Prediction of subtropical forest parameters using airborne laser scanner

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Abstract: Light Detection and Ranging (LiDAR) is one of the most promising technologies in forestry, which shows potential for timely and accurate measurements of forest biophysical properties over time. This study explores several regression models relating variables derived from airborne laser scanner for the estimation of various forest metrics, and discusses the results of prediction concluding accuracy. These prediction models use 78 plots with radius of 7.5 m or 15 m in Kunming, Yunnan province, China. Two series of variables are provided from the airborne laser scanner data, one is canopy height and to the other canopy density. These variables are used as independent variables in the regressions. The stepwise regression analysis has been used to select various independent variables. The results show high correlation between forest metrics and variables derived from airborne laser scanner. For the three different forest types (coniferous, broad-leaf and mixed), all the prediction of mean heights are accurate. However, for the predictions of above ground biomass, the result of coniferous is better than broad-leaf, while there is no significant correlation between the biomass of mixed and the laser variables. Finally, the results of regression and factors affect the accuracy of prediction are discussed. The accuracy of prediction may be relate to the forest type, sampling time and density of laser scanning and position errors.

Key words: airborne laser, scannersub-tropical forest, mean height, above ground biomass
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1 INTRODUCTION

Forest resource is one of the most important natural resources, and plays an important role in the sustainable development of mankind. In the past, the forest resource survey has been dependent on the time-consuming and labor-intensive manual inventory methods, and therefore, forestry researchers are hoping to find a more convenient method of investigation. Light Detection and Ranging (LiDAR) is an active remote sensing technology, which can determine the distance between the sensor and the target by emitting laser from sensors. It has been applied to forestry research in the mid-80s of 20th century. Early researches find that canopy closure is most strongly related to the penetration capability of the laser pulse, and indicates that the pulsed laser system may be used to remotely sense the vertical forest canopy profile and assess tree height. The forest biomass and volume are estimated in related researches which also obtain good results (Nelson, *et al.,* 1984, 1988). Then, many work expose the enormous potential of laser applications in the forestry, which demonstrate that forest variables such as tree height, basal area, biomass, *etc.* can be estimated accurately using airborne laser scanner data (Nasset, 1997; Nelson, *et al.*, 1997; Popescu, *et al.*, 2002; Maltamo, *et al.*, 2004; Pang, *et al.*, 2008). Studies based on small footprint, high sampling density LiDAR data at individual tree level are reported later (Brandtberg, *et al.*, 2003; Maltamo, *et al.*, 2004; Holmgren & Persson, 2004a). However, some studies show that the relationships between forest biophysical properties and airborne laser scanner data are different for the different geographical location, species composition, site quality, *etc.* (Holmgren, 2004b; Hall, *et al.*, 2005; Nasset & Gobakken, 2008). In the case that remote sensing becoming more popular, the LiDAR technology has increasingly being used in the forestry as a new means of remote sensing.

The objectives of this study are (1) to explore 2 regression models for the estimation of forest variables at plot level, (2) discuss the results of methods and the factors that affect the prediction accuracy.

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2 MATERIALS AND METHODS

2.1 Study area

Test area is located in central Yunnan Province, including Xishan forest of Kunming and Hongta forest of Yuxi with complex terrain, with altitude varies from 1750 m to 2641 m above sea level. The area belongs to subtropical sub-humid monsoon climate in low latitude and high altitude where the local microclimate is obvious. The main conifer species are Yunnan pine (*Pinus yunnanensis*), Huashan pine (*Pinus armandii*), Yunnan keteleeria (*Keteleeria evelyniana Mast*) *etc.* Major hardwood species are *Alnus nepalensisi*, *Lithocarpus dealbatus*, *Herba glauca Cyclobalanopsis delavayi etc.*. Other associated species including *Cyclobalanopsis glaucoides*, *Populus davidiana*. The main forest type of plots in this study is young natural coniferous forest, dominated by Yunnan pine and Huashan pine, and other a few middle-aged to mature natural hardwood forest dominated by Alnus nepalensisi.

2.2 Field data

The plots are selected based on the LiDAR data coverage. According to tree species, tree height and canopy density, 78 circular plots (radius of 7.5 m or 15 m) data were collected from July 16th to August 4th, 2008 in Xishan forest of Kunming and Hongta Forest of Yuxi, Yunnan province(24°9′N—25°28′N, 102°23′E—102°36′E). Each tree was recorded in details with a stem diameter⩾5 cm, including tree species, diameter at breast height (DBH, D), tree height (H) *etc.*. DBH were measured using PI tape. Tree height and canopy base height were measured using laser altimeter. Crown widths of the two main directions were measured using the tape measure. The centers of plots were positioned using a differential global positioning system (DGPS). Most selected plots were natural forest dominated by single tree species, and there were 50 coniferous plots, 18 broadleaf plots and 10 mixed plots.

Then several forest variables were calculated based on the investigated data, containing basal area (m^2·ha^{-1}), Lorey's mean height, *i.e.*, mean height weighted by basal area (m). And above ground total, stem wood, live branch and foliage biomass (Mg·ha^{-1}) were calculated using species-specific allometric equations. A summary of plot data is shown in Table 1.

Table 1 Summary of plot data

Forest metrics	Coniferous(n=50)			Broad-leaved(n=18)			Mixed(n=10)		
	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean
Lorey's mean height/m	4.600	21.500	9.800	4.200	19.300	13.700	4.200	18.100	9.800
Total above ground biomass/(Mg·ha^{-1})	7.345	282.248	63.629	17.726	167.399	75.318	16.024	90.907	39.647
Stem biomass/(Mg·ha^{-1})	4.233	233.513	45.098	14.206	107.682	50.077	9.804	44.045	25.125
Live branches biomass/(Mg·ha^{-1})	1.624	45.426	14.130	2.369	45.2772	19.566	3.8998	40.322	11.222
Foliage biomass/(Mg·ha^{-1})	0.794	21.019	4.401	0.697	14.44	5.675	1.278	8.588	3.2995

2.3 ALS data

The ALS data was collected using LiteMapper-5600 in December of 2008. The relative height of flying altitude was 650 m, with the laser-scanning angle of 60°, frequency of 50 kHz, and the laser scanning frequency of 48 lines / s, and the average point density of 1.08 m×1.04 m. The aircraft attitude maintenance was supported using GPS equipment of aircraft navigation, inertial measure unit (IMU) and global positioning system (GPS) of airborne laser radar. The track amendment, the aircraft's pitch, the control of roll and lateral roll were able to achieve a high precision.

