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Large biases and inconsistent climate change signals in ENSEMBLES regional projections

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Abstract In this paper we analyze some caveats found in the state-of-the-art ENSEMBLES regional projections dataset focusing on precipitation over Spain, and highlight the need of a task-oriented validation of the GCM-driven control runs. In particular, we compare the performance of the GCM-driven control runs (20C3M scenario) with the ERA40-driven ones (”perfect” boundary conditions) in a common period (1961-2000). Large deviations between the results indicate a large uncertainty/bias for the particular RCM-GCM combinations and, hence, a small confidence for the corresponding transient simulations due to the potential nonlinear amplification of biases. Specifically, we found large biases for some RCM-GCM combinations attributable to RCM in-house problems with the particular GCM coupling. These biases are shown to distort the corresponding climate change signal, or ”delta”, in the last decades of the 21^{st} century, considering the A1B scenario. Moreover, we analyze how to best combine the available RCMs to obtain more reliable projections.

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1 Introduction

Regional Climate Models (RCMs) are one of the main tools available to produce climate change projections at the regional scale needed for many impact studies (Foley, 2010). These models run over a limited area of interest (e.g. Europe), driven at the boundaries by the output of a particular Global Climate Model (GCM), thus providing a regional (downscaled) version of the corresponding global simulation. Nowadays, a number of public multi-model databases of regional climate change projections are available for several regions of the world (see, e.g. the WCRP CORDEX initiative, Giorgi et al., 2009). For instance, the state-of-the-art ENSEMBLES database provides the biggest available ensemble of regional projections over Europe at an unprecedented 25km resolution (van der Linden and Mitchell, 2009). These simulations were produced by more than ten RCMs which were initialized and driven by lateral boundary conditions from the ERA40 reanalysis (Uppala et al., 2005) as well as from several GCM simulations —considering both the control 20C3M and transient A1B scenario runs—. The ERA40-driven runs allow evaluating the skill of the RCMs with so-called "perfect" boundary conditions (Brands et al., 2011; Eum et al., 2011). On the other hand, GCM driven RCM simulations allow to assess the uncertainty introduced by the particular RCM-GCM coupling (20C3M scenario) and to estimate the climate change signal (usually obtained applying the "delta rule", as the difference between the results in a future A1B period and the control 20C3M one). Evaluation results usually rely in the skill of the RCMs with reanalysis boundary conditions analyzing, e.g., the resulting biases w.r.t. observations (see, e.g. Christensen et al., 2010; Rummukainen, 2010 and references therein). However, although the additional need of evaluating the GCM-driven runs in the control scenario for climate change studies has been pointed out in several works (see, e.g. Kjellström et al., 2011), this task is still neglected in some recent impact studies (Mittal et al., 2013; Zhang and Huang, 2013).

In this paper we analyze the performance of each particular RCM-GCM coupling in the ENSEMBLES dataset by comparing the biases of the control GCM-driven run with the ERA40-driven one in a common period (1961-2000). Large deviations between both results indicate a large uncertainty/bias for the particular RCM-GCM combination and, hence, a small confidence for the corresponding transient simulations for future scenarios, due to the potential nonlinear amplification of biases (Christensen et al., 2008a). We found that some particular RCM-GCM combinations exhibit large outlier-like biases in the control runs, much larger than the corresponding reanalysis driven biases. Moreover, these combinations yielded inconsistent climate change signals (as compared with the rest of the ensemble) when applying the delta rule to the transient A1B and the control 20C3M runs. This indicates that there is some non-linear amplification of the bias in the transient run, thus questioning the application of bias correction techniques —calibrated with control run data— in those cases. We also analyze how to best combine the available projections in the light of these results, in order to obtain more reliable scenarios.

We focus on precipitation, a key variable for many impact sectors (agriculture, hydrology, etc.) which has a large uncertainty in RCMs. In particular we consider the Spanish Iberian Peninsula, a challenging domain with great climatic variability due to its complex orography and particular location, at the transition between extra-tropical and subtropical influence, with both Atlantic and Mediterranean influences (Giorgi and Lionello, 2008). Moreover, Spain is near the southern boundary of the different integration domains used by the ENSEMBLES RCMs, and consequently, the possible modelling errors and biases could be further amplified (Rummukainen et al., 2001).

