- elaboration (2) from the *SI* applied to the dynamically downscaled *GCM* scenarios.
- elaboration (3) from the *SI* applied to the *SD* of the dynamically downscaled *GCM* scenarios.
- elaboration (4) from the *SI* applied to the *SD* of the *GCM* scenarios.
- the reference dataset (ref) obtained from the *SI* of the land control network.

(c) Indicators of performance

Aim of the indicators of performances: to quantify the ability of each downscaling method and their combination in reproducing the land observed temperature and precipitation patterns, in order to be used for hydrological simulation at local and/or basin scale.

1- Reducing the meteorological bias between GCM and land data, that is the mean error.

The mean bias is defined for each variable, at each *SI* node *n*, for each elaboration *e*, as : $M_n^e = \overline{SI_n^e - SI_n^{ref}}$ *(1)* where SI_n^e stands for the monthly time series resulting from the *SI* of elaboration *e* the *SI* node n (the overbar stands for the mean over time, at monthly scale).

2- Improving the GCM ability in reproducing the observed climate and its non stationarity.

The local climate is represented by the SI_n^e quantiles computed at each season *s*, at each node *n*, using a 21 year sliding time window centered on the year I, and referred as $Q_{n,s,y}^e$. The $Q_{n,s,y}^e$ are then compared with quantiles of the same node computed over the whole period $Q_{n,s}^e$ using the same plotting position. The non stationarity in the climate means is then revealed by the $Q_{n,s,y}^e$ -$Q_{n,s}^e$ quantiles-quantiles residues means time variation : $Qmb_{n,s,y}^e = \frac{1}{L}\sum_{k=1}^{L}\left[Q_{n,s,y}^e(k) - Q_{n,s}^e(k)\right]$ *(2)*

3- Improving the GCM ability in reproducing the observed trends and their spatial heterogeneity.

The annual Sen's slope (Gilbert, 1987) and associated significativity (through the associated Man Kendall coefficients) over the whole study period are computed at each node of the SI_n^e grid on the annual variables and referred as SS_n^e. The SS_n^e spatial distribution of each elaboration and associated variance are computed as an indicator of the trend amplitude spatial heterogeneity: $Var^e = E[(SS_n^e - E[SS_n^e])^2]$ *(3)*

(d) Results & discussions

1-MEAN BIAS

Indicator of performance: The 5th, 25th, 50th, 75th and 95th percentile of the M_n^e cumulative spatial frequency distribution over the 10^2 km² grid SI nodes (figure 3). Same elaboration performed after splitting residues into four seasonal sub dataset: winter (Dec, Jan, Feb), spring (Mar, Apr, May), summer (Jun, Jul, Ago) and autumn (Sep, Oct, Nov).

How to read the results: The closer the mean bias to zero, the higher the ability of the method to reproduce the spatial mean of each variable; The narrower the distribution, the higher the ability of the elaboration to reproduce the spatial variability of each variable.

