Forest Aboveground Biomass Estimation using ICESat/GLAS and Imagery Remote Sensing Data in the Greater Mekong Subregion: 1st result from Yunnan Province, China

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Abstract: This study aims to develop a forest aboveground biomass (AGB) mapping method in the Greater Mekong Subregion (GMS). Vertical structure of forest parameters of two forest farms in Yunnan province, China were derive using airborne LiDAR system (ALS). Regression models were built between field data of forest AGB and percentiles of canopy height, canopy density which derived from ALS point cloud data. The high accuracy ALS estimated forest aboveground biomass (AGB) were used as training data for building forest AGB estimation model with ICESat GLAS waveform indices. Then the forest ABG was estimated at ICESat GLAS footprint level in the whole province. The regression tree and MAXENT methods were investigated to extend the AGB estimation from GLAS footprint to continuous mapping using imagery remote sensing data of ENVISAT MERIS and EOS MODIS data.

The preliminary results showed that: 1) The integrated method based on field measurements, airborne and spaceborne LiDAR data can be used to estimate forest aboveground biomass effectively. 2) The estimation agreed well with inventory based results, and the average difference was about 10%. 3) Both regression tree and MAXENT methods predicted AGB spatial distribution well. 4) These methods will be investigated further and used to the entire Greater Mekong Subregion with more reference training data.

INTRODUCTION

Forests play an irreplaceable role in maintaining regional ecological environment, global carbon balance and mitigating global climate change. Forest aboveground biomass (AGB) is an important indicator of forest carbon stocks. Estimating forest aboveground biomass accurately could significantly reduce the uncertainties in terrestrial ecosystem carbon cycle. The Greater Mekong Subregion (GMS) is rich in forest resources, the change of forest resources affect the regional even global climate change.

It is important to estimate forest AGB with high accuracy methods in this region. Remote sensing is an efficient way to estimate forest parameters in large area, especially at regional scale where field data is scarce. LIDAR (Light Detection And Ranging) provides accurate information on the vertical structure of forests. Combining airborne LiDAR and spaceborne LiDAR for regional forest biomass retrieval could provide a more reliable and accurate quantitative information in regional forest biomass estimate.

Foody et al (2003) estimated tropical forest biomass from Landsat TM data between sites in Brazil, Malaysia and Thailand and results showed that for each test site, the vegetation indices of Landsat TM data most strongly related to the biomass of the training data. Muukkonen et al (2007) used forest inventory data and MODIS data to estimate forest biomass and compared the results with National Forest Inventory data found the relative RMSE was 9.9%. These researchers showed that optical remote sensing can be used to build empirical relationships between the forest biomass and spectral reflectance, especially at regional scale where field data is scarce (Lim et al., 2003).

Light Detection and Ranging (LiDAR) is one of the most promising technologies for retrieval of various forest biophysical properties (Lefsky et al., 1999; 2005). Although airborne LiDAR can estimate tree height with sub-meter vertical accuracy and spatial resolution but its utility is limited in large area for its high cost (Boudreau et al. 2008). The first spaceborne large footprint LiDAR sensor (ICESat/GLAS) acquired over 250 million LiDAR observations over forest regions globally and has been used successfully for forest height and biomass estimation in various sites (Lefsky et al., 2007; Boudreau et al. 2008; Duncanson et al., 2010; Pang et al., 2011). Lefsky et al (2005) used ICESat/GLAS and SRTM data to estimate forest height and aboveground biomass and demonstrated that GLAS data were able to predict forest heights successfully over a wide range of canopy height and aboveground biomass. (Nelson et al., 2009) used optical data from the MODIS and waveform data from ICESat/GLAS to estimate timber volume in Central Siberia. The encouraging result showed that GLAS and MODIS data can be used to develop accurate regional estimates of timber volume.

In this paper, airborne LiDAR and ICESat/GLAS data were used to estimate forest aboveground biomass at footprint level in Yunnan Province of China and a continue forest biomass map was generated by combined optical data and LiDAR estimated biomass samples.

STUDY SITE AND DATA

1) Study site

The Yunnan Province in the southwest of China extends from 97°19′ E to 106°07′ E and 21°04′ N to 29°09′ N, bordered by Myanmar, Laos, and Vietnam (Fig. 1).

