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Editorial Department of *Hydrology and Earth System Sciences*

Dear Dr. Miriam Coenders-Gerrits,

Please find enclosed the revised version of the manuscript (reference hess-2018-208) entitled "*Mapping the suitability of groundwater dependent vegetation in a semi-arid Mediterranean area*".

All the reviewer and editor suggestions were carefully considered and addressed accordingly. In the response to reviewers you will find the responses to all comments and all changes made, point by point, as suggested by the reviewers. In the present cover letter, you will find the response to the editor comments, as well as all changes made.

We are very thankful for all the comments, which allowed an improvement of the manuscript quality.

To facilitate the identification of changes along the manuscript, a version of the manuscript with tracked changes was uploaded in the journal platform.

We kindly ask the editor to add another institutional e-mail correspondence of the first author. This e-mail has already been added in the submitted manuscript with tracked changes and in the final manuscript.

All the information included in this manuscript is completely original and has been approved by all authors. The authors declare no conflict of interest. This manuscript has not been published previously or concurrently submitted for publication elsewhere.

Thank you for considering this revised manuscript for publication. Please do not hesitate to contact me if you require further details.

With our best regards, sincerely,

Inês Gomes Marques (on behalf of all authors)

Editor Decision: Reconsider after major revisions (further review by editor and referees) (07 Dec 2018) by Miriam Coenders-Gerrits

Comments to the Author:

Dear authors,
As can be seen by the comments of the 2 reviewers they are rather positive. In your reply you addressed correctly to the comments and proposed some major improvements. Nonetheless, I think the paper can be improved by making it less case specific. How general are the results for other (semi)-arid regions?

***Answer:** Due to the similar climatic conditions and physiological responses of other semi-arid regions, the approach presented in this study can be applied as a first approximation to model the phreatophyte species. However, the model coefficients are highly and spatially variable and specific, which reinforces the need for model calibration on other regions, even though presenting the same climatic conditions. This was explained in lines 611-618, 657-660 of the discussion and 695-699 of the conclusion, and the possible applications, based on validations results, are presented in lines 706-713.*

The applied regression model is highly sensitive for the input as shown by your own correction to remove soil type from the analysis. Hence a proper sensitivity analysis plus a more elaborated discussion on the limitations of regression model would benefit the manuscript.

***Answer:** As suggested by the editor, a sensitivity analysis was performed to the model outputs. The applied methodology was explained in the chapter 2.8, in lines 377-390. The respective results were presented in the chapter 3.6 (in lines 523-535).*

Furthermore, I had a minor comment on the use of symbols. I highly recommend to use single characters. So not Dd as in equation 1, but D_d (subscript). Otherwise Dd could be confused with D*d. Please check this throughout the entire manuscript. Related to this, it's also better to not use words in equations. So in the case of equation 4, please define symbols for density, depth, soil type, etc.

***Answer:** All symbols were changes according to the editor suggestion. Drainage density symbol is now D, Aridity Index is A_i, Ombrothermic index is O_4, Groundwater depth is W and Slope is s. Equation 6 (lines 436-437) was changed accordingly, as well as all figures, tables and in the text.*

Dear Referee1,

Please find enclosed the revised version of the manuscript “Mapping the suitability of groundwater dependent vegetation in a semi-arid Mediterranean area”.

All the suggestions were carefully considered and addressed accordingly. In the present letter, you will find the responses to all comments and all changes made, point by point. Particularly, we have clarified the comments on the methodology to calculate the map to water table and changes the validation method as suggested. As a result of the introduction of a new remote sensing for the suitability map validation we added the author Célia M. Gouveia to the authors list.

We are very thankful for all the comments, which allowed a very significant improvement of the manuscript quality.

To facilitate the identification of changes along the manuscript, a version of the manuscript with tracked changes was uploaded in the journal platform.

All the information included in this manuscript is completely original and has been approved by all authors. The authors declare no conflict of interest. This manuscript has not been published previously or concurrently submitted for publication elsewhere.

Thank you for considering this revised manuscript for publication. Please do not hesitate to contact us if you require further details.

<u>Referee Comments 1</u>

General Comments

Gomes Marques et al. present an analysis of the spatial distribution of groundwater dependent vegetation across the Iberian Peninsula. While the method used is perhaps not as novel as suggested in the text, the paper’s main strength lies in the validation of the maps created against a fairly robust eternal dataset. The text is generally well written, although it is not as clear as it could be when discussing how the "model" was parameterized and validated. In general, the paper is a solid contribution to the literature on phreatophytes, but needs revision to enhance its clarity and address some lingering questions about the work.

Specific Comments

1. Throughout: What exactly is meant by a "suitability map"? Suitability for what? Or do you mean suitability of the terrain for hosting phreatophtyes? The concept is fine, but the word choice seems odd.

Answer: *We appreciate the reviewer’s comment on this matter. With a suitability map we aim to ascertain the suitability of the arboreous phreatophyte species to the climatic and local conditions. To clarify this matter, this information was provided in lines 122-123 of the introduction.*

2. Line 147 - 149: How heavily managed are these forestry systems? What species are harvested? And with what methods?

Answer: *In the Alentejo region, Cork oak, Holm oak and Stone pine represent 83% of the forest cover, covering about 36% of the geographical area. Cork oak covers 46% of the total forest area of the region, Holm oak 30%, and Stone pine only 7%, according to the last forest inventory. These species were already dominant species in the region and in Portugal two millennia after the beginning of holocene (Bugalho et al. 2009, Proença 2009). Since the 15th century, the agro-silvopastoral systems is largely dominant and steady in the province of Alentejo, on flat terrain. The system has a low tree density (40 to 80 trees/ha), trees being exploited for cork or seeds to feed cattle and the understory cleared of shrubs for pasture, crops (mainly wheat, barley and oats), or both. Tree density is determined by the need for space for pasture or cereal cultivation in the understory (Acacio & Holmgreen 2014) and by climate drivers, especially mean annual precipitation (Joffre 1999, Gouveia & Freitas 2008). Agro-silvopastoral systems are considered semi-natural ecosystems, which must be continually maintained through human management by thinning and understory use through grazing, ploughing and shrub clearing (Huntsinger and Bartolome 1992) to maintain a good productivity, biodiversity and ecosystem services. Cork oak trees are protected and cannot be harvested unless the tree has died, while holm oak trees are maintained with a low tree density (20 to 40 trees/ha) to guard against soil erosion and to provide shelter and shadow for cattle. Holm oaks are known to be more resilient to drought (David et al. 2007) and are mostly distributed in the most xeric area, on the oriental part of the Alentejo region. Some of this information has been added to the introduction section in lines 83-88 and in the discussion section in lines 547-550.*

Bugalho M *, Plieninger T, Aronson J , Ellatifi M, Gomes D Crespo 2009. Revista especializada. Cork oak woodlands on the edge. Ecology, adaptive management, and restoration, 1st edn. Society for Ecological Restoration International, Island Press, WashingtonChapter 3. Open Woodlands: A Diversity of Uses*
Proença *2009, Galicio-Portuguese oak forest of Quercus robur and Quercus pyrenaica: biodiversity patterns and forest response to fire. PhD Thesis, https://core.ac.uk/download/pdf/12421965.pdf*
Acácio *V. & Holmgreen M. 2009 Pathways for resilience in Mediterranean cork oak land use systems. Annals of Forest Science 71:5-13. DOI: 10.1007/s13595-012- 0197-0*
Joffre *R, Rambal S, Ratte PJ. 1999 The dehesa system of southern Spain and Portugal as a natural ecosystem mimic. Agrofor Syst 45:57–79*
Gouveia *A. & Freitas H., 2008 Intraspecific competition and water use efficiency in Quercus suber: evidence of an optimum tree density? Trees, 22 (2008), pp. 521-530*
Huntsinger *L, Bartolome JW. 1992 Ecological dynamics of Quercus dominated woodlands in California and southern Spain: a state transition model. Veg 99–100:299–305*
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 Physiology 27(6): 793-803*
https://doi.org/10.1093/treephys/27.6.793

3. Line 170: Cite ASTER GDEM data in the manner requested on the NASA webpage (https://lpdaac.usgs.gov/citing_our_data).

Answer: *Done. The missing citation was added in the proper place, in line 171-174. The acknowledgement is already properly done in the acknowledgement section.*

4. Line 172: What is meant by superficial water use? Shallow groundwater? Surface water in streams? It's used several places but isn't well defined.

Answer: *We substituted the expression superficial water/groundwater by shallow soil water, which refers to the water between 0 and 1.5 m depth, in line 175. All water below 1.5 m depth was considered as groundwater. This was clarified in lines 306-308.*

5. Line 179: What were the three classes? How did soil parameters influence in classification?

Answer: *The three classes are presented in Table 4 and an additional explanation to clarify the conditions who led to each scoring was added to lines 182-186. After revision of the suitability model the predictor soil type was no longer included in model fitting, and therefore no further explanation on its effect on the suitability to GDV was added.*

6. Line 187-202, Figure 2: The location of piezometer data and well data are quite biased. What is this attributable to and how might it affect the results? It seems like the kriging in the south-central region could be quite problematic. Also, what is the distinction between a well and a piezometer here? This is also concerning because the most dense of the GDV species are roughly in this corridor as well.

Answer: *The region under study is an area with a very low population density, which reflected in the lack of points for piezometric level measurement, mainly in unconfined aquifers (~96% of the total area). Once the correlation between the piezometric level and the topography was successfully tested it was possible to estimate the piezometric level by kriging with external drift in areas where information was not enough. We added one reference to line 601 to support this methodology.*

In the studied area, the presence of piezometers (exclusively dedicated structures for piezometric observations) is mostly associated with karst aquifers and areas with high abstraction volumes for public water supply. Oppositely, large wells are mainly devoted to private use and low volume abstractions. To complement the information given on the groundwater level estimation the following sentence was added to the ms, in lines 199-202: "In the studied area, piezometers are exclusively dedicated small diameter boreholes for piezometric observations, in areas with high abstraction volumes for public water supply. Large diameter wells in this region are usually low yielding and mainly devoted to private use and irrigation."

7. Line 199 -202: I disagree with this method - the groundwater elevations should be determined by first determining the groundwater elevation at the piezometers and then interpolating that through kriging. This should introduce fewer errors and be more realistic.

Answer: *The relation between piezometric level and topography is quite high in most of the unconfined aquifers (Marcily, 1986). This relation allows to estimate the piezometry in areas with few piezometric points with enough confidence using external drift kriging. On the other hand, through this method the piezometric surface respects the orographic structures such as valleys, which is not the case with traditional interpolation methods.*

"In the aquifer, the water flows toward the outlets, which are the low points in the topography (springs, streams in the surface flow network)." from Ghislain de Marsily, 1986. Quantitative Hydrogeology, Academic Press, Orlando. ISBN: 9780122089169, 9780080917634.

8. Line 303 - 312: The rationale for this validation method is a bit shaky and could use more explanation. If the presence/absence of these trees is a good indicator, why is the rest of the analysis necessary? Is it more expansive? Precise? Also, how is this not a bit autoregressive, given that it sounds like kernal density was derived from the tree data. It starts to make more sense as the results are discussed, but it needs more clarity here. What about using a remote sensing method for validation instead (e.g., Munch et al. 2007, Barron et al. 2012, Gou et. al 2014)? How would that compare?

> ***Answer:*** *After consulting the authors of the EPIC suitability maps (Magalhães M. and Mesquita S.) we understood that the latter were indeed constructed based on the last forest inventories. Therefore, there was indeed autoregression in our validation (see Mesquita, S. and Capelo, J. (2016). Aptidão Bioclimática às Espécies Arbóreas. In Magalhães, M.R. coord): Ordem Ecológica e Desenvolvimento - o futuro do território português. Pp. 63-85. Centro de Estudos de Arquitectura Paisagista "Professor Caldeira Cabral". ISA Press. Lisboa. ISBN: 978-972-8669-64-5).*
>
> *We thus followed the reviewer suggestion to use remote sensing data to validate our GDV suitability map. We therefore compared our GDV suitability map with NDWI anomalies of June 2005 (extremely dry hydrological year in Portugal) with the median June NDWI of year 1999-2009 with a dataset shared by Gouveia et al. (2012). We chose the Normalized Difference Water Index (NDWI) for being more representative of water content in vegetation's leaves. This index is thus a proxy for vegetation stress, with low NDWI values representing less leave water content, corresponding to a higher drought stress. The NDWI map we present show in yellow and brown color the areas were the vegetation was more sensitive to the extreme drought of 2005. We obtain a very good agreement between maps that we commented in the results and discussion sections, in the section 3.5 – Map Validation, 634-639 and 641-644. The method and dataset used are described in the M&M section lines 349-374.*

9. Line 389-397: What soil types were the most likely to host phreatophtyes? What does "soil type 3" represent?

Answer: *Soil type 3 represented soils with prevailing water storage at deeper soil depths, and therefore these soils were considered as more likely to host phreatophytes.*

10. Line 480-484: This paragraph seems to be saying that there must be some threshold by which no woody species can be supported, even if they are GDVs. These species get replaced by shortlived grasses and forbes, converting savanna to grassland. Is this correct? If so, this seems to contradict the next line about woody vegetation being replaced by shrublands. Wouldn't that presume shrubs are less susceptible to drought than trees? Please clarify.

Answer: *The referenced paragraph was removed from the discussion, after the calculation of a new suitability map. Instead we discussed the strong relation between aridity and tree density and the degradation of ecosystems linked to increasing water scarcity, in lines 608-615.*

11. Line 495-511: This part of the discussion is problematic, because, as the authors note, the factor expected to be most key is poorly mapped. Regardless, they still say that soil type, as opposed to groundwater depth, is the most influential and claim that soil type defines the capacity for "groundwater storage". This appears to be overreach.

> ***Answer:*** *The most influential factors in the reviewed version of the manuscript are climate drivers. After removing soil types from the final GWR model, the contribution of*

the W variable in the model improved (now corresponding to the 3rd most relevant variable in the model), but still remained far less relevant than climate drivers. The part of the discussion was slightly modified according to new results, lines 592-598.

12. Figure 7: This figure needs more color variation. It is difficult to tell moderate, good, and very good apart.

Answer: *Done. The color scale was modified to improve readability in Figure 09.*

Technical Corrections

13. Line 88: Replace "genders" with genre

Answer: *Done in line 93.*

14. Line 102: Replace "5m" with "5 m". Noticed number/unit spacing issues in several other locations as well.

Answer: *Done in line 108. All other places where the same issue was found, were corrected.*

15. Lines 132 - 135: Replace "chapters" with "sections". But really, this whole paragraph isn't necessary, as the format doesn't deviate from standard expectations.

Answer: *Done. The paragraph was eliminated from the manuscript.*

16. Line 154: "Proxy for" not "proxy to".

Answer: *Done in line 154.*

17. Line 175: Is the copyright symbol here a typo?

Answer: *No, the copyright symbol is requested to reference the database.*

18. Line 201: Don't need to repeatedly cite Spatial Analyst and its version so frequently. Can this be converted to one mention at the beginning of the section?

Answer: *Done. We added the sentence "The software used in spatial analysis was ArcGIS® software version 10.4.1 by Esri and R program software version 3.4.2 (R Development Core Team, 2016)." to the ms, under the chapter 2.3 in lines 167-168. All mentions to R and ArcGIS software versions were removed from the text.*

19. Line 295: Put equation right after fist mention.

Answer: *We have added a general equation of the model (Eq. 4) in lines 337-338 and maintained the equation with the final predictors (Eq. 6) in lines 436-437 so that only in the results section we would present the final model equation used to calculate the suitability map.*

20. Line 306: Replace "to a" with "of a".

Answer: *This paragraph has been deleted from the ms, after the validation was performed with a different dataset.*

21. Line 434, Line 454: Delete first names of authors.

Answer: *The first reference has been removed from the paragraph. On lines 58, 303 and 563 however, the name "Condesso de Melo" was right, thus remained unchanged.*

22. Line 450: Pinpoint is one word.

    Answer: *Done in line 559.*

23. Lines 451-453: Awkward wording makes the sentence hard to parse.

    Answer: *The sentence was improved in lines 559-562.*

24. Line 466: Delete stray "s".

    Answer: *This paragraph was completely re-structured.*

Dear Referee2,

We are very grateful for your rigorous assessment and the valuable comments and suggestions you provided to improve our manuscript.

Please find enclosed the revised version of the manuscript "Mapping the suitability of groundwater dependent vegetation in a semi-arid Mediterranean area".

We believe that all your suggestions were carefully addressed. In the present letter, you will find our responses to each comments and changes made.

Particularly, we have corrected the methodology to calculate drainage density. We also clarified the error you detected regarding a mistake in the map of Figure 7 where for a low aridity index (AI) we predicted a high suitability value (Figure B1b), which you attributed to the negative sign assigned to AI used as weighting factor. We evaluated the impact of each predictor on the final model and discovered that soil type actually considerably worsened the performance of the GWR model. We therefore decided to remove it from the final model equation selected to build the suitability map.

We also attempted to provide a better evaluation of the importance of each predictor in the final model and improved the discussion section accordingly.

To facilitate the identification of changes along the manuscript, a version of the manuscript with tracked changes was uploaded in the journal platform. All the information included in this manuscript is completely original and has been approved by all authors. The authors declare no conflict of interest. This manuscript has not been published previously or concurrently submitted for publication elsewhere.

Also, we thank you for considering this revised manuscript for publication. Please do not hesitate to contact us for any further needed detail.

With our best regards, sincerely

<u>Referee Comments 2</u>

General comments

The current manuscript provides an interesting insight into the use of mapping and spatial regression to assess the occurrence of groundwater dependent vegetation (GDV). Such maps can subsequently be used to predict the effect of change in any of the explanatory variables, such as climate or groundwater depth, on the spatial distribution of GDV in an area. The paper is well written and structured, and is subdivided into two parts: the first on the building of regression models for predicting GDV occurrence based on actual data, and the second part where a parameter-based index is calculated to construct so-called "suitability maps" for GDV. While I find the first part strong and with high potential of publication by adding a scenario analysis, my main concern lies with the second part. In my opinion this part is less well developed and the interpretation of the results is largely straightforward, and to a certain degree incorrect. Interpretation is largely straightforward because of the large bias in weighting of the parameters, where the contribution of soil largely exceeds all other parameters, thus making it essentially a soil map. Additionally, interpretation is to a certain degree incorrect, due to an apparent mistake in the generation of the suitability map, where (inadvertently) a negative weighting was assigned to the aridity index, resulting in the inverse impact of this parameter on the soil map. I would therefore recommend focusing and further elaborating on the regression modelling, as I will specify in my detailed comments below.

