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Quercus suber Allometry in the West Mediterranean Basin

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Abstract: The necessity for accurate biomass estimates is greater than ever for the sustainable management of forest resources, which is an increasingly pressing matter due to climate change. The most used method to estimate biomass for operational purposes is through allometric equations. Typically, each country develops their own models to be applied at the local scale because it is more convenient. But, for *Quercus suber*, a joint regional model can be more beneficial, since the species is distributed across the Mediterranean and is challenging to account for due to felling limitations and the nature of mature cork biomass itself. We found that these characteristics are reflected in the biomass datasets and compatibility was, perhaps, the largest impediment to such a model. The use of dummy variables to differentiate between countries, as well as compromises in the limits of biomass compartments, allowed us to develop two joint models to estimate aboveground biomass in Portugal, Spain and Tunisia. One model as a function of diameter and another as a function of diameter and total tree height. In addition, we developed a separate model for roots (modelling efficiency of fitting = 0.89), since it was not possible to assure additivity of the whole tree. All coefficients were estimated using Seemingly Unrelated Regressions (SUR) and model fitting assured additivity in the aboveground compartments—leaves and woody biomass (modelling efficiency of fitting = 0.89 and 0.93, respectively). This work proves that it is possible to have a biologically sound and efficient model for the three countries, despite differences in the observed allometric patterns.

Keywords: biomass estimation; cork oak; seemingly unrelated regression; allometry; regional equations; Portugal; Spain; Tunisia; *montado*; *dehesa*

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1. Introduction

The nature of carbon is temporary. It moves from one ecosystem to the next, changing its form. Excess of carbon residing in the atmosphere has caused severe global changes [1]; however, it is possible to slow the rate of climate change by increasing residence time in terrestrial carbon pools [2]. Forests are a significant part of that carbon pool, as regulators of the carbon global cycle. Furthermore, forests store carbon in their soils and biomass, both above and belowground, and many countries in the European Union have made carbon neutrality commitments [3] using carbon sequestration by forests as a strategy to deal with climate change [4]. So, accurately quantifying carbon biomass in trees, while only part of the solution, is of the utmost importance, either to evaluate stand productivity, the success of forest policies, or to study the processes involved in carbon sequestration [5].

The most accurate method to quantify tree biomass is through tree felling and weighting after drying (destructive sampling), which is always an onerous task. But, even if slightly less accurate, biomass estimates can alternatively be obtained from non-destructive biometric measures using allometric equations e.g., [6,7]. The development of such equations relies on statistical concepts and the existence of suitable datasets obtained from destructive sampling that will ultimately dictate the circumstances in which the models should be applied. A comprehensive review on this subject has been made elsewhere [8], pointing out that models are often developed from small and geographically limited datasets, while discussing the limitations.

An adequate equation to estimate biomass within a given region should ideally be based on a set of trees harvested in stands with different site conditions, so as to encompass the variability of growth patterns observed in trees. The biomass data should preferably be kept without any transformation, in order to avoid biased parameter estimates [9], even if it means that it might be necessary to model the error term variance [10]. It is also important to incorporate the property of biomass additivity, i.e., predicted estimates for the different tree components adding up to the total biomass, to preserve the coefficients biological meaning [11,12]. Furthermore, estimator efficiency is another important aspect to consider, since providing narrower confidence intervals for the equation parameters will ensure better biomass estimates [13]. When attempting to incorporate all these aspects, one of the most commonly used methodologies is an additive system of equations where parameters are estimated with seemingly unrelated regression (SUR) [14–16]. Despite these guidelines, the greatest source of error in biomass predictions can be the choice of the model [17], and often times, the performance metrics reported and error procedure methodology can be insufficient [18]. In this regard, well evaluated allometry studies are relevant to understand the adequacy of a model.

Cork oak (*Quercus suber* L.) is a tree species with economic importance and carbon sink potential in the West Mediterranean basin [19–21]. The most commonly used tree variable to model cork oak biomass is diameter at breast height under bark (*du*); when using two variables, it is customary to add total tree height (*h*). Portugal has developed a system of equations as a function of *du* to estimate crown biomass—encompasses leaves and smaller branches—woody and total aboveground biomass [22], but has developed no model for roots. Both Spain and Tunisia have two sets of models: one with *du* as a regressor, to estimate stem wood, branches of diverging thickness, leaves and belowground biomass; and another set of models that add the *h* variable to estimate the biomass of aboveground components only [23–25]. Several studies have quantified cork oak biomass [26–31], but these were focused on individual countries. The use of distinct models and tree compartments in each country is an issue to compare biomass estimates [32], as it makes it difficult to disentangle whether the differences in estimates are due to sampling and data treatment, environmental conditions or allometry. Given these issues, the present work has several objectives to accomplish and questions to investigate:

1. join *Quercus suber* biomass datasets and compare the different allometries in cork oak growth among three countries—Portugal, Spain and Tunisia;
2. is it feasible to develop a joint model that can consistently estimate biomass in the regions where cork oak is prevalent?
3. is the addition of total tree height significant for biomass prediction?
4. provide two alternative root biomass models and two additive SUR aboveground biomass models—one set as a function of *du*, to be used when tree height has not been measured, and the other as a function of *du* and *h*.

