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Title: Occlusion probability in operational forest inventory field sampling with ForeStereo

Authors: Fernando Montes, Álvaro Rubio-Cuadrado, Mariola Sánchez-González, Isabel Aulló-
Maestro, Miguel Cabrera, Cristina Gómez

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1 Occlusion probability in operational forest inventory field sampling 2 with ForeStereo

3 Accuracy of plot-level estimates of number of trees and basal area using ForeStereo fixed-
4 point sampling improves with correction of instrument bias and tree occlusions.

5 Abstract

6 Field data in forest inventories are increasingly obtained using proximal sensing
7 technologies, often under fixed-point sampling. Under fixed-point sampling some trees are
8 not-detected due to instrument bias and occlusions, hence involving an underestimation of
9 the number of trees per hectare (N). The aim here is to evaluate various approaches to
10 correct tree occlusions and instrument bias estimates calculated with data from ForeStereo
11 (proximal sensor based on stereoscopic hemispherical images) under a fixed-point sampling
12 strategy. Distance-sampling and the new hemispherical photogrammetric correction (HPC),
13 which combines image segmentation-based correction for instrument bias with a novel
14 approach for estimating the proportion of shadowed sampling area in stereoscopic
15 hemispherical images, best estimated N and basal area (BA). Distance-sampling slightly
16 overestimated N (11% bias and 0.60 Pearson coefficient with the reference measures) and
17 BA (4%, 0.82). HPC provided less biased N estimates (-6%, 0.61) but underestimated BA (-8%,
18 0.83). The diameter distribution was more accurately retrieved through HPC.

1. Introduction

Understanding forests dynamics is necessary for sustainable forest management. Forest inventories supported by data measured on the ground and data acquired remotely via aerial or satellite platforms enable the monitoring of forest structure, growth, change in composition, responses to silvicultural traits and decline originated by climatic or biotic factors. Continuous development of technology for data acquisition, processing, and analysis contributes to improving the quality of forest inventories. Remote sensing provides information on forest variables such as cover (Morsdorf et al. 2006), structure (Gómez et al. 2011), volume (Vauhkonen et al. 2011) or biomass (Næsset and Gobakken 2008), with complete spatial coverage. A wide range of sensors with different spatial resolutions (from hundreds to less than 1 m) are suitable for forest applications (White et al. 2016). Satellite imagery and aerial LiDAR data support mapping and updating National Forest Inventory estimations (e.g. in Finland, Tomppo et al. 2008, or in Canada, Hilker et al. 2008). Changes in land cover and forest variables like biomass are mapped and monitored with optical and radar satellite sensors (White et al. 2017; Matasci et al. 2018; Santoro et al. 2018). For height retrieval and assessment of vertical structure Synthetic Aperture Radar may be employed by itself (e.g. Garestier et al. 2008; Tebaldini and Rocca 2012) and its combination with LiDAR data is expected to provide improved resolution and accuracy for large scale assessments (Qi et al. 2019). For estimation of forest inventory variables at regional scale LiDAR is the most precise technology (Wulder et al. 2013) enabling structural characterization (Valbuena et al. 2013; Bottalico et al., 2017) and measurement of individual tree attributes (Hauglin et al. 2014). LiDAR provides precise digital elevation models and metrics for characterization of height distribution (Lindberg et al. 2012) and is increasingly being used to generalize the sampling plot data to the whole area through area-based models (Næsset 2002; Bouvier et

al. 2015). Research is ongoing to overcome LiDAR limitations in the estimation of tree diameter distribution (Magnussen et al. 2013) or species composition (Maltamo et al. 2009), which may benefit from the combination with other sensors (Holmgren et al. 2008; Puttonen et al. 2010; Zhao et al. 2018). Forest canopy surface height can also be estimated comparing image-based point clouds derived from digital aerial photography and terrain elevation models of high spatial resolution generated with LiDAR (Leberl et al. 2010). Digital aerial photography is less costly than LiDAR (White et al. 2013) and provide spectral information to support species classification (St-Onge et al. 2015); however, image-based point clouds do not penetrate through tree crowns in dense stands (White et al. 2013) being LiDAR more informative for forest inventory applications. Equipped with optical sensors unmanned aerial vehicles (UAVs) can retrieve photogrammetric surface models at local scale with very high spatial resolution, and spectral vegetation indices to support species classification (Tuominen et al. 2018). To date practical concerns in the use of UAVs include data processing, power autonomy, payload weight, and local regulations (Gómez and Green, 2017; Manfreda et al. 2018).

Although the contribution of remotely sensed data to forest inventories is constantly increasing, field data is needed to calibrate and validate the models (Broszofske et al. 2014). Field data is expensive to acquire, therefore a sampling survey approach is generally used (Mandallaz and Ye 1999). Proximal sensing (PS) techniques, which refer to the acquisition of data with a sensor from a relatively short distance, may provide information on variables which are complex to measure manually, such as spatial arrangement and dimensions of trees (Rodríguez-García et al. 2014), canopy features (Seidel et al. 2012), stand volume (Astrup et al. 2014) or forest fuel (Pimont et al. 2015), complementing the field measurement and enhancing performance (Dassot et al. 2011). The combination of remote

67 sensing and proximal sensing may improve estimations and reduce the cost of inventories
68 (Lindberg et al. 2012).

69 The development of point sampling PS technologies—based on laser distance or
70 photogrammetry—to measure tree dimensions and to estimate forest parameters at plot or
71 stand level began in the early 2000s (Clark et al. 2000; Lovell et al. 2003). Some PS
72 technologies have been optimized for forestry, such as ForeStereo (a camera system with
73 fish-eye lenses, Montes et al. 2009) and Terrestrial Laser Scanning (TLS, Liang et al. 2016;
74 Newnham et al. 2015).

75 ForeStereo is a passive optical sensor composed of two hemispherical cameras capturing the
76 visible radiation reflected by the surface of surrounding objects (e.g. trees) in a single shot.
77 The stereoscopic hemispherical images were firstly used for measurement of tree diameter,
78 height, and volume by Rodríguez-García et al. (2014). ForeStereo technology has been
79 incorporated into the Spanish National Forest Inventory (Sánchez González et al. 2016) and
80 National Parks forest monitoring in Spain (Sangüesa-Barreda et al. 2015, Rubio-Cuadrado et
81 al. 2018a, Rubio-Cuadrado et al. 2018b). ForeStereo is widely used as part of the field survey
82 in natural forests and plantations of different species in Spain and it is being tested in Brazil
83 and Chile. Computer vision techniques have been developed for the segmentation of
84 ForeStereo images to identify trees (Sánchez-González et al. 2016) and a methodology has
85 been proposed for the 3D reconstruction of stem profiles from the angular disparity
86 between the matched stem sections in both stereoscopic images and epipolarity restrictions
87 (Rodríguez-García et al. 2014). ForeStereo has been specifically developed for forestry and
88 employs software designed specifically to estimate stand variables such as basal area (BA) or
89 number of trees per hectare (N) (Sánchez-González et al. 2016). Applications for vertical

distribution of forest fuel assessment (Marino et al. 2018) or species classification (Gea-Izquierdo et al. 2015) have also been developed.

