

Modeling above-ground carbon storage: a remote sensing approach to derive individual tree species information in urban settings

Jan Tigges¹ · Galina Churkina^{1,2} · Tobia Lakes¹

Published online: 20 August 2016
© Springer Science+Business Media New York 2016

Abstract Vegetation has gained importance in respective debates about climate change mitigation and adaptation in cities. Although recently developed remote sensing techniques provide necessary city-wide information, a sufficient and consistent city-wide information of relevant urban ecosystem services, such as carbon emissions offset, does not exist. This study uses city-wide, high-resolution, and remotely sensed data to derive individual tree species information and to estimate the above-ground carbon storage of urban forests in Berlin, Germany. The variance of tree biomass was estimated using allometric equations that contained different levels of detail regarding the tree species found in this study of 700 km², which had a tree canopy of 213 km². The average tree density was 65 trees/ha per unit of tree cover and a range from 10 to 40 trees/ha for densely urban land cover. City-wide estimates of the above-ground carbon storage ranged between 6.34 and 7.69 tC/ha per unit of land cover, depending on the level of tree species information used. Equations that did not use individually localized tree species information undervalued the total amount of urban forest carbon storage by up to 15 %. Equations using a generalized estimate of dominant tree species information provided rather precise

city-wide carbon estimates. Concerning differences within a densely built area per unit of land cover approaches using individually localized tree species information prevented underestimation of mid-range carbon density areas (10–20 tC/ha), which were actually up to 8.4 % higher, and prevented overestimation of very low carbon density areas (0–5 tC/ha), which were actually up to 11.4 % lower. Park-like areas showed 10 to 30 tC/ha, whereas land cover of very high carbon density (40–80 tC/ha) mostly consisted of mixed peri-urban forest stands. Thus, this approach, which uses widely accessible and remotely sensed data, can help to improve the consistency of forest carbon estimates in cities.

Keywords Climate change mitigation · Urban ecosystem services · Uncertainty · Urban remote sensing · Individual tree detection · Tree species composition

Introduction

Reducing carbon emissions is important to avoid a steep increase in the effects of climate change (IPCC 2013). Cities are among the key contributors of carbon emissions, and many have set up mitigation strategies with a focus on infrastructure and energy (Castán Broto and Bulkeley 2013). However, green infrastructures like urban forests have hardly been addressed as an additional source of climate change mitigation, partly because of the lack of consistent area-wide urban forest carbon estimates (Davies et al. 2013; Demuzere et al. 2014; Hutya et al. 2011; Pickett et al. 2011).

Studies of above-ground carbon storage have been applied on forestry at the national level; however, most studies do not address urban forests (McHale et al. 2009). Carbon estimates from urban forests focused US cities starting from the 1990s, and have spread across selected global cities to the present

✉ Jan Tigges
jan.tigges@tum.de

Galina Churkina
galina.churkina@iass-potsdam.de

Tobia Lakes
tobia.lakes@geo.hu-berlin.de

¹ Department of Geography, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany

² Institute for Advanced Sustainability Studies e.V. (IASS), Berliner Straße 130, 14467 Potsdam, Germany

(Chen 2015; Liu and Li 2012; Nowak and Crane 2002; Stoffberg et al. 2010; Strohbach and Haase 2012). Davies et al. (2013) investigated 13 independent urban forest studies and demonstrated multiple reasons for the high variability that exists between urban carbon estimates—most of which either under- or overestimate the carbon storage of urban forests. They found that a lack of uniform methods and standardized metrics makes it difficult to conduct comparisons within and between cities. Therefore, the precision of carbon estimates is likely to get affected by a patchwork of different data sources, lack of up-to-date information, varying data quality, and inconsistency of input parameters. Furthermore, the assessment of parameters like the tree canopy size might vary concerning the methodology and data used, which causes additional uncertainty for following applications like carbon estimates (Richardson and Moskal 2014). For example, Raciti et al. (2014) accounted for 14 % variability in class accuracy occurring by chance concerning the tree canopy mapping. Urban forest carbon estimates of different land use classes can be beneficial to account for a heterogeneous urban structure, as Hutyra et al. (2011) used different degrees of urbanization in the US city of Seattle. Strohbach and Haase (2012) applied multiple land use classes in the German city of Leipzig, and also pointed out, an even higher level of details would better address the variability within certain land use classes, and therefore could provide more precise estimates of urban forest carbon storage. Most challenging of all is the lack of up-to-date data, in particular, that regarding vegetation on private property.

In fact, globally available city-wide studies showed differences, as selected US cities had a city-wide average of 26.9 tC/ha per unit of land cover compared to the city of Leipzig with 11.81 ± 3.25 tC/ha. Though, the heterogeneity of tree canopies and different land covers showed high variability of urban forest carbon storage from below 10 tC/ha to above 100 tC/ha per unit of tree cover, which would require improved assessments of more refined estimates between and within cities. (Nowak et al. 2013b; Strohbach and Haase 2012) Besides, the contribution of urban vegetation to the total carbon storage of cities should not be underestimated, as it can add a considerable amount—as much as 20 %—as shown by Churkina et al. (2010).

Recent research has further illustrated the importance of urban forests by investigating the role such forests play as carbon sinks. For example, carbon offset analyses have indicated that using vegetation to reduce urban CO₂ emissions has positive correlations with sequestration, storage, and reduced energy demand because of the shading and cooling provided by vegetation (Akbari et al. 2001; Liu and Li 2012; Zhao et al. 2010). The positive effects of highly vegetated urban areas acting as a carbon sink have also been shown through urban CO₂ flux models (Grimmond et al. 2002). Other selected surveys of urban forests have hinted at potential future applications for carbon credits as part of the governments' ongoing mitigation strategies (O'Donoghue and Shackleton 2013;

Poudyal et al. 2011). Further studies have suggested integrating urban forests into regional carbon balancing, since the contribution of urban forests has been underestimated in past decades (Churkina et al. 2010; Zhang and Hu 2012).

Ground-based methods currently provide the most accurate carbon storage estimates; however, such approaches rely on the harvesting and weighing of trees and have been rarely applied to urban and non-commercial forestry because of their destructive nature (Jo and McPherson 2001; McHale et al. 2009). Findings from ground-based samples are frequently used to model woody biomass using growth functions for general or species-specific allometric equations (Weissert et al. 2014). The most common input variables for allometric equations include the dendrometric parameters of diameter at breast height (dbh), height, volume, number (quantity), age, and type of species (Nowak and Crane 2002).

McHale et al. (2009) showed, that specific urban conditions might cause an increase in variability of forest carbon storage, which depended on multiple factors like the allometric equations used, scale, species, population, and community characteristics. Therefore, urban forest carbon estimates might require a more standardized methodology or even allometric equations adapted to urban conditions. As Zhao et al. (2012) pointed out, carbon storage of densely vegetated areas can be underestimated when using national equations similar to that used by Jenkins et al. (Jenkins et al. 2003). The availability of specific urban allometric equations is not likely to rise rapidly any time in the near future because creating such specific equations is highly labor intensive. Thus, other studies have suggested carefully selecting allometric equations before drawing a final conclusion regarding urban forest carbon estimates (Aguaron and McPherson 2012). Important decisive parameters regarding urban carbon estimates are tree size, tree density and tree species composition (McPherson et al. 2013). Schmitt-Harsh et al. (2013) pointed out the necessity of addressing species-specific size distributions on private parcels, in particular, those of dominant trees, which contribute most to above-ground carbon storage. Though, most studies apply tree species information for forest carbon estimates (Nowak et al. 2002; Ren et al. 2011; Zhao et al. 2010), remotely sensed individual tree species data has rarely been analyzed in urban studies so far. Developments in urban remote sensing techniques are very promising as far as assessing the necessary data to estimate the carbon stored in urban vegetation, and particularly, in urban trees in a consistent and comparable manner (Weng et al. 2012). Therefore, remote sensing data can be seen as a highly useful complementary source of information beside field surveys. Laser scanners and high-resolution multi-spectral sensors show promising applications for area-wide estimates of the location, height, crown shape, and species of individual trees (Holopainen et al. 2013; Nielsen et al. 2014; Shrestha and Wynne 2012; Tigges et al. 2013; Zhao et al. 2009). Remotely sensed light detection and ranging (LiDAR) height metrics have

been successfully used for individual tree detection and classification in urban areas (Dandois and Ellis 2013; Jung et al. 2011; Koch 2010; Kwak et al. 2007; Yao et al. 2012; Zarco-Tejada et al. 2014). Field surveys have been supplemented by terrestrial (TLS) and mobile laser scanning (MLS), which can offer accurate measures of an individual tree's shape, quick estimates for a larger number of trees, and support for ground-based validation (Gibbs et al. 2007; Hyyppä et al. 2008; Nielsen et al. 2014). Combining recently available satellite data of RapidEye's multispectral, high-spatial, and temporal information with LiDAR-derived height information might allow for improved assessment of individual trees in cities. On the one hand, existing ground sampling approaches already provide accurate information for carbon estimates. On the other hand, remote sensing provides more comprehensive coverage of tree variables across the city, which might help to better assess variability of urban forest carbon estimates.

In this study we estimate the above-ground carbon storage of urban forests in Berlin, Germany. We use a remote sensing approach to derive individual tree species information, which are input for allometric biomass equations. The tree species composition data used is derived from RapidEye satellite data, and the dendrometric parameters of individual trees are derived from airborne LiDAR data. The major aim is to assess the variability of carbon estimates concerning tree species information of each individual tree compared to more general tree coverage information. Our approach might improve the retrieval of urban forest carbon estimates' details across large cities, and indicate spatial differences within cities. Furthermore, this might also assist sampling approaches to better address differences within land use classes.

