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Potential Use of Remote Sensing to Assess Effects of Wave Action on Plant Re-establishment

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ABSTRACT

We evaluated the potential for remote sensing to detect a relationship between wave action factors and plant re-establishment after a habitat enhancement at Lake Kissimmee, Florida. Using Geographic Information Systems (GIS) and remote sensing, wave action factors were found to be inversely related to the probability of plant re-establishment. This corresponded with our expectation that more exposed areas would experience less plant re-establishment than areas protected from wind. However, when we tried to correlate these wave action factors with areal coverage of aquatic plants based on field measurements, we were unable to detect a significant relationship. Other factors aside from wave action, including littoral slope and the presence of offshore vegetation, may have influenced plant re-establishment in these sites. Remote sensing techniques may be useful to detect large changes in plants communities, but our results suggest that small changes in plant coverages are not detectable using this technique.

Key words: exposure, effective fetch, GIS, remote sensing, satellite imagery.

INTRODUCTION

In 1996, a habitat enhancement project was conducted at Lake Kissimmee, a 14,143-ha eutrophic lake located in the upper Kissimmee River Basin in Osceola County, Florida (Moyer et al. 1993). The project included a major drawdown and mechanical removal of dense aquatic vegetation and associated organic matter from approximately half of the lake's 80-km shoreline. Using large machinery, these aquatic plant communities which consisted primarily of primrose willow (*Ludwigia peruviana* (L.) Hara), duck potato (*Sagittaria lancifolia* L.), pickerelweed (*Pontederia cordata* L.), and cattail (*Typha* spp.) were removed leaving behind a hard sandy bottom habitat devoid of vegetation. The purpose of this project was to enhance fish habitat by reducing vegetation biomass and creating areas with intermediate plant coverages. However, the pattern and colonization rate of aquatic plants in scraped areas were variable around Lake Kissimmee following the enhancement (Tugend and Allen 2004).

Remote sensing offers a potentially cost-effective way to study aquatic plants over a large area through time, as field studies can be time consuming and cover only a small area. In addition, some remote sensing data, such as Thematic Mapper (TM) images, are acquired and archived on a regular schedule and can be accessed at a later date. This allows researchers the ability to assess long-term temporal trends using previously-collected, as well as current, data. Remote sensing technology has been used to map the distribution of aquatic plants (Raitala and Lampinen 1985, Welch et al. 1988, Marshall and Lee 1994, Rutchey and Vilcheck 1994) and document changes in plant distributions through time (Jensen et al. 1993, 1995, Robbins 1997, Williams and Lyon 1997). For example, Systeme Pour l'observation de la Terre (SPOT) imagery was used to map changes in the distribution of cattail (*Typha latifolia* L.) and white waterlily (*Nymphaea odorata* Ait.) in a South Carolina reservoir (Jensen et al. 1993). Raitala and Lampinen (1985) used Landsat Multispectral Scanner (MSS) imagery to classify and map aquatic macrophytes in a western Finland reservoir. Thus, studies utilizing these technologies have been useful in detecting and monitoring aquatic plant distributions and can further be used to assess possible environmental factors influencing these distributions.

We investigated the effects of effective fetch and exposure on plant re-establishment in enhanced areas of Lake Kissimmee, Florida, following the completion of the habitat enhancement project. Wave action factors were chosen because of our ability to back-calculate these values for previous years using archived wind data and because of its established role in shaping aquatic plant community dynamics in other systems (Jupp and Spence 1977, Keddy 1982, 1983, Dieter 1990, Engel and Nichols 1994). Our objectives were to 1) identify areas of plant re-establishment in enhanced sites using remotely-sensed and field-collected data; and 2) assess and compare relations between wave action factors and changes in plant abundance using the two methods.

METHODS

Satellite Detection of Plant Changes

Three satellite images (WRS-2 Path 41/Row 16) were obtained from the United States Geological Survey (USGS). Landsat 5 TM images were obtained for September 20, 1996

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and June 22, 1998, and the Landsat 7 TM image was acquired for July 5, 2000. These satellite images were used to assess changes in the distribution of aquatic macrophytes between years using Erdas IMAGINE 8.4 computer software (Erdas 1997).

