Postprint: Estimation of Vegetation Biomass in Desert Areas Based on Five Vegetation Indices

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Abstract

Aboveground biomass of vegetation in desert areas is an important indicator for monitoring land desertification and extracting remote sensing information of desert vegetation. This study used Minqin County, Gansu Province as the experimental area and Sentinel-2 imagery as the data source to develop estimation models (univariate linear, exponential, logarithmic, and polynomial models) for aboveground biomass based on five vegetation indices: Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI), Soil-Adjusted Vegetation Index (SAVI), and Optimized Soil-Adjusted Vegetation Index (OSAVI), and estimated the aboveground biomass of the study area using the selected optimal model. The results show that SAVI had the highest correlation with aboveground biomass compared to RVI, NDVI, DVI, and OSAVI indices (r=0.79), and the polynomial model based on SAVI was the optimal model for estimating aboveground biomass in the study area (R2=0.76) with relatively high accuracy (R2=0.73, RMSE=0.12). The relatively dense vegetation areas in Minqin County are mainly distributed in the four major irrigation districts (Hongyashan, Huanhe, Changning, Nanhu), around Qingtu Lake, and in the northwestern region of Hongshagang Town, while vegetation in other areas is relatively sparse. The proportions of non-vegetation area [<0.005 kg · (100m2)- 1], low vegetation area [0.005~0.2 kg · (100m2)- 1], medium vegetation area [0.2~0.5 kg · (100m2)- 1], and high vegetation area [>0.5 kg · (100m2)-1] are 66%, 21%, 5%, and 8%, respectively.

Full Text

Extraction of Desert Vegetation Biomass Based on Five Vegetation Indices

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Abstract

Aboveground vegetation biomass in desert areas serves as a crucial indicator for monitoring land desertification and extracting desert vegetation information through remote sensing. This study selected Minqin County in Gansu Province as the experimental area and utilized Sentinel-2 imagery as the data source. We constructed estimation models (unitary linear, exponential, logarithmic, and binomial) for five vegetation indices—ratio vegetation index (RVI), normalized difference vegetation index (NDVI), difference vegetation index (DVI), soil-adjusted vegetation index (SAVI), and optimized soil-adjusted vegetation index (OSAVI)—and the measured aboveground biomass. The aboveground biomass in the study area was then estimated using the selected optimal model. The results demonstrated that SAVI exhibited the highest correlation with aboveground biomass ($r = 0.79$) among the five indices. The binomial model based on SAVI proved to be the optimal model for estimating aboveground biomass in the study area ($R^2 = 0.76$), with satisfactory accuracy ($R^2 = 0.73$, RMSE = 0.12). In Minqin County, relatively dense vegetation was primarily distributed in four major irrigation districts (Hongyashan, Huanhe, Changning, and Nanhu), the periphery of Qingtu Lake, and the northwest region of Hongshagang Town, while vegetation in other areas remained relatively sparse. The proportions of non-vegetation area [<0.005 kg · $(100\text{m}^2)^{-1}$], low vegetation area [0.005–0.2 kg · $(100\text{m}^2)^{-1}$], medium vegetation area [0.2–0.5 kg · $(100\text{m}^2)^{-1}$], and high vegetation area [>0.5 kg · $(100\text{m}^2)^{-1}$] were 66%, 21%, 5%, and 8%, respectively.

Keywords: desert vegetation; aboveground biomass; vegetation index; information extraction; Sentinel-2 imagery

1 Introduction

1.1 Study Area Overview

This study focused on Minqin County in Gansu Province, geographically located between 101°47 39 –104°57 3 E and 38°0 39 –39°27 49 N, covering a total area of 1.58×10^4 km^2. Situated in the northeastern part of the Hexi Corridor and the lower reaches of the Shiyang River basin, Minqin is surrounded by the Tengger Desert on three sides and the Badain Jaran Desert to the northeast, with elevations ranging from 1298 to 1936 m. The region experiences a typical temperate continental arid climate, with a multi-year average temperature of 8.5°C, average precipitation of 114 mm, and average evaporation of 2412 mm. The vegetation characteristics are distinct, with simple community structures dominated by shrub-grass formations. The landscape comprises three typical surface morphologies of northwest arid regions: desert, desert-oasis transition zone, and oasis, forming a typical desert-oasis ecosystem that serves as an ideal site for desert vegetation biomass research.

