Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions

Mapping the suitability of groundwater dependent vegetation in a semi-arid Mediterranean area

Inês Gomes Marques[1]; João Nascimento[2]; Rita M. Cardoso[1]; Filipe Miguéns[2]; Maria Teresa Condesso de Melo[2]; Pedro M. M. Soares[1]; Cathy Kurz Besson[1]

[1] Instituto Dom Luiz; Faculty of Sciences, University of Lisbon, Campo Grande, Ed. C8, 1749-016, Lisbon, Portugal

[2] CERIS; Instituto Superior Técnico, University of Lisbon, 1049-001, Lisbon, Portugal

Correspondence to: Inês Gomes Marques (icgmarques@fc.ul.pt)

Abstract. The forecasted groundwater resource depletion under future climatic conditions will greatly influence groundwater dependent ecosystems and their associated vegetation. In the Mediterranean region this will create harsh conditions for the maintenance of agroforestry systems dependent on groundwater, such as cork oak woodlands. The threat of increasing aridity conditions will affect their productivity and eventually induce a shift in their geographical distribution. Thus, characterizing and modelling the relationship between environmental conditions and groundwater dependent vegetation (GDV) will allow to identify the main drivers controlling its distribution and predict future impacts of climate change.

In this study, we built a model that explains the distribution of deep-rooted woody species in southern Portugal from climatic, hydrological and topographic environmental variables. To achieve this, we relied on the density of *Quercus suber*, *Quercus ilex* and *Pinus pinea* as proxy species of GDV. Model fitting was performed between the proxy species Kernel density and the selected environmental predictors using 1) a simple linear model and 2) a Geographically Weighted Regression (GWR), to account for auto-correlation of the spatial data and residuals. When comparing the results of both models, the GWR modelling results showed improved goodness of fitting, as opposed to the simple linear model. Soil type was the main driver of GDV density closely followed by the aridity index. Groundwater depth did not appear to be as pertinent in the model as initially expected.

Model predictor coefficients were used as weighting factors for multicriteria analysis, to create a suitability map to the GDV in southern Portugal. A validation of the resulting map was performed using independent data of integrated potential distribution of each proxy tree species in the region and overall, there was a good accordance between areas of good suitability to GDV. The model was considered reliable to predict the distribution of the studied vegetation, however, lack of data quality and information was shown to be the main cause for suitability discrepancies between maps.

Our new methodology on mapping of GDV's will allow to predict the evolution of the distribution of GDV according to climate change scenarios and aid stakeholder decision-making concerning priority areas of water resources management.

Keywords: Groundwater dependent ecosystems, aridity, agroforestry, suitability map

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

1 Introduction

Groundwater is the largest subsurface water reservoir and supports valuable ecosystems (Eamus et al., 2006). Mediterranean forests, woodlands and shrublands, mostly growing under restricted water availability, are one of the terrestrial biomes with higher volume of groundwater used by vegetation (Evaristo and McDonnell, 2017). Future predictions of decrease precipitation (Giorgi and Lionello, 2008; Nadezhdina et al., 2015), decreased runoff (Mourato et al., 2015) and aquifer recharge (Ertürk et al., 2014) in the Mediterranean region threaten the sustainability of groundwater reservoirs and the corresponding dependent ecosystems. Therefore, a sustainable management of groundwater resources and the Groundwater Dependent Ecosystems (GDE) is of crucial importance.

Mapping GDE constitutes a first and fundamental step to their active management. Several approaches have been proposed, including remote sensing techniques (e.g. Normalized Difference Vegetation Index – NDVI) (Barron et al., 2014; Eamus et al., 2015; Howard and Merrifield, 2010), remote-sensing combined with ground-based observations (Lv et al., 2013), based on geographic information system (GIS) (Pérez Hoyos et al., 2016a) or statistical approaches (Pérez Hoyos et al., 2016b). Integrated multidisciplinary methodology (Condesso de Melo et al., 2015) has also been used. A widely used classification of GDE was proposed by Eamus et al. (2006). This classification distinguishes between three types: 1) Aquifer and cave ecosystems, which includes all subterranean waters; 2) Ecosystems reliant on surface groundwater (e.g. estuarine systems, wetlands; riverine systems) and 3) Ecosystems reliant on subsurface groundwater (e.g. systems where plants remain physiologically active during extended drought periods, without visible water source).

Despite of a wide-ranging body of literature regarding GDE, most of the studies did not included Mediterranean regions (Doody et al., 2017; Dresel et al., 2010; Münch and Conrad, 2007). Moreover, studies on ecosystems relying on subsurface groundwater frequently only focused on riparian environments (Lowry and Loheide, 2010; O'Grady et al., 2006), with few examples in Mediterranean areas (del Castillo et al., 2016; Fernandes, 2013; Hernández-Santana et al., 2008; Mendes et al., 2016). There is a clear knowledge gap concerning the identification of such ecosystems, their phreatophyte associated vegetation (Robinson, 1958) in the Mediterranean region and the management actions that should be taken to decrease the adverse effects of climate change.

In the driest regions of the Mediterranean basin, the persistent lack of water during the entire summer periods selected plants with drought-avoiding strategies, like those that reach deeper stored water up to the point of relying on groundwater (Canadell et al., 1996; Miller et al., 2010). Groundwater access by deep rooting species is often associated to hydraulic lift and/or hydraulic redistribution mechanisms (Orellana et al., 2012). Those mechanisms provide the ability to move water from deep soil layers, where water content is higher, to more shallow layers where water content is lower (Horton and Hart, 1998; Neumann and Cardon, 2012). Hydraulic lift and redistribution have been reported for several woody species of the Mediterranean basin (David et al., 2007; Filella and Peñuelas, 2004) and noticeably for Cork oak (*Quercus suber* L.) (David et al., 2013; Kurz-Besson et al., 2006; Mendes et al., 2016).

Cork oak woodlands are agro-silvo-pastoral systems of the southwest Mediterranean basin (Joffre et al., 1999) who have already been referenced has a groundwater dependent terrestrial ecosystem (Mendes et al., 2016). In the ecosystems of this geographical area, the dominant tree species are the cork oak (*Quercus suber* L.) and the Portuguese holm oak (*Quercus ilex* subs *rotundifolia* Lam.*)* (Pinto-Correia et al., 2011). Additionally, stone pine (*Pinus pinea* L.) has become a commonly co-occurrent species in the last decades (Coelho and Campos, 2009). The use of groundwater has been frequently reported for both Pinus (Filella and Peñuelas, 2004; Grossiord et al., 2016; Peñuelas and Filella, 2003) and Quercus (Barbeta and Peñuelas, 2017; David et al., 2007, 2013, Kurz-Besson et al., 2006, 2014; Otieno et al., 2006) genders. Furthermore, the contribution of groundwater to tree physiology has been shown to be of a greater magnitude for *Quercus* sp. as compared with *Pinus* sp. (del Castillo et al., 2016; Evaristo and McDonnell, 2017).

Q. suber and *Q. ilex* have been associated with high resilience and adaptability to hydric and thermic stress, and to recurrent droughts in the southern Mediterranean basin (Barbero et al., 1992). In Italy and Portugal, during summer droughts *Q. ilex* used a mixture of rain-water and groundwater and was able to take water from very dry soils (David et al., 2007; Valentini et al., 1992). An increasing contribution of groundwater in the summer has also been shown for this species (Barbeta et al., 2015). Similarly, *Q. suber* showed a seasonal shift in water sources, from shallow soil water in the spring to the beginning of the dry period followed by a progressive higher use of deeper water sources throughout the drought period (Otieno et al., 2006). In addition, the species roots are known to reach depths as deep as 13m in southern Portugal (David et al., 2004). Although co-occurrent to cork and holm oaks species, there is still no evidence yet that *P. pinea* relies on groundwater resources during the dry season. However it shows a very similar root system (Montero et al., 2004) as compared to cork oak (David et al., 2013), with large sinker roots reaching 5m depth (Canadell et al., 1996). Given the information available on water use strategies by the phreatophyte arboreous species of the cork oak woodlands, we considered *Q. ilex*, *Q. suber* and *P. pinea* as proxies for vegetation that belongs to GDE relying on subsurface groundwater (from here onwards designed as Groundwater Dependent Vegetation – GDV).

GDV of the Mediterranean basin is often neglected in research. Indeed, still little is known about the GDV distribution, but research has already been done on the effects of climate change in specific species distribution, such as *Q. suber*, in the Mediterranean basin (Duque-Lazo et al., 2018; Paulo et al., 2015). While the increase in atmospheric CO_2 and the raising temperature can boost tree growth (Barbeta and Peñuelas, 2017; Bussotti et al., 2013; Sardans and Peñuelas, 2004), water stress can have a counteracting effect on growth of both *Quercus ilex* (López et al., 1997; Sabaté et al., 2002) and *P. pinaster* (Kurz-Besson et al., 2016). Therefore, it is of crucial importance to identify geographical areas where subsurface GDV is present and characterize the environmental conditions this vegetation type is thriving in. This would contribute to the understanding of how to manage these species under unfavorable future climatic conditions.

The aim of this study was to create a suitability map of the current distribution of GDV in southern Portugal, based on the occurrence of known and foreseen subsurface phreatophyte species and well-known environmental conditions affecting groundwater storage. Several environmental predictors were

selected according to their impact on groundwater use and storage and then used in a Geographically Weighted Regression (GWR) to model the density of *Q. suber*, *Q. ilex* and *P. pinea* occurrence in the Alentejo region (NUTSII) of southern Portugal. So far, very few applications of this method have been used to model species distribution and only recently its use has spread in ecological research (Hu et al., 2017; Li et al., 2016; Mazziotta et al., 2016). The coefficients obtained from the model equation for each predictor were used as weights to build the suitability map with GIS multi-factor analysis, after reclassifying each environmental predictor.

Based on the environmental conditions of the study area and the species needs, we hypothesized that 1) groundwater depth together with climatic conditions play one of the most important environmental roles in GDV's distribution and 2) a more superficial access to groundwater and less arid conditions should allow a higher density of GDV. Therefore, a higher suitability should be expected under such conditions.

We start by presenting the methodology used to create the environmental variables for the study area of Alentejo, followed by an explanation of how the model was constructed and lead to the GDV suitability map and subsequent validation. In the result section in chapter 3, we display the maps for the environmental variables and parameters from the model fitting, the final suitability map and respective validation. The results are discussed in the fourth chapter and the conclusions are presented in the fifth chapter.

2 Material and Methods

2.1 Study area

The administrative region of Alentejo (NUTSII) (fig01) covers an area of 31 604.9 km^2, between the latitude 37.22º to 39.39º N and longitude 9.00º to 6.55º W. This study area is characterized by a Mediterranean temperate mesothermic climate with hot and dry summers, defined as Csa in the Köppen classification (APA, n.d.; ARH Alentejo, 2012a, 2012b). It is characterized by a sub-humid climate, which has recently quickly drifted to semi-arid conditions (Ministério da Agricultura do Mar do Ambiente e do Ordenamento do Território, 2013). A large proportion of the area (above 40%) is covered by forestry systems (Autoridade Florestal Nacional and Ministério da Agricultura do Desenvolvimento Rural e das Pescas, 2010) providing a high economical value to the region and the country (Sarmento and Dores, 2013).

2.2 Kernel Density estimation of GDV

Presence datasets of *Quercus suber*, *Quercus ilex* and *Pinus pinea* of the last Portuguese forest inventory achieved in 2010 (ICNF, 2013) were used to calculate Kernel density (commonly called heat map) as a proxy to GDV suitability. Only data points with one of the three proxy species selected as primary and secondary occupation were used. The resulting Kernel density was weighted according to tree cover percentage and was calculated using a quartic biweight distribution shape, a search radius of 10km, and an output resolution of 0.018 degrees, corresponding to a cell size of 1 km. This variable was computed using QGIS version 2.14.12 (QGIS Development Team, 2017).

2.3 Environmental variables

Species distribution is mostly affected by limiting factors (controlling ecophysiological responses), disturbances and resources (Guisan and Thuiller, 2005). To characterize the study area in terms of GDV suitability, environmental variables expected to affect GDV's density were selected according to their constraint on groundwater uptake and soil water storage. Within possible abiotic variables, landscape topography, geology, groundwater availability and regional climate were considered to map GDV density in the study area. The twelve selected variables for modeling purposes, retrieved from different data sources are listed on Table 1.

