



RESEARCH PAPER

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Allometric models for above-ground biomass, carbon and nutrient content of wild cherry (*Prunus avium* L.) trees in agroforestry systems

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Abstract

Key message We provide a set of allometric models for wild cherry trees (*Prunus avium* L.) established in agroforestry systems. A total of 70 trees in southwestern Germany were surveyed using terrestrial laser scanning and analysed using quantitative structure models. The derived allometric models provide a stable base for biomass estimation in comparable agroforestry systems. Our biomass model, based on volume estimates converted to biomass, shows no significant differences to a previous study in the same region on the same species, although it was conducted on agroforestry trees under a different management regime.

Context Wild cherry (*Prunus avium* L.) is a common tree species in agroforestry systems (AFS). Utilised for either fruit production or for high-value timber production, it is a highly relevant species, yet even basic allometric models are lacking.

Aims The aim of this study was to develop a set of allometric models for wild cherry trees in AFS. Within this context, we present an innovative non-destructive approach to estimate bark and wood volume separately by applying bark thickness models to 3D models of trees. To assess model applicability to different AFS, we compared our allometric model for above-ground biomass with a previous biomass model for wild cherry trees under different management in the same region.

Methods Wild cherry trees ($n = 70$) located within AFS in southern Germany were scanned with a terrestrial laser scanner. Quantitative structure models were used to derive tree dimensions and above-ground volume per tree. Using additional auxiliary data, the target variables were derived, and corresponding allometric models were fitted.

Results The allometric models estimating above-ground volume, oven-dry biomass, carbon content and nutrient content based on diameter at breast height (DBH) showed excellent fits ($R^2_{adj} \geq 0.97$). The comparisons with a similar study conducted in the same region suggested that management practices such as pruning have only a minor influence on the relationship between DBH and above-ground tree biomass. The nutrient content in the trees decreased in the order $Ca > N > K > Mg > P$.

Handling editor: Erwin Dryer

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Conclusions The derived allometric models provide valuable information on this important agroforestry tree species. Our findings can both inform management practices in AFS and advance ecological understanding of these systems. Future research should focus on developing allometric models for other tree species relevant to AFS.

Keywords Allometry, LiDAR, TLS, Terrestrial laser scanning, QSM, Tree volume, Carbon sequestration

1 Introduction

Climate change is heavily impacting ecosystems as well as people around the globe and is expected to progressively cause more damage with increasing global warming (IPCC 2022a). To reduce projected damages and losses, global warming has to be limited through the reduction of greenhouse gas (GHG) emissions. While being one of the most severely impacted sectors of climate change (Malhi et al. 2021), the agricultural sector is also a major emitter of GHGs (IPCC 2022b). However, by implementing agroforestry systems (AFS), the carbon sequestration potential of agricultural systems can be greatly enhanced to reduce net emissions of agriculture (Montagnini and Nair 2004; Abbas et al. 2017; Kay et al. 2019). AFS are commonly defined as agricultural systems for animal or crop production which are deliberately combined and interact with woody perennials such as trees and shrubs (Nair et al. 2021). When compared to conventional agricultural systems, AFS are capable of sequestering and storing larger amounts of carbon in both the above- and below-ground system compartments (Nair et al. 2009, 2010).

Despite the fact that AFS are known to potentially have various environmental and economic benefits (Jose 2009; Torralba et al. 2016), there is still a lack of knowledge on the growth of trees in AFS and their interactions with their surroundings (Schnell et al. 2015; Cardinael et al. 2020). For example, trees influence carbon and nutrient cycling in AFS (Nair et al. 1995; Jose and Bardhan 2012). While growing, they sequester carbon and store large amounts of carbon and nutrients in their biomass. Upon harvesting or pruning, carbon and nutrients from the above-ground fractions are removed from the system. While carbon and nutrient removal upon harvest has been thoroughly investigated in forestry situations (Kimmins 1977; Merino et al. 2005; Paré and Thiffault 2016), for AFS, this has hardly been investigated (Morhart et al. 2016). Since growing conditions and nutrient supply inside and outside forests are distinctly different, this type of information cannot simply be transferred from forests to agricultural landscapes (Nair 2012; Schnell et al. 2015). The quantification of tree growth and ecological interactions, however, is important to enable modelling and subsequent optimisation of AFS.

At present, even basic knowledge on the allometry of many tree species in AFS is lacking. Allometric models

quantitatively describe the relationship between different tree parameters. They can relate parameters which are difficult or time-consuming to measure to other parameters which are easier obtained (Picard et al. 2012). Typical predictors are stem diameter at breast height (DBH, measured at 1.3 m above the ground) and tree height. Allometric models for trees in AFS could be applied for various purposes. For example, allometric models for tree dimensions could facilitate the planning of future AFS by providing appropriate planting distances between trees. They might also be used for efficient and straightforward quantification of carbon stocks and subsequently carbon storage and substitution potential. These data could be used to establish directed financial compensation to land managers for providing ecosystem services. Tree nutrient content quantification, on the other hand, could be used to assess nutrient loss from AFS when trees are felled or pruned. Once nutrient loss is quantified, land managers could fertilise their land accordingly to prevent nutrient depletion or surplus caused by inadequate management.

While there are many allometric functions available for trees growing in forests, there is a lack of such information for trees in AFS. Since growing conditions inside and outside forests differ substantially, especially in terms of density and competition, it is likely that trees in AFS follow distinct growth patterns (Nair 2012; Schnell et al. 2015). For example, tree density in AFS is usually lower than in forests, resulting in lower competition among trees (Balandier and Dupraz 1999). Competition is known to alter tree growth, in terms of growth rates and crown development (Perry 1985). Due to the different light conditions between closed canopy forests and AFS, light-demanding tree species can be used in AFS, which might suffer under the lower light availability in forests (Nair 1993). In AFS, trees are also frequently pruned to increase fruit yield of fruit (Mika 2011) or to produce high-quality timber (Coello et al. 2013). Other management techniques that alter growing conditions are, for example, ploughing and fertilisation. Due to all these differences, there is a need for allometric models specifically derived for AFS.

The lack of models may be attributed to the diverse range of AFS types, each with varying degrees and types of competition and management (Nair 1985). While certain tree characteristics, such as crown width and base height, are most certainly influenced

by management practices like pruning, the impact of management on other parameters is not yet known. For instance, the generalisability of biomass models, which are crucial for estimating carbon sequestration potential and stocks in the context of climate change mitigation, across different management styles is unknown. Nevertheless, establishing allometric models for very common AFS, such as grazed orchards, is very valuable for the description of these specific systems. Wild cherry (*Prunus avium* L.) is a common tree species in AFS and offers diverse ecosystem services. It has been cultivated for its fruit in traditional AFS in temperate Europe for centuries (Herzog 1998). This species is also a popular choice for the production of high-quality timber due to its relatively fast growth and the high price that can be realised in the veneer industry (Coello et al. 2013).

To determine biomass for individual trees and tree compartments, which is required to derive tree carbon and nutrient content, traditionally destructive sampling is applied. This method, however, is both time and labour intensive (Vashum and Jayakumar 2012; Seifert and Seifert 2014). An alternative to destructive sampling is the use of remote sensing to estimate single-tree volume, which can be used to derive biomass. Remote-sensing techniques are faster, less laborious and, due to their noninvasive nature, allow for repeated measurements over time (Kunneke et al. 2014). One of the most prominent remote-sensing technologies for above-ground biomass estimation is terrestrial laser scanning (TLS), which uses laser-based distance measurements and positioning estimates to produce highly accurate 3D point clouds of the surroundings (Calders et al. 2015; Kunz et al. 2017; Disney et al. 2018). To extract volumetric data from point clouds, quantitative structure models (QSMs) can be applied. QSMs are simplified 3D models that represent trees based on geometric primitives such as cylinders. They can be derived from single-tree point clouds in various ways, as summarised by Kunz et al. (2017).

In this study, we used a combination of TLS and QSMs to derive various single-tree parameters of wild cherry trees in AFS which in turn were used to derive models that enable the estimation tree volume, biomass and carbon content of trees with different dimensions.

Against this backdrop, our research goals were as follows:

- (1) To develop allometric models relating tree dimensions (height, crown base height, crown diameter, crown projection area), woody above-ground volume, oven-dry biomass, carbon content and nutrient content to easily measurable parameters such as DBH.
- (2) To test whether there is a significant ($p < 0.05$) difference between our allometric model for above-ground biomass and previous biomass models for wild cherry trees under a different management from the same region.

2 Materials and methods

2.1 Study sites

The majority of the studied trees were located in Ebringen (47°57'1" N, 7°47'15" E, 407 m a.s.l.) in southwestern Germany (Fig. 1A). The system is a so-called *Streuobst* system, a traditional meadow orchard AFS in temperate Europe which is characterised by widely spaced fruit trees (Herzog 1998). This particular system is a silvopastoral system that is extensively managed for nature conservation purposes. Additional trees with smaller dimensions, which were located on a nearby agroforestry research plot in Breisach (48°4'13" N, 7°35'23" E, 188 m a.s.l.), were also surveyed. The study sites are within the temperate oceanic climate zone (Köppen-Geiger: Cfb; Peel et al. 2007) characterised by warm summers, classically with no significant precipitation differences between seasons. In the recent climatological period from 1991 to 2020, the average annual temperature was 11 °C, and the average annual precipitation sum amounted to 896 mm (Deutscher Wetterdienst 2022). The vegetation period ranges from April to September and is typified by a long-term average temperature of 16.5 °C with an average precipitation sum of 510 mm. A total of 70 trees with varying dimensions and unknown ages were sampled. The trees were selected to cover a wide range of diameters and ages to increase the generalisability of the resultant allometric models. Due to the wide spacing between tree rows, all trees had a near solitary growth form (Fig. 1B, C). Although we have no knowledge of the exact management treatments applied at either site in the past, the trees on the Ebringen site display wide crowns with no dominant lateral shoots on the trunk basis suggesting the application of one or more formative pruning treatments.

