TIDAL WETLAND CLASSIFICATION FROM LANDSAT IMAGERY USING AN INTEGRATED PIXEL-BASED AND OBJECT-BASED CLASSIFICATION APPROACH

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ABSTRACT

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 resolution Landsat ETM+ and Terra ASTER satellite imagery and high resolution QuickBird satellite and Leica ADS40 aerial imagery in conjunction with *in situ* field measurements of plant spectra. This paper will detail research to classify tidal wetlands throughout Long Island Sound from Landsat satellite imagery. The goal of this portion of the project was to produce an accurate base map that identifies the location of tidal wetlands. An integrated classification approach which uses both pixel-based and object-based classification techniques was utilized. The classification serves as a base map to compare with subsequent dates of imagery to monitor any changes in tidal wetland extent and also compared with existing land cover maps to identify any upland changes in close proximity to the wetlands that could cause potential detrimental impacts to the tidal marsh system. The results of this research will provide a beneficial tool for coastal wetland management and monitoring along the Long Island Sound estuary.

INTRODUCTION

Tidal marshes are among the most productive environments in the northeastern United States and serve as a critical component of the Long Island Sound ecosystem. However, over the past century, a significant amount of these wetlands has been lost due to development, filling, and dredging, or damaged due to other anthropogenic disturbance and modification and natural events. Global sea level rise is also likely to have a significant impact on the condition and health of these tidal marshes, particularly if the marshes have no place to migrate due to dense coastal development (*e.g.,* Donnelly and Bertness, 2001).

Due to these anthropogenic and natural influences on tidal marsh areas, it is becoming increasingly important to identify and inventory the current extent and condition of tidal marshes located throughout the Long Island Sound estuary and to assess what is changing in the upland regions in close proximity to the individual marsh ecosystems. Currently the State of Connecticut acquires high-resolution color infrared photographs at approximately five-year intervals to monitor environmental conditions and landscape changes along the Connecticut coast. New York State collects similar color aerial photographs for Long Island which are interpreted by experienced analysts to produce useful information in terms of the extent of coastal land cover. With the rapid change in land cover occurring in the upland regions, 5-year intervals may not be frequent enough. More frequent collection of digital, multispectral remote sensing image data may provide an intermediate approach to monitoring the location and changes to the tidal marsh ecosystems. With revisit periods as frequent as every four days with ASTER and 16 days with Landsat, satellite remote sensing affords the opportunity to monitor intra-seasonal change. This capability is critical to identifying times when marsh species are most distinctive during the growing season. Digital remote sensing data are radiometrically and geometrically corrected and can be immediately compared to other data sets using GIS. Digitization, radiometric calibration, geometric correction, and mosaicking of analog aerial photographs are time-consuming, complicated processes, but are necessary if this form of imagery is to be computer-processed and integrated into a GIS. Radiometry is also preserved and recorded directly in a digital remote sensing image, whereas the same information must be derived from an aerial photograph (*e.g*., using a densitometer). Lastly, non-photographic remote sensing systems typically have greater spectral range than black-and-white or color infrared photographs, and, in the case of Landsat and ASTER 30-meter resolution images, include several measurements of middle infrared reflected energy. These data are sensitive to variations in moisture content in vegetation and soils and thus vital to the delineation of coastal marshes. While coarser in spatial resolution, these image types are still capable of identifying a vast majority of the tidal marshes within Long Island Sound.

STUDY AREA

The area of interest consists of the entire Long Island Sound coastal region located in the Northeastern United States (Figure 1). 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. Long Island Sound is bordered to the north by the states of Connecticut and New York, and to the south by Long Island, New York. Long Island Sound is approximately 177 km long (oriented east to west) and 34 km across at the widest point and contains 965 km of coastline (Tedesco, 1995). Its maximum depth is 91 meters with an average depth of 20 meters. The entire Long Island Sound watershed area is approximately 41,440 square km extending from the Canada and United States border in the north to the Sound in the south and the extreme north shore of Long Island (Figure 1) (LISS, 2003). 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. Within the entire watershed area live approximately eight million people and more then 20 million people live within 80 km of the shores of Long Island Sound. The commercial and recreation value of the Sound contributes upwards of $5.5 billion annually to the regional economy. 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 (Patton and Kent, 1992). This significant difference is due to tidal resonance and the shape of the Sound.

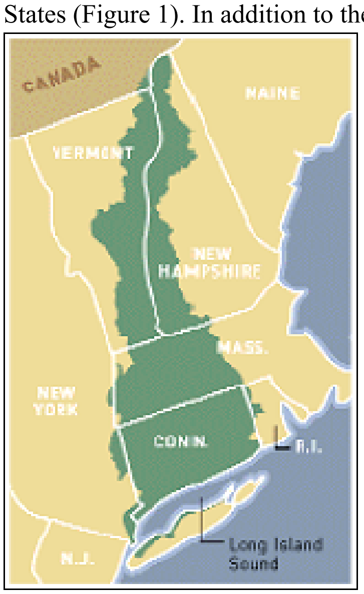


Figure 1. Location of Long island Sound in the Northeastern United States.

