Learning from forest trees: improving urban tree biomass functions

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Abstract Trees are one of the few carbon sinks in urban areas. Different methods are available to assess biomass of urban trees, one of it being biomass functions. One advantage of biomass functions is their easy and low-cost application because required data like diameter and height are directly available from tree inventories.

Our data show that it is not suitable to use forest tree biomass functions as size and biomass allocation differ between both ecospheres. Hence, it is important to apply specific urban tree biomass function if biomass or carbon storage is of interest. We started to develop new urban tree aboveground biomass functions using 144 measured deciduous trees of fourteen tree species in Karlsruhe, Germany. Conifers are also of interest but not covered in this data, so we explored several possibilities to build more general models incorporating deciduous and conifer tree species from urban and forest origin. Among others, we tested adjusted forest biomass models and a cross-classified mixed model using data from urban and forest origin holding more than 2200 conifer and deciduous trees. This last model shows best predictive performance for deciduous urban tree species, assured by ten-fold cross-validation on group- and population level. We also compared performance to conifer forest biomass functions, showing slightly improved BIAS values. As a feature, the model is also able to make predictions also for non-observed conifers in urban space, under the assumption of comparable urban-forest differences between deciduous and conifer species. A sample application shows results for a small subset of data of a urban tree inventory, collected in a residential area in the city of Munich, Germany.

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1 Introduction

Urban trees provide several ecosystem services, one of them being a carbon storage (Konijnendijk et al, 2005; McGovern and Pasher, 2016; Moser et al, 2017). During the last decades,

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a lot of research was undertaken to bring light into the role of urban forests for carbon sequestration (e. g. Nowak, 1993; Vonderach et al, 2012; Pasher et al, 2014; Zhao et al, 2018; Trlica et al, 2020, and many others). In comparison to traditional forests, tree density in urban forests is much lower, but nevertheless urban trees represent a relevant reservoir of carbon and eventually a sink of carbon dioxide in the urban context (e. g. Nowak et al, 2002; Kändler et al, 2011). Management of urban forests might additionally focus on increasing the amount of stored carbon. For this, methods to derive current state of carbon storage are necessary to be able to evaluate the development of this reservoir.

Knowledge about the urban carbon reservoir and possibly the associated fluxes help understand the role of urban trees in carbon dioxide emission mitigation for single trees (e. g. Brianezi et al, 2013), on local (Xie et al, 2007; Kändler et al, 2011; Strohbach and Haase, 2012; Russo et al, 2014; Schreyer et al, 2014; Gardi et al, 2016; Tigges et al, 2017; Boukili et al, 2017; Trlica et al, 2020), or nation-wide scale (Nowak, 1993; Nowak and Crane, 2002; Nowak et al, 2013; Pasher et al, 2014; McGovern and Pasher, 2016), to deduce the total net balance for a specific area (Nowak et al, 2002; Timilsina et al, 2014; Orozco-Aguilar et al, 2018), to conduct demand-supply analysis (Timilsina et al, 2014; Zhao and Sander, 2015; Russo et al, 2015) for reporting in context of United Nations Framework Convention for Climate Change (UNFCCC) (Pasher et al, 2014), to assess their potential in carbon credit markets (e. g. McHale et al, 2007), to draw comparisons to other urban (e. g. Tigges et al, 2017) or traditional forests (e. g. Nowak and Crane, 2002), build storage maps (Raciti et al, 2014; Strohbach and Haase, 2012) or to develop management options (O'Donoghue and Shackleton, 2013; Raciti et al, 2014) with regard to climate change and carbon dioxide mitigation.

For the estimation of stored carbon in urban space, several methods were developed and applied. On the one hand, there are approaches using remote sensing (Xie et al, 2007; Kändler et al, 2011; Strohbach and Haase, 2012; Pasher et al, 2014; Schreyer et al, 2014; Tigges et al, 2017; Trlica et al, 2020), either based on airborne photogrammetry and/or airborne lidar. Ground based lidar, i. e. terrestrial laser scanning (TLS), was applied to estimate single trees biomass (e. g. Vonderach et al, 2012; Zhao and Sander, 2015; Zhao et al, 2018; Xu et al, 2018; Velasco and Chen, 2019). On the other hand, several remote sensing studies make also use of allometric biomass functions. These serve for direct estimation of single tree biomass, which might be upscaled to the required spatial level. In these cases, biomass functions with predictors originating from remote sensing analysis are used (Kändler et al, 2011; Strohbach and Haase, 2012; Schreyer et al, 2014; Tigges et al, 2017). Some studies developed specific biomass functions (e. g. Johnson and Gerhold, 2003; Yoon et al, 2013), used equations from near-by locations (e. g. Lv et al, 2016) or used forest tree biomass function for comparison (e. g. Gardi et al, 2016). Yet another option is to estimate biomass based on data and attributes stored in an (existing) tree inventory.

When it comes to applying existing methods to new areas, applicability (Russo et al, 2014) and comparability of results (Strohbach and Haase, 2012) need to be assessed. McPherson et al (2016, p. 8ff) point out that several factors might influence tree growth within and between cities. The authors highlight management practice in this context, which also dependent on regulatory rules. They also state, that urban trees exhibit higher variability in habitus than rural trees.

Since the amount of stored carbon cannot simply be accessed using existing forest tree biomass functions (McHale et al, 2009; Velasco and Chen, 2019) there is a need to develop specific functions for urban trees. But developing tree biomass functions is more demanding in the urban space than in traditional forests, due to comprehensible limitations in availability of trees for cutting. Hence, if one aims at calculating stored carbon using acquired data of well-established management tools like tree inventories – as in this study – new approaches are required.

The aim of this study is to develop a set of urban biomass functions to estimate the total aboveground biomass (*agb*) based on individual tree attributes usually available at tree inventories. In the following, we describe our data for model building which encompass both, urban and forest trees. Subsequently, methodological steps are described starting from a simple urban trees mixed non-linear allometric biomass model, enhancing it using additional predictors, adjusting existing forest biomass models and finally building models based on data including urban and forest trees. We show results based on cross-validation and discuss the different approaches. Finally, the new models are applied on example data from a tree inventory.

2 Material and Methods

2.1 Data

In this study, we could revert on previously generated biomass data from both urban trees (Kändler et al, 2011) and forest trees (Vonderach et al, 2018). The first set contains data of 164 non-destructively sampled urban trees of fourteen different tree species from a field study in 2011 in Karlsruhe, Germany. These trees were non-destructively sampled by skilled arborists using the randomized-branch-sampling (RBS) protocol (c.f. Gaffrey and Saborowski, 1999; Saborowski and Gaffrey, 1999; Good et al, 2001).