2.3.1 Topography and Geology

NASA and METI ASTER GDEM product (https://lpdaac.usgs.gov) was retrieved from the online Data Pool. Spatial Analyst Toolbox from ArcGIS® software version 10.4.1 by Esri was used to calculate the

slope from the digital elevation model. Slope was used as proxy for the identification of superficial water interaction with vegetation.

The map of soil type was obtained from the Portuguese National Information System for the Environment - SNIAmb (© Agência Portuguesa do Ambiente, I.P., 2017) and uniformized to the World Reference Base with the Harmonized World Soil Database v 1.2 (FAO et al., 2009). The vector map was converted to raster using the Conversion Toolbox from ArcGIS® software version 10.4.1 by Esri. To reduce the analysis complexity involving the several soil types present in the map, soil types were regrouped in three classes, according to their capacity to store or drain water. The classification was based on the characteristics of each soil unit (available water storage capacity, drainage and topsoil texture) from the Harmonized World Soil Database (FAO et al., 2009).

Effective soil thickness (Table 1) represents the maximum soil depth explored by the vegetation roots. It constrains the expansion and growth of the root system, as well as the available amount of water that can be absorbed by roots.

2.3.2 Groundwater availability

Root access to groundwater is one of the most limiting factors for GDV's growth and survival, especially during the dry season. The map of depth to water table was interpolated from piezometric observations from the Portuguese National Information System on Water Resources (SNIRH) public data base (http://snirh.apambiente.pt, last accessed on March 31st 2017) and the Study of Groundwater Resources of Alentejo (ERHSA) (Chambel et al., 2007). Data points of large-diameter wells and piezometers were retrieved for the Alentejo region (fig02) and sorted into undifferentiated, karst or porous geological types to model groundwater depth. Due to the large heterogeneity of geological media, groundwater depth was calculated separately for each sub-basin. A total of 3158 data points corresponding to large wells and piezometers were used, with uneven measurements between 1979 and 2017. For each piezometer an average depth was calculated from the available observations and used as a single value. In areas with undifferentiated geological type, piezometric level and elevation were highly correlated (>0.9), thus a linear regression was applied to interpolate data. Ordinary kriging was preferred for the interpolation of karst and porous aquifers, combining large wells and piezometric data points. To build a surface layer of the depth to water table, the interpolated surface of the groundwater level was subtracted from the digital elevation model. Geostatistical Analyst ToolBox from ArcGIS® software version 10.4.1 by Esr was used for this task.

Drainage density is a measure of how well the basin is drained by stream channels. It is defined as the total length of channels per unit area. Drainage density was calculated for each of the six hydrographic basins of the Alentejo region, by the division between the total stream length (L) in km and the basin area (A) in km^2, as in Eq. (1).

$$Dd = \frac{L}{A}, \quad (1)$$

208

209 **2.3.3 Regional Climate**

210 Temperature and precipitation datasets were obtained from the E-OBS
211 (http://eca.knmi.nl/download/ensembles/ensembles.php, last accessed on March 31st 2017) public
212 database (Haylock et al., 2008). Standardized Precipitation Evapotranspiration Index (SPEI), Aridity
213 Index (AI) and Ombrothermic Indexes were computed from long-term (1951-2010) monthly temperature
214 and precipitation observations. The computation of potential evapotranspiration (PET) was performed
215 according to Thornthwaite (1948) and was assessed using the SPEI package (Beguería and Vicente-
216 Serrano, 2013) in R program software version 3.4.2 (R Development Core Team, 2016).

217 SPEI multi-scalar drought index (Vicente-Serrano et al., 2010) was calculated over a 6 month interval to
218 characterize drought severity in the area of study using SPEI package (Beguería and Vicente-Serrano,
219 2013) for R program. SPEI is based on the normalization of the water balance calculated as the difference
220 between cumulative precipitation and PET for a given period at monthly intervals. Normalized values of
221 SPEI typically range between -3 and 3. Drought events were considered as severe when SPEI values were
222 between -1.5 and -1.99, and as extreme with values below -2 (Mckee et al., 1993). Severe and extreme
223 SPEI predictors were computed as the number of months with severe or extreme drought, counted along
224 the 60 years of the climate time-series.

225 Aridity index gives information related to evapotranspiration processes and rainfall deficit for potential
226 vegetative growth. It was calculated following Eq. (2) according to Middleton et al. (1992), where PET is
227 the average annual potential evapotranspiration and P is the average annual precipitation, both in mm for
228 the 60 years period of the climate time-series. Dry lands are defined by their degree of aridity in 4 classes:
229 Hyperarid (AI<0.05); Arid (0.05<AI<0.2); Semi-arid (0.2<AI<0.5) and Dry Subhumid (0.5<AI<0.65)
230 (Middleton et al., 1992).

231 $$AI = \frac{P}{PET}, \quad (2)$$

232 Ombrothermic Indexes were used to better characterize the bioclimatology of the study region (Rivas-
233 Martínez et al., 2011), by evaluating soil water availability for plants during the driest months of the year.
234 Four ombrothermic indexes were calculated following Eq. (3), where Pp is the positive annual
235 precipitation (accumulated monthly precipitation when the average monthly mean temperature is higher
236 than 0°C) and Tp is the positive annual temperature (total in tenths of degrees centigrade of the average
237 monthly temperatures higher than 0°). If the ombrothermic index presents values above 2 for the analyzed
238 months, the area cannot be considered as Mediterranean bioclimatically. For non-Mediterranean areas,
239 there is no dry period in which, for at least two consecutive months, the precipitation is less than or equal
240 to twice the temperature. Each ombrothermic index differed in the examined period of the year (Table1).

241 $$Io = \frac{Pp}{Tp}, \quad (3)$$

242

243 **2.4 Predictors selection**

The full set of environmental variables were evaluated as potential predictors for the suitability of GDV (based on the Kernel density of the proxy species). A preliminary selection was carried out, first by computing Pearson's correlation coefficients between environmental variables and second by performing a Principal Components Analysis (PCA) to detect multicollinearity. Covariates were discarded for modeling according to a sequential procedure. Whenever pairs of variables presented a correlation value above 0.4, the variable with the highest explained variance on the first axis of the PCA was selected. Variables showing low correlations and explaining a higher cumulative proportion of variability with the lowest number of PCA axis were later selected as predictors for modeling. PCA was performed using the GeoDa Software (Anselin et al., 2006) and Pearson's correlation coefficients were computed with Spatial Analyst Tool from ArcGIS ® software version 10.4.1 by Esri.

2.5 Model development

When fitting a linear regression model to the selected variables, we must assure a normal distribution and stationarity of the model residuals. However, spatial autocorrelation and non-stationarity are common when using linear regression on spatial data. To overcome these issues, Geographically Weighted Regression (GWR) was used to allow model coefficients to adjust to each location of the dataset, based on the proximity of sampling locations (Stewart Fotheringham et al., 1996). In this study, simple linear regression and GWR were both applied to the dataset and their performances compared. Models were fitted on a 5% random subsample of the entire dataset (6242 data points), due to computational restrictions.

Adaptive Kernel bandwidths for the GWR model fitting were used due to the spatial irregularity of the random subsample. Bandwidths were obtained by minimizing the CrossValidation score (Bivand et al., 2008). To analyze the performance of the GWR model alone, the local and global adjusted R-squared were considered. To compare between the GWR model and the simple linear model, we considered the distribution of the model residuals, e.g. whether there were visible clustered values. The second-order Akaike Information Criterion (AICc) was also contemplated. The spatial autocorrelation of the models residuals was evaluated with the Moran's I test (Moran, 1950) using the Spatial Statistics Tool from ArcGIS ® software version 10.4.1 by Esri, and also graphically. GWR model was fitted using the *spgwr* package from R program version 3.4.2 (Bivand and Yu, 2017).

2.6 Suitability map building

To create the suitability map we proceeded with the classification of all predictor layers included in the GWR model, similarly to Condesso de Melo et al. (2015) and Aksoy et al. (2017) . The likelihood of an interaction between the vegetation and groundwater resources was scored from 0 to 3 for each predictor. Scores were assigned after bibliographic review and expert opinion. The higher the score, the higher the likelihood, 1 corresponding to a weak likelihood and 3 indicating very high likelihood. Groundwater depth was divided in two classes, according to the accessibility to superficial water above 1.5m and the maximum rooting depth for Mediterranean woody species reaching 13 m, reported by Canadell et al.

(1996). The minimum score was given to areas where groundwater depth was too shallow (below 1.5m). This allowed to identify species dependent on more superficial groundwater which were considered to belong to other types of groundwater dependent vegetation. Areas with steep slope were considered to have superficial water flow (e.g. areas with permanent water table close to the surface due to proximity to permanent streams) and influence negatively tree density (Costa et al., 2008). Those areas were treated as less suitable to GDV. Aridity Index and Ombrothermic Index of the summer quarter and the immediately previous month (Ios4) values were split in 3 classes according to Jenks natural breaks, with higher suitability scores corresponding to higher aridity.

A direct compilation of the predictor layers could have been performed, however not all predictors influence in the same measure the distribution of this type of vegetation. Therefore, there was a need to define weighting factors for each layer of the final GIS multicriteria analysis. Yet, due to the intricate relations between all environmental predictors and their effects on the GDV, experts and stakeholders provided very different scoring for a same layer. Subsequently, we instead chose to use the coefficients of the GWR model (Eq. 4) as weighting factors. The final GIS multicriteria analysis was performed using the Spatial Analyst Tool ArcGIS® software version 10.4.1 by Esri, resulting in the final suitability map.

In the latter, lower values indicate a lower probability of GDV occurrence while higher values correspond to a higher suitability. To allow for an easier interpretation, the data on suitability to GDV was subsequently classified based on their distribution value, according to Jenks natural breaks. This resulted in 5 suitability classes: “Very poor”, “Poor”, “Moderate”, “Good” and “Very Good”.

2.7 Map validation

To assess the quality of the suitability map obtained in the present study, independent maps of integrated suitability to *Q. suber*, *Q. ilex* and *P. Pinea* were retrieved from the EPIC WebGIS Portugal (http://epic-webgis-portugal.isa.ulisboa.pt/) public data base (Magalhães et al., 2015a, 2015b, 2015c). Those distribution maps represent the suitability to a tree species according to bioclimatic, soil morphological conditions and best silvicultural practices (Magalhães et al., 2015a). By overlapping the maps of the three species in ArcGIS, we obtained a synthetic independent map where it was possible to identify suitable areas to none, one, two or three of the tree species, considered good proxies of GDV (fig. C1). Artificialized areas, rocky outcrops, rivers and humid areas were eliminated from the evaluation and validated maps before performing an analytical comparison using the Analysis Tool ArcGIS® software version 10.4.1 by Esri.

315 **3 Results**

316

317 **3.1 Kernel Density**

318 Within the studied region of Portugal, the phreatophyte species *Quercus suber*, *Quercus ilex* and the
319 suspected phreatophyte species *Pinus pinea* were not distributed uniformly throughout the territory. Areas
320 with higher Kernel density (or higher distribution likelihood) were mostly spread between the northern
321 part of Alentejo region and the western part close to the coast, with values ranging between 900 and 1200
322 (fig03). Two clusters of high density also appeared below the Tagus river. The remaining study area
323 presented mean density values, with a very low density in the area of the river Tagus.

324

325 **3.2 Environmental conditions**

326 The exploratory analysis of the variables, performed through the PCA and Pearson correlation matrix
327 confirmed the presence of multicollinearity. From the initial variables (Table 1), Thickness, Drainage
328 Density, Spei_severe, Spei_extreme, Annual Ombrothermic Index (Io), Ombrothermic Index of the
329 hottest month of the summer quarter(Ios1) and Ombrothermic Index of the summer quarter **(**Ios3) were
330 discarded, while the variables slope, soil type, depth, AI and Ios4 were maintained for analysis (fig. A1
331 and Table A1 in appendix). Therefore, five environmental variables out of the initial 12 considered
332 (fig04) were endorsed to explain the variation of the Kernel density of GDV in Alentejo: soil type,
333 ombrothermic index of the summer quarter and the immediately previous month (ios4), slope, aridity
334 index and groundwater depth.

