

Characterization of Coastal Wetland Systems using Multiple Remote Sensing Data Types and Analytical Techniques

Daniel Civco, James Hurd, and Sandy Prisloe

Center for Land use Education and Research

University of Connecticut

Storrs, CT 06269-4087 USA

daniel.civco@uconn.edu

james.hurd_jr@uconn.edu

michael.prisloe@uconn.edu

Matha Gilmore

Earth and Environmental Sciences

Wesleyan University

Middletown, CT 06459-0139 USA

mgilmore@wesleyan.edu

Abstract — A multistage process for classifying coastal marshes using a rule-based object-oriented procedure applied to Landsat ETM data is discussed. The method, which uses both spectral and spatial criteria, produces classifications more useful than those based on per-pixel, spectral data-alone techniques. Analysis of co-registered high resolution LIDAR-derived elevation and ADS40 CIR imagery has demonstrated it is possible to discriminate among areas dominated by *Phragmites australis*, *Typha spp.* and *Spartina patens*.

Keywords—Connecticut; Long Island Sound; salt marsh; vegetation, classification; Landsat; LIDAR; ADS-40

I. INTRODUCTION

The tidal wetlands within the Long Island Sound estuary serve a critical role in maintaining the health of the Sound. Over the past two centuries, there has been significant disturbance and loss of tidal wetlands along the Sound due primarily to anthropogenic activities. Researchers at the University of Connecticut and Wesleyan University are continuing on the second year of a two year project to document the extent and vegetative composition of coastal marshes using moderate to high resolution satellite imagery from Landsat ETM+, Terra ASTER and QuickBird sensors, very high resolution airborne ADS40 imagery and high density LIDAR data in conjunction with *in situ* field measurements of plant spectra.

This paper details continuing work on two of the major aspects of the overall project: (1) tidal wetland classification from Landsat imagery, and (2) use of LIDAR data to aid in discriminating and mapping tidal marsh plant communities. Another key aspect of this research addresses the classification of tidal wetland communities using multi-temporal, single-season Quickbird imagery and *in situ* spectroradiometry.

The collective results of this research will provide a beneficial tool for coastal wetland management and monitoring along the Long Island Sound estuary.

II. PROCEDURES

A. Study Areas and Data

1) Landsat-based Sound-wide Coastal Marsh Mapping

The area of interest consists of the entire Long Island Sound coastal region located in the Northeastern United States. In addition to the coastal regions, the study area extends up the tidally-influenced portions of the three rivers (Housatonic, Connecticut, and Thames) that serve as the primary source of freshwater to the Sound. Of the three major rivers that drain into the Sound, the Connecticut River watershed covers 71% of the overall area and contributes about 64% of the fresh water. The Sound is classified as an estuary because it is a place where salt water and fresh water mix, but unlike most estuaries, the Long Island Sound is open on both ends – at the Race at the eastern end, and the much more narrow East River and New York City Harbor at the western end. Mean tidal range varies from 0.7 meters in the east to 2.3 meters in the west. This significant difference is due to tidal resonance and the shape of the Sound.

This analysis focuses on just the coastal region of Long Island Sound. A Landsat ETM image acquired on September 8, 2002 was clipped to create an analysis region that includes tidal marshes and adjacent uplands. This region was created based on the (1) generation of a *wetness* layer using the difference between Landsat bands 2 and 5, (3) the application of a threshold to this layer to discriminate upland from coastal water and wetland areas, (4) the buffering of the water-land layer to 1.2 km inland, and (5) the extraction of pixels from the original September 8, 2002 Landsat ETM image from within just the buffer to be used in the image analysis.

2) LIDAR-based Analysis of Marsh Plant Species

The Ragged Rock tidal marsh is approximately 1.4 km² in area, located on the west bank of the Connecticut River approximately 3 km from where the river discharges into Long Island Sound. The marsh is a brackish tidal marsh subject to diurnal flooding. Much of the area of the marsh has been ditched to provide drainage of the marsh surface in an effort to reduce mosquito breeding areas, but the marsh has been spared other modifications including any *Phragmites* control

measures. A small rectangular section of the southwest corner of the marsh and adjacent upland areas was selected for the study. The study area covered approximately 0.4 km² and measures approximately 0.6 km east-west by 0.6 km north-south.

