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ASSESSING INVASIVE PLANT INFESTTAION IN
FRESHWATER WETLANDS

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Nathan M. Torbick

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ASSESSING INVASIVE PLANT INFESTATION IN FRESHWATER WETLANDS.

By

Nathan M. Torbick

A DISSERTATION

Submitted to
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ABSTRACT

ASSESSING INVASIVE PLANT INFESTATION IN FRESHWATER WETLANDS.

By

Nathan M. Torbick

Recent shifts in wetland ecosystem management goals have directed efforts toward measuring ecological integrity, rather than only using physical and chemical measures of ecosystems as health indicators. Invasive species pose one of the largest threats to wetlands integrity. Resource managers can benefit from improved methods for identifying invasive plant species, assessing infestation, and monitoring control measures. The utilization of advanced remote sensing tools for species-level mapping has been increasing and techniques need to be explored for identifying species of interest and characterizing infestation.

The overarching goal of this research was to develop monitoring technologies to map invasive plants and quantify wetland infestation. The first field-level objective was to characterize absorption and reflectance features and assess processing techniques for separating wetland species. The second field-level objective was to evaluate the abilities of a shape filter to identify wetland invasive plant species. The first landscape-level objective was to classify hyperspectral imagery in order to identify invasives of interest. The second landscape-level objective was to quantify infestation within the study area.

Field-level hyperspectral data (350-2500nm) were collected for twenty-two wetland plant species in a wetland located in the lower Muskegon River watershed in Michigan, USA. The Jeffries-Matusita distance measure, continuum removal, and a

shape-filter were applied to hyperspectral species reflectance data to characterize spectral features. Generally, continuum removal decreased separation distance for the invasive species of interest. Using the shape-filter, *Lythrum salicaria*, *Phragmites australis*, and *Typha latifolia* possessed maximum separation (distinguished from other species) at the near-infrared edge (700nm) and water absorption region (1350nm), the near-infrared down slope (1000 and 1100nm), and the visible/chlorophyll absorption region (500nm) and near-infrared edge (650nm), respectively.

Airborne hyperspectral imagery was classified using a two-step approach in order to obtain an optimal map (overall accuracy ~ 70%). Information in the near-infrared enabled relatively accurate classification for *Phragmites australis* using the Spectral Angle Mapper algorithm and image-derived training, while *Typha latifolia* signatures possessed high spectral overlap and required ISODATA clustering techniques. Landscape pattern metrics relate infestation to disturbances and hydrological controls. The highest levels of infestation and infestation patterns coincide with the most substantial levels of hydrological modifications indicating human disturbances are correlated with *Typha* and *Phragmites* percentages in the landscape.

Overall the approach was successful and increased the level of information ultimately desired by decision makers. The rapidly advancing field of wetland remote sensing science can obtain more meaningful information from hyperspectral imagery; however, the data are challenging to work with and only the most precisely calibrated datasets will provide utility. Combining these data with traditional wetland assessment techniques can substantially advanced goals of preserving and restoring wetland ecosystem integrity.

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Chapter 1: INTRODUCTION

Global inventories estimate that approximately half of the world's wetlands have been lost due to human activities (Mitsch and Gosselink 2000). Over 50% of the 90 million hectares of wetlands estimated in the lower 48 states at the time of European settlement have been lost due to human activities (Figure 1). In the Great Lakes regions, some states have lost 90% of the original wetlands primarily to intense agricultural expansion, resource use, and urbanization (Dahl 2000).

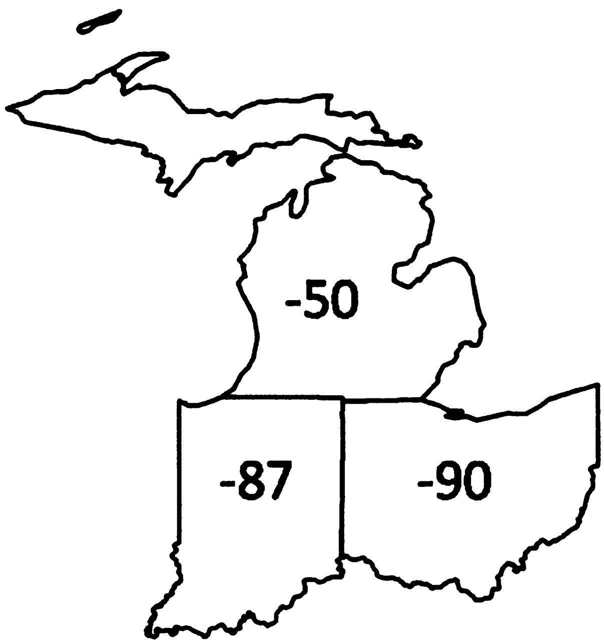


Figure 1. Wetlands percentage loss in the past 150 years (Source: Dahl 2000).

The substantial loss of wetland area has gained attention over the past few decades. The environmental and socioeconomic benefits of wetland ecosystems are now well recognized. These benefits are in the form of services provided by the ecosystem functions wetlands perform. These range from ground water recharge and flood control to providing habitat and promoting biodiversity. Current policies and regulations at various government levels require wetlands management practices to conserve and promote the benefits wetlands provide. No net loss and assessment policies are in place which requires monitoring and inventory to conserve the remaining wetlands.

Traditionally, wetland assessment techniques have largely relied on a few physiochemical measurements as indicators of condition. Recent shifts in ecosystem management goals have redirected efforts toward measuring ecological and biological integrity, rather than only using physical and chemical measures of ecosystems as health indicators (USEPA 1998, EMAP 2002). Here, integrity refers to a condition that is determined to be characteristic of its natural condition considering history, regionalization and scale, and levels of diversity and resiliency. Preserving and restoring the ecological integrity of the remaining wetlands has become a priority (Danielson 2001, NRC 1995, 2000). This shift is part of a growing consensus that wetland assessments require a set of complementary indicators for a complete 'check-up' and assessment of the threats to ecosystem functions (Paulsen et al. 1991, US EPA 1996, 1998).

Currently an overarching goal for wetlands assessment is to provide improved information on invasive species (EMAP 2002, NRC 1995, 2000). Invasive species are one of the largest threats to wetlands biodiversity and ecosystem functioning. In the US, invasive species are estimated to cause $120 billion dollars per year in environmental damage and associated control costs: *Lythrum salicaria* (purple loosestrife) alone is estimated to cost $45 million per year as it spreads at a rate of 115,000 ha/yr across wetlands in the US (Pimentel *et al.* 2005).

The term invasive is sometimes used interchangeably with exotic, alien, foreign, introduced, and nonindigenous among others. The National Invasive Species Information Center (USDA) defines an invasive species as non-native to an ecosystem and whose introduction is likely to cause economic or environmental harm (USDA NRCS 2007). The EPA and other organizations tend to focus on *likelihood to cause ecological harm or economic damage* and not so much on alien categorization (EMAP 2002, NRC 2000). The pre-industrial revolution (circa 1750) is often set as a benchmark for determining whether a species is native or foreign. Currently there are approximately 7000 non-native species introduced in the US, about 15% become invasive, and only a smaller percent of those become a nuisance or cause harm (USDA NRCS 2007).

Ecologically, invasive refers to a set of characteristics that a species possess that enable that species to establish, often aggressively, or invade. Those characteristics include a plants reproduction ability (e.g., seed- abundance, persistence, vigor), growth pattern (e.g., moisture use, anaerobic tolerance, density), and morphological adaptations (e.g., foliage porosity, shape, form). The degree of invasiveness will vary by region and environmental conditions. Generally, invasives have been found to alter ecosystem functions and services such as hydrology, soil moisture, disturbance regimes, and ecosystem resiliency. Invasives have a wide tolerance to environmental conditions (e.g., soil and water pH, temperature, and hydroperiod fluctuations), possess phenotypic plasticity and unique life cycle features (e.g., reproduction, seed crop intervals), and can often undergo rapid evolution.

1.1 Wetlands Remote Sensing

Wetlands mapping programs have largely focused on identifying extent or total area. The National Wetlands Inventory (NWI) program has relied extensively on fine-scale aerial photography as its primary source of data. Human photo interpretation techniques are utilized to delineate the extent of wetlands in a given area based on these photos. This technique is by nature somewhat subjective as visual interpretation approaches rely on an expert to delineate wetland boundaries. While acceptable accuracy can be achieved for a region, the approach can be time consuming, expensive, and extrapolation to other regions is problematic. The last large-area NWI application is now more than two decades old. Further, when using subjective approaches, discrepancies exist between classifications (e.g., NWI vs. Michigan Land Use Land Cover), program objectives, and definitions used to map wetlands.

Satellite and airborne remote sensing has been utilized for nearly three decades to inventory and identify wetlands (Hardinsky 1986). Similar to aerial photography, remote sensing techniques are often less costly and time-consuming compared to conventional field methods. Advantages of satellite and airborne data include regular overpass intervals with capabilities for the mapping of wetlands and adjacent land use/covers, monitoring human activities and impacts on wetlands, assessing wetland changes seasonally, and extrapolation of information over large regions. Sensor instruments record measurements in spectral regions outside of the visible spectrum. Additionally, advances in technology and computer capabilities allow advanced modeling and integration of remotely sensed data within a Geographic Information System (GIS).

Many wetlands mapping studies discuss the limitations of remote sensing technology. Data resolution has been the foremost limiting factor in obtaining high precision and detailed information on wetlands vegetation and biophysical characteristics (Ozemsi and Bauer 2002). Coarse spatial resolutions have made delineations of wetland boundaries challenging (Fortin *et al.* 2000, Torbick *et al.* 2006), while broad radiometric and spectral resolutions prohibit species level separability (Becker *et al.* 2005, Schmidt and Skidmore 2003). Generally fewer types, or categories, of wetlands can be mapped due to complications with spatial resolution, temporal overpass constraints, and spectral variability and overlap. In response to these limitations, the NWI program (in the USA) has used color infrared aerial photography exclusively (Cowardin 1979, Tiner 1999).

New state of the art remote sensing technology can contribute to advancing wetlands mapping and monitoring. Recent advances in sensor technology and remote sensing science have promoted an interest in hyperspectral data for mapping wetlands at the species level (Artigas and Yang 2006, Becker *et al.* 2005, Schmidt and Skidmore 2003, Thiemann and Kaufmann 2002, Thomas *et al.* 2002). Advanced spectroscopic systems possess capabilities to capture data at narrow spectral bandwidths on the order of three to ten nanometers (nm) contiguously covering large portions of the spectrum (e.g., 350-2500nm). This allows for small variations in plant/substrate absorptance and reflectance to be recorded (Figure 2). Incorporating such relatively high spectral detail makes it possible to explore species separability and precise ecological process monitoring (Schmidt and Skidmore 2003, Ustin *et al.* 2004).