Material and methods

Study area

The city of Berlin (52° 31' N, 13° 24' E) has a moderate climate and is characterized by a mostly flat topography. Its administrative area is approximately 890 km², 40 % of which is covered by vegetation such as urban forests, parks, street trees, and urban agriculture (Berlin Department of Urban Development 2010a). More than 290 km² of Berlin is taken up by urban forests, which constitutes the largest urban forest in Germany; Berlin's public parks cover approximately 55 km². Deciduous broadleaf tree species are prevalent on public land: according to official statistics, the most frequent street or park tree species (100 %) are the lime tree (*Tilia*, 35 %), maple (*Acer*, 20 %), oak (*Quercus*, 9 %), plane tree (*Platanus*, 6 %), chestnut (*Aesculus*, 5 %), birch (*Betula*, 3 %), and locust (*Robinia*, 3 %) (Berlin Department of Urban Development 2010b). The remaining percentage of public street and park trees are mostly dominated by mixed deciduous trees. The forest of Berlin is dominated by pine

(*Pinus*), oak (*Quercus*) and beech (*Fagus*) (Berlin Department of Urban Development and Ministry of Infrastructure and Agriculture Brandenburg 2014). According to the authors' knowledge, there is no statistical data regarding different tree species on private property.

Data

Tree species classification from 2009 (Tigges et al. 2013) and a normalized digital surface model (nDSM) derived from airborne laser scanning data from 2007 and 2008 (Berlin Partner GmbH 2007) were available for this study. The overlapping area of both datasets covers approximately 700 km² of the city of Berlin, resulting in a study area that is 78 % of the total area of Berlin (Fig. 1). Tree canopy covered 30.4 % (213 km²) of the study area. Eight dominant tree species (Table 1) were classified with a high degree of accuracy (kappa values of 0.83) (Tigges et al. 2013). Because of the pixel size of RapidEye imagery (6.5 m), high accuracy of classified tree species data was limited to large groups of trees, trees aligned in a linear manner (i.e., alley), and large individual trees. We did not consider further corrections of those trees due to its already high accuracy. Though, small sized fragments of the tree canopy were likely to be a source of error. Therefore, we assigned fragments of grouped pixels covering less than 100 m² to a mixed class of dominant tree species in our case study area (Classes 1–10, Table 1), which should avoid potential over- or underestimation of a specific tree species.

An individual tree with a stem diameter of 40 cm is listed as an example in Table 1, which we applied its associated allometric biomass equation. The carbon weight accounts for 50 % of above-ground tree biomass (dry) (Table 1). We calculated the final percentage of tree species pixels assigned to each class. Fig. 1 shows the spatial distribution of the tree canopy and tree species classification across the study area.

A normalized height model (nDSM) with a minimum height of 3 m is used for the tree crown height estimates (ALS data, winter 2007–08, 4 points/m², first pulse) (Kolbe et al. 2008; Tigges et al. 2013). A 3 × 3 median filter was applied to the nDSM during preprocessing to smooth gaps in the tree crown values that were caused during leaf-off data acquisition (Ben-Arie et al. 2009; Popescu et al. 2003).

Two field surveys of trees were conducted in the city of Berlin in late autumn of 2011 and summer of 2014. Different plots included a total of 318 trees. Two plots comprising 220 trees were used for calibration and four plots comprising 98 trees were used for validation of an individual tree detection approach. In these surveys, tree locations were mapped using global position system and the number of trees and their stem diameters (dbh) 1.3 m above-ground were assessed. Sites considered the spatial heterogeneity of urban trees by including public and private property; isolated, lined, and grouped trees; different species; and various tree crown conditions. We defined a tree as dominant if its tree crown covered other trees.

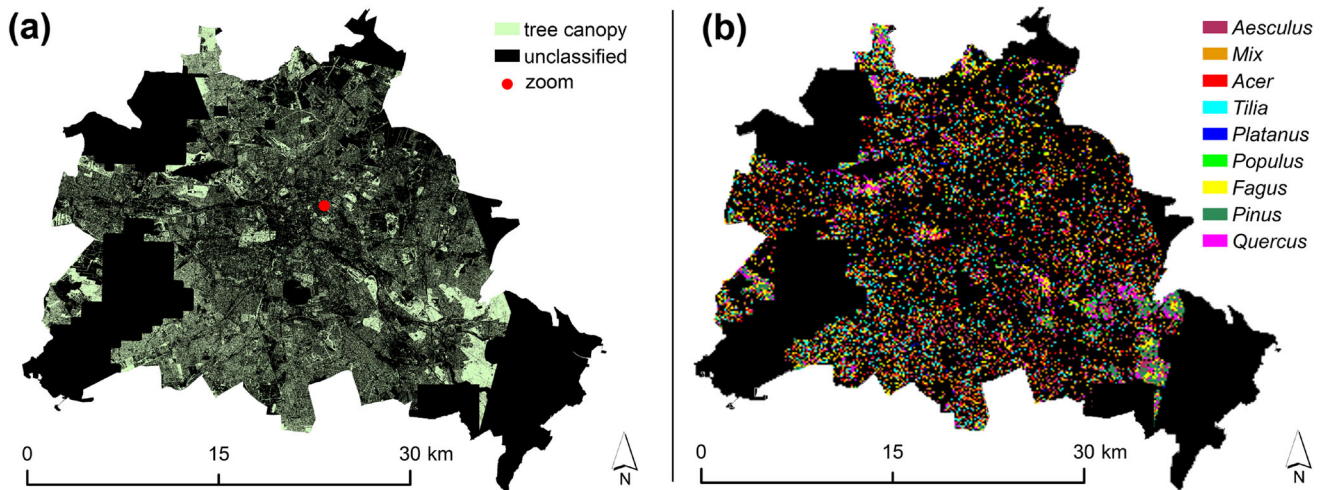


Fig. 1 a Tree canopy inside the administrative boundaries of Berlin. “Unclassified” refers to areas where either RapidEye or LiDAR data were not available for classification. The red dot represents a densely built part of the city and is shown in greater detail in Figs. 3 and 6. b

Spatial distribution of eight dominant tree species classified using multitemporal RapidEye satellite imagery. Class “mix” refers to difficult-to-classify tree species in the tree canopy

Modeling above-ground carbon storage estimates

Our major aim was to derive urban forest carbon estimates and analyze the effects concerning the availability of tree species information details (Table 2). Therefore we used dbh estimates of individual trees in allometric equations for biomass approximations. We derived the stem diameter (dbh) of each tree by applying an individual tree detection (ITD) approach and high-resolution remotely sensed LiDAR data. Tree species information were allocated from our remotely sensed RapidEye tree species classification data.

The ITD approach refers to a local maxima filter algorithm that is integrated into Fusion software (McGaughey 2013); this approach proved to be applicable to both natural and urban forests as well as to parks (Holopainen et al. 2013). The absolute tree height (LH) of individual trees and their tree crown diameters (LCD) could be estimated using this approach. The stem diameter (dbh) of individual trees was derived using laser scanning calculations from Zhao et al. (2009).

$$dbh = 0.95 + 0.7 * LH + 3.14 * LCD + 0.37 * LCBH, \quad (1)$$

where *LH*: tree height; *LCD*: tree crown diameter; and *LCBH*: crown base height with several constants for mixed forests (Hyypää et al. 2001).

LCBH values were simplified using half of the maximum tree height, which reflects a growth form used in forestry (McGaughey 2013). Other *LCBH* data were not available for calibration or validation of urban deciduous trees. Wack et al. (2003) successfully applied a similar approach combining local maxima and a decreasing height order to define edges of individual tree crowns (Hyypää et al. 2008). The algorithm in the Fusion software sets local maxima as the highest location of surrounding pixels, and thus estimates the absolute tree height

of an individual tree (Popescu and Wynne 2004). That algorithm uses a moving, circular, and variable size evaluation window that varies with the CHM’s height information. It assumes that local minima are the edge of a rounded tree crown and a linear regressive dependency of *LH* and *LCD* as follows:

$$LCD = a + b * LH^2, \quad (2)$$

Furthermore, the edge of a tree crown will be set if the absolute height value falls below 66 % of the local maxima height value within a 3-pixel distance (McGaughey 2013). The local conditions of our case reflect a dominant deciduous stand of trees. This could be adapted by using 220 trees from the field survey to calibrate the variable evaluation window size equation with coefficients $a = 3.09632$ and $b = 0.00895$ (Popescu and Wynne 2004).

Stem diameter estimates from this method were systematically below the values derived from field data and were corrected by multiplying an overall weighted arithmetic mean previously developed by Schreyer et al. (2014) for Berlin as follows:

$$dbh_{cor} = dbh * 1.36, \quad (3)$$

This correction factor is based on the average stem diameter of each plot used for calibration, weighted according to the number of trees per plot. Classified results of the stem diameter (dbh) were validated by 98 trees from the field survey. High cranes on construction sites and voltage electricity lines led to classification errors. These were avoided after implementing a height threshold of 30 m, which did not affect very tall trees. Using dendrometric data, we calculated the tree density and stem diameter. Individual tree data was stored in a geospatial database and used to calculate carbon storage estimates as follows: We applied and compared four methods to

Table 1 Most dominant tree species in the study area are listed as classes 1–10. Classes 1–8 are classified using RapidEye satellite data. Class “mix” includes all other species of the total tree canopy, mostly comprising classes 9 and 10. The area and fraction of the total tree canopy

(CHM) taken by each classified class is listed. The allometric equation used with an example of the above-ground carbon storage of an individual tree is shown for classes 1–10

