Evaluation of the mean and extreme precipitation regimes from the ENSEMBLES regional climate multimodel simulations over Spain

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Received 25 January 2010; revised 2 August 2010; accepted 16 August 2010; published 9 November 2010.

A state-of-the-art ensemble of regional climate model (RCM) simulations provided by the European Union–funded project ENSEMBLES is used to test the ability of RCMs to reproduce the mean and extreme precipitation regimes over Spain. To this aim, ERA-40–driven simulations at 25 km resolution are compared with the 20 km daily precipitation grid Spain02, considering the period 1960–2000. This gridded data set has been interpolated from thousands of quality-controlled stations capturing the spatial variability of precipitation over this RCM benchmark–like area with complex orography and influence of both Atlantic and Mediterranean climates. The results show a good representation of the mean regimes and the annual cycle but an overestimation of rainfall frequency leading to a wrong estimation of wet and dry spells. The amount of rainfall coming from extreme events is also deficient in the RCMs. The use of the multimodel ensemble improves the results of the individual models; moreover, discarding the worst performing models for the particular area and variable leads to improved results and reduced spread.


1. Introduction

[2] Dynamical downscaling of a global climate model (GCM) using a regional climate model (RCM) is a widely used technique to obtain high-resolution information about projected climate change scenarios [Leung et al., 2003; Wang et al., 2004; Laprise, 2008]. Basically, this technique consists of solving the governing equations of the atmosphere at high resolution in a particular region (e.g., Europe) using the coarse GCM output as boundary conditions. In this way, it is expected that the RCM dynamics will provide highly resolved climatic information that the coarse resolution GCM cannot obtain [Elía and Laprise, 2002; Vidale et al., 2003; Castro et al., 2005]. High-resolution climatic information is demanded by end users to analyze the impacts produced in different sectors by changes in the mean or extreme regimes of a variety of meteorological variables [Fronzek and Carter, 2007]. Precipitation is a key variable in sectors such as agriculture and hydrology and it is one of the variables with the largest uncertainty in RCMs, due to the large number of parameterized processes involved in its determination. The present study analyzes the performance of several RCMs from the European Union (EU)–funded project ENSEMBLES [van der Linden and Mitchell, 2009] nested in a common global reanalysis to reproduce the observed mean and extreme regimes of precipitation over Spain. The combined use of the ensemble of RCMs (multimodel ensemble) is compared with the individual RCM results.

[3] Since RCMs are limited to the quality of the GCM information [Déqué et al., 2007], the evaluation of the skill of an RCM in reproducing the observed climate should be done by providing reanalysis data (as a surrogate of a perfect GCM) as boundary conditions. Even though different RCMs can be compared when forced by the same GCM boundaries [Jacob et al., 2007], this kind of experiment makes difficult to discern whether the observed biases arise from the global or the regional model.

[4] ENSEMBLES is the latest in a series of EU-funded projects dealing with multimodel dynamical downscaling of large-scale climate information over Europe: Regionalization (1993–1994), RACCs (1995–1996) [Machenhauer et al., 1998], MERCURE (1997–2000), and PRUDENCE (2001–2004) [Christensen et al., 2007]. These projects paved the way for ENSEMBLES, where the latest-generation RCMs downscaled with unprecedented resolution a set of GCM simulations (for present control and the future scenario A1B) and also “perfect” boundaries from reanalysis. The perfect boundary approach was missing in the predecessor project PRUDENCE, where RCMs where only nested into GCMs. Thus, ENSEMBLES enables, one decade after MERCURE, a direct comparison of the performance of different state-of-the-art RCMs over Europe.
Several works deal with the performance of ensembles of RCM simulations over Europe [Frei et al., 2003; Jacob et al., 2007; Boberg et al., 2009, 2010]. Frei et al. [2003] performed a detailed evaluation of the precipitation from MERCURE RCMs over the Alps, stressing the need for very dense station networks in the evaluation of RCM results over complex terrain. Boberg et al. [2010] evaluates daily precipitation distributions in ENSEMBLES RCMs and compares them with observations. Their analyses were performed over large European subregions, as in several other studies [Christensen and Christensen, 2007; Jacob et al., 2007]. They found a poor performance in reproducing the precipitation PDF over the Iberian Peninsula region. However, this region is not climatically homogeneous [De Castro et al., 2007] and, additionally, the station coverage used in previous studies over this area is poor and not spatially uniform. Then, analyses of variables averaged over the whole Iberian Peninsula should be taken with caution.