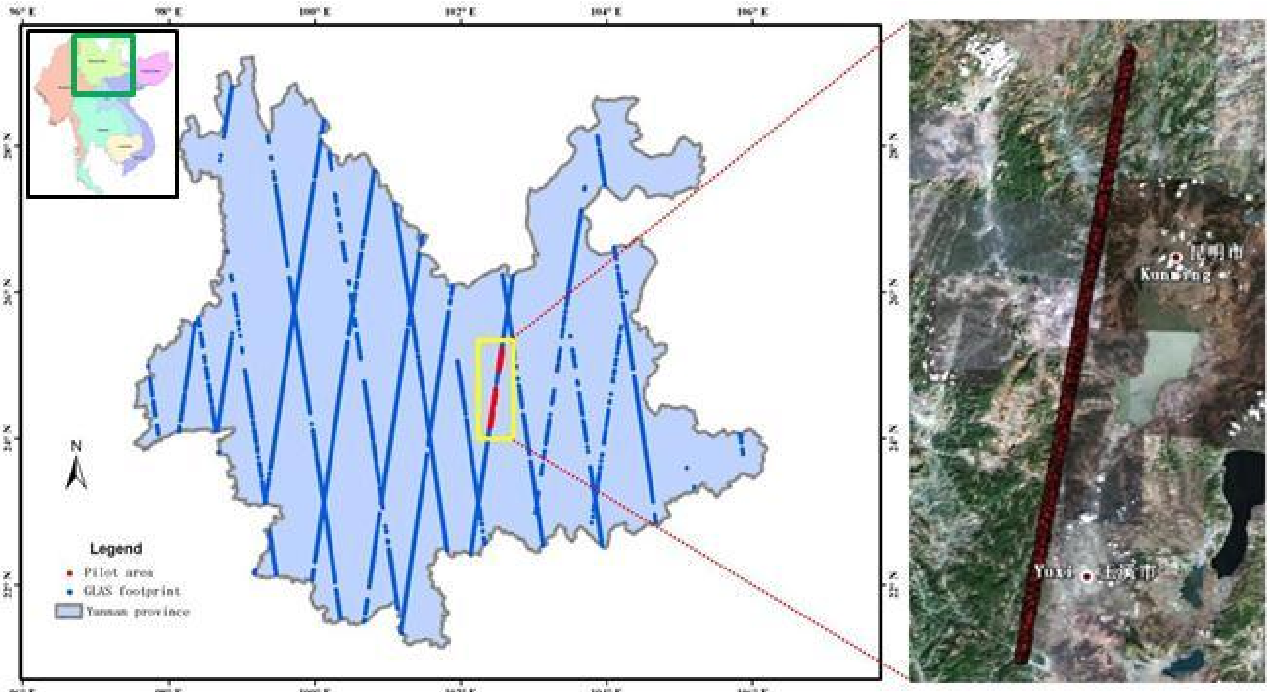

Figure 1: Study area in Yunnan, China (blue points represent GLAS shots and the zoom in map of yellow rectangle are covered by airborne LiDAR data in Kunming and Yuxi)

Yunnan is situated in a mountainous area, with highest elevations in the northwest reaching more than 5,000 m and lowest elevations of 76.4 m in the southeast. Average annual rainfall ranges from 600 mm to 2,300 mm. It is rich in natural resources and has the largest diversity of plant life in China. The dominant tree species are coniferous (*Pinus yunnanensis*, *Pinus kesiya var. langbianensis*, *Pinus armandii*, *Picea asperata Mast* and *Keteleeria evelyniana*). There are also some broadleaf forests, primarily in regenerated forests (*Alnus nepalensis*, *Hevea brasiliensis*, *Quercus variabilis* and *Quercus cautissima*).

2) Remote sensing data

Airborne lidar waveform data was collected using the LiteMapper 5600 system flown an orbit of ICESat/GLAS in December of 2007. The Riegl LMS-Q560 laser was used. This system has a wavelength of 1550 nm, with a 0.5 mrad beam divergence and 3 ns pulse length. It operated at a 50 kHz pulse rate at 650 m relative flight height. The resulting footprint size was 35 cm with a point density of approximately 2 points/m^2.

