Ecological Informatics 35 (2016) 43–54

Contents lists available at ScienceDirect

Ecological Informatics

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

Multi-temporal change detection of seagrass beds using integrated Landsat TM/ETM+/OLI imageries in Cam Ranh Bay, Vietnam

Chi-Farn Chen [a,b], Va-Khin Lau [a,c,*], Ni-Bin Chang [d], Nguyen-Thanh Son [b], Phuoc-Hoang-Son Tong [c], Shou-Hao Chiang [b]

[a] Department of Civil Engineering, National Central University, Taoyuan City 32001, Taiwan
[b] Center for Space and Remote Sensing Research, National Central University, Taoyuan City 32001, Taiwan
[c] Institute of Oceanography, Vietnam Academy of Science and Technology, 01 Cau Da, Nha Trang City, Khanh Hoa Province, Vietnam
[d] Department of Civil, Environmental, and Construction Engineering, University of Central Florida, Orlando, FL 32816, USA

ARTICLE INFO

Article history:
Received 24 December 2015
Received in revised form 23 July 2016
Accepted 24 July 2016
Available online 26 July 2016

Keywords:
Seagrass beds
Landsat data
Linear mixture model
Change analysis
Cam Ranh Bay

ABSTRACT

Seagrass beds comprise a unique marine ecosystem that acts as a biofilter in marine environments and serves as a spawning ground and nursery for various species of fish. Long-term monitoring of seagrass beds is critical to understanding the dynamic relationships between the ecosystems and the stresses from natural systems and society. This study investigated temporal changes of seagrass beds in Cam Ranh Bay (CRB), Vietnam using multi-temporal Landsat data from 1996 to 2015. The data were processed through 5 main steps including: (1) image preprocessing to convert Landsat data to the top of atmosphere reflectance (TOA) and to correct atmospheric effects, (2) water column correction to eliminate effects on remotely sensed data of aquatic environments, (3) image classification using a linear mixed model, (4) accuracy assessment using the ground reference data, and (5) change detection of seagrass beds. The classification results compared with the ground reference data indicated that the overall accuracies and Kappa coefficients were higher than 91.7% and 0.8, respectively, in all cases. From 1996 to 2015, the total area of seagrass beds had declined by approximately 25% (66 ha), mainly attributed to coastal development and infrastructure construction.

1. Introduction

Seagrasses are flowering plants commonly distributed in shallow water along coastlines, estuaries, bays, and lagoons. They serve as direct and indirect food for marine animals, including fish, dugong, and green turtles (Dai, 2011; Duarte, 2002; Fortes, 1990; Heck et al., 2003; Short et al., 2001). Seagrass beds provide the habitat for marine animals, stabilize sediments, and prevent soil erosion (Cabaço et al., 2008; Dai, 2011; Dai et al., 1999; Fortes, 1990), and their leaves can act as a biofilter by absorbing nutrients from coastal run-off (Spalding et al., 2014; Stapel et al., 1996; Vonk et al., 2008). They can also store organic carbon at levels two times higher than typical terrestrial forests per each km^2 (Fourqurean et al., 2012). In recent years, the seagrass loss rate has been increasing due to impacts of economic development, infrastructure, aquaculture farm constructions, urbanization, dredging, and turbidity and eutrophication in many locations such as, in the Gulf of Mexico, Indonesia, Philippines, Singapore, Thailand and Vietnam (Duarte, 2002; Erftemeijer and Robin Lewis Iii, 2006; Green and Short, 2003; Vo et al., 2013; Walker, 1996; Walker and McComb, 1992). It is thus necessary to monitor seagrass beds for environmental management and conservation.

