Remote Sensing of Environment 158 (2015) 193–206

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Mapping dynamic cover types in a large seasonally flooded wetland using extended principal component analysis and object-based classification

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ARTICLE INFO

Article history:
Received 25 August 2012
Received in revised form 15 October 2014
Accepted 29 October 2014
Available online xxxx

Keywords:
Dynamic cover types
Wetland remote sensing
Object-based image analysis
PR China
Extended PCA
Phenology
Change trajectory analysis

ABSTRACT

Periodically inundated wetlands with high short-term surface variation require special approaches to assess their composition and long-term change. To circumvent high uncertainty in single-date analyses of such areas, we propose to characterize them as dynamic cover types (DCTs), or sequences of wetland states and transitions informed by physically and ecologically plausible surface processes. This study delineated DCTs for one 2007–2008 flood cycle at Poyang Lake, the largest freshwater wetland in China, using spatial and temporal orientation modes of extended principal components analysis (EPCA) and supervised object-based classification of multi-spectral and radar image series. Classification accuracy was compared among three sets of attributes selected by machine-learning optimization from object-level mean and standard deviations of: 1) image time series alone; 2) the most informative EPCA outputs alone and 3) image time series and EPCA results together. Classification uncertainty was additionally assessed as low values of object's maximum class membership (<0.5). The highest accuracy was achieved with a larger set of 33 attributes selected from combined time series and EPCA results (overall accuracy 95.0%, kappa 0.94); however, accuracies with smaller sets of variables from input image series or EPCA results alone were comparably high (93.1% and 94.7%, respectively). All three selected attribute sets included standard deviations of image and/or EPCA values, suggesting the utility of object texture in dynamic class discrimination. The highest classification uncertainty was observed primarily along the mapped class boundaries, in some cases indicating minor change trajectories for which prior reference data were not available. Results indicate that DCTs provide a reasonable classification framework for complex and variable Poyang Lake wetlands that can be facilitated by EPCA transformation of complementary remote sensing time series. Future work should test this approach over multiple change cycles and assess sensitivity of results to temporal frequency of input image series, alternative variable selection algorithms and other remote sensors.

1. Introduction

Landscape ecosystems are never truly static; they constantly vary due to physical processes, biological interactions, phenology and disturbance. For a given ecosystem property, the assumption of "change" versus "no change" over a time frame of interest is important for understanding long-term resilience and response to natural and anthropogenic change drivers (Foley et al., 2005; Liu & Cai, 2011; Neuenschwander & Crews, 2008). Remote sensing platforms greatly facilitate studies of landscape change by providing repeated monitoring over large areas and locations with difficult ground access (Gong et al., 2010; Ordoyne & Friedl, 2008; Ozesmi & Bauer, 2002; Rebelo, Finlayson and Nagabhatla, 2009). However, the accuracy of detection and interpretation of change may be constrained by spatial resolution, extent and acquisition frequency of the data (Assendorp, 2010; Coppin, Jonckheere, Nackaerts, Muys and Lambin, 2004; Liu & Cai, 2011; Lunetta, Johnson, Lyon and Crotwell, 2004), and by the short-term variation of land surface properties (Crews-Meyer, 2008; Dronova, Gong and Wang, 2011; McCleary, Crews-Meyer and Young, 2008).

Traditional mapping approaches have often focused on static classes representing discrete states of surface cover observable for extended periods of time. The "change" is assumed to occur for a given location if the highest-probability cover classes differ among successive points in time, and various change detection techniques have been summarized in several reviews (Coppin et al., 2004; Gong & Xu, 2003; Lu, Mausel, Brondizio and Moran, 2004; Mas, 1999). However, both

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http://dx.doi.org/10.1016/j.rse.2014.10.027
0034-4257/© 2014 Published by Elsevier Inc.

classification and change detection are challenging in rapidly varying areas such as periodically inundated wetlands, where short-term surface dynamics produce transitional states and fine-scale mixtures of classes and may obscure long-term surface trends. Notably, such complex landscapes often support unique ecological services and high biological diversity (Dudgeon et al., 2006; Gibbs, 2000; Ordoyne & Friedl, 2008; Wang et al., 2012) and thus call for alternative approaches to characterize them in order to assess their response to climate change and human activities.