The Geoscience Laser Altimeter System (GLAS) board on ICESat (Ice, Cloud, and land Elevation Satellite) launched on Jan. 12, 2003, is the benchmark Earth Observing System mission for measuring ice sheet mass balance, cloud and aerosol heights, as well as land topography and vegetation characteristics. GLAS Level-1A altimetry data (GLA01), level-1B waveform parameterization data (GLA05) and level-2 land altimetry product (GLA14) were used to estimate forest height and biomass. The GLA01 data include the transmitted and received waveform from the altimeter. The GLA05 data contain waveform-based range corrections and surface characteristics. The GLA14 data contain the land elevation and land elevation distribution data. A dataset of 20,317 GLAS full waveforms with cloud-free profiles during period L3E (Feb. 22 to Mar. 27, 2006) over the study area was downloaded from the National Snow and Ice Data Center (NSIDC) (http://nsidc.org/data/icesat/). There were 260 filtered GLAS shots from L3E period within the coverage of the airborne LiDAR over pilot sites used to link with airborne LiDAR data.

MODIS Vegetation Continuous Field (VCF) (MOD44B) product of 2005 was used for extending the GLAS estimates. The VCF product shows the coverage of vegetation such as "forest" or "grassland" exists in each pixel. The product is derived from all seven bands of was estimated from MODIS 1-7 bands using supervised regression tree algorithm (Hansen et al., 2003). Globcover Land Cover product of ENVISAT MERIS is 300 m resolution with a legend defined and documented using the UN Land Cover Classification System (LCCS). The product has 22 different land cover classes at the global level (Defourny et al., 2006). Class ID for 40, 50, 60, 70, 100, 110 and 120 were defined as forest covers in this study (Table 1). The GlobCover Land Cover product of central Asia for the period from Dec., 2004 to Jun., 2006 and GlobCover Annual MERIS FR mosaic product which computed by averaging the surface reflectance values of these bimonthly products generated over the year 2005 were used in this study.

Table 1: Forest Classes used in Globcover Product

Class ID	Globcover legend
40	Closed to open (>15%) broadleaved evergreen or semi-deciduous forest (>5m)
50	Closed (>40%) broadleaved deciduous forest (>5m)
60	Open (15-40%) broadleaved deciduous forest/woodland (>5m)
70	Closed (>40%) needleleaved evergreen forest (>5m)
100	Closed to open (>15%) mixed broadleaved and needleleaved forest (>5m)

110	Mosaic forest or shrubland (50-70%) / grassland (20-50%)
120	Mosaic grassland (50-70%) / forest or shrubland (20-50%)

3) Ground measurement data

Field data were collected from Xishan Forest Farm of Kunming and Hongta Forest Farm of Yuxi from Jul. 16 to Aug. 4, 2008 in Yunnan Province. A total number of 78 circular plots were set and surveyed with radius of 7.5 m or 15 m within the coverage of airborne LiDAR. The centers of the plots were positioned by Trimble GEOXT GPS. Trees with a DBH of 5 cm and larger were measured within those plots. For each plot, biophysical parameters such as species of dominant trees, DBH and height of trees were calculated. DBH was measured by diameter tape, tree heights were measured by Impulse-200 laser altimeter.

DATA PROCESSING METHOD

NSIDC provided IDL tools to read and processing binary data of GLA01, GLA05 and GLA14. GLAS waveforms contain lots of noise. In our work, the threshold was set to the background noise plus 4.5 times the standard deviation (Lefsky et al. 2005). We exclude abnormal data that with low signal to noise ratio or influenced by cloud (e.g., maximum intensity value of waveform under 80). Three variables of GLAS waveform by Lefsky et al (2005) were used in our study which including width, trailing edge and leading edge.

Aboveground biomasses of 40 sample plots were calculated from field measurement using species specific algometric equations. Height and density percentiles of airborne LiDAR data were used to develop regression equations with field measurements and model of aboveground biomass was developed (Fu et al., 2011).