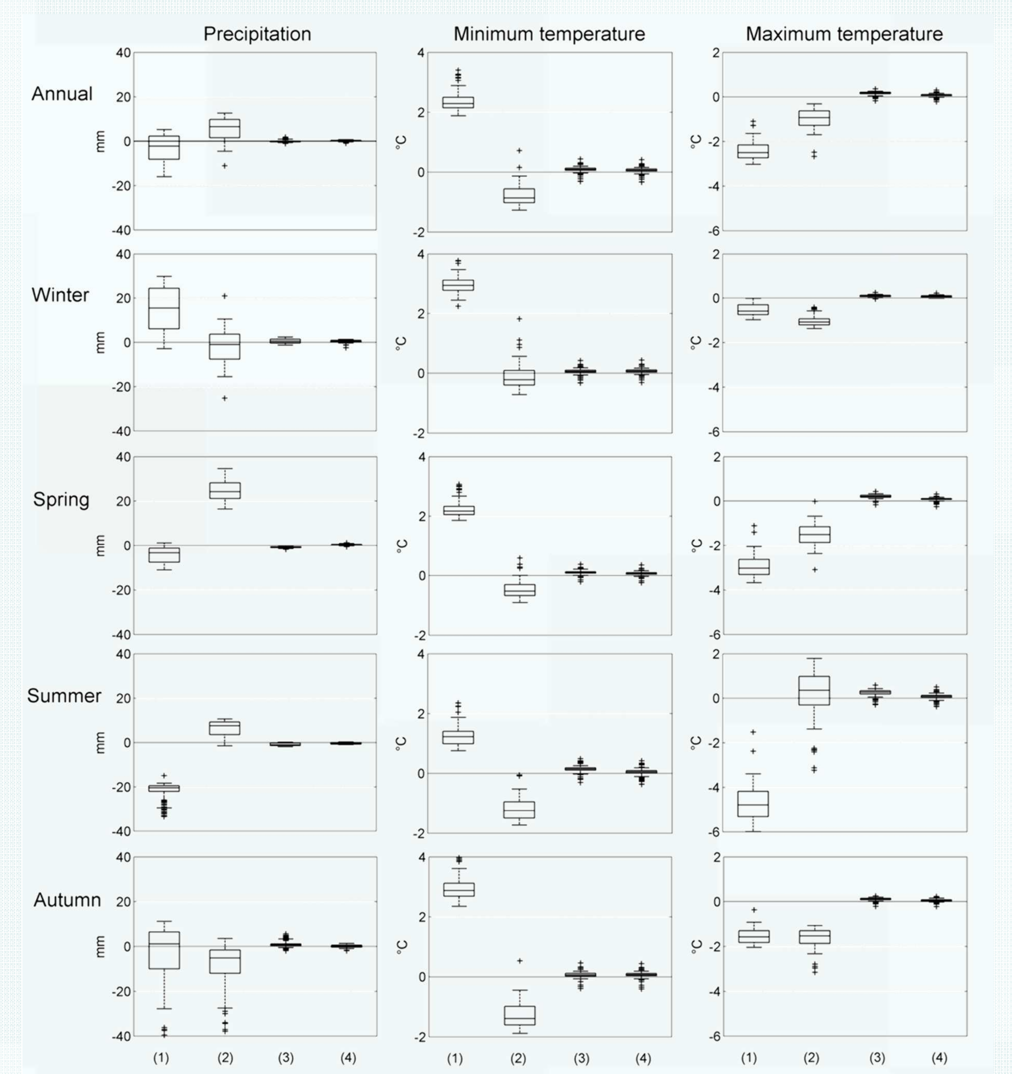

Fig.3 Monthly and seasonal spatial distribution of mean bias

- *GCM* (1): large mean bias in seasonal precipitation, overestimates and underestimates in minimum and maximum temperature, respectively (2°C). These GCM bias are associated with large spatial heterogeneity.
- *DD* (2): reduction of the mean bias, keeping almost unchanged the spatial heterogeneity.
- *SD* (3): reduction of the annual and seasonal mean bias and associated spatial heterogeneity by an order of magnitude.
- *DD-SD* (4) : further and statistically significant improvement,.

2-QUANTILES NON STATIONARITY

Indicator of performance: spatial mean of the quantiles mean bias $Qmb_{n,s,y}^e$ computed between the 21 years window quantiles and the whole period quantiles of reference and each elaboration (figure 4).

How to read the results: The absolute value of each $Qmb_{s,y}^e$ indicates, for each elaboration, how the mean value of the quantiles arising from the consider 21 years window differs from the associated mean value of the full period quantiles. A linear signal stands for a monotonic trend.