2.2 Terrestrial laser scanning

The TLS data were collected using the RIEGL VZ-400i (RIEGL Laser Measurement Systems GmbH, Horn, Austria) during the winter dormancy of the trees in February and March 2022 and during January 2023. To ensure full coverage of the trees and to reduce occlusion from neighbouring trees, a multi-scan approach was employed. This means that each tree was scanned from multiple directions and distances (Fig. 2). The single-scan point clouds were automatically co-registered by the TLS device, which uses positioning data and the point clouds

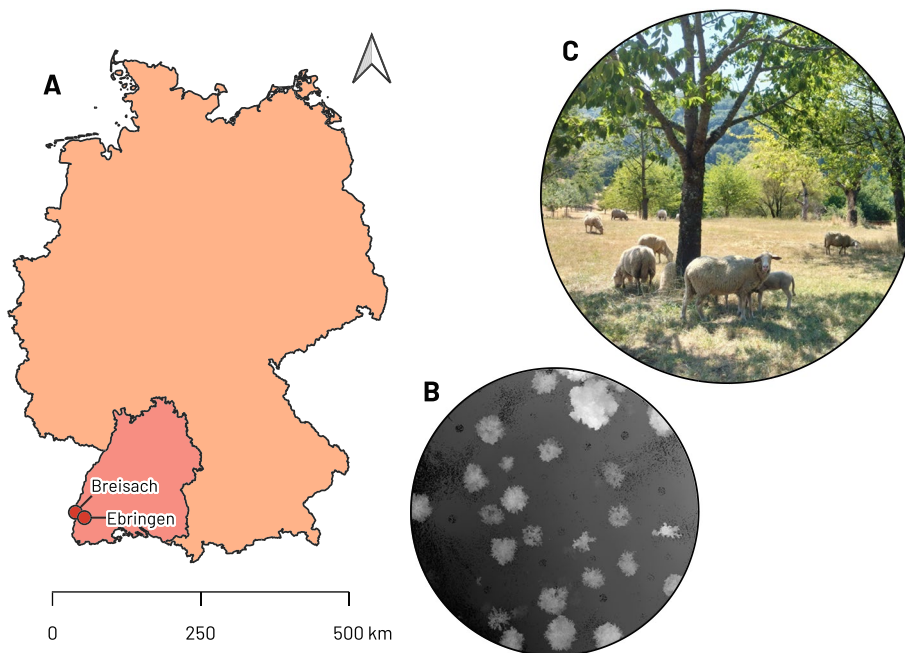


Fig. 1 Overview of the agroforestry systems studied. **A** Map of Germany (light orange), Baden-Württemberg (dark orange) and the locations of the two research sites (red dots), Geodata: © GeoBasis-DE/BKG (2023). **B** Top view on the TLS point cloud from Ebringen, dark pixels indicate low, and light pixels indicate high height above ground. **C** Photo of the agroforestry system in Ebringen

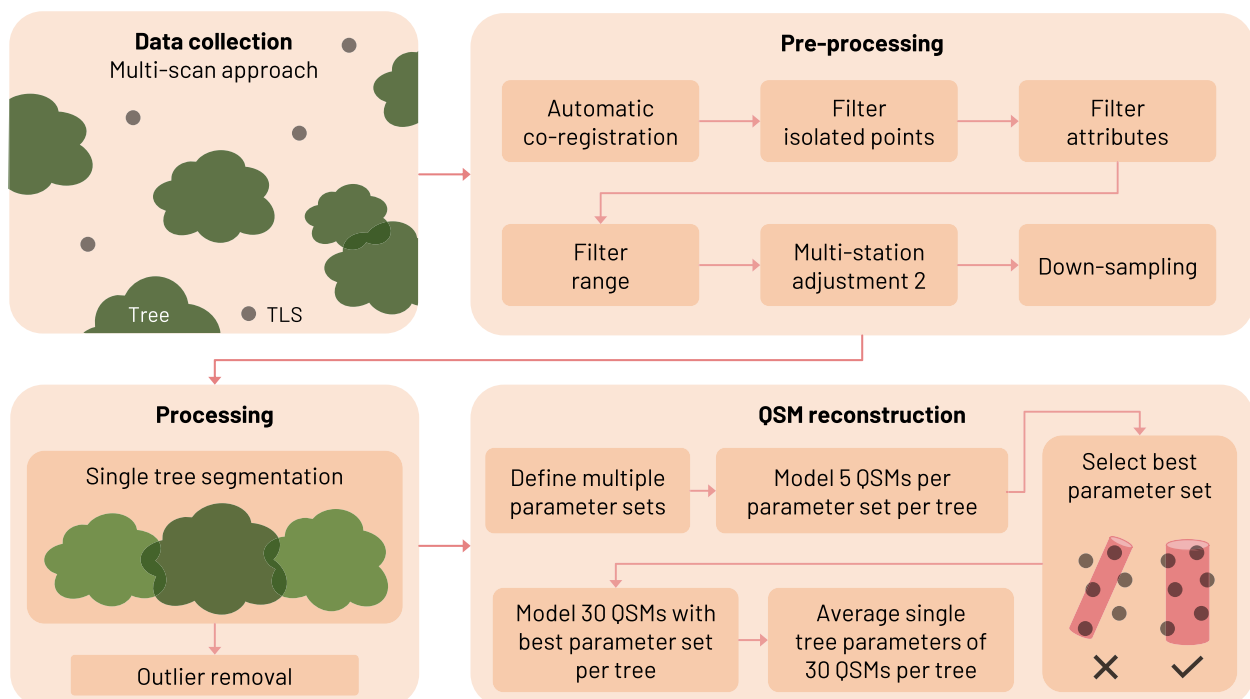


Fig. 2 Workflow for deriving QSMs from TLS data. The diagram shows the workflow for deriving QSMs starting from the TLS data collection. The two graphics on the left display the scan setup and overlapping tree crowns as seen from above. The trees are coloured green for better visualisation, although the trees were scanned during winter dormancy. The graphic on the right demonstrates how the best parameter set is chosen based on distances between points and fitted cylinders

themselves to co-register the single scans. The registered point clouds were further preprocessed using the RiSCAN PRO v2.15 (RIEGL Laser Measurement Systems GmbH, Horn, Austria) software. To remove erroneous points, several filters were applied to the point clouds. The filters removed isolated points (<5 neighbours in 10 cm radius), points with a low reflectance (< -15 dB) or high deviation (>15) and points with a large distance to the scanning position (>50 m). When the filtered point clouds showed slight misalignment in the crown, an additional multi station adjustment (MSA2) was carried out (Demol et al. 2022). Eventually, the point clouds were down-sampled to 1 point per cubic centimetre to increase computational efficiency of the next steps. To enable the derivation of single-tree parameters, single-tree point clouds were filtered and segmented manually using CloudCompare v2.11.3 (2022). Noisy point clouds, i.e. point clouds containing many erroneous points arising from data collection, were additionally filtered using the statistical outlier removal tool in CloudCompare, which removes points that have less than a specified number of neighbours in a specified radius around them. Depending on the noisiness of the point clouds and their point density, points with fewer than five neighbours within a radius of the arithmetic mean plus two or three times the standard deviation of the point density were removed. The larger radius was used on low-density point clouds to avoid information loss, while the smaller radius was used on higher-density point clouds to remove as much noise as possible. Remaining noise was removed manually.

2.3 Quantitative structure models

Using TreeQSM v2.4.1 (Raumonen and Åkerblom 2022), QSMs were derived for the single-tree point clouds (Fig. 3). This software package is a well-established tool for the creation of QSMs that uses cylinders for the construction of 3D tree models. TreeQSM has been validated in several studies in which it demonstrated a high level of agreement with manual measurements (Raumonen et al. 2013; Calders et al. 2015; Gonzalez de Tanago et al. 2018). Since the construction algorithm is based on stochastic elements, marginally different results are obtained each time a model is fitted to the same data using the same hyperparameters. Therefore, it is suggested to fit multiple models to the same tree and to average derived outputs (Raumonen 2022). Before the final QSMs are derived from the data, the hyperparameters of the algorithm must be optimised. Depending on the respective tree height, a set of hyperparameters was selected, and five models were fitted for each tree and hyperparameter combination. The best combination of hyperparameters was selected based on the lowest average distance between the points and the fitted cylinder models. Using the optimised hyperparameters, for each tree, 30 models were created, and derived parameters were averaged to produce robust estimates. This data is available online on the Zenodo repository (Schindler et al. 2023). All subsequent data processing and analysis steps were performed using the statistical software R v4.2.1 (R Core Team 2023).

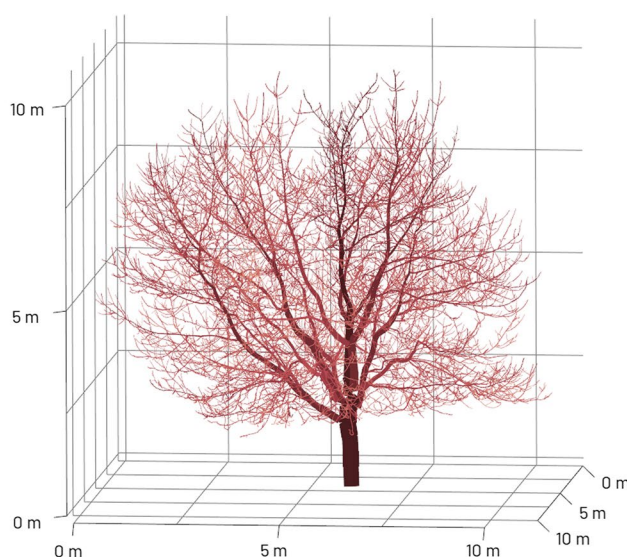


Fig. 3 Single cherry tree in the real world and as a QSM. Left: Photo of one of the cherry trees in Ebringen. Right: Visualisation of one of the QSMs of the same tree. The cylinders of the QSM are coloured according to their branch order

