Referee #1

This manuscript aims to assess the sensitivity of vegetation types to drought across Spain, using a high-resolution (1.1 km) spatial dataset of the Normalized Difference Vegetation Index (NDVI) and the Standardized Precipitation Evapotranspiration Index (SPEI) for Spain for the period from 1981 to 2015. In particular, an analysis of the drought time scales at which vegetation activity aims to show the highest response to drought severity at different moments of the year. The study is exhaustive, taking advantage of the two high resolution datasets computed by the authors, the methods are adequate and the results are in accordance with previous works and are discussed in a detailed way. The overall context of the subject is very important in Mediterranean and Iberian context, taking in account the importance of drought subject for the region within the context of warming tendency. Therefore, the work seems to be appropriate for this journal. However, some aspects could be improved in order to increase the intelligibility and readability of the paper.

We strongly appreciate the positive comment on the manuscript by the reviewer#1. Really she/he has appreciated that this study contains a considerable amount of work, including the use of high resolution datasets and different spatial-temporal analysis.

MAJOR As I said the subject and results of this manuscript are of great interest for a wide range of readers. However, the reading of the paper is very tiring, the number of figures in the manuscript and supplementary information is 'astronomic', the figures are really small, the axis information and titles are unreadable and the results and discussion is really hard to follow. Nevertheless, I recognize that present these results is a very hard task. Therefore, my next comments are suggestion that may increase the readability and increase the number or interested readers that should be attracted to the important results of the manuscript.

We have reduced some parts of the results section and removed around ½ of the supplementary figures that were not very informative.

The semi-monthly analysis is interesting and aimed to take advantage of the higher temporal resolution of the datasets. However, the temporal changes in correlation are slow and I do not see the add-value of presenting 24 graphs instead of 12. As a matter of fact, the graphs for each month are very similar and if you increase the size of the figures (taking in account that you may present only one figure for each month, e.g., 2nd January, 2nd Feb,. . .) the analysis will be much more easy.

We understand this comment but given the high temporal resolution of both climate and NDVI datasets, it would be a pity to reduce the temporal resolution of the data. Usually these analysis are done at monthly resolution, but really the motivation of this choice is usually the availability of the data, which is usually available at the monthly resolution. Nevertheless, here we had access to a high temporal resolution data, which allows identifying very interesting patterns, difficult to be observed with data at the monthly resolution. An excellent example is the seasonal transitions in the relationships between the spatial patterns of aridity (and temperature) and the correlations between the SPEI and the sNDVI. These plots clearly show that the changes in the role of drought on the vegetation activity show a seasonal transition, which is clearly appreciated using a detailed temporal resolution (semi-monthly). For this

reason we prefer to maintain the analysis at the original temporal resolution better than focusing on specific semi-monthly periods.

Another issue related with the 12 new bigger figures is the possibility ´ of presenting all the land cover inside each graph, maybe with different colours. This allows a better comparison between land covers and reduce drastically the number of figures in supplementary information.

Really we understand that we are including a high amount of figures in our ms. But we are mostly making use of supplementary information. Of course, in the main manuscript we do not describe in depth these figures but we provide the main results. Moreover, we do not think possible to include in a single figure the information corresponding to the different land cover scatter plots since they are already containing different colors. In any case, we have reduced the number of supplementary figures in ½.

The result section is very exhaustive and ´ hard to follow. Please consider to resume.

We have removed some sections of the text but also some figures from the supplementary information that were not very informative.

The discussion and conclusions section ´ is very long and also hard to follow, although with a huge amount of very interesting points. I would suggest to separate discussion from conclusion and introduce sub sections in discussion in order to organized the main findings.

We appreciate this comment. We have including different sub-headings in the discussion section but also developed a new section that states the main conclusions of the manuscript.

I also would suggest to add in conclusion section some paragraphs highlighting the new insights of this work in comparison with previous ones and the usefulness and need of this type of analysis.

We have included an independent conclusions section in which the different main findings obtained in the manuscript are clearly stated.

Furthermore, some methodological issues are not very clear. 1) (Lines 189-193) The authors said "computed the atmospheric evaporative demand (AED), reference evapotranspiration (ETo), and the Standardized Precipitation Evapotranspiration Index (SPEI)." Please explain the advantage of using AED AND ET0. Which is used to computed SPEI? SPEI in Vicente-Serrano eta al., 2010 is computed using PET. What is the difference between AED and ET0? Which method is used to compute AED? Maybe the readers of the journal are not very familiarized with these differences and should understand the biophysical add value of using AED. Please clarify the innovation of this new approach and the need of this innovation. Additionally, in several figures (e.g. Figure 8) the author mentioned AED in figure caption and ET0 is written in axis. Please try make it more consistent.

The ETo is one of the forms in which we can express the AED. The potential evaporation is a form of the AED. The pan evaporation is also a form of the AED (which can be estimated using the PenPan model or measured by means of evaporation pans). But the ETo is also a form of

the AED since it includes a constant surface resistance. The ETo can be compared spatially and temporally and it only depends of meteorological factors. To avoid any possible misleading by the readers we have clarified this issue in the revised manuscript:

"Based on this gridded dataset, we computed the atmospheric evaporative demand (AED) and the Standardized Precipitation Evapotranspiration Index (SPEI). We used the reference evapotranspiration (ETo) as the most realibale way of estimating the AED. ETo was calculated using the physically based FAO-56 Penman-Monteith equation (Allen et al., 1998)."

In addition, we have removed the term AED in different parts of the manuscript and replaced by ETo.

2) (Lines 170-172): Please clarify which variable is really used for the correlation assessment: is it the standardized NDVI (sNDVI) or NDVI magnitude with residuals? Figure captions mentioned sNDVI. I am confused with these definitions. Please clarify and justify those options with more clarity and detail.

This has been justified in the revised manuscript:

"Correlations with the drought dataset were based on the sNDVI."

3) (Lines 220-223): Why CLC2000 and not the most recent version? The land cover is not static, are always changing. The classification of 2000 does not represent the average state of land cover during the period, Please, justify this choice taking in account this changeable character of land cover. As the authors have removed the pixels that they say are corresponding to land cover change, I would suggest to use the versions of CLC for 1990, 2000, 2006 and 2012 and considered only the pixels that are corresponding to unchangeable land covers, as coded using CLC.

As we justified in the manuscript, we have chosen the CLC2000 because it is the most representative over the entire study period. The suggestion by the reviewer of using different land cover maps do not solve the problem of having a baseline for the beginning of the study period (1981). Moreover the selection of the pixels that have not showed a land cover change would strongly reduce the analysed surface area since in a period of 30 years the land cover change processes that are recorded in Mediterranean areas may affect large regions (see e.g. Lasanta and Vicente-Serrano, 2012).

There are several land cover changes processes which are not characterized by an abrupt change in the land cover type. Of course, we are aware that possible abrupt modifications of the land cover type could affect the relationship between the SPEI and the sNDVI. For this reason we removed those pixels characterized by abrupt changes (quantified by means of the selection of a high value in the magnitude of change of the sNDVI, e.g. non-irrigated arable lands transformed to irrigated lands, urbanization, etc.) ,but we maintained those that showed more gradual changes. In any case this did not affect the quality of our analysis since before the temporal correlations were calculated for each time series we removed the trend of the series (both for SPEI and sNDVI).

4) (Lines 159- 166): What means strong changes in NDVI? The author said "the annual NDVI higher than 0.05 units or an increase higher than 0.15 units between 1981 and 2015", but what does it means in terms of variability (in terms of std). Why do you choose this value? Please fundament the choice.

This was explained in more depth in the manuscript. As indicated, these thresholds were defined after an exploratory analysis and in areas in which we have strong knowledge in relation to the occurrence of abrupt changes in the land cover, such as the creation of new irrigated lands:

"In order 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 of these pixels (not shown here) concurs well with the areas identified in earlier studies over Spain in which it was an abrupt modification of the land cover type (e.g. creation of new irrigated lands) (Lasanta and Vicente-Serrano, 2012; Vicente-Serrano et al., 2018)."

5) Please clarify what means the time-scales between 1- and 48-semi-months? Did you compute SPEI with a bi-monthly accumulation? In line 202 you said that "the SPEI was calculated for the common 1- to 24-month time scales". please explain the difference between both computation approaches and the advantage of the last one (bi-monthly accumulation). What is the advantage of doing this instead of computing the monthly mean of NDVI? I do not see the add value of this approach

In the revised manuscript we have clarified that the 1- to 24-month time scales correspond to 1- to 48- semi-monthly periods:

"In this work, the SPEI was calculated for the common 1- to 24-month time scales but here given the semi-monthly availability of the data, we calculated the corresponding 1- to 48- semi-monthly time-scales."

6) Figures: For the majority of the figures in the manuscript and supplementary information is not possible to read the axis of the figures. The axis number, the axis titles and the titles of figures are not readable at all. Please increase the font size (probably only for the bottom and left figures in order to save space). Supp Figure 5: provide a title for each graph Figure 12: the tile of previous figures should be like the ones in this figure (e.g., 1st Jan, 2nd Jan,...). This will increase significantly the readability of figures.

We have increased the size of the fonts for the different figures and added axis labels in all of the cases.

7) (Lines 454-458): Difficult to follow. Please consider to rephrase.

The sentences have been rephrased.

8) (Lines 505-507): Difficult to follow. Please consider to rephrase.

Rephrased.

9) (Lines 555): When? in spring and autumn. Please consider to rephrase, clarifying and detailing.

We have detailed that the comments refer to the cold season.

10) (Lines 585-589): Very good point!

Thanks a lot for your comment.

11) (Lines 607-609): Another important finding of this work!

Thanks again.

MINOR 1) (Line 22): rephrase 'a another newly developed. . .'

Rephrased

2) (Line 57): move the data of access to the reference list

Data access moved to references.

3) (Line 157): rephrase 'In out attemp'

Replaced: "in order to…"

4) (Line 158): NDVI or sNDVI

NDVI is correct in this case.

5) (Line 353): make the sentence consistent with the figure caption. Is it P-AED or P-ET0

AED has been replaced by ETo throughout the manuscript.

6) (Line 359): "July to August" or July to September???

Replaced

7) (Line 388): "March to April" or March to May???

Replaced.

Reviewer 2

The authors present a very detailed, innovative analysis (fine-scale spatial resolution) of the relationships between SPEI and NDVI measurements in the Iberian Peninsula. A large number of interesting figures, tables and supplementary figures are presented. I think that this data paper is very informative and the methods are robust. I would suggest to the authors to address the following points, if possible and easily achievable:

We would like to appreciate the positive assessment of our manuscript by the reviewer#2. We have followed most of his/her recommendations in order to improve our manuscript.

Major comments - The manuscript is very interesting but lacks a clear focus.

We do not exactly agree with this comment since we think our manuscript has a clear focus, which was detailed in the objectives stated in the introduction:

"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."

A very large number of results, hypotheses and figures are described and commented. Please consider somehow reducing the number of main figures and tables in the main manuscript, providing more focus, and shortening the manuscript. Please focus on the more interesting results and move some of the non central figures and the associated text to the supplementary materials.

According to the comments by the reviewers 1 and 2, we have reduced the number of figures but also the length of the manuscript.

- Please clearify in all the figures which SPEI temporal scale/s are considered. for example, in Fig 8 it not clear to me which SPEI time scale are considered. –

The reviewer is right. This was not detailed in the original manuscript and it can be a source of confusion for the readers. We have clarified this point in the methods section:

"Given that it is not possible to know a priori the best cumulative period to explain the response of the vegetation activity to drought variability, we retained for further analysis the maximum correlation, independently of the time scale at which this is obtained."

Pleae define sNDVI on line 217. –

This was described previously in line 150, in which it is indicated that the sNDVI corresponds to the standardized NDVI:

"Herein, it is noteworthy indicating that the data from the Sp_1Km_NDVI dataset was standardized (sNDVI),"

Please clarify this sentence. Line 163. "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)."

This has been rewritten and detailed in the revised manuscript:

"The spatial distribution of these pixels (not shown here) concurs well with the areas identified in earlier studies over Spain in which it was an abrupt modification of the land cover type (e.g. creation of new irrigated lands) (Lasanta and Vicente-Serrano, 2012; Vicente-Serrano et al., 2018)."

Minor comments: - Figure 10. if easily achievable, using a unique name for the response variable would clarify the figure (increasing at the same time the font size). This may apply to many other figures in the suppl. mat and the main manuscript. –

We have improved the figures of the manuscript including Figure caption in the cases in which this was not available and increasing the font size of some of the figures.

Figure 10. There is a typographic error in the legend. Please check this detail. –

Corrected in the revised manuscript.

Please simplify/clarify the following sentence: On line 290: "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)"

This section has been removed from the revised manuscript in order to improve readability.

Line- 204. please correct the following typographic error. "... 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)."

Corrected.

Line 295. Please correct the following typographic error: "Interestingly, this , this pattern is not driven by the presence of different land cover types,"

This paragraph has been removed in the revised manuscript.

Line 61. Check the following sentence. "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)"

Rephrased.

