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Title: Estimation of canopy attributes in beech forests using true colour digital images from a small fixed-wing UAV

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Keywords: drone; leaf area index; cover photography; hemispherical photography; *Fagus sylvatica*

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Abstract: Accurate estimates of forest canopy are essential for the characterization of forest ecosystems. Remotely-sensed techniques provide a unique way to obtain estimates over spatially extensive areas, but their application is limited by the spectral and temporal resolution available from these systems, which is often not suited to meet regional or local objectives. The use of unmanned aerial vehicles (UAV) as remote sensing platforms has recently gained increasing attention, but their applications in forestry are still at an experimental stage. In this study we described a methodology to obtain rapid and reliable estimates of forest canopy from a small UAV equipped with a commercial RGB camera. The red, green and blue digital numbers were converted to the green leaf algorithm (GLA) and to the CIE $L^*a^*b^*$ color space to obtain estimates of canopy cover, foliage clumping and leaf area index (L) from aerial images. Canopy attributes were compared with in situ estimates obtained from two digital canopy photographic techniques (cover and fisheye photography).

The method was tested in beech forests. UAV images accurately quantified canopy cover even in very dense stand conditions, despite a tendency to not detecting small within-crown gaps in aerial images, leading to a measurement of a quantity much closer to crown cover estimated from in situ cover photography. Estimates of L from UAV images significantly agreed with that obtained from fisheye images, but the accuracy of UAV estimates is influenced by the appropriate assumption of leaf angle distribution.

We concluded that true colour UAV images can be effectively used to obtain rapid, cheap and meaningful estimates of forest canopy attributes at medium-large scales. UAV can combine the advantage of high resolution imagery with quick turnaround series, being therefore suitable for routine forest stand monitoring and real-time applications.

Opposed Reviewers:

F. van der Meer,

Editor-in-Chief

International Journal of Applied Earth Observation and Geoinformation

Dear Editor-in-Chief,

please find enclosed the article “*Estimation of canopy attributes in beech forests using true colour digital images from a small fixed-wing UAV*” by F. Chianucci, L. Disperati, D. Guzzi, D. Bianchini, V. Nardino, C. Lastri, A. Rindinella and P. Corona, which we are submitting for consideration for publication as a research article.

The manuscript presents original data on the accuracy of true colour UAV imagery to estimate forest canopy attributes. The results have not previously been submitted for publication in any other journal. The topic is crucial, given that accurate data on forest canopy attributes are strongly required for a wide range of studies, including processed-based models, hydrology, carbon and nutrient cycling. Recent technological innovations have led to an upsurge in the availability of UAV platform and lightweight sensors, but their application in forestry is still at an experimental stage.

Estimates of canopy cover and foliage clumping were obtained from UAV images combining a visible vegetation index (GLA) with a colour-space conversion (RGB to CIE $L^*a^*b^*$); leaf area index (L) was then derived from a radiative transfer model. Results were validated against ground estimates obtained from two well-established canopy photographic methods (cover and fisheye photography). The method was tested in beech forests. Results indicated that UAV accurately estimates canopy cover even in very dense stand conditions, despite a tendency to not detecting many small within-crown gaps in aerial images, leading to a measurement of a quantity much closer to crown cover estimated from *in situ* cover photography. Estimates of L from UAV images significantly agreed with that obtained from fisheye images, but the accuracy of UAV estimates is influenced by the appropriate assumption of leaf inclination angle distribution.

We concluded that true colour UAV images acquired with a commercial digital camera can be effectively used to obtain rapid, cheap and meaningful estimates of forest canopy attributes at medium-

large scales. UAV can combine the advantage of high resolution imagery with quick turnaround series, being therefore suitable for routine forest stand monitoring and real-time applications.

As qualified reviewers I would suggest the following:

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Many thanks for your attention.

Arezzo, September 29th, 2015

Yours sincerely,

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Highlights

- Forest canopy estimates were obtained using a small UAV and a commercial RGB camera
- True colour UAV images accurately quantified canopy cover
- Leaf area index from UAV is influenced by leaf angle distribution assumption

Estimation of canopy attributes in beech forests using true colour digital images from a small fixed-wing UAV

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Abstract

Accurate estimates of forest canopy are essential for the characterization of forest ecosystems. Remotely-sensed techniques provide a unique way to obtain estimates over spatially extensive areas, but their application is limited by the spectral and temporal resolution available from these systems, which is often not suited to meet regional or local objectives. The use of unmanned aerial vehicles (UAV) as remote sensing platforms has recently gained increasing attention, but their applications in forestry are still at an experimental stage. In this study we described a methodology to obtain rapid and reliable estimates of forest canopy from a small UAV equipped with a commercial RGB camera. The red, green and blue digital numbers were converted to the green leaf algorithm (GLA) and to the CIE $L^*a^*b^*$ color space to obtain estimates of canopy cover, foliage clumping and leaf area index (L) from aerial images. Canopy attributes were compared with *in situ* estimates obtained from two digital canopy photographic techniques (cover and fisheye photography).

The method was tested in beech forests. UAV images accurately quantified canopy cover even in very dense stand conditions, despite a tendency to not detecting small within-crown gaps in aerial

images, leading to a measurement of a quantity much closer to crown cover estimated from *in situ* cover photography. Estimates of L from UAV images significantly agreed with that obtained from fisheye images, but the accuracy of UAV estimated is influenced by the appropriate assumption of leaf angle distribution.

