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Article *in* Wetlands · January 2008

DOI: 10.1672/08-34.1

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WETLANDS, Vol. 28, No. 4, December 2008, pp. 1028–1039

ASSESSING THE USE OF MULTISEASON QUICKBIRD IMAGERY FOR MAPPING INVASIVE SPECIES IN A LAKE ERIE COASTAL MARSH

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Abstract: QuickBird multispectral satellite images taken in September 2002 (peak biomass) and April 2003 (pre-growing season) were used to map emergent wetland vegetation communities, particularly invasive *Phragmites australis* and *Typha* spp., within a diked wetland at the western end of Lake Erie. An unsupervised classification was performed on a nine-layer image stack consisting of all four spectral bands from both dates plus a September Normalized Difference Vegetation Index image. The resulting eight cover classes distinguished three monodominant genera (*Phragmites australis*, *Typha* spp., *Nelumbo lutea*), three multigenera plant communities (wet meadow, other non persistent emergents, woody vegetation), and two unvegetated cover types (water, bare soil). Field validation at 196 data points yielded an overall classification accuracy of 62%, with producer's accuracy for the eight individual classes ranging from 41 to 91% and user's accuracy from 17 to 90%. Three-fourths of areas designated as *Phragmites* were correctly mapped, but 14% were found to be cattail (*Typha*) during field validation. Lotus (*Nelumbo lutea*) beds were accurately mapped on multiseason imagery (producer's accuracy = 91%); these beds had not yet emerged above water in April, but were fully developed in September. Other types of non persistent vegetation were confused with managed areas in which vegetation had been cut and burned to control invasive *Phragmites*. Multiseason QuickBird imagery is promising for distinguishing certain wetland plant species, but should be used with caution in highly managed areas where vegetation changes may reflect human alterations rather than phenological change.

Key Words: *Phragmites*, remote sensing, *Typha*, wetland mapping

INTRODUCTION

Satellite remote sensing has many advantages for mapping wetlands, including frequent acquisition, repeat coverage for monitoring changing conditions, and low image cost in comparison to high-altitude photography (Ozesmi and Bauer 2002). The ability to remotely identify dominant wetland plant species is desirable, because plant species are indicators of wetland condition (Johnston et al. 2007a). It would be particularly useful to identify the presence and spread of invasive plant species that displace native vegetation and degrade wetland habitat values (Madden 2004). One such species is common reed (*Phragmites australis*), which has been the subject of remote sensing research in coastal brackish marshes (Bachman et al. 2002, Artigas and Yang 2006) as well as coastal freshwater marshes of the North American Great Lakes (Arzandeh and Wang 2003, Wilcox et al. 2003, Lopez et al. 2004, Pengra et al. 2007).

The identification of non persistent emergents would also be desirable, because non persistent coastal wetlands provide important faunal habitat (Burton et al. 2004, Brazner et al. 2007). As defined by the U.S. National Wetlands Inventory, non persistent emergents are a subclass "dominated by plants which fall to the surface of the substrate or below the surface of the water at the end of the growing season so that, at certain seasons of the year, there is no obvious sign of emergent vegetation" (Cowardin et al. 1979). Examples of non persistent emergents include arrow arum (*Peltandra virginica* (L.) Schott), pickerelweed (*Pontederia cordata* L.), and arrowheads (*Sagittaria*). Non persistent wetlands were poorly mapped by the National Wetlands Inventory due to its use of "leaf-off" aerial photography that was taken too early in the growing season to detect non persistent emergents (Johnston and Meysembourg 2002). Accurate remote identification of non persistent emergents requires images representing both mature and senescent vegetation periods.

Imagery from early satellite sensors such as Landsat (30 m resolution) was inadequate for many wetland mapping applications due to coarse spatial resolution, but newer finer-resolution imagery offers promise for more detailed classification of wetland vegetation. Multispectral SPOT (10 m and 20 m resolution) or IKONOS images (4 m resolution) have been used to identify multiple classes of emergent wetlands, with mapping accuracies of 79.5 to 85.1% (Rutchey and Vilchek 1999, Sawaya et al. 2003, Phillips et al. 2005). Airborne hyperspectral imagery (5 m resolution) improved mapping of *Phragmites* and *Typha* in Great Lakes coastal wetlands, with estimated accuracies of 80% based on photointerpreted aerial imagery and 91% based on field measurement data (Lopez et al. 2004).

Multiseason remote sensing has aided discrimination of wetland types by detecting hydrological and phenological changes characteristic of those types (Jensen et al. 1993b, Sersland et al. 1995, Wolter et al. 2005, Baker et al. 2006). The advantage of using multiseason imagery is that it provides additional classification information for distinguishing plant species within a single growing season. This information is especially important given that many wetland species have overlapping spectral reflectances at peak biomass (Ernst-Dottavio et al. 1981, Spanglet et al. 1998, Schmidt and Skidmore 2003).

To the best of our knowledge, QuickBird imagery, with resolution of less than 3 m, has not been previously used for mapping individual wetland species. The goal of this research was to evaluate the use of multiseason QuickBird imagery for mapping emergent wetland vegetation. Our primary objective was to distinguish invasive emergent species that occurred in monodominant stands, including *Phragmites australis*, and *Typha* spp. A secondary objective was to distinguish persistent from non persistent emergents.

METHODS

Study Site

Erie Marsh (41°45′05″ N, 83°27′18″ W) is located at the west end of Lake Erie in North Maumee Bay, Monroe County, Michigan (Figure 1). This 918 ha area is situated 10 km north of Toledo, Ohio, and 70 km south of Detroit, Michigan. Major land holdings include the Michigan Department of Natural Resources' Erie State Game Area and the Erie Marsh Preserve, an area protected by The Nature Conservancy (TNC). Erie Marsh represents 11% of the remaining marshland in southeastern Michigan and is one of the largest marshes on Lake Erie (TNC 2006). Two state-threatened vascular species, American lotus (*Nelumbo lutea* Willd.) and swamp rose-mallow (*Hibiscus moscheutos* L.), are found on the preserve. The marsh also serves as a migratory and nesting area for shorebirds and waterfowl.