Terrestrial Laser Scanner used in forest inventories provides a dense point cloud that enables the 3D structural reconstruction (Strahler et al. 2008; Yao et al. 2011) and estimation of forest inventory variables such as *N*, BA, volume or biomass (Lovell et al. 2011; Astrup et al. 2014; Liang et al. 2016). TLS provides detailed data of below-canopy forest structure that can be used for precise biomass estimations and development of allometric equations, as well as crown shape and tree morphology modelling (Côte et al. 2012; Raunonen et al. 2013; Hauglin et al. 2013). However, the big amount of beam returns generated by TLS requires complex data processing to select returns from stems, foliage or shrubs and to fit geometrical models for diameter and volume estimation (Newnham et al. 2015). In addition, TLS devices are expensive and its use for the field stage in large scale forest inventories usually is not justified (White et al. 2016). Modern TLS devices reduce weight, and 2D laser scanner offers an easy to handle solution, but data is limited to the sensors plane (Ringdahl et al. 2013; Brunner and Gizachew 2014). Compared with TLS, photogrammetric PS techniques (including ForeStereo) have better battery performance and reduced device weight, and faster image processing through computer vision techniques (Herrera et al. 2009; Herrera et al. 2011). Photogrammetric PS technologies employing conventional lenses require multiple image acquisitions (Clark et al. 2000; Varjo et al., 2006; Forsman et al. 2012), and processing becomes complicated. ForeStereo employs fisheye lenses with 180° field of view, so all features above the horizontal plane passing through the lens are projected in the image, enabling the 3D forest structural reconstruction around the sampling point from a single pair of images.

Large-scale operational forest inventories require a large number of sampling points covering the target area, therefore single scan plots are an economically advantageous option (Ducey et al. 2014). In order to become functional, a PS instrument for use in operational forest inventories should provide repeatable measures of the forest variables in a fast and economic manner, as well as a measure of the accuracy and reliability of the acquired data. For estimation of stand level variables like BA or N , the fixed point techniques are based on the angle count sampling method, which is the basis of the Relaskop (Bitterlich 1947). In the angle count sampling method, those stems projected in the visor which are wider than a reference threshold are sampled, so the maximum distance of detection depends on the size of each tree. Fixed point sampling typically underestimates the number of trees for two main reasons: (1) the instrument bias derived from a limited range of detection, which depends on the resolution of the scan or image and the diameter of trees (Seidel and Ammer 2014) and (2) the process of tree retrieval from a single scan or image: some trees actually present in the plot are occluded by others, hence reducing the tree detection rate (Lovell et al. 2011). The underestimation issue becomes more important in very dense forests and has been analysed in recent studies (Yang et al. 2013; Brunner and Gizachew 2014). Three main methods have been proposed to correct the effects of tree occlusion on the estimation of plot and stand level variables, leading to less biased estimations:

i) Attenuation model (Strahler et al. 2008). This method assumes that the gap probability - where a gap is the area between trees that allows clear visibility to more distant trees - decreases exponentially as a function of the distance to the sensor and an effective diameter of trees, following a Poisson model. The effective diameter includes branches, foliage,

shrubs, and any other intercepting elements. This method has been used for counting stems and for estimation of biomass from TLS data (Yao et al. 2011).

ii) Modelling a detection function based on distance-sampling (Ducey et al. 2013). In this case, the probability of detecting a tree depends on its distance from the sensor. The function to model probabilities is fitted to the distribution of distances of trees that are actually detected (apparent trees). Distance-sampling methods are widely used in ecology, where the mathematical framework for population summary statistics and variance estimation has been established (Buckland et al. 2001). Astrup et al. (2014) employed two functions to model the probability of tree detection, namely Half-Normal and Hazard-Rate, and estimated volumes with data from TLS.

iii) Estimation of the proportion of sampling area shadowed by the apparent trees (Seidel and Ammer 2014). The plot area shadowed by trees can be calculated from the diameter and the actual distance from the sensor of all retrieved trees. This method was adapted by Sánchez-González et al. (2016) for ForeStereo.

These methods have been tested with TLS data mainly focused on plantations of even-aged stands managed for timber production, but comparative works using ForeStereo data are lacking. The first two methods depend on parameters linked to the stand conditions (density, beam interception by foliage or shrubs, and other features hampering the detection of trees) and may show limitations in natural heterogeneous forests, where the method proposed by Seidel and Ammer (2014) seems more suitable. Under the last method the apparent trees generate a shadowed angular sector behind them. The shadowed area is then subtracted from the sampling plot area. However, this method may underestimate the number of trees of smaller DBH classes for which the probability of non-detection is greater (Sánchez-Gonzalez et al. 2016). Moreover, the method proposed by Seidel and Ammer

(2014) must be adapted for use with ForeStereo because in the case of stereoscopic hemispherical images, mensuration requires correspondence between the projection of the tree in both images of the stereoscopic pair, so occlusion in either of the two images hampers tree detection.

The incorporation of PS technologies in operational forest inventories requires information on the accuracy of methods implemented in end-user tools. The accuracy of individual tree diameter at 1.3 m height (DBH) estimation using ForeStereo has been demonstrated in previous studies: Rodríguez-García et al. (2014) reported a RMSE of 0.015 m for DBH in 8 m radius plots, whereas Sánchez-González et al. (2016) obtained a Pearson coefficient between DBH field measurement and ForeStereo estimates of 0.86. Sánchez-González et al. (2016) also analysed stand level estimation of N , BA and mean DBH from ForeStereo data, reporting high agreement between field measurements and ForeStereo estimates in the case of BA but a notable underestimation of N , especially for smaller DBH classes. We present a comparative work in which a ForeStereo dataset is used to estimate plot level variables (N , BA and DBH distribution) with the aforementioned inference methods, and compared with the non-corrected estimates. We adapt the method proposed by Seidel and Ammer (2014) for estimating the proportion of the sampling area shadowed in the case of stereoscopic hemispherical images acquired with ForeStereo.

2. Material and methods

2.1 Data set

Data from mixed stands of *Pinus sylvestris* L. and *Fagus sylvatica* L. were used in this work. Stereo-pairs of hemispherical photos were captured using ForeStereo from the centre of 44 plots randomly selected from a management inventory in a public forest at Ansó, located in the Spanish Pyrenees (Figure 1), and covering a broad range of stand densities and light

conditions. The stand originates from natural regeneration and timber is the main production, although it also contains protected areas. The ForeStereo device was located in the plot centre, displacing the centre if necessary just to ensure that the nearest tree was at least 0.5 m distant. In addition to the pair of hemispherical photos, the field crew measured the diameter at breast height (DBH) with a calliper and the distance from the plot centre of all trees with DBH > 0.075 m was also measured using a Vertex IV (©Haglöf Sweden 2016). These values were used to calculate basal area and number of trees in fixed radius circular plots of 8 m and 9.8 m, to serve as ground truth reference. The mean N was 1167 trees/ha (SD = 681) and the mean BA was 41 m²/ha (SD = 18).