335 The Alentejo region showed high heterogeneity of soil types, with 27 different categories (fig04a). In
336 most part of the region, slope was below 10% (fig04b), coastal areas presenting the lowest values and
337 variability. Highest values of groundwater depth (fig04c), reaching a maximum of 255m, were found in
338 the Atlantic margin of the study area, mainly in Tagus and Sado river basins. Several other small and
339 confined areas in Alentejo also showed high values, corresponding to aquifers of porous or karst
340 geological types. Most of the remaining study area showed groundwater depths ranging between 1.5m
341 and 15m. Figures 4d and 4e indicate the southeast of Alentejo as the driest area, given by minimum
342 values of the aridity index (0.618), and potential evapotranspiration much higher that precipitation.
343 Besides, Ios4 presented a maximum value (0.714) for this region (meaning that water availability in the
344 soil was not compensated by the precipitation of the previous months).

345 Combining all variables, it was possible to distinguish two sub-regions with distinct conditions: the
346 southeast of Alentejo and the Atlantic margin. The latter is mainly composed of podzols and regosols,
347 low slope areas and more humid climatic conditions than the southeast of Alentejo.

348

349 **3.3 Regression models**

The Kernel density of the proxy GDV species, *Q. suber*, *Q. ilex* and *P. pinea*, showed a skewed normal distribution. Therefore, a square-root normalization of the data was applied on this response variable, before model fitting. To be able to compare the resulting model coefficients and use them as weighting factors of the multi-criteria analysis to build the suitability map, the predictor variables were normalized using the z-score function. The equation resulting from the GWR model fitting, featuring the predictor coefficients (Table 2) used later for the computation of the GDV suitability map corresponds to Eq. (4).

Local adjusted R-squared was highly variable throughout the study area, ranging from 0.25 to 0.95 (fig05). Lower R-squared values were clustered, near the Tagus river basin and in central and northern Alentejo. The overall fit of the GWR model was high (Table 3). The adjusted regression coefficient indicated that 92% of the variation in the data was explained by the GWR model, while only 11% was explained by the simple linear model (Table 3). Accordingly, GWR had a substantially lower AICc when compared with the simple linear model, indicating a much better fit.

The analysis of spatial autocorrelation, given by the Moran Index, showed a Z-score of 107.79 for the GWR model, with a considerable reduction of the Moran Index between models, from 0.94 in the simple linear regression model to 0.67 in the GWR model. From figures 06a and 06b there is an evident decrease in clustered residual values from the simple linear model to GWR. In the linear model (fig06a), positive residuals were condensed in the right side of Tagus and Sado river basins, while negative values were mainly present on the left side of the Tagus river and in the center-south of Alentejo. In GWR model (fig06b) the condensed positive and negative residual values were much more scattered throughout the study region, highlighting a much better performance of the GWR, which minimized residual autocorrelation.

$$Density = 23.88 + 0.22\ Ios4 - 1.61\ AI + 0.06\ Depth + 1.33\ Soil\ type\ 2 + 2.46\ Soil\ type\ 3 + 0.14\ Slope\ , \quad (4)$$

3.4 GDV Suitability map

The classification of the 5 endorsed environmental predictors is presented in Table 4 and their respective maps in figure B1 in appendix. Rivers Tagus and Sado had a positive impact on GDV's suitability to each predictor. This is due to a higher water availability reflected by the values of omborthermic and aridity indexes (figs. B1a and B1b in appendix) and a higher groundwater depth in the surroundings of the rivers (fig. B1c in appendix). Optimal conditions for groundwater access were mainly gathered in the interior of the study region (fig07), with the exception for some confined aquifers. Favorable slopes for GDV were mostly highlighted in the Tagus river basin area, where a good likelihood of interaction between GDV and groundwater could be identified (fig. B1d in appendix). However, this high likelihood was hindered by the type of soil present in that area (fig. B1e in appendix).

The final map illustrating the suitability to GDV is shown in Fig. 7. The largest part of the study area (17 538 km^2), representing more than half of the total area (55.8%) showed a very good suitability to the occurrence of GDV. The rest of the territory showed a "Moderate" to "Poor" suitability, representing

387 5 037 km^2 and 4 313 km^2, respectively. Altogether, 1/3 of the total area showed "Very poor" to
388 "Moderate" suitability to GDV, corresponding to the most southern and eastern part of the study region.

389 The suitability to GDV in the Alentejo region was mainly driven by soil type, given by the similar
390 distribution pattern between the suitability map and the soil type predictor (fig04a and fig07). This was
391 also confirmed by the high coefficient obtained for the soil type predictor in the GWR model equation.
392 The aridity index also showed a strong influence on GDV's suitability, mostly for the intermediate and
393 good classes. Areas with high suitability classes corresponded to the most northern and coastal areas of
394 Alentejo region. Areas with intermediate class in the north of the study region mostly matched with soil
395 type polygons, with score 1 and 2 (figB1e in appendix), while high aridity values restricted GDV's
396 suitability in the south. Areas with a good suitability mostly coincided with polygons of soil type 3 and
397 with lower values of aridity index in the northern region of Alentejo.

398

399 **3.5 Map validation**

400 To assess the quality of the suitability map developed in the present study, we compared our results with
401 integrated suitability maps, from different data sources than those used in this study, for each of the
402 previously considered proxy species. The integrated suitability maps of each proxy species were
403 aggregated into one validation map.

404 Both the result and validation maps were highly coincident, especially with respect to areas with lower
405 and moderate suitability to GDV (Table 5). Areas with very poor GDV suitability corresponded to almost
406 76% of the non-suitable areas for proxy species in the validation map. Accordingly, poor suitability areas
407 for GDV matched 36.65% of the non-suitable areas for proxy species and 45.27% of areas suitable to
408 only one of the proxy species. Besides, areas with moderate GDV suitability matched almost half of the
409 suitable areas for two of the proxy specie in the validation map. Classes with higher GDV suitability did
410 not show a good agreement with the validation map.

411 When juxtaposing both maps (fig07 and fig08), there was an overall correspondence between areas with
412 higher suitability to the proxy species. In both maps the northern and coastal area of the Alentejo region,
413 south of the Tagus river basin, showed a matching higher suitability to the proxy species and the GDV.
414 The Sado region was a common area of high suitability in both maps as well. The largest mismatches
415 between maps were found in the center and southeast of the study region.

416 Temporary irrigated areas matched non-suitable areas for proxy species in the validation map (fig C1 in
417 appendix). This could explain some of the mismatches highlighted before, particularly where a large
418 percentage of good and very good GDV suitability (28 and 41% respectively) corresponds to a non-
419 suitable area for each of the proxy species in the validation map (Table5).

420

421

4 Discussion

4.1 Modeling approach

Mapping the suitability of regional Groundwater Dependent Vegetation in southern Portugal proved to be a challenge because of the intricate relations between topographical, hydrological and biotic conditions in this specific area of the Mediterranean basin. Only 50% of the initial predictors were assigned for model fitting, due to a high collinearity between variables of the same type (e.g. aridity index and SPEI variables). Nevertheless, the small number of elected predictors for modeling will provide a higher reliability of the forecast of GDV suitability under future predicted environmental conditions.

Despite the exclusion of redundant predictors, the spatial distribution of residues after fitting the simple linear model still showed a significant clustered pattern, which violated the basic assumption of independence between samples. Therefore, a Geographically Weighted Regression model was used according to Stewart Fotheringham et al. (1996). This spatial variation of the linear model has been used before in ecological studies (Li et al., 2016; Mazziotta et al., 2016), but never for the mapping of GDV, to our knowledge. This approach considerably improved the goodness of fit, with a coefficient of regression (R^2) increasing from 0.11 to 0.92 at the global level, and an obvious reduction of residual clustering. Despite those improvements, it has not been possible to completely eliminate the residual autocorrelation after fitting the GWR model.

Kernel density for the study area provided a strong indication of presence and abundance of the tree species considered as GDV proxy for modeling. Mediterranean cork woodlands are very particular agroforestry systems present in a confined area of the Mediterranean basin, where sparse tree distributions dominate, because of silvicultural management to increase cork and acorn production, while providing a large grassland area for cattle (Bugalho et al., 2009). However, anthropologic management of agroforestry systems in this region has not been considered in the model. This could, at least partially, explain the non-randomness of the residual distribution after GWR model fitting.

Another explanation of the reminiscent autocorrelation after GWR fitting could be the lack of groundwater dependent species in the model. For example, we decided to exclude *Pinus pinaster* Aiton due to its more humid distribution in Portugal, and due to conflicting conclusions driven from previous studies to pin point the species as a potential groundwater use (Bourke, 2004; Kurz-Besson et al., 2016). In addition, only recently the use of groundwater by an olive orchard has been proved (Ferreira et al., 2018), however with little groundwater flow amount of the daily root flow, and so with no significant impact for the species physiological conditions.

Methods previously used by Doody et al., (2017) and Condesso de Melo et al. (2015) to map specific vegetation relied solely on expert opinion, e.g. Delphi panel, to define weighting factors of environmental information for GIS multicriteria analysis. In our study, we used GWR to assess weighting factors for each environmental predictor in the study area, to build a suitability map for the GDV in southern

458 Portugal. This allowed an empirical determination of the relevance of each environmental predictor in
459 GDV distribution, thus avoiding the inevitable subjectivity of Delphi panels.

460

461 **4.2 Suitability to Groundwater Dependent Vegetation**

462 As shown by the simulations of future climate conditions based on RCP4.5 and RCP8.5 emission
463 scenarios (Soares et al., 2015, 2017), a significant decrease of precipitation for the Guadiana basin and
464 overall decrease for the southern region of Portugal are expected. Agroforestry systems relying on
465 groundwater resources, such as cork oak woodlands, may show a decrease in productivity and ecosystem
466 services or even face sustainability failure. Therefore, linking s GDV to key environmental drivers and
467 especially climate, will allow to forecast ecological changes under future climatic conditions and spot
468 priority areas for adaptation and stakeholder decision.

469 According to our results, more than half of the study area appears suitable for GDV. However, one third
470 of the studied area showed the lowest suitability to GDV. The lower suitability to this vegetation in the
471 eastern part of the studied area can be explained by less favorable climatic and geological conditions,
472 resulting from the combination of a high aridity index and low water retention at deep soil layers. Soils
473 with lower water capacity further lowered GDV suitability in the most southeastern region of the studied
474 area.

475 An increase in aridity and drought frequency for the Mediterranean (Spinoni et al., 2017) will most
476 probably induce plant physiological adaptations (Peñuelas and Filella, 2001) as well as species
477 substitution (Lloret et al., 2004). In the Mediterranean environment, Peñuelas et al. (2011) distinguished
478 two plant communities regarding water consumption, one with deep roots, able to constantly access water
479 and nutrients and a second community with shallow roots, depending on superficial water from rainfall.
480 Due to climate change conditions, in the Alentejo region of Portugal, we should expect GDV of the less
481 suitable areas to be replaced by the community with shallow roots using rainfall water exclusively. This
482 has already been reported for a Mediterranean woodland of the Iberian Peninsula, where extreme drought
483 conditions led to a shift in vegetation cover from deep-rooting species to water spending species (Caldeira
484 et al., 2015). Groundwater reservoirs would thus no longer be a constraint for plant survival during
485 summer droughts, because the supplanting vegetation community, namely annuals that stop their growing
486 cycle or die before the onset of the dry season, would no longer need constant access to water. Such
487 species substitution would be associated with ecological and biodiversity costs, by shifting from
488 woodland to shrubland ecosystems.

489 In environments with scarce water sources such as the Mediterranean basin, many tree species have
490 adapted to the precipitation's seasonality and its large variability by developing dimorphic root systems.
491 When comparing different water limited ecosystems from a global dataset, Schenk and Jackson (2002)
492 showed that rooting depth increased with aridity. Our results agree with these findings since the aridity
493 index was the second most important predictor of GDV density, according to our equation. Nevertheless,
494 the soil type turned out to be the most important predictor of GDV density. This is comprehensible
495 because the soil type defines the capacity for groundwater storage and the accessibility for deep root

system (Centenaro et al., 2017; Grimaldi et al., 2015). However, the soil type component is not expected to change as dramatically as the aridity index in response to climate change, leaving the aridity index as the main driver for the GDV density under climatic changes in southern Portugal.