1   **A high-resolution spatial assessment of the impacts of drought variability on**
2   **vegetation activity in Spain from 1981 to 2015**

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17   **Abstract:** Drought is a major driver of vegetation activity in Spain, with significant

18   impacts on crop yield, forest growth, and the occurrence of forest fires. Nonetheless, the

19   sensitivity of vegetation to drought conditions differs largely amongst vegetation types

20   and climates. We used a high-resolution (1.1 km) spatial dataset of the Normalized

21   Difference Vegetation Index (NDVI) for the whole Spain spanning the period from

22   1981 to 2015, combined with a ~~another newly developed~~ dataset of the Standardized

23   Precipitation Evapotranspiration Index (SPEI) to assess the sensitivity of vegetation

24   types to drought across Spain. In specific, this study explores the drought time scales at

25   which vegetation activity shows its highest response to drought severity at different

26   moments of the year. Results demonstrate that –over large areas of Spain– vegetation

27   activity is controlled largely by the interannual variability of drought. More than 90% of

28   the land areas exhibited statistically significant positive correlations between the NDVI

29   and the SPEI during dry summers (JJA). Nevertheless, there are some considerable

30   spatio-temporal variations, which can be linked to differences in land cover and aridity

31   conditions. In comparison to other climatic regions across Spain, results indicate that

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).~~(FAO, 2018). To

handle these 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~~active 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 well-

documented. 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

108   northeast and southeast Spain, respectively. Albeit with these comprehensive efforts, a

109   detailed spatial assessment of the links between droughts and vegetation activity, which

110   covers a long time period (decades), is highly desired for Spain to explore the

111   differences in the response of vegetation activity to drought under different

112   environments with various land cover and vegetation types.

113   The overriding objectives of this study are: i) to determine the possible differences in

114   the response of vegetation activity to drought over Spain, as a function of the different

115   land cover types and climatic conditions; and ii) to explore the drought time scales at

116   which vegetation activity highly responds to drought severity. An innovate aspect of

117   this study is that it provides –for the first time– a comprehensive assessment of the

118   response of vegetation activity to drought using a multidecadal (1981-2015) high spatial

119   resolution (1.1 km) NDVI dataset over the study region.

120

121   **2. Data and methods**

122   ***2.1. Datasets***

123   *2.1.1. NDVI data*

124   Globally, there are several NDVI datasets, which have been widely used to analyze

125   NDVI variability and trends (e.g. Slayback et al., 2003; Herrmann et al., 2005;

126   Anyamba and Tucker, 2005) and to assess the links between NDVI and climate

127   variability and drought (e.g. Dardel et al., 2014; Vicente-Serrano et al., 2015; Gouveia

128   et al., 2016). Amongst these global datasets, the most widely used are those derived

129   from the Advanced Very High Resolution Radiometer (AVHRR) sensor on board of the

130   NOAA satellites and those retrieved from the Moderate Resolution Imaging

131   Spectroradiometer (MODIS) data. Both products have been widely employed to

132   evaluate the possible influence of drought on vegetation dynamics in different regions

133   worldwide (e.g. Tucker et al., 2005; Gu et al., 2007; Sona et al., 2012; Pinzon and

134   Tucker, 2014; Ma et al., 2015). While the Global Inventory Modeling and Mapping

135   Studies (GIMMS) dataset from NOAA-AVHRR is available at a semi-monthly

136   temporal resolution for the period from 1981 onwards (Tucker et al., 2005; Pinzon and

137   Tucker, 2014), its spatial resolution is quite low (64 km^2), which makes it difficult to

138   capture the high spatial variability of vegetation cover over Spain. On the other hand,

139   the NDVI dataset derived from MODIS dates back only to 2001 (Huete et al., 2002),

140   which is insufficient to give insights into the long-term response of vegetation activity

141   to drought. To overcome these spatial and temporal limitations, our decision was made

142   to employ a recently developed high-resolution spatial NDVI dataset (Sp_1Km_NDVI),

143   which is available at grid interval of 1.1 km, spanning the period from 1981 onwards. In

144   accordance with GIMMS dataset, Sp_1Km_NDVI is available at a semi-monthly

145   temporal resolution. This dataset has already been validated (Vicente-Serrano et al.,

146   2018), showing high performance in comparison to other available NDVI datasets. As

147   such, it can be used -with confidence- to provide a multidecadal assessment of NDVI

148   variability at high-spatial resolution, especially in areas of highly variable vegetation.

149   Herein, it is noteworthy indicating that the data from the Sp_1Km_NDVI dataset was

150   standardized (sNDVI), so that each series has an average equal to zero and a standard

151   deviation equal to one. This procedure is motivated by the strong seasonality and spatial

152   differences of vegetation activity over Spain. Following this procedure, the magnitudes

153   of all NDVI time series are comparable over space and time. To accomplish this task,

154   the data were fitted to a log-logistic distribution, which shows better skill in

155   standardizing environmental variables, in comparison to other statistical distributions

156   (Vicente-Serrano and Beguería, 2016).

In ~~out attempt~~order 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 of these pixels (not shown here) ~~of these pixels~~ concurs well with the areas identified in earlier studies over Spain in which it was an abrupt modification of the land cover type (e.g. creation of new irrigated lands) (Lasanta and Vicente-Serrano, 2012; ~~Vicente-Serrano et al., 2018~~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~~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). Correlations with the drought dataset were based on the sNDVI.

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,

182 drought indices can be an appropriate tool to make this assessment, particularly with

183 their calculation at multiple time scales. These time scales summarize the accumulated

184 climatic conditions over different periods, which make drought indices closely related

185 to impact studies. Overall, to calculate drought indices, we employed data for a set of

186 meteorological variables (i.e. precipitation, maximum and minimum air temperature,

187 relative humidity, sunshine duration, and wind speed) from a recently developed

188 gridded climatic dataset (Vicente-Serrano et al., 2017). This gridded dataset was

189 developed using a dense network of quality-controlled and homogenized meteorological

190 records. Data are available for the whole Spanish territory at a spatial resolution of 1.1

191 km, which is consistent with the resolution of the NDVI dataset (section 2.1.1). Based

192 on this gridded dataset, we computed the atmospheric evaporative demand (AED~~,~~

193 ~~reference evapotranspiration (ETo),)~~ and the Standardized Precipitation

194 Evapotranspiration Index (SPEI). We used the reference evapotranspiration (ETo) as the

195 most realibale way of estimating the AED. ETo was calculated using the physically

196 based FAO-56 Penman-Monteith equation (Allen et al., 1998). On the other hand, the

197 SPEI was computed using precipitation and ~~AED~~ETO data (Vicente-Serrano et al.,

198 2010). The SPEI is one of the most widely used drought indices and has thus been

199 employed to quantify drought in a number of agricultural (e.g. Peña-Gallardo et al.,

200 2018b), environmental (e.g. Vicente-Serrano et al., 2012; Bachmair et al., 2018), and

201 socioeconomic applications (e.g. Bachmair et al., 2015; Stagge et al., 2015). The SPEI

202 is advantageous compared to the Palmer Drought Severity Index (PDSI), as it is

203 calculated at different time scales. In comparison to the Standardized Precipitation

204 Index (SPI) (McKee et al., 1993), the SPEI does not account only for precipitation, but

205 it also considers the contribution of ~~AED~~ETO in drought evolution.

In this work, the SPEI was calculated for the common 1- to 24-month time scales. but here given the semi-monthly availability of the data, we calculated the corresponding 1- to 48- semi-monthly 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 which antecedent climate conditions are accumulated and it allows to adapt adapting 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. Given that it is not possible to know a priori the best cumulative period to explain the response of the vegetation activity to drought variability, we retained for further analysis the maximum correlation, independently of the time scale at which this is obtained.

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 AEDETO) 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-

256 and 12-months (2-, 6-, 12- and 24-semi-monthly periods). Results are shown only for

257 the second semi-monthly period of each month between April and July. The differential

258 response of the NDVI to the different time scales of the SPEI is illustrated. As depicted,

259 the 6-month time scale was more relevant to vegetation activity in large areas of

260 Southwestern and Southeastern Spain during the second half of April. On the other

261 hand, vegetation activity was more determined by the 12-month SPEI across the Ebro

262 basin in northeastern Spain. This stresses the need of considering different drought time

263 scales to know the climate cumulative period that mostly affects vegetation activity. The

264 6-month and 12-month SPEI produced similar results during the second period of May,

265 while the 12-month time scale is more related to vegetation activity in June and July.

266 ~~The density plots (supplementary Figures 1 to 4) summarize the magnitude of~~

267 ~~correlations between the SPEI and sNDVI for Spain, as a function of the semi-monthly~~

268 ~~period as well as the SPEI time scale. It can be seen that correlations tend to be higher~~

269 ~~during the warm season (May to August), and at time scales between 6 and 24 months.~~

270 Figure 2 summarizes the maximum correlation between the sNDVI and the SPEI,

271 providing insights into the differential response of the NDVI to drought. It can be noted

272 that there are clear seasonal and spatial differences in the response of sNDVI to the

273 SPEI. The sNDVI is more related to the SPEI during the warm season (MJJA). In

274 contrast, the response of the sNDVI to drought is less pronounced from September to

275 April, albeit with some exceptions. One example is the response of vegetation to

276 drought alongside the southeastern Mediterranean coastland, where the correlation

277 between sNDVI and SPEI is almost high all the year around. Table 1 summarizes the

278 percentage of the total area exhibiting significant or non-significant correlations over

279 Spain during the different semi-monthly periods. Positive (lower sNDVI with drought)

280 and statistically significant correlations are dominant across the entire territory, but with

281   a seasonal component. In particular, a higher percentage of the territory shows positive

282   and significant correlations during the warm season (MJJA). From mid of May to mid

283   of September, more than 80% of the study domain show positive and significant

284   correlations between the sNDVI and the SPEI. A similar finding is also found between

285   the mid of June and the beginning of August. Figure 3 summarizes the average

286   correlations between the SPEI and sNDVI. As illustrated, there is a gradual increase in

287   the response of the sNDVI to the SPEI from the beginning of May to the end of July,

288   when the maximum average correlation is recorded. In contrast, the correlations

289   between the SPEI and sNDVI decrease progressively from August to December.

290   The response of the sNDVI to different times scales of the SPEI and seasons is quite

291   complex. Figure 4 shows the spatial distribution of the SPEI time scale at which the

292   maximum correlation was found for each one of the 24 semi-monthly periods of the

293   year. It can be noted that there are considerable seasonal and spatial differences.

294   Nonetheless, these differences are masked with the estimated average values of the

295   SPEI time scale recorded for the semi-monthly periods (Figure 5) which are less

296   variable (oscillating between 18 and 22 semi-monthly periods -9 to 11 months-)

297   throughout the year. In general, the areas and periods with higher correlations are

298   recorded at the time scales between 7 and 24 semi-months (3-12 months). This pattern

299   is mostly recorded in the period between May and July (Supplementary Figure 5), in

300   which the sNDVI variability is more sensitive to drought. Nevertheless, there are no

301   general spatial patterns in the response of the NDVI to SPEI, indicating that there is a

302   dominance of the maximum correlations associated with a certain SPEI time scale

303   (Supplementary Figure 6). Interestingly, this , this pattern is not driven by the presence

304   of different land cover types, given that the correlation coefficients between the sNDVI

305 ~~and SPEI are quite similar, irrespective of the land cover type (Supplementary Figures 7~~

306 ~~to 17).~~

307

3.2. Land cover differences

309 There are differences in the magnitude and seasonality of the Pearson's r correlation

310 coefficients among all land cover types. Figure 6 shows the average and standard error

311 of the mean of the maximum Pearson's r coefficients between the sNDVI and SPEI for

312 the different land cover types and the 24 semi-monthly periods. The magnitudes of

313 correlation vary considerably, as a function of land cover type, as well as the period of

314 the year in which the highest correlations are recorded. The non-irrigated arable lands

315 show a peak of significant correlation between April and June. However, this

316 correlation decreases towards the end of the year. The majority of ~~the surface dominated~~

317 ~~by~~ this land cover shows positive and significant correlations between May and

318 September (Supplementary Table 1), with percentages almost close to 100%. On the

319 contrary, irrigated lands do not show such a strong response to drought during the warm

320 season. Even with the presence of a seasonal pattern, it is less pronounced than the one

321 observed for non-irrigated arable lands. Overall, irrigated areas are characterized by

322 positive and significant correlations between sNDVI and SPEI during summertime

323 (Supplementary Table 2). Similarly, vineyards show a clear seasonal pattern, albeit with

324 a peak of maximum correlations during the late summer (July-August) and early

325 autumn (September-October) (Supplementary Table 3). On the other hand, olive groves

326 show of the highest correlation between the sNDVI and SPEI during the second half of

327 May and in October, suggesting a quasi bi-modal response of the NDVI to drought.

328 This pattern is also revealed in the percentage of the surface area with significant

329 correlations (Supplementary Table 4). In the same context, the areas of natural

330   vegetation exhibit their maximum correlation between the sNDVI and SPEI during

331   summer months. The highest correlations are found in July and August for the forest

332   types, compared to earlier June for the natural grasslands and the areas of sclerophillous

333   vegetation. On the other hand, the mixed forests tend to show lower correlations than

334   broad-leaved and coniferous forests. A quick inspection of all these types of land cover

335   indicates that the correlations between the sNDVI and SPEI are generally positive and

336   significant during summer months (Supplementary Tables 5 to 11).