Class	Dominant Species of Study Site	Area	CHM	Allometric Equation	Carbon Storage
1	<i>Acer</i> (<i>Acer campestre</i> , <i>Acer platanoides</i> , <i>Acer sp.</i>)	2744	12.9	Equation 2, <i>Acer saccharum</i> (Ter-Mikaelian and Korzukhin 1997)	588
2	<i>Aesculus</i> (<i>Aesculus hypocastanum</i>)	2852	13.4	Table 1, <i>Aesculus indica</i> (horse chestnut) (Adhikari et al. 1995)	687
3	<i>Fagus</i> (<i>Fagus sylvatica</i>)	2216	10.4	Appendix A, Eq. 89, <i>Fagus sylvatica</i> (Zianis et al. 2005)	585
4	<i>Pinus</i> (<i>Pinus sylvestris</i>)	2397	11.3	Table 3, <i>Pinus sylvestris</i> (Muukkonen 2007)	260
5	<i>Platanus</i> (<i>Platanus hispanica</i>)	402	1.9	Volume Equation, <i>Platanus acerifolia</i> (London Plane), average specific gravity of <i>Platanus</i> (Alden 1995; Pillsbury et al. 1998)	342
6	<i>Populus</i> (<i>Populus nigra</i> , <i>Populus alba</i>)	387	1.8	<i>Populus tremula</i> (Zianis et al. 2005)	310
7	<i>Quercus</i> (<i>Quercus robur</i> , <i>Quercus rubra</i> , <i>Quercus sp.</i>)	1839	8.6	Table 3, <i>Quercus sp.</i> (Muukkonen 2007)	568
8	<i>Tilia</i> (<i>Tilia cordata</i> , <i>Tilia × vulgaris</i> , <i>Tilia platyphyllos</i>)	2810	13.2	Appendix A, Equation 607, <i>Tilia cordata</i> (Jenkins et al. 2003; Zianis et al. 2005)	299
9 (extra)	<i>Betula</i> (<i>Betula pendula</i>)	not classified	/	Appendix A, Equation 31, <i>Betula pendula</i> (Zianis et al. 2005)	387
10 (extra)	<i>Robinia</i> (<i>Robinia pseudoacacia</i>)	not classified	/	Table 2, Equation 6, <i>Robinia pseudoacacia</i> (Böhm et al. 2011)	400
mix	grouped pixel < 100 m ²	5643	26.5	Mixture of different tree species concerning equations of class 1–10	443

estimate tree biomass (Table 2, methods 1–4) concerning the availability of additional tree species information. The previously built basic dataset of remotely sensed individual dbh estimates were input in allometric biomass equations, if no local tree species information were available (methods 1), and contrasted by adding higher details of local information regarding our high resolution remotely sensed RapidEye tree species classification data (Table 1). Methods 2–3 were set up to reflect only general local information, such as dominance or fraction of dominant species, rather than the highest level of details by allocating remotely sensed RapidEye species information to each LiDAR derived individual tree (method 4).

Method 1 (Eq. 4): We applied the allometric equation developed for mixed deciduous forests of the US to each

individual dbh tree estimate (Jenkins et al. 2003). This equation was frequently used for miscellaneous tree types if no site- or species-specific information or equations are available (Hutyra et al. 2011; McHale et al. 2009).

$$\text{biomass} = \sum_{i=1}^n x_i, \tag{4}$$

where x : biomass; i : individual tree; and n : total number of trees.

Method 2 (Eq. 5): We formed a generalized above-ground carbon estimate based on the suggestions of McHale et al. (2009) and Aguaron and McPherson (2012). This estimate reflected the general knowledge of local dominant tree species, but had no further additional or spatial species information. Therefore we used data on the 10 most dominant tree species of Berlin (classes 1–10, Table 1), applied those

Table 2 Methods used to estimate biomass using different levels of tree species information

Method		Tree Species Information				Allometric Equations
#	Details	Level	Dominant	Fraction	Location	
1	low	general				national scale, mixed deciduous forest (Jenkins et al. 2003)
2	medium	general	x			averaged using general information of dominant tree species (class 1–10, Table 1)
3	high	general	x	x		averaged and weighted by each class fraction of the tree canopy (class 1–8 and “mix”, Table 1)
4	very high	specific	x	x	x	specific using tree species information of each individual tree (class 1–8 and “mix”, Table 1)

species-specific allometric equations to each individual dbh tree estimate, and finally averaged the results to create a generalized biomass estimate.

$$\text{biomass} = \sum_{i=1}^n \bar{x}(c_1 + c_2 \dots + c_{10})_i, \quad (5)$$

where \bar{x} : averaged total tree biomass; i : individual tree; n : total number of trees; and c_{1-10} : tree biomass concerning each class 1–10 (Table 1).

Method 3 (Eq. 6): We formed a generalized estimate as in method 2 based on the suggestions of McHale et al. (2009) and Aguaron and McPherson (2012). Furthermore, we

$$\text{biomass} = \sum_{i=1}^n x(c_1 * CHM_1 + c_2 * CHM_2 + \dots + c_8 * CHM_8 + c_{MIX} * CHM_{MIX})_i, \quad (6)$$

where x : total tree biomass; i : individual tree; n : total number of trees; c_{1-MIX} : tree biomass concerning classes 1–8 and “mix” (Table 1); and CHM_{1-MIX} : fraction of the tree canopy taken up by each class 1–8 and “mix” (Table 1).

Method 4 (Eq. 7): We applied species-specific equations to each individual dbh tree estimate. Each individual dbh estimate was assigned the class concerning our remotely sensed RapidEye tree species classification data

$$\text{biomass} = \sum_{i=1}^n x(c_{class})_i; c_{class} = c_1 \text{ or } c_2 \text{ or } c_3 \text{ or } c_4 \text{ or } c_5 \text{ or } c_6 \text{ or } c_7 \text{ or } c_8 \text{ or } c_{MIX}, \quad (7)$$

where x : total tree biomass; i : individual tree; n : total number of trees; and c_{class} : tree biomass concerning the specific class (classes 1–8 and “mix”, Table 1) of each individual tree.

We examined the differences that occurred between these methods in both the complete study area as well as in a selected and densely built area that is typical of such areas in Berlin. We matched equations to our case study tree species (Table 1), and if no species-specific equations were available, we followed the approach taken by Hutyra et al. (2011): selecting equations for trees in the same genus. We multiplied our biomass estimates by 0.5 to convert above-ground dry biomass into units of carbon (C) (Nowak and Crane 2002). Because we did not include root biomass, we expected the actual total carbon storage of the urban trees included in our study to be higher than our estimates. However, we did not include a correction factor for root biomass as Nowak and Crane (2002) because of lack of data and a high degree of uncertainty regarding species and local growth conditions in the urban area studied (Johnson and Gerhold 2003).

included additional information regarding the amount of tree canopy (CHM) considered by each dominant species. Therefore we applied species-specific allometric equations to each individual dbh tree estimate regarding the availability of data on the fraction of dominant tree species (classes 1–8 and “mix”, Table 1). We could not assign a specific dominant tree species to the fraction of our mixed class, and applied an average of most dominant tree species as in method 2. Each result was weighted by multiplying its percentage fraction of the total CHM (Table 1). The final sum was a general estimate concerning the fraction of prevalent dominant tree species.

(classes 1–8 and class “mix”, Table 1). Input class “mix” refers to classified trees less than 100 m², to which we could not assign a specific dominant tree species. Therefore, we assigned a general estimate from method 2 to class “mix”, which comprised all available information of dominant tree species. Estimates of method 4 were expected to provide the highest level of detail by providing individual tree species information.

Results

Our methods show a variability of urban forest carbon storage estimates up to 21 % (Table 3). Most of the differences can be explained by the use of different carbon equations by either integrating local knowledge of tree species information or not having any local tree species information available. The maximum variability was 9 % concerning tree species information of each individual tree and more general and aggregated coverage information of local tree species. In other words, individual tree species information notably but slightly affected our urban forest carbon estimates. If tree species information of each individual tree were used in method 4, we can claim that method 1, which used no local tree species information, results in an underestimation of 15 %. We can also state, that more general and aggregated coverage information of local tree species information either underestimated carbon storage by 3 % (method 2, 7.08 tC/ha) or overestimated it by 6 % (method 3, 7.69 tC/ha) compared to tree species information of each individual tree (method 4, 7.32 tC/ha). Therefore, method 2, which provides a generalized estimate using information regarding the most dominant tree species, and method

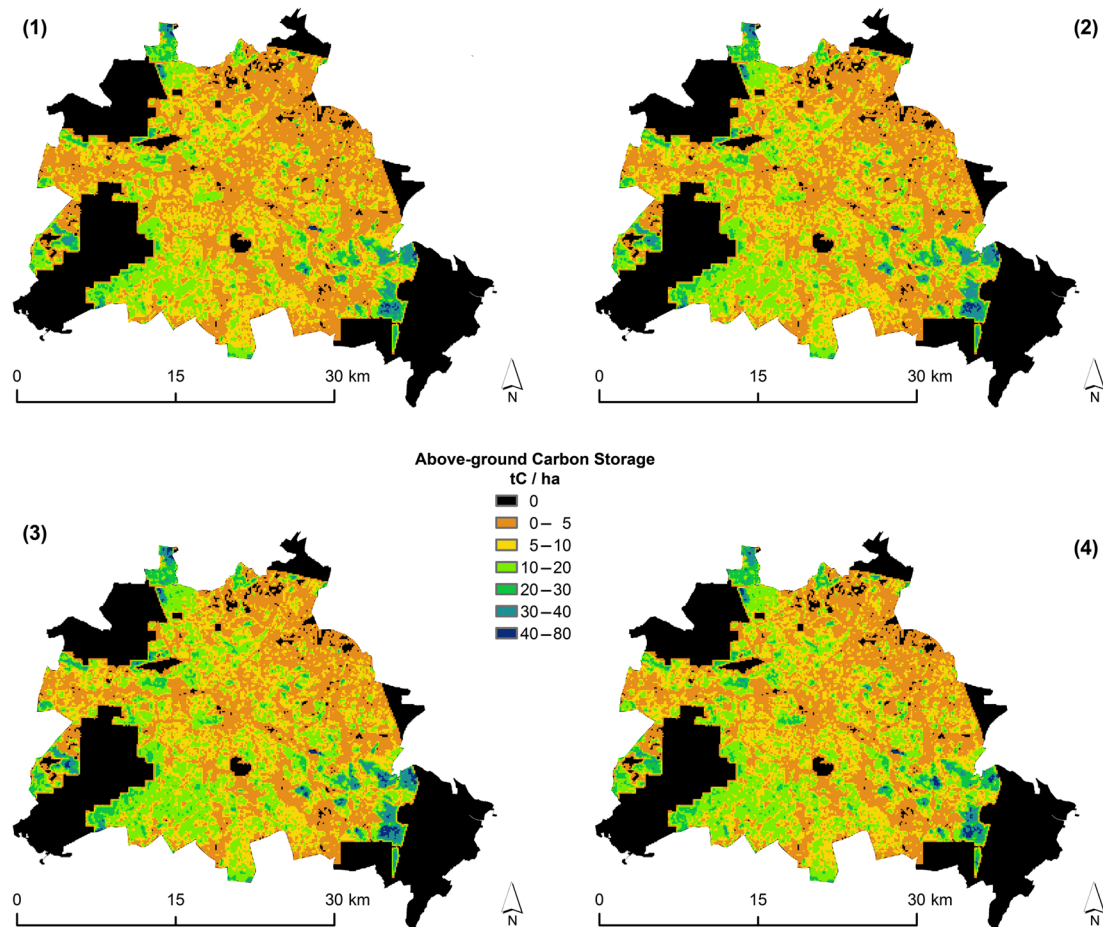
Table 3 City-wide average of carbon estimates of trees in Berlin obtained using different levels of input detail (Table 2)