2 Data and verification method

In this study we use the daily high-resolution gridded precipitation dataset over Spain (*Spain02*), which cover the period 1950–2008 with a regular 0.2° resolution —approximately 20 km— which is publicly available for research activities (at http://www.meteo.unican.es/datasets/spain02). This grid was produced from 2756 quality-controlled pluviometric stations, obtained from the Spanish Meteorological Agency (AEMET). To ensure spatial and temporal homogeneity, these series were quality and homogeneity tested (see Herrera et al., 2012 for more details).

On the other hand, we consider an ensemble of eleven state-of-the-art RCMs (see Table 1) at a 25 km resolution produced in the EU-funded project ENSEMBLES (van der Linden and Mitchell, 2009). The dataset includes reanalysis-driven simulations using the ERA-40 reanalysis (Uppala et al., 2005) and GCM-driven simulations for the 20C3M scenario (for the period 1961-2000) as well as for the A1B scenario (2001-2050, or 2001-2100, depending on the particular model). Most of the RCMs are nested on a single GCM with only two exceptions —which are nested onto three different GCMs—, thus resulting in an ensemble of 15 RCM-GCM combinations (see Table 1). For practical reasons, the outputs of the RCMs were bilinearly interpolated from their original resolution (aprox. 25 km) to the Spain02 grid (approx. 20 km).

In the following we investigate the uncertainty of each RCM-GCM coupling by comparing the performance of the 20C3M GCM-driven run (control) with the ERA40-driven one in a common period (1961-2000). Specifically, we compare the seasonally-averaged spatial patterns of the mean and the standard deviation (not shown) of daily precipitation. For this aim we use Taylor diagram (Taylor, 2001), which synthesizes three standard metrics of spatial similarity —standard deviation, centered root-mean-square difference (RMSD) and correlation— in a single bidimensional plot. Note that the statistics are normalized dividing both the centered root-mean-square and the standard deviations by the standard deviation of the observations. Besides, in order to include information about overall biases, the color of each point indicates the difference between the simulated and observed mean, normalized by the observed mean. Better performance models are close to observation, on the x-axis (labelled as OBS in the figures).

Note that an evaluation of the ERA40-driven RCMs has been already performed for this variable and region (Herrera et al., 2010; Turco et al., 2011) considering both the mean and extreme spatial precipitation regimes and the spatially

Table 1 RCM-GCM couplings from the ENSEMBLES project used in this study. The numbers are used to facilitate the reading of the Taylor diagrams presented later (see Fig. 1). The acronyms correspond to that ones in the ensemble web page http://ensemblesrt3.dmi.dk. The asterisks indicate the best performing RCM models for precipitation in this region according to the evaluation of Herrera et al. (2010), based on the accuracy to reproduce the mean precipitation regime and the annual cycle.

Number - Acronym	**RCM**	**Driving GCM**	**Reference**
1 - C4I	RCA3	HadCM3Q16	Samuelsson et al. (2011)
2 - CNRM	ALADIN	ARPEGE	Radu et al. (2008)
3 - DMI	HIRHAM	ARPEGE	Christensen et al. (2008b)
4 - DMI-BCM	HIRHAM	BCM	Christensen et al. (2008b)
5 - DMI-ECHAM5	HIRHAM	ECHAM5-r3	Christensen et al. (2008b)
6 - *ETHZ	CLM	HadCM3Q0	Jaeger et al. (2008)
7 - *HC	HadRM3Q0	HadCM3Q0	Haugen and Haakensatd (2005)
8 - ICTP	RegCM3	ECHAM5-r3	Pal et al. (2007)
9 - *KNMI	RACMO	ECHAM5-r3	van Meijgaard et al. (2008)
10 - *MPI	M-REMO	ECHAM5-r3	Jacob (2001)
11 - OURANOS	MRCC4.2.1	CGCM3	Plummer et al. (2006)
12 - SMHI-BCM	RCA	BCM	Samuelsson et al. (2011)
13 - SMHI-ECHAM5	RCA	ECHAM5-r3	Samuelsson et al. (2011)
14 - SMHI-HCQ3	RCA	HadCM3Q3	Samuelsson et al. (2011)
15 - *UCLM	PROMES	HadCM3Q0	Sanchez et al. (2004)

averaged annual cycle. The RCMs with better performance according to Herrera et al. (2010) have been highlighted with an asterisk in Table 1.

