

# Dynamical and statistical downscaling of precipitation and temperature in a Mediterranean area

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## Abstract

In this paper we present and discuss a comparison between statistical and regional climate modeling techniques for downscaling GCM prediction. The comparison is carried out over the *Capitanata* region, an area of agricultural interest in south-eastern Italy, for current (1961-1990) and future (2071-2100) climate. The statistical model is based on Canonical Correlation Analysis (CCA), associated with a data pre-filtering obtained by a Principal Component Analysis (PCA), whereas the Regional Climate Model REGCM3 was used for dynamical downscaling. Downscaling techniques were applied to estimate rainfall, maximum and minimum temperatures and average number of consecutive wet and dry days. Both methods have comparable skills in estimating stations data. They show good results for spring, the most important season for agriculture. Both statistical and dynamical models well reproduce the statistical properties of precipitation, the crucial variable for the growth of crops.

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## Introduction

The fourth report of the Intergovernmental Panel on Climate Change (IPCC, 2007) concluded that warming of the climate system is unequivocal, and that most of the observed increase in global average surface temperatures since the mid 20<sup>th</sup> century is very likely due to the observed increase in the concentration of CO<sub>2</sub> and other greenhouse gases. The increase is expected to continue in the future, even in the most optimistic of the greenhouse gas emission scenarios, described in the IPCC Special Report on Emissions Scenarios (IPCC, 2000) and based on expected socio-economical evolutions. The most appropriate approach to obtain information on global climate is the use of Atmospheric-Ocean Global Climate Models (GCMs). They can simulate the processes of the atmosphere-ocean system relevant at global and continental scale and, although there are many uncertainties in their formulation, they can be confidently used to assess climate changes resulting from increases of atmospheric greenhouse gases concentration. Recent advances in climate change modelling now enable better estimates than in the past and likely assess uncertainty ranges. In fact, in the framework of intercomparison projects (e.g., EU FP6 Ensembles project), simulations of future climate are performed using different GCMs and for different emissions scenarios. Unfortunately, GCMs climate projections cannot be used directly in impact studies, due to difference between the coarse spatial (and temporal) resolution of GCMs (generally of order 100 km) and the small scale resolution needed by environmental impact models (typically of order 10 km or less), that are very sensitive to local climate. Thus, downscaling techniques have been developed, which use the large-scale predictions provided by a GCM to assess climate change information on a regional scale. This approach has been widely used in impact studies, such as the statistical evaluation of river flows (DiazNieto and Wilby, 2003), floods (Charlton *et al.*, 2006), groundwater recharge (Holman *et al.*, 2009), and, more in general, water resource planning (Prudhomme and Davies, 2009a,b). The downscaling models can be divided into two main categories: the statistical models, which are based on regression analysis used to derive semi-empirical statistical relationships between the large-scale predictors and local (station) scale predictands; the dynamical models, which are *high-resolution* Regional Climate Models (RCMs) nested in a coarser resolution GCM. In the statistical approach, the empirical relationships are derived by using historical meteorological series defined at the coarse GCM grid resolution and historical series from a set of stations available in the area of interest, typically characterized by a small

distance. The dynamical approach is similar to the grid one-way nesting technique used in weather forecast and other meteorological applications. However, both the downscaling approaches have some drawbacks. For example, the dynamical downscaling needs large computing resources and is strongly dependent on the boundary conditions that are provided by GCMs; also, it is based on the assumption that the actual parameterization schemes are still valid in a future climate; the statistical downscaling needs long time series (that are available for long periods only in limited regions) to build statistical relationships, that are supposed to be still valid in the future. Also, both methods inherit the inaccuracies present in the GCM outputs: Prudhomme and Davies (2009a,b) observed that the existing bias in reproducing the present climate is likely to be transferred to simulations in future time horizons. In order to partially overcome this problem, they suggest to use more than one downscaling technique and to compare the results to get a more reliable picture. Haylock *et al.* (2006) agreed with this consideration and noticed that the differences between different downscaling models are at least as large as the differences between different SRES (Special Report on Emissions Scenarios, the most widely used and cited scenarios, that form the basis for the IPCC assessments). As a consequence, they suggested to include different types of downscaling models and emission scenarios when developing climate-change projections at the local scale. One of the first comparisons between different downscaling models is given by Wilby *et al.* (1998). They compared only statistical models and found that neural networks were the last skilful in reproducing observed rainfall, mainly due to wrong estimation of wet-day occurrence. Kidson and Thomson (1998) found that dynamical and statistical approaches have similar skills in downscaling daily precipitation, minimum and maximum temperature. Murphy (1999) found that a Linear Regression Statistical Model (LRSM) has skills comparable to a Regional Climate Model (RCM) in downscaling monthly precipitation and temperature over Europe. Wilby *et al.* (2000) also compared the results obtained from a LRSM and a RCM relative to daily precipitation, runoff and temperature in the Animas River basin (Colorado) and reached a similar conclusion for daily data. Also, they noticed that both the methods were more skilful than the raw National Center for Environmental Prediction ([www.cdc.noaa.gov](http://www.cdc.noaa.gov)) analysis precipitation data. Haylock *et al.* (2006) compared several statistical and dynamical downscaling models with a new version of a non-linear artificial neural network, finding that the latter was the best at reproducing inter-annual variability, but that also has the tendency to underestimate the extremes.