Long Island Sound Tidal Marsh Characteristics

The coastal marshes in Long Island Sound are technically classified as estuarine emergent wetlands, because the vegetation emerges above the water level. Most of the wetlands are true salt marshes where salt marsh plant species dominate and salinity levels average about 20 to 30 ppt (parts per thousand). In the riverine systems where marshes are also abundant, the marshes become more brackish with salinity levels dropping to 15 ppt. Further up the rivers the marshes eventually become dominated by freshwater wetland plant species and the salt marsh plants largely disappear although these areas are still affected by tidal influences. Unlike the southeast and southern regions of the United States, the marsh systems in Long Island Sound are small with a mean area of approximately 39 ha (Roman *et al*., 2000). A typical coastal salt marsh is a relatively simple system comprised of a few dominant species which exhibit a distinct pattern of vegetation across a gradient of tidal flooding and salinity (Ewanchuk and Bertness, 2004). In the low marsh, which receives twice daily tidal flooding, pure stands of the tall form of *Spartina alterniflora* can be found. *S. alterniflora* is also common in a narrow band along mosquito ditches and creeks. The high marsh, flooded frequently, exhibits a mosaic of vegetation types. Common species here include *Spartina patens*, *Distichlis spicata*, *Juncus gerardii* and the short form of *S. alterniflora* among others. In the brackish marshes, *Typha* spp. also becomes prominent. *Phragmites australis* is also found in over 50% of the tidal marshes along the Connecticut coast (Barret and Prisloe, 1998). As an invasive species it is rapidly changing the character of the tidal marshes in Long Island Sound.

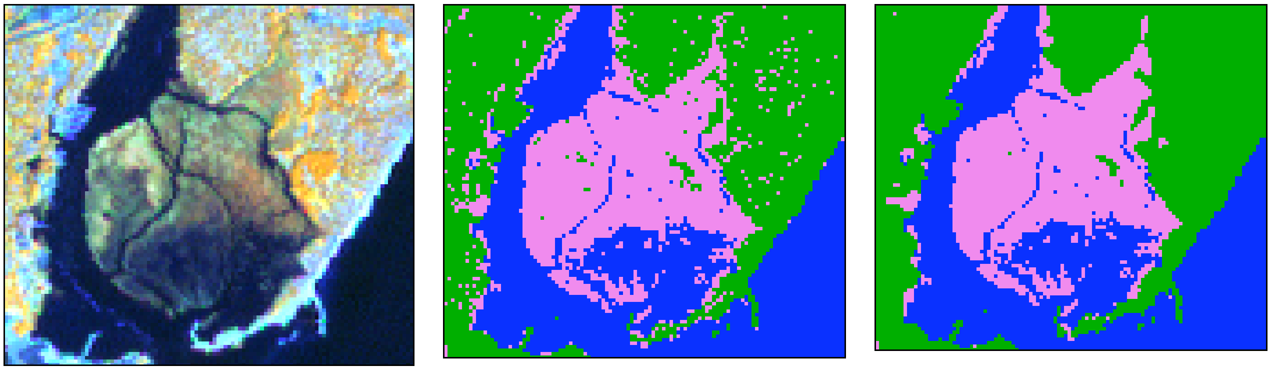
METHODOLOGY

Extracting the Analysis Area

To focus analysis 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 generation of a wetness layer using the difference between Landsat bands 2 and 5. The output is a grayscale image with values ranging from a possible -255 to 255. The higher positive values representing more water like pixels. A threshold was identified (between "wetness" values 27 and 28) that delineated between a likely water pixel and an upland pixel. Pixels that contained mixed features, such as streams that have pixels that contain both water and upland, were not sufficiently identified using the wetness layer, where needed were digitized on-screen. The wetness layer was then processed to group contiguous water pixels into individual objects of water pixels. A buffer operation was then performed to identify pixels within 1,200-meters (40 pixels) from an identified water object. The 1,200-meter distance is arbitrary and was selected only to ensure all tidal marshes were captured within the buffered region since some of these can exist some distance from water features. This buffer layer was then used to extract pixels from the original September 8, 2002 Landsat ETM image to be used in the image analysis.

ISODATA "Cluster-busting"

A first classification was performed using the ISODATA clustering algorithm found in Leica Geosystem's ERDAS Imagine 8.7 image processing software. The procedure was conducted using a "cluster-busting" approach. First, 150 separate spectral clusters were classified using ISODATA and labeled into one of four categories: water, tidal marsh, upland, and other. The other category contained pixels that were not readily identified as belonging to one of the primary three informational classes. These "other" pixels were extracted from the Landsat image and a second ISODATA classification performed, specifying 100 clusters. Again, the clusters were identified and labeled into one of the four categories. Pixel remaining in the "other" category were once again extracted from the Landsat image, and classified specifying 50 clusters. These clusters were labeled and the procedure repeated a final time, again specifying 50 clusters. The results of the four cluster-busting procedures were recoded and combined to generate a final classification layer with each pixel being labeled as water, tidal marsh, and upland . 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 described in the next section. A sample of the classification is provided in Figure 2.



