INDIVIDUAL TREE AGB ESTIMATION BASED ON FRACTAL PARAMETERS AND TREE VOLUME

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Commission II, WG II/2

KEY WORDS: LiDAR points, Individual tree, AGB, Fractal geometry, Tree volume.

ABSTRACT:

Forest is an important component of ecosystem. To estimate forest above-ground biomass (AGB) accurately, this paper proposed an individual tree AGB estimation method based on fractal geometry and individual tree volume. In this study, fractal parameters, such as fractal dimension and intercept were first calculated. And then, a fast tree volume estimation method based on point clouds voxelization was proposed. By combining fractal parameters, tree volume and specific wood density together, an individual tree AGB estimation method was developed. The datasets of three different tree species with harvest referenced AGB values were used for evaluating the performance of the developed model. Experimental results showed that the coefficient of determination (R^2) of the developed model was 0.853. Compared with other four traditional allometric models, the proposed model performs the best no matter which accuracy indicator was adopted.

1. INTRODUCTION

Forest is an important part of terrestrial ecosystem, which holds 70-80% terrestrial biomass (Disney et al. 2018; Houghton et al. 2009). Forests can fix atmospheric carbon dioxide into vegetation and soil through photosynthesis, which enables it to play an extremely important role in maintaining the global climate system, regulating the global carbon balance and slowing down the rise of greenhouse gas concentration (Kukenbrink et al. 2021). The inventory of Swiss greenhouse gas indicates that 9.4 million tons of carbons are stored in trees within Switzerland (Price et al. 2017). Conversely, deforestation will lead to forest carbon loss resulting to climate change acceleration (Demol et al. 2022). To protect ecological environment and improve forest management, it is urgent to monitor forest carbon stocks accurately.

An effective way to assess carbon storage is through aboveground biomass (AGB) estimation, which is defined as dry mass of above ground standings (Latella et al. 2021). A direct way for AGB acquisition is destructive harvesting which involves the felling of trees with each tree segments measured separately. To obtain AGB, the ratio of dry mass to fresh mass of wood segments must be calculated. Hackenberg et al. (2015) weighted fresh woods in the field, while dry weight was determined after drying for 72 hours at 106 $^{\circ}C$ (Hackenberg et al. 2015). Obviously, the destructive AGB harvesting methods are timeconsuming and uneconomic. More importantly, this kind of methods cannot be applied to forest in large areas. Thus, an alternative way for AGB estimation is developing allometric equations based on tree metrics of destructive tree samples, such as tree height, diameter at breast height (DBH), crown width, etc. To build accurate AGB allometric models, extensity

destructive samplings are generally required (Roxburgh et al. 2015), which is not always economically or legally permissible. Moreover, the established allometric models in literature can only be applied to specific forest sites or species (Yang et al. 2022).

Compared with traditional destructive measurements, Light Detection and Ranging (LiDAR), especially terrestrial laser scanning (TLS) provide a non-touching way for AGB estimation. TLS can achieve high precision three-dimensional point clouds for trees, which lead to breakthroughs in forest inventory (Goldbergs et al. 2018; Hui et al. 2021; Magnussen et al. 2018). With fast developments of TLS instruments, more details can be achieved for tree structures (Hui et al. 2022; Morsdorf et al. 2018). Therefore, tree metrics can be calculated directly from point clouds without felling down trees. For example, DBH can be estimated by circle fitting towards points within 1.25 m to 1.35 m from tree root, while tree height can be acquired as the highest point within an individual tree. Since these tree metrics can be achieved in a cheaper way, numerous allometric equations are developed based on one (DBH) or two variables (DBH and height) (Altanzagas et al. 2019; Xue et al. 2016). However, DBH estimating generally involves error. Moreover, LiDAR pulses may miss actual tree tops, which will lead to tree heights underestimation (Yang et al. 2022). Consequently, the AGB estimation results using the developed allometric models always suffer from biases and low accuracy especially for different forest sites or tree species. Existed studies have shown that the developed models underestimated AGBs for large tropical trees and eucalypt trees more than 35% (Calders et al. 2015; de Tanago et al. 2018). In addition to the allometrics equations built upon tree metrics, Wang et al. (2021) presented a new indicator named as LiDAR biomass index (LBI)

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for AGB estimation. Experimental results show that comparative performance can be achieved based on LBI. However, LBI should be first calculated using point clouds of analytical trees. Another kind of AGB estimation methods is based on tree volume and species-specific wood density (Demol et al. 2021; Stovall et al. 2017; Takoudjou et al. 2018). Tree volumes can be calculated by voxelizing (Hosoi et al. 2013; McHale and Melissa 2008) or cylinder-fitting (Hackenberg et al. 2015; Hui et al. 2022; Raumonen et al. 2013). The voxelizing method is easy to over-estimate stem volume, while the cylinder-fitting method has difficulties in fitting non-cylindrical tree structures. Moreover, determining species-specific wood density is still a challenge. To sum up, the main challenges of AGB estimation using TLS mainly includes the following four aspects:

i In general, AGB estimation of individual tree heavily relies on its size and architecture. However, the current calculated tree metrics used for AGB estimation, such as DBH, height, etc., cannot reflect the overall structure of the tree in threedimensional space. As a result, AGB estimation cannot be obtained using the descriptors in a global perspective with higher accuracy.