Prior to image analysis, all images were geometrically and radiometrically rectified. The 1998 image was geometrically corrected using ground control points (GCPs) obtained from 1:24,000 USGS topographic quad maps. After geo-rectifying the 1998 image, the 1996 and 2000 images were georeferenced to that image so that all images were correctly aligned. Once a root mean square error (RMSE) <15 m was attained, images were resampled using bilinear interpolation. This method assigns a data value to each pixel in the rectified image by taking a weighted average of the four closest pixels (Erdas 1997).

To correct for differences in sun angle, atmospheric conditions, detectors and sensor systems between dates, the images were normalized (Jensen et al. 1995). Because clouds were present in the 1996 and 2000 images, atmospheric attenuation effects were removed prior to normalization. An unsupervised classification was conducted, and the classes associated with clouds and cloud shadows were identified and masked out of the image by assigning the pixels a value of zero. The 1996 and 2000 images were then normalized to the 1998 image using the histogram matching function (Erdas 1997).

In addition to atmospheric factors, water level differed among dates. Water level in the 1996 image was approximately 0.8 m higher than that in the 1998 and 2000 images. Therefore, a bathymetric map was used to standardize all images for water level. A georeferenced bathymetric map which was obtained from ReMetrix LLC, a private mapping firm, was used to subset all images so that they only included areas of water. Although the 1996 image had higher water levels and thus a larger surface area of water, only the area which also contained water in 1998 and 2000 was used in the analysis.

Change vector analysis (CVA) was used to assess changes in aquatic plant distributions between 1996 and 1998 and between 1996 and 2000 (Michalek et al. 1993). We performed this analysis for both time periods (1996 to 1998 and 1996 to 2000) as a means to validify the technique. We expected unenhanced areas to show the same changes in both analyses as they should have remained relatively unchanged through this period of time. Thus, if comparisons of these areas depicted different changes in each analysis, then we would deem this technique unsuitable for this study. Total change magnitude for each pixel was computed as:

$$\sum_{i=1}^{n} (X_2 - X_1)_i^2 \tag{1}$$

where X is the brightness value of the pixel for each date, and i is the TM band (Michalek et al. 1993, Jensen 1996). A threshold value of no change was chosen as 100 by investigating deep water areas in the lake, which should remain unchanged through time (Jensen 1996). Pixel values exceeding this threshold were then considered an area of change. For each band, the change direction was determined for each pixel with a "+" indicating an increase in the brightness value and a "-" indicating a decrease in the brightness value through time. For this study, the three visible bands (1,2,3) (450 to 630 nm) were used, which resulted in $2^3 = 8$ possible change combinations or sector codes. Pixels within each enhanced site were then assigned a sector code. Each sector code often relates to specific types of changes (Lillesand and Kiefer 1994). However, in this study, we categorized change as either: 1) a decrease in brightness due to increases in vegetation or 2) an increase in brightness due to increased turbidity or lower water level in the later image. Michalek et al. (1993) hypothesized that areas of plant growth would result in decreases in the brightness value of all three bands, because the sediment in the study areas was bright sand. Our study sites were also predominantly sand (authors, pers. obs.), and we expected similar decreases in brightness with the establishment of vegetation. Therefore, we combined the sector codes into two groups according to changes in brightness. Sector codes 1 to 4 characterized pixels which became "darker" as they contained more negatives than positives, whereas sector codes 5 to 8 characterized pixels which became "lighter" (Table 1). These groupings resulted in categorical data and magnitude of change was not revealed.