2. Materials and Methods

2.1. Dataset Description

A total of 212 trees from Portugal, Spain and Tunisia were gathered into a dataset to fit allometric models. Trees that had already been debarked were considered adult, while trees that were never debarked were considered juvenile. There was a total of 158 juvenile trees (152 from Portugal and 6 from Spain) and a total of 54 adult trees (12 from Portugal, 16 from Tunisia and 26 from Spain). Every country considered different tree compartments in the field procedure to determine biomass, which is described in detail by the respective authors: adult trees in Portugal [33,34], juvenile trees in Portugal [35], trees in Tunisia [24] and trees in Spain [23]. The majority of differences were found in the diameter values to separate branch size along the tree crown architecture. So, in order to make biomass contents compatible, the dataset was homogenized into the three following compartments: leaves, woody biomass—includes stems, branches and virgin cork—and roots. Total aboveground biomass results from the sum of leaves and woody biomass, while belowground biomass is comprised of roots. Mature cork biomass was not considered, as it is periodically extracted. In the case of trees from Spain and Tunisia, it was necessary to estimate the amount of mature cork present in the stem at the moment of felling, since it had not been accounted for in the harvest procedure. This was done in three steps, requiring cork thickness and cork age at felling [36]. When *du* was not directly measured, it was calculated by deducting the cork thickness. A summary of all available variables for the dataset and basic descriptive statistics is given in Table 1 (full dataset available in the supplementary materials, Table S1).

Table 1. A summary of the available tree variables.

Variable [1]	n	Min.	Median	Mean	Max.	sd
du (cm)	212	2.45	5.95	13.49	79.44	14.68
h (m)	212	1.52	2.44	4.75	15.80	3.93
wl (kg)	212	0.10	1.25	4.95	51.28	8.52
ww (kg)	212	0.64	6.51	178.86	3032.49	412.02
wa (kg)	212	0.99	7.67	183.81	3078.68	418.79
wr (kg)	26	7.42	116.67	132.10	454.06	88.89

[1] du: diameter at breast height under bark, h: total height, wl: leaf biomass, ww: woody biomass, wa: aboveground biomass and wr: root biomass.

2.2. Model Fitting

The biomass models were based on the allometric model that has been recognized as appropriate to establish the relationship between two parts of the same organism [37,38]:

$$Biomass\ Compartment = a \times x^b, \tag{1}$$

where, x is a tree variable (du, in this case); a and b are parameters. The value of the allometric scalar—a—is heavily influenced by the actual values of the tree variables used to build the power law and the respective units, while the allometric exponent—b—is much more stable and captures the growth pattern of a species [9,39].

The model described by Equation (1) will henceforth be referred to as the reduced model. However, the allometric model in its generalized form to two variables, has also been used and will be referred to as the full model:

$$Biomass\ Compartment = a \times x^b \times y^c, \tag{2}$$

where, x and y are tree variables (du and h, in this case); a, b and c are parameters.

The biomass models were developed in the following steps:

(1) fitting individual allometric equations for each biomass compartment using the reduced and full model, without differentiating between countries;
(2) addition of dummy variables for each country at each individual equation and selection of a model for each biomass compartment, in which all the parameters were significantly different from zero;
(3) fitting aboveground components in a system of equations, in order to guarantee the additivity between total biomass and the other two biomass components.

The full model fitting procedure was done for both SUR models (reduced and full) and the biomass model for roots did not require step 3, since the additivity property could not be taken into account because root biomass was only available for a small subset of the total trees sampled.

Basic descriptive statistics and scatterplots were produced in the R software [40], while all steps of the model fitting procedure were carried out in SAS software [41] with the MODEL procedure. Steps 1 and 2 used ordinary least squares (OLS) as estimator for all biomass components and step 3 used iterated SUR for the aboveground biomass components only.

The aboveground biomass system has three equations, according to the compartments: leaves, woody biomass and one for the sum of leaves and woody biomass. The starting point to fit the system was to use the best individual model for each compartment selected in step 2. Furthermore, in order to separate the observations by country, two dummy variables were created: *SP* and *TUN*. If the tree belonged to Spain, *SP* = 1 and 0 otherwise. If the tree belonged to Tunisia, *TUN* = 1 and 0 otherwise. So, if both dummy variables were 0, then the model applied to the trees from Portugal. The general equation with dummy variables is defined as follows:

$$Biomass\ Compartment = (a_1 + a_2 \times SP + a_3 \times TUN) \times du^{(b_1+b_2\times SP+b_3\times TUN)} \times h^{(c_1+c_2\times SP+c_3\times TUN)}, \quad (3)$$

where a_i, b_i and c_i are the parameters associated with each dummy variable (i = 1, 2 and 3). It is important to note that if *SP* = 1 or *TUN* = 1, parameter values are presented taking into account a_1, b_1 and c_1, i.e., taking into account similarities between countries through the common parameters. In addition, there were no roots from Portugal, so the baseline of that model was Spain and the only dummy variable is *TUN*. Parameters were added in a forward stepwise procedure until all were significantly different from zero (α = 0.05), while minimizing the sum of squared errors (SSE).

Reporting metrics of model fit is imperative in order to guarantee model adequacy [42–44]. Several performance metrics were used to compare models, namely: SSE, Root Mean Squared Error (RMSE), a measure equivalent to the adjusted coefficient of determination—the modelling efficiency of fitting (EF_{fit}). However, we report only EF_{fit}, as this is the only comparable measure when different weights are applied to the models. Since the dataset was small and it was not feasible to collect an additional independent dataset, model validation was done using the so called PRESS residuals, that are successively computed for each data point with the parameter estimates obtained with a model fitted without this particular data point (leave-one-out jackknife method) [45]. The following validation statistics were computed: mean of PRESS residuals (mPRESS), mean of absolute PRESS residuals (maPRESS) and predictive modelling efficiency ($EF_{pred.}$).

The usual plots to test the regression assumptions of normality and heteroscedasticity of the residuals were evaluated. Weighted regression was applied when heteroscedasticity was not verified and several weight functions were tested, namely the inverse of the response variable, the inverse of the squared fitted values and fitted values, the inverse of the dependent variable and similar variations, following the method described by Parresol [12].

3. Results

3.1. The Need for Country Specific Models and for including Total Height

Step 1 of the fitting procedure (Section 2.2) allowed confirmation that the height variable is significant, but most importantly, suggested the need for a dummy variable to differentiate between countries. Step 2 showed the results reported in Table 2, where the need to have country specific models, at least in the aboveground compartments, is clear.

