High resolution WRF climatic simulations for the Iberian Peninsula: Model validation

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Abstract

A high resolution atmospheric modelling study was done for a 20-year recent historical period. The dynamic downscaling approach adopted used the Max Planck Institute Earth System Model (MPI-ESM) to drive the WRF running in climate mode. Three online nested domains were used covering part of the North Atlantic and Europe, with a resolution 81 km, and reaching 9 km in the innermost domain which covers the Iberian Peninsula.

For validation purposes, an additional configuration forced by the ERA-Interim reanalysis was also run. Validation was based on comparison of probability distributions between model results and observational datasets of near surface temperature and precipitation. The comparison was based on daily climatologies, spatially averaged inside subdomains obtained with cluster analysis of the observations, for each of the four seasons. The validation of the historic simulation was done in order to assess if the climate mode can be used to drive the regional WRF configuration, to estimate climate change projections for future time periods.

Considering the difficulty to simulate extremes in long term simulations, the results showed a confortable comparison of both models (forced by climate model and reanalysis results) with observations. This provides us confidence on the continuity of using MPI-ESM to perform climate simulations of the future.

Keywords: Dynamical Downscaling, Climate Modelling, WRF, MPI-ESM, ERA-Interim, Iberian Peninsula

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1. Introduction

Global Climate Models (GCM) have been in use for more than a decade to study the impact of anthropogenic emission scenarios on global climate change. These models, albeit useful to understand global trends and climate change behaviour, lack the spatial resolution to solve meso to local scale phenomena. Therefore, in order to assess the impact of climate change at local scales in activities of interest such as agriculture, forestry and energy production, regional climate change modelling is needed. Various techniques have been developed to downscale GCM scenarios (Hewitson and Crane, 1996; Lo et al., 2008; Racherla et al., 2012). A review of the different downscaling methods can be found in Wilby and Wigley (1997) and Giorgi et al. (2004), as well in the Intergovernmental Panel on Climate Change (IPCC) Third (Giorgi et al., 2001; Mearns et al., 2001) and Fourth (Christensen et al., 2007) Assessment Reports. The dynamical downscaling approach relies on coarse-resolution large-scale fields from either GCMs or global reanalysis, which are used to provide the initial and boundary conditions to a nested Regional Climate Model (RCM). The pioneer European project PRUDENCE followed by ENSEMBLES (Van der Linden and Mitchell, 2009) provided multi-model ensembles of RCM simulations for Europe which has been extensively analysed not only by the official modelling groups but also by the word scientific community. When constrained by a large-scale model, the RCM does not change the large-scale circulation of the GCM, while adding regional detail in response to the large scale forcing, simulating more realistically surface winds and temperatures over complex terrain and coastlines, as well as mesoscale processes and its variability (Giorgi, 2006; Lo et al., 2008). The result is typically a highly detailed and accurate model solution over the region of interest.

Such implementations have been broadly used and the value added with the downscaling technique has been often debated. Castro et al. (2005) and Rockel et al. (2008) have shown that the RCM can not add skill to simulations of large-scale weather features beyond what is already in the parent global model or reanalysis, since the RCM is strongly influenced by the parent model. Moreover, Castro et al. (2005) classified the dynamical downscaling into (1) numerical weather prediction, in which the memory of the initial conditions are not lost due to the short-term model integration; (2) regional climate simulations driven by global reanalysis, in which memory is lost, but the periodically enforced lateral boundary conditions contain atmospheric observations; (3) GCMs, in which the real-world influence comes indirectly via the observed ocean boundary conditions driving the GCM; and (4) GCMs real-world constraints are completely absent. Considering this, the authors observed that model skill worsens as the parent global input goes from a reanalysis to a global prediction model (in which all aspects of the climate system are predicted), with intermediate steps where only some aspects of the system are prescribed (e.g., sea surface temperature).

In the past decade, the most common approach in regional climate simulations was to have a single initialization of large-scale fields and frequent updates of lateral boundary conditions. This approach has been shown to have several drawbacks, namely the development of flow within the RCM domain inconsistent with the driving boundary conditions. Furthermore, the internal solution generated by RCMs may vary with the size of the simulation domain, as well as location and season (Miguez-Macho et al., 2004; Castro et al., 2005). To overcome this issue, the use of nudging or relaxation of large-scale atmospheric circulations within the interior of the computational domain of the RCM has been applied and proven to produce successful results (Miguez-Macho et al., 2004; Bowden et al., 2012; Spero et al., 2014). This method prevents the RCM solution to drift away from the large-scale driving fields. In addition, Spero et al. (2014) has shown that the spectral nudging method was successful in keeping the simulated states close to the driving state at large scales, while generating small-scale features and thus improving model skill.

The implementation of a dynamical downscaling technique using a single initialization and spectral nudging to the large-scale patterns allows to perform a single spin-up while obtaining a structured and consistent solution of the regional scale climate, coping with the the soil moisture initialization as shown by Khodayar et al. (2014), while maintaining consistency between the large-scale fields of the forcing GCM (Spero et al., 2014).

The objective this work is to compare the results obtained with a regional scale modelling configuration for the Iberian Peninsula, forced with a GCM and forced with a global reanalysis. This validation will give us confidence of the usage of the GCM to force the regional model in forecast simulations of the future climate under predefined anthropogenic emission scenarios.

The manuscript provides a description of the downscaling parametrizations and a comparison of model results with observations in terms of precipitation and mean and extreme values of surface temperature.

2. Methods

2.1. Regional Model

The community model WRF version 3.5 (Skamarock et al., 2005) with the modifications performed by Fita et al. (2010) for regional climate simulation has been broadly used to produce climatological downscaling (Gula and Peltier, 2012; Bowden et al., 2012; Pinto et al., 2014) and was applied in this work to produce a dynamical climate downscaling for the Iberian Peninsula. Two sets of atmospheric global simulation results, from different sources, were used to provide initial and boundary conditions to the regional configuration. Firstly the MPI-ESM (LR) model with the r1i1p1 initialization, with 1.9° horizontal resolution and 47 hybrid sigma-pressure levels (Giorgetta et al., 2013) was used. This model participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5). As a representation of the recent-past climate, the last 20 years (1986-2005) Secondly the ERA-Interim reanalysis (Dee et al., 2011). The model used to generate the reanalysis uses a 4D-variational analysis on a spectral grid with triangular truncation of 255 waves T255 with 80km (N128) - reduced points - Gaussian grid and a hybrid coordinate system with 60 vertical levels.

These two configurations are named WRF-MPI (WRF driven by MPI-ESM) and WRF-ERA (WRF driven by ERA-Interim) hereinafter.

