

The impact of drought on the productivity of two rainfed crops in Spain

Marina Peña-Gallardo¹, Sergio Martín Vicente-Serrano¹, Fernando Domínguez-Castro¹, Santiago Beguería²

¹ Instituto Pirenaico de Ecología, Consejo Superior de Investigaciones Científicas (IPE-CSIC), Zaragoza, Spain.

² Estación Experimental de Aula Dei, Consejo Superior de Investigaciones Científicas (EEAD-CSIC), Zaragoza, Spain.

Abstract

Drought events are of great importance in most Mediterranean climate regions because of the diverse and costly impacts they have in various economic sectors and on the environment. The effects of this natural hazard on rainfed crops are particularly evident. In this study the impacts of drought on two representative rainfed crops in Spain (wheat and barley) were assessed. As the agriculture sector is vulnerable to climate, it is especially important to identify the most appropriate tools for monitoring the impact of the weather on crops, and particularly the impact of drought. Drought indices are the most effective tool for that purpose. Various drought indices have been used to assess the influence of drought on crop yields in Spain, including the standardized precipitation and evapotranspiration index (SPEI), the standardized precipitation index (SPI), the Palmer drought indices (PDSI, Z-Index, PHDI, PMDI), and the standardized Palmer drought index (SPDI). Two sets of crop yield data at different spatial scales and temporal periods were used in the analysis. The results showed that drought indices calculated at different time scales (SPI, SPEI) most closely correlated with crop yield. The results also suggested that different patterns of yield response to drought occurred depending on the region, period of the year, and the drought time scale. The differing responses across the country were related to season and the magnitude of various climate variables.

Key words: crop yields, drought, Spain, standardized precipitation index, standardized precipitation evapotranspiration index, standardized Palmer drought severity index

1. Introduction

The Mediterranean region is one of the major areas in Europe likely to be subject to the potential impacts of climate change. Many semiarid regions of southwestern Europe are expected to undergo a critical decline in water availability as a consequence of reduced precipitation and an increase in interannual and intra-annual rainfall variability (IPCC, 2014, EEA, 2017). It is also expected that future changes in the precipitation regime, along with a rise in temperature, will inevitably bring more extreme and severe weather events (Giorgi and Lionello, 2008; Webber et al., 2018; Wigley, 2009) that will impact ecosystems and economic sectors (Asseng et al., 2014; Tack et al., 2015). It has been suggested that precipitation and temperature changes in the western Mediterranean region will lead to more severe and longer drought events in coming decades (Alcamo et al., 2007; Dai, 2011; Forzieri et al., 2016; Giorgi and Lionello, 2008; Spinoni et al., 2018; Vicente-Serrano et al., 2014). This is significant because agriculture plays a key role in food supply; in 2017 it accounted for 2.59% of GDP in Spain, 1.92% in Italy, and 3.53% in Greece (World Bank, 2017).

The agriculture sector is highly vulnerable to drought, as it depends directly on water availability (Hanjra and Qureshi, 2010; Meng et al., 2016; Tsakiris and Tigkas, 2007). Although each crop differs in its resilience to water stress (Liu et al., 2016; Lobell et al., 2011), droughts can cause crop failure if the weather conditions are adverse during the most sensitive stage of crop growth (Lobell and Field, 2007). The adverse impacts of drought have been highlighted in recent severe events, including in 2003 when the agricultural and forestry losses from drought in France, Italy, Germany, Spain, Portugal, and Austria were approximately 13 billion Euros (Fink et al., 2004; García-Herrera et al., 2010). The most recent drought, which mostly affected north–central Europe, caused European farmers to claim agricultural aid because of the low production that resulted (European Commission, 2018).

For these reasons the vulnerability of agricultural production to extreme events, and the quantification of drought impacts on crop yields, have become a focus of interest. In recent years diverse studies in the Mediterranean region have assessed these issues from multiple perspectives. For example, Capa-Morocho et al. (2016) investigated the link between seasonal climate forecasts and crop models in Spain, Loukas and Vasiliades, (2004) used a probabilistic approach to evaluate the spatio-temporal characteristics of drought in an agricultural plain region in Greece, and Moore and Lobell, (2014) estimated the impacts of climate projections on various crop types across Europe.

Droughts are difficult to measure and quantify (Vicente-Serrano et al., 2016), and consequently a wide range of drought indices has been developed to provide tools for quantifying the effects of drought across different sectors (Zargar et al., 2011). In this respect, drought indices are the most widely used method for monitoring drought impacts on agriculture; examples of their use available in the scientific literature include in Europe (Hernandez-Barrera et al., 2016; Potopová et al., 2016a; Sepulcre-Canto et al., 2012; Vergni and Todisco, 2011), America (McEvoy et al., 2012; Quiring and Papakryiakou, 2003) and Asia (Ebrahimpour et al., 2015; Wang et al., 2016a). However, there is no general consensus on the most suitable indices for this purpose (Esfahanian et al., 2017). Despite the existing literature, very few studies (Peña-Gallardo et al., 2018a; Tian et al., 2018) have compared drought indices to

46 identify their appropriateness for monitoring drought impacts on agriculture and for various
47 crop types.

48 Among Mediterranean countries, agriculture in Spain is particularly sensitive to climate
49 because of the low average precipitation level and its marked interannual variability (Vicente-
50 Serrano, 2006). Spain has been subject to multiple episodes of drought (Domínguez-Castro
51 et al., 2012), with those in the last century being amongst the most severe to have occurred in
52 Europe (González-Hidalgo et al., 2018; Vicente-Serrano, 2006). In 2017 the agricultural and
53 livestock losses caused by drought were estimated to be at least 3600 million Euros (UPA,
54 2017), highlighting the need to establish appropriate tools for monitoring drought impacts on
55 crops. Recent studies as the conducted by Ribeiro et al. (2019) in Iberian Peninsula stressed
56 the risk of this region to suffer from yield losses in the context of climate change. For that
57 purpose, these authors analysed the exposure of cereal rainfed crops to drought conditions
58 using remote sensing information and performing a multi-scalar drought index.

59 Information on crop production is commonly limited in terms of spatial or temporal availability.
60 Recent studies in Spain have analyzed the impact of climate on various crops since the early
61 21st century at national or provincial scales (Cantelaube et al., 2004; Hernandez-Barrera et
62 al., 2016; Páscoa et al., 2016; Ribeiro et al., 2019), but few have used yield data at finer
63 resolution (García-León et al., 2019). In this study we compared different drought indices using
64 two datasets at different spatial scales: provincial information provided by the national
65 statistical services, and a regional dataset specifically developed for the study. The objectives
66 of this study were: (1) to determine the most appropriate and functional drought index among
67 four Palmer-related drought indices (Palmer drought severity index: PDSI; Palmer hydrological
68 drought index: PHDI; Palmer Z index: Z-index; Palmer modified drought index: PMDI), and the
69 standardized precipitation evapotranspiration index (SPEI), the standardized precipitation
70 index (SPI), and the standardized Palmer drought index (SPDI); (2) to identify the temporal
71 response of two main herbaceous rainfed crops (wheat and barley) to drought; and (3) to
72 determine whether there were common spatial patterns, by comparing the two datasets at
73 different spatial scales.

74

75 **2. Methods and datasets**

76 **2.1.Crop yield data**

77 The statistical analysis was conducted using an annual dataset of crop yields for peninsular
78 Spain and the Balearic Islands at two spatial scales for the two main herbaceous rainfed crops
79 (barley and wheat). We obtained provincial annual yield data from the National Agricultural
80 Statistics Annularies published by the Spanish Ministry of Agriculture, Fishing and Environment
81 (MAPA), available at: [https://www.mapa.gob.es/es/estadistica/temas/publicaciones/anuario-
82 de-estadistica/default.aspx](https://www.mapa.gob.es/es/estadistica/temas/publicaciones/anuario-de-estadistica/default.aspx) (last accessed: March 2018); these include agricultural statistics
83 since the early 20th century. We used data from 1962 to 2014, to match climate data that was
84 available for this period. The Gipuzkoa and Vizcaya provinces were not used in the analysis
85 at the province scale as wheat has not been cultivated there since 1973 and 1989, respectively.
86 We used crop production data collected by the *Encuesta sobre Superficies y Rendimientos de*
87 *Cultivos-Survey on surface and crop yields* (Esyrce), an agrarian yield survey undertaken by
88 the MAPA since 1990. This survey records information about crop production at parcel scale

89 every year from a sample of parcels. Yield observations were aggregated to the main spatial
90 unit defined for agricultural districts by the MAPA (Fig. 1). As not all territories were included
91 in this survey until 1993, we only considered the period 1993–2015. Data on barley production
92 is limited in the ESYRCE database, and the agricultural districts considered in this study did not
93 correspond to all the areas where this crop is cultivated.

94 For both datasets the unit of measure was the harvested production per unit of harvested area
95 (kg/ha); it did not include any measure of production related to the area of the crop planted in
96 each province or region. To consider the total area covered by the crops we used the defined
97 rainfed crop delimited area for Spain, derived from the Corine land cover 2000 database
98 (<http://centrodedescargas.cnig.es/CentroDescargas/catalogo.do?Serie=MPPIF> ; last
99 accessed: March 2018).

100 The spatial resolution of yield data can influence the interpretation of drought impacts on
101 agriculture. Figure 2 shows a comparison of crop yields for the common period of available
102 information in both datasets (1993–2014). Overall, the average production was greater at the
103 agricultural district scale than at the provincial scale. Tables S1 and S2 summarize the
104 relationships between the datasets for each province for the available common period, based
105 on Pearson's correlations coefficients for wheat and barley yields, respectively. It was
106 surprising that both datasets showed very different temporal variability in crop yields in the
107 analyzed provinces. Wheat yields showed good agreement and highly significant correlations
108 between both datasets in provinces including Ávila ($r = 0.77$), Barcelona ($r = 0.69$), Burgos (r
109 $= 0.82$), Cuenca ($r = 0.86$), Guadalajara ($r = 0.87$), León ($r = 0.69$), Palencia ($r = 0.73$),
110 Salamanca ($r = 0.87$), Segovia ($r = 0.94$), Teruel ($r = 0.83$), Valladolid ($r = 0.92$), and Zamora
111 ($r = 0.75$), while in other provinces including Castellón, Málaga, Murcia, and Navarra the
112 correlations were non-significant or negative. Thus, the national statistics for these districts
113 were unreliable. For barley yields the available regional data were more limited, but similar
114 relationships with good agreement and more highly significant correlations were found among
115 the datasets for the provinces where wheat was also cultivated, including Cáceres ($r = 0.48$),
116 Cuenca ($r = 0.88$), Granada ($r = 0.51$), Guadalajara ($r = 0.86$), La Rioja ($r = 0.76$), and
117 Tarragona ($r = 0.88$); however, for Sevilla the correlation was negative and significant ($r =$
118 -0.35).

119 Mechanization and innovation in agriculture have increased since last century, resulting in a
120 trend of increased yields (Lobell and Field, 2007), that is also evident in data for Spain. To
121 remove bias introduced by non-climate factors, and to enable comparison of yields between
122 the two crop types, the original series were transformed to standardized yield residuals series
123 (SYRS) by using the following quadratic polynomial equation:

$$124 \quad SYRS = \frac{y_a - \mu}{\sigma}$$

125 where y_a is the residuals of the de-trended yield obtained by fitting a linear regression model,
126 μ is the mean of the de-trended series, and σ is the standard deviation of the de-trended yield.

127 This methodology has been applied in other similar studies (Chen et al., 2016; Tian et al.,
128 2018). First announced as 'SYRS' by Potopová et al. (2015), the full procedure of the following
129 methodology is described by Lobell and Asner, (2003) and Lobell et al. (2011). In Fig. S1 an

130 example of the positive trend (more evident in the provincial data due to the length of available
131 data) and the temporal evolution of SYRS is illustrated for both type of crops and spatial scale.

132 **2.2. Climate data**

133 We used a weekly gridded dataset of meteorological variables (precipitation, maximum and
134 minimum temperature, relative humidity and sunshine duration) at 1.1 km resolution for
135 peninsular Spain and the Balearic Islands for the period 1962–2015. The grids were generated
136 from a daily meteorological dataset provided by the Spanish National Meteorological Agency
137 (AEMET), following quality control and homogenization of the data. Further details on the
138 method and the gridding procedure are provided by [Vicente-Serrano et al. \(2017\)](#). Reference
139 evapotranspiration (ET_o) was calculated using the FAO-56 Penman-Monteith equation ([Allen
140 et al., 1998](#)). Weekly data were aggregated at the monthly scale for calculation of the various
141 drought indices.

142 **2.3. Methods**

143 **2.3.1. Drought indices**

144 **Palmer Drought Severity Indices (PDSIs)**

145 [Palmer \(1965\)](#) developed the Palmer drought severity index (PDSI). Variations of this index
146 include the Palmer hydrological drought index (PHDI), the Palmer moisture anomaly index (Z-
147 index), and the Palmer modified drought index (PMDI). Computation of the Palmer indices
148 (PDSIs) is mainly based on estimation of the ratio between the surface moisture and the
149 atmospheric demand. Subsequent studies have revealed that spatial comparison among
150 regions is problematic ([Alley, 1984](#); [Doesken and Garen, 1991](#); [Heim, 2002](#)). In this context
151 we followed the variation introduced by [Wells et al. \(2004\)](#); this enables spatial comparison
152 when determining a suitable regional coefficient, developing the self-calibrated PDSIs. PDSIs
153 are also referred to as uni-scalar indices, which can only be calculated at fixed and unknown
154 timescales ([Guttman, 1998](#); [Vicente-Serrano et al., 2010](#)); this is a limitation of these indices.

155 **Standardized Precipitation Index (SPI)**

156 The standardized precipitation index (SPI) was introduced by [Mckee et al. \(1993\)](#), and
157 provided a new approach to the quantification of drought at multiple time scales. The index is
158 based on the conversion of precipitation series to a standard normal variable having a mean
159 equal to 0 and variance equal to 1, by adjusting an incomplete Gamma distribution. The SPI
160 is a meteorological index used worldwide, and is especially recommended by The World
161 Meteorological Organization ([WMO, 2012](#)) for drought monitoring and early warning.

162 **Standardized Precipitation Evapotranspiration Index (SPEI)**

163 [Vicente-Serrano et al. \(2010\)](#) proposed the standardized precipitation evapotranspiration index
164 (SPEI) as a drought index that takes into consideration the effect of atmospheric evaporative
165 demand on drought severity. It provides monthly climate balances (precipitation minus
166 reference evapotranspiration), and the values are transformed to normal standardized units
167 using a 3-parameter log-logistic distribution. Following the concept of the SPI, the SPEI
168 enables comparison of drought characteristics at various time scales among regions,
169 independently of their climatic conditions. The SPEI has been widely used in drought-related

170 studies, including to investigate the impacts of drought on various crops worldwide (Chen et
171 al., 2016; Kuhnert et al., 2016; Peña-Gallardo et al., 2018b; Potopová et al., 2016b; Vicente-
172 Serrano et al., 2012).

173 **Standardized Precipitation Drought Index (SPDI)**

174 The standardized precipitation drought index (SPDI) was developed by Ma et al. (2014), and
175 relies on the concept of time scales. It is considered to be a combined version of the PDSI and
176 the SPEI, because the SPDI accumulates the internal water valance anomalies (D) obtained
177 in the PDSI scheme at various time scales, and the values are later transformed into z-units
178 following a standard normal distribution. For this purpose a log-logistic distribution has been
179 used, because this has been shown to be effective at the global scale (Vicente-Serrano et al.,
180 2015).