The coefficient a_2 in both of the root biomass models displayed a high p-value at any of the usual significance levels. But it cannot be dropped since it is not an additive term in the model. We opted to keep the estimate fixed because assuming a_2 = 1 was not correct, as it does not fall within the confidence interval for the estimate.

Table 2. Coefficients and performance metrics for the weighted models described by Equation (3).

Model Description		Coefficients									Performance
		a_1	a_2	a_3	b_1	b_2	b_3	c_1	c_2	c_3	EF_{fit}
Reduced model	*wl*	0.09 ***	0.02 ***	0.06 ***	1.58 ***						0.86
	ww	0.08 ***	0.24 *		2.60 ***	2.13 ***	2.49 ***				0.87
	wa	0.15 ***			2.42 ***	2.23 ***	2.31 ***				0.88
	wr [1]		0.26 [2]			1.76 ***	1.86 ***				0.87
Full model	*wl*	0.10 ***	0.02 ***	0.05 ***	1.21 ***			1.80 ***			0.89
	ww	0.10 ***			2.07 ***	1.48 **	1.84 ***	0.75 ***	1.41 *		0.92
	wa	0.14 ***			1.97 ***	1.81 ***	1.75 ***	0.74 ***			0.89
	wr [1]		0.16 [2]			1.43 ***			0.76 ***		0.89

All coefficients a_i, b_i and c_i, were marked with symbols according to the following: *** indicates $p < 0.001$, ** $p < 0.01$ and * $p < 0.05$. Empty cells indicate that the parameter was not significantly different from zero at the usual α levels. Greyed out cells indicate that the parameter is not part of the model fitting. *wl*: leaf biomass, *ww*: woody biomass, *wa*: aboveground biomass, *wr*: root biomass. EF_{fit}: modelling efficiency of fitting, calculated with non-weighted residuals. [1] Both models for roots do not have weights. [2] The coefficient estimate was fixed.

As expected, the coefficients b_i are generally always significant and the addition of h always improves model performance. But it is interesting to note that the coefficients b_i and c_i associated with Spain and Tunisia were not statistically significant for leaves (*wl*). In addition, coefficient a_2 loses significance when height is added in the woody compartment (*ww*).

3.2. Two Systems of Equations for Aboveground Biomass

Step 3 of the fitting procedure (simultaneous fitting of the aboveground biomass compartments, Section 2.2) provided the results reported in Table 3, where all parameters remained with the same level of significance as reported in Table 2, or even higher.

Table 3. Coefficients and performance metrics for the SUR weighted systems of equations.

Model Description		Coefficients									Performance
		a_1	a_2	a_3	b_1	b_2	b_3	c_1	c_2	c_3	EF_{fit}
Reduced model	*wl*	0.09 ***	0.02 ***	0.06 ***	1.60 ***						0.86
	ww	0.08 ***	0.26 **		2.59 ***	2.09 ***	2.48 ***				0.89
	wa	*wl* + *ww*									0.89
Full model	*wl*	0.11 ***	0.03 ***	0.05 ***	1.13 ***			0.65 ***			0.89
	ww	0.10 ***			2.07 ***	1.40 ***	1.84 ***	0.75 ***	1.54 **		0.93
	wa	*wl* + *ww*									0.93

All coefficients a_i, b_i and c_i, were marked with symbols according to the following: *** indicates $p < 0.001$ and ** $p < 0.01$. Empty values indicate that the parameter was not significantly different from zero at the usual α levels. Greyed out cells indicate that the parameter is not part of the model fitting. *wl*: leaf biomass, *ww*: woody biomass, *wa*: aboveground biomass. EF_{fit}: modelling efficiency of fitting, calculated with non-weighted residuals.

As expected, the metric EF_{fit} improved or was maintained from the individual fits to the simultaneous equation fits. A graphical representation of all final reduced models are shown in Figure 1, where it is possible to see that the compartments with the greatest variability are woody and aboveground biomass. However, their patterns are nearly identical, since most of the biomass can be found in wood at the moment of sampling. Leaves show less variability of observed values but starkly different patterns.

