Individual tree early growth models for ten valuable broadleaves in Mediterranean conditions

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Abstract

Valuable broadleaved species are an essential, although often sporadic, element of forests in Europe. They provide multiple benefits, including high-quality timber, biodiversity and social values. Despite their importance, these tree species are often overlooked in forest management. As a consequence, there is a general lack of growth models of these species, and the effects of tree characteristics, site conditions, and weather on their growth has not been studied in depth, particularly in Mediterranean conditions. In this study linear mixed-effect models using R programming language was applied to develop early individual tree diameter and height increment models and to identify the drivers of growth for ten valuable broadleaves in Mediterranean conditions: *Acer campestre*, *A. pseudoplatanus*, *Fraxinus angustifolia*, *F. excelsior*, *Juglans regia*, *J. x intermedia*, *Prunus avium*, *Pyrus communis*, *Sorbus domestica*, and *S. torminalis.* The data were collected in 34 plots (experimental forest restoration trials) in a wide range of conditions in Catalonia, NE Spain, with a total of 5,390 experimental trees, with data collected between 2001 and 2019. The total explanatory power of the models ranged ($R2 = 0.58$ to 0.91) for diameter increment and ($R2 = 0.34$ to 0.84) for height increment. The study identified the most relevant drivers of the valuable broadleaved tree growth in the Mediterranean context: previous dimensions and seasonal precipitation (specially summer, followed by winter and autumn precipitation). Other variables related to planting techniques, topography, and soil conditions were less relevant and therefore not considered in the models. These models can be used to estimate the expected annual diameter or height growth and the time needed to reach a certain diameter during the first growing seasons. Besides, they can be used to design tailored management alternatives (i.e. irrigation plan) to enhance tree growth.

Key words: Growth model, Individual tree diameter increment model, Individual tree height increment model, Linear Mixed effect model, Valuable broadleaved trees

1. Introduction

1.1. Main features of valuable broadleaves

Valuable broadleaved tree species such as walnut, cherry, maple, ash, service tree, wild pear, and European nettle tree are among the most important elements of the European forest in terms of economic potential and biodiversity (Hemery et al. 2008, 2010; Oosterbaan et al. 2009; Spiecker et al. 2009; Coello et al. 2013). The occurrence of these species ranges from the Northern and eastern continental zone to the Mediterranean and Atlantic areas (Spiecker et al. 2009). These species often occur within forests dominated by other species, either conifers or broadleaved species.

The species commonly known as "valuable", "noble" or "sporadic" can include most or all of the above-mentioned ones and may also include other such as lime tree, apple tree and others. They have the following common features: they can provide high-quality timber, grow at an intermediate or fast rate, they do not form large pure stands (their contribution in terms of area and volume at forest scale rarely exceeds 5%) and have relatively high site quality requirements, especially with regard to soil fertility and balanced texture and to water availability without waterlogging (Hemery et al. 2008; Savill et al. 2009; Spiecker et al. 2009). Despite their importance, these species have been largely neglected for decades as a result of the promotion of pure stands, which are easier to manage, prioritizing the most abundant, less demanding and fast-growing species. This has considerably affected the composition of mixed forests and the presence of broadleaved tree species in Europe (Hemery et al. 2008). In the last decades, the interest in planting valuable broadleaved species increased among forest owners and farmers for economic (valuable timber production), ecological (habitat diversification) and social and aesthetic reasons (Hemery et al. 2008). They may also enhance climate change adaptation through forest resilience and reduce the impact of ecological risks such as pests and pathogens, fire and habitat loss (Hemery et al. 2010). Besides, plantation of these broadleaved tree species may provide multiple benefits for the management of the landscapes and biodiversity in the Mediterranean region. By increasing forest diversity, these tree species may play a key role in increasing forest vitality against global change.

The valuable broadleaves can be grown successfully on marginal or abandoned agricultural lands (either as an afforestation or as an agroforestry system), orchards, along roadsides (Hemery et al. 2008) and as enrichment plantings in forests dominated by conifers or other broadleaves (Kerr and Haufe 2016). Sometimes, these species tend to occur on sites where no other common species will thrive and this could be one of the reasons why the valuable broadleaved trees are an overlooked group of trees compared to other species such as oak (*Quercus robur L.*) and beech (*Fagus sylvatica L.*) (Savill et al. 2009). These species are generally light-demanding, especially in adult stages, which poses a difficulty for growing them in closed-canopy forest conditions (Savill et al. 2009; Spiecker et al. 2009). Similarly, compared to other species, they are considered more site demanding (Miller 1984; Savill et al. 2009).

1.2. Growth models

Growth models are systems of mathematical equations used to predict the growth and yield of forest stands or trees under a wide range of conditions (Vanclay 1994). Forest researchers and managers use growth models for many purposes: to predict the future yield, to develop silvicultural alternatives and management options, to identify the most important drivers of tree growth and to know tree growth dynamics (Vanclay 1994). They also provide information on both the current and the future state of the forest (Sharma et al. 2019). Growth models can be conducted at a tree or stand level. Individual tree growth models estimate the development and growth, regeneration, and survival of single trees (Dale et al. 1985). On the other hand, the stand-level growth models project the growth and development of entire forests (Dale et al. 1985). They are not precise in describing individual tree growth dynamics (Dale et al. 1985). So, the individual tree growth models such as diameter and height increment models are becoming more popular as they provide more detailed information on tree growth dynamics irrespective of the stand complexities, species composition, and management history (Hasenauer and others 2006). With individual tree growth models, variability within and between forest systems can be projected, and hence, individual tree traits can be examined (Dale et al. 1985). They are also useful as they allow preparing detailed management options, simulating silvicultural alternatives, and can be used instead of the traditional yield tables for efficient decision making (Pretzsch 2009; Vospernik 2017).

1.3. Growth models of valuable broadleaves

Despite the importance of valuable broadleaved species, there is a general lack of individual tree growth models for these species, particularly in Mediterranean conditions. Only a few growth models are available for these particular species in Europe. Even though there are some studies on the autecology and site requirements of these species in Europe by different scholars including (Dobrowolska et al. 2008; Hemery et al. 2008, 2010; Oosterbaan et al. 2009; Savill et al. 2009; Spiecker et al. 2009; Coello et al. 2013; Gonin et al. 2013), there is still limited scientific literature and reviews on the main drivers that influence the growth of valuable broadleaved trees in Europe in general and in the Mediterranean in particular.

1.4. Objectives

The current study aims at contributing to bridging the knowledge gap on the factors influencing the primary and secondary growth of valuable broadleaved tree species in Mediterranean conditions. In particular, the study aimed to build early individual-tree diameter and height increment models for ten (10) valuable broadleaved tree species using variables from tree characteristics, site conditions, and weather parameters in order to identify the most relevant drivers of tree growth. These early individual tree growth models can also assist in species' specific management measures under the global change context.

2. Materials and methods

2.1. Data

The data used for this study came from a network of 34 experimental plots in former arable or grassland fields planted with valuable broadleaves in Catalonia between 2001 and 2019 (**Fig.1**, described in **Table 1**). The study area is characterized by varying altitudes, ranging from 80 m a.s.l at the coastal area to 1,450 m a.s.l at the Pyrenees. This altitudinal range results in a wide variety of climatic conditions. The plots were planted in open areas and the effect of tree competence is considered negligible in all cases because of the generally young age and wide planting frame.

Data from 5,390 individual trees of ten valuable broadleaved tree species were used. The response variables were annual diameter and height growth at tree level. The data was collected by the Forest Science and Technology Centre of Catalonia (CTFC) from 2001 to 2019. Growth measurements were calculated as the difference of dimensions between two consecutive years. Diameter was measured with digital calliper at constant points (painted) at 4-5 cm above the root collar. When there are no branches below breast height (1.3 m) then we started measuring diameter at breast height, assuming that the annual diameter growth at breast height is similar to basal diameter growth from this moment onwards. Total height was measured as the height of the bud of the main shoot.

The predictor variables were 129, organised in three categories: site features (6 variables), tree-level data (8 variables) and weather (115 variables), as provided in **Table 2**. Site features refer to the main physical and soil features related to tree growth. Tree level data include the type of vegetative material, the planting techniques utilized to mitigate the negative impact of drought, competing vegetation and browsing damage and the diameter and height value at the end of the previous growing season. Weather data were temperature, precipitation and potential evapotranspiration, provided by the Catalan Meteorological Service and interpolated to the plot's location. Monthly, seasonal (i.e: winter consisting of December, January and February), and annual values were used. The minimum, maximum, and mean values were considered for temperature, while, for precipitation and potential evapotranspiration, the sum of seasonal and annual values were considered.

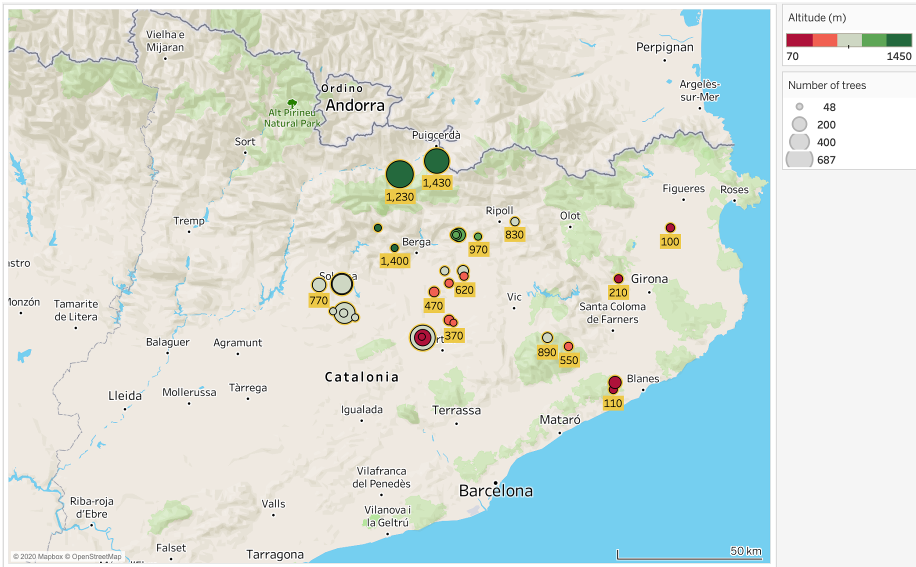

Figure 1: Distribution of the plots. (Map produced by: Tableau software)

