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

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[1] 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.

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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.

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Table 1. Summary of the RCM Simulations Nested in ERA-40 Data Produced for the ENSEMBLES Project[a]

Acronym	Institution	Model	Reference
CNRM*	Centre National de Recherches Meteorologiques	ALADIN-Climat	*Radu et al.* [2008]
DMI*	Danish Meteorological Institute	HIRHAM	*Christensen et al.* [2006]
ETHZ*	Swiss Institute of Technology	CLM	*Jaeger et al.* [2008]
KNMI*	Koninklijk Nederlands Meteorologisch Instituut	RACMO	*van Meijgaard et al.* [2008]
HC*	Hadley Center/UK Met Office	HadRM3 Q0	*Collins et al.* [2006]
ICTP	Abdus Salam International Centre for Theoretical Physics	RegCM3	*Pal et al.* [2007]
METNO*	The Norwegian Meteorological Institute	HIRHAM	*Haugen and Haakensatd* [2005]
MPI*	Max Planck Institute for Meteorology	M-REMO	*Jacob et al.* [2001]
SMHI*	Swedish Meteorological and Hydrological Institute	RCA	*Kjellström et al.* [2005]
UCLM*	Universidad de Castilla la Mancha	PROMES	*Sánchez et al.* [2004]

[a]The columns are the acronym used in the paper, the institution running the simulation, the model used, and a reference publication. Only the simulations highlighted with an asterisk were used in the study.

[5] 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.

[6] 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° × 0.2° 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).

[7] 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

[8] 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

[9] 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.

[10] Within ENSEMBLES, an initial RCM verification experiment was carried out using the reanalyses 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 20C3M 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].

[11] 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 gridded 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

[12] Spain02 is a regular 0.2° (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 (24h 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