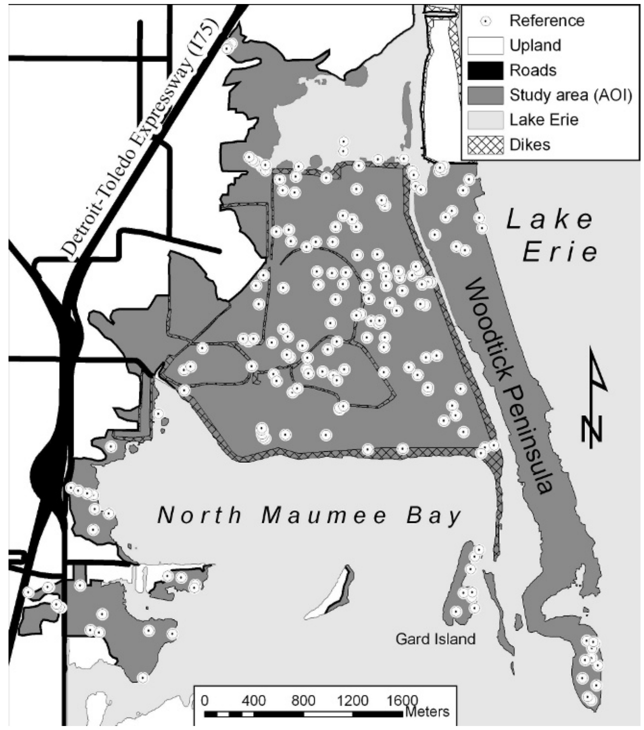

Figure 1. Study area and reference point locations.

The hydrology of Erie Marsh has been altered over the past century by construction of dikes for water level control that was initiated by waterfowl hunting clubs in the early 1900s (Johnston et al. 2007b). Although the dikes alter the natural dynamics of water level change in Erie Marsh, they also give wetland managers greater control over the vegetation within the dikes. The Nature Conservancy's management plan for controlling invasive *Phragmites* within the Erie Marsh Preserve involves a sequence of draining, prescribed burning, herbiciding of *Phragmites*, and reflooding (NOAA 2006).

Satellite Imagery

We utilized two QuickBird images of the Erie Marsh Area: an early fall image (6 September 2002), when vegetation was at peak biomass, and an early spring image (10 April 2003) when deciduous trees were leafless and non persistent vegetation was absent (Figure 2). The QuickBird images covered a 10 km × 10 km area, with a pixel size of 2.8 m × 2.8 m. The QuickBird images were orthorectified by the vendor to 1:24,000 base maps with RMS error of 7.7 m. The projected coordinate system was UTM Zone 17, North American Datum 1983. Each image

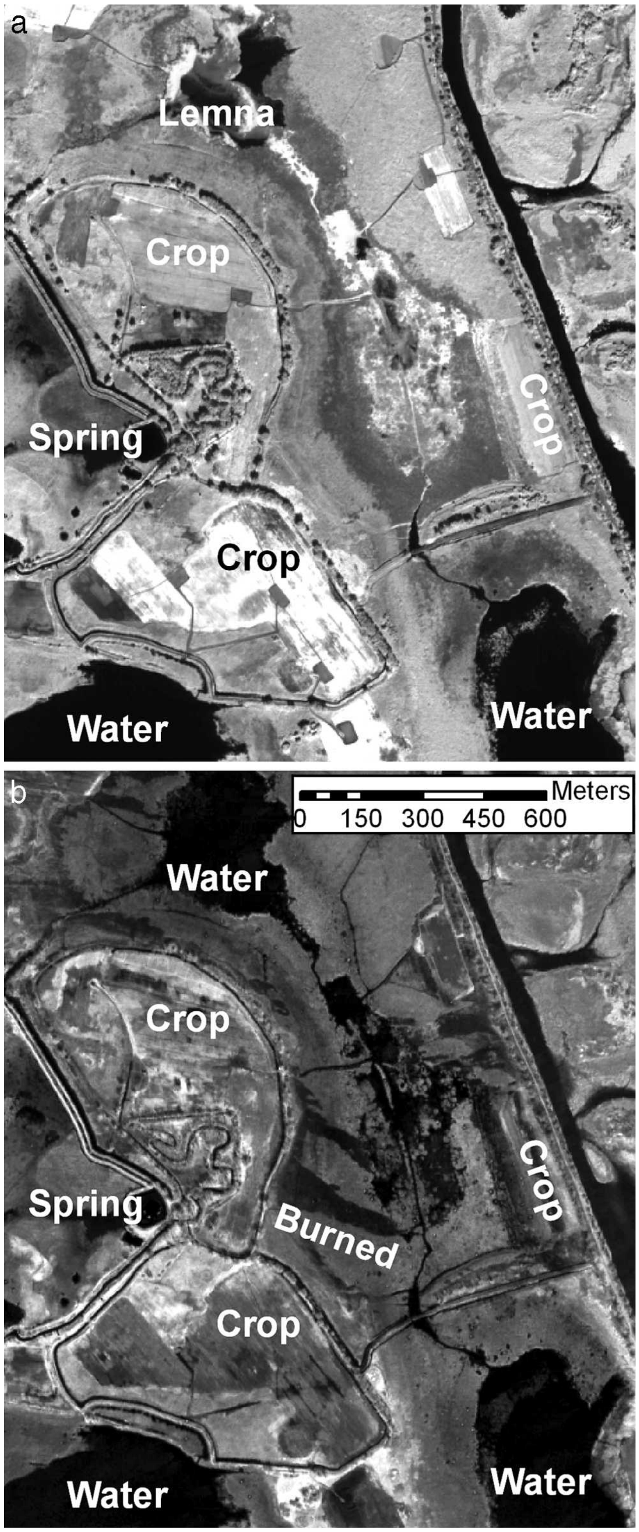

Figure 2. NIR band images of highly managed portion of Erie Marsh showing selected types of vegetation change during September (top image) and the following April (bottom image). "Spring" is the location of a diked sulphur spring visible on both images.

includes four layers, corresponding to blue, green, red, and near-infrared (NIR) wavelengths. The QuickBird images were initially acquired for a previous study of submergent aquatic vegetation (Wolter et al. 2005).

