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A new approach for land cover classification and change analysis: Integrating backdating and an object-based method

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ABSTRACT

Accurate information on land use and land cover (LULC) change is crucial for ecosystem monitoring and environmental change studies. Updating/backdating approaches have been increasingly used for LULC classification and change analysis, but mostly based on pixels. Here, we presented a new approach, an object-based backdating approach which integrates the backdating approach with an object-based method, and further compared it with the pixel-based backdating approach. We tested the new approach by using Landsat TM data collected in 2001 and 2009 at the Beijing metropolitan region. We found that: 1) an object-based backdating approach achieved higher accuracy for change detection, LULC classification and change analysis than the pixel-based backdating approach. With the object-based approach, the overall accuracies for the classification and change analysis were 84.33% (versus 69.33% for a pixel-based approach), and 80.00% (versus 70.50% for a pixel-based approach), respectively. 2) The object-based backdating approach greatly increases the efficiency because classification and change analysis are only conducted for locations with changes. The increase in efficiency is particularly important for LULC classification and change analysis conducted at a large area, for example, at the national or global scale.

1. Introduction

Land use/land cover (LULC) change affects local and regional climate, carbon, water, and biodiversity, and therefore has been recognized as one of the major components of environmental change (Grimm et al., 2008; Turner, Lambin, & Reenberg, 2007). Accurate information on LULC and change is crucial for ecosystem monitoring, environmental change studies, and land management and planning (Turner et al., 2007). Remote sensing data have been widely used for LULC classification and change analysis, as these data explicitly reveal spatial patterns of LULC and change over a large geographic area in a recurrent and consistent way (De Fries, Hansen, & Townshend, 1998; Homer et al., 2007; Peng, Liu, Shen, Han, & Pan, 2012; Vogelmann, Howard, & Yang, 2001; Zhang et al., 2014).

Various methods have been developed for land cover change analysis using remotely sensed data (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 2004; Hussain, Chen, Cheng, Wei, & Stanley, 2013; Lu, Mausel, Brondizio, & Moran, 2004; Tewkesbury, Comber, Tate, Lamb, & Fisher, 2015). These methods may be broadly classified into two categories: post-classification comparison and pre-classification change detection (Lu et al., 2004; Singh, 1989; Zhou, Troy, & Grove, 2008). The first approach generates the multi-temporal LULC maps independently, and then identifies and quantifies the changes by comparing the classification maps (Deng, Wang, Hong, & Qi, 2009; Ellis & Porter-Bolland, 2008; Yuan, Sawaya, Loeffelholz, & Bauer, 2005). Pre-classification change detection techniques typically identify changes by comparing multi-temporal imagery directly, without classification. With high temporal resolution data, such as AVHRR, SPOT-VEGETATION and MODIS data, change detection can be conducted based on characterizing spectral trajectories of land cover by dense time series data (Bontemps, Bogaert, Titeux, & Defourny, 2008; Eklundh, Johansson, & Solberg, 2009; Hansen & DeFries, 2004). With the opening of Landsat data archive on the long-term data accumulation, there has been increasing interest in applying dense time series Landsat data on change detection (Wulder, Masek, Cohen, Loveland, & Woodcock, 2012; Zhu & Woodcock, 2014). Because of the advantage of high temporal frequency, many quite subtle disturbance events of forest, such as defoliation, diseases, insect pests and regeneration, can be captured based on the change of vegetation spectral attribution (Goodwin et al., 2008; Hermosilla, Wulder, White, Coops, & Hobart, 2015; Zhu, Woodcock, & Olofsson, 2012). In addition to its wide applications in forest ecosystems, such method has also been applied to quantify changes of impervious surfaces in urban environments (Powell, Cohen, Yang, Pierce, & Alberti, 2008; Schneider, 2012), coral reef health (Palandro et al., 2008) and fire events (Röder, Hill, Duguy, Alloza, & Vallejo, 2008). Pre-classification change detection techniques, whether using dense time series image data or not, generally only generates "change" vs. "no-change" maps, but do not specify the type of change (Berberoglu & Akin, 2009; Lu et al., 2004; Singh, 1989).

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Updating/backdating, an approach that has long been used in visual interpretation (Linke et al., 2009; McDermid et al., 2008; Zhou, Huang, & Cadenasso, 2011), has been increasingly applied in automatic change analysis and classifications (e.g., Xian & Homer, 2010, Jin et al., 2013). An updating/backdating approach can be considered as a synthesis of the post-classification comparison and pre-classification change detection (Xian & Homer, 2010). This approach typically started with an existing map, frequently referred as the reference map, based on which the classification and change analysis are conducted. One of the most remarkable examples is the generation of the 2006 National Land Cover Database (NLCD 2006) by updating the NLCD 2001 (Xian & Homer, 2010), which is now used as the reference dataset to create the 2011 NLCD, also using an updating approach (Jin et al., 2013).

Previous research has shown that an updating/backdating approach has several advantages in terms of both efficiency and accuracy (Linke et al., 2009; Xian, Homer, & Fry, 2009). For example, with this approach, classification is only conducted at locations with changes, which greatly reduce the time for classifications of the entire area of interest, compared with the post-classification comparison approach (Xian et al., 2009). An updating/backdating approach also helps maintain the consistency of the features with on changes, and largely reduce “false changes” (Xian et al., 2009). In addition, this approach provides an opportunity to correct the errors of reference map in the change analysis process, which greatly improving the reliability of change analysis (Perdigao & Annoni, 1997).