(a) Landsat ETM image bands 4,5,3 displayed

(b) Raw ISODATAClassification

(c) ISODATA Classification following 3x3 majority filter

Figure 2. Sample of the ISODATA cluster-busting tidal marsh classification. Pixels colored magenta represent classified tidal wetlands, green is upland, blue is water.

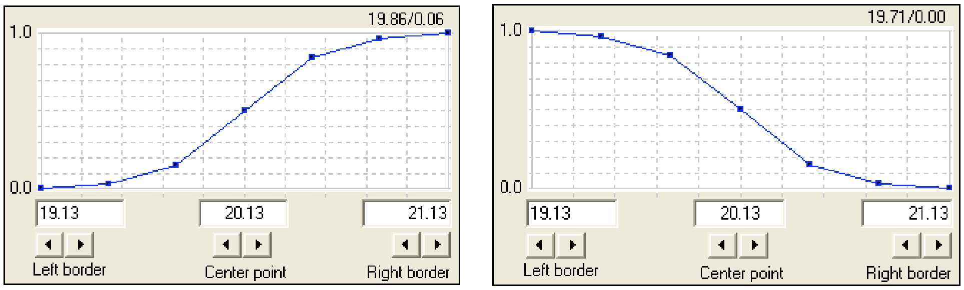
Object-based Classification

Object-based classification is the process of classifying image objects rather then 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. The benefit of object-based classification over per-pixel classifiers is that the image objects contain more information then just spectral information provided by single pixels. In addition to spectral information, summarized from the collection of pixels composing the image object, each image object also contains information regarding the texture, size, shape, and context of that image object to surrounding image objects. The spectral and spatial attributes of each image object are utilized to assign the object to a specific classification category, paralleling somewhat the human visual cognitive process. Advantages to this technique are a more robust classification due to the increased information, reduction in the number of units (pixels versus objects) to be classified, and the elimination of the "salt-and-pepper" effect which is common in per-pixel classifiers. For this research, image segmentation and object-based classification was performed using eCognition, produced by Definiens Imaging.

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 derived wetness layer. All of these layers were utilized for the object-based classification. To perform the multiresolution segmentation to derive the image objects, however, only four Landsat reflective bands (red, NIR, SWIR1 and SWIR2), NDVI (a greenness layer), principal component 1 (a brightness layer), and the wetness layer were used. These layers were equally weighted in their contribution to the segmentation process.

Level 2 Segmentation and Classification. A general image segmentation was performed first to produce larger image objects which were used in a basic binary classification to separate upland objects from water objects. The results of this classification were used to assist with a more detailed classification process based on smaller image objects. This will be discussed in detail in the next section. eCognition allows for the creation of objects at various resolutions (sizes) depending on user specified variables. These include a scale parameter which determines the maximum size of the objects and the composition of the homogeneity criterion which uses settings of color, shape, smoothness and compactness that roughly determine the shape of the objects using spectral and shape information. The assignment of these parameters to generate image objects is based on knowledge of the software, input data used, the classification procedure to be followed, and what features are to be identified. For the generation of larger image objects from the seven input layers used in the segmentation process, 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 then the shape parameter, the spectral information from the input layers was the most significant contributor to the creation of the level 2 image objects.

