USING HIGH RESOLUTION SATELLITE IMAGERY TO MAP AQUATIC MACROPHYTES ON MULTIPLE LAKES IN NORTHERN INDIANA

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ABSTRACT

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Resource managers need to be able to quickly and accurately map aquatic plants in freshwater lakes and ponds for regulatory purposes, to monitor the health of native species and to monitor the spread of invasive species. Site surveys and transects are expensive and time consuming, and low resolution imagery is not detailed enough to map multiple, small lakes spread out over large areas. This study evaluated methods for mapping aquatic plants using high resolution Quickbird satellite imagery obtained in 2007 and 2008. The study area included nine lakes in northern Indiana chosen because they are used for recreation, have residential development along their shorelines, support a diverse wildlife population, and are susceptible to invasive species. An unsupervised classification was used to develop two levels of classification. The Level I classification divided the vegetation into detailed classes of emergent and submerged vegetation based on plant structure. In the Level II classification, these classes were combined into more general categories. Overall accuracy of the Level I classification was 68% for the 2007 imagery and 58% for the 2008 imagery. The overall accuracy of the Level II classification was higher for both the 2007 and 2008 imagery at 75% and 74%, respectively. Classes containing bulrushes were the least accurately mapped in the Level I classification. In the Level II classification, the least accurately mapped class was submerged vegetation. Water and man-made surfaces were mapped with the highest degree of accuracy in both classification schemes. Overhanging trees and shore vegetation contributed to classification error. Overall, results of this research suggest that high resolution imagery provides useful information for natural resource managers. It is most applicable to mapping general aquatic vegetation categories, such as submerged and emergent vegetation, and providing general estimates of plant coverage in lakes. Better

methods for mapping individual species, species assemblages, and submerged vegetation constitute areas for further research.

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INTRODUCTION

Inland wetlands, lakes, and ponds are important environmental resources that store excess floodwaters, improve water quality, provide habitat for fish and wildlife, and recharge groundwater aquifers (Ozesmi and Bauer 2002). Aquatic plants have been recognized as important components of these freshwater ecosystems (Olmanson et al. 2002). Emergent aquatic macrophytes provide shade, cover, and help maintain cooler water temperatures necessary for fish and other aquatic organisms (Jakubauskas et al. 2000; Vis et al. 2003). Submerged aquatic macrophytes form diverse habitats that are utilized by fish, invertebrates and algae, and they can also be an early indicator of declining wetland health (Lehmann and Lachavanne 1999; Vis et al. 2003; Wolter et al. 2005). In recent years, better environmental protection of aquatic environments has created a need for increased mapping of aquatic vegetation by consultants, citizen groups, and state and local agencies (Madden 2004; Olmanson et al. 2002; Shuman and Ambrose 2003).

Standard methods of mapping aquatic macrophytes beds involve surveys of vegetation using sampling and field observations along quadrants or transects. These methods are often expensive and time consuming (Jakubauskas et al. 2002; Nelson et al. 2006; Vis et al. 2003). Extensive field data collection in areas of dense vegetation or wetland and aquatic environments that are difficult to access make traditional methods impractical (Jakubauskas et al. 2002; Jensen et al. 1986). In addition, ground sampling and mapping techniques can disturb the vegetative beds and wildlife (Shuman and Ambrose 2003). These techniques are also impractical to use when inventorying many lakes spread out over large distances (Nelson et al. 2006). Standard mapping methods are also challenging to implement when it’s necessary to account for rapid changes in aquatic macrophyte extent and density, especially when looking at a seasonal or interannual time scale (Jakubauskas et al. 2002).

Despite difficulties in obtaining the information, being able to quickly and economically map aquatic macrophyte beds is vital for their effective management. Accurate maps allow resource managers to assess the composition of plant beds and the abundance of species either directly or indirectly (Turner et al. 2003; Olmanson et al. 2002; Wolter et al. 2005). Changes in growth patterns of aquatic plants are important indicators of water quality which can impact humans, wildlife, and fisheries (Jakubauskas et al. 2000; Valta-Hulkkonen et al. 2005). High resolution satellite imagery is a potentially cost-effective way to gather information about aquatic macrophyte communities. In particular, remote sensing can be used to economically map aquatic vegetation in lakes spread out over a large area, costing as little as one half traditional surveying methods (Valta-Hulkkonen et al. 2005).

Previous studies have shown that remote sensing can be an effective tool for mapping aquatic macrophyte beds in saltwater, brackish water, and freshwater environments (Ciraolo et al. 2006; Everitt et al. 2005; Jakubauskas et al. 2002; Laba et al. 2008; Marshall and Lee 1994; Sawaya et al. 2003; Underwood et al. 2006; Wolter et al. 2005). Remote sensing is most effective in mapping emergent and floating macrophyte beds, and less so with submerged macrophytes (Laba et al. 2008; Marshall and Lee 1994; Nelson et al. 2006; Underwood et al. 2006; Valta-Hulkkonen et al. 2005; Vis et al. 2003). Historically, aerial photography has been the most widely used method of obtaining detailed aquatic vegetation data and is still used today (Jensen et al. 1986; Marshall and Lee 1994; Valta-Hulkkonen et al. 2005). However, as the spatial resolution of satellites has improved, there has been a shift to using satellite imagery to map aquatic vegetation (Everitt et al. 2005; Everitt et al. 2008; Jakubauskas et al. 2002; Laba et al. 2008; Madden 2004; Nelson et al. 2006; Olmanson et al. 2002; Ozemi and Bauer 2002; Sawaya et al. 2003; Wolter et al. 2005). Satellite imagery is more effective than aerial photography when researchers need high resolution imagery that covers a large geographic area (Madden 2004). Using satellite imagery produces maps which can be used to prioritize areas of vegetation removal and allows for the assessment of the success or failure of aquatic plant control efforts (Jakubauskas et al. 2002; Madden 2004).

Satellite imagery has also been used to track and monitor the spread of invasive species (Madden 2004). Such monitoring across multiple sites could facilitate the detection of new or spreading invasive species early enough that eradication efforts could be successful (Laba et al. 2008). Information from these monitoring systems could then be used as input into models which can predict future plant distribution and assist in

making future management decisions (Mironga 2004). Information on changes in the surrounding land uses over time is also provided (Ozesmi and Bauer 2002).
An invasive species is any species of plant or animal that is not native to that ecosystem and “whose introduction does or is likely to cause economic or environmental harm or harm to human health” (Executive Order 13112 1999). Invasive aquatic plant species can have severe ecological and economic impact and can adversely impact navigation, nutrient cycling in wetlands and lakes, water quality, drinking water supplies, hydropower facilities, irrigation, fisheries, recreation, wildlife, and native vegetation diversity (Jakubauskas et al. 2002; Laba et al. 2008; Madden 2004; Underwood et al. 2006). Federal and state governments spend millions of dollars annually on plant management programs (Jakubauskas et al. 2002). A major proportion of these budgets are targeted towards the monitoring and control of invasive plant species.

Starting in 1988, the Indiana Department of Natural Resources (IDNR) created the Lake and River Enhancement program (LARE). Aquatic vegetation management plans for many of the lakes in Indiana were created as part of this program. The aquatic vegetation plans consisted of a survey of the plant communities present in the lakes, a catalogue of invasive species, fisheries data, and methods for managing any nuisance or invasive species. In order to prepare these plans, either IDNR personnel or private companies have been contracted to survey aquatic macrophytes using traditional field-based plant survey methods.

The purpose of this study was to test a method for mapping aquatic macrophyte vegetation, both emergent and submerged, using Quickbird satellite imagery so that the resulting maps will be useful to resource managers in a variety of ways including:

1) Outlining the extent of vegetative beds for management purposes
2) Monitoring the extent and health of native plant species
3) Monitoring the current extent and spread of invasive plant species
4) Identification of man-made shoreline and lake structures such as docks, erosion control structures, etc.

These goals were chosen for several reasons. Outlining the extent of vegetative beds has important management implications. Under Indiana law, vegetative beds larger than 58 m^2 (625 ft^2) are considered areas of “special concern” by the Indiana Administrative Code Title 312 Article 11 (2005). Disrupting, spraying to control vegetation, or otherwise impacting such beds requires both permits and special review. However, vegetative beds with a surface area of less than 58 m^2 (625 ft^2) that are near a boat landing can be managed without the use of pesticides and without a permit if they meet certain other conditions (IDNR LARE Reports: Adams Lake 2008; Indiana Administrative Code Title 312 Article 11). In addition, owners must obtain a permit and go through a special review in order to disrupt these large beds by building a permanent pier or other structure. Outlining the extent of current vegetative beds would allow for better enforcement of this law and would allow the IDNR to better target areas which can be managed without a permit. Being able to identify man-made structures from satellite imagery would allow the IDNR to better track permanent structures already in place and to locate areas where permits are needed for further construction. Currently, pesticide applications partially funded by the LARE program are used to control invasive species in Indiana lakes. Examples of lakes in the northern Indiana study area include Adams, Little Turkey, and Messick (IDNR LARE Reports: Adams Lake 2008; IDNR LARE Reports: Five Lakes 2007; IDNR LARE Reports: Little Turkey Lake 2008). The use of high resolution satellite imagery provides maps of the distribution of aquatic macrophyte communities and offers the potential to greatly reduce the need for ground surveys to monitor the impact of aquatic vegetation control programs.

Both emergent and submerged vegetation were mapped in this study. Mapping at the species level was preferred, but broader categories of plant structure were the primary focus of the current study given the limitations of species-level identification from remotely sensed imagery. Special attention was given to finding an efficient, repeatable process that can then be applied to many lakes spread across a region.

To this end, ten lakes in northern Indiana were chosen by the IDNR as representative of the type of lakes found in the study area that had available ground-truth data available. These lakes were all small (less than 125.45 surface hectares (310 acres)) and covered a wide variety of depths, water qualities, and aquatic macrophyte bed composition. In addition, problem or invasive species were found in all ten of the lakes. Invasive species occurring in the lakes included Eurasian watermilfoil (*Myriophyllum* *spicatum*), purple loosestrife (*Lythum salicaria)*, curly leaf pondweed (*Potamogeton crispus*), and brittle naiad (*Najas minor*). Eurasian watermilfoil was of particular concern because of its aggressive growth, detrimental effects on native plant communities, and ability to impede human recreational activities (IDNR LARE Reports: Adams Lake 2008; IDNR LARE Reports: Five Lakes 2007; IDNR LARE Reports: Indian Lakes 2001; IDNR LARE Reports: Little Turkey Lake 2008; Jakubauskas et al. 2002). These lakes are used extensively for recreation, have residential development along their shorelines, support a diverse and healthy wildlife population, and are susceptible to invasive species (IDNR LARE Reports: Adams Lake 2008; IDNR LARE Reports: Cree Lake 2005; IDNR LARE Reports: Five Lakes 2007; IDNR LARE Reports: Indian Lakes 2001; IDNR LARE Reports: Little Tueky Lake 2008).

BACKGROUND

The study of aquatic macrophytes using remote sensing techniques has been less comprehensive than that of terrestrial vegetation because of the additional challenges associated with water reflectance, differentiating between different macrophyte species, and the small scale of freshwater aquatic environments compared to the resolution of most sensors (Nelson et al. 2006; Underwood et al. 2006). It is known that different types of aquatic vegetation have subtly different spectral reflectance signatures, which differ greatly from open water and non-vegetated areas (Marshall and Lee 1994; Ozesmi and Bauer 2002; Peñuelas et al. 1993; Underwood et al. 2003). However, in the case of mixed beds, the varying contribution of each emergent macrophytes species to the total coverage remains difficult (Underwood et al. 2006; Vis et al. 2003).

Mapping submerged aquatic vegetation with remote sensing can be problematic. The electromagnetic radiation reflected or radiating from submerged vegetation must cross the air-water interface (Wolter et al. 2005). In addition, because water absorbs much of the electromagnetic spectrum used in remote sensing, a major complication in remotely sensing submerged vegetation is depth of the macrophyte canopy in the water column (Han and Rundquist 2003; Peñuelas et al. 1993; Wolter et al. 2005). Non-canopy forming submerged vegetative species are the most commonly misclassified submerged vegetation (Valta-Hulkkonen et al. 2005; Vis et al. 2003; Wolter et al. 2005).

Studies that have been able to map submerged vegetation have reported that it can be sensed and classified to a maximum depth between 2 m and 3 m (6.5 ft and 9.8 ft) (Han 2002; Sawaya et al. 2003; Welch and Remillard 1988). However, submerged vegetation is harder to remotely sense when concentrations of algae increase and in water with increased turbidity (Han and Rundquist 2003; Underwood et al. 2006; Valta-Hulkkonen et al. 2005; Vis et al. 2003). When submerged vegetation is mapped, researchers often label it only as “submerged” with no attempt to differentiate between species or plant structure types (Saway et al. 2003; Welch and Remillard 1988; Wolter et al. 2005). For this reason, researchers have primarily used remote sensing to detect dense homogenous clusters of submersed vegetation (Nelson et al. 2006; Underwood et al.

2006; Vis et al. 2003; Zhu et al. 2007). At least one study has shown that it is possible to differentiate between different submerged macrophytes using remote sensing. Pinnel et al. (2004) were able to distinguish between the two submerged macrophyte groups *Chara* and *Potomageton* using hyperspectral sensors.

Previous work has approached the problem of aquatic vegetation remote sensing from a number of different directions. Ackleson (2003) reviewed historical and recent efforts to model light fields in shallow, marine environments. More advanced remote sensing systems and a better understanding of what the current remote sensing systems are finding can be achieved by understanding how light propagates through the water column. This work is geared more towards submerged vegetation than to emergent vegetation.

Researchers have also done experimental work on how various environmental characteristics affect the spectral signature of aquatic vegetation. Han (2002) examined the effects of depth on reflectance from marine species of sea grass. As depth increased, the reflectance decreased. Han and Rundquist (2003) studied the effects of depth on the spectral signatures of coontail (*Ceratophyllum demersum*), a submerged, freshwater macrophyte. They also considered the effects of depth in both clear and algae-laden waters. In the study, the authors found that as depth increased, the amount of reflectance from the submerged macrophyte decreased, particularly in the infrared and green parts of the spectrum. Another study on submerged vegetation examined a type of eel grass (*Vallisneria spiralis)* but focused on coverage as opposed to depth in both a laboratory and in algae-laden waters in the field (Yuan and Zhang 2007). As the amount of coverage of the submerged macrophyte decreased, the amount of reflectance decreased; again, most heavily in infrared and green wavelengths. Of particular interest is that Yuan and Zhang (2007) found that the "green peak" was more evident in algae-laden waters and did not decrease as quickly with a decrease in coverage in algae-laden waters as in clear waters. The presence of algae emphasizes the green portion of the spectrum and masks the decrease in the spectral signature with respect to coverage that is normally seen in non-algae laden waters. Jakubauskas et al. (2000) studied the effects of canopy coverage on the spectral signature of the emergent macrophyte spatterdock or yellow pond lily (*Nuphar polysepalum*). The authors found that as the coverage of emergent macrophyte decreased, the amount of reflectance decreased in the green and infrared parts of the spectrum. Similar results were also found using water hyacinth (*Eichornia crassipes*) and percent coverage in Texas waterways (Jakubauskas et al. 2002). The researchers concluded that even though this work was done at close range with hand-held hyperspectral sensors, the high correlations between vegetation cover and infrared reflectance should be transferable to satellite sensors with broader bandwidths (Jakubauskas et al. 2000).

Aerial photography, hyperspectral airborne imagery, and satellite imagery are all used to map aquatic vegetation remotely (Madden 2004). Aerial photography is relatively inexpensive and there is a large amount of archival data available for researchers to utilize (Underwood et al. 2003; Welch and Remillard 1988). Historically satellite imagery was preferred over aerial photography when mapping macrophyte species that were closely spaced or intermixed with each other (Jensen et al. 1986). This was because aerial photography had poor spectral resolution when compared to multispectral remote sensors and could contain variations in brightness caused by light fall off and bi-directional effects (Jensen et al. 1986; Valta-Hulkkonen et al. 2004). For this reason, Jensen et al. (1986) and Moore et al. (2000) stated that aerial photography is best suited to interpretation of homogenous emergent beds and is not adequate to map most submerged vegetation. Another problem was that visual interpretation of aerial photography was a labor intensive process (Marshall and Lee 1994; Nelson et al. 2006).

Advances in aerial photography have improved both the spatial and spectral resolution in some cases making aerial photograph equivalent or superior to high resolution satellite imagery (Madden 2004). However, aerial photography still has limited use when assessing macrophyte distributions across many small bodies of water spread across a large geographical area (Nelson et al. 2006). This is because even high resolution cameras mounted on an aircraft do not have as great a field of view as a sensor on a satellite (Madden 2004). For this reason, aerial photography requires multiple passes to cover the same area acquired at one point in time by satellite imagery. These additional passes can introduce changes in light and atmospheric conditions, which in turn can affect classification attempts (Jensen 2007; Valta-Hulkkonen et al. 2004).

High spectral and spatial resolution satellite imagery provides more detailed spectral information relative to traditional photography that can be used to classify aquatic macrophyte species (Jensen et al. 1986). Early satellites, such as Landsat TM, with moderate spatial and spectral resolutions were unable to identify mixed beds or invasive species unless they dominated the beds (Laba et al. 2008). Coarser resolutions have also been linked to lower accuracies in classifications (Everitt et al. 2008) and are not suited to mapping most submerged aquatic vegetation (Underwood et al. 2006). Newer satellites, such as Quickbird and IKONOS, have provided more detailed results when it comes to spatial and spectral resolution (Everitt et al. 2005; Everitt et al. 2008; Jakubauskas et al. 2002; Laba et al. 2007; Olmanson et al. 2002; Sawaya et al. 2003).

Hyperspectral satellites and airborne scanners have been used to map submerged vegetation in shallow water lagoons (Ciraolo et al. 2006), and in mapping invasive species over an entire freshwater delta (Underwood et al. 2006). While hyperspectral imagery can be useful in discriminating between vegetation and exotic species, the large data volume inherent in this method makes it challenging for use by resource managers without sufficient expertise and data processing capabilities (Madden 2004).

Generally, permanently flooded or open water ponds and lakes are the easiest freshwater ecosystems on which to map aquatic macrophytes (Ozesmi and Bauer 2002). The majority of existing studies focus on one lake or wetland, though some cover large lakes or whole regions (Underwood et al. 2006; Wolter et al. 2005; Zhu et al. 2007). One of the reasons that studies have focused on single locations is that lakes can vary widely in suspended sediments, Secchi depth transparency, and chlorophyll content, all of which can influence how aquatic macrophytes are remotely sensed, though there is some debate about this (Nelson et al. 2006). Studies that focused on a large number of lakes spread out over a large area are fewer in number and often broader in scope than just mapping aquatic macrophytes (Nelson et al. 2006; Sawaya et al. 2003; Valta-Hulkkonen et al. 2005).

The number of vegetative and non-vegetative classes that authors attempt to map varies greatly from study to study. Most of the studies reviewed have used 5-10 classes (Everitt et al. 2005; Everitt et al. 2008; Jensen et al. 1986; Mackey et al. 1992; Olmanson et al. 2002; Sawaya et al. 2003; Valta-Hulkkonen et al. 2005; Vis et al. 2005; Wolter et al. 2005). These studies rarely map to the species level; instead, plant types are aggregated by either leaf or plant structure (Mackey et al. 1992; Nelson et al. 2006; Olmanson et al. 2002; Saway et al. 2003; Valta-Hulkkonen et al. 2005; Vis et al. 2003) into ecological categories (Everitt et al. 2005; Jensen et al. 1986), or a mixture of the two (Welch and Remillard 1988). Laba et al. (2008) mapped twenty classes, some at the species level. The rest were classified using ecological categories (such as wooded swamp, scrub/shrub, salt meadow, etc). Others chose to group plants based on criteria known to cause differences in spectral signature, such as plant cover (Nelson et al. 2006; Wolter et al. 2005) or in the case of submerged vegetation, depth (Olmanson et al. 2002; Sawaya et al. 2003). In some cases, such as Everitt et al. (2005, 2008) and Underwood et al. (2006), the focus was on mapping a particular invasive species instead of mapping a broad range of macrophytes. Therefore, all other plants were grouped into a few broad categories.

