Improving precision of field inventory estimation of above ground biomass through an alternative view on plot biomass

Christoph Kleinn (CKleinn@gwdg.de)
Georg-August-Universitat Gottingen Gottinger Graduiertenschule fur Neurowissenschaften Biophysik und Molekulare Biowissenschaften https://orcid.org/0000-0002-8625-3492

Steen Magnussen
Natural Resources Canada

Nils Noelke
Georg-August-Universitat Gottingen

Paul Magdon
Georg-August-Universitat Gottingen

Juan Gabriel Álvarez-González
Universidade de Santiago de Compostela

Lutz Fehrmann
Georg-August-Universität Göttingen

César Pérez-Cruzado
Universidade de Santiago de Compostela

Research

Keywords: Branch biomass, foliage biomass, stem biomass, biomass surface plots, sampling surfaces, standard error of estimation

Posted Date: August 14th, 2020

DOI: https://doi.org/10.21203/rs.3.rs-29694/v2

Version of Record: A version of this preprint was published on October 23rd, 2020. See the published version at https://doi.org/10.1186/s40663-020-00268-7.

Abstract

We contrast a new continuous approach (CA) to estimation of plot level above-ground biomass (AGB) in forest inventories with the current approach of deriving the AGB estimate exclusively from the tree-level AGB predicted for each tree in a plot; henceforth called DA (discrete approach). In CA the AGB in a forest is modelled as a continuous surface and the AGB estimate for a fixed area plot is computed as the integral of the AGB surface taken over the plot. Hence with CA, the portions of biomass in plot-trees that extend across a plot perimeter is ignored while the biomass from trees outside the plot reaching inside the plot is added. We use a sampling simulation with data from a fully mapped 2 ha area to illustrate, that important differences in plot-level AGB estimates can emerge, and that one should expect CA-based estimates of AGB to be less variable than with the DA, which translates to a higher precision of estimates from field plots: in our case study, for a target precision of estimation of 5%, the required sample size was 27% lower for small plots of 100m 2 when using the CA and 10% lower for larger plots of 1700m 2 . We discuss practical issues to implementing CA in field inventories and discuss the expected potential for applications that model biomass from remote sensing data.

Background

Fixed-area field plots constitute a plot design with a long history in forest inventory which is part of the plot design of most national forest inventories. In the early 19th century at the latest fixed-area plots were used to expand plot observations to entire stands (e.g. König 1835, Heyer 1861). That was long before statistical sampling had been established; which was called the “representative method” (Kiaer 1895-96) at the time.

When sampling for tree attributes, there are at least two different views on fixed-area plots each of which carries a different analytical approach: (1) The plot cuts out a sample area from a population (defined as the horizontally projected surface of a defined area of forest land) with recordings of all observations exactly above that area; this may be individual objects but also a continuously distributed variable (henceforth, we call this approach the “continuous approach to plot-level biomass”, CA); and (2), the plot serves as a selection tool and defines the discrete set of sample trees to be included into this particular plot from the population of all trees in a defined area of forest land (we will call this approach the “discrete approach to plot-level biomass” DA in what follows). In CA, the per-plot observation is the total of the target variable exactly above the horizontal projection of the plot area (for circular plots, the biomass within a cylinder on the plot perimeter), and in DA the per-plot observation comes from the total of the target variable over all included sample objects (trees). In remote sensing, the CA is the natural approach when the plot area is matched as accurately as possible with the image data (pixels). Naesset (2002) named this the “area-based approach” (ABA), which, in remote sensing is contrasted to the “individual tree detection” approach. In field sampling, it is commonly the DA which is applied, with a recording of tree variables for all sample trees on the plot, regardless of whether a sample tree has parts of its stem and crown outside the plot area. Both approaches CA and DA and their corresponding different analytical approaches have been applied in plot design comparisons when sampling for dead

wood: Gove and Van Deusen (2011) introduced the instructive terms “chainsaw method”, when only those parts of the deadwood are recorded that are exactly above the plot area (as if cut out by a chainsaw; this corresponds to our CA), and “stand-up method”, when all those deadwood pieces with their thicker end within the plot area are included and recorded (as if these dead wood pieces would stand up within the plot; this corresponds to our DA). In forest inventory field sampling, both approaches may be applied, and they differ in efforts and in precision of estimation while for both, unbiased estimators are available.

To the best of our knowledge, these two approaches have not been compared for other variables than dead wood, and certainly not for above-ground biomass, which has become a core variable in forest monitoring. The role of forests in the global carbon cycling accentuates the importance of quantifying both state and trends in forest biomass (IPCC 2006) and points to the demand for altogether “credible” estimates: for forest biomass and carbon monitoring, the Conference of the Parties (COP) to the UN-Climate Convention (UN-FCCC) explicitly requests the countries (Parties to the Convention) to establish “A robust and transparent national forest monitoring system …”; and these monitoring systems should “Provide estimates that are transparent, consistent, as far as possible accurate, and that reduce uncertainties” (UNFCCC COP decisions 4/CP.15, 1/CP.16, 9/CP19). That is: there is an important call to investigate opportunities for improvements of precision of forest biomass estimation; as we do it here.

Above-ground biomass is defined as “all living biomass above the soil … including stem, stump, branches, bark, seeds and foliage” (IPCC 2006, Annex 4A.1, 4.72). To bypass issues of destructive biomass sampling, tree biomass is predicted with models linking biomass to easy-to-measure tree variables, in particular the diameter at breast height (*dbh*) given its correlation with stem basal area, and tree height (Brown et al. 1989, Fehrmann et al. 2008, Picard et al. 2012, Chave et al. 2015, Magnussen and Carillo Negrete 2015).

In this study, we compare the precision of estimation of AGB from fixed-area field inventory plots under the two approaches CA and DA. The DA is the textbook approach to plot-level biomass observation and estimated as the sum over the trees in a plot from the biomass predicted for each tree using an appropriate model (Kershaw et al. 2016). A DA estimate of plot-level biomass may also include crown parts of sample trees that extend outside the plot perimeter or biomass in oblique stems leaning outside the plot area.

