INVENTORY OF VEGETATION SPECTRAL PROPERTIES IN THE SOUTH BAY SALT PONDS: A DATABASE FOR ENHANCING DECISION SUPPORT AND RESTORATION MAPPING

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ABSTRACT

In the past century, more than 85% of the historical marshlands in the San Francisco Bay were converted to salt ponds or filled for urban development, resulting in a loss of biodiversity. The municipalities along the southern margin of the San Francisco Bay are in the process of one of the most extensive tidal wetland restoration projects ever undertaken, the South Bay Salt Pond Restoration Project (SBSPRP). The goal of this project was to perform an analysis of the spectral variation between different salt pond vegetation types and to track the changes in vegetation distribution from 2000 to 2010. These data will be shared with the SBSPRP partners to aid in their three-year classification of vegetation. This project has identified the spectral characteristics of dominant salt marsh vegetation through the use of in-situ spectral measurements and classification of remotely sensed imagery from EO-1 Hyperion and Landsat TM 5. Fieldwork included the use of a handheld spectroradiometer to gather spectral curves for analysis as well as obtaining point vegetation information for image classification. Comparison of the spectral signatures of the dominant vegetation showed little distinction among vegetation species. Field data and IKONOS imagery were used to identify presence of vegetation throughout the study area to aid in the classification of Landsat imagery, and to track the yearly changes in vegetation colonization for the region between 2000-2010. The spectral angle mapper classification algorithm was applied to a July 2010 Hyperion scene to classify pickleweed in the Alviso area. For this study area, it was determined that Landsat is better suited at detecting overall changes in vegetation. Additional field data could improve the classification of Hyperion imagery.

KEYWORDS: hyperspectral monitoring, vegetation, wetlands, pickleweed, NASA Hyperion

INTRODUCTION

Tidal marshes, the ecotones between estuaries and upland habitats, are some of the most highly productive ecosystems on the planet (Kelly and Tuxen, 2009). These marshes provide habitat for birds, breeding grounds for fish and crabs, flood protection, and improved water quality through pollutant filtration. The edges of San Francisco Bay, California once consisted primarily of salt water marshes and mudflats. However, within the past century, an estimated 85% of these historic tidal marsh ecosystems were converted to salt ponds or otherwise altered or filled for urban and industrial uses (South Bay Salt Pond Restoration Project, SBSPRP, 2010). The South Bay salt ponds, located at the southern end of San Francisco Bay, lie on the Pacific flyway, which provides good roosting and over-wintering sites for migratory bird species. A diverse gradient of habitats and ecosystems exist within the ponds, including shallow open water and salt marsh that is utilized by various waterfowl, shorebirds, and mammals (Siegel and Bachand 2002). In recent years, support for tidal marsh restoration has gained strength, and many of the San Francisco Bay salt ponds and marshes are currently undergoing restoration or have been targeted for restoration in the future.

The first phase of the South Bay Salt Pond Restoration Project (South Bay Salt Pond Restoration Project 2010), the largest tidal wetland restoration effort on the West Coast of the United States, began in 2006 after a multi-year collaborative public planning process involving the United States Fish and Wildlife Service, California Coastal Conservancy, and California Department of Fish and Game. Once construction/restoration is completed for the salt ponds, many wildlife species will benefit from the restored habitat; it will provide more nesting, foraging, and over-wintering areas. When completed, 15,100 acres of commercial salt ponds will be converted into tidal marsh, mudflat and other wetland habitats (SBSPRP 2010). The objectives of this project were to restore and enhance wetland habitats, to provide wildlife-oriented public access and recreation, and to improve flood management in the South Bay (SBSPRP 2010). The SBSPRP is an adaptive management project. Currently it is investigating scientific uncertainties and making decisions by combining in-situ monitoring, modeling, and experimental research with a high level of attention to information management and continuing data synthesis. Included in this effort is a multi-year vegetation identification and classification project which will aid in determining how marsh restoration is progressing.

Studies indicate that remote sensing is highly effective for monitoring wetlands, coastal systems and estuaries (Kelly and Tuxen 2009, Trabucco et al. 2009). Among remote sensing's advantages are non-invasiveness, cost-effectiveness, and the potential for encouraging public participation and communication. Remote sensing allows for a "high intensity of measurements" to be taken in often inaccessible or sensitive sites, thus eliminating the need for more invasive traditional field methods that could damage sensitive marsh and endangered species habitat. Additionally, remote sensing eliminates the need for expensive and labor intensive field methods inherent in accessing the soft sediment and dense vegetation that characterize tidal marsh ecosystems (Kelly and Tuxen 2009).