We concluded that true colour UAV images can be effectively used to obtain rapid, cheap and meaningful estimates of forest canopy attributes at medium-large scales. UAV can combine the advantage of high resolution imagery with quick turnaround series, being therefore suitable for routine forest stand monitoring and real-time applications.

Keywords: drone; leaf area index; cover photography; hemispherical photography; *Fagus sylvatica*

1. Introduction

Accurate estimates of forest canopy are central for a wide range of studies including hydrology, carbon and nutrient cycling, and global change. Leaf area index (L), canopy cover and clumping index are amongst the most widely used canopy attributes. Ground-based methods to estimate these variables include either direct contact (destructive sampling) or indirect optical methods (for a review, see Jonckheere et al., 2004). Generally, both approaches are time consuming and unpractical for large forest areas. In addition, these methods are unsuitable for real-time application such as monitoring wildfire spread or plant disease outbreaks (Anderson and Gaston, 2013). Remotely-sensed information offers a unique way to obtain large scale mapping of forest canopy attributes. In particular, several studies indicated that space-borne sensors can be used to obtain spatially extensive information from landscape to the global scale (e.g., Davi et al., 2006; Turner et al. 1999; Hu et al., 2007; Lamonaca et al., 2008; Pellikka et al., 2009; Prospatin and Panferov, 2013). However, the spatial and temporal resolutions of satellite-based data are often not suited to meet regional or local objectives. New satellite sensors have become operational over the past decade, offering data at finer spatial scale and more responsive capabilities. Notwithstanding these improvements, high-cost per scene and not profitable revisit time remain significant obstacles for many remote sensing applications. Airborne platforms may theoretically be used to obtain more scale-appropriate data, but they are so expensive to prevent regular time-series monitoring.

Recent technological advances have led to an upsurge in the availability of unmanned air vehicles (UAV). UAVs can combine high spatial resolution and quick turnaround times together with lower operational costs and complexity. However, low-cost and light-weight sensors are required for UAVs, particularly for small-sized vehicles that make use of commercial digital cameras (Hunt et al.2008,). Commercially available sensors like RGB cameras are highly suitable for use with UAV platform but their reliability still need to be accurately verified. (Clemens, 2012).

Recent studies have tested the use of UAV-derived vegetation indices to monitor canopy attributes of field crops (e.g., Hunt et al., 2005; Hunt et al., 2010; Guillen-Climent et al., 2012). The majorities of the adopted indices involve use of NIR bands, because the near infrared portion of the electromagnetic spectrum provides strong information on both the physiological status and the geometric properties of vegetation (Houborg and Boegh, 2008; Breuning et al., 2013). On the contrary, relatively few studies have tested the applicability of UAV-derived vegetation indices based on solely the visible portion of the electromagnetic spectrum (VIs) (e.g., Hunt et al., 2005; Jannoura et al., 2015). Nonetheless, VIs are particularly interesting for UAV applications because they can be obtained from commercial RGB digital cameras; therefore, this option holds great potential for expanding the range of sensors and platforms available for UAV sensing of vegetation.

In this study we tested whether true colour (RGB) digital photography can be used to obtain estimate of forest canopy attributes from unmanned aerial vehicles. For this purpose we used a small fixed-wing UAV equipped with a standard RGB digital camera, which was tested in pure beech stands. Canopy attributes derived from true colour UAV imagery were calibrated against ground estimates of canopy cover and leaf area index, which were obtained from well-established canopy photographic techniques.

2. Material and methods

2.1 Study sites and field data collection

The study was carried out on July 2015 in a mountain forest in Central Italy (Alpe di Catenaia, 43°48'N, 11°49'E). The climate at the study site was temperate, with warm, dry summers and cold, rainy winters. The mean annual rainfall was 1224 mm, and the mean annual temperature was 9.5°C.

Ten 0.5-ha beech stands were sampled, which were located within a radius of 2 km each other. The stands showed differences in stand density (ranging from 108 to 3324 trees ha⁻¹), basal area

(ranging from 14.7 to 45.3 m²ha⁻¹) and mean height (ranging from 26.4 to 29.9 m). Species composition in the stands was nearly pure (beech contribution >90% of basal area).

Within each stand, canopy attributes were estimated *in situ* using two canopy photographic techniques, namely cover photography (DCP) and fisheye photography (DHP), which were used as benchmark to validate UAV-based indices. All photographs were acquired as ‘fine’ quality and at maximum resolution (2272x1704 pixels) jpeg using a Nikon Coolpix 4500. Photographs were collected close to sunrise or sunset at a height of 1 m along a grid of sampling points, following the protocols by Macfarlane et al. (2007) and Chianucci and Cutini (2013) as described below.

In each stand, 36 cover images were collected with the fixed lens set to F2, minimum aperture (F 9.6), automatic exposure. RGB images were sharpened (medium) and analysed in Winscanopy 2012a (Regent Instruments, Ste-Foy, Quebec, Canada). Two distinct estimates of canopy cover were obtained and used as ground truth for comparison with UAV estimates: foliage cover (f_F), which was calculated as the complement of total gap fraction, and crown cover (f_C), which was calculated as the fraction of pixels that do not lie in between-crowns gaps, considering between-crown gaps as those exceeding the 0.3% of the image area; this threshold value was set in a previous study (Chianucci et al., 2014a). Foliage clumping $\Omega(0)$ was also calculated from gap size distribution (Chen and Cihlar, 1995, as modified by Leblanc, 2002).

