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Post-processing methods for COSMO-CLM precipitation over Italy

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SUMMARY To produce regional climate scenarios, traditionally, the statistical downscaling has been considered as an alternative to dynamical downscaling. However, the use of the two kinds of downscaling approaches together consents, at least to some extent, to combine their advantages. This report presents the preliminary results of combined downscaling methods for precipitation. The dynamical downscaling is the COSMO-CLM regional climate model applied to ERA40 Reanalysis over the control period 1971-2000. The statistical post-processing of the COSMO-CLM outputs is performed through three different methods following the MOS (Model Output Statistic) approach: linear-scaling, quantile mapping and MOS analogs. The performances of the RCM and of the joint RCM-MOS simulations are evaluated in terms of spatial similarity of three ETCCDI indices (characterizing total precipitation, number of rainy days and maximum precipitation) between observed dataset and downscaled fields at seasonal scale. Three Italian test cases have been considered: Orvieto, Po river basin, and Sardinia. Preliminary results indicate that the application of MOS techniques generally improves the performances of the COSMO-CLM model, regardless the season or the index considered, and, among the MOS methods, better results have been generally obtained with the quantile mapping technique.

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INTRODUCTION

Developing regional climate scenarios is a key problem for climate change impact/adaptation studies, especially for geographically complex and heterogeneous regions that are sensible to climate change. Italy, a typical Mediterranean region, is one of the most vulnerable regions in Europe to natural hazards relate to precipitation like droughts, floods and landslides [7]. These reasons have motivated this study that has been conducted within the framework of the Italian project GEMINA. Its main objective is to develop regional scenarios to support mitigation and adaptation policies [30].

Usually, two different methodologies are used to downscaling the General Climate Models (GCMs) outputs: (i) the *dynamical downscaling*, that is based on high resolution (e.g. 10 km) Regional Climate Models (RCMs, [9]), or (ii) the *statistical downscaling* techniques [29, 1], that are based on statistical models that exploit the historical relationship between large-scale GCM variables (the predictors, e.g. 500mb geopotential) and local variables (the predictands, e.g. precipitation at a given location).

In this study we test an alternative approach combining these two downscaling methods together. This hybrid method constitutes an advanced calibration method for end-users, allowing the calibration of RCM outputs for climate change impact studies. The idea is to apply the statistical post-processing directly to the RCM outputs following the Model Output Statistics (MOS) approach [15]. In this case the predictor is directly the RCM output variable (i.e. the RCM precipitation) which is calibrated to match the observed variable (local precipitation at a station or interpolated grid point). Note that the RCM post-processing methods are still in a rather premature state of development, and substantial improvements are currently under development [15].

Specifically, we evaluate three different MOS (Model Output Statistics) methods to refine the precipitation output of the COSMO-CLM model over Italy. These three methods are of increasing complexity: (i) the simple linear-scaling (LS), (ii) the quantile mapping (QM), and (iii) the MOS Analog method (MA), recently proposed by Turco et al. (2011, [27]). Each method has its strengths and its weakness [22]. The simple linear-scaling is routinely applied in climate change studies when only climatic means are needed. More sophisticated methods are used when other statistical moments are required. The quantile mapping tries to correct the distribution function of the RCM values and it is largely used for climate change impact studies. Finally, we test the MOS Analog method, which proved to perform well in regions of similar climate like Spain, it is parsimonious (so that one can assume that it is also robust to climate change conditions) and maintains the spatial coherence of the daily precipitation fields (which is important for hydrogeological impact studies).

To minimize the error relate to the GCM model, this comparison is based on the "perfect" global model (ERA40 reanalysis), downscaled by the COSMO-CLM. Then, the three MOS methods are applied over three Italian areas (Figure 1): (i) Po river basin, (ii) Orvieto and (iii) Sardinia. These sites are interesting domains to study the impact of climate change on the hydrogeological risk, and, besides, they are also covered by high-resolution data over the baseline period 1971-2000.

Orvieto is an historical town located at about 100km north of Rome. Orvieto represents an excellent case study to estimate the impact of climate change on landslide risk, mainly for these two reasons: i) it appears quite representative, as regards hydro-mechanical properties of involved soils and rainfall regime, of many other central southern Italian Apennines cases; ii) moreover, over the last years, the "in situ" soils have been deeply investigated by laboratory tests, displacements and soil pore water pressures have been continuously monitored at several observation points and soil depths while numerical analysis aimed to characterize and reproduce the observed trends have been performed ([25], [24], [26],[12], [14]). Specifically, to detect how the rainfall regime can affect soil pore water pressure and hence the movement rates, the observed data of daily precipitation related to Orvieto station are used. It is located on top of tuff slap (315 m a.s.l.) and, surely, represents the nearest measurement point to slopes affected by instability phenomena.

The choice of the Po river as case study is justified by its national and European relevance. The Po river is the longest (652 km) in Italy and, with an area of about 71000 km^2 in Italy and about 3000 km^2 between France and Switzerland, its basin is the widest of Italy. This basin is characterized by a complex orography, with around 50% of its surface is covered by mountains (Alps in the north and Apennines in the south). The Po basin is one of the mostly populated areas in Italy, with about 16 million inhabitants, mainly concentrated in the cities like Milan and Turin, and one of the most important Italian areas in terms of productive enterprises and water utilization. This basin is prone to hydrogeological disasters related to severe floods and droughts.

Finally, the last chosen domain is Sardinia. Sardinia is an island located in the Western Mediterranean Sea characterised by a dry summer and a rather wet winter with highly irregular precipitations, both in time ([5]), and in space [2, 5], due to its position and the presence of high and steep mountains near the sea. Besides this area is highly vulnerable to flash flooding and landslides ([3]). This is a challenging domain to perform a precipitation downscaling since this field is highly variable in this relatively small area, and our predictands are 39 stations of daily rainfall records, representative of the local scale.

The present study is organized as follows. First, the model data and the three MOS methods are presented. Then, the Sections ”Orvieto”, ”Po river basin” and ”Sardinia” describe the observed data used and the results for these areas. Finally, Section ”Conclusion” resumes the main findings of this report.

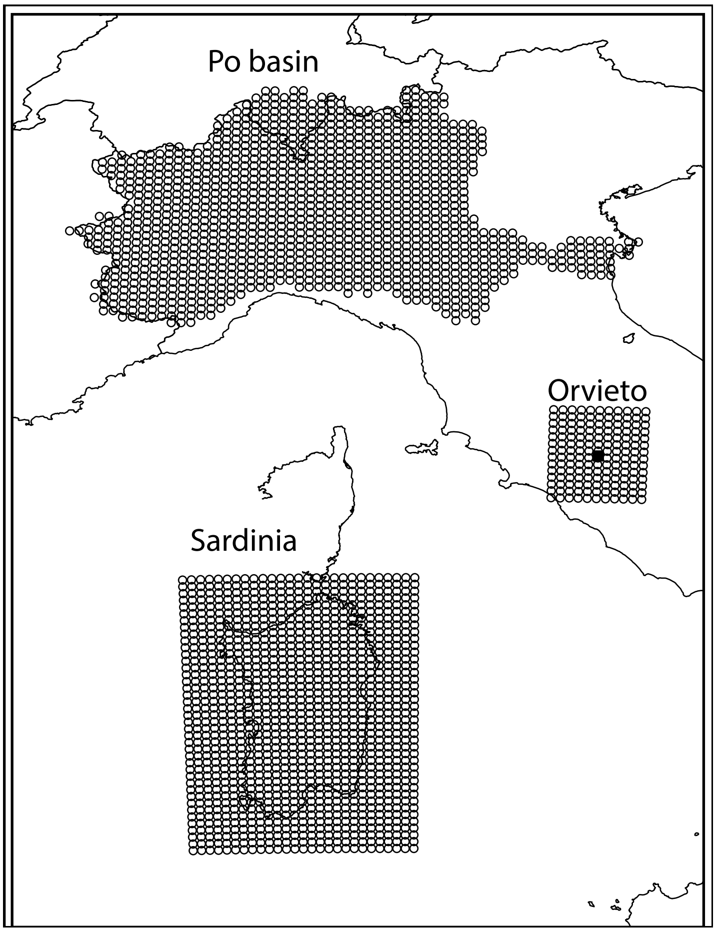


Figure 1:
The three domains of the study: (i) Po river basin, (ii) Orvieto, (iii) Sardinia. The black circles indicate the gridpoints of the COSMO-CLM model over these areas used in the MOS approaches. The black filled square indicates the position of the Orvieto station.

DATA AND METHODS

COSMO-CLM REGIONAL CLIMATE MODEL

In this study, we consider the ERA40-driven COSMO-CLM model [19] for the baseline period 1971-2000. The COSMO-CLM regional climate model is the climate version of the COSMO-LM non-hydrostatic limited area model [20]. A detailed description of this RCM and its evaluation is given in Zollo et al. (2012, [31]). The horizontal resolution is $0.0715°$ (about 8 km). The model domain is $3°$-$20°$E / $36°$-$50°$N. Table 1 summarizes the main features of the COSMO-CLM set-up.

Driving data	ERA40 Reanalysis
Horizontal resolution	$0.0715°$ (about 8km)
Num. of grid points	224 x 230
Num. of vertical levels in the atm.	40
Num. of soil levels	7
Soil scheme	TERRA_ML
Time step	40 s
Melting processes	yes
Convection scheme	TIEDTKE
Frequency of radiation computation	1 hour
Time integration	Runge-Kutta (3rd ord.)
Frequency update boundary cond.	6 hours

Table 1
Main features of the COSMO-CLM set-up.