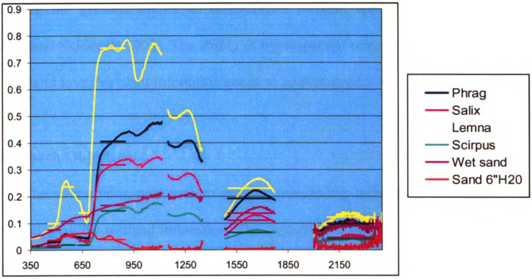


Figure 2. Example plant signatures recorded using a hyperspectral instrument with rescaled Landsat resolutions signatures overlaid.

1.2 Problem Statement

Traditionally most ecosystem assessment techniques have relied on a few physical and chemical measures of systems as indicators of health. In order to meet future goals for enhancing wetland ecosystem integrity, resource managers and decision makers need advanced information and improved methods for identifying wetland stressors and ecological indicators, such as invasive plants, and for monitoring response to control measures. Multispectral remote sensing has been a useful tool in monitoring and mapping aquatic vegetation and stressors; however, the information provided is limited in achievable detail by sensor resolutions.

Hyperspectral sensing technologies that capture narrow spectral and spatial resolution data can advance assessment techniques for addressing complex wetland assessment questions. A few studies have explored methods to identify wavelengths possessing the greatest ability to differentiate wetland species (Becker et al 2005, Schmidt and Skidmore 2003). The ability of hyperspectral remote sensing technologies to map wetland invasive plant infestation needs to be evaluated.

1.3 Research Objectives

The overarching goal was to develop monitoring technologies to map invasive plants and quantify wetland infestation. The objectives were broken into two categories: field-level and landscape-level. The first field-level objective was to characterize absorption and reflectance features and assess processing techniques for separating wetland species. The second field-level objective was to evaluate the abilities of a shape filter, which requires unique absorption features for successful implementation, to identify wetland invasive plant species. The overarching landscape-level goal was to map invasive plant infestation. The first landscape-level objective was to classify hyperspectral imagery in order to identify invasives of interest. The second landscape-level objective was to quantify infestation within the study area.

Chapter 2: HYPERSEPCTRAL REMOTE SENSING

Satellite remote sensing has been a useful tool in providing general information on wetlands types (Ozesmi and Bauer 2002); however, both spatial and spectral resolutions have limited the level of detail ultimately required for comprehensive wetland assessments. Recent advances in sensor technology and remote sensing science have promoted an interest in hyperspectral data for mapping wetlands at the species level (Artigas and Yang 2006, Becker *et al.* 2005, Hirano *et al.* 2003, Schmidt and Skidmore 2003, Thomas *et al.* 2002). Advanced spectroscopic systems possess capabilities to capture data at narrow spectral bandwidths on the order of three to ten nanometers (nm) contiguously covering large portions of the spectrum (e.g., 350-2500nm). This allows for small variations in plant/substrate absorptance and reflectance to be recorded. Incorporating such relatively high spectral detail makes it possible to explore species separability and precise process monitoring (Schmidt and Skidmore 2003, Ustin *et al.* 2004).

The underlying theory of hyperspectral science is that increased spectral detail, along with improved or adequate spatial resolution, can provide increased information such as species-level mapping. Generally, the higher resolutions a sensor possess, the greater the level of detail can be extrapolated. In the last few years several studies have applied hyperspectral data for wetlands mapping. A primary goal in these investigations was to evaluate and develop methods to utilize the increased level of data supplied via hyperspectral instruments. The studies can be grouped into methods to identify wavelengths of particular utility (processing techniques to extract and identify the most useful bands) and evaluating classification algorithms to map species of interest.

Approaches to identify wavelengths that possess separation abilities are an interest because of the large amount of spectral information and fact that much is redundant. With hyperspectral instruments recording near-continuously, large portions of the data tend to be highly correlated. At the same time the amount of storage space required can be quite large as these sensors do in fact capture hundreds of narrow bands. Processing protocols and limitations on spatial resolutions can be problematic due to the large file sizes. Therefore identifying wavelengths of particular utility allows less spectral information to be required simultaneously allowing for increases in spatial resolutions.

Becker et al. (2005) performed derivative analysis to identify unique points of inflection along spectra for wetland plants in a Great Lakes coastal wetland and identified eight bands as possessing the most utility for separation. The bands are located across the visible (VIS) and near-infrared (NIR) portions of the spectrum and are affiliated with domains that represent unique biophysical characteristics. The red-edge was highlighted as having particular strength in separation. Artigas and Yang (2006) also identified the NIR region using a discrimination metric (Cochrane 2000) and derivative analysis for a New Jersey coastal wetland. This research concluded that monotypic stands of Phragmites could be identified by using the unique NIR response. Schmidt and Skidmore (2003) found significant differences between salt marsh species using field-level reflectance data from coastal Netherlands wetlands.

Developing and improving classifications has been a focus of hyperspectral wetland remote sensing. Becker et al. (2007) examined the optimal spectral and spatial resolutions for mapping Great Lakes coastal wetlands. A series of experiments tested different bands, band combinations, and pixels sizes to identify the most advantageous configurations to accurately map coastal wetlands. The results showed that narrow, strategically located bands were necessary to achieve acceptable resiliency levels when trying to limit the number of bands to maintain small pixel sizes. The research also found that spatial resolutions of 1 meter or under were best situated to map coastal wetlands. Obtaining pixels this size essentially requires use of airborne remote sensing platforms as no satellite instruments possess hyperspectral spatial resolutions less than 20m.

Rosso et al. (2005) used Spectral Mixture Analysis (SMA) and Multiple End-member (MESMA) techniques on airborne data to map a portion of coastal marshes in central California. They found MESMA appropriate allowing for multiple end-members. However, when similar end-members, defined by root-mean-square-error, were utilized accuracy decreased substantially highlighting the need to carefully choose them for image training. Rosso et al. (2005) further found that using less than half a dozen end-members in a more homogeneous environment produced optimal results.

Some recent research focused on evaluating image processing techniques to map wetlands has come to different conclusions. Underwood et al (2003) found increased accuracy in using Minimum Noise Fraction (MNF), a data reduction technique, to map *Carpobrotus edulis* in coastal California; while Artigas and Yang (2006) found less separation ability after applying MNF for salt-marsh species in a New Jersey meadowland. Underwood et al (2003) found band ratio techniques to perform moderately well as an image processing technique to identify coastal *Cortaderia jubuta*, but it did not outperform MNF enhancements. Artigas and Yang (2006) were able to distinguish

Phragmites australis from *Spartina* and *Distichlis* in the NIR region of imagery when only these species were dominant. These papers highlight the fact that biological community composition (number of species and level of heterogeneity) will largely determine selection of image processing methodologies.

Chapter 3: METHODS

3.1 Study Area

The investigation was carried out in an expansive wetland complex in the lower Muskegon River Watershed (MRW) located on the western side of central Michigan (W86° 09' 45", N43° 16' 10"). The MRW is almost 7000 km^2 in size, includes 94 tributaries and 183 stream segments (interrupted by 95 dams), and hundreds of lakes and wetlands (Figure 3). Glacial deposits reach as much as 300m deep over bedrock and create conditions with substantial ground-surface water exchange.

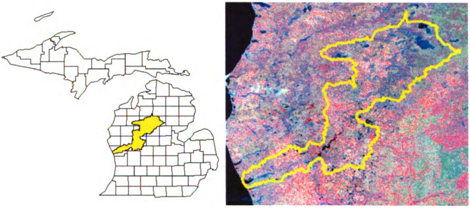


Figure 3. Location of MRW (left) within Michigan and overlay on false color (4:3:2) Landsat ETM+ scene.

Fed from the Muskegon River and an extensive tributary network, the wetland complex serves as the last land-water interface before draining into Lake Muskegon, which flows directly into Lake Michigan (Figure 4). Lake Muskegon was recognized as an Area Of Concern by the 1987 Great Lakes Water Quality Agreement due to poor water quality conditions. Projections show that a 50% urban sprawl increase by 2040 is likely in the coastal sub-watershed under current land use trends (Pijanowski *et al.* 2002). Adjacent land uses in the immediate subwatershed are residential and urban neighborhoods, industrial zones including a pulp and paper mill, chemical and petrochemical companies, and recreation parks, along with expansive agriculture and forest patches. NWI data classify the majority of the wetland complex as palustrine with seasonally and semiperimanently flooded regions with scrub-shrub, forest, and emergent covers.

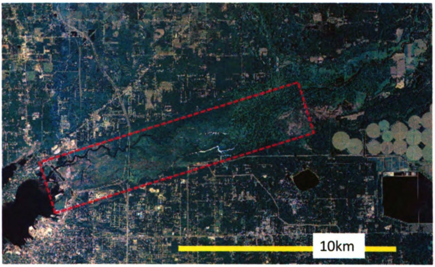


Figure 4. Wetland complex resides adjacent to Lake Muskegon. Dashed red line approximates hyperspectral imagery footprint overlaying 2006 aerial photo.

The two most problematic invasive species in the study area are *Phragmites australis* and *Typha latifolia*. *P. australis,* is a perennial grass species that has strains native to temperate wetlands for at least the past thousand years. Recently, however, Saltonstall (2002) found that nonnative strains of *P. australis* have aggressively spread throughout the northeastern US and Great Lakes region. *T. latifolia* is a herbaceous, rhizomatous perennial plant and is common throughout the US and temperate and tropical places worldwide. *T. latifolia* is exploitative in its ability to clone rapidly and produce a large litter amounts and biomass, which may contribute to its superior competitive ability (Grace and Wetzel 1982). Every state in the US has now reported the presence of *Phragmites australis* and *Typha latifolia*.

The increasing rate of expansion is now a primary concern. Regionally, Lynch and Saltonstall (2002) found that *P. australis* invasion in Lake Superior wetlands was dominated by native strains, although nonnatives were present. Wilcox et al. (2004) found that 90% of *P. australis* populations expanding into Long Point, Ontario on Lake Erie were nonnative strains of the species, and suggested that declining water levels in the Great Lakes may have contributed to its expansion. Given that fluctuations in water levels are associated with high plant diversity in coastal wetlands (Wilcox and Meeker 1991), stable water levels caused by management or natural climate change may favor the spread of dominant invasive species. Nonnative or native classification is less relevant as these two species are both considered a nuisance species because they are persistent, produce large amounts of biomass, propagate easily, and are difficult to control with mechanical, biological, or chemical means.

