Grassland Biomass Estimation Based on MODIS Data and Vegetation Characteristics (Postprint)

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Date: 2017-11-09T00:00:00+00:00

Abstract

Accurate estimation of grassland biomass is of significant importance for research on terrestrial ecosystem carbon cycling under the background of global climate change. Over the past few decades, grassland biomass estimation studies have predominantly concentrated in northern regions, while southern grasslands, characterized by diverse types and scattered distribution, have been seldom reported for biomass assessment. This study takes Yunnan Province as a case study, employing field survey data of grassland biomass from 2012–2014 and concurrent MODIS remote sensing data to establish a remote sensing estimation model for grassland aboveground biomass (AGB); subsequently, vegetation community characteristic information (height and coverage) of grasslands is introduced to optimize the statistical model and conduct spatial inversion of biomass. The results indicate that the estimation accuracy of the optimized model increased from 35.0% to 43.7%; the total annual average AGB of Yunnan Province for the three years derived from inversion ranges between 10.2686 million–14.0854 million t, averaging 12.2111 million t; in terms of spatial distribution, the AGB density of grasslands in Yunnan Province generally displays a pattern of high in the west and low in the east, high in the south and low in the north. This study represents the first integration of remote sensing vegetation index data with measured vegetation community characteristic parameters, substantially improving estimation accuracy by 24.9% compared to traditional pure optical remote sensing simulation methods; however, accurate estimation of large-area grassland AGB necessitates further exploration of how to apply vegetation characteristic information extracted from LiDAR data or remote sensing stereo imagery to grassland AGB estimation research.

Full Text

Estimation of Grassland Biomass Using MODIS Data and Plant Community Characteristics

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Abstract: Accurate estimation of grassland biomass is critical for terrestrial ecosystem carbon cycling research in the context of global climate change. Over the past several decades, most grassland biomass estimation studies in China have concentrated on northern regions, while southern grasslands—characterized by diverse types and fragmented distribution—have received limited attention. This study takes Yunnan Province as a case study, using field survey data of grassland biomass from 2012–2014 and concurrent MODIS remote sensing data to establish a remote sensing estimation model for aboveground grassland biomass (AGB). Plant community characteristics (height and coverage) were then incorporated to optimize the statistical model, which was subsequently applied for spatial inversion of biomass. Results show that the optimized model improved estimation accuracy from 35.0% to 43.7%. The estimated annual total AGB in Yunnan Province for the three-year period ranged from 10.27 to 14.09 million tons, with an average of 12.21 million tons. Spatially, AGB density exhibited a pattern of higher values in the west and south compared to the east and north. This study represents the first integration of remote sensing vegetation index data with measured plant community parameters, achieving a 24.9% improvement in accuracy over traditional optical remote sensing methods alone. However, precise large-scale AGB estimation requires further exploration of how to incorporate vegetation structural information derived from LiDAR data or stereo remote sensing imagery.

Keywords: Yunnan Province; MODIS data; Aboveground biomass; Plant community characteristics; Spatial inversion

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Introduction

Grasslands constitute a vital component of terrestrial ecosystems and play a significant role in global climate change and carbon cycling [1]. Grassland biomass serves as an indicator of vegetation condition and production potential, and its accurate estimation is essential for studying global carbon cycles and assessing ecological benefits of grassland vegetation [2-3]. China possesses 3.55×10 hm² of grassland area, accounting for 41.7% of its total territory [4]. Since the mid-1990s, scholars have conducted numerous studies on grassland biomass estimation in China [5-8], focusing primarily on northern regions [9] including Tibet, Inner Mongolia, Qinghai, and Xinjiang. For instance, Niu et al. [7] established a remote sensing monitoring model for grassland vegetation biomass in the Qinghai Lake region using TM imagery and concurrent field data, while Zhang et al. [10] validated the CASA model for ecosystem carbon cycling processes in Inner Mongolia' s typical grasslands using 13 years of AGB data and analyzed temporal variation in net primary productivity and its driving factors from 1982–2002. Southern China contains over 60 million hm² of grassland slopes, representing nearly one-sixth of the national grassland area [11]. As northern grasslands face degradation [12-13], southern grasslands have become increasingly important in China' s grassland ecosystem. However, complex terrain, significant climate variation, and pronounced spatial heterogeneity in southern regions result in diverse and fragmented grassland types, leaving research on biomass estimation for Yunnan' s grasslands largely unaddressed [14].