The WRF lateral boundary conditions were provided to the model at six hour intervals, including the sea surface temperature update, and a spectral nudging for wave length larger than 1000 km was considered (Miguez-Macho et al., 2004). Ferreira (2007) has tested several model parametrizations configuration for the Iberian Peninsula using the WRF model, comparing the model outputs against observations. Considering his findings, the set of parametrizations used in the model physical configuration were: WRF Single-moment 6-class Microphysical Scheme (Hong et al., 2006); Dudhia Shortwave radiation scheme (Dudhia, 1989); RRTMG (Rapid Radiative

Transfer Model) longwave radiation model (Mlawer et al., 1997); MM5 similarity surface layer scheme (Zhang and Anthes, 1982); Noah Land Surface Model (Tewari et al., 2004); Yonsei University Planetary Boundary Layer scheme (Hong and Lim, 2006) and Grell-Freitas Ensemble Scheme for cumulus parametrization (Grell and Freitas, 2013).

A similar set of parameterisations are used by the Group of Meteorology and Climatology from Aveiro University (`http://climetua.ua.pt`) to perform analysis and forecasts for the Portuguese region. Data produced by the group has been successfully used for weather forecasting and to force a biogeochemical ocean model for the Portuguese and Galician waters (Marta-Almeida et al., 2012).

Due to the importance of land use accuracy, the Coordination of Information on the Environment Land Cover (CORINE, Bossard et al. (2000)) was implemented recategorized to be recognizable by the WRF model. This conversion of CORINE data into WRF categories followed Pineda et al. (2004). Teixeira et al. (2014) performed sensitivity test for the usage of this dataset in WRF simulations obtaining positive results.

The regional WRF implementation uses three domains online nested with increasing resolution at a downscalling ratio of 3. The domains are illustrated in Figure 1. The coarser domain, D-1, covers part of the North Atlantic ocean and most of Europe, using a horizontal resolution of 81 km. The smallest domain, with 9 km resolution, solves the Iberian Peninsula extending off-coast several hundreds of km.

2.2. Model validation

Observational data for model validation was obtained for Spain and Portugal independently. The Spanish dataset (Spain02, Herrera et al. (2012, 2014-submitted)), developed by the University of Cantabria, includes long term (from 1971 to end of 2010) gridded daily precipitation and near surface temperature (daily maximum, minimum and mean) at 0.11° resolution. The Portuguese dataset, created by the Portuguese Institute of Meteorology, includes only precipitation and at a lower horizontal resolution (0.2°), but it is still the best observational product available. It includes data from 1950 to the end of 2013 (Belo-Pereira et al., 2011).

From these datasets of temperature and precipitation it was created a daily climatology. Then a temporal K-Means cluster analysis (MacQueen, 1967) was performed on the seasonal subsets resulting in a spatial subdivision of the domain in regions with similar temporal behaviour (magnitude and variability). The model results, from the higher resolution domain D-3, were then compared with observations using the clusters as a natural division of the domain. Daily climatologies of modelled precipitation and, maximum, minimum and mean temperature were created to compare with the daily climatologies of the observed data. Finally, the probability distributions of the model output variables inside each cluster and for each season were compared with the corresponding probability distributions of the observations. The data inside each cluster was, thus, spatially averaged and the mean of the resulting time series was removed. The result was a centred probability distributions of precipitation and temperature, in distinct regions of Portugal and Spain, for the four seasons. The aim was to access if the shape of the observational distributions could be reproduced by the model forced by both a GCM and a reanalysis. If WRF-MPI and WRF-ERA probability distributions present similar differences to the observational distributions, we have the confidence to use the GCM MPI-ESM (LR) to drive WRF for climatic simulations of future scenarios.

The K-Means cluster analysis is a non-hierarchical clustering method which starts by computing the centroids for each cluster and then calculates the distances between the current data vector and each of the centroids, assigning the vector to the cluster whose centroid is closest to it. Since this is a dynamic method, meaning that vectors can change cluster after being assigned to it, this process is repeated until all vectors are assigned a cluster and their members are closest to the centroid than to the mean of other clusters (Wilks, 2011). The determination of the number of clusters was done using the Caliński and Harabasz (1974) pseudo F-statistic, which is based on the maximization of the ratio of between-cluster variance to within-cluster variance. This approach of domain decomposition has been successfully applied for European temperature and precipitation by Carvalho et al. (2015), and for Iberian Peninsula precipitation by Parracho et al. (2015). This clustering regionalisation technique is a robust method and with physical significance, since it gathers points with comparable variability. Arbitrary methods of domain partitioning, like the usage of political boundaries or a fixed number of empirical regions based on distance to coast or other frontiers, for instance, lacks physical meaning, although still being commonly employed in climate and modeling studies.

Our domain decomposition, using the observational datasets, identified four clusters for each season of Spanish temperatures and precipitation, and three clusters for Portuguese precipitation.

The probability density functions were estimated using a Gaussian Kernel Density Estimator (Rosenblatt, 1956; Parzen, 1962) with automatic bandwidth determination using the Scott's Rule (Scott, 2009). The comparison of probabability distributions of the observed and modelled variables was done via the Kolmogorov-Smirnov test (KS-test, Kolmogorov (1933); Smirnov (1948)). KS-test is a nonparametric test that compares the cumulative distributions of two datasets. This test is robust to outliers, just like the other commonly used Mann-Whitney test (MW-test, Mann and Whitney (1947)), but is more robust to detect changes in the shape of the distribution than the MW-test (Lehmann and D'Abrera, 2006).

3. Results

The validation of WRF forced by the climate model (WRF-MPI) and by the reanalysis (WRF-ERA) is made by comparing the probability distributions of the average daily climatologies inside regions with temporal similarities (clusters). This analysis was done for each of the four seasons and for temperature and precipitation over Spain, and for precipitation over Portugal.

The results for the maximum near surface temperature is shown if Figure 2. The figure is organised so that each row corresponds to one season, the first column shows the clusters subdivision and the other columns show the probability distributions of the observations (Ob) and model results. The KS-test statistic (d-value, maximum distance between the cumulative distributions) and p-value of the pairs Ob vs WRF-ERA and Ob vs WRF-MPI are shown inside each subplot. High p-values or low d-values indicate the null hypothesis that both groups were sampled from populations with similar distribution, cannot be rejected.

The results of maximum temperature identify a hotter region in southern Spain and a colder region occupying in general all the north of the Peninsula and a small region in the south (west Andalucía). The winter (DJF) and summer (JJA) results clear show a larger departure of WRF-MPI from the observations, both in terms of magnitude and shape of the distribution, with associated p-values decreasing to 0.02 and 0.05 in the summer. Spring WRF-MPI has a much better correspondence to the observations. In autumn we have a mixed WRF-MPI behaviour, with regions with high p-values and regions with low p-values. WRF-ERA has much higher p-value in all the regions and all seasons, as can be easily observed by the shape of the distributions which are very close to the Ob distributions.