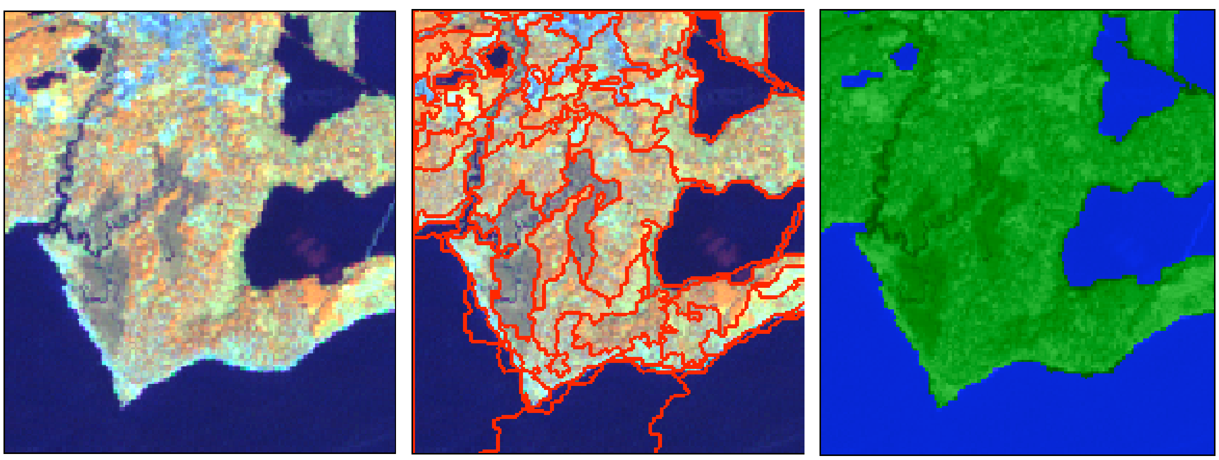
To classify the level 2 image objects into water or upland, the wetness layer was used exclusively as the identifying feature. Data exploration of the image objects identified a wetness value of 20.13 as a probable threshold between water and upland objects. Tidal wetlands would be expected to fall in one or the other category based on their level of wetness. To assign objects to a specific class, eCognition allows for absolute thresholds for assigning classes or fuzzy rules can be applied. For the process of identifying water and upland image objects, it was decided to use a fuzzy rule where the center point of the membership function was assigned a value of 20.13 with a range of 19.13 to 21.13. To identify water objects, any segment with a value larger then 21.13 was absolutely classified as water with a decreasing function slope to 19.13 (Figure 3a). Inversely, uplands were identified as any image object having a wetness value below 19.13 with a decreasing function slope to 21.13 (Figure 3b). By using a fuzzy rule, those image objects bordering between water and upland (*i.e.*, wetness value between 19.13 and 21.13) are more easily recognized. Figure 4 shows an example of the result of this level of object-oriented classification.



(a) Membership function used to identify water objects.

(b) Membership function used to identify upland objects.

Figure 3. Fuzzy rule membership functions used to classify level 2 image objects into water or upland categories.



Landsat ETM image bands 4, 5, 3 displayed.

Landsat ETM image with Level 2 image objects outlined in red

Level 2 object-oriented classification

Figure 4. Sample of the Level 2 object-oriented classification. Green represents upland image objects, blue are water image objects.

Level 1 Segmentation and Classification. To extract additional thematic information, a more detailed image object layer was created (Level 1). As with the generation of the larger image objects in the level 2 segmentation, the same seven input layers were used in this segmentation process. The scale parameter was set to 15 to generate smaller objects, color 0.9, shape 0.1, smoothness 0.5 and compactness 0.5. During the creation of multiple levels of image objects (*i.e.*, level 1 and level 2), the more detailed objects (level 1) will be nested within larger objects (level 2). Any characteristic of a larger image object can be applied to the smaller image objects nested within it and, therefore, aid in the classification of the more detailed image objects.

As mentioned in a previous section, the classification of image objects can utilize more then just spectral information, but include spatial information such as the texture, size, shape, and context to other image objects. While having additional information to help with the classification is beneficial, it becomes increasingly difficult to identify what characteristic of an object are most important for identifying the features of interest. To assist in the determination of important characteristics that can be applied to the classification, a data mining tool was used. See5, developed by RuleQuest Research, was used to assess a database of input information from the image objects to analyze and extract patterns and identify those input characteristics that are deemed most important for identifying features of interest. The output from See5 is a decision tree that can be re-created in eCognition and used to classify the image objects.

To develop the database, however, it was necessary to export the image object information from eCognition and select those image objects that would be representative of the classification categories of interest. Following several attempts, the following categories were identified for classification from the level 1 image objects: 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. Image objects were exported from eCognition into an ESRI polygon shapefile and included information such as the mean value for each input data layer (*i.e.*, blue band, NIR band, NDVI, PCA 1, etc…), the standard deviation for each input data layer, object brightness, object area, object length, object width, object length to width ratio, object shapeindex, and object density. In all there were 35 unique characteristics that describe each image object. Polygons were draped over the Landsat image in ESRI ArcMAP and several representative polygons of each classification category were manually selected. In all, 2,294 polygons were selected as training polygons. The attributes of these polygons were saved in a database file and converted to a format usable by See5.

One of the options in See5 allows for Winnowing the data. This process assesses the input characteristics and determines which contribute the most to the final classification decision tree. Essentially, the process weeds out those characteristics that are found to not be significant contributors to the classification and exclude them from the decision tree creation process. Of the 35 image object characteristics provided to See5, only 22 were used in the construction of the decision tree. Of these, only six were considered to by highly significant: mean band 5 (SWIR), mean NDVI, mean band 1 (blue), mean wetness, mean panchromatic, and mean band 2 (green). The output decision tree from See5 was then re-created in eCognition using membership functions similar to that used in the level 2 classification. See5 provided significantly more branches of the decision tree then is depicted in the eCognition classification decision tree shown in Figure 5. Since tidal marshes were the target feature, only those branches and thresholds that classified these features were used. If the branch continued further separating other upland or water classes a generic class was given and the branch ended. A sample of the result of the level 1 classification is provided in Figure 6.