MOS METHODS

Here we describe the three MOS methods that we compare: (i) the linear-scaling, (ii) the quantile mapping, and (iii) the MOS Analog method.

The linear-scaling approach consists in correcting the monthly differences between observed and simulated values:

$$P^*(d) = P(d) \cdot \frac{\mu_m(P_{obs}(d))}{\mu_m(P_{rcm}(d))} \qquad (1)$$

where, for the day d, P^* is the corrected value, $P(d)$ is the original daily precipitation value from the RCM, $\mu_m(P_{obs}(d))$ is the observed monthly average for the month m, and $\mu_m(P_{rcm}(d))$ is the simulated monthly average.

The quantile mapping correction, instead, tries to adjust all the moments of the probability distribution function (PDF) of the precipitation field. The idea is to calculate the correct variable P^* as a function of the original simulated variable P using a transfer function calculated forcing the equality between the CDF (cumulative distribution function F) of the observed and simulated variables [18]:

$$F_{rcm}(P_{rcm}) = F_{obs}(P_{obs}) \qquad (2)$$

Where F_{rcm} and F_{obs} are, respectively, the CDF of simulated and observed precipitation. So the corrected value of precipitation is obtained using the following equation:

$$P^*(d) = F^{-1}_{obs}(F_{rcm}(P(d))) \qquad (3)$$

We applied the quantile mapping assuming that both observed and simulated distributions are well approximated by a Gamma distribution. This distribution, dependent only on two parameters, is commonly used for representing the PDF of precipitation [17] and several studies have proved that it is effective for modelling rainfall data ([22], [11], [10]).

The analog method was first developed for weather forecasting [13, 6, 16] and later applied to climate scales [32, 4, 33, 23], so it is nowadays a popular and widely used technique in climate change studies. The analog method is based on the hypothesis that ”analogue” weather patterns (predictors, e.g. $500mb$ geopotential) should cause ”analogue” local effects (predictands, e.g. precipitation at a given location).

Figure 2 illustrates this relatively simple

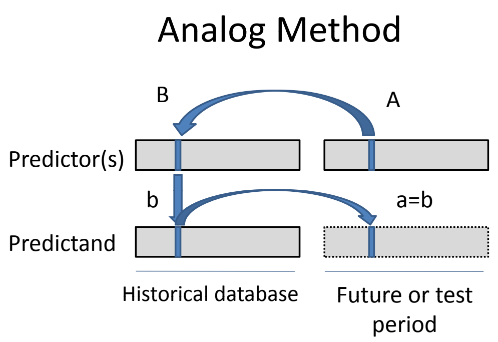


Figure 2:
Schematic illustration of the analog method (adapted from [8])

method. It basically consists in two steps. For the day A to be downscaled, in a future or in a test period:

1. The closest historical predictor B (the analog) is found.
2. Then, the observed local precipitation b, correspondent to the analog day B, is used as the downscaled precipitation a.

Then these steps are repeated for each day to downscale. Turco et al. (2011, [27]) positively tested over Spain a new implementation of the standard analogs method, in which the predictor is the RCM precipitation. This approach it is tested here for the first time over Italy.

CROSS-VALIDATION

It is important to verify the ability of any statistical model to perform out-of-sample prediction, i.e. to reproduce the downscaling from the knowledge of climatic data outside the period used to test the model. Generally, the out-of-sample prediction involves determining the model parameters on one subset of the data (training set), and validating the prediction on the other (testing set). Here a leave-one-out-cross-validation is applied [28], in which a moving window of 1 year is used as the validation data, and the remaining observations as the training data (Figure 3). For example, the first test year is 1971, and the MOS analog method is calibrated over the period 1972-2000; the second test year is 1972 and is trained with the complementary years, and so on. Consequently, a total of 30 (equal to the total length of the series) test periods were considered. Finally, we analyse the union of these 30 test periods. The monthly means for the LS, and the CDF of both observed and simulated precipitation for the QM, are calculated for every month of the year following this cross-validation approach.

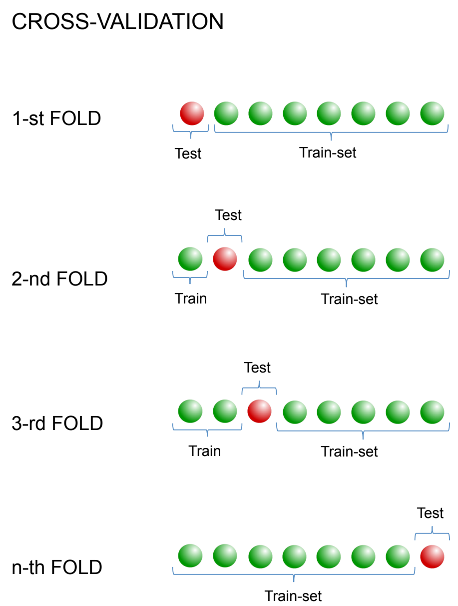


Figure 3:
A schematic view of the leave-one-out cross-validation approach. Iteratively, all the single samples (in our case years) from the original sample set are used as the test data, and the remaining samples as the training data.

We evaluate the ability of the COSMO-CLM model and of the post-processing methods to reproduce the seasonal climatology (spatial pattern) for three precipitation indices proposed by ETCCDI (http://cccma.seos.uvic.ca/ETCCDI) and shown in Table 2.

Simple performance scores (i.e. bias or mean error M, correlation C, standard deviation S, and centred root mean square error R) were computed for the spatial pattern of the seasonal indices averaged over the control period (1971-2000). The statistics were normalized dividing both the centred root mean square error, and the standard deviations of the simulated fields, by the standard deviation of the observations. In this way it is possible to compare the different indices. Besides, the comparison between the simulated (both RCM and MOS downscaled outputs) and observed climatologies (spatial patterns) are resumed by the Taylor diagram [21]. The Taylor diagram consents to summarize the three metrics of spatial similarity, C, S and R, in a single bidimensional plot. To include information about overall biases, the colour of each point indicates the difference between the simulated and observed mean, normalized by the observed mean. In the Taylor diagrams reported in this study, the same structure is used in the different case studies (unless otherwise specified). Specifically, the dots with the numbers indicate the RCM results while the squares with the letter "M" followed by a number indicates the MOS results. Number 1, 2, and 3 stand for $PRCPTOT$, $R1$ and $RX1DAY$ respectively. In the Taylor diagram, the more the points are close to the observation point labelled "OBS", the better are the performances.

Label	Description	Units
PRCPTOT	total precipitation	mm
R1	number of days with precipitation over 1 mm/day	days
RX1DAY	maximum precipitation in 1 day	mm

Table 2
Climatic mean and extreme ETCCDI indices for precipitation used in this work (see also http://cccma.seos.uvic.ca/ETCCDI).

ORVIETO

OBSERVED DATA

The data cover the time window 1921-2010; the dataset is based on daily values available in the Hydrological Annals Part I; the rainfall values time series result quite complete; major gaps concern the period 1943-1946 (for which are not available reliable observations even for neighbours station) and the data related to years 1966,1979 and 1980 (in part); for these ones, the data are replaced by measurements supplied by Acquapendente station (425 m a.s.l.; about 20 km away from the slopes to investigate). The choice is carried out verifying the good agreement between the two observation points in terms of cumulated precipitation values on seasonal and annual scale during the periods when both worked (not shown).

MOS RESULTS

For this case study, the simple linear-scaling and the quantile mapping methods are applied not only to single grid-point, but to the ensembles of grid-points that surround the station in a square of 1° (see Fig. 1). This has been done taking into account the reliable scale of the model. Indeed it should be noted that the direct model output is not a point value but an average (over a grid) value, reliable considering only from 4 to 10 times the nominal resolution of the model.

In Figure 4 the three proposed methods are compared in terms of probability distribution, CDF (top) and PDF (bottom). The linear-scaling and the MOS analogs results are not satisfactory, while, as expected, a better agreement between observed and corrected distributions is reached using the quantile mapping method.

As shown in Table 3, the QM approach also allows to correctly reproduce the seasonal means for the three indices $PRCPTOT$, $R1$ and $RX1DAY$ (described in Table 2). The best performances are reached for $PRCPTOT$ and $R1$ indices.

		DJF	MAM	JJA	SON
PRCPTOT (mm)	**OBS**	184	190	114	268
	RCM	144 (109,181)	176 (138,241)	95 (60,149)	192 (117,254)
	QM	186 (151,219)	195 (143,244)	119 (72,165)	269 (199,337)
R1 (days)	**OBS**	21	22	12	21
	RCM	20 (17,24)	27 (23,32)	13 (9,17)	19 (15,23)
	QM	21 (18,24)	22 (19,26)	12 (9,15)	21 (18,24)
RX1DAY (mm/day)	**OBS**	32	29	29	50
	RCM	24 (15,34)	23 (16,39)	24 (11,44)	42 (20,59)
	QM	32 (21,45)	34 (21,54)	35 (15,59)	59 (31,86)

Table 3

Seasonal means for the three indices $PRCPTOT$, $R1$ and $RX1DAY$. The mean value for each index and for each season, averaged over the period 1971-2000, is shown. The values are relative to observations (OBS), original simulation (RCM) and corrected simulation using the quantile mapping approach (QM). For both original and corrected simulation the nearest grid point to Orvieto station has been considered together with 5° and 90° percentile (in brackets) of the ensembles of grid-points that surround the station in a square of 1° .