2.4 Volume, biomass, carbon and nutrients

When estimating volume and subsequently biomass using QSMs, bark thickness models can be applied to the fitted cylinders in order to derive separate wood and bark volumes. Here, we used the diameter-dependent bark thickness model for *P. avium* introduced by Pryor (1988), who measured bark thickness and disk diameter at varying heights on stems to acquire Eq. 1. The resulting model relates the diameter over bark *DOB* (cm) to the double bark thickness *DBT* (cm). To derive bark and wood biomass from volume, we measured the dry density of bark and wood for 35 samples of wild cherry. The samples were extracted from one sample tree and were then dried at 105 °C until constant weight was reached. Bark and wood density were then determined using the Archimedean principle (Seifert and Seifert 2014). By combining the dry density (ρ_{dry}) with volumetric shrinkage (β_v), the basic density (ρ_{basic}) was derived (Eq. 2). In the equation, m_{dry} corresponds to the dry mass, while V_{fresh} and V_{dry} correspond to the fresh and dry volumes, respectively. Here, we used $\beta_v = 13.7\%$ as provided by Bosshard (1982). Carbon and nutrient concentrations of wild cherry were adopted from Morhart et al. (2016), who studied widely spaced wild cherry trees from a site in the same geographic region near Breisach, Germany (Table 1). The biomass was partitioned into four different compartments (wood and bark in stem and branches) to which the corresponding carbon and nutrient concentrations were applied.

$$DBT = 0.367 + 0.0353 \times DOB + \varepsilon \quad (1)$$

$$\rho_{basic} = \frac{m_{dry}}{V_{fresh}} = \frac{m_{dry}}{V_{dry}} \times \frac{100 - \beta_v}{100} = \rho_{dry} \times \frac{100 - \beta_v}{100} \quad (2)$$

2.5 Statistical analysis

The derived data were used to fit allometric models relating the variables to the DBH. Although the addition of more predictors, such as tree height, would likely have improved the model fit for some variables (Picard et al. 2015), we chose not to include any additional predictors. Including tree parameters that are

more difficult to measure could affect model applicability for land managers. Models were chosen based on fit statistics (AIC, RMSE, R^2), plausibility of model behaviour in the interpolation and extrapolation range up to a DBH of 80 cm and normality and homoskedasticity of the residuals.

Regressions on tree dimension variables, above-ground volume, dry biomass, carbon content and nutrient content were modelled according to Eq. 3 using linear models. Since both the response variable and the predictors are log transformed, this function is equivalent to a power function. To account for the bias resulting from back transforming the response variable, for each affected model, a correction factor as given in Eq. 4 was calculated (Baskerville 1972; Sprugel 1983; Mascaro et al. 2011). The model fits of the power models were assessed using the adjusted R^2 (R^2_{adj}).

$$\ln(\hat{y}) = \beta_0 + \beta_1 \times \ln(DBH) \quad (3)$$

$$CF = \exp\left(\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{(n-2) \times 2}\right) \quad (4)$$

Additional beta regressions were fitted to describe the allocation of volume, biomass, carbon and nutrients among different sections of the tree. We employed beta regressions instead of modelling each component with a separate power function to ensure additivity of all components (Douma and Weedon 2019). For fitting the regressions, we used the R-package *betareg* (Cribari-Neto and Zeileis 2010). Respective confidence intervals were derived by bootstrapping each model 1000 times. The distribution of total volume in the branch-free bole up to the first branch and in the remaining woody biomass within the crown was modelled using Eq. 5. The distribution of total biomass, carbon content and nutrient content in the bark and wood was modelled using Eq. 6. To assess the fit of the beta regressions, the pseudo R^2 (R^2_{pseudo}) was employed. This goodness-of-fit statistic is the squared correlation between the predictor and the link-transformed response (Cribari-Neto and Zeileis 2010).

Table 1 Carbon and nutrient content of wood and bark of *P. avium* after Morhart et al. (2016). Both the carbon and the nutrient contents are given in g kg^{-1} of dry wood and bark sampled from the tree stem or branches

Segment		C (g kg^{-1})	Ca (g kg^{-1})	K (g kg^{-1})	Mg (g kg^{-1})	N (g kg^{-1})	P (g kg^{-1})
Wood	Stem	478.0	01.27	0.94	0.24	1.03	0.18
Wood	Branch	478.0	02.58	1.08	0.34	1.47	0.26
Bark	Stem	503.5	20.94	3.18	0.57	6.24	0.74
Bark	Branch	513.4	18.10	2.87	0.46	5.18	0.62

$$\text{logit}(\hat{y}) = \beta_0 + \beta_1 \times DBH \tag{5}$$

$$\text{logit}(\hat{y}) = \beta_0 + \beta_1 \times \ln(DBH) + \beta_2 \times DBH + \beta_3 \times \ln(DBH) \times DBH \tag{6}$$

To test the difference between our allometric model for above-ground dry biomass and previous biomass models for wild cherry from the same region, we compared our model to that of Morhart et al. (2016). Using both models, we predicted biomass for DBH values from 1 to 50 cm in steps of 1 cm. The differences between the predictions for these 50 values were then tested for normality using the Kolmogorov–Smirnov test. As the differences were not normally distributed ($p < 0.05$), a paired Wilcoxon signed-rank test was used to test the two sets of predictions for significant differences.

3 Results

For all the regression models produced, the model coefficients and either R^2_{adj} or R^2_{pseudo} are shown in Tables 2 and 3. The residuals of all models were successfully tested for normality using the Kolmogorov–Smirnov test ($p \geq 0.05$). All regression models showed a significant effect of DBH, either transformed or untransformed, on the respective response variable ($p < 0.05$).

The sampled trees ($n=70$) comprised free standing individuals with a DBH range of 1 to 50 cm and a tree height of 1.9 to 15.1 m. The corresponding crown base height ranged between 0.4 and 2.8 m. Crown base height correlated only weakly with the DBH (Fig. 4). The weak functional relationship between crown base height and DBH is underlined by the low R^2_{adj} of the associated regression model ($R^2_{adj}=0.47$, Table 2). Crown diameters of the trees varied from 0.1 to 13.8 m. The crown

Table 2 Overview of the regression models describing total single-tree parameters. All regressions were modelled according to Eq. 3, with correction factors (CF) derived according to Eq. 4. In each model, the predictor is the logarithm of the DBH in centimetre. For each model, the response variable and its unit, the model coefficients, the CF, the R^2_{adj} and the p -values of the model are reported

Response (\hat{y})	Unit	Intercept (β_0)	Slope (β_1)	CF	R^2_{adj}	p -value
Tree height	m	0.7421	0.4603	1.0150	0.8831	<0.001
Crown base height	m	-0.2801	0.2468	1.0368	0.4677	<0.001
Crown diameter	m	-1.2619	0.9772	1.0653	0.8887	<0.001
Crown projection area	m ²	-1.7834	1.6680	1.1751	0.9013	<0.001
Above-ground volume	m ³	-8.0157	2.2960	1.0502	0.9828	<0.001
Above-ground biomass	kg	-1.6740	2.2865	1.0517	0.9821	<0.001
Above-ground carbon	kg	-2.3786	2.2819	1.0527	0.9817	<0.001
Above-ground Ca	kg	-6.1680	2.1162	1.0890	0.9653	<0.001
Above-ground K	kg	-7.8585	2.1948	1.0688	0.9746	<0.001
Above-ground Mg	kg	-9.5174	2.2479	1.0627	0.9778	<0.001
Above-ground N	kg	-7.3125	2.1617	1.0759	0.9713	<0.001
Above-ground P	kg	-9.3780	2.1967	1.0711	0.9739	<0.001

Table 3 Overview over the regression models describing above-ground volume and mass fractions. In each model, the predictor is the logarithm of the DBH in centimetre. For each model, the response variable, the modelled fraction, the equation the model was fitted to, the model coefficients, the R^2_{pseudo} and the p -values are reported. The explicitly modelled section is highlighted in bold, while the implicitly modelled section is not. The p -values were derived by performing likelihood ratio tests comparing each model with the respective intercept-only model

Response (\hat{y})	Section	Eq	Intercept (β_0)	Slope (β_1)	Slope (β_2)	Slope (β_3)	R^2_{pseudo}	p -value
Volume	Bole Crown	(5)	-0.7389	-0.0226	n.a	n.a	0.3008	<0.001
Biomass	Bark Wood	(6)	-0.3430	0.9208	-0.1674	0.0321	0.7829	<0.001
Carbon	Bark Wood	(6)	-0.4039	0.9234	-0.1694	0.0326	0.7780	<0.001
Ca	Bark Wood	(6)	-2.8383	0.9983	-0.1612	0.0307	0.9194	<0.001
K	Bark Wood	(6)	-1.4817	0.9931	-0.1832	0.0353	0.8346	<0.001
Mg	Bark Wood	(6)	-1.0126	0.9554	-0.1551	0.0294	0.8892	<0.001
N	Bark Wood	(6)	-1.9599	1.0016	-0.1736	0.0333	0.8852	<0.001
P	Bark Wood	(6)	-1.5711	0.9821	-0.1663	0.0318	0.8854	<0.001

