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Vegetation Colonization in a Restoring Tidal Marsh: A Remote Sensing Approach

Karin A. Tuxen,[1,2,*] Lisa M. Schile,[3,*] Maggi Kelly,[1] and Stuart W. Siegel[4]

Abstract

Although remote sensing offers the ability to monitor wetland restoration, few have tested automated methods for quantifying vegetation change. We implemented a semiautomated technique using color infrared aerial photography and a common vegetation index, Normalized Difference Vegetation Index (NDVI), to document vegetation colonization in a restoring salt marsh. Change in vegetation over a period of 10 years was analyzed using a postclassification comparison technique where each image year was classified individually into vegetated and nonvegetated areas using NDVI thresholds and then differenced between years to identify areas of vegetation change. Vegetated and nonvegetated areas were identified using this technique, as were areas and time periods of vegetation change. By comparing classified NDVI imagery, we calculated that 90% of our study site was vegetated 10 years after restoration. This study demonstrated that high-resolution remotely sensed data can be analyzed with common geospatial software to monitor change in a rapidly vegetating wetland and that long time frames with yearly image acquisition are needed to quantify plant colonization rates. This method was effective at detecting change in vegetation over time in a variable tidal marsh environment using imagery that had inconsistent specifications and quality across years. Inconsistencies included interannual climate variation, phenology, and presence of algae, as well as differences in pixel size and image brightness. Our findings indicate that remote sensing is useful for postrestoration monitoring of tidal marsh ecosystems.

Key words: change detection, NDVI, Petaluma River Marsh, remote sensing, San Francisco Bay-Delta, tidal marsh restoration.

Introduction

Wetland habitat is being secured and restored throughout the world (Zedler & Kercher 2005); however, achieving conservation goals and objectives requires knowledge of vegetation composition, structure, and change over time in attributes such as percent cover, biomass, and plant diversity (Phinn et al. 1999). Unfortunately, postrestoration monitoring is commonly underfunded, understaffed, or short term, and the data collected are rarely published (Zedler 2000). Therefore, there is a need to further develop, refine, and disseminate site and landscape-level monitoring methods (Simenstad et al. 2006). We present a method for monitoring vegetation change over time in restoring wetlands using simple remote sensing techniques and common geospatial software.

[1] Department of Environmental Sciences, Policy and Management, University of California, Berkeley, 137 Mulford Hall #3114, Berkeley, CA 94720-3114, U.S.A.
[2] Address correspondence to K. A. Tuxen, email karin@nature.berkeley.edu
[3] Department of Biology, San Francisco State University, 454 Hensill Hall, San Francisco, CA 94132, U.S.A.
[4] Wetlands and Water Resources, 818 Fifth Avenue, Suite 208, San Rafael, CA 94901, U.S.A.
* These authors both had primary roles in research and writing; therefore, they share first authorship.

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Remote Sensing for Wetland Monitoring

Remote sensing involves the acquisition of information about the Earth's surface at a remote distance, usually by airplane or satellite (Jensen 2000), offering tools to map, measure, model, and evaluate wetland restoration efforts in a non-invasive, cost-effective manner. The use of this technology is rapidly growing in the ecological sciences because ecosystems, such as wetlands, can be monitored at various spatial and temporal scales (Jensen et al. 1995; Guo & Psuty 1997; Michener & Houhoulis 1997; Apan et al. 2002; Heinl et al. 2006; Papa et al. 2006).

Despite the growing use of remote sensing for wetland inventory and monitoring (Phinn et al. 1996; Zhang et al. 1997), there has been limited use of this technology on restoring wetlands (Phinn et al. 1999; Hinkle & Mitsch 2005). Furthermore, there is growing consensus about the need to examine restoration projects at the landscape scale and to develop landscape-based tools for monitoring restoration progress (Simenstad et al. 2006). Remote sensing is ideal for monitoring restored wetlands because it allows for a high spatial and temporal intensity of measurements in relatively inaccessible and sensitive sites, without the potential invasiveness that traditional field methods present to delicate habitat conditions, bird nesting territories, or endangered species habitat (Shuman & Ambrose 2003). In addition, many wetlands are physically inaccessible due to soft sediment or dense vegetation. Remote sensing allows for broad-scale estimation of many parameters valuable to ecologists, including land cover, vegetation structure, biophysical characteristics, and habitat areas (Smith et al. 1998; Thomson et al. 2003; Higinbotham et al. 2004; Wulder et al. 2004), in a noninvasive manner.

Both aerial photography and satellite imagery have been used for wetland vegetation classification and monitoring. High-resolution multispectral satellite imagery offers some advantages over aerial photography in terms of geometric control, radiometric precision, spectral range, and image processing and allows for the same ability as aerial photography to map vegetation composition and structure. Past work has shown that both types of imagery offer different, but complementary, information (Ozesmi & Bauer 2002), and many studies have combined the two platforms in order to benefit from the advantages of both (Jensen et al. 1984, 1986; Ramsey & Laine 1997; Palandro et al. 2003; Everitt et al. 2004). However, much of the wetland science still requires the very high resolution and flexible flight times offered by aerial photography (Harvey & Hill 2001). For these same reasons, some organizations choose aerial photography over satellite imagery for their wetland monitoring projects (Jensen et al. 1986). Furthermore, the use of historical imagery is often required in long-term studies (Van Dyke & Wasson 2005), and researchers are therefore restricted in the imagery that is available.

