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Salt marsh elevation and habitat mapping using hyperspectral and LIDAR data

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ABSTRACT

Accurate mapping of both elevation and plant distributions in salt marshes is important for management and conservation goals. Although light detection and ranging (LIDAR) is effective at measuring surface elevations, laser penetration is limited in dense salt marsh vegetation. In a previous study, we found that LIDAR-derived digital elevation model (DEM) error varied with vegetation cover. We derived cover-class-specific correction factors to reduce these errors, including separate corrections for three different height classes of *Spartina alterniflora*, the dominant macrophyte in southeastern U.S. salt marshes. In order to apply these cover class-specific corrections, it is necessary to have information on the distribution of cover classes in a LIDAR-derived DEM. Hyperspectral imagery has been shown to be suitable for the separation of salt marsh vegetation species by spectral signatures, and can be used to determine cover classes; however, there is persistent confusion both among the different height classes of *S. alterniflora* and between plants and mud (the *Spartina* problem). This paper presents a method to overcome the respective limitations of LIDAR and hyperspectral imagery through the use of multisensor data. An initial classification of hyperspectral imagery based on the maximum likelihood classification algorithm was used in a decision tree in combination with elevation and normalized difference vegetation index (NDVI) derived from the hyperspectral imagery to map nine salt marsh cover classes. The decision tree appreciably reduced the *Spartina* problem by reassigning classes using these ancillary data and resulted in a final overall classification accuracy of 90%, with a quantity disagreement of 1% and an allocation disagreement of 9%. The resulting hyperspectral image classification was then used as the basis for applying cover class-specific elevation correction factors to the LIDAR-derived DEM. Applying these correction factors greatly improved the accuracy of the DEM: overall mean error decreased from 0.10 ± 0.12 (SD) to -0.003 ± 0.10 m, and root mean squared error from 0.15 to 0.10 m. Our results suggest that the use of decision trees to combine elevation and spectral information can aid both hyperspectral image classification and DEM elevation mapping.

1. Introduction

Salt marshes are intertidal wetlands typically found in association with estuaries in temperate coastal areas. Salt marshes are susceptible to habitat loss due to changes in sea level and coastal flooding, and there is growing interest in obtaining accurate elevation maps for these areas in order to understand how small topographic differences affect water flow, sediment distribution, and the extent and frequency of tidal inundation (Gesch, 2009; Sanders, 2007). Salt marshes occupy a narrow vertical range of less than a meter to 2 m and small differences in elevation can alter flooding regimes. For example, in a Dutch salt marsh a 4 cm elevation difference resulted in 15 to 20 minute changes in the duration of tidal submergence (Scholten and Rozema, 1990). Differences in elevation also affect plant distributions, as salt marsh macrophytes exhibit characteristic patterns of vertical zonation: elevation differences of less than 10 cm have been shown to significantly influence species patterns in marshes (Callaway et al., 1990; Silvestri, Marani, & Marani, 2003; Suchrow and Jensen, 2010). In salt marshes in the southeastern U.S., the height of *Spartina alterniflora*, the dominant plant, is affected by elevation, with taller plants found growing in low areas closest to the water's edge and medium and shorter plants at higher elevations (Weigert & Freeman, 1990). A variety of other plants, including *Juncus roemerianus*, *Salicornia virginica*, *Batis maritima*, *Distichlis spicata* and *Borrichia frutescens*, are typically found in the highest parts of the marsh. Gradients in elevation are also associated with a range of changes in soil characteristics, including oxygen availability and redox potential (Mitsch & Gosselink, 2000; Pezeshki, 2001), soil moisture and porewater salinity (Adam, 1990), and concentrations of sulfides and nutrients (Gallagher, 1975; Mendelssohn & Morris, 2000). Elevation maps at the resolution that controls both flooding and vegetation patterns are therefore important for understanding inundation patterns

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and for determining habitat characteristics of salt marshes (Adam, 1990; Silvestri et al., 2003; Zedler et al., 1999).

Many coastal researchers use light detection and ranging (LIDAR) to produce digital elevation models (DEMs) of salt marshes, as LIDAR provides broad coverage for areas that are large and sometimes difficult to access on the ground. However, there are several drawbacks to this approach. First, LIDAR tends to overestimate salt marsh elevations due to poor laser penetration of the dense canopy (Montane & Torres, 2006; Rosso, Ustin, & Hastings, 2006; Sadro, Gastil-Buhl, & Melack, 2007; Schmid, Hadley, & Wijekoon, 2011). The majority of prior studies have focused on improving techniques to separate LIDAR returns (Wang et al., 2009) and optimizing DEM interpolation methods (Schmid et al., 2011; Toyra, Pietroniro, Hopkinson, & Kalbfleisch, 2003), both of which can help to reduce errors. These corrections have been applied without taking plant species into account, and have had vertical accuracies (mean error) ranging from −0.02 to 0.12 m. In a previous study (Hladik & Alber, 2012), we found that LIDAR-derived DEM mean error varied with vegetation cover in salt marshes. Of particular importance was the finding that tall, medium, and short height classes of *S. alterniflora* required significantly different correction factors, ranging from 0.05 to 0.25 m. However, overall mean error could be reduced to −0.01 m by applying cover-class-specific correction factors to four test areas (total area of 0.107 km^2). Using these correction factors requires information on the distribution of cover classes throughout the study area, which was not available in the earlier study. A second, related limitation of topographic LIDAR is that it only receives spectral information at one wavelength in the near infrared (NIR). It therefore cannot be used to distinguish among plant species, which requires information from the visible portion of the electromagnetic spectrum (Campbell, 2006). It should be noted that bathymetric or dual-band LIDAR systems are able to measure green, red and NIR wavelengths and have been successfully used to assess salt marshes as well as other coastal habitats without visible imagery (see Collin, Long, & Archambault, 2010, 2012 and references therein).