In addition, 9 fisheye images were collected in each stand with the camera equipped with a FC-E8 fisheye lens converter set to F1, minimum aperture (F 5.3), and with the exposure set two-stops lower than that measured in a clearing close to each stand. The gamma function of the fisheye images was corrected to 1.0; the blue channel was then sharpened (medium) and analyzed in Winscanopy 2012a. The hemisphere of each image was divided into seven zenith angle rings and eight azimuth segments; the zenithal angle range used for the analyses was 0°-70°. L without correction for clumping was obtained by averaging the generalized method (Welles and Norman, 1991) and the ellipsoidal method (Campbell, 1986) from linearly-averaged gap fraction. L corrected for clumping was obtained by averaging the generalized method (Welles and Norman, 1991) and the ellipsoidal method (Campbell, 1986) from logarithmically-averaged gap fraction (Chianucci et al., 2015). Estimated L served as ground truth for modelling UAV-based L (see section 2.2).

2.2 True color UAV images collection and pre-processing

Aerial images were collected with a commercially available fixed-wing eBee (SenseFly, Cheseaux-Losanne, Switzerland) equipped with a commercial 16MP Canon Power Shot/ELPH 110 RGB camera. The eBee is a hand-launched, autonomous flying drone with an electric motor-driven pusher propeller. It has a 96 cm wingspan and a weight of about 700 g including camera, inertial measuring unit, GPS and battery payloads. The maximum flight time (with RGB camera) was about 50 min and can cover a maximum area of about 10 km² per flight. The eBee flight plan was managed through SenseFly's eMotion software and the flight monitored through a laptop; the software requires initial parameter like area of interest, desired ground pixel resolution, side and longitudinal image overlap; it then automatically calculates the number of stripes to cover the area of interests and the flight height. Take-off and landing are also planned and managed by the software and monitored through the laptop. Remote controller by operator is still possible during flight by means of wireless modem connected to the laptop up to a maximum distance of 3 km from the vehicle.

Images were collected in TIFF format with the camera set in automatic mode at noon under clear sky and calm conditions to minimize wind and shadows effects on photographs; ground pixel resolution was set to 7.5 cm, corresponding to an altitude of about 170 m. The longitudinal and lateral image overlap was set respectively to 80% and 30%. The take-off/landing area was located about 1 km from the studied stands in a clearing close to the beech forest. Two subsequent flights covered the entire study areas in approximately 30'. Another flight was executed immediately after the previous ones to cover the take-off/landing area, which was used as calibration site for performing spectral field measurements of vegetation (see section 2.3). Absolute positioning was based on a direct georeferencing approach using the position/attitude measurements acquired by the UAV-embedded GPS/IMU instrumentation. Images were then process using the APS software (Menci Software, Arezzo, Italy; www.menci.com). The software processing is based on a conventional photogrammetric approach: an automated image matching algorithm identifies tie points in the images which were used to retrieve orientation parameters of the aerial triangulation (bundle-block adjustment). Once oriented, the software allows DSM extraction and the generation of orthomosaic from images. A colour balancing between images with histogram matching was applied during orthomosaicking.

2.3 True color UAV image processing and analysis

True colour orthomosaic images were cropped to fit each of the targeted stand extent. Each cropped image was then processed to estimate canopy cover, clumping index and leaf area index as described below.

Canopy cover (c_c) was estimated using an image classification methods developed by Macfarlane and Ogden (2012), namely LAB2, and the relative routine coded by the authors in MATLAB (Mathworks Inc., MA, US). Previous studies indicated the method is particularly suited for estimating cover in dense stands (Chianucci et al., 2014a; Macfarlane and Ogden, 2012). Four groups of pixels used as training sets were automatically detected for each image using logical tests based on the DNs of the original RGB image (Table 1).

The DNs of each RGB channels were transformed to calculate a visible-spectrum vegetation index (Eq. (1)):

$$GLA = \frac{2G - R - B}{2G + R + B} \quad (1)$$

Where G, R and B are the green, red and blue channel of the image, respectively; values ≤ 0 were classified as definite background (Group 1, Table 1). The camera-based GLA was checked against reflectance-based GLA derived from spectral field measurements, which were performed during the flight in the calibration site using an ASD spectroradiometer (Analytical Spectral Devices Inc., Boulder, Co, US). The two indices showed comparable results ($GLA_{UAV} = 0.92 GLA_{ASD} - 0.02$, $R^2=0.85$, $p < 0.01$); therefore, no radiometric corrections were applied to the DNs of the UAV images.

The RGB images were then converted to the CIE $L^*a^*b^*$ colour model, whose coordinates represent the lightness of the color (L^*), its position between magenta and green (a^*) and its position between yellow and blue (b^*). The mean values of GLA, a^* and b^* of both the background and foreground training sets were calculated (Groups 1 and 2, Table 1), and the LAB2 classifier was performed based on the Euclidean distance from the group means. An object-noise filtering was applied to remove potentially misclassified pixels.

Once classified, LAB2 binary images were further analysed for estimation of clumping index $\Omega(0)$ using a gap-size distribution approach. Each classified image was divided into a number of sub-images. To speed up calculation, we observed that dividing the entire scene from 5x5 up to 9x9 sub-images gives similar gap size estimates, therefore we adopted a 7x7 sub-images division. Gap fraction of each sub-image was classified on the basis of its size as large, non-random gaps and

small, random gaps. A large gap threshold for each image classification method was set based on visual image inspection: large gaps were considered those larger 15% of the sub-image area. The clumping index was then calculated at image level from gap-size distribution (Chen and Cihlar, 1995, as modified by Leblanc (2002)):

$$\Omega(0) = \frac{\ln[\overline{P(0)}] [1 - F_{mr}(0)]}{\ln[F_{mr}(0)] [1 - \overline{P(0)}]} \quad (2)$$

Where $F_{mr}(0)$ is the reduced gap-size accumulated fraction after removal of large, non-random gaps (also called crown porosity). Although the gap size image analysis described above was not completely operator-free, the method is simple, automated and it was successfully applied in previous studies (Chianucci et al., 2014a, 2014b).