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 rules-based approach to classification that utilizes a decision tree. The decision tree is comprised of variables and a hierarchy of rules, which are conditional statements, to produce a final classification output. The decision tree used for this project to combine the ISODATA and object-oriented classifications is simple. Input variables consist of the final ISODATA classification and the object-oriented classification. In addition, the following data layers were also included to improve the final classification result: PCA1 (brightness), NDVI, Wetness, and elevation DEM. Output classes consisted of water, upland, low marsh, and high marsh. Figure 7 shows the design of the decision tree in the Knowledge Engineer.

To summarize the output results shown in Figure 7:

1. Water is classified using the Wetness layer and PCA1. Following an attempt to utilize the classified water from both the ISODATA classification and Object-based classification, it was determined that a pixel with a wetness value greater then or equal to 20.4 and PCA1 value less then or equal to 34 gave a superior result. Values were selected based on visual examination of the data layers.

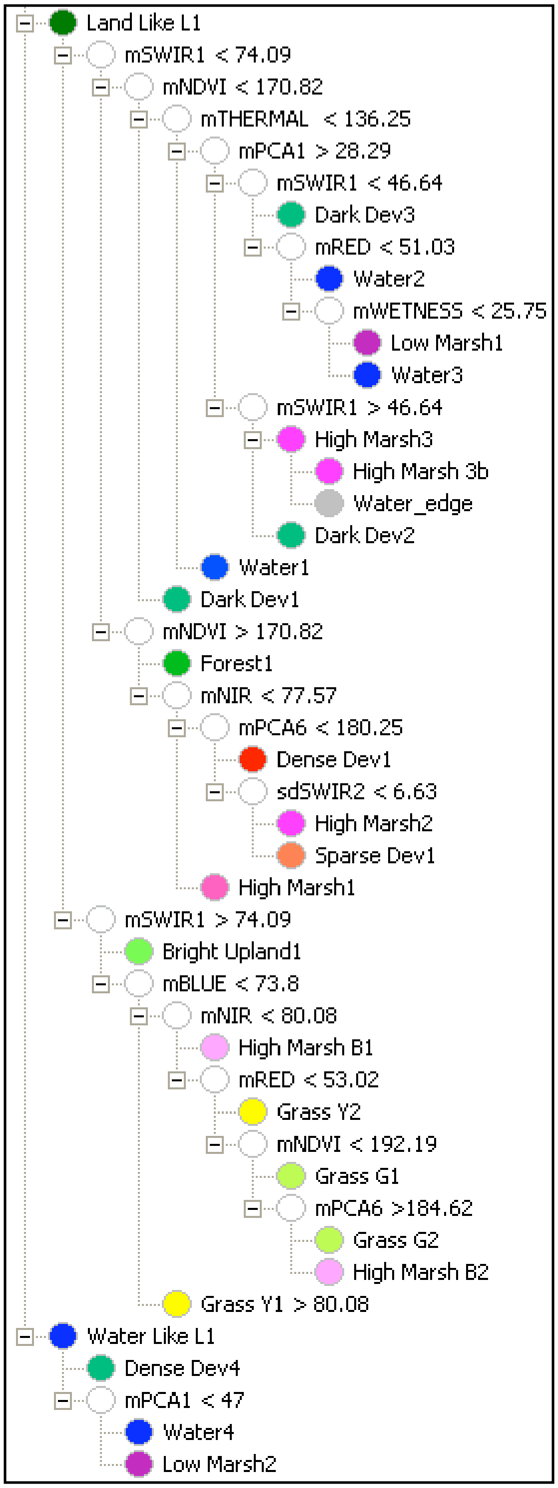
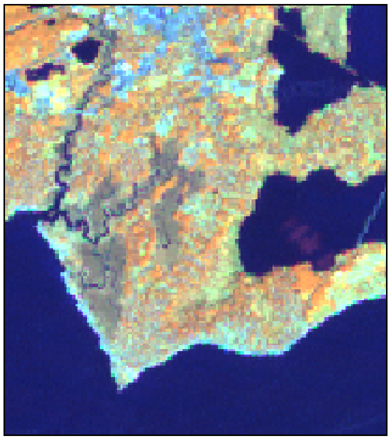


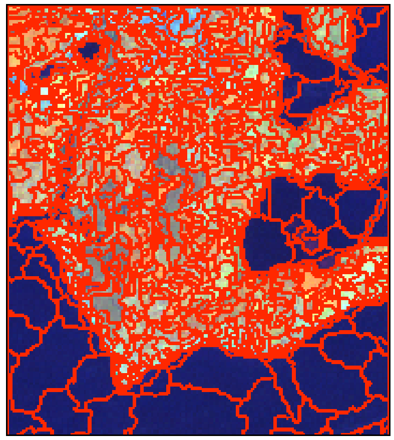
Figure 5. Classification decision tree created in eCognition based on thresholds generated from See5.

