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Uncertainty of remotely sensed aboveground biomass over an African tropical forest: Propagating errors from trees to plots to pixels

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ABSTRACT

Quantifying the uncertainty of the aboveground biomass (AGB) and carbon (C) stock is crucial for understanding the global C cycle and implementing the United Nations Program on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD). The uncertainty analysis of remotely sensed AGB is tricky because, if validation plots or cross-validation is used for error assessment, the AGB of validation plots does not necessarily represent the actual measurements but estimates of the true AGB. Leveraging a recently published pan-tropical destructively measured tree AGB database, this study proposed a new method of characterizing the uncertainty of the remotely sensed AGB. The method propagates errors from tree- to landscape-level by considering errors in the whole workflow of the AGB mapping process, including allometric model development, tree measurements, tree-level AGB prediction, plot-level AGB estimation, plot-level remote sensing based biomass model development, remote sensing feature extraction, and pixel-level AGB prediction. Applying such a method to the tree AGB mapped using airborne lidar over tropical forests in Ghana, we found that the AGB prediction error is over 20% at 1 ha spatial resolution, larger than the results reported in previous studies for other tropical forests. The discrepancy between our studies and others reflects not only our focus on African tropical forests but also the methodological differences in our uncertainty analysis, especially in the aspect of comprehensively addressing more sources of uncertainty. This study also highlights the importance of considering the plot-level AGB estimate uncertainty when field plots are used to calibrate remote sensing based biomass models.

1. Introduction

Tropical forests contain ~50% of the aboveground carbon (C) in global vegetation (Hunter, Keller, Vitoria, & Morton, 2013), account for ~33% of terrestrial net primary productivity (Bonan, 2008), and play a crucial role in global C cycle and climate change (Grace, Mitchard, & Gloor, 2014). Tropical forests have also been experiencing intense pressure from land use changes such as deforestation and degradation (Berenguer et al., 2014). However, substantial uncertainty remains in estimating tropical forest C emissions from those human activities (Clark, Roberts, Ewel, & Clark, 2011). Because land use change is a patchy process (Ometto et al., 2014), accurately mapping the spatial distribution of tropical C stock and its dynamics is vital to reduce such uncertainty (Achard et al., 2014). Remote sensing is a promising technology to achieve this goal with its ability of providing synoptic view of the whole study area (Chen, 2013; DeFries et al., 2007).

Considerable efforts have been devoted to map tropical forest biomass at the landscape (e.g., Dubayah et al., 2010; Mascaro, Detto, Asner, & Muller-Landau, 2011; Vaglio Laurin et al., 2014), national (Asner et al., 2012), continental (Baccini, Laporte, Goetz, Sun, & Dong, 2008; Goetz et al., 2009), and even cross-continental (Baccini et al., 2012; Saatchi et al., 2011) scales using remote sensing technology. However, accompanying with the sheer number of biomass mapping studies is the substantial variations among the various estimates of biomass and C stock (Houghton, Lawrence, Hackler, & Brown, 2001; Mitchard et al., 2013; Ometto et al., 2014), which makes it difficult to choose a product for making forest management decision in mitigating the impacts of climate change.

Central to understanding the quality of remotely sensed biomass and C maps is to quantify the uncertainty of the estimated biomass from remote sensing based models (Lu et al., 2014; Wang et al., 2009). Root mean square errors (RMSE) is the most common statistic to characterize the error of remote sensing based biomass models (Zolkos, Goetz, & Dubayah, 2013) and it is calculated by comparing model prediction to "true" biomass over a sample of forest plots. One of the key distinctions of mapping biomass, compared to mapping many other vegetation attributes such as tree height and basal area, is that the ground truth biomass for calibrating a remote sensing model has rarely been directly measured (Clark & Kellner, 2012). Instead, it is estimated using allometric models with other tree- and site-level attributes, such

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as DBH (diameter at breast height), tree height and wood density, as predictors. Both the allometric model predictions and tree attributes could have errors, which can be propagated to the plot-level biomass estimates and thus affect the uncertainty of the biomass estimation from a remote sensing based model.

Remotely sensed biomass mapping involves the combined use of two types of models: 1) allometric models for estimating tree- and plot-level biomass using tree attributes such as DBH, tree height, and wood density, 2) models for predicting pixel-level biomass using remote sensing derived variables. Both models have parameters, the uncertainty of which could lead to uncertainty in biomass estimation. The omission of model parameter uncertainty will underestimate the biomass prediction uncertainty (Yanai et al., 2010).

Overall, the uncertainty assessment of remotely sensed biomass needs to consider errors and uncertainty in the whole process of upscaling biomass from tree to plot and landscape levels, including those related to field measurements, allometric models, lidar data, and statistical modeling. Many of these issues have been investigated in the past (see McRoberts and Westfall (2014) for a recent review), especially from the perspective of estimating the mean statistic of forest attributes (e.g., volume, biomass) and its uncertainty over a large area (e.g., Berger, Gschwantner, McRoberts, & Schadauer, 2014; Breidenbach, Antón-Fernández, Petersson, McRoberts, & Astrup, 2014; Gregoire et al., 2010; McRoberts & Westfall, 2014; Ståhl, Heikkinen, Petersson, Repola, & Holm, 2014). However, only a few studies (e.g., Gonzalez et al., 2010) have quantified the biomass uncertainty at the pixel level when remote sensing data are used for biomass estimation.