The obtained canopy cover c_c and $\Omega(0)$ was used to estimate leaf area index using the Beer-Lambert's law (Equation (3), after Nilson, 1971):

$$L = -\frac{\ln(1 - c_c)}{\Omega(0) \times G(0)} \quad (3)$$

Equation (3) requires a foliage projection function $G(0)$ to calculate L ; this attribute is mainly related to the mean leaf angle and the leaf angle distribution of the target species. For the remainder of the study, we adopted either the spherical leaf angle distribution (foliage projection function at nadir of 0.50), which was often assumed in these studies (e.g., Chianucci and Cutini, 2013; Macfarlane et al., 2007), and the planophile leaf angle distribution (foliage projection function at nadir of 0.85), which was inferred from leaf inclination measurements of beech trees collected in a previous study (Chianucci et al., 2014a) The woody material contribution in Eq. 3 was considered negligible in nadir images.

2.4 Statistical analyses

We compare canopy attributes from aerial photographs (UAV) with that obtained from ground photography (DCP and DHP) by fitting simple regression lines. Since all methods are subject to measurements errors and are therefore not “independent” variables, we used reduced-major-axis (RMA) linear regression. The coefficient of determination (R^2), deviation of the slopes from unity and deviation of the intercepts from zero were assessed. All statistical analyses were performed using R version 3.0.2 (R Development Core Team, 2013).

3. Results

The studied stands were characterized by dense canopy, as indicated by the canopy attributes estimated from ground (cover and fisheye) photography. From DCP, foliage cover, crown cover and crown porosity ranged from 0.81 to 0.95 (average $\pm$ s.e. 0.90 ± 0.07), 0.87 to 1.00 (0.96 ± 0.06) and 0.04 to 0.08 (average 0.06 ± 0.01), respectively. Clumping index estimated from DCP ranged from 0.72 to 0.99 (0.90 ± 0.03). When no correction for clumping was applied, leaf area index estimated from DHP ranged from 3.65 to 7.15 m^2m^{-2} (average 5.71 ± 0.42); when correction for clumping was applied, leaf area index estimated from DHP ranged from 5.33 to 8.40 m^2m^{-2} (average 6.87 ± 0.41). Clumping index estimated from DHP ranged from 0.69 to 0.89 (0.83 ± 0.02).

Canopy cover estimated from UAV images ($c_{C \text{ UAV}}$) ranged from 0.85 to 0.99 (average 0.95 ± 0.01). The classification methods yielded estimates of canopy cover which agreed with foliage cover estimates obtained from DCP:

$$c_{C \text{ UAV}} = 0.83 f_{\text{F DCP}} + 0.20, n=10, R^2 = 0.62, p < 0.01 \quad (4)$$

However, the LAB2 showed a tendency to overestimate f_{F} (Figure 1), resulting in estimates of canopy cover which significantly differed from foliage cover (t -test, $p < 0.05$). Closer inspection of classified LAB2 images revealed that the method poorly detect small within-crown gaps. This was confirmed by the better agreement observed with crown cover estimates obtained from DCP (Figure 1), and by the non-significant differences found between the two estimates (t -test):

$$c_{C \text{ UAV}} = 0.89 f_{\text{C DCP}} + 0.09, n=10, R^2 = 0.70, p < 0.01 \quad (5)$$

The estimated clumping index from UAV images ranged from 0.75 to 1.00 (average 0.94 ± 0.03) and agreed closely to that estimated from cover photography ($\Omega(0)_{\text{UAV}} = 0.77 \Omega(0)_{\text{DCP}} + 0.25, R^2 = 0.80, p < 0.01$). Crown porosity $F_{\text{mr}}(0)$ ranged from 0.01 to 0.12 (average 0.05 ± 0.01) but was not correlated with that estimated from DCP. Both foliage cover and clumping index from UAV increased as leaf area index increased, while crown porosity decreased (Figure 2).

With regard to leaf area index, estimates from UAV measurements agreed well with those obtained from fisheye photography (Table 2). The adoption of a planophile leaf angle distribution provided more accurate estimates of L , based on the closer-to-unity slopes and the closer-to-zero intercepts compared to those obtained adopting the spherical leaf angle distribution (Table 2), even though a tendency to underestimate L in the former (Figure 3). When no correction for clumping was applied, on average UAV acquisitions underestimated L by 30% when assuming a planophile leaf angle distribution while overestimated L by 18% when assuming a spherical leaf angle distribution. When correction for clumping was applied, on average UAV measurements underestimated L by values 39% when assuming a planophile leaf angle distribution while overestimated L by only 3% when assuming a spherical leaf angle distribution.

4. Discussion

The studied stands were characterized by dense canopy cover yet characteristic of beech. The observed leaf area index values were in accordance with the range 7-10 observed in other pure beech stands (Breda et al., 2003; Chianucci and Cutini, 2013; Fleck et al., 2003; Lebourgeois et al., 2005; Meier and Leuschner, 2008).