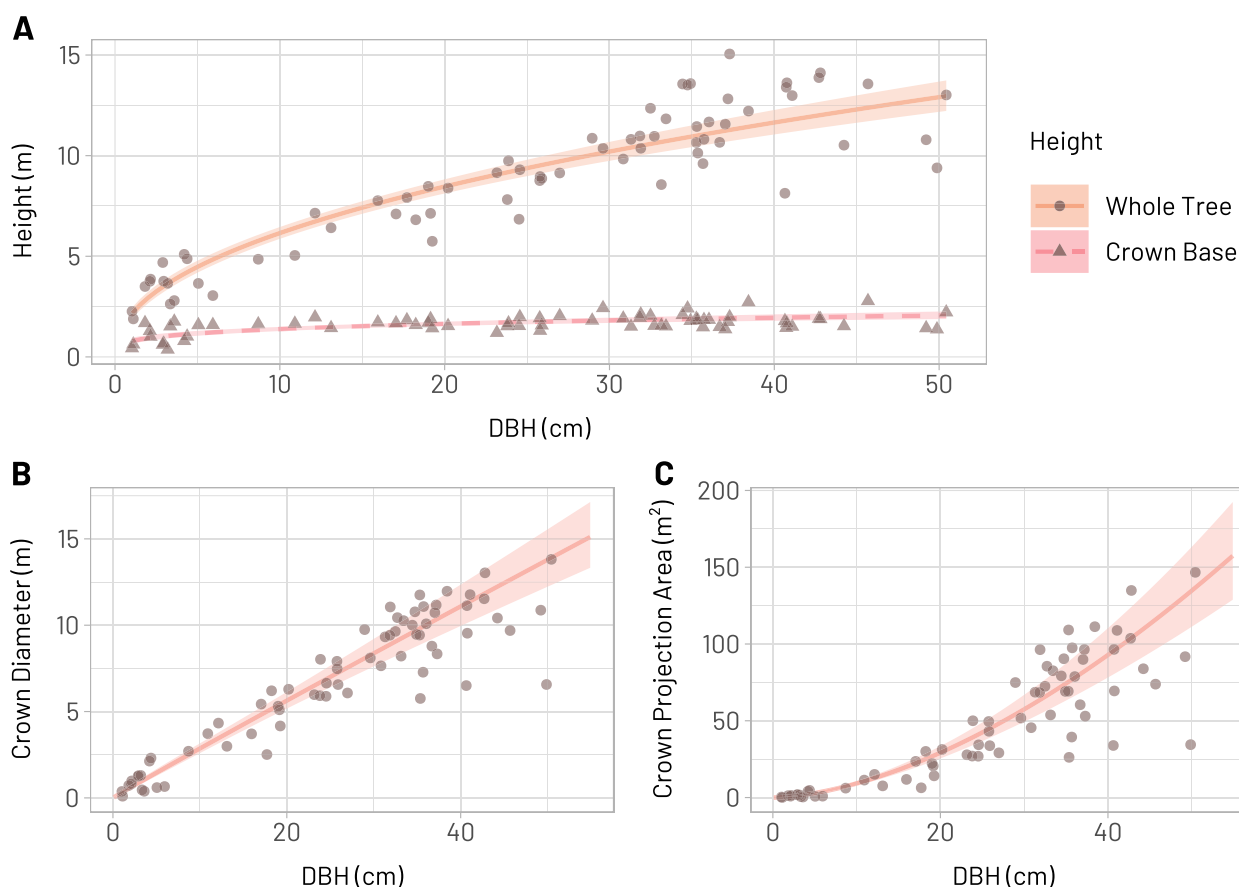


Fig. 4 Tree dimension variables. The lines and shaded areas show the bias-corrected regression models with their respective 95% confidence intervals. The dots represent data derived from the QSMs. **A** Tree height (solid orange line, circles) and crown base height (dashed pink line, triangles). **B** Crown diameter. **C** Crown projection area

diameter of individual trees was calculated as implemented in TreeQSM, by dividing the crown projection area into 36 conical sections at angles of 10° and averaging the maximum crown extent of all opposing sections. Meanwhile, the crown projection area of the trees ranged from 0.04 to 146.6 m² (Fig. 4). Except for the crown base height, all tree dimension variables could be described well ($R^2_{\text{adj}} \geq 0.88$, Table 2) as functions of the DBH.

To derive biomass from bark and wood volumes, the density of 35 individual bark and wood samples was determined. On average, the dry wood density was 0.619 ± 0.034 g/cm³ SD, and the dry bark density was 0.697 ± 0.073 g/cm³ SD. The average basic density of wood was 0.534 ± 0.029 g/cm³ SD, and the basic density of bark was 0.602 ± 0.063 g/cm³ SD.

Overall, the maximum above-ground volume of a single tree reached 3.4 m³. The same tree reached the maximum above-ground dry woody biomass of 1853 kg (Fig. 5). The share of branch-free bole volume ranged between 8 and 73% of the total above-ground volume. As DBH increased, the fraction of branch-free bole volume

decreased. The proportion of wood biomass to total above-ground biomass ranged from 39 to 84%, with the proportion of bark biomass decreasing with increasing DBH. The models relating total above-ground volume and biomass to DBH showed excellent fits ($R^2_{\text{adj}} = 0.98$, Table 2). Upon comparing the predictions of our biomass model with those of the model by Morhart et al. (2016), we did not find a significant difference between the models. While still showing a significant relationship between DBH and response, the fractional model for branch-free bole and crown volume displayed a worse fit ($R^2_{\text{pseudo}} = 0.3$, Table 3). Conversely, the model attributing total biomass to wood and bark showed a reasonable fit ($R^2_{\text{pseudo}} = 0.78$, Table 3).

The maximum amount of carbon which was stored in the above-ground biomass of a tree amounted to 901 kg, which is equivalent to 3307 kg of sequestered CO₂. From this amount, about 75% was stored in the wood, and 25% was stored in the bark. In general, the proportion of above-ground carbon stored in wood ranged from 37 to 84% of the total above-ground carbon. The nutrient

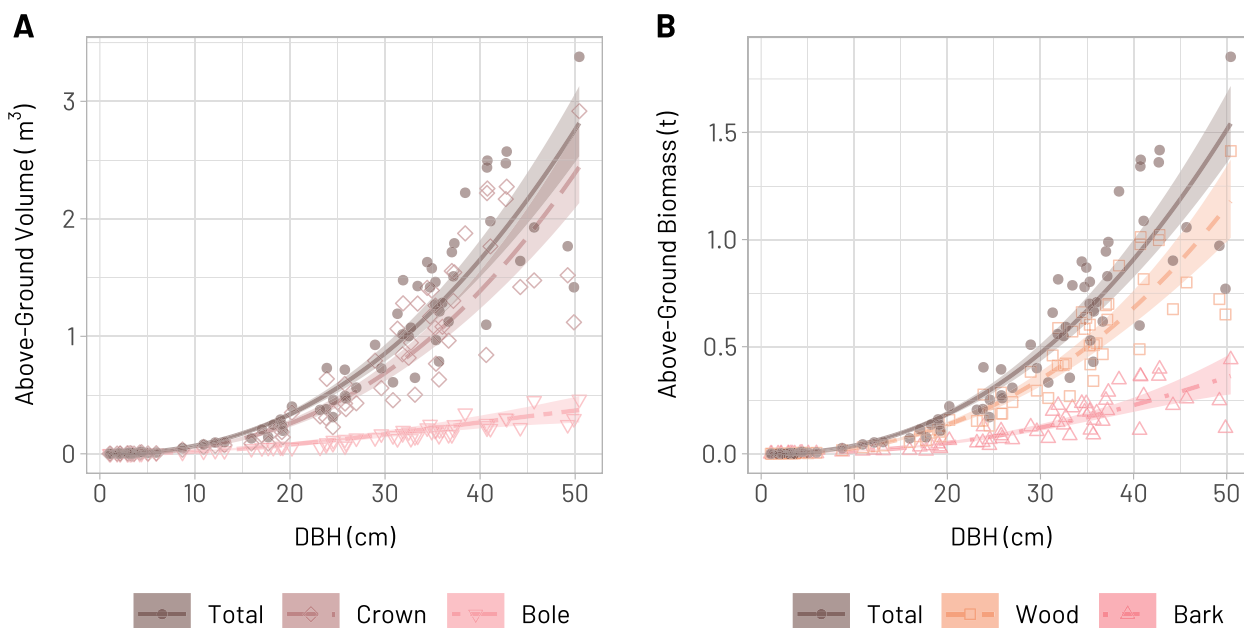


Fig. 5 Above-ground volume and biomass. The lines and shaded areas show the bias-corrected combined total and fractional regression models with their respective 95% confidence intervals. The dots represent data derived from the QSMs. **A** Above-ground woody volume, including total volume (solid dark line, filled circles), crown volume (brown dashed line, empty diamonds) and volume of the branch-free bole (pink double-dashed line, empty triangles). **B** Dry woody above-ground biomass in metric tonnes, including total biomass (solid dark line, filled round dots), wood biomass (orange dashed line, empty squares) and bark biomass (pink dot-dashed line, empty triangles)

content in the trees showed the following order of magnitude: Ca > N > K > Mg > P (Fig. 6). Of the most prevalent nutrient, calcium, a maximum of 11 kg occurred in a single tree. Nutrient proportions between wood and bark were dependent on the individual nutrient element. Nevertheless, with increasing DBH, the share of nutrients

stored in the wood increased regardless of the nutrient (Fig. 7). Similar to the biomass model, total carbon and nutrient content could be modelled precisely ($R^2_{adj} \geq 0.97$, Table 2) as functions of the DBH. In comparison, the models describing the proportion of nutrients in wood and bark displayed inferior fits ($R^2_{pseudo} \geq 0.78$, Table 3).

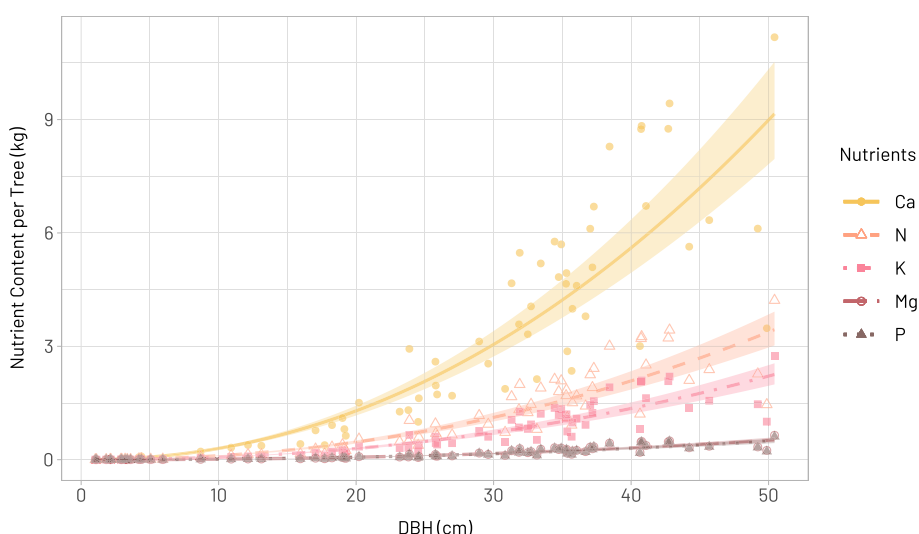


Fig. 6 Nutrient content in the above-ground tree biomass. The lines and shaded areas show the bias-corrected regression models with their respective 95% confidence intervals. The dots represent data derived from the QSMs. The plot shows the total nutrient content of the above-ground biomass, including calcium (yellow solid line, filled circles), nitrogen (orange short-dashed line, empty triangles), potassium (pink dot-dashed line, filled rectangles), magnesium (red long-dashed line, empty circles) and phosphorus (brown dotted line, filled triangles)