Specific comments

Abstract

Line 13-19: The first part of the abstract is more of an introduction. I suggest starting with what was actually done (line 20). Moreover, groundwater depletion will not occur merely as a result of climate change. Finally, as groundwater level seems to have such a low impact in the regression model, the question rises to what extent groundwater depletion will play a role in the spatial distribution of GDV.

> ***Answer:*** *The first paragraph of the abstract was rearranged. The abstract was corrected according to new results.*

Line 48: When referring to climate change impact studies on recharge in Mediterranean areas add the paper of doi.org/10.1007/s10113-012-0377-3, where such a study is being reported.

Answer: *Done. The suggested reference has been added in the text lines 49-50 and reference list lines 1083-1086.*

PART 1: REGRESSION MODELLING

Parameter selection for the regression model

Soil type: the authors only use the first layer of the soil. To understand the importance of capillary rise feeding into the root zone, the texture of deeper soils also needs to be considered. The latter could further affect the role of groundwater depth in the model, as fine soils have a much higher capillary (and water-holding) capacity. In the model, soil type is subdivided into two sub-parameters (2 and 3, Equation 4 and Table 2), but this is not further explained. Evidently, this increases the weight of soil type in the regression model.

> ***Answer:*** *The classification of soils into 3 categories was explained in lines 182-186 of the M&M section and in Table A1 in appendix A. This predictor was removed from the model fitting after revision from the authors. It has not been possible to add the texture of deeper horizon into our study because such information was only available on inaccessible printed maps. Unfortunately, no such digital data were available when the manuscript was prepared or revised.*

Groundwater depth: please comment on the reliability of the results in the empty areas (areas without wells or piezometers). Can wells and piezometers be used together, in other words, are all wells installed in unconfined aquifers?

> ***Answer:*** *Please notice the previous answer to the reviewer 1.*
> *The region under study is an area with a very low population density, which reflected in the lack of points for piezometric level measurement, mainly in unconfined aquifers (~96% of the total area). Once the correlation between the piezometric level and the topography was successfully tested it was possible to estimate the piezometric level by kriging with external drift in areas where information was not enough. We added one reference to line 601 to support this methodology.*

The estimation of the groundwater depth did not consider the simultaneous use of large wells and piezometers, with exception of the northwestern area, due to the lack of large wells.

In the studied area, the presence of piezometers (exclusively dedicated structures for piezometric observations) is mostly associated with karst aquifers and areas with high abstraction volumes for public water supply. Oppositely, large wells are mainly devoted to private use and irrigation.

Drainage density: Drainage density was calculated for six river basins. That gives little variation across the area. Is it possible to map drainage density at a higher resolution, e.g. sub-basin scale, or a 10 km grid size? This would increase the importance of this parameter.

Answer: *Indeed, there was little spatial variation of the drainage density for the studied area, therefore, as suggested by the reviewer, we recalculated this variable considering a 10km resolution grid. The methodology concerning this calculation was corrected in the ms, in lines 212-213. Due to the creation of a new drainage density map, we performed a reassessment of the multicollinearity between variables and the selection of predictors (see section 2.4). This implied recalculating Pearson's coefficients and Principal Components Analysis (PCA), presented in table A2 and figure A2 both in appendix A. It also affected predictors and coefficients in the model linking GDV density to environmental predictors). By affecting model development, model performance (Tables 2 and 3), suitability and coefficient maps were also affected (Figures 7 to 9).*

Climate: The authors should provide a bit more explanation on the SPEI and particularly the ombrothermic index calculations. Please explain how/where the latter differs significantly from (and is thus not correlated to) the aridity index.

Answer: *Done. Clear explanations on SPEI calculations were already provided in lines 225-228. Since the SPEI predictor was excluded from modeling further explanation would unnecessarily extend the manuscript length. We however briefly altered paragraph lines 233-235, to better explain the discrepancies between SPEI and Ombrothermic indices, and to clarify the Ombrothermic indices calculation according to Table 1.*

Model development

It is not clear how the parameters were normalized before entering the regression model.

Answer: *The explanation of the normalization based on the z-score function was improved and changed to the M&M section, under the chapter 2.5 - Model development. Variables were standardized before entering the regression model through the calculation of a z-score. To clarify how the standardization was done the following sentence was added to lines 274-276 of the ms: "This allows to create standardized scores for each variable, by subtracting the mean of all data points from each individual data point, then divide those points by the standard deviation of all points, so that the mean of each z-predictor is zero and the deviation is 1.".*

How was the soil parameter transformed into a quantitative variable? If all parameters were classified/categorized (as is often done in e.g. factorial regression analysis), this can explain the low influence of the groundwater depth parameter, as there is very little variation (in large part of the area groundwater depth is between 1.5 and 15 m). In this case, I strongly suggest increasing the number of classes for groundwater depth.

Answer: *We greatly appreciate your comment. First, we would like to clarify that the main purpose of the model construction is to attribute coefficients of importance to each variable, so that these coefficients can be applied to classification scores given to each variable by expert judgement (table 4) and return a suitability map to groundwater dependent vegetation. This will allow the production of a suitability map where the coefficients of importance applied to each variable were calculated empirically. Therefore, the classification scores given to each variable were not applied in the model calculation, but rather after the local model coefficients were calculated (as a mean to construct the suitability map).*

The soil parameter was used has a numeric categorical variable (with the values given initially from 1 to 3), through the use of the function as.factor() in R. The usage of this function will insure that the factor is seen as nominal and not as ordinal. Because the remaining variables showed continuous values, only the soil type variable was categorized, and the remaining variables used to run the model were continuous. The scoring applied is presented is Table A1and the explanation in lines 182-186 of the methods section.

The reviewer is correct about the groundwater depth variable and its very low variation above 15 m. As further explained below, it has not been possible to increase the number of classes for GWDepth, for the weighting factors to be correctly applied to the GWDepth layer in the multicriteria analysis. To overcome this situation the values of water depth above 15 m were replaced by a value above 15m (15.1 m), in order to emphasize the variation observed between 0 and 15 m depth, which matters the most to GDV. These values were only used for the model fitting. The species used as proxies for groundwater dependent vegetation are less probable to use water at depths lower than 15m, and so all the range of values above this threshold would be considered as inaccessible by those species.

Please provide references showing that it is common practice to fit the model on a 5% random subsample. Also explain more lines 264-265.

Answer: *The sub-sampling size was mostly dictated by computing limitation in the sense that the random subsample size was decreased down to 5% until the GWR model could be fitted. The mean distance between neighbor points using 5% of the original dataset was about 6 km, with a maximum distance of 15km. Nevertheless, we could find a few studies using a 10% random sub-sample of the data corresponding to a 10km resolution grid to perform GWR modeling (Bertrand R., 2017), as well as linear regression (Bertrand et al. 2016). The authors were using such subsampling to restrain autocorrelation issues according to Kühn (2007). We modified our text to include those references as well as the benefit for autocorrelation issues in our study, lines 281-287 and in the reference list, lines 785-787 and 946-947*

In addition, we calculated basic statistic indicators for the totality of the data and compared with the random subsample. Results are presented in line 284-286 of the ms and in Figure A1 in appendix A.

Bertrand R. Unequal contributions of species' persistence and migration on plant communities' response to climate warming throughout forests. bioRxiv, doi.org/10.1101/217497, 2017.
Bertrand R., Riofrío-Dillon G., Lenoir J., Drapier J., de Ruffray P., Gégout J.C., Loreau M.. Ecological constraints increase the climatic debt in forests. Nature Communications 7, 12643, doi: 10.1038/ncomms12643, 2016.

Kühn, I. Incorporating spatial autocorrelation may invert observed patterns. Divers. Distrib. 13, 66–69 (2007).

Results

Overall section 3.2 on environmental conditions mainly consists of an explanation of each of the maps. To support the selection of the five parameters, the authors should provide all the results on correlation and PCA as supplementary material.

> ***Answer:*** *Done. PCA results have now been provided as supplementary material in Table A2 in appendix A and was modified according to new results, due to the construction of a new map of drainage density.*

The results of the model suggest, as stated by the authors, a low importance of the groundwater depth on explaining the spatial distribution of GDV (eq. 4). However, nothing is said on how this varies locally within in the area. Are there regions where the role of groundwater is larger? Can these regions be identified?

> ***Answer:*** *We have plotted the local coefficients of all predictors and present it in Figures 07 and 08. In addition, we added some paragraphs with an explanation of the spatial variation of each predictor in the results section, in lines 455-461 and in the discussion section in lines 578-583.*

Line 343-344: This requires quite a bit more explanation, but can be easier to follow once the calculation of Ios4 has been better explained in the methods section.

> ***Answer:*** *We altered lines 233-235 and 243-245 to better explain the discrepancies between SPEI and O and to clarify the O calculation according to Table 1.*

Line 362-364: Please elaborate on this outcome on the Moran index.

> ***Answer:*** *Bibliographic references for the Moran Index were added in line 446 and the respective references were added to the bibliography. In addition, we extended the results explanation on the Moran Index and the z-score, in lines 446-450.*

In eq. 4 the appearance of Soil type 2 and Soil type 3 is not explained.

> ***Answer:*** *After revising the methodology and predictors selection, the predictor soil type was no longer included in the model.*

The results would become more interesting with:
1) a more local/regional analysis of the explanatory model and the importance of each of the parameters (in particular groundwater depth);

> ***Answer:*** *The model equation was substituted by a local one including the proportion of the local coefficients from the total variability of all the coefficients for each local GWR model. Local relative coefficients were considered as weighting factors instead of median values (please see revised Equation 6 in the manuscript). We also added a figure corresponding to the local variation of each coefficient in Figure 07 and commented the variations in the result section, in lines 455-461 and in the discussion section, lines 578-583. The relative importance of each variable in the final model is now shown in Figure 08, representing the distribution of the local coefficient values in a box plot.*

2) an assessment of the use of more/less/different parameters on the final model. It seems the soil type and to a lesser extent the aridity index are the dominating parameters in the regression model. How does a model based solely on these two parameters perform? And what about including a deeper (2nd-3rd layer) soil parameter to account for water holding and capillary rise capacity? Not much can be stated on the importance of soil type for the groundwater storage (as mentioned in line 495) if only the first soil layer is assessed.

Answer: *We tested the effect of removing one of the variables on the model performance and found out that the model performance increased notably when soil types was removed (AIC divided by factor 2, Table 2). The removal of any other variable however, did not seem to impact the model performance as compared to the equation including all formerly selected variables. Therefore, we excluded soil types from the final GWR model and the rest of our analyses and multicriteria analysis. Data on deeper soil parameters was not available for the study area and therefore that information could not be included in the model.*

3) scenario analysis: what happens if one or more of the parameters (such as climate or groundwater level) change? You do not have to develop climate scenarios, but an assessment of the impact of a relative change in aridity index or groundwater level on the resulting map would be of high added value.

Answer: *The development of climate scenarios or the assessment of the impact of aridity change on GDV suitability was out of the scope of this manuscript, since the actual manuscript is quite long already. The full assessment of climate changes impacts and corresponding uncertainties will be the focus of our next publication.*

We calculated preliminary results of the relative change of A_i and O_4 expected for the near future (Table a and b below). Our ongoing calculations based on scenarios RCP 4.5 and 8.5 show that A_i and O_4 climate indexes are going to decrease in the studied region (-14 to -33% within 2099), drifting from a mostly dry sub-humid climate ($0.5<A_i<0.65$) to a mostly semi-arid one ($0.2<A_i<0.5$) by 2099 in scenario RCP8.5, and according to the classification of Middleton et al. (1992). Ios4 is also going to suffer a huge drop (-42 to -58% within 2099). Also, while most of the territory could be considered as non-Mediterranean based on the ombrothermic index ($O_4>2$) during the historical period 1971-2000, it is becoming mostly Mediterranean by 2099 in scenario RCP8.5 and according to the classification of Rivas-Martínez et al. (2011).

To include such preliminary results in the M&M, result and discussion regarding climate change impact would imply to considerably increase the manuscript, while providing an incomplete picture of the changes and associated uncertainties. We therefore chose not to include the suggested assessment of the impact of a relative change in aridity index or groundwater level on the resulting map in this manuscript.

Nevertheless, we discussed the relative importance of each predictor in our final map, which give an insight of how the groundwater dependent- vegetation is expected to be affected according to the predicted increased aridity, lines 676-684 and 708-713.

Table a. *Mean relative changes expected for AI and IOS4 in the near future according to climate changes scenarios RCP 4.5 and 8.5, and respective standard deviations. Changes were computed considering 30 yr means obtained from an ENSEMBLE of eleven EU-CORDEX climate models.*

	Mean	Stdev
AI_rcp45_2011-2040	-8.1	1.5
AI_rcp45_2041-2070	-16.0	1.5
AI_rcp45_2071-2099	-14.5	1.7
AI_rcp85_2011-2040	-12.4	1.8
AI_rcp85_2041-2070	-22.1	2.0
AI_rcp85_2071-2099	-33.0	2.1
IOS4_rcp45_2011-2040	-21.2	2.3
IOS4_rcp45_2041-2070	-37.8	1.3
IOS4_rcp45_2071-2099	-42.1	2.4
IOS4_rcp85_2011-2040	-29.7	2.4
IOS4_rcp85_2041-2070	-44.4	1.6
IOS4_rcp85_2071-2099	-57.8	1.3

Table b. *Evolution of percentiles 10 and 90 values of AI and IOS4 in Alentejo from the present to the near future according to scenarios RCP 4.5 and 8.5. ECAD are observed values for the reference period 1971-2000. Historical values for the reference period 1971-2000 as well as predicted values for the future were simulated by an Ensemble of EU-Cordex models.*

	AI		IOS4	
	P10	**P90**	**P10**	**P90**
AI_ECAD_1971-2000	0.37	0.53	2.29	4.06
AI_historical_1971-2000	0.37	0.66	2.46	4.10
AI_rcp45_2011-2040	0.34	0.60	1.88	3.28
AI_rcp45_2041-2070	0.31	0.55	1.53	2.58
AI_rcp45_2071-2099	0.31	0.55	1.39	2.42
AI_rcp85_2011-2040	0.32	0.58	1.66	2.97
AI_rcp85_2041-2070	0.28	0.51	1.39	2.24
AI_rcp85_2071-2099	0.25	0.44	1.05	1.70

Discussion

Much of the discussion on the modelling approach is more of a summary of the manuscript, particularly lines 425-439. I miss the interpretation of the results obtained by regression modelling, and the this could further be enriched by the discussion of the added results as proposed above.

> ***Answer:*** *The discussion section has been considerably modified. The dominant impact of aridity on tree density and GDV suitability is now much more discussed, as well as the lower impact of groundwater depth. The relative weight of each predictor is also discussed and considered in the key limitations and conclusions sections. (see mostly lines 586-591, 676-681 and 693-702).*

PART 2: SUITABILITY MAPPING

Suitability map building

The authors decide to attribute the minimum score (in terms of suitability) to areas where groundwater depth is smaller than 1.5 m, considering that vegetation extracting water from shallow depths belongs to another type of GDV. This distinction between shallow and deep groundwater dependent vegetation, which I indeed think is useful (as most vegetation can use water in the first 1.5 m if present) needs to be briefly elaborated upon.

> ***Answer:*** *Providing a less probable score to host the GDV to the 0-1.5m GWDepth was made to exclude riparian vegetation and shrubby species which primarily use the water from streams and the superficial soil layer. An additional explanation and references were added to the manuscript in lines 310-314: "The depth class between 0 and 1.5m was based on the riparian vegetation in semi-arid Mediterranean areas which is mainly composed of shrub communities (Salinas et al., 2000) and present a mean rooting depths between 1 and 2m (Schenk and Jackson, 2002). The most common tree species rooting depth in riparian ecosystems is normally similar to the depth of fine sediment not reaching gravel substrates (Singer et al., 2012), but not reaching levels as deep as deep-rooted species.".*

Line 284-286. I do not understand why shallow groundwater flow would be expected at steep slopes. Normally steeper slopes are found in mountainous areas, where groundwater levels are deep.

> ***Answer:*** *The reviewer is correct, and we appreciate for noticing the error. The sentence was corrected in lines 316-317 and the term water flow was substituted by runoff.*

Results

The main finding here is that "suitability to GDV in the Alentejo region was mainly driven by soil type". That is obvious, as the weight of this parameter is by far the largest in the suitability index (and given by two soil type variables)! The same holds for the observation "The aridity index also showed a strong influence on GDV's suitability", as the weight of the aridity index is highest following that of soil type. I would strongly suggest analysing alternative weights for each parameter (based for instance on the Delphi panel) and evaluating the corresponding sensitivity of the outcome, as well as the degree of success in the validation procedure.

> ***Answer:*** *Unfortunately, it has not been possible for us to perform this analysis within the time provided to review our manuscript. We hope that the discussion on the relative importance of each predictor in the model will be satisfactory enough for the reviewer, considering that every other request was fulfilled.*

Line 395-396: "high aridity values restricted GDV's suitability in the south". Again, in my view it is exactly the opposite, as a high aridity is classified as class 3, i.e. of high suitability. In the south in fact aridity index is lowest, indicating the highest aridity and therefore higher suitability for GDV.

I think I might have detected a mistake in the resulting map of Figure 7. Where aridity index (AI) values are low, corresponding suitability value is high (Figure B1b), which means that overall suitability should also increase in those areas (towards the southeast). In the map of Figure 7 the values actually decrease in that area, which is contrary to what would be expected and could result from a negative weight being assigned to this parameter (as it also has a negative coefficient in the regression equation). If this is the case, the presentation and interpretation of the results on suitability mapping needs to be redone.

> ***Answer:*** *After thoroughly verifying the model calculations (Eq. 6) and the weighting factors used for the final multicriteria analysis (Figure 09), we must agree with the reviewer that it was a mistake to apply a negative weighting to the Aridity Index layer. Indeed, where real values of A_i were low (indicating a more arid area), our scoring was high in the multicriteria analysis. To directly apply a negative weight, we should have the real predictor values and the predictor scores co-varying (or growing) accordingly. We*

also verified that the same logic should be applied to the other quantitative variables Slope, O_4 and Groundwater Depth, since scoring and real values variation were opposite.