Indicators of seagrass distribution are critically important for monitoring coastal ecosystem health. The presence/absence and spatial distribution of seagrasses are commonly used ecological indicators representing the status of seagrass ecosystems and the response to surrounding environments at the landscape scale. These response patterns or changes may be intimately tied to anthropogenic impacts, such as eutrophication, land-use changes, coastal development, boating, dredging, and agriculture. Cam Ranh Bay (CRB) is a region in Vietnam that has a large meadow of seagrasses with a high diversity of species. Because of aquaculture activities and socioeconomic development, however, seagrasses in the region have been seriously degraded; approximately 20–30% of the total area of seagrass was lost between 1998 and 2002 (Dai et al., 2002). Studies indicated that *Enhalus acoroides*, a dominant seagrass species usually flowering and fruiting during July to August, almost disappeared in this region because of anthropogenic activities (Dai et al., 2002). Despite these observations, no formal ecological study of seagrass monitoring has been conducted in the region. Thus,

* Corresponding author at: Department of Civil Engineering, National Central University, Taoyuan City 32001, Taiwan.
E-mail address: khinlau@yahoo.com (V.-K. Lau).

http://dx.doi.org/10.1016/j.ecoinf.2016.07.005
1574-9541/

understanding the spatiotemporal changes of seagrasses is critical to provide ecologists and economists in the region with information to improve sustainable management strategies for marine ecosystems.

Mapping seagrass beds in the study region is traditionally implemented through costly and time-consuming field surveys limited to small areas in either shallow (<10 m) or deeper (>10 m) waters by snorkeling or diving using 50 × 50 cm quadrat frames, cover sheets, and waterproof cameras (Green et al., 1996, 2000; Komatsu et al., 2003a; Komatsu et al., 2003b; Mumby et al., 1999; Sagawa et al., 2010). Remote sensing technologies such as aerial photography and satellites have been an indispensable tool for marine ecosystem monitoring, including change detection of seagrasses, because they can acquire data over larger regions. Mapping seagrass distributions by remote sensors could be influenced by various contributions from the atmosphere, water column, and sea bottom. Because the bottom signal is not always distinct, the signal received by remote sensors may be compromised by bottom features that appear as variations in the radiance directed toward the sensor. For example, seagrasses present in shallow waters with a light sandy bottom are distinguished easily by remote sensing images (Andréfouët et al., 2001; Andréfouët et al., 2003; Hochberg et al., 2003), yet a wide dynamic range of colors are required to distinguish a dark silty bottom with mixed seagrasses, mussel beds, and other covers types in deeper waters (Botha et al., 2013; Lyzenga, 1981).

Images of turbid and deep water with other dark features such as mussel beds, stones, or macroalgae are much more difficult to interpret than clear and shallow water environments where seagrasses grow in dense beds and constitute the only dark features on a sandy bottom (Andréfouët et al., 2001; Andréfouët et al., 2003; Hochberg et al., 2003). Low spatial resolution satellite images can be used only for macroscale mapping to catalogue the presence and absence of seagrass beds or coarsely assess the area distribution of seagrass beds (Ferguson and Korfmacher, 1997; Pu et al., 2014; Wabnitz et al., 2008). Many mapping methods use high spatial resolution satellite images to map macroalgae and seagrasses in the intertidal regions at a scale of 2 to 20 m pixel size to investigate the distribution of seagrass beds for change detection or to estimate the biomass (Mumby and Edwards, 2002; Phinn et al., 2008; Sagawa et al., 2010; Valle et al., 2015). The use of high spatial and spectral resolutions of hyperspectral satellite images for seagrass mapping usually produces results with wide coverage and are easily georectified, enabling a photo-interpreter to differentiate between objects with colors that appear identical (Table 1).

