Computers and Electronics in Agriculture 115 (2015) 1–11

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

High-resolution Leaf Area Index estimation from synthetic Landsat data generated by a spatial and temporal data fusion model

Mingquan Wu [a,*], Chaoyang Wu [a,b], Wenjiang Huang [c], Zheng Niu [a], Changyao Wang [a]

[a] The State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, P.O. Box 9718, Datun Road, Chaoyang, Beijing 100101, PR China

[b] Department of Geography, University of Toronto, 100 St. George Street, Room 5047, Toronto, Ontario M5S 3G3, Canada

[c] Key laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, P.O. Box 9718, Datun Road, Chaoyang, Beijing 100101, PR China

ARTICLE INFO

Article history:
Received 20 October 2014
Received in revised form 10 March 2015
Accepted 7 May 2015
Available online 24 May 2015

Keywords:
Leaf area index
Spatial and temporal data fusion
Remote sensing
Winter wheat

ABSTRACT

Leaf area index (LAI) is an important input parameter for biogeochemical and ecosystem process models. Mapping LAI using remotely sensed data has been a major objective in remote sensing research to date. However, the current LAI product mapped by remote sensing is both spatially and temporally discontinuous as a result of cloud cover, seasonal snows, and instrumental constraints. This has limited the application of LAI to ground surface process simulations, climatic modeling, and global change research. To fill these gaps in LAI products, this study develops an algorithm to provide high spatial and temporal resolution LAI products with synthetic Landsat data, generated by a spatial and temporal data fusion model (STDFA). The model has been developed and validated within the Changping District of Beijing, China. Using Moderate Resolution Imaging Spectroradiometer (MODIS) reflectance data and real Landsat data, this method can generate LAI data whose spatial (temporal) resolution is the same as that of the Landsat (MODIS) data. Linear regression analysis was performed to compare the modeled data with field-measured LAI data, and indicates that this new method can provide accurate estimates of LAI, with R^2 equal to 0.977 and root mean square error (RMSE) equal to 0.1585 $m^2\,m^{-2}$ ($P < 0.005$), which is superior to the standard MODIS LAI product. Further, various STDFA model application strategies were tested, with the results showing that the application strategy of the STDFA model has an important influence on the accuracy of LAI estimation: the vegetation index fusion strategy produced a better result than the reflectance fusion strategy. The applications of the STDFA model to eight commonly used vegetation indices were also compared. The results show that some vegetation indices (e.g., Enhanced Vegetation Index (EVI), Normalized difference vegetation index (NDVI), and Normalized difference infrared index (NDII)) exhibited better performance than others (e.g., Infrared simple ratio (ISR), Reduced infrared simple ratio (RISR), Reduced normalized difference vegetation Index (RNDVI), Reduced simple ratio (RSR), and Simple ratio (SR)). However, ISR, RISR, and NDII data produced lower saturation effects than other spectral vegetation indices in the estimation of LAI values higher than 2 $m^2\,m^{-2}$.

1. Introduction

Biogeochemical and ecosystem process models are increasingly run in a spatially explicit mode, requiring model drivers in the form of multi-scale and multi-data biogeophysical parameters, such as leaf area index (LAI), which are derived mainly from satellite imagery (Running et al., 1999; Cohen et al., 2003; Gonsamo and Pellikka, 2012). As a key parameter of ecosystem processes, leaf area index has attracted considerable attention (Weiss et al., 2004), and mapping LAI using remotely sensed data has been a major objective of remote sensing research (Soudani et al., 2006; Song and Dickinson, 2008). For example, a LAI product is currently provided based on observations acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments aboard NASA's Terra and Aqua satellites (Maire et al., 2011; Zhang et al., 2012; Leonenko and Los, 2013).

There are two methods for mapping LAI using remotely sensed data. One is through the inversion of canopy reflectance models (Myneni et al., 1997; Knyazikhin et al., 1998; Peddle et al., 2004; Duan et al., 2014). Inversion methods have a firm physical foundation and can be applied across large areas, as they are not restricted by biome type. However, such methods are usually difficult to parameterize and may be mathematically ill-posed, in that their

* Corresponding author. Tel./fax: +86 10 6480 6258.
E-mail address: wumq@radi.ac.cn (M. Wu).

http://dx.doi.org/10.1016/j.compag.2015.05.003
0168-1699/

solutions may not be unique (Gray and Song, 2012). The second method, which is perhaps the most commonly employed, involves the development of empirical relationships between single spectral vegetation indices (SVIs) and ground-based LAI (Cohen et al., 2003; Wu et al., 2007; Hasegawa et al., 2010; Viña et al., 2011; Zarate-Valdez et al., 2012; Li and Wang, 2013). Among these, the normalized difference vegetation index (NDVI) is the most commonly used index for mapping LAI (Chen and Cihlar, 1996). Regression analysis is usually used to link field-measured LAI to remote sensing vegetation index data (Cohen et al., 2003; Gonsamo and Pellikka, 2012). Empirical models have been widely used due to their ease of implementation. However, these methods cannot be applied across large areas due to the fact that their parameters are restricted to specific biome types. Additionally, there is a tendency for SVIs to saturate at moderately high LAIs (Gray and Song, 2012; Yang et al., 2012; Heiskanen et al., 2012; Gu et al., 2013; Potithep et al., 2013).

