RETRIEVAL OF TIME SERIES LAI BY COUPLING AN EMPIRICAL CROP GROWTH MODEL WITH A RADIATIVE TRANSFER MODEL

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1. INTRODUCTION

Traditional LAI retrieval methods are based on physical models inversion of the bidirectional reflectance or statistical regression with the vegetation index. However, the variable weather condition often makes the retrieval process failed. As a result, remote sensing LAI product often shows some holes in both of the spatial and temporal dimensions. On the other hand, even if no cloud covers a region for many days, LAI is not yet produced every day. For example, MODIS's LAI is produced every 8 days [1]. Such a temporal resolution is not enough for crop growth monitoring.

Since the 80s and 90s of last century, some scientists tried to combine the crop growth model and the remote sensing inversion to predict the crop yield. Two types of methods were proposed. One uses the remotely sensed LAI values to adjust the growth model's parameters [2-4], and the other one uses the canopy reflectance or vegetation index [5, 6]. Even if these kind of retrieval algorithms and assimilation algorithms were able to consider the growth of crop, nearly all of the parameters except LAI were assumed to be known in their radiative transfer (RT) models based inversion [2, 7]. However, in many cases, LAI is not the most sensitive parameter, fixing the other spatial and temporal variable parameters may cause significant errors in LAI retrieval.

In this paper, we developed an empirical crop growth model and coupled this model with a RT model SAILH to retrieve the continuous time series LAI. In stead of fixing the unknown parameters, the sensitive spectral parameters in the RT model were also retrieved. To minimize the random noise in the observations, we further proposed a rolling inversion strategy for LAI inversion in the crop growth period. From the simulation based retrieval results, it was found that this method improve both of the accuracy and the temporal resolution of LAI.

2. AN EMPIRICAL CROP GROWTH MODEL

LOGISTIC function is popular in the modeling of regional crop growth processes, such as dry matter accumulation, leaf area growth, and so on. Using the relative accumulation temperature (DVS) to denote the time variable in the crop growth period, and using the relative LAI value (RLAI, that is LAI/LAI_{max}, where LAI_{max} is the largest LAI during the whole growing period) to denote the state variable in the crop growth period, we can get the relative LAI growth model of winter wheat as:

$$RLAI_i = \frac{C}{1 + EXP(A0 + A1 * DVS_i + A2 * DVS_i^2)} \tag{1}$$

Where ,C, A0，A1 and A2 are coefficients that can be fitted using the continuous field measured LAI values.

As many as 865 sets of ground measured LAIs in Shunyi and Changping of Beijing were collected. Some of them were measured in the same day at the same site. Consequently, such data sets were averaged to be one typical LAI measurements. We get 103 data sets of RLAI after the data processing. All of the 103 data sets were used to fit the Eq. (1), and we got:

$$RLAI_i = \frac{2.5}{1 + EXP(7.76 - 12.75 * DVS_i + 5.63 * DVS_i^2)} \tag{2}$$

3. RETRIEVAL STRATEGY

3.1. Selection of the retrieval parameters

It is some times a trick to determine how many variables should be inverted in an algorithm. But generally the most sensitive and uncertain parameters, such as the spectral parameters in the RT model, should be inverted together with LAI. Unfortunately, only the state variables in the crop growth model were usually adjusted in the past. The parameters of the RT models except LAI were often fixed as known values in inversion or assimilation. However, for the daily operational parameters production, it is hard to get such values by ground measurements, and set values of the sensitive parameters in RT models according to the experience may lead into more errors. We choose the SAILH model as the RT model in this paper [8]. The spectral parameters of SAILH include leaf reflectance, leaf transmittance and soil reflectance which are all sensitive parameters. All of these spectral parameters were adjusted together with LAI in inversion.

Eq. (2) can give a good statistical description of the growth of winter wheat in Beijing, however, such an expression may not be the best candidate in the other region. By the sensitivity analysis of Eq. (1), we found that the coefficients A0, A1 and A2 show different sensitivity in different growth stage. A0 is the most sensitive at the beginning and middle of the growth period, on the contrary, A2 is the most sensitive parameter in the last stage of growth. In our work, besides LAI_{max}, A0 was chosen as variables at the beginning and middle growth period, and A2 was chosen as variables in the last growth stage. As a result, our inversion algorithm is expected to do well in large area for winter wheat LAI retrieval.

3.2. Description of the retrieval algorithm

There are always random noises in the measured data, and this will affect the retrieval result. In order to deduce this effect, we designed the retrieval strategy as follows: Taking 8 days as a retrieval period, the overlapped days between the former and the later periods are 6 days. The time window rolls ahead step by step. The final continuous time series LAI values can be got by the average of the output in four periods. By using this rolling retrieval strategy, we not only coupled the growth model with the RT model, but also reduced the random noise in the measured data. That is, we used as many information as possible to do the best inversion.