This project team assists the SBSPRP with vegetation classification by providing spectral measurements and image analysis of four dominant salt marsh vegetation types: annual pickleweed (*Salicornia europease*), perennial pickleweed (*Salicornia virginica*), cordgrass (*Spartina foliosa*), and bulrush (*Scirpus maritimus*). These vegetation types were chosen for their abundance and function. For example, pickleweed provides nesting and cover for birds and small mammals, and is the primary host for parasitic salt marsh dodder (*Cuscuta salina*). It is also vital to the survival of several endangered species, including the salt marsh harvest mouse (*Reithrodontomys raviventris*) and the California clapper rail (*Rallus longirostris obsoletus*) (Taylor 2010). The California clapper rail also uses cordgrass, but the native cordgrass cannot out-compete the non-native invasive cordgrass (*Spartina aleniflora*) also found in the marshes. This invasive species stabilizes the sediment which encourages further invasion and alters marsh hydrology, affecting shore birds. Native cordgrass is threatened with local extinction as a result of hybridization with *S.alteniflora* (Invasive Spartina Project 2010). Bulrush provides erosion control, protection from erosive wave action and stream currents, food and cover for wildlife, and waste treatment. It also restores and creates wetlands and improves plant diversity in wetland and riparian communities (USDA-NRCS 2010). Pepperweed (*Lepidium latifolium*) is an herbaceous perennial that invades a wide range of ecosystems such as riparian areas, mountain meadows, marshes, and wetlands (Renz and Blank 2004). Pepperweed can spread and form dense monospecific stands that can displace native plants and animals.

As temperate tidal wetlands have limited numbers of species and genera (even considering world-wide distributions) it is feasible to develop a useful and functional spectral library for wetland managers (Trabucco et al. 2009). Developing these libraries is important to improving our capacity to utilize the full mapping potential from emerging sources of data provided by airborne and advanced space-borne hyperspectral sensors (Trabucco et al. 2009).

The goals of this project were:

1. Create a spectral library of four primary salt marsh vegetation types
2. Classify the vegetation types using Landsat and Hyperion satellite imagery
3. Assess the historical progression of vegetation growth in the south San Francisco Bay

METHODOLOGY

Study Area

The South Bay Salt Pond Restoration Project is located at the southern end of San Francisco Bay and consists of three primary restoration sites: Ravenswood, Eden Landing and Alviso (Figure 1). Ground truth measurements, polygons, and spectroradiometer readings for this project were performed in each of the three primary restoration sites.

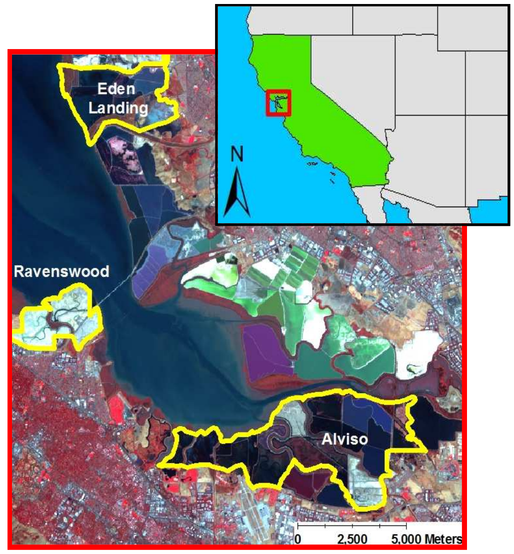

Figure 1: Study location of Alviso, Eden Landing, and Ravenswood. The salt ponds are located at the southern end of San Francisco Bay, California.

Field Work and Data Processing

The locations of four dominant salt marsh vegetation types in the salt ponds in the form of GIS shapefiles were used. After studying the locations of the four selected vegetation species, several field days in June 2010 were spent taking ground measurements to verify the existence of the particular species at the documented locations. If other acceptable study sites were discovered during field work, observations and notes were recorded for them. GPS coordinates were taken at each observed site using a handheld Garmin GPSMAP 76 chart plotting receiver. Accuracy of the GPS measurements at each point ranged between approximately 11 and 19 feet. Sites were deemed appropriate for measuring and recording if they contained a homogenous sample (coverage of 80% or greater) of one of the four selected vegetation species. Sites were also recorded where a mixture of species of interest occurs (i.e. 50% pickleweed, 50% cordgrass). In addition, at study sites where the vegetation patch was homogenous and at least 30m x 30m, a polygon measurement for the plot was taken using measuring tape and GPS coordinates. The plot measurements were uploaded and the center pixels of the polygon were used as training sites for unsupervised and supervised classifications for Landsat TM (Thematic Mapper) 5 scenes. Plots were required to be at least 30m x 30m to match the pixel size of the majority of Landsat TM5 bands.

