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Linking lidar and forest modeling to assess biomass estimation across scales and disturbance states

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ABSTRACT

Light detection and ranging (lidar) is currently the state-of-the-art remote sensing technology for measuring the 3D structures of forests. Studies have shown that various lidar-derived metrics can be used to predict forest attributes, such as aboveground biomass. However, finding out which metric works best at which scale and under which conditions requires extensive field inventories as ground-truth data. The goal of our study was to overcome the limitations of inventory data by complementing field-derived data with virtual forest stands from a dynamic forest model. The simulated stands were used to compare 29 different lidar metrics for their utility as predictors of tropical forest biomass at different spatial scales. We used the process-based forest model FORMIND, developed a lidar simulation model, based on the Beer-Lambert law of light extinction, and applied it to a tropical forest in Panama. Simulation scenarios comprised undisturbed primary forests and stands exposed to logging and fire disturbance regimes, resulting in mosaics of different successional stages, totaling 3.7 million trees on 4200 ha. The simulated forest was sampled with the lidar model. Several lidar metrics, in particular height metrics, showed good correlations with forest biomass, even for disturbed forest. Estimation errors (nRMSE) increased with decreasing spatial scale from < 10% (200-m scale) to > 30% (20-m scale) for the best metrics. At the often used 1-ha scale, the top-of-canopy height obtained from canopy height models with fine to relatively coarse pixel resolutions (1 to 10 m) yielded the most accurate biomass predictions, with nRMSE < 6% for undisturbed and nRMSE < 9% for disturbed forests. This study represents the first time dynamic modeling of a tropical forest has been combined with lidar remote sensing to systematically investigate lidar-to-biomass relationships for varying lidar metrics, scales and disturbance states. In the future, this approach can be used to explore the potential of remote sensing of other forest attributes, e.g., carbon dynamics, and other remote sensing systems, e.g., spaceborne lidar and radar.

1. Introduction

Due to their important role in the global carbon cycle and ongoing deforestation and degradation, tropical forests are of particular interest to biomass remote sensing. Tropical forest carbon accounting and monitoring of deforestation are important tasks in the context of REDD + and global climate modeling. In recent years, remote sensing has led to considerable improvements in this field (Gibbs et al., 2007; De Sy et al., 2012; Pan et al., 2013). Airborne small-footprint lidar (light detection and ranging) is currently the state-of-the-art technology for measuring the 3D structure of forests (Lefsky et al., 2002b; Wulder et al., 2012; Mascaro et al., 2014). Various lidar metrics correlate well with different forest attributes. In particular, lidar-derived height metrics have commonly been used to predict forest aboveground biomass (AGB) and carbon density (ACD) (Drake et al., 2002; Asner et al., 2009; Dubayah et al., 2010; Jubanski et al., 2013; Asner and Mascaro, 2014). The major challenges in biomass estimation based on lidar data are that 1) the calibration of the prediction functions relies on field data that must be collected manually in inventory plots; and 2) there are many different metrics available using different spatial scales, and the task is to find the combination that provides accurate AGB predictions.

In inventory plots, tree diameters at breast height (DBH) are typically measured, from which AGB is calculated via known allometric equations (e.g., Chave et al., 2005, 2014; Chen, 2015). Lidar data are acquired for the same inventory plots to build regression models between lidar-based structure metrics and ground-based AGB. A wide range of metrics can be calculated from lidar data. To date, no standard approach for AGB estimation from lidar has been established and

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different studies have applied different metrics (Chen, 2013; Lu et al., 2014). Several publications have compared metrics among each other for different forest types (e.g., Lefsky et al., 1999, 2002a; Dubayah et al., 2010; Jubanski et al., 2013). However, there has not been a comparison of a wide range of metrics on a single tropical forest dataset. Lidar metrics can generally be divided into metrics which are based on the full 3D point cloud of lidar returns and metrics which are based on canopy height models (CHM), i.e., the rasterized canopy surfaces which are derived from the uppermost returns of the point clouds (Chen, 2013). The full 3D point cloud contains more information about the vertical canopy structure than the corresponding CHM. On the other hand, the vertical distribution of lidar returns also depends on technical properties of the specific sensor, making point-cloud-based metrics less robust and comparable between different studies than CHM-based metrics (Næsset, 2009; Asner and Mascaro, 2014). Many commonly used metrics can be calculated based on both types of data. Those metrics include mean heights (Lefsky et al., 2002a; Asner and Mascaro, 2014), relative height quantiles (the heights below which a certain percentage of returns or pixels falls) (Patenaude et al., 2004; Dubayah et al., 2010; Meyer et al., 2013), and metrics of heterogeneity such as the standard deviation of heights or the Shannon diversity index of the height profiles (Stark et al., 2012). Other metrics, such as the ratio of above ground returns to total returns or fractional canopy cover above a certain height, that can be derived either from point clouds or CHMs describe relative vegetation cover.