TABLE 1. NUMBER AND PERCENTAGE OF PIXELS (PARENTHESES) CORRESPONDING TO ASSIGNED SECTOR CODES IN ENHANCED AREAS OF LAKE KISSIMMEE, FLORIDA. A SECTOR CODE OF ZERO INDICATES PIXELS OF NO DETECTABLE CHANGE (I.E., PIXELS WITH CHANGE MAGNITUDES <100). SECTOR CODES 1-4 CORRESPOND TO DECREASED BRIGHTNESS, WHEREAS SECTOR CODES 5 TO 8 CORRESPOND TO INCREASED BRIGHTNESS. CHANGE COMBINATION REFERS TO THE RELATIVE INCREASE (+) OR DECREASE (-) IN THE BRIGHTNESS VALUE IN THE 1,2,3 BANDS OF THE TM IMAGES.

		Pixels		
Sector code	Change combination	1996 to 1998	1996 to 2000	
0	—	1611 (56)	1578 (50)	no change
1	(-,-,-)	13 (0.4)	260 (8)	decreased brightness
2	(-,-,+)	1 (0.0)	1 (0.0)	
3	(-,+,-)	2 (0.1)	1 (0.0)	
4	(+,-,-)	263 (9)	17 (0.5)	
5	(-,+,+)	942 (33)	119 (4)	increased brightness
6	(+,-,+)	6 (0.2)	0 (0.0)	
7	(+,+,-)	2 (0.1)	0 (0.0)	
8	(+,+,+)	51 (2)	1151 (37)	

Wave Action Factors

Wind data were used to estimate different wave action parameters which were incorporated into GIS layers and compared with the satellite-derived change maps. Daily wind data were acquired from the Orlando International Airport weather station (28.42°N, 81.33°W) from September 21, 1996 through June 30, 2000. The airport is about 50 km north of Lake Kissimmee. Wind data were not available at Lake Kissimmee, and we assumed that patterns in wind direction and speed at the airport were comparable to those at the lake. Wind speed was averaged for every 10 degrees of direction for the period between the acquisition dates of the two satellite images used to create each of the change maps. For this same period, percent of days wind blew in each 10-degree increment and percent of days wind ≥15 km/h blew in each 10-degree increment were determined.

In order to calculate potential wave exposure and effective fetch, Lake Kissimmee was first divided into a grid containing points approximately 150 m apart. All calculations for these points assumed no or very little interference of offshore aquatic vegetation on surface waves. For each of the grid points, effective fetch was calculated every 10 degrees for a total of 36 measurements. Effective fetch (L_f) for a given wind direction, *i*, is defined by the following equation:

$$L_f = \frac{\sum_{\gamma_i = -42}^{+42} x_i \cos\gamma_i}{\sum_{\gamma_i = -42}^{+42} \cos\gamma_i} \tag{2}$$

where $\gamma_i = 0, \pm 6, \pm 12, \ldots, \pm 42$ and is the angle to the given wind direction, and x_i is the distance from the given point to land (Håkanson and Jansson 1983). A weighted mean effective fetch, L_p, was calculated by taking the effective fetch for each 10-degree increment and multiplying it by the percent of days wind blew in that direction, then summing over all 36 directions. Using effective fetch, two measures of potential wave exposure were calculated for each point using a process similar to that of Keddy (1982):

$$E_M = \sum_{i=1}^{36} \text{mean wind speed*percent frequency*effective fetch} \tag{3}$$

$$E_X = \sum_{i=1}^{36} \text{percent frequency*effective fetch} \tag{4}$$

where E_M is exposure based on mean wind speed; E_X is exposure based on exceedance of 15 km·h^{-1}; and *i* is the 10-degree wind direction increment. Mean wind speed is the mean wind speed for the days when wind blew in the given *i* direction. Percent frequency for E_M is the percent of days wind blew in the given *i* direction, and percent frequency for E_X is the percent of days wind ≥15 km·h^{-1} blew in the given *i* direction. Fifteen km·h^{-1} was chosen as the exceedance value, because daily wind speed only equaled or exceeded this value 14 and 12% of the time between 1996 and 1998 and between 1996 and 2000, respectively. E_M and E_X are expressed in km^2·h^{-1} and km, respectively. However, these measurements are considered indices and so were treated as unitless values (Keddy 1982). Once computed, mean effective fetch and potential wave exposure for each georeferenced point were mapped. The points were then converted into a 30-m grid to match the resolution of the satellite change maps.

