Agricultural and Forest Meteorology 259 (2018) 23–38

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Annual forest aboveground biomass changes mapped using ICESat/GLAS measurements, historical inventory data, and time-series optical and radar imagery for Guangdong province, China

Wenjuan Shen[a,b], Mingshi Li[a,b,*], Chengquan Huang[c], Xin Tao[d], Anshi Wei[e]

[a] College of Forestry, Nanjing Forestry University, Nanjing, 210037, China
[b] Co-Innovation Center for Sustainable Forestry in Southern China, Nanjing Forestry University, Nanjing, 210037, China
[c] Department of Geographical Sciences, University of Maryland, College Park, MD, 20742, USA
[d] Department of Geography, University at Buffalo, Buffalo, NY 14261, USA
[e] Guangdong Provincial Center for Forest Resources Monitoring, Guangzhou, 510173, China

ARTICLE INFO

Keywords:
Forest aboveground biomass
Forest inventory data
ICESat/GLAS
Multisource remotely sensed data
Stochastic models
Southern China

ABSTRACT

Forest aboveground biomass (AGB) assessments are essential for accurate understanding of carbon accounting under forest disturbance effects and climate change. We mapped AGB data (from 1986 to 2016) by combining the forest inventories and multisource remotely sensed data, including the Ice, Cloud, and Land Elevation Satellite data and Landsat dense time series imagery, and L-band Synthetic Aperture Radar (PALSAR) mosaic data in Guangdong, China. We used random forest (RF) and stochastic gradient boosting (SGB) algorithms to determine the optimal variables of statistical models for mapping and validation of the AGB purpose. Our results showed that the Geoscience Laser Altimeter System (GLAS)-based AGB correlated well (R^2_{adj} = 0.89, n = 277, p < 0.001, RMSE = 21.24t/ha) with those obtained using the field-based method that used an RF-based approach, although inevitably, there is a saturation problem. The combined remotely sensed optical and radar imagery and ancillary data sets for mapping AGB using the RF algorithm yielded a stronger (R^2_{adj} = 0.86, n = 558, p < 0.001, RMSE = 11.35t/ha) linear correlation with those produced using the GLAS waveform data than that produced using the SGB algorithm. The overall accuracy and Kappa coefficient of mapping forests based on the PALSAR-forest/non-forest Landsat-based phenology for AGB masking were approximately 92.1% and 0.83, respectively. Additionally, the total amount of AGB had increased from 1986 to 2016 by 55.9%. The same increasing trend was observed for total AGB in both mid-subtropical (from 42% to 62%) and south-subtropical (from 38% to 57%) evergreen broadleaved forests, whereas a decreasing trend was witnessed in the tropical forest, particularly after 2010. There was an upward trend of total AGB among the four economic zones of Guangdong; the mountainous area had the highest AGB value distribution, accounting for 58%–70%, followed by the Pearl River Delta region (20%–30%), the western coast of Guangdong (3%–9%), and the eastern coast of Guangdong (2%–7%). The resulting provincial continuous forest AGB maps will provide a better evaluation of carbon dynamic in southern China.

1. Introduction

Accurate forest biomass assessments are important for evaluating forest carbon stocks and terrestrial carbon dynamics (Fang et al., 2001; Houghton et al., 2009; Le Toan et al., 2011; Tian et al., 2017). Traditional forest inventories (Lu, 2006) or field-based allometric equations (Lucas et al., 2006) have been conducted for the calculation of forest aboveground biomass (AGB). A major barrier to quantifying AGB has

Abbreviations: NFI, National Forest Inventory; FMPI, forest management planning inventory; Annual Landsat data, Landsat data per year; extrapolated, using model to extrapolate to where there is no AGB value; scene, Landsat word reference system-2 path/row level; GLC, China's 30 m GlobeLand30 land cover data; ntree, number of random forest trees; mtry, number of variables to try at each node of random forest trees; nodesize, minimum size of terminal nodes; n.trees, the number of stochastic gradient boosting trees for an SGB model; shrinkage, shrinkage parameter applied to each tree in the expansion; interaction.depth, maximum depth of variable interactions; bag.fraction, fraction of the training set observations randomly selected to propose the next tree in the expansion; n.minobsinnode, minimum number of observations in the trees terminal nodes; v.fold, the number of cross-validation folds; varselect.thres, a vector of indexes of variables selected after "thresholding step"; varselect.interp, a vector of indexes of variables selected after "interpretation step"; varselect.pred, a vector of indexes of variables selected after "prediction step"; OOB, out of bag; VI, variable importance

