Trees (2017) 31:1859–1874
DOI 10.1007/s00468-017-1592-9

ORIGINAL ARTICLE

Biomass and volume modeling in *Olea europaea* L. cv "Leccino"

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Received: 14 November 2016 / Accepted: 31 July 2017 / Published online: 11 August 2017

Abstract

Key message **This work demonstrates that the Olive tree, which is managed and pruned as a fruit tree, can be treated as a forest tree using allometric equations, to estimate both biomass production and volumes.**

Abstract The Olive tree (*Olea europaea* L.) is an evergreen tree that can grow and accumulate a relatively high amount of dry matter, even in dry environmental conditions common in the Mediterranean basin and typical of traditional rain-fed agriculture. The objective of this research was to develop a tool to predict woody biomass and tree component volume for the olive tree, to be used for different agricultural and environmental purposes. The study was carried out in six olive groves across three locations in Italy, collecting data on the "Leccino" cultivar, which is spread worldwide. Models for volume and biomass were developed for the whole tree and its different components. Basal diameter and a diameter of 80 cm of the trunk height were explored as independent variables for modeling. The results of this study demonstrate a high correlation between the two selected variables and total biomass, above and below-ground biomass and tree component volumes. The same variables show high correlation with total leaf area, but no correlation with the root/shoot ratio, and Leaf Area Index.

Keywords Woody biomass · Tree component volume · *Olea europaea* · Allometric relationship · "*Leccino*" *cv*

Introduction

The olive tree (*Olea europaea* L.) is the most widespread cultivated tree species in the Mediterranean basin. It represents an extended horticultural crop not only in Mediterranean regions, reaching 10.3 Mha worldwide in 2015 (FAO Statistics Division 2014). The impact of olive growing in agricultural production is important, especially in countries where the cultivation of olive trees covers extensive areas, such as in Spain, Italy or Greece (Beaufoy 2000); the production of olives by these Countries accounts for 57% of the world's total output (FAO Statistics Division 2013). There is also an increase of the dedicated area for olive tree cultivation, such as in North Africa and Middle Eastern Countries. Recently, olive production has expanded into non-traditional areas like Argentina, South Africa, Australia, and Chile. The olive tree is extensively cultivated for its fruits while it is also appreciated for its multi-functionality, such as the hydrogeological safeguarding of mountains and hills, climate mitigation actions, and landscape enhancement. Although the role of the olive tree in the environment is well recognized, some information about its capacity to grow and accumulate dry matter is missing. The olive tree is an exciting natural

Communicated by R. Grote.

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resource because it is considered a xerophytic plant, able to withstand drought conditions and to maintain the right balance between water intake and uptake. This quality is vital in a world facing the greatest challenge of meeting the increase in food demand with the consistent reduction of water resources available to the population (Pellegrini et al. 2016). The in-depth knowledge of the olive trees' ability to grow and to accumulate woody biomass is a key factor in pursuing sustainable agriculture. It is necessary to assess carbon storage, potential carbon emission reduction, and water usage. The production of woody biomass from the olive tree, always an ancillary aim of the olive grove system, could also be taken into consideration and evaluated. Some information about olive groves' biomass production has only recently been published, little information is available regarding the potential of this species, and little data has been issued regarding an estimation of its wood or biomass production (Cantini et al. 1998; Velazquez-Marti et al. 2014). Biomass may be calculated directly from measured tree attributes using biomass prediction equations or estimated indirectly with the IPCC formula by multiplying the stem volume estimates by basic wood density (D) and biomass expansion factors (BEF) that convert stem volume into above-ground biomass (AGB). This kind of information is more common in forestry than in agricultural science. As regards forestry, the estimation of growth, biomass, accumulation, and carbon storage is usually carried out using 'indirect' methods, which rely on forest inventories instead of complex and costly direct estimation. The classical non-destructive method to evaluate a plant growth rate uses tree allometric equations based on forest inventories or field measurement. Hence biomass models, which relate to the dendrometry variables up to the tree biomass components such as BEF and stand volume, are particularly useful tools in biomass estimation of forests and plantations (Brown 2002; Somogyi et al. 2007). Biomass models require tree-level data, which are usually recorded in forest inventories, such as diameter and sometimes height (Teobaldelli et al. 2009). Biomass variable like BEF could depend on the site (Wirth et al. 2004), age (Lehtonen et al. 2004), or stand timber volume (Fang et al. 2001). However, since BEF is not reliable for biomass calculation in pruned or pollarded trees (BEF is studied for trees in their natural habitat), it is preferable to adopt biomass prediction equations in olive groves. Allometric equations are the best and most affordable tool to predict forest tree biomass and volume development (Zianis et al. 2005; Paine et al. 2012; Henry et al. 2013; Mandal et al. 2013). Many allometric equations were recently developed for tropical, subtropical, and boreal trees or forests (de Jong et al. 2009; Henry et al. 2011; Návar 2009). Though studies on temperate species and research on commercial orchards (i.e., with harvesting, pruning, fertilization, etc.) are limited or absent in olive groves. Indeed, GlobAllomeTree (Henry et al. 2013), the most important international platform for tree allometric equations that contains over 5000 tree allometric equations classified according to 73 fields, does not report any information on *Olea europaea*.

Recently, Velazquez-Marti et al. (2014) have developed dendrometry algorithms to estimate the woody biomass of olive trees cultivated in Eastern Spain, using the stem and crown volume as variables with a non-destructive method, without defining the influence that cultivars or management systems might have on the algorithms.

In Spain in 2012, the first research on wild olive (*Olea europaea var. sylvestris*) was performed to estimate biomass equations (Ruiz-Peinado et al. 2012). Research activities on the role of olive tree groves in sequestering atmospheric CO_2 are scarce (Ilarioni et al. 2013; Villalobos et al. 2005) but relevant (Nardino et al. 2013; Proietti et al. 2014). The development of allometric equations to predict olive tree biomass would be very useful in the correct estimation of olive grove biomass accumulation and related to CO_2 sequestration. Also, both genetic and environmental effects (Marra et al. 2013) influence plant volume and biomass. Allometric data can be useful in supporting grove management, and agronomic choices (level of fertilizers, density, tree shape, pruning, pesticide dose, and irrigation (Marra et al. 2016).

To date, only olive pruning residues are commonly used for their energy content (Cantini and Sani 2011; Spinelli et al. 2011), but this undervalues the olive tree's potential, considering its widespread coverage and its capability in dry matter stocking (Proietti et al. 2014). Moreover, the methodology applied to this work could also be adopted to estimate biomass and volumes of other commercial tree orchards, such as fruit plantations.

These estimates are used in the elaboration of the sustainable planning of forest resources, assessment of merchantable timber, and also the estimation of carbon stock, especially as requested by the Kyoto protocol. Considering the potential of the olive tree in carbon storage and reduction of carbon emissions (Proietti et al. 2016), this work intends to propose allometric equations as supporting tools for the estimation of olive woody biomass and volumes.

Materials and methods

Olive groves and trees

For this research, 14 olive trees cv "Leccino" were selected in six different experimental orchards, managed by the University of Perugia in Umbria, by the National Research Council CNR-IVALSA in Tuscany and by the

University of Palermo in Sicily (Fig. 1). The selection of the groves was made to process data from plants growing under similar agronomical conditions but in various environmental conditions to manage data of general interest and correlated to genetic and dimensional traits of the plants. All of the plants were trained using a "vase system" with planting density ranging from 70 to 250 trees/ha in traditional rain-fed conditions. A detailed explanation of each grove and study area is reported in Table 1.

