



Mapping seasonal impervious surface dynamics in Wuhan urban agglomeration, China from 2000 to 2016

Lei Zhang^a, Ming Zhang^{b,*}, Yibin Yao^a

^a School of Geodesy and Geomatics, Wuhan University, 129 Luoyu Road, Wuhan 430079, China

^b School of Resources and Environmental Engineering, Wuhan University of Technology, Wuhan 430070, China

ARTICLE INFO

Keywords:

Impervious surfaces
Landsat
Wuhan urban agglomeration

ABSTRACT

Numerous methods have been successfully applied to estimate the regional impervious surface dynamics based on spectral or spatial information from remote sensing imagery. However, previous methods mainly focused on mapping impervious surfaces at annual or decadal time scales. Few studies have attempted to map impervious surface dynamics at finer time scales, such as on a seasonal time scale using temporal information. This study aims to map regional impervious surface dynamics on a seasonal time scale by using time series Landsat data. The semi-supervised support vector machine (SVM) algorithm was employed for classifying impervious surfaces based on temporal characteristics, which were derived from seasonal time series biophysical composition index (BCI) and seasonal time series modified normalized difference impervious surface index (NDISI). The proposed method was validated over the Wuhan urban agglomeration (WUA) in China from 2000 to 2016. The results showed that impervious surfaces in the Wuhan urban agglomeration increased from 903.24 km² in 2000 to 3989.49 km² in 2016, with an annual growth rate of 20.10%. Additionally, the proposed method yielded reasonable average overall classification accuracy (up to 88%). Our results demonstrated that the proposed method could accurately map seasonal impervious surface dynamics based on temporal characteristics. This study could enable the monitoring of time-intensive impervious surfaces at a regional scale using remote sensing data.

1. Introduction

Impervious surfaces are mainly artificial structures such as pavement, building roofs, roads, sidewalks, driveways, parking lots, etc. Dramatic expansion of impervious surfaces is the result of the rapid urbanization process (Liu et al., 2013). Impervious surfaces, as one of the most important land cover type in urban areas, are a key indicator used to analyze the urbanization process and assess the environmental quality in cities (Arnold and Gibbons, 1996; Fan et al., 2015; Li et al., 2018). Numerous studies have examined changes in impervious surfaces and their impacts on the environment in the age of economic globalization. Satellite data has become one of the key data sources used to map regional impervious surfaces, such as DMSP/OLS nighttime light data (Liu et al., 2012; Ma et al., 2012; Zhang and Seto, 2011), Landsat archive (Ahmed and Ahmed, 2012; Bagan and Yamagata, 2012; Bhatta, 2009), MODIS imagery (Mertes et al., 2015), and multi-sensor imagery (Pandey et al., 2013; Shao and Liu, 2014; Zhang et al., 2012; Zhang et al., 2014).

Landsat data provides spatially consistent data at a fine spatial resolution and with a temporal frequency suitable for evaluating long-

term regional impervious surface dynamics. Time series Landsat imagery has been successfully applied to characterize the dynamics of impervious surfaces. Zhang et al. (2013) applied time series classification to monitor impervious surface dynamics in the Zhoushan Islands from 1986 to 2011 (Zhang et al., 2013). Zhang and Weng (2016) monitored the annual dynamics of impervious surfaces in the Pearl River Delta, China, from 1988 to 2013, using time series Landsat imagery (Zhang and Weng, 2016). Gao et al. (2012) used the decision tree model to map the continuous expansion of impervious surfaces in the lower Yangtze River Delta region with time series Landsat imagery (Gao et al., 2012). Song et al. (2016) proposed a post-classification method to derive the magnitude, timing and duration of impervious surface changes from Landsat data in the Washington DC-Baltimore metropolitan region at an annual resolution from 1984 to 2010 (Song et al., 2016). Powell et al. (2008) demonstrated the value of a 35-year Landsat archive for monitoring impervious surface trends in areas undergoing rapid urbanization (Powell et al., 2008). Li et al. (2016) analyzed the spatial patterns of impervious surface distribution and its dynamic changes in various directions using Landsat imagery in the Hangzhou metropolis (Li et al., 2016). Previous methods typically

* Corresponding author.

E-mail address: zhangming_88@whut.edu.cn (M. Zhang).

focused on studying the annual or decadal changes in impervious surfaces. However, changes in impervious surfaces have no fixed date, because impervious surfaces were associated with human activities and urban construction. As a result, changes in impervious surfaces may occur within one year or less. This is especially true for rapidly urbanized areas. Thus, mapping impervious surface dynamics on a finer time scale is required.

In addition, previous studies typically differentiated impervious surfaces from other land cover types based on the spectral and spatial characteristics of land covers. However, for regional level impervious surface estimation, using only spectral and spatial characteristics was considered ineffective due to the limited spectral and spatial resolutions of Landsat data (Li et al., 2013; Weng and Hu, 2008; Zhang and Weng, 2016). Researchers have increasingly explored the potential of land cover temporal characteristics for mapping impervious surface dynamics using time series Landsat data. Zhang and Weng (2016) mapped annual pixel-based impervious surface dynamics based on temporal spectral differences, and the proposed method performed well when applied to the Pearl River Delta in southern China between 1988 and 2013 (Zhang and Weng, 2016). This study reduced the impact of the limited spatial resolution of Landsat images and spectral confusion of land covers. However, this study still monitored impervious surfaces at an annual time scale. Zhang et al. (2017) mapped impervious surface dynamics on a monthly time scale by fusing Landsat and MODIS time series in the Pearl River Delta, China from 2000 to 2015, and the results showed that distinguishability of land covers with similar spectral characteristics was enhanced because of the temporal information (Zhang et al., 2017). However, this study required additional data (MODIS data) for the generation of monthly time series data. Recently, few studies have introduced temporal characteristics of land covers to identify seasonal impervious surfaces. Schneider (2012) revealed the need to consider seasonality when attempting to identify urban change (Schneider, 2012). Therefore, in this study, the intent was to use the temporal characteristics of land covers to map impervious surface dynamics at a seasonal time scale.