Raw data contains a large number of gross errors or irrelevant information, such as data produced by local terrain mutation, reflected signal resulted from flying birds or other moving objects, or other local empty formed by no echo. In the data pre-processing, the data process software provided by equipment supplier should use artificial interactive editing to ensure the accuracy of terrain model and vegetation model generated later. The GPS carried by aircraft and DGPS on the ground positioned in real time during the flight for unifying and correcting the coordinates of data so that the ALS data and ground data can match exactly.

The laser data can be classified into 3 classes: ground points, vegetation points and others. LiDAR data distributes irregularly as discrete three-dimensional point cloud in space, and each point has a precise three-dimensional coordinates, namely, the horizontal coordinates (x, y) and vertical elevation values z. For building's roofs with no coverage and bare ground surface, the laser returns only once generally. Therefore, the point cloud is regular in discrete distribution. For vegetation, the pulse can penetrate the vegetation to return echoes many times that formed by transmission or reflection (Zeng, *et al.*, 2008). In the area covered by dense vegetation, the echoes are more complicated, some may return from top vegetation, and some from the lower branches, or some from the surface below vegetation. The last return received is usually from the surface. This feature of LIDAR data can be used for classification. From the point of morphological view, the elevation change between adjacent ground points is usually not severe. You can compare the points one by one in a specific region, and the points which angle change exceeds a certain threshold can be considered as non-ground points, and the rest can be classified as ground points. General LiDAR data processing software are able to achieve such classification.

Digital elevation model (DEM) is generated using TIN interpolation method with the ground point data classified. Then, the elevation values of vegetation points are normalized by DEM to remove the terrain elevation, so that the height values of vegetation points are the heights relative to the ground.

Only the first returns are used to estimate the forest variables because previous research has shown that properties of first return echoes tend to be more stable across different ALS equipment configuration and flying altitudes than other echo categories (Nasset & Gobakken, 2008). Normally, the points with a height value > 2 m are considered to belong to the tree canopy (Nilsson, 1996). Percentiles can represent the distribution situation of laser point (Pang, *et al.*, 2008). So the percentiles of the canopy height distributions for 10% (h_{10}), 20% (h_{20}), ... , and 90% (h_{90}) were computed, and also the mean values (h_{mean}) were computed. The range between the lowest canopy height and the maximum canopy height was divided into 10 fractions of equal length. Canopy density were then computed as the proportions of laser points above fraction #0(>2 m), #1, …, #9 to total number of points. In addition, the density variable c was extracted, defined as the proportion of points higher than 1.8 m to total number of points.

2.4 Statistical analysis

With the assumption that the laser data relates to the content expected to estimate, the variables were derived from airborne laser scanner data after height being normalized. The Pearson correlation analysis between the variables from "2.3" and forest parameters shows that the Pearson correlation coefficients can be higher than 0.6 with significant relationships, indicating that there are linear relationship. The correlation coefficient between laser height variables and Lorey's mean height is the highest, reaching about 0.8. Therefore, considering height variables as candidate of independent variables, a simple linear regression model could be created to estimate the Lorey's mean height. The variables are logarithmic transformed for overcoming the nonlinear problem of variables, and then the logarithmic linear regression is generated for estimating the aboveground biomass.

$$h_L = \beta_0 + \beta_1 h_{10} + \beta_2 h_{20} + \ldots + \beta_9 h_{90} + \beta_{10} h_{mean} + \varepsilon$$

$$\ln W_i = \beta_0' + \beta_1' \ln h_{10} + \beta_2' \ln h_{20} + \ldots + \beta_9' \ln h_{90} + \beta_{10}' \ln h_{mean} + \beta_{11}' \ln d_0 + \beta_{12}' \ln d_1 + \ldots + \beta_{20}' \ln d_9 + \beta_{21}' \ln c + \varepsilon$$

where h_L is the Lorey's mean height (mean height weighted by basal area) (m); W_i = above ground total, stem wood, live branch or foliage biomass (Mg·ha^{-1}); h_{10}, h_{20}, …, h_{90} = percentiles corresponding to 10, 20, …, 90% of laser canopy heights (m); h_{mean} is mean of the laser canopy heights (m); d_0, d_1, …, d_9 represent the canopy densities corresponding to the proportions of laser echoes above fraction #0, #1, …, #9 to total number of echoes; c is canopy density corresponding to the proportions of laser echoes with a height value > 1.8 m to total number of echoes; ε is a normally distributed error term [$\varepsilon \sim N(0, \sigma^2)$].

Multiple linear regression is a common method to distinguish the causal relationship between multiple variables, and the relationship between each independent variable should be linear. Both stepwise variable selection and the maximum R^2 improvement variable selection techniques were applied to select the ALS-derived variables to be included in the models (Nasset & Gobakken, 2008). Independent variables could be removed if the value of statistic F value is too small and the result of T-test do not reach the level of significance (P >0.1). On the contrary, independent variables are allowed to entered regression model (P < 0.05). The least squares method was used generally, and repeated until the independent variables of the regression equation are all accord with the requirements of entering models.

Following indicators are used to verify the stability of models. (1) High R^2 indicates the high correlation between variables and independent variables. This is a test on the effect of regression linear superposition. (2) The mean relative error (*MPE*) between the true values and predicted values is also an indicator. The *MPE* is smaller, the better the effect of predication. (3) Durbin - Watson test was used to test the independence of the residuals, and denoted the results with D that its range is $0 < D < 4$. When the residuals and independent variables are independent of each other, $D = 2$. So since the value of D close to 2, it means the random errors are essentially independent of each other, and there is no problem of serial correlation.

In the statistical analysis course, there were two cases. First, all plots was analyzed with no distinction. Then the plots divided into coniferous forest, broadleaf forest and mixed forest by species were analyzed.

3 RESULTS

3.1 Lorey's mean height

Lorey's mean height is estimated by regression model, the results show that there is a high correlation between laser-predicted and field-measured mean tree heights. The correlation coefficients are all higher then 0.8. For all plots with no partition analysis, 83% of the variability could be explained, and the mean relative error (*MPE*) between predicted and true value is –2.6%, with standard error (*SE*) of 1.62 m which accounted for 10% of the average Lorey's mean height. For coniferous plots, 79% of the variability could be explained, and the *MPE* is –2.3%, with *SE* of 0.81 m which accounted for 8.3% of the average. For broad-leaf plots, 75% of the variability could be explained, and the *MPE* is –1.4%, with *SE* of 1.98 m which accounted for 14.5% of the average. For mixed plots, 95% of the variability could be explained, and the *MPE* is 0.01%, with *SE* of 0.81 m which accounted for 8.2% of the average.Details values of these results are shown in Fig. 1 and Table 2.