General Carbon Estimates					Individual Tree Statistics		
Method		Total	Land Cover (Tree cover)	Δ	Maximum	Mean	SD
#	Details	[MtC]	Average [tC/ha]	[%]	[kg]	[kg]	[kg]
1	low	0.444	6.34 (20.83)	reference	3151	322	200
2	medium	0.496	7.08 (23.29)	12	2838	360	195
3	high	0.538	7.69 (25.29)	21	2728	391	195
4	very high	0.512	7.32 (24.06)	15	4500	372	227

3, which uses information regarding the most dominant tree species and their percentage of the total tree canopy, were slightly off results of method 4, which required higher input details concerning species information of each individual tree.

The different methods tested in this study (Table 2) clearly affect carbon storage density numbers. Methods of increasing details show both over- and underestimations. The area classified as very low carbon densities (0–5 tC/ha) decreases if methods involving greater levels of detail are used for calculation (Figs. 2 and 4). For example, method 1 overestimates areas of very low

carbon densities by 11.4 %. Areas of low carbon density (5–10 tC/ha) show the smallest differences between methods (with maximum differences of 1 % in the study area and 3.3 % in densely built areas). Densely built areas (Figs. 3 and 4) show a high level of very low to low carbon densities (0–10 tC/ha). The largest discrepancies occur between areas of very low (0–5 tC/ha) and mid-range (10–20 tC/ha) carbon densities. Very low and mid-range carbon density areas take up a major fraction (60 %) of the total tree canopy. This is important because the percentage of very low carbon density is overestimated and that of mid-

**Fig. 2** Estimated average carbon density (tC/ha) per unit of land cover for urban trees in Berlin. Spatial distributions of carbon densities are displayed for each method from Table 2. Areas with zero carbon density either did not contain trees or did not have data available for classification

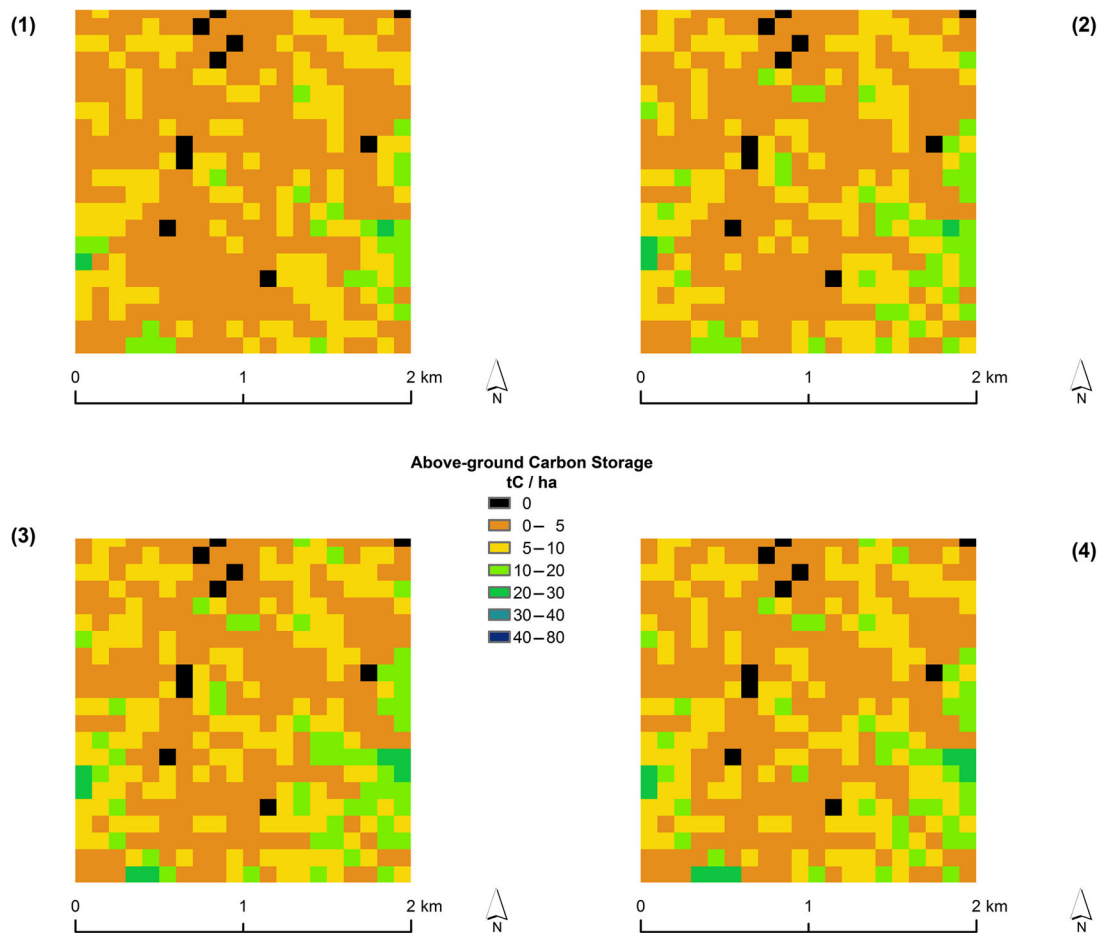


Fig. 3 Spatial distribution of tree carbon density (tC/ha) per unit of land cover in a densely built part of Berlin (red dot, Fig. 2). Differences in spatial distribution are displayed at a given density range for each method

listed in Table 2. Areas with zero carbon density did not contain trees. Areas with low carbon density (0–5 tC/ha) had few trees and contained a higher number of buildings and impervious surfaces

range carbon density is underestimated if high levels of tree species detail are not used. In particular, areas of medium (20–30 tC/ha) carbon density (such as in park-like areas) increase

when higher levels of tree species detail are used. Areas with very high (40–80 tC/ha) densities comprise only a small part of the study area, though individual tree species information shows

Percentage Area of Different Methods on Carbon Storage Density

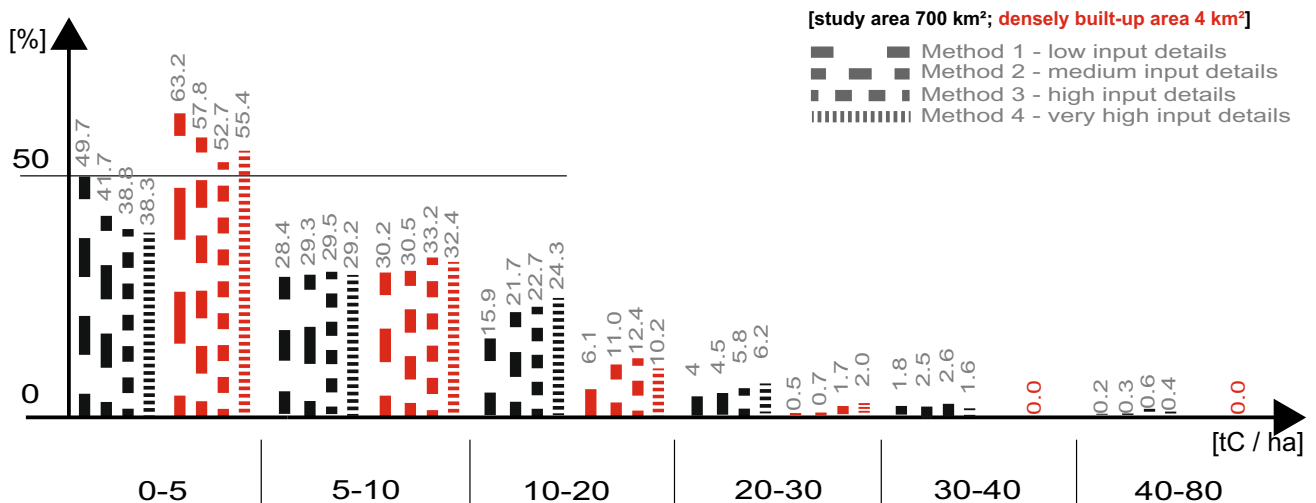


Fig. 4 Differences in carbon storage density (tC/ha) per unit of land cover within the city of Berlin for methods listed in Table 2

a notable impact on carbon densities. High (30–40 tC/ha) and very high (40–80 tC/ha) carbon densities are not found at the selected densely built area (Fig. 4).

The mean stem diameter (dbh) for all detected trees is 36 cm. Few mature trees exhibit a dbh up to 92 cm. Most trees within a densely built area show an average dbh of 30–35 cm (Figs. 5b and 6a). Trees with the largest stem diameter values are found in parks and forests (Fig. 5b). Densely built areas contain approximately 3 % of the total number of large trees with dbh of 80 cm (Fig. 6a). The spatial distribution of individual trees and tree species are heterogeneous in our study area, which is densely built (Fig. 6b). Validation of the stem diameter (dbh) shows moderate to good accuracy. This study's classified average mean diameter of 36 cm differs by 11 % (4.1 cm) from the average mean of our field survey data (40.10 cm). From 98 trees of the field survey, 80.1 % of dominant trees and 65.3 % of less dominant trees are classified.