Dense forest stands usually represents a challenge for accurate estimation of canopy attributes (Angelini et al., 2015). Optical measurements often saturate at leaf area index values of about 5 (Gower et al., 1999; Jonckheere et al., 2004), while vegetation indices may saturate at lower values (Davi et al., 2006; Turner et al. 1999). In this study we obtained accurate measurements of canopy structure from true colour UAV images even in very dense stand conditions. We attributed the result mainly to the high image resolution obtainable from UAV platforms. Closer inspection of UAV images revealed that LAB2 accurately detects large gaps between crown boundaries, resulting in accurate retrieval of canopy cover, which is comparable with that obtained from ground cover photography. On the other hand, we observed that the method poorly detect many small within-crown gaps even at the obtained high spatial resolution, leading to a measurement of a quantity much closer to crown cover (Macfarlane et al., 2007). When removing object-noise filtering, LAB2 was able to detect many small gaps but it was also more prone to misclassify shaded leaves in crowns as gaps, confirming the sensitivity of the method to shaded pixels (Macfarlane and Ogden, 2012; Song et al., 2015). The results indicated that much higher spatial resolution may be required to improve the performance of the method in very dense stands; this can be easily achieved using

UAV platforms by acquiring images at lower altitudes and/or utilizing cameras with higher pixel resolution.

A great advantage of the proposed method was that we demonstrated the reliability of using a commercially available RGB camera to obtain estimates of canopy attributes from UAV imagery. This allows a significant reduction of the camera equipment cost when compared e.g., with thermal or near-infrared cameras. Furthermore, this option is particularly interesting for UAV applications, as it allows a significant extension of the range of sensors and platforms available from these systems, in particular for small-sized vehicles. However, many commercial cameras are not radiometrically calibrated. The camera itself in the experiment was not calibrated. Even if we checked the accuracy of UAV-derived vegetation indices with field spectral-derived vegetation indices, we recommend whenever possible to check the radiometry of any adopted camera (Swain et al., 2010).

The only pre-processing step performed in UAV imagery was a colour balancing between images with histogram matching during orthomosaicking. We did not apply further atmospheric correction in the images as we assumed that solar irradiation and sky conditions did not vary very much during images acquisition; this was a reasonable assumption considering the UAV acquired the experimental sites in approximately 30' at noon during clear and calm sky conditions. Moreover, the $L^*a^*b^*$ colour space is less sensitive to changing irradiation conditions than the RGB colour space, because their a^* and b^* channels are independent from the luminance, which is stored in the L^* channel (Liu et al., 2012). Larger variation are expected when comparing different places and time (Hunt et al., 2010) which may require more effort to reduce spectral effects caused by external factors like atmosphere and soil background (Demarez and Gastellu-Etchegorry, 2000). This goal is perhaps less of an issue in the LAB2 classification method, which was originally developed for analysing DN of images acquired from nadir photography (Macfarlane and Ogden, 2012). Use of training set based on DN test can provide an alternative, fairly robust option to compensate for lack of radiometric and atmospheric corrections of the images.

A comparison with leaf area index estimates from fisheye photography revealed that leaf inclination strongly influences optical properties of vegetation, and thus the indirect estimation of L from optical sensors (Pisek et al., 2013; Prosspatin and Panferov, 2013; Ryu et al., 2010). While hemispherical sensors were able to eliminate the influence of leaf angle by integrating measurements over the entire zenith range (Miller, 1967) restricted view angle methods are strongly influenced by the foliage projection coefficient. Moreover, the differences between theoretical foliage projection functions are largest at lower view zenith angles, namely across the field of view

usually considered from aerial imagery; under such circumstances, the common assumption of a spherical leaf angle distribution may lead to large errors in the leaf area inversion (Pisek et al., 2013). In the current study, good estimates of L were obtained by adopting a planophile leaf angle distribution, which was inferred from a previous study conducted in young beech trees (about 0.5 m tall; Chianucci et al., 2014a). However, our result suggest that the optimal foliage projection coefficient value occupies an intermediate value between the planophile and the spherical leaf angle distribution; that is, the plagiophile leaf angle distribution appears more suited for leaf area inversion in the studied stands. This was also confirmed by regression testing against leaf area index values from DHP, based on the closer-to-unity slopes obtained from adopting a plagiophile distribution ($L_{NC \text{ UAV}} = 1.11 L_{NC \text{ DHP}} - 1.39$, $R^2 = 0.70$, $p < 0.01$; $L_{C \text{ UAV}} = 0.95 L_{C \text{ DHP}} - 1.29$, $R^2 = 0.59$, $p < 0.01$), compared with those obtained from adopting either the planophile or the spherical leaf angle distribution. This does not necessarily imply that the plagiophile leaf angle distribution was the dominant distribution in the observed canopies; it has been noted previously that leaf angle distribution might change with canopy height (Hutchinson et al., 1986; Raabe et al., 2015). At the top of canopy light is frequently received in excessive amount, and more inclined distribution of foliage can allow trees to reduce photo-inhibition and optimizing light interception (Ball et al., 1988); conversely, more horizontally leaves at the bottom of the canopy allows increasing light use efficiency at lower light intensities (Ford and Newbould, 1971). Based on the above considerations we concluded that direct leaf angle measurements are strongly recommend to model leaf area index from optical sensors. This can be easily achieved by a recently developed ground levelled photographic method (Ryu et al., 2010), which can provide ancillary data to improve the indirect retrieval of canopy attributes.

5. Conclusions

We demonstrated that true colour UAV images acquired with a commercial digital camera can be effectively used to obtain rapid, cheap and meaningful estimates of forest canopy attributes at medium-large scales. UAV can combine the advantage of high resolution imagery with quick turnaround series, being therefore suitable for routine forest stand monitoring and real-time applications.

