Spectral Discrimination of Phragmites Australis at Different Phenological Stages in Saginaw Bay, Michigan

Trenton Benedict

Western Michigan University, trentonbenedict322@yahoo.com

Follow this and additional works at: https://scholarworks.wmich.edu/masters_theses

Part of the Physical and Environmental Geography Commons, and the Plant Sciences Commons

Recommended Citation
https://scholarworks.wmich.edu/masters_theses/3430
SPECTRAL DISCRIMINATION OF *PHRAGMITES AUSTRALIS* AT DIFFERENT PHENOLOGICAL STAGES IN SAGINAW BAY, MICHIGAN

by

Trenton Benedict

A thesis submitted to the Graduate College
in partial fulfillment of the requirements
for the degree of Master of Science
Geography
Western Michigan University
April 2018

Thesis Committee:

Charles Emerson, Ph.D., Chair
Lisa DeChano-Cook, Ph.D.
Chansheng He, Ph.D.
Copyright by
Trenton Benedict
2018
Michigan Great Lakes wetlands are among Michigan’s most significant bio-diversified ecosystems. One threat to this ecosystem is invasive species. *Phragmites australis* is one of these invasive species creating problems in the wetlands. Identifying *Phragmites* through satellite imagery creates difficulties in discriminating *Phragmites* from other vegetation accurately. This study used an ASD HandHeld 2 field spectroradiometer to identify the phenological spectral properties between *Phragmites* and cattails. The Euclidean distance was analyzed the spectral curves from the spectroradiometer to determine the separability between *Phragmites* and cattails. The largest Euclidean distance determined the best month to separate the spectral signatures of *Phragmites* and cattails. The spectroradiometer hyperspectral data for *Phragmites* and cattails were averaged to coincide with National Agriculture Imagery Program imagery bandwidths. Applying Normalized Difference Vegetation Index (NDVI) to the averaged bandwidths for *Phragmites* and cattails, the value for each month was analyzed using Euclidean distance. Results showed that the best time of the year to distinguish *Phragmites* from cattails was in the fall.
ACKNOWLEDGEMENTS

I am thankful for the guidance I received throughout this research. I would like to give a special thanks to my committee members, Dr. Charles “Jay” Emerson, Dr. Lisa DeChano-Cook, and Dr. Chansheng He.

I would like to acknowledge the Saginaw Basin Land Conservancy and Saginaw Valley State University for permitting me to use the Michigan Sugar Trails and private university land, respectively. Without the access permission, I would not have been able to start my research within the studied period. I would also like to acknowledge Dr. Rhett Mohler and Dr. Andrew Miller for pushing me onto my Master’s Degree and lending me their Garmin for the research. Additional acknowledgments are owed to Dr. Ben Ofori-Amoah and Mary Lou Brooks for keeping a friendly humor throughout the stressful times, and the Lucia Harrison Endowment Fund for supporting my research and my assistantship.

None of this would have been possible without the support of my family and fiancé for believing in me to complete my degree. They helped push me to do my best and kept my mind sane during the long hours of work.

Trenton Benedict
TABLE OF CONTENTS

ACKNOWLEDGMENTS .................................................................................................................. ii

LIST OF TABLES .......................................................................................................................... v

LIST OF FIGURES ........................................................................................................................ vi

CHAPTER

I. INTRODUCTION ......................................................................................................................... 1

   Research Questions .................................................................................................................. 1

   Definition of Terms ............................................................................................................... 1

   Background .......................................................................................................................... 3

   Significance of the Research ............................................................................................... 6

   The Objectives of the Study ................................................................................................. 6

II. REVIEW OF LITERATURE ...................................................................................................... 8

   Spectroscopy ......................................................................................................................... 8

   Phenological Signatures ...................................................................................................... 10

   Vegetation Separability ....................................................................................................... 12

   Satellite Imagery .................................................................................................................. 16

III. METHODOLOGY .................................................................................................................... 21

   Study Area .......................................................................................................................... 21

   Methods and Materials ....................................................................................................... 25

   Imagery ............................................................................................................................... 28
Table of Contents – Continued

CHAPTER

Data Analysis ................................................................. 32
Imagery Interpretation ....................................................... 34

IV. RESULTS ............................................................................ 36
Seasonal Separability .......................................................... 36
Accuracy Assessment ............................................................ 41
Mapping the Rate of Change ............................................... 46

V. DISCUSSION ...................................................................... 53
Study Limitations ................................................................. 56

VI. CONCLUSION ................................................................... 58
Considerations for Future Research ....................................... 60

APPENDICES

A. Spectral Reflectance Integrated to NAIP Multispectral Bands .............. 63
B. Averaged Location’s Multispectral Reflectance Values ......................... 65
C. Euclidean Distances .................................................................. 67

BIBLIOGRAPHY ...................................................................... 69
LIST OF TABLES

1. Spectralon average reflectance data for the HandHeld 2 ........................................... 27
2. NAIP imagery acquisition dates ...................................................................................... 29
3. ESUN values per spectral band ...................................................................................... 32
4. Leica ADS100 spectral bands ......................................................................................... 33
5. Data collection information ............................................................................................ 37
6. Error matrix for the MS 2014 accuracy assessment ......................................................... 45
7. Error matrix for the MS 2016 accuracy assessment ......................................................... 45
8. NAIP imagery and solar information ............................................................................... 46
LIST OF FIGURES

1. Map of the Saginaw Bay watersheds ................................................................. 22
2. Map of the path and waypoints at MS study area NAIP 2016 imagery ................. 23
3. Map of the path and waypoints at SVSU study area NAIP 2016 imagery ............. 24
4. ASD HandHeld 2 with handle attachment ................................................................ 26
5. Phenological spectral curves of Phragmites and cattails ......................................... 39
6. NDVI values for averaged Phragmites and cattails ............................................... 40
7. NDVI values for the MS site .................................................................................. 40
8. NDVI values for the SVSU site .............................................................................. 41
9. Boundary for the MS 2014 accuracy assessment of the vegetation classification .................................................................................................................. 43
10. Boundary for the MS 2016 accuracy assessment of the vegetation classification .................................................................................................................. 44
11. Masked MS land displayed as NDVI, green, and red, RGB .................................... 48
12. MS 2016 NAIP supervised classification ............................................................... 50
13. Distribution of Phragmites and cattails based on supervised classification .......... 51
14. Distribution of Phragmites and cattails manually mapped between 2014 and 2016 .................................................................................................................. 52
CHAPTER I
INTRODUCTION

Research Questions

Great Lakes coastal wetlands are some of the most biologically diversified areas in Michigan (Department of Environmental Quality or DEQ, 2017). In danger of being lost due to human interaction and invasive species, Michigan’s wetlands are considered some of the rarest communities. Of the 33 wetland types in Michigan, 26 are rare wetland communities, and eight are on the edge of extinction (DEQ, 2018). Michigan’s Department of Environmental Quality works with public and private agencies to manage and preserve wetlands. The DEQ creates protocols and regulations when it comes to the massive wetland management areas.

This research investigates the invasive wetland species Phragmites australis (hereafter Phragmites) and Michigan’s native Typha latifolia (broadleaf cattail) which tend to grow in the same wetlands on the Saginaw River in Saginaw Bay, Michigan. Two research questions are, how can we more efficiently identify and map the occurrence of Phragmites and separate it from the cattails and other surrounding vegetation? Is the Phragmites spreading? The researcher considered these questions throughout the research process.

Definition of Terms

Spatial resolution is the ability for a remotely sensed image such as a satellite image to identify the smallest detail in the image pixel (Mapping European Seabed Habitat, 2010). The spatial resolution is mentioned with satellite imagery, where the images are grids of millions of pixels, or cells, which are different shades of grey or color. High spatial resolution means that the pixel size is minimal and can detect an object’s more significant details (MESH, 2010). Satellites data consists of bands, which are recordings of the amount of energy reflectance from a
segment of the electromagnetic spectrum. These bands range from the visible light through the infrared portion of the electromagnetic spectrum. The number of bands that a satellite has can determine the bandwidth. The bandwidth is how much of the electromagnetic spectrum each band covers. A multispectral satellite image consists of several spectral bands that have a broad bandwidth, whereas hyperspectral satellite imagery consists of hundreds of spectral bands with a smaller bandwidth.

Different surface materials such as vegetation, water, and pavement reflect different amounts of radiation in different wavelengths, which is the surface’s spectral signature (European Space Agency, 2014). For example, a blue ball absorbs nearly all the visible light waves except for the reflected blue wavelength. The spectral signature of the blue ball would have a peak in the blue wavelengths with the rest having a low reflection value. The spectral curve is the graph that illustrates the object’s reflectance percentage. With the spectral signatures of an object or plant, one can use the spectral curve to determine which object is reflecting the different wavelengths, which is spectral discrimination.

One way to enhance the ability to discriminate the spectral curves of a plant is by characterizing the plant’s phenology. Phenology is the study of the plants’ seasonal cycles and how the life cycle is influenced by each season (National Phenology Network, n.d.). For example, deciduous trees have the life cycle of sprouting in the spring and then losing its leaves in the fall, whereas, an evergreen tree continuously keeps its needles throughout the year. One can distinguish between deciduous and evergreen trees in satellite image by looking at the spectral curves in the fall, where deciduous trees reflect less infrared radiation than the evergreen trees. Studying the plants’ phenological spectral signature help with spectral discrimination.
Background

Wetlands are essential habitats for many plant and animal species. Invasive species, such as the *Phragmites australis* (common reed), are causing disturbances in the wetlands. *Phragmites* take over the wetland ecosystem by out-competing native vegetation, like *Typha latifolia* (broadleaf cattails) (Bellavance & Brisson, 2010). *Phragmites* is a wetland grass that grows about 15 feet tall in very densely packed stands (Avers, 2007). These reeds are reported invasive in 18 of the lower 48 states. Most of these states are along the East Coast and Midwest (Saltonstall, 2005). They are known to thrive in saltmarshes on the Atlantic coast, so they can tolerate high soil salinity, which explains how they survive in highway ditches after repeated winter salt applications. The migration from the Atlantic coast occurred by water and wind dispersal, transporting their seeds throughout the region and sprouting in different wetland habitats. Once *Phragmites* establish themselves, they spread rapidly with their roots, and disperse from fragments of their rhizomes (Saltonstall, 2005).