181 The SPEI, SPI, and SPDI are referred to here as multi-scalar indices, and the PDSIs as uni-
182 scalar indices. Thus, the multi-scalar indices were computed at scales of 1, 12, 18, and 24
183 months, and along with the PDSIs series were de-trended by adjusting a linear regression
184 model to enable accurate comparisons with de-trended crop yield information. Following the
185 same procedure used for the yield series, the residual of each monthly series was summed to
186 the average value for the period.

187 **2.3.2. Correlation between drought indices and crop yields**

188 The relationship between the drought indices and the SYRS for both datasets was assessed
189 by calculating polynomial correlation coefficients (c) (Baten and Frame, 1959). We used a
190 second-order polynomial regression model, given the common nonlinear relationship between
191 drought indices and crop production (Páscoa et al., 2016; Zipper et al., 2016). Hereafter, the
192 references made to correlations refer to results obtained using the polynomial approach. The
193 months of August and September were excluded from the analysis because they correspond
194 to the post harvest period, and we were considering only the period from sowing to harvest.

195 As the month of the year when the greatest correlation between the drought index and the crop
196 yield was not known beforehand, all 10 monthly series for each index were correlated with the
197 annual yield, and the highest correlation value was used. In the case of the multi-scalar indices,
198 for each monthly series and time scale we obtained 10 correlations (one for each of the 10
199 months and the 14 time scales considered in the analysis). Thus, 140 correlations were
200 obtained for each crop and spatial unit considered in the analysis (only correlations significant
201 at $p < 0.05$ were considered). In addition, we used the time scale (in the case of multi-scalar
202 drought indices) and the month in which the strongest correlation was found.

203 A t-test was performed to assess the significance of the differences in the polynomial
204 regression correlation coefficients obtained from the drought–yield relationships, to determine
205 whether there were significant similarities or differences among the indices.

206 **2.4. Identification of spatial patterns for crop yield response to drought.**

207 A principal component analysis (PCA) was performed to identify general patterns in the effect
208 of drought on crop yields, in relation to seasonality of the effects. PCA is a mathematical
209 technique that enables the dimensionality of a large range of variables to be reduced, by fitting
210 linear combinations of variables. We conducted a T-mode analysis, and used the varimax

211 method to rotate the components to obtain more spatially robust patterns (Richman, 1986).
212 The monthly series of the monthly maximum correlation values found from the yield–drought
213 relationship were the variables (one data point per month), and the provinces and agricultural
214 districts were the cases. We selected two principal components (PC) that in combination
215 explained > 60% of the variance (individually the other components explained < 5% of the
216 variance), and aggregated each province or agricultural district according to the maximum
217 loading rule (i.e., assigning each spatial unit to the PC for which the highest loading value was
218 found). The loadings were expressed in the original correlation magnitudes using the matrix of
219 component weights.

220 3. Results

221 3.1. Relationship of drought indices to crop yields

222 Figure 3 shows the strongest correlation found between the crop yield for each dataset and
223 the monthly drought indices. The correlations differed substantially between the two groups of
224 indices. Independently of the crop type, month of the year, or the drought time scale
225 considered, the correlation coefficients for the multi-scalar indices were much higher than
226 those for the uni-scalar indices. In both cases weaker correlations were found for the wheat
227 crops compared with the barley crops. The PDSI, PHDI, and PMDI correlations were non
228 significant ($p < 0.05$), but the correlations for the Z-index and the multi-scalar indices were
229 significant for most provinces and agricultural districts. The correlation values for the three
230 multi-scalar drought indices were similar. At district scale the average values were $c = 0.57$
231 and $c = 0.6$ for wheat and barley, respectively, and $c = 0.41$ and $c = 0.48$ at the provincial
232 scale. Thus, the datasets showed a stronger correlation for the drought indices at district scale
233 than at the provincial scale. In addition, more variability was found in the provincial data than
234 in the regional data, associated with the length of the available records.

235 The spatial distribution of the maximum correlation coefficients between the drought indices
236 and the crop yields are shown in figures 4 and 5, for the province and district scales,
237 respectively. The wheat and barley yield–drought correlations showed a similar spatial pattern
238 among indices at the province scale. Stronger correlations ($c \geq 0.7$) were found for the SPEI
239 and SPI for the provinces of Castilla y León (Valladolid, Zamora, Segovia, and Soria), Aragón
240 (Zaragoza and Teruel), Castilla La Mancha (Guadalajara, Albacete, and Toledo), and the
241 province of Valencia (particularly the cereal agricultural districts). The weakest correlations
242 were found for the southern (Andalusian) provinces. For the Palmer drought indices, the PMDI
243 and Z-index showed similar spatial patterns to the multi-scalar indices (especially in the central
244 and northern provinces), but the correlations were weaker ($c = 0.25–0.6$). For most provinces
245 the weakest correlations were found for the PDSI and PHDI ($c = 0.1–0.25$) for both crops, with
246 no clear spatial difference in the correlations.

247 The spatial distribution of correlations between wheat yields and the drought indices at the
248 agricultural district scale showed clearer patterns than those for the province level. Thus, the
249 response of drought indices at district scale is similar to the response observed at provincial
250 scale, showing stronger correlations for the multi-scalar indices and weaker correlations for
251 the Palmer indices, especially the PDSI and PHDI. The distribution of correlations among the
252 multi-scalar indices was very similar. The most correlated agricultural districts ($c \geq 0.8$) were
253 in Castilla y León, especially Valladolid, Segovia, north of Ávila, and northeast of Salamanca.

254 Similar correlations were found for areas of northeast Spain. There was a gradient in
255 correlations from north to south, with the exception of some districts in northwestern Málaga,
256 where wheat is extensively cultivated. In addition, in some districts of Galicia, where expansion
257 of the planted wheat area has not been large, there was a strong relationship between drought
258 indices and crop yields. The results for barley suggest a similar spatial relationship for the
259 various drought indices. The highest coefficients were found for the multi-scalar indices,
260 followed by the Z-index and the PMDI, with districts north of Cáceres, north of Galicia, and in
261 Guadalajara showing correlations in the order of $c = 0.8$, while the correlations were weaker
262 ($c = 0.25\text{--}0.4$) in districts in the south of Córdoba and Jaén.

263 **3.2. Relationship of drought indices to crop yields: temporal responses**

264 [Table 1](#) summarizes the time scales at which the strongest correlations were found for each
265 of the three multi-scalar indices. Strongest correlations were found for short time scales (1–3
266 months) for both datasets and both crops, in general with little difference between the indices.
267 For wheat, for 52.6% of the agricultural districts the yield was most strongly correlated with all
268 three drought indices at a time scale of 1–3 months; this was also the case for 49.6% of
269 provinces. In agricultural districts where wheat is cultivated the strongest correlations were
270 predominantly at the 1-month scale (20.37%), especially for the SPDI, while for most of the
271 provinces this occurred at the 3-month scale, particular for the SPEI and SPI (23.26%). For
272 barley, 57.4% of the districts and 58.7% of provinces where this crop was grown the strongest
273 correlations were predominantly at 1- to 3-month time scales. Among the various indices for
274 districts, the SPI showed the strongest correlation at the 1-month scale, while for provinces
275 the SPEI showed the strongest correlation at the 3-month scale (33.33%).

276 The multi-scalar drought indices showed similar results. Among these, the SPEI was the index
277 most strongly correlated with yield in the highest percentage of provinces and districts ([Table](#)
278 [2](#)). For wheat crops the SPEI was the most strongly correlated index with yield in ~37% of the
279 agricultural districts and ~58% of the provinces; these correlations were found predominantly
280 at the 3-month time scale. For this crop the SPDI was most strongly correlated with yield in a
281 similar proportion of districts (~33%), primarily at the 1-month scale, but only ~14% at the
282 province scale. In general, most of the maximum correlations corresponded to short time
283 scales.

284 [Figure 6](#) shows the spatial distribution of the most strongly correlated drought indices. For most
285 of the provinces the SPEI was the index most strongly correlated with crop yield. For the
286 agricultural districts there was substantial spatial variability and, along with the provincial
287 results, no well-defined spatial pattern that distinguished specific areas for which one index
288 was most effective at monitoring drought. For barley the SPDI showed the best correlation with
289 yield among districts (~44%), while in provinces the SPEI was best correlated (~69%). No clear
290 spatial patterns were evident. The similarities in the magnitude of the correlations between
291 multi-scalar drought indices and crop yields were statistically significant. A t-test ([Fig. S2](#)) was
292 used to determine whether there were significant differences in the magnitude of correlations
293 obtained using the various multi-scalar drought indices. This showed significant differences
294 between the SPEI and the SPDI in ~30% of agricultural districts where wheat was grown; these
295 were districts that showed a weaker correlation of yield with drought indices. The results
296 suggest that, for districts having strong correlations between drought indices and crop yields,

297 the two indexes were equally useful. A lower proportion of districts where barley is planted
298 showed that statistical differences among indices exist. In contrast, for provinces no significant
299 differences were found. Overall, this suggests the appropriateness of using any of these multi-
300 scalar indices indistinctly.

301 **3.3. Spatial patterns of drought index correlations at the monthly scale**

302 Regionalization of the crop yield response to drought based on monthly correlations with the
303 drought indices was undertaken in relation to the most correlated drought index in each region,
304 independently of the month in which this maximum correlation occurred. Thus, in this analysis
305 the results obtained using the various multi-scalar drought indices were merged. General
306 spatial patterns in the effect of drought conditions on yield were identified using a T-mode PCA.
307 [Figures 7 and 8](#) show the results for the provincial and regional datasets, respectively. We
308 selected two components that explained more than the 60% of the variance in each case. This
309 classification reinforced the north–south pattern of correlations previously found for both
310 datasets. [Figure 9](#) shows the time scales for which the maximum monthly correlations were
311 found for the provinces and agricultural districts for each of the defined components, using a
312 maximum loading rule.

313 **3.3.1. Wheat**

314 *Agricultural district scale*

315 At the district scale the PCA for wheat ([Figure 7a](#)) showed more defined spatial patterns
316 than did the PCA at the provincial scale. PC1 explained 43.36% of the variance, and was
317 characterized by stronger correlations ($c = 0.7\text{--}0.9$) in districts mainly located on the north and
318 central plateau; these were stronger than those recorded for the same locations at the
319 provincial scale. Weaker correlations ($c = 0.15\text{--}0.5$) were dispersed, although these were
320 found predominantly in the south and northwest. The scores for PC1 showed particular
321 sensitivity to drought during spring, although strong correlations were also found during
322 autumn. PC2 explained 18.63% of the variance, and the loading coefficients also showed a
323 clear spatial pattern, with the agricultural districts north of Sevilla and east of Castilla La
324 Mancha having the highest values. The weakest correlations were found for the districts of
325 Andalucía, Extremadura, and Aragón. Lower scores in PC2 characterized the interannual
326 response to drought relative to PC1. These districts in PC2 also showed a stronger response
327 during spring but not autumn, as was found for PC1. The distribution of PCs according to the
328 maximum loading rule enabled identification of a north–south component in the sensitivity of
329 wheat yields to the drought index. The time scales at which wheat yields in agricultural districts
330 responded most during spring varied from shorter time scales (3-month) in districts in PC1 to
331 longer time scales (5- to 6-month) for those in PC2 ([Fig. 9e, 9f](#)), which also showed greater
332 variability in most months relative to districts from PC1. Greater variability for wheat at the
333 district scale was observed relative to that at the provincial scale. Due to the major number of
334 observations considered, the response to drought in Spain when considering district scale
335 shows more heterogeneity than at provincial scale.

336 *Provincial scale*

337 The results for wheat at the provincial scale ([Fig. 7b](#)) showed that the first (PC1) and second
338 (PC2) components explained 51.7% and 20.8% of the variance, respectively. The loadings of

339 the first component were higher for the central plateau and the east of Spain. These represent
340 provinces in the Castilla y León and Castilla y La Mancha districts, and the provinces of
341 Castellón, Valencia, Alicante, Cantabria and Huelva, and Sevilla and Almería in Andalucía. In
342 these provinces there was a strong correlation between drought indices and crop yields,
343 especially during spring, with particularly strong correlations in May. In contrast, during winter
344 the correlations were weaker, especially in February. PC2 showed greater spatial
345 heterogeneity, with strong correlations in the east (Zaragoza and Tarragona provinces) and
346 south (Cádiz, Córdoba, Málaga, Granada, and Jaén provinces) of Spain. For this component
347 the temporal response to drought was not as strong as that for PC1, but the maximum
348 correlation was also found during May. The distribution of the maximum loadings showed a
349 dispersed pattern, with PC1 grouping provinces in the central plateau and east of Spain, and
350 PC2 grouping those in southern and some northeastern provinces. The averaged temporal
351 response to drought during spring is set at medium time scales (4–7 months). In particular, in
352 May most of the provinces correlated at 5 months (Fig. 9a, 9b), indicating the importance of
353 climatic conditions during winter and spring to the crop yields obtained. This was also evident
354 for the longer time scales at which most of the provinces correlated during the winter months
355 (11–18 months). It is noteworthy that there was great variability in the temporal response of
356 provinces in PC1 in October, February, March, and April.

357 **3.3.2. Barley**

358 *Agricultural district scale*

359 For barley crops (Fig. 8a) both components showed strong correlations ($c = 0.6–0.9$) in most
360 of the agricultural districts. In general, the districts showing the strongest correlations in PC1
361 and PC2 were those located in Castilla La Mancha, and north of Cáceres and Córdoba. Scores
362 for PC1 for barley crops were similar to those for PC1 for wheat during spring and autumn, but
363 the results for PC2 suggest that there was little interannual sensitivity to drought. Most of the
364 correlations for spring indicate that barley responded to drought conditions at the 3–4 month
365 scale, mainly in those districts associated with PC1. Barley yields in districts associated with
366 PC2 were more affected by drought conditions in May at 7–9 month time scales (Fig. 9g, 9h).

367 *Provincial scale*

368 For barley at the provincial scale (Fig. 8b) we found more variability in the magnitude of
369 correlations. For PC1 (explaining 43.22% of the variance) strong correlations ($r = 0.7–0.9$)
370 were found for the north and central provinces of Castilla y León, the central provinces of
371 Castilla y la Mancha, and Madrid, Teruel, Valencia and Castellón. The provinces associated
372 with PC2 (explaining 27.91% of the variance) were more dispersed than those in PC1, and
373 those showing strong correlations included Zaragoza and Guadalajara in the north,
374 Barcelona and Balearic Islands in the northeast and east, Cáceres in the west, and Cádiz,
375 Córdoba, Málaga, Granada and Jaén in the south. Provinces showing weaker correlations in
376 PC1 were spread in the northeast (e.g., Navarra, Zaragoza, and Lleida) and west of Spain
377 (e.g., Cáceres and Badajoz). Component scores for PC1 were higher than for PC2, although
378 for wheat crops both showed maximum scores during spring (March) and minimum scores in
379 autumn and winter. More provinces in May were correlated with drought indices at medium
380 drought time scales (4–8 months). During spring, provinces in PC1 showed correlations at

381 longer time scales (7–8 months), while provinces in PC2 showed responses at shorter time
382 scales (3–4 months) (Fig. 9c, 9d).

383 3.3.3. General climatological characteristics for the PCA components

384
385 Figures S3-12 show the distribution of climatic characteristics including precipitation,
386 atmospheric evaporative demand (AED), maximum and minimum temperature, and the
387 hydroclimatic balance (precipitation minus AED) at the district scale for the two PCA
388 components. For those districts where wheat was cultivated, no major differences in AED
389 values were found among the components. However, minor differences were observed in
390 precipitation among districts belonging to different PCA components. Those in PC2 had on
391 average less precipitation than those in PC1, especially during autumn, but the difference was
392 not substantial. Greater differences were observed for temperature, with PC1 mainly
393 characterized by districts that had higher maximum temperatures in autumn and spring, and
394 with higher minimum temperatures than the districts in PC2. These results highlight the
395 important role of temperature in the different responses of crop yield to drought, and
396 demonstrate that, contrary to what may have been expected, temperature and not precipitation
397 was the main factor constraining crop growth. Thus, changes in extreme temperature levels
398 may influence future crop yields. Districts in PC2 where the barley yield correlated with drought
399 indices were characterized by lower levels of precipitation and higher maximum and minimum
400 temperatures than districts represented by PC1, and by higher AED, especially from April to
401 July. Extremes of temperature also seemed to be the major factor determining barley crop
402 yield.