In this work, an analysis at basin scale is performed to assess the usefulness of RCMs in different regions of interest for hydrological studies (and also for many other fields since the river basins correspond to climatically uniform regions in this area). The evaluation of the model performance is done against a new $0.2^\circ \times 0.2^\circ$ gridded interpolated data set (Spain02) [Herrera et al., 2010] for the region, which includes thousands of stations (as compared with a few tens used in previous studies).

Section 2 briefly describes the data used and the indices and techniques considered for verification. Section 3 gives a short description of precipitation regimes in Spain. Section 4 analyzes the observed and RCM simulated mean precipitation regime in terms of total accumulated amounts and the monthly annual cycle on the river basins. Section 5 analyzes the extreme regimes in terms of extreme precipitation indices. Section 6 summarizes the conclusions of the study.

2. Data and Methodology

In this study we used RCM data from the ENSEMBLES project and the Spain02 data set (interpolated observations), which are described next. The indices and validation measures used in the paper are also briefly described here.

2.1. ENSEMBLES RCM Data Set

The EU-funded project ENSEMBLES (http://www.ensembles-eu.org) is a collaborative effort of different European meteorological institutions focused on the generation of climate change scenarios over Europe. ENSEMBLES studies climate change from different perspectives and includes a large variety of communities and state-of-the-art methodologies and techniques. In particular, dynamical downscaling of GCM simulations was performed using nine different RCMs run by different institutions (see a list in Table 1) over a common area covering the entire continental European region and with a common resolution of 25 km.

Within ENSEMBLES, an initial RCM verification experiment was carried out using the reanlaysis from the European Centre for Medium Range Weather Forecasts (ECMWF) (ERA-40 [Uppala et al., 2005]) as boundary conditions for the RCMs. All RCMs were run over the common 30 year period 1961–1990 (although some of them simulated longer periods). A second experiment for climate change studies was done nesting the RCMs into different GCM simulations for a control climate (forced with the A2C3M scenario) and future projections (forced with the A1B scenario). These runs were used to produce regional climate change scenarios over Europe with different weighting techniques [van der Linden and Mitchell, 2009].

In this paper we used a total of 9 RCM simulations (shown with an asterisk in Table 1) taken from the RCM verification experiment. These 9 models were those providing (by the end of summer 2009) the daily precipitation output required in our study. Thus, we evaluated the performance of the RCMs with realistic (reanalysis) boundary conditions. To this aim, we could use the 25 km grided interpolated observations data constructed within ENSEMBLES using observations all over Europe (EOBS [Haylock et al., 2008]). Unfortunately, the station density over Spain is only of a few tens and, thus, it does not appropriately represent the spatial precipitation variability in this area.

In section 2.2 we describe an alternative gridded precipitation data set focused on Spain and based on thousands of stations, which were used in this paper to test the performance of the RCMs.

2.2. Spain02 Gridded Observations Data Set

Spain02 is a regular $0.2^\circ$ (approximately 20 km) daily gridded precipitation data set obtained from 2772 quality-controlled surface stations from the Agencia Estatal de Meteorología (AEMET, Spanish Meteorological Agency), covering continental Spain and the Balearic Islands during the period 1950–2003. This data set was obtained following a two-step process. First, the occurrence was interpolated.
applying a binary kriging and, in a second step, the amounts were interpolated using ordinary kriging for the occurrence outcomes. Thus, both precipitation frequencies and amounts are properly represented in this gridded data set (see Herrera et al., submitted manuscript, 2010 and http://www.meteo.unican.es/datasets/spain02 for more details). Moreover, since the kriging methodology performs weighted averages of station data, it is more comparable to the grid point average given by an RCM than the individual observations, which can be affected by very local features not represented by the models [Osborn and Hulme, 1998].

