SHADOW BASED NEW REMOTE SENSING METRICS FOR MOSO BAMBOO BIOMASS PREDICTION USING UNMANNED AERIAL VEHICLE PHOTOGRAMMETRIC DATA

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ABSTRACT: Bamboo is one of the most important and fast growing species in the planet and it accounts for 1% of the earth's forest areas. Naturally, the specie has extremely high efficiency for carbon absorption. Therefore, monitoring its biomass changes can provide a good reference for global carbon cycle research. In recent years, the development of unmanned aerial vehicles (UAVs) has led to the rapid development of regional high-precision remote sensing biomass monitoring technology. However, the explanatory variables based on UAVs photography are mostly characterized by spectral, texture, and point cloud height parameters. Therefore, based on the explanatory variables of UAV image photography, we propose a new method for predicting the biomass of Moso bamboo (*Phyllostachys pubescens*). A series of shadow-based remote sensing variables were developed for bamboo biomass estimation, such as shadow fraction, shadow perimeter, shadow perimeter standard deviation, shadow count, average area for each shadow, shadow perimeter/area ratio, etc. Through regression analysis, we can understand the relationship between the shadow-based remote sensing variables and the bamboo biomass. The results indicate that shadow-based remote sensing metrics have potential predictive Moso bamboo biomass. The shadow-based remote sensing metrics proposed in this study can be used as an aid to the estimation of bamboo biomass.

1. MANUSCRIPT

Bamboo forest is one of the most important and fast-growing species in the planet and it accounts for 1% of the earth's forest areas. Approximately 15% of world's bamboo forests are concentrated in China (Yuen et al., 2017), and Moso bamboo (*Phyllostachys pubescens*) accounts for approximately 70% of the bamboo in China (Xu et al., 2011). Moso bamboo is also the most important economic bamboo in China. Naturally, the specie has extremely high efficiency for carbon absorption. Therefore, monitoring its biomass changes can provide a good reference for global carbon cycle research.

In recent years, the development of unmanned aerial vehicles (UAVs) has led to the rapid development of regional high-precision remote sensing biomass monitoring technology (Wallace et al., 2016; Puliti et al., 2015). However, the explanatory variables for estimating forest biomass based on UAV photography are mainly characterized by spectral, texture and point cloud height parameters. In fact, less scholars pay attention to the information in the shadow of the image. In fact, the image shadow hides some information, such as remote sensing for forests. At present, remote sensing image shading is considered to be the last important image feature and is highly correlated with the canopy structure (Peddle et al., 1999). The heterogeneity of the canopy canopy produces a large number of shadows and is reflected in remote sensing images. These shades are related to many biophysical factors such as biomass, net productivity, and leaf area index (Seed and King, 2003). Some studies have shown that the shadow fraction of high-resolution images is related to some stand parameters (Leboeuf et al., 2007; Leboeuf et al., 2012; Leboeuf et al ., 2013). The shadow feature parameters also bring some important information that provides new options for high-resolution imagery in forest biomass estimation. However, the shadow characteristic parameters are less common in previous studies, with the shadow fraction as the main shadow feature parameter. On the other hand, according to Hsieh et al. (2016) research, the spectral features of the shaded areas are quite different from those of the non-shaded areas. Therefore the characteristics of the spectrum of the shaded area, it should be possible to build shadow spectrum metrics for analysis testing.

Therefore, this study attempts to develop a series of shadow-based variables based on the explanatory of UAV image photography. A series of shadow-based remote sensing variables were developed for bamboo biomass estimation.