The probability distributions of the mean temperature (Figure 3) show a similar spatial pattern of the cluster subdivisions, with a northward decrease of temperature. The KS-test exhibits in general improved values for WRF-MPI (compared to the values obtained for maximum temperature), especially for the summer months, showing an increase in the p-values above the 0.05 threshold and a decrease in the d-values of all the cluster regions.

Minimum temperatures (Figure 4) show better agreement for WRF-MPI, comparable to WRF-ERA in some seasons/regions, and even higher for the colder summer regions. A much closer shape of the distributions is evident, relatively to the maximum and mean temperatures.

Regarding daily climatological total precipitation over Spain (Figure 5), a very well defined subdivision of the region was obtained with the cluster analysis, with Galicia and Northern Spain having higher precipitation and the central and Mediterranean regions with lower values. An overall agreement between model results and observations was obtained, considering the difficulty to model the convective precipitation (e.g. Yang et al., 2012). Still, low p-values are obtained for high precipitation regions during winter. There is not a clear definition of which model results perform better (WRF-MPI or WRF-ERA). During the summer, the lowest precipitation region shows a very high p-value for WRF-MPI (0.99) and very low for WRF-ERA (0.00). Spring and autumn show reasonably good and comparable p-values for both models. The worst season/region combination in terms of model capacity to follow observations is the winter high precipitation Galician region, where p-values are below 0.05.

The results for precipitation over Portugal, depicted in Figure 6, show maximum values in the North Atlantic region through all the year. Lowest precipitation is found in the southern region and in general in all the eastern side. The best comparison of probability distributions occur during the autumn. In all other seasons, p-values are notoriously low. In the three regions and for the seasons winter to spring, WRF-MPI values are three times lower than 0.05 and WRF-ERA values are seven times below 0.05.

4. Analysis

The regionalisation of the observational domains, followed by spatial averanging in each subregion, decreased the dimension of the data, allowing the representation of the annual cycle of temperature and precipitation fields by probability distributions for each season, appears to be a successful technique. The subregions obtained obey the empirical and bibliographic knowledge on the intensity and variability of temperature and precipitation of the Iberian Peninsula, namely the high rain in northwest Portugal, Galicia and the rest of northern Spain, the drier southern Portugal and southern/central Spain, and the higher temperatures in southern Spain.

The subregions have complex geometries, and even having been calculated according to the intensity and variability of daily climatologies, we get satisfied whenever the statistical test comparing the distribution of observed data and model result return a p-value above the threshold 0.05 (the usual level of significance). Values higher than this indicate we should not reject the hypothesis that the sets belong to populations with the same probability distribution. This happened in most of the regions/seasons for Spanish temperature and precipitation. The zero p-value obtained for the WRF-ERA Spanish summer precipitation in the lowest precipitation region is not significant because the days without precipitation were not removed before the analysis. So, even a small precipitation difference may result in high relative differences an hence a bad comparison with the KS-test. Low p-values are also obtained for the high precipitation region (west Galicia) during the winter. This may be associated with the difficulty of simulating convective precipitation (e.g. Yang et al., 2012), even using convective resolving resolution. Some effort could be positive on the attempt to improve the capacity of the model to reproduce the highest precipitation value, namely by assessing the model performance with different combinations of horizontal and vertical resolution and convective parameterisations.

The highest temperatures returned by the model forced by the CGM (WRF-MPI) also show poor comparison with observations. On the other hand, the model forced by reanalysis compares very well. Reanalysis is based on the usage of realistic initial conditions and continuous assimilations. So, in the end, the result obtained for the very difficult to reproduce maximum temperature (e.g. Sillmann et al., 2014), is not strange. We accept the result specially because the probability distributions of WRF-MPI actually exhibit, with distortions, the same features of the observations.

The results for the Portuguese precipitation are quite surprising. Over Spain, the comparison among the datasets is fairly good, but over Portugal the distributions differ substantially, even without important geographic differences that could justify such behaviour. Basically the unique distinction is the source of the datasets. The Portuguese dataset has about half the resolution of the Spanish dataset and was created based on Ordinary Kriging Interpolation, and a sparse observational network in large portions of the country. The Spanish higher resolution dataset is continuously evolving and includes improved interpolation methodologies and data correction schemes.

5. Conclusion

The atmospheric model WRF was parameterised to perform high resolution climate simulations of a nested configuration of the Iberian Peninsula. In order to validate the model ability to simulate scenarios for the future, driven by a GCM, we decided to do two simulations for the past (20 years, 1996 to 2005), one forced by the GCM, other forced by ERA-Interim. The chosen GCM was MPI-ESM (LR). If historic simulations with both forcings result in a similar comparison with observations, we shall feel justified the continuity of the usage of the GCM to force future climate simulations of WRF.

The observational datasets used include extremes and mean temperature over Spain and precipitations for both Portugal and Spain. The comparison was done in terms of probability distribution of daily climatologies inside subregions of the observational domain. These subregions were calculated using a cluster analysis technique, which gathers spatially points with similar temporal behaviour. Inside each cluster, observed and modelled data was spatially averaged and the probability distribution of the resulting time series was estimated. This procedure was done for each season separately.

The results show an overall acceptable comparison of both models with observations, with seasons/regions where model forced with reanalysis (WRF-ERA) performs better, but also occasions when the comparison for WRF-MPI was better. In general, however, WRF-ERA gave probability distributions closer to the observed ones.

In spite of the difficulty of simulate extremes of atmospheric variables, like maximum temperature and extreme precipitation, in continuous long term simulations, without reinitialisation and/or data assimilation, the statistical test used to compare the probability distributions gave in general good results, i.e., in most of the occasions it cannot be rejected that the datasests compared belong to the same distribution.

The worst results were obtained for the precipitation over Portugal, in disagreement with the comparison done for precipitation over Spain. Since apparently more effort has been dedicated to the Spanish dataset, we are forced to trust our comparison with the Spanish precipitation. Also, even assuming the same quality of the observations, the differences in the observational network, differences in the resolution of the final dataset, in the data correction approaches and interpolations methodologies employed, may result in important discrepancies among the observational datasets.

Considering the results obtained, we feel confidence on the usage of the WRF-MPI to perform climate simulations of the future. Such task is already underway and the results will be analysed soon.

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6. References

Belo-Pereira, M., Dutra, E., Viterbo, P., 2011. Evaluation of global precipitation data sets over the Iberian Peninsula. Journal of Geophysical Research 116.