2.2. Modelling approach

For modeling individual tree diameter and height increment (DI and HI), linear mixed effect model (LMM) was fitted with covariates (Pinheiro and Bates 2000). Mixed-effect models (MM) are statistical models that constitute fixed-effects parameters and random effects (Bates 2010). Lang wu (2009) defined MMs as an extension of the regression model, which incorporates random effect parameter/s in the model to account for the variability between individuals and correlation within individuals (Wu 2009). The applications of LMM are increasingly common in the analysis of ecological, forestry, and social data (Zuur et al. 2009; Kuznetsova et al. 2017; Harrison et al. 2018). These models consist of random and fixed effects as predictor variables, and the inclusion of random variables in the model helps to account for the non-independence nature of biological data (Harrison et al. 2018). The LMM accounts for non-independence data through the random component of the model by constraining non-independent units to have the same intercept and/or slope (Zuur et al. 2009; Zuur and Ieno 2016; Harrison et al. 2018). These random effects minimize the probability of false-positive type I error and false-negative type II error (Crawley 2007; Harrison et al. 2018). There are two major types of MM. These are (i) random intercept model and (ii) random slope model. The former allows the group means (intercept) to vary and assumes that all groups (random effects) have similar slopes. The latter allows the slope of the explanatory variables to change based on the random grouping variables (Harrison et al. 2018). The random slope model in MM requires more extensive data than the random intercept model. Even though it is recommended to use the random slope model

Table 1: Main features of the study plots

Plot_ID	Altitude (m)	Number of trees	Number of species	First growing season	T (°C)	P (mm)
Plot 1	770	169	3	2002	13.6	725
Plot 2	1070	108	3	2003	12.0	806
Plot 3	430	90	2	2005	15.0	568
Plot 4	320	261	4	2008	15.8	603
Plot 5	680	592	4	2008	14.0	638
Plot 6	1070	172	2	2008	12.3	913
Plot 7	320	48	7	2009	15.7	623
Plot 8	370	48	7	2009	15.2	658
Plot 9	520	66	10	2009	14.3	853
Plot 10	710	48	7	2009	13.7	582
Plot 11	760	48	7	2009	13.6	688
Plot 12	760	48	7	2009	13.3	618
Plot 13	760	48	7	2009	13.3	583
Plot 14	760	414	4	2009	13.3	581
Plot 15	760	64	1	2009	13.2	627
Plot 16	970	48	7	2009	12.7	905
Plot 17	1070	48	7	2009	11.8	895
Plot 18	1400	48	7	2009	9.8	855
Plot 19	1450	48	7	2009	9.4	909
Plot 20	80	144	1	2010	16.8	750
Plot 21	100	72	10	2010	16.3	753
Plot 22	110	71	10	2010	16.7	739
Plot 23	210	72	10	2010	15.8	827
Plot 24	550	66	10	2010	14.5	897
Plot 25	620	72	10	2010	13.7	892
Plot 26	830	66	10	2010	13.2	875
Plot 27	670	362	1	2011	14.5	605
Plot 28	670	432	1	2011	14.5	604
Plot 29	680	108	1	2012	14.5	754
Plot 30	700	72	1	2012	14.5	762
Plot 31	1230	687	6	2012	11.5	805
Plot 32	470	90	2	2014	15.7	633
Plot 33	890	90	3	2014	13.5	801
Plot 34	1430	570	1	2014	10.2	922
Total number of species						**10**
Total number of trees						**5390**
Total number of plots						**34**

* P: Mean annual precipitation (mm); T: Mean annual temperature (°C), Source: Meteorological Service of Catalonia

Table 2: Predictor variables used in the modelling of individual tree growth

Variables	Description	Type	Units	Source
Site characteristics				
Latitude	Latitudinal location data of the study sites	Continuous	Decimal degrees	CTFC
Longitude	Longitudinal location data of the study sites	Continuous	Decimal degrees	CTFC
Soil pH	pH of the soil calculated for each plot	Continuous	pH	CTFC
Organic matter	Soil organic matter content	Continuous	Percentage (%)	CTFC
Soil texture	Soil texture	Categorical	No unit	CTFC
Altitude	Average altitude above sea level	Continuous	Meter (m)	CTFC
Tree characteristics				
Previous diameter	Tree basal diameter at the end of the previous growing season	Continuous	Millimeter (mm)	CTFC
Previous height	Tree height at the end of the previous growing season	Continuous	Meter (m)	CTFC
Tree Variety	Tree variety, progenies or clone	Categorical	No unit	CTFC
Mulch type	The types of much applied	Categorical	Mulch model	CTFC
Mulch dimension	Dimensions of the mulch	Categorical	Centimeter (cm)	CTFC
Conditioner type	Type of soil conditioner applied	Categorical	Soil conditioner formulation	CTFC
Conditioner dose	Dose of soil conditioner applied	Categorical	Gram (g)	CTFC
Tree shelter	Type of tree shelter installed	Categorical	Shelter type and height	CTFC
Weather variables				
Temperature (T)	Minimum, mean and maximum temperature calculated monthly, seasonally and annually	Continuous	Degree Celsius (°C)	MSC
Precipitation (P)	Monthly, seasonal and annual precipitation	Continuous	Millimeter (mm)	MSC
Potential evapotranspiration (PET)	Monthly, seasonal and annual PET	Continuous	Millimeter (mm)	MSC

* CTFC: Forest Science and Technology Centre of Catalonia; MSC: Meteorological Service of Catalonia

as it provides more accurate P-values than the random intercept model and gives more power to detect among-individual variation; however, this technique relies on the availability of intensive data (Schielzeth and Forstmeier 2009).

For the current study, data was obtained from repeated measurements or longitudinal data in which the same trees were measured at multiple time points, violating the assumption of independence of observation. LMM was used for the data analyses and modeling, as often recommended by several authors and statisticians (Pinheiro and Bates 2000; Zuur et al. 2009). Random intercept modeling approach was used due to the limited and unbalanced nature of the data. The plot/trial, year of measurement, and trees nested in the plots were considered the random effects in our model. In the cases when the number of categories in the random effect is below five, the variable was considered as a fixed effect. R version 3.5.2 was used for all the statistical analyses and modeling (R Core Team 2018).

The mathematical notation for linear mixed effect model takes the form (Wu 2009):

$$y_i = x_i\beta + z_i * b_i + e_i,\ i = 1, 2, ..., n,$$
$$b_i \sim N(0, D),\ e_i| \sim N(0, R_i),$$

where $\beta = (\beta_1, ..., \beta p)^T$ is a $p * 1$ vector of fixed effects, $b_i = (b_{i1}, ..., b_{iq})^T$ is a $q * 1$ vector of random effects,the $n_i * p$ matrix X_i and then $n_i * q$ matrix Z_i are known design matrices which may contain covariates, $e_i = (e_{i1}, e_{i2}, ..., e_{ini})^T$ represents random errors of the repeated measurements within individual i, D is a $q * q$ covariance matrix of the random effects, and R_i is a $n_i * n_i$ covariance matrix of the within-individual errors.

2.3. Model fitting process

Before fitting the LMM models, data arrangement were performed by species; more important predictor variables were selected using the *random forest* package (Liaw and Wiener 2002), and outliers and multicollinearity issues were checked using visual and statistical tools such as the Cleveland dot-plot, box-plot, and variance inflation factors (VIF for multicollinearity). To avoid the use of collinear predictors in the same model, VIF below five were used.

The two most common R packages used for fitting LMM are *lme4* (Bates et al. 2015) and *lmerTest* (Kuznetsova et al. 2017). The *lme4* package is well known and widely applied in fitting linear and nonlinear mixed effect models. However, it does not provide the p-value for F and t-test statistics. In comparison, the *lmerTest* package extends the lme4 package by overloading the *anova* and *summary* functions and gives P-values for the fixed effect parameters (Kuznetsova et al. 2017). Besides, it provides type I-III ANOVA tables; it also has other interesting functions such as *ranova* (to test the significance of random effects); *drop1* function (for single term deletion, model selection and testing marginal terms), and *step-function* (for automatic backward model selection of fixed and random components of LMM). For the above reasons, the *lmerTest* package was applied to fit linear mixed effect model.

Step up model building approach was used, and it is one method of model building for repeated or longitudinal data (Pinheiro and Bates 2000). In this approach, model fitting was started with the simplest model and then continued to a more complex model until the selected model is not significantly different from the more complex model. Using this approach, first, intercept only model was fitted, in which all the random effects were included in the model, but no fixed effect parameters. *Ranova* function of the *lmerTest* package was used to check whether the random variables are statistically significant or not. In the cases when a given random variable is not statistically significant, it was removed from the model using the *step* function. After identifying the optimal random effect model, the predictor variables were added one by one. The covariates that improved the model performance significantly were kept in the model, and those that had a minimal effect were excluded. Using these steps, candidate models were built for all the 10 valuable broadleaved tree species considered in the study. Restricted maximum likelihood estimation (REML) was used for fitting the linear mixed effect models. The LMM with different fixed effect structures fit using REML cannot be compared directly based on their restricted likelihoods (Pinheiro and Bates 2000). Therefore, for comparison of models with different fixed effect covariates, maximum likelihood estimation (ML) was used instead of REML.

2.4. Model selection and evaluation

After identifying candidate models for the diameter and height growth for all the tree species, goodness of fit statistics and biological knowledge/reasoning were used to select the most meaningful model. Information criteria (IC) are widely used to compare and select models (Müller et al. 2013). There are two commonly used IC in regression and mixed-effect model selection: Akaike Information Criteria (Akaikei 1973) and Bayesian Information Criteria (Schwarz and others 1978). Both Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were applied to select the best model for each tree species. Besides, conditional R2, which shows the variability explained by fixed and random effects, and marginal R2 that shows the variability explained by only the fixed effect parameters, root mean square error (RMSE), and Intraclass Correlation Coefficient (ICC) were used as a basis of model selection.

Following the identification of the best model for each tree species from both statistical and ecological perspectives, the models were evaluated against the mixed model assumptions. To check the homogeneity of variance assumptions, plots of residuals versus fitted values were examined for the entire model and also residuals versus all the predictor variables to look for the patterns. Besides, as recommended by several authors, residuals versus fitted values were inspected for each grouping level of random factors (Zuur et al. 2010; Zuur and Ieno 2016). In addition, *check_heteroscedasticity* function of the *performance* package in R was used to check for heteroscedasticity of the variance (Lüdecke et al. 2020). Square root and logarithmic transformations were used in the cases when heteroscedasticity of variance were detected.