Biomass estimation models generally fall into four categories: (1) process-based models, (2) empirical models, (3) biomass expansion/conversion factor methods, and (4) integration of field data with remote sensing data [15]. Among these, the integration of field and remote sensing data is widely applied for large-scale vegetation biomass estimation, particularly in regions with established field biomass survey databases [15]. However, existing inventory and field survey data suffer from limitations for annual dynamic assessments, including lack of continuous spatial coverage, low spatial resolution, discontinuities across administrative boundaries, and significant time lags [16]. Remote sensing data offer extensive spatial coverage, high spatiotemporal resolution, and good consistency and stability [17-20], which can compensate for these deficiencies. Vegetation remote sensing quantitative research utilizes field survey data to establish regression models with remote sensing vegetation indices or environmental factors as independent variables and biomass as the dependent variable, thereby extrapolating biomass across entire regions [21]. Among various vegetation indices calculated from remote sensing imagery (e.g., Landsat and MODIS), the Normalized Difference Vegetation Index (NDVI) is a commonly used indicator for vegetation biomass, providing an ideal quantifiable parameter for monitoring spatiotemporal variation in vegetation biomass across scales [22-23]. Nevertheless, NDVI-based biomass estimation has limitations, including remote sensing platform and sensor performance constraints, susceptibility to cloud and aerosol interference, and NDVI saturation issues [24-26]. Previous studies have shown that biomass varies with species composition and vegetation height [27], and LiDAR' s capability to directly measure canopy height distribution makes it suitable for large-scale biomass estimation [20]. Therefore, integrating vegetation community characteristics (e.g., height and coverage) with NDVI offers a new approach for vegetation biomass research. Considering data accessibility and the correlation between vegetation height and species composition [26], this study incorporated grassland community characteristic parameters into biomass inversion to provide a methodological basis for large-scale estimation.

This research focuses on Yunnan Province, using NDVI calculated from MODIS data combined with concurrent field AGB measurements to establish an NDVI-based grassland AGB estimation model. Plant community height and coverage were applied to optimize the model, addressing three key questions: (1) Does incorporating vegetation community characteristics improve estimation accuracy? (2) What are the spatial distribution patterns of grassland AGB in Yunnan? (3) What is the significance of southern grasslands, represented by Yunnan, in China' s grassland ecosystem? The findings aim to provide scientific support for grassland biomass estimation, carrying capacity assessment, and sustainable utilization in China.

1.1 Study Area

Yunnan Province is located in southwestern China between 21°09 -29°15 N and 97°30 -106°00 E [Figure 1: see original paper], with elevation ranging from 76.4 to 6,740 m. The province covers a total land area of 3.94×10 hm^2, including 1.527×10 hm^2 of grassland (38.7% of total land area), with 1.187×10 hm^2 of usable grassland [28]. The climate is characterized as plateau tropical monsoon, featuring small annual temperature variation, large diurnal temperature range, and abundant rainfall. The average annual temperature is 24°C, with average annual precipitation of 1,100 mm, though winter and spring precipitation accounts for only about 20% of annual totals. The favorable natural environment provides suitable light, soil, and climate conditions for plant growth, fostering biodiversity in biological resources. Based on field investigations, Yunnan' s vegetation types primarily include alpine meadow, temperate steppe, montane meadow, warm-temperate (shrub) herbosa, tropical (shrub) herbosa, and arid-tropical shrub herbosa scattered with trees.

1.2 Data and Methods

1.2.1 Field Survey of Grassland Biomass Field surveys were conducted during the 2012-2014 growing seasons. Based on spatial distribution characteristics and area sizes of grassland types, 305 sample plots were designed across Yunnan. Surveys of major grassland types were carried out from August to October each year, covering 58 counties/county-level cities. After removing anomalous data points, 684 samples remained for modeling and validation (138 in 2012, 230 in 2013, and 316 in 2014 after expanding survey scope) [Figure 1: see original paper]. Sample plots were established in typical locations with uniform grassland vegetation distribution. In homogeneous vegetation communities, one or two 0.5 m × 0.5 m quadrats were set; in heterogeneous areas with complex vegetation types, three or four 1.0 m × 1.0 m quadrats were established. Basic plot characteristics recorded included administrative region, grassland type, topography, seasonal utilization patterns, and usage status. GPS was used to determine quadrat coordinates and elevation, while conventional vegetation survey methods measured species number, vegetation coverage, average community height, and total aboveground biomass.