1.2 Data Collection

1.2.1 Field Measurement Data Field measurement points were primarily located in the desert-oasis transition zone, which functions as an ecological buffer area. The sampling design accounted for vegetation distribution differences across the region and encompassed all vegetation types within the county. Data collection was conducted during the peak vegetation period from July 20–30, 2021. To maintain consistency with the spatial resolution of Landsat satellite remote sensing data, 10 m × 10 m sample plots were established. Within each plot, a five-point sampling method was employed to set up 1 m × 1 m sub-quadrats, where all plants were recorded, numbered, and classified. After clipping at ground level, samples were oven-dried in the laboratory, and the average dry weight was calculated and multiplied to obtain the aboveground biomass per 100 m^2 area. A total of 30 sampling points were established across the study area [Figure 1: see original paper].

1.2.2 Remote Sensing Data Sentinel-2 Level 2A data products from July 2021 were selected to match the ground measurement period. Five scene images were obtained from the Copernicus Open Access Hub (https://scihub.copernicus.eu/) and underwent preprocessing including mosaicking and clipping to the study area boundary .

1.3 Methods

1.3.1 Vegetation Index Selection and Correlation Analysis Five vegetation indices were selected for their established effectiveness in desert vegetation biomass estimation: the ratio vegetation index (RVI), normalized difference vegetation index (NDVI), difference vegetation index (DVI), soil-adjusted vegetation index (SAVI), and optimized soil-adjusted vegetation index (OSAVI). These indices were calculated using the formulas presented in . Pearson correlation analysis was performed between each vegetation index and the measured aboveground biomass to evaluate their relationships for subsequent biomass inversion.

1.3.2 Optimal Model Selection and Accuracy Validation To prevent overfitting, the 30 sample points were randomly divided into training (21 samples, 70%) and validation (9 samples, 30%) sets. Using empirical statistical methods, we constructed unitary linear, logarithmic, exponential, and binomial estimation models for aboveground biomass based on each vegetation index. The optimal model was selected according to the coefficient of determination (R^2). The accuracy of the selected model was then evaluated using the linear fit between estimated and observed values from the validation set, employing both R^2 and root mean square error (RMSE) as evaluation metrics:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(M_i - O_i)^2}{n}}$$

where n represents the number of data points, M and O are the estimated and observed aboveground biomass values, respectively.

1.3.3 Vegetation Biomass Inversion in the Study Area Given the generally low-statured, sparse vegetation and low biomass characteristics of the study area, we established classification standards for vegetation distribution in Minqin County based on biomass magnitude , incorporating both the actual proportion of vegetation types and interspecies relationships.

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2 Results

2.1 Correlation Between Vegetation Indices and Aboveground Biomass

All five vegetation indices exhibited significant positive correlations with aboveground biomass ($P < 0.05$), with correlation coefficients ranging from 0.67 to 0.79, indicating their suitability for vegetation biomass estimation. SAVI demonstrated the highest correlation coefficient ($r = 0.79$) .

2.2 Optimal Model Selection

The estimation models constructed for each vegetation index are presented in . The SAVI-based binomial model achieved the best performance with $R^2 = 0.76$, followed by RVI. While the logarithmic models showed relatively high average R^2 values (with the SAVI logarithmic model performing best among the four indices at $R^2 = 0.44$), the exponential and binomial models for DVI and OSAVI performed poorly. Consequently, the binomial model based on SAVI was selected as the optimal model for estimating aboveground biomass in the Minqin desert region.

