Title:

Influence of variations in climate on primary production indicators and on the resilience of forest ecosystems in a future scenario of climate change: application to sweet chestnut agroforestry systems in the Iberian Peninsula

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Abstract

Sweet chestnut agroforestry systems make valuable contributions to the landscape and environment, fulfilling fundamental functions and processes. Net primary production (NPP) and carbon use efficiency (CUE) are commonly used as ecological indicators to evaluate the responses of the terrestrial carbon cycle to climate change. Nonetheless, although climate-induced primary production changes have been widely documented at the global scale, few studies have addressed this issue at local scale in relation to sweet chestnut forests. Data from 65 climate maps and MODIS remote-sensed data captured in the Iberian Peninsula between 2000 and 2015 were analysed in this study. Statistical methods (Lineal Regression and Classification and Regression Trees) were used to analyse the potential influence of climate change on sweet chestnut primary production, thus enabling assessment of ecosystem and ecosystem service (ES) supply and of the resilience of these systems in a future scenario of climate change in the Iberian Peninsula. The findings for the whole of the Iberian Peninsula show that NPP and CUE are negatively correlated with temperature variables and positively correlated with latitude. High NPP values mainly corresponded to northern Spain, characterised by cold, humid conditions. The CUE values were highest in the north of Portugal, mainly in monospecific managed forest. Overall, the fitted models showed a temporary response in which the monthly variables were particularly important and water availability was more important than temperature. The findings suggest that precipitation is not a limiting factor in Atlantic areas, but that water availability tends to be a limiting factor in Mediterranean areas. However, mean annual temperature (MAT) is also an important driver of sweet chestnut production and may be a limiting factor in a future scenario of climate change. Regions of Provenance (RoP) proved useful for explaining NPP and CUE and classifying the sweet chestnut agroforestry systems. Finally, the study findings also revealed that Iberian sweet chestnut ecosystems and the associated ES supplies are at risk of being seriously affected or even disappearing as a result of climate change, especially in some Mediterranean areas of southern and central Spain.

Keywords

Carbon use efficiency

Climate

Ecosystem resilience

Net primary production

Remote sensing

Ecosystem services risks

1 Introduction

Climate is considered one of the main drivers of biodiversity and ecosystem change (IPBES, 2019; Millennium Ecosystem Assessment, 2005), and it is expected to become a major stressor (Bellard et al., 2012; Urban, 2015; Willeit et al., 2019) and a determining factor for ecosystem resilience (Moritz and Agudo, 2013) in the future. Resilience management in social-ecological systems (Berkes and Folke, 1998; Gunderson and Holling, 2002) involves providing the information necessary for activating institutional, adaptive governance (Berkes et al., 2017; Folke et al., 2016, 2005). In this study we focus on the analysis of the potential influence of climate change on sweet chestnut forests, considered examples of socio-ecological agroforestry systems (Diaz-Varela et al., 2018; Roces-Diaz et al., 2018). Sweet chestnut (*Castanea sativa* Mill.) has a scattered distribution throughout Europe and Western Asia. In Europe, the species covers more than 2.5 million hectares of land (Conedera et al., 2016; Fernández-López and Alía, 2003), with more than 10% located in the Iberian Peninsula, 58,000 ha in Portugal (DGT, 2015) and about 239,000 ha in Spain (available data to date, from the III and IV Spanish National Forest Inventory). Sweet chestnut is one of the most important native broadleaved tree species in the Iberian Peninsula, where it has a discontinuous distribution. The species mainly occurs in the northwest of Spain and north of Portugal, with isolated stands in south, centre and east of Spain. It is found at elevations ranging between sea level and 1,800 m and tolerates a wide range of climate conditions, varying from cold, wet conditions in the Atlantic bioclimatic region to hot, dry conditions in the Mediterranean bioclimatic region. Chestnut is generally a temperate deciduous species that prefers temperatures between 10ºC and 14ºC with minimum annual rainfall of 700mm (Álvarez Álvarez et al., 2000). It can also be sensitive to summer drought (Conedera et al., 2010).

Sweet chestnut is therefore found in natural and semi-natural forest formations, as well as in managed cultivations, including both traditional orchards (with specific techniques for pruning and grafting) and modern plantations for producing wood or chestnut fruit (Míguez-Soto et al., 2019; Roces-Diaz et al., 2018). In addition, wild Iberian *C. sativa* populations can be divided in two ecotypes; the Northern Iberian gene pool (mesophytic with higher growth rates), and the

Mediterranean Iberian gene pool (more xeric traits and more adaptable to drought) (Míguez-Soto et al., 2019).

C. sativa orchards traditionally constitute multifunctional agroforestry systems (AFS) that can take the form of high-forest, simple coppices, coppices with standards or grafted orchards (Míguez-Soto et al., 2019). These systems provide valuable contributions to the landscape and environment (Díaz Varela et al., 2009; Martín et al., 2012; Roces-Diaz et al., 2018), fulfilling fundamental functions and processes such as primary productivity, soil formation, nutrient cycling, regulation of hydrological flows and biological diversity. This finally produces a number of types of ecosystem services (ES), including provision (food, wood and biomass production, etc.), regulation (water quality, erosion control, pollination, disturbance prevention, gene pool, climate regulation, etc.), and cultural services (aesthetic landscape, sense of place, traditional knowledge, etc.) (Jose, 2009; Roces-Diaz et al., 2018). In addition, sweet chestnut orchards may constitute biodiversity spots with important roles in alternative area-based biodiversity conservation strategies (Diaz-Varela et al., 2018). Consequently, sweet chestnut forests and orchards play a fundamental role in the human life and well-being, as well as in wildlife conservation.

Sweet chestnut ecosystems in the Iberian Peninsula are currently threatened by different stressors, both natural and human-induced, including climate change, abandonment of traditional orchards, wildfire and an increased incidence of diseases and pests. As the impact of these factors on ecosystems may involve a risk of loss of ecological processes and properties (Mooney et al., 2009; Schröter et al., 2005, 2019), these in turn may seriously affect the provision of ecosystem services to society, and a reduction in human well-being. Owing to the increase in emissions of greenhouse gases (GGG), such as CO_2 (IPCC, 2007), climate change is one of the most outstanding drivers of ecosystem changes. Anomalies in mean temperatures could affect the Iberian Peninsula, with increments of 1.7 to 4.8 ºC, while yearly precipitation could fall by as much as 20 % (Christensen et al., 2007; IPCC, 2001, 2013). Consequently, climate change could have serious consequences for chestnut ecosystems in the Iberian Peninsula, possibly leading to significant loss of the goods and services provided. Impacts on the physiological functioning of the plants can be both direct (e.g. by hydric stress) or and indirect (via effects on interspecific interactions). Thus, some authors suggest that the increasing temperatures may favour the spread of *Cryphonectria parasitica* (chestnut blight) and reduce the systematically acquired resistance of the host trees (Anderson et al., 2004; Wilhelm et al., 1998). In addition, moisture is considered a key factor for the establishment, spread and longevity of *Phytophthora cinnamomi* (ink disease) (Hardham, 2005).

Indicators are required to enable assessment of the current state of sweet chestnut ecosystems and their related services and of the effects of climate change on development of these ecosystems (Schröter et al., 2005). Specifically, owing to the major role of plants fixing atmospheric CO_2 via photosynthesis (Falkowski et al., 2000; Sekercioglu, 2010), primary production (i.e. the rate of carbon fixation) is a major ecosystem function that is sensitive to changes in climate (Huang et al., 2019; Stocker et al., 2019; Tang et al., 2019). As a result of the relationship between ecosystem function and the service provision capacity (Costanza et al., 2017, 2007), primary production may thus be considered a useful indicator for climate-induced risks in ecosystems and ecosystem services. Among the indicators of primary production, both net primary production (NPP) and carbon use efficiency (CUE) are widely used to evaluate ecosystems and ES supply (Tang et al., 2019; Zhang et al., 2014), especially regarding land use and climate change effects on ecosystems. NPP is the net carbon stored after respiration and transformed into biomass. CUE represents the efficiency of plants to sequester carbon from the atmosphere through photosynthesis and is calculated as the ratio of NPP to gross primary production (GPP), i.e. the total amount of carbon stored by plants. Remote sensing techniques enable primary production indicators to be monitored at global or regional scales (Ma et al., 2019; Running et al., 2004). Open data captured by moderate resolution imaging spectroradiometer (MODIS) provides an opportunity to study the state of ecosystems and the associated risks (He et al., 2018).

