Postprint: Quantitative Remote Sensing Retrieval of Vegetation Leaf Area Index Based on BP Neural Networks, 1988-2013

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Abstract

Leaf Area Index (LAI) comprehensively integrates vegetation horizontal coverage conditions and vertical structure, as well as litter layer thickness and underground biomass, representing the primary aspect of vegetation' s influence on soil erosion. Time-series LAI at the regional scale reveals the evolution process of regional soil erosion. Therefore, timely and accurate acquisition of long-term vegetation LAI at the regional scale is crucial for studying the relationship between soil erosion dynamics and vegetation. This study selected 10 phases of remote sensing images from Nanjing City between 1988-2013, constructed an LAI inversion model based on Back Propagation (BP) neural network, and performed long-term time-series LAI inversion. Combining measured LAI values from 2009 and 2010, the model' s evaluation accuracy and adaptability were validated and discussed. The results indicate: (1) The model demonstrates high fitting performance, with mean relative error, Root Mean Square Error, and correlation coefficient for 2009 and 2010 being 0.2395 and 0.2174, 0.2962 and 0.2581, 0.7713 and 0.6844 respectively, with all accuracy evaluation metrics performing well; (2) Statistical analysis of LAI changes across the city after removing cropland shows that low vegetation coverage areas (LAI<2) continuously increased, high vegetation coverage areas (LAI>3) first decreased then increased, and cropland area continuously decreased, consistent with Nanjing' s development patterns; (3) Interannual LAI variations in the main urban area align with the vegetation coverage change trends obtained by other scholars for Nanjing, demonstrating high temporal consistency of the inversion results. The proposed long-term time-series LAI inversion based on the Back Propagation neural network model is feasible, providing a new approach for quantitative remote sensing monitoring of soil erosion at the regional scale.

Full Text

Preamble

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Quantitative Inversion of Long Sequential Leaf Area Index Using Remote Sensing Based on BP Neural Network from 1988 to 2013

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Abstract

Leaf Area Index (LAI) comprehensively integrates vegetation horizontal coverage, vertical structure, litter layer thickness, and underground biomass, representing the primary aspects through which vegetation influences soil erosion. Regional-scale time series LAI reveals the evolution of regional soil erosion processes, making timely and accurate acquisition of long-term sequential vegetation data critical for studying the dynamic relationship between soil erosion and vegetation. This study selected Nanjing City as the research area and constructed a long-term LAI inversion model based on Back Propagation (BP) neural networks. The model's evaluation accuracy and adaptability were verified and discussed. The results demonstrated high model fitting performance, with mean absolute percentage errors (MAPE), root mean square errors (RMSE), and correlation coefficients (R) of 0.2395 and 0.2174, 0.2962 and 0.2581, and 0.7713 and 0.6844 for 2009 and 2010, respectively. All accuracy evaluation indices were satisfactory. Statistical analysis after removing cultivated land revealed that low vegetation coverage areas (LAI $<$ 2) continuously increased, high vegetation coverage areas (LAI $>$ 3) first decreased then increased, while cultivated land area continuously decreased—patterns consistent with Nanjing' s development trajectory. The interannual variation trends aligned with vegetation coverage changes reported by other scholars. The temporal sequence of inversion results was robust. This BP neural network-based approach for long-term LAI inversion provides a new method for quantitative remote sensing monitoring of regional soil erosion.

Keywords: Nanjing City; BP neural network; long time series; Leaf Area Index (LAI); soil erosion

1. Study Area Overview

Nanjing City is located in the lower Yangtze River region, southwestern Jiangsu Province (31°14 -32°37 N, 118°22 -119°14 E). The terrain features low mountains and hills forming the skeleton of the landscape, with a basin-shaped topography as the main characteristic. The total administrative area is 6,587.02 km². Nanjing has a north subtropical monsoon climate with an average annual temperature of 16°C, average annual rainfall of 1,106 mm, and 237 rainy days annually.

Soils in the Nanjing region are primarily yellow-brown soils in the vast central and northern areas, the zonal soil type, with small areas of red soil near the border with Anhui Province in the south. Vegetation belongs to the evergreen deciduous broad-leaved mixed forest type. Nanjing has a dense population and intense agricultural activity. Natural vegetation has been severely damaged throughout history and has almost completely disappeared; current vegetation is predominantly secondary, with planted forest area exceeding that of naturally recovered secondary forest. Existing forest land within the jurisdiction covers approximately 570 km², with timber and ecological forests accounting for about 210 km² and economic forests and bamboo forests covering 840 km². Main timber and ecological forest species include Masson pine, while economic forests are dominated by tea, fruit, and mulberry, and bamboo forests consist primarily of moso bamboo, concentrated in hilly and mountainous areas.