3 Results and discussion

Figure 1 shows the performance of the different RCM-GCM couplings (see Table 1) in order to reproduce the spatial pattern of the seasonal climatology for precipitation. Each arrow in the diagram is associated with a particular coupling. The starting point indicates the performance of the ERA40-driven run for the corresponding RCM, while the end (denoted with a colored circle, labelled according to Table 1) indicates the performance of the GCM-driven simulation for the 20C3M control scenario. The color of the circle indicates the bias of the latter simulation. Note that the longer the length of the arrow, the bigger the differences/inconsistencies between the ERA40- and GCM- driven simulations. Overall, the main conclusion is that some couplings exhibit significantly larger differences than the others. This is the case of couplings 4, 5 and 12 (corresponding to DMI-BCM, DMI-ECHAM5 and SMHI-BCM, respectively) in all seasons but Summer (JJA), and couplings 4, 12 and 14 (DMI-BCM, SMHI-BCM and SMHI-HCQ3) in Summer. These differences are associated with a low performance of the GCM-driven simulations which exhibit large biases and standard deviations (larger than 2.5 times the observed ones in all cases). Note that these simulations correspond to couplings of the two RCMs which have been nested into three different GCMs in the ENSEMBLES datasets (see Table 1). The spatial structure of the RCM seasonal climatologies is in a relatively good agreement with observations, with spatial correlations between 0.65 and 0.85 and RMSD smaller than 1.5 in most cases. Besides the mean climatologies, we have also analyzed the variability (i.e.

the standard deviation of daily precipitation in each season), obtaining similar conclusions (the results are not shown).

Besides, contrary to the behaviour seen in all the other seasons, the majority of RCMs (except the low-performing ones) improve their performance in summer when the boundary conditions are provided by the GCMs. This is the season with less precipitation in Spain, which is influenced by local factors (e.g. convection) in addition to large scale circulation in some regions, leading to a North-South spatial gradient with smaller influence of the orography than in other seasons (see Herrera, 2011, for further details). Note that all the components in the downscaling process have the same common problem to reproduce local drivers (Hohenegger et al., 2008; Rummukainen, 2010) and, therefore, further research is necessary in order to investigate potential explanatory factors, such as soil moisture accumulation in previous months (see, e.g., Quesada et al., 2012).

As an illustrative example of the low-performing RCM-GCM combinations, Figure 2 shows the mean daily precipitation maps corresponding to the DMI runs for winter (DJF), including (b) the ERA40 driven outputs, (c-f) the reanalysis ERA40 and the three GCM model outputs and (g-i) the corresponding three GCM-driven DMI outputs. For the sake of comparison, the observations from Spain02 are also included in panel (a). Overall, this figure shows that those runs driven by the global models BCM and ECHAM5 have a very large bias, as compared to the ARPEGE-driven one, which is much closer to the observations and to the reanalysis-driven results. Note that the precipitation magnitude is similar among the corresponding global models (panels c-e) and, thus, the different RCM outputs could be attributed to the particular RCM-GCM coupling. The same is true for the SMHI model, where the BCM- and HCQ3-driven runs exhibit very large biases, as compared to the ECHAM5-driven ones (not shown). Similar coupling problems have been reported in the NARCCAP project (Mearns et al., 2012) where one of the RCMs —the HadRM3 model— yielded very large biases when driven by the NCEP/NCAR reanalysis (done for the first time in that project), as compared with the corresponding results from other RCMs. However, rerunning HadRM3 using the ERA-Interim data (an alternative reanalysis previously used to drive the HadRM3 model) resulted in biases of similar magnitude to those for the other RCMs.