Preliminary field work conducted in summer 2005 found more than 30 plant species in the marsh portion of the study area; however, the dominant species were *Phragmites australis*, *Typha angustifolia*, *Typha xglauca* and *Spartina patens*. Other common species included *Spartina cynosuroides*, *Solidago sempervirens*, *Panicum virgatum*, *Schoenoplectus americanus* and *Schoenoplectus pungens*. In general, the *Phragmites* and *Typha spp.* tend to grow as dense monocultures except at the stand edges where newer growth tends to be less dense and intermixed with other plant species. Distinct communities of *Spartina patens* also are located throughout the study site. In many cases they exist as complex mosaics with intermixed areas of *S. sempervirens*, *P. virgatum*, *S. americanus*, *S. pungens* and other less common species.

LIDAR data, collected on October 8, 2004 as part of a NOAA Coastal Services Center Coastal Remote Sensing project, were provided by Woolpert LLP. LIDAR data were collected at a height of 3,000 feet (914 m) using a Leica ALS50 airborne laser scanner. Two returns per pulse (first and last) were recorded. LIDAR data points had a nominal ground sampling distance of 0.9 m. The reported horizontal accuracy was 0.5 m and the reported vertical accuracy was 0.002 m based on the average error between the bare-earth DEM and 21 ground control points.

16-bit Leica ADS40 color and CIR orthoimagery with 0.5 m resolution were acquired on September 20 and 22, 2004 by EarthData, Inc. The data were delivered as two sets of 122 tiles each (one RGB and one CIR) referenced to UTM Zone 18N, NAD83, GRS80.

B. Methods

1) Landsat-based Sound-wide Coastal Marsh Mapping

The classification of coastal marshes was accomplished through a series of image processing and pattern recognition procedures.

a) Unsupervised Classification (ISODATA clustering)

Cluster-busting was employed to refine iteratively the results of unsupervised classification. One-hundred fifty initial clusters were labeled as water, tidal marsh, upland, or other (uncertain) in a first pass. Of the remaining 100 uncertain clusters, 50 were assigned to a land cover class, and in a final third pass, the remaining uncertain clusters were labeled. To remove many of the isolated coastal marsh pixels falsely identified in the upland regions, and to smooth the overall result, a 3x3 majority filter was used. This resulting layer serves as the pixel-based classification that is applied to the integration with the object-based classification.

b) Object-oriented Classification

Object-oriented classification is the process of classifying image objects rather than individual pixels. Image objects are

created through multiresolution segmentation which is the process of grouping contiguous pixels with similar qualities (i.e., spectral similarity) based on information from one or more input layers. For this research, image segmentation and object-based classification was performed using Definiens Imaging's eCognition.

Input data to the eCognition project consisted of the six Landsat ETM reflective bands, Landsat ETM thermal band, Landsat ETM panchromatic band, derived NDVI, principal components 1, 2, 4, and 6, and the wetness layer. All layers were utilized for the object-based classification. To perform the multiresolution segmentation to derive the image objects, however, only four ETM reflective bands (red, NIR, MIR₁ and MIR₂), NDVI, PC₁, and the wetness layer were used. These layers were equally weighted in their contribution to the segmentation process.

Two hierarchical levels of segmentation were derived and used for classification. For large objects, the scale parameter was set to 75, color 0.9 (from 0 to 1), shape 0.1 (color and shape must sum to 1), smoothness 0.5 and compactness 0.5 (smoothness and compactness must sum to 1). Since the color parameter was set much higher than the shape parameter, the spectral information from the input layers was the most significant contributor to the creation of the larger image objects. These objects were classified as either water or upland, using exclusively the wetness layer as the identifying feature. Further, by employing a fuzzy decision rule, the class between that which is clearly upland and that which is clearly water (i.e., wetland) was distinguished.