Statistical Analyses

Comparison of the satellite change map and the GIS layers depicting effective fetch and wave exposure was only done for enhanced littoral areas, which generally ranged in width from 100 to 200 m (Figure 1). Logistic regression was then used to determine if effective fetch and wave exposure were significantly related to changes in the distribution of aquatic plants in enhanced littoral areas (Narumalani et al. 1997). Pixels corresponding to a decrease in brightness were thought to represent areas of change from no plants to plants and were assigned a value of one. All other change pixels and pixels corresponding to no change were assigned a value of zero. Therefore, the binary response was either zero if no change in plants was detected or one if change was detected. Logistic regression was run separately for E_M, E_X, and with an alpha level of 0.05. The linear model used was:

$$\operatorname{logit}(p_j) = a + b_i(x_i) \tag{5}$$

where logit(p_j) is the logistic probability of no increase in plants through time, *a* is the y-intercept and b_i is the parameter estimate, and x_i is the independent variable. The best model was chosen based on the Akaike's information criterion (AIC) and the percent effectiveness of the model for predicting the binary response (*c*) (SAS 1994). The logit(p_j) value was then used to calculate the predicted probability of no increase in plants through time as determined by the following equation:

$$p = \frac{e^{\operatorname{logit}(p)}}{(1 + e^{\operatorname{logit}(p)})} \tag{6}$$

(SAS 1994). Thus, this type of analysis would indicate the probability that plants would not establish in enhanced sites given a particular wave action value.

Field Data

In October 2000, we mapped the percent area coverage of aquatic plants in enhanced areas of Lake Kissimmee. While circling the lake in a boat, we visually estimated percent coverage within enhanced sites (Figure 1). Every time PAC shifted in value within each of these sites, the geographic location was recorded using a Trimble GeoExplorer® Global Positioning (GPS) receiver with differential correction. Thus, each set of points was used to mark the beginning and end of each section characterized by a given PAC. Using the ArcView 3.2® computer program, we created a digital map

