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Mapping mangrove forests using multi-tidal remotely-sensed data and a decision-tree-based procedure

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ABSTRACT

Mangrove forests grow in intertidal zones in tropical and subtropical regions and have suffered a dramatic decline globally over the past few decades. Remote sensing data, collected at various spatial resolutions, provide an effective way to map the spatial distribution of mangrove forests over time. However, the spectral signatures of mangrove forests are significantly affected by tide levels. Therefore, mangrove forests may not be accurately mapped with remote sensing data collected during a single-tidal event, especially if not acquired at low tide. This research reports how a decision-tree −based procedure was developed to map mangrove forests using multi-tidal Landsat 5 Thematic Mapper (TM) data and a Digital Elevation Model (DEM). Three indices, including the Normalized Difference Moisture Index (NDMI), the Normalized Difference Vegetation Index (NDVI) and $NDVI_L \cdot NDMI_H$ (the multiplication of $NDVI_L$ by $NDMI_H$, L: low tide level, H: high tide level) were used in this algorithm to differentiate mangrove forests from other land-cover and land-use types in Fangchenggang City, China. Additionally, the recent Landsat 8 OLI (Operational Land Imager) data were selected to validate the results and compare if the methodology is reliable. The results demonstrate that short-term multi-tidal remotely-sensed data better represent the unique nearshore coastal wetland habitats of mangrove forests than single-tidal data. Furthermore, multi-tidal remotely-sensed data has led to improved accuracies using two classification approaches: i.e. decision trees and the maximum likelihood classification (MLC). Since mangrove forests are typically found at low elevations, the inclusion of elevation data in the two classification procedures was tested. Given the decision-tree method does not assume strict data distribution parameters, it was able to optimize the application of multi-tidal and elevation data, resulting in higher classification accuracies of mangrove forests. When using multi-source data of differing types and distributions to map mangrove forests, a decision-tree method appears to be superior to traditional statistical classifiers.

1. Introduction

Mangrove forests are widely distributed in tropical and subtropical regions of the world, forming important intertidal ecosystems that link terrestrial and marine systems (Giri et al., 2011a; Zhang and Tian, 2013). They are typically distributed from mean sea level to the highest spring tide (Alongi, 2009). Mangrove ecosystems can provide a wide variety of important ecological and economical ecosystem services to coastal communities, e.g., water filtration, storm protection, shoreline stabilization (Alongi, 2008; Blasco et al., 1996; Kuenzer et al., 2011). However, their health and existence are seriously threatened by relative sea-level rise as well as coastal development and various forms of anthropogenic activities, such as conversion to agriculture, aquaculture, tourism, urban development and overexploitation (Farnsworth and Ellison, 1997; Giri and Muhlhausenet, 2008; Giri et al., 2008; Lovelock et al., 2015). In the past several decades, the world's mangrove ecosystems have been destroyed at a rate of 1%–2% per annum (Jones et al., 2016).

Rapid and accurate mapping techniques are required to effectively monitor and manage mangrove resources. Conventional field surveying is time-consuming and labor-intensive. It is also difficult to determine mangrove distribution and abundance with field surveying due to the inaccessibility of mangrove communities. Rapid progress in sensor technologies and remote sensing methods have brought land-cover detection into a new era (Zhang et al., 2013) and have proven to be effective for monitoring mangrove forests (Everitt et al., 2010; Giri et al., 2011a,b, 2015). Numerous studies have employed remotely-sensed data to analyze the relationship between changes in coastal land

