CHARACTERIZATION OF DROUGHT EVENTS OVER SPAIN USING THE WEATHER RESEARCH & FORECASTING MODEL

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ABSTRACT

This work examines the ability of the Weather Research & Forecasting (WRF) model to capture drought spatiotemporal variability over a topographically complex region such as Spain. For this, two well-known drought indices, i.e. the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) were used. Thus, we compared the results of an index based solely on precipitation data (i.e. the SPI) and another one that takes into account the temperature effect (i.e. the SPEI). The evaluation was based on a grid-to-grid comparison between the drought indices computed using downscaled fields from a WRF simulation conducted by ERA-Interim and those calculated from the MOPREDAS and MOTEDAS observational databases, for the period 1980-2010. Additionally, in order to determine the added value obtained by applying downscaled climate data, the drought indices computed from WRF outputs were also compared with those computed from ERA-Interim fields.

Key Words: Weather Research & Forecasting, regional climate models, drought, dynamical downscaling, Spain.

RESUMEN

Este trabajo evalúa la habilidad del modelo Weather Research & Forecasting (WRF) para representar la variabilidad espacio temporal de las sequías en una región topográficamente compleja como es España. Para ello, se han usado dos índices, el índice de precipitación estandarizado (SPI) y el índice de precipitación evapotranspiración estandarizado (SPEI). Así, se comparó los resultados de un índice basado únicamente en valores de precipitación, el SPI, y otro que tiene en cuanta el efecto de la temperatura, el SPEI. La evaluación aquí realizada se ha basado en una comparación punto a punto de los resultados de los índices obtenidos usando las salidas del modelo WRF conducido por los datos de ERA-Interim y aquellos calculados a partir de los datos observacionales de MOPREDAS y MOTEDAS para el periodo 1980-2010. Además, con el objetivo de determinar el valor añadido proporcionado al aplicar el *downscaling* dinámico, los índices de sequía calculados con WRF se han comparado con los índices obtenidos a partir de ERA-Interim.

Palabras clave: Weather Research & Forecasting, modelos climáticos regionales, sequía, *downscaling* dinámico, España.

1. INTRODUCTION

In broad terms, drought can be defined as the scarcity of precipitation over a prolonged time period. Such kind of phenomenon causes serious social and environmental impacts leading to tremendous losses, particularly in vulnerable regions to global warming such as the Mediterranean region.

In order to detect, monitor and analyze droughts events, the World Meteorological Organization recommends the Standardized Precipitation Index (SPI, McKee et al., 1993) due to its simplicity, robustness, easy interpretation, and especially for its multiscalar character. This last characteristic is essential to detect different drought types and their impacts (Beguería et al., 2014). Furthermore, the SPI has the advantage of being comparable across regions with markedly different climates. Nevertheless, it is based solely on precipitation. Another index, the Standardized Precipitation Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2010) is a relatively new index widely used because it combines the benefit of taking into account the effect of the temperature throughout the reference evapotranspiration (ET_0), with the simplicity, robustness, and the multiscalar properties of the SPI.

Global climate models (GCMs) are the first source of information to study future changes in drought events. However, due to their coarse resolution, the GCMs are unable to capture the regional behavior of the droughts, especially in those regions characterized by high precipitation variability such as the Mediterranean region (Vicente-Serrano et al., 2004). This problem could be solved by the application of regional climate models (RCMs), which are able to capture different processes related to drought episodes at a finer scale. This work aims to ascertain the added value provided by the WRF model as RCM to detect dry and wet periods for Spain, a topographically complex area.

2. DATA AND METHODS

2.1. Data

In this work the precipitation, maximum (T_{max}) and minimum (T_{min}) temperature from a WRF simulation were used to compute drought indices. To do this, the WRF-ARW (Skamarok et al., 2008) version 3.6.1 was run for a 31-year (1980-2010) period over a domain (Fig. 1) centered over the Iberian Peninsula (IP) at 0.088º of spatial resolution, and nested in a coarser domain that corresponds to the 0.44 EURO-CORDEX (Jacob et al., 2014) region, using as lateral boundary conditions (LBCs) the ECMWF ERA-Interim reanalysis dataset (Berrisford et al., 2011). For more details of the model configuration see García-Valdecasas Ojeda et al. (2017).