The effect of this rapid expansion is largely unknown, but is generally believed to be negative (Roman et al. 1984; Marks et al. 1994). Plants can influence ecosystem functions like nutrient cycling through their morphological, phenological, and metabolic traits (Windham and Ehrenfeld 2003). Increasing cover of these invaders has known multiple impacts on the ecology of wetlands, as it can reduce nutrient availability to native species, shift community composition, and alter food webs (Mack and D'Antonio 2003, Saltonstall 2002, Uzarski and Burton 2005, Windham 2001, Windham and Ehrenfeld 2003).

3.2 Data

3.2.1 Field-level data

A field campaign was conducted during mid-August (2005 and follow up 2006), which generally represents the peak of the growing season for wetland species within the study area. Capturing data during peak phenological cycles has been shown to increase the separability of invasive wetland plants (Laba *et al.* 2005). Due to the expansive nature of the wetland complex and the challenge of moving through a wetland, a compromise between operational feasibility and statistical sampling rigor was required. Both logistical constraints (equipment setup and takedown) and traveling throughout the wetland complex required a substantial amount of time. Reconnaissance field work identified two primary emergent pools where high biodiversity and ecologically noteworthy species of interest (i.e., invasives) were present. Focusing our efforts around these two regions of the wetland complex allowed the largest number of species spectra to be collected with minimal time required between sampling sites. An airboat provided the most efficient access for traveling around the wetland complex. Data acquisition focused on the dominant terrestrial-, emergent-, and submergent- species. Dominance was qualitatively identified during reconnaissance field work by evaluating percent cover and the approximate size of a patch for a species. Eight measurements were averaged for one spectrum and approximately nine spectra were collected in each homogeneous plot. A total of twenty-two (*Vallisneria americana* repeated for two different water depth conditions) wetland plant species were recorded (Table 1). Eight species are identified as being invasive (USDA, NRCS 2006). Note that not all the species identified as invasive are classified as exotic and the degree of 'invasiveness' can vary by region and conditions.

Table 1. Plant species sampled in the study area.

Common Name	Genus	Species	Invasive
Arrowhead, broadleaf	*Sagittaria*	*latifolia*	Invasive
Bulrush, softstem	*Scirpus*	*validus*	
Cattail, broad-leaved	*Typha*	*latifolia*	Invasive
Cutgrass	*Leersia*	*oryzoides*	
Eelgrass	*Vallisneria*	*americana*	
Spikerush, beaked	*Eleocharis*	*rostellata*	
Canadian waterweed	*Elodea*	*canadensis*	Invasive
Bur-reed, branched	*Sparganium*	*androcladum*	
Filamentous green algae			
Grassleaf mudplatain, water star grass	*Heteranthera*	*dubia*	
Iris, harlequin blue flag	*Iris*	*versicolor*	
Common duckweed	*Lemna*	*minor*	
Watermilfoil, whorl-leaf	*Myriophyllum*	*verticillatum*	
Mowed field grass			
Pennsylvania smartweed	*Polygonum*	*pensylvanicum*	Invasive
Common reed	*Phragmites*	*australis*	Invasive
Pickerelweed	*Pontederia*	*cordata*	Invasive
Spiral pondweed	*Potamogeton*	*spirillus*	
Purple loosestrife	*Lythrum*	*salicaria*	Invasive
White water lily	*Nymphaea*	*odorata*	Invasive
Willow	*Salix*	*eriocephala*	
Yellow pond lily	*Nuphar*	*lutea*	

We used a portable spectroradiometer (FieldSpec Pro FR®, Analytical Spectral Devices, Inc., Boulder, Colorado) to collect *in situ* radiance between 350-2500 nm (visible to shortwave infrared). Spectral resolution (full width half maximum) was recorded at 3 nm in the visible wavelengths and 10 nm in the infrared region. The sensor was equipped with a 24 degree field-of-view (FOV) optic and held approximately 1-meter above the target at nadir for measurements representing field-canopy conditions. Sun-target-sensor geometry was repeated as best as possible under these difficult field conditions. The viewing geometry configuration approximately represents the spatial resolution current airborne hyperspectral sensors can achieve. A reference Spectralon® panel (Labsphere, Inc., North Sutton, New Hampshire) was used for calibration during processing and atmospheric adjustments. During data acquisition, the sensor was first placed over the reference panel to record the panel-reflected radiance. Then the sensor was placed over the target to record the target-reflected radiance. Then, by ratioing the radiance measurements, surface *reflectance factor* was calculated. By definition, the term *reflectance factor* is the ratio of radiant emittance of a target (i.e., wetland plant) to that reflected into the same reflected-beam geometry and wavelength range by an ideal and diffuse standard surface (i.e., Spectralon calibration panel) irradiated under the same conditions (Schaepman-Strub et al. 2006). The reflectance factor was calculated based on the following equation:

$$\rho = tE \uparrow / cpE \uparrow \qquad (1)$$

where ρ is *in situ* reflectance factor for target of interest (wetland plant species), $tE \uparrow$ is target (wetland plant species) *in situ* radiance, and $cpE \uparrow$ is the calibration panel *in situ* radiance.

Subsequent data processing in this study also removed wavelength regions severely affected by atmospheric absorption in the spectral ranges of 1350-1480 nm, 1775-2000 nm, and >2400 nm (Thenkabail et al. 2004).

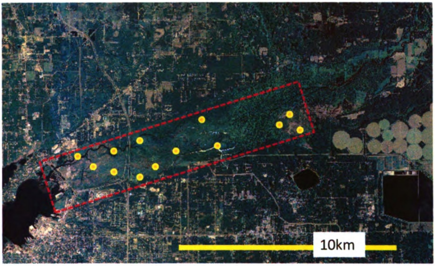


Figure 5. Ground control marking data collection locations. Polygons were stratified throughout the complex and included a range of shapes and sizes.

Field-level ground control was collected during August 2005 and 2006 (Figure 5). The 2005 field campaign was within a few days of the airborne imagery fly over but not simultaneous. The ground control was collected in order to characterize the accuracy of the classified airborne imagery. The ground control was focused on collecting reference data for the invasive plant species of interest, primarily large *Typha latifolia* and *Phragmites australis* patches as these are the two primary invasives of concern in the region. A Trimble Pro XR Global Positioning Systems (GPS) was utilized to record ground polygons. A suite of polygons ranging in size, shape, and location were collected.

Potential sites were identified using airborne photographs and on-the-fly sites were collected while traversing the study area.

3.2.2 Landscape-level data

A flyover was performed on the 24th of August 2005. A light aircraft was equipped with a push-broom Airborne Imaging Spectroradiometer for Applications (AISA) and a GPS differential navigation system. The AISA sensor (16-bit) is a linear array sensor (push-broom) that uses a system of semiconductive elements (e.g., charge-coupled device array) to record one line of an image simultaneously. Concurrent downwelling radiance was integrated using a Fiber Optic Downwelling Irradiance System (FODIS) configured to match the upwelling radiance measurements. Twelve overlapping flight lines and AISA configuration calculated apparent at sensor reflectance covering the VIS–NIR domains (Table 2). AISA pre-processing (CaliGeo) included geometric correction and image rectification. Flown at an above ground altitude of approximately 1000m, one meter pixels were obtained for twenty bands in the visible through near infrared.

Table 2. AISA hyperspectral configuration and resolutions for airborne data-collection performed during August 2005.

nbr	min. wvl	center wvl	max. wvl	ch.width	avg. offset	avg. gain
1	434.45	438.43	442.4	7.95	0	21.8771
2	451.94	455.92	459.89	7.95	0	17.8561
3	459.89	463.87	467.84	7.95	0	15.9328
4	499.64	503.62	507.59	7.95	0	7.1509
5	518.72	522.7	526.67	7.95	0	5.6548
6	575.56	579.73	583.91	8.35	0	3.382
7	585.58	589.75	593.93	8.35	0	3.2076
8	620.65	624.82	629	8.35	0	2.9989
9	644.03	648.2	652.38	8.35	0	2.9429
10	654.05	658.22	662.4	8.35	0	2.8382
11	674.09	676.6	679.1	5.01	0	3.9341
12	684.11	685.78	687.45	3.34	0	5.3284
13	689.12	691.62	694.13	5.01	0	3.4042
14	723.06	725.65	728.25	5.19	0	3.4821
15	731.71	734.31	736.9	5.19	0	3.5483
16	738.63	741.23	743.82	5.19	0	3.6101
17	757.66	760.25	762.85	5.19	0	4.0223
18	783.61	786.21	788.8	5.19	0	5.2317
19	833.78	836.38	838.97	5.19	0	5.8467
20	877.03	879.62	882.22	5.19	0	7.3689

3.3 Quantifying separation

A variety of separability measures can be used on spectral signatures to identify similar and divergent spectra. The Jeffries-Matusita (JM) distance measure has been utilized successfully to quantify the divergence of spectral signatures including wetland vegetation (Schmidt and Skidmore 2003). Slight variations of the JM formula exist. The Ayala and Menenti (2002) algorithm (Eq. 2 & 3) was used to evaluate spectral separability and the impacts of processing techniques executed:

$$JMij = \sqrt{2(1-e^{-a})} \qquad (2)$$

$$a = \frac{1}{8}(U_i - U_j)^T \left[\frac{(C_i + C_j)^{-1}}{2} \right] (U_i - U_j) + \frac{1}{2} Ln \left[\frac{\left| [C_i + C_j] \right| / 2}{\sqrt{\left| C_i * C_j \right|}} \right] \tag{3}$$

where *JMij* is the Jeffries-Matusita distance between signatures i and j, T is transpose, C_i is the variance-covariance matrix of signature i, Ui is the mean vector of signature i, $| C_i |$ is the determinant of C_i.

3.4 Continuum removal

A processing technique that allows for the extraction and modeling of individual spectral features (absorptance and reflectance) is continuum removal (Clark and Roush 1984). This technique is increasingly being implemented in hyperspectral vegetation investigations as a processing technique to extract parameters of interest (Huang *et al.* 2004, Kokaly *et al.* 2003, Schmidt and Skidmore 2003, Underwood *et al.* 2003). Used extensively in geological applications, continuum removal disregards albedo, or background, to obtain individual features (absorption/reflectance) such as peak wavelength position and depth (van der Meer 2004). Schmidt and Skidmore (2003) found that applying continuum removal to salt-marsh vegetation spectra improved species separation in the visible spectrum, but decreased it in the near-infrared (NIR) and shortwave-infrared (SWIR) regions of the spectrum. This is important as the NIR domain is often identified as an area of key utility for separation. Underwood *et al.* (2003) found that continuum removal performed moderately well in improving hyperspectral image classifications when trying to identify species with high leaf water content.

