Mapping leaf area index of maize in tasseling stage based on Beer-Lambert law and Landsat-8 image

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Abstract: *Leaf area index (LAI) is one of the important structural parameters of crop population, which could be used to monitor the variety of crop canopy structure and analyze photosynthesis rate. Mapping leaf area index of maize in a large scale by using remote sensing technology is very important for management of fertilizer and water, monitoring growth change and predicting yield. The Beer-Lambert law has been preliminarily applied to develop inversion model of crop LAI, and has achieved good application results. Most of current applications were concentrated in wheat and paddy rice, but less in maize. Because the population characteristics of maize are different from wheat and paddy, mapping maize LAI based on Beer-Lambert law will be helpful to improve the application ability of remote sensing in crop growth monitoring and management of fertilizer and water. In this paper, with the support of in-situ samples and Landsat 8 multispectral image in the tasseling stage, the Beer-Lambert law was used to analyze the influence of reducing solar radiation by the maize canopy structure. The light reduction coefficient was derived from the NDVI of soil samples and maize samples by using the least square method. The inversion model was developed to map the spatial distribution of maize LAI in the study area. The in-situ samples of maize LAI were used to evaluate the accuracy of the model with cross validation. Results showed that the relationship between NDVI of Landsat-8 image and LAI of maize was positively correlated. The determination coefficient of inversion model of maize LAI based on Beer-Lambert law could reach 0.97. The spatial distribution of maize LAI in the study area was consistent with the information of local agricultural management department. These indicated that the Beer-Lambert law could effectively reflect the influence of light reduction from maize canopy structure. It was feasible to map maize LAI by Beer-Lambert law and multispectral image.*

Keywords: *leaf area index, maize, Beer-Lambert law, multispectral image, light reduction*

0 Introduction

Leaf area index (LAI) is one of the important structural parameters of crop population, which could be used to monitor the variety of crop canopy and growth condition [1-2]. LAI plays an important role in crop photosynthesis, crop management and grain yield [3-6]. The traditional method of obtaining LAI mainly depends on the field measurement, which can only obtain the LAI information of the limited sample points. The field measurement can't meet the application needs of crop growth monitoring at a large scale. In recent years, remote sensing technology is increasingly becoming an important method of monitoring crop LAI at a large scale, which is helpful to improve scientific decision-making level of field management, variety optimization and disaster evaluation.

There are two main types of remote sensing inversion of crop LAI, including empirical regression model and physical model [7-9]. Experience regression method is mainly establish regression model between vegetation index and LAI by using multi-spectral satellite remote sensing image, which can map the distribution of crop LAI at a large scale. He Jia et al found that the winter wheat leaf area index under different nitrogen and phosphorus level increasing trend with the increase of fertilizer rate, linear regression method was used to construct monitoring winter wheat leaf area index at different development model [10]. Chen et al analyzed the response relationship between the index and LAI by using correlation analysis method, and chose RVI as the optimal model for inversion of winter wheat LAI [11]. Guo et al. established the sugarcane LAI remote sensing monitoring model using support vector machine regression method based on NDVI data of HJ-CCD image [12]. Liang et al. used support vector machine regression method to filter more band information as input parameters to improve the inversion precision of winter wheat LAI [13]. Experience regression method principle are simple and easy to calculate, but poor universality, for planting conditions, geographic location, crop varieties has great dependence, such as the training sample of representative determines the accuracy of the regression model. The physical model method has a good explanation for the physiological and biochemical processes of crops, and the general adaptability is better. Sugiura et al. obtained the information of small area farmland by using UAV imaging sensors and mapped the distribution of crop LAI in the study area [14]. Corcoles et al. realized the non-destructive measurement of onion canopy by using UAV, and analyzed the relationship between canopy density and leaf area index [15]. The Beer-Lambert extinction law had been preliminary applied in the inversion model of crop LAI, such as wheat and paddy, and achieved good application effect, but less reported on the application of maize. The population and individual of maize are different from wheat and paddy. The inversion model of maize LAI based on Beer-Lambert law will be help to improve the application ability of monitoring maize growth and water-fertilize management by using remote sensing technology.

