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# Estimation of Remote Sensing and Analysis of Temporal and Spatial Distribution of Grassland LAI

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**Abstract** To estimate the leaf area index (LAI) in large areas, this paper analyzes the relationships between normalized difference vegetation index (NDVI) and the grassland LAI based on MODIS data in the southern grassy mountains and slopes of China. By using nonlinear fitting equation we constructed the basic estimation model of grassland LAI with NDVI as the independent variable and introduced precipitation and temperature as regulatory factors. The model was validated with observed data in different years and the results showed that there was a good correlation between the simulated and observed LAI value with a statistically significant level of $R^2$. RMSE was 0.302 and RRMSE was 0.154. It was also found that the spatial distribution of grassland LAI in south China showed a remarkable zonal characterization, and temporal distribution showed a single peak curve. These results provided a theoretical basis for the effective management of southern grassland resources and the carbon sink estimation of the nationwide grasslands.

**Key words** Estimation model, Grassland LAI, MODIS, NDVI, Temporal and spatial characteristics

LAI, one of the most important structural parameters for terrestrial ecosystems, is closely linked to evapotranspiration, canopy light interception, surface net primary productivity and energy exchange *etc*. Therefore, LAI inversion has been a hot topic on quantitative remote sensing research[1-3]. LAI, which involves in the establishment of remote sensing-photosynthetic model is not only associated with light interception but also has a direct impact on plant photosynthesis time and photosynthetic area. Yet it is difficult and time-consuming to obtain the LAI value from ground measurements and the characteristic of remote sensing data which were obtained from a large-scale area and repeated time series, provided with valid data sources for estimating the LAI in large areas. The change information on the surface could be reflected on the observed data of remote sensing on time series; and for vegetation, the vegetation index and LAI could be used to monitor and forecast their growth[4-6]. The vegetation growth and MODIS reflectance show a good consistency in red and near infrared bands, so MODIS data is often used to estimate vegetation LAI[7,8]. The vegetation LAI estimation based on MODIS and its data products have been investigated in many studies, such as LAI inversion about rice, wheat, corn and other crops[9-12], as well as the LAI inversion of global forest vegetation[13-17]. Some studies on remote sensing estimation of grassland LAI have also been reported[18-22], but few about grassland in China[23,24], and the remote sensing estimation of grassland LAI in south China has not been studied yet. China has rich grassland resources with grassland areas of nearly 400 million $hm^2$, and more than 60 million $hm^2$ are grassy mountains and slopes. South grassland ecosystem could not be ignored under the adverse conditions that northern grassland had been deteriorated constantly. Therefore, studying the dynamic changes of south grassland LAI is important to promote the global change research. The estimation model of the southern grassland LAI according to regression equations is constructed in this study which aims to provide a scientific basis for the effective management of grassland resources.

## 1 Materials and methods

**1.1 Study area** The study area includes the grassy mountains and slopes in south China, the regional center located at 11000′ E, 27030′ N, mainly including hills and mountains in Yunnan, Guizhou, Sichuan, Guangxi, Jiangxi, Anhui and other 17 provinces, the areas of grassy mountains and slopes are more than 60 million $hm^2$. The climate of this area is characterized by high temperature, more rain in summer and a mild winter with a lot of rain. The frost-free period is more than 300 days with plenty of precipitation. The annual precipitation is between 800 - 1 600 mm in most areas, which is suitable for the growth of grass (Fig. 1).

**1.2 Measurement data acquisition** The experiments were implemented in Anhui, Guizhou, Sichuan and other provinces in July of 2009 and 2010. There were 118 sample plots in studied area and a big quadrat was set in each sample plot (10 m × 10 m). In the big quadrat, 5 small quadrants were set at four corners and the center position. The longitude and latitude data at the same plot were measured too. The LAI data were acquired using the LAI-2000 Canopy Analyzer manufactured by the LI-COR company of United States[25,26], then rectified by LAI which was measured by dry weight method.

**1.3 Vegetation index selection** Vegetation index could be divided into several species according to different monitoring methods and calculation approaches, such as NDVI, Ratio Vegetation

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Index (RVI), Soil Adjusted Vegetation Index (SAVI) and Global Vegetation Index (GVI), etc. NDVI is one of the most widely used vegetation index. NDVI is also called as standardization vegetation index, and it is widely used in the study of vegetation and plant phenology when using remote sensing images. It is the best indicator for plant growth states and density of vegetation spatial distribution. There is a linear correlation between NDVI and vegetation distribution density. Therefore, NDVI was selected in this study as an input factor of MODIS data, and the longitude and latitude of NDVI data were the same as LAI data.