An Area of Interest (AOI) mask was created to exclude non-wetland areas (Figure 1). The lakeward side of the mask was determined digitally by computing the Normalized Difference Vegetation Index (NDVI) for the September image and selecting the NDVI threshold between water and vegetation, which was used with the ERDAS Imagine 8.7 (LEICA Geosystems, Norcross, GA, USA) CLUMP command to generate a GIS file of contiguous water pixels. The pixel clump representing the waters of Lake Erie and Maumee Bay was converted into a water mask polygon. The landward side of the mask (i.e., the upland-wetland boundary) was digitized manually based on visual interpretation by an experienced aerial photo interpreter (Johnston et al. 2007b), because upland areas could not be distinguished from wetland areas by a simple elevation threshold. This process masked out such features as the J. R. Whiting Power Plant and associated facilities, seasonal hunting cabins owned by the Erie Shooting and Fishing Club, coastal residential areas, marinas, upland forest on Indian Island, and agricultural lands outside of the diked areas. Crops planted to attract waterfowl within diked portions of Erie Marsh were not masked out. Although paved roads in areas surrounding Erie Marsh were masked out of the image, dirt roads on top of dikes were not. The AOI thus created contained shallow water areas in the interior of Erie Marsh, excavated ponds on the western edge of Erie Marsh, the Woodtick Peninsula south of the Whiting Power Plant fly ash pit, dikes and their associated dirt roads, and emergent and woody wetlands.

Unsupervised Classification

An eight-layer stack of all four bands from both dates was initially used for image analysis. During test runs, dark tree shadows appearing on the September image were sometimes misclassified as water, so we added the September NDVI layer as a ninth layer to alleviate this problem (tree shadows were not a problem on the April image due to the lack of deciduous foliage). Because we had minimal knowledge of the site prior to image classification, we opted to use unsupervised classification, which is recommended when not much is known about the data before classification (Leica Geosystems 2003). We performed an unsupervised classification (ISO-

Table 1. Category names and descriptions used to classify wetlands, spring and summer field appearance, and area mapped in each class at Erie Marsh, North Maumee Bay, Michigan.

Category	Spring Appearance	Summer Appearance	Typical Species	Area (ha)
Unvegetated or cultivated				
1 – Water	Water	Water, may contain floating or submerged aquatic vegetation	*Lemna minor* L., *Stuckenia pectinata* (L.) Böerner	212.4
2 – Soil	Beach, bare moist soil, stubble in cultivated lands	Beach, sparsely vegetated moist soil, crops in cultivated lands	corn (*Zea mays* L.)	54.2
Emergent, nonpersistent				
3 - *Nelumbo*, monodominant	Water	Large, circular leaves that may float on water surface or be on emergent petioles; growing in shallow water	*Nelumbo lutea* Willd.	33.5
4 - Other nonpersistent, multidominant	Water	Various plant species that emerge out of shallow water; may be mixed with *Nelumbo*	*Sagittaria latifolia* Willd., *Eleocharis* R. Br.	50.6
Emergent, persistent				
5 - *Phragmites*, monodominant or dominant mix	Dense standing and fallen plant litter	Dense reeds with alternate leaves on very tall (2–4 m) stems, flowering heads plumelike; growing in shallow water or moist soil	*Phragmites australis* (Cav.) Trin. ex Steud.	349.8
6 - *Typha*, monodominant	Dense standing and fallen plant litter	Long, erect leaves emerging from base of plant, stems 1.5–3 m, flowering heads brown & cylindrical; growing in shallow water or moist soil	*Typha angustifolia* L., *Typha* x *glauca* Godr. (pro sp.)	119.3
7 - Wet meadow, multidominant	Primarily fallen plant litter	Various plant species growing in moist soil; canopy height 1.5 m or shorter	*Phalaris arundinacea* L., *Carex* L.	67.7
Woody				
8 - Trees, shrubs	Woody stems without leaves	Woody stems with leaves	*Populus deltoides* Bartram ex Marsh., *Salix* L.	30.5

DATA) with 100 classes in ERDAS Imagine 8.7, selecting to initialize means along the Principal Axis and limiting the processing operation to 25 iterations or until it converged to the 0.95 threshold level.

The 100 ISODATA classes were grouped into eight classes (Table 1) using a classification scheme developed from ground reconnaissance conducted contemporaneously with summer image acquisition (28 August 2002) and on quantitative vegetation cover data collected for the Great Lakes Environmental Indicators project on 20 July 2002 and 25–26 June 2003 (Johnston et al. 2007a). The classification distinguished three monodominant genera (*Phragmites australis*, *Typha* spp., and *Nelumbo lutea*), three multi-genera plant communities (wet meadow, non persistent emergents, and woody vegetation), and two unvegetated cover types (water and soil). The *Phragmites* class was initially divided into two water depth classes, but field measurements showed that they could not be consistently distinguished and we collapsed the two *Phragmites* classes into a single class.

Accuracy Assessment

The initial reconnaissance data were unsuitable for accuracy assessment because they had been used for image analysis and were non-random. Therefore, we conducted field accuracy assessment of the maps on 17–19 July 2005 (27 points) and 4–16 July 2006 (169 points). A minimum of 18 data points were collected per class, with a greater number (51 points) being collected for the species of greatest interest and coverage, *Phragmites*. We developed a stratified random sampling scheme, using ERDAS Imagine and ArcView (ESRI, Redlands, CA, USA) to generate random points. Each random point was defined as a group of 3 $\times$ 3 neighboring pixels and belonging to the same class. In the field these random points represented approximately 8 m $\times$ 8 m plots. The random locations were uploaded into a handheld GPS unit with accuracy to within 30 cm (Geo XH 2005 Series, Trimble Navigation Limited, Sunnyvale, CA, USA). We then used the GPS unit in the field to navigate to the reference points (i.e., accuracy assessment points) (Johnston et al. in press).