Aspects of continuum removal not previously addressed in detail relate to the role of plant canopy architecture and the impacts of continuum removal on separating individual species of interest such as invasives. Schmidt and Skidmore (2003) suggest that if continuum removal eliminates noise from the soil background, moisture content, and canopy structure, then only the varying biogeochemical content of a species would determine separability levels. The impact of continuum removal related to species canopy architecture needs to be investigated to assess its contribution to distinguishing wetland invasive species.

A modified continuum removal technique was developed for the wetland vegetation spectra following methods outlined in Schmidt and Skidmore (2003). For wetland spectra, amplitudes in the near-infrared can be large enough to disregard absorption features in other spectral regions, such as the visible portion of the spectrum. Therefore, a modified convex hull was forced to include seven primary spectral reflectance maxima distributed among spectral regions. Once the modified continuum removal was forced, the continuum was removed by dividing the reflectance by the convex hull (Clark and Roush 1984). The seven primary spectral regions that isolate the major reflectance features were:

- Visible domain and chlorophyll absorption region (350-675 nm)
- Near-infrared edge (676-780 nm)
- Near-infrared plateau (781-975 nm)
- Near-infrared down slope (976-1190 nm)
- Upper near-infrared shoulder (1191-1450 nm)
- First shortwave infrared plateau (1451-2000 nm)

- Second shortwave infrared plateau (2001-2400 nm)

3.5 Shape filter

In reality, plant canopy architecture and other factors create reflectance variability and reflectance overlap between plant species that makes species-level identification challenging. Vegetation reflectance varies across the spectrum with the visible domain largely determined by the chlorophyll content, the NIR region a function of leaf structure and biomass volume, and the SWIR region largely determined by leaf water content and biomass volumes (Cochrane 2000, Danson 1995). Generally, differences in absorption determine the amount of variation and spectral overlap between vegetation species. To examine variability, a shape filter (Cochrane 2000) that incorporates species reflectance variability was applied to evaluate separability of wetland invasive species in the study area based on spectra shape. The maximum (Max) and minimum (Min) spectral reflectance creates the shape-space for the species (Eq. 4).

$$\text{Shape-space} = Max\rho : Min\rho / \lambda \qquad \text{(Eq.4)}$$

3.6 Image classification

The primary objective associated with the imagery was to characterize infestation. In order to complete this objective an accurate map was needed. Becker et al. (2007) assessed classification algorithms and image resolutions for mapping coastal wetland imagery. The research here is intended to build upon these efforts and not repeat classification technique assessment. A series of classification algorithms were applied and evaluated in order to achieve the most accurate depiction of the invasive plants of interest within the landscape. An expert system approach was carried out that primarily relied on two classification algorithms. A basic unsupervised clustering algorithm was first executed and refined, then combined with a more advanced supervised algorithm using image derived training data.

An unsupervised classification is generally considered a straightforward, basic approach to group pixels based on spectral properties in n-dimensional space. The Iterative Self-Organizing Data and Analysis Technique (IOSDATA) algorithm was applied. Using a set of defined criteria that have been developed over the past two decades, ISODATA approaches can be very effective and sophisticated. The approach here included:

- The maximum number of classes was defined at forty based on reconnaissance field work, ancillary data, and expert judgment
- Statistical initialization was based on diagonal axis means which are computed to be along a diagonal vector and are evenly distributed within the scaling range for each band
- The number of iterations was set at ten to recalculate cluster mean vectors each iteration
- Convergence threshold was set to ninety-five percent. The convergence threshold is the maximum percentage of pixels whose cluster assignments can go unchanged between iterations

A second, more advanced supervised approach was carried out to classify the species of interest in the landscape using ground-truthed training data rather than image statistics. The Spectral Angle Mapper (SAM) algorithm (Kruse et al. 1993) was used in this context. This algorithm relies on spectra shape and angles formed between a reference spectrum and an unclassified pixel in n-dimensional space where n represents the number of bands. The primary advantage of SAM is that the classifier is insensitive to albedo and illumination effects (Sohn et al. 1999). The SAM approach has been shown to correctly classify spectrally similar targets (South et al. 2004).

Using the ground-truthed GPS collected data, image training sites were developed. Slight spatial adjustments were required due to registration and georeferencing discrepancies. NRCS aerial color photographs were used as reference data to assist in spatial adjustments. Spectral signatures were used to create a signature library. Forty total signatures were created including the two primary species of interest- *Typha latifolia* and *Phragmites australis*. This library was developed within ENVI and fed into the SAM protocol using imagery mosaics.

3.7 Landscape pattern metrics

Landscape-pattern metrics provide a means to quantify ecosystem characteristics at various scales. In the past two decades an increasing number of investigations have explored landscape-stressor relationships for wetland ecosystems using pattern metrics (Liu and Cameron 2001, Lopez et al. 2002, Kearns et al. 2005, Torbick et al. 2006). In general, all landscape pattern metrics have strengths and weaknesses. When using metrics to explore relationships and patterns, it is important to understand their limitations, appropriate applications, inter-relationships, and possible interpretations of results (Gustafson 1998, Hargis et al. 1998, Li and Wu 2004). Identifying specific thresholds of indices to guide decision making and management practices individually has proven to be a challenge when using landscape pattern measures. By comparing characteristics and ecosystem attributes across the landscape at various scales using complementing measures, a more thorough indication of relationships is possible. This can help focus decision making and monitoring.

Several studies have used pattern metrics to indicate landscape patterns and wetland stressors. The methods vary widely and range in results. The overarching goal of using the landscape pattern metrics was to quantify and assess relationships between hydrology and infestation. Simple metrics that describe the percentage and distribution of the invasives of interest were generated using Fragstats v3.3 (McGarigal and Marks 1995) for the class (species) and landscape level. Composition measures, including percent cover, were generated to calculate the total area covered by the invasives. Configuration metrics, including the Aggregation Index and the Interspersion and Juxtaposition Index (IJI), were generated to identify large homogenous patches and assess dispersion. The Simpson Diversity Index (SDI), dependant only on the class of interest, was chosen as the diversity metric.

Area-based metrics are a suite of measures quantifying fundamental information on the ecological utility of a patch. Basic area metrics are perhaps the most important metrics and provide information for many other metrics (Hargis et al 1998). Therefore area and percent of landscape (PLAND) were generated to illustrate landscape composition-invasive relations.

$$\text{Area} = a_{ij}\left(\frac{1}{10{,}000}\right) \qquad \text{(Eq.5)}$$

Area equals the area of a patch, class, or landscape. a_{ij} is the area of patch ij.

$$\text{PLAND} = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100) \qquad \text{(Eq.6)}$$

PLAND is the sum of the areas of all patches of the corresponding patch type, divided by the total landscape area (converted into units of preference). Pi=proportion of the landscape occupied by patch type (class) i, a_{ij} = area of patch ij, A=total landscape area.

Aggregation Index is calculated from the number of like adjacencies of corresponding classes (types), divided by the maximum possible number of like adjacencies (McGarigal and Marks 1995).

$$AI = \left(\frac{g_{ii}}{\max > g_{ii}}\right) \qquad \text{(Eq.7)}$$

g_{ii} equals the number of like adjacencies (joins) between pixels of patch type *i* based on the single-count method, max-g_{ii} is maximum number of like adjacencies (joins) between pixels of patch type *i* based on the single-count method.

A disturbance metric was developed to assess relationships between infestations and hydrogeomorphic modifications (HGMM) and human disturbances. The study area was divided into contiguous 1km wide transects, or sections, for a total of 15 full sections. Using a knowledge-based evaluation system, each section was assessed for level of human disturbance and given a rating between 1 to 5 representing low to high disturbance and/or activities. Human activities and/or disturbances were measured in terms land use pressures and landscape modifications (agriculture, urban), intensity of managements and disturbances (continuous crop fields, dense impervious road network, etc…), and hydrological modification (river channelization, dredging). Following the river continuum framework, adjacency and spatial dependence was incorporated into the knowledge-based ratings. The river continuum framework emphasizes a holistic approach considering system openness, or the notion of spatial scaling, in a landscape adjacency context (Naiman et al 1988, Weins 1989). For example, if a section had intense agriculture along its boundary this increases the disturbance rating. Further, if a pristine section was adjacent to a highly disturbed section, this would cause an increase.

Chapter 4: RESULTS AND DISCUSSION

4.1 Spectral separation

The wetland plant spectra displayed a range of JM distance values. Table 3 displays the JM distance values in a matrix against the invasive species (USDA, NRCS 2006). According to the JM values, *Heteranthera dubia* (grassleaf mudplain) and *Lythrum salicaria* (purple loosestrife) are relatively easy to separate with the highest JM value of 1.2645. *Heteranthera dubia* has the highest separability from most of the invasives compared to the other species collected (Table 3). The invasive with the lowest separation value from *Heteranthera dubia* is *Elodea canadensis* (Canadian waterweed) at 0.8599, still a moderate separation value.

Table 3. JM distance matrix for invasive species. *Vallisneria americana*-18 refers to a collection of spectra made with *Vallisneria americana* located approximately 18inches below the water surface (averaged spectra n=32). Low, medium, high detail three evenly divided categories.

Wetland species	*Elodea canadensis*	*Lythrum salicaria*	*Nymphaea odorata*	*Phragmites australis*
Eleocharis rostellata	0.9258	*0.4213*	*0.1124*	*0.3245*
Elodea canadensis	-	1.066	0.9693	1.0357
Filmacutee	0.9468	0.3406	0.0969	0.2435
Heteranthera dubia	0.8599	1.2645	1.228	1.2528
Iris versicolor	0.6335	0.7902	0.5909	0.7293
Leersia oryzoides	1.1229	0.2365	0.5282	0.3381
Lemna minor	1.1257	0.2525	0.5408	0.353
Lythrum salicaria	1.066	-	0.3251	0.1093
Mowed field grass	1.0351	0.1132	0.2187	0.0051
Myriophyllum verticillatum	0.3723	0.9407	0.7983	0.8968
Nymphaea odorata	0.9693	0.3251	-	0.2225
Nuphar lutea	0.6966	0.7317	0.5134	0.6647
Phragmites australis	1.0429	0.1093	0.2225	-
Ponterderia cordata	1.0093	0.1818	0.1585	0.078
Polygonum pensylvanicum	1.0429	0.0763	0.2712	0.0643
Potamogeton spirillus	0.9264	0.418	0.1094	0.321
Sagittaria latifolia	1.0421	0.079	0.2551	0.0388
Salix eriocephala	0.9616	0.3141	0.0593	0.2127
Scirpus validus	0.7527	0.6696	0.435	0.599
Sparganium androcladum	0.6413	1.215	1.1649	1.199
Typha latifolia	0.7354	0.6946	0.4629	0.6234
Vallisneria americana	0.079	1.1444	0.9486	1.0194
Vallisneria americana-18	0.8	1.0515	1.2098	1.2371

Table 3 (cont).