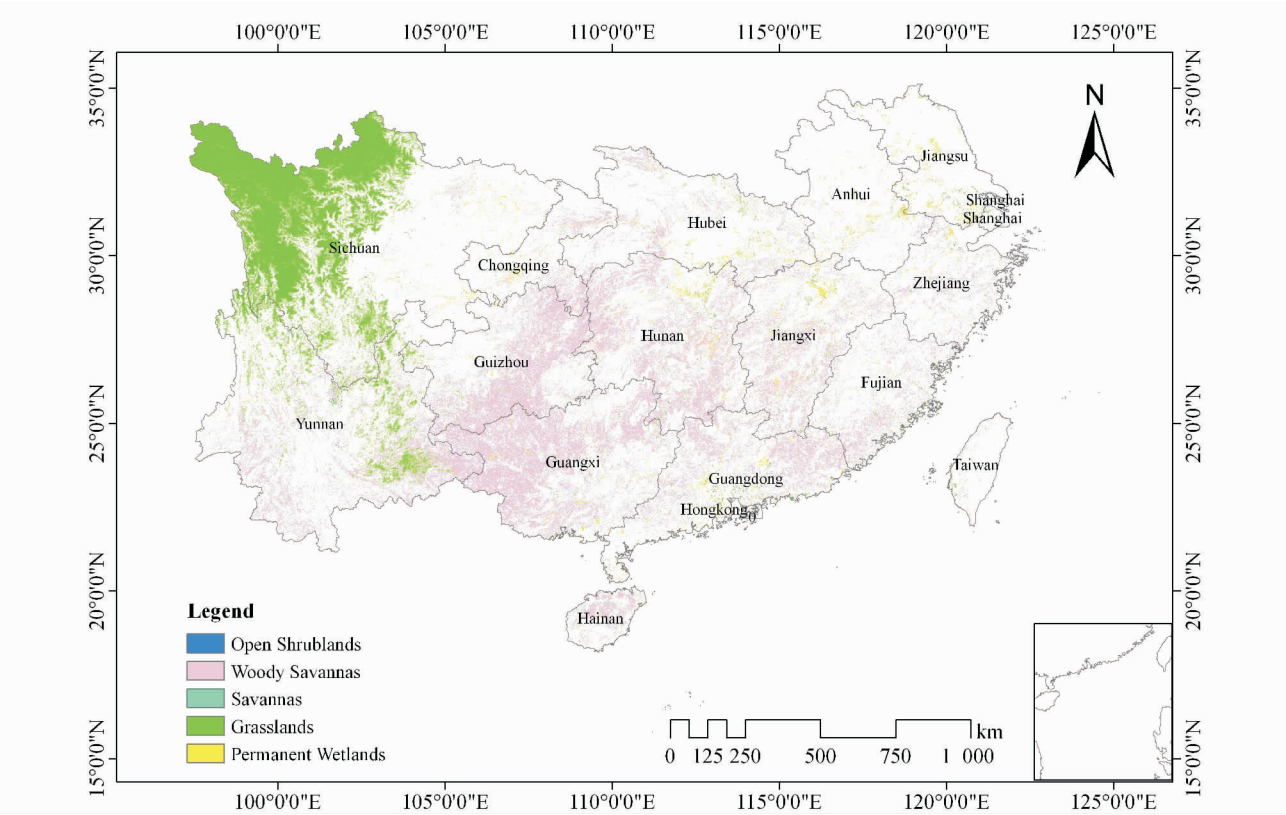


**Fig. 1 Study area and grassland distribution**

### 1.4 Remote sensing image acquisition and processing

MOD13 vegetation index products with a standard header file downloaded from the EOS data center of NASA are used in this study. The product was synthetic of 16 days and had 500 meters spatial resolution; the observation time was from May to October of 2009 and the same period of 2010. The image data were spliced with the band spliced method by using ENVI software, and then NDVI data were directly extracted. Then the re-projection was implemented to convert the hyperbolic sinusoidal projection to UTM/WGS84 format[27]. Finally, the images after conversion were cut in ArcMap by using the distribution map of southern grassy mountains and slopes and the NDVI distribution map was obtained.

**1.5 Climate data acquirement** The monthly mean temperature, monthly precipitations from year 2009 to 2010 were acquired from 752 ground stations of China Meteorological data sharing service system (http://cdc.cma.gov.cn/). By using geographic information system (GIS) interpolation tool, Kriging interpolation was applied to those meteorological data according to the latitude and longitude information of each station. Then image projection transformation was applied to the data. They were all converted to latitude and longitude network projected raster image with a spatial resolution of 1000m. Temperature and precipitation information was obtained by taking survey into points corresponding to the latitude and longitude information.