403 4. Discussion

404 In this study we investigated the impacts of drought on two rainfed crops in Spain, as measured
405 by a variety of drought indices. We used two datasets of annual crop yields, one from
406 agricultural statistics at the provincial scale spanning the period 1962–2013, and the other a
407 new database at the agricultural district scale from the available parcel data from the national
408 survey covering the period 1993–2015. To identify the best indicator of the impact of drought
409 on yields and their sensitivity to climate, we evaluated the performance of seven drought
410 indices. The selection of drought indices was based on those commonly used to monitoring
411 droughts worldwide, including the standardized precipitation and evapotranspiration index
412 (SPEI), the standardized precipitation index (SPI), the Palmer drought indices (PDSI, Z-Index,
413 PHDI, and PMDI), and the standardized Palmer drought index (SPDI).

414 Independently of the type of crop and the temporal scale considered, our results showed that
415 drought indices calculated at different time scales (the SPEI, the SPI, and the SPDI) had
416 greater capacity to reflect the impacts of climate on crop yields, relative to uni-scalar drought
417 indices. The better performance of these multi-scalar drought indices was mainly because of
418 their flexibility in reflecting the negative impacts of drought over a range of regions having very
419 different characteristics (Vicente-Serrano et al., 2011). This issue is especially relevant in
420 agriculture, as vegetation components do not respond equally to water deficit. The sensitivity
421 and vulnerability of each type of crop to drought, and the characteristics of the specific region
422 influence the variability evident in the response to droughts (Contreras and Hunink, 2015).
423 Nonetheless, the results of the assessment of the performance of the PDSIs demonstrated

424 that correlations varied markedly among them, showing some exceptions that may affect their
425 usefulness for monitoring purposes. Overall, our results showed that the PHDI had the weakest
426 relationship to crop yields, followed by the PDSI and the PMDI. The better performance of the
427 PDSI over the PHDI was expected, as the latter was primarily developed for hydrological
428 purposes. Likewise, our results confirmed a better performance of the PMDI (a modified
429 version of the PDSI) over the original PDSI for both crops. Our results are consistent with those
430 of previous studies assessing agricultural drought impacts on crop yields at the global (Vicente-
431 Serrano et al., 2012) and regional (Peña-Gallardo et al., 2018b) scales. The Z-index was the
432 best uni-scalar index among the set analyzed in our study. This index measures short-term
433 moisture conditions, which is a major factor in crop stress (Quiring and Papakryiakou, 2003).
434 Thus, the Z-index was more closely correlated with crop yield than any of the other Palmer
435 indices, indicating its usefulness relative to other PDSIs (Karl, 1986).

436 Although our findings point to poorer performance of the Palmer drought indices relative to the
437 multi-scalar drought indices, they remain among the most widely accepted indices. Numerous
438 studies have used the Palmer indices in assessments of the use of drought indices for
439 monitoring agricultural drought in various regions worldwide, and have reported the superiority
440 of the Z-index (Mavromatis, 2007; Quiring and Papakryiakou, 2003; Sun et al., 2012;
441 Tunalioğlu and Durdu, 2012); our results confirm its usefulness among the Palmer drought
442 indices.

443 Nevertheless, it is important to stress that the usefulness of PDSIs is less than drought indices
444 that can be computed at different time scales (Vicente-Serrano et al. 2012). We demonstrated
445 that the three multi-scalar drought indices in our study (SPEI, SPI, and SPDI) were able to
446 detect drought at different time scales, enabling past weather conditions to be related to
447 present conditions in regions characterized by diverse climatic conditions. This is consistent
448 with previous comparative studies in various regions that reported multi-scalar drought indices
449 were effective for monitoring drought impacts on agricultural lands (Blanc, 2012; Kim et al.,
450 2012; Potopová, 2011; Potopová et al., 2016a; Tian et al., 2018; Zhu et al., 2016; Zipper et al.,
451 2016). Although previous studies reported differences among some of the above three indices
452 (e.g., the SPDI and the SPEI; Ghabaei Sough et al., 2018), others have reported similarities
453 in their performance in assessing agricultural drought impacts (Labudová et al., 2016; Peña-
454 Gallardo et al., 2018a). The similar magnitudes of their correlations suggest a similar ability to
455 characterize the impact of drought on crop yields. However, minor differences among these
456 indices suggested the SPEI performed best. First, for both crops slightly stronger correlations
457 were observed with the SPEI, although the SPDI was superior in relation to barley yields at
458 the agricultural district scale. In general, the SPEI was found to be the most suitable drought
459 index in the majority of agricultural districts and provinces, in accordance to Ribeiro et al.
460 (2018) who also found it suitable in Spain for relating drought conditions and yields variability.
461 This suggests that inclusion of AED in the drought index calculation, as occurs in the SPEI,
462 provides greater capacity to predict drought impacts on crop yields compared with the use of
463 precipitation only. Variation in the maximum and minimum temperatures has been found to be
464 the major factor differentiating agricultural districts and provinces having greater sensitivity to
465 drought. Previous studies have stressed the risks associated with an increase in global
466 temperatures, particularly maximum temperatures, and the possible effects on crop yields
467 (Lobell and Field, 2007; Moore and Lobell, 2014). Thus, a ~5.4% reduction in grain yields

468 resulting from an increase in average temperature is expected to occur under the current global
469 warming scenario (Asseng et al., 2014; Zhao et al., 2017).

470 The temporal and spatial effects of drought on yields seem to be very complex, given the
471 observed variability in Spain. In this respect, significant yield effects of drought were found in
472 both datasets. Nevertheless, at the agricultural district scale there was a more evident spatial
473 effect of drought on agricultural yields. This is a key finding for spatial-scale analyses, although
474 the lack of long time series datasets on regional yields is a common constraint.

475 Drought effects on barley and wheat were similar in space and time, although their sensitivity
476 to drought differed, as shown by differences in the magnitude of the correlations with the
477 drought indices, with wheat yields showing stronger correlations than barley yields. This can
478 be explained by the different physiological characteristics of the two crops, as barley is less
479 dependent on water availability at germination and the grain filling stage than wheat
480 (Mamnouie et al., 2006). Although the transpiration coefficient for barley is higher, this crop is
481 not as subject as wheat to water stress under drought conditions (Fischer et al., 1998). Our
482 results indicate that the temporal responses of barley and wheat to drought conditions were
483 very similar, despite the fact that in Spain barley is typically cultivated later than wheat, and in
484 soils having poor moisture retention. Therefore, the phenological characteristics of each type
485 of crop determine how drought affects yields. The results showed that temperature had a more
486 important role than precipitation, suggesting that extreme variations in average temperature
487 conditions during the most sensitive growth stages may have a negative impact on crops.

488 Overall, crop yields in Spain tend to respond to short drought time scales (1–3 months).
489 However, the sensitivity of crops to drought is greater during spring at medium (4–6 months)
490 time scales. These results are in line with previous studies conducted in Iberian Peninsula with
491 a similar database at provincial scale that also point at shorter time-scales, mostly during
492 spring months (1-6 months) (Ribeiro et al., 2018). This highlights that moisture conditions
493 during winter (the period corresponding to planting, and the first growth stages of tillering and
494 stem elongation), are crucial for the successful development of the plants (Çakir, 2004;
495 Moorhead et al., 2015; Wang et al., 2016a, 2016b).

496 We found a stronger response of crops to climatic conditions in provinces and agricultural
497 districts in the central plateau, and unexpectedly a weaker response in southwestern districts.
498 This reflects the inconsistencies reported for the Iberian Peninsula by Páscoa et al. (2016) ,
499 who argued that spatial differences can be explained mainly by the differing productivities in
500 the various districts; we noted this for the mainly agrarian areas of peninsular Spain (Castilla
501 y León and Castilla La Mancha), and the characteristically heterogeneity of this territory. In the
502 southwestern agricultural areas, where the precipitation rates are lower and temperatures
503 higher, the correlations of yield with drought were weaker. In addition, conclusions achieved
504 by Gouveia et al. (2016) in the same region supported the statement of the strong control of
505 drought on plants activity, especially in semiarid areas. Even though our findings from crop
506 yields suggest the contrary due to the predominance of cereal croplands in north-central
507 regions of Spain, this can be attributed to episodes of abnormal extreme temperatures, such
508 as the very low temperatures in early spring or warmer than usual temperatures in winter.
509 These would affect the expected low evapotranspiration rates during the cold season (Fontana
510 et al., 2015; Kolář et al., 2014). A recent study by Hernandez-Barrera et al. (2016)

511 demonstrated that during autumn and spring, precipitation deficit is the most influential climate
512 factor affecting wheat growth, while an increase in the diurnal temperature range causes a
513 reduction in wheat yield. We found no major differences in precipitation among districts
514 belonging to any of the two defined components, but found other differences including in the
515 average maximum and minimum temperatures. These findings highlight the complexity in
516 choosing a useful drought index that encompasses the specificities of each crop, including its
517 sensitivity to moisture and environmental conditions throughout the entire growth cycle, and
518 its seasonality. This underscores the importance of testing and comparing the appropriateness
519 of different drought indices to ensure accurate identification of the multi-temporal impacts of
520 drought on natural systems.

521 **5. Conclusions**

522 The main findings of this study are summarized below.

523 (1) Assessment of the efficacy of drought indices for monitoring the effect of climate on
524 agricultural yields demonstrated the better performance of multi-scalar indices. The
525 ability to calculate these indices at various time scales enabled drought impacts to be
526 more precisely defined than with the use of indices lacking this characteristic. The multi-
527 scalar drought indices assessed also had fewer computational and data requirements
528 (particularly the SPEI and the SPI), which is a significant consideration when
529 performing analyses based on scarce climate data.

530

531 (2) From a quantitative evaluation of the relationship of drought indices to crop yields we
532 determined that both of the multi-scalar drought indices tested were useful for
533 assessment of agricultural drought in Spain. However, the SPEI had slightly better
534 correlations and is the most highly recommended for the purpose.

535

536 (3) The spatial definition of yield responses to drought was clearer at the district scale,
537 where the finer spatial resolution enabled better definition of the patterns of responses
538 because the climatic variability of each region was better captured at this scale.

539

540 (4) Barley and wheat yields were more vulnerable to drought during spring, both at short
541 (1–3 months) and medium (4–6 months) time scales. Moisture conditions during late
542 autumn and winter also had an impact on the crop yields.

543

544 (5) The strongest relationships between drought indices and crop yields were found for the
545 northern and central agricultural districts. The relationships for the southern districts
546 were weaker because of the difficulty of characterizing drought impacts over the
547 diverse and complex territory involved.

548

549 (6) The climatic and agricultural conditions in Spain are very diverse. The large spatial
550 diversity and complexity of droughts highlights the need to establish accurate and
551 effective indices to monitor the variable evolution of drought in vulnerable agriculture
552 areas. Climate change is likely to lead to yield losses because of increased drought
553 stress on crops, so in this context effective monitoring tools are of utmost importance.
554 The authors consider that further analysis complementing this study may help to
555 unravel the climate mechanisms that influence the spatio-temporal responses of yields
556 to climate in Spain.

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565

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864

Tables

Table 1. Percentage of analyzed agricultural districts and provinces where wheat and barley are cultivated, at which the maximum correlations per time scale were found using the multi-scalar indices.

Time-scale		1	2	3	4	5	6	7	8	9	10	11	12	18	24
a) Agricultural district data															
Wheat	SPI	18.38	15.38	13.68	9.83	4.27	7.26	2.56	5.13	1.28	3.42	6.41	2.14	5.98	4.27
	SPEI	16.67	14.96	17.09	9.83	6.41	3.42	5.13	4.7	3.42	2.56	3.85	4.27	5.13	2.56
	SPDI	26.07	21.79	13.68	5.13	3.42	2.99	2.56	2.56	2.14	5.13	1.71	3.85	3.42	5.56
Averaged %		20.37	17.38	14.82	8.26	4.70	4.56	3.42	4.13	2.28	3.70	3.99	3.42	4.84	4.13
Barley	SPI	29.63	14.81	14.81	12.96	0	3.7	3.7	1.85	3.7	1.85	1.85	3.7	3.7	3.7
	SPEI	24.07	12.96	22.22	9.26	1.85	3.7	5.56	3.7	3.7	1.85	0	5.56	1.85	3.7
	SPDI	24.07	14.81	14.81	7.41	7.41	3.7	11.11	1.85	0	3.7	0	0	3.7	7.41
Averaged %		25.92	14.19	17.28	9.88	3.09	3.70	6.79	2.47	2.47	2.47	0.62	3.09	3.08	4.94
b) Provincial data															
Wheat	SPI	6.98	13.95	23.26	6.98	2.33	6.98	6.98	6.98	6.98	2.33	4.65	4.65	4.65	2.33

	SPEI	9.3	11.63	23.26	11.63	9.3	0	6.98	6.98	2.33	2.33	4.65	4.65	4.65	2.33
	SPDI	13.95	32.56	13.95	2.33	2.33	4.65	4.65	6.98	0	2.33	6.98	2.33	0	6.98
Averaged %		10.08	19.38	20.16	6.98	4.65	3.88	6.20	6.98	3.10	2.33	5.43	3.88	3.10	3.88
	SPI	7.14	19.05	30.95	9.52	4.76	7.14	0	2.38	2.38	0	0	11.9	0	4.76
Barley	SPEI	11.9	11.9	33.33	7.14	4.76	4.76	7.14	4.76	7.14	0	0	2.38	2.38	2.38
	SPDI	9.52	38.1	14.29	4.76	4.76	7.14	0	0	7.14	0	2.38	4.76	2.38	4.76
Averaged %		9.52	23.02	26.19	7.14	4.76	6.35	2.38	2.38	5.55	0.00	0.79	6.35	1.59	3.97

Table 2. Percentage of analyzed agricultural districts and provinces where wheat and barley are cultivated, where the maximum correlations with the multi-scalar indices were found. Information in parentheses show the time scale at which the provinces and agricultural districts correlate most and the percentage of the provinces and district.