Classification of nested, finer scale objects (scale parameter=15, color=0.9, shape=0.1, smoothness=0.5 and compactness=0.5) was performed using a combination of eCognition and RuleQuest Research's See5, a data mining tool producing a decision tree classifier developed by way of supervised training. At this finer scale, spatial as well as spectral variables were used, the former including measures such as object length, width, l-w ratio, shape index, and other spatial information such as the texture, size, shape, and context to other image objects. The set of classes identified at this finer scale included: Water-Rounded (ocean & lake), Water-Elongated (tidal creeks), Low Marsh, High Marsh, High Marsh-bright, Grass-yellow, Grass-green, Forest, Barren, Bright-Development, Dark-Development, Dense-Development, and Sparse-Development. The output decision tree from See5 was then re-created in eCognition using membership functions. Since tidal marshes were the target feature, only those branches and thresholds that classified these features were used.

c) Classification Integration

To combine the results of the ISODATA cluster-busting and object-oriented classifications, ERDAS Imagine's Knowledge Engineer was utilized. The Knowledge Engineer is a GUI used to design a rule-based, decision tree approach to classification. The decision tree is comprised of variables and a hierarchy of rules, which are conditional statements, to produce a final classification output. Input variables consist of the final ISODATA classification and the object-oriented classification. The following data layers were also included to improve the final classification result: PC₁, NDVI, Wetness, and elevation.

Final output classes consisted of water, upland, low marsh, and high marsh.

2) LIDAR-based Analysis of Marsh Plant Species

ASCII files of LIDAR data were added to ArcGIS 9.1 as an XY event layer and exported to shapefiles in UTM Zone18N, NAD83, coordinates. Nine tiles were merged into a single point shapefile and those points that fell within the area of the Ragged Rock tidal marsh were selected and exported as a shapefile. This file contained just over 3.75×10^6 point features. A subset of LIDAR point features also was extracted to cover the smaller study area. The file, which contained just over 1.0×10^6 point features, was used for analysis.

A question the research team wanted to investigate was the degree to which plant height and structure in the study area could be characterized using LIDAR non-ground returns. Field observations demonstrated that at this site there is distinct height stratification among marsh plant communities and it was hypothesized that comparable height classes could be derived from the LIDAR data.

In ArcGIS, several transects were digitized across the study area using an ADS40 CIR image for reference (see Figure 2 for example). All LIDAR point features within 0.5 m of each transect were selected and UTM XY coordinates were added as attributes to these data subsets. The UTM XY coordinates, Z values and class values were exported to Excel[®]. In general, *S. patens* is the dominant plant at lower height classes and *Typha* and *Phragmites* are the two higher classes.

Polygon boundaries of relatively pure patches of *P. australis*, *Typha spp.* and *S. patens* and edge patches between *P. australis* and *Typha spp.* and between *Typha spp.* and *S. patens* were digitized in ArcGIS using ADS40 CIR imagery for reference. Interestingly, within the study area there were no clearly visible large edge patches where *P. australis* transitioned directly into *S. patens*. The polygons were manually classified based on visual interpretation and with the aid of a set of GPS field points, collected in summer 2005, which recorded dominant plant species information. Polygons were overlaid on the LIDAR points and all non-ground LIDAR point features were extracted into a dataset. Descriptive statistics for LIDAR Z-values (in our case, height of plant canopy) for each class of vegetation were generated using JMP statistical software.

III. RESULTS

1) Landsat-based Sound-wide Coastal Marsh Mapping

Figure 1 provides a sample of the final integrated tidal marsh classification for a site near Stratford, CT, which can be compared to the September 8, 2002 Landsat ETM image used for the classification and a high spatial resolution ADS-40 image collected on September 22, 2004.

In addition, tidal marshes digitized by the Connecticut Department of Environmental Protection from color aerial imagery are outlined in white on each of the images. The sample shown here is representative of the quality of the tidal wetland detection from the Landsat ETM imagery throughout the Sound. As would be expected, larger marsh complexes are

identified more easily. The classification does only a fair job at identifying the smaller marsh complexes. Problem areas occur