**1.6 Modeling method** The relationship between MODIS-NDVI and the grassland LAI was modeled by using statistical analysis method, and the factors of temperature and precipitation were introduced as regulatory factors. The NDVI data had the same longitude and latitude value with ground LAI data.

**1.7 Data analysis and test** The experiment data was analyzed by Matlab software and EXCEL 2003. The root mean square error (RMSE) and relative root mean square error (RRMSE) between observed values and simulation results were used to describe precision of the model. A 1:1 relation graph of observed and simulated values was plotted based on this model.

## 2 Results

**2.1 Relationships between LAI and NDVI** Remote sensing information could be used to indicate the accumulation of dry matter and the quantity of biomass. Different vegetation index have good relationships with LAI, leaf weight, biomass, etc., and

plant growth, coverage, seasonal dynamic are directly responded to the quantity change of NDVI. This study analyzed the relevance between the measured LAI data of the ground square and the NDVI data of the corresponding position to LAI, and their relationship was shown in the scatter-plot (Fig. 2). As seen from Fig. 1, with the increasing of the NDVI value, the grassland LAI value also increases. There is a statistical positive correlation between the grassland LAI and NDVI. So it was feasible to estimate grassland LAI by using NDVI as a vegetation index of remote sensing.

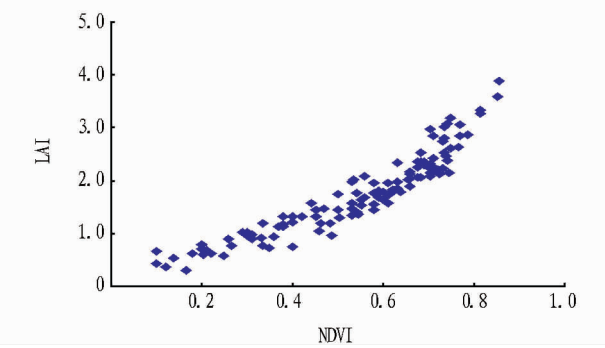


**Fig. 2 Relationships between LAI and NDVI (July of 2009)**

**2.2 Model establishment and parameter confirmation** The regression analysis was implemented between the grassland LAI and NDVI with linearity equation, logarithm equation, polynomial equation, power equation and exponent equation; the results are in Table 1. It can be seen from Table 1 that the correlation of five regression equations are significant level ($P<0.01$). The exponent equation had the highest correlation, $R^2$ reached 0.9152. Followed by polynomial equation, $R^2$ was 0.9051. The logarithm equation has the minimum $R^2$ value, 0.7258.

**Table 1 Analysis on the fitting results of regression equations between grassland LAI and NDVI**

| Related types | Regression equation | $R^2$ | Significant Level | Sample size |
|---|---|---|---|---|
| Linearity | y = 4.24x − 0.476 | 0.8654 | $P<0.01$ | 118 |
| Logarithm | y = 1.88Ln(x) + 3.105 | 0.7258 | $P<0.01$ | |
| Polynomial | y = 6.46x2 − 2.55x + 1.113 | 0.9051 | $P<0.01$ | |
| Power | y = 3.56x1.2 | 0.8762 | $P<0.01$ | |
| Exponent | y = 0.44e2.44x | 0.9152 | $P<0.01$ | |

**2.2.1** Basic model confirmation. According to the above results, the exponent equation was the most reliable to express the correlation between grassland LAI and NDVI, so the estimation model could be expressed as:

$$Y = ae^{bX} \quad (1)$$

where $Y$ is grassland LAI, $X$ is MODIS-NDVI, a and b are coefficients of the model, and the value of them are 0.38 and 2.48 respectively.

**2.2.2** Influencing factors of precipitation and temperature. In order to avoid the interannual fluctuation of the regression model, the regulatory factors of annual precipitation and mean annual temperature were introduced into the estimation model. The annual precipitation factor could be expressed as:

$$W_F = Sqrt(W/w_1 + 1) \quad (2)$$

where $W_F$ was the regulatory factor of precipitation, $W$ was annual precipitation (mm), $w_1$ was the model coefficient. In this paper, the value of $w_1$ was 84.5.

In a similar way, the mean annual temperature factor could be expressed as:

$$T_F = Ln(T/t_1 + 1.6) \quad (3)$$

where $T_F$ was the regulatory factor of temperature, $T$ was mean annual temperature (℃), $t_1$ was he model coefficient. In this paper, the value of $t_1$ was 16.7.