The Gaocheng city of Hebei province in China was chosen as study area. The multi-spectral LandSat-8 image was obtained in the tasseling stage of maize. After analyzing extinction coefficient of maize canopy, the inversion model of maize LAI were developed based on Beer-Lambert law. The in-situ samples were used to evaluate the model accuracy by Cross validation. Through the developed model, the maize LAI in the study area was mapped by LandSat-8 image.

1 Material and method

1.1 Study area

The Gaocheng city is located in the south central plain in the Hehei province in China, nearby eastern foot of Taihang Mountain. Its geographic coordinates is from 37° 51' 00" to 38°18′44″ N and from 114° 38' 45" to 114° 58' 47", where is belong to sub-humid warm temperate continental monsoon climate zone. Because the study area is located in the plain, the topography and geomorphology have little influence on climate. The distribution of climate factors is relatively uniform, which is characterized by the climatic characteristics of cold winter and heat summer. The study area has four distinct seasons, the spring is dry and windy, the summer is hot and rainy, the autumn is cool, and the winter is cold and short of snow and rain. The annual average temperature of study area is 12.5 ℃, while the annual average rainfall is 494 mm. The annual sunshine hours are 2711 hours. It is the major producing areas of maize in Hebei province, where the perennial planting area of maize is around 33000 hectares.

1.2 Data preparation

1.2.1 In-situ samples

The field observation experiment was carried out On August 13, 2015 in tasseling period of the summer maize. The sixteen random sample parcels of maize were observed. Each sample parcel were larger than 1.3 ha. The spatial positions of the sample parcels were obtained by using the submeter GPS, which were evenly distributed in the study area. The observation content of the sample parcel included planting density, relative chlorophyll content (SPAD) and plant height. The function of LAI was showed as follows.

$$LAI_{\mathrm{i}} = 0.75*(\sum_{j=1}^{n} a_{i,j} * b_{i,j}) / \mathrm{S}$$

Here, the $a_{i,j}$ was the length of maize leaf in the No.i sample parcel. The $b_{i,j}$ was the width of maize leaf in the No.i sample parcel. The n was the number of maize leaves in a sample parcel. The S was sampling area.

1.2.2 Acquisition and preprocessing of remote sensing image

The LandSat-8 multispectral image was obtained as the main data used for monitoring maize LAI. The imaging time was August 13 in the tasseling stage of maize. The image quality was very good, without cloud covering. The parameters of LandSat-8 image were shown in table 1.

Table 1 Landsat-8 images of the main parameters

Sensor type	Band	Wavelength range (μm)	Spatial resolution /m	Revisiting period /d
Landsat-8 OLI	Coastal Blue Green Red NIR SWIR 1 SWIR 2	0.433 - 0.453 0.450 - 0.515 0.525 - 0.600 0.630 - 0.680 0.845 - 0.885 1.560 - 1.660 2.100 - 2.300	30	16

The preprocessing of Landsat-8 image included three steps. The first step was radiation calibration. The digital number of Landsat-8 image was transformed to radiance with absolute calibration gain coefficient and offset. The seven bands were lay stack as multispectral image in the ENVI 5.1 software. The second step was atmospheric correction. The FLAASH module in the ENVI 5.1 was used to eliminate the influence of atmosphere on the reflectivity of ground objects and obtain the true reflectance of ground objects. The third step was geometric correction by three times convolution interpolation in the ENVI 5.1. The registration error was lower than 0.5 pixels.

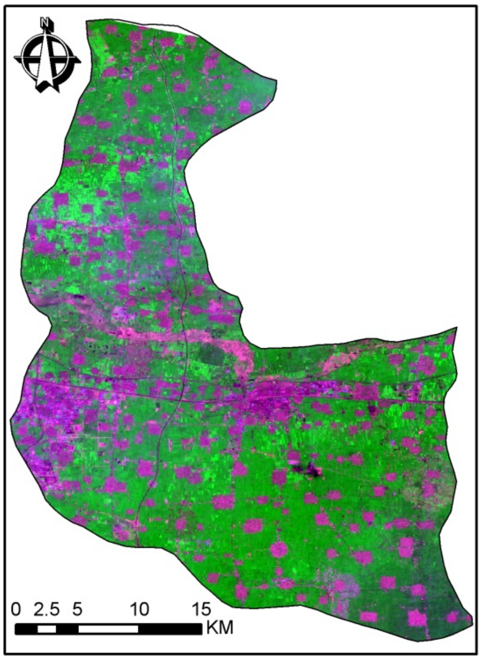

Fig.1 LandSat-8 image of study area on Aug. 13

1.3 Extracting planting distribution of maize

Maize is one of main summer crops in the study area. The soybean and vegetable are apt to mix with maize in the classification. With the support of in-situ samples, the classification system was developed, mainly including maize, soybean, vegetable, fruit tree, residential land and water. The maximum likelihood supervised classification was used to recognize the above objects. The spatial distribution of maize in the study area was mapped.

