ESTIMATION OF CROP LEAF AREA INDEX USING MODIS DIRECTIONAL REFLECTANCES DATA

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1. INTRODUCTION

Leaf Area Index, LAI is a key parameter which determines mass, energy and momentum exchange between land surface and atmosphere. Monitoring global vegetation state and changes is necessary under global change. Large area LAI dynamic observation is essential in global carbon circle and climate change researching [1].

Remote sensing provides a powerful tool to estimate of large area LAI. There are two main methods to estimate LAI from remote sensing observation. One is based on the relationship between field measured LAI and remote sensing spectral index [2]. The other is based on canopy radiation models which characterize the relationship between canopy reflectance and biophysical parameters [1, 3]. Although the VIs-based approach is more computation efficient, it is very difficult to gather representative field measurements to fit the empirical model for large-scale application [2]. The physically based models have been proved to be more suitable to large area LAI retrieval as they describe the physical process of transfer and interaction of radiation inside the canopy. Directly inversions of canopy radiation model are often not practical for global applications due to its significant computational resources and time needs. Several inversion techniques have been employed, such as look-up tables (LUT) and neural networks [1, 3]. Neural network simulation is more efficient compared to LUT method, which is essential in large scale application [4].

The remote sensed land surface reflectances depend on the observational geometry and the vegetation structure. LAI is a key vegetation structure parameter, so observational geometric information would be important for retrieval of LAI from land surface reflectances. CYCLOPES algorithm utilizes the BRDF normalized spectral reflectances of the VEGETATION to produce 10 days composite LAI products [3]. However, BRDF normalization probably induced uncertainty for large area application because the solar zenith angle varies significantly for any given date and large normalization errors may occur when the reflectance is forced to a standard geometry [5]. This uncertainty is particularly of concern as kernel-driven BRDF models are widely used in this normalization. For this reason, GlobalCarbon algorithm explicitly considers the BRDF effect of vegetation and produces global LAI using 4-scale geometrical optical model and VI-based LAI algorithm to simulate the relationship between LAI and the directional spectral properties without BRDF normalization of reflectance [5]. However, this LAI product tends to display erratic variations [6].

In this paper, an algorithm based on neural network to derive leaf area index from MODIS directional reflectance and geometry data is presented. This algorithm directly utilizes the directional reflectances instead of the BRDF normalized data to avoid complex BRDF normalization and the error occurred in this process. The estimated LAI is finally compared against existing MODIS/CYCLOPES LAI products and ground measurements of annual crop LAI in 2004 in Hengshui, China.

2. METHOD

The algorithm utilizes remote sensing directional land surface reflectances and geometry data to retrieve LAI. We use Four-Scale model combined with neural network to apply this algorithm. Firstly, Four-Scale model is used to simulate LAI at different land surface and geometric situations for crop. Then, the neural networks are trained with the simulated LAI dataset. After the neural network is calibrated, the MODIS directional land surface reflectances and geometry data are used as network inputs to efficiently produce LAI.

2.1 Radiative transfer model

The algorithm is developed based on the Four-scale Bidirectional Reflectance model. This geometric-optical model developed by Chen and Leblanc considers four scales of canopy architecture [7]. Compared with other radiative transfer models, this GO model is easier in investigating BRDFs for a large set of input parameters [8].

A large number of simulations are made using a large combination of input model variables and observation geometries to produce training dataset. Simple Ratio (SR) is used to combine the information of red and near-infrared bands and form the training dataset. Besides the conventional red and NIR bands, the shortwave infrared (SWIR) band is also used to replicate better the behavior of the vegetation reflectance in satellite images. In total, 23040 simulations were performed for crop. Two third of these were randomly selected to compose the learning database, the others were used as testing database to evaluate the neural network performances.

2.2 Networks design and calibrate

In this paper, a two-layer back-propagation artificial neural network was trained. Inputs of the network are Simple ratio, short wave infrared reflectance, solar zenith angle, and view zenith angle as well as cosine value of relative azimuth angle. Network output is LAI.

The learning database made of pairs of inputs and outputs were first normalized according to: $X_{norm} = (X - X_{\min})/(X_{\max} - X_{\min})$ where $X_{\min}$ and $X_{\max}$ are respectively the minimum and maximum values for variable X. Then two third of the standardized learning database cases were used to train the network. After several tests, the network provided the best performance with relative simple architecture was selected. The optimal network is made of one input layer with 5 linear neurons, one hidden layer of 11 tangent-sigmoid transfer functions and one output layer with 1 linear neuron. The network was calibrated by minimizing of a misfit function, which was defined as the mean square error (MSE) between the targeted variables and the network outputs. The Levenberg-Marquardt minimization algorithm was used in the learning process due to its efficient convergence performances.

