A Protocol of Using High Spatial Resolution Satellite Imagery to Map Salt Marshes: Towards Long Term Change Detection

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0. Executive Summery

Productivity of salt marshes is a primary indicator of ecosystem health. Nationwide, emergent salt marshes declined by an estimated 14,450 acres in ten years from 1986 to 1997. In November 2000, the New York Department of Environmental Conservation (NYDEC) released a study that shows a sustained trend of significant salt marsh loss in Jamaica Bay over the past 100 years. The Jamaica Bay Wildlife refuge encompasses 2,500 acres within the boroughs of Brooklyn and Queens in the New York City. This refuge, the only one in the national park system, provides a variety of habitats for more than 300 kinds of waterfowl and shorebirds. It is a critical stopover area along the Eastern Flyway migration route and is one of the best bird-watching locations in the Western Hemisphere. Interpretation of historical aerial photographs shows that 51% of salt marshes in the Bay had been lost between 1924 and 1999. Although the salt marshes have been protected since 1972 as part of the Gateway National Recreation Area, a recent study shows that 38% of salt marshes in Jamaica Bay have been lost since 1974. The salt marsh decrease in the Jamaica Bay has caught attentions of scientific communities and the media such as the New York Times, Columbia News, and NASA's Goddard Institute for Space Study. The salt marsh change in the Jamaica Bay is similar to the trends found in other salt marshes elsewhere in the northeastern United States. Therefore, Jamaica Bay is ideal for developing a protocol for salt marsh mapping and change detection for monitoring future extents of salt marshes in the northeast U.S.

Extensive studies have been conducted for monitoring and quantifying salt marsh dynamics. Methods for examining salt marsh changes vary with project goals, compliance requirements, organization priorities, and financial limitations. In remote sensing and GIS perspectives, timely and repeated data acquisition, quick and easy information extraction, low cost in data acquisition and processing, as well as available baseline referencing data are key considerations in protocol development.

Remote sensing and GIS have been applied in wetland and salt marsh habitat monitoring (*e.g.*, Zhang, *et al.*, 1997; Ritter and Lanzer, 1997). The U.S. Fish and Wildlife Service Natural Wetland Inventory has used aerial photography imagery and direct on-the-ground observations to record and monitor wetland changes over time. Given that salt marsh monitoring requires repeatable and reliable updates of land cover maps, exploration of new data and approaches that could efficiently update the salt marsh maps is necessary. Recent development of high spatial resolution satellite remote sensing data can be helpful in salt marsh change detection. For example, Space Imaging's IKONOS satellite data, consisting of 1-meter spatial resolution for the panchromatic band and 4-meter spatial resolution for the multispectral bands (visible to near infrared), have been applied in resource mapping. Digital Globe's QuickBird-2 satellite data possess 0.61-meter spatial resolution for the panchromatic band and 2.5-meter spatial resolution for the multispectral bands (visible to near infrared). These new satellite data can meet the requirements of salt marsh mapping. The capability of repeated data acquisition by high spatial resolution satellite imageries and relatively low cost can facilitate the routine practice in salt marsh change detection.

In this project, we developed a protocol using Quickbird-2 high spatial resolution satellite imagery as the primary data source. There were two goals of this project. The first was to test the reliability of satellite remote sensing data for long term change detection of salt marshes. The second was to examine the ability of data generated with high spatial resolution satellite imagery in comparison with historical data generated from aerial photography. We used the unsupervised classification scheme available at the ERDAS Imagine software system to extract information of salt marsh coverage from Quickbird-2 images. With consultation from the NPS experts we defined three categories to characterize the overall salt marsh composition in the Jamaica Bay, including (1) *Spartina* area coverage in excess of 50%, (2) *Spartina* area coverage of 10-50%, (3) areas consisting of mudflats. For specific islands a category of High Marsh was added. The high marsh areas can have a variety of different plants, such as *Spartina paten*s, *Phragmites*, *Distichlis spicata* and others. These classes allowed us to compare the new data with historical salt marsh data of the park.

We began the project by compiling all existing information, such as historical aerial photographs, interpretation of salt marsh areas and the maps, as well as other GIS data. Predominately these data came from previous projects conducted by the NPS. We purchased the Quickbird-2 satellite remote sensing imageries acquired September 10 and October 6, 2003. We merged the 2.5-m spatial resolution multispectral image data and the 0.6-m panchromatic image data from the original Quickbird-2 image to create a new dataset that possesses 0.6-m spatial resolution and 4 spectral bands. The new dataset took advantage of high spatial resolution of the panchromatic band and broader spectral coverage from the multispectral data. This new dataset was used in the classification process to extract salt marsh and related information.

To support the classification we conducted GPS-guided ground checking and verification. We employed a Trimble ProXR and a Kodak Field Imaging System to document sampling locations throughout the salt marshes. At each sampling point, a GPS location was recorded and at least one georeferenced digital photograph was taken with identification of the geographic coordinate and compass facing direction. The georeferenced photographs were compiled to create a virtual field reference database (VFRDB). The VFRDB provides valuable benchmark records for monitoring future salt marsh changes in the Jamaica Bay.

The final salt marsh map (Figure 0-1) and the area calculations (Table 0) provide the most up-to-date status and coverage of the salt marshes in the Jamaica Bay area. The overall accuracy of the salt marsh map is about 84.6%. Figures 0-2 to 0-5 show examples of the QuickBird-2 satellite images and the corresponding salt marsh classification maps.

We concluded that unsupervised classification using high spatial resolution Quickbird-2 satellite imagery is a rapid, cost effective and accurate approach to map salt marshes in the Jamaica Bay. The protocol provides detailed steps to achieve the goal of salt marsh information extraction. With comparable spatial resolution, the salt marsh information extracted from classification of Quickbird-2 image can be used for change detection against existing digital GIS format data derived from interpretation of aerial photographs. However validation and justification must be conducted when a comparison is to be done between data from different sources and using different methodologies. Details of digital satellite imagery data involved in change detection, such as minimum mapping unit, classification system, projection and registration, purpose of original map data, *etc.*, need to be considered.

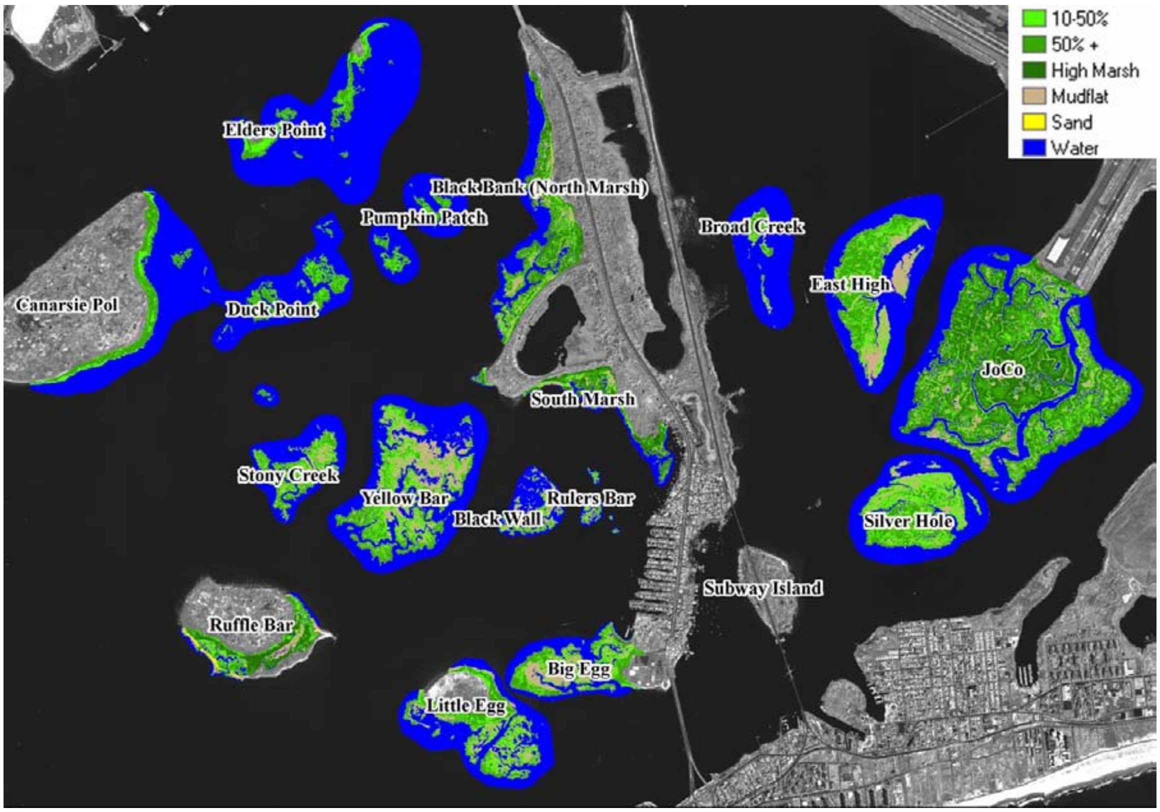


Figure 0-1. Final map of salt marsh classification in the Jamaica Bay, New York.

Table 0. Mapping result of the salt marsh in the Jamaica Bay area.

Class Name	Acres	Hectares
Mudflat	220.013	89.0362
10-50% *Spartina alterniflora*	298.534	120.813
Greater than 50% *Spartina alterniflora*	421.246	170.472
High Marsh	155.727	63.0204
Total	1095.52	443.3416

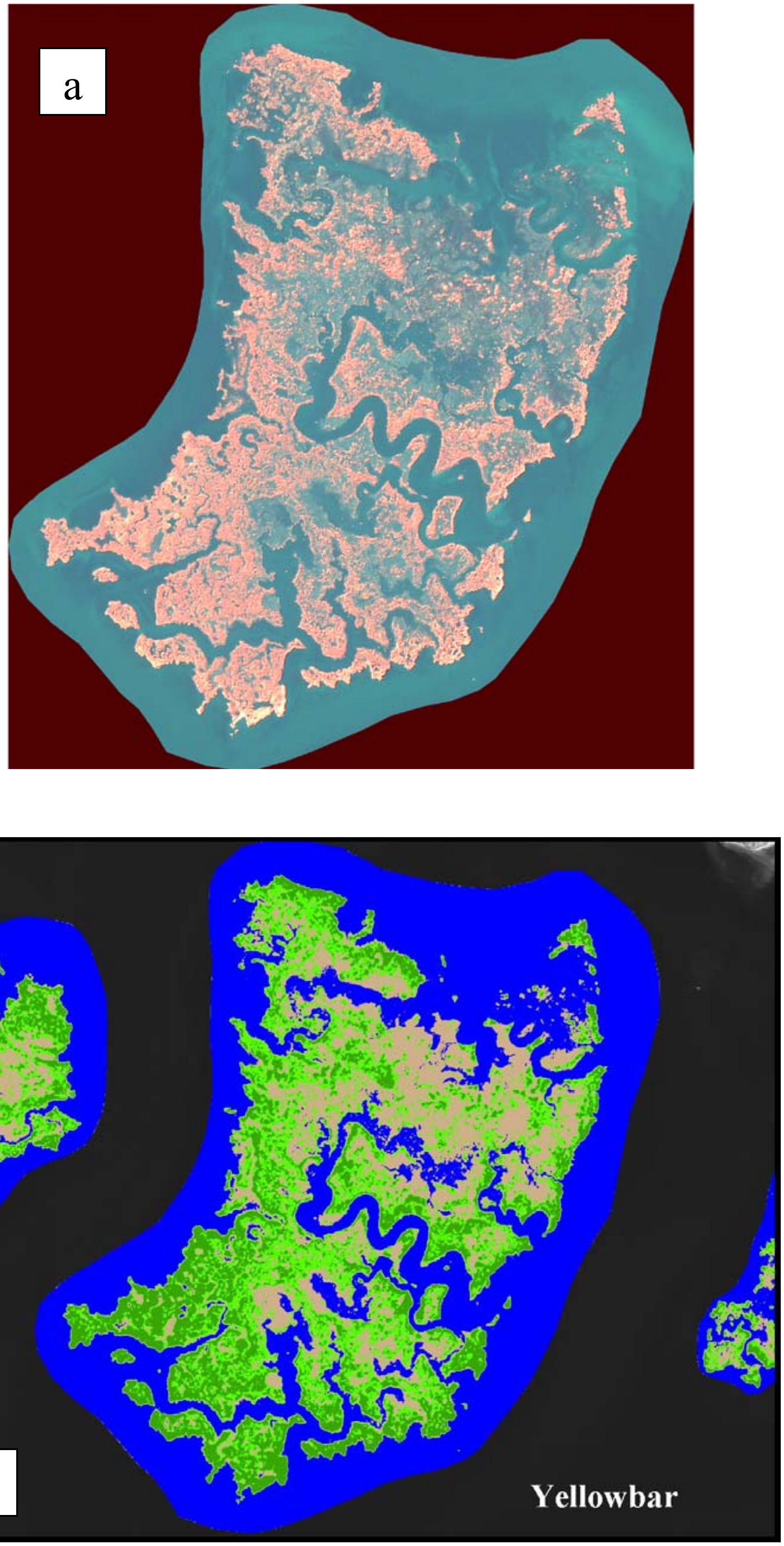


Figure 0-2. QuickBird-2 satellite image of the Yellowbar marsh (a) and the classification map (b).

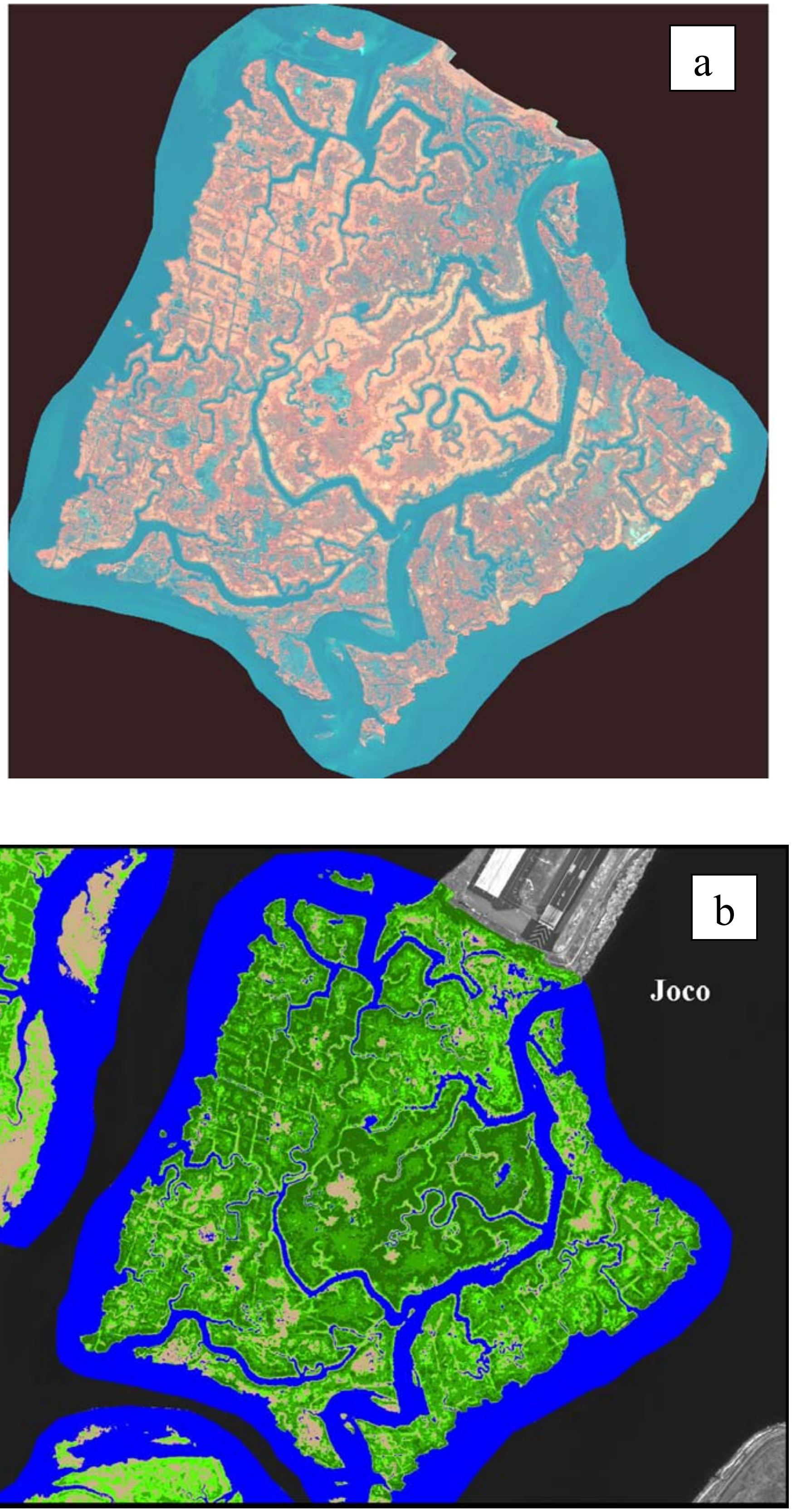


Figure 0-3. QuickBird-2 satellite image of the Joco marsh (a) and the classification map (b).

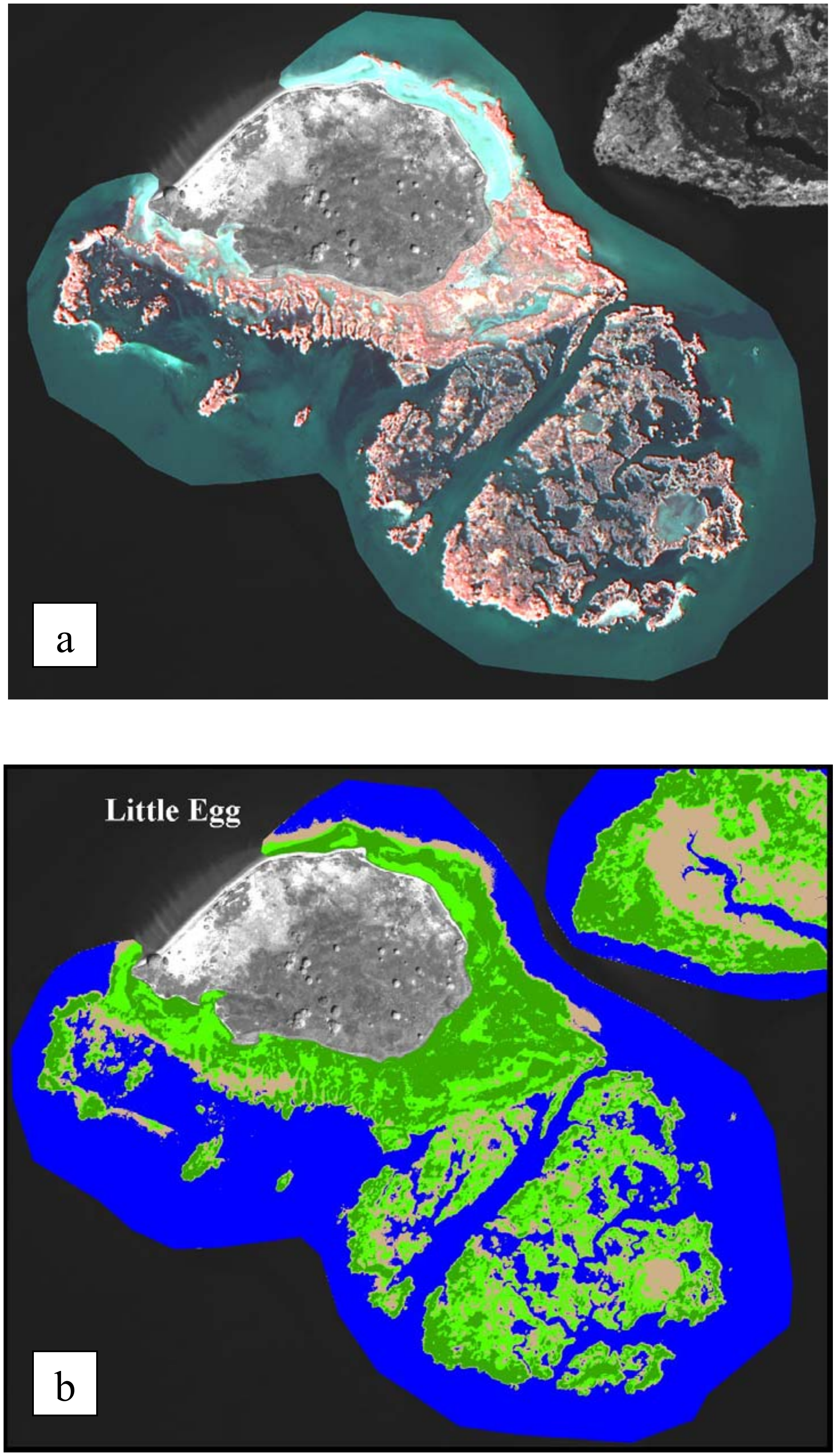


Figure 0-4. QuickBird-2 satellite image of the Little Egg marsh (a) and the classification map (b).

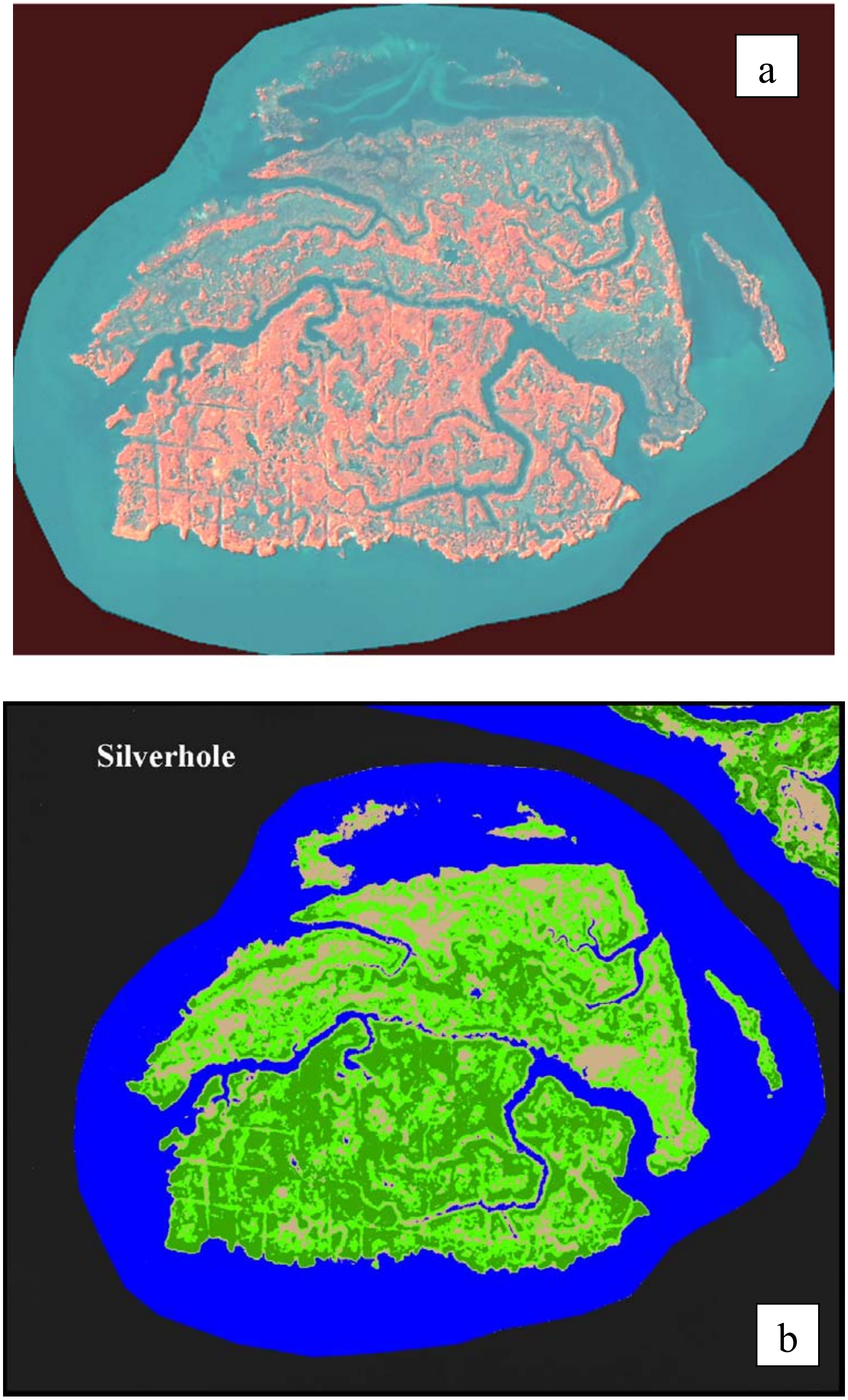


Figure 0-5. QuickBird-2 satellite image of the Silverhole marsh (a) and the classification map (b).