Table 2 Regression models and parameters used for estimation of basal area weighted mean tree height (h_L) and above ground biomass (W_i)

regression models	*P*	R^2	*SE*	*MPE*	*D*
a.all plots					
h_L=1.809+0.018×h_{50}	0.000	0.83	1.62	–2.6%	2.116
lnW_a=6.887+0.815×lnd_9	0.000	0.37	0.64	–21.3%	2.404
lnW_s=6.581+0.835×lnd_9	0.000	0.39	0.63	–21.3%	2.378

to be continued

continue

regression models	*P*	R^2	*SE*	*MPE*	*D*
$\ln W_b$=6.730+1.313×$\ln d_9$ – 0.996×$\ln d_0$	0.000	0.37	0.68	–24.9%	2.363
$\ln W_f$=2.441+0.513×$\ln d_9$+0.394×$\ln h_{30}$	0.001	0.35	0.58	–16.5%	2.141
b. *coniferous*					
h_L=1.229+0.998×h_{60}	0.000	0.79	0.81	–2.3%	2.077
$\ln W_a$=2.278+1.170×$\ln h_{30}$+0.991×$\ln d_0$	0.000	0.68	0.426	–9.7%	2.125
$\ln W_s$=1.962+1.158×$\ln h_{30}$+1.034×$\ln d_0$	0.000	0.68	0.43	–10%	1.940
$\ln W_b$= 2.676+1.040×$\ln d_7$ 0.938×$\ln h_{80}$	0.000	0.7	0.426	–9.9%	2.049
$\ln W_f$=1.828+0.752×$\ln d_8$+1.452×$\ln h_{40}$–0.863×$\ln h_{10}$	0.001	0.69	0.35	–6.7%	2..056
c. *broad-leaved*					
h_L=2.360+1.040×h_{40}	0.000	0.75	1.98	–1.4%	1.793
$\ln W_a$=6.494+0.673×$\ln d_9$	0.000	0.43	0.46	–12%	1.925
$\ln W_s$=5.016+0.777×$\ln d_5$	0.000	0.42	0.44	–10.7%	1.797
$\ln W_b$=5.605+0.822×$\ln d_9$	0.000	0.42	0.57	–16.8%	2.044
$\ln W_f$=4.671+0.908×$\ln d_9$	0.000	0.57	0.47	–12%	2.018
d. *mixed*					
h_L=0.006+0.941×h_{90}	0.000	0.95	0.81	0.01%	2.077
Biomass	No significant relationship				

Note: h_L = Lorey, s mean height (mean height weighted by basal area); W_a= total above ground biomass; W_s = stem wood biomass; W_b = live branch biomass ;W_f = foliage biomass

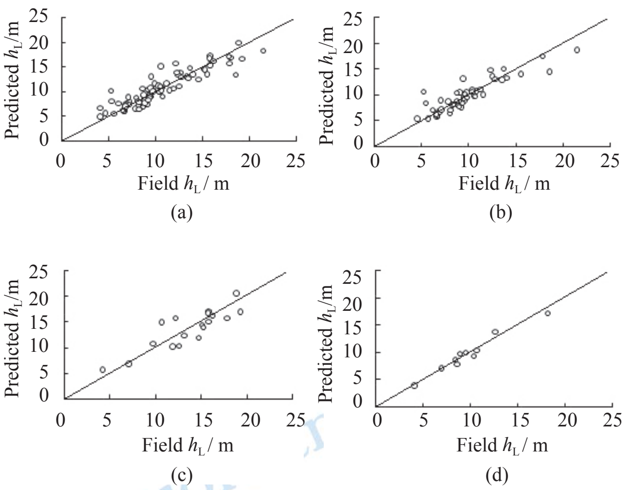

Fig. 1 Observed field Lorey's mean height plotted against predicted data

(a) All plots; (b) Coniferous plots; (c) Broad-leaved plots; (d) Mixed plots

3.2 Above ground biomass

Using regression model generated by variables related to canopy height and canopy density as combinations to estimate above ground biomass, high correlation between the laser data and above ground biomass is observed. For all plots with no partition analysis, correlation coefficients of each part of biomass are all higher than 0.4, above 35% of the variability could be explained. Standard error (*SE*) of above ground total, stem wood, live branch and foliage biomass are 1.89 Mg·ha^{-1} (3% of average value), 1.88 Mg·ha^{-1} (4.3% of average value), 1.97 Mg·ha^{-1} (13.1% of average value) and 1.79 Mg·ha^{-1} (39.3% of average value), respectively. The mean relative error (*MPE*) between predicted and true value are –21.3%, –21.3%, –24.9% and –16.3%, respectively.

For coniferous plots, correlation coefficients of each part of biomass are all higher than 0.8, above 68% of the variability could be explained. The *SE* of above ground total, stem wood, live branch and foliage biomass are 1.53 Mg·ha^{-1} (2.4% of average value), 1.54 Mg·ha^{-1} (3.4% of average value), 1.53 Mg·ha^{-1} (10.8% of average value) and 1.42 Mg·ha^{-1} (32.3% of average value), respectively. The *MPE* between predicted and true value were –9.7%, –10%, –9.9% and –6.7%, respectively.

For broad-leaf plots, correlation coefficients of each part of biomass are all higher than 0.5, above 40% of the variability could be explained. The *SE* of above ground total, stem wood, live branch and foliage biomass are 1.58 Mg·ha^{-1} (2.1% of average value), 1.55 Mg·ha^{-1} (3.1% of average value), 1.76 Mg·ha^{-1} (9% of average value) and 1.6 Mg·ha^{-1} (28.2% of average value), respectively. The *MPE* between predicted and true value were –12%, –10.7%, –16.8% and –12%, respectively.

However, there is no clear relationship between laser variables and mixed plots' biomass. Details are shown in Fig. 2 and Table 2.