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Figure captions

Figure 1 . Canopy cover estimates from aerial UAV images using LAB2 classification method vs foliage cover (top) and crown cover (bottom) estimates from ground cover photography. The dashed line indicates the 1:1 relationship.

Figure 2. Canopy cover (empty triangles), clumping index (filled circles), crown porosity (filled triangles) from UAV images vs leaf area index (corrected for clumping) from fisheye photography. The trends are reported (dashed lines).

Figure 3. Leaf area index from aerial UAV images using the LAB2 method and either the spherical leaf angle distribution (empty circles) and the planophile leaf angle distribution (filled circles) vs leaf area index from ground fisheye photography. The dashed line indicates the 1:1 relationships.

Table captions

Table 1. Identification of training sets for foliage cover classification (for meaning of abbreviations, see section 2.3).

Table 2. RMA regression coefficients for leaf area index (L) from UAV images and from fisheye images (DHP). The expression used for regression was: $L_{\text{UAV}} = a L_{\text{DHP}} + b$. Highlighted in bold are intercepts whose 95% confidence interval includes zero, and slopes that do not significantly differ from unity ($p < 0.05$). Estimates from DHP were calculated either assuming a spherical distribution or a planophile distribution of foliage. NC: No clumping correction. CC: Clumping correction

Figure 1
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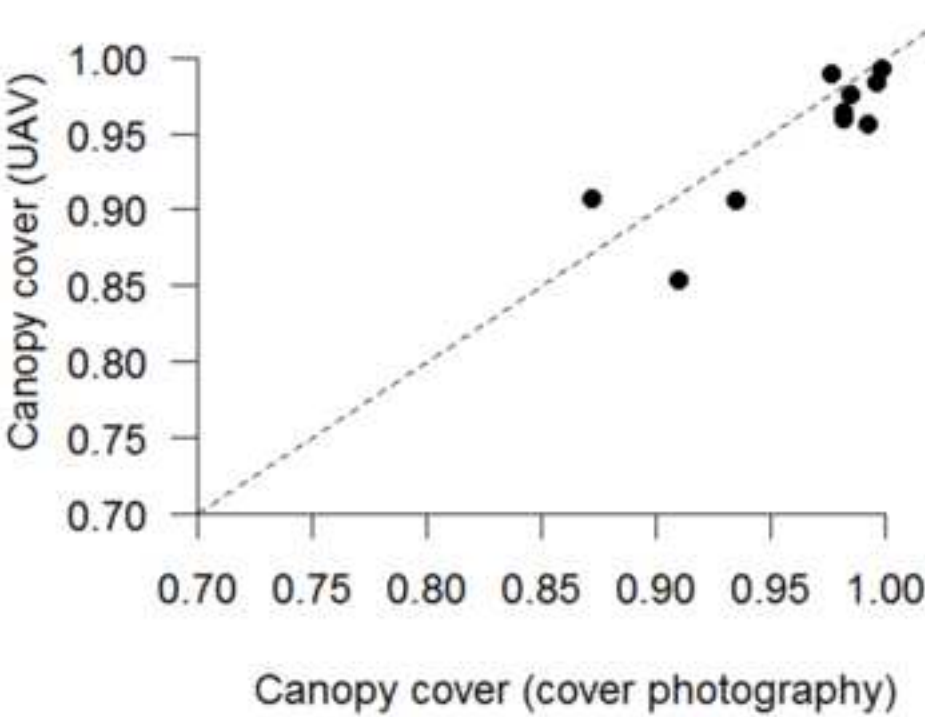
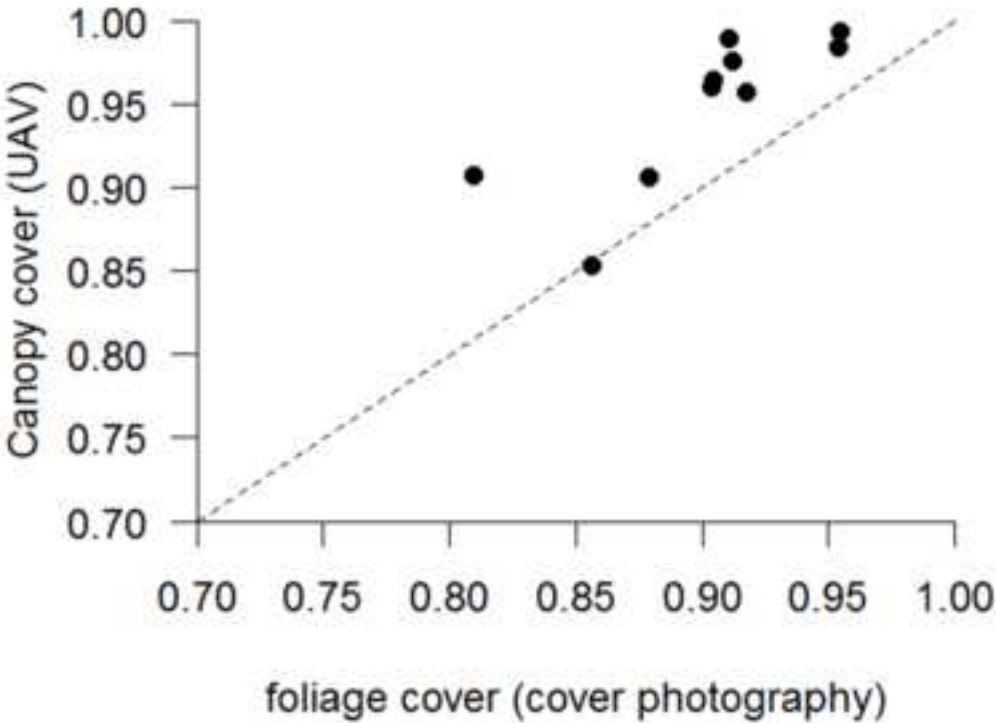