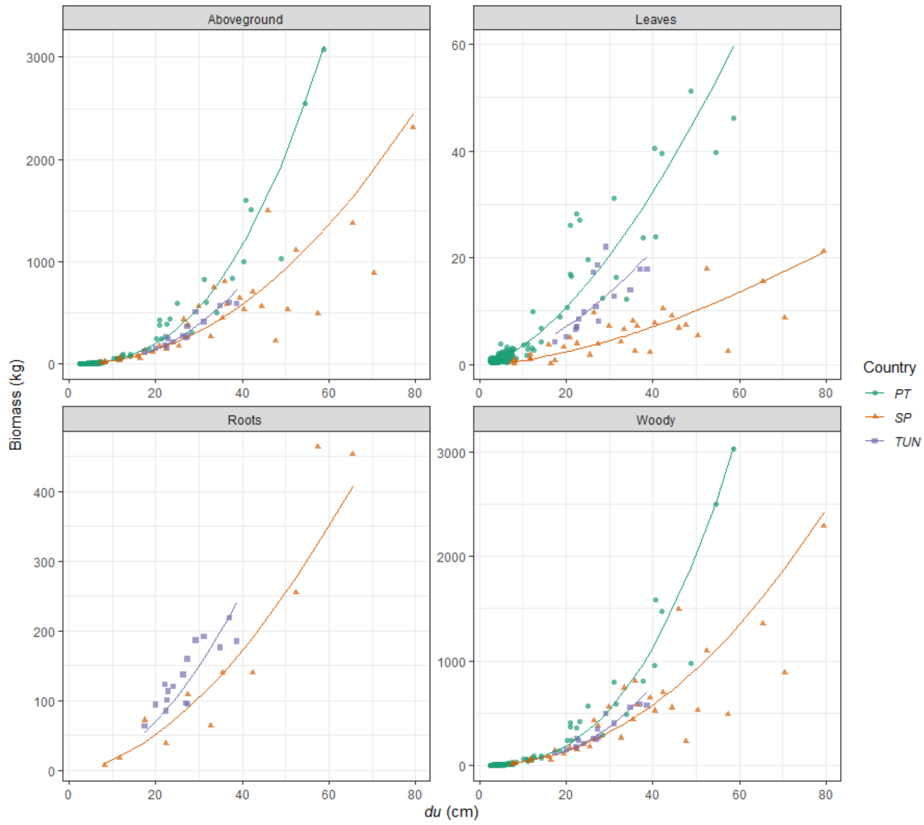

Figure 1. Best reduced models with weights for all biomass compartments: leaves, woody and aboveground show the simultaneous equations fit, while roots show the individual equation fit. The green dots represent the models for Portugal, orange triangles represent Spain and purple squares represent Tunisia.

3.3. Evaluating the Models

Regarding model validation (Table 4), the best performance was found to be in the SUR full model for aboveground compartments (*wl*, *ww* and *wa*). Roots also had better predictive ability in the full model.

Table 4. Cross-validation metrics for all models.

Model Description			Cross-Validation Metrics		
			mPRESS	**maPRESS**	$EF_{pred.}$
INDIVIDUAL EQUATIONS	Reduced model	*wl*	−0.0032	0.14	0.84
		ww	−0.0005	0.06	0.85
		wa	−0.0286	0.36	0.86
		wr	3.17	25.50	0.59
	Full model	*wl*	−0.0013	0.08	0.87
		ww	0.0002	0.04	0.90
		wa	0.0002	0.05	0.88
		wr	1.48	24.28	0.84
SUR	Reduced model	*wl*	0.0029	0.14	0.86
		ww	0.0020	0.04	0.89
		wa	0.0053	0.08	0.89
	Full model	*wl*	−0.0060	0.08	0.89
		ww	−0.0002	0.04	0.93
		wa	−0.0007	0.05	0.93

wl: leaf biomass, *ww*: woody biomass, *wa*: aboveground biomass, *wr*: root biomass. mPRESS: mean of PRESS residuals, maPRESS: mean of absolute PRESS residuals and $EF_{pred.}$: predictive modelling efficiency.

There were issues with heteroscedasticity for all aboveground compartments. The best method to solve the issues was Parresol's method to model the error term by taking the logarithm of the squared residuals and the logarithm of the original dependent variable. There were no serious issues with heteroscedasticity for roots. Figure 2 shows all the plots of studentized residual for each compartment.

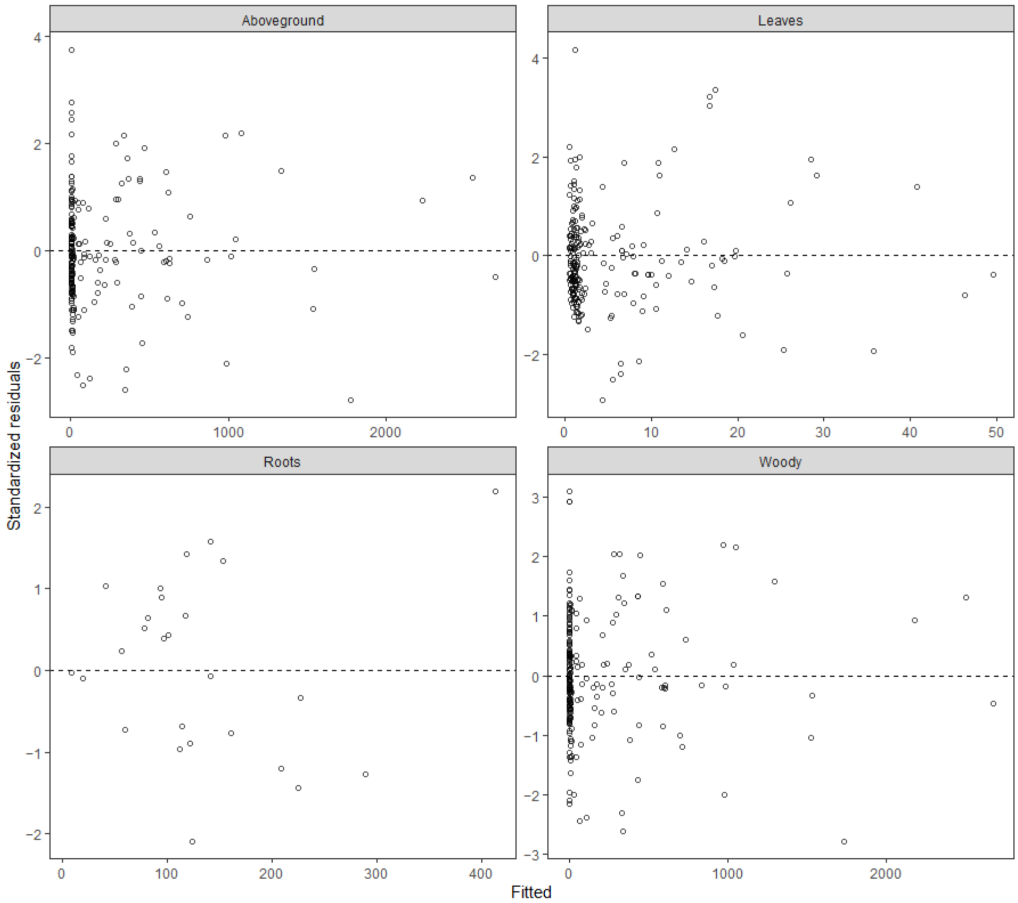

Figure 2. Fitted values *versus* studentized residuals of the best models for all biomass compartments: the fitted values for leaves, woody and aboveground are from the full SUR model and the residuals are weighted; the fitted values for roots are from the individual full model and the residuals are not weighted.