Using RBS, the main bole was measured at 0.5 m and 1 m above ground, followed by 2 m-sections up to the crown. Inside the tree crown, each of three paths from crown base to bud end were measured for segment length as well as bottom and top diameter between all knots, i. e. branching points. Total volume is then estimated by expanding measured segment volume by the path-wise cumulated selection probability based on all branch base diameters at each knot (for details see Gaffrey and Saborowski, 1999; Good et al, 2001). Aggregated volume is transferred to biomass using specific gravity values from literature (Kollmann, 1982). The processed data include information about total aboveground biomass, several diameters along the stem (of which here we use the diameter in 1 m height above ground, further called *d1* as predictor), tree height (*h*), height of green crown (*hgc*) and remotely sensed crown diameter (*cd*, see Kändler et al, 2011). The required *d1*-diameter was not available for all trees due to early branching. Hence, only 144 complete observations were available, spread over fourteen deciduous species, each holding three to thirty-two observations. Further biometric information is given in table 1, a graphical overview is given in figure 1.

As preliminary results during model building have shown, the use and incorporation of tree data from traditional forests can enhance the final biomass model. Hence, we additionally used data from a meta-study aiming at building additive component biomass functions for the most frequent forest tree species in Germany (Vonderach et al, 2018). This data (n=2061 complete observations) originate from different sources (both with regard to geographic origin and sampling method), but a substantial part of the trees was also sampled using RBS (in contrast to the urban tress, forest trees were cut before sampling). The data contains the same variables as the urban tree data set, except remotely sensed *cd*. Missing *d1* was estimated based on the other predictors using the taper curve library BDAT (Kublin, 2003; Vonderach et al, 2022). Here, eight tree species, including four conifers, are given holding 25 to 666 observations (for a data summary see table 2).

species	name	n	dbh	d1	h	hgc	cd	agb
Acer campestre	field maple	5	21.6	21.9	8.8	2.2	6.1	206.3
Acer platanoides	Norway maple	32	47.6	48.4	13.9	2.3	10.5	1372.5
Acer pseudoplatanus	sycamore maple	3	47.0	48.0	15.6	2.5	10.6	1267.2
Aesculus hippocastanum	sweet chestnut	6	53.6	52.8	12.7	2.7	10.4	1658.9
Betula spp.	birch spp.	3	40.9	43.0	17.3	3.9	8.2	866.8
Carpinus betulus	common hornbeam	12	30.0	31.3	11.5	2.6	7.1	570.5
Fraxinus excelsior	common ash	15	48.9	50.3	14.7	3.0	10.6	2110.6
Platanus × acerifolia	London plane	14	79.2	83.4	20.8	3.6	12.1	4601.7
Prunus avium	wild cherry	4	25.4	26.0	12.2	2.9	4.6	308.6
Quercus robur	common oak	21	40.5	42.1	13.8	2.9	9.1	1750.4
Quercus rubra	red oak	8	75.6	75.8	19.6	2.5	15.6	5319.6
Robinia pseudoacacia	black locust	6	37.5	38.9	14.5	3.9	7.3	1406.9
Tilia × euchlora	Caucasian lime	7	49.9	50.9	14.9	3.5	8.4	1412.6
Tilia cordata	small-leafed lime	8	29.6	31.5	12.9	3.7	7.0	392.0

Table 1 Overview on sampled urban trees per species. Given are the number of sampled trees per species (n), mean values for diameter in breast height (*dbh*, measured in 1.3 m above ground), diameter in 1 m above ground (*d1*), tree height (*h*), height of green crown (*hgc*), crown diameter (*cd*) and aboveground biomass (*agb*), calculated from volume and specific gravity.

species	name	n	dbh	d1	h	agb
Abies alba	silver fir	29	41.8	43.4	25.8	1255.2
Acer pseudoplatanus	sycamore maple*	25	28.3	29.1	22.6	493.2
Fagus sylvatica	European beech	666	32.2	33.1	24.8	1078.8
Fraxinus excelsior	common ash*	37	33.2	34.2	25.6	1144.5
Picea abies	Norway spruce	616	32.7	34.3	24.9	581.0
Pinus sylvestris	Scots pine	311	31.7	32.9	23.0	516.2
Pseudotsuga menziesii	Douglas fir	130	31.0	32.0	24.7	580.5
Quercus spp.	oak spp.*	247	31.9	32.9	22.9	955.7

Table 2 Overview on sampled forest trees per species. Species names with asterix (*) indicate availability in both data sets. Besides, number of sampled trees per species, mean values for diameter in breast height (*dbh*), diameter in 1m above ground (*d1*), tree height (*h*) and aboveground biomass (*agb*) are given.

2.2 Methods

The urban tree data set consists of fourteen tree species. Because the number of observations are rather low for some species, which prohibits stable biomass models for each species individually, a mixed model approach was chosen in the first step. Hence, we modelled the aboveground biomass (*agb*) for all species in one model, but allowed for structured deviations from this population average given the factor species (*spp*). Additionally, we chose to fit the models on the (nonlinear) data scale to avoid the need of back-transformation and bias correction (c. f. Sprugel, 1983). We started by modeling the response y (=*agb*) by allometric models of the general form

$$y = (\alpha + a) \prod_{i=1}^{p} X_i^{\beta_i + b_i} + \varepsilon \tag{1}$$

with predictors $X_i, i = 1 \ldots p$ and fixed effect parameters α and β_i for the population average, random terms a and b_i for species specific deviations and investigating *d1* and further predictors, namely tree height (*h*), height of green crown (*hgc*) and crown diameter (*cd*). The known phenomenon of heteroscedastic errors in biomass data was treated by modelling the increasing variance species-wise as power of a variance covariate ν, using *d1* or the estimated *agb* (c. f. table 3), i. e. $var(\varepsilon) = \sigma^2 |\nu|^{2\delta}$ (see Pinheiro and Bates, 2004, p. 210f).