Soomers et al. (2013) studied the *Phragmites*’ dispersal patterns caused by wind and water in the Netherlands. They noticed that dispersal by water transported seeds farther than wind dispersal. Although in the Netherlands *Phragmites* is native, Soomers et al. (2013) suggest connecting suitable habitats for *Phragmites* with drainage ditches. Ditches would connect riparian wetlands for *Phragmites* to disperse farther in Europe (Soomers et al., 2013). In North America where *Phragmites* is invasive, this information is useful to understand how *Phragmites* transport long distances. Conservation specialists can use this information to manage drainage ditches to prevent *Phragmites* seed dispersal.

In Quebec, Canada, the wetland surface area covered by *Phragmites* increased by 18% from 1980 to 2002 (Gucker, 2008). In central Washington, U.S.A, the spread rate was 39 acres
in three years. Along the Atlantic coast, the spread rate averaged around 10 acres a year. Areas that were already occupied by *Phragmites* had an increase in land cover by 20% per year until they covered 50% to 80% of the wetland (Gucker, 2008). The spread rate mentioned by Gucker (2008) is significant because rare wetlands in Michigan are infected by *Phragmites* and can experience this 20% increase. In roughly three years, the infected land cover will be greater than 50% if the wetland is left untreated.

These invasive reeds are causing adverse impacts to the Great Lakes wetland ecosystems, such as the Saginaw Bay region in Michigan. Negative impacts identified in the coastal Great Lakes study by Bourgeau-Chavez et al. (2006) include displacing native vegetation, reducing biological diversity, changing nitrogen and phosphorous nutrient cycles, increasing air temperature within wetlands, changing rates of plant decomposition, drying out wetland soils, and trapping sediments. Biodiversity in habitat creates a healthy ecosystem that fulfills many species’ role in the environment. Invasive species damage these ecosystem roles by spreading rapidly and displacing other species. Resource managers have compiled plans to remove the threat of *Phragmites* (DEQ, 2017; Michigan Department of Natural Resources or DNR, 2017).

There have been multiple practices to remove the *Phragmites* from coastal and inland wetland locations (DEQ, 2017). Some practices include herbicide applications, mechanical treatment (such as mowing), prescribed fires, and water level management flooding. Sometimes the removal processes are not successful on their own, and reeds reappear or disperse to more places because of fragmented rhizomes. Mechanical removal is a successful method that consists of mowing the plant during winter (Avers, 2007). DEQ (2018) recommends mechanical treatments at least two weeks after applied chemical treatments for best results.
One challenge in controlling the *Phragmites* is identifying where it is thriving. One can chemically treat *Phragmites*, but as time moves forward, it reappears. The problem could be from a nearby source that keeps dispersing seeds to the area. To identify the source, one must map the surrounding wetlands. Researchers may find it difficult to identify the *Phragmites*’ local source in Michigan’s wetlands without the right tools.

One way to view areas affected by *Phragmites* is remote sensing. Satellite imagery can estimate the location of this species in a large area of land with ground-truthed field observations. Depending on the spatial resolution, coarse resolution imagery can cause different types of vegetation to look identical in images. Viewing distinct vegetation is best practiced with high spatial resolution satellite imagery such as WorldView 2 satellite with a spatial resolution of 1.84 meters (pan-sharpened to 0.46 m), whereas Landsat 8 satellite imagery has a spatial resolution of 30 meters (or when pan sharpened 15 m). Identifying the distinct vegetation is difficult when other vegetation is present, causing vegetation color pattern values to blend. Landsat 4-7 satellite sensors can record 256 different shades of grey, whereas Landsat 8 has 4096 shades of grey, which is a representation of reflected light energy recorded from the feature (United States Geological Survey, 2017).

Aerial images are another type of remotely sensed digital imagery that offers a high spatial resolution. Aerial images are collected from an aircraft carrier such as a plane, helicopter, or an Unmanned Aerial Vehicle, which provides a finer spatial resolution that is also cloud-free (Humboldt State University, 2014). An example of aerial collected imagery is the National Agriculture Imagery Program (NAIP) images from the United States Department of Agriculture (USDA). NAIP images are gathered using the Leica ASD100 sensor to collect four bands of spectral data (USDA, 2013). These NAIP bands are further discussed throughout this research.
To relate the phenology to remote sensing, one can use a spectroradiometer that detects and measures the light reflectance spectrum from a specific plant. Studying the reflectance with a portable spectroradiometer for the *Phragmites* and surrounding vegetation during the growing season, allows one to determine the spectral discrimination at multiple phenological stages. Using the seasonal reflectance, the researcher can determine the best time to map the invasive *Phragmites*. *Phragmites*’ spectral curves determine the best wavelengths to separate different vegetation types in a similar area to separate different vegetation during a specific season. Understanding distinct species’ reflectance values throughout a growing season will increase the ability to map the *Phragmites* using remote sensing.

*Significance of the Research*

This research is significant to land management agencies throughout the Saginaw Bay area. The research enhances the identification of the *Phragmites*’ occurrence and spread. The spread rate determines if the *Phragmites* in the study area need to be eradicated before it causes more harm to the wetland. With the concern for biodiversity in the Great Lakes wetlands, this research provides information on the Great Lakes freshwater ecosystem’s overall health, specifically Saginaw Bay.

*The Objectives of the Study*

The *Phragmites* is reducing wetland biodiversity. These changes displace the local vegetation and disrupt the balanced wetland ecosystem. To find areas that will be significantly affected by *Phragmites*, infected wetlands would need to be mapped at multiple dates to determine the rate of change. The first objective of this research is to identify the phenological spectral characteristics of *Phragmites* and the surrounding cattails using a spectroradiometer. The second objective is determining the best time of year for distinguishing between *Phragmites*
and cattails using the phenological spectral signatures. The third objective of this research is to map the *Phragmites* expanse from multiple dates to determine whether, and to what amount, they are spreading.
CHAPTER II
REVIEW OF LITERATURE

Spectroscopy

In remote sensing, there are many ways to gather information about specific vegetation’s distribution. One way to gather this information is by using a spectroradiometer, which was applied by Gao & Zhang (2006), Gilmore et al. (2008), and Ouyang et al. (2013) in their research. Gao & Zhang (2006) used a spectroradiometer from Analytical Spectral Devices Inc. (ASD) called the Fieldspec Pro JR Field Portable Spectroradiometer. Ouyang et al. (2013) used a UniSpec-DC Spectral Analysis System. The spectroradiometer used by Gilmore et al. (2008) was an ASD Fieldspec FR spectroradiometer. A white reference surface called a spectralon, is used to calibrate spectroradiometers when sampling for the spectral curves of the vegetation (Gao & Zhang, 2006; Gilmore et al., 2008; Ouyang et al. 2013). The known reflectance from the white reference surface allows the spectroradiometer to identify the vegetation reflectance percentage when compared to the white reference surface. The calibrated spectroradiometer can then record the reflectance values throughout a wide range of wavelengths.

Spectroradiometers used by Gao & Zhang (2006) and Gilmore et al. (2008) collected data with wavelengths ranging from 350 – 2500 nm, with sampling intervals of 1.4 nm. With these intervals, one can measure the spectral curves of Phragmites and other marsh vegetation. Sample vegetation areas were a one squared meter area, and one meter above the vegetation canopy (Gao & Zhang, 2006; Gilmore et al., 2008; Ouyang et al. 2013). Ouyang et al. (2013) collected spectral curves from Spartina, Phragmites, and Scirpus monthly throughout the year in China. Each plant had a total of 12 spectral curve samples to interpret. The spectral discrimination of those plants demonstrates that during different seasonal periods, all plants have
different spectral identifications (Gao & Zhang, 2006; Zomer et al. 2009; Peña-Barragán et al., 2010; Ouyang et al., 2013). Finding these spectral curves help determine where *Phragmites* are in satellite multispectral and hyperspectral images. Understanding when *Phragmites* and cattails have different spectral curves can help separate these two vegetation species in a satellite image, which is how Peña-Barragán et al. (2010) and Ouyang et al. (2013) identified their studied species.

Ullah et al. (2000) also used a spectroradiometer to gather spectral curves of *Typha latifolia*, *Scirpus americanus*, and *Phragmites communis/australis* in Nebraska, U.S.A. In this study, they used a portable spectroradiometer through the 1998 growing season and collected data on May 28th, June 16th, July 20th, and August 11th. These researchers chose those months because they represented various stages of the phenological cycle: early emergence stage, fully grown stage, flowering stage, and seed stage, respectively. The spectroradiometer collected data between 11 am and 2 pm, to reduce the solar angle (Ullah et al., 2000).

Peña-Barragán et al. (2010) studied the spectral curves of bare soil, sunflowers, and a weed called *Ridolfia segetum Moris*. In their study, they used high spatial resolution satellite imagery, along with an ASD HandHeld spectroradiometer to map the vegetation. They gathered both the sunflower’s and the weed’s spectral curves with field measurements. Peña-Barragán et al. (2010) chose to gather field measurements in mid-May, mid-June and mid-July, based on the phenological stages of both plants. In their study, they found that the best time to determine the sunflower yield, with the identification of weeds, was in mid-June. These results demonstrate that all plant species have different spectral curves, and a different time of year produces a more significant spectral difference between plant species.
**Phenological Signatures**

Vegetation spectral curves are reliable indicators for identifying the plant’s health status. Healthy plants follow seasonal patterns, which identify plants’ phenological spectral patterns. These phenological changes help identify thriving invasive species’ spectral signatures compared to the starving native vegetation. Studying the leaf phenology of invasive species can help detect where those plants thrive in the thicker brush (Resasco et al., 2007; Wilfong et al., 2009). Studying when the plants blossom and when they fall into dormancy is a crucial research method for monitoring the invasive species. Not only should one know the invasive species phenology patterns, but they should also acknowledge temporal phenological patterns of native plants. Temporal phenology patterns distinguish the native and non-native plants in the spring and fall months (Resasco et al., 2007; Wilfong et al., 2009).