To sum up, the estimation model of grassland LAI in south China could be expressed as:

$$LAI = Y \times W_F \times T_F \quad (4)$$

**2.3 Model test** In this study, the results of simulation model were verified using the observations of the grassland and the corresponding MODIS-NDVI in July of 2010. The results showed that the simulated and observed LAI value had a good correlation with $R^2$ value of 0.8927, and it is statistically significant ($P<0.01$). RMSE of the simulated and observed values was 0.263, RRMSE was 0.145. The promising results indicated that the inversion simulation of LAI in southern grassy mountains and slopes is feasible. In addition, the trend of simulation results and the observed values were consistent, as shown in the 1:1 relationship figure (Fig. 3) between simulated and observed values of grassland LAI.

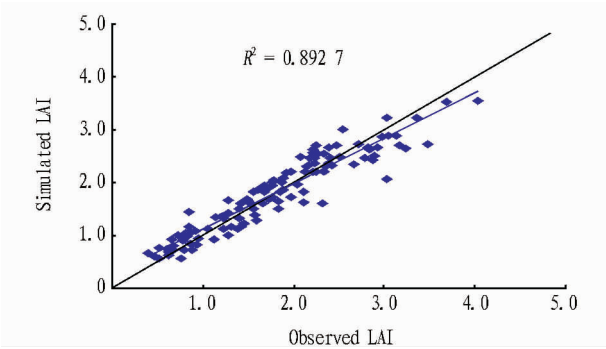


**Fig. 3 Comparison between the simulated and observed grassland LAI (2010)**

**2.4 Grassland LAI distribution**

**2.4.1** Spatial distribution. The spatial distribution map of grassland LAI produced by remote sensing technology was beneficial to monitor grassland resource that grow rapidly[28]. This paper built the spatial distribution map of southern grassy mountains and slops LAI using the estimation model of grassland LAI based on MODIS − NDVI (Fig. 4). The inversion LAI of southern grassy mountains and slopes had obvious zonal distribution. The LAI aggregation is lower in southeast and northeast regions, higher in southwest and northwest regions, especially in the northwest which is bordered on Sichuan and Qinghai, followed by Yunnan and northern Guizhou adjacent to Hunan. The grassland LAI values are affected by the zonality and seasonality.

**2.4.2** Temporal distribution. Based on the above analysis, samples were collected randomly from the spatial distribution map of grassland LAI in the study region, and 120 valid samples were ex-