Trees selection and data recording

The 14 trees were chosen among the most representative trees of different classes (from 5 to 45 cm) of basal diameter (DB) and diameter at 80 cm height (D80) that were selected to proceed to the destructive test. Basal diameter is the stem diameter that can be measured over the stump (Villalobos et al. 2005, suggest to measure the stem diameter at 0.3-m height). Olive trees were sampled and eradicated after winter pruning, by their belonging to a diameter class of the trunk, with no interest in age. Before and after pruning, the height of the trunk and total tree height was recorded. The maximum north–south and left–right diameters of the tree canopy were measured, and the average was determined; the volume of the canopy was calculated by assimilating it to a cylinder. All the plants were cut at the base, then the root system was excavated by machine, and the roots were manually separated to recover the maximum quantity of below-ground material (root diameter >2 mm). The fresh tree biomass was weighed in the field using a dynamometer (KERN CH 50K 50G) and then dissected into six biomass components: foliage, small branches (with diameter less than 5 cm), branches, stem, roots, and stump (basal part of the trunk remaining after removing the stem) (Villalobos et al. 2005). When the tree had a basal diameter (BD) of less than 5 cm, branches were not considered separately from the main stem, or trunk. All tree components were further cut into pieces, and branches, stem, roots, and stump volumes were calculated measuring the heights and diameters of single pieces using equations of Huber (La Marca 1999) in the field. Twig (foliage and small branches with diameter less than 5 cm) volume was calculated by using the measured weight of foliage and small branches and the measured density value obtained in the laboratory.

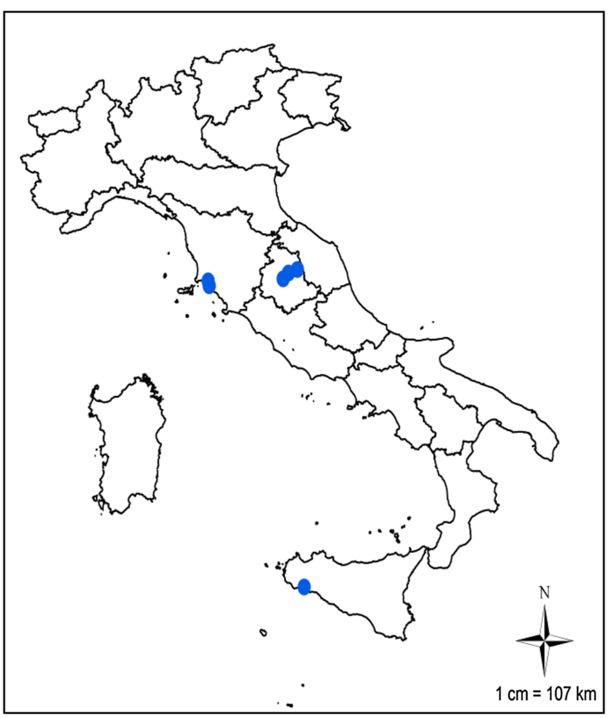

Fig. 1 Location of the survey areas

A cubic sample (3 × 3 × 3 cm) of stem, stump, branches, and root were taken from each selected tree. The volume of each sample was measured using a xylometer in the laboratory the same day of the field operation. The weight of trunk, stem, root, branch, small branches, and foliage samples were measured using electronic balances (Gibertini TMB 45/N) in the laboratory. All samples were oven-dried at 105 °C for more than a week, and weighed until they reached constant weight (evaluated by two measurements with the same results). Then the basic density of wood (D) of each stem, root, branches, and stump was calculated using the ratio between samples DM by dividing fresh cut wood volumes.

Total foliage area was measured sampling 100 leaves equally distributed throughout the canopy. This sample was weighed using electronic balances (Gibertini TMB 45/N) in the laboratory. The area of the leaf samples was measured calculating the diameters as an ellipse. Foliage samples were oven-dried at 105 °C to a constant weight, as described above, to determine the dry matter content (DM). Total foliage dry mass was calculated from foliage samples fresh weight, DM of foliage samples, and the total foliage fresh weight. Specific leaf area (SLA) was determined by dividing the total leaf area of sample to its dry mass. The total leaf area (TLA) per tree was calculated multiplying SLA to total leaf dry mass (Bréda 2003).

Leaf Area Index (LAI) was finally calculated by dividing the total leaf canopy area by the area of canopy projection on the soil (Bréda 2003). Root volume was calculated by dividing the dry weight by its density.

Statistical analysis

Data of all the plants were processed together in a random design since the primary variable for modeling was the measure of the trunk independently from the variables of

Table 1 Environmental characteristics of studied areas

Region	Area	Coordinate	Elevation (m a.s.l.)	Planting year	Planting distance (m)	N. tree/ha	N. Sampled tree	Climate type	Temperature (mean annual °C)	Precipitation (mm)	pH	Texture	N (%)	P (ppm)	K (ppm)
Umbria	Assisi	43° 11′N, 12° 56′E	400	2000	5.5 × 5.5	330	3	Continental	13.5	810	8.1	Loam	0.07	17	143
	Deruta	42° 96′N, 12° 40′E	350	2000 1st 2009 2nd	6 × 6	277	4	Continental	15	767	7.6	Medium	0.06	5.7	175
	Perugia	43°5′N, 12°23′E,	400	1986	5 × 5	300	2	Continental	15	767	7.7	Medium	0.07	4.8	186
Tuscany	Follonica	42° 56′N, 10° 46′E	40	1997	7.0 × 5.0	285	3	Mediterranean sub arid	16	650	7.46	Sandy-loam	0.09	3.5	677
	Scarlino	42°51′N, 10°47′E	32	1950	12.0 × 12	70	1	Mediterranean sub arid	16	650	7.46	Sandy-loam	0.09	3.5	677
Sicily	Castel-vetrano	37°35′N 12°53′E	50	1987	5 × 7	286	1	Mediterranean semi-arid	17.2	494	7.8	Sandy clay loam	0.14	57	767

age or location. Linear and non-linear equations were applied to describe the relation between the two independent variables (DB, D80) and the dependent variables (biomass, volumes, leaf area, and root/shoot ratio). Fourteen trees were used from their basal diameter data, but only 12 were used concerning their diameter at 80 cm because two plants were pollarded and did not reach the stem height of 80 cm.

As is known, exponential and power law functions are usually applied for forest trees to predict below-ground biomass and above-ground biomass. In this research, those functions are used (Zianis et al. 2005; Matula et al. 2015) to create new formulas for olive trees for the very first time.

The formula used in the models were:

(a) Linear: $y = b + ax$.
(b) Power law: $y = \mathrm{b} * x^{a.}$
(c) Exponential: $y = a * \mathrm{e}^{bx}$.

where x is the independent variable (base diameter or diameter at 80 cm), y is the expected value of the measured variable, (above-ground biomass, AGB; below-ground biomass, BGB; total biomass, TotB; branches biomass, Bra; twigs biomass, Twi; foliage biomass, Fol; canopy volume CanV; above-ground volume, AGV; total leaf area, TLA) and a and b are the model parameters.