Recent advancements in imaging science have also provided finer spatial, spectral, and temporal resolutions, as well as reduced price (Hirano et al. 2003; Schmidt & Skidmore 2003; Rosso et al. 2005*a*). In addition, nonoptical data sources, such as radar data (e.g., SAR, RADAR) and laser altimetry (e.g., LiDAR), have been shown to add value when combined with optical remote sensing data (Ramsey et al. 1998; Rosso et al. 2005*b*). Although this can be highly useful for studies that use satellite imagery, it does not substitute the frequent need for resolutions finer than 1 m.

Change Detection

There are many ways of utilizing remotely sensed data, such as aerial photography, to monitor landscape changes. Change detection measures differences in a variable, such as vegetation cover, over time and many methods are available (Singh 1989; Lu et al. 2004). Change detection is an important tool for wetland restoration monitoring because it provides measurements of incremental changes that can be used for inventory and benchmark purposes, which then can be integrated with adaptive management plans and targeted for specific restoration goals. Effective change detection can help to track changing boundaries between mudflat and vegetation patches, characterize vegetation dynamics and spatial patterning, and gain a better understanding of biotic and abiotic interactions (Smith et al. 1998).

Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index for discriminating between vegetated and nonvegetated areas in environments with low-to-moderate vegetation cover on light soils or backgrounds (Eastwood et al. 1997; Jensen 2000) and has been used in change detection methods (Singh 1989; Apan et al. 2002; Lu et al. 2004). In some cases, NDVI can be used to differentiate plant species or growth types, as well as be used as an indicator of plant productivity that can be correlated with biophysical parameters such as live plant biomass (Jensen 2000). In past studies, NDVI was found to most accurately represent vegetation change when compared to six other vegetation indexes (Lyon et al. 1998).

Automated and semiautomated change detection methods ideally should not require a largely technical skill set. We demonstrate the use of a semiautomated change detection technique utilizing common Geographic Information Systems (GIS) packages on the market. Although we consider this method *semi*automated due to a small amount of manual work, the amount of manual work is on par with supervised image classification, which is considered automated. This study addresses one potential monitoring method through the use of remote sensing to map vegetation cover and measure the amount, location, and spatial pattern of vegetation change at a recently restored salt marsh. Although this study does not use new techniques or data types, it effectively illustrates successful change detection in a highly dynamic restoring ecosystem.

Methods

Study Site

Petaluma River Marsh, which is also known as Carl's Marsh, is located near the mouth of the Petaluma River (lat 38°7′17″N, long 122°30′25″W) in San Pablo Bay in the northern reaches of the San Francisco Bay-Delta, California, U.S.A. (Fig. 1). The site is surrounded by agriculture to the immediate east and north but is in close proximity to many marshes. Petaluma River Marsh was restored to tidal action in 1994 following the dredging of two main channels from the breaches in the north and the south ends of the outboard levee and the removal of soil from the site to heighten and strengthen the inboard levee, which created linear features within the site. No vegetation was planted (Siegel 2002).

Petaluma River Marsh accumulated sediment rapidly (Siegel 2002). After only 4 years of tidal flow, plant colonization by California cordgrass, native (*Spartina foliosa*) began to occur and radial, clonal growth continued. Over the next 2 years, additional species, such as Alkali bulrush[1] (*Bolboschoenus maritimus*) and Annual pickleweed (*Salicornia europaea*), colonized the site along both levee and channel edges. Presently, the site is almost entirely vegetated with the three aforementioned species, as well

[1] *Bolboschoenus maritimus* is formerly known as *Scirpus maritimus*.

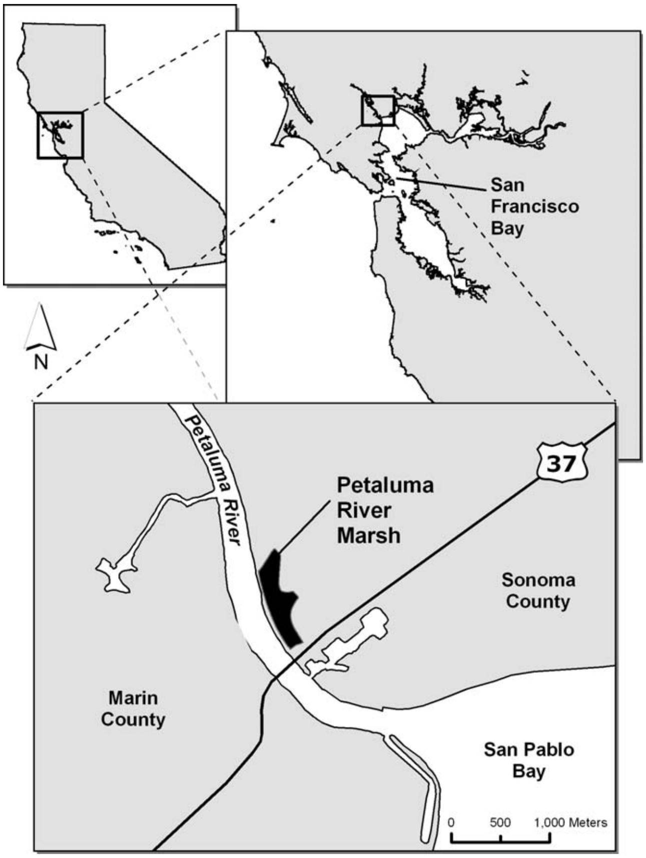

Figure 1. Petaluma River Marsh is located near the mouth of the Petaluma River along the northwestern reaches of the San Francisco Bay-Delta, California, U.S.A.

as Perennial or Common pickleweed[2] (*Sarcocornia pacifica*) and contains eight native plant species. The surrounding levee contains multiple invasive species; however, none have encroached upon the site.