The aims of the present study were (i) to evaluate the influence of climate variability on sweet chestnut AFS production in the Iberian Peninsula by using primary production indicators (NPP and CUE) to assess ES supply and associated risks, and (ii) to analyse the resilience of sweet chestnut AFS in a future scenario of climate change.

2 Materials and methods

2.1 Study area and climate data

The study in the Iberian Peninsula focused on mainland Portugal and Spain, without including the islands (Figure 1). The land covers an area of 582,000 km², in which forest and other woodland systems comprised about 54.4% and 55.4% in respectively Portugal and Spain in 2015 (Forest Europe, 2015).

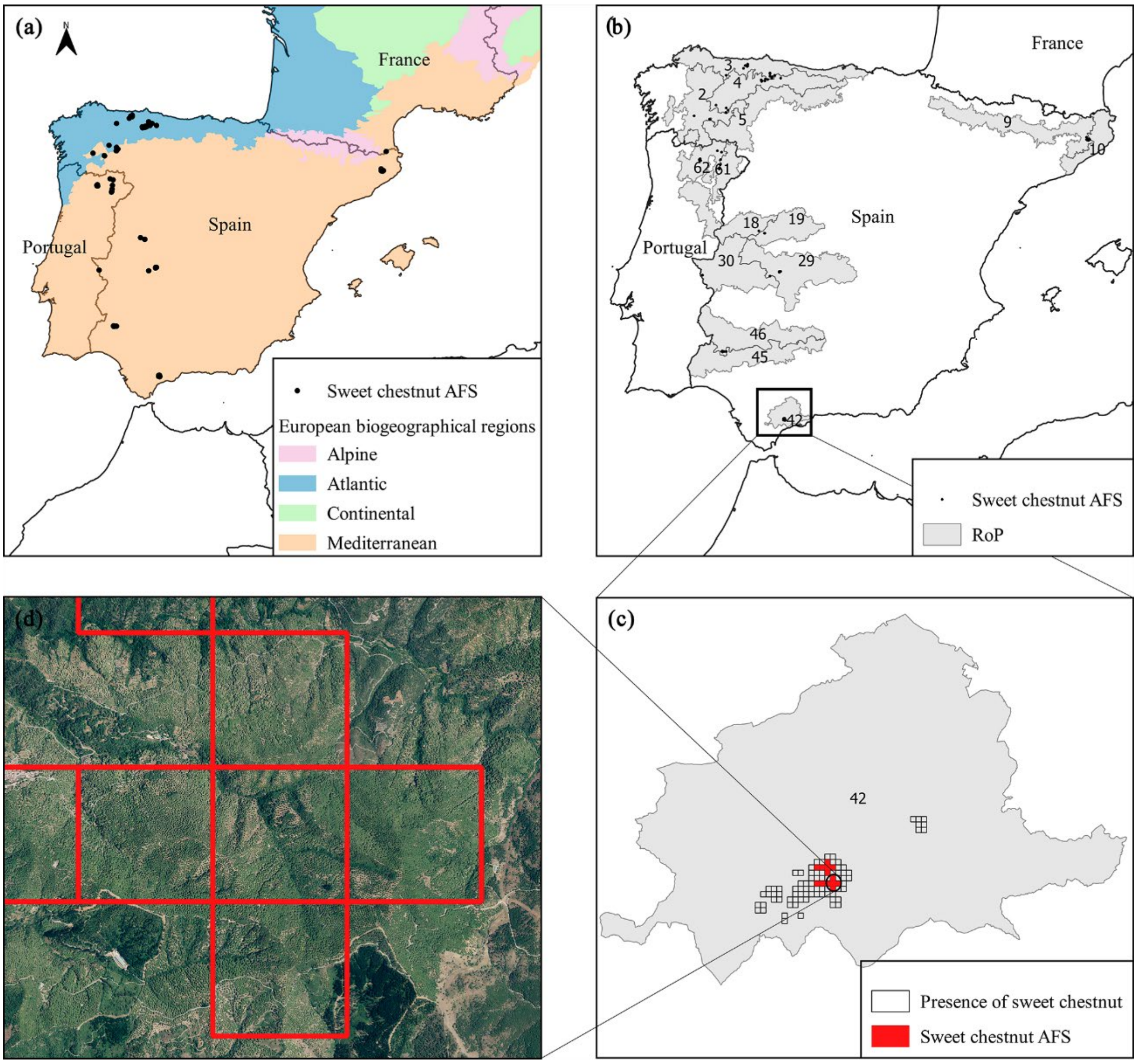

Figure 1. (**a)** Study area and location of the sweet chestnut AFS (black points), (**b)** distribution of the Region of Provenance (RoP), (**c)** details of the selected pixels (red squares) within the RoP and (**d)** zoom of selected pixels.

In terms of climate, the area is very heterogeneous and broadly speaking can be divided into three zones: dry climate zones (widespread in the south and southeast); temperate zones with dry, hot summers (most of the Iberian peninsula, i.e. approximately 40% of its surface); and temperate zones with dry, temperate summer climates (most of the northeast of the Peninsula, as well as almost all of the west cost of mainland Portugal) (AEMET, 2011).

The climate data mainly comprises air temperature (minimum, mean and maximum), precipitation and solar radiation. The data set was downloaded from the Digital Climatic Atlas for the Iberian Peninsula (http://opengis.uab.es/wms/iberia/) (Ninyerola et al., 2005), developed by the Autonomous University of Barcelona. The data were included in 65 climate maps (raster maps, resolution 200m), with climate variables computed monthly and annually from 2285 weather stations between 1951 and 1999. These data were resampled to 1-km resolution to correspond to the spatial resolution of the MODIS data set and projected to the ETRS89-UTM zone 30N.

2.2 MODIS data

The global MODIS data collection was obtained from the Numerical Terradynamic Simulation Group (NTSG), University of Montana, Public Data Repository. We downloaded the MOD17A3 product, which provides GPP and NPP data (in kg carbon m^{-2}) from 2000 to 2015 at 1-km resolution. The GPP and NPP were computed individually (Running et al., 2004) in raster files in TIF format and assigned to the WGS84 geographic coordinate system. GPP and NPP values of non-vegetated or artificial areas were excluded from the analysis (Zhang et al., 2014), and the land pixel values were multiplied by a scale factor of 0.0001 (Running and Zhao, 2015), as ordered in the metadata file, to return the original value at those pixels.

Subsequently, in the QGIS geographic information system (QGIS Development Team, 2019) the MODIS data set was converted into the ETRS89-UTM zone 30N and a data set of points was created using the “pixels to points” tool. The “point sampling tool” complement was then used to extract pixel data for each raster layer, so that each point was the pixel centroid and each point contained the data information of GPP and NPP for all years evaluated. CUE was also calculated as the NPP/GPP ratio.

Validation of MODIS dataset at local scale for sweet chestnut ecosystem is challenging because of the lack of available field data to compare with MOD17 data (Zhao et al., 2005). Nevertheless, other researchers have reported that the MODIS product is strongly correlated with data from eddy covariance (EC) towers in Spain, although they also observed a slight decrease in the correlation in high precipitation (Northern Spain) and high water stress areas (Southern Spain) (e.g. Gilabert et al., 2015).

2.3 Land use maps

Land use data sources (which are required to identify sweet chestnut agroforestry systems) were different for Portugal and Spain, due to the different approaches used in both countries to data collection and production.