With the range of the spectroradiometer, researchers can measure the vegetation reflectance and produce their spectral curves. The spectral curve of each plant differs throughout the electromagnetic light spectrum. In Gao and Zhang’s (2006) study, they measured the spectral signatures of *Phragmites, Spartina alterniflora, Scirpus marriqueter,* and *Carex scabrifolia,* during the spring, summer, and fall. After analyzing the four vegetation groups, Gao & Zhang (2006) concluded that the different salt marshes produced unique spectral properties during different times of the year. Another example of phenology signatures is the Rosso et al. (2005) study, who also identified four different vegetation species reflecting different amounts of the same spectral band. Rosso et al. (2005) studied marshland vegetation, which has a range of different vegetation types. These plants develop different spectral reflectance values while existing in the same region. Their study illustrates that different marshland vegetation types have different spectral curves from each other (Rosso et al., 2005). According to Adam et al.
(2010), this is a common trait with wetland species. Wetland species vary in their “chlorophyll and biomass reflectance as a function of plant species and hydrologic regime” (Adam et al., 2010 p. 283). Appling these reflectance values can determine the most separable wavelengths to increase the accuracy of discriminating distinct species.

Resasco et al. (2007) described the Amur honeysuckle’s seasonal patterns. This article used the Soil Adjusted Atmospheric Resistant Vegetation Index (SARVI2) rather than Normalized Difference Vegetation Index (NDVI). NDVI is calculated from near-infrared and visible red light reflected by vegetation, which identifies healthy green vegetation compared to unhealthy and non-vegetation objects (Ichoku & Przyborski, 2017). The SARVI2 is less sensitive to atmospheric effects and soil background, which enhances the greenness of the biomass compared to NDVI (Resasco et al., 2007). These researchers applied the Jeffries-Matusita distance calculation to determine the best season to separate native and non-native vegetation species. The article is beneficial for determining the best season to monitor invasive species. One can repeat Resasco et al. (2007) process to find when Amur honeysuckles or any other invasive bush are best identified during spring or fall.

These phenology patterns have been researched by many scholars such as Ouyang et al. (2013). They gathered these signatures throughout the growing season to identify spectral curves related to the plant’s phenological status. Carvalho et al. (2013) also noted the importance of these phenology signatures when studying the spectral reflectance of Jacobaea vulgaris. They mentioned that, due to the chemical structures of J. vulgaris, reflectance signatures in both the flower and the leaves provide the information needed to determine if plants are thriving during their successional stages (Carvalho et al., 2013). Their study identifies that the chemical structures vary from plant to plant during phenological stages, which create the various
reflectance signatures. Identifying these phenological signatures is essential when dealing with hyperspectral information. There are gaps between many different vegetation species which is why identifying the phenological cycles of many species is completed at the same time. Being able to identify these phenological signatures enhances the ability to discriminate between different plant species using satellite imagery during corresponding dates. Different dates are essential when creating phenological signatures on *Phragmites* and cattails to identify species’ spectral properties during those stages.

*Vegetation Separability*

There are several methods to separate the vegetation species in the literature. One influence on separating the vegetation types is through the different phenological cycles. For this reason, Gao & Zhang (2006), Gilmore et al. (2008), and Ouyang et al. (2013) observed the growing season of *Phragmites* to distinguish them from other marsh vegetation. Identifying plants’ spectral curves can measure the separability by applying statistical analysis. The spectroradiometer data was first averaged to 5 nm spectral bandwidths before being analyzed by the researchers (Ouyang et al., 2013). After averaging this data, statistical processes were applied to determine if the different vegetation spectral curves were significant. The Mann-Whitney U-test determines if population means are significant from each other (Ouyang et al., 2013). If these means are significant, then determining how significant the spectral curves are from each other requires a distance formula. Ouyang et al. (2013) used the Jeffries-Matsushita (JM) distance formula. The JM distance determined how separable the vegetation hyperspectral bands were from each other. This process was repeated with the averaged multispectral bands.

Murakami et al. (2001) also applied the Jeffries-Matsushita and Euclidean distance formulas to determine the spectral band's separability. Separability is defined as a statistical
measurement of the distance between two points, such as the Euclidean distance (Murakami et al., 2001). Murakami et al. (2001) applied NDVI to multiple scenes of rice, soybeans, and winter cereal crops. The Euclidean distance formula (Eq. 1) determined which temporal scene created the most separable distinction among different crops.

\[ ED = \sqrt{\sum_{i=1}^{n} (u_i - v_i)^2} \]  

(Eq.1)

Where \( u_i \) and \( v_i \) are the \( i^{th} \) band or element in the vegetation’s spectral curve where \( u_i \) and \( v_i \) are different vegetations. The Euclidean distance showed the stronger separability by determining the largest distances between the crops. When the Euclidean distance equaled zero, there was no separability between the vegetation (Murakami et al., 2001). The Euclidean distance is a more straightforward method to produce separability on large data sets, such as hyperspectral data.

Researchers in this study applied this method to determine the most separable spectral bands and vegetation indices throughout the phenological stages.

Ullah et al. (2000) determined the separability of three plants by using analyses of variance (ANOVA). ANOVA and the F-test were applied to identify if the three plants’ spectral curves were significantly different from each other. Before finding the significant difference, researchers averaged the narrow hyperspectral bands into multispectral bands, blue, green, red and near-infrared. Each band from the distinct species were then statistically tested for significance through ANOVA. Results showed that all species were separable throughout May, June, July, and August data (Ullah et al., 2000). Applying ANOVA to the spectral bands was another way to identify separability as oppose to indicating distances. This method worked to identify the most significant differences between spectral means, but results needed a post hoc test to identify where ANOVA indicated significant differences.
When utilizing multispectral bands, another way to identify vegetation separation is through vegetation indices. The most common index is NDVI (Eq. 2), which applies near-infrared bands and red bands to a normalizing ratio and compares these values to find healthy vegetation (Gao & Zhang, 2006; Gilmore et al., 2008; Ouyang et al. 2013). Other vegetation indices used in the literature include: Ratio Vegetation Index (RVI), Red Blue (RB), Green Normalized Difference Vegetation Index (GNDVI), Atmospheric Near-Infrared Vegetation Index (ANVI), and Enhanced Vegetation Index (EVI) (Gao & Zhang, 2006; Ouyang et al. 2013, Harris, 2013). In the Gao & Zhang (2006) and Ouyang et al. (2013) studies, they discovered that NDVI, ANVI, GNDVI, and RVI could enhance marsh vegetation separations. The JM distance formula determined the separability of vegetation index values produced by each species (Ouyang et al., 2013).

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}} \quad \text{(Eq. 2)}$$

Resasco et al. (2007) and Wilfong et al. (2009) studied the Amur honeysuckle using Landsat 5 and Landsat 7. To find the Amur honeysuckle’s leaf phenology, Resasco et al. (2007) applied spring and fall images from 1999 to 2006. Spectral readings equivalent to NDVI determined the amount of honeysuckle land cover. Resasco et al. (2007) omitted NDVI and used SARVI2 because SARVI2 is less sensitive to atmospheric and soil noise, and more sensitive to indirect differences in biomass. After obtaining 15 cloud-free spring and fall images from the two Landsat satellites, these researchers converted the imagery to Landsat 7 ETM+ and applied the cosine of the solar zenith angle (COST) model to create the top-of-the-atmosphere reflectance (Resasco et al., 2007; Wilfong et al. 2009). The COST model was used to reduce atmospheric haze. After producing reflectance values, they used two vegetation indices (SARVI2, and Tasseled Cap transformation) (Resasco et al., 2007). Once those values were
created, JM distances were calculated to determine which images (spring or fall) were best to identify the honeysuckle. Resasco et al. (2007) analyzed the mean of SARVI2 greenness values using ANOVA and Tukey’s honestly significant difference test (Resasco et al., 2007). After these calculations were produced, Resasco et al. (2007) found that the best images to identify invasive honeysuckle was in the fall. They found that October is too early to distinguish leaves, but the best time is early to mid-November in Southwest Ohio (Resasco et al., 2007).

Spectral curves gathered from spectroradiometers are used for calculating the vegetation separability. Most of the research that Ouyang et al. (2013) referenced dealt with statistical separation methods. Like Ouyang et al. (2013), Artigas and Yang (2005) used the non-parametric Mann-Whitney U-test for comparing the medians of different wavelengths. This method compares medians of wavelengths from different plant reflectance data. With these data, they found that the invasive Phragmites is significantly separable in the visible light spectrum from other marsh species (Artigas & Yang, 2005).

Another method using the vegetation spectral curve is by looking at the first derivative of the spectral curve. Gao and Zhang (2006) studied four different marsh species’ first derivatives in their research. The first derivative produces peaks at wavelengths where the curve increase or decrease rapidly. The first derivative was helpful for identifying where the spectral curve’s slopes were significantly different. They found that the wavelengths to concentrate on were bands of visible light, green peak (around 550 nm), red-edge peak (around 720nm), and the near-infrared wavelengths (Gao & Zhang, 2006). These results differ from Artigas and Yang’s (2005) and Ouyang et al.’s (2013) studies because they did not consider the first derivatives of the reflectance curves.
Another study that analyzed the first derivative was Cochrane (2000). This study compared different tree species’ spectral curves by using the root-mean-square difference between two distinct vegetation species. The first derivative compared the different vegetation red-edge reflectance and found that it was most significant for identifying specific vegetation types (Cochrane, 2000). The first derivative of spectral curves could be another approach for separating distinct vegetation species.

Another way to enhance the separability between different species is by analyzing phenological spectral data. More phenological studies help differentiate the studied vegetation species from the dominant vegetation in the area (Carvalho et al., 2013; Fernandes et al., 2013; Gao & Zhang, 2006; Peña-Barragán et al., 2006; Ullah et al., 2000). Artigas and Yang (2005) compared spectral curves of desired plant species each month between April and October. This study demonstrates how vital the phenology spectral separation is when mapping a distinct vegetation species. Artigas and Yang (2005) mentioned that collecting data throughout a growing season provided efficient information to identify the most active period for vegetation. The most active period indicates the peak of the season for each distinct vegetation species. Identifying where the active or non-active periods are during the growing season for different vegetation can enhance the separation.

