THE TEMPORAL CHANGING INFORMATION EXTRACTION ON SPECTRAL REFLECTANCE AND GROWTH PARAMETERS OF TYPICAL CROPS

Xiao Yueting, Song Jinling, Wang Jindi

School of Geography and Remote Sensing Science, State Key Laboratory of Remote Sensing Science, Beijing Key Laboratory of Environmental Remote Sensing and Digital City, Beijing Normal University, 100875, Beijing, China
xiaoyueting2099@163.com, wangjd@bnu.edu.cn, songjl@bnu.edu.cn

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ABSTRACT:

When we estimate the land surface variables by remote sensing model inversion, *a priori* knowledge is needed for given the initial values of the model parameters to be retrieved. In this paper, based on the measured datasets accumulated in the Spectrum Database of Typical Land Objects, we analyzed the measured data of typical crops and presented the parameters prior knowledge as the statistics data on canopy spectral reflectance and leaf spectral reflectance. We calculated the mean values and variances for constructing the initial values and uncertainties of model parameters. By taking the winter wheat as the typical crop, with the ground measured crop canopy spectral reflectance and leaf spectral reflectance data in the spectrum database, integrating the spectral response function of Beijing-1 multi-spectral sensor, we got the needed *a priori* spectral knowledge in three spectral band (Green: 523nm－605nm, Red: 630nm－690nm and Near Infrared: 774nm－900nm) and achieved the transformation from narrow band to broad band in order to get the corresponding vegetation index, such as RVI,NDVI,SAVI and so on. With this method, we obtained the statistical relationship between vegetation index and LAI for estimate LAI using Beijing-1 data. The Beijing-1 multi-spectral data with DN value is transformed into different vegetation index. Then we could get LAI data from Beijing-1 multi-spectral image with the statistical relationship expressed above. The data and methods presented in this paper could be considered as valuable reference while estimating model parameter's initial value and its associated uncertainty in physical model inversion.

1. INTRODUCTION

New views are provided to understand the earth system more comprehensively for people via remote sensing ways. Beijing-1 small satellite was launched in Oct.10, 2005 in China successfully. Two type of sensors were carried on the satellite, the 3-band multi-spectral sensor with 32m spatial resolution and the the panchromatic sensor with 4m spatial resolution. Preliminary processing system has been developed for Beijing-1 data receiving, preprocessing, and distribution (Han Dong, 2007). Some relative research works are needed for retrieving more information on land surface.

Taking the remotely sensed data application in Beijing region as sample, MU Fengyun concluded the land use characteristic of Beijing between I984~2005 urbanization based on three Landsat TM images of 1984, 1996, 2001 and one "Beijing-1" data obtained in 2005, which shows that "Beijing-1" data could service as the data base for the studies on the city planning, the ecological environment monitoring, etc (Mu Fengyun, 2007). Yang Shengtian integrated "Beijing-1", SPOT5 and QuickBird images to detect and analyze the vegetation fractional coverage in riparian buffer zones of Guanting Reservoir. For reed marshes, compared with the result of using vegetation fractional coverage calculation equation, the mean absolute error of vegetation fractional coverage measured by "Beijing-1"image was reduced by 22.7 % after applying statistic models (Yang Shengtian, 2006). Wangqian studied "Beijing-1" satellite image application potential in land use field, showed that "Beijing-1" image quality is fine and land use classification precision is high (Wang Qian, 2007).

For applying broadband and high spatial resolution remotely sensed data in agricultural applications at the field measurement scale, an improve method was developed to evaluate commonly used broadband vegetation indices (VIs) for the estimation of LAI with VI–LAI relationships. For the agricultural applications, MSAVI–LAI relationships are easy-to-apply and reasonably accurate for estimating LAI. (Wu Jindong, 2007). Researchers also have found that the broadband SAVI2 index is least affected by background reflectance for both LAI and CCD estimation, and is also the best predictor of LAI. RVI is marginally better than SAVI2 for CCD estimation in terms of canopy effects, but it becomes increasingly sensitive to atmospheric effects and solar zenith angle with increasing vegetation densities. Further, SAVI2 proved to be least affected by illumination geometry changes (N.H. Brogea, 2000).