We used the land use map of Portugal developed by the Portuguese Geographic Institute (Carta de Uso e Ocupação do Solo de Portugal Continental – COS) (DGT, 2015), with the aim of characterizing land cover in 2015. In addition, we used the Forest Map of Spain (MFE), at scale 1:25000 (MFE25) or 1:50000 (MFE50) (depending on availability, because it was created with the information captured in national forest inventories carried out in different years, between 1997 and 2006 the MFE50 project was completed and after 2007 the MF25 is being developed). In both cases, data were downloaded in vector format and geo-processed in order to identify sweet chestnut agroforestry systems. For this purpose, we first projected into ETRS89-UTM zone 30N and then merged both maps. The Iberian Peninsula is located between UTM zones 29, 30 and 31 (with extreme longitudes spanning from 9º 30’ W to 3º 14’ E), and we considered the geodesic distortion as negligible for the aims of the study. We selected areas designated as “Florestas de castanheiro” from the COS maps as those with sweet chestnut presence and those in which the main species was identified as *Castanea sativa* in MFE (MFE25 where is available, and MFE50 for the rest of Spain)

To ensure that GPP and NPP values corresponded to sweet chestnut AFS, we only selected these areas if more than 80% of MODIS pixels were fully occupied by areas in which sweet chestnut was present. Finally, exhaustive visual inspection of the areas corresponding the selected pixels was conducted to confirm the presence of sweet chestnut (Figure 2).

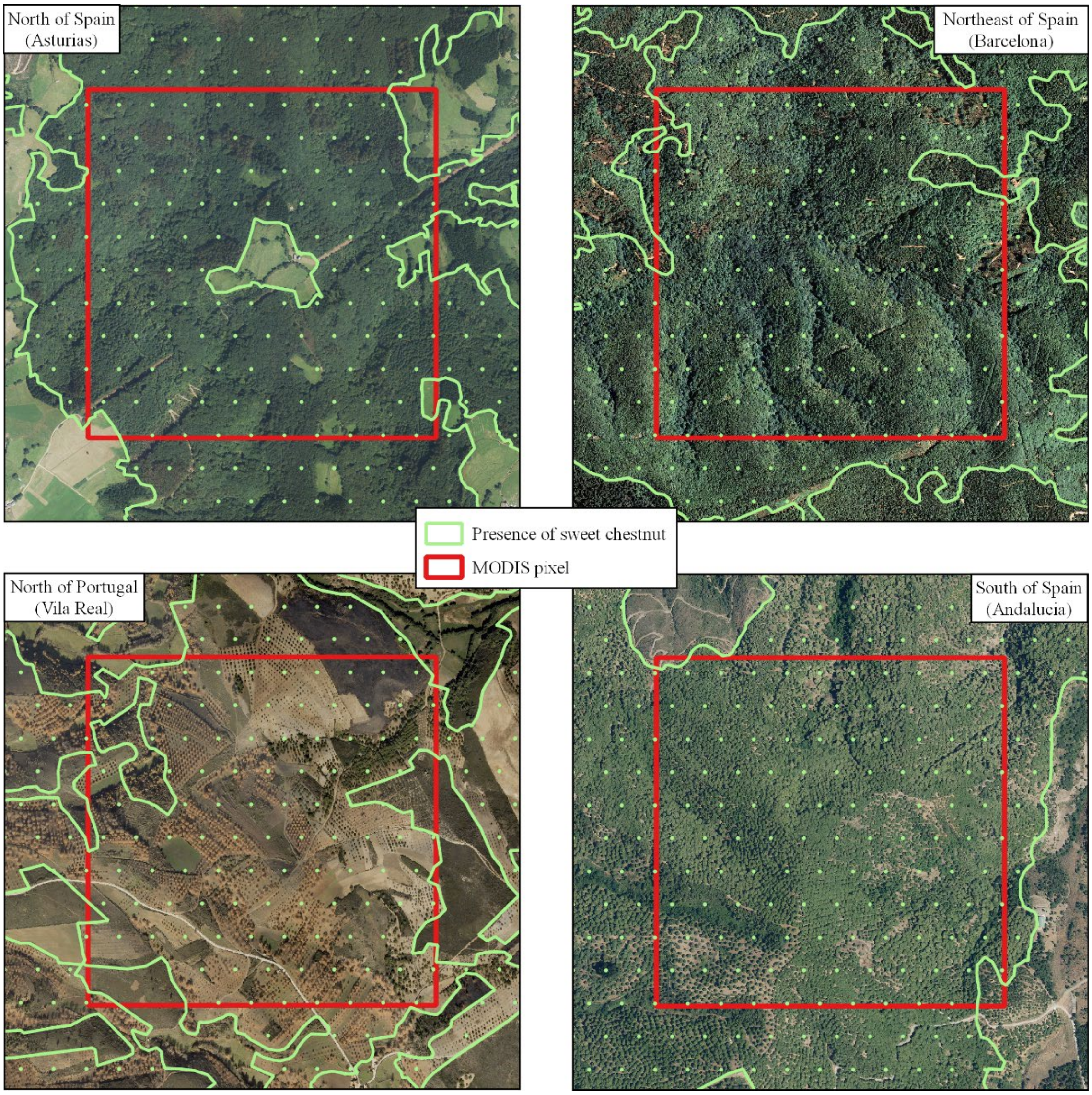

Figure 2. Pixels randomly selected from those areas selected as sweet chestnut AFS.

2.4 Region of Provenance data

The Region of Provenance (RoP) is defined in the EC/1999/105 Directive as "the area or group of areas subject to sufficiently uniform ecological conditions in which stands or seed sources showing similar phenotypic or genetic characters are found, taking into account altitudinal boundaries where appropriate", which should be demarcated by the EU countries following their own criteria. Two classifications are available for the study area. We therefore used RoP to classify and compare sweet chestnut AFS with different ecological traits.

For the Portuguese region, we used the RoPs available from Instituto da Conservação da Natureza e das Florestas (ICNF, 2018) for *C. Sativa* . For the Spanish region, we used the divisive RoP method developed by Alía Miranda et al., (2009), in which the territory is divided into ecologically similar zones and it is independent of species because no accumulative RoP system has yet been developed for *C. sativa*.

2.5 Statistical analysis

Several statistical methods can be used in ES supply studies. In this study, two well-defined and complementary parametric and non-parametric fitting methods were used to predict the risks to ecosystem and ecosystem services. Both fitting methods were used for comprehensive analysis of the data and because they provide important complementary information. SPSS software version 23.0 (IBM Corp, 2015) was used for the calculations of parametric and non-parametric methods. R software version 3.5.3 (R Core Team, 2019) was used for descriptive statistics and graphs. Table 1 shows a summary of the structural characteristics statistics for the study areas (complete summary table given in supplementary material).

Table 1. Summary statistics for study variables

Type	Code	Description variable	Unit	Mean	Std. Deviation	Min	Max	N
Primary production	NPP	Net primary production	Kg C m^{-2} yr^{-1}	0.8205	0.3710	0.0751	1.6911	94
	GPP	Gross primary production	Kg C m^{-2} yr^{-1}	1.4933	0.5313	0.7677	2.7026	94
	CUE	Carbon use efficiency	Dimensionless	0.5336	0.1422	0.0646	0.6798	94
Precipitation	MAP	Mean annual precipitation	mm	1020.2	171.6	683.0	1762.3	94
Temperature	MAT	Mean annual temperature	°C	12.6	1.4	9.3	15.6	94

	MATmin	Mean minimum annual temperature	°C	7.1	1.5	3.9	10.3	94
	MATmax	Mean maximum annual temperature	°C	18.1	1.6	14.5	20.9	94
Solar radiation	MAPSR	Mean annual solar radiation	kJ m^{-2} day^{-1} μm^{-1}	195.9	12.7	161.2	221.2	94
Topographic	P_CS	Percentage occupied by chestnut stand within the pixel	%	87.6	5.8	80	100	94
	Slope	Terrain slope	%	28.6	11.9	7	54	94
	Elevation	Terrain elevation	m	714.8	175.1	270	1055	94
	LAT	Latitude	Geographic coordinates EPSG:4258	40.799314	2.343386	36.599908	43.463517	94
	LON	Longitude		-4.637072	3.478571	-7.682393	2.746181	94

2.5.1 Parametric methods

Multiple linear regression (MLR) was used to model the relationships between primary production indicators (NPP and CUE) and the climatic and topographic variables in order to produce general models and models based on RoP classification.