This poses some caveats on the use of the ENSEMBLES transient projections in impact studies which typically use either daily data (to run impact models in future climate conditions) or climatological climate change ”deltas” (to modify a baseline climatology to obtain the future climatology). On the one hand, when daily data is required, the control run is typically used for calibrating bias-correction techniques (factor scaling, quantile-quantile mapping, etc.) which are commonly applied in this case (see Ehret et al., 2012, and references therein for a debate on this topic). However, these techniques assume bias stationarity between the control and transient runs, which can pose significant limitations in cases with large biases —such as those presented in this study— and/or with systematic conditional biases —such as biases in warm months (Boberg and Christensen, 2012)—. On the other hand, although a linear cancellation of bias is performed when taking the difference (or ratio) of the transient and control climatologies for the climate change signal (delta), the resulting signal could still be affected by nonlinear amplifications of biases in an unpredictable form (Christensen et al., 2008a).

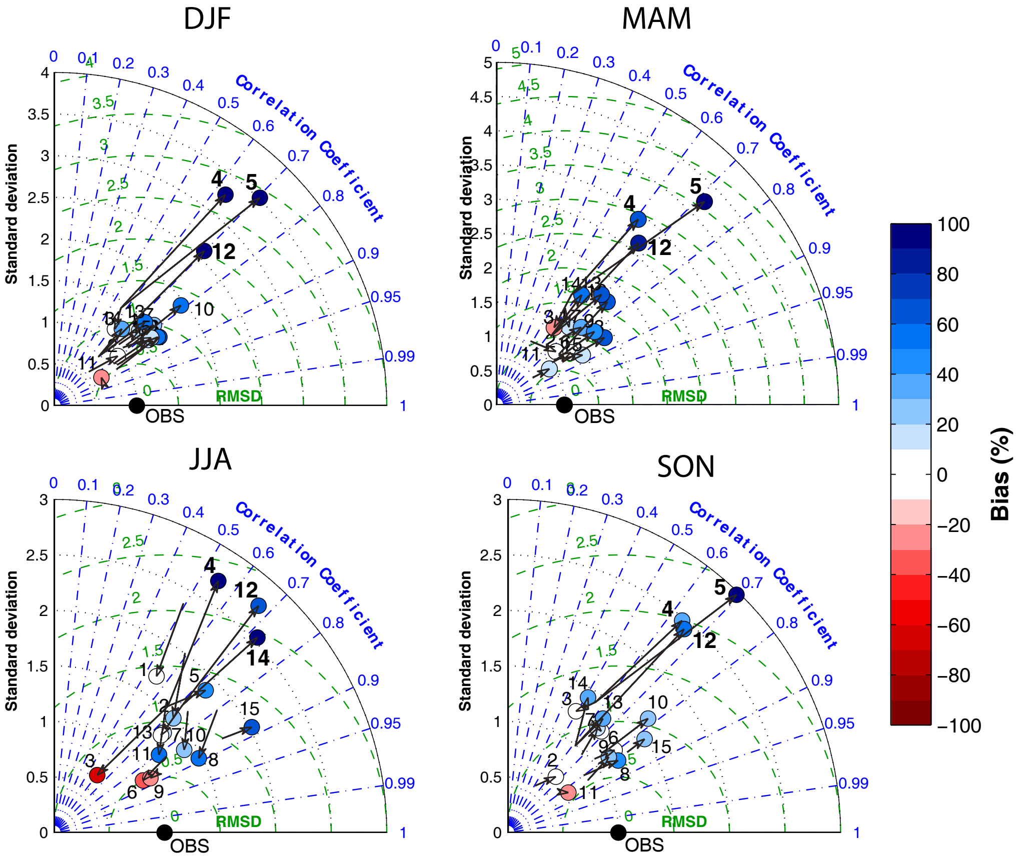

Fig. 1 Taylor diagrams for the seasonal precipitation climatology. Models with better performance are close to the observations (labelled as OBS). The starting point of the arrow indicates the performance of the ERA40-driven runs, while the end (denoted with a coloured circle, labelled according to Table 1) indicates the performance of GCM-driven runs. The colors indicate the bias (in percentage respect to the observed value) of the GCM-driven runs. Bold face indicates particularly low-performing models.