2. Low Marsh is classified using the results of the ISODATA classification and the Object-based classification. In addition, elevation information was utilized. If the ISODATA classification equals marsh (ISODATA class 2) and The Object-based classification equals low marsh (Object-based class 2) and the elevation is less then or equal to 5.33, the pixel is assigned as low marsh. The elevation value was determined by selecting multiple points both within the marshes and uplands from the Landsat imagery then analyzed with the elevation data to identify an appropriate elevation threshold.
3. High Marsh is classified using a similar rule to the Low Marsh classification. In this case, however, the object-based class equals high marsh (Object-based class 3).
4. Upland is classified using three separate rules. The first rule (D1 in Figure 7) identifies a pixel as upland if the ISODATA classification equals upland (ISODATA class 3) and The Object-based classification equals upland (Object-based class 4) and the elevation is less then or equal to 5.33. These upland pixels occur at low elevations in close proximity to the coastal marshes and coastal waters. The second rule (D2 in Figure 7) assigns any pixel above an elevation of 5.33 as upland. This comprises the vast majority of the upland. pixels. The last rule (D3 in Figure 7) uses the NDVI layer to identify pixels of high vegetation biomass that are not wet. In this rule, the elevation is less then or equal to 5.33 and NDVI is greater then or equal to 191 when stretched to an 8-bit dataset. This rule was developed to capture more of the low lying upland pixels not captured using rule D1.

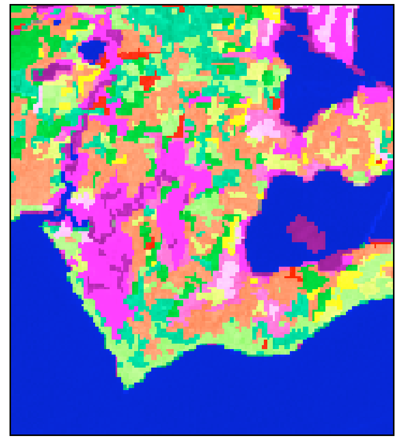
The manner in which the Knowledge Engineer functions, lower rules in the hierarchy are superseded by rules located higher in the hierarchy. Pixels that meet the criteria of more then one rule will be assigned the value identified by the top most rule in the decision tree. The order of each rule in the decision tree is therefore important. It is also possible to have pixels not classified by any of the rules. This was the case using this decision tree. An attempt was made to alter the rules to classify all the pixels in the study area. This, however, resulted in adverse affects on some of the previous results. It was decided instead to extract those pixels not classified and run an ISODATA classification to assign them to one of the final four categories. These pixels were merged with the integrated classification to produce a final tidal marsh classification map.



Landsat ETM image bands 4, 5, 3 displayed.



Landsat ETM image with Level 1 image objects outlined in red



Level 1 object-oriented classification

Figure 6. Sample of the Level 1 object-oriented classification. Greens, yellows and orange represent upland image objects, blue are water image object, and magenta, purple and pink are tidal wetland objects.

