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Developing indices of temporal dispersion and continuity to map natural vegetation

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ABSTRACT

An accurate and updated natural vegetation map is imperative for sustainable environmental management. This paper proposed a novel natural vegetation mapping algorithm based on time series images. Several indices of temporal dispersion and continuity were established for this purpose: low density (LD), medium density (MD), high density (HD) and medium continuity (MC). These indices were developed based on the particular percentiles-determined section of the EVI2 temporal profiles obtained through continuous wavelet transform. The natural vegetation was generally characterized as with lower temporal dispersion and greater temporal continuity compared with agricultural crops. The proposed methodology incorporated the indices of temporal dispersion and continuity and was applied to 13 provinces in central East China based on 500 m 8-day composite Moderate Resolution Imaging Spectroradiometer (MODIS) Enhanced Vegetation Index with two bands (EVI2) in 2013. An overall accuracy of 92.97% was obtained when compared with 2715 ground truth sites. There was also a good agreement (kappa index = 0.8049) on the distribution and areas of different vegetation types between the MODIS-estimated image and the Landsat 8 OLI interpreted data on two test regions. This study demonstrated the efficiency of the transform and metric integrated time series classification approaches in the fields of land and vegetation cover mapping.

1. Introduction

The vegetation cover of the Earth surface plays an important role in global climate regulation (Avissar et al., 2002; Bonan, 2008). Threats to natural vegetation such as urban growth and agricultural intensification are clearly identified but their spatio-temporal dynamics are largely unknown by environmental managers (Rapinel et al., 2014). Timely and accurate information on natural vegetation is essential for sustainable environmental management (Lapola et al., 2008; Rapinel et al., 2014). Remote sensing has been utilized for vegetation cover monitoring for decades at regional and global scales (Jin and Sader, 2005; Xiao et al., 2009; Dong et al., 2012; Senf et al., 2013; Jiang et al., 2015; Rapinel et al., 2014). Several global land cover maps exit, such as the University of Maryland's 1 km Global Land Cover products (UMD) (Hansen et al., 2000), 1 km Global Land Cover 2000 (GLC2000) (Bartholomé and Belward, 2005), 500 m Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Collections (MAD12C5) (Friedl et al., 2010), and 300 m Global composites and land cover maps (Glob Cover) based on Medium Resolution Imaging Spectrometer (MERIS) data (Arino et al., 2007). The inconsistencies and uncertainties among these global land cover maps were highlighted by several recent studies (Herold et al., 2008; Lapola et al., 2008; Tchuenté et al., 2011). Existing global land cover maps have approximately 70% area-weighted thematic overall accuracy when compared with reference datasets (Mora et al., 2014). There is a clear need to improve its quality and acquire more accurate forest cover (Zhao et al., 2013; Mora et al., 2014). Land cover products based on remote sensing imagery can be significantly improved by using smarter algorithms, more appropriate image acquisition time and improved class definitions (Tchuenté et al., 2011).

Land cover mapping methods can be divided into two groups (Biradar and Xiao, 2011). The first group relied on training datasets and image statistics for various spectral bands from individual images in order to generate land cover map (Biggs et al., 2006). This space or individual image-oriented approach faces challenges

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in its extension over time due to spectral variability across different periods and regions (Cihlar, 2000). The second group is the time-oriented approach based on time series images (Qiu et al., 2014a). The time-series approach provides an alternative way to identify land cover types through considerations of a time series of spectral reflectance or vegetation indices for individual pixels (Dong et al., 2015). Recently, the time-oriented method has been successfully utilized for forest cover and land cover mapping (Xiao et al., 2002, 2009; Senf et al., 2013; Zhao et al., 2013; Song et al., 2014; Yan and Roy, 2015). Since vegetation indices time series are considered to be appropriate representations of vegetation activities (Yan et al., 2015), pixels with similar characteristics of vegetation indices time series was classified as the vegetation type in these studies.

The time series classification methods by similarity calculation could be divided into three categories (Lhermitte et al., 2011): (1) the original time-series based approaches, including the distance measure and correlation measure (Li and Fox, 2012); (2) the time series transformation-based approaches such as the principal component analysis (PCA) and the Fourier transform (Galford et al., 2008); and (3) the metric-based approaches such as the beginning and end dates of growing season, maximum, minimum, mean values and variance (Zhao et al., 2013; Qiu et al., 2015). The original time-series based approaches directly measure the similarity without any transformation. Their major challenge was the intra-class variability of Vegetation Indices (VIs) temporal profiles (Lunetta et al., 2010; Qiu et al., 2015). The time series transformation-based approaches assess the similarity based on specific components, and the metric-based methods calculate the similarity based on statistical characteristics of time series (Lhermitte et al., 2011; Yan et al., 2015). The latter two approaches have been successfully applied in the fields of land cover mapping and crop identification (Broich et al., 2011; Qiu et al., 2015; Yan et al., 2015).