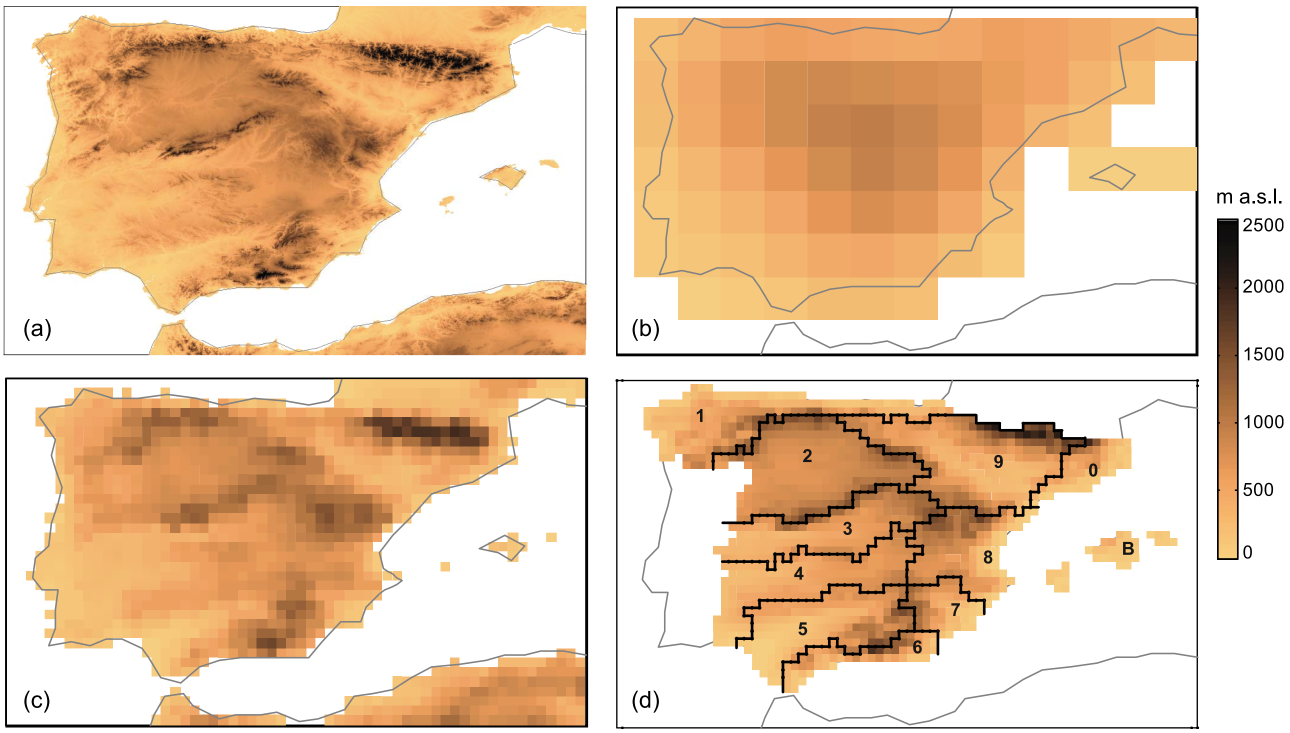

Figure 1. Topography of the Iberian peninsula and the Balearic Islands as given by (a) GTOPO30 (approximately 1 km) and as represented by (b) ERA-40 reanalysis at 1.125°, (c) RCM members at 25 km resolution, and (d) Spain02 at 0.2°. River basins are shown in Figure 1d. Basin names and number of grid points are as follows: 0, Catalana (57 grid points); 1, North (178 grid points); 2, Duero (225 grid points); 3, Tajo (150 grid points); 4, Guadiana (159 grid points); 5, Guadalquivir (163 grid points); 6, South (59 grid points); 7, Segura (56 grid points); 8, Levante (127 grid points); 9, Ebro (234 grid points); B, Baleares (37 grid points). All panels show the area from 10°W to 5°E in longitude and from 35°N to 44°N in latitude.

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.

[21] 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%.

[22] 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).

[23] 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.

[24] 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

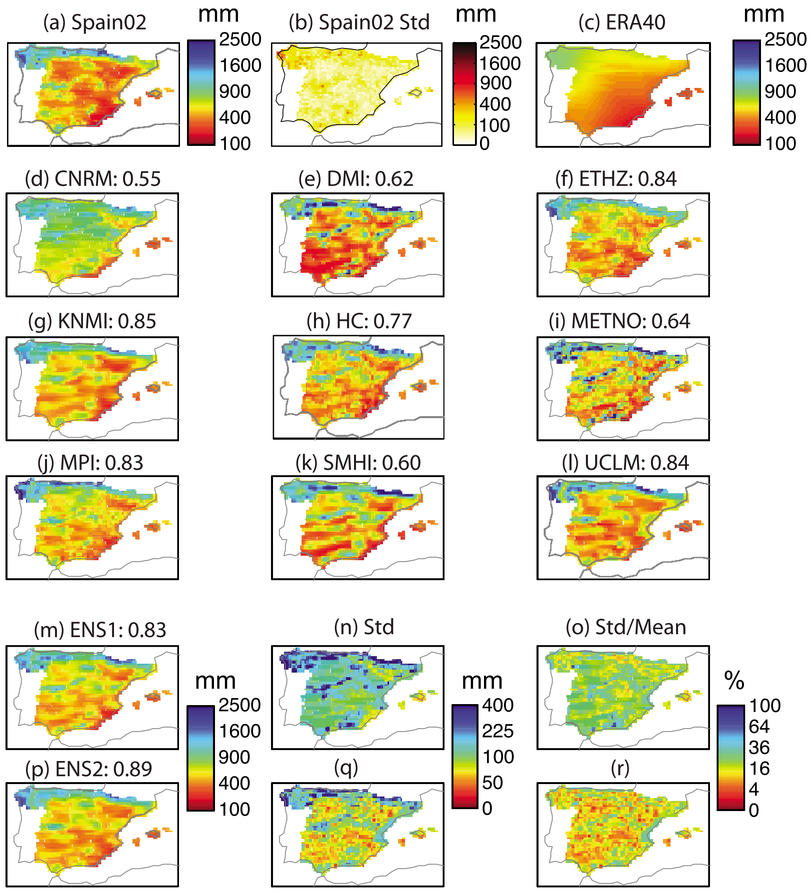

Figure 2. Annual precipitation climatology of (a) the Spain02 grid and (b) its standard error (see text). (c) ERA-40 annual precipitation climatology. Annual precipitation climatologies interpolated to the Spain02 grid of the models (d) CNRM, (e) DMI, (f) ETHZ, (g) KNMI, (h) HC, (i) METNO, (j) MPI, (k) 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 bestcorrelated 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.

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

[25] 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.

[26] 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].