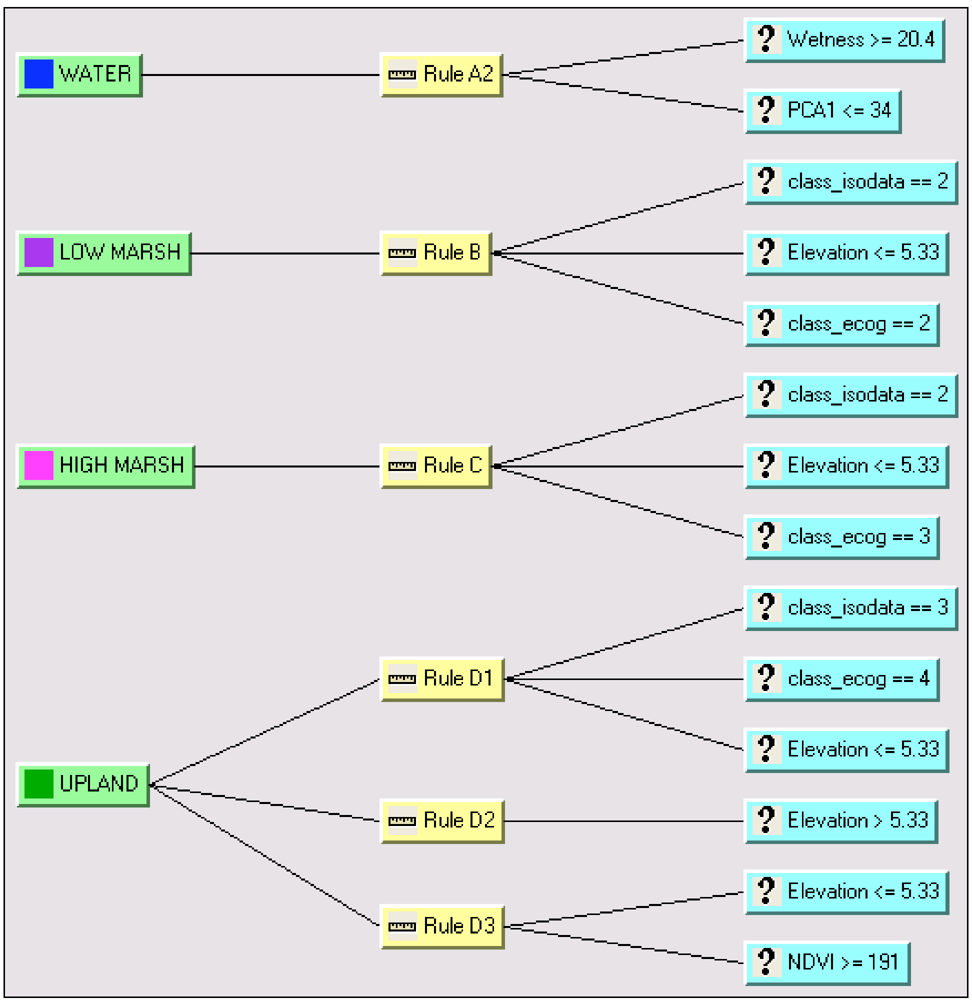


Figure 7. Graphic showing the design of the decision tree used to integrate the ISODATA classification with the object-based classification

EFFECT OF TIDAL STAGE

It is readily accepted that the tidal stage will influence the ability to classify tidal wetlands accurately. Ideally acquiring image data captured within 1-2 feet of mean low tide would be preferable and anything over this would be considered unacceptable (Dobson *et al*., 1995; Jensen *et al*., 1993). In reality, however, acquisition and use of satellite image data is also dependent on atmospheric conditions. In the northeast region of the United States, it is rare to have two or more cloud-free images collected for a given growing season due to significant cloud cover. Because of this, we used the most recently acquired Landsat image we had in our archive that was cloud-free and also captured during the August-early September timeframe which is the height of the growing season in the northeastern United States. In Long Island Sound, the mean tidal range varies from east to west. The eastern end of the Sound, being more open to the Atlantic Ocean has a mean tidal range of 2.7 feet. The western end of the Sound has a mean tidal range up to 7.3 feet. The September 8, 2002 Landsat ETM image used in this research was captured at high tide in the eastern end, and over two hours prior to high-tide at the western end of the Sound. What impact this might have on the resulting tidal wetland classification has yet to be assessed.

RESULTS AND DISCUSSION

Figure 8 provides samples of the final integrated tidal marsh classification for three sites along the Connecticut coast. These can be compared to the September 8, 2002 Landsat ETM image used for the classification and also a high spatial resolution ADS-40 image collected on September 22, 2004 that provides a more detailed view of each area. 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. As can be seen, the classification performs well at capturing the general location of tidal marshes throughout the Long Island Sound. The samples shown here are indicative 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 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 then 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.

At the time of this writing, a comprehensive accuracy assessment has not been conducted. Preliminary results, comparing the Connecticut DEP digitized tidal wetlands with the Landsat ETM classified tidal wetlands for just the Connecticut coast indicate significant omission is occurring. The digitized tidal marsh layer indicates that there are 5,895 hectares of tidal wetlands along the Connecticut coast. The Landsat ETM classification identifies 4,054 hectares. Of the 5,895 hectares digitized, 3,023 hectares were classified as tidal wetlands (51 percent) from the Landsat image. Of the remaining digitized tidal wetland areas, 2,213 hectares (37 percent) were classified as upland and 676 hectares (11 percent) classified as water.

FUTURE EFFORTS

Currently, a second tidal marsh classification is being conducted following the same methodology described in this paper. The September 8, 2002 Landsat ETM scene used for this project does not cover the entire Long Island Sound region. As such, the very extreme eastern portion of the Sound is missed by the WRS Path 13 scene. The second classification is utilizing a July 31, 2002 Landsat ETM scene from WRS Path 12. There is significant overlap between scenes from these two paths. This will provide an opportunity to assess the repeatability of the classification technique by comparing the overlap areas in addition to providing complete coverage for all of Long Island Sound. Further, the result of this July 31, 2002 classification can be used to diminish the impact of the high tide in the September 8, 2002 classification because of the presence of near low tide conditions.