Bossard, M., Feranec, J., Otahel, J., 2000. CORINE land cover technical guide - Addendum 2000. Tech. Rep. 40, European Environmental Agency, Copenhagen.

Bowden, J. H., Otte, T. L., Nolte, C. G., Otte, M. J., 2012. Examining interior grid nudging techniques using two-way nesting in the WRF model for regional climate modeling. Journal of Climate 25, 2805–2823.

Caliński, T., Harabasz, J., 1974. A dendrite method for cluster analysis. Communications in Statistics-theory and Methods 3, 1–27.

Carvalho, M. J., Melo-Gonçalves, P., Teixeira, J. C., Rocha, A. M., 2015. Regionalization of Europe based on a K-Means Cluster Analysis of the climate change of Temperatures and Precipitation. Physics and Chemistry of the Earth (current issue).

Castro, C. L., Pielke, R. A., Leoncini, G., 2005. Dynamical downscaling: Assessment of value retained and added using the Regional Atmospheric Modeling System (RAMS). Journal of Geophysical Research: Atmospheres 110.

Christensen, J., Hewitson, B., Busuioc, A., Chen, A., Gao, X., Held, I., Jones, R., Kolli, R., Kwon, W.-T., Laprise, R., na Rueda, V. M., Mearns, L., Menéndez, C., Räisänen, J., Rinke, A., Sarr, A., Whetton, P., 2007. Regional climate projectios. Cambridge University Press.

Dee, D., Uppala, S., Simmons, A., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M., Balsamo, G., Bauer, P., et al., 2011. The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society 137, 553–597.

Dudhia, J., 1989. Numerical study of convection observed during the winter monsoon experiment using a mesoscale two-dimensional model. Journal of the Atmospheric Sciences 46, 3077–3107.

Ferreira, A., 2007. Sensibilidade às parametrizações físicas do WRF nas previsões à superfície em Portugal Continental. Relatório de estágio em meteorologia e oceanografia Física. Universidade de Aveiro.

Fita, L., Fernández, J., Garcıa-Dıez, M., 2010. CLWRF: WRF modifications for regional climate simulation under future scenarios. In: 11^{th} WRF Users's Workshop. NCAR Boulder CO.

Giorgetta, M. A., Jungclaus, J., Reick, C. H., Legutke, S., Bader, J., Böttinger, M., Brovkin, V., Crueger, T., Esch, M., Fieg, K., et al., 2013. Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the Coupled Model Intercomparison Project phase 5. Journal of Advances in Modeling Earth Systems 5, 572–597.

Giorgi, F., dec 2006. Regional climate modeling: Status and perspectives. Journal de Physique IV France 139, 101–118.

Giorgi, F., Bi, X., Pal, J., 2004. Mean, interannual variability and trends in a regional climate change experiment over Europe. I. Present-day climate (1961–1990). Climate Dynamics 22, 733–756.

Giorgi, F., Jones, R., P, W., H, V. S., Fu, G., Mearns, L. O., Hewitson, B., Christensen, H., Hulme, M., 2001. Regional climate information evaluation and projections. Cambridge University Press, Cambridge, pp. 583–638.

Grell, G. A., Freitas, S. R., 2013. A scale and aerosol aware stochastic convective parameterization for weather and air quality modeling. Atmospheric Chemistry and Physics 13, 845–23.

Gula, J., Peltier, W. R., 2012. Dynamical downscaling over the Great Lakes basin of North America using the WRF regional climate model: The impact of the Great Lakes system on regional greenhouse warming. Journal of Climate 25, 7723–7742.

Herrera, S., Gutiérrez, J. M., Ancell, R., Pons, M., Frías, M., Fernández, J., 2012. Development and analysis of a 50-year high-resolution daily gridded precipitation dataset over Spain (Spain02). International Journal of Climatology 32, 74–85.

Herrera, S., et al., 2014-submitted. Update of the Spain02 gridded observational dataset for Euro-CORDEX evaluation: Assessing the effect of the interpolation methodology. International Journal of Climatology.

Hewitson, B., Crane, R., 1996. Climate downscaling: techniques and application. Climate Research 7, 85–95.

Hong, S.-Y., Lim, J.-O. J., 2006. The WRF single-moment 6-class microphysics scheme (WSM6). Asia-Pacific Journal of Atmospheric Sciences 42, 129–151.

Hong, S.-Y., Noh, Y., Dudhia, J., 2006. A new vertical diffusion package with an explicit treatment of entrainment processes. Monthly Weather Review 134 (9), 2318–2341.

Khodayar, S., Sehlinger, A., Feldmann, H., Kottmeier, C., 2014. Sensitivity of soil moisture initialization for decadal predictions under different regional climatic conditions in Europe. International Journal of Climatology.

Kolmogorov, A. N., 1933. Sulla determinazione empirica di una legge di distribuzione. Giornale dell Istituto Italiano degli Attuari 4, 83–91.

Lehmann, E. L., D'Abrera, H. J., 2006. Nonparametrics: statistical methods based on ranks. Springer New York.

Lo, J. C.-F., Yang, Z.-L., Pielke, R. A., 2008. Assessment of three dynamical climate downscaling methods using the Weather Research and Forecasting (WRF) model. Journal of Geophysical Research: Atmospheres 113.

MacQueen, J. B., 1967. Some methods for classification and analysis of multivariate observations. In: 5^{th} Berkeley Symposium on Mathematical Statistics and Probability. University of California Press, University of California Press, Berkeley, pp. 281–297.

Mann, H. B., Whitney, D. R., mar 1947. On a test of whether one of two random variables is stochastically larger than the other. The Annals of Mathematical Statistics 18, 50–60.

Marta-Almeida, M., Reboreda, R., Rocha, C., Dubert, J., Nolasco, R., Cordeiro, N., Luna, T., Rocha, A., e Silva, J. D. L., Queiroga, H., Peliz, A., Ruiz-Villarreal, M., may 2012. Towards Operational Modeling and Forecasting of the Iberian Shelves Ecosystem. PLoS ONE 7, e37343.

Mearns, L. O., Hulme, M., Carter, T. R., P, W., 2001. Climate scenario development. Cambridge University Press, Cambridge, pp. 739–768.

Miguez-Macho, G., Stenchikov, G. L., Robock, A., 2004. Spectral nudging to eliminate the effects of domain position and geometry in regional climate model simulations. Journal of Geophysical Research: Atmospheres 109.

Mlawer, E. J., Taubman, S. J., Brown, P. D., Iacono, M. J., Clough, S. A., 1997. Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. Journal of Geophysical Research: Atmospheres 102, 16663–16682.