[13] In this work, Spain02 was used to obtain a reference climatology for the 30 year period 1961–1990 suitable for the validation of RCMs. To this aim, RCM outputs were bilinearly interpolated from their respective native grids at 25 km resolution to the Spain02 resolution (0.2° × 0.2°).

2.3. Comparison Measures

[14] All the statistics computed were compared using the standard Pearson’s correlation of the spatial patterns. This measure is insensitive to biases and focuses on the ability of the models to reproduce the geographical details and contrasts. Thus, even assuming that RCM results have biases, the correlation will represent the degree of agreement between the position and shape of the simulated precipitation areas and the observed ones. We also computed the Spearman’s rank correlation, which is less sensitive to the underlying distribution of the data, and the results obtained were fairly similar to those shown for the Pearson’s correlation. Additionally, quantile-quantile plots (q–q plots) were used to compare the whole probability density function. Quantile-quantile plots represent on a Cartesian plane the quantiles of the simulated distribution versus the quantiles of the observed distribution. Given the large amount of data available, we used percentiles on the q–q plots. We considered only the distribution of the precipitation on rainy days. Otherwise, the dry days would dominate the PDF on most regions and the ability of the RCMs to represent the occurrence of precipitation would mix with their ability to represent the intensity distribution. The ability of the models to represent the occurrence of precipitation can be observed in the wet day frequency maps (also shown).

3. Precipitation Regimes in Spain

[15] Different studies devoted to the Spanish climatological features show the complexity and variability of precipitation all over the region [Esteban-Parra et al., 1998; Muñoz-Díaz and Rodrigo, 2004]. A significant northwest-southeast precipitation gradient is observed with characteristic Atlantic and Mediterranean precipitation regimes, respectively. Broadly speaking, Spain can be divided into 5 main climatically homogeneous precipitation regions [Muñoz-Díaz and Rodrigo, 2004]: a dry desert-like southern region (precipitation amounts less than 100 mm/yr in the southeastern area) with an upland wet region due to the Sierra Nevada mountains; the southwestern region is influenced by Atlantic winds (rainfall about 900 mm/yr). The eastern coast is characterized by low annual amount of precipitation (less than 700 mm/yr), but with a large variability including significant frequency of severe events (24 h precipitation larger than 200 mm). This specific pattern is elongated all over the Ebro River basin (northeast) due to intrusions of wet and warm air from the Mediterranean Sea [García-Ortega et al., 2007]. The Balearic Islands have a low regime of precipitation (less than 500 mm/yr) except in the mountain ranges of Mallorca (about 900 mm/yr). The central part of continental Spain contains low precipitation amounts (less than 500 mm/yr) except in the Tajo River basin (with 900 mm/yr) along which wet and cold air masses from Atlantic frontal systems can reach on Spanish territory. Finally, almost all of the North Atlantic coast of the peninsula has large amounts of precipitation (from 900 to 2500 mm/yr) with remarkable climatological regularity, mainly due to the continuous arrival of Atlantic frontal systems.

[16] Due to the strong spatial variability of precipitation, this is a challenging area for RCMs, since models must be able to simulate very different precipitation regimes in a relatively small area with remarkable topographic complexity (Figure 1a). The 25 km resolution topography of the RCMs (Figure 1c) provides a realistic picture of the real topography (Figure 1a), distinguishing the main orographic barriers leading to the precipitation regimes described above. The Spain02 data set provides a similar representation of the orography (see Figure 1d) in order to compare the results with those of the RCMs (see Figure 1c). Finally, note that the ERA–40 resolution (Figure 1b) misses most of the orographic details.

