Ecological Indicators 73 (2017) 105–117

Contents lists available at ScienceDirect

Ecological Indicators

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

Comparison of object-based and pixel-based Random Forest algorithm for wetland vegetation mapping using high spatial resolution GF-1 and SAR data

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ARTICLE INFO

Article history:
Received 20 May 2016
Received in revised form 11 August 2016
Accepted 18 September 2016

Keywords:
Wetland vegetation mapping
Image fusion
Random Forest classifier
GF-1
SAR
Northeast China

ABSTRACT

Vegetation is an integral component of wetland ecosystems. Mapping distribution, quality and quantity of wetland vegetation is important for wetland protection, management and restoration. This study evaluated the performance of object-based and pixel-based Random Forest (RF) algorithms for mapping wetland vegetation using a new Chinese high spatial resolution Gaofen-1 (GF-1) satellite image, L-band PALSAR and C-band Radarsat-2 data. This research utilized the wavelet-principal component analysis (PCA) image fusion technique to integrate multispectral GF-1 and synthetic aperture radar (SAR) images. Comparison of six classification scenarios indicates that the use of additional multi-source datasets achieved higher classification accuracy. The specific conclusions of this study include the followings:(1) the classification of GF-1, Radarsat-2 and PALSAR images found statistically significant difference between pixel-based and object-based methods; (2) object-based and pixel-based RF classifications both achieved greater 80% overall accuracy for both GF-1 and GF-1 fused with SAR images; (3) object-based classifications improved overall accuracy between 3%-10% in all scenarios when compared to pixel-based classifications; (4) object-based classifications produced by the integration of GF-1, Radarsat-2 and PALSAR images outperformed any of the lone datasets, and achieved 89.64% overall accuracy.

1. Introduction

Wetland vegetation is adapted to thrive in hydric soil and plays a vital role in distinguishing wetlands from other land cover or open water (Kokaly et al., 2003; Floyd and Anthony, 2008). Wetland vegetation serves as indicators of ecosystem health and provide early signs of physical or chemical degradation (Dennison et al., 1993; Silva et al., 2008). Accurately mapping the distribution, quality and quantity of wetland vegetation is an essential first step for wetland management that protects and restores the ecosystems at risk (Henderson and Lewis, 2008). The Honghe National Nature Reserve is a Ramsar designated wetland which provides important habitat for many birds including 10 endangered avifauna (Luan et al., 2003). The site has been mapped in the past with medium spatial resolution remote sensing imagery demonstrating that the reserve is experiencing irrigation driven wetland loss (Zhou et al., 2009). *In situ* floristic mapping and data collection can be expensive, labor intensive and even dangerous due to difficulties of navigating wetlands. Remote sensing provides a practical means in data collection and wetland mapping to inform management. In particular, repeated coverage of remote sensing data offer the capability for monitoring spatial distribution of wetland vegetation over time.

Remote sensing images are increasingly utilized for mapping wetland vegetation from optical to synthetic aperture radar (SAR) sensors. While optical image has long been the main data source for wetland vegetation mapping, SAR data with different wavelength and polarization modes have been reported such applications over the last decade (Martinez and Le Toan, 2007; Sartori et al., 2011). The classification of wetland vegetation from remote sensing data can be divided into two general image analysis techniques, i.e., pixel-based image analysis and object-based image analysis. Comparative studies of pixel-based, and/or object-based image analysis

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http://dx.doi.org/10.1016/j.ecolind.2016.09.029
1470-160X/

using high spatial resolution optical or SAR data have been implemented to examine the relative performance of these classification algorithms (Wang et al., 2004; Harken and Sugumaran 2005; Demers et al., 2015; Dingle Robertson et al., 2015). The studies found that object-based classification typically outperform pixel-based classification when comparing overall classification accuracy in setting ranging from agricultural to urban land cover classes. However, there has been lack of comparison of pixel-based with object-based image analysis using the multi-sensor remote sensing images for mapping wetland vegetation. With the progress of computer technology, different classification algorithms have been used in the identification of wetland vegetation including ISODATA (McCarthy et al., 2015) and maximum likelihood classification (MLC) (Tuxen et al., 2011), spectral mixture modelling (LSMM) (Delalieux et al., 2012) and fuzzy classification techniques (Gong et al., 2014), artificial neural network (ANN) (Szantoi et al., 2015), decision trees (DTs) (Cordeiro and Rossetti, 2015), support vector machines (SVMs) (Betbeder et al., 2015) and random forest (RF) (Kopeć et al., 2016). RF has demonstrated robust and accurate performance for the analyses of multi-source remote sensing data in land cover studies (Myint et al., 2011; Millard and Richardson, 2013; Stefanski et al., 2013). The consistency of RF led to the utilization of that algorithm with both the object and pixel-based methods, facilitating comparisons between all classifications. The objective of this study was to fill the gap by comparisons of pixel-based and object-based RF classification of wetland vegetation using the optical and SAR data.

