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Estimating aboveground biomass of broadleaf, needleleaf, and mixed forests in Northeastern China through analysis of 25-m ALOS/PALSAR mosaic data

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A B S T R A C T

Aboveground biomass (AGB) of temperate forest plays an important role in global carbon cycles and needs to be estimated accurately. ALOS/PALSAR (Advanced Land Observing Satellite/Phased Array L-band Synthetic Aperture Radar) data has recently been used to estimate forest AGB. However, the relationships between AGB and PALSAR backscatter coefficients of different forest types in Northeastern China remain unknown. In this study, we analyzed PALSAR data in 2010 and observed AGB data from 104 forest plots in 2011 of needleleaf forest, mixed forest, and broadleaf forest in Heilongjiang province of Northeastern China. "*Poisson*" regression in generalized linear models (GLMs) and *BRT* (boosted regression tree) analysis in generalized boosted models (GBMs) were used to test whether the constructed PALSAR/AGB models based on individual forest types have better performance. We also investigated whether adding topographical and stand structure factors into the regression models can enhance the model performance. Results showed that GBM model had a better performance in fitting the relationships between AGB and PALSAR backscatter coefficients than did GLM model for needleleaf forest ($RMSE$ = 3.81 Mg ha^{-1}, R^2 = 0.98), mixed forest ($RMSE$ = 17.72 Mg ha^{-1}, R^2 = 0.96), and broadleaf forest ($RMSE$ = 19.94 Mg ha^{-1}, R^2 = 0.96), and performance of nonlinear regression models constructed on individual forest types were higher than that on all forest plots. Moreover, fitting results of GLM and GBM models were both enhanced when topographical and stand structure factors were incorporated into the predictor variables. Regression models constructed based on individual forest types outperform than that based on all forest plots, and the model performance will be enhanced when incorporating topographical and stand structure factors. With information of forest types, topography, and stand features, PALSAR data can express its full ability in accurate estimation of forest AGB.

1. Introduction

Temperate forests cover more than 6.4 billion hectares on the Earth, and approximately 41 Pg carbon is stored in its vegetation carbon pools, most of which is held in aboveground live biomass (AGB) (Dixon et al., 1994). In Northeastern (NE) China, the area of temperate forest is more than 38.3 million hectares and accounts for more than one third of the total forest area in China, and the carbon storage of forests in this area is about 1.4 Pg C and also accounts for about 30% of the total carbon storage in forests of China (Wang, 2006). Many factors have both positive and negative influence on forest aboveground biomass. On the one hand, human and natural disturbances, such as harvesting, fire, and pest disease, in history decreased the carbon density in NE China, which is lower than that in temperate forests of other regions over the world (Fang et al., 2001). Forests in NE China tended to be carbon source due to overharvesting and degradation during 1980s and 1990s (Piao et al., 2009). On the other hand, NE China locates in high latitude region where the climate has changed intensely since last century, and forest biomass in this region is boosted by the climate warming (Yang and Wang, 2005). More-

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over, although forests in NE China have experienced severe harvesting in history (Jiang et al., 2002; Yu et al., 2011), they had been one of the key objectives for conservation and reforestation in Natural Forest Resource Conservation Project of China since 2000 (Wei et al., 2014), and forest biomass in this region increased rapidly (Ma et al., 2016). Forest biomass in NE China has changed greatly during the past several decades. Therefore, accurate estimation of forest aboveground biomass has important significance in estimating the role of temperate forests in regional and global carbon cycle (Laurin et al., 2016) and developing science-based forest management practices.

There are a number of ways to estimate and monitor forest AGB (Brandeis et al., 2006; Soenen et al., 2010; FAO, 2015). Directly weighing individual components of trees is the most accurate way to estimate the biomass of trees (Parresol, 1999), but the method is hardly adopted because of its high cost of labor, money, and time. Conducting forest inventory and calculating forest biomass using allometric biomass equations based on DBH (diameter at breast height) and height of each tree is an efficient way (Gower et al., 1999; Wang, 2006). Although rich data of forest composition and structure can be obtained in forest inventory, it still has some deficiency in evaluating spatial distribution of forest biomass (Brown et al., 1999; Houghton et al., 2001). Moreover, it is also difficult to calculate the biomass of some tree species, as their allometric equations haven't been established yet. Remote sensing has offered a viable mean for estimating forest AGB at large spatial scales (Hansen et al., 2000; Myneni et al., 2001; Brown, 2002).

