Postprint of Aboveground Biomass Estimation of Vegetation in the Desert-Oasis Ecotone at the Northeastern Margin of the Ulan Buh Desert

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Date: 2018-03-08T00:00:00+00:00

Abstract

Above-ground biomass of desert vegetation in arid regions is an important indicator for evaluating vegetation growth status and monitoring desertification. A typical area was selected in the desert-oasis transition zone on the northeastern edge of the Ulan Buh Desert, where allometric equations for major plant species were constructed based on ground survey data to estimate vegetation above-ground biomass within quadrats; regression models between vegetation indices and above-ground biomass of artificial sand-fixing forests and desert vegetation were respectively established based on quadrat survey data and QuickBird imagery data, and vegetation above-ground biomass in the study area was estimated. The results showed that canopy volume V was a good predictor variable, and the obtained allometric equations for desert plants had high accuracy, meeting the needs for estimating desert vegetation above-ground biomass within quadrats; the RVI logarithmic model yielded the best results for estimating above-ground biomass of artificial sand-fixing forests (R^2=0.72, RMSEP=56.15), while the RVI linear model performed best for estimating desert vegetation above-ground biomass (R^2=0.82, RMSEP=15.07); the above-ground biomass per unit area of desert vegetation and artificial sand-fixing forests in the study area was 90.73 g/m^2 and 105.28 g/m^2, respectively. This study can provide a reference for desertification monitoring and remote sensing information extraction of desert vegetation.

Full Text

Preamble

ACTA ECOLOGICA SINICA
ChinaXiv Partner Journal

Vol. 38, No. 4, Feb. 2018
DOI: 10.5846/stxb2016122719

Estimation of Aboveground Biomass of Vegetation in the Desert-Oasis Ecotone on the Northeastern Edge of the Ulan Buh Desert

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Abstract

Aboveground biomass (AGB) of desert vegetation in arid regions serves as a critical indicator for evaluating vegetation growth status and monitoring desertification. This study selected a typical area in the desert-oasis ecotone on the northeastern edge of the Ulan Buh Desert. Based on field survey data, we constructed allometric equations for major plant species to estimate vegetation AGB within sample plots. Using QuickBird imagery, we extracted three vegetation indices—the Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index (NDVI), and Modified Soil-Adjusted Vegetation Index (MSAVI)—and established regression models between these indices and the AGB of artificial sand-fixing forests and desert vegetation. The results demonstrated that: (1) Crown volume (V) was the optimal predictive variable for allometric equations of desert shrub species such as *Tamarix ramosissima*, *Haloxylon ammodendron*, *Caragana korshinskii*, *Artemisia desertorum*, *Nitraria tangutorum*, and *Elaeagnus angustifolia*, with all R^2 values exceeding 0.7, while crown area (S) was optimal for *Hedysarum scoparium*, yielding an R^2 of 0.63; (2) Among regression models constructed using RVI, NDVI, and MSAVI, the RVI logarithmic model performed best for estimating artificial sand-fixing forest AGB ($R^2 = 0.72$, RMSEP = 56.15), whereas the RVI linear model was optimal for desert vegetation AGB ($R^2 = 0.82$, RMSEP = 15.07); (3) The per-unit-area AGB of desert vegetation and artificial sand-fixing forests in the study area was 90.73 g/m^2 and 105.28 g/m^2, respectively. This research provides a reference for desertification monitoring and remote sensing information extraction of desert vegetation.

Keywords: allometric equation; vegetation index; QuickBird imagery; desert vegetation; sparse vegetation

1. Introduction

Aboveground biomass (AGB) estimation methods primarily include ground-based measurements and remote sensing approaches. Traditional ground measurement methods offer high accuracy and can reflect terrestrial vegetation productivity, serving as essential tools for studying ecosystem carbon sources and sinks. However, these methods are time-consuming, labor-intensive, and destructive to vegetation, making them suitable only for small-scale studies. For large-scale regions, uniform field surveys are often impractical, and extrapolating biomass from limited sample points to entire areas introduces significant errors [1-4].

Remote sensing methods for AGB estimation have largely compensated for the limitations of ground surveys due to their high efficiency and broad applicability. Systematic research on biomass in high-density forest and grassland ecosystems has been conducted extensively [5-6]. For instance, Liu et al. [7] estimated China’ s forest biomass spatial distribution using MODIS data and detailed inventory data, while Chen et al. [8] assessed AGB and carbon storage in the Hulunbuir Plateau using remote sensing technology. Sun et al. [9] developed a high-precision surface modeling method for grassland AGB based on field survey and concurrent remote sensing data.