Image Preprocessing

Color infrared (CIR) aerial photography was collected for this site once a year between 1995 and 2004 (Table 1), with the exception of 1996 and 1997. CIR photographs are multispectral and have three bands in the green, red (R), and near-infrared (NIR) spectral regions. For this project, no satellite imagery was obtained over this site. No airborne GPS or inertial measurements were taken during image acquisition. All photographs were scanned at 1,200 dpi and were georeferenced to Universal Transverse Mercator Zone 10 projection and 1983 North American Datum using 4–10 ground control points (GCPs). GCPs were surveyed with differential correction to submeter accuracy using survey-grade equipment by a professional licensed surveyor. All georeferencing work was performed using the Georeferencing toolbar in ESRI's ArcGIS 9.0 software (Environmental Science Research Institute 1995–2007). Root mean squared errors (RMSE) are listed in meters in Table 1. All images prior to 2003 were resampled to a pixel size of 20 cm to match the resolution of years 2003 and 2004 (Table 1).

Change Detection

The NDVI was calculated for each image using the formula:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}.$$

Because live vegetation reflects highly in the NIR wavelength region and absorbs in the red region, higher NDVI values indicate vegetated areas. NDVI values range from -1 to 1. ERDAS Imagine software (Leica Geosystems, Inc. 2006) was used to perform the NDVI calculation, which rescaled the -1 to 1 NDVI values to 0–255 in order to provide numbers that are appropriate to display as gray scale and standardize the range of pixel values in an eight-bit image.

For each NDVI eight-bit image, a NDVI threshold was visually determined between vegetated and nonvegetated pixels, meaning values equal to and above this threshold represented vegetation and values below the threshold were bare or nonvegetated (Fig. 2). This determination was made through prior knowledge of the site (i.e., photographs and field visits), as well as visual determination and agreement by K.T. and L.S. Although the optimum threshold level can be chosen based on the histogram or standard deviations from the mean, Singh (1989) proposed that the best threshold level can be determined by prior knowledge of the site. We reclassified, or recoded, the NDVI image into two classes: vegetation and nonvegetation. We then performed this recoding process on three NDVI values above and below (±3 NDVI values) the optimum threshold to account for subjectivity in threshold determination by human interpreters, as well as radiometric differences between image years, which would affect change detection (Lu et al. 2004). Digitization of the aerial photographs was not considered due to concerns of accuracy of the delineation of very fine-scale patches, as well as subjectivity of the visual interpreter. This process was applied to all images except for the one flown in 1999. Image date 1999 was mosaicked from three separate aerial photograph tiles or image segments that together comprised the entire image, and variable camera angle for each tile caused abrupt changes in pixel values at the seams of the tiles. This variation prevented us from assigning the same threshold value for the entire image. A threshold value that differentiated vegetation from bare areas in the middle tile overestimated vegetation for the bottom tile and underestimated vegetation for the top tile. As a result, we analyzed each tile separately, determined

[2] *Sarcocornia pacifica* is formerly known as *Salicornia virginica*.

Table 1. Summary of image specifications used in change detection analyses.

Image Year	*Image Date*	*Image Ratio Scale*	*Original Pixel Size (cm)*	*RMSE (m)*	*Pixel Size after Resampling (cm)*	*Camera Type*
1995	29 November 1995	1:7,200	20	0.1326	20	Unknown
1998	9 September 1998	1:2,400	24	0.0475	20	Zeiss RMK Top 15 camera, with Zeiss pleogon lens
1999	26 August 1999	1:2,400	24	0.0660	20	Zeiss RMK Top 15 camera, with Zeiss pleogon lens
2000	29 September 2000	1:3,600	7	0.0638	20	Wild RC30 lens
2001	8 August 2001	1:7,200	11	0.4654	20	Unknown
2002	8 August 2002	Not available	22	0.2905	20	Unknown
2003	14 August 2003	1:7,200	20	1.0068	20	Zeiss RMK Top 15 camera, with Zeiss pleogon lens
2004	19 August 2004	1:9,600	20	1.1012	20	Zeiss RMK Top 15 camera, with Zeiss pleogon lens

the optimum NDVI threshold value ±3 threshold levels, reclassified each tile, and joined the reclassified tiles together. The resulting image was used when calculating vegetation change over time.

Each reclassified image was clipped to include only the levees and interior of the site. The total area of vegetated and nonvegetated pixels was calculated for each image year and plotted as a time series. In addition, each reclassified image was compared to its previous year, and areas of vegetation gain, loss, and no change were calculated. A Student's *t* test was performed to determine significant differences, if any, between yearly changes in area of vegetation loss and gain across all years.

