Vol. 76: 95–113, 2018
https://doi.org/10.3354/cr01521

CLIMATE RESEARCH
Clim Res

Published online October 10

# Climate-driven variability in vegetation greenness over Portugal

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ABSTRACT: The role of climatic variability on vegetation greenness over mainland Portugal (2000–2014) was assessed using the Normalized Difference Vegetation Index (NDVI) as a measure of vegetation greenness. The gridded Standardized Precipitation Evapotranspiration Index (SPEI), gridded maximum (TX) and minimum (TN) temperatures, defined on a monthly basis, were used to assess climatic variability. Different vegetation classes were studied separately: grasslands, holm oak and cork oak, shrubland, deciduous forests and other evergreen forests. Type-specific models were developed to represent NDVI variability, using lagged monthly anomalies (up to 6 mo) of SPEI, TX and TN as exploratory variables. For southern Portugal, occupied mainly by grassland and low density woodland, vegetation greenness is very sensitive to precipitation. This sensitivity is particularly clear in February–March and September. Conversely, in the northwestern regions, where shrubland and evergreen/deciduous forests prevail, vegetation greenness is much less sensitive to precipitation seasonality. After cross-validation, the type-specific vegetation models explained 50–88% of the observed NDVI variability (relative errors of 3–7%). Models showed that SPEI significantly correlates with vegetation greenness at 3 and 6 mo timescales. At the same timescales, anomalously low TX and, to a much lower extent, anomalously high TN tend to favour vegetation greenness. It is thus possible to predict vegetation greenness in Portugal, up to 3 mo in advance and for different vegetation types, with some accuracy. A thorough understanding of the relationships between vegetation greenness and precipitation variability may promote a better management of forest/agroforestry systems, water resources, ecosystems and landscapes, particularly under changing climates.

KEY WORDS: SPEI · NDVI · Vegetation · Greenness · Greenness forecast · Vegetation types · Portugal



## 1. INTRODUCTION

Weather and climate have a key influence in determining vegetation dynamics and growth. Particularly, drought and heat events are an important threat to forestry, agricultural, economic and environmental systems (Prasad et al. 2008, Beguería et al. 2010, Vicente-Serrano et al. 2011). Previous studies have shown that droughts and extreme temperatures (e.g. cold spells, heat waves) have strong impacts on vegetation greenness and health (Potter et al. 2007). Drought has long been recognized as a main driving factor of forest health and species distribution. Drought-induced disturbances depend on drought intensity and duration, as well as on the developmental stage of plants (Beguería et al. 2010). Drought detection is strongly influenced by the time lag between anomalies in precipitation and vegetation activity, since droughts are caused by persistent lack of precipitation over a certain time period (van Hoek et al. 2016). As such, drought indices are essential to monitor vegetation health, supporting decision-making (Sánchez et al. 2016).

Drought indices can be used to determine different drought conditions for e.g. crops (Potopova et al.

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2016), plant growth (Oliveira et al. 2016, Zhang et al. 2016), afforestation (Abiodun et al. 2013), fire danger (Goodrick 2002), soil water availability (van der Burg et al. 2016) and climate change impact assessment (Li et al. 2015). Subjectivity in defining drought, including its multi-scale nature, has made it very difficult to establish a unique and universal drought index (Vicente-Serrano et al. 2010, Paulo et al. 2012, Banimahd & Khalili 2013, Sun et al. 2016, Yoo et al. 2016). However, the Standardized Precipitation Evapotranspiration Index (SPEI) is one of the most widely used indices (Vicente-Serrano et al. 2010). SPEI is based on normalized differences between precipitation and evapotranspiration and can be calculated over a wide range of climates (Beguería et al. 2010). It combines the sensitivity of the self-calibrated Palmer drought severity index to evapotranspiration (Beguería et al. 2010) with the simple mathematical formulation and multi-scale nature of the standardized precipitation index (Vicente-Serrano et al. 2010, van der Burg et al. 2016). Hence, it combines temperatures and precipitation in its definition, being a robust index that allows comparisons of drought severity through time and space.

Plant vigour (or greenness) can be assessed through satellite-derived vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) (Huete et al. 1999). NDVI combines spectral reflectance measurements within specific near-infrared (NIR) and red (Red) electromagnetic bands as follows: NDVI = (NIR − Red) / (NIR + Red). NDVI provides a measure of vegetation greenness; i.e. the larger the difference between NIR and red reflectances, the higher the NDVI and vegetation greenness (Roderick et al. 1996). The use of satellite remote sensing data has many advantages, such as global coverage and frequent (and regular) measurements, making NDVI useful to support field observations and estimate forest biophysical parameters (Brooks et al. 2016). NDVI is widely applied in ecological research and management as a proxy for vegetation quantity and quality (Garroutte et al. 2016), and it has been used to estimate plant production (Brooks et al. 2016), forest biomass (e.g. net primary productivity) (Myneni et al. 1997, Tum et al. 2011), leaf area index (Verger et al. 2016) and plant growth and photosynthetic activity (Decuyper et al. 2016, Ganjurjav et al. 2016). The NDVI is also related to other variables, such as phenology (Fraga et al. 2014), surface water (Decuyper et al. 2016), drought (Klisch & Atzberger 2016), soil cover (Tian et al. 2016), soil sealing (Perez & Garcia 2016), live fuel moisture content for fire danger rating (Chuvieco et al. 2004) and pests and diseases (Olsson et al. 2016).

In Portugal, forests occupy approximately 35% of the country (INE 2010). Typical Mediterranean flora dominated by the 'montado' (cork and holm oak woodlands) predominates in the south, while shrubland and denser forests prevail in the northern mountains, including Eurosiberian species (Godinho-Ferreira et al. 2005). Maritime pine *Pinus pinaster* and eucalypt *Eucalyptus globulus* forest stands and cork oak *Quercus suber* montado woodland jointly represent 72% of the forested area and are the most economically important species in Portugal (ICNF 2013). Although 6.0 Mha are potentially suited for forest, part of this area is occupied by shrubland (ICNF 2013). Grasslands are relevant in the southern half of the country and, essentially, alternate in the landscape with evergreen oak woodlands. Portuguese forests have been subjected to anthropogenic influences over the last millennia, which has resulted in a significant replacement of oak-dominated native forests by agriculture, shrubland and forest plantations (Reboredo & Pais 2014).

Portuguese forests are usually exposed to warm and dry periods as a result of the Mediterranean-type climate, particularly during summers. The effects of recent-past temperature rise and rainfall reduction have been observed in southern Portugal, an area highly susceptible to desertification and one of the most vulnerable regions worldwide (Vicente-Serrano et al. 2012, Mühlbauer et al. 2016). In fact, Portuguese forests are expected to be severely affected by climate change owing to the projected warming and drying trends, which are expected to favour non-forest vegetation types (Costa et al. 2012, 2017, Andrade et al. 2014). As future projections show increases in both droughts and extreme temperatures, understanding the patterns of mortality and plant responses to severe drought is of great relevance to resource managers (Andrade et al. 2014, Assal et al. 2016).

Previous studies have analyzed the relationships between climatic variables and either vegetation greenness (Gonsamo et al. 2016) or SPEI (Vicente-Serrano et al. 2013). Nonetheless, the climate-driven variability of forest vegetation greenness has not yet been assessed in Portugal. Given the strong sensitivity of the Portuguese forestry system to drought and air temperatures, and the climate change projected for the next decades, the assessment of these connections is of foremost relevance. In the present study, the climate-driven variability of vegetation greenness was assessed in Portugal over the time period of 2000–

2014. Owing to the large diversity of land-use in Portugal, the study individualized the different main vegetation types, which provided important information regarding response heterogeneity throughout the country. Our main objectives were 4-fold: (1) to identify the mean vegetation greenness conditions over mainland Portugal and associated trends; (2) to identify temporal and spatial correlations between drought/air temperatures (SPEI/minimum and maximum temperatures) and vegetation greenness (NDVI); (3) to analyse these associations separately for each vegetation type in Portugal; and (4) to develop corresponding type-specific models for predicting NDVI.

## 2. MATERIALS AND METHODS

### 2.1. Vegetation indices

A NDVI dataset was used to evaluate vegetation greenness, based on measurements taken by the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the National Aeronautics and Space Administration (NASA) Terra satellite. The 15 yr MODIS-derived NDVI data (MOD13Q1, Collection 5), tiles h17v04 and h17v05, were extracted from the NASA Land Processes Distributed Active Archive Center (LP DAAC; https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod13q1). These data consist of 16 d composites at near 250 m spatial resolution (231.75 meter pixel size) covering the study area during the period of 2000–2014. Monthly NDVI values were computed and re-projected from the original sinusoidal grid onto the UTM-WGS84 reference grid. NDVI dimensionless values range from −1 to 1. Overall, values $>0.1$ indicate the level of greenness and intensity of vegetation. Values between 0 and 0.1 are commonly characteristic of rocks or bare soil, whereas negative values may indicate clouds, rain or snow (Holm et al. 1987). Low values of NDVI (typically $<0.4$) do not necessarily mean a lack of vegetation, since e.g. deciduous forests may have very low greenness during winter (Roderick et al. 1996).

### 2.2. Vegetation types in Portugal

The COS2007 land use and land cover dataset for mainland Portugal (Caetano et al. 2009) was used for analyzing the spatial distribution of the main non-agricultural vegetation types (Source: Direção-Geral do Território, http://mapas.dgterritorio.pt/geoportal/catalogo.html). The third level of COS2007 was used for grassland, shrubland, deciduous and evergreen forest vegetation types, while the fifth level was considered to differentiate holm and cork oak vegetation types. The digital land use and land cover dataset for 2007 is suitable for our study as it corresponds to the middle of the study period. This data set has a minimum mappable area of 1.0 ha, positional accuracy of ≤5.5 m and thematic accuracy of 85%, and was produced from orthophotomaps with a spatial resolution of 0.5 m. The spatial distributions of the different vegetation types were obtained from COS2007. For this purpose, the individual polygons of a given vegetation type were used for the analysis. The geographical coordinate system used was PT-TM06/ETRS89.