Several strategies to characterize highly variable landscapes were offered by previous research. One of them defines classes as static cover types prevalent over the whole time range of the data but classified based on their multi-temporal signatures, such as in studies of crop dynamics (Zhong, Hawkins, Biging and Gong, 2011) and in the National Dynamic Land Cover Dataset for Australia (Lymburner et al., 2011). This approach reveals class-specific phenological spectral trajectories (Wang et al., 2012; Zhong et al., 2011) and early signals of potential state shifts (Lymburner et al., 2011); however, "single class representation of dynamic behavior" (Lymburner et al., 2011) may prohibit detection of the actual changes between classes (Sun, Zhao, Gong, Ma and Dai, 2014).

With the second strategy, land-cover change pathways are derived from multi-date images (Lawrence & Ripple, 1999; Liu & Cai, 2011; Mertens & Lambin, 2000; Vågen, 2006) as multi-temporal transition classes (Hess, Melack, Novo, Barbosa and Gastil, 2003) or as the outputs of multi-date image series transformations with principal component analysis (PCA), Kauth–Thomas algorithm and other methods (Byrne, Crapper and Mayo, 1980; Collins & Woodcock, 1996; Coppin, Nackaerts, Queen and Brewer, 2001; Ribed & Lopez, 1995; Seto et al., 2002b). A promising but under-explored strategy is using different forms of PCA to highlight recurring temporal patterns in space (S-mode PCA), prevalent spatial patterns over time (T-mode) (Cattell & Murphy, 1973; Richman, 1986), or shared temporal and spatial patterns among different datasets (extended PCA, or EPCA; Neeti & Eastman, 2014).

The third type of studies aims to distinguish longer-term changes from short-term variation caused by phenology or disturbance. Such analysis may be implemented by comparing inter- and intra-annual land cover changes as a panel approach described by Crews-Meyer (2008) and McCleary, Crews-Meyer and Young (2008), or by fitting regression to long-term data series and analyzing residuals for signals of non-recurring disturbance and unusual events (Neuenschwander & Crews, 2008).

While all these approaches offer useful strategies for complex landscapes such as periodically flooded wetlands, they also highlight an important challenge. Complex surface composition and dynamics may result in a large number of detected unique change pathways, some of which may not be physically plausible (Hess et al., 2003; Liu & Cai, 2011; Villa, Boschetti, Morse and Politte, 2012), representing error and noise (McCleary et al., 2008). This issue may be addressed by using ancillary information in class definition, transforming the images to highlight relevant patterns (Neeti & Eastman, 2014) and by reducing pixel-level local heterogeneity using primitive objects as mapping units (Chen, Hay, Carvalho and Wulder, 2012). In dynamic landscapes, periodic processes often produce regimes of change, sometimes along the gradients of change drivers such as inundation (Assendorp, 2010; Lenssen, Menting, van der Putten and Blom, 1999). These regimes may shape unique ecosystem types, functions and species assemblages and thus may be useful in landscape management, planning and conservation (Parrott & Meyer, 2012; Watson, Luck, Spooner and Watson, 2014). We will refer to these regimes as "dynamic cover types" (DCTs), or distinct sequences of wetland cover states and transitions observed within a given period of change cycle.