A powerful tool for comparing models is the Akaike information criteria (AIC), Akaike (1973). The AIC is widely used in the biological, environmental, marine, watershed, and pharmacological sciences. A wmodel would be able to capture the variability of a dataset (under-fitting) and not losing generality (overfitting), AIC is a way to select the model that best balances these drawbacks. An AIC score determines the selection of the "best" model:

$$\mathrm{AIC} = 2K - 2\log\left(L\left(\hat{\theta}|y\right)\right),$$

where K is the number of estimable parameters (degrees of freedom), and $\log\left(L\left(\hat{\theta}|y\right)\right)$ is the log-likelihood at its maximum point of the model estimated (Akaike 1973). The best is then the model with the lowest AIC score. It is important to note that the AIC scores are ordinal and mean nothing on their own. They are simply a way of ranking the models.

For the "best" model, the measured and the modeled data set are compared to estimate the performance of fitting. The goodness of fit was evaluated using traditional statistical parameters: the coefficient of the correlation (r), the statistical significance of the estimation (p), the Mean Absolute Error (MAE), the total root mean square error (RMSEabs) (Moffat et al. 2007). Model selection, model fitting, and model evaluation were performed in "R" software (R Core Team 2015) using the functions "lm", "AIC", and the "NLS" package (Bates and Chambers 1992) and MATLAB (MATLAB and Statistics Toolbox Release 2012).

To test the reliability of the selected allometric equation parameters, the "bootstrap analysis" was performed. The bootstrap method is a resampling technique for estimating the properties, such as the variance, of an estimator or statistic. This approach has been widely applied in several fields to assess the uncertainties of parameters in simple time series and its variations, such as in hydrological models (Li et al. 2010), in pharmacology (Paixão et al. 2017) and in economy (González-Rodríguez and Colubi 2017).

In this work, we applied observed data "resampling with replacement" technique to generate bootstrapped samples and evaluate the uncertainty of the parameters in the equations linked to measured values. The resampling process was repeated 1000 times, and for each iteration, the parameters of the model were estimated.

The extra data for each allometric equation ($N\Delta$) were calculated and then standardized using the formula:

$$N\Delta = \frac{(\mathrm{OD} - \mathrm{PD})}{\mathrm{OD}},$$

(where PD stands for predicted data and OD for observed data).

Results

Power law models and, in some cases, linear models have the lowest AIC scores. The statistical estimators were applied to estimate the performance of fitting (r, MAE, RMSEabs) and the results are shown in Table 2a for the basal diameter and Table 2b for the D80 diameter. Selected equations belong to both power law and linear models, and these show the high value of the coefficient of correlation (r) (Table 2). MAE values remained below 0.61935 for DB and below 3.3266 for D80; RMSEabs values remained below 23.5802 for DB and below 16.6826 for D80 (Table 3) for each power law selected. MAE values remained below 2.0038e−14 for DB and 1.7895e−14 for D80; RMSEabs values below 119.0454 for DB and 111.5512 for D80 (Table 3) for each linear model selected. The developed exponential models are not shown in this text, because they show higher AIC values than both linear and power law models and r value lower than 0.5 (data not showed).

Root/shoot ratio and LAI did not show any correlation with the selected independent variables since all relationships elaborated on during the work have no significant r values.

Uncertainty evaluation

The bootstrap analysis, with resampling technique, was performed to estimate the uncertainty of power models and linear models. The Table 3a, b show the range of the parameters, "a" and "b" for each dependent variables vs. BD and vs. D80. The power law models show the "b" parameters between 2.0829 (shape of the pattern near to linear regression) and 0.0022983. For BD and between 3.7379 and 0.015403 for the D80; while for the linear model between 20.5332 and 0.40264 for BD and between 21.54 and 0.40652 for D80.

The BD vs. Twi, BD vs. Fol and BD vs. TLA power law models (Figs. 2e, f, 4f) have a linear shape and the "a" values are 1.0503, 1.0008, and 1.0008, respectively. The models with "a" parameter greater than two shows the typical power design shape, for example, the BD vs. CanV model (Fig. 4d) shows an "a" values near to 1.4 and the form of fitting is intermediate between linear and power model. The models with the parameters named "a" lower than two show an uncertainty (the area between the blue lines) greater than other models: in particular, the BD vs. CanV and the BD vs. TLA power law models (Fig. 4d, f). The measured BD values between 20 and 30 cm show a deep uncertainty in the BD vs. AGV power law models (Fig. 4e). In this case, the area between the blue lines decreases with the BD those are greater than 30 and lower than 15 cm. In general, the deep uncertainty is shown by models with "a" values comprised between 2.4 and 2.9 (ABG, TotB, and Bra).

Biomass evaluation

Linear and non-linear models evaluated the relations between the independent variable DB and the dependent variables of the olive trees (AGB, BGB, twigs, branches, and total biomass). A graphical visualization of the plotted data suggested that both power law and linear model describe the data trend (Figs. 2, 3) correctly; the allometric equations were selected using AIC values, MAE, and RMSEabs.

Following this method, the power law equations were selected to describe the relation between AGB, BGB, TotB, Bra, and both the independent variables (Figs. 2a–d, 3a–d); these models also show r values equal to 0.997, 0.986, 0.996, and 0.996 for BD; and 0.998, 0.996, 0.999, and 0.997 for D80.

The other two tree components, twigs, and foliage were also considered (Figs. 2e, f, 3e, f). In these cases, both power law and linear models efficiently describe the relationship between the components and the two diameters, as showed by the AIC values. Linear and power law models

Table 2 Allometric equations, *r* value, MAE, RMSEabs, AIC value of the Basal diameter (a), and of the Diameter at 80 cm (b) (root/shoot ratio and LAI are not shown)

Independent variable	Dependent variable	Abbreviation	Unit	Model	Equation	*r*	MAE	RMSEabs	a parameter *t* value	b parameter *t* value	AIC value
(a)											
DB	Above-Ground Biomass DM	AGB	kg	Linear	$y = 11.0749\ x - 101.8103$	0.909***	−4.7088e−14	54.8952	6.55e−06***	0.00706**	158
				Power law	$y = 0.0538\ x$^2.4208	0.997***	−2.0512	9.6909	8.27e−14***	0.00114**	102
	Below-Ground Biomass DM	BGB	kg	Linear	$y = 9.4583\ x - 106.3572$	0.841***	−8.5376e−14	65.7644	0.000166***	0.015495*	162
				Power law	$y = 0.0023\ x$^3.2249	0.986***	−0.28781	20.3243	8.55e−09***	0.267	130
	Total biomass DM	TotB	kg	Linear	$y = 20.5332\ x - 208.1660$	0.882***	−9.4188e−14	119.0454	3.11e−05***	0.0101*	179
				Power law	$y = 0.0282\ x$^2.7608	0.996***	−1.9215	23.5802	2.89e−12***	0.0182*	134
	Branches biomass DM	Bra	kg	Linear	$y = 9.2834\ x - 135.0020$	0.947***	2.0038e−14	28.9053	9.65e−06***	0.000452***	111
				Power law	$y = 0.0096\ x$^2.7544	0.996***	0.61935	8.1462	8.47e−10***	0.03*	83
	Twigs biomass DM	Twi	kg	Linear	$y = 1.2235\ x - 2.1561$	0.967***	−3.8332e−14	3.4636	1.61e−08***	0.298	80
				Power law	$y = 0.9620\ x$^1.0503	0.966***	1.5963	3.5899	2.83e−07***	0.0133*	81
	Foliage biomass DM	Fol	kg	Linear	$y = 0.4026\ x - 0.3953$	0.926***	−3.5904e−14	1.7687	1.93e−06***	0.703	61
				Power law	$y = 0.3857\ x$^1.0008	0.927***	1.4046	1.7799	1.95e−05***	0.0651	61
	Canopy volume	CanV	m^3	Linear	$y = 3.8364\ x - 23.4286$	0.933***	−5.5348e−14	16.5663	1.62e−06***	0.0295*	124
				Power law	$y = 0.7215\ x$^1.4158	0.927***	3.9494	17.0008	2.07e−05***	0.194	125
	Above-ground volume	AGV	m^3	Linear	$y = 12.0271\ x - 127.6723$	0.867***	−9.164e−14	74.7894	5.96e−05***	0.0115*	359
				Power law	$y = 0.0081\ x$^2.9527	0.996***	−1.4394	14.203	5.18e−12***	0.0323*	313
	Total leaf area	TLA	m^2	Linear	$y = 2.1742\ x - 2.1348$	0.926***	−5.0532e−14	9.5511	1.93e−06***	0.703	108
				Power law	$y = 2.0829\ x$^1.0008	0.926***	1.4046	9.6115	1.95e−05***	0.0651	109