4. Discussion

4.1. Advantages and Disadvantages of Joining a Dataset from Three Countries

The most obvious limitation to joining separate datasets is the difference in sampling procedures. This is especially true for foliage and roots [8,32], which can have considerable differences due to the practical difficulties associated with the sampling process. Furthermore, there is no standard definition of compartments, so in order to join a dataset the modeler is forced to group compartments to achieve data compatibility. These issues are exacerbated in cork oak trees for two reasons: cork can be extremely heterogeneous and each country accounts for cork biomass with its own guidelines. Another important issue is that cork oak trees are usually protected by legislation which prevents their felling and determines a reduced number of observations. Thus, the gain in joining datasets in the Mediterranean region, for cork oak particularly, could far outweigh the weaknesses.

The advantages of joining datasets are the increase in range of tree characteristics—*du* and *h*, in this case—and a higher level of geographical representation. It is common practice to build allometric models based on *du* alone, since it is highly correlated with biomass growth, while also being relatively easy, accurate and inexpensive to measure. However, this practice assumes a constant $\frac{du}{h}$, which is not true due to tree competition e.g., [46,47] further deviates from the truth in larger scale models [48]. Several authors support the idea that more complex regional models with a greater availability of data and variables can be useful, especially in regions that are underrepresented [49,50], provided that due diligence in model use and dataset compatibility is exerted.

4.2. Is It Feasible to Develop a Joint Model That Can Consistently Estimate Biomass in the Regions Where Cork Oak Is Prevalent?

It was not possible to develop a system of equations with additivity for the whole tree, since Portugal had no data on root biomass and in Spain and Tunisia not all trees had been sampled for roots. Therefore, it was necessary to separate between belowground and aboveground biomass.

Belowground biomass models used only data from two countries—Spain and Tunisia—which show that there are significant differences in root allometry (Figure 1 and Table 2). These differences are related to climatic and stand characteristics, as well as soil type and soil water dynamics, since these factors have a great influence in root development [51,52]. However, the best general model for roots is the full model, in which no significant allometric differences were found, but both the fit and predictive modeling efficiencies (Tables 2 and 4) were better.

Aboveground biomass data allowed a joint model with no distinction between countries, i.e., no dummy variables. However, such a model would not be accurate for any one country. This inadequacy is especially noticeable in the leaves compartment (Figure 1), which was to be expected due to their intrinsic variability [53,54]. But we found that all aboveground biomass estimates for each particular country can be significantly improved by including dummy variables (Equation (3) and Table 2). Furthermore, the full model for woody biomass required dummies for coefficients related to du and h only—b_i and c_i—which are more related to growth patterns, and thus, indicating that each country has indeed significantly different allometries. On the other hand, the equation for leaf biomass required only dummies for the a_i coefficient, which is sensitive to the choice of independent variables and its units [9,39], suggesting that the growth patterns exhibited by tree foliage were masked either by du or by its measurement units.

The growth pattern of tree foliage is influenced by different management practices related to pruning, thinning and stand density and several authors have found that crown variables are tremendously important in describing the leaf allometry of cork oak [6,55,56]. These variables were not available for this study. However, some information on stand density (N, trees/ha) was accessible. Portugal and Tunisia were found to be more similar in the aboveground compartments, despite extremely different stand densities: 4–304 *versus* 512–560, respectively. The stands in Los Alcornocales Natural Park, Spain, where many biomass samples were collected, have a density in the range 87–334 [57,58]. So it seems that stand density cannot explain all the variability in leaves, at least not straightforwardly. Furthermore, cork oak forests of low density don't exhibit signs of tree competition and we can expect the management options often applied in these systems, namely pruning, to be the dominant cause of differences [59–62]. It is also possible that differences in leaf biomass could simply be from a distinct timing in the sampling method itself, since leaf biomass is not static. But a more detailed exploratory analysis of the effect of stand density, crown width and crown length in future studies would be highly enlightening.

Regardless, it is clear that the full SUR model is superior to the individual allometric models, which has been shown by other authors to be true when there is some correlation between the response variables and restrictions on the coefficients are necessary e.g., [11,13]. In addition, and as expected, forcing additivity is a suitable pre-requisite for biomass modelling, since the quality of the SUR model is not worsened by imposing such a restraint (Tables 2 and 3).

4.3. Is the Addition of Total Tree Height Significant for Biomass Prediction?

The full model with *du* and *h* provide better estimates of biomass, in all compartments, than the reduced models (Tables 2 and 4). But it should be noted that when *h* was added to the roots reduced model, the coefficients associated with dummy variables were not significant. This indicates that a model with no distinction between countries works well for roots, provided that enough information about tree characteristics, namely *du* and *h*, are used. Despite this, we provide the reduced models for every compartment because on its own, *du* is the best, most common regressor of biomass and *h* might not be available. Furthermore, *h* estimation in cork oak could be a bit inaccurate in comparison with other species due to the crown architecture.

5. Conclusions

The biomass estimates for leaves, woody, total aboveground and roots always improve with the addition of height, even though height is not the most adequate variable to estimate leaf biomass. We found that by making reasonable compromises in the level of detail with which biomass compartment limits are set, it is possible to join datasets from three different countries and mitigate the scarcity of cork oak destructive sampling data. Furthermore, each country had significantly different allometries in every biomass compartment, but these differences can be accounted for with dummy variables, thereby allowing a regional model that can harmoniously quantify the carbon stocks of cork oak.

Supplementary Materials: The biomass datasets with which the models were developed are available online at https://www.mdpi.com/article/10.3390/f14030649/s1, Table S1: Dataset_SupMaterials.

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Data Availability Statement: The different datasets analyzed in this research were gathered, homogenized and made available in the Supplementary Materials as an excel file.

