

# Monitoring crop leaf area index time variation from higher resolution remotely sensed data

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**Abstract.** The leaf area index (LAI) is significant for research on global climate change and ecological environment. China HJ-1 satellite has a revisit cycle of four days, providing CCD data (HJ-1 CCD) with a resolution of 30 m. However, the HJ-1 CCD is incapable of obtaining observations at multiple angles. This is problematic because single angle observations provide insufficient data for determining the LAI. This article proposes a new method for determining LAI using HJ-1 CCD data. The proposed method uses background knowledge of dynamic land surface processes that are extracted from MODerate resolution Imaging Spectroradiometer (MODIS) LAI 1-km resolution data. To process the uncertainties that arise from using two data sources with different spatial resolutions, the proposed method is implemented in a dynamic Bayesian network scheme by integrating a LAI dynamic process model and a canopy reflectance model with remotely sensed data. Validation results showed that the determination coefficient between estimated and measured LAI was 0.791, and the RMSE was 0.61. This method can enhance the accuracy of the retrieval results while retaining the time series variation characteristics of the vegetation LAI. The results suggest that this algorithm can be widely applied to determining high-resolution leaf area indices using data from China HJ-1 satellite even if information from single angle observations are insufficient for quantitative application.

## 1. Introduction

Satellite remote sensing is an effective way to obtain regional LAI. Currently, most systems that can operationally determine LAI from remotely sensing data are based in North America and Europe, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI, the VEGETATION CYCLOPES global products and the Advanced Very High Resolution Radiometer (AVHRR) LAI products[1]. In the past decades, many studies have attempted to produce higher resolution LAI products[2]. However, higher resolution products still cannot be practically achieved. The main reason for this is a deficiency in satellite observation information.

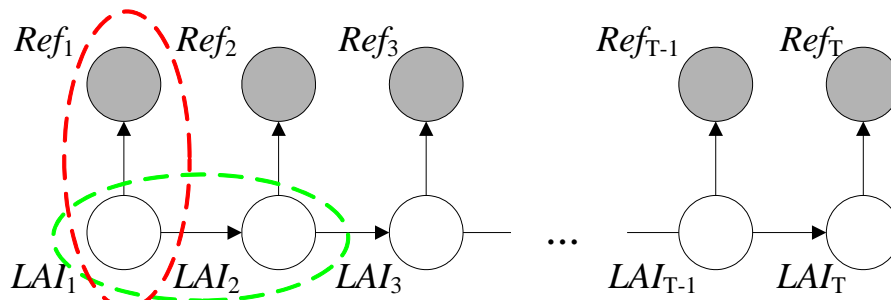
The first land environment satellite (HJ-1) launched by China in 2009 has a revisit cycle of 4 days, and has a 4-band CCD camera with a 30-m spatial resolution. Data from this satellite can be freely accessed, making its data a central to the production of high-resolution land surface products. Researchers have started to retrieve LAI of high-resolution based on HJ-1 satellite data using physically based algorithm[3]. It is generally thought that retrieving the LAI from a physical model based on remote sensing data allows a wider range of applications. However, this requires inverting a physical model, which results in several unknown parameters that make the model complicated and will make the inverse problem ill posed, inducing difficulties and inaccuracies in the search for the solution[4]. As a result, large quantities of remotely sensed data may be necessary to guarantee the



reliability and correctness of the results. This is also the reason why the MODIS LAI products need 8 days of multi-angle observations[5]. This paper investigates a feasible method for incorporating additional information into high-resolution LAI estimations by inverting a physical canopy reflectance model and using time series satellite observation data. The purpose of the present paper is to study the use of dynamic information on land surface parameters extracted from low to medium resolution historical data to produce higher resolution LAI products.

## 2. Algorithm and model

The essence of Bayesian time series retrieval is the extensional iteration of a time series using a static Bayesian model. The retrieval process of the algorithm is shown in Figure 1.