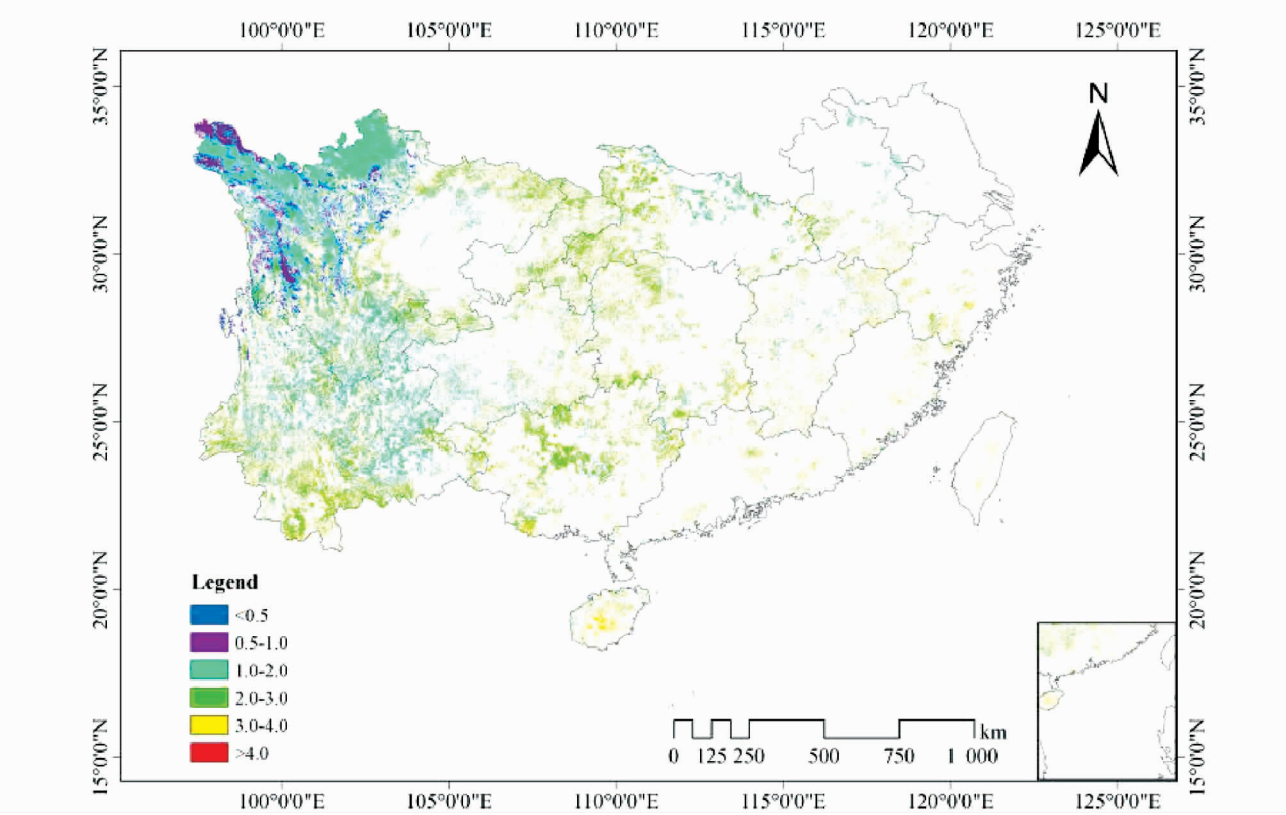


**Fig. 4 Spatial distribution of LAI in southern grasslands (2011)**

tracted as the research object. Through averaging the LAI values, the LAI time series of southern grassy mountains and slops were obtained[24]. Since grassland vegetation growth was affected by temperature and water conditions before April and after October, this study only analyzed the changes of LAI from April to October, the results were showed in Fig. 5. In the average values of the selected samples, the distribution of grassland LAI had time distribution difference. The change of LAI showed a single peak curve along with time changing, the time of peak was in July, and the average value of LAI was about 2.7 which may be related to the fact that there was better water and heat conditions in July (close to August) for the southern areas.

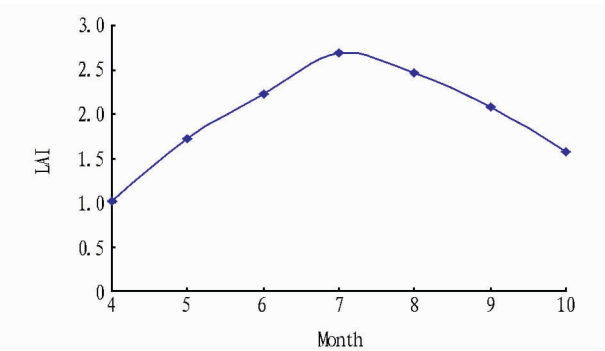


**Fig. 5 Temporal distribution of LAI in southern grassland (2011)**

## 3 Discussions and conclusions

LAI is a key parameter of the ecosystem productivity pattern, global climate pattern, hydrological pattern and biochemical and ecological patterns. It controls many vegetation biophysical processes such as photosynthesis, respiration, transpiration, carbon cycle and intercepted precipitation, etc. It could provide structured quantitative information for the energy changes of vegetation canopy surface. Therefore, LAI inversion technique has always been a very important content in global change research. In this study, , the remote sensing inversion model of grassland LAI was established with MODIS data as the information source by combining the ground measurement results of southern grassy mountain and slops LAI. Through validation by using measurement values obtained from different times, the results showed that the simulation is reliable and it is feasible to invert southern grassy mountains and slops LAI using the model. MODIS has a series of processed data products which could provide enormous potential for regional land ecosystem monitor service. Remote sensing data used in this study were the MODIS – NDVI data products which were widely used and were one of the best indicator factors for the vegetation spatial distribution density. This study showed that NDVI and grassland LAI had significant correlation, and this enables the construction of a linear regression model and curve regression model of LAI by using NDVI directly. The remote sensing inversion of grassland LAI is a comprehensive technology process, which is affected not only by the remote sensing data but also by the grassland vegetation types and the geographic location and other factors. Southern grassy mountains and slopes distribute widely and include many vegetation types. But the LAI distribution is not well

balanced, although the estimation effect of the model is better, the performance of the model is limited by the environment conditions. The first limitation is the lack of investigation on classifying the southern grassy mountains and slopes, hence the result of LAI estimation is a single type. The second is that the measurement samples were scarce. If the samples in other southern provinces and regions could be collected, the estimation results would be more representative. The last is the sensitivity of the model. Research showed that the model was not sensitive to relatively large LAI (when NDVI = 1, LAI = 5.17) and relatively small LAI (when NDVI = 0, LAI = 0.38). When LAI is greater than 5.17 or less than 0.38, the model would be unable to express, which may be related to NDVI saturation and background interference and other factors[29, 30]. These problems require further investigation.

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