In the field, each plot was divided in four subplots oriented towards each cardinal direction. For each plot we recorded the elevation (m). Maximum water depth (cm) was measured at most plots (166 out of 196). We estimated the vegetation/bare soil/water cover (%) in each of the four subplots and calculated average cover for each plot. Based on the dominant cover type, one of the eight classes was assigned to each plot. Some plots have several layers of dominant vegetation on vertical structure; we assigned classes based on the tallest vegetation layer which likely would have determined the spectral value of a pixel. For emergent vegetation (persistent and non persistent) we used a threshold of 30% vegetation cover (Cowardin et al. 1979).

To assess the accuracy of the classification, we constructed an error matrix and computed the overall, producer's, and user's accuracy values. We computed average digital numbers (DN) for green, red, and NIR bands for both QuickBird images to assess the spectral differences among the reference classes. We also calculated $\hat{k}$ = (observed accuracy - chance accuracy)/(1-chance accuracy), as an indicator of the extent to which the percentage correct values of an error matrix are due to the "true" agreement versus "chance" agreement (Congalton and Green 1999, Lillesand and Kiefer 2000).

RESULTS

Wetland Classes and Reference Data

Human activity has altered most of the vegetation within the 918 ha study area. Erie Marsh is actively managed for waterfowl hunting, and grain crops are planted on plowed fields within the marsh to attract waterfowl (Figure 2). Trails and staging areas are mowed within the planted crops for hunter access into the interior of the wetland. Diked areas are periodically flooded. Control efforts for *Phragmites* include mowing, herbicide spraying, burning, and reflooding. Such types of alteration are typical of managed Lake Erie coastal marshes, but complicate remote sensing of vegetation.

The eight classes utilized were ecologically fairly distinct. In addition to differences in dominant plant species (Table 1, Figure 3), these classes had different water depths (Table 2). Sampled open water areas and *Nelumbo* beds had water depths of about 50 cm, whereas other non persistent emergents grew in water averaging 38 cm in depth. Water depth ranges were similar for *Typha* and *Phragmites*, but average water depth was different: *Typha* grew in water averaging 16 cm in depth, whereas *Phragmites* tended to grow in drier areas (mean water depth = 5 cm). Sites with woody vegetation had little standing water, and the wet meadows and bare soil/cultivated areas had no standing water when the field work was conducted in July. As mapped, *Phragmites* was the most extensive class, covering 38% of the study area, followed by open water and *Typha* (Table 1).

The eight classes were also spectrally distinct. The spectral characteristics of the eight wetland classes were very different in September versus April due to the overwinter change from photosynthesizing vegetation to dead plant litter or water, and the average digital number (DN) in the NIR band was much greater in September than it was in April (Figure 4). The *Nelumbo* and non persistent emergent classes changed the most, from dense vegetation in September to open water areas with very low NIR values in April (Figures 4 and 5). The average NIR DN for these two classes was about five times greater in September than in April. Stands confirmed in the field to be *Phragmites* and *Typha* had distinct September NIR DN values, with the average DN values for *Phragmites* being 69% greater than those of *Typha*. Both *Phragmites* and *Typha* had similar NIR DN values in April. Woody vegetation had September NIR DN values intermediate between those of *Phragmites* and *Typha*, and lower September DN values in the visible light bands than other vegetation types. The wet meadow class differed from the other vegetation classes in April due to its high DN values in the visible light bands. We believe that this difference is due to the lack of subcanopy water and the reflectivity of prostrate grass detritus from the previous growing season. The wet meadow class also had higher NIR DN values in April than all other classes, which may be due to earlier green-up of vegetation in these drier areas of the wetland. The magnitude of change in the NIR DN values of the soil/sand/cultivated class was surprising, nearly three times greater in September than in April. This change is attributed to the growth of cultivated crops on portions of this