		SPEI	SPDI	SPI
Agricultural districts	Wheat	36.75 (3, 7.26)	33.33 (1, 7.69)	29.91 (2, 4.70)
	Barley	35.19 (3, 11.11)	44.44 (1, 12.96)	20.37 (1, 11.11)
Provinces	Wheat	58.14 (3, 18.60)	13.95 (24, 4.65)	27.9 (3, 4.65)
	Barley	69.04 (3, 16.66)	9.52 (1, 7.14)	21.42 (5,24, 4.76)

Figures

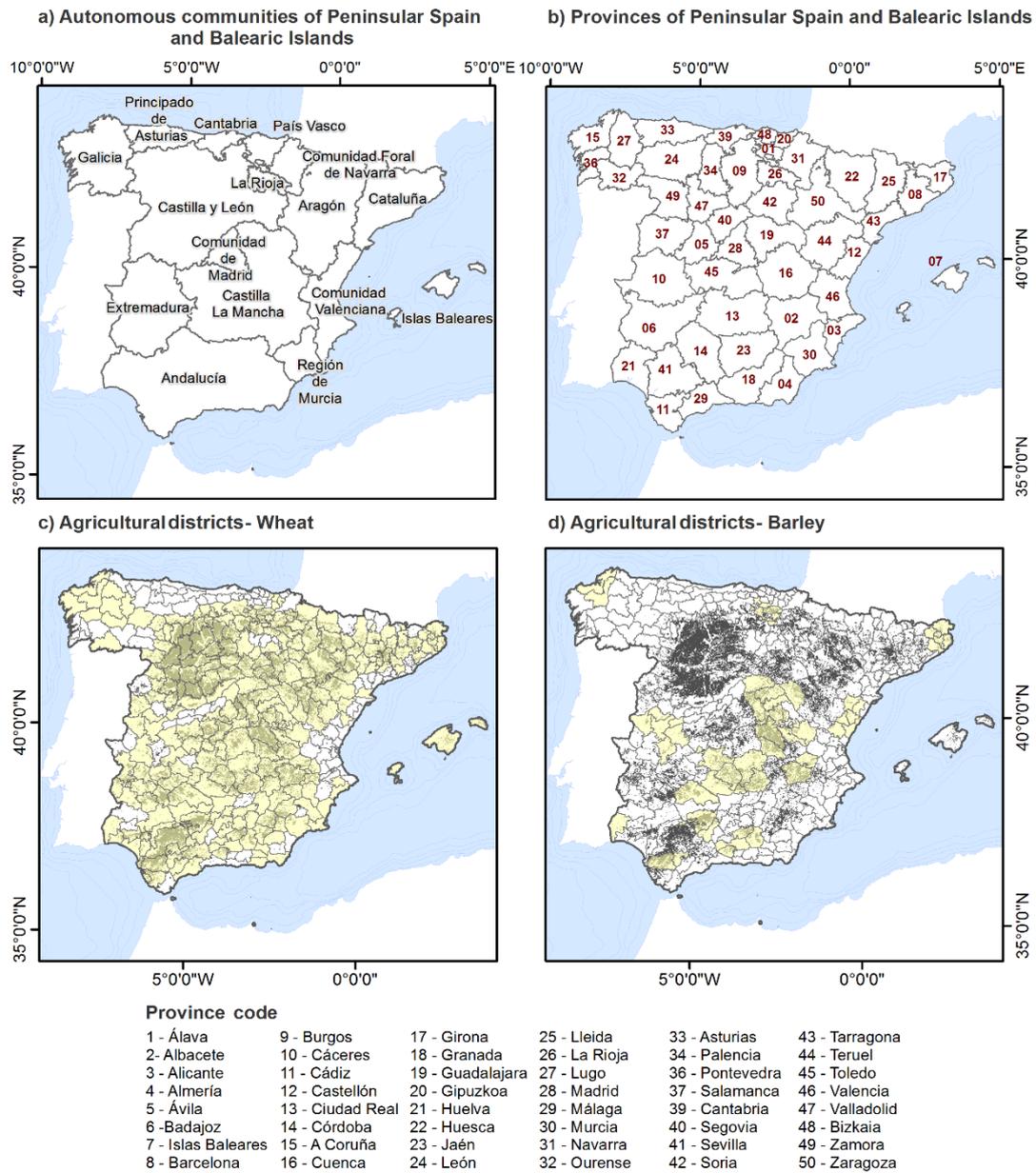


Fig. 1. Location of Spanish Autonomous Communities (a) and provinces (b), and the distribution of agricultural districts having data available (yellow) for wheat (c) and barley (d) yields for the period 1993–2015. Areas where rainfed cereal crops are cultivated (Corine Land Cover 2006) are shown in grey.

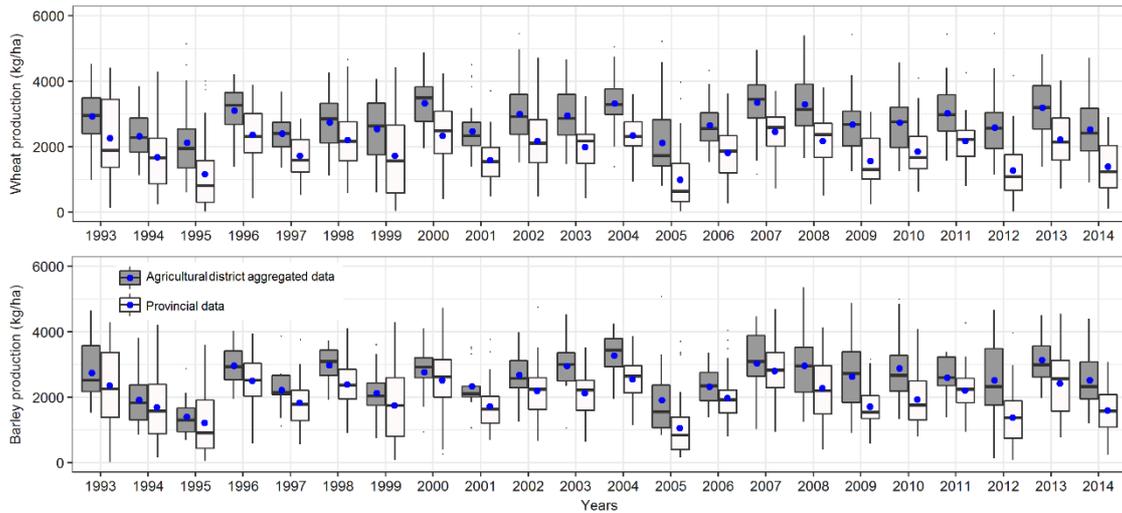


Fig. 2. Temporal series of wheat (top) and barley (bottom) yields for the provincial data, and the aggregated agricultural district data at the province scale for the common period 1993–2014. The solid black line shows the median and the blue dot shows the mean.

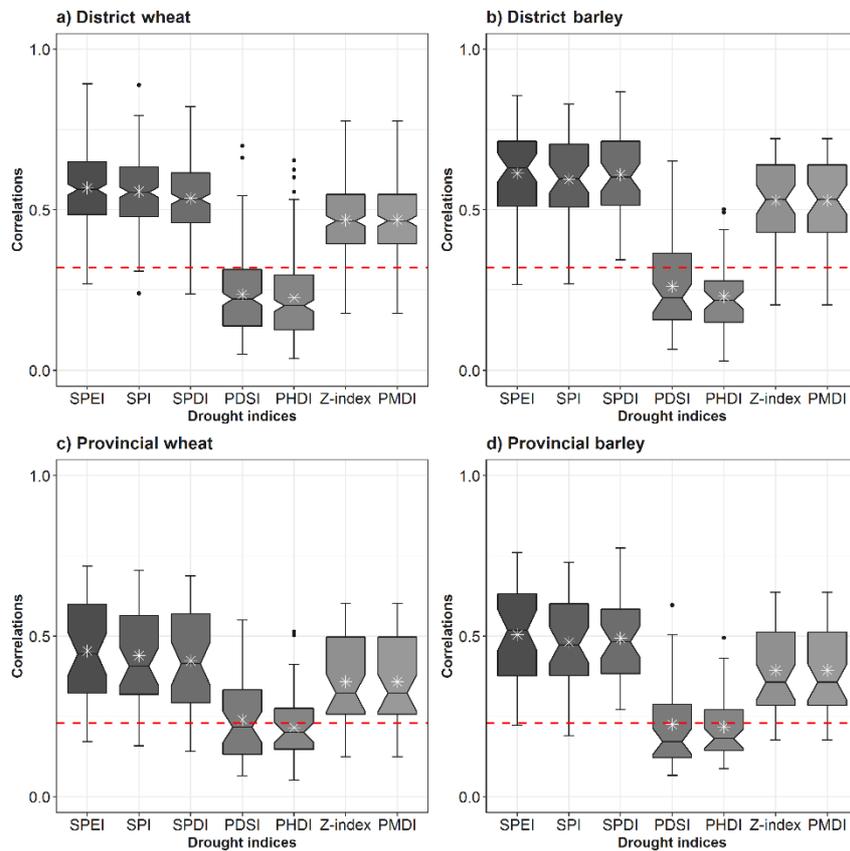


Fig. 3. Box plots showing the strongest correlation coefficients found between drought indices and wheat and barley yields at the agricultural district (a and b) and provincial (c and d) scales, for all districts and provinces analysed. The solid black line shows the median, the white asterisk shows the mean, and the dashed red lines show the $p < 0.05$ significance level.

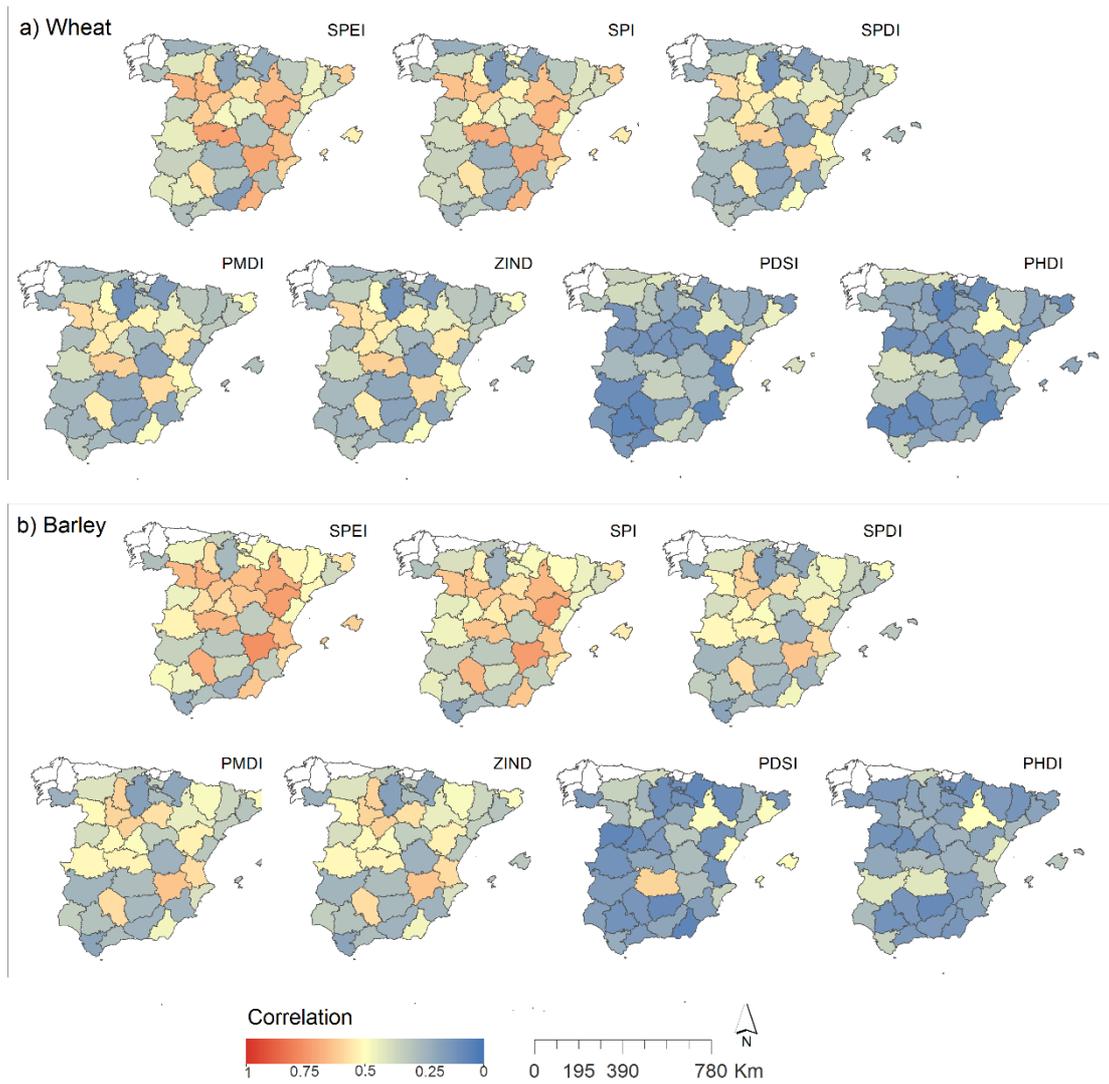


Fig. 4. Spatial distribution of the highest correlation coefficients between the drought indices and the wheat (a) and barley (b) yields at the provincial scale, independently of the time scale.

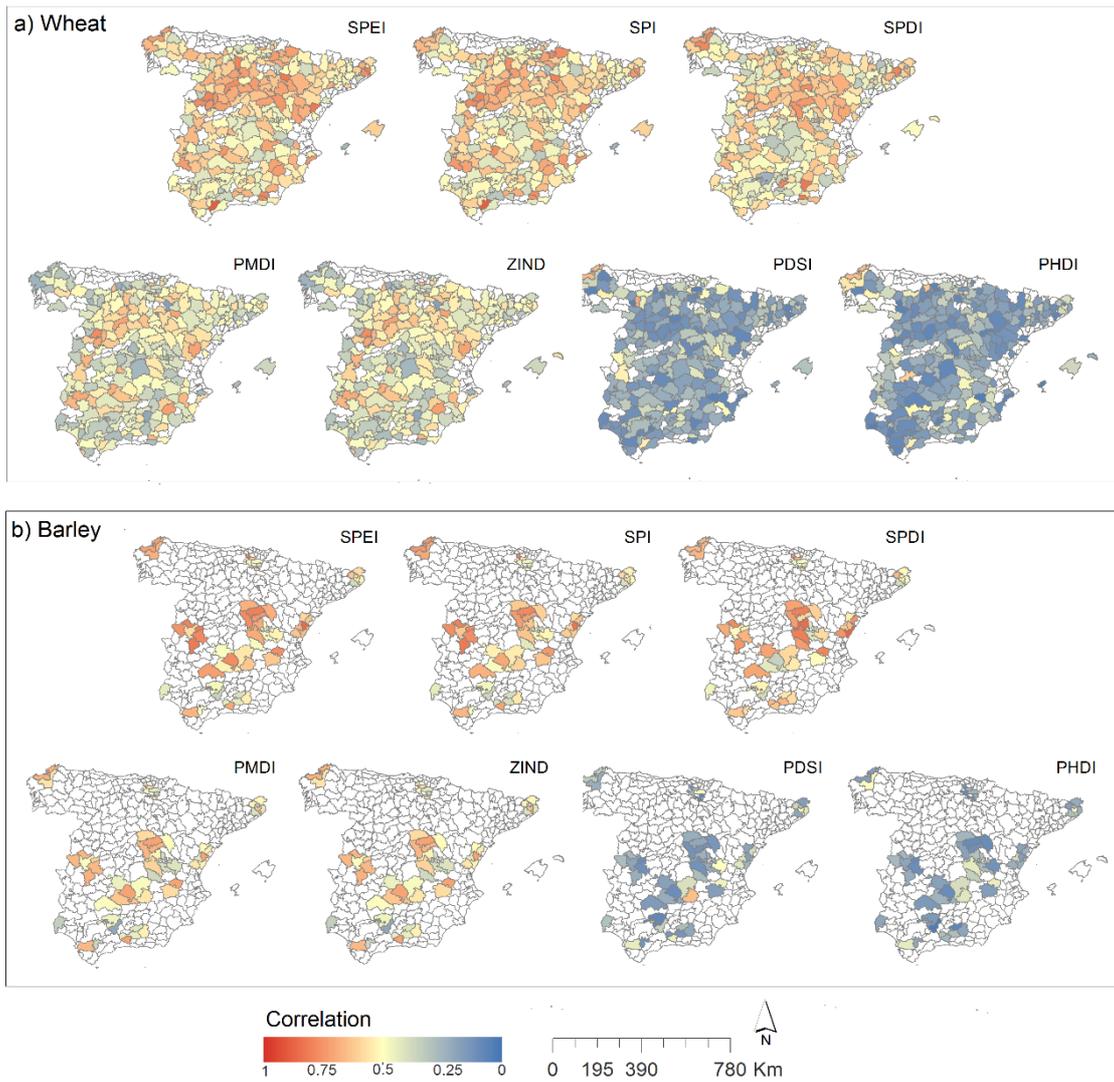


Fig. 5. Spatial distribution of the highest correlation coefficients between the drought indices and the wheat (a) and barley (b) yields at the agricultural district scale, independently of the time scale.