3. Results

3.1. Individual tree diameter and height increment models

Individual tree diameter and height increment models were developed using the *lmerTest* package (Kuznetsova et al. 2017), which applies Satterthwaite's method of estimating the degree of freedom and generate p-values for mixed effect models. Linear mixed-effect models were fitted using restricted maximum likelihood estimation (REML) to predict the early diameter and height growth of ten valuable broadleaved tree species in Mediterranean conditions. The model included trees nested in the plot, plot, and year_id as a random effects. The effect sizes were labelled following Funder's recommendations (Funder and Ozer 2019). The general formula used for the LMM in R is presented as follows:

$$Model_{code} = Response \sim predictor/s + (1|plot/tree) + (1|Year), data = data)$$

where:

Model code: is the code or name of the model. Response: the response variable (Diameter or height increment). Tilde (~): shows "as a function of". Predictor/s: Predictor or explanatory or covariate variable/s used in the model. It is a fixed effect part of the model. (1 | plot/tree): assumes an intercept that's different for each tree within the plot. "plot/tree" indicates that the trees are nested within plots. (1 | Year_id): assumes an intercept that's different for each Year_id. Data: the data used for the analyses.

The model's total explanatory power ranged from (**0.58 to 0.91**) for diameter increment and (**0.34 to 0.84**) for height increment models (**Table 3 & 4**). In both cases, *Sorbus domestica* models explained less variability for diameter and height growth, which was 0.58 and 0.34, respectively. The total number of covariates used in the diameter increment models was five. These covariates are the previous dimension, precipitation of summer, winter, autumn, and July. In all cases, they had a highly significant positive effect on early diameter growth with p-values less than 0.001. Except *Fraxinus excelsior* which had only one predictor variable, all other species had two to four predictors for diameter increment models. In the case of height increment models, there was less consistency in the models. The number of covariates used for the height increment models was ten. Most of the covariates positively influenced the height growth except the minimum winter temperature, which negatively impacted the *Fraxinus angustifolia* species' height growth.

For both diameter and height increment models, Previous dimension and precipitation were the most important predictors. The summarized information of the individual tree growth models with covariate effect are indicated in **Table 3**. Other detailed information on parameter estimates and fitting statistics of the individual tree diameter and height increment models are shown in **Table 4 and 5**.

Table 3: Predictors and their effects on individual tree diameter and height growth models

Species	Response	AIC	BIC	RMSE	P_D	P_win	P_sum	P_aut	P_jul	P_nov	Variety	WintMinT	P_year	P_dec
Acer campestre	DI	521	543	0.49	+++		+++							
	HI	1004	1021	1.74			++							
Acer pseudoplatanus	DI	372	395	0.36	+++		+++							
	HI	664	695	1.23					+		+++			
Fraxinus angustifolia	DI	1935	1984	0.49	+++	+++	+++							
	HI	3896	3931	1.32			+++					- - -		
Fraxinus excelsior	DI	2148	2175	0.43		+++								
	HI	3351	3375	1.30		+++								
Juglans regia	DI	3452	3486	1.46	+++		+++							
	HI	694	721	0.31				+						
Juglans x intermedia	DI	19167	19230	0.67	+++	+++	+++	+++						
	HI	36775	36831	1.89	+++		+++	+++						
Prunus avium	DI	7671	7709	2.72	+++	+++								
	HI	5165	5201	1.71	+++		+++			+++				
Pyrus communis	DI	971	1003	0.38	+++		+++							
	HI	2404	2431	1.42	+								+++	
Sorbus domestica	DI	253	270	0.50	+++				+++					
	HI	535	549	1.88										+
Sorbus torminalis	DI	1254	1289	0.32	+++	+++								
	HI	3847	3882	1.20	++			+						

Note:
AIC:Akaike information criterion; BIC: Bayesian information criteria; RMSE: Root-mean-square error; P_D: Previous dimension (mm/cm); P_win: Precipitation of winter (mm); P_sum: Precipitation of summer (mm); P_aut: Precipitation of autumn (mm); P_jul: Precipitation of July (mm); P_nov: Precipitation of November (mm); WintMinT: Winter minimum tempreture temperature (°C); P_year: Annual Precipitation (mm); P_dec: Precipitation of December (mm);
+++: shows positive effect and level of significance ($P < 0.001$). DI: Diameter increment (mm); HI: Height increment (cm)

Table 4: Parameter estimates and fitted statistics of the individual tree diameter increment models

Species	Predictors	Estimates	CI	P.value	SD	ICC	N_plot	N_Year	N	Marginal.R2	Conditional.R2
Acer campestre	Intercept	1.09	0.71 – 1.48	<0.001	0.26	0.55	17	8	287	0.183	0.631
	PD	0.02	0.02 – 0.03	<0.001							
	Summer P	0.00	0.00 – 0.00	<0.001							
Acer pseudoplatanus (LOG)	Intercept	0.20	-0.31 – 0.72	0.441	0.20	0.70	12	7	184	0.105	0.727
	PD	0.02	0.01 – 0.03	<0.001							
	Summer P	0.00	0.00 – 0.00	0.006							
Fraxinus excelsior	Intercept	0.81	0.31 – 1.32	<0.002	0.20	0.76	15	11	1620	0.143	0.794
	Winter P	0.01	0.01 – 0.01	<0.001							
Fraxinus angustifolia	Intercept	0.20	-0.85 – 1.24	0.713	0.29	0.89	16	9	1008	0.181	0.912
	PD	0.02	0.02 – 0.03	<0.001							
	Winter P	0.01	0.01 – 0.02	<0.001							
	Summer P	0.00	0.00 – 0.00	0.032							
Juglans regia	Intercept	0.72	0.31 – 1.13	0.001	0.21	0.62	9	11	858	0.227	0.704
	PD	0.01	0.00 – 0.02	0.001							
	Summer P	0.00	0.00 – 0.01	<0.001							
Juglans x intermedia	Intercept	-2.55	-3.07 – -2.03	<0.001	0.46	0.74	33	17	8961	0.443	0.857
	PD	0.33	0.31 – 0.35	<0.001							
	Autumn P	0.01	0.01 – 0.01	<0.001							
	Summer P	0.00	0.00 – 0.00	<0.001							
	Winter P	0.01	0.01 – 0.01	<0.001							
Prunus avium	Intercept	2.27	-0.17 – 4.71	0.068	8.09	0.69	17	16	1502	0.139	0.734
	PD	0.04	0.03 – 0.05	<0.001							
	Winter P	0.02	0.00 – 0.03	0.009							
Pyrus communis	Intercept	1.38	1.00 – 1.76	<0.001	0.17	0.72	20	8	706	0.106	0.747
	PD	0.02	0.02 – 0.03	<0.001							
	Summer P	0.00	0.00 – 0.00	<0.001							
Sorbus domestica	Intercept	0.90	0.39 – 1.42	0.001	0.29	0.50	12	8	122	0.144	0.576
	PD	0.04	0.01 – 0.08	0.004							
	July P	0.01	0.00 – 0.01	0.001							
Sorbus torminalis	Intercept	0.05	-0.63 – 0.73	0.878	0.13	0.89	21	9	1028	0.224	0.913
	PD	0.02	0.01 – 0.03	<0.001							
	Winter P	0.01	0.01 – 0.01	<0.001							

Note:

CI: Confidence interval; P: Precipitation (mm); SD: Standard deviation; ICC: interclass correlation coefficient; N_plot: Number of plots; N_year: Number of years; N: Number of trees; PD: Previous diameter (mm)

Table 5: Parameter estimates and fitted statistics of the individual tree height increment models

Species	Predictors	Estimates	CI	P.value	SD	ICC	N_plot	N._Years	N	Marginal.R2	Conditional.R2
Acer campestre	Intercept	3.74	2.55 – 4.93	<0.001	3.33	0.40	17	10	233	0.081	0.450
	Summer P	0.01	0.00 – 0.01	0.001							
Acer pseudoplatanus	Intercept	-0.13	-3.37 – 3.11	0.936	2.05	0.65	12	10	161	0.314	0.761
	variety [FNAN]	0.42	-1.82 – 2.65	0.716							
	variety [GdlsAF400]	-0.32	-2.75 – 2.11	0.797							
	variety [MasPir]	7.59	3.89 – 11.28	<0.001							
	variety [MasPirAN]	4.19	1.12 – 7.26	0.007							
	P_jul	0.01	0.00 – 0.03	0.022							
Fraxinus angustifolia	Intercept	4.71	3.34 – 6.08	<0.001	2.01	0.71	16	11	1031	0.086	0.736
	Summer P	0.01	0.00 – 0.01	<0.001							
	Winter P	-0.68	-0.98 – -0.39	<0.001							
Fraxinus excelsior	Intercept	2.70	0.98 – 4.43	0.002	1.75	0.82	15	11	952	0.128	0.845
	Winter P	0.02	0.02 – 0.03	<0.001							
Juglans regia	Intercept	0.89	0.53 – 1.24	<0.001	0.11	0.64	9	13	768	0.040	0.652
	Autumn P	0.00	0.00 – 0.00	0.018							
Juglans x intermedia	Intercept	1.22	0.22 – 2.21	0.016	3.78	0.53	33	17	8641	0.157	0.600
	PH	0.00	0.00 – 0.00	<0.001							
	Autumn P	0.02	0.02 – 0.02	<0.001							
	Summer P	0.00	0.00 – 0.01	<0.001							
Prunus avium	Intercept	2.54	1.17 – 3.91	<0.001	3.01	0.56	16	16	1276	0.136	0.621
	PH	0.00	0.00 – 0.00	<0.001							
	Summer P	0.01	0.00 – 0.01	<0.001							
	November P	0.02	0.01 – 0.02	<0.001							
Pyrus communis	Intercept	2.22	0.35 – 4.09	0.02	2.10	0.52	20	10	643	0.090	0.564
	PH	0.00	0.00 – 0.01	0.009							
	Annual P	0.00	0.00 – 0.01	0.001							
Sorbus domestica	Intercept	4.49	3.28 – 5.69	<0.001	3.89	0.28	12	10	120	0.085	0.344
	December P	0.03	0.01 – 0.06	0.01							
Sorbus torminalis	Intercept	2.53	1.40 – 3.66	<0.001	1.62	0.55	21	11	1088	0.031	0.566
	PH	0.00	0.00 – 0.01	0.007							
	Autumn P	0.01	0.00 – 0.01	0.016							

Note:
CI: Confidence interval; P: Precipitation (mm); SD: Standard deviation; ICC: interclass correlation coefficient; N_plot: Number of plots;
N_year: Number of years; N: Number of trees; PH: Previous height (cm)

3.2. Drivers of valuable broadleaved tree growth in Mediterranean conditions

3.2.1. Drivers of diameter growth

Previous dimension (diameter at the end of the previous growing season) was among the most relevant drivers of early diameter growth, having a significantly positive effect in 9 out of 10 species, with *F. excelsior* as the only exception. In addition, significant effect of precipitation was found on early diameter growth. Summer and winter precipitation had a substantial impact on the diameter growth of six and five species, respectively. Comparing drivers of diameter growth between similar genus, some level of consistency was identified. For example, a significant positive effect of winter precipitation was found on both *F. excelsior* and *F. angustifolia*. Similarly, for *A. campestre*, *A. pseudoplatanus* and for *J. regia* and *J x intermedia* species a significant positive effect of summer precipitation was found.

