Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2018-356
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 27 November 2018

Natural Hazards and Earth System Sciences
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A high-resolution spatial assessment of the impacts of drought variability on vegetation activity in Spain from 1981 to 2015

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Abstract: Drought is a major driver of vegetation activity in Spain, with significant impacts on crop yield, forest growth, and the occurrence of forest fires. Nonetheless, the sensitivity of vegetation to drought conditions differs largely amongst vegetation types and climates. We used a high-resolution (1.1 km) spatial dataset of the Normalized Difference Vegetation Index (NDVI) for the whole Spain spanning the period from 1981 to 2015, combined with a another newly developed dataset of the Standardized Precipitation Evapotranspiration Index (SPEI) to assess the sensitivity of vegetation types to drought across Spain. In specific, this study explores the drought time scales at which vegetation activity shows its highest response to drought severity at different moments of the year. Results demonstrate that –over large areas of Spain– vegetation activity is controlled largely by the interannual variability of drought. More than 90% of the land areas exhibited statistically significant positive correlations between the NDVI and the SPEI during dry summers (JJA). Nevertheless, there are some considerable spatio-temporal variations, which can be linked to differences in land cover and aridity conditions. In comparison to other climatic regions across Spain, results indicate that

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vegetation types located in arid regions showed the strongest response to drought. Importantly, this study stresses that the time scale at which drought is assessed is a dominant factor in understanding the different responses of vegetation activity to drought.

Key-words: Drought, NDVI, Vegetation activity, Climatic change, Spain.

1. Introduction

Drought is one of the major hydroclimatic hazards impacting land surface fluxes (Baldocchi et al., 2004; Fischer et al., 2007; Hirschi et al., 2011), vegetation respiration (Ciais et al., 2005), net primary production (Reichstein et al., 2007; Zhao and Running, 2010), primary and secondary forest growth (Allen et al., 2015), and crop yield (Lobell et al., 2015; Asseng et al., 2015). Recently, numerous studies suggested an accelerated impact of drought on vegetation activity and forest mortality under different environmental conditions (Allen et al., 2010, 2015; Breshears et al., 2005) with a reduction in vegetation activity and higher rates of tree decay (e.g. Carnicer et al., 2011; Restaino et al., 2016). Nevertheless, a comprehensive assessment of the impacts of drought on vegetation activity is a challenging task. This is particularly because data on forest conditions and growth are partial, spatially sparse, and restricted to a small number of sampled forests (Grissino-Mayer and Fritts, 1997). Furthermore, the temporal resolution of forest data is insufficient to provide deep insights into the impacts of drought on vegetation activity [e.g. the official forest inventories (Jenkins et al., 2003)]. In addition to these challenges, the spatial and temporal data on crops are often limited, as they are mostly aggregated to administrative levels and provided at the annual scale, with minor information on vegetation activity across the different periods of the year (e.g. http://faostat.fao.org; https://quickstats.nass.usda.gov/#AF9A0104-19EF-3BFE-90D2-C67700892F3E; last access on 1st October 2018). To handle these

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limitations, numerous studies have alternatively employed the available remotely sensed data to assess the impacts of drought on vegetation activity (e.g. Ji and Peters, 2003; Wan et al., 2004; Rhee et al., 2010; Zhao et al., 2017).

Several space-based products allow for quantifying vegetation conditions, given that both health and dry vegetation biomass respond dissimilarly to the electromagnetic radiation received in the visible and near-infrared parts of the vegetation spectrum (Knipling, 1970). As such, with the available spectral information recorded by sensors on board of satellite platforms, it is possible to calculate vegetation indices and accordingly assess vegetation activity (Tucker, 1979). In this context, several studies have already employed vegetation indices not only to develop drought-related metrics (e.g. Kogan, 1997; Mu et al., 2013), but to determine the impacts of drought on vegetation conditions as well (García et al., 2010; Vicente-Serrano et al., 2013; Zhang et al., 2017). An inspection of these studies reveals that drought impacts can be characterized using vegetation indices, albeit with a different response of vegetation dynamics as a function of a wide-range of factors, including –among others– vegetation type, bioclimatic conditions, and drought severity (Bhuiyan et al., 2006; Vicente-Serrano, 2007; Quiring and Ganesh, 2010; Ivits et al., 2014).

Given high interannual variability of precipitation, combined with the prevailing semi-arid conditions across vast areas of the territory, Spain has suffered from frequent, intense and severe drought episodes during the past decades (Vicente-Serrano, 2006). Nonetheless, in the era of temperature rise, the observed increase in atmospheric evaporative demand (AED) during the last decades has accelerated the severity of droughts (Vicente-Serrano et al., 2014c), in comparison to the severity caused only by precipitation deficits (Vicente-Serrano et al., 2014a; González-Hidalgo et al., 2018). Over Spain, the hydrological and socioeconomic impacts of droughts are welldocumented. Hydrologically, droughts are often associated with a decrease in streamflow and reservoir storages (Lorenzo-Lacruz et al., 2010; Lorenzo-Lacruz et al., 2013). The impacts of drought can extend further to crops, leading to crop failure due to deficit in irrigation water (Iglesias et al., 2003), and even in arable non-irrigated lands (Austin et al., 1998; Páscoa et al., 2017). Over Spain, numerous investigations also highlighted the adverse impacts of drought on forest growth (e.g. Camarero et al., 2015; Gazol et al., 2018; Peña-Gallardo et al., 2018) and forest fires (Hill et al., 2008; Lasanta et al., 2017; Pausas, 2004; Pausas and Fernández-Muñoz, 2012).

Albeit with these adverse drought-driven impacts, there is a lack of comprehensive studies that assess the impacts of drought on vegetation activity over the entire Spanish territory, with a satisfactorily temporal coverage. While numerous studies employed remotely sensed imagery and vegetation indices to analyze spatial and temporal variability and trends in vegetation activity over Spain (e.g. del Barrio et al., 2010; Julien et al., 2011; Stellmes et al., 2013), few attempts have been made to link the temporal dynamics of satellite-derived vegetation activity with climate variability and drought evolution (e.g. Vicente-Serrano et al., 2006; Udelhoven et al., 2009; Gouveia et al., 2012; Mühlbauer et al., 2016). An example is González-Alonso and Casanova (1997) who analyzed the spatial distribution of droughts in 1994 and 1995 over Spain, concluding that the most affected areas are semiarid regions. In their comparison of the MODIS Normalized Difference Vegetation Index (NDVI) data and the Standardized Precipitation Index (SPI) over Spain, García-Haro et al. (2014) indicated that the response of vegetation dynamics to climate variability is highly variable, according to the regional climate conditions, vegetation community, and growth stages. A similar finding was also confirmed by Vicente-Serrano (2007) and Contreras and Hunink (2015) in their assessment of the response of NDVI to drought in semiarid regions of

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northeast and southeast Spain, respectively. Albeit with these comprehensive efforts, a detailed spatial assessment of the links between droughts and vegetation activity, which covers a long time period (decades), is highly desired for Spain to explore the differences in the response of vegetation activity to drought under different environments with various land cover and vegetation types.

The overriding objectives of this study are: i) to determine the possible differences in the response of vegetation activity to drought over Spain, as a function of the different land cover types and climatic conditions; and ii) to explore the drought time scales at which vegetation activity highly responds to drought severity. An innovate aspect of this study is that it provides –for the first time– a comprehensive assessment of the response of vegetation activity to drought using a multidecadal (1981-2015) high spatial resolution (1.1 km) NDVI dataset over the study region.

2. Data and methods

2.1. Datasets

2.1.1. NDVI data

Globally, there are several NDVI datasets, which have been widely used to analyze NDVI variability and trends (e.g. Slayback et al., 2003; Herrmann et al., 2005; Anyamba and Tucker, 2005) and to assess the links between NDVI and climate variability and drought (e.g. Dardel et al., 2014; Vicente-Serrano et al., 2015; Gouveia et al., 2016). Amongst these global datasets, the most widely used are those derived from the Advanced Very High Resolution Radiometer (AVHRR) sensor on board of the NOAA satellites and those retrieved from the Moderate Resolution Imaging Spectroradiometer (MODIS) data. Both products have been widely employed to evaluate the possible influence of drought on vegetation dynamics in different regions worldwide (e.g. Tucker et al., 2005; Gu et al., 2007; Sona et al., 2012; Pinzon and Tucker, 2014; Ma et al., 2015). While the Global Inventory Modeling and Mapping Studies (GIMMS) dataset from NOAA-AVHRR is available at a semi-monthly temporal resolution for the period from 1981 onwards (Tucker et al., 2005; Pinzon and Tucker, 2014), its spatial resolution is quite low (64 km^2), which makes it difficult to capture the high spatial variability of vegetation cover over Spain. On the other hand, the NDVI dataset derived from MODIS dates back only to 2001 (Huete et al., 2002), which is insufficient to give insights into the long-term response of vegetation activity to drought. To overcome these spatial and temporal limitations, our decision was made to employ a recently developed high-resolution spatial NDVI dataset (Sp_1Km_NDVI), which is available at grid interval of 1.1 km, spanning the period from 1981 onwards. In accordance with GIMMS dataset, Sp_1Km_NDVI is available at a semi-monthly temporal resolution. This dataset has already been validated (Vicente-Serrano et al., 2018), showing high performance in comparison to other available NDVI datasets. As such, it can be used -with confidence- to provide a multidecadal assessment of NDVI variability at high-spatial resolution, especially in areas of highly variable vegetation. Herein, it is noteworthy indicating that the data from the Sp_1Km_NDVI dataset was standardized (sNDVI), so that each series has an average equal to zero and a standard deviation equal to one. This procedure is motivated by the strong seasonality and spatial differences of vegetation activity over Spain. Following this procedure, the magnitudes of all NDVI time series are comparable over space and time. To accomplish this task, the data were fitted to a log-logistic distribution, which shows better skill in standardizing environmental variables, in comparison to other statistical distributions (Vicente-Serrano and Beguería, 2016).