We consider the CA that looks at tree biomass as a variable that is continuously distributed horizontally. Its application requires for each inventory plot a prediction of the continuous horizontal biomass distribution (HBD) since the biomass is determined strictly above the plot area. A continuous view is also adopted in forest monitoring when defining an infinite population of sample elements (plots) in an area sampling frame (Mandallaz 1991), but applying a continuous view to the inventory variable biomass is new; to the best of our knowledge, modelling the continuous horizontal biomass distribution to produce plot-level observations of biomass has not been reported before. Outside forest inventories, a continuous

view is not uncommon, like, for example, topographic variables such as height above sea level, and remotely-sensed crown surfaces.

Figure 1 illustrates the key difference between DA and CA for the estimation of AGB.

While the vertical distribution of forest biomass has been researched intensively (e.g. Nemec et al. 2012, Jiménez et al. 2013, Ruiz-González and Álvarez-González 2011, Tahvanainen and Forss 2008), studies that address the horizontal forest or tree biomass distribution are sparse. Kershaw and Maguire (1996) and Xu and Harrington (1998), modelled the horizontal distribution of leaf biomass - but not AGB. Affleck et al. (2012) also noted an absence of HBDs for modelling of fuel load where HBDs would be required to take full advantage of next-generation fire behaviour simulators, and to improve fuel management strategies to reduce fire hazard. Mascaro et al. (2011) considered a uniform HBD across the crown projection area in a study on uncertainty of carbon estimation, and may have been the first to work the DA/CA issue in the context of airborne laser scanning (ALS) for forest carbon. They named the approaches “stem-localized” (corresponding to our DA and Gove’s and Van Deusen’s (2011) “stand-up” approach) and “crown-distributed” (corresponding to our CA and Gove and Van Deusen’s (2011) “chainsaw” method). Mascaro et al. (2011) investigated the issue in a remote-sensing based modelling context. Their main finding was that RMSEs were lower for the “crown-distributed” approach when modelling biomass from ALS data. As expected, the results varied with field plot size. Packalen et al. (2015) suggested a different approach to the edge tree issue in the area based approach in ALS based modelling: they modify the plot area so that the crown of in-trees is fully contained in that extended plot while overlapping crown parts of out-trees are zeroed. This allows them to compute the predictor variables tree-wise for the extended plot, while predictions are still made for the original plots.

This study is a first step towards integrating the horizontal distribution of forest biomass into AGB estimation from forest inventory field sampling. To that end, we provide a case study where DA estimates of AGB are compared to CA estimates derived by considering AGB as a continuous variable across an area of interest. This case allows us to draw first conclusions about the CA´s statistical performance, and identify pathways for further developments.

Materials And Methods

2.1. Study area

Data for our simulations come from a two ha (100 m × 200 m) area within a stand dominated by beech (*Fagus sylvatica* L., 92.3 % in both basal area and number of trees) near Göttingen, Germany (51°33'52.3" N 9°57'53.8" E). The stand was fully tallied: for each tree, species was identified and its *dbh* (cm) measured with a tape to the nearest millimeter. Summary statistics are in Table 1.

Table 1. Characteristics of the 2ha study area. *N* = stand density, *G* = basal area, and *dg* = quadratic mean diameter.

	Total	Beech	Other Broadleaves	Conifers
N (trees·ha^{-1})	183.0	169.0	9.0	5.0
G (m^{2}·ha^{-1})	25.1	23.1	0.9	1.1
dg (cm)	41.8	41.7	35.7	54.1

Tree heights and maximum crown diameters (*CDmax* = diameter of crown projection area) were predicted from *dbh* via local models (Guericke, 2001). The crown projection for a tree is assumed circular.

2.2 Construction of a tree-level HBD

The cornerstone in the CA is a tree specific HBD for all trees in a plot, and for trees outside the plot with a biomass from branches and foliage inside the plot perimeter. The HBD distributes a predicted tree biomass over a tree's crown projection area.

Mascaro et al. (2011) proposed a uniform distribution assigning, unrealistically, the same biomass density to the inner and outer parts of a tree crown. To improve realism, we develop a per-tree crown horizontal biomass distribution by combining a simple model for the stem with models for branch-wood, and foliage biomass derived from allometry, and horizontal foliage distribution.

First, we predicted the AGB for each tree separately for the compartments stem, branches and foliage with models provided in Bartelink (1997). Next, we addressed the spatial distribution of each biomass component across a horizontally projected crown area: for the stem biomass, we assumed a distribution within the confinements of a cone (centered at the tree position) with a basal diameter (*BD*) at ground level (height zero) predicted from the *dbh* (assuming a cone shape) and tree height.

To predict branch biomass at a given distance from the stem center we used models developed by Pérez-Cruzado et al. (in preparation) for beech from nearby the study stand. The branch biomass at a given distance from the stem center was estimated using a model proposed by Max and Burkhardt (1976) for stem taper:

$$wb = \left(-0.0047 \cdot (RCR - 1) + 0.0024 \cdot (RCR^2 - 1) + 0.0366 \cdot (0.6654 - RCR)^2 \cdot \frac{max\big((0.6654 - RCR), 0\big)}{(0.6654 - RCR)}\right)^{0.5} + \varepsilon \quad [1]$$

where *wb* is the standardized branch biomass density at the relative crown radius *RCR* ($RCR = CR_i / CDmax_i/2$) for the tree *i;* and ε is a random error term. Thus branch biomass is assumed to decrease with the distance to the center of the stem. At a distance of *CDmax*/2, the branch biomass density approaches zero (Figure 2).

The horizontal distribution of foliage biomass is modelled as two-parameter Weibull probability density function. This approach has been previously used to characterize horizontal distribution of foliage for different species and crown positions (e.g. Kershaw and Maguire, 1996; Xu and Harrington, 1998). We chose a location parameter equal to 0, a scale parameter of 0.61, and a shape parameter equal to 3.55. These parameter values are based on Pérez-Cruzado (in preparation).

The 3D HBD for each biomass component (stem, branches and foliage) was generated by rotating the corresponding functions around the stem axis. We standardized the *X* axis of the distribution (distance from the tree axis in Fig. 2) to the *CDmax*/2 of each tree and distributed the volume under the rotation solid over the horizontal plane. Hence, we assume that the HBD is isotropic in the horizontal plane and we assume the same standardized distribution for all trees. Figure 2 illustrates the horizontal profile distribution of biomass for a tree with known crown diameter *CDmax, DBH,* and *height*.