As stated by our model equation, groundwater depth appeared to have little influence on GDV density. This disagrees with our initial hypothesis. However, this disagreement should be regarded cautiously due to the poor quality of the data used. On one hand, data points in the study region were highly heterogeneous, and certain areas showed a better statistical representation than others. Moreover, the high variability in geological media, topography and vegetation cover at the regional scale did not allow to account for small changes in groundwater depth (<15m deep), which has a huge impact on GDV suitability (Canadell et al., 1996; Stone and Kalisz, 1991). Indeed, a high spatial resolution of hydrological database is essential to characterize the spatial dynamics of groundwater depth between hydrographic basins (Lorenzo-Lacruz et al., 2017). However, such resolution was not available for our study area. In addition, the lack of temporal data did not allow the calculation of seasonal trends in groundwater depth, which are essential under Mediterranean conditions to build a reliable interpolation of observed data. Temporal data would also further help discriminate areas of optimal suitability to GDV, either during the wet and the dry seasons.

Overall, the map of suitability to GDV showed good results, compared with the validation maps showing the proxy species integrated suitability (Magalhães et al., 2015a, 2015b, 2015c). However, areas of high suitability to GDV matched areas of the validation that were non-suitable areas for the proxy species. This can be explained by the lack of information in the model concerning main land occupation and land management in the studied region. We found that areas where the main land occupation is non-silvicultural (e.g. temporary irrigation fields), corresponded to non-suitable areas for proxy species in the validation map. Several other discrepancies can be explained by additional information considered in the validation map by their authors, such as the current occupation type (e.g. olive orchards, vineyards or urban).

The main areas showing good suitability are mostly matching in both maps. Furthermore, our results highly agree with Paulo et al. (2015) who predicted site productivity index and soil variables for cork oak (*Q. suber*) stands in Portugal with a stochastic modelling approach. This allows us to apply the methodology to extend our findings for larger geographical areas such as the Iberian Peninsula. Also, the model equation can be considered reliable to simulate the impact of future climatic conditions on the distribution of GDV in southern Portugal.

4.3 Key limitations

With the methodology applied in this study, weighting factors can be easily evaluated solely from local and regional observations of the studied area. Nonetheless, either the computation of model coefficients or expert opinion to assess weighting factors, require update, and/or environmental data, species distribution and revised expert knowledge (Doody et al., 2017).

Changes in climate conditions only represents part of the water resources shortage issue in the future. Global-scale changes in human populations and economic progresses also rules water demand and supply, especially in arid and semi-arid regions (Vörösmarty et al., 2000). A decrease in useful water resources for human supply can induce an even higher pressure on groundwater resources (Döll, 2009), aggravating the water table drawdown caused by climate change (Ertürk et al., 2014). Therefore, additional updates of the model should include human consumption of groundwater resources, identifying areas of higher population density or intensive farming. Future model updates should also account for the interaction of deep rooting species with the surrounding understory species. In particular, shrubs surviving the drought period, which can benefit from the redistribution of groundwater by deep rooted species (Dawson, 1993; Zou et al., 2005).

5 Conclusions

The current pressure applied by human consumption of water sources has reinforced the concern on the future of economic activities dependent on groundwater resources. To address this issue, several countries have developed national strategies for the adaptation of water sources for Agriculture and Forests against Climate Change, including Portugal (FAO, 2007). In addition, local drought management as long-term adaptation strategy has been one of the proposals of Iglesias et al. (2007) to reduce the climate change impact on groundwater resources in the Mediterranean. The preservation of Mediterranean agroforestry systems, such as cork oak woodlands and the recently associated *P. pinea* species, is of great importance due to their high socioeconomic value and their supply of valuable ecosystem services (Bugalho et al., 2011). Management policies on the long-term should account for groundwater resources monitoring, accompanied by defensive measures to ensure agroforestry systems sustainability and economical income from these Mediterranean ecosystems are not greatly and irreversibly threatened.

Our present study, and novel methodology, provides an important tool to help delineating priority areas of action for species and groundwater management, at regional level, to avoid the decline of productivity and cover density of the agroforestry systems of southern Portugal. This is important to guarantee the sustainability of the economical income for stakeholders linked to the agroforestry sector in that area. Furthermore, mapping vulnerable areas at a small scale (e.g.by hydrological basin), where reliable groundwater depth information is available, should provide further insights for stakeholder to promote local actions to mitigate climate change impact on GDV.

Based on the methodology applied in this work, future predictions on GDV suitability, according to the RCP4.5 and RCP8.5 emission scenarios will be shortly computed, providing guidelines for future management of these ecosystems in the allocation of water resources.

572 **6 Acknowledgements**

573

574 The authors acknowledge the E-OBS dataset from the EU-FP6 project ENSEMBLES (http://ensembles-
575 eu.metoffice.com) and the data providers in the ECA&D project (http://www.ecad.eu). The authors also
576 wish to acknowledge the ASTER GDEM data product, a courtesy of the NASA Land Processes
577 Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS)
578 Center, Sioux Falls, South Dakota, https://lpdaac.usgs.gov/data_access/data_pool. We are grateful to
579 ICNF for sharing inventory database performed in 2010 in Portugal continental. We also thank Célia
580 Gouveia, Cristina Catita, Ana Russo and Patrícia Páscoa for the advice and helpful comments. We are
581 very grateful to Eric Font for the useful insights on soil properties. I Gomes Marques and research
582 activities were supported by the Portuguese National Foundation for Science and Tecnhology (FCT)
583 through the PIEZAGRO project (PTDC/AAG-REC/7046/2014).

584

585 The authors declare that they have no conflict of interest.

586

587

588 **References**

589 Aksoy, E., Louwagie, G., Gardi, C., Gregor, M., Schröder, C. and Löhnertz, M.: Assessing soil
590 biodiversity potentials in Europe, Sci. Total Environ., 589, 236–249, doi:10.1016/j.scitotenv.2017.02.173,
591 2017.

592 Anselin, L., Ibnu, S. and Youngihn, K.: GeoDa: An Introduction to Spatial Data Analysis, Geogr. Anal.,
593 38(1), 5–22, 2006.

594 APA: Plano de Gestão da Região Hidrográfica do Tejo: Parte 2 - Caracterização e Diagnóstico da Região
595 Hidrográfica. [online] Available from:
596 https://sniambgeoviewer.apambiente.pt/Geodocs/geoportaldocs/Planos/PGRH5-
597 TEJO/RB%5Cpgrhtejo_p2.pdf (Accessed 1 February 2018), n.d.

598 ARH Alentejo: Plano de Gestão das Bacias Hidrográficas integradas na RH7 - Parte 2. [online] Available
599 from:
600 https://sniambgeoviewer.apambiente.pt/Geodocs/geoportaldocs/Planos/PGRH7/VolumeI_Relatorio%5CP
601 arte2%5CTomo1%5CP2_T1A_RH7_VF.pdf (Accessed 1 February 2018a), 2012.

602 ARH Alentejo: Planos de Gestão das Bacias Hidrográficas integradas na RH6 - Parte 2. [online]
603 Available from:
604 https://sniambgeoviewer.apambiente.pt/Geodocs/geoportaldocs/Planos/PGRH6/VolumeI_Relatorio%5CP
605 arte2%5CTomo1%5CP2_T1A_RH6_VF.pdf (Accessed 1 February 2018b), 2012.

606 Autoridade Florestal Nacional and Ministério da Agricultura do Desenvolvimento Rural e das Pescas: 5o
607 Inventário Florestal Nacional, 2010.

608 Barata, L. T., Saavedra, A., Cortez, N. and Varennes, A.: Cartografia da espessura efectiva dos solos de
609 Portugal Continental. LEAF/ISA/ULisboa. [online] Available from: http://epic-webgis-
610 portugal.isa.utl.pt/, 2015.

611 Barbero, M., Loisel, R. and Quézel, P.: Biogeography, ecology and history of Mediterranean Quercus ilex
612 ecosystems, in Quercus ilex L. ecosystems: function, dynamics and management, edited by F. Romane
613 and J. Terradas, pp. 19–34, Springer Netherlands, Dordrecht., 1992.

614 Barbeta, A. and Peñuelas, J.: Increasing carbon discrimination rates and depth of water uptake favor the
615 growth of Mediterranean evergreen trees in the ecotone with temperate deciduous forests, Glob. Chang.
616 Biol., 1–15, doi:10.1111/gcb.13770, 2017.

617 Barbeta, A., Mejía-Chang, M., Ogaya, R., Voltas, J., Dawson, T. E. and Peñuelas, J.: The combined
618 effects of a long-term experimental drought and an extreme drought on the use of plant-water sources in a
619 Mediterranean forest, Glob. Chang. Biol., 21(3), 1213–1225, doi:10.1111/gcb.12785, 2015.

620 Barron, O. V., Emelyanova, I., Van Niel, T. G., Pollock, D. and Hodgson, G.: Mapping groundwater-
621 dependent ecosystems using remote sensing measures of vegetation and moisture dynamics, Hydrol.
622 Process., 28(2), 372–385, doi:10.1002/hyp.9609, 2014.

623 Beguería, S. and Vicente-Serrano, S. M.: SPEI: Calculation of the Standardized Precipitation-
624 Evapotranspiration Index. R package version 1.6., 2013.

625 Bivand, R. and Yu, D.: spgwr: Geographically Weighted Regression. [online] Available from:
626 https://cran.r-project.org/package=spgwr, 2017.

627 Bivand, R. S., Pebesma, E. J. and Gómez-Rubio, V.: Applied Spatial Data Analysis with R, edited by G.
628 P. Robert Gentleman, Kurt Hornik, Springer., 2008.

629 Bourke, L.: Growth trends and water use efficiency of Pinus pinaster Ait. in response to historical climate
630 and groundwater trends on the Gnangara Mound, Western Australia. [online] Available from:
631 http://ro.ecu.edu.au/theses_hons/141 (Accessed 29 January 2018), 2004.

632 Bugalho, M. N., Plieninger, T. and Aronson, J.: Open woodlands: a diversity of uses (and overuses), in
633 Cork oak woodlands on the edge, edited by J. Aronson, J. S. Pereira, and J. G. Pausas, pp. 33–48, Island
634 Press, Washington DC., 2009.

635 Bugalho, M. N., Caldeira, M. C., Pereira, J. S., Aronson, J. and Pausas, J. G.: Mediterranean cork oak
636 savannas require human use to sustain biodiversity and ecosystem services, Front. Ecol. Environ., 9(5),
637 278–286, doi:10.1890/100084, 2011.

638 Bussotti, F., Ferrini, F., Pollastrini, M. and Fini, A.: The challenge of Mediterranean sclerophyllous
639 vegetation under climate change: From acclimation to adaptation, Environ. Exp. Bot., 103(April), 80–98,
640 doi:10.1016/j.envexpbot.2013.09.013, 2013.

641 Caldeira, M. C., Lecomte, X., David, T. S., Pinto, J. G., Bugalho, M. N. and Werner, C.: Synergy of
642 extreme drought and shrub invasion reduce ecosystem functioning and resilience in water- limited
643 climates, Sci. Rep., 5(15110), 1-9, doi:10.1038/srep15110, 2015.

644 Canadell, J., Jackson, R., Ehleringer, J., Mooney, H. A., Sala, O. E. and Schulze, E.-D.: Maximum
645 rooting depth of vegetation types at the global scale, Oecologia, 108, 583–595, doi:10.1007/BF00329030,
646 1996.

647 del Castillo, J., Comas, C., Voltas, J. and Ferrio, J. P.: Dynamics of competition over water in a mixed
648 oak-pine Mediterranean forest: Spatio-temporal and physiological components, For. Ecol. Manage., 382,
649 214–224, doi:10.1016/j.foreco.2016.10.025, 2016.

650 Centenaro, G., Hudek, C., Zanella, A. and Crivellaro, A.: Root-soil physical and biotic interactions with a
651 focus on tree root systems: A review, Appl. Soil Ecol., doi:10.1016/J.APSOIL.2017.09.017, 2017.

652 Chambel, A., Duque, J. and Nascimento, J.: Regional Study of Hard Rock Aquifers in Alentejo, South
653 Portugal: Methodology and Results, in Groundwater in Fractured Rocks - IAH Selected Paper Series, pp.
654 73–93, CRC Press., 2007.