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References

1. Pörtner, H.-O.; Roberts, D.C.; Tignor, M.; Poloczanska, E.S.; Mintenbeck, K.; Alegría, A.; Craig, M.; Langsdorf, S.; Löschke, S.; Möller, V.; et al. *Climate Change 2022: Impacts, Adaptation, and Vulnerability*; IPCC: Geneva, Switzerland, 2022.
2. Keenan, T.F.; Williams, C.A. The Terrestrial Carbon Sink. *Annu. Rev. Environ. Resour.* **2018**, *43*, 219–243. [CrossRef]
3. Santos, F.D.; Ferreira, P.L.; Pedersen, J.S.T. The Climate Change Challenge: A Review of the Barriers and Solutions to Deliver a Paris Solution. *Climate* **2022**, *10*, 75. [CrossRef]
4. Andersen, S.P.; Allen, B.; Domingo, G.C. *Biomass in the EU Green Deal: Towards Consensus on the Use of Biomass for EU Bioenergy*; Policy Report; Institute for European Environmental Policy (IEEP): Brussels, Belgium, 2021.
5. Brown, S. Measuring Carbon in Forests: Current Status and Future Challenges. *Environ. Pollut.* **2002**, *116*, 363–372. [CrossRef] [PubMed]
6. António, N.; Tomé, M.; Tomé, J.; Soares, P.; Fontes, L. Effect of Tree, Stand, and Site Variables on the Allometry of Eucalyptus Globulus Tree Biomass. *Can. J. For. Res.* **2007**, *37*, 895–906. [CrossRef]
7. Zianis, D.; Muukkonen, P.; Mäkipää, R.; Mencuccini, M. *Biomass and Stem Volume Equations for Tree Species in Europe*; Silva Fennica, The Finnish Society of Forest Science: Helsinki, Finland, 2005; Volume 4, ISBN 9514019830.
8. Weiskittel, A.R.; MacFarlane, D.W.; Radtke, P.J.; Affleck, D.L.R.; Temesgen, H.; Woodall, C.W.; Westfall, J.A.; Coulston, J.W. A Call to Improve Methods for Estimating Tree Biomass for Regional and National Assessments. *J. For.* **2015**, *113*, 414–424. [CrossRef]
9. Ter-Mikaelian, M.T.; Korzukhin, M.D. Biomass Equations for Sixty-Five North American Tree Species. *For. Ecol. Manag.* **1997**, *97*, 1–24. [CrossRef]