Vegetation AGB represents a crucial indicator for evaluating vegetation growth and monitoring desertification in arid regions. While remote sensing technology provides multi-band and multi-temporal data sources for vegetation information extraction, desert vegetation is extremely sparse. When vegetation cover falls below a certain threshold, the spectral information of vegetation becomes difficult for sensors to detect, causing general remote sensing models to lose their universality in extracting desert vegetation information [10]. The weak green signal, small leaf area index, and large branch-to-leaf ratio of desert vegetation further complicate information extraction.

Some scholars have attempted to improve desert vegetation information extraction by leveraging the high lignin and cellulose content in desert plants [11, 14]. Others have employed linear pixel unmixing models [10] or improved multi-endmember spectral mixture analysis [12] to extract sparse vegetation cover. Li et al. [13] used Hyperion vegetation indices to estimate sparse vegetation cover in arid regions. However, reliable methods for extracting sparse desert vegetation information using multi-source remote sensing data remain an area requiring further exploration.

This study focuses on the desert-oasis ecotone on the northeastern edge of the Ulan Buh Desert. Using ground survey data and QuickBird imagery, we constructed allometric equations for major desert plant species and developed regression models between vegetation indices and AGB to estimate the aboveground biomass of both desert vegetation and artificial sand-fixing forests, providing a scientific basis for desertification monitoring and carbon storage estimation in desert ecosystems.

2. Study Area Overview

The Ulan Buh Desert is located in western Inner Mongolia, within Bayannur City and Alxa League. It borders the Hetao Plain to the northeast, reaches the northern foothills of Helan Mountain to the south, and extends to Jilantai Salt Lake to the west, covering approximately 17,000 km². The study area is situated in the desert-oasis ecotone between the northeastern edge of the Ulan Buh Desert and Bayangaole Town in Dengkou County, Inner Mongolia, forming a rectangular region extending from northeast to southwest between 40°3 40 -40°9 35 N and 106°2 42 -107°14 45 E, with an elevation of 1,028–1,054 m.

The region features a temperate continental monsoon climate with an average annual precipitation of 145 mm, concentrated in July–September, and an average annual evaporation of approximately 2,397 mm. The mean annual temperature is 7.6°C, and the terrain slopes gently from south-southwest to north-northeast.

Zonal vegetation consists of desert vegetation, with *Artemisia desertorum* and *Nitraria tangutorum* as dominant species. Associated species include *Caragana korshinskii*, *Hedysarum scoparium*, and *Tamarix ramosissima*. Herbaceous plants are primarily *Salsola collina*, *Inula salsoloides*, and *Bassia dasyphylla*. Soils are mainly aeolian sandy soil and desert soil.

In 1999, artificial sand-fixing forests were established in the study area, covering approximately 15.69 km² and distributed in the northeastern part near the oasis. The dominant species in these forests are *Elaeagnus angustifolia* and *Haloxylon ammodendron*, with community coverage of 50–70%. Sparse desert vegetation covers about 16.19 km², primarily distributed in the northwestern part near the desert, with community coverage of 3–36.9%. Farmland is present in the southeastern portion of the study area.

3. Field Survey

Field surveys were conducted in August 2015 using the quadrat method. We established 10 m × 10 m sample plots in typical, accessible areas representing both desert vegetation and artificial sand-fixing forest communities. A total of 30 plots were set up: 15 in artificial sand-fixing forests and 15 in desert vegetation. For each plot, we measured and recorded the base diameter, height, and long and short axes of the crown for every tree and shrub, along with the GPS coordinates of the plot center.

Along each plot' s diagonal, we established 1 m × 1 m subplots to measure herbaceous biomass using the harvest method. Fresh herbaceous biomass was weighed in the field, then oven-dried in the laboratory to calculate dry weight, which was extrapolated to the entire plot based on area.

To construct allometric equations, we selected healthy individuals of various sizes for *Elaeagnus angustifolia*, *Haloxylon ammodendron*, and *Tamarix ramosissima* near the sample plots. We measured base diameter and height, harvested entire plants at ground level, weighed fresh biomass, and took samples for oven-drying to obtain dry weight. Ten individuals per species were surveyed.

