Neural Network-Based Retrieval of Vegetation Above-Ground Biomass in the Manas River Basin: Postprint

Authors: Zhang Yuan, Wang Ling, Bao Anming, Liu Hailong, Liu Hailong

Date: 2019-09-10T00:00:00+00:00

Abstract

Vegetation biomass reflects the capacity of ecosystems to capture energy, and analysis of its distribution characteristics is of paramount importance for understanding ecosystem structure and function. Conventional approaches for retrieving vegetation aboveground biomass often yield low estimation accuracy due to scarcity of samples and uncertainty of influencing factors. This study utilizes ELM to train on remote sensing variables (10 factors including TM image grayscale values and vegetation factors) from 105 measured samples, with the remaining 34 samples used for validation. Results indicate that ELM can achieve high accuracy for retrieving vegetation aboveground biomass, with the coefficient of determination (R^2) for curve fitting between model predictions and measured results reaching 0.89. Additionally, vegetation aboveground biomass in the Manas River Basin from 2010 to 2015 was retrieved, revealing that biomass in the upstream mountainous areas remained relatively stable, biomass in the midstream plain areas showed an increasing trend, while biomass in the downstream desert areas exhibited a degrading trend.

Full Text

Inversion of Vegetation Above-ground Biomass in the Manas River Basin Based on Neural Network Model

ZHANG Yuan[1], WANG Ling[2], BAO An-ming[3], LIU Hai-long[1]

[1]College of Water Conservancy and Architectural Engineering, Shihezi University, Shihezi 832003, Xinjiang, China
[2]School of Civil Architecture and Environment, Xihua University, Chengdu 610039, Sichuan, China
[3]Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, Xinjiang, China

Abstract

Above-ground biomass reflects the capability of ecosystems to obtain energy, and analysis of its spatial distribution pattern is of great significance for understanding ecosystem structure and function. The accuracy of conventional approaches for inverting above-ground biomass is low due to the lack of samples and uncertainty of impact factors. In this study, Extreme Learning Machine (ELM) was used to train remote sensing factors from 105 samples, which included seven-band pixel values of TM imagery and vegetation factors, while the remaining 34 samples were used for verification. The results confirmed that the ELM approach could invert vegetation above-ground biomass with high accuracy, achieving a determination coefficient of curve fitting of 0.89. Additionally, the inversion of vegetation above-ground biomass in the Manas River Basin from 2010 to 2015 revealed that biomass was relatively stable in the upper reaches of the basin, showed an increasing trend in the middle plains, and exhibited a deterioration trend in the downstream desert area.

Keywords: vegetation; above-ground biomass; neural network model; land use; Manas River Basin; Xinjiang

1. Methods

1.3.3 Data Processing and Variable Extraction The study utilized Landsat TM imagery, DEM data, and field-measured biomass samples. Vegetation indices including the Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI), green band reflectance (GREEN), and functional group parameters (FG) were calculated. The square root of RVI (SQRT(RVI)) was also derived as an additional predictor variable. Topographic variables of slope and aspect were extracted from DEM data using ArcGIS 3D Analyst. All remote sensing variables were processed at a spatial resolution of 30 m, consistent with the GDEM DEM data. Field sampling followed the "Specifications for Observation of Terrestrial Ecosystem Carbon Fluxes" (LY/T 1812-2009), with sample plots established at scales of 15 m and 5 m × 5 m. The remote sensing data processing and spatial analysis were performed using ENVI 4.8 and ArcMap 10.2.2 software platforms.

1.4.2 Model Construction and Parameter Optimization The ELM model was constructed using the TM1, TM2, TM3, TM4, TM5, and TM7 bands along with NDVI, RVI, and DVI as input variables. The SQRT(RVI) transformation was applied to improve linearity. Model performance was evaluated using the coefficient of determination (R^2) between predicted and observed biomass values. The optimal number of hidden nodes was determined through iterative testing, revealing that 50 hidden nodes yielded the best performance with $R^2 = 0.89$. When hidden nodes were varied between 20 and 60, R^2 values ranged from 0.79 to 0.67, with 50 nodes providing the optimal balance between model complexity and predictive accuracy. The final model architecture consisted of input layers corresponding to the remote sensing variables, a single hidden layer with 50 nodes, and an output layer predicting above-ground biomass.

---

2. Results

[Figure 3: see original paper] shows the inversion results of the neural network model for vegetation biomass. The model demonstrated strong predictive capability across the 34 validation samples, with minimal deviation between predicted and measured values. The spatial distribution of biomass across the Manas River Basin [Figure 5: see original paper] exhibited distinct patterns: areas with biomass ranging from 0–200 g · m ^{2} were predominantly located in downstream desert regions, while higher biomass values were concentrated in the middle plains. The upper basin maintained relatively stable biomass levels between 2010 and 2015.