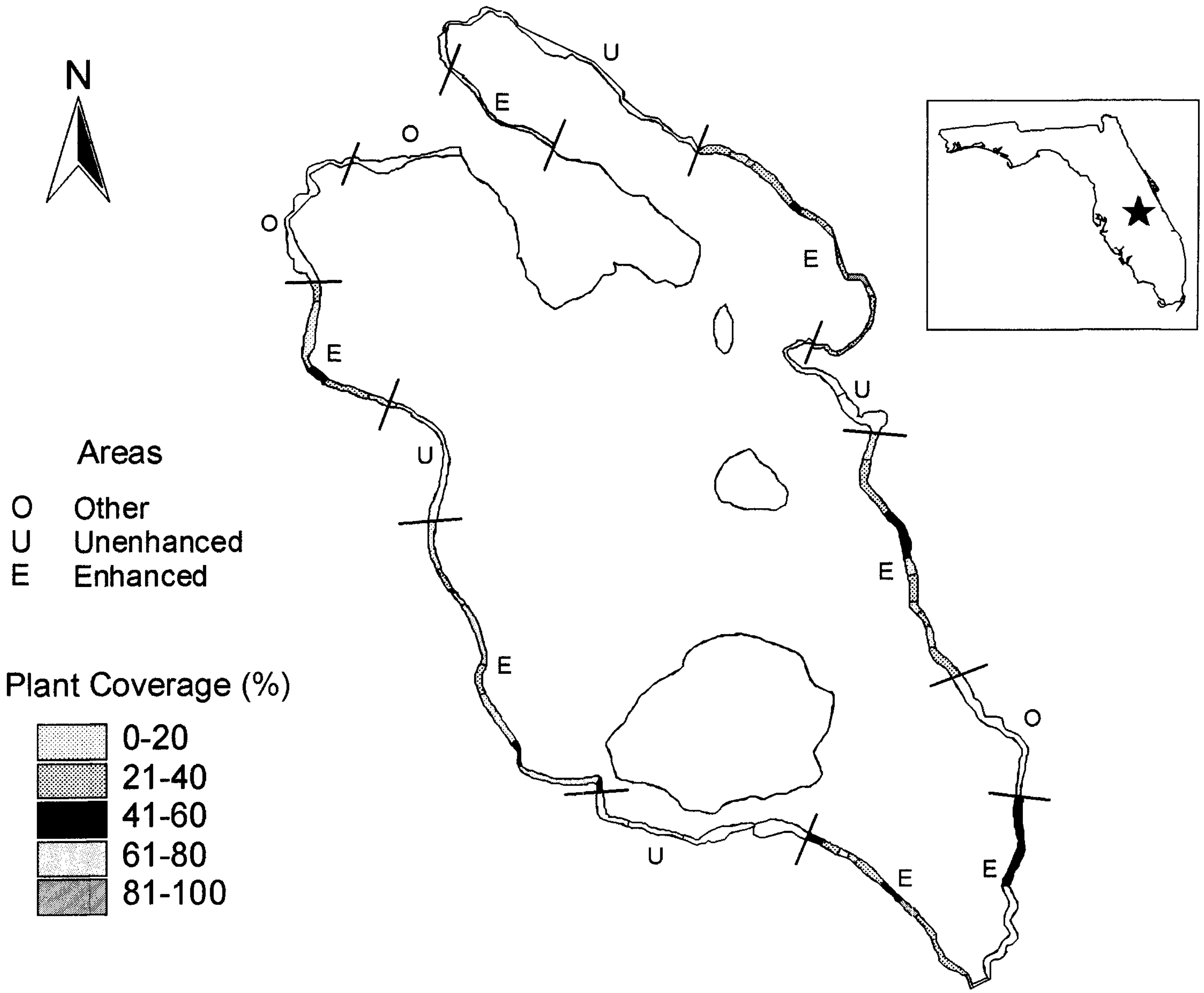

Figure 1. Map depicts the visually estimated plant coverage data obtained for enhanced areas of Lake Kissimmee, Florida, in October 2000. Lines mark the boundaries of the enhanced (E) and unenhanced (U) areas following the 1996 habitat enhancement project. 'Other' refers to unenhanced areas that did not contain appreciable levels of aquatic plants.

of enhanced areas which consisted of polygons formed from the sections marked in the field. We then calculated mean exposure and effective fetch for each polygon. We used correlation analysis to assess relations between PAC and mean exposure and effective fetch.

RESULTS AND DISCUSSION

The two methods employed in this study to investigate the relationship between wave action factors and plant re-establishment yielded different results. Although a low proportion of pixels depicted a decrease in brightness with the remote sensing technique (~9%, Table 1), logistic regression revealed that the probability of plants increasing in enhanced areas was inversely related to wind exposure. Models were highly significant and the percent effectiveness of the model predictions (*c*) ranged from 0.55 to 0.78 (Table 2). As expected, enhanced sites that were exposed to high wind and wave action exhibited lower plant re-establishment than areas protected from wind in the 4-year period following habitat enhancement. This corresponds to the results of previous research (Jupp and Spence 1977, Keddy 1982, 1983, Dieter 1990) and suggests that wave action is an important factor influencing plant community dynamics in enhanced areas of Lake Kissimmee. Wind-induced wave action has been shown to influence plant community dynamics by increasing sediment resuspension (Dieter 1990), uprooting existing plants (Engel and Nichols 1994), and decreasing the organic content and nutrients of the sediment (Keddy 1983). Similar mechanisms may be responsible for the observed relation-

TABLE 2. LOGISTIC REGRESSION RESULTS FOR THE 1996 TO 1998 AND 1996 TO 2000 CHANGE MAPS. *P* IS THE PROBABILITY THAT PLANTS WILL NOT RE-ESTABLISH ENHANCED SITES, *EXC* IS EXPOSURE BASED ON EXCEEDANCE, *EXP* IS EXPOSURE BASED ON MEAN DAILY WIND SPEED, AND *FETCH* IS MEAN EFFECTIVE FETCH. WALD'S χ^2, AKAIKE'S INFORMATION CRITERION (AIC), PERCENT EFFECTIVENESS OF THE MODEL FOR PREDICTING THE BINARY RESPONSE (CHANGE OR NO CHANGE, *C*), AND SAMPLE SIZE (N) ARE GIVEN.