Section 1
Protocol Overview

1. Introduction

Salt marshes have been disappearing in the continental United States at an ever increasing rate (Dahl, 2000). Marshes within the boundaries of National Parks are no exception. This protocol is designed to aid in the long term monitoring of the salt marshes and assess the effect of restoration and erosion on the marshes. The first objective was to provide detailed instructions to facilitate salt marsh information extraction from high spatial resolution digital satellite imagery. The mapping result can provide park managers quantified information for a long-term salt marsh monitoring and change analysis. The second objective was to generate compatible information with previous efforts of the National Park Service in mapping salt marshes. This would allow for long term trend analysis of the salt marsh. This protocol has been divided into two sections. The first section explains the general methodology giving and explanation of how, why and the value of mapping a salt marsh. This is intended for resource managers to get a better sense of how this type of mapping can be valuable to National Parks and gain an overall sense of the process. The second section details the specific steps that need to be taken in setting up and documenting such a program; going into cost, selecting and ordering of data, all the way though map creation. This protocol was developed based on the Jamaica Bay, a part of the Gateway National Recreation Area in the State of New York (Fig. 1).

Wetland Mapping

In 1979, the Department of the Interior published a book "Classification of Wetlands and Deepwater Habitats of the United States" (Cowardin, 1979). This document was prepared by several noted wetland scientists to provide a universal system to describe the characteristics of wetlands. It explains in detail the concepts and terms of wetlands that need to map and categorize though a hierarchal system. This document became the federal standard for wetland classification, mapping and data reporting activities since 1997 (Executive Order 12906). This document provided the basis for the wetland categories used in this protocol.

Photogrammetry has long been used for mapping salt marshes. It is the art and science of making accurate measurements by means of aerial photography (Jensen, 2000). Through aerial photographs an interpreter can derive many attributes from a salt marsh, such as the size, shape, tone/color, texture and pattern. With photo interpretation, it is possible to distinguish wetland plant species through stereoscopic viewing.

With the advancements of computers, on-screen or "heads-up" digitizing can replace manual delineation methods. For on-screen digitizing the aerial photo is scanned into a digital format image and georectified. The user can then trace the areas of identified marshes and calculate the areas using GIS software.

Satellite Imagery and Mapping

Satellite imagery mapping started during the 1970s with the launch of Landsat series satellites. Satellites can pass over with sensors on board scanning the Earth on regular time intervals. Satellite imagery is well suited for mapping coastal wetlands. Schmidt and Skidmore (2003) tested the spectral discrimination of salt marsh plants and studied the spectral reflectance of 27 different species of salt marsh vegetation. It was concluded that the reflectance of vegetation is statistically different. Using the hyperspectral libraries of vegetation, different plant species could be identified, and the marshes could be mapped.

In the last several years satellite sensors have been developed to acquire high spatial resolution imagery. The spatial resolution can be comparable to orthophotos. For example, using IKONOS imagery with a resolution of 4-meters, the minimum mapping unit can be 0.08 ha. IKONOS imagery data have been applied to map emergent and aquatic wetland vegetation. Ozesmi and Bauer (2002) employed an unsupervised classification to map five different types of emergent vegetation, including cattail, sedge, brush, water lily, and mudflat areas, and four types of submerged vegetation in the levels of abundance. Sawaya *et al.* (2003) concluded that they had high success using high resolution imagery to map wetlands, reporting an overall accuracy of 79.5%. When comparing the high-resolution mapping of marshes to field surveys of marshes a strong agreement between the two studies was reported (Sawaya *et al.* 2003).

Image Classification and Mapping Approach

Image classification is the process by which raw data is transformed into information. With increasing availability of satellite imageries, two basic approaches of digital image classifications have been broadly used, *i.e.* the supervised and unsupervised classifications. Supervised classification is an interactive process, requiring the skills of an image analyst knowledgeable of the field conditions. The image analyst selects training samples that have distinctive spectral signatures and then use the statistics of the signatures to classify digital images (Marshall and Lee, 1995). The advantage of this method is that the image analyst specifies desired information classes. The disadvantage is that the desired classes may not be spectrally unique. For example, certain vegetation types share similar spectrums, which make the classification difficult. Unsupervised classification groups (clusters) of pixels that have similar spectral values. The advantage of this method is that the user does not have to create training signatures. However, the spectral clusters of pixels may not correspond to the desired classes. The image analyst will be responsible to label and name the clusters of pixels. Both approaches are acceptable for image classification and have been used to map wetlands (Ozesmi and Bauer, 2002).

Digital image analysis has a distinct advantage over manual delineation of wetlands. With manual delineation, the common approach is to trace boundaries around identified land feature patterns to encompass salt marsh vegetations. Unfortunately, this process often includes open water patches in low-density areas. This has the effect of over inflating estimates of marsh vegetation coverage. With a pixel-based classification, measurements of marsh vegetation areas can be more precise (Marshall and Lee, 1995).

Several studies have compared different types of imagery classifications. It has been found that computer driven mapping, either though supervised or unsupervised classification, is less time consuming than manual delineation (Marshall and Lee, 1995). Schmidt *et al.* (2004) reported a 27% reduction in the amount of time it took to create their coastal vegetation maps. Marshall and Lee's (1995) study concluded that digital imagery analysis produced more accurate and efficient maps of the wetlands than manual delineations. The study showed that unsupervised classification produced comparable result to supervised classification.

Aerial photography, which offers high spatial resolution of a site, has been successfully used to map salt marshes through both manual delineation and digital image classification. Satellite sensors can generate images with comparable spatial resolution to aerial photographs. The advantages of satellite imagery can be applied at local scales to better understand ecological phenomena and can meet the requirements of management decisions of natural resources.

We used unsupervised classification for this study. The goal of this protocol was for a long term change detection of the salt marshes. We decided to use a method that has less influence from human errors. Also, in experiments with supervised classification, it could be difficult to create spectral signatures that could be used for all marshes. In our testing unsupervised classification yielded satisfied results for mapping marshes. It would also not require complicated skills to replicate the procedures.

The Study Site

Salt marshes in the Jamaica Bay have been the subject of several studies in the past few years. Hartig *et al.* (2002) conducted a study to examine the trend of salt marsh loss in the bay since 1924. From 1924 to 1974, over 205 hectares of salt marsh were lost. This constitutes a salt marsh loss of approximately 4 hectares per year. Most of this loss was caused by filling, dredging or drainage. From 1974 to 1994, the rate of loss increased from 4 to 12 hectares per year, resulting in 304 hectares of salt marsh disappeared in the span of 30 years. More recently, in examining aerial photography from 1994 to 1999, it was found that the rate of loss had increased to 18 hectares per year. Because marshes in the Jamaica Bay have been mapped several times, it was the ideal site to develop a long term change detection protocol.

The United States Congress created the Gateway National Recreation Area in 1972. The Jamaica Bay wildlife refuge, which is one portion of the Gateway NRA, encompasses 9,100 acres within the boroughs of Brooklyn and Queens (Fig. 2).

The Jamaica Bay islands are a mix of salt mashes and upland islands. These islands provide habitats for over 300 different species of birds. Some of the species found there are glossy ibises, great blue herons, snowy egrets, marsh hawks, eastern kingbirds, terns and a variety of gulls.

The bay also supports a large number of fish. Several studies have been conducted over the past 5 years that have found 81 different species of fish in the bay. These species are an integral part of the ocean's food web and contribute to both the local and regional fish population. The marshes provide habitat during the development portion of the fishes' life cycle. Figure 3 displays a Quickbird-2 satellite image with the mapped islands labeled.

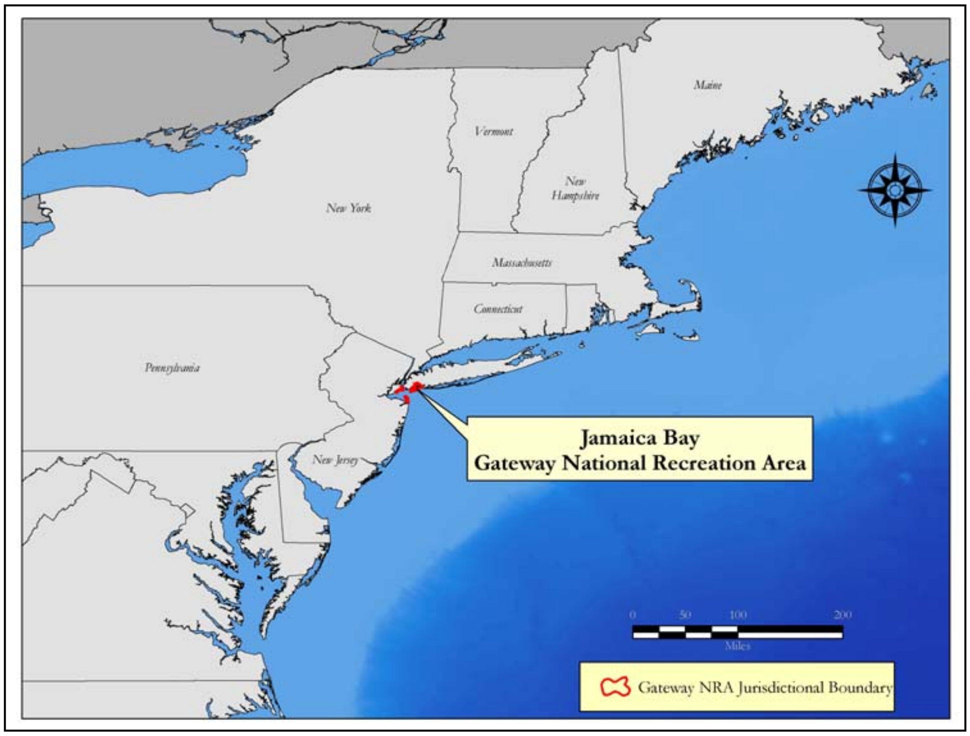


Figure 1 – Location map for the Gateway National Recreation Area.

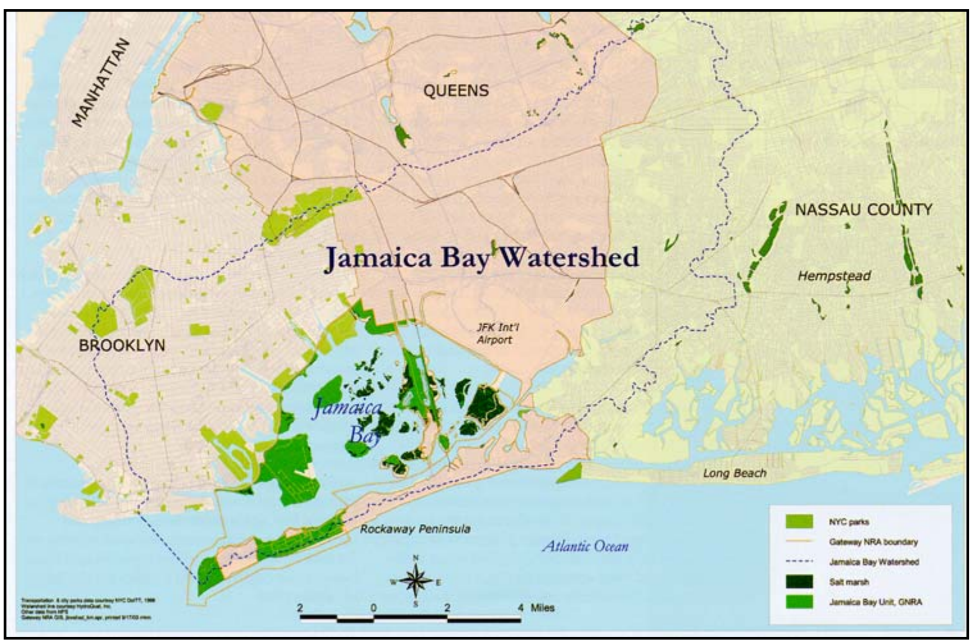


Figure 2 – Jamaica Bay watershed map.

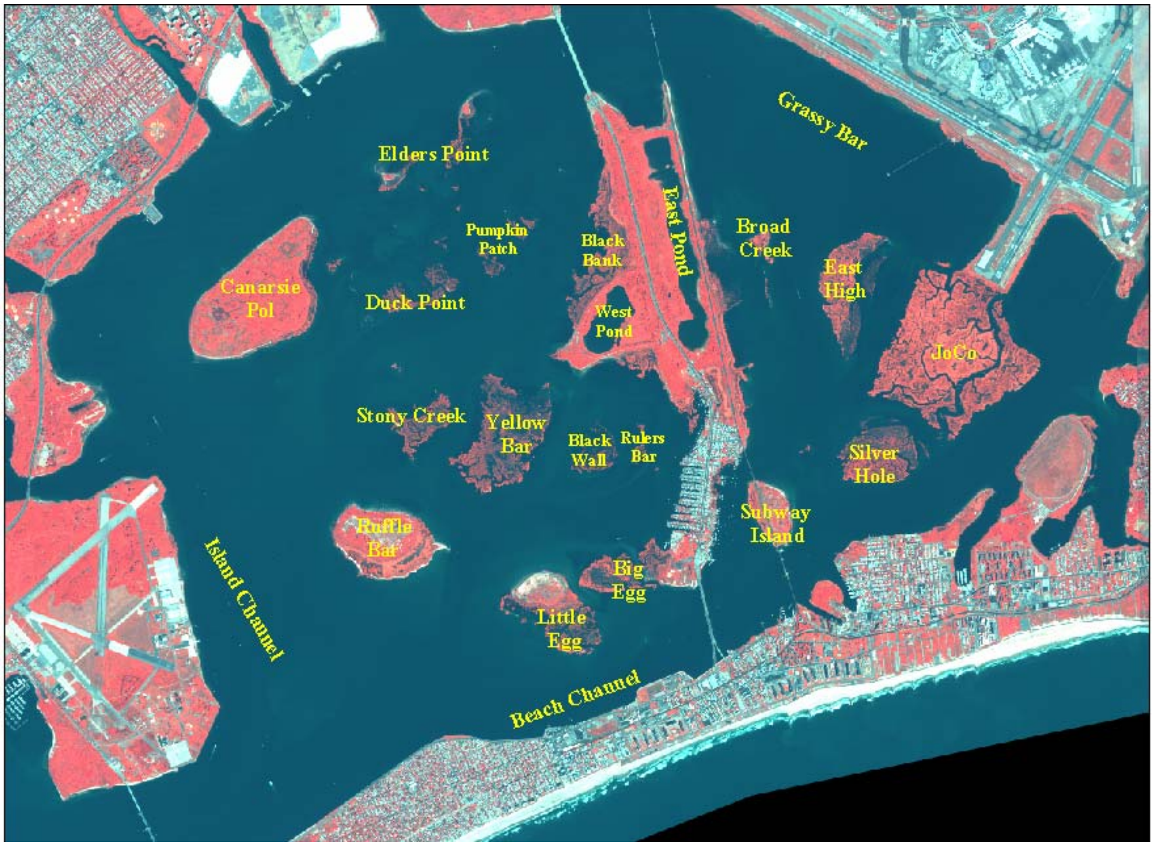


Figure 3 – Islands in the Jamaica Bay displayed by pseudo color combination of Quickbird satellite image (Bands 4, 2, 1 in RGB).

Table 1 describes basic characteristics of the islands. All of the islands support *Spartina alterniflora* also known as smooth cordgrass. Six of the islands are attached in some way to upland areas. In the case of Ruffle Bar, the salt marsh lies between two uplands areas. Three of the islands support high marsh vegetation. (See section 2.4 Classes for specific marsh definitions)

For the purposes of testing, fringe marshes were excluded from this study. However in general practice they can be included using the same methodology used for island with upland components.

Table 1- Island Variables.

Island Name	Upland	*Spartina alterniflora*	High Marsh
Big Egg	Y	Y	N
Black Bank	Y	Y	Y
Black Wall	N	Y	N
Broad Creek	N	Y	N
Canarsie Pol	Y	Y	N
Duck Point	N	Y	N
East High	N	Y	N
Elders Point	N	Y	N
Joco	Y	Y	Y
Little Egg	Y	Y	N
Pumpkin Patch	N	Y	N
Ruffle Bar	Y	Y	Y
Rulers Bar	N	Y	N
Silver hole	N	Y	N
Stony Creek	N	Y	N
Yellowbar	N	Y	N

2 Mapping the Salt Marsh

2.1 Overview

This protocol took existing, matured methods of image processing that have been applied to coarser spatial resolution imageries and applies them to the finer spatial resolution satellite imagery. Classification is the primary process to obtain land cover types or attribute information from remote sensing data. Multispectral classification is the process of sorting pixels into a finite number of individual classes, or categories of data, based on their spectral data values. If the data for a pixel location satisfy a certain set of criteria, the pixel is assigned to the class that corresponds to the criteria. One of the difficulties in attempting classifying finer spatial resolution imagery is that the large amount of pixels that provide spectral details prevents creation of unique spectral signatures. This creates the salt and pepper effects in the classification map. With moderate resolution imagery, some of the variations of the landscape are generalized into one pixel. With high resolution imagery, such as the 0.6-m imagery data, the subtle feature of the landscape may increase the noise level. In order to deal with this problem we isolate the study area by removing all areas that are not necessary in the classification. This masking process involves clipping out the salt marshes and removing upland and bay water areas. Specifics on clipping out the imagery and preparing it for classification can be found in the technical section of this report. The final products of those steps are multi-band high resolution images that can undergo classification and provide quality information.

2.2 Unsupervised Classification

Unsupervised classification offers the easiest approach to classifying salt marshes as this technique relies upon the computer algorithm to extract spectral clusters from the digital image pixels. The data, once prepared, are processed by the computer algorithm, whereby numerical operations are performed that search for natural groupings of the spectral properties of the pixels, as examined in multi-spectral feature space (Jensen, 1996). Because we have removed unnecessary portions of the images except the areas with salt marshes, the software can classify the marshes into different classes of vegetation coverage, so that classifying the marsh area can be accomplished quickly and the area calculations can be generated easily. Since unsupervised classification is based on spectral values of the pixels, human decision in selection of spectral signatures can be avoided. This will be helpful for the follow up classifications in the future. With reduced human influence, it will increase the consistency, accuracy and efficiency in salt marsh mapping and change analysis.

2.2.1 Digital Image Classification vs. Manual Delineation

Digital image classification offers advantages over manual delineation in certain cases. When performing manual delineation, errors of inclusion maybe created when an interpreter traces polygons around marsh areas. Often there are small ponds or mudflats within manually delineated polygons. Although those small areas are too subtle to map, they should not be mapped as marsh vegetation. This can produce an exaggerated calculation of marsh vegetation areas. When mapping using digital image classification, each pixel is treated individually and placed into a corresponding category, which can greatly reduce the amount of inclusion error.

Figure 4 shows a portion of the Yellowbar marsh mapped by manual delineation. The portion labeled as Marsh contains many areas of mudflats and pools. These pixels should belong to different classes but salt marsh vegetation. In Figure 5 the same areas were mapped using unsupervised classification. This time the areas of marsh vegetation were classified more precisely. Since much of the inclusion error was removed, it provides a more precise and accurate area calculation for the marsh vegetation.

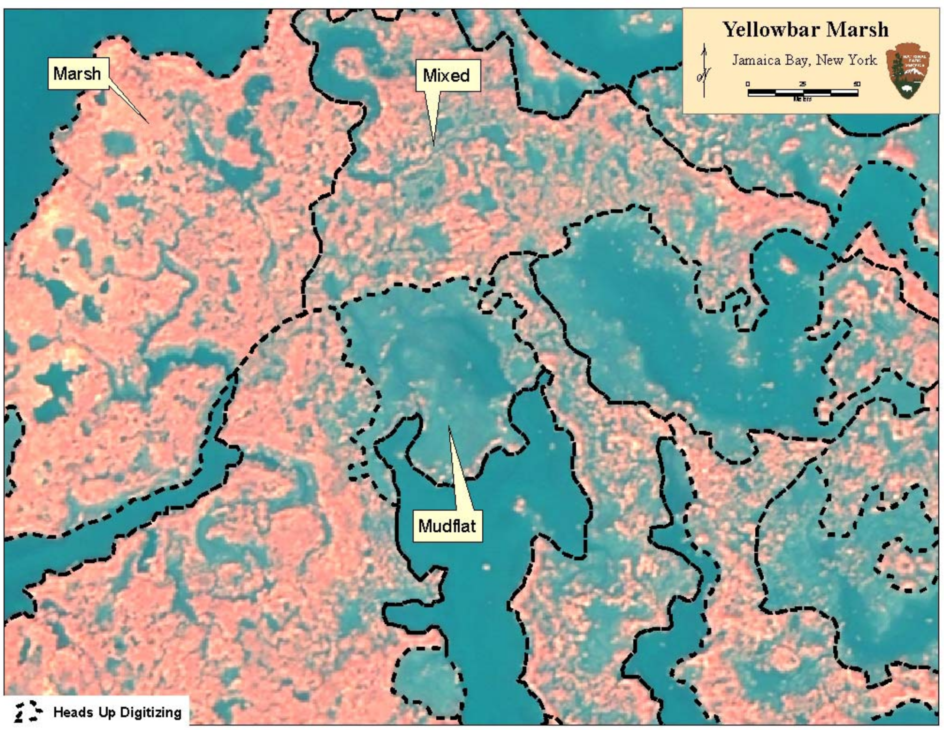


Figure 4. Manual delineation result of the Yellowbar marshes.