Airborne LiDAR system was flight along the orbits of ICESat/GLAS data. Coincidence airborne LiDAR data with GLAS elliptical footprints were extracted. The GLAS footprint size varies with laser operating periods. In the research of (Pang et al., 2008), the azimuth angle, major axis radius and eccentricity fields in the ICESat/GLAS GLA05 product were used to extract Airborne discrete LiDAR data within ICESat/GLAS footprint (Equation 1):

$$\frac{((x_i * \cos(azimuth) - y_i * \sin(azimuth))^2}{ellipse\_a^2} + \frac{((x_i * \sin(azimuth) - y_i * \cos(azimuth))^2}{ellipse\_b^2} \le 1 \qquad (1)$$

where x_i and y_i are the central coordinates of airborne discrete LiDAR point i, and $ellipse\_a$ and $ellipse\_b$ can be calculated by equation 2 using the records of GLA05 data:

$$\begin{aligned} &ellipse\_a = (i\_tpmajoraxis * sqrt(1 - i\_tpeccentricity^2))/2 \\ &ellipse\_b = i\_tpmajoraxis/2 \qquad (2) \\ &azimuth = i\_beam\_azimuth \end{aligned}$$

where $i\_tpmajoraxis$ and $i\_tpeccentricity$ are the major axis and eccentricity of GLAS shot; $azimuth$ represent the vector from the ground to the spacecraft.

Forest biomass within GLAS footprints were estimated by airborne LiDAR. Then we developed a predictive regress model between airborne LiDAR estimated biomass and GLAS waveform parameters.

Models between GLAS waveform parameters and airborne LiDAR estimates of biomass were developed and applied to quality-filtered GLAS footprints of L3E period in the study area to estimate the biomass. The biomass within GLAS footprints of the study area were used to fusion with optical data.

Then the regression tree and maximum entropy methods were used to extend the AGB estimation from GLAS footprint to continuous mapping using imagery remote sensing data of ENVISAT MERIS and EOS MODIS data. According to different types of ecological zones, a set of categorical regression models was built between ICESat GLAS estimates and optical spectral variables. The cubist software was used for regression tree analysis (Pang et al., 2011). The MAXENT software was used for maximum entropy analysis (Philips, et al, 2006; Saatchi, et al, 2010).

RESULTS

The stepwise regression analysis method was used to select airborne LiDAR variables which contribute biomass estimates. The results showed that forest AGB could be well estimated by airborne LiDAR with an R^2 of 0.68. The RMSE of the regression was 1.54 Mg/ha (2.5% of average value).

A dataset of 260 GLAS shots in L3E period which covered by airborne LiDAR scans were extracted for developing regression equations of forest AGB. Three parameters of GLAS waveform including width, trailing edge, leading edge and some transformations of these three basic waveform parameters were used to develop regression equations with airborne LiDAR estimates (Equation 3).

$$w_a = -48.67 + 7.22 * width - 44.31 * \sqrt{trail} + 2133.08 * \frac{trail}{width^2} \qquad (3)$$

where w_a is aboveground biomass; $width$ is GLAS waveform extent; $trail$ and $lead$ represent Trailing edge and Leading edge respectively which mentioned in 1.7. Results showed that the regression equation of biomass has an R^2 of 0.52 and RMSE of 30.96 Mg/ha (Fig 2).

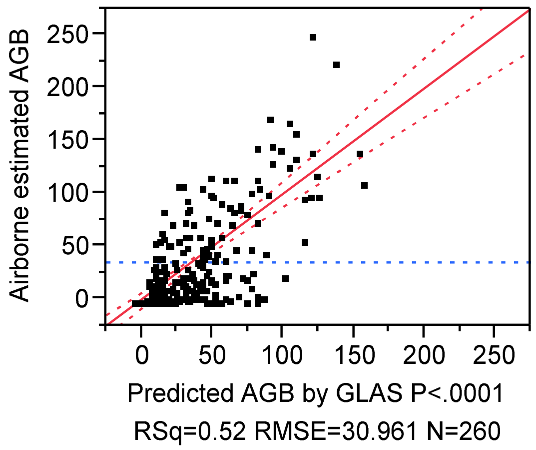

Figure 2: Forest aboveground biomass estimated using GLAS-airborne LiDAR equations.

Then the continuous forest aboveground biomass map was generated using the basic estimates by ICESat/GLAS (total footprints of 20,317) and extrapolated by MODIS and MERIS products in study area. In the regression tree model evaluation, the overall average error of the estimation models was 34 ton/ha, with a correlation coefficient of 0.7. The Figure 3 showed the estimated forest aboveground biomass using maximum entropy method. The regression method gave similar spatial pattern.

