Applying Remote Sensing and GIS to quantify marsh dynamics in the Plum Island Ecosystems

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1. Introduction

The Plum Island Ecosystems (PIE) site consists of a linked watershed-marsh-estuarine system located north of Boston, Massachusetts. The brackish and saline tidal wetlands of the PIE site form the major portion of the "Great Marsh", the largest contiguous acreage of intact marsh on the northeast coast of the United States. However, recent studies have shown that the marsh in PIE is under threats from rising sea level. Triggered by global warming, sea level rise is leading to pond expansion and channel widening, which subsequently alters the shapes of tidal marshes. Geomorphic change of the marshes will potentially affect the whole regional ecological process. The quantitative and accurate mapping over marsh landscape is therefore of extreme importance for understanding the implication of marsh change as well as predicating the future change. Also, river and pond network information are important as they can be used to analyze the relationship between water level rise and marsh change.

My internship is about using advanced GIS and remote sensing technology to quantify various land cover types in the Plum Island Ecosystems, and to characterize the changes happening among these types. The change of marsh and ponds usually happens at a fine spatial scale given a time interval of less than a decade. Thus images with spatial resolution of less than 1 meter are preferred in this project. However, the use of fine resolution imagery poses new challenges because it can produce greater within-class variance and lower classification reliability. This problem can be worse in heterogeneous landscapes such as marsh mosaics consisting of various land cover types such as soil, water, marsh. Another challenge of this project is mapping marsh species. We want to distinguish between two primary marsh types, specifically *Spartina Alternflora* and *Spartina Patens*. However, little is known about their spectral difference in remotely sensed data due to the lack of literature. This suggests both an innovative method design and exhaustive field work are required in order to reliably discriminate these two dominant marsh species. The third difficulty of this project is at accurately mapping the river network. It is difficult to map a complete river network from aerial photos because most of the images were collected at low tides when tidal flats are exposed. Also, leaves often cover small ditches, making it difficult to discern river networks from remote sensing images.

The objectives of this internship are two-fold. First is to design a novel mapping approach using object-based classification. Object-based classification firstly subdivides images into clusters of pixels called segments, which are homogeneous in themselves relative to nearby regions, and then uses the segments as the analysis units. Second is to delineate the river network by using fine-resolution topographic maps generated from Light Detection and Ranging (LIDAR) data. LiDAR sensor has the capability of penetrating the water surface to measure directly water depths in clear water environments (Höfle et al., 2009), thus can provide representation of topographic features.

2. Dataset and preprocessing

Two fine resolution images came from MassGIS, the state GIS agency of Massachusetts (MassGIS, 2016). Fine-resolution topographic data was obtained from the satellite data manager (Hap Garritt hgarritt@mbl.edu) at the Marine Biological Lab, Woods Hole MA. Two fine-resolution aerial datasets were collected respectively on April 9th, 2005 (Four bands: Red, Green, Blue, Near-infrared; resolution: 0.5m), and on April 15-30, 2013 (Four bands: Red, Green, Blue, Near-infrared; resolution: 0.3m). We resampled the image of the year of 2013 into the resolution 0.5. Due to both the large image size (32000 rows by 32000 columns), we split each image into 16 tiles. Using tile-by-tile processing enables using suitable classification parameter setting for each tile instead of using only one global parameter setting for the whole image, and also facilitates manual refinement subsequent to classification.

Fine-resolution topographic data were generated by using Terrasolid's TerraScan Lidar processing software, based on airborne LiDAR data collected on April 19th to 25th, 2005.

3. Method

3.1 Field work

The fieldwork aims mainly at collecting ground information to assist in training sample selection for subsequent object-based classification. Considering our budget and project duration, our fieldwork didn't perform exhaustive sampling for each class, but focused on two marsh types that are the most confused among all categories from aerial images. Forty sampling points for these two marsh species (*Spartina Alternflora*: 17 points; *Spartina Patens: 23 points*) were collected along the Rowley River. Through analyzing these sample points in the 2013 imagery, we found *Spartina Alternflora* appears to be black or dark green in the true color composite image, while *Spartina Patens* appeaers gray. This is because *Spartina Alternflora* are often more spatially sparse than *Spartina Patens*, and the water in the gaps among *Spatina alternflora* absorb electromagnetic energy and make the surface reflectance much lower than *Patens*. In the subsequent supervised classification procedure, we used this finding to collect enough training samples for *Spatina alterniflora* and *Spatina patens* marsh. For the other land cover types, we applied visual inspection to select samples because those categories are discernable from high-resolution images.

