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Technical note

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Influence of image pixel resolution on canopy cover estimation in poplar plantations from field, aerial and satellite optical imagery

Francesco Chianucci[1*], Nicola Puletti[1], Mirko Grotti[1], Carlo Bisaglia[3], Francesca Giannetti[4], Elio Romano[3], Massimo Brambilla[3], Walter Mattioli[1], Giovanni Cabassi[5], Sofia Bajocco[6], Linyuan Li[7,8], Gherardo Chirici[4], Piermaria Corona[1], Clara Tattoni[4]

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ABSTRACT Accurate estimates of canopy cover (CC) are central for a wide range of forestry studies. As direct measurements are impractical, indirect optical methods have often been used to estimate CC from the complement of gap fraction measurements obtained with restricted-view sensors. In this short note we evaluated the influence of the image pixel resolution (ground sampling distance; GSD) on CC estimation in poplar plantations obtained from field (cover photography; GSD < 1 cm), unmanned aerial (UAV; GSD <10 cm) and satellite (Sentinel-2; GSD = 10 m) imagery. The trial was conducted in poplar tree plantations in Northern Italy, with varying age and canopy cover. Results indicated that the coarser resolution available from satellite data is suitable to obtain estimates of canopy cover, as compared with field measurements obtained from cover photography; therefore, S2 is recommended for larger scale monitoring and routine assessment of canopy cover in poplar plantations. The higher resolution of UAV compared with Sentinel-2 allows finer assessment of canopy structure, which could also be used for calibrating metrics obtained from coarser-scale remote sensing products, avoiding the need of ground measurements.

KEYWORDS: foliage cover, crown cover, canopy photography, unmanned aerial vehicles, Sentinel-2.

Introduction

Canopy cover (CC), defined as the average proportion of forest covered by the vertical projection of tree crowns (Jennings et al. 1999, Paletto and Tosi 2009), is a common variable used in forestry. This variable is strongly required for modelling leaf area index using radiative transfer theory (Nilson 1999, Nilson and Kuusk 2004). In addition, CC is a major determinant of forest reflectance from optical remote sensing and is, therefore, widely used to calibrate and validate satellite remotely-sensed information (Chianucci et al. 2016, Prospatin and Panferov 2013). CC is also often used in national forest inventories (Angelini et al. 2015) as well as in land-use/land-cover (LULC) analyses. Accordingly, accurate estimates of CC are essential for a wide range of studies and applications (Chianucci 2020).

As no direct method exists to retrieve this variable in the field, optical instruments have been frequently used *in situ* to indirectly estimate CC in forest stands from the complement of vertically-resolved gap fraction (Chianucci 2016). Optical instruments with hemispherical view have been often used to estimate this variable from gap fraction data at narrow viewing zenith angle range (typically 0-15°; (Rautiainen et al. 2005, Seed and King 2003, Chianucci 2016, Grotti et al. 2020, Chianucci et al. 2019, Chianucci 2020). However, the gap fraction readings obtained at this view are often biased in hemispherical sensors, because of the limited spatial resolution near the zenith (Chianucci 2020). The vertical nature of CC makes this variable more efficiently measured using optical instruments with restricted field of view (FOV). For instance, digital cover photography (DCP) is an optical method based on acquiring images using a normal lens fitted to a camera oriented upward, which yields a restricted 30° FOV (Macfarlane et al. 2007); the resulting combination of high resolution and mainly vertical sampling allowed to separate total gap fraction into large, between-crowns gaps and small, within-crown gaps, yielding two distinct estimates of CC from DCP (see Macfarlane et al. 2007 and Equations 1 and 2). Due to the similar FOV, DCP is considered the ideal ground-based instrument to calibrate optical measurements obtained from aerial and satellite sensors (Pekin and Macfarlane 2009, Chianucci 2020).