Candidate predictor variables were required to have an input F-statistic with a significance level of 0.05 or less for inclusion in the model, and no predictor was left in the model with a partial F-statistic with a significance level greater than 0.05.

The model estimates were compared using the adjusted coefficient of determination (R_{fit}^2) and the root mean square error (RMSE). R_{fit}^2 compares the descriptive power of regression models that include a diverse numbers of predictors. The RMSE is a quadratic scoring rule that measures the average magnitude of the error (the square root of the average of squared differences between prediction and actual observation) and was calculated to provide additional information. Finally, residual plots were checked in order to validate the model fit. The variance inflation factor (VIF) was also used to quantify the severity of multicollinearity in the ordinary least squares regression analysis and also provided an index that measures the extent to which the variation in an estimated regression coefficient increased due to collinearity. Only models in which all parameters were significant at the 5% level and with VIF <10 were included, thus ensuring that predictions were not highly correlated (Bollinger, 1981; Castaño-Díaz et al., 2017; Mandeville, 2008).

Pearson correlation coefficient was used to determine the strength of the linear relationship between the different variables. A high R value signifies a stronger relationship while a low R value represents the opposite. Positive R values indicate the same trend, while low R values represent the opposite trend (Benesty et al., 2009). This analysis was conducted based on the package "corrplot" (Wei and Simko, 2013) in R software v3.6.1. In addition, the remaining graphics were developed with the package "ggplot2" (Wickham, 2009).

Finally, to determine the resilience to climate change of sweet chestnut AFS and their ability to recover, we used parametric simple linear regression to predict when the dependent variable becomes zero and to make comparisons for different climate change scenarios. The reference scenarios for the increase in the global mean surface temperature were the correspondent with the representative concentration pathways (RCP) developed by the (IPCC, 2013). Specifically, we compared with the RCP2.6 scenario, which predicts by year 2100 an increase by up to 1.7 ºC; and with the RCP8.5 scenario, which predicts an increase of as much as 4.8 ºC. MAT was the variable selected for simple projections, because it is expected to be correlated with the dependent variables and it is the main variable used in climate change scenarios (IPCC, 2018, 2013).

2.5.2 Non-parametric method

The Classification and Regression Trees (CART) method was selected for use because it provided good fits to the data, with high R^2 values and low RMSE, and it is a good exploratory technique that aims to determine classification and prediction rules.

The main advantages of the CART method can be summarised as follows (Gordon, 2013; Timofeev, 2004): (i) it does not require specification of any functional form; (ii) it does not require variables to be selected in advance; (iii) it can easily handle outliers; (iv) it does not require the assumptions of statistical models and is computationally fast; (v) it is flexible and can deal with missing data; and (vi) the results are easy to interpret.

The objective of CART is usually to classify a data set into several groups by use of a rule that displays the groups in the form of a binary tree (Breiman et al., 2017), which is determined by a procedure known as recursive partitioning, where each group is the node for the next partition. In this study, the CART method was used to classify the primary production indicators considered (NPP and CUE) in relation to the climate and topographic variables.

Each tree branch is described by the value of one descriptor, chosen so that the values of the response variables for all objects in a daughter group are more similar. The split for continuous variables is defined by $x_i<a_j$, where x_i is the selected descriptor or explanatory variable and a_j is its split value. To choose the most appropriate descriptor x_i and value a_j, CART uses an algorithm in which all descriptors and all split values are considered, selecting those producing the best reduction in impurity between the mother group (t_p) and the daughter groups (t_L and t_R)(Álvarez-Álvarez et al., 2013; Deconinck et al., 2005). This process is repeated for each daughter group until the maximal tree height is reached. Mathematically this is expressed as follows:

$$\Delta i(s, t_p) = i(t_p) - p_L\, i(t_L) - p_R\, i(t_R) \qquad (Eq.1)$$

where i_t is the impurity, s is the candidate split value, and p_L and p_R are the fractions of the objects in respectively the left and right daughter groups.

The impurity is defined as the total sum of squares of the deviations of the individual responses from the mean response of the group and is expressed as follows:

$$i(t) = \sum_n (y_n - \bar{y}\,(t))^2 \qquad (Eq.2)$$

where i(t) is the impurity of group t, y_n is the value of the response variable for object x_n and $\bar{y}\,(t)$ is the mean value of the response variable in group t.

CART methods are not required to conform to probability distribution restrictions, and there is no assumption of linearity or any need to pre-specify a probability distribution for the errors (Bell, 1999).

Complexity and robustness are competing characteristics that must be considered simultaneously during construction of statistical models. The more complex a model is, the less reliable it will be for purposes of prediction. To prevent this from occurring, stopping rules must be applied during elaboration and development of decision trees, to prevent the model from becoming overly complex. Common parameters used in stopping rules include (a) the minimum number of observations in a leaf, (b) the minimum number of observations in a node prior to splitting and (c) the depth (i.e. number of levels) of any leaf from the root node (Song and Lu, 2015). The risk estimate, which is a measure of the within-node variance, was used as an indicator of model performance (IBM Corp, 2015).

3 Results

3.1 Annual trends in NPP and CUE

Mean annual NPP and CUE between 2000 and 2015 (16 years) were calculated using the procedure described above. Figure 3 shows the dispersion and annual trends in GPP, NPP and CUE in the total sweet chestnut AFS for each year. NPP varied slightly, between 0.66 Kg C m^{-2} yr^{-1} and 0.92 Kg C m^{-2} yr^{-1}, while CUE varied between 0.50 and 0.59, with important within-year variability (see supplementary material). In 2004, a possible mismatch in the MODIS data led to loss of data and deviations (Fig. 3). The general trend for these three different indicators was homogeneous, with no large variations around mean values.