**Satellite Imagery**

Most researchers collected imagery from different satellite databases. Bourgeau-Chavez et al. (2013) collected their data from a high spatial resolution satellite from Phased Array Type L-band Synthetic Aperture Radar (PALSAR) aboard the Advanced Land Observing Satellite (ALOS). This satellite was an excellent choice to distinguish the *Phragmites* from other wetland species because the sensor is an excellent beam dual polarized sensor and has been known to be
useful for flooding under vegetation canopies (Bourgeau-Chavez et al., 2013). This satellite had a 10-meter spatial resolution with 70 km by 70 km image (Bourgeau-Chavez et al., 2013). Researchers gathered images from the spring, summer, and fall between 2008 and 2010. Here they only used three seasons of imagery and omitted the months in-between because Bourgeau-Chavez et al. (2013) felt that those three seasons represent the three life stages of vegetation. Those three life stages of vegetation are the germination, primary vegetation growth, and flowering stage. Images were only gathered for the coastal Great Lakes wetlands. To map out the *Phragmites* they used unsupervised classifications to group similar pixels together to classify distinct vegetation species.

Gilmore et al. (2008) used Quickbird high-resolution imagery in their Connecticut *Phragmites* study. This satellite has a spatial resolution of 2.4 meters at nadir (Gilmore et al. 2008). This satellite is an excellent high spatial resolution satellite for identifying invasive species with temporal differences in images. Gilmore et al. (2008) applied nine images from July 2003 to November 2006 throughout the growing season. In their study, they found that *Phragmites* displayed a high NDVI and near-infrared/ red band ratio late in the growing season (Gilmore et al., 2008). Gilmore et al. (2008) found that when implementing seasonal images, the *Phragmites* was the most accurately mapped compared to the other vegetation. Their study is an example of the success Quickbird high-resolution imagery has on mapping salt marsh vegetation.

Another study that used Quickbird imagery was Ghioca-Robrecht et al. (2008). In this study, they researched two images in southeast Michigan. They used an image from September 6, 2002, and another image from April 10, 2003. Using these satellite images and a September NDVI image, an unsupervised classification was applied and created eight land cover classes (Ghioca-Robrecht et al., 2008). Ghioca-Robrecht et al. (2008) identified three land cover classes
as *Phragmites*, cattails, and *Nelumbo lutea* (lotus) by comparing these multiseasonal images. The accuracy was tested by applying the collected 196 ground-truthed GPS points to these images. The unsupervised classification results accurately identified three-fourths of the *Phragmites*, but 14% of the classified *Phragmites* were ground-truthed as cattails; and lotus beds were mapped with a producer accuracy of 91% (Ghioca-Robrecht et al., 2008). Multiseason Quickbird imagery can distinguish certain wetland vegetation types as long as natural phenological changes are not affected by human impacts (Ghioca-Robrecht et al., 2008).

A different approach to mapping the *Phragmites* was taken by Liu et al. (2016) when they used National Agriculture Imagery Program (NAIP) high-resolution imagery. Their study took place at the Detroit River International Wildlife Refuge. Their research objectives were to increase the historical training samples for detecting *Phragmites*. To create these historical training samples, they interpreted NAIP imagery from 2001 to 2010 and applied an automatic sample recognition algorithm called intersection analysis algorithm (IIAA) to supply the training samples (Liu et al., 2016). The IIAA identified where the *Phragmites* classification intersects the *Phragmites* classifications from other classified images. They analyzed NDVI calculations on Landsat TM images which created rough patches of *Phragmites* due to the coarse spatial resolution of 30-meter pixels. NAIP imagery was applied by interpreting field surveys on the imagery and extracting the sample to utilize as training data to Landsat imagery. Although they are unable to travel to the past years of 2001, 2005, and 2010 imagery, they extracted some of these samples by visual interpretation. Their results of visual interpretation outcome were “satisfactory” according to Liu et al. (2016 p. 273).

Visual interpretations of NAIP imagery were possible due to the high spatial resolution the sensor acquires. NAIP is a United States Department of Agriculture (USDA) program that
funds an aerial sensor to annually be flown during the leaf-on-season for the USDA Farm
Service Agency (FSA) (United States Department of Agriculture, 2013). Images contain three to
four spectral bands depending on the year they were obtained. Beginning in 2007 some states
had four-band imagery because of their contract with USDA FSA. These images have a one-
meter spatial resolution, with the exception 2011 images, where states had an option of half
meter spatial resolution depending on their contract (USDA, 2013). The fourth spectral band
scans the surface in the near-infrared spectrum (808-882 nm) which is ideal for interpreting
vegetation (USDA, 2013). One limitation using NAIP imagery is the inability to perform
radiometric calibrations accurately due to the lack of metadata.

This thesis attempted to produce a radiometric calibration to derived vegetation indices
for enhancing the Phragmites and cattail separation. Reflectance values are needed to compare
different image acquisition dates (Chander et al., 2009). Reflectance values are needed because
digital numbers are based on the grey scale of 0-255 value, which identifies as darkest to
brightest values in each spectral band, and can vary from date to date (Irons et al., 2018).
Identifying radiometric calibration for NAIP imagery can benefit vegetation visual identification
due to the no-cost imagery of high spatial resolution.

After reviewing the literature for this study, the common method for data collecting was
using a spectroradiometer above the vegetation’s canopy. Some researcher’s measurements were
collected three times in a year (spring, summer, and fall) to represent the phenological properties
of distinct vegetation types. The vegetation’s phenological spectral curves were then statistically
analyzed to identify the season that had the largest separability between the studied vegetation.
The largest separability would determine which month would best be used to separate distinct
vegetation with satellite imagery. There has been a lot done for separating *Phragmites* from other vegetation, but most of those studies have not been in Michigan’s inland wetlands.

This thesis used a HandHeld 2 portable spectroradiometer to identify the spectral curves of *Phragmites* and broadleaf cattails. The spectral curves showed the difference between recording reflectance values with water in the background compared to densely packed stands on land. The methodology for this thesis is unique compared to the other research done on *Phragmites* identification. The research recorded the reflectance curves almost every month to represent the spring, summer, and fall vegetations’ spectral properties. Instead of using satellite imagery, this research implemented NAIP imagery to map and distinguish the *Phragmites*’ spread rate in Michigan. Michigan’s inland wetlands were used to research the *Phragmites*’ phenological spectral properties, as opposed to the Great Lakes coastal wetlands. This research identified details about inland wetlands that can be managed for to prevent the *Phragmites* from spreading to the coastal wetlands.
CHAPTER III

METHODOLOGY

Study Area

The study area is within the Saginaw Bay Basin which is full of rivers and tributaries that feed Lake Huron’s Saginaw Bay (Figure 1). This study chose sites that were safely and legally accessible on the Saginaw River and Saginaw Valley State University’s (SVSU) property. The area of interest is on Middle Ground Island in Bay City along the Saginaw River with coordinates 43°34’38.91” N, 83°54’08.18” W (Figure 2). This became the Michigan Sugar (MS) site because of the associated Michigan Sugar Bike Trails on the island. MS has an abundance of Phragmites and patches of cattails. The researcher used the separated section of cattails (the southern patch of study points in figure 2) for the cattail data collection.

The second study area is a flooded wetland on SVSU’s property at the corner of Davis Road and West Freeland Road with coordinates 43°31’17.57” N, 83°57’23.10” W (Figure 3). Data collected on SVSU’s property was named SVSU for the associated property owners. This study site was accessible from the road and had a mixture of cattails and Phragmites. The flooded area had about 0.5 meters of water in the spring. The southern part of the wetland is dominated by Phragmites whereas the western edge of the wetland is full of cattails (Figure 3). This isolated wetland is an ideal area to collect data due to low traffic and minimal disturbance from the public. The researcher had permission from SVSU’s land management department to access their property to conduct the research.
Figure 1. Map of the Saginaw Bay watersheds (Partnership for the Saginaw Bay, 2018).
Figure 2. Map of the path and waypoints at MS study area NAIP 2016 imagery.
Figure 3. Map of the path and waypoints at SVSU study area NAIP 2016 imagery.
Although Phragmites dominate many areas in the Saginaw Bay watershed, the hard part was finding areas that contained both cattails and Phragmites. While those areas were identified, they were not included in this research because they were on private property. The two sites that were chosen had the cattails and Phragmites coexisting and the easiest accessibility to the wetlands. Phragmites dominated most wetlands, which outcompeted local cattails. Collecting field data, represented by similar solar radiation, was made possible with the Phragmites and cattails within the same wetland creating a short time interval between data collection.

**Methods and Materials**

To collect the vegetation’s spectral signatures, the researcher used an ASD Hand-Held 2 Spectroradiometer (Figure 4). The spectroradiometer measured the wavelengths from 325 nm – 1075 nm and had an accuracy of plus or minus one nanometer and a resolution of fewer than three nanometers at 700 nm (ASD, 2010). The wavelengths range included the visible light spectrum through the near-infrared spectrum. The near-infrared spectrum is ideal for relating the vegetation spectral curves to the areal imagery, such as NAIP imagery because vegetation reflects a significant amount of near-infrared light (Harris, 2013).