As field-based instruments are unpractical for large forest areas, remotely-sensed information is often considered for larger scale applications. Several studies indicated that spaceborne sensors can be used to obtain spatially-extensive information from landscape to the global scale. New satellite sensors have also recently become operational, offering data at finer spatial scale. An example is the recent Sentinel-2 (S2) mission, started on June 2015, which features visible and NIR bands at a 10 m spatial resolution, being highly suited for forestry applications

1 CREA – Research Centre for Forestry and Wood - Italy
2 Sapienza University of Rome, Department of Architecture and Design - Italy
3 CREA – Research Centre for Engineering and Agro-Food Processing - Italy
4 University of Florence, Department of Agriculture, Food, Environment and Forestry – DAGRI - Italy
5 CREA – Research Centre for Animal Production and Aquaculture - Italy
6 CREA – Research Centre for Agriculture and Environment - Italy
7 State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and Institute of Remote Sensing and Digital Earth of Chinese Academy of Sciences - China
8 Beijing Engineering Research Center for Global Land Remote Sensing Products, Institute of Remote Sensing Science and Engineering, Faculty of Geographical Science - China
* Corresponding author: francesco.chianucci@crea.gov.it

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(Puletti et al. 2017). Notwithstanding these improvements, the spatial scale available from satellite sensors is often not suited to meet local or regional objective. An open question is whether the available spatial resolution from optical satellite imagery is adequate to estimate canopy cover at the stand or plot level.

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. Due to the spatial resolution achievable (<10 cm), UAV can bridge the data gap between the field scale and the satellite scale, potentially providing an estimate of canopy cover closer to field optical measurements than is possible with coarser scale remotely-sensed products.

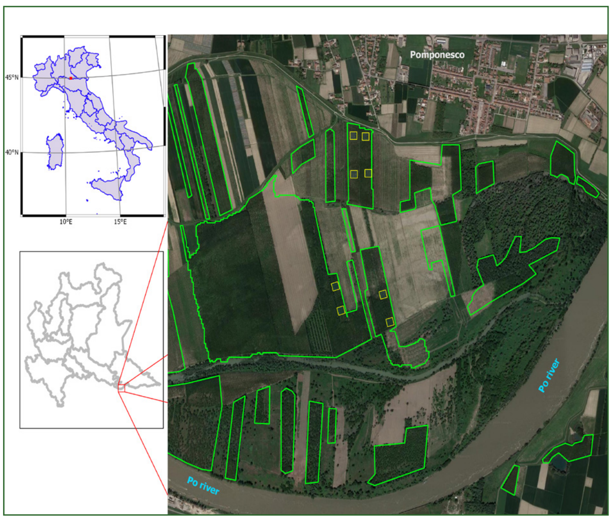
In this short note, we presented the first results of a trial aimed at evaluating the influence of the image resolution (as determined from ground sampling distance; GSD) on CC estimation in poplar plantations. Reference measurements obtained from *in situ* canopy photography (DCP) were compared with both aerial (UAV) and remotely-sensed (S2) estimates obtained from optical imagery.

Material and methods

Study area

Data were collected in poplar plantations located in Viadana, Mantova, Northern Italy (44°55'N; 10°35'E; Fig. 1) on 22-24th July 2019. The plantations grew in a flat and uniform terrain. Eight 50x50 m plots were randomly established in poplar plantations ranging from 5 to 10 years.

Figure 1 - Study area and experimental plots (yellow squares). The green polygons indicated poplar plantations obtained from photointerpretation of aerial orthoimagery



In-situ canopy cover estimates from cover photograph

Sixteen cover photographs were acquired in each plot under overcast sky conditions along a grid of sampling points using a digital single-lens reflex camera (Nikon D90) fitted with an AF Nikkor 50mm 1:1.8 D fixed lens, which yields a FOV of about 30°. The images were acquired in raw format (Nikon's NEF). The camera was placed at about 1.3 m height and oriented upward. The camera was set in aperture-priority mode, with the aperture set to F10.0; exposure was set to underexpose the image by one stop (REV -1) to improve contrast between sky and canopy pixels (Macfarlane et al. 2014).