No ground reference data were available for years prior to 2003; therefore, no accuracy assessment could be performed for these image years. However, accuracy assessments were performed on vegetated/nonvegetated classifications for 2003 and 2004 with vegetation field surveys that were conducted during those years. The surveys consisted of visiting point locations each year (194 points in 2003 and 163 in 2004) using handheld Garmin GPS units with a horizontal accuracy of 3–6 m (using Wide Area Augmentation System [WAAS] differential correction) and recording species presence and bare area in a 3-m radius relevé (circular plot). The points were randomly generated in GIS and were stratified between vegetated and nonvegetated areas. Overall accuracy was calculated by comparing the ground data to the reclassified maps and dividing the total number of accurate classifications by the total number of ground reference points. This calculation was performed for the optimum threshold as well as the ±3 NDVI thresholds. We also computed errors of omission and commission, two commonly measured indexes for map accuracy assessment, in addition to overall accuracy (Congalton 2004). The omission error, also known as the "producer's accuracy," measures the probability of a ground point being correctly classified. The commission error indicates the probability of a ground point on the map representing what is truly on the ground and is often called the "user's accuracy" (Congalton 2004).

Results

The RMSE for all sites ranged from 0.04 to 1.10 m (Table 1). Although some of the historical imagery had been georectified previously and the RMSE for the past rectifications were unknown, it is estimated that RMSE for all image dates are roughly 1 m. Using NDVI threshold classifications, we differentiated vegetated from nonvegetated pixels successfully and calculated total acreage of each classification for all images, with the exception of the 2001 image (Fig. 3). Pixels that were clearly visible as being vegetated in the 2001 CIR photograph were not classified

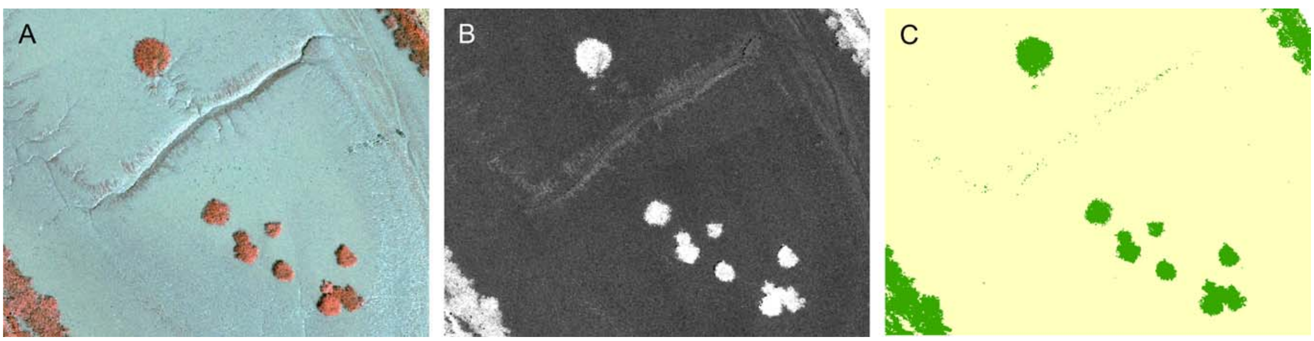

Figure 2. Each CIR image (A) was transformed to NDVI (B), after which pixels were reclassified as vegetated or nonvegetated (C).

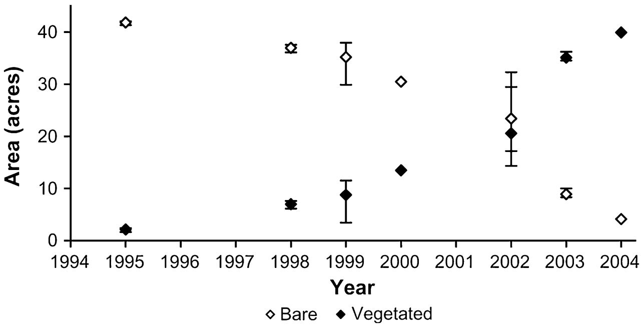

Figure 3. Change in cover of vegetated and bare areas at Petaluma River Marsh following tidal restoration was calculated for each image date between 1995 and 2004 (error bars = ±3 values from NDVI threshold).

as vegetation in the NDVI image, despite the fact that these pixels were categorized as vegetated in 2000 and 2002. We did not use the 2001 data in our subsequent analyses because methods other than those presently mentioned were required to classify the land cover types.

The colonization and growth rate of vegetation were slow during the first 5 years after tidal restoration but began to increase more rapidly between 1999 and 2000 (Fig. 3). As more colonization occurred, we experienced more variability in the vegetated/nonvegetated NDVI classifications for each year; the largest difference in our NDVI thresholds buffers occurred in 1999 and 2002. By August 2004, the site was 90% covered in native vegetation (Fig. 4).

We documented the location of vegetation colonization, growth, and loss over time (Fig. 5). The initial colonization occurred along levee edges and in a few scattered patches in the interior (Fig. 5A). Marked radial clonal growth was evident between 1998 and 1999 (Fig. 5B), and there was an increase in vegetation growth along the interior channel edges between 1999 and 2000, as well as vegetation loss along the interior levee due to new channel formation (Fig. 5C). Colonization along channel edges continued between 2000 and 2002 (Fig. 5D), and the greatest peak in vegetation growth occurred between 2002 and 2003 (Figs. 5E & 6). At any given period, vegetation gain was greater than vegetation loss ($t_5 = 3.53$, $p = 0.017$; Fig. 6). The accuracy assessments conducted on the optimum threshold classification for image years 2003 and 2004 rendered overall accuracy rates of 84.1 and 96.3%, respectively (Table 2; Fig. 7).