In order to reduce the number of the retrieved parameters, we assumed that the spectral parameters in a retrieval period (8 days) are stable. Furthermore, the *a priori* knowledge of LAI_{max}, A0(or A2)were given according to the fitting result in section 2, and the *a priori* knowledge of leaf reflectance, leaf transmittance and soil reflectance were obtained from the ground measurements. Other model parameters, such as C, A1、A2 (or A0) in the growth model and the left RT model parameters were all fixed as the fitting results or the ground measured data.

SCE-UA (Shuffled Complex Evolution method developed at the University of Arizona) Global optimization algorithm [9] was used to search the optimum values. The final time series LAI values were calculated using the LOGISTIC model developed in section 2 after the coefficients LAI_{max} , A0 and A2 had been retrieved.

4. METHOD EVALUATION

In order to evaluate the rolling retrieval strategy, we compared three kinds of retrieval algorithm:1) Retrieval in single period by fixing the spectral parameters; 2) Retrieval in single period with the spectral variables in inversion; 3) Retrieval using rolling strategy with the spectral variables in inversion. In the test, we set the initial values of the spectral parameters 20% bigger or smaller than the true values, and added Gaussian random noise with 20% standard deviation on the simulated reflectance as the "observed values". After repeating the process of adding noise and inversion for 200 times, we got the root mean square error (RMSE) of the retrieved LAI values. Because there are few remote sensors can achieve as many multi-angle observations as the ground-based measurements, we only considered the observation geometries of MODIS sensor over Beijing.

The comparison of the retrieval results of these 3 retrieval algorithms from April, 19, 2001 to May, 2, 2001 is shown in figure 1. What can be found from figure 1 is that the retrieval errors increase with the increase of LAI values for all of these 3 retrieval algorithms. Because in the simulation based retrieval, 30% relative error was added to the *a priori* knowledge of LAI_{max}, the absolute errors of the retrieval results were large. On the other hand, the sensitivity of reflectance to LAI may decrease for large LAI values, and this may be another reason for the increasing retrieval errors with the increasing LAI values. We can also find that, if we fix the spectral parameters in the retrieval algorithm, 20% overestimate or underestimate of their values may cause LAI retrieval errors from 0.91 to 2.25. On the contrary, our rolling inversion strategy can significantly decrease the inversion errors. More inversion using the field measured data showed that the spectral parameters in SAILH model were sensitive and could not be fixed.

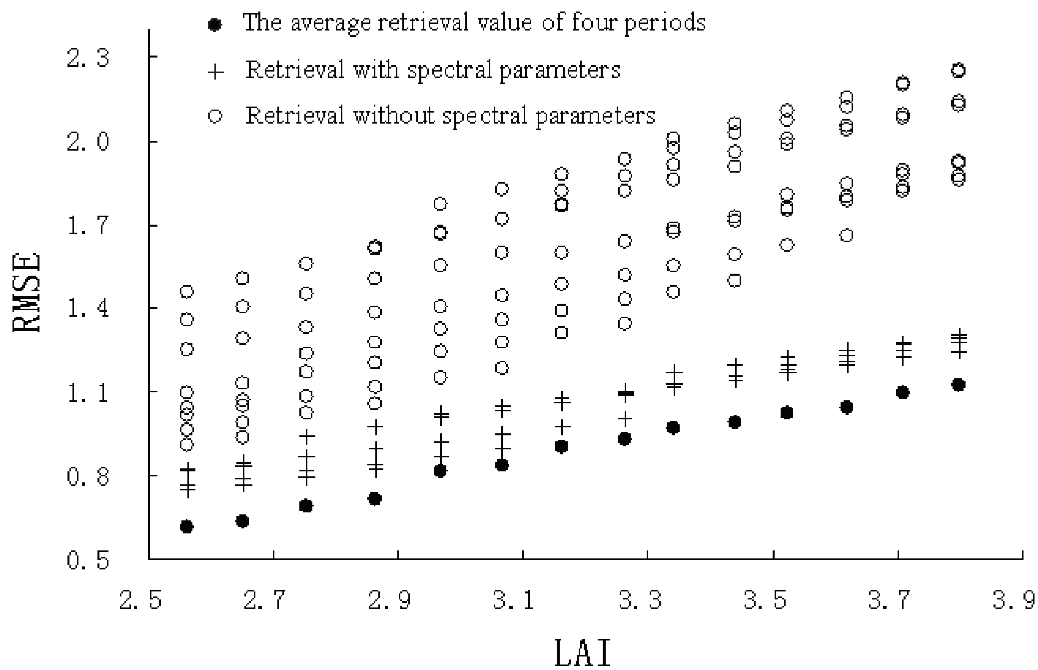

Figure 1 Comparison of 3 inversion algorithms

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