3.2 Object-based classification approach

As mentioned in introduction, salt marshes (both *Spatina alterniflora* and *Spatina patens*) are very spectrally similar with grass. To avoid misclassification led by this problem, a wetland mask is used to separate marsh area from other land cover types. This mask map is downloaded from MassGIS (2016). Because the wetland map has questionable accuracy, around 20 hours was spent first to manually refine this mask using our latest 2013 fine-resolution image. After the 'wetland' part and 'no-wetland' part were separated from the original image, object-based classification was performed for each part. For the 'wetland' part, we defined the classification system as four categories, i.e. 'Water', 'Tidal flats/soil', '*Spartina alterniflora*' and '*Spartina patens*'. For the 'non-wetland' part, we defined five categories, i.e. 'water', 'Tidal flats/soil', 'Trees', 'Grass' and 'Impervious'. This approach enables separately classifying 'grass' and two marsh species without confusing these two.

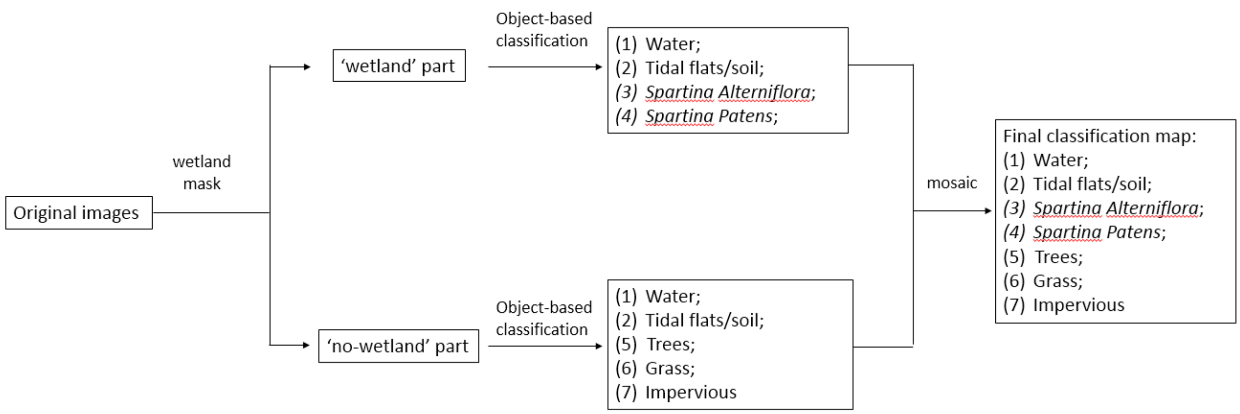


Figure 1 the schematic representation of our object-based classification approach by using wetland mask.

Object-based classification was performed using the module 'Example-based feature selection' in the software Exelis Visual Information Solutions 5.0 (ENVI 5.0). The following is the detailed description for object-based classification. First, the image was segmented into many homogeneous 'objects' by using a segmentation technique; the best parameters for segmentation were determined by a trial-and-error procedure. Then, we selected 'blue band', 'green band', 'red band', 'NIR' and 'NDVI' as five properties for each object, and performed supervised classification using k-NN algorithm. For more details, we refer readers to the help document in ENVI software.