**Figure 1.** Schematic diagram of time series Bayesian retrieval

Figure 1 is a schematic diagram of the Bayesian retrieval of time series data, extended to the T time slices. The round nodes represent random variables, the gray nodes Ref represent the reflectance data from remote sensing observation, RefT is the reflectance data from remote sensing observation at the time T; the non-filled node LAI is the target variable, and LAIT is the LAI at time T. The directional arcs connecting the nodes represent the dependence or influence relationship between variables. The arcs pointing to the right in Figure 1 represent the state transition relation between two adjacent time slices of the LAI (the green dashed frame in Figure 1). The transition relation is represented quantitatively as a dynamic process. The arcs pointing upwards represent the mapping relationship between the target variable LAI and the observation variable Ref (the part in the red curved frame). The mapping relationship is represented as a canopy reflectance model.

In practice, the time series Bayesian method consists of the following four steps: (1) obtaining the LAI posterior distribution of the estimation on the previous moment  $P(LAI_{T-1} | Ref_{1:T-1})$ ; (2) calculating the state transition probability from the dynamic process model  $P(LAI_T | Ref_{T-1})$ ; (3) calculating the likelihood probability  $P(Ref_T | LAI_T)$  of the observational data using the look-up table generated by canopy reflectance model; (4) calculating the posterior probability of the LAI at the Tth time slice based on Bayesian Principle. Using a sequential iteration of the four steps above, the LAI results can be obtained.

The dynamic process information of land surface parameters that change with time can be expressed by the state transition probability of the LAI between different time-steps. In terms of dynamic changes of the LAI, many crop growth mechanism models originate from following two formulas.

During the vegetation growth period,

$$LAI_{t+1} = LAI_t + \Delta LAI \quad (1)$$

and during vegetation senescence,

$$LAI_{t+1} = LAI_t \times \alpha \quad (2)$$

where  $\Delta LAI$  represents the LAI increase from  $t$  to  $t+1$  and  $\alpha$  represents the attenuation speed of the LAI from time  $t$  to  $t+1$ . The LAI increase is the result of interactions between the temperature, water, soil, fertilization, etc. The attenuation speed is an exponential function of factors that can affect crop growth, such as temperature or the number of days without sowing. During the vegetation growth period,  $\Delta LAI$  can be obtained by calculating the difference in the LAI at two adjacent time steps. During the vegetation senescence,  $\alpha$ , the LAI attenuation speed equals the ratio of the LAI at two adjacent time steps. The fitting of Equations (1) and (2) can be accomplished using time series LAI products, even with a coarse resolution. In this work, the standard MODIS LAI products are chosen and re-analyzed for dynamic process fitting and for calculating the state transition probability.

Under ideal conditions, one can assume that the changing tendency of the time series of MODIS LAI data coincides with that of vegetation LAI. This implies that Equations (1) and (2) can be used to represent dynamic vegetation processes. However, many studies have shown that MODIS LAI data are likely to be overestimated or underestimated in some regions, leading to temporal and spatial discontinuities. The influence of these factors should be reduced or eliminated before using the MODIS LAI data in the dynamic process model used to conduct the LAI estimation. In this work, the MODIS time series LAI were filtered to reduce or eliminate possible temporal and spatial discontinuities. This will produce temporally and spatially continuous MODIS LAI data. The filtered MODIS LAI data were used to simulate the dynamic process of vegetation growth. Because the MODIS LAI overestimates or underestimates in some regions, a proportional factor was introduced to correct the MODIS LAI estimation values:

$$k = LAI_t / l_t \quad (3)$$

where  $k$  is a proportional factor that represents the overestimation or underestimation factor,  $LAI_t$  is the LAI value at time step  $t$ , and  $l_t$  is the MODIS LAI value after filtering the corresponding moment. Equation (3) can be derived as follows:

$$LAI_{t+1} = LAI_t + \Delta LAI = LAI_t + \frac{LAI_t \times (l_{t+1} - l_t)}{l_t} = LAI_t \times l_{t+1} / l_t \quad (4)$$