1.4 Developing the inversion model of maize LAI based on Beer-Lambert law

Based on the process of optical transmission reduction, the Beer-Lambert law is widely used in the field of physical optics. The Beer-Lambert law widely used in the vegetation remote sensing depends on the phenomenon of light reduction through crop canopy. Considering the approximate isotropic distribution of maize leaves, the canopy NDVI could be used to develop the inversion model of maize LAI based on Beer-Lambert law.

$$NDVI = NDVI\infty + (NDVIpw - NDVI\infty) * \exp(-K\mathrm{n}dvi * LAI)$$

Here, the $NDVI\mathrm{pw}$ was the NDVI of soil. The $NDVI\infty$ was the NDVI value when LAI reached infinite. The $Kndvi$ was coefficient of light extinction, which was closely linked with maize canopy structure.

2 Result and analysis

2.1 Extracting spatial distribution of maize

The maximum likelihood method was used to carry out supervised classification of LandSat-8 multispectral image. The in-situ samples were used to establish the confusion matrix to evaluate the accuracy of classification. The total accuracy was 85.2%, while the Kappa was 0.801. The spatial distribution of maize in the study area was mapped as fig.2.

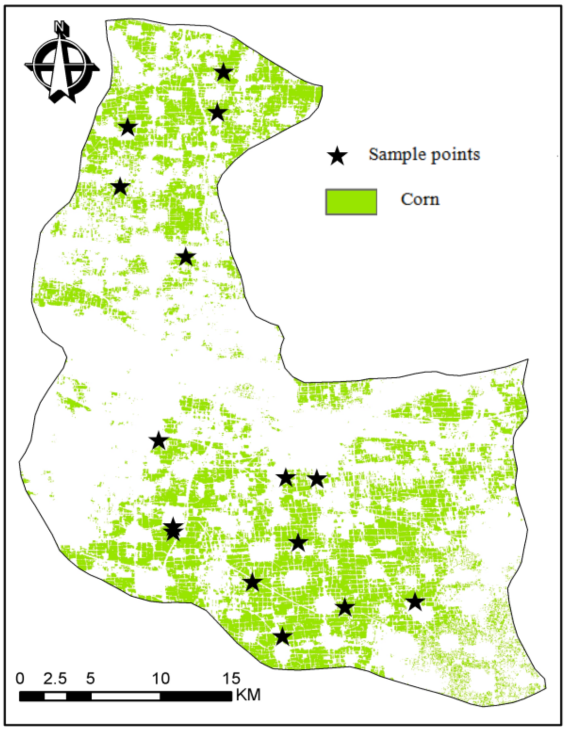

Fig.2 Spatial distribution of maize in the study area

2.2 Inversion model of maize LAI by using Beer-Lambert law

The twenty pixels of exposed soil were chosen from LandSat-8 image, of which the NDVI were calculated by near-red band and red band. The $NDVI_{pw}$ was 0.1594. The LAI and NDVI of in-situ sample were used to fit the $NDVI\infty$ and $Kndvi$, which were respectively 0.8311 and 0.2811. So the inversion model of maize LAI at the tasseling stage was expressed as follows.

$$LAI = \ln((0.8311 - 0.1594) / (0.8311 - NDVI)) / 0.2821$$

The determination coefficient (R^2) of the developed model was 0.9602, while the root-mean-square error (RMSE) was 0.0086. At the tasseling stage of maize, the LAI increased exponentially with the NDVI.

2.3 Accuracy evaluation

Considering the small size of in-situ samples, the cross validation method was adopted to evaluate the accuracy of the developing model.