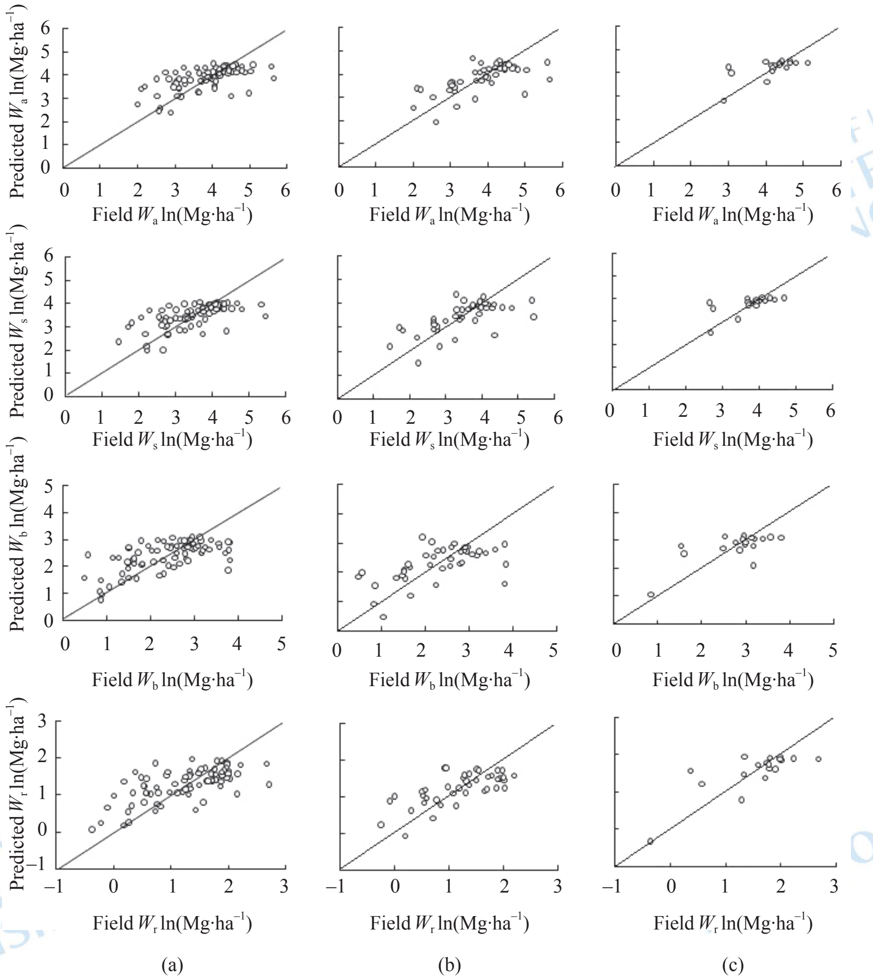

Fig. 2 Observed field biomass plotted against predicted data

W_a= total above ground biomass; W_s = stem wood biomass; W_b = live branch biomass ; W_f = (foliage biomass)

(a) All plots; (b) Coniferous plots; (c) Broad-leaved plots

4 DISCUSSION

The application of high percentiles for the estimation of basal-area-weighted mean tree height and basal area has been analyzed in other studies. Holmgren (2004b) estimates the mean tree height and basal area on 29 forest stands (each containing 16 field plots) in the south-western Sweden with forest dominated by Norway spruce, Scots pine and birch. The 95th percentile is selected for estimating mean tree height and the coefficient of relationship r equals to 0.995. Næsset and Gobakken (2008) estimates the above-ground and under-ground bio-mass for 1395 sample plots located in the boreal zone of Norway. Plots are classified by species composition, age classes, and site indexes. The canopy height percentiles and canopy density are used as independent variables. The site indexes and age classes are dummy variables, and species composition is continuous variable. The coefficients of determination for final regression models are above 0.7. Similar laser variables are selected for estimation of biomass in this study.

In this study, variables selected by stepwise regression method for different species are different. The variables for estimating the Lorey's mean height of all plots, coniferous forest, broadleaf forest and mixed forest are 50th , 40th, 60th, 90th percentile of laser height, respectively. Only the variable for mixed forest shows higher percentile, probably due to the little difference in height between the trees of mixed plots. The variables for biomass estimate of coniferous forest are composed of height variables and density variables in pairs. However, analysis of all plots and broad-leaved forest only using density variables and their relations are lower than the coniferous forest. The species-specific biomass equations show that the biomass and tree height, diameter should have a certain relationship. This is reasonable as the relationship between biomass and height of coniferous tree is more obvious and biomass of broad-leaved trees is related with DBH.

The accuracy of Lorey's mean height estimation is closely related with the extraction of laser height. Airborne laser system samples discretely, the sampling points have a certain interval. It may miss the top of tree easily, resulting in height underestimation. The weighted mean height algorithm also makes large trees influencing the mean height of plots than small ones, and there is no connection with species. However, increasing sampling accuracy can improve the precision of tree height estimation, but it compensates for excessively high costs. On the other hand, ground points used to generate digital elevation model (DEM) may be covered in the dense forest, causing height errors of canopy height model (CHM). Reutebuch, *et al.* (2003) investigate the accuracy of digital terrain models (DTM) for four different stand density forests and the results show that the greater DTM errors can cause greater canopy density.

The accuracy of biomass estimations may be influenced by cumulative errors. First, the measured errors of plot data acquisition are inevitable. Second, the scanning time of LIDAR data is at the turn of autumn and winter, not summer with dense foliage, so the echoes returned from leaves decreases. Plot coordinates errors and sampling density of LIDAR data could affect the laser height distribution, and ultimately affect the estimation of foliage biomass (Lim, *et al.*, 2003; Lim & Treitz, 2004). In addition, underestimation of tree height leads to the underestimation of the biomass directly. It can be seen that estimation precision of foliage biomass is relatively low. In addition, it is necessary to consider the impact of different geographical regions and forest types on the estimation of biomass. Stem biomass is the main part of tree biomass, and stem shape variations directly affect stem biomass, and may affect other biomass components. Therefore, the impact of geographic regions and forest types should be controlled in a minimum range, classifying the plots in accordance with site quality and tree species is expected to improve prediction accuracy.

5 CONCLUSIONS

This study investigated sub-tropical forest in central Yunnan Province. Through the LiDAR cloud data processing analysis and measurements of tree height, the forest parameters are predicted using LiDAR technology. The conclusions as follow:

(1) The variables and regression coefficients selected by stepwise regression analysis are able to achieve significant level, and ensure good prediction results. It indicates that forest parameters of different forest types could be predicted accurately using the regression models. In which the tree height estimation models' coefficients of determination are higher than 0.75, while biomass estimation models' coefficients of determination are relatively low (lower than 0.7). For biomass estimation of different forest types, coniferous forest's coefficient of determination higher than the broad-leaved forest, then all the plots are followed. Biomass of mixed forest represents no relationship with LIDAR data.

(2) For different forest types, tree height estimation errors are tiny, and the average relative errors are controlled around 2%. That means LIDAR data can reflect tree height, and different species composition effect little the height predictions. The results show that the height variable (h_{40}, h_{50}, h_{60} and h_{90}) can provide accurate estimates of the tree heights. In the future, this extraction method can be applied to the tree height estimation of other regions if the estimation accuracy satisfies requirements and the results are stable.

(3) For different forest types, the biomass precision estimates are significantly different. The accuracy of coniferous forest biomass is the highest, followed by broad-leaved forest, and the results of all the plots. In this study, mixed forest biomass has no relationship with laser variables. But this may because the limited of number of small plots that are insufficient for analysis. For each part of the biomass estimation, the results of total aboveground biomass and stem biomass estimation are better than other parts, and the leaf biomass estimation results are the worst. This mainly due to stem is the largest proportion of the total biomass, and the scan time of 12 months is not conducive to leaf biomass estimation.