Spectral measurements of the different vegetation types were taken on June 25, 2010 and July 1, 2010 using a GER 1500 Spectroradiometer (Spectra Vista Corporation). The GER 1500 has a spectral range of 350-1050 nm. Prior to scanning the vegetation, reference scans were taken using a 99% reflectance panel. An 8° lens was used to take scans of the vegetation. Between five and ten scans were taken at each vegetation sample site. Within each sample site, each of the spectroradiometer scans was aimed at a different vegetation points so that a representative spectrum of the vegetation type could be recorded. The measurements were taken between the hours of 10:00am and 2:00pm in order to minimize the variance of the sun angle. At each site, the following data were recorded:

- Vegetation species
- Percent cloud cover
- Universal Transverse Mercator (UTM) coordinates
- Time of measurement
- Photos
- General descriptions of the site

To create the spectral library and to qualitatively compare spectral profiles, percent reflectance of each vegetation type was calculated by dividing the digital number radiance of the vegetation target by the digital number radiance of the reference scans.

Satellite Image Processing

Both multispectral and hyperspectral satellite imagery were used for the classification. One L1R Hyperion image from July 7th, 2010 was acquired from the United States Geological Survey (USGS) Earth Observing 1 (EO-1) website. There were 130 images acquired from the USGS Glovis website between the years 2000 - 2010. The number of Landsat images analyzed is significantly higher than the number of Hyperion images analyzed because of the limited temporal and spatial availability of Hyperion images. Although all available Landsat images were inspected for approximately the past ten years, the only images used for classification were taken between the months of May and August (inclusive), on days with tides of six feet or less, and on days with minimal cloud cover. After narrowing the selection of Landsat images using these criteria, one image from each year was selected for a supervised classification (Table 1).

Table 1: Landsat images used for vegetation classification

Landsat Imagery		
August 2, 2000	June 26, 2004	June 5, 2008
June 18, 2001	June 13, 2005	July 26, 2009
July 7, 2002	May 31, 2006	June 11, 2010
May 23, 2003	August 22, 2007	

Landsat Processing and Classification

Landsat TM5 orbits the earth every 90 minutes and crosses the equator at approximately 10:30 am Pacific Time and acquisition is made continuously in a 16-day repeated cycle. Landsat TM5 is a multispectral satellite sensor that collects seven spectral channels with 30m spatial resolution in bands 1-5 and in band 7. Band 6 is a thermal band and is collected at 120m resolution, which is then resampled to 30m resolution. ERDAS Imagine 9.3.2 was used to perform image stacking, radiometric correction and calculation of reflectance values for Landsat images. For Landsat, only bands in the visible (1-3) and infrared (4-5, 7) ranges were used. One of the project goals was to determine whether Landsat could be used to identify the location of four designated species of salt marsh vegetation (annual and perennial pickleweed, bulrush, and cordgrass). The collected field data were used to run a 200-class unsupervised classification on the 2009 Landsat image. In addition to the four species of vegetation, four other categories of vegetation also needed to be identified, making it a total of eight different vegetation categories (Table 2).

Table 2: Summary of Vegetation

Study Specific Vegetation Species	Other Vegetation Species
Annual Pickleweed	Pepperweed
Perennial Pickleweed	Pickleweed/Cordgrass Mix
Bulrush	Pickleweed/Dodder Mix
Cordgrass	Pepperweed/Pickleweed

The unsupervised classification of the 2009 image was used to run supervised classifications on the selected images from 2000-2010. An accuracy assessment was then run on the 2009 supervised classification image. Following the first round of classifications, a second round of classifications was conducted using additional ground truth data. These additional field data were used in an attempt to increase the accuracy of the original classification process. The combined field data were used to run a 200-class unsupervised classification on the 2009 Landsat image and this unsupervised classification was used to run a supervised classification on the images from 2000-2010. An accuracy assessment was then run on the 2009 supervised classification to determine whether adding more data points increased the accuracy of the supervised classification process. Details of the classification process and accuracy assessment are described below.

As a result of low accuracy in the supervised and unsupervised classifications of vegetation species, a third round of classification was conducted to identify only vegetated areas versus non-vegetated areas in the study sites. In an attempt to improve accuracy results, this round of classification did not attempt to distinguish vegetation at a species level. Instead, the classification attempted to identify the location of any vegetation in the South Bay salt ponds, track its presence from 2000 through 2010, and determine whether restoration of the salt ponds (as evidenced by increased vegetation) has progressed. To accomplish this, a 200-class unsupervised classification was run on the 2009 image using the combined data described above. In ArcMap, this unsupervised image was then layered over a June 2009 IKONOS image of the study sites to aid in the identification of the presence or absence of vegetation. The IKONOS image was then set to NIR so that vegetation became easily identifiable. The Swipe tool in ArcMap was used to compare the Landsat and IKONOS images and appropriate changes were made to the unclassified image by altering the signature file to include pixel classes of vegetation that were missed by the original unsupervised classification. After all vegetation classes were identified, a supervised classification was run on all images and an accuracy assessment was performed on the 2009 image. Accuracy assessment results are also shown below.