* Corresponding author at: Department of Forest Resources Management, College of Forestry, Longpan Road 159, Nanjing Forestry University, Nanjing, Jiangsu Province, China.
E-mail address: nfulms@njfu.edu.cn (M. Li).

https://doi.org/10.1016/j.agrformet.2018.04.005
Received 1 November 2017; Received in revised form 8 April 2018; Accepted 9 April 2018

been identified as being the ground-based inventory that lacks timeliness and spatial coverage (Lu, 2006), especially for large-scale AGB measurements. For this reason, remotely sensed data have been widely applied in detecting forest biomass (Dong et al., 2003; Foody et al., 2003; Lefsky et al., 2002; Lu, 2006; Lu et al., 2016).

Integration of both optical data (e.g., HJ-1, MODIS, and Landsat) and radar data (Synthetic Aperture Radar (SAR); e.g., Phased Array L-band Synthetic Aperture Radar (PALSAR) on the Advanced Land Observing Satellite (ALOS) satellite) captures more useful information from canopy cover and canopy structure (Guo et al., 2010; Shen et al., 2016; Xing et al., 2016). Additionally, full-waveform, large-footprint, satellite-based Geoscience Laser Altimeter System (GLAS) data (Schutz et al., 2005) overcomes both the cost intensiveness of airborne LIDAR (light detection and ranging) data or high-resolution images, and the spatial limitations of field-based techniques. The GLAS-based waveform can be used to estimate large-scale forest structures, such as height and AGB (Chi et al., 2015; Duncanson et al., 2010; Huang et al., 2017; Lefsky et al., 2005; Mitchard et al., 2012; Saatchi et al., 2011; Simard et al., 2011; Sun et al., 2008; Yu et al., 2015).

Many studies have found the value of gaining high-quality field measurements when monitoring and validating AGB (Chen, 2013; Su et al., 2016; Wulder et al., 2008). A direct geolocation linkage between the field inventories and GLAS waveforms is the most straightforward approach to solve the spatially discontinuous GLAS footprints (its footprints with a nominal diameter of 70 m are spaced at 170 m along tracks and tens of kilometers across tracks) (Schutz et al., 2005) and ultimately estimate AGB (Baccini et al., 2012; Chi et al., 2015, 2017; Saatchi et al., 2011; Zhang et al., 2014b). Two major field measurement sources called National Forest Inventory(NFI) (Shen et al., 2016; Zhao et al., 2012) and Forest Management Planning Inventory (FMPI) (Lei et al., 2009; Xie et al., 2011) in China can be applied to estimate GLAS waveform-based AGB, excluding the different resolution sizes of airborne LIDAR data (Nelson et al., 2017).

Extrapolating GLAS-based biomass estimates to MODIS has been successfully utilized over the past few years (Chi et al., 2015; Hu et al., 2016; Margolis et al., 2015; Su et al., 2016; Zhang et al., 2014b). The disadvantage of this approach is the mismatch in spatial resolutions between MODIS and field measurements, and inability to capture multi-year biomass dynamic changes evaluation. Landsat data of 30 m spatial resolution could match a majority of plots to predict spectrally forest biomass (Lu et al., 2016; Main-Knorn et al., 2013; Powell et al., 2010); for example, a study with two cloudless Landsat data from two different years for GLAS-based AGB extrapolation (Chi et al., 2017). The PALSAR image pixels are similar to the size of Landsat pixels and plot (Yu and Saatchi, 2016). The trend is to use multi-sensor remote-sensing systems integration, including optical, radar, and space-borne LIDAR data (i.e., GLAS), in view of the weakness of a single sensor, which indicates the great potential of GLAS-based forest biomass estimation.