During the senescence of vegetation, Equation (2) can be rewritten as follows:

$$LAI_{t+1} = LAI_t \times \alpha = LAI_t \times (k \times l_{t+1}) / (k \times l_t) = LAI_t \times l_{t+1} / l_t \quad (5)$$

Using Equations (4) and (5), it can be concluded that the expressions of the dynamic process model constructed by the MODIS LAI data are identical for the growth and senescence periods. The equation is:

$$LAI_{t+1} = LAI_t \times l_{t+1} / l_t \quad (6)$$

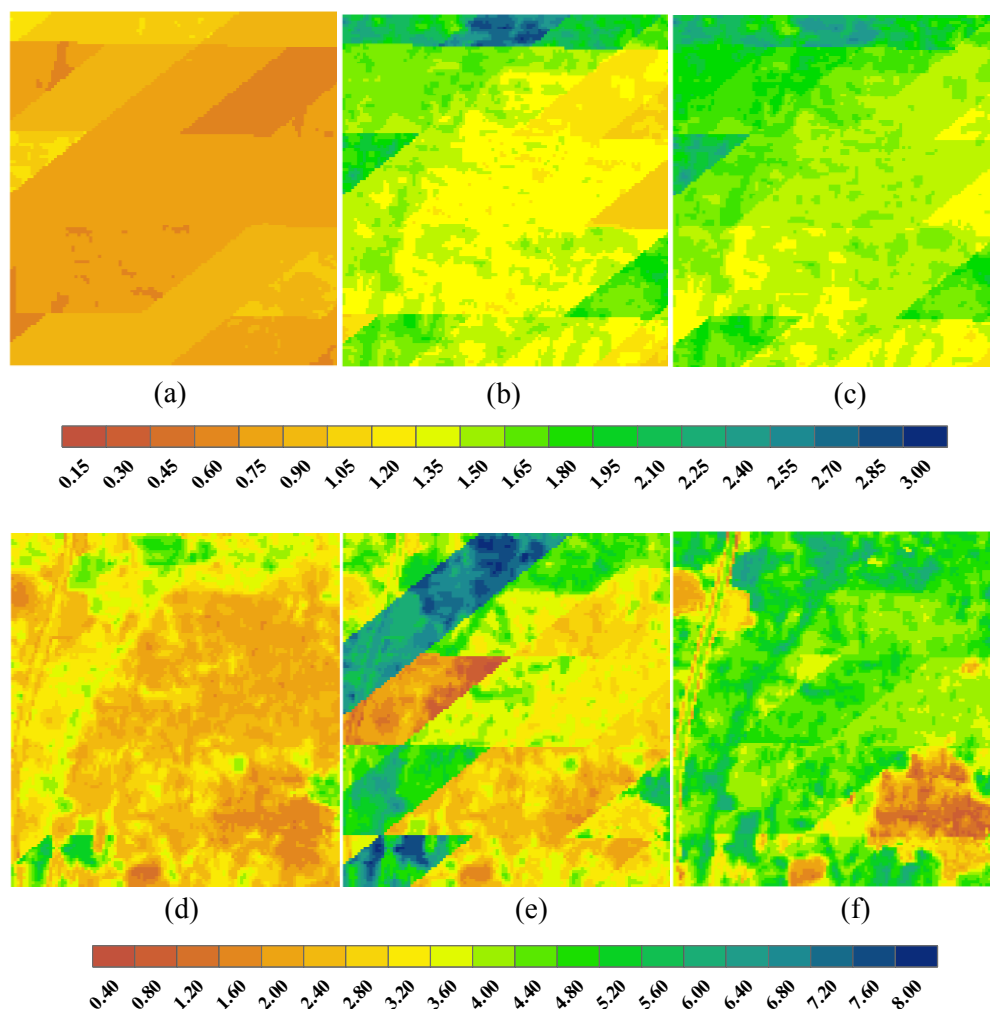
This model is a dynamic iteration equation. The value of  $LAI_{t+1}$  is a function of the retrieved LAI from the previous time step  $LAI_t$ .