Table 2 continued

Independent variable	Dependent variable	Abbreviation	Unit	Model	Equation	r	MAE	RMSEabs	a parameter t value	b parameter t value	AIC value
(b)											
D80	Above-ground biomass DM	AGB	kg	Linear	$y = 11.3640\ x - 87.8966$	0.923***	1.7523e−14	53.848	1.88e−05***	1.88e−05***	135
				Power law	$y = 0.1202\ x$ ^2.2159	0.998***	-2.5703	10.3327	1.96e−11***	0.00245**	95
	Below-ground biomass DM	BGB	kg	Linear	$y = 10.1759\ x - 98.3776$	0.891***	1.2279e−14	58.8627	0.000102***	0.015779*	137
				Power law	$y = 0.0154\ x$ ^2.7322	0.996***	1.7276	11.1255	4.09e−10***	0.0771	97
	Total biomass DM	TotB	kg	Linear	$y = 21.5400\ x - 186.2727$	0.91***	1.7895e−14	111.5512	4.06e−05***	0.0158*	153
				Power law	y = 0.0950 x ^2.4484	0.999***	−1.2432	10.1921	4.38e−14***	6.02e−05***	95
	Branches biomass DM	Bra	kg	Linear	$y = 9.6475\ x - 131.1098$	0.962***	1.2549e−13	26.3666	3.35e−05***	0.00105**	90
				Power law	$y = 0.0206\ x$ ^2.5611	0.997***	−0.11863	7.0187	2.48e−08***	0.0245*	66
	Twigs biomass DM	Twi	kg	Linear	$y = 1.1997\ x + 0.2984$	0.961***	−9.1667e−15	3.9188	6.51e−07***	0.894	72
				Power law	$y = 1.5402\ x$ ^0.9277	0.964***	1.399	3.826	4.78e−06***	0.0166*	72
	Foliage biomass DM	Fol	kg	Linear	$y = 0.4065\ x + 0.5709$	0.956***	−1.1712e−14	1.4218	1.27e−06***	0.502	48
				Power law	$y = 0.6922\ x$ ^0.8558	0.963***	1.4118	1.3172	5.91e−06***	0.0119*	46
	Canopy volume	CanV	m^3	Linear	$y = 3.7357\ x - 16.5020$	0.933***	8.6461e−15	16.3473	9.58e−06***	0.11	107
				Power law	$y = 1.1676\ x$ ^1.2887	0.932***	3.3266	16.6826	8.66e−05***	0.186	107
	Above-ground volume	AGV	m^3	Linear	$y = 12.6258\ x - 114.9777$	0.895***	−2.7643e−14	71.4891	8.58e−05***	0.019*	308
				Power law	$y = 0.0286\ x$ ^2.6280	0.998***	−1.0367	10.3749	1.38e−11***	0.00635**	261
	Total leaf area	TLA	m^2	Linear	$y = 2.1952\ x + 3.0829$	0.956***	1.0845e−14	7.6778	1.27e−06***	0.502	88
				Power law	$y = 3.7379\ x$ ^0.8558	0.963***	1.4118	7.113	5.91e−06***	0.0119*	87

*** $p < 0.001$, ** $p < 0.005$, * $p < 0.01$

Table 3 Ranges of a and b parameters in power models and linear model estimated with bootstrapping technique for BD (a) and D80 (b)

Independent variable	Dependent variable	Abbreviation	Model	*a*	Min *a*	Max *a*	*b*	Min *b*	Max *b*
(a)									
DB	Above-Ground Biomass DM	AGB	Linear	−101.8103	−222.3472	−27.0946	11.0749	5.8216	15.9636
			Power law	2.4208	1.8821	2.5764	0.05379	0.029975	0.28775
	Below-Ground Biomass DM	BGB	Linear	−106.3572	−251.9551	−5.8901	9.4583	1.6486	15.7114
			Power law	3.2249	1.3924	7.5094	0.0022983	1.4075e−09	0.66095
	Total biomass DM	TotB	Linear	−208.166	−569.8799	−47.0675	20.5332	8.5338	32.9282
			Power law	2.7608	1.723	3.0475	0.028189	0.0095534	0.71707
	Branches biomass DM	Bra	linear	−135.002	−183.1771	−52.6364	9.2834	4.8547	11.2171
			Power law	2.7544	2.1357	3.2952	0.0096083	0.0017436	0.071498
	Twigs biomass DM	Twi	Linear	−2.1561	−7.7582	1.5731	1.2235	1.0731	1.6097
			Power law	1.0503	0.92859	1.5785	0.96202	0.19258	1.507
	Foliage biomass DM	Fol	Linear	−0.39533	−2.1182	1.7617	0.40264	0.31812	0.53106
			Power law	1.0008	0.71987	1.5372	0.38573	0.08422	0.95986
	Canopy volume	CanV	Linear	−23.4286	−66.669	−11.0427	3.8364	2.9189	6.1492
			Power law	1.4158	1.0496	3.7815	0.72146	0.00081741	2.8803
	Above-ground volume	AGV	Linear	−127.6723	−264.7092	−3.306	12.0271	1.8806	17.9159
			Power law	2.9527	2.2343	4.2669	0.0080791	9.1281e−05	0.080273
	Total Leaf Area	TLA	linear	−2.1348	−16.0321	11.7191	2.1742	1.5164	3.2085
			Power law	1.0008	0.75296	1.6367	2.0829	0.38193	4.7273
(b)									
D80	Above-Ground Biomass DM	AGB	Linear	−87.8966	−222.4386	−5.2747	11.364	4.5787	16.7855
			Power law	2.2159	1.3295	2.3334	0.12016	0.076901	1.585
	Below-Ground Biomass DM	BGB	Linear	−98.3776	−213.3325	−7.9669	10.1759	2.9793	15.1907
			Power law	2.7322	2.1786	5.6144	0.015403	3.2796e−06	0.087986
	Total biomass DM	TotB	Linear	−186.2727	−368.6323	−35.179	21.54	8.7835	30.0503
			Power law	2.4484	2.0363	2.7538	0.095009	0.041682	0.35105
	Branches biomass DM	Bra	Linear	−131.1098	−187.4461	−41.8495	9.6475	4.1563	11.5702
			Power law	2.5611	1.984	3.0189	0.020612	0.0052491	0.13601