In this paper, based on the spectrum database of typical land surface objects, we first statistically analyze the collected data(including five typical crops, such as winter wheat, summer maize, cotton, rice and rape) and construct the prior knowledge of the canopy and leaf reflectance(obtaining the mean values and variances of measured canopy reflectance). Then we applied the prior knowledge to estimate LAI by using VI-LAI relationship from "Beijing-1" images obtained in 2006.

2. MATERIALS

2.1 Spectral Reflectance Datasets

The five typical crops included in this study are winter wheat, summer maize, cotton, rice and rape. These datasets come from the Spectral Database System of Typical Objects in China (http://spl.bnu.edu.cn): the data of winter wheat is measured in Beijing, China, in 2001, 2003 and 2004; summer maize is measured in Hebei province, in 2000 and 2003; cotton is measured in Xinjiang province, in 2003 and 2004; rice is measured in Zhejiang province, in 2002 and 2003; and rape is measured in Zhejiang, in 2003 and 2004.

2.2 "Beijing-1" imagery

The study area stands in Beijing and Tianjin Cites located in North China Plane under typical continental monsoon climate characterized by hot and rainy summers, cold and dry winters. The three scenes of Beijing-1 images (UTM projection, pixel resolution of 32m) were obtained in 16 March, 2006, 14 May, 2006 and 17 June, 2006, respectively. Radiation corrections were performed using the radiation correction coefficients supplied by Dr. Chen Zhengchao in Institute of Remote Sensing Applications Chinese Academy of Sciences. The major crop species in the area are winter wheat and summer maize.
The ground-based optical LAI measurements were obtained in 2004 using the instrument LAI2000 from spectrum database of typical land surface objects. The work in this paper was to extract the datasets from the Spectral Database System of Typical Objects in China (http://spl.bnu.edu.cn), analyze systematically and apply the prior knowledge to remote sensing scale.

3. METHODS

3.1 The statistical analysis of spectrum datasets

The overall statistical analysis of spectrum datasets depends on two steps that influence the expression of the prior knowledge. The first step is to specify the growth stages of crops for every measured spectral data, because the work of wrongly divided growth stages will lead to different sample quantity and disharmony with others' work. The second step is to calculate the mean values of measured spectrum of these crops in their growth stages and assess the data uncertainty.

In this study we classified the data extracted from the spectrum database by variety and growth stages. And we analyzed the measured data of typical crops and presented the statistics data on canopy spectral reflectance and leaf spectral reflectance by their mean values and the uncertainties. We did statistical analysis, obtaining statistical parameters such as mean values, minimum values, maximum values and variance. In this way, we calculated the mean values and variances for constructing the initial values and uncertainties of model parameters. Thus the calculated results are shown in Fig. 1 and Fig.2. The important *a priori* knowledge could be used in calculating spectral VI and LAI retrieval.

3.2 "Beijing-1"data process

With Maximum Likelihood Method, we classified the "Beijing-1" images into six targets: water, forest, grass, crop, city and the unused. We classified the three images (16-March-2006, 14-May-2006 and 17-June-2006) respectively. Comparing these three classification images with Beijing LULC data, we used the 14-May-2006 classification image as the reference to make sure the certain ground species. With this method, we obtain our final classification image (Fig.3). As is shown in Fig.3, there are 7 classification classes, of which the winter wheat and summer maize are reclassified from crop.
We got the needed *a priori* spectral knowledge of winter wheat and summer maize in three spectral band (Green: 523nm－605nm, Red: 630nm－690nm and Near Infrared: 774nm－900nm) and achieved the transformation from narrow band to broad band in order to get the corresponding vegetation index, such as RVI,NDVI,SAVI and so on. The arithmetic for transformation is seen in Equation (1)

$$R = \sum_{\lambda=a}^{b} \alpha_{\lambda} \rho_{\lambda} \Big/ \sum_{\lambda=a}^{b} \alpha_{\lambda} \qquad (1)$$

where λ is wavelength, [a, b] stands for the wavelength bound, α_{λ} is the band response function for "Beijing-1" image, ρ_{λ} is the ground high spectrum reflectance on the wavelength of λ.