This study integrated high spatial resolution optical sensor data from the Chinese GF-1 satellite with, C-band Radarsat-2 and L-band PALSAR images, and compared the performance of object-based and pixel-based RF algorithms for mapping wetland vegetation in six classification scenarios for the Honghe National Nature Reserve (HNNR) in Northeast China.

2. Study area and data source

2.1. Study area

The Sanjing Plain in the Northeast China is an extensive alluvial plain by the Amur, Ussuri and Songhua rivers. Also known as the Three River Plain, the region has a low and flat topography with a slope grade less than 1:10,000, which forms the largest wetland concentration in China. Extensive wetland areas of the Sangjiang Plain were reclaimed as paddy field and cropland in the past 50 years. Honghe National Nature Reserve (HNNR), 251 km^2 in size and located in Heilongjiang Province (Fig. 1), was established in 1984 as a wetland of international importance due to being a typical fresh water herbaceous wetland ecosystem in the Northern Temperate Zone (Ramsar Secretariat, 2015). The Nongjiang and Woyalan rivers pass through the reserve. The climate is humid temperate with four distinct seasons, including six months of freezing conditions. The mean annual temperature is 1.9 °C and annual precipitation is 585 mm. The landscape of HNNR is dominated forest, shrub and herbaceous vegetation (Table 1). HNNR provides a critical habitat for the endangered red-crowned Crane (*Grus japonensis*).

2.2. Data source

2.2.1. Remote sensing and ancillary data

The optical remote sensing data comes from a Chinese GF-1 environmental satellite which was launched in April 26, 2013, and possesses 2 m and 8 m spatial resolutions in panchromatic and multispectral bands, respectively. The GF-1 multispectral data contain 4 spectral bands covering blue, green, red and near-infrared spectrum. The SAR imageries includes the Japanese Earth Resources Satellite 1 ALOS-PALSAR (PA) with fine beam dual polarization and C-band wide fine quad-polarization Canadian Radarsat-2 (RA). Technical details of the datasets are described in Table 2.

Table 1
Classification scheme for mapping wetland vegetation in HNNR.

	Vegetation species	Class codes
Open water	None	1
Cropland	*Sorghum*	2
Paddy field	*Rice*	3
Forest	*Quercus mongolica, Populus davidiana, Betula platyphylla*	4
Shrub	*Betula fruticasa, Salix brachypoda*	5
Shallow-water herbaceous vegetation	*Calamagrostis angustifolia, Calamagrostis angustifolia–Carex* spp.	6
Deep-water herbaceous vegetation	*Carex pseudocuraica, Carex lasiocarpa, Carex lasiocarpa*	7

Additional data included 1:10,000 topographic map with 1 m elevation interval developed by the Chinese National Administration of Surveying, Mapping and Geoinformation; 1:25,000 vegetation map derived from field measurements; and Shuttle Radar Topographic Mission (SRTM) generated Digital Elevation Model data at 30 m spatial resolution.

2.2.2. Training and validation data

The field investigations were conducted in August-October 2013, May and September 2014. Field data were collected in 63 1 × 1 m sampling plots. To augment the plot data, training and assessment data were chosen from remote sensing imageries with reference to 1:10,000 topographic map and 1:25,000 vegetation map. The sampling data were divided randomly in half for training and testing, respectively. The training and testing sample size for classification is described in Table 3.

3. Methods

3.1. Data processing

3.1.1. Data preprocessing

The GF-1 imagery data were georeferenced based on 1:10,000 topographic maps with error controlled less than 0.5 pixels. The georeferenced images were processed for atmospheric correction using Fast Line-of-Site Atmospheric Analysis of Spectral Hypercubes (FLAASH) (Adler-Golden et al., 1999).

The SAR data of PALSAR and Radarsat-2 were processed by a series of procedures, including multi-looking, refined Lee filter, geocoding, radiometric calibration, Range-Doppler terrain correction. The PALSAR SLC data was first multilooked with 4 looks in azimuth and 1 in range, resulting in approximately 14 × 14 m ground-range resolution. Radarsat-2 SLC data was used as it is without multilook, resulting in 6.3 × 5.2 m ground-range resolution. Later, the images were filtered using Lee refined with 7 × 7 window to remove the speckle noise. The images were geocoded to WGS-84 datum and Universal Transverse Mercator (UTM) Zone 53 North coordinate system by Range-Doppler terrain correction using the SRTM 30 m DEM. Finally, the SAR images were georeferenced the GF-1 image with error controlled less than 0.5 pixels. In this study, the SAR polarization data was processed in intensity format and resampled to 2 m pixel size for classification. The SAR RGB image was derived from assigning backscatter coefficients of HH and HV polarization to R and G components, and the ratio of backscatter coefficients of HH and HV polarization to B color combination.