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亚热带森林参数的机载激光雷达估测

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摘　要：通过应用机载激光雷达数据，在分析云南省中部的78块样地的基础上提出2个预测森林不同生物特性的统计模型(加权平均高度的预测模型和生物量的预测模型)，并讨论了预测结果及其精确性。从激光雷达数据中提取了2组变量(树冠高度变量组和植被密度变量组)作为自变量，采用逐步回归方法进行自变量选择。结果表明，激光雷达数据与森林的平均树高和地上各部分生物量有很强的相关性。对于3种不同森林类型(针叶林，阔叶林和混交林)，平均树高估测均能达到比较高的精度；生物量的估测结果是针叶林优于阔叶林，混交林的生物量与激光雷达数据则没有明显相关性。最后，对回归分析的结果和影响预测精度的因素进行讨论,认为预测结果的精度可能与森林类型、激光雷达采样时间和采样密度以及坐标误差等因素有关。

关键词：机载激光雷达，亚热带森林，平均树高，地上生物量

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1　引　言

森林资源是地球资源中最为重要的自然资源之一，对人类的可持续发展有着极其重要的作用。在遥感技术广泛应用于林业清查之前，森林资源调查一直依赖于耗时、耗力的人工清查手段，林学研究者希望能找到一种更为方便的调查方式。激光雷达(Light Detection And Ranging，LiDAR)是一项通过由传感器所发出的激光脉冲来测定传感器与目标物之间距离的主动遥感技术。它应用于林业研究始于20世纪80年代中期，早期的研究发现激光脉冲的穿透力与冠层郁闭度高度相关，并指出激光雷达系统可以用于遥感森林垂直结构并估测林木高度(Nelson 等，1984，1988)。随后，许多研究证明激光雷达扫描数据能够准确地估测森林参数，如树高、胸高断面积和生物量等(Nasset，1997，Nelson，等，1997；Popescu 等，2002；Maltamo 等，2004；庞勇 等，2008)。基于小光斑、高密度激光雷达数据的单木水平估测研究也有报道(Brandtberg 等，2003；Maltamo 等，2004；Holmgren和Persson，2004a)。另外，有研究表明森林参数与激光雷达数据之间的关系受地域、树种构成和立地质量等条件的影响(Holmgren，2004b；Hall 等，2005；Nasset和Gobakken，2008)。在航空遥感日益普及的情况下，激光雷达技术作为一种新型遥感手段在林学方面的应用也越来越广泛。

研究目的：(1)探讨两个预测样地水平的森林不同生物物理特性的统计模型；(2)讨论这些模型的预测结果及影响预测精度的因素。

2　材料与方法

2.1　研究区域

试验区位于云南省中部，包括昆明市西山区林场和玉溪市红塔区林场。地形复杂，起伏较大，地

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势南高北低，其海拔高度是1750—2641 m。该地区属于低纬度高海拔亚热带半湿季风性气候，区内小气候明显。植被类型多样，主要针叶树种有云南松(Pinus yunnanensis)、华山松(Pinus armandii)和云南油杉(Keteleeria evelyniana Mast)等；主要阔叶树种为旱冬瓜(Alnus nepalensisi)、滇石栎(Lithocarpus dealbatus)和黄毛青冈(Cyclobalanopsis delavayi)等；其他伴生树种包括滇青冈(Cyclobalanopsis glaucoides)和山杨(Populus davidiana)等。林区内主要森林类型为幼龄到中龄天然针叶林，优势树种为云南松和华山松；还有少量中龄到过熟天然阔叶林，优势树种为旱冬瓜。

2.2 地面数据

根据机载数据覆盖情况，选取试验区的代表树种，分别对树高和郁闭度等级进行了外业样地选择。2008-07-16—2008-08-04在云南省昆明市西山区林业局和玉溪市红塔区林业局开展了外业测量，总共选取了78块圆形样地(半径为7.5 m或15 m)，地理范围是24° 9′N—25° 28′N；102°23′E—102°36′E。进行每木检尺，起测直径为5 cm，逐一测定树木种类、胸高直径(DBH，简写为D)和树高(H)等测树因子。单株木的胸径使用围尺进行测量，树高和枝下高使用激光测高仪进行测量，冠幅的两个主方向使用皮尺进行测量，使用DGPS定位样地中心地理坐标。选择的大多数样地是优势树种为单一树种的天然林，所有样地中有50块针叶树样地，18块阔叶树样地和10块针阔混交样地。

然后根据调查数据计算相关森林参数，包括：每块样地以$m^2 \cdot ha^{-1}$为单位的胸高断面积(G)，胸高断面积加权的平均树高(h_L)，应用特有树种生长方程计算每块样地的树干生物量(W_s)、活枝生物量(W_b)和叶生物量(W_f)，地上总生物量(W_a)由以上3项相加得出(表1)。

表1 样地数据汇总

森林参数	针叶林(n=50)			阔叶林(n=18)			混交林(n=10)		
	最小值	最大值	平均值	最小值	最大值	平均值	最小值	最大值	平均值
平均树高/m	4.600	21.500	9.800	4.200	19.300	13.700	4.200	18.100	9.800
地上总生物量/($Mg \cdot ha^{-1}$)	7.345	282.248	63.629	17.726	167.399	75.318	16.024	90.907	39.647
树干生物量/($Mg \cdot ha^{-1}$)	4.233	233.513	45.098	14.206	107.682	50.077	9.804	44.045	25.125
活枝生物量/($Mg \cdot ha^{-1}$)	1.624	45.426	14.130	2.369	45.2772	19.566	3.8998	40.322	11.222
叶生物量/($Mg \cdot ha^{1}$)	0.794	21.019	4.401	0.697	14.44	5.675	1.278	8.588	3.2995

2.3 激光雷达数据获取及处理

研究采用的激光雷达数据是2007年12月获取的LiteMapper-5600数据。航飞相对高度为650 m，激光扫描角度为60°，激光发射频率为50 kHz；激光扫描频率为48线/s；激光间距为1.08 m × 1.04 m。飞机姿态保持由惯性导航系统IMU和GPS全球定位系统共同承担，在航迹修正、飞机的俯仰、横滚与侧滚的控制方面均能达到较高的精度要求。

原始点云数据会包含大量粗差、错误或无关信息。如局部地形突变产生的跳变数据、飞鸟等运动目标物的遮挡产生的反射信号或无回波信号的局部空洞等。为保证后期生成地面模型及植被模型的精确性，在前期数据处理过程中采用人工交互编辑的方法，利用仪器供应商提供的数据处理软件，剔除错误信息并补足遗漏信息。飞机上装载的全球定位系统(GPS)和地面设置的差分全球定位系统(DGPS)在飞行过程中实时定位，用于数据坐标的统一和校正，以保证激光雷达数据与地面实测数据的精确匹配。