Table 3 continued

Independent variable	Dependent variable	Abbreviation	Model	*a*	Min *a*	Max *a*	*b*	Min *b*	Max *b*
	Twigs biomass DM	Twi	Linear	0.29843	−5.6183	6.6949	1.1997	0.97183	1.6874
			Power law	0.92766	0.75987	1.613	1.5402	0.20231	2.8597
	Foliage biomass DM	Fol	linear	0.57091	−1.5485	2.8661	0.40652	0.31988	0.56231
			Power law	0.85583	0.68215	1.2956	0.69221	0.19741	1.3016
	Canopy volume	CanV	Linear	−16.502	−41.2651	−2.6871	3.7357	1.9069	5.7731
			Power law	1.2887	0.88083	2.7024	1.1676	0.017519	4.603
	Above-ground volume	AGV	Linear	−114.9777	−279.2074	−9.2954	12.6258	3.1205	18.1628
			Power law	2.628	2.1142	3.1597	0.028587	0.0048968	0.16123
	Total Leaf Area	TLA	Linear	3.0829	−11.0142	20.0888	2.1952	1.6507	3.2319
			Power law	0.85583	0.73403	1.3774	3.7379	0.79685	5.8594

that describe the relation between Twi and Fol and both the independent variables, show *r* values higher than 0.927 (Table 2).

Volume estimation

The correlation between size and both diameters (DB and D80) were investigated. According to the AIC value, both linear and power law models describe the relationship between CanV and both the widths (Table 2) efficiently. Power law model presents r values equal to 0.927 (Fig. 4a) for BD and 0.933 for D80. Linear model has a coefficient of correlation equal to 0.927 (Fig. 4d) and 0.932, respectively for DB and D80.

AGV (representing trunk, stump, and branches) is also analyzed, and power law model was selected, using AIC values (Fig. 4b, e). Above-Ground volume in the power law model shows high correlation values, 0.996 for BD and 0998 for D80 (Table 2).

Total leaf area and LAI determination

The graph of the related measure of diameters and Total Leaf Area (TLA) are reported in Fig. 4c, f. Linear and power law models for TLA and both the diameters are comparable, with similar AIC values. Power law models have coefficients of correlation equal to 0.926 and 0.963, respectively for DB and D80; while the linear model has a coefficient of correlation equal to 0.926 and 0.956, respectively for DB and D80. On the contrary, the diameter was not a good estimate of LAI as can be seen from the plot (data not shown).

Plant biomass allocation

The above-ground tree biomass is divided into four elements, and its distribution is changed concerning the increasing diameters, as shown in Table 4 and Fig. 5. In particular Fig. 5 shows how the plant 'growth is allocated to different tissues: foliage, small branches (without foliage) and trunk biomass partitioning coefficients decrease with time, while branch biomass partitioning coefficient increases. For example, for an olive tree with 8 cm DB the partitioning coefficient for foliage, small branches, branches, and trunk are 0.2, 0.35, 0.15, and 0.3, while in an olive tree with 44.5 cm DB, it becomes 0.03, 0.06, 0.63, and 0.28, respectively.

While AGB parameters seem to follow an allometric model, no significant relation between both independent variables and root/shoot ratio were observed.

Furthermore, the relation between plant age and root/shoot ratios doesn't show significant correlation (data not shown); consequently, the root/shoot ratio of the olive plants cannot be described with simple allometric equations.

Models evaluation

An overall assessment of all the tested power law models and all the linear models are shown in Figs. 6 and 7, where types' divergences are related to each of the dependent

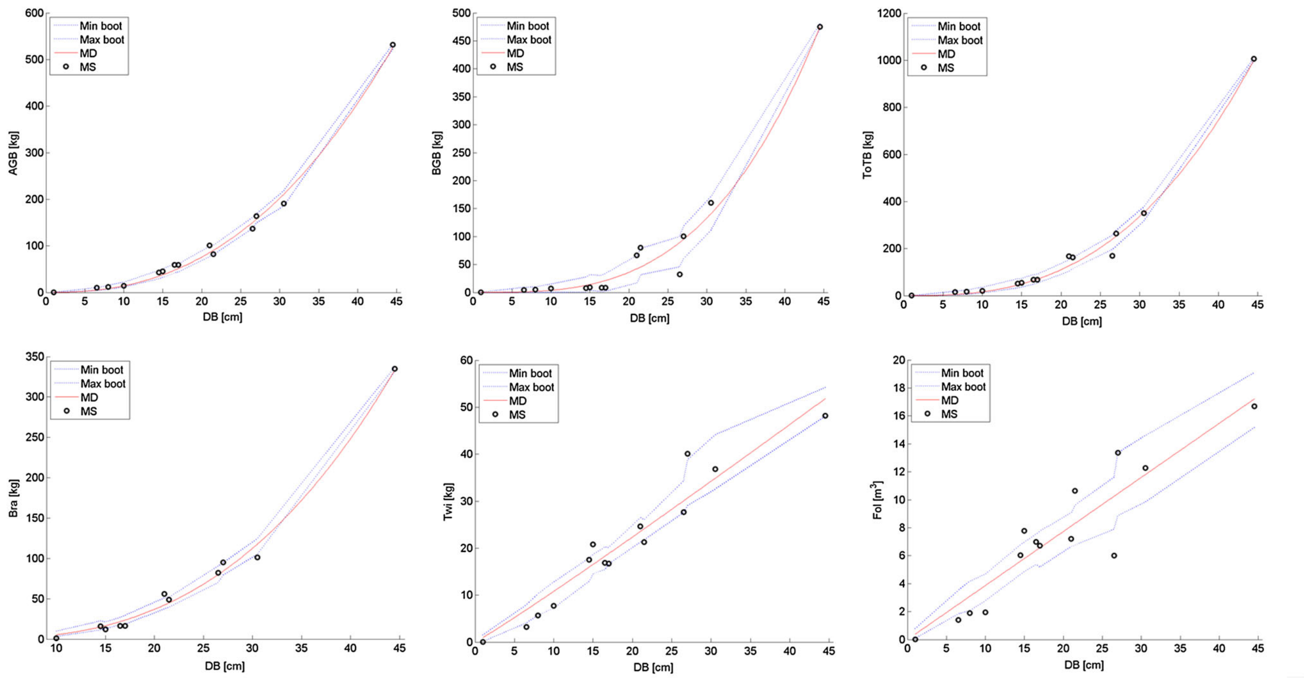

Fig. 2 Power models between dependent variables: **a** AGB; **b** BGB; **c** ToTbio; **d** BRA; **e** Twi; Fol (**f**) and olive base diameter (BD). *Black circle* are observed data; *red line* is expected data; *blue lines* containing bootstrapped uncertainty values

