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Mapping and assessing seagrass along the western coast of Florida using Landsat TM and EO-1 ALI/Hyperion imagery

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A B S T R A C T

Seagrass habitats provide a variety of ecosystem functions thus monitoring of seagrass habitat is a priority of coastal management. Remote sensing techniques can provide spatial and temporal information about seagrass habitats. Given the availability and accessibility of Landsat-5 Thematic Mapper (TM) and the advanced nature of Earth Observing-1 Advanced Land Imager (ALI) and Hyperion (HYP), we compared the capability of the three 30 m resolution satellite sensors and tested regression models based on two seagrass metrics [percent cover of submerged aquatic vegetation (%SAV) and leaf area index (LAI)] for mapping and assessing seagrass habitats within a shallow coastal area along the central western coast of FL, USA. We also evaluated a water depth correction approach to create water depth-invariant bands calculated from the three sensors' data. Then a maximum likelihood classifier was used to classify the %SAV cover into two classification schemes (3-class and 5-class). Based upon the two seagrass metrics measured in the field, six multiple regression models were developed and %SAV and LAI were estimated with spectral variables derived from the three sensors to assess the seagrass habitats in mapped units. Our results indicate that the HYP sensor produced the best seagrass cover maps in the two classification schemes: 3-class [overall accuracy (OA) = 95.9%] and 5-class (OA = 78.4%) and the best %SAV and LAI estimation models [R^2 = 0.78 and 0.59, and cross-validation (CV) = 18.1% and 1.40 for %SAV and LAI, respectively] for assessing seagrass habitats. These results are likely due to the many narrow bands in the visible spectral range and rich subtle spectral information available in the HYP hyperspectral data. ALI outperformed TM (OA = 94.6% *vs*. 92.5% for the 3-class scheme, and OA = 77.8% *vs*. 66.0% for the 5-class scheme) for mapping %SAV likely due to its higher radiometric resolution. Our findings also demonstrate that the water depth correction approach was effective in mapping the detailed seagrass habitats with the data from the three sensors. The protocol developed and utilized here represents a new contribution to the existing set of tools used by researchers for documenting the amount of seagrass and which can guide future studies.

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1. Introduction

Seagrass meadows are characteristic features of shallow marine waters worldwide and are extensive in the Gulf of Mexico (Iverson and Bittaker, 1986). Seagrass habitats provide a variety of ecosystem functions including the provision of food and shelter for many fauna, imparting stability to sediments, and the regulation of nutrient cycles and water turbidity. Thus preservation of seagrass habitats is intimately related to the sustainability of overall coastal ecosystem function (Bell et al., 2006; Sagawa et al., 2010). Quantification of the extent and persistence of seagrass habitats remains an important component of nearshore monitoring and management of this underwater resource (Phinn et al., 2008).

For decades, a variety of methods have been used for mapping and monitoring of seagrass habitats in shallow coastal waters including the use of optical remote sensing in many locations. Traditionally this relied on the use of aerial photography (e.g., Chauvaud et al., 1998; Meehan et al., 2005), and more recently moderate-spatial resolution multispectral satellite image data: Landsat Multispectral Scanner (MSS) (e.g., Ackleson and Klemas, 1987), Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+) (e.g., Schweizer et al., 2005; Dekker et al., 2005; Shapiro and Rohmann, 2006; Gullström et al., 2006; Roelfsema et al., 2009), and Satellite Pour l'Observation de la Terre (SPOT) image

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data (e.g., Pasqualini et al., 2005). Recent developments and improvements in multispectral and hyperspectral remote sensing have raised interest in the possible use of these methods to map and monitor benthic habitats. For example, researchers have used high-spatial resolution satellite image data such as IKONOS and QuickBird image data (e.g., Fornes et al., 2006; Mishra et al., 2006), and hyperspectral remote sensing data (e.g., Peneva et al., 2008) and have provided improvements in mapping and monitoring seagrass habitats under some conditions. Each method has advantages and limitations however. For example, optical imagery is limited to optically shallow waters (i.e., generally between 0 and 20 m depth) (Mount, 2007) and is less useful in highly turbid locations, often observed in shallow water settings. Yet optical imagery remains one of the most widely used data sources for mapping seagrass habitats and enables comparisons with historic archives (Leriche et al., 2004).