Approximately 1.4 million trees are classified within our highly heterogeneous urban area using an individual tree detection approach. The maximum tree height is set at 30 m since higher values tend to be misclassified. We visually verified that the majority of tall, dominant trees are not affected by this threshold. The mean height for all detected trees is 15 m. The average tree density is 65 trees/ha per unit of tree cover. This accounts for trees classified using first pulse LiDAR height data, which is less appropriate to account for potential understory. Though, in situ observations revealed a majority of large open grown trees in Berlin. The spatial distribution of tree density per unit of land cover varies greatly across the city (Fig. 5a). Most areas have an average tree density of between 10 and 40 trees/ha. Urban parks have large patches of high tree densities (40–80 trees/ha). Very high tree densities (80–160 trees/ha) are found in the forests located in the southeastern portion of our study site (Fig. 5a).

Discussion

The tree information we derived from remote sensing could improve our assessment of the above-ground carbon storage of urban forests and provided a high degree of detail that allowed carbon estimates to be analyzed across the city of Berlin. The combination of RapidEye satellite data and airborne LiDAR data was beneficial in providing important details of individual trees for biomass equations. Regarding additional tree species information we determined that city-wide carbon estimates are sufficient when an average of dominant tree species information is used. Further precision of carbon estimates could be enhanced on a city-wide scale if we considered the spatial distribution of tree species. Not using individual tree species information undervalued urban forest carbon estimates by up to 15 %.

Including high levels of detail for dominant tree species has a notable effect on the precision of carbon storage estimates, i.e., 15 %–21 % higher values in our case study (methods 3 and 4, Table 3). Zhao et al. (2012) obtained similar results for forests; in their study, selection of specific allometric equations and individual trees could provide notable improvements concerning the precision of regional carbon estimates. Our reference method, Jenkins' national scaled approach for mixed deciduous forest (method 1, Tables 2 and 3), considers an average from all national forests in the US and does not reflect the local tree species composition of our study site (Jenkins et al. 2003). Such averaged conditions tend to level results. Our results also suggest, that the fraction or exact location of tree species (methods 3 and 4, Table 3) might be less important for city-wide carbon estimates than for an analysis of differences within a city since results differ only slightly from an averaged general carbon estimate of dominant tree species (method 2, Table 3). Concerning

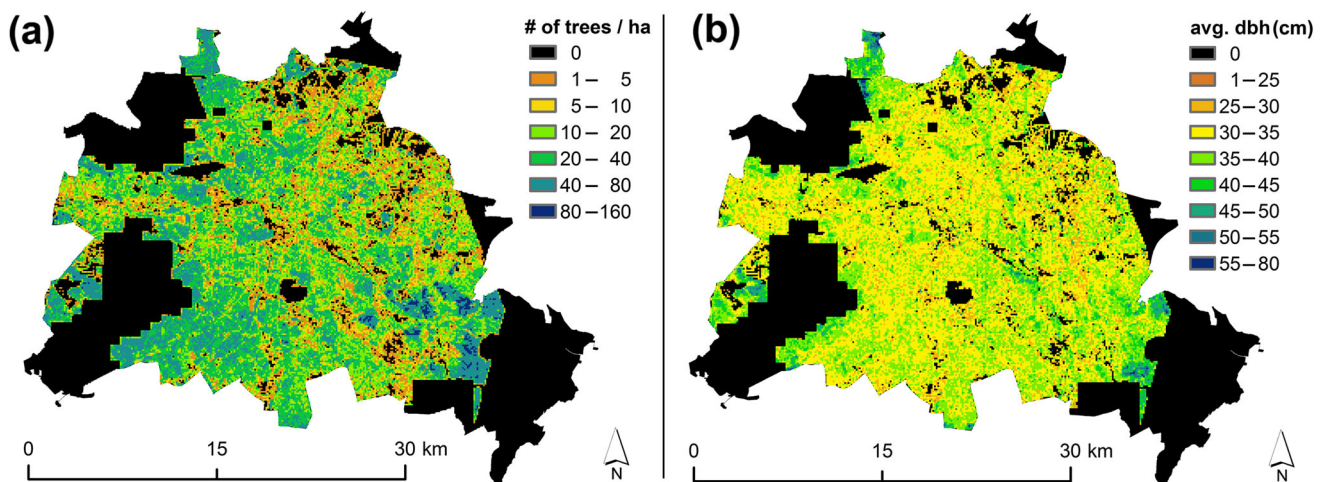


Fig. 5 **a** Spatial distribution of the average tree density (#/ha) per unit of land cover. **b** Spatial distribution of the average tree diameter at breast height (dbh in cm) across the study area. For **a** and **b**, black areas indicate that no data was available for classification

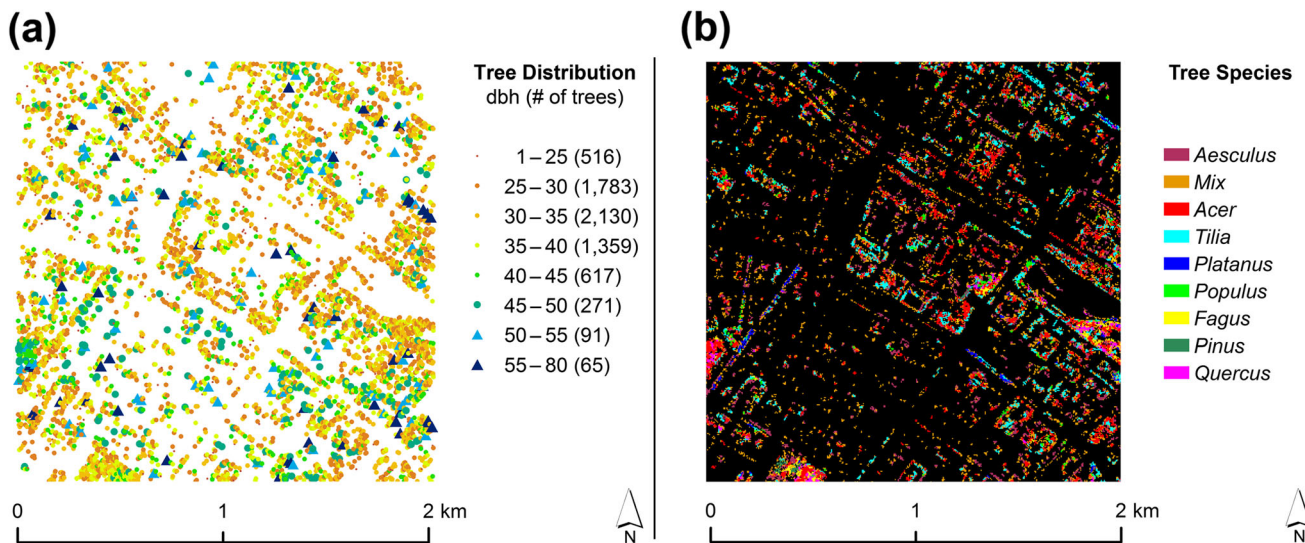


Fig. 6 **a** Spatial distribution of the average tree diameter at breast height (dbh in cm) of a densely built area. Individual trees are grouped at different ranges of dbh. The absolute number of individual trees

classified is shown in brackets. Very large trees are marked with a triangle or star symbol. **b** Spatial distribution of tree species classified for the same area

differences within a typical densely built area using individual tree species information prevented underestimation of mid-range carbon density areas (10–20 tC/ha), which were actually up to 8.4 % higher, and prevented overestimation of very low carbon density areas (0–5 tC/ha), which were actually up to 11.4 % lower. However, further studies are needed to prove those assumptions.

Our area-wide remote sensing approach uses individual tree detection and tree species information instead of averaged results from large regional areas, because these appear better suited to consider spatial differences within a highly heterogeneous urban forest structure (Figs. 2 and 4). However, results of our Berlin case study appear to be a substantial underestimation of carbon and tree density compared to other cities due to various reasons of local differences: The urban forest carbon estimates we obtained using the highest level of detail have a total of 0.512 megatons C (tree cover of 213 km², average of 65 trees per hectare of tree cover, and a total area of 700 km²). The total case study area of Berlin showed an average of around 7 tC/ha, whereas Strohbach and Haase (2012) showed an average of about 11 tC/ha for the city of Leipzig, which has a similar built structure like Berlin. However, 22 % of Berlin's administrative area (ca. 190 km²) was unavailable for our case study, which makes it difficult to compare differences between and within cities. That unavailable area is mostly covered by dense broad-leaf and mixed woodlands (Berlin Department of Urban Development and Ministry of Infrastructure and Agriculture Brandenburg 2014). It shows similarities to the Leipzig case study concerning land cover of high tree coverage like broad-leaf (68 tC/ha; 80 tC/ha per unit of tree cover) and mixed urban forests (76 tC/ha; 77 tC/ha per unit of tree cover). A high fraction of those forest-like areas in the city of Leipzig

certainly contributed to a high city-wide average of 68 tC/ha per unit of tree cover compared to our Berlin case study of around 24 tC/ha per unit of tree cover (Strohbach and Haase 2012). Therefore including such less urbanized land of high tree coverage in our calculations could have substantially affected and increased the average urban forest carbon density of the city of Berlin. Schreyer et al. (2014) calculated the carbon densities of urban trees for selected urban Berlin structure types. Those calculations were extrapolated across the total city including those dense woodlands resulting in an average density of 11.53 tC/ha for the city of Berlin. Similar differences were shown for the city of Karlsruhe, Germany, which stated urban forest carbon estimates of 9.5 tC/ha carbon for highly urbanized areas, and an exponential increase to a total average of 32.3 tC/ha, if state and city forests were included as they are part of the administrative boundaries of Karlsruhe (Kändler et al. 2011). Tree density is influenced by various factors in different case studies such as land use, differences between countries and city development. For example, our results of Berlin had an average range of 10–40 trees/ha across densely built areas (excluding parks and forest-like areas), which is close to the average of 30.7 trees/ha in the city of Karlsruhe, Germany (Kändler et al. 2011). Residential areas of Cambridge, UK, showed a range from 33.7 to 55.7 trees/ha (Wilson et al. 2015). Almost 80 % of 167 cities in the state of Gujarat, India, showed values below 30 trees/ha compared to its capital Gandhinagar with an average of 152 trees/ha (Singh 2013). For selected US cities, the average tree density had a large range from below 25 (Casper, Wyoming) up to 280 trees/ha (Atlanta, Georgia) (Nowak et al. 2008). Hence, tree density differences certainly have a large impact on carbon density values, which needs to be considered for comparisons between and within cities. Additionally, carbon density

would slightly increase, if we included root biomass. Though, our case study excluded it since little research has been conducted on the carbon storage of urban tree root systems and high uncertainty surrounds the research that has been conducted (Johnson and Gerhold 2003; Nowak and Crane 2002).