3.2.2. Drivers of height growth

Early height growth drivers were more variable than in the case of diameter growth. For early height growth models, a total of ten (10) predictors were used in the models considering all species. Four out of ten individual tree height increment models include previous height as predictor. It was also found that seasonal precipitation plays a crucial role in the trees' early height growth, especially in summer and autumn. In addition to the previous height and seasonal precipitation effects, the study also revealed that annual and monthly rainfall (such as; July, November, and December rains) had vital roles in early individual tree height growth (**Table 4**). Besides, variety had a significant effect on the early height growth of A. pseudoplatanus. *Massís Pirinenc* and *Massís Pirinenc Arrel nua* varieties showed better growth performance compared to other varieties considered (*França Nord AF500, França Nord arrel nua, and Gerri de la sal AF400*) (**Fig 3**). Moreover, a significant negative impact of winter minimum temperature on the early height growth was detected for *F. angustifolia*.

No similarities between species of the same genus with regard to the variables considered in the individual height growth models.

Plantation techniques, topography, and soil conditions seem not to influence the tree species' early diameter and height growth.

3.3. Predictors effect

Predictor effect plots offer graphical summaries for regression models with linear predictors, including linear models, linear and generalized linear mixed models, and many others (Fox and Weisberg, 2018). They are applied in R using the *effects* package (Fox and Weisberg, 2019). These plots were used to summarize the role of a given predictor in fitted linear mixed models with varying values when all other predictors in a model held constant (also known as ceteris paribus). As shown in **Fig 2**, the predictor effect plot was used to evaluate the effect of individual predictors in a particular model. For example, for *F.*

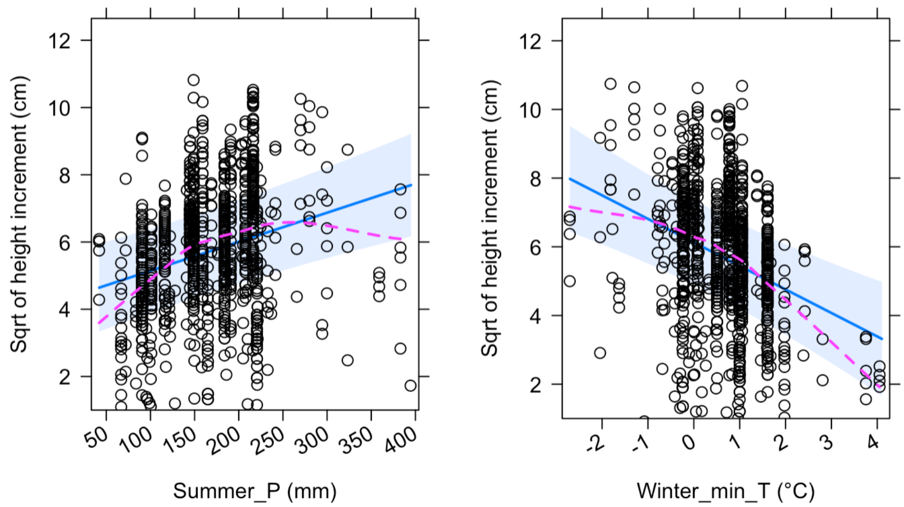

Figure 2: Effect of summer precipitation and minimum winter temperature on height growth of *F. angustifolia.*

angustifolia species, we can observe the positive effect of summer precipitation and the negative effect of the minimum winter temperature separately (**Fig 2**).

Similarly, the significant positive effects of predictors used on early diameter and height growth for the *A. pseudoplatanus*, *F. excelsior*, and *S. torminalis* models are illustrated in **Fig 3, 4 and 5**.

In the predictor effect plots, the shaded area represents a confidence band for the fitted values based on the standard error calculated from the covariance matrix of the fitted mixed effect model coefficients. The solid blue line indicates the fitted model. The dashed magenta line is known as LOESS (Locally Weighted Smoothing). It was used to create a smooth line through the scatter plots to understand more the relationship between the response and predictor variables.

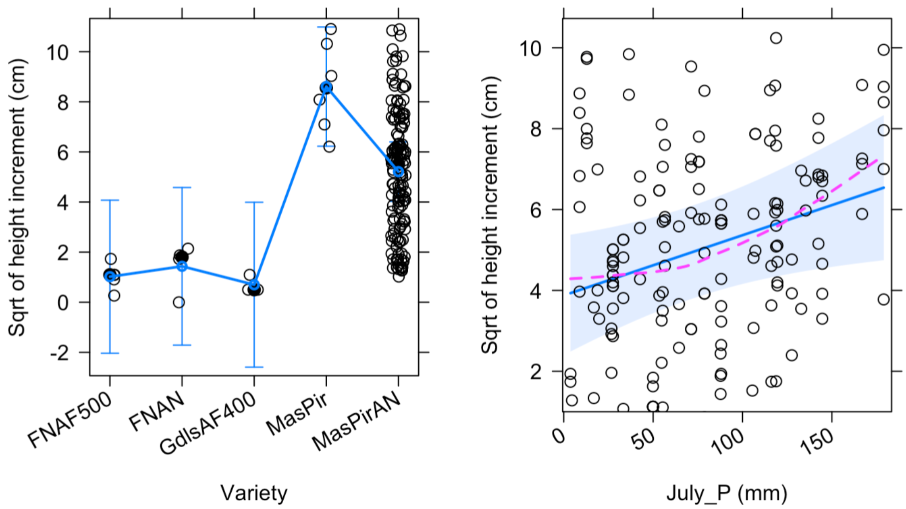

Figure 3: Effect of variety and July precipitation on height growth of *A. pseudoplatanus*

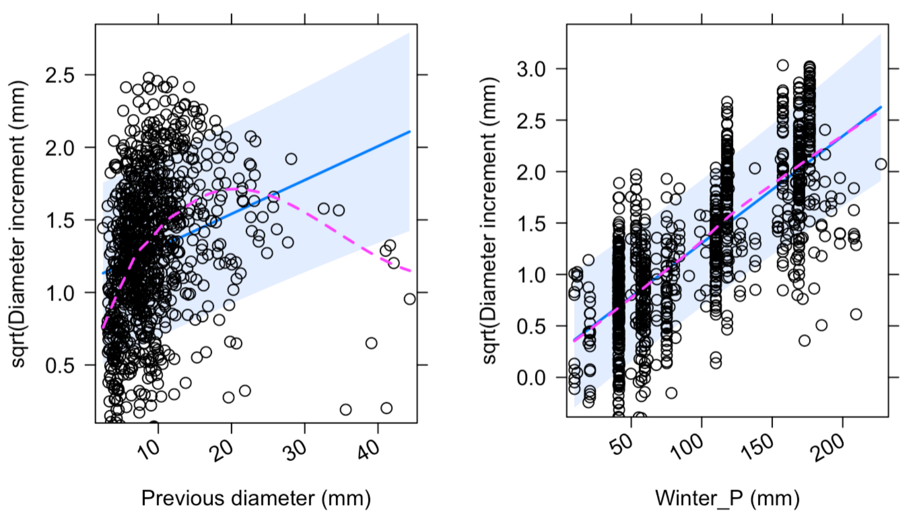

Figure 4: Previous dimension and winter precipitation effect on diameter growth of *S. torminalis*

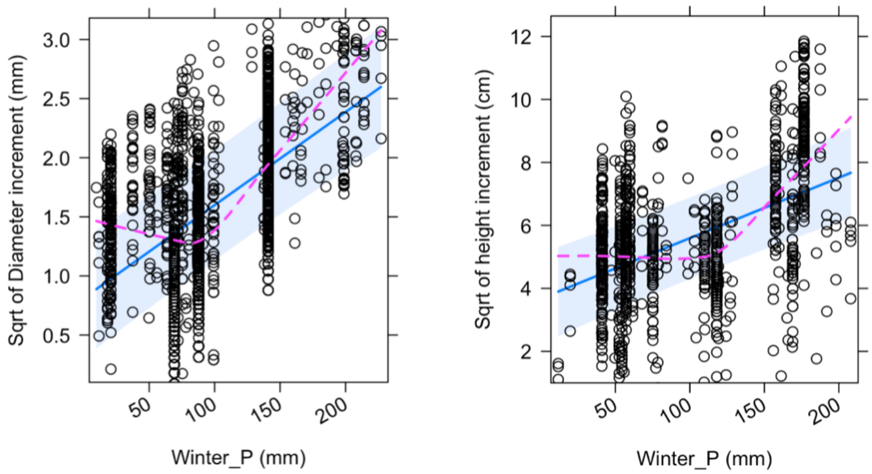

Figure 5: Effect of winter precipitation on both height and diameter growth of *F. excelsior*

4. Discussion

4.1. Model quality

The overall performance of the models developed can be considered reasonably good. The conditional R^2, attributed to the variability explained by the fixed and random effects, ranged from 0.58 to 0.91 for early diameter growth and 0.34 to 0.84 for early height growth (**Table 4 and 5**). On the other hand, the variability explained only by the fixed effects ranged from 0.1 to 0.44 for early diameter growth and 0.03 to 0.31 for the early height growth. These differences in the explained variability between the species might indicate different responses of the species towards weather variables (specially precipitation) or the different levels of impact of the weather variables on the tree growth. For illustration purposes, the best model fitted for the early diameter growth of *Juglans x intermedia* was plotted for all the plot random effects separately to observe the goodness of fit and model performance (**Fig 6**). Besides, the same model fit was plotted for all the sites together (**Fig 7**).