Estimation of forest AGB from remote sensing data starts with analysis of the relationship between remote sensing signals and AGB of training samples, and then applies this relationship (statistical model) to calculate AGB over the entire study area (Bastin et al., 2014). Data from optical sensors were used to estimate forest biomass, based on the relationship between forest AGB and vegetation indices, such as NDVI (normalized difference vegetation index) and EVI (enhanced vegetation index) (Huete et al., 2002; Nakaji et al., 2008). However, the applications with optical data are often limited by the lack of high quality images due to frequent clouds and saturation at low biomass level by the spectral bands and spectral indices (Nichol and Sarker, 2011). Data from LiDAR (Light detection and ranging) provide accurate three-dimension information like tree height and canopy vertical structure (Naesset, 2002; Goetz et al., 2009), and AGB is calculated using empirical equation of tree height and biomass (Lefsky et al., 1999; Zhao et al., 2009). Because of sophisticated technical equipment and high cost, airborne LiDAR images are not widely available and are less often used in biomass estimation at large spatial scales, including temperate forest of NE China (Tang et al., 2012; Zhang and Ni-meister, 2014).

Synthetic Aperture Radar (SAR) data such as L-band ALOS/PALSAR (Advanced Land Observing Satellite/Phased Array L-band Synthetic Aperture Radar) and X-band TerraSAR-X are widely available and have been increasingly used in estimation of forest AGB (Karjalainen et al., 2012; Vastaranta et al., 2014). PALSAR data were used to estimate AGB of forest plots from tropic and temperate forests to boreal forests in Africa, North America, Australia, and Russia (Lucas et al., 2007; Thiel et al., 2009; Lucas et al., 2010; Cartus et al., 2012; Sarker et al., 2012). Nonlinear regression models were developed to estimate forest AGB based on PALSAR backscatter coefficients; but the model structure and parameters vary substantially among these studies (Lucas et al., 2010; Englhart et al., 2011; Carreiras et al., 2012; Peregon and Yamagata, 2013). In addition, other forest stand properties (stand structure and complexity of understory layer) and topographical features vary among different forest types and affect forest AGB (Conard and Ivanova, 1997; Jobidon, 2000; Ma et al., 2015b). These factors also have influence on PALSAR backscatter coefficients (Lucas et al., 2010; Whittle et al., 2012; Atwood et al., 2014). Therefore, it may be useful to incorporate forest stand and topographical factors in the nonlinear regression models and to construct various regression models of different forest types for the purpose of accurate estimation of AGB.

In this study, we constructed the nonlinear relationship between PALSAR backscatter coefficients and forest AGB of different forest types in NE China, based on forest inventory data of 104 plots and PALSAR data. Forest types in NE China were divided into broadleaf forest, needleleaf forest, and mixed forest in our study. The objectives of this study were twofold: (1) determine the relationships between AGB and PALSAR backscatter coefficients by different forest types; (2) test the hypothesis that adding forest stand and topographical factors in the predictor variables of regression models can improve estimation of forest AGB.

2. Materials and methods

2.1. Study area

Our study area is the forest zone in Heilongjiang province of NE China, and it extends across 43.42°N–52.58°N, 118.06°E–135.16°E (Fig. 1). The topography is characterized by low mountains with elevation of 120–1000 m. The climate types are mid-temperate continental monsoon climate and cold- temperate continental monsoon climate. The annual mean temperature ranges from −2.8 °C in southern part to −3.2 °C in northern part. The average annual rainfall ranges from 530 mm to 800 mm, falling most in summer. Three main forest types are located in our study area, needleleaf forest in the northern part, mixed forest in the central part, and broadleaf forest in the southern part (Fig. 1). Based on our inventory data and previous studies (Ma et al., 2016; Ma et al., 2015b), species compositions of the three forest types are listed in Table 1.

2.2. Field inventory data and AGB calculation

In 2011, field inventory was carried out in various types of forests in Heilongjiang province. A total of 104 forest plots (Fig. 1) with the size of 20 m $\times$ 50 m were surveyed. These plots belong to three forest types: needleleaf forest, mixed forest, and broadleaf forest (Table S2). For each plot, location (latitude and longitude) of the central point, species name, diameter at breast height (DBH), and height of individual trees in the overstory layer were recorded. Because the lower limit of the applicable range of most biomass allometric equations in this study is about 5 cm, we only measured the trees that with a minimum DBH of 5 cm. trees with DBH less than 5 cm will be regarded as shrubs, and their biomass was calculated by direct measurement. Each plot was regarded as an individual sample in our analysis. The number of dead trees was quite few, therefore they were not included in the AGB of our survey. Within each tree plot, three 2 m $\times$ 2 m shrub plots and three 1 m $\times$ 1 m herb plots were selected randomly. Species name and abundance of each shrub and herb were recorded, and then the aboveground part of shrub and herb was harvested. These shrub and herb samples were taken into laboratory for further processing, and they were dried to a constant weight at 105 °C and then weighed. Considering the low growth rate of forests in this high latitude region, the increment of forest AGB for one year is negligible. Therefore, forest inventory results in 2011 were matching with PALSAR data in 2010.

The DBH-based allometric equations from previous studies (Chen and Zhu, 1989; Wang, 2006) were adopted to calculate tree AGB (Table S1). The dry weight of shrub and herb samples of the three subplots within a tree plot represented the AGB of under-