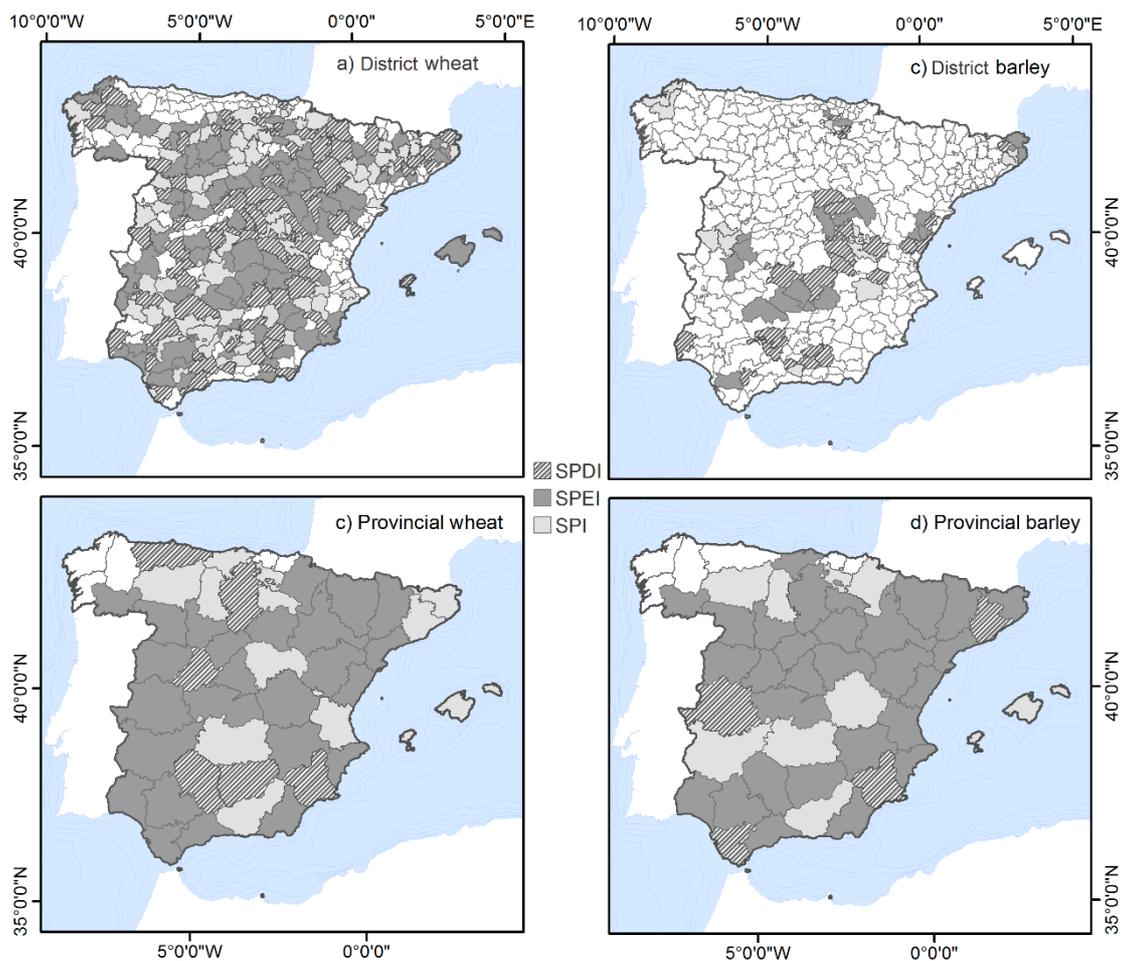


Fig. 6. Spatial distribution of the drought indices having the strongest correlations with wheat (left) and barley (right) at the province (bottom) and agricultural district (top) scales.

a) Agricultural district wheat PCA

b) Provincial wheat PCA

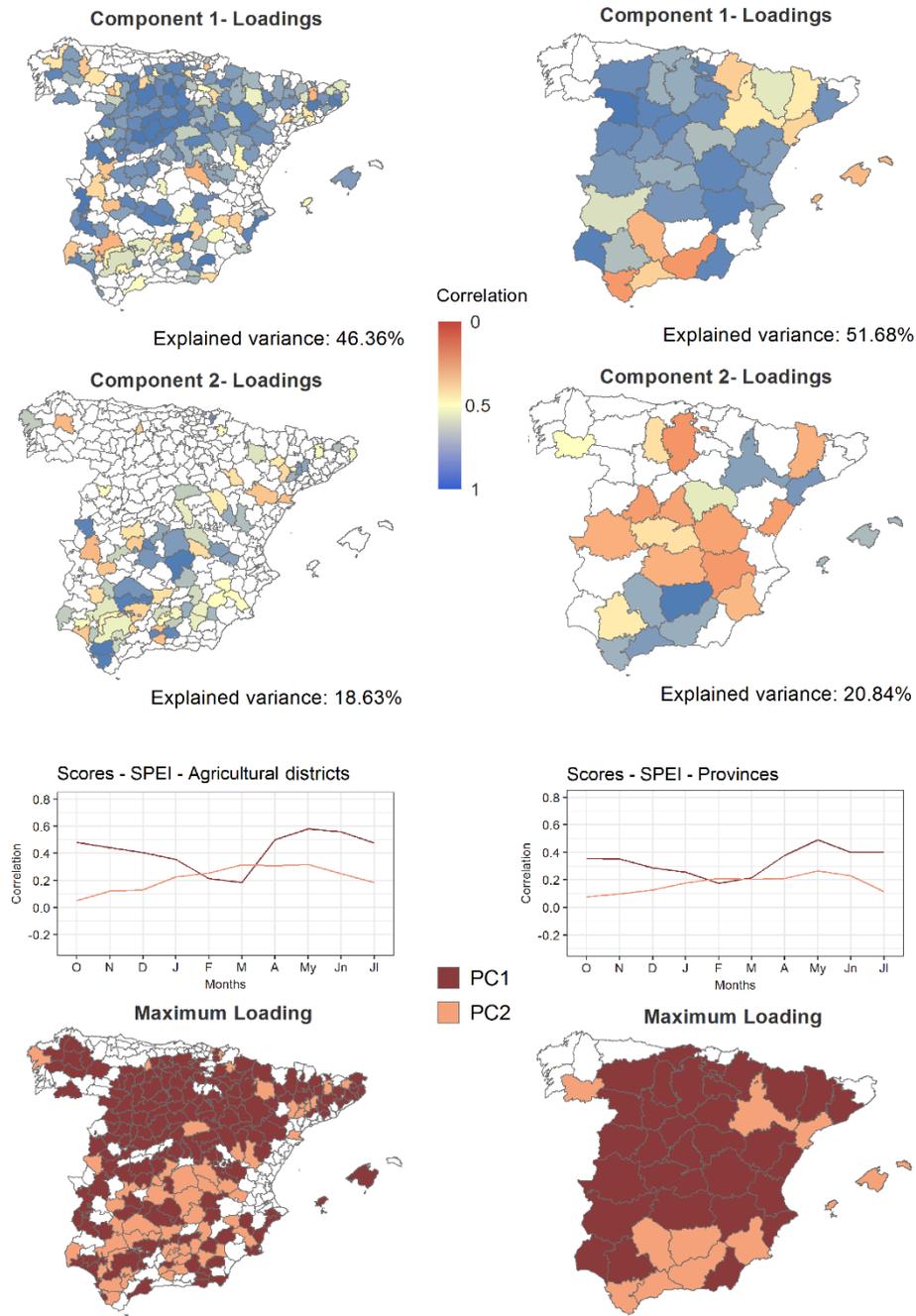


Fig. 7. PC loadings, PC scores, time scales, and maximum loading rules from the PCA for monthly maximum correlation coefficients between the SPEI and wheat yields at the agricultural district (a) and provincial (b) scales, independently of the time scale. The PC loadings and maximum loadings were significant at $p < 0.05$.

a) Agricultural district barley PCA

b) Provincial barley PCA

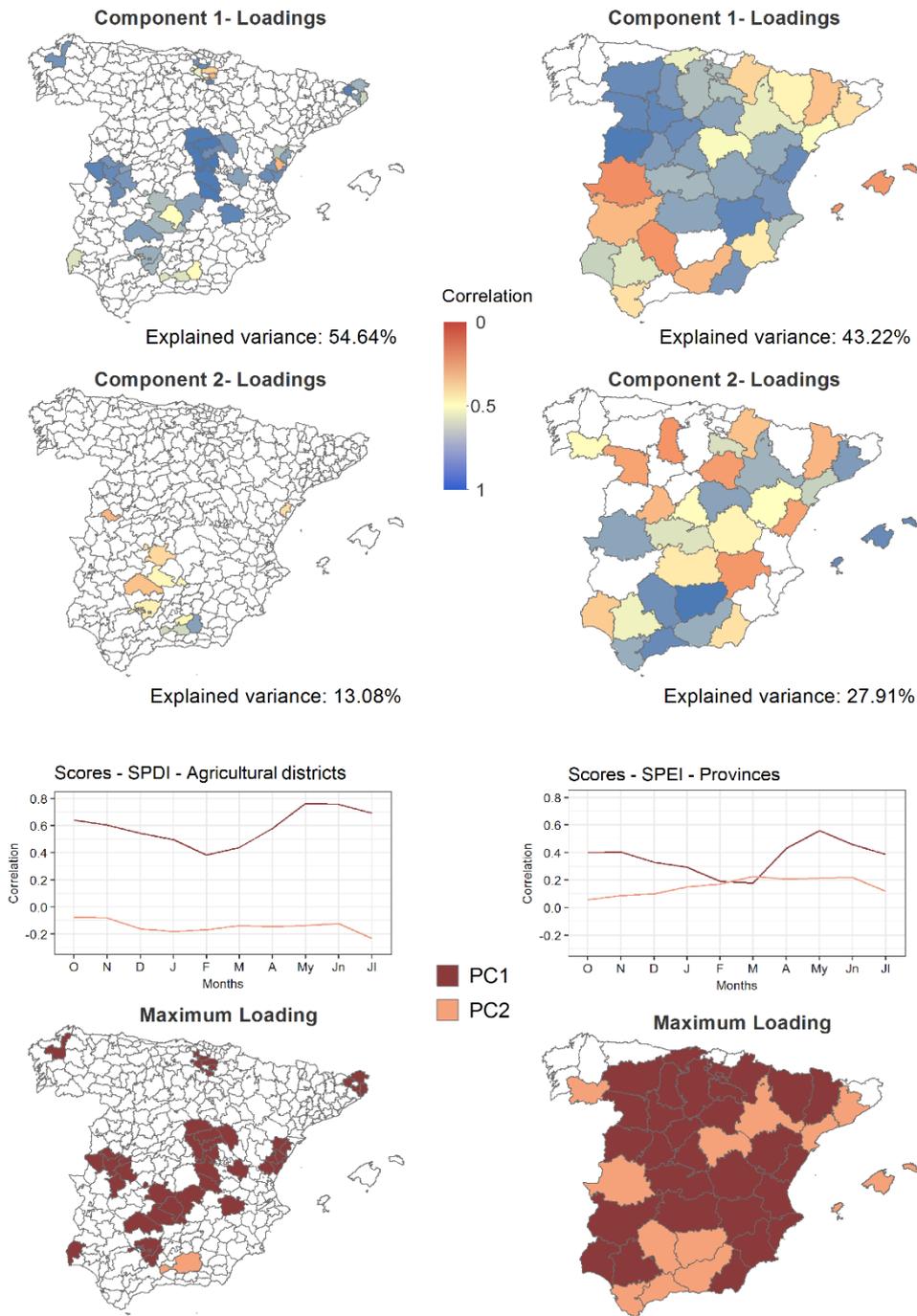
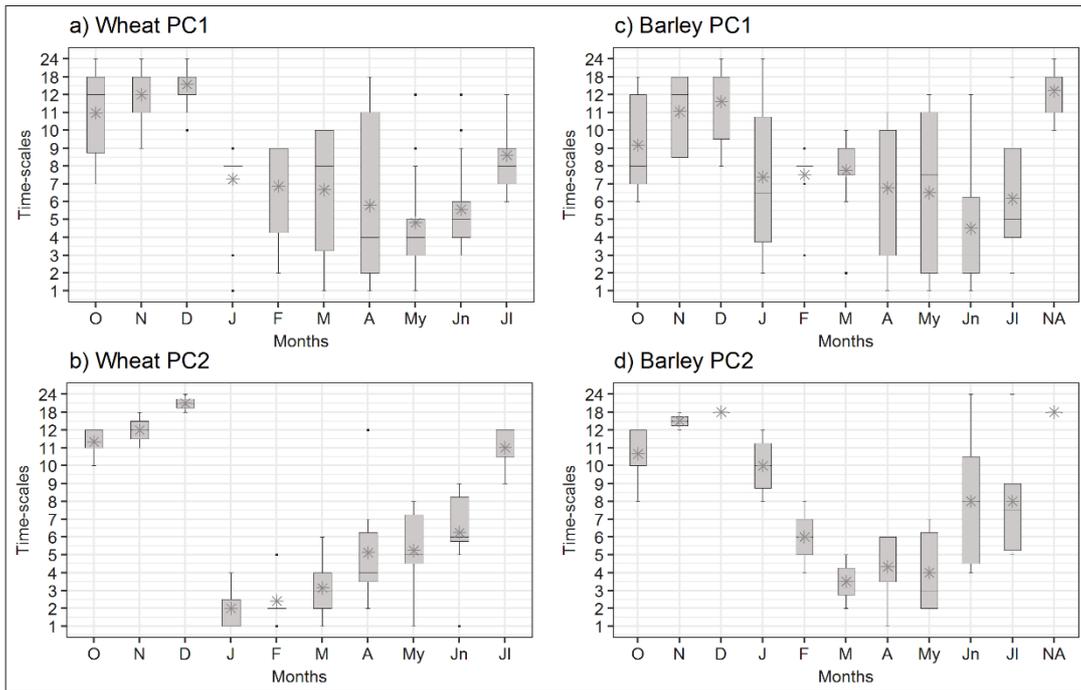


Fig 8. PC loadings, PC scores, time scales, and maximum loading rules from the PCA for monthly maximum correlation coefficients between the SPEI and barley yields at the agricultural district scale (a), and the SPDI and barley yields at the provincial scale (b), independently of the time scale. The PC loadings and maximum loadings were significant at $p < 0.05$.