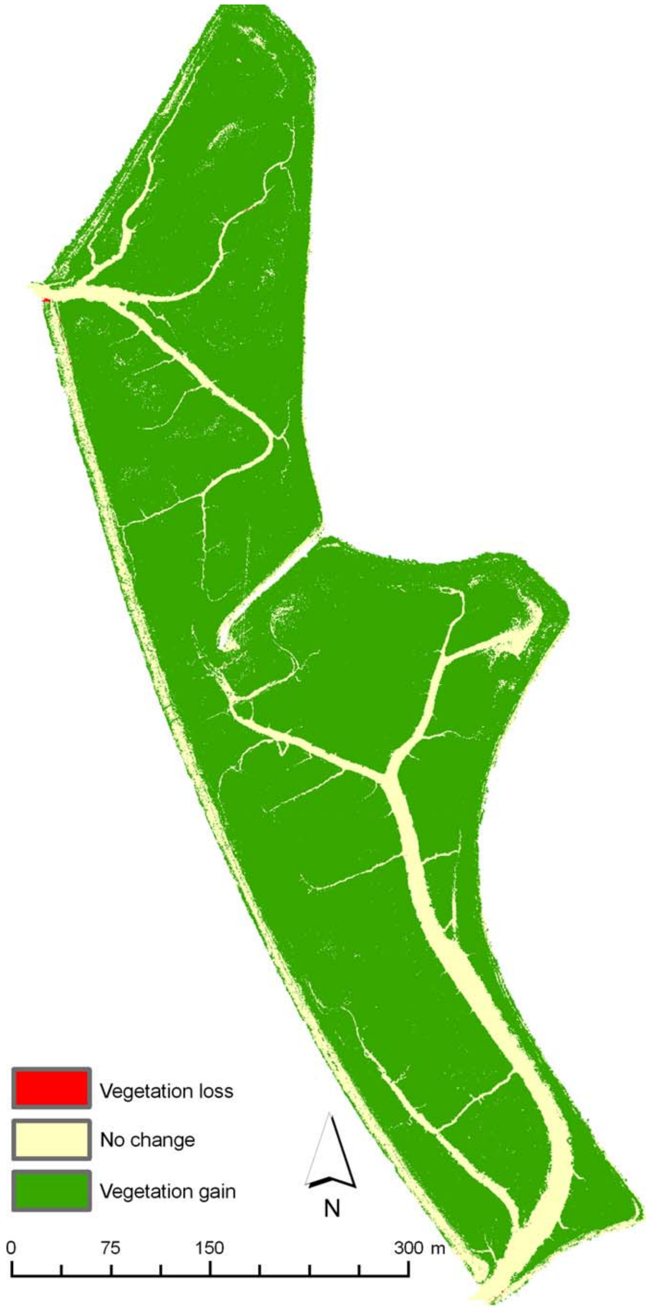

Figure 4. Spatial representation of total vegetation colonization that occurred between 1995 and 2004. Ten years after tidal restoration, Petaluma River Marsh was 90% covered in native vegetation.

Discussion

In this study, change in vegetation over time was analyzed using the postclassification comparison technique, where each image year was classified individually into vegetated and nonvegetated areas using NDVI thresholds and then differenced between years to identify places of vegetation gain, loss, or no change. This change technique method is semiautomated, allows for the use of common geospatial software, and is easy to analyze using the sometimes inconsistent historical data that may exist for many wetland sites. In addition, this method reduces errors caused by atmospheric, soil moisture, and sensor differences across images because it can be used to consider each date individually (Singh 1989). We recommend this technique for tidal marsh change detection because it reduces effects