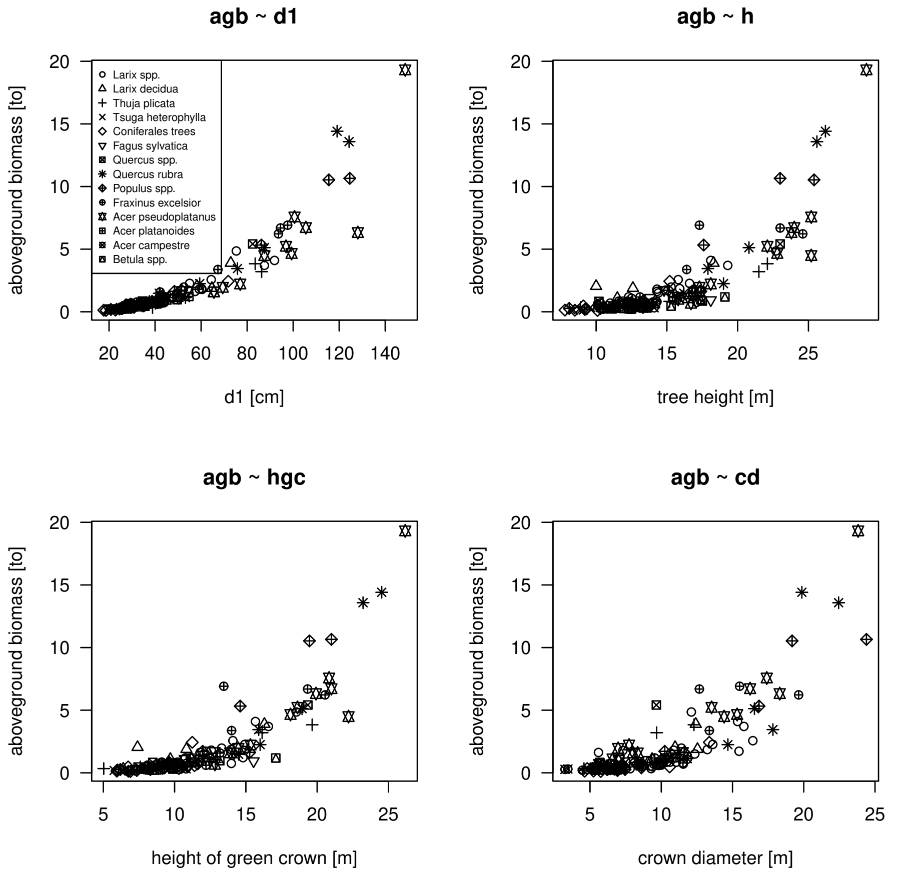

Fig. 1 Relation between predictors and agb for different species. Legend for all graphs is given in top left panel.

To check if a generalized model fits all species without grouping satisfies our requirements, such a model was implemented as well. So far, all models were fit using R (R Core Team, 2019) and the *nlme*-package (Pinheiro et al, 2019).

Since the urban tree data set misses conifer species, which in fact occur in urban space as well, the question arose how to estimate *agb* for those trees, if no models can be developed. We explored several possibilities:

One option would be to use biomass functions from traditional forests as a surrogate for the urban landscape, possibly incorporating a compensating additive term or scaling factor. We tested such an approach on the deciduous tree species using the biomass functions from the German National Forest Inventory (NFI) (f_{NFI}, which were developed for 18 species, c. f. Riedel and Kaendler, 2017), estimated agb_{NFI} and modeled the difference as well as the ratio to the observed *agb*. Different nonlinear and hierarchical models were tested and a species-mixed allometric model (c. f. equation 1) also proved to be a reasonable choice, both from theoretical and practical considerations. Only *d1* was required for modeling the absolute or relative deviations from the NFI biomass functions (notation as in equation 1).

$$
\begin{aligned}
y &= f_{NFI}(spp, dbh, h) + (\alpha + d1^{\beta+b}) \\
y &= f_{NFI}(spp, dbh, h) \cdot (\alpha + d1^{\beta+b})
\end{aligned}
\tag{2}
$$

A second option for modeling *agb* for urban areas is to include tree data of urban and traditional forests and let the mixed model framework statistically separate the available information. Unfortunately, the merged data (a combination of table 1 and 2) misses complete information on crown attributes (*hgc* and *cd*) as these are not available in the forest data set, therefore only *d1* and *h* are available predictors. The more challenging part in such a model is that we now need to include two factor variables (*species* and *origin*) which are not hierarchically organised, but instead are *cross-classified*. This means that each species can (potentially) occur in each level of origin. The following (potential) function is used as starting model equation:

$$
y = (\alpha + a_{aoo} + a_{spp}) \cdot d1^{(\beta + b_{aoo} + b_{spp})} \cdot h^{(\gamma + c_{aoo} + c_{spp})} \tag{3}
$$

Here again, greek letters refer to fixed effects and the latin letters are used for the random effect terms, which are indexed for area of origin (*aoo*) and species (*spp*). The complexity of such nonlinear cross-classified mixed model makes convergence often difficult. Indeed, we also experienced convergence issues also with models of reduced complexity (i. e. less random effects), so that we switched to the log-scale, imposing back-transformation and bias correction on predictions (e. g. 'naive estimate', see Sprugel, 1983; Duan, 1983). The model equation of the final best cross-classified mixed model (CCMM), fitted using the R-package *lme4* (Bates et al, 2015), is:

$$
log(y) = (\alpha + a_{aoo} + a_{spp}) + (\beta + b_{spp}) \cdot log(d1) + (\gamma + c_{spp}) \cdot h \tag{4}
$$

using tree height (h) untransformed, which yielded better results.

As a last approach, we simplified this model and included the area of origin as a binary variable, being *zero* and *one* in case of forest and urban origin (FU). This reduces complexity and the 1-level mixed model can be fitted on the data-scale making a bias correction obsolete but predictions for conifers in urban areas possible. The equation of this 'factor' model (FM) is:

$$
y = (\alpha + a_{spp} + b \cdot FU) \cdot d1^{(\beta + b_{spp})} \cdot h^{(\gamma + c_{spp})} \tag{5}
$$

All models were examined for the urban trees using leave-one-out cross-validation, both on population and on species level. The indicators of interest were RMSE and BIAS:

$$
\begin{aligned}
RMSE &= \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \\
BIAS &= \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}
\end{aligned}
\tag{6}
$$

Additionally, for the species specific evaluation, we calculated relative RMSE and BIAS by dividing each by the species-specific mean *agb*. For all models, *agb* was estimated as described, taking back-transformation and BIAS-correction into account where necessary.

The predictions of the final CCMM model were also checked against the estimates of the NFI biomass functions (Riedel and Kaendler, 2017) using the R-package *rBDAT* (Vonderach et al, 2022) with respect to absolute and relative RMSE and BIAS for the forest tree species of our data set. The data was used during both model developments, and hence, concerns regarding improper comparison are unfounded.

2.3 Sample application

We evaluated the CCMM model using a small subset of a tree inventory containing a subset of areas in Munich, Germany, at two different points in time (2007 and 2019). All registered trees are characterised by species name and the required model predictors. In rare cases, trees were recorded as groups, i. e. data holds the number of trees of these groups, mean diameter and height. Diameter was measured using caliper, rounded towards full centimeter, and height was estimated by experienced arborists and given as full meters. No measured aboveground biomass is available. For tree species, which were not covered by the set of species for which biomass functions were developed, we applied a mapping based on genus, habitus and expert knowledge. For few species (mainly genus *Populus*) a biomass estimation correction was applied due to very unequal specific gravity values between model species (using *Acer*, being the best covered genus in our model data) and assigned species. For that purpose, we used the specific gravity proportion between both species according to Kollmann (1982).

3 Results

Urban trees show different biomass accumulation with size, e. g. *dbh*, when compared to forest trees (figure 2). This finding is even more pronounced if tree height is considered additionally. Tree height is very different for deciduous urban trees given diameter when comparing to forest trees. Based on our data, we can state that the measured deciduous urban trees are 10 to 15 m smaller than their forest counterpart (figure 3). Interestingly, there is virtually no overlap in tree height between both origins for all diameter classes. If we consider *d1* and *h* when looking at biomass, we find that deciduous urban trees have higher biomass values for the same dimensions than forest trees. This is also shown in figure 3 by the modeled contour lines (see also the figure caption for an explanation and example). In consequence, we can state that deciduous urban trees usually hold less biomass than forest trees if only diameter, i. e. *d1*, is considered. If comparison includes both thickness and height, deciduous urban trees accumulate more biomass. This seemingly contradictory result is resolved by the fact that urban trees (in our data) never reach the same tree heights as forest trees and show a different morphology. This observed difference in biomass diminishes as trees get larger and almost vanishes for trees above 100 cm *d1*. This at least is shown by our data, although only a small share of thick trees are present. Hence, for modelling and application it is important to include a height measure into the biomass models.