10. Trautenmüller, J.W.; Péllico Netto, S.; Balbinot, R.; Watzlawick, L.F.; Dalla Corte, A.P.; Sanquetta, C.R.; Behling, A. Regression Estimators for Aboveground Biomass and Its Constituent Parts of Trees in Native Southern Brazilian Forests. *Ecol. Indic.* **2021**, *130*, 108025. [CrossRef]
11. Parresol, B.R. Assessing Tree and Stand Biomass: A Review with Examples and Critical Comparisons. *For. Sci.* **1999**, *4*, 573–593.
12. Parresol, B.R. Additivity of Nonlinear Biomass Equations. *Can. J. For. Res.* **2001**, *31*, 865–878. [CrossRef]
13. Behling, A.; Netto, S.P.; Sanquetta, C.R.; Corte, A.P.D.; Affleck, D.L.R.; Rodrigues, A.L.; Behling, M. Critical Analyses When Modeling Tree Biomass to Ensure Additivity of Its Components. *An. Acad. Bras. Cienc.* **2018**, *90*, 1759–1774. [CrossRef]
14. Carvalho, J.P.; Parresol, B.R. Additivity in Tree Biomass Components of Pyrenean Oak (*Quercus pyrenaica* Willd.). *For. Ecol. Manag.* **2003**, *179*, 269–276. [CrossRef]
15. Poudel, K.P.; Temesgen, H. Methods for Estimating Aboveground Biomass and Its Components for Douglas-Fir and Lodgepole Pine Trees. *Can. J. For. Res.* **2015**, *46*, 77–87. [CrossRef]
16. Xie, L.; Li, F.; Zhang, L.; Widagdo, F.R.A.; Dong, L. A Bayesian Approach to Estimating Seemingly Unrelated Regression for Tree Biomass Model Systems. *Forests* **2020**, *11*, 1302. [CrossRef]
17. Picard, N.; Boyemba Bosela, F.; Rossi, V. Reducing the Error in Biomass Estimates Strongly Depends on Model Selection. *Ann. For. Sci.* **2015**, *72*, 811–823. [CrossRef]
18. Sileshi, G.W. A Critical Review of Forest Biomass Estimation Models, Common Mistakes and Corrective Measures. *For. Ecol. Manag.* **2014**, *329*, 237–254. [CrossRef]
19. Oubrahim, H.; Boulmane, M.; R Bakker, M.; Augusto, L.; Mohammed, H. Carbon Storage in Degraded Cork Oak (*Quercus suber*) Forest on Flat Lowlands in Morocco. *Iforest Biogeosci. For.* **2016**, *9*, 125–137. [CrossRef]
20. Palma, J.H.N.; Paulo, J.A.; Tomé, M. Carbon Sequestration of Modern *Quercus suber* L. Silvoarable Agroforestry Systems in Portugal: A YieldSAFE-Based Estimation. *Agrofor. Syst.* **2014**, *88*, 791–801. [CrossRef]
21. Correia, A.C.; Costa e Silva, F.; Correia, A.V.; Hussain, M.Z.; Rodrigues, A.D.; David, J.S.; Pereira, J.S. Carbon Sink Strength of a Mediterranean Cork Oak Understorey: How Do Semi-Deciduous and Evergreen Shrubs Face Summer Drought? *J. Veg. Sci.* **2014**, *25*, 411–426. [CrossRef]
22. Paulo, J.A.; Tomé, M. *Equações Para Estimação Do Volume e Biomassa de Duas Espécies de Carvalhos: Quercus Suber e Quercus Ilex*; Publicações GIMREF RC1/2006; Universidade Técnica de Lisboa—Instituto Superior de Agronomia, Centro de Estudos Florestais: Lisboa, Portugal, 2006.
23. Ruiz-Peinado, R.; Montero, G.; Del Rio, M. Biomass Models to Estimate Carbon Stocks for Hardwood Tree Species. *For. Syst.* **2012**, *21*, 42. [CrossRef]
24. Zribi, L.; Chaar, H.; Khaldi, A.; Hanchi, B.; Mouillot, F.; Gharbi, F. Estimate of Biomass and Carbon Pools in Disturbed and Undisturbed Oak Forests in Tunisia. *For. Syst.* **2016**, *25*, e060. [CrossRef]
25. Montero, G.; Ruiz-peinado, R.; Muñoz, M. *Producción de Biomasa y Fijación de CO_2 Por Los Bosques Españoles*; INIA-Instituto Nacional de Investigación y Tecnología Agraria y Alimentaria: Madrid, Spain, 2005; Volume 13, ISBN 84-7498-512-9.
26. Laporta, L.; Domingos, T.; Marta-Pedroso, C. It's a Keeper: Valuing the Carbon Storage Service of Agroforestry Ecosystems in the Context of CAP Eco-Schemes. *Land Use Policy* **2021**, *109*, 105712. [CrossRef]
27. von Essen, M.; do Rosário, I.T.; Santos-Reis, M.; Nicholas, K.A. Valuing and Mapping Cork and Carbon across Land Use Scenarios in a Portuguese Montado Landscape. *PLoS ONE* **2019**, *14*, e02121. [CrossRef] [PubMed]
28. Coelho, M.B.; Paulo, J.A.; Palma, J.H.N.; Tomé, M. Contribution of Cork Oak Plantations Installed after 1990 in Portugal to the Kyoto Commitments and to the Landowners Economy. *For. Policy Econ.* **2012**, *17*, 59–68. [CrossRef]
29. Cañellas, I.; Sánchez-González, M.; Adame, P.; Moreno-Fernández, D.; Bogino, S.M.; Herrero, C.; Roig, S.; Tomé, M.; Paulo, J.A.; Bravo, F. Carbon Sequestration in Mediterranenan Oak Forests. In *Managing Forest Ecosystems: The Challenge of Climate Change*; Bravo, F., LeMay, V., Jandl, R., Eds.; Springer: Cham, Switzerland, 2017; pp. 403–427.
30. Demertzi, M.; Sierra-Pérez, J.; Paulo, J.A.; Arroja, L.; Dias, A.C. Environmental Performance of Expanded Cork Slab and Granules through Life Cycle Assessment. *J. Clean. Prod.* **2017**, *145*, 294–302. [CrossRef]
31. Demertzi, M.; Paulo, J.A.; Arroja, L.; Dias, A.C. A Carbon Footprint Simulation Model for the Cork Oak Sector. *Sci. Total Environ.* **2016**, *566–567*, 499–511. [CrossRef]
32. Neumann, M.; Moreno, A.; Mues, V.; Härkönen, S.; Mura, M.; Bouriaud, O.; Lang, M.; Achten, W.M.J.; Thivolle-Cazat, A.; Bronisz, K.; et al. Comparison of Carbon Estimation Methods for European Forests. *For. Ecol. Manag.* **2016**, *361*, 397–420. [CrossRef]
33. Paulo, J.; Tomé, M. *Recolha de Dados Para Determinação de Biomassas e Volumes de Sobreiro (Quercus suber). Protocolo Para a Instalação de Parcelas Temporárias e Medição de Árvores Amostra*; Publicações FORCHANGE RT3/2008; Universidade Técnica de Lisboa—Instituto Superior de Agronomia, Centro de Estudos Florestais: Lisboa, Portugal, 2008.
34. Paulo, J.A.; Tomé, M.; Uva, J.S. *Recolha de Dados de Biomassa de Azinheiras (Quercus Ilex). Protocolo Para a Instalação de Parcelas Temporárias e Medição Das Árvores Amostra.*; Publicações GIMREF RT6/2001; Universidade Técnica de Lisboa—Instituto Superior de Agronomia, Centro de Estudos Florestais: Lisboa, Portugal, 2001.
35. Varela, M.C.; Bellarosa, R.; Eriksson, G.; Bariteau, M.; Catalan, G.; Branco, T.; Barros, I.R.; Almeida, H.; Chambel, R.; Sbay, H.; et al. *Handbook of the Concerted Action "European Network for the Evaluation of Genetic Resources of Cork Oak for Appropriate Use in Breeding and Gene Conservation Strategies". Reference—FAIR 1 CT 95-0202*; Varela, M.C., Ed.; Estação Florestal Nacional: Lisboa, Portugal, 2000; ISBN 972-95736-7-0.