[27] 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

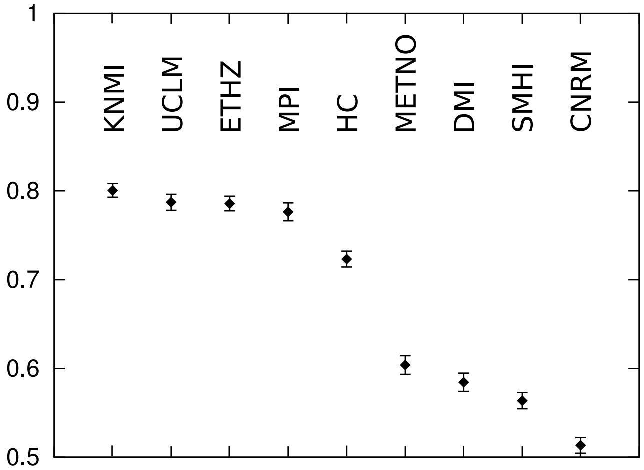

Figure 3. Spatial correlation between the yearly climatology given by Spain02 and the different RCMs. Correlations are sorted in decreasing order along the horizontal axis. The error bars show the standard deviation obtained from a Monte Carlo simulation (see text).

the anomalous March precipitation is shown (this was also found by *Fernández et al.* [2007] using the MM5 model on this area). There is a tendency to overestimate precipitation on nearly every basin, though (except in the North and Catalana basins). The five-member ensemble (ENS2), simply defined in section 4.1 by means of the spatial correlation of the yearly precipitation pattern, performs remarkably better than the full ensemble (the dark shade corresponding to ENS2 is closer to the Spain02 line). ENS2 shows a smaller bias on nearly every month and region and the spread of the ensemble (i.e., the uncertainty) is also noticeably smaller. This is apparent in the reduced overestimation of spring precipitation in most of the basins or on the more balanced estimation of the winter precipitation in the North basin.

[28] Late spring precipitation (months 4–6) exhibits the highest spread in most of the basins for the whole ensemble of RCMs. During this period precipitation is the mixture of two different origins: last intrusions of Atlantic cold air fronts and the beginning of convective activity in the area. The presence of a thermal low due to solar radiation that dominates all of the Iberian peninsula that might help to trigger convection is almost constant during the summer season [*Alonso et al.*, 1994]. An analysis of the large-scale and convective components of the RCMs could provide insight into this problem but this is out of the scope of this paper.

4.3. q-q Plots

[29] The results presented in the previous sections show that RCMs can consistently reproduce the yearly and seasonal climatology of the observed precipitation in Spain. Here we consider not only the mean values but the whole distribution of daily precipitation provided by the RCMs and compare it with the observed one using q-q plots. As before, we proceed separately on each basin. In this case, we used two different methods to build the q-q plots: (1) considering the sample $\{x_{ij}; i, j\}$ to estimate the empirical cumulative distribution function (ECDF) and the percentiles for the q-q plot, where i stands for the different days within the period 1961–1990 and j stands for the different grid points within the basin, and (2) averaging the daily precipitation of all grid points in the basin, $\{y_i = \Sigma_j x_{ij}; i\}$, to build the ECDF. The percentiles for the q-q plot are computed in both cases considering only wet days from the RCM and for Spain02, respectively (a wet day is defined by precipitation >1 mm).

[30] As shown in Figure 5, q-q plots for the grid points in the basins reveal an underestimation of the larger daily precipitation quantiles as compared with Spain02. Figure 5 also shows a smaller spread for the five-model ensemble ENS2 than for full-ensemble ENS1, with no significant improvement of the results, although in some particular basins the ENS2 ensemble gets closer to the observed quantiles. Figure 5 shows how the spread increases quasi-linearly as quantiles increase, showing the lack of consistency of RCMs in correctly reproducing the extreme values of precipitation. However, when considering spatially averaged values (Figure 6) the RCMs better reproduce the observed quantiles, particularly when considering the ENS2 ensemble. In this case, the RCMs show a distribution similar to Spain02 in almost all river basins. Note that the better results of the spatially averaged values reflect a limitation of the RCMs in simulating the intensity of precipitation at the small intrabasin scales. This is not surprising since the Spain02 resolution is slightly higher than that of the RCMs. It not clear whether the RCM precipitation should be interpreted as the precipitation on the center of the grid cell [*Gutowski et al.*, 2007] or an average precipitation for the grid cell [*Osborn and Hulme*, 1998]. Using the latter interpretation, the Spain02 averages of station point values on smaller cells would lead naturally to more extreme precipitation values than those provided by the RCMs. In any case, the RCMs cannot be expected to be skillful at their grid point scale [*von Storch et al.*, 1993; *Frei et al.*, 2003]. The spatial average over several grid points smoothes out the errors at the grid point scale leading to better estimates. The smallest basin considered (Baleares) contains 37 Spain02 grid points, that is, around 23 grid points in the native RCM grids.

