A simple data assimilation method for improving the MODIS LAI time-series data products based on the object analysis and gradient inverse weighted filter

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A simple data assimilation method for improving estimation of moderate resolution imaging spectroradiometer (MODIS) leaf area index (LAI) time-series data products based on the gradient inverse weighted filter and object analysis is proposed. The properties and quality control (QC) of MODIS LAI data products are introduced. Also, the gradient inverse weighted filter and object analysis are analyzed. An experiment based on the simple data assimilation method is performed using MODIS LAI data sets from 2000 to 2005 of Guizhou Province in China.

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Leaf area index (LAI) is an important parameter for describing vegetation canopy structure in the terrestrial ecosystem on the global, continental, and regional scales. Although the moderate resolution imaging spectroradiometer (MODIS) LAI data products have been successfully used in research regarding global environment change, crop growth estimation and so on, residual noise in the MODIS LAI time-series data, even after applying strict pre-processing, impedes further analysis and risks generating erroneous results. There are several generic issues that affect the quality of MODIS LAI[1]. Firstly, estimating LAI from one satellite instrument MODIS is an ill-posed inversion problem because the number of unknowns is always larger than the available bands, due to the nature of the earth's complex environment. Furthermore, most MODIS LAI data products are not continuous in both space and time because of a variety of reasons, e.g., cloud contamination, insufficient number of data points for retrieval. As a result, MODIS LAI products need significant improvements. For this reason, some methods for reducing noise and constructing high-quality MODIS time-series data sets for further analysis have been formulated, applied, and evaluated[1−4]. Furthermore, some methods have also been used to improve other time-series remote sensing data quality[5−9].

Quality control (QC) information of MODIS LAI product is represented by two data layers (FparLai_QC and FparExtra_QC) in the file with MOD15A2 product. QC measures are produced at the file (containing one MODIS tile) and at the pixel level for the MOD15A2 product. The LAI/fraction of photosynthetically active radiation (FPAR) algorithm is executed irrespective of input quality. Therefore user should consult the QC layers of the LAI/FPAR product to select reliable retrievals. The key indicator of retrieval quality of the LAI/FPAR product is SCF_QC bitfield. In this paper, a simple data assimilation method for improving estimation of MODIS LAI time-series data products based on the gradient inverse weighted filter and object analysis coupling quality control information of MODIS LAI product is proposed. Meanwhile, an experiment based on the simple data assimilation method is performed using MODIS LAI data sets from 2000 to 2005 of Guizhou Province in China.

Gradient weighted smoothing filters are locally adaptive weighted mean filters[10]. Smoothing filter design in image processing basically depends on the types of noise. Rank order based filters such as median filters are good at removing additive impulsive noise and linear filters are good at suppressing Gaussian noise. However, most of them suffer from the trade-off between removing noise and preserving details. Moreover, as the types and the amount of noise are mixed diversely, noise removal continues to provide a challenge to smoothing filter designers. Weighted mean filters are commonly used spatial filters based on the local intensity information directly. They replace the intensity of the pixel to be processed by the weighted average of the intensities of its neighbors. One major drawback of these filters is that they will blur the sharpness of edges. Adaptive weighted filters are then proposed to avoid this drawback. Most of them are based on local gradient information. Examples of such gradient-based filters include gradient inverse weighted filters, sigma filters, adaptive Gaussian weighted filters, and rational filters. The smoothing scheme of the gradient inverse weighted filters is based on the observation that the variations of grey levels inside a region are smaller than those between regions[10]. In other words, the absolute value of gradient at the edge is higher than that within the regions. The weighting coefficients are the normalized gradient inverses between the center point and its neighbours. Its basic principle is as follows[10].

For a 3×3 windows, suppose that the grey value of point (x, y) is $f(x, y)$. The inverse of absolute gradient at (x, y) is

$$g(x, y; i, j) = \frac{1}{|f(x+i, y+j) - f(x, y)|}, \tag{1}$$

where $i, j = -1, 0, 1$, but i and j are not equal to zero at the same time.

If $f(x+i, y+j) = f(x, y)$, the gradient is equal to zero.