Provincial scale



Agricultural district scale

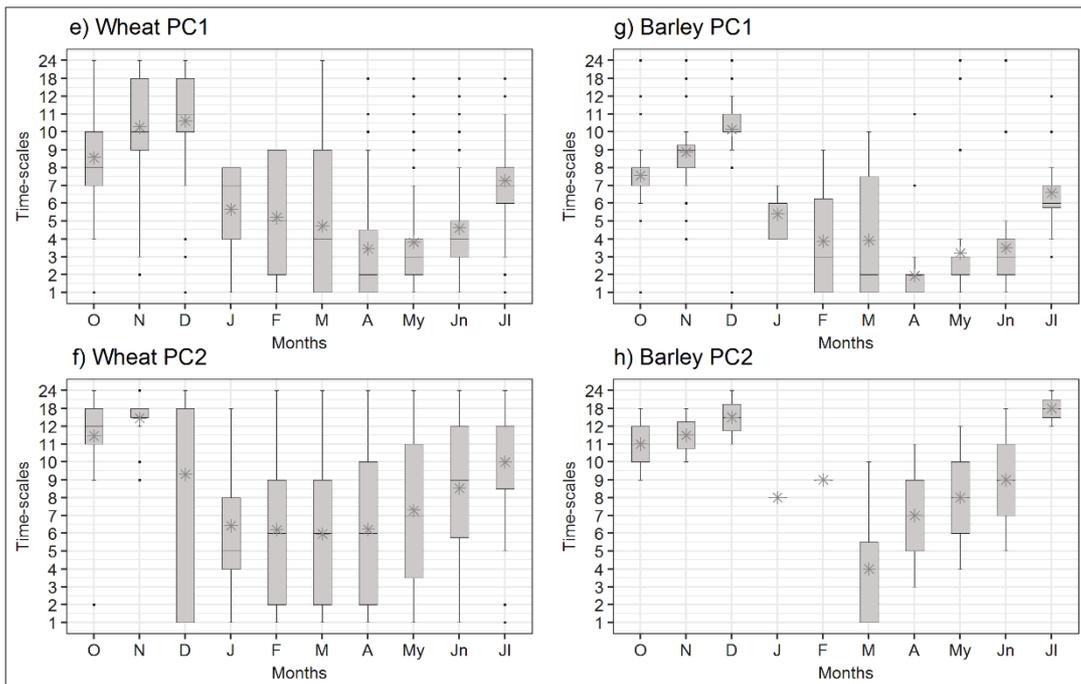


Fig. 9. Box plots showing the time scale at which significant monthly correlations were found in the provinces (top) and agricultural districts (bottom) for wheat and barley for each of the components defined in the PCA.

Supplementary Material

Supplementary Table 1. Relationship between provincial and agricultural district data, aggregated at the provincial scale, for wheat cultivation for the common period 1993–2014.

Codes	Provinces	r	Codes	Provinces	r
1	Álava	0.16	23	Jaén	0.38*
2	Albacete	0.41*	24	León	0.69*
3	Alicante	0.1	25	Lleida	0.52*
4	Almería	0.47*	26	La Rioja	0.35*
5	Ávila	0.77*	28	Madrid	0.81*
6	Badajoz	0.49*	29	Málaga	0.11
7	Islas Baleares	-0.22	30	Murcia	0.13
8	Barcelona	0.69*	31	Navarra	-0.25
9	Burgos	0.82*	32	Ourense	0.37*
10	Cáceres	0.34*	33	Asturias	-0.16
11	Cádiz	0.32*	34	Palencia	0.73*
12	Castellón	-0.19	37	Salamanca	0.87*
13	Ciudad Real	0.43*	40	Segovia	0.94*
14	Córdoba	0.46*	41	Sevilla	0.25
15	A Coruña	0.1	42	Soria	0.89*
16	Cuenca	0.86*	43	Tarragona	0.54*
17	Girona	0.1	44	Teruel	0.83*
18	Granada	0.3	45	Toledo	0.48*
19	Guadalajara	0.87*	46	Valencia	0.2

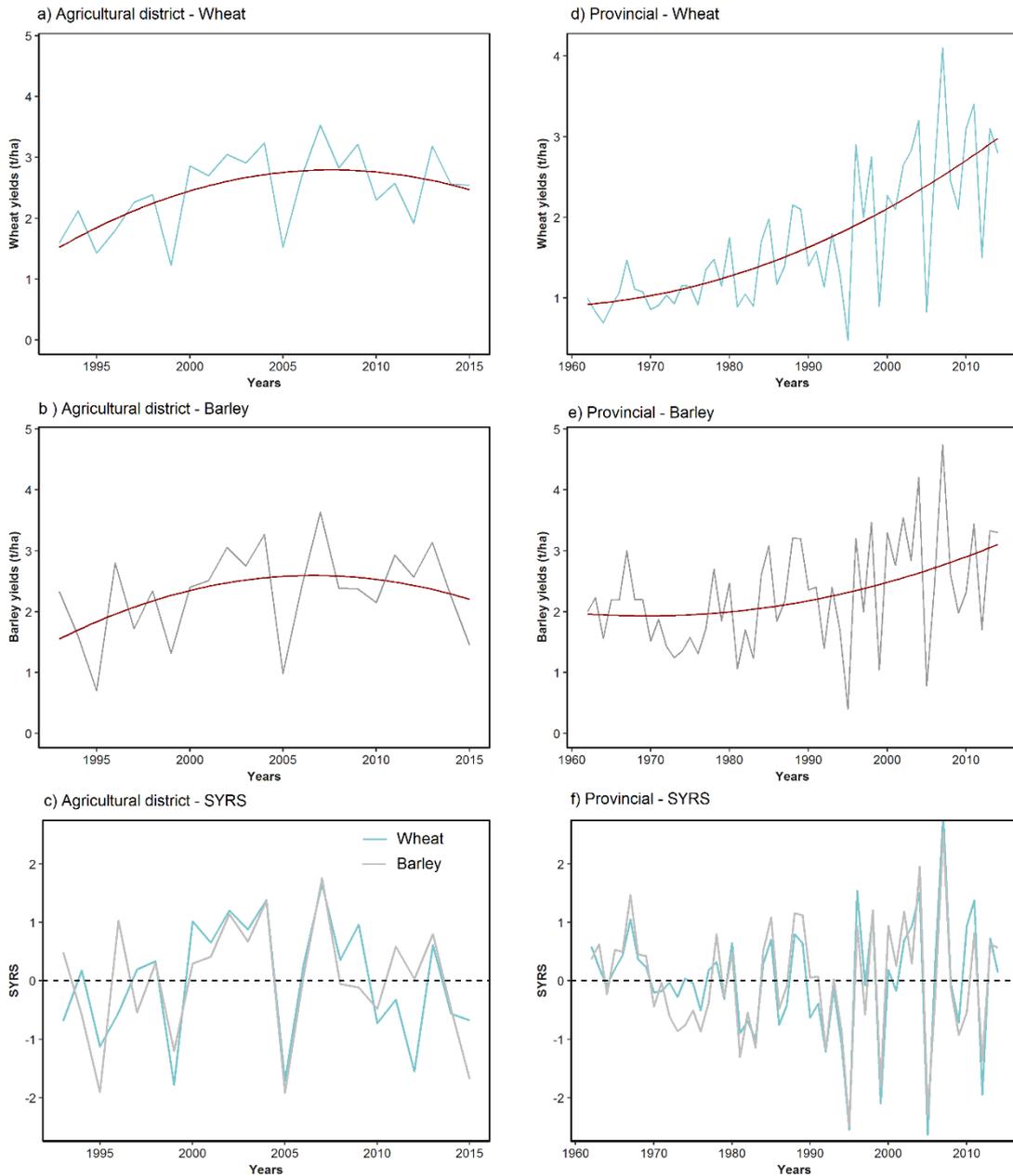
21	Huelva	0.29	47	Valladolid	0.92*
22	Huesca	0.4*	49	Zamora	0.75*
			50	Zaragoza	0.51*

(*) correlations are significant at $p < 0.05$

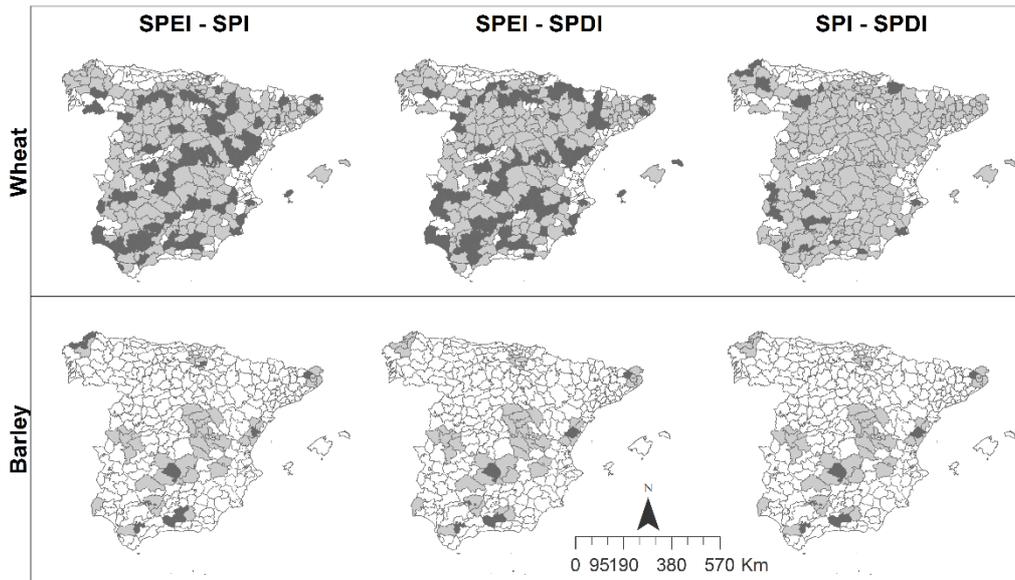
Supplementary Table 2. Relationship between provincial and agricultural district data, aggregated at provincial scale, for barley cultivation for the common period 1993–2014.

Code s	Provinces	r
1	Álava	0.11
2	Albacete	0.2
10	Cáceres	0.48*
11	Cádiz	0.32*
12	Castellón	-0.14
13	Ciudad Real	0.28
14	Córdoba	0.54*
15	A Coruña	-0.09
16	Cuenca	0.88*
17	Girona	0.08
18	Granada	0.51*
19	Guadalajar a	0.86*
22	Huelva	0.57*
26	La Rioja	0.76*
31	Navarra	0.01
41	Sevilla	- 0.35*
43	Tarragona	0.88*

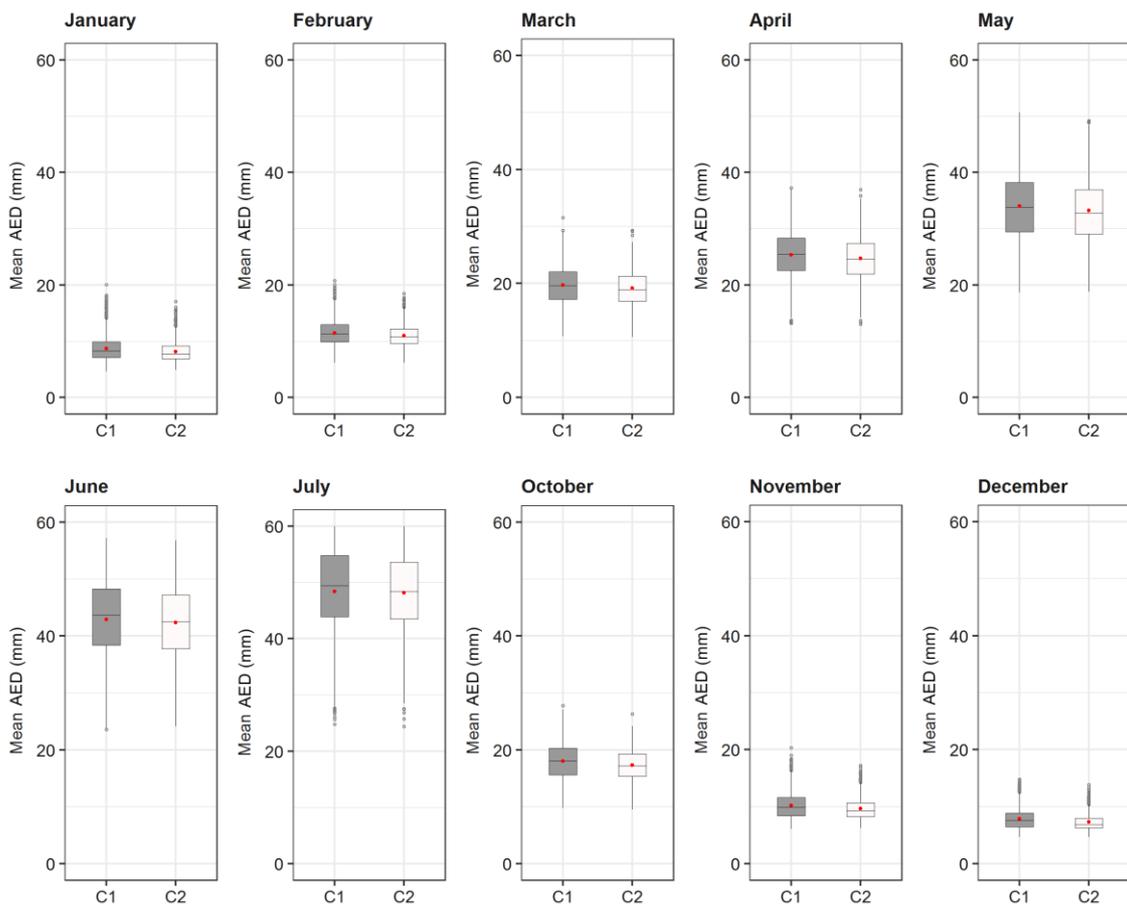
(*) correlations are significant at $p < 0.05$



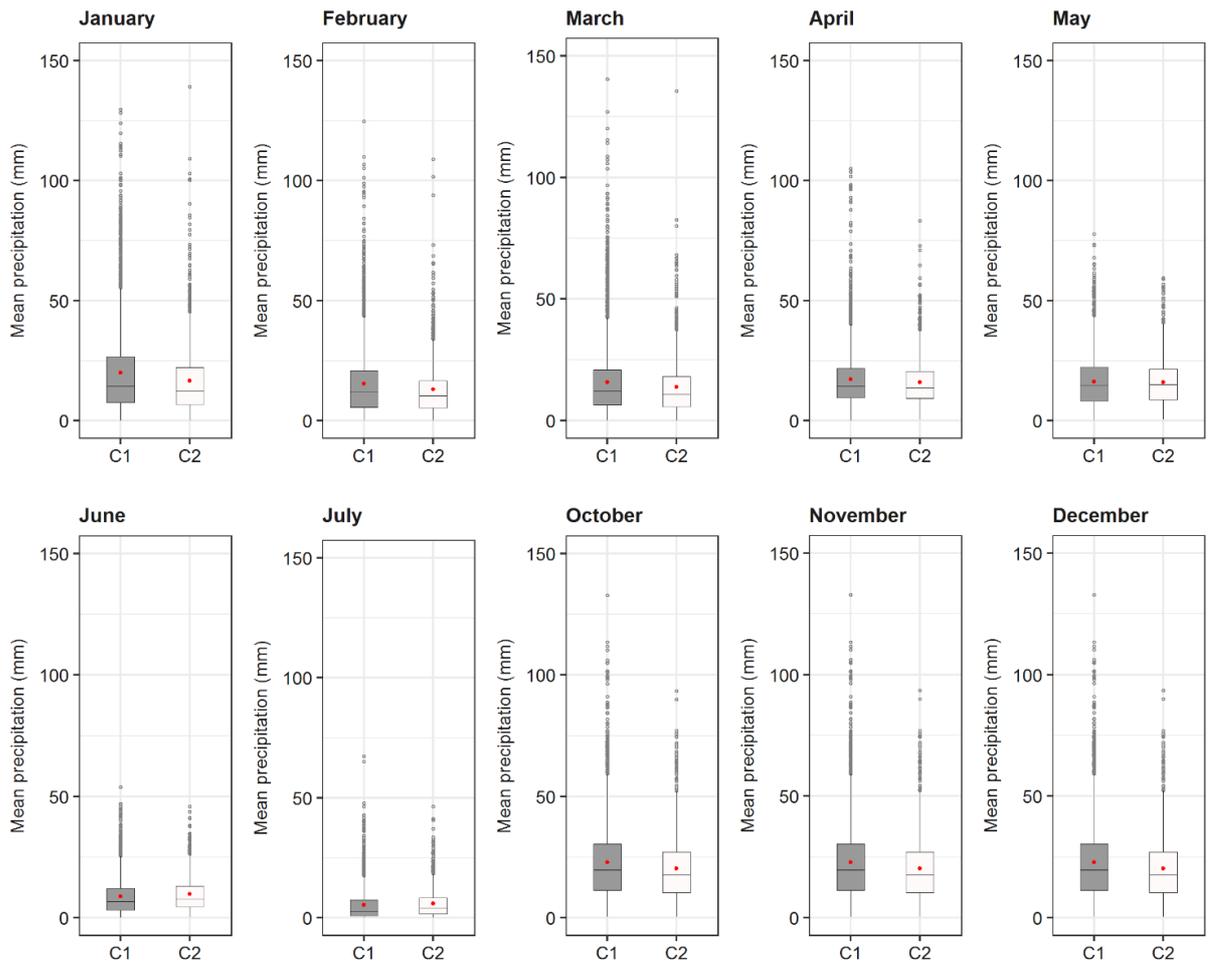
Supplementary Fig. 1. Example of temporal trends of provincial and agricultural district yields of wheat (a, d) and barley (b, e) in the province of Cáceres and the district Navalmoral de la Mata (Cáceres) and the temporal evolution of the SYRS at both scales (c, f) for the available period of time in each case. Red line represents the fitting of a quadratic function. Dashed black line represents the threshold 0-value.