Fig. 1 shows the spatial distribution of the 6 selected vegetation types in Portugal: grasslands, holm oak, cork oak, shrubland, deciduous forests and other evergreen forests. Deciduous and evergreen forests (mostly pines and eucalypts), as well as shrublands are more conspicuous in the north of the country, particularly in its inner north-central regions, whereas grassy oak woodlands prevail in its southern half (Fig. 1). Differences in physiognomy, phenology and stand density, as determined by land management and environmental limitations, potentially influence the NDVI and justify a separate analysis for each type. NDVI and SPEI values were extracted for the points corresponding to each type separately. The resulting data were then used for the vegetation-type specific analysis.

### 2.3. Climatic indices

Regarding droughts, SPEI data were retrieved from the Global SPEI database v.2.4 (http://sac.csic.es/spei/database.html; Beguería et al. 2010), for the period of 2000–2014 (15 yr) and within a sector that comprises mainland Portugal (36°–43° N, 5°–11° W). Data is available over a grid of 0.5° latitude × 0.5° longitude. For the SPEI calculation, the differences between precipitation and potential evapotranspiration were calculated on a monthly basis, providing a simple measure of monthly water balance. In this data set, potential evapotranspiration was estimated by the Penman-Monteith equation. As the difference time series was also standardized (to zero mean and unit variance) using a 3 parameter log-logistic distribution, it can be compared with other SPEI values in time and space. A SPEI = 0 indicates a cumulative probability of 50% in the difference time series. Although SPEI values for different timescales were retrieved, only the 1 mo (SPEI-1), 3 mo (SPEI-3) and

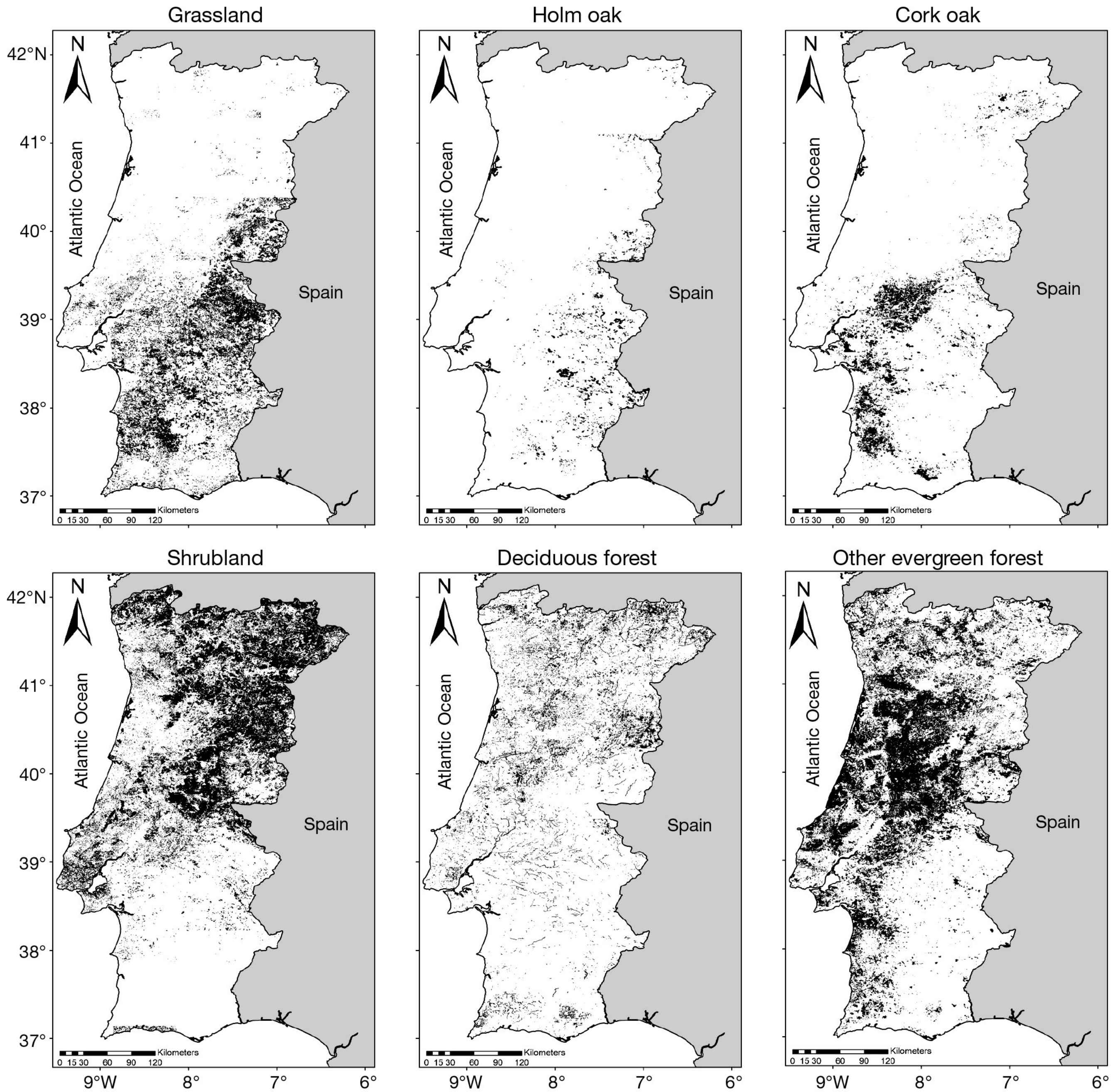


Fig. 1. Spatial distribution of the selected vegetation types over mainland Portugal: grassland, holm oak and cork oak, shrubland, deciduous forests and other evergreen forests. Black shading represents the respective vegetation cover. Source: COS2007 (Caetano et al. 2009) (Geographic coordinate system: ETRS89)

6 mo (SPEI-6) timescales were selected. Further information on the SPEI dataset can be found in Beguería et al. (2014). In fact, SPEI-1, SPEI-3 and SPEI-6 are commonly used for assessing drought impacts on agroforestry systems, while SPEI-9 and SPEI-12 (or even higher timescales) are mostly applied to hydrological systems (Meresa et al. 2016).

In order to assess the likely influence of air temperatures on NDVI, monthly means of maximum (TX) and minimum (TN) temperatures were calculated from the E-OBS gridded daily TX and TN (Haylock et al. 2008). Data is available on a 0.25° latitude × 0.25° longitude grid (~25 km spatial resolution) and were retrieved for the period of 1999–2014 (1999 was used for estimating lagged temperatures in 2000) and within a sector that covers mainland Portugal. The 1 mo, 3 mo and 6 mo timescales (lags) for both TX and TN were then computed.

### 2.4. NDVI modelling

In order to test the potential use of SPEI/TX/TN in modelling NDVI, point-by-point Pearson correlation coefficient patterns between NDVI and SPEI/TX/TN were used to assess their co-variability on the space domain. Cross-wavelet spectral analysis was also applied for identifying non-stationarity in their co-variability on the time domain (Grinsted et al. 2004). A set of potential predictors was then defined for the 3 variables (SPEI, TX and TN) at timescales from 1 to 6 mo, being e.g. SPEI-*x*, the *x*-lagged average of SPEI. Monthly anomalies with respect to the corresponding monthly climate-means for the full period (2000–2014) were computed for NDVI and for all predictors, thus removing seasonality from the analysis.

The modelling approach was applied to each vegetation type separately so as to highlight different responses to climate variables, i.e. the NDVI time series for each vegetation type over Portugal was retrieved and modelled. Stepwise multivariate linear regressions were applied, with robust fitting using bi-square weighting. As the NDVI time series length was not long enough (15 yr) for defining the conventional training/testing periods for each model, a leave-one-out (1 full year) cross-validation analysis was carried out to avoid model overfitting. The normal distribution and independency of residuals were checked using respectively the Lilliefors and Durbin-Watson tests. In order to mitigate the inability of regression models to replicate the observed variance, a multiplicative scaling factor was applied to the modelled time series, i.e. the ratio between observed and modelled time series variance. Lastly, for each vegetation type, the mean seasonal cycle (seasonal component) was added to the corresponding estimated NDVI anomalies, obtained from the multivariate linear regression, so that the final modelled monthly NDVI values were recovered. The model performances were assessed using the following measures: Fisher's test measure ($F$), R-squared value ($R^2$), R-squared value after leave-one-out cross-validation ($R^2_{cv}$), difference between estimated and observed averages (BIAS), mean absolute error (MAE) and root-mean squared error (RMSE).

## 3. RESULTS AND DISCUSSION

### 3.1. NDVI versus climatic indices

The NDVI annual mean pattern shows that the northern half of Portugal, apart from some innermost regions, clearly has higher greenness than the south (Fig. 2a), depicting a strong southeast–northwest gradient as the Mediterranean influences are gradually mitigated by the Atlantic influences towards the northwest. The effect of the largest urban areas, bare rock or snow areas and artificial water surfaces (dams) are also clearly displayed (NDVI < 0.2).