Change map	Model	χ^2 value	P-value	AIC	c	n
1996-1998	logit(P) = 1.4833 + 0.0223(exc)	8.0733	0.004	1830.79	0.55	2891
	logit (P) = 0.5262 + 0.0008(exp)	43.7283	<0.001	1792.92	0.63	2891
	logit(P) = 0.2156 + 0.0010(fetch)	61.2449	<0.001	1773.32	0.65	2891
1996-2000	logit(P) = -0.2307 + 0.0882(exc)	119.6162	<0.001	1770.02	0.72	3127
	logit (P) = -1.3762 + 0.0021(exp)	154.7573	<0.001	1677.32	0.77	3127
	logit(P) = -1.5818 + 0.0021(fetch)	170.5391	<0.001	1656.57	0.78	3127

ship between wave action and plant re-establishment in Lake Kissimmee.

When we attempted to verify this relationship using field-collected data, the results were not significant ($P > 0.05$). Wave action factors explained less than 3% of the variation in percent coverage of aquatic plants. The measure we used, percent coverage of aquatic plants, has commonly been used to estimate plant abundance in aquatic systems, but because it is determined visually by individual observers, it may also be variable and unreliable (Orth 1983). Thus, variability or inconsistency in this estimate, particularly with respect to submersed species, may have masked any effect of wave action on plant re-establishment in enhanced sites.

Alternately, the remote sensing technique contained a number of potential problems that may have limited our results. We used change vector analysis (CVA) to identify enhanced areas that experienced an increase in plants. With this technique, we categorized change as either a decrease in brightness which would indicate the establishment of plants or an increase in brightness which would indicate changes in other environmental variables such as turbidity. To evaluate sector code groupings, we compared the spatial distribution of the dominant sector codes in the original change maps. We found that many of the unenhanced areas, which should have remained similar between years, were assigned different sector codes in the two change maps. By categorizing the codes as either a decrease (codes 1-4) or increase (codes 5-8) in brightness (Table 1), similar patterns between the two change maps were observed. Thus, these groupings appeared to be an appropriate index of changes in brightness.

Although a previous field study indicated that both plant abundance and biomass increased significantly from 1998 to 2000 in two enhanced sites (Tugend and Allen 2004), these changes may not have been large enough to be detected with this method. Mean coverage of aquatic plants at one site increased from approximately 20 to 30% between 1998 and 2000 (Tugend and Allen 2004). At the other site, these values increased from approximately 35 to 40% between the 2 years (Tugend and Allen 2004). We had expected the plants to re-establish much more rapidly as was previously observed (Moyer et al. 1995). Following a similar enhancement at Lake Tohopekaliga, Florida, which is located in the same chain of lakes as Lake Kissimmee, plants reached pre-enhancement levels of near 100% coverage within three years (Moyer et al. 1995). Nonetheless, aquatic plants re-colonized enhanced areas at a slower rate at Lake Kissimmee, and it is unlikely that a procedure such as CVA would be able to detect such small magnitude changes in vegetation coverage (Johnson and Kasischke 1998).

Plants are known to reflect highly in the near-infrared portion of the electromagnetic spectrum (TM band 4, 700 to 900 nm), but water absorbs highly in this region (Gates et al. 1965). As a result, the presence of water hinders the ability to detect submersed plants by remotely sensed methods. This was a concern in the current study as previous field work conducted at two enhanced sites of Lake Kissimmee revealed that the re-established plant communities consisted of many submersed species (Tugend 2001). The dominant species in these study sites in 1998 and 2000 were eel grass (*Vallisneria americana* Michx.), hydrilla (*Hydrilla verticillata* (L.f.) Royle), and dwarf arrowhead (*Sagittaria subulata* (L.) Buch.) (Tugend 2001). As a result, the inclusion of the near-infrared band would be of limited use, and we used only the visible portion of the spectrum in the analysis in order to detect submersed plants. However, the absolute reflectance of submerged species decreases with depth and may not differ from that of background water (Penuelas et al. 1993). This may have resulted in the misclassification of deeper areas containing submersed plants. Although Michalek et al. (1993) used the same CVA approach to identify loss and gain of submersed vegetation in a coastal marine environment, their study did not include ground truthing data, so its effectiveness could not be assessed (Michalek et al. 1993).