In order to test this problem in an illustrative case, we consider the five different runs driven by the same GCM (the ECHAM5 model), which include the low-performing ECHAM5-driven DMI model. In all cases we computed the "deltas" given by the ratios of the winter precipitation in the period 2071-2100 w.r.t. the control run 1971-2000 (see Fig. 3). This figure shows that in the case of the largest bias (DMI-ECHAM5), the deficiencies of the coupling in the control scenario seem to propagate to the corresponding delta (panel b), leading to a doubtful and inhomogeneous wetter climate change signal (with a relative increase over 60% in some regions and without the negative signal of the south/south-east), while the other ECHAM5-driven runs show a spatially consistent pattern similar to the GCM one

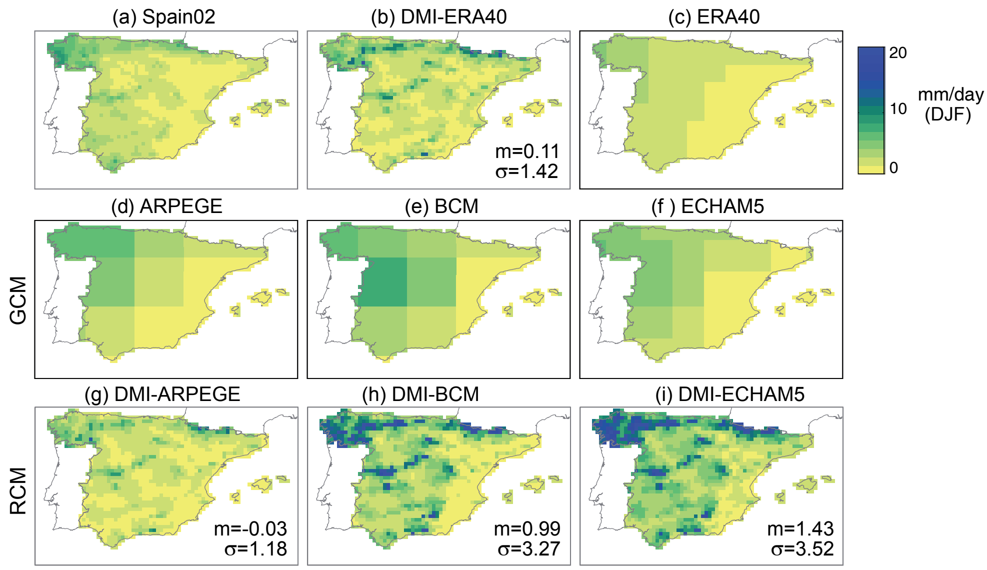

Fig. 2 Maps of winter precipitation climatology (in mm/day) as given by (a) the Spain02 interpolated data set, (c) the reanalysis ERA40 and the DMI (b) ERA40- and (g-i) GCM-driven simulations (for the control 20C3M period). The numbers below the figures indicate the spatial mean error (m), w.r.t. Spain02, and standard deviation of those errors (σ). Panels (d)-(f) show the precipitation climatologies for the GCMs.

(both in terms of spatial correlation and climate change signal). Note that the mean spatial signal from the DMI model is positive, as opposite to the negative values in all other cases. Moreover, the correlation of the regional climate change signal with the global one is close to 0.5 in this case, whereas it is over 0.7 in all other cases. Therefore, it is not advisable to work directly with the delta signals, ignoring the performance of the RCM-GCM runs in the control period and the side effects of large biases.

In the following we analyze how to best combine the available RCMs to obtain more reliable projections. We consider four different ensembles: The ensemble mean of the eleven ERA40-driven RCMs (E1 hereinafter), the mean of the fifteen GCM-driven RCMs members (E2), the ensemble mean of the eleven best performing RCMs, i.e. excluding models 4, 5, 12 and 14 (E3) and, finally the ensemble of five models according to Herrera et al. (2010) (E4); these RCMs are indicated with an asterisk in Table 1.