However, this general pattern has been changing through the years, mostly owing to both land-use changes and wildfires. The NDVI trends highlight that most of the western northern-central regions of the country exhibit decreasing greenness (Fig. 2b), whereas NDVI has experienced slight increases in the inner north and south of the country. In the first case, a very densely populated area, forest replacement by agriculture, wildfire incidence and urbanization might have played an important role in the NDVI lowering. In the second case, gradual afforestation and abandonment of some agricultural areas, subsequently encroached with woody vegetation or converted to shrubland might explain the NDVI increase (Ogaya et al. 2015). It was also possible to identify localized areas with strong positive (dark blue) or negative (orange) trends (Fig. 2b). The strongest negative trends can be due to different factors, namely large wildfires at the end of the analyzed period (2000–2014), large water surfaces from new dams (e.g. Alqueva in the southeast) and forest harvested because of the pine wilt nematode (in the southwest). The strongest positive trends (e.g. in central Portugal) result from vegetation recovery after the extremely large fires of 2003 and 2005.

The NDVI intra-annual variability is quite strong owing to the prevailing Mediterranean conditions, with mild-wet winters and warm-dry summers, which can be illustrated by the January and August NDVI mean patterns (Fig. 2c,d). These maps highlight that NDVI is greatly influenced by precipitation (and soil water availability), showing a relatively homogeneous pattern in January with relatively high NDVI values, and a highly heterogeneous pattern in August. Summertime NDVI is typically much lower than wintertime NDVI. The south and inner regions reveal quite strong intra-annual variability, particularly in the south, where high greenness in winter is replaced by very low greenness in summer. The northwest presents much lower intra-annual variability.

The NDVI intra-annual variability (seasonality) varies significantly among different vegetation types, despite the important within-class ranges (Fig. 3). Seasonal patterns in the NDVI are evident for grasslands, holm oak and cork oak (winter maximum and

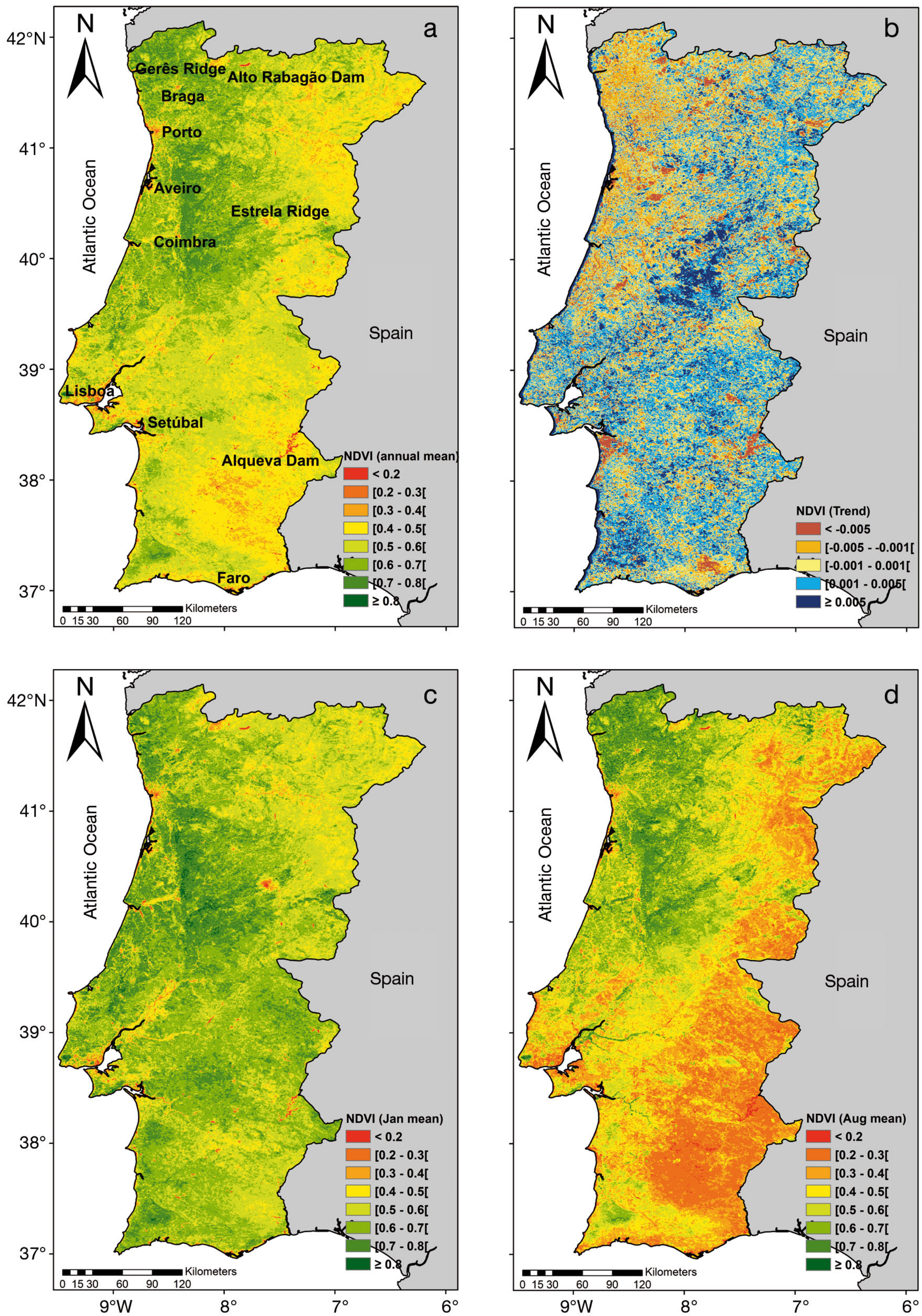


Fig. 2. Normalized Difference Vegetation Index (NDVI) patterns (dimensionless) over mainland Portugal for the period of 2000–2014: (a) annual mean, (b) linear trend of annual mean, (c) January mean, and (d) August mean. Geographic coordinate system: WGS 1984

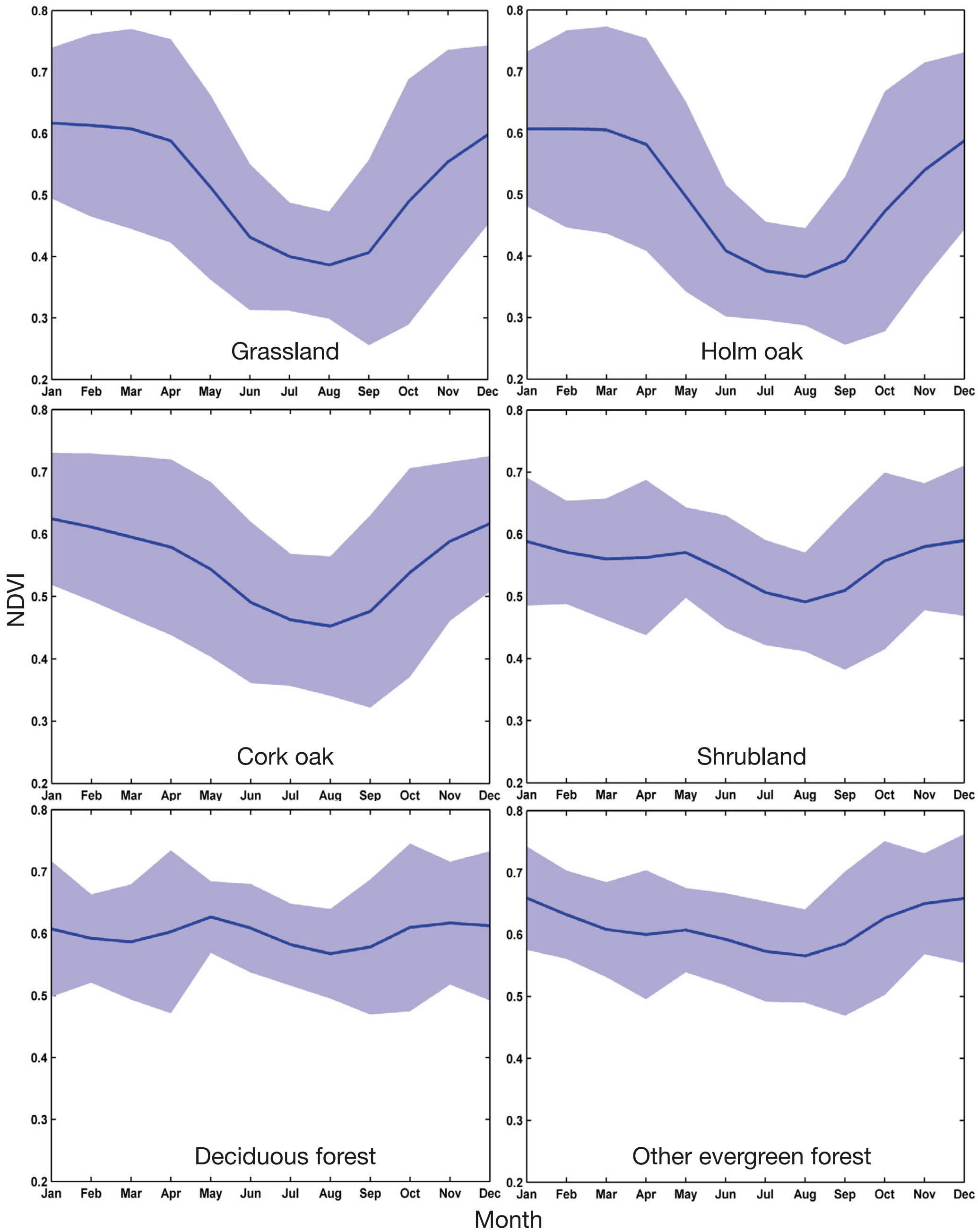


Fig. 3. Monthly means of the Normalized Difference Vegetation Index (NDVI) for the period of 2000–2014 and for each selected vegetation type. The curves correspond to the averages, while shading represents maximum–minimum monthly ranges

summer minimum), but are much weaker for shrubland and deciduous or evergreen forests. For grasslands, this strong seasonality is explained by the archetypal annual growing cycle of herbaceous species in Mediterranean ecosystems, with vigorous growth in winter/spring under wet and mild conditions, and subsequent curing in summer. Since holm oak and cork oak are generally low-density woodlands, canopy density is low enough to allow widespread grass coverage. Hence, their corresponding NDVI seasonality mainly reflects the growing cycle of grasses — particularly for holm oak, as it typically grows in the driest regions of southern Portugal, with the strongest winter–summer contrast (Figs. 1 & 2).