In out attempt to limit the possible impact of changes in land cover on the dependency between drought and vegetation cover, we assumed that strong changes in NDVI can be seen as an indicator of changes in land cover. As such, those pixels with strong changes in NDVI during the study period were excluded from the analysis. These pixels were defined after an exploratory analysis in which we tested different thresholds. In specific, we excluded those pixels, which exhibited a decrease in the annual NDVI higher than 0.05 units or an increase higher than 0.15 units between 1981 and 2015. The spatial distribution (not shown here) of these pixels concurs well with the areas identified in earlier studies over Spain (e.g. Lasanta and Vicente-Serrano, 2012; Vicente-Serrano et al., 2018). Furthermore, to avoid the possible influence of spatial autocorrelation, which can occur in areas with dominant positive changes in NDVI due to excessive rural exodus and natural revegetation processes (Hill et al., 2008; Vicente-Serrano et al., 2018), we detrended the standardized NDVI series by means of a linear model. We then add the residuals of the linear trend to the average of NDVI magnitude over the study period. A similar approach has been adopted in several environmental studies (Olsen et al., 2013; Xulu et al., 2018; Zhang et al., 2016).

2.1.2. Drought dataset

Due to its complicated physiological strategies to cope with water stress, vegetation can show specific and even individual resistance and vulnerability to drought (Chaves et al., 2003; Gazol et al., 2017; Gazol et al., 2018). As such, it is quite difficult to directly assess the impacts of drought on vegetation activity and forest growth. Alternatively, drought indices can be an appropriate tool to make this assessment, particularly with their calculation at multiple time scales. These time scales summarize the accumulated climatic conditions over different periods, which make drought indices closely related to impact studies. Overall, to calculate drought indices, we employed data for a set of meteorological variables (i.e. precipitation, maximum and minimum air temperature, relative humidity, sunshine duration, and wind speed) from a recently developed gridded climatic dataset (Vicente-Serrano et al., 2017). This gridded dataset was developed using a dense network of quality-controlled and homogenized meteorological records. Data are available for the whole Spanish territory at a spatial resolution of 1.1 km, which is consistent with the resolution of the NDVI dataset (section 2.1.1). Based on this gridded dataset, we computed the atmospheric evaporative demand (AED), reference evapotranspiration (ETo), and the Standardized Precipitation Evapotranspiration Index (SPEI). ETo was calculated using the physically based FAO-56 Penman-Monteith equation (Allen et al., 1998). On the other hand, the SPEI was computed using precipitation and AED data (Vicente-Serrano et al., 2010). The SPEI is one of the most widely used drought indices and has thus been employed to quantify drought in a number of agricultural (e.g. Peña-Gallardo et al., 2018b), environmental (e.g. Vicente-Serrano et al., 2012; Bachmair et al., 2018), and socioeconomic applications (e.g. Bachmair et al., 2015; Stagge et al., 2015). The SPEI is advantageous compared to the Palmer Drought Severity Index (PDSI), as it is calculated at different time scales. In comparison to the Standardized Precipitation Index (SPI) (McKee et al., 1993), the SPEI does not account only for precipitation, but it also considers the contribution of AED in drought evolution.

In this work, the SPEI was calculated for the common 1- to 24-month time scales. The preference to use various time scales is motivated by our intention to characterize the response of different hydrological and environmental systems to drought It is well-recognized that natural systems can show different responses to the time scales of drought (Vicente-Serrano et al., 2011, 2013). The time scale refers to the period in

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which antecedent climate conditions are accumulated and it allows to adapt the drought index to the drought impacts since different hydrological and environmental systems show different responses sensitivities to the time scales of climate variability. This has been shown for hydrological systems (López-Moreno et al., 2013; Barker et al., 2016), but also ecological and agricultural systems show strong differences in the response to different time scales of climatic droughts (Pasho et al., 2011; Peña-Gallardo et al., 2018b) given different biophysical conditions, but also the different strategies of vegetation types to cope with water stress (Chaves et al., 2003; McDowell et al., 2008), which are strongly variable in complex Mediterranean ecosystems. For instance, drought indices can be calculated on flexible time scales since it is not known a priori the most suitable period at which the NDVI is responding. Herein, we also detrended and standardized the semi-monthly SPEI data to be comparable with the de-trended sNDVI.

Finally, we used the CORINE Land Cover for 2000 (https://land.copernicus.eu/pan-european/corine-land-cover) to determine how land cover can impact the response of NDVI to drought severity. This map is representative of the main classes of land cover in the study domain over the period of investigation.

2.2. Statistical analysis

We used the Pearson's *r* correlation coefficient to assess the relationship between the interannual variability of the sNDVI and SPEI. This association was evaluated independently for each semi-monthly period of the year. In specific, we calculated the correlation between the sNDVI for each semi-monthly period and SPEI recorded in the same period, at time-scales between 1- and 48-semi-months. Significant correlations were set at $p < 0.05$. Importantly, as the data of the sNDVI and SPEI were de-trended, the possible impact of serial correlation on the correlation between sNDVI and SPEI is minimized, with no spurious correlation effects that can be expected from the co-occurrence of the trends. Similarly, as the data were analyzed for each semi-monthly period independently, our results are free from any seasonality effect.

Based on the correlation coefficients between the sNDVI and SPEI in the study domain, we determined the semi-monthly period of the year and the SPEI time scale at which the maximum correlation is found. This information was then used to determine the spatial and seasonal variations according to the different land cover categories. Finally, the average climate conditions over the study domain, including aridity (precipitation minus AED) and average temperature, were related to the time-scales at which the maximum correlation between the sNDVI and SPEI was found.

3. Results

3.1. General influence of drought on the sNDVI

Figure 1 shows an example of the spatial distribution of the Pearson's r correlation coefficients calculated between the sNDVI and the SPEI at the time-scales of 1-, 3-, 6- and 12-months (2-, 6-, 12- and 24-semi-monthly periods). Results are shown only for the second semi-monthly period of each month between April and July. The differential response of the NDVI to the different time scales of the SPEI is illustrated. As depicted, the 6-month time scale was more relevant to vegetation activity in large areas of Southwestern and Southeastern Spain during the second half of April. On the other hand, vegetation activity was more determined by the 12-month SPEI across the Ebro basin in northeastern Spain. This stresses the need of considering different drought time scales to know the climate cumulative period that mostly affects vegetation activity. The 6-month and 12-month SPEI produced similar results during the second period of May, while the 12-month time scale is more related to vegetation activity in June and July. The density plots (supplementary Figures 1 to 4) summarize the magnitude of correlations between the SPEI and sNDVI for Spain, as a function of the semi-monthly period as well as the SPEI time scale. It can be seen that correlations tend to be higher during the warm season (May to August), and at time scales between 6 and 24 months.

Figure 2 summarizes the maximum correlation between the sNDVI and the SPEI, providing insights into the differential response of the NDVI to drought. It can be noted that there are clear seasonal and spatial differences in the response of sNDVI to the SPEI. The sNDVI is more related to the SPEI during the warm season (MJJA). In contrast, the response of the sNDVI to drought is less pronounced from September to April, albeit with some exceptions. One example is the response of vegetation to drought alongside the southeastern Mediterranean coastland, where the correlation between sNDVI and SPEI is almost high all the year around. Table 1 summarizes the percentage of the total area exhibiting significant or non-significant correlations over Spain during the different semi-monthly periods. Positive (lower sNDVI with drought) and statistically significant correlations are dominant across the entire territory, but with a seasonal component. In particular, a higher percentage of the territory shows positive and significant correlations during the warm season (MJJA). From mid of May to mid of September, more than 80% of the study domain show positive and significant correlations between the sNDVI and the SPEI. A similar finding is also found between the mid of June and the beginning of August. Figure 3 summarizes the average correlations between the SPEI and sNDVI. As illustrated, there is a gradual increase in the response of the sNDVI to the SPEI from the beginning of May to the end of July, when the maximum average correlation is recorded. In contrast, the correlations between the SPEI and sNDVI decrease progressively from August to December.

The response of the sNDVI to different times scales of the SPEI and seasons is quite complex. Figure 4 shows the spatial distribution of the SPEI time scale at which the maximum correlation was found for each one of the 24 semi-monthly periods of the year. It can be noted that there are considerable seasonal and spatial differences. Nonetheless, these differences are masked with the estimated average values of the SPEI time scale recorded for the semi-monthly periods (Figure 5) which are less variable (oscillating between 18 and 22 semi-monthly periods -9 to 11 months-) throughout the year. In general, the areas and periods with higher correlations are recorded at the time scales between 7 and 24 semi-months (3-12 months). This pattern is mostly recorded in the period between May and July (Supplementary Figure 5), in which the sNDVI variability is more sensitive to drought. Nevertheless, there are no general spatial patterns in the response of the NDVI to SPEI, indicating that there is a dominance of the maximum correlations associated with a certain SPEI time scale (Supplementary Figure 6). Interestingly, this , this pattern is not driven by the presence of different land cover types, given that the correlation coefficients between the sNDVI and SPEI are quite similar, irrespective of the land cover type (Supplementary Figures 7 to 17).