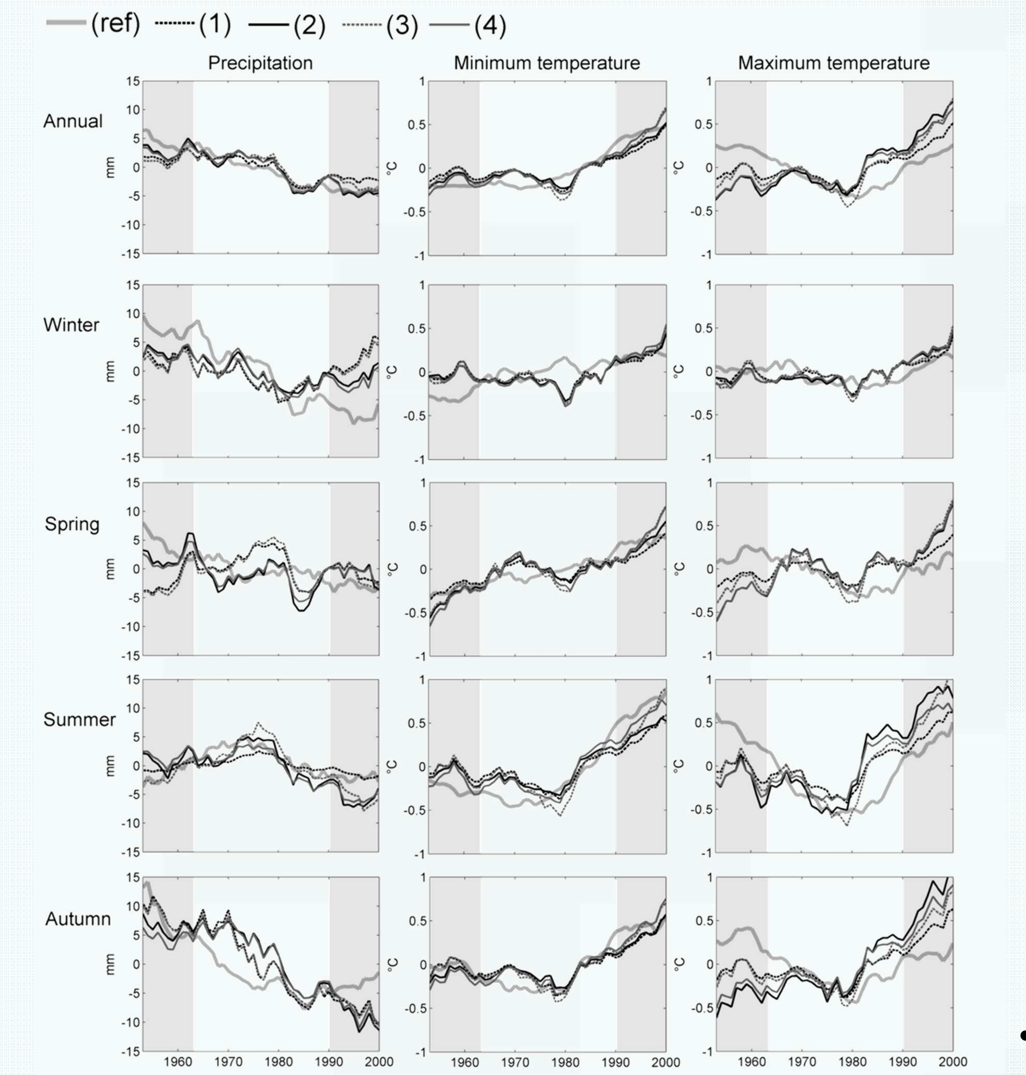

Fig.4 Annual and seasonal non stationarity in the quantiles distribution means.

- The *GCM* (1) reproduces correctly the non stationarity of the annual and seasonal quantiles, but mostly underestimates trends.
- The *DD* (2) modulates the non stationarity of the *GCM* quantiles, mostly by increasing trends when presents in the GCM, improving correlation with reference.
- The *SD* (3) does not modulate the *GCM* non stationarity.
- The combined *DD-SD* (4) presents the same results as the *DD*.

3-SPATIAL HETEROGENEITY OF TRENDS

Indicator of performance: annual Sen's slopes SS_n^e computed at each *SI* node are plotted in figure 5. The significativity of the trends is indicated with stars centered in each *SI* cells.