4.2. The most influential drivers of valuable broadleaved tree growth in Mediterranean conditions

The most relevant drivers of early individual tree growth are the previous dimensions and precipitation. Significant positive effect of previous dimensions were found on early diameter and height growth. The effect of previous dimensions was more consistent for diameter growth than for height growth. Although a general positive effect of previous dimensions on early tree growth, looking at the predictor effect plot, it seems that the previous dimension effect is not homogenous. It seems that tree size has a significant positive effect until a certain threshold and then it has a negative or no effect (**Fig 8**). This result is

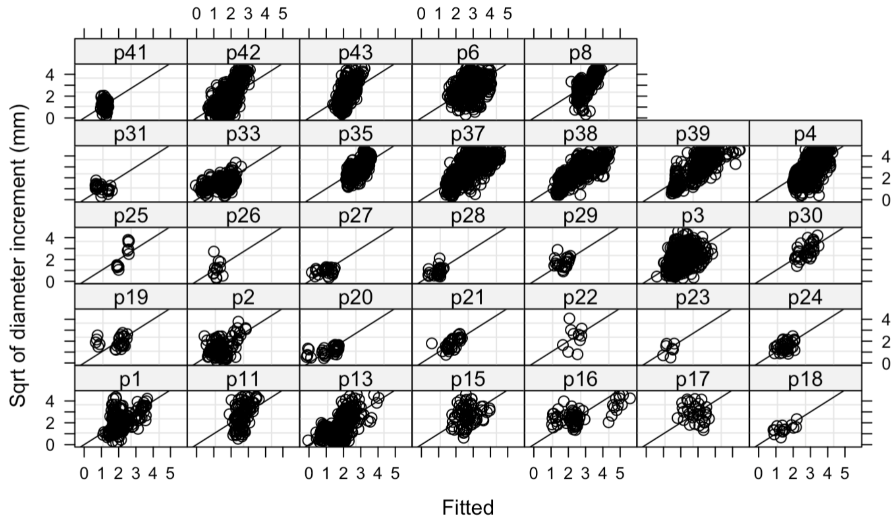

Figure 6: Graphical illustration of the best model for *Juglans x intermedia* species considering the random permanent plots

consistent with other studies that have indicated the relationship between tree dimension and growth does not seem to follow a single rule (Muller-Landau et al. 2006; GÓMEZ-APARICIO et al. 2011). The typical pattern observed for Iberian tree species followed a maximum peak of growth at intermediate d.b.h and subsequent decreases with size (GÓMEZ-APARICIO et al. 2011).

Besides previous dimensions, a significant positive effect of seasonal precipitation was found on early diameter and height growth. Previous literatures also revealed the positive effect of rainfall and the availability of water for the growth of valuable broadleaved trees (Delzon and Loustau 2005; Hemery 2007; Linder et al. 2008; Hemery et al. 2010; Gonin et al. 2013; Coello and Piqué 2016). From all the precipitation variables tested, the seasonal rainfall, especially the summer, winter, and autumn precipitation, were among the most crucial ones. Several authors also recognize that increased drought (specially in summer) is likely to result in reduced tree growth and primary productivity (Ogaya and Peñuelas 2003; Llorens et al. 2004; Linder et al. 2008; Coello and Piqué 2016).

Another study conducted in the Iberian Peninsula also showed a positive effect of increased annual precipitation on tree growth of both conifer (*pines*) and broadleaved species (*Quercus*) (GÓMEZ-APARICIO et al. 2011). This positive effect of precipitation on tree growth is more likely due to the evidence that Iberian tree species are becoming increasingly more water-stressed in summer (Gea-Izquierdo et al. 2009; GÓMEZ-APARICIO et al. 2011).

Site characteristics is another essential factor affecting tree growth. In the current study, no significant effect of site conditions was found on either the early diameter or height growth. This could be due to the sound choice of the species

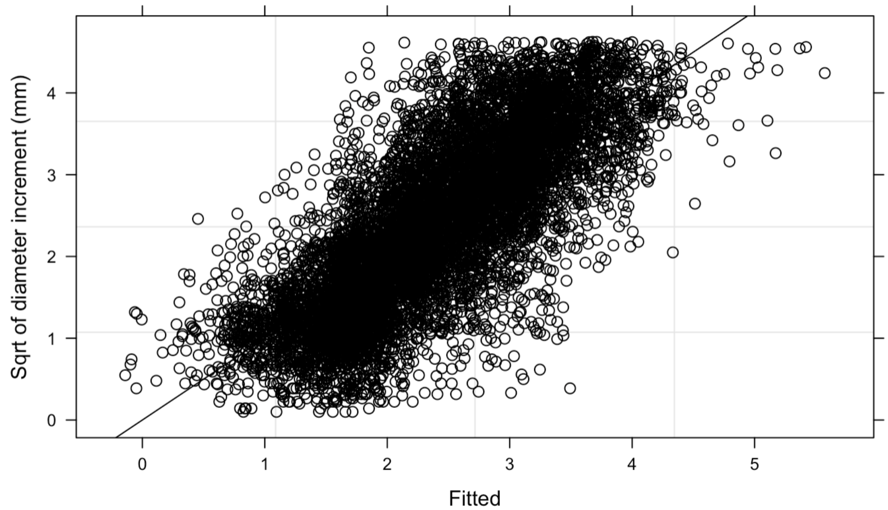

Figure 7: Graphical illustration of the best model for *Juglans x intermedia* species for the entire permanent plots.

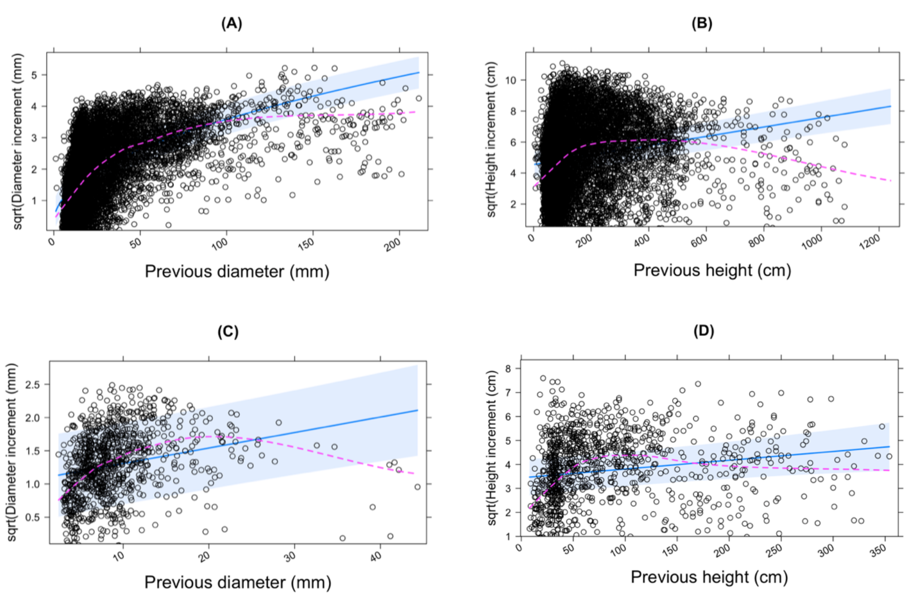

Figure 8: The pattern and effect of previous dimensions on tree growth for *Juglans x intermedia* (A and B) and *Sorbus torminalis* (C and D)

to all sites. Previous findings indicated that site conditions (such as topography and soil characteristics) influence tree growth. It is possible that outcomes might vary if data is collected from more plots in various countries from the Mediterranean region. Therefore, future researchers and studies should consider investigating the impact of site conditions on the growth of valuable broadleaves using a higher number of plots from different Mediterranean countries.

Another limitation of the current study was the minimal observations for some species, which could affect the detection of some drivers' significant effect on tree growth. Future studies should also consider using more observations to detect the in-depth effect of different factors on tree growth.

4.3. Implications in the global change context

The present study found that winter precipitation tends to influence more diameter growth than height growth. The effect of winter precipitation was found in five species (*Fraxinus angustifolia*, *Fraxinus excelsior*, *Juglans x intermedia*, *Prunus avium*, and *Sorbus torminalis*)(**Table 3**). In all the five species', winter precipitation had a significant positive effect on early diameter growth; on the other hand, summer precipitation tends to impact both the diameter and height growth of most tree species' studied: *Acer campestre*, *Acer pseudoplatanus*, *Fraxinus angustifolia*, *Juglans regia*, *Juglans x intermedia*, *Prunus avium*, and *Pyrus communis*(**Table 3**). This indicates that most of the study species are vulnerable to summer drought and predicted future climate change. In the Mediterranean, models predict a decrease in precipitation and an increase in temperature leading to the occurrence of drought periods (Parry et al. 2007; Linder et al. 2008; Hemery et al. 2010; Garcı'a-Ruiz et al. 2011; Peñuelas et al. 2017). Due to this, the water supply will increasingly become the future critical limiting factor of tree growth and survival in plantation forests (Linder et al. 2008). Globally, changes in land use and climate are increasing at faster rates, causing more considerable changes to the forest landscapes worldwide (Mery et al. 2010; Acácio et al. 2017). The Mediterranean region is projected to be highly vulnerable to global change (Acácio et al. 2017) which leads to shifts in forest species composition in different geographic locations (Kelly and Goulden 2008) by increasing the frequency and intensity of disturbances, such as pathogen outbreaks (Edburg et al. 2012), increased in wildfires (Westerling et al. 2006), and escalate tree mortality and enhance extreme weather events (Allen et al. 2015).

The study also revealed that there are differences between species in the requirements of precipitation. While most species' growth was influenced by single seasonal, monthly, or annual precipitation, other species' (*Fraxinus angustifolia*, *Juglans x intermedia*, and *Prunus avium*) growth was impacted by multiple seasons of precipitation (**Table 3**). *Juglans x intermedia* was affected by summer, winter, and autumn precipitation. While *Fraxinus angustifolia* and *Prunus avium* were influenced by summer and winter precipitations. This could tell us that the species which are influenced by multiple seasonal precipitations could be more susceptible to the impact of climate change. Besides, it is an indication of different water requirements between the species for growth and development.