2. Remote Sensing Image Data and Processing

2.1 Remote Sensing Image Data

The remote sensing images used for LAI inversion in this study consisted of 10 scenes. Selection criteria required images from the month when vegetation growth was most vigorous and rainfall was most concentrated—the period when soil erosion is most likely to occur. Image acquisition times were selected during July-October each year. To ensure inversion accuracy, high-quality images with minimal cloud cover over the study area were prioritized. When no suitable images were available for a given month, alternatives were selected. The final image dataset is shown in .

Landsat 5 Thematic Mapper (TM) is an optical Earth observation satellite and the fifth in the US Landsat series. The US Geological Survey announced that due to rapid amplifier aging, data acquisition has currently ceased. Landsat 8 Operational Land Imager (OLI) multispectral remote sensing imagery was provided by the US Geological Survey. To avoid atmospheric absorption features, bands were adjusted, with the most significant modification being OLI Band 5 (0.845-0.885 m) compared to Landsat 5' s 0.825 m band.

2.2 Other Data Sources

Additional data sources included: high-resolution imagery from Google Earth; land use/cover data for 1986, 1996, 2002, and 2013 based on Landsat 8 OLI data; and land use data from the National Science and Technology Infrastructure Platform' s Earth System Science Data Sharing Network. Land use/cover data were obtained through manual interactive interpretation, with interpretation accuracy verified through field sampling.

2.3 Data Preprocessing

Atmospheric correction is essential for obtaining true ground reflectance from remote sensing imagery and is particularly important for quantitative vegetation remote sensing [24-25]. The FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) model was used for atmospheric correction. Using Nanjing boundary vector data, geometric precision correction was performed on the images using quadratic polynomial fitting. The preprocessing workflow for the 10 scenes of imagery is shown in [Figure 1: see original paper].

2.4 Field Measured Data

To verify the effectiveness of the neural network inversion model for time series LAI, measured values from 2009 and 2010 were used for accuracy validation. LAI measurements were conducted using the LI-COR LAI-2000 plant canopy analyzer. In 2009, samples were mainly distributed in Jiangning District and Pukou District; in 2010, samples were mainly distributed in Tongshan and Jiangning Districts. All measurements were conducted between 6:30–9:00 and 16:30–19:00 to avoid direct sunlight and minimize testing errors caused by it. At each sample plot, measurements were taken at four corners and the center, with each point measured repeatedly and averaged. GPS receivers were used for positioning (WGS-84). The spatial resolution was 30 m, with sampling intervals greater than 30 m to avoid spatial autocorrelation.

The multispectral remote sensing imagery included all bands from the Landsat 5 TM sensor and the Enhanced Thematic Mapper Plus (ETM+), with two additional bands: a deep blue band (Band 1; 0.433–0.453 m) and a shortwave infrared band (Band 9; 1.360–1.390 m) for water vapor absorption features. Although sensor differences cause some variation in reflectance for the same ground objects across images, the model established with Landsat 8 OLI data was applicable to previous TM data. This study applied a BP neural network model with a hidden layer to invert LAI [18]. Due to sensor differences, normalization processing was performed on each scene separately to reduce the impact of reflectance differences on inversion accuracy.

5. Accuracy Evaluation Methods

Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and correlation coefficient (R) were used to measure and characterize model accuracy:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i^{\text{BP}} - x_i}{x_i}\right| \times 100\%$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i^{\text{BP}} - x_i)^2}$$

$$R = \frac{\sum_{i=1}^{n}(x_i^{\text{BP}} - \bar{x}^{\text{BP}})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^{n}(x_i^{\text{BP}} - \bar{x}^{\text{BP}})^2}\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}}$$

where x_i^{BP} is the model inversion value (LAI(BP)), x_i is the measured value, $\bar{x}$ is the mean of measured values, σ^2 is sample variance, and n is the sample size.

1. Error Analysis Based on Ground Measured Data

To further verify the accuracy of time series LAI inversion, measured values from 2009 and 2010 were used for validation. The fitting results are shown in [Figure 2: see original paper], and simulation accuracy is presented in .

The results demonstrate that the model effectively simulated LAI, with high agreement between simulated and measured values. In 2009 and 2010, the mean absolute percentage errors were 0.2395 and 0.2174, root mean square errors were 0.2962 and 0.2581, and correlation coefficients were 0.7713 and 0.6844, respectively. All accuracy evaluation indices were satisfactory. The BP neural network model trained with Landsat 8 OLI data successfully simulated the LAI time series.