Shrublands, deciduous forests and other evergreen forests are also characterized by a wintertime maximum and a summertime minimum, but their intra-annual variability is much less apparent. Mediterranean forest species are evergreen, with only small changes due to foliage renewal, and are sclerophylous and adapted to drought, thus explaining the weak seasonality. Although deciduous forest species are leafless during part of the dormant season, the rapid growth of understory herbaceous species in winter/spring tends to offset this effect and maintains greenness, explaining minimal NDVI changes (Figs. 2 & 3). A joint effect resulting from the herbaceous coverage plus foliage renewal of deciduous trees occurs in May, underlying the second peak of NDVI.

To assess the relevance of water availability in the previously described NDVI intra-annual variability, monthly correlation coefficients between the spatial means of NDVI and SPEI are presented for each type separately. For the 6 types, the highest correlations were found between NDVI and SPEI-6, while SPEI-1 showed much lower correlations (Fig. 4). The SPEI-1 correlations highlighted a strong sensitivity of NDVI to SPEI in 2 well-defined periods: February–March and September. This suggests that soil water status in early spring and by the end of summer tends to play a key role in vegetation greenness. As these are transitional periods between the wet and dry seasons, a delay or advancement in the dry/wet season can have significant implications for vegetation greenness. As the transition from the wet to the dry season (spring) is much slower than from the dry to the wet season (late summer/early autumn), correlations are stronger and spikier in September than in February–March. As the SPEI timescale increases, the correlations tend to increase — apart from September, when SPEI-6 tends to reveal lower correlations than SPEI-1 or SEPI-3. The inclusion of longer periods in SPEI calculations gradually overrides intra-annual differences in the sensitivity of NDVI to SPEI, justifying the general increase and evenness of correlations throughout the year.

Despite the above-described intra-annual variability, the inter-annual variability in both indices can be illustrated by the highly contrasting conditions for September 2005 and 2010 (Fig. 5), which were extremely dry and wet years, respectively (Costa et al. 2012, Andrade et al. 2014). As stated above, September's NDVI is the most sensitive to soil water status. The NDVI spatial pattern for September 2005 (Fig. 5a) reveals relatively low NDVI values (<0.3) throughout the country, particularly in the southern and inner regions, while only a few areas in northern and central Portugal present NDVI > 0.6. For September 2010 (Fig. 5c), however, the NDVI spatial pattern is remarkably different from 2005, showing much greater values of NDVI (>0.6) over large areas of northern and central Portugal, with the exception of the innermost regions and in the southwest. Yet low NDVI values (<0.3) were also found over most of southern and inner Portugal. There was also a clear association between NDVI and SPEI-6 for both months (positively correlated), i.e. low/high NDVI vs. low/high SPEI-6. SPEI-6 was lower in September 2005, revealing dry conditions throughout the country, particularly in southern and central Portugal (Fig. 5c). Conversely, September 2010 presented lower dryness and even humid conditions in some northeastern areas (Fig. 5d).

The monthly anomalies of NDVI (baseline of 2000–2014) were jointly represented with the corresponding anomalies for SPEI-1, SPEI-3 or SPEI-6 so as to determine relationships between the indices (Fig. 6). The connection between SPEI-1 and NDVI was not clear on a monthly basis (Fig. 6a), but a noteworthy association can be found for SPEI-3 (Fig. 6b) and SPEI-6 (Fig. 6c). In effect, the area-mean SPEI-6 (2000–2014, 180 months), computed over mainland Portugal, has the strongest relationship with the corresponding area-mean NDVI ($r = 0.60$), followed by SPEI-3 ($r = 0.55$) and SPEI-1 ($r = 0.26$) (see Fig. S1 in the Supplement at www.int-res.com/articles/suppl/c076p095_supp.pdf). These correspondences were weaker for higher SPEI timescales (data not shown). This is in clear agreement with the increasing correlation coefficient as the SPEI timescale increases from 1 to 6 mo, highlighting that vegetation typically integrates the signal of precipitation variability into a lagged and low-pass filtered response. This outcome is also corroborated by previous studies that showed that 6 mo SPEI is optimally correlated with land biomes over Portugal (Vicente-Serrano et al. 2013). The corresponding chronograms for SPEI-6 and for each type separately showed similar behaviour (Fig. S2). Therefore, the inter-annual variability in NDVI over Portugal is better represented by SPEI-6.

Despite the general agreement between NDVI and SPEI-6, it was also possible to identify periods where SPEI-6 influences NDVI more clearly. The cross-wavelet spectrum between the monthly anomalies of NDVI and of SPEI-6 over the same time period displays periods with primarily in-phase relationships (forward arrows in Fig. 6d). In this spectrum, thick black lines outline statistically significant co-variability at the 95% confidence level, while the 5% significance level against red noise is shown as a thick contour. Furthermore, the most significant and persistent associations were found in the low frequencies (periods >12 mo), particularly in the second half of the time period, when there is a much clearer corres-

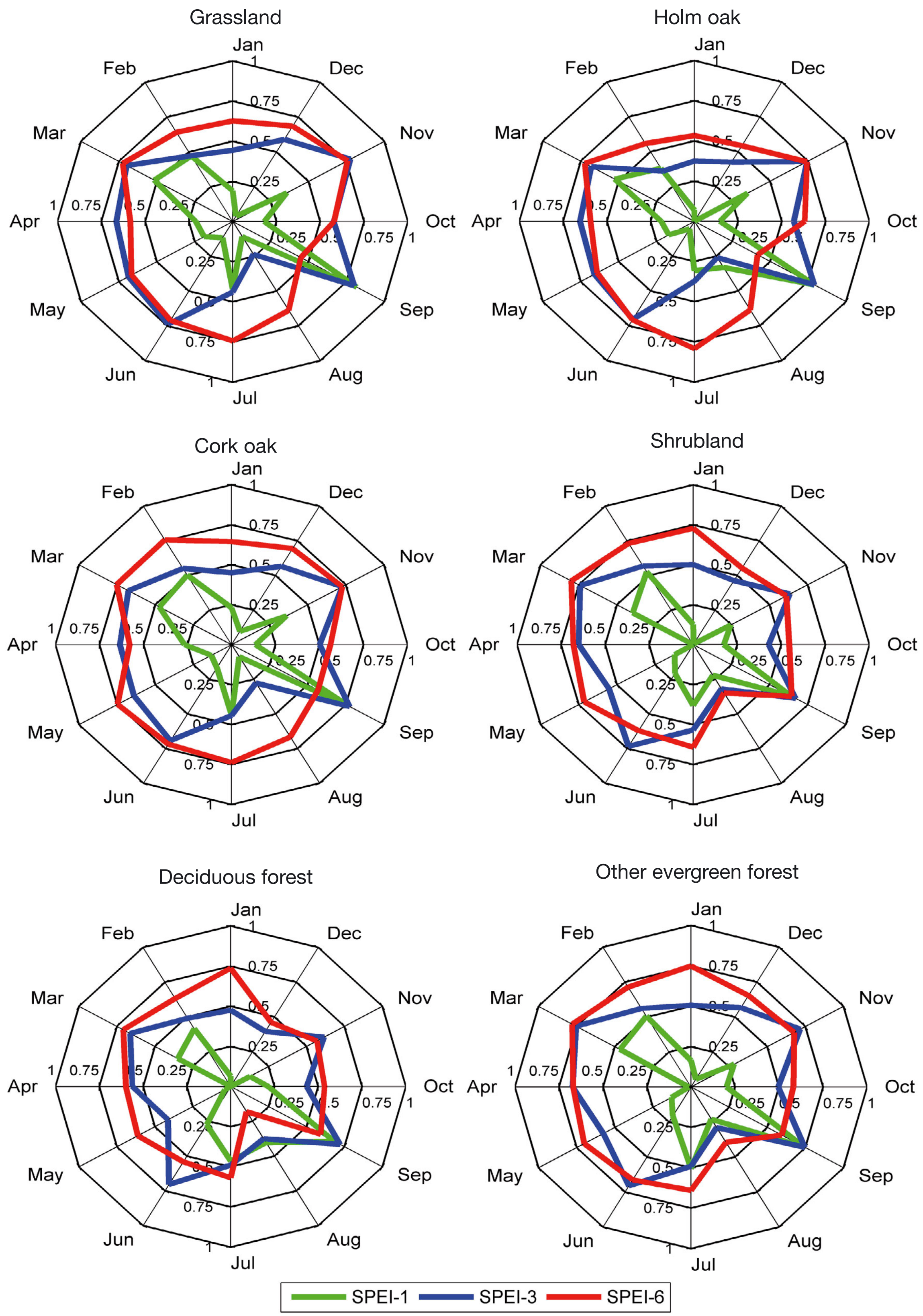


Fig. 4. Radar plots of the monthly correlation coefficients between the Normalized Difference Vegetation Index (NDVI) and 1 mo (SPEI-1), 3 mo (SPEI-3) and 6 mo (SPEI-6) Standardized Precipitation Evapotranspiration Index (SPEI) for the period of 2000–2014 and for each selected vegetation type (see legends for details)