Downscaling of GCM model output is particularly important for assessing regional climate change for a region like the Mediterranean area, which is characterized by high space variability and many climate types. This variability is due to a combination of different factors: the complex orography; the complicated land-sea patterns of the basin; the Mediterranean Sea itself, that influences the genesis and the distribution of cyclones through air-sea interaction mechanisms and latent heat release (Lionello *et al.*, 2006, Moscatello *et al.*, 2008). Also, the position of the Mediterranean region makes the regional climate dependent on both mid-latitude climate in the north and on tropical climate in the south. In fact, mid-latitude regimes, such as the North Atlantic Oscillation (NAO) and the East Atlantic pattern (Trigo and Palutikof, 2001), and tropical phenomena, like El Niño Southern Oscillation (ENSO), affect the weather regimes during Winter; the Asian and the African monsoon and geopotential blocking anomalies over central Europe influence the climate during Summer (Alpert *et al.*, 2006). About historical records, trends from 1900 show that precipitation declined in the Mediterranean basin; also, a temperature increase larger than the global average (especially during Summer) as well as an increase in the number of heat waves have been recorded. Giorgi and Lionello (2008) show that GCMs generally agree on a substantial future dry-

ing of the Mediterranean region in all the different (SRES) scenarios, especially in the warm season. In IPCC (2007), the authors show that different GCM experiments agree in a regional mean temperature increase of 0.5-1°C for the period 2011-2030 (with respect to the period 1960-1990) which is insensitive to the choice of the SRES scenario. These results point out that, with high confidence, the Mediterranean basin will suffer from a decrease in water resources due to climate change in the near future. Thus, drought-affected areas are expected to increase in extent, with adverse impact on multiple sectors, such as water resources, energy production, agriculture, ecosystems. The projected changes are, however, not uniform in the whole region, stressing the need of downscaling techniques able to resolve internal differences in the basin and to reproduce the detailed spatial distribution. Statistical downscaling has been applied to precipitation climate change in several studies in different Mediterranean areas (e.g., von Storch *et al.*, 1993; Corte-Real *et al.*, 1995; Goodess and Palutikof, 1998; Palatella *et al.*, 2010). More recently, different GCMs, scenarios and predictors, have been tested for statistical downscaling of precipitation during the wet season (Hertig and Jacobeit, 2008a), reporting different climate change signals in different areas and confirming the need of an analysis that is capable of resolving internal differences within the Mediterranean region. Statistical downscaling for temperature has shown a projected increase for the whole Mediterranean area for all months of the year in the period 2071-2100 compared to 1990-2019; the assessed temperature rise varies depending on region and season, but overall substantial temperature changes of partly more than 0.5-1°C have to be anticipated by the end of this century under enhanced greenhouse warming conditions (Hertig and Jacobeit, 2008b). For the European continent, a number of studies with regional climate models focused on future changes in extreme events (e.g., Frei *et al.*, 2006; Beniston *et al.*, 2007). In this context, the STARDEX project (the Statistical and regional dynamical downscaling of extremes for European regions; Goodess, 2005) provided a rigorous and systematic inter-comparison and evaluation of statistical, dynamical and statistical-dynamical downscaling methods for the construction of scenarios of extremes for six different European regions. The EU project PRUDENCE (Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects) provided an ensemble of high-resolution climate change scenarios for Europe at the end of the twenty-first century by means of dynamical downscaling (Christensen *et al.*, 2007). The simulations in PRUDENCE have been compared with global simulations (Deque *et al.*, 2005), and have been used to assess temperature and precipitation change signals, e.g. in Italy (Coppola and Giorgi, 2010) and Greece (Zanis *et al.*, 2009), and changes in European drought characteristics (Blenkinsop and Fowler, 2007). The EU project ENSEMBLES (Hewitt, 2005) will further advance the state-of-the-art by comparing different methods for representing climate model uncertainty and linking these methods to downscaling techniques in order to improve the robustness of climate change impact assessments.

In the present study a comparison of temperature and precipitation future projections, obtained from a dynamical and a statistical downscaling model, are presented and discussed. The study is focused on the *Capitanata* plane (Apulia), a region of agricultural interest in the Mediterranean area, positioned in South Italy. An intercomparison between these methods is important in order to provide an estimate of the uncertainties of future projections in this small area. In the present study, the analysis of the future local scenarios in this region is crucial to evaluate the effect of climate change on local agriculture and can also provide a better understanding of the future climate in the South Mediterranean. In this context, the European Project MedClivar, aims to coordinate and promote the study of this area.

## Materials and methods

### Predictor: Sea Level Pressure from EMULATE dataset and T1000 from ECMWF

The Sea Level Pressure (SLP) EMULATE dataset (Ansell *et al.*, 2006) is based on daily averaged sea level pressure values for the period from January 1850 to December 2003. The data cover the region from 70°W-70°N (top left corner) to 50°E-25°N (bottom right corner). The grid resolution is 5°×5° in latitude and longitude. This means that at each time step the dataset consists of 250 SLP values. The dataset covers the region involved in the North Atlantic Oscillation (NAO) and in the dynamical features responsible for precipitation in Europe. The National Centers for Environmental Prediction ([www.cdc.noaa.gov](http://www.cdc.noaa.gov)) monthly averaged 1000 hPa temperature reanalysis (T1000) is retrieved from the National Oceanic and Atmospheric Administration (NOAA) data server, for the period from 1948 to 2007. The data cover Europe and Asia and are distributed on a Gaussian grid of 73×37 grid points with a resolution of 2.5°×2.5°. To obtain a resolution comparable with that of SLP, we upscale the data on the same grid points of the EMULATE dataset. The upscaling is recommended because in this way the resolution of both predictors is comparable with that of the GCM data available for future scenarios (temperature).

### Predictands for the *Capitanata* region

Regarding the predictands needed in the statistical approach, a dataset of historical local scale meteorological variables were made available in the framework of the Italian Research Project on the *Evolution of cropping systems as affected by climate change* (CLIMESCO). The downscaling technique was applied in two sub-regions characterised by intense agricultural activity: the *Capitanata* plain and Delia-Nivolelli basin. The *Capitanata* plain (about 4000 km<sup>2</sup>) is located in the Northern part of Apulia region and is one of the most important areas for the Italian agriculture; the most widespread crop is wheat. The Delia-Nivolelli basin, with an extension of about 60 km<sup>2</sup>, is located in south-western Sicily. In the present paper, we will consider only the first basin. In these areas, the annual evapotranspiration is generally greater than rainfall, determining drought conditions that make irrigation necessary for agriculture. Thus, climate changes in temperature and pluviometric regime could have a substantial impact on some agronomical practices as the choice of the crops to be included in the rotations, the sowing time and the irrigation scheduling in both regions. Based on the available datasets, the following predictands have been chosen for the *Capitanata* area: the daily series of maximum and minimum temperature in the city of Foggia (in the station named *Podere 124*) (from 1951 to 2005), monthly precipitation data recorded in six stations in the sub-region (from 1935 to 2003). The location of the stations is shown in Figure 1.