However, in the revised manuscript we have adopted different scores for the Aridity Index (scores 1, 3, 2) which were not varying linearly, and it was no longer possible to apply a linear scoring. The same was applicable in the case of Groundwater Depth, when we came to a dead end because scoring was not varying linearly according to class values (scores 1, 3, 1). As a solution we calculated the proportion of each local coefficients from the total variability of all the coefficients for each local GWR model (Eq. 6) as a local weighting factors reflecting the relative relevance of each predictor locally. This allowed us to apply scores not varying linearly and still interpreting the results easily. This way, the weighting factor obtained in from the proportions could be directly and correctly applied to the Groundwater Depth and Aridity Index layers.

One example of this wrong interpretation is in lines 376-378, where the authors state that the positive impact of the rivers on the GDV suitability "is due to a higher water availability reflected by the values of omborthermic and aridity indexes. In my view it should be the contrary, i.e. due to a lower water availability, indicating a higher suitability for GDV. Moreover, the positive impact is not visible in the map of Figure 7. And why is there a higher groundwater depth near the river? You would expect groundwater levels to be shallowest near the river.
Another example of this is in discussion section, where the authors state that "The lower suitability to this vegetation in the eastern part of the studied area can be explained by less favorable climatic and geological conditions, resulting from the combination of a high aridity index and low water retention at deep soil layers". It is again the contrary, as the ariditiy index in this (south)eastern area is lower, indicating a higher suitability and therefore higher values on the map of Figure 7. Moreover, it is not clear why the "deep soil" layer is mentioned here now, if only the first soil layer has been analysed.

***Answer:** We appreciate the referee comment and agree with it. Indeed, groundwater levels are expected to be higher near the river, mainly in alluvial aquifers (associated with gentle slopes). However, the opposite also occurs in areas where the rivers are associated with hard rock aquifers (generally associated with steep slopes) and where the relation surface/groundwater is more heterogeneous. The slope predictor, also considered in the presented methodology, distinguishes these occurrences.*

In Figure 7 please indicate how the values were calculated.

***Answer:** A thorough explanation was added in the methods section, in lines 335-341. The explanation in the methods section in the ms reads: "The final GIS multicriteria analysis was performed using the Spatial Analyst Tool by applying local model equations obtained for each of the 6214 coordinates of the Alentejo map (Eq.4),*

$$Suitability = Intercept + coef_1 * [real\ value\ X_1] + coef_2 * [real\ value\ X_2] + coef_3 * [real\ value\ X_3] + \ldots, \quad (4)$$

with brackets representing the reclassified GIS X layer corresponding to the scoring and $coef_{px}$ indicating the relative proportion for the predictor x.".

The final equation used for the calculation of the suitability map is presented in the results section, in lines 436-437, and is presented in the Equation 1 below.

$$S_{GDV} = Intercept + A_i\ coef_p * [reclassified\ A_i\ value] + O_4\ coef_p * [reclassified\ O_4\ value] + W\ coef_p * [reclassified\ W\ value] + D\ coef_p * [reclassified\ D\ value] + s\ coef_p * [reclassified\ s\ value], \quad (1)$$

If the authors decide to do the analysis per river basin, they should indicate the river basin boundaries in Figure 1.

> ***Answer:*** *As suggested by reviewer 1, we decided to use a 10 km grid mesh instead. The methodology was corrected in lines 212-213.*

Line 382-383: “this high likelihood was hindered by the type of soil present in that área In terms of soil type in the Tagus basin”. That is not true, as the suitability is mostly class 3 in the Tagus river basin.

> ***Answer:*** *The sentence was deleted according to the new results of the revised manuscript.*

Line 416-419 belongs to the discussion section, not the results section.

> ***Answer:*** *The paragraph was deleted according to the new validation performed in the revised manuscript.*

Technical corrections
Overall the text is well written and structured, the main comments above concern the content of the manuscript.
Line 47: decreased precipitation

> ***Answer:*** *Done in line 48.*

Line 56: An integrated multidisciplinary methodology

> ***Answer:*** *Done in lines 57-58.*

Line 63: do not include

> ***Answer:*** *Done in line 64.*

Line 167: listed in Table 1

> ***Answer:*** *Done in line 167.*

Line 169: 2.3.1 Slope and soil characteristics

> ***Answer:*** *Done in line 170.*

Line 205: division of the basin area by the total stream length

> ***Answer:*** *Done in line 213.*

Line 244: was evaluated

> ***Answer:*** *Done in line 255.*

Line 256: based on the selected variables

Answer: *Done in line 268.*

Line 277: score from 1 to 3

Answer: *Done in line 304.*

Line 367: In the GWR model

Answer: *Done in line 450.*

Line 380: with the exception of

Answer: *Done in line 478.*

Line 948: Table 2: Groundwater Depth

Answer: *This table was eliminated from the revised manuscript. The variable Groundwater Depth was, from now on, referenced as W.*

Line 956: suitable areas for GDV

Answer: *Done in line 1190, in Table 4.*

Figure 1: add catchment limits

Answer: *Done in the new version of fig01.*

Figure 4: change soil colours, or combine

Answer: *The map of soil type was removed form Figure 04.*

Line 990: what kind of residuals?

Answer: *This was clarified in lines 1213-1214.*

Figure 7: consider changing the colour coding

Answer: *A new suitability map was calculated, with new colors by classes, and was added as Figure09.*

Figure B1: present the maps in the same order as in Figure 4.

Answer: *Done in Figure B1.*

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

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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.~~

Mapping the suitability of groundwater dependent vegetation in semi-arid Mediterranean areas is fundamental for the sustainable management of groundwater resources and groundwater dependent ecosystems (GDE) under the risks of climate change scenarios. For the present~~In this~~ study~~, we built a model that explains~~ the distribution of deep-rooted woody species in southern Portugal was modeled ~~from~~ using climatic, hydrological and topographic environmental variables; and the ~~. To achieve this, we relied on the~~ density of *Quercus suber*, *Quercus ilex* and *Pinus pinea* were used as proxy species of Groundwater Dependent Vegetation (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~~Climatic indices ~~was~~were the main drivers of GDV density closely followed by groundwater depth, drainage density and slope~~the aridity index~~. Groundwater depth did not appear to be as pertinent in the model as initially expected, accounting only for about 7% of the total variation against 88% for climate drivers~~.~~

The relative proportion of m~~M~~odel predictor coefficients ~~were~~ was used as weighting factors for multicriteria analysis, to create a suitability map to the GDV in southern Portugal showing where the vegetation most likely relies on groundwater to cope with aridity. A validation of the resulting map was

performed using independent data of the Normalized Difference Water Index (NDWI) a satellite-derived vegetation index. June, July and August of 2005 NDWI anomalies, to the years 1999-2009, were calculated to assess the response of active woody species in the region after an extreme drought. The results from the NDWI anomaly~~integrated potential distribution of each proxy tree species in the region~~ provided an overall good agreement~~and overall, there was a good accordance between areas of good~~ with the suitability to host 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~~The methodology developed~~on~~ to map~~ping 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~~vegetation, aridity, agroforestry, suitability map, Normalized Difference Water Index

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 decreased precipitation (Giorgi and Lionello, 2008; Nadezhdina et al., 2015), decreased runoff (Mourato et al., 2015) and aquifer recharge (Ertürk et al., 2014; Stigter 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). An i~~I~~ntegrated 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) that ~~. 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 do~~id~~ not include~~d~~ 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 on~~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 gave an adaptive advantage to the vegetation ~~selected~~ that could either avoid or escape drought by reaching deeper stored water up to the point of relying in groundwater (Chaves et al., 2003;~~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). This drought-avoiding strategy~~Groundwater access by deep rooting species~~ is often associated to the development of a dimorphic root systems in woody species (Dinis 2014, David et al., 2013) or 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).

Mediterranean~~C~~ cork oak woodlands (Montados) are agro-silvo-pastoral systems considered as semi-natural ecosystems of the southwest Mediterranean basin (Joffre et al., 1999) that~~who~~ have already been referenced has a groundwater dependent terrestrial ecosystem (Mendes et al., 2016). Montados must be continually maintained through human management by thinning, understory use through grazing, ploughing and shrub clearing (Huntsinger and Bartolome, 1992) to maintain a good productivity, biodiversity and ecosystems service (Bugalho et al., 2009). 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* genre (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 5 m 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* were considered as proxies for arboreous 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 the arboreous phreatophyte species considered here as GDV in southern Portugal, based on the occurrence of known ~~and foreseen~~ subsurface phreatophyte species and well-known environmental conditions affecting ~~groundwater storage~~water resources availability. Several environmental predictors were selected according to their impact on ~~ground~~water 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 proportions 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 depth between 1.5 and 15 m associated with xeric~~and less arid~~ conditions should favor~~allow~~ a higher density of GDV and thus a larger use of groundwater by the vegetation. ~~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 and~~to~~ 39.39º N in latitude and between~~longitude~~ 9.00º and~~to~~ 6.55º W in longitude. 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 for~~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 10 km, 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's 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 ~~o~~in Table 1. The software used in spatial analysis was ArcGIS® software version 10.4.1 by Esri and R program software version 3.4.2 (R Development Core Team, 2016).

2.3.1 ~~Topography and Geology~~Slope and soil characteristics

The NASA and METI ASTER GDEM product ~~(https://lpdaac.usgs.gov)~~ was retrieved from the online Data Pool, courtesy of the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, https://lpdaac.usgs.gov/data_access/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~~ shallow soil 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 (Table A1 in appendix A). 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 v 1.2 (FAO et al., 2009). In the presence of dominant soil with little drainage capacity, mainly topsoil clay fraction and high available water content (AWC), lower scores were given in association to decreased suitability for GDV. Otherwise, when soil characteristics suggested water storage at deeper soil depths, lower AWC, drainage and sandy topsoil texture, higher scores were given.

Effective soil thickness (Table 1) was also considered for representing~~s~~ 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 ~~ground~~water resources 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 (W). In the studied area, piezometers are exclusively dedicated small diameter boreholes for piezometric observations, in areas with high abstraction volumes for public water supply. Large diameter wells in this region are usually low yielding and mainly devoted to private use and irrigation. 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 a 10km grid size ~~each of the six hydrographic basins of~~for the Alentejo region, by the division of the 10km square area (A) in km^2 by~~between~~ the total stream length (L) in km ~~and the basin area (A) in km^2~~, as in Eq. (1).

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

2.3.3 Regional Climate

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

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

While the SPEI index used in this study identifies geographical areas affected with more frequent extreme droughts, the Aridity index distinguishes arid geographical areas prone to annual negative water balance (with low A_i value) to more mesic areas showing positive annual water balance (with high A_i value). A_i gives information related to evapotranspiration processes and rainfall deficit for potential vegetative growth. It was calculated following Eq. (2) according to Middleton et al. (1992), where PET is the average annual potential evapotranspiration and P is the average annual precipitation, both in mm for the 60 years period of the climate time-series. Dry lands are defined by their degree of aridity in 4 classes: Hyperarid ($A_i\cancel{I}<0.05$); Arid ($0.05<A_i\cancel{I}<0.2$); Semi-arid ($0.2<A_i\cancel{I}<0.5$) and Dry Subhumid ($0.5<A_i\cancel{I}<0.65$) (Middleton et al., 1992).

$$A_i\cancel{I} = \frac{P}{PET}, \quad (2)$$

Ombrothermic Indexes (O) were used to better characterize the bioclimatology of the study region (Rivas-Martínez et al., 2011), by evaluating soil water availability for plants during the driest months of the year. Four ombrothermic indexes were calculated according to a specific section of the year stated in Table 1, and following Eq. (3), where Pp is the positive annual precipitation (accumulated monthly precipitation when the average monthly mean temperature is higher than 0°C) and Tp is the positive annual temperature (total in tenths of degrees centigrade of the average monthly temperatures higher than 0°). ~~If the o~~Ombrothermic index presenting~~s~~ values below~~above~~ 2 for the analyzed months, ~~the area~~ can~~not~~ be considered as Mediterranean bioclimatically. For non-Mediterranean areas, there is no dry period in which, for at least two consecutive months, the precipitation is less than or equal to twice the temperature. ~~Each ombrothermic index differed in the examined period of the year (Table1).~~

$$O\cancel{Io} = \frac{Pp}{Tp}, \qquad (3)$$

2.4 Selection of model p~~P~~redictors~~ selection~~

The full set of environmental variables was~~ere~~ 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. In addition, selected variables had to show the lowest possible correlation values between them. 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 based on~~to~~ the selected variables, ~~we must assure a~~the normal distribution and stationarity of the model predictors and residuals must be assured.

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 the 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. This allows to create standardized scores for each variable, by subtracting the mean of all data points from each individual data point, then dividing those points by the standard deviation of all points, so that the mean of each z-predictor is zero and the deviation is 1.

~~However, s~~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 (6214~~42~~ data points), due to computational restrictions and to decrease the spatial autocorrelation effect (Kühn, 2007). This methodology has already been applied with a subsample of 10%, with points distant 10km from each other (Bertrand et al., 2016). In spite of the subsampling, the mean and maximum distance between two random data points were, respectively, 3.6 km and 16.7 km, providing a good representation of local heterogeneity, as shown in figures 05 and 06. An additional analysis showing an excellent agreement between the two datasets is presented in FigA1 in appendix A.

Initially the model was constructed containing all selected predictors through the PCA and Pearson's correlation analysis. Afterwards, predictors were sequentially discarded to ascertain the model presenting lower second-order Akaike Information Criteria (AICc) and higher quasi-global R^2 chosen to predict the suitability of GDV.

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 was used~~, e.g. whether there were visible~~ to identify clustered values as well as the~~. 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 were classified, 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 1~~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 shallow soil ~~superficial~~ water above 1.5 m and the maximum rooting depth for Mediterranean woody species reaching 13 m, reported by Canadell et al. (1996). Throughout the manuscript water between 0 and 1.5 m depth was designated as shallow soil water, while water below 1.5 m depth was considered as groundwater. The depth class between 0 and 1.5m was based on the riparian vegetation in semi-arid Mediterranean areas which is mainly composed of shrub communities (Salinas et al., 2000) and presents a mean rooting depth of 1.5m (Silva and Rego, 2004). The most common tree species rooting depth in riparian ecosystems is normally similar to the depth of fine sediment not reaching gravel substrates (Singer et al., 2012) and not reaching levels as deep as deep-rooted species. The minimum score was given to areas where groundwater depth was too shallow (below 1.5 m)~~. This allowed to identify species dependent on more superficial groundwater which were~~ considered to belong to ~~other types of~~surface groundwater dependent vegetation. Areas with steep slope were considered to have superficial ~~water flow~~runoff and less recharge ~~(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~~Values of the Ombrothermic Index of the summer quarter and the immediately previous month (O~~Ios~~$_4$) ~~values~~ were split in 3 classes according to Jenks natural breaks, with higher suitability ~~scores~~ corresponding to higher aridity. The higher values of A_i, corresponding to lower aridity had a score of 1, because a higher humid environment would decrease the necessity of the arboreous species to use deep water sources. Accordingly, an increase in aridity (lower values of A_i) has already been shown to increase tree decline (Waroux and Lambin, 2012) and so higher A_i values corresponded to a score of 2, leaving the score 3 to intermediate values of A_i. Drainage density scoring was based on the capability of drainage of the water through the hydrographical network of the river. When drainage density was lower (below 0.5), a higher suitability scoring was given because the water lost from runoff through the hydrographic network would be less available to the vegetation thus favoring a higher use of water from groundwater reservoirs (Rodrigues, 2011).

A direct compilation of the predictor layers could have been performed for the multicriteria analysis.~~,~~ H~~h~~owever, some~~not all~~ predictors might have a stronger influence ~~in the same measure~~ on ~~the~~ GDV's distribution and density than others~~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 suggested~~provided~~ very different scoring for a same layer. ~~Subsequently, we i~~Instead ~~chose to use~~ the relative proportion of each predictor was used ~~coefficients~~ locally, according to the~~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,~~ by applying local model equations obtained for each of the 6214~~42~~ coordinates of the Alentejo map (Eq.4), ~~resulting in the final suitability map.~~

$$S_{GDV} = Intercept + coef_{p1} * [real\ value\ X_1] + coef_{p2} * [real\ value\ X_2] + coef_{p3} * [real\ value\ X_3] + \ldots, \quad (4)$$

with S_{GDV} representing the suitability to Groundwater Dependent Vegetation, brackets representing the reclassified GIS X layer corresponding to the scoring and $coef_x$ indicating the relative proportion for the predictor *x*.

According to this equation,~~In the latter,~~ lower values indicate a lower ~~probability~~ occurrence of groundwater use referred a lower GDV suitability~~occurrence~~ while higher values correspond to a higher use of groundwater referred a higher GDV 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 eval~~id~~uation

~~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/) (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.~~

Satellite derived remote-sensing products have been widely used to follow the impact of drought on land cover and the vegetation dynamics (Aghakouchaket al. 2015). Vegetation indexes offer excellent tools to assess and monitor plant changes and water stress (Asrar et al. 1989). The Normalized Difference Water Index (NDWI) (Gao, 1996) is a satellite-derived index that aims to estimate fuel moisture content (Maki et al., 2004) and leaf water content at canopy level, widely used for drought monitoring (Anderson et al., 2010, Gu et al., 2007; Ceccato et al., 2002a). This index was chosen to be more sensitive to canopy water content and a good proxy for water stress status in plants. Moreover, NDWI has been shown to be best related to the greenness of Cork oak woodland’s canopy, expressed by the fraction of intercepted photosynthetically active radiation (Cerasoli et al., 2016).

NDWI is computed using the near infrared (NIR) and the short-wave infrared (SWIR) reflectance, which makes it sensitive to changes in liquid water content and in vegetation canopies (Gao, 1996; Ceccato et al., 2002a, b). The index computation (Eq. 5) was further adapted by Gond et al. (2004) to SPOT-VEGETATION instrument datasets, using NIR (0.84 µm) and MIR (1.64 µm) channels, as described by Hagolle et al. (2005).

$$NDWI = \frac{\rho_{NIR} - \rho_{MIR}}{\rho_{NIR} + \rho_{MIR}}. \qquad (5)$$

Following Eq. (5), NDWI data was computed using B3 and MIR data acquired from VEGETATION instrument on board of SPOT4 and SPOT5 satellites. Extraction and corrections procedures applied to optimize NDWI series are fully described in Gouveia et al. (2012).