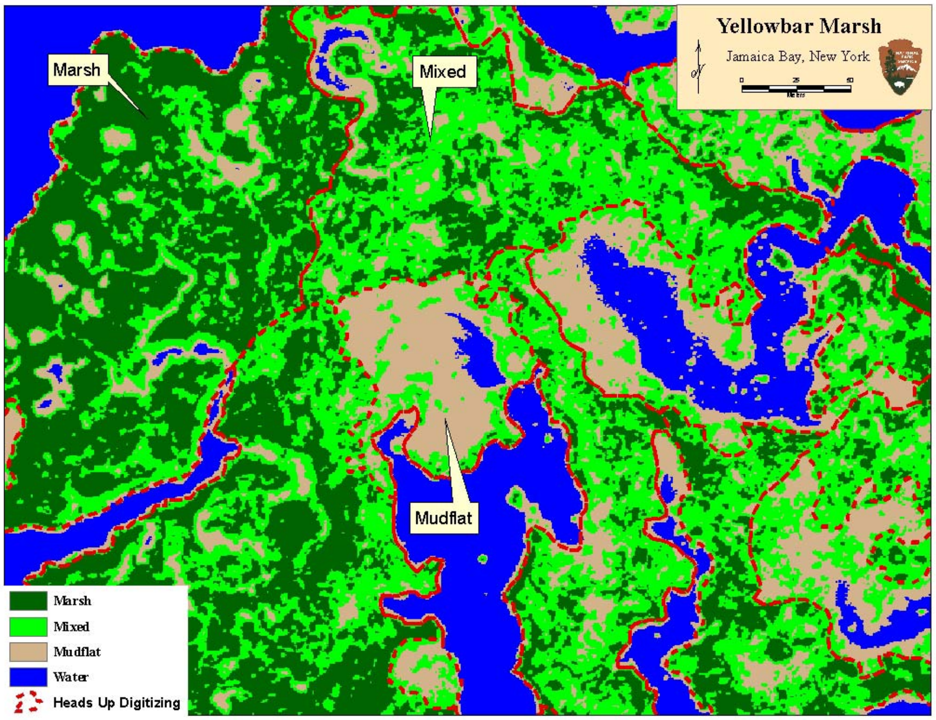


Figure 5. The result of unsupervised classification of the Yellowbar marshes.

Digital image classification of high spatial resolution QuickBird-2 data also allows the user to see details in specific areas of the marsh. By examining the trends between years, the user can see more precisely where the marsh is failing and use that type of information to aid in management decisions. User could not accomplish in a timely fashion with the manual delineation at this level of finer spatial resolution.

2.3 How It Works

This protocol employed the ISODATA algorithm for unsupervised classification. ISODATA stands for **I**terative **S**elf-**O**rganizing **D**ata **A**nalysis **T**echnique. ISODATA makes a large number of passes over the dataset until specified results are obtained.

Figure 6 explains the concepts of the ISODATA algorithm. The algorithm starts by examining the 4 spectral bands of digital image data to determine the mean and standard deviation of the dataset (Fig. 6 (a)). The algorithm then places points and cluster means evenly across the data range, between one standard deviation on either side of the mean, equal to the number of classes the image analyst wants to generate. In the first iteration, each candidate pixel is compared to each cluster mean and assigned to the cluster whose mean is closest in Euclidean distance in spectral domain (Fig. 6 (b)). During the second iteration, a new mean is calculated for each cluster based on the actual spectral locations of the pixels assigned to each cluster, instead of the initial arbitrary calculation (Fig. 6(c)). After the new cluster mean vectors are selected, every pixel in the scene is once again assigned to one of the new clusters. This process continues until there is little change between classes in new iterations (Fig. 6 (d)). For the demonstrative purposes, Figure 6 is only displaying the concept of clustering between spectral band 3 and band 4. When this process is performed, all spectral bands in the dataset are used.

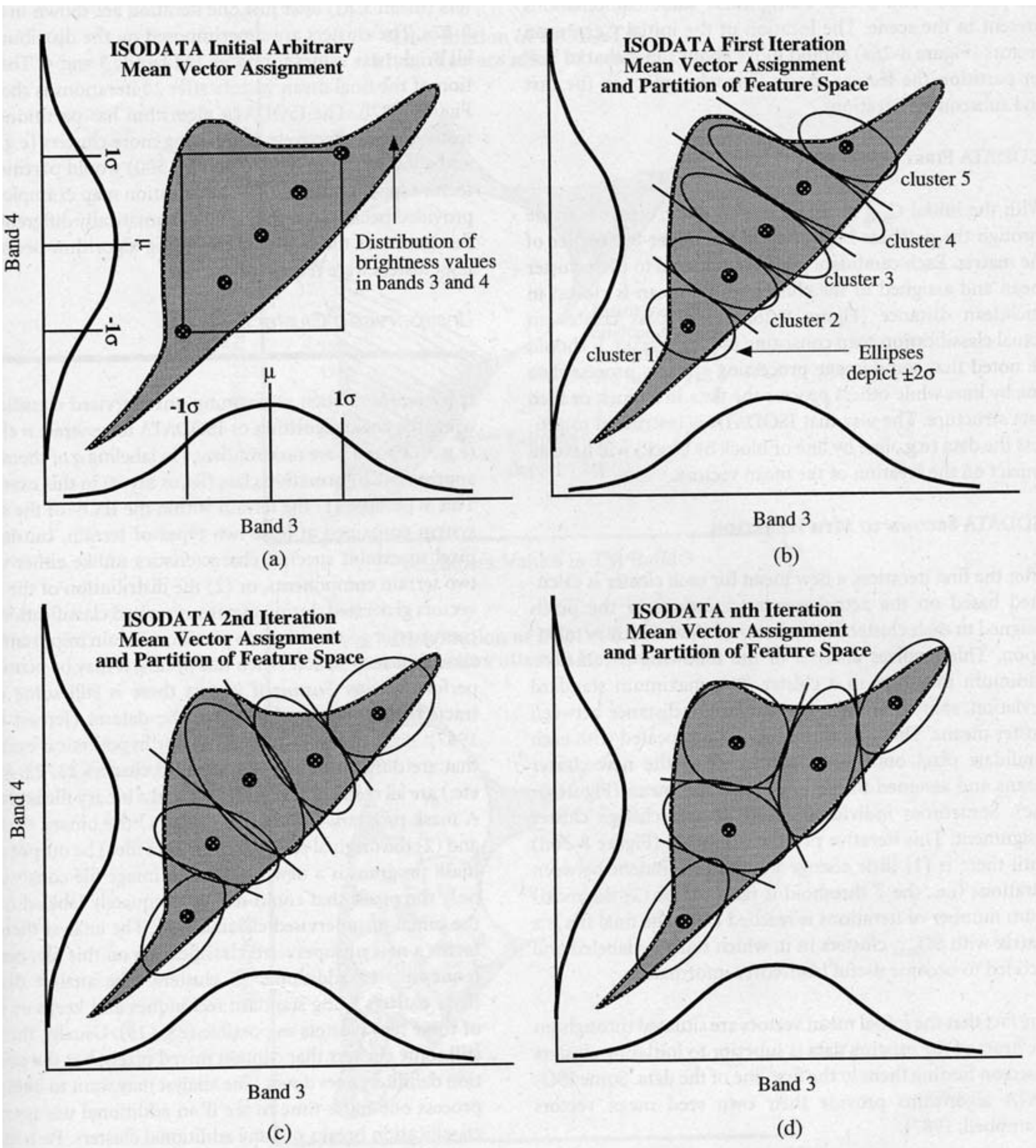


Figure 6 – Explanation of ISODATA (Jenson, 1996, p. 237).

2.4 Classes

We decided, by consulting with the experts of the National Park Service, to classify the Jamaica Bay marsh areas into categories of Mudflat, *Spartina* 10-50% cover, *Spartina* > 50% cover, and Open Water. For specific islands a fifth category of High

Marsh was added. These classes were chosen because they represent the process of marsh loss within the Jamaica Bay. As the marshes degrade and break up they tend to follow the path shown in Figure 7.

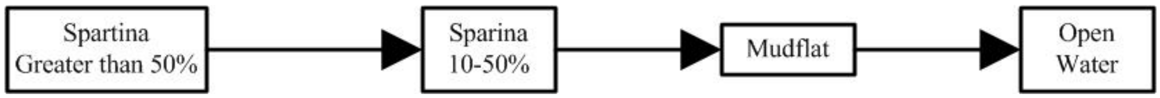


Figure 7. Path of marsh loss.

As marsh vegetation degrades, proceeding along the path from left to right, it breaks into smaller isolated marsh islands. The density of marsh patch begins to decrease, marsh areas break up, turning from marsh vegetation to mud, and finally to open water. This path is not reversible for growth. Growth of marsh vegetation tends to follow a different pattern with solid piece of marsh expanding outward. There is no fragmentation during growth.

2.4.1 Manual Interpretation Classes

Traditionally, the National Park Service has used manual interpretation to map the salt marshes of the Jamaica Bay. The classification scheme included nine categories as described in Table 2. These classes have been converted and updated to fit our classification scheme that can be mapped using unsupervised classification of QuickBird-2 data. We grouped some categories from the manual delineation classes and eliminated several others because they were not relevant to this protocol development project.

***Spartina* < 10% -** We decided that if an area has less than 10% of *Spartina* and over 90% as mudflat, this area should be considered as the mudflat class.

Mucky Peat – Mucky peat is a mudflat habitat that retains some remnants of decomposing salt marsh peat. During image classification process, mucky peat could not be distinguished from mudflat.

Mud Flat (interior vs. exterior) – The difference between interior and exterior of mud flat is a user distinction and cannot be reproduced during digital image classification.

Tidal Creek and Pools – We grouped all water bodies as one category. The interior and exterior mudflats are user distinctions and could not be reproduced during digital satellite image classification.

Artifact, Sand Artifact – This class was part of an archeological study performed at Jamaica Bay. This class was removed for this protocol development.

Table 2. Comparison of classification schemes between manual delineation and unsupervised classification.

Manual Delineation Classes	***Unsupervised Classification Classes***
Spartina greater than 50%	Marsh - *Spartina* >50%
Spartina 10 – 50%	Mixed Mudflat / Marsh - *Spartina* 10-50%
Spartina less than 10%	Mudflat - *Spartina* <10% - Mucky Peat - Mudflat, Interior - Mudflat, Exterior
Mucky Peat	
Mudflat, Interior	
Mudflat, Exterior	
Tidal Creek	Open Water - Tidal Creek - Pool
Pool	
Sand	
Artifact, Sand Artifact	

2.4.2 Mudflat

Areas classified as mudflat have little to no vegetation cover. Mudflats are typically inundated with water for longer periods of time then the areas covered by vegetation. These areas are similar in appearance to those shown in Figure 8, where there are small islands of marsh vegetation surrounded by mud. There are often subtle elevation difference between the mudflat and vegetated areas.

Figure 8. An example of Mudflat.

2.4.3 10 to 50% *Spartina alterniflora*

The class of 10 to 50% *Spartina* cover is made up of mixed mudflat marsh areas. Figure 9 shows an area that is closer to the 50% coverage. Interior areas have started to degrade but coverage is still mostly complete. Some areas of this field photo would be classified greater than 50%.

Figure 9. An example of 10 to 50% Marsh cover.

Figure 10 shows an area that is closer to the 10% boundary for coverage. There are large visible areas without coverage of marsh vegetation. Most likely portions of this area will be classified as mudflat.

Figure 10. An example of 10 to 50% Marsh cover.

2.4.4 Greater than 50% *Spartina alterniflora* cover

Areas classified as greater than 50% cover represent relatively dense expanses of *Spartina alterniflora*. These areas are usually firm enough to walk on. There are no breaks in the vegetation. Figures 11 and 12 are good examples of areas with *Spartina alterniflora* cover greater than 50%.

Figure 11. An example of areas with *Spartina alterniflora* cover greater than 50%.

Figure 12. An example of areas with *Spartina alterniflora* cover greater than 50%.

2.4.5 High Marsh

The high marsh does not exist on all salt marshes in the Jamaica Bay. High marsh is typically found on marshes that have upland components. The high marsh areas can have a variety of different plants, such as *Spartina patens*, *Phragmites*, *Distichlis spicata* and others. Figure 13 shows an example of high marsh area adjacent to upland. High marsh can be found in Joco, Black Bank and Ruffle Bar islands.

Figure 13. An example of High Marsh.

2.5 *Spectral Separation*

In an unsupervised classification, the algorithm searches for natural breaks of statistics in the data. In the data preparation section of this protocol, all of the unrelated external data were removed, leaving mainly the areas with salt marshes. The algorithm then searches only for breaks of statistics in the data for the salt marshes coverage. Figure 14 shows the histograms of digital pixel values that each spectral class had for each spectral band in the QuickBird-2 dataset. For bands 1, 2, and 3 the histogram of pixel values are clustered together. In Band 4 the groupings are spread out. The pixel values for band 4 (near-IR band) are driving the classification. The histogram is tied to the amount of vegetation cover in the pixels. The more the vegetation cover, the higher the digital pixel value in the IR band. It should also be noted that pixels of mudflat are contained within a very specific spectral region, because of their low value for vegetation cover. The pixel values for categories of 10-50% and Greater than 50% *Spartina* covers are spread out more because these classes represent different biomass accumulation on the ground.

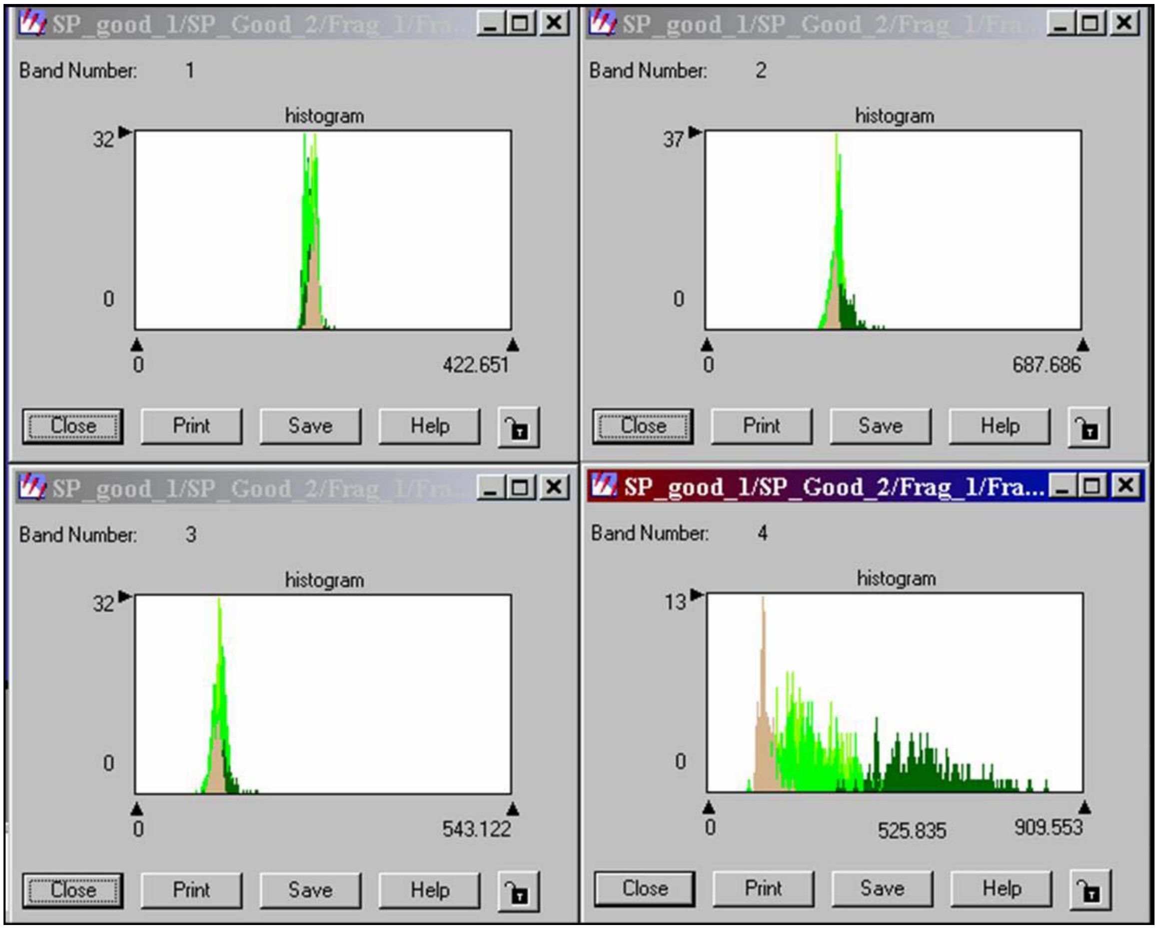
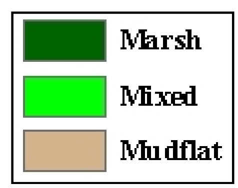


Figure 14. The spectral seprability for classes.



We tested classifications with different numbers of spectral clusters. We found that for the Jamaica Bay, the best results came from using four clusters only. We also tested unsupervised classification with 10, 25, and 100 clusters. While more clusters yielded maps with higher precision, the differences were marginal. More clusters added huge amount of extra work. Expanding to additional groups may be necessary if the differences in classes are more subtle. The number of groups created may change also based on the goal of the mapping project. Experiments with the data are necessary for a site to determine the appropriate number of clusters for image classifications.

3 Field Reference Database

A field reference database contains digital records of landscape conditions of sites at the time close to that the satellite images were taken. Such a database can provide a historical record of the points, which can be used to aid in image classification. Digital photographs of the site can be taken with GPS coordinates. This will allow land managers to record the conditions of the sites. If these photographs are taken every year, land managers can look back and observe how the marsh areas have been changing. The GPS coordinate insures that the same location is observed in different years. This type of field reference database will aid in checking classification results and provide benchmark data for long term monitoring. Once the classification is completed, the GPS coordinates of the field photos can be placed over the mapped site. The landscape recorded by the field photos can be compared with the classifications to examine the mapping accuracy. In this project we created a field reference database for the Jamaica Bay study area. Some of the field sites are marked in Figure 15.

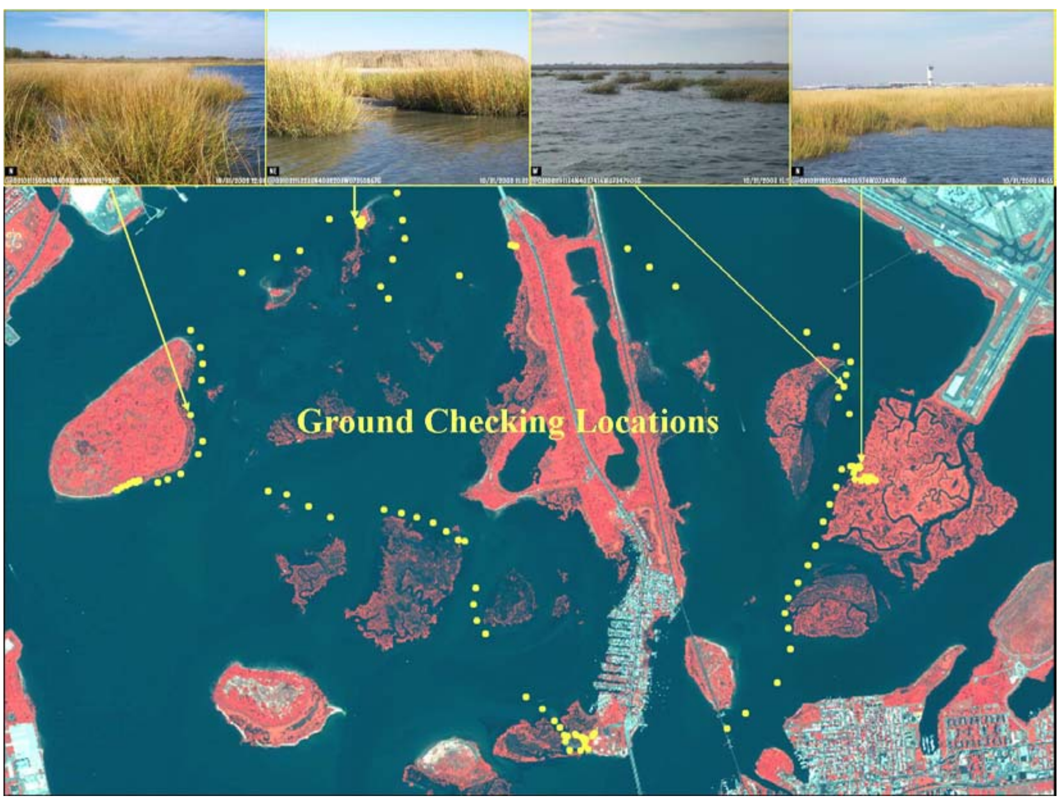


Figure 15 – Locations of example field photos with GPS coordinates.

4 Other Mapping Techniques

Unsupervised classification is not the only method for mapping salt marsh. This section describes other techniques that are commonly used and acceptable to map salt marshes.

4.1 "Heads-Up Digitizing

Heads-up digitizing was the first computerized method to map salt marshes. It is similar to mapping salt marshes using a stereoscope and aerial photos. Heads-up digitizing involves displaying the digital images from satellite or aerial photos on a computer screen and the image interpreter drawing polygons around the salt marshes and classifying (labeling) them. Figure 16 shows an example result from heads-up digitizing. This method allows the interpreter to have a complete control over how the marshes are delineated and classified. This method is most commonly used with aerial photos. Heads-up digitizing can yield accurate results. However, this process can be very time consuming, especially for large areas.

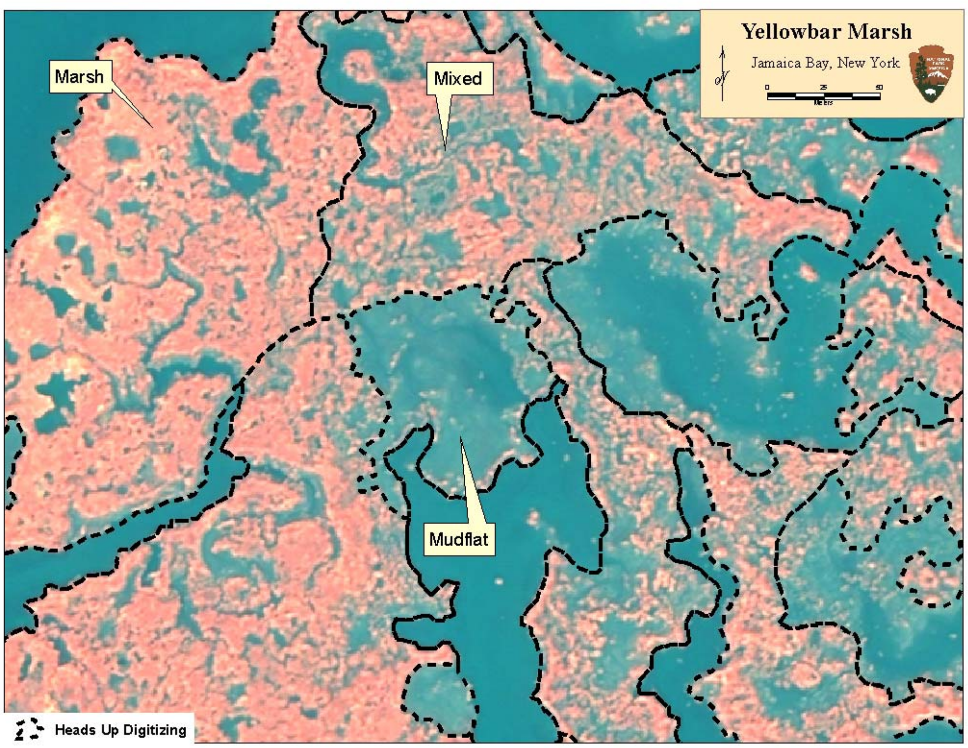


Figure 16. Heads-up digitizing of marshes.