4 Discussion

In the context of increasing the carbon storage potential of conventional agricultural systems by adding a tree component, we analysed 70 wild cherry trees from an AFS using TLS and QSMs. This approach has been widely applied in forestry (Calders et al. 2015; Raunonen et al. 2015; Gonzalez de Tanago et al. 2018) but seldom in agroforestry (Hackenberg et al. 2014). We enhanced the methodology by distinguishing between bark and wood volume. Using this data, we derived allometric models that may be used likewise by researchers for understanding tree characteristics and their impacts on the other components in AFS, as well as by land managers for planning and optimising AFS. Apart from crown base height, all tree dimension variables, above-ground volume, oven-dry woody biomass, carbon content and nutrient content could be modelled as a function of DBH ($R^2_{adj} \geq 0.88$, Tab. 2). The normality of the residuals, goodness-of-fit statistics and significance of all predictor terms indicate that appropriate models were selected. Although the trees most likely belonged to different age classes and might not have been managed in the same way, the DBH

provided sufficient information to adequately model the response variables. Model fits possibly could have been improved by including additional predictors such as tree height or age (Picard et al. 2015), yet additional predictors can present difficulties in accurate measurement. We are confident that the models are sufficiently accurate and straightforward to apply at the same time. The limitations of the applicability of our models are discussed in Sect. 4.5.

4.1 Tree dimensions

Tree height is a key characteristic of orchard trees that has major economic consequences, as larger trees may produce more fruit per tree (Wünsche et al. 2000) but can also increase labour costs for harvesting (Hester and Cacho 2003). Crown base height is highly dependent on management practices, such as pruning, and other external factors that are not species specific. Trees in *Streuobst* systems are usually formatively pruned to retain low crown base heights between 1.6 and 1.8 m (Herzog 1998). This is probably the reason for the mediocre fit ($R^2_{adj} = 0.47$, Table 2) of the crown base height model.

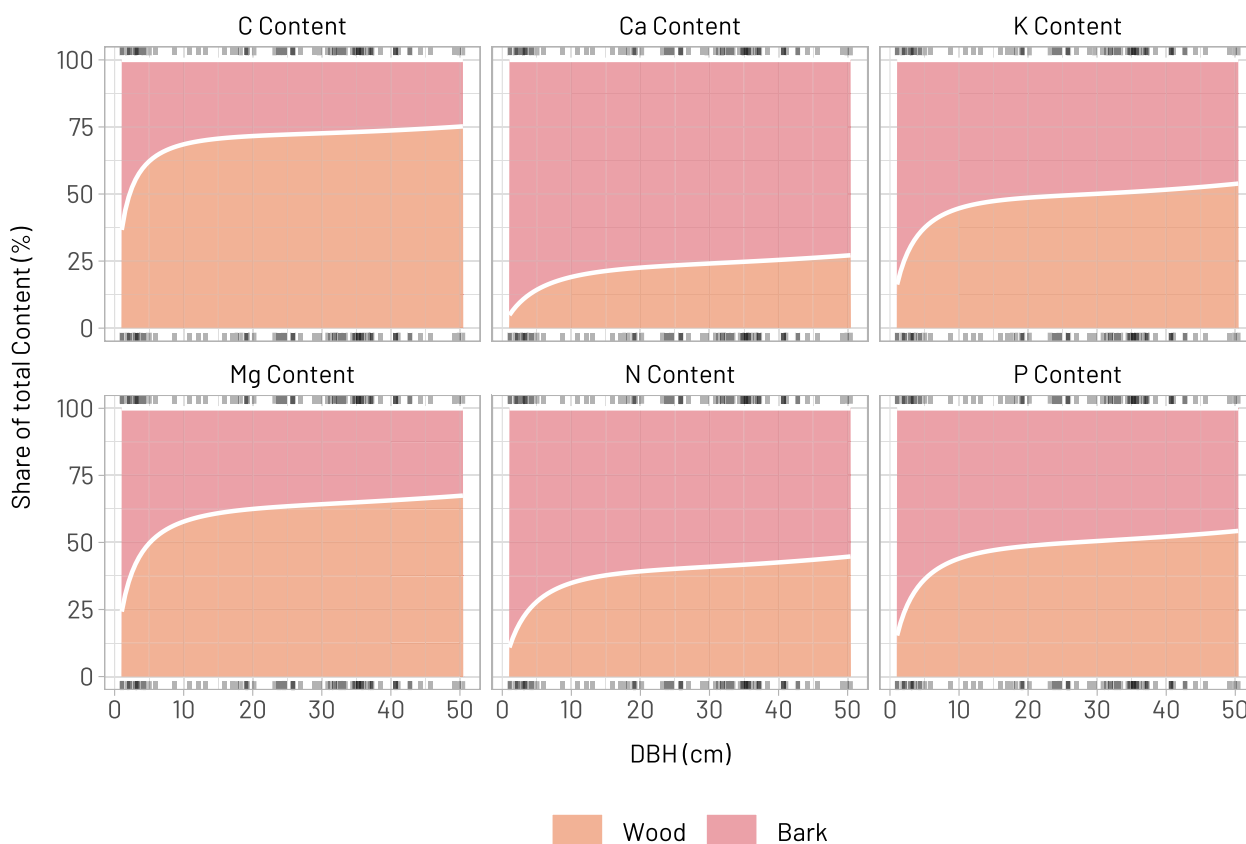


Fig. 7 Nutrient distribution in the above-ground bark and wood. The white lines show the regression models, while the areas specify the wood (orange) and bark (pink) fractions. The grey vertical lines above and below the graphs indicate DBH values derived from the QSMs. The plots show carbon, calcium, potassium, magnesium, nitrogen and phosphorus content (from left to right and from top to bottom)

Crown diameter, on the other hand, is relevant when planning AFS as it determines the required planting distance if crowns are not to interfere with each other. Tree spacing is not only important for crown development but can hinder or even prevent the use of heavy machinery, which might not fit between the tree rows. Low crown base heights can hamper management in a similar way. Therefore, allometric models for tree dimensions are particularly useful in AFS planning.

In general, tree dimensions are strongly influenced by management practices which ultimately depend on the production goals. For example, crown size affects several factors such as growth, carbon sequestration and shading (Pretzsch et al. 2015). Large crowns can increase light interception and thus photosynthesis of the individual tree, which can lead to higher fruit yields and carbon sequestration (Robinson and Lakso 1991; Wünsche et al. 2000), but they also shade larger portions of agricultural land beneath the trees. Shading can be beneficial for light-sensitive crops (Bellow and Nair 2003) and the welfare of grazing animals (Mele et al. 2019), especially in the light of changing climatic conditions due to global warming, but equally, it may adversely affect light-demanding crops (Artru et al. 2017). In addition, shading can alter fruit traits such as weight, colour, firmness and the occurrence of blemishes on the fruits (Wünsche et al. 2000).

4.2 Volume

As most of the studies conducted on *P. avium* trees so far sampled data destructively and focused on tree biomass, which is easier to measure manually than volume, there are few allometric models for the volume of wild cherry. In a previous study by Hackenberg et al. (2014), a model for total tree volume was developed based on TLS data and QSMs. They investigated trees on the same study site in Breisach that was also used within this study (Fig. 1). However, they only sampled 24 trees within a narrow DBH range between 7 and 16 cm. Up to a DBH of 10 cm, both models are very similar, but with increasing DBH, their model predicts increasingly less volume than our model. As our model contains data from larger trees, we deem our model to be more robust for trees with higher DBH values.

The model describing the relationship between DBH and relative bole volume showed a weak fit ($R^2_{\text{pseudo}}=0.3$, Tab. 3). This can be attributed to the fact that bole volume, defined as the volume of the stem up to the first branch, is strongly influenced by crown base height. Since crown base height itself is subject to high variability due to its dependence on external factors, the poor fit of the model was not unexpected. With increasing DBH, the proportion of branch-free bole volume decreased. Miguel

et al. (2017), who conducted a study on trees in a forest savannah in Brazil, observed a similar trend. The reason for this relationship is probably that in the crown, there is length and diameter growth, whereas on the trunk, only diameter growth occurs, and thus, the volume increases less. By combining the above-ground volume models presented, the potential yield of high-quality (bole volume) and low-quality timber (crown volume) can be estimated. However, pruning the lower parts of the crown can increase crown base height and bole length, thus increasing the production of high-value wood, which can then be sold at higher revenues (Balandier and Dupraz 1999).

4.3 Biomass

In the GlobAllomeTree database (Henry et al. 2013), a centralised repository of allometric models, no biomass models for *P. avium* are currently listed. In a study by Alberti et al. (2006), wild cherry trees from a closed forest plantation in the Udine region of Italy were studied ($n=18$, 23 years old). Starting at a DBH of about 10 cm, their model consistently predicts less biomass than our model, with discrepancy increasing at larger DBH values. Differences between the models may be attributable to different climatic conditions, tree density and management treatments.

Presenting the best opportunity for comparison given the similarities in the study region, the models proposed by Morhart et al. (2016) compare well with those presented within this study. We did not find a significant difference between the predictions of this model and our biomass model. This outcome validates the alternative methodology utilising TLS while also validating an extrapolation of the previously proposed model for larger DBH values. Morhart et al. (2016) sampled cherry trees from the same region using an intensive destructive sampling method ($n=39$, 15 years old). Their resultant allometric models for biomass apply to trees with a DBH range of 2 to 26 cm, thus limiting the predictive ability of the models. Our data covers a wider DBH range with a larger sample size (DBH 1 to 50 cm, $n=70$), making the presented models applicable to larger trees within the study region. The trees sampled in the aforementioned study were not subject to any management procedures such as thinning and pruning to the point of sampling. Thus, the growth form and management of these trees are in direct contrast to the majority of the trees examined in this current study. Nonetheless, the close relation of the two biomass curves between these two studies suggests that growth form and management practices like thinning and pruning have only a minor influence on the relationship between DBH and total above-ground biomass. Differences, nevertheless, may arise in biomass partitioning, growth rates and other attributes such as

tree height. Since both carbon and nutrient content depend primarily on biomass, this indicates that the carbon and nutrient models are probably also transferable to some extent to differently managed wild cherry trees under similar environmental conditions. The close relationship between these variables can also be seen in the very similar model fit statistics (Table 2).