With this method, we obtained the statistical relationship between ground based vegetation indexes and LAI, and discovered better parameter inversion way. Then we simply applied this ground relationship to the "Beijing-1" images.

4. RESULTS AND DISCUSSION

4.1 The statistical results of the measured spectral reflectance in time sequence

Fig.1 and Fig.2 include all crop species from measured crop spectral reflectance data based on the Spectral Database System of Typical Objects in China. In two figures, each colored lines show the mean values of leaf and canopy spectrum in different crop growth stages. Along each colored line, there is a range in black which stands for the variance calculated from the whole measured data. The wider as the black depicted in the figure, the larger the variances is.

Form Fig.1 and Fig.2, we can see that the mean values of measured canopy and leaf reflectance change in different growth stages and the uncertainty in the near infrared region is higher than in the visible region.

From Fig.1, we could see that each of rice, rape , maize and winter wheat only have one-year data in 2002, 2004, 2003 and 2004, respectively, while cotton have two-year data in 2003 and 2004. The measured growth stages in 2003 are more than in 2004 for cotton. The leaf reflectance in green light and the near-infrared region reach the peak in grain-filling stage for early rice, while for the late rice, it is the ripen stage and milky stage, respectively. The leaf reflectance in green and the near-infrared bands reaches the peak in ripen stage and returning green stage respectively for winter wheat. In general, the temporal changing information of the five crops' leaf reflectance agrees with others' work.

And from Fig.2, we could see that each of rice, rape and maize only have one-year data in 2003, 2004 and 2003, respectively, while cotton and winter wheat have two-year data in 2003, 2004 and 2001, 2004, respectively. The measured growth stages in 2003 are more than in 2004 for cotton, and for winter wheat the measured growth stages in 2004 are more than in 2001.The canopy reflectance in green light reach the peak in flourishing flowering stage for rape, in flourishing flowering stage and flourishing belling stage for cotton, in early stage for maize and winter wheat under the effect of soil. In general, the temporal changing information of the five crops canopy reflectance is similar with others' work.