[31] In general, the worst results are obtained for the Mediterranean and Sur river basins. This is mainly due to the large temporal and spatial variability of precipitation in these regions. Section 5 will show the importance of the extreme events to the total annual precipitation amount in these basins.

5. Verification of the Extreme Regimes

[32] 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 Roeckner*, 2008] related to precipitation, listed in Table 2. For the sake of simplicity, we show results from 6 of them (the results of rx1day and r20 are similar to rx5day and r10, 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).

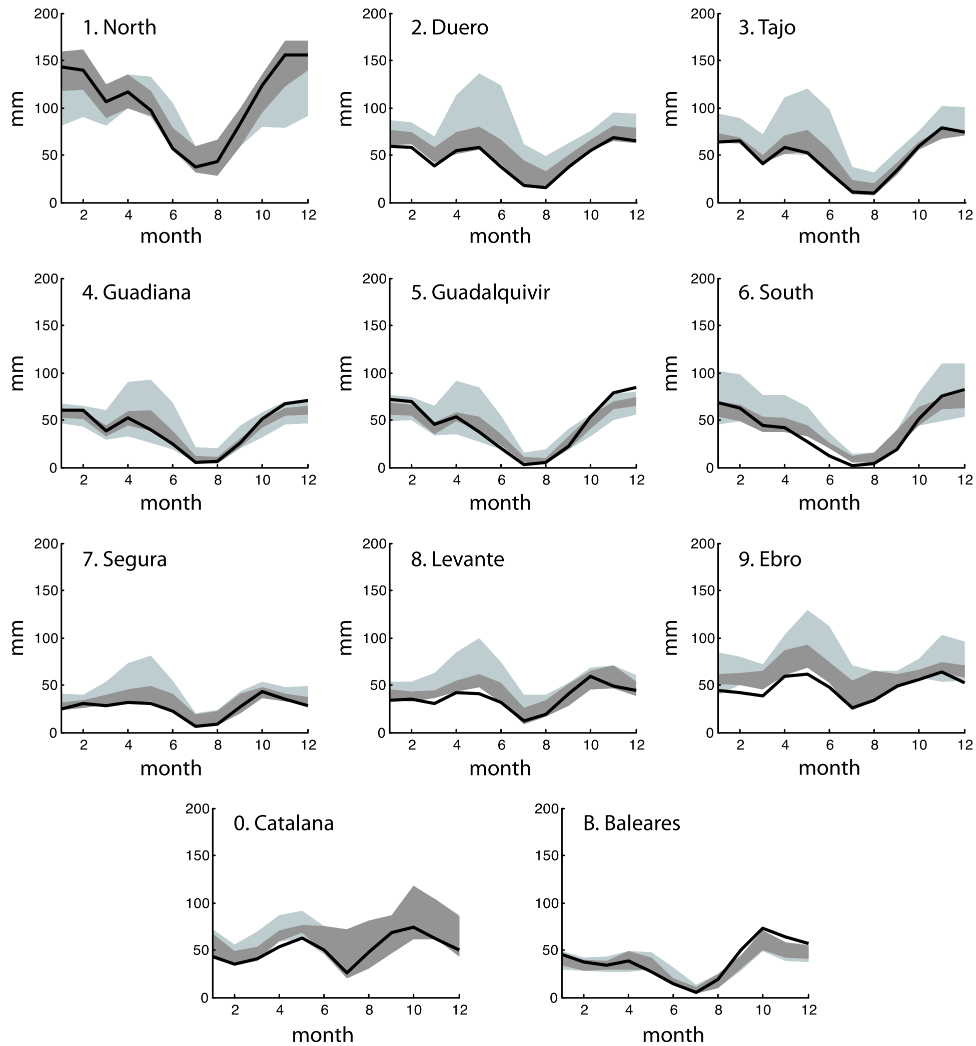

Figure 4. Monthly climatology of the spatially averaged precipitation for each river basin (in millimeters). The thick black line shows the Spain02 (i.e., observed) climatology. The light shaded area spans the values for all members (ENS1), while the dark shaded area spans the values for the five members of ENS2 (see text). The basins correspond to those shown in Figure 1d.

[33] 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).

[34] 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.