Creating polygons around the marshes also promotes inclusive errors that can skew area calculations for the marsh vegetation. Heads-up digitizing may have potential problems in long-term change detection analysis. Often, different interpreters will perform the process for different years. Because heads-up digitizing relies on interpreters' decisions, different interpreters may yield different mapping results. This is even common for the same interpreters performing the task in different years.   Some of the human errors can be avoided by the unsupervised classification method described by this protocol.

4.2 Supervised Classification

In Supervised classification the image analyst defines ideal groups of pixels that represent the training signatures for corresponding classes. The classification algorithm groups the pixels into classes based on the statistics of the signature pixels. In general, this method is considered more informational because it has image analyst involved in creating the signatures. This method may re-introduce human judgment and errors in the classifications. However as different image analysts may choose different spectral signatures the end results could be altered significantly.

5 Conclusion

This protocol lays out the methodology for using unsupervised classification to map salt marshes in the Jamaica Bay. By taking advantage of the most recent satellite technology we were able to map the salt marsh areas in the Jamaica Bay to compare with the map results acquired from manual digitizing techniques. Unsupervised classification can reduce the level of human influence in image analysis and provide a reliable mapping result. Overall this protocol can provide data for a long term monitoring of a dynamic salt marsh ecosystems and aid in management decisions.

Section 2
Technical Instructions

Overview

This section of the protocol details the process for one cycle of image collection. Images can be collected in different frequencies depending on the time intervals that the park wants to monitor the changes. This technical document outlines the procedures of ordering data, data preparation, creating polygons to extract the areas of interest, unsupervised classification and finally for accuracy assessment. In this protocol we use the ERDAS Imagine[1] software as the program base. However ERDAS is just one of many software packages. While the exact steps would change using a different software package, the basic methodology and procedures would remain the same.

6. Acquiring QuickBird-2 Imagery

6.1 QuickBird-2 Data

The Quickbird-2 satellite was launched October 18, 2001 by the Digital Globe[2] company. Currently it provides the highest spatial resolution imagery data available from commercial satellites. The Quickbird-2 orbits 450 km above the Earth's surface and revisits most locations of the Earth between 30 degrees north and south every 1 to 4 days. Quickbird-2 imagery data include a panchromatic band (450-900nm) with 0.61-m spatial resolution (Fig. 17) and multispectral bands of blue (450-520nm), green (520-600nm), red (630-690nm), and near IR (760-900nm) spectrum with 2.5-m spatial resolution (Fig. 18). The swath width is 16.5km. The maximum order polygon size for a single scene is approximately 14 x 14km.

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1 Leica Geosystems Geospatial Imaging (http://gis.leica-geosystems.com)
2 Digital Globe: www.digitalglobe.com

Figure 17– Quickbird-2 panchromatic data with 0.6-meter spatial resolution.

Figure 18 – Quickbird-2 Multi-Spectral data with 2.5-meter spatial resolution.

Figure 19 is a pseudo color display of the Joco island marsh adjacent to the JFK International Airport. Since the near IR band is sensitive to vegetation and the band is displayed using red color, the brighter red color represents more abundant vegetation on the ground.

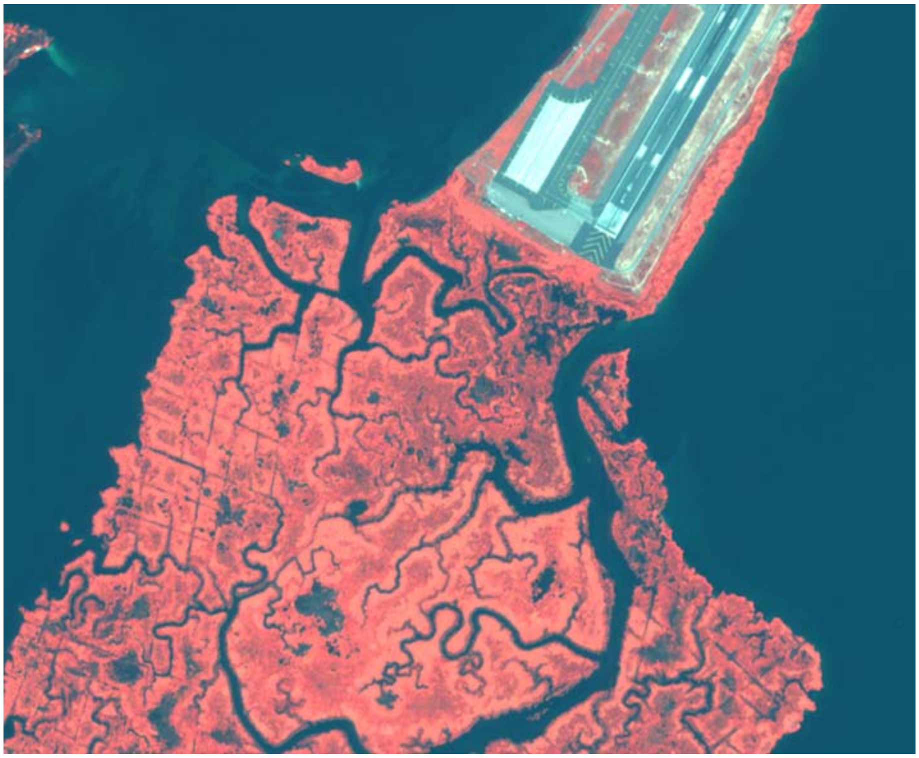


Figure 19. A pseudo color display of Quickbird-2 satellite image of the Joco marsh displayed as Bands 4, 2, 1 in RGB color combination. The spatial resolution is 2.5-meter.

6.2 *Imagery Parameters*

A variety of parameters and information that will be required to order satellite imagery from a data provider. This information can range from data acquisition times, to cloud cover specifications, to the size of imaging site.

6.2.1 Outline of Site

One of the most important aspects of ordering satellite imagery is communicating about what area you are interested in. While Digital Globe provides several ordering options, the most efficient way to insure the site is covered is to provide an ArcView shape file or other GIS file of the study area. Figure 20 shows the outline that was used for data ordering in the Jamaica Bay. The red line shows the outline of the area that was provided to the Digital Globe in an ArcView GIS shape file. Instead of just presenting the park boundaries, we recommend that a buffer around the park be applied to ensure that all the study area is covered by the data acquisition. This information can be very valuable in assessing what impacts are affecting the resources being studied.

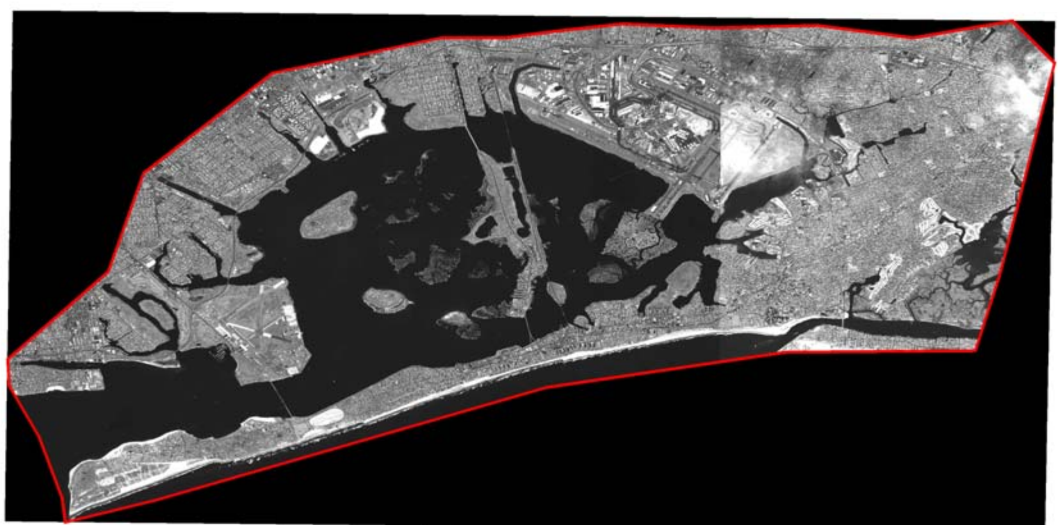


Figure 20. Outline of the Jamaica Bay study site.

6.2.2 Standard Imagery

When ordering the imagery, standard image processing from data provider should be selected. It is recommended that the same parameters are used for future imagery acquisitions. For the Jamaica Bay project, we ordered data with the following parameters:

Projection: UTM Zone 18N
Datum: NAD 83
Resampling Method: 4x4 Cubic Convolution
Bit Depth: 16 Bit
File Format: GeoTiff
Tile Overlap: 200m
Cloud Cover: Less than 20%

Cloud cover represents the greatest hindrance to image collection. The ideal situation for image acquisition is cloud free. As part of the contract, Digital Globe or other company's may insist 20% cloud cover as the minimum requirement in the contract. This percentage is the amount of cloud cover over the entire image acquired. The cloud may not necessarily cover the site of interests. Most of the image providers, including the Digital Globe, will provide quick view images to the end users for inspection before sending the data. This will be the good time to examine the imagery data and determine if the data quality is acceptable.

6.2.3 Time of Year Consideration

For mapping salt marshes the ideal time window (for this protocol development study) for data acquisition is at the end of August or the beginning of September, when the salt marsh plants are at the maximum height at the peak growing season. The vegetation height and biomass will enhance the spectral signals that will help in the classification of the marsh vegetation. This time window is also good for image acquisition because it has the greatest probability for cloud free or near cloud free skies at this particular study site.

The imageries for the Jamaica Bay were collected on September 10, 2003 and October 06, 2003. A window from 08/06/03 to 10/20/03 was requested at data ordering. Digital Globe asks for a collection window of 90 days to insure enough time to meet the specifications.

6.2.4 Tidal Considerations

The ideal tide situation for image acquisition would be the time near low tide. However, tide height is difficult to predict at time of image acquisition in the Jamaica Bay. One should consult the NOAA Tide charts to account for local variations and regional characteristics. While the lunar and tide cycles can be predicted, different parks will have regional characteristics that affect the tides. For example, Jamaica Bay has a constricted out flow. The tide waters "back-up" in the bay and can delay the drop in the tide height several hours past the predicted peak. The winds can also affect the tides and drive water into the bay further affecting the tide heights. These factors make it difficult to predict when low tide will occur in regards to satellite orbit. Waiting for perfect tide condition when the satellite passes overhead would reduce the chances of image acquisition. Wind or cloud cover could easily spoil the quality of image data collected. Some flexibility is required in acquiring satellite imagery.

The ideal image should be collected 2 hours before or after low tide. Anything beyond that range will affect the quality of mapping results. The class that is most susceptible to tide height is the mudflat class.

6.2.5 Cost Consideration

To acquire both the panchromatic and multispectral data, as was done for this project, the cost was \$30 per km^2. The Jamaica Bay site was about 216 km^2 in area (Figure 20). Digital Globe has a minimum order size for standard imagery of 64 km^2. Special contract rates may apply with certain agencies. If an image for the area of interest has been archived with earlier orders by other customers the price will be less expensive. Therefore we recommend a search for possible available data from data providers prior putting a data order.

7 Image Processing

The goal of image processing is to prepare the image for classification. Due to the size limit of the image acquisition, the QuickBird-2 data are provided in tiles of GeoTiff images. The tiles of images from the data provider may need to be mosaicked into a seamless dataset. The areas of interest, the salt marshes in this case, need to be clipped out of the mosaic, and then the 2.5-m spatial resolution multispectral images are merged with the 0.6-m spatial resolution panchromatic images to increase the spatial resolution. Once these steps are completed, the images are ready for the classification process.

All of the image processing and classification in this project was conducted using ERDAS Imagine software system. When using ERDAS Imagine, each image processing function in the toolbox has a help button, which will provide the user with information on what that function in the toolbox can do. In addition, if pointing at a button with computer mouse, a brief description of the button's function will appear on the computer screen. The image provider also provides GIS shape files that display the swath width and when the image data were collected.

7.1 Mosaic Imagery

In order for ERDAS Imagine to work with the data effectively the tiles should be converted into "image" format or ".img" files. This is accomplished using ERDAS Imagine's import function.

7.1.1 Steps to Convert GeoTiff files into .img Files

1. On the main toolbar (Fig. 21), click on the Import button. This will bring up the Import/Export tool (Fig. 22).

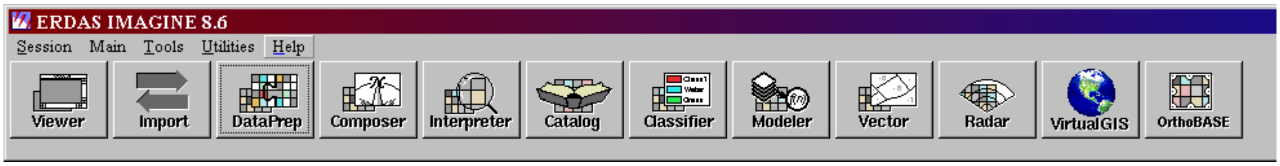


Figure 21. ERDAS Imagine Main Tool Bar.

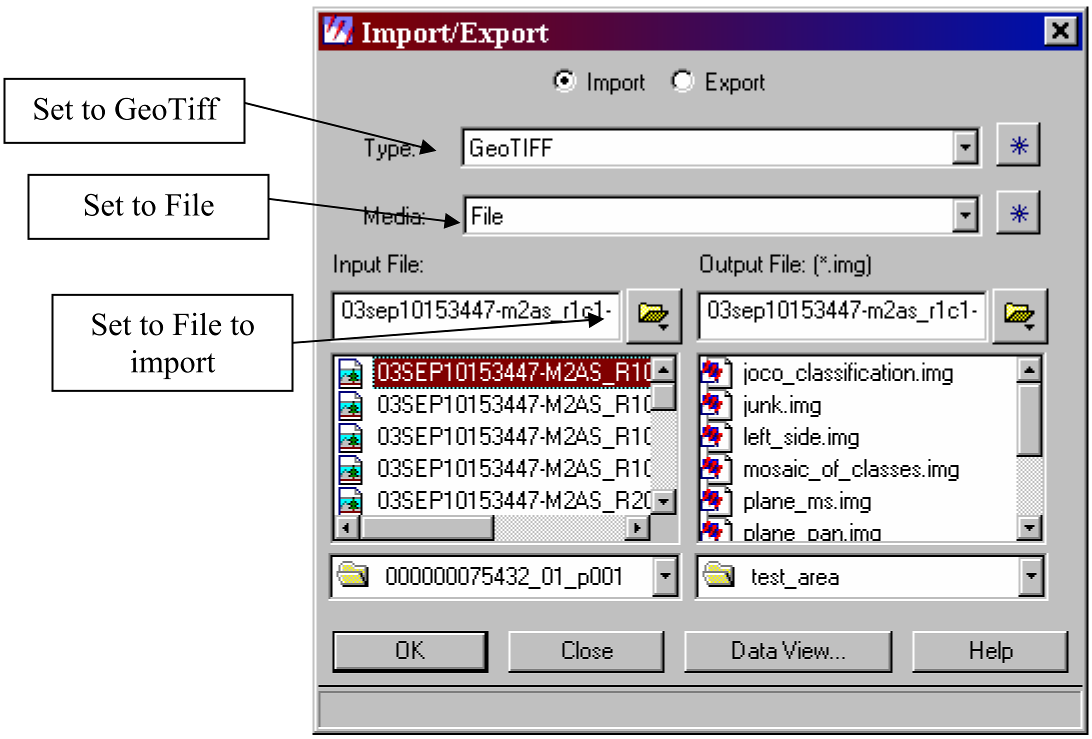


Figure 22. Import/Export Tool Box.

2. The media dropdown menu needs to be set to file

3. The Type needs to be set to GeoTiff

4. Using the Input file folder button navigate to the CD or to the directory on the hard drive where the images are stored. This process will go faster if the files are saved on the computer hard drive, which is recommended.

5. Click the Output File folder button and navigate to where the new images are to be saved, enter a name. Click the Ok button.

6. Back in the Import/Export window, the two view windows are now set to the two locations where the data is coming from and where it is going to. Click on the file you want to import. This will cause the same name to appear in the output box, in the new location. Click the Ok button.

7. This process needs to be repeated until all the images have been imported. If the tool box window remains up, the computer will retain the path names and you can keep selecting the images you need to import.

Once the images have been imported they need to be stitched together into one seamless mosaic. As display in the left side of Figure 23, image tiles are visible due to the display stretch function in ERDAS Imagine. After the images are brought together into one mosaic, the image is seamless and color balanced (Fig. 23 right).

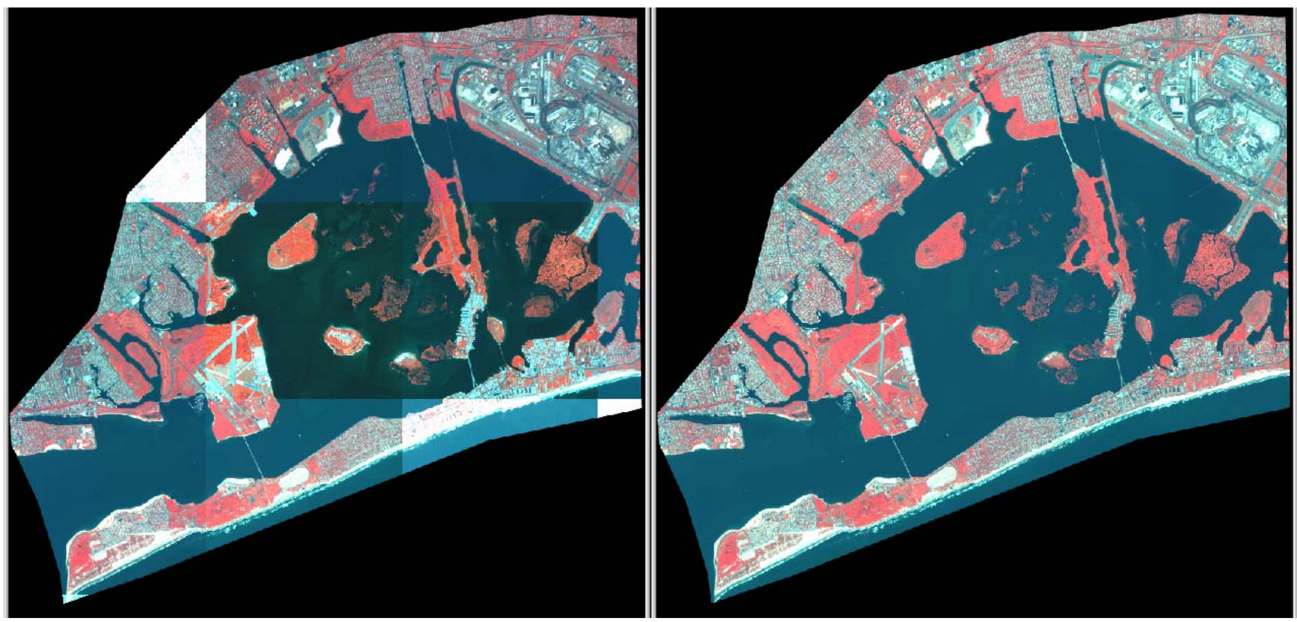


Figure 23. Titles of images before and after the mosaic.

7.1.2 Steps to Mosaic the Images

1. Click on Data Prep button on the ERDAS Imagine Main Tool Bar.
This will bring up the Data Preparation Tool Bar (Fig. 24).

2. Click on Mosaic Images…Button on the Data Preparation Tool Bar. This will launch the Mosaic Tool (Fig. 25).

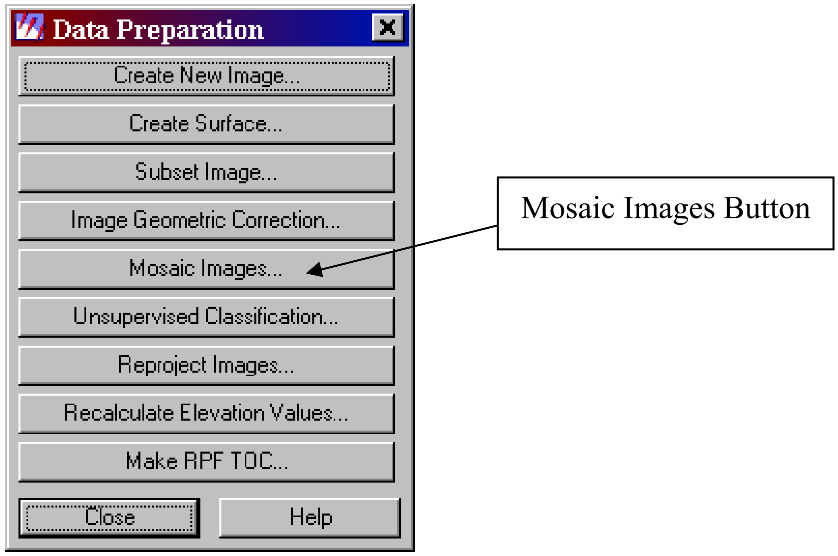


Figure 24. Data Preparation Tool Bar.

The mosaic tool window will be empty to start. You need to load all of the images you wish to be in the mosaic tool window. This will need to be done twice, once for the multispectral image tiles, and once for the panchromatic image tiles.

3. Click on "Add Image Display Box" Button

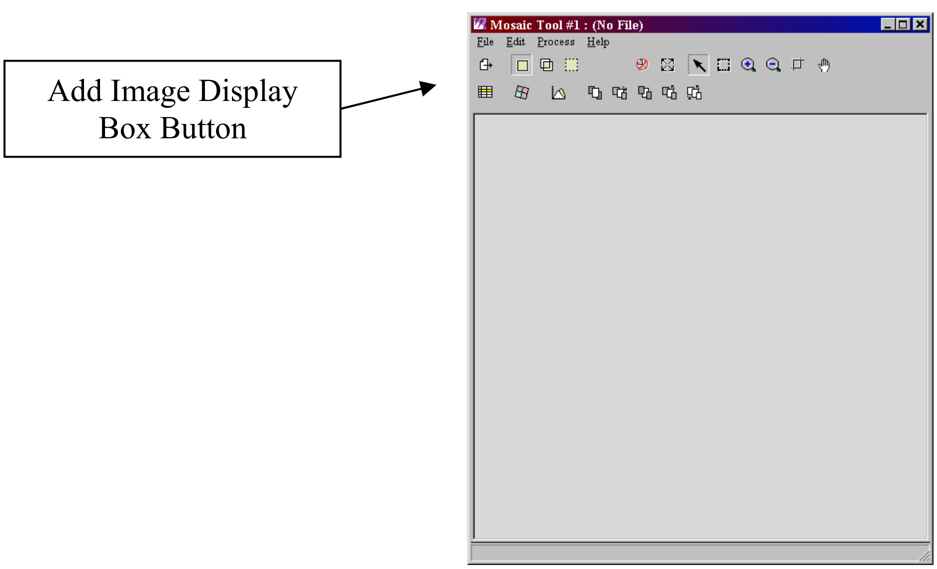


Figure 25. The Mosaic Tool.

