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Assessing the performance of aerial image point cloud and spectral metrics in predicting boreal forest canopy cover

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ABSTRACT

Canopy cover (CC) is a variable used to describe the status of forests and forested habitats, but also the variable used primarily to define what counts as a forest. The estimation of CC has relied heavily on remote sensing with past studies focusing on satellite imagery as well as Airborne Laser Scanning (ALS) using light detection and ranging (lidar). Of these, ALS has been proven highly accurate, because the fraction of pulses penetrating the canopy represents a direct measurement of canopy gap percentage. However, the methods of photogrammetry can be applied to produce point clouds fairly similar to airborne lidar data from aerial images. Currently there is little information about how well such point clouds measure canopy density and gaps.

The aim of this study was to assess the suitability of aerial image point clouds for CC estimation and compare the results with those obtained using spectral data from aerial images and Landsat 5. First, we modeled CC for n = 1149 lidar plots using field-measured CCs and lidar data. Next, this data was split into five subsets in north-south direction (y-coordinate). Finally, four CC models (*AerialSpectral*, *AerialPointcloud*, *AerialCombi* (spectral + pointcloud) and *Landsat*) were created and they were used to predict new CC values to the lidar plots, subset by subset, using five-fold cross validation.

The Landsat and *AerialSpectral* models performed with RMSEs of 13.8% and 12.4%, respectively. *AerialPointcloud* model reached an RMSE of 10.3%, which was further improved by the inclusion of spectral data; RMSE of the *AerialCombi* model was 9.3%. We noticed that the aerial image point clouds managed to describe only the outermost layer of the canopy and missed the details in lower canopy, which was resulted in weak characterization of the total CC variation, especially in the tails of the data.

1. Introduction

Forest canopy cover (CC) is an important ecological indicator and is commonly used in the estimation of habitat suitability (Jennings et al., 1999). CC is also one of the main criteria in the international definition of forests (FAO, 2005). A definition of CC according to Jennings et al. (1999) is "*the proportion of the forest floor covered by the vertical projection of tree crowns*". Following this definition, CC has traditionally been estimated with upward-looking sighting-tubes, but different remote sensing techniques have also been used to predict CC, especially over large areas. Of these techniques, Airborne Laser Scanning (ALS) using Light Detection and Ranging (lidar) has been proven to be highly accurate in estimating CC (Korhonen et al., 2011). It has even been suggested that lidar data can be used to give validation data about the quality of the field measurements (Smith et al., 2009).

Canopy cover has been commonly estimated from satellite images with varying resolutions (e.g. Hansen et al., 2003; Chopping, 2011; Halperin et al., 2016) and in different types of forests (Sexton et al., 2013; Korhonen et al., 2015; Hadi et al., 2016). Compared to satellite images, aerial images usually have fewer spectral bands, but higher spatial resolution, typically 25–50 cm. Yet, they have other problems caused by the low flying altitude, such as relief displacement. Also, the solar zenith angles can vary according to the flight time. These can all have significant effects when predicting CC (Culvenor, 2003; Pouliot et al., 2002; Mikhail et al., 2001). Recent work with aerial images has been done by Chianucci et al. (2016), who used RGB images taken from Unmanned Aerial Vehicle (UAV) to estimate canopy attributes such as CC and Leaf Area Index (LAI) in Italian beech forests. Using aerial images to estimate the canopy cover of urban forests has also been a topic of interest, with recent works done by Nowak and

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Greenfield (2012), Merry et al. (2014) and Ucar et al. (2016). Aerial images can, however, also provide some of the 3D information present in lidar point clouds by photogrammetric techniques such as image matching. Recently, the utility of such point clouds has been demonstrated in the estimation forest attributes (Bohlin et al., 2012; Puliti et al., 2016; Tanhuanpää et al., 2016).

The interest of the forest science community in image matching can be attributed to the development of computer vision algorithms and hardware, as well as cost control and the quality of aerial images (White et al., 2013). Although creating surface models from overlapping aerial images has transitioned from analogue workstations (Hobrough, 1959) to the digital environment, the underlying method relies on the same fundamental collinearity equations (Schindler, 2014). The process is similar to that of human vision; closer objects seem to move faster than objects at a greater distance when the viewing position changes. This is called a parallax, an apparent shift of the relative position of an object due to a change in the position of the observer (Wolf et al., 2014). Stereo photogrammetry, therefore, requires the identification of common features from multiple images, which can be difficult in surveys spanning across large areas. The reason for this is the apparent change in canopy composition resulting from a change in the sun's elevation angle (Martha et al., 2010), which often results in different representations of the canopy surface in different parts of the study area. When comparing digital photogrammetry data to lidar, it is important to note that image point clouds contain significantly less information from the understory, because only the outermost part of the canopy is visible in an image. Even though photogrammetric point clouds are being increasingly used in forestry, we are not aware of studies that have utilized photogrammetric point clouds in CC estimation. One of the aims of this paper is to fill this gap.