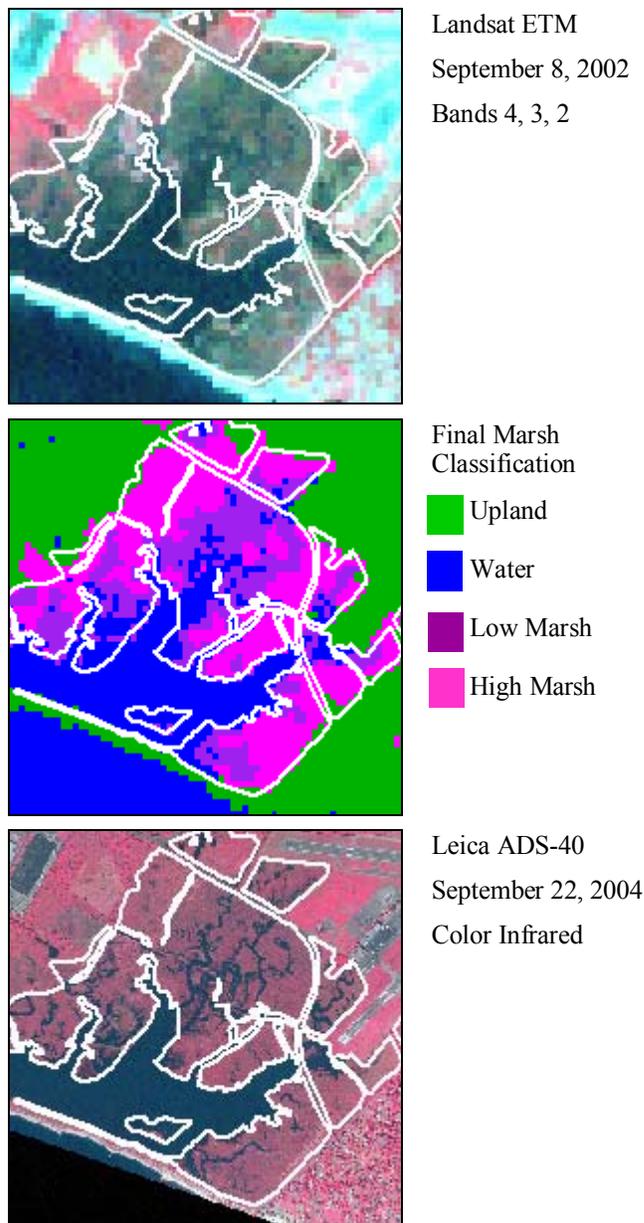


Figure 1. Results of the final integrated tidal marsh classification for a salt marsh near Stratford, CT compared with the Landsat ETM image used for classification and a high spatial resolution ADS-40 image. The white outlines represent tidal marshes delineated from aerial imagery by Connecticut Department of Environmental Protection personnel.

near the boundary between the tidal marshes and upland forested areas and within the high marsh complex where there is confusion between tidal marsh and upland image objects. Small tidal marsh complexes are difficult to detect due to the spatial resolution of the Landsat ETM sensor being larger than many of these areas and the associated mixed pixels that subsequently occur. As a note, the distinction between high marsh and low marsh is a result of how wet the area is as opposed to specific vegetative cover.

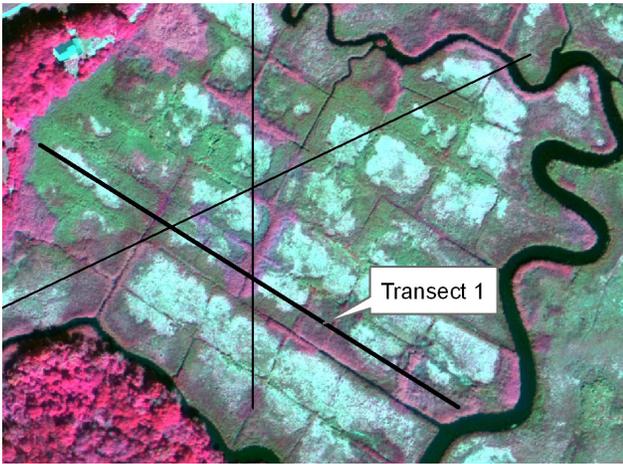


Figure 2. Leica ADS40 color infrared image of a portion of the Ragged Rock salt marsh study area.

2) LIDAR-based Analysis of Marsh Plant Species

Values for relatively pure stands of *P. australis*, *Typha spp.* and *S. patens* and for the two edge patch classes are reported in Table 1. Frequency distributions and box plots of the same data are shown in Figure 3.

Figure 4 shows the grid data reclassified into four height groups; three which represent the dominant vegetation classes and the fourth group being upland areas outside the marsh. Vegetation class breaks were set at 2 standard deviations above the mean LIDAR heights for the 3 dominant plant communities (see Table 1).