<FIGURE 1 around here>

The ForeStereo device used for measurement is a prototype of the MU2005-01738. It is composed of two Fujinon FE185C057HA-1 fish-eye lenses and two Hitachi Kokusai Electric Inc. KP-FD500GV cameras with 5 Mp, a 2/3' CCD sensor wired to a laptop through Gigabit Ethernet interface (Figure 2). The two cameras are 0.5 m apart and mounted on a light framework. The optical axes of the lenses are parallel and should be vertically aligned when shooting. The image acquisition software was developed using GENICAM TM with a shooting sequence that automatically acquires 4 pairs of stereoscopic hemispherical photos at 1/9 s, 1/60 s, 1/200 s and 1/1000 s exposures, as proposed by Pueschel (2012) for gap fraction retrieval from hemispherical photos.

<FIGURE 2 around here>

Of the four pairs captured by default, the light conditions at the time of data acquisition determine the most suitable pair of hemispherical photos for identification of trees in the sampling plot. To identify the apparent trees (those viewed in the hemispherical photos) and to estimate the stand variables, an automatic process, fully described in Sánchez-González et

al. (2016) is implemented in a Matlab® software package developed for the purpose. Basically, the image is segmented into basic components: sky, tree stems, and foliage (Figure 3). During the image segmentation process tree stems are identified in each image through a pixel-based dichotomous hierarchical classification followed by a region-growing process for individual tree labeling. The pixel-based classification establishes four criteria: *intensity* to discriminate the sky, *ratio* between green intensity and the sum of RGB intensities to separate the foliage from the stems; and *local color variance* in the radial and tangential directions to identify homogeneity of texture along the stem and stem boundaries, respectively. The computation of these criteria requires a minimum window size of 7x7 pixels, which in turn determines the minimum size of projected stems identifiable during segmentation. Cross-sectional slices are extracted from the classified image, connected under geometrical constraints, and labelled as individual stems in the region-growing process.

The correspondence process, that is, the matching of a tree identified in both images of a pair, establishes the correspondence between the homologous cross-sectional slices of the segmented stem requiring identification of at least three sections of the tree. The correspondence between sections in both images is determined under restrictions of *epipolarity* (homologous points lie over the epipolar line in the other image), *ordering* (height order of sections is maintained), *similarity* (diameter disparity is minimized), and *uniqueness* (points have a single match) (Herrera et al. 2009). A user-guided matching method was used for identification of apparent trees missed by the automatic matching process (Sánchez-González et al. 2016).

<FIGURE 3 around here>

The distance from the left camera (d_1) is calculated with the equations developed by Rodríguez-García et al. (2014):

$$d_1 = d_b / \left(\frac{\sin(\alpha_1)}{\sin(\alpha_2)} \cos(\alpha_2) - \cos(\alpha_1) \right) \quad (1)$$

where d_b is the distance between the optical axes of the cameras, and α_1 and α_2 are the azimuth angles between the base-line and the visual to the target point in the images 1 and 2 respectively. The diameter (D_1) of each stem section is then calculated through the covering angle of the stem section in the left image ε_1 (Figure 4).

$$D_1 = 2 * d_1 * \sin(\varepsilon_1/2) \quad (2)$$

<FIGURE 4 around here>

The accuracy of the distance calculation is limited in the proximity of the base line, where α_1 and α_2 form a very acute angle. For this reason the alignment of trees with the base line was avoided during image acquisition.

Due to the equidistant projection of fish-eye lenses and the verticality of the lens optical axis, the zenith direction (θ_1 and θ_2 in the left and right images respectively) is proportional to the projected radius. The height of the stem section with respect to the lens plane can be determined as:

$$h = d_1 * \cos(\theta_1) / \sin(\theta_1) \quad (3)$$

For each matched section, the correspondence process provides the azimuth direction, horizontal distance, height referred to the lens plane, and diameter. To determine each section height (i.e. the distance to the base of the stem, H), a terrain plane is defined using information self-contained in the images, by fitting the projected horizon line. Species specific linear taper equations are fitted to the diameter (D) and height (h) of the sections obtained in the matching process as follows:

$$D = a_i + b_s H \quad (4)$$

where D is the stem diameter at height H from the base of tree i of species s , a_i is the intercept parameter and b_s is the regression coefficient, which is unique for all trees of the

same species measured in the plot. We are interested in the diameter at 1.30 m height (DBH), necessary for estimation of BA. To calculate the DBH of each tree i we obtain D at $H = 1.30$ m through Eq.4.

2.2 Estimation of plot level variables

To characterize the forest stand structure N and BA were used. These variables are calculated for a circular sample plot of radius R as:

$$N = n * 10000 / (\pi R^2) \quad (5)$$

$$AB = \sum_{i=1}^n \pi (DBH_i / 2)^2 * 10000 / (\pi R^2)$$

Diameter classes of 50 mm intervals were considered, with the smaller trees accounted for (50-100 mm) belonging to the 75 mm class. The number of trees in each diameter class is calculated analogously to N .

These variables are estimated from the trees identified in the ForeStereo images. During measurements, the sensor resolution limits the maximum range of detection and, as a consequence, the sampling area, particularly for the smaller diameter classes. This effect is known as instrument bias. Furthermore, occlusions by nearby stems hamper the detection of other trees, so shaded sectors should be discounted from the sampling area (Appendix 1). In this work, plot estimates calculated according to three methods that treat occlusions and instrument bias differently have been compared: Relaskop-based estimation to deal with instrument bias combined with the Poisson attenuation model to correct the effect of occlusions; distance-sampling based correction of instrument bias and occlusions; and a new method termed hemispherical photogrammetric correction (HPC), that combines the segmentation based correction for instrument bias proposed by Sánchez-González et al. (2016) with a new approach for estimation of occlusion probability which adapts the method proposed by Seidel and Ammer (2014) to the case of stereoscopic hemispherical images.