The main goal of this study is to develop a methodology to assess the uncertainty of remotely sensed aboveground biomass (AGB) at the pixel level over western African tropical forests in Ghana with a synergistic use of field data, airborne lidar, allometric modeling, and remote sensing based biomass modeling. This study addresses these questions: 1) what the errors associated with allometric models and lidar-based biomass models are, 2) how the errors of tree measurements collected in a forest plot will be propagated to the biomass estimates at the tree- and plot-level when an allometric model is used to predict biomass, 3) how the errors in lidar metrics will be propagated to AGB prediction, 4) how the plot-level AGB errors affect the lidar-biomass AGB modeling and prediction errors, and 5) what the major error sources in AGB prediction at the tree- and pixel levels are.

2 . Study area and data

2.1. Study area

Our study area transverses transects along a ~100 km latitudinal gradient in Southwest Ghana close to the border with Ivory Coast (Fig. 1). These transects are along the orbits of ICESat and were mapped with airborne lidar with width of ~250 m to 750 m. The first group of transects is located in the Bia Conservation Area that comprises of Bia National Park (BNP) and Bia Resource Reserve (BRR). The area covers the transition between two of Ghana's forest types, Moist Evergreen forest in the south and Moist Semi-deciduous forests in the north. BRR was logged in 1980–90, and possibly even after; it can be impacted by natural (fire, elephants' damages) and illegal human-related disturbance. BNP has a better protection status and no logging records, but fires, elephants' damages and illegal access could occur. The second group of transects is located in the Dadieso Forest Reserve (DFR), which lies south of the Bia Conservation Area but north of Boin river Forest Reserve and Disue Forest Reserve. The vegetation of the reserve is transitional between Moist Evergreen and Wet Evergreen types. DFR was illegally logged and surrounded by communities and coffee farms; furthermore it has swampier characteristics, and flooding can represent a frequent natural disturbance.

2.2. Field measurements

Along the ICESat orbits, the field plots were set up at the footprints of GLAS laser shots with the goal of upscaling biomass from local to regional scale. The GLAS waveforms were first screened to exclude the shots that are saturated or contaminated by clouds (Chen, 2010). So, the plots can be considered as a quasi-transect sample of the forests. The field plots have a square shape of 40 m by 40 m. For each plot, DBH, tree height, and species information was collected for all trees having DBH > 20 cm. For trees with DBH in the 10–20 cm range, the same information was collected in subplots of 400 m^2. We did not measure wood density but use estimates from Chave et al. (2009). A total of 36 field plots are used in our analysis (13 in BNP, 3 in BRR, and 20 in DFR).

2.3. Airborne lidar data

The study area was surveyed by an airborne campaign in March 2012 over pre-defined flight lines covering the field plots, using a Pilatus PC-6 Porter aircraft equipped with lidar and hyperspectral sensors and a digital camera for aerial photographs. The lidar sensor ALTM GEMINI (Optech Ltd.), characterized by a 1064 nm laser wavelength and able to record up to 4 range measurements, was operated 650–850 m above ground level. The minimum laser density was set to 11 points/m^2. The positional errors of the laser returns in the horizontal and vertical dimensions were lower than 0.27 m.

The raw all-returns point cloud was processed using the Toolbox for Lidar Data Filtering and Forest Studies (TIFFS) (Chen, 2007) to derive a range of metrics for AGB estimation from each plot, including: mean height, quadratic mean height, standard deviation height, height bins at 5 m intervals and 10% percentile heights. TIFFS used the ground returns identified by the data provider to generate a DTM (Digital Terrain Model) and calculated the relative height above terrain of each laser return by subtracting the corresponding DTM elevation from its original Z value. The lidar metrics were derived using the relative height of all laser points. We generated lidar metric maps of 40 m by 40 m cell size, equivalent to the field plot size.

2.4. Pan-tropical tree AGB database

We developed an allometric model from a pan-tropical destructive tree database compiled by Chave et al. (2014) (see http://chave.ups-tlse.fr/pantropical_allometry.htm) to fully characterize the tree AGB prediction errors. This database (called Chave14 hereinafter) includes a total of 4004 trees from 53 undisturbed and five secondary forest sites across tropics in Latin America, Southeast Asia, and Africa. The tree measurements include DBH (cm), tree height (m), wood specific gravity or wood density (g/cm^3), and total oven-dry AGB (kg).

3 . Methods

3.1. Errors of tree-level AGB prediction

We first developed a pan-tropical allometric model from the Chave14 tree database. An allometric model is used to predict AGB using other easily measurable tree attributes such as DBH, tree height, and wood density (denoted as $\boldsymbol{x}$ as a whole). The model is usually calibrated from a sample of trees for which AGB has been measured via destructive sampling and $\boldsymbol{x}$ has been obtained by direct measurements or estimation:

$$E(B_{tree}|\boldsymbol{x}) = f_{tree}(\boldsymbol{\beta}, \boldsymbol{x}) \quad (1)$$

$$\mathrm{var}(B_{tree}|\boldsymbol{x}) = {\sigma_{\varepsilon,tree}}^2 \quad (2)$$

where $E()$ and var() represent the expectation and variance of a variable; f_{tree} is the allometric model with parameter(s) $\boldsymbol{\beta}$ to predict tree