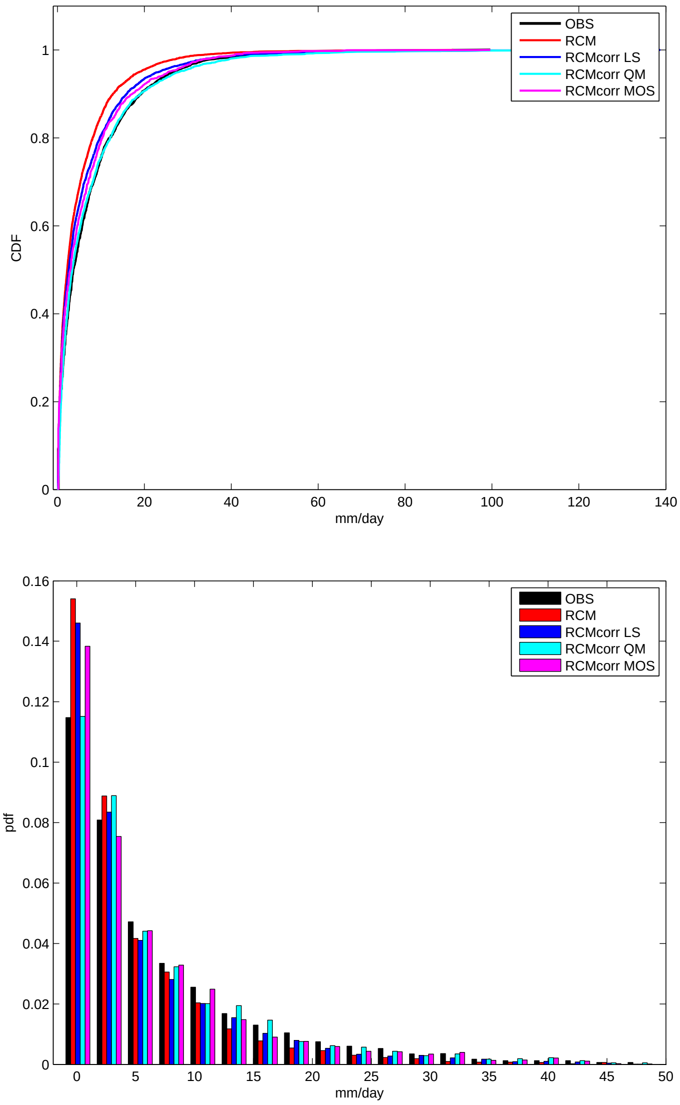


Figure 4:
Probability distributions of the three proposed methods: Linear-Scaling (LS), Quantile mapping (QM) and MOS analogs (MOS). The first figure is relative to the CDF and the second one to the PDF.

PO RIVER BASIN

OBSERVED DATA

The observed data of daily precipitation are provided by ARPA Emilia Romagna over a gridded dataset (based on the Inverse Distance Weighting interpolation method) of $0.0715°$ (about 8 km) of spatial resolution. This horizontal resolution is the same of the nominal resolution of the COSMO-CLM model, and it facilitates the comparison and the MOS application.

This dataset is based on daily observed precipitation available in the Hydrological Annals - Part I, for the period 1971-2000. Hydrological Annals - Part 1 for the period 1971 to 1991 were published by the National Hydrographic Service and are available at the website `http://www.acq.isprambiente.it/annalipdf/`. Data for the following years are available at the regional ARPA website, e.g. for Emilia Romagna at `http://www.arpa.emr.it/sim/?idrologia/annali_idrologici/`. The database is based on 1128 precipitation stations (Fig. 5 (a)). On average 459 stations were active each year, with a maximum of 636 stations in 1975 and a minimum of 54 stations in 1985. Figure 5 (b) shows the consistency of this dataset.

MOS RESULTS

The ability of COSMO-CLM and MOS methods to reproduce the seasonal climatologies (spatial pattern) in terms of the precipitation indices shown in Table 2 has been investigated.

As example, the results for the winter season (DJF) are summarised in Figure 6 through comparison maps for the observed dataset (left column), the COSMO-CLM model (center) and the corresponding MOS analog (right column). Each rows is representative of one index, $PRCPTOT$ (top), $R1$ (middle), and $RX1DAY$ (bottom). The seasonal values of the indices are averaged over the common period 1971-2000. Below each subplot is indicated the bias (or mean error M), relative standard deviations (S), the correlation (C), and centred root-mean-square (R) for the MOS analog and RCM. These numbers indicate the similarity scores and are plotted in the Taylor diagrams.

Figure 6 shows an overestimation of the COSMO-CLM model in terms of total precipitation and number of rainy days (respectively 23% and 16% of the observed values). The overestimation is larger over the Alps, while the maximum values over the Apennines are underestimated. These biases lead to a low spatial correlation between model and observations. Surprisingly, the results are better for the extreme index RX1DAY. These results suggest that, in addition to possible model limitations, its overestimation could also be related to the well-known problem in measuring the winter precipitation at high altitudes. This problem could affect both the RCM validation and its downscaling and, unfortunately, there are not trivial solutions. Figure 7 summarizes the verification results for all the seasons and indices. The $MOS\ analog$ downscaled values show a higher agreement with the observations and clearly outperform the uncalibrated RCM outputs for all the indices and seasons (Fig. 7).

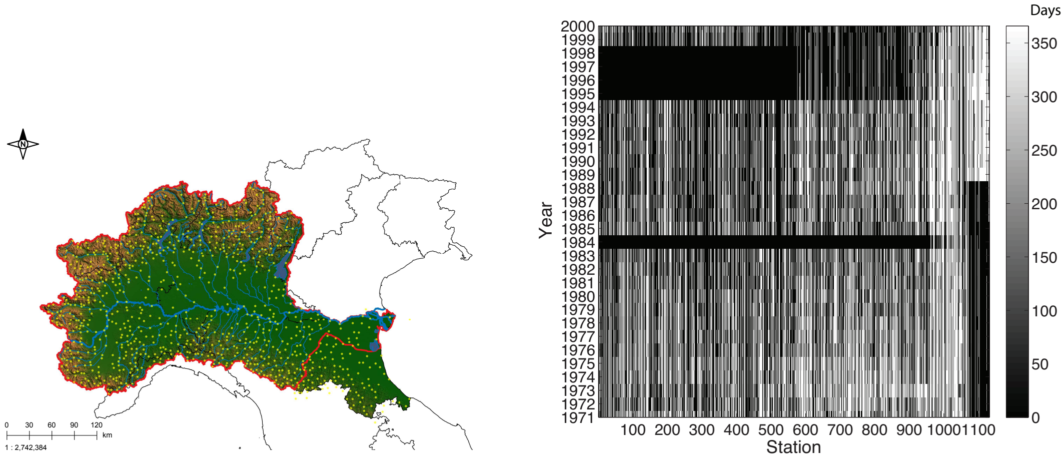
The MOS analog also reduced the bias of the RCM, except for the autumn season, when the MOS analog shows an underestimation (around 25%) of the observed values. Unfortunately, floods are expected in autumn in Po river basin, thus a correct simulation of the precipitation in this season is important to study the flood hazard.

The MOS underestimation in autumn could be due to the seasonal dependent bias of the predictor, that is, of the precipitation simulated by the COSMO-CLM run. Indeed, in the other seasons, COSMO-CLM tends to overestimate the observed precipitation, while in autumn the model presents an underestimation. Thus, the autumn days to downscale have more chance to find an analogue in which the bias have opposite sign, thus increasing the systematic error. Consequently, to test a potential solution to this problem, we here evaluate a different implementation of the MOS analog, in which the closest historical predictor (the analog) is sought within the same season of the day which should be downscaled. Preliminary results of this $MOS\ seasonal\ analogs$ are resumed in the Taylor diagram in the Figure 9. The $MOS\ seasonal\ analogs$ improves the COSMO-CLM model and reduced the autumn bias of the original MOS analogs (from -25% to -12%, Fig. 10), but slightly deteriorates its performance in terms of bias in summer (Fig. 9). These results are probably due to the balance between a potential improving searching analogues with similar bias and the potential worsening due to the reduced sample of analogues.

Figure 11 shows that the linear-scaling, that is based on a mean correction factor at monthly scale, not only improves the representation of the $PRCPTOT$ index, as expected, but also the other two indices, although to a lesser extent (e.g. the bias for the $RX1DAY$ in autumn is +18%).

The aim of the quantile mapping is to improve the representation not only of mean values but the entire PDF of the precipitation. Figure 11 shows that this method clearly improves the direct output of the COSMO-CLM model.

Finally, to facilitate the comparison among the three MOS methods, Figure 13 shows the results for the three methods. The quantile mapping method have the best scores for most indices and seasons, while the linear-scaling shows the worst results in most cases.



(a) (b)

Figure 5:
Location (a) and consistency (b) of precipitation stations used in ARPA EMR dataset.