4. This will bring up the Add Images for Mosaic Tool Box (Fig. 25). Use the folder button to navigate to the directory containing the QuickBird-2 image tiles that need to be mosaicked. Load one image at a time. Click the Add button to add the image. The images come from data provider as geo-referenced. Each time an image is loaded its outline will be added to the mosaic box. Use the folder button if you need to navigate to a different folder. When adding an image the "Use Entire Image" button should be checked. This is the default setting.

It is recommended to help balance the whole image that all of the tiles be loaded to create the overall scene. The areas of interest will be clipped out later in the Protocol.

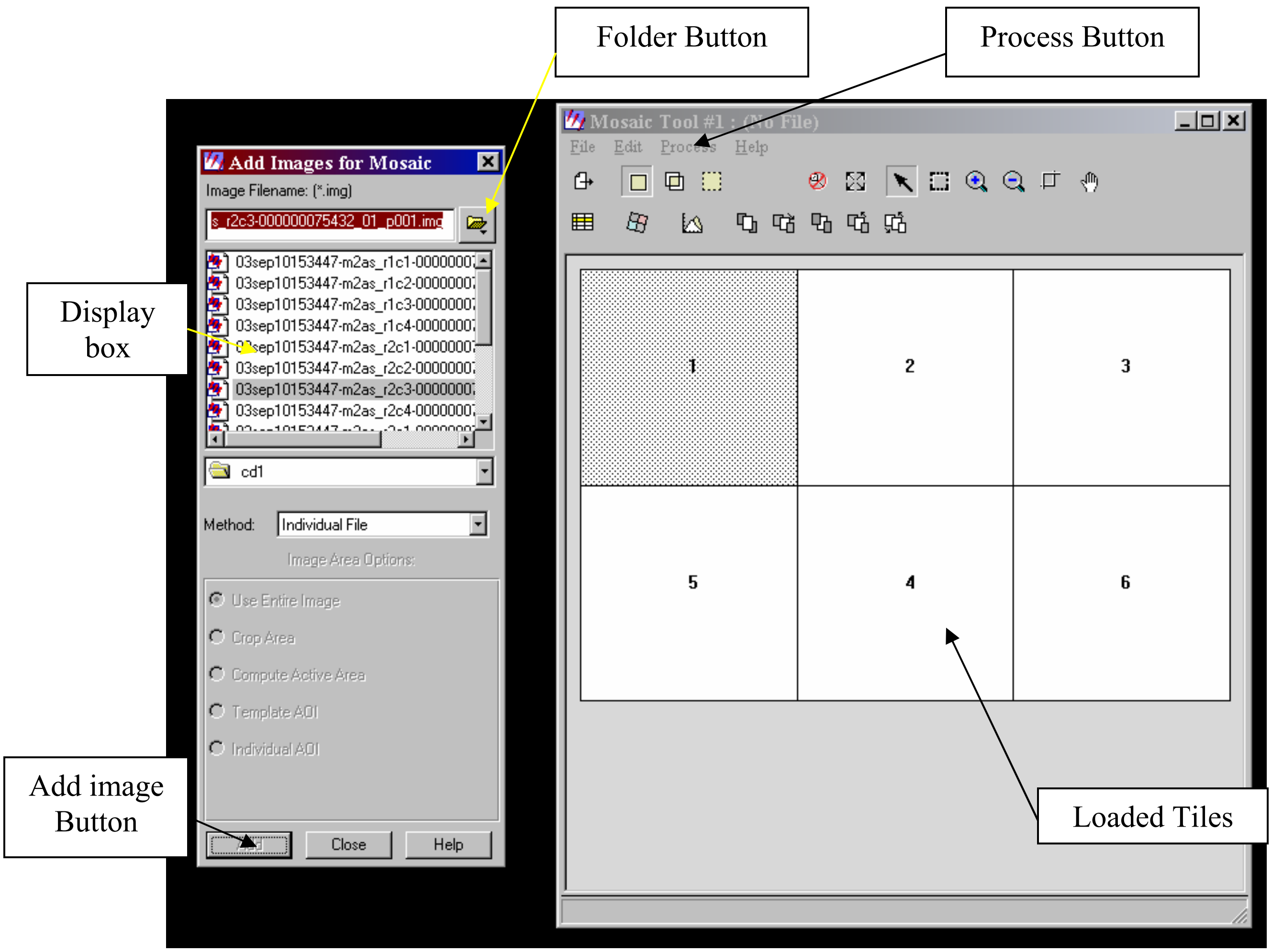


Figure 26. Add Images Toolbox and Mosaic Toolbox.

5. Once all of the tiles that need to be mosaicked are loaded, click on the Process button (Fig. 26). This will bring up two options, click the Run Mosaic.

6. This will bring up the Run Mosaic Dialog box (Fig. 27). Click on the folder button and navigate to the directory where the final image to be stored. Once a name has been entered, click OK, and then click OK on the Run Mosaic dialog box.

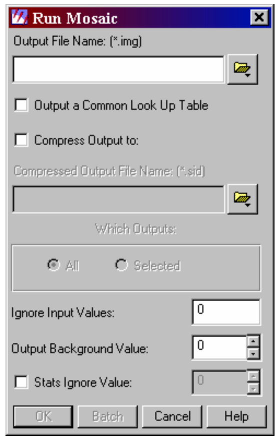


Figure 27. Run Mosaic Dialog Box.

7. The Mosaic will now run. This may take a few minutes to complete.

7.2 Creating Area-Of-Interest Polygons for Islands

The goal of this protocol is to map the salt marshes. To reduce the spectral confusion and misclassification between salt marsh and upland vegetation it is helpful to clip out the salt marsh areas much like a cookie cutter. This step will aid in classification later by restricting classification to salt marsh areas.

ERDAS Imagine requires an Arc Coverage file or an Area-of-Interest (AOI) file to act as the cookie cutter. The directions below describe how to create AOI files using ERDAS Imagine. Other software packages such as ArcInfo or ArcMap can also be used to create the AOI files. ERDAS can convert Arc coverage files into AOI files. Once the AOI polygons are created, they can be used again in subsequent image acquisitions. For the purpose of change detection, the AOI polygons can be updated each year or when it is necessary. The AOI files for Jamaica Bay were generated in this project.

7.2.1 Steps to Create AOI Polygons

1. Upload the image to a viewer and zoom to the area of interest.

2. On the Viewer window click File ➔ New ➔ AOI layer…
This will lead to create an AOI layer over your image

3. On the viewer window, click AOI ➔ Tools
This will bring up the AOI Toolbar (Fig. 28).

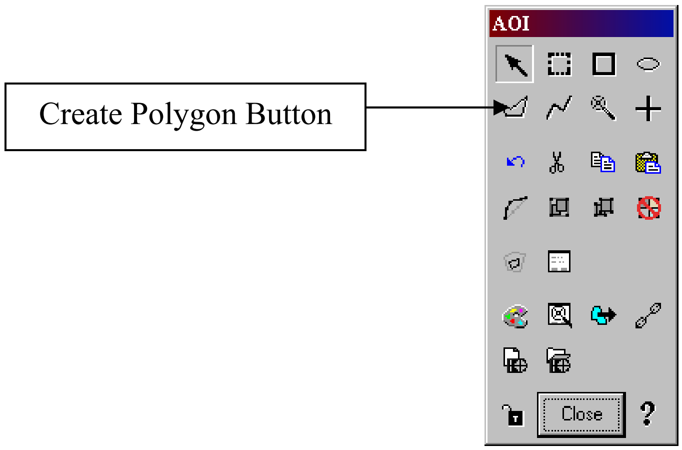


Figure 28. AOI Toolbar.

4. Click the Create Polygon Button. This will allow you to draw a polygon around the salt marsh areas. One click starts the line. Double clicking will close and end the polygon drawing.

For islands with no upland components, the line around the island can be rough. Make sure to include the whole island. For islands with upland components, carefully delineate the boundary between the upland and marsh area visually identifiable on the image.

Figure 29 shows the AOI boundary in red. The water around the island is rough, however the portion between the marsh and the upland is carefully delineated.

TIP – The best way to draw the polygons for marsh areas with upland components is to do a rough delineation of the marsh, creating more vertexes. Then go back and carefully delineate the marsh areas using the edit feature. Also, using both images, the panchromatic and multi-spectral, can help to delineate the marsh boundaries.

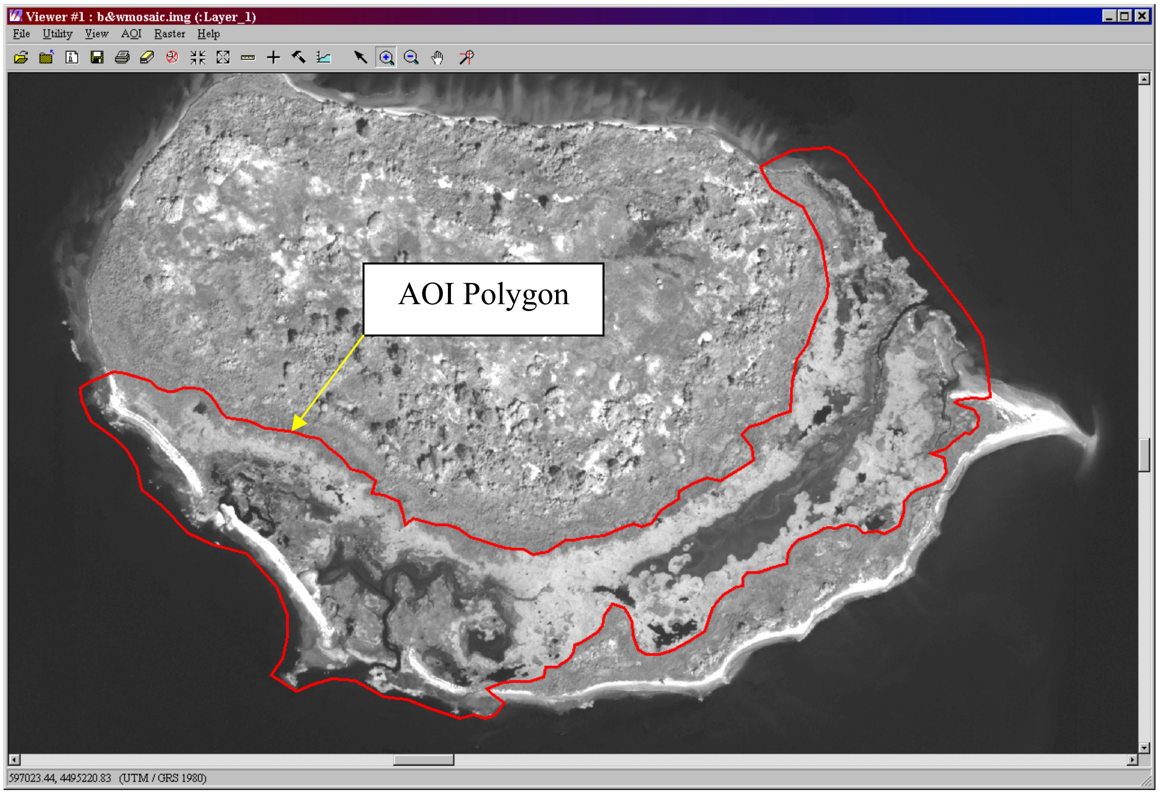


Figure 29. Example of AOI delineated on the Yellowbar Island.

5. On the Viewer click File ➔ Save ➔ AOI Layer as…
Label the new AOI layer with a name, and navigate to the directory to store the file, click OK. This AOI file is ready to be used in subsetting the image.

7.2.2 Editing the Polygon AOI Layers

For Marsh areas with upland components it is recommended to clip out the upland area. Or with time it may be necessary to adjust the boundaries of the marshes due to its growth or loss. The following steps describe how to edit an existing AOI file.

1. In the viewer, upload the image to work with and the AOI file to edit. Open the tools for the AOI file.

2. With the AOI polygon highlighted click on the Reshape polygon button on the AOI Toolbox (Fig. 30).

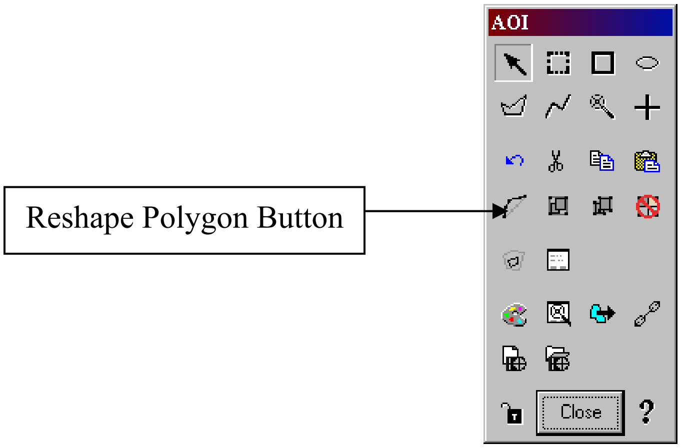


Figure 30. AOI Toolbox – Reshape Polygon Button.

3. When click this button, the polygon should change from a dashed line to a solid line with the nodes of vertexes (Fig. 31).

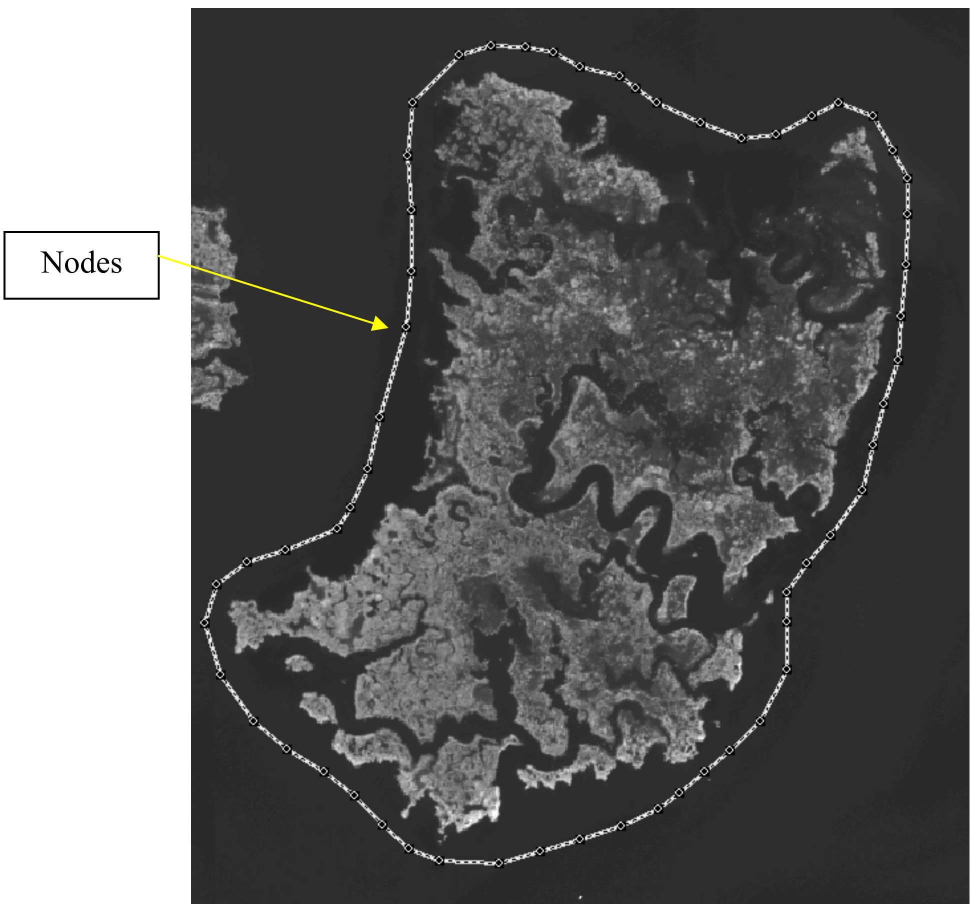


Figure 31. Yellowbar marsh with an editable AOI polygon around it.

4. Click on the Arrow button on the AOI toolbox. Then point the arrow at the node one wish to move. Left click and hold, then move the node to the location it should be placed.

7.3 Clipping and Subsetting Marsh Areas

Once the AOI files for each island are created you can use them to clip out the portions of the satellite images that are needed.

7.3.1 Steps to Subset Image

1. Using ERDAS Imagine, click on Data Prep on the main tool bar. Click on Subset image. This will bring up the Subset image toolbox. (Fig. 32)

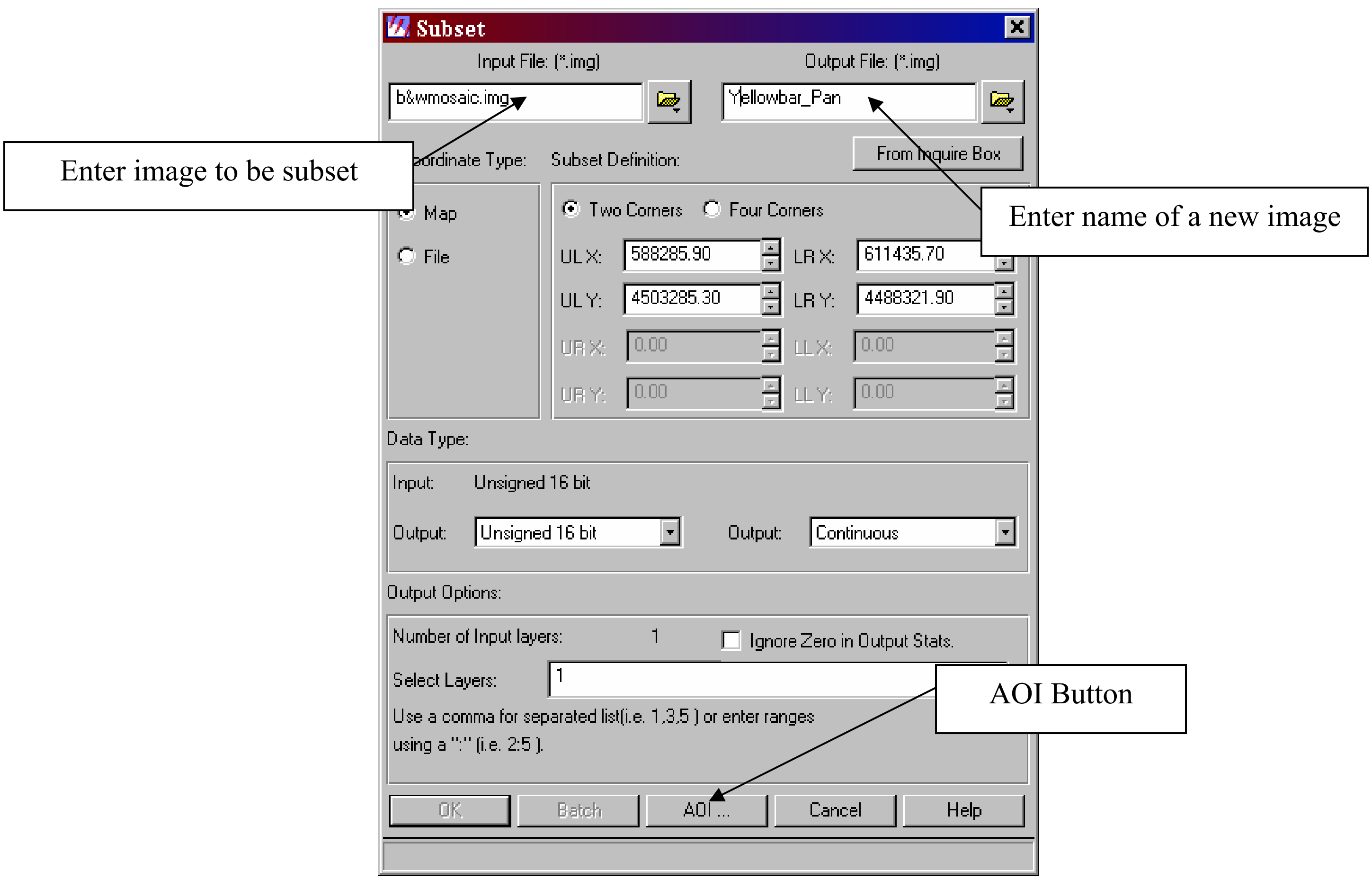


Figure 32 – Subset Image Toolbox.

2. Using the folder button next to the input file box, navigate to the image that will be subsetted. (This will be the mosaic of the panchromatic or multi-spectral images made in Section 3.1).

3. Click on the folder button next to output file box; navigate to the directory to store the new image in. Name the new image.

   TIP: Name the new image after the island you are clipping out and the type of imagery it is. For example: Yellowbar_Pan.

4. Click on the AOI button. Select the AOI File for the marsh (Fig. 33). This will allow you to select an AOI file. Select the AOI file that you have created for this island. This will clip the island areas specifically as you have drawn it. Once it has been selected click OK.

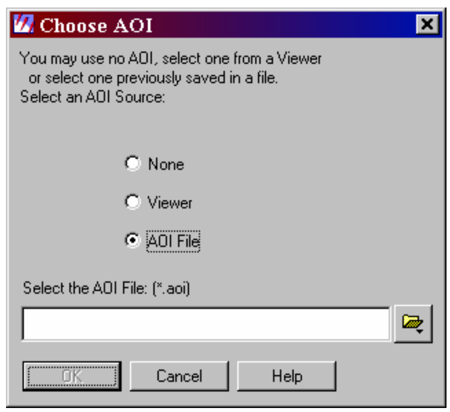


Figure 33 - AOI file selection box.

5. Click OK on the Subset toolbox.

6. Repeat this process until all of the islands have been clipped out of the image.

7.4 Resolution Enhancement

To take a full advantage of both the spatial and spectral qualities of the Quickbird-2 imagery data, a resolution merge is recommended. The process takes the high spatial resolution qualities of the panchromatic imagery (0.6-m) and combines them with the spectral qualities of the multispectral imagery (Fig. 34). While this process does create a very clear color image, it increases the file size and requires a large amount of computing power. We recommend that a resolution merge to be conducted only on the clipped images, not the entire image.