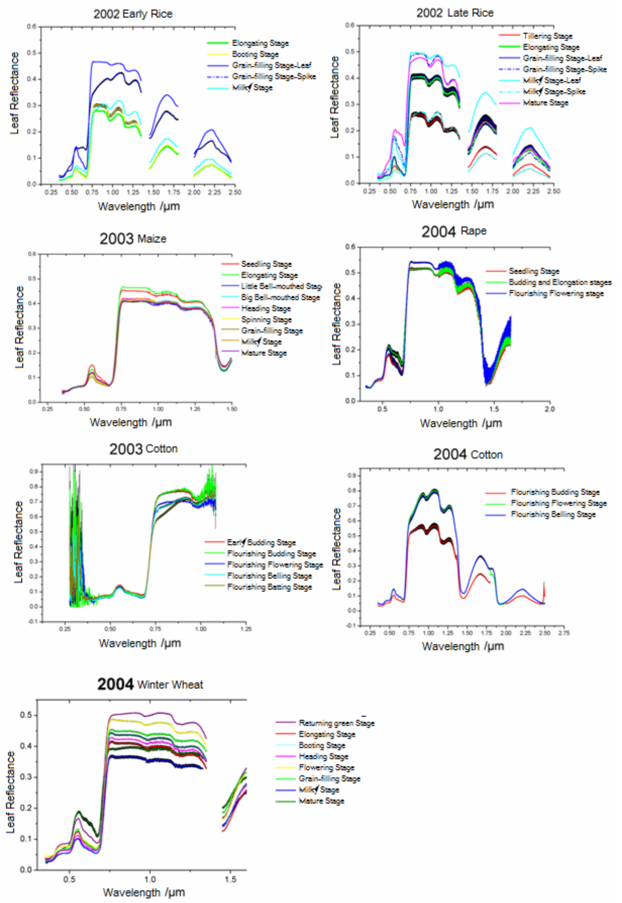

Figure 1: Statistical analysis of crop leaf reflectance

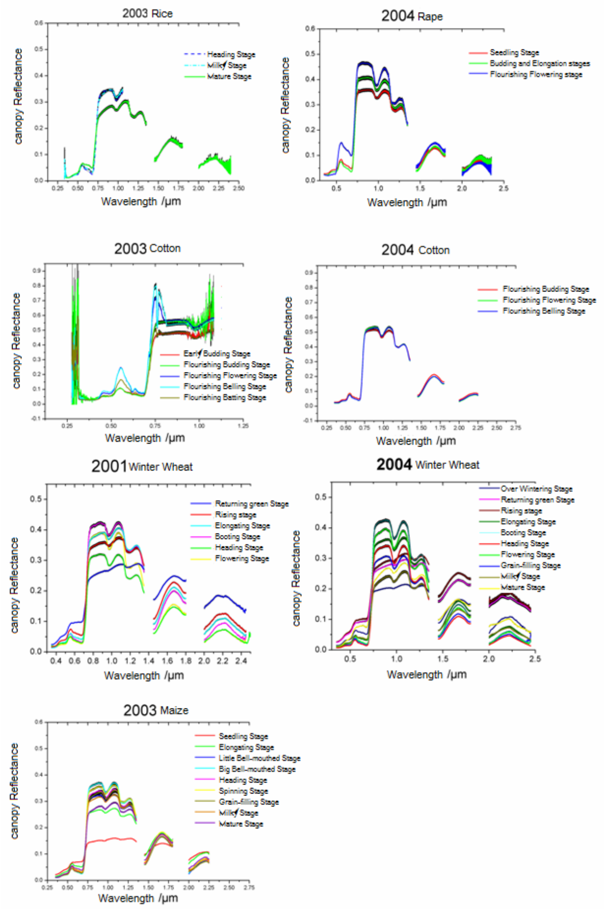

Figure 2: Statistical analysis of crop canopy reflectance

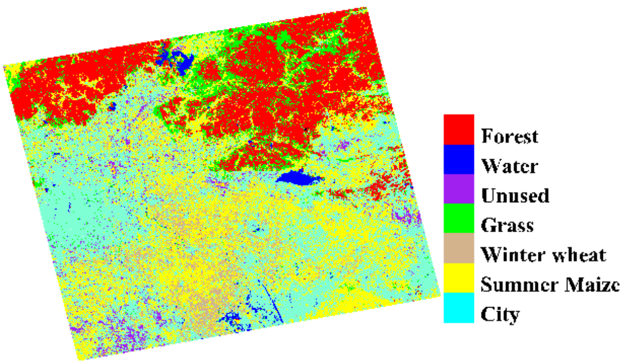

Figure 3: Study area classification map

4.2 "Beijing-1" LAI image

Table 1 lists the linear and non-linear regression functions between LAI and several VIs created by spectral reflectance in broad red and near IR bands of winter wheat. The best linear regression function is the relationship between RVI and LAI (R^2=0.939), while the best non-linear regression function was relationship between SAVI and LAI (R^2=0.0.678). The parameters in different VI are: PVI (a=0.96916, b=0.084726), SAVI (L=0.5).

Baret and Guyot put forward a semi-empirical regression function between VI and LAI, as shown in Equation (2)

$$VI = VI_{\infty} - (VI_{\infty} - VI_g)\exp(-K_{VI} LAI) \qquad (2)$$

where VI_{∞} is the asymptotically limiting value of a specific VI when LAI approaches a very large value; VI_g is the index value corresponding to bare soil conditions (LAI = 0). The dynamic range of the VI (i.e., VI_{∞} -VI_g) is the difference between its maximum (VI_{∞}) and minimum value (VI_g). K_{VI} is the absorption-scattering coefficient that determines the sensitivity of the VI to a unit increase of LAI (Baret, F. 1991).