Wetland species	*Polygonum pensylvanicum*	*Pontederia cordata*	*Sagittaria latifolia*	*Typha latifolia*
Eleocharis rostellata	0.3663	0.2579	0.3535	0.7354
Elodea canadensis	1.0429	1.0093	1.0421	1.062
Filmacutee	0.2753	0.168	0.2672	0.3305
Heteranthera dubia	1.2552	1.2424	1.255	1.248
Iris versicolor	0.7487	0.68	0.7445	0.675
Leersia oryzoides	0.2949	0.4004	0.307	0.302
Lemna minor	0.309	0.4139	0.3218	0.4126
Lythrum salicaria	0.0763	0.1818	0.079	0.6946
Mowed field grass	0.0693	0.0761	0.0438	0.1546
Myriophyllum verticillatum	1.2182	1.202	1.218	0.8988
Nymphaea odorata	0.2712	0.1585	0.2551	0.4629
Nuphar lutea	0.6865	0.6108	0.6816	0.6578
Phragmites australis	0.0643	0.078	0.0388	0.6234
Ponterderia cordata	0.1179	-	0.1044	0.1224
Polygonum pensylvanicum	-	0.1179	0.0275	0.6474
Potamogeton spirillus	0.3625	0.254	0.3499	0.318
Sagittaria latifolia	0.0275	0.1044	-	0.0988
Salix eriocephala	0.2519	0.1389	0.2404	0.6418
Scirpus validus	0.6207	0.5378	0.6149	0.5982
Sparganium androcladum	1.2023	1.1848	1.2021	1.188
Typha latifolia	0.6474	0.5671	0.6418	-
Vallisneria americana	1.0276	0.9919	1.0264	1.0023
Vallisneria americana-18	1.2398	1.2256	1.2396	1.2217

Heteranthera dubia and *Elodea canadensis* are both perennial forbs with somewhat similar morphology and physiology, growing at the water-surface with a mat-like foliage texture. *Elodea canadensis* tends to grow at a higher density, with toothed leaves (6-15mm) in whorls, mostly floating just under the water surface; whereas *Heteranthera dubia* tends to grow along the water surface with long, linear leaves (10-15cm) joined at the base to a tubular sheath wrapped around a stem. Therefore, both species often have substantial amounts of water present in their spectra under field-canopy conditions resulting in distinguishable signatures compared to the other emergent- and upland- aquatic invasive species in the study area. The VIS, NIR, and SWIR reflectance for *Heteranthera dubia* and *Elodea canadensis* spectra never surpassed ten percent reflectance factor because of the high amounts of water absorbing energy in the FOV.

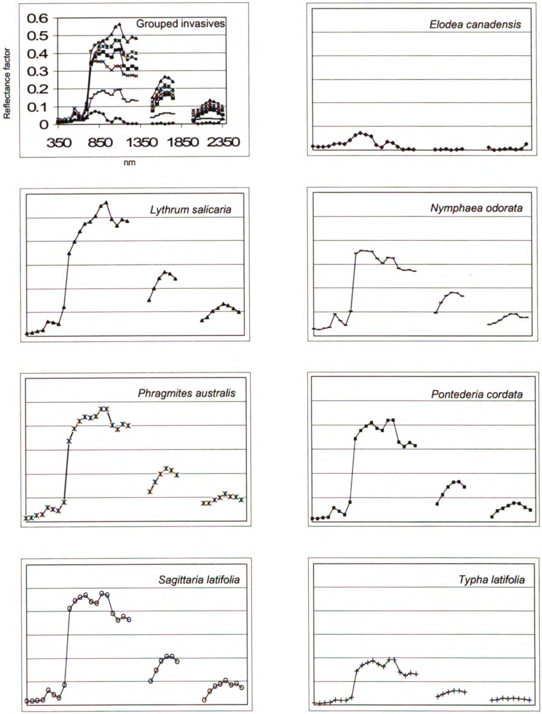


Figure 6. Reflectance factor at 50nm intervals for selected invasive plant species. Pre-processing removed wavelength regions severely affected by atmospheric absorption in the spectral ranges of 1350-1480 nm, 1775-2000 nm, and >2400 nm. Averaged spectra (n=32).

Nymphaea odorata (water lily) had the lowest separation distance from all other species, while *Sagittaria latifolia* (arrowhead) had the lowest separability value against the other invasive species. *Sagittaria latifolia* had a relatively high separability measure from submergent and emergent species such as the invasive *Elodea canadensis* at 1.0421, but very low separation scores from the other six invasives with an average of 0.1006 indicating difficulty in identifying this species. *Sagittaria latifolia* had a very small separation distance from *Polygonum pensylvanicum* (Pennsylvania smartweed) and the two are likely to cross-classify. These two plant species have relatively similar plant architectures and inhabitat very similar niches in this ecosystem. *Sagittaria latifolia* is a medium height perennial herb with erect orientation that can grow upwards of a few feet from the water surface. Its structure has arrow-shaped, simple leaves (6-40cm) with small white flowers arranged in whorls on the stalk (present during data collection) that fills out to reach medium foliage texture with moderate porosity. *Polygonum pensylvanicum* is an annual herb with lance-shaped leaves (25cm) that grows a few feet upward from the water with flowering branches that has moderate porosity with medium foliage texture. The similarity of these two species with respect to the JM index lends support to the claim that plant canopy structure plays a large role in species separability. In contrast, *Sagittaria latifolia* also had very low separation values from *Phragmites australis* (common reed), an aggressive, very densely growing erect stalk with coarse texture that extends upwards of 2m, and *Nymphaea odorata*, a floating-leaf forb with large, thick circular leaves (25cm) that rest on the water surface, which suggests that plant canopy structure does not play a singularly strong role in differentiating spectra.

4.2 Continuum removal

In theory, a normalization process based on continuum removal can remove albedo, or background signal, from a spectral signature. In this study, the modified continuum removal mostly decreased separation abilities (Table 4). The differentiation of *Lythrum salicaria* from *Sagittaria latifolia*, *Potamogeton spirillus* (spiral pondweed), and *Polygonum pensylvanicum* increased slightly, although these species had very high JM separation values before the continuum removal was applied. The separability of *Potamogeton spirillus* from five of the invasives also increased slightly. *Potamogeton spirillus* can be submerged or float on the water surface with long (20cm), simple leaves. Therefore, an increase in species separability for *Lythrum salicaria*, *Nymphaea odorata*, *Phragmites australis*, *Pontederia cordata* (pickerelweed), and *Sagittaria latifolia* was contrary to expected results based on plant architecture, while emphasizing the role of leaf water content in separation. The decrease in separability from *Elodea canadensis* further suggests that background signal and canopy architecture were indeed removed via continuum removal.

Table 4. Change in JM distance values with modified continuum removal applied. Negative values indicate increase in separation values. *Vallisneria americana*-18 refers to a collection of spectra made with *Vallisneria americana* located approximately 18inches below the water surface (averaged spectra n=32).

Wetland species	*Elodea canadensis*	*Lythrum salicaria*	*Nymphaea odorata*	*Phragmites australis*
Eleocharis rostellata	0.5615	0.3275	0.0344	0.1982
Elodea canadensis		0.7279	0.6421	0.7038
Filmacutee	0.5976	0.2086	-0.0111	0.0843
Heteranthera dubia	0.8599	1.2645	1.228	1.2528
Iris versicolor	0.3549	0.6905	0.5135	0.6105
Leersia oryzoides	0.8061	0.2127	0.5114	0.2968
Lemna minor	0.8418	0.2326	0.5038	0.3382
Lythrum saicaria	0.7279		0.3017	0.0765
Mowed field grass	0.739	0.0626	0.1648	-0.0329
Myriophyllum verticillatum	0.0678	0.8029	0.6837	0.7336
Nymphaea odorata	0.6421	0.3017		0.1707
Nuphar lutea	0.4064	0.6282	0.433	0.5388
Phragmites australis	0.7134	0.0401	0.1707	
Pontederia cordata	0.7275	0.1201	0.1103	0.0087
Polygonum pensylvanicum	0.797	-0.0207	0.1822	-0.0273
Potamogeton spirillus	0.5914	-0.0948	-0.4067	-0.1708
Sagittaria latifolia	0.7686	-0.0081	0.164	-0.0274
Salix eriocephala	0.6238	0.2438	-0.0147	0.1607
Scirpus validus	0.4855	0.602	0.3898	0.5023
Sparganium androcladum	0.5946	0.9468	1.1649	1.199
Typha latifolia	0.3958	0.6254	0.4134	0.5229
Vallisneria americana	-0.0509	0.8959	0.7165	0.7411
Vallisneria americana-18	0.6076	0.6523	0.8297	0.8302

Table 4 (cont).

Wetland species	*Polygonum pensylvanicum*	*Pontederia cordata*	*Sagittaria latifolia*	*Typha latifolia*
Eleocharis rostellata	0.2157	0.1488	0.1879	0.4562
Elodea canadensis	0.797	0.7275	0.7686	0.3958
Filmacutee	0.1221	0.0495	0.0859	0.2067
Heteranthera dubia	1.2552		1.255	1.2567
Iris versicolor	0.6689	0.6248	0.6279	0.5645
Leersia oryzoides	0.2194	0.3624	0.2326	0.2826
Lemna minor	0.2221	0.355	0.2523	0.3565
Lythrum saicaria	-0.0207	0.1201	-0.008	0.6254
Mowed field grass	0.0157	0.0362	0.0063	0.1058
Myriophyllum verticillatum	1.0843	1.0943	1.2034	0.8955
Nymphaea odorata	0.1822	0.1103	0.1641	0.4134
Nuphar lutea	0.5914	0.5437	0.5517	0.6245
Phragmites australis	-0.0273	0.0087	-0.0273	0.5229
Pontederia cordata	0.1179		0.0401	0.4901
Polygonum pensylvanicum		0.0748	-0.0202	0.5285
Potamogeton spirillus	0.3194	-0.232	-0.0926	-0.0264
Sagittaria latifolia	0.0078	0.0401		-0.0065
Salix eriocephala	0.2054	0.088	0.2232	0.2036
Scirpus validus	0.5166	0.4748	0.4916	0.5062
Sparganium androcladum	0.7865	1.1033	1.2021	1.1462
Typha latifolia	0.5285	0.4901	0.5072	
Vallisneria americana	0.8655	0.8042	0.8221	0.8634
Vallisneria americana-18	0.9187	0.8852	0.8752	0.6947

The continuum removal results suggest that the processing technique is not necessarily useful for all vegetation applications. While continuum removal might be effective in identifying absorption feature characteristics or particular wavelengths associated with biophysical attributes, applying the technique for separating plant species (or classifying image data) might be disadvantageous. Clearly, for wetland ecosystems, continuum removal decreased abilities to distinguish invasives species. These results further suggest that background and canopy architecture may contribute to improving separation of wetland plant species. The results here advocate emphasizing plant canopy architecture when attempting to map wetland invasive species.