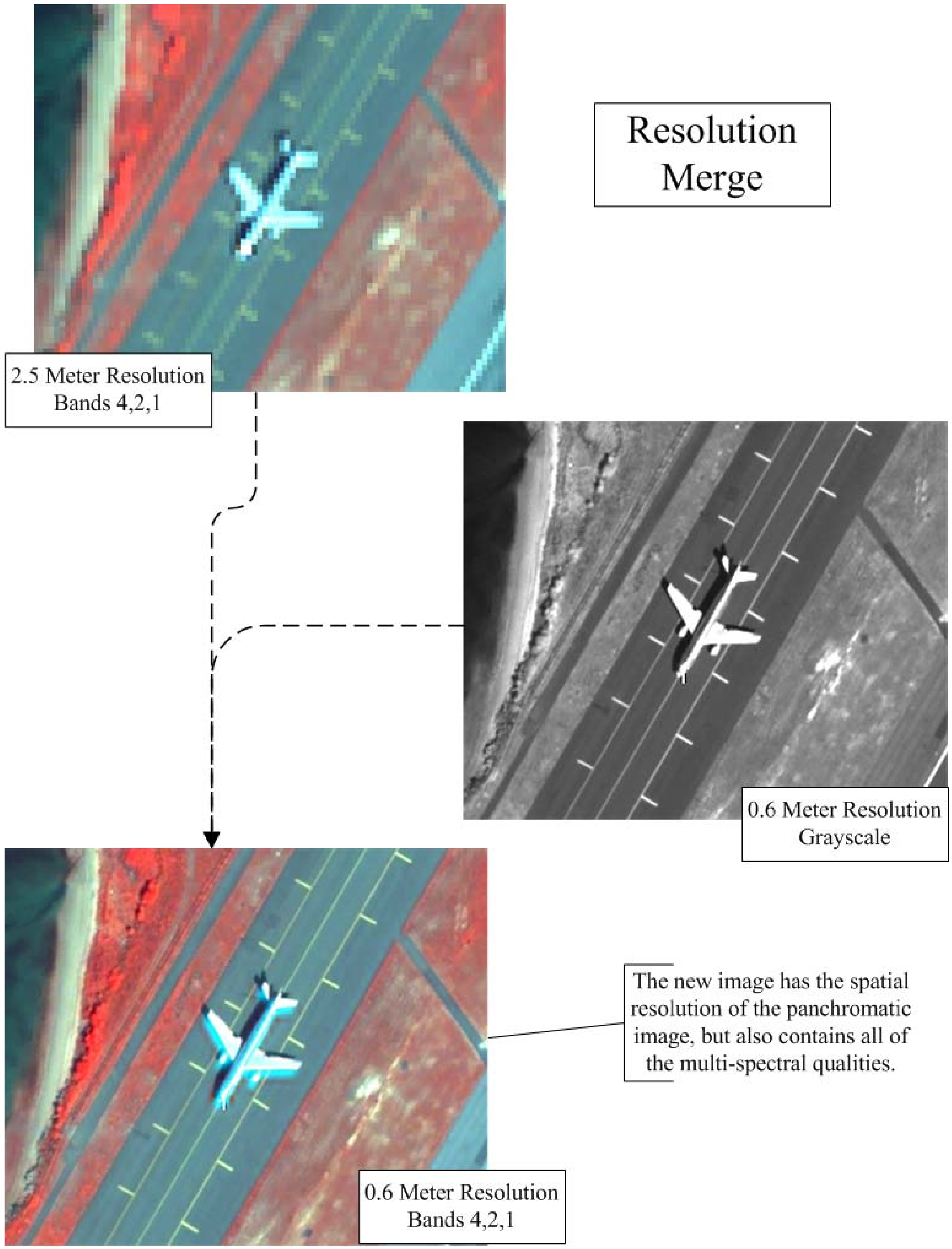


Figure 34 – Diagram of resolution merge process.

7.4.1 Steps for Performing a Resolution Merge.

2. Click on the interpreter button on the main toolbar. This will bring up the Image Interpreter toolbar. Click on the Spatial Enhancement button on the Interpreter toolbar (Fig. 35). Click on the Resolution Merge toolbar. This will bring up the Resolution Merge toolbox (Fig. 36).

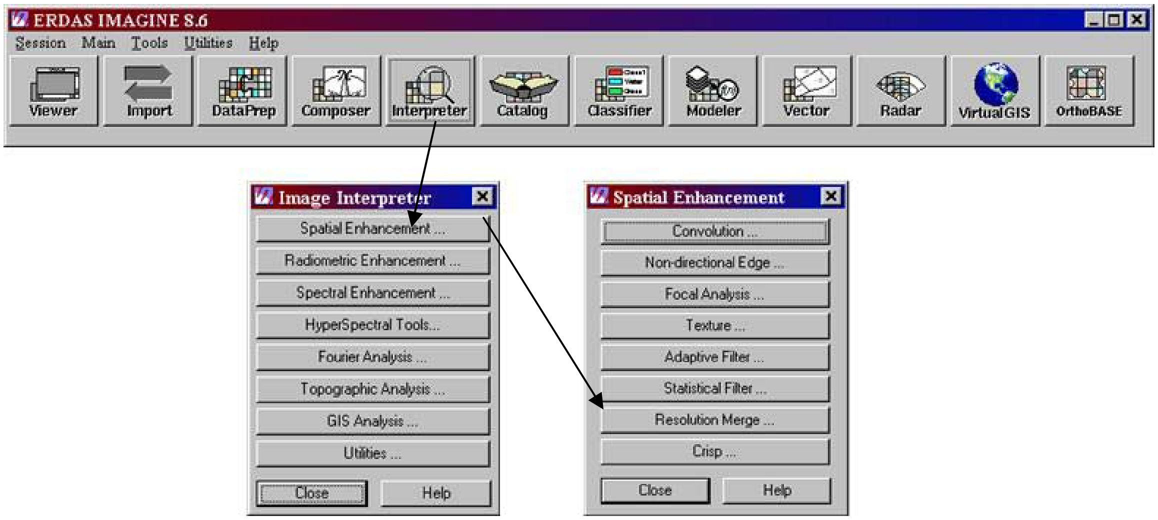


Figure 35. Resolution merge path.

3. There are three fields that need to be filled out in the Resolution Toolbox.

High Resolution Input File – Use the folder button and navigate to the clipped panchromatic image of the island.

Multispectral File – Use the folder button and navigate to the clipped multispectral image of the island.

Output file – Use the folder button to navigate to the directory you want to save the new image in. TIP: Name the new file the way that can be easily recognized.

The following methods should be the default. Make sure they are selected (Fig. 36).

Method: Principal Component

Resampling Techniques: Cubic Convolution

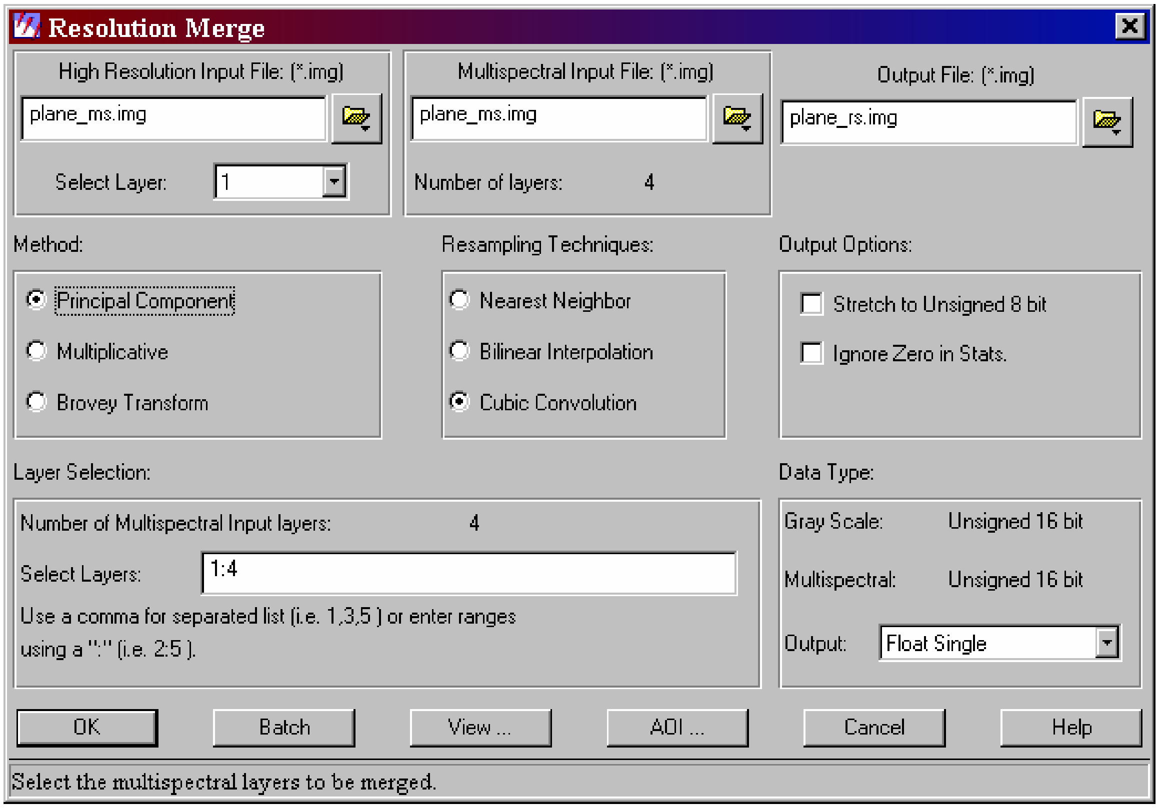


Figure 36. - Resolution Merge Tool Box.

4. Click on the AOI Button. Select the AOI for the island you are performing the Resolution Merge on. This will clip the island and maintain the rest of the image area as black background.

5. Click Ok. This may take a few minutes to process depending on the size of the images.

After completing section 7.1 to 7.4, the imagery is prepared for classification. Figure 37 shows an example of what one island looks like after the subsetting.

Figure 37. Quickbird-2 imagery data of the Stony Creek Island after spatial resolution merge (Displayed as bands 4,2,1 in RGB).

7.5 Steps for Unsupervised Classification

1. On the main toolbar click “Classifier”. This will bring up the classification toolbar (Fig. 38). Click on the unsupervised classification button.

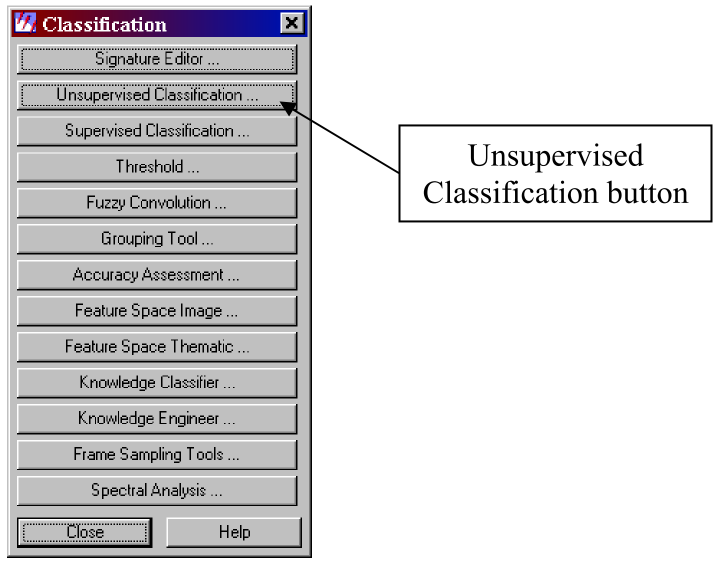


Figure 38. Classification tools.

2. This will bring up the unsupervised classification toolbar (Fig. 39).

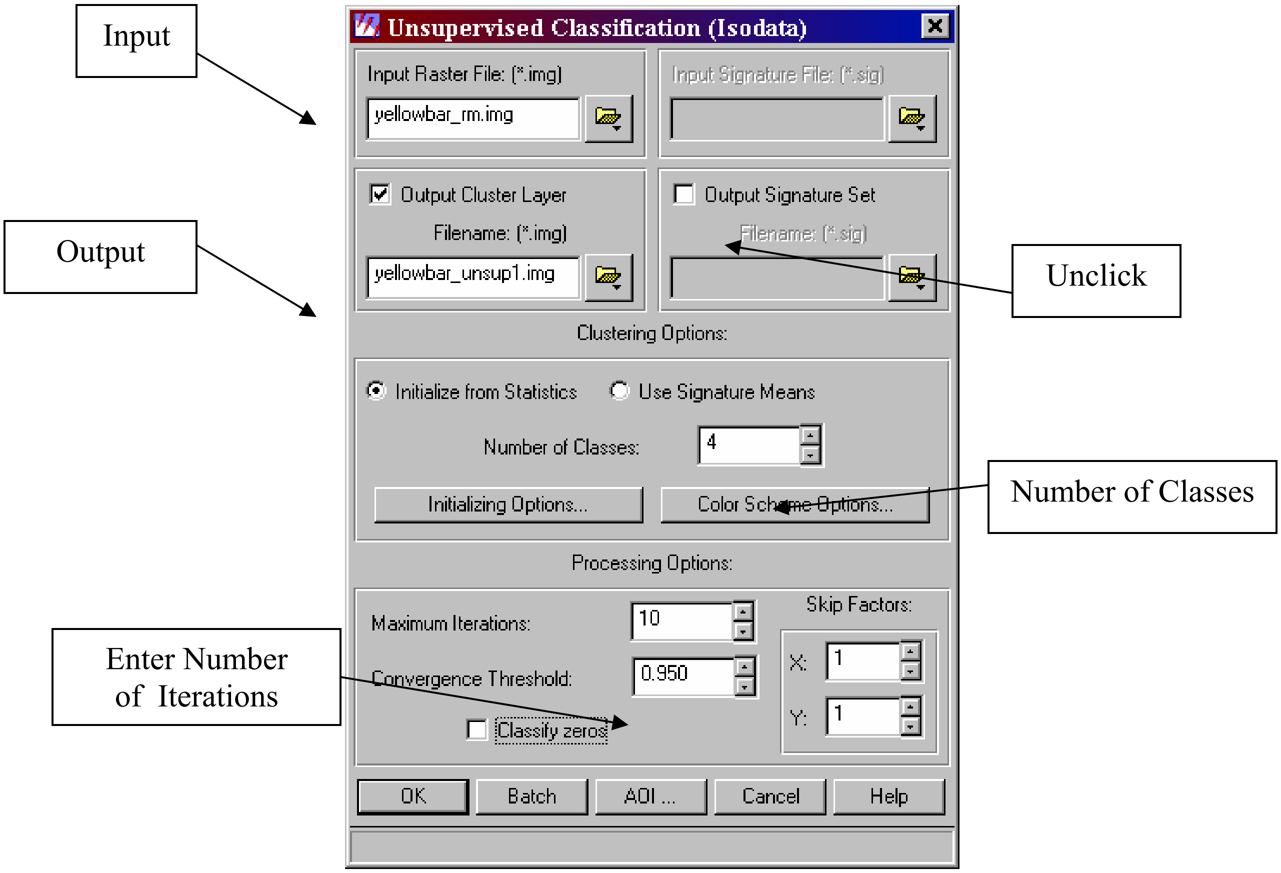


Figure 39. Unsupervised Classification Toolbar.

3. Using the folder button next to the input box, navigate to the directory where image to be classified is stored.

4. Using the folder button next to the output box, navigate to the folder where the classified image is to be stored.

5. Unclick the Output signature set box. This option would generate the spectral signatures for each class made. If one has interest in supervised classification afterward, leave the box checked. It will not affect the classification outcome.

6. Enter the number of clusters (classes) to be generated. In this protocol project, the number was 4 for the islands where High Marsh does not exist. For the islands where High Marsh exists, then the number was 5. Typically more classes are needed to achieve more details of spectral groups.

7. Enter the maximum number of iterations that should be performed. This is more of a safety feature. If the convergence threshold was set to 95 percent for 4 classes it is possible the classification process would stop after less than 10 passes. It is important that the computer algorithm reach its convergence

threshold in the number of iterations. In most cases 10 passes should be enough. If it times out due to the number of iterations instead of reaching a convergence threshold of 95%, increase the iterations to a higher number, such as 20.

8. Once all of the information has been entered, click Ok. The process will show how much percentage of the data is converging and what iteration it is on. This may take a few minutes.

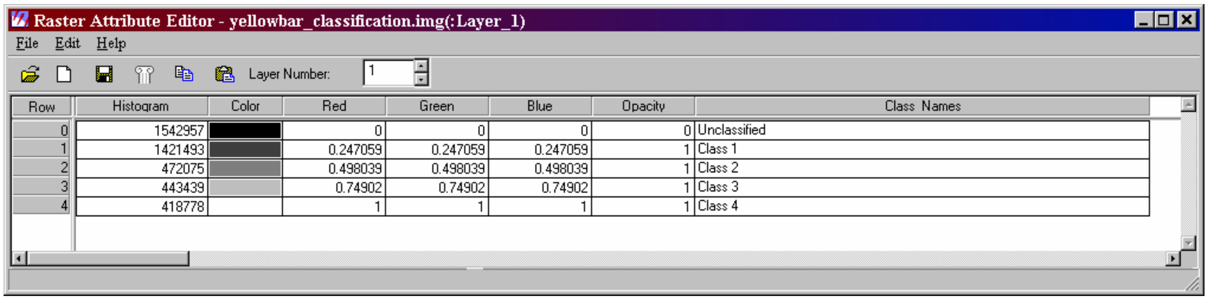
7.5.1 Unsupervised Classification Output

The unsupervised classification process will output the results of clusters of pixels. These clusters, or classes, need to be labeled and colored to reflect the different classes that are being mapped.

1. Load the new classification over the resolution merge image that was created early (Fig. 40).

Figure 40. Classification result of the Yellowbar island before labeling and assigning colors.

2. In the viewer toolbar, click on Raster ➔ Attributes… This will bring up the Attribute table for the image (Fig. 41).


Raster Attribute Editor - yellowbar_classification.img(:Layer_1)

File Edit Help

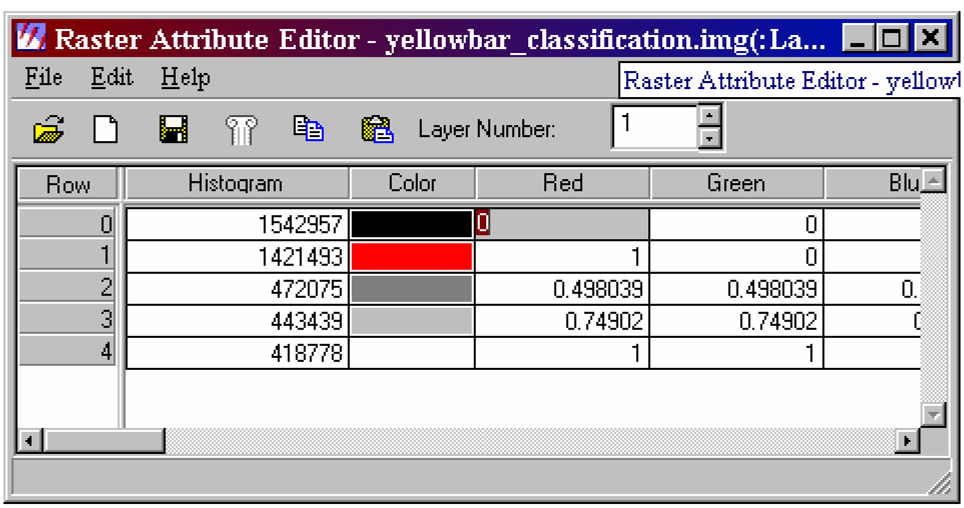
Layer Number: 1

Row	Histogram	Color	Red	Green	Blue	Opacity	Class Names
0	1542957		0	0	0	0	Unclassified
1	1421493		0.247059	0.247059	0.247059	1	Class 1
2	472075		0.498039	0.498039	0.498039	1	Class 2
3	443439		0.74902	0.74902	0.74902	1	Class 3
4	418778		1	1	1	1	Class 4

Figure 41. Raster Attribute Table.

The table will have the number of rows that match the number of clusters defined in the unsupervised classification. Row 0 represents the background class. The Color column defines the color assigned to each class for displaying in the viewer. Opacity shows how transparent the class will be in the view. Class name can be assigned and changed for each class.

3. To change the color, point at color square of the row you want to change and right click the computer mouse. This will bring up a color palette. Select the color (*e.g.*, red). This will change all the pixels in this cluster to the color selected. Figure 42 shows that the class 1 is assigned the red color in the attribute table. Figure 43 shows the result after assigning the color to the class.


Raster Attribute Editor - yellowbar_classification.img(:La...

File Edit Help

Layer Number: 1

Row	Histogram	Color	Red	Green	Blu
0	1542957		0	0	
1	1421493		1	0	
2	472075		0.498039	0.498039	0.
3	443439		0.74902	0.74902	(
4	418778		1	1	

Figure 42. Raster Attribute with color change.

Figure 43. Yellowbar island with class 1 color change.

4. Class 1 is identified as the water class. Then change the color of class 1 to blue. On the Rater Attribute table, assign the name for class 1 as Water. Continue changing the colors until all classes have been identified, labeled and colored. Figure 44 and 45 show an example of how the classes can be colored and labeled. By changing the setting of Opacity the colors can be transparent or hidden. This will allow the user to see though to the satellite image underneath, if both original and classified images have been loaded. This may aid in identifying the different classes with visual interpretation of the displayed satellite image.

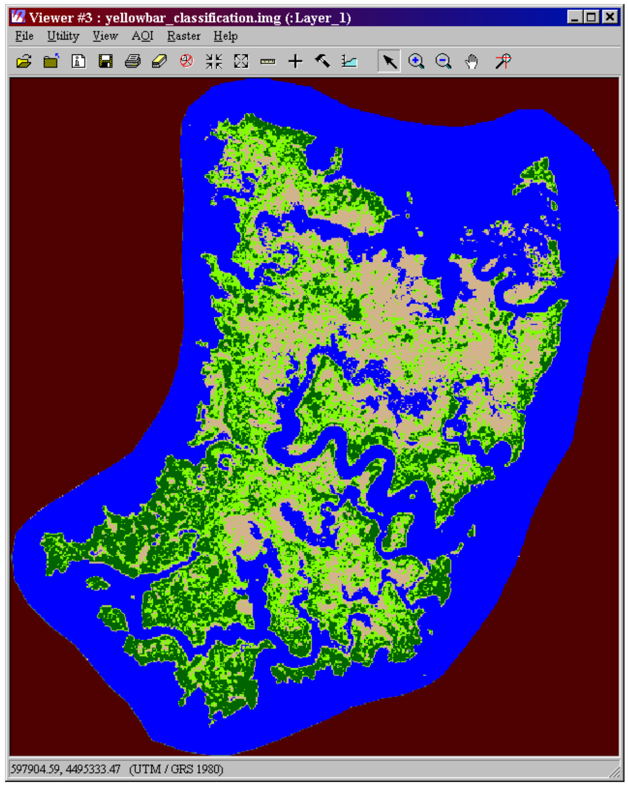
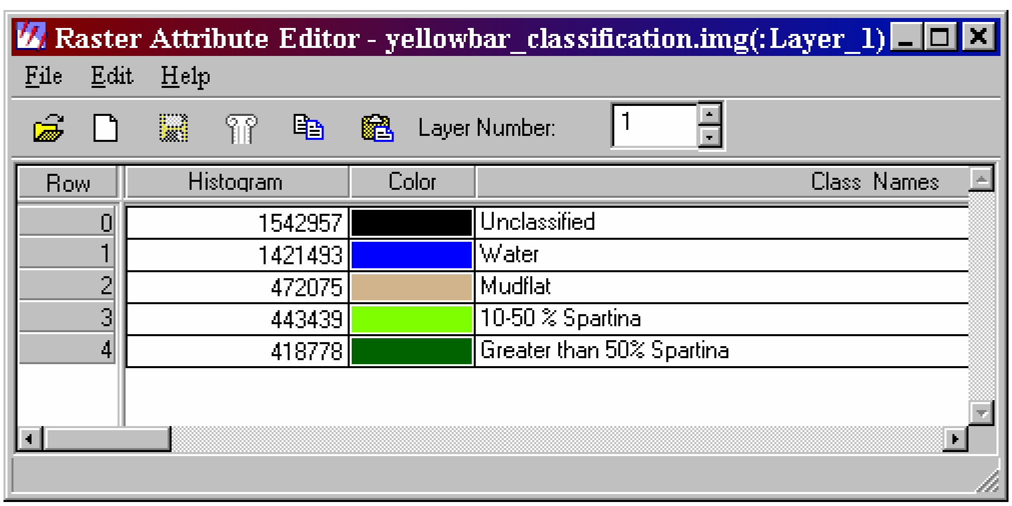


Figure 44. An example of final color scheme for unsupervised classification of Yellowbar site.