ii The calculated tree metrics used for AGB estimation is generally prone to errors. For example, the DBH calculation usually relies on the least squares fit which cannot give accurate estimation of DBH when data gap caused by shielding is encountered. For tree height calculation, due to the canopy cover, tree tops cannot be acquired effectively using TLS. Obviously, inaccurate tree metrics cannot lead to accurate AGB estimation results.

To solve these challenges, this paper proposed an individual tree AGB estimation method based on fractal geometry and individual tree volume. In this method, fractal parameters, including fractal dimension and intercept were first calculated. And then, tree volume was estimated by voxelizing the individual tree points. By combining the fractal parameters, individual tree volume and specific wood density together, an individual tree AGB estimation model was developed. Experimental results showed that the proposed model can achieve promising AGB estimation results.

2. METHOD

2.1 Fractal geometry

Fractal geometry is a concept that describes mathematical patterns found in nature. One important characteristic of fractal geometry is self-similarity, which means that each part of a fractal looks like a smaller version of the whole. Another characteristic of fractals is their dimensionality. Unlike traditional shapes with integer dimensions (such as squares or cubes), fractals have non-integer dimensions, which means they occupy more space than you might expect based on their size. Nowadays, fractal geometry has been applied in many practical applications fields such as computer graphics, physics, biology and engineering.

On plants specifically, fractal geometry has been applied to determine bifurcation patterns in trees or to predict tree metrics. Guzm án Q. et al. (2020) have proven that there is a strong relationship between fractal parameters and tree metrics, such as tree height, DBH and crown area. In this paper, fractal geometry was applied to estimate AGB of individual trees. Fractal parameters can be calculated using the box-counting method. As shown in Figure 1, the individual tree point clouds can be covered by a series of voxels. Initially, the individual tree can be covered by a larger voxel, whose voxel side length is equal

to the maximum length of the three sides of the bounding box of the individual tree. With the size of the voxel (S) changes from larger to smaller, the number of voxels (N) covering the individual tree will be increased distinctly. Thus, a log-log regression model can be built between the changing voxel size and corresponding number of voxels as Equation (1).

$$\log(N) = d \cdot \log\left(\frac{1}{S}\right) + Inter$$
(1)

where d = fractal dimension

Inter = fractal intercept



Figure 1. Individual tree point clouds voxelization. (a) side length is equal to one thirty-second of the initial setting size; (b) side length is equal to one sixty-four of the initial setting size.

2.2 AGB estimation based on fractal parameters and tree volume

In traditional AGB estimation methods, individual tree AGB can be estimated by multiplying the tree volume (V) by its corresponding specific wood density (ρ). However, how to calculate the individual tree volume from tree LiDAR points is still a challenge. One way is building an individual tree model using the quantitative structural model (QSM) building method, such as TreeQSM proposed by Raumonen et al. (2013). And then, the tree volume can be calculated as the sum of volumes of each cylinder formed the individual tree model. Obviously, QSM construction is a prerequisite for volume calculation. The QSM construction accuracy will affect the result of volume calculation greatly. Moreover, when processing larger number of trees, this process will be time consuming. Thus, this paper proposed a fast tree volume estimation method based on voxelizing the individual tree points. As shown in Figure 1 (b), when the voxel size is smaller, the individual tree can be covered compactly by a series of voxels. In this paper, the side length of the voxel is set as the mean point spacing (dis). Here,

the voxel volume is equal to \overline{dis}^3 . Then, tree volume can be estimated by summarizing all the voxel volumes together. The specific wood density of different tree species provided in Hackenberg et al. (2015) was used for calculation in the current study.

Although the tree volume can be used for AGB estimation, the exiting studies do not consider how tree architecture is distributed in the space, especially in the dense forest environments. Obviously, tree architecture is related to the individual tree AGB. As mentioned in section 2.1, fractal dimension and intercept can be used to describe the distribution of tree architecture. Thus, fractal dimension and intercept were applied to achieve better AGB estimation result. The proposed AGB estimation model can be expressed as Equation (2).

$$AGB = a \cdot d^b \cdot Inter^c \cdot V^d \cdot \rho^e \tag{2}$$

By making logarithm operation to Equation (2), a log-log linear regression model can be derived as Equation (3).

$$\log(AGB) = a_0 + a_1 \cdot \log(d) + a_2 \cdot \log(Inter) + a_3 \cdot \log(V) + a_4 \cdot \log(\rho)$$
(3)

where a_0 , a_1 , a_2 , a_3 , a_4 = linear model fitting coefficients.