The NDWI anomaly was computed as the difference between NDWI observed in June, July and August of 2005 and the median NDWI for the considered month for the period 1999 to 2009. June was selected to provide the best signal from a still fully active canopy of woody species while the herbaceous layer had usually already finished its annual cycle and dried out. The hydrological year of 2004/2005 was characterized by an extreme drought event over the Iberian Peninsula, where less than 40% of the normal precipitation was registered in the southern area (Gouveia et al., 2009). Thus, in June 2005 the vegetation of the Alentejo region was already coping with an extreme long-term drought, which was well captured by the anomaly of the NDWI index (negative values), as shown by Gouveia et al. 2012.

2.8 Sensitivity analysis

Sensitivity analyses are conducted to identify model inputs that cause significant impact and/or uncertainty in the output. They can be used to identify key variables that should be the focus of attention to increase mode robustness in future research or to remove redundant inputs from the model equation because they do not have significant impact on the model output. Based on bootstrapping simulations (Tian et al., 2014), a sensitivity analysis was conducted on the GWR model by perturbing one input predictor at time while keeping the rest of the equation unperturbed. To simulate perturbations, 10000 values were randomly selected within the natural range of each input variable observed in the Alentejo region. Those random values were then used to run 10000 simulations of the local equation of the GWR model for each of the 6214 coordinates of the geographical area. Local outputs corresponding to the predicted GDV density were then calculated for each perturbed input variable (A_i, O_4, W, D and s). The range of output values was calculated to reflect the sensibility of the model for the perturbed input variable. The overall sensibility of the model to all input variables was estimated as the absolute difference between the minimum output value and the sum of maximum output values of all predictors, thus representing the maximum possible output range observed after perturbing all predictors.

3 Results

3.1 Kernel Density

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

3.2 Environmental conditions

The exploratory analysis of the variables~~,~~ performed through the PCA and Pearson correlation matrix confirmed the presence of multicollinearity. From the initial variables (Table 1), Thickness (T), ~~Drainage Density,~~ number of months with severe and extreme SPEI (respectively, SPEI$_s$ and~~pei_severe,~~ SPEI$_e$)~~Spei_extreme~~, Annual Ombrothermic Index (O~~Io~~), Ombrothermic Index of the hottest month of the summer quarter(O~~Ios~~$_1$) and Ombrothermic Index of the summer quarter **(**~~Ios~~O$_3$) were discarded, while the variables slope (s), drainage density (D), soil type (S$_t$), groundwater depth (W), A$_i$~~I~~ and ~~Ios~~O$_4$ were maintained for analysis (fig~~.~~ A2~~1~~ and Table A2~~1~~ in appendix). A sequential removal of one predictor from the initial modeling including six variables was performed (Table 2), after which the model was reduced to 5 variables, with the highest global R^2 (0.99) and the lowest AICc (18050.34). Therefore, ~~five environmental variables~~ out of the initial 12 considered (fig04) were endorsed to explain the variation of the Kernel density of GDV in Alentejo the following variables: A$_i$,~~soil type,~~ ~~ombrothermic index of the summer quarter and the immediately previous month (ios~~O$_4$~~)~~, W, D and s~~lope, aridity index and groundwater depth~~.

~~The Alentejo region showed high heterogeneity of soil types, with 27 different categories (fig04a).~~ In most part of the Alentejo region, slope was below 10% (fig04e~~b~~) and~~,~~ coastal areas presented~~ing~~ the lowest values and variability. Highest values of groundwater depth (fig04c), reaching a maximum of 255 m, were found in the Atlantic margin of the study area, mainly in Tagus and Sado river basins. Several other small and confined areas in Alentejo also showed high values, corresponding to aquifers of porous or karst geological types. Most of the remaining study area showed groundwater depths ranging between 1.5 m and 15 m. Figures 04a~~d~~ and 04b~~e~~ indicate the southeast of Alentejo as the driest area, given by minimum values of the aridity index (0.618), and much higher potential evapotranspiration ~~much higher~~ that precipitation. Besides, O~~Ios~~$_4$ presented a maximum value (0.714) for this region (meaning that soil water availability ~~in the soil~~ was not compensated by the precipitation of the previous M-J-J-A months). This is also supported by the higher drainage density in the southeast which indicates a lower prevalence of shallow soil water due to higher stream length by area.

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

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).~~The best model to describe the GDV distribution was found through a sequential discard of each variable (Table 2) and corresponded to the model with a distinct lower AICc (18050.76) compared with the second lowest AICc (27389.74) and showed an important increase in quasi-global R^2 (from 0.926 for the second best model to 0.992 for the best one). The best model fit was obtained with A_i, O_4, W, D and s. This final model was then applied to the GIS layers to map the suitability of GDV in Alentejo, according to Eq. 6.

$$S_{GDV} = Intercept + A_i\, coef_p * [reclassified\ A_i\ value] + O_4\, coef_p * [reclassified\ O_4\ value] + W\, coef_p * [reclassified\ W\ value] + D\, coef_p * [reclassified\ D\ value] + s\, coef_p * [reclassified\ s\ value], \tag{6}$$

Local adjusted R-squared of the GWR model was highly variable throughout the study area, ranging from 0~~.25~~ to 0.9~~9~~5 (fig05). Also, the local R^2 values below 0.5 corresponded to only 0.3% of the data. The l~~L~~ower R^2 values were distributed throughout the Alentejo area, with no distinct pattern.~~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 99~~2~~% of the variation in the data was explained by the GWR model, while only 2~~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~~The spatial autocorrelation~~,~~ given by the Moran Index (Griffith, 2009; Moran 1950) retrieved from the geospatial distribution of residual values~~,~~ was~~showed~~ significant for both the GWR and the linear models, indicating that observations geospatially are dependent on each other to a certain level . However, this dependence was substantially lower for the GWR model than for the linear model (~~a Z~~ z-score of ~~107.79~~50.24 ~~for the GWR model~~and 147.56 respectively). ~~, 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 GWR model (fig06a) the positive and negative residual values were much more randomly scattered throughout the study region than in the linear model (fig06b), highlighting a much better performance of the GWR, which minimized residual autocorrelation. Indeed, i~~I~~n the linear model (fig06b~~a~~), 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.~~

The spatial distribution of the coefficients of GWR predictors is presented in Fig07. They were later used for the computation of the GDV suitability score for each data point (Eq.6). The coefficient variability was three times higher for the A_i as compared to O_4 (fig08a), reaching 66% and 22% respectively. For W, D and s, the coefficient variation was much lower, representing only about 6.2%, 3.8% and 1.2% of the total variation observed in the coefficients, respectively. The remaining variables showed a median close to 0 and the O_4 was the second with higher variability followed by the W. The coefficient median values were, respectively, -3.40, 0.29, -0.015, -0.018 and 0.022 for A_i, O_4, W, D and s variables.

The distributions of negative coefficients were similar for A_i and the O_4 variables (fig07a and fig07b), with lower values in the southern coastal area, and in the Tagus river watershed. The highest absolute values were mostly found for A_i in the southern area of the Alentejo region and on smaller patches in the northern region. In the center and eastern areas of Alentejo, a higher weight of the groundwater depth coefficient could be found (fig07c), approximately matching a higher influence of slope (fig07e). The groundwater depth seemed to have almost no influence on GDV density in the Tagus river watershed, expressed by coefficients mostly null around the riverbed (fig07c). The coefficient distribution of D and O_4 shows some similarities, mostly in the center and southeast of Alentejo (fig07d). Extreme values of O_4 coefficients were mostly concentrated in the eastern part of the Tagus watershed and in the southern coastal area included in the Sado watershed. Slope coefficient values showed the lowest amplitude throughout the study area (fig07e), with prevailing high positive values gathered mainly in the center of the study area and in the Tagus river watershed (northwest of the study center).

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

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 B. Rivers Tagus and Sado had an overall large~~positive~~ impact on GDV's suitability for~~to~~ each predictor, with the exception of W. This is due to a higher water availability reflected by the values of ~~omborthermic~~O_4, D and lower slopes due to the alluvial plains of the Tagus river~~ and aridity indexes~~ (figs. B1b,~~a, and B1~~d and e~~b~~ in appendix B)~~ and a higher groundwater depth in the surroundings of the rivers (fig. B1c in appendix)~~. Moreover, those regions presented higher humidity conditions (through analysis of the A_i in fig B1a in appendix B) and groundwater depths outside the optimum range (Fig. B1c in appendix B), therefore less suitable for GDV. Optimal conditions for groundwater access were mainly gathered in the interior of the study region (fig. B1c in appendix B~~07~~), with the exception of~~for~~ some confined aquifers in the northeast and southeast of the study region. 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. B1e~~d~~ in appendix B). ~~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. 09~~7~~. ~~The~~ The largest classified area (8 787km^2) presented a very poor suitability to GDV but corresponded only to approximately a quarter of the total study area (29%). This percentage was followed closely by the moderate suitability to GDV which occupied 26% (8000km^2). Overall, the two less suitable classes (very poor and poor) represented 47% of the study area, whilst the two best ones and the moderate class (very good, good and moderate) represented 53%. Consequently, most of the study area showed moderate to high suitability to GDV. The very good and good suitability classes cover an arch from the most south and northeastern area of the Alentejo region, passing through the Sado and southern and northern Guadiana river basins and close to the coastal line at 38ºN. Most of the center of the study area showed moderate to very good suitability do GDV, while the areas corresponding to the alluvial deposits of the Tagus river showed poor to very poor suitability. ~~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 5 037 km^2 and 4 313 km^2, respectively. Altogether, 1/3 of the total area showed "Very poor" to "Moderate" suitability to GDV, corresponding to the most southern and eastern part of the study region.~~

The suitability to GDV in the Alentejo region was mainly driven by ~~soil type~~ A_i, given that~~by~~ the highest coefficient variability was associated to the A_i predictor in the GWR model equation. This is also supported by the similar distribution pattern observed between the suitability map and the aridity index predictor (fig04a and fig09). Areas with good or very good suitability mostly matched areas of A_i with score 3, corresponding to aridity index values above 0.75 (Fig. B1a in appendix B). On the other hand, the lowest suitability classes showed a good agreement with the lowest scores given to W (fig. B1c in appendix B), mostly in the coastal area and in the Tagus river basin. ~~similar distribution pattern between the suitability map and the soil type predictor (fig04a and fig07). This was also confirmed by the high coefficient obtained for the soil type predictor in the GWR model equation. The aridity index also showed a strong influence on GDV's suitability, mostly for the intermediate and good classes. Areas with high suitability classes corresponded to the most northern and coastal areas of Alentejo region. Areas with intermediate class in the north of the study region mostly matched with soil type polygons, with score 1 and 2 (figB1e in appendix), while high aridity values restricted GDV's suitability in the south. Areas with a good suitability mostly coincided with polygons of soil type 3 and with lower values of aridity index in the northern region of Alentejo.~~

3.5 Map evalu~~id~~ation

To evaluate~~assess the quality of~~ the suitability map developed in the present study, the~~we compared our~~ results were compared with the NDWI anomaly considering the month of June of the dry year of 2005 in the Alentejo area (fig10). Both maps (figs 09 and 10) showed similar patterns, with higher presence of GDV satisfactorily matching areas with the lowest NDWI anomaly. The NDWI anomaly was mostly negative over the Alentejo territory indicating water stress in the vegetation leaves. Water stress due to the extreme drought was maximum (green color) in geographical areas matching the highest GDV suitability (fig09). It was less pronounced (mostly yellowish) in the central area of the Alentejo region between the Guadiana and Sado river basins where the vegetation presents a lower density (fig03). Areas with positive/null values of NDWI anomaly (corresponding to geographical areas with a higher water availability) were mostly distributed on the coastal area of the Atlantic ocean or close to riverbeds, namely in the Tagus and Sado floodplains (brown color, fig10), matching areas of poor suitability for GDV in Figure 09. Note that green and yellow areas in June 2005 (fig 10a) progressively turned to brown color in July and August 2005 (fig10c), suggesting that the corresponding vegetation recovered from the increasing water stress, despite the intensification of drought throughout the summer period. ~~integrated suitability maps, from different data sources than those used in this study, for each of the previously considered proxy species. The integrated suitability maps of each proxy species were aggregated into one validation map.~~

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

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

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

3.6 Sensitivity analysis

The sensitivity of the model in response to the perturbation of each one of the input variables (A_i, O_4, W, D and s) is presented on Figure 11a to Figure11e. The overall sensitivity of the model is further presented on Figure 11f. For any input variable, the model sensitivity (fig11a to 11e) was higher where absolute values of local coefficients were also higher (fig07a to 07e). The maximum impact on GDV's density, corresponding to the maximum output range observed after perturbation (fig08b), was observed when perturbing the Aridity index, accounting for 66% of the total variability. The second highest impact was observed after perturbing the ombrothermic index. The variability in the model outputs observed after perturbing the remaining variables O_4, W, D and s accounted for 22, 7, 4 and 1% of the total accumulated variability, respectively (fig08b). The highest variability in the GWR model output was mostly observed in the central part of the southern half of the Alentejo region, as well as close to the main channels of the Guadiana and Tagus rivers (fig11f). Furthermore, areas with higher model sensitivity (fig11f) significantly matched higher model performance expressed by R^2 (fig05), assessed with a Kruskall-Wallis test ($p<0.0001$***).

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.~~ The~~refore, a~~ Geographically Weighted Regression model has been ~~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 when compared to the linear model, with a coefficient of regression (R^2) increasing from 0.02~~11~~ to 0.99~~2~~ 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).~~ The Mediterranean cork woodlands dominate about 76% of the Alentejo region (while only 7% is covered by stone pine). In those systems, tree density is known to be a tradeoff between climate drivers (Joffre 1999, Gouveia & Freitas 2008) and the need for space for pasture or cereal cultivation in the understory (Acacio & Holmgreen 2014). In our study, ~~However,~~the anthropologic management of agroforestry systems in the Alentejo~~is~~ region has not been taken into account~~considered in the model~~. According to a recent study of Cabon et al. (2018) where thinning played an important role in *Q. ilex* density in a Mediterranean climate site, anthropologic management~~This~~ could, at least partially, explain the non-randomness of the residual distribution after GWR model fitting as well as the mismatches between the GDV and the NDWI evaluation maps.

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 was excluded 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 user (Bourke, 2004; Kurz-Besson et al., 2016). In addition, olive trees were also excluded although ~~only recently~~ the use of groundwater by an olive orchard has been recently proved (Ferreira et al., 2018), however with a weak contribution of ~~little~~ groundwater ~~flow amount of~~to the daily root flow, and thus~~so~~ with no significant impact of groundwater on ~~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~~ the GWR modelling approach was used to assess weighting factors for each environmental predictor in the study area, to build a suitability map for the GDV in southern Portugal. This allowed an empirical determination of the local relevance of each environmental predictor in GDV distribution, thus avoiding the inevitable subjectivity of Delphi panels.

Modelling of the entire study area at a regional level did not provide satisfactory results. Therefore, we developed a general model varying locally according to local predictor coefficients. The local influence of each predictor was highly variable throughout the study area, especially for climatic predictors reflecting water availability and stress conditions. The application of the GWR model did not only allowed for a localized approach, by decreasing the residual error and autocorrelation over the entire studied region, but also provided insights on how GDV's density can be explained by the main environmental drivers locally.

The GWR model appeared to be highly sensitive to coefficient fitting corresponding to a good model fit, as expected in a spatially varying model. As so, high coefficients are highly reliable in the GWR model in our study. Predictor coefficients showed a similar behavior in the spatial distribution of the coefficients. This was noticeable for the aridity index and the groundwater depth in the Tagus and Sado river basins. Groundwater depth had no influence on GDV's density in these areas and similarly, the coefficient of aridity index showed a negative effect of increased humidity on GDV's density. In addition, a cluster of low drainage density values matched these areas. Due to the lower variability and impact of the drainage density and slope on the GDV's density, these variables might not impact significantly this vegetation density in future climatic scenarios.

4.2 Suitability to Groundwater Dependent Vegetation

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

According to our results, more than half of the study area appeared~~s~~ suitable for GDV. However, one quarter~~third~~ of the studied area showed ~~the lowest~~lower suitability to GDV. The lower suitability to this vegetation in the ~~eastern~~ more northern and western part of the studied area can be explained by less favorable climatic and hydrological conditions~~geological conditions~~, resulting from the combination of a high aridity index and ~~low water retention at deep soil layers~~low groundwater depth scores (equivalent to high shallow soil water availability), corresponding to the coastal area and in the Tagus river basin. ~~Soils with lower water capacity further lowered GDV suitability in the most southeastern region of the studied area.~~

Groundwater depth appeared to have a lower influence on GDV density than climate drivers, as reflected by the relative low magnitude of the W coefficient and outputs of our model outcomes. This surprisingly disagrees with our initial hypothesis because groundwater represents a notable proportion of the transpired water of deep-rooting phreatophytes, reaching up to 86% of absorbed water during drought periods and representing about 30.5% of the annual water absorbed by trees (David et al. 2013, Kurz-Besson et al. 2014). Nonetheless, this disagreement should be regarded cautiously due to the poor quality data used and the complexity required for modelling the water table depths. Besides, the linear relationship between water depth and topography applied to areas of undifferentiated geological type can be weakened by a complex non-linear interaction between topography, aridity and subsurface conductivity (Condon and Maxell, 2015). 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 (<15 m 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 rigorously characterize the spatial dynamics of groundwater depth between hydrographic basins (Lorenzo-Lacruz et al., 2017). Unfortunately, such resolution was not available for our study area.

The aridity and ombrothermic indexes were the most important predictors of GDV density in the Alentejo region, according to our model outcomes. Our results agree with previous findings linking tree cover density and rooting depth to climate drivers such as aridity, at a global scale (Zomer et al., 2009; Schenk and Jackson, 2002) and specifically for the Mediterranean oak woodland (Gouveia and Freitas 2008, Joffre et al. 1999). Through previous studies showing the similarities in vegetation strategies to cope with water scarcity in the Mediterranean basin (Vicente-Serrano et al., 2013) or the relationship between rooting depth and water table depth increased with aridity at a global scale (Fan et al., 2017) we can admit that the most relevant climate drivers in this study are similarly important to map GDV in other semi-arid regions. In this study, the most important environmental variables that define GDV's density in a semi-arid region were identified, helping to fill the gap of knowledge for modelling this type of vegetation. However, the coefficients to be applied when modelling each variable need to be calculated locally, due to their high spatial variability.