We have tested different approaches to develop urban tree biomass functions. The first set of models are based on the 144 urban trees, the second set encompassed 2205 trees, including forest trees. We evaluated these models using AIC (Akaike, 1974, where applicable), model residual error, leave-one-out cross-validated root mean squared error (RMSE) and mean error (BIAS).

The first set of models, fitted using the urban tree data only, show that all four selected variables (*d1*, *h*, *hgc* and *cd*) contribute to explain aboveground biomass of urban trees. This is coherent, since all variables describe trees in their volumetric extent (see also figure 1). The fitted mixed models had the random effect terms for factor *species* usually placed on the parameter β_1 belonging to *d1*. Heteroscedasticity (c. f. section 2.2) was best treated also by this covariate, except for model mm4, which makes use of the model predictions to weight the errors (see table 3). The best model by AIC (mm4, AIC=1905.4) makes use of *d1*, *hgc* and *cd* for the fixed effects with random effects set on the exponent of *d1*. Other models are

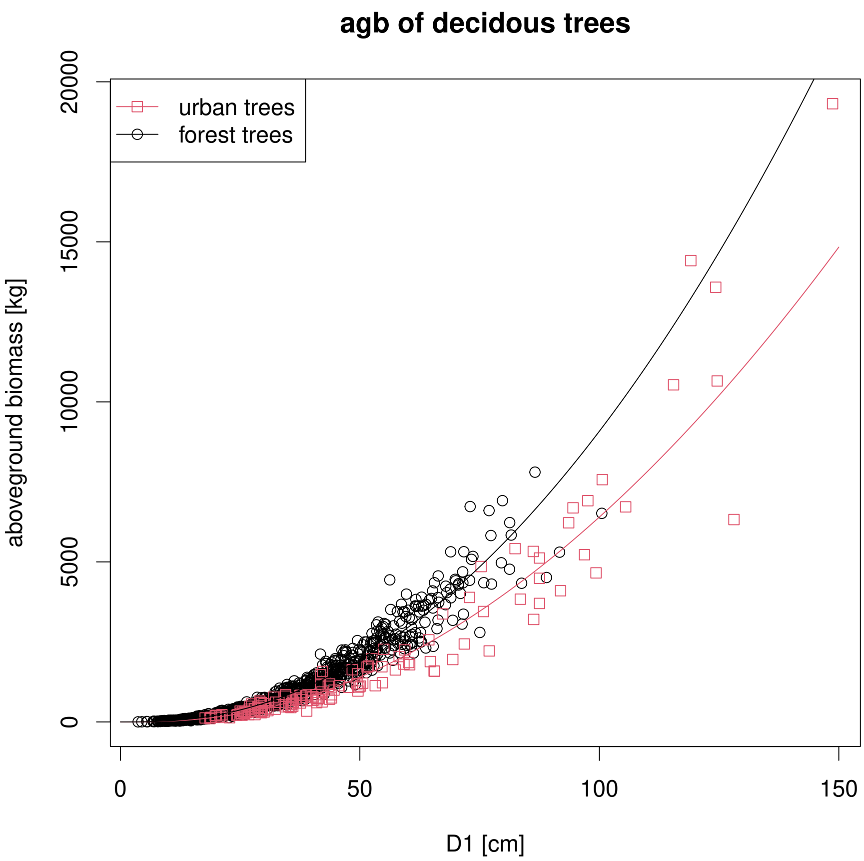

Fig. 2 Aboveground biomass (*agb*) of deciduous forest trees (black circles) and urban trees (red squares) in relation to diameter in 1 m above ground. The continuous lines show modeled relationship between *agb* and *d1*.

not much worse, or — especially when evaluated in terms of residual standard error (σ) and cross-validated RMSE and BIAS (see tables 3 and 4) — even better. In terms of predictive performance, mm5 shows lowest group-level cross-validated RMSE and BIAS (see table 4, index 'g' and 'cv'). When it comes to applicability, the model mm1 seems to be a good choice as well, because it only requires easy to measure quantities (*d1* and *h*, no laborious crown measurements) and exhibit only a slightly higher bias than mm5. The model results also indicate that height of green crown (*hgc*) might offer more information than does tree height (*h*) – at least for model fitting. Comparing cross-validated results, it seems that using *h* instead of *hgc* delivers more accurate predictions on average (models mm1 and mm5). The model gm6, a species-independent generalized nonlinear least squares model, was fitted as a reference without an hierarchical approach and, indeed, shows smallest residual standard error. But all other fit statistics do not show any advantage of that model.

As mentioned above, our full data clearly indicates, that there is a difference in aboveground biomass between urban and forest trees of same diameter class. Especially, urban

name	model	formula	v	RE	AIC	σ
mm0	nlme	$\alpha \cdot \mathrm{d1}^{\beta_1}$	d1	a	1982.5	0.057
mm1	nlme	$\alpha \cdot \mathrm{d1}^{\beta_1} \cdot \mathrm{h}^{\beta_2}$	d1 | spp	b_1	1944.8	0.035
mm2	nlme	$\alpha \cdot \mathrm{d1}^{\beta_1} \cdot \mathrm{hgc}^{\beta_3}$	d1 | spp	b_1	1939.2	0.028
mm3	nlme	$\alpha \cdot \mathrm{d1}^{\beta_1} \cdot \mathrm{hgc}^{\beta_3} \cdot \mathrm{cd}^{\beta_4}$	d1 | spp	b_1	1907.3	0.030
mm4	nlme	$\alpha \cdot \mathrm{d1}^{\beta_1} \cdot \mathrm{hgc}^{\beta_3} \cdot \mathrm{cd}^{\beta_4}$	$\hat{y}$ | spp	b_1	1905.4	0.122
mm5	nlme	$\alpha \cdot \mathrm{d1}^{\beta_1} \cdot \mathrm{h}^{\beta_3} \cdot \mathrm{cd}^{\beta_4}$	d1 | spp	b_1	1922.2	0.021
gm6	gnls	$\alpha \cdot \mathrm{d1}^{\beta_1} \cdot \mathrm{h}^{\beta_3} \cdot \mathrm{cd}^{\beta_4}$	d1 | spp	-	1940.4	0.012

Table 3 Structural representation of the first set of fitted models (urban trees only). 'mm' and 'gm' in column name refer to 'mixed model' and 'generalized model', respectively. In column model, the applied methodological framework is indicated, column formula refers to the fixed effects, column v gives details about covariate and grouping applied in modeling heteroscedasticity, with $\hat{y}$ refering to fitted values. Column RE indicates on which parameter random effects are finally placed. Column σ refers to residual standard deviation.