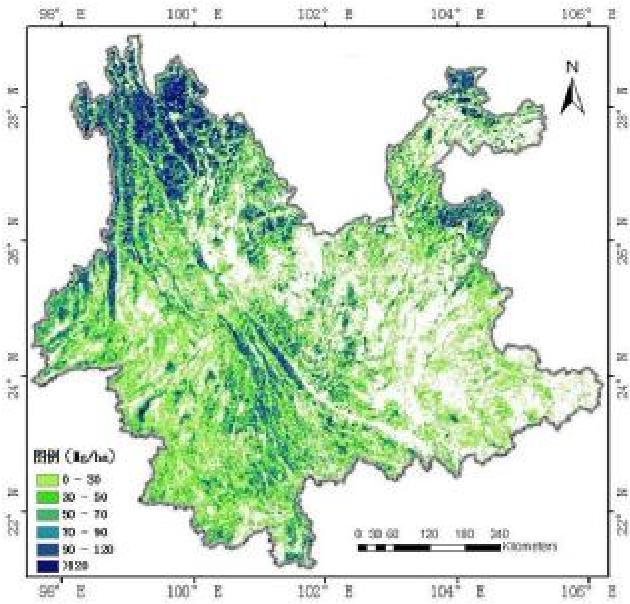

Figure 3: Estimated forest aboveground biomass of Yunnan Province

The total estimated AGB by GLAS in study area were 1272 and 1173 million tons by regression tree and maximum entropy method respectively. The remote sensing estimations from regression tree and maximum entropy method showed good consistent. These remote sensing estimations were compared with results from traditional ground inventory method. As shown in Figure 4, our estimation is comparable with the early research of Li et al (2010) which reported that total forest biomass (including underground biomass) of Yunnan was 1735 million tons (Based on data of The 7th National Forest Inventory during 2004-2008). According to the root-shoot ratios which suggested by IPCC, we used 0.32 as the root-shoot ratio considering the forest composition in the study area. Then the transformed AGB is 1180 from inventory estimation.

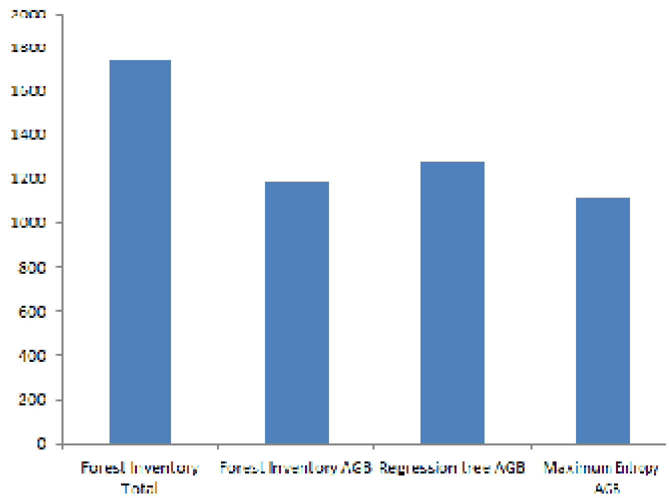

Figure 4: The comparison of total biomass from different estimation methods

Despite of total biomass in the area, the remote sensing estimations provide spatial distribution of these biomass. Result showed that high AGB levels were distributed in northwest and center southern of the study area. This spatial pattern is reasonable since most of the nature reserves are located in these regions. For example, there are several forest nature reserves located in northwest of Yunnan such as Yulong Snow Mountain, Baima Snow Mountain, Haba Snow Mountain and Bita Lake. In southern central of Yunnan, there are nature reserves of Wuliangshan, Ailaoshan, Xishuangbanna and Daweishan which were all rich in forest resource.

DISCUSSION & CONCLUSIONS

Regional forest biomass was estimated by combining airborne LiDAR, spaceborne LiDAR of ICESat/GLAS and optical remote sensing data. To conclude, the result of this study is encouraging that ICESat/GLAS can estimate forest above ground biomass successfully in regional scale which described the amount and distribution of forest AGB well in the study area. It makes a significant sense in regional forest biomass and carbon estimates. These methods will be investigated further and used to the entire Greater Mekong Subregion with more reference data.

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