Vegetation coverage in artificial sand-fixing forest plots ranged from 3% to 80%

(mean 55.8%), with average per-unit-area AGB of 217.9 g/m². Desert vegetation plots had coverage ranging from 3% to 36.9% (mean 15.4%), with average per-unit-area AGB of 55.5 g/m².

4. Sample Plot Aboveground Biomass Estimation

We employed the allometric equation method commonly used in forest management and plant ecology to estimate plot-level AGB. Using biomass data from 70 surveyed plants, we established species-specific allometric equations for *Elaeagnus angustifolia*, *Haloxylon ammodendron*, and *Tamarix ramosissima*. These equations were then applied to calculate individual tree and shrub biomass in each plot, which was summed with herbaceous biomass to obtain total plot AGB.

The allometric growth equation follows the relationship:

$$Y = \beta X^{\alpha}$$

where Y represents plant aboveground biomass dry weight, X is an external morphological characteristic, β is a normalization constant, and α is the allometric scaling exponent [15-16]. Compared to other biomass equations, allometric equations better reflect the relationship between external morphological characteristics and cumulative individual plant biomass [17-18].

We used ordinary least squares regression (OLS) to construct biomass fitting equations. The coefficient of determination (R^2), mean absolute error (MAE), and mean symmetric error (MSE) served as evaluation metrics:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

$$MAE = \frac{\sum |y_i - \hat{y}_i|}{n}$$

$$MSE = \frac{\sum(y_i - \hat{y}_i)}{\sum \hat{y}_i} \times 100$$

where y_i is measured biomass, $\hat{y}_i$ is estimated biomass, $\bar{y}$ is the mean measured biomass, and n is sample size.

5. Remote Sensing Data Processing

We used high-resolution QuickBird multispectral imagery (2.4 m spatial resolution) acquired on August 26, 2015, covering the entire study area. The FLAASH module performed atmospheric correction to eliminate atmospheric and illumination effects. The imagery contained minor cloud patches in the upper-right and lower-left corners, with clear conditions elsewhere. Geometric precision correction was applied using differential positioning.

Land cover types were classified into artificial sand-fixing forest, desert vegetation, and cloud patches. The Support Vector Machine (SVM) method was employed with training samples (>30 per class) selected uniformly across the image. Post-classification clustering and merging produced the final land cover map.

6. Remote Sensing Estimation of Aboveground Biomass

Due to soil background noise, sparse desert vegetation information is difficult to extract accurately. We selected three vegetation indices commonly used for sparse desert vegetation AGB estimation [20]: Normalized Difference Vegetation Index (NDVI), Ratio Vegetation Index (RVI), and Modified Soil-Adjusted Vegetation Index (MSAVI).

The vegetation indices were calculated as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

$$RVI = \frac{NIR}{RED}$$

$$MSAVI = \frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - RED)}}{2}$$

where NIR and RED represent near-infrared and red band reflectance, respectively.

Studies indicate that the optimal sample plot size for remote sensing validation is 10 m × 10 m, which matches well with QuickBird's 2.4 m resolution, as geometric accuracy can be controlled within one pixel [25]. We extracted vegetation index values for pixels corresponding to each plot' s center coordinates and established regression models between these indices and field-measured plot AGB.

Model performance was evaluated using coefficient of determination (R^2), root mean square error of calibration (RMSEC), root mean square error of prediction (RMSEP), and relative root mean square error:

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$$

Higher R^2 and lower RMSEP indicate better predictive capability. A ratio of RMSEC to RMSEP between 0.8 and 1.2 suggests robust model performance [26].

7. Results

7.1 Allometric Equations

Literature review shows that common predictive variables for allometric equations include base diameter (D), height (H), and composite variables such as D^2H and DH [27]. Crown volume (V) and crown area (S) are also frequently used.

We tested power, exponential, and quadratic polynomial models for seven species. Power function models showed the best fit. For six species (*Nitraria tangutorum*, *Artemisia desertorum*, *Haloxylon ammodendron*, *Caragana korshinskii*, *Tamarix ramosissima*, and *Elaeagnus angustifolia*), crown volume (V) was the optimal predictor, with R^2 values exceeding 0.7. For *Hedysarum scoparium*, crown area (S) performed best, yielding an R^2 of 0.63.