METHODS

Study Area:

The study area consisted of ten lakes in Lagrange Co. and Noble Co. in northern Indiana spread out over 220 km^2. These lakes include Adams Lake, Cree Lake, Jones Lake, Latta Lake, Little Turkey, Messick Lake, Steinbarger Lake, Tamarack Lake, Waldron Lake, and Witmer Lake (Fig. 1). Waldron, Jones, Steinbarger, and Tamarack are a chain lake system connected by a series of narrow waterways. They are collectively referred to as the WJST chain. These lakes range in size from Adams with a total surface area of 125 ha (308 acres) to Latta with a surface area of just 18 ha (45 acres). The maximum depth of the lakes is 28.35 m (93 ft) in Adams with average depths in the lakes ranging from 10.67 m to 2.59 m (25 ft to 8.5 ft). Lake clarity varies from very good in Cree with secchi depths between 2.47 m to 2.59 m (8.1 ft to 8.5 ft) to poor in Little Turkey with a secchi depth of less than 0.98 m (< 3.2 ft). Table 1 shows size, depth, and clarity information for all the lakes in the study area with the exception of Latta, where there is no depth or clarity information available.

Table 1
Lake and water characteristics of the lakes utilized in this study.

Lake Name	County	Surface Area in hectares (acres)	Max Depth in meters (ft)	Avg. Depth in meters (ft)	Clarity	Secchi Depth in meters (ft)	2007 Recorded Secchi Depth in meters (ft)
Adams	Lagrange	125 (308)	28.35 (93)	7.62 (25)	Good	1.52 – 2.74 (5 – 9)	
Cree	Noble	31 (76)	7.92 (26)	4.79 (15.7)	Very good	2.47 – 2.59 (8.1 – 8.5)	2.83 (9.3)
Jones	Noble	46 (114)	7.62 (25)	2.59 (8.5)	Low	1.22 (4)	-
Latta	Noble	18 (45)	-	-	-	-	-
Little Turkey	Lagrange	55 (135)	10.97 (36)	3.51 (11.5)	Low	< 0.98 (< 3.2)	0.58 (1.9)
Messick	Lagrange	28 (68)	16.46 (54)	6.40 (21)	Intermediate	-	-
Steinbarger	Noble	30 (73)	11.89 (39)	6.71 (22)	Intermediate	1.07 – 2.90 (3.5 – 9.5)	0.64 (2.1)
Tamarack	Noble	20 (50)	11.28 (37)	5.33 (17.5)	Intermediate	1.07 – 2.44 (3.5 – 8)	-
Waldron	Noble	87 (216)	13.72 (45)	4.27 (14)	Low	1.22 (4)	-
Witmer	Lagrange	83 (204)	16.46 (54)	10.67 (35)	Low	1.07 (3.5)	-

Source: IDNR Lake Reports: Adams Lake 2008; IDNR LARE Reports: Cree Lake 2005; IDNR LARE Reports: Five Lakes 2007; IDNR LARE Reports: Indian Lakes 2001; IDNR LARE Reports: Little Turkey Lake 2008; 2007 Field Data

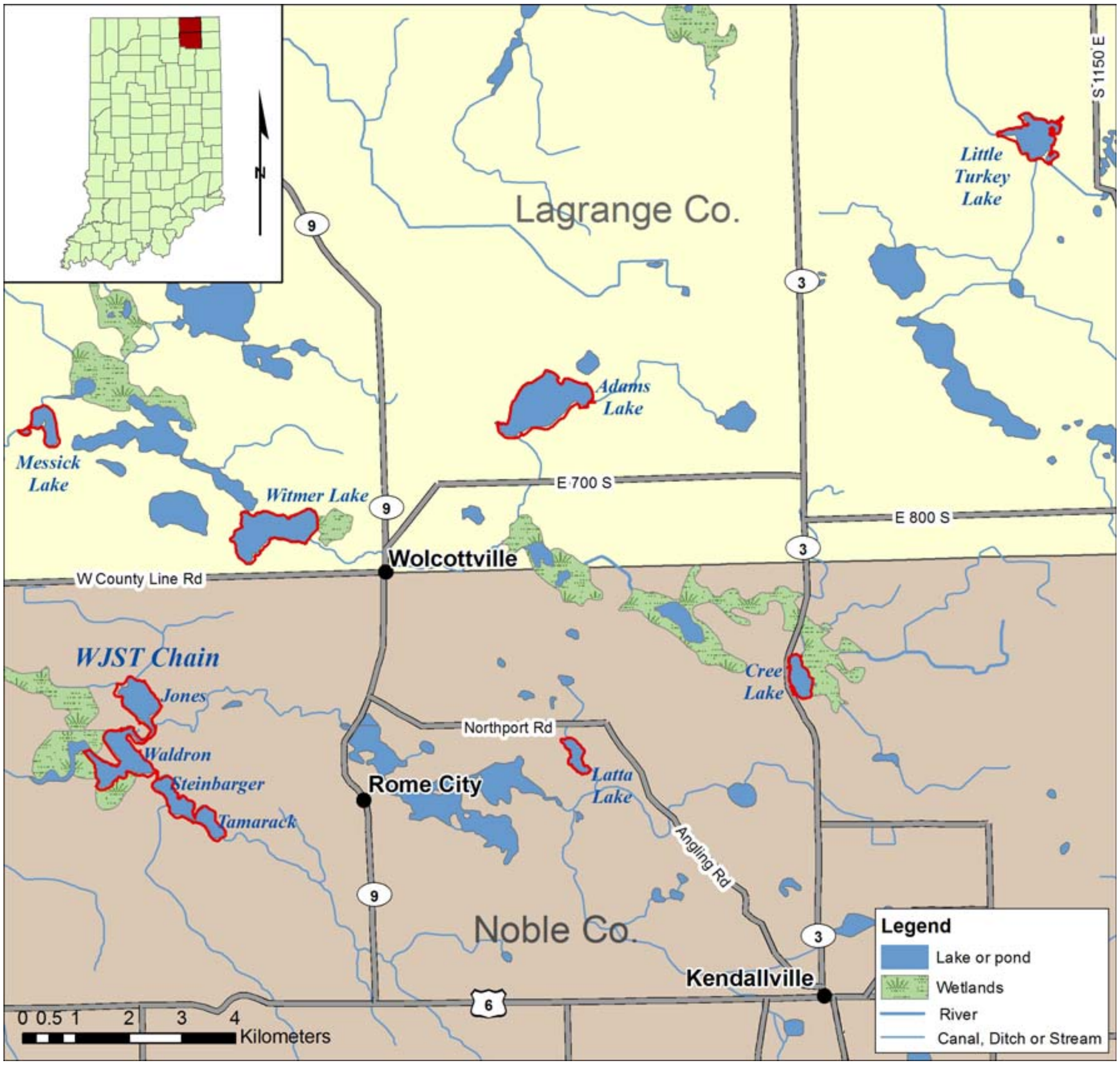

Fig. 1. Locations of the lakes in Lagrange and Noble counties. The ten lakes outlined in red are the focus of this study.

Satellite Imagery:

Multispectral satellite imagery was acquired for the study area using DigitalGlobe's Quickbird sensor. The Quickbird sensor has a spatial resolution of 2.4 m (7.87 ft) for multispectral images with four bands in the blue (450 to 520 nm), green (520 to 600 nm), red (630 to 690 nm) and near-infrared (760 to 900 nm) wavelength. It also produces panchromatic imagery with a resolution of 60 cm (1.97 ft). Quickbird was chosen because a high spatial resolution was needed to map the aquatic macrophytes in the small lakes.

Satellite imagery was acquired for the study area on September 15, 2007, August 6, 2008, and September 6, 2008. These late summer dates were used because the optimal time to map the areal extent of emergent and submerged vegetation is late in the growing season when full emergence has occurred but before the beds have begun to senesce or die back due to frost (Mackey 1992; Marshall and Lee 1994; Nelson et al. 2006; Wolter et al. 2005).

Each of the satellite images is less than optimal in some way. Heavy cloud cover over the study area obscured all of the study lakes but Cree Lake in the September 15, 2007 imagery. Cree Lake had some cloud effects over the southern portion of the lake in this image date, but was otherwise of good quality (Fig 2). The image acquired on September 6, 2008 covers Adams, Latta, Messick, Witmer, and the WJST chain. It was of good quality with minimal effects of wind drift, sun glint, and cloud cover. Witmer and Waldron Lake are impaired by thin cloud cover in this image. In Witmer Lake, a shadow cast from a cloud affects less than 5% of the shoreline. Shadows and clouds on Waldron Lake obscure about 40% of the shoreline (Fig. 3).

Fig. 2. Cree Lake from the September 15, 2007 imagery. The white circle shows an area of cloud interference.

Fig. 3. Waldron and Witmer Lakes in the September 6, 2008 imagery showing the cloud and shadow interference.

The August 6, 2008 image includes Cree, Little Turkey, Adams, and Latta Lakes. Reflectance from the lakes in this image appears to be adversely impacted by sun glint, wind effects, cloud cover, and turbidity. Figure 4 shows imagery for Latta Lake acquired on August 6, 2008 and September 6, 2008, and demonstrates the problems with the August imagery. In the August imagery, Cree Lake has over 50% of its surface obscured by cloud cover or shadows cast by clouds, in addition to the other reflectance problems. Previous work has shown that wind conditions and turbidity can greatly influence the ability to classify aquatic macrophytes (Ozesmi and Bauer 2002). Due to the problems with the August 6, 2008 imagery, the analysis focused on the imagery obtained on September 6, 2008 and September 15, 2007. This cut the number of lakes examined in the study from ten to nine with Little Turkey Lake no longer considered.

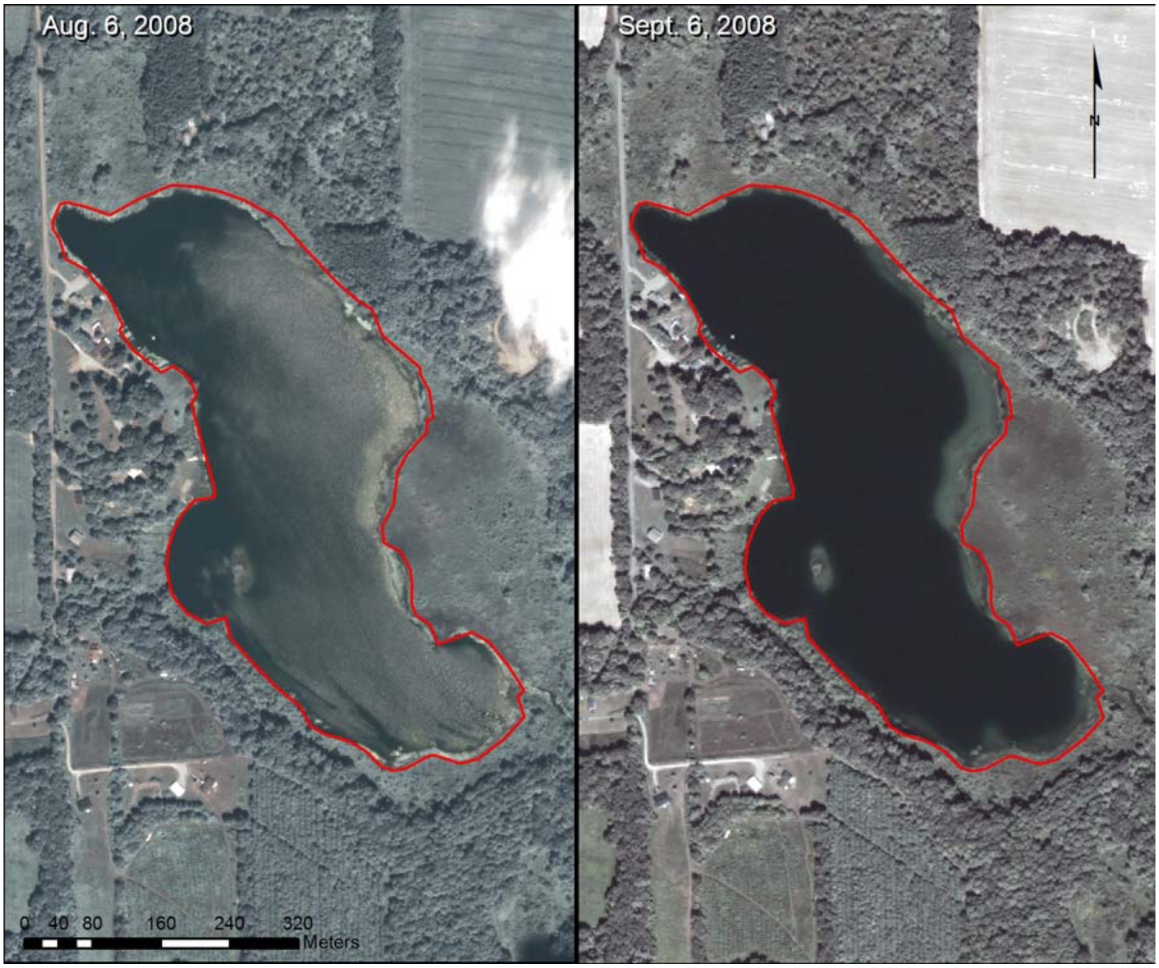

Fig. 4. Latta Lake from August 6, 2008 and September 6, 2008. The image from August 6 on the left shows the effects of wind and sun glint on the lake's surface while the September 6 image has no such problems.

Field Data:

Field reconnaissance of the lakes was conducted in early August of the 2007 and 2008 field seasons to ground truth the satellite imagery interpretation and document the general variability in aquatic macrophyte beds present. In 2007, field work emphasized collection of information on large emergent and submerged beds. A Trimble Differential GPS unit was used to map the farthest extent of the bed from the shoreline, field notes about the composition of the beds were recorded and beds were photographed. The 2007 field data covered all the lakes in the study area except Adams and Witmer Lakes.

During the 2008 field season, all beds larger than 2 m^2 (21.5 ft^2) in size were mapped using a Garmin GPSmap 76CSx. Waypoints were taken at the start of each bed when vegetation increased to approximately 25% coverage, at the farthest point of the bed from shore, and at the end of each bed. Waypoints were also recorded where the composition of the bed changed and where the beds were photographed. Plant identification, bed composition estimates, and distance to shore measurements were recorded. Table 2 gives a list of the major species and bed formers found in the lakes in the two field seasons.

Ground photographs of macrophyte beds and of individual plant species were collected in both field seasons. The photographs of the mixed beds were used to help identify composition variation within the beds. Some of the beds within the lakes showed distinct zonation, with one species dominating the shoreline, another dominating the nearshore, and a third composing the outer edge of the bed (Fig. 5). Other beds were not zoned and two or more plant species were intermingled in the bed. The photos also served as a way of cross-checking the accuracy of notes taken in the field. Individual species photographs were used to verify plant identifications and to illustrate the variety of macrophyte species found in the lakes.

In the 2007 field season, over 720 photographs were taken on eight of the lakes in the study area using a Nikon D2H digital SLR camera. The eight lakes covered in the 2007 field season were Cree, Latta, Little Turkey, Messick, and the WJST chain.

Fig. 5. A zoned mixed bed of pickerelweed (*Pontederia cordata*), white water lily (*Nymphaea orderata*), and the invasive Eurasian watermilfoil (*Myriophyllum spicatum*) in front of a house with lawn. Latta Lake, GPS point 1179, 2007.

In the 2008 field season, over 150 photographs were taken on six of the lakes in the study area using a Kodak Easyshare P850 camera. The six lakes photographed in the 2008 field season were Adams, Cree, Latta, Little Turkey, Messick, and Witmer Lake. The WJST chain was not photographed during the 2008 field campaign due to technical issues with the camera. Field notes about the plant bed composition were recorded for each picture.

Table 2
Plant species seen in the field.

Species Code	Scientific Name	Common Name	Vegetation Type
ALGA	Any species of filamentous algae	Algae	N
CEPOCC	*Cephalanthus occidentalis*	Buttonbush	E
CERDEM	*Ceratophyllum demersum*	Coontail	S
CHARA	*Chara sp.*	Chara, any species	S
DECVER	*Decodon verticillatus*	Swamp loosestrife or water willow	E
ELOCAN	*Elodea canadensis*	Canada waterweed	S
LEMMIO	*Lemna minor*	Small or common duckweed	N
*LYTSAL	*Lythum salicaria*	Purple loosestrife	E
*MYRSPI	*Myriophyllum spicatum*	Eurasian watermilfoil	S
NAJGUA	*Najas guadalupensis*	Southern naiad	S
*NAJMIN	*Najas minor*	Brittle naiad	S
NELLUT	*Nelumbo lutea*	American lotus	F
NUPADV	*Nuphar advena*	Spatterdock	F, E
NUPVAR	*Nuphar variegata* (formerly *N. luteum*)	Bullhead lily or yellow pond lily	F
NYMODT	*Nymphaea oderata subsp. tuberosa*	White water lily or fragrant water lily	F
PELVIR	*Peltandra virginica*	Arrow arum	E
PERAMP	*Persicaria amphibia*	Water knotweed or water smartweed	F
PHAARU	*Phalaris arundinacea*	Reed canary grass	E
PONCOR	*Pontederia cordata*	Pickerelweed	E
*POTCRI	*Potamogeton crispus*	Curly-leaf pondweed	S
POTILL	*Potamogeton illinoensis*	Illinois pondweed	S
POTNLV	*Potamogeton foliosus, P. pusillis,* or any other unidentified narrow-leaved pondweeds	Narrow-leaved pondweeds	S
POTZOS	*Potamogeton zosteriformis*	Flat-stemmed pondweed	S
SAGLAT	*Sagittaria latifolia*	Arrowhead	E
SAUCER	*Saururus cernuus*	Lizard’s Tail	E
SCIACU	*Scirpus acutus*	Hard-stem bulrush	E
SCIVAL	*Scirpus validus*	Soft-stem bulrush	E
SPIPOL	*Spirodela polyrhiza*	Greater duckweed	N
STUPEC	*Stuckenia pectinata*	Sago pondweed	S
TYPHA	*Typha sp.*	Cattails	E
VALAME	*Vallisneria americana*	Wild celery or eel grass	S

Key to Vegetation Types:
E = emergent, rooted vegetation
F = floating-leaved, rooted vegetation
N = non-rooted floating vegetation
S = submersed vegetation
* = invasive species

Source: IDNR Lake Reports: Adams Lake 2008; IDNR LARE Reports: Cree Lake 2005; IDNR LARE Reports: Five Lakes 2007; IDNR LARE Reports: Indian Lakes 2001; IDNR LARE Reports: Little Turkey Lake 2008; 2007 Field notes

Classification:

The shorelines of the nine lakes were outlined using heads-up digitizing with the 60 cm Quickbird panchromatic image. The boundary between water and land was traced on screen and converted into a file that represented the shoreline of the lakes at the time the satellite imagery was captured. In areas where there was there was doubt as to where the boundary was, the line was drawn to maximize the amount of aquatic vegetation included even if that meant that shore vegetation was sometimes included in the study area. This effectively masked out the land, leaving only the lakes in the study area to be analyzed.

One of the goals of the study was to find an efficient, non-labor intensive way of classifying the aquatic macrophyte beds. Marshall and Lee (1994) found that the process of selecting training classes and the subsequent signature evaluation needed in a supervised classification was a time consuming process. An added problem was that the majority of the aquatic macrophyte beds in the lakes chosen by the IDNR varied in either composition or in coverage. Such variability within the beds made finding suitable training classes for a supervised classification difficult. Finally, work done by Everitt et al. (2005, 2008) showed that a supervised classification does not produce significantly better results than an unsupervised classification when mapping macrophyte species.