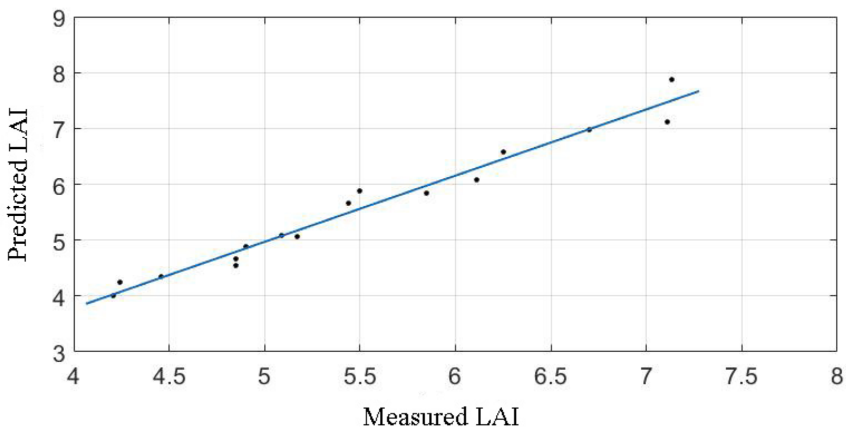

Fig. 3 Relationship between predicted LAI and measured LAI of in-situ samples

The figure 3 showed the predicted LAI of the inversion model agreed well with the measured LAI of in-situ samples. The determination coefficient between predicted LAI and measured LAI reached 0.97. It indicated that the inversion model of maize LAI developed in the study had good accuracy and stability.

2.4 Mapping the maize LAI

Based on Beer-Lambert law and LandSat-8 image, the maize LAI at tasseling stage in the study area were mapped as figure 6. The map showed that in the area north of Gaocheng city, the maize LAI mainly fluctuated from 5.0 to 6.5. It was caused by the soil desertification in the north of Gaocheng city. The water conservation in soil was poor, leading to poor growth of maize. In the central south of Gaocheng city, the maize LAI fluctuated between 7.0 and 8.0. The better growth of maize was closely linked with the fertile soil and good water holding capacity. In the southeast region of Gaocheng city, the parcels of maize were relatively broken, where the LAI generally fluctuated between 6.0 and 6.5. The interplanting of maize and fruit tree affected the light and air flow, which depressed the maize growth. In general, the spatial distribution of maize LAI in the study area based on Beer-Lambert law was consistent with the actual growth of maize in the local agricultural department.

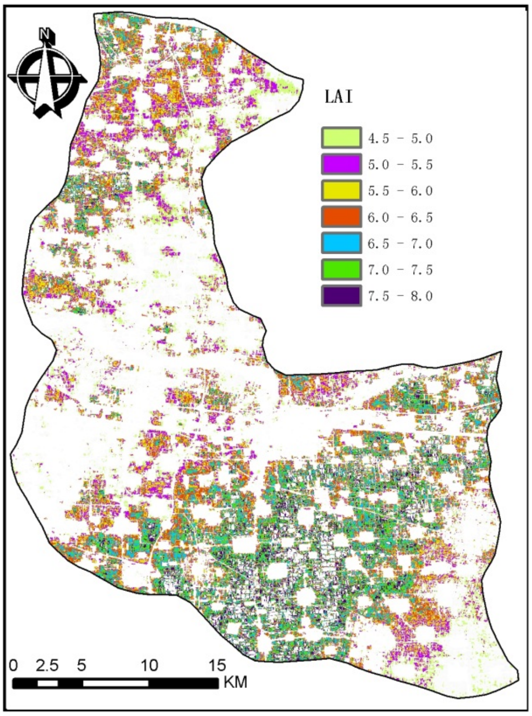

Fig.4 Spatial distribution of maize LAI in the study area

3 Discussion

The study extracted NDVI in the study area from LandSat-8 multi-spectral image on August 13, 2015. The light extinction coefficient of maize canopy was analyzed by the in-situ samples. The inversion model of maize LAI was developed by Beer-Lambert law, which was used to monitor the spatial distribution of maize LAI in the study area.

The tasseling stage is chosen to monitor maize LAI in the study, which is the most important period of maize growing. The LAI in the tasseling stage will reach the biggest and determine the final grain yield to a great degree. So it is significant for water and fertilizer management to monitor LAI at tasseling stage. All leaves of maize at tasseling stage have been expanded, which leads to improve photosynthesis. The population structure has great difference with wheat and paddy. When the maize population is too large, the NDVI will be apt to be saturated. It is necessary to analyze the influence on LAI derived from NDVI saturation.