Plant canopy architecture is not only the morphological and biophysical structure of a species. The plant canopy architecture is also representative of the microenvironment; the background removed via continuum removal. The background signal, or local environment, is what often creates conditions that support hydrophytic plants. The background signal includes variations in soil moisture or water content along with understory debris and previous plant growth. These background factors provide useful biophysical information that is well-known to be measured spectrally. Therefore, when continuum removal techniques are applied, the loss of these background signals is detrimental to spectral separation of species in many cases. In other ecosystems or applications, such as geological and mineral identification, background signal may not be useful; in wetland ecosystems these are critical.

4.3 Absorption feature characteristics

The peak reflectance and wavelength location in each of the seven spectral regions varies by species. This is important because identifying the *best* wavelengths can be arbitrary if those wavelengths are not unique to an invasive species of interest. The SWIR plateaus (1451-2000 nm, 2001-2400 nm) have the largest variation in peak reflectance wavelength. When normalized by the number of wavelengths in each spectral domain (range of peak wavelengths/number of wavelengths in spectral domain), the second SWIR plateau has the greatest range in peak wavelength locations, followed by the NIR edge (781-975 nm) and first SWIR plateau (1451-2000 nm). This indicates that these three spectral domains possess the largest variation in peak reflectance wavelength location, which can assist in species discrimination. These results are consistent in identifying the NIR edge as this wavelength region has been recognized as a useful spectral domain for distinguishing wetlands plants using other statistical techniques, namely second derivative analysis and Mann-Whitney U-testing (Artigas and Yang 2006, Becker *et al.* 2005, Schmidt and Skidmore 2003).

Peak reflectance wavelength locations for *Lythrum salicaria* are furthest from the average of all other species in the first SWIR and NIR domains and to a lesser extent the NIR down slope and second SWIR domains. The peak reflectance wavelengths in these spectral domains are, therefore, more useful for discriminating *Lythrum salicaria* from the other wetland species compared to the chlorophyll absorption region, NIR edge, and the water absorption region. As such, the leaf moisture content and internal leaf structure (Cochrane 2000, Danson 1995) of *Lythrum salicaria* are more useful characteristics for separation than are plant pigmentation differences represented by the visible and chlorophyll domain. However, when background was eliminated via continuum removal, little increase in separation scores resulted.

The NIR regions (edge, plateau, and down slope) have the greatest range of reflectance maxima between species. The visible domain and SWIR plateaus have relatively narrow ranges between the peak reflectance of the wetland species. The differences between species' leaf structure, largely represented by the NIR and water absorption regions, make the differences in reflectance amplitude a useful characteristic for separation. However, for a particular species of interest, the most unique peak reflectance feature might reside within a different wavelength domain. For *Lythrum salicaria*, the water absorption region, followed by the NIR down slope, possess peak reflectance features furthest from the average of all other species. The peak reflectance features of the two SWIR plateaus have relatively equivalent separation abilities as the NIR edge and NIR plateau for *Lythrum salicaria* (reflectance factor for *Lythrum salicaria* – average reflectance factor for all species). The NIR edge is often emphasized as a useful wavelength region for distinguishing species (Artigas and Yang 2006, Becker et al 2005, Schmidt and Skidmore 2003, Thenkabail et al. 2004); however, for identifying *Lythrum salicaria* other wavelength regions show larger distances in terms of peak reflectance maxima and peak reflectance wavelength location. Thus, individual plant absorption/reflectance features should receive some consideration when attempting to map invasives or species of interest.

4.4 Shape filter

While the absorption/reflectance features from average species spectra provide useful information, in reality the reflectance for individual wetland plant spectra display considerable variation. Figure 7 illustrates the reflectance variability for *Scirpus validus* (softstem bulrush), *Phragmites australis*, *Lythrum salicaria*, and *Typha latifolia* (broad leaved cattail). Recall that the shape filter method (Cochrane 2000) is intended to identify species of interest, such as invasives, using the uniqueness of the absorption features and reflectance variability. In essence, the more unique an absorption feature of a given species is, the easier that species can be distinguished.

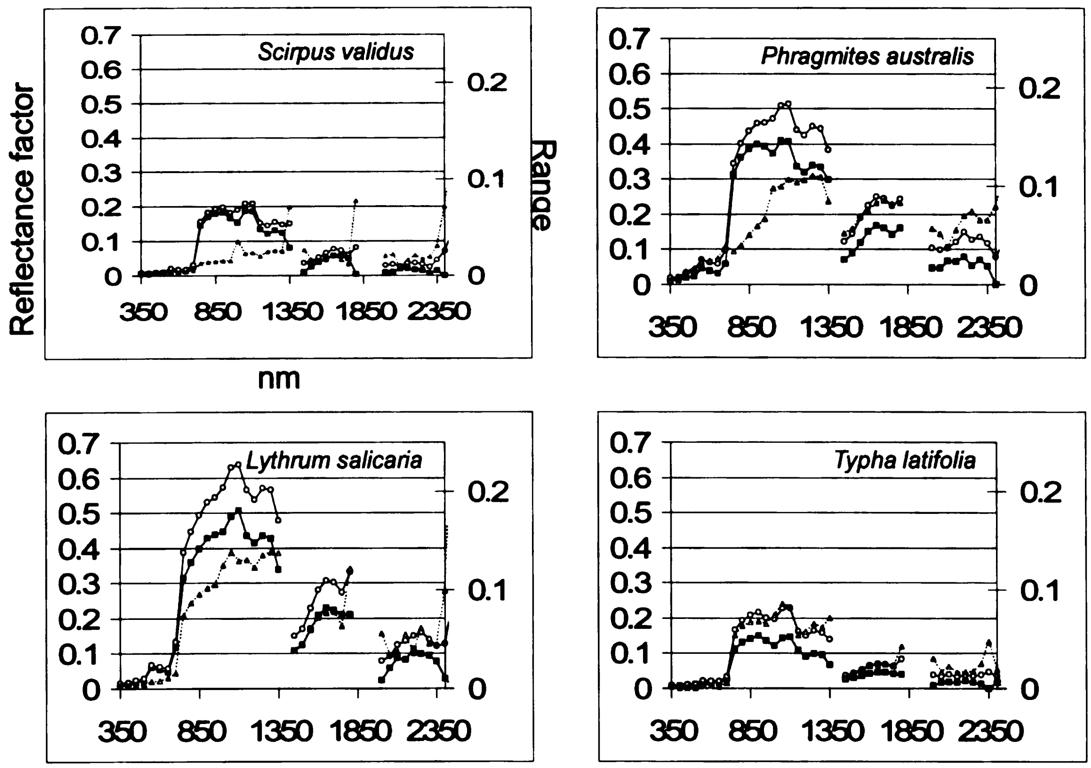


Figure 7. Reflectance factor (n=32) variability, or *shape-space*, (maximum●, minimum▲, range-▲-) illustrated for *Scirpus validus*, *Phragmites australis*, *Lythrum salicaria*, and *Typha australis* at 50nm intervals. Pre-processing removed wavelength regions severely affected by atmospheric absorption in the spectral ranges of 1350-1480 nm, 1775-2000 nm, and >2400.

The shape space varies by wavelength domain and by species. For example, *Scirpus validus* had relatively less variation compared to *Phragmites australis*, *Lythrum salicaria*, and *Typha latifolia.* The variation *Scirpus validus* did possess occurred primarily in the water absorption region, first SWIR plateau, and second SWIR plateau while increasing respectively. This is likely due to the erect, small diameter structured growth and the fact that *Scirpus validus* tends to occur as a transitional plant between standing water and higher substrate on a microtopographic scale. Thus only minute differences were detected in leaf water content and plant biomass volume compared to variation in soil moisture and understory debris, again emphasizing the utility in background signal for identification purposes. *Phragmites australis* and *Typha latifolia* have larger reflectance variability in the NIR down slope (976-1190nm) and the water absorption region (1191-1450nm); however, both these regions have high separation abilities when the shape filter was applied (Figure 8).