337   Large differences across vegetation types were found for the SPEI time scales at which

338   maximum correlations between sNDVI and the SPEI are found (Figure 7). For example,

339   for non-irrigated arable lands, the maximum correlation between SPEI and sNDVI is

340   found for time scales between 11 and 21 semi-monthly periods. This indicates that

341   crops in May-June (the period in which higher correlations are recorded) respond

342   mostly to the climate conditions recorded between June and December of the preceding

343   year. Irrigated lands show a clear seasonal pattern, as maximum correlations are

344   recorded at time scales between 12 and 18 semi-monthly periods (i.e. 6 to 9 months),

345   mainly between November and May. On the other hand, the maximum correlations

346   between sNDVI and SPEI during summer are found for time scales between 25 and 28

347   semi-monthly periods. Similar to irrigated lands, vineyards show a strong seasonality,

348   responding to longer time-scales at the end of summertime. In contrast, natural

349   vegetation areas show less seasonality to SPEI time scales, which mostly impact the

350   interannual variability of sNDVI. The SPEI time scales, at which the maximum

351   correlation is found between sNDVI and SPEI, vary from 20 semi-monthly periods

352   during the warm season (MJJAS) to 30 semi-monthly periods during the cold season

353   (ONDJFMA). This finding is evident for all forest types and areas of sclerophillous

354   vegetation and mixed wood-scrub. The only exception corresponds to natural

355 grasslands, which show a response to shorter SPEI time scales (i.e. 20 semi-monthly

356 periods in winter and 15 in spring and early summer).

357

358 *3.3. Influence of average climatic conditions*

359 In addition to the impact of the time scale at which drought is quantified, the response

360 of vegetation activity to drought can also be closely related to the prevailing climatic

361 conditions. Figure 8 summarizes the spatial correlation between aridity (P-AEDETo)

362 and the maximum correlation between the sNDVI and SPEI. For most of the semi-

363 monthly periods of the year aridity is negatively correlated with the maximum

364 correlation between sNDVI and SPEI, indicating that vegetation activity in arid sites is

365 more responsive to drought variability. This correlation is more pronounced for the

366 period between December and June. In contrast, this negative association becomes

367 weaker and statistically non-significant during warmer months (e.g. July andto August).

368 Figure 9 illustrates the spatial correlation between mean air temperature and the

369 maximum correlation between the sNDVI and SPEI. Results demonstrate similar results

370 to those found for aridity, with a general positive and significant correlation from March

371 to June, followed by a non-significant and weak correlation during summer months.

372 Nonetheless, these general patterns vary largely as a function of land cover type

373 (Supplementary Figures 181 to 2811). For example, in non-irrigated arable lands, there

374 is strong negative correlation between aridity and the sNDVI/SPEI maximum

375 correlation from March to May: a period that witnesses the peak of vegetation activity

376 in this land cover type. This also coincides with the period of the highest average

377 correlations between the sNDVI and SPEI. Taken together, this demonstrates that non-

378 irrigated arable lands located in the most arid areas are more sensitive to drought

379 variability than those located in humid regions. As opposed to non-irrigated arable

380 lands, the correlations with aridity are found statistically non-significant in all periods of

381 the year for irrigated lands, vineyards and olive groves. Nevertheless, for the different

382 natural vegetation categories, the correlations are negative and statistically significant

383 during large periods. The mixed agricultural/natural vegetation areas show a significant

384 correlation between October and July, with stronger association at the beginning of

385 summer season. Broadleaved and coniferous forests, scrubs, and pasture lands also

386 show a negative relationship between the spatial patterns of the sNDVI/SPEI

387 correlations and aridity.

388 As depicted in Figure 9, the relationship between the sNDVI/SPEI correlation and air

389 temperature shows that the response of vegetation activity to drought is modulated by

390 air temperature during springtime. This implies that warmer areas are those in which the

391 sNDVI is more controlled by drought. A contradictory pattern is found during warmer

392 months, in which the role of air temperature in modulating the impact of drought on

393 vegetation activity is minimized. The relationships between air temperature and the

394 NDVI-SPEI correlation vary among the different land cover types (Supplementary

395 Figures 2912 to 3922). For example, in non-irrigated arable lands, the positive and

396 statistically significant correlation is found in the period from March to AprilMay,

397 indicating that the response of the sNDVI to SPEI tends to coincide spatially with areas

398 of warmer conditions. As observed for aridity, the relationship between the sNDVI and

399 SPEI in irrigated lands is less associated with the spatial patterns of air temperature. A

400 similar pattern is recorded for vineyards and olive groves. Nevertheless, the areas of

401 natural vegetation show a clear relationship between air temperature and the

402 sNDVI/SPEI correlations. In the mixed agriculture and natural vegetation areas, we

403 found a statistically significant positive association between the sNDVI and SPEI from

404 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)~~(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~~shows 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 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).

4.1. The response of vegetation activity to drought variability

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

504 the recorded drought conditions, the response of vegetation to drought would be low

505 during wintertime. This behaviour is also enhanced by the atmospheric evaporative

506 demand (AED), which is generally low in winter in Spain (Vicente-Serrano et al.,

507 2014d), with a lower water demand of vegetation and accordingly low sensitivity to soil

508 water availability. Austin et al. (1998) indicated that soil water recharge occurs mostly

509 during winter months, given the low water consumption by vegetation. However, in

510 spring, vegetation becomes more sensitive to drought due to temperature rise.

511 Accordingly, the photosynthetic activity, which determines NDVI, is highly controlled

512 by soil water availability (Myneni et al., 1995). In this study, the positive spatial

513 relationship found between air temperature and the sNDVI/SPEI correlation reinforces

514 this explanation. In spring, we found low correlations between the NDVI and SPEI,

515 even in cold areas. In contrast, ~~warmer air~~summer warm temperatures ~~during summer~~

516 ~~months~~ reinforce vegetation activity, but with some exceptions such as cereal

517 cultivations, dry pastures and shrubs~~, which record their maximum vegetation activity~~

518 ~~during spring.~~. This would explain why the response of vegetation activity to the SPEI

519 is stronger during summer in vast areas of Spain.

520 Also, this study suggests clear seasonal differences in the response of the NDVI to

521 drought, and in the magnitude of the correlation between the NDVI and the SPEI, as a

522 function of the dominant land cover. These differences are confirmed at different spatial

523 scales, ranging from regional and local (e.g. Ivits et al., 2014; Zhao et al., 2015;

524 Gouveia et al., 2017; Yang et al., 2018) to global (e.g. Vicente-Serrano et al., 2013),

525 Over Spain, the non-irrigated arable lands, natural grasslands and sclerophyllous

526 vegetation show an earlier response to drought, mainly in late spring and early summer.

527 This response is mainly linked to the vegetation phenology dominating in these land

528 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

554   sub-humid and humid vegetation (Schultz and Halpert, 1995; Abrams et al., 1990;

555   Nicholson et al., 1990; Herrmann et al., 2016). Vicente-Serrano et al. (2013) analysed

556   the sensitivity of the NDVI in the different biomes at a global scale and found a spatial

557   gradient in the sensitivity to drought, which was more important in arid and semiarid

558   regions.

559

560   *4.2. Response to the average climatology*

561   In this study we have shown a control in the response of the NDVI to drought severity

562   by the climatic aridity. Thus, there is a significant correlation between the spatial

563   distribution of the climatic aridity and the sensitivity of the NDVI to drought, mostly in

564   spring and autumn. This could be explained because in more humid environments the

565   main limitation to vegetation growth is temperature and radiation rather than water, so

566   not all the water available would be used by vegetation reflected in a water surplus as

567   surface runoff. This characteristic would make the vegetation less sensitive to drought

568   in the cold season. Drought indices are relative metrics in comparison to the long term

569   climate with the purpose of making drought severity conditions comparable between

570   areas of very different climate characteristics (Mukherjee et al., 2018). This means that

571   in humid areas the corresponding absolute precipitation can be sufficient to cover the

572   vegetation water needs although drought indices inform on below-of-the-average

573   conditions. On the contrary, in arid regions a low value of a drought index is always

574   representative of limited water availability, which would explain the closer relationship

575   between the NDVI and the SPEI.

576   Here we also explored if the general pattern observed in humid and semi-arid regions is

577   also affected by the land cover, and found that the behaviour in the non-irrigated arable

578   lands is the main reason to explain the global pattern. Herbaceous crops show that

579   aridity levels have a clear control of the response of the NDVI to drought during the

580   period of vegetation activity. Nevertheless, after the common harvest period (June) this

581   control by aridity mostly disappears. This is also observed in the grasslands and in the

582   sclerophyllous vegetation, and it could be explained by the low vegetation activity of

583   the herbaceous and shrub species during the summer, given the phenological strategies

584   to cope with water stress with the formation of the seeds before the period of dryness

585   (Chaves et al., 2003). The limiting aridity conditions that characterises the regions in

586   which these vegetation types grow would also contribute to explain this phenomenon.

587   On the contrary, the forests, both broad-leaved and coniferous, also show a control by

588   aridity in the relationship between the NDVI and the SPEI during the summer months

589   since these land cover types show the peak of the vegetation activity during this season.

590   In any case, it is also remarkable that the spatial pattern of the NDVI sensitivity to

591   drought in forests is less controlled by aridity during the summer season, curiously the

592   season in which there are more limiting conditions. This could be explained by the

593   NDVI saturation under high levels of leaf area index (Carlson and Ripley, 1997), since

594   once the tree tops are completely foliated the electromagnetic signal is not sensitive to

595   additional leaf growth. This could explain the less sensitive response of the forests to

596   drought in comparison to land cover types characterised by lower leaf area (e.g. shrubs

597   or grasslands). Nevertheless, we do not think that this phenomenon can explain totally

598   the decreased sensitivity to drought with aridity in summer since the dominant

599   coniferous and broad-leaved forests in Spain are usually not characterised by a 100%

600   leaf coverage (Castro-Díez et al., 1997; Molina and del Campo, 2012), so large signal

601   saturation problems are not expected. On the other hand, the ecophysiological strategies

602   of forests to cope with drought may help explain the observed lower relationship

603   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.

4.3. The importance of drought time scales

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

629 simply because soil moisture is impacted largely by precipitation and the atmospheric

630 evaporative demand over previous cumulative periods (Scaini et al., 2015). Moreover,

631 the different morphological, physiological and phenological strategies would also

632 explain the varying response of vegetation types to different drought time scales. This

633 finding is confirmed in previous works using NDVI and different time scales of a

634 drought index (e.g. Ji and Peters, 2003; Vicente-Serrano, 2007), but also using other

635 variables like tree-ring growth (e.g. Pasho et al., 2011; Arzac et al., 2016; Vicente-

636 Serrano et al., 2014a). This study confirms this finding, given that there is a high spatial

637 diversity in the SPEI time scale at which vegetation has its maximum correlation with

638 the NDVI. These spatial variations, combined with strong seasonal differences, are

639 mainly controlled by the dominant land cover types and aridity conditions. In their

640 global assessment, Vicente-Serrano et al. (2013) found gradients in the response of the

641 world biomes to drought, which are driven mainly by the time scale at which the biome

642 responds to drought in a gradient of aridity. Again, the response to these different time

643 scales implies not only different vulnerabilities of vegetation to water deficits, but also

644 various strategies from plants to cope with drought. In Spain, we showed that the NDVI

645 responds mostly to the SPEI at time scales around 20 semi-monthly periods (10

646 months), but with some few seasonal differences (i.e. shorter time scales in spring and

647 early autumn than in late summer and autumn). Herein, it is also noteworthy indicating

648 that there are differences in this response, as a function of land cover types. Overall,

649 during the periods of highest vegetation activity, the herbaceous land covers (e.g. non-

650 irrigated arable lands and grasslands) respond to shorter SPEI time-scales than other

651 forest types. This pattern can be seen in the context that herbaceous covers are more

652 dependent on the weather conditions recorded during short periods. These vegetation

653 types could not reach deep soil levels, which are driven by climatic conditions during

654   longer periods (Changnon and Easterling, 1989; Berg et al., 2017). In contrast, the tree

655   root systems would access to these deeper levels, having the capacity of buffering the

656   effect of short term droughts, albeit with more vulnerability to long droughts that

657   ultimately would affect deep soil moisture levels. This pattern has been recently

658   observed in southeastern Spain when comparing herbaceous crops and vineyards

659   (Contreras and Hunink, 2015). Recently, Okin et al. (2018) linked the different

660   responses to drought time scales between scrubs and chaparral herbaceous vegetation in

661   California to soil water depletion at different levels.

662   Albeit with these general patterns, we also found some relevant seasonal patterns. For

663   example, irrigated lands responded to long SPEI time scales (> 15 months) during

664   summer months, whilst they responded to shorter time scales (<7 months) during spring

665   and autumn. This behaviour can be linked to water management in these areas. In

666   specific, during spring months, these areas do not receive irrigation and accordingly

667   vegetation activity is determined by water stored in the soil. On the contrary, summer

668   irrigation depends on the water stored in the dense net of reservoirs existing in Spain;

669   some of them have a multiannual capacity. Water availability in the reservoirs usually

670   depends on the climate conditions recorded during long periods (one or two years)

671   (López-Moreno et al., 2004; Lorenzo-Lacruz et al., 2010), which determine water

672   availability for irrigation. This explains why vegetation activity in irrigated lands

673   depends on long time scales of drought. Similarly, vineyards and olive groves respond

674   to long SPEI time-scales during summer. These cultivations are highly resistant to

675   drought stress (Quiroga and Iglesias, 2009). However, these adapted cultivations can be

676   sensitive to severe droughts under extreme summer dryness. In comparison to other

677   natural vegetation, mixed forests show response to shorter SPEI time scales. This could

678   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.