name	$\mathrm{rmse_g}$	$\mathrm{rmse_{g,\,cv}}$	$\mathrm{rmse_p}$	$\mathrm{rmse_{p,\,cv}}$	$\mathrm{bias_g}$	$\mathrm{bias_{g,\,cv}}$	$\mathrm{bias_p}$	$\mathrm{bias_{p,\,cv}}$
mm0	695.3	777.9	804.4	825.3	-36.9	-40.7	-80.8	-81.6
mm1	631.7	723.8	730.3	745.6	14.2	16.7	32.1	38.4
mm2	619.9	714.4	711.2	738.8	30.1	27.7	53.3	55.0
mm3	653.2	726.0	772.7	783.6	86.6	97.4	143.1	142.9
mm4	664.7	792.4	764.6	804.5	91.4	118.5	135.9	147.7
mm5	591.8	688.8	659.0	684.5	15.0	13.6	38.4	37.0
gm6	690.8	740.1	690.8	740.1	94.6	100.0	94.6	100.0

Table 4 Performance for the first set of urban trees models expressed in the form of the RMSE and BIAS for the group (Index g) as well as the population effects (Index p) of the model fit as well as for the cross-validation (Index cv).

trees exhibit less biomass for a given diameter (c. f. figure 2). Including forest data into model building not necessarily improve the models. Modeling the deviation between urban and forest biomass to be able to use well approved forest biomass functions using an additive or multiplicative correction factor does not lead to satisfactory results: these types of models, based on adjusting forest tree biomass functions, turn out to have the highest $\mathrm{RMSE_{cv}}$ values of all tested models and moderately high $\mathrm{BIAS_{cv}}$ values (see table 5). The additive model shows lower $\mathrm{RMSE_{cv}}$ but higher $\mathrm{BIAS_{cv}}$ than the multiplicative model.

Alternatively, the CCMM model of equation 4, being an extension of the well suited mm1-model incorporating both urban and forest trees and only requiring available *d1* and *h*, shows best values for both $\mathrm{RMSE_{cv}}$ and $\mathrm{BIAS_{cv}}$, whereas the simplified FM model, implementing equation 5 using a binary variable encoding forest and urban origin, exhibits an $\mathrm{BIAS_{cv}}$ high as −90.6 kg (almost nine times higher than the best model in absolute values) and moderately high $\mathrm{RMSE_{cv}}$ (see table 5). Clearly, the best model in this regard is the CCMM. To assure, that the CCMM also reproduces measured forest biomass equally well, we compared the bias-adjusted predictions against the NFI functions (Riedel and Kaendler, 2017) for Norway spruce, Scots pine, Douglas fir, European beech, oak and sycamore and found slightly higher RMSE values for all species except Douglas fir and sycamore (max. +4.1 %) and smaller absolute BIAS values for all species except for Norway spruce (NFI: +8.0 kg, CCMM: -12.8 kg). Maximum deviation of relative BIAS of the CCMM model is −3.2 %.

When evaluating the different models for single species results, especially for species of particular interest, results might show different patterns (see tables 8 and 9 in appendix for absolute and relative RMSE and BIAS). In this case, no model exhibits best results for all of the 14 considered deciduous tree species. The 'best' models show smallest $\mathrm{BIAS_{cv}}$

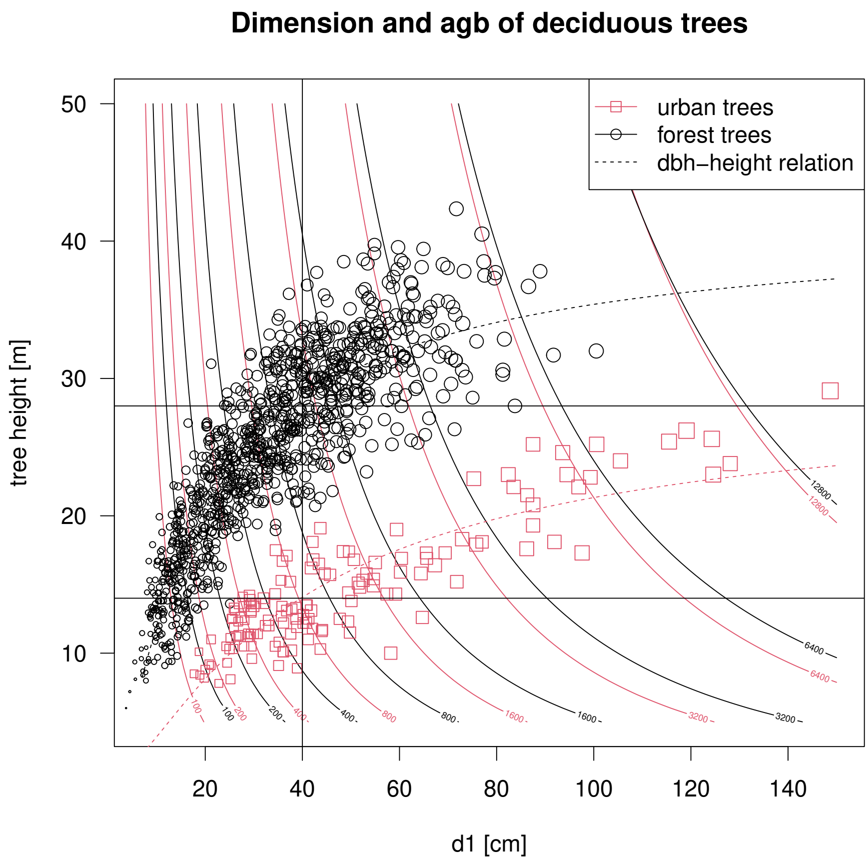

Fig. 3 Comparison of observed (circles and squares, size proportional to biomass) and modeled (contour lines) *agb* for deciduous forest (black circles) and urban trees (red squares) with respect to *d1*, *h* and *agb* No consideration of *species* in this graph. Each observed tree is given by its diameter and height, while *agb* (modeled by a simple allometric model using these two predictors) is given as contour lines in the background. Additionally, a functional relationship between *d1* and *h* is modeled and included (dashed lines). Horizontal and vertical lines are included to ease the interpretation of the graph: a tree with *d1*=40 cm shows an average height of 28 m in forests and only 14 m in urban space. Of course, a forest tree given these dimensions exhibits an *agb* of approx. 1200 kg while an urban tree, which is only half in height, shows only 800 kg. Interestingly, the models indicate for trees with the comparable dimension in *d1* and *h*, that urban trees theoretically exhibit more *agb* than forest trees.

values for only four species and smallest $RMSE_{cv}$ values for only five species, respectively. In this regard, the well performing CCMM also shows very good results: in particular, the largest relative Bias is −9.7 % (Robinia) and relative RMSE ranges between 10 and 36 % (cf. table 9). Similarly, mm1 and mm5 models also perform well, but the largest BIAS is higher (for sycamore and birch, respectively). Only for black locust, the result of mm1 is better than that of CCMM considering RMSE and BIAS. But both models (mm1 and mm5) exceed 10 % BIAS for 3 and 4 tree species, respectively. Moreover, both models, mm1 and mm5, can only predict deciduous trees. This is an advantage of the CCMM model, because coniferous trees in urban areas can be represented by the integration of coniferous tree species data and the methodology of cross-classified mixed models. Unfortunately, an independent evaluation of the performance for these additional tree species in the city is currently not possible (no data available).