Combinations of the transformation-based and metric-based approaches were proved to be very promising and efficient for agricultural crop mapping (Qiu et al., 2014a, 2014b). However, few studies have utilized the combined approaches for identifying other land cover types such as natural vegetation. The objective of this study is twofold: (1) to provide a new approach of natural vegetation mapping through developing indices of temporal dispersion (VMTD for short) and continuity based on continuous wavelet transformed time series images; (2) to generate an accurate natural vegetation cover map in China through VMTD and compare it with two global land cover datasets, Global Land Cover Map with MERIS (GLOBCOVER) and the MODIS Terra + Aqua Land Cover Type product (MCD12Q).

2. Study area and methods

2.1. Study area

Our study area is located between 27°9′36″ N–42°33′36″ N latitude, 105°18′36″ E–22°40′48″ E longitude, in central East China. It includes Hebei, Shanxi, Shaanxi, Henan, Shandong, Jiangsu, Anhui, Zhejiang, Hubei, Shanghai provinces, and three direct-controlled municipalities (Beijing, Tianjing and Chongqing) (Fig. 1). This region covers 2.254×10^6 km^2, accounting for around a quarter of the national territory. The whole terrain is composed of three parts: mountainous, hilly, and plain areas (Fig. 1). The mountains are mainly distributed in the surroundings such as the Taihang, Qi and Wu Mountains. The central and east parts are dominated by North China Plain and the Middle-lower reaches of the Yangtze River Plain. Elevation ranges from −10 m to 3733 m. The study area is divided into two climate regions by the Qin Mountains and Huai River. The north portion is characterized as temperate continental monsoon, with mean temperature in January −16 to 0 °C and annual precipitation of 200–800 mm. The south portion belongs to subtropical continental monsoon climate, with mean temperature in January 0–8 °C and annual precipitation of 800–1600 mm.

2.2. Proposed methodology

A new forest mapping approach was proposed (Fig. 2). It included the following procedures: data preprocessing, developing indices of temporal dispersion, classification algorithm and validations. The entire procedure was executed using the Matlab software package (The MathWorks, Natick, MA, USA). Detailed descriptions of these steps were provided in the following sections.

2.3. Continuous wavelet transform

The 500 m 8-day composite MODIS surface reflectance products (MOD09A1) from 2012 to 2014 were utilized. The Enhanced Vegetation Index with two bands (EVI2) was calculated using surface reflectance values from red (620–670 nm) and near infrared red bands (841–875 nm) (Jiang et al., 2008). The EVI2 time series were utilized since it eliminated most of the problems associated with sub-pixel and residual clouds (Jiang et al., 2008). A total of 46 composites were available each year. A daily continuous smoothed EVI2 time series was established through linear interpolation with reference to the dates of composites (Qiu et al., 2014b).

For the purpose of land/vegetation cover mapping, the procedure of VI time series reconstruction through continuous wavelet transform was described as follows. First, a two-dimensional wavelet scalogram was obtained through continuous wavelet transform performed on the daily VI time-series based on the Morlet wavelet. The VI time series in 2013 along with its neighboring years were applied in order to eliminate the edge effects. Second, the appropriate scale range was selected from the wavelet scalogram for the purpose of signal reconstruction. The noise present in the signal was usually high frequency (Ebadi et al., 2013). The scale range utilized for land/vegetation cover mapping was determined as 15–45 through some comparative experiments. Third, the values of 2D matrix of wavelet coefficients were set to zero outside the scale range 15–45. Finally, reverse wavelet transform was performed based on the 2D matrix of wavelet coefficients achieved in step 3 and the smoothed daily continuous vegetation indices time series were obtained (Fig. 3).

2.4. Developing indices of temporal dispersion

2.4.1. EVI2 temporal profiles from forests and other vegetation

Distinct EVI2 temporal profiles were observed from different vegetation types. For deciduous broadleaf, needle-leaf forest, the EVI2 values increased dramatically from around 0.1 in late March to 0.5 in early June, then leveled off for several months, and finally descended gradually in early autumn (Fig. 4). Compared with deciduous broadleaf forest and needle-leaf forest, the evergreen broad-leaf forest generally exhibited less distinct seasonal patterns and obtained relatively high EVI2 values even in winter. For single agricultural crop sites, the EVI2 values started to increase when it was planted, reached its peak one or two months later, then declined quickly when it was harvested. Double cropping sites had two distinct growth cycles (Fig. 4).

2.4.2. Developing indices of temporal dispersion and continuity

A schematic diagram illustrated the process for developing indices of temporal dispersion and continuity (Fig. 5). First, the sequence signal was developed through ordering numbers from the daily continuous EVI2 profile. Second, several important percentiles, the 50th, 65th and 75th percentiles, were identified based