IV. CONCLUSIONS

The primary objective of Long Island Sound-wide aspect of this research was to produce a robust yet repeatable method to identify tidal marshes of various sizes from readily available image and ancillary data. Preliminary results indicate a moderate level of success in meeting this goal. Future work will validate further the success of this classification technique in terms of providing an accurate, quick, and repeatable method of identifying tidal marshes. Is there a benefit in integrating two different classification techniques to improve the overall classification accuracy? An initial response would be “yes” each method serves to validate the result of the other. The problem still exists, however, of how to deal with classified pixels that do not agree. This remains a subjective issue that must be resolved during the integration process either by favoring one technique over the other, or by extracting pixels that do not agree and classifying them further as in this project. In addition, the inclusion of elevation data proved extremely valuable in eliminating misclassification of tidal marshes in the upland areas. Despite some of the shortcomings, it is believed

that the final resulting tidal marsh classification provides a beneficial tool for coastal wetland management and monitoring of tidal wetlands along the Long Island Sound estuary.

Preliminary work with the LIDAR data has demonstrated that it effectively can be used to help characterize plant heights for the three species of interest. Based solely on LIDAR non-ground returns, it is possible to discriminate among areas dominated by *P. australis*, *Typha spp.* and *S. patens*. Since we were unable to extract a bare-earth DEM from the LIDAR data, we were unable to use the data to measure actual plant heights and to map subtle changes in the marsh surface.

A visual comparison of Figures 2 and 4 shows a strong correlation between the vegetation groups that can be seen in the ADS40 CIR image and the vegetation height classes created from the LIDAR data. Future image classification and field work will provide additional data with which we will assess the LIDAR data and their potential uses to improve classification.

The next phase of the research will involve two activities; (1) extending the LIDAR analysis to the entire area of the Ragged Rock tidal marsh, and (2) segmenting LIDAR data and Quickbird imagery in eCognition and developing a rule-based classification hierarchy to produce more detailed and accurate vegetation maps of the marsh. Of particular interest will be assessing the degree to which mixed vegetation communities, typical of portions of the *S. patens* dominated pans, can be identified through a combination of LIDAR and Quickbird data.

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Table 1. Descriptive LIDAR plant top-of-canopy height statistics for vegetation patches

	Count	Mean (meters)	Median (meters)	Standard deviation	Minimum Height	Maximum Height
<i>P. australis</i>	20780	3.0133	3.06	0.5210	-0.16	4.92
<i>Typha spp.</i>	9453	1.3670	1.37	0.2391	0.42	3.46
<i>S. patens</i>	13693	0.6390	0.63	0.0763	0.49	1.65
<i>Phrag-Typha edge</i>	2699	1.8124	1.81	0.7305	0.53	4.02
<i>Typha-patens edge</i>	1554	1.0337	0.98	0.3745	0.51	2.99