[17] In order to study different regional aspects, river basins were used to divide Spain into eleven regions (shown in Figure 1d). The mountain ranges on the basin borders act as natural barriers modifying the distribution of precipitation. For instance, the Cantabrian mountain range near the North Atlantic coast blocks the moist Atlantic air leading to enhanced precipitation in the North basin yielding to a different precipitation regime downwind. In this paper we shall present results both at a grid point scale and at a basin scale; in the latter case we assume a uniform precipitation regime within each basin and aggregate the corresponding grid points. Although this assumption is not exact (e.g., in the North basin there is a west–east precipitation gradient), we consider this division more sensible than a subjective rectilinear division. Additionally, basin averaged results provide useful information for hydrological impact studies.

4. Verification of the Mean Precipitation Regime

[18] Here we analyze the skill of the different RCMs in reproducing the mean precipitation regime, the seasonal cycle and the distributions of daily precipitation (using q–q plots).

4.1. Yearly Climatology

[19] The yearly precipitation climatology for the period 1961–1990 for each of the nine RCMs is shown in Figures 2d–2l; for the sake of comparison, Figures 2a and 2c show the Spain02 and ERA–40 climatologies. Figure 2 shows that the RCMs present a great diversity of results as compared with Spain02, although all of them represent the north–south precipitation gradient and exhibit signatures of the most influential mountain ranges in the area.

[20] The lowest spatial correlation with the Spain02 climatology is shown by the CNRM model (r = 0.55), whereas the largest correlation is obtained with KNMI model (r = 0.85). KNMI used a wider boundary relaxation zone for the
wind than the rest of the models. This helps keeping the circulation inside the RCM domain closer to the forcing fields [Lenderink et al., 2003] and could be responsible for the better performance. CNRM overestimates precipitation over most of continental Spain (except on the northern coast where it is underestimated). SMHI shows longitudinal patterns all over Spain and DMI has a climatology with overestimation of both maximum and minimum annual precipitation. METNO climatology shows very strong spatial precipitation gradients with low spatial continuity (this effect is even stronger on the native noninterpolated grid, not shown). The rest of the models (HC, MPI, ETHZ, UCLM and KNMI) show similar spatial patterns to those shown in Spain02, with large spatial correlations.

The ensemble mean of the nine members (Figure 2m) shows a relatively good agreement with Spain02 in terms of amounts and spatial distributions (spatial correlation of 0.83). The ensemble mean also has the signature of the main mountain ranges and a north–south precipitation gradient as observed. However, the standard deviation of the ensemble (Figure 2n) has a large spread; the spread is larger in the areas where the precipitation is larger (a small relative error in an area with large precipitation gives rise to an absolute deviation much larger than in dryer areas). To avoid that effect, Figure 2o shows the value of the standard deviation relative to the mean precipitation (the coefficient of variation). In most places, this coefficient of variation has values around 25%.

According to the individual spatial correlations of the ensemble members with respect to Spain02, the results from the RCMs can be grossly divided in two groups. First, a group of four members with spatial correlations around 0.6. Second, five members with values over 0.75: ETHZ, HC, KNMI, MPI and UCLM. This clear difference (there is a gap in the correlations from 0.64 to 0.77) between the ensemble members leads us to consider a second ensemble using only a set of five members. We will refer to this ensemble as ENS2, while the ensemble composed of all nine members will be referred to as ENS1. The Ensemble ENS2 mean (Figure 2p) is comparable to that of ENS1, but the variability (uncertainty) is reduced (Figures 2o–2r).

ENS2 mean presents a good agreement with Spain02. However, it still has some deficiencies in representing the yearly climatology. Although, in general, the spatial pattern is similar to the observed one, the amounts are smaller.

Note that when comparing models against observations, the uncertainties in the later must be taken as part of the analysis. Therefore, we estimated the uncertainty of the kriging gridded data set applying the method introduced by Yamamoto [2000] to the yearly accumulated values. Then, we analyzed the impact in the above spatial correlation values by means of a Monte Carlo simulation. We performed 1000
realizations of the observations by adding normal random errors with standard deviation given by the uncertainty computed before (and shown in Figure 2b). The results obtained (Figure 3) show a small impact of the uncertainty on the resulting correlation values, with standard deviations lower than 0.01 in most of the cases and still showing a robust correlation gap between the models in ENS2 and the rest.