During the image segmentation and correspondence processes some error from classification of pixels and their correspondence may occur. Missing identification of matching trees leads to some underestimation of N , whereas pixel classification errors and erroneous matching lead to stem diameter measurement errors, and affect the estimation of DBH and BA through the fitting of taper equations. In addition, since DBH is not directly measured at 1.3 m height in the hemispherical images (it is estimated through the linear taper equations) and the height to the measured sections is derived from the fitted terrain model (assumed to be plane for the sampling area), this may contribute to the estimation error in DBH and BA estimations. The quality of N and BA estimates was evaluated comparing the outcomes with reference data measured in the field, through values of the Pearson correlation coefficient (r) and bias, calculated as the mean of differences between estimated minus field values as a percentage of the mean value measured in field (ME). The histograms of diameter distribution were obtained from ForeStereo data with each of the four methods as well as with the caliper measurements, establishing a bin interval of 0.05 m and a minimum value of DBH = 0.075 m. The histograms derived from ForeStereo data and from caliper measurements were compared through the *quadratic-form distance* (eq. 6), proposed by Hafner et al. (1995) to assess the similarity between histogram distributions.

$$d(\mathbf{H}_{GroundTruth}, \mathbf{H}_F) = \sqrt{(\mathbf{H}_{GroundTruth} - \mathbf{H}_F)^T \mathbf{A} (\mathbf{H}_{GroundTruth} - \mathbf{H}_F)} \quad (6)$$

Where $(\mathbf{H}_{GroundTruth})$ is the matrix of histogram bin values as derived from caliper measurements and $(\mathbf{H}_F)$ the matrix of histogram bin values derived from ForeStereo data. $\mathbf{A}$ is a similarity matrix with $[a_{ij}]$ denoting the similarity between histogram bins i and j , calculated as $a_{ij} = 1 - |i - j| / \max(|i - j|)$. Lower values of the quadratic-form distance indicate higher similarity between histogram distributions.

2.2.1 Relaskop-based estimation combined with correction of occlusion effect based on Poisson attenuation model

The Relaskop-based approach for estimation of plot or stand level variables is based on the angle-count sampling and has frequently been used in TLS measurement to reduce the instrument bias (e.g. Strahler et al. 2008, Lovell et al. 2011). Only trees with DBH apparently wider than an angular span κ (which depends on a pre-defined *basal area factor*, BAF) are included in the sample. The BAF is typically (and for convenience) set as $0.0002 \text{ m}^2/\text{m}^2$. With our dataset, the number of trees per m^2 (λ) was calculated from the n trees included in the sample as (eq. 7):

$$\lambda = \sum_{i=1}^n \frac{\text{BAF}}{\pi * (\text{DBH}_i/2)^2} \quad (7)$$

where

$$\text{BAF} = \sin^2(\kappa/2) \quad (8)$$

The gap probability decreases exponentially with distance r following a Poisson model of the form $P_{\text{gap}} = \exp(-\lambda D_E r)$. The number of trees n_{corr} expected to actually exist in an area of radius r_{max} (including detected and occluded trees), is expressed as a product of the number of trees actually measured n and a factor of attenuation $F(t)$:

$$n_{\text{corr}} = n * F(t) \quad (9)$$

$F(t)$ depends on λ , the effective diameter calculated for all the trees of the plot (D_E) and the distance r_{max} :

$$F(t) = \frac{2}{t^2} (1 - \exp(-t)(1 + t)) \quad (10)$$

$$t = \lambda D_E r_{\text{max}}$$

The effective diameter takes into account the occlusive effect of stems, low branches and understory. Strahler et al. (2008) proposed considering a D_E which depends on the average

327 diameter of the trees actually measured and their variability (eq. 11, where C_v is a
328 coefficient of variation):

$$329 \quad D_E = \overline{DBH}(1 + C_v^2)^2 \quad (11)$$

330 $(n_{corr})_i$ is then estimated for each detected tree and summarized to estimate N :

$$331 \quad N = \sum_{i=1}^n (n_{corr})_i * 10000 / (\pi r_{max}^2)_i \quad (12)$$

332 *2.2.3 Distance-sampling based correction of instrument bias and occlusion effect*

333 In this approach the probability of detecting trees in the plot is modelled through the
334 *detection function* $g(r, \theta)$. As in Astrup et al. (2014), we employed the Half-Normal function:

$$335 \quad g(r, \theta) = \exp(-r^2 / (2\sigma^2)) \quad (13)$$

336 and the Hazard-Rate function:

$$337 \quad g(r, \theta) = 1 - \exp(-(r/\sigma)^{-b}) \quad (14)$$

338 In $g(r, \theta)$ the parameter θ comprises both the scale (σ) (in the Half-Normal and the Hazard-
339 Rate functions) and shape (b) (only in the Hazard-Rate function) parameters. The inclusion of
340 DBH as a covariate was explored in both models, as in Ducey et al. (2014), expanding the
341 scale parameter $\sigma = \alpha_0 \cdot \exp(\alpha_1 \cdot DBH)$.

342 The parameters $\hat{\theta}$ are obtained by maximum likelihood (Marques and Buckland 2003, Miller
343 and Thomas 2015, Clark 2016). The probability of detection for tree i in a plot of radius R is
344 given by eq. 15. Our sampling was truncated at 8 m, 9.8 m, and 15 m to analyze the effect of
345 different R values on estimates:

$$346 \quad P_i = \frac{2}{R^2} \int_0^R r * g(r, \hat{\theta}) \quad (15)$$

347 Finally, N is estimated as in eq. 16. Note that P_i is identical for all i in models without
348 covariate:

$$349 \quad N = \sum_{i=1}^n 10000 / (P_i * \pi R^2) \quad (16)$$

2.2.4 Hemispherical photogrammetric correction (HPC)

Here we propose a new approach for estimating forest variables at plot and stand level from data obtained using ForeStereo. This approach combines the segmentation based correction for instrument bias described with detail in Sánchez-González et al. (2016), and a new method for estimating the probability of occlusions which adapts the method proposed by Seidel and Ammer (2014) to the case of stereoscopic hemispherical images.

In the equation for instrument bias correction proposed by Sánchez-González et al. (2016) the range of detection depends on the stem diameter and the inclination angle of the viewing direction. Stem sections thinner than the minimum window size, defined in pixels as p_{sel} , are not detected (as mentioned in the segmentation process description). Assuming there are no occlusions, each tree sampling area A_i is calculated integrating a circular area of radius defined by the user (R) or by the maximum horizontal distance r_{max} at which the section of the tree wider than p_{sel} is projected on the images (Sánchez-González et al. 2016) (eq. 17):

$$A_i = \int_0^{2\pi} \frac{1}{2} (\min(R, r_{\text{max}}))^2 d\alpha \quad (17)$$

$$r_{\text{max}} = \frac{D_m * \cos\left(\frac{\pi}{2} - \theta(\alpha)\right)}{2 * \sin\left(\frac{\frac{\pi}{2} p_{\text{sel}}}{2\theta(\alpha)r_{\text{image}}}\right)}$$

where D_m is the mean diameter of the target tree i three lowest sections matched (see full description of the matching process in Sánchez-González et al. 2016) and the $\theta(\alpha)$ is the zenith angle of the viewing direction at each azimuthal direction for the three lowest sections estimated from all the matched trees using cubic splines (Sánchez-González et al. 2016).