Temporal data would further help discriminate areas of optimal suitability to GDV, either during the wet and the dry seasons, because the seasonal trends in groundwater depth are essential under Mediterranean conditions. Investigations efforts should be invested to fill the gap either by improving the Portuguese piezometric monitoring network, or by assimilating observations with remote sensing products focused on soil moisture or groundwater monitoring. This has already been performed for large regional scale such as GRACE satellite surveys, based on changes of Earth's gravitational field. So far, these technologies are not applicable to Portugal's scale, since the coarse spatial resolution of GRACE data only allows the monitoring of large reservoirs (Xiao et al. 2015).

~~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.~~

4.3 Validation of the results

The understory of woodlands and the herbaceous layer of grasslands areas in southern Portugal usually ends their annual life cycles in June (Paço et al. 2007), while the canopy of woody species is still fully active with maximum transpiration rates and photosynthetic activities (Kurz-Besson et al. 2014, David et al. 2007, Awada et al. 2003). This is an ideal period of the year to spot differential response of the canopy of woody species to extreme droughts events using satellite derived vegetation indexes (Gouveia 2012).

The spatial patterns of NDWI anomaly in June 2005 seem indicate that the woody canopy showed a strong loss of canopy water in the areas were tree density and GDV suitability were higher (figs03, 09 and 10). This occurred although trees minimized the loss of water in leaves with a strong stomatal limitation in response to drought (Kurz-Besson et al. 2014, Grant et al. 2010). In the most arid area of the region were Holm oak is dominant but tree density is lower, the NDWI anomaly was generally less negative thus showing a lower water stress or higher canopy water content. Holm oak (*Quercus ilex* spp *rotundifolia*) is well known to be the most resilient species to dry and hot conditions in Portugal, due to its capacity to use groundwater and associated to a higher water use efficiency (David et al. 2007). Furthermore, the dynamics of NDWI anomaly spatial patterns over the summer period (fig10a, b and c) pointed out that the lower water stress status on the map is progressively spreading from the most arid areas to the milder ones from June to August 2005, despite the intensification of drought conditions. This endorses the idea that trees manage to cope with drought by relying on deeper water sources in response to drought, replenishing leaf water content despite the progression and intensification of drought conditions. Former studies support this statement by showing that groundwater uptake and hydraulic lift were progressively taking place after the onset of drought by promoting the formation of new roots reaching deeper soil layers and water sources, typically in July, for cork oak in the Alentejo region (Kurz-Besson et al., 2006, 2014). Root elongation following a declining water table has also been reported in a review on the effect of groundwater fluctuations on phreatophyte vegetation (Naumburg et al. 2005).

Our results and the dynamics of NDWI over summer 2005 tend to corroborate the studies of Schenk and Jackson (2002) and Fan et al. (2017), by suggesting a larger/longer dependency of GDV on groundwater with higher aridity. Further investigation needs to be carried on across aridity gradients in Portugal and the Iberian Peninsula to fully validate this statement, though.

Overall, the map of suitability to GDV showed an excellent ~~good results~~ agreement with the NDWI validation maps.~~, compared with the validation maps showing the proxy species integrated suitability (Magalhães et al., 2015b, 2015a, 2015c). However, areas of high suitability to GDV matched areas of the validation that were non-suitable areas for the proxy species.~~ 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.~~The good agreement between our GDV suitability maps, and NDWI dynamic maps opens the possibility to apply and extend the methodology to larger geographical areas such as the Iberian Peninsula, or the simulation of the impact of climate changes on the distribution of groundwater dependent species in the Mediterranean basin. ~~As shown by the simulations~~Simulations of future climate conditions based on RCP4.5 and RCP8.5 emission scenarios (Soares et al., 2015, 2017) predict~~,~~ a significant decrease of precipitation for the Guadiana basin and overall decrease for the southern region of Portugal ~~are expected~~within 2100. Agroforestry systems relying on groundwater resources, such as cork oak woodlands, may show a decrease in productivity and ecosystem services or even face sustainability failure. Many studies carried out on oak woodlands in Italy and Spain identified drought as the main driving factor of tree die-back and as the main climate warning threatening oak stands sustainability in the Mediterranean basin (Gentilesca et al. 2017). An increase in aridity and drought frequency for the Mediterranean (Spinoni et al., 2017) will most probably induce a geographical shift of GDV vegetation toward milder/wetter climates (Lloret et al., 2004; Gonçalez P., 2001). ~~plant physiological adaptations (Peñuelas and Filella, 2001) as well as species substitution (Lloret et al., 2004). In the Mediterranean environment, Peñuelas et al. (2011) distinguished two plant communities regarding water consumption, one with deep roots, able to constantly access water and nutrients and a second community with shallow roots, depending on superficial water from rainfall. Due to climate change conditions, in the Alentejo region of Portugal, we should expect GDV of the less suitable areas to be replaced by the community with shallow roots using rainfall water exclusively. This has already been reported for a Mediterranean woodland of the Iberian Peninsula, where extreme drought conditions led to a shift in vegetation cover from deep-rooting species to water spending species (Caldeira et al., 2015). Groundwater reservoirs would thus no longer be a constraint for plant survival during summer droughts, because the supplanting vegetation community, namely annuals that stop their growing cycle or die before the onset of the dry season, would no longer need constant access to water. Such species substitution would be associated with ecological and biodiversity costs, by shifting from woodland to shrubland ecosystems.~~

~~In environments with scarce water sources such as the Mediterranean basin, many tree species have adapted to the precipitation's seasonality and its large variability by developing dimorphic root systems.~~

~~When comparing different water limited ecosystems from a global dataset, Schenk and Jackson (2002) showed that rooting depth increased with aridity. Our results agree with these findings since the aridity index was the second most important predictor of GDV density, according to our equation. Nevertheless, the soil type turned out to be the most important predictor of GDV density. This is comprehensible 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.~~

~~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.~~

4.4~~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 recurrent ~~update~~amendments, associated with updated~~and/or~~ environmental data, species distribution and revised expert knowledge (Doody et al., 2017).

The evolution of groundwater depth in response to climate change is difficult to model on a large scale based on piezometric observations because it requires an excellent knowledge of the components and dynamics of water catchments. Therefore, a reliable estimation of the impact of climate change on GDV suitability in southern Portugal could only been performed on small scale studies. However, the GWR model appeared to be much more sensitive to climate drivers than the other predictors, given that 88% of the model outputs variability was covered by climate indexes A_i and O_4. Nevertheless, changes in climate conditions only represent~~s~~ 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

Our results show a highly dominant contribution of water scarcity of the last 30 years (Aridity and Ombrothermic indexes) on the density and suitability of deep-rooted groundwater dependent species in southern Portugal. Therefore, in geographical regions of the world with similar semi-arid climate conditions (Csa according to Köppen-Geigen classification, Peel et al. 2007) and similar physiological responses of the groundwater dependent vegetation (Vicente-Serrano et al., 2013), the use of the aridity and ombrothermic indexes could be used as first approximation to model and map deep rooted phreatophyte species and the evolution of their distribution in response to climate changes. The contribution of groundwater depth was lower than initially expected, however, this might be underestimated due to the poor quality of the piezometric network, especially in the central area of the studied region.

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~~ by 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~~introduced, providing guidelines for future management of these ecosystems in the allocation of water resources.

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Figure and Table Legends

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

Table 2: Effect of variable removal in the performance of GWR model linking the Kernel density of *Quercus suber, Quercus ilex* and *Pinus pinea* (S_{GDV}) to predictors Aridity Index (A_i); Ombrothermic Index of the summer quarter and the immediately previous month (O_4); Slope (s); Drainage density (D); Groundwater Depth (W) and Soil type (S_t). The model with all predictors is highlighted in grey and the final model used in this study is in bold. ~~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 the simple regression and the GWR models.

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~~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: Classification scores for soil type predictor.

Table A2: ~~Squared c~~Correlations between predictor variables and principal component~~s~~ axis. The most important predictors for each axis (when squared correlation is above 0.3) are showed in bold. The cumulative proportion of variance explained by each principal component axis is shown at the bottom of the table.

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 groundwater depth~~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)~~ and~~;~~ (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 model residuals from the fitting of the Simple Linear model (a) and Geographically Weighted Regression (b).

Figure 07: Map of local model coefficients for each variable. (a) – Aridity Index; (b) - Ombrothermic Index of the summer quarter and the immediately previous month; (c) – Groundwater Depth; (d) – Drainage density and (e) - Slope.

Figure 08: Boxplot of GWR model coefficient values for each predictor (a) and boxplot of the GWR model outputs, corresponding to GDV's density after each of the predictors was disturbed for the sensitivity analysis (b). A_i stands for

Aridity Index; O_4 for the ombrothemic index of the hottest month of the summer quarter and the immediately previous month; W for the groundwater depth; D for the drainage density and s for the slope. Error bars represent the 25th and 75th percentile while crosses indicate the 95th percentile.

~~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 09~~7~~: Suitability map for Groundwater Dependent Vegetation.

Figure 10~~08~~: ~~Validation map corresponding to the~~ NDWI anomaly considering the months of June, July and August of the extremely dry year of 2005, in reference to the same months of the period 1999-2009, in the Alentejo region. Green colors (corresponding to low NDWI values) indicates vegetation canopy undergoing a higher water stress than the average reference period 1999-2009. ~~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 11: Sensitivity analysis performed on the GWR model by perturbing one of the predictors, while remaining the rest of the model equation constant. Graphics present the output range of GDV's density when the aridity index (a), the ombrothermic index (b), the groundwater depth (c), the drainage density (d) or the slope variable (e) was perturbed; and the maximum possible range combining all predictors (f). The 95th percentile was used for the maximum value of the color bar for a better statistical representation of the spatial variability.

Figure A1: Boxplot of the main predictors used for the Geographically Weighted Regression model fitting (top) and the response variable (below), for the total data (left) and for the 5% subsample (right).

Figure A2: Correlation plot between all environmental variables expected to affect the presence of the Groundwater Dependent Vegetation. O_1, O_3 and O_4 are ombrothermic indices of, respectively, the hottest month of the summer quarter, the summer quarter and the summer quarter and the immediately previous month; O is the annual ombrothermic index, $SPEI_e$ and $SPEI_s$ are, respectively, the number of months with extreme and severe Standardized Precipitation Evapotranspiration Index; A_i is Aridity index; W is groundwater depth; D is the Drainage density; T is thickness and S_t refers to soil type.

~~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.~~

Figure B1 – Predictors maps after score classification. (a) – Aridity Index; (b) – Ombrothermic Index of the summer quarter and the immediately previous month; (c) – Groundwater Depth; (d) – Drainage density and (e) – Slope.

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

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

Variable code	Variable type	Source	Resolution and Spatial extent
s~~Slope~~	**Slope (%)**	This work	0.000256 degrees (25m) raster resolution
S~~oil~~ t~~ype~~	**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
T~~hickness~~	**Soil thickness (cm)**	EPIC WebGIS Portugal (Barata et al., 2015)	Converted from vectorial to 0.000256 degrees (25m) resolution raster
W~~Depth~~	**Groundwater Depth** ~~**to groundwater**~~ **(m)**	This work	0.000256 degrees (25m) raster resolution
D~~d~~	**Drainage Density**	This work	0.000256 degrees (25m) raster resolution
SPEI$_s$~~pei_severe~~	**Number of months with severe SPEI**	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
SPEI$_e$~~_extreme~~	**Number of months with extreme SPEI**	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
A$_i$~~I~~	**Aridity Index**	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
O~~Io~~	**Annual Ombrothermic Index** Annual average (January to December)	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
O~~Ios~~$_1$	**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
O~~Ios~~$_3$	**Ombrothermic Index of the summer quarter** (J, J and A)	This work	0.000256 degrees (25m) raster resolution Time coverage 1950-2010
~~Ios~~O$_4$	**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

Table 2: Effect of variable removal in the performance of GWR model linking the Kernel density of *Quercus suber, Quercus ilex* and *Pinus pinea* (S_{GDV}) to predictors Aridity Index (A_i); Ombrothermic Index of the summer quarter and the immediately previous month (O_4); Slope (s); Drainage density (D); Groundwater Depth (W); and Soil type (S_t). The model with all predictors is highlighted in grey and the final model used in this study is in bold.~~Coefficients of determination resulting from the application of GWR model between GDV density 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~~

Type	**Model**	**Discarded predictor**	**AICc**	**Quasi-global R^2**
GWR	$S_{GDV} \sim O_4 + A_i + s + D + W + S_t$		27389.74	0.926481
GWR	$S_{GDV} \sim O_4 + s + D + W + S_t$	A_i	28695.14	0.9085754
GWR	$S_{GDV} \sim A_i + s + D + W + S_t$	O_4	28626.88	0.9095033
GWR	$S_{GDV} \sim O_4 + A_i + s + W + S_t$	D	27909.86	0.9184337
GWR	$S_{GDV} \sim O_4 + A_i + D + W + S_t$	S	27429.55	0.924176
GWR	$S_{GDV} \sim O_4 + A_i + s + D + S_t$	W	27742.67	0.9208344
GWR	$S_{GDV} \sim O_4$ **+ A_i + s + D + W**	S_t	**18050.76**	**0.9916192**

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

Model	R^2~~-squared~~	AICc	p-value
OLS	0.02~~11~~	42720~~76~~	<0.001
GWR	0.99~~2~~ *	18851~~27795~~	-

*Quasi-global R^2

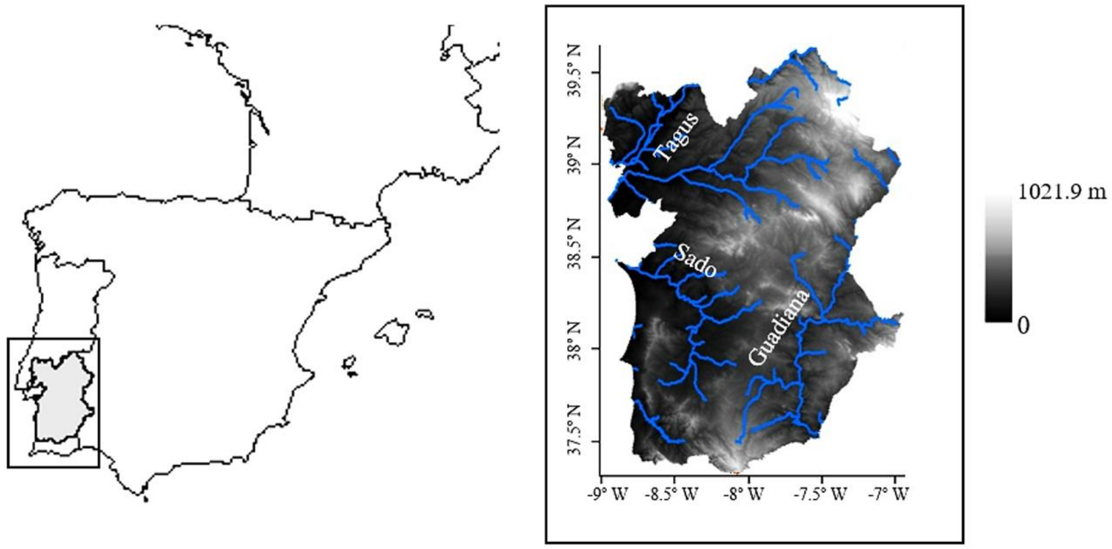
Table 4: Classification scores for each predictor. A score of 3~~1~~ was given to highly~~areas less~~ suitable areas and 1~~3~~ to highly less suitable areas for GDV.

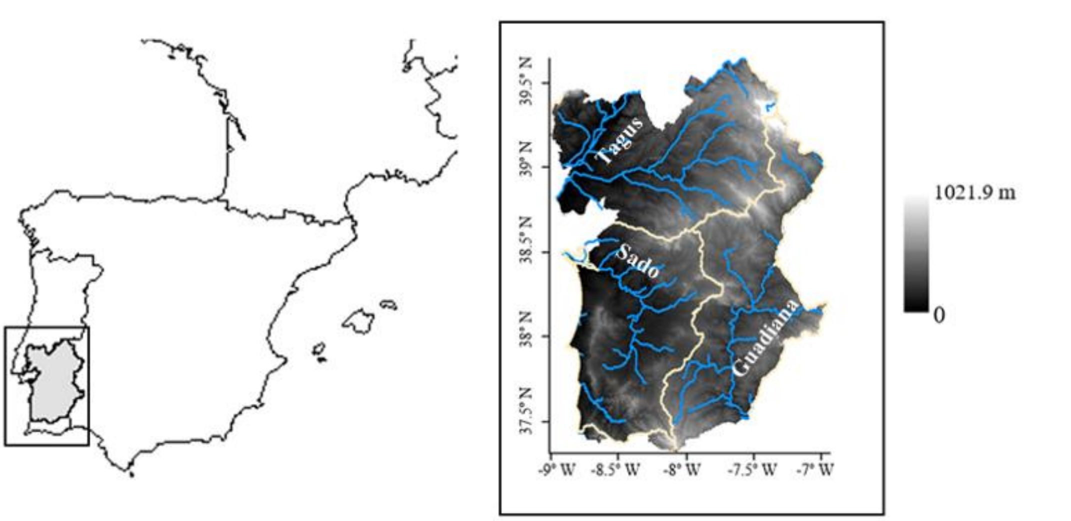
Predictor	Class	Score
Slope	0%-5%	1~~3~~
	5%-10%	2~~2~~
	>10%	3~~1~~
~~Soil type~~	~~Eutric Cambisols; Dystric Regosol; Humic Cambisols; Haplic Luvisols; Gleyic Luvisols; Ferric~~	~~3~~

	~~Luvisols; Chromic Luvisols associated with Haplic Luvisols; Ortic Podzols~~	
	~~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 1.5m-15m ≤1.5m	1 3 1
Aridity Index	0.6-0.68 0.68-0.75 ≥0.75	1~~3~~ 2~~2~~ 3~~1~~
Ombrothermic Index of the summer quarter and the immediately previous month~~Ios4~~	<0.28 0.28-0.64 ≥0.64	1~~3~~ 2~~2~~ 3~~1~~
Drainage Density	≤0.5 >0.5	3 1

~~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.~~

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





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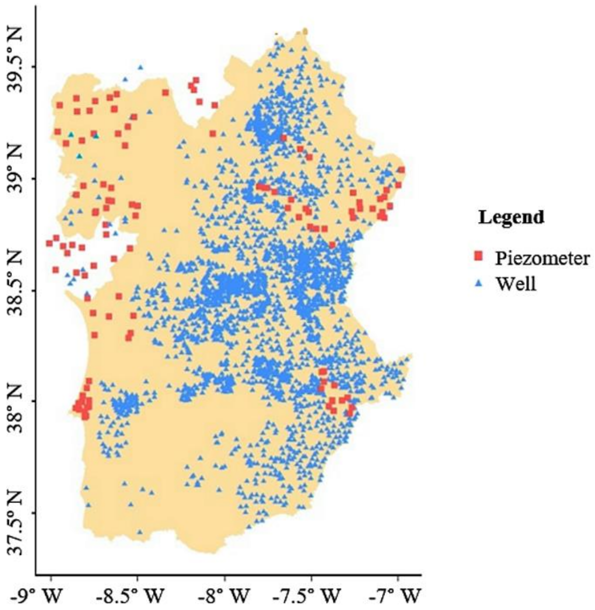


Figure 02: Large well and piezometer data points used for ~~Water Table Depth~~groundwater depth calculation. Squares represent piezometers data points and triangle represent large well data points.