Even high-resolution satellite images have several limitations: (1) narrow coverage of spectral bands in hyperspectral remote sensing; (2) limited temporal resolution; (3) high photographic distortion; (4) low radiometric resolution; (5) cloud contamination (i.e., in optical remote sensing); (6) mapping inaccuracies of seagrass meadows caused by the growth of epiphytes, seagrasses cover density, varying water depth, and changing optical properties of overlying water driven by seagrass die-back in anoxia and high temperature environment; (7) interpretation difficulty in deep and turbid waters, especially in low light or when water transparency is disturbed by high nutrient concentrations; (8) highly variable sun-glint reflection from all directions in image (i.e., especially in air-borne remote sensing); (9) errors due to converting analogue air-borne photos to digital images, and (10) high costs when high spatial and spectral resolutions are required (Mumby et al., 1999). Nevertheless, multispectral Landsat data with 30 m spatial resolution are a good candidate for this monitoring purpose over a multi-decadal scale because they are free of charge, and historic archives from Landsat TM to Landsat ETM+ and to Landsat OLI have existed since the 1970s. Integration of these three satellite sensors without the need for extra bias corrections in the cross-sensor data merging allows homogeneous multisensor image processing to support a long-term seagrass monitoring mission.

Sophisticated feature extraction and content-based mapping are essential to retrieving useful information in many circumstances, especially when interpretation becomes difficult in deep and turbid waters, triggering formulation of additional semiempirical or empirical feature extraction models. A number of methods have been developed for feature extraction and for seagrass mapping, including principal component analysis (PCA) (Ferguson and Korfmacher, 1997; Pasqualini et al., 2005), normalized difference vegetation index (NDVI) (Barillé et al., 2010), and leaf area index (LAI) combined with additional in-situ optical data of water leaving radiance and attenuation coefficient (Yang et al., 2011). These studies did not consider effects of the water column, however, and ignoring this processing step could reduce the mapping accuracy by approximately 22% and 17% when using an airborne hyperspectral imaging device such as Compact Airborne Spectrographic Imager (CASI) and satellite data, respectively (Mumby et al., 1998).

The depth invariant index (DII) (Lyzenga, 1981) and bottom reflectance index (BRI) (Sagawa et al., 2010) are two commonly used water column correction methods based on the bottom reflectance equation that considers the reflectance through water decreasing exponentially with an increase in water depth. The DII used to indicate sea bottom types without using bathymetry data is based on the unchanged characteristic of the y-intercept value (i.e., invariant index) of relations between two visual bands associated with the water depth on the same substrate (Lyzenga, 1981). The BRI uses bathymetry data of a substrate to obtain attenuation coefficients from a reflectance function using exponential regression analysis; the coefficients are then used to obtain the BRI, which is then used to indicate the bottom type (Sagawa et al., 2010). The classification of seagrass beds using BRI could improve the overall accuracy by 21–36% compared to DII (Sagawa et al., 2010; Sagawa et al., 2012).

The main objective of this study was to investigate the potential use of multi-temporal Landsat data with appropriate water column corrections for seagrass mapping and conduct multi-temporal change detection of five key seagrass beds in CRB of Vietnam (i.e., five key study regions) during the periods 1996–2001, 2001–2005, 2005–2010, 2010–2013, and 2013–2015. The case study allows us to determine if the integrated Landsat data could support a holistic seagrass mapping over the anticipated spatial and/or temporal time scales. To overcome water column impact on reflectance, we used the BRI to remove the water column effects followed by the linear mixed model (LMM) to quantify the abundance fraction of seagrass beds in each pixel (Gokul et al., 2014; Philpot, 1989; Schroeder et al., 2006). This type of multi-temporal change detection may help answer the following questions: 1) which key study region suffered from the biggest net loss of the seagrass bed over the five study periods; and 2) can the new seagrass bed outweigh the loss of seagrass bed over the five study periods? The

Table 1
Accuracy consideration for mapping seagrass beds with satellite and air-borne sensors (Blakey et al., 2015; Lyons et al., 2012; Mumby et al., 1997; Pasqualini et al., 2005; Sagawa et al., 2010; Wabnitz et al., 2008).

Type of images	Landsat TM/ETM	SPOT XS/5	CASI	Aerial photography
	Space-borne high resolution multispectral images	Space-borne high resolution multispectral images	Air-borne high resolution hyperspectral images	Air-borne high resolution multispectral images
Accuracy of the map (%)	≤88	≤96	<90	≤90
Coverage per scene (km)	185 × 185	60 × 60	Variable	Variable