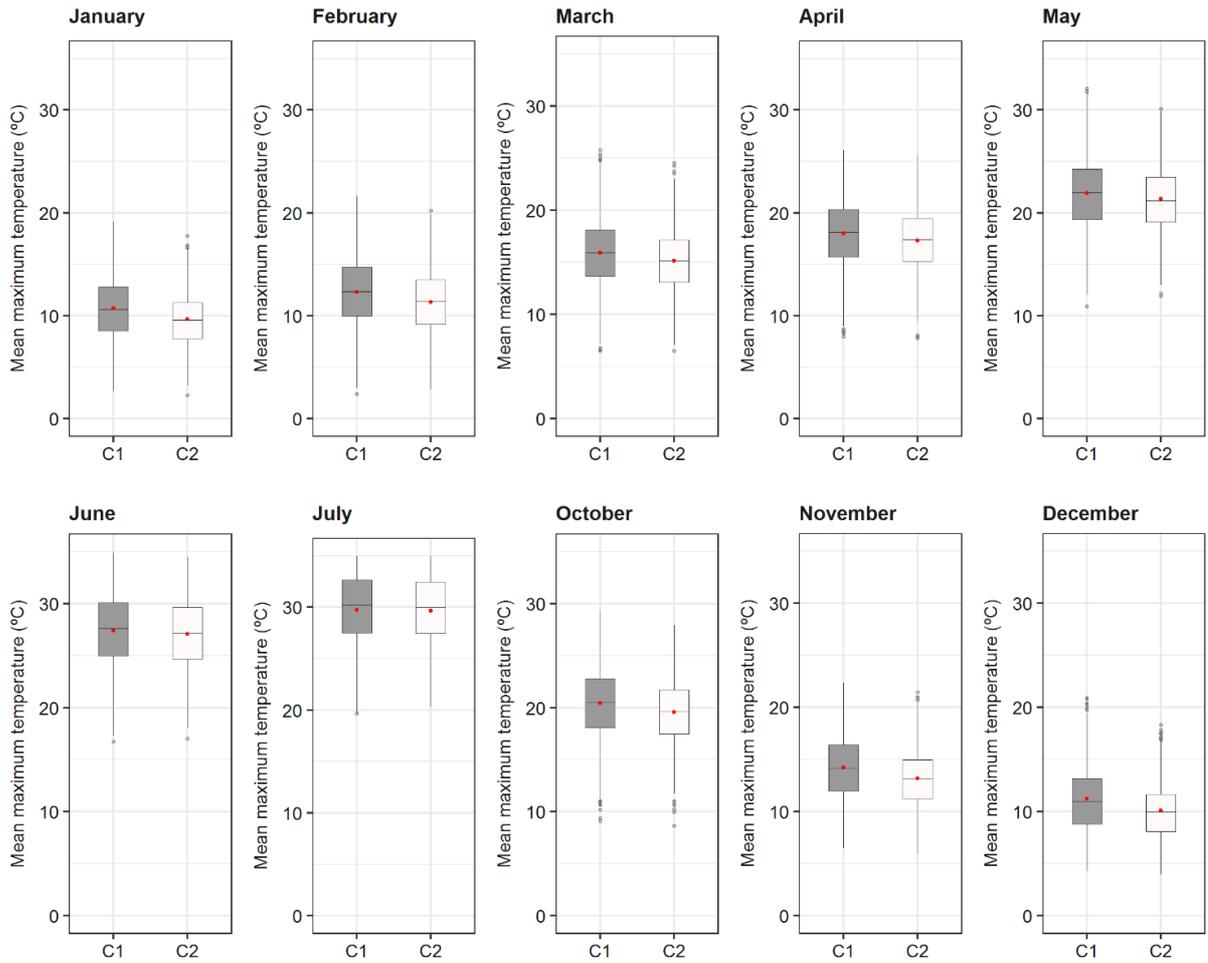
Supplementary Fig. 2. Spatial distribution of regions where significant differences (dark grey) and non significant differences (light grey) were found in the t-tests.



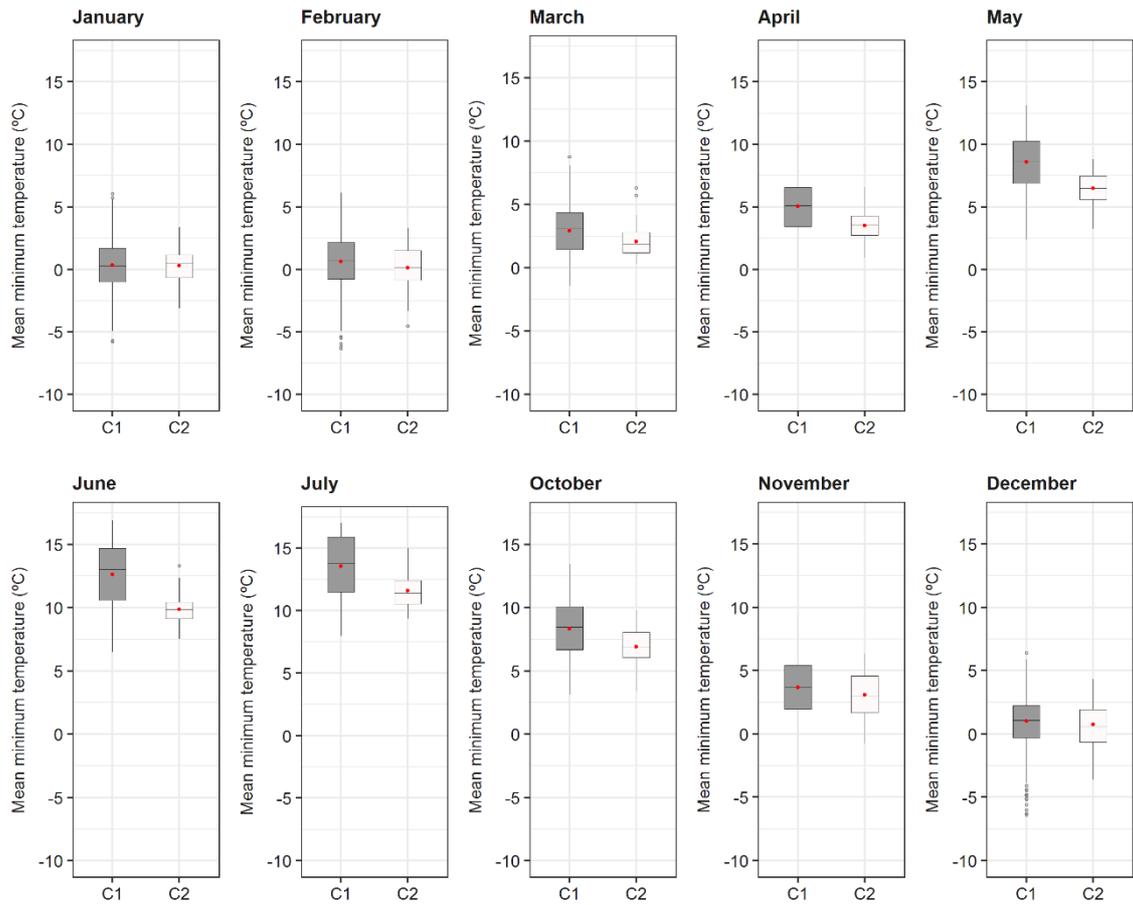
Supplementary Fig. 3. Monthly mean AED conditions in the agricultural districts where wheat was cultivated, classified into principal components (C1 and C2) for the period 1993–2015. The red dot shows the mean, and the black line shows the median.



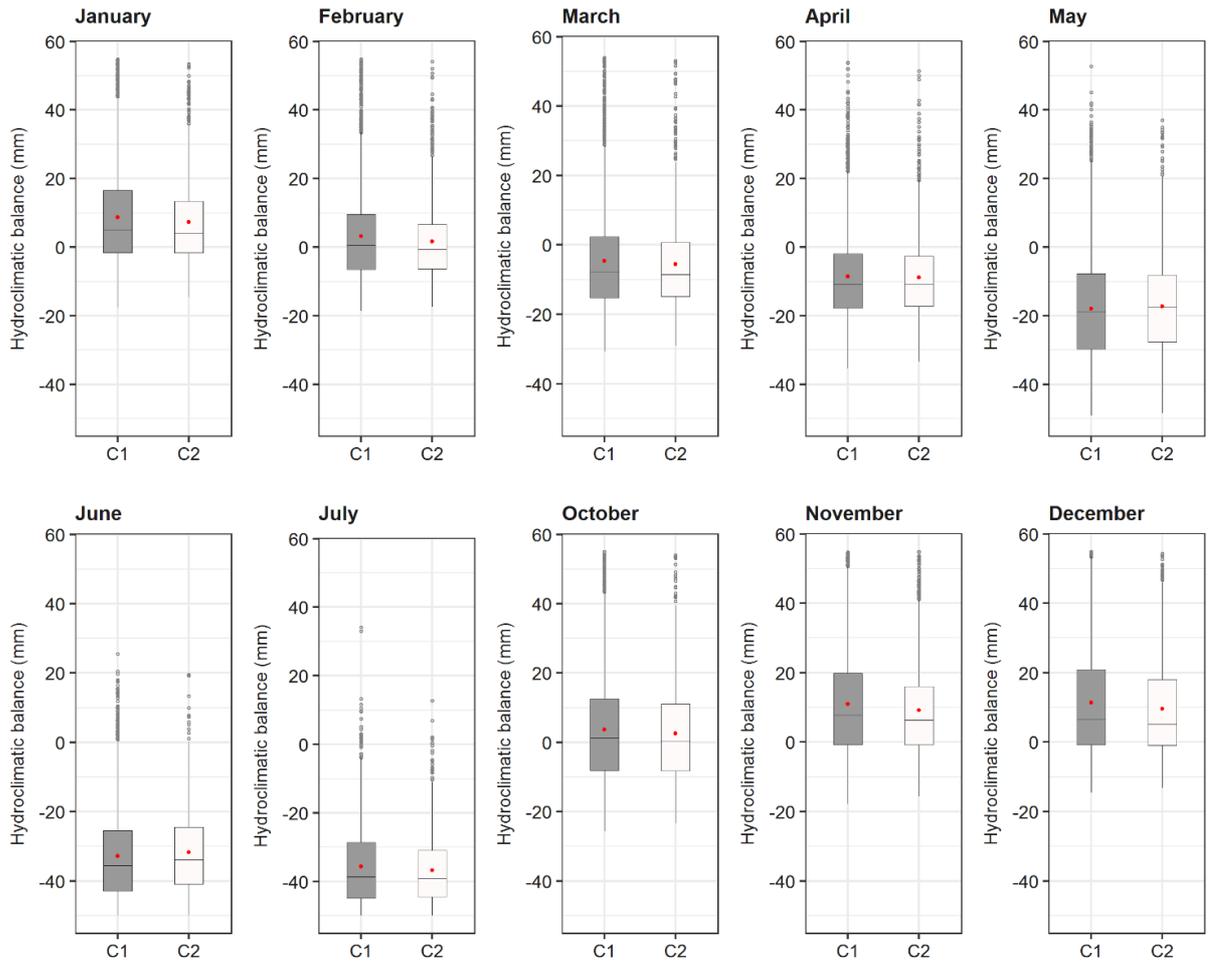
Supplementary Fig. 4. As for Supplementary Fig. 3, but for the monthly mean precipitation.



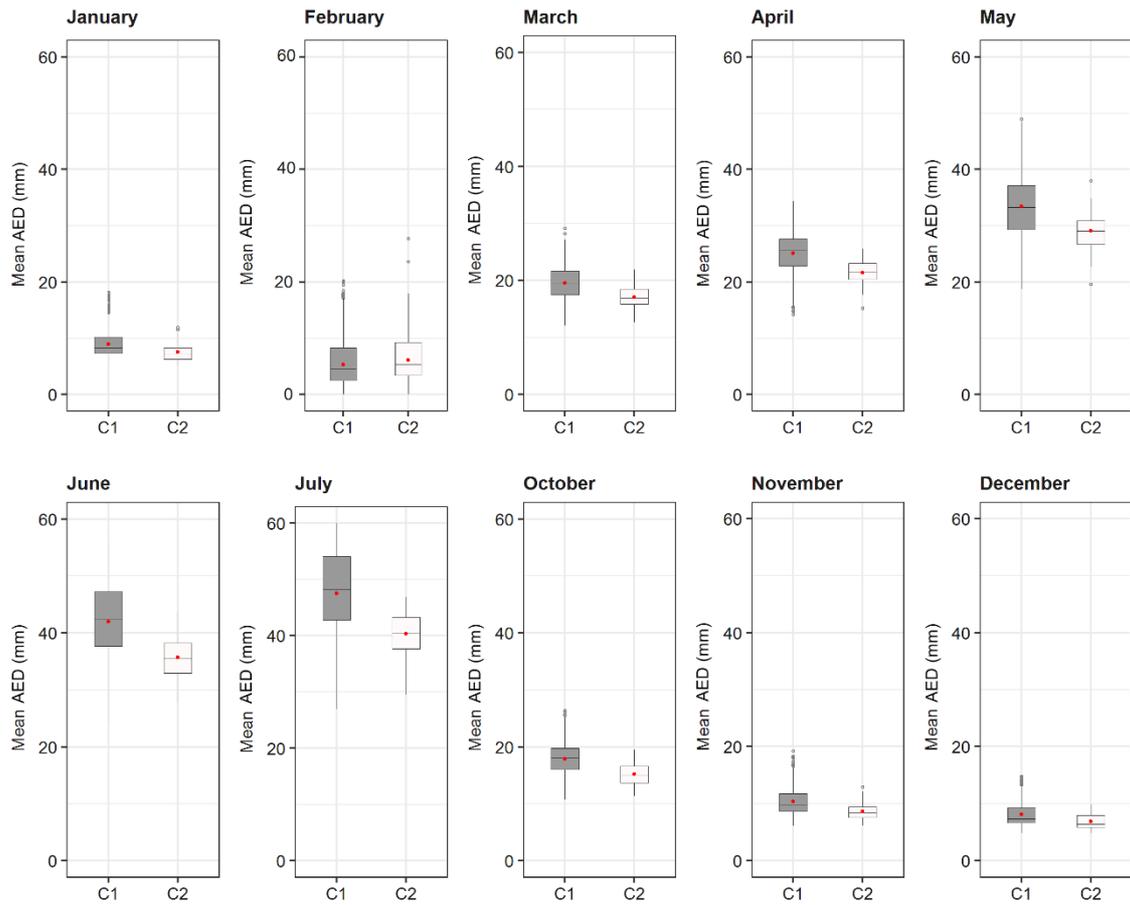
Supplementary Fig. 5. As for Supplementary Fig. 3, but for the monthly mean maximum temperature.