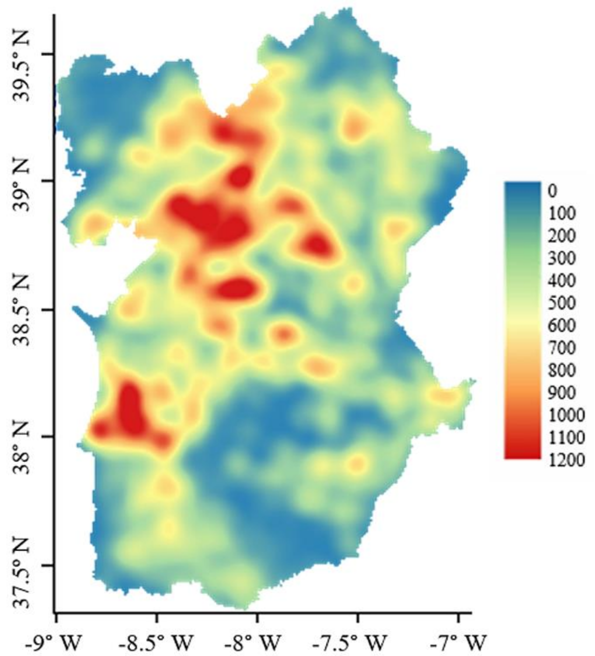
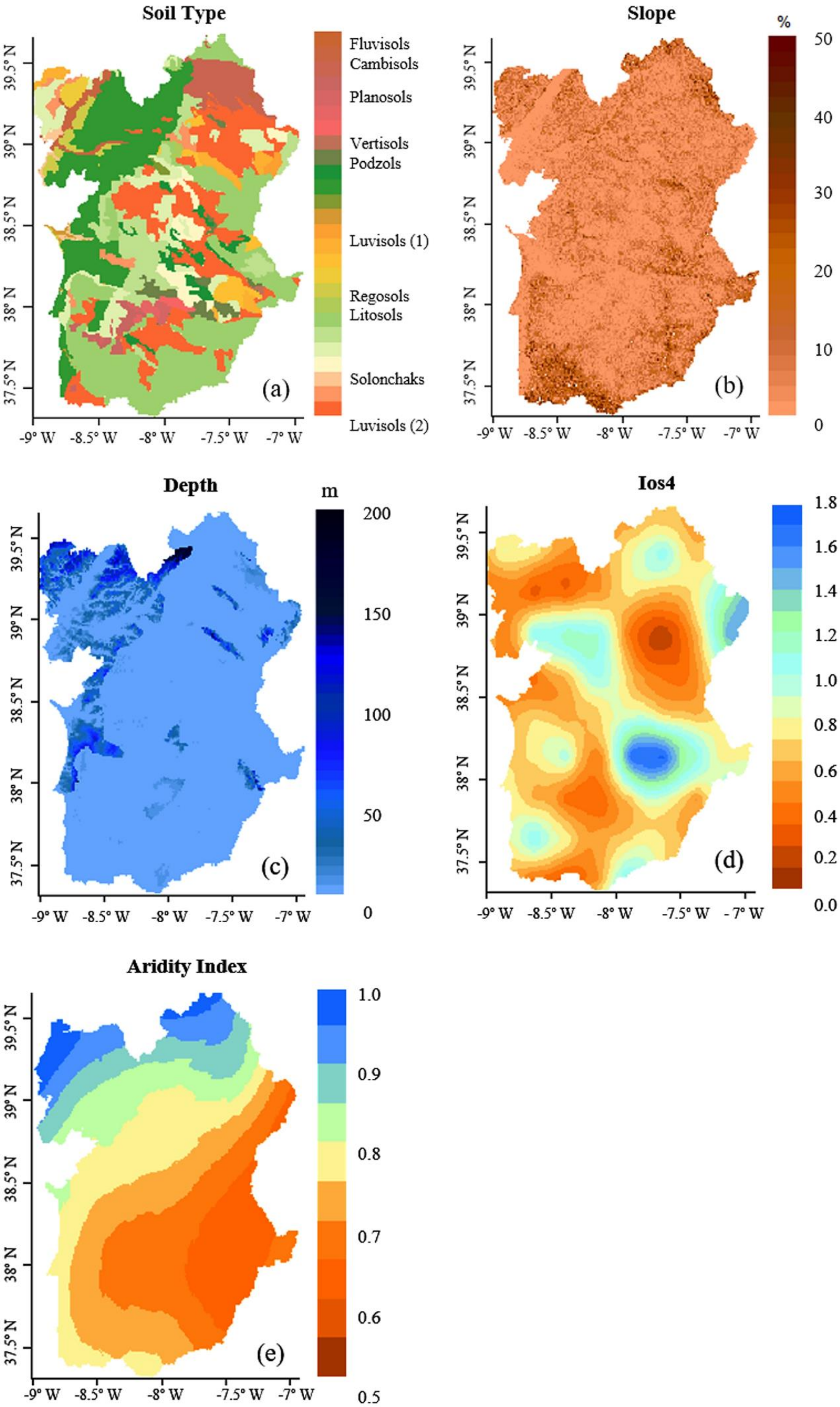


Figure 03: Map of Kernel Density weighted by cover percentage of *Q. suber, Q. ilex* and *P. pinea*.


Soil Type
Fluvisols
Cambisols
Planosols
Vertisols
Podzols
Luvisols (1)
Regosols
Litosols
Solonchaks
Luvisols (2)
(a)
Slope
%
50
40
30
20
10
0
(b)
Depth
m
200
150
100
50
0
(c)
Ios4
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
(d)
Aridity Index
1.0
0.9
0.8
0.7
0.6
0.5
(e)
39.5° N
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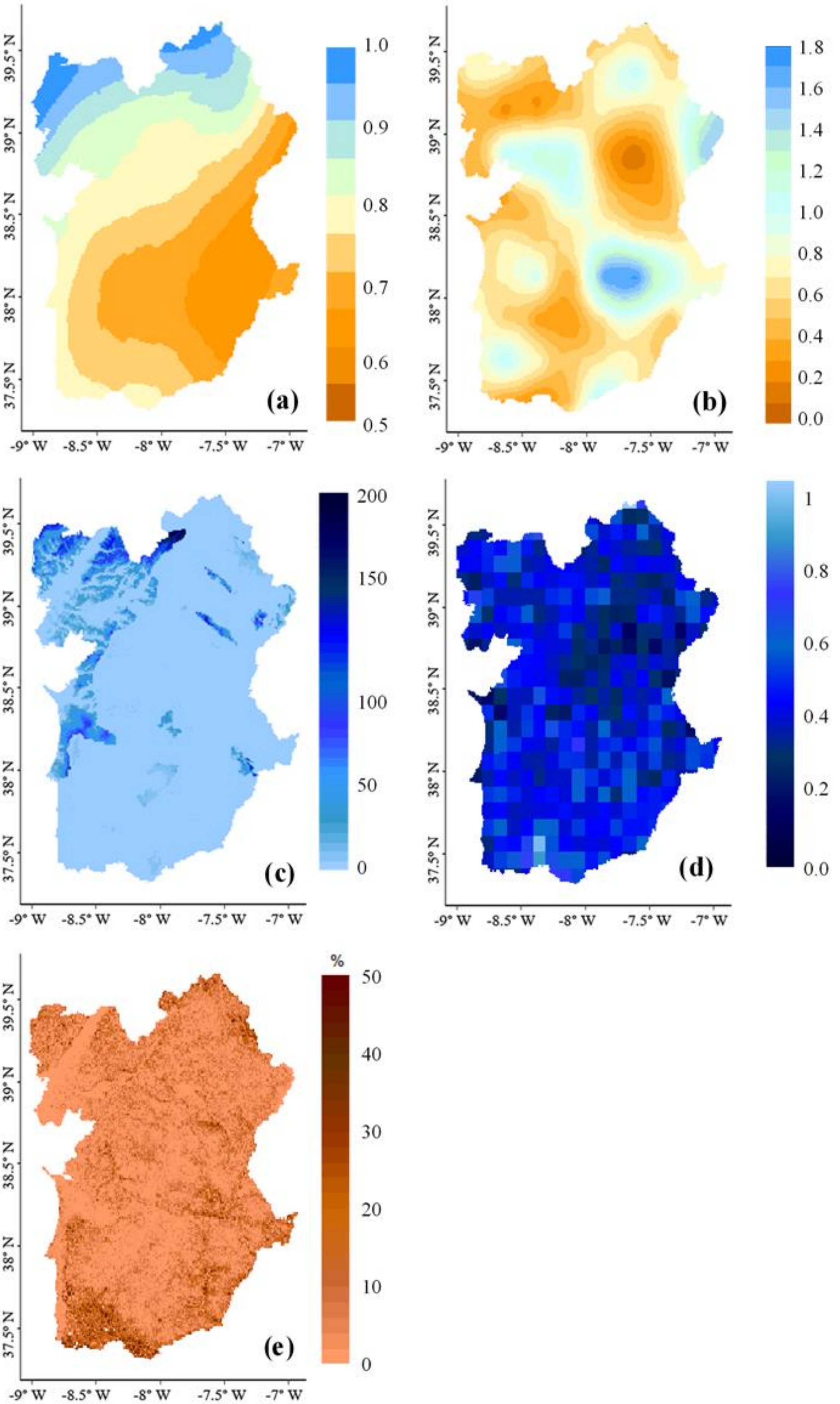
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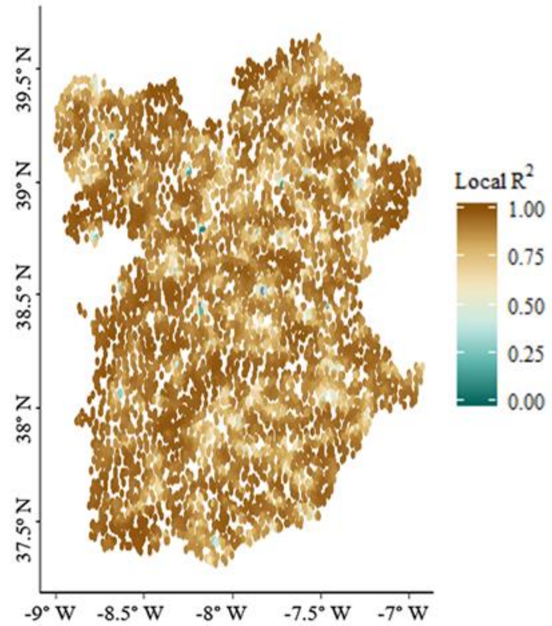
Figure 04: Map of environmental layers used in model fitting. (a) – Soil type; (b) – Slope; (c) – Groundwater Depth~~ (Depth)~~; (d) – Ombrothermic Index of the summer quarter and the immediately previous month~~ (Ios4)~~; (e) – Aridity Index~~ (AI)~~.



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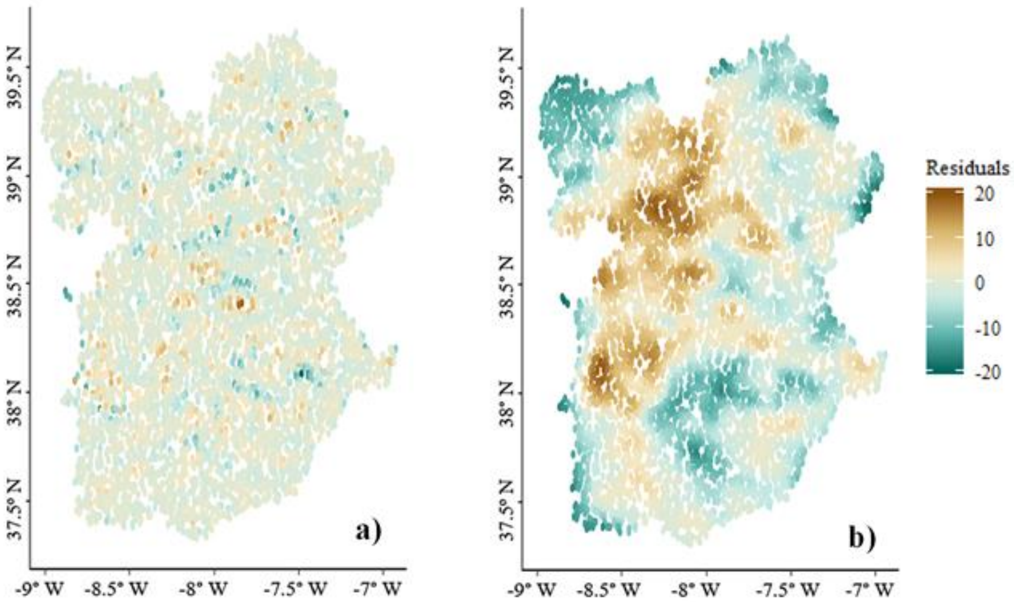
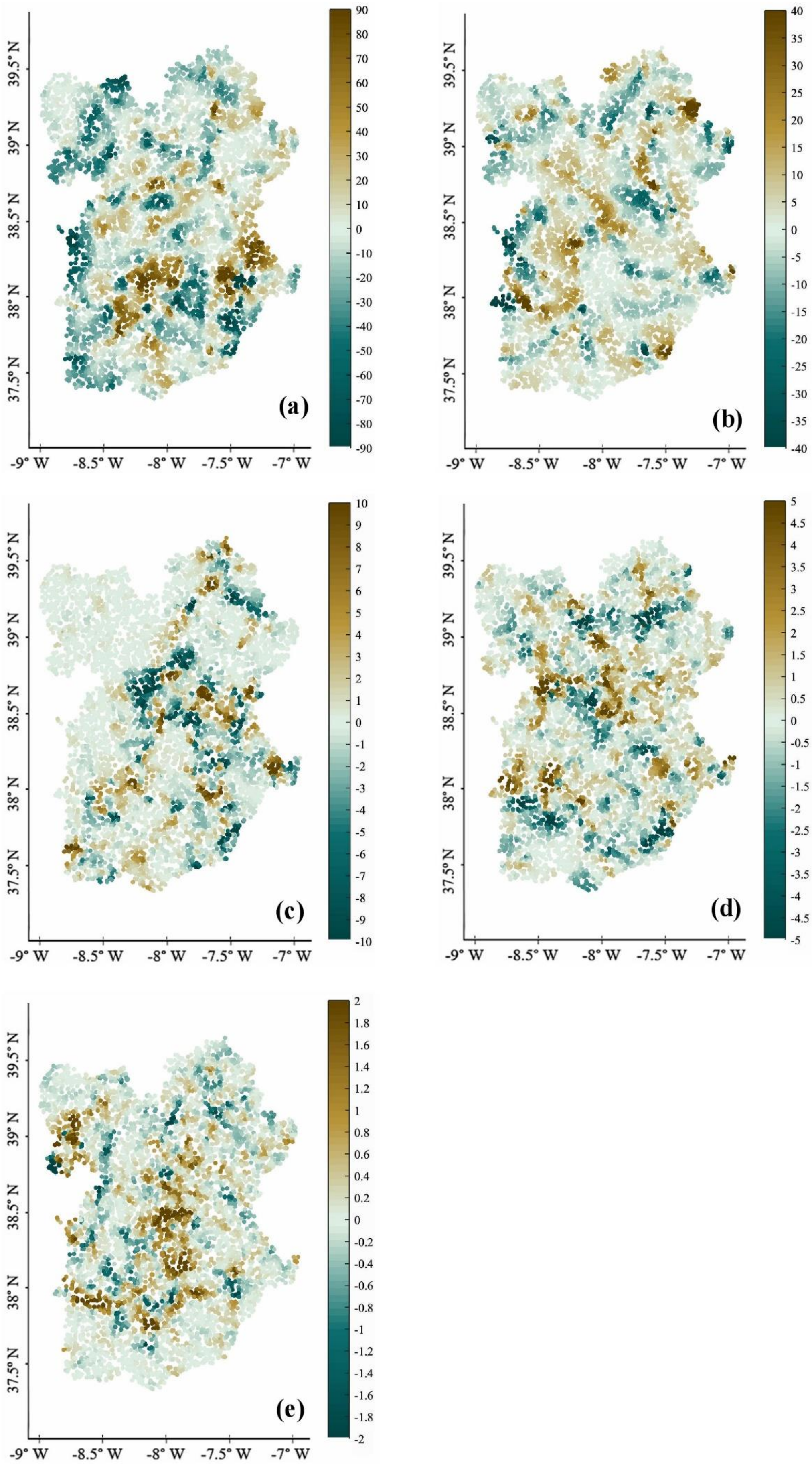


Figure 06: Spatial distribution of model residuals from the fitting of the Geographically Weighted Regression (a) and Simple Linear model (b).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35
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25
20
15
10
5
0
-5
-10
-15
-20
-25
-30
-35
-40
10
9
8
7
6
5
4
3
2
1
0
-1
-2
-3
-4
-5
-6
-7
-8
-9
-10
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
-4.5
-5
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
-1.8
-2

Figure 07: Map of local model coefficients for each variable. (a) – Aridity Index; (b) - Ombrothermic Index of the summer quarter and the immediately previous month; (c) – Groundwater Depth; (d) – Drainage density and (e) – Slope.