2. MATERIALS

2.1 Field data

A total of 88 ground sample plots were used in this study (Figure 1). The ground sample plots size was 20 m × 20 m. Within each plot, all bamboo and trees were measured. Their species, dbh (1.3 m), tree height, bamboo age was measured and recorded (dbh > 5 cm). In order to calculate the biomass of bamboo, we adopt the empirical equation to estimate bamboo biomass of each plot as follows (Zhou & Jiang 2004):

$$M = 747.787D^{2.771}\ [0.148A/(0.028 + A)]^{5.555} + 3.772$$

Where, M is biomass of single bamboo plant in kg; D is DBH of the bamboo culm in cm; and A is a value related to bamboo age, which is dimen-sionless. In China, a new Moso bamboo culm grows usually every 2-years. Thus, A = 1 corresponds to 1-2 years of bamboo age, and A = 2, 3 and 4 correspond to 3 - 4, 5 - 6 and 7 - 8 year-old culms, respectively.

2.2 UAV image

UAV images in Yongan were collected in June 2018 under good conditions with sunny weather and wind speeds of <1 m/s. The flight altitude was set to 300 m above ground and the images were acquired using a Micasense camera. Micasense camera has 5 multi-spectral bands (blue, green, red, near-infrared, red-edge). The overlap was set to 85% along the tracks and 75% between the tracks. UAV images are processed using Pix4d to create a 3D point cloud. Pix4d combines SfM and photogrammetric stereo matching algorithms to perform 3D reconstruction of overlapping images.

3. METHODOLOGY

3.1 Shadow detection

For the image shadow, the shadow bitmap was produced by applying a threshold value to the calculations of modified intensity from Nagao et al. (1979). The thresholds were determined using the first valley detection method, as in Equation (1) (Adeline et al. 2013):

$$I = \frac{1}{6} \times (2RED + GREEN + BLUE + 2NIR)$$

where I = Nagao’s modified intensity; RED = red waveband; GREEN = green waveband; BLUE = blue waveband; and NIR = near-infrared waveband.

The difference between the shadowed and non-shadowed areas was enhanced using Nagao *et al.*’s (1979) modified intensity image prior to dividing it into shadowed and non-shadowed areas. Because of the location of the shadows in the histograms, mainly occupying the first mode, the thresholds of the shadowed areas were determined using the first valley detection method (Adeline et al. 2013).

3.2 Extraction of explanatory variables

In this study, we get the shape and distribution of shadows through shadow detection. The following shadow shape metrics are constructed based on the shape features such as the area, perimeter, and number of shadows. Table 1 provides a detailed description of the shadow shape image explanatory metrics.

Table 1 Summary of the shadow shape metrics

Metric	Description
SF	Shadow fraction is the sum of all areas occupied by the shadow of a given tree divided by the total area of the ground
SP	Shadow perimeter per ha (m/ha)
SC	Shadow count per ha (count/ha)
SA/C	Average area for each shadow (m^2)
SP/C	Average perimeter for each shadow (m)
SP/A	Shadow perimeter/area ratio

This study proposes the following basic shadow spectrum metrics. The spectral spectrum of each band of the shaded area is statistically analyzed to construct a shadow spectrum metrics. Table 2 provides a detailed description of the shadow spectrum metrics.

Table 2 Summary of the shadow spectrum metrics

Metrics	Description
SNDVI_mean	Mean NDVI in shadow area
SNDVI_max	Maximum NDVI in shadow area
SNDVI_min	Minimum NDVI in shadow area
SNDVI_range	Difference between maximum and minimum NDVI values in shadow area
SNDVI_STD	Standard deviation of NDVI in shadow area
Smean_R, Smean_G, Smean_B, Smean_NIR, Smean_Red-edge	Mean value of R, G, B, NIR, and Red-edge bands in shadow area
Smax_R, Smax_G, Smax_B, Smax_NIR, Smax_Red-edge	Maximum value of R, G, B, NIR, and Red-edge bands in shadow area
Smin_R, Smin_G, Smin_B, Smin_NIR, Smin_Red-edge	Minimum value of R, G, B, NIR, and Red-edge bands in shadow area
Srange_R, Srange_G, Srange_B, Srange_NIR, Srange_Red-edge	Difference between maximum and minimum values of R, G, B, NIR, and Red-edge bands in shadow area
SSTD_R, SSTD_G, SSTD_B, SSTD_NIR, SSTD_Red-edge	Standard deviation of NDVI in shadow area

3.3 Regression models and Accuracy assessment

First, this study separately analyzes each shadow-based metrics and field-measured bamboo biomass data by typical correlation analysis, to see the relationship between each metric and field-measured bamboo biomass.