4.2. Annual Cycle

The previous analysis showed the ability of the models to represent the spatial pattern of precipitation. Yearly precipitation was accumulated and the seasonal variability was disregarded. Seasonal variability is important because in this area rainy seasons differ from region to region. To account for this seasonal variability, we analyze here the monthly annual cycle averaged over each of the basins defined in Figure 1d. The different seasonal precipitation regimes are illustrated in Figure 4. The black line in Figure 4 shows the observed monthly (spatially averaged) climatologies for each of the basins according to Spain02. For a better comparison, the scale for precipitation is the same in all the plots (ranging from 0 to 200 mm). In most of the basins, the seasonal cycles present their minimum values in July; moreover, there is almost no precipitation during this month in Sur, Guadiana, and Guadalquivir river basins. The seasonal cycle in Segura, Levante, Ebro, Catalana, and Baleares basins present two peak precipitation periods (weakly in the Catalana basin), the main one during autumn and a secondary one during spring (note that the precipitation amounts are different in these basins). This was defined as a typical feature of the western Mediterranean seasonal precipitation climatology [Romero et al., 1998]. Contrarily, in the basins under Atlantic influence (1–5) the main rainy season is winter; the secondary maximum in spring is due to an anomalous low precipitation in March. This phenomenon was related to anomalies in the Atlantic circulation during this month [Paredes et al., 2006].

In general terms, the RCMs (shaded areas in Figure 4) perform remarkably well in reproducing the monthly annual cycle in every basin. Peak seasons are reproduced and even

Figure 2. Annual precipitation climatology of (a) the Spain02 grid and (b) its standard error (see text). (c) ERA-40 annual precipitation climatology. Annual precipitation climatologies interpolated to the Spain02 grid of the models (d) CNRM, (e) DMI, (f) ETHZ, (g) KNMI, (h) HC, (i) METNO, (j) MPI, (k) SMHI, and (l) UCLM. Results for two different ensembles showing the ensemble mean, standard deviation, and coefficient of variation for (m–o) the nine-member ensemble (ENS1) and (p–r) the five best correlated members with Spain02 (ENS2). Values on the top of each panel, next to the labels, show spatial correlation values of each individual panel with Spain02. The scale is linear in the square root of the precipitation (millimeters) to gain details on the low precipitation areas. All panels show the area from 10°W to 5°E in longitude and from 35°N to 44°N in latitude.
stands for the different grid points within the basin, and $S_{ij}$ stands for the different days within the period 1961–1990.

In section 4.3 we showed some results concerning the extremes of the precipitation distribution by means of upper percentiles. Additionally, in section 5 we compute standard indicators commonly used to account for extreme events and other local features related to precipitation (e.g., rain frequency). In particular, we selected a subset of the standard Intergovernmental Panel on Climate Change (IPCC) indicators of extreme events [Sillman and Roeker, 2008] related to precipitation, listed in Table 2. For the sake of simplicity, we show results from 6 of them (the results of $r_{x1\text{day}}$ and $r_{x20}$ are similar to $r_{x5\text{day}}$ and $r_{x10}$, respectively, and only the spatial correlation of the resulting values is shown). All indices are computed using daily precipitation data from each of the ENSEMBLES models, and compared with that from Spain02. The suitability of this gridded data set for the analysis of extreme events was tested by Herrera et al. (submitted manuscript, 2010).