数据预处理完成后，再将激光点分为3类：地面点、植被点和其他。地面点指裸露地面的激光回波，植被点则是指植被的激光回波。LiDAR数据在空间的分布为不规则的离散三维点云，每个点具有精确的三维坐标，即水平方向的地理坐标(x，y)及垂直方向的高程值z。对于没有被遮盖的建筑物屋顶和光秃的地表面，激光点一般只返回一次回波。因此，所形成的点云呈离散的规则分布。对于植被，激光脉冲可以

穿透植被，通过透射或折射作用返回多次回波，点云分布呈团状聚集等不规则形状(曾奇红 等，2008)。在植被密集的地方，激光回波的情况比较复杂，有些来自于植被顶部，有些来自于下层的树枝，还有一些来自于植被覆盖下的地表。接收到的最后一次回波通常是植被覆盖下的地表回波。激光雷达点云的这个特性可以用于激光点分类。另外，从形态学的角度出发，地面相邻点的高程变化通常不会很剧烈，可以逐个比较区域内的点，如果变化超过一定的角度阈值就可判断为非地面点，其他的则归为地面点。一般的激光雷达数据处理软件均能做以上点云分类处理。

将分类后的地面激光点数据使用TIN插值方法生成DEM。然后利用DEM的高程值对植被回波点的高度进行归一化处理，即去除地形的高程，使植被点的高度值为相对于地面的高度值。

对于不同的ALS仪器的不同构造和飞行高度而言，第一回波更趋于稳定，因此多采用第一回波来计算森林参数(Nasset和Gobakken，2008)。一般情况下，植被点是取高于地面2 m的回波点(Nilsson，1996)。百分位数能很好的体现激光点数据的分布情况(庞勇 等，2008)，因此，提取一组变量取每块样地中的激光雷达植被回波点的百分位高度10%(h_{10})，20%(h_{20})，…，90%(h_{90})，还有激光雷达平均高度(h_{mean})。然后将激光雷达最低高度值(>2 m)到最大高度值之间范围10等分,冠层密度就是高于每等分高度的点在所有点中所占的比例。另外，再提取密度变量c，定义为高于1.8 m的回波点在所有回波点中所占的比例。

2.4 统计分析

在假设激光雷达数据与所要估测的内容存在相关性的情况下，对所得到的高度归一后的激光雷达数据进行变量的提取。将2.3节中得到的变量与需要预测的参数进行了Pearson相关分析，结果显示激光雷达变量与所需估测的森林参数之间的Pearson相关系数均高于0.6，且关系显著，说明它们之间有较好的线性关系。其中激光雷达高度变量与森林胸高断面积加权平均高之间的相关系数最高，达到0.8左右。因此，把得到的激光雷达高度变量均作为候选的独立变量，可以建立一个简单的线性回归模型来估测森林平均高度。为了克服变量的非线性问题，对变量进行对数变换，用对数变量线性回归来估测地上生物量：

$$h_{\mathrm{L}} = \beta_0 + \beta_1 h_{10} + \beta_2 h_{20} + \ldots + \beta_9 h_{90} + \beta_{10} h_{\mathrm{mean}} + \varepsilon$$

$$\begin{aligned}\ln W_i = {} & \beta_0' + \beta_1' \ln h_{10} + \beta_2' \ln h_{20} + \ldots + \beta_9' \ln h_{90} + \\ & \beta_{10}' \ln h_{\mathrm{mean}} + \beta_{11}' \ln d_0 + \beta_{12}' \ln d_1 + \ldots + \\ & \beta_{20}' \ln d_9 + \beta_{21}' \ln c + \varepsilon\end{aligned}$$

式中，h_{L}为胸高断面积加权平均高；W_i为地上总生物量(W_{a})或树干生物量(W_{s})或活枝生物量(W_{b})或叶生物量(W_{f})；h_{10}，h_{20}，…，h_{90}为激光雷达树高的10%，20%，…，90%分位数高度值；h_{mean}为激光雷达树高的平均值；d_0为所有植被点在所有回波点中所占的比例，d_1，d_2，…，d_9为将最低树高到最高树高范围10等分,取高于每等分高度#0 (>2 m)，#1，…，#9的点在所有点中所占的比例；c为取高于1.8 m的回波点在所有回波点中所占的比例；ε为正态分布误差项[$\varepsilon - N(0，\sigma^2)$]。

多元线性回归是研究多个变量之间因果关系最常用的方法之一，并且每个自变量与因变量之间的关系都应该是线性的。建立回归模型的过程中，运用逐步进入法(stepwise)和观察决定系数R^2的变化情况来选择进入模型的合适变量(Nasset和Gobakken，2008)。如果有自变量使统计量F值过小并且T检验达不到显著水平(P值>0.1)，则予以剔除；F值较大且T检验达到显著水平(P值<0.05)则得以进入。一般采用最小二乘法。这样重复进行，直到回归方程中所有的自变量均符合进入模型的要求，方程外的自变量均不符合进入模型的要求为止。

回归方程可靠性的由以下几个指标进行检验。(1)R^2值越大，则因变量与自变量之间相关性越强,这是对回归直线拟合优度的检验。(2)实际值与预测值之间的平均相对误差(MPE)，MPE越小，则表明预测值的效果越好。(3)采用Durbin-Watson检验考察残差的独立性，Durbin-Watson检验的参数用D表示，其取值范围是$0<D<4$，当残差与自变量相互独立时，$D = 2$。当D的值接近2时，可以认为随机误差项基本上是相互独立的，不存在序列相关的问题。

在统计分析过程中，分成两种情况进行了分析。首先是对所有样地无区分的统计分析，再将样地按树种分成针叶林、阔叶林和混交林分别进行分析。

3　研究结果

3.1　平均树高

应用回归模型对胸高断面积加权平均树高进行估测，结果表明激光雷达数据中提取的高度信息与平均树高高度相关，相关系数r均高于0.8。对所有样地无区分分析的估测结果中可解释的变异占总变异的83%；实测值与预测值之间的平均相对误差(MPE)为–2.6%；标准误差(SE)为1.62 m，占平均值的15.1%。针叶林的估测结果中可解释的变异占总变异的79%；实测值与预测值之间的MPE为–2.3%；SE为0.81 m，占平均值的8.3%。阔叶林的估测结果中可解释的变异占总变异的75%；实测值与预测值之间的MPE为–2.3%；SE为1.98 m，占平均值的14.5%。混交林的估测结果中可解释的变异占总变异的95%；实测值与预测值之间的MPE为0.01%；SE为0.81 m，占平均值的8.2%(图1，表2)。