To build a prediction model for bamboo biomass through shadow-based metrics, a set of multiple regression models were built using the selected metrics and the field-measured bamboo biomass data to predict bamboo biomass. A stepwise regression approach was then employed to search the best fit model using the shadow-based metrics from the preliminary bamboo biomass model. In our regression analyses of the relationship between shadow-based metrics and field-measured data, the values of the former served as the independent variable to establish a statistical relationship that was used to predict the bamboo biomass. To develop the regression model, 70% of the ground sample plots (63) were randomly selected as a training or modeling dataset. An adjusted regression coefficient (R^2_{adj}) was calculated as a representative indicator of the fit quality. Supplemental statistics were calculated to evaluate the accuracy of the shadow fraction regression model. We used the remaining 30% of the ground sample plots (25) to calculate the absolute and relative root mean square errors (RMSE and $RMSE_r$) of the regression model.

4. Results and Discussion

4.1 Correlation of shadow-based metrics with bamboo biomass

Through regression analysis, we can understand the relationship between the shadow-based remote sensing variables and the bamboo biomass. The relationship between each metrics and biomass was known from the results of the correlation analysis. In the shadow shape metrics, SP had a significant correlation with biomass ($p<0.05$) (Table 3). SP is the unit perimeter of the shadow, and the relationship between the perimeter of the shadow and the biomass of the bamboo can be discussed later. From the results, it can be found that there is no significant relationship between SF and bamboo biomass. In the past, the research on the use of SF for the stand parameters of conifers was estimated (Leboeuf et al., 2007; Leboeuf et al., 2012; Leboeuf et al., 2013). SF has no obvious benefit for the estimation of the bamboo forest biomass.

Table 3 Correlation analysis of shadow shape metrics and bamboo biomass

Metrics	R	p-value
SF	-0.165605	p=0.121
SP	-0.224429	p=0.034*
SC	-0.045424	p=0.673
SA_C	-0.157881	p=0.139
SP_C	-0.176328	p=0.098
SP_A	0.151789	p=0.156

In shadow shape metrics, SNDVI_min, SNDVI_max, SNDVI_range, SNDVI_mean, SNDVI_STD, Srange_B, Smax_R, Srange_R, SSTD_R, Smin_NIR, Smean_NIR, SSTD_NIR were significantly correlated with biomass ($p<0.05$, $p<0.01$)(Table 4). Among them, the NDVI metrics of the shaded area can be found to have a higher R value, which indicates that it has a higher contribution (Table 4).

Table 4 Correlation analysis of shadow spectrum metrics and bamboo biomass

Metrics	R	p-value	Metrics	R	p-value
SNDVI_min	0.474279	p=0.000**	Smin_R	0.185130	p=0.082
SNDVI_max	0.361661	p=0.000**	Smax_R	-0.323324	p=0.002*
SNDVI_range	-0.316389	p=0.003**	Srange_R	-0.366190	p=0.000**
SNDVI_mean	0.444703	p=0.000**	Smean_NIR	-0.064858	p=0.546
SNDVI_STD	-0.398905	p=0.000**	SSTD_R	-0.269050	p=0.011
Smin_B	0.347573	p=0.001**	Smin_NIR	0.365205	p=0.000
Smax_B	-0.105279	p=0.326	Smax_NIR	0.173640	p=0.104
Srange_B	-0.251932	P=0.017*	Srange_NIR	-0.160786	p=0.132
Smean_B	0.199901	P=0.060	Smean_NIR	0.320567	p=0.002*
SSTD_B	-0.163152	p=0.127	SSTD_NIR	-0.232124	p=0.029*
Smin_G	0.171039	p=0.109	Smin_Red-edge	0.163725	p=0.125
Smax_G	-0.103347	p=0.335	Smax_Red-edge	0.078955	p=0.462
Srange_G	-0.145277	p=0.174	Srange_Red-edge	-0.008836	p=0.935
Smean_G	0.154784	p=0.148	Smean_Red-edge	0.139213	p=0.193
SSTD_G	0.041876	p=0.697	SSTD_Red-edge	0.038087	p=0.723