1.2.2 Remote Sensing Data Acquisition and Processing Remote sensing data consisted of EOS/MODIS MOD13Q1 products from USGS (United States Geological Survey) with 250 m spatial resolution and 16-day composite intervals in EOS-HDF format. Data covered two tiles (h26v06 and h27v06) in the global sinusoidal projection system for the 2012–2014 growing seasons (August–October), comprising six cloud-free (<10% cloud cover) images. MODIS Reprojection Tools (MRT) were used for projection and format conversion to unified Albers projection (Standard Parallel 1: 25°N, Standard Parallel 2: 47°N, Central Meridian: 105°E, Datum: WGS84). Based on regional vegetation characteristics and referencing domestic and international grassland AGB studies, ENVI and ArcGIS software were used to extract NDVI from MODIS data, calculated as [29]:

$$NDVI = (NIR - R) / (NIR + R)$$

where NIR represents near-infrared band reflectance and R represents red band reflectance. Due to the significant linear correlation between vegetation coverage and NDVI, NDVI can be used to extract vegetation coverage information [30-31]. Based on the pixel dichotomy model, each pixel' s NDVI value comprises contributions from green vegetation (NDVIveg) and bare soil (NDVIsoil). Vegetation coverage (fc) is calculated as [32]:

$$fc = (NDVI - NDVIsoil) / (NDVIveg - NDVIsoil)$$

where NDVIsoil represents NDVI values for completely bare soil or non-vegetated areas (taken as the 0.5% cumulative frequency NDVI value in this study), and NDVIveg represents NDVI values for fully vegetated areas (taken as the 99.5% cumulative frequency NDVI value).

1.2.3 Model Development and Accuracy Assessment SPSS statistical software was used for correlation and regression analysis between NDVI, vegetation characteristics (height and coverage), and field-measured AGB data to develop regression models for AGB estimation. Model accuracy was evaluated using reserved field samples by comparing measured AGB with model-estimated values through Root Mean Square Error (RMSE) and Accuracy [33]:

$$RMSE = \sqrt{[\Sigma(Yi - Yi')^2 / N]}$$
$$Accuracy = (1 - RMSE / \bar{Y}) \times 100\%$$

where Yi is measured grassland AGB (g · m ²), Yi' is estimated AGB (g · m ²), $\bar{Y}$ is mean measured AGB (g · m ²), and N is sample size.

Results

2.1 AGB-NDVI Model Development and Validation

From 684 AGB samples collected during 2012–2014, 600 data points were randomly selected. Corresponding concurrent NDVI values were extracted from MODIS data using ArcGIS to establish a linear regression equation between unit area AGB and NDVI. Results showed a significant positive linear correlation ($R = 0.297$, $P < 0.01$) with the regression equation:

$$y = 2280.171x - 2015.156$$

where y represents AGB and x represents NDVI. Validation using the remaining 84 samples yielded an estimation accuracy of 35.0% [Figure 2: see original paper].

2.2 Vegetation Characteristics and Biomass of Different Grassland Types

Field survey data revealed nine major grassland vegetation types in Yunnan [Figure 3: see original paper]. As grassland types transitioned from alpine to temperate to tropical, average vegetation height (AH) gradually increased, while average coverage (AC) showed no significant change, and AGB exhibited an increasing trend. Standard errors for AGB and AH were relatively large, while AC showed small variation, indicating greater within-type variability in AGB and AH compared to AC. Correlation analysis demonstrated significant positive relationships between AGB and both AH and AC , suggesting that incorporating community characteristics (height and coverage) improves AGB estimation accuracy.

2.3 Optimization of Grassland AGB Estimation Model

Vegetation community characteristics were integrated into the regression model using 600 samples for multiple linear regression with AGB as the dependent variable and NDVI, height, and coverage as independent variables. The optimized model showed substantially improved fit ($R = 0.614$, $P < 0.01$) with no multicollinearity among variables . The regression equation was:

$$y = 2280.171x + 36.842x + 15.892x - 2015.156$$

where y is AGB, x is NDVI, x is average vegetation height, and x is vegetation coverage. Validation with 84 reserved samples improved estimation accuracy to 43.7% [Figure 4: see original paper], representing a 0.289 increase in goodness-of-fit and 8.7 percentage point improvement in accuracy. The optimized model demonstrated substantial benefits for accurately estimating Yunnan' s grassland AGB.