Other studies have pointed out the importance of precipitation and water availability for these species' optimal growth and performance(Dobrowolska et al. 2008; Hemery et al. 2008, 2010; Spiecker et al. 2009; Coello et al. 2013; Gonin et al. 2013). Previous studies have shown that *Fraxinus angustifolia* and *Juglans x intermedia* are resistance to drought provided that there is an adequate water supply in the soil (Cisneros et al. 2002; Gonin et al. 2013). However, the present study found that these species' early growth relies on adequate precipitation in the summer and winter seasons. This could be associated with less water availability in the soil, especially in the summer season in the Mediterranean condition. Regarding *Prunus avium*, studies have shown that it is vulnerable to drought and needs significant water reserve for optimal growth which is consistent with the finding of the present study (Hemery et al. 2010; Gonin et al. 2013). In general, even though there are species-specific differences, it was found that precipitation was among the most critical factor contributing to the early growth of all the ten valuable broadleaved trees studied in Mediterranean conditions. Therefore, the predicted decrease in precipitation in the Mediterranean region might significantly affect the growth of these species unless proper management measures are not in place.

Studies have also shown the effect of the predicted increase in temperature on the tree growth in the Mediterranean areas. Loustau et al. (2005) found a detrimental effect of an increase in temperature if the precipitation does not increase in the case of the Mediterranean regions. Other studies also showed the negative effect of increased temperature on photosynthesis (Rennenberg et al. 2006); reduced CO2-uptake and biomass production (Granier et al. 2007); and aggravated competition of seedlings with ground vegetation (Linder et al. 2008). In the current study, only little effect of temperature was detected on the studied species' early growth and performance, negative effect of winter minimum temperature was only found on the early height growth of *F. angustifolia.* This could be due to the species adaptation and plasticity to a range of temperature values and to the use of species within their adequate climatic range.

4.4. Management implications

The tree early growth models obtained for ten Mediterranean valuable broadleaved species are a first approach to the knowledge of the growth of these species and the main factors that influence annual diameter and height growth. Between those factors that can be modified by management (i.e. irrigation), seasonal precipitation appears to be the most important. Forest managers can estimate from these models, approximately, the expected annual growth, which is important for economical assessment of broadleaves plantations. The expected annual growth for all the species can be achieved using *ciTools* package in R, which provides the expected annual mean growth with 95% confidence interval . **Table 6** shows example of predicted mean annual diameter growth for *Fraxinus excelsior* with 95% confidence limit. We can estimate the expected annual growth with varying precipitation for a given plot and year. This can be done for certain species, and in many cases it is also needed to consider

Table 6: Estimated annual diameter growth of *Fraxinus excelsior* with changing winter precipitation

Plot_ID	Winter_P (mm)	Year_id	PV (mm)	LL 95% CI (mm)	UL 95% CI (mm)
p1	150	2019	2.89	2.76	2.97
p1	200	2019	3.22	3.04	3.33
p1	290	2019	3.80	3.53	3.97
p1	800	2019	7.05	6.38	7.61
p1	1200	2019	9.62	8.57	10.47
p16	150	2019	2.86	2.69	3.01
p16	200	2019	3.18	2.98	3.34
p16	290	2019	3.75	3.53	3.98
p16	800	2019	7.08	6.27	7.59
p16	1200	2019	9.62	8.45	10.44
p41	150	2019	2.76	2.61	2.85
p41	200	2019	3.07	2.92	3.18
p41	290	2019	3.64	3.46	3.83
p41	800	2019	6.92	6.26	7.42
p41	1200	2019	9.48	8.44	10.31
p25	150	2019	2.52	2.35	2.74
p25	200	2019	2.84	2.64	3.06
p25	290	2019	3.42	3.16	3.70
p25	800	2019	6.72	6.02	7.33
p25	1200	2019	9.31	8.20	10.15

Note:
CI: Confidence interval; LL: Lower limit; P: Precipitation; PV: Predicted value (mm); UL: Upper limit

the previous dimensions. Besides, we can estimate minimum precipitation desired for obtaining a specific annual growth. However, it is important to stress when using these models that the range of models application is in early stages (plantation no older than 10-12 years).

Several studies have described the effect of global change including the increased irregularity of precipitation and increased temperature on the Mediterranean forests (Kirschbaum 2004; Räisänen et al. 2004; Fuhrer et al. 2006; Rennenberg et al. 2006; Granier et al. 2007; Linder et al. 2008; Peñuelas et al. 2017). From the management point of view, our study indicated that the water inputs are particularly effective in some particular periods of the year, especially during the summer, winter, and autumn seasons depending on the species. This informs the most effective time to apply irrigation to maximize the trees' growth and performance. Therefore, the irrigation measures should consider the species-specific most performing time.

5. Conclusion

Individual tree early diameter and height growth models were developed using a linear mixed effect modeling approach, and the main drivers influencing tree species' primary and secondary development were identified. The main drivers explaining the annual diameter and height growth of ten valuable broadleaved trees in Mediterranean conditions are previous dimensions and seasonal precipitation. Differences between species were observed in terms of drivers of tree growth. While most of the species were mainly influenced by summer precipitation, others were more impacted by winter, autumn, and monthly rains than summer precipitation. The models developed can be used to estimate the annual diameter and height growth of the ten valuable broadleaves considered. Furthermore, forest managers and practitioners can use these models to estimate the minimum precipitation required to obtain specific diameter or height growth and apply irrigation and other management alternatives during minimal and erratic rainfall.

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Annex 1: Plots of residuals versus fitted values and Q-Q plot to check for homogeneity of variance and normality of residual assumptions

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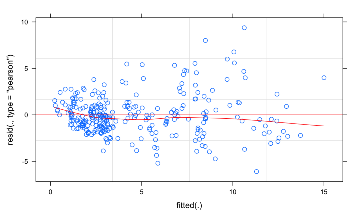
<td>
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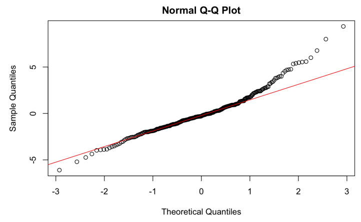
<td>
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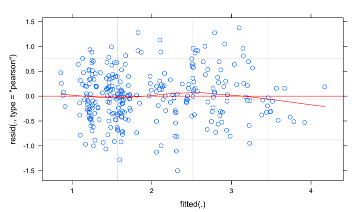
<td>
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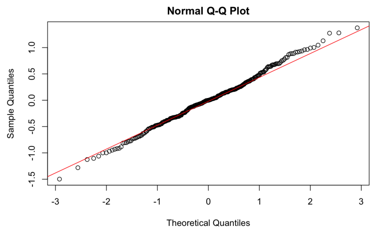
<td>
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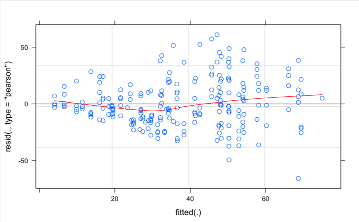
<td>
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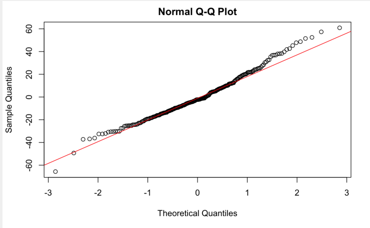
<td>
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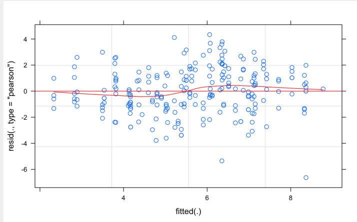
<td>
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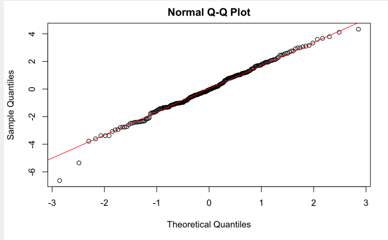
<td>
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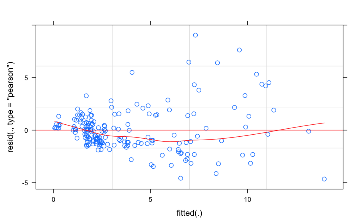
<td>
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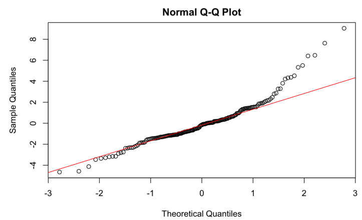
<td>
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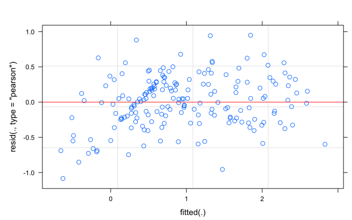
<td>
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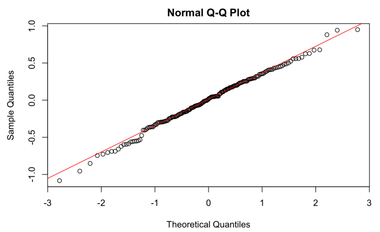
<td>
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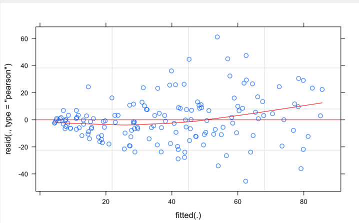
<td>
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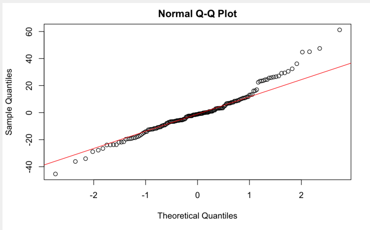
<td>
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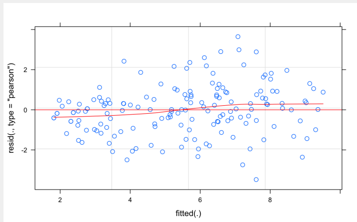
<td>
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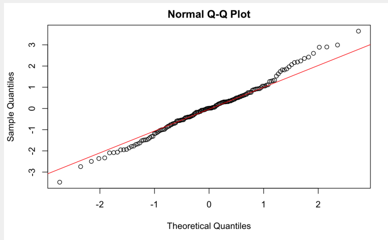
<td>
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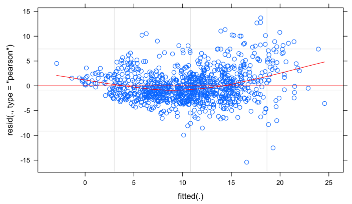
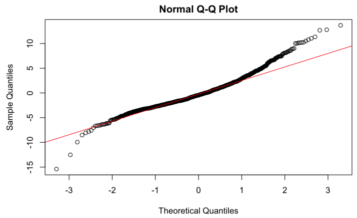
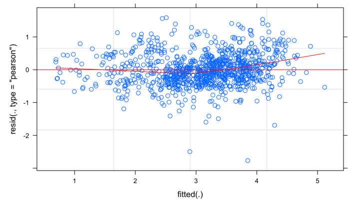
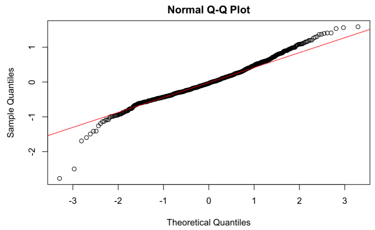
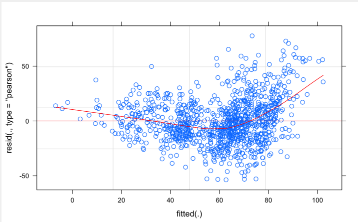
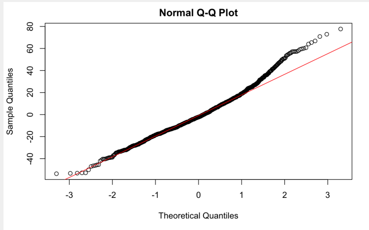
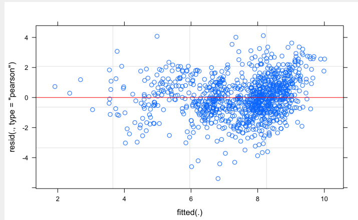
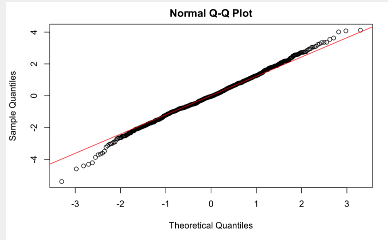
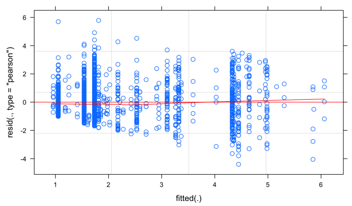
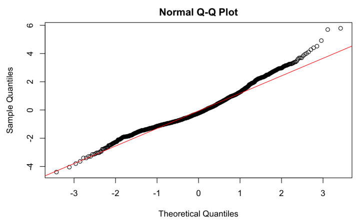
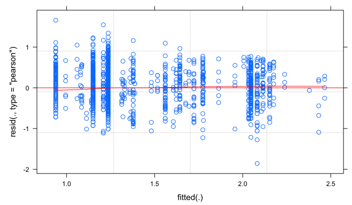
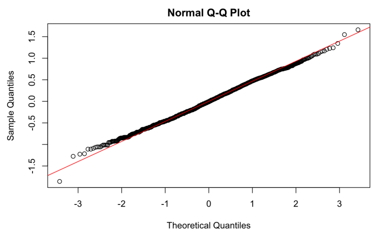
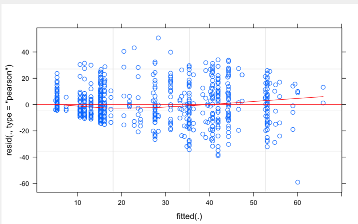
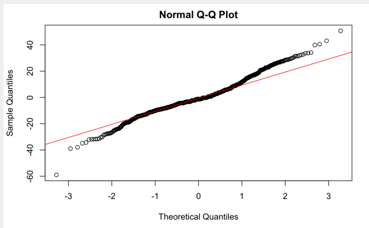
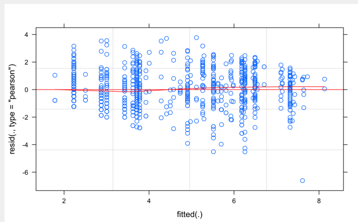
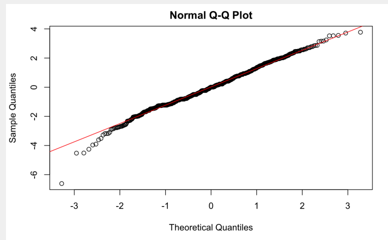
Fraxinus angustifolia	DI				
	HI				
Fraxinus excelsior	DI				
	HI				