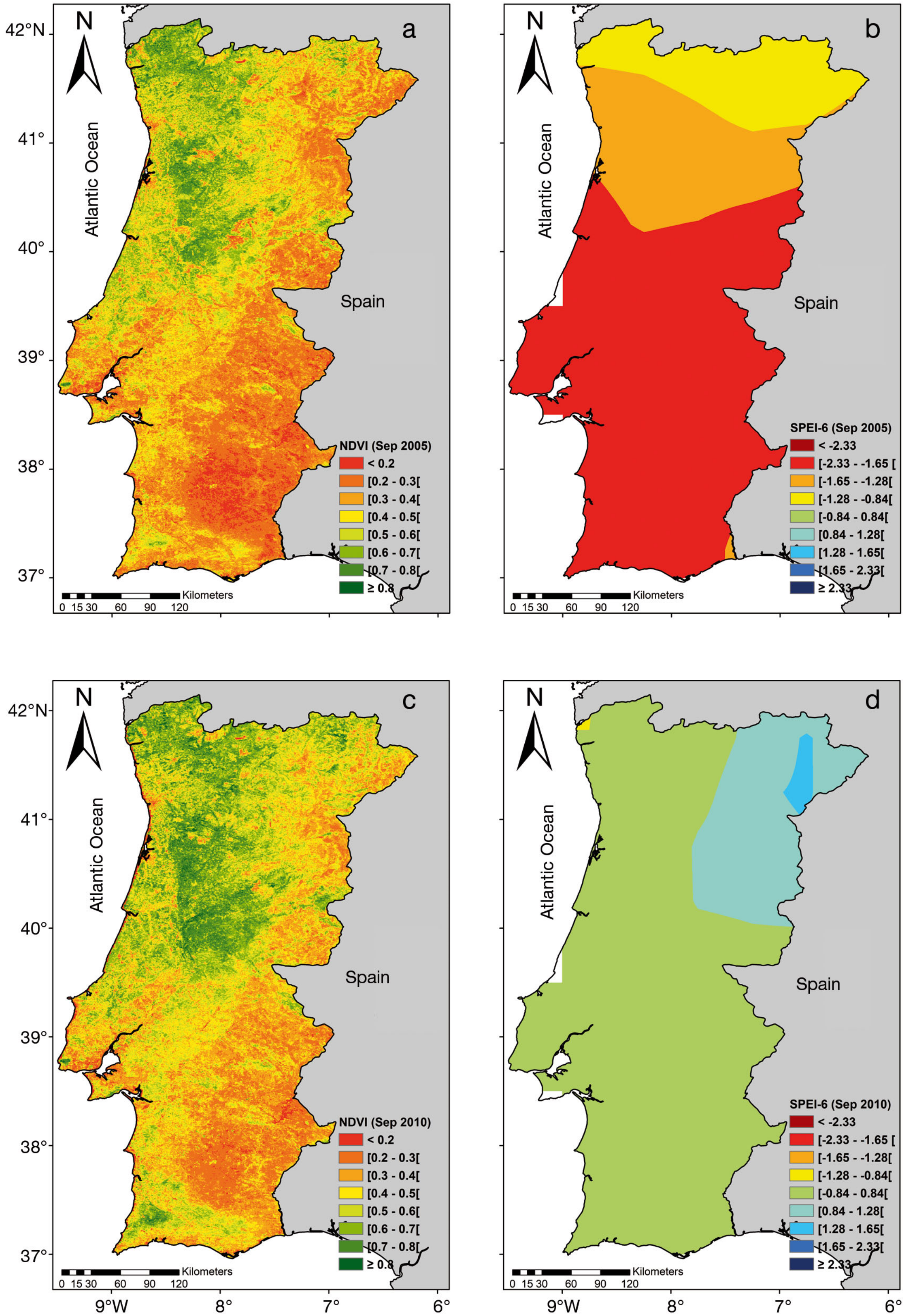


Fig. 5. (a) Normalized Difference Vegetation Index (NDVI) pattern for September 2005 and (b) corresponding 6 mo Standardized Precipitation Evapotranspiration Index (SPEI-6) pattern; (c,d) same as in (a,b) but for September 2010. Geographic coordinate system: WGS 1984

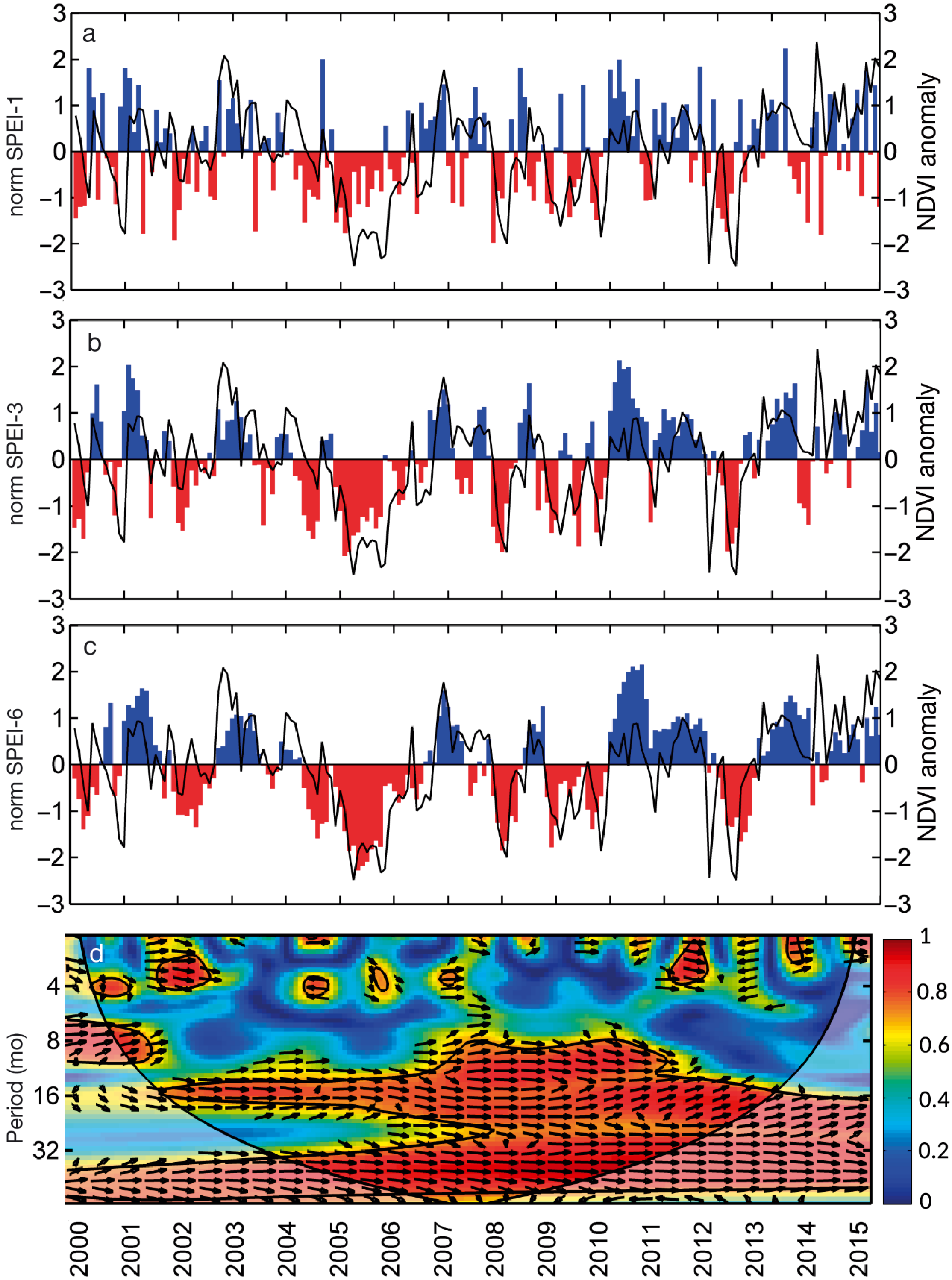


Fig. 6. Chronograms (2000–2014) of the monthly anomalies (departures from the corresponding monthly means for the full period) of the Normalized Difference Vegetation Index (NDVI, black lines) and of the Standardized Precipitation Evapotranspiration Index (a) 1 mo (SPEI-1), (b) 3 mo (SPEI-3) and (c) 6 mo (SPEI-6) timescales (blue bars for positive and red bars for negative values). (d) Cross-wavelet spectrum between the monthly anomalies of NDVI and of SPEI-6 for the same time period. Thick black lines outline statistically significant co-variability at the 95 % confidence level (5 % significance level against red noise is shown as a thick contour). The cone of influence is also represented by lighter shading. The relative phase relationship is shown as arrows (with in-phase pointing right, anti-phase pointing left)

pondence between drought/wet periods and NDVI anomalies (i.e. departures from its corresponding monthly means computed over the full period of 2000–2014). Besides the temporal correlation analysis, the spatial correlation between NDVI and SPEI-6 was also analyzed (Fig. S3). Apart from January, April and September, remarkably lower correlations were found over northwestern Portugal, which can be explained by regional vegetation features (Fig. 1) and by their different sensitivities to water availability. In effect, dense evergreen and deciduous forests are mostly located in the northwest and tend to be less sensitive to precipitation regime seasonality (Fig. 3). Therefore, SPEI is expected to be an important predictor of NDVI anomalies in Portugal, particularly at the longer timescales. A similar analysis was also carried out for TX and TN, but showed much weaker associations between the NDVI anomalies and these variables (Figs. S4 & S5). However, some correlations at 3 and 6 mo timescales are still apparent, thus also being potential predictors of NDVI.