An updating/backdating approach can be implemented on pixels, or image objects (Linke et al., 2009; Xian et al., 2009). Object-based image analysis is quickly gaining acceptance among remote sensors, and has demonstrated great potential for classification and change detection, compared to pixel-based approach (Blaschke, 2010; Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011; Zhou et al., 2008). A considerable amount of research have shown that an object-based approach is superior to a pixel-based approach because it can greatly reduce the “salt and pepper” effect, provide an effective way in incorporating spatial, textural, and neighborhood relation in classification and change analysis (Blaschke, 2010; Hansen & Loveland, 2012; Zhou & Troy, 2008). However, previous studies using an automatic updating/backdating approach, have been largely applying a pixel-based method (e.g., Xian & Homer, 2010, Jin et al., 2013). Relatively few studies have investigated how an object-based updating/backdating approach performs. This study aims to fill this gap.

Here, we present a new approach that integrates the backdating approach with an object-based method for LULC classification and change analysis. We tested this approach using the Beijing metropolitan region as a case study, where great changes occurred during the time period (i.e., 2001–2009) we chose. We further compared this new approach with the typically used pixel-based backdating approach.

2. Study area and data acquisition

Our research focused on the Beijing metropolitan region (Fig. 1). This study area contains an urban–suburban–rural gradient which presents the land use intensity diminishes from the central Beijing city to the rural fringe. During the period of 2001 to 2009, Beijing metropolitan has experienced a dramatic LULC change from agriculture land to developed land in the suburban area. In addition, a mix of farmland and forest in the rural fringe was also highly dynamic. Therefore, this study area is well suited for the goals of this research.

We used two scenes of Landsat TM data collected in 2001 (2001/08/31) and 2009 (2009/09/22), and a land cover thematic map of 2009 (Hereinafter referred to as Map2009) (Fig. 1). These two images were obtained from United States Geological Survey (USGS), with primary process through Level 1 Product Generation System (LPGS), which included systematic radiometric and geometric corrections (Chander, Markham, & Helder, 2009). We further normalized the 2001 TM data using the 2009 TM data as the reference (Yang & Lo, 2000). Map2009 has six land cover types including forest, grass, water, farmland, developed land and barren. Developed land includes urban residential, commercial, industrial and transportation lands, and rural residential lands (Homer et al., 2007). It generated from the 2009 TM data, using an object-based classification approach, and thus had the spatial resolution of 30 m. We did extensive manual editing to refine the classification by referring to higher resolution SPOT image data (2.5 m). Therefore, Map2009 had an overall accuracy of 96%.

3. Methods

For comparison purpose, we implemented the backdating approach with two different methods: 1) the one integrating backdating and an object-based method (BOB, hereafter); and 2) the other integrating backdating and pixel-based method (BPB, hereafter). For both methods, we first used change vector analysis (CVA) to identify areas with changes (image objects in BOB, and pixels in BPB) from 2001 to 2009. We then classified these areas with changes, and backdated the areas with no changes based on Map2009 (Fig. 2). We did not use any ancillary data to aid in classification, and not conduct manual editing.

3.1. Integrating backdating and an object-based method

3.1.1. Image segmentation

With the BOB approach, we first segmented the 2001 image into objects. We used the multi-resolution segmentation algorithm that was embedded in eCognition software (Baatz & Schäpe, 2000). When implementing the segmentation, the classification map, Map2009, was used as the thematic layer. Consequently, the generated objects were not allow to across any of the borders separating different thematic classes of Map2009, and thus fell within or shared the boundaries of different land cover class of the thematic layer (Zhou et al., 2008) (Fig. 3).

The multi-resolution segmentation algorithm uses a bottom-up region merging technique, with each pixel initialized as a single segment (Baatz & Schäpe, 2000). Spatially adjacent segments are then merged based on the degree of heterogeneity that is largely defined by the parameter - scale. The process stops when there are no more possible merges given the defined scale parameter (Zhou & Troy, 2008). The greater the scale parameter, more heterogeneity allowed within each object, and the larger the average size of the objects. Two other parameters, color and shape, can also be set to determine the relative weighting of reflectance and shape in defining segments. The total weighted value of color and shape equals to one (Trimble, 2012). Previous studies showed that a higher weight, typically up to 0.9, should be given to color for better segmentation results (Mathieu, Aryal, & Chong, 2007; Pu, Landry, & Yu, 2011). Therefore, we set the weights as 0.9 and 0.1, respectively.

As the average size of land cover patches and their changes varied by different types, there was no one scale fitting for all the land cover types. For example, the forest patches were larger than patches of water and grass. Therefore, we created a 3-level hierarchy of image objects with the scale parameters setting as 10 (Level 1), 30 (Level 2), and 50 (Level 3) (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). The three values of the scale parameter were determined by testing different parameter values and visually interpreting the image segmentation results (Mallinis, Koutsias, Tsakiri-Strati, & Karteris, 2008; Zhou & Troy, 2008). Specifically, Objects created at Level 1 were used to detect changes for the classes of water, grass and barren, the size of whose changes tended to be small. Objects at Level 2 were created to identify changes for farmlands and developed lands, and those at Level 3 for forested land (Fig. 3).

3.1.2. Change detection

Change vector analysis has been widely used for land cover change detection (Chen, Gong, He, Pu, & Shi, 2003; Johnson & Kasischke, 1998; Nackaerts, Vaesen, Muys, & Coppin, 2005; Xian et al., 2009).