Variation in environmental conditions between dates may impede interpretation and must also be considered. For example, water clarity may have differed between dates. Bartolucci et al. (1977) found that turbid water yielded a higher spectral response than clear water in the red region (600 to 700 nm). The importance of water depth has also been noted. Tidal stage influenced the detection of areas containing vegetation and may result in misclassifications (Jensen et al. 1993). It is likely that differences in environmental conditions between images influenced our results. Water levels at Lake Kissimmee differed between dates with water level approximately one meter higher in the 1996 image as compared to the 1998 or 2000 image. Even though only areas containing water were included in the analysis, the effect of water depth was apparent with the presence of large numbers of pixels that increased in brightness (Table 1). This increase likely occurred because low water level in the latter images (1998 and 2000) allowed more sandy bottom to become visible, resulting in a "brighter" pixel. Likewise, lower water levels resulted in the omission of many pixels from the analysis as portions of the enhanced areas were not inundated during these times. The presence of clouds in the 1996 and 2000 images also resulted in the omission of approximately 10% of pixels from the analysis.

The amount of resolution in remote sensing data may not be adequate to detect desired changes (Michalek et al. 1993, Robbins 1997). We used Landsat TM imagery which has a resolution of 30 m. As a result, substantial establishment of plants would be needed for the change magnitude to exceed the threshold value and be identified as vegetation using this method. Furthermore, plants were patchily distributed in enhanced sites. Based on field data, most patches were less than 25 m^2 in area (Tugend 2001), so a remote sensing technique with a resolution ≤5 m, such as color aerial photography, would be ideal for this type of study. Although color aerial photography was not available for the scope of this study, future investigations should employ this method when possible.

The inclusion of other or more accurate variables may improve the predictability and significance of the models created by both the remote sensing and field methods. For example, in addition to fetch, slope and depth were also found to be significant predictors of the presence/absence of plants in Par Pond, South Carolina (Narumalani et al. 1997) and were not considered in this study. We also did not take into account the presence of offshore vegetation, which may influence the effect of wave action on nearshore plant communities. Much of the shallow littoral areas of Lake Kissimmee are buffered by bands of offshore vegetation. It is unclear how much these bands of vegetation would affect wave action, but their presence would probably reduce the effect of waves in these areas. For example, the presence of offshore vegetation has been shown to stabilize shallow areas by reducing water current velocity and sediment resuspension. Madsen and Warncke (1983) found that current velocity was reduced by 58 to 92% by submerged vegetation in a Danish stream. Hamilton and Mitchell (1996) further emphasized the importance of macrophytes in reducing the effects of waves on sediment resuspension. Lastly, the use of wind data collected at the airport may have introduced error into our models due to site differences; however, we feel that the general pattern in wind conditions were similar (authors, pers. obs.). Nonetheless, the inclusion of on-site wind data may have strengthened our models.

In this study, we assessed the relationship between wave action and plant re-establishment following a habitat enhancement at Lake Kissimmee. We detected significant relationships between wave action factors and changes in vegetation in enhanced areas using remotely sensed data. However, we were unable to support these relationships using visually estimated percent area coverage of aquatic macrophytes as an index of plant re-establishment. This study has provided valuable information for scientists and managers interested in using these methods to detect long-term changes in plant abundance or investigate relationships between plant establishment and other factors in large aquatic systems. Detecting submersed species using widely available remotely-sensed data continues to be limited and detailed field studies may be preferred despite the often large time and effort commitment required.

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