3. EXPERIMENTAL RESULTS AND ANALYSIS

To evaluate the performance of the proposed model, three datasets of different tree species, including Erythrophleum fordii, Pinus massoniana and Quercus petraea, were adopted for the testing (Hackenberg et al. 2015). Several individual trees of these three tree species were shown in Figure 2. Each dataset of different tree species contains twelve individual trees. Trees of Erythrophleum fordii were scanned in subtropical China by the Z+F IMAGER 5010c, while trees of Pinus massoniana and Quercus petraea were scanned by Z+F IMAGER 5010 in subtropical China and southern Germany, respectively. All the thirty-six individual trees were destructively harvested to obtain referenced AGB values.





Figure 2. Individual trees of different tree species. (a) Erythrophleum fordii; (b) Pinus massoniana; (c) Quercus petraea.

The log-log regression result between AGB referenced values and estimated values were shown in Figure 3. It can be found that the estimated AGB values using the proposed model are close to the referenced AGB values. Almost all the blue points are distributed around the 1:1 line. As a result, the coefficient of determination (R^2) of the developed model is 0.853.



Figure 3. Log-log regression result between AGB referenced values and estimated values. The blue dotted line is the fitted line, while the black solid line represents 1:1 line.

Five accuracy metrics were used for testing the performance of the proposed method, including mean bias (*mBias*), relative

mean bias (*rmBias*), root mean square error (*RMSE*), relative RMSE (*rRMSE*) and coefficient of determination (R^2). Other four traditional AGB allometric models based on DBH ($AGB = aD^b$), tree height ($AGB = aH^b$), DBH and tree height ($AGB = aD^bH^c$), and tree volume and specific wood density ($AGB = aV^b\rho^c$) were used for comparison. The comparison results were shown in Table 1. It can be found that the proposed model performs the best no matter which accuracy indicator is adopted. In terms of R^2 , the proposed model improved by nearly 30% compared to the allometric model built upon DBH. In terms of *mBias*, the proposed model also performs much better than other four allometric models. Thus, it can be concluded that it is effective when combining fractal parameters, tree volume and specific wood density together to estimate AGB values.

Allometric models	$\frac{R^2}{R^2}$	mBias (kg)	rmBias	RMSE (kg)	rRMSE
$AGB = aD^b$	0.565	103.521	0.314	119.927	0.364
$AGB = aH^b$	0.638	75.001	0.228	101.987	0.310
$AGB = aD^bH^c$	0.711	76.687	0.233	96.379	0.293
$AGB = aV^b\rho^c$	0.775	66.520	0.202	86.585	0.263
The proposed model	0.853	48.093	0.146	61.104	0.186

Table 1. Comparison with commonly used allometric models.

As mentioned above, there are three different tree species, including Erythrophleum fordii, Pinus massoniana and Quercus petraea, were used in this study. To test the performance of the proposed model towards different tree species, the proposed model was applied to these three different tree species separately. The results were shown in Table 2. It can be found that all the R^2 values are greater than 0.65. Among these three tree species, Erythrophleum fordii achieves the highest R^2 and smallest *rmBias* and *rRMSE*. The AGB estimation results are also shown in Figure 4. It can also be found that trees of Erythrophleum fordii obtained the best AGB estimation result.

Species	R^2	mBias (kg)	rmBias	RMSE (kg)	rRMSE
Erythrophleum fordii	0.903	30.721	0.090	37.375	0.110
Pinus massoniana	0.671	29.408	0.178	39.831	0.241
Quercus petraea	0.659	50.775	0.105	58.729	0.122

Table 2. The performance of the developed model towards different tree species.



Figure 4. Log-log regression result between AGB referenced values and estimated values of different tree species.

4. CONCLUSION

AGB is an important indicator for assessing carbon storage. To estimate AGB of individual tree accurately, this paper proposed an AGB estimation method based on fractal geometry and individual tree volume. In this paper, fractal parameters including fractal dimension and intercept were first computed for each individual tree point clouds. And then, an AGB estimation model was proposed by combining these two fractal parameters, tree volume and specific wood density. The datasets of three different tree species were used for testing the performance of the proposed model. Experimental results indicate that the proposed model can achieve satisfied AGB estimation results. Meanwhile, R^2 of all the three tree species are above 0.65. Thus, the proposed model can achieve promising results in all these three tree species.

ACKNOWLEDGEMENTS

The authors would like to thank the Funds from National Science Foundation (NSF) (42161060, 41801325), Jiangxi Province Outstanding Youth Fund (20232ACB213017), Jiangxi Province "Double Thousand Plan" High-level Talent Project (S2021GDQN2699), the Science Foundation of Jiangxi Province (20192BAB217010), and the China Post-Doctoral Science Foundation (2019M661858) for their financial support.

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