3.2. Land cover differences

There are differences in the magnitude and seasonality of the Pearson's r correlation coefficients among all land cover types. Figure 6 shows the average and standard error of the mean of the maximum Pearson's r coefficients between the sNDVI and SPEI for the different land cover types and the 24 semi-monthly periods. The magnitudes of correlation vary considerably, as a function of land cover type, as well as the period of the year in which the highest correlations are recorded. The non-irrigated arable lands

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show a peak of significant correlation between April and June. However, this correlation decreases towards the end of the year. The majority of the surface dominated by this land cover shows positive and significant correlations between May and September (Supplementary Table 1), with percentages almost close to 100%. On the contrary, irrigated lands do not show such a strong response to drought during the warm season. Even with the presence of a seasonal pattern, it is less pronounced than the one observed for non-irrigated arable lands. Overall, irrigated areas are characterized by positive and significant correlations between sNDVI and SPEI during summertime (Supplementary Table 2). Similarly, vineyards show a clear seasonal pattern, albeit with a peak of maximum correlations during the late summer (July-August) and early autumn (September-October) (Supplementary Table 3). On the other hand, olive groves show of the highest correlation between the sNDVI and SPEI during the second half of May and in October, suggesting a quasi bi-modal response of the NDVI to drought. This pattern is also revealed in the percentage of the surface area with significant correlations (Supplementary Table 4). In the same context, the areas of natural vegetation exhibit their maximum correlation between the sNDVI and SPEI during summer months. The highest correlations are found in July and August for the forest types, compared to earlier June for the natural grasslands and the areas of sclerophillous vegetation. On the other hand, the mixed forests tend to show lower correlations than broad-leaved and coniferous forests. A quick inspection of all these types of land cover indicates that the correlations between the sNDVI and SPEI are generally positive and significant during summer months (Supplementary Tables 5 to 11).

Large differences across vegetation types were found for the SPEI time scales at which maximum correlations between sNDVI and the SPEI are found (Figure 7). For example, for non-irrigated arable lands, the maximum correlation between SPEI and sNDVI is found for time scales between 11 and 21 semi-monthly periods. This indicates that crops in May-June (the period in which higher correlations are recorded) respond mostly to the climate conditions recorded between June and December of the preceding year. Irrigated lands show a clear seasonal pattern, as maximum correlations are recorded at time scales between 12 and 18 semi-monthly periods (i.e. 6 to 9 months), mainly between November and May. On the other hand, the maximum correlations between sNDVI and SPEI during summer are found for time scales between 25 and 28 semi-monthly periods. Similar to irrigated lands, vineyards show a strong seasonality, responding to longer time-scales at the end of summertime. In contrast, natural vegetation areas show less seasonality to SPEI time scales, which mostly impact the interannual variability of sNDVI. The SPEI time scales, at which the maximum correlation is found between sNDVI and SPEI, vary from 20 semi-monthly periods during the warm season (MJJAS) to 30 semi-monthly periods during the cold season (ONDJFMA). This finding is evident for all forest types and areas of sclerophillous vegetation and mixed wood-scrub. The only exception corresponds to natural grasslands, which show a response to shorter SPEI time scales (i.e. 20 semi-monthly periods in winter and 15 in spring and early summer).

3.3. Influence of average climatic conditions

In addition to the impact of the time scale at which drought is quantified, the response of vegetation activity to drought can also be closely related to the prevailing climatic conditions. Figure 8 summarizes the spatial correlation between aridity (P-AED) and the maximum correlation between the sNDVI and SPEI. For most of the semi-monthly periods of the year aridity is negatively correlated with the maximum correlation between sNDVI and SPEI, indicating that vegetation activity in arid sites is more

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responsive to drought variability. This correlation is more pronounced for the period between December and June. In contrast, this negative association becomes weaker and statistically non-significant during warmer months (e.g. July and August). Figure 9 illustrates the spatial correlation between mean air temperature and the maximum correlation between the sNDVI and SPEI. Results demonstrate similar results to those found for aridity, with a general positive and significant correlation from March to June, followed by a non-significant and weak correlation during summer months.

Nonetheless, these general patterns vary largely as a function of land cover type (Supplementary Figures 18 to 28). For example, in non-irrigated arable lands, there is strong negative correlation between aridity and the sNDVI/SPEI maximum correlation from March to May: a period that witnesses the peak of vegetation activity in this land cover type. This also coincides with the period of the highest average correlations between the sNDVI and SPEI. Taken together, this demonstrates that non-irrigated arable lands located in the most arid areas are more sensitive to drought variability than those located in humid regions. As opposed to non-irrigated arable lands, the correlations with aridity are found statistically non-significant in all periods of the year for irrigated lands, vineyards and olive groves. Nevertheless, for the different natural vegetation categories, the correlations are negative and statistically significant during large periods. The mixed agricultural/natural vegetation areas show a significant correlation between October and July, with stronger association at the beginning of summer season. Broadleaved and coniferous forests, scrubs, and pasture lands also show a negative relationship between the spatial patterns of the sNDVI/SPEI correlations and aridity.

As depicted in Figure 9, the relationship between the sNDVI/SPEI correlation and air temperature shows that the response of vegetation activity to drought is modulated by air temperature during springtime. This implies that warmer areas are those in which the sNDVI is more controlled by drought. A contradictory pattern is found during warmer months, in which the role of air temperature in modulating the impact of drought on vegetation activity is minimized. The relationships between air temperature and the NDVI-SPEI correlation vary among the different land cover types (Supplementary Figures 29 to 39). For example, in non-irrigated arable lands, the positive and statistically significant correlation is found in the period from March to April, indicating that the response of the sNDVI to SPEI tends to coincide spatially with areas of warmer conditions. As observed for aridity, the relationship between the sNDVI and SPEI in irrigated lands is less associated with the spatial patterns of air temperature. A similar pattern is recorded for vineyards and olive groves. Nevertheless, the areas of natural vegetation show a clear relationship between air temperature and the sNDVI/SPEI correlations. In the mixed agriculture and natural vegetation areas, we found a statistically significant positive association between the sNDVI and SPEI from October to May. On the contrary, this association is less evident during summer months. This general association during springtime, combined with the lack of association during summertime, can also be seen for other natural vegetation types such as broad-leaved and coniferous forests, natural grasslands, sclerophillous vegetation and mixed wood-scrubs.

We also analyzed the dependency between climatic conditions (i.e. aridity and air temperature) and the SPEI time scale(s) at which the maximum correlation between the sNDVI and SPEI is recorded. Figure 10 shows the values of aridity corresponding to SPEI time scales at which the maximum correlation between the sNDVI and SPEI is found for each semi-monthly period. The different box-plots indicate complex patterns, which are quite difficult to interpret. Overall, less arid areas show stronger correlations at longer time-scales (25-42 semi-monthly periods) during springtime. In the same context, the regions with maximum correlations at short time scales (1-6 months) tend to be located in less arid regions that record their maximum correlations at time scales between 7 and 24 semi-monthly periods. This suggests that the most arid areas mostly respond to the SPEI time scales between 6 and 12 months, compared to short (1-3 months) or long (> 12 months) SPEI time-scales in more humid regions. In contrast, during summer season, the interannual variability of the sNDVI in the arid areas is mostly determined by the SPEI recorded at time scales higher than 6 months (12 semi-monthly periods), while responding to short SPEI time scales (< 3 months) over the most humid regions.

Again, this general pattern is highly dependent on the land cover type (Supplementary Figures 40 to 50). In the non-irrigated arable lands, there are no noticeable differences in aridity in response to the SPEI time scale that recorded the maximum correlation with the sNDVI. A similar finding is also found irrespective of the considered semi-monthly period. In the vineyards, we noted that the sNDVI responds to short SPEI time scales in areas characterized by lower aridity conditions during summer months. This pattern is less evident for olive groves. In contrast, we observed clear patterns for natural vegetation. In particular, those areas characterized by mixed agriculture and vegetation show high complexity during winter and spring, with no specific patterns in relation to the SPEI time-scales with maximum correlations with the sNDVI. In contrast, we found a clear pattern during warmer months (June to September), with stronger correlations at shorter time scales in the most humid areas and at longer SPEI time-scales (> 12 months) over the most arid regions. The pattern is less pronounced in broad-leaved forests, although the response to short SPEI time scales seems to be more frequent in the less arid broad-leaved forests. On the other hand, in coniferous forests, sclerophylous vegetation, and the transition wood-scrub, we noted a relationship between the aridity and the SPEI time-scales with maximum correlation with the sNDVI during summer months. Natural grassland areas show clear seasonal differences. In spring, the grasslands located in the most arid sites show higher correlation at short SPEI time scales, while they exhibit similar patterns (i.e. maximum correlations at short SPEI time scales under less arid conditions) to those of other natural vegetation areas during summer.

Also, we found links between the spatial distribution of air temperature and the SPEI time scales at which maximum correlation between the sNDVI and SPEI is recorded (Figure 11). In early spring, short SPEI time scales dominate in warmer areas, compared to long SPEI time scales in colder regions. A contradictory pattern is observed from June to September, with a dominance of shorter SPEI time scales in colder areas and longer SPEI time scales in warmer regions. In terms of vegetation types, natural vegetation areas tend generally to reproduce similar pattern in comparison to cultivation types (Supplementary Figures 51 to 61).