After collection, raw images were first pre-processed using the 'RAW2JPG' software (Macfarlane et al. 2014). The NEF format was converted to 12-bit linear (demosaiced), uncompressed portable gray map (pgm) format using the 'dcraw' (Coffin 2011) functionality. The blue channel of the pgm image was selected and a linear contrast stretch was applied using the 'imadjust' functionality of MATLAB's (MathWorks Inc., USA) Image Processing Toolbox. Images were then converted to 8 bits per channel and saved as JPG files for subsequent analysis. A gamma adjustment was also applied to the raw images (Macfarlane et al. 2014). This pre-processing made it possible to capture the full dynamic range of the image, while enhancing the contrast between gap and canopy pixels. Finally, JPG images were classified using the two-corner method (Macfarlane 2011). This method first identifies the unambiguous sky and canopy peaks of the image histogram and then detects the point of maximum curvature to the right of the canopy peak and to the left of the sky peak. Mixed pixels containing a portion of canopy and sky, located between the peaks, were classified with a dual threshold (Macfarlane 2011, Macfarlane et al. 2014); this procedure yielded a binary image of sky or canopy pixels. Once classified, total gap fraction was also further classified into large between-crowns gaps and small, within-crown gaps. Gaps larger than 1.3% of the image area were classified as between-crowns gaps as proposed by Macfarlane et al. (2007). Two distinct canopy cover estimates were then derived from classified gap size. Crown cover (CCO; *sensu* Macfarlane et al. 2007) was defined as the complement of large between-crowns gap, including within-crown gap as part of the canopy:

$$CCO = 1 - \frac{N_L}{N_T} \quad (1)$$

where N_T is the total number of pixels and N_L is the total number of pixels located in the large gaps. Conversely, foliage cover (FCO) was defined as the complement of total gap fraction (including within-crown and between-crowns gaps):

$$FCO = 1 - GF \quad (2)$$

where GF is the total gap fraction at the considered restricted view (0°-15°). See Figure 2 for graphical explanation of the estimated CC variables

The two-corner classification method and gap size classification were implemented using the 'DCP 3.15' software (Macfarlane et al. 2014).

Figure 2 - An example of a cover image that has been classified into canopy (black), small within-crown gaps (white) and large between-crowns gaps (grey). Crown cover is the fractional cover of black and white pixels, foliage cover is the fractional cover of black pixels. From Chianucci (2020), modified.

Aerial estimates from UAV

Aerial images were collected with a multirotor "STC_X8_U5" UAV. The UAV is an octocopter with eight co-axial propellers. It has a maximum payload mass of 4 kg and a maximum flight time of about 25' per flight. The UAV has a maximum cruising speed of 18 $m \cdot s^{-1}$. The UAV was equipped with the MicaSense (MicaSense, Seattle, WA, USA) RedEdge multispectral camera. The camera is a 12 bit, 1.2 megapixels camera with tree visible (RGB) spectral bands and two non-visible (red-edge, near-infrared (NIR)) bands.

Images were acquired in TIFF format with the camera set in automatic mode; photographs were collected at noon under clear sky and calm conditions, to minimize wind and shadows effects on photographs. GSD was set to about 8 cm, corresponding to an altitude of about 120 m. The longitudinal and lateral image overlap was set respectively to 85% and 82%. Three subsequent flights covered the entire study areas in approximately 42'. An image of a calibrated reflectance panel was acquired prior of each flight, for the conversion of digital number to reflectance of image pixel values.

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 PIX4D software (Pix4D S.A., Prilly, Switzerland). 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. The software also allows the correction of raw digital number of pixel values to reflectance values, using the camera's specific calibration factor for conversion to radiance, and the calibrated panel reflectance values and sun irradiance data from the downwelling light sensor (DLS), for conversion to reflectance.