Although the current LAI product mapped using remotely sensed data has been widely used, it is spatially and temporally discontinuous as a result of cloud cover, seasonal snows, and instrumental constraints. This has limited the application of LAI to ground surface process simulations, climatic modeling, and global change research (Fang et al., 2008). Image fusion technology has already been important in mapping LAI using spatial, spectral, and temporal information from multiple sensors (Gray and Song, 2012; Hernández et al., 2014). The spatially and temporally discontinuous of LAI was caused by the gaps of remote sensing data. A solution to fill the gaps of remote sensing data is to develop high spatial and temporal multi-source remote sensing data fusion methods. Several spatial and temporal data fusion approaches have been proposed to blend high spatial and high temporal data to generate synthetic high spatial resolution imagery with high temporal resolution. These methods can be classified into two categories. The first category is the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) developed by Gao et al. (2006). Several studies applied and demonstrated the STARFM for mainly coniferous areas, urban environmental variables extraction, vegetated dry-land ecosystems monitoring, public health studies, and generating daily land surface temperatures (Hilker et al., 2009; Walker et al., 2012; Liu and Weng, 2012; Weng et al., 2014; Schmidt et al., 2015). Zhu et al. (2010) enhanced the STARFM for complex heterogeneous regions. Emelyanova et al. (2013) assessed the accuracy of STARFM and ESTARFM for two landscapes with contrasting spatial and temporal dynamics. The second category is based on linear mixing theory, called unmixing method. Here, the coarse resolution images are disaggregated by solving linear mixed models based on the assumption that the reflectance of each coarse spatial resolution pixel is a linear combination of the responses of each land-cover class contributing to the mixture (Settle and Drake, 1993; Maselli et al., 1998; Duran and Petrou, 2014). However, this assumption is violated in many situations because of the spatial variability of surface reflectance. Several methods have been proposed to address this problem based on the assumption that spectral properties of a land-cover class do not show great variations in the surroundings of a pixel (Zhukov et al., 1999; Maselli, 2001; Lorenzo et al., 2008; Wu et al., 2012). Gevaert and García-Haro (2015) compared the STARFM and an unmixing-based algorithm and recommended using unmixing-based data fusion in situations where the spectral characteristics of the medium-resolution input imagery is downscaled.

To fill the gaps in the current LAI products, the overall aim of this study is to develop an algorithm to generate high spatial and temporal resolution LAI products with synthetic Landsat data, generated by an unmixing-based spatial and temporal data fusion model. The objectives of this study, therefore, are: (1) to analyze the ability of a spatial and temporal data fusion model to generate high spatial and temporal resolution synthetic LAI data; (2) to test and compare various Spatial Temporal Data Fusion Approach (STDFA) application strategies in the estimation of high spatial and temporal resolution LAI.

2. Materials and methods

2.1. Study area

The Xiaotangshan National Demonstration Base of Precision Agriculture Research in the Changping District of Beijing, China was selected as the study area for this research. The Xiaotangshan National Demonstration Base is the first experimental, research and demonstration base for precision agriculture technology in China, and covers a total area of 2500 acres. The precision production testing and demonstration areas of the large fields in this base integrate modern information technology and intelligent equipment technologies. Fertilization, irrigation, and spraying operations in the large fields can been precisely controlled by machines on site (Changping district association for science and technology 2012). One of the fields in this Demonstration Base, centered on 40°10′44″N, 116°26′23.3″E and with an area 450×820 m planted with winter wheat, was used in this study (Fig. 1).

2.2. Satellite data and pre-processing

One Landsat-7 Enhanced Thematic Mapper Plus (ETM+) image and a time series of the MODIS surface reflectance product were used in this study. The Landsat-7 ETM+ image was acquired on May 17, 2012. It has no missing lines in our study area as the Scan Line Corrector (SLC) has been switched off. The image was atmospherically corrected using the 6S radiative transfer code. The atmospherically corrected image was then georeferenced using a second order polynomial warping approach, based on the selection of 21 Ground Control Points (GCPs) using a 1:10,000 topographic map, and application of the nearest neighbor resampling method with a position error of less than 0.5 pixels for the Landsat-7 ETM+ images.

MODIS surface reflectance products (MOD09GA, 500 m), obtained in clear sky conditions from April 11, 2012 to June 9, 2012, were used in this study (Table 1). Images affected by clouds were not used; therefore, only 17 days of MOD09GA data acquired with clear sky conditions were used. The MOD09GA product has six spectral bands at 500 m spatial resolution. All MODIS images were re-projected from the native Sinusoidal projection to a UTM-WGS84 reference system, and were resized to select the study area using MODIS Reprojection Tool (MRT) software. All MODIS data were then georeferenced by a second order polynomial warping approach based on the selection of 26 of GCPs on the 480 m Landsat ETM+ images, and the application of a nearest neighbor resampling method with a position error of less than 0.6 MODIS pixels. The 480 m Landsat ETM+ images were generated from georeferenced Landsat ETM+ images by a pixel aggregate resampling method.

2.3. Generation of high spatial and temporal resolution synthetic Landsat ETM+ data

The Spatial Temporal Data Fusion Approach (STDFA) proposed by Wu et al. (2012) was used to generate high spatial and temporal resolution synthetic Landsat ETM+ data. The STDFA algorithm comprises three steps: (1) mapping medium resolution spatial Landsat-7 ETM+ images using the IsoData classification method