2.3 Construction of an area-level HBD

To illustrate the difference between AGB estimates from DA and CA for an area of interest, we need an HBD model for the entire area (here: our 2 ha study area). In principle this is done by predicting the HBD for each tree and adding these predicted biomasses for each location in the study area. To be practical, we chose to rasterize the study area into cells of 2 cm × 2 cm (resulting in a total of 50×10^6 cells). The high spatial resolution of the horizontal distribution of biomass over the study area provides an approximation to the continuous biomass distribution.

To facilitate a comparison between DA and CA estimates of AGB, and to better illustrate their differences, we also produced an HBD model for the study area as it would emerge with the DA. In contrast to CA, the DA specific HBD model assigned the predicted AGB of a tree to the single 2 cm × 2 cm cell containing the stem position; resulting in a HBD map where the biomass values are concentrated at the tree positions in peaks whose height depends on the respective tree´s biomass.

The DA and CA area-level HBD models are used next in a sample simulation as a basis for comparison.

2.4 Sample simulation

To capture effects of plot-size and shape, we carried out simulations with two common plot shapes (circles as preferred in forest inventory and squares as preferred in ecological surveys), and 17 plot sizes (100, 200, …, 1700 m^2). As our DA-CA comparison should not be influenced by Monte-Carlo errors (Rao 1973, Koehler 2009) we opted for simulating all possible samples through the construction of a sampling surface (Van Deusen et al. 1986, Roesch et al. 1993, Hradetzky 1995). A sampling surface is specific to a plot design, and provides - for each point within a defined sampling frame (area) - the AGB value that would be realized (from either a DA or CA HBD area level model) had the point been selected for sampling. Our sampling frame was the grid with the total of 50 x 10^6 square units of 4 cm^2. Upon completion we have, for each plot design, two sampling surfaces of AGB, one for DA, and one for CA.

In our simulations we eliminated boundary effects by excluding sample locations with a distance less than or equal to 23.26 m from a study area border. The width of this sample exclusion zone corresponds to the radius of the largest circular plot. In actual applications, boundary effects will be different for DA and CA, but they are beyond the scope of our study.

The standard deviation of all AGB values across all 4 cm^2 units in a sampling surface for a specific plot design and approach (DA or CA), corresponds to the standard error under simple random sampling and a sample size of n =1. Standard errors for larger sample sizes are not needed; they are covered by the central limit theorem (Johnson 2004) and may directly be derived.

To illustrate our results, also in more practical terms, we defined a target relative standard error of 5% and compared the expected sample sizes required to reach this target with DA and CA under the various plot designs. All statistical analyses and computations were made in R (R Core Team, 2018).

Results

We first build the HBDs for the study area for both approaches, CA and DA. The enlarged 20 m × 20 m sections in Figure 3 illustrate the difference between the two, where the biomass distribution for DA is characterized by high peaks at the tree positions while under CA the tree biomass is distributed isotropically over each crown area as per our example in Figure 2.

From the HBD of the study stand we calculated the AGB sampling surfaces both for the DA and the CA (Figure 4, [$Mg \cdot ha^{-1}$]). A sampling surface is specific for a defined plot design and gives per point (cell of 2 cm × 2cm) the per-plot biomass value that results for a sample plot centred at this particular point. While the topography of a sampling surface map varies by the two approaches and by plot design, the overall mean of AGB computed for the sampling frame of 4 cm^2 units remains almost constant at 279.25 $Mg \cdot ha^{-1}$. As expected, for a given plot size, the sampling surfaces (Figure 4) are smoother for the HBD of the CA than for the HBD of the DA. Equally, these differences diminish with an increase in plot size due to a lowering of the within-surface variance. With plot sizes above 900 m^2 the difference in the smoothness of the DA and the CA sampling surface were minor and without practical importance (not shown).

A smoother (less variable) sampling surface translates to a lower standard error in a mean estimated from a probability sample. Figure 5 depicts the standard deviations of the DA and CA HBD sampling surfaces by plot size. The CA sampling surface has consistently a smaller standard deviation for all plot sizes and the two plot shapes (circular, square). The relative reduction in variability is more pronounced for smaller plots and decreases as plot size is increased. This can be explained by a higher perimeter-to-area ratio of a smaller plot, so that per unit area, the frequency of crowns intersecting a smaller plot is higher than for a larger plot. Figure 5 also indicates a (small – but consistently) superior performance of the circular plot shape, a feature in line with the minimum perimeter-to-area ratio of a circle.

We also used the DA and CA sampling surfaces of plot-level AGB estimates to gauge the required sample size for a target relative standard error of 5 % in an estimate of the mean AGB in the studied sample frame. The results are in Figure 6. As alluded to, the CA can achieve the target with a smaller sample size. In our study area, a reduction of 27.1 % was achieved with our smallest plots of 100 m^2. For the largest plots considered (1,700 m^2), the reduction was 10.4 %. We noted a slightly but consistently greater (1.4 %) reduction with circular plots than with square plots, in agreement with their more favourable perimeter-to-area ratio.

Discussion

For field sampling, our case study indicates that the CA approach to estimation of AGB tends to be more efficient in terms of precision of estimation than the traditional DA. This advantage of CA over DA will depend however, in a rather complex way, on tree species, tree and crown sizes, stand structures, stem densities, and interactions of these factors with plot size and shape (in particular perimeter length). In our case study, for a defined target precision of estimation, we observed a reduction of required sample size of 10.4 % for larger plots (1700 m^2) and 27.1 % for small plots (100 m^2). It will be instructive to look in more detail into the factors influencing this gain in precision.

We may compare our findings regarding the precision of estimation with those of a dead wood sampling study by Gove and Van Deusen (2011), who compared the performance of their “stand-up method” (corresponding to our DA) to their “chainsaw method” (corresponding to our CA) to estimate the volume of downed coarse woody debris. They found the CA to be superior: in their study, the standard deviations for the sample surfaces were 135.48 m^3 and 120.18 m^3, respectively so that their (continuous) chainsaw approach was approximately 12 % more precise than the (discrete) stand-up approach. Mascaro et al (2011) did also observe superiority of their version of the CA when they derived a remote sensing-based model for forest biomass prediction.