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use and mangrove distribution (Bird et al., 2004; Chen et al., 2013; Cornforth et al., 2013; Tran et al., 2015) and to characterize change (Murray et al., 2003; Ramírez-García et al., 1998). In particular, medium-resolution (e.g. 10–30 m) multispectral data provides surface information at regional scales (Kuenzer et al., 2011) and has been applied to monitor and map mangrove forests over large areas. These data include: (i) Landsat Multispectral Scanner (MSS) (Giri and Muhlhausen, 2008; Giri et al., 2008; Howari et al., 2009; Prasad et al., 2009; Seto and Fragkias, 2007; Tran et al., 2015); (ii) Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper Plus (ETM+) (Andriamparany and Francois, 2010; Ferreira et al., 2009; Howari et al., 2009; Tran et al., 2015; Zhang et al., 2013); (iii) SPOT (Gao, 1999; Prasad et al., 2009; Thu and Populus, 2007; Pu et al., 2012; Tran et al., 2015; Vo et al., 2013); (iv) Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (Giri and Muhlhausenet, 2008; Seto and Fragkias, 2007; Vaiphasa et al., 2006); and (v) radar imagery (Cornforth et al., 2013; Rao et al., 1999).

Over the past few decades, various methods have been employed to map mangrove forests or other aquatic vegetation from remotely-sensed images, ranging from visual to semi-automated and unsupervised approaches, and pixel to object-based approaches (Andriamparany and Francois, 2010; Everitt et al., 2010; Ferreira et al., 2009; Giri and Muhlhausenet, 2008; Giri et al., 2007; Heenkenda et al., 2014; Heumann, 2011; Howari et al., 2009; Kanniah et al., 2015; Paling et al., 2008; Prasad et al., 2009; Seto and Fragkias, 2007; Shapiro et al., 2015; Vo et al., 2013; Wang et al., 2004; Zhang et al., 2013). More recently, machine learning algorithms such as neural network classification (Ferreira et al., 2009; Mas, 2004; Seto and Fragkias, 2007) or decision trees (Heumann, 2011; Liu et al., 2008; Luo et al., 2014, 2016, 2017) have also been applied.

The majority of previous studies have used single-tidal (i.e., single-date) remotely-sensed data to map mangrove forests. However, mangroves are located in nearshore coastal wetlands and are periodically submerged by incoming tides. The moderate/lower intertidal mangrove forests are likely to be submerged at high tide, as demonstrated in Fig. 1 (Zhang and Tian, 2013). Consequently, changes in tide levels often result in contrasting spectral signatures for mangrove forests and lead to different mapping results, especially in areas with large tidal ranges. As demonstrated in previous studies the tidal effect frequently results in underestimating the mapped area of mangrove forests from single-tidal remotely-sensed data, particularly at high tide (Lin and Fu, 1995; Zhang and Sui, 2001). Meanwhile, spectral signatures for mangrove forests contain a mixture of information related to vegetation and wetland conditions due to the unique characteristics of nearshore coastal wetland habitats. As Luo et al. (2017) reported, aquatic vegetation can be effectively mapped by considering life history information on aquatic vegetation with multi-seasonal satellite images. If we can make good use of the unique habitat characteristics of mangrove forests, i.e. the wetland background and periodic variation of the tide level, mapping accuracy of mangrove forests using remotely-sensed data may be improved (Zhang and Tian, 2013; Zhang et al., 2013).

Vegetation Indices (VIs) have been extensively used to describe vegetation growing state and cover condition (Yu et al., 2005). In particular, the Normalized Difference Vegetation Index (NDVI) is a widely used VI for mapping and monitoring a vast array of ecosystems (Pettorelli et al., 2005; Rouse et al., 1973) including mangrove forests (Green et al., 1998; Jensen et al., 1991; Panigrahy et al., 2012). Moreover, numerous studies have shown that mangrove NDVI values are highly correlated with mangrove biomass, canopy cover, and leaf area index (LAI) (Green et al., 1997, 1998; Jensen et al., 1991). In addition, the Normalized Difference Moisture Index (NDMI), calculated using the near infrared (NIR) and shortwave infrared (SWIR) bands, can effectively estimate vegetation water content (Chen et al., 2005; Huang et al., 2009; Wilson and Sader, 2002). However, to our knowledge, NDMI has seldom been incorporated into the classification of mangrove forests.