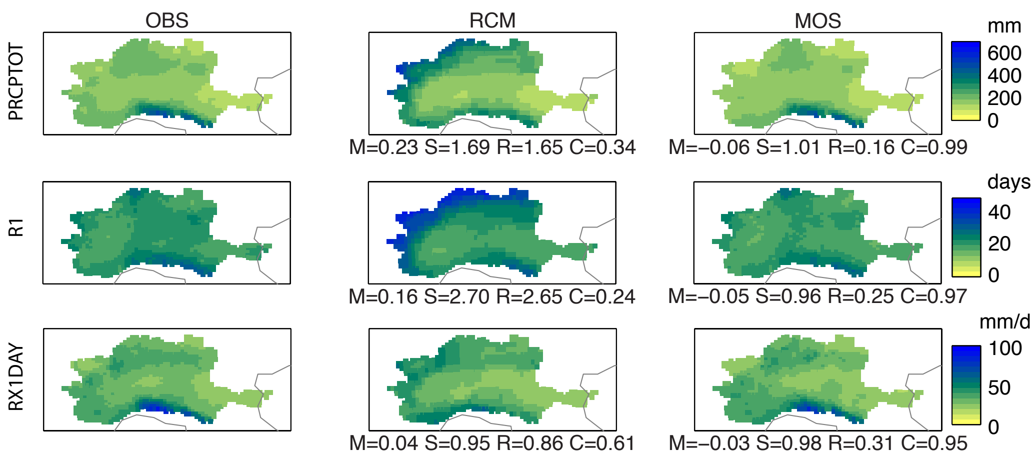


Figure 6:
Spatial distribution of the observed (left), COSMO-CLM (central) and downscaled (right) mean values (averaged over the control period 1971-2000) for the precipitation indices shown in Table 2. The spatial validation scores for the RCM and *MOS analog* simulated values are given below the corresponding panels: bias (or mean error M), relative standard deviations (S), correlation (C) and centred root-mean-square (R).

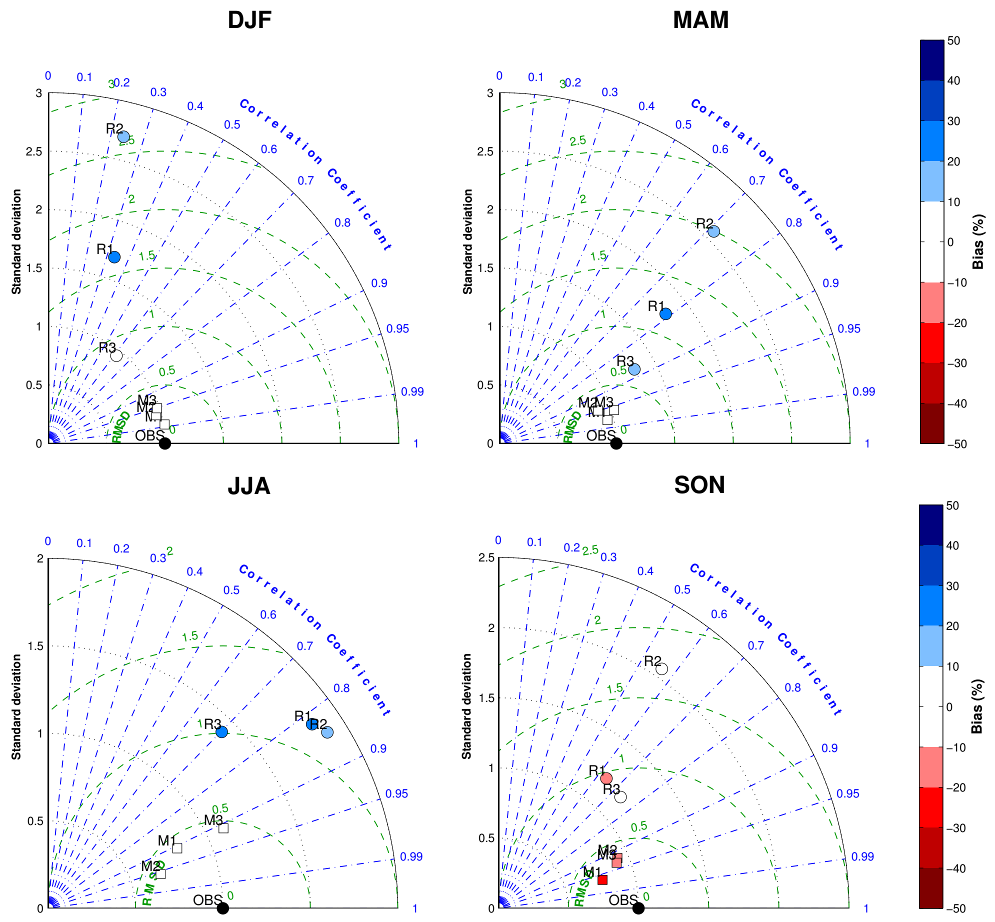


Figure 7:
Taylor diagrams for the seasonal precipitation climatology. Better results are closer to observation (OBS). The circles are used for the original COSMO-CLM model, while the squares for the MOS analogs method. The colours indicate the bias (in percentage respect to the Observed mean). The numbers correspond to the different indices: 1=PRCPTOT; 2=R1; 3=RX1DAY.

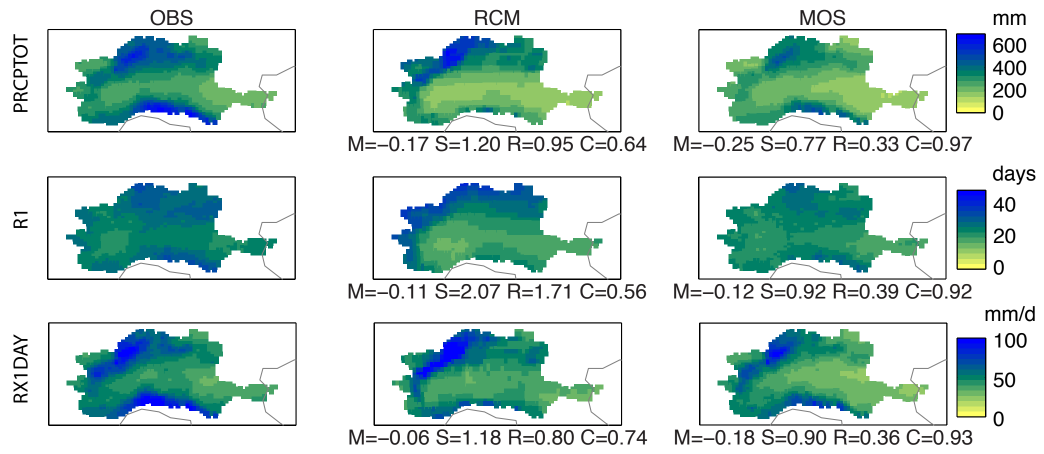


Figure 8:
Same as Figure 6, but for autumn.