Although *Hedysarum scoparium*' s R^2 was the lowest at 0.63, its MAE and MSE were only 195.82 g and 1.088%, respectively, indicating good fit quality. Since *Hedysarum scoparium* is not a dominant community species, its lower precision has minimal impact on overall plot biomass estimation.

shows the allometric equation parameters for each species, including coefficients, exponents, MAE, MSE, and significance levels.

7.2 Aboveground Biomass Estimation Models

We extracted vegetation indices from the QuickBird imagery for each plot center and established regression models between these indices and plot AGB. For artificial sand-fixing forests, 12 plots were used for model construction and 3 for validation. For desert vegetation, 12 plots were used for modeling and 3 for validation.

Among the three vegetation indices, RVI-based models showed the best performance. For desert vegetation, the RVI linear model was optimal ($R^2 = 0.82$, RMSEP = 15.08), while for artificial sand-fixing forests, the RVI logarithmic model performed best ($R^2 = 0.72$, RMSEP = 56.15). compares model parameters across vegetation types and indices.

The desert vegetation model showed higher R^2 and lower RMSEP compared to the artificial sand-fixing forest model, reflecting the substantially lower per-unit-area biomass of desert vegetation. [Figure 2: see original paper] illustrates the regression relationships between AGB and vegetation indices.

Model validation [Figure 3: see original paper] revealed that for desert vegetation, errors concentrated in plots with AGB around 70 g/m^2, while for artificial sand-fixing forests, estimation errors increased when measured AGB exceeded 300 g/m^2. The ratio of estimated to measured AGB was more concentrated for artificial forests, whereas desert vegetation showed greater dispersion.

7.3 Study Area Aboveground Biomass Estimation

Based on the land cover classification, we masked out non-vegetation areas and cloud patches. Artificial sand-fixing forest AGB was calculated using the RVI logarithmic model, while desert vegetation AGB used the RVI linear model.

The total area of desert vegetation and artificial sand-fixing forests was 16.189 km^2 and 15.685 km^2, respectively. Despite similar areas, their per-unit-area AGB differed dramatically: 90.73 g/m^2 for desert vegetation versus 105.28 g/m^2 for artificial sand-fixing forests. Consequently, total AGB was approximately 3.12 t, with artificial forests contributing substantially more. AGB decreased from east to west across the study area [Figure 4: see original paper].

8. Conclusions and Discussion

This study established allometric equations for major desert plant species using ground survey data and developed regression models between vegetation indices and AGB using QuickBird imagery to estimate vegetation biomass in the desert-oasis ecotone on the northeastern edge of the Ulan Buh Desert. Key findings include:

1. Crown volume (V) was the optimal predictor for allometric equations of most desert shrubs, while crown area (S) performed best for *Hedysarum scoparium*. All equations achieved satisfactory precision for plot-level biomass estimation.

2. Among vegetation indices, RVI-based models performed best. The logarithmic model excelled for artificial sand-fixing forests ($R^2 = 0.72$, RMSEP = 56.15), while the linear model was superior for desert vegetation ($R^2 = 0.82$, RMSEP = 15.07).

3. The study area contained 16.189 km^2 of desert vegetation and 15.685 km^2 of artificial sand-fixing forests, with per-unit-area AGB of 90.73 g/m^2 and 105.28 g/m^2, respectively. Total AGB was approximately 3.12 t, decreasing from east to west.

The superior performance of the desert vegetation model compared to the artificial forest model may relate to vegetation index saturation at higher cover levels. The MSAVI did not significantly improve desert vegetation AGB estimation, possibly because soil background effects were less pronounced given the relatively high vegetation cover in our study area.

Allometric equations effectively capture growth patterns but have limited mechanistic explanatory power. The optimal use of V (combining crown diameter and height) aligns with previous research [31-32], though *Hedysarum scoparium*' s radiating morphology made crown area (S) more suitable, albeit with lower R^2 (0.63).

Sparse desert vegetation commonly faces mixed-pixel issues [3]. Our high-resolution QuickBird data (2.4 m) yielded higher precision than medium- or lowresolution data, demonstrating that increased spatial resolution reduces mixed-pixel errors. Such high-precision models can serve as intermediaries between ground measurements and coarse-resolution remote sensing data, enabling accurate large-scale biomass estimation through spectral scaling principles [33-34].

Current methods still face challenges in meeting the needs of desertification monitoring and vegetation biomass estimation [35-36]. Further research should explore reliable methods for extracting sparse desert vegetation information using multi-source remote sensing data.

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