About local climate, Figure 2 shows the monthly averaged precipitation amount and the number of WET days for each month, while Figure 3 shows the annual cycle of  $T_{min}$  and  $T_{max}$ . The region shows a typical semi-arid Mediterranean climate, with hot and dry summer and rather mild and humid winter. The rainfall is mainly concentrated in fall and winter, while weak precipitation is recorded in late spring and summer, with a few tens of mm recorded throughout summer.

### Global climate model data

We retrieved the SLP and T1000 projections relative to the A2 and B1 scenarios of the Third Assessment Report (TAR) from the International Panel on Climate Change IPCC-Data server (<http://cera-www.dkrz.de/>). The data from ECHAM5 developed by the Max Planck Institute for Meteorology (MPI-M) is considered here. The data are available on a 192×96 grid.

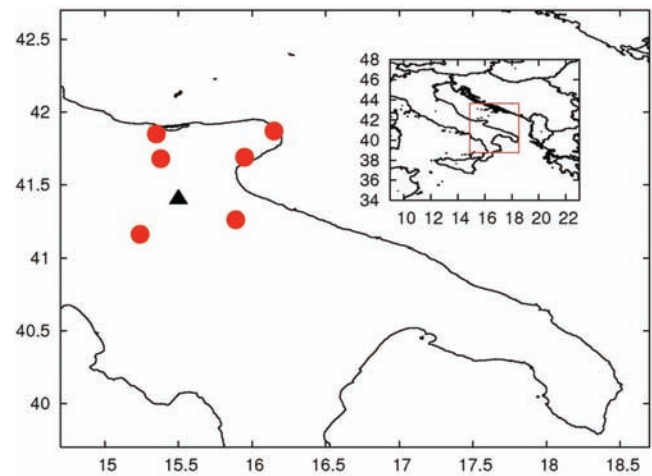


Figure 1. Temperature (triangle) and precipitation (circles) stations used for the statistical downscaling.

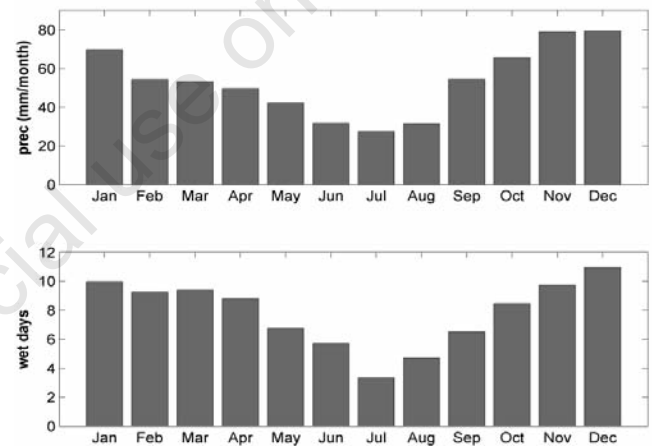


Figure 2. Monthly precipitation amount (upper panel) and number of wet days (bottom panel) averaged across all stations for each month.

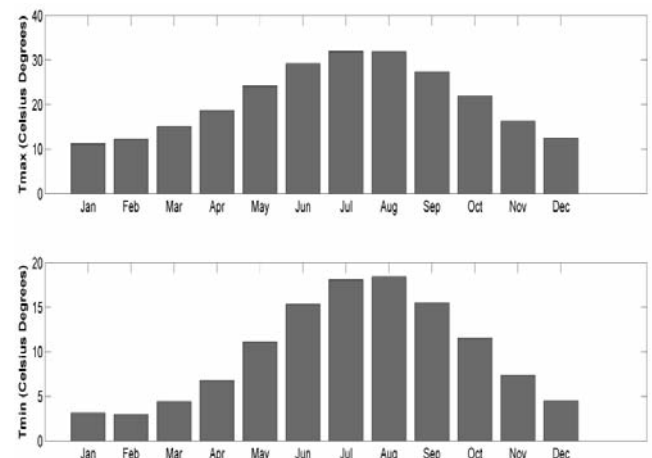


Figure 3. Maximum (upper panel) and minimum temperature (bottom panel) averaged in Foggia Podere 124 station for each month.

### Statistical downscaling - canonical correlation analysis

Statistical downscaling is a computer-wise cheap method for the description of seasonal climate variability at regional and local scale, i.e. local meteorological variables that are not adequately described in climatic projections of GCM's. Statistical downscaling is based on statistical relationships linking regional climate variables (predictands) to large-scale atmospheric variables (predictors). Such links are determined during an observational period, tested with independent data outside this period, and used for computing future climate projections.

In this study canonical correlation analysis (CCA) is applied, associated with a data pre-filtering obtained by a principal component analysis (PCA) (von Storch and Zwiers, 1999). CCA belongs to the class of direct methods, i.e. methods directly applied to seasonal or monthly indices, so differing from other methods that are focused on the modelling of daily data, from which seasonal or monthly averages are computed in a second step. In the CCA technique, a regional scale field (e.g. precipitation) – the predictand – is derived by a large scale field (e.g. SLP) – the predictor – through a set of linear statistical relationships. The linearity is a basic assumption of CCA. Further, a stationarity hypothesis is given by assuming that the linear correlation between predictors and predictands, which is found in the observational period, is valid also in the future scenario provided by the runs of the GCM. The calibration of the CCA model is obtained by searching the most correlated couples of patterns, the canonical patterns (CP), made up of a vector for the predictor and another for the predictand. It is important to note that CCA must be applied to the difference between real observations and their time averaged value. In this study we adopt the sea level pressure (SLP) or the 1000 hPa temperature (T1000) as large scale predictor, and monthly average of number of consecutive dry days and monthly average of number of consecutive wet days, precipitation, or maximum and minimum temperature as predictand. Moreover, we decided to put to zero the negative precipitation values in order to give a physical meaning to the CCA predictions.