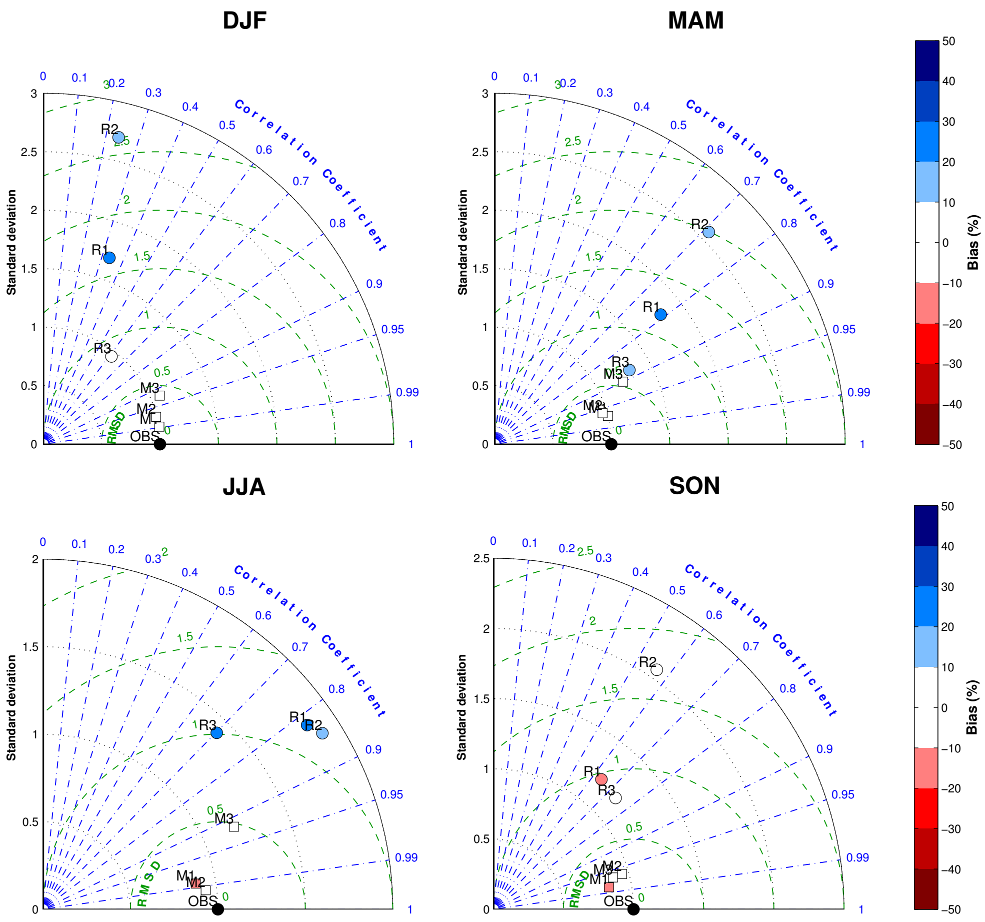


Figure 9:
Same as Figure 7, but for the *MOS seasonal analogs.*

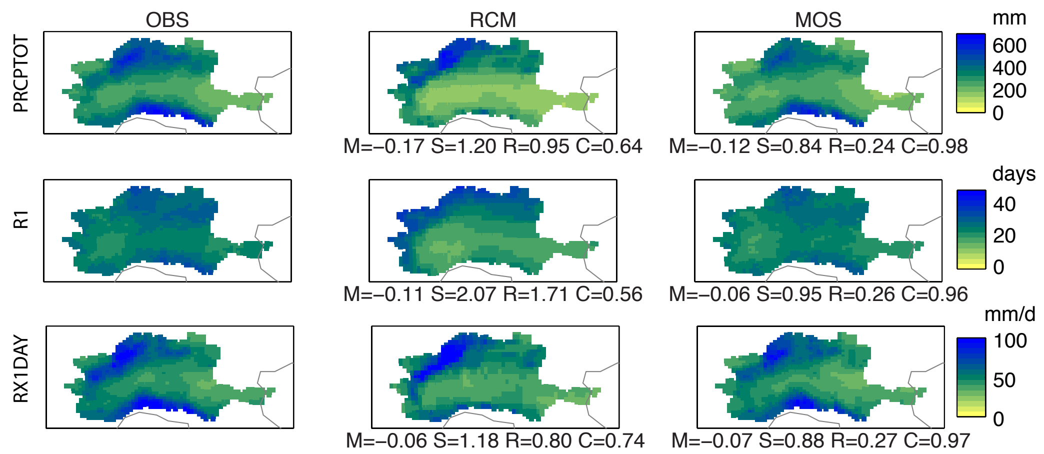


Figure 10:
Same as Figure 6, but for autumn, considering the *MOS seasonal analogs*.

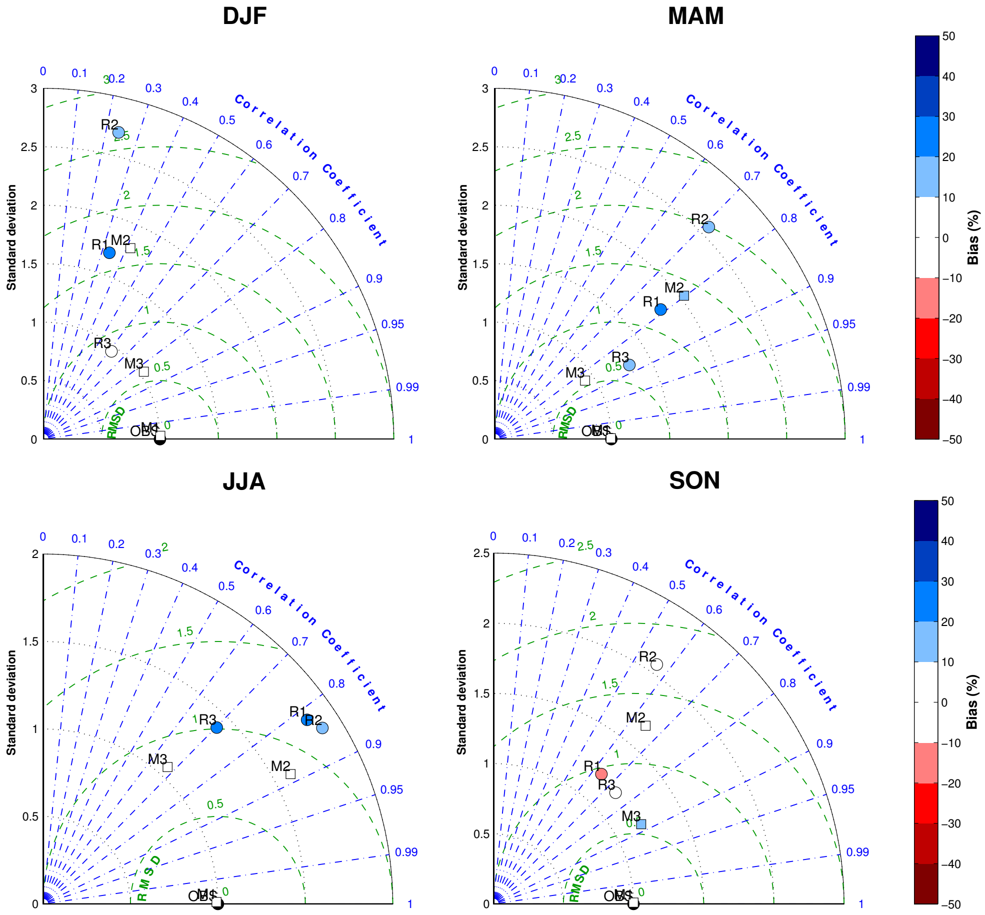


Figure 11:
Same as Figure 7, but for the linear-scaling method.

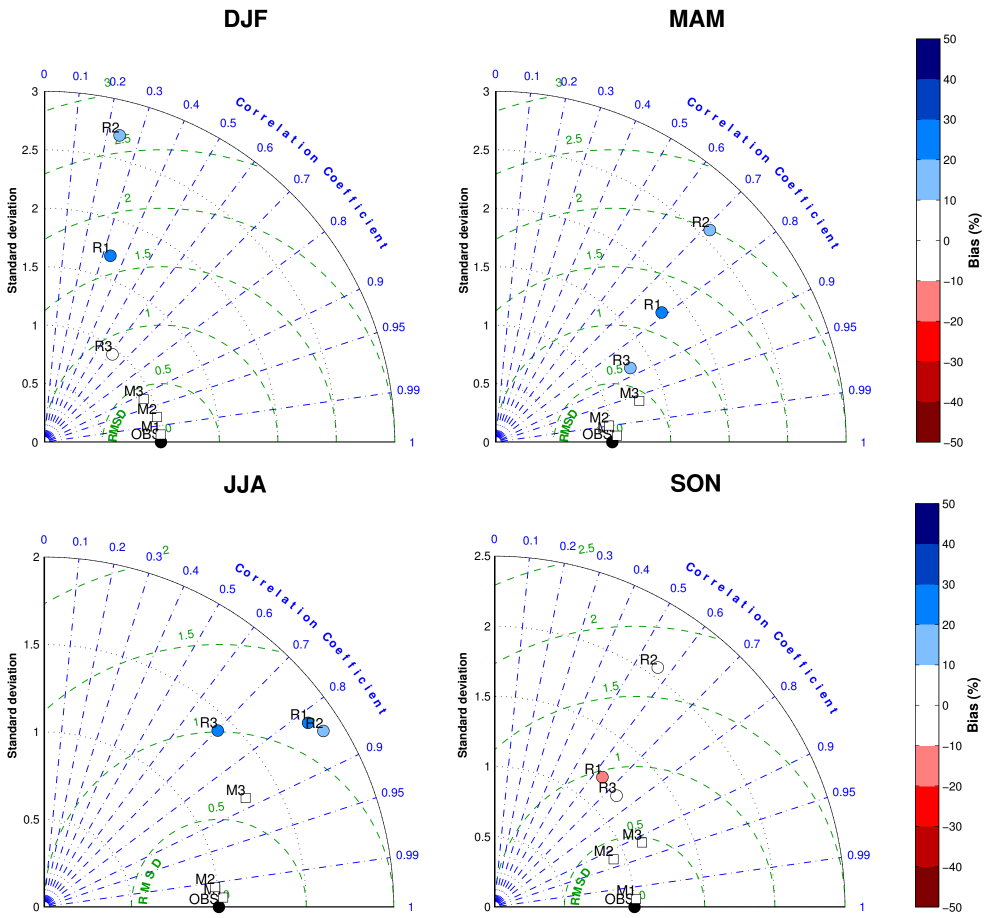


Figure 12:
Same as Figure 7, but for the quantile mapping method.

