ESTIMATING REGIONAL ABOVEGROUND FOREST BIOMASS USING HJ-1 SATELLITE DATA AND ICESAT

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1. INTRODUCTION

Concerns about global climate change have highlighted the significance of finding efficient ways of quantifying terrestrial carbon stocks at regional, continental and global scales [1]. Inventories of monitoring changes could be available in evaluating the impacts of climate change, natural disturbances, deforestation and forest management on the amount and distribution of regional carbon stocks. It also provided useful information for ecosystem management and biodiversity conservation.

Estimation of Aboveground biomass (AGB) is necessary for studying productivity, carbon cycles, nutrient allocation and fuel accumulation in terrestrial ecosystems [2][3]. We deal with biomass initially because the available ground-based, tree species allometric equations and forest stand map (two forest farms) could estimate biomass. AGB is defined in this study as a biomass growing stock tree great than 5cm in diameter at breast height (DBH) for stand greater than or equal 5 years and all trees taller than 1.3m for stand less than 5 years.

2. STUDY SITE AND DATA

The study area is located in the contiguous areas between China and Russia comprises about 28000km^2. Most area is within the territory of China. The area is characterized by diverse land cover and topography. This boreal forest area belongs to the southern taiga forest of East Siberia, which is the key forestry base in China. There are two forest farms in the test site, called Changqing (CQ) and Zhuanglin (ZL). The climate is marked by cool temperature continental climate.

Both HJ-1 satellite and ICESat data were used in this study. HJ-1 includes HJ-1A, Huan Jing-1A, and HJ-1B, Huan Jing-1B (Huan Jing means Environment). They are the first two satellites of a small constellation for environmental and disaster monitoring and prediction. On board, the satellites comprise a CCD imaging system, hyperspectral camera and infrared camera. The observed image in our study captured on May 13, 2009 by CCD imaging system (HJ-1A) with 30m resolution.

The other satellite Ice, Cloud and land Elevation Satellite (ICESat) took the Geoscience Laser Altimeter System (GLAS), which is the first spaceborne lidar instrument for continuous global observation of the earth. The GLAS sensor using a 1064nm laser pulses operating at 40Hz and records a continuous record of the amplitude of the returned laser energy, from top to bottom, resulting in a ellipsoidal footprint of about 65m diameter. It acquires information on topography and the vertical structure of the vegetation [4].The Lidar waveform from large-footprint Lidar instruments has been successfully used to estimate the canopy height, stand volume, basal area and aboveground biomass [5][6][7][8].

3. METHODOLOGY

3.1. Data processing

The HJ-1 image was orthorectified and georeferenced to Universal Transverse Mercator (UTM) projection. A nearest-neighbour resampling technique was used and root mean square error of less than 0.5 pixels. After atmospheric correction and radiometric calibration, the image was used to the biomass estimation.

The primary GLAS data used in this study was the waveform data (GLA01) and standard height products (GLA14, land/canopy elevation) acquired between October 2003 and November 2006. The location accuracy of the GLAS footprints was evaluated by matching the elevation profile from GLAS with the existing DEM data. The flow for calculating the heights of quartile waveform energy from GLAS form as follows [6], the waveform was first filtered by Gaussian filter of a width similar to the transmitted laser pulse. Consequently, we estimated the noise levels before the signal beginning and after the signal ending from the original waveform separately using a method based on the histogram. Starting from the signal ending, the position of the 25%, 50% and 75% of energy were located by comparing the accumulated energy with total energy. There are 6 Gaussian peaks fit sequentially to a given waveform in the GLA14 products. The last fitted Gaussian peak is assumed to be the ground peak. The distance between signal beginning and this peak will be the maximum canopy height.

3.2. Analysis

The supervised maximum likelihood decision rule is used for the HJ-1 image classification to identify the footprints whether locate in the forest area. Then, three classes were discriminated, including conifer forest, broadleaf forest and nonforest and the average class accuracy is above 90%. Several GLAS waveforms variables were evaluated to find high accuracy relationship between GLAS waveforms parameters and tree height in CQ firstly [6]. The coefficient of determination (R^2), which is used to evaluate a regression mode performance, is 0.70 (n=47). Then, the model was used to estimate tree height within other GLAS footprints. Allometric equations were developed relating component biomass to DBH [9], which is calculated by the empirical equation as a function of tree height derived from our forest inventory. And then, AGB within each footprint could be estimated. Meanwhile, the HJ-1 image in the study area was acquired to calculate various vegetation indices. The study incorporated reflectance in four individual bands (blue, green, red and infrared (NIR)) and six vegetation indices calculated from individual bands as independent variables as follows: (1) ratio of blue and NIR (blue/NIR); (2) ratio of NIR and sum of four individual bands (NIR/ (NIR + red + green + blue)); (3) Normalized Difference

Vegetation Index (NDVI) ((NIR - red) / (NIR + red)) [10]; (4) Soil-Adjusted Vegetation Index (SAVI) ((L+1)*(NIR - red)/ (NIR + red + L)), L is a soil reflect adjustment factor [11]; (5) Modified Soil-Adjusted Vegetation Index (MSAVI) (((2NIR+1-((2NIR+1)2-8(NIR- red)) 1/2)/2) [12]; (6) Modified Vegetation Index (MVI) (((NIR - red)/((NIR + red)+0.5)) 1/2) [13]. Lastly, AGB within the GLAS footprints in the model application extrapolation process used to create forest AGB map in the whole study site.