The NDVI can be influenced by non-climatic factors; namely, by wildfires. However, we found no clear association between the evolution of NDVI anomalies and burnt area in Portugal, obtained from Portuguese Forest Service (ICNF) official records (http://www2.icnf.pt/portal/florestas/dfci/inc/estat-sgif#tot) (Fig. S6). The burnt area attained a maximum of 3.5% of the total area of Portugal, illustrating that the influence of wildfires in areal-mean NDVI is marginal. Therefore, wildfire effects on the NDVI are neglectful beyond the local scale.

### 3.2. NDVI models

Although the time series of the NDVI anomalies (departures from the mean seasonal cycle) for each vegetation class are highly correlated, some important differences can still be found; namely, the stronger variability and magnitude of the anomalies in grasslands, holm and cork oaks compared to deciduous forests and other evergreen forests (Fig. S7). Therefore, 6 type-specific NDVI models, one for each vegetation class, were developed using SPEI, TX and TN as potential regressors (defined for timescales from 1–6 mo). These models are statistically significant ($p < 0.01$) according to Fisher's test (Table 1), and the residuals are normally distributed and independent according to the Lilliefors and Durbin-Watson tests ($p < 0.05$). The resulting estimated time series accounted for 37–49% of the observed variance ($R^2$ values in Table 1). However, after cross-validation, as expected, these values lower to 30–37%, i.e. the model explains about one-third of the withheld variance of the seasonality-removed monthly NDVI anomalies.

The scatterplots between observed and modelled NDVI highlight the different model performances (Fig. 7, left panels). Despite the post-processing scaling of the modelled time series, there is still some underestimation of the variability in the modelled time series (regression slopes <1), which is a common limitation of regression analysis. Furthermore, the corresponding chronograms depict an overall agreement between estimated and observed monthly NDVI (Fig. 7, middle panels). However, the models show noteworthy deviations, e.g. on the estimation of NDVI for 2010 (anomalously wet conditions; Fig. 6), overestimating NDVI. Modelling extreme events often requires specific models for these events, which is out of the scope of the present study owing to the insufficient sample size for such a study (15 yr).

For all vegetation classes, no biases between observed and modelled NDVI were found (Table 1). The corresponding MAE varied from 0.02–0.04, while the RMSE ranged from 0.03–0.05 (Table 1). For each model, the correlation coefficients between

Table 1. Stepwise-selected predictors (Standardized Precipitation Evapotranspiration Index [SPEI], maximum [TX] and minimum [TN] temperatures at 3 and 6 mo timescales) and corresponding performance parameters of the multivariate linear regression modelling of Normalized Difference Vegetation Index (NDVI) monthly anomalies (dependent variable): Fisher's test measure ($F$), R-squared value ($R^2$), R-squared value after leave-one-out cross-validation ($R^2_{cv}$), bias between estimated and observed averages (BIAS), mean absolute error (MAE) and root-mean squared error (RMSE)

| | Predictors | $F$ (p-value) | $R^2$ | $R^2_{cv}$ | BIAS | MAE | RMSE |
|---|---|---|---|---|---|---|---|
| Grassland | SPEI-3, SPEI-6, TX-6 | 47.59 (<0.01) | 0.44 | 0.34 | 0.00 | 0.04 | 0.05 |
| Holm oak | SPEI-3, SPEI-6, TX-6, TN-3 | 32.84 (<0.01) | 0.42 | 0.31 | 0.00 | 0.04 | 0.05 |
| Cork oak | SPEI-3, SPEI-6, TX-6 | 57.68 (<0.01) | 0.49 | 0.37 | 0.00 | 0.03 | 0.04 |
| Shrubland | SPEI-1, SPEI-3, SPEI-6 | 44.31 (<0.01) | 0.42 | 0.36 | 0.00 | 0.03 | 0.03 |
| Deciduous forest | SPEI-1, SPEI-3, SPEI-6, TX-6 | 26.38 (<0.01) | 0.37 | 0.30 | 0.00 | 0.02 | 0.03 |
| Evergreen forest | SPEI-3, SPEI-6, TX-6 | 38.83 (<0.01) | 0.39 | 0.31 | 0.00 | 0.02 | 0.03 |

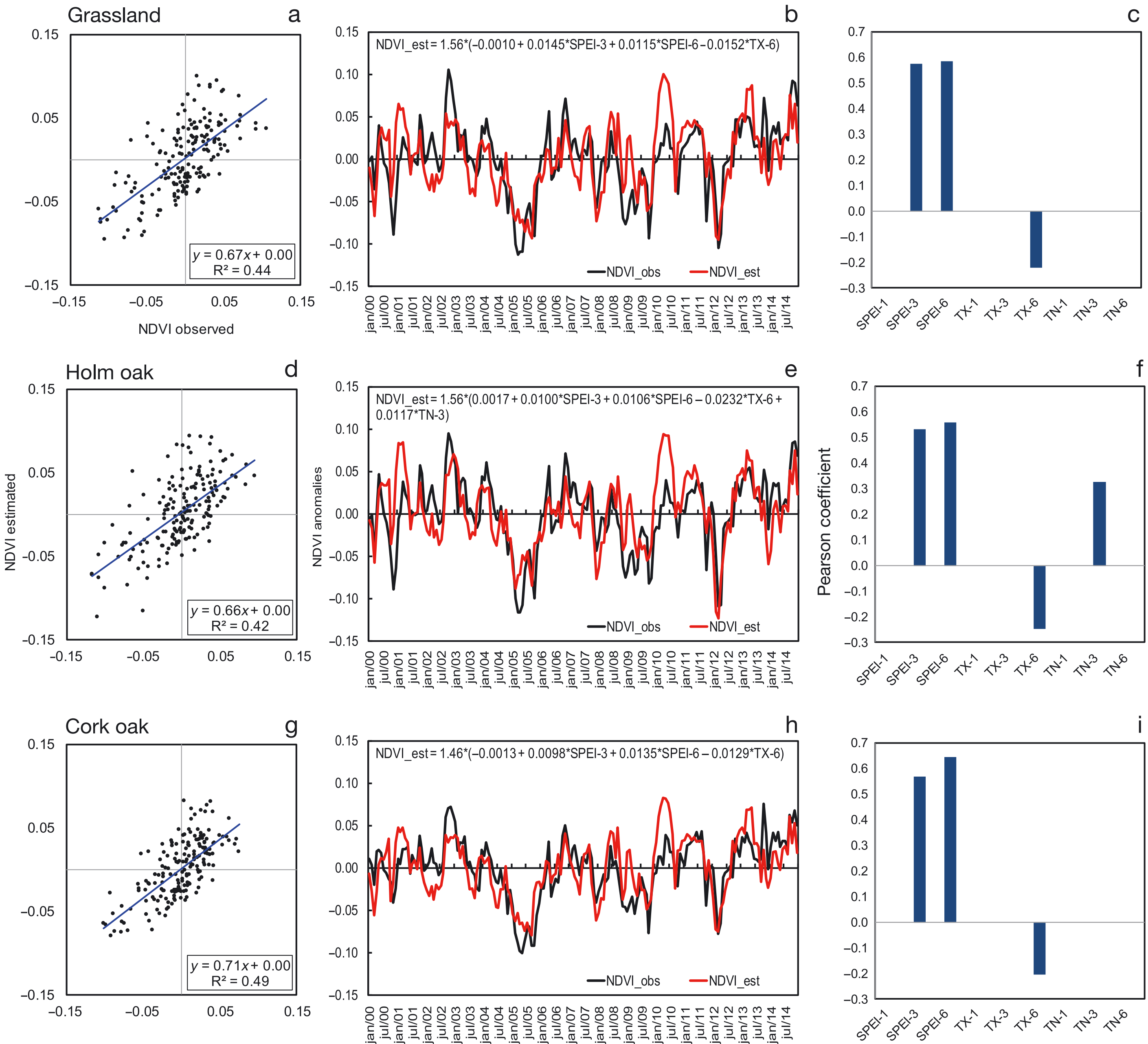


Fig. 7. Regression on the Normalized Difference Vegetation Index (NDVI) anomalies: (a,d,g,j,m,p) scatterplots of observed vs. modelled NDVI anomalies for each outlined vegetation type, along with the respective linear regression lines; (b,e,h,k,n,q) chronograms of the observed and modelled NDVI anomalies over the period of 2000–2014 (cf. legends for details). The corresponding regression equations with the multiplicative factors are also outlined. (c,f,i,l,o,r) Bar charts of the Pearson product-moment correlation coefficients between the observed NDVI anomalies and the stepwise-selected predictors over the period of 2000–2014 and for each vegetation type (continued on next page)

NDVI and the stepwise-selected regressors confirmed that SPEI largely controls NDVI variability, particularly at the 6 mo scale (correlation coefficients 0.55–0.65 for SPEI-6 in all vegetation types; Fig. 7, right panels). Nevertheless, TX-6 also presented significant negative correlations with observed NDVI for all classes except shrublands (correlation coefficients from −0.25 to −0.15). In the latter case, SPEI is an important factor for 1, 3 and 6 mo timescales and no significant association with temperatures was found, as in the global empirical model of Del Grosso et al. (2008) for net primary production. TN-3 influ-

