Tidal Marsh Restoration in the South Bay Salt Ponds: Mapping Vegetation Re-establishment Patterns with Remote Sensing in Pond A21 and North Creek Marsh

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ABSTRACT

Tidal wetlands provide a large variety of important ecosystem services, but are extremely vulnerable to environmental changes and have experienced high losses globally. Without intervention, these losses will increase because of stresses from climatic events and urban development. Many efforts have been made to conserve and restore wetlands around the San Francisco Bay, but the progress of restoration projects have been seen to be highly variable and difficult to monitor. Remote sensing and change analysis can alleviate some of those difficulties and provide information on long-term monitoring. I used Object Based Image Analysis (OBIA) on 1 meter resolution IKONOS imagery and performed change analysis to assess the patterns of vegetation change between 2009 and 2011 in two breached restoration sites managed by the South Bay Salt Pond Restoration Project: Pond A21 in Alviso and North Creek Marsh (NCM) in Eden Landing. NCM experienced increases in vegetation throughout the site, while vegetation growth in A21 remained limited to areas near water channels. Image segmentation based on scale parameter was variable between sites, but other parameters within segmentation and classification rule sets can be saved and applied to monitor additional restored wetlands. This information gives adaptive management projects greater insight on the effectiveness and limitations of using these remote sensing methods to monitor wetland response to environmental changes.

KEY WORDS

Remote Sensing, Object Based Image Analysis, San Francisco Bay, Wetland Restoration, Adaptive Management

INTRODUCTION

Tidal marshes and coastal wetlands provide a variety of ecosystem services. These wetlands improve storm and wastewater quality, mitigate climate change through carbon sequestration, and provide habitat for many endangered species (Zedler and Kercher 2005, Crooks et al. 2011, Demers and Robinson-Nilsen 2012). However, freshwater and brackish water ecosystems are highly sensitive to environmental changes such as sea level rise and drought (Thomas et al. 2011). Globally, the land cover area of tidal marshes have been reduced by 50%, and these habitats are projected to decrease even further from environmental stress caused by land use change (Crooks et al. 2011). In South San Francisco Bay, 85% of the historical tidal marsh areas have been lost to urban development along with other ecosystem engineering projects (Trulio et al. 2007). Currently there are many efforts being made to restore and conserve the remaining wetlands.

Wetland restoration projects on the West Coast of the United States began only recently, leaving much more to learn about how these ecosystems function. Prior to the 1970s, tidal marshes were recognized as areas in need of conservational efforts, because they are complex ecosystems at risk of being forever lost in their entirety (Williams and Faber 2001). Early San Francisco Bay restoration efforts used approaches originally developed for wetlands on the Atlantic Coast; however these new restoration projects faced many problems. As a result, Pacific Coast wetland restoration became very experimental to address these differences. Issues included the accidental introduction of non-native Atlantic Coast cordgrass, which now is treated as an invasive species and is a focus of current restoration efforts (Williams and Faber 2001). Vegetation establishment on restoration sites is also highly variable between wetlands. A decade after restoration projects began, a summary study on the early progress of these projects concluded that restored marshland around San Francisco Bay still required monitoring, continued experimentation, and long-term documentation to determine the success of these projects (Race 1985).

With recent climatic changes in California, restoration projects require even more monitoring to ensure the resiliency of restoration efforts. Factors such as sedimentation rates, which are dependent on hydrological flows for particle transport, can be greatly affected by hydrological changes caused by both natural events, like drought and El Niño, and anthropogenic modifications. These rates are highly important to the survival of tidal marsh ecosystems, because the inflow of new sediment is required for maintaining sediment quality (McKee et al. 2013). Changes in water salinity also affects the types and rates of vegetation re-establishment in the area, because of the differing salinity tolerances between wetland plant species and overall increased stress to vegetation caused by increased salinity (Thomas et al. 2011). Variables as simple as sediment dispersal patterns can cause some locations to be much more ideal for restoration than adjacent sites (Brand et al. 2012, Shellenbarger et al. 2013). Because each wetland has different characteristics, each may respond differently to the same restoration approach.

The past management of wetlands in South and East San Francisco Bay makes restoration on these sites unique. As mid 1800's industrialization and urbanization spread around San Francisco Bay, many tidal wetlands were blocked and converted to salt ponds for salt production (California Research Bureau 2002). Salt production expansion continued through the 1950's, by which half of the wetlands in the South Bay were already lost to salt production. In the late twentieth century, wetlands became protected areas and the previous industrial salt production sites were returned to wildlife habitat. Currently the South Bay Salt Pond Restoration Project manages wetland conservation and restoration from salt production activity on these sites. Restoration strategies of these areas include the elimination of some of the constructed ponds to return to tidal marsh, while strategically preserving some pond ecosystems to support the wildlife that has established (Trulio et al. 2007, Athearn et al. 2012). The breaching process, or the opening up of the constructed ponds to allow inflow of seawater, will affect the sedimentation rates and salinity of the wetlands (Rey 2015). The change in salinity will in particular affects the conditions of the areas in which vegetation is re-establishing; increases in salinity causes stress on the vegetation in the area (Callaway et al. 2007). In addition to the changes caused by natural events, these newly breached tidal wetlands are facing sudden new changes in tidal activity, erosion, and sedimentation, which all affect the rates and patterns of vegetation re-establishment in the different former pond areas.

Long term progress monitoring is in itself a major challenge for wetland restoration projects. Areas within project sites could be inaccessible for fieldwork due to natural conditions, such as tides, or habitat sensitivity to disturbances (Tuxen et al. 2008, Klemas 2013). Remote sensing and geographical information systems (GIS) provide the ability to include inaccessible areas in analysis, and the advantages of being time and cost effective. Surface heterogeneity in wetlands can increase the difficulty in classifying land cover for restoration monitoring by creating noise in remote sensing imagery, but Object Based Image Analysis (OBIA) can eliminate some of those effects (Dronova 2015). Using remote sensing in monitoring wetland restoration is a growing field, and can provide great advantages in adaptive management projects.