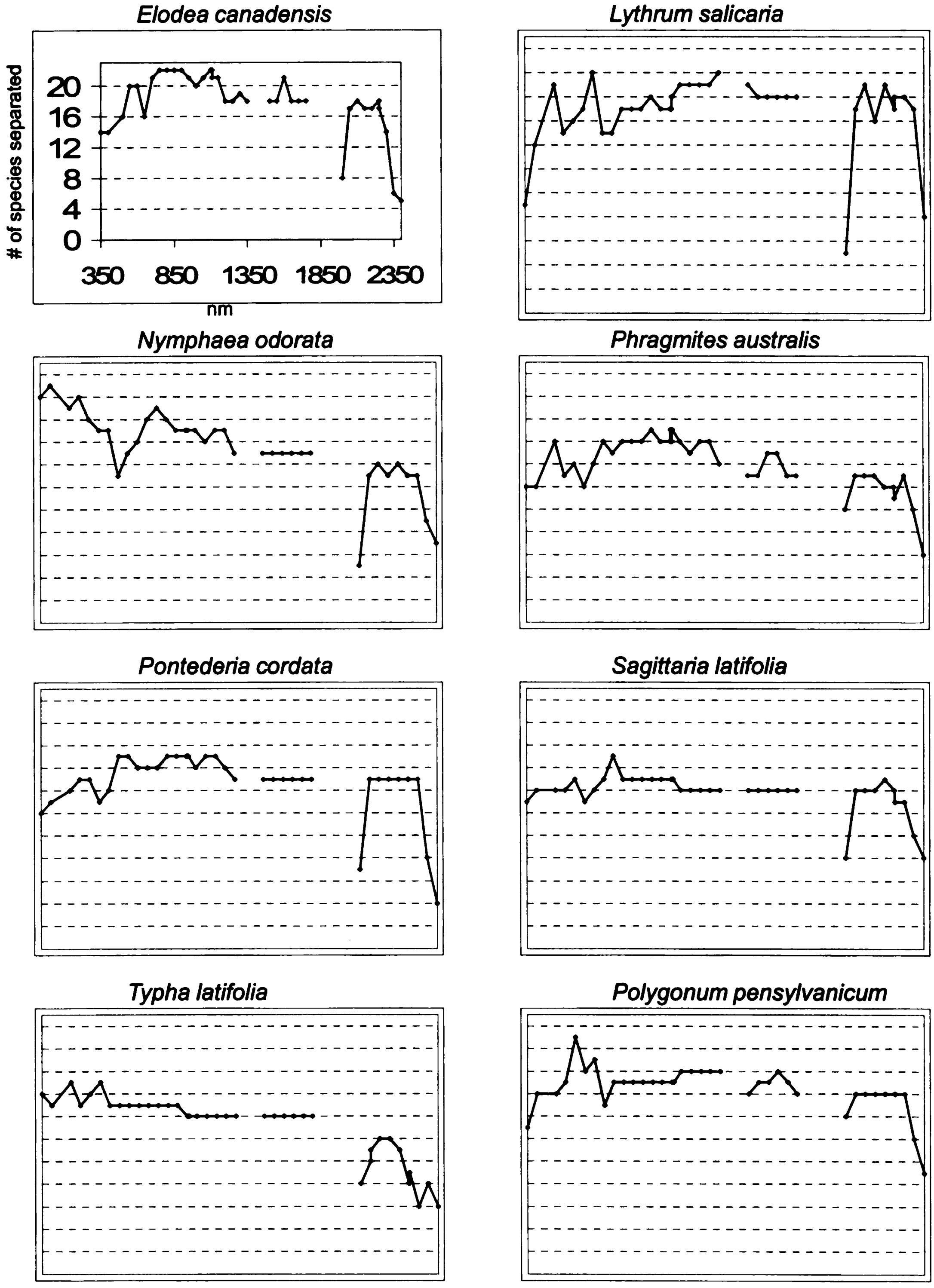


Figure 8. Number of plants species separated (displayed at 50nm intervals) by shape filtering for the wetland invasive plant species.

The wavelengths identified as most useful for separating invasive species by the shape filter vary by species (Figure 8). This is critical as classification and processing techniques and/or choice of wavelengths might require evaluation based on the species on interest. Further, the biophysical properties influencing reflectance become valuable as background and plant canopy architecture vary by species thus potentially improving identification. *Polygonum pensylvanicum* has the most separation around 605nm. Compared to the other invasives this wavelength has low separation value using the shape filter method. *Nymphaea odorata* is most separable from the other species in the visible and chlorophyll domain (350-600nm) likely due to the plant canopy architecture possessing large (24cm), round leaves that float on the water surface. Using the shape filter technique, the invasive *Lythrum salicaria* had between five (minimum at 2000nm) and 20 (maximum at 700nm) species distinguished.

The results from applying the shape filtering technique confirm that information provided by increased spectral data does increase abilities to distinguish plants of interest. The wavelength domains of utility vary by species therefore data reduction and wavelength selection methods need to consider evaluating species of interest and their particular absorption/reflectance features. The concept of spectral libraries and classification techniques based on shape filtering is promising for distinguishing invasive species. In the wetland ecosystem where this study was conducted, even very similar spectra were able to be filtered.

4.5 Characterizing Infestation

Complications due to shifts in aircraft flight path and multiple flight lines, lack of simultaneous ground control, and high landscape heterogeneity required a multi-step approach in order to obtain the most accurate map possible for the species of interest. A series of classification runs were executed. The more advanced SAM approach using the signature library developed from field-collected spectra resulted in very poor classification accuracy results. SAM classifications carried out on image-derived training data had satisfactory results for *Phragmites*, but the *Typha* delineation was poor. Therefore, a simplified approach was executed to identify *Typha* in the form of unsupervised algorithms. Qualitative inspections confirmed that the unsupervised classification accurately depicted landscape structure and biological communities within the study area. Figure 9 illustrates a subset of the 40-class unsupervised ISODATA classification. Apparent is landscape structure with deep pools, biological communities, forest regions, road networks, and tributary systems. Using GPS ground data, *Typha* polygons were created and merged within the classification.

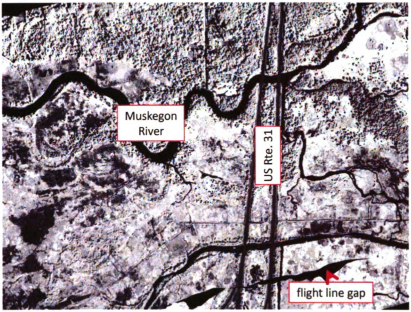


Figure 9. Unsupervised classification depicts landscape structure and man-made features for adjacent buffer around Route 31 which bisects the wetland complex.

The SAM *Phragmites* classification was fused with the *Typha* unsupervised classification for the optimal product. A total of twelve polygons were used to assess the accuracy of the combined classification. Overall accuracies for each individual polygon ranged from 39%-81% (Table 5). Figure 10 illustrates two *Typha latifolia* assessment polygons located on opposite ends of the study area. P6 shows a high accuracy (73%) while P3 shows a poor overall accuracy (39%). P6 was surrounded by lower strata canopy (submergents/emergents) while the P3 assessment polygon area tended to have similar strata canopy (rushes/sedges) which likely contributed to the confusion and ultimately the misclassification. The overall accuracy (weighted average by # pixels) was 70%. Considering the level of detail, overlapping signatures, and imagery complications, this is a fair (~industry standard is 85%) overall accuracy. When referencing the field-level signatures, *Typha* tends to have common reflectance values within the wavelength domains covered by the imagery. *Phragmites,* on the other hand, has a relatively unique spike in the NIR.

Table 5. Accuracy assessment for the *Typha* and *Phragmites* classes.

Poly #	Overall	# Pixles	Plant
1	66.97%	445	Typha
2	80.00%	70	Typha
3	39.45%	844	Typha
4	62.67%	150	Typha
5	63.03%	238	Typha
6	73.33%	896	Typha
7	81.40%	328	Phrag
8	55.45%	101	Phrag
9	46.39%	761	Phrag
10	67.08%	814	Phrag
11	76.56%	3720	Phrag
12	79.63%	2573	Phrag
Weighted average 70%		10665	Typha & Phrag

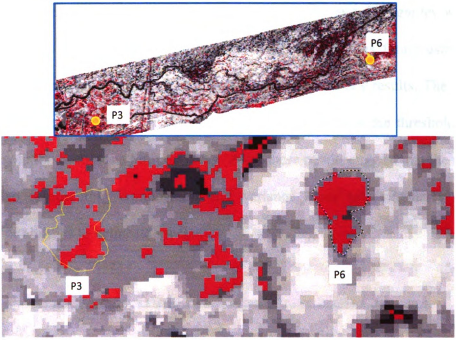


Figure 10. Example accuracy assessment points for *Typha latifolia*. P3 shows a poorly captured patch whereas P6 illustrates a patch captured very accurately with the imagery.

Heterogeneous environments are challenging to classify and the desired level of classification detail and pixel size often influence methodology, objectives, and overall goals. Becker et al. (2007) evaluated classification algorithms and the optimal spatial resolutions for mapping coastal wetlands. The research concluded that strategic wavelengths and spatial resolutions of a few meters meter or under were required for accurate maps. Li et al. (2004) found that increasing levels of landscape heterogeneity required higher spatial and spectral resolutions. Large homogeneous stands have less variance compared to smaller mixed stands and, essentially, large homogenous areas are easier to map. Smaller mixed stands have greater spectral overlap and a larger amount of species contributing toward the spectral signature. However, in this study no relationship between patch size and accuracy was found. Both *Typha* and *Phragmites* were tested individually and collectively, and no significant relationship was found using 1m size pixels. Two related points can be extrapolated from the accuracy results. The first being that the fine resolution imagery used in this study was not near the threshold in which spatial resolution becomes a limiting factor. Also, these results suggest that the size of the patch, also representing composition and variance, does not singularly determine accuracy or abilities to delineate species.

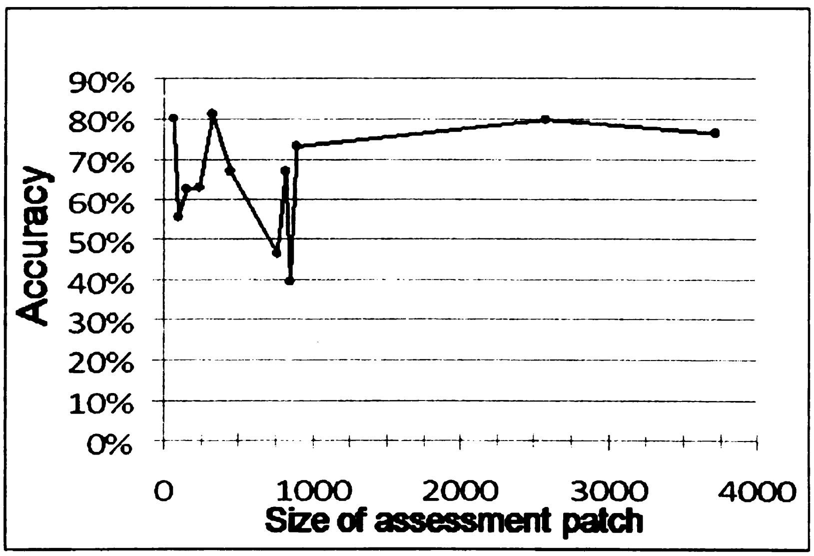


Figure 11. No relationship between accuracy and patch size was found. Combined *Typha* and *Phragmites* ground control and overall accuracy for each polygon.

Assessing infestation required an expert system framework that depicted a variety of disturbances and scale. Using a knowledge-based evaluation system, each section was assessed for level of human disturbance and given a rating between 1 to 5 representing low to high disturbance and/or activities. Human activities and/or disturbances were measured in terms land use pressures and landscape modifications (e.g., agriculture, urban), intensity of managements and disturbances (continuous crop fields, dense impervious road network, etc…), and hydrological modification (river channelization, dredging). Following the river continuum framework, adjacency and spatial dependence was incorporated into the knowledge-based ratings. If a section had intense agriculture along its boundary, the disturbance rating will increase. Further, if a pristine section was adjacent to a highly disturbed section, this would cause an increase. Figure 12 displays transects across the study area. Transects were aligned N-S in order to complement the imagery and locate the Rte 31 bridge into one transect.