[35] 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)

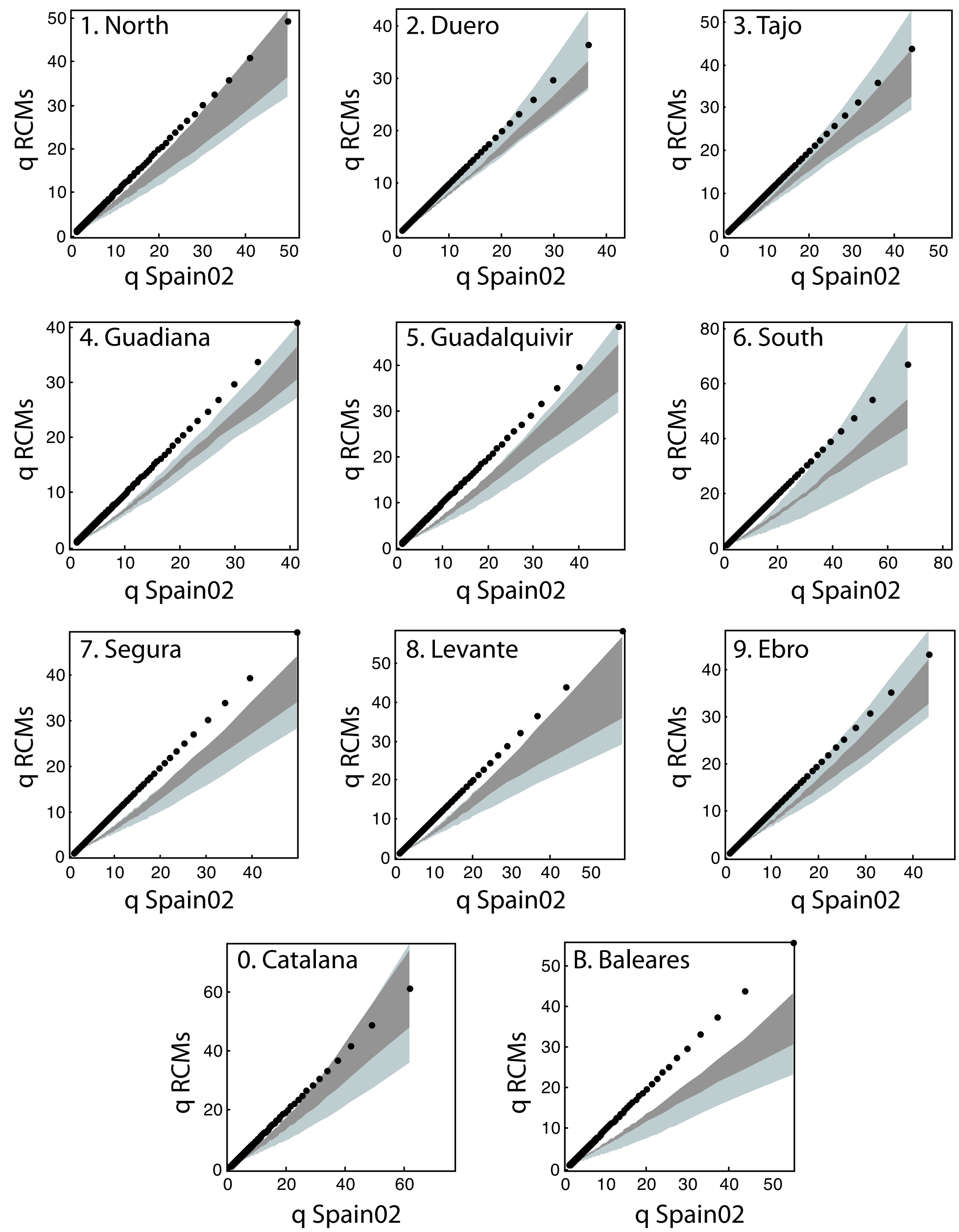

Figure 5. Here q-q plots for the daily distributions of Spain02 versus the RCM ensembles for the different basins using percentiles are shown; the black dots indicate the percentiles of Spain02 drawn over the diagonal, whereas the light and dark shaded areas indicate the q-q plots for ENS1 and ENS2, respectively. In all cases the percentiles are estimated from the empirical distributions formed by gathering in a single sample the daily values of the different grid points within the basin.

are, of course, present in both ensemble results since there is no compensation of errors.

[36] 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.