655 Coelho, I. S. and Campos, P.: Mixed Cork Oak-Stone Pine Woodlands in the Alentejo Region of
656 Portugal, in Cork Oak Woodlands on the Edge - Ecology, Adaptive Management, and Restoration, edited
657 by J. Aronson, J. S. Pereira, J. Uli, and G. Pausas, pp. 153–159, Island Press, Washington. [online]

Available from:
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.732.5454&rep=rep1&type=pdf (Accessed 2 February 2018), 2009.

Condesso de Melo, M. T., Nascimento, J., Silva, A. C., Mendes, M. P., Buxo, A. and Ribeiro, L.: Desenvolvimento de uma metodologia e preparação do respetivo guia metodológico para a identificação e caracterização, a nível nacional, dos ecossistemas terrestres dependentes das águas subterrâneas (ETDAS). Relatório de projeto realizado para a Agência P., 2015.

Costa, A., Madeira, M. and Oliveira, C.: The relationship between cork oak growth patterns and soil, slope and drainage in a cork oak woodland in Southern Portugal, For. Ecol. Manage., 255, 1525–1535, doi:10.1016/j.foreco.2007.11.008, 2008.

David, T. S., Ferreira, M. I., Cohen, S., Pereira, J. S. and David, J. S.: Constraints on transpiration from an evergreen oak tree in southern Portugal, Agric. For. Meteorol., 122(3–4), 193–205, doi:10.1016/j.agrformet.2003.09.014, 2004.

David, T. S., Henriques, M. O., Kurz-Besson, C., Nunes, J., Valente, F., Vaz, M., Pereira, J. S., Siegwolf, R., Chaves, M. M., Gazarini, L. C. and David, J. S.: Water-use strategies in two co-occurring Mediterranean evergreen oaks: surviving the summer drought., Tree Physiol., 27(6), 793–803, doi:10.1093/treephys/27.6.793, 2007.

David, T. S., Pinto, C. A., Nadezhdina, N., Kurz-Besson, C., Henriques, M. O., Quilhó, T., Cermak, J., Chaves, M. M., Pereira, J. S. and David, J. S.: Root functioning, tree water use and hydraulic redistribution in Quercus suber trees: A modeling approach based on root sap flow, For. Ecol. Manage., 307, 136–146, doi:10.1016/j.foreco.2013.07.012, 2013.

Dawson, T. E.: Hydraulic lift and water use by plants: implications for water balance, performance and plant-plant interactions, Oecologia, 95, 565–574 [online] Available from: https://link.springer.com/content/pdf/10.1007%2FBF00317442.pdf (Accessed 31 January 2018), 1993.

Döll, P.: Vulnerability to the impact of climate change on renewable groundwater resources: a global-scale assessment, Environ. Res. Lett., 4(4), 35006–12, doi:10.1088/1748-9326/4/3/035006, 2009.

Doody, T. M., Barron, O. V., Dowsley, K., Emelyanova, I., Fawcett, J., Overton, I. C., Pritchard, J. L., Van Dijk, A. I. J. M. and Warren, G.: Continental mapping of groundwater dependent ecosystems: A methodological framework to integrate diverse data and expert opinion, J. Hydrol. Reg. Stud., 10, 61–81, doi:10.1016/j.ejrh.2017.01.003, 2017.

Dresel, P. E., Clark, R., Cheng, X., Reid, M., Terry, A., Fawcett, J. and Cochrane, D.: Mapping Terrestrial Groundwater Dependent Ecosystems: Method Development and Example Output., 2010.

Duque-Lazo, J., Navarro-Cerrillo, R. M. and Ruíz-Gómez, F. J.: Assessment of the future stability of cork oak (Quercus suber L.) afforestation under climate change scenarios in Southwest Spain, For. Ecol. Manage., 409(June 2017), 444–456, doi:10.1016/j.foreco.2017.11.042, 2018.

693 Eamus, D., Froend, R., Loomes, R., Hose, G. and Murray, B.: A functional methodology for determining
694 the groundwater regime needed to maintain the health of groundwater-dependent vegetation, Aust. J.
695 Bot., 54(2), 97–114, doi:10.1071/BT05031, 2006.

696 Eamus, D., Zolfaghar, S., Villalobos-Vega, R., Cleverly, J. and Huete, A.: Groundwater-dependent
697 ecosystems: Recent insights from satellite and field-based studies, Hydrol. Earth Syst. Sci., 19(10), 4229–
698 4256, doi:10.5194/hess-19-4229-2015, 2015.

699 Ertürk, A., Ekdal, A., Gürel, M., Karakaya, N., Guzel, C. and Gönenç, E.: Evaluating the impact of
700 climate change on groundwater resources in a small Mediterranean watershed, Sci. Total Environ., 499,
701 437–447, doi:10.1016/j.scitotenv.2014.07.001, 2014.

702 Evaristo, J. and McDonnell, J. J.: Prevalence and magnitude of groundwater use by vegetation: a global
703 stable isotope meta-analysis, Sci. Rep., 7, 44110, doi:10.1038/srep44110, 2017.

704 FAO: Adaptation to climate change in agriculture, forestry and fisheries: Perspective, framework and
705 priorities, Rome. [online] Available from:
706 http://www.fao.org/nr/climpag/pub/adaptation_to_climate_change_2007.pdf (Accessed 31 January 2018),
707 2007.

708 FAO, IIASA, ISRIC, ISS-CAS and JRC: Harmonized World Soil Database (version 1.1), 2009.

709 Fernandes, N. P.: Ecossistemas Dependentes de Água Subterranea no Algarve - Contributo para a sua
710 Identificação e Caracterização, University of Algarve., 2013.

711 Ferreira, M. I., Green, S., Conceição, N. and Fernández, J.-E.: Assessing hydraulic redistribution with the
712 compensated average gradient heat-pulse method on rain-fed olive trees, Plant Soil, 1–21,
713 doi:10.1007/s11104-018-3585-x, 2018.

714 Filella, I. and Peñuelas, J.: Indications of hydraulic lift by Pinus halepensis and its effects on the water
715 relations of neighbour shrubs, Biol. Plant., 47(2), 209–214, doi:10.1023/B:BIOP.0000022253.08474.fd,
716 2004.

717 Giorgi, F. and Lionello, P.: Climate change projections for the Mediterranean region, Glob. Planet.
718 Change, 63(2–3), 90–104, doi:10.1016/j.gloplacha.2007.09.005, 2008.

719 Grimaldi, S., Orellana, F. and Daly, E.: Modelling the effects of soil type and root distribution on shallow
720 groundwater resources, Hydrol. Process., 29(20), 4457–4469, doi:10.1002/hyp.10503, 2015.

721 Grossiord, C., Sevanto, S., Dawson, T. E., Adams, H. D., Collins, A. D., Dickman, L. T., Newman, B. D.,
722 Stockton, E. A. and Mcdowell, N. G.: Warming combined with more extreme precipitation regimes
723 modifies the water sources used by trees, New Phytol., doi:10.1111/nph.14192, 2016.

724 Guisan, A. and Thuiller, W.: Predicting species distribution: Offering more than simple habitat models,
725 Ecol. Lett., 8(9), 993–1009, doi:10.1111/j.1461-0248.2005.00792.x, 2005.

726 Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., Jones, P. D. and New, M.: A European
727 daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006, J. Geophys.
728 Res. Atmos., 113(20), doi:10.1029/2008JD010201, 2008.

729 Hernández-Santana, V., David, T. S. and Martínez-Ferná Ndez, J.: Environmental and plant-based
730 controls of water use in a Mediterranean oak stand, For. Ecol. Manage., 255, 3707–3715,
731 doi:10.1016/j.foreco.2008.03.004, 2008.

732 Horton, J. L. and Hart, S. C.: Hydraulic lift: a potentially important ecosystem process, Tree, 13(6), 232–
733 235, doi:0169-5347/98, 1998.

734 Howard, J. and Merrifield, M.: Mapping groundwater dependent ecosystems in California, PLoS One,
735 5(6), doi:10.1371/journal.pone.0011249, 2010.

736 Hu, X., Zhang, L., Ye, L., Lin, Y. and Qiu, R.: Locating spatial variation in the association between road
737 network and forest biomass carbon accumulation, Ecol. Indic., 73, 214–223,
738 doi:10.1016/j.ecolind.2016.09.042, 2017.

739 ICNF: IFN6 – Áreas dos usos do solo e das espécies florestais de Portugal continental. Resultados
740 preliminares., Lisboa. [online] Available from:
741 http://www2.icnf.pt/portal/florestas/ifn/resource/ficheiros/ifn/ifn6-res-prelimv1-1 (Accessed 9 January
742 2018), 2013.

743 Iglesias, A., Garrote, L., Flores, F. and Moneo, M.: Challenges to manage the risk of water scarcity and
744 climate change in the Mediterranean, Water Resour. Manag., 21, 775–788, doi:10.1007/s11269-006-
745 9111-6, 2007.

746 Joffre, R., Rambal, S. and Ratte, J. P.: The dehesa system of southern Spain and Portugal as a natural
747 ecosystem mimic, Agrofor. Syst., 45, 57–79, doi:10.1023/a:1006259402496, 1999.

748 Kurz-Besson, C., Otieno, D., Lobo Do Vale, R., Siegwolf, R., Schmidt, M., Herd, A., Nogueira, C.,
749 David, T. S., David, J. S., Tenhunen, J., Pereira, J. S. and Chaves, M.: Hydraulic lift in cork oak trees in a
750 savannah-type Mediterranean ecosystem and its contribution to the local water balance, Plant Soil, 282(1–
751 2), 361–378, doi:10.1007/s11104-006-0005-4, 2006.

752 Kurz-Besson, C., Lobo-do-Vale, R., Rodrigues, M. L., Almeida, P., Herd, A., Grant, O. M., David, T. S.,
753 Schmidt, M., Otieno, D., Keenan, T. F., Gouveia, C., M??riaux, C., Chaves, M. M. and Pereira, J. S.:
754 Cork oak physiological responses to manipulated water availability in a Mediterranean woodland, Agric.
755 For. Meteorol., 184(December 2013), 230–242, doi:10.1016/j.agrformet.2013.10.004, 2014.

756 Kurz-Besson, C., Lousada, J. L., Gaspar, M. J., Correia, I. E., David, T. S., Soares, P. M. M., Cardoso, R.
757 M., Russo, A., Varino, F., Mériaux, C., Trigo, R. M. and Gouveia, C. M.: Effects of recent minimum
758 temperature and water deficit increases on Pinus pinaster radial growth and wood density in southern
759 Portugal, Front. Plant Sci, 7, doi:10.3389/fpls.2016.01170, 2016.

760 Li, Y., Jiao, Y. and Browder, J. A.: Modeling spatially-varying ecological relationships using
761 geographically weighted generalized linear model: A simulation study based on longline seabird bycatch,
762 Fish. Res., 181, 14–24, doi:10.1016/j.fishres.2016.03.024, 2016.

763 Lloret, F., Siscart, D. and Dalmases, C.: Canopy recovery after drought dieback in holm-oak
764 Mediterranean forests of Catalonia (NE Spain), Glob. Chang. Biol., 10(12), 2092–2099,
765 doi:10.1111/j.1365-2486.2004.00870.x, 2004.

766 López, B., Sabaté, S., Ruiz, I. and Gracia, C.: Effects of Elevated CO2 and Decreased Water Availability
767 on Holm-Oak Seedlings in Controlled Environment Chambers, in Impacts of Global Change on Tree
768 Physiology and Forest Ecosystems: Proceedings of the International Conference on Impacts of Global
769 Change on Tree Physiology and Forest Ecosystems, held 26--29 November 1996, Wageningen, The
770 Netherlands, edited by G. M. J. Mohren, K. Kramer, and S. Sabaté, pp. 125–133, Springer Netherlands,
771 Dordrecht., 1997.

772 Lorenzo-Lacruz, J., Garcia, C. and Morán-Tejeda, E.: Groundwater level responses to precipitation
773 variability in Mediterranean insular aquifers, J. Hydrol., 552, 516-531, doi:10.1016/j.jhydrol.2017.07.011,
774 2017.

775 Lowry, C. S. and Loheide, S. P.: Groundwater-dependent vegetation: Quantifying the groundwater
776 subsidy, Water Resour. Res., 46(6), doi:10.1029/2009WR008874, 2010.