The finally proposed CCMM model (equation 4) uses only *d1* and *h* as predictors due to data limitations, but includes independent random effects given *species* for the intercept and the two parameters. Random effects based on *origin* (traditional forest vs. urban area) were significant only for the intercept (a_{aoo}), making it a scaling parameter (this finding provoked the development of the factor model of equation 5). The estimated parameters for the CCMM model are given in table 6, the random effects for different species are given in table 10 in the appendix. The factor for correcting bias is estimated to be 1.012081 (see Sprugel, 1983; Duan, 1983). As long as predictions correspond to the group-level, i. e. refer to a certain species and location as in our example, the given approach for bias-correction by $e^{0.5\sigma^2}$ is valid and corrects for the bias of transformation of the common within-group error. On higher level, e. g. on population level, the uncertainty of the between-group error must be incorporated as well (see e. g. Wirth et al, 2004, appendix 1).

no	model	n_{fit}	n_{cv}	n_{dec}	n_{con}	RMSE	Bias	RMSE_{cv}	Bias_{cv}
1	mm1	144	144	14	0	631.7	14.2	724.0	13.3
2	mm5	144	144	14	0	591.8	15.0	688.8	13.6
3	FB+D	144	144	14	0	790.1	22.0	802.2	21.7
4	FB*R	144	144	14	0	842.1	32.7	849.4	12.8
5	CCMM	2205	144	15	4	598.6	-10.7	667.1	-10.7
6	FM	2205	144	15	4	693.1	-76.8	780.9	-90.6

Table 5 Comparison of the different modeling approaches.'mm1' and 'mm5' refer to the mixed models from table 3 without forest trees and with resp. without crown diameter (*cd*). 'FB+D' and 'FB*R' are adjusted forest tree biomass functions (equation 2), 'CCMM' refers to the cross-classified mixed model (equation 4) and 'FM' is the factor model from equation 5. Column headings 'n' show the number of observations of model fit (index *fit*) and for the cross-validation (index *cv*), respectively. The indices 'dec' und 'con' refer to deciduous and conifer tree species.

model	α	β	γ	$Std.a_{spp}$	$Std.b_{spp}$	$Std.c_{spp}$	$Std.a_{aao}$	σ
CCMM	-1.50880	2.02329	0.03487	0.13843	0.04568	0.00349	0.16024	0.15498

Table 6 Parameter estimates of the CCMM model from equation 4. The first three columns (α, β and γ) give the estimated fixed effects. Column four to seven give the estimated standard deviations of the independent random effect terms. σ gives the residual standard deviation of the model. Estimated random effects for different species can be found in the table 10 in the appendix.

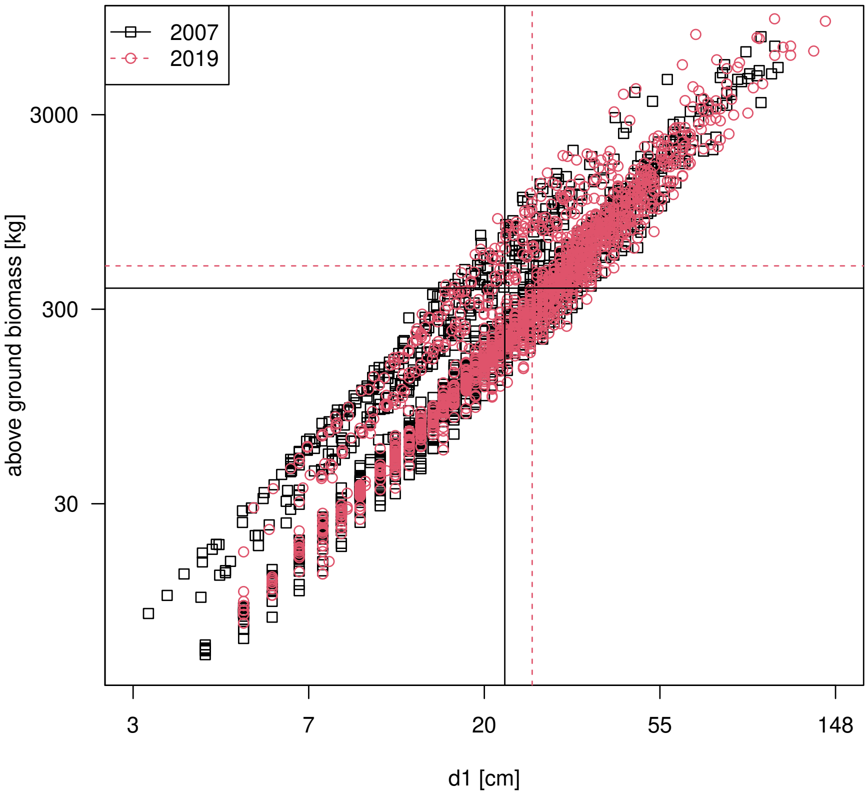

Fig. 4 Predicted above ground biomass of the Munich data against *d1* on double log scale. Black squares indicate 2007 data and red circle refer to 2019 data. Vertical and horizontal lines mark the average biomass and diameter. The two-part pattern is due to differences in tree heights and applies to almost all tree species. On average, tree height remains constant and biomass increase is driven by diameter increase.

3.1 Sample application

year	stems	agb	C	CO_2	$d1_m$	h_m	agb_m	$d1_{med}$	h_{med}
[a]	[n]	[kg]	[kg]	[kg]	[cm]	[m]	[kg]	[cm]	[m]
2007	2763	854176	411950	1511856	22.6	10.2	309.1	19.1	9.0
2019	2260	941050	453472	1664241	26.4	10.2	416.4	23.9	9.0

Table 7 Carbon storage and *agb* for the example area in Munich by urban trees for 2007 and 2019. Indices ‘m’ and ‘med’ refer to mean and median values. A clear increase of storage can be highlighted (+10.2 %) despite a decrease in number of trees.

To show the applicability of the developed model, we applied the CRM with iSiMan5 tree management software (Brudi and Akontz, 2022) to a small subset of data, collected in a residential area in the city of Munich, Germany. The model makes use of variables, which are easy to measure and are regularly collected during urban tree inventory. The model can estimate stored *agb* of the urban trees, which can also be easily translated into stored amount of carbon by applying the respective carbon content factor (see e. g. Paustian et al, 2006; Calvo Buendia et al, 2019). If data for multiple points in time are available, in this case for 2007 and 2019 (see figure 7), it even is possible to calculate the respective net carbon fluxes.

The results for our example data show that in 2019 the urban trees store about 941 tons of biomass, i. e. about 453 tons of carbon (c. f. table 4). This amount of storage was achieved by 2260 trees, meaning an average amount of stored biomass of 416 kg per tree. Compared to 2007, this is an increase of about 86 tons of biomass or a plus of 10.2 %. The average sink capacity is thus approx. 3.5 tons of carbon per year. At the same time, 503 trees were lost (−18.2 %) and the compensation of loss and increase in carbon storage is a result of an increased average diameter. Average tree height remained constant. Since the developed equation takes into account the different tree species and their sizes, further analyses in combination with the data from the tree inventory are possible. These results highlight the importance of managing, tending and conserve especially old urban trees, which not only act as a carbon storage but also serve further ecosystem services (social, economic, ecological, climatic and aesthetical, see further e. g. Konijnendijk et al, 2005; Moser et al, 2017).