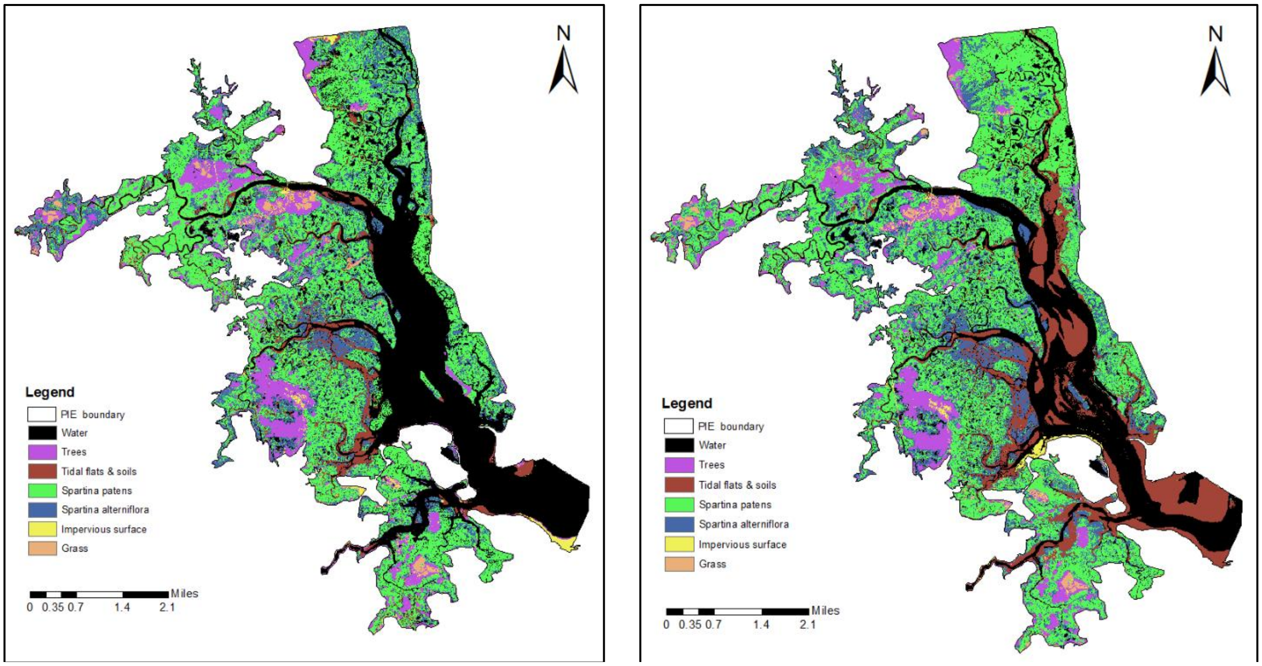
We applied the procedure described above to every tile for each image. After classification, approximately 30 additional hours were taken to perform manual edition for each map in order to guarantee the thematic accuracy in our final maps.

3.3 Water network generation

The whole water network was generated using Arc Hydro package (http://resources.arcgis.com/en/communities/hydro/01vn0000000s000000.htm) in ArcGIS software. We followed the procedure: (1) DEM Reconditioning; (2) Fill sinks; (3) Flow direction; (4) Flow accumulation; (5) Stream definition; (6) Stream segmentation. Additional 20 hours were spent on manual edition based on the latest fine-resolution 2015 image after we processed topographic data in Arc Hydro.

4. Result and analysis

4.1 Land cover and water network maps



(a) 2005 (b) 2013

Figure 2 Land-cover maps of 2005 (a) and 2013 (b) for Plum Island Ecosystems.

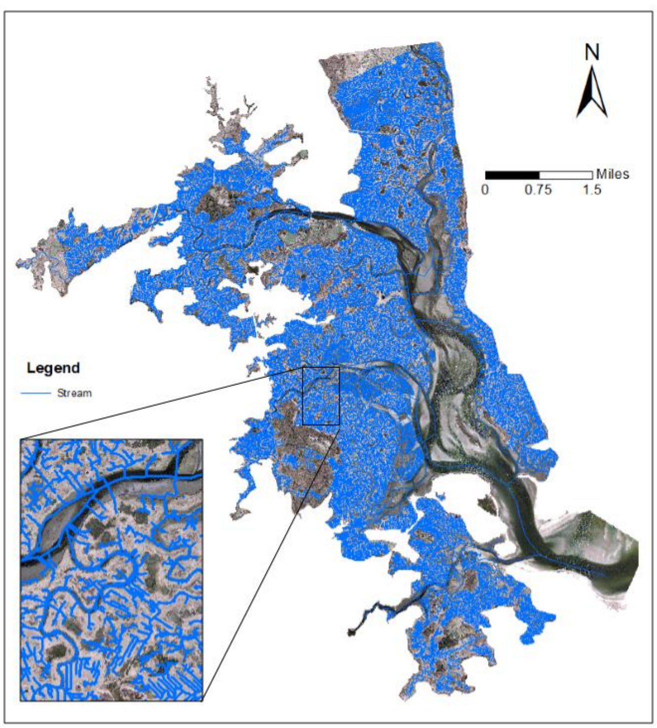


Figure 3 Water network map for Plum Island Ecosystems. Tthe background image is the true color composite of the fine-resolution aerial image of the year of 2013.

