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Removing bias from LiDAR-based estimates of canopy height: Accounting for the effects of pulse density and footprint size

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ABSTRACT

Airborne laser scanning (LiDAR) is used in forest inventories to quantify stand structure with three dimensional point clouds. However, the structure of point clouds depends not only on stand structure, but also on the LiDAR instrument, its settings, and the pattern of flight. The resulting variation between and within datasets (particularly variation in pulse density and footprint size) can induce spurious variation in LiDAR metrics such as maximum height (h_{max}) and mean height of the canopy surface model (C_{mean}). In this study, we first compare two LiDAR datasets acquired with different parameters, and observe that h_{max} and C_{mean} are 56 cm and 1.0 m higher, respectively, when calculated using the high-density dataset with a small footprint. Then, we present a model that explains the observed bias using probability theory, and allows us to recompute the metrics as if the density of pulses were infinite and the size of the two footprints were equivalent. The model is our first step in developing methods for correcting various LiDAR metrics that are used for area-based prediction of stand structure. Such methods may be particularly useful for monitoring forest growth over time, given that acquisition parameters often change between inventories.
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1. Introduction

Airborne laser scanning (LiDAR) is a remote sensing technology for characterizing the surface of the earth using a cloud of georeferenced points. A single point records the height at which the emitted light was reflected back to the sensor with enough energy to generate a “spike of intensity”. During the last two decades, the adoption of this technology has increased rapidly, along with the number of applications, particularly in the fields of topography and forest inventory. In the forestry sector, LiDAR has the potential to reduce the need for intensive ground-based measurement of stand structure, making it a valuable tool for “wall-to-wall” forest inventory and mapping (Thomas et al., 2006).

1.1. Prediction methods and their limits

The most common approach for describing forest structure is referred to as the “area-based approach” (ABA), because the point cloud is aggregated and summarized into LiDAR metrics that reflect the structure of the forest at the stand level (usually square pixels of 400 m^2) (Woods et al., 2011; White et al., 2013). This method is dependent on plot-based inventory data, which is used for the calibration of statistical models relating LiDAR metrics to variables of interest, such as stand height, stand wood volume, and stand aboveground biomass (e.g. Holmgren, 2004; Ioki et al., 2009; Lim et al., 2014; Bouvier et al., 2015).

The alternative “individual tree based approach” of delineating and measuring individual tree crowns is rapidly gaining in importance (e.g. Pyysalo and Hyyppä, 2002; Morsdorf et al., 2004; Reitberger et al., 2009; Kwak et al., 2010; Yao et al., 2012; Vega et al., 2014). However, despite the decreasing costs of data acquisition and the constant increase of computing power, the ABA remains the most practical approach for large-scale inventories because it needs lower point density and is therefore cheaper. For example, due to the large landbase of the Canadian province of Quebec, the Ministry of Forests, Wildlife and Parks (MFWPQ) has recently made the decision to run a province-wide survey at a low to medium pulse density ($\sim$ 2 to 4 pulses/m^2). This will not be sufficient for delineating individual tree crowns in closed-crown forests, so we expect that the ABA will remain relevant for some years to come.

However, one drawback of the ABA is that the statistical models used cannot be generalized in every configuration. For example, when relating two metrics X and Y to a quantity of interest Q by the equation

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$Q = \alpha X^{\beta} Y^{\gamma}$, the model is not only specific to the forest type being sampled (Van Leeuwen and Nieuwenhuis, 2010; Coomes et al., 2017), because α, β and γ have been estimated using a local inventory, but is also likely to be specific to the LiDAR campaign, because X and Y could be specific to the instrument, its settings, and the pattern of flight.

Beyond the bias potentially included in existing models, the fact that ABA-based descriptions of forest structure cannot be generalized is important because in practice this might limit the usage of LiDAR for wide-scale or multi-temporal inventory surveys in forestry. Datasets acquired from different flights, and often different providers, may not be perfectly compatible. In the operational context of the province-wide survey described above, statistical incompatibility of datasets acquired with different device parameters has been observed in contiguous areas leading to a spatial discontinuities of predictions at the exact boundary of the datasets using a metric derived from the canopy surface model that was expected to emulate a measure of stand height made in classical optical imagery (Ferland-Raymond B. & Lemonde M.-O. – MFWPQ, personal communication).

One way to avoid this issue when implementing the ABA on a large scale is to collect inventory data for each LiDAR survey, and to fit the statistical models separately. However, this is not ideal in the case of two contiguous datasets that share the same forest type. Also, such a solution implies a new ground inventory and a new calibration is necessary for each dataset, which is both time-consuming and costly. An ideal automated approach would involve the development of models that remain stable for any LiDAR settings and could therefore be applied to various datasets sampled at different times and by different providers.