Parracho, A. C., Melo-Gonçalves, P., Rocha, A. M., 2015. Regionalization of precipitation for the Iberian Peninsula. Physics and Chemistry of the Earth (current issue).

Parzen, E., sep 1962. On estimation of a probability density function and mode. The Annals of Mathematical Statistics 33, 1065–1076.

Pineda, N., Jorba, O., Jorge, J., Baldasano, J., 2004. Using NOAA AVHRR and SPOT VGT data to estimate surface parameters: application to a mesoscale meteorological model. International Journal of Remote Sensing 25, 129–143.

Pinto, J. O., Monaghan, A. J., Delle Monache, L., Vanvyve, E., Rife, D. L., 2014. Regional assessment of sampling techniques for more efficient dynamical climate downscaling. Journal of Climate 27, 1524–1538.

Racherla, P. N., Shindell, D. T., Faluvegi, G. S., 2012. The added value to global model projections of climate change by dynamical downscaling: A case study over the continental US using the GISS-ModelE2 and WRF models. Journal of Geophysical Research: Atmospheres 117.

Rockel, B., Castro, C. L., Pielke, R. A., von Storch, H., Leoncini, G., 2008. Dynamical downscaling: Assessment of model system dependent retained and added variability for two different regional climate models. Journal of Geophysical Research: Atmospheres 113.

Rosenblatt, M., sep 1956. Remarks on some nonparametric estimates of a density function. The Annals of Mathematical Statistics 27, 832–837.

Scott, D. W., 2009. Multivariate density estimation: theory, practice, and visualization. Vol. 383. John Wiley & Sons.

Sillmann, J., Donat, M. G., Fyfe, J. C., Zwiers, F. W., 2014. Observed and simulated temperature extremes during the recent warming hiatus. Environmental Research Letters 9, 064023.

Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Wang, W., Powers, J. G., 2005. A description of the advanced research WRF version 2. Tech. rep., DTIC Document.

Smirnov, N., 1948. Table for estimating the goodness of fit of empirical distributions. The Annals of Mathematical Statistics 19, 279–281.

Spero, T. L., Otte, M. J., Bowden, J. H., Nolte, C. G., 2014. Improving the representation of clouds, radiation, and precipitation using spectral nudging in the Weather Research and Forecasting model. Journal of Geophysical Research: Atmospheres 119, 11–682.

Teixeira, J., Carvalho, A., Carvalho, M., Luna, T., Rocha, A., 2014. Sensitivity of the WRF model to the lower boundary in an extreme precipitation event–Madeira island case study. Natural Hazards and Earth System Science 14, 2009–2025.

Tewari, M., Chen, F., Wang, W., Dudhia, J., LeMone, M., Mitchell, K., Ek, M., Gayno, G., Wegiel, J., Cuenca, R., 2004. Implementation and verification of the unified NOAH land surface model in the WRF model. 20^{th} conference on weather analysis and forecasting/16^{th} conference on numerical weather prediction, pp. 11–15.

Van der Linden, P., Mitchell, JFB, e., 2009. ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project. Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK 160.

Wilby, R. L., Wigley, T., 1997. Downscaling general circulation model output: a review of methods and limitations. Progress in Physical Geography 21, 530–548.

Wilks, D. S., 2011. Statistical methods in the atmospheric sciences. Vol. 100. Academic press.

Yang, B., Qian, Y., Lin, G., Leung, R., Zhang, Y., 2012. Some issues in uncertainty quantification and parameter tuning: a case study of convective parameterization scheme in the WRF regional climate model. Atmospheric Chemistry and Physics 12, 2409–2427.

Zhang, D., Anthes, R. A., 1982. A high-resolution model of the planetary boundary layer-sensitivity tests and comparisons with SESAME-79 data. Journal of Applied Meteorology 21, 1594–1609.

7. List of Figures

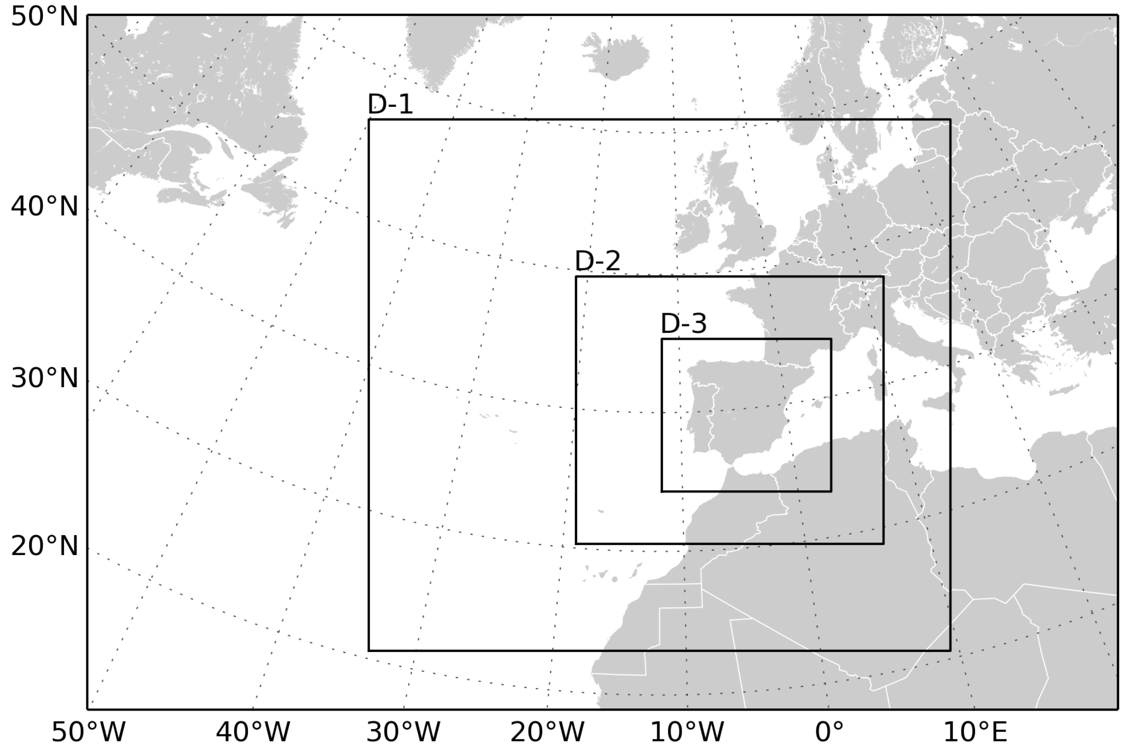

Figure 1: Model domain used in the regional WRF implementation. Model ran in 2-way nesting mode with increasing domain resolutions of 81, 27 and 9 km.