[Figure 3: see original paper] shows the LAI distribution maps of Nanjing from 1988 to 2013. The maps reveal that LAI < 2 areas were mainly distributed in densely built urban areas with sparse vegetation, including northern Jiangning District, southern Liuhe District, southeastern Pukou District, Qixia District, and the municipal district. LAI values of 2–3 were primarily found in areas with moderate building density and some vegetation, distributed relatively dispersedly. LAI values of 3–4 occurred mainly in suburban areas with fewer buildings and more vegetation. LAI > 4 areas were concentrated in mountainous regions with dense vegetation such as Purple Mountain and Tongshan.

2. Vegetation Change Analysis in Nanjing

Since Nanjing has extensive farmland distribution around the city and farmland is significantly affected by human activities, LAI changes are related not only to farmland area changes but also to crop growth conditions. To exclude the influence of crops on LAI changes, land use classifications from 1988, 1994, 2002, and 2013 were used to mask cultivated land, generating LAI distribution maps of Nanjing without cultivated land [Figure 4: see original paper].

The analysis shows that from 1988 to 2013, built-up areas in Nanjing increased annually, expanding from the main urban area outward. To quantitatively understand LAI trends, this study statistically analyzed the changes in low vegetation coverage (LAI < 2) and high vegetation coverage (LAI > 3) areas after removing cultivated land [Figure 5: see original paper].

Overall, the area of low vegetation coverage showed an increasing trend, first rising from 203.97 km^2 in 1988 to 270.15 km^2 in 1996, then decreasing to 71.41 km^2 in 2002, and finally increasing to 335.81 km^2 in 2013. The area of high vegetation coverage showed a decreasing-then-increasing pattern, declining from 798.87 km^2 in 1988 to 335.81 km^2 in 1996, then increasing to 798.87 km^2 in 2013. Cultivated land area continuously decreased. These patterns align with Nanjing' s development trajectory: during 1988–1996, urban expansion and large-scale real estate development severely damaged vegetation, causing rapid reduction in high vegetation coverage areas (decreasing by 78.19%) and continuous increase in low vegetation coverage areas. However, due to national policies and increased environmental awareness, vegetation restoration improved conditions, though urban expansion continued.

To compare with other studies, Li Mingshi et al. used Landsat TM/ETM+ imagery to extract vegetation coverage in Nanjing' s main urban area (1986–2009) using a linear spectral mixture model [27]. This study selected the main urban area for comparative analysis of LAI distribution changes from 1988–2013. The results showed that LAI > 3 areas continuously decreased (from 50.49% to 35.75%), while LAI < 2 areas increased (from 27.58% to 42.20%), consistent with Li Mingshi' s findings on spatiotemporal dynamics of urban green space in Nanjing.

3. Conclusions and Discussion

This study applied a BP neural network model to invert the 26-year time series of LAI in Nanjing (1988–2013). By analyzing model accuracy and the relationship between interannual LAI changes and land cover dynamics, the following conclusions were drawn:

(1) The model demonstrated high fitting performance. Validated against measured data from 2009 and 2010, the mean absolute percentage errors, root mean square errors, and correlation coefficients were 0.2395 and 0.2174,

0.2962 and 0.2581, and 0.7713 and 0.6844, respectively. All accuracy indices were satisfactory.

(2) Spatial analysis revealed that LAI < 2 areas were mainly distributed in densely built urban areas with sparse vegetation, while LAI > 4 areas were concentrated in mountainous regions with dense vegetation such as Purple Mountain.

(3) From 1988–2013, statistical analysis after removing cultivated land showed that low vegetation coverage (LAI < 2) areas continuously increased, high vegetation coverage (LAI > 3) areas first decreased then increased, and cultivated land area continuously decreased—patterns consistent with Nanjing' s development trajectory. The interannual variation of LAI in Nanjing' s main urban area aligned with vegetation coverage trends reported by other scholars.

The results demonstrate high temporal consistency, indicating that the BP neural network model provides high accuracy for time series LAI inversion. This offers a new approach for quantitative remote sensing monitoring of regional soil erosion dynamics and vegetation cover management factors in soil erosion models. However, due to potential limiting factors such as BP neural network model errors, large inversion area, complex vegetation types, and diverse community structures, the LAI inversion accuracy through remote sensing still requires improvement. Future research should focus on establishing multi-angle LAI inversion methods, constructing coupling models between LAI and soil erosion, and quantitative fusion of multi-source remote sensing imagery.

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