Figure 2
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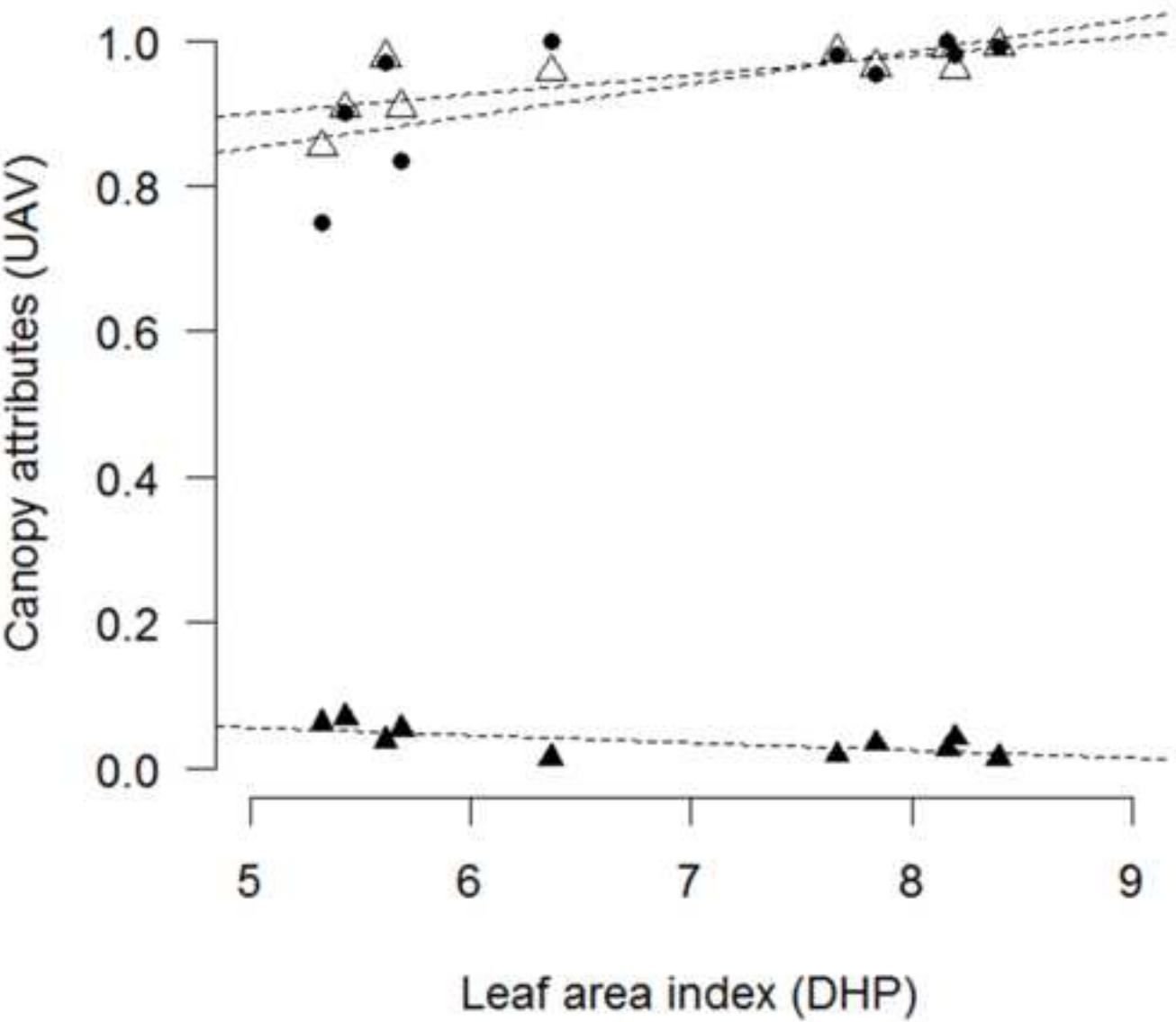