[37] 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

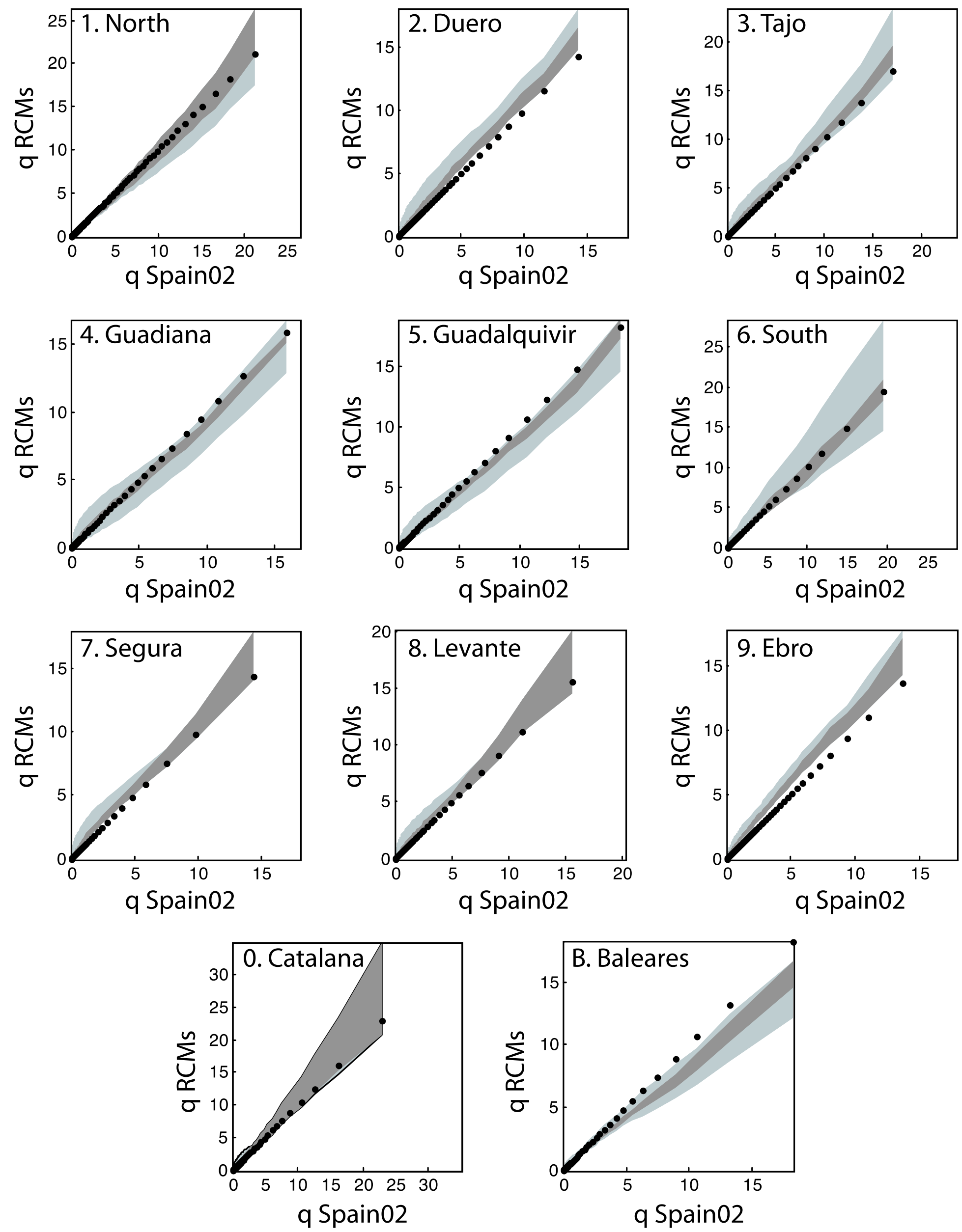

Figure 6. As in Figure 5 but for the spatially averaged values of each river basin.

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 rx5day 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[a]

Label	Description	Units
Cdd	consecutive dry days (<1 mm)	day
Cwd	consecutive wet days (>1 mm)	day
rx1day	maximum precipitation in 1 day	millimeter
rx5day	maximum precipitation in 5 days	millimeter
r10	number of days with precipitation over 10 mm/d	day
r20	number of days with precipitation over 20 mm/d	day
r95p	percentage over the total of precipitation due to 95th percentile events	percent

[a]See also ETCCDI (http://cccma.seos.uvic.ca/ETCCDI).