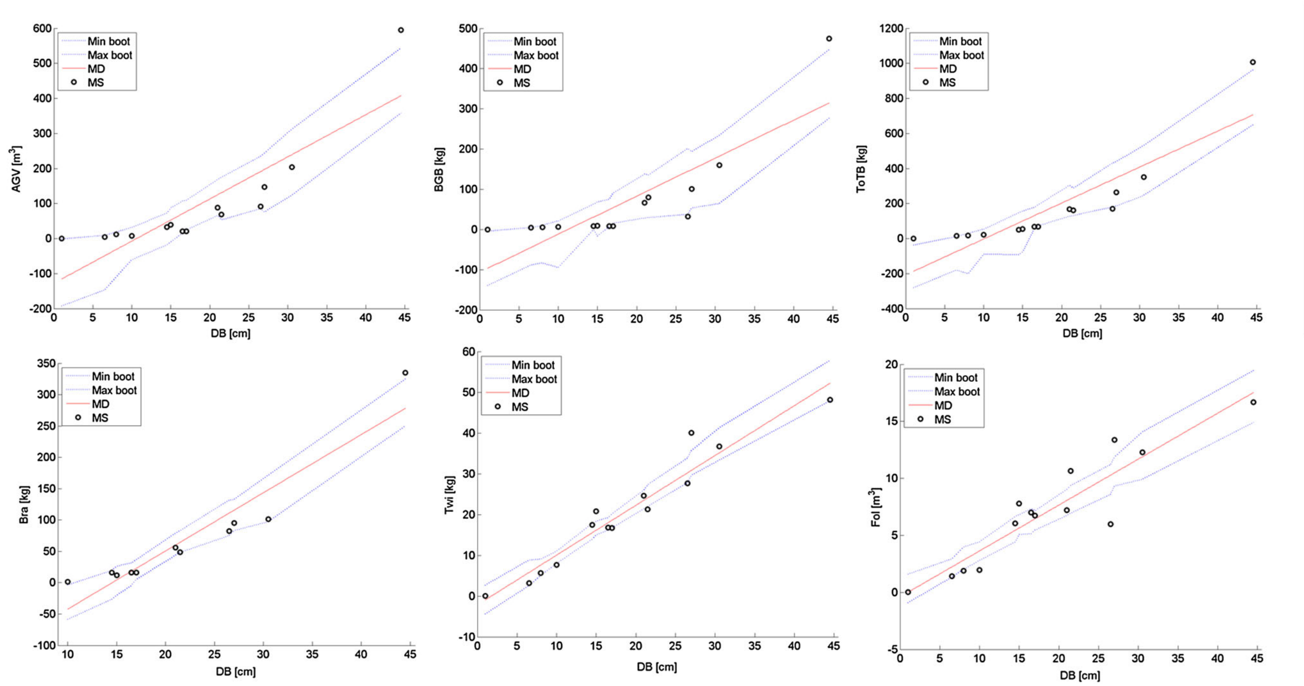

Fig. 3 Linear models between dependent variables: **a** AGB; **b** BGB; **c** ToTbio; **d** BRA; **e** TWI, Fol (**f**) and olive base diameter (BD). *Black circle* are observed data; *red line* is expected data; *blue lines* containing bootstrapped uncertainty values

variables. The graphs show how the differences between the observed data and data estimated values decline when the plant diameters increase, for all the allometric equations.

Figure 6 represents the $N\Delta$ values obtained from the divergences between observed data and linear model-estimated data, and shows the absence of a correlation between BD and the selected dependent variables. These linear

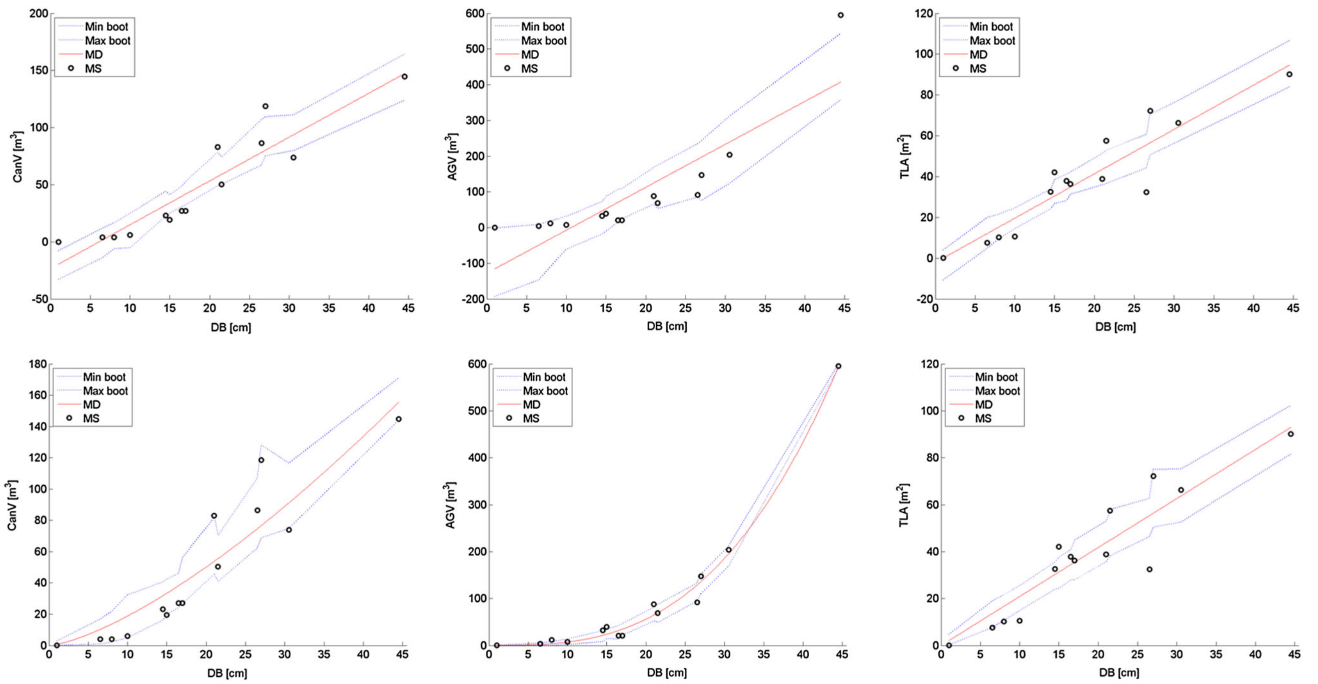

Fig. 4 Linear model between dependent variables: **a** CanV; **b** AGV; **c** TLA and olive base diameter (BD). Power law model between dependent variables: **d** CanV; **e** AGV; **f** TLA olive base diameter (BD). The *black circle* is observed data; the *red line* is expected data; *blue lines* are containing bootstrapped uncertainty values

models, in fact, result in an over-estimation or an under-estimation of the observed data. Overall, when DB is over 30 cm, $N\Delta$ values remain between 0.5 and −0.5; while with DB under 30 cm, $N\Delta$ values are between −0.6 e+5.5. Linear models always give negative results with DB under 15 cm (with the exception of FOL and TLA where the estimated data are correct also for smaller DB). BGB and BVG show larger differences between estimated values and biomass; probably due to sampling uncertainty and also to the simplicity of the models. The above-ground-compartments models, describing AGV and AGB, are discordant one to another when DB is in the range of 15 and 21 cm (AGB show higher estimated values in respect to the AGV estimated value).