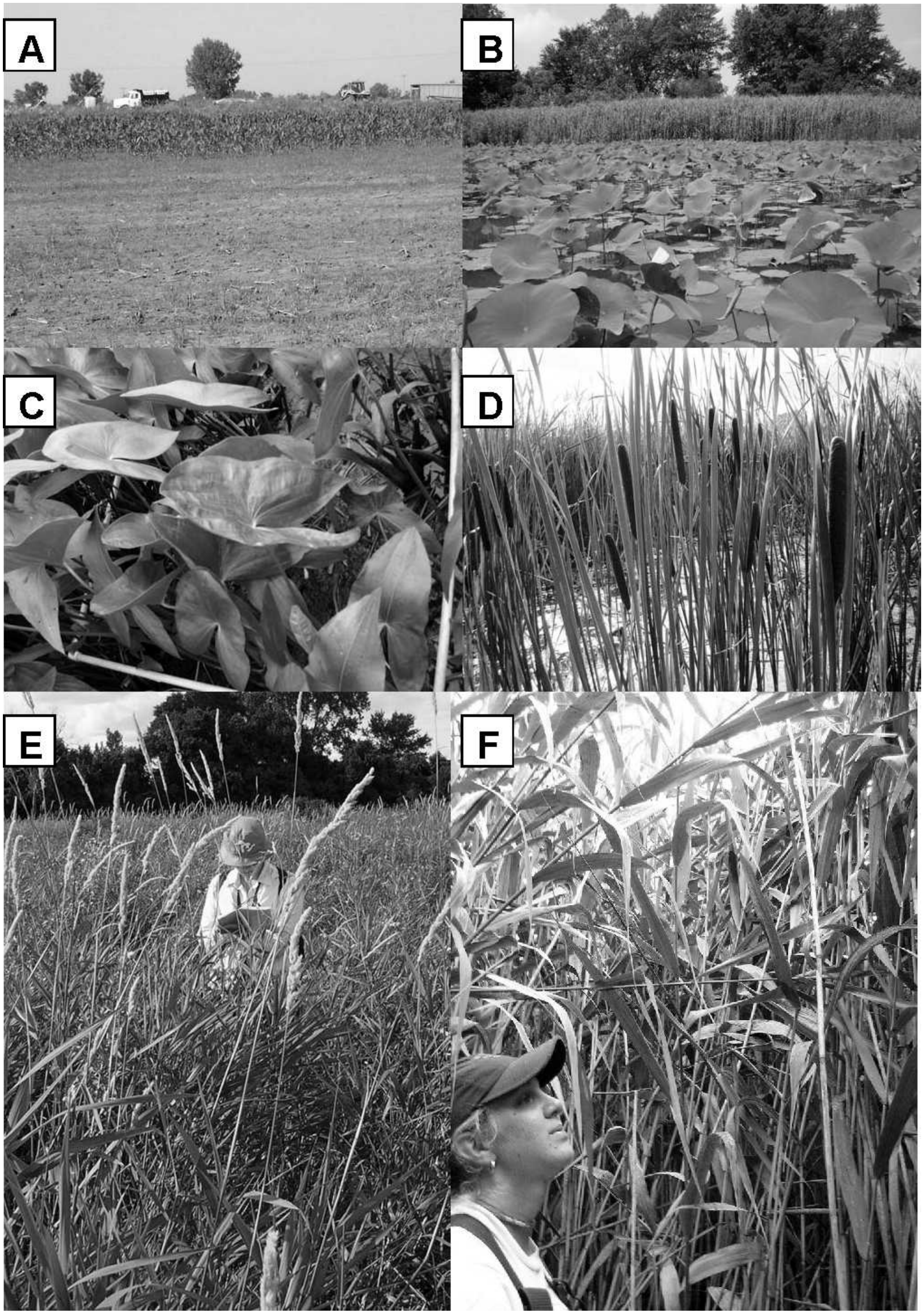

Figure 3. Field photos of the eight cover types mapped. A) Soil/cultivated (plowed ground in foreground, corn in background); B) *Nelumbo* beds (foreground) and woody vegetation (background); C) *Sagittaria latifolia*, a non persistent emergent; D) *Typha* spp.; E) wet meadow dominated by *Phalaris arundinacea*; and F) *Phragmites australis*.

Table 2. Average water depth for the eight classes, based on field measurements made at 166 reference points at Erie Marsh, North Maumee Bay, Michigan.

Class	Water depth (cm)	SE	Min	Max	N
1–Water	48.40	12.71	20.00	150.00	10
2–Soil	0.00	0.00	0.00	0.00	18
3–*Nelumbo*	51.00	9.80	20.00	80.00	5
4–Other non persistents	37.50	7.27	5.00	50.00	6
5–*Phragmites*	4.81	1.18	0.00	45.00	70
6–*Typha*	16.00	2.50	0.00	40.00	26
7–Meadow	0.00	0.00	0.00	0.00	9
8–Woody	1.59	1.37	0.00	30.00	22

category (Figure 2); sandy beach areas on the Woodtick Peninsula did not exhibit a similar increase. Predictably, water had the lowest NIR DN values of any class on both dates, and the two non persistent emergent classes had April DN values similar to that of water. The September NIR DN value of the "water" class was twice greater than its April value, which we attribute to the presence of submergents, algae, and duckweed, a tiny free-floating plant that covered some wind-protected water areas in the marsh during September (e.g., area marked "*Lemna*" on Figure 2).

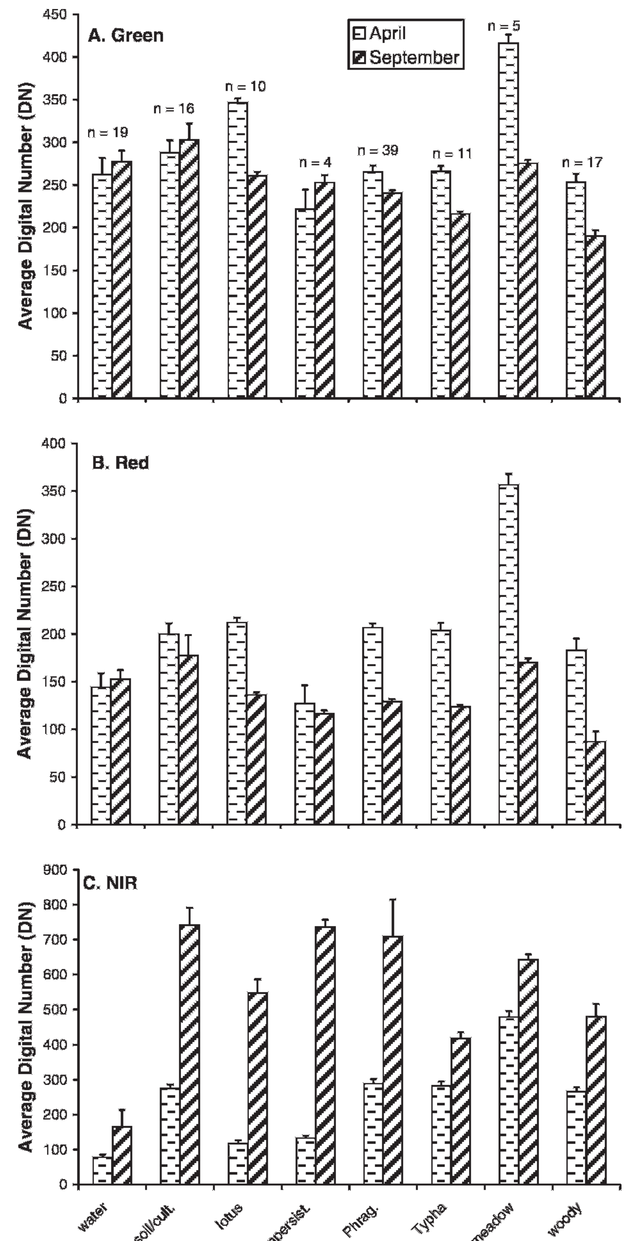

Figure 4. Digital numbers (mean + SE) for green, red, and NIR bands at points confirmed to be correctly mapped within the eight wetland classes.