To monitor the progress of vegetation re-establishment in areas breached and restored from pond to tidal marsh, I used IKONOS remote sensing data from 2009 and 2011 and OBIA to classify changes in vegetation cover, water channels, and mudflats for Pond A21 in Alviso and North Creek Marsh (NCM) in Eden Landing over this 3-year period. Both sites are managed by the South Bay Salt Pond Restoration Project (SBSPRP). These changes were visually assessed with proximity to water channels, and compared to expected site differences to estimate their impacts on vegetation re-establishment behavior. In addition, I assessed the replicability of OBIA processes across multiple SBSPRP sites. I hypothesized that both sites will have more vegetation re-establishment closer to the water channels, but NCM will have less overall vegetation than pond A21 because of higher salinity. This study improves the understanding of the variables that cause differences in response to restoration practices in tidal marshes, and of the effectiveness of using OBIA in monitoring SBSPRP project sites.

METHODS

Study Site

The South Bay salt ponds are located along the Tidal Terrestrial Transition Zone of San Francisco Bay. Its northern-most ponds are located just south of the Hayward San Mateo Bridge entrance, extending south through the cities of Fremont, Milpitas, Mountain View, and Palo Alto. SBSPRP manages 15,100 acres South Bay salt ponds (SBSPRP 2009). They are divided between three complexes: Eden Landing Ecological Reserve, Alviso, and Ravenswood (Figure 1).

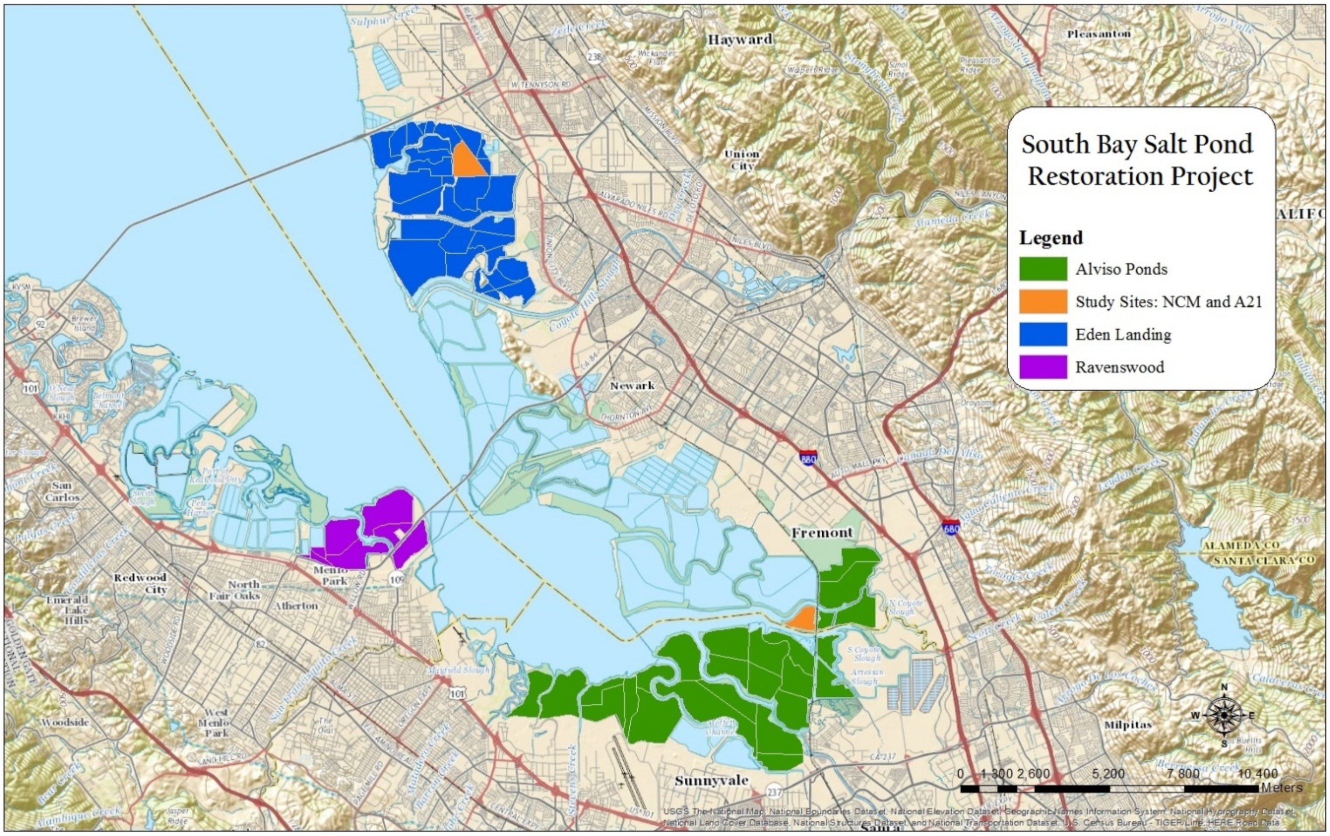

Figure 1. South Bay Salt Pond Restoration Project Map. The South Bay Salt Pond Restoration Project manages Alviso, Eden Landing, and Ravenswood. North Creek Marsh and A21 are highlighted in orange.