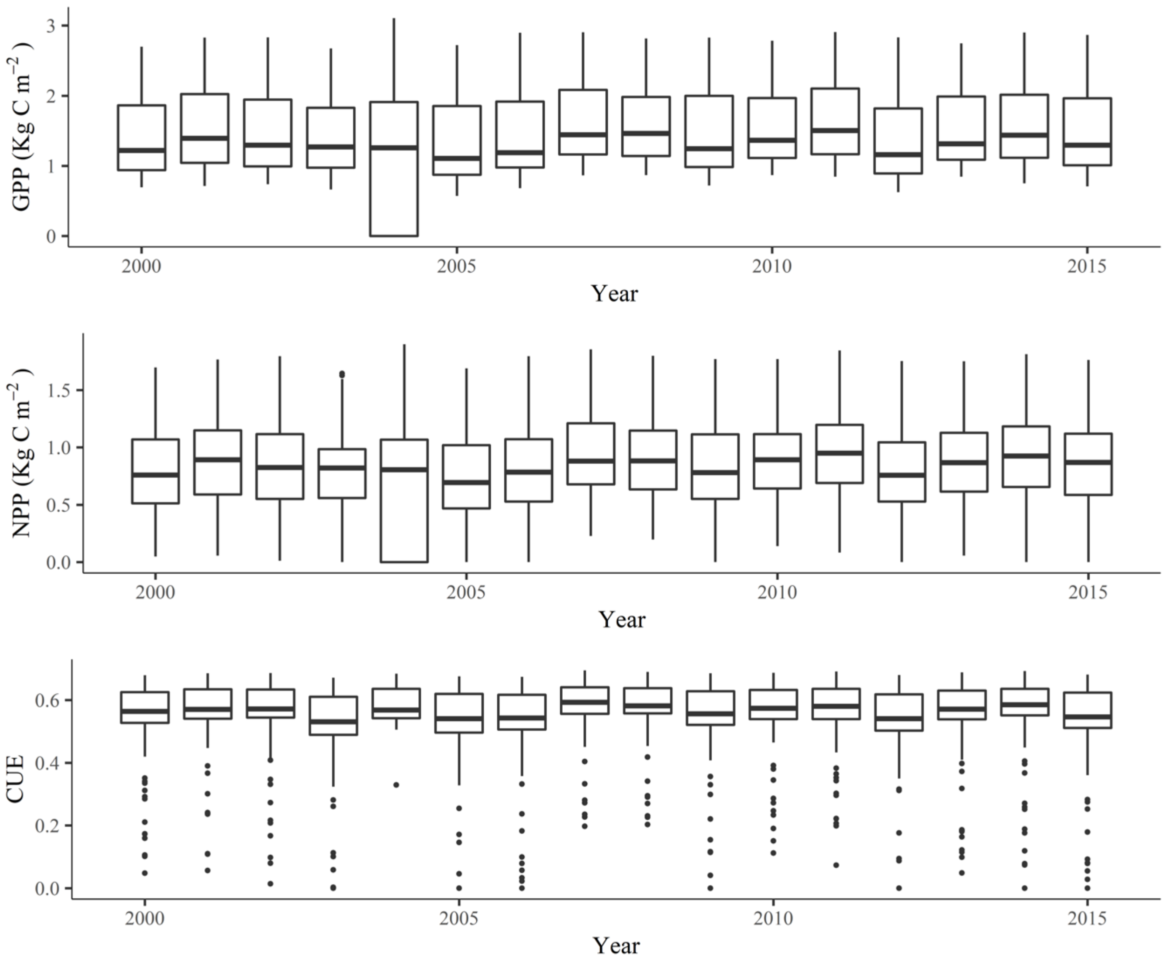

Figure 3. Mean annual trends in GPP, NPP and CUE shown in a box-and-whisker plot. Points show outliers.

When the RoP classification was applied, the homogeneity in the values of the different variables disappeared (Figure 4). As expected, high values of both NPP and CUE were obtained for sweet chestnut AFS in the north and northwest of Iberian Peninsula (RoP 02, 03, 04, 05, 09 and 10): NPP was greater than 1.04 Kg C m^{-2} yr^{-1} and CUE varied from 0.54 to 0.64. In the north of Portugal (RoP 61 and 62) and RoP 30, although NPP was lower, CUE values were higher (< 0.66), possibly due to the fact that most of the stands are young fruit plantations. Finally, the lowest values with the maximum deviations corresponded to RoP 29 and 42.

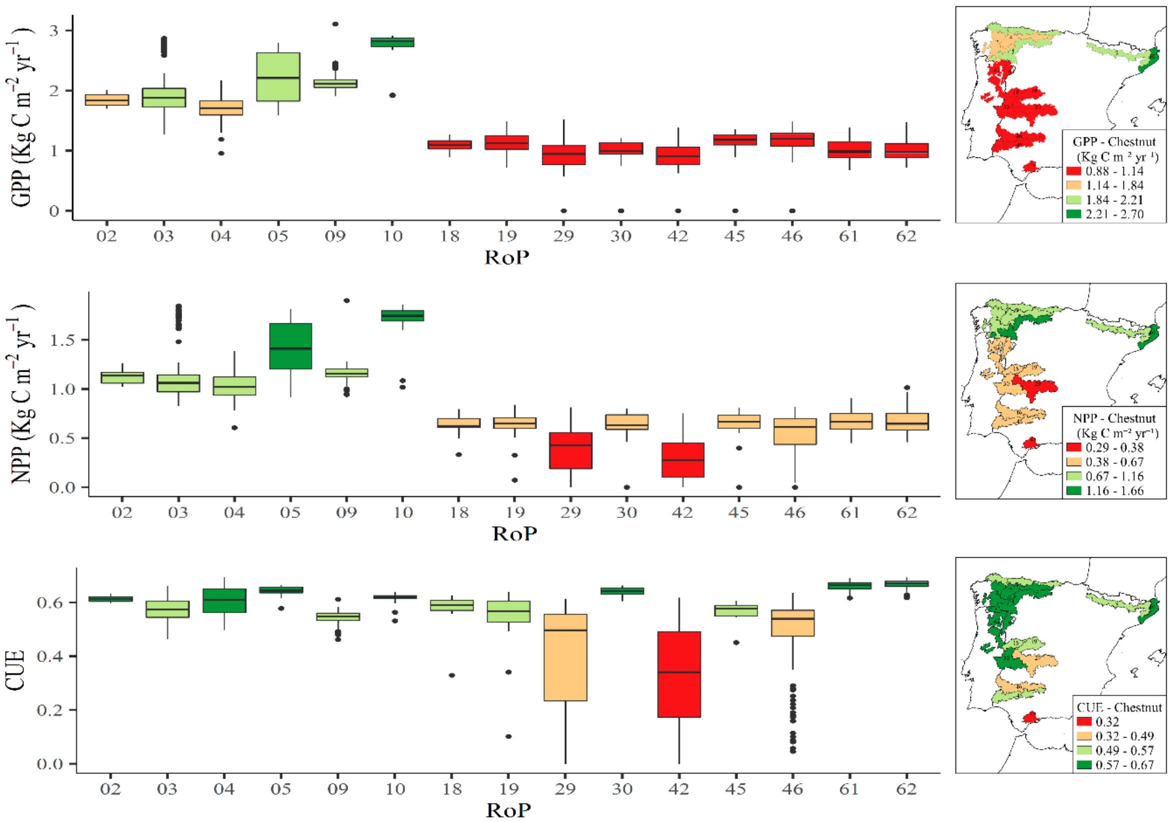

Figure 4. Mean trends in GPP, NPP and CUE for sweet chestnut AFS grouped by RoP.

The Atlantic area of Spain and the northern of Portugal may be more strongly influenced by the stand factors or characteristics (fruit plantations, simple coppices, mixture of coppices with standards and abandoned grafted orchards) than by climatic factors, which may partly account for the high values and the variability. By contrast, climate may be the main limiting factor in the Mediterranean area.

3.2 Influence of climate on NPP and CUE

To analyse the responses of vegetation NPP and CUE to the climatic and topographic variables, we used two well-defined and complementary parametric and non-parametric fitting procedures. In general, both NPP and CUE were negatively correlated with mean temperature variables (MAT, MATmin and MATmax) and positively correlated with latitude, and neither were correlated with MAP (Figure 5). The correlation values for CUE were always lower than for NPP. Thus, for NPP values inversely correlated with the mean temperature variables, “r” ranged between -0.62 to -0.70, while despite following the same trend, CUE ranged from -0.41 to -0.52. Furthermore, MAT was highly and positively correlated with MATmin and MATmax, and "r" = 0.96 in both cases. As the three variables are highly correlated, they explain the same components of the variance; thus, we focus the analysis in just one of them.