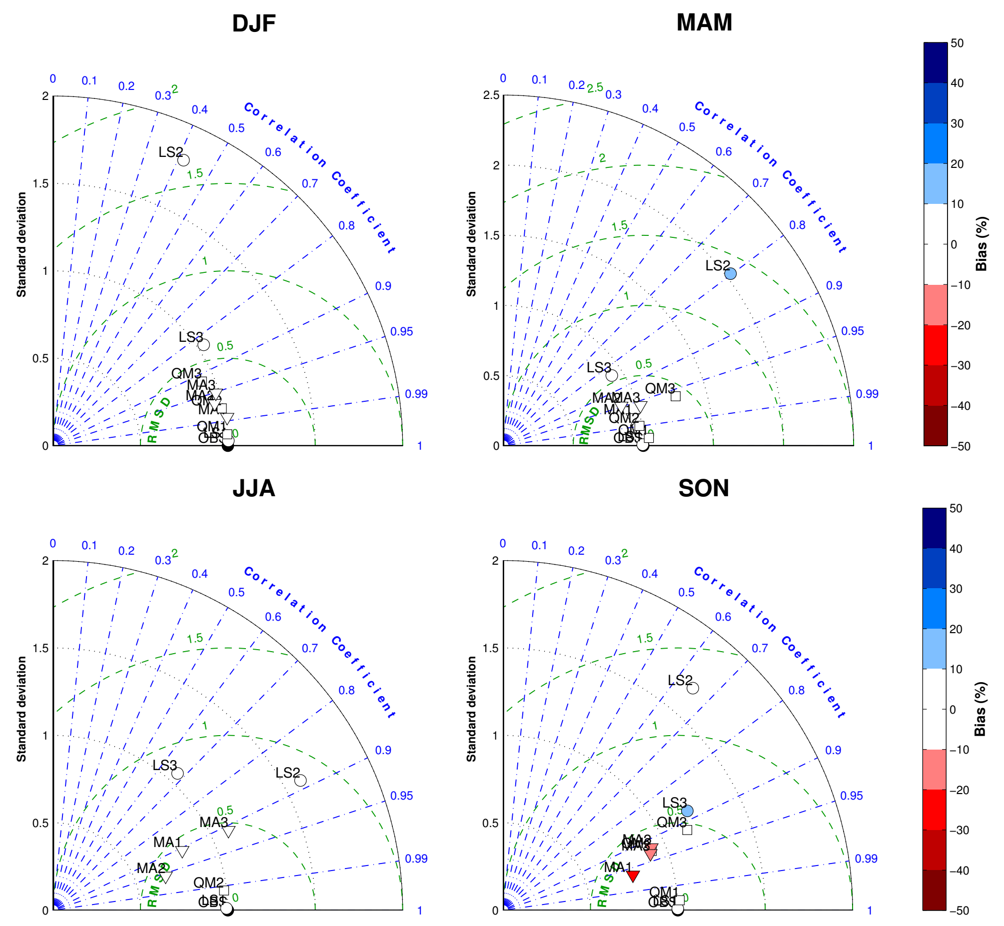


Figure 13:
Taylor diagrams for the seasonal precipitation climatology. Better results are closer to observation (OBS). The circles with LS are used for the linear-scaling method, the squares with QM for the quantile mapping, while the triangles with MA for the MOS analogs method. The colours indicate the bias (in percentage respect to the Observed mean). The numbers correspond to the different indices: 1=PRCPTOT; 2=R1; 3=RX1DAY.

SARDINIA

OBSERVED DATA

The observed data used for this domain are time series of daily cumulated precipitation, measured by an observational network located in Sardinia region and managed by *Ente Idrografico della Sardegna*. This dataset has been provided by the CMCC IAFENT division (Sassari). The considered observational stations are listed in Table 4 and their geographical distribution is shown in Figure 14.

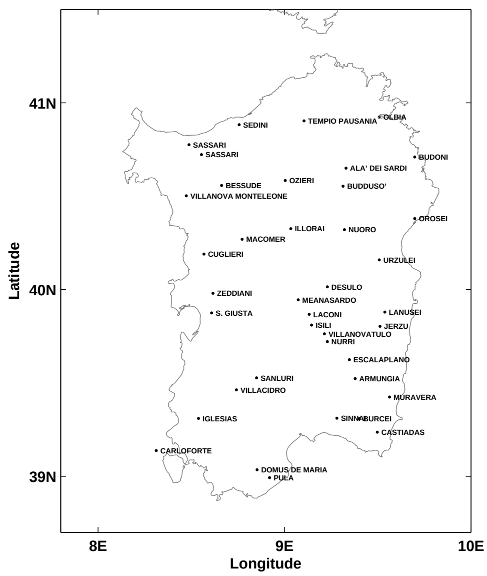


Figure 14:
Map of the Sardinia and geographical distribution of meteorological stations.

	Station	Longitude	Latitude
1	ALA' DEI SARDI	9,33	40,65
2	ARMUNGIA	9,38	39,52
3	BESSUDE	8,66	40,56
4	BUDONI	9,70	40,71
5	BURCEI	9,40	39,31
6	CARLOFORTE	8,31	39,14
7	CASTIADAS	9,50	39,24
8	ISILI	9,14	39,81
9	SINNAI	9,28	39,31
10	CUGLIERI	8,57	40,19
11	DESULO	9,23	40,01
12	ESCALAPLANO	9,35	39,62
13	URZULEI	9,51	40,16
14	IGLESIAS	8,54	39,31
15	DOMUS DE MARIA	8,85	39,04
16	JERZU	9,51	39,80
17	LANUSEI	9,54	39,88
18	MACOMER	8,77	40,27
19	MEANASARDO	9,07	39,95
20	MURAVERA	9,56	39,42
21	NUORO	9,32	40,32
22	NURRI	9,23	39,72
23	OLBIA	9,51	40,92
24	OROSEI	9,70	40,38
25	SASSARI	8,49	40,78
26	OZIERI	9,00	40,58
27	PULA	8,92	38,99
28	ILLORAI	9,03	40,33
29	SEDINI	8,76	40,88
30	S. GIUSTA	8,61	39,87
31	SANLURI	8,85	39,53
32	ZEDDIANI	8,62	39,98
33	LACONI	9,13	39,87
34	SASSARI	8,55	40,72
35	BUDDUSO'	9,31	40,55
36	TEMPIO PAUSANIA	9,10	40,90
37	VILLACIDRO	8,74	39,46
38	VILLANOVA MONTELEONE	8,47	40,50
39	VILLANOVATULO	9,21	39,76

Table 4
Location of the meteorological stations.

The available period is 1961-2000. In Figure 15 the number of available measurements is reported, for each year and for each station. The availability of pluviometric data in the considered period is quite good for almost all the stations, and only few stations have incomplete or missing data for some years. Figure 15 shows that the year 1981 is characterised by the highest number of station without data and that only three stations (Pula, S. Giusta and Sassari, Table 4) have more than two years of missing data.

The data variability for each station is displayed in the box plots of Figure 16.

The variability ranges of the different stations are almost the same, with mean values between 4 and 7 mm/day. Only one station shows precipitation significantly smaller than the others (Carloforte station, number 6 of Table 4).

These observed precipitation data could provide useful information on the climatology of the island. The three indices PRCPTOT, R1, and RX1DAY (described in Table 2), have been calculated at annual and seasonal timescales. The indices have been calculated only if no more than 10% of the days in the considered period is missing. Figure 17 shows the results for each index (column) and timescales (row).

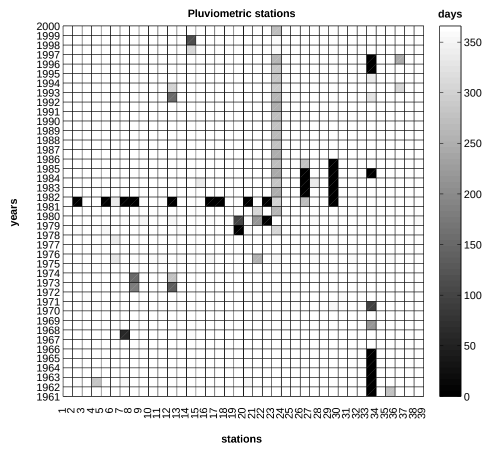


Figure 15:
Number of days with valid data in each year and for each pluviometric station.

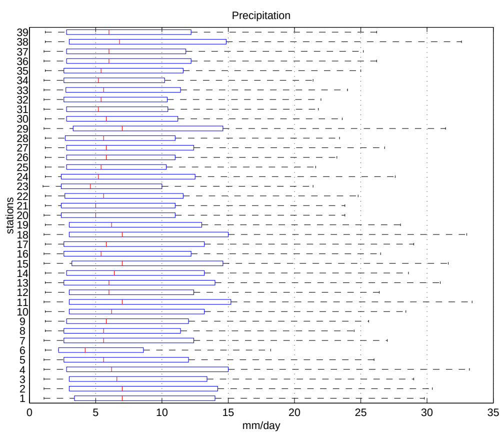


Figure 16:
Box plots of precipitation for each station.

The first column of pictures in Figure 17 is relative to the total precipitation, at annual and seasonal scale. Concerning the annual case, there is only one station with annual precipitation lower than 500 mm per year (Carloforte station in the south west part of island), while most of the values are between 600 and 800 mm. Stations near the Gennargentu massif have the highest values of annual precipitation, greater than 1000 mm per year. The seasons with more rain are winter and autumn. The second column of Figure 17 is relative to the number of rainy days (index R1), and it shows that in the east coast of the island there is a lower number of rainy days with respect to other regions, both at annual and seasonal scale. In particular, the number of rainy days in summer is very low, with less than 7 days in the inland of the island, and with less than 5 days near the coastline. Finally, in terms of maximum daily precipitation (index RX1DAY, third column of Figure 17) there is a quite high spatial variability, with higher values on the south-eastern coast, especially in winter and in autumn.

MOS RESULTS

Figure 18 summarizes the verification results of MOS analog for all the seasons and indices. Also in this case, the *MOS analog* downscaling method generally improves the RCM results for all the indices and seasons. However, for JJA and SON, the *MOS analog* does not eliminate the (seasonal) bias of the RCMs.

As for the Po river basin, also in this case we have evaluated the MOS analogs approach applied at seasonal level, but without obtaining encouraging results. Instead, better performance have been obtained by reducing the seasonal bias of the regional model through the linear-scaling method (Figure 19), or through the quantile mapping, which is effective even for the extremes (Figure 20).

Finally, the comparison among the three MOS methods is reported in Figure 21. As for the Po river basin, also in this case the quantile mapping method usually have the best scores, while the linear-scaling shows the worst results in most cases.