Pond A21 in Alviso and North Creek Marsh in Eden Landing were selected as study sites because of their similarities in management practices. This allows for easier isolation of factors that affect vegetation re-establishment within each pond from restoration methods used by SBSPRP. Both ponds were breached to become tidal wetland in 2006. Eden Landing is among the northern-most sites of the South Bay Salt Ponds, just south of the San Mateo Bridge and Hayward Shoreline (a salt marsh restoration site not managed by SBSPRP). The Alviso ponds are located in the south-most area managed by the SBSPRP. Pond A21 in particular was breached at two points to Coyote Creek (Callaway et al. 2013). The freshwater from the creek causes the salinity of the salt marsh to decrease (Saiki and Mejia 2009).

Imagery

I obtained IKONOS imagery and a polygon shapefile of the South Bay salt ponds from my mentor, Dylan Chapple (University of California, Berkeley), who received the data from the San Francisco Estuary Institute (http://www.sfei.org/). The image data covers three years: 2009, 2010, and 2011. The 2010 dataset was omitted from this study because of poor data quality. These images have three 4m resolution bands (red, green, and blue) and one 1m resolution panchromatic band (Fulfrost et al. 2012). Images were taken in June or July for each year, when water levels were closest to the Mean Lower Low Water, or the average height of the lowest tide recorded for the area. This timing allows for the images to be taken during the period of maximum vegetation growth in the study area, when marsh and mudflat are fully exposed from the tide. The imagery is a composite of three snapshots taken over three days, one for each of three passes of the satellite.

Using ArcGIS 10.3 (Environmental Systems Research Institute 2014), I converted the project ponds polygon map and imagery to the same projection: GCS WGS 1984. Using the Clip (Data Management) tool, I exported the data for each individual pond polygon along with corresponding clipped images from the original IKONOS imagery. To include only the restoration project area, I used the Extract by Mask tool to create boundaries around each pond.

To compare different project sites, I used supervised classification and Object Based Image Analysis to categorize areas of water, vegetation, and mudflat after normalizing and correcting the imagery. This was done using eCognition software (Trimble Geospatial 2013), with a rule set similar to that used by my mentor in previous trials for NCM. A 4-3-2 band false color display was used with the Histogram Equalization stretch to allow for interpretation of vegetation and water from mudflat. The Multiscale Resolution Segmentation tool was used with different parameters to produce objects that captured the vegetation patterns in the images. An Image Layer weight of 1 was placed for bands 1 (blue) and 2 (green), and a weight of 2 was placed on bands 3 (red) and 4 (near-infrared). Because the previous analysis on NCM was unable to detect smaller surface water channels, smaller scale parameters were tested to improve delineation of water (Moffett and Gorelick 2013). In the final segmented images, the scale value of 5 was used for both NCM images to more effectively capture smaller water channel details that had been missed previously, while the higher scale value 7 was used for A21 to smooth some of the variation caused by the greater amount of water and algae on the mudflat areas of this site.

After segmentation, training samples were collected in North Creek Marsh for mudflat, water/channels, roads, and *Salicornia pacifica* (commonly known as Pickleweed, the dominant colonizing vegetation type), while in A21 training samples were collected for mudflat, water/channels, *Salicornia pacifica* and *Spartina foliosa* (or California cordgrass, a native colonizing vegetation type). *Spartina foliosa* was differentiated from *Salicornia pacifica* based off its distinct circular growth patterns (see Appendix A1). However, it was only classified for the 2011 imagery because differences in color between the two sets of A21 imagery made it difficult to visually determine cordgrass from Pickleweed in the 2009 image. The images for both sites were then classified using the nearest neighbor configuration algorithm with features Brightness, Mean NIR, and Standard deviation Red.

To assess the accuracy of these classifications, sets of 100 random points covering the extent of each classified image were generated using ArcGIS. The 4-3-2 band display images and historical Google Earth (Google Earth 2015) images were used to verify the classifications of the collection points. The class values from the classified image were extracted to each point, and the frequency tool was used to create a table with the frequencies of each predicted class matching with each actual class. The pivot table tool was used to generate a confusion matrix to assess classification accuracy.

The 2009 and 2011 classified images for each pond were combined using the Combine tool to produce a table of unique combinations of input and output values. These combinations were grouped by no change, change (+) of vegetation, change (-) of vegetation, and non-vegetation class changes. For the 2011 A21 image, Pickleweed and cordgrass were analyzed together as one class: vegetation. Symbology was adjusted to emphasize the patterns of vegetation gain and loss.

Comparisons with other factors

To compare factors within the individual study sites with vegetation patterns, data for salinity, water channel cover, and *Spartina foliosa* cover was downloaded or extracted from the imagery. Salinity data was acquired from the USGS data archive (http://sfbay.wr.usgs.gov/access/wqdata/overview/examp/charts/salin.html) for San Francisco Bay. The average elevation for each site was calculated using Google Earth Engine (Google Earth Engine Team 2015). Using the USGS National Elevation Dataset available within Google Earth Engine, each site was clipped to polygon outline layers of A21 and NCM and processed through the reducer (mean).

The water channels were extracted by converting the raster image into a vector shapefile, then exporting the polygons of selected water channel areas. The water shapefile was visually compared with the original imagery to assess how well the smaller water channels were captured by the classification. The *Spartina foliosa* data was extracted in a similar way, with confirmation from the Invasive Spartina Project (http://www.spartina.org/) that the vegetation classified is the native cordgrass species (D. Chapple, *personal communication*).

RESULTS

Alviso Pond A21

Between the years 2009 and 2011, the change analysis for Pond A21 in Alviso (Figure 3) resulted in a net loss of vegetation habitat by -10.002156%, while mudflat experienced a small increase (Figure 2). 99076 pixels of mudflat and water transitioned to vegetation, but this gain was smaller than the loss of 115101 pixels of vegetation to mudflat and water. The accuracy of classification for 2009 was 82% with a Kappa statistic of 0.673024523, and the accuracy for 2011 was 89% with a Kappa statistic of 0.83899297 (see Appendix B1 and B2 for confusion matrices).