As observations, the data from the MOPREDAS (González-Hidalgo et al., 2011) and MOTEDAS (González-Hidalgo et al., 2015) were selected, which are two observational gridded products of monthly precipitation and extreme temperatures (T_{max} and T_{min}), respectively. These datasets cover the Peninsular Spanish region for a period between 1950 and 2010. Additionally, precipitation, T_{max} and T_{min} from ERA-Interim reanalysis were also used to compute drought indices.

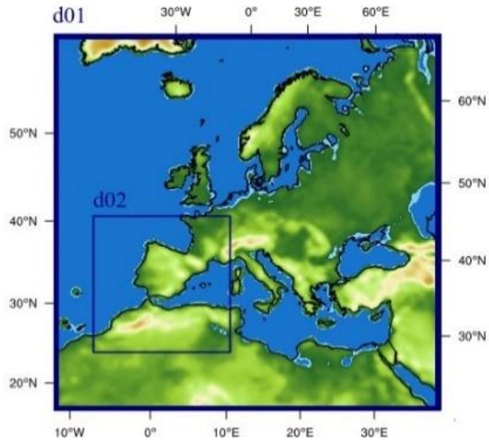

Fig. 1: The WRF domains used in this study: the EURO-CORDEX (d01) and a domain centered in the IP (d02).

2.2. Method

The ability of the WRF model to detect dry and wet periods was analyzed by a direct comparison in a local analysis (grid-to-grid). For this, both drought indices, the SPI and the SPEI, were computed using the SPEI R-package (Beguería and Vicente-Serrano, 2013). This code allows the formulation of both indices, also providing an additional function to estimate the ET_0. Among the different approaches available, the Modified Hargreaves equation (HG-PP, Droogers and Allen, 2002) was used, which is appropriated for estimating ET_0 values in Spain (Vicente-Serrano et al., 2014). Thus, through the HG-PP, the results proved similar to those from the Penman-Monteith equation (Allen et al., 1998), which is the method adopted by the Food and Agriculture Organization to estimate this variable, but with the advantage that only precipitation and temperature (maximum and minimum) are required to calculate it (Beguería et al., 2014).

Drought indices were computed at two different time scales, the 3-month time scale, which allows us to the study of episodes related to meteorological drought, and the 12-month time scale, commonly used to detect hydrological drought.

For comparative purposes, both the SPEI and the SPI were fitted to the log-logistic probability distribution. Thus, we can ensure that the differences between them were related to the effect of the temperature and not to the probability distribution used.

3. RESULTS

3.1. Temporal Analysis

Fig. 2 shows the root mean squared errors (RMSEs) of the simulated drought indices (ERA and WRFERA) with respect to the observations (mprmt) for both indices (the SPEI and the SPI) and for the two time scales (3- and 12-months) analyzed. In general, the ERA drought indices presented higher RMSE values than those from WRFERA, so this result is suggesting that WRF adds value with respect to its driving data (e.g., Ebro Valley or Cantabrian Range). Such added-value appeared to be higher for the SPI than for the SPEI, and particularly for 12-month time scale in the Cantabrian, northeastern and southeastern regions of Spain.