Figure 4 confirms that, except for JJA, the best ensemble is E1, i.e. the reanalysis-driven ensemble. Moreover, the E2 is the ensemble with lowest performance for all the seasons. Overall, the best GCM-driven results are obtained removing the four GCM-driven RCM runs with lowest performance. The performance of the ensemble E4 (based on the skill of the ERA40-driven RCMs) is similar or slightly lower than the one of the ensemble E3 (i.e. based on the skill of the GCM-driven RCMs). Note that all the four ensembles overestimate the seasonal average precipitation. The GCM-driven ensembles (E2, E3 and E4) have stronger

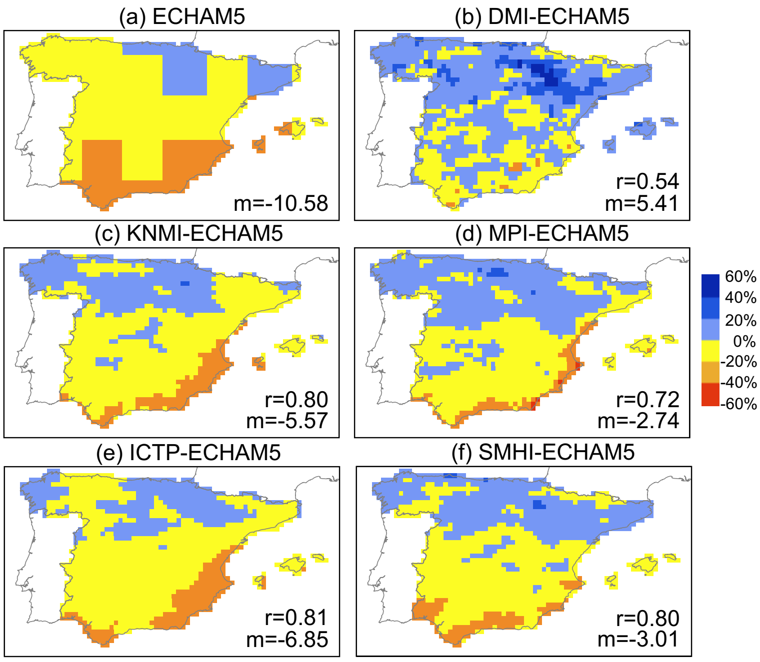

Fig. 3 Winter climate change signal (”deltas”) given by the ratios (in %) of the precipitation in the period 2071-2100 (A1B scenarios) over the control run 1971-2000 (20C3M scenario) for (a) ECHAM5-r3 outputs and (b,f) the corresponding RCM-driven simulations. The numbers inside the panels indicate the spatial correlation with the ECHAM5 results (to check spatial consistency with the GCM) and the spatial mean climate change signal (in %).

bias than the ERA40-driven runs, except for JJA. These results suggest that the problem of constructing an optimum ensemble is delicate since both reanalysis- and GCM-driven control simulations have to be evaluated to detect potential low-performing RCMs and/or couplings, respectively.

4 Conclusion

In this paper we have shown that the assessment of regional climate projections in control conditions is necessary to avoid low-performing RCM-GCM couplings which may bias the resulting transient projections and the corresponding climate change signals. This was done by comparing the GCM-driven control run (20C3M) with the ERA40-driven one (”perfect” boundary conditions) in a common period (1961-2000). Large deviations between both results indicate a large bias for the particular RCM-GCM combination, which might affect the future transient projections due to the possible nonlinear amplification of biases. We analyzed the state-of-the-art ENSEMBLES dataset focusing on precipitation in the Spanish Iberian Peninsula and found very large biases for some particular RCM-GCM couplings which can be considered outliers/errors of the ensemble. Indeed, the performance of the ensemble clearly improved discarding those simulations.