	Unclassified	Vegetation	Mudflat	Water	Row Total	Class Total (final)
Unclassified	572005	160	298	343	572806	572806
Vegetation	409	42465	68908	30168	141950	141950
Mudflat	189	73583	307464	120593	501829	501829
Water/Channels	358	41518	108311	84249	234436	234436
Class Total (initial)	572961	157726	484981	235353		
Class Changes	956	115261	177517	151104		
Image Difference	-155	-15776	16848	-917		
Percent Change	-0.02705%	-10.002156	3.474%	-0.389%		

Figure 2. Alviso Pond A21 Area (pixels) and Percent Change. Columns represent initial state classes (2009) while Rows represent final state classes (2011).

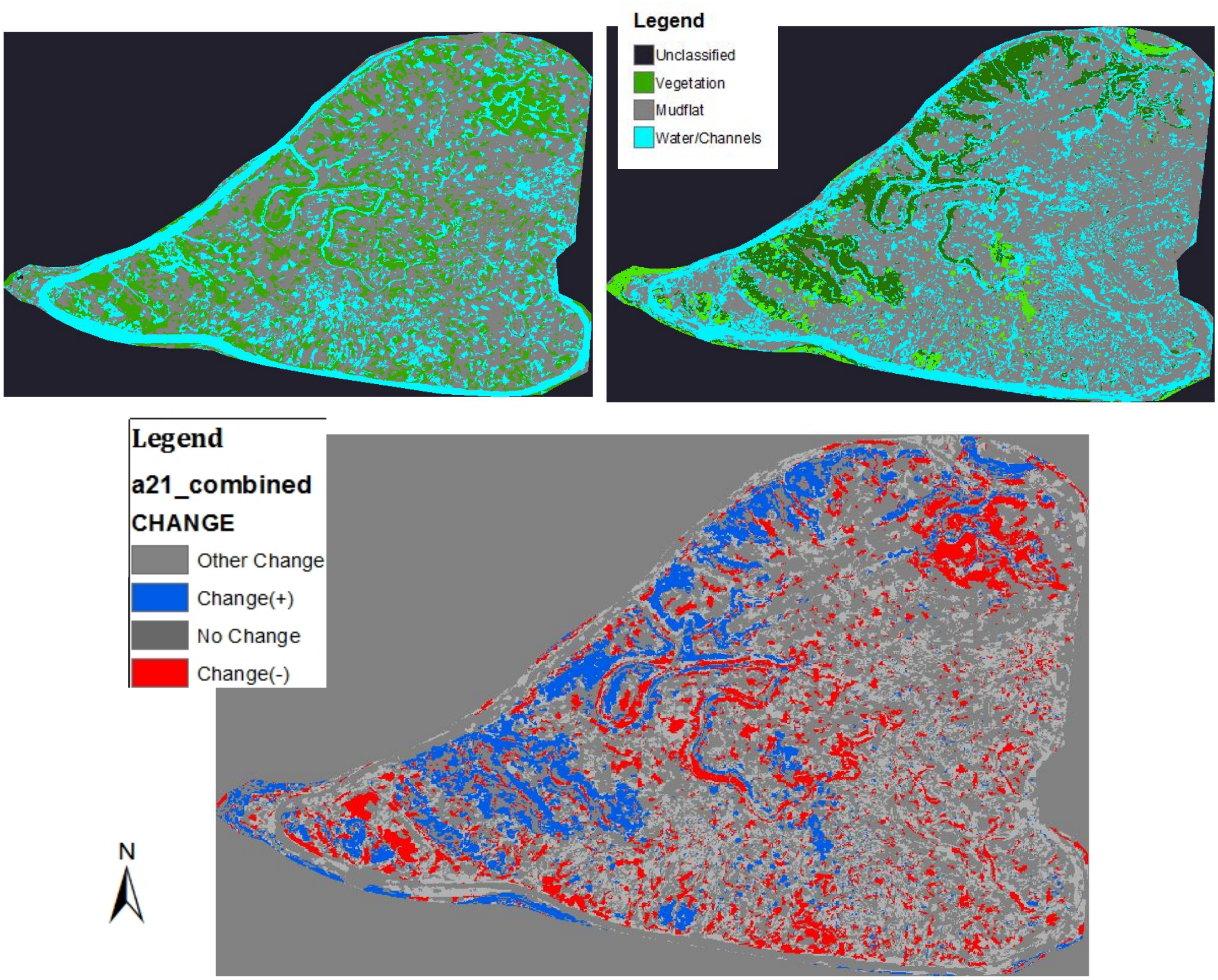

Figure 3. Change Analysis of A21. Classifications for A21 in 2009 (top left), 2011 (top right), and change analysis map highlighting areas of vegetation gain and loss between 2009-2011 (bottom)

North Creek Marsh

For the same time period, North Creek Marsh (Figure 5) experienced an overall increase in vegetation habitat. There was a 52.9% increase in vegetation (Figure 4). However, water and roads experienced large losses of -46.3% and -65.97% respectively. 1284 pixels that had been classified in 2009 became unclassified pixels in 2011. The accuracy of classification for 2009 was 84% (Kappa = 0.80941) and the accuracy for 2011 was 83% (Kappa = 0.764934) (see Appendix B3 and B4 for confusion matrices).

	Unclassified	Vegetation	Mudflat	Water	Roads	Row Total	Class Total (final)
Unclassified	199744	266	241	162	931	201344	201344
Vegetation	43	55724	132933	22740	6178	217618	217618
Mudflat	168	75177	191707	32747	14518	314317	314317
Water	0	9427	12981	14951	755	38114	38114
Roads	105	1698	772	414	7014	10003	10003
Class Total (initial)	200060	142292	338634	71014	29396		
Class Changes	316	86568	146927	56063	22382		
Image Difference	1284	75326	-24317	-32900	-19393		
Percent Change	0.641807%	52.9376%	-7.181%	-46.3%	-65.97%		

Figure 4. North Creek Marsh Area (pixels) and Percent Change. Columns represent initial state classes (2009) while Rows represent final state classes (2011).