4. RESULT

A number of multiple regression models were developed to infer AGB from GLAS and HJ-1 data. Combined with total ten variables mentioned above, the result models demonstrated that AGB estimates for conifer forest were stronger than broadleaf forest relate to the blue band and NDVI. AGB estimation for conifer forest (R^2=0.56, n=949) was much better than the result for broadleaf forest (R^2=0.44, n=454). In order to decrease the uncertain effect of these models, the study area was stratified into graded serious map.

The validation results are comparable to forest stand map in ZL. Forest inventory plots consist of many compartment polygons, which record tree height, DBH and stands volume. For every polygon, AGB was estimated by allometric equations based on DBH and tree height record. The R^2 between AGB predicted from GLAS and field investigated was 0.52.

5. DISCUSSION

The major deficiency of the ground based forest inventory is the uncertain in the inventory data. Considering the forest inventory that existing for ZL is several years old, drawn in 1999, the time periods will be a major factor to affect the accuracy of AGB estimation. This study is an attempt to estimate AGB based on GLAS data and new satellite HJ-1 data. It is meaningful to explore the degree of relationship between AGB and spectral responses. Once again, the study result has shown potential application in aboveground biomass estimation of ICESat/ GLAS.

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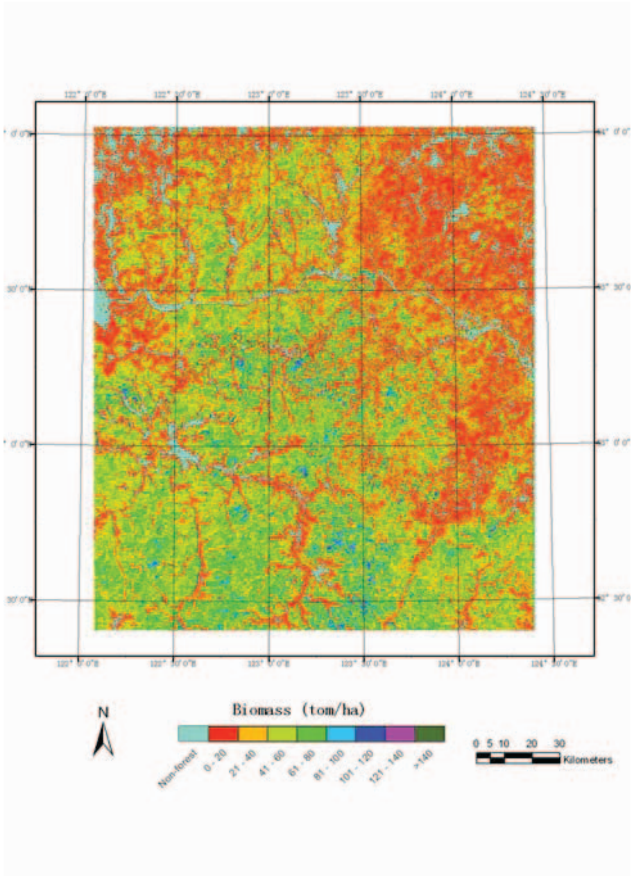

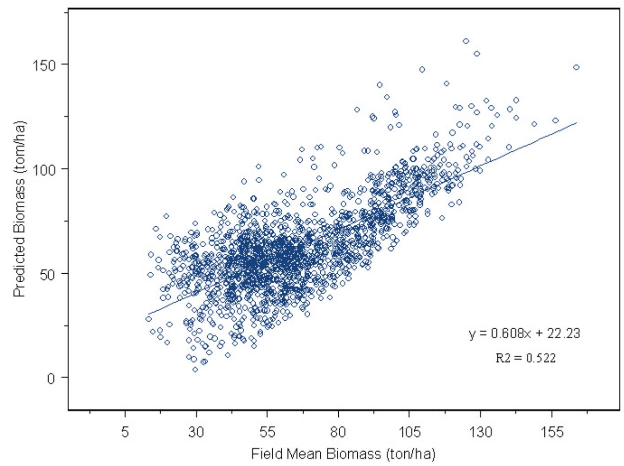

Figure.1 (left): Forest AGB
Figure.2 (up): Forest AGB predicted from GLAS data compared with field investigated biomass

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