Table 2 lists the semi-empirical regression function between LAI and VI created with broad red and near IR bands of winter wheat. The best semi-empirical regression function is between SAVI and LAI. However, the L parameter of SAVI is simplified to 0.5, we couldn't prove its applicability for the "Beijing-1" images, and then we just used the NDVI instead since the NDVI-LAI relationship is the best in relationships between RVI-LAI, PVI-LAI and MSAVI-LAI except SAVI-LAI relationship.

With the same method, we got the semi-empirical regression functions for summer maize, grass and forest. The datasets of summer maize were extracted from the Spectral Database System of Typical Objects in China, while grass and forest datasets were obtained using Computer Simulation Model.

Since the ground based minimum NDVI value is higher the minimum NDVI value in remote sensing scale, we advanced a simpler semi-empirical relationship between NDVI and LAI as shown in Table 3. The advanced arithmetic for transformation is seen in Equation (3)

$$VI = VI_{\infty} - (VI_{\infty} - 0)\exp(-K_{VI}\, LAI) \qquad (3)$$

where VI_{∞} and K_{VI} are consistent with Equation (2).

The original and advanced semi-empirical regression functions are shown in Table 3.

After all these work, with the foregoing classification map (Fig. 3), we applied the relationship between NDVI and LAI for estimating the LAI of different species, and to see how these LAI change in different crop growth stages. As shown in Figure 4, we could see that the LAI value of crop is the highest in May 14, since the winter wheat grows best in May 14 and are harvested in June 17. And LAIs value of grass and forest are the highest in June 17.

The LAI temporal distribution characteristic is shown in Fig.5; there are several high LAI values in March and June, which locate in the forest area. In 16-March-06 LAI image, 99% of LAI values are below 1.6, in 14-May-06 LAI image, 99% of LAI values are below 1.8, and in 17-June-06 LAI image, 99% of LAI values are below 4.2. After checking the whole data, we found that there were a few high NDVI value points in March and June, that's why the LAI got high value in those areas.

Linear Regression Function	R^2	F	Sig.	Non-Linear Regression Function	R^2	F	Sig.
LAI=0.397*RVI	0.939**	3077.24	0.000	LAI=0.487*exp(0.236 *RVI)	0.655**	376.101	0.000
LAI=3.599*NDVI	0.902**	1833.453	0.000	LAI =0.218*exp(3.345*NDVI)	0.661**	385.627	0.000
LAI=17.201*PVI	0.934**	2816.534	0.000	LAI =0.629*exp(8.554 *PVI)	0.641**	353.635	0.000
LAI=5.439*SAVI	0.927**	2525.258	0.000	LAI =0.290*exp(4.369*SAVI)	0.678**	416.311	0.000
LAI=5.493*MSAVI	0.938**	3005.292	0.000	LAI =0.361*exp(3.904*MSAVI)	0.676**	414.030	0.000

Table 1: Regression functions between VI (x) and LAI (y).
RVI is Ratio Vegetation Index, NDVI is Normalized Differenced Vegetation Index,
PVI is Perpendicular Vegetation Index, SAVI is Soil Adjusted Vegetation Index, MSAVI is Modified SAVI.

RVI= $\frac{NIR}{R}$ **, NDVI=** $\frac{NIR-R}{NIR+R}$ **, PVI=** $\frac{NIR-aR-b}{\sqrt{a^2+1}}$ **, SAVI=** $\frac{NIR-R}{NIR+R+L}(1+L)$ **, MSAVI=** $\frac{2NIR+1-\sqrt{(2NIR+1)^2-8(NIR-R)}}{2}$