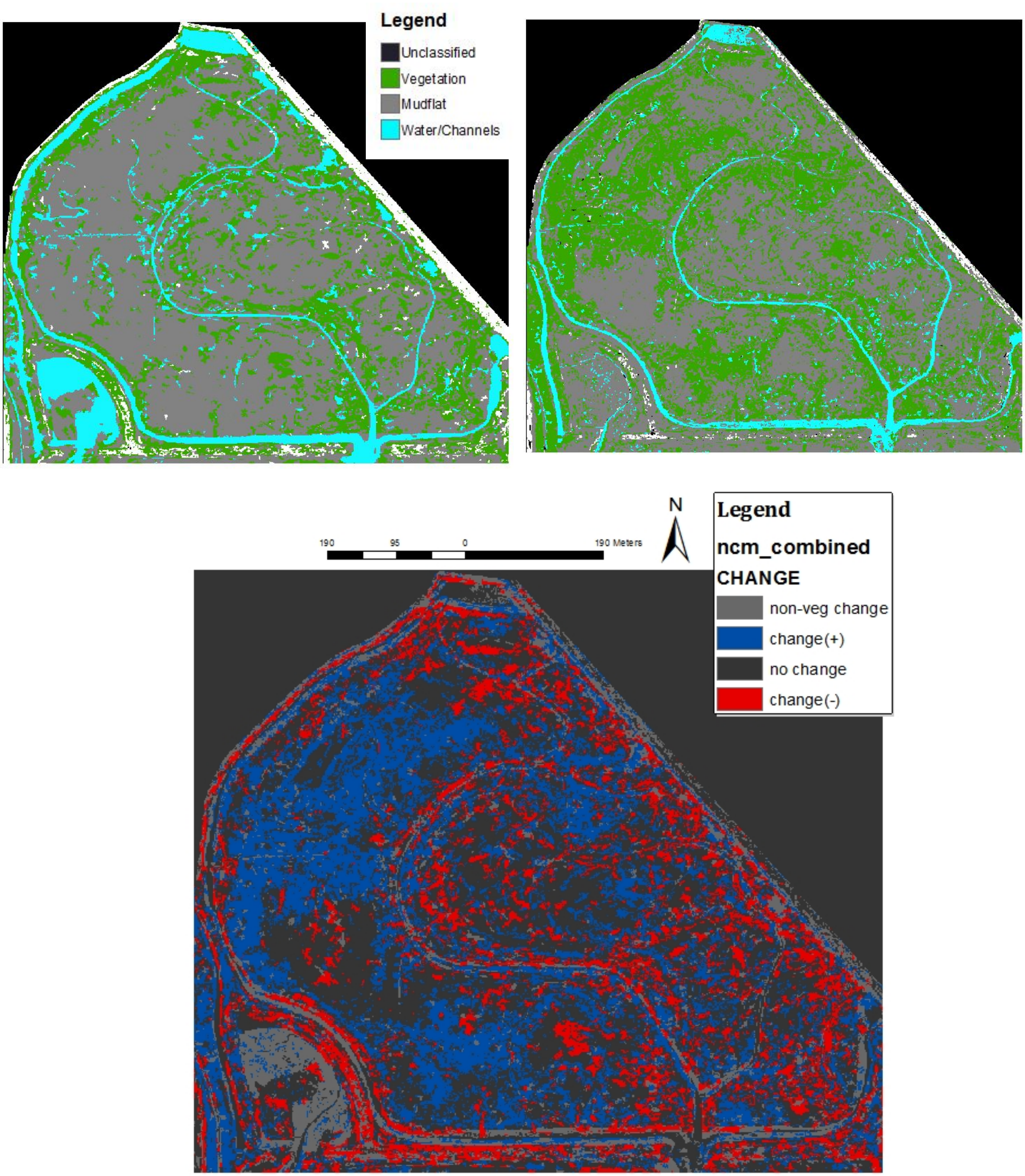

Figure 5: Change Analysis of North Creek Marsh. North Creek Marsh in 2009 (top left), 2011 (top right), and change in vegetation between 2009-2011 (left)

The average elevation of A21 was lower than the elevation of NCM (Table 1). Although A21 was breached to a freshwater creek, the average and median salinity of San Francisco Bay at the monitoring station nearest to the site was generally similar to the salinity at the monitoring station near NCM (see Appendix C for additional information on salinity values).

Table 1. Summary of Differences between A21 and NCM. Data was acquired from Google Earth Engine (United States Geological Survey National Elevation Dataset), personal communication, and United States Geological Survey San Francisco Water Quality database

Factors	A21	NCM
Average Elevation (m)	1.430668	1.565355
Colonizing Vegetation Type	*Spartina foliosa* and *Salicornia pacifica*	*Salicornia pacifica*
Water Source	SF Bay, possibly mixing with freshwater from Coyote Creek	SF Bay
Annual Salinity (psu)	*Average, median*	*Average, median*
2009	26.7275, 26.6083	28.67674, 2.584231
2010	24.80187, 26.58714	26.36975, 26.91
2011 (Jan-Jul 22)	18.3721, 1.751833333	19.29723, 21.38117

DISCUSSION

Wetland restoration attempts along the California Coast have had differing degrees of effectiveness. By monitoring the progress of vegetation re-establishment in response to varying environmental factors in individual ponds, restoration managers can make more informed decisions in prioritizing sites and choosing restoration practices. NCM experienced faster rates of vegetation re-establishment than A21, despite being breached in the same year. Of the parameters used in the OBIA rule set, scale value had the greatest variability between each site. Besides adjustments to the scale parameter, the rule set was able to classify imagery in multiple restoration sites relatively effectively for use in change analysis.