For these reasons, an unsupervised classification using the Iterative Self-Organizing Data Analysis Technique (ISODATA) algorithm was run on the eight lakes in the September 2008 imagery and separately on Cree Lake in the September 15, 2007 imagery. The unsupervised classification was limited to a maximum of 300 spectral clusters for the eight lakes in the 2008 imagery because of the large number of differing bed characteristics and environments found within the eight lakes. The 2007 imagery covers a smaller area, contains fewer macropyhte species and does not show as much variation in lacustrine environments as the 2008 imagery. For this reason, a maximum of only 50 clusters was chosen for 2007 imagery covering just Cree Lake. The convergence threshold was left at the default of 0.95 and the maximum number of iterations in both cases was set to fifty (ERDAS 2009; Jensen 2005). Since the two images were processed separately, no radiometric correction, atmospheric correction, or normalization was performed.

Both unsupervised classifications produced similar patterns in the number of pixels assigned to spectral clusters. Some of these clusters contained very low pixel counts, ranging from 0 to 100 pixels, while others were very large; the largest cluster occurred in the 2008 imagery and contained 25,961 pixels.

When the unsupervised classification was run on both sets of imagery, an unusual pattern was noticed. Many of the clusters that were separated out towards the beginning and middle of the analysis contained a relatively low number of pixels, while those that were separated out towards the end of the analysis contained a much greater number of pixels. In the 2008 imagery, seven of the last eight clusters were 2 to 6 times larger than other clusters. A similar pattern emerged in the 2007 imagery, with the last two clusters being more than 2 times the size of previous clusters. Looking at the average spectral signatures for these clusters showed that in both cases all of the larger clusters had a "typical" vegetation curve with high reflectance in green and NIR bands, indicating that they corresponded to emergent vegetation. In order to capture as much detail as possible on emergent vegetation, these clusters were subject to cluster busting with the maximum number of clusters set at 30 in the 2008 imagery and at 10 in the 2007 imagery. In both cases, all clusters resulting from the cluster busting were populated with pixels.

The average spectral signatures of all clusters were examined. The clusters were divided into rough categories based on their spectral signature as an initial step in the classification process. These initial classes were shadowed water, water, water/unknown, submerged vegetation, possible submerged vegetation, man-made surfaces, and emergent vegetation (Fig. 6).

A Normalized Difference Vegetation Index (NDVI) was calculated using the red and NIR bands of the satellite imagery with the following formula:

$$\mathrm{NDVI} = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$$

Previous studies have shown that NDVI has positive correlation with aquatic macrophyte plant cover (Jakubauskas et al. 2000; Peñuelas et al. 1993) and can be used to help

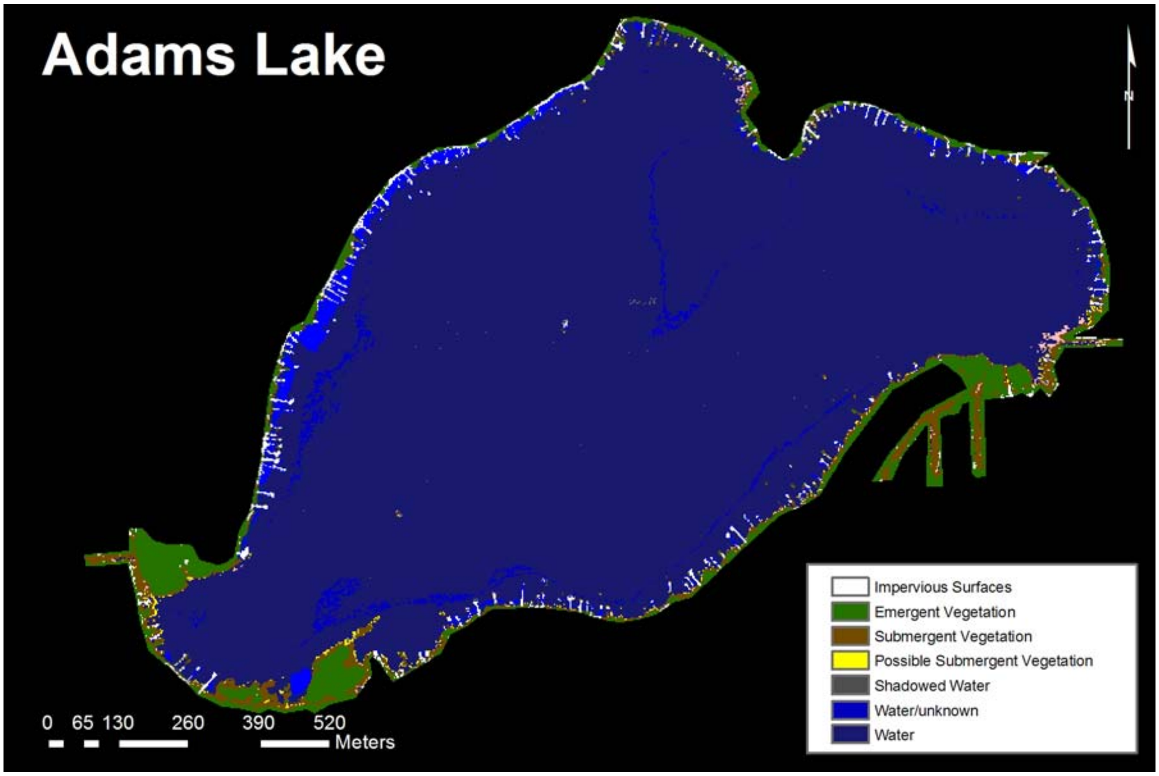

Fig. 6. The initial classification for Adams Lake in the September 2008 imagery.

differentiate vegetation and other surfaces from one another (Ozesmi and Bauer 2002). Because the NDVI is a ratio, it reduces many forms of multiplicative noise such as shadows. This is particularly important in the current study because two of the study lakes have significant effects caused by cloud shadow. In addition, several of the lakes have a large number of man-made structures, such as docks, which extend into macrophyte beds. Some of these structures are narrow enough that pixels are mixed with vegetation, and throw shadows onto nearby beds. NDVI was evaluated as a potential tool in addition to the unsupervised classification to help decrease the pixel confusion and help separate these man-made structures from the vegetation beds.

The next step was to match field data to the spectral clusters resulting from the unsupervised classification of the 2007 and 2008 imagery. The classified image was imported into ArcGIS. The GPS data for the 2007 and 2008 field seasons were overlaid on the cluster image. Clusters were assigned a highly visible color and the type of vegetation contained in each cluster based on the GPS points was noted. The location of the pixels in each cluster was also compared to both the field notes and digital photographs of the bed from the 2008 field season. In the case of the WJST chain, no digital photographs were available for the 2008 field season so the field notes for 2008 were supplemented by the digital photographs collected in 2007. The 2007 digital photographs were also used in areas where the 2008 photographs were not taken. Based on this information, the rough spectral classes (depicted in the legend of Figure 6) were assigned to one of the 15 classes shown in Table 3.

Table 3
Level I Classes

Class name	**Symbol**	**Explanation**
Broad-leafed emergent	B	Broad-leafed emergent vegetation with little or no other types of vegetation
Broad-leafed emergent/*Chara*	BC	Bed dominated by broad-leafed emergent vegetation and underlain by *Chara*
Broad-leafed emergent/ bulrushes/*Chara*	BRC	Bed dominated by broad-leafed emergent vegetation intermixed with stands of bulrushes (*Scirpus acutus* and *Scirpus validus.*) and underlain by *Chara*
Broad-leafed emergent/submerged vegetation	BS	Bed dominated by broad-leafed emergent vegetation underlain by submerged vegetation
Chara/bulrushes	CR	*Chara* dominates, but contains bulrushes
Chara	C	*Chara* with little or no other types of vegetation
Chara/ broad-leafed emergent	CB	Bed dominated by *Chara*, but contains broad-leafed emergent vegetation with <30% coverage
Man-made surfaces	MS	Docks, concrete, rip-rap, boats, etc.
Overhanging trees/shore vegetation	OT/SV	Overhanging trees and other shore vegetation such as grass, loosestrife, sedge, etc.
Shadowed water	WS	Water impacted by shadows
Submerged vegetation	S	Submerged vegetation with no emergent vegetation
Submerged vegetation/ broad-leafed emergent	SB	Bed dominated by submerged vegetation, but containing broad-leafed emergent vegetation with <30% coverage
Submerged vegetation/ algae	SA	Submerged vegetation covered in algae or growing among algae mats
Submerged vegetation/ algae/broad-leafed emergent	SAB	Bed dominated by submerged vegetation covered in algae or growing among algae mats but containing broad-leafed emergent vegetation with <30% coverage
Typha/broad-leafed emergent	T	Bed dominated by *Typha* (cattails), but containing some broad-leafed emergent vegetation
Water	W	Open water

The classes were developed using previous literature on mapping aquatic macrophytes. It is known that the density of the vegetation, the openness of the canopy, and the number, forms, and orientation of the leaves all affect the spectral signature of emergent aquatic macrophytes (Marshall and Lee 1994; Peñuelas et al. 1993; Valta-

Hulkkonen et al. 2005). In particular, four major types of emergent vegetation existed within the lakes in this study. One is broad-leafed surface vegetation such as white water lilies (*Nymphaea oderata*), bullhead lilies (*Nuphar variegata*), and American lotus (*Nelumbo lutea*). Another is broad-leafed above surface vegetation such as spatterdock (*Nuphar advena*), arrow arum (*Peltandra virginica*), and pickerelweed (*Pontederia cordata*). A third type is tall, broad-leafed vegetation, such as cattails (*Typha sp.*). The final type of vegetation is tall and thin with small or no leaves such as the bulrushes *Scirpus acutus* and *Scirpus validus.*

Past studies suggested classification would be able to separate out the broad-leafed vegetation that floated on the surface of the water from the broad-leafed vegetation that rose above the water surface (Laba et al. 2008; Nelson et al. 2006; Peñuelas et al. 1993; Sawaya et al. 2003). Initially, an additional set of classes was developed showing this distinction. However, as the clusters were assigned to different classes it became obvious that broad-leafed surface vegetation and broad-leafed above surface vegetation were highly confused with each other. A contributing factor may be that one of the species that normally lays flat on the water, *Nymphaea oderata*, was observed with leaves curled or entirely above the water's surface in several parts of the study area (Fig. 7). This added an additional complication when assigning classes to a particular category. In the end, surface and above surface vegetation was assigned to one class designated as "broad-leafed emergent." At least one other study has reported similar problems with classification algorithms being unable to separate different types of broad-leafed vegetation (Marshall and Lee 1994).

One of the goals of this study was to attempt to map the invasive species within the lakes. Since it was a major component of submerged beds, special focus was placed on mapping Eurasian watermilfoil (*Myriophyllum spicatum*). Work by previous authors has shown that it is possible to differentiate between different submerged vegetation to a limited extent (Pinnel et al. 2004; Peñuelas et al. 1993). Pinnel et al. (2004) concluded that the spectral differences detected between the submerged macropyhtes *Chara* and pondweeds *(Potamogeton)* is a function of their growth heights and that the spectral response is dependent on water depth and clarity. Size, density, and the homogeneity of

Fig. 7. The image on the left (Adams Lake, pt. 474) shows the typical, floating habit of white water lilies (*Nymphaea oderata*) while the image on the right (Cree Lake, pt. 920) shows the vegetation with leaves extending above the water surface.

the beds also determine how well one submerged macropyhte can be differentiated from another (Pinnel et al. 2004; Peñuelas et al. 1993). Early on in the classification, it was noted that there was no discernible spectral difference between two of the major types of submerged vegetation in the study area: the native coontail (*Ceratophyllum demersum*) and the invasive Eurasian watermilfoil (*Myriophyllum spicatum*). These were combined into the class labeled "submerged vegetation". Because of previous studies had been able to differentiate between *Chara* and other submerged vegetation and the fact that *Chara* has calcium deposits on its surface which could affect its spectral signature, it was placed in a separate class (IDNR LARE Reports: Adams Lake 2008).

Classes were then divided based on the following critera: type of submerged vegetation and presence and type of emergent vegetation. The presence or absence of macrophytic green algae was added because previous work suggests that its presence can affect the recorded spectral signature (Han and Rundquist 2003; Yuan and Zhang 2007). Classes for man-made surfaces and overhanging trees/shore vegetation were added because they make up a significant part of the study area. A class for shadowed water was added to better track the impact of cloud shadows on the classification of aquatic macrophytes.

During the assignment of classes it was noted that once the number of pixels within a cluster fell below 150, it became difficult to locate pixels within the smaller clusters that occurred near GPS points or in areas where digital photographs had been taken. For this reason, a transformed divergence separability analysis (TDSA) was implemented. TDSA compares spectral data associated with each cluster and provides an index of the separability between all cluster pairs. The index can be used as guide in making decisions about whether or not clusters should or should not be combined (ERDAS). Based on the TDSA results, clusters containing a small number of pixels were either combined with other small clusters to produce results that could be more easily assigned to a macrophyte class, or they were combined with already assigned classes. Five of the clusters were not close enough spectrally to any other class to be combined. Because of the small number of pixels within these clusters, they were assigned to the most common macrophyte mix surrounding the pixel locations.

In addition to the detailed classification, a more general classification was derived by aggregating the Level I classes to the six classes depicted in Table 4. The Level II classification provides more general thematic information for resource managers. Evaluating the Level II classification also provides an indication of the utility of the data and methods used to derive more general thematic information on macrophytes from satellite imagery.

Table 4
Level II Classes

Class name	Symbol	Explanation
Emergent vegetation	E	All beds dominated by emergent vegetation
Man-made surfaces	MS	Docks, concrete, rip-rap, boats, etc.
Overhanging trees/shore vegetation	OT/SV	Overhanging trees and other shore vegetation such as grass, loosestrife, sedge , etc.
Submerged vegetation	S	Submerged vegetation with no emergent vegetation
Submerged vegetation/ emergent vegetation	SE	Bed dominated by submerged vegetation, but containing broad-leafed emergent vegetation with <30% coverage
Water	W	Open water

Accuracy Assessment:

The conventional method of assessing the accuracy of a classification is to use an error matrix that compares the agreement between classes predicted through image processing to those observed independently of the classification. Independent observations are collected either through visual interpretation of imagery, by visiting selected sample sites or doing field work in the study area (Congalton and Green 1999). Error matrixes were used to assess the classification results in the current study. Accuracy assessments were run separately on the 2007 and 2008 imagery because the images were analyzed and classified separately. Additionally, independent error matrixes were derived for both the Level I and Level II classifications. Congalton and Green (1999) recommended that a stratified random sample of at least 50 points per class be used to populate error matrixes for an accuracy assessment. For the fifteen Level I classes, that would mean using 750 points. Another option is using the binomial distribution formula, which says that a minimum of 203 sample points is an acceptable sample size when the expected accuracy is 85% and an acceptable error is 5% (Congalton and Green 1999; Jensen 2005). A review of the literature shows that the number of points used in accuracy assessment in similar studies tends to be lower than even this. In general, the number of points chosen to assess accuracy in the literature ranges from 100 to 200 points per site (Everitt et al. 2005; Everitt et al. 2008; Laba et al. 2008; Sawaya et al. 2003; Wolter et al. 2005). This was used as the guideline for determining the number of points used in the current study.

In order to assess the accuracy of all of the classes, a stratified random sample was used to select points for both images in the Level I classification using the sampling tools in ERDAS Imagine 9.3. Because of the large amount of noise inherent in creating thematic maps using classification methods, a smoothing function was used to preferentially select pixels that were surrounded by other pixels of the same class. A minimum of fifteen points per class was specified, but this was not achieved in smaller classes that contained small clusters or scattered pixels. On Cree Lake in the 2007 imagery, 150 points were selected across twelve classes present in Cree Lake. A total of 350 points across fifteen classes were selected for the 2008 imagery because it contained more pixels and more classes.

Certain points were eliminated from this first selection because they fell within the “unclassified” portion of the image. Another selection was run using the same criteria to select additional points to bring the final number up to 150 for the 2007 imagery and 350 for the 2008 imagery.

A second accuracy assessment was completed for the Level II classification using the same methods as in the accuracy assessment for the Level I classification with one change. Because there were fewer classes in the Level II classification, a minimum of thirty points per class was specified for the 2008 imagery and a minimum twenty points per class in the 2007 imagery. The same number of total points and the smoothing function was held constant for the second accuracy assessment.

RESULTS

Level I:

The nine maps presented in Appendix A depict the results of the Level I classifications in each of the study lakes. The man-made structures seen in the maps include docks, boats, rip-rap, and concrete lining along the edges of the lakes. The edges of the large macrophyte beds in the study lakes appear to be accurately mapped and the channels cut through the beds by boats going to and from docks are visible. Most of the areas classified as shadowed water in Latta Lake and Adams Lake result from radiometric noise in the imagery, though in Adams Lake the outline in the north central portion of the lake corresponds to a large underwater feature that is visible in aerial photographs (Fig. 8).

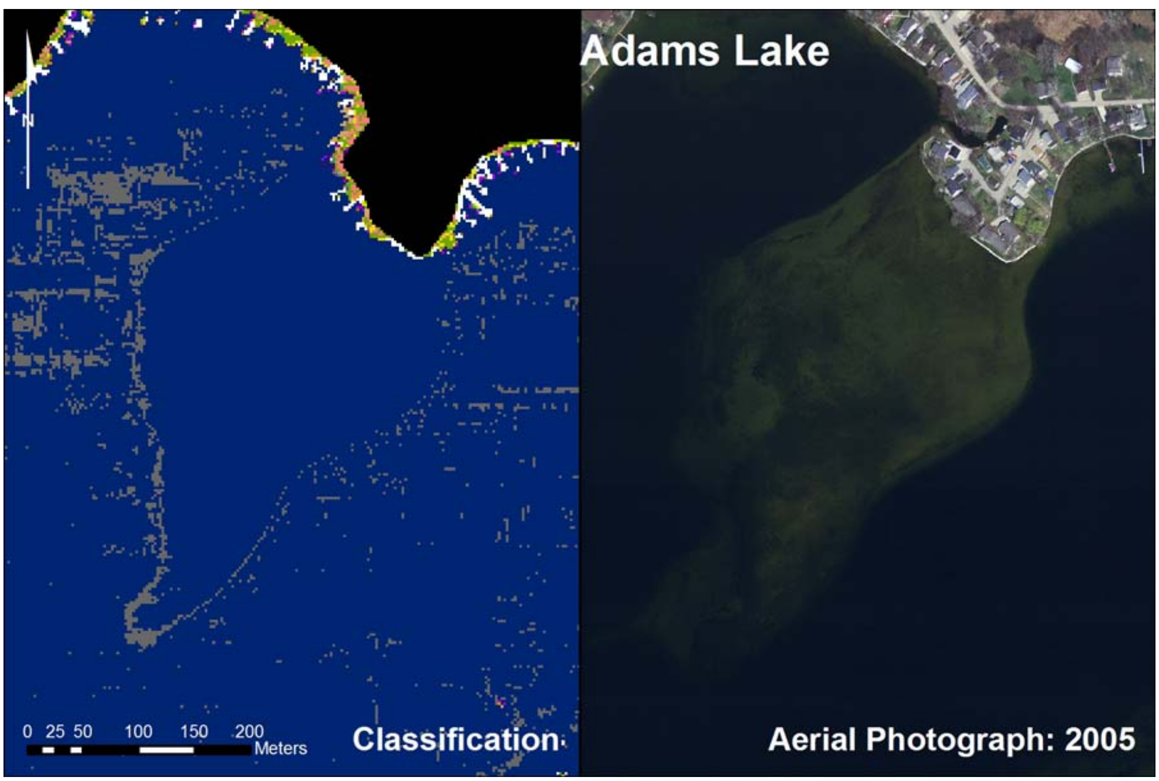

Fig. 8. The classified September 6, 2008 image of Adams Lake on the left and an aerial photograph of Adams Lake on the right.

In the Level I classification, the largest category in each of the nine lakes is water with no detectable aquatic vegetation. Water with no detectable aquatic vegetation covered 386.75 ha (955.7 acres) of the 458.74 ha (1133.7 acres) classified across all nine of the study lakes. This is not surprising given that most of the vegetation found in these lakes occurs along the shoreline with only a few larger beds in Adams Lake, Jones Lake, Tamarack Lake, and Waldron Lake.