The aim of this study was to develop a new methodology to map impervious surface dynamics on a seasonal basis using temporal characteristics from time series Landsat data. The procedures of the proposed method were as follows: (1) to generate a seasonal time series biophysical composition index (BCI) (Deng and Wu, 2012) and a seasonal time series normalized difference impervious surface index (NDISI) (Xu, 2010); (2) to develop an improved partial least squares regression (IPLSR) for extracting the temporal characteristics of impervious surfaces, pervious surfaces, and water from seasonal time series BCI and NDISI; (3) to classify temporal characteristics using semi-supervised support vector machine (SVM); (4) to develop seasonal scale temporal filtering to check the classification consistency and correct unreasonable land cover changes; and (5) to map the dynamics of impervious surfaces at a seasonal frequency in the Wuhan urban agglomeration of China from 2000 to 2016.

2. Methodology

To map the seasonal dynamics of impervious surfaces, original, unevenly sampled time series BCI and NDISI were first reconstructed as seasonal time series BCI and NDISI. Then IPLSR was proposed to derive the temporal characteristics from reconstructed time series BCI and NDISI. Next, the semi-supervised SVM algorithm was implemented to map seasonal impervious surfaces based on temporal characteristics. Finally, seasonal scale temporal filtering was proposed to improve the classification accuracies. The experiments were performed using MATLAB (MATLAB R2013a, MathWorks Inc. Natick, MA). The procedures for mapping the seasonal dynamics of impervious surfaces are as follows (Fig. 1).

2.1. Study area and datasets

The Wuhan urban agglomeration (WUA) is in the eastern part of Hubei Province (upper left longitude 112°30'E and latitude 29°05'N, lower right longitude 116°10'E and latitude 31°50'N) (He et al., 2017; Lu et al., 2014). The WUA centers on Wuhan within a radius of 100 km and includes the cities of Wuhan, Huangshi, Ezhou, Huanggang, Xianning, Xiaogan, Xiantao, Tianmen, and Qianjiang. The WUA covers an area of 58,000 square kilometers, which is less than one third the size of Hubei Province (Tan et al., 2014). However, the WUA accounts for more than 50% of the population and GDP of the Hubei Province (Zeng et al., 2016). It has a humid subtropical climate with abundant rainfall. The average temperature ranges from 15 °C to 20 °C, and the mean annual precipitation is approximately 1300 mm (Zhang, 2017). The mainly reason for selecting the WUA as the suitable study area is because the area has experienced dramatic urban expansion in the past two decades. Since the theme of Wuhan (center of the WUA) is “Wuhan, Different Every Day”, the WUA is very representative of urbanization.

In this study, 150 Landsat surface reflectance climate data record (Landsat CDR) images were ordered and downloaded from the United States Geological Survey (USGS) Earth Explorer (reference system: WRS-2, path: 123, row: 39) for Landsat TM, ETM+, and OLI data. The day of the year (DOY) distribution of the collected Landsat data is shown in Fig. 2. Land cloud covers in the downloaded images were less than 10% of the data. Image subsets including Wuhan, Xiantao, Xiaogan, Xianning, and Tianmen were used to monitor impervious surface dynamics in the WUA area. The subsets covered an area of 23,426 square kilometers. The geographic location of the study area is shown in Fig. 3 with a true color composite image using Landsat TM 5 (October 31, 2000) bands 3, 2, and 1.

All the Landsat data were registered to the 1984 World Geodetic System Universal Transverse Mercator (WGS-84 UTM) Zone 49 North projection system and resampled at 30-m spatial resolution. Landsat 4–5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) surface reflectance data were generated from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al., 2006), which applied MODIS atmospheric correction routines to Landsat L1 data products. Landsat 8 surface reflectance data were generated from the L8SR algorithm and were downloaded from the USGS products web portal (<https://landsat.usgs.gov/provisional-landsat-8-surface-reflectance-data-available>). Cloud, cloud shadow, and snow mask were calculated using the Fmask algorithm for all scenes (Zhu and Woodcock, 2012). The scan-line corrector (SLC) of the Landsat 7 ETM+ sensor failed in 2003, which resulted in approximately 22% of the pixels per scene not being scanned. The locations of SLC-off data were identified using band-specific gap mask files in each SLC-off data product.

2.2. Generation of seasonal time series BCI, NDISI

Seasonal time series BCI and NDISI contributed to increase the temporal resolution of original time series Landsat data and provided a regular time series for extracting temporal characteristics. BCI was used to differentiate urban biophysical compositions. It was effective in identifying the characteristics of impervious surfaces and vegetation, and distinguishing bare soil from impervious surfaces (Deng and Wu, 2012). BCI, which involves Tasseled Cap (TC) transformation and V-I-S triangle model, is given as follows:

$$BCI = \frac{\frac{TC_1 + TC_3}{2} - TC_2}{\frac{TC_1 + TC_3}{2} + TC_2} \quad (1)$$

where TC_1 was high albedo, TC_3 was low albedo, and TC_2 was vegetation. Each derived TC component was then linearly normalized to a range of 0–1. That is, TC_i ($i = 1, 2, \text{ and } 3$) were three normalized TC components. For calculating BCI, water bodies were masked out before

Download English Version:

<https://daneshyari.com/en/article/8867852>

Download Persian Version:

<https://daneshyari.com/article/8867852>

[Daneshyari.com](https://daneshyari.com)