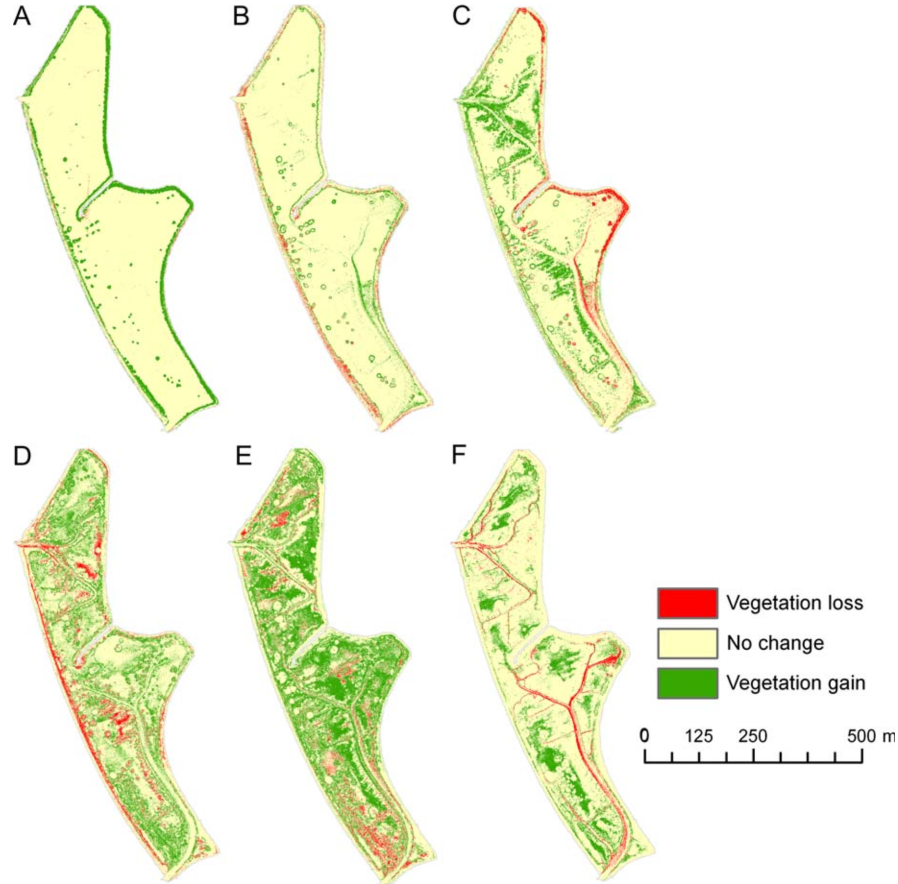

Figure 5. Spatial representation of vegetation change at Petaluma River Marsh between (A) 1995 and 1998, (B) 1998 and 1999, (C) 1999 and 2000, (D) 2000 and 2002, (E) 2002 and 2003, and (F) 2003 and 2004.

from variability in image acquisition and climate. NDVI was chosen to differentiate between vegetation and nonvegetation for each year because it is an effective and commonly used vegetation index in both remote sensing and ecology.

This approach is more automated than hand-digitizing vegetated areas via photointerpretation because each pixel is automatically assigned as vegetated or nonvegetated based on the chosen threshold. However, because the choice of threshold takes human visual interpretation, we

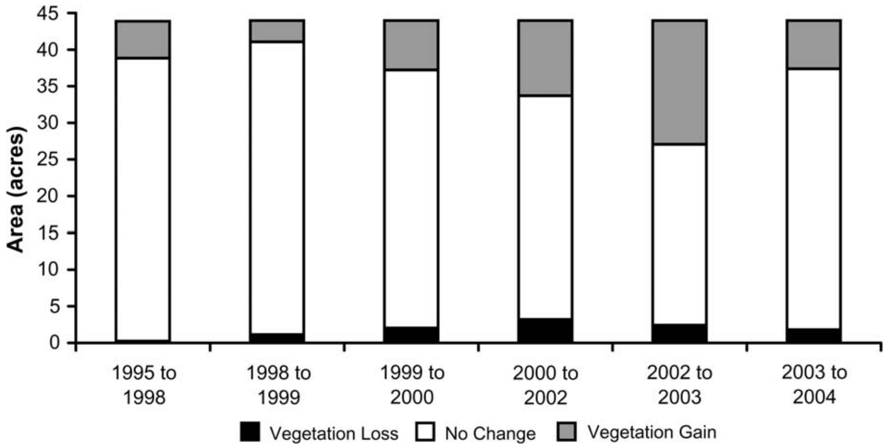

Figure 6. The area of vegetation gain and loss, as well as the area not changing, between image dates was calculated for Petaluma River Marsh using NDVI classifications.

Table 2. Error matrices and accuracy measures were generated for vegetated and nonvegetated classifications for the 2003 and 2004 image dates.

		Ground Data		
		Nonvegetated	*Vegetated*	*Total*
2003[a]				
Map data	Nonvegetated	12	14	26
	Vegetated	22	146	168
	Total	34	160	194
2004[b]				
Map data	Nonvegetated	7	2	9
	Vegetated	4	150	154
	Total	11	152	163

[a]Overall accuracy: (12 + 146) = 158/194 = 81.4%; producer's accuracy: nonvegetated = 12/34 = 35.3%; vegetated = 146/160 = 91.3%; user's accuracy: nonvegetated = 12/26 = 46.2%; vegetated = 146/168 = 86.9%.
[b]Overall accuracy: (7 + 150) = 157/163 = 96.3%; producer's accuracy: nonvegetated = 7/11 = 63.6%; vegetated = 150/152 = 98.7%; user's accuracy: nonvegetated = 7/9 = 77.8%; vegetated = 150/154 = 97.4%.

consider the methods used in this study to be semiautomated, even though the amount of manual work is on par with automated supervised classification techniques. The only data needed are NIR and red bands, which can be obtained using CIR imagery. Often, this is the most affordable option for monitoring.

In an ideal situation, remotely sensed images are acquired when decisions can be made about imagery specifications and field data collection that will make change detection accurate and applicable to the monitoring of a restoring wetland. When collecting imagery to monitor marsh restoration, it is important to acknowledge the multiple purposes for which the imagery will be used (vegetation type mapping, vegetation type change detection, channel delineation) and to choose image specifications that are optimal for as many purposes as possible. For accurate change detection, imagery should have (1) the same spatial and spectral resolution across years, (2) precise spatial registration across years, (3) precise radiometric/atmospheric calibration, and (4) similar phenological states (Lu et al. 2004). These characteristics affect the data accuracy from each image date, as well as the comparison between years. Precise spatial registration for each year can be attained by collecting many GCPs (5–15) and using the combination of four or more that renders the highest accuracy (or lowest RMSE value) for each year. Imprecise registration across years, which is often easily noticed visually as linear features falsely disguised as change, can produce large errors in change detection analysis (Singh 1989; Dai & Khorram 1998). For vegetation change detection, imagery should be acquired at similar phenological states across years and should be timed with daily tides and the sun, especially if a particular level of detail regarding the channels, mudflats, or low-lying vegetation is desired. This will also keep effects from the water level and sun angle consistent across time because sunlight and shadows can cause inaccuracies in the detection of vegetation.