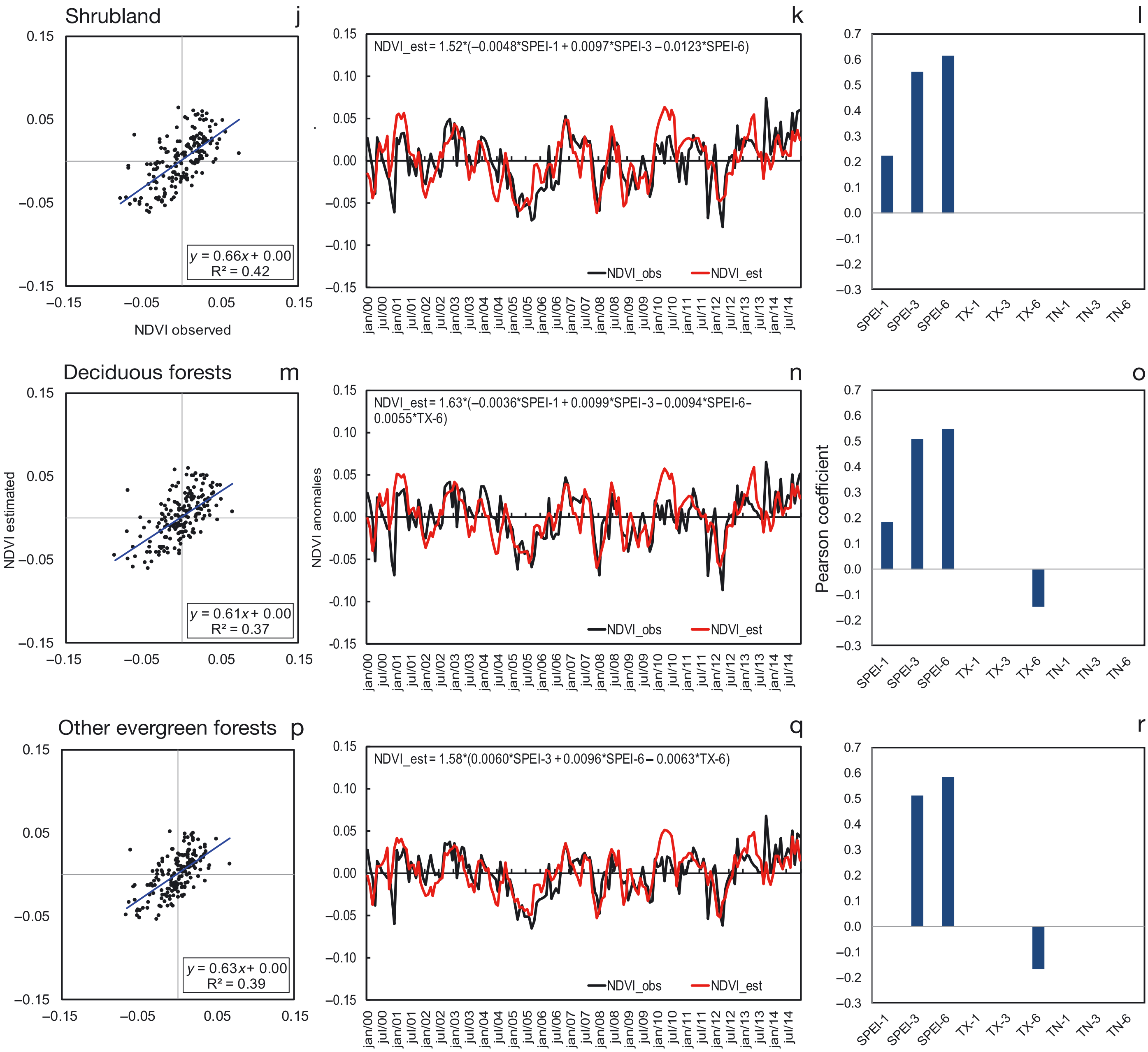


Fig. 7 (continued)

ences NDVI in the case of holm oak (correlation coefficient of 0.33). Hence, monthly greenness fluctuations with respect to the seasonal cycle depend primarily on SPEI-6, but TX-6 and TN-3 may have a moderate influence on greenness of some specific vegetation classes. Therefore, anomalously high SPEI generally favours greenness (higher water availability leads to higher NDVI), as well as moderate air temperatures (lower TX and higher TN). These results are indeed supported by previous studies (De Dato et al. 2008, Del Grosso et al. 2008, Fang et al. 2016). The diurnal temperature range at the different timescales was also tested based on previous studies (Scheitlin 2013, Hatfield & Prueger 2015), but no statistically significant improvements in the models were achieved.

For each vegetation type, the NDVI values can be recovered by adding the corresponding mean seasonal cycle to the predicted anomalies. Therefore, as a final step of the NDVI modelling, the mean seasonal cycle (second model component) of each vegetation type was added to the corresponding NDVI cross-validated monthly anomalies in Fig. 7. The final results are displayed in Fig. 8 (multivariate lin-

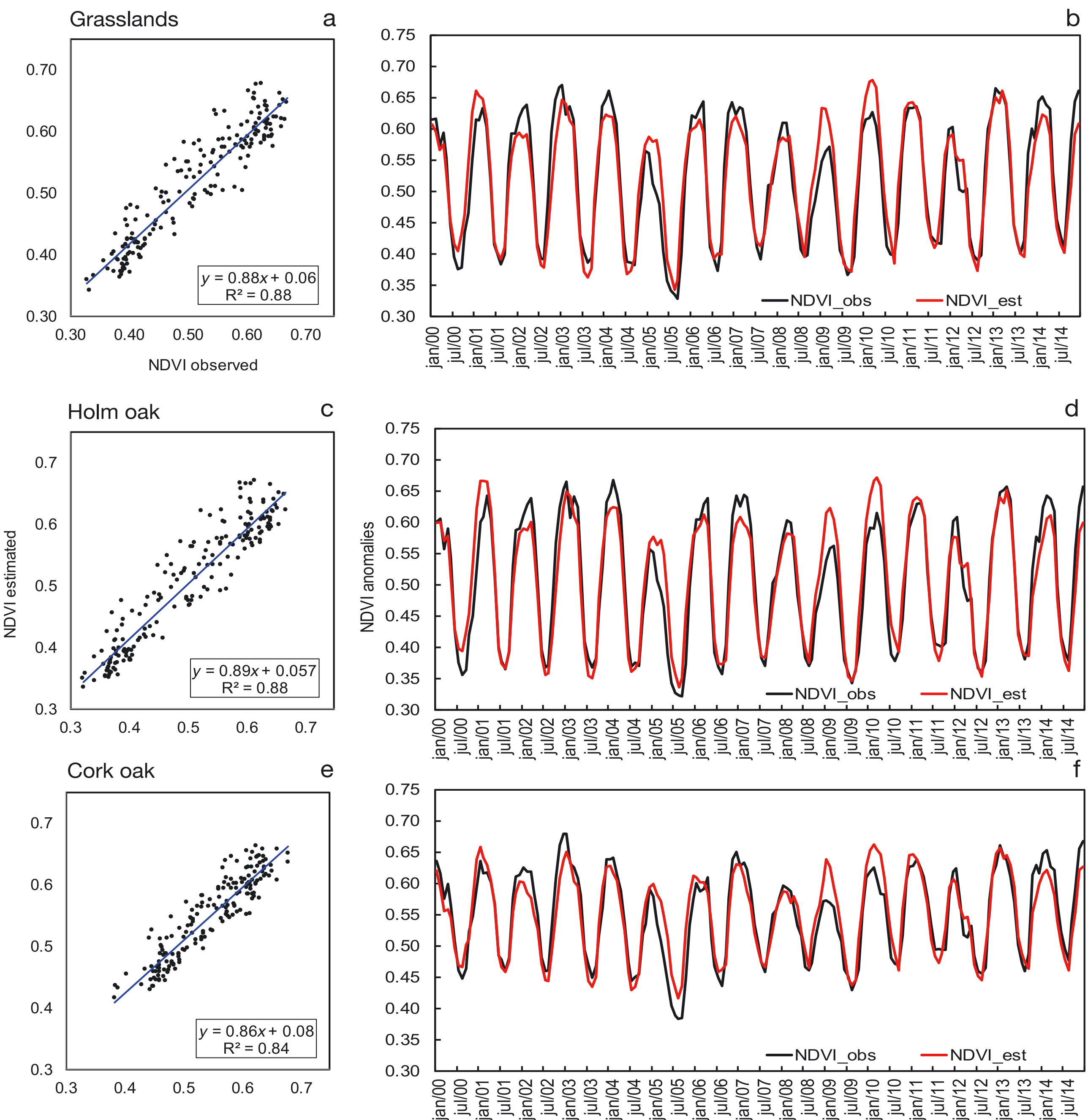


Fig. 8. Final Normalized Difference Vegetation Index (NDVI) models: (a,c,e,g,i,k) scatterplots of observed vs. modelled NDVI values for each outlined vegetation type, along with the respective linear regression lines; and (b,d,f,h,j,l) chronograms of the observed and modelled NDVI over the period of 2000–2014 (cf. legends for details) (continued on next page)

ear regression + mean seasonal cycle). The model performances increased significantly when the seasonal cycle was incorporated (Table 2), as it is a very strong component of the NDVI monthly variability. Overall, the final NDVI model performances were very satisfactory at simulating the observed monthly variability of NDVI, explaining 50–88% of the observed variability, with relative RMSE of 3–7% (Table 2). The BIAS was zero for every type, while the MAE varied from 0.02–0.03 (Table 2). As expected, this improvement is particularly noteworthy for the vegetation types with stronger seasonality (Fig. 3), such as grasslands (88%), holm (88%) or cork (84%) oaks, while for shrublands (71%), deciduous forests (50%) and other evergreen forests (74%), with weaker seasonality, the improvements in