2.4 Spatial Inversion and Distribution Characteristics of AGB in Yunnan

For spatial inversion across Yunnan, vegetation community characteristic data were simplified due to data availability constraints. Mean heights for different grassland types were used to represent actual heights in the regression model, with GIS raster calculator tools applied for spatial inversion. The 1:1,000,000 grassland type classification system did not include four minor types (alpine meadow, alpine meadow-steppe, temperate meadow-steppe, and arid-tropical shrub herbosa), so grasslands were categorized into six types: lowland meadow, montane meadow, warm-temperate herbosa, warm-temperate shrub herbosa, tropical herbosa, and tropical shrub herbosa. Height data were available from field surveys for all types except lowland meadow; based on previous studies [5,34], lowland meadow height ranged from 18.77–31.00 cm, with a mean of 24.89 cm used .

Using NDVI data extracted from MODIS for 2012–2014, ArcGIS calculated maximum, minimum, and mean NDVI values [Figure 5: see original paper]. Maximum AH was calculated as mean plus standard error, and minimum AH as mean minus standard error. Vegetation coverage maximum, mean, and minimum values were derived from NDVI [Figure 6: see original paper]. These values were input into regression model (6) using GIS raster calculator to spatially invert grassland biomass, yielding maximum, minimum, and mean AGB density maps [Figure 7: see original paper]. The results revealed distinct spatial patterns, with higher AGB density in western and southern Yunnan compared to eastern and northern regions, likely related to temperature, precipitation, and other environmental factors.

Yunnan's grassland AGB density ranged from 1,376.76–1,888.51 kg·hm ^{2} (mean: 1,637.21 kg·hm ^{2}) during 2012–2014. With total grassland area of 7,458,498.06 hm^{2}, annual total AGB ranged from 10.27-14.09 million tons (mean: 12.21 million tons). At the prefecture level , high-density grasslands occurred in Xishuangbanna, Dehong, and Puer (southern and southwestern Yunnan), while low-density grasslands were found in northwestern Diqing and eastern Qujing. Honghe Hani and Yi Autonomous Prefecture had the largest total AGB (1.48 million tons), followed by Puer and Zhaotong, while Dehong and Nujiang Lisu Autonomous Prefecture had the smallest totals.

Significant differences in AGB existed among grassland types . Montane meadow (lowest density) was primarily distributed in northwestern Yunnan, while tropical and warm-temperate herbosa (highest density) occurred mainly in central and southern regions. Warm-temperate herbosa and shrub herbosa were most extensive, contributing large total AGB values of 6.11 and 4.13 million tons, respectively.

Spatial heterogeneity is a key characteristic of grassland ecosystems [35], with distinct differences in vegetation features among grassland types. Xu et al. [34] monitored annual variation in coverage, height, and yield of Hebei grasslands, finding substantial coverage differences among seven grassland types (montane meadow: 93.97%; temperate steppe: 57.63%) and significant height variation (warm-temperate herbosa: 49.25 cm; lowland meadow: 18.77 cm). Gao et al. [36] also reported significant differences in coverage and height among forest steppe, typical steppe, and desert steppe. Yunnan' s mountainous terrain (94% of area) features steep, fragmented topography [37] with elevation differences up to 6,663.6 m [38], creating diverse climates that control complex hydrothermal conditions, drive species selection and competition, and generate ecosystem diversity [39] and pronounced spatial heterogeneity. This study' s results align with Xu et al. [34], showing clear differences in coverage and height among Yunnan' s grassland types.

Vegetation height and coverage are ideal characteristics for describing community condition and reflecting productivity [40]. Most studies show positive correlation between vegetation height growth and biomass accumulation, with peak biomass coinciding with peak height [41]. This study found significant positive correlation between vegetation height and biomass ($R = 0.539$, $P < 0.001$). Coverage is also an important biomass indicator; Chen et al. [42] reported extremely significant linear correlation between community coverage and biomass ($R = 0.96$, $P < 0.001$), consistent with this study' s results ($R = 0.104$, $P < 0.001$, TABLE:2). Integrating MODIS data with measured grassland characteristic data improved estimation accuracy by 24.9% compared to traditional optical remote sensing methods alone, representing a novel approach for grassland AGB estimation. Numerous studies have confirmed that forest vertical structure parameters improve biomass estimation; Yu et al. [43] achieved 91.3% theoretical accuracy in forest biomass estimation using large-footprint LiDAR (GLAS) waveform data. This study provides a new methodology for future grassland biomass estimation.