5. Conclusions

The main conclusions of this study are:

- Vegetation activity over large parts of Spain is closely related to the interannual variability of drought.
- The response of vegetation activity to drought is more pronounced during the warm season, which is attributed to the phenology of vegetation under different land cover types.
- There are clear seasonal differences in the response of the NDVI to drought.
- Natural grasslands and sclerophyllous vegetation show an earlier response to drought.

707 - There is a control in the response of the NDVI to drought severity by the climatic aridity, which is partially controlled by the land cover.
709 - The response of the NDVI is highly dependent on the time scale at which drought is quantified although there are differences in this response, as a function of land cover types.

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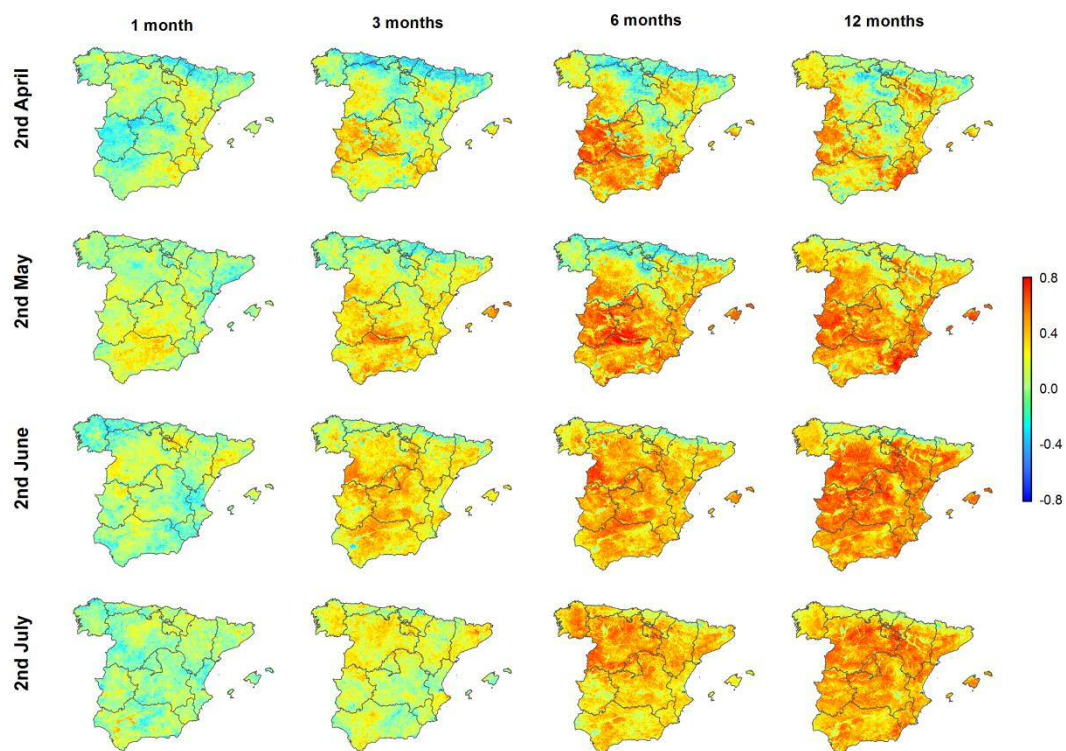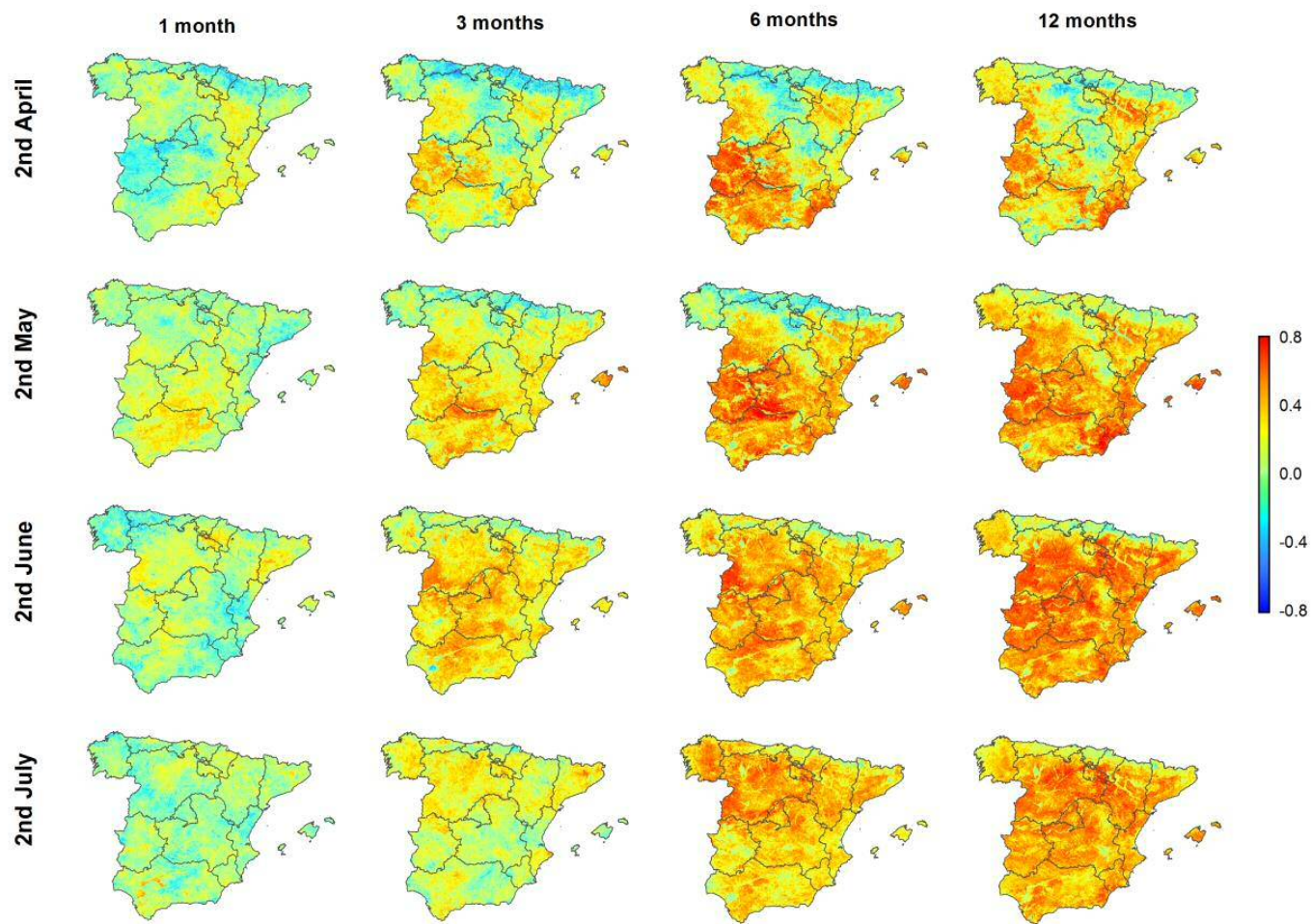
Figure 1: Spatial distribution of the Pearson's r correlation coefficient calculated between the sNDVI and different SPEI time scales for different

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1187 semi-monthly periods.

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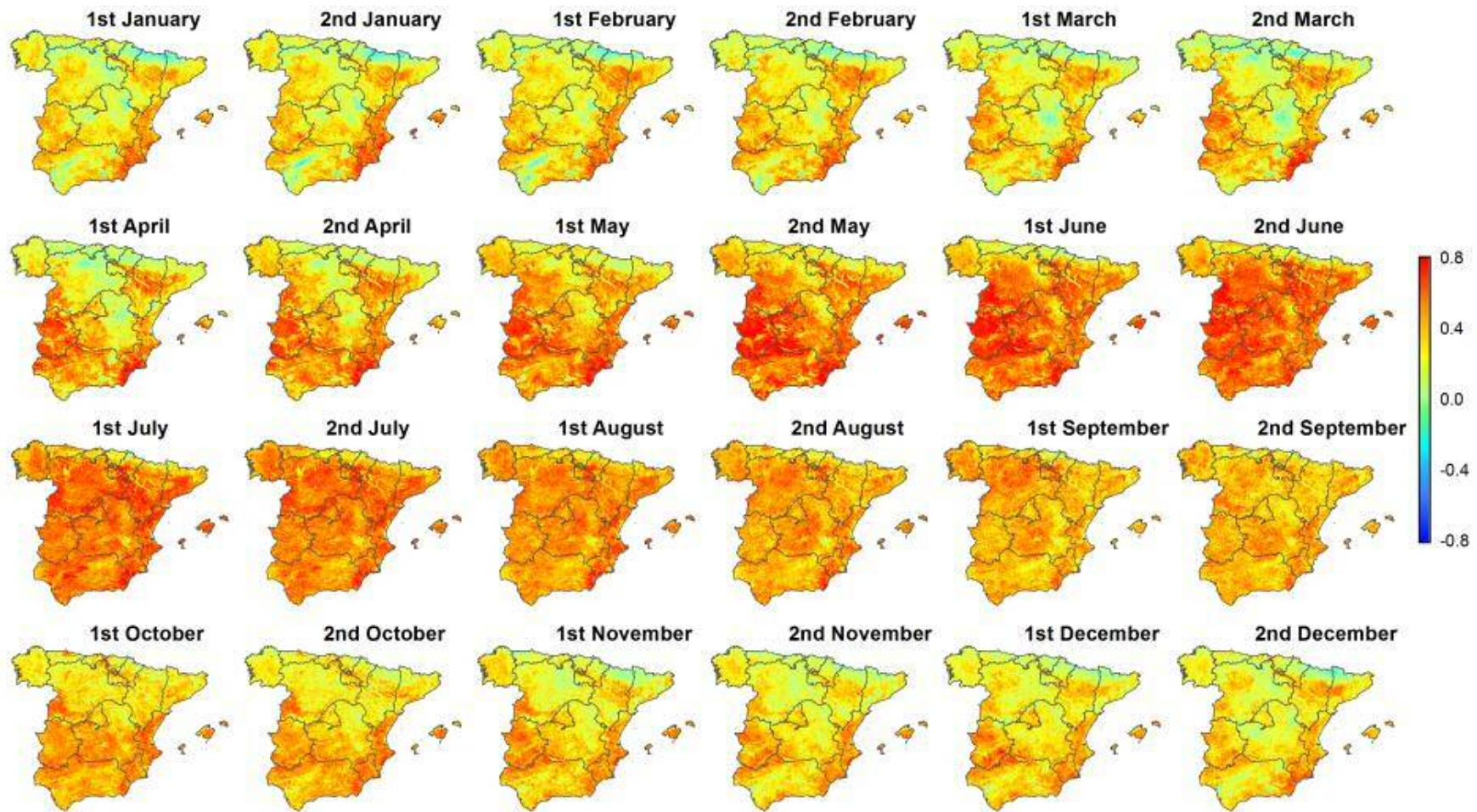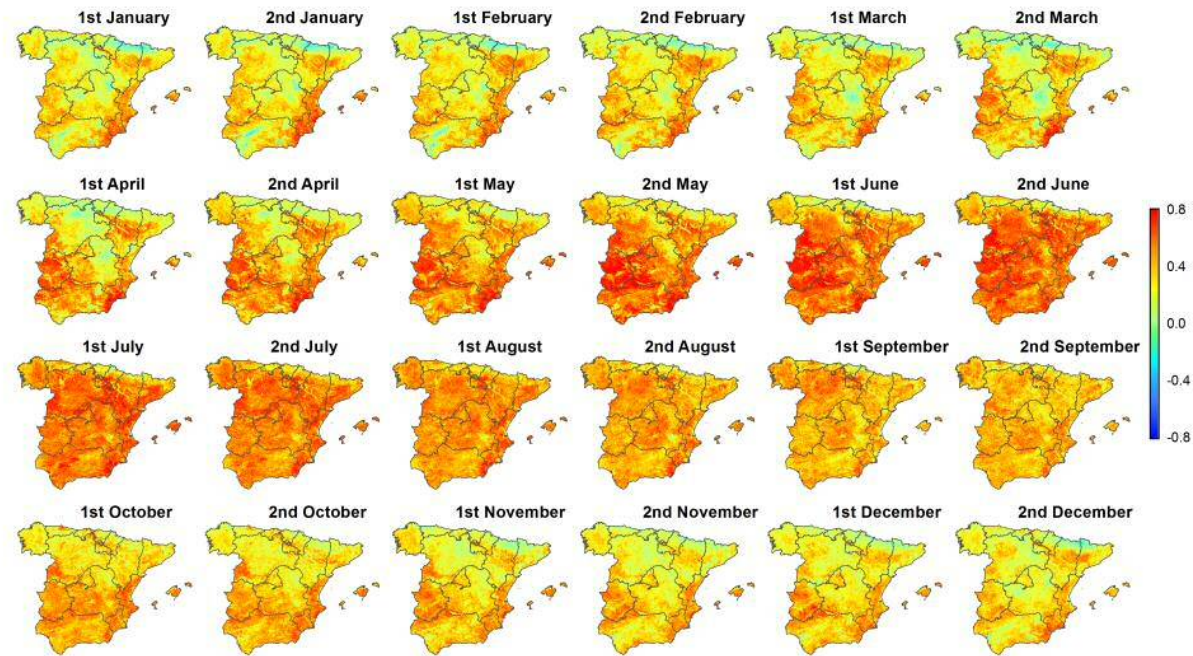
1191   Figure 2: Spatial distribution of the maximum correlation between the sNDVI and the SPEI during the different semi-monthly periods.