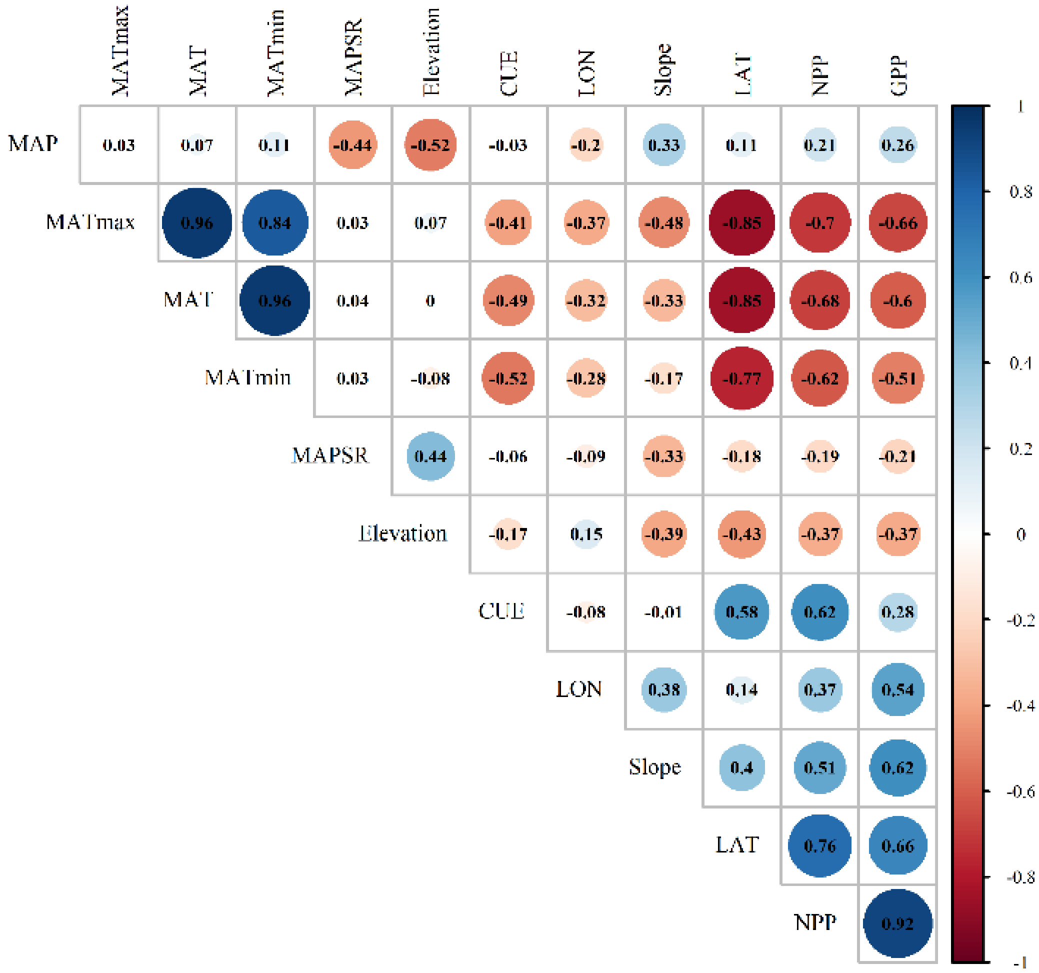

Figure 5. Correlation matrix for the variables selected in Table 1.

The main results of both fitting methods are shown in Tables 2 and 3. The parameter estimates and goodness of fit statistics for the parametric models (multiple linear regression) are summarized in Table 2, and non-parametric (CART) models are summarized in Table 3. For the whole of the Iberian Peninsula, the linear model for NPP provided a good fit, with a high level of variance explained (R_{fit}^2 = 77.78%). The model was only influenced by precipitation variables such as mean precipitation for the months of September, November and December (MP09, MP11 and MP12). Less variance was explained for CUE than for NPP (R_{fit}^2

= 45.49%). In this case, the variables involved were latitude and mean precipitation of July (MP07) (see Table 2 for parameter estimates and model errors).

Table 2. Results of multiple regression showing the best models obtained for NPP and CUE.

Region	Dependent variable	Independent variable	Parameter estimate	Std. Error	RMSE	R^2	R_{fit}^2
Iberian Peninsula	**NPP (Kg C m^{-2} yr^{-1})**	(Constant)	0.3565	0.1123	0.1749	0.785	0.7778
		MP09	0.0162	0.0010			
		MP11	-0.0081	0.0019			
		MP12	0.0040	0.0013			
	CUE	(Constant)	-1.9133	0.3036	0.105	0.467	0.4549
		LAT	0.0624	0.0079			
		MP07	-0.0031	0.0008			
Mediterranean biogeographical region	**NPP (Kg C m^{-2} yr^{-1})**	(Constant)	-4.6636	0.8936	0.1582	0.825	0.8170
		MP09	0.0154	0.0017			
		LAT	0.1017	0.0197			
		MT12	0.0904	0.0249			
	CUE	(Constant)	-1.7244	0.2729	0.1146	0.496	0.4811
		LAT	0.0547	0.0067			
		LON	-0.0124	0.0038			
Atlantic biogeographical region	**NPP (Kg C m^{-2} yr^{-1})**	(Constant)	0.3818	0.2397	0.1767	0.313	0.2786
		MP08	0.0114	0.0038			

When we split the sample into Atlantic and Mediterranean bioclimatic regions, we found that the linear model for Atlantic bioclimatic region did not provide a good fit to the data. The R_{fit}^2 value was 27.86%, for the amount of variance explained by the best model of NPP, including only one variable, mean precipitation of August (MP08). On the contrary, one of the best fits was obtained for the Mediterranean bioclimatic region. With mean precipitation of September (MP09), latitude, and mean temperature of December (MT12), the variance explained in the linear model for NPP yielded $R_{fit}^2 = 81.70\%$. One of the best fits was obtained for CUE, with only latitude and longitude included in the model, yielding $R_{fit}^2 = 48.11\%$.

Table 3 shows the results for the CART models for NPP and CUE, divided in the climate variables (upper section) and the RoP (lower section). Nodes defining the partitions are hierarchically numbered, and show the values for the independent classification variables. Globally, the proportion of variance explained was slightly lower than in the linear models

(Table 3), but with satisfactory results. For fitting with all variables, the variance explained for NPP yielded a R^2 value of 74.57% while for CUE, the R^2 value was 25.61%. In both cases, the model included geodetic longitude (LON) together with climatic variables such as mean precipitation in August (MP08) for NPP fit, and with mean precipitation of December (MP12) and latitude for CUE fit.

Table 3. Results of the non-parametric fitting (CART) of the models obtained for NPP and CUE. Upper section shows the results for climatic variables, and lower section for the RoP.

Variable	R^2	RMSE	Node	Mean	Standard Deviation	Number	Percent	Predicted mean	Parental Node	Independent variable		
										Variable	Improvement	Value
NPP (Kg C m^{-2} yr^{-1})	**0.75**	**0.17**	0	0.82	0.37	94	1	0.82				
			1	0.51	0.21	48	0.5	0.51	0	MP08	0.10	<= 21.10
			2	1.14	0.19	46	0.5	1.14				> 21.10
			3	0.64	0.12	28	0.3	0.64	1	LON	0.01	<= -5.66
			4	0.34	0.19	20	0.2	0.34				> -5.66
CUE	**0.26**	**0.14**	0	0.53	0.14	94	1	0.53				
			1	0.40	0.18	29	0.3	0.40	0	LAT	0.01	<= 39.48
			2	0.59	0.05	65	0.7	0.59				> 39.48
			3	0.33	0.19	19	0.2	0.33	1	MP12	0.00	<= 182.95
			4	0.53	0.05	10	0.1	0.53				> 182.95
			5	0.65	0.03	23	0.2	0.65	2	LON	0.00	<= -6.63
			6	0.56	0.03	42	0.4	0.56				> -6.63
NPP (Kg C m^{-2} yr^{-1})	**0.69**	**0.17**	0	0.82	0.37	94	1	0.82				
			1	1.14	0.19	46	0.5	1.14	0	RoP	0.10	03; 04; 10; 02; 05; 09
			2	0.51	0.21	48	0.5	0.51				62; 61; 18; 19; 29; 30; 46; 45; 42
			3	0.64	0.12	28	0.3	0.64	2	RoP	0.01	62; 61; 18; 19; 30; 46; 45
			4	0.34	0.19	20	0.2	0.34				29; 42
CUE	**0.40**	**0.10**	0	0.53	0.14	94	1	0.53				
			1	0.58	0.07	74	0.8	0.58	0	RoP	0.01	03; 04; 10; 02; 05; 09; 62; 61; 18; 19; 30; 46; 45
			2	0.35	0.18	20	0.2	0.35				29; 42
			3	0.64	0.04	31	0.3	0.64	1	RoP	0.00	04; 10; 02; 05; 62; 61; 30
			4	0.54	0.07	43	0.5	0.54				03; 09; 18; 19; 46; 45

Nevertheless, the variability of both NPP and CUE can be explained with only RoP. For NPP, the R^2 value was 69.49% while for CUE, the corresponding value was 40.49%. In this case, the NPP fit was slightly lower than the previous fit with all variables, but CUE fit with RoP was better.

3.3 Resilience capacity

MAT shows a strong inverse correlation with GPP, NPP and CUE (Figure 5). The adjusted model for NPP had better fit with MAT than CUE (fitting graphs in supplementary material). In both cases a clear trend was observed: as MAT increased the dependent variable decreased until reaching zero. NPP reached zero at 16.6 ºC, beginning the survival phase of the ecosystem, while CUE reached zero at 18.4 ºC when the chestnut ecosystem and their functions may disappear, or are at risk of disappearing.