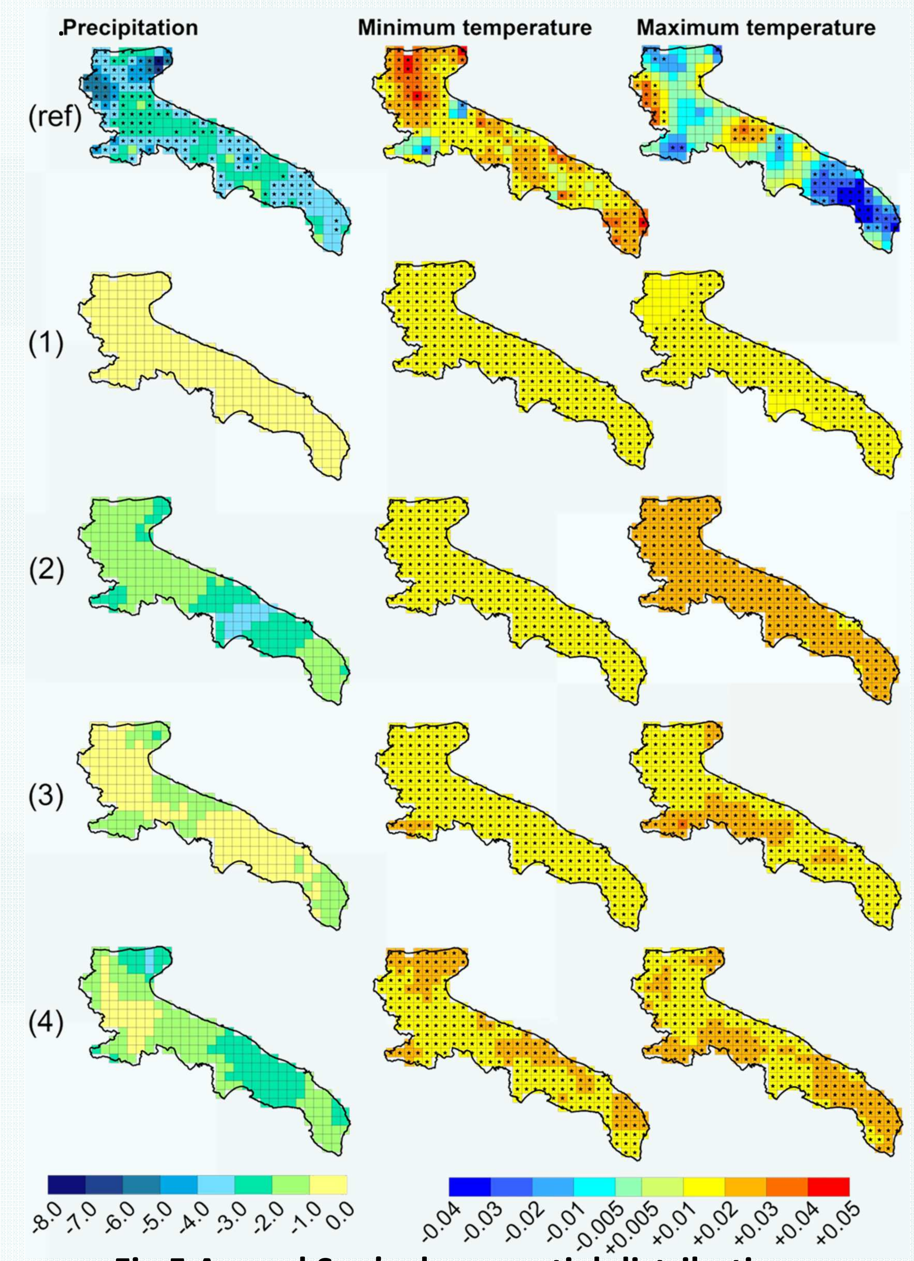

Fig.5 Annual Sen's slope spatial distribution

- Any spatial heterogeneity from *CGM (1)* (low resolution with regard to the case study dimension).
- Modulation of the GCM trends by *DD* (2) by introducing half of the observed variance for precipitation and by increasing trends amplitude for maximum temperature.
- The *SD* (3) generates less spatial variance in the precipitation slope than the DD but slightly more for temperature.
- The combine *DD-SD* (4) presents the highest variance in the trend spatial distribution and the best results in terms of covariance with the reference, but still fails in correctly representing the observations.

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