The fore-optics’ field of view is 25 degrees, with measurements being recorded from 1.5 meters above ground, yielding a ground resolution of about 0.665 meters. These measurements were equivalent to the researcher’s arm span with the added trigger mounted to the instrument (Figure 4). The trigger mount added length, so waders used in the field did not interfere with measurements.
Some internal instrument specifications included changing the spectral scans in the system to optimize the signal-to-noise ratio before the calibration process. The user manual determined this, noting that when using the instrument outside, 30 scans should be set for spectrum averaging for samples, and 60 scans should be set for spectrum for the white reference and dark current averaging count (Analytical Spectral Devices, 2010). When the researcher pulled the trigger, 10 samples were taken, starting with the first index value as one, to easily separate the different samples based on the tens digit place. The spectroradiometer required bright sunny days to record the most accurate reflectance values. Clear skies replicated the satellite or areal images that were obtained with zero percent cloud cover. Along with clear skies, the optimal time to collect data was solar noon. Solar noon allows for minimum shadows from the tall vegetation stands, which is needed for the spectroradiometer to reduce shadow noise.
Once the researcher set the averaging counts, a spectalon calibration disk was used to calibrate the instrument before each measurement. The calibration disc is a white four-inch diameter disc that has a uniform reflectance across the range of wavelengths measured by the spectroradiometer. The researcher recalibrated the instrument every 10 minutes and before every measurement. When calibrating, the spectroradiometer was placed approximately six inches perpendicularly above the disc while facing south towards the sun. The instrument is first optimized using the calibration disc, which calibrates the gain values for the instrument’s sensitivity to the sun’s brightness. Next, the spectroradiometer was calibrated for the white reflectance the same way using the calibration disc (ASD, 2010). When done correctly, the calibrated spectroradiometer has a horizontal line equaling one or 100% reflection, while pointed at the white disc. The horizontal line signifies that the spectroradiometer was calibrated for reflectance value since the sensor was created to identify the exact value the white reflectance disk (Table 1).

Table 1. Spectralon average reflectance data for the HandHeld 2.

<table>
<thead>
<tr>
<th>Wavelength (nm)</th>
<th>SRM-990 Spectralon® Uncalibrated Reflectance (plus/minus 0.5 percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>300</td>
<td>0.985</td>
</tr>
<tr>
<td>400</td>
<td>0.99</td>
</tr>
<tr>
<td>500</td>
<td>0.991</td>
</tr>
<tr>
<td>600</td>
<td>0.992</td>
</tr>
<tr>
<td>700</td>
<td>0.992</td>
</tr>
<tr>
<td>800</td>
<td>0.991</td>
</tr>
<tr>
<td>900</td>
<td>0.991</td>
</tr>
<tr>
<td>1000</td>
<td>0.993</td>
</tr>
<tr>
<td>1100</td>
<td>0.993</td>
</tr>
</tbody>
</table>

Source: (ASD, 2010 p. 20)

When the spectroradiometer was used to gather reflectance values, the instrument was held by its trigger adaptor 1.5 meters above and perpendicular to the ground. Having the
instrument 90 degrees to the earth imitates the satellite or aircraft flying directly over the area to record imagery. The spectroradiometer recorded reflectance values while facing south towards the sun to avoid shadows created by the instrument and the observer. There were still shadows created by *Phragmites* stands since they are 3.6-4.6 meters (12 – 15 feet) tall and the instrument recorded the stems and leaves of the densely packed *Phragmites*.

Another instrument used during the collection process was a Garmin Oregon 450t Global Positioning System (GPS) unit. The GPS had an accuracy of fewer than 10 meters (95% Root-Mean Squared error [RMSE]), and a differential GPS (DGPS) accuracy from three to five meters 95% RMSE as well (Garmin, 2010). With the use of the GPS, waypoints for each sample site were recorded, along with the route from point to point. Figures 2 and 3 illustrate the paths recorded by the GPS along with the waypoints. The path and waypoints recorded at the SVSU site and MS site are the reference points for the respective study area. The GPS receiver was used to validate the same points and were repeatedly measured each month to represent the same patch of *Phragmites* and cattails throughout the growing season.

*Imagery*

The separability information is essential for indicating what satellite imagery to obtain. Some free satellite imagery, such as Landsat 8 imagery, consists of pixels sizes too large to identify detailed information in a small study area. Having a smaller study area requires high spatial resolution satellite imagery which becomes expensive, and most people are unable to afford this imagery. The solution was NAIP imagery. NAIP is not satellite imagery, but instead, images are gathered by the Leica ADS100 Aerial Digital Scanner that is commercially flown and funded by the USDA Farm Service Agency (FSA) (USDA, 2013). NAIP imagery started in 2002 with three spectral bands (blue, green and red). The four-band (blue, green, red, and near-
infrared) spectral resolution is ideal for studying vegetation because of the near-infrared band. This high spatial resolution imagery has an advantage of identifying the *Phragmites* and other vegetation when using the four-band spectral resolution imagery.

When determining dates necessary for this study, the researcher looked for the most recent available NAIP image for MS and SVSU study area (Table 2). The most recent date acquired by NAIP was July 10, 2016. Then for the earlier date, the researcher chose the earliest NAIP imagery with four bands. EarthExplorer results indicated that 2010 was the earliest imagery with four-band spectral resolution. The earliest NAIP imagery chosen was July 24, 2014, so the radiance could be compared to Landsat 8 imagery. The USDA FSA revealed dates and times the NAIP imagery was collected for Bay City and Saginaw (Table 2). Data gathered from USDA FSA was used for solar calculations for calibrating digital number to reflectance values.

**Table 2. NAIP imagery acquisition dates.**

<table>
<thead>
<tr>
<th>Study Area</th>
<th>NAIP imagery dates acquired</th>
<th>Time Flown</th>
<th>Spectral Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS</td>
<td>July 10, 2017</td>
<td>1:55 – 2:40 PM</td>
<td>4 Bands</td>
</tr>
<tr>
<td>MS</td>
<td>July 24, 2014</td>
<td>1:49 – 2:08 PM</td>
<td>4 Bands</td>
</tr>
<tr>
<td>SVSU</td>
<td>July 10, 2017</td>
<td>1:55 – 2:40 PM</td>
<td>4 Bands</td>
</tr>
<tr>
<td>SVSU</td>
<td>July 24, 2014</td>
<td>1:49 – 2:08 PM</td>
<td>4 Bands</td>
</tr>
</tbody>
</table>

Source: USDA FSA

Landsat 8 imagery was used to help normalize the two NAIP imageries by utilizing radiance values calculated for Landsat 8. The researcher used Landsat 8 imagery based on the Landsat Science Team’s calibration techniques for the Google Earth Engine App for Residential Water Use and Preservation (G.E.A.R.U.P.) (Kilic et al., 2017). They used Landsat reflectance values to calibrate NAIP’s digital numbers into reflectance values. To do so, they compared the NDVI values from both Landsat imagery and NAIP imagery for their calibration (Kilic et al., 2017).
The researcher used the dark object method to determine if the Landsat 8 imagery was useful for normalizing the NAIP imagery (Chavez, 1988). The dark object method comparison would determine if Landsat 8 can be used for the NAIP radiance calibration. Landsat 8 dark object comparison for 2014 and 2016 imagery resulted in a 4.75% percent difference. The dark object comparison for NAIP imagery resulted in a 2.68% percent difference. The values were only different by 2.07%, which made Landsat 8 feasible for the radiance calibration.

One issue with NAIP imagery is the radiometric calibration process, which is the process of converting images’ digital number to radiance, reflectance, or brightness temperatures (Harris, 2013). Digital numbers that come with the imagery when downloaded from earthexplorer.usgs.gov are values of 0-255 for each pixel. These digital numbers do not come with metadata that can be used to calibrate them into radiance or reflectance values. Gains and offsets of each band are needed to change digital numbers to radiance values (Harris, 2013). Usually, the metadata contains this information with the downloaded imagery; this is not the case for NAIP imagery. The equation used to form the radiance calibration process is

\[ L_{γ} = Gain \times DN + offset \]  

(Eq.2)

where \( L_{γ} \) is the radiance value; Gain refers to the radiometric gain value; DN is the pixel’s digital number; and offset is the radiometric offset (Harris, 2013). Since gains and offsets were not provided, the linear equation (Eq. 3) creates a linear regression between the DN of NAIP and the radiance value computed for Landsat 8 imagery. Imagery from July 23, 2014, and July 12th, 2016, covered the SVSU and MS study areas. The radiometric calibration for Landsat 8 was performed using ENVI software for the near-infrared band (Band 5 in Landsat 8), red band (Band 4 in Landsat 8), green band (Band 3 in Landsat 8), and blue band (Band 2 in Landsat 8).
(Irons et al., 2018). Applying the linear regression to the NAIP imagery gave an estimation of a radiance calibrated NAIP imagery.

Once digital numbers were calibrated to radiance values, the reflectance equation (Eq. 4) was applied. The reflectance equation used is the Top-of-Atmosphere (ToA) reflectance with values from 0 – 1 (Harris, 2013). This equation is

$$\rho_{\gamma} = \frac{\pi L_{\gamma} d^2}{ESUN_{\gamma} \cos \theta}$$  

(Eq. 4)

Where $$\rho_{\gamma}$$ is the reflectance values; $$L_{\gamma}$$ is the radiance values of the cell; $$d$$ refers to the Earth- sun distance in astronomical units; $$ESUN_{\gamma}$$ is the solar irradiance in units of W/(m$$^2$$ * µm); and $$\theta$$ is the solar zenith angle in degrees (Chander et al., 2009; Harris, 2013). To find these variables, the date and time for the given image was required (Table 2), along with the coordinates, so they could be entered in NOAA’s Solar Position Calculator and GLOBE’s Program Solar position/ air mass calculator (Cornwall et al., 2018; GLOBE, 2010). To find the solar irradiance ($$ESUN_{\gamma}$$), Chander et al.’s (2009) research collaborated multiple irradiance values from several different satellites and sensors. They did not have Leica ADS100 sensor solar irradiance spectral band widths, so the constant that resembled the bandwidth of ADS100 were chosen (Table 3). The results for Band 1 $$ESUN_{\gamma}$$ value came from averaging Earth-Observing 1 Advanced Land Imager (EO-1 ALI) Sensor Band 1P and Band 1, since NAIP’s Band 1 width included those two bands. Band 2 and Band 3 $$ESUN_{\gamma}$$ value was produced by using the nearest bandwidth from EO-1 ALI Sensor, which was Band 2 and Band 3, respectively. Band 4 $$ESUN_{\gamma}$$ value was produced from Multispectral Scanner (MSS) Sensor Level 1 (National Landsat Production System) (Chander et al., 2009).
Table 3. ESUN values per spectral band.