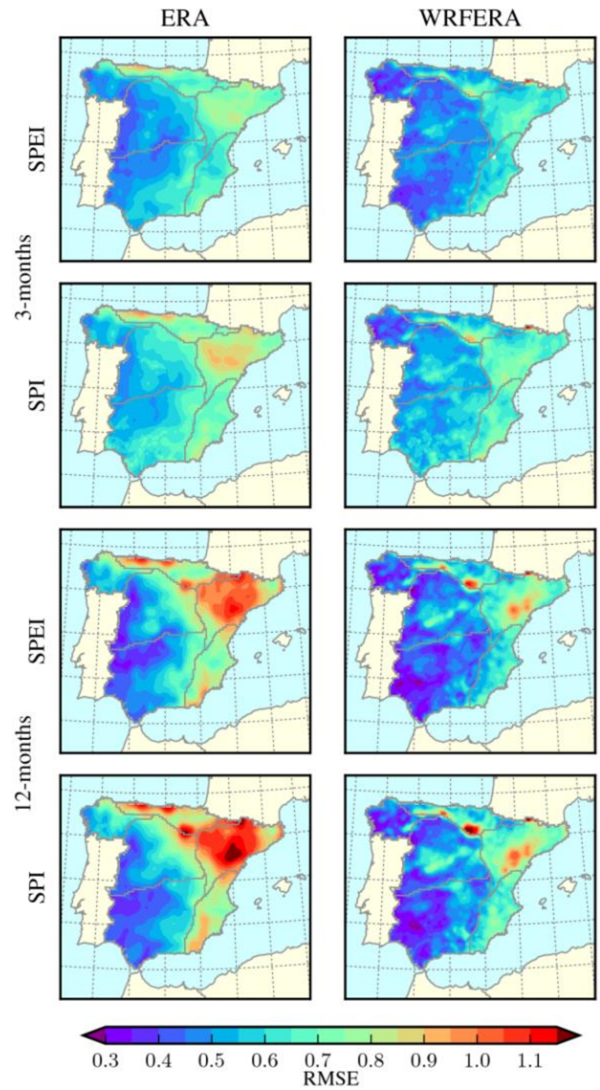

Fig. 2: Root mean squared errors (RMSEs) for drought indices computed from the ERA and the WRFERA with respect to those from the mprmt. In rows, both the two indices and time scales used.

3.2. Categorical Analysis

An added-value analysis was also performed through a categorical viewpoint, using the critical success index (CSI, Kang et al., 2005). Such a measurement is based on the ability of the model to detect occurrence above or below a given threshold. The CSI is defined as:

$$CSI(\%) = \frac{TP}{TP + FP + FN} \times 100$$

where *TP* are the true positives, i.e. positive predictions corroborated by observations, *FP* are the ones found by using ERA (or WRFERA) that are not accompanied by a true event (false positives), and *FN* the events occurred non-captured by simulated data (false negatives).

Fig. 3 depicts the CSI for moderate-to-extreme dry and wet periods (drought indices below -1 and above 1). The significant relative differences between WRFERA and ERA (third column) were also computed to quantify the benefit of using downscaling fields. Here, to determine the statistical significance of such CSI differences, we applied the two-proportional z-test at the 95% confidence level.

As can be seen through the significant relative differences of the CSI, the results indicated that the WRF model provided an added value in certain regions of northern Spain, slightly higher for the SPI and for the indices computed at 12-month time scale. These results agree with those found in the analysis of the RMSE values.

3.3. Spatial Analysis

The potential WRF benefit was also assessed in the context of the spatial variability. Here, the procedure detailed in Wang et al. (2015) was applied, which consists of calculating the Pearson correlation coefficients at different spatial intervals (or lags) over the longitude and latitude. Thereby, the spatial correlations are calculated by:

$$r_{L,I,s_1,s_2} = \frac{\sum_{i=1}^{n}(x_{i,L,I} - \overline{x}_{L,I})(x_{i,L+s_1,I+s_2} - \overline{x}_{L+s_1,I+s_2})}{\sqrt{\sum_{i=1}^{n}(x_{i,L,I} - \overline{x}_{L,I})^2}\sqrt{\sum_{i=1}^{n}(x_{i,L+s_1,I+s_2} - \overline{x}_{L+s_1,I+s_2})^2}}$$

where x corresponds to the drought index values for every i month with coordinates (L, I) in latitude and longitude respectively; s_1 is the south-to-north interval and s_2 the west-to-east interval. From this way, the added value can be analyzed through the difference between the spatial correlation from simulations and observations; positive differences mean that two points from the simulated drought indices are more similar than the same points from the observational data, and therefore, the simulations are unable to capture the spatial variability of drought indices. Conversely, a negative difference means that the simulated fields are more sensitive to spatial variability than the observational data.

Fig. 4 displays the spatial correlation between one grid and another along the south-to-north with a lag of 0.4º. The spatial correlations from mprmt are shown in the first row and the differences from simulations against observations appear in the second and third rows, respectively. In general, results indicate that the ERA drought indices provided positive differences with respect to the observations, suggesting that they are unable to represent the spatial variations and the local characteristics in the main mountain ranges of Spain. By contrast, the WRFERA indices adequately reproduced the spatial variability, even more than the observational data (the differences are negative in general), leading therefore an added value with respect to its LBCs. These results were similar for the two drought indices and more evident at 12-month time scale.