A validation of the statistical model was done by splitting the historical time series into two periods. We use the first period as the *training* series, in order to build the statistical model, and the second one as the *validation* one. The first period was chosen considering the period covered by predictands and making some tests to have the best statistical model. Whereas the downscaling of all variables is done on a monthly basis to increase the statistical consistency, the output analysis is seasonal where winter (DJF), spring (MAM), summer (JJA) and fall (SON) seasons are defined by grouping months from December to February, March to May, June to August and September to November, respectively. In Table 1 the training and validation periods are reported for each predictand.

Agreement between the original data and the predicted ones during the validation period is used to assess the quality of the methods. For this purpose, we have computed the mean relative error and the Spearman correlation coefficient between the historical experimental data and the validation series (von Storch and Zwiers, 1999). The mean relative error in the prediction during the validation period is defined as  $\sigma / \bar{\rho}$ , with

$$\sigma^2 = \frac{\sum_{i=1}^{\tau} \sum_{j=1}^N (Y_j(i) - \tilde{Y}_j(i))^2}{\tau N}; \quad \bar{\rho} = \frac{\sum_{i=1}^{\tau} \sum_{j=1}^N (Y_j(i))^2}{\tau N} \quad (1)$$

where  $N$  denotes the number of stations in each area,  $\tau$  the number of time steps in the validation period, and  $Y_j(i)$  and  $\tilde{Y}_j(i)$  represent the CRU and downscaled precipitation (at point  $j$  and time  $i$ ), respectively ( $\sigma^2$  is the mean squared error as discussed in Von Storch and Zwiers, 1999, pag. 396. Here it is divided by the mean observed value  $\bar{\rho}$ ,

thus obtaining a relative error). The Pearson correlation coefficient was also evaluated. This is defined as:

$$r = \frac{\sum_{i=1}^{\tau} \sum_{j=1}^N (Y_j(i) \cdot \tilde{Y}_j(i))^2}{\left( \sum_{i=1}^{\tau} \sum_{j=1}^N (Y_j(i))^2 \right)^{1/2} \cdot \left( \sum_{i=1}^{\tau} \sum_{j=1}^N (\tilde{Y}_j(i))^2 \right)^{1/2}} \quad (2)$$

with

$$\tilde{Y}_j(i) = \tilde{y}_j(i) - \bar{y}_j(i) \quad (3)$$

$$Y_j(i) = y_j(i) - \bar{y}_j(i) \quad (4)$$

being  $\bar{y}_j(i)$  the time average value of the predictand corresponding to the  $j$ -th station. The Spearman correlation coefficient is obtained by substituting, in Eq. 2, the predictand values  $Y_j(i)$  with the corresponding ranks  $R_j(i)$ , that is, the number of data with a value greater than  $Y_j(i)$  itself. In other terms, the Spearman correlation coefficient is the Pearson coefficient between ranked variables. At variance with Pearson, the Spearman correlation is used as a nonparametric test. This means that a perfect Spearman correlation follows when  $X$  and  $Y$  are related by any monotonic function. On the contrary, the Pearson correlation only gives a perfect value when  $X$  and  $Y$  are related by a linear function. The correlation gives a good validation of the inter-annual variability, independently of any bias or incorrect variance. Modelling the inter-annual variability is particularly important as it indicates that the models are correctly reproducing the predictor predictand relationships and it is well known that a basic assumption of statistical downscaling models is that the predictor-predictand relationships remain stationary under different future climate conditions.

In Table 2 the results for the mean relative error ( $MRE = \sigma / \bar{\rho}$ ), described in Eq. 1, and the Spearman correlation coefficients are shown. The Pearson coefficient is not reported, as it is very similar to the Spearman, with the exception of WET and DRY, where significant-

**Table 1. Training and validation periods for each predictand.**

	Training	Validation
Precipitation, Wet and dry	1935-1969	1970-2003
T-max and T-min	1951-1992	1993-2005

**Table 2. Mean relative error and Spearman coefficient for each predictand and season.**

	Precipitation	T-max	T-min	Wet	Dry
DJF					
MSE	0.29	0.10	0.41	0.19	0.26
Spearman	0.37	0.61	0.44	0.22	0.41
MAM					
MSE	0.32	0.08	0.18	0.19	0.47
Spearman	0.44	0.89	0.90	0.21	0.35
JJA					
MSE	0.41	0.05	0.06	0.31	0.46
Spearman	0.56	0.83	0.87	0.29	0.42
SON					
MSE	0.28	0.06	0.11	0.20	0.39
Spearman	0.43	0.96	0.91	0.23	0.55

DJF, winter; MAM, spring; JJA, summer; SON, fall; MSE, mean relative error.

ly better values are found for the latter coefficient, probably a consequence of the particular definition of WET and DRY indicators. The table shows that a better agreement (lower mean relative error and higher Spearman correlation) between modelled and observed data is obtained for temperatures and, in minor way, for precipitation. The different seasons show a similar behaviour, apart from a lower correlation and higher error in temperature (especially in  $T_{\min}$ ) in DJF, and a larger RMSE in precipitation in JJA.

### Dynamical downscaling

The dynamical downscaling simulations are carried out with the regional climate model RegCM (Giorgi *et al.* 1993a,b) driven at the boundaries by fields from the ECHAM5 GCM output (Roeckner *et al.*, 2003) for two 30-year periods starting on 1<sup>st</sup> January 1961 and 1<sup>st</sup> January 2071, respectively. RegCM is a primitive equation, hydrostatic, compressible, sigma-vertical coordinate model. Version 3 of the model is used in this study. It includes a number of parameterization schemes, like the convective (Pal *et al.*, 2000) and large-scale (Grell, 1993) precipitation schemes, the land surface and ocean flux schemes (Dickinson *et al.*, 1993). The radiative transfer package and planetary boundary layer scheme are still essentially those described by Giorgi and Mearns (1999). The model is implemented on a rotated grid of 100 by 75 points centered on 40° N-15° E, the horizontal resolution is 55.5 km and the model domain covers the central and southern European region and adjacent oceans, including all the Mediterranean sea. The vertical grid is composed of 18 unequally spaced levels, the higher resolution being close to the surface and in the boundary layer. The model needs initial and boundary conditions for geopotential, temperature, humidity and horizontal wind components in the atmosphere and sea surface temperature. The data to drive the regional model are produced by the 5<sup>th</sup> generation of the ECHAM general circulation model. The same model is also used to provide the future scenario conditions to the statistical downscaling. ECHAM5 is implemented on a linear Gaussian grid corresponding to the spectral truncation T63 (1.875 degrees) and 31 vertical levels. It is coupled with the MPI-OM1 ocean general circulation model, that is the next generation of the HOPE model (Marsland *et al.*, 2003), running at 1.5 degrees with 40 vertical levels. Flux adjustment is not adopted in the coupled runs. The data produced for the Fourth IPCC Assessment Report are downloaded from the CERA WWW-Gateway of the Hamburg World Data Center for Climate (<http://cera-www.dkrz.de/>). For each scenario (Nakicenovic, 2000) 3 different runs are available. The first run corresponding to scenario 20C3M is used for the simulation of recent climate (1961-1990 period), while the first runs of the SRESA2 and SRESB1 scenarios are used for the two time slices (2071-2100 period).