777 Lv, J., Wang, X. S., Zhou, Y., Qian, K., Wan, L., Eamus, D. and Tao, Z.: Groundwater-dependent
778 distribution of vegetation in Hailiutu River catchment, a semi-arid region in China, Ecohydrology, 6(1),
779 142–149, doi:10.1002/eco.1254, 2013.

780 Magalhães, M. R., Müller, A. and Ferreira Silva, J.: Aptidão Integrada à Azinheira (Quercus rotundifolia)
781 para Portugal Continental. LEAF/ISA/ULisboa., [online] Available from: http://epic-webgis-
782 portugal.isa.utl.pt/, 2015a.

783 Magalhães, M. R., Müller, A. and Ferreira Silva, J.: Aptidão Integrada ao Pinheiro-manso (Pinus Pinea
784 L.) para Portugal Continental. LEAF/ISA/ULisboa., [online] Available from: http://epic-webgis-
785 portugal.isa.utl.pt/, 2015b.

786 Magalhães, M. R., Müller, A. and Ferreira Silva, J.: Aptidão Integrada ao Sobreiro (Quercus suber L.)
787 para Portugal Continental. LEAF/ISA/ULisboa., [online] Available from: http://epic-webgis-
788 portugal.isa.utl.pt/, 2015c.

789 Mazziotta, A., Heilmann-Clausen, J., Bruun, H. H., Fritz, Ö., Aude, E. and Tøttrup, A. P.: Restoring
790 hydrology and old-growth structures in a former production forest: Modelling the long-term effects on
791 biodiversity, For. Ecol. Manage., 381, 125–133, doi:10.1016/j.foreco.2016.09.028, 2016.

792 Mckee, T. B., Doesken, N. J. and Kleist, J.: The relationship of drought frequency and duration to time
793 scales, in AMS 8th Conference on Applied Climatology, pp. 179–184., 1993.

794 Mendes, M. P., Ribeiro, L., David, T. S. and Costa, A.: How dependent are cork oak (Quercus suber L.)
795 woodlands on groundwater? A case study in southwestern Portugal, For. Ecol. Manage., 378, 122–130,
796 doi:10.1016/j.foreco.2016.07.024, 2016.

797 Middleton, N., Thomas, D. S. G. and Programme., U. N. E.: World atlas of desertification, UNEP, 1992.,
798 London., 1992.

799 Miller, G. R., Chen, X., Rubin, Y., Ma, S. and Baldocchi, D. D.: Groundwater uptake by woody
800 vegetation in a semiarid oak savanna, Water Resour. Res., 46(10), doi:10.1029/2009WR008902, 2010.

801 Ministério da Agricultura do Mar do Ambiente e do Ordenamento do Território: Estratégia de Adaptação
802 da Agricultura e das Florestas às Alterações Climáticas, Lisbon, 2013.

803 Montero, G., Ruiz-Peinado, R., Candela, J. A., Canellas, I., Gutierrez, M., Pavon, J., Alonso, A., Rio, M.
804 d., Bachiller, A. and Calama, R.: El pino pinonero (Pinus pinea L.) en Andalucia. Ecologia, distribucion y
805 selvicultura, edited by G. Montero, J. A. Candela, and A. Rodriguez, Consejeria de Medio Ambiente,
806 Junta de Andalucia, Sevilla., 2004.

807 Moran, P. A. P.: Notes on continuous stochastic phenomena, Biometrika, 37(1–2), 17–23 [online]
808 Available from: http://dx.doi.org/10.1093/biomet/37.1-2.17, 1950.

809 Mourato, S., Moreira, M. and Corte-Real, J.: Water resources impact assessment under climate change
810 scenarios in Mediterranean watersheds, Water Resour. Manag., 29(7), 2377–2391, doi:10.1007/s11269-
811 015-0947-5, 2015.

812 Münch, Z. and Conrad, J.: Remote sensing and GIS based determination of groundwater dependent
813 ecosystems in the Western Cape, South Africa, Hydrogeol. J., 15(1), 19–28, doi:10.1007/s10040-006-
814 0125-1, 2007.

815 Nadezhdina, N., Ferreira, M. I., Conceição, N., Pacheco, C. A., Häusler, M. and David, T. S.: Water
816 uptake and hydraulic redistribution under a seasonal climate: Long-term study in a rainfed olive orchard,
817 Ecohydrology, 8(3), 387–397, doi:10.1002/eco.1545, 2015.

818 Neumann, R. B. and Cardon, Z. G.: The magnitude of hydraulic redistribution by plant roots: a review
819 and synthesis of empirical and modeling studies, New Phytol., 194(2), 337–352, doi:10.1111/j.1469-
820 8137.2012.04088.x, 2012.

821 O'Grady, A. P., Eamus, D., Cook, P. G. and Lamontagne, S.: Groundwater use by riparian vegetation in
822 the wet–dry tropics of northern Australia, Aust. J. Bot., 54, 145–154, doi:10.1071/BT04164, 2006.

823 Orellana, F., Verma, P., Loheide, S. P. and Daly, E.: Monitoring and modeling water-vegetation
824 interactions in groundwater-dependent ecosystems, Rev. Geophys., 50(3), doi:10.1029/2011RG000383,
825 2012.

826 Otieno, D. O., Kurz-Besson, C., Liu, J., Schmidt, M. W. T., Do, R. V. L., David, T. S., Siegwolf, R.,
827 Pereira, J. S. and Tenhunen, J. D.: Seasonal variations in soil and plant water status in a Quercus suber L.

stand: Roots as determinants of tree productivity and survival in the Mediterranean-type ecosystem, Plant Soil, 283(1–2), 119–135, doi:10.1007/s11104-004-7539-0, 2006.

Paulo, J. A., Palma, J. H. N., Gomes, A. A., Faias, S. P., Tomé, J. and Tomé, M.: Predicting site index from climate and soil variables for cork oak (Quercus suber L.) stands in Portugal, New For., 46, 293–307, doi:10.1007/s11056-014-9462-4, 2015.

Peñuelas, J. and Filella, I.: Responses to a Warming World, Science. 294(5543), 793–795, doi:10.1126/science.1066860, 2001.

Peñuelas, J. and Filella, I.: Deuterium labelling of roots provides evidence of deep water access and hydraulic lift by Pinus nigra in a Mediterranean forest of NE Spain, Environ. Exp. Bot., 49(3), 201–208, doi:10.1016/S0098-8472(02)00070-9, 2003.

Peñuelas, J., Terradas, J. and Lloret, F.: Solving the conundrum of plant species coexistence: Water in space and time matters most, New Phytol., 189(1), 5–8, doi:10.1111/j.1469-8137.2010.03570.x, 2011.

Pérez Hoyos, I., Krakauer, N., Khanbilvardi, R. and Armstrong, R.: A Review of advances in the identification and characterization of groundwater dependent ecosystems using geospatial technologies, Geosciences, 6(2), 17, doi:10.3390/geosciences6020017, 2016a.

Pérez Hoyos, I., Krakauer, N. and Khanbilvardi, R.: Estimating the probability of vegetation to be groundwater dependent based on the evaluation of tree models, Environments, 3(2), 9, doi:10.3390/environments3020009, 2016b.

Pinto-Correia, T., Ribeiro, N. and Sá-Sousa, P.: Introducing the montado, the cork and holm oak agroforestry system of Southern Portugal, Agrofor. Syst., 82(2), 99–104, doi:10.1007/s10457-011-9388-1, 2011.

QGIS Development Team: QGIS Geographic Information System. Open Source Geospatial Foundation Project., 2017.

R Development Core Team: R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, 2016.

Rivas-Martínez, S., Rivas-Sáenz, S. and Penas-Merino, A.: Worldwide bioclimatic classification system, Glob. Geobot., 1(1), 1–638, doi:10.5616/gg110001, 2011.

Robinson, T. W.: Phreatophytes, United States Geol. Surv. Water-Supply Pap., (1423), 84, 1958.

Sabaté, S., Gracia, C. A. and Sánchez, A.: Likely effects of climate change on growth of Quercus ilex, Pinus halepensis, Pinus pinaster, Pinus sylvestris and Fagus sylvatica forests in the Mediterranean region, For. Ecol. Manage., 162(1), 23–37, doi:10.1016/S0378-1127(02)00048-8, 2002.

Sardans, J. and Peñuelas, J.: Increasing drought decreases phosphorus availability in an evergreen Mediterranean forest, Plant Soil, 267(1–2), 367–377, doi:10.1007/s11104-005-0172-8, 2004.

Sarmento, E. de M. and Dores, V.: The performance of the forestry sector and its relevance for the portuguese economy, Rev. Port. Estud. Reg., 34(3), 35–50 [online] Available from: http://www.apdr.pt/siterper/numeros/RPER34/34.4.pdf (Accessed 16 February 2018), 2013.

Schenk, H. J. and Jackson, R. B.: Rooting depths, lateral root spreads and belowground aboveground allometries of plants in water limited ecosystems, J. Ecol., 480–494, doi:10.1046/j.1365-2745.2002.00682.x, 2002.

Soares, P. M. M., Cardoso, R. M., Ferreira, J. J. and Miranda, P. M. A.: Climate change and the Portuguese precipitation: ENSEMBLES regional climate models results, Clim. Dyn., 45(7–8), 1771–1787, doi:10.1007/s00382-014-2432-x, 2015.

Soares, P. M. M., Cardoso, R. M., Lima, D. C. A. and Miranda, P. M. A.: Future precipitation in Portugal: high-resolution projections using WRF model and EURO-CORDEX multi-model ensembles, Clim Dyn, 49, 2503–2530, doi:10.1007/s00382-016-3455-2, 2017.

Spinoni, J., Vogt, J. V., Naumann, G., Barbosa, P. and Dosio, A.: Will drought events become more frequent and severe in Europe?, Int. J. Climatol., 38(4), 1718–1736, doi:10.1002/joc.5291, 2017.

Stewart Fotheringham, A., Charlton, M. and Brunsdon, C.: The geography of parameter space: an investigation of spatial non-stationarity, Int. J. Geogr. Inf. Syst., 10(5), 605–627, doi:10.1080/02693799608902100, 1996.

Stone, E. L. and Kalisz, P. J.: On the maximum extent of tree roots, For. Ecol. Manage., 46(1–2), 59–102, doi:10.1016/0378-1127(91)90245-Q, 1991.

Thornthwaite, C. W.: An approach toward a rational classification of climate, Geogr. Rev., 38(1), 55–94, 1948.

Valentini, R., Scarascia, G. E. and Ehleringer, J. R.: Hydrogen and carbon isotope ratios of selected species of a Mediterranean macchia ecosystem, Funct. Ecol., 6(6), 627–631, 1992.

Vicente-Serrano, S. M., Beguería, S. and López-Moreno, J. I.: A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index, J. Clim., 23(7), 1696–1718, doi:10.1175/2009JCLI2909.1, 2010.

Vörösmarty, C. J., Green, P., Salisbury, J. and Lammers, R. B.: Global water resources: Vulnerability from climate change and population growth, Science (80-.)., 289, 284–288, doi:10.1126/science.289.5477.284, 2000.

Zou, C. B., Barnes, P. W., Archer, S. and Mcmurtry, C. R.: Soil moisture redistribution as a mechanism of facilitation in savanna tree–shrub clusters, Ecophysiology, (145), 32–40, doi:10.1007/s00442-005-0110-8, 2005.

Figure and Table Legends

Table 1: Environmental variables for the study area characterization in suitability to Groundwater Dependent Vegetation.

Table 2: Coefficients of determination resulting from the application of GWR model between GDV density and the selected predictive variables.

Table 3: Comparison of Adjusted R-squared and second-order Akaike Information Criterion (AICc) between simple regression and GWR models.

Table 4: Classification scores for each predictor. A score of 1 was given to areas less suitable and 3 to highly suitable areas.

Table 5: Interception (in %) between the classes of the GDV suitability map classes and the Overlapped Integrated suitability map. Value of "0" in overlapped integrated suitability map represent the non-suitable area for all the proxy species; value of "1" represent the suitable area for 1 of the proxy species; value of "2" represent the suitable area for 2 of the proxy species and value of "3" represent the suitable area for all the proxy species.

Table A1: Squared correlations between predictor variables and principal components axis. The most important predictors for each axis (when squared correlation is above 0.3) are showed in bold.