An important aspect of AGB prediction from remote sensing is spatial resolution. Resolution means, first, spatial resolution of the remote sensing data from which different metrics are calculated and, second, the spatial resolution of the output map, i.e., the grain size of the units for which the metrics are calculated to produce an AGB prediction. The resolution of the data is determined by the sensor's technical specifications and the capacities to store and process data. The resolution of the mapping units is influenced by the desired estimation accuracy and the desired spatial detail of the mapped product. Köhler and Huth (2010), Mascaro et al. (2011b) and Chen et al. (2016) showed how errors in AGB estimations from mean lidar heights decreased with increasing grain sizes and that a grain of approximately 1 ha is required to achieve errors of < 10%.

Fitting any of the described lidar metrics to measured AGB relies on field inventory data. Forest inventory plots are limited in number, size and structural variety. The collection of inventory data is costly and laborious and most studies in the past made use of tens to a few hundred plots (Fassnacht et al., 2014). Those plots are often located in old growth forests. Hence, available data sets might not cover the full structural complexity of forests over their entire successional range (noteworthy exceptions are e.g., Dubayah et al., 2010, Poorter et al., 2016). For lidar-to-AGB-calibration, a broad range of different forest succession states that cover the range of all possible AGB stocks and associated forest structures is preferable. To overcome this limitation, we propose a new approach in which we complement in situ measurements with simulated forest stands (Fig. 1). We used an individual-based forest model (FORMIND, Fischer et al., 2016) to simulate a large virtual inventory dataset, covering the full range of succession stages by including forest disturbances in the simulations. The model was parameterized to represent the well-studied lowland tropical rainforest of Barro Colorado Island, Panama (Condit et al., 2001; Kazmierczak et al., 2014). We developed a lidar model to sample lidar data of simulated forest stands.

The research goals of this study were 1) to establish a lidar simulation model that is able to produce synthetic lidar-like data for dynamic forest model output; 2) to test a wide variety of lidar metrics for their ability to predict AGB of a tropical rainforest at various spatial scales; and 3) to investigate the influence of disturbances on the lidar-to-biomass relationships.

2. Material & methods

2.1. Study area

The study focused on the tropical forest on Barro Colorado Island (BCI), Panama (9.15° N, 79.85° W). BCI is a 15 km^2 island located in Lake Gatun, an artificial water body created by the construction of the Panama Canal (Condit et al., 2001). It is covered with semi-deciduous tropical lowland rainforest, the minimum forest age is estimated to range from 300 to 1500 years (Bohlman and O'Brien, 2006; Meyer et al., 2013; Lobo and Dalling, 2014). The climate is characterized by average daily maximum and minimum temperatures of 30.8 and 23.4 °C and an annual precipitation sum of approximately 2600 mm, with a dry season from January to April (Condit et al., 2001). A 50-ha rainforest observation plot is located on the central plateau of the island, with terrain altitudes varying between 120 and 160 m above sea level (Lobo and Dalling, 2014). Since the establishment of the plot in the early 1980s, each tree in the 1000 m × 500 m area with a DBH ≥ 1 cm has been measured during censuses in five year intervals (Condit, 1998; Hubbell et al., 1999, 2005). Estimates of the mean canopy height are 24.6 ± 8.2 m, and those of the mean AGB are 281 ± 20 t/ha (Chave et al., 2003).

2.2. Lidar data

An airborne discrete point cloud lidar dataset was collected on BCI in August 2009 with a multi-pulse scanning laser altimeter (Optech ALTM Gemini system; BLOM Sistemas Geoespaciales SLU, Madrid, Spain, Lobo and Dalling, 2014). The terrain elevation was subtracted from the point cloud to obtain the relative height above ground. Point densities ranged from 0 to 60 m^{-2} with a median of 10 m^{-2} and a 5th-percentile of 4 m^{-2}. To avoid locally varying point densities, caused by flight swath overlaps, the point clouds were thinned by random subsampling of 4 returns in each square meter. A 1-m resolution canopy height model (CHM) was derived from the highest returns in each square meter. Data processing was performed using LAStools (Isenburg, 2011) and R (R Development Core Team, 2014).

2.3. Lidar model description

The purpose of the lidar model is the simulation of a lidar scan of a given forest stand. More specifically, it generates point clouds of discrete returns as usually produced by small-footprint lidar systems. As input, a tree list has to be provided. The list can either be real forest inventory data or data generated by a forest model (Fig. 2a). The basic elements of the model are trees, lidar pulses and lidar returns. Trees are characterized by their position (X- and Y-coordinate), height, crown length, crown radius, crown shape and leaf area index (LAI). The model operates in a 3D space represented by an array of cuboid voxels. Each vertical column of voxels represents one modeled lidar pulse. Lidar returns are points in 3D space, characterized by their X-, Y- and Z-coordinates.

From the tree list, a voxel representation of the entire forest is created. Thus, voxels that could potentially produce a lidar return, because they belong to a tree crown or the ground, are distinguished from empty space voxels. The voxel forest is then scanned with a virtual lidar. The simulation follows a probabilistic approach. Instead of explicitly simulating the branches and foliage and their interaction with laser beams within the tree crowns, the model assumes that the tree crown space is a homogeneous, turbid medium filled with a certain leaf area density (LAD). The probability of having a lidar return from a certain point decreases as the distance the laser beam has to travel through the medium before reaching the point increases. This relationship is analogous to the Beer-Lambert light-extinction law (Campbell and Norman, 2012). Thus, the probability for a lidar return P for each tree and ground voxel (Fig. 2c) can be calculated as a function