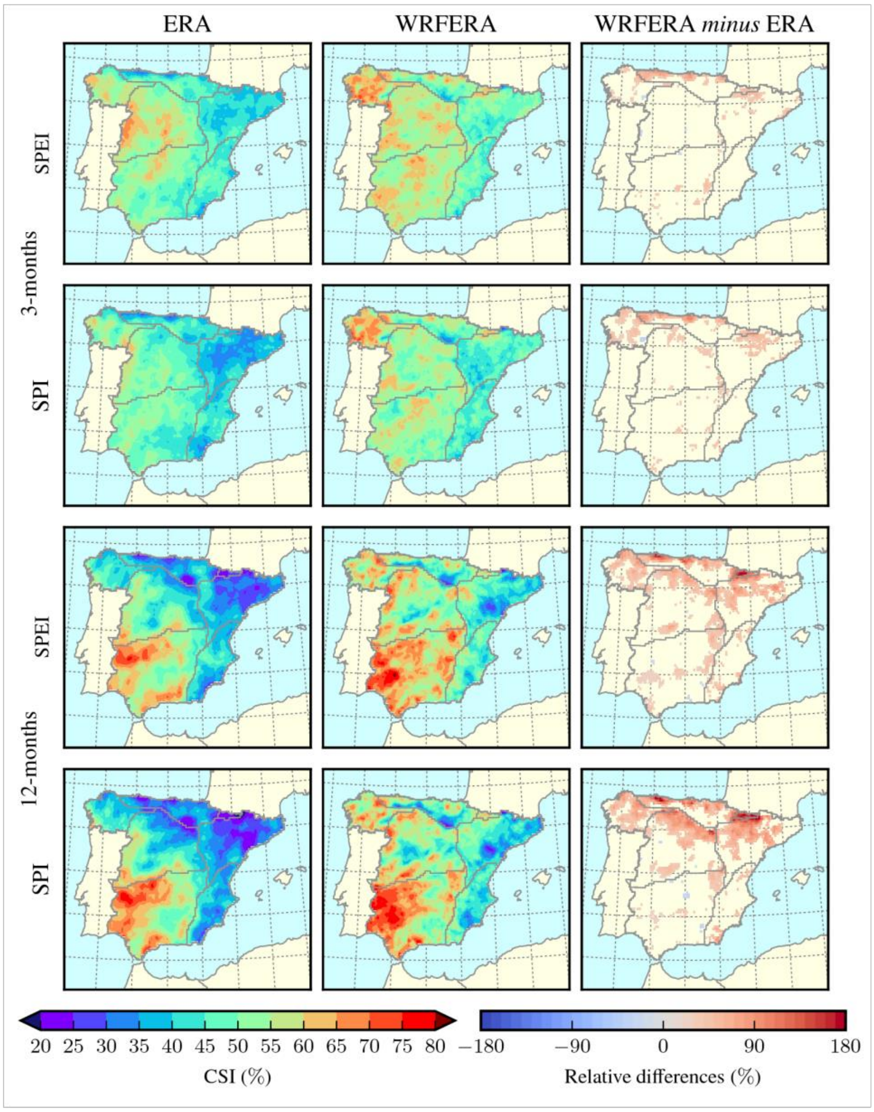

Fig. 3: Critical Success Index (CSI) between simulated (ERA and WRFERA) and observed (mprmt) for the SPEI and the SPI at 3- and 12-month time scales (first and second columns). The third column represents the significant relative differences ((WRFERA minus ERA) / ERA) according to a two proportional z-test at the 95% confidence level.

3.4. Event Evaluation Based on the SPEI and SPI

Finally, the behavior of the drought indices during an extreme dry period using downscaled fields was also investigated. For this, we selected a severe drought event occurred over the IP during 2005, which has been considered as the driest event in the last 140 years (García-Herrera et al., 2007).