<table>
<thead>
<tr>
<th>Spectral Band</th>
<th>Wavelength (nm)</th>
<th>ESUN (W/(m² * µm))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>435-495</td>
<td>1926.5</td>
</tr>
<tr>
<td>Green</td>
<td>525-585</td>
<td>1807</td>
</tr>
<tr>
<td>Red</td>
<td>619-651</td>
<td>1536</td>
</tr>
<tr>
<td>Near-infrared</td>
<td>808-882</td>
<td>880.1</td>
</tr>
</tbody>
</table>

Source: Chander et al. (2009)

Data Analysis

Analytics Spectral Devices (ASD) ViewSpec Pro Version 6.0 software analyzed the descriptive statistics of all 1,680 spectral curves exported from the spectroradiometer (ASD, 2010). The ASD software packages of HH2 Sync and ViewSpec Pro extracted the data from the spectroradiometer. The extraction was done on the day of the collection because HH2 Sync would automatically create a folder named after the date these data were downloaded. These dates kept the files organized and accessible for analysis. The first process was averaging the 10 spectral curves gathered at each measuring point. The researcher applied the ASD software to create the 10 reflectance curves’ mean for each patch measured. The 10 reflectance curves resulted in one reflectance curve file for each measured patch labeled SVCT1-SVCT6, SVP1-SVP6, MSC1-MSC6, and MSP1- MSP6, for each respective gathering date. The averaged 10 reflectance curves condensed the 1,680 spectral files into 168 files.

The next process was integrating wavelengths to correspond with NAIP’s multispectral bands’ wavelengths (Table 4). Table 4 illustrates the spectral ranges and respective multispectral bands for the sensor. The ViewSpec Pro’s lambda integration process integrated the spectroradiometer wavelengths to match Leica ADS100’s spectral band range (Table 4). Within the lambda integration, there is an input window to specify the band range to integrate, such as the spectral bands from Leica ADS100 sensor. The process output resulted in each of the 168
files integrated into four bands, which created 672 files. The lambda integration process was vital to integrate the hyperspectral bands into the multispectral bands of NAIP imagery, which were the files used for data analysis.

Table 4. Leica ADS100 spectral bands (USDA, 2013)

<table>
<thead>
<tr>
<th>Spectral Range</th>
<th>Spectral bands (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>435-495</td>
</tr>
<tr>
<td>Green</td>
<td>525-585</td>
</tr>
<tr>
<td>Red</td>
<td>619-651</td>
</tr>
<tr>
<td>Near-infrared</td>
<td>808-882</td>
</tr>
</tbody>
</table>

The 672 files that consisted of NAIP band wavelengths were used to analyze the seasonal separability. Separability is a statistical measurement of the distance between two data points (Murakami et al., 2001). The researcher used the separability to identify which seasonal spectral curve creates the best separation between *Phragmites* and cattails to distinguish them in seasonal imagery. The Euclidean distance (ED) formula (Eq. 5) is evaluated to find the separability distance. The Euclidean distance is the shortest straight-line distance between two points in a plane. The distance formula between two spectral band vectors, \( u \) and \( v \), represented by

\[
ED = \sqrt{\sum_{i=1}^{n}(u_i - v_i)^2} \quad \text{(Eq. 5)}
\]

Where \( u_i \) consists of the measured hyperspectral and multispectral bands for *Phragmites* \([u_1, u_2, \ldots, u_n]\) and \( v_i \) is the measured hyperspectral and multispectral bands for cattails \([v_1, v_2, \ldots, v_n]\) from the spectroradiometer.

For this research, the researcher measured the distance between the *Phragmites* and cattails on their specified collection date. The Euclidean distance formula produced a value of zero to positive infinity, where zero means the points have no distance from one another, (they have same reflectance value), and therefore they are not separable. The larger the distance, the better separability the corresponding phenological stage creates. The limitation to the Euclidean
distance is that it is not standardized for comparing separability, so the best separability of the dates was determined by the largest Euclidean distance, and the least separable were the dates when the Euclidean distance was closest to zero. Collected spectroradiometer data determined what time of the year has the most separable spectral signature.

*Imagery Interpretation*

Once images were calibrated to reflectance values, the discrimination of *Phragmites* and cattails were analyzed. Reflectance values allowed for two images to be compared because reflectance values are more normalized than digital numbers. When analyzing vegetation, understanding spectral properties of vegetation enables one to identify the vegetation’s reflectance performance based on ecological differences (Harris, 2013). Vegetation indices are combinations of surface reflectance between two or more wavelengths, which is used to enhance properties of vegetation (Harris, 2013). The vegetation index analyzed to enhance the separability was NDVI (Eq. 6) based on Ouyang et al.’s (2013) results. The vegetation index examined to enhance spectral separability is:

\[
\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}}
\]

(Eq. 6)

Where NIR is the near-infrared spectral band, R is the red spectral band (Harris, 2013; Ouyang et al., 2013). NDVI was calculated using ArcGIS Raster Calculator and the reflectance values from NIR and Red bands. The researcher applied NDVI to the NAIP spectral bands produced by the spectroradiometer. NDVI was also applied to the NAIP imagery gathered on July 24, 2014, and July 10, 2016, to enhance the separability. The researcher used the ground-truthed waypoints to identify regions of interest for cattails and *Phragmites* which were used for supervised classification in ENVI. Once both 2014 and 2016 images were classified, the digitized area was calculated and compared to each other. Then, using the Raster Calculator function in ArcMap,
the two images were added together to identify the *Phragmites*’ new growth between 2014 and 2016. The calculated raster identified the spread rate for *Phragmites* in the Saginaw River wetland.

The vegetation index and NAIP bands were stacked using ENVI layer stacker function, which would allow the values to be viewed in Red, Green, Blue (RGB) colored image. A shapefile made from the NDVI values of less than zero created the mask of the land from Saginaw River study site. Creating this shapefile omitted the water, roads, and other non-vegetation surfaces within the study area (Harris, 2013). This shapefile was used to build a mask in ENVI and applied the mask to the stacked layers. The resulted image consisted of the vegetation at MS site, which was used to interpret the *Phragmites* and cattails.
CHAPTER IV  
RESULTS

Seasonal Separability

The researcher collected field data from May 2017, through November 2017. Table 5 outlines the dates and times of data collection. The significant description of the day includes the Phragmites and cattail conditions, rainfall and notable weather conditions. On each collection day, the routine was constant; the first location was always SVSU cattails moving towards the Phragmites (Figure 3, SVC1 to SVP6 in ascending order). The observer collected the cattails and Phragmites spectral reflectance at the MS site (Figure 2, MSC1 to MSP6 in ascending order) following the SVSU site. The regular pattern resulted in collecting data each day during similar sun intensity.

Once the spectral reflectance values from the spectroradiometer were integrated to represent the four-band NAIP imagery, the Euclidean distance was analyzed. The researcher calculated the Euclidean distance for the four bands at both locations (Appendix A) and then averaged the reflectance values for Phragmites and cattails (Appendix B). The distance determined which month was most separable via the largest distance value.

The Euclidean distance was calculated between Phragmites and cattails by separating locations, which resulted in different significant separable months between MS and SVSU site. Appendix C demonstrates the Euclidean distances between Phragmites and cattails. These results illustrate that Phragmites and cattails had the most substantial separability on September 15, 2017, at the MS site, but at the SVSU site, Phragmites and cattails were most separable on August 25, 2017. When combining the location’s vegetation reflectance (Appendix B), the
Euclidean distance between *Phragmites* and cattails was most separable on May 30, 2017 (Appendix C).

Table 5. Data collection information.

<table>
<thead>
<tr>
<th>Date</th>
<th>Time (24 hour)</th>
<th>Temperature</th>
<th>Sky Conditions</th>
<th>Significant descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>May 3, 2017</td>
<td>10:45-12:35</td>
<td>58°F-60°F</td>
<td>Clear and sunny</td>
<td><em>Phragmites</em> were sprouting between dead stands</td>
</tr>
<tr>
<td>May 30, 2017</td>
<td>10:45-13:00</td>
<td>67°F-70°F</td>
<td>Sunny-Partly Cloudy</td>
<td>Gathered data between cloud shadows</td>
</tr>
<tr>
<td>June 21, 2017</td>
<td>10:40-12:35</td>
<td>68°F-69°F</td>
<td>Clear and sunny</td>
<td>A couple of days of significant rainfall before</td>
</tr>
<tr>
<td>August 25, 2017</td>
<td>11:30-13:30</td>
<td>68°F-72°F</td>
<td>Clear and sunny</td>
<td>SVSU water level dropped</td>
</tr>
<tr>
<td>September 15, 2017</td>
<td>10:40-12:35</td>
<td>71°F-80°F</td>
<td>Clear and sunny</td>
<td>Cattail leaves were turning brown</td>
</tr>
<tr>
<td>October 18, 2017</td>
<td>11:00-12:55</td>
<td>60°F-61°F</td>
<td>Clear and sunny</td>
<td>Strong gusts of wind</td>
</tr>
<tr>
<td>November 29, 2017</td>
<td>11:00-13:00</td>
<td>36°F-37°F</td>
<td>Clear and sunny</td>
<td><em>Phragmites</em> and cattails were brown</td>
</tr>
</tbody>
</table>

The researcher examined the spectroradiometer’s raw hyperspectral data for each date. These spectral curves of *Phragmites* and cattails were compared to the spectral curves from Zomer et al. (2009) along with the *Phragmites* spectral curves in Ouyang et al. (2013). The comparison ensured that the spectral curves from this research are approximately identical to other spectral curves. Figure 5 illustrates the spectral curves recorded by the spectroradiometer. The Euclidean distance formula was applied to *Phragmites*’ and cattails’ hyperspectral vectors using Microsoft Excel (Appendix C). Microsoft Excel calculated the squared difference between each *Phragmites*’ and cattails’ hyperspectral vector element, which was then added together to create the sum of differences. The sum of squared differences was then square rooted to calculate the Euclidean distance (Eq. 5). With a Euclidean distance of 2.15, September 15, 2017, emerged as the most separable date for *Phragmites* and cattails at the MS site. For the SVSU...
site, the most separable date was August 25, 2017, with a distance of 1.26 (Appendix C). The most separable date is influenced by the plant’s chlorophyll, which reflects more near-infrared energy. Hyperspectral curves of *Phragmites* at MS site illustrate the abundance of chlorophyll compared to the cattails’ spectral curve. **MS Phragmites’** spectral curves identify that *Phragmites* hold more chlorophyll than cattails, which is displayed as the large jump in near-infrared reflectance (National Aeronautics, 2010).