The spatial distribution of all land cover types, after excluding irrigated lands in which the anthropogenic factors dominate, is illustrated in Figure 12. Mixed forests are located in the most humid areas, while vineyards, olive groves, non-irrigated arable lands and the sclerophyllous natural vegetation are distributed in the most arid sites. Nevertheless, there is a gradient of these land cover types in terms of their response to drought, as those types located under more arid conditions show a stronger response of vegetation activity to drought than those located in humid environments. For example, the mixed forests show lower correlations than crop types and other vegetation areas. This may suggest that there is a linear relationship between climate aridity corresponding to each land cover and how vegetation activity will respond to drought. This pattern is more evident during the different semi-monthly periods of the year, albeit with more differences during spring and autumn. In summer, these differences are much smaller between land cover categories, irrespective of aridity conditions.

There are also differences in the average SPEI time scale at which the maximum sNDVI/SPEI correlation is obtained (Figure 13). However, these differences are complex, with noticeable seasonal differences in terms of the relationship between climate aridity and land cover types. In spring and late autumn, land cover types located in more arid conditions tend to respond to shorter SPEI time scales than those located in more humid areas. This pattern can be seen in late summer and early autumn, in which the most arid land cover types (e.g. vineyards and olive groves) tend to respond at longer SPEI time scales, compared to forest types (mostly the mixed forests), which are usually located under more humid conditions.

4. Discussion and conclusions

This study assesses the response of vegetation activity to drought in Spain using a high-resolution (1.1 km) spatial NDVI dataset that dates back to 1981 (Vicente-Serrano et al., 2018). Based on another high-resolution semi-monthly gridded climatic dataset, drought was quantified using the Standardized Precipitation Evapotranspiration Index (SPEI) at different time scales (Vicente-Serrano et al., 2017).

Results demonstrate that vegetation activity over large parts of Spain is closely related to the interannual variability of drought. In summer more than 90% of the study domain show statistically significant positive correlations between the NDVI and SPEI. A similar response of the NDVI to drought is confirmed in earlier studies in different semi-arid and sub-humid regions worldwide, including Northeastern Brazil (e.g. Barbosa et al., 2006), the Sahel (e.g. Herrmann et al., 2005), Central Asia (e.g. Gessner

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et al., 2013), Australia (e.g. De Keersmaecker et al., 2017) and California (e.g. Okin et al., 2018). Albeit with this generalized response, our results also show noticeable spatial and seasonal differences in this response. These differences can be linked to the time scale at which the drought is quantified, besides the impact of other dominant climatic conditions (e.g. air temperature and aridity).

This study stresses that the response of vegetation activity to drought is more pronounced during the warm season (MJJAS), in which vast areas of the Spanish territory show statistically significant positive correlation between the sNDVI and SPEI. This seasonal pattern can be attributed to the phenology of vegetation under different land cover types. In the cold season, some areas, such as pastures and non-permanent broad leaf forests, do not have any vegetation activity. Other areas, with coniferous forests, shrubs and cereal crops, show a low vegetation activity. As such, irrespective of the recorded drought conditions, the response of vegetation to drought would be low during wintertime. This behaviour is also enhanced by the atmospheric evaporative demand (AED), which is generally low in winter in Spain (Vicente-Serrano et al., 2014d), with a lower water demand of vegetation and accordingly low sensitivity to soil water availability. Austin et al. (1998) indicated that soil water recharge occurs mostly during winter months, given the low water consumption by vegetation. However, in spring, vegetation becomes more sensitive to drought due to temperature rise. Accordingly, the photosynthetic activity, which determines NDVI, is highly controlled by soil water availability (Myneni et al., 1995). In this study, the positive spatial relationship found between air temperature and the sNDVI/SPEI correlation reinforces this explanation. In spring, we found low correlations between the NDVI and SPEI, even in cold areas. In contrast, warmer air temperatures during summer months reinforce vegetation activity, but with some exceptions such as cereal cultivations, dry pastures and shrubs, which record their maximum vegetation activity during spring. This would explain why the response of vegetation activity to the SPEI is stronger during summer in vast areas of Spain.

Also, this study suggests clear seasonal differences in the response of the NDVI to drought, and in the magnitude of the correlation between the NDVI and the SPEI, as a function of the dominant land cover. These differences are confirmed at different spatial scales, ranging from regional and local (e.g. Ivits et al., 2014; Zhao et al., 2015; Gouveia et al., 2017; Yang et al., 2018) to global (e.g. Vicente-Serrano et al., 2013), Over Spain, the non-irrigated arable lands, natural grasslands and sclerophyllous vegetation show an earlier response to drought, mainly in late spring and early summer. This response is mainly linked to the vegetation phenology dominating in these land covers, which usually reach their maximum activity in late spring to avoid dryness and temperature rise during summer months. The root systems of herbaceous species are not very deep, so they depend on the water storage in the most superficial soil layers (Milich and Weiss, 1997), and they could not survive during the long and dry summer in which the surface soil layers are mostly depleted (Martínez-Fernández and Ceballos, 2003). This would explain an earlier and stronger sensitivity to drought also showed in other world semiarid regions (Liu et al., 2017; Yang et al., 2018; Bailing et al., 2018). On the contrary, maximum correlations between the NDVI and the SPEI are recorded during summer months in the forests but also in wood cultivations like vineyards and olive groves. In this case, the maximum sensitivity to drought coincides with the maximum air temperature and atmospheric evaporative demand (Vicente-Serrano et al., 2014d). This pattern would be indicative of a different adaptation strategy of trees in comparison to herbaceous vegetation, since whilst herbaceous cover would adapt to the summer dryness generating the seed bank before the summer (Peco et al., 1998; Russi et al., 1992), the trees and shrubs would base their adaptation on deeper root systems, translating the drought sensitivity to the period of highest water demand and water limitation.

In addition to the seasonal differences among land cover types, we have shown that in Spain herbaceous crops show a higher correlation between the NDVI and the SPEI than most of natural vegetation types (with the exception of the sclerophyllous vegetation). This behaviour could be explained by three different factors: i) a higher adaptation of natural vegetation to the characteristic climate of the region where drought is a frequent phenomenon (Vicente-Serrano, 2006); ii) the deeper root systems that allow shrubs and trees to obtain water from the deep soil; and iii) cultivated lands tend to be typically located in drier areas than natural vegetation. Different studies showed that the vegetation of dry environments tends to have a more intense response to drought than sub-humid and humid vegetation (Schultz and Halpert, 1995; Abrams et al., 1990; Nicholson et al., 1990; Herrmann et al., 2016). Vicente-Serrano et al. (2013) analysed the sensitivity of the NDVI in the different biomes at a global scale and found a spatial gradient in the sensitivity to drought, which was more important in arid and semiarid regions.

In this study we have shown a control in the response of the NDVI to drought severity by the climatic aridity. Thus, there is a significant correlation between the spatial distribution of the climatic aridity and the sensitivity of the NDVI to drought, mostly in spring and autumn. This could be explained because in more humid environments the main limitation to vegetation growth is temperature and radiation rather than water, so not all the water available would be used by vegetation reflected in a water surplus as surface runoff. This characteristic would make the vegetation less sensitive to drought. Drought indices are relative metrics in comparison to the long term climate with the purpose of making drought severity conditions comparable between areas of very different climate characteristics (Mukherjee et al., 2018). This means that in humid areas the corresponding absolute precipitation can be sufficient to cover the vegetation water needs although drought indices inform on below-of-the-average conditions. On the contrary, in arid regions a low value of a drought index is always representative of limited water availability, which would explain the closer relationship between the NDVI and the SPEI.

Here we also explored if the general pattern observed in humid and semi-arid regions is also affected by the land cover, and found that the behaviour in the non-irrigated arable lands is the main reason to explain the global pattern. Herbaceous crops show that aridity levels have a clear control of the response of the NDVI to drought during the period of vegetation activity. Nevertheless, after the common harvest period (June) this control by aridity mostly disappears. This is also observed in the grasslands and in the sclerophyllous vegetation, and it could be explained by the low vegetation activity of the herbaceous and shrub species during the summer, given the phenological strategies to cope with water stress with the formation of the seeds before the period of dryness (Chaves et al., 2003). The limiting aridity conditions that characterises the regions in which these vegetation types grow would also contribute to explain this phenomenon. On the contrary, the forests, both broad-leaved and coniferous, also show a control by aridity in the relationship between the NDVI and the SPEI during the summer months since these land cover types show the peak of the vegetation activity during this season.

In any case, it is also remarkable that the spatial pattern of the NDVI sensitivity to drought in forests is less controlled by aridity during the summer season, curiously the season in which there are more limiting conditions. This could be explained by the NDVI saturation under high levels of leaf area index (Carlson and Ripley, 1997), since once the tree tops are completely foliated the electromagnetic signal is not sensitive to additional leaf growth. This could explain the less sensitive response of the forests to drought in comparison to land cover types characterised by lower leaf area (e.g. shrubs or grasslands). Nevertheless, we do not think that this phenomenon can explain totally the decreased sensitivity to drought with aridity in summer since the dominant coniferous and broad-leaved forests in Spain are usually not characterised by a 100% leaf coverage (Castro-Díez et al., 1997; Molina and del Campo, 2012), so large signal saturation problems are not expected. On the other hand, the ecophysiological strategies of forests to cope with drought may help explain the observed lower relationship between aridity during the summer months. Experimental studies suggested that the interannual variability of the secondary growth could be more sensitive to drought than the sensitivity observed by the photosyntetic activity and the leaf area (Newberry, 2010). This could be a strategy to optimize the storage of carbohydrates, suggesting that forests in dry years would prioritize the development of an adequate foliar area in relation to the wood formation in order to maintain respiration and photosynthetic processes. Recent studies by Gazol et al. (2018) and Peña-Gallardo et al. (2018b) confirmed that, irrespective of forest species, there is a higher sensitivity of tree-ring growth to drought, as compared to the sensitivity of the NDVI. The different spatial and seasonal responses of vegetation activity to drought in our study domain can also be linked to the dominant forest species and species richness, which has been evident in numerous studies (e.g. Lloret et al., 2007). Moreover, this might also be attributed to the ecosystem physiological processes, given that vegetation tends to maintain the same water use efficiency under water stress conditions, regardless of vegetation types and environmental conditions (Huxman et al., 2004). This would explain that -independently of the aridity conditions- the response of the NDVI to drought would be similar. Here, we demonstrated that the response of the NDVI to drought is similar during summer months, even with the different land cover types and environmental conditions.