The effect of occlusions should be corrected using the information contained in the sample of apparent (i.e. not occluded) trees. To estimate the actual non-shaded sampling area, the theoretical sampling area A_i (eq. 17) is multiplied by the probability of detection P_i of each apparent tree i . N is then computed as:

$$N = \sum_{i=1}^n 10000 / (P_i * A_i) \quad (18)$$

If S_0 is the non-shaded area, the probability of detecting tree 0 in a sampling plot of radius $r_{\max}$, considering the potential shadowing of all other apparent trees is determined as:

$$P_0 = S_0 / \pi r_{\max}^2 \quad (19)$$

The term shadowing in this case refers to non-detection during the matching process. Matching fails to detect or identify a tree when the stem is partially or completely missed in any of the two stereo-images. In contrast, the method developed for application to TLS data by Seidel and Ammer (2014) estimates the shadowed area for a single scan.

In order to calculate S_0 , let d_{01} and d_{02} be the horizontal distances from the left and right cameras to tree 0 (Figure 5a) and analogously d_{i1} and d_{i2} the horizontal distances from the left and right cameras to tree i , ($i = 1 \dots n$, being n the number of apparent trees). S_0 can be computed as the integral of the circumference length, from $d_{01} = 0$ to the maximum sampling radius $r_{\max}$ (remember $r_{\max}$ depends on the tree size) multiplied by the probability of no occlusion at d_{01} :

$$S_0 = \int_0^{r_{\max}} d_{01} * 2\pi * P(d_{01}) dd_{01} \quad (20)$$

For each distance d_{01} , the probability of no occlusion $P(d_{01})$ is the product of no occlusion probability in the left image $P(S_{01})$ and no occlusion probability in the right image, conditional on being visible in the left image $P(S_{02} | S_{01})$:

$$P(d_{01}) = P(S_{01}) \cdot P(S_{02} | S_{01})$$

$$P(S_{01}) = S_{01} / 2\pi \quad (21)$$

395 $P(S_{02}|S_{01}) = S_{02}/S_{01}$

396 where S_{01} is the angle where there is no occlusion in the left image and S_{02} is the angle
 397 where there is no occlusion in the right image conditional on being visible in the left image.

398 In order to calculate S_{01} and S_{02} , let ε_{01} and ε_{02} be the angle span covered by tree 0 in the left
 399 and right images respectively (Figure 5b) -and analogously ε_{i1} and ε_{i2} for tree i -. S_{01} equals a
 400 complete sampling round 2π minus the sum of occlusion angles in the left image o_{i01}
 401 produced by all shading trees i closer to the device (eq. 22, where $I(d_{01} < d_{i1})$ equals 1 if $d_{01} <$
 402 d_{i1} and 0 in any other case).

403
$$S_{01} = 2\pi - \sum(o_{i01} \cdot I(d_{01} < d_{i1})) \quad (22)$$

404 Likewise, S_{02} can be computed as the difference of the visible angle in the left image S_{01}
 405 minus the sum of occlusion angles o_{i02} of trees located closer to the device:

406
$$S_{02} = S_{01} - \sum(o_{i02} \cdot I(d_{02} < d_{i2})) \quad (23)$$

407 Tree 0 occlusion angle produced by tree i (o_{i01}) is the angle at which tree 0 is totally or
 408 partially shaded by tree i , calculated as a sum of covering angles:

409
$$o_{i01} = \varepsilon_{i1} + \varepsilon_{01} \quad (24)$$

410 The occlusion angle o_{i02} conditional on no occlusion in the left image require that the
 411 projection of tree 0 in the right image be conditioned by it being visible in the left image.

412 Moreover, in order to estimate the integral in eq. 20, o_{i01} and o_{i02} , and henceforth ε_{01} and ε_{02} ,
 413 should be expressed as a function of d_{01} . Thus, let α_{01} and α_{02} be the azimuthal angles
 414 formed by the visual line from the left and right cameras to tree 0 with the camera baseline
 415 (Figure 5a) and α_{i1} and α_{i2} the analogous angles for tree i . ε_{01} depends on the diameter and
 416 distance to the device of tree 0, which in turn depends on the horizontal distance and the

417 terrain slope in the direction towards tree 0 (eq. 25), $\sigma_{\max}$ being the maximum slope in the
 418 plot and $\alpha_{\sigma_{\max}}$ the direction upslope.

$$419 \quad \varepsilon_{01} = 2 \cdot \operatorname{asin} \left(\frac{\operatorname{DBH}_0}{2d_{01} / \cos(\operatorname{atan}(\tan(\sigma_{\max}) \cos(\alpha_{01} - \alpha_{\sigma_{\max}})))} \right) \quad (25)$$

420 <FIGURE 5 around here>

421 Analogously, the covering angle of tree 0 in the right image is:

$$422 \quad \varepsilon_{02} = 2 \cdot \operatorname{asin} \left(\frac{\operatorname{DBH}_0}{2d_{02} / \cos(\operatorname{atan}(\tan(\sigma_{\max}) \cos(\alpha_{02} - \alpha_{\sigma_{\max}})))} \right) \quad (26)$$

423 If δ_0 is the angular displacement between the projection of tree 0 in the left and right images
 424 (Figure 5a) then:

$$425 \quad \alpha_{02} = \alpha_{01} + \delta_0 \quad (27)$$

426 The displacement between tree 0 projected in the left and right images can be expressed by
 427 eq. 21 (Rodríguez-García et al. 2014 and Figure 5a). For convenience, we refer d_{02} to d_{01} :

$$428 \quad \delta_0 = \operatorname{asin} \left(\operatorname{baseline} \frac{\sin(\alpha_{01})}{d_{02}} \right)$$

$$429 \quad d_{02} = \sqrt{\operatorname{baseline}^2 + d_{01}^2 - 2 \cdot \operatorname{baseline} \cdot d_{01} \cos(\alpha_{01})} \quad (28)$$

430 In order to calculate α_{i02} , we should define $\alpha_{i01\min}$, $\alpha_{i01\max}$ as the enclosing angles of α_{i01} . As
 431 Figure 5b shows, $\alpha_{i01\min}$ and $\alpha_{i01\max}$ can be expressed as:

$$432 \quad \alpha_{i01\min} = \alpha_{i1} - \frac{\alpha_{i01}}{2} \quad \alpha_{i01\max} = \alpha_{i1} + \frac{\alpha_{i01}}{2} \quad (29)$$

433 Analogously, $\alpha_{i02\min}$, $\alpha_{i02\max}$ are the enclosing angles of the non-conditioned occlusion angle
 434 in the right image and can be expressed as:

$$435 \quad \alpha_{i02\min} = \alpha_{i2} - \frac{(\varepsilon_{i2} + \varepsilon_{02})}{2} \quad \alpha_{i02\max} = \alpha_{i2} + \frac{(\varepsilon_{i2} + \varepsilon_{02})}{2} \quad (30)$$

To calculate the occlusion angle in the right image conditional on being visible in the left image, we must subtract the azimuth angles in the right image corresponding to occluded angles in the left image. Depending on the distance from the tree to the device, the projection angle in the right image is displaced along the epipolar line. Thus the projection of tree 0 in the right image conditional on no occlusion in the left image should be in the range between $\alpha_{i01\max} + \delta_{0\max}$ and $\alpha_{i01\min} + \delta_{0\min}$. Three cases can be distinguished (Figure 6) to calculate α_{i02} , depending on the angular displacement of trees i and 0:

<<FIGURE 6 around here>>

Case 1. $\alpha_{i02\min} > \alpha_{i01\max} + \delta_{0\max}$

In this case the angle shaded by tree i in the right image lies completely within the range of tree 0 projection in the right image conditional on no occlusion in the left image. Therefore, in the right image, the occlusion angle conditional on no occlusion in the left image coincides with the shaded angle:

$$\alpha_{i02} = \alpha_{i02\max} - \alpha_{i02\min} \quad (31)$$

Case 2. $\alpha_{i02\min} > \alpha_{i01\max} + \delta_{0\max}$ & $\alpha_{i02\min} > \alpha_{i01\min} + \delta_{0\min}$

In this case the angle shaded by tree i in the right image lies partially within the range of tree 0 projection in the right image conditional on no occlusion in the left image, and the angular displacement of tree i (from left to right image) is greater than the angular displacement of tree 0. The occlusion angle in the right image conditional on no occlusion in the left image coincides with the intersection of the total shaded angle and the range in the right image corresponding to being visible in the left image:

$$\alpha_{i02} = \alpha_{i02\max} - (\alpha_{i01\max} + \delta_{0\max}) \quad (32)$$

458 Case 3. $\alpha_{i02\min} < \alpha_{i01\min} + \delta_{0\min}$

459 In this case the angle shaded by tree i in the right image lies partially in the range of tree 0
460 projection in the right image conditional on no occlusion in the left image. Also, the angular
461 displacement of tree i (from left to right image) is smaller than the angular displacement of
462 tree 0. The occlusion angle in the right image conditional on no occlusion in the left image
463 coincides with the intersection of the angle shaded and the range in the right image
464 corresponding to being visible in the left image:

$$465 \quad o_{i02} = \alpha_{i01\min} + \delta_{0\min} - \alpha_{i02\min} \quad (33)$$

466 We calculated $\alpha_{i02\max}$ and $\alpha_{i02\min}$ for both $\alpha_{01} = \alpha_{i01\max}$ and for $\alpha_{01} = \alpha_{i01\min}$, obtaining the
467 maximum and minimum (not necessarily in that order) values for o_{i02} . The final o_{i02} is the
468 average of o_{i02} calculated for $\alpha_{i01\max}$ and for $\alpha_{i01\min}$.

469 **3. Results**

470 **3.1 Number of trees**

471 As expected, N was largely underestimated with the ForeStereo sample of matched trees
472 when not corrected for instrument bias and occlusion effect; the bias increased with the
473 maximum sampling distance and the mean error ranged from 42% to 77% (Table 1). The
474 underestimation of N was more relevant in plots of higher density (Figure 7) —those
475 occupied by smaller trees. The Relaskop-based sampling with Poisson attenuation model for
476 correction of occlusions reduced the estimation bias slightly, to between 35% - 69%. Among
477 the distance-sampling options the Hazard-Rate function performed better than the Half-
478 Normal function in terms of bias, although the latter showed higher values of correlation
479 with field data. Although the distance-sampling method tends to overestimate N , this
480 overestimation is more notable with the Half-Normal function. The Half-Normal model does

not accurately fit the distribution of distances: the $r \cdot g(r, \theta)$ function should be proportional to the frequency histogram by distance bins, however, the curve (scaled to make the integral of the curve between 0 and R equal to the number of detected trees) is over the detected frequencies at short as well as large distances and below the detected frequencies for intermediate distances (Figure 8). As most detected trees are located at intermediate distances (3-5 m), the underestimation of the sampling probability for these distances results in an overestimation of N . HPC estimates had the lowest bias for 8 m and 9.8 m sampling distances (-6% and -10% respectively), but tended to underestimate N when the distance sampled increased to 15 m (bias of -33%). To help disentangle the effect of instrument bias and occlusion effect corrections, Figure 9 compares the distribution of sampling areas of all detected trees in the 15 m plots in the cases of instrument bias correction alone and instrument bias combined with the occlusion corrections for the Relaskop-based sampling with Poisson attenuation model and for the HPC. The first method bases the instrument bias correction on DBH, whereas HPC employs the diameters detected during image segmentation, which are usually over 1.30 m height and are smaller than the DBH, resulting in a greater reduction in sampling area for most trees (Figure 9). Moreover, the Poisson attenuation model mainly depends on plot density, providing a similar reduction in sampling area for all trees in the plot, whereas the occlusion correction proposed by HPC varies for each tree depending on the size and position of all other trees within the plot.

<<FIGURE 7 around here>>

<<TABLE 1 around here>>

<<FIGURE 8 around here>>

<<FIGURE 9 around here>>

3.2 Diameter distribution

The distributions of DBH derived from field data and from ForeStereo estimates are compared in Figure 10. The histograms derived from ForeStereo estimates without correction and those corrected using Relaskop-based estimation combined with the Poisson attenuation model are similar; tending to underestimate the number of trees by diameter class, especially for the smaller diameters (0.075 m-0.125 m class) and in larger plots. The majority of approaches correcting instrument bias and tree occlusions improved the non-corrected estimates and had lower quadratic-form distances than the field measured distribution (Table 2). The distance-sampling method using Hazard-Rate function without covariate underestimates the smallest diameter class (0.075 m) and overestimates classes over 0.125 m. As observed in Figure 8, the globally adjusted distance distribution function $g(r, \theta)$ for the Hazard Rate model without covariate is influenced by the distance distribution of the smaller classes, which are not detected at long distances. This may be the reason for the underestimation of the detection probability of larger trees at greater distances, leading to an over-correction for these trees. This problem is solved when DBH is included as covariate. The distance-sampling with Half-Normal function overestimates the number of trees with DBH < 0.275 m as a consequence of the underestimation of the detection probability for these diameter classes, shown as a flattening of the $r * g(r, \theta)$ curve (Fig. 8). When DBH is included as covariate, the distance-sampling with Hazard-Rate function results in a diameter distribution with greater similarity to the diameter distribution measured in the field –as assessed by the quadratic form distance— when the maximum sampling distance is 9.8 or 15 m (Table 2).

<<FIGURE 10 around here>>

The DBH distribution obtained with HPC showed the closest agreement with field data measured in 8 m plots and the overall minimum quadratic form distance (Table 2 and Figure

10). When the distance was increased to 15m HPC underestimated the density of most DBH classes (Figure 10 right).