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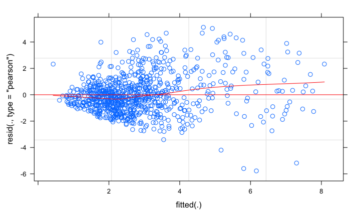
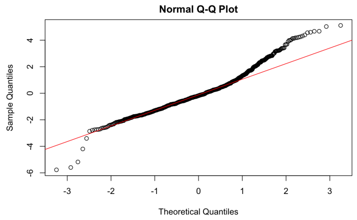
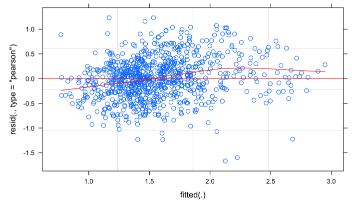
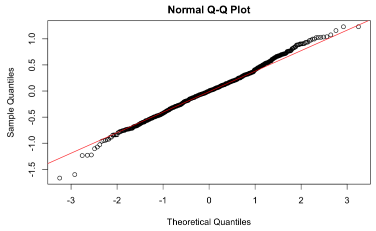
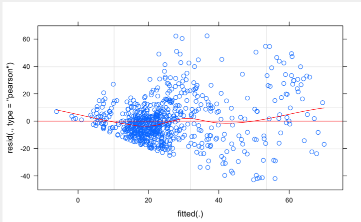
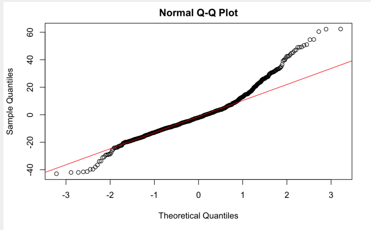
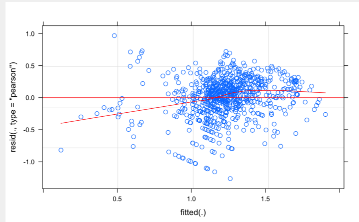
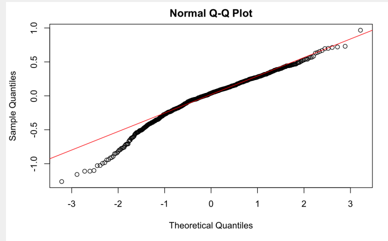
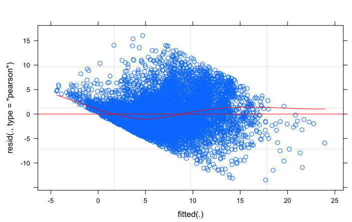
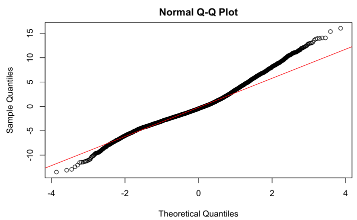
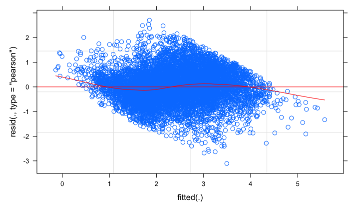
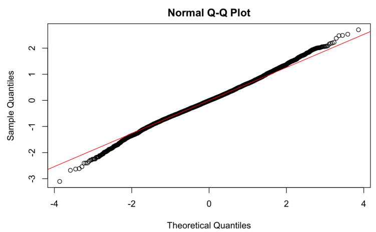
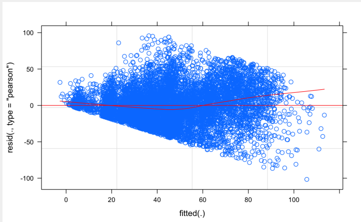
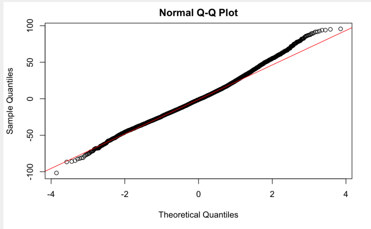
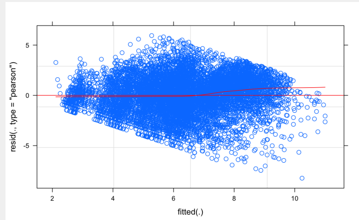
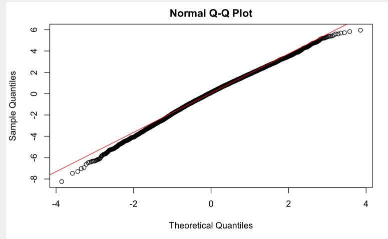
Juglans regia	DI				
	HI				
Juglans x intermedia	DI				
	HI				