4 Discussion

There are several other, supposedly more modern, approaches to determine the biomass and C-sink potential of urban trees (e.g. aerial and terrestrial laser scanning). But the use of the close allometric relationships between simple to measure tree attributes and the target variables biomass or carbon storage, especially in combination with regular and repeated inventory data, remains an accurate and low-cost (or even no-cost) method to determine urban tree carbon storage. Additionally, the method allows for more modern techniques (e. g. terrestrial laser scanning) for data acquisition to extent the data basis of model building.

There is a clear need for urban tree biomass functions in addition to forest tree biomass functions. Our data analysis shows that a simple transfer of forest biomass functions into urban space needs adjustment because the allometry of urban trees differs strongly from those of forest trees. Although the same tree size in terms of diameter (e. g. *d1*) can be found in both landscapes, tree heights (and also crown habitus) differ significantly. In our data set, there was virtually no overlap in tree heights given diameter, making both origins separate units. Still, both units are made up of trees, obeying allometric rules. Differences in biomass between urban and forest trees are more pronounced in smaller dimensions and diminish as trees mature. One explanation could be that urban trees grow in less confined spaces, are less affected by inter- or intraspecies competition, grow less tall and form larger crowns from early live on. The larger trees get, both origins resemble a more unconstrained habitus and thus show more comparable biomass and carbon storage. The application of forest biomass models in an urban setting is an extrapolation of those models, which requires correction. Our approaches using the NFI biomass functions including correction performed worse in comparison to most other tested models.

The developed models make use of the predictors *d1* and *h* which are regularly measured during urban tree inventories. In case of using a diameter measured in a different height, e. g. in 1.3 m (*dbh*) as regularly used in forestry, a simple linear regression can convert between both variables. It turned out by model cross-validation that additional variables like height of green crown (*hgc*) or crown diameter (*cd*) do not or only slightly improve the models. Actually, our CCMM model shows best overall statistics only using *d1* and *h*.

We propose to use the CCMM model, which fits several species and origins (urban and forest areas) at once. This model shows best performance compared to models only using data from urban areas and, hence, the model learns from forest trees and improves the modeled relationship. Besides, it is possible to estimate unmeasured crossings (here: conifer species in urban areas). This advantage should be used with care as no validation could be conducted. In particular, the difference between urban trees and forest trees is contained only in the random effect of the scaling parameter and applies to both hardwood and softwood. Thus, a similar difference of these two tree species groups is assumed, which is not necessarily true. In principle, however, it can be assumed that both deciduous and coniferous trees in urban areas grow with more space and less competition as compared to forest trees, so that crown formation and height growth are modified in a similar direction.

The CCMM uses the mixed-effects modelling framework. From a theoretical perspective, the validity of a model is assured, among other things, by checking the assumption of normality for the estimated random effects. This is difficult if the factor variable has only two levels, and often 5–6 factor levels are recommended as a minimum. Nevertheless, the case of less factor levels is not uncommon (e. g. female vs. male) and some authors see no reason to prevent the use of mixed models in such cases (e. g. Gelman and Hill, 2007, p. 247/275f). Our results indicate convergence and suitable parameter estimates of the CCMM model as well as proper fit statistics so that we can assume correctness and applicability of the model.

The set of (urban) tree species included reflects the situation in Karlsruhe, Germany, and, hence, is not necessarily representative for other cities, not even in Germany. Some tree species are represented only by small numbers of samples. It is important to enhance our data by more tree species, especially, if considering future development eventually aiming at more suited tree species in a changing urban climate. There might also be differences within tree species depending on different urban regions (c. f. McPherson et al, 2016), requiring more specific and localised models. Using the mixed-models approach new tree species can be added into the model by estimating their random effect even with a few observations only, so that local situations can be handled with little effort (Mehtätalo and Lappi, 2020). Beside that, collecting data from different cities might help building a more general model, which includes random effect terms for each city and makes it possible to expand the model geographically.

As an example, we applied the CCMM model to a subset of a tree inventory in Munich, Germany. The additional encountered tree species were assigned to the model tree species. Of course, this results in a degree of uncertainty that has an impact on the results, but is unavoidable in this context of application from our point of view. Such uncertainty can only be resolved by additional data. In our data set, only 196 (138) trees out of 2763 (2260) were conifers in 2007 (2019), i. e. significantly less than 10 % and with a higher proportion of trees removed than in the hardwoods. In consequence, we do not expect an excessive impact on the result by the invalidated part of the model, nevertheless it is important to be aware of it.

5 Conclusions

Biomass functions are an easy and low-cost method to estimate biomass and carbon storage, both in forests and urban landscapes. Although trees are the main carbon sink and obey close allometric relationships in both ecosystems, the simple use of widely available forest biomass functions in urban areas is not recommended. Our data show clear differences in dimensions and biomass allocation. Hence, the development of specific urban biomass functions is important. Based on data from urban and forest areas, we present a new biomass model fitted for multiple species at once. This model is capable of differentiating between both origins and at the same time improving predictive power compared to single-origin-models, i. e. the model 'learns' from the allometric relation of forest trees. Besides, the cross-classified mixed model can also estimate unobserved groups, which in this case are conifers in urban areas. Regrettably, we could not check the performance of these groups due to missing data. Although conifer tree species are of minor importance in urban areas, there is still lack of such data. The presented approach deserves further attention because it is capable of further extensions like e. g. including a city-group level or random effects estimation for further tree species by means of the mixed effects modeling framework. The assumption of comparable differences in habitus and biomass allocation between urban and forest trees for both deciduous and conifer species needs to be further investigated.

As an exemplary application, we used the model to estimate carbon storage for a subset of Munich for two points in time showing an increase in biomass and carbon storage despite a reduced number of stems and a constant tree height. Main driver is an average increase of diameter of about 4 cm in 12 years. Further work should concentrate on currently less frequent species especially in view of rapid climate change and subsequent changes in tree species composition. With that, a closer look into the carbon sink potential of different species over time is possible and improves knowledge of ecosystem services provided by urban trees.

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Statements and Declarations

Ethics approval

not applicable

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Authors' contributions

All authors contributed to the study. Material preparation, data collection, model building and analysis was performed by Christian Vonderach. Application and analysis of the sample application were performed by Adrienne Akontz and Christian Vonderach. The first draft of the manuscript was written by Christian Vonderach and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Availability of data and material

The datasets analysed during the current study are available from the corresponding author on reasonable request.