Hyperion Processing and Classification

The EO-1 Hyperion is a hyperspectral satellite sensor that collects a total of 220 spectral channels with a 10-11nm bandwidth at a 30m resolution for every channel (Simon and Beckmann 2005). Hyperion scenes are acquired when requested by the general public and therefore, are not collected at regular intervals.

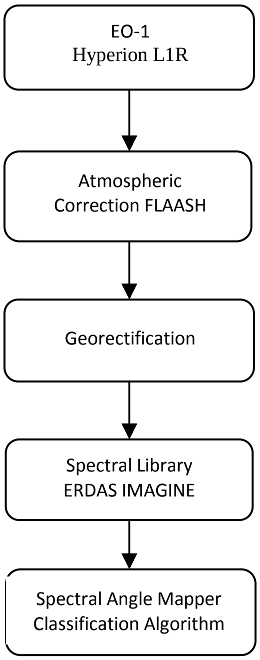

Figure 2: Flow Chart Showing Methods for Processing Hyperion Image **.**

The L1R EO-1 July 7, 2010 Hyperion image downloaded and used for classification included radiometric correction. ENVI 4.7 and the plug-in module, FLAASH (Research Systems) were used to perform atmospheric correction and to convert radiance to surface reflectance values for the image. Only 154 of the total 242 Hyperion bands were used in the analysis. A total of 46 bands from the radiometrically corrected image were removed following steps described in the EO-1 User Guide (Beck 2003). An additional 42 bands with excessive noise, particularly at the water vapor absorption region were also removed.

The Hyperion image was then georectified using a total of 20 ground control points (GCP) and two georeferenced vector files: one shapefile outlining the Alviso salt ponds and one vector file containing California highways. Orthorectification of the Hyperion image was omitted because the terrain in the study area was relatively flat and close to sea level.

A total of two spectral libraries were constructed using the spectral analysis workstation in ERDAS IMAGING, and the libraries were used as the reference or target spectra to classify the Hyperion image. The first library used the GER 1500 data (converted to apparent reflectance), and the second library used image derived spectral data based on the known locations of vegetation polygons mapped during fieldwork using GPS coordinates.

The Material Mapping Wizard (MMW) in ERDAS IMAGINE was used to apply the spectral angle mapper (SAM) algorithm on the Hyperion data (Equation 1). The image spectrum (X in equation 1), corresponds to the pixels in the image that are to be analyzed. The reference or target spectra can be obtained from field or laboratory spectral measurements, or extracted from the satellite image. Pickleweed, the most prevalent vegetation type in the study sites, was used as the input target spectrum for both classifications using GER 1500 as well as image derived spectral data. Following the MMW steps, additional bands, particularly in the three water vapor absorption regions, were removed and the minimal noise fraction (MNF) transformation was used on the Hyperion to further remove noise in the data (Shippert 2003).

$$\alpha = \cos^{-1}\left(\frac{\sum_{i}^{n} X_i Y_i}{\sqrt{\sum_{i}^{n} X_i^2}\sqrt{\sum_{i}^{n} Y_i^2}}\right) \tag{1}$$

n = number of bands
α = angle formed between reference spectrum and image spectrum
X = image spectrum
Y = reference or target spectrum

Hyperion-Spectral Angle Mapper (SAM):

The cosine mode of the spectral angle mapper (SAM) classification algorithm was applied to the July 7th, 2010 Hyperion image in ERDAS IMAGINE. The cosine SAM algorithm computes a spectral angle between a target spectrum and each pixel in the image using all of the bands in the image (Shippert 2003). The lower the spectral angle value between a pixel and a target spectrum, the more similar the pixel and target. The output result from cosine SAM displays the image in a scale of gradient color corresponding to the cosine of spectral angle value from -1 to 1. Determination of the threshold values was based on two of the field polygons of known pickleweed locations.

RESULTS

Comparison of Spectral Profiles

Spectral profiles were compared for four different vegetation types: perennial and annual pickleweed, bulrush, and cordgrass. Table 3 summarizes the number and location of spectroradiometer readings taken for each vegetation type. Figure 3 shows the spectral profiles for each vegetation type. Each spectral profile represents the average of the spectroradiometer scans taken at that site. Pickleweed was more prevalent in large patches than cordgrass and bulrush. Therefore, more samples were collected of pickleweed than of other vegetation types.