<<TABLE 2 around here>>

3.3 Basal area

BA was underestimated in the majority of plots when no correction was applied to the sample of detected trees (Figure 11). The degree of underestimation is greater in dense plots with high values of BA and for large maximum sampling distances. Relaskop-based estimations with the Poisson attenuation correction reduced the estimate bias from 35% to 28% (Table 3). Distance-sampling using the Hazard-Rate function without covariate and with Half-Normal function with covariate resulted in a notable overestimation of BA. However, this method showed better results in terms of bias when the detection function used was the Hazard-Rate with covariate (4% - 11%). The HPC method with 8 m plots slightly underestimated BA (-8%) but showed the highest Pearson correlation coefficient between BA estimated from ForeStereo data and field measurements (0.83)

<<FIGURE 11 around here>>

<<TABLE 3 around here>>

4. Discussion and Conclusions

Estimation of forest stand variables from sample data captured using ForeStereo requires precise knowledge of the sources of error associated with sampling schemes, image processing, and estimation methods. This work analyzed the performance of different methods for estimating sampling probability. Working with a single point sampling design the probability of sampling a tree depends on two factors: the relationship between the distance range of detection and the tree size, and the probability of being occluded by

another tree. In addition, in order to attain unbiased estimations, the locations of the plot centres should be selected randomly or on a regular grid, but not prevailing open locations within the plot. The displacement of the device to a distance of 0.5 m from the nearest tree is necessary as the variability of textures within the stem associated with the macro-acquisition of images hampers stem segmentation. Due to the wide field of view of the fish eye lens, the size of the features projected decreases rapidly at 0.5 m and the occlusion effect is reduced substantially. However, this displacement is small when compared with the tree spacing and should not cause a noticeable bias. The relationship between the distance range of detection and the tree size is defined by the image resolution and by the algorithms used in the segmentation process. The probability of occlusion has to be inferred from the actual distribution of the apparent trees. Employing ForeStereo data from a forest inventory, we tested and compared three approaches for estimating the sampling probability and calculating plot level variables: Relaskop-based sampling and correction of occlusions with Poisson attenuation model, distance-sampling based correction for instrument bias and occlusions, and the proposed HPC, which combines the segmentation based correction for instrument bias method (Sanchez-González et al. 2016) and a new correction of occlusions effect calculating the shadowed area, based on the Seidel and Ammer (2014) method. The three approaches incorporate some kind of correction for instrument bias and occlusion of trees, and all three led to an improvement in the raw estimates; reducing the estimate bias and increasing the correlation with ground truth data.

Each method for estimating sampling probability is supported by different assumptions, and the suitability of one or other method depends on the forest structure and on the characteristics of the PS technology employed. For example, the approach consisting of Relaskop-based sampling and correction of occlusions with Poisson attenuation model

(Strahler et al. 2008) depends on the DBH of the apparent trees and on the basal area factor selected, and assumes a Poisson distribution of tree distances from the sensor. For an accurate determination of the effective tree diameter D_e , this method may require calibration (e.g. with traditionally measured plots). Ducey et al. (2014) and Astrup et al. (2014) proposed a distance-sampling based approach relying on the actual distribution of the apparent tree distances. Under this approach, the assumptions are implicit in the model selected for probability of detection (e.g. Half-Normal or Hazard-Rate functions). Employing actual distances makes this approach more adaptable than the attenuation model to the forest stand conditions that affect the detection of trees (e.g. presence of under-canopy vegetation). However, the parameterization of the detection function is based on the distances actually measured in all plots within a stand or strata, so this method would seem to be more appropriate for homogeneous stands. Unlike applications described in Ducey et al. (2014) and Astrup et al. (2014), where the inclusion of covariates in the models did not significantly improve the estimates, we achieved the better performance by incorporating DBH as covariate in the detection probability. Sánchez-González et al. (2016) proposed an approach for estimating sampling probability which combines an instrument bias correction based on the minimum window size allowed by the process of image segmentation and an occlusion effect correction adapted to ForeStereo from that of Seidel and Ammer (2014) using TLS data. The hemispherical photogrammetric correction (HPC) described here combines the instrument bias correction proposed by Sánchez-González et al. (2016) with an improved correction of the occlusion effect. This method integrates the probability of no occlusion for the entire sampling range calculated from the size and position of apparent trees. Seidel and Ammer (2014) worked with circular plots of 2 m radius in dense poplar plantations and obtained correlations of 0.9 between BA estimates from data captured with TLS and ground truth data; the estimate bias was reduced by 1.4% (from -9.8% to -8.4%)

after correction. The HPC approach reduced the bias of BA estimates in plots of 8 m radius from -35% to -8% in structurally diverse forests (i.e. with irregular distribution of tree sizes). Notwithstanding the differences in stand structure and between TLS data and stereo-hemispherical photos, the more significant improvement in our analysis may be related to the integration of the instrument bias correction and to an improved estimation of the area occluded. In the estimation of the occlusion probability with stereo-hemispherical photos, partial blockage hinders tree matching; therefore the occlusion angle is the sum of the coverage angles of the occluded and shading trees (Ducey et al. 2014).

Correspondence between the projections of a tree in both stereo images captured with ForeStereo is necessary in order to detect the tree. The probability of detection has therefore to be computed as a product of the probability of no occlusion in the left image, by the probability of no occlusion in the right image conditional on being visible in the left. This need for this correspondence may explain the underestimation of BA and N in our analyses with the Poisson attenuation model correction of occlusions. The distance-sampling based approach relies on the distance distribution of apparent trees and, in contrast, is not affected by the correspondence issue. Single scan sampling with TLS typically overestimates the mean DBH, since the occlusion probability is greater for smaller trees (Strahler et al. 2008, Lovell et al. 2011, Yao et al. 2011, Seidel and Ammer 2014). We estimated the occlusion probability as an integral over the range of detection for each tree, and the relation between the covering angles of the target and shading trees is recalculated for each distance, providing a reduced bias in the estimation of the number of trees of smaller DBH classes.

The Relaskop-based method for correction of instrument bias combined with the Poisson attenuation model for correction of occlusions has proved to substantially reduce bias in N

(Strahler et al. 2008) and BA (Strahler et al. 2008; Lovell et al. 2011) estimated with single scan TLS data. Likewise, Yao et al. (2011) reported correlations of 0.902 and 0.656 with field data when estimating N and BA with the Poisson attenuation model for correction of occlusions without the Relaskop sampling. However, in our analysis using ForeStereo data this method yields biased results when compared with HPC estimates. In contrast to TLS, where tree detection is better at the lower part of the stem, stem sections viewed under an inclination angle over the crown of more distant trees—seen against the sky—are most accurately detected in the hemispherical images. The Relaskop-based method selects trees depending on DBH, whereas the method based on image segmentation considers the diameter at the height corresponding to the inclination angle of view, making the latter preferable for the RGB photos acquired using ForeStereo. However, the Relaskop-based and Poisson attenuation model methods performance may be improved through the adjustment of BAF and D_E .