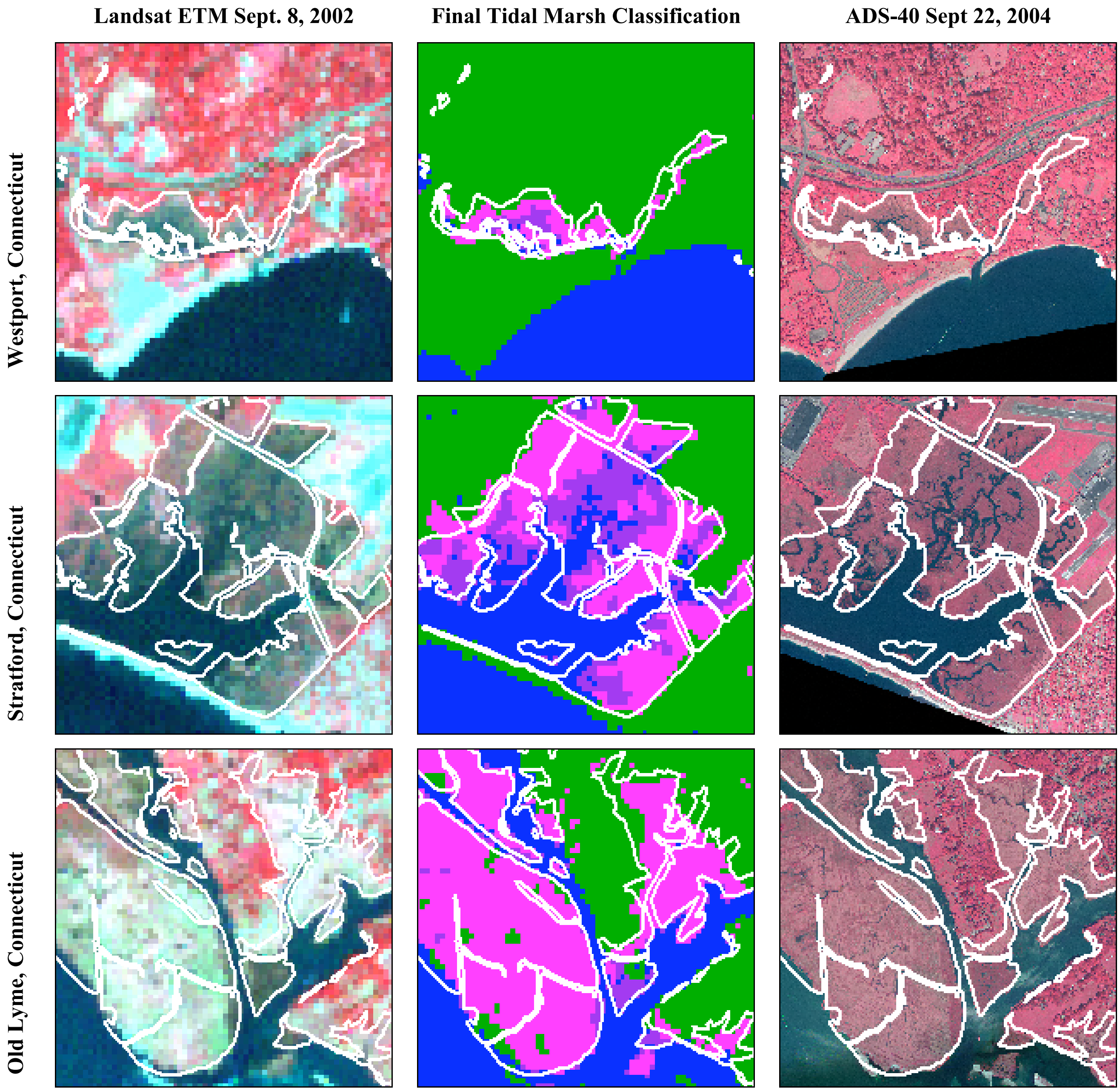


Figure 8. Results of the final integrated tidal marsh classification for selected areas along the Connecticut coast compared with the Landsat ETM image used for classification and a high spatial resolution ADS-40 image. The white outlines represent tidal marshes delineated from aerial imagery by Connecticut Department of Environmental Protection personnel. In the classification, green represents upland, blue is water, magenta is high marsh, and purple is low marsh.

Upon completion of the classification process for the entire Long Island Sound, the tidal marsh data will be analyzed with existing land cover information derived by the Center for Land use Education And Research (CLEAR) at the University of Connecticut. CLEAR has created land cover and land cover change information in addition to impervious surface information from four dates of Landsat TM and ETM imagery spanning a 17 year period. These data will allow for the analysis of landscape change in the upland areas surrounding and/or directly draining into the tidal marsh ecosystems which will permit the identification of tidal marshes that are at risk of potential detrimental impacts due to anthropogenic activities in the adjacent uplands.

CONCLUSIONS

The primary objective of this work 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 better validate 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.

ACKNOWLEDGEMENTS

The work reported in this paper was supported by the United States Environmental Protection Agency Office of Long Island Sound Studies under the project "Application of Remote Sensing Technologies for the Delineation and Assessment of Coastal Marshes and their Constituent Species". [CLEAR Publication Number 060213.1]

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