4.4 Carbon and nutrients

Woody biomass represents carbon storage in both above- and below-ground portions (Cardinael et al. 2017) and is qualifiable utilising biomass models. Our model describing the relationship between above-ground carbon content and DBH showed an excellent fit ($R^2_{adj}=0.98$, Table 2). The model derived by Morhart et al. (2016) was to their maximum observed DBH very similar to our model. With increasing DBH, the discrepancy between the models increased with their model estimating a higher carbon content than our model. The similarity of the two models was anticipated, however, as both models were based on the same conversion factor of biomass to carbon content and as the models on total woody above-ground biomass already demonstrated strong agreement. We were unable to find any other allometric models for the carbon content of *P. avium* trees to compare with our models.

Carbon stored within vegetation represents a larger global carbon sink than the atmosphere (Bombelli et al. 2009), so the inclusion of trees within agricultural landscapes presents a potential for increased carbon storage over a low baseline. The agricultural sector is currently a net emitter of anthropogenic GHG emissions (IPCC 2022b), but adding trees to agricultural landscapes could reduce net GHG emissions (Montagnini and Nair 2004; Abbas et al. 2017). Our results show that an AFS composed of 40 cherry trees with a DBH of 50 cm could store an additional 29 t of carbon solely in the above-ground tree parts. Our carbon models presented provide a valuable tool for assessing carbon stocks of the wood and bark of wild cherry trees in AFS and can inform discussions about their carbon sequestration and substitution potential. It should be emphasised that carbon storage and substitution effects within AFS depend on management practices and how the produced wood is utilised. Retaining large trees on the sites increases in situ carbon storage. Managing trees to produce high-value timber can provide ex situ carbon storage if the timber is used for durable products such as furniture. If trees are not pruned appropriately, more low-grade wood is produced that is likely to be used as firewood, which, nevertheless, can replace carbon arising from fossil fuel combustion.

The nutrient content within the woody above-ground biomass followed the order $Ca > N > K > Mg > P$, with the total magnesium and phosphorus content being very

similar (Fig. 6). Although Morhart et al. (2016) sampled wild cherry trees in the same region and used the same nutrient concentrations, their trees contained slightly more phosphorus than magnesium. This is likely due to the different bark thickness models, as we chose to use the model suggested by Pryor (1988) that covers a wider range of diameters. Nevertheless, they also found the relative nutrient content of the bark to decrease with increasing DBH due to the lower proportion of bark biomass.

4.5 Limitations

To date, numerous studies have compared volume and biomass estimates obtained from TLS and QSMs with field measurements, with most studies showing good agreement (Hackenberg et al. 2014; Calders et al. 2015; Raunonen et al. 2015; Kükenbrink et al. 2021). Factors affecting point cloud and hence QSM quality include the TLS sensor type (Calders et al. 2020), scanning setup (Wilkes et al. 2017) and point cloud processing (Demol et al. 2022). To reduce possible errors, we used techniques known to improve point cloud quality. During data acquisition, we performed multiple scans per tree to ensure full crown coverage without occlusion effects, as proposed by Wilkes et al. (2017). In forests, canopy occlusion by the trees themselves and their neighbours is a major source of errors that deteriorates as stand complexity and tree height increase (Wang et al. 2019). The comparatively low height of our trees (Fig. 4) and the large spacing between them (Fig. 1) created more favourable conditions. Resultant point clouds were filtered for noise, and co-registration was improved using multistation adjustments (Demol et al. 2022). Although QSM-based volume estimates are subject to inherent uncertainty, this method still provides the best currently available non-destructive estimates.

Since the TLS data as well as the carbon and nutrient concentrations in wood and bark were obtained in the same geographical region, our allometric models are potentially limited to that region (Fig. 1). They might be applicable to regions with similar climate and soil but should be applied with caution. For example, it is known that wood nutrients can vary with soil nutrient availability (Heineman et al. 2016), and that tree height is linked to climate, soil and stand structure (Cysneiros et al. 2021). Furthermore, some of the allometric models might be restricted to comparable AFS in which the trees were managed in a comparable way. Most of the trees studied were grown in a system similar to a meadow orchard. In orchards, trees are usually managed in a specific way to promote and maximise fruit production (Mika 2011). Trees pruned for the production of high-value timber (Coello et al. 2013) or damaged by browsing

livestock (Triches et al. 2020), in contrast, might behave differently in terms of their growth, i.e. rate of diameter or height increment or crown architecture. The growth of trees in AFS with varying tree density, and thus competition, might also differ (Perry 1985). Furthermore, our data included a heterogeneous age distribution to cover a wide range of DBH values. We cannot be sure that the models are transferable to systems with a very different age distribution, for example planted systems with trees of the same age, as age can have an effect on biomass allocation (Forrester et al. 2017). Moreover, although we selected models that show a plausible behaviour in the extrapolation range, model uncertainty increases after the maximum observed DBH of 50 cm.

4.6 Outlook

As an outlook, we recommend researchers to employ TLS and QSM in agricultural and agroforestry research to a greater extent. Using this methodology, topological and volumetric data can be collected accurately and efficiently without the necessity for destructive sampling. From these data, as this study presents, a wealth of information can be derived. Ironically, this methodology is most often used in forests, where challenging conditions lead to suboptimal data quality. Within AFS, on the other hand, TLS is used much less frequently, even though the conditions allow for better data quality. Using TLS alongside supplementary data, further interactions between the woody and the agricultural component of AFS should be explored to foster our understanding of AFS. For example, TLS has previously been used to assess shading cast by trees (Roskopf et al. 2017; Bohn Reckziegel et al. 2021), additionally harnessing the spatial information of TLS-derived point clouds to dissect and shape trees to implement distinct shading scenarios (Bohn Reckziegel et al. 2022). The precise 3D data collected with TLS opens up possibilities for addressing complex and previously almost unanswerable research questions on a single-tree basis. As there is currently little knowledge about trees in AFS, there are many questions that still need to be answered. For example, to our knowledge, it is currently unknown how fertilisation affects nutrient content and allocation in trees in AFS. Depending on management practices such as pruning and fertilisation, the applicability of the allometric models is likely affected. Future research should make efforts to quantify differences in tree growth induced by different management practices more thoroughly.

5 Conclusion

In this study, a set of allometric models for *P. avium* trees in AFS was derived based on TLS, QSMs and further auxiliary data. In particular, we modelled tree dimensions,

above-ground volume, oven-dry biomass and carbon and nutrient content. For all parameters not related to crown base height, our models achieved good to excellent fits (total: $R^2_{\text{adj}} \geq 0.88$, fractions: $R^2_{\text{pseudo}} \geq 0.78$), although we relied on DBH as the only predictor to facilitate application. Although models related to crown base height showed significant effects of DBH, the models show weaker fits (total: $R^2_{\text{adj}} = 0.47$, fractions: $R^2_{\text{pseudo}} = 0.3$), demonstrating the dependence of this variable on external factors. It should be emphasised that the allometric models presented here are likely limited in their applicability to comparable AFS systems with comparable management and environmental conditions. Our most interesting finding is the apparent transferability of biomass models for wild cherry to differently managed trees in other AFS under similar environmental conditions. However, as with any allometric models, applying the models outside their calibration range should be avoided or carried out with caution. With this paper, we are able to provide a scientific basis for the inclusion of wild cherry trees in AFS and, moreover, to supply land managers with additional tools and information to plan AFS according to their individual demands and production goals. Our models can be used, for example, to estimate the space required per tree, to approximate shaded area or to derive the potential revenue from the sale of bole wood. Furthermore, our models may be used to assess above-ground carbon stocks within comparable existing and future AFS. This kind of information can assist policy makers in appropriately subsidising carbon sequestration in agricultural systems and increases the resolution of information regarding carbon storage within above-ground woody biomass in temperate AFS. The models on the above-ground nutrient content, on the other hand, can be used to assess nutrient removal from AFS upon harvesting trees. This could aid land managers to adapt fertilisation measured accordingly. Though AFS have a long history in Europe, it is only now that such innovative systems are starting to receive more attention. Therefore, there is still much to be uncovered and understood about these complex systems which could prove invaluable for climate change adaptation and mitigation.

Acknowledgements

We would like to thank Melchior Schliephack for his assistance with the data collection in Ebringen and Robert Dietrich for sample preparation.

Authors' contributions

Conceptualization, ZS, CM and TS; methodology, ZS, CM and TS; formal analysis and investigation, ZS and CM; visualisation, ZS; writing — original draft preparation, ZS, JS and CM; writing — review and editing, ZS, CM, JS and TS; funding acquisition, CM and TS; and supervision, CM and TS. All authors read and approved the final manuscript.

Funding

Open Access funding enabled and organized by Projekt DEAL. The project INTEGRA is supported by funds of the Federal Ministry of Food and Agriculture

(BMEL) based on a decision of the parliament of the Federal Republic of Germany via the Federal Office for Agriculture and Food (BLE) under the Federal Programme for Ecological Farming and Other Forms of Sustainable Agriculture (support code 2819NA071). The article processing charge was funded by the Baden-Württemberg Ministry of Science, Research and Art and the University of Freiburg in the funding programme Open-Access Publishing.

Availability of data and materials

The datasets generated and/or analysed during the current study are available on the Zenodo repository (<https://doi.org/10.5281/zenodo.8068348>) and from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors gave their informed consent to this publication and its content.

Competing interests

The authors declare that they have no competing interests.