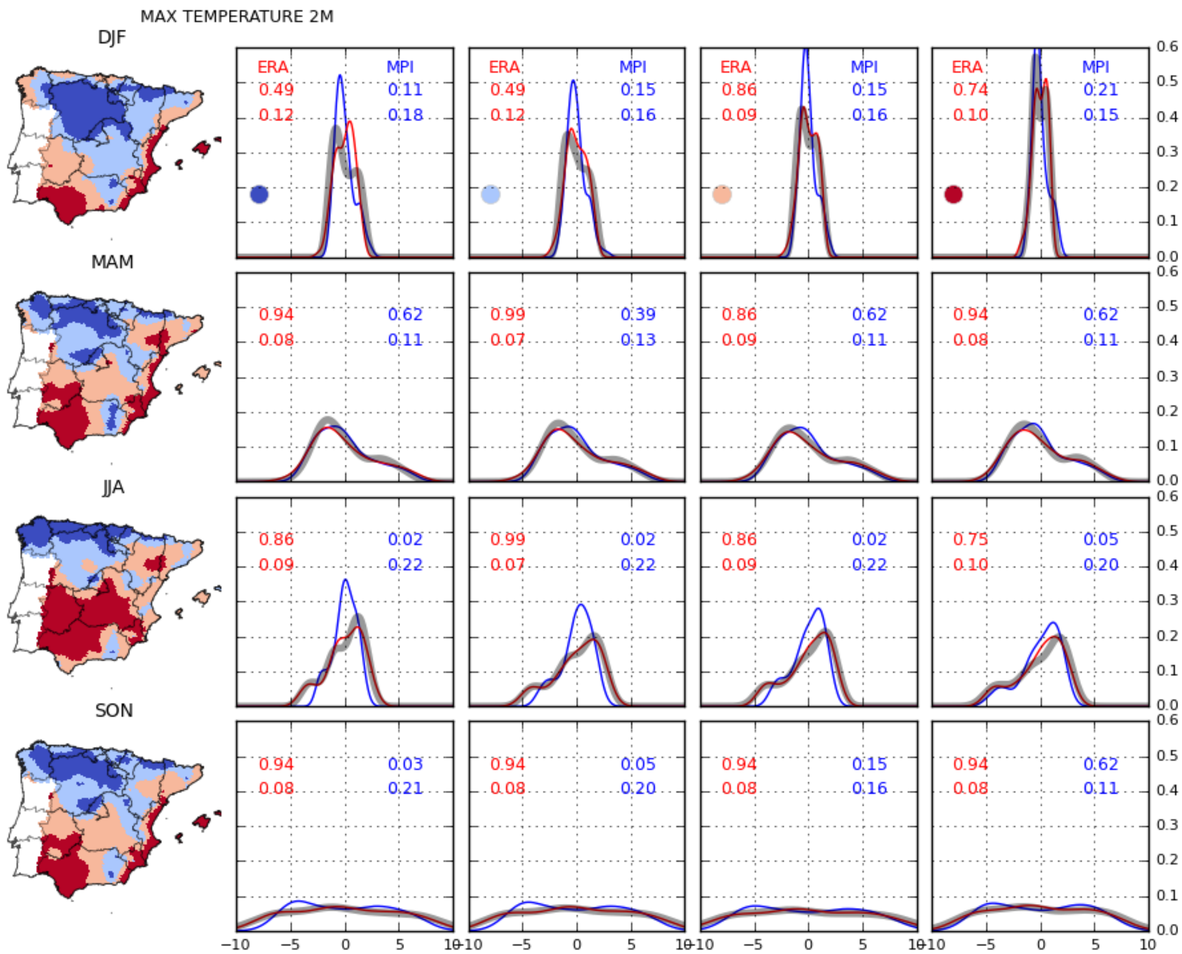

Figure 2: Regionalisation of the observed Spanish maximum temperature (°C) daily climatology and comparison of observed and modelled probability distribution of the spatial average inside each subregion. The probability distribution of the observations corresponds to the grey line; red line corresponds to the model forced by the ERA-Interim reanalysis (WRF-ERA); blue line corresponds to WRF model results forced with the MPI GCM (WRF-MPI). The numbers inside the subplots indicate the KS-test statistic (down) and p-value (up) corresponding to the comparison of observations with WRF-ERA (red) and with WRF-MPI (blue). Each row refers to one season (DJF means December, January and February, etc). The subplots are ordered with increasing mean value of the observed variable (subtracted from the data prior to the estimation of the probability distributions), and the corresponding cluster is indicated by the colour of the circular marker inside the winter subplots (1^{st} row).