### 3. Study area and data set

The performance of the proposed method was validated using field collected data sets. The field experiment was conducted in Guantao County, Hebei Province (115.13 ° E, 36.52 ° N). The MCD15A2 product was adopted as the data source for constructing background information. The temporal distribution is from the 161th day (DOY161) to the 273rd day (DOY273) of 2010. We chose images with low cloud cover (< 10% overall) for LAI retrieval. There are four HJ-1 CCD images satisfying this requirement during the period from June 22, 2010 to September 16, 2010, when the field LAI measurements were available. The satellite data was available on June 28, 2010, July 6, 2010, July 20, 2010, and August 16, 2010.

#### 4. Results

Based on the HJ-1 CCD surface reflectance data, as well as the process model fit by the MODIS LAI and the look-up table generated by a canopy reflectance model, a Bayesian retrieval algorithm for time series was used for the LAI retrieval experiment. The results are shown in Figure 2.



**Figure 2.** LAI retrieval results of time series of the study area.

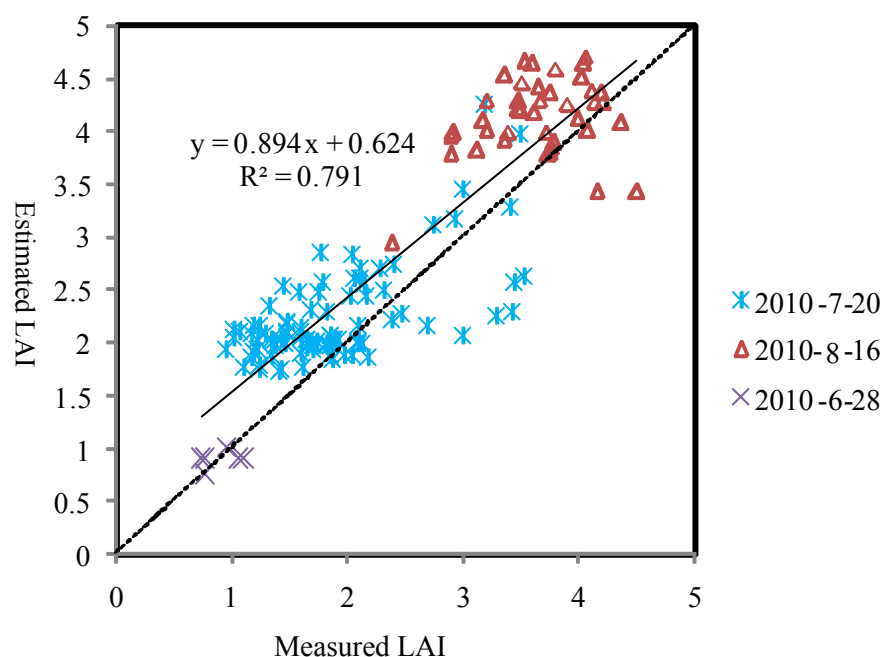
Figure 2 shows the temporal and spatial distribution of the LAI in one growth season in the study area. As mentioned in Section 3.3, the satellite observations were available at four days: June 28, 2010, July 6, 2010, July 20, 2010, and August 16, 2010. The corresponding retrieval results are shown as images (a), (b), (d), and (f) in Figure 2. The spatial distribution of the retrieved LAI values is the result of the dynamic process model and the HJ-1 satellite observation. Figure 2 (c) and (e) are the retrieval results that do not use HJ-1 satellite data. Therefore, their corresponding LAI distributions are only predictions of the dynamic process model. Figure 2 (c) was estimated using the dynamic process model based on the previous results obtained using the HJ-1 satellite CCD on July 6, 2010 (Figure 2(b)). Its corresponding DOY was 193-200. Figure 2 (e) was estimated using a dynamic process model based on results from HJ-1 CCD data obtained on July 20, 2010 (Figure 2(d)). Its corresponding DOY was 209-216.