A relevant finding of this study is that the response of the NDVI is highly dependent on the time scale at which drought is quantified. Numerous studies indicated that the accumulation of precipitation deficits during different time periods is essential to determine the influence of drought on the NDVI (e.g. Malo and Nicholson, 1990; Liu and Kogan, 1996; Lotsch et al., 2003; Ji and Peters, 2003; Wang et al., 2003). This is simply because soil moisture is impacted largely by precipitation and the atmospheric evaporative demand over previous cumulative periods (Scaini et al., 2015). Moreover, the different morphological, physiological and phenological strategies would also explain the varying response of vegetation types to different drought time scales. This finding is confirmed in previous works using NDVI and different time scales of a drought index (e.g. Ji and Peters, 2003; Vicente-Serrano, 2007), but also using other variables like tree-ring growth (e.g. Pasho et al., 2011; Arzac et al., 2016; Vicente-Serrano et al., 2014a). This study confirms this finding, given that there is a high spatial diversity in the SPEI time scale at which vegetation has its maximum correlation with the NDVI. These spatial variations, combined with strong seasonal differences, are mainly controlled by the dominant land cover types and aridity conditions. In their global assessment, Vicente-Serrano et al. (2013) found gradients in the response of the world biomes to drought, which are driven mainly by the time scale at which the biome responds to drought in a gradient of aridity. Again, the response to these different time scales implies not only different vulnerabilities of vegetation to water deficits, but also various strategies from plants to cope with drought. In Spain, we showed that the NDVI responds mostly to the SPEI at time scales around 20 semi-monthly periods (10 months), but with some few seasonal differences (i.e. shorter time scales in spring and early autumn than in late summer and autumn). Herein, it is also noteworthy indicating that there are differences in this response, as a function of land cover types. Overall, during the periods of highest vegetation activity, the herbaceous land covers (e.g. non-irrigated arable lands and grasslands) respond to shorter SPEI time-scales than other forest types. This pattern can be seen in the context that herbaceous covers are more dependent on the weather conditions recorded during short periods. These vegetation types could not reach deep soil levels, which are driven by climatic conditions during longer periods (Changnon and Easterling, 1989; Berg et al., 2017). In contrast, the tree root systems would access to these deeper levels, having the capacity of buffering the effect of short term droughts, albeit with more vulnerability to long droughts that ultimately would affect deep soil moisture levels. This pattern has been recently observed in southeastern Spain when comparing herbaceous crops and vineyards (Contreras and Hunink, 2015). Recently, Okin et al. (2018) linked the different responses to drought time scales between scrubs and chaparral herbaceous vegetation in California to soil water depletion at different levels.

Albeit with these general patterns, we also found some relevant seasonal patterns. For example, irrigated lands responded to long SPEI time scales (> 15 months) during summer months, whilst they responded to shorter time scales (<7 months) during spring and autumn. This behaviour can be linked to water management in these areas. In specific, during spring months, these areas do not receive irrigation and accordingly vegetation activity is determined by water stored in the soil. On the contrary, summer irrigation depends on the water stored in the dense net of reservoirs existing in Spain; some of them have a multiannual capacity. Water availability in the reservoirs usually depends on the climate conditions recorded during long periods (one or two years)

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(López-Moreno et al., 2004; Lorenzo-Lacruz et al., 2010), which determine water availability for irrigation. This explains why vegetation activity in irrigated lands depends on long time scales of drought. Similarly, vineyards and olive groves respond to long SPEI time-scales during summer. These cultivations are highly resistant to drought stress (Quiroga and Iglesias, 2009). However, these adapted cultivations can be sensitive to severe droughts under extreme summer dryness. In comparison to other natural vegetation, mixed forests show response to shorter SPEI time scales. This could be explained by the low resistance of these forest species to water deficits [e.g. the different fir species located in humid mountain areas, (Camarero et al., 2011; Camarero et al., 2018)].

Here, we also showed that climate aridity can partially explain the response of the NDVI to the different SPEI time scales. In Spain, the range of the mean aridity recorded by the mean land cover types is much lower than that observed at the global scale for the world biomes (Vicente-Serrano et al., 2013). This might explain why there are no clear patterns in the response of the land cover types to the aridity gradients and the SPEI time scales at which the maximum correlation between the NDVI and SPEI is found. Nevertheless, we found some seasonal differences between the cold and warm seasons. In summer, the NDVI responds to longer SPEI time scales, as opposed to the most humid forests that respond to shorter time scales. This stresses that – in addition to aridity- the degree of vulnerability to different duration water deficits, which are well-quantified using the drought time scales, may contribute to explaining the spatial distribution of the main land cover types across Spain given different biophysical conditions, but also the different strategies of vegetation types to cope with water stress (Chaves et al., 2003; McDowell et al., 2008), which are strongly variable in complex Mediterranean ecosystems.

Acknowledgements

This work was supported by the research projects PCIN-2015-220, CGL2014-52135-C03-01 and CGL2017-82216-R financed by the Spanish Commission of Science and Technology and FEDER. IMDROFLOOD financed by the Water Works 2014 co-funded all of the European Commission and INDECIS, which is part of ERA4CS, an ERA-NET initiated by JPI Climate, and funded by FORMAS (Sweden), DLR (Germany), BMWFW(Austria), IFD (Denmark), MINECO(Spain) and ANR (France), with co-funding by the European Union (Grant 690462), FORWARD financed under the ERA-NET Cofund WaterWorks2015 Call EU and Innovation Fund Denmark (IFD). This ERA-NET is an integral part of the 2016 Joint Activities developed by the Water Challenges for a Changing World Joint Programme Initiative (Water JPI). Marina Peña-Gallardo was supported by the Spanish Ministry of Economy and Competitiveness

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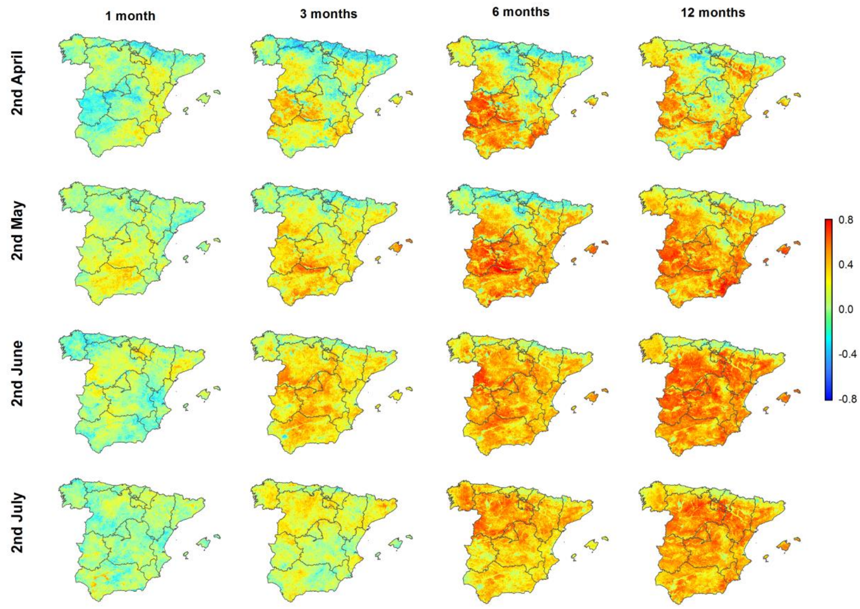

Figure 1: Spatial distribution of the Pearson's r correlation coefficient calculated between the sNDVI and different SPEI time scales for different semi-monthly periods.

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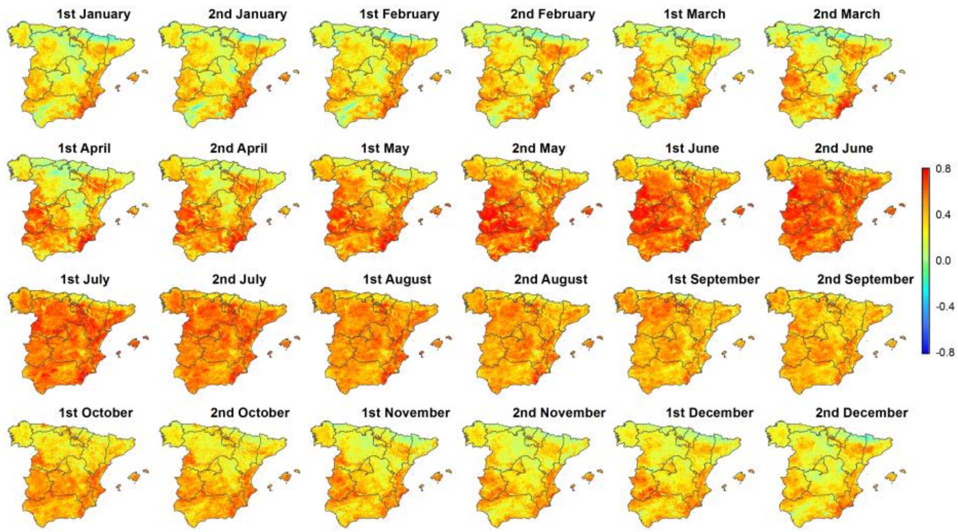

Figure 2: Spatial distribution of the maximum correlation between the sNDVI and the SPEI during the different semi-monthly periods.