Table 3. Number of GER 1500 Scans Taken by Location

	Alviso	**Ravenswood**	**Eden Landing**
Bulrush	10 scans at 1 site	10 scans at 1 site	10 scans at 1 site
Cordgrass	5 scans at 1 site	10 scans at 1 site	--
Annual Pickleweed	5 scans at 1 site	25 scans at 5 sites	--
Perennial Pickleweed	25 scans at 3 sites	20 scans at 2 sites	20 scans at 2 sites

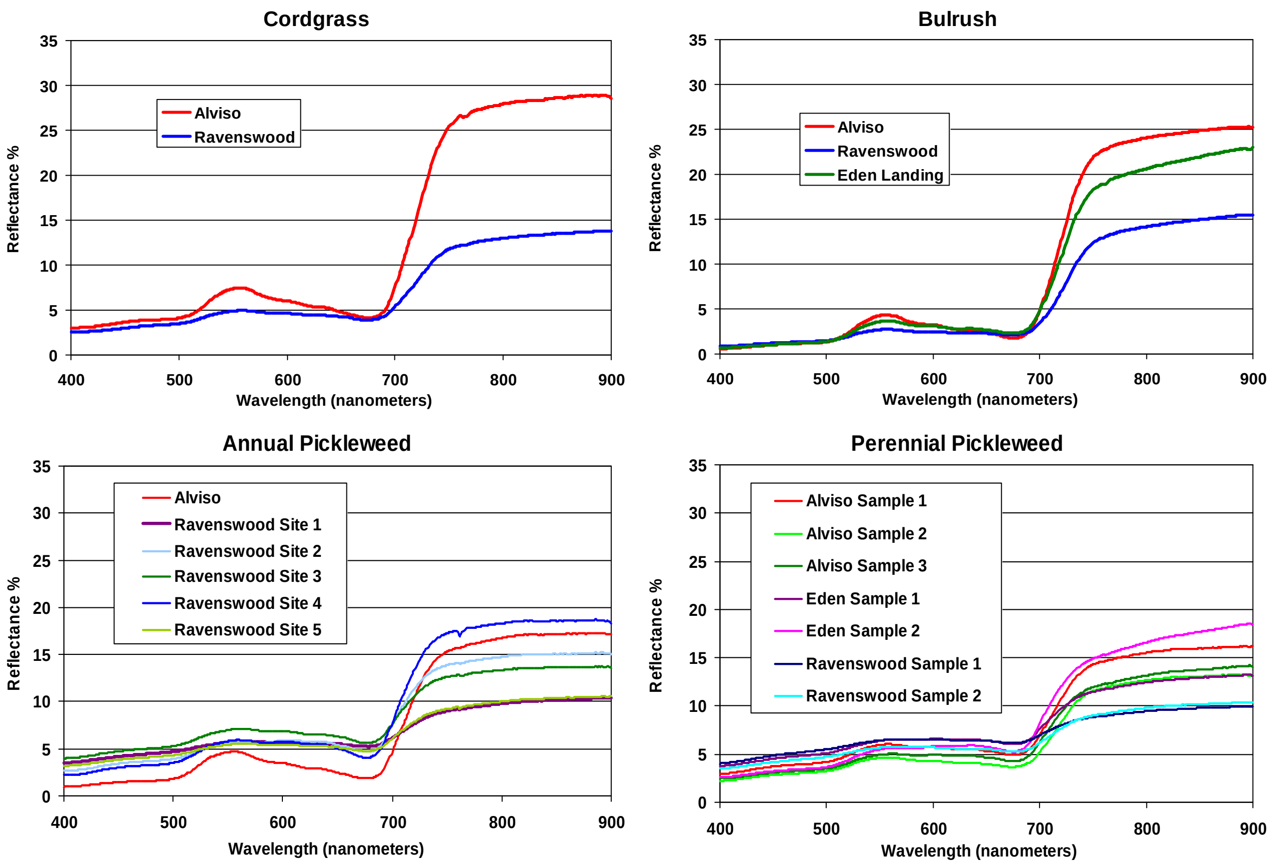

Figure 3. Spectral Profiles by Vegetation Type.

Figure 4 shows the average reflectance (by wavelength) and standard deviation for the samples of each vegetation type. Although the vegetation spectral profiles have similar shapes, the individual reflectance values vary and the mean appears different for each vegetation type. However, when dispersion of the samples is considered, it is evident that the spectral profile samples could have significant overlap and be difficult to distinguish within the bands shown here. This dispersion is evident in figure 4, which shows the mean compared to one standard deviation above and below the mean for each vegetation type. The majority of the means and standard deviations for the vegetation types fall within one standard deviation above and below the cordgrass mean.