Trends in Vegetation Re-establishment

In the multiple classifications and change assessments run on the imagery, A21 tended to have lower rates of vegetation re-establishment than NCM. Visually we can see that there is more widespread vegetation development across NCM (Figure 5), while the patches of vegetation development in A21 (Figure 2) remain near the west regions of the site along the water channels. This is likely attributed to A21 being at a lower elevation than NCM (Table 1), because plant development occurs at targeted elevations (Callaway et al. 2013, Williams and Orr 2002). In restored wetlands, vegetation tends to begin establishing near water channels because of the high rates of sedimentation in those areas (Callaway et al. 2013, Newcomer et al. 2013). Vegetation development in areas further away from these channels indicates that a site has reached later stages of restoration (Tuxen 2008). The more widespread vegetation covering NCM indicates that the site has experienced a faster rate of vegetation re-establishment compared to A21. Although it was expected that A21 would have faster rates of vegetation re-establishment due to lower salinity, elevation appears to have greater impact on the site. The salinity levels of San Francisco Bay at monitoring stations closest to the sites show that average water salinity was similar near the two sites (see Appendix C). However, the data was measured from the bay rather than within the project sites, where the impact of freshwater directly entering from the Coyote Creek breach points would have a greater impact on salinity. Assessment of salinity could be improved with measurements taken within each wetland site and comparing with the change maps to measure the possible impact salinity may have on vegetation re-establishment.

Using OBIA and IKONOS imagery

Object Based Image Analysis has many strengths for use in wetland monitoring, but it also has challenges. In the previous study on NCM, there was false change noticeable along some of the main water channels caused to tidal effects and variability during the day the images were collected (Fulfrost 2012). There was also difficulty in distinguishing smaller, finer water channels from vegetation, as well as shallow areas within the water channels where the channel banks were more exposed and appeared similar to mudflat (Appendix A2). Many initial attempts at classifying these sites lead to high overestimations of water. One study found that while high resolution imagery, such as this set of 1m resolution IKONOS imagery of the SBSPRP sites, was effective at mapping vegetation, water channels required imagery at even higher resolutions to be accurately mapped (Moffett and Gorelick, 2012). When analyzing vegetation change maps using this data, the inaccuracies of water should be taken in consideration. However, these maps can still be highly informative for assessing relative changes in spatial structure of vegetation patterns (Kelly et al. 2011). Because many restoration projects use remote sensing to monitor vegetation change, it would be more useful to use a larger scale parameter to accurately map vegetation changes at the expense of inaccuracies in mapping surface water channels.

Another effect of using a smaller scale parameter in segmentation was confusion between mudflat and vegetation. Some areas of mudflat ended up over segmented and small algae patches were mistakenly classified for colonizing vegetation. The over segmentation also caused difficulty in quantifying accuracy because many of the random testing points landed between areas where mudflat and vegetation objects were small and heterogeneous in the classified image, making it difficult to match with the test point classifications based on the false color and Google Earth imagery (Figure 7). The subjectivity and bias with using expert knowledge to perform supervised classification of land cover can also contribute to the inaccuracies in the classified images, bringing them below the 85% accuracy benchmark (Dronova 2015). To minimize the effects of this confusion between classes, validation with field work, groundtruthed data, and expert knowledge from the field can be used to more accurately distinguish between difficult areas like patches of algae from vegetation (Tuxen 2008). Taking these extra steps to ensure better map accuracy will improve the quality of information we can extract from remote sensing data.

Variations in the results of segmentation and classification occurred between each different site. A21 appeared to have higher amounts of noise from water and algae on the mudflats because it is at a lower elevation, so it required a different scale parameter than NCM. While the need to use trial and error in finding the ideal scale parameter for each new site makes it more difficult to apply the same segmentation and classification process across many ponds, the other parameters used in segmentation and classification for NCM worked successfully for A21. Finding the ideal scale parameter for other sites to monitor can be time consuming, but the ability to save rule sets within the eCognition software helps with setting up other parameters to make the process of applying OBIA to new restoration sites easier.

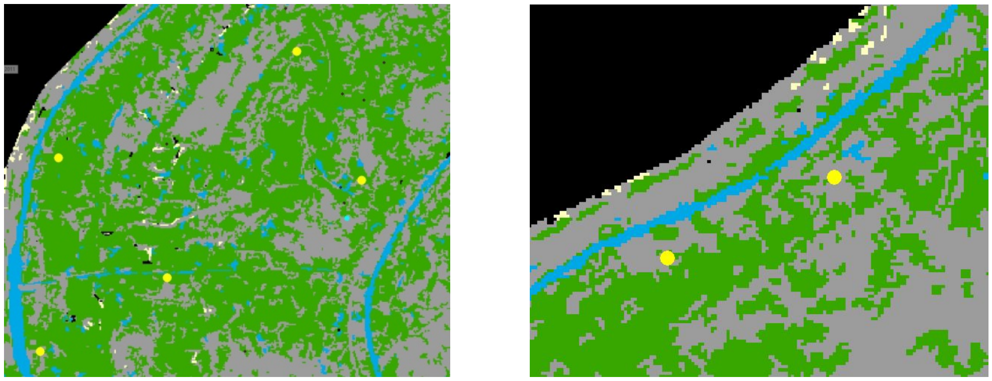

Figure 7. Accuracy Error in NCM: Because the scale parameter of the objects was smaller to capture finer water channel details, validation point classifications created by assessing the original imagery were difficult to match with areas classified as a heterogeneous mix of mudflat and vegetation. The yellow points in these images show pixels that had been classified as vegetation based off Google Earth imagery and the false color display of the original IKONOS imagery, but were classified as mudflat with the nearest neighbor configuration algorithm.