For the majority of the lakes, the second largest class is broad-leafed emergent vegetation that is underlain by submerged vegetation. The exception is Cree Lake, where the second largest class is broad-leafed emergent vegetation underlain by *Chara.* All classes containing *Chara* are larger in area in Cree Lake than in any of the other lakes. This observation is supported by the field data collected in 2007 and 2008 which shows that in Cree Lake *Chara* is the dominant submerged vegetation while in the other lakes, Eurasian watermilfoil (*Myriophyllum spicatum*) and coontail (*Ceratophyllum demersum)* make up the majority of submerged beds. Large *Chara* beds can also be found in Witmer Lake and Adams Lake.

Jones Lake had the largest area covered in cattails (*Typha sp.*) at 2.02 ha (5 acres), which is not surprising given the large cattail beds on the western portion of the lake. Both Waldron Lake and Jones Lake have very large areas of submerged vegetation with visible algae at 3.80 ha (8.8 acres) and 3.56 ha (9.4 acres), respectively, compared to the other lakes. Overall, the most common macrophyte class in the lakes was broad-leafed emergent vegetation with underlying submerged vegetation. This covered 22.78 ha (56.3) acres. The IDNR LARE Report (2008) states that 95% of the shoreline of Adams Lake is developed. These data are consistent with the results of the image classifications developed in the current study, which show that the proportional area covered by man-made surfaces is highest in Adams Lake. The area covered by each class by lake is provided in Table 5. Table 6 summarizes the proportional area of each class.

Using the information from Tables 5 and 6, some general estimates can be calculated about the lakes in the study. On average, 81.9% of the lakes are covered by water with no detectable aquatic vegetation. Macrophyte coverage averages about 15% across all the lakes. Broad-leafed surface vegetation underlain by submerged vegetation is the largest class percentage-wise, covering about 5.8% of the lakes on average. Man-made surfaces cover about 1% of the lakes.

Adams Lake has the largest percentage of water, with 91.4% of its area being covered by water with no discernible aquatic vegetation. Jones Lake has the lowest percentage of its area covered with water at 70.4%. Given this, it is unsurprising that Adams Lake has the lowest percent coverage of all macrophytes at 5.8% while Jones Lake has over a quarter of its area covered by aquatic vegetation. Adams Lake also has 2.0% of its 123.81 ha (306 acres) classified as man-made surfaces. Latta Lake had the lowest amount of man-made surfaces with 0.4% of its 17.99 ha (44.6 acres). While Witmer Lake has the highest amount of bulrushes underlain by *Chara* in terms of hectares, Latta Lake has a higher percentage of its area covered in bulrushes underlain by *Chara.* Nearly 1% of Latta Lake's is covered by this class, while the average across the lakes is only 0.3%. Messick Lake has the highest percentage of overhanging tree/shore vegetation at 3.4%, which is not surprising given the relatively low amount of residential development along its shoreline.

The overall Level I accuracy for the 2007 classification was 68.0%. The overall Level I accuracy of the 2008 imagery was lower at 57.7%. Both of these overall accuracies are low when compared to other studies mapping aquatic macrophytes, where the majority fall in the 80% range (Everitt et al. 2005; Everitt et al. 2008; Jensen et al. 1986; Nelson et al. 2006; Valta-Hulkkonen et al. 2005; Wolter et al. 2005), though both Sawaya et al. (2003) and Laba et al. (2008) reported lower accuracies (79.5% and 68.4% respectively). Producer's accuracies ranged from 44.4% to 100% in the 2007 imagery and from 11.1% to 87.2% in the 2008 imagery. User's accuracies ranged from 25% to 100% in the 2007 imagery and from 20% to 100% in the 2008 imagery. The literature reports much wider ranges for producer's and user's accuracies with some reporting a user's and producer's accuracies in the 30% to 50% range (Everitt et al. 2005; Laba et al. 2008; Sawaya et al. 2003). Detailed error matrixes for the 2007 and the 2008 Level I classifications are presented in Tables 7 and 8.

Table 5
Level I vegetation coverage summary for all lakes in hectare (acres)

Lake	W	CR	C	CB	S	SB	SA	SAB	BC	BS	T	M	OT/SV	Total
Adams	113.15	0.20	0.48	0.08	0.24	0.20	1.29	0.40	0.53	2.79	0.93	2.47	1.05	123.81
	(279.6)	(0.5)	(1.2)	(0.2)	(0.6)	(0.5)	(3.2)	(1.0)	(1.3)	(6.9)	(2.3)	(6.1)	(2.6)	(306)
Cree	19.30	-	0.85	0.45	0.32	0.45	-	-	1.70	0.89	-	0.16	0.32	24.44
	(47.7)		(2.1)	(1.1)	(0.8)	(1.1)			(4.2)	(2.2)		(0.4)	(0.8)	(60.3)
Jones	36.14	0.08	0.12	0.04	0.32	0.20	3.56	0.40	0.36	6.68	2.02	0.28	1.13	51.33
	(89.3)	(0.2)	(0.3)	(0.1)	(0.8)	(0.5)	(8.8)	(1.0)	(0.9)	(16.5)	(5.0)	(0.7)	(2.8)	(126.9)
Latta	15.46	0.16	0.16	0.04	0.08	0.08	0.28	0.04	0.24	0.93	0.28	0.08	0.16	17.99
	(38.2)	(0.4)	(0.4)	(0.1)	(0.2)	(0.2)	(0.7)	(0.1)	(0.6)	(2.3)	(0.7)	(0.2)	(0.4)	(44.6)
Messick	23.19	0.08	0.16	0.04	0.12	0.08	1.09	0.16	0.12	1.46	0.36	0.32	0.97	28.17
	(57.3)	(0.2)	(0.4)	(0.1)	(0.3)	(0.2)	(2.7)	(0.4)	(0.3)	(3.6)	(0.9)	(0.8)	(2.4)	(69.6)
Steinbarger	26.87	0.08	0.16	0.04	0.12	0.12	1.38	0.20	0.20	1.25	0.36	0.28	0.81	31.87
	(66.4)	(0.2)	(0.4)	(0.1)	(0.3)	(0.3)	(3.4)	(0.5)	(0.5)	(3.1)	(0.9)	(0.7)	(2.0)	(78.8)
Tamarack	15.66	0.04	0.04	-	0.12	0.12	1.01	0.12	0.24	1.94	0.61	0.16	0.53	20.59
	(38.7)	(0.1)	(0.1)		(0.3)	(0.3)	(2.5)	(0.3)	(0.6)	(4.8)	(1.5)	(0.4)	(1.3)	(50.9)
Waldron	46.94	0.20	0.32	0.08	0.32	0.20	3.80	0.49	0.28	4.82	1.09	0.77	1.58	60.89
	(116.0)	(0.5)	(0.8)	(0.2)	(0.8)	(0.5)	(9.4)	(1.2)	(0.7)	(11.9)	(2.7)	(1.9)	(3.9)	(150.5)
Witmer	90.04	0.28	0.61	0.08	0.28	0.12	1.90	0.24	0.12	2.02	0.73	1.70	1.46	99.59
	(222.5)	(0.7)	(1.5)	(0.2)	(0.7)	(0.3)	(4.7)	(0.6)	(0.3)	(5.0)	(1.8)	(4.2)	(3.6)	(246.1)
Total	386.75	1.12	2.90	0.85	1.92	1.57	14.31	2.05	3.79	22.78	6.38	6.22	8.01	458.74
	(955.7)	(2.8)	(7.2)	(2.1)	(4.7)	(3.9)	(35.4)	(5.1)	(9.4)	(56.3)	(15.8)	(15.4)	(19.8)	(1133.7)

Key: W – Water, CR – *Chara/*bulrushes, C – *Chara*, CB – *Chara/*broad-leafed emergent, S – Submerged vegetation, SB - Submerged vegetation/ broad-leafed emergent, SA - Submerged vegetation/ algae, SAB – Submerged vegetation/algae/broad-leafed emergent, BC - Broad-leafed emergent/*Chara*, BS - Broad-leafed emergent/submerged vegetation, T - *Typha*/broad-leafed emergent, M - Man-made surfaces, OT/SV - Overhanging trees/shore vegetation

Table 6
Level I amount of coverage for all lakes

Lake	W	CR	C	CB	S	SB	SA	SAB	BC	BS	T	M	OT/SV	All macrophytes
Adams	91.4%	0.2%	0.4%	0.1%	0.2%	0.2%	1.0%	0.3%	0.4%	2.3%	0.8%	2.0%	0.8%	5.8%
Cree	79.0%	0.0%	3.5%	1.8%	1.3%	1.8%	0.0%	0.0%	7.0%	3.6%	0.0%	0.7%	1.3%	19.1%
Jones	70.4%	0.2%	0.2%	0.1%	0.6%	0.4%	6.9%	0.8%	0.7%	13.0%	3.9%	0.5%	2.2%	26.8%
Latta	85.9%	0.9%	0.9%	0.2%	0.4%	0.4%	1.6%	0.2%	1.3%	5.2%	1.6%	0.4%	0.9%	12.7%
Messick	82.3%	0.3%	0.6%	0.1%	0.4%	0.3%	3.9%	0.6%	0.4%	5.2%	1.3%	1.1%	3.4%	13.0%
Steinbarger	84.3%	0.3%	0.5%	0.1%	0.4%	0.4%	4.3%	0.6%	0.6%	3.9%	1.1%	0.9%	2.5%	12.3%
Tamarack	76.1%	0.2%	0.2%	0.0%	0.6%	0.6%	4.9%	0.6%	1.2%	9.4%	3.0%	0.8%	2.6%	20.6%
Waldron	77.1%	0.3%	0.5%	0.1%	0.5%	0.3%	6.2%	0.8%	0.5%	7.9%	1.8%	1.3%	2.6%	19.1%
Witmer	90.4%	0.3%	0.6%	0.1%	0.3%	0.1%	1.9%	0.2%	0.1%	2.0%	0.7%	1.7%	1.5%	6.4%
Average	81.9%	0.3%	0.8%	0.3%	0.5%	0.5%	3.4%	0.5%	1.4%	5.8%	1.6%	1.0%	2.0%	15.1%

Key: W – Water, CR – *Chara/*bulrushes, C – *Chara*, CB – *Chara/*broad-leafed emergent, S – Submerged vegetation, SB - Submerged vegetation/ broad-leafed emergent, SA - Submerged vegetation/ algae, SAB – Submerged vegetation/algae/broad-leafed emergent, BC - Broad-leafed emergent/*Chara*, BS - Broad-leafed emergent/submerged vegetation, T - *Typha*/broad-leafed emergent, M - Man-made surfaces, OT/SV - Overhanging trees/shore vegetation

Table 7
Level I accuracy assessment, September 2007 imagery

	W	**CR**	**C**	**CB**	**SAB**	**S**	**SB**	**SA**	**BC**	**BS**	**M**	**OT/ SV**	**User's Accuracy**
W	31					2							93.9%
CR													0.0%
C			13	1	1	1	1	2					68.4%
CB			3	8	1		3			2			47.1%
SAB													0.0%
S				1		4							80.0%
SB		1	3	3			3		1		1		25.0%
SA													0.0%
BC				2		1			17	5		4	58.6%
BS			1			1			4	8			57.1%
M											12		100%
OT/SV									3			6	66.7%
													Overall Accuracy
Producer's Accuracy	100%	0.0%	65.0%	53.3%	0.0%	44.4%	42.9%	0.0%	68.0%	53.3%	92.3%	60.0%	**68.0%**

Key: W – Water, CR – *Chara*/bulrushes, C – *Chara*, CB – *Chara*/broad-leafed emergent, SAB – Submerged vegetation/algae/broad-leafed emergent, S – Submerged vegetation, SB - Submerged vegetation/ broad-leafed emergent, SA - Submerged vegetation/ algae, BC - Broad-leafed emergent/*Chara*, BS - Broad-leafed emergent/submerged vegetation, M - Man-made surfaces, OT/SV - Overhanging trees/shore vegetation

Table 8
Level I accuracy assessment, September 2008 imagery

	WS	W	CR	C	CB	BRC	SAB	S	SB	SA	BC	BS	M	T	OT/ SV	User's Accuracy
WS	16	5	1					5		1	1					55.2%
W	2	95		1				2	1				1			93.1%
CR	2	1		1	3					1	1	1	1			0.0%
C		2	2	3	1			1			2		1		1	23.1%
CB				1	2		2	1	1	1		2				20.0%
BRC																0.0%
SAB		1							1	2					2	0.0%
S	2							2	2			2	1			22.2%
SB				1				1	1	2						20.0%
SA	1	2			1		2	3	1	15		2	1		2	50.0%
BC					1	4				2	6	2		1		37.5%
BS	1		1		1	1	2	2	1	2		22		5	16	40.7%
M	1	2						1					12		1	70.6%
T		1			1		1				1	7		10	9	33.3%
OT/SV															18	100%
Producer's Accuracy	64.0%	87.2%	0.0%	42.9%	20.0%	0.0%	0.0%	11.1%	12.5%	57.7%	54.6%	57.9%	70.6%	62.5%	36.7%	**Overall Accuracy 57.7%**

Key: W – Water, WS - Shadowed water, CR – *Chara/*bulrushes, C – *Chara*, CB – *Chara/*broad-leafed emergent, BRC - Broad-leafed emergent/ bulrushes/*Chara*, SAB – Submerged vegetation/algae/broad-leafed emergent, S – Submerged vegetation, SB - Submerged vegetation/ broad-leafed emergent, SA - Submerged vegetation/ algae, BC - Broad-leafed emergent/*Chara*, BS - Broad-leafed emergent/submerged vegetation, M - Man-made surfaces, T - *Typha*/broad-leafed emergent, OT/SV - Overhanging trees/shore vegetation

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All eight lakes in the 2008 imagery were classified together in an attempt to reduce the amount of processing time and to make the classification scheme more uniform across all lakes. One of the issues with this approach is that the aquatic vegetation and lake characteristics differ from one lake to the next and these differences can be lost when classifying all lakes together. An example of this is the macrophyte American lotus (*Nelumbo lutea*). American lotus (*Nelumbo lutea*) has leaves up to 100 cm (3.28 ft) in diameter and is a significant component of the beds along the southern shore of Waldron Lake, but was not observed in any of the other study lakes. No classes show the presence of this distinct emergent species. Another problem is that areas can be classified as macrophytes that do not exist in that lake, but exist in others. One example of this is the submerged aquatic plant *Chara sp.* This macrophyte forms large beds in Adams Lake and Latta Lake, smaller beds in Messick Lake, but is not present in significant amounts in the WJST chain or Witmer Lake. However, as seen in Table 7, *Chara* appears in all the lakes in the classification. Marshall and Lee (1994) came to the conclusion that spectral signatures, especially at the species level, were not fully transportable to other lakes in their study of mapping freshwater aquatic vegetation in Walkinshaw and Big Pearl Lakes in northwestern Ontario. It is likely that simultaneous classification is one of the reasons why the overall Level I accuracy of the 2008 imagery is lower than that of the 2007 imagery, which focused solely on Cree Lake.

Some of the highest accuracies in the Level I assessment were found in the categories of water and man-made structures in both the 2007 and 2008 imagery. Water had a user's accuracy of 93.9% and a producer's accuracy of 100% in the 2007 imagery and a similarly high user's accuracy of 93.1% and a lower producer's accuracy of 87.2% in the 2008 imagery. Man-made structures had a user's accuracy of 100% and a producer's accuracy of 92.3% in the 2007 imagery. The user's and producer's accuracy in the 2008 imagery is lower at 70.6% for both.

The lowest accuracies in the Level I assessment were for beds that contained bulrushes, *Scirpus acutus* and *Scirpus validus.* All of the beds containing bulrushes in both the 2007 and 2008 imagery have a user's and producer's accuracy of 0%. In general, bulrushes and other tall, thin macrophytes with no prominent leaves (such as horsetails) are the least accurately mapped aquatic macrophyte (Laba et al. 2008; Marshall and Lee

1994). In the current study, bulrushes were most often mischaracterized as *Chara* or as broad-leafed emergent vegetation underlain by *Chara.* Marshall and Lee (1994) state that while bulrushes are easily visible when viewed laterally from a boat, it is difficult to discern these plants from an overhead position. This could explain the low accuracies in classes containing bulrushes, despite the fact that areas with large and relatively dense bulrush beds exist in the study area, such as in the southwest corner of Adams Lake.

One of the major sources of error in the Level I classification of the 2008 imagery was the confusion between aquatic macrophytes and shoreline vegetation, usually in the form of overhanging trees and mowed grass. The user's accuracy for the overhanging tree/shore vegetation class was 100%, indicating that when an area is classified as overhanging tree or shore vegetation, it has a high chance of actually being an overhanging tree or shore vegetation. However, the producer's accuracy for this class is 46.2%. The error matrix shows that the overhanging tree/shore vegetation is often classified as broad-leafed emergent vegetation and occasionally as cattails (*Typha sp.*). This explains the low producer's accuracy for the category.

Work by Han and Rundquist (2003) has shown that the reflectance in the NIR is relatively low for submerged vegetation when compared to terrestrial vegetation. Equivalent work comparing emergent aquatic macrophytes and terrestrial vegetation was not found in a literature review. In some areas around the study lakes, grass and other non-aquatic vegetation grew right up to the water's edge while in the water, aquatic vegetation formed dense beds that also extended to the water's edge. Parts of tree canopies were included in the image because these trees overhang the water. Since many of the smaller aquatic macrophyte beds grow very near to the shore, effort was made to come as close to the shoreline as possible so as to include these smaller beds. In many cases, identifying the exact shoreline was difficult in the panchromatic imagery and, when digitizing, preference was given to including more terrestrial vegetation rather than excluding aquatic vegetation. This additional terrestrial vegetation contributed to confusion with macrophytes in the accuracy assessment.

Cattails (*Typha sp.*) and other broad-leafed emergent vegetation had a relatively high producer's accuracy compared to other categories in the 2008 imagery, but a low user's accuracy. In addition to being confused with different types of shoreline vegetation, such as grass and overhanging trees, it was often confused with broad-leafed emergent vegetation. It is known that *Typha sp.* has variations in growth patterns which can complicate classifications (Ozesmi and Bauer 2002). A review of the field data shows that the class containing cattails (*Typha sp.*) was more often confused with broad-leafed emergent vegetation classes that did not contain cattails in areas where the vegetation was dense (canopy coverage between 80-100%) and in areas where the vegetation was dominated by above surface species such as spatterdock (*Nuphar advena*) and arrow arum (*Peltandra virginica*).

Another problem classifying aquatic macrophytes in small lakes is that the shadows of trees along the shoreline or from obstructions in the water, such as docks, can interfere with spectral signatures (Sawaya et al. 2003; Valta-Hulkkonen et al. 2005). Cloud shadows also contribute to this problem. While the classification was able to differentiate shadows when they occurred in areas of open water, it was not able to do the same for vegetation. Often in areas where shadows occurred, emergent vegetation was classified as submerged vegetation and submerged vegetation was classified incorrectly as *Chara*.

Submerged vegetation in all forms had relatively low accuracies in both the 2007 and 2008 images. *Chara* had a much higher user's accuracy and producer's accuracy in the 2007 imagery than in the 2008 imagery. The same trend holds for the submerged vegetation class. In the 2008 imagery, areas classified as *Chara* or submerged vegetation were not confused with each other. Instead, most of the confusion with *Chara* was with categories that also contained *Chara* such as bulrushes with *Chara* and broad-leafed emergent vegetation with *Chara.* This is also true for the submerged vegetation class in the 2008 imagery, with most of the confusion being between classes containing submerged vegetation and broad-leafed emergent vegetation or classes with submerged vegetation and algae.