Currently the majority of tools and methods developed for mapping seagrass habitats using optical remote sensing classify seabed habitats only into several broadly defined classes and usually lack details on seagrass species composition or measures of seagrass canopy, such as LAI (e.g., Yang and Yang, 2009). For example, in the regional-scale seagrass habitat mapping using multi-scene Landsat sensors (TM/ETM+) in the Caribbean region, Wabnitz et al. (2008) used a total of 40 Landsat scenes to classify the region into dense seagrass, medium-sparse seagrass and a generic 'other' class after carrying out processing steps including geomorphologic segmentation, contextual editing and supervised classifications. The overall classification accuracies ranged from 46% to 88%. Similar seagrass and benthic habitat mapping was conducted by Cerdeira-Estrada et al. (2008) in the Gulf of Batabanó, southwest of the island of Cuba. Five benthic habitats types (medium to high density seagrass, low-density seagrass, sand with scarce vegetation, mud with scarce vegetation and rock) were identified and mapped using a supervised classification technique with Landsat ETM+ imagery. Gullström et al. (2006) and Shapiro and Rohmann (2006) mapped benthic habitats with Landsat TM/ETM+ images, and used a grouping method that included distinguishing among three benthic habitat types [seagrass, other submerged aquatic vegetation (e.g., macroalgae) (SAV), and non-vegetated sediments]. The results of both studies demonstrated the efficacy of using moderate-spatial resolution satellite imagery to map benthic habitats, including seagrass beds. Detailed studies, such as that by Roelfsema et al. (2009), which created five cover classes for seagrasses (0%, 1–25%, 25–50%, 50–75%, 75–100%) from a classification of Landsat TM images and accompanying field data, are generally lacking. In general, the "coarse" information currently reported at moderate-spatial resolution may not be useful for decision-making activities that require assessment of changes in extent and abundance of seagrass beds.

Although the importance of characterizing seagrass habitats as a tool/product for seagrass management and monitoring is likely well-recognized, only a few of studies have utilized products from satellite imagery to assess seagrass habitat, typically linked to measuring seagrass abundance (canopy cover or biomass) and/or productivity. Among such studies, a diversity of approaches (sensors used; protocols developed) have been employed. Phinn et al. (2008) used Landsat TM, QuickBird and hyperspectral airborne CASI-2 images to map seagrass resources using above ground biomass and seagrass species in shallow waters. Dierssen et al. (2003) discussed development of a methodology to quantify the distribution and LAI of the seagrass, *Thalassia testudinum*, using a hyperspectral sensor which they argued could be used in seagrass assessment or monitoring. Schweizer et al. (2005) characterized SAV by mapping biomass using images provided by Landsat ETM+ data, although the classification scheme was limited. Mumby et al. (1997a, b) also estimated seagrass standing crop (biomass) from Landsat TM which could be compared over time, but they also recognized some major limitations of their approach, especially for low to moderate levels of seagrass cover. Therefore, it would be instructive to evaluate and compare the advantages of different satellite sensors with same spatial resolution for monitoring and assessing seagrass from the same location while also applying the same spectral data processing.

The main purpose of our study was to expand upon past studies and evaluate the relative effectiveness of data of three moderate-spatial resolution satellite sensors [Landsat-5 TM, Earth Observing-1(EO-1) Advanced Land Imager (ALI) and Hyperion (HYP) hyperspectral sensor] as tools for mapping and assessing seagrass habitats in coastal areas along the mid-western coast of Florida, USA. Of special interest was a comparison of data provided by each sensor spectral characteristics (spectral resolution and number of bands) at the same spatial resolution. Specifically, in this study, we: (1) compared the capability of the three satellite sensors for mapping detailed 3- and 5-class seagrass classes; (2) evaluated the applicability of a water depth correction approach to optical image data in an effort to improve the overall accuracy of classification; (3) tested the use of multiple regression models for estimating two seagrass metrics, %SAV (here defined as all seagrasses plus infrequently encountered rhizophytic algae) and Leaf Area Index (LAI) of multiple seagrass species, based upon spectral variables extracted from the three sensors's data; and (4) assessed relationships between spectral features extracted from the three sensors and two metrics of seagrass abundance: %SAV and LAI.

2. Materials and methods

Fig. 1 presents a flowchart of mapping and assessing seagrass habitats with the three satellite sensors' data and field survey data. After image preprocessing, the depth-invariant bands calculated from the visible bands of the three sensors, together with field survey data, were used to map 3- and 5-class detailed seagrass groupings using a supervised classifier. Meanwhile, spectral features/variables (individual reflectance bands, depth-invariant bands, and vegetation indices) extracted from the preprocessed image data were used to develop regression models with two seagrass metrics: %SAV and LAI, based upon field survey data. Finally, the detailed 5-class seagrass maps and developed seagrass metric regression models were used to create pixel-based %SAV and LAI maps in order to quantify seagrass resources in the study area.

2.1. Study area and data sets

2.1.1. Study area

The study area (center: 28°03′36″N, 82°48′45″W), approximately 105 km^2, is located along the northwest coastline of Pinellas County (Fig. 2), FL, USA. These areas are characterized by extensive development of subtropical seagrass meadows in shallow, relatively clear waters (Meyer and Levy, 2008). The substrate consists of unconsolidated soft sediments including a range of muddy to shelly sands with occasional hard bottom areas. The water depth ranges from 0 to 4 m (mean low water, MLW) with the majority of seagrass habitats limited to water depths of $<$3 m. Three seagrass species are numerically dominant: *Syringodium filiforme*, *Thalassia testudinum*, and *Halodule wrightii*. Occasionally *Halophila engelmanni* occurs sparsely within the seagrass beds. In addition, a variety of marine rhizophytic algae, with values up to 80% coverage in selected locations, are mixed with seagrass, based on field observations.

2.1.2. Data sets

2.1.2.1. Satellite imagery. Data from three satellite sensors were acquired. Landsat TM data were acquired on Oct. 1, 2009 while

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