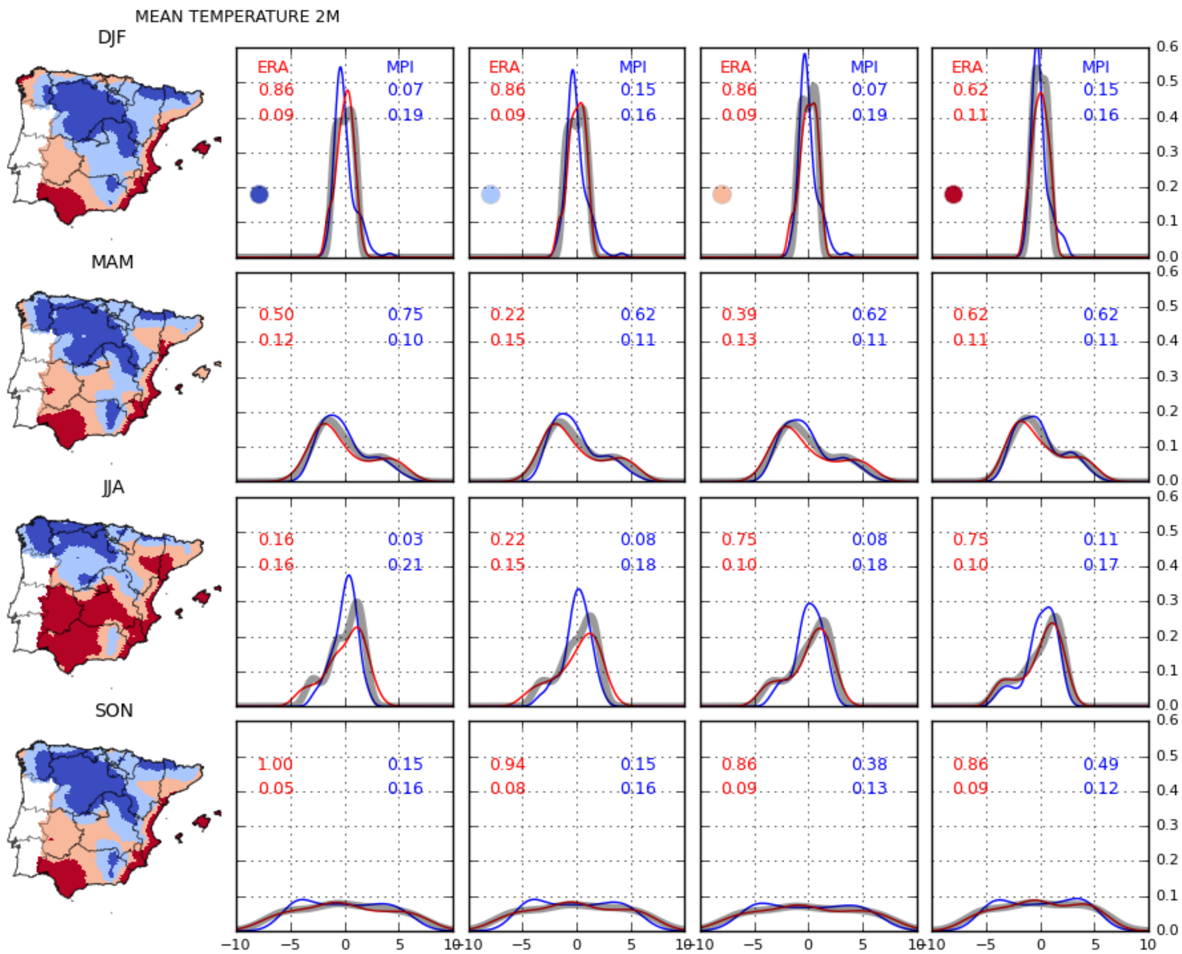

Figure 3: Same as Figure 2 but for mean temperature.

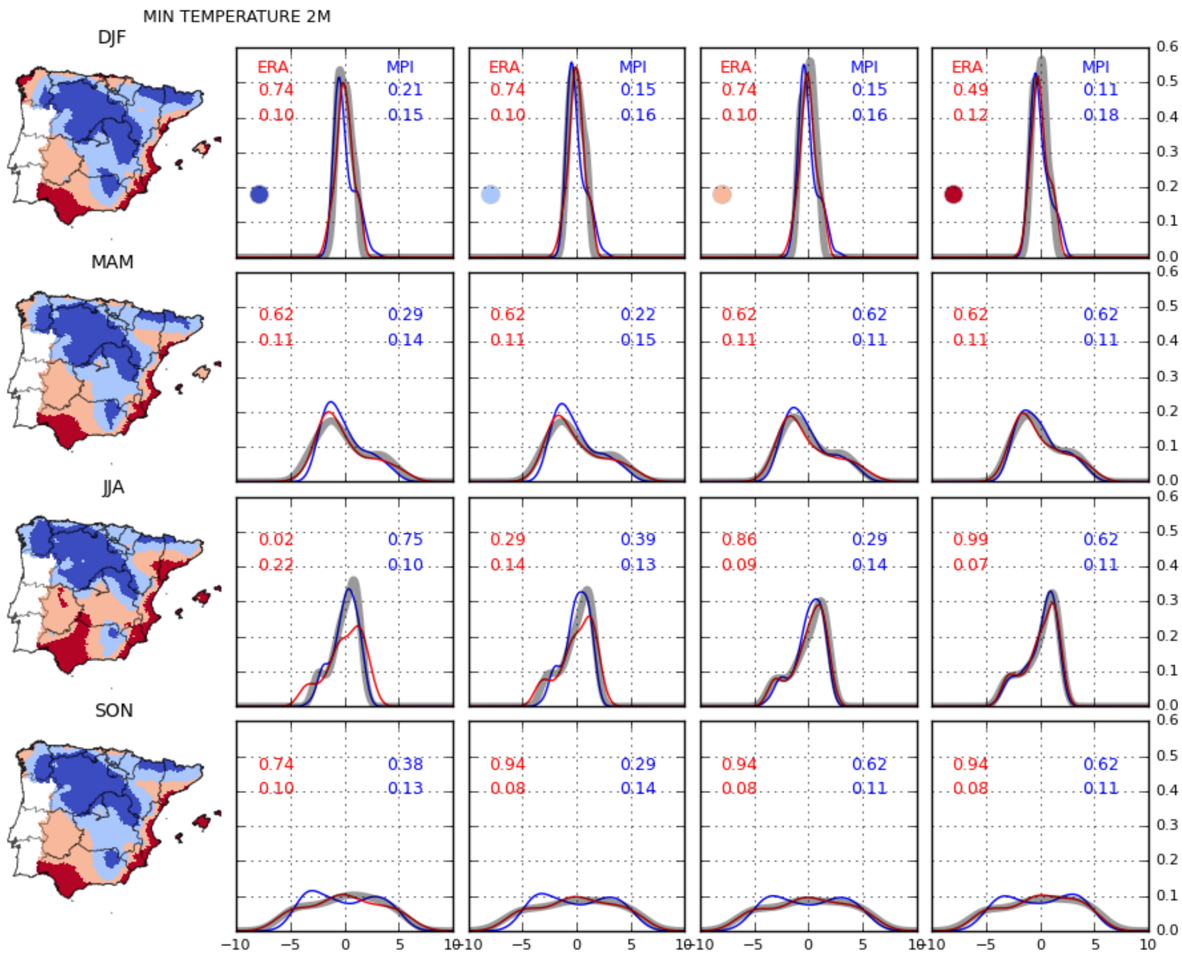

Figure 4: Same as Figure 2 but for minimum temperature.