Our city-wide average of carbon density in Berlin, Germany, most likely falls in the lower range of urban forest studies obtained from globally selected cities of temperate climate zones (11–38 tC/ha) (Strohbach and Haase 2012). Hutyra et al. (2011) related the average carbon estimates of urban forests in Seattle, WA, US to the degree urbanization, which means that Berlin's results (approximately 7 tC/ha) are comparable with values between their class of heavy (2 ± 2 tC/ha) and medium urbanized areas (15 ± 8 tC/ha). Most of Berlin's residential areas are less dispersed than for example US suburbs of detached houses, which are most likely to have a high tree coverage. As well as European cities show a tendency towards higher densification, which is likely to decrease carbon estimates. (Davies et al. 2011) In this context, a high range of carbon density values are mainly due to the different structures of the urban forests, higher tree density and tree coverage in particular (Liu and Li 2012). For example, carbon density values between US cities showed values from 31.4 tC/ha to 141 tC/ha concerning differences per unit of tree cover (Nowak et al. 2013b), 14.6 tC/ha to 54.1 tC/ha between different forest types within the city of Changchun, China (Zhang et al. 2015), or from 6.8 tC/ha to 98.5 tC/ha per unit of tree cover concerning differences between afforestation areas and riparian forests in the city of Leipzig, Germany (Strohbach and Haase 2012).

Our individual tree detection approach has a good level of accuracy (>80 %) compared with other studies, such as that previously published by Schreyer et al. (2014). As Schreyer et al. pointed out, less dominant trees were likely to be overlooked in their study, which would have led to them calculating a lower level of total carbon storage than what actually exists. Temporal changes, such as leaf-dropping, pruning, and cutting, add further challenges for obtaining accurate carbon estimates of urban trees (McPherson 1998). However, the application of different methodological approaches and levels of detail for urban forest carbon estimates makes it difficult to compare results (Hutyra et al. 2011; Kändler et al. 2011; Nowak and Crane 2002). Thus, previous studies on forest carbon estimates have demanded more detailed data and methods (Nowak and Crane 2002; Nowak et al. 2013b). Differences in sampling sizes, data types, and prediction methods are also important factors not to be forgotten when comparing carbon estimates between cities (Fassnacht et al. 2014). Future applications should follow a more generic approach concerning methodology and the general availability of data to improve comparisons between urban forest carbon estimates, similar to what Pasher et al. (2014) established for Canadian cities. To improve the evaluation of results and track

changes over time, we suggest that researchers at least provide additional information regarding the spatial distribution of individual trees concerning the total city area, tree canopy, and tree density.

The selection of appropriate allometric biomass equations will remain a major source of uncertainty since few equations are adapted to the local urban environment. High expertise will be necessary to complete the selection process of allometric biomass equations (Zhao et al. 2012). Different climate conditions influence urban growth functions, and species-specific equations lack established accuracy or general availability, which might affect large-scale estimates (McHale et al. 2009). Averaged equations, such as method 2 (Table 1), may be a way to reduce the variability for city-wide estimates (McHale et al. 2009). Sileshi (2014) pointed out, that various reports on allometric models are often uninformative, in particular, as regards the selection of criteria, adaptation, and validation. Sileshi also calls attention to so-called “locally tailored” models, which tend to be less transferable to other study sites. Creating new equations will be both labor- and time-intensive and will require further improvements. Therefore, Zapata-Cuartas et al. (2012) suggest an approach that requires less destructive sampling of trees. Even though less bias by a higher number of equations is likely to cause a higher variance of carbon estimates (Weissert et al. 2014), other studies recommend the use of generalized results from a group of equations to reduce biased estimates (Aguaron and McPherson 2012; McHale et al. 2009). Such bias could affect the results we obtain using the highest level of detail regarding individual tree species (method 4, Table 3). A higher variance is expected for our input class “mix” (Table 1), and further uncertainty might be caused by differences in the classification accuracy of input data.

Automatic processing of tree species classification can be a future goal since information regarding dominant tree species is important for biomass estimates. Our multitemporal remote sensing approach on tree species classification should therefore be extended at different study sites since different species show correlation to tree phenology (Tigges et al. 2013). For example, high-resolution and carrier systems like unmanned aerial vehicles (UAV) might easily offer accessible information on temporal differences and tree phenology. Further information could be used to address either temporal changes or the prevalence of other native and alien species, which still contains an information gap (Kowarik et al. 2013; Nowak et al. 2013a). The combination of different remotely sensed data can further improve the classification of forest details and be beneficial for carbon modeling approaches (Popescu and Wynne 2004; Yu et al. 2011). Very high resolution data have become more available for cities and can be used for improved delineation of individual trees, e.g., airborne UltraCamX data with a pixel size of 10 cm for downtown Berlin (Berlin Department of Urban Development 2014). The application

of very-high-resolution data should still consider the potential over-segmentation of individual trees, which would reduce overall accuracy (Holopainen et al. 2013). Even manual delineation of trees does not always provide superior results as input for biomass estimates stated by Gleason and Im (2012). Ground-truth data for training and validation should be extended by terrestrial laser scanning since studies show that dendrometric measures of individual trees are highly accurate (Holopainen et al. 2013).

Common approaches to estimating the above-ground carbon storage of urban forests often use random sampling and generalized estimates of land use classes, which can consider high levels of detail. Though, they can lack expansive spatial data in extent of area, which might cause higher variability of carbon estimates within a certain land use class (Davies et al. 2011; Hutyra et al. 2011; Strohbach and Haase 2012). Therefore, high resolution remote sensing could be recommended as a cost-efficient methodology to supply more sufficient data on local differences and temporal changes (Raciti et al. 2014), and as a necessary standard inventory procedure (Davies et al. 2013; McPherson et al. 2013). This would help to better reflect local differences of land use patterns and processes, or differences in tree canopy structure. Future applications can use remotely sensed carbon storage estimates as a consistent baseline reference that is annually updated by sequestration estimates. Additionally, more site-specific information has helped to refine that high range of estimates. For example, the availability and improvements of remotely sensed imagery and interpretation contributed to correct the average forest carbon density of US cities (2002: 92.5 tC/ha per unit of tree cover; corrected 2013: 76.9 tC/ha per unit of tree cover). (Nowak et al. 2013b) Following recent approaches like the first global map on tree density by Crowther et al. (2015), future availability of global (very) high resolution remote sensing imagery might help to give more precise answers to the questions of how much urban forests contribute to carbon offset. The CO₂ emissions offset might be another marketable regulating option to allow for an improved consideration of urban forests (Poudyal et al. 2010). This implies, that urban forests can act as a carbon sink, which has been indicated by some studies, but they lack future usage and climate mitigation strategies for urban vegetation (Weissert et al. 2014). This will also require appropriate information regarding tree species that maximize sequestration capacity, water use efficiency, and stress resistance (Muñoz-Vallés et al. 2013). Furthermore, the capacity of trees to act as a system should be continued to be considered in more detail, as a recent study by Klein et al. (2016) showed, that trees do not use carbon for themselves in particular, but also trade large quantities of carbon even between different tree species using fungi in the soil. Moreover, the benefits of high-

resolution, remotely sensed, tree species information should be evaluated with regard to other ecosystem services, such as cooling and shading (Demuzere et al. 2014), which are still less prevalent in recent urban forest management plans (Ordóñez and Duinker 2013).

Conclusion

Our remote sensing approach allows us to retrieve area-wide and consistent information regarding urban heterogeneous forest structures, and our results show a measurable impact of tree species composition on urban carbon estimates. To the authors' knowledge, this is the first study that applies city-wide, high-resolution, and remotely sensed data to individual tree detection and tree species information. Providing additional sensitive information when assessing the uncertainty of carbon estimates can be beneficial, and furthermore, the methods discussed in this study may provide new techniques to increase the comparability of different cities with specific heterogeneous urban forest structures. Our findings may provide a baseline of urban forest carbon storage for future climate action planning, for identifying conservation areas where urban forest carbon densities are highest, and for identifying areas in which carbon density may be expanded in the long-term. Further studies will have to demonstrate whether a higher spatial resolution or LiDAR point density might address very heterogeneous areas more adequately on a consistently comparable basis. This applies for dendrometric estimates, species richness, and information on private property, in particular.

ALS, airborne laser scanning; C, carbon; CHM, canopy height model; dbh, diameter at breast height; Δ , delta; GPS, global position system; kg, kilogram; ITD, individual tree detection; LCBH, LiDAR crown base height; LCD, LiDAR crown diameter; LH, LiDAR height; LiDAR, Light Detection And Ranging; Mt., megatons; MLS, mobile laser scanning; nDSM, normalized digital surface model; SD, standard deviation; t, tons; TLS, terrestrial laser scanning; UAV, unmanned aerial vehicle.