The estimated mean AGB for Yunnan' s grasslands (12.21 million tons, 2012–2014) was 1.85 million tons higher than Piao et al.' s [8] national-scale estimate for Yunnan under equivalent grassland area. Xu et al. [44] estimated China's six major grassland regions using MODIS imagery and field data, reporting Yunnan' s productivity as 15.20 million tons (2004) and 11.55 million tons (2005), similar to this study' s results. However, Xu et al. [44] used a larger grassland area for Yunnan (104,274 km^2), yielding lower unit area biomass (1,108 kg · hm ^{2}) than this study. Compared with northern China studies, Yunnan' s average AGB density was substantially higher: Ma et al. [45] calculated northern grassland AGB density as 790 kg · hm ^{2}, and Jia et al. [46] reported 1,112 kg · hm ^{2} for northern typical steppe. With China's total grassland AGB estimated at 292.32 million tons [8], Yunnan' s contribution (10.27–14.09 million tons) represents 3.5–4.8% of the national total, demonstrating its non-negligible role.

This study improved grassland biomass estimation accuracy in complex terrain by incorporating vegetation community characteristics, though several uncertainties remain. First, the 1:1,000,000 grassland classification map may omit small grassland patches, potentially underestimating total grassland area and total biomass. Second, spatial scaling conversion may introduce errors [47]: the 250 m resolution MODIS imagery may misclassify scattered small grassland patches and edges of large grassland blocks as non-grassland vegetation, causing NDVI values to mismatch field biomass data and potentially overestimate biomass. Additionally, spatial matching between the 1:1,000,000 map and 250 m imagery creates edge pixel errors that are difficult to avoid and assess. Third, a single model for all Yunnan grasslands without stratification by vegetation type introduces uncertainty, as different grassland types have distinct characteristics and patterns. Higher-resolution imagery (e.g., Landsat) could reduce scaling errors but would require mosaicking 17 scenes for Yunnan, potentially creating boundary artifacts and cloud contamination issues that affect vegetation index calculation. Therefore, MODIS data were selected as a compromise. LiDAR-derived vegetation height could improve accuracy [20], but such data remain immature for grassland applications from acquisition to processing [48]. This study employed simplified mean heights by grassland type as an exploratory approach; precise large-scale AGB estimation requires further investigation of vertical structural information extraction from LiDAR or stereo imagery.

Conclusions

This study integrated remote sensing data with field measurements using an optimized estimation model to analyze Yunnan’ s grassland AGB and spatial patterns, yielding three main conclusions:

1) Incorporating vegetation characteristic information (height and coverage) significantly optimized the grassland AGB remote sensing estimation model, increasing goodness-of-fit by 0.289 and improving estimation accuracy by 24.9%. This approach is particularly suitable for complex terrain with variable climate and fragmented grassland distribution.

2) Yunnan’ s annual mean grassland AGB for 2012–2014 ranged from 10.27–14.09 million tons (average: 12.21 million tons), accounting for 4.1% of China’ s total and demonstrating the importance of southern grasslands in national biomass calculations. Spatially, AGB density showed a clear pattern of higher values in western and southern regions compared to eastern and northern regions.

3) Prefecture-level AGB densities ranged from 1,130.12–2,116.03 kg · hm ^{2}. Substantial differences existed among grassland types, with increasing trends from montane meadow to warm-temperate herbosa to tropical herbosa: montane meadow (1,071.73 kg · hm ^{2}) < lowland meadow (1,552.45 kg · hm ^{2}) < tropical shrub herbosa (1,579.80 kg · hm ^{2}) < warm-temperate shrub herbosa (1,588.12 kg · hm ^{2}) < warm-temperate herbosa (1,771.02 kg · hm ^{2}) < tropical herbosa (2,004.37 kg · hm ^{2}).

Acknowledgments

We sincerely thank the staff who assisted with field surveys in Yunnan Province and Dr. Zhu Zaichun for manuscript revisions.

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Note: Figure translations are in progress. See original paper for figures.