2.3 Theoretical performances

After the network calibrated, its performances were evaluated on the testing database of 7680 cases. The network inversion to retrieve LAI with a fairly good accuracy (RMSE=0.1808). The network simulated and targeted LAI keep good consistent with correlation coefficient of 0.97. And the majority of difference between network simulated and targeted LAI centralized at zero.

3. RESULTS AND VALIDATION

The neural network performances are evaluated by analyzing the consistency between the results and the MODIS and CYCLOPES LAI products. Then, directly validation with ground measurements of annual crop LAI of 2004 in Hengshui is presented.

3.1. Comparison with 2001-2003 MODIS\CYCLOPES LAI products

MODIS clear-sky non-snow high-quality land surface reflectance and geometry data were selected over 33 winter wheat experimental sites in Hengshui. Then the extracted data were used to drive the network and simulate LAI. The simulated LAI were matched with the most spatial and temporal proximal MODIS and CYCLOPES LAI data from 2001-2003. Figure 1 and 2 shows a good agreement between simulated and MODIS and CYCLOPES LAI both in spatial pattern and Interannual as well as seasonal variations.

3.2 Validation against ground LAI measurements in Hengshui

The network LAI algorithm was validated against ground-based LAI data in Hengshui from 2003 to 2004. Seven fine-resolution (30m) Landsat ETM+ scenes from October, 2003 to April, 2004 were used to map the LAI images of study area. For the sample sites, vegetation index NDVI was computed from these ETM+ images, and the relationship between measured LAI and ETM+ NDVI was established. The relationship is $LAI=1.747\times\ln(NDVI) + 3.240$. Then, a fine resolution LAI map was produced using this relationship based on ETM+ image acquired on Julian day 190, 2002. The validation results are shown in Figure 3. The spatial structure of LAI map using our algorithm is consistent with the corresponding MODIS and CYCLOPES products at 1km resolution.

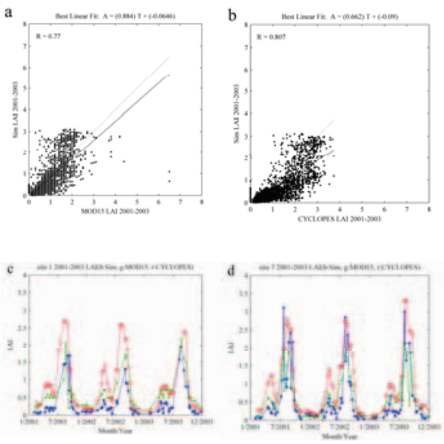

Figure 1. network simulated LAI Comparison with: a) MODIS LAI product, b) CYCLOPES LAI, Interannual and seasonal variations over c) site 1, d) site 7

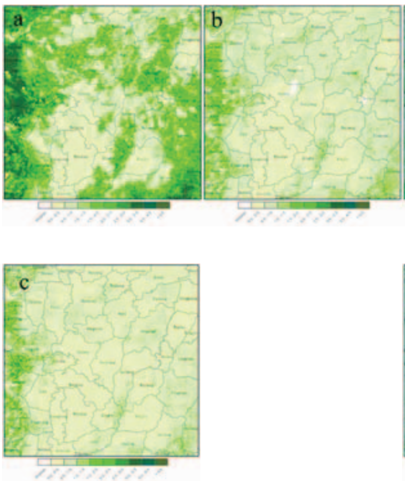

Figure 2. Maps of a) CYCLOPES, b) MODIS c)network simulated LAI in April, 2002

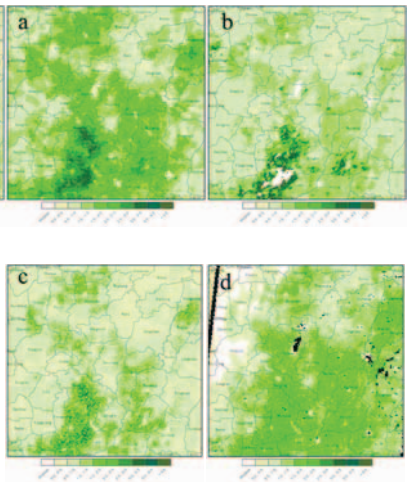

Figure 3. Validation of LAI. a) CYCLOPES LAI product in Hengshui at Julian Day 190, 2002; b) MODIS LAI product; c) our algorithm results; d) ETM+ LAI

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