## Results and discussion

### Comparison of dynamical and statistical downscaling for the period 1961-1990

Hereafter, we perform a statistical comparison between (dynamical and statistical) downscaled data and observations for each station and for the period 1961-1990 (CTR). Comparison is performed applying the Mann-Whitney test to the datasets. The Mann-Whitney test is a non-parametric test for assessing whether two independent samples of data come from the same distribution. This is inferred by computing an index, obtained by comparing the ranks of the two samples. The probability that the two samples come from the same distribution increases as this index decreases, so that it is possible to choose a threshold value below which the two samples can be considered significantly similar. In Table 3 the results for the Mann-Whitney test are reported. The samples are considered to come from the same distribution when the

index is below 1.645, and in this case the value is written in italic. Table 3 shows good results for spring, the most important season for agriculture, in particular both statistical and dynamical models represent well the statistical properties of precipitation, one of the most crucial variable for the growth of crops. Regarding the other seasons and variables, the agreement is not so good for both models. In winter we can infer from Table 3 that, regarding precipitation, the statistical model is more representative of the observations with respect to the dynamical model. One way to visualize and compare data from non-gaussian distributions is to compute median and percentiles and to plot these values through a box-plot. Figure 4 shows box-plots for precipitation, maximum and minimum temperatures, consecutive wet and dry days, comparing statistical model data, dynamical model data and observation data. The lower and upper lines of the *box* are the 25<sup>th</sup> and 75<sup>th</sup> percentiles of the sample. The distance between the top and bottom of the box is the interquartile range. The line in the middle of the box is the sample median. If the median is not centered in the box, that is an indication of skewness. The lines extending above and below the box show the extent of the 95% of the sample. The plus signs are an indication of *outliers*, data out of the 95<sup>th</sup> percentile of the sample. Box-plots confirm that the best agreement between models and observed data is in spring, while the largest precipitation discrepancies are in summer. About the different parameters:

- both models generally underestimate precipitation;
- the discrepancy is generally small, but it is larger for the dynamical downscaling and in JJA;
- the dynamical downscaling overestimates the number of consecutive wet days, apart from JJA;
- the statistical downscaling overestimates the number of consecutive dry days, especially in summer;

**Table 3. Mann-Whitney test for each season and applied to observation and respectively to statistical and dynamical model.**

Season	Model	Precipitation	T-max	T-min	Wet	Dry
DJF	Dynamical	3.36	<i>1.43</i>	2.71	6.06	6.20
	Statistical	<i>1.53</i>	5.12	0.78	<i>0.54</i>	4.47
MAM	Dynamical	<i>1.15</i>	<i>0.05</i>	2.71	5.69	4.63
	Statistical	<i>0.10</i>	1.75	<i>0.39</i>	1.94	2.62
JJA	Dynamical	4.82	3.66	<i>0.02</i>	<i>0.79</i>	<i>0.14</i>
	Statistical	4.15	6.14	<i>0.76</i>	2.76	5.15
SON	Dynamical	3.16	1.75	2.09	3.84	2.26
	Statistical	2.28	1.69	2.00	1.09	3.33

DJF, winter; MAM, spring; JJA, summer; SON, fall.

**Table 4. Comparison dynamical-statistical (CTR, 1961-1990).**

	Precipitation	T-max	T-min	Wet	Dry
DJF					
MSE	0.38	0.23	0.25	0.52	1.45
Spearman	0.42	0.56	0.50	0.28	0.34
MAM					
MSE	0.35	0.07	0.16	0.58	0.87
Spearman	0.65	0.91	0.89	0.32	0.29
JJA					
MSE	1.12	0.13	0.07	0.34	0.54
Spearman	0.39	0.61	0.63	0.10	0.30
SON					
MSE	0.56	0.10	0.13	0.55	0.74
Spearman	0.35	0.90	0.89	0.43	0.30

DJF, winter; MAM, spring; JJA, summer; SON, fall; MSE, mean relative error.

- maximum and minimum temperatures are generally well reproduced, apart from a reduced interannual variability of the maximum temperature by the statistical model.

Finally, a comparison in terms of Spearman correlation and RMSE between statistical and dynamical models is shown in Table 4. Correlations between models are better for temperature, especially in MAM and SON; for precipitation the best agreement occurs in MMA, while MSEs are generally high and correlations low for the number of consecutive wet and dry days.

### Comparison of dynamical and statistical downscaling, scenario A2 and B1

The results of downscaling for A2 scenario are shown in Figures 5, 6 and 7, relative respectively to precipitation, maximum and minimum temperatures. While Figure 5 does not show any significant trend for precipitation in any month, Figures 6 and 7 show an increase in both maximum and minimum temperatures, that is particularly clear in Summer and for the dynamical downscaling. For what concerns A2 scenario, Table 5 shows that both downscaling methods have a pretty good correlation and low relative error for temperature, apart from DJF, while for precipitation the correlation is better for DJF as compared to the other months. Similar results can be inferred from Table 6 for B1 scenario.