Figure 01: Study area. On the left the location of Alentejo in the Iberian Peninsula; on the right, the elevation characterization of the study area with the main river courses from Tagus, Sado and Guadiana basins. Names of the main rivers are indicated near to their location in the map.

Figure 02: Large well and piezometer data points used for Water Table Depth calculation. Squares represent piezometers data points and triangle represent large well data points.

Figure 03: Map of Kernel Density weighted by cover percentage of *Q. suber*, *Q. ilex* and *P. pinea*.

Figure 04: Map of environmental layers used in model fitting. (a) – Soil type; (b) – Slope; (c) – Groundwater Depth (Depth); (d) – Ombrothermic Index of the summer quarter and the immediately previous month (Ios4); (e) – Aridity Index (AI).

Figure 05: Spatial distribution of local R^2 from the fitting of the Geographically Weighted Regression.

Figure 06: Spatial distribution of residuals from the fitting of the Simple Linear model (a) and Geographically Weighted Regression (b).

Figure 07: Suitability map for Groundwater Dependent Vegetation.

Figure 08: Validation map corresponding to the juxtaposition of the integrated suitability maps for each of the proxy species *Q. suber*, *Q. ilex* and *P. pinea*. Areas suitable for more than 1 or more proxy species are represented with a gradient of brown colors. Rivers and dams are indicated in blue and artificialized areas in grey.

Figure A2: Correlation plot between predictors used for fitting the simple linear model and the GWR model. AI is Aridity Index; Depth is Groundwater Depth (Depth) and Ios4 is the Ombrothermic Index of the summer quarter and the immediately previous month.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions

931 Figure B1 – Predictors maps after classification. (a) – Ombrothermic Index of the summer quarter and the
932 immediately previous month (Ios4); (b) – Aridity Index (AI); (c) – Groundwater Depth (Depth); (d) – Slope; (e) –
933 Soil type.

934

935

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions

936 **Table 1: Environmental variables for the study area characterization in suitability to Groundwater Dependent**
937 **Vegetation.**

Variable code	Variable type	Source	Resolution and Spatial extent
Slope	**Slope (%)**	This work	0.000256 degrees (25m) raster resolution
Soil type	**Soil type in the first soil layer**	SNIAmb (© Agência Portuguesa do Ambiente, I.P., 2017)	Converted from vectorial to 0.000256 degrees (25m) resolution raster
Thickness	**Soil thickness (cm)**	EPIC WebGIS Portugal (Barata et al., 2015)	Converted from vectorial to 0.000256 degrees (25m) resolution raster
Depth	**Depth to groundwater (m)**	This work	0.000256 degrees (25m) raster resolution
Dd	**Drainage Density**	This work	0.000256 degrees (25m) raster resolution
Spei_severe	**Number of months with severe SPEI**	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
SPEI_extreme	**Number of months with extreme SPEI**	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
AI	**Aridity Index**	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
Io	**Annual Ombrothermic Index** Annual average (January to December)	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
Ios1	**Ombrothermic Index of the hottest month of the summer quarter** (J, J and A)	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
Ios3	**Ombrothermic Index of the summer quarter** (J, J and A)	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
Ios4	**Ombrothermic Index of the summer quarter and the immediately previous month** (M, J, J and A)	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010

938
939
940
941
942
943
944
945

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions

946

947 **Table 2: Coefficients of determination resulting from the application of GWR model between GDV density**
948 **and the selected predictive variables.**

Variables	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Global
Intercept	-48.55	16.01	23.88	29.16	94.65	13.86
Ios4	-18.31	-2.47	0.22	3.13	16.29	-0.22
AI	-48.27	-11.22	-1.61	5.48	64.87	-0.72
Depth	-32.30	-1.08	0.06	0.95	33.25	0.43
Soil type (2)	-19.78	-1.34	1.33	3.97	24.32	3.98
Soil type (3)	-20.18	-0.48	2.46	5.13	23.17	7.62
Slope	-2.88	-0.18	0.14	0.68	4.75	-0.13

949

950 **Table 3: Comparison of Adjusted R-squared and second-order Akaike Information Criterion (AICc) between**
951 **simple regression and GWR models.**

Model	R-squared	AICc	p-value
OLS	0.11	42276	<0.001
GWR	0.92 *	27795	-

952 *Quasi-global R^2

953

954

955 **Table 4: Classification scores for each predictor. A score of 1 was given to areas less suitable and 3 to highly**
956 **suitable areas.**

Predictor	Class	Score
Slope	0%-5%	3
	5%-10%	2
	>10%	1
Soil type	Eutric Cambisols; Dystric Regosol; Humic Cambisols; Haplic Luvisols; Gleyic Luvisols; Ferric Luvisols; Chromic Luvisols associated with Haplic Luvisols; Ortic Podzols	3
	Calcaric Cambisols; Dystric Regosol associated with Umbric Leptosols; Eutric Regosols; Vertic Luvisols; Eutric Planosols; Cambic Arenosols	2
	Chromic Cambisols; Eutric fluvisols; Chromic Luvisols; Gleyic Solonchak; Eutric Vertisols	1
Groundwater Depth	>15 m	1
	1.5m-15m	3
	≤1.5m	1
Aridity Index	0.6-0.68	3
	0.68-0.75	2
	≥075	1
Ios4	<0.28	3
	0.28-0.64	2
	≥0.64	1

957

958

959

960

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions

961

962

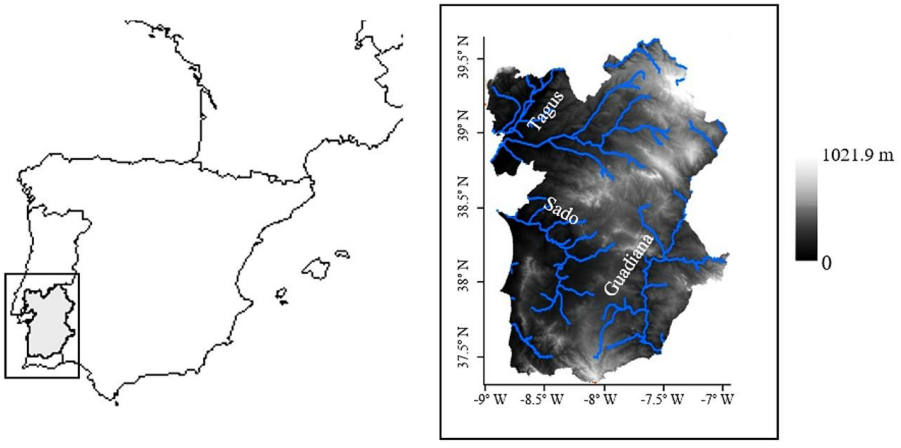
963 **Table 5: Interception (in %) between the classes of the GDV suitability map classes and the Overlapped**
964 **Integrated suitability map. Value of "0" in overlapped integrated suitability map represent the non-suitable area**
965 **for all the proxy species; value of "1" represent the suitable area for 1 of the proxy species; value of "2" represent**
966 **the suitable area for 2 of the proxy species and value of "3" represent the suitable area for all the proxy species.**

967

GDV suitability	Validation map (Integrated Suitability for 0 to 3 of the proxy species)	%968
Very Poor	0	75.67
	1	19.78
	2	2.8
	3	0.23
Poor	0	36.65
	1	45.27
	2	14.90
	3	0.02
Moderate	0	33.17
	1	15.53
	2	49.15
	3	0.03
Good	0	38.38
	1	29.51
	2	30.48
	3	0.15
Very Good	0	41.124
	1	18.38
	2	37.81
	3	0.57

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

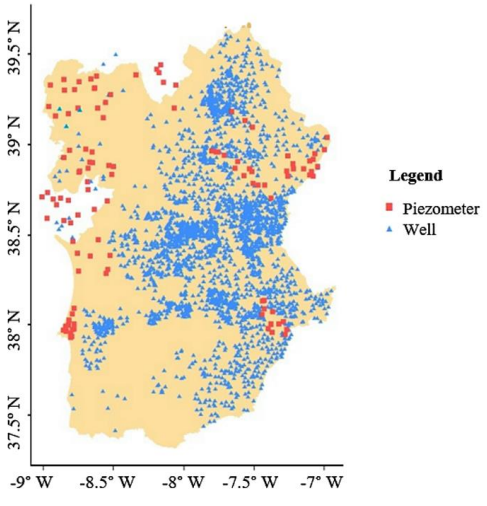
Hydrology and Earth System Sciences
Discussions
Open Access
EGU



969
970

971 **Figure 01: Study area. On the left the location of Alentejo in the Iberian Peninsula; on the right, the elevation**
972 **characterization of the study area with the main river courses from Tagus, Sado and Guadiana basins. Names**
973 **of the main rivers are indicated near to their location in the map.**

974



975

976 **Figure 02: Large well and piezometer data points used for Water Table Depth calculation. Squares represent**
977 **piezometers data points and triangle represent large well data points.**

978

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions
Open Access
EGU

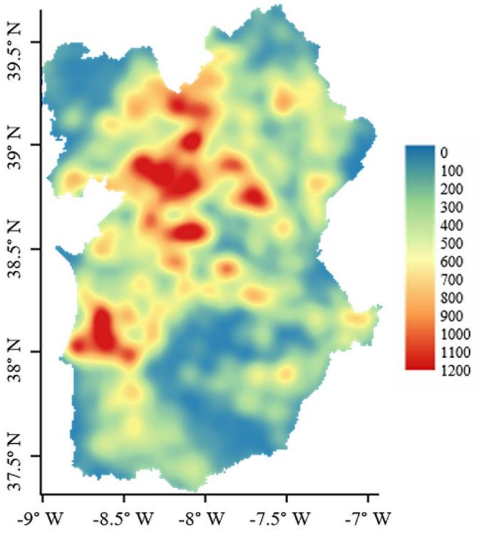
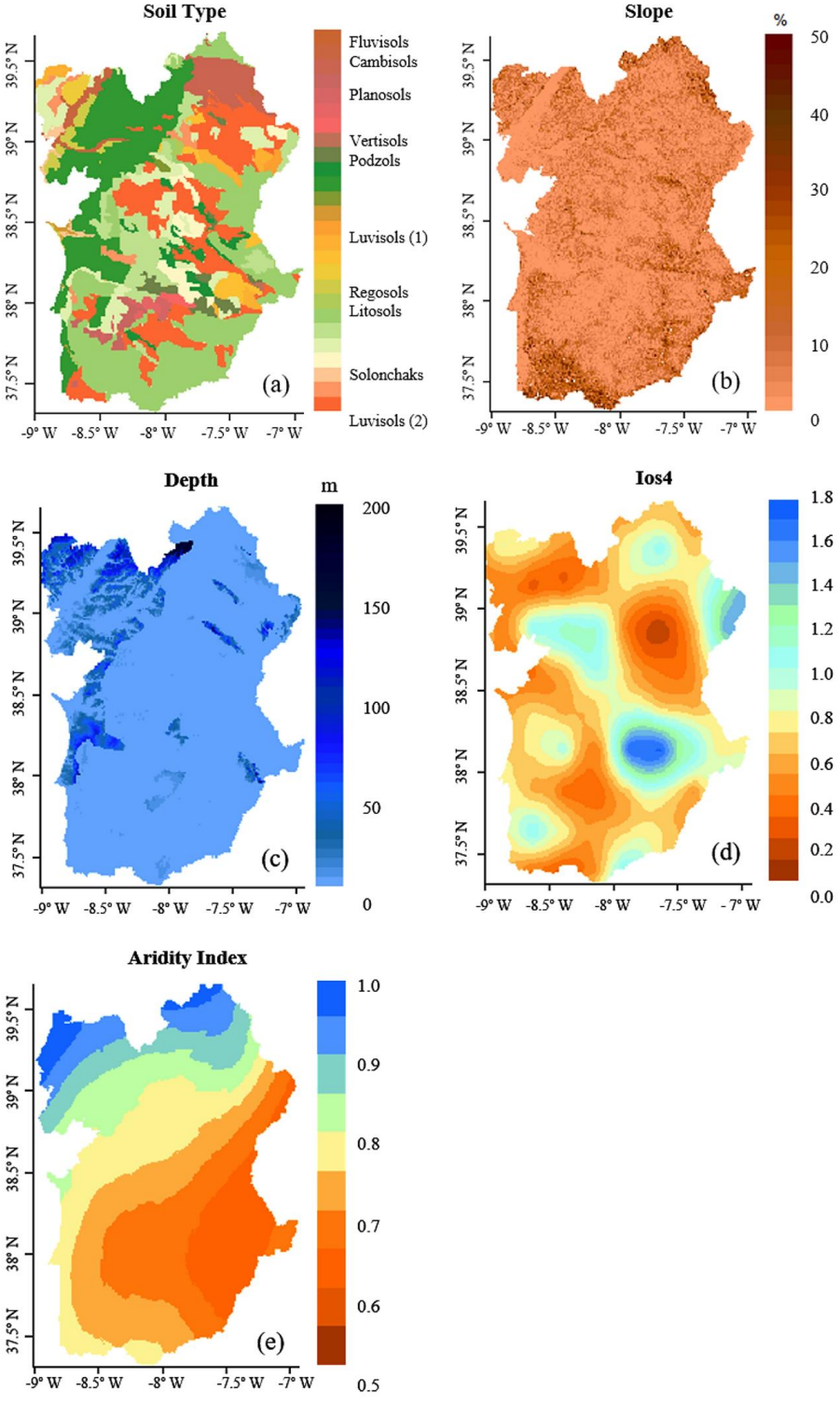