For consistency and comparability with S2, we calculated the normalized difference vegetation index (NDVI) as a proxy of canopy cover (Prospatin and Penferov 2013), which was calculated from the reflectance values of the NIR and RED bands as:

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad (3)$$

The mean NDVI was calculated at plot scale and used for comparison with plot-averaged canopy cover measurements obtained from DCP.

Satellite estimates from Sentinel-2

Sentinel-2 features 13 spectral bands with 10, 20 and 60 m spatial resolution at 12 bit radiometric resolution (see Puletti et al. 2017). For the remainder of the analysis, we focused only on visible (RGB) and NIR 10 m bands. A S2 image (date 2019 July 23rd) was downloaded as Level-1C Top-of-Atmosphere (TOA) reflectance product from the Scientific Hub (https://scihub.copernicus.eu; product code "S2A MSIL1C 20190723T101031 N0213 R022 T32TPQ 20190723T125722"). TOA reflectance was then corrected to Bottom-of-Atmosphere (BOA) reflectance, using the Sentinel Application Platform (SNAP), available at the ESA website (http://step.esa.int/main/toolboxes/snap). The 10 BOA bands were then imported in ENVI software, stacked and cropped over the area of interest. We calculated the normalized difference vegetation index (NDVI; Eq. 3) as a proxy of canopy cover. The mean NDVI was calculated at plot scale and used for comparison with plot-averaged canopy cover measurements obtained from DCP and plot-averaged NDVI estimates obtained from UAV.

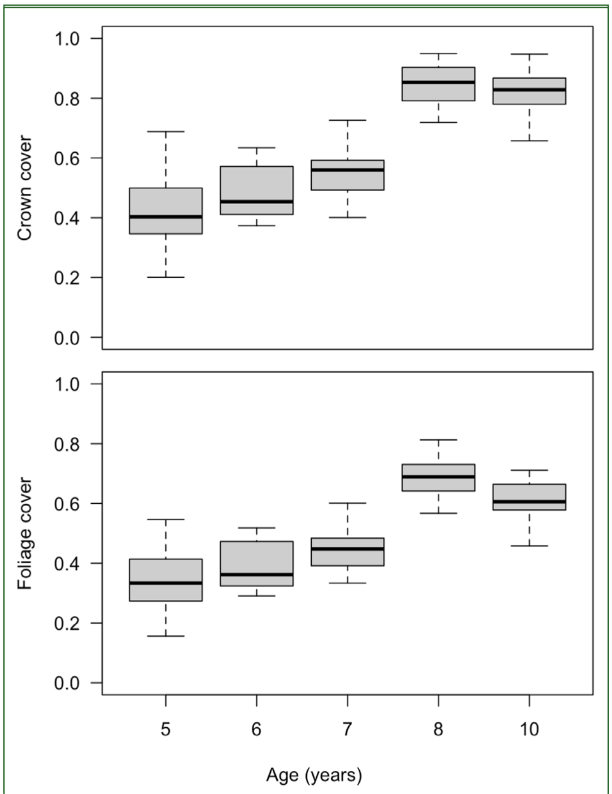
Statistical analyses

We compared canopy cover estimates obtained from DCP, and NDVI estimates obtained from both UAV and S2, using Reduced-Major Axis (RMA) regression. Statistical analyses were performed in R (CRAN R development Team) with the 'lmodel2' package (Legendre and Oksanen 2018) uploaded.