For this first of its kind case study on the comparison of the CA and the DA for forest biomass, we needed to work with various simplifying assumptions regarding regular and symmetric (rotational) stem and crown shapes, branch allometry, profile distributions of foliage, isotropic distribution of biomass within the volumetric confinements of a biomass component, and perfectly upright stem axes. Combined, these assumptions may have impacted the results of our sampling study. Refinements are clearly needed, and in light of our results we will pursue improvements in the next iteration At any rate, it will be important to research if using more realistic models for each biomass component will significantly change the performance differential between CA and DA.

From a practical perspective, the DA method for estimation of AGB has well-established advantages in terms of expediency because measurements and model-based predictions are straightforward and apply

only to the sample trees within a plot. With the DA, there is neither need for a map of tree locations in the plot nor measurements (*dbh* and location) of trees in the surrounding vicinity of a plot as required by the CA. It is obvious, that additional measurements come at a cost detrimental to existing budgets to support already costly field work. However, one may realistically expect the future to bring forest mensuration devices that allow to automatically and simultaneously measure the distance to sample trees, the height 1.3 m, and the diameter at this reference height. This would accelerate field work on mapped forest inventory plots and their surrounds, and render practical applications of the CA approach more feasible.

We compared DA and CA from a perspective of field plot sampling. The theoretical consistency of the CA in terms of estimating AGB over a specifically defined piece of forest (the plot area) is, however, of particular relevance in model-assisted and model-based estimation problems in which remotely-sensed auxiliary variables are linked to per-plot values of AGB (Nelson et al. 2000, Mascaro et al 2011, Magdon et al. 2018). Conceptually, the remotely-sensed auxiliary variable only registers the biomass proxies within the confinements of a field plot while the field data from the DA – that are used to build the remote sensing based biomass model - include biomass of plot trees extending beyond the plot perimeter, and ignore the biomass from outside trees overhanging a plot. The extent of the misalignment depends (to a large degree) on the spatial resolution or density of the remotely-sensed data, plot size and in particular plot perimeter. This has also been described, for example, by Packalen et a. (2015) with respect to the ABA in lidar remote sensing who present an interesting approach in which the plot area is extended to accommodate the complete tree crowns also of those in-trees whose crowns are partly outside the plot area.

In cases where the spatial resolution is much finer than the size of most crown areas, the CA approach should, *a priori*, tend to generate a stronger correlation between the auxiliaries in an assisting model and AGB than possible with DA because the misalignment of biomass vis-à-vis the confinements of a plot will act as a measurement error - with an attenuation of correlations (Fuller 1987, Carroll 2006). In fact, Mascaro et al. (2011) in their ALS study, addressed three major sources of errors: (1) GPS positional error, (2) temporal differences between the field and lidar data, and (3) a lack of consistency between lidar and field plot measurements rooted in the uncertainty of deciding on whether a tree or any part of it resides inside the confinements of a field plot. With respect to the third source of error, which relates to our study, they found that the root mean square error (RMSE) of the model that links the lidar with the ground data could be consistently improved with a CA approach replacing the traditional DA. This ‘third’ error has so far not been explicitly recognized in otherwise detailed error budgets for AGB estimates in forest monitoring (Chave et al. 2004, Ståhl et al. 2014, Molto et al. 2013, Magnussen et al. 2014, Chen et al. 2016).

Conclusions

Our overall goal was to contribute to improving the precision of forest biomass estimation from field sampling by suggesting the novel CA to observing plot-biomass which may be applied to any forest inventory sampling design. From our piloting simulation study and the fact that the CA produces a

smoother (less variable) sampling surface , we may conclude that the CA has the potential to improve the precision of field estimated AGB. However, the CA approach is unlikely to be operational until issues related to field measurement efforts can be resolved. Moreover, the inroad of CA in forest inventory will not only depend on the availability of measurement devices for rapid mapping of trees around a sample point, recordings of *dbh* and delineation of crown projection areas, but also on an expansion of our arsenal of models for crown sizes, foliage distribution, and branch architectures.

Acknowledgements

The authors are grateful to two anonymous reviewers for their detailed and thoughtful review observations which helped to improve the manuscript.

References

Affleck, D.L.R., Keyes, C.R., Goodburn, J.M. 2012. Conifer crown fuel modeling: Current limits and potential for improvement. West. J. Appl. For. 27, 165-169.

Bartelink, H.H. 1997. Allometric relationships for biomass and leaf area of beech (*Fagus sylvatica* L). Ann. For. Sci. 54, 39-50.

Brown, S., Gillespie, A., Lugo, A.E. 1989. Biomass Estimation Methods for Tropical Forests with Applications to Forest Inventory Data. Forest Science 35(4):881-902.

Brown, S., 1997. Estimating biomass and biomass change of tropical forests – a primer. FAO Forestry Paper 134. 55p.

Chave, J., Condit, R., Aguilar, S., Hernandez, A., Lao, S., Perez, R. 2004. Error propagation and scaling for tropical forest biomass estimates. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences 359(1443):409-420.

Chave J., Rejou-Mechain, M., Burquez, A., Chidumayo, E., Colgan, M.S. Delitti, W.B.C., Duque, A., Eid, T., Fearnside, P.M., Goodman, R., Henry, M., Martinez-Yrizar, A., Mugasha, W.A., Muller-Landau, H.C. , Menuccini, M., Nelson, B.W., Ngomanda, A., Nogueira, E.M., Ortiz-Malavassi, E., Pelissier, R., Ploton, P., Ryan, C.M., Saldarriaga, J.G., Vielleedent G. 2015. Improved allometric models to estimate the above-ground biomass of tropical trees. Global Change Biology (2015) 20, 3177–3190.

Chen Q., McRoberts, R.E., Wang, C., Radtke 2016Forest aboveground biomass mapping and estimation across multiple spatial scales using model-based inference. Remote Sensing of Environment 184 (2016) 350–360

Enquist, B.J. 2002. Universal scaling in tree and vascular plant allometry: toward a general quantitative theory linking plant form and function from cells to ecosystems. Tree Physiol. 22, 1045-1064.