Because field observation of maize is much more difficult than those of other crops, it is an inevitable trend to reduce the workload of maize field observation in the management of water and fertilizer. The remote sensing technology can provide more extensive, objective and rapid monitoring of crop growth and improve the practicality and accuracy of monitoring result. It is helpful for agricultural department to master the growth dynamics of maize in regional scale accurately. Meanwhile, the remote sensing technology reduces the workload of field observation and improves the representativeness of in-situ samples.

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Reference

[1] Hasegawa K, Matsuyama H, Tsuzuki H,*et al*.. Improving the estimation of leaf area index by using remotely sensed NDVI with BRDF signatures [J]. Remote Sensing Environ., 2010, 114: 514-519.

[2] Zhiqiang Xiao, Shunlin Liang, Jindi Wang, et al.Real-time retrieval of Leaf Area Index from MODIS time series data[J]. Remote Sensing of Environment, 2011,115: 97－106.

[3] Darvishzadeh R, Atzberger C, Skidmore A K, et al. Leaf Area Index derivation from hyperspectral vegetation indicesand the red edge position[J]. International Journal of Remote Sensing, 2009, 30(23): 6199－6218.

[4] Chen J M, Cihlar J. Retrieving leaf area index of boreal conifer forests using landsat TM images[J]. Remote Sensing of Environment, 1996, 55(2): 153－162.

[5] Rasmus Houborg, Martha Anderson, Craig Daughtry. Utility of an image-based canopy reflectance modeling tool for remote estimation of LAI and leaf chlorophyll content at the field scale[J]. Remote Sensing of Environment, 2009, 3(1): 259－274.

[6] Jianxi Huang, Yuan Zeng, Andres Kuusk et al. Inverting a forest canopy reflectance model to retrieve the overstorey and understorey leaf area index for forest stands[J]. International Journal of Remote Sensing, 2011, 32(22): 7591－7611.

[7] Vuolo F, Dini L, D'Urso G. Retrieval of leaf area index from CHRIS/PROBA data: an analysis of the directional and spectral information content[J]. International Journal of Remote Sensing, 2008, 29 (17/17): 5063－5072.

[8] Meng Jihua, Wu Bingfang, Li Qiangzi. Method for estimating crop leaf area index of China using remote sensing[J]. Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE), 2007, 23(2): 160 － 167. (in Chinese with English abstract)

[9] The application of remotely sensed data to the estimation of the leaf area index[J]. Remote Sensing For Land and Resources, 2003(3): 58－62. (in Chinese with English abstract)

[10] HE Jia, LIU Bing-feng, LI Jun.Halloon Area Indices Hyperspectral Remote Sensing Monitoring Model for Winter Wheat at Different Growth Stages [J] .Journal of Agricultural

Engineering, 2014,30 (24): 141-150. (in Chinese with English abstract)
[11] Chen Xueyang, Meng Jihua, Du Xin, et al. The monitoring of the winter wheat leaf area index based on HJ 1 CCD data[J]. Remote Sensing for Land and Resource, 2010, 21(2): 55－58. (in Chinese with English abstract)
[12] Guo Lin, Pei Zhiyuan, Zhang Songling, et al. Estimation method of sugarcane leaf area index using HJ CCD images[J]. Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE), 2010, 26(10): 201－205. (in Chinese with English abstract)
[13] Liang Dong, Guan Qingsong, Huang Wenjiang, Huang Linsheng, Yang Guijun.Remote Sensing of Leaf Area Index of Winter Wheat Based on Support Vector Machine Regression [J] .Journal of Agricultural Engineering, 2013,29 (07): 117-123.
[14] Sugiura R, Noguchi N, Ishii K. Remote Sensing Technology for Vegetation Monitoring Using an Unmanned Helicopter[J]. Biosystems Engineering, 2005, 90 (4): 369-379.
[15] Córcoles J I, Ortega J F, Hernández D, et al.Estimation of Leaf Area Index in Onion (Allium cepa L.) Using an Unmanned Aerial Vehicle[J].Biosystems Engineering, 2013, 115 (1) :31-42.