There is confusion between classes containing *Chara* and classes containing submerged vegetation in the 2007 imagery of Cree Lake. In particular, a large *Chara* bed on the eastern side of Cree Lake is classified as submerged vegetation or submerged vegetation with broad-leafed emergent vegetation. A possible reason for this confusion is reflectance off of the lake bottom. Lake bottoms have been shown to cause confusion in classification of aquatic macrophytes, especially when classifying submerged vegetation (Marshall and Lee 1994; Valta-Hulkkonen et al. 2005; Wolter et al. 2005). Peñuelas et al. (1993) suggested the reason that *Chara* could be differentiated from other submerged vegetation, such as coontail (*Ceratophyllum demersum*) and *Myriophyllum*, was because it had slightly lower reflectance values. In areas such as the shelf on the east side of Cree Lake, it is possible that bottom reflectance in addition to the reflectance from *Chara* is causing the misclassification.

The confusion between areas with different submerged vegetation and emergent vegetation, particularly in areas where the emergent vegetation coverage is less than 30%, can be explained. As the depth of submerged vegetation in the water column increases, there is a dramatic drop in reflectance in the NIR band and a corresponding drop in the green part of the spectrum (Han and Rundquist 2003). This drop in the NIR band also occurs as the percentage of coverage in submerged vegetation decreases (Yuan and Zhang 2007). In addition, as the percentage of cover in emergent, floating vegetative beds decreases, there is also a dramatic drop in reflectance in the NIR band and again, a less dramatic decrease in the green part of the spectrum (Jakubauskas et al. 2000). These effects occur because of the increase in water area exposed to the sensor (Han and Rundquist 2003; Jakubauskas et al. 2000; Yuan and Zhang 2007). An attempt was made to separate areas with low emergent coverage into different classes from areas with higher emergent coverage, and areas with solely submerged vegetation. The low accuracies shown for these classes indicate that this was not particularly successful.

The presence of algae, both in the water column and growing on the submerged vegetation, is another confounding factor in differentiating between different submerged macrophytes, and between emergent and submerged vegetation. There is some debate about whether and how much the presence of algae disrupts the detection of submerged macrophytes. At least one study has found no correlation between water clarity or algae concentrations and the ability of sensors to detect submerged macrophytes (Nelson et al. 2006). Empirical work suggests that submerged macrophyte signatures become confused in algae laden waters. Submerged vegetation still shows a rapid decreased in the NIR band with depth, but a large "green peak" occurs due to the algae (Han and Rundquist 2003; Yuan and Zhang 2007). Even as depth increases or the coverage of the submerged macrophyte bed decreases, the amount of green light reflected back remains relatively high. In this study, dense algae mats were sometimes confused with submerged vegetation. Algae growing on the submerged macrophytes is thought to have caused some of the confusion between different species and between submerged macrophyte beds and beds containing low, broad-leafed emergent vegetation.

Finally, a possible issue contributing to error in the classifications was bottom reflectance. Stumpf and Holderied (2003) indicate that high-resolution satellite imagery can detect bottom reflectance up to 20 m (65.6 ft) in depth. Early analysis indicated that only limited areas within the lakes showed signs of bottom reflectance in their spectra and these areas were incorporated into the water category. For this reason, bottom reflectance was initially not thought to be an issue. After the final classification had been completed, the IDNR provided bathymetry maps derived from hydroaccoustic data obtained during 2007. This led to a review of the water classes for possible reflectance. A comparison of the bathymetry maps and several of the water classes that have possible bottom reflectance shows a distinct similarity between the two within Adams Lake, Latta Lake, Messick Lake, and Witmer Lake. No such correlation exists in the WJST chain in the 2008 imagery or within Cree Lake in the 2007 imagery.

Level II:

The nine maps presented in Appendix B depict the results of the Level II classifications in each of the study lakes. As in the Level I classification, in the Level II classification of the 2008 imagery the largest category for all the lakes is water with no detectable aquatic vegetation. The second largest class for all lakes is emergent vegetation which covers a total of 32.97 ha (81.5 acres) across all nine lakes. The smallest class is man-made surfaces, which only cover 6.22 ha (15.4 acres) across all nine of the lakes.

Jones Lake had the largest amount of emergent vegetation at 9.06 ha (22.4 acres), again probably due to the large cattail bed in northwestern portion of the lake as well as large beds in the channel leading to Witmer Lake. At 4.37 ha (10.8 acres), Waldron Lake has the largest amount of submerged vegetation of any of the lakes. It also has the largest amount of overhanging tree/shore vegetation of any of the lakes in terms of area. As the smallest lake in the study, Latta Lake had the smallest area of each of the classes in the Level II classification. The sole exception was with the mixed submerged/emergent vegetation class where Tamarack Lake, the second smallest lake in the study, had only 0.28 ha (0.7 acres). Latta Lake had 0.36 ha (0.9 acres). Adams Lake had the largest area covered by the mixed submerged/emergent vegetation class with 1.21 ha (3 acres). A detailed breakdown of the Level II classes by lake can be seen in Table 9.

The percent coverage for the Level II classes is summarized in Table 10. The average proportion covered by emergent vegetation is 8.8%. Submerged vegetation, on average, covers about 4.6% of the lakes while the mixed submerged/emergent vegetation class covers, on average, only 1.7% of the lakes. Jones Lake, which as previously stated has the highest percentage of its surface covered by macrophytes, has the highest percentage of its area covered by emergent macropyhtes at 17.7% and by submerged macropyhtes at 7.7%. Waldron Lake has the highest area of submerged vegetation at 4.37 ha (22.4 acres), but it only covers 7.2% of the 60.89 ha (150.5 acres) that make up its area. Cree Lake had the highest amount of its area covered by the mixed emergent/submerged vegetation class at 3.6%.

Table 9
Level II vegetation summary for all lakes in hectare (acres)

Lake	**Water**	**Submerged**	**Submerged/ Emergent**	**Emergent**	**Man-made surfaces**	**OT/SV**	**Total**
Adams	113.15 (279.6)	1.74 (4.3)	1.21 (3.0)	4.25 (10.5)	2.47 (6.1)	1.05 (2.6)	123.87 (306)
Cree	19.30 (47.7)	1.13 (2.8)	0.89 (2.2)	2.59 (6.4)	0.16 (0.4)	0.32 (0.8)	24.44 (60.3)
Jones	36.14 (89.3)	3.97 (9.8)	0.77 (1.9)	9.06 (22.4)	0.28 (0.7)	1.13 (2.8)	51.33 (126.9)
Latta	15.46 (38.2)	0.53 (1.3)	0.36 (0.9)	1.50 (3.7)	0.08 (0.2)	0.16 (0.4)	17.99 (44.6)
Messick	23.19 (57.3)	1.25 (3.1)	0.45 (1.1)	1.90 (4.7)	0.32 (0.8)	0.97 (2.4)	28.17 (69.6)
Steinbarger	26.87 (66.4)	1.58 (3.9)	0.53 (1.3)	1.78 (4.4)	0.28 (0.7)	0.81 (2.0)	31.87 (78.8)
Tamarack	15.66 (38.7)	1.17 (2.9)	0.28 (0.7)	2.79 (6.9)	0.16 (0.4)	0.53 (1.3)	20.59 (50.9)
Waldron	46.94 (116.0)	4.37 (10.8)	1.09 (2.7)	6.23 (15.4)	0.77 (1.9)	1.58 (3.9)	60.89 (150.5)
Witmer	90.04 (222.5)	2.47 (6.1)	1.05 (2.6)	2.87 (7.1)	1.70 (4.2)	1.46 (3.6)	99.59 (246.1)
Total	386.75 (955.7)	18.21 (45.0)	6.63 (16.4)	32.97 (81.5)	6.22 (15.4)	8.01 (19.8)	458.74 (1133.7)

Table 10
Level II amount of coverage for all lakes

Lake	Water	Man-made surfaces	Emergent	Submerged/Emergent	Submerged	All macropyhtes
Adams	91.3%	2.0%	3.4%	1.0%	1.4%	5.8%
Cree	79.1%	0.7%	10.6%	3.6%	4.6%	18.9%
Jones	70.4%	0.6%	17.7%	1.5%	7.7%	26.9%
Latta	85.5%	0.4%	8.3%	2.0%	2.9%	13.2%
Messick	82.6%	1.2%	6.8%	1.6%	4.5%	12.8%
Steinbarger	84.4%	0.9%	5.6%	1.7%	5.0%	12.2%
Tamarack	76.0%	0.8%	13.6%	1.4%	5.7%	20.6%
Waldron	77.0%	1.3%	10.2%	1.8%	7.2%	19.2%
Witmer	90.4%	1.7%	2.9%	1.1%	2.5%	6.4%
Average	81.9%	1.1%	8.8%	1.7%	4.6%	15.1%

Error matrixes for the 2007 and the 2008 Level II classifications are presented in Tables 11 and 12. The overall accuracies for both maps increased in the Level II classification. The overall Level II accuracy for the 2007 classification of Cree Lake was 74.6% while the overall Level II accuracy of the eight lakes in the 2008 map was 74.3%. Producer's accuracies ranged from 52.4% to 100% in the 2007 classification and 51.7% to 85.8% in the 2008 classification. These error ranges are more narrow relative to the Level I classification and indicate that the Level II classification does a better job of correctly classifying aquatic vegetation. The user's accuracies range from 27.8% to 98% in the 2007 classification and 33.3% to 97.1% in the 2008 classification. These results are comparable to those derived from the Level I classification.

While the Level I classification was more detailed than the Level II, it also had a lower accuracies in most categories. The highest accuracies in the Level II classification were found in the categories of water in both the 2007 and 2008 imagery. Water had a user's accuracy of 98% and a producer's accuracy of 90.4% in the 2007 imagery and user's accuracy of 97.1% and a lower producer's accuracy of 85.8% in the 2008 imagery. Man-made structures had lower user's accuracies than in the Level I classification of the 2007 imagery at 63.2% but had a producer's accuracy of 100%. There was an increase in the confusion between man-made structures and both emergent and submerged vegetation. Confusion between man-made structures and submerged and emergent vegetation is also seen in the Level II 2008 imagery. The user's accuracy is 71% and producer's accuracy is 73.3%. In the Level II classification of the 2007 imagery, the mixed class of submerged/emergent vegetation had a high user's and producer's accuracy at 75%.

Table 11
Level II accuracy assessment, September 2007 imagery

	Water	Submerged	Submerged/ Emergent	Emergent	Man-made surfaces	OT/SV	User's Accuracy
W	47	1					98.0%
S	4	11	4	2			52.4%
SE	1	1	15	2		1	75.0%
E				22		2	91.7%
MS		3		4	12		63.2%
OT/SV			1	12		5	27.8%
							Overall Accuracy
Producer’s Accuracy	90.4%	68.8%	75.0%	52.4%	100%	62.5%	**74.6%**

Table 12
Level II accuracy assessment, September 2008 imagery

	Water	Submerged	Submerged/ Emergent	Emergent	Man-made surfaces	OT/SV	User's Accuracy
W	133	2			2		97.1%
S	9	15	5	6	3	7	33.3%
SE	7	8	13	2	1	1	40.6%
E	1	1	1	46	2	20	64.8%
MS	5	2		2	22		71.0%
OT/SV		1		2		31	91.2%
							Overall Accuracy
Producer’s Accuracy	85.8%	51.7%	68.4%	79.3%	73.3%	52.5%	**74.3%**

Although the Level II classification had higher overall accuracies, it suffered from some of the same problems as the Level I classification. The most significant of these is the confusion between shore vegetation and aquatic macrophytes. The user's accuracy for the overhanging tree/shore vegetation class in the 2008 imagery was 91.2%, indicating that when an area is classified as overhanging tree or shore vegetation, it has a high chance of actually being an overhanging tree or shore vegetation. However, the producer's accuracy for this class is 52.5%. As in the Level I classification, overhanging trees and other types of shore vegetation were most often misclassified as emergent vegetation.

It is interesting to note that in the Level II assessment for the 2007 imagery, the exact opposite phenomenon happened. In the 2007 imagery overhanging trees/shore vegetation had a very low user's accuracy of 27.8% but a higher producer's accuracy of 62.5%. Areas of emergent vegetation were often misclassified as overhanging trees/shore vegetation (13 cases) with at least one case of mixed submerged/emergent being misclassified as overhanging trees/shore vegetation. This indicates that the amount of vegetation classified as shore vegetation in the 2007 imagery is exaggerated in the classification.

Confusion between the mixed emergent/submerged vegetation beds and submerged vegetation becomes more evident in the Level II analysis than in the Level I analysis as does the confusion between emergent and submerged vegetation. As in the Level I analysis, this is probably because of similar spectral responses of emergent macrophytes as the density of the canopy decreases and as the depth of submerged macrophytes increases.

CONCLUSIONS

Using high spatial resolution imagery and unsupervised classification to map aquatic macrophytes in small lakes for management purposes is possible. This study presents maps of the distribution of aquatic macrophyte beds in nine northern Indiana lakes and provides estimates of the area covered by different macrophyte classes and man-made structures. Two of the four management objectives outlined by the IDNR were met. First, it was possible to outline the extent of emergent and submerged vegetative beds within these lakes for management purposes. Second, the classification was able to accurately map man-made structures in both sets of imagery. The analysis was unable to differentiate the invasive species Eurasian watermilfoil (*Myriophyllum spicatum*) from the native species coontail (*Certatophyllum demersum*), and these two submerged macrophytes were grouped into one class. The analysis was able to differentiate between *Chara* and other submerged macrophytes to a limited extent, but accuracies were still low. Therefore, two of the study goals are topics for further research: mapping the health and extent of native species, and the extent and spread of invasive species.

The study results provide information important for management decisions. For example, while coontail (*Ceratophyllum demersum*) and *Chara* were considered nuisance plants in Cree Lake, funding was not available through the LARE program to control them because they are not invasive plants (IDNR LARE Reports: Cree Lake 2005). However, monitoring is still needed in Cree Lake because of the threat of invasive species, like Eurasian watermilfoil (*Myriophyllum spicatum)*, spreading within the lake. Since the high resolution satellite imagery mapping methods tested in this study cannot differentiate between Eurasian watermilfoil (*Myriophyllum spicatum)*, and the native species coontail (*Certatophyllum demersum*), a sudden spread of the invasive species within the lake could go unnoticed without field data. These results also cast doubt onto whether image-based methods would be useful in monitoring the spread of invasive species such as hydrilla (*Hydrilla verticillata*), which has recently been found in Indiana (IDNR LARE Reports: Adams Lake 2008).

The Level II analysis accurately mapped of vegetative beds in the study lakes and was effective in mapping man-made surfaces in both analyses. Pesticides are often used to manage invasive species in the vegetative beds in the lakes. Their use requires monitoring to track the effectiveness of the pesticides and to track their effect on native species. While using the satellite imagery cannot differentiate what species are being affected within the bed, it can be used to track the reduction in size of the beds that result from pesticide applications. Once this occurs, a field team could document what species recolonize the area. In addition, the analysis provides a lake-wide view of all the man-made structures and the locations of large beds within the lakes. Maps made with this information could be useful to resource managers in matching existing permits with structures and determining which structure are in violation. Again, a ground check would be necessary to confirm the presence of structures for legal purposes, but maps derived using the image processing methods in this study can help to guide this process. Overall, mapping using high resolution satellite imagery cannot completely replace traditional field surveys, but can be used to guide these processes and provide overview information that would be difficult to collect using field methods alone.

This study revealed several problems that should be addressed in future work. The accuracies in the Level I classification were low, but comparable to results of similar studies in the peer-reviewed literature. Laba et al. (2008) reported a result of 68.4% for the overall accuracy while classifying invasive wetland species using Quickbird satellite imagery of in the Hudson River National Estuarine Research Reserve, which is similar to the 68% for Cree Lake in the 2007 imagery. The Level II classification was more successful and the smaller number of classes is more comparable (in terms of thematic detail) to other work on aquatic macrophyte mapping (Everitt et al. 2005; Everitt et al. 2008; Jensen et al. 1986; Mackey et al. 1992; Olmanson et al. 2002; Sawaya et al. 2003; Valta-Hulkkonen et al. 2005; Vis et al. 2005; Wolter et al. 2005). In an attempt to comprehensively map the aquatic plants in the study lakes, the heads-up digitizing process used to identify shorelines from the panchromatic imagery included overlapping shore vegetation. Since most macrophyte beds in the study lakes grow up to the water's edge, the problem becomes which is more important in the heads-up digitization process: inclusion of all possible aquatic macropyhte beds or exclusion of shore vegetation? In future applications, the tradeoffs between these approaches need to be considered carefully.

Another issue to consider in future work is the impact of bottom reflectance on spectral signatures captured in imagery, which can impact classification results. The IDNR has recently made available bathymetric data that could help inform and potentially improve mapping results in future studies. While bathymetric data for the lakes did not become available until after much of the current study was completed, initial inspection of these data suggests a potential correlation between water depth and several spectral features apparent in visual interpretation of the imagery. It is known that sandy bottoms are more often confused with submerged vegetation than muck bottoms (Wolter et al. 2005) and it is possible that areas in the study lakes with sandy bottoms have more confusion than areas without. This is an issue that needs to be explored in further studies.

Classifying all eight lakes together in the 2008 imagery instead of processing each lake separately may have contributed to lower accuracies, particularly in the Level I maps. This approach may also have masked areas in lakes with unique environments. However, classifying all eight lakes simultaneously did allow for a large area to be classified in a relatively short amount of time. Resource managers will need to decide whether time or accuracy is more vital when determining whether to classify lakes in bulk or separately. When making these types of decisions, the desired thematic detail should also be considered. It is likely that more accurate species-level maps could be developed by processing lakes individually. More general maps designed to inform decisions about total aquatic plant cover can be created using the simultaneous classification approach.

The less-detailed Level II maps were developed by aggregating the results of the more detailed Level I classifications. Future studies could explore the effect of an alternative approach on accuracy assessment. For example, less detailed Level II classes could be generated first, then sub-analyses of these more general classes could be conducted to evaluate the potential to discern more thematically detailed classes.

One of the issues with using Quickbird imagery is that standard orders can be preempted by priority orders (Wolter 2005). Given the very narrow optimal window for mapping aquatic macrophytes in these lakes, this could be a potential problem in using satellite imagery in the future. In this study only nine lakes from the imagery were analyzed in the September 2008 imagery. The imagery covers an additional thirteen named lakes as well as numerous smaller unnamed lakes and ponds (Fig. 9). Using this study as a starting point, further analysis on these additional lakes could be done with the data already available. Additionally, this study used individual dates of imagery to derive classifications for the lakes. The potential to use multi-temporal imagery, which would provide additional information on aquatic plant spectral variation, could be considered in future work.