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Received: 14 March 2023 Accepted: 28 June 2023

Published online: 21 July 2023

References

- Abbas F, Hammad HM, Fahad S, Cerdà A, Rizwan M, Farhad W, Ehsan S, Bakhat HF (2017) Agroforestry: a sustainable environmental practice for carbon sequestration under the climate change scenarios—a review. *Environ Sci Pollut Res* 24:11177–11191. <https://doi.org/10.1007/s11356-017-8687-0>
- Alberti G, Marelli A, Piovesana D, Peressotti A, Zerbi G, Gottardo E, Bidese F (2006) Carbon stocks and productivity in forest plantations (Kyoto forests) in Friuli Venezia Giulia (Italy). *Forest@* 3:488–495. <https://doi.org/10.3832/efor0414-0030488>
- Artru S, Garré S, Dupraz C, Hiel M-P, Blitz-Frayret C, Lassois L (2017) Impact of spatio-temporal shade dynamics on wheat growth and yield, perspectives for temperate agroforestry. *Eur J Agronomy* 82, Part A:60–70. <https://doi.org/10.1016/j.eja.2016.10.004>
- Balandier P, Dupraz C (1999) Growth of widely spaced trees. A case study from young agroforestry plantations in France. *Agroforest Syst* 43:151–167. <https://doi.org/10.1023/A:1026480028915>
- Baskerville GL (1972) Use of logarithmic regression in the estimation of plant biomass. *Can J for Res* 2:49–53. <https://doi.org/10.1139/x72-009>
- Bellow J, Nair PKR (2003) Comparing common methods for assessing understory light availability in shaded-perennial agroforestry systems. *Agric for Meteorol* 114:197–211. [https://doi.org/10.1016/S0168-1923\(02\)00173-9](https://doi.org/10.1016/S0168-1923(02)00173-9)
- Bohn Reckziegel R, Larysch E, Sheppard JP, Kahle H-P, Morhart C (2021) Modelling and comparing shading effects of 3D tree structures with virtual leaves. *Remote Sensing* 13:532. <https://doi.org/10.3390/rs13030532>
- Bohn Reckziegel R, Sheppard JP, Kahle H-P, Larysch E, Spiecker H, Seifert T, Morhart C (2022) Virtual pruning of 3D trees as a tool for managing shading effects in agroforestry systems. *Agrofor Syst* 96:89–104. <https://doi.org/10.1007/s10457-021-00697-5>
- Bombelli A, Avitabile V, Baltzer H, Belelli Marchesini L, Bernoux M, Brady M, Hall R, Hansen M, Henry M, Herold M, Janetos A, Law BE, Manlay R, Marklund L, Olsson H, Pandey D, Saket M, Schmillius C, Sessa R, Shimabukuro YE, Valentini R, Wulder MA (2009) Assessment of the status of the development of the standards for the Terrestrial Essential Climate Variables. Rome
- Bosshard HH (1982) *Mikroskopie und Makroskopie des Holzes*, 2nd edn. Lehrbücher und Monographien aus dem Gebiete der exakten Wissenschaften Reihe der experimentellen Biologie, vol 18. Birkhäuser, Basel
- Calders K, Adams J, Armston J, Bartholomeus H, Bauwens S, Bentley LP, Chave J, Danson FM, Demol M, Disney M, Gaulton R, Krishna Moorthy SM, Levick SR, Saarinen N, Schaaf C, Stovall A, Terry L, Wilkes P, Verbeeck H (2020) Terrestrial laser scanning in forest ecology: expanding the horizon. *Remote Sensing of Environment* 251:112102. <https://doi.org/10.1016/j.rse.2020.112102>
- Calders K, Newnham G, Burt A, Murphy S, Raunonen P, Herold M, Culvenor D, Avitabile V, Disney M, Armston J (2015) Nondestructive estimates of above-ground biomass using terrestrial laser scanning. *Methods Ecol Evol* 6:198–208. <https://doi.org/10.1111/2041-210X.12301>
- Cardinael R, Chevallier T, Cambou A, Béal C, Barthès BG, Dupraz C, Durand C, Kouakoua E, Chenu C (2017) Increased soil organic carbon stocks under agroforestry: a survey of six different sites in France. *Agr Ecosyst Environ* 236:243–255. <https://doi.org/10.1016/j.agee.2016.12.011>
- Cardinael R, Mao Z, Chenu C, Hinsinger P (2020) Belowground functioning of agroforestry systems: recent advances and perspectives. *Plant Soil* 453:1–13. <https://doi.org/10.1007/s11104-020-04633-x>
- CloudCompare (2022) CloudCompare. <http://www.cloudcompare.org/>
- Coello J, Desombre V, Becquey J, Gonin P, Ortisset J-P, Baiges T, Piqué M (2013) Wild cherry (*Prunus avium*) for high quality timber. In: Government of Catalonia MoALFFaNE, Catalan Forest Ownership Centre (ed) Ecology and silviculture of the main valuable broadleaved species in the Pyrenean area and neighbouring regions, Santa Perpètua de Mogoda, Spain. pp 13–20
- Cribari-Neto F, Zeileis A (2010) Beta regression in R. *J Stat Soft* 34. <https://doi.org/10.18637/jss.v034.i02>
- Cysneiros VC, Coelho de Souza F, Gai TD, Pelissari AL, Orso GA, Machado SdA, de Carvalho DC, Silveira-Filho TB (2021) Integrating climate, soil and stand structure into allometric models: an approach of site-effects on tree allometry in Atlantic Forest. *Ecological Indicators* 127:107794. <https://doi.org/10.1016/j.ecolind.2021.107794>
- Demol M, Wilkes P, Raunonen P, Krishna Moorthy SM, Calders K, Gielen B, Verbeeck H (2022) Volumetric overestimation of small branches in 3D reconstructions of *Fraxinus excelsior*. *Silva Fennica* 56. <https://doi.org/10.14214/sf.10550>
- Disney MI, Boni Vicari M, Burt A, Calders K, Lewis SL, Raunonen P, Wilkes P (2018) Weighing trees with lasers: advances, challenges and opportunities. *Interface Focus* 8. <https://doi.org/10.1098/rsfs.2017.0048>
- Douma JC, Weedon JT (2019) Analysing continuous proportions in ecology and evolution: a practical introduction to beta and Dirichlet regression. *Methods Ecol Evol* 10:1412–1430. <https://doi.org/10.1111/2041-210X.13234>
- Forrester DI, Tachauer I, Annighoefer P, Barbeito I, Pretzsch H, Ruiz-Peinado R, Stark H, Vacchiano G, Zlatanov T, Chakraborty T, Saha S, Sileshi GW (2017) Generalized biomass and leaf area allometric equations for European tree species incorporating stand structure, tree age and climate. *Adaptation of Forests and Forest Management to Changing Climate Selected papers from the conference on "Adaptation of Forests and Forest Management to Changing Climate with Emphasis on Forest Health: A Review of Science, Policies and Practices"*, Umeå, Sweden, August 25–28, 2008 396:160–175. <https://doi.org/10.1016/j.foreco.2017.04.011>
- Gonzalez de Tanago J, Lau A, Bartholomeus H, Herold M, Avitabile V, Raunonen P, Martius C, Goodman RC, Disney M, Manuri S, Burt A, Calders K (2018) Estimation of above-ground biomass of large tropical trees with terrestrial LiDAR. *Methods Ecol Evol* 9:223–234. <https://doi.org/10.1111/2041-210X.12904>
- Hackenberg J, Morhart C, Sheppard JP, Spiecker H, Disney M (2014) Highly accurate tree models derived from terrestrial laser scan data: a method description. *Forests* 5:1069–1105. <https://doi.org/10.3390/f5051069>
- Heineman KD, Turner BL, Dalling JW (2016) Variation in wood nutrients along a tropical soil fertility gradient. *New Phytol* 211:440–454. <https://doi.org/10.1111/nph.13904>
- Henry M, Bombelli A, Trotta C, Alessandrini A, Birgazzi L, Sola G, Vieilledent G, Santenoi P, Longuetaud F, Valentini R, Picard N, Saint-André L (2013) GlobAllomeTree: international platform for tree allometric equations to support volume, biomass and carbon assessment. *iForest - Biogeosciences Forestry* 6:326–330. <https://doi.org/10.3832/for0901-006>
- Herzog F (1998) Streuobst: a traditional agroforestry system as a model for agroforestry development in temperate Europe. *Agroforest Syst* 42:61–80. <https://doi.org/10.1023/A:1006152127824>