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Table 1: Percentage of the total surface area according to the different significance categories of Pearson's r correlations between the sNDVI and SPEI.

	Negative ($p < 0.05$)	Negative ($p > 0.05$)	Positive ($p > 0.05$)	Positive ($p < 0.05$)
1st Jan	0.3	9.8	41.3	48.6
2nd Jan	0.4	8.7	40.2	50.7
1st Feb	0.3	7.5	39.9	52.3
2nd Feb	0.1	7.5	39.0	53.4
1st Mar	0.2	8.9	41.6	49.4
2nd Mar	0.2	11.3	38.2	50.3
1st Apr	0.0	7.6	34.9	57.5
2nd Apr	0.0	3.4	27.0	69.7
1st May	0.0	1.6	19.0	79.4
2nd May	0.0	0.9	14.2	84.9
1st Jun	0.0	1.2	10.8	88.0
2nd Jun	0.0	0.5	7.4	92.0
1st Jul	0.0	0.3	5.3	94.4
2nd Jul	0.0	0.1	4.5	95.4
1st Aug	0.0	0.1	5.9	94.1
2nd Aug	0.0	0.2	10.6	89.2
1st Sep	0.0	0.6	14.0	85.4
2nd Sep	0.0	0.4	16.9	82.6
1st Oct	0.0	1.5	24.5	74.0
2nd Oct	0.0	1.9	31.1	67.0
1st Nov	0.0	4.5	35.6	59.8
2nd Nov	0.0	4.8	41.8	53.4
1st Dec	0.0	4.4	38.9	56.7
2nd Dec	0.2	5.9	43.1	50.8

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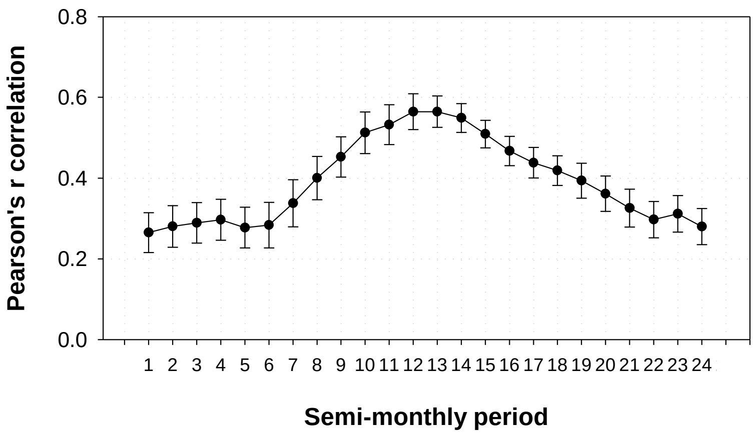

Figure 3: Spatial Average and standard error of the Pearson's r correlation coefficient between the sNDVI and SPEI time series.

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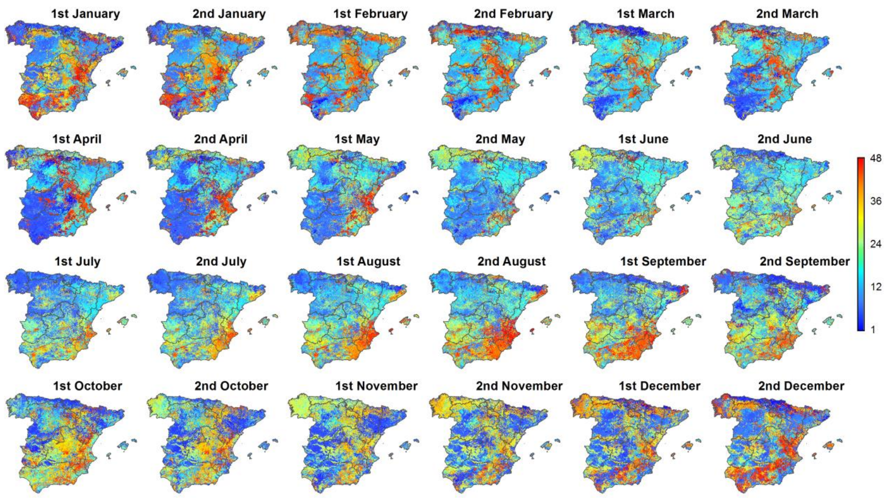

Figure 4: Spatial distribution of the SPEI time scales at which the maximum correlation between the sNDVI and SPEI is found for each one of the semi-monthly periods.

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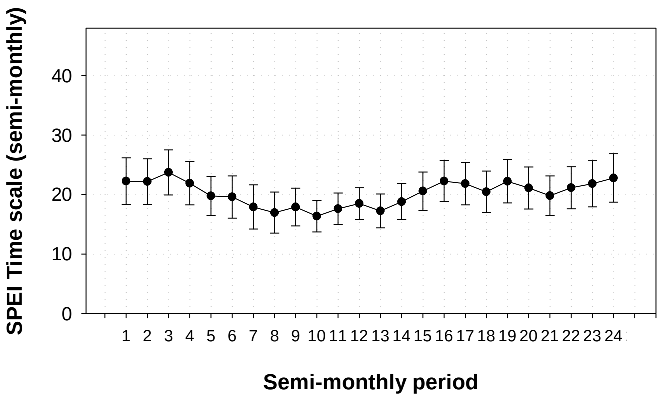

Figure 5: Average and standard error of the SPEI time scale at which the maximum Pearson's r correlation coefficient between the sNDVI and SPEI is found.

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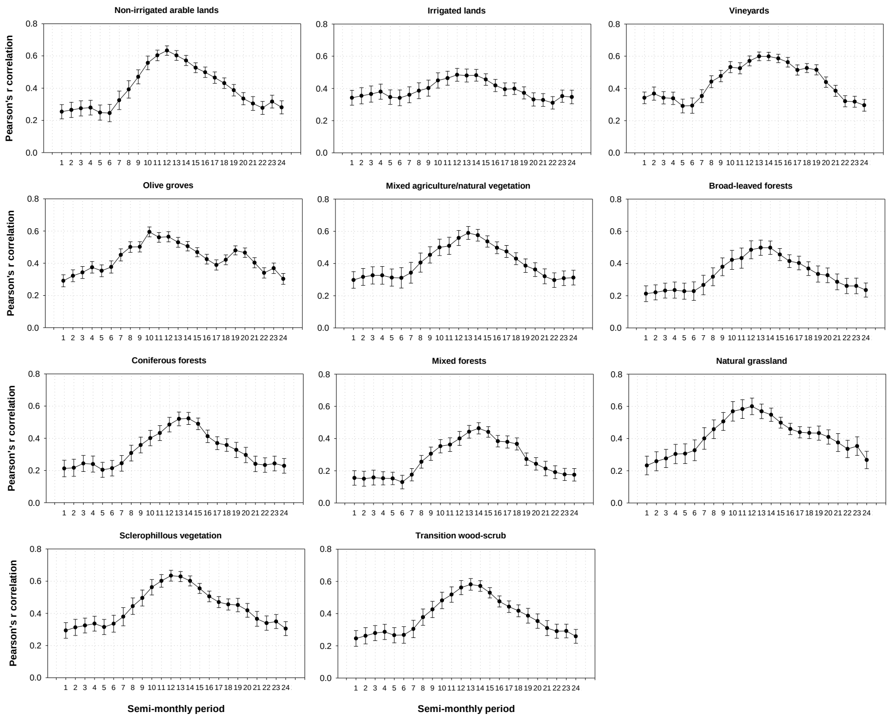
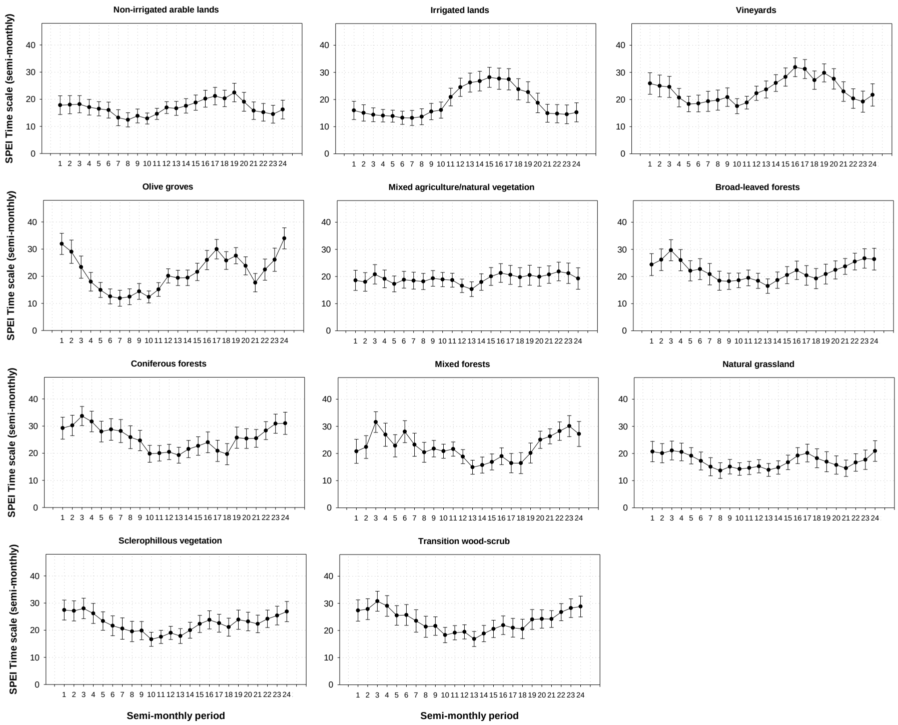


1178 Figure 6: Average and standard error of the Pearson's r correlation coefficient between
1179 the sNDVI and SPEI for the different land cover types.