4.2 **Change analysis**

Table 1 summarizes individual class area and change statistics from 2005 to 2013. Water area decreased approximately 666 ha (30%), while Tidal flats & Soil increased 527 ha (134%). This is because these two images were collected at different tidal times. The 2013 image has lower tide, so less water and more soil were exposed at 2013 compared with 2005. The area for two marsh species both experienced a slight increase (*Spartina alterniflora* increased 99 ha; *Spartina patens* increased 105 ha), which supports the previous hypothesis that salt marshes are able to keep with sea level rise (Morris et al, 2013). Table 1 indicates is a large area of exchange between *Spartina alterniflora* and *Spartina patens* despite their relatively consistent total area: 474 ha of *Spartina alterniflora* transitioned to *Spartina patens* while 455 ha of *Spartina Patens* transitioned to *Spartina alterniflora*. Impervious surface experienced a slight decrease (13 ha), which is counter to intuition. We believed that the decrease might be related to classification inconsistency between the two dates.

Table 1 Transitions from 2005 to 2013 in hectares

	2013							
2005	Water	Tidal flats & Soil	Spartina alterniflora	Spartina patens	Trees	Grass	Impervious	2005 Total
Water	1326.29	595.82	126.49	94.14	12.61	3.08	16.59	2175.03
Tidal flats\Soil	80.69	187.24	60.60	47.93	10.20	2.64	4.87	394.17
Spartina alterniflora	47.68	42.83	472.94	473.63	37.11	2.41	2.11	1078.71
Spartina patens	38.65	46.19	455.10	1923.72	24.41	3.86	6.77	2498.69
Trees	13.47	23.59	52.52	32.12	497.90	32.01	14.24	665.85
Grass	0.55	0.63	8.20	24.16	16.83	44.01	1.60	95.98
Impervious	2.02	24.55	2.01	7.73	15.80	7.12	20.17	79.40
2013 Total	1509.36	920.84	1177.85	2603.43	614.88	95.13	66.34	6987.83

5. Conclusion

Fine-resolution aerial image and topological processing is still a very challenging topic for the remote sensing and GIS community. A variety of errors in the intermediate maps mainly came from inappropriate segmentation scale, inefficient training samples, spectral variability within geographic objects, etc. Therefore, the intermediate maps required many hours of manual corrections based on visual inspection. Error concerning change are even more complicated to understand due to the inconsistency among multiple classification processes between the two time points. This research shows a procedure for generating fine-resolution land-cover map and water network map for a complex marsh landscape, which could be used in the future for similar fine-resolution marsh mapping.

All the maps we created have been submitted to the PIE data manager for official inclusion in the PIE database. Also, Professor Pontius is using the data during his course and his students will use the data for American Association of Geographers Annual meeting presentations during spring 2017. Future research will focus on how to alleviate the impacts of the inconsistency among independent mapping processes for land cover change characterization.

6. Acknowledgement

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References

MassGIS, 2016. Massachusetts Geographic Information Systems office. http://www.mass.gov/mgis/. Accessed May 16, 2016.

Morris, J. T., Sundberg, K., & Hopkinson, C. S. (2013). Salt marsh primary production and its responses to relative sea level and nutrients in estuaries at Plum Island, Massachusetts, and North Inlet, South Carolina, USA. *Oceanography*, *26*(3), 78-84.

Hofle, B., Vetter, M., Pfeifer, N., Mandlburger, G., & Stotter, J. (2009). Water surface mapping from airborne laser scanning using signal intensity and elevation data. *Earth Surface Processes and Landforms*, *34*(12), 1635.