Figure 7 represents the $N\Delta$ values obtained from the divergences between observed data and data estimated with power law models. When DB values are lower than 10 cm the allometric equations for BGB, BGV, TOTB e AGV underestimate the measurement based calculations, while the allometric equations for Twi e TLA overestimate them. The application of the ABG allometric equation, however results in a correct estimation.

As regards DB values between 10 and 20 cm, only the allometric equations for TotB, Twi, AGB, and TLA give acceptable results. For larger DB values, all equations perform sufficiently well.

Comparing the results shown in Figs. 6 and 7, the selected power law models have lower deviations between observed and estimated data than linear models (NΔ in power law is between −0.8 and 1 while $N\Delta$ in linear model is between −0.6 and +5.6). Estimates are restricted to DB larger than 1 cm.

Discussion

Non-destructive tests used to estimate the biomass of olive groves are still not available in the literature. On the other hand, some remote sensing research has already been conducted and validated to predict tree height (Zarco-Tejada et al. 2014) and canopy volume (Sánchez et al. 2014; Caruso et al. 2014; La Scalia et al. 2016) in the olive grove. Therefore, it is relevant to develop useful tools to estimate tree biomass components and related volumes in *Olea europaea* trees which are managed and pruned.

According to the dendrometry method, at least two hypotheses exist to predict the biomass of a forest tree, even though they are not universally recognized:

1. the metabolic scaling theory (Enquist et al. 1998), that predicts a power relationship with exponent −4/3 between tree biomass and diameter;
2. the diameter-height relationships theory described in Chave et al. (2014), where the allometry between tropical tree biomass and rD^2H (where r is wood density, D diameter, H height) is considered universal.

Table 4 Tree component allocation

Base diameter	Diameter at 80 cm	Foliage biomass (%)	Small branches biomass (%)	Branches biomass (%)	Trunk biomass (%)	ABG (%)	BGB (%)	Root/shoot ratio
1.0	0.5	20.0	40.0	0.0	40.0	87.0	13.0	0.15
6.5	5.0	13.9	17.9	0.0	68.3	68.5	31.5	0.46
8.0	7.0	19.7	30.5	15.5	34.3	64.7	35.3	0.55
10.0	0.0	13.8	40.6	9.4	36.2	67.1	32.9	0.49
14.5	13.5	14.1	28.0	37.6	21.3	84.2	15.8	0.19
15.0	11.5	17.3	29.0	26.5	27.2	83.3	16.7	0.20
16.5	15.0	13.2	18.6	32.7	35.4	78.6	21.4	0.27
17.0	15.0	12.7	18.9	21.5	35.5	78.8	21.2	0.27
21.0	20.0	7.1	19.3	55.6	19.9	60.3	39.7	0.66
21.5	20.5	12.9	13.4	59.1	14.6	50.7	49.3	0.97
26.5	0.0	4.4	15.8	60.2	19.6	80.8	19.2	0.24
27.0	26.0	8.1	16.3	58.0	17.6	62.0	38.0	0.61
30.5	29.0	6.4	12.9	53.1	27.6	54.3	45.7	0.84
44.5	44.0	3.1	5.9	62.9	28.2	52.8	47.2	0.89

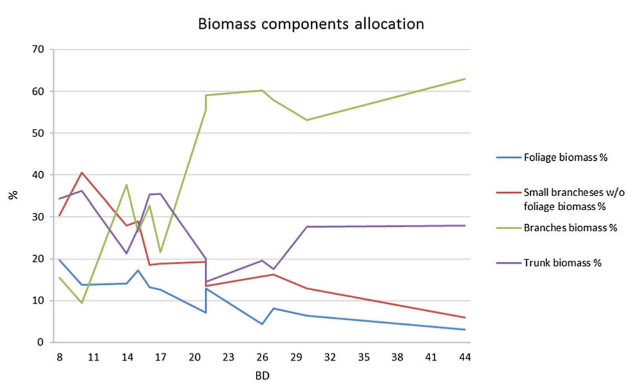

Fig. 5 Tree components allocation (foliage, small branches without leaves, branches and trunk included stump) vs. base diameter (BD)

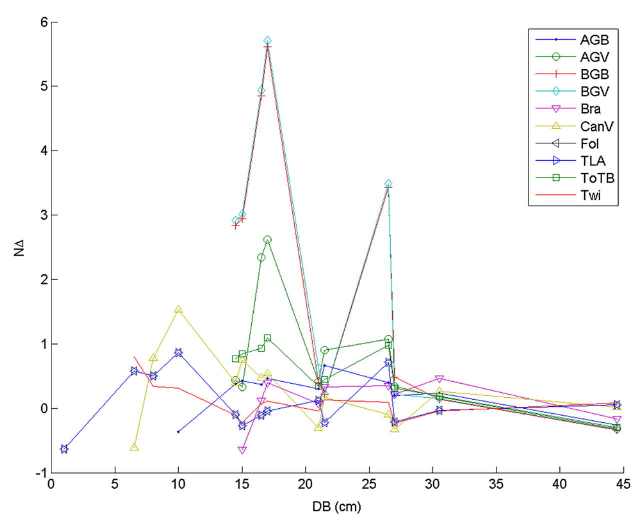

Fig. 6 Combined graph of percentage differences between the obtained predicted data from all the tested linear models and their observed data

The authors believe that testing these theories on olive trees would guide towards biased results, because both height and tree biomass are periodically modified by human intervention, adding a variable that is not considered by the theories mentioned above. Moreover, both theories have some contraindications, since the metabolic scaling theory received many criticisms (Coomes et al. 2012; Mäkelä and Valentine 2006), while the second theory is considering only tropical trees (and it is not a biomass equation as such since it requires wood density as input). For this reason, an allometric approach for *Olea europaea* biomass prediction was tested and verified. Elaborations of statistical biomass equations are assumed to be preferable compared to the IPCC formula because the size of the olive stem is always artificially manipulated by pollarding operations. The IPCC formulation uses a simple Biomass Expansion Factor (BEF) which is constant over time. However, as shown by Sanquetta et al. (2011), BEF is not constant in time but decreases with plant age and size. In fact, as regards olive trees, BEF is even less predictable since the trunk height changes from place to place, making BEF an unreliable index in a broader contest.

Pollarding operations and pruning intensities, that change from place to place, unpredictably influence the tree height, making this data an unreliable independent variable in allometric equations for biomass prediction. Another variable that the authors did not consider in building the allometric relationships (after testing it—data

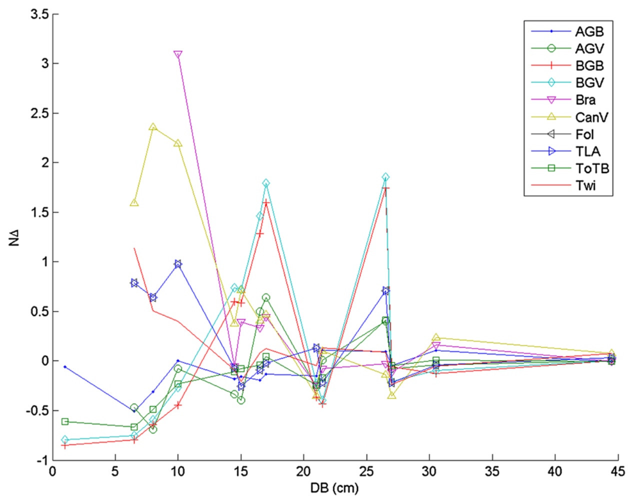

Fig. 7 Combined graph of percentage differences between the obtained predicted data from all the tested power law models and their observed data

not shown) is the age since the size of an olive tree appears to be influenced by site conditions and human intervention. In this study, non-linear models, and in few cases linear models, were selected to describe the relationship between trunk diameters and the most important tree parameters. The authors generated allometric equations deriving from both the independent variables DB and D80. As a matter of fact, it was preferred to show DB correlation curves with dependent variables because DB is a parameter always available in the field, while D80 sometimes is not measurable (in many Mediterranean traditional and commercial orchards the trunk reaches a height of 60–80 cm). However, D80 shows acceptable values regarding RMSEabs and this independent variable should be investigated by increasing the number of sampled trees.