The results of the Mann-Whitney test, applied to compare scenarios (2071-2100) with CTR period (1961-1990), are shown for A2 and B1 scenarios in Tables 7 and 8, respectively. In italic values greater than 1.64, meaning that the samples are considered to come from different distributions (trend). For A2, Table 7 confirms Figure 5, in fact precip-

**Table 5. Comparison dynamical-statistical, A2 scenario. Mean relative error and Spearman correlation coefficient.**

	Precipitation	T-max	T-min	Wet	Dry
<b>DJF</b>					
MSE	0.36	0.09	0.30	0.54	1.62
Spearman	0.60	0.45	0.41	0.33	0.32
<b>MAM</b>					
MSE	0.42	0.13	0.21	0.37	0.75
Spearman	0.42	0.57	0.79	0.32	0.32
<b>JJA</b>					
MSE	2.50	0.07	0.07	0.54	0.36
Spearman	0.22	0.75	0.72	0.14	0.16
<b>SON</b>					
MSE	0.80	0.10	0.10	0.44	0.62
Spearman	0.25	0.81	0.89	0.33	0.22

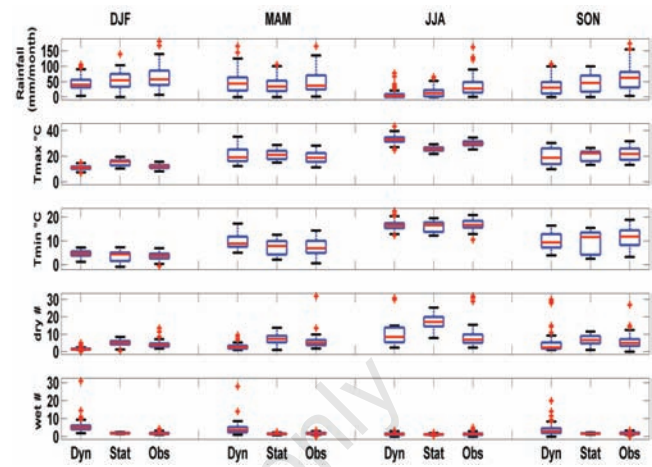
DJF, winter; MAM, spring; JJA, summer; SON, fall; MSE, mean relative error.

**Table 6. Comparison dynamical-statistical, B1 scenario. Mean relative error and Spearman correlation coefficient.**

	Precipitation	T-max	T-min	Wet	Dry
<b>DJF</b>					
MSE	0.34	0.11	0.30	0.48	1.61
Spearman	0.68	0.32	0.41	0.20	0.22
<b>MAM</b>					
MSE	0.44	0.10	0.19	0.52	0.73
Spearman	0.49	0.79	0.91	0.25	0.31
<b>JJA</b>					
MSE	2.38	0.09	0.06	0.42	0.35
Spearman	0.27	0.74	0.74	0.30	0.43
<b>SON</b>					
MSE	0.77	0.10	0.11	0.49	0.59
Spearman	0.17	0.83	0.92	0.43	0.15

DJF, winter; MAM, spring; JJA, summer; SON, fall; MSE, mean relative error.

itation does not show any significant trend in any season. A significant trend for maximum and minimum temperatures is present only for dynamical downscaling in winter and spring, whereas both methods display the same behaviour (trend) in summer and fall. For the number of consecutive wet and dry days, the distribution is the same as the control run (no trend) in SON and, mostly, in DJF and MAM. Similar



**Figure 4. Box-plot for Capitanata region. The considered period is 1961-1990. From the top to the bottom: precipitation, maximum temperature, minimum temperature, number of consecutive dry days, number of consecutive wet days.**

**Table 7. Mann-Whitney between A2 scenario and CTR for dynamical and statistical model and for all seasons.**

Season	Model	Precipitation	T-max	T-min	Wet	Dry
<b>DJF</b>						
Dynamic	0.11	5.20	5.69	0.55	1.20	
Statistical	1.25	0.14	0.33	1.33	2.14	
<b>MAM</b>						
Dynamic	0.39	2.27	3.32	3.01	0.57	
Statistical	0.07	0.57	0.82	1.15	0.86	
<b>JJA</b>						
Dynamic	1.03	4.92	5.52	1.95	2.76	
Statistical	1.07	6.53	4.75	3.75	2.53	

DJF, winter; MAM, spring; JJA, summer; SON, fall; MSE, mean relative error.

**Table 8. Mann-Whitney between B1 scenario and CTR for dynamical and statistical model and for all seasons.**

Season	Model	Precipitation	T-max	T-min	Wet	Dry
<b>DJF</b>						
Dynamic		0.32	5.02	5.12	0.49	1.12
Statistical		1.29	0.21	0.39	1.23	1.96
<b>MAM</b>						
Dynamic		1.63	2.66	3.26	2.92	0.58
Statistical		0.33	0.11	0.86	1.12	0.83
<b>JJA</b>						
Dynamic		2.02	3.76	4.95	1.96	2.06
Statistical		2.48	6.12	4.13	3.07	2.85
<b>SON</b>						
Dynamic		0.11	1.68	2.70	0.13	0.46
Statistical		1.19	3.27	3.27	0.38	1.01

DJF, winter; MAM, spring; JJA, summer; SON, fall.

results are shown in Table 8 for B1 scenarios, except for precipitation in JJA (P values greater than 1.64).

The results in terms of box-plots for the two scenarios are shown respectively in Figures 8 and 9. For A2 scenario, the main results in Figure 8 are:

- an increase in summer precipitation predicted by the statistical method, due to an increase in the number of consecutive wet days;
- both downscaling techniques predict an increase in the number of dry days in summer. Thus, according to statistical downscaling, summer in A2 is characterised by an alternative presence of persistent anticyclonic conditions, associated with drought, and long periods of rainfall, probably associated with local thunderstorms;
- an increase in temperatures, that is particularly apparent for the minimum temperature and in summer and fall.

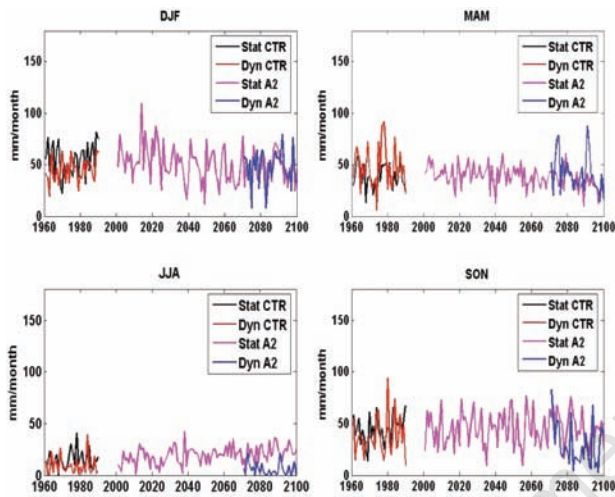


Figure 5. Temporal series of precipitation from statistical and dynamical model and for CTR and A2 scenario.