Regression Function	R^2	SSE	SSY	F
$LAI = -1.711 * Ln(\frac{10.67-RVI}{10.67-1.45})$	-	336.559	280.210	-
$LAI = -1.227 * Ln(\frac{0.83-NDVI}{0.83-0.18})$	0.622	105.983	280.210	325.495
$LAI = -2.706 * Ln(\frac{0.29-PVI}{0.29+0.01})$	0.402	167.588	280.210	133.059
$LAI = -2.018 * Ln(\frac{0.66-SAVI}{0.66-0.12})$	0.629	103.991	280.210	335.523
$LAI = -2.010 * Ln(\frac{0.69-MSAVI}{0.69-0.10})$	0.496	141.299	280.210	194.654

Table 2: Semi-empirical regression functions between VI (x) and LAI (y)

Species	Improved Regression Function		Original Regression Function	
	Regression Function	R^2	Regression Function	R^2
Winter Wheat	$LAI = -1.155 * Ln(\frac{0.83 - NDVI}{0.83})$	0.623	$LAI = -1.26 * Ln(\frac{0.83 - NDVI}{0.83 - 0.16})$	0.622
Summer Maize	$LAI = -2.111 * Ln(\frac{0.90 - NDVI}{0.90})$	0.638	$LAI = -2.314 * Ln(\frac{0.90 - NDVI}{0.90 - 0.19})$	0.595
Grass	$LAI = -0.873 * Ln(\frac{0.87 - NDVI}{0.87})$	0.961	$LAI = -1.067 * Ln(\frac{0.87 - NDVI}{0.87 - 0.42})$	0.827
Forest	$LAI = -1.702 * Ln(\frac{0.90 - NDVI}{0.90})$	0.564	$LAI = -2.69 * Ln(\frac{0.90 - NDVI}{0.90 - 0.58})$	-

Table 3: Semi-empirical regression functions between NDVI (x) and LAI (y) for different crops