Fehrmann L., Lehtonen, A., Kleinn, C., Tomppo, E. 2008.Comparison of linear and mixed-effect regression models and a k-nearest neighbour approach for estimation of single-tree biomass. Canadian Journal of Forest Research 38(1): 1-9.

Fuller, W.A. 1987. Measurement error models. Wiley, New York. 440p.

Gove, J.H., Van Deusen, P.C. 2011. On fixed-area plot sampling for downed coarse woody debris. Forestry 84, 109-117.

Guericke, M. 2001. Growth dynamics of mixed stands of Beech and European Larch (*Larix decidua*, Mill.). Georg August Universität Göttingen 273.

Hradetzky, J. 1995. Concerning the precision of growth estimation using permanent horizontal point samples. For. Ecol. Manage. 71, 203-210.

Heyer G. 1861. Notizen: A. Über die Größe der Probeflächen (in German: Notes: A. About the size of sample plots). Allgemeine Forst- und Jagdzeitung AFJZ. Oktober 1861:399.

IPCC. 2006. Guidelines for National Greenhouse Gas Inventories. https://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_04_Ch4_Forest_Land.pdf

Jiménez, E., Vega, J.A., Ruiz-González, A.D. , Guijarro, M., Alvarez-González, J.G., Madrigal, J., Cuiñas, P., Hernando, C., Fernández-Alonso, J.M. 2013. Carbon emissions and vertical pattern of canopy fuel consumption in three *Pinus pinaster* Ait. active crown fires in Galicia (NW Spain). Ecol. Eng. 54:202-209.

Kershaw, J.A., Maguire, D.A. 1996. Crown structure in western hemlock, Douglas-fir, and grand fir in western Washington: trends in branch-level mass and leaf area. Can. J. For. Res. 25, 1897-1912.

Kershaw, J.A., Ducey, M.J., Beers, T. W., Husch, B. 2016. Forest Mensuration. 5th edition. Wiley-Blackwell. 630p.

Kiaer AN. 1895-96. Observations et expériences concernant des dénombrements representatives. Bulletin of the International Statistical Institute, IX, Book 2: 176-183.

König G. 1835. Forstmathematik (in German: ”Forest Mathematics”). Gotha, in Commission der Beckerschen Buchhandlung.436p. + 56p of tables (2nd edition 1854).

Koehler, E., E. Brown, and J.-P.A. Haneuse. 2009. On the assessment of Monte Carlo error in simulation-based statistical analyses. Am. Stat. 63(2):155-162.

Magdon, P., González-Ferreiro, E., Pérez-Cruzado, C., Purnama, E.S., Sarodja, Y., Kleinn, C. 2018. Evaluating the Potential of ALS Data to Increase the Efficiency of Aboveground Biomass Estimates in Tropical Peat-Swamp Forests. Remote Sensing 10 (9), 1344.

Magnussen, S., M. Köhl, K. Olschofsky. 2014. Error propagation in stock-difference and gain–loss estimates of a forest biomass carbon balance. Eur. J. For. Res. 133(6):1137-1155. DOI: 10.1007/s10342-014-0828-0

Magnussen, S., Carillo Negrete, O.I. 2015. Model errors in tree biomass estimates computed with an approximation to a missing covariance matrix. Carbon Balance Manag. 10: 21.

Mandallaz, D. 1991. A unified approach to sampling theory for forest inventory based on infinite population and superpopulation models [online]. Diss. Techn. Wiss. ETH Zürich 9378.

Mascaro, J., Detto, M., Asner, G.P., Muller-Landau, H.C. 2011. Evaluating uncertainty in mapping forest carbon with airborne LiDAR. Remote Sens. Environ. 115, 3770-3774.

Max, T.A., Burkhart, H.E., 1976. Segmented polynomial regression applied to taper equations. For. Sci.22, 283-289.

McRoberts, R.E., Næsset, E., Saatchi, S., Liknes, G.C., Walters, B.F. Chen, Q. 2019. Local validation of global biomass maps. International Journal of Applied Earth Observation and Geoinformation. Volume 83, November 2019, 101931.

Molto, Q., V. Rossi, L. Blanc. 2013. Error propagation in biomass estimation in tropical forests. Methods in Ecology and Evolution 4(2):175-183. 10.1111/j.2041-210x.2012.00266.x

Montero, G., Ruiz-Peinado, R., Nuñoz, M. (2005). Producción de biomasa y fijación de CO2 por los bosques españoles. Monografías INIA. Serie Forestal nº 13. 270 pp.

Næsset, E., 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sens. Environ. 80, 88–99. doi:10.1016/S0034-4257(01)00290-5

Nemec, A.F.L., Parish R., Goudie, J.W. 2012. Modelling number, vertical distribution, and size of live branches on coniferous tree species in British Columbia. Can. J. For. Res. 42(6):1072-1090.

Nelson, R., Jimenez, J., Schnell, C. E., Hartshorn, G. S., Gregoire, T. G., Oderwald, R. 2000. Canopy height models and airborne lasers to estimate forest biomass: Two problems. International Journal of Remote Sensing 21:2153–2162.

Packalen, P., Strunk, J. L., Pitkänen, J. A., Temesgen, H., Maltamo, M. 2015. Edge-Tree Correction for Predicting Forest Inventory Attributes Using Area-Based Approach With Airborne Laser Scanning. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 8(3):1274-1280.

Pérez-Cruzado, C., Merino, A., Rodríguez-Soalleiro, R. 2011. A management tool for estimating bioenergy production and carbon sequestration in *Eucalyptus globulus* and Eucalyptus nitens grown as short rotation woody crops in north-west Spain. Biomass and Bioenergy 35:2839-2851.

Pérez-Cruzado, C., Nölke, N., Magdon, P., Álvarez-González, J.G., Fehrmann, L., Kleinn, C. In preparation. The horizontal distribution of branch biomass of European beech: a TLS study with subsequent destructive measurements. Remote Sensing.

Picard, N., Saint-André, L., Henry, M. 2012. Manual for building tree volume and biomass allometric equations - From field measurement to prediction. CIRAD et FAO. 215p.