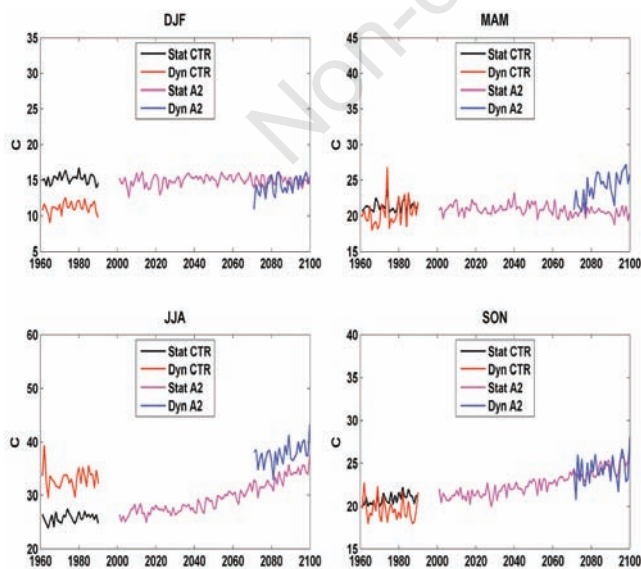


Figure 6. Temporal series of maximum temperatures from statistical and dynamical model and for CTR and A2 scenario.

For B1 scenario, a similar trend emerges for temperatures, while the increase in rainfall amount and in the number of consecutive wet days is no more present in summer. Also, only the dynamical downscaling predicts an increase of drought periods.

The monthly cycle of temperatures and precipitation for A2 is shown in Figure 10. The dynamical downscaling predicts a generalised increase of temperatures and a decrease in precipitation in each season apart from winter. The statistical method predicts an increase in precipitation from May to September and a decrease in the other months and a warmer scenario in summer and fall, while there is no clear trend for temperatures in the other seasons. Figure 11 shows that the results are similar for B1 scenario, but the trends are smaller as compared to A2 scenario.

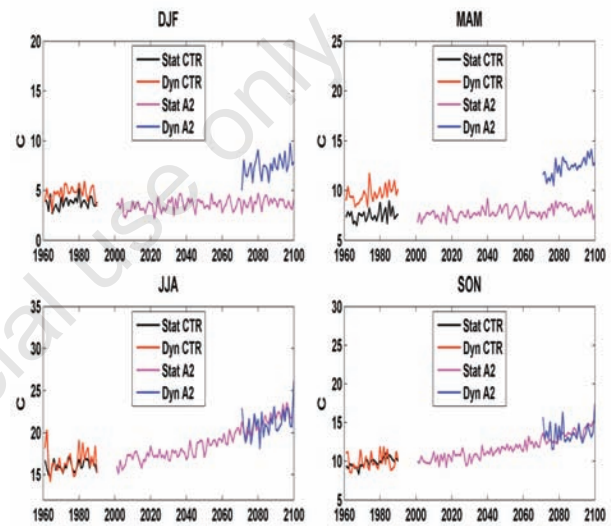


Figure 7. Temporal series of minimum temperatures from statistical and dynamical model and for CTR and A2 scenario.

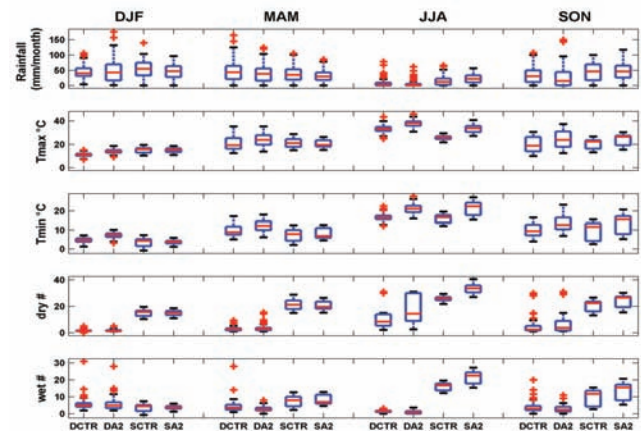


Figure 8. Box plots for precipitation, maximum and minimum temperature, for CTR and A2 scenario, for both statistical and dynamical model.

## Conclusions

In this paper, two downscaling models have been applied to produce future scenarios in a sub-region of agricultural interest in South Italy (*Capitanata* plain in Apulia region): a statistical downscaling model (CCA) and a dynamical downscaling model (RegCM). The A2 and B1 emission scenarios were used. The work has been carried out in the framework of the Italian Research Project *Evolution of cropping systems as affected by climate change* (CLIMESCO). The main goal was to perform an impact study on the role of climate change in future cropping systems.

Then, the evaluation of climate change starting from the available global simulations, associated with given emission scenarios, has been

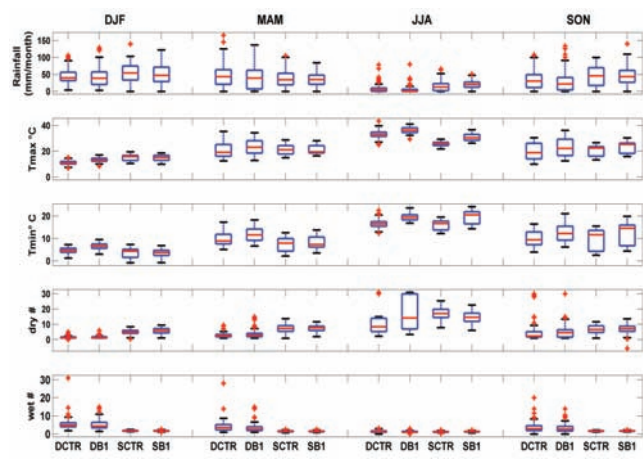


Figure 9. Box plots for precipitation, maximum and minimum temperature, for CTR and B1 scenario, for both statistical and dynamical model.