Hyperspectral imagery in the visible and NIR portion of the electromagnetic spectrum has been shown to be suitable for the separation of salt marsh vegetation species based on their spectral signatures (Artigas & Yang, 2005; Schmidt & Skidmore, 2003). Hyperspectral sensors are ideal for this purpose as they are able to collect a high number of contiguous spectral bands (sometimes greater than 200 bands) with narrow bandwidths and at a fine spatial resolution. Hyperspectral imagery has been used extensively in salt marshes to map vegetation patterns (Belluco et al., 2006; Hirano, Madden, & Welch, 2003; Silvestri et al., 2003; Wang, Menenti, Stoll, Belluco, & Marani, 2007), monitor invasive species (Gilmore et al., 2008; Rosso et al., 2006), document erosion and vegetation succession (Thomson, Huiskes, Cox, Wadsworth, & Boorman, 2004), measure biomass and species abundance (Lucas & Carter, 2008; Wang et al., 2007) and detect vegetation change (Klemas, 2011), among other applications.

There are several challenges in using hyperspectral imagery in salt marshes, particularly with respect to accurately classifying *Spartina* species. First, the different height classes of *S. alterniflora* (short, medium and tall), which represent user-defined classes along a height continuum, are commonly confused in hyperspectral imagery classifications due to their spectral similarity in both the visible and NIR portions of the spectrum (Artigas & Yang, 2005; Schmidt & Skidmore, 2003). Another source of error results from mixed pixels that include either more than one class of vegetation and/or mud. Both of these complications are observed with *S. alterniflora*: the different height classes can be found adjacent to one another, and *S. alterniflora*'s erect structure and often sparse density mean that mud is spectrally mixed with vegetation (Belluco et al., 2006; Silvestri et al., 2003; Thomson et al., 2003). Silvestri et al. (2003) found that *S. maritima* is often misclassified because it is found in low-lying areas where mud and water interfere with its spectral signature. Thomson et al. (2003) hypothesized that microphytobenthos on mud may also cause mud to resemble *Spartina* spectrally. The inability to accurately classify the three height classes of *S. alterniflora*, compounded by the presence of mud in mixed pixels, is what we term the *Spartina* problem. A solution to the *Spartina* problem is especially important for ecological studies as the *S. alterniflora* height classes can have significantly different biomass and productivity values (Morris & Haskin, 1990; Schalles et al., 2013; Turner, 1979).

One way to potentially overcome the individual limitations of LIDAR-derived DEMs and hyperspectral imagery, and to potentially address the *Spartina* problem, is through the use of multisensor data. Multisensor data integration combines data from different sources to improve classification performance and can include spectral, texture and/or ancillary data such as DEMs (Lu & Weng, 2007; Pohl & van Genderen, 1998). LIDAR-derived DEMs have been included as a component band with multispectral and hyperspectral imagery to classify coastal habitats (Chust, Galparsoro, Borja, Franco, & Uriarte, 2008; Sadro et al., 2007; Yang & Artigas, 2010) and as data layers in object-orientated classifications of salt marsh habitats (Brennan & Webster, 2006; Gilmore et al., 2008), resulting in improved classification accuracies. LIDAR-derived DEMs have also been combined with land cover classifications post hoc to refine and improve classification products for urban areas (Lu & Weng, 2004; Pal & Mather, 2003), to extract salt marsh species elevation ranges and distributions (Morris et al., 2005; Sadro et al., 2007), monitor the spread of invasive species (Rosso et al., 2006), model species habitat (Moeslund, Arge, Bocher, Nygaard, & Svenning, 2011; Sellars & Jolls, 2007), and predict the effects of sea level rise (Webster, Forbes, MacKinnon, & Roberts, 2006). The above studies have all used multisensor data for classification purposes or for extracting additional elevation information. However, none have used elevation data to refine their existing classification of salt marshes.

This paper describes our approach for combining hyperspectral imagery of the salt marshes surrounding Sapelo Island, GA with a LIDAR-derived DEM through a decision tree. A decision tree is a non-parametric multistage or hierarchical classifier that can be applied to a single image or multiple co-registered images (Breiman, Feidman, Olshen, & Stone, 1984). Using a multistage approach, a decision tree breaks down a complex decision into a series of nodes, or branches, where binary decisions are made to sequentially subdivide the data into predetermined classes. Data sources that can be used in decision trees include classified images, DEMs and vegetation indices. Although Pal and Mather (2003) found that decision trees performed poorly with high-dimensional hyperspectral data, we used a classified map (single band) as an input rather than the entire hyperspectral data set. Our workflow was: (1) to use hyperspectral imagery to initially classify nine salt marsh cover classes; (2) to improve vegetation classification accuracy and address the *Spartina* problem by incorporating elevation information and the normalized difference vegetation index through a decision tree; and (3) to combine the final vegetation classification with a LIDAR-derived DEM to produce corrected DEM elevations. The method we outline produced both an accurate habitat classification and DEM for the study area. This approach will be of specific use to those interested in developing accurate maps of salt marshes, but will also be more broadly applicable as a demonstration of the combined power of LIDAR and hyperspectral imagery through the iterative use of multisensor data.

2. Methods

2.1. Study site

This study included a total of 13.82 km^2 of salt marsh habitat in and around the Duplin River, a 13-km long tidal inlet that flows into Doboy Sound and forms the western boundary of Sapelo Island, Georgia, USA (UTM Zone 17 N, 471480 E 3473972 N, Fig. 1). The site is located in the Georgia Coastal Ecosystems Long Term Ecological Research domain and the Sapelo Island National Estuarine Research Reserve. The inlet is surrounded by a complex of salt marshes, tidal creeks and back barrier