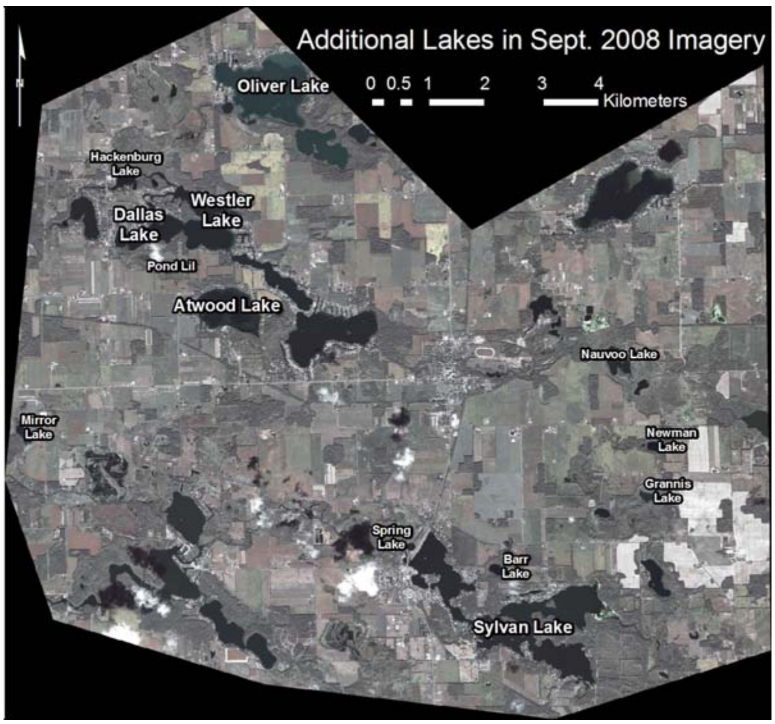
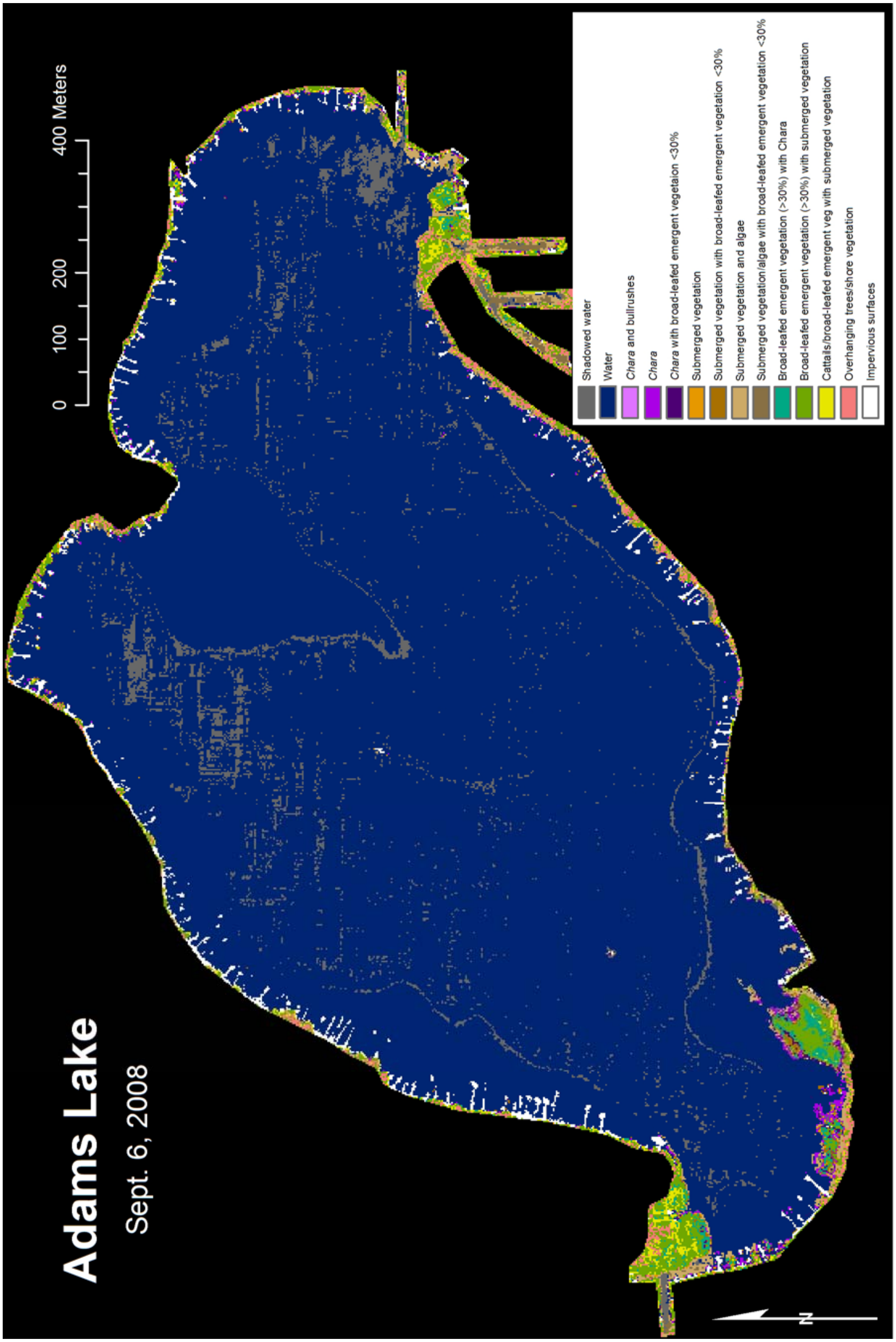


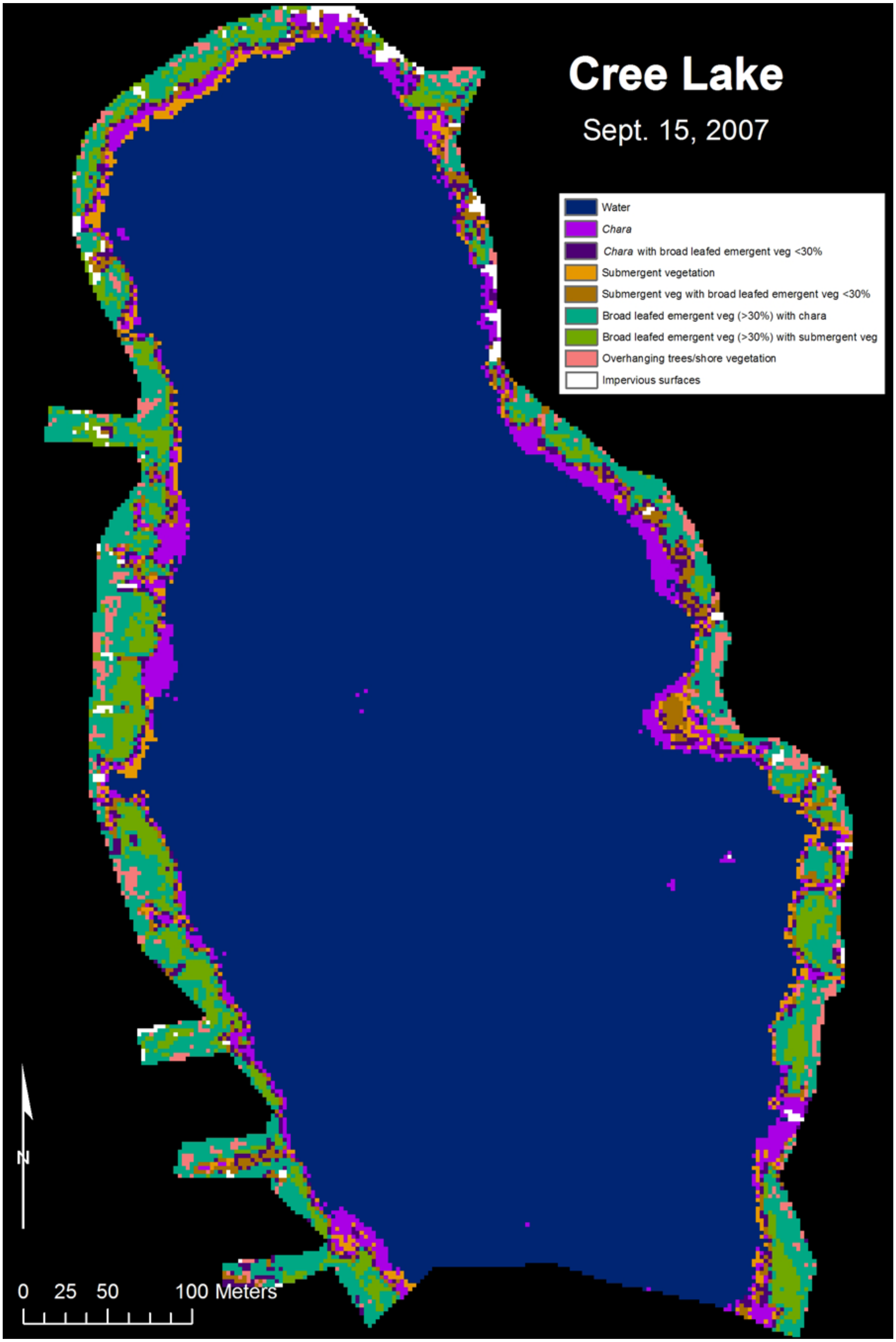
Fig. 9. The location of lakes in the September 2008 imagery that were not a part of this study.

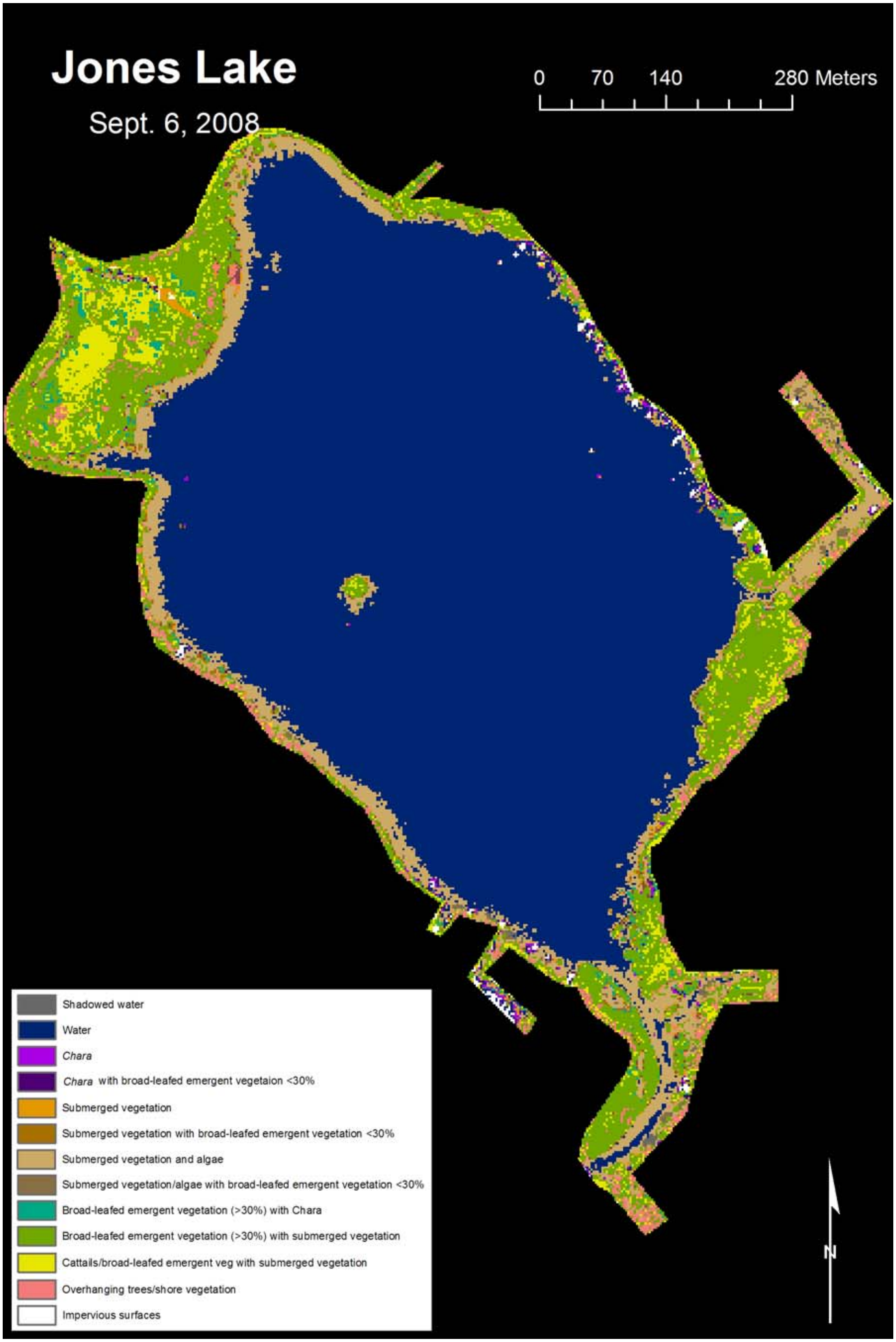
In summary, this study has shown that high resolution satellite imagery can be used to map aquatic vegetation in small lakes for management purposes. Areal estimates of general thematic classes, such as submergent and emergent vegetation, can be generated for multiple lakes simultaneously. High resolution satellite imagery was also successfully used to identify the presence of man-made structures in lakes that could help guide more detailed field assessments for regulatory purposes. Further study is needed to determine whether alternative methods and data sources (such as multi-temporal imagery, bathymetric data, and different image processing approaches), can be used to derive more detailed maps with species-level classes that important for natural resource management decisions.

Appendix A

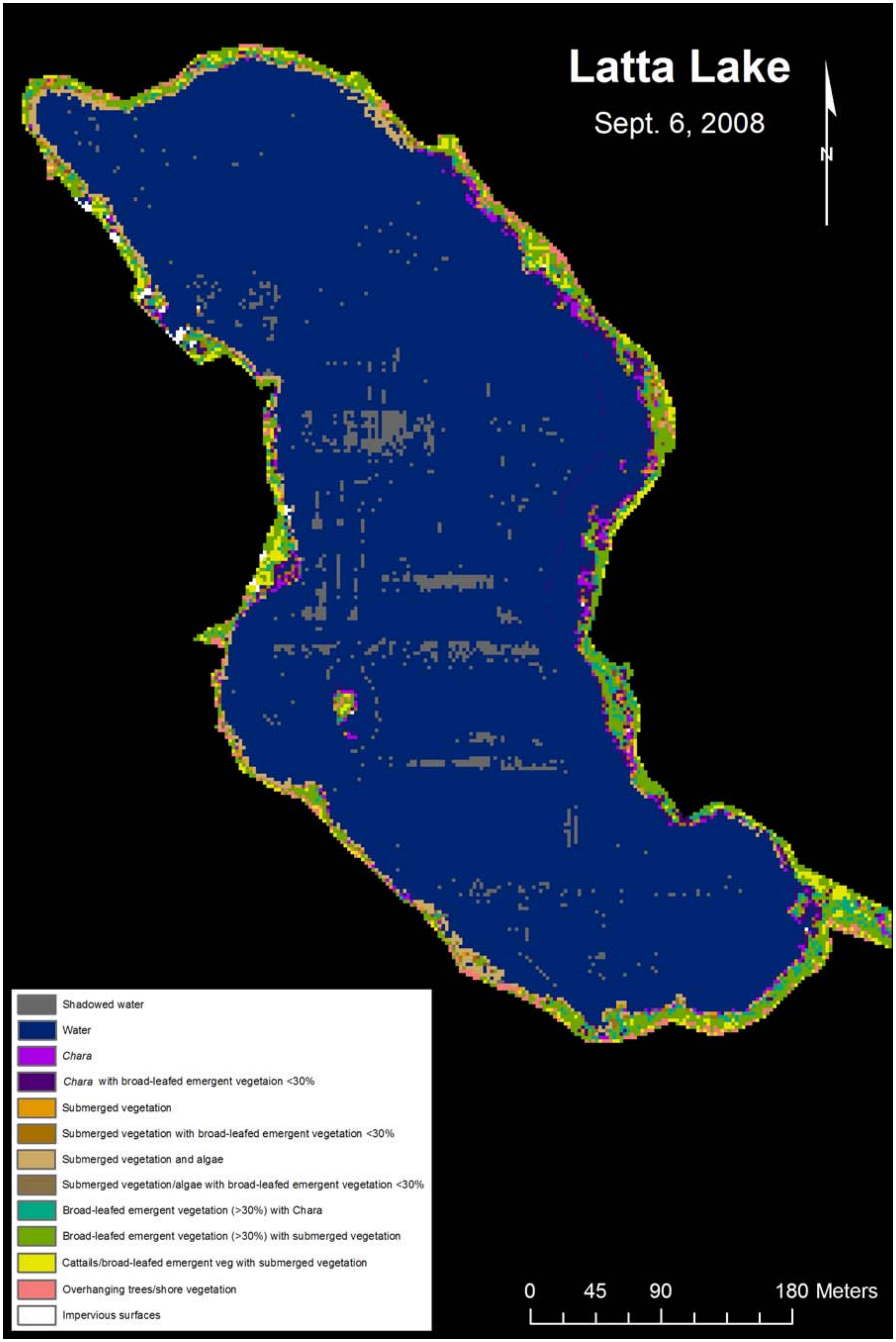
Level I Classification Maps

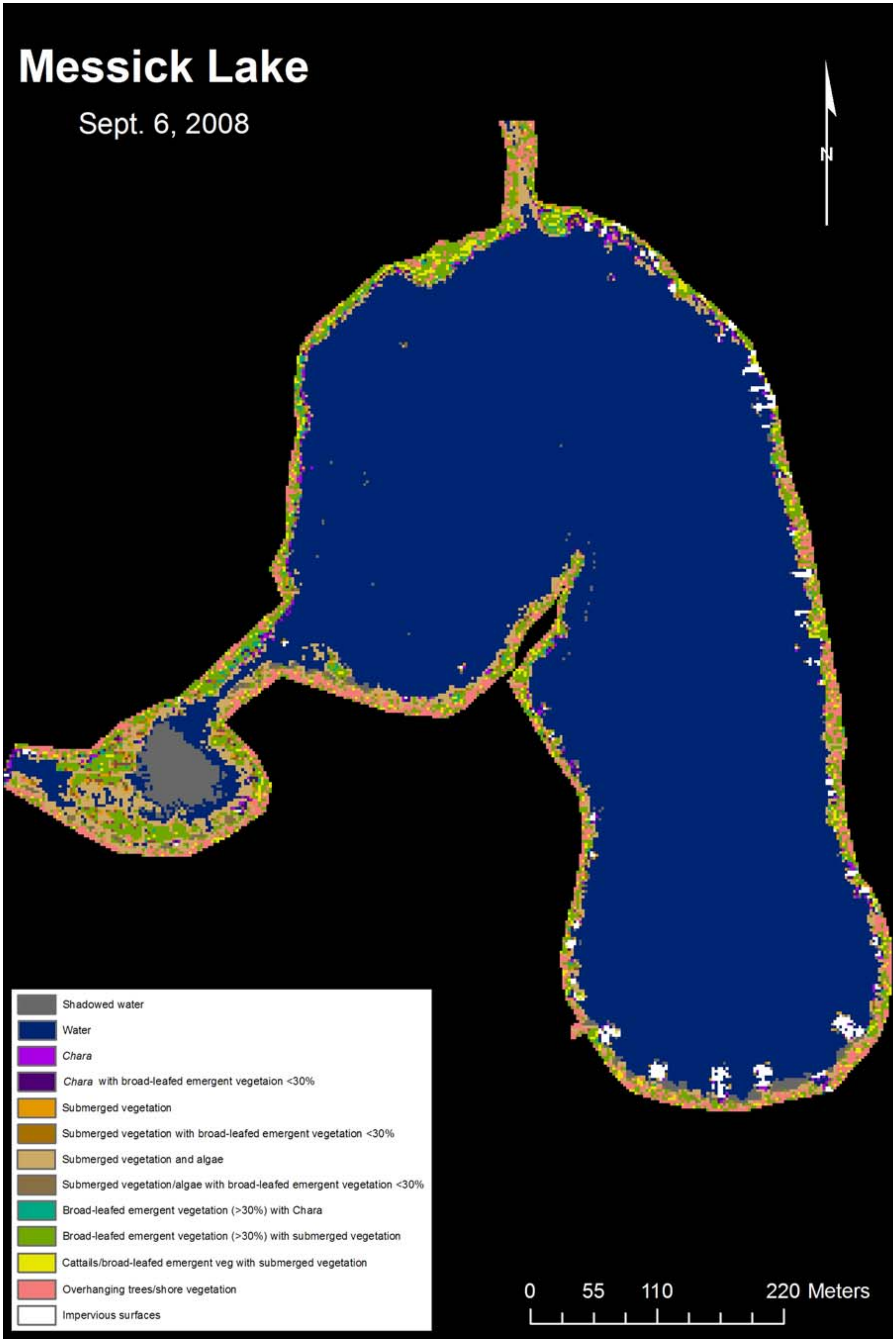

Adams Lake
Sept. 6, 2008
0
100
200
400 Meters
N
Shadowed water
Water
Chara and bullrushes
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces


Cree Lake
Sept. 15, 2007
Water
Chara
Chara with broad leafed emergent veg <30%
Submergent vegetation
Submergent veg with broad leafed emergent veg <30%
Broad leafed emergent veg (>30%) with chara
Broad leafed emergent veg (>30%) with submergent veg
Overhanging trees/shore vegetation
Impervious surfaces
N
0 25 50 100 Meters