Acknowledgments This study was supported by the German Research Foundation (DFG) as part of the Research Training Group 780 3 and 4 on "Perspectives on Urban Ecology" (project numbers: 32108303 and 32108304). The authors would like to thank Berlin Partner GmbH and virtualcitySYSTEMS GmbH for providing pre-processed LiDAR data of Berlin. We particularly thank Johannes Schreyer (Geography Department, Humboldt-Universität zu Berlin) for his support and willingness to share data and knowledge. We thank the anonymous reviewers for their very useful input.

Compliance with ethical standards

Competing interests The authors declare that they have no competing interests.

References

- Adhikari BS, Rawat YS, Singh SP (1995) Structure and function of high altitude forests of central Himalaya I. Dry matter dynamics. *Ann Bot* 75:237–248. doi:10.1006/anbo.1995.1017
- Aguaron E, McPherson EG (2012) Comparison of Methods for Estimating Carbon Dioxide Storage by Sacramento's Urban Forest. In: Lal R, Augustin B (eds) *Carbon Sequestration in Urban Ecosystems*. Springer, Netherlands, pp. 43–71. doi:10.1007/978-94-007-2366-5_3
- Akbari H, Pomerantz M, Taha H (2001) Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. *Sol Energy* 70:295–310. doi:10.1016/S0038-092X(00)00089-X
- Alden, HA (1995) *Hardwoods of North America*. FPL-GTR-83. Madison, WI
- Ben-Arie JR, Hay GJ, Powers RP, Castilla G, St-Onge B (2009) Development of a pit filling algorithm for LiDAR canopy height models. *Comput Geosci* 35:1940–1949. doi:10.1016/j.cageo.2009.02.003
- Berlin Department of Urban Development (2010a) *Natur + Grün* [online] Available from: www.stadtentwicklung.berlin.de/umwelt/stadtgruen [accessed: 09–30-2011]
- Berlin Department of Urban Development (2010b) *Straßenbaum-Zustandsbericht Berliner Innenstadt 2010* [online] Available from: www.stadtentwicklung.berlin.de/umwelt/stadtgruen/stadtbaeume/downloads/strb_zustandsbericht2010.pdf [accessed: 09–30-2010]
- Berlin Department of Urban Development (2014) *Gebäude- und Vegetationshöhen (Ausgabe 2014)* Available from: www.stadtentwicklung.berlin.de/umwelt/umweltatlas/ki610.htm [accessed: 05–09-2014]
- Berlin Department of Urban Development and Ministry of Infrastructure and Agriculture Brandenburg (2014) *Waldzustandsbericht 2014 der Länder Brandenburg und Berlin* Available from: www.stadtentwicklung.berlin.de/forsten/waldzustandsbericht2010/de/download/wzb2010.pdf [accessed: 12–22-2014]
- Berlin Partner GmbH (2007) *Geodatenmanagement in der Berliner Verwaltung – Amtliches 3D Stadtmodell für Berlin* [online] Available from: www.businesslocationcenter.de/imperia/md/content/3d/efre_ii_projektdokumentation.pdf. Accessed: 23 Oct 2010
- Böhm C, Quinkenstein A, Freese D (2011) Yield prediction of young black locust (*Robinia pseudoacacia* L.) plantations for woody biomass production using allometric relations. *Ann For Res* 54:215–227
- Castán Broto V, Bulkeley H (2013) A survey of urban climate change experiments in 100 cities. *Glob Environ Chang* 23:92–102. doi:10.1016/j.gloenvcha.2012.07.005
- Chen WY (2015) The role of urban green infrastructure in offsetting carbon emissions in 35 major Chinese cities: a nationwide estimate. *Cities* 44:112–120. doi:10.1016/j.cities.2015.01.005
- Churkina G, Brown DG, Keoleian G (2010) Carbon stored in human settlements: the conterminous United States. *Glob Chang Biol* 16:135–143. doi:10.1111/j.1365-2486.2009.02002.x
- Crowther TW et al. (2015) Mapping tree density at a global scale. *Nature* 525:201–205. doi:10.1038/nature14967
- Dandois JP, Ellis EC (2013) High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. *Remote Sens Environ* 136:259–276. doi:10.1016/j.rse.2013.04.005
- Davies ZG, Edmondson JL, Heinemeyer A, Leake JR, Gaston KJ (2011) Mapping an urban ecosystem service: quantifying above-ground carbon storage at a city-wide scale. *J Appl Ecol* 48:1125–1134. doi:10.1111/j.1365-2664.2011.02021.x
- Davies ZG, Dallimer M, Edmondson JL, Leake JR, Gaston KJ (2013) Identifying potential sources of variability between vegetation carbon storage estimates for urban areas. *Environ Pollut* 183:133–142. doi:10.1016/j.envpol.2013.06.005
- Demuzere M et al. (2014) Mitigating and adapting to climate change: multi-functional and multi-scale assessment of green urban infrastructure. *J Environ Manag* 146:107–115. doi:10.1016/j.jenvman.2014.07.025
- Fassnacht FE, Hartig F, Latifi H, Berger C, Hernández J, Corvalán P, Koch B (2014) Importance of sample size, data type and prediction method for remote sensing-based estimations of aboveground forest biomass. *Remote Sens Environ* 154:102–114. doi:10.1016/j.rse.2014.07.028
- Gibbs HK, Brown S, O Niles J, Foley JA (2007) Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environ Res Lett* 2:045023
- Gleason CJ, Im J (2012) Forest biomass estimation from airborne LiDAR data using machine learning approaches. *Remote Sens Environ* 125:80–91. doi:10.1016/j.rse.2012.07.006
- Grimmond CSB, King TS, Cropley FD, Nowak DJ, Souch C (2002) Local-scale fluxes of carbon dioxide in urban environments: methodological challenges and results from Chicago. *Environ Pollut* 116:243–254. doi:10.1016/S0269-7491(01)00256-1
- Holopainen M et al. (2013) Tree mapping using airborne, terrestrial and mobile laser scanning – A case study in a heterogeneous urban forest. *Urban For Urban Green* 12:546–553. doi:10.1016/j.ufug.2013.06.002
- Hutyra LR, Yoon B, Alberti M (2011) Terrestrial carbon stocks across a gradient of urbanization: a study of the Seattle, WA region. *Glob Chang Biol* 17:783–797. doi:10.1111/j.1365-2486.2010.02238.x
- Hyypää J, Kelle O, Lejikonen M, Inkinen M (2001) A Segmentation-Based Method to Retrieve Stem Volume Estimates from 3-D Tree Height Models Produced by Laser Scanners. *IEEE Trans Geosci Remote Sens* 39:969–975
- Hyypää J, Hyypää H, Leckie D, Gougeon F, Yu X, Maltamo M (2008) Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *Int J Remote Sens* 29:1339–1366
- IPCC (2013) *Summary for Policymakers*. Cambridge University Press, Cambridge
- Jenkins JC, Chojnacky DC, Heath LS, Birdsey RA (2003) National-Scale Biomass Estimators for United States tree species. *For Sci* 49:12–35
- Jo HK, McPherson EG (2001) Indirect carbon reduction by residential vegetation and planting strategies in Chicago, USA. *J Environ Manag* 61:165–177. doi:10.1006/jema.2000.0393
- Johnson AD, Gerhold HD (2003) Carbon storage by urban tree cultivars, in roots and above-ground. *Urban For Urban Green* 2:65–72. doi:10.1078/1618-8667-00024
- Jung S-E, Kwak D-A, Park T, Lee W-K, Yoo S (2011) Estimating crown variables of individual trees using airborne and terrestrial laser scanners. *Remote Sens* 3:2346–2363
- Kändler G, Adler P, Hellbach A (2011) Wie viel Kohlenstoff speichern Stadtbäume? – Eine Fallstudie am Beispiel der Stadt Karlsruhe FVA-einblick 2/2011 2011:7–10
- Klein T, Siegwolf RTW, Kömer C (2016) Belowground carbon trade among tall trees in a temperate forest. *Science* 352:342–344. doi:10.1126/science.aad6188
- Koch B (2010) Status and future of laser scanning, synthetic aperture radar and hyperspectral remote sensing data for forest biomass assessment ISPRS-J Photogramm. *Remote Sens* 65:581–590. doi:10.1016/j.isprsjprs.2010.09.001
- Kolbe TH, König G, Nagel C, Stadler A (2008) 3D-Geo-Database Berlin Berlin: Senatsverwaltung für Stadtentwicklung Berlin
- Kowarik I, von der Lippe M, Cierjacks A (2013) Prevalence of alien versus native species of woody plants in Berlin differs between habitats and at different scales. *Preslia* 85:113–132