R Core Team. 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing.

Rao, C.R. 1973. Linear Statistical Inference and its Applications. In 2nd edition. John Wiley &Sons, New York (NY).

Roesch, F.A., Green, E.J., Scott, C.T. 1993. An alternative view of forest sampling. Surv. Methodol. 19, 199-204.

Ruiz-González, A.D., Álvarez-González, J.G. 2011. Canopy bulk density and canopy base height equations for assessing crown fire hazard in *Pinus radiata* plantations. Can. J. For. Res. 41(4):839-850.

Schepaschenko, D. and 144 co-authors. 2019. The Forest Observation System, building a global reference dataset for remote sensing of forest biomass. Nature | Scientific Data 6:198.

Ståhl G., Heikkinen J., Petterson, H., Repola J., Holm S. 2014. Sample-Based Estimation of Greenhouse Gas Emissions From Forests—A New Approach to Account for Both Sampling and Model Errors. For. Sci. 60(1):3–13.

Tahvanainen, T., Forss, E. 2008. Individual tree models for the crown biomass distribution of Scots pine, Norway spruce and birch in Finland. For. Ecol. Manage. 255(3):455-467.

Tesfaye, M.A., Bravo-Oviedo, A., Bravo, F., Ruiz-Peinado, R. 2016. Aboveground biomass equations for sustainable production of fuelwood in a native dry tropical afro-montane forest of Ethiopia. *Annals of Forest Science* **73**:411–423.

UNFCCC COP decisions

4/CP.15: https://unfccc.int/sites/default/files/resource/docs/2009/cop15/eng/11a01.pdf

1/CP.16: https://unfccc.int/sites/default/files/resource/docs/2010/cop16/eng/07a01.pdf

9/CP19: https://unfccc.int/sites/default/files/resource/docs/2013/cop19/eng/10a01.pdf

Van Deusen, P.C., Dell, T.R., Thomas, C.E. 1986. Volume growth estimation from permanent horizontal points. For. Sci.32, 415-422.

Xu, M., Harrington, T.B. 1998. Foliage biomass distribution of loblolly pine as affected by tree dominance, crown size, and stand characteristics. Can. J. For. Res. 28, 887-892.

Declarations

- Ethics approval and consent to participate

Not applicable

- Consent for publication

The authors confirm that the agree to publication of the manuscript

- Availability of data and material

Data and material will be made available upon reasonable request.

- Competing interests

There are no competing interests

- Funding

This study was entirely self-funded, no external funding.

- Authors' contributions

CK developed the idea, drafted the research design and wrote the first draft, CPC: developed the models and programed them. JGAG, PM: supported in programming and writing; SM, LF, NN: supported implementation of the study, and data.
All authors critically participated in internal review rounds and read the final manuscript and approved it.

- Acknowledgements

The authors will formulate an acknowledgement to the reviewers, then.

Figures

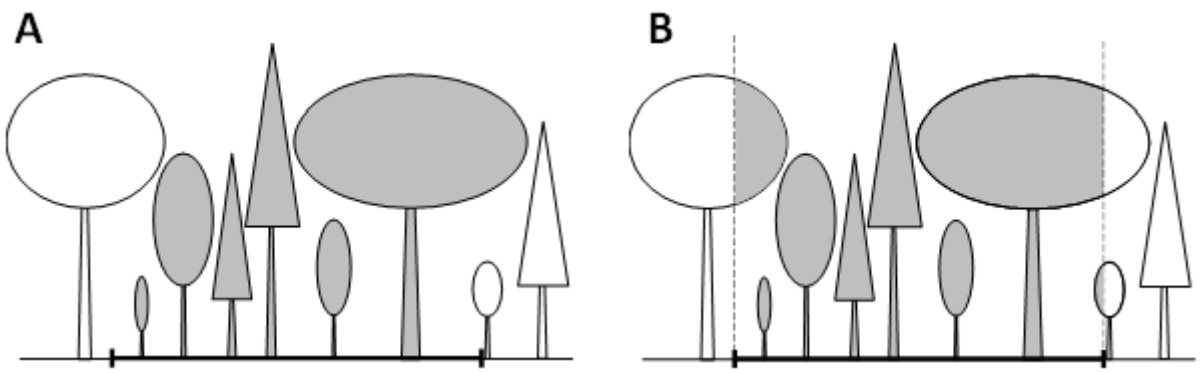

Figure 1

Schematic comparison of (A) the discrete approach DA and (B) the continuous approach CA to determining plot-level biomass. The plot size is represented by the bold black line at ground level, and for the CA, the vertical dashed lines mark the positions between which the biomass is considered.

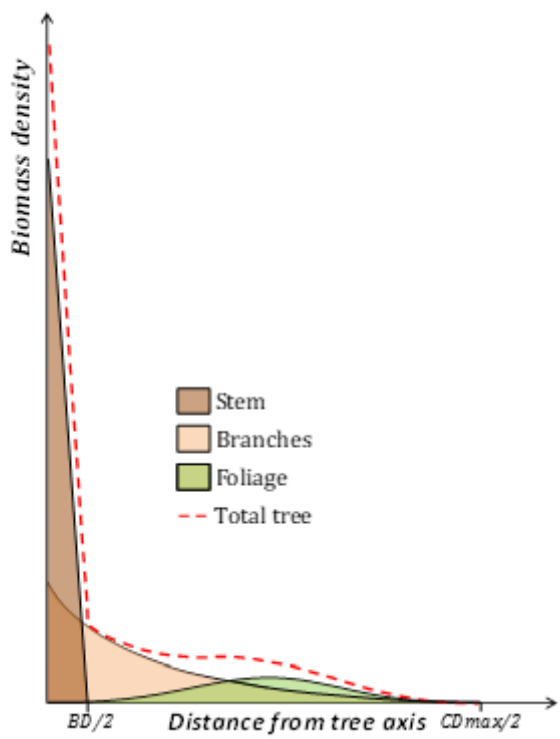

Figure 2

Schematic profile of the horizontal distribution of stem, branches, foliage biomass, and combined (AGB) in an individual tree and arbitrary direction. BD is the basal diameter of the stem, derived from dbh

(assuming cone shape); CDmax is the maximum crown diameter.