One potential solution to this problem is to develop models using metrics that remain stable when acquisition parameters change. Such considerations are rarely presented in the literature, though Næsset (2004) reported that the height of first returns did not vary significantly with flight altitude or footprint diameter (footprint size ranged between 16 and 26 cm), while last returns were more sensitive to variation in footprint diameter. The most common practice is to process a large number of candidate metrics and aim for the highest possible goodness-of-fit by automatically selecting the best combination of usually 3 or 4 of them (for model parsimony) to predict a variable of interest. This approach generally includes little consideration for metric stability. Moreover, the intrinsic nature of LiDAR point clouds implies that there are endless possibilities to develop new variants of each metric, a fact that limits the possibility to make general assessments of their robustness.

A second solution is to examine the effect that acquisition parameters have on the structure of the point cloud, and hence on metrics and model predictions. This option has received more attention in the literature, particularly the influence of pulse density on model predictions (e.g. Lovell et al., 2005; Anderson et al., 2006; Thomas et al., 2006; Gobakken and Næsset, 2008; Lim et al., 2008; Pirotti and Tarolli, 2010; Jakubowski et al., 2013). Most of these studies reached the conclusion that pulse density has little or no effect on predictions because many statistical metrics remain stable when pulse density is artificially reduced (by definition of what a statistic is). Some studies concluded that pulse density affects the accuracy of the predictions without necessarily introducing bias (Magnusson et al., 2007; Magnussen et al., 2010; Ruiz et al., 2014). However, metrics such as maximum height and its derivations are not stable because they are not statistics. Models that rely on unstable metrics can yield biased predictions at low pulse densities (e.g. Nilsson, 1996; Næsset, 1997; Evans et al., 2001; Sadeghi et al., 2015) especially for multi-temporal or multi-provider datasets.

Prior studies generally use an empirical (data-driven) approach to test if acquisition parameters have a measurable effect on particular metrics. However, hypothesis-driven efforts dedicated to correcting the bias that such effects may cause have mainly been restricted to the normalization of signal intensity (e.g. Höfle and Pfeifer, 2007; Kukko et al., 2008). This approach can also be used to recompute LiDAR metrics as if they were obtained from an idealize "standard device". Such a standardization method should yield the same metrics that would be obtained with an infinite pulse density, a null footprint size and a constant scan angle at nadir as it has been achieved for signal intensity.

1.2. The specific case of maximum height (h_{max}) and derived metrics

In this paper we focus on the metric h_{max} expressed in two different ways. We derive a mathematical model for understanding how bias in h_{max} varies as a function of pulse density, forest structure, and the scale at which it is computed (the window size). We also examine effect of the footprint size, and a derived metric called C_{mean}, which allows us to further examine the issue of scale dependency.

We examine two sources of variation in pulse density: variation between datasets and variation within datasets. Variation between datasets is mainly attributable to fixed differences in device and flight parameters. Finer scale variation within a single dataset is due to overlaps between flightlines (twice as many pulses per square meter on average), and variation in aircraft speed and attitude (mainly pitch adjustments), which are rarely discussed in the literature. Aircraft pitch adjustments are unavoidable because of the need to maintain the specified altitude. Direction and speed corrections are also common and may result in local variations in pulse density. The local pulse density variations that result from pitch corrections create a clear geometric pattern perpendicular to the flight direction (Fig. 1). Gatziolis and Andersen (2008) presented a similar pattern and highlighted the fact that its effects on predictions remain unknown.

2. Methods

2.1. Study area

The study area is located within the Haliburton Forest and Wildlife Reserve (Fig. 2). The forest is a 32 , 000 ha privately owned

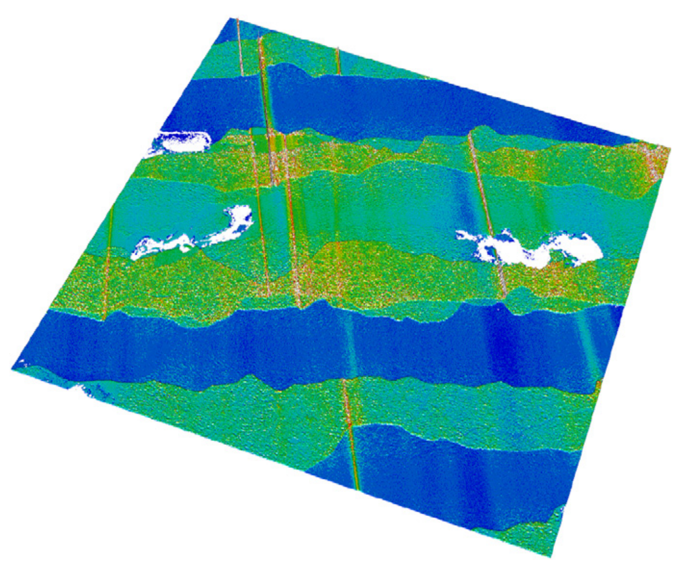

Fig. 1. Heat map of the variation in pulse density across a 4 km^2 area. Dark blue: low density; light blue and green: intermediate density; yellow and red: high density. Variation is due to overlap between adjacent flight lines (running from left to right) and aircraft pitch corrections, which cause the perpendicular stripes (running from top to bottom). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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