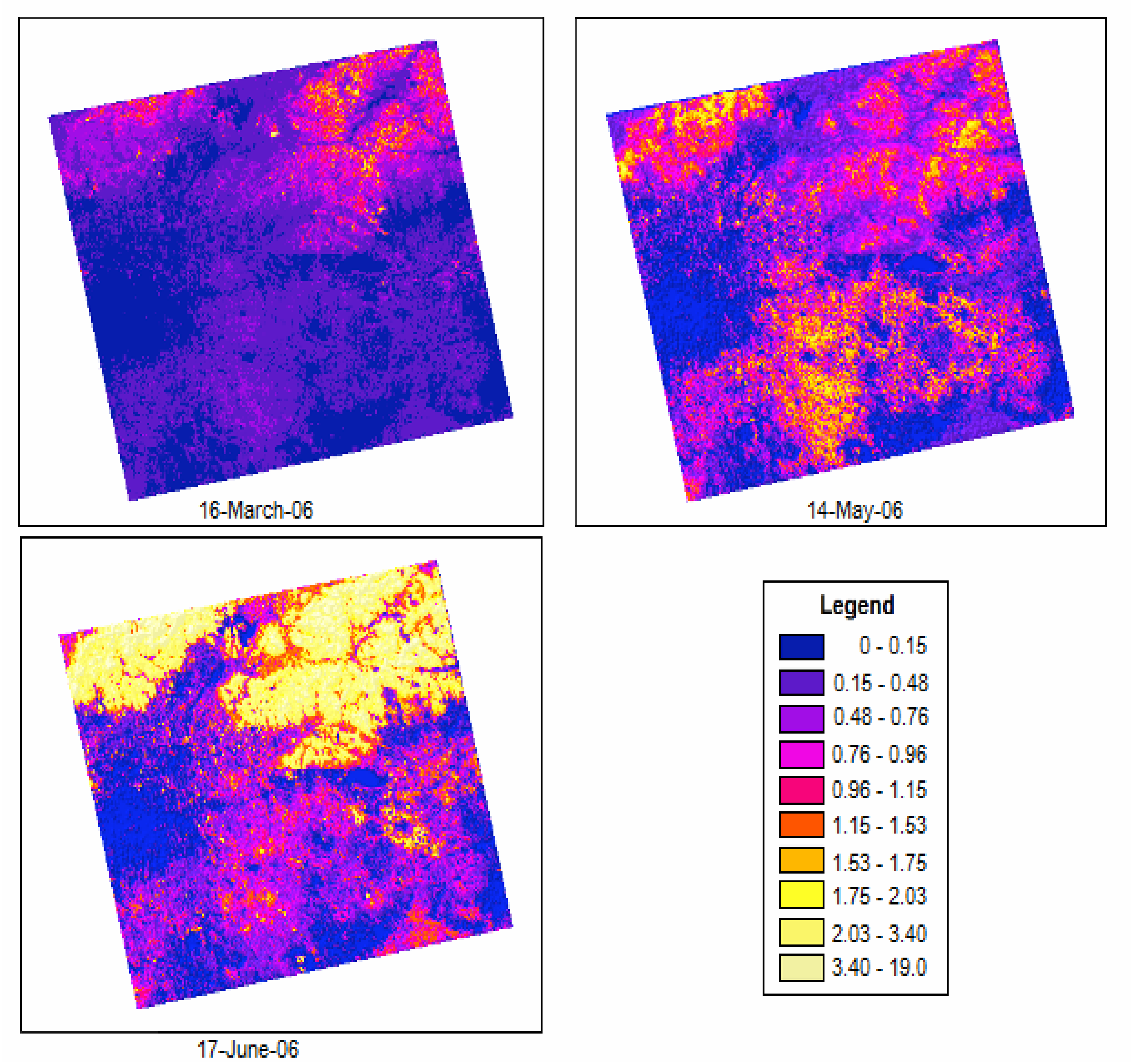

Figure 4: “Beijing-1” LAI images of Time series

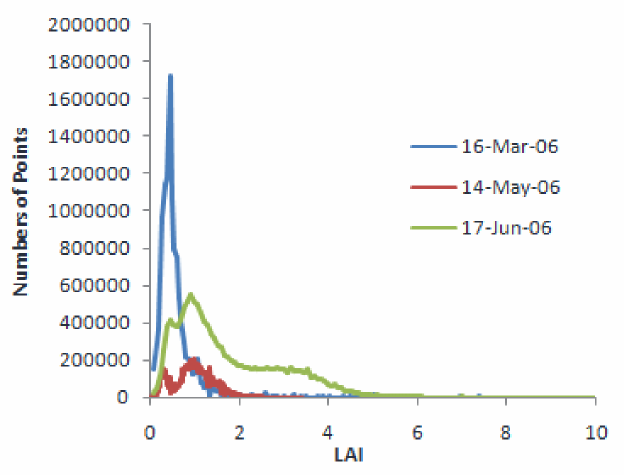

Figure 5: scatter plot between LAI and numbers of points

5. CONCLUSIONS AND FUTURE WORK

This research is focused on the temporal changing information extraction both from the Spectral Database System of Typical Objects in China (http://spl.bnu.edu.cn) and the "Beijing-1" imagery supplied by Beijing Landview Mapping Information Technology Co. Ltd. This work was carried out by means of applying ground relationship between VI and LAI to the "Beijing-1" images in 16-March-2006, 14-May-2006 and 17-June-2006, respectively. We built the ground crop temporal canopy and leaf reflectance changing information, and then compared different relationships between VIs and LAI using empirical way and semi-empirical way. The best linear regression function was relationship between RVI and LAI, the best non-linear regression function was relationship between SAVI and LAI, and the best semi-empirical function was relationship between SAVI and LAI, however SAVI was not a perfect VI for large-extent apply, since L parameter varied with the region, thus we finally chose NDVI to acquire the "Beijing-1" LAI product. With this prior knowledge, a reasonable semi-empirical relationship was found between NDVI and LAI.
The results of this study suggest that the new "Beijing-1" imagery could be a useful way to detect the LAI temporal change. However, more work is waiting to validate the precise of estimated LAI of Beijing-1 images.

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