Accuracy Assessment

Assignment of field vegetation to a wetland cover class for reference data was done without knowledge of the mapped class that might bias the assignment. An error matrix of the image analysis yielded an overall accuracy of 62% and a $\hat{k}$ value of 0.542, but map accuracy varied substantially among the eight classes mapped (Table 3). Both user's and producer's accuracies were $> 70\%$ for water, soil/cultivated, and woody vegetation, but there was moderate to severe misclassification of the five emergent wetland classes. Inspection of the imagery after field data collection revealed a variety of reasons for these errors.

All but two of the points mapped as water were found to be water in the field (90% user's accuracy); the two erroneous points were located on a boundary between water and cattail. Eight points were found in the field to be water but not mapped as such (70% producer's accuracy). Inspection of the September 2002 imagery showed that five of these were clearly vegetated as of that date, so this "error" actually represents a change in conditions between the image date and the date of the reference data. The three points mapped as *Nelumbo* but found to be water were all east of Gard Island, and visual inspection of the imagery confirmed the mapped classification (Figure 5). However, this area of North Maumee Bay is experiencing active erosion, so a change in wetland configuration near Gard Island is likely. The points classified as soil and *Typha* that were found to be water were within diked areas that had clearly been flooded since the image date. The producer's accuracy for water was increased to 86% by assuming that these five points correctly portrayed conditions as of the image date, and overall accuracy was raised to 64% (Table 3).

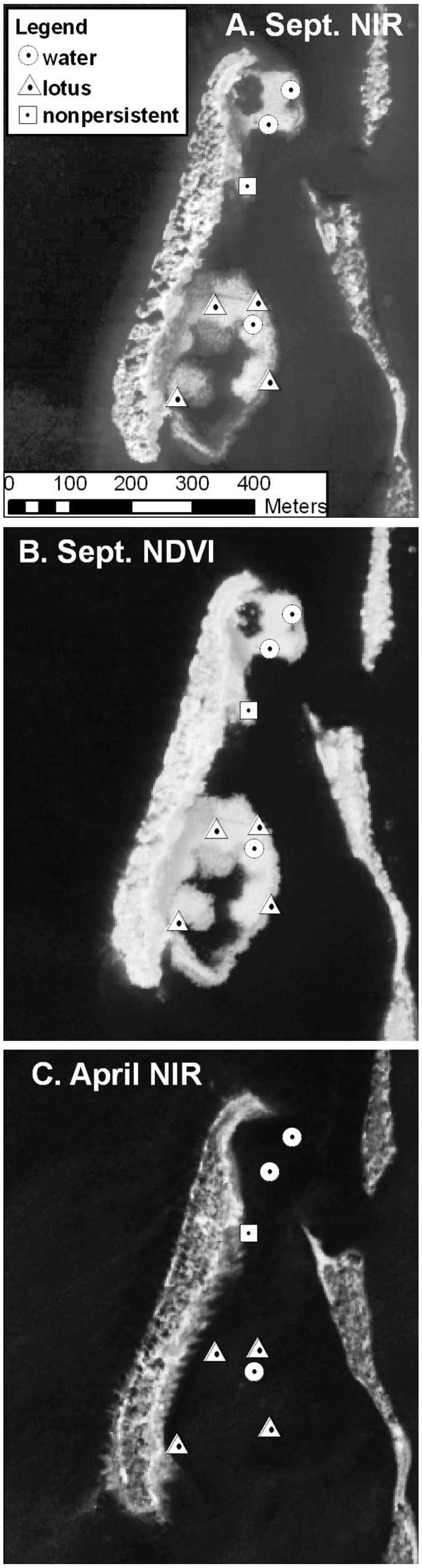

Figure 5. *Nelumbo lutea* beds near Gard Island, showing appearance on selected image layers and field determination of reference point classes. A. *Nelumbo* beds are clearly visible on September NIR image. B. bright photosynthesizing vegetation contrasts with dark water on September ←

NDVI image, and tree shadows are minimized. C. *Nelumbo* beds are undetectable on April image, prior to emergence.

The high level of accuracy for the soil/beach/cultivated class was surprising given the diversity of conditions represented by this class and its propensity for change (Figure 2). All but two of the points found in the field to be bare soil/cultivated were correctly mapped (89% producer's accuracy), and inspection of those points suggested that cultivation changes may have occurred between the time of image acquisition and field checking. Five points mapped as bare soil/cultivated were other classes in the field. Excluding the diked flooded soil (see above) yielded an 81% user's accuracy. One of the erroneous soil/cultivated points was at the edge of a field, and the error could be due to expansion of field boundaries or georeferencing error.

All of the 11 *Nelumbo* beds visited in the field were correctly mapped except for one mapped as non persistent (producer's accuracy = 91%). User's accuracy was much lower (50%). Already noted was the problem of *Nelumbo* bed loss in the vicinity of Gard Island. Five points classified as *Nelumbo* beds were found in the field to be *Phragmites*; all five had unvegetated April soils that were dark due to wetness or burn scars. Two points classified as *Nelumbo* were found to be other non persistents, which is not considered to be a serious error.

The other non persistents class was quite inaccurate (17% user's accuracy, 50% producer's accuracy). Only eight points were actually found to have this type of vegetation in the field. Areas mapped as non persistent based on the multiseason image were usually found to be managed vegetation, where mowing and/or raised water levels within diked areas of the wetland caused the April image to appear as water (e.g., areas marked as ''burned'' on Figure 2). Nearly half of the points mapped as non persistent were found to be *Phragmites* in the field, and another three points were found to be *Typha*. This class represents a disadvantage of using multiseason imagery to infer non persistent vegetation: anthropogenically caused vegetation changes cannot be distinguished from natural phenological changes by spectral reflectance alone.