Figure 03: Map of Kernel Density weighted by cover percentage of *Q. suber*, *Q. ilex* and *P. pinea*.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018



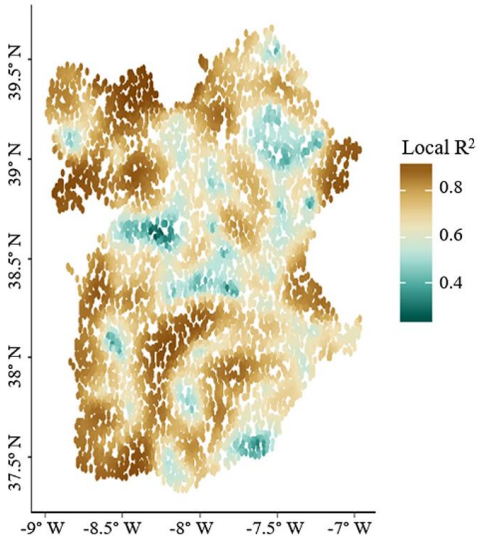
981

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions

982 **Figure 04: Map of environmental layers used in model fitting. (a) – Soil type; (b) – Slope; (c) – Groundwater**
983 **Depth (Depth); (d) – Ombrothermic Index of the summer quarter and the immediately previous month (Ios4);**
984 **(e) – Aridity Index (AI).**

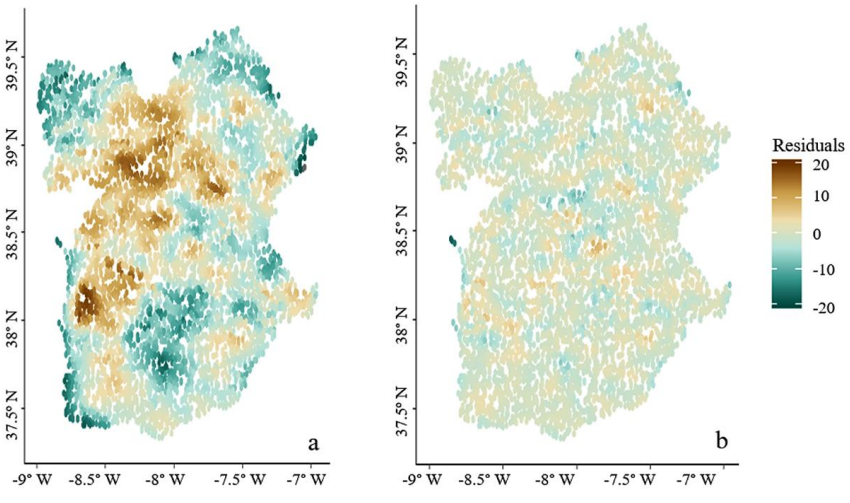
985



986

987 **Figure 05: Spatial distribution of local R^2 from the fitting of the Geographically Weighted Regression.**

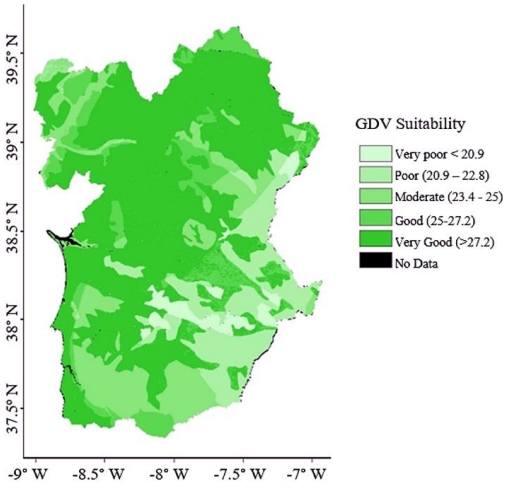
988



989

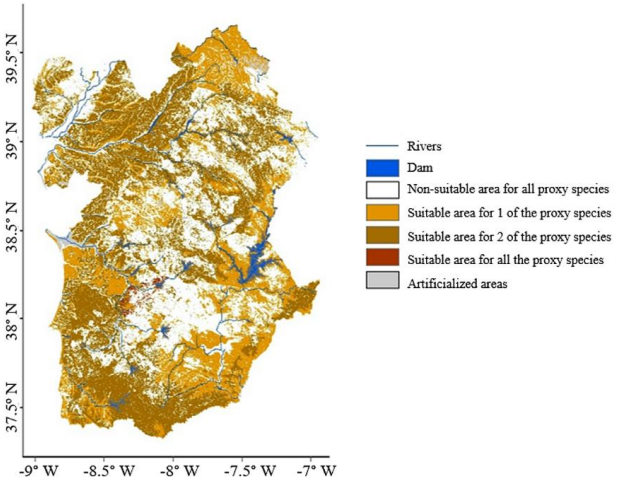
990 **Figure 06: Spatial distribution of residuals from the fitting of the Simple Linear model (a) and Geographically**
991 **Weighted Regression (b).**

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018



992

993 **Figure 07: Suitability map for Groundwater Dependent Vegetation.**



994

995 **Figure 08: Validation map corresponding to the juxtaposition of the integrated suitability maps for each of the**
996 **proxy species *Q. suber*, *Q. ilex* and *P. pinea*. Areas suitable for more than 1 or more proxy species are represented**
997 **with a gradient of brown colors. Rivers and dams are indicated in blue and artificialized areas in grey.**

998

999

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Appendix A

Table A1: Squared correlations between predictor variables and principal components axis. The most important predictors for each axis (when squared correlation is above 0.3) are showed in bold.

	PC1	PC2	PC3	PC4	PC5
Slope	<0.01	**0.34**	**0.63**	0.03	<0.01
AI	**0.67**	0.02	<0.001	<0.01	**0.31**
Ios4	0.18	**0.45**	0.24	0.03	0.10
Depth	**0.43**	<0.01	0.06	**0.45**	0.06
Soil type	**0.33**	0.25	0.05	0.29	0.08

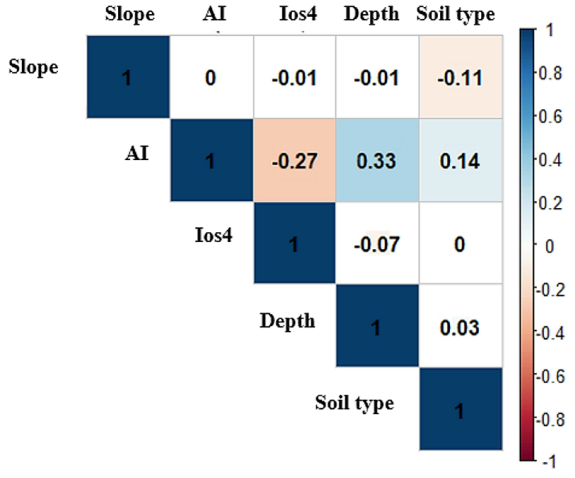
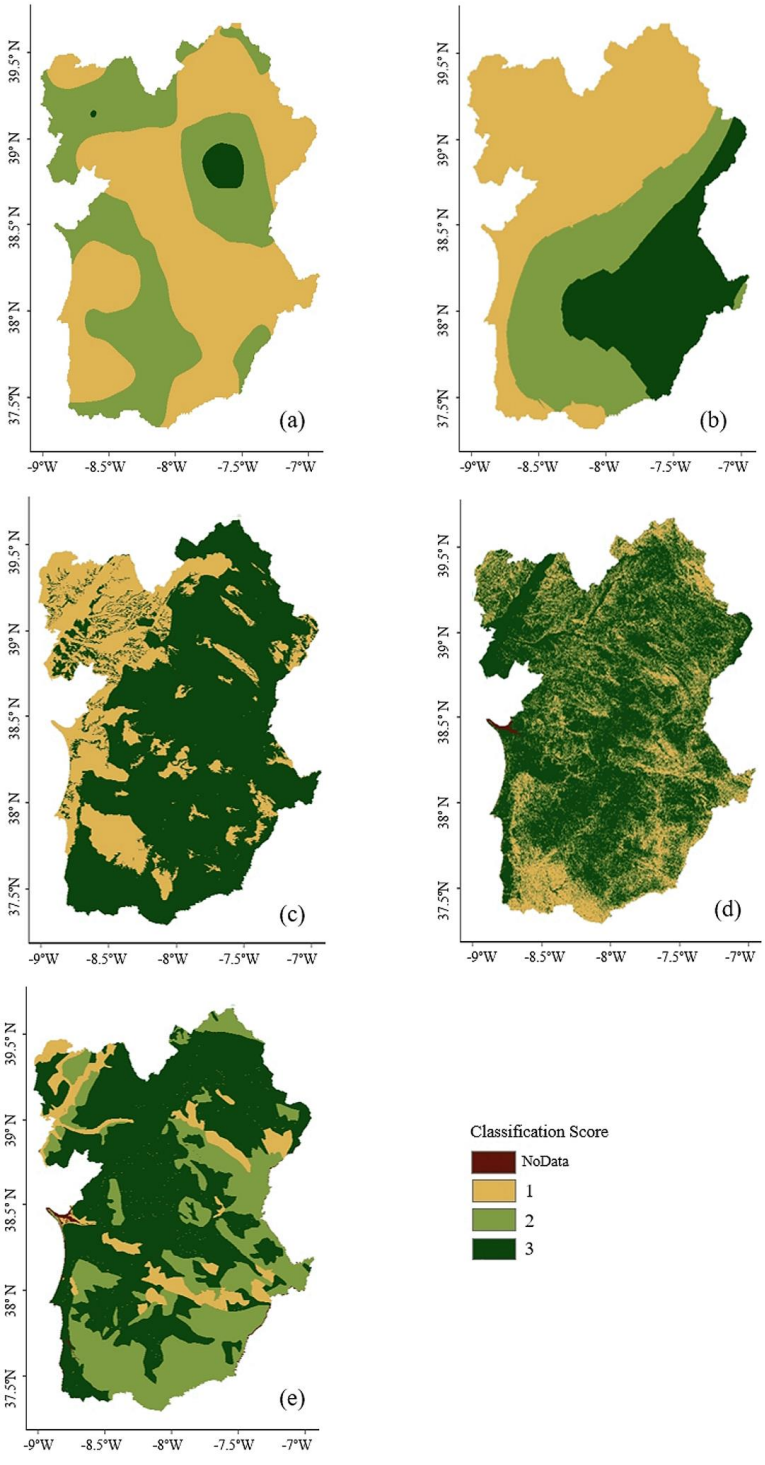


Figure A2: Correlation plot between predictors used for fitting the simple linear model and the GWR model. AI is Aridity Index; Depth is Groundwater Depth (Depth) and Ios4 is the Ombrothermic Index of the summer quarter and the immediately previous month.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

1011 **Appendix B**



1012

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2018-208
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 22 May 2018

Hydrology and Earth System Sciences
Discussions

1013 **Figure B1 – Predictors maps after classification. (a) – Ombrothermic Index of the summer quarter and the**
1014 **immediately previous month (Ios4); (b) – Aridity Index (AI); (c) – Groundwater Depth (Depth); (d) – Slope;**
1015 **(e) – Soil type.**

1016

1017

1018

1019

1020

1021

1022