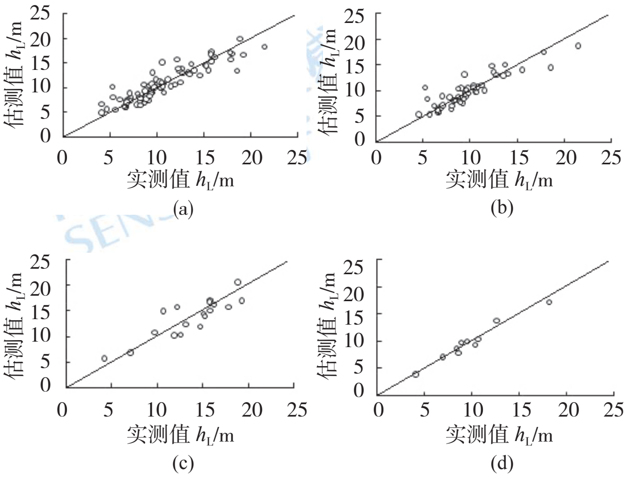

图1　样地胸高断面积加权平均树高(h_L)实测值与预测值的对比

(a) 所有样地；(b) 针叶林；(c) 阔叶林；(d) 混交林

3.2　地上生物量

估测地上生物量部分，将所有高度变量和密度变量均带入方程进行了逐步回归分析，结果表明激光雷达数据与地上各部分生物量相关性较高。所有样地无区别分析的预测结果中，各部位生物量的相关系数r均高于0.4，可解释的变异占总变异的比例均在35%以上；总的地上、树干、树枝和树叶生物量的标准误差(SE)分别为1.89 Mg·ha^{-1}(为平均值的3%)，1.88 Mg·ha^{-1}(为平均值的4.3%)，1.97 Mg·ha^{-1}(为平均值的13.1%)和1.79 Mg·ha^{-1}(为平均值的39.3%)。实测值与预测值之间的平均相对误差(MPE)则分别为–21.3%，–21.3%，–24.9%和–16.3%。针叶林各部位生物量的相关系数r均高于0.8，可解释的变异占总变异的比例均在68%以上；总的地上、树干、树枝和树叶生物量的SE分别为1.53 Mg·ha^{-1} (为平均值的2.4%)，1.54 Mg·hm^{-1} (为平均值的3.4%)，1.53 Mg·ha^{-1}(为平均值的10.8%)和1.42 Mg·ha^{-1}(为平均值的32.3%)。实测值与预测值之间的MPE则分别为–9.7%，–10%，–9.9%和–6.7%。阔叶林各部位生物量的相关系数r均高于0.5，可解释的变异占总变异的比例均在40%以上；总的地上、树干、树枝和树叶生物量的SE分别为1.58 Mg·ha^{-1}(为平均值的2.1%)，1.55 Mg·ha^{-1}(为平均值的3.1%)，1.76 Mg·ha^{-1}(为平均值的9%)和1.6 Mg·ha^{-1}(为平均值的28.2%)。实测值与预测值之间的MPE则分别为–12%，–10.7%，–16.8%和–12%。混交林各部位生物量与激光雷达变量则没有明显关系(图2，表2)。

表2　估测胸高断面积加权平均高(h_L)和地上生物量(W_i)的回归方程及参数情况

回归模型	P	R^2	SE	MPE	D
a. 所有样地					
h_L=1.809+0.018×h_{50}	0.000	0.83	1.62	–2.6%	2.116
lnW_a=6.887+0.815×lnd_9	0.000	0.37	0.64	–21.3%	2.404
lnW_s=6.581+0.835×lnd_9	0.000	0.39	0.63	–21.3%	2.378
lnW_b=6.730+1.313×lnd_9 – 0.996×lnd_0	0.000	0.37	0.68	–24.9%	2.363
lnW_f=2.441+0.513×lnd_9+0.394×lnh_{30}	0.001	0.35	0.58	–16.5%	2.141
b. 针叶林					
h_L=1.229+0.998×h_{60}	0.000	0.79	0.81	–2.3%	2.077
lnW_a=2.278+1.170×lnh_{30}+0.991×lnd_0	0.000	0.68	0.426	–9.7%	2.125
lnW_s=1.962+1.158×lnh_{30}+1.034×lnd_0	0.000	0.68	0.43	–10%	1.940

续表

回归模型	P	R^2	SE	MPE	D
$\ln W_b$= 2.676+1.040 × $\ln d_7$ 0.938 × $\ln h_{80}$	0.000	0.7	0.426	−9.9%	2.049
$\ln W_f$=1.828+0.752 × $\ln d_8$+1.452 × $\ln h_{40}$ −0.863 × $\ln h_{10}$	0.001	0.69	0.35	−6.7%	2.056
c. 阔叶林					
h_L=2.360+1.040 × h_{40}	0.000	0.75	1.98	−1.4%	1.793
$\ln W_a$=6.494+0.673 × $\ln d_9$	0.000	0.43	0.46	−12%	1.925
$\ln W_s$=5.016+0.777 × $\ln d_5$	0.000	0.42	0.44	−10.7%	1.797
$\ln W_b$=5.605+0.822 × $\ln d_9$	0.000	0.42	0.57	−16.8%	2.044
$\ln W_f$=4.671+0.908 × $\ln d_9$	0.000	0.57	0.47	−12%	2.018
d. 混交林					
h_L=0.006+0.941 × h_{90}	0.000	0.95	0.81	0.01%	2.077
生物量	无明显关系				