Results

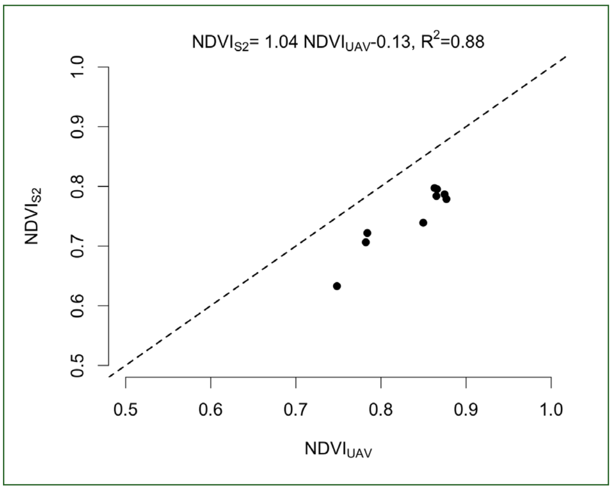
Crown cover estimated from DCP ranged between 0.38 to 0.85 (mean ± standard deviation 0.66 ± 0.19). Foliage cover ranged between 0.30 to 0.69 (0.52 ± 0.14). Both attributes increased with plantation age (Fig.3).

Figure 3 - Variability of crown cover (top) and foliage cover (bottom) estimates obtained from DCP with poplar plantation age.



NDVI estimated from UAV ranged between 0.75 to 0.88 (0.83 ± 0.05) while it ranged between 0.63 and 0.80 (0.76 ± 0.06) when estimated from Sentinel-2. Comparison between the two sensors further indicated that S2 systematically underestimated NDVI, when compared with UAV (Fig.4).

Figure 4 - Comparison with plot-averaged NDVI obtained from Sentinel-2 (y-axis) against estimates obtained from UAV (x-axis). The dashed line indicates the 1:1 relationship with UAV estimates



Comparison between NDVI estimated from the two sensors and *in situ* estimates of canopy cover indicated that both sensors yielded quantities which are correlated with ground measurements of canopy cover (Fig.5 and 6). In addition, in both sensors the NDVI showed higher correlations with CCO than FCO, indicating that the resolution of aerial and satellite optical data is unable to detect small gaps within crowns boundaries. Overall, S2 showed higher correlation with *in situ* canopy cover than UAV, based on the closer to unity slopes, and the higher coefficient of determination of regressions (Fig.5 and 6).

Figure 5 - Comparison with canopy (crown and foliage) cover estimates obtained from DCP (y-axis) against plot-averaged NDVI estimates obtained from UAV (x-axis). The dashed line reports the regression fittings; intercepts were forced to pass through the origin. Blue color: CCO; red color: FCO.

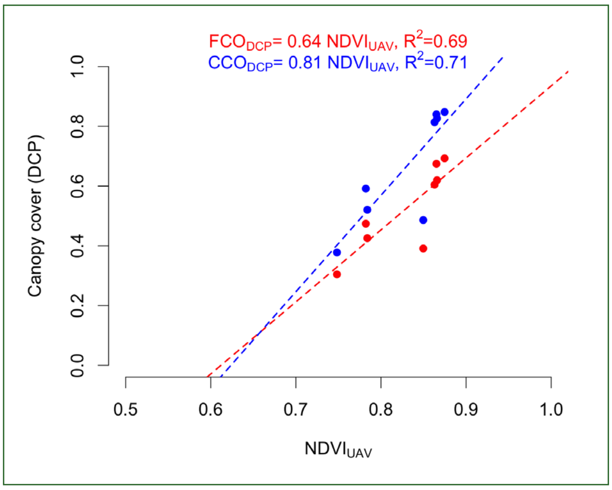
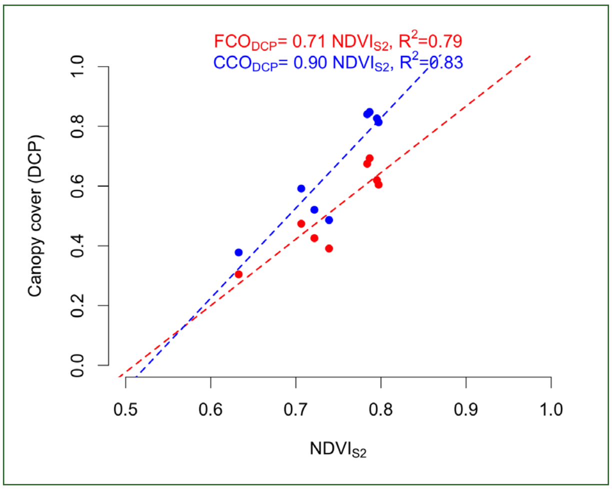