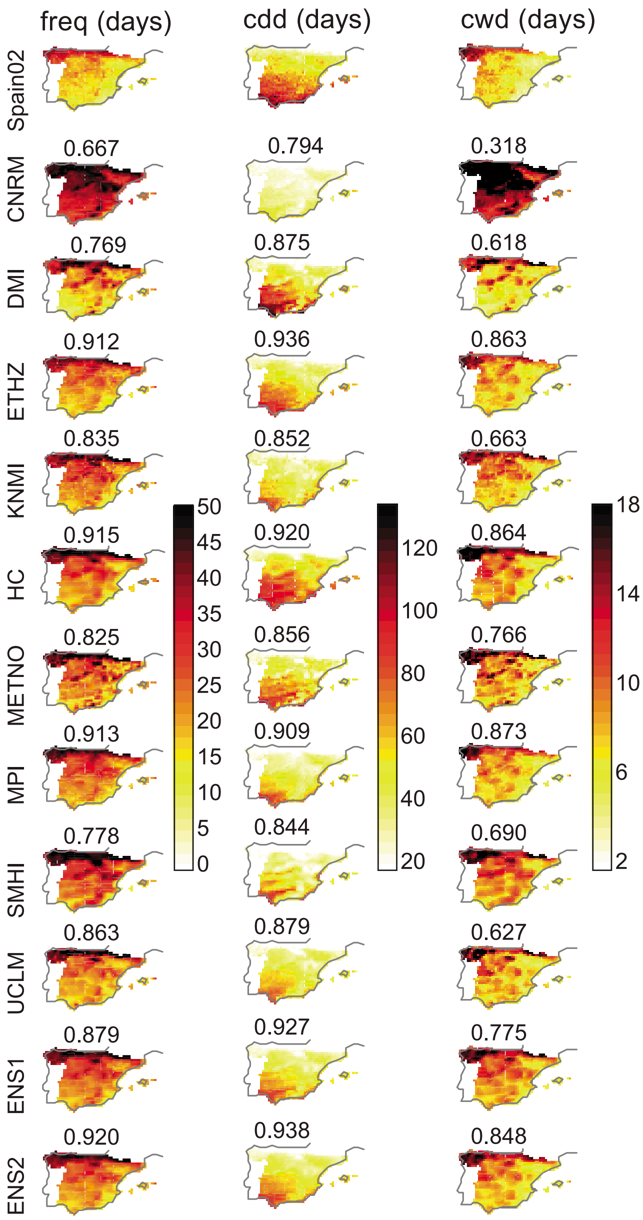

Figure 7. (left) Mean values of frequency of precipitation occurrence (in percentage of days). (middle) Mean maximum number of consecutive days without precipitation in 1 year (cdd). (right) Mean maximum number of consecutive days with precipitation in 1 year (cwd). From top to bottom: Spain02, CNRM, 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.

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).