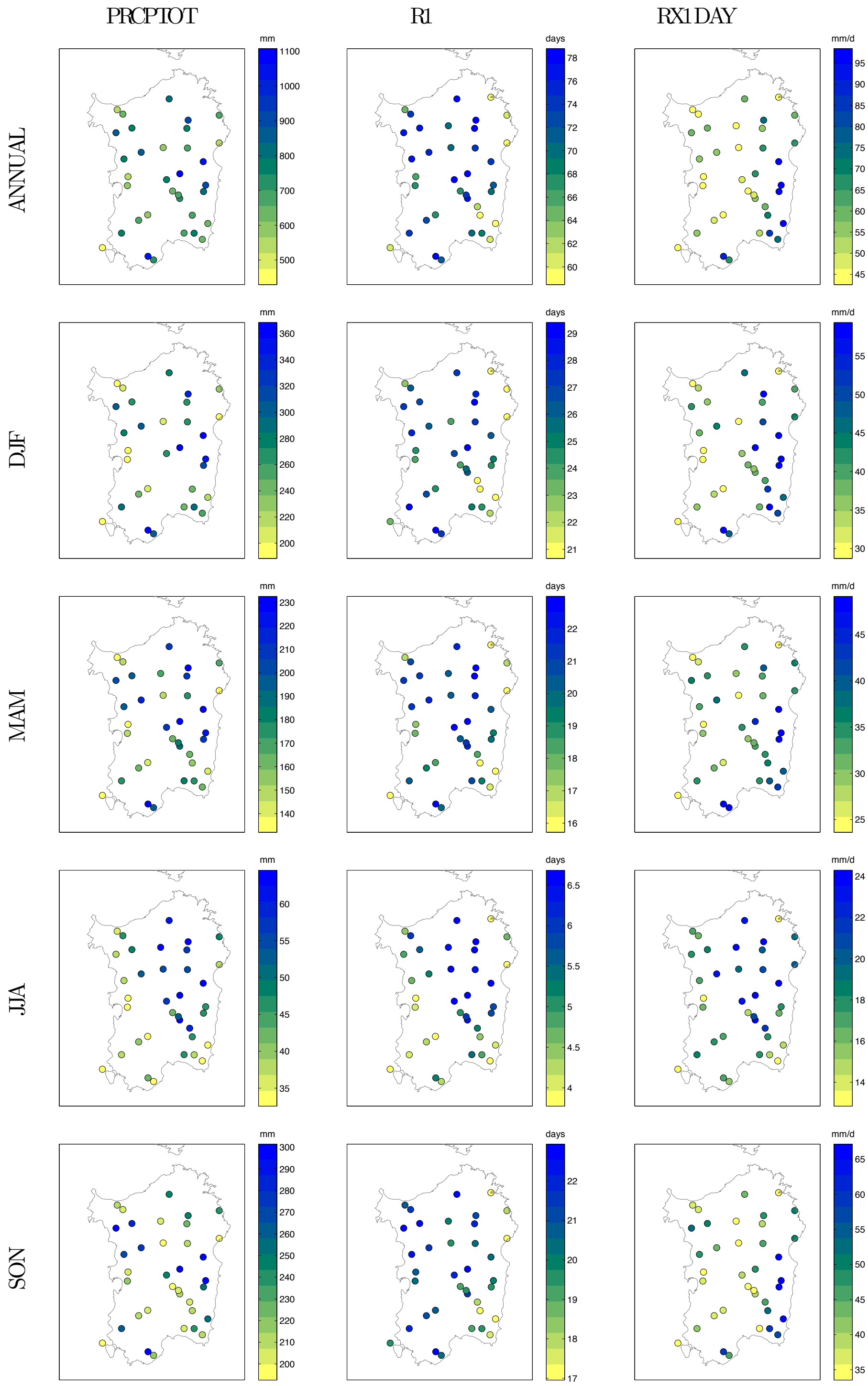


Figure 17:
Annual and seasonal climatologies for the three indices PRCPTOT, R1, RX1DAY (Table 2), calculated from time series of daily cumulated precipitation.

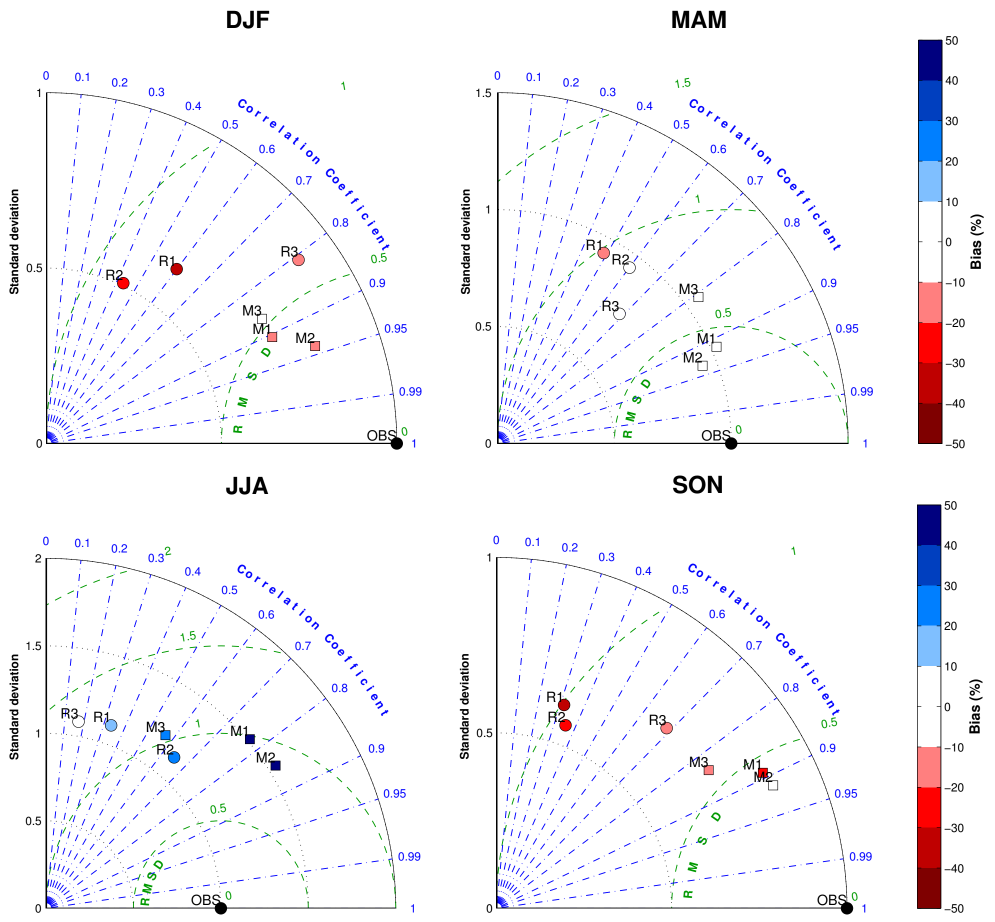


Figure 18:
Taylor diagrams for the seasonal precipitation climatology. Better results are closer to observation (OBS). The circles are used for the original COSMO-CLM model, while the squares for the MOS analogs method. The colours indicate the bias (in percentage respect to the Observed mean). The numbers correspond to the different indices: 1=PRCPTOT; 2=R1; 3=RX1DAY.

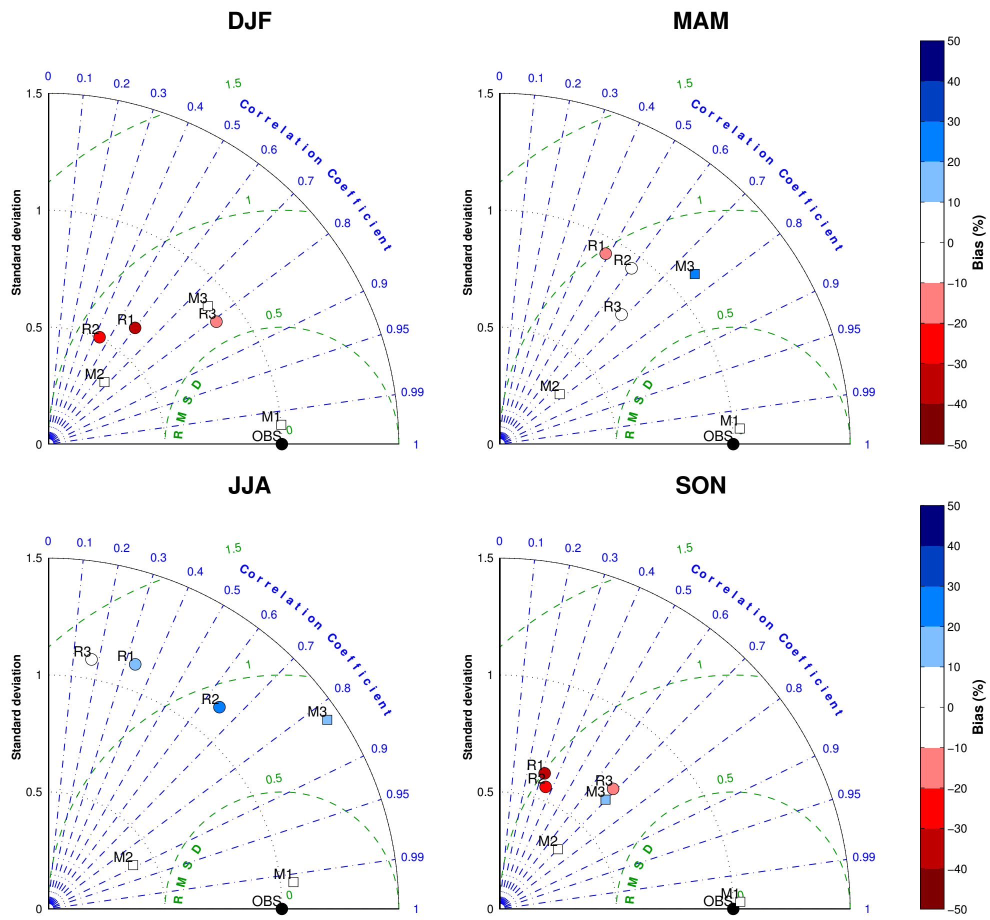


Figure 19:
Same as Figure 18, but for the linear-scaling method.