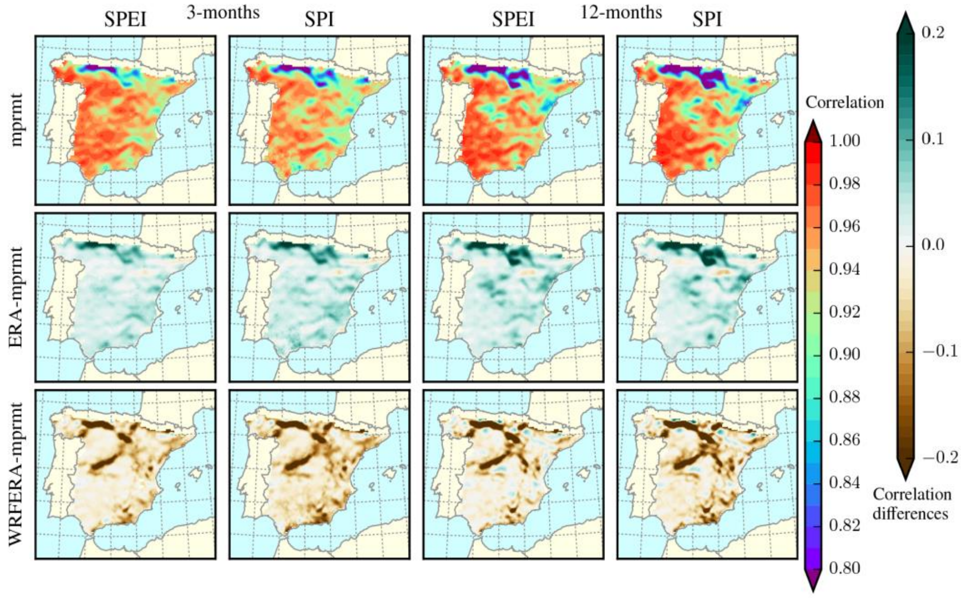

Fig. 4: Spatial correlation coefficients from the mprmt and the differences between the ERA and the WRFERA with respect to the mprmt for a lag of 0.4º along the south-to-north direction. In columns, the drought indices at a time scale of 3 (first and second columns) and 12 (third and fourth columns) months.

Fig. 5 depicts the spatial distribution of drought indices from the mprmt, the ERA, and the WRFERA data, corresponding to September. In brackets are displayed the pattern correlations between simulated (ERA and WRFERA) drought indices and those from observational datasets.

At 3-month time scale (Fig. 5a), the ERA drought indices reliably represented the broad patterns of drought (r values of 0.44 and 0.34 for the SPEI and the SPI, respectively). However, the WRFERA fields provided substantial improvements (r values of 0.76 and 0.70 for the SPEI and SPI, respectively). At this time scale, certain benefits of using the WRF model were clearly displayed. For example, over northeastern Spain, the ERA drought indices showed moderate-to-severe droughts (drought indices below -1), whereas the mprmt indicated values above 1 (wet episode). However, WRF correctly represented the behavior of the mprmt drought indices in such region. At 12-month time scale (Fig. 5b), both indices presented similar spatial patterns, as reflected Fig. 5b. At this time scale, the ERA indices depicted suitable results showing pattern correlations of 0.57 and 0.64 for the SPI and SPEI, respectively. However, again, WRFERA outperforms ERA with patterns correlations of 0.76 for the SPEI and 0.77 for the SPI. Therefore, in general, we can conclude that the WRF model provided an improvement with respect to the ERA data to detect the 2005 extreme event at local scale, with a major benefit at 3-month time scale in this case.