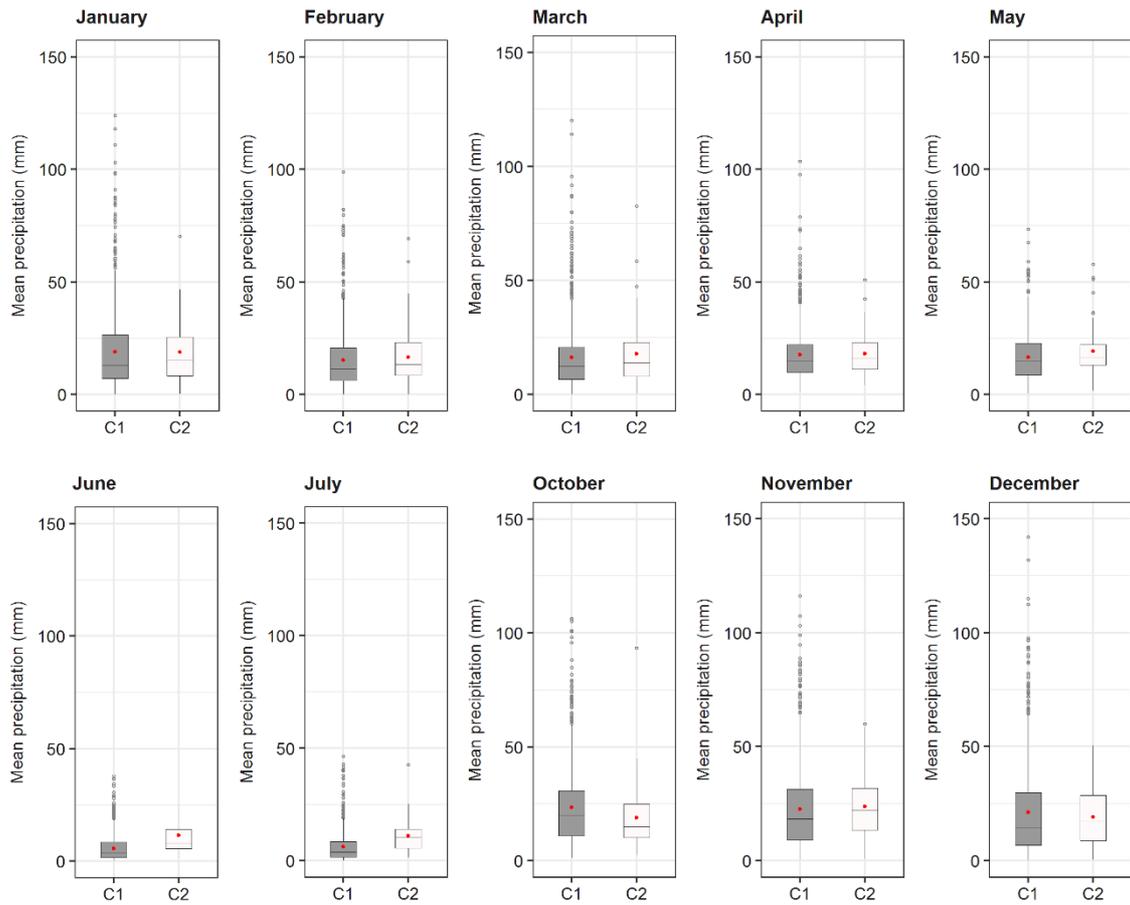
Supplementary Fig. 6. As for Supplementary Fig. 3, but for the monthly mean minimum temperature.



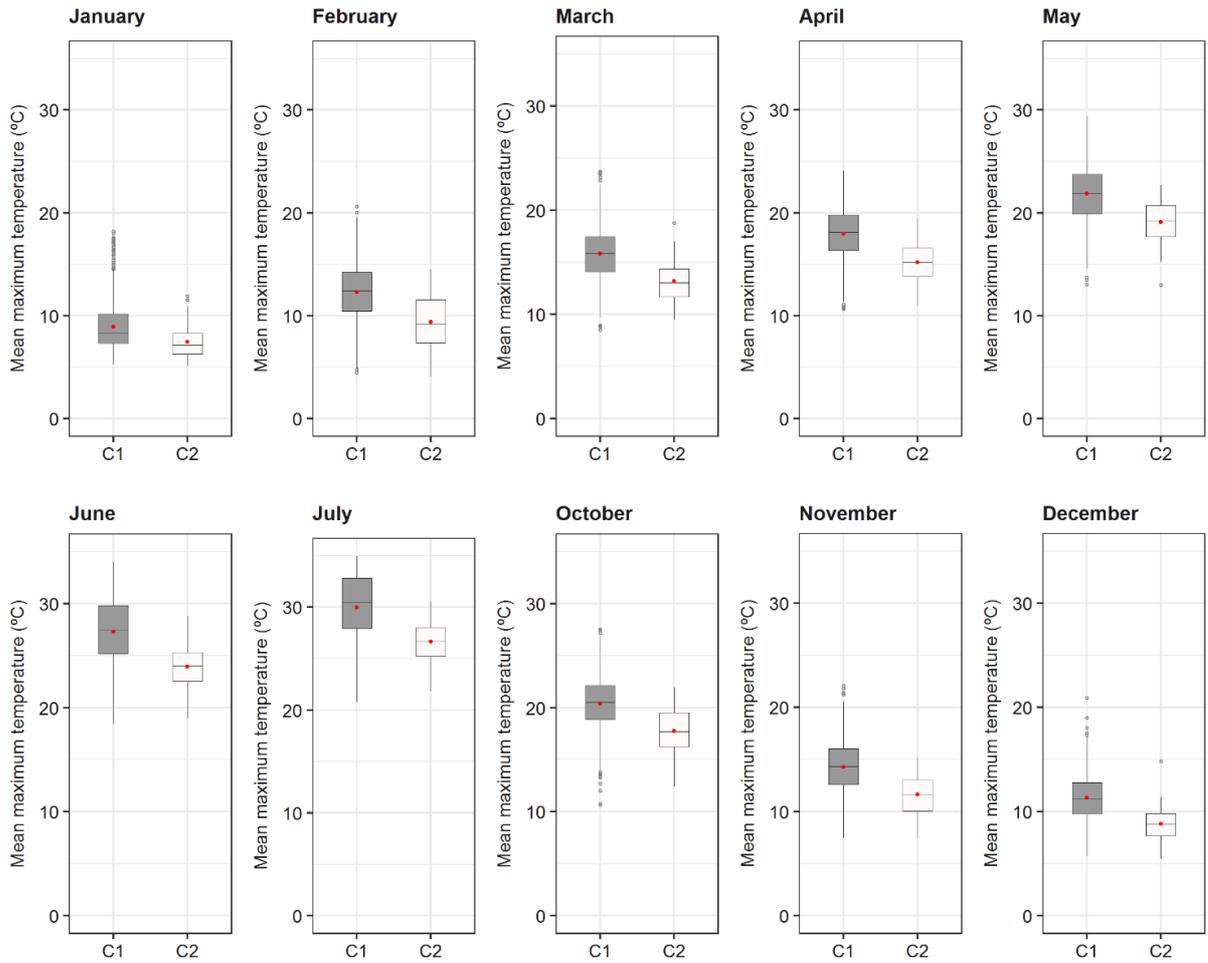
Supplementary Fig. 7. As for Supplementary Fig. 3, but for the monthly mean hydroclimate balance.



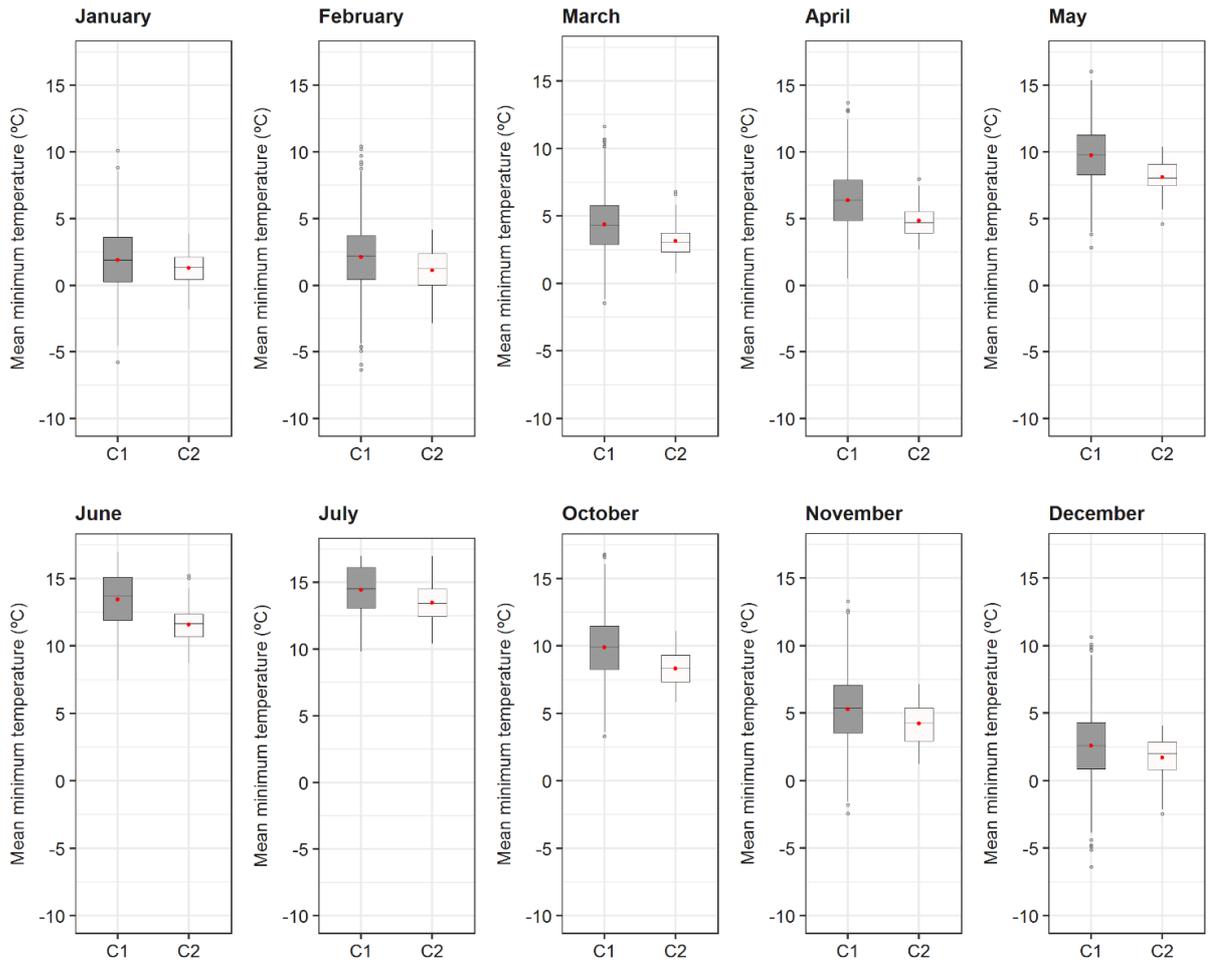
Supplementary Fig. 8. Monthly mean AED conditions in the agricultural districts where barley was cultivated, classified into principal components (C1 and C2) for the period 1993–2015. The red dot show the mean, and black line shows the median.



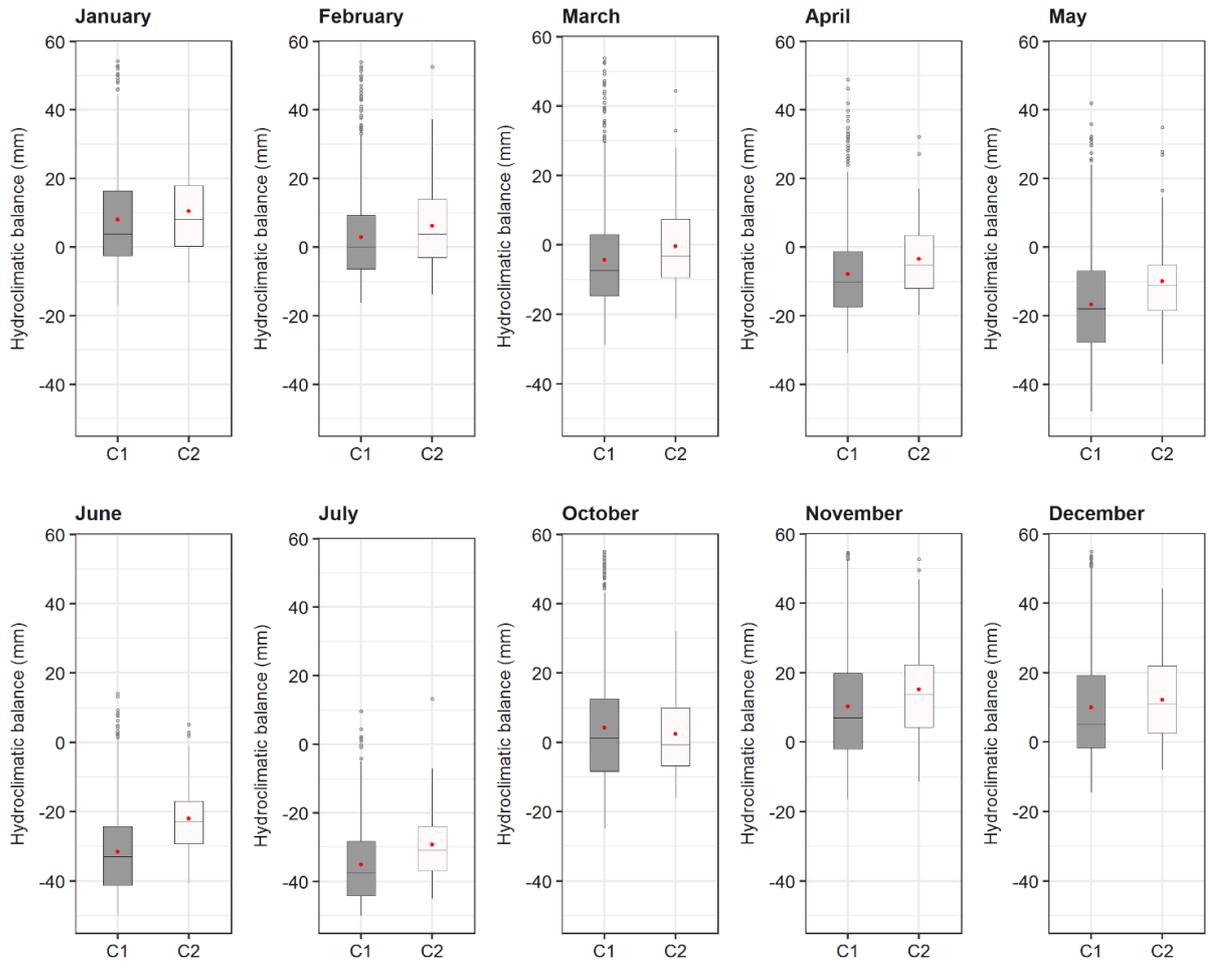
Supplementary Fig. 9. As for Supplementary Fig. 8, but for the monthly mean precipitation.



Supplementary Fig. 10. As for Supplementary Fig. 8, but for the monthly mean maximum temperature.



Supplementary Fig. 11. As for Supplementary Fig. 8, but for the monthly mean minimum temperature.



Supplementary Fig. 12. As for Supplementary Fig. 8, but for the monthly mean hydroclimatic balance.