- Hester SM, Cacho O (2003) Modelling apple orchard systems. *Agric Syst* 77:137–154. [https://doi.org/10.1016/S0308-521X\(02\)00106-3](https://doi.org/10.1016/S0308-521X(02)00106-3)
- IPCC (2022a) Climate change 2022: impacts, adaptation and vulnerability: Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, NY, USA
- IPCC (2022b) Climate change 2022: mitigation of climate change: contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, NY, USA
- Jose S (2009) Agroforestry for ecosystem services and environmental benefits: an overview. *Agroforest Syst* 76:1–10. <https://doi.org/10.1007/s10457-009-9229-7>
- Jose S, Bardhan S (2012) Agroforestry for biomass production and carbon sequestration: an overview. *Agrofor Syst* 86:105–111. <https://doi.org/10.1007/s10457-012-9573-x>
- Kay S, Rega C, Moreno G, den Herder M, Palma JH, Borek R, Crous-Duran J, Freese D, Giannitsopoulos M, Graves A, Jäger M, Lamersdorf N, Memedemin D, Mosquera-Losada R, Pantera A, Paracchini ML, Paris P, Roces-Diaz JV, Rolo V, Rosati A, Sandor M, Smith J, Szerencsits E, Varga A, Viaud V, Wawer R, Burgess PJ, Herzog F (2019) Agroforestry creates carbon sinks whilst enhancing the environment in agricultural landscapes in Europe. *Land Use Policy* 83:581–593. <https://doi.org/10.1016/j.landusepol.2019.02.025>
- Kimmins JP (1977) Evaluation of the consequences for future tree productivity of the loss of nutrients in whole-tree harvesting. *For Ecol Manage* 1:169–183. [https://doi.org/10.1016/0378-1127\(76\)90019-0](https://doi.org/10.1016/0378-1127(76)90019-0)
- Kükenbrink D, Gardi O, Morsdorf F, Thürig E, Schellenberger A, Mathys L (2021) Above-ground biomass references for urban trees from terrestrial laser scanning data. *Ann Bot* 128:709–724. <https://doi.org/10.1093/aob/mcab002>
- Kunneke A, van Aardt J, Roberts W, Seifert T (2014) Localisation of biomass potentials. In: Seifert T (ed) *Bioenergy from Wood*, vol 26. Springer, Netherlands, Dordrecht, pp 11–41
- Kunz M, Hess C, Raunonen P, Bienert A, Hackenberg J, Maas HG, Härdtle W, Fichtner A, von Oheimb G (2017) Comparison of wood volume estimates of young trees from terrestrial laser scan data. *iForest-Biogeosciences Forestry* 10:451–458. <https://doi.org/10.3832/for2151-010>
- Malhi GS, Kaur M, Kaushik P (2021) Impact of climate change on agriculture and its mitigation strategies: a review. *Sustainability* 13:1318. <https://doi.org/10.3390/su13031318>
- Mascaro J, Litton CM, Hughes RF, Uowolo A, Schnitzer SA (2011) Minimizing bias in biomass allometry: model selection and log-transformation of data. *Biotropica* 43:649–653. <https://doi.org/10.1111/j.1744-7429.2011.00798.x>
- Mele M, Mantino A, Antichi D, Mazzoncini M, Ragagnini G, Cappucci A, Serra A, Pelleri F, Chiarabaglio P, Mezzalana G et al (2019) Agroforestry system for mitigation and adaptation to climate change: effects on animal welfare and productivity. *Agrochimica* 2019:91–98
- Merino A, Balboa MA, Rodríguez Soalleiro R, González JÁ (2005) Nutrient exports under different harvesting regimes in fast-growing forest plantations in southern Europe. *Adaptation of Forests and Forest Management to Changing Climate Selected papers from the conference on "Adaptation of Forests and Forest Management to Changing Climate with Emphasis on Forest Health: A review of science, policies and practices"*, Umeå, Sweden, August 25–28, 2008 207:325–339. <https://doi.org/10.1016/j.foreco.2004.10.074>
- Miguel EP, Rezende AV, Pereira RS, Azevedo GB de, Mota FCM, Souza AN de, Joaquim MS (2017) Modeling and prediction of volume and aerial biomass of the tree vegetation in a Cerradão area of Central Brazil. *Interciencia* 42
- Mika A (2011) Physiological responses of fruit trees to pruning. *Hortic Rev* 8:337–378
- Montagnini F, Nair PKR (2004) Carbon sequestration: an underexploited environmental benefit of agroforestry systems. *Agroforest Syst* 61–62:281–295. <https://doi.org/10.1023/B:AGFO.0000029005.92691.79>
- Morhart C, Sheppard JP, Schuler JK, Spiecker H (2016) Above-ground woody biomass allocation and within tree carbon and nutrient distribution of wild cherry (*Prunus avium* L.) – a case study. *Forest Ecosystems* 3:1–15. <https://doi.org/10.1186/s40663-016-0063-x>
- Nair PKR, Kang BT, Kass DCL (1995) Nutrient cycling and soil-erosion control in agroforestry systems. In: Joo ASR, Freed RD (eds) *Agriculture and the Environment*. American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America, Madison, WI, USA, pp 117–138
- Nair PKR (1985) Classification of agroforestry systems. *Agroforest Syst* 3:97–128. <https://doi.org/10.1007/BF00122638>
- Nair PKR (1993) An introduction to agroforestry, p. 499. Kluwer Academic Publishers (in cooperation with the International Centre for Research in Agroforestry), Dordrecht, Netherlands
- Nair PKR (2012) Carbon sequestration studies in agroforestry systems: a reality-check. *Agroforest Syst* 86:243–253. <https://doi.org/10.1007/s10457-011-9434-z>
- Nair PKR, Kumar BM, Nair VD (2009) Agroforestry as a strategy for carbon sequestration. *J Plant Nutr Soil Sci* 172:10–23. <https://doi.org/10.1002/jpln.200800030>
- Nair PKR, Kumar BM, Nair VD (2021) Definition and concepts of agroforestry. In: Nair PKR, Kumar BM, Nair VD (eds) *An introduction to agroforestry*. Springer International Publishing, Cham, pp 21–28
- Nair PKR, Nair VD, Kumar BM, Showalter JM (2010) Carbon sequestration in agroforestry systems. *Adv Agron* 108:237–307. [https://doi.org/10.1016/S0065-2113\(10\)08005-3](https://doi.org/10.1016/S0065-2113(10)08005-3)
- Paré D, Thiffault E (2016) Nutrient budgets in forests under increased biomass harvesting scenarios. *Curr Forestry Rep* 2:81–91. <https://doi.org/10.1007/s40725-016-0030-3>
- Peel MC, Finlayson BL, McMahon TA et al (2007) Updated world map of the Köppen-Geiger climate classification. *Hydrol Earth Syst Sci Discuss* 4:439–473
- Perry DA (1985) The competition process in forest stands. *Attributes of trees as crop plants*:481–506
- Picard N, Rutishauser E, Ploton P, Ngomanda A, Henry M (2015) Should tree biomass allometry be restricted to power models? *For Ecol Manage* 353:156–163. <https://doi.org/10.1016/j.foreco.2015.05.035>
- Picard N, Saint-André L, Henry M (2012) Manual for building tree volume and biomass allometric equations: from field measurement to prediction. Food and Agricultural Organization of the United Nations and Centre de Coopération Internationale en Recherche Agronomique pour le Développement, Rome, Montpellier
- Pretzsch H, Biber P, Uhl E, Dahlhausen J, Rötzer T, Caldentey J, Koike T, van Con T, Chavanne A, Seifert T, du Toit B, Farnden C, Pauleit S (2015) Crown size and growing space requirement of common tree species in urban centres, parks, and forests. *Urban Forestry & Urban Greening* 14:466–479. <https://doi.org/10.1016/j.ufug.2015.04.006>
- Pryor SN (1988) The silviculture and yield of wild cherry. *Forestry Commission bulletin*, vol 75. Her Majesty's Stationery Office, London
- R Core Team (2023) R: a language and environment for statistical computing. <https://www.R-project.org/>
- Raunonen P, Casella E, Calders K, Murphy S, Åkerblom M, Kaasalainen M (2015) Massive-scale tree modelling from TLS data. *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci.* II-3/W4:189–196. <https://doi.org/10.5194/isprsannals-II-3-W4-189-2015>
- Raunonen P, Åkerblom M (2022) InverseTampere/TreeQSM: Version 2.4.1. Zenodo. <https://doi.org/10.5281/ZENODO.6539580>
- Raunonen P (2022) Instructions for MATLAB-software TreeQSM, version 2.4.1. https://github.com/InverseTampere/TreeQSM/blob/master/Manual/TreeQSM_documentation.pdf
- Raunonen P, Kaasalainen M, Åkerblom M, Kaasalainen S, Kaartinen H, Vastaranta M, Holopainen M, Disney M, Lewis P (2013) Fast automatic precision tree models from terrestrial laser scanner data. *Remote Sensing* 5:491–520. <https://doi.org/10.3390/rs5020491>
- Robinson TL, Lakso AN (1991) Bases of yield and production efficiency in apple orchard systems. *J Am Soc Hortic Sci* 116:188–194. <https://doi.org/10.21273/JASHS.116.2.188>
- Roskopf E, Morhart C, Nahm M (2017) Modelling shadow using 3D tree models in high spatial and temporal resolution. *Remote Sensing* 9. <https://doi.org/10.3390/rs9070719>
- Schindler Z, Seifert T, Sheppard JP, Morhart C (2023) *Prunus avium*, agroforestry trees, South-Western Germany. Zenodo. <https://doi.org/10.5281/zenodo.8068348>
- Schnell S, Klein C, Stähl G (2015) Monitoring trees outside forests: a review. *Environ Monit Assess* 187:600. <https://doi.org/10.1007/s10661-015-4817-7>
- Seifert T, Seifert S (2014) Modelling and simulation of tree biomass. In: Seifert T (ed) *Bioenergy from Wood: Sustainable Production in the Tropics*. Springer Netherlands, Dordrecht, pp 43–65

- Sprugel DG (1983) Correcting for bias in log-transformed allometric equations. *Ecology* 64:209–210. <https://doi.org/10.2307/1937343>
- Torralba M, Fagerholm N, Burgess PJ, Moreno G, Plieninger T (2016) Do European agroforestry systems enhance biodiversity and ecosystem services? A meta-analysis. *Agr Ecosyst Environ* 230:150–161. <https://doi.org/10.1016/j.agee.2016.06.002>
- Triches GP, Moraes A de, Porfirio-da-Silva V, Lang CR, Lustosa SBC, Bonatto RA (2020) Damage caused by cattle to *Eucalyptus benthamii* trees in pruned and unpruned silvopastoral systems. *Pesq Agropec Bras* 55. <https://doi.org/10.1590/S1678-3921.pab2020.v55.01275>
- Vashum KT, Jayakumar S (2012) Methods to estimate above-ground biomass and carbon stock in natural forests - a review. *J Ecosyst Ecogr* 02. <https://doi.org/10.4172/2157-7625.1000116>
- Wang Y, Lehtomäki M, Liang X, Pyörälä J, Kukko A, Jaakkola A, Liu J, Feng Z, Chen R, Hyyppä J (2019) Is field-measured tree height as reliable as believed – a comparison study of tree height estimates from field measurement, airborne laser scanning and terrestrial laser scanning in a boreal forest. Theme issue 'State-of-the-art in photogrammetry, remote sensing and spatial information science' 147:132–145. <https://doi.org/10.1016/j.isprsjprs.2018.11.008>
- Deutscher Wetterdienst (2022) Climate data center. https://www.dwd.de/EN/climate_environment/cdc/cdc_en.html. Accessed 27 May 2022
- Wilkes P, Lau A, Disney M, Calders K, Burt A, Gonzalez de Tanago J, Bartholomeus H, Brede B, Herold M (2017) Data acquisition considerations for terrestrial laser scanning of forest plots. *Remote Sens Environ* 196:140–153. <https://doi.org/10.1016/j.rse.2017.04.030>
- Wünsche JN, Lakso AN et al (2000) Apple tree physiology: implications for orchard and tree management. *Compact Fruit Tree* 33:82–88

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