When mapping vegetation, vegetation indices are incorporated by combining different spectral bands to enhance the separability. The goal of this thesis was to identify the best month to apply NDVI for separating *Phragmites* and cattails. Executing NDVI (Figure 6) on *Phragmites’* and cattails’ reflectance values on NAIP bandwidths showed the largest distance was on October 18, 2017 (Appendix C). Figures 7 and 8 represent the NDVI values for the separated MS and SVSU vegetation, respectively. After applying the Euclidean distance, the most separable dates for NDVI on MS data was June 21st, whereas SVSU data was October 18, 2017 (Appendix C).
Figure 5. Phenological spectral curves of *Phragmites* and cattails. The x-axis for the graphs is the wavelengths (nm), and the y-axis is the reflectance value (%).
Figure 6. NDVI values for averaged *Phragmites* and cattails.

Figure 7. NDVI values for the MS site.
Figure 8. NDVI values for the SVSU site.

**Accuracy Assessment**

The accuracy matrix (Table 6 and Table 7) was created to find the user’s accuracy, producer’s accuracy, percent correctly classified (PCC), and Cohen’s Kappa Statistic (KHAT) for MS 2014 and MS 2016 Supervised Classifications (Figure 9 and Figure 10, respectively). The researcher used 50 random points created by ArcMap’s Create Random Points tool to create the accuracy matrices. The random points were placed within each dissolved shapefile of *Phragmites*, cattails, trees, and other vegetation, resulting in a total of 200 points. The Dissolve tool is used to break down the borders of the individual polygons created within the class, this way the random points were placed throughout the shapefile. The referenced land cover for MS 2016 was the GPS tracks overlaid on NAIP 2016 imagery. The reference land cover for MS 2014 used Google Earth September 26, 2014, historical imagery to identify the land cover.

Results for MS 2014 and MS 2016 classifications’ PCC were 64% and 57%, respectively.
The producer’s accuracy and user’s accuracy results for MS 2014 *Phragmites* classification were 75% and 66%, respectively (Table 6). The producer’s accuracy and user’s accuracy results for MS 2016 *Phragmites* classification were 86.5% and 64%, respectively (Table 7). The *Phragmites* and cattails producer’s and user’s accuracy results were not the most significantly accurate, but the supervised classifications were used to determine the spread rate.

For a more accurate spread rate, the *Phragmites* and cattails were manually mapped by visual discrimination. The manually mapped vegetation accuracy was only comparing the manually classified *Phragmites* and cattails in the 2014 and 2016 NAIP imagery. The researcher used the 2017 GPS tracks as the referenced land cover information to create the accuracy. The percent correctly classified results for the manually mapped *Phragmites* and cattails in 2016 was 83.33%, whereas 2014 the accuracy was 89.17%. The producer’s accuracy results for 2016 *Phragmites* and cattails were 91.18% and 100%, respectively. The user’s accuracy produced from *Phragmites* and cattails were 77.5% and 75%, respectively. When comparing the accuracy of the 2014 image the producer’s and user’s accuracy results were greater than 2016. For *Phragmites* and cattails mapped in 2014, the producer’s accuracies were 94.59% and 100%, and the user’s accuracies were 87.5% and 82.5%, respectively.
Figure 9. Boundary for the MS 2014 accuracy assessment of vegetation classification.
Figure 10. Boundary for the MS 2016 accuracy assessment of the vegetation classification.
Table 6. Error matrix for the MS 2014 accuracy assessment.

<table>
<thead>
<tr>
<th>Reference Land Cover</th>
<th>Phragmites</th>
<th>Cattails</th>
<th>Trees</th>
<th>Other Vegetation</th>
<th>Class. Total</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>33</td>
<td>2</td>
<td>3</td>
<td>12</td>
<td>50</td>
<td>66%</td>
</tr>
<tr>
<td>Cattails</td>
<td>6</td>
<td>19</td>
<td>16</td>
<td>9</td>
<td>50</td>
<td>38%</td>
</tr>
<tr>
<td>Trees</td>
<td>5</td>
<td>1</td>
<td>28</td>
<td>16</td>
<td>50</td>
<td>56%</td>
</tr>
<tr>
<td>Other Vegetation</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>48</td>
<td>50</td>
<td>96%</td>
</tr>
<tr>
<td>Reference Total</td>
<td>44</td>
<td>22</td>
<td>49</td>
<td>85</td>
<td>200</td>
<td></td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>75%</td>
<td>86.4%</td>
<td>57.1%</td>
<td>56.5%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCC</td>
<td>64%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHAT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.52</td>
</tr>
</tbody>
</table>

Table 7. Error matrix for the MS 2016 accuracy assessment.

<table>
<thead>
<tr>
<th>Reference Land Cover</th>
<th>Phragmites</th>
<th>Cattails</th>
<th>Trees</th>
<th>Other Vegetation</th>
<th>Class. Total</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>32</td>
<td>0</td>
<td>5</td>
<td>13</td>
<td>50</td>
<td>64%</td>
</tr>
<tr>
<td>Cattails</td>
<td>2</td>
<td>12</td>
<td>23</td>
<td>13</td>
<td>50</td>
<td>24%</td>
</tr>
<tr>
<td>Trees</td>
<td>3</td>
<td>0</td>
<td>25</td>
<td>22</td>
<td>50</td>
<td>50%</td>
</tr>
<tr>
<td>Other Vegetation</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>45</td>
<td>50</td>
<td>90%</td>
</tr>
<tr>
<td>Reference Total</td>
<td>37</td>
<td>12</td>
<td>58</td>
<td>93</td>
<td>200</td>
<td></td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>86.5%</td>
<td>100%</td>
<td>43.1%</td>
<td>48.4%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCC</td>
<td>57%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.427</td>
</tr>
<tr>
<td>KHAT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


Mapping the Rate of Change

Before mapping the rate of change, NAIP imagery needed radiometric calibration for radiance and reflectance. Applying the ENVI radiometric calibration function, radiance values for Landsat 8 imagery were produced. Choosing 30 random points on near-infrared and red separate spectral bands for NAIP imagery and referencing them to intersecting cloud free cells on Landsat spectral bands created a linear regression for NAIP NIR and red band radiance. NAIP band digital numbers were then transformed to radiance values using the linear regression equation.

When calculating reflectance values with equation 4, constants had to be calculated using the date and time for the respective image coordinates (Table 8). The researcher entered the coordinates in the NOAA Solar Position Calculator and GLOBE’s Program Solar position/air mass calculator (Cornwall et al., 2018; GLOBE, 2010). The returned results included Earth-sun distance in astronomical units (d) and the cosine of solar zenith angle in degrees (cosθ) (Table 8) (Cornwall et al., 2018; GLOBE, 2010). The gathered constants for equation (4) calculated the reflectance values of the radiance values ($L_y$) from the NAIP 2014 and 2016 imagery. Equation (4) was applied to NAIP Bands 1, 2, 3, and 4 to calculate the reflectance values for NAIP imagery by using the solar properties from Table 8.

Table 8. NAIP imagery and solar information.

<table>
<thead>
<tr>
<th>Location</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Date</th>
<th>Time (24 hr)</th>
<th>Earth-Sun distance</th>
<th>cosθ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bay City</td>
<td>43°34’38.91” N</td>
<td>83°54’08.18” W</td>
<td>7/10/2016</td>
<td>14:15:42</td>
<td>1.016622</td>
<td>0.6573</td>
</tr>
<tr>
<td>Bay City</td>
<td>43°34’38.91” N</td>
<td>83°54’08.18” W</td>
<td>7/24/2014</td>
<td>13:58:30</td>
<td>1.015819</td>
<td>0.6795</td>
</tr>
<tr>
<td>SVSU</td>
<td>43°31’17.57” N</td>
<td>83°57’23.10” W</td>
<td>7/10/2016</td>
<td>14:15:42</td>
<td>1.016622</td>
<td>0.6579</td>
</tr>
<tr>
<td>SVSU</td>
<td>43°31’17.57” N</td>
<td>83°57’23.10” W</td>
<td>7/24/2014</td>
<td>13:58:30</td>
<td>1.015819</td>
<td>0.6802</td>
</tr>
</tbody>
</table>

Source: USDA FSA Geospatial Services Branch Chief, GLOBE (2010), and Cornwall et al. (2018).
The researcher implemented the ground-truthed waypoints to identify the locations of *Phragmites* and cattails in the imagery. The five-layer raster (Blue, Green, Red, Near-Infrared, and NDVI raster bands) was displayed in different combinations of RGB, resulting with NDVI, Green, and Red, respectively, being the most contrasting combination. The cattails along the river appeared to have a darker tint of red in the image, whereas the *Phragmites* had a blue tint (Figure 11).

The researcher classified 2014 and 2016 NAIP images into four classes, which included *Phragmites*, cattails, trees, and other vegetation (Figure 12). The other vegetation class included dead vegetation, shrubs, grass, aquatic vegetation such as algae, and smaller wetland vegetation. The features that were unclassified included water, roads, and any cell that had a negative NDVI value, which included shadows for MS 2014 image. ENVI software identified these classes using the Regions of Interests (ROI) in a Supervised Maximum Likelihood Classifications of Figure 11.