Areas mapped as *Phragmites* were generally so in the field (76% user's accuracy), but *Phragmites* was much more prevalent than expected (53% producer's accuracy). Most of the points erroneously mapped as *Phragmites* were actually *Typha* (7 out of 51), and a number of points mapped as *Typha* were actually

Table 3. The error matrix and producer's and user's accuracies resulting from an unsupervised classification with eight final classes and based on QuickBird high-resolution imagery of the Erie Marsh, North Maumee Bay, Michigan. Numbers in parentheses and bold represent corrected values based on visual interpretation of the images.

		Reference Classification									
		1	2	3	4	5	6	7	8	Raw Total	User's Accuracy
Unsupervised Classification	1 – Water	**19**			1	1				21	90%
	2 – Soil	1 (0)	**16 (17)**		1	1	1	1		21	76% (81%)
	3 – *Nelumbo*	3 (0)		**10 (13)**	2	5				20	50% (65%)
	4 – Other nonpersistent	3		1	**4**	11	3	1	1	24	17%
	5 – *Phragmites*		1			**39**	7	2	2	51	76%
	6 – *Typha*	1 (0)				8	**11 (12)**		1	21	52% (57%)
	7 – Meadow		1			8	3	**5**	1	18	28%
	8 – Woody					1	2		**17**	20	85%
	Column Total	27 (22)	18 (19)	11 (14)	8	74	27 (28)	9	22	196	
	Producer's Accuracy	70% (86%)	89% (90%)	91% (93%)	50%	53%	41% (43%)	56%	77%		Overall Accuracy 62% (64%)

Phragmites (8 out of 21), illustrating that the separation between these two species was imperfect. Most of the errors of *Phragmites* omission were due to confusion between managed *Phragmites* and non persistent emergents (see preceding). Eight points found to be *Phragmites* were mapped as wet meadow; most of these points were located at the end of the Woodtick Peninsula, and may be due to differences in substrate that were misinterpreted as vegetation differences. Points on the Woodtick Peninsula had sandy soils, whereas points elsewhere in the marsh generally did not.

Typha was inconsistently mapped. Nearly half of the points mapped as *Typha* were actually *Phragmites*, and only 41% of the points found in the field to be *Typha* were mapped as such. In addition to confusion with *Phragmites*, errors of omission included all classes except for *Nelumbo* and water.

Wet meadow was much less common than anticipated, occurring in the field at only nine points. Of these, five were correctly mapped. Of the 18 field check points mapped as wet meadow, eight were actually *Phragmites*, as discussed above. The resulting accuracies were low (28% user's accuracy, 56% producer's accuracy).

Points mapped as woody vegetation were usually correct (85% user's accuracy). Two points erroneously mapped as woody vegetation were actually *Typha*, which had a very similar spectral signature (Figure 4). The other point misclassified as woody was a *Phragmites* stand that fell within a tree shadow on the September image. Producer's accuracy was 77%, with errors partly due to confusion with *Typha* and misclassification of a dense stand of sandbar willow (*Salix interior* Rowlee) as *Phragmites*.

DISCUSSION

Using multiseason imagery to map Erie Marsh aided detection of some plant species but confused interpretation of others. Multiseason imagery was essential for identifying *Nelumbo* beds, which emerge anew from the waters of coastal wetlands every year. *Nelumbo lutea* is listed as "threatened" by the state of Michigan, but in other states (e.g., Connecticut) it is banned as a potentially invasive species (USDA 2008). In either case, the ability to detect *Nelumbo* beds with satellite imagery is beneficial.

The use of multiseason imagery was expected to aid identification of other non persistent emergents, but problems arose due to confusion with areas where anthropogenic action had artificially removed overlying plant material. For example, vegetation changes that occurred within a burned area of the wetland ("burned," Figure 2) were misclassified as non persistent emergents because of the change from extensive vegetation in September 2002 (before the burn) to shallow open water in April 2003 (after the burn). It was clear from visual inspection of the imagery prior to classification that these areas were not true non persistent emergents, but they were spectrally inseparable because of the comparable temporal change from photosynthesizing vegetation to water. The multiseason analysis was responding to two different causes of change, plant phenology and anthropogenic alteration, that had the same ultimate result but affected very different plant species. We easily could have improved our classification accuracy by masking out these human-altered areas prior to digital image analysis, but human alteration of wetland vegetation is a common occurrence in coastal wetlands, so our work provides a more realistic analysis of potential application problems.

The ability to reliably distinguish *Phragmites* from *Typha* is desirable because rapid invasion by the invasive Eurasian *Phragmites* genotype is an increasing problem in Great Lakes coastal wetlands (Johnston et al. 2007b, Pengra et al. 2007, Tulbure et al. 2007). Although we achieved moderate success at identifying *Phragmites*, the level of confusion between *Typha* and *Phragmites* was greater than we hoped for. Our overall accuracy would have improved from 64% to 72% by merging the *Phragmites* and *Typha* classes, but that would have defeated our objective to differentiate major wetland species. Other workers have also found that *Phragmites* and *Typha* are spectrally similar, but that airborne hyperspectral imagery has promise for differentiating them (Lopez et al. 2004). Future studies should also investigate the use of LiDAR to distinguish *Phragmites* and *Typha* stands based on height differences.

Phragmites and *Typha* have overlapping water depth preferences (Table 2), so some of the reported errors may have been due to actual vegetation changes that occurred between the time of image acquisition and reference data collection. *Phragmites* could have invaded *Typha* stands or vegetation management could have promoted *Typha* over this time period. *Typha* is a preferred food of muskrats, so herbivory could have influenced its abundance (Kroll and Meeks 1985); muskrat lodges were clearly visible to the human eye on the April image. We know that the lag time between image and reference data acquisition caused fictional errors in our mapping of *Nelumbo* beds (Figure 5), but we have no way to assess whether this happened between *Phragmites* and *Typha*. Optimally, reference data should be collected at the same time as image acquisition.