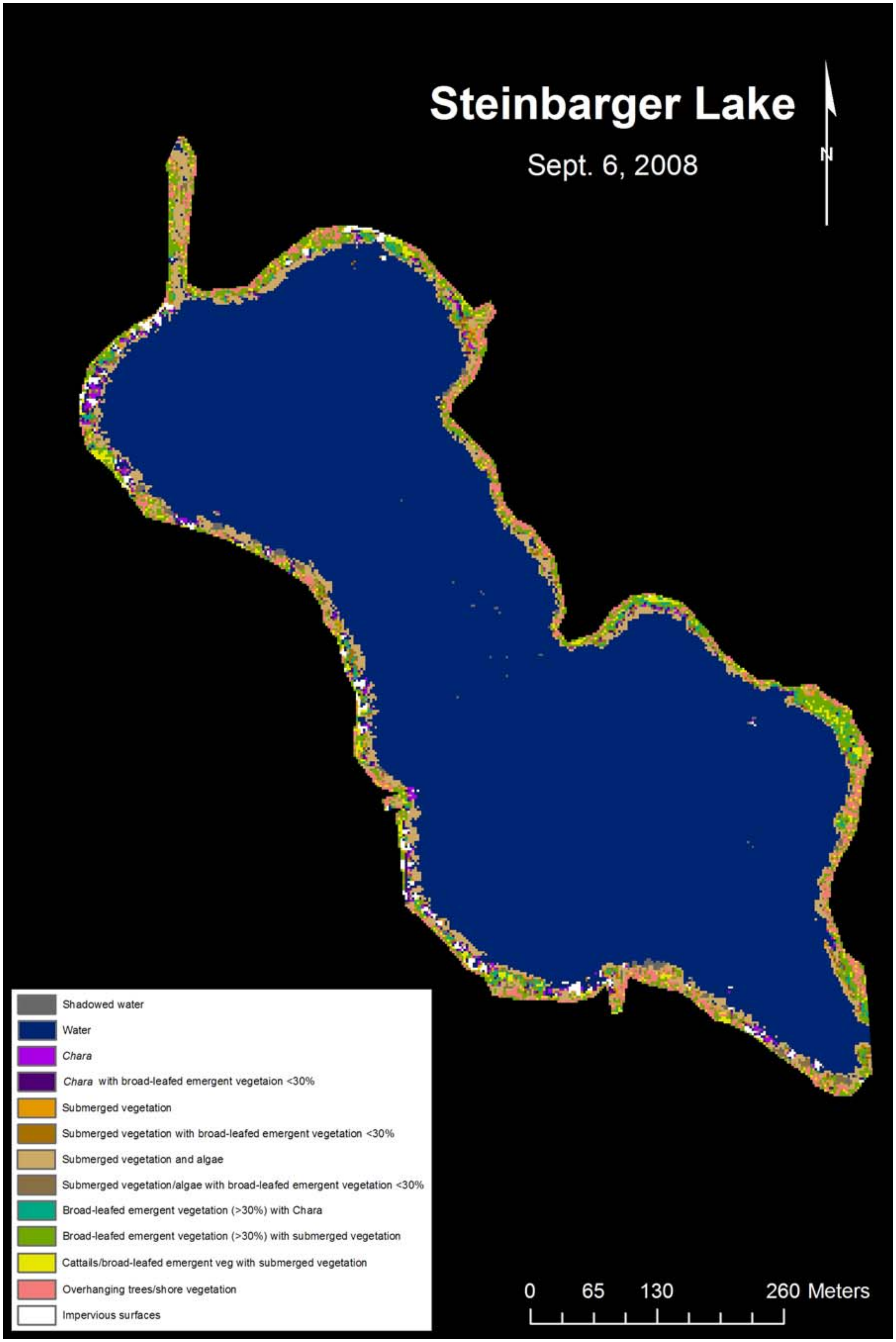


Jones Lake
Sept. 6, 2008
0 70 140 280 Meters
Shadowed water
Water
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces
N


Latta Lake
Sept. 6, 2008
N
Shadowed water
Water
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 45 90 180 Meters

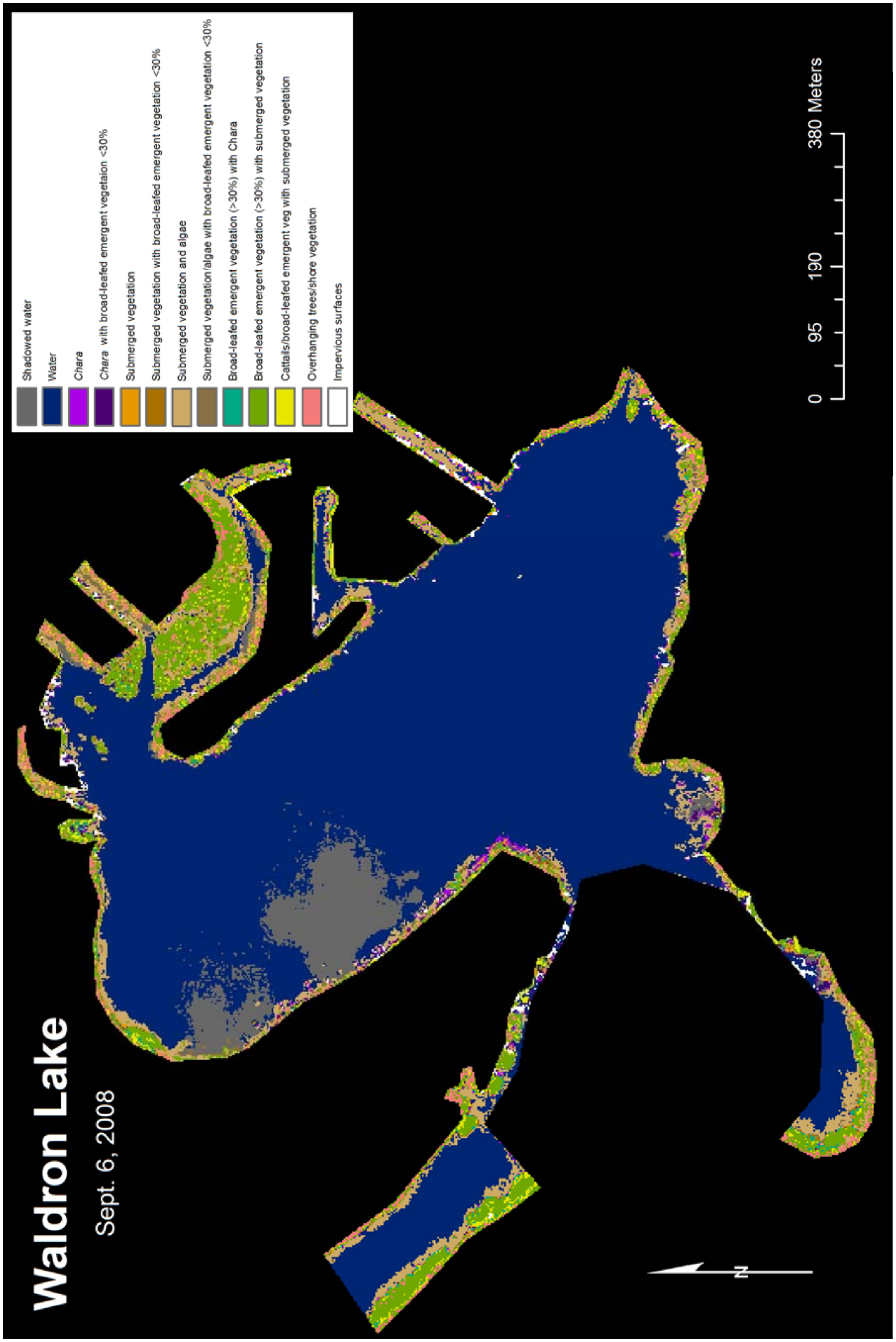


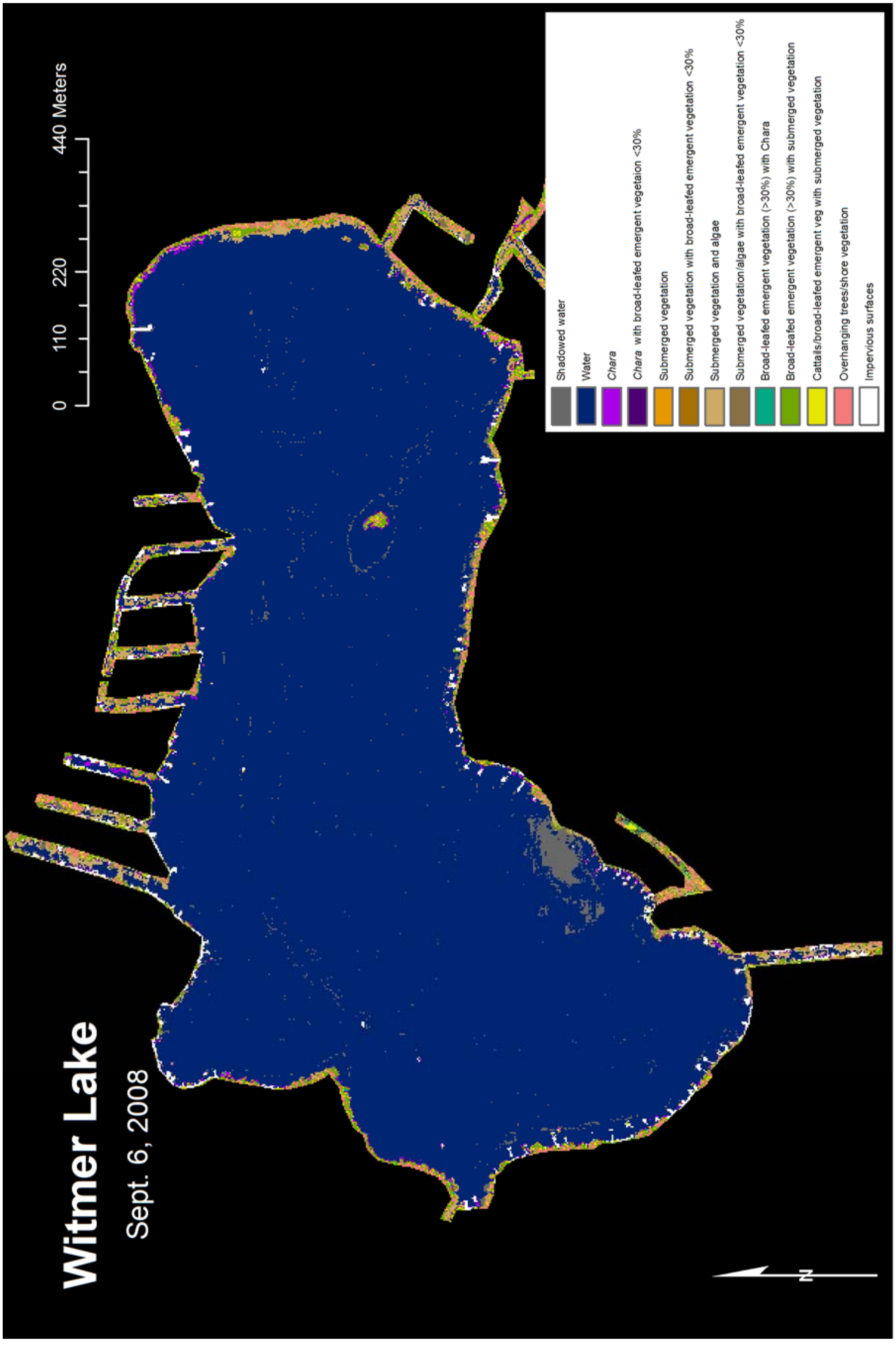
Messick Lake
Sept. 6, 2008
N
Shadowed water
Water
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 55 110 220 Meters



Steinbarger Lake
Sept. 6, 2008
N
Shadowed water
Water
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 65 130 260 Meters

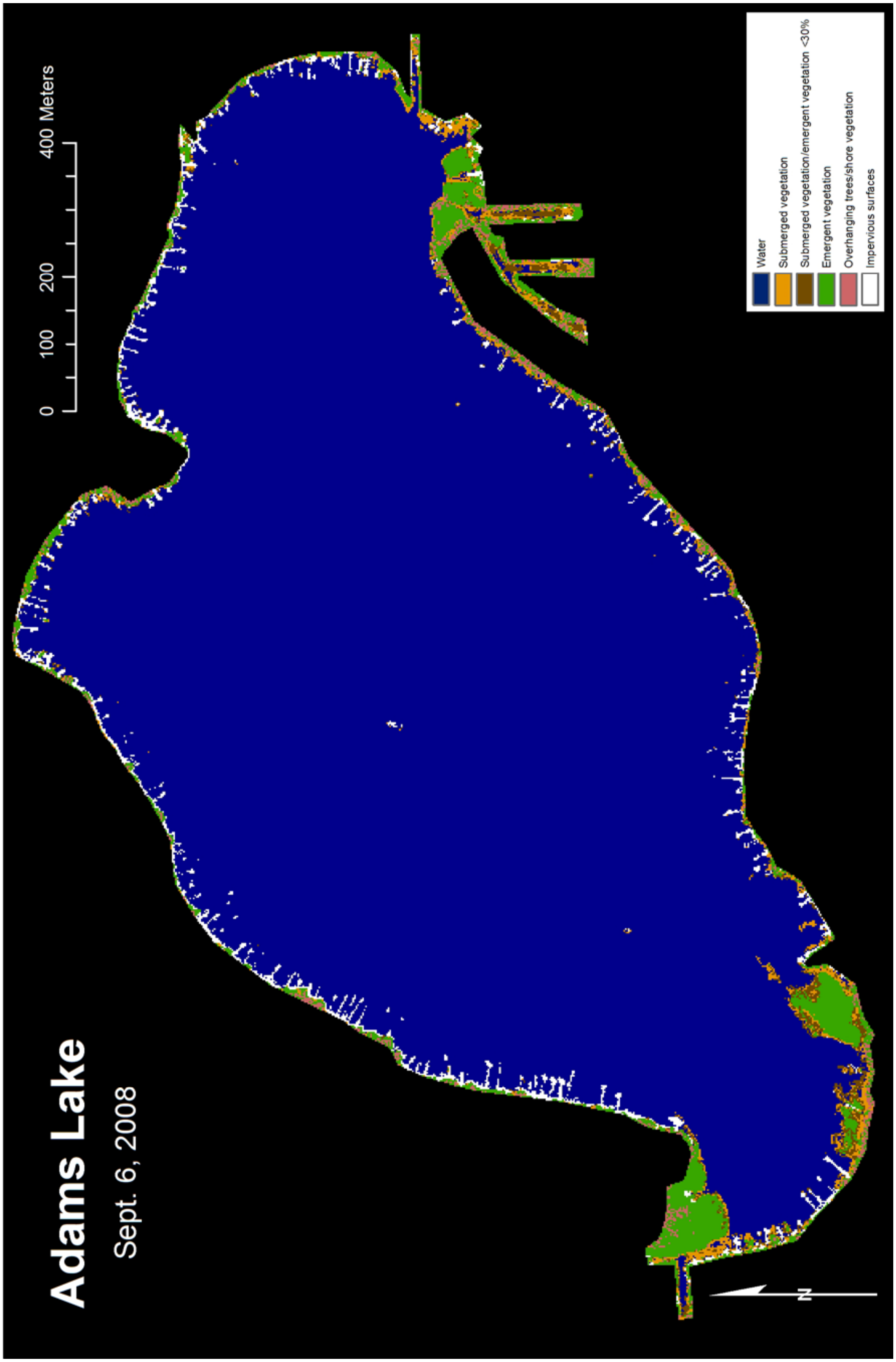

Tamarack Lake
Sept. 6, 2008
N
Shadowed water
Water
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 45 90 180 Meters

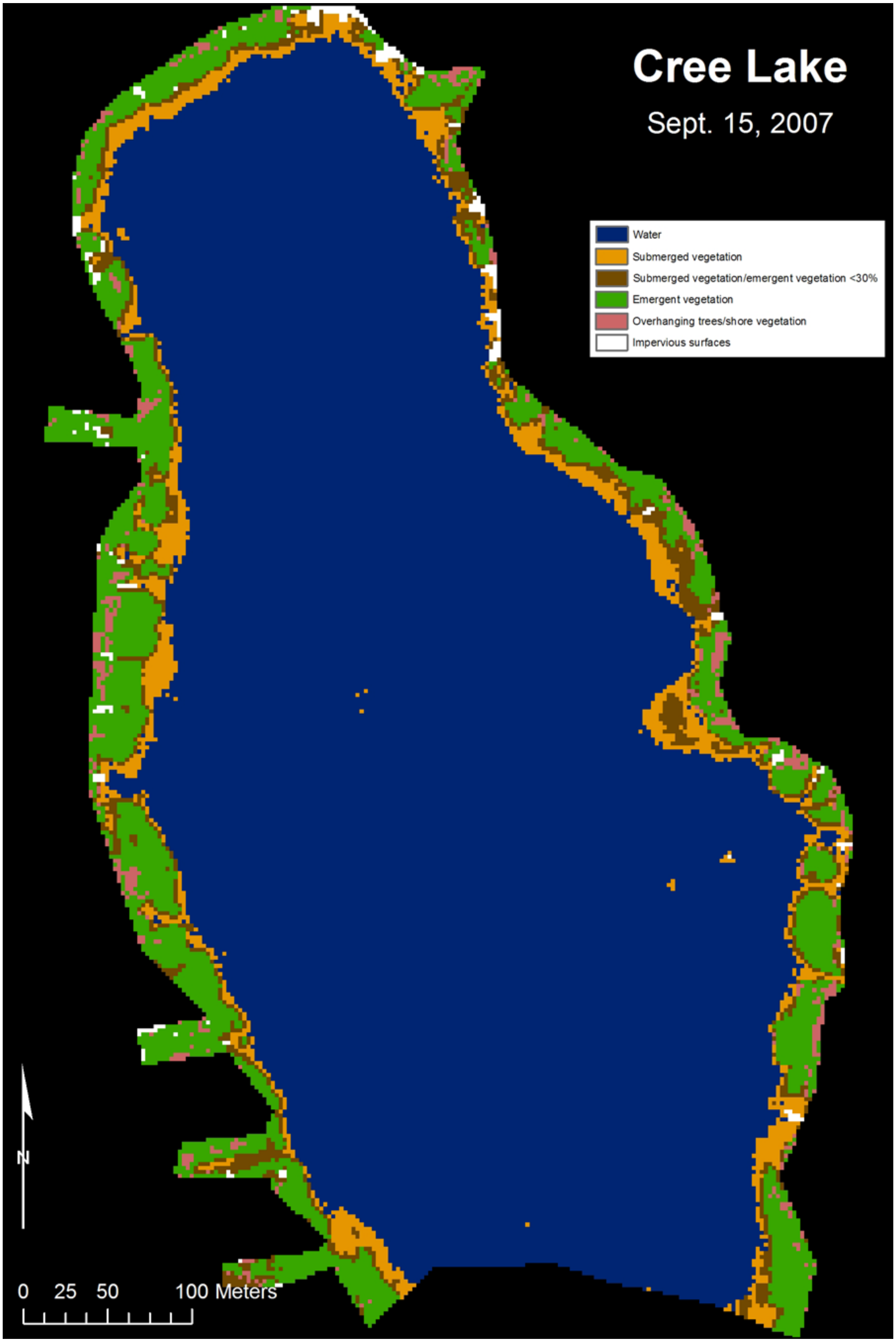

Waldron Lake
Sept. 6, 2008
Shadowed water
Water
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0
95
190
380 Meters
N


Witmer Lake
Sept. 6, 2008
0 110 220 440 Meters
N
Shadowed water
Water
Chara
Chara with broad-leafed emergent vegetaion <30%
Submerged vegetation
Submerged vegetation with broad-leafed emergent vegetation <30%
Submerged vegetation and algae
Submerged vegetation/algae with broad-leafed emergent vegetation <30%
Broad-leafed emergent vegetation (>30%) with Chara
Broad-leafed emergent vegetation (>30%) with submerged vegetation
Cattails/broad-leafed emergent veg with submerged vegetation
Overhanging trees/shore vegetation
Impervious surfaces