36. Paulo, J.A.; Tomé, M. Predicting Mature Cork Biomass with t Years of Growth from One Measurement Taken at Any Other Age. *For. Ecol. Manag.* **2010**, *259*, 1993–2005. [CrossRef]
37. Attiwill, P.M.; Ovington, J.D. Determination of Forest Biomass. *For. Sci.* **1968**, *14*, 13–15.
38. O'Brien, S.T.; Hubbell, S.P.; Spiro, P.; Condit, R.; Foster, R.B. Diameter, Height, Crown, and Age Relationships in Eight Neotropical Tree Species. *Ecology* **1995**, *76*, 1926–1939. [CrossRef]
39. Thornley, J.H.M.; Johnson, I.R. *Plant and Crop Modelling*; Oxford University Press: Oxford, UK, 1990.
40. *R Core Team R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2021.
41. *SAS/ETS 13.2 User's Guide*; SAS Institute Inc.: Cary, NC, USA, 2014.
42. Jara, M.C.; Henry, M.; Réjou-Méchain, M.; Wayson, C.; Zapata-Cuartas, M.; Piotto, D.; Alice Guier, F.; Castañeda Lombis, H.; Castellanos López, E.; Cuenca Lara, R.; et al. Guidelines for Documenting and Reporting Tree Allometric Equations. *Ann. For. Sci.* **2015**, *72*, 763–768. [CrossRef]
43. Soares, P.; Tomé, M.; Skovsgaard, J.P.; Vanclay, J.K. Evaluating a Growth Model for Forest Management Using Continuous Forest Inventory Data. *For. Ecol. Manag.* **1995**, *71*, 251–265. [CrossRef]
44. Vanclay, J.K.; Skovsgaard, J.P. Evaluating Forest Growth Models. *Ecol. Modell.* **1997**, *98*, 1–12. [CrossRef]
45. Myers, R.H. *Classical and Modern Regression with Applications*, 2nd ed.; Duxbury Press: Belmont, CA, USA, 1990.
46. Assmann, E. *The Principles of Forest Yield Study*; Pergamon Press: Oxford, UK, 1970.
47. Burkhart, H.E.; Tomé, M. *Modeling Forest Trees and Stands*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2012; ISBN 978-94-007-1597-4. [CrossRef]
48. Temesgen, H.; Affleck, D.; Poudel, K.; Gray, A.; Sessions, J. A Review of the Challenges and Opportunities in Estimating above Ground Forest Biomass Using Tree-Level Models. *Scand. J. For. Res.* **2015**, *30*, 326–335. [CrossRef]
49. Forrester, D.I.; Tachauer, I.H.H.; Annighoefer, P.; Barbeito, I.; Pretzsch, H.; Ruiz-Peinado, R.; Stark, H.; Vacchiano, G.; Zlatanov, T.; Chakraborty, T.; et al. Generalized Biomass and Leaf Area Allometric Equations for European Tree Species Incorporating Stand Structure, Tree Age and Climate. *For. Ecol. Manag.* **2017**, *396*, 160–175. [CrossRef]
50. Dutcă, I.; Mather, R.; Ioraș, F. Sampling Trees to Develop Allometric Biomass Models: How Does Tree Selection Affect Model Prediction Accuracy and Precision? *Ecol. Indic.* **2020**, *117*, 106553. [CrossRef]
51. David, T.S.; Pinto, C.A.; Nadezhdina, N.; Kurz-Besson, C.; Henriques, M.O.; Quilhó, T.; Cermak, J.; Chaves, M.M.; Pereira, J.S.; David, J.S. Root Functioning, Tree Water Use and Hydraulic Redistribution in *Quercus suber* Trees: A Modeling Approach Based on Root Sap Flow. *For. Ecol. Manag.* **2013**, *307*, 136–146. [CrossRef]
52. David, T.S.; Pinto, C.A.; Nadezhdina, N.; David, J.S. Water and Forests in the Mediterranean Hot Climate Zone: A Review Based on a Hydraulic Interpretation of Tree Functioning. *For. Syst.* **2016**, *25*, eR02. [CrossRef]
53. Paulo, J.A.; Tomé, J.; Tomé, M. Ajustamento Simultâneo de Equações de Biomassa de Azinheira. In Proceedings of the Actas do X Congresso da Sociedades Portuguesa de Estadística, Porto, Portugal, 25–28 September 2002.
54. Andivia, E.; Bou, J.; Fernández, M.; Caritat, A.; Alejano, R.; Vilar, L.; Vázquez-Piqué, J. Assessing the Relative Role of Climate on Litterfall in Mediterranean Cork Oak Forests. *IForest* **2018**, *11*, 786–793. [CrossRef]
55. Sánchez-González, M.; Cañellas, I.; Montero, G. Generalized Height-Diameter and Crown Diameter Prediction Models for Cork Oak Forests in Spain. *Investig. Agrar. Sist. Recur. For.* **2007**, *16*, 76. [CrossRef]
56. Menéndez-Miguélez, M.; Calama, R.; Del Río, M.; Madrigal, G.; López-Senespleda, E.; Pardos, M.; Ruiz-Peinado, R. Species-Specific and Generalized Biomass Models for Estimating Carbon Stocks of Young Reforestations. *Biomass Bioenergy* **2022**, *161*, 10645. [CrossRef]
57. Sánchez-González, M.; Calama, R.; Cañellas, I.; Montero, G. Variables Influencing Cork Thickness in Spanish Cork Oak Forests: A Modelling Approach. *Ann. For. Sci.* **2007**, *64*, 301–312. [CrossRef]
58. Sánchez-González, M.; Tomé, M.; Montero, G. Modelling Height and Diameter Growth of Dominant Cork Oak Trees in Spain. *Ann. For. Sci.* **2007**, *62*, 633–643. [CrossRef]
59. Pasalodos-Tato, M.; Pukkala, T.; Cañellas, I.; Sánchez-González, M. Optimizing the Debarking and Cutting Schedule of Cork Oak Stands. *Ann. For. Sci.* **2018**, *75*, 61. [CrossRef]
60. Faias, S.P.; Paulo, J.A.; Tomé, M. Inter-Tree Competition Analysis in Undebarked Cork Oak Plantations as a Support Tool for Management in Portugal. *New For.* **2020**, *51*, 489–505. [CrossRef]
61. Palma, J.H.N.; Paulo, J.A.; Faias, S.P.; Garcia-Gonzalo, J.; Borges, J.G.; Tomé, M. Adaptive Management and Debarking Schedule Optimization of Quercus Suber L. Stands under Climate Change: Case Study in Chamusca, Portugal. *Reg. Environ. Chang.* **2015**, *15*, 1569–1580. [CrossRef]
62. Campos, P.; Daly-Hassen, H.; Oviedo, J.L.; Ovando, P.; Chebil, A. Accounting for Single and Aggregated Forest Incomes: Application to Public Cork Oak Forests in Jerez (Spain) and Iteimia (Tunisia). *Ecol. Econ.* **2008**, *65*, 76–86. [CrossRef]