Delineation of dynamic classes may benefit from data transformations that accentuate both prevalent types of surface cover and key transitions — such as extended PCA searching for patterns recurring in both space and time (Cattell & Murphy, 1973; Neeti & Eastman, 2014; Richman, 1986). It may be also useful to map DCTs with object-based image analysis (OBIA) where prior to classification, image pixels are segmented into "objects" matching spatial entities (Blaschke, Lang, Lorup, Strobl and Zeil, 2000; Dronova et al., 2011, 2012; Lyons, Phinn and Roelfsema, 2012). Even small "primitive" objects have been shown to improve classification accuracy relative to pixels by smoothing local noise and enhancing class contrasts with non-spectral attributes (Conchedda, Durieux and Mayaux, 2008; Grenier et al., 2007; Kim, Warner, Madden and Atkinson, 2011; Lyons et al., 2012). Using prior knowledge to define DCTs may facilitate differentiating among long-term change and short-term variation for the processes of interest, while novel change or sporadic disturbances can be detected as deviations from DCT trajectories.

Our study aimed to delineate DCTs as major trajectories of annual wetland change cycle at Poyang Lake, the largest freshwater lake-wetland complex in China (Fig. 1). Dynamics of monsoon-driven inundation (Andreoli et al., 2007; Qi et al., 2009), vegetation phenology (Wang et al., 2012) and disturbance affect important ecological properties of this wetland, such as nutrient and greenhouse gas fluxes (Liu, Xu, Lin and Zhang, 2013), habitat for migratory waterbirds including critically endangered species (Barzen, Engels, Burnham, Harris and Wu, 2009) and life cycle of the snail species *Oncomelania hupensis*, the intermediate host to the parasite *Schistosoma japonica* causing severe human disease in the region and globally (Seto et al., 2002a). While "characteristic" dynamics of Poyang Lake's surface are still insufficiently understood (Feng et al., 2012; Sun et al., 2014), they are likely to change in the near future due to hydrological effects of the Three Gorges Dam upstream Yangtze River and local dams (Barzen et al., 2009; Finlayson, Harris, McCartney, Young and Chen, 2010; Guo, Hu, Zhang and Feng, 2012). Remote sensing classifications of this area from single-date images exhibit high uncertainty due to complex wetland cover and frequent transitional mixtures of classes (Dronova et al., 2011). These issues call for new strategies to address spatial and temporal complexity of this unique wetland ecosystem in order to improve the capacity for monitoring and, ultimately, landscape-level modeling of its change.

We focused on one flood cycle from summer 2007 to spring 2008 and seven dominant DCTs representing changes in water coverage, surface composition and plant phenology informed by previous research (Barzen et al., 2009; De Leeuw et al., 2006; Dronova et al., 2011, 2012; Qi et al., 2009; Wang et al., 2012). Our specific objectives were to 1) determine whether ecologically informed Poyang Lake DCTs could be distinguished with multi-temporal multi-spectral and microwave radar satellite images; and 2) assess the utility of S- and T-mode EPCA to highlight prevalent wetland cover states and key transitions (Cattell & Murphy, 1973; Neeti & Eastman, 2014; Richman, 1986) to facilitate DCT mapping from these different data types. Given spatial complexity of Poyang Lake's surface, we mapped DCTs by supervised classification of primitive image objects derived by multiresolution segmentation of the multi-date images. We further assessed the accuracy of DCT classifications with different sets of discriminating variables based on the image time series and EPCA outputs, assessed the uncertainty in class membership and discussed the strategies to enhance DCT analyses and extend them to multi-temporal framework in the future.

2. Methods

Our analysis was organized as follows (Fig. 2): we first performed the T- and S-mode EPCA transformation of the input remote sensing data and examined which spatial and temporal patterns in EPCA results corresponded to DCTs (Table 1). We then segmented the input image series into primitive objects and assigned training and test reference samples for DCT mapping using field data and high-resolution imagery. The statistics of training objects were examined to determine DCT class differences in 1) temporal trajectories calculated from the input image series; and 2) EPCA component (T-mode) and loading (S-mode) images. Next, we performed supervised object-based classification of DCTs followed by assessments of classification accuracy and uncertainty.