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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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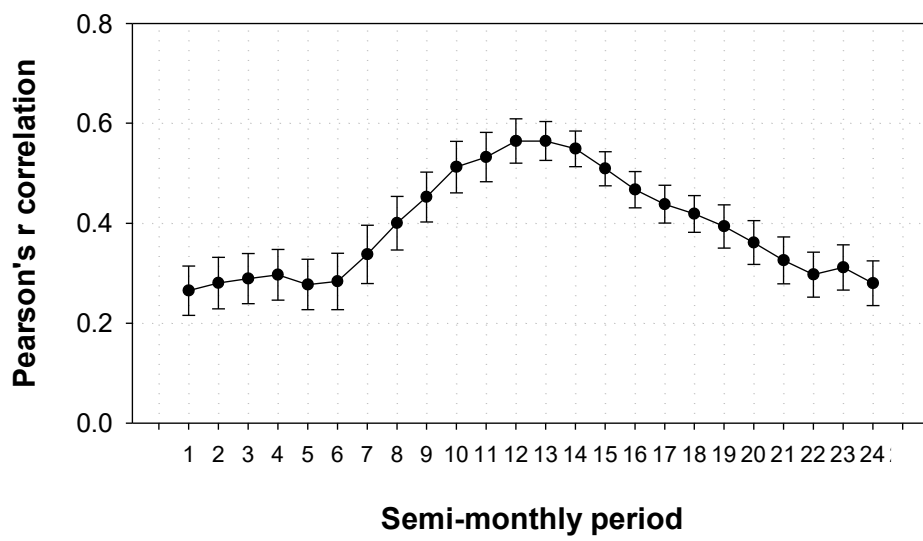
1198 Figure 3: Spatial Average and standard error of the Pearson's r correlation coefficient
1199 between the sNDVI and SPEI time series.

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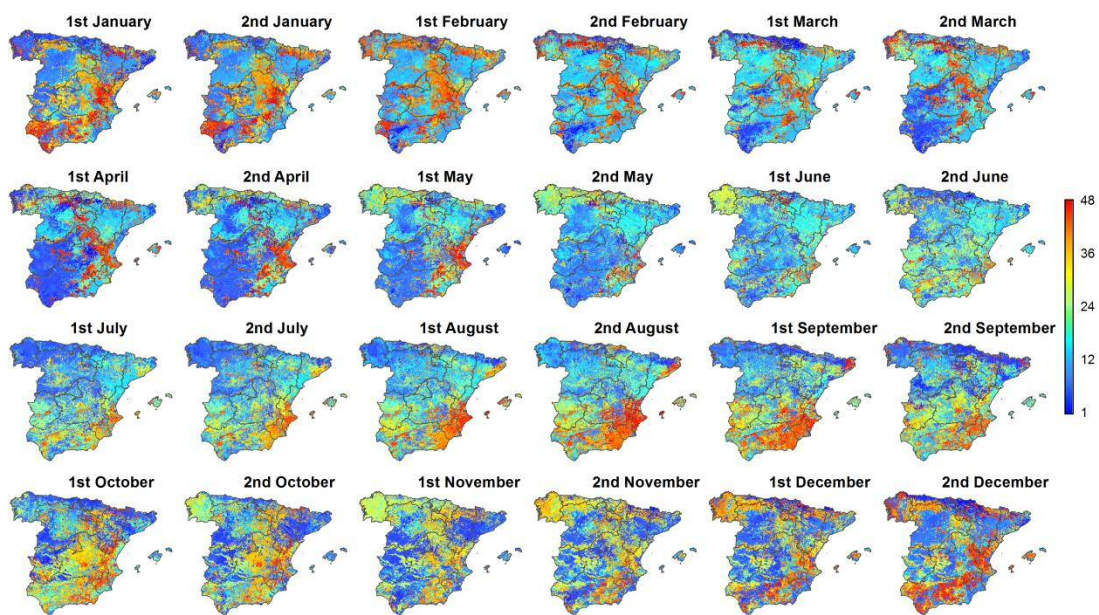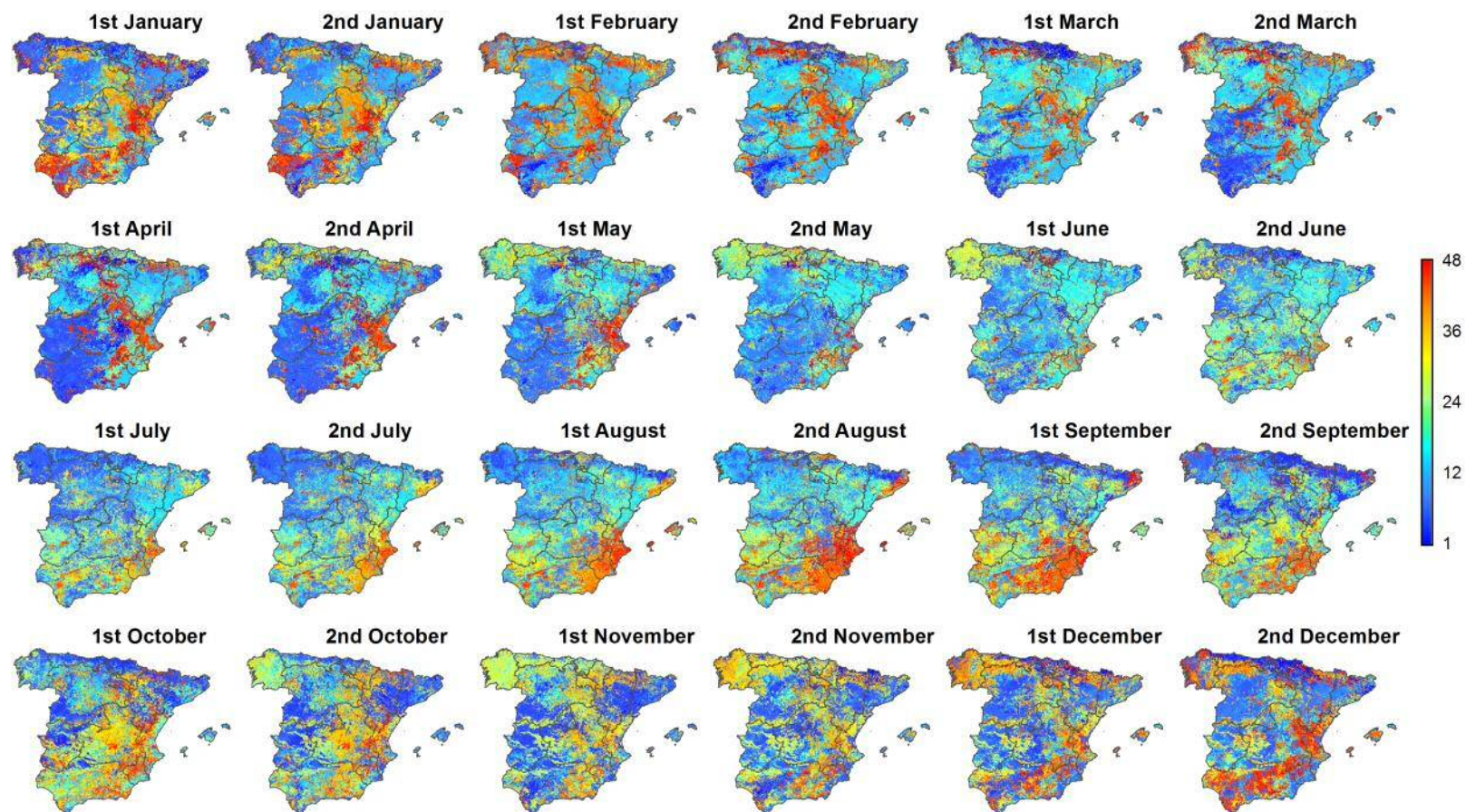
1203 Figure 4: Spatial distribution of the SPEI time scales at which the maximum correlation between the sNDVI and SPEI is found for each one of
1204 the semi-monthly periods.

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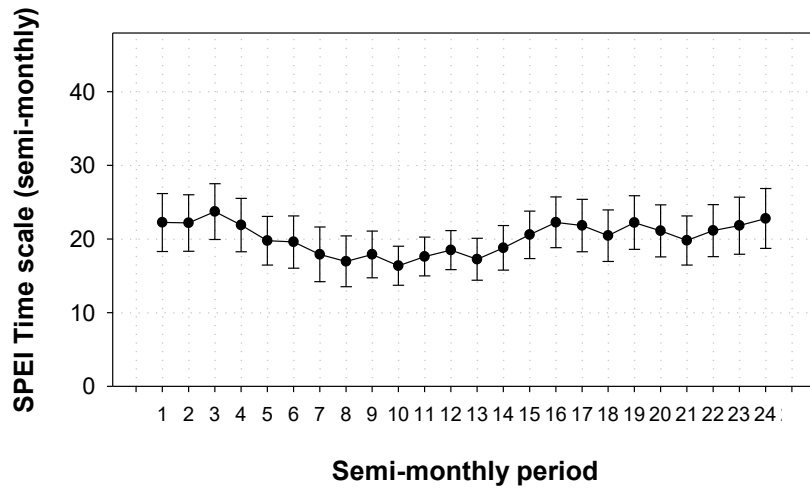
Figure 5: Average and standard error of the SPEI time scale at which the maximum
Pearson's r correlation coefficient between the sNDVI and SPEI is found.