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Then define $g(x,y;i,j) = 2$. So the scope of $g(x,y;i,j)$ is $[0,2]$. The normalized weight matrix W of smoothing is

$$W = \begin{bmatrix} w(x-1,y-1) & w(x-1,y) & w(x-1,y+1) \\ w(x,y-1) & w(x,y) & w(x,y+1) \\ w(x+1,y-1) & w(x+1,y) & w(x+1,y+1) \end{bmatrix}, \tag{2}$$

generally, the coefficient value of central elements is 1/2, the sum of other elements is 1/2. So besides $f(x,y)$, other elements of W are computed as

$$w(x+i,y+j) = \frac{1}{2} * \frac{g(x,y,i,j)}{\sum\limits_i \sum\limits_j g(x,y,i,j)}, \tag{3}$$

where $i,j = -1,0,1$, but i and j are not equal to zero at the same time.

The smoothed pixel (x,y) is computed as

$$G(x,y) = \sum_i \sum_j w(x+i,y+j) f(x+i,y+j), \tag{4}$$

where $i,j = -1,0,1$, but i and j are not equal to zero at the same time.

In this paper, based on the QC information of MODIS LAI product and gradient inverse weighted filter, a simple data assimilation method named objective analysis is adopted, which sets observed values as the values of the model variables at the observation location[2]. The values of the model variables at other locations are interpolated. We denote x_b by the first guess of the model state (background), and by $x_0(r_j)$, $j = 1,2,\cdots,n$, a set of observations of the same parameter, where r defines the spatial location in a one-, two- or three-dimensional domain[2]. The model state x_a defined at each gridpoint i can be determined by

$$x_\mathrm{a}(r_i) = x_\mathrm{b}(r_i) + \frac{\sum\limits_{j=1}^{n} w(r_i,r_j)[x_0(r_j) - x_\mathrm{b}(r_j)]}{\sum\limits_{j=1}^{n} w(r_i,r_j)}, \tag{5}$$

where $w(r_i,r_j)$ is the weighting function dependent on the distance $d_{i,j}$ between points r_i and r_j, R the distance constant. In following experiments, $R = 2.0$.

$$w(r_i,r_j) = \max\left(0, \frac{R^2 - d_{i,j}^2}{R^2 + d_{i,j}^2}\right). \tag{6}$$

The simple data assimilation method and algorithm is shown in Fig. 1.

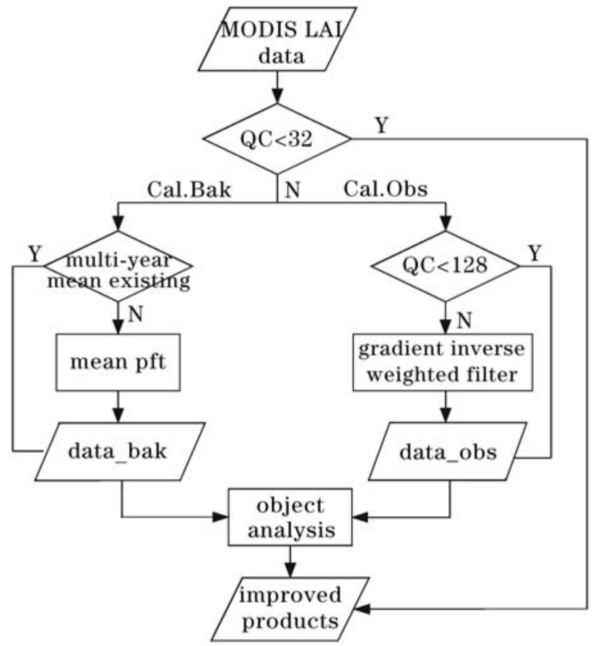

Fig. 1. Flowchart of data assimilation for MODIS LAI.