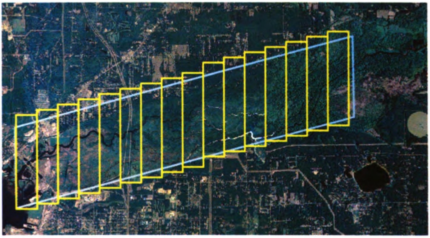


Figure 12. Illustration of infestation transects used to assess *Typha* and *Phragmites* distribution and develop the disturbance metric.

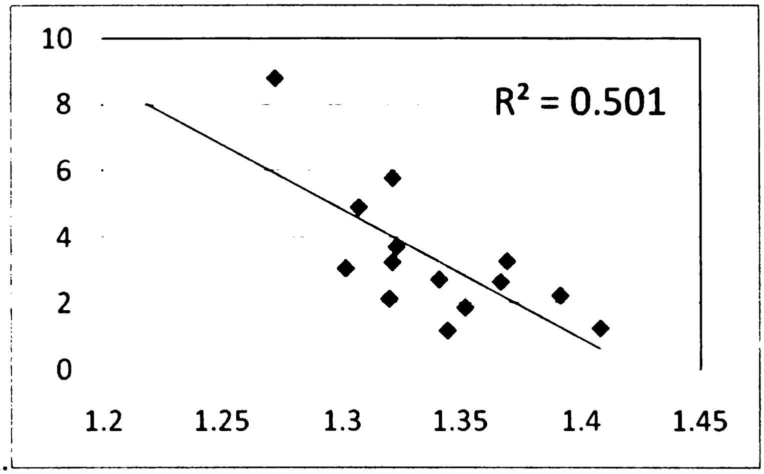
The expert-system values are displayed in table six. Transects start upstream, which is the eastern most portion of the classification in this case. Transects one and two received the highest hydrogeomorph rating because the river in these transects has undergone substantial channelization altering the hydrological flow of the main branch of the Muskegon. As the river resumes natural meandering toward transect three, hydrogeomorph disturbance ratings decrease. As the river branches into its delta-like pattern in transect five ratings receive their lowest scores. At transect eleven substantial modification is present as the Route 31 bridge bisects the wetland complex. A channel was dredged running parallel to the bridge creating an artificial, slow moving branch. Dredging and miniature dikes for several rail bridges and old transport channels are present closer toward the City of Muskegon resulting in increased modification ratings.

Table 6. Disturbance ratings for the study area east to west.

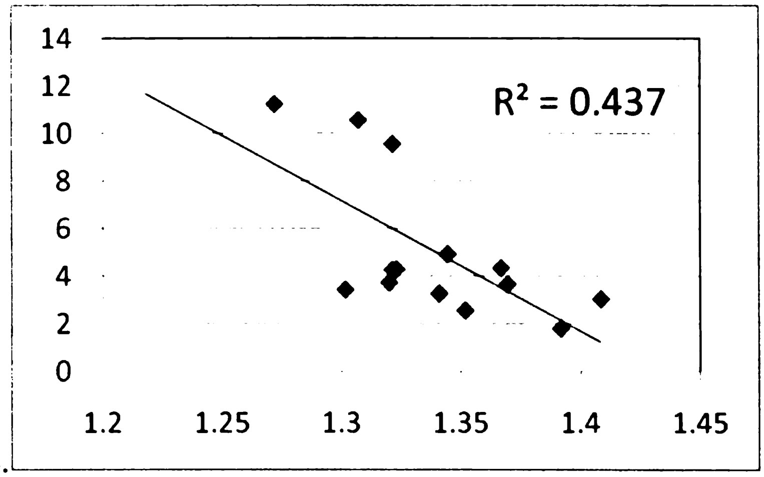
Transect	LU/LANDP	HGMM	Rating
1	5	5	5
2	2	5	3.5
3	2	2	2
4	1	1	1
5	2	2	2
6	3	1	2
7	3	1	2
8	3	2	2.5
9	3	2	2.5
10	2	2	2
11	5	5	5
12	4	4	4
13	4	4	4
14	5	5	5
15	5	5	5

The human disturbances in transects one and two are relatively moderate. As the wetland complex resides in essentially a valley, adjacency disturbances play a role. The northern buffer of the study area remains relatively consistent. Clearings for power lines aiming westward starting in transect six and seven increased the rating. Transect eleven and the western most transect have the highest amounts of impervious surfaces causing the highest possible rating.

For replication, quantitative approaches are desired. Therefore, a fractal metric was derived to quantify the shape of the Muskegon River and its tributaries to assess changes in hydrogeomoprh across the study area. Figure 13 displays the area-weighted fractal metric for the water class against *Phragmites australis* (A) and *Typha latifolia* (B). Although sample size was limited to the number of transects (15), moderately strong (.5 and .44 respectively) relationships are evident with decreasing PLAND values as the shape complexity of the water class increases. This supports the interpretation that as the river becomes channelized and impacted by human activities infestation is higher, and as the river flow reflects the delta-like hydrology of the complex, *Phragmites* PLAND decreases.



A.



B.

Figure 13. Moderately strong relationships exist between Phragmites australis (A) and Typha latifolia (B) PLAND metric and the shape complexity of the water class.

The spatial pattern of *Typha* and *Phragmites* are closely correlated in addition to the percentage of areal coverage these two invaders occupy. Their area-weighted fractal was strongly positive correlated (.69) across the study site and these two species appear to mimic the other species pattern and distribution. The shape complexity, as measured by area-weighted fractal, of *Typha* was highly correlated (.76) to the aggregation index of *Phragmites* patches across the landscape. As *Typha* patch shape becomes more complex, *Phragmites* tends to become more aggregated and decrease in complexity within the landscape. Figure 14 displays the assessment metric showing the relationship between disturbance and infestation. The quantitative fractal metric indicates that the hydrological modifications are significantly related to pattern of infestation.

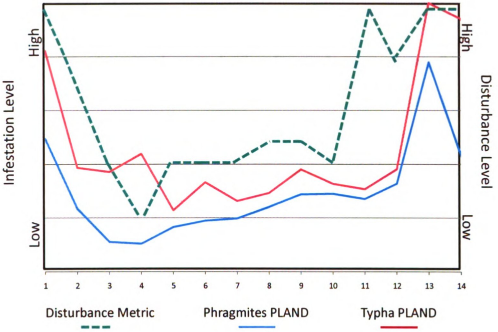


Figure 14. displays the relationship between infestation level and disturbance ratings for the transects contiguously covering the study site.

Chapter 5: CONCLUSIONS

The research carried out in this investigation was focused on distinguishing wetland invasive plant species of interest and mapping infestation. Field-level hyperspectral reflectance factor was characterized to identify unique wavelength regions for dominant invasive plant species within the study area. Processing techniques were evaluated and showed varying degrees of utility. Relatively accurate maps for *Typha latifolia* and *Phragmites australis* were developed from airborne hyperspectral imagery. The mouth and western portion of the study site were identified as having higher levels of infestation. These infested regions coincide with relatively higher human land use intensities and slow-moving hydrological conditions.

Specific and general conclusions are as follows:

1. Characterizing absorption/reflectance features for particular species of interest should be considered when determining processing and classification techniques. When an overarching goal is to identify and map species of interest, such as *Phragmites australis*, techniques should consider absorption/reflectance features of that species response, since wavelengths of utility might vary. 'Universally' applied processing techniques are not always applicable as shown in this research. Shape filtering, which is a relatively straightforward approach, is one useful method to isolate wavelengths and/or biophysical attributes of interest for individual species. Useful wavelengths, according to shape-filtering approaches, can be species specific as shown in this work.

2. Continuum removal largely decreased separation abilities. The understory and previous plant growth are critical for identifying wetland species and play a role in creating unique signatures. Removing these features ultimately removed biophysical characteristics that aided in identification. Unless an absorption feature is identified as having a particular utility in aiding identification, continuum removal decreases separation and should not be used. Plant canopy structure had mixed results in terms of whether continuum removal disregarded structure, yet it did emphasize the utility of background signal.
3. In this study, basic pattern metrics were most applicable. While more complex metrics exist, describing infestation is really a factor of basic area, percentages covered, and distribution of those species across the study site. Straightforward metrics that describe percentage of landscape and aggregation measures illustrated infestation which was a primary goal. The infestation maps developed through this work can help assist management plans and efforts to control invasive species in the future. The framework developed in this work should be applicable to many regions and many species.
4. The concept of signature libraries (or building a database of signatures to feed into imagery for classification) for species-level mapping in wetland environments with current technologies is very challenging. In environments where species reflectance ranges widely and landscape heterogeneity is high, classification accuracies will rarely achieve levels above the industry standard threshold of 85%. Ground control and collection ***must*** occur simultaneously (i.e., radiometric calibration) to overpass for successful implementation. The highest

quality imagery is also necessary as slight reflectance differences between species are often smaller than signal to noise ratios of imagery. If species have unique spectral characteristics, if those characteristics are distinguishable in the wavelength captured by the imagery, if simultaneous ground control is collected, if the landscape has lower levels of dominant species and low levels of mixed pixels, and imagery is of the highest caliber, it will improve mapping accuracies and signature library concepts might be capable of discriminating covers.

5. The highest quality data is required. Issues related to multiple flight lines and no simultaneous ground control created calibration problems and limited imagery accuracy. Field work in diverse, wetland environments is extremely challenging and obtaining a large ground control dataset is extremely useful. In this study, several trips to the field were required and more data was always useful.
6. As eluded to in conclusion four and five, operational monitoring using hyperspectral wetland imagery for invasives monitoring is challenging. Data quality issues and landscape conditions produce *'thresholds of utility'* where the framework developed here is and is not useful. Operational monitoring might be possible with lower diversity in simpler landscapes where large, dominant patches of spectrally unique species are the plants of interest.
7. Future work needs to explore fusing advanced hyperspectral remote sensing technologies with other sensors such as LiDAR (providing topographic information) and RADAR (providing moisture information). Hyperspectral sensing provides advanced canopy and biological community (e.g., species) information. By combining these data with geomorphology and hydroperiod data

increased assessment information can possibly be provided. Wetlands health assessment approaches that can link all these technologies together and link with traditional field-based measures (e.g., HGM) is the next step in this field.

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