Raster Attribute Editor - yellowbar_classification.img(:Layer_1)

File Edit Help

Layer Number: 1

Row	Histogram	Color	Class Names
0	1542957		Unclassified
1	1421493		Water
2	472075		Mudflat
3	443439		10-50 % Spartina
4	418778		Greater than 50% Spartina

Figure 45. An example of raster attributes for the classification of the Yellowbar site.

5. Click on the disk symbol to save these changes.

7.6 *Minimum Mapping Unit*

Given the high spatial resolution of the QuickBird-2 data, the minimum mapping unit is two pixel cells together following the 4 Cell Rule (See section 7.6.1 for definition). Together the total area of the smallest mapped patch in the marsh is 0.72 m^2. Figure 46 compares the 0.25 ha NPS standard for a minimum mapping unit, to a Landsat Pixel size, to the minimum mapping unit for this QuickBird-2 image-derived mapping result.

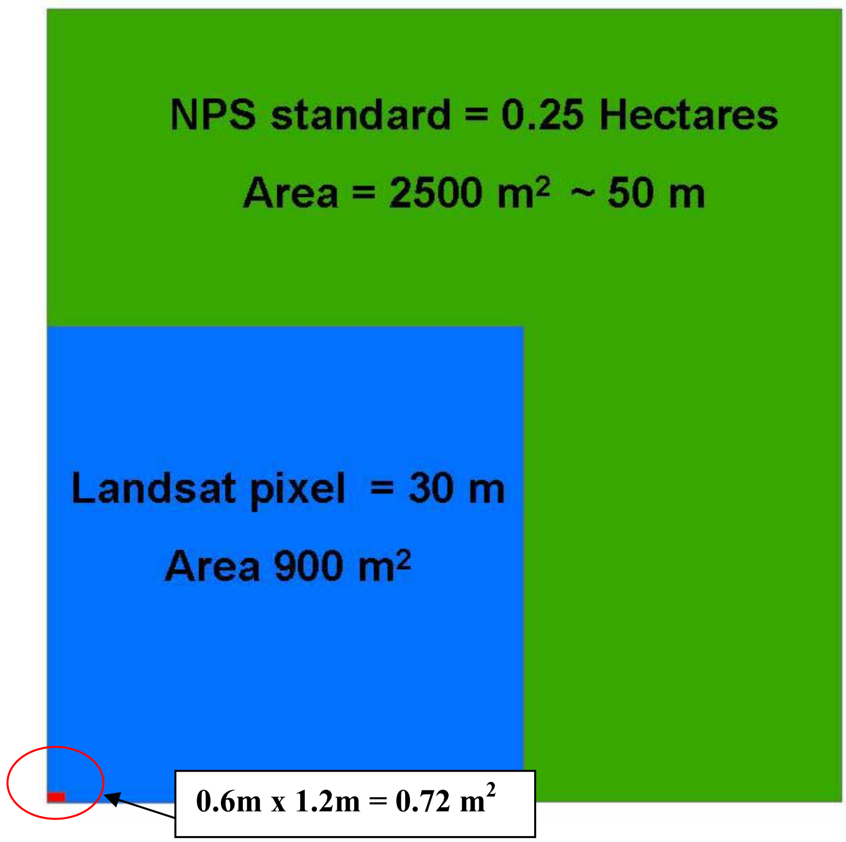


Figure 46. Comparison of minimum mapping units.

7.6.1 4 Cell Rule vs. 8 Cell Rule

The 4 cell rule and the 8 cell rule are two different ways to consider how pixels are grouped together to make patches. If the 4 cell rule is applied then connections between diagonal pixels cannot be made. Connections between pixels can only be made North, South, East, and West. If the 8 cell rule is applied then connections can be made in a 3 x 3 pixel window in any direction (Fig. 47). Because of the high spatial resolution of the pixels, if there was only a diagonal connection between two pixels (the pixels only touched at the corners), this would represent a break in patches, so the 4 cell rule was applied.

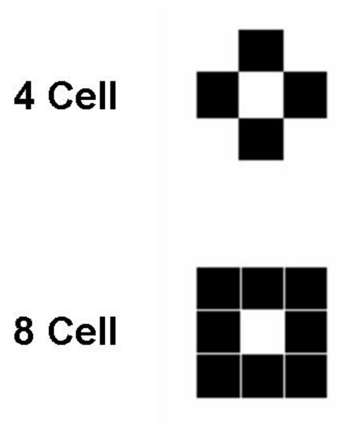


Figure 47. 4 Cell Rule vs. 8 Cell Rule.

7.6.2 Elimination Function

In order to make the data conform to the minimum mapping standard, the “salt and pepper” effect needs to be removed (Fig. 48). This is done though the elimination command in ERDAS Imagine. This command removes solitary pixels. The individual pixel is changed to the pixel class of the pixels sounding it. In the case where there are different types of pixels, the pixel class that is most abundant (majority rule) is selected.

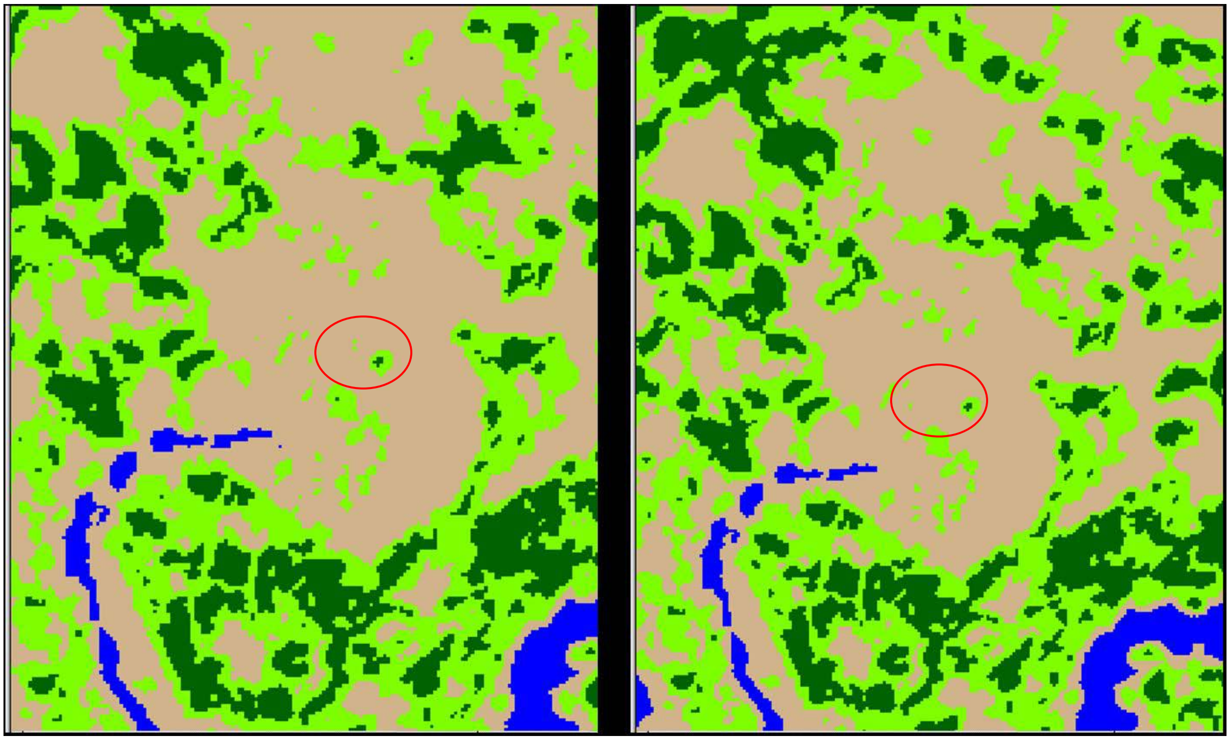


Figure 48. Comparison of removing "salt and pepper" pixels. Original unsupervised classification (left) and the result after the "salt and pepper" pixels were removed (right).

7.6.2.1 Steps to Perform Elimination Command

Before the eliminate command can be used, the image must first be processed with the Clump function. The clump function groups the connected pixels into patches according to the 4 cell or 8 cell rule.

Clump Function

1. Click on the Interpreter button on the ERDAS Imagine main tool bar. This will bring up the interpreter toolbar. Click on the GIS Analysis button. Click on the Clump Button. This will bring up the Clump toolbox (Fig. 49).

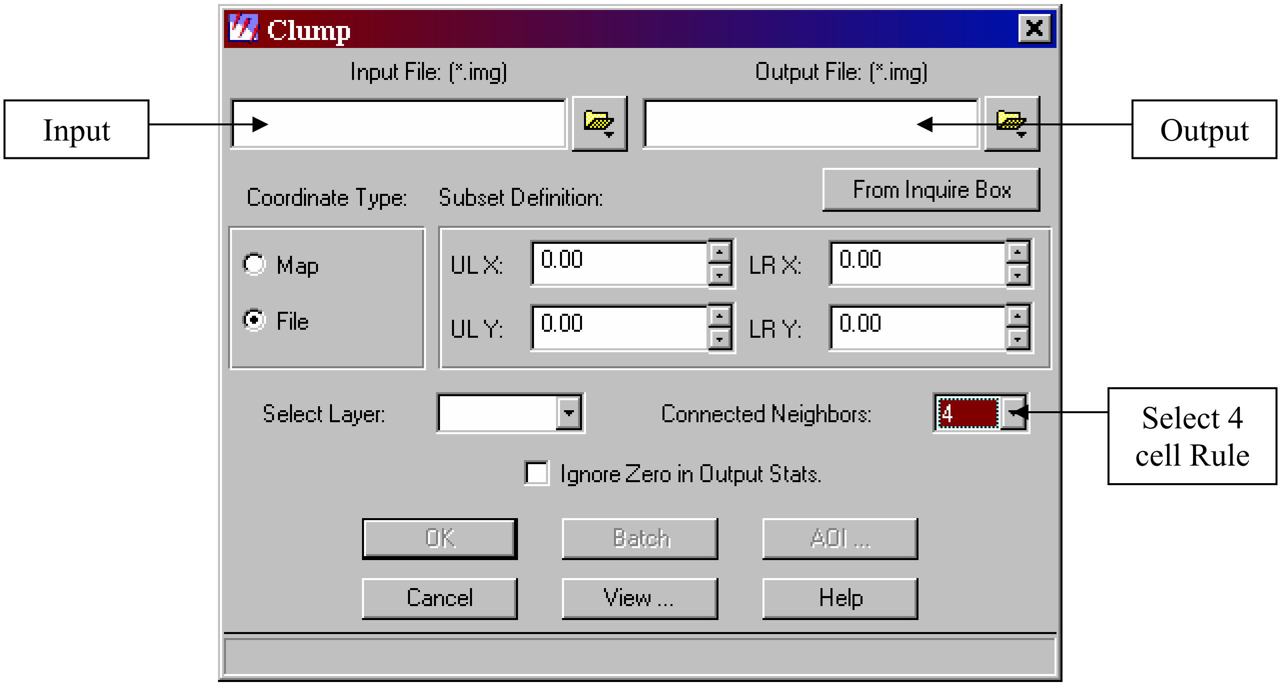


Figure 49. Clump Function.

2. Input the file to be clumped. Use the folder button to navigate to the directory where the new image is to be stored. Enter the new file name.

3. Under the Connected Neighbors box, select "4", so that the 4 cell rule will be applied.

4. Click Ok.

Eliminate Function

1. This command is on the same toolbar as the clump command (Fig. 50).

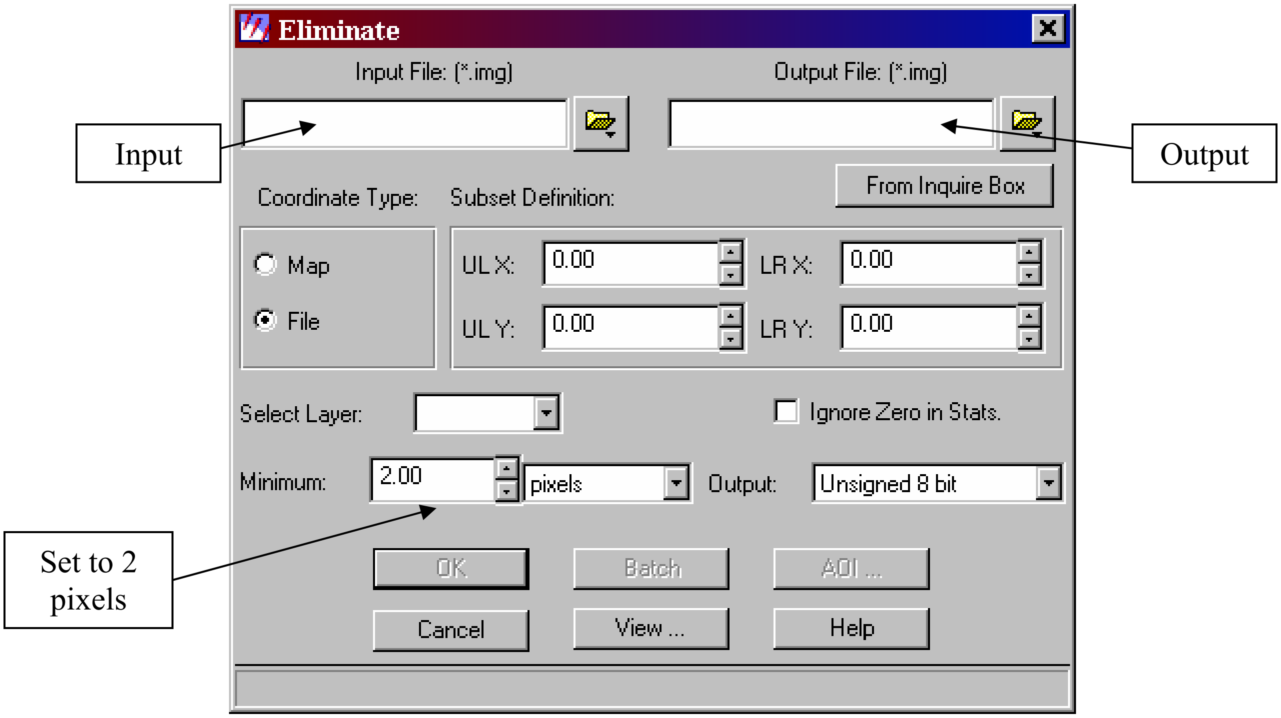


Figure 50. Eliminate Function.

2. Using the Input folder button, navigate to the image that was created using the clump command. Using the output folder button, set the source for the new file, with a new name.

3. Set the minimum number for pixels to "2". Set the type to "Pixel".

4. Click Ok.

7.7 Final Result and Area Calculations

Once all of the classifications of the islands have been generated they can be mosaicked together for the entire study area. This is the same process used in section 7.1 when the tiles were merged together into a mosaic. The class names may have to be re-entered after the mosaicking process. Once the mosaic has been created, it should look similar to Figure 0-1 in the Executive Summary.

Generating Area Calculations

1. Using ERDAS Imagine, load the mosaic image of the islands into the view. Bring up the Attribute Table (Fig. 51).

2. On the Raster Editor Toolbar, click edit. A drop down menu will appear, select the add area column.

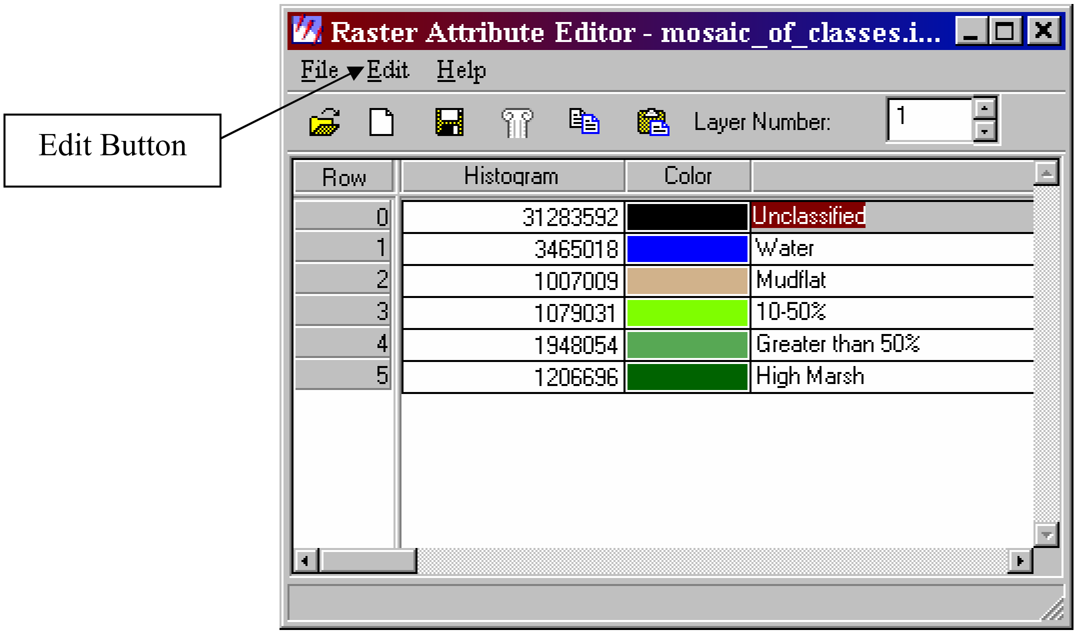


Figure 51. Raster Attribute Editor.

3. This will bring up the add area column window. Select the units. Rename the the column to reflect this (Fig. 52).

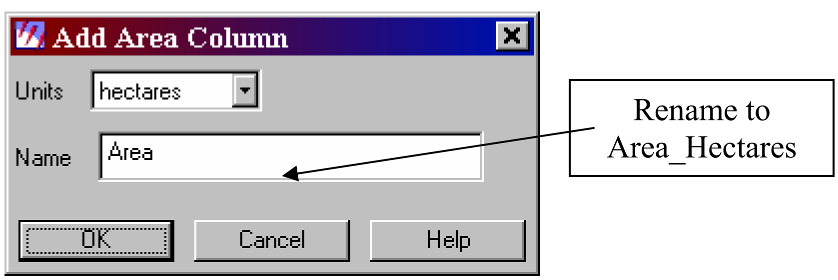


Figure 52. Add Area Column.

4. This will generate a new column in the attributes table.

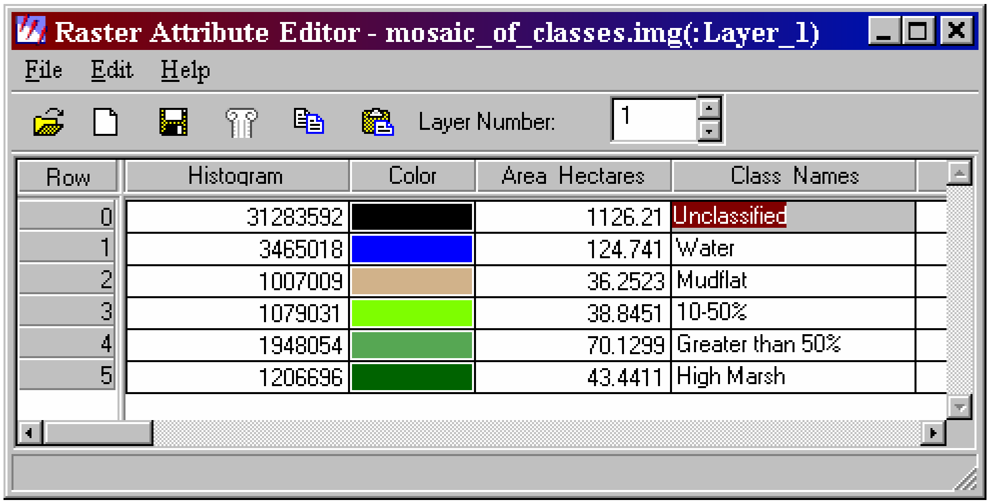


Figure 53. Raster Attributes with Area Column.

7.8 Accuracy Assessment

Accuracy assessment is a general term for comparing the classification to geographical data that are assumed to be true, in order to determine the accuracy of the classification process. Usually, the assumed-true data are derived from ground truth data. It is usually not practical to ground truth or otherwise test every pixel of a classified image. Therefore, a set of reference pixels is usually used. **Reference pixels** are points on the classified image for which actual data are (or will be) known. The reference pixels are randomly selected (Congalton 1991).

NOTE: You can use the ERDAS IMAGINE Accuracy Assessment utility to perform an accuracy assessment for any thematic layer. This layer did not have to be classified by IMAGINE.

When reference pixels are selected by the analyst, it is often tempting to select the same pixels for testing the classification as were used in the training samples. This biases the test, since the training samples are the basis of the classification. By allowing the reference pixels to be selected at random, the possibility of bias is lessened or eliminated (Congalton 1991). The number of reference pixels is an important factor in determining the accuracy of the classification. It has been shown that more than 250 reference pixels are needed to estimate the mean accuracy of a class to within plus or minus five percent (Congalton 1991).

ERDAS IMAGINE uses a square window to select the reference pixels. The size of the window can be defined by the user. Three different types of distribution are offered for selecting the random pixels:

• random - no rules will be used

• stratified random - the number of points will be stratified to the distribution of thematic layer classes
• equalized random - each class will have an equal number of random points

Use the Accuracy Assessment utility of the ERDAS Imagine can generate random reference points.

An Accuracy Assessment CellArray (error table) is created to compare the classified image with reference data. This CellArray is simply a list of class values for the pixels in the classified .img file and the class values for the corresponding reference pixels. The class values for the reference pixels are input by the user. The CellArray data reside in an .img file. (*See ERDAS Tour guide for more professional descriptions*)

We used the stratified random strategy to generate 500 points in testing the classification result at this protocol (Fig. 54). We displayed the QuickBird-2 satellite image as the background against the classification result. We add the reference categories for each randomly selected pixels without knowing the results from unsupervised classification. Once all 500 points have been labeled, the computer algorithm compared the reference pixels between the labeled categories and the classification results to generate an error table (Table 3).