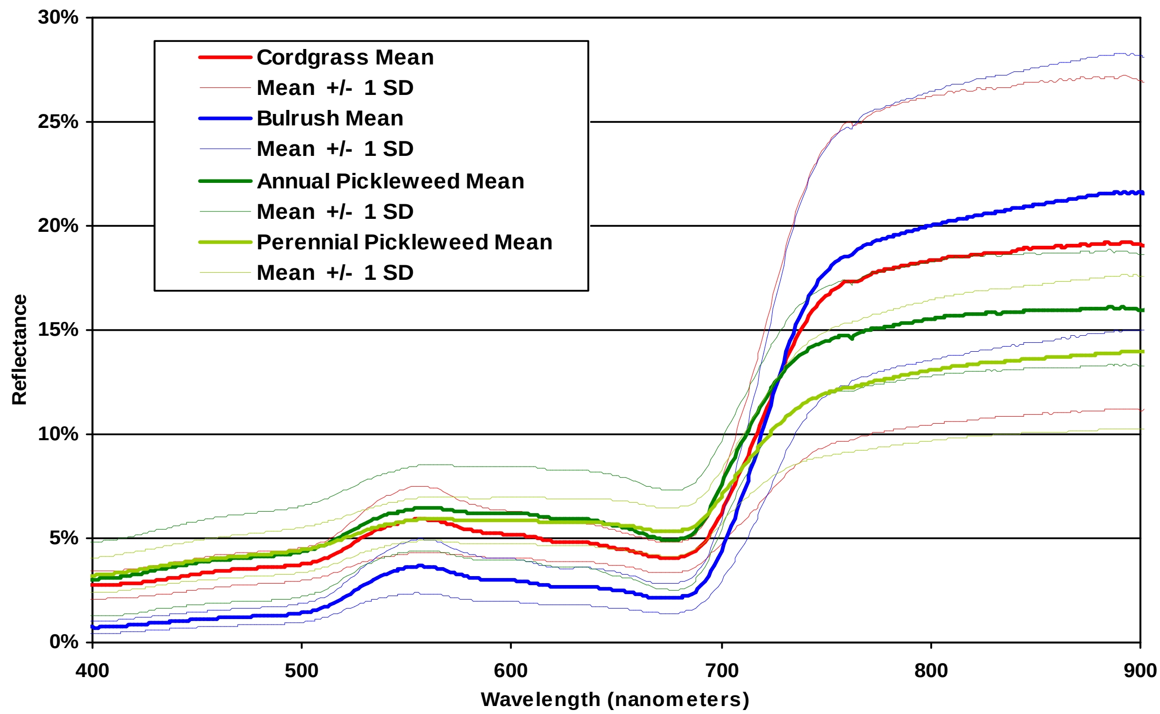

Figure 4. Means and Standard Deviations for Vegetation Samples.

The spectral library created for classification of the Hyperion image was based on these spectral signatures. This spectral library could be improved by spending more time gathering spectral data of other endmembers found in the salt marshes (other vegetation types, soil, silt, water, etc.). The similarity of spectral signatures among the four vegetation types suggests that more sampling and analysis of vegetation spectral signatures is needed to fully distinguish them using remote sensing techniques. Using the current data, only bulrush has a distinct signature and this distinctness only occurs at lower wavelengths (below 700nm). Additional sampling of vegetation could aid in classification by reducing dispersion among the signatures. Once dispersion is reduced, it would be advisable to analyze imagery from sensors focusing on wavelengths where the dispersion is the lowest. Alternatively, if dispersion is not reduced significantly by obtaining more samples, more sophisticated classification algorithms than those used in this study could be applied to the data.

Satellite Data

The Landsat unsupervised classification data were applied to other images through a supervised classification. The accuracy assessment produced a result of 32.56% accuracy from the supervised classification of an image. An accuracy assessment was then done on the supervised images and produced a result of 32.66% accuracy. Unable to distinguish between the different species of salt marsh vegetation, the decision was made to broaden the scope of concentration and try to identify the presence of all types of vegetation within the salt ponds. Unsupervised classification with the field work polygons yielded to 26% accuracy for a 2009 image. These data with SBSPRP's polygons yielded to 32% accuracy for a 2009 image. The spectral signature from the 2009 image was applied to a 2006 image, yielding to 1% accuracy. The vegetation change over time model has a 92% accuracy displaying the areas that have vegetation versus distinct species.