2.3 Accuracy Assessment

The linear fitting relationship between estimated and observed aboveground biomass values from the validation set yielded $R^2 = 0.73$, with RMSE = 0.12, passing the significance test at $P < 0.05$ [Figure 2: see original paper]. These results indicate that the model meets accuracy requirements and can be applied for desert vegetation aboveground biomass estimation in Minqin.

2.4 Vegetation Biomass Inversion

The spatial distribution of aboveground biomass in Minqin, derived using the SAVI binomial model [Figure 3: see original paper], reveals that non-vegetation areas (desert, Gobi, bare land, etc.) constitute the largest proportion at 66%. Low vegetation areas account for 21% of the county, primarily distributed along the Minqin-Hongyashan highway and the periphery of oasis plantations. Medium vegetation areas represent the smallest proportion at only 5%, occurring mainly in artificial vegetation plantations and the outer zones of high vegetation areas. High vegetation areas are concentrated in the four major irrigation districts (Hongyashan, Huanhe, Changning, and Nanhu) as well as in Qingtu Lake and the northwest region of Hongshagang Town (natural vegetation), comprising less than 8% of the county's total area.

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3 Discussion

Minqin is located at the junction of the Tengger and Badain Jaran deserts, characterized by arid land and sparse vegetation. Aboveground biomass represents the most important indicator of vegetation growth status, with its magnitude directly reflecting vegetation health in the region. To better characterize biomass distribution, this study employed high-spatial-resolution, low-cloud-cover Sentinel-2 imagery combined with field-measured aboveground biomass to estimate desert vegetation biomass.

Analysis of biomass extraction in the sparsely vegetated desert region indicates that SAVI exhibits the strongest correlation with aboveground biomass and superior simulation performance compared to other indices, consistent with findings from studies in Kangbao County, Hebei Province and the Junggar Basin. This is attributed to SAVI's introduction of a soil adjustment coefficient (L) in the denominator, which further reduces the influence of soil background variations. The L coefficient is critical for vegetation information extraction, with its value range indicating vegetation cover conditions—when L = 0.5, it signifies very high vegetation cover. This aligns with Huete's research on adjusting L values to account for vegetation index variations caused by different factors, demonstrating that SAVI can effectively exclude noise from soil background and other factors.

Using empirical statistical methods, we constructed various aboveground biomass estimation models (unitary linear, logarithmic, exponential, and binomial) based on different vegetation indices, and further investigated the spatial distribution patterns using the optimal model. This approach requires minimal parameters and involves simple calculations, making it commonly applicable for model development combining remote sensing imagery with field measurements. The method yielded satisfactory results in this study and provides a basis for aboveground biomass research in desert regions.

4 Conclusions

Based on the investigation of vegetation aboveground biomass and vegetation indices in Minqin, the following conclusions were drawn:

1. All five vegetation indices (RVI, NDVI, DVI, SAVI, and OSAVI) showed significant positive correlations with aboveground biomass ($P < 0.05$), with correlation coefficients ranging from 0.67 to 0.79, making them suitable for vegetation biomass estimation.

2. SAVI exhibited the highest correlation with aboveground biomass ($r = 0.79$). The binomial model based on SAVI was identified as the optimal model for estimating aboveground biomass in the Minqin desert region ($R^2 = 0.76$), with satisfactory accuracy ($R^2 = 0.73$, RMSE = 0.12).

3. Relatively dense vegetation in Minqin County was primarily distributed in four major irrigation districts (Hongyashan, Huanhe, Changning, and Nanhu), the periphery of Qingtu Lake, and the northwest region of Hongshagang Town. Other areas exhibited sparse vegetation, with non-vegetation area [<0.005 $kg \cdot (100m^2)^{-1}$], low vegetation area [0.005–0.2 $kg \cdot (100m^2)^{-1}$], medium vegetation area [0.2–0.5 $kg \cdot (100m^2)^{-1}$], and high vegetation area [>0.5 $kg \cdot (100m^2)^{-1}$] accounting for 66%, 21%, 5%, and 8% of the total area, respectively.

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