- Kwak D-A, Lee W-K, Lee J-H, Biging G, Gong P (2007) Detection of individual trees and estimation of tree height using LiDAR data. *J For Res* 12:425–434. doi:10.1007/s10310-007-0041-9
- Liu C, Li X (2012) Carbon storage and sequestration by urban forests in Shenyang, China. *Urban For Urban Green* 11:121–128. doi:10.1016/j.ufug.2011.03.002
- McGaughey, RJ (2013) FUSION/LDV (version 3.x) [Software]. United States Department of Agriculture (USDA) and Pacific Northwest Research Station (UAS)
- McHale M, Burke I, Lefsky M, Peper P, McPherson E (2009) Urban forest biomass estimates: is it important to use allometric relationships developed specifically for urban trees? *Urban. Ecosystems* 12: 95–113. doi:10.1007/s11252-009-0081-3
- McPherson EG (1998) Atmospheric carbon dioxide reduction by Sacramento's urban forest. *J Arboric Urban For* 24:215–223
- McPherson EG, Xiao Q, Aguaron E (2013) A new approach to quantify and map carbon stored, sequestered and emissions avoided by urban forests. *Landsc Urban Plan* 120:70–84. doi:10.1016/j.landurbplan.2013.08.005
- Muñoz-Vallés S, Cambrollé J, Figueroa-Luque E, Luque T, Niell FX, Figueroa ME (2013) An approach to the evaluation and management of natural carbon sinks: From plant species to urban green systems. *Urban For Urban Green* 12:450–453. doi:10.1016/j.ufug.2013.06.007
- Muukkonen P (2007) Generalized allometric volume and biomass equations for some tree species in Europe. *Eur J For Res* 126:157–166. doi:10.1007/s10342-007-0168-4
- Nielsen AB, Östberg J, Delshammar T (2014) Review of urban tree inventory methods used to collect data at single-tree level. *Arboricult Urban For* 40:96–111
- Nowak DJ, Crane DE (2002) Carbon storage and sequestration by urban trees in the USA. *Environ Pollut* 116:381–389. doi:10.1016/S0269-7491(01)00214-7
- Nowak DJ, Stevens JC, Sisinni SM, Luley CJ (2002) Effects of urban tree management and species selection on atmospheric carbon dioxide. *J Arboric Urban For* 28:113–121
- Nowak DJ, Crane DE, Stevens JC, Hoehn RE, Walton JT, Bond J (2008) A ground-based method of assessing urban forest structure and ecosystem services *Arboricult Urban For* 34:347–358
- Nowak D, Hoehn R, Bodine A, Greenfield E, O'Neil-Dunne J (2013a) Urban forest structure, ecosystem services and change in Syracuse, NY. *Urban Ecosystems*:1–23. doi:10.1007/s11252-013-0326-z
- Nowak DJ, Greenfield EJ, Hoehn RE, Lapoint E (2013b) Carbon storage and sequestration by trees in urban and community areas of the United States. *Environ Pollut* 178:229–236. doi:10.1016/j.envpol.2013.03.019
- O'Donoghue A, Shackleton CM (2013) Current and potential carbon stocks of trees in urban parking lots in towns of the Eastern Cape, South Africa. *Urban For Urban Green* 12:443–449. doi:10.1016/j.ufug.2013.07.001
- Ordóñez C, Duinker PN (2013) An analysis of urban forest management plans in Canada: implications for urban forest management. *Landsc Urban Plan* 116:36–47. doi:10.1016/j.landurbplan.2013.04.007
- Pasher J, McGovern M, Khoury M, Duffe J (2014) Assessing carbon storage and sequestration by Canada's urban forests using high resolution earth observation data. *Urban For Urban Green* 13:484–494. doi:10.1016/j.ufug.2014.05.001
- Pickett STA et al. (2011) Urban ecological systems: scientific foundations and a decade of progress. *J Environ Manag* 92:331–362. doi:10.1016/j.jenvman.2010.08.022
- Pillsbury N, Reimer J, Thompson R (1998) Tree Volume Equations for Fifteen Urban Species in California, Technical Report No. 7. Urban Forest Ecosystems Institute, California Polytechnic State University, San Luis Obispo
- Popescu SC, Wynne RH (2004) Seeing the trees in the forest: using lidar and multispectral data fusion with local filtering and variable window size for estimating tree height. *Photogramm Eng Remote Sens* 70:589–604
- Popescu SC, Wynne RH, Nelson RF (2003) Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Can J Remote Sens* 29:564–577
- Poudyal NC, Siry JP, Bowker JM (2010) Urban forests' potential to supply marketable carbon emission offsets: a survey of municipal governments in the United States. *Forest Policy Econ* 12:432–438. doi:10.1016/j.forpol.2010.05.002
- Poudyal NC, Siry JP, Bowker JM (2011) Quality of urban forest carbon credits. *Urban For Urban Green* 10:223–230. doi:10.1016/j.ufug.2011.05.005
- Raciti SM, Hutrya LR, Newell JD (2014) Mapping carbon storage in urban trees with multi-source remote sensing data: relationships between biomass, land use, and demographics in Boston neighborhoods science of the Total Environment 500–501:72–83 doi:10.1016/j.scitotenv.2014.08.070
- Ren Y et al. (2011) Relationship between vegetation carbon storage and urbanization: a case study of Xiamen, China. *For Ecol Manag* 261: 1214–1223. doi:10.1016/j.foreco.2010.12.038
- Richardson JJ, Moskal LM (2014) Uncertainty in urban forest canopy assessment: Lessons from Seattle, WA, USA. *Urban For Urban Green* 13:152–157. doi:10.1016/j.ufug.2013.07.003
- Schmitt-Harsh M, Mincey SK, Patterson M, Fischer BC, Evans TP (2013) Private residential urban forest structure and carbon storage in a moderate-sized urban area in the Midwest, United States. *Urban For Urban Green* 12:454–463. doi:10.1016/j.ufug.2013.07.007
- Schreyer J, Tigges J, Lakes T, Churkina G (2014) Using airborne LiDAR and QuickBird data for modelling urban tree carbon storage and its distribution—a case study of Berlin. *Remote Sens* 6:10636–10655
- Shrestha R, Wynne RH (2012) Estimating biophysical parameters of individual trees in an urban environment using small footprint discrete-return imaging Lidar. *Remote Sens* 4:484–508
- Sileshi GW (2014) A critical review of forest biomass estimation models, common mistakes and corrective measures. *For Ecol Manag* 329: 237–254. doi:10.1016/j.foreco.2014.06.026
- Singh HS (2013) Tree density and canopy cover in the urban areas in Gujarat, India. *Curr Sci* 104:1294–1299
- Stoffberg GH, van Rooyen MW, van der Linde MJ, Groeneveld HT (2010) Carbon sequestration estimates of indigenous street trees in the City of Tshwane, South Africa. *Urban For Urban Green* 9:9–14. doi:10.1016/j.ufug.2009.09.004
- Strohbach MW, Haase D (2012) Above-ground carbon storage by urban trees in Leipzig, Germany: analysis of patterns in a European city. *Landsc Urban Plan* 104:95–104. doi:10.1016/j.landurbplan.2011.10.001
- Ter-Mikaelian MT, Korzukhin MD (1997) Biomass equations for sixty-five north American tree species. *For Ecol Manag* 97:1–24. doi:10.1016/s0378-1127(97)00019-4
- Tigges J, Lakes T, Hostert P (2013) Urban vegetation classification: benefits of multitemporal RapidEye satellite data. *Remote Sens Environ* 136:66–75. doi:10.1016/j.rse.2013.05.001
- Wack R, Schardt M, Lohr U, Barrucho L, Oliveira T (2003) Forest inventory for eucalyptus plantations based on airborne laser scanner data. *Int Arch Photogramm Remote Sens Spat Inf Sci* 34:40–46
- Weissert LF, Salmond JA, Schwendenmann L (2014) A review of the current progress in quantifying the potential of urban forests to mitigate urban CO₂ emissions. *Urban Climate* 8:100–125. doi:10.1016/j.uclim.2014.01.002
- Weng Q, Quattrochi DA, Carlson TN (2012) Remote sensing of urban environments: special issue. *Remote Sens Environ* 117:1–2. doi:10.1016/j.rse.2011.08.005
- Wilson LA, Davidson R, Coristine H, Hockridge B, Magrath M (2015) Enhancing the Climate Change Benefits of Urban Trees in Cambridge. In: Johnston M, Percival G (eds) *Trees, People and the Built Environment II*, Institute of Chartered Foresters, Edinburgh, 2014.

- Yao W, Krzystek P, Heurich M (2012) Tree species classification and estimation of stem volume and DBH based on single tree extraction by exploiting airborne full-waveform LiDAR data. *Remote Sens Environ* 123:368–380. doi:[10.1016/j.rse.2012.03.027](https://doi.org/10.1016/j.rse.2012.03.027)
- Yu X, Hyyppä J, Vastaranta M, Holopainen M, Viitala R (2011) Predicting individual tree attributes from airborne laser point clouds based on the random forests technique ISPRS-J Photogramm. *Remote Sens* 66:28–37. doi:[10.1016/j.isprsjprs.2010.08.003](https://doi.org/10.1016/j.isprsjprs.2010.08.003)
- Zapata-Cuartas M, Sierra CA, Alleman L (2012) Probability distribution of allometric coefficients and Bayesian estimation of aboveground tree biomass. *For Ecol Manag* 277:173–179. doi:[10.1016/j.foreco.2012.04.030](https://doi.org/10.1016/j.foreco.2012.04.030)
- Zarco-Tejada PJ, Diaz-Varela R, Angileri V, Loudjani P (2014) Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle (UAV) and automatic 3D photo-reconstruction methods. *Eur J Agron* 55:89–99. doi:[10.1016/j.eja.2014.01.004](https://doi.org/10.1016/j.eja.2014.01.004)
- Zhang K, Hu B (2012) Individual urban tree species classification using very high spatial resolution airborne multi-spectral imagery using longitudinal profiles. *Remote Sens* 4:1741–1757
- Zhang D et al. (2015) Effects of forest type and urbanization on carbon storage of urban forests in Changchun, Northeast China. *Chin Geogr Sci* 25:147–158. doi:[10.1007/s11769-015-0743-4](https://doi.org/10.1007/s11769-015-0743-4)
- Zhao K, Popescu S, Nelson R (2009) Lidar remote sensing of forest biomass: a scale-invariant estimation approach using airborne lasers. *Remote Sens Environ* 113:182–196. doi:[10.1016/j.rse.2008.09.009](https://doi.org/10.1016/j.rse.2008.09.009)
- Zhao M, Kong Z-h, Escobedo FJ, Gao J (2010) Impacts of urban forests on offsetting carbon emissions from industrial energy use in Hangzhou, China. *J Environ Manag* 91:807–813. doi:[10.1016/j.jenvman.2009.10.010](https://doi.org/10.1016/j.jenvman.2009.10.010)
- Zhao F, Guo Q, Kelly M (2012) Allometric equation choice impacts lidar-based forest biomass estimates: a case study from the sierra National Forest, CA. *Agric For Meteorol* 165:64–72. doi:[10.1016/j.agrformet.2012.05.019](https://doi.org/10.1016/j.agrformet.2012.05.019)
- Zianis D, Muukkonen P, Mäkipää R, Mencuccini M (2005) Biomass and Stem Volume Equations for Tree Species in Europe vol 4. The Finnish Society of Forest Science