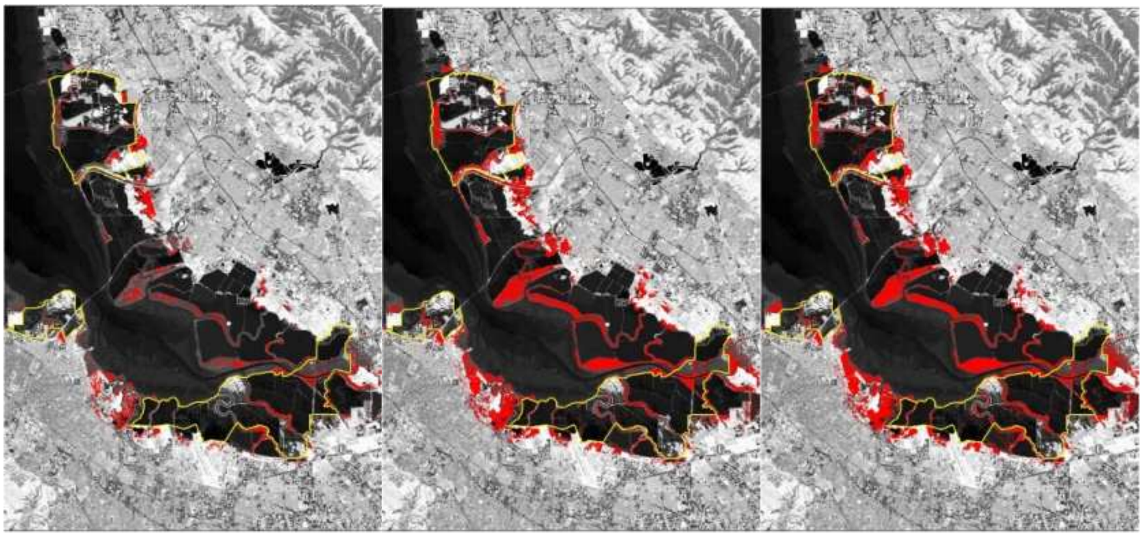

Figure 5: Supervised Classification of Landsat Images. From left to right: August 2, 2000; June 13, 2005; June 11, 2010. These three images show the increase of vegetation (shown in red) over the past decade in the south bay area of San Francisco Bay. The three study sites are outlined in yellow.

Table 4. Change in Vegetation over time

Years	Increased	Decreased
2000-2001	General increase	No visible decrease
2001-2002	No visible increase	General decrease
2002-2003	No visible increase	No visible decrease
2003-2004	No visible increase	Slight decrease
2004-2005	General increase	No visible decrease
2005-2006	General increase	No visible decrease
2006-2007	No visible increase	General decrease
2007-2008	General increase	No visible decrease
2008-2009	No visible increase	Slight decrease
2009-2010	General increase	No visible decrease

Hyperion

The results of the SAM classification algorithm are shown in Figure 6, with pickleweed showing in red. Pixels representing areas of pickleweed were classified using cosine SAM threshold value of 0.993936 from GER 1500 spectral data, and 0.993687 from the image derived spectral data.

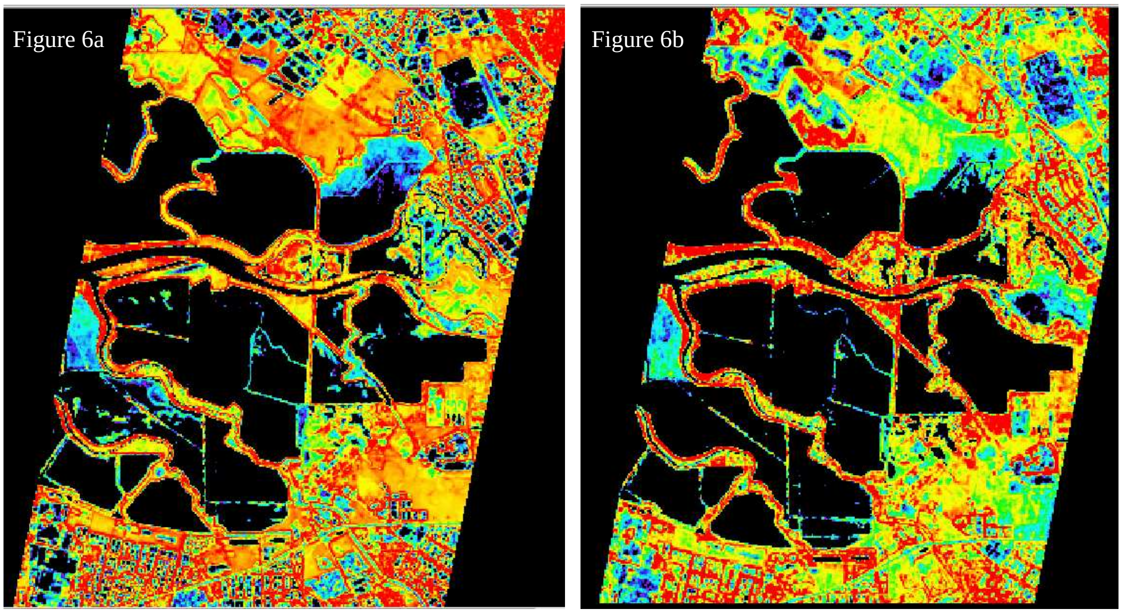

Figure 6. A subset image of the classified July 7th, 2010 Hyperion data showing the Alviso area using the SAM classification algorithm with spectral library constructed in ERDAS IMAGINE. Figure 6a is the classification using GER 1500 spectral data. Figure 6b shows the classification using image derived spectral data. Pickleweed is displayed in red.