In this paper, we investigated the unique characteristics of nearshore coastal wetland habitats for mapping mangrove forests in Fangchenggang City, China and developed and evaluated a decision-tree algorithm for mapping mangrove forests using multi-tidal remote sensing data. Specifically, two objectives were addressed: (1) to evaluate the ability to discriminate mangrove forests from other land cover types using two spectral indices, i.e., NDVI and NDMI; and (2) to compare the decision-tree algorithm to a traditional classification algorithm (i.e., maximum likelihood classification − MLC) using multi-tidal remotely-sensed data to map mangrove forests.

2. Study area

The study area is located in Fangchenggang City, Guangxi Zhuang Autonomous Region of China, which is in a tropical rainforest and monsoon forest zone (Fig. 1). The area covers a wide range of vegetation types, including: coniferous forests (China fir [*Cunninghamia lanceolata*], masson pine [*Pinus massoniana*]); broad-leaved forests (*eucalyptus urophylla*, *Schima superba*, Camphor [*Cinnamomum camphora*]); mangrove forests; orchards (Leechee [*Litchi chinemis*], Longan [*Dimocarpus longgana Lour.*], aniseed [*Illicium verum*]); bushwood (Myrtle [*Rhodomyrtus tomentosa*], *Rhus chinensis*, *Phyllanthi Fructus, Melastoma candidum*); and grassland (*Deyeuxia Clarion*, *Heteropogon contortus*, *Dicranopteriis dichotoma (Thunb.) Bernh* and *Arundinella hirta*). Mangrove forests are distributed at Pearl Bay (21°28′–21°37′N, 108°2′–108°16′E) within the Beilunhekou National Nature Reserve Area. The species communities include *Avicennia marina*, *Aegiceras corniculatum*, *Kandelia candel*, *Bruguiera gymnorrhiza* and *Acanthus ilicifolius*. The hierarchy of mangrove plant communities was simple and most of them were single layer. In addition, the height of mangrove plant communities is usually less than 5 m in the study area (Liang et al., 2004). The tidal type is regularly diurnal, and the mean and maximum tidal ranges are 2.24 m and 5.64 m above the Fangchenggang datum plane, respectively (Zhang and Tian, 2013).

3. Data and methodology

3.1. Datasets

The data used for this study include satellite remote sensing data (Table 1), high resolution images from Google Earth (acquired on November 16, 2007 and December 25, 2013), in situ measurements, and ancillary spatial data (e.g., topographic maps and a DEM). Two-dates of Landsat 5 TM data were collected on October 30, 2006 (Fig. 1A) and November 15, 2006 (Fig. 1B) for tide levels of 417 cm and 282 cm (National Marine Data and information Service, 2005), respectively. The tidal datum was 230 cm below the mean sea level. Moreover, to validate the mapping results of mangrove forests, two Landsat 8 OLI data (https://lta.cr.usgs.gov/L8) were also employed. They were collected on December 20, 2013 (Fig. 1C) and December 4, 2013 (Fig. 1D) for tide levels of 362 cm and 265 cm (National Marine Data and information Service, 2012), respectively. Additionally, though there was a time lag of 16 days between image acquisitions, the land cover/land use for the study can be considered unchanged. To geometrically correct the Landsat data, a 1:50,000 topographic map was used for planimetric reference. In our study area, mangrove forests are generally limited to elevations below 10 m above sea level (a.s.l.) and found within 1 km from the coastline in the study area (Liu et al., 2008). To establish elevation limits, the SRTM (Shuttle Radar Topographic Mission) DEM data with 90 m spatial resolution, resampled to 30 m spatial resolution, was used. The vertical accuracy of SRTM is approximately 2.39 m in the low altitude areas where the elevation value is less than 20 m (Du et al., 2013).

The field survey was carried out during the period of November 1–5, 2006. The surveying sites are shown in Fig. 1 and include 15 mangrove forest sites, 20 terrestrial vegetation sites (including 2 shaded forest