[39] 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

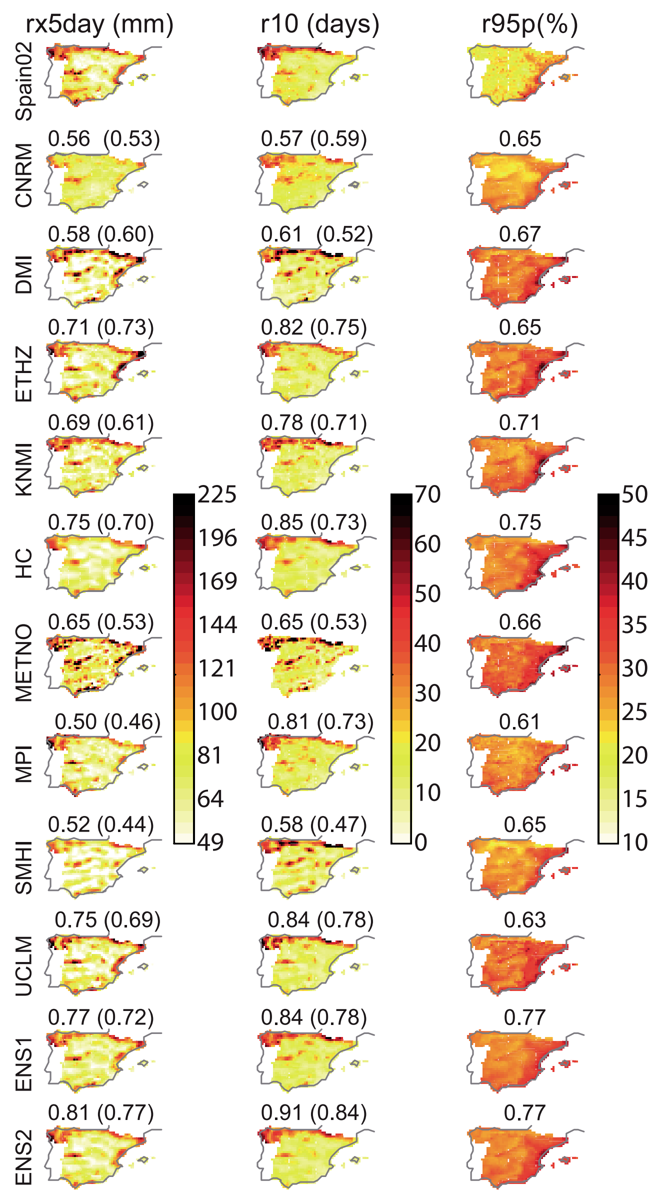

Figure 8. As in Figure 7 but for extreme indicators. (left) Maximum of precipitation during 5 days (rx5day); values in parentheses are spatial correlations for rx1day. (middle) Number of days with a maximum precipitation over 10 mm/d (r10); values in parentheses are spatial correlations for r20. (right) Percentage of precipitation due to 95th percentile events (r95p). All panels show the area from 10°W to 5°E in longitude and from 35°N to 44°N in latitude.

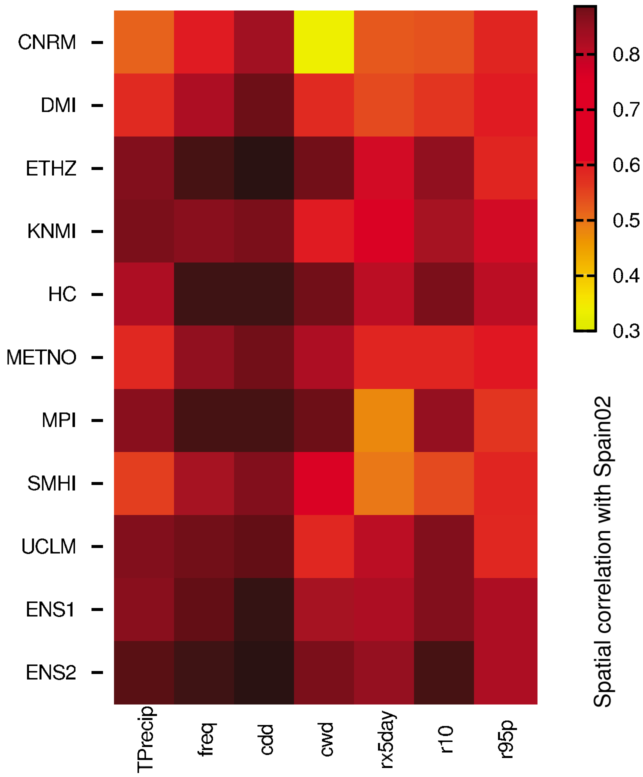

Figure 9. Spatial correlations of each indicator for each RCM with respect to Spain02. Shaded values range from 0.3 to 1.

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). 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].

[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.

6. Summary and Conclusions

[43] We used a state-of-the-art ensemble of RCM simulations provided by the EU-funded project ENSEMBLES to test the ability of RCMs to reproduce the mean and extreme precipitation regimes over Spain. The complexity of the precipitation regimes over the area was described and illustrated using a gridded precipitation database built from thousands of quality controlled stations. A northwest area with large and frequent precipitation, a desert-like southern region and the infrequent and extreme precipitation along the Mediterranean coastal area makes the Spanish territory an ideal benchmark for RCMs.

[44] In general, the RCMs show a good agreement with the observed mean precipitation regime. They capture the north-south gradient and the modulation of precipitation by the orography. The total amounts are overestimated in most areas, though. The monthly annual cycle is also well captured, correctly reproducing the peak precipitation seasons in each basin. The main deficiency is the overestimation of spring precipitation by some of the models. However, the frequency of days with precipitation is overestimated by all models. This leads to a low number of consecutive dry days and overestimated consecutive wet days. The spatial pattern for consecutive dry days is well captured, though.

[45] The main limitation of the RCMs is the misrepresentation of extreme regimes. In particular, upper percentiles are underestimated and the amount of the total rainfall coming from extreme events is especially poor, both in the amount and the spatial distribution.

[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.

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