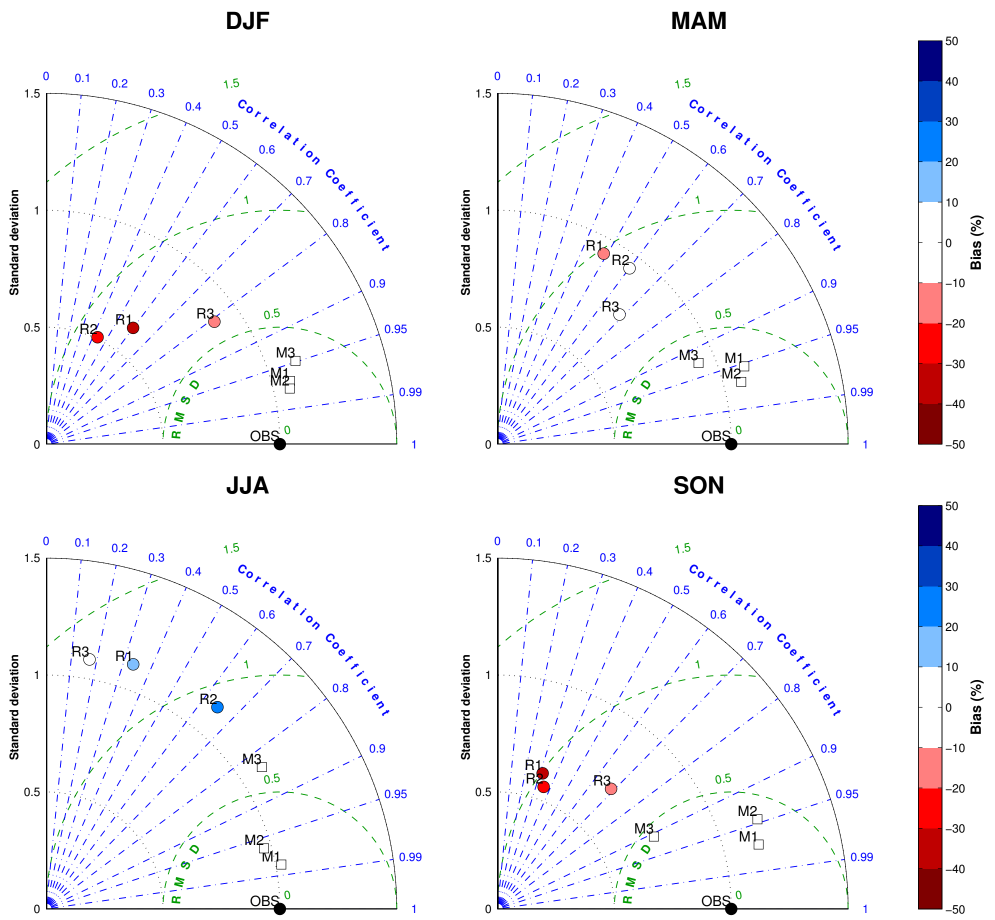


Figure 20:
Same as Figure 18, but for the quantile mapping method.

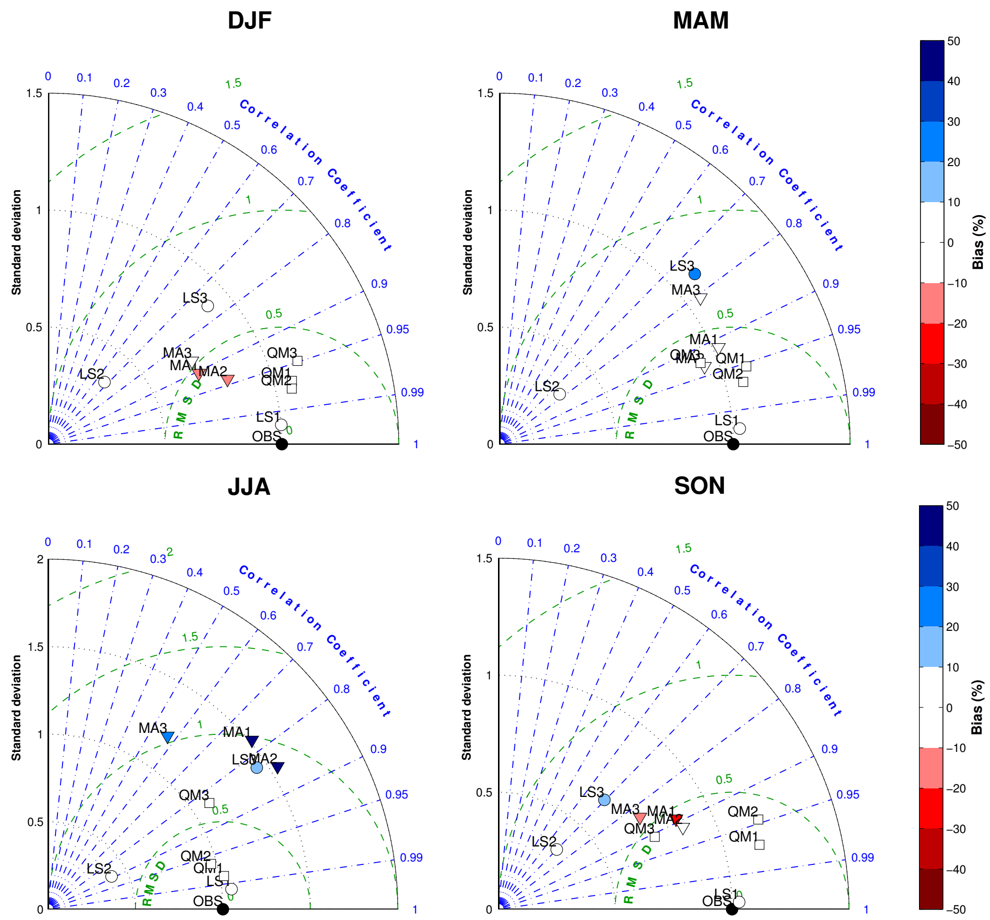


Figure 21:
Taylor diagrams for the seasonal precipitation climatology. Better results are closer to observation (OBS). The circles with LS are used for the linear-scaling method, the squares with QM for the quantile mapping, while the triangles with MA for the MOS analogs method. The colours indicate the bias (in percentage respect to the Observed mean). The numbers correspond to the different indices: 1=PRCPTOT; 2=R1; 3=RX1DAY.

CONCLUSION

The objective of this report was to test and to compare the performances three MOS techniques of increasing complexity - linear-scaling, quantile mapping, and MOS analogs - to refine the precipitation output of the COSMO-CLM regional model over three Italian case study, Orvieto, Po basin, and Sardinia. These domains are covered by high resolution data, and by the ERA40-driven COSMO-CLM model over the control period 1971-2000. The performance of the RCM and of the RCM-MOS simulations are cross-validated in terms of spatial similarity of the seasonal climatology (spatial pattern) for three ETCCDI indices (characterizing total precipitation, number of rainy days and maximum precipitation) between observed dataset and downscaled fields at seasonal scale.

This comparison shows that the *MOS* downscaled values generally outperform the uncalibrated RCM outputs, and the quantile mapping have often the best scores for most precipitation indices and seasons. These results highlight the MOS applicability, especially useful for those users that need high–resolution simulations for climate change impact studies.

Specifically, the main results of this study are:

- Over Orvieto, the best MOS results derives from the application of the quantile mapping approach: the preliminary result of this method give some confidence in its use to study the impacts of climate change on landslide risk in this area.
- Over the Po basin the *MOS analog* improves the representation of the mean regimes the frequency and the extremes of precipitation, regardless of the season (except an underestimation in autumn). This is probably due to the seasonal bias of the RCM. An alternative implementation of this approach, finding the analogs in the same season of the predictor, led to better results. Also the linear-scaling improves the RCM outputs, except for the index relate to the maximum precipitation, while the QM usually gives better results.
- Over Sardinia the *MOS analog* generally improves the RCM results for all the indices and seasons. However, for JJA and SON, the *MOS analog* does not eliminate the bias of the RCMs. Comparing the three MOS approaches, the QM often gives better results while the linear-scaling is the worst performing in most the cases.

To sum up, our strategy to bridge the gap between dynamical models and the end user shows promising results. However further research is recommendable to apply these post-processing methods to refine the RCM values, taking into account the impact user needs and the overall uncertainties that characterize the climate model chains. Indeed, even if, in general, the model chain ERA40-RCM-MOS reproduce quite well the spatial distribution of precipitation, its application in a climate change context requires further research. For this reason we plan to test these methods under "sub-optimal" conditions (using RCM driven by GCM in current climate) and to future RCM scenarios. In this case, it will be necessary to do additional analysis of the robustness of these MOS methods in climate change conditions.

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