Limitations

This study had considerations for differences in proximity to water channels, elevation, salinity, and major colonizing cover types as factors that affect vegetation re-establishment patterns; however there are many other factors that can be compared with the change analysis results to find the influence they have on restoration sites. For example, nutrients such as nitrogen and phosphorus mobilized in runoff may increase the rates of vegetation growth.

The timing of the available high-resolution imagery also limits the usefulness of this analysis to managers. Because the 2010 IKONOS imagery was omitted in this study because of the quality of the data, it is possible for there to be small changes missed that could have been informative to why the change analysis resulted in a loss of vegetation between 2009 and 2011 (Tuxen 2008). The assessment of only a two year data timespan also limits detection of longer term trends, such as increases in vegetation cover in A21 observed in field assessments occurring after 2011 (Tuxen 2011, Callaway et al. 2013).

Since the year of the most recent image, California has experienced a multi-year drought and El Niño, both which affect the hydrology of the sites. If high resolution imagery were available of these sites taken during the drought period and before El Niño, and again after the El Niño period, the change analysis process using OBIA rulesets can be used with same methods as the 2009-2011 imagery to assess the changes to vegetation colonization.

Conclusion

Many factors affect ecosystem responses to restoration practices in California coastal wetlands. Comparing vegetation re-establishment patterns in breached salt pond restoration sites to major factors is especially informative for ongoing, adaptive management restoration projects of these unique systems. With the many variables affecting wetland vegetation response, it is difficult to predict the effectiveness of restoration work in different sites. Remote sensing with OBIA is an effective tool in assisting with monitoring for these restoration projects. Analysis of high resolution remote sensing data, such as IKONOS imagery, can give meaningful information on how vegetation patterns change over time in different restoration project sites. Understanding how different factors can affect patterns of vegetation re-establishment can help managers decide on project sites to prioritize. Depending on funding and available resources, this information helps managers choose between areas where vegetation re-establishment is likely to occur faster, because it is cheaper, or slower, because the site needs more assistance in returning to a tidal wetland ecosystem (D. Chapple, *personal communication*). A greater understanding of vegetation re-establishment trends will allow for restoration efforts to be more effective in restoring and conserving the remaining wetlands in San Francisco Bay.

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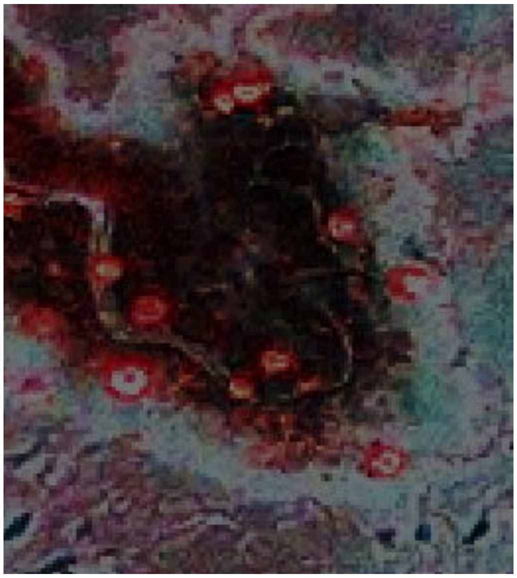
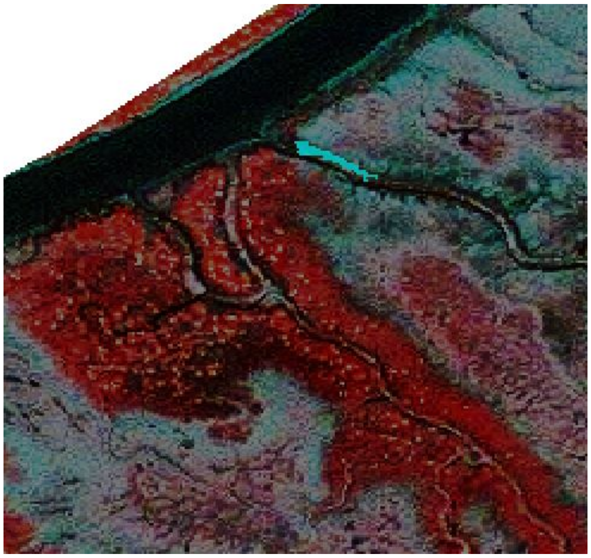
APPENDIX A: *Spartina foliosa*



Appendix A1. *Spartina foliosa.* Patches of native California cordgrass can be seen in the 2011 A21 using a 4-3-2 band false color display.



Appendix A2. Water Channel and Mudflat Confusion. An area in the NCM 2011 imagery, shown here as the false color display, that had difficulty classifying water channels from mudflat because areas of water channel had areas with exposed banks.

APPENDIX B: Classification Accuracy Assessment

	Reference	Classes					
Map Classes	Unclassified	Vegetation	Mudflat	Water	Row Total	User's Accuracy	Commission Error
Unclassified	39	0	0	0	39	100%	0%
Vegetation	0	7	4	1	12	58.33333%	41.66667%
Mudflat	0	2	29	1	32	90.625%	9.375%
Water	0	2	8	7	17	41.17647%	58.82353%
Column Total	39	11	41	9			
Producer's Accuracy	100.00%	63.64%	70.73%	77.78%	Kappa Statistic	=	0.673024523
Omission Error	0.00%	36.36%	29.27%	22.22%	Total Accuracy	=	82%

Appendix B1. Confusion Matrix, Pond A21 2009. Classifications were reviewed to confirm their accuracy. Rows represent predicted classifications, while columns represent the actual classes of the samples