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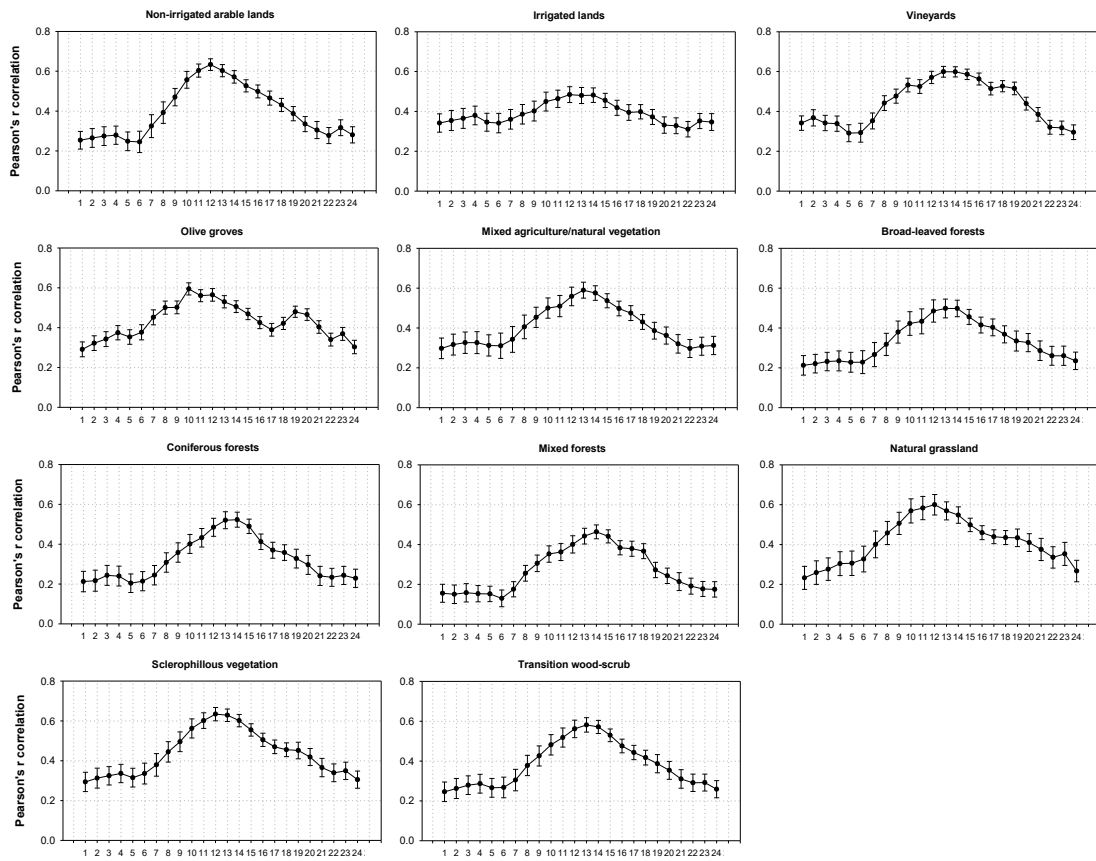
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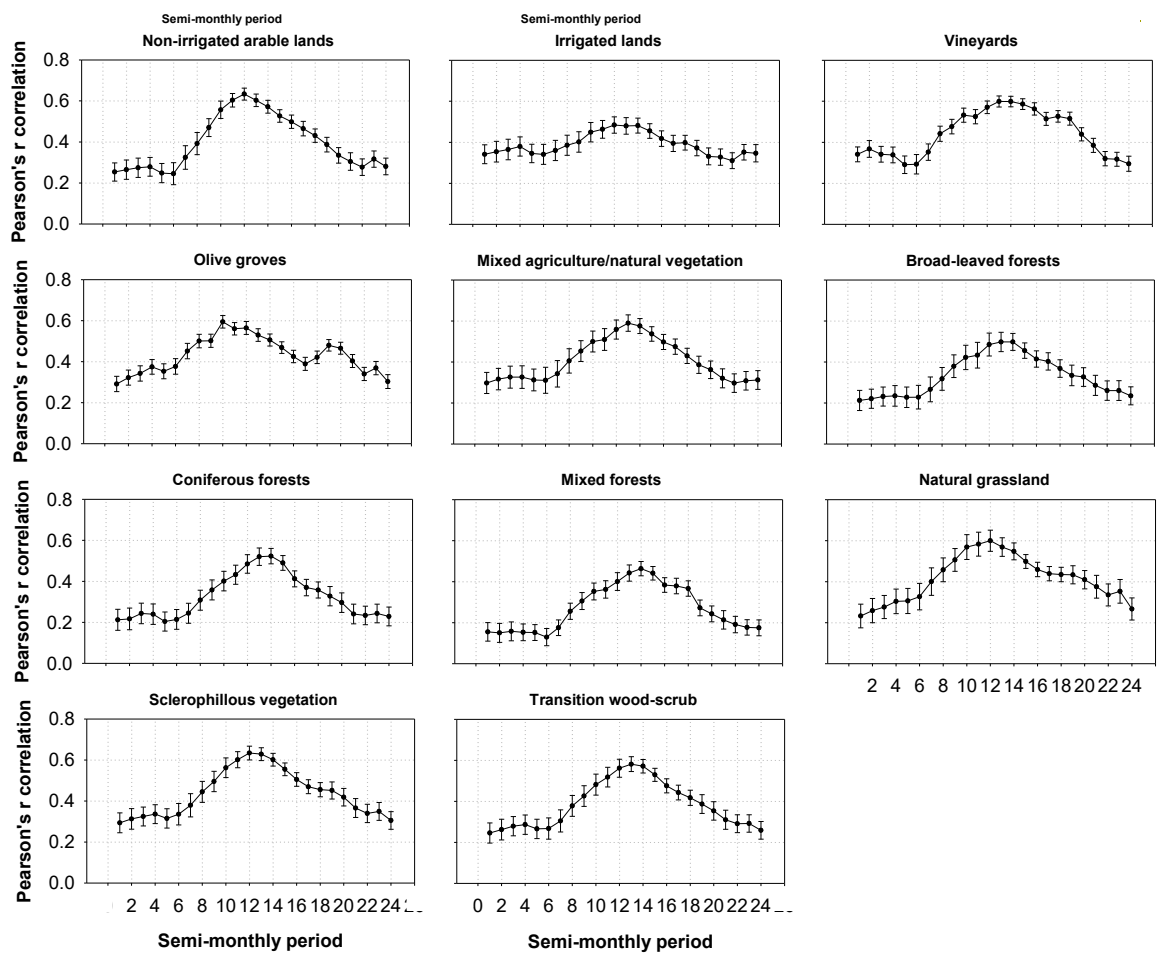
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1213   Figure 6: Average and standard error of the Pearson's r correlation coefficient between
1214   the sNDVI and SPEI for the different land cover types.