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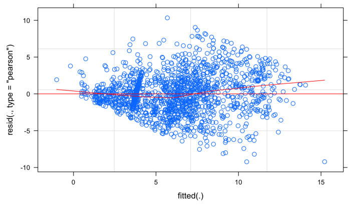
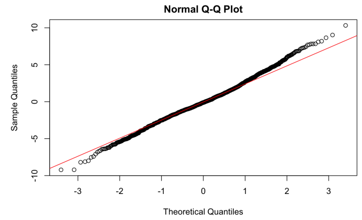
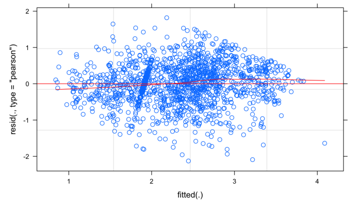
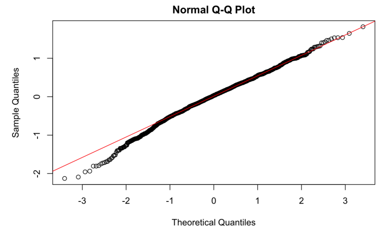
<td></td>
<td></td>
<td></td>
<td></td></tr>
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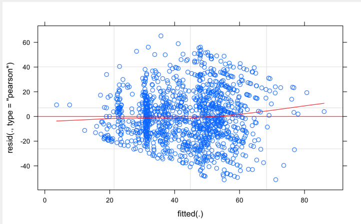
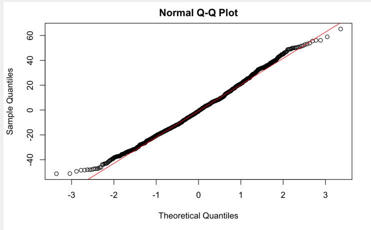
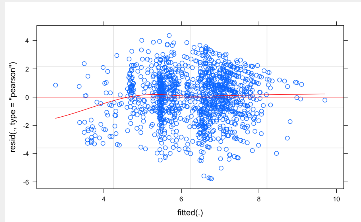
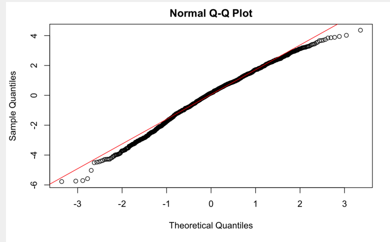
<td></td>
<td></td>
<td></td>
<td></td></tr>
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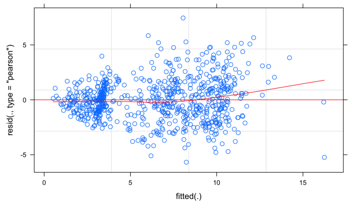
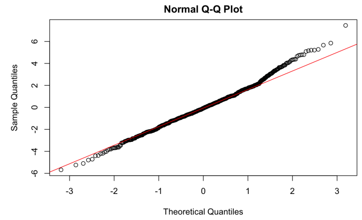
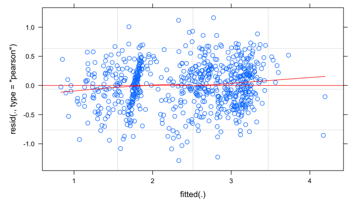
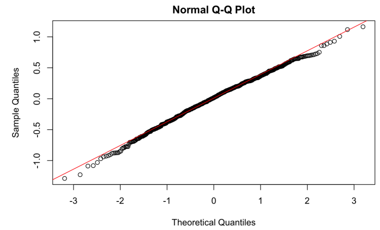
<td></td>
<td></td>
<td></td>
<td></td></tr>
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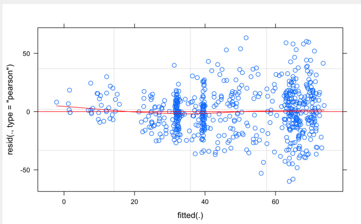
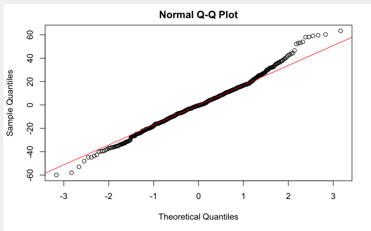
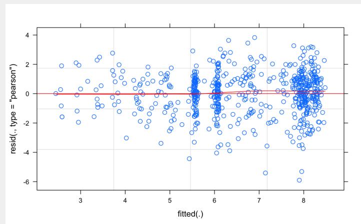
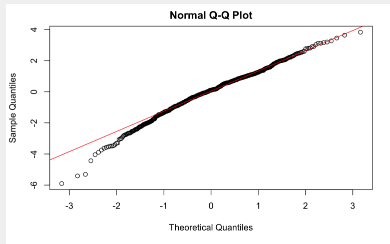
<td></td>
<td></td>
<td></td>
<td></td></tr>
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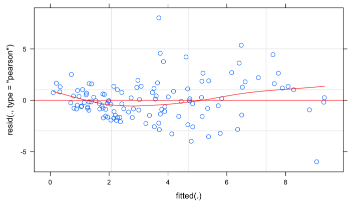
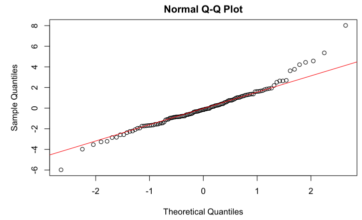
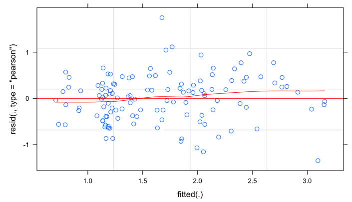
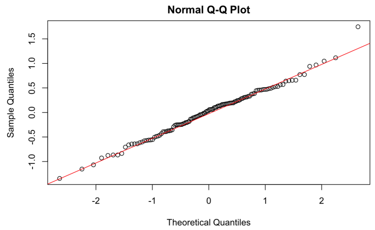
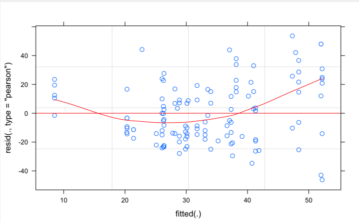
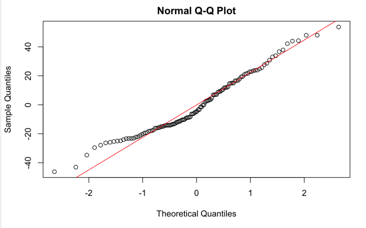
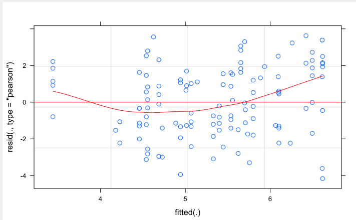
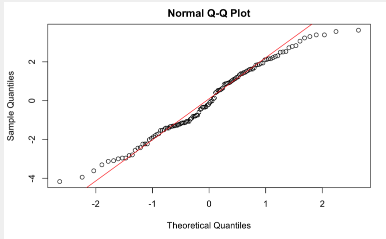
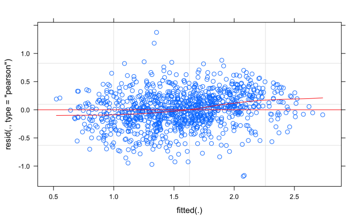
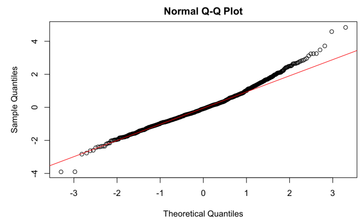
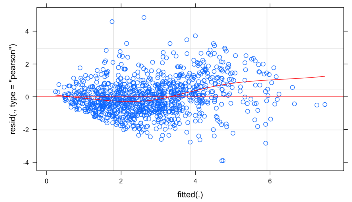
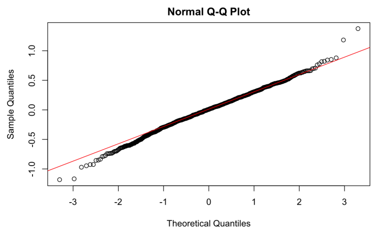
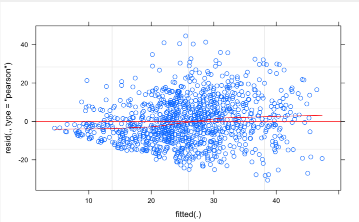
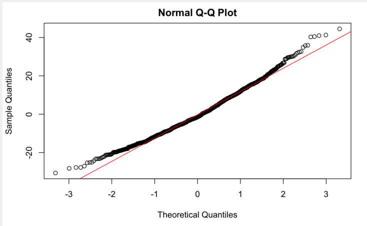
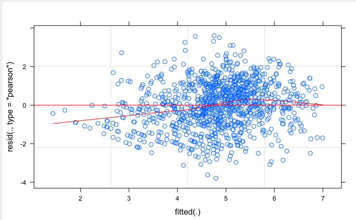
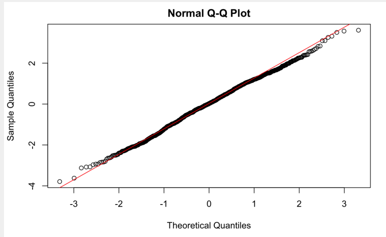
Species	Responce variable	Before transformation of data		After transformation	
Sorbus domestica	DI				
	HI				
Sorbus torminalis	DI				
	HI				

Annex 2: Early diameter and height increment model formula by species

Species	Response	Formula
Acer campestre	DI	sqrt(DI) ~ PD + Summer_P + (1 | plot) + (1 | Year_id)
	HI	sqrt(HI) ~ Summer_P + (1 | plot) + (1 | Year_id)
Acer pseudoplatanus	DI	log(DI) ~ PD + Summer_P + (1 | plot/arbol2) + (1 | Year_id)
	HI	sqrt(HI) ~ Variety + P_july + (1 | plot/arbol2) + (1 | Year_id)
Fraxinus angustifolia	DI	sqrt(DI2) ~ PD + Winter_P + Summer_P + (1 | plot/arbol2) + (1 | Year_id)
	HI	sqrt(HI2) ~ Summer_P + winterMinT + (1 | plot/arbol2) + (1 | Year_id)
Fraxinus excelsior	DI	sqrt(DI) ~ Winter_P + (1 | plot) + (1 | Year_id)
	HI	sqrt(HI2) ~ Winter_P + (1 | plot) + (1 | Year_id)
Juglans regia	DI	sqrt(DI2) ~ PD + Summer_P + (1 | plot/arbol2) + (1 | Year_id)
	HI	log10(HI2) ~ Autumn_P + (1 | plot/arbol2) + (1 | Year_id)
Juglans x intermedia	DI	sqrt(DI2) ~ sqrt(PD) + Autumn_P + Summer_P + Winter_P + (1 | plot/arbol2) + (1 | Year_id)
	HI	sqrt(HI2) ~ PD + Autumn_P + Summer_P + (1 | plot/arbol2) + (1 | Year_id)
Prunus avium	DI	sqrt(DI2) ~ PD + Winter_P + (1 | plot/arbol2) + (1 | Year_id)
	HI	sqrt(HI2) ~ PD + Summer_P + P_nov2 + (1 | plot) + (1 | Year_id)
Pyrus communis	DI	sqrt(DI2) ~ PD + Summer_P + (1 | plot/arbol2) + (1 | Year_id)
	HI	sqrt(HI2) ~ PD + AnnualSumP + (1 | plot) + (1 | Year_id)
Sorbus domestica	DI	sqrt(DI2) ~ PD + P_July + (1 | plot) + (1 | Year_id)
	HI	sqrt(HI2) ~ P_December + (1 | plot) + (1 | Year_id)
Sorbus torminalis	DI	sqrt(DI2) ~ PD + Winter_P + (1 | plot/arbol2) + (1 | Year_id)
	HI	sqrt(HI2) ~ PD + Autumn_P + (1 | plot/arbol2) + (1 | Year_id)

[1]DI: Diameter increment; HI: Height increment; P: Precipitation; PD: Previous dimension; “~/tilde”: as a function of .

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