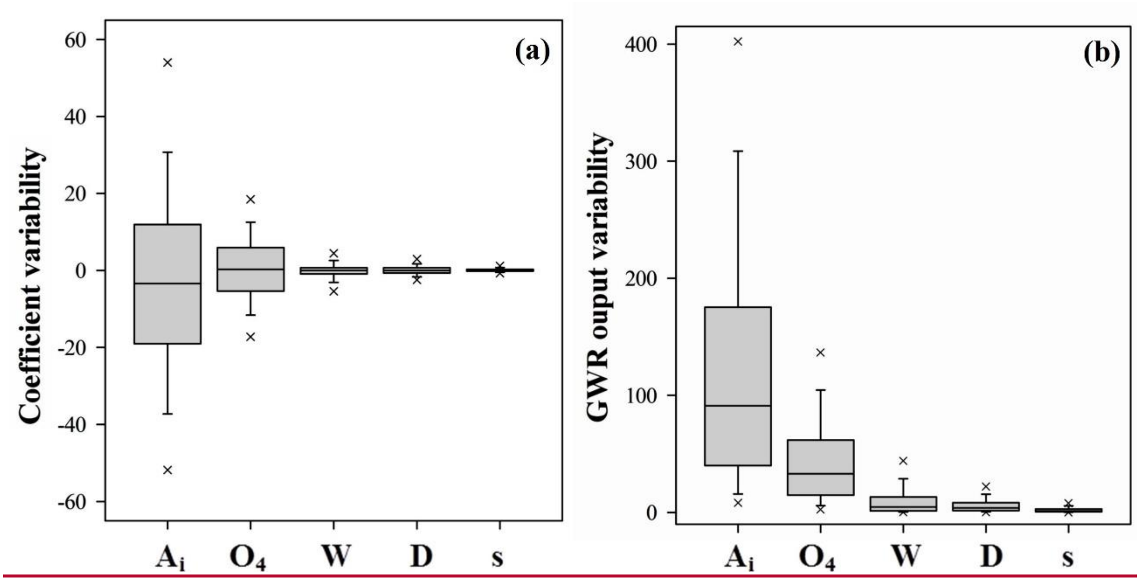
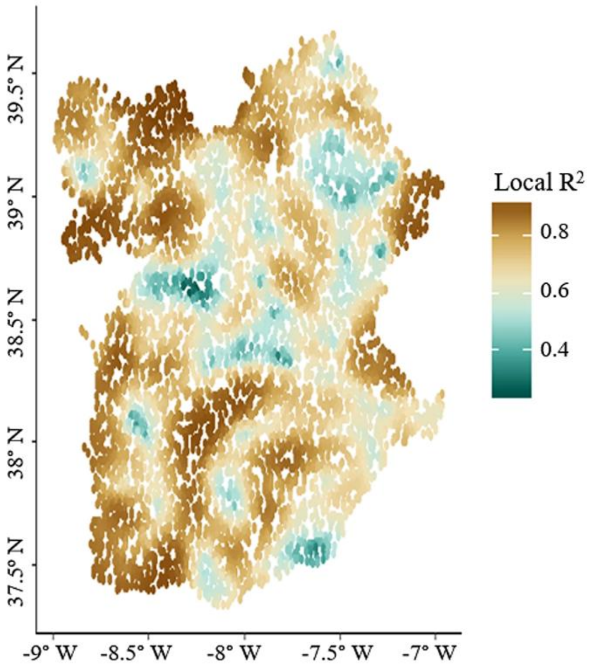
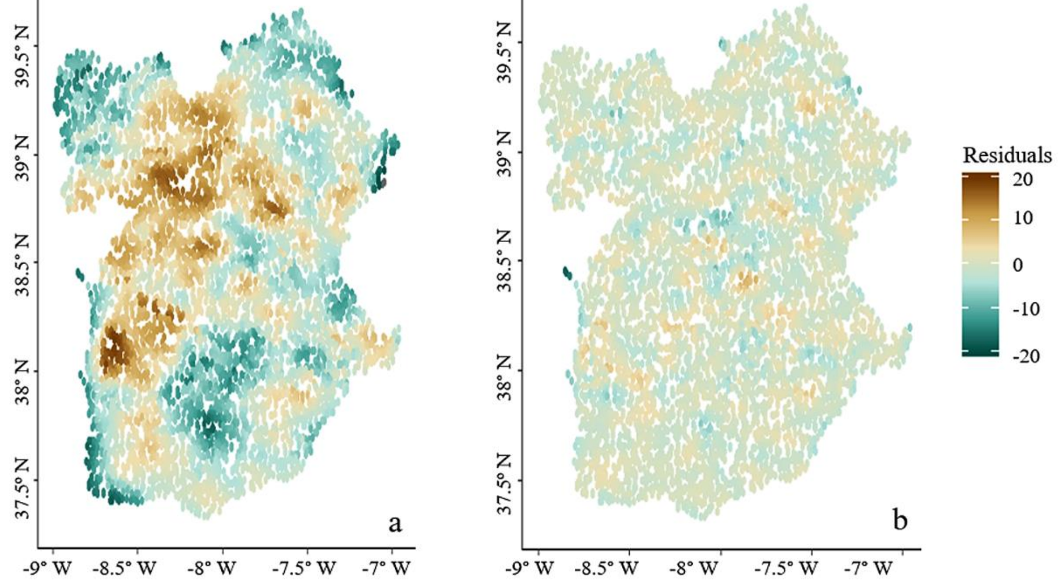


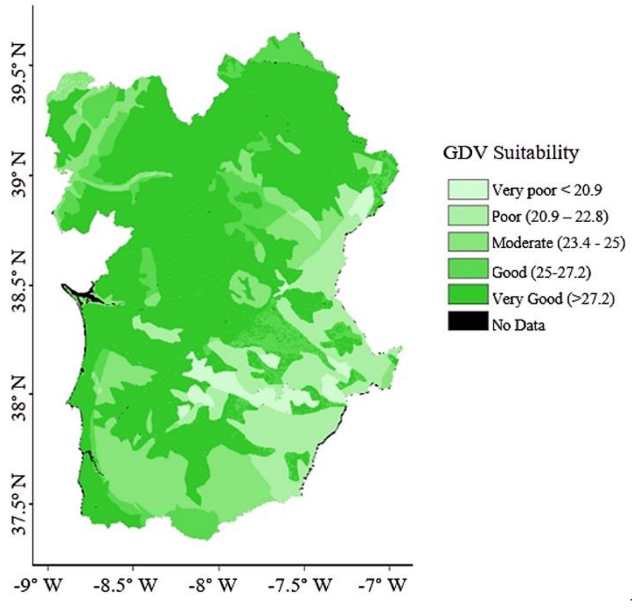
Figure 08 – Boxplot of GWR model coefficient values for each predictor (a) and boxplot of the GWR model outputs, corresponding to GDV's density after each of the predictors was disturbed for the sensitivity analysis (b). A_i stands for Aridity Index; O_4 for the ombrothemic index of the hottest month of the summer quarter and the immediately previous month; W for the groundwater depth, D for the drainage density and s for the slope. Error bars represent the 25th and 75th percentile while crosses indicate the 95th percentile.



~~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).**~~



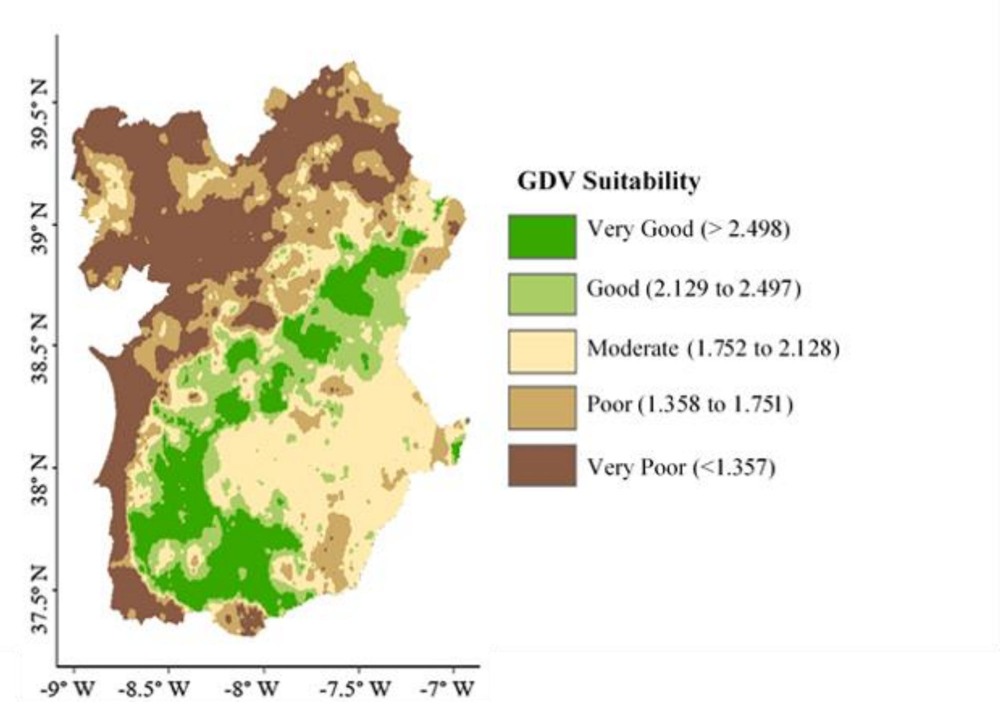
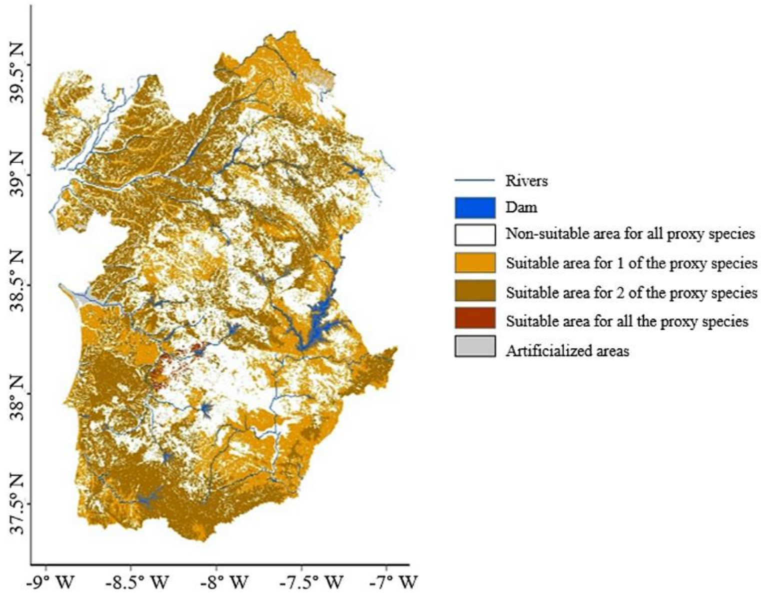


Figure 09~~7~~: Suitability map for Groundwater Dependent Vegetation.



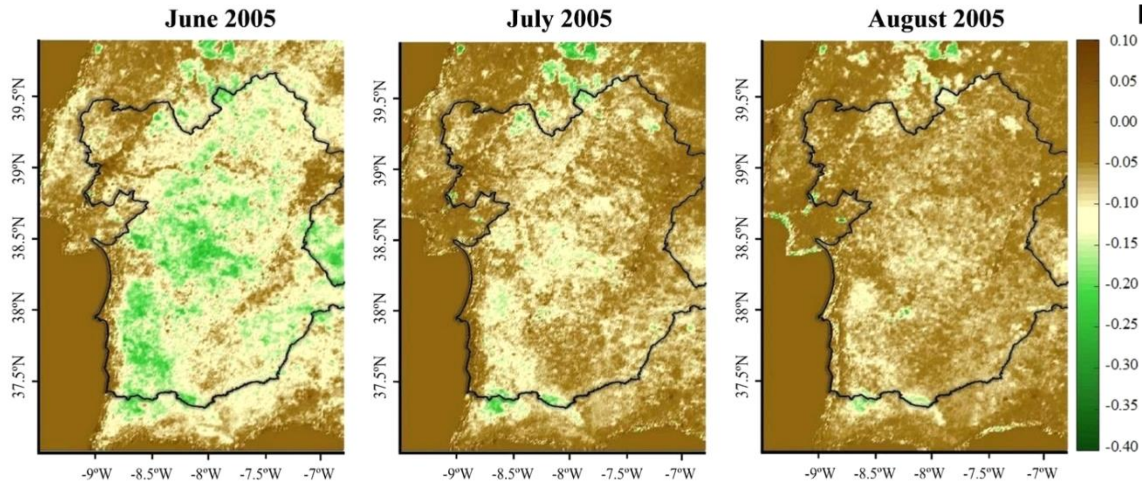


Figure ~~08~~10: NDWI anomaly considering the months of June, July and August of the extremely dry year of 2005, in reference to the same months of the period 1999-2009, in the Alentejo region. Green colors (corresponding to low NDWI values) indicates vegetation canopy undergoing a higher water stress than the average reference period 1999-2009. ~~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.~~

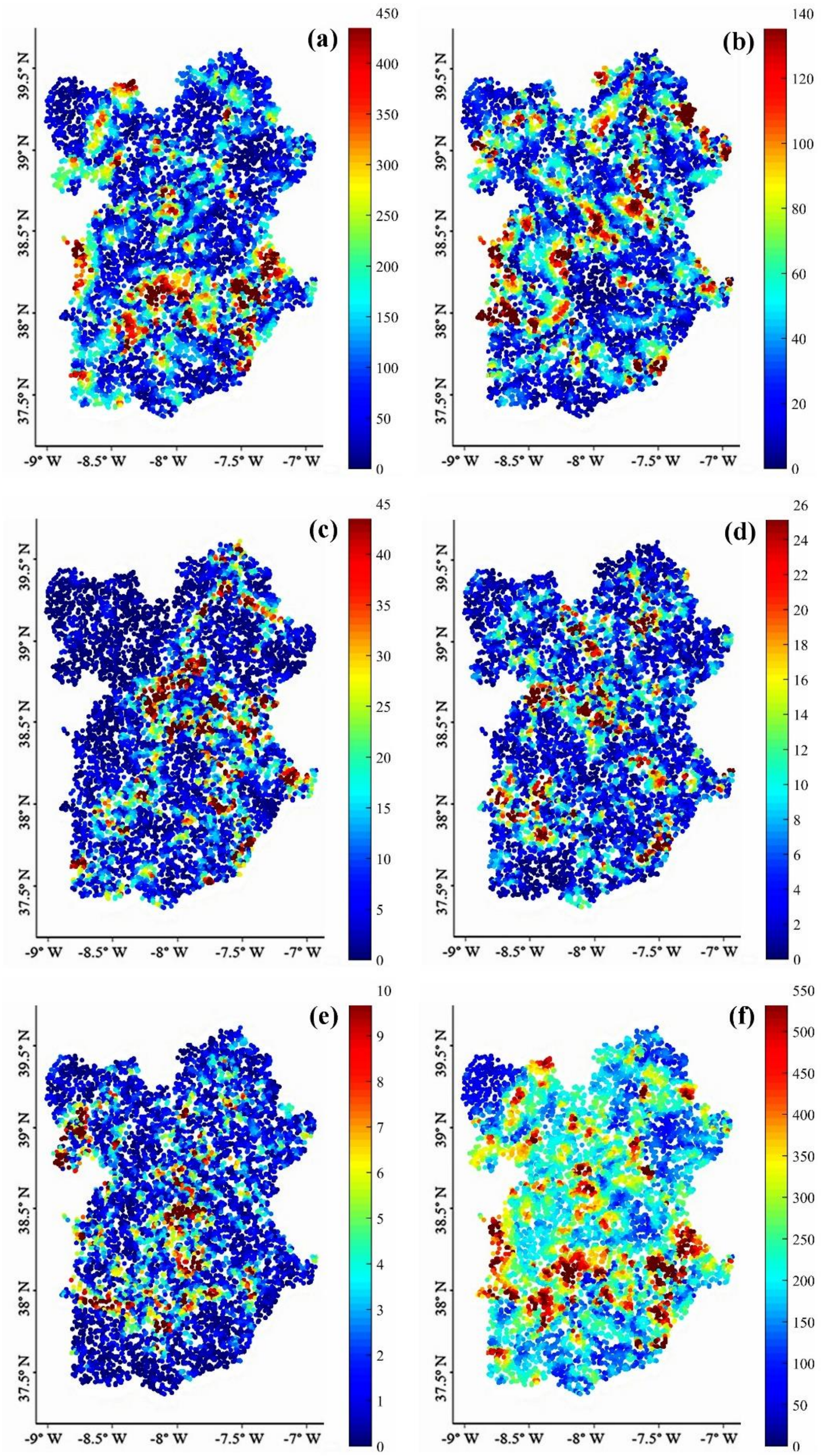


Figure 11: Sensitivity analysis performed on the GWR model by perturbing one of the predictors, while remaining the rest of the model equation constant. Graphics present the output range of GDV's density when the aridity index (a), the ombrothermic index (b), the groundwater depth (c), the drainage density (d) or the slope variable (e) was perturbed; and the maximum possible range combining all predictors (f). The 95th percentile was used for the maximum value of the color bar for a better statistical representation of the spatial variability.

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Appendix A

Table A1: Classification scores for the soil type predictor.