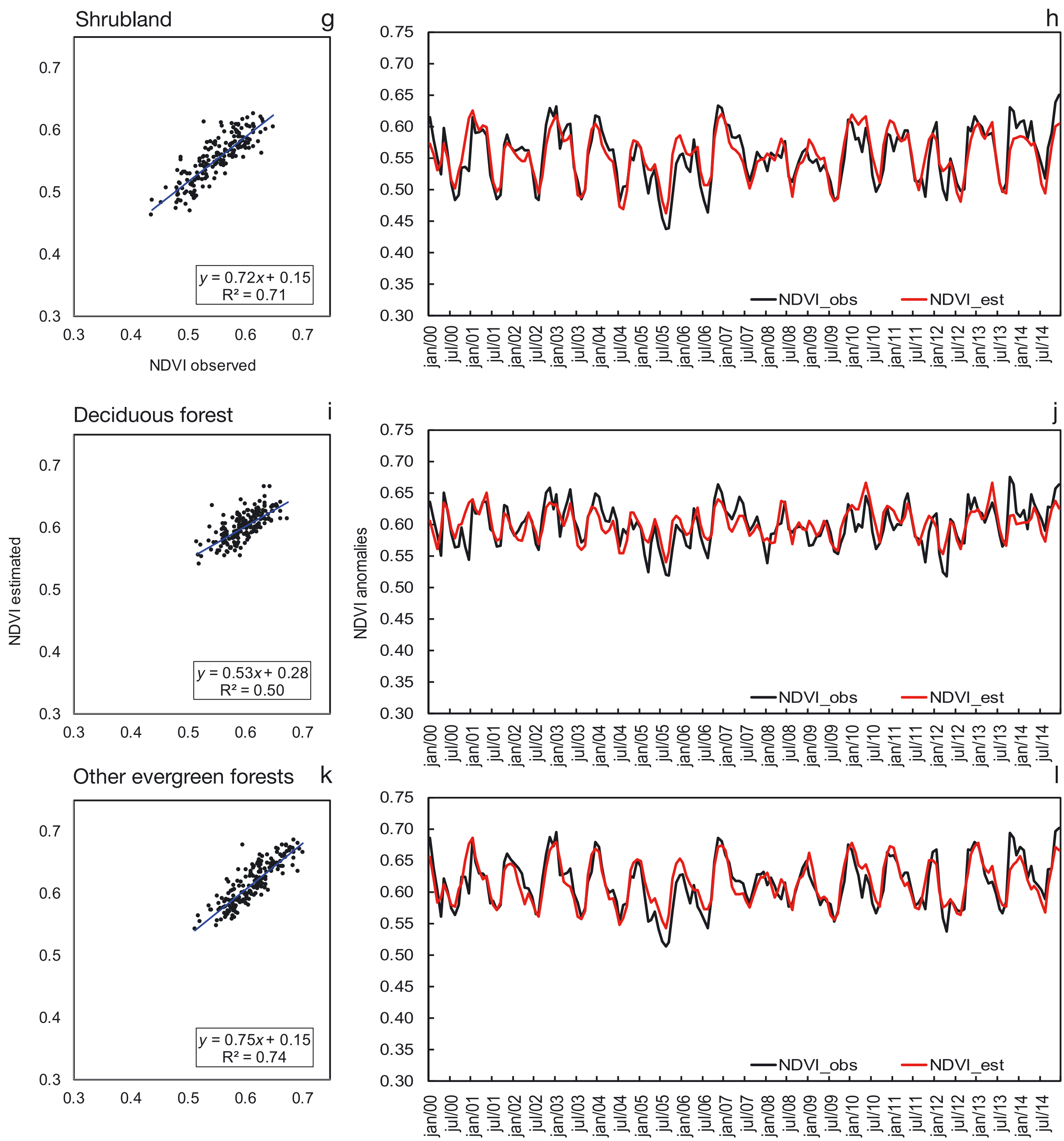


Fig. 8 (continued)

the model performances are more modest. In fact, the seasonal cycle has higher contributions to the explained variance than the climatic anomalies (regression models) in the former 3 types, but has similar contributions in the latter 3 types. For deciduous forests, the seasonal cycle has indeed lower contribution than the climatic anomalies.

By applying the previous models, it is possible to predict, with relatively high accuracy, vegetation greenness in Portugal up to 3 mo (1 mo) in advance for grasslands, holm or cork oaks and other evergreen forests (shrublands and deciduous forests). Furthermore, these models enable predicting the NDVI in future conditions, including under climate change scenarios, which should be done in a follow-up study. Predicting NDVI is useful e.g. for forest and fire management; namely, to anticipate and prepare for particularly severe and prolonged fire seasons.

Table 2. Performance parameters of the final models (multivariate linear regression + mean seasonal cycle) of monthly Normalized Difference Vegetation Index (NDVI): R-squared value after leave-one-out cross-validation ($R^2_{cv}$), the change in $R^2_{cv}$ after adding the mean seasonal cycle ($\Delta R^2_{cv}$), bias between estimated and observed averages (BIAS), mean absolute error (MAE), root-mean squared error (RMSE) and relative RMSE (%) of observed NDVI average

| | $R^2_{cv}$ | $\Delta R^2_{cv}$ | BIAS | MAE | RMSE | RMSE (%) |
|---|---|---|---|---|---|---|
| Grassland | 0.88 | +0.54 | 0.00 | 0.03 | 0.03 | 7 |
| Holm oak | 0.88 | +0.57 | 0.00 | 0.03 | 0.04 | 7 |
| Cork oak | 0.84 | +0.47 | 0.00 | 0.02 | 0.03 | 5 |
| Shrubland | 0.71 | +0.35 | 0.00 | 0.02 | 0.02 | 4 |
| Deciduous forest | 0.50 | +0.20 | 0.00 | 0.02 | 0.02 | 4 |
| Evergreen forest | 0.74 | +0.43 | 0.00 | 0.02 | 0.02 | 3 |

An evident example is the abnormally high burnt area in 2005, which was preceded by, and coincided with, the strongest and longest drought during the study period (cf. Figs. 6 & S6).

The ability to predict the NDVI is also pertinent in the face of on-going and future warming, with substantial increase of dry and arid lands in the Iberian Peninsula indicating changes in vegetation cover (Vicente-Serrano et al. 2012). As such, given the projected warming and decrease in precipitation, particularly during spring and summer (Fraga et al. 2016, Santos et al. 2016, Costa et al. 2017), as well as the projected increases in the occurrence of extreme droughts (Costa et al. 2012) such as the aforementioned 2005 drought in Portugal, an enhancement of these negative impacts is envisioned. Furthermore, intensified human-related activities, such as overgrazing, cultivation of steep slopes and development of intensive crops may also decrease vegetation cover, consequently influencing soil fertility and triggering or intensifying vegetation degradation processes (Vicente-Serrano et al. 2012). Conversely, many regions are currently undergoing declining agriculture and forest use, which may lead to natural vegetation recovery. Nonetheless, successful recovery will be influenced by several environmental and socioeconomic limitations, such as the degree of prior agricultural intensity and the land economic interest.

## 4. CONCLUSIONS

Over the study time period, a general increasing trend in NDVI values over southern Portugal and a decrease along coastal northern areas were found. However, despite these long-term trends, landscape greenness in Portugal is largely governed by climatic factors, especially the precipitation regime. This dependency is particularly apparent in the more typically Mediterranean regions of southern/inner Portugal. Furthermore, the identified regional discrepancies are mostly attributable to different vegetation types. Therefore, in the present study, these associations were analyzed using vegetation-type specific analyses, which helped explaining spatial and temporal (intra- and inter-annual) variability of NDVI in Portugal in response to different timescales of precipitation and temperature variability. In fact, despite the key role played by precipitation/soil water variability in monthly anomalies of vegetation greenness, maximum and, to a much lower extent, minimum temperatures are also relevant forcing factors. In effect, several previous studies have identified clear connections between NDVI and land surface/near-surface temperatures in different regions worldwide, though these relationships are often modulated by precipitation (e.g. Karnieli et al. 2010). Other studies also suggest that medium to long-term water stress plays an important role on NDVI variability (e.g. Gouveia et al. 2009, Ferreira et al. 2012), which is also in accordance with the high relevance of the 3–6 mo SPEI timescales the present study models.

Understanding the vegetation greenness versus climatic variability relationship is of foremost relevance in land monitoring and management (e.g. crop phenology and development, forest degradation/health assessments and wildfires), water resources management (e.g. water stress assessments), ecosystem monitoring and landscape planning, all of which are pertinent under changing climates and environments. These relationships may provide clues about the ecosystem impacts of climate change, allowing developing guidelines to improve forest and water resources management.

*Acknowledgements*. This study was funded by the 'Integrative Research in Environment, Agro-Chains and Technology' project (INTERACT; NORTE-010145-FEDER-000017) in its line of research entitled BEST-T4, co-financed by the European Regional Development Fund (ERDF) through NORTE 2020 (North Regional Operational Program 2014/2020). It was also supported by FEDER/COMPETE/POCI (Operational Competitiveness and Internationalization Programme), POCI-01-0145-FEDER-006958, and by FCT (Portuguese Foundation for Science and Technology), UID/AGR/04033/2013. The authors also acknowledge the FCT scholarship given to R.C., PD/BD/135326/2017, under the Doctoral Programme 'Agricultural Production Chains – from fork to farm' (PD/00122/2012).

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*Editorial responsibility: Gerrit Hoogenboom, Gainesville, Florida, USA*

*Submitted: November 3, 2017; Accepted: May 11, 2018*
*Proofs received from author(s): August 21, 2018*