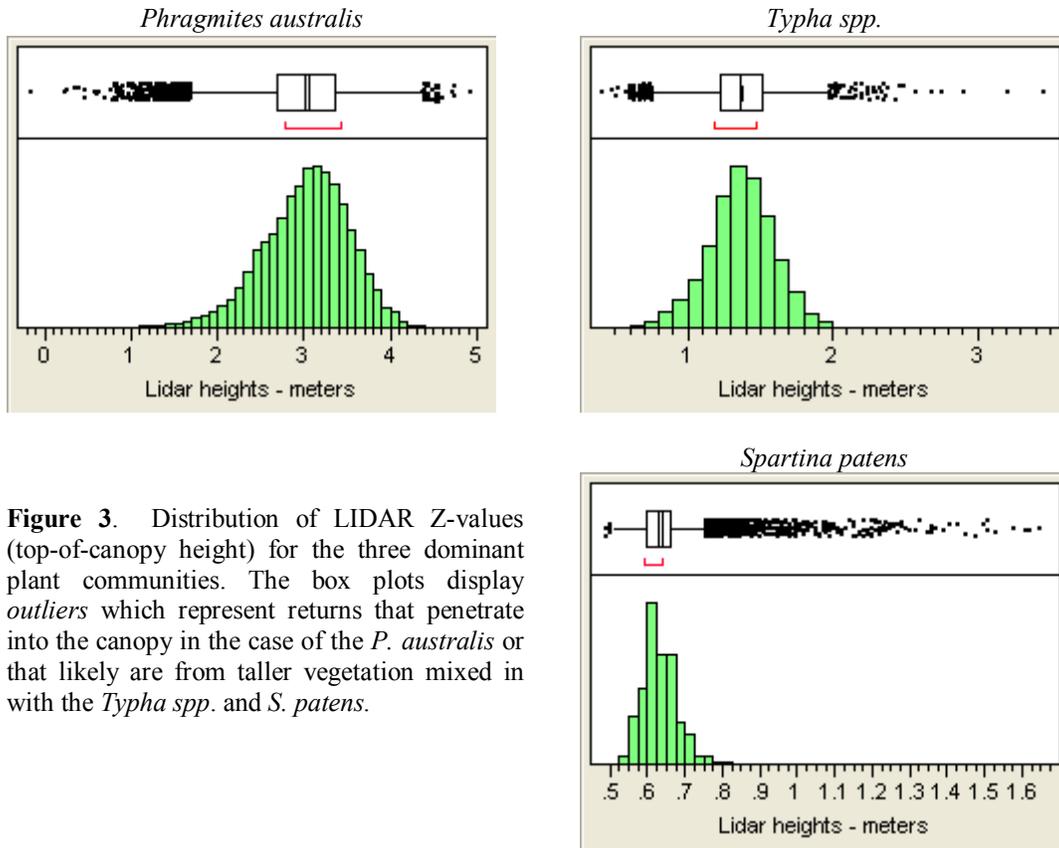


Figure 3. Distribution of LIDAR Z-values (top-of-canopy height) for the three dominant plant communities. The box plots display *outliers* which represent returns that penetrate into the canopy in the case of the *P. australis* or that likely are from taller vegetation mixed in with the *Typha spp.* and *S. patens*.

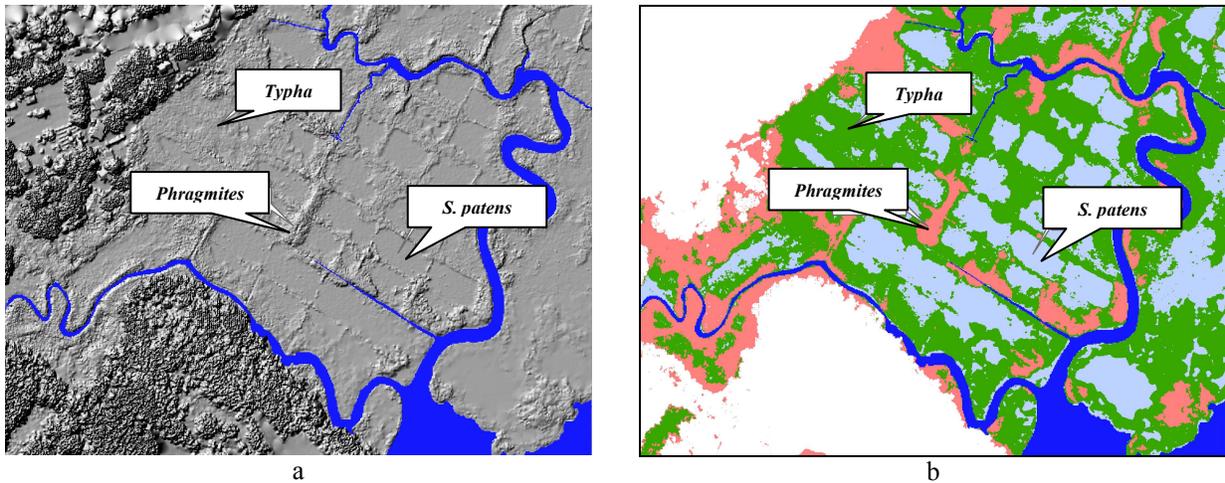


Figure 4. Shaded relief map of LIDAR generated vegetation canopy surface (a) and a grid reclassification of the vegetation canopy into 3 classes (b) that represent the general distribution of *P. australis*, *Typha spp.* and *S. patens*.