Predictor	Class	Score
	Eutric Cambisols; Dystric Regosol; Humic Cambisols; Haplic Luvisols; Gleyic Luvisols; Ferric Luvisols; Chromic Luvisols associated with Haplic Luvisols; Ortic Podzols	3
Soil type	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

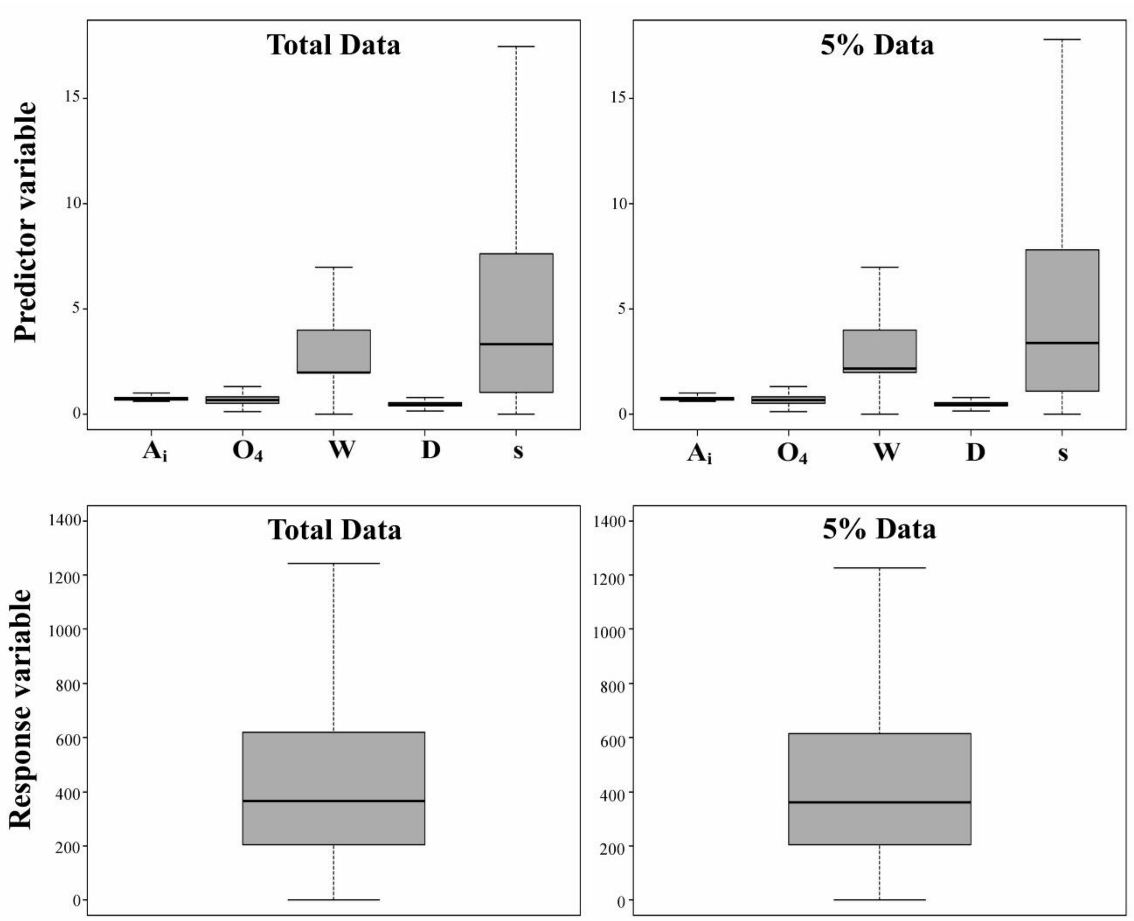
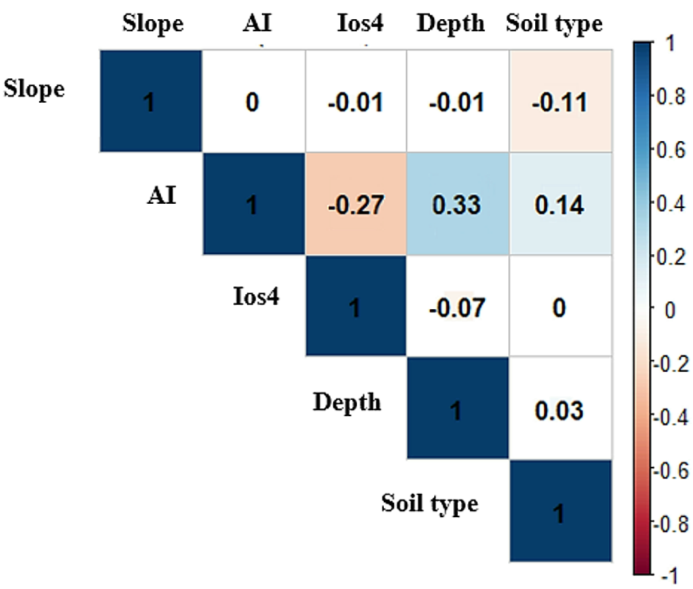


Figure A1: Boxplot of the main predictors for the final Geographically Weighted Regression model fitting (top) and the response variable (below), for the total data (left) and for the 5% subsample (right).

~~**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.**~~



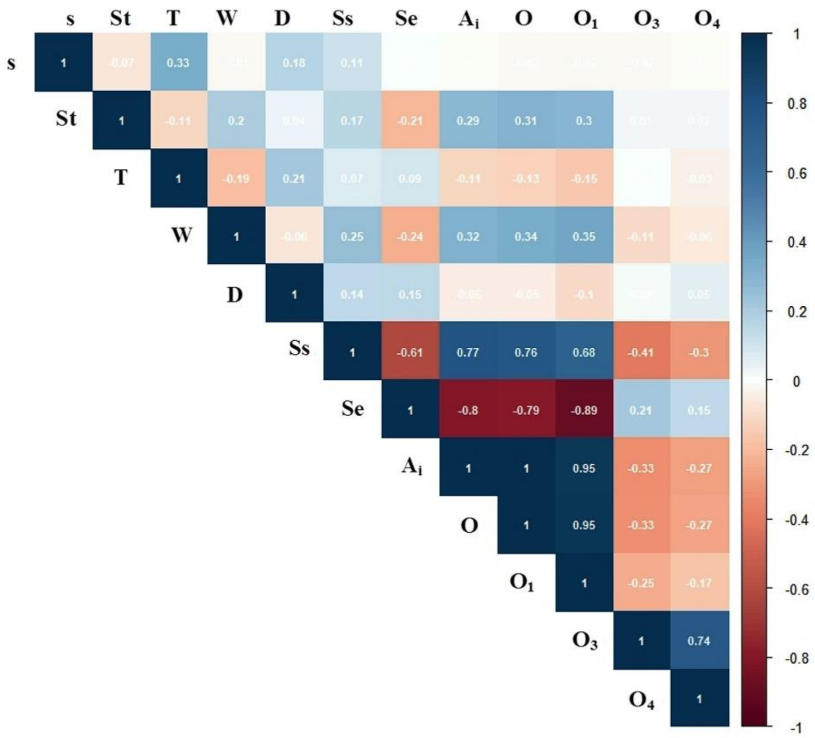


Figure A2: Correlation plot between all environmental variables expected to affect the presence of the Groundwater Dependent Vegetation. O_1, O_3, O_4 are ombrothemic indices of, respectively, the hottest month of the summer quarter, the summer quarter and the summer quarter and the immediately previous month; O is the annual ombrothermic index, $SPEI_e$ and $SPEI_s$ are, respectively, the number of months with extreme and severe Standardized Precipitation Evapotranspiration Index; A_i is Aridity Index; W is Groundwater Depth; D is the Drainage density; T is thickness and S_t refer to soil type.

Table A2~~1~~: ~~Squared c~~Correlations between predictor variables and principal component~~s~~ axis. The most important predictors for each axis (when squared correlation is above 0.3) are showed in bold. The cumulative proportion of variance explained by each principal component axis is shown at the bottom of the table. s is slope; A_i is Aridity Index; O, O_1, O_3, O_4 are ombrothemic indices of, respectively, the year, the hottest month of the summer quarter, the summer quarter and the summer quarter and the immediately previous month; $SPEI_s$ and $SPEI_e$ are, respectively, the number of months with severe and extreme Standardized Precipitation Evapotranspiration Index; W is Groundwater Depth; D is the Drainage density; S_t refer to soil type and T is thickness.

	~~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~~

	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**PC11**	**PC12**
s	<0.001	**0.32**	0.13	0.06	0.14	0.18	0.18	<0.001	0.03	0.03	<0.01	<0.01
A_i	**0.94**	<0.001	0.01	<0.01	<0.001	<0.01	<0.001	<0.001	0.22	**0.33**	**0.40**	**0.68**
O	**0.93**	<0.01	0.01	<0.01	<0.001	<0.01	<0.001	<0.001	0.24	**0.38**	0.24	**0.72**
O_1	**0.89**	0.02	0.04	0.01	<0.001	<0.001	<0.001	0.02	0.03	0.14	**0.82**	0.10
O_3	0.21	0.18	**0.47**	<0.01	<0.01	<0.001	<0.01	0.11	**0.64**	**0.33**	<0.01	<0.01
O_4	0.15	0.19	**0.53**	<0.001	<0.001	<0.01	<0.001	**0.33**	**0.53**	**0.33**	0.05	<0.01
$SPEI_s$	**0.66**	0.08	0.01	<0.01	<0.001	-0.02	<0.01	**0.77**	0.08	**0.40**	0.11	0.01
$SPEI_e$	**0.72**	0.01	0.04	0.05	<0.01	<0.001	<0.01	**0.36**	**0.44**	0.57	0.29	0.05
W	0.16	0.05	0.01	**0.33**	0.14	0.26	0.06	0.06	0.04	0.06	0.04	0.01
D	<0.01	0.25	0.11	0.20	0.08	**0.32**	<0.01	0.29	0.06	0.04	<0.01	<0.01
S_t	0.02	0.19	0.03	0.22	**0.46**	0.05	0.02	0.06	0.03	0.05	0.03	<0.01
T	0.02	**0.46**	0.09	0.03	0.06	0.01	**0.32**	0.11	0.03	0.09	0.01	<0.01
Cumulative proportion	0.39	0.54	0.66	0.74	0.81	0.88	0.93	0.96	0.98	0.99	0.99	1

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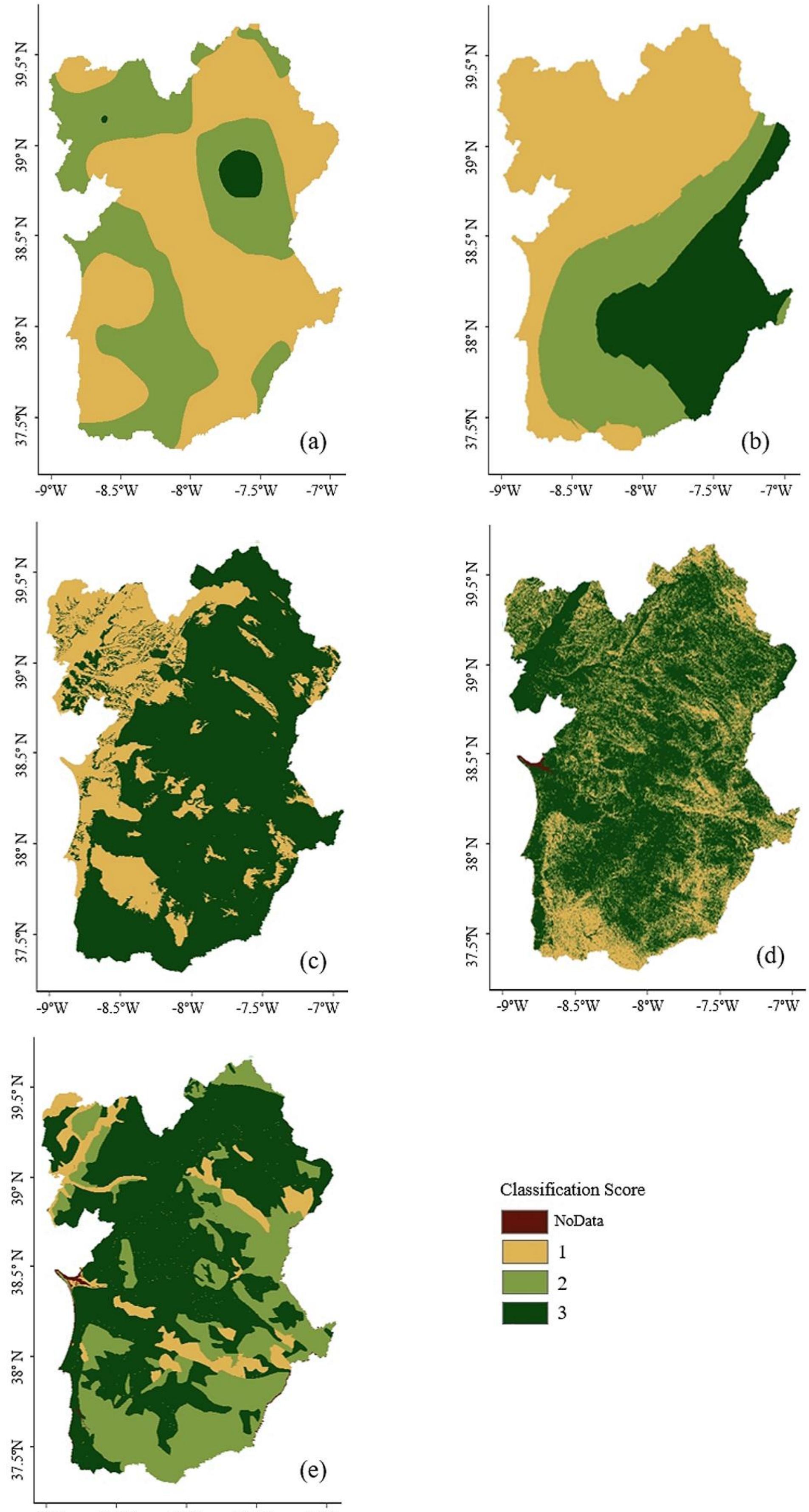
Appendix B



39.5° N
39° N
38.5° N
38° N
37.5°N
-9°W
-8.5°W
-8°W
-7.5°W
-7°W
(a)
(b)
(c)
(d)
(e)
Classification Score
NoData
1
2
3

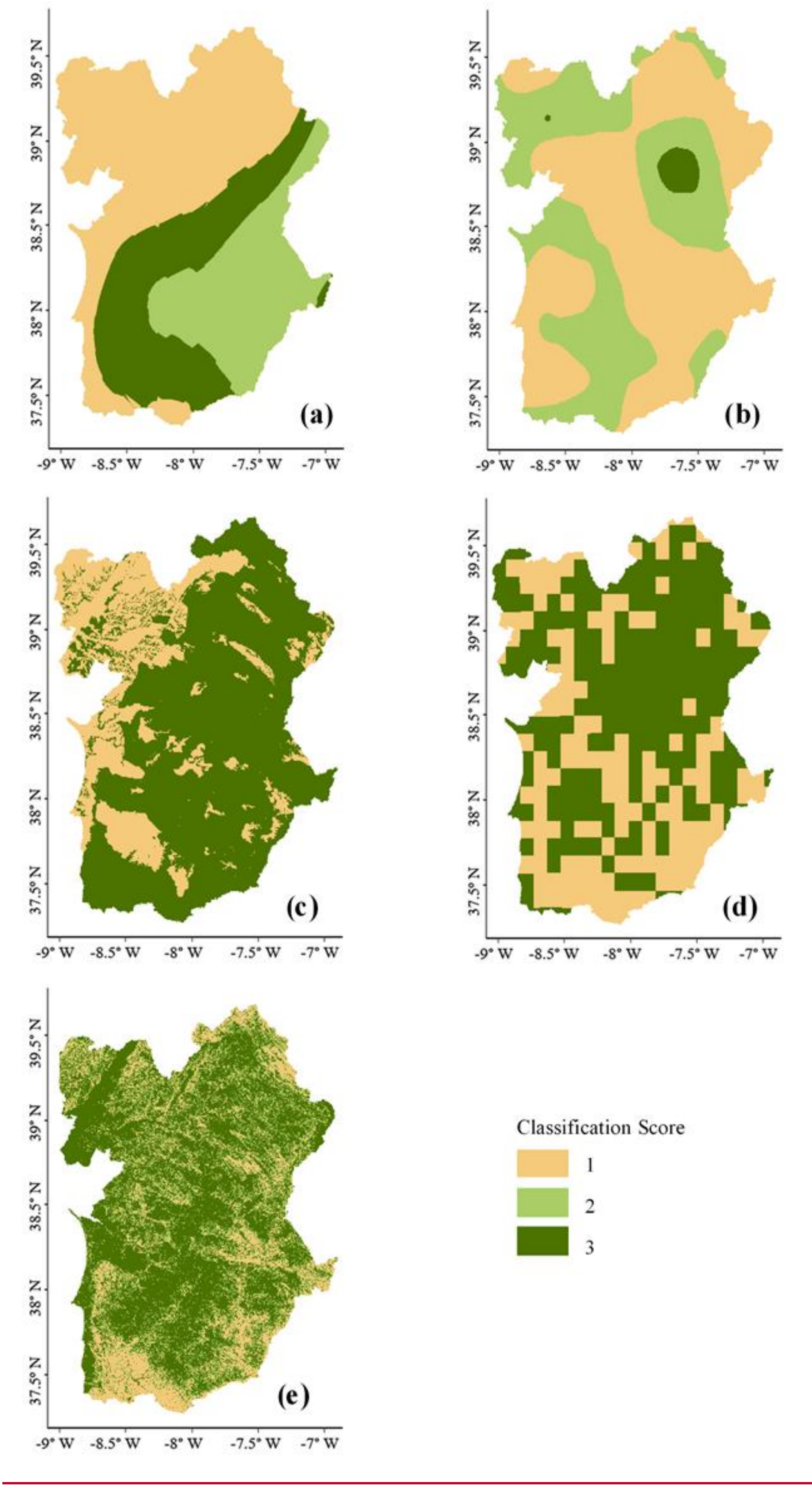

39.5° N
39° N
38.5° N
38° N
37.5° N
-9° W
-8.5° W
-8° W
-7.5° W
-7° W
(a)
(b)
(c)
(d)
(e)
Classification Score
1
2
3

Figure B1 – Predictors maps after score reclassification. (a) – Aridity Index~~Ombrothermic Index of the summer quarter and the immediately previous month (Ios4)~~; (b) – Ombrothermic Index of the summer quarter and the immediately previous month~~Aridity Index (AI)~~; (c) – Groundwater Depth~~ (Depth)~~; (d) – Drainage density~~Slope~~ and~~;~~ (e) – Slope~~oil type~~.