Figure 3. Spatial correlation between the yearly climatology given by Spain02 and the different RCMs. Correlations are sorted in decreasing order along the horizontal axis. The error bars show the standard deviation obtained from a Monte Carlo simulation (see text).
Figure 7 shows the results for the frequency of rain occurrence and the dry and wet spells. Note the frequency differences for the different basins in our area of study. These differences are not only in the amounts as shown before, but also in the way the precipitation is distributed. The observed frequency ranges from the extreme dry conditions of southern Spain, with less than 10% wet days per year, to the northern coast where the precipitation is distributed among more than 50% of the days of the year. The different regimes can also be shown in terms of the maximum number of consecutive dry/wet days (cdd/cwd) in a year with mean values of about 100 days for cdd in southern Spain (Figure 7, top middle) and up to 18 consecutive wet days (cwd) in the north as shown in Figure 7 (top right).

The ability of the RCMs to represent the frequency of precipitation varies significantly from one RCM to another. In general, the frequency is overestimated in the RCMs and the region with frequencies around 50% span a larger area than seen in observations. Apart from this apparent bias, the spatial structure is, in general, well captured with spatial correlations with Spain02 ranging from 0.67 to 0.91. Similar patterns and conclusions can be obtained for the consecutive wet days, with correlations ranging from 0.32 to 0.87. The consecutive dry days show a different pattern, with the southern half of the area exhibiting a clear dry season with an average of 90 or more consecutive dry days; in this case the correlation ranges from 0.79 to 0.92. Thus, in general all RCMs have good correlations of rain frequency and dry spells (cdd). However, they do not represent well the continuous wet spells (cwd). This indicator is overestimated in almost all models. This seems to be a contradictory result, since models can deal with normal precipitation and drought periods, but they cannot maintain long periods of precipitation. The too frequent light precipitation is a well-known problem of RCMs and GCMs.

Figure 7 also shows the results for the full ensemble (ENS1) and the ENS2 ensemble means, with a slight improvement (in terms of spatial correlation) of the results when using the latter. The deficiencies of the individual models (excessive rain frequency and smaller values of cdd)
are, of course, present in both ensemble results since there is no compensation of errors.

Figure 8 shows the results for the indices accounting for the maximum rainfall accumulated in a 5 day period (rx5day), the number of days exceeding 10 mm (r10) and the percentage of the total precipitation coming from events with precipitation over the 95th percentile (r95p). In all cases, the index is computed yearly and the 30 year average is shown. The results for rx1day and r20 are very similar to rx5day and r10, respectively. Although maps are not shown for these indices, their spatial correlation is shown in parenthesis to the right of the correlations for rx5day and r10. The indices shown should be the most advantageous for RCMs, since the 5 day accumulation compensates small localization and time shift errors commonly present in the models and the 10 mm threshold is not very extreme so as to be reached by the model underestimated precipitation.

Concerning the observations, the rx5day climatology resembles the mean precipitation climatology (Figure 2b), mainly modulated by the orographic barriers. The number of days exceeding 10 mm (r10) is similar to rx5day except for the Mediterranean area, where the number of days is small. This is explained by the r95p index, which clearly shows that in the Mediterranean area, a large part of the annual rainfall
comes from events exceeding the 95th percentile. Thus, the total rainfall comes from a few days with strong precipitation. Notice that this area includes the Ebro basin, which is also exposed to intrusions of Mediterranean air.

[38] The RCMs capture the orographic features of \(rx5\text{day}\) and \(r10\) as shown by the large correlation values. However, concerning the amount of rainfall arising from extreme events \((r95p)\), the models are not able to reproduce the marked