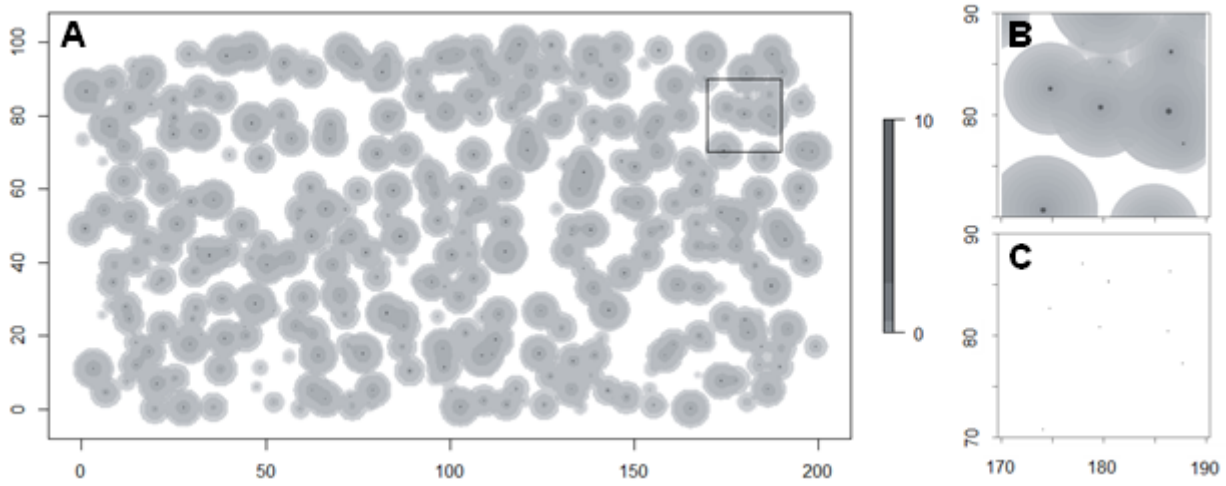

Figure 3

Horizontal above-ground biomass distribution for all tree components (stem + branches + foliage) for CA (maps A and B) and DA (map C). Map A shows the entire 2 ha study area. Maps B and C amplify the 20 m × 20 m square shown in map A. The units of the grey values are “kg per 4 cm2 ” (i.e. per raster cell of 2 cm × 2 cm).

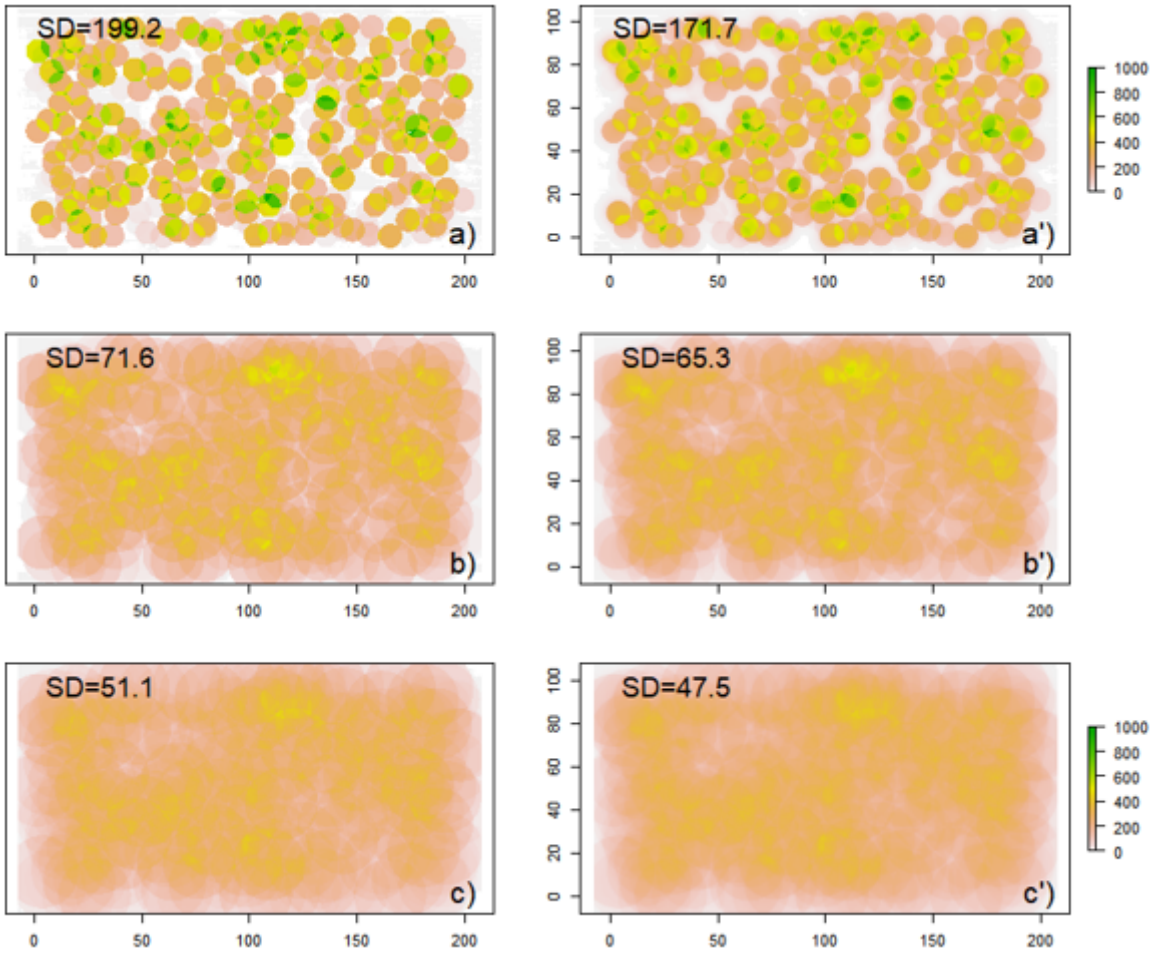

Figure 4

Sampling surfaces for the DA (left, a-c) and the CA (right, a'-c') approaches for estimation of AGB with a circular plot with an area of: 100 m2 (a, a'); 500 m2 (b, b'); and 900 m2 (c, c'). The color scale illustrates the values of the observed plot-level biomass in Mg·ha-1 and SD is the standard deviation (Mg·ha-1) of surface values of AGB.