Figure 6 - Comparison with canopy (crown and foliage) cover estimates obtained from DCP (y-axis) against plot-averaged NDVI estimates obtained from Sentinel-2 (x-axis). The dashed line reports the regression fittings; intercepts were forced to pass through the origin. Blue color: CCO; red color: FCO.



Discussion and conclusions

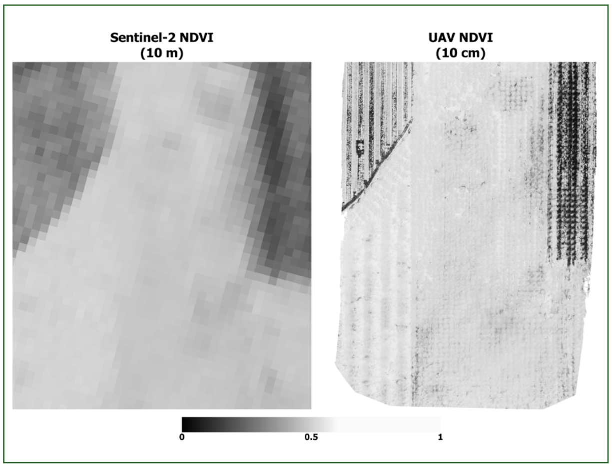
The main finding of the study is that canopy cover (as approximated from NDVI) can indeed be estimated at the (coarser) 10 m spatial resolution available from Sentinel-2 in poplar plantations. The results are attributable to the homogeneity and relatively-low canopy density (Leaf area index in the plots was <3.5; data not published) of poplar plantations, for which the 10 m is suitable for characterize canopy structure in these stands.

The comparison with aerial and satellite estimates also showed some specific trends:

- Both UAV and S2 yielded plot-averaged estimates of NDVI that are more correlated with CCO than FCO, which indicates that the both sensors failed to detect many small within-crown gaps even at the higher spatial resolution of UAV (<10 cm). The result is in accordance with that observed by Chianucci et al. (2016) in beech forests.
- Plot-averaged NDVI values obtained from UAV are systematically higher than those obtained from S2. We attributed these differences to the higher spatial resolution of UAV, which can allow more understory cover to be detected, which explained the higher NDVI values obtained as compared to S2, being the sum of overstory cover and (higher) understory cover. Conversely, the coarser scale of S2 is unable to detect small understory patches at scales lower that that available from the sensor's GSD (Fig. 7) (Korhonen et al. 2017).
- The Plot-averaged NDVI in S2 showed higher correlation than UAV with canopy cover estimates obtained from DCP. The results can be explained as *in situ* canopy cover estimates from DCP did not consider the understory contribution to total canopy cover, as the camera is placed above the forest floor layer. By contrast, both aerial and satellite imagery are affected by understory (Eriksson et al. 2006, Kodar et al. 2011, Chianucci 2020). These results confirm the hypothesis that S2 capture less understory cover contribution than UAV, which in turns explain the higher correlation of S2 data with field canopy cover.

Based on the results, we concluded that S2 can be used to larger scale monitoring and routine assessment of canopy cover in poplar plantations. The higher resolution of UAV allows finer assessment of canopy structure, which could also be used for calibrating metrics obtained from coarser-scale remote sensing products and/or analyses that use morphological processing (rather than relying only on vegetation indices), avoiding the need of ground measurements (Chianucci et al. 2016, Chianucci et al. 2020).

Figure 7 - CComparison of NDVI maps obtained from Sentinel-2 (left) and UAV (right; resampled at 10 cm) optical imagery.



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