The total area with biomass below 200 g · m ^{2} covered approximately 12,841.47 km^2 in 2010, with a mean biomass of 259.01 g · m ^{2}. In contrast, areas with biomass exceeding 200 g · m ^{2} spanned 7,953.18 km^2, with a mean of 1,341.90 g · m ^{2}. By 2015, the high-biomass area had decreased to 6,572.26 km^2, indicating a reduction in vegetation productivity in the downstream regions. The middle plains showed an increasing trend, with biomass values rising from 504.99 km^2 to 1,572.90 km^2 in the highest biomass class (>2000 g · m ^{2}), reflecting improved vegetation conditions.

---

3. Discussion

The ELM-based inversion approach proved superior to conventional methods, achieving an R^2 of 0.89 compared to typical values below 0.70 reported in previous studies. This improvement is attributed to the ELM’ s ability to handle nonlinear relationships between remote sensing variables and biomass while requiring minimal training time. The model successfully captured the spatial heterogeneity of vegetation across the basin’ s diverse landscapes, from alpine meadows in the upper reaches to irrigated croplands in the middle plains and desert steppe in the downstream areas.

The temporal analysis from 2010 to 2015 revealed that land use changes, particularly agricultural expansion in the middle plains and desertification in the lower basin, were the primary drivers of biomass variation. The stable biomass in the upper basin reflects the conservation effectiveness of protected alpine ecosystems, while the increasing trend in the middle plains correlates with intensified irrigation and land management practices. The deterioration downstream underscores the need for sustainable water resource management in arid watersheds.

References

[1] Cheng Xiaoli, An Shuqing, Qin Pei, et al. The heterogeneity in spatial distribution of the above-ground biomass in the degraded grasslands of Ordos [J]. *Acta Ecologica Sinica*, 2003, 23(8): 1526–1532.

[2] Wu Guiping, Ye Chun, Liu Yuanbo. Spatial distribution of wetland vegetation biomass in the Poyang Lake National Nature Reserve, China [J]. *Acta Ecologica Sinica*, 2015, 35(2): 361–369.

[3] Wang Shujun, Guan Dongsheng. Remote sensing method of forest biomass estimation by artificial neural network models [J]. *Ecology and Environment*, 2007, 16(1): 108–111.

[4] Moreau S, Toan TL. Biomass quantification of Andean wetland forages using ERS satellite SAR data for optimizing livestock management [J]. *International Journal of Remote Sensing*, 2003, 84(4): 477–492.

[5] Cao L, Coops NC, Innes JL, et al. Estimation of forest biomass dynamics in subtropical forests using multi-temporal airborne LiDAR data [J]. *Remote Sensing of Environment*, 2016, 178(14): 158–171.

[6] Sarabandi K, Polatin P. An iterative inversion algorithm with application to the polarimetric radar response of vegetation canopies [J]. *IEEE Transaction Geosciences Remote Sensing*, 1994, 32(1): 62–71.

[7] Ma C, Ouyang JH, Chen HL, et al. A novel kernel extreme learning machine algorithm based on self-adaptive artificial bee colony optimization strategy [J]. *International Journal of Systems Science*, 2016, 47(6): 1342–1357.

[8] Wang Yuangang, Luo Geping, Feng Yixing, et al. Effects of land use/land cover change on carbon storage in Manas River Watershed over the past 50 years [J]. *Journal of Natural Resources*, 2013, 28(6): 994–1006.

[9] He Ke, Wu Shixin, Zhou Hongfei, et al. Two typical land use modes in the Manas River Basin [J]. *Arid Zone Research*, 2018, 35(4): 954–962.

[10] Li Jurong, Wang Yanhua, Tang Xiangling, et al. The spatial-temporal characteristics of land use change in the Manas River Basin and influencing factors [J]. *Chinese Journal of Soil Science*, 2018, 49(1): 61–68.

[11] Li-ang Jiang, Liu Hailong, Bao Anming, et al. Analysis on landscape pattern change and driving mechanism in Manas River Watershed [J]. *Research of Soil and Water Conservation*, 2014, 21(4): 256–262.

[12] Feng Yixing, Luo Geping, Zhou Decheng, et al. Effects of land use change on landscape pattern of a typical arid watershed in the recent 50 years: A case

study on Manas River Watershed in Xinjiang [J]. *Acta Ecologica Sinica*, 2010, 30(16): 4295-4305.

[13] Jiang Liangliang, Liu Hailong, Bao Anming, et al. Analysis on landscape pattern change and driving mechanism in oasis of the Manas River Basin [J]. *Research of Soil and Water Conservation*, 2014, 21(4): 256-262.

[14] Li Hui, Lei Xiaoyun, Bao Anming, et al. Application of simulation about montanic daily runoff volume in the Manas River Basin based on SWAT model [J]. *Arid Zone Research*, 2010, 27(5): 686-690.

[15] Ding SF, Zhang YN, Xu XZ, et al. A novel extreme learning machine based on hybrid kernel function [J]. *Journal of Computers*, 2013, 8(8): 2110-2117.

[16] Huang GB, Zhu QY, Siew CK. Extreme learning machine: Theory and applications [J]. *Neurocomputing*, 2006, 70(1): 489-501.

[17] Liu Xiaotong. Study on data normalization in BP neural network [J]. *Mechanical Engineering and Automation*, 2010(3): 122-123.

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