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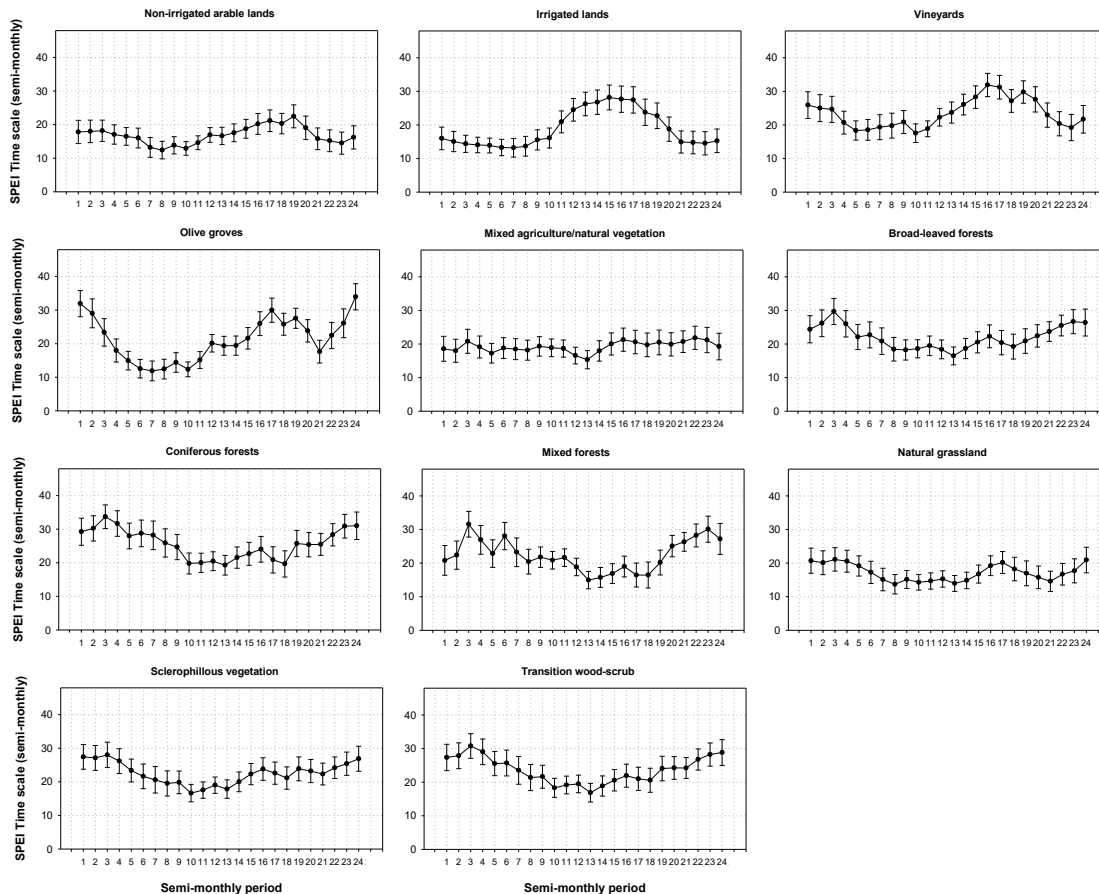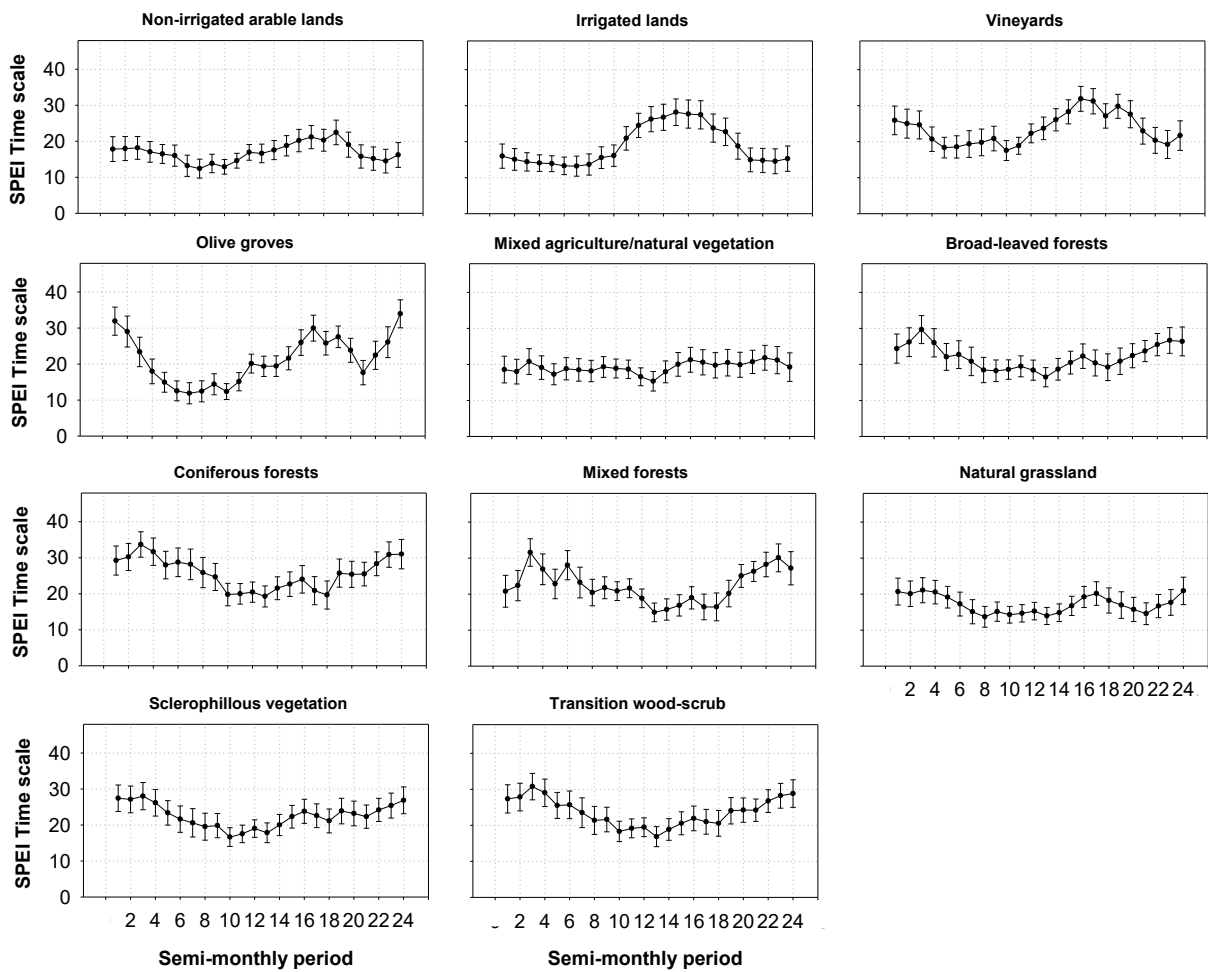
Figure 7: Average and standard error of the SPEI time scale at which the maximum Pearson's r correlation coefficient was found between the sNDVI and SPEI for the different land cover types.
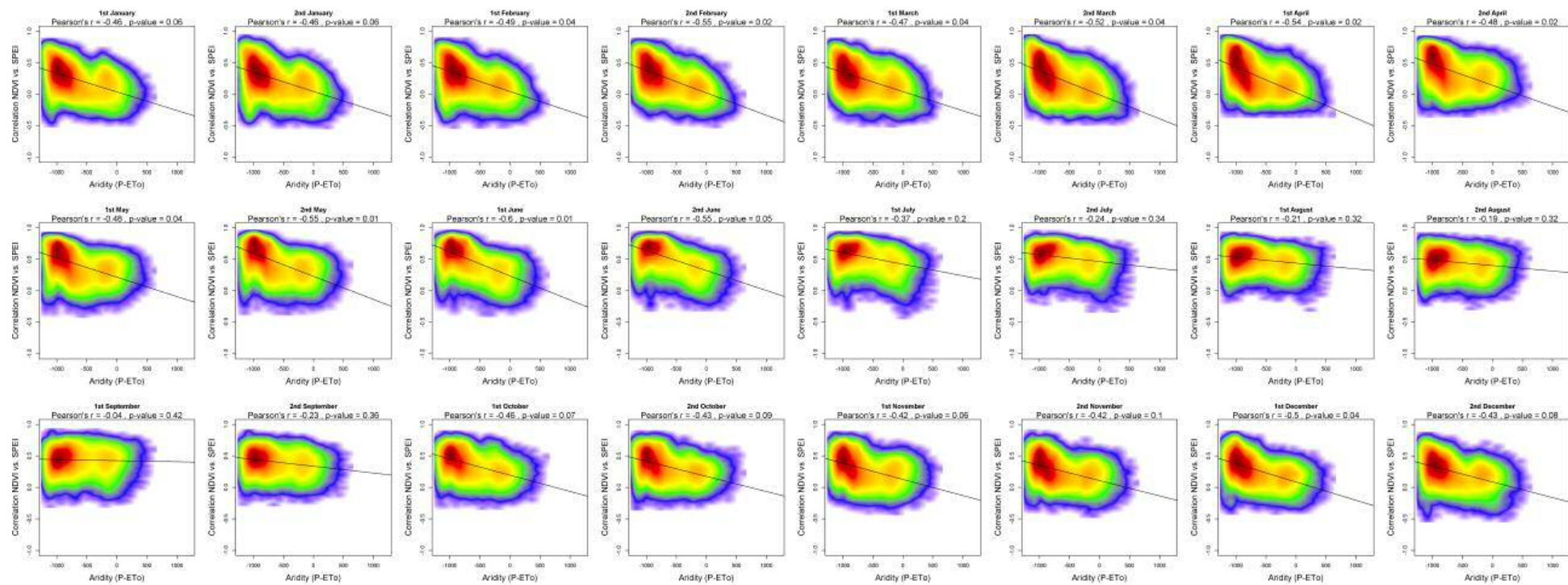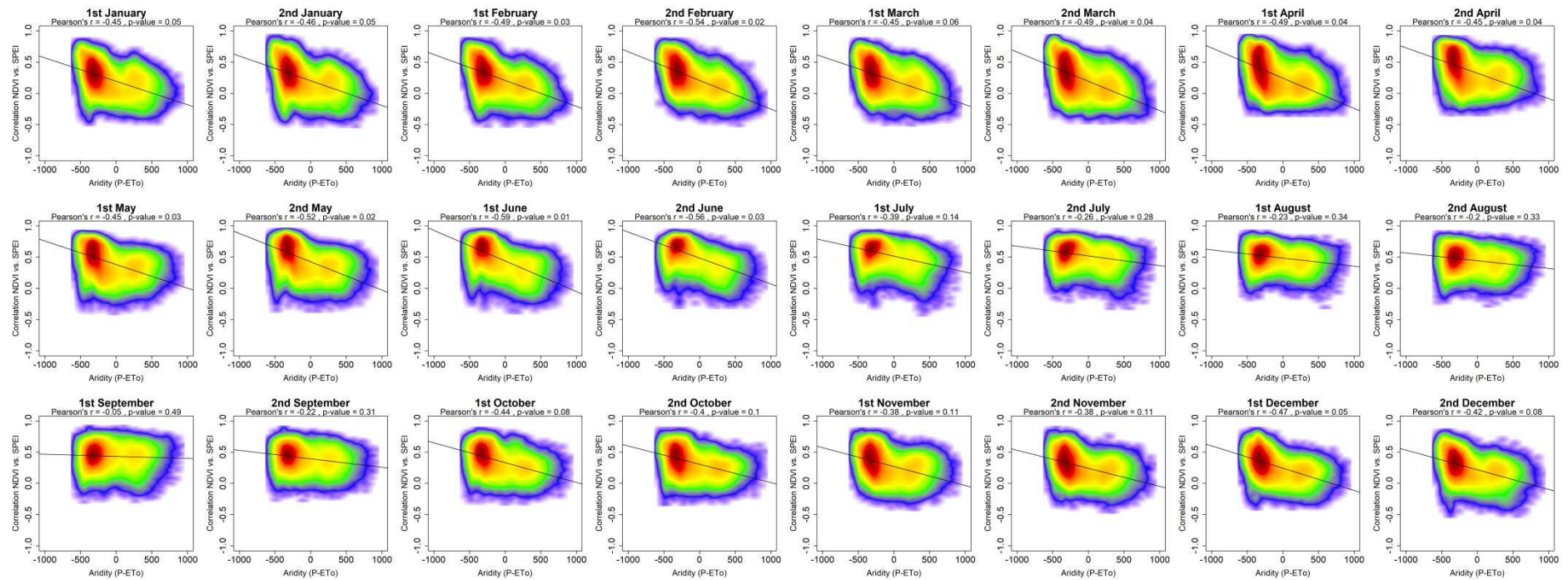
Figure 8. Scatterplots showing the relationships between the maximum correlation obtained between the sNDVI and the SPEI and the climate aridity (Precipitation minus ~~Atmospheric Evaporative Demand).~~ETo). Given the high number of data, the signification of the correlation was obtained by a bootstrap 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.
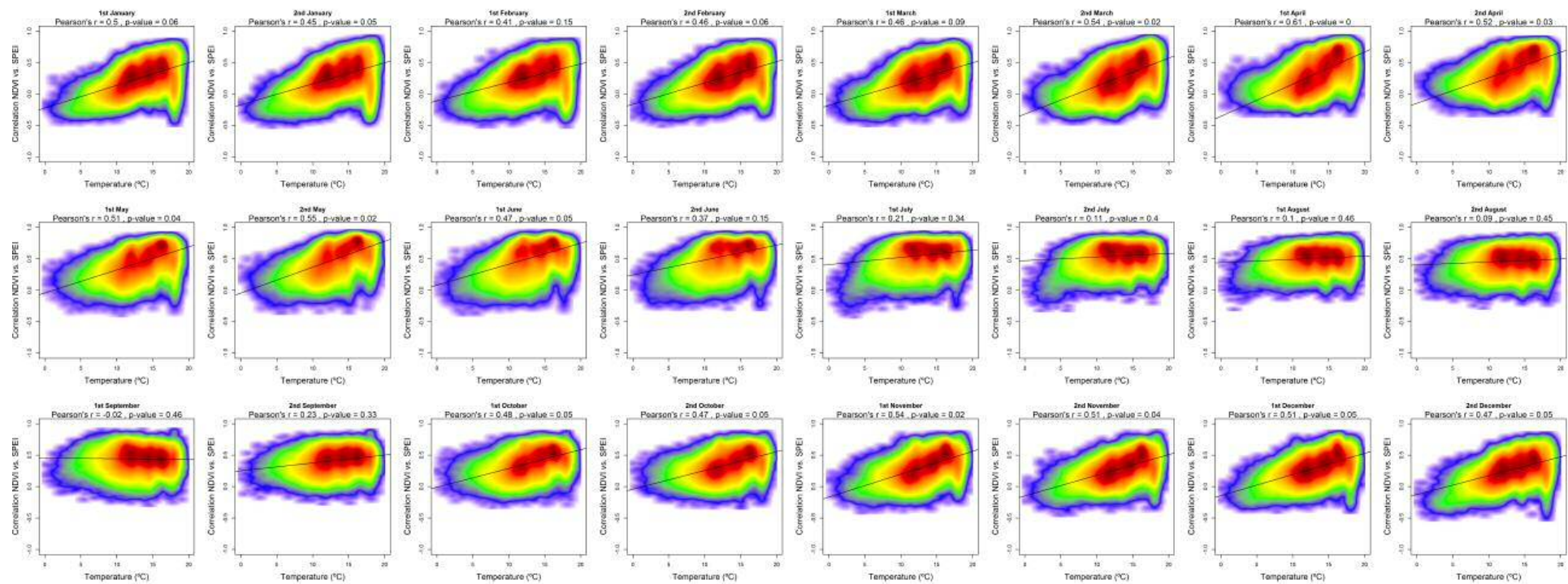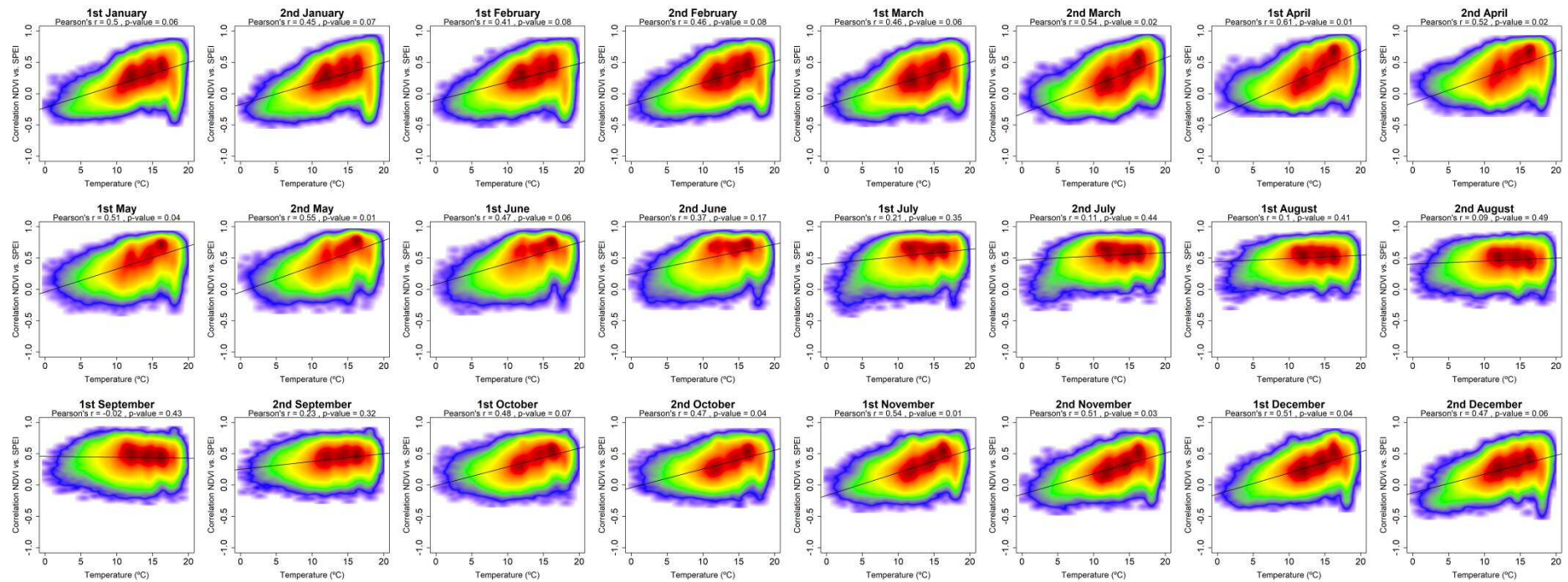
Figure 9. Scatterplots showing the relationships between the maximum correlation obtained between the sNDVI and the SPEI and the average air temperature. Given the high number of points the signification of correlation was obtained by means of 1000 random samples of 30 cases from which correlations and p-values were obtained. The final signification was assessed by means of the average of the obtained p-values.