Table 2. IPCC Extreme Precipitation Indicators

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
<th>Units</th>
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<tbody>
<tr>
<td>Cdd</td>
<td>consecutive dry days (&lt;1 mm)</td>
<td>day</td>
</tr>
<tr>
<td>Cwd</td>
<td>consecutive wet days (&gt;1 mm)</td>
<td>day</td>
</tr>
<tr>
<td>rx1day</td>
<td>maximum precipitation in 1 day</td>
<td>millimeter</td>
</tr>
<tr>
<td>rx5day</td>
<td>maximum precipitation in 5 days</td>
<td>millimeter</td>
</tr>
<tr>
<td>r10</td>
<td>number of days with precipitation over 10 mm/d</td>
<td>day</td>
</tr>
<tr>
<td>r20</td>
<td>number of days with precipitation over 20 mm/d</td>
<td>day</td>
</tr>
<tr>
<td>r95p</td>
<td>percentage over the total of precipitation due to 95th percentile events</td>
<td>percent</td>
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*See also ETCCDI (http://cccma.seos.uvic.ca/ETCCDI).*
gradient due to the Atlantic/Mediterranean influences, with values lower than 20% over all of continental Spain. A closer look at small regions shows mixed results from the different models, leading to a good performance of the ensemble mean, which cancels out the differences and reinforces the overall pattern. In this case, the spatial correlations of ENS1 and ENS2 are larger than that of any of the members. For this indicator the lowest spatial correlation is given by the MPI member ($r = 0.61$) and the largest one by HC ($r = 0.75$).

A cautionary remark must be made regarding the extreme indicators computed from the daily gridded observations. In the case of the annual precipitation climatology, we computed the associated errors in the mean, which yield small values (Figure 2b). A similar analysis to get the error associated to the extreme indicators would require the computation of the error on a daily basis for the 50 year period, followed by a Monte Carlo sampling. This is a very intensive

Figure 7. (left) Mean values of frequency of precipitation occurrence (in percentage of days). (middle) Mean maximum number of consecutive days without precipitation in 1 year (cdd). (right) Mean maximum number of consecutive days with precipitation in 1 year (cwd). From top to bottom: Spain02, CNRM, DMI, ETHZ, KNMI, HC, METNO, MPI, SMHI, UCLM, ENS1 mean, and ENS2 mean. The values on top of each map correspond to the spatial correlation with Spain02. All panels show the area from 10°W to 5°E in longitude and from 35°N to 44°N in latitude.

Figure 8. As in Figure 7 but for extreme indicators. (left) Maximum of precipitation during 5 days ($r_{5\text{day}}$); values in parentheses are spatial correlations for $r_{1\text{day}}$. (middle) Number of days with a maximum precipitation over 10 mm/d ($r_{10}$); values in parentheses are spatial correlations for $r_{20}$. (right) Percentage of precipitation due to 95th percentile events ($r_{95\text{p}}$). All panels show the area from 10°W to 5°E in longitude and from 35°N to 44°N in latitude.
task which is being pursued at the moment to confirm the robustness of the extreme indicators computed. In this case, the errors are expected to be larger than in the climatology, where the average tends to cancel out the daily errors. The daily errors may affect more significantly extreme indicators such as the duration of wet/dry spells.

[40] As a summary of all indices considered, Figure 9 shows the spatial correlation of each of the indices (columns) for each of the RCMs and for the two ensembles considered (rows). The correlations with the yearly precipitation climatology from section 4.3 are also shown. In such a plot, the good performance of a model in all indicators would show up as a tendency to see dark horizontal lines. On the contrary, the tendency of an indicator to be well represented by all models would show dark vertical lines.

[41] From a subjective point of view, there are no clear horizontal nor vertical lines in the plot, suggesting that there is no best model or best reproduced indicator. The most clear hint of a vertical line is that of the consecutive dry days. The correlations of this indicator are all over 0.79. However, despite the well represented spatial pattern, we just showed that it suffers from an overall underestimation due to the tendency of the models to overestimate rain frequency. On the other hand, the indicator worst represented by all RCMs is the amount of rainfall coming from extreme events (r95p); the best correlation in this case is 0.75 (HC). Moreover, there are models with varying skill for the indices; for instance the MPI model is able to represent the frequency of precipitation (with $r = 0.91$) and total amount ($r = 0.83$), but it does not represent well extreme indicators ($r_{rx5day} = 0.50$ and $r_{r95p} = 0.61$).

6. Summary and Conclusions

[42] Not all models selected for ENS2 keep good correlation in all indices. KNMI and UCLM showed problems with the consecutive wet days and the MPI model failed with the 5 day maximum. According to this measure (we are considering only the spatial structure and disregarding biases or spatial variability) the RCMs from ETHZ and HC would be the most skillful for our region and variable (precipitation). Anyway, the consideration of all (or a selection of) RCMs seems to be the best option. Not just because the mean value performs better than any single model, but mainly because they provide information about the uncertainty. Disregarding poor-performing models for the region/variable also seems beneficial, even if using a simple method such as the one used in this study.