The results described in this work demonstrate the effectiveness of ForeStereo as a PS technology for field sampling in operational forest inventories. Cost analyses are beyond the scope of this study, but the performance capacity shown by ForeStereo in field surveys for this study—a team of two people surveyed 16 sampling points located on a systematic grid of 400 x 400 m, covering 256 ha per day on average—enables increased sampling and cost optimization of the forest inventory field stage. Two stage sampling design, combining PS technologies and spatially explicit remotely sensed data, may improve the accuracy of inference estimations in forest inventories (Brososke et al. 2014). Precise and unbiased estimators for plot and stand level variables are still to be developed. The approaches tested in this work can be used to deal with bias, our results pointing to the distance-sampling using DBH as covariate and the HPC method proposed here as suitable approaches with

ForeStereo data. Other sources of error affecting ForeStereo estimates —light conditions, stand density or species on image segmentation, or the limited accuracy of distance estimations in the proximity of the base line— are beyond the scope of this study and should be the subject of future research. As an alternative, remote sensing and PS data may be integrated during data processing: Korpela et al. (2007) combined photogrammetry and field triangulation for complete mapping of the stand, whereas Liang et al. (2016) suggested the use of TLS for retrieval of individual tree attributes and airborne remote sensing data to extend the estimation of tree attributes to all trees within the stand, which renders the estimation of stand-level summary statistics from TLS data unnecessary. Whichever approach is chosen, the next step is to implement these methods in user-friendly software packages—such as the ForeStereo software presented in Sánchez-González et al. (2016), which has been used for this study—so that these methods can be made available for foresters and stakeholders.

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Tables

Table 1. Bias (ME) and Pearson coefficient (r) of the relationship between measured and estimated number of trees per ha (N) in plots of 8 m, 9.8 m and 15 m radius R .

	$R = 8$ m		$R = 9.8$ m		$R = 15$ m*	
	ME (%)	r	ME (%)	r	ME (%)	r
ForeStereo sample without correction	-42	0.54	-52	0.50	-77	0.40
Relaskop sampling + Poisson attenuation model	-35	0.52	-46	0.49	-69	0.53
Distance-sampling (Hazard-Rate)	16	0.54	31	0.50	26	0.40
Distance-sampling (Hazard-Rate + covariate)	11	0.60	22	0.60	12	0.58
Distance-sampling (Half-Normal + covariate)	33	0.62	53	0.62	49	0.59
HPC	-6	0.61	-10	0.59	-33	0.56

*ForeStereo estimates with 15 m maximum distance are compared with the values calculated with the 9.8 m radius field plot

Table 2. Quadratic form distance between the DBH histograms derived from the field data and the DBH histograms derived from ForeStereo data in plots of 8 m, 9.8 m and 15 m radius R .

	$R = 8$ m	$R = 9.8$ m	$R = 15$ m
ForeStereo sample without correction	501.84	561.57	854.03
Relaskop sampling + Poisson attenuation model	425.53	497.09	762.19
Distance-sampling with Hazard-Rate function	209.07	319.80	273.75
Distance-sampling with Hazard-Rate function + covariate	78.50	78.96	139.26
Distance-sampling with Half-Normal function+ covariate	424.35	583.97	543.91
HPC	72.65	117.22	373.75

898 Table 3. Bias (ME) and Pearson coefficient (r) between measured and estimated basal area
 899 (m^2/ha) in plots of 8 m, 9.8 m and 15 m radius R .

	$R = 8 \text{ m}$		$R = 9.8 \text{ m}$		$R = 15 \text{ m}^*$	
	ME (%)	r	ME (%)	r	ME (%)	r
ForeStereo sample without correction	-35	0.78	-42	0.67	-66	0.48
Relaskop sampling + Poisson attenuation model	-28	0.79	-36	0.68	-61	0.51
Distance-sampling (Hazard-Rate)	29	0.78	57	0.66	92	0.47
Distance-sampling (Hazard-Rate + covariate)	4	0.82	13	0.71	5	0.59
Distance-sampling (Half-Normal + covariate)	16	0.82	36	0.71	35	0.59
HPC	-8	0.83	-11	0.78	-35	0.60

900 *ForeStereo estimates with 15 m maximum distance are compared with the values calculated with
 901 the 9.8 m radius field plot

Figure captions

Figure 1. Study area map

Figure 2. ForeStereo prototype used in this study

Figure 3. Above: pair of stereoscopic hemispherical images. The colored point series indicate the matched sections; below: classified image of the sky, foliage, and stems.

Figure 4. Representation of ForeStereo geometry.

Figure 5. (a) Angular displacement δ_0 between tree 0 projection in the left and right images and (b) tree i (with covering angle in the left image ε_{i1}) shading angle over tree 0 (with covering angle ε_{01}).

Figure 6. Geometric relationships between tree 0 projected on the right image conditional on being visible in the left image, and the shaded angle by tree i in the right image in the case 1), case 2) and case 3); grey lines correspond to the occlusion angle in the left image; continuous black lines correspond to the occlusion angle in the right image; discontinuous black lines correspond to maximum and minimum displacement of tree 0 projection from right to left image when tree 0 is occluded by tree i in the left image. The grey area correspond to the conditional occluded angle in the right image (ϕ_{02}).

Figure 7. Number of trees per ha (N) estimates from ForeStereo vs N estimated from field measurements and regression line of linear models in plots of 8 m (empty triangles and dashed line) and 9.8 m radius (filled squares and dash-dot line). A: uncorrected, B: Relaskop-based sampling and Poisson attenuation model C: distance-sampling with Hazard-Rate function, D: distance sampling with Hazard-Rate function and DBH as covariate, E: distance sampling with Half-Normal function and DBH as covariate, F: hemispherical photogrammetric correction.

Figure 8. Number of trees by distance bins detected by ForeStereo compared with the scaled $r^*g(r, \theta)$ of distance-sampling with Hazard-Rate function (left), Hazard-Rate function with DBH as covariate (middle) and Half-Normal function with DBH as covariate (right) for distance of truncation 8 m (above) and 15 m (below).

929 Figure 9. Estimated sampling areas corresponding to all detected trees in the 15 m radius
930 plots when applying instrument bias correction (black filled dots) and instrument bias and
931 occlusion corrections (grey empty dots) for Relaskop-based sampling and Poisson
932 attenuation model (A) and hemispherical photogrammetric correction (B)

933 Figure 10. DBH distribution from ForeStereo up to a maximum sampling distance of 8 m (A),
934 9.8 m (B) and 15 m (C) vs DBH distribution measured in the field.

935 Figure 11. Basal area (BA) estimates from ForeStereo vs BA derived from field data and
936 regression line of linear models in plots of 8 m (empty triangles and dashed line) and 9.8 m
937 radius (filled squares and dash-dot line). A: uncorrected, B: Relaskop-based sampling and
938 Poisson attenuation model C: distance-sampling with Hazard-Rate function, D: distance
939 sampling with Hazard-Rate function and DBH as covariate, E: distance sampling with Half-
940 Normal function and DBH as covariate, F: hemispherical photogrammetric correction

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942 **Appendix 1**

943 Figure A1. Example of instrument bias: the stem section marked with a red arrow cannot be
944 detected due to instrument bias because the pixel size is of similar magnitude to the stem
945 projection width.

946 Figure A2. Example of occlusion: the tree marked with an arrow in the right image is
947 occluded by tree marked with a triangle in the left image.

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Figure 8

Figure 9

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