Recent scientific studies on conifer forests prove that linear models, commonly used in the forest sector, are inadequate to describe tree growth because they cannot efficiently show the growth rate of the whole plant and its components at different ages (Parresol 2001; Calama and Montero 2004; Matula et al. 2015). The ultimate limit of traditional forest biomass and volume calculation is due to the assumption of constant absolute growth rate (AGR), and so the same quantity of biomass is added in each unit of time. Biomass acquisition is independent of current biomass. This assumption is unacceptable for the initial stage of tree life, as AGR should depend on leaf area when resources are unlikely to be limiting (Paine et al. 2012; Matula et al. 2015). Then the best way to accommodate temporal variation in growth rates is with non-linear growth models for trees growing in a natural environment.

It was taken into consideration that olive tree pruning alters body size and biomass distribution, influencing all canopy parameters (canopy volume, twigs biomass, foliage biomass, and TLA) and probably the root development related to the TLA. Statistical parameters (r value and AIC) prove that both linear and power law models are equivalent in describing the studied relationships (Fol, CanV, TLA), and are accepted to predict the above-ground-mentioned parameters.

The power law model describes more efficiently parameters like AGB, BGB, TotB, BRA, and AGV, confirming the rapid initial growth and the subsequent slowdown of the trees growth.

The authors decided to consider two volume regression equations (CanV, AGV) since these could be applied to the prediction of olive biomass using non-destructive methodologies such as remote sensing, LIDAR, or photographic surveys.

Results obtained from the relations between volumes/diameters and total leaf area/diameters demonstrate an opportunity to estimate biomass for managed olive trees. Such prediction is more reliable for plants that are measured at its BD from 10 cm onward as demonstrated by Figs. 6 and 7. Although the produced equation could efficiently describe the biomass and volume of olive trees, the uncertainty of the estimated parameters is large, probably due to the low number of plants analyzed and the management techniques applied to the olive grove that modifies the natural plant growth. Indeed, human activities influence the growth of olive trees, changing biomass production and allocation on forest trees; for this reason, allometric equations usually applied to forest species could show wider intervals of confidence.

This work also illustrates how the biomass allocation varies in relation to the tree components during its growth: small plants, between 1 and 15 cm of BD, mainly accumulate biomass into the trunk (around 45%) and foliage (around 17%) while in bigger trees, biomass allocations are collected in branches (around 65%). The marked tendency is explained by the constant pruning activity influencing the quantity of twig biomass and canopy volume, while trunk increasing biomass regards only diameter. The only tree component which increases its volume and its biomass is the branch element because pruning influences its growth less intensively than that of twigs.

Above mentioned equations are also relevant determining the role of olive groves for carbon sequestration as reported in Ilarioni et al. (2013) and Villalobos et al. (2005). As demonstrated by Proietti et al. (2016), olive groves are agricultural systems that can contribute regarding sequestered $CO_{2\text{-eq}}$ and possible avoided emissions as a result of sustainable practices. These activities are identified by the Kyoto Protocol and then in the Paris agreement to actually reduce GreenHouse Gas (GHG) emissions, since they are closely related to land use, included in the category of Agriculture, Forestry and Land Uses (AFOLU); and then in the Paris agreement as the instrument that will allow valuing forest carbon stocks in the UNFCCC framework. Considering, for example, the intensively managed olive groves in the Umbria region, one of the three areas in which this study was carried out, they could contribute to the 10% emission allowances of the entire region (in 2015). These carbon credits, even though at this moment considered ineligible under the Kyoto Protocol, could be valued within the Voluntary Market by profit and non-profit organizations, local administrations and even individuals, to offset, entirely or partially, the emissions for which they are responsible. Nevertheless, uncertainties in the relationship between BD and biomass that might origin from variations in leaf area index or root/shoot ratios needs to be addressed in future research. Considering that the LAI value is the relationship between total leaf area and the area of the ground covered by the crown projection, results can be explained by the difference in pruning among plants. Even with the same training system (in this case polyconic vase), pruning cannot be standardized regarding intensity and/or height of the crown because the capacity of the plant to maintain a very dense or sparse foliage is related to the intensity of the light. Also, the root/shoot ratio was not efficiently described by an equation nor related to BD or age. As reported by Mokany et al. (2005), this is an important descriptor of the relationship between root and shoot biomass. Carbon sequestration would in particular benefit from an improved root/shoot ratio that is currently mainly determined for forest trees.

Conclusions

This work generated allometric equations that can be used to assess olive tree volume and biomass for *Olea europaea* "Leccino" cultivar in their components trained using a "vase system." This study demonstrates that when facing a uniform genotype and training system, the resulting allometric equations for AGB, BGB, total biomass, and individual volumes are reliable and statistically significant. These results offer a tool to estimate biomass and volumes of commercial olive orchards, which are relatively easy and cost-efficient to execute. This approach is supposed to be applicable to predict volumes and biomass of other trees that are cultivated for fruit production.

DB is a reliable parameter to predict olive tree biomass and volume of "Leccino" cultivar. The allometric equations could be usefully adopted for olive cultivars that have similar habit and vigor. It is recommended that the methodology is tested also for other cultivars and training systems to find characteristic equations to be adopted to predict biomass and volumes of *Olea europaea* L. species.

Acknowledgements This work was financially supported by the MIUR-PRIN Project 'Climate change mitigation strategies in tree crops and forestry in Italy' (CARBOTREES). We gratefully acknowledge the valuable collaboration of Adele Amico Roxas, Laura Macaluso, and the workers of ESA (Ente di Sviluppo Agricolo) for help during the operations in the field. We are grateful to the two anonymous reviewers and the Editor that gave important and useful suggestions to improve this paper.

Author contribution statement AB: study conception and design; collection, analysis, and interpretation of data; article drafting; final draft revision; final approval of the manuscript. FD: statistical analysis of data; analysis and interpretation of data; article drafting; final draft revision. CC: study conception and design; field data collection; final draft revision. GS: Field data collection and analysis; critical revision of the manuscript. TLM: Field data collection and analysis; critical revision of the manuscript. TC: Field data planning and collection; critical revision of the manuscript. MFP: analysis and interpretation of data; critical revision of the manuscript. CT: statistical analysis of collected data; graph construction; critical revision of the manuscript. LN: Field data collection and critical revision of the manuscript. LR: Field data collection; critical revision of the manuscript. PP: study conception and design; final approval of the manuscript.

Compliance with ethical standards

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

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