In reality, however, conditions for monitoring salt marshes are less than ideal, both with site-specific issues and with use of historical imagery. Although some wetland areas are relatively amenable to image processing, tidal ecosystems are challenging because the marshes are inundated by high tides that obscure boundaries of vegetation and mudflats. Our study illustrates the many challenges of monitoring with a limited budget. We used preexisting data (e.g., historical imagery) that were collected for purposes other than detecting vegetation change, so the image specifications, flight times, and ground reference data might not exist. Thus, features like pixel size, number of tiles, time of year, and plant phenology were not consistent across image dates. For most years, we had no reliable field data. Despite these shortcomings, we were able to document vegetation change with adequate accuracy.

Although aerial photography is a relatively inexpensive way to acquire high-resolution remotely sensed imagery, often costing less than its satellite-borne counterparts, there are problems inherent in airborne imagery, all of which we faced in this study. The original pixel sizes of the images were not identical and ranged from 7 to 25 cm. Image dates were resampled up or down to produce 20-cm-pixel sizes across all images. Resampling to a larger pixel size resulted in data loss but was necessary to gain consistency in spatial resolution across image dates. Registration problems are often difficult to overcome with ultra

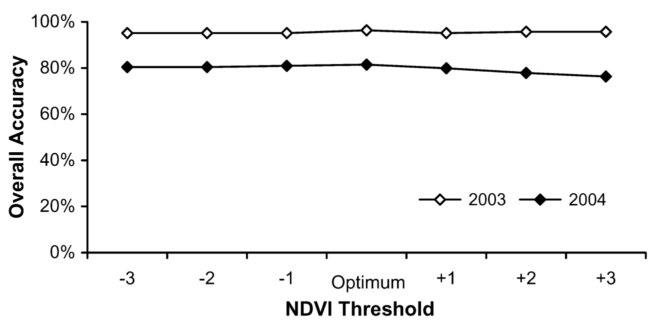

Figure 7. The overall accuracy of the optimum NDVI threshold did not vary much within the ±3 threshold buffer, illustrating that changing the NDVI threshold slightly does not cause the accuracy of the classification to change drastically.

high-resolution imagery such as the 0.2-m imagery used in this study; however, we avoided this problem by using multiple high-accuracy GCPs and observed no obvious signs of misregistration in the change maps.

In order to get the extremely high spatial resolutions often required when mapping wetland vegetation, it is often necessary to collect several tiles to cover a large wetland area. These tiles can have varying radiometric and sensor gradients due to camera tilt and image distortion, both of which are common in aerial photography, creating seams across the mosaicked tiles and complicating the registration, classification, and change detection procedures. The 1999 mosaicked image provides an example of this issue, where we had to apply NDVI to each of the three tiles separately, choose a separate NDVI threshold for each tile, and recode for each accordingly. Doing this removed error caused by radiometric differences between the three tiles. Likewise, because we classified each image date individually, we removed error caused by radiometric differences between the annual images. The use of satellite imagery would overcome many of these problems, particularly when higher resolution data become more available; however, no satellite images were available for analysis and comparison in this study.

While the imagery was acquired at roughly the same seasonal time each year, issues arose with differing phenological states, tidal level, and sun angles. Even though the 2001 image date was flown during the same month as the majority of the other images, we were unable to use NDVI to distinguish between bare and vegetated areas because many of the plants appeared to have senesced by the time of the image acquisition. Live vegetation reflects highly in the NIR region, which results in larger NDVI values; however, many of the areas that appeared to be vegetated in the CIR image showed low NIR reflectance values. Differences in the growth cycle due to climatic variability can cause differences in phenology and recruitment in tidal salt marshes between years (Callaway & Sabraw 1994; Noe & Zedler 2001*a*,*b*). Although we were not present to ground reference the site in 2001, rain and temperature data suggested a hotter, drier environment earlier in the season (University of California Statewide Integrated Pest Management Program, Agriculture and Natural Resources 2006), which would have resulted in increased plant stress due to higher salinity levels and premature tissue senescence. Greater loss was measured between 2000 and 2002 than between other years, suggesting that the premature senescence in 2001 also affected vegetation growth in 2002.

We experienced false change because of tidal differences, algae occurrences, and shadows. The 2003 image was acquired at low tide to capture all low-lying *Spartina foliosa* on the mudflats, whereas 2004 image was flown when the channels approached bank-full for the purposes of delineating channels. This led to detection of false change along the channel margins. Applying a "mask" over the channels could alleviate this problem but might be outside the technical expertise of some restoration projects. We also encountered the presence of algae on mudflats, which was often classified as vegetation. Algal coverage is not inherently an image error but is instead a land cover residual that complicates the differentiation between vegetated and bare mudflats; oftentimes, widespread algal growth occurs before vascular plant colonization. Because algae are photosynthetically active, they reflect strongly in the NIR and can complicate vegetation discernment when ground reference data are not available. Because we did not have ground reference data for the majority of years since tidal restoration, we were unable to identify areas with high algal cover conclusively and might have overestimated vegetative cover in some years. However, many photos and conversations with researchers involved in the tidal restoration aided our identification of years and particular areas of high algal cover. Further investigation into the spectral qualities of algae would allow for remote discrimination between algae and vascular vegetation. Finally, shadows from an electrical tower located along the center levee of the site and the deep linear features created from prerestoration dredging resulted in overestimation of vegetated areas in some years, particularly in 1995. Altering the threshold levels to reduce the influence of shadows erroneously decreased the cover of vegetation on the levees; therefore, we had to compromise on a threshold value that minimized the influence of shadows yet maintained an accurate representation of vegetation.