Various approaches could be used to derive GLAS-based AGB from the field plot observations, including stepwise regression, SR; partial least-squares regression, PLSR; ordinary least squares, OLS; support vector regression, SVR; k nearest neighbors, kNN (Duncanson et al., 2010; Guo et al., 2010; Margolis et al., 2015; Zhang et al., 2014b). SR provided the widest range of biomass estimates, but with the greatest uncertainty in overfitting (Chi et al., 2017; Zhang et al., 2014a, b); poor validation performance of SR and PLSR was found (Zhang et al., 2014b). Few studies, however, have explored the random forest (RF) approach in GLAS-derived AGB. RF and stochastic gradient boosting (SGB) are both nonparametric modeling techniques. RF outperformed other regression methods (Coulston et al., 2012), although previous studies looking at individual year continuous models for AGB estimation pointed out that the SGB approach outperformed the RF, or both approaches showed extremely similar performance (Dube et al., 2014; Freeman et al., 2015). There has been little direct comparison of RF and SGB for continuous GLAS waveform-extrapolated footprint AGB.

The specific objectives of the current study were as follows: (i) constructing RF-based GLAS waveform-derived AGB model from field inventory data; (ii) capturing GLAS waveform- extrapolated footprint AGB to the scene level based on Landsat time-series data (1986–2016) and PALSAR data (2007–2016); (iii) exploring and validating the ability of RF and SGB for quantifying AGB; and (iv) identify and map of annual forests for AGB masking from 1986 to 2016 based on the integration of the PALSAR-based forest/non-forest (FNF) and Landsat-based phenology variables.

2. Materials and data

2.1. The study area

Guangdong Province (17.97×10^4 km^2) is located at 20°13′N to 25°31′N and from 109°39′E to 117°19′E (Fig. 1). Most of the areas have a mid-subtropical or south-subtropical monsoon climate–southern coastal region being a tropical monsoon climate. Its mean annual precipitation and temperature ranges from 1300 to 2500 mm and 19 to 24 °C, respectively. According to the Chinese climatic zones and geographic characteristics of forests (Ren et al., 2013), from north to south, Guangdong Province is divided into three forest zones (Fig. 1(b)): mid-subtropical typical evergreen broadleaved forest region, south-subtropical monsoon evergreen broadleaved forest region, and tropical monsoon forest or rainforest region (Zhou et al., 2017). Guangdong has a wet season from April to September and a dry season from November to January. February, March, and October are transition months (Wang et al., 2009). During these months, the wetness conditions can differ substantially across the province. For example, in March and April, the northern region is often wet, but the south is dry. In September, the pattern is reversed. According to the status of economic development, Guangdong Province has four economic regions, including the Pearl River Delta economic zone (PRD), the east coast economic zone (EasternGD), the west coast economic zone (WesternGD), and the northern Guangdong mountainous zone (Mountainous). Northern Guangdong is located in the valley basin and is surrounded by mountains, the PRD mainly consists of hilly lands and plains, the WesternGD is a large platform area, and the EasternGD is mostly plains.

2.2. Data acquisition and preprocessing

2.2.1. Forest inventory plots

China has a three-tiered inventory system: the first level is the NFI, the second level is the FMPI, and the third level is the Forest Operation Design Inventory (FODI) (Xie et al., 2011). A subcompartment or forest stand in FMPI is a contiguous trees region that is quite homogeneous or contains a bunch of forest features, such as species, age, site quality, average stand height, average stand diameter at breast height, and stem volume. Two years (2002 and 2007) of NFI data for the entire province and five years (2005–2009) of subcompartment data ("xiaoban" (XB)) from five cities (Guangzhou, Heyuan, Huizhou, Qingyuan, and Shaoguan) located within the study area were available for use in this study. NFI AGB (25.82 m × 25.82 m in size) was calculated from the dominant trees AGB by using the allometric equations (Shen et al., 2016). Forest stand (XB) (a range between 0.006 ha and 68 ha in size) AGB was derived from stand volume based on a biomass expansion factor developed by the Guangdong Provincial Center for Forest Resources Monitoring. GLAS footprints were overlaid onto the subcompartments and NFI data to derive the field inventory-based AGB (Fig. 2). The overall data processing and analysis workflow was summarized in Fig. 3.

2.2.2. ICESat GLAS data

The GLAS's laser footprint on the surface is elliptical, with an