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1182 Figure 7: Average and standard error of the SPEI time scale at which the maximum
1183 Pearson's r correlation coefficient was found between the sNDVI and SPEI for the
1184 different land cover types.

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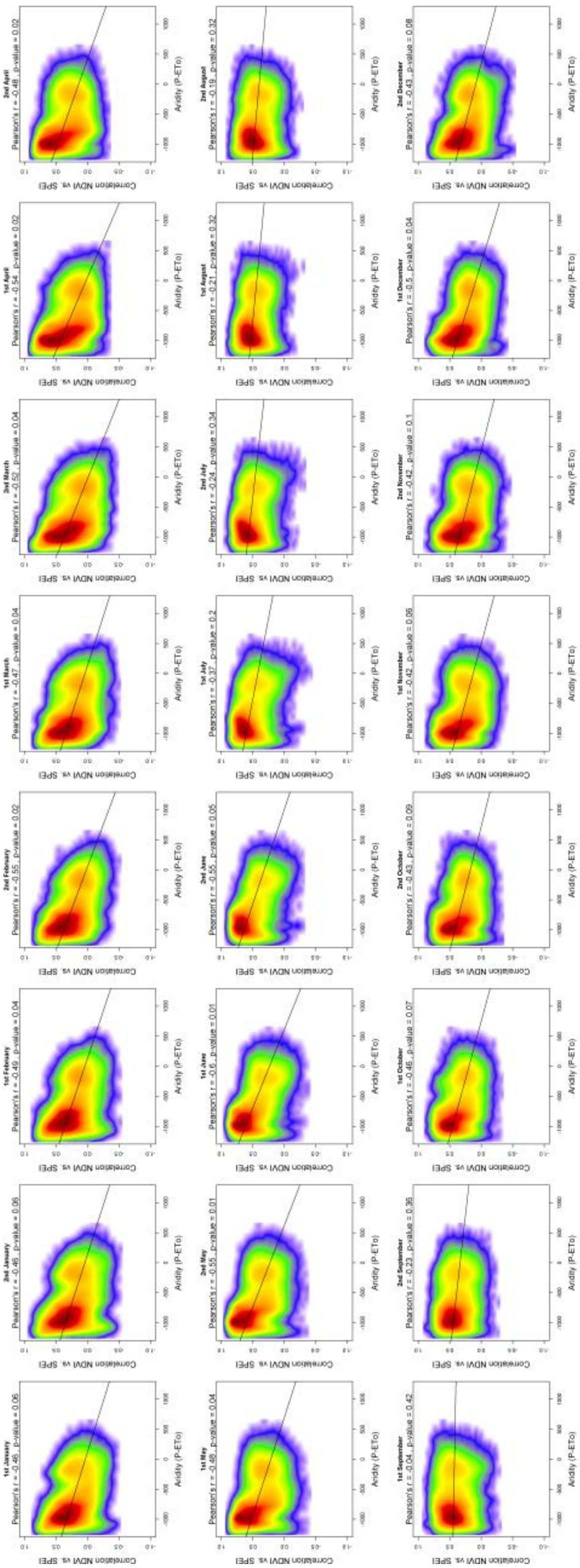

Figure 8. Scatterplots showing the relationships between the maximum correlation obtained between the sNDVI and the SPEI and the climate aridity (Precipitation minus Atmospheric Evaporative Demand). Given the high number of data, the signification of the correlation was obtained by a bootstrap method. 1000 random samples were extracted of 30 data points each, from which correlations and p-values were obtained. The final signification was assessed by means of the average of the obtained correlation coefficients and p-values, which are indicated in the figure.

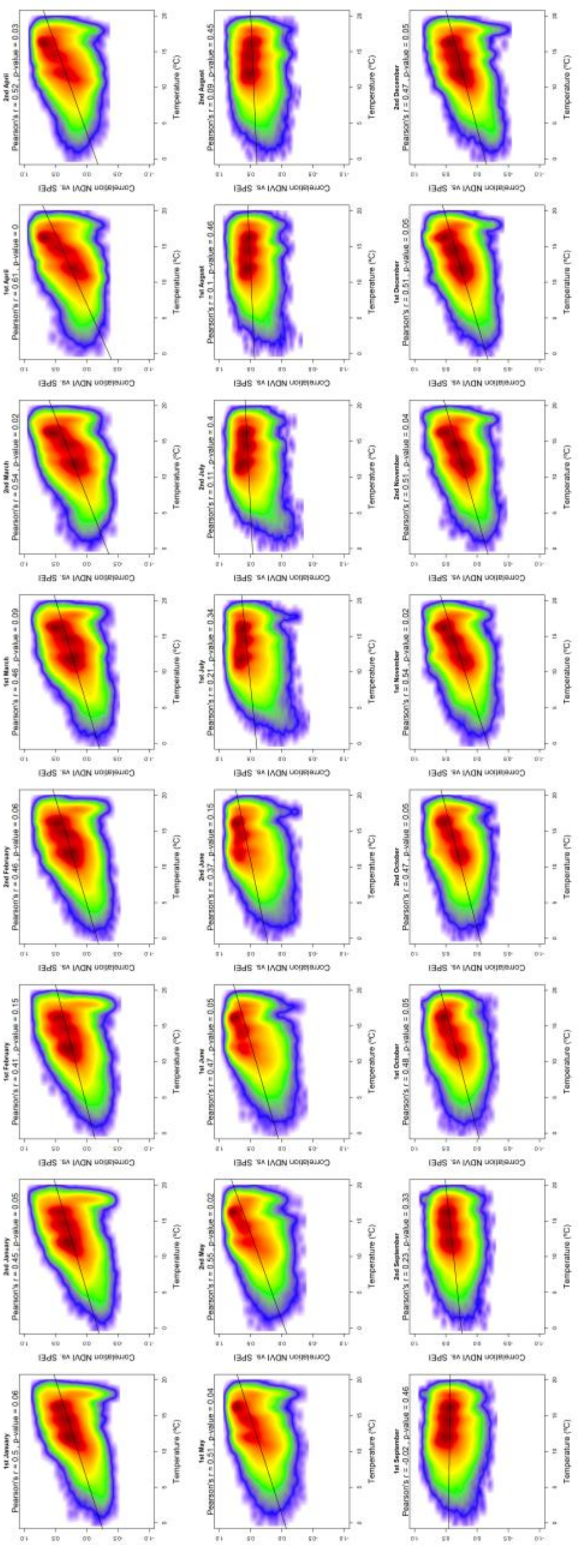

Figure 9. Scatterplots showing the relationships between the maximum correlation obtained between the sNDVI and the SPEI and the average air temperature. Given the high number of points the signification of correlation was obtained by means of 1000 random samples of 30 cases from which correlations and p-values were obtained. The final signification was assessed by means of the average of the obtained p-values.

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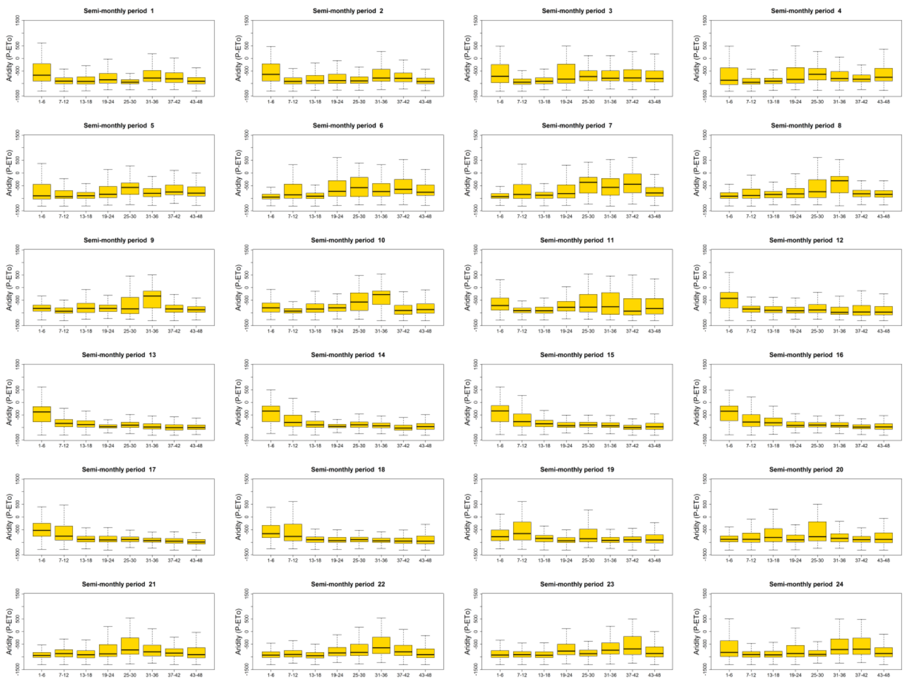

Figure 10: Box plots showing the climate aridity values , as a function of the SPEI time scales at which the maximum correlation between the sNDVI and SPEI is recorded