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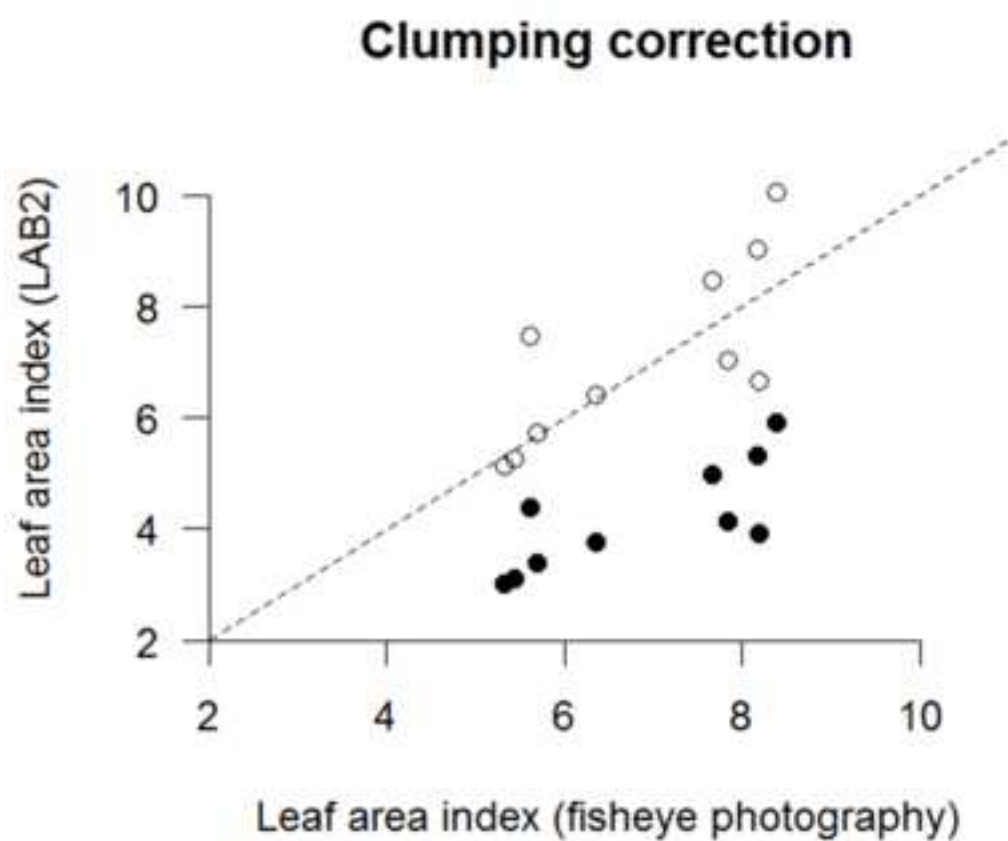
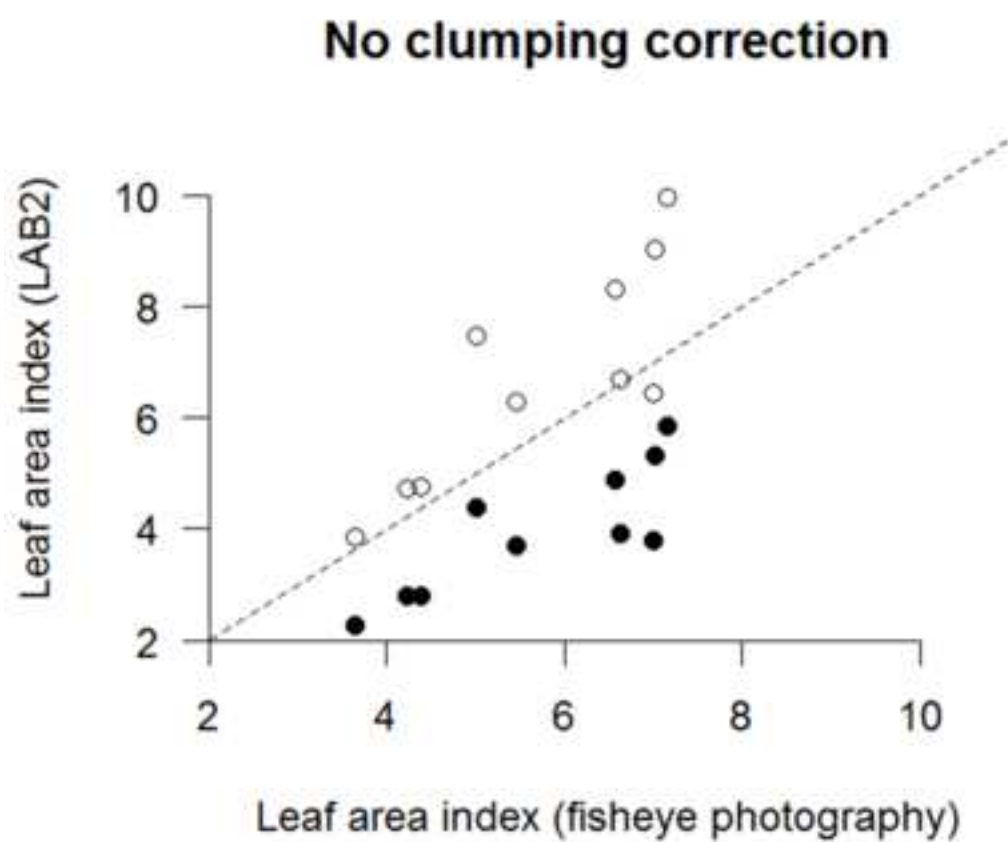


Table 1. Identification of training sets for foliage cover classification
(for meaning of abbreviations, see section 2.3).

Group ID	Note
1	Non vegetation materials (background)
2	Green vegetation (foreground)
3	Dark pixels, non vegetation materials
4	Residuals from previous classifications

Table 2

Table 2. RMA regression coefficients for leaf area index (L) from UAV images and from fisheye images (DHP). The expression used for regression was: $L_{UAV} = a L_{DHP} + b$. Highlighted in bold are intercepts whose 95% confidence interval includes zero, and slopes that do not significantly differ from unity ($p < 0.05$). Estimates from DHP were calculated either assuming a spherical distribution or a planophile distribution of foliage. NC: No clumping correction. CC: Clumping correction

Clumping	Distribution	<i>a</i>	<i>b</i>	R ²	<i>p</i>
NC	Spherical	1.51	-1.89	0.70	0.01
NC	Planophile	0.89	-1.12	0.70	0.01
CC	Spherical	1.29	-1.76	0.59	0.01
CC	Planophile	0.76	-1.04	0.59	0.01