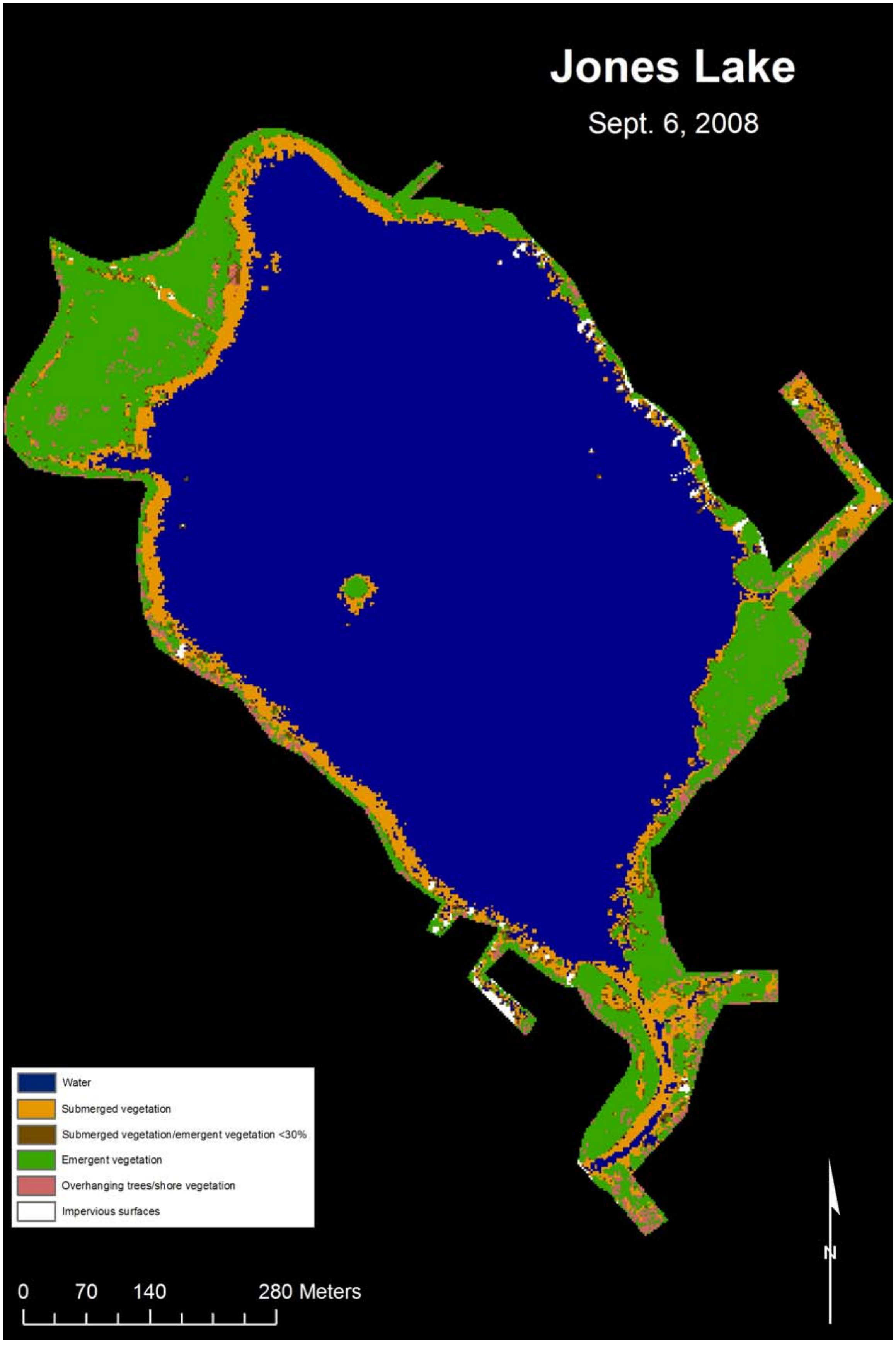
Appendix B

Level II Classification Maps

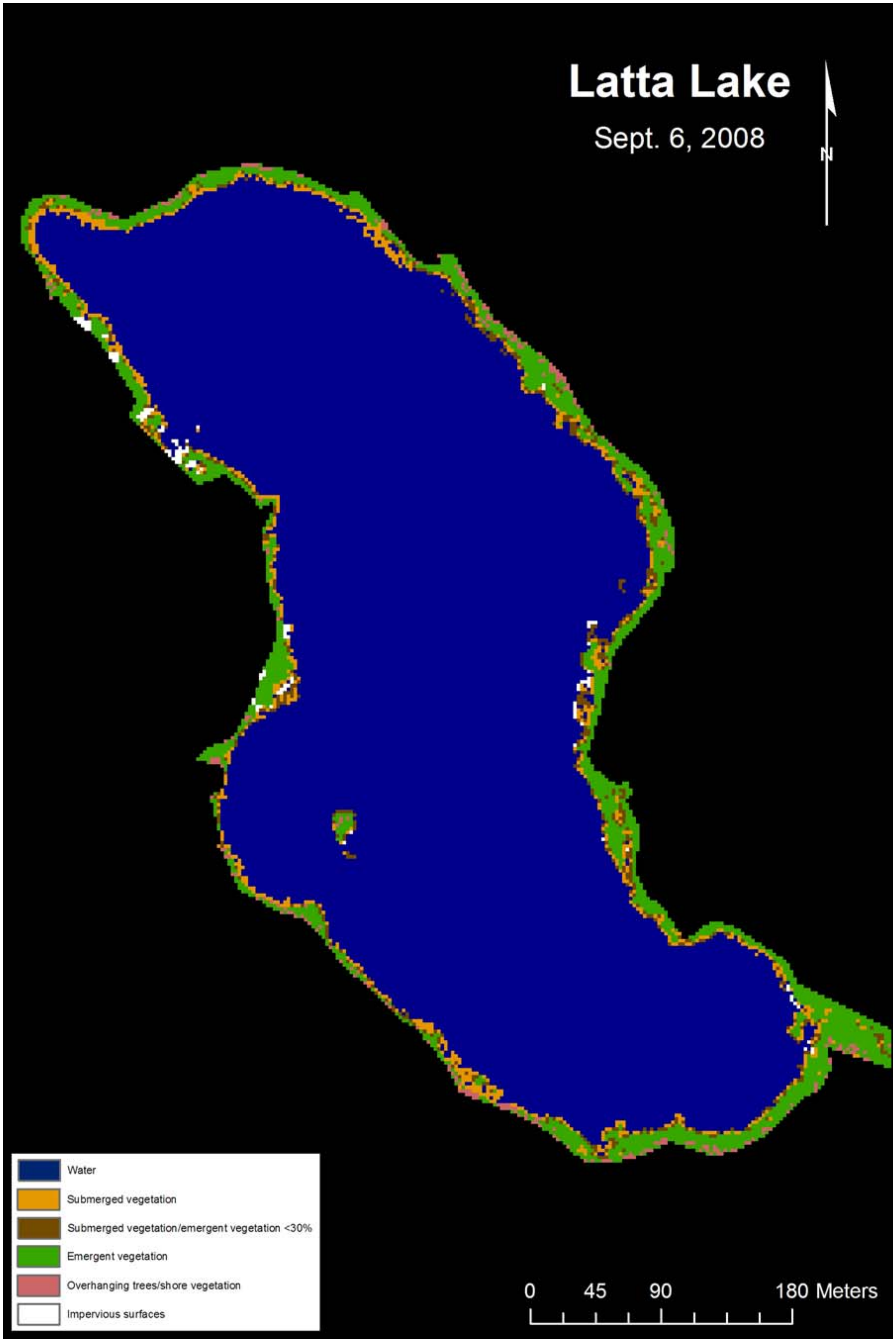

Adams Lake
Sept. 6, 2008
0
100
200
400 Meters
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
N



Cree Lake
Sept. 15, 2007
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
N
0 25 50 100 Meters

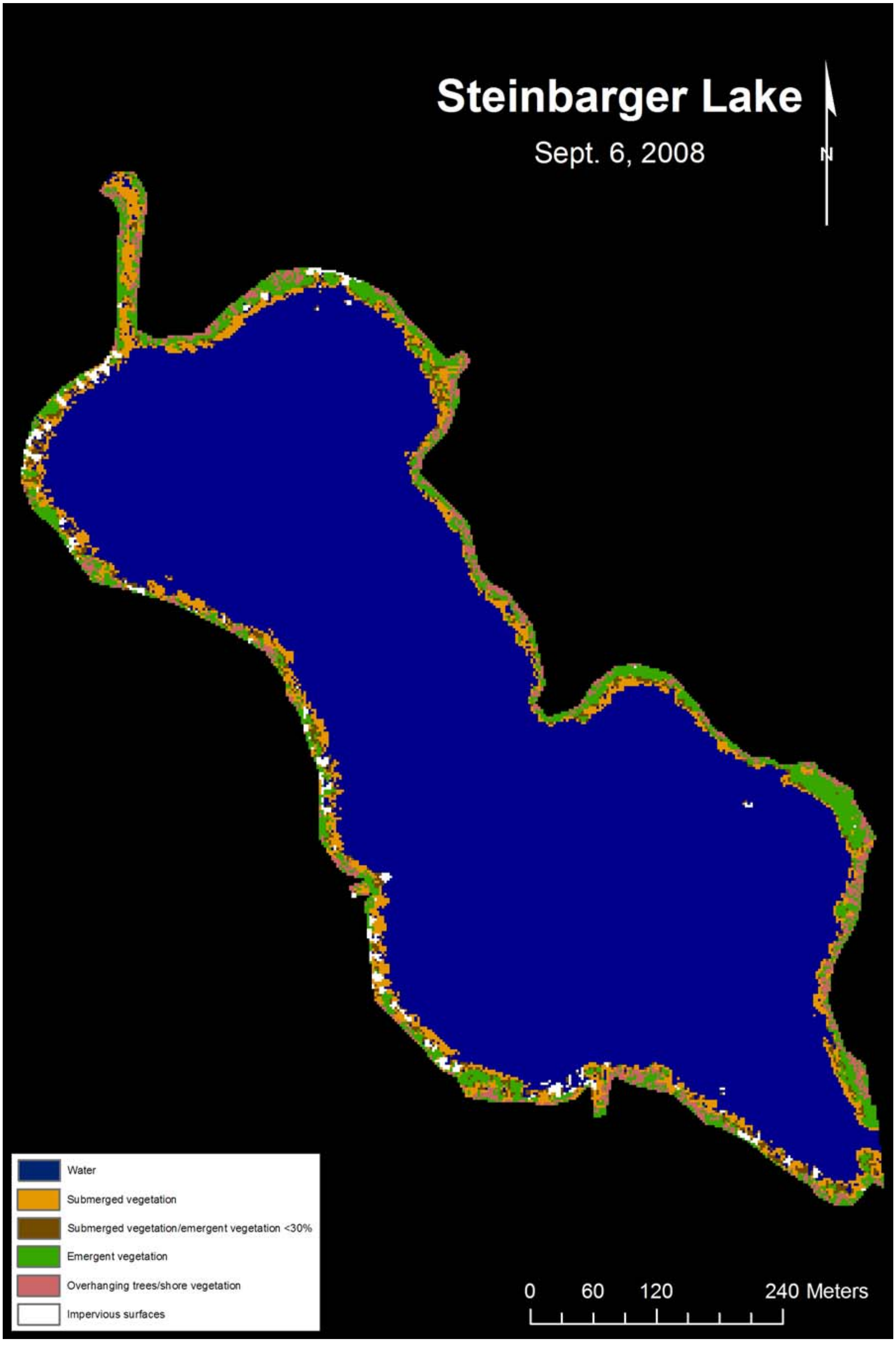


Jones Lake
Sept. 6, 2008
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 70 140 280 Meters
N

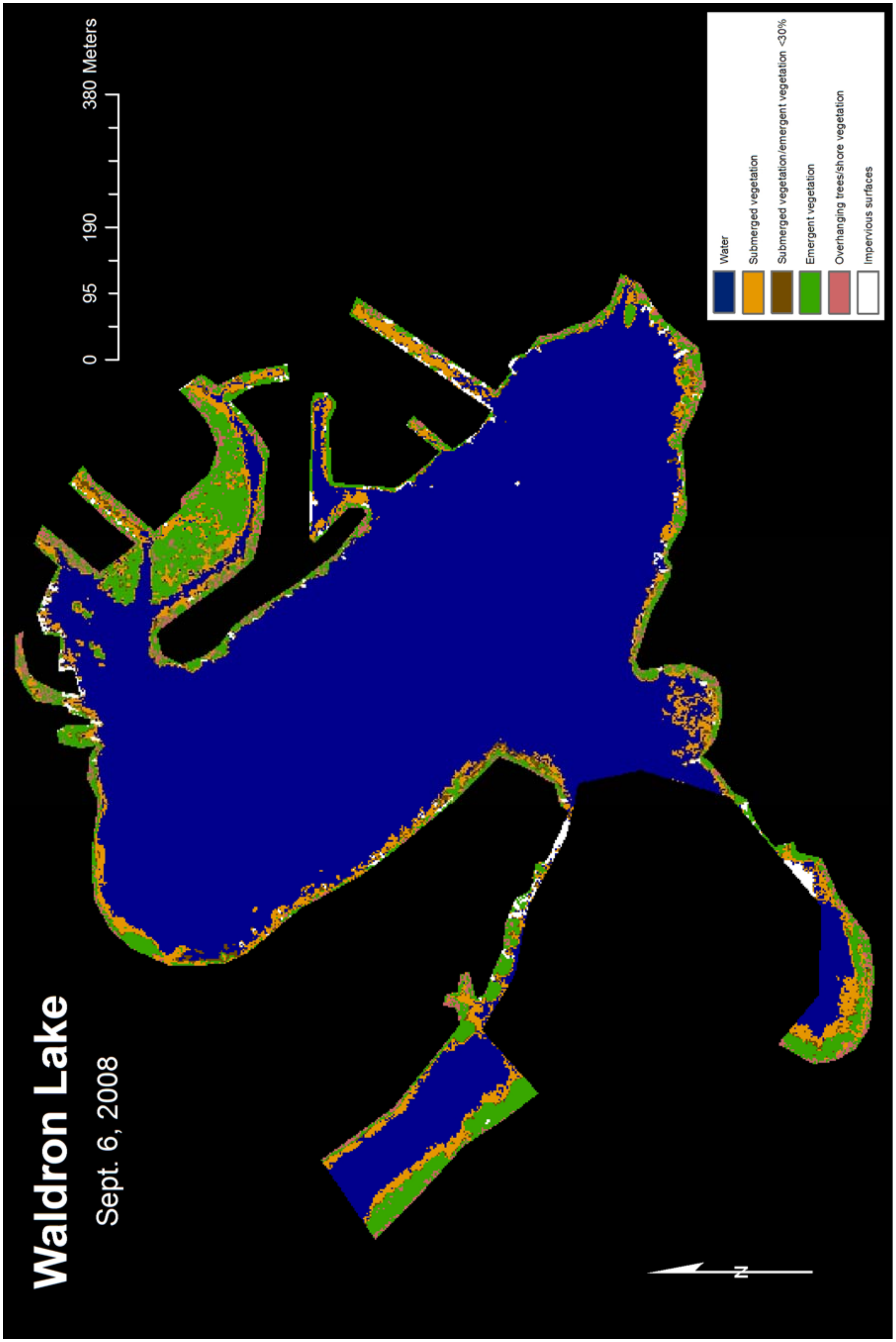


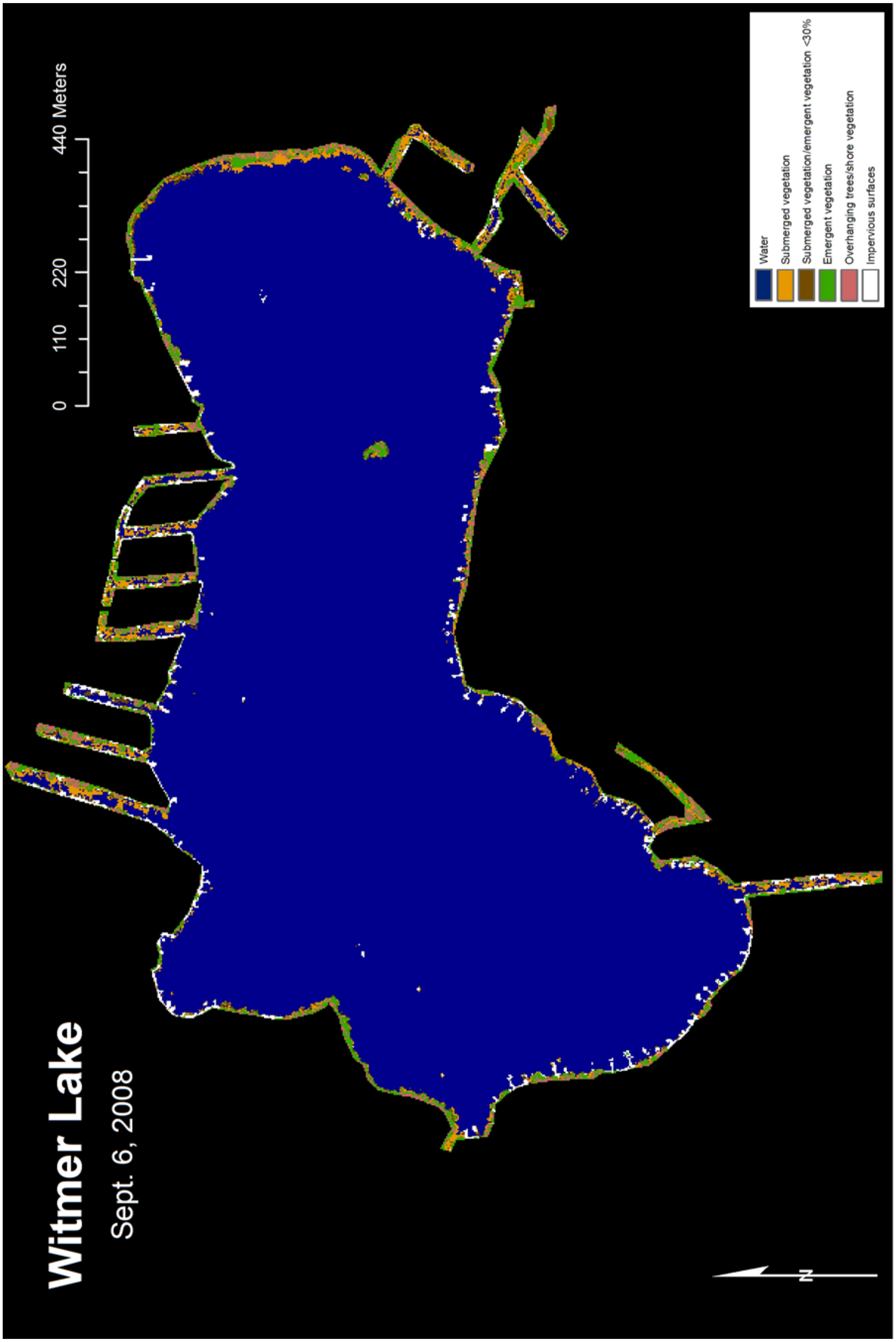
Latta Lake
Sept. 6, 2008
N
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 45 90 180 Meters

Messick Lake
Sept. 6, 2008
N
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 55 110 220 Meters


Steinbarger Lake
Sept. 6, 2008
N
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 60 120 240 Meters


Tamarack Lake
Sept. 6, 2008
N
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
0 45 90 180 Meters


Waldron Lake
Sept. 6, 2008
0 95 190 380 Meters
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
N


Witmer Lake
Sept. 6, 2008
0
110
220
440 Meters
Water
Submerged vegetation
Submerged vegetation/emergent vegetation <30%
Emergent vegetation
Overhanging trees/shore vegetation
Impervious surfaces
N

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