	Reference	Classes					
Map Classes	Unclassified	Vegetation	Mudflat	Water	Row Total	User's Accuracy	Commission Error
Unclassified	38	0	0	0	38	100%	0%
Vegetation	0	10	1	0	11	90.909%	9.090909%
Mudflat	1	2	34	1	38	89.47368%	10.52632%
Water	0	4	2	7	13	53.84615%	46.15385%
Column Total	39	16	37	8			
Producer's Accuracy	97.44%	62.50%	91.89%	87.50%	Kappa Statistic	=	0.83899297
Omission Error	2.56%	37.50%	8.11%	12.50%	Overall Accuracy	=	89%

Appendix B2. Confusion Matrix, Pond A21 2011. Classifications were reviewed to confirm their accuracy. Rows represent predicted classifications, while columns represent the actual classes of the samples

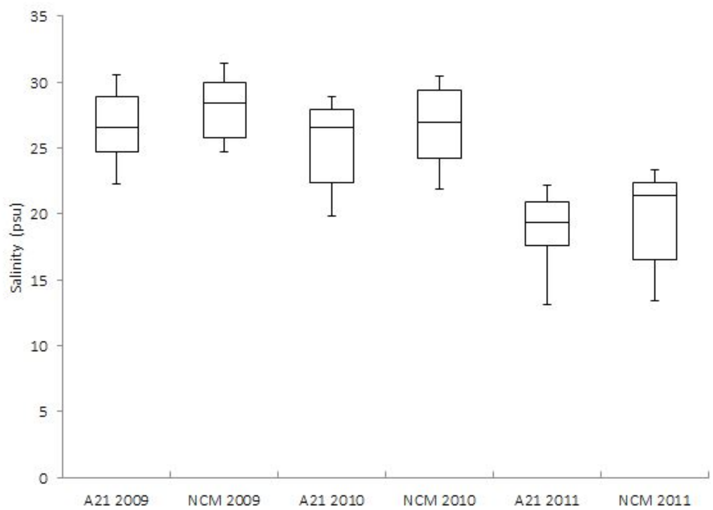
Map Classes	Unclassified	Vegetation (Reference Classes)	Mudflat	Roads	Water	Row Total	User's Accuracy	Commission Error
Unclassified	35	0	0	0	0	35	100%	0%
Vegetation	0	13	4	1	2	20	65%	35%
Mudflat	1	2	27	1	0	31	87.09677%	12.90323%
Roads	0	1	0	2	0	3	66.66667%	33.33333%
Water	0	3	1	0	7	11	63.63636%	36.36364%
Column Total	36	19	32	4	9			
Producer's Accuracy	97.22%	68.42%	84.38%	50.00%	77.78%	Kappa Statistic	=	0.80941
Omission Error	2.78%	31.58%	15.63%	50.00%	22.22%	Overall Accuracy	=	84%

Appendix B3. Confusion Matrix, North Creek Marsh 2009. Classifications were reviewed to confirm their accuracy. Rows represent predicted classifications, while columns represent the actual classes of the samples

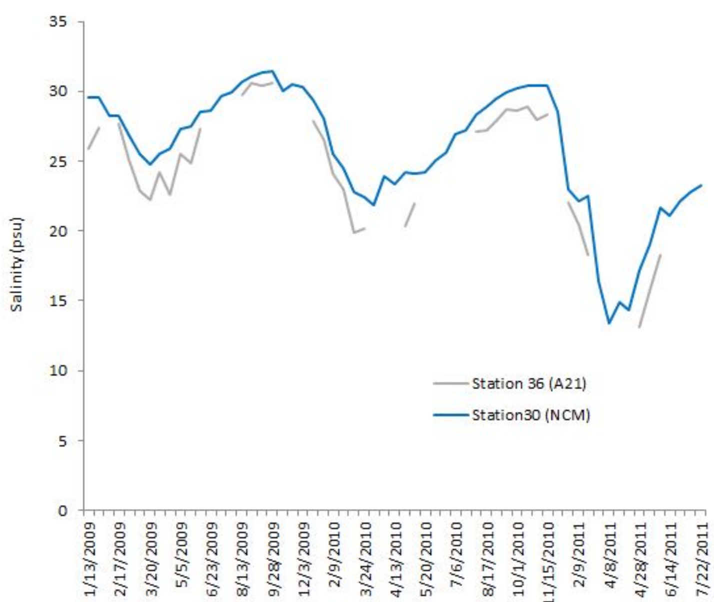
Map Classes	Unclassified	Vegetation (Reference Classes)	Mudflat	Roads	Water	Row Total	User's Accuracy	Commission Error
Unclassified	28	0	0	0	0	28	100.00%	0.00%
Vegetation	0	18	1	0	1	20	90.00%	10.00%
Mudflat	0	11	30	0	1	42	71.43%	28.57%
Roads	0	0	0	2	1	3	66.67%	33.33%
Water	0	2	0	0	5	7	71.43%	28.57%
Column Total	28	31	31	2	8			
Producer's Accuracy	100.00%	58.06%	96.77%	100.00%	62.50%	Kappa Statistic	=	0.764934
Omission Error	0.00%	41.94%	3.23%	0.00%	37.50%	Overall Accuracy	=	83.00%

Appendix B4. Contingency Matrix, North Creek Marsh 2011. Classifications were reviewed to confirm their accuracy. Rows represent predicted classifications, while columns represent the actual classes of the samples

APPENDIX C: Annual Salinity Comparisons



Appendix C1. Annual Salinity 2009- July 2011 Box and Whisker plot of salinity data in San Francisco Bay, taken from monitoring station 30 and 36. Data was downloaded from the United States Geological Survey San Francisco Water Quality database. Data for 2011 was only taken up to July because the 2011 imagery was collected in late June-early July in 2011.



Appendix C2. Salinity 2009- July 2011 Line graph of the same salinity data of San Francisco Bay. Annual trends in salinity tended to be similar for both monitoring stations.