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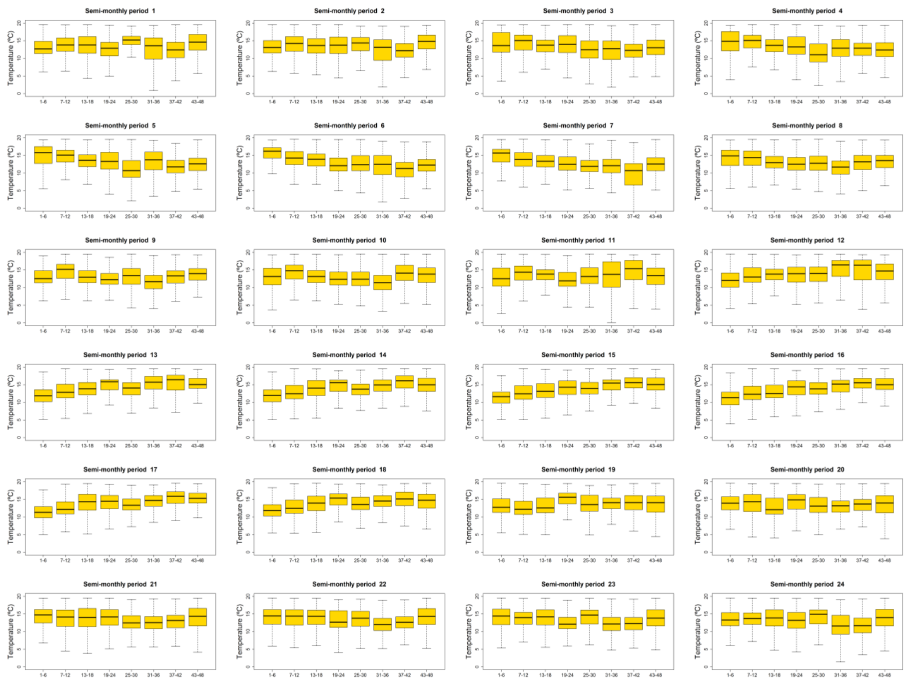

Figure 11: Box plots showing air temperature values, as a function of the SPEI time scales at which the maximum correlation between the sNDVI and SPEI is recorded.

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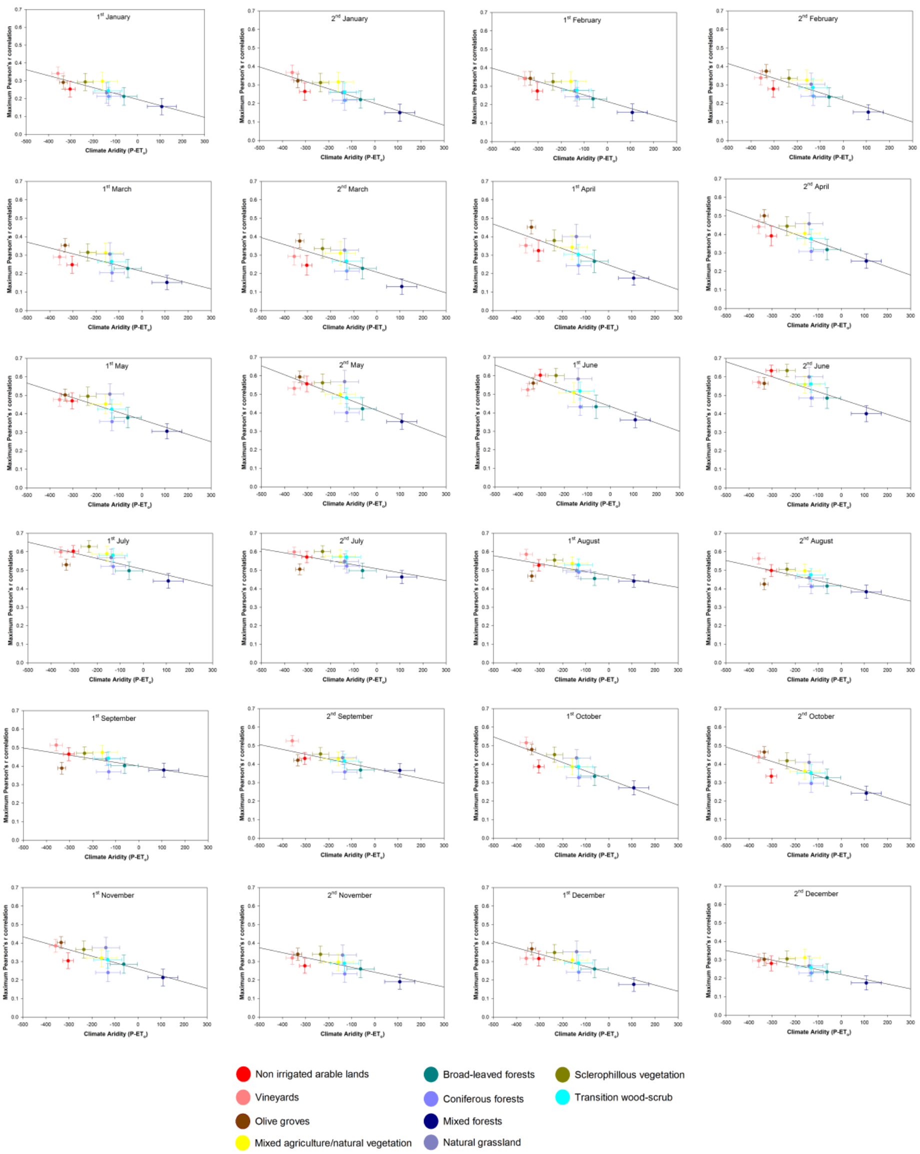

Figure 12: Scatterplots showing the relationship between the mean annual aridity and the maximum correlation found between the sNDVI and the SPEI in the different land cover types analysed in this study. Vertical and horizontal bars represent ¼ of standard deviation around the mean values.

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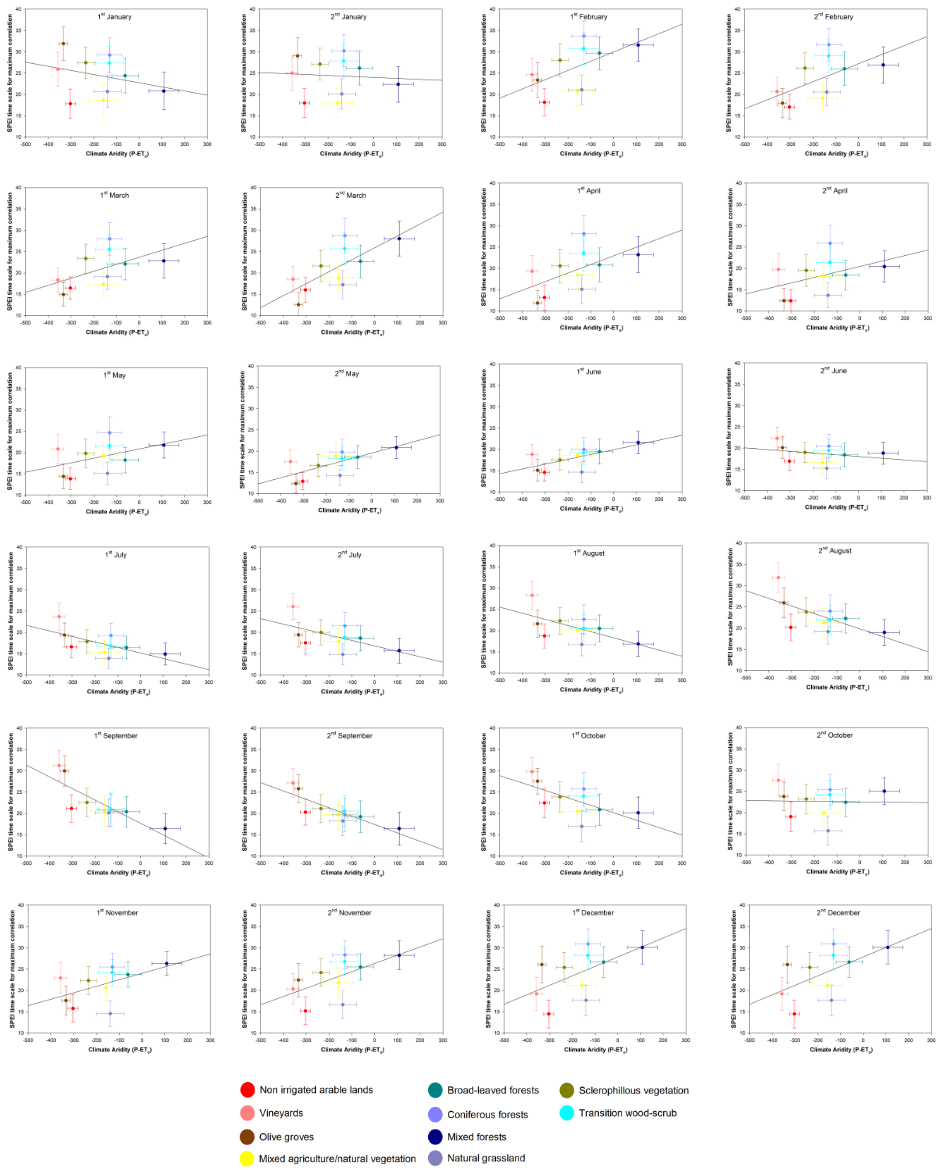

Figure 13: Scatterplots showing the relationship between the mean annual aridity and the SPEI time scale at which the maximum correlation is found between the sNDVI and SPEI for the different land cover types. Vertical and horizontal bars represent ¼ of standard deviation around the mean values.