The capabilities of lidar data in accurately predicting boreal forest CC have been demonstrated e.g. by Korhonen et al. (2011). In this paper, we used a set of field plots to calculate CCs for 1149 lidar plots (Wulder et al., 2012), which were then used to train and test the models from other remote sensing datasets. Our objective was specially to assess the CC estimation results obtained using aerial image point clouds and aerial image spectral data. For reference, the accuracy of CC estimation based on an additional spectral dataset, multispectral satellite imagery, is also tested.

2. Materials and methods

2.1. Study area and field data collection

The CC measurements were conducted between 8 May and 8 June 2006, at 30 field plots located in boreal forests of Koli, Eastern Finland, (63°04′N, 29°51′E). Fifteen plots were located on fertile site types and they were dominated by Norway spruce (*Picea abies L. H. Karst*), birch (*Betula* spp. *L.*), or European aspen (*Populus tremula L.*). The other 15 plots were Scots pine (*Pinus sylvestris L.*) dominated and they were located in barren site types. The study area is mostly located inside a national park, but many of the pine plots were located in an area that had been under silvicultural management until 1991. The field plots were subjectively placed, 30×30 m rectangular plots intended for biodiversity or individual tree detection studies (Säynäjoki et al., 2008; Peuhkurinen et al., 2011). Table 1 shows measured attributes from the plots.

The CC measurements were made using a Cajanus tube (Korhonen et al., 2006; Sarvas, 1953). This is a sighting tube (skyward-looking periscope) where the user observes whether a crosshair at the top of the tube is pointing at a crown or open sky. All foliage lower than 1.3 m was ignored. A grid of sampling points was established on each plot by sample transects at 2.5 m intervals and point observations were made at 1 m intervals along the transects. This resulted in each plot having at least 250 observations. The CC was then calculated as the fraction of crown observations. Johansson (1985) and Korhonen et al. (2011) suggest that the risk of serious errors in these kinds of measurements is small. For more details on the field data collection, see Korhonen et al. (2011).

2.2. Lidar data and lidar plots

Lidar data were collected on 13 July 2005 using an Optech ALTM 3100 laser scanner. A total of nine transects were flown at an altitude of 900 m and a flight speed of 75 m/s. The pulse repetition rate was 100 kHz and the scanning frequency of a swath was 70 Hz, at a half angle of 11°. The nominal density of the data was 3.9 submitted pulses per m^2, but because of a side overlap of 35% and the variation in terrain, the actual ground hit density was 3.2–7.8 pulses/m^2. The scanner captured a maximum of four echoes per one submitted pulse: *first of many*, *intermediate*, *last of many*, or *only*. Here, we used echoes only from the categories *first of many* and *only*, because they represented surface hits. The echoes were classified into ground and vegetation hits using the method by Axelsson (2000). Using Delaunay triangulation, the ground hits were interpolated to a 1-m resolution DTM, which was then subtracted from all of the echoes to scale their heights to above ground level (AGL).

An earlier study based on this particular data set showed that the fraction of first and single echoes above a 1.3 m height threshold had nearly a 1:1 relationship with the field-measured CC values (absolute root mean square error = 3.7%, bias −3.1%) (Korhonen et al., 2011). Thus, we used the available lidar and field data sets to predict canopy cover for 1149 lidar plots. The lidar plots enabled us to have a larger CC data set with accuracy comparable to that of field measurements. The lidar plots were 30×30 m plots that were placed in the study area in a regular 120 m grid (water bodies were excluded). Fig. 1 shows the study area and the lidar plots.

Next, a regression model was used to predict the CC for the lidar plots. This model was based on the field-measured CC data and lidar data extracted from the area of the field plots. The lidar variable used in the prediction was termed *p1* and it accounted for the proportion of echoes that came above the height of 1 m. The model used to link the CC with *p1* was based on an ellipsoidal function defined as:

$$CC = 1 - (1 - p1^{t})^{1/t}$$

where t is a parameter to be estimated from the model shape.

2.3. Aerial imagery

Aerial images were captured on 1 September 2005 with a Vexcel UltraCamD digital frame camera. The area was covered by two 10 km long flight lines. The images were taken from an altitude of 3000 m above ground level with a side lap of 67% and an end lap of 80%. The data used for this study comprised the red, green, blue, and near-infrared spectral bands. The images were pansharpened (Vexcel's Level-3 product) and then orthorectified to a pixel size of 25 cm and an image mosaic was built from near-nadir parts of the orthorectified images. Due to the high overlap, majority of the plots were located within 0–800 m of the nadir point.

The image point cloud datasets were created with ERDAS's implementation of the Semi-Global Matching (SGM) algorithm (ERDAS, 2016). The point clouds were created from images captured with the panchromatic sensor. In general, image-matching methods can be divided into two categories: area-based and