Based on the methodology described in Fig. 1, an experiment is performed using MODIS LAI data products from 2000 to 2005 of Guizhou Province in China. Figure 2 is MODIS/Terra land cover types (plant functional types, PFT) over the Guizhou Province of China, which indicates that most of land cover types are trees (evergreen needleleaf trees, evergreen broadleaf trees, deciduous needleleaf trees, deciduous broadleaf trees), shrub, grass and crop (cereal crop, broadleaf crop), whereas urban and built up, barren or sparse vegetations are very little. Figure 3 is original MODIS LAI data products (MOD15A2) over Guizhou Province of China on day 169 and 265 in 2004, which indicate that the LAI in most of areas is very little. Figure 4 is the QC data of MODIS LAI over Guizhou Province of China on day

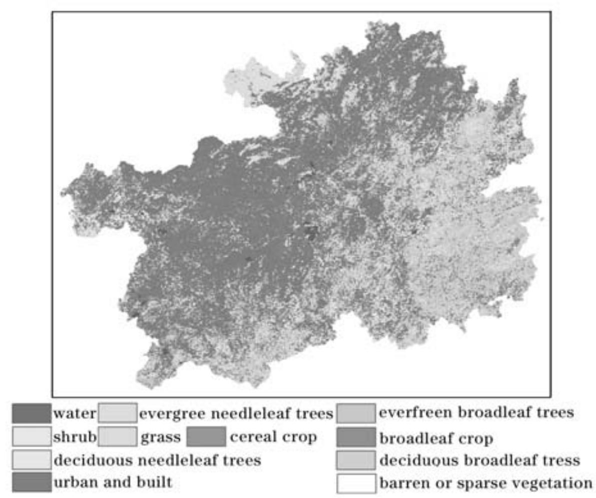

Fig. 2. MODIS/Terra land cover type PFT over the Guizhou Province of China.

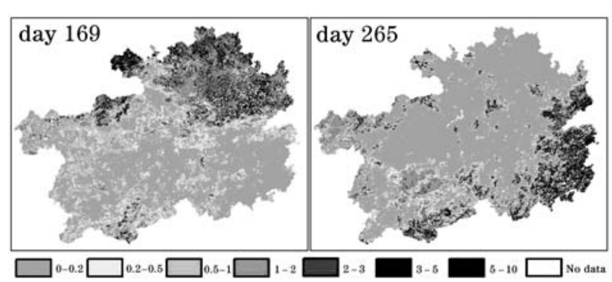

Fig. 3. Original MODIS LAI data products over the Guizhou Province of China on day 169 and 265 in 2004.

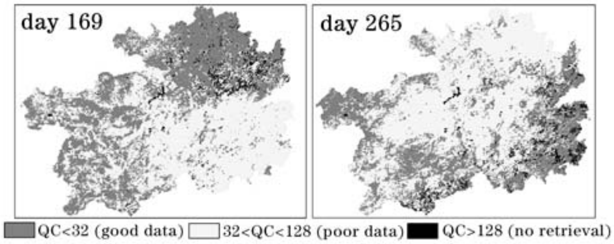

Fig. 4. QC data of MODIS LAI over the Guizhou Province of China on day 169 and 265 in 2004.

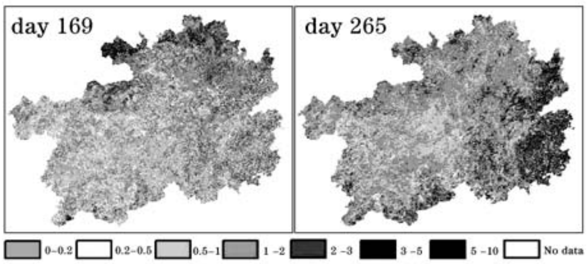

Fig. 5. Improved MODIS LAI data products over the Guizhou Province of China on day 169 and 265 in 2004.

169 and 265 in 2004, which indicates that the quality of most areas is very poor due to cloud contamination. Figure 5 shows the corresponding improved results of MODIS LAI data products based on the simple data assimilation method, which indicates that the low quality MODIS raw LAI data are greatly improved.

In summary, we propose a new approach to improve MODIS LAI time-series data products. The method is very suitable for improving estimation of MODIS time-series data products mainly due to cloud contamination and three types of data, including MODIS time-series data products and its QC data, land cover types data, are needed. In order to improve the quality of MODIS time-series data products utterly, the coupling remote sensing observation and growth model for improving the MODIS time-series data products is our following task.

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