In the field, vegetation interspersion and alteration sometimes made it difficult to assign a reference point to a particular class. Our requirement that reference points be restricted to 3 × 3 neighboring pixels belonging to the same class slightly reduced interspersion, but a number of reference points were within areas where patch sizes were small and interspersed, or at the edge between two different classes. Because minor georeferencing errors in the imagery and/or the field GPS unit might have caused a spatial mismatch between the image point and its field reference point, choosing reference points within a larger contiguous clump of same-class pixels might have reduced such edge effects. Assignment of field vegetation to a class was done without knowledge of the mapped class that might bias the assignment, but the field assignment was sometimes ambiguous, and later inspection of the field data for erroneously mapped points often revealed that the reference point had some attributes of the mapped class. For example, a point mapped as *Nelumbo* that contained 20% *Nelumbo* and 20% *Sagittaria* cover was field-assigned to the non persistent emergent class and considered incorrectly mapped. Utilization of a fuzzy matrix approach that incorporates variability into the reference data might have reduced the effect of such minor errors (Congalton and Green 1999).

Collection of reference data at random points was extremely difficult. We walked to most of the reference points because much of the study area was inaccessible by canoe, but walking through *Phragmites* stands was difficult due to slippery clay soils and dense, tall vegetation (Figure 3f). Access on foot was sometimes impeded by deep ditches. Thus, some sections of the area of study had fewer data points than intended (e.g., Woodtick Peninsula). The final reference data set contained 196 points, an average of one point per every 4.7 ha.

Our number of reference points was less than the recommended "rule-of-thumb" of 50 points per mapped class (Congalton 1991). However, this rule-of-thumb is rarely adhered to in remote sensing studies of freshwater emergent wetlands due to the logistical difficulties of obtaining field data. For example, Phillips et al. (2005) used 10, 14, and 59 reference points for their mapped classes of deep marsh, wet meadow, and prairie grassland. Sawaya et al. (2003) used only 5 to 27 field reference points per mapped class (83 reference points total) when they mapped wetlands of the > 3600 ha Swan Lake, an average of one reference point per every 43 ha. Furthermore, their points were not randomly generated as ours were, but were selected by taking the classified image into the field so that they could "identify unique areas with different spectral-radiometric responses on the image and target them for field identification" (Sawaya et al. 2003:152). Our approach of randomly selecting points in advance of the field work and of gathering field data without knowledge of the mapped class imposed a much more statistically rigorous test that should be considered when comparing our overall accuracy with that of other studies.

Digital analysis combined with visual interpretation of displayed satellite imagery might yield the best results. The high resolution QuickBird imagery can be visually interpreted much like digital aerial photography, a capability which Johnston et al. (2007b) used to map land use. The size, shape, location, and context of mowed and burned areas made them easily discernable on the imagery by a trained air photo interpreter (co-author Johnston). Improved results might have been obtained by inferring the vegetation present in human-altered areas from these contextual clues, rather than trying to use spectral characteristics alone. Alternatively, an object-oriented image classification system such as eCognition that takes into consideration some of these size, shape, and contextual clues might improve the classification (Hurd et al. 2006).

QuickBird imagery has only four spectral bands. Unlike Landsat TM, ETM+ or SPOT imagery, QuickBird does not have a mid-IR band, but only NIR (760 to 900 nm). The fact that mid-IR bands and hyperspectral imagery have been demonstrated to provide separability between wetland types (Jensen et al. 1993a, Hirano et al. 2003, Bachmann et al. 2002, Lopez et al. 2004), constitutes a disadvantage of using QuickBird for wetland mapping. However, QuickBird's fine spatial resolution offers advantages over course resolution hyperspectral satellite imagery, such as Hyperion, in instances where wetlands are configured in strips narrower than image pixel dimensions (Pengra et al. 2007). Thus, there are trade-offs between QuickBird's higher spatial resolution and its lower spectral resolution.

Despite our somewhat low accuracy, we felt that the QuickBird imagery itself was very appropriate for use in wetland vegetation mapping. The fine pixel resolution allowed us to reliably distinguish features that were long and narrow, such as rows of trees growing on dikes and berms. Coastal wetland vegetation often occurs in narrow bands controlled by water depth or may invade in linear anthropogenic features, such as roadside ditches (Maheu-Giroux and de Blois 2007), so fine resolution is crucial for detecting such zonation. Multiseason, multispectral, high-resolution imagery such as QuickBird could be successfully used for mapping certain wetland plant communities such as invasive *Phragmites* in unaltered wetlands, but in highly fragmented and managed areas, multiseason imagery may not reflect natural processes but rather human alterations of the landscape.

ACKNOWLEDGMENTS

We thank Heidi Walking for field assistance and Tami Watson for assistance with figures. Peter Wolter collected the 2002 field reconnaissance data and provided helpful comments on a manuscript draft. Special thanks go to Jeff Savino at University of Toledo Lake Erie Center for help with the logistics in the field. We also thank Joseph Robison at Michigan DNR and Douglas Pearsall at East Michigan TNC for allowing us access on their properties. This research was supported by a grant from the National Aeronautics and Space Administration (NAG5-11262-Sup 5) and through a cooperative agreement with U.S. Environmental Protection Agency's Science to Achieve Results Estuarine and Great Lakes program through funding to Great Lakes Environmental Indicators, U.S. EPA Agreement R828675-00. Although the research described in this article has been funded in part by the U. S. EPA, it has not been subjected to the agency's required peer and policy review and therefore does not necessarily reflect the views of the agency and no official endorsement should be inferred.

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Manuscript received 19 February 2008; accepted 28 July 2008.