注h_L为胸高断面积加权平均高；W_a为地上总生物量；W_s为树干生物量；W_b为活枝生物量；W_f为叶生物量

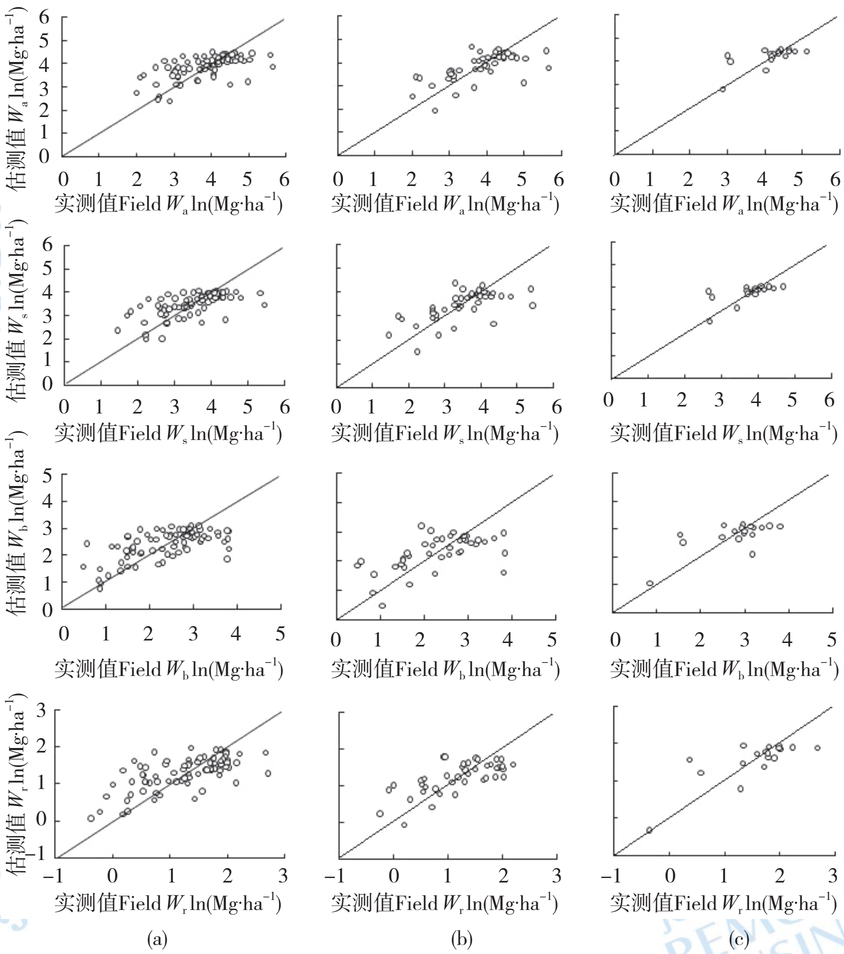

图2 样地生物量实测值与预测值的对比(W_a为地上总生物量；W_s为树干生物量；W_b为活枝生物量；W_f为叶生物量)
(a) 所有样地；(b) 针叶林；(c) 阔叶林

4 讨 论

应用分位数高度来估测森林参数的方法在激光雷达反演森林参数中广泛应用。Holmgren(2004b)对瑞典西南部Remningstorp地区的优势树种为挪威云杉、苏格兰松和桦树的29块森林立地估测了平均树高。若干激光雷达分位数高度数据被带入并采用逐步回归分析选出了95th分位数高度来估计。平均树高，其关系

系数r达到0.995。本研究中，由激光雷达分位数高度变量构建的树高预测模型也得到了比较好的结果。Nasset和Gobakken (2008)对挪威北部森林公园的1395块样地做了地上和地下生物量估测研究，将样地按照树种组成、龄级和立地等级进行分类，把树冠分位数高度和树冠密度作为独立变量，立地和龄级等作为虚变量，树种组成作为连续变量构建了回归模型，其决定系数也达到了0.7以上。类似的变量选择也成功用于本研究中的生物量估计。

在本研究中，采用逐步回归方法对不同树种选择出的变量区别很大。所有样地、针叶林、阔叶林和混交林用于估测平均高度的变量分别为50^{th}，40^{th}，60^{th}和90^{th}激光雷达分位数高度。唯混交林选择的变量为较高的分位数高度，其原因可能是混交林内树木间高度差别不大。针叶林用于生物量估测的变量是由高度变量和密度变量成对组成，而对所有样地和只有阔叶林样地的分析结果则都只选出了密度变量，且其关系差于针叶林的分析结果。特有树种的生物量方程表明生物量与树高、胸径是有一定关系的，这个结果可以理解为针叶树的生物量与树高的关系更为明显，而阔叶树的生物量则与胸径更有关联。

估测平均树高的精度与激光雷达树冠高度的提取有密切关系。机载激光雷达系统是离散采样，其采样点有一定间隔，容易错失树顶，造成树高的低估。加权平均树高的算法也使得大树对平均树高的影响比小树大，树种的影响则很小。虽然提高采样精度能提高估测树高的精度，但要面对成本过高的问题。另一方面，在比较茂密的林地，用于生成数字高程模型的地面点也可能被遮挡，造成树冠高程模型的高度误差。Reutebuch等人(2003)在研究中考察了针对4种不同林分密度林地的数字地形模型(DTM)生成的精确度，结果表明郁闭度越大对DTM造成的误差越大。

影响森林生物量估测精度的原因可能是一种误差的累积。首先，在样地实测数据的采集中出现的误差不可避免。其次，激光雷达数据的采集时间不是在枝叶茂密的夏季，而是在秋冬之交，从叶上返回的回波数有所减少。样地坐标的误差与激光雷达采样密度可能同时影响到激光雷达高度的分布情况，最终影响到叶生物量的估测(Lim 等，2003; Lim和Treitz，2004)。另外，树高的低估也直接造成了生物量的低估。从研究结果中可以看出，叶物量的估测精度相对最低，地上总生物量、树干生物量与活枝生物量受到的影响相对较小。另外，不能忽略地理区域和森林类型不同对生物量估测所造成的影响。树干生物量是树的主要生物量部分，树干形状的变化必然直接影响到树干生物量，并可能影响到其他生物量组成部分。因此，将地理区域与森林类型的影响控制在最小范围内，将样地进行按立地质量和树种构成进行分类处理，有望提高预测精度。

5 结 论

以云南中部的亚热带森林为研究对象，通过对机载LiDAR点云数据的处理分析和外业树高的测量，进行了机载LiDAR技术进行林分参数反演的试验。结论如下：

(1)通过逐步回归分析选出的变量和回归系数均能达到显著水平，且得到了较好的预测结果，说明针对不同森林类型选出的变量组成的各预测模型可以进行高精度的森林参数预测。其中树高估测模型的决定系数均大于0.75，生物量估测模型的决定系数则相对较低(均低于0.7)。对于不同森林类型的生物量估测，针叶林生物量估测模型的决定系数高于阔叶林生物量估测模型的决定系数，其次是所有样地生物量估测模型的决定系数，混交林则未选出具有高相关性的变量。

(2)对于不同森林类型，树高估计精度的差异不大，其平均相对误差均能控制在2%左右。说明激光雷达数据能很好的反映森林高度，且树种构成不同对其影响不大。此结果表明，激光雷达高度变量(h_{40}，h_{50}，h_{60}和h_{90})能够准确估测树高，今后可以对其他地区进行此类树高估测的研究，如果估测精度达到要求且结果稳定，那么此激光雷达变量提取方法应用于其他地区的树高估计是可行的。

(3)对于不同森林类型，生物量估计的精度有明显区别，其中针叶林的估测精度相对最高，其次是阔叶林，最后是所有样地的结果。本研究中，混交林生物量与激光雷达变量无明显联系。但这可能是因为样地数少不利于统计分析。而对于各部分生物量的估测，总的地上生物量和树干生物量的估测结果要优于其他部分，叶生物量的估测结果最差。主要原因是树干占总生物量的比重最大，且激光雷达的扫描时间为12月，不利于叶生物量的估测。

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