In this study, NDVI metrics (including shadow and non-shadow images) in the sample area was also calculated, and correlation analysis with bamboo biomass was also carried out. The analysis results are shown in Table 4. Among them, NDVI_min, NDVI_max, NDVI_range, NDVI_mean had significant correlation with biomass ($p<0.05$, $p<0.01$). However, compared to the shadow-based NDVI metrics (SNDVI_min, SNDVI_max, SNDVI_range, SNDVI_mean, SNDVI_STD), the R values are higher than the NDVI metrics, such as the R values of SNDVI_min and NDVI_min are 0.371101, 0.474279. The NDVI in the shaded area is better correlated with the biomass.

Table 5 Correlation analysis of NDVI metrics and bamboo biomass

Metrics	Description	R	p
NDVI_min	Minimum NDVI	0.371101	p=0.000**
NDVI_max	Maximum NDVI	0.281464	p=0.008**
NDVI_range	Difference between maximum and minimum NDVI values	-0.306068	p=0.004**
NDVI_mean	Mean NDVI	0.241748	p=0.022*
NDVI_STD	Standard deviation of NDVI	-0.200153	p=0.060

4.2 Bamboo-based biomass estimation model for shadow-based metrics

Through stepwise learning analysis, the obtained model R^2_{Adj}=0.446 is slightly lower, whereas $RMSE_r$=25.65% is still an acceptable range (Table 6). In a study comparing past telemetry to estimate bamboo biomass, Cao et al (2019) used LiDAR metrics predicted Moso bamboo biomass (R^2=0.59–0.87, $RMSE_r$=11.92–21.11%) with LiDAR percentile heights and the coefficient of variation of height. Although the $RMSE_r$ of this study is slightly higher than that of Cao et al. (2019), this study mainly uses low-cost UAV images, and its shooting cost is unmatched by LiDAR.

The selected parameters are SNDVI_min, SSTD_G, Srange_R, SP, SNDVI_max. Visible by the selected metrics, shadow spectrum metrics dominates the model (Table 6). The main component, the parameters of the shaded area NDVI are selected by two parameters. The NDVI in the shaded area has high importance; the SP is also selected, and the SP is the unit perimeter of the bamboo forest shadow. This parameter is also a parameter not mentioned in the past literature. The results indicate that shadow-based remote sensing metrics have potential predictive Moso bamboo biomass.

Table 6 Summary of the regression analysis for the estimation of biomass with the explanatory shadow-based metrics.

Model	R^2	Adj. R^2	RMSE (Mg ha^{-1})	$RMSE_r$(%)
26.705 SNDVI_min + 1796.882 SSTD_G**-381.175 Srange_R*-0.002 SP+ 72.575 SNDVI_max**-6.269	0.491	0.446	7.48	25.65

* b0.05 level of significance.
** b0.01 level of significance.
*** b0.001 level of significance.

5. Conclusions

The shadow-based remote sensing metrics proposed in this study can be used as an aid to the estimation of bamboo biomass. The NDVI in the shaded area is significantly helpful for the estimation of bamboo biomass, and the correlation is better than the NDVI that is generally not considered for shadow. Subsequent development of other shadow-related metrics, such as the combination of shadow metrics of UAV matching point clouds, etc., in order to facilitate subsequent enhancement of model accuracy.

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