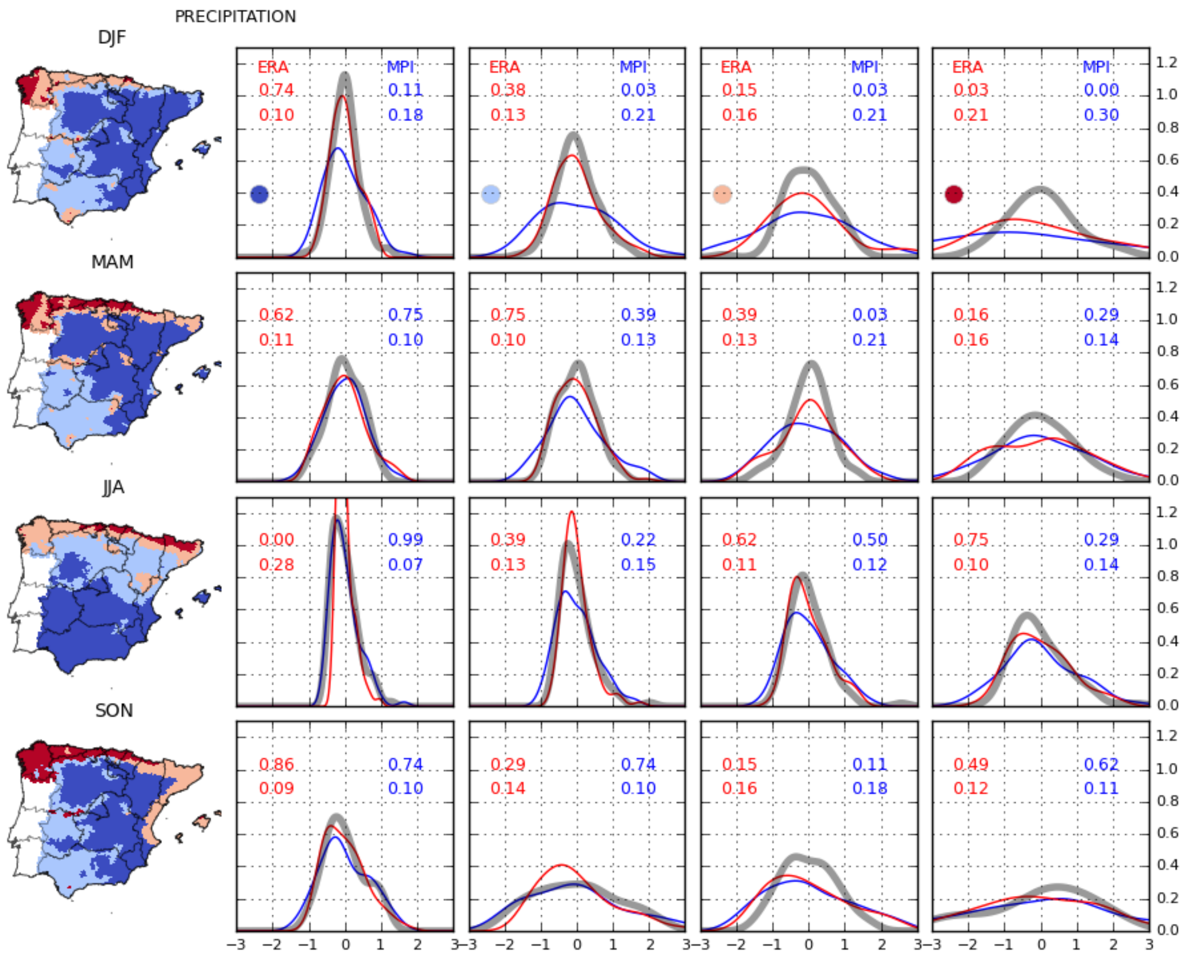

Figure 5: Same as Figure 2 but for total precipitation (mm day^{-1}).

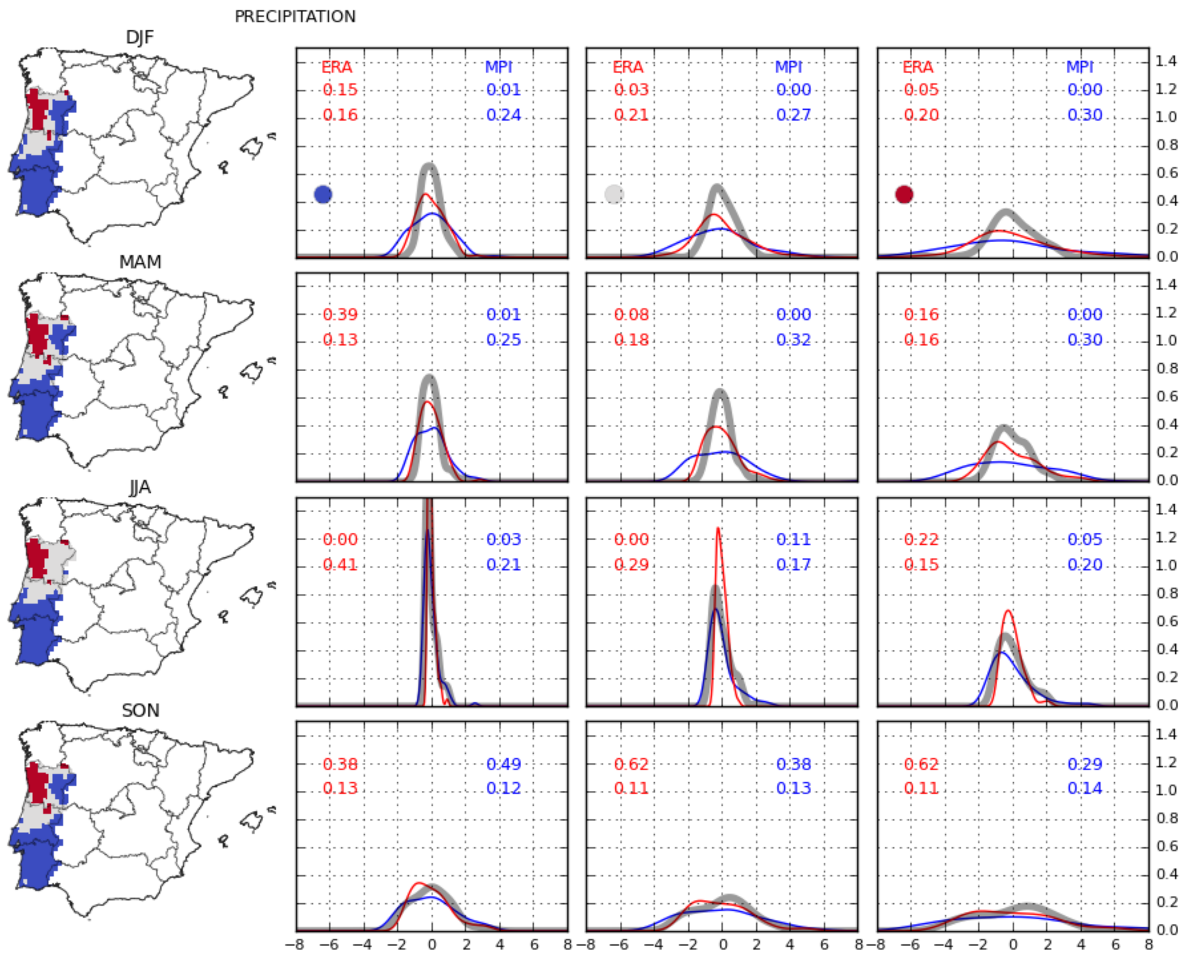

Figure 6: Same as Figure 5 but for the total precipitation (mm day^{-1}) over Portugal.