This might be due to the misrepresentation of deep convection and/or other extreme precipitation related events. Therefore, a selection of models should be carefully designed for each particular application. Bear in mind that this study has mainly focused on the reproduction of the spatial patterns of the different statistics and several biases were quite apparent and do not affect our scores. These biases may be crucial for some applications and, moreover, usually several variables (not just the precipitation considered in this study) are used by the impact applications. Also, compensating errors may lead to the right scores for the wrong reasons. For instance, the reasonable reproduction of the total precipitation (Figure 2) or the annual cycle (Figure 4) even though the rainfall frequency is overestimated can only be explained by compensation with the overall underestimation of precipitation intensity. Similar results were found in other studies [e.g., Frei et al., 2003].
[46] Ensemble means produce better results and provide an estimation of the uncertainty. We selected 5 RCMs for their good performance in the yearly precipitation climatology to build a smaller ensemble that performed better than the full ensemble in all indices. In some cases, this reduction of the ensemble size by less than 50% (we removed 4 out of 9 RCMs) produced much larger reductions of the spread (i.e., uncertainty) while driving the new ensemble mean closer to the observed values.

[47] The results found for these RCM simulations are likely to be dependent on the region under study and the variable considered. Thus, RCM simulations showing poor performance in this region could possibly be well suited in other regions or when considering other variables. However, common features of the RCMs found in all of the precipitation regimes in this region are likely to be of a general scope (e.g., features such as the overestimation of rainfall frequency or the ability to capture the seasonal cycle on different precipitation regimes). Also, our results may vary depending on aspects not considered in this work such as the resolution, or not considered within ENSEMBLES, such as the location of the boundaries, the domain size, the reanalysis used as boundary condition, the physical parameterizations or even the models considered (e.g., non-European models may perform differently when used out of their “home domain” [Takle et al., 2007]).

[48] The overestimation of the frequency of wet days leading to the wrong duration of dry/wet spells is a critical problem for impact studies. Given the biases found in these critical indicators in the ENSEMBLES RCMs, impact research fields such as agriculture may benefit from the use of calibrated RCM precipitation. In this study we focused on analyzing the raw RCM precipitation output, but simple corrections such as the selection of an RCM-dependent wet day threshold to match the observed rainfall frequency [Schmidli et al., 2006] may lead to improved dry/wet spell durations and more useful precipitation input for impact models. More sophisticated methods have proved useful in correcting the raw RCM precipitation output [Piani et al., 2010].

[49] This study is a first approach to the analysis of RCM precipitation data from ENSEMBLES in Spain. Further analyses such as a deeper analysis of the causes behind the over/under estimation of certain features are out of the scope of the present paper, but are interesting topics for future research.

[50] Acknowledgments. This work is supported by projects ESCENA and esTcena from the Spanish Strategic Action on Energy and Climate Change, funded by the Ministerio de Medio Ambiente, Rural y Marino. The ENSEMBLES data used in this work were funded by the EU FP6 Integrated Project ENSEMBLES (contract GOCE-CT-2003-505539) whose support is gratefully acknowledged: we also acknowledge DMI for hosting the RCM repository. We also thank three anonymous reviewers who contributed to improve the final manuscript.

References
Herrera, S., J. Gutiérrez, R. Ancell, M. Pons, M. Frías, and J. Fernández (2010), Development and analysis of a 50 year high-resolution daily gridded precipitation dataset over Spain (Spain02), Int. J. Climatol., in press.


van der Linden, P., and J. Mitchell (Eds.) (2009), *ENSEMBLES: Climate change and its impacts: Summary of research and results from the ENSEMBLES project*, 160 pp., Met Off. Hadley Cent., Exeter, U. K.


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