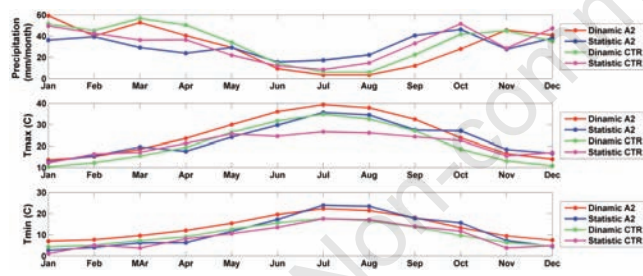


Figure 10. From the top to the bottom the annual cycle for precipitation, maximum and minimum temperatures, for A2 scenario and CTR and both statistical and dynamical models.

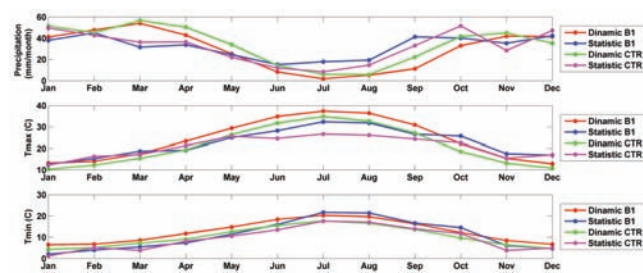


Figure 11. From the top to the bottom the annual cycle for precipitation, maximum and minimum temperatures, for B1 scenario and CTR and both statistical and dynamical models.

carried out. A set of stations with monthly data of precipitation and one station with daily data of temperature were available in the *Capitanata* plain. These data were used as predictands in the statistical model. Haylock *et al.* (2006) highlighted the importance of comparing different types of downscaling models to generate reliable future climate-change projections at the local scale. In fact, they noticed that the differences between different downscaling models are at least as large as the differences between different scenarios. As a consequence, they suggest to include different types of downscaling (dynamical and statistical) models and emission scenarios when developing climate-change projections at the local scale. Also, they found that all the different models they used perform better in winter than in summer.

The latter result is consistent with the present work; in fact, in our study the skill of both statistical and dynamical downscaling models is much worse in summer than in winter. This result could be related to a much lower intensity of rainfall in Summer than in the other seasons, due to very long dry periods. Consequently, the relevance of the rainfall future trends in Summer is probably not really significative. Also, it must be stressed that the dynamical models have a tendency to significantly underestimate the rainfall, especially in summer (as shown in Figure 4). This can be probably ascribed to the limitations in numerical models, that cannot properly represent convective rainfall. In fact, they can only parameterise this type of precipitation, that prevails during summer. This limitation can significantly affect the triggering and development of convection especially in a coarse resolution model, such as GCM's but also RCM's at the resolution actually used for climate simulations. Also, *Capitanata* sub-region is in the proximity of Gargano, a 65 km long and 40 km wide promontory, high more than 1000 m, and in its western side borders Appennines. As a consequence of the rough representation of the orography in a coarse numerical model, the airflow over and around the orographic obstacles cannot be properly represented and the intensity of the rainfall can be significantly affected.

The differences between downscaling models and emission scenarios are considered as an important source of uncertainty. However, it is nowadays recognized that GCM data are still the largest source of uncertainty in regional climate-change projections (Giorgi *et al.*, 2001; Prudhomme and Davies, 2009a,b). In fact, the greatest contribution to the uncertainty in impact studies was found to be related to GCM's, while scenarios and downscaling models give smaller contributions, and impact model uncertainty is found to be of the same magnitude as the natural climate variability (Arnell, 2004). This means that the presence of biases in the downscaled variables is mainly associated with biases in the GCM outputs. As an example, it is well known that GCM's display the SLP field problem (Trigo and Palutikof, 2001), i.e. the average mean sea level pressure observed in the actual climate (e.g., 1961-1990) is not yet well reproduced by GCM's in the control run. Thus, our analysis is potentially affected by this problem. In particular, there is a tendency to overestimate the pressure difference between the Azores' high and the Iceland low, leading to serious doubts about the capacity of GCM's to simulate precipitation properly. As a consequence, all GCM's show deficiencies in reproducing the current seasonal pattern of the rainfall. From downscaling techniques perspective this is a very serious problem, because precipitation over Europe is strongly correlated to the difference between Azores' high and Iceland low (linked to the NAO index). A wrong SLP mean field would prevent the statistical downscaling from computing the correct mean precipitation.

Outputs from statistical and dynamical downscaling models can be used directly input into a crop model (Mearns *et al.*, 1999). An intercomparison between different methods and different scenarios allows to estimate the uncertainties of future projections of the climate variables. However, crop production is a function of dynamic, nonlinear interactions between weather, soil water and nutrient dynamics, management and physiology of the crop; thus it is not straightforward to



relate predicted climatic variations (averaged in time and space) to crop response, that is nonlinearly, and sometimes non-monotonically, dependent on a realistic range of environmental variability. Furthermore, crops do not respond to conditions averaged through the growing season. To capture the dynamic, nonlinear interactions responsible for the crop production, process-oriented crop simulation models typically operate on a daily time step and on a spatial scale of a homogeneous plot (although sampling the heterogeneity of soil, weather and management inputs allows simulated results to be interpreted over a range of scales). To overcome this problem, when daily in situ data are available for a long period (minimum 30 years) a weather generator (Semenov *et al.*, 1998; Richardson, 1981; Onof *et al.*, 2000) can be applied to the output of both statistical and dynamical models. A weather generator is able to simulate site-specific daily weather data. In the framework of the project *Evolution of cultural systems as a consequence of climate changes* (CLIMESCO), the stochastic weather generator LARS-WG (Semenov *et al.*, 1998) was used: the output from the statistical downscaling model provided the climatological input for a crop model in order to reproduce the evolution of the crop systems in the *Capitanata* plane.

The details of the study performed with the LARS-WG model are out of the purposes of this paper and will be the subject of a forthcoming study.

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