In order to assess the resilience capacity, we also examined the MAT range occupied by RoP and sweet chestnut AFS in these RoP (Figure 6). Sweet chestnut stands in the south of Iberian Peninsula and at north of the valley of the Guadalquivir (RoP 45 and 46), the hottest location in Europe, preferentially occupied the cold range of MAT in these regions. A similar trend was observed in RoP 10, which also inhabited the highest elevations, ranging from 900 to 1250 m. In the south of the valley of the Guadalquivir with oceanic influence, sweet chestnut AFS occurred in RoP 42 occupying the middle MAT of this region. Portuguese sweet chestnut AFS (RoP 61 and 62) and those in inland areas of Iberian Peninsula (RoP 18, 19, 29, 30) tend to survive at temperatures around the half the range of the RoP. On the contrary, on the northern (RoP 02, 03, 04 and 05) tend to occupy the hottest locations, according to the temperature distribution of chestnut within the RoP temperature variability.

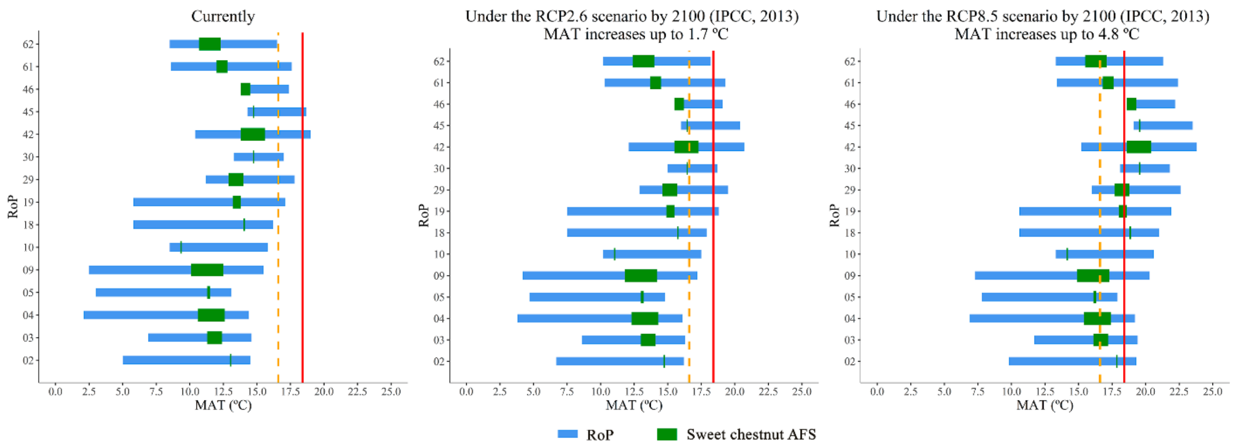

Figure 6. Current resilience of sweet chestnut AFS, under RCP2.6 scenario and under RCP8.5 scenario by 2100 (IPCC, 2013). Dashed orange line indicates the moment that NPP=0 (survival

begins), and the continuous red line represents CUE=0 (the chestnut ecosystem and their functions could disappear).

As shown in Figure 6, currently all sweet chestnut AFS were below the survival threshold, being the RoP 42 and 45 the closest to it, which are at 1ºC and 1.8ºC to exceed it respectively. A bit further are sweet chestnut AFS in northern areas (RoP 02, 03, 04 and 05), which ranges between 3.5ºC and 5.1ºC up to edge, and the Portuguese zones (RoP 61 and 62) and RoP 09 with an average of 4ºC. By last, the furthest are in RoP 10 with more than 7ºC until threshold. For the most favourable climate change scenario (RCP2.6, MAT increases up to 1.7ºC), only sweet chestnut AFS in RoP 42 will surpass this limit. However, all of centre of Spain (RoP 18, 19, 29, 30, 45 and 46) is below 1ºC of the aforementioned limit. In the worst possible scenario (RCP8.5, MAT increases up to 4.8ºC), almost all sweet chestnut AFS have crossed the survival edge marked by the threshold, while some of them, mainly those of centre of Spain (RoP 18, 19, 29, 30, 42, 45 and 46) may even disappear. In this case, only sweet chestnut AFS in RoP 05 and 10, would have a considerable margin, 2ºC and 4ºC respectively until threshold of death, while the others would have a margin of around 0.5-1.3ºC.

4 Discussion

4.1 Harmonization of data

In this work, spatially-explicit data developed and provided by institutions from two different countries was used. In order to detect monospecific chestnut forest patches, the typologies better suited to this land cover were selected both in the COS (Portugal) and IFN (Spain) maps. Nevertheless, each cartography was developed aiming to slightly different objectives: the first is a land cover map, and the second, is the map created as a support for the national forest inventory. This conditioned our methodological approach, which had to solve differences between geodesic reference systems, associated thematic information (i.e. forest data) and typological categories. Specifically, in the absence of similar and coordinated spatial-explicit databases and information, the results of the forest patch selection have been contrasted with ortorectified remote sensed data uniform for both countries to ensure the comparability of data.

This fact highlights the importance of the harmonization of mapping processes and protocols between countries, especially regarding thematic data developed at intermediate scales.

4.2 Annual NPP and CUE trends

The climate-sensitive parameters vegetation NPP and CUE are widely modelled in carbon cycle-related studies at global scale (Field et al., 1995). The spatio-temporal response defines the context in which sweet chestnut AFS of the Iberian Peninsula are currently located. In the present study, only minor differences were observed in the general trend for annual mean NPP and CUE between different years, possibly because the stand characteristics have not undergone important changes in most of the AFS during the study period. This may be due to the stability of relatively large and continuous sweet chestnut stands, which theoretically should span more than 80% of the MODIS pixel area, i.e. 100 ha (1km x 1km resolution). Consequently, perturbations smaller than the pixel area may be averaged and thus be difficult to detect. Nevertheless, calculation of NPP and CUE for each RoP revealed a high level of variability. Consistently with Gilabert et al., (2015), the highest annual NPP and GPP values appeared in the most humid areas in the northern of Iberian Peninsula, which are also the coldest regions. However, the highest CUE values did not follow the same pattern. The highest CUE values corresponded to stands in Portugal, where young plantations are destined for fruit production, or areas where sweet chestnut plantations for fruit are traditionally well established (Fernandez-Lopez et al., 2005). These findings confirm that managed forests (such as fruit plantations, simple coppices, coppices with standards and grafted orchards) have a higher CUE than unmanaged forests (Campioli et al., 2015; Fernández-Martínez et al., 2014), particularly considering monospecific stands (Kunert et al., 2019). Nonetheless, Atlantic regions with highest NPP also have higher CUE values than in Mediterranean regions, owing to the strong influence of climate.

4.3 Responses of NPP and CUE to climate influence

As argued elsewhere (Kato and Tang, 2008), both precipitation and temperature, together with others factors not considered in this study (e.g. extreme climate events, management regime, soil characteristics, ecological traits, age and disturbance), play a fundamental role as drivers of primary production indicators. In general, due to the scale characteristics used in other studies, (mainly global and regional), MAT and MAP have been the main climate-related drivers identified (He et al., 2018; Khalifa et al., 2017; Reichstein et al., 2007; Zhang et al., 2014, 2009). On the other hand, although latitude and longitude are not climatic variables per se, these entail a mixture of factors including temperature and precipitation among others (Valentini et al., 2000), so that the geographic variations implicitly include an intrinsic change in climatology. In addition, we also used monthly climatic variables, which may provide a better ecological explanation of influence of climate for sweet chestnut ecosystems in the Iberian Peninsula.