Spectral similarity to picklweed

DISCUSSION

Landsat imagery with 30m pixel resolution is too coarse to distinguish among the different vegetation species in the salt marsh environment, although it is very accurate with classifying vegetation vs. non-vegetation. Many Landsat images had qualities such as banding, noise, clouds, a fog layer, and high tides that precluded their use. However, because of Landsat's frequent overpasses and good availability, it is likely that enough high-quality Landsat images could be selected to potentially enable tracking of large scale changes in marsh vegetation over time. According to the classification, the vegetation in the study sites has generally increased over the past decade, though in some years the vegetation cover decreased. (Based on a cursory analysis of rainfall, this decrease could possibly have been due to years with below normal precipitation.)

With the capability of hyperspectral data, a pickleweed map was produced using the July 7th, 2010 Hyperion image and the SAM classification algorithm. The classification from both the GER 1500 data and the image derived data are able to identify the occurrence of pickleweed in the Alviso area based on the field observations and knowledge of the area. However, the SAM algorithm misclassified portions of urban vegetation features as pickleweed. The low number of field polygons used to determine the threshold for pickleweed could have contributed to the misclassification. In addition, a sufficient number of large, homogeneous field polygons would need to be obtained to perform an accuracy assessment for the SAM classification.

Attempts were made to use all of the GER 1500 spectral data collected in the field to classify Hyperion at the sub-pixel level using multiple endmember spectral mixing analysis (MESMA) (Roberts et al. 2007). The classification was unsuccessful in unmixing the different endmembers within the 30 m pixel of Hyperion image. This suggests that additional GER 1500 spectral data are needed to achieve a full classification using hyperspectral data.

More time is needed in the field to collect additional spectroradiometer readings of the four vegetation types as well as readings of mud, water, silt and other land types commonly found in the salt ponds to distinguish between marsh vegetation types. Spectroradiometer readings were taken for annual and perennial pickleweed, cordgrass, bulrush, and pepperweed. Readings were attempted in all three ponds to determine whether vegetation in the three ponds have uniform signatures. However, certain ponds had significantly more vegetation eligible for sampling (e.g. much of the Eden Landing cordgrass had recently been sprayed with pesticides which would affect the spectral signature).The experience in the field taking readings also shows that many factors need to be considered when attempting to obtain spectral vegetation data and apply spectral profiles to image analysis. For example, when taking readings of perennial and annual pickleweed, it was noticed that annual pickleweed is generally found on mud (of various wetness) that could potentially affect the spectral readings. It was also noticed that dodder is commonly found on perennial pickleweed and affects the spectral profile of pickleweed.

CONCLUSION

The first round of classification yielded an accuracy of 32.56%. This was unsuccessful possibly due to insufficient field data being collected. In particular, large homogenous plots of marsh vegetation were not prevalent throughout the study sites. Even if plots at least 30mx30m were located, it is difficult to know whether these plots were contained within one pixel on the image. It is likely that each pixel contained multiple species of vegetation. The classification process was also challenging due to the existence of certain field data indicating a pixel class should be labeled as one species (e.g. pepperweed), while other field data (collected from nearby sites) indicated that the same pixel class should be labeled as multiple species (e.g. pickleweed/cordgrass mix). More categories of vegetation (e.g. pepperweed/ pickleweed/cordgrass mix) could have been created, but the goal of the study was to identify the originally designated categories rather than create additional categories to validate results.

The second round of classification, which included additional field data samples during the classification process, also produced low accuracy results. After multiple attempts to identify the presence of the four vegetation species, the conclusion was reached that identification of individual salt marsh vegetation could not be achieved by applying our classification methods to Landsat imagery.

The third round of classification, which did not attempt to distinguish vegetation species, yielded a much higher accuracy than the two previous classification attempts. This shows that although Landsat is not able to identify individual species of vegetation in this ecosystem, Landsat is able to adequately identify the presence of vegetation in the South Bay Salt Ponds. After running the supervised classification on the images from 2000-2010, changes in the presence of vegetation were evident, though lack of ground truth measurements data from 2000-2008 prevented an accuracy assessment from being performed. Since the amount of vegetation pixels present can be calculated for each image (one image per year), an extrapolation could be obtained of the relative amount of vegetation present for that image based on how many vegetation pixels are present. After graphing the amount of vegetation pixels in each image for each year, it can then be roughly stated that the amount of vegetation in the South Bay Salt Ponds has increased from 2000-2010. Certain factors must be taken into account when analyzing the amount of vegetation present in each image, such as the month the image was taken (vegetation present varies due to season and time of bloom), the amount of annual rainfall for each year, and other environmental variables.

Using Hyperion imagery, a classification of one vegetation species was obtained using the SAM algorithm. However, additional data are needed to improve and assess classification accuracy. The preliminary classification from the Hyperion image showed that it could be used for vegetation detection. Further research with Hyperion imagery could be performed using a more powerful sub-pixel level classification with additional field and spectral data to distinguish between multiple vegetation species.

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