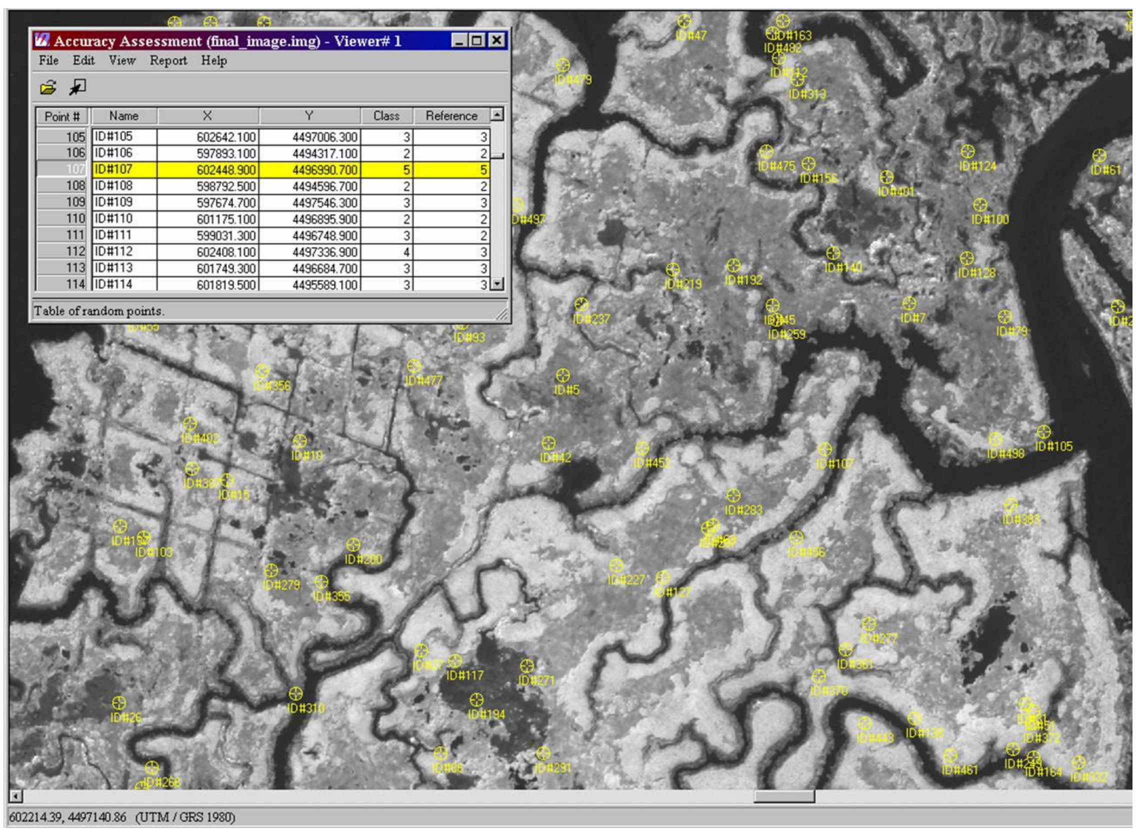


Figure 54. Randomly selected reference points for accuracy assessment.

Table 3 – Accuracy Assessment.

		Reference Data				
	423	Mudflat	10-50% Spartina	50% + Spartina	High Marsh	Row Totals
Classification	Mudflat	95	6	0	0	101
	10-50% Spartina	22	99	15	0	136
	50% + Spartina	3	12	170	7	192
	High Marsh	0	0	12	59	71
	Column Total	120	117	197	66	500

The data in the accuracy assessment table show the correctly classified pixels and misclassified pixels within the randomly selected testing pixels. High lighted diagonal pixels represent correctly classified pixels as the reference labels agreed with the classification results. The off diagonal columns and rows show the number of misclassified pixels among selected testing pixels. For example, the comparison shows that 22 pixels classified as 10-50% *Spartina* cover should be in the category of Mudflat. 12 pixels classified as > 50% *Spartina* should be classified as 10-50% *Spartina,* and 12 pixels classified as High Marsh should be classified as > 50% *Spartina*.

The overall classification accuracy is the percentage of correctly classified pixels among total randomly selected reference pixels. In this case, the sum of the diagonal cells is 423. Therefore the overall accuracy should be 423/500=84.6%.

7.8.1 Performing an Accuracy Assessment on Your Data

1. Using ERDAS Imagine, load the final mosaicked QuickBird-2 image to the viewer.

2. On the main toolbar click "Classifier" button. This will bring up the classification toolbar. Click the Accuracy Assessment button (Fig. 55).

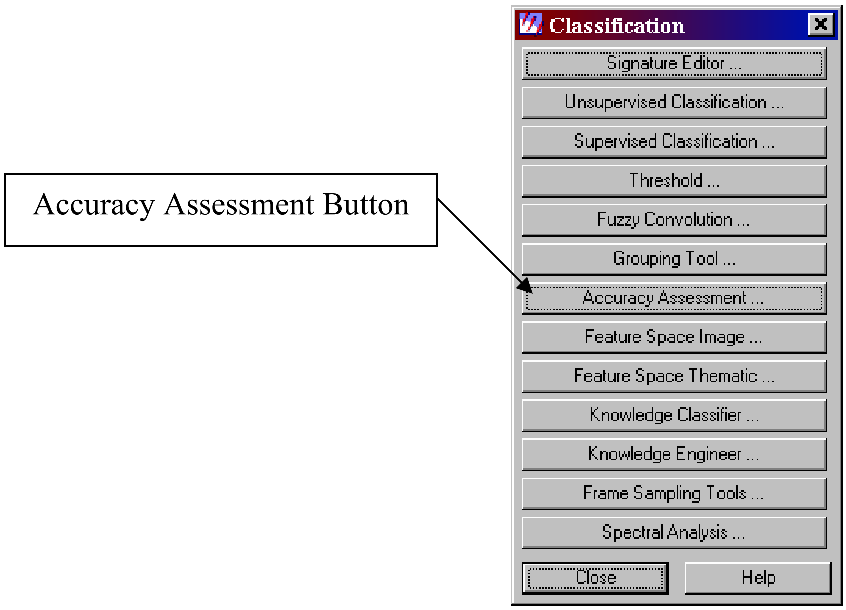


Figure 55. Classification Toolbar.

3. This will bring up the Accuracy Assessment viewer. When the viewer first comes up it will be empty. The top should say "No File" (Fig. 56). It should also display which viewer the accuracy assessment is tied to.

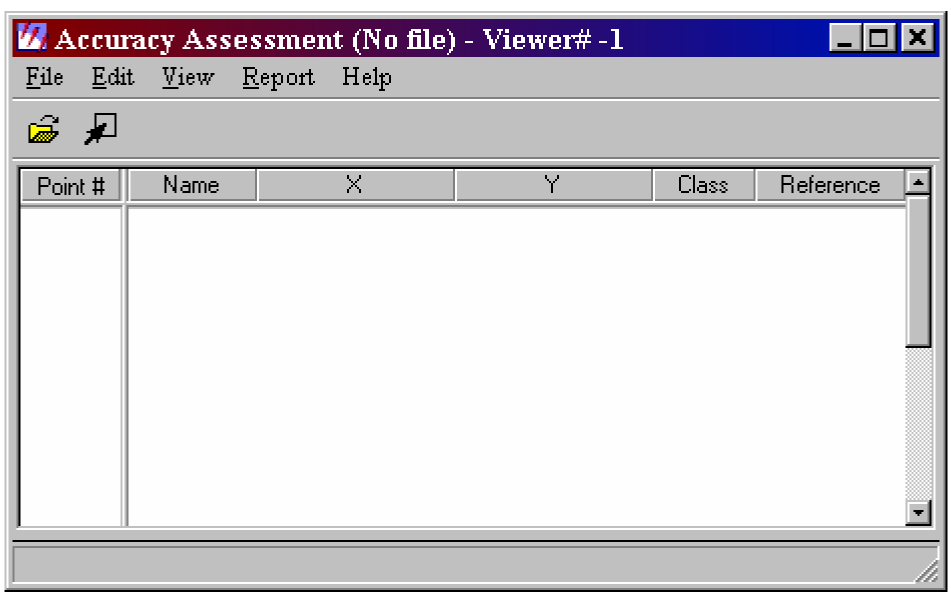


Figure 56. Accuracy Assessment viewer (No File).

4. Click File ➔ Open on the Accuracy Assessment viewer. Select the final mosaicked classification result file that was created early. Instead of displaying No File at the top, the viewer will change to display the file that was selected (Fig. 57).

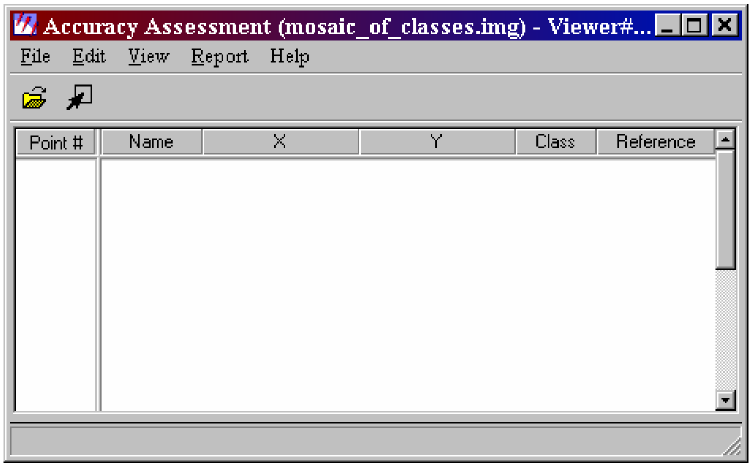


Figure 57. Accuracy Assessment - with classified file loaded.

5. Select Edit➔ Create/Add Random Points. This will bring up the Add Random Points Viewer. The search count can remain the default. The number of points need, by the rule of thumb, should be at least 50 points per class. The Distribution Parameters should be set to Stratified Random. Click the minimum number box and set the number to 50 points per class. Click the "select classes" box. Select the classes that should be tests. This is done by highlighting the numbers in the row column (Fig. 58).

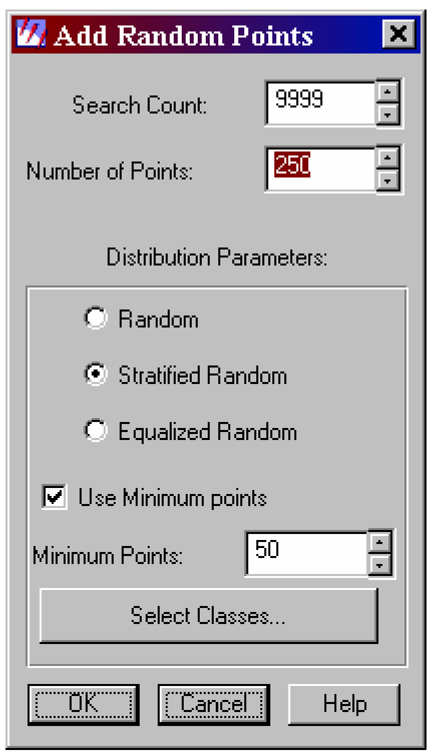


Figure 58. Add number of random points.

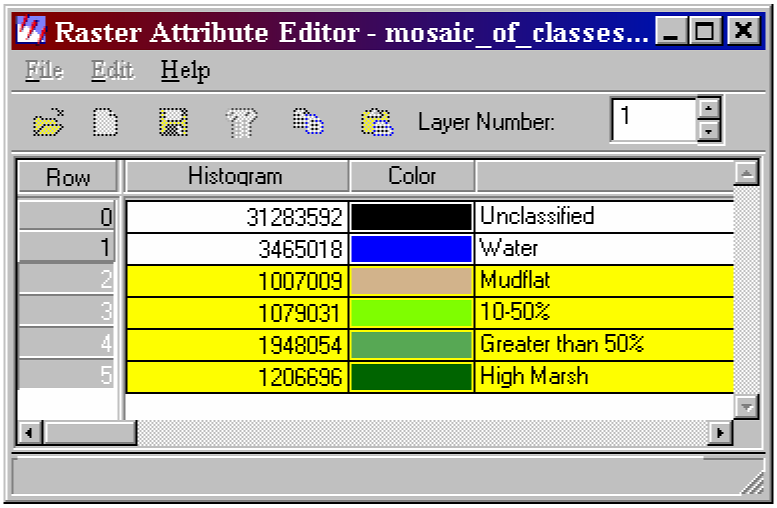


Figure 59. Selecting Classes.

6. Once the classes are set click ok. The computer program may tell you it reached the maximum number of selections, and if it should continue. Continue to say yes until it finds all the number of reference points requested (Fig. 59).

7. The Accuracy Assessment viewer will now have the points. Each point has an ID number and X-Y coordinate. The Class and Reference columns are left blank (Fig. 60).

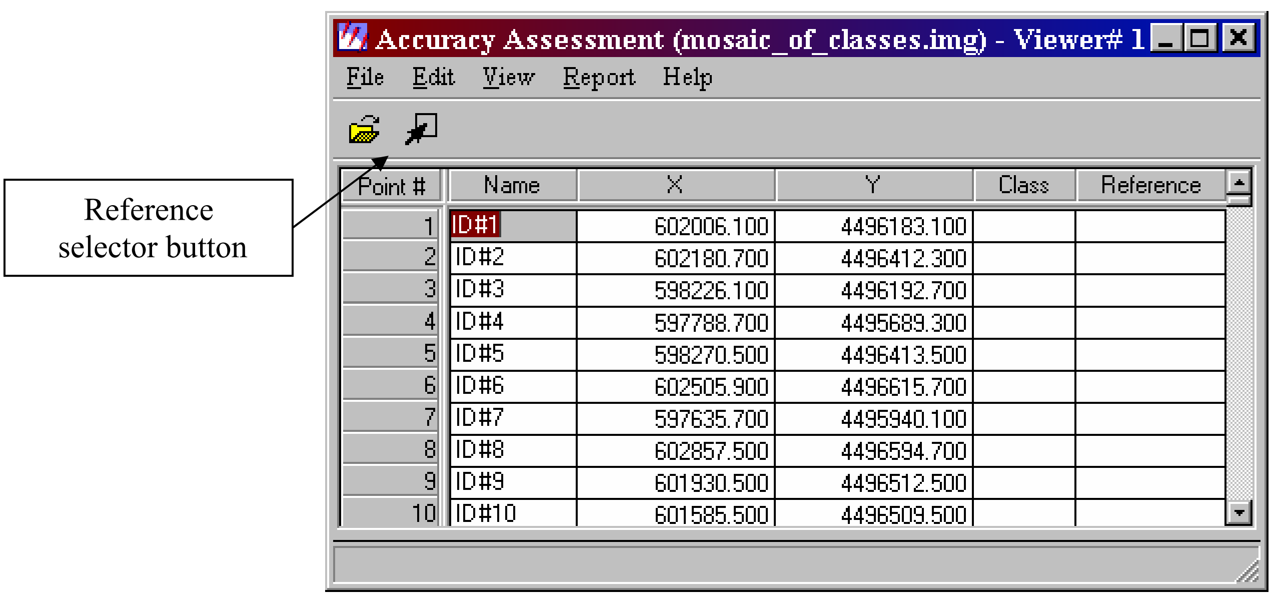


Figure 60. Accuracy Assessment Table.

8. Click on the Reference selector button. This allows the user to select the view to display each of the point location and label the point based on visual judgment of the class that this reference pixel should be classified.

For example, checking point number 3 would bring up point number 3 in the view with the resolution merge image behind it (Fig. 61).

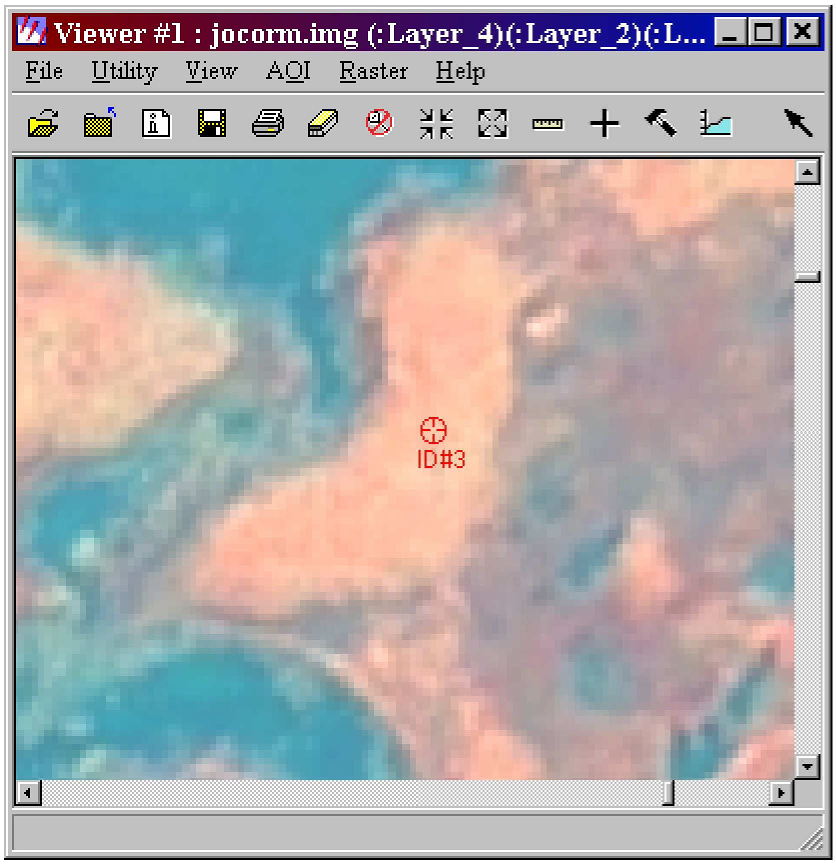
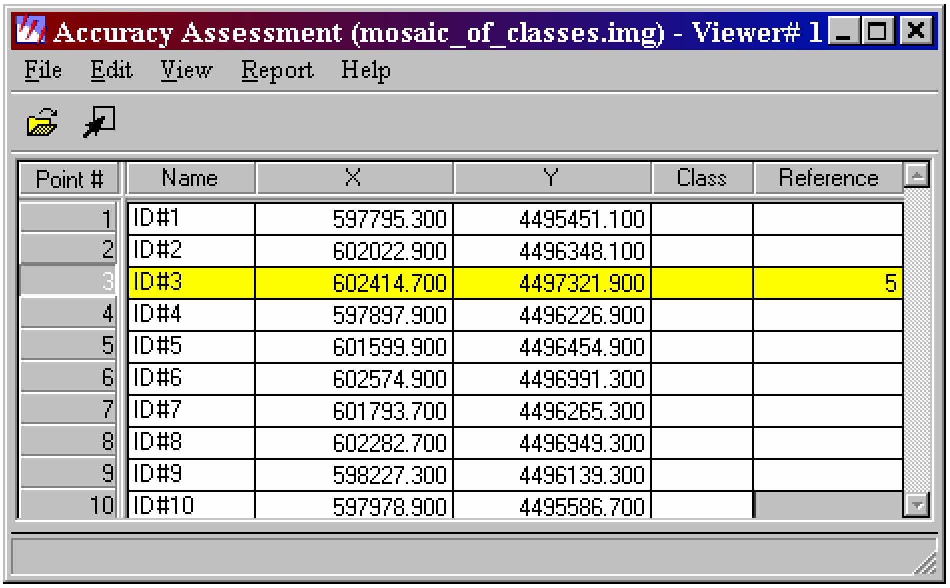


Figure 61. Viewer with reference point # 3.

The user would identify this point as High Marsh which is class # 5. This is entered in the reference column in row 3 as 5 (Fig. 62)

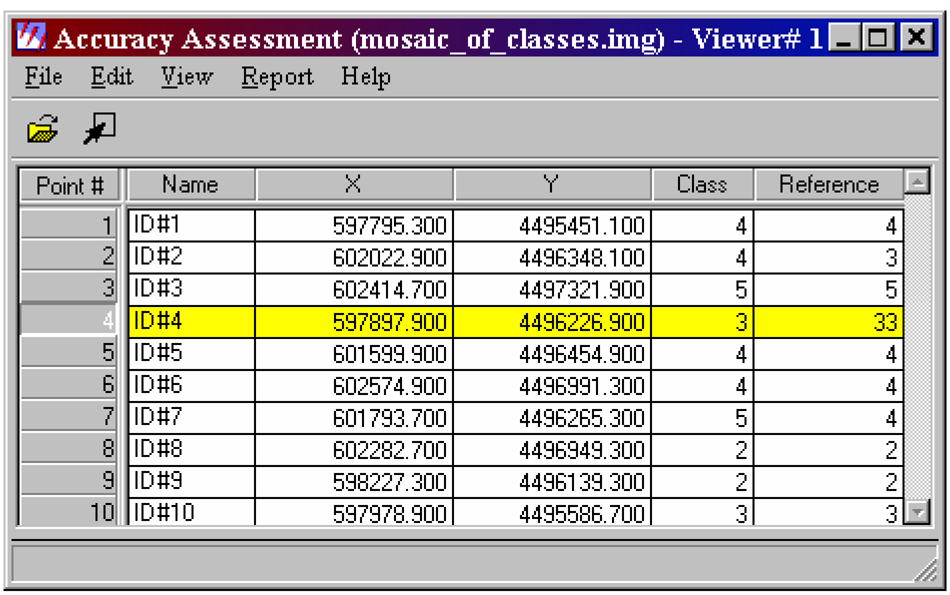

Accuracy Assessment (mosaic_of_classes.img) - Viewer# 1

File Edit View Report Help

Point #	Name	X	Y	Class	Reference
1	ID#1	597795.300	4495451.100		
2	ID#2	602022.900	4496348.100		
3	ID#3	602414.700	4497321.900		5
4	ID#4	597897.900	4496226.900		
5	ID#5	601599.900	4496454.900		
6	ID#6	602574.900	4496991.300		
7	ID#7	601793.700	4496265.300		
8	ID#8	602282.700	4496949.300		
9	ID#9	598227.300	4496139.300		
10	ID#10	597978.900	4495586.700		

Figure 62. Data entry for accuracy assessment.

This process continues for all selected reference pixels. Once it is done, the user may choose to reveal the class values and see which ones are right and wrong between the results of unsupervised classification and the reference given by visual judgments. In order to generate an accurate error table, the numbers must be checked. Figure 63 shows one type of error that can occur. In this example it is a typographic error. The number should have been recorded as 3, but it was put in as 33. Go back and check the values to insure that the value that was entered was actually what is on the ground. If you are unsure, a field check can be done do discover the true type of marsh.


Accuracy Assessment (mosaic_of_classes.img) - Viewer# 1

File Edit View Report Help

Point #	Name	X	Y	Class	Reference
1	ID#1	597795.300	4495451.100	4	4
2	ID#2	602022.900	4496348.100	4	3
3	ID#3	602414.700	4497321.900	5	5
4	ID#4	597897.900	4496226.900	3	33
5	ID#5	601599.900	4496454.900	4	4
6	ID#6	602574.900	4496991.300	4	4
7	ID#7	601793.700	4496265.300	5	4
8	ID#8	602282.700	4496949.300	2	2
9	ID#9	598227.300	4496139.300	2	2
10	ID#10	597978.900	4495586.700	3	3

Figure 63. An example of accuracy assessment type-o.

9. Once all of the points have been entered, Click Report → Accuracy Report. This will generate the error matrix and kappa statistic.

7.8.2 Interpreting the Results

Once you have the accuracy assessment result a determination can be made on how accurate the mapping was. If the accuracy is too low, there are several options depending on where the error occurred. One problem may be that the area of interest needs to be mapped more accurately, which would involve editing the polygons. If the area of interest is fine, then possibly the number class needs to be changed, expanding the different types of class present. A third possibility is expanding the number of groups created by the unsupervised classification; a site might need 10 or more clusters to capture the subtle differences to distinguish the classes.

Further details about ERDAS Imagine functions can be found in the Field Guide and Tour Guide document, which should be available for the users with ERDAS Imagine software system.

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