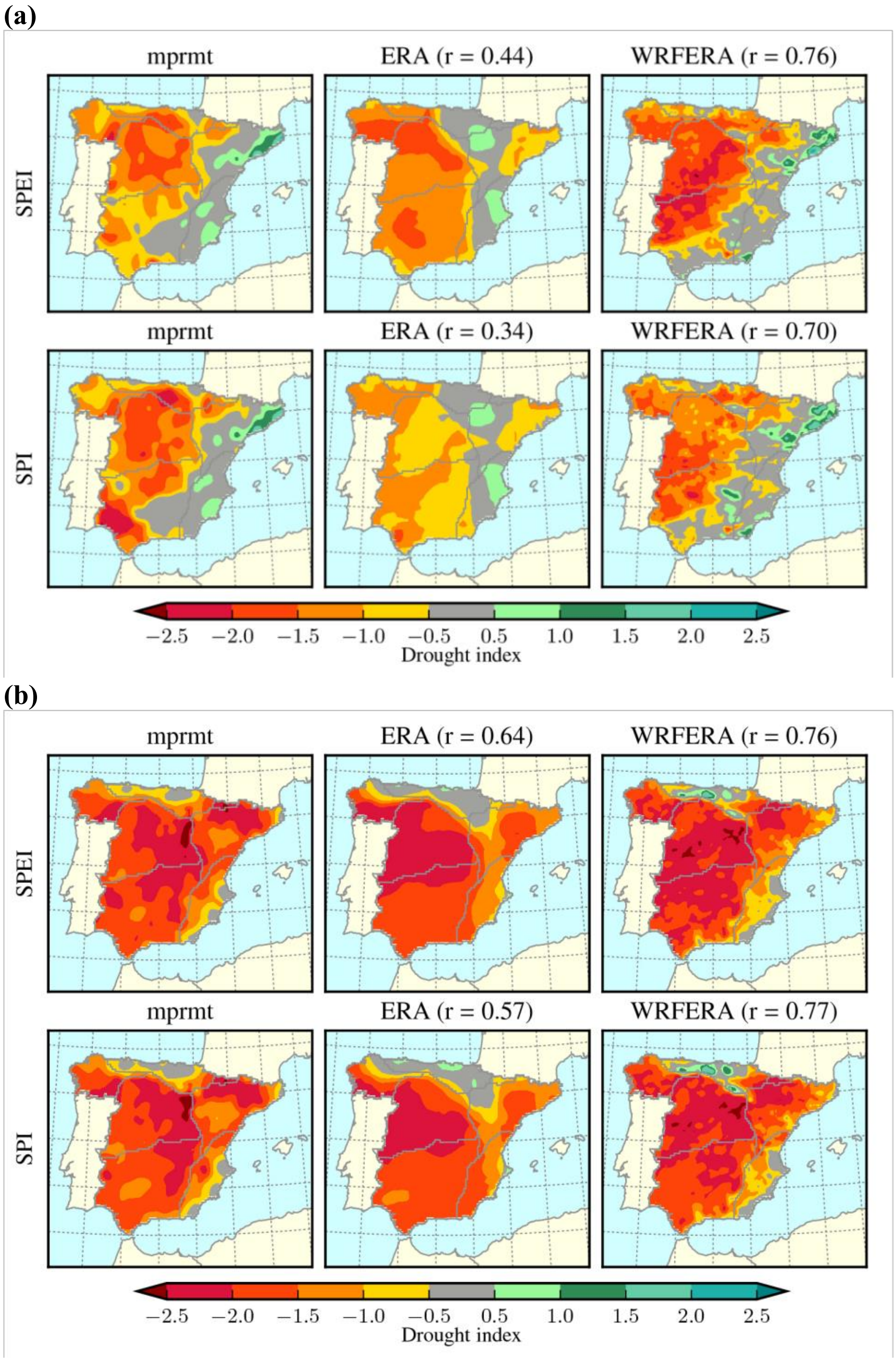

Fig. 5: Drought indices ending in September 2005 at (a) 3-month and (b) 12-month time scales. The pattern correlations of the simulated indices values with respect to those from the mprmt are shown in brackets.

4. DISCUSSION

This work aims to assess the ability of the WRF model to capture dry and wet periods using two drought indices, the SPEI and the SPI. These drought indices were used to evaluate whether the downscaled fields offer a benefit to detect, analyze and monitor drought at local scale. In this context, the results showed that the WRF model generally captures well the main spatiotemporal pattern of drought in Spain, showing an added value with respect to its driving data in many cases. In the study of the RMSE and CSI values, the results indicate that the WRF model achieved an overall improvement with better results at 12-month time scale. Moreover, RMSE values reflect that the highest improvements provided by WRF are in regions where the ERA data presented the worst results. Similarly, in the spatial analysis, the WRF model proved an added value clearly shown over high altitude regions. This study also reveals that there is no substantial difference between the SPEI and the SPI in the evaluation of the ability of the WRF model to simulate droughts in Spain. Such results prove the benefit of using WRF for drought analysis in a topographically complex region such as Spain, which is relevant for drought-related decision making, particularly, for water-resource management.

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