Most climatic variables involved in parametric and non-parametric models for NPP are precipitation variables (Tables 2 and 3), as in previous studies indicating that water availability is more important than temperature (Garbulsky et al., 2010; Heimann and Reichstein, 2008; Zhang et al., 2009; Zhao and Running, 2010). In this sense, only MP09 explained 72% of the NPP in the Iberian Peninsula and 75% of NPP for the Mediterranean area. As this was only detected in monthly variables, we can therefore interpret precipitation as a limiting factor only in a short period of the year, specifically when sweet chestnut fruit is ripening or during summer drought months (MP07, MP08 and MP09), and when precipitation at the end of autumn is low (MP11 and MP12) (Gandullo Gutiérrez et al., 2004). In the NPP linear model for the Iberian Peninsula, the monthly precipitation variables explained the model variance and yielded a good fit (R_{fit}^2 = 77.78%). Nevertheless, different responses were found for different areas: precipitation does not appear to be a limiting factor in Atlantic areas, as it is rarely water-limited, while water availability becomes limiting in Mediterranean areas (Reichstein et al., 2007). As argued by Liu et al., (2018), one possible explanation is that precipitation is sufficient for the regular growth of vegetation in relatively humid areas, but that excessive water input may lead to soil erosion. In the present study, the precipitation in Atlantic areas varies within specific limits depending on how vegetation is locally adapted. The average values of MAP and MP09 for Atlantic regions are 1182.6 mm yr^{-1} and 74.5 mm yr^{-1} respectively, while for the

Mediterranean region the corresponding values are 970.6 mm yr^{-1} and 49.8 mm yr^{-1}. However, the central and southern RoP of Mediterranean regions, where some areas such as RoP 30 or 42 have MP09 values close to 30 mm yr^{-1}, is what confirm this hypothesis.

Regarding temperature, the general model fits only seem to be influenced by one monthly temperature variable (MT12), which explains around 40% of NPP in Mediterranean region, without affecting the Atlantic region (Tables 2 and 3). However, temperature plays a fundamental role, because it affects both the photosynthesis and autotrophic respiration (R_a), the rates of which increase exponentially with temperature by increasing the maintenance cost by plants (Ryan, 1991; Ryan et al., 1994). Respiration rates are lower in the Atlantic region, causing an increase in the CUE, while MAT is higher in the Mediterranean region where the maintenance cost increases and CUE decreases. Although monthly temperature variables do not seem to have much influence, the findings revealed that MAT is an important driver of primary production in sweet chestnut stands. MAT explains the variations in NPP and also in CUE (Fig. 6). According to Chen et al., (2019), MAT may explain 50% of variations in NPP, whereas for CUE, MAT may explain 30% of variations and both decrease quadratically when MAT increases. Hence, in sweet chestnut AFS in the Iberian Peninsula, CUE is more strongly influenced by MAT than by MAP, indicating a relationship between climate warming and CUE (He et al., 2018).

4.4 Ecosystem and Ecosystem Services risks

The findings presented above indicate the usefulness of primary production indicators as proxies for assessing ecosystems and the associated risks, given the goodness of fit of the parametric and non-parametric models used in this study. However, primary production indicators may vary among or within ecosystems with climate change and other factors (such as management, ecological traits and age), and the ranges of NPP and CUE that do not entail risks for sweet chestnut are not known. NPP can theoretically be negative (R_a > GPP) for limited periods (Collalti and Prentice, 2019; Roxburgh et al., 2005). Therefore, when NPP reaches zero, the maintenance cost will be equal to the GPP and the plant will begin a survival phase. Moreover, several authors have reported a minimum value for CUE of 0.2 as the threshold below which the physiological activity of plants cannot be maintained (Amthor, 2000; Keith et al., 2010; Van Iersel, 2003). Our findings show that the NPP values are sometimes equal or close to zero for periods of 1 year in the south of the Mediterranean region (RoP 29, 30, 42 ,45 and 46), and chestnut of RoP 29 and 42 the regions with most years with minimum values of NPP (equal or close to zero) keeping the ecosystem alive. However, our data correspond to regions with low CUE values (such as RoP 29, 42 and 45) close to or below 0.2 (at risk), and we believe that values below 0.3 may also indicate ecosystems at potential risk, increasing considerable additional respiratory cost, reducing growth and new tissue formation, or even plant collapse . The sustainability of sweet chestnut AFS in north of Portugal and north of Spain does not depend on current climatic conditions, and therefore ecosystem provision would not be at risk in a hypothetically stable situation. However, and regarding future scenarios of climate change, our projections do not indicate a good future for sweet chestnut. This particularly applies to the Mediterranean regions of the central and southern part of the Iberian Peninsula where the influence of climate drivers is currently high, and the weather is expected to become warmer and drier in the coming years. Our findings suggest that by 2100, under the most favourable scenario (RCP2.6, MAT increases up to 1.7ºC), chestnut ecosystems will begin the survival phase in the south of the Iberian Peninsula, where some CUE values below 0.2 have already been observed. This hypothetical situation may be even worse under the RCP8.5 scenario (when MAT increases up to 4.8ºC), where is foreseen that all sweet chestnut in the Iberian Peninsula, except in RoP 10 and 05, surpass the survival threshold (R_a > GPP) and some (e.g. those in the most strongly affected regions specified above) may even disappear.

The most recent IPCC Report (IPCC, 2018) indicates temperature increases between 1.5 ºC and 2 ºC as the most likely scenario, as also suggested by Cox et al., (2018), although neither report dismisses the worst scenario established in the IPCC Report 2013. Keeping this in mind, it is uncertain how sweet chestnut AFS will adapt to these conditions. Some authors argue that plant species will adapt to climate change by altering their physical traits (Moritz and Agudo, 2013) with the consequent alteration of plant trait distributions (Madani et al., 2018) or by occupying current ecological niche spaces but under new environmental conditions (Dubuis et al., 2013) where local state for plants are more favourable. However, recent research suggests an insufficient acclimatization response to climate change by ecosystems during the last 30 years (Huang et al., 2019). While the focus of the present research is not to predict whether these ecosystems will be able to adapt via alteration of physical traits or whether they will occupy new ecological niches, the latter is probably most likely. However, the situation will differ depending on the type of sweet chestnut formations: in the long term, natural or semi-natural chestnut forests may adapt to new and favourable geographical locations (depending on competition with other species and/or land use types). Similarly, chestnut plantations may be established in different locations according to climate tolerance. Nevertheless, the resilience and adaptation of well-established and traditional AFS will ultimately depend on the variations in climatic conditions. Accordingly, ecosystem services provision will be affected in different ways due to the variations in provision related to the type of formation (see e.g. Roces-Diaz et al., 2018). Considering the multifunctional character of the traditional AFS (resulting in a greater capacity to supply bundles of ecosystem services, including provision, regulation and cultural services), climate change may negatively affect the provision of ecosystem services in many regions.

5 Conclusions

In this study, we assessed the influence of variations in climate on primary production indicators (NPP and CUE) in sweet chestnut AFS in the Iberian Peninsula and the resilience of these systems in a future scenario of climate change. Overall, the data is robust due to the selection criteria and the use of relatively large and continuous sweet chestnut stands. The annual NPP and CUE show homogenous temporal trends, with no large variations along the studied time frame, but their values show high spatial variation for each year considered. However, there are large differences between the mean trends in the different RoP, which were used to represent ecologically homogeneous areas. The highest NPP values corresponded to the north of Spain, associated with the coldest and wettest regions. The highest CUE values corresponded to in the north of Portugal, but very close to some areas of northern and central Spain. Furthermore, the model fitting results show a close relationship between primary production indicators and climate variables in sweet chestnut, highlighting the importance of including monthly climatic variables, such as summer precipitation, in the models. The findings also revealed that MAT is an important driver of primary production in sweet chestnut AFS, while MAP is not related to any indicator.

Further analysis of the explanatory power of the models, together with the scenarios predicted by IPCC, revealed that sweet chestnut AFS and their ecosystem services supply will be at risk due to the effects of climate change in the Iberian Peninsula. In RCP2.6, the most likely scenario according to IPCC 2018, important risks of loss of ecosystems and their associated functions will first appear in the south of Iberian Peninsula, while under the RCP8.5 scenario, the risk will be especially high in Mediterranean areas of southern and central Spain. Thus, because of the different ways that the physiological conditions of sweet chestnut may be affected by climate variations (i.e. increases in mean temperature), ecosystems will be affected, and their services reduced. In the worst case, if climate continues to change according to the worse predictions, ecosystems will be lost. In addition, both physical traits and the resilience and adaptation capacity for well-established and traditional AFS will play a fundamental role, always under the influence of final climatic conditions.

Acknowledgements

Pérez-Girón, JC. is in receipt of a “Severo Ochoa” PhD Grant provided by the Government of Principado de Asturias (PA-18-PF-BP17-026).

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