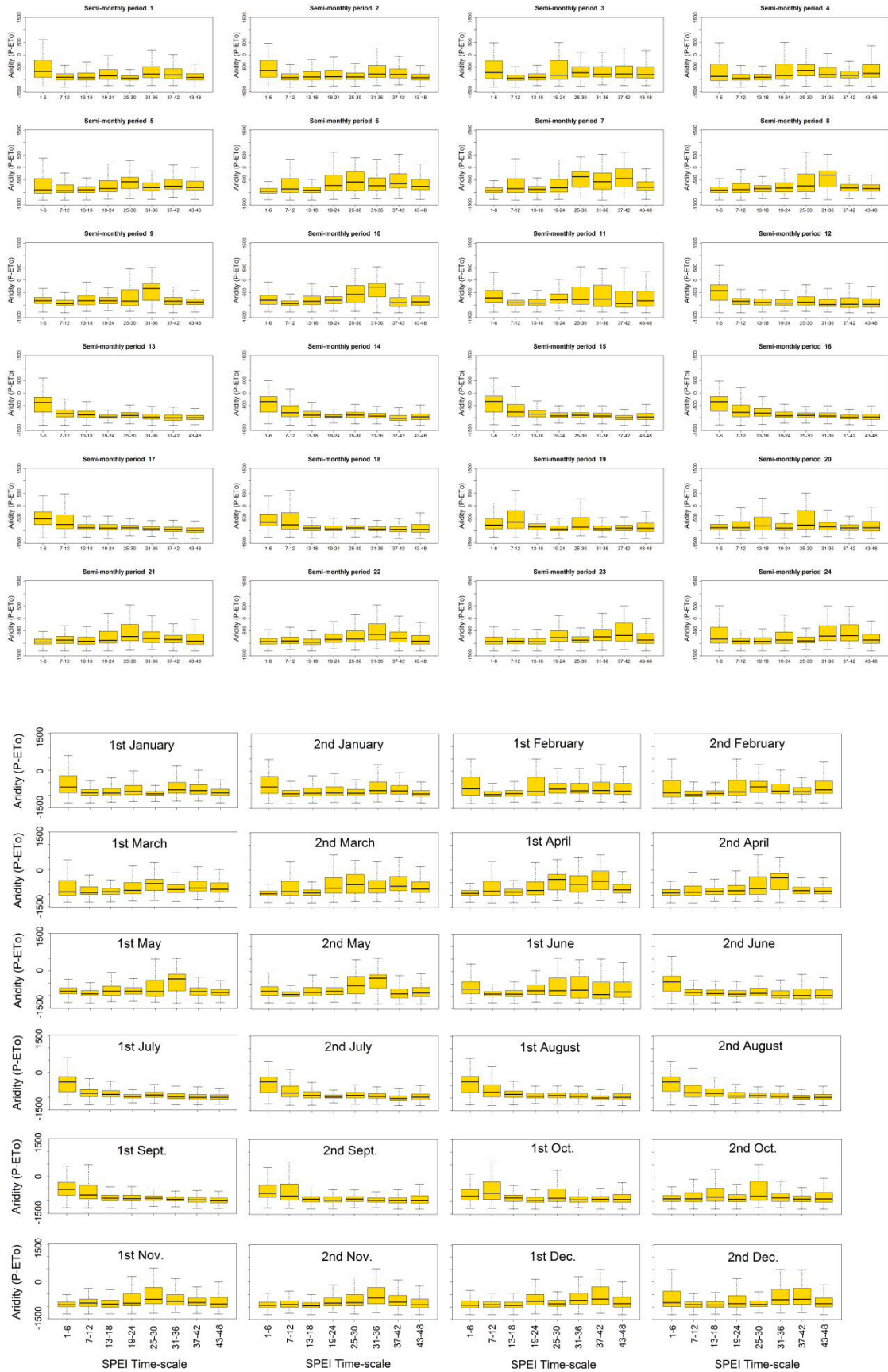
Figure 10: Box plots showing the climate aridity values-, as a function of the SPEI time scales at which the maximum correlation between the sNDVI and SPEI is recorded
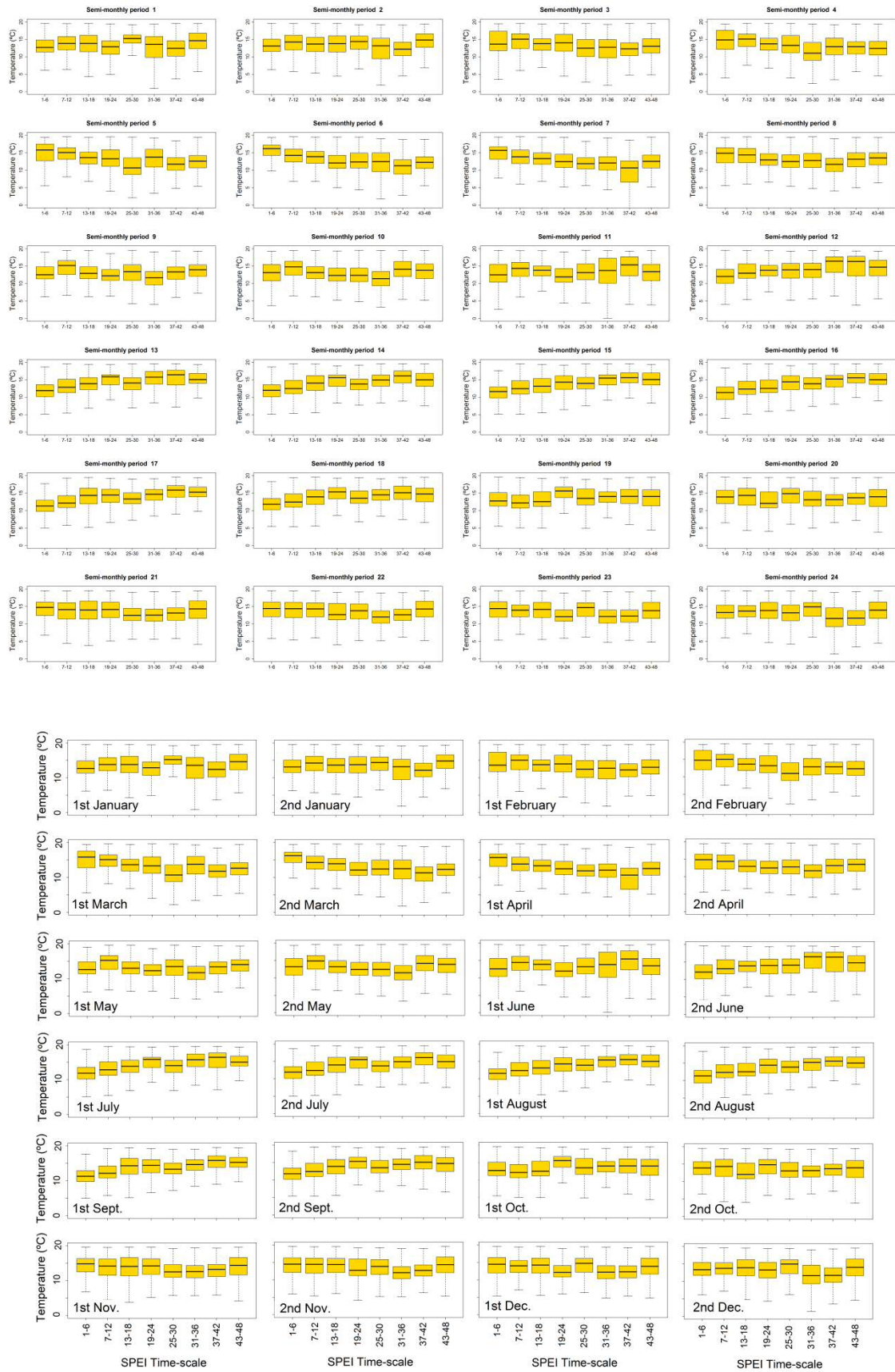
Figure 11: Box plots showing air temperature values, as a function of the SPEI time scales at which the maximum correlation between the sNDVI and SPEI is recorded.
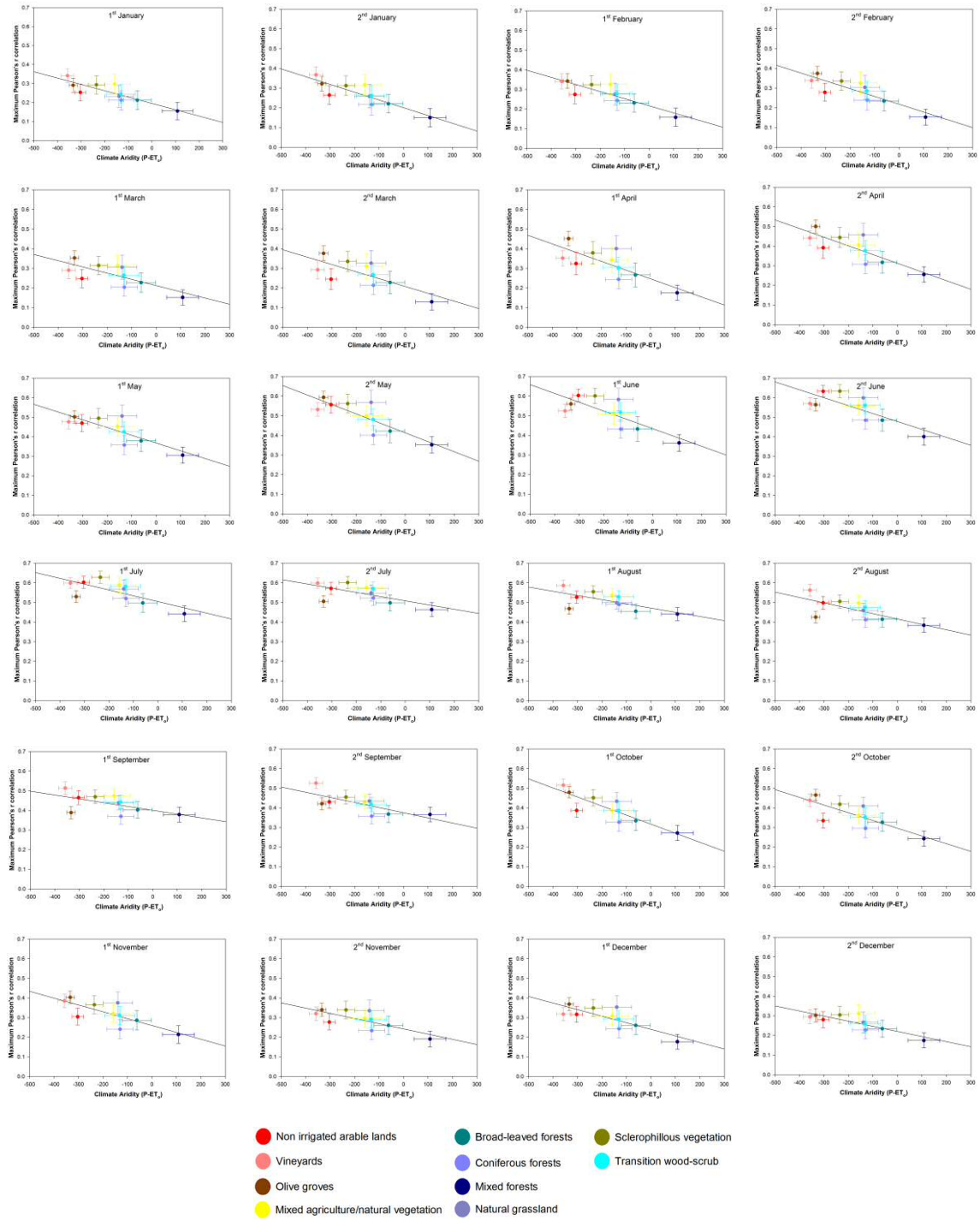
Figure 12: Scatterplots showing the relationship between the mean annual aridity and the maximum correlation found between the sNDVI and the SPEI in the different land cover types analysed in this study. Vertical and horizontal bars represent ¼ of standard deviation around the mean values.
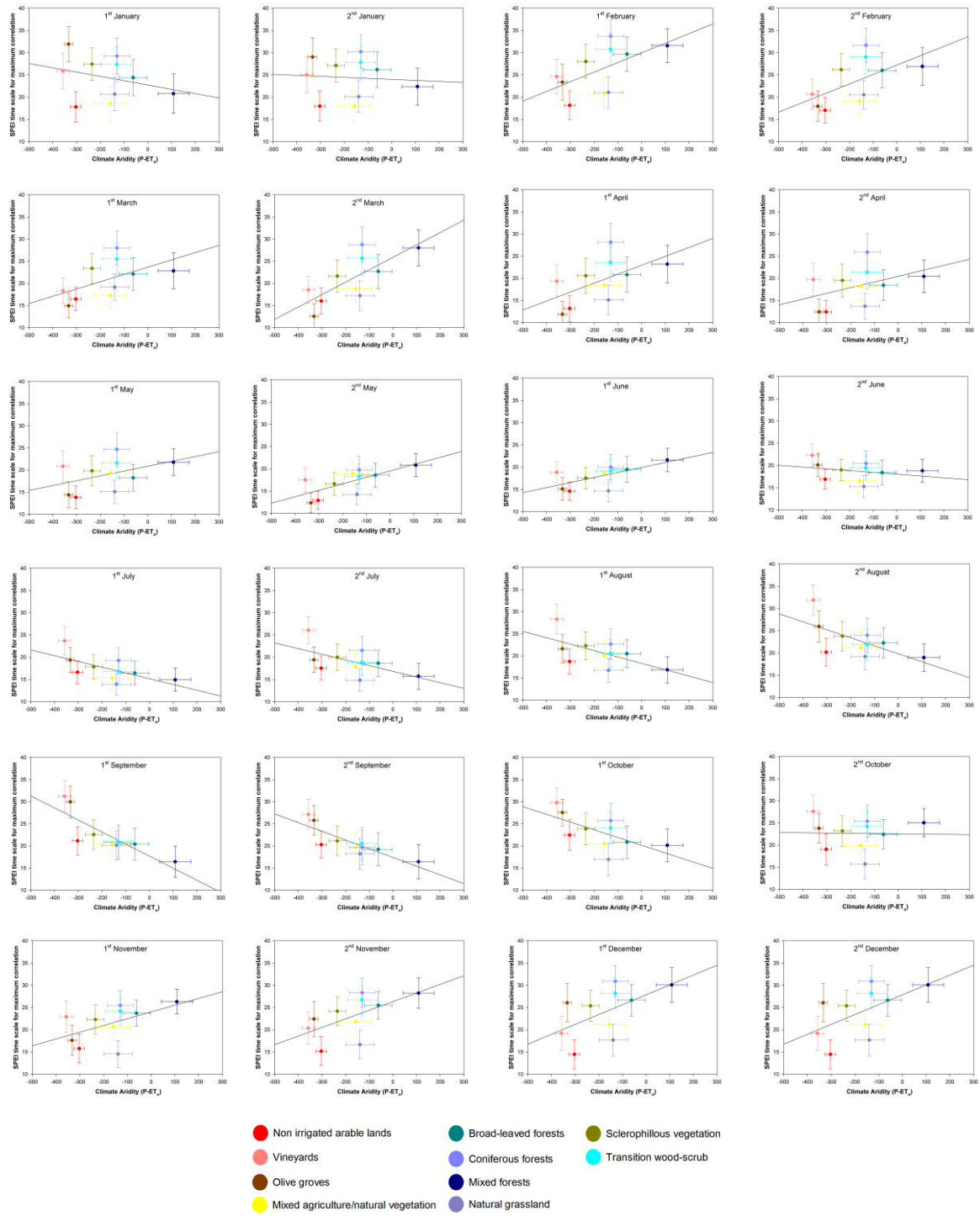
Figure 13: Scatterplots showing the relationship between the mean annual aridity and the SPEI time scale at which the maximum correlation is found between the sNDVI and SPEI for the different land cover types. Vertical and horizontal bars represent ¼ of standard deviation around the mean values.