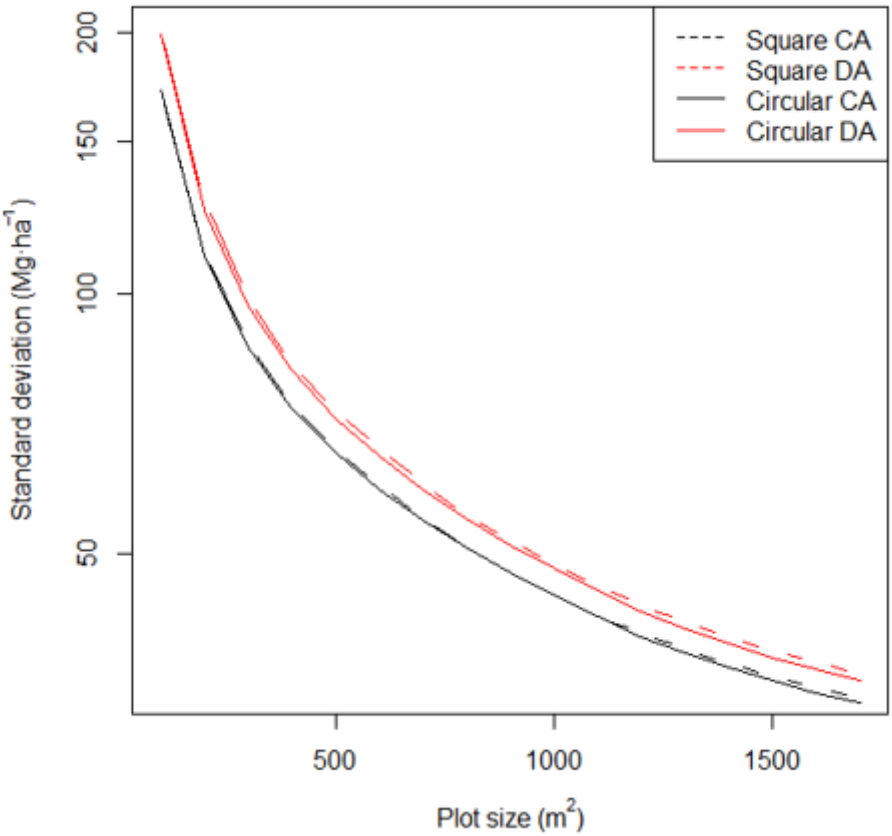

Figure 5

Standard deviation (log scale) of the DA and CA sampling surfaces of AGB as a function of plot area (and shape). Differences between square and circle shape are small, but CA produces clearly lower standard deviations.

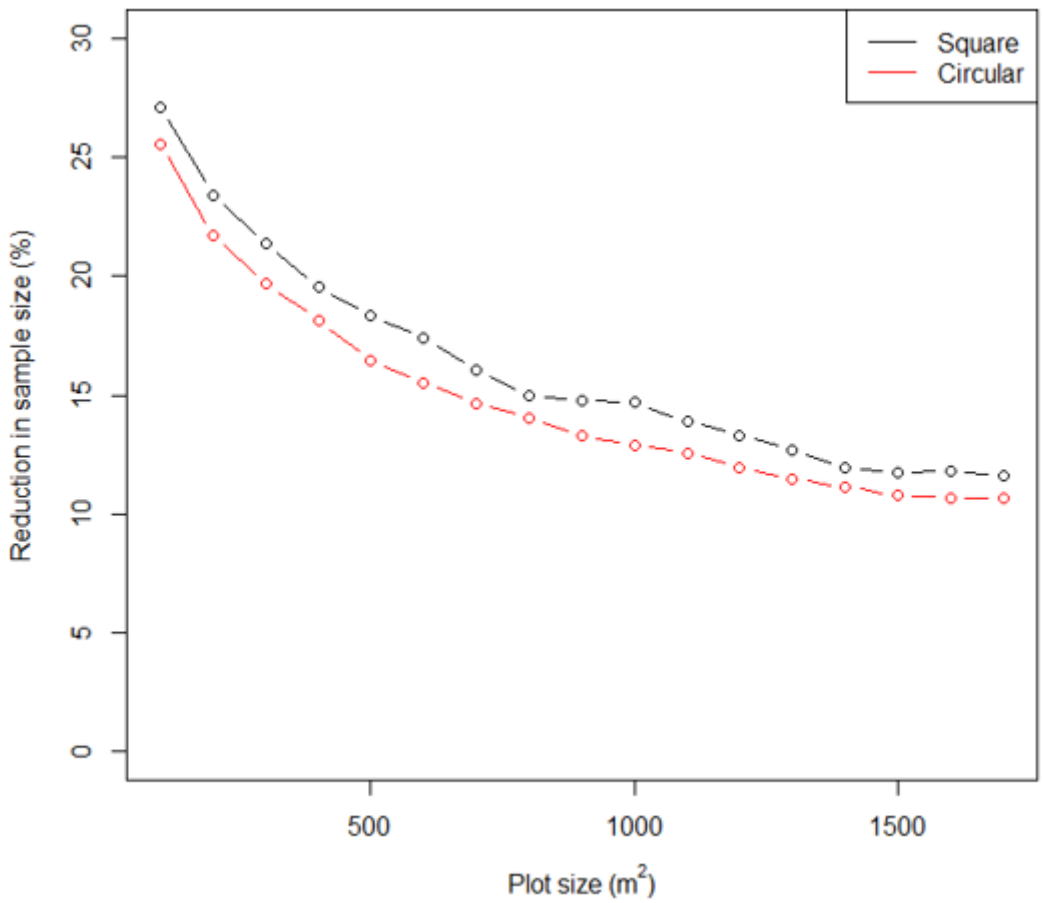

Figure 6

For the 2 ha study area: reduction in required sample size as a function of plot area for the DA and the CA with a fixedtarget standard error of 5 % in AGB.