A cross-validated species specific results

species	n	R_1	B_1	R_2	B_2	R_3	B_3	R_4	B_4	R_5	B_5	R_6	B_6
sycamore maple	3	191.7	-173.0	216.8	-184.5	167.2	25.9	166.1	4.0	262.6	88.0	263.7	60.1
birch spp.	3	314.3	-64.1	210.4	-190.0	228.7	-96.3	218.8	-98.0	258.2	-5.3	137.1	-137.1
oak spp.	21	381.4	-49.4	562.4	-99.8	243.5	85.0	321.8	97.4	623.9	-149.9	963.0	-286.2
common ash	15	549.3	-14.3	675.9	9.8	274.9	4.9	360.8	-61.0	497.4	-47.0	753.7	-193.8
field maple	5	40.5	5.6	43.2	4.7	32.1	6.3	35.4	14.5	40.6	-2.1	44.4	1.1
common hornbeam	12	137.0	-16.4	138.9	-12.9	152.1	-22.3	165.0	-33.2	164.1	-9.4	259.5	-59.5
Caucasian lime	7	449.3	-182.0	241.7	-98.3	708.5	-234.7	890.6	-318.3	386.2	-105.9	576.8	-235.0
London plane	14	1848.9	121.2	1523.3	-67.5	2269.8	109.2	2381.7	168.9	1633.9	98.4	1669.5	-11.2
black locust	6	344.1	-86.5	253.3	145.3	101.6	75.1	81.9	52.1	426.4	-136.1	733.0	-243.4
horse chestnut	6	450.6	216.3	497.7	252.0	356.2	-89.2	402.1	24.8	432.0	150.3	394.8	152.9
red oak	8	1207.5	402.9	1363.3	449.7	1166.3	274.1	1167.3	208.0	898.6	236.9	839.2	116.6
Norway maple	32	346.4	-18.8	342.6	11.4	270.0	0.7	250.3	-8.4	368.6	-13.2	401.4	-53.3
wild cherry	4	78.1	-8.2	98.6	1.5	49.2	-9.9	56.4	-17.0	60.0	-3.8	76.6	-0.7
small-leafed lime	8	70.6	8.1	60.9	6.2	99.5	-32.0	196.3	-74.9	40.9	1.5	33.0	3.4

Table 8 Overview on cross-validated measures of the different model approaches. The abbreviation 'R' and 'B' refer to RMSE and BIAS, respectively. The corresponding indices relate to column 'no' of table 5.

species	n	rR_1	rB_1	rR_2	rB_2	rR_3	rB_3	rR_4	rB_4	rR_5	rB_5	rR_6	rB_6
sycamore maple	3	15.1	-13.6	17.1	-14.6	13.2	2.0	13.1	0.3	20.7	6.9	20.8	4.7
birch spp.	3	36.3	-7.4	24.3	-21.9	26.4	-11.1	25.2	-11.3	29.8	-0.6	15.8	-15.8
oak spp.	21	21.8	-2.8	32.1	-5.7	13.9	4.9	18.4	5.6	35.6	-8.6	55.0	-16.3
common ash	15	26.0	-0.7	32.0	0.5	13.0	0.2	17.1	-2.9	23.6	-2.2	35.7	-9.2
field maple	5	19.6	2.7	20.9	2.3	15.6	3.0	17.2	7.0	19.7	-1.0	21.5	0.6
common hornbeam	12	24.0	-2.9	24.4	-2.3	26.7	-3.9	28.9	-5.8	28.8	-1.7	45.5	-10.4
Caucasian lime	7	31.8	-12.9	17.1	-7.0	50.2	-16.6	63.0	-22.5	27.3	-7.5	40.8	-16.6
London plane	14	40.2	2.6	33.1	-1.5	49.3	2.4	51.8	3.7	35.5	2.1	36.3	-0.2
black locust	6	24.5	-6.1	18.0	10.3	7.2	5.3	5.8	3.7	30.3	-9.7	52.1	-17.3
horse chestnut	6	27.2	13.0	30.0	15.2	21.5	-5.4	24.2	1.5	26.0	9.1	23.8	9.2
red oak	8	22.7	7.6	25.6	8.5	21.9	5.2	21.9	3.9	16.9	4.5	15.8	2.2
Norway maple	32	25.2	-1.4	25.0	0.8	19.7	0.1	18.2	-0.6	26.9	-1.0	29.2	-3.9
wild cherry	4	25.3	-2.7	32.0	0.5	15.9	-3.2	18.3	-5.5	19.4	-1.2	24.8	-0.2
small-leafed lime	8	18.0	2.1	15.5	1.6	25.4	-8.2	50.1	-19.1	10.4	0.4	8.4	0.9

Table 9 Overview on cross-validated measures of the different model approaches. The abbreviation 'rR' and 'rB' refer to the relative RMSE (coefficient of variation) and relative BIAS. The corresponding indices relate to column 'no' of table 5. Relative RMSE and BIAS are scaled by species specific mean observed aboveground biomass.

B parameter estimates of the CCMM

species	α	a_{aao}	a_{spp}	β	b_{spp}	γ	c_{spp}
birch spp.	-1.50880	0.15417	-0.05195	2.02329	-0.01990	0.03487	-0.00017
black locust	-1.50880	0.15417	0.13679	2.02329	0.04328	0.03487	0.00066
Caucasian lime	-1.50880	0.15417	-0.02768	2.02329	-0.02594	0.03487	0.00012
common ash	-1.50880	0.15417	0.12836	2.02329	0.01542	0.03487	0.00143
common hornbeam	-1.50880	0.15417	0.01220	2.02329	0.01543	0.03487	0.00200
douglas fir	-1.50880	0.15417	-0.09424	2.02329	-0.01337	0.03487	-0.00441
European beech	-1.50880	0.15417	-0.01902	2.02329	0.05054	0.03487	0.00331
field maple	-1.50880	0.15417	0.04772	2.02329	0.01217	0.03487	0.00015
horse chestnut	-1.50880	0.15417	0.00105	2.02329	0.02287	0.03487	0.00038
London plane	-1.50880	0.15417	-0.01711	2.02329	-0.03266	0.03487	0.00054
Norway maple	-1.50880	0.15417	0.02568	2.02329	0.00816	0.03487	0.00147
Norway spruce	-1.50880	0.15417	0.18834	2.02329	-0.10420	0.03487	-0.00453
oak spp.	-1.50880	0.15417	0.01319	2.02329	0.04164	0.03487	0.00117
red oak	-1.50880	0.15417	0.04590	2.02329	0.02222	0.03487	0.00134
Scots pine	-1.50880	0.15417	-0.28100	2.02329	-0.00441	0.03487	0.00027
silver fir	-1.50880	0.15417	-0.03706	2.02329	-0.02470	0.03487	-0.00202
small-leafed lime	-1.50880	0.15417	-0.10021	2.02329	-0.03197	0.03487	-0.00072
sycamore maple	-1.50880	0.15417	-0.00223	2.02329	0.01602	0.03487	-0.00079
wild cherry	-1.50880	0.15417	0.03127	2.02329	0.00939	0.03487	-0.00017

Table 10 Parameter estimates of the cross-classified mixed model of equation 4 for different species. Parameter a_{aoo} would take the value -0.15417 in case of forest trees.

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