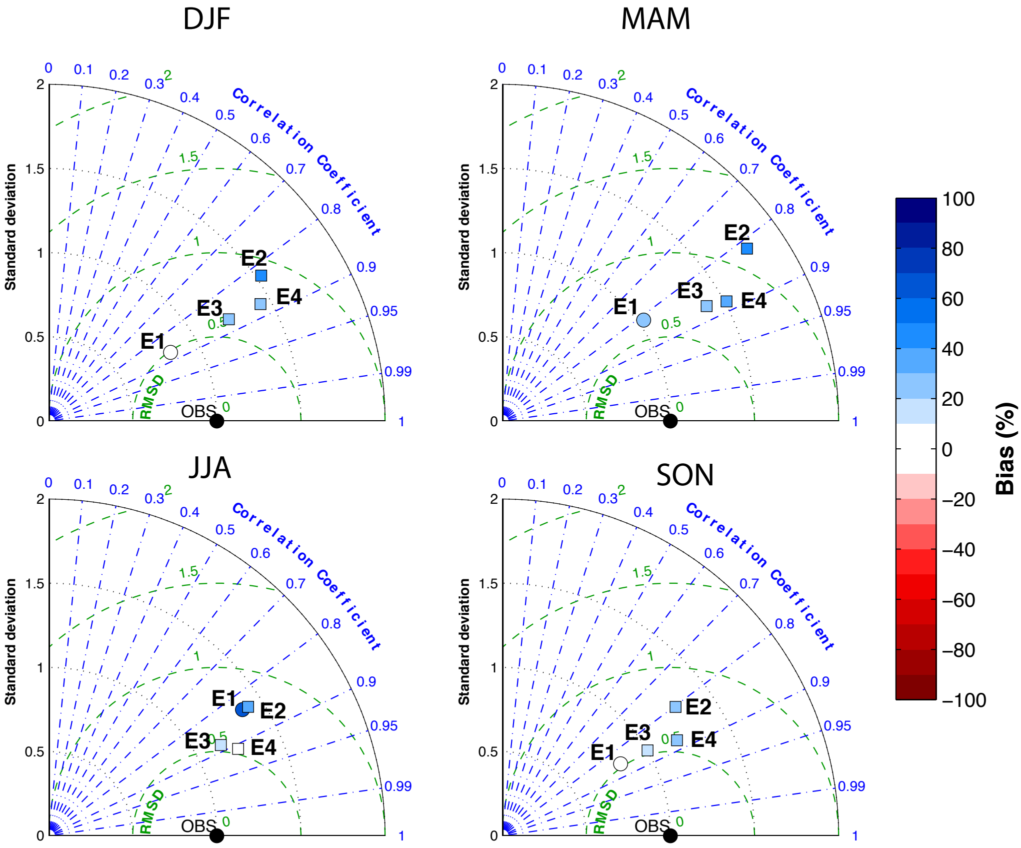

Fig. 4 Taylor diagrams for different ensembles: (E1) the eleven ERA40-driven runs; (E2) all the GCM-driven runs; (E3) as E2, but discarding the four deficient runs; (E4) ensemble formed by the runs of the best five 5 ERA40-driven RCMs. See running text for more details.

Rummukainen et al. (2001) found that the RCM precipitation patterns substantially follow those of the driving GCM, but with local features mainly related to the orographic details. Therefore, it could be argued that the GCMs could be responsible of the deficient runs. However, in our analysis we found that the same GCM (e.g. ECHAM5) can lead to inconsistent projections when driving different RCMs (e.g. runs 5 and 13, see Table 1). Therefore, the problem seems to be related to the coupling of some specific GCM with some RCM, more than to particular deficiencies of the individual models. This is bad news, since it might indicates that we cannot run freely whatever RCM-GCM combination.

The large biases found in some RCM-GCM couplings are shown to affect the corresponding "deltas" for a transient future period (w.r.t. the control run) leading to inconsistent climate change projections which should not be used in impact studies. Similar problems are expected to occur when applying bias corrections to these couplings, thus warning on the systematic application of those techniques, although they may improve climate scenarios in most cases (Maraun, 2012).

As a final conclusion, this study highlights the importance of performing task-oriented validation of the control runs to identify and discard low-performing (as compared with the corresponding reanalysis-driven runs) RCM-GCM couplings.

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