Accurate change detection methodology includes documenting (1) area change and change rate, (2) spatial distribution of changed types, (3) change trajectories of land cover types, and (4) accuracy assessment of change detection results (Lu et al. 2004). Our methodology captured all four of these requirements and differentiated vegetated and nonvegetated areas accurately, even though there were no ground reference data for years prior to 2003. The accuracy rates of 81 and 96% for 2003 and 2004, respectively, are considered high (Congalton & Green 1999) and were achieved even with the use of handheld GPS units, with horizontal error ranging from 3 to 6 m with WAAS positional correction at the study site. Due to budget constraints, use of handheld GPS units was required over the use of more accurate units. WAAS improved our position accuracy in this site, as there was an open sky and a clear view of the southern horizon. Without these criteria, accuracy could be worsened as the GPS unit looks for the WAAS signal. In addition, WAAS correction is only available for North America, and while the European Geostationary Navigation Overlay Service is WAAS's equal in Europe, all other international areas will not have access to the differential correction that these services provide. The 2003 and 2004 ground reference data were initially intended for accuracy assessment of detailed vegetation type maps. Six vegetation types were combined into one vegetation class and two nonvegetation types (water and mudflat) were combined to one nonvegetation class; therefore, nonvegetated points were under-represented in this study, which contributed to the low accuracies for the nonvegetation classes. The producer's and user's accuracies for both 2003 and 2004 were higher for the vegetated areas than for the nonvegetated areas. This difference is most likely due to more points falling into the vegetated zones, thus allowing for better representation. Additionally, the data were collected for species diversity studies and therefore consisted of a plot size (3 m radius) that was larger than typical accuracy assessments require. Because the 3-m radius plots were much larger than the pixel size of the 2003 and 2004 image dates (20 cm), it is difficult to compare the units of measurement. Even with this potential error, the accuracy rates calculated for this study in vegetated areas are considered to be high (Congalton & Green 1999). Furthermore, changing the optimal NDVI threshold slightly, which might happen with different human photointerpreters, did not cause the overall accuracy to change drastically, as illustrated by the relatively shallow slopes between thresholds in. This may indicate that postclassification change detection does very well with this site, which is the case in many change detection studies (Lu et al. 2004).

Although change detection studies using remote sensing can take much time and resources, they are usually more cost-effective than field-based studies for quantifying landscape-scale change across an entire restoration site. For this study, time and resources were spent on three major efforts: image acquisition (i.e., the flyover), field visits to gather ground data, and methods (including georectification, NDVI transformation, recoding, image comparison, area calculations, and accuracy assessment). Each effort used various levels of time and resources, and costs varied between $1,500 and $3,000. Costs would increase for larger sites and if certain services were purchased in addition to simple image flyover and acquisition. For example, georectification, orthorectification[3], and photogrammetry[4] would cost upward of $50,000 on much larger sites (S. Siegel 2006, Wetlands and Water Resources, San Rafael, CA, personal communication). The study required one field visit to gather accurate benchmark position information to use for georectification and about 6 person-days of ground referencing for 2003 and 2004 image dates each. Field personnel used handheld GPS units to collect location information of field points, which cost between $300 and $600 each. Field personnel recorded all species and absolute percent cover for all ground reference and accuracy assessment data. The time spent performing methods, including georectification, NDVI transformation, recoding, image comparison, area calculations, and accuracy assessment, was roughly 6 person-hours per image date. This time estimate would increase if more detailed image processing, such as vegetation classification and mapping, was performed. A study using satellite imagery would expect to spend roughly the same amount of time and resources as this study; however, because satellite imagery might need a higher level of preprocessing (i.e., atmospheric correction) before imagery can be used for analysis, satellite imagery might require additional costs.

[3] Orthorectification is similar to georectification in that it places the imagery accurately in real-world location, but it also takes into account elevation and camera position at time of image capture.

[4] Photogrammetry is the three-dimensional measurement of objects using two or more two-dimensional images.

Conclusions

Remote monitoring of vegetation is useful where access on the ground is constrained by soft sediment, remote location, or the presence of endangered species. Remote sensing allows assessment of patterns of composition, configuration, diversity, and structure of land cover types. In addition, attributes of restoration sites are readily compared with reference sites (Parker 1997). Colonizing species can be tracked accurately in a cost-effective way when remote sensing is combined with ground-based surveys. Acquiring images over the long term allows capture and understanding of vegetation colonization dynamics with spatially explicit data. Without annual imagery, we would have missed unpredictable changes such as premature senescence in 2001 and increased colonization between 2002 and 2003. Although completely bare when the levee was breached in 1994, the site was 90% vegetated by year 10 as measured by our relatively inexpensive, semiautomated, change detection technique.

Implications for Practice

- Remote sensing offers accurate automated methods for detecting change in restored wetlands.
- Vegetation change detection is a powerful indicator of restoration success.
- Remote sensing in tidal environments necessitates particular considerations to maintain consistency among image dates for accurate vegetation change detection.

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