The result at the initial observation (Figure 2(a)) was based on prior information provided by the MODIS LAI that was updated with reflectance data from the HJ-1 satellite. In this context, the dynamic process model was used for further estimation of the LAI distribution with a 30-m pixel

resolution. The reflectance data was also updated with new observations (Figure 2(b)). Repeating such iterations, the LAI distribution was obtained for the time series. During the time series retrieval process, one of the key roles of the observed data was to update the existing background information. At the initial stage of retrieval in Figure 2, a period in which the HJ-1 CCD reflectance was not updated (Figures 3(c) and 3(e)), the retrieved LAI spatial distribution better reflected the MODIS background information. However, the retrieved results showed some strip features. This is related to the low spatial resolution of the MODIS LAI employed as the a priori knowledge and the large weight of the MODIS LAI data in these images. When new reflectance data were added, the spatial distribution of the LAI tended to reveal the real growth status of land surface vegetation, and the strip phenomenon disappeared. Therefore, the texture of these images became smoother (Figures 3(d) and 3(f)).

## 5. Validation

The retrieved LAI in Figures 2(d) and (f) are the joint results from updating the HJ-1 CCD reflectance data and the dynamic process model. The dynamic process model represents a certain spatial heterogeneity after having been updated twice using remote sensing observations (Figures 2(a) and (b)). Compared with other images, the spatial distributions of LAI were more reasonable, which is shown in Figure 2(c). To verify the LAI retrieval results, the field measurement from June 22, 2010, July 24, 2010, and August 14, 2010 were used to verify the LAI values of the corresponding pixels on 2010-06-28 (Figure 2(a)), 2010-07-20 (Figure 2(d)) and 2010-08-16 (Figure 2(f)), respectively. The results are shown in Figure 3.



**Figure 3.** Validation of the retrieval results of the study area

The determination coefficient ( $R^2$ ) between measured value and estimated value was 0.791 and the RMSE was 0.61. This showed a high consistency between the retrieved value and the measured value. But it also can be found that the retrieved values for some pixels had large deviations from the real measured values. This is partially due to the fact that the measured LAI and retrieved LAI were not temporally matched. For example, the retrieved LAI from 2010-07-20 and the observed LAI from July 24, 2010 had a 4-day lag. During periods of rapid vegetation growth, a four-day lag could cause a significant deviation. In addition, errors in the HJ-1 CCD surface reflectance data could also cause a

large deviation for some pixels. When the observed reflectance had errors in a specific spectra band, the weight of a prior of LAI increased compared to the reflectance data, and the retrieved result would deviate towards a prior of LAI. In such cases, the accuracy of the retrieved results of corresponding pixels would be compromised.

## 6. Conclusion

To overcome difficulties in the retrieval of high-resolution quantitative products from remotely sensed data obtained by China environmental satellite HJ-1, this paper proposed a method that utilizes prior knowledge extracted from low and medium resolution historical data products. By expanded from the traditional Bayesian retrieval model, dynamic changes in the land surface LAI were introduced to form a new method for the Bayesian retrieval of time series LAI. In the proposed method, the dynamic process model, canopy reflectance model, and remotely sensed data are combined. Algorithm validation was conducted using LAI data based on HJ-1 CCD data and field measurements. The validation results show that the LAI retrieved using the time series Bayesian algorithm developed in this paper were consistent with measured values. The retrieval algorithm fully utilized the high spatial resolution of HJ-1 CCD data and the time series information of the MODIS LAI. This allowed for the extraction of land surface parameter dynamic information from low-resolution data, which assisted in LAI retrieval. This method has the potential application of generating high-resolution LAI products with the assistance of low-resolution remote sensing data.

## 7. References

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