After computing the MS 2014 and 2016 NAIP Supervised Classification, there was a definite accuracy issue for calculating the spread rate of *Phragmites*. There were pixels highlighted as *Phragmites* that should have been trees or other vegetation. The researcher kept the accuracy in mind and still calculated the spread rate between 2014 and 2016. Figure 13 illustrates the spread rate between the two years classified. The result from the supervised classified images was a total of 2,022 pixels that were classified as *Phragmites*’ spread in 2016. The size of each pixel is 1 $m^2$ which means the area covered by the 2016 spread is 2,022$m^2$. The spread rate between the two years resulted in a 1,011$m^2$/year. To omit the pixels that were inaccurately classified, 2014 and 2016 images were manually digitized (Figure 14).
Figure 11. Masked MS land displayed as NDVI, green, and red, RGB.
Since *Phragmites* and cattails were visibly distinguishable, the researcher classified the vegetation manually. NAIP 2014 and NAIP 2016 *Phragmites* and cattails were mapped by polygons and then transformed to 1-meter raster cell image to identify the spread rate. Applying Raster Calculator to 2014 and 2016, a digitized map of the distributions between *Phragmites* and cattails was produced (Figure 14). After evaluating the cell count for each classification, the total area of *Phragmites* in 2014 was 6356 $m^2$ and the cattails’ area was 1074 $m^2$. For the distribution in 2016, *Phragmites* had an area of 4193 $m^2$ and the cattails’ area was 713 $m^2$. This created a decreasing spread rate for *Phragmites* and cattails at a loss of 1081.5 $m^2$/ year and 180.5 $m^2$/ year, respectively. The *Phragmites*’ width showed a positive spread rate for the *Phragmites* present in 2016 (Figure 14).

The researcher measured the *Phragmites*’ width in 2016 to determine the spread rate. Mapping out the difference between the *Phragmites*’ edge in 2014 to the widest edge in 2016 created the 2016 spread rate area (Figure 14). The total amount of cells in this area was 1835, making the area 1835 $m^2$. With the difference of two years between the image, the *Phragmites* spread rate was 917.5 $m^2$/year.
Figure 12. MS 2016 NAIP supervised classification.
Figure 13. Distribution of *Phragmites* and cattails based on supervised classification.
Figure 14. Distribution of *Phragmites* and cattails manually mapped between 2014 and 2016.
CHAPTER V
DISCUSSION

The spectroradiometer identified the Phragmites’ and cattails’ phenological spectral curves. After analyzing these spectral curves at the SVSU site and MS site separately, the Euclidean distances demonstrated different phenological reflectance values. Phragmites’ and cattails’ hyperspectral data’s most separable date at the MS site was September 15, 2017, with a distance of 2.150 and at the SVSU site with a distance of 1.258 on August 25, 2017. When hyperspectral data were averaged to the multispectral NAIP bands, they showed the same separability results as the hyperspectral data.

The reason for the different separable dates between the MS and SVSU sites could have been the water noise on the spectroradiometer, which could have affected the reflectance values for both Phragmites and cattails. The water noise did not affect the spectral readings for the Phragmites at Saginaw River because they were on drier land. Cattails on the south end of the MS study site were thriving in water, but they were thick enough to block the water noise in the reflectance values. This noise was hard to avoid as these species originate in wetlands. Another explanation could be that the Phragmites at SVSU was a hybrid species that have been known to survive the same as the non-native Phragmites.

The best separable dates between the Phragmites and cattails based on NAIP NDVI values were June 21st with a distance of 0.082 for MS site and October 18th with a distance of 0.223 for SVSU site. The second largest distance for MS site was August 25 at 0.070 and SVSU with a distance of 0.117 on May 3rd. Euclidean distance, measured using the NDVI values for the averaged Phragmites and cattails NAIP bands, was largest on October 18th with a distance of 0.101, and the second largest distance of 0.071 on May 30th. Combining the Phragmites and
cattails reflectance values from both sites created different outcomes for the most separable date. The SVSU Phragmites and cattails may be the cause of these altered results because of the water background.

When mapping the Phragmites and cattails using NAIP imagery, NDVI was most separable in June and August. June and August's data were the closest dates to represent the July characteristics of NAIP imagery. The MS site was essential to map the Phragmites on the Saginaw River since the river discharges into the Saginaw Bay. The reason for this was because Soomers et al. (2013) found that the Phragmites seeds disperse farther by water than by wind. Mapping MS site would be more beneficial for conservation specialist to benefit from the research to protect the Saginaw Bay. Observing the MS vegetation index with the RGB combinations (NDVI, green, and red bands, respectively) produced the best visual contrast between Phragmites and cattails.

Mapping the Phragmites from cattails created difficulties in separating trees and other vegetation from the Phragmites and when applying Supervised Classification techniques. The percent correctly classified result for MS 2014 was 64% and MS 2016 was 57%. The producer’s and user’s accuracy results for classifying Phragmites in 2014 were 75% and 66%, respectively, and in 2016 were 86.5% and 64%, respectively. The producer’s accuracy means that over 75% of the referenced Phragmites pixels were accurately classified as Phragmites. The user’s accuracy suggests that over 64% of the classified Phragmites appear as Phragmites on the referenced image. These percentages were not as high as they should have been to be used for classification; however, since the producer’s accuracy was over 75% for Phragmites, it was used to predict the spread rate. The spread rate produced was 1,011 m²/year.
Results from the manually mapped *Phragmites* spread rate at MS site resulted in a negative spread of 1081.5 \( m^2/\text{year} \). Although the *Phragmites* appeared to have a decreasing spread rate, the unknown light area between the *Phragmites* and the river could be fallen *Phragmites* stands. The researcher noted seeing large patches of *Phragmites* toppled over during data collection, which could have been by the weight of old *Phragmites* or by wind gusts. The *Phragmites* edge near the grass, appeared to have increased in size. This area gave a positive spread rate of 917.5 \( m^2/\text{year} \) (Figure 14). The results for the cattails had a decreasing spread rate of 180.5 \( m^2/\text{year} \). In the south patch of cattails (Figure 14), the 2016 data shows no *Phragmites* in the patch, but the 2014 data indicated *Phragmites*. An explanation for this is that the dead brown color in the natural color image of RGB (Band 1, 2, and 3, respectively) could be dead *Phragmites* stands that have fallen over. These sites could have unknowingly been treated with herbicides. This may have been the reason for fallen stands in 2016, however, this research took place in 2017. Stands between the *Phragmites* and the river appeared healthy like the other *Phragmites*.

The interesting part is that the separation is visibly noticeable and to an extent, the computer mapped the most significant separation contrasts. The results for the 2014 imagery, the PCC was 89.17%. The user’s accuracy results for *Phragmites* and cattails were 87.5% and 82.5%, respectively. The PCC result for 2016 manually mapped distribution of *Phragmites* and cattails was 83%. The results for 2016 manually mapped *Phragmites* and cattail’s user’s accuracy were 77.5% and 75%, respectively. With the manually mapped accuracies greater than the supervised maximum likelihood classification, digitizing became more accurate when the observer visually interpreted the RGB image with NDVI, green, and red bands, respectively.
Study Limitations

During this research, there were some apparent limitations. The first significant limitation dealt with the HandHeld 2 spectroradiometer instrument used for collecting data. The spectroradiometer used as a handheld instrument was not sufficient for vegetation taller than 1.5 meters. With the Phragmites over this benchmark, limited possibilities for measuring the canopies reflectance was an issue. This limitation required the researcher to adapt to the equipment and measure the vegetation at 1.5 meters above ground. This spectroradiometer was the only instrument the Department of Geography at Western Michigan University owned, and due to the extreme cost of a different spectroradiometer, it was the one available.

Another limitation dealing indirectly with the spectroradiometer was the weather. Having no control in the weather, and the weather being hard to predict, there were times when the researcher canceled field work due to rain or a clear sunny day turning cloudy. Creating a plan to collect data between equivalent dates to represent the best seasonal change was difficult when the weather was involved. Snow also limited data collection during the spring months, as snow would reflect the sun’s illumination and create noise in the spectroradiometer.

One limitation dealing with the tall Phragmites was the shadows they created. There was a small-time window to eliminate the shadows during solar noon. There were slight shadows created in the morning, and with the sun in the south, there were still shadows created on the north side of the vegetation. When measuring the reflectance in a cluster of tall reeds, there were shadows within the cluster mixed with the sun directly between weeds.

There was prior knowledge of not having reflectance values or a straightforward way to find those reflectance values for NAIP imagery. Reflectance values were a way to normalize the imagery to compare two different dates. Understanding that reflectance and radiance values can

56
change daily, and there are so many factors that can create a different value, the two dates would have different gains and offsets. Leica Geosystems was unable to produce the offset values for the Leica ADS100 sensor. Therefore, the researcher applied the radiance values of Landsat 8 satellite imagery to compute the linear regression for NAIP imagery, which has some error to the values. There are also some downsides to this imagery, which include temporal resolution and radiometric calibration. The issue with temporal resolution is that the sensor is flown biannually during the peak of the growing season in Michigan (USDA, 2013).

Another project limitation was finding an accessible undisturbed area to record the *Phragmites*’ and cattails’ reflectance values. Optional sites were either inaccessible or were *Phragmites* dominant and could not be used to identify the spread rate. At the MS site, they managed the *Phragmites*’ width by mowing the area frequently to manage the park’s aesthetics. Also, when comparing the images, some stands in the 2016 imagery were knocked over. These fallen stands could be from herbicide applications. These limitations can play a significant role when identifying vegetation spread rate.
CHAPTER VI

CONCLUSION

This research was about identifying the best time of year to use satellite imagery when distinguishing *Phragmites* from cattails. After conducting the research and analysis, the Euclidean distance suggested the most separable time of the year to identify the *Phragmites* from cattails was in the fall around September 15th. The Euclidean distance for MS *Phragmites* in September was an example of when *Phragmites* retain more chlorophyll than cattails. This retention can be used to discriminate *Phragmites* from cattails in September satellite imagery and can be viewed on Google Earth’s September historical image. The vegetation index, NDVI, was most separable on June 21st for the MS site. However, when averaging the *Phragmites* and cattail reflectance from both locations the most separable date to apply NDVI was in the late fall.

When using NAIP imagery, the most useful information was data collected near July because of NAIP’s acquisition dates. The most contrasting RGB image (NDVI band, green band, and red band, respectively) was used for supervised classifications. The supervised classification’s PCC was over 57% which did not prove to be most effective. Nevertheless, the researcher’s visual interpretation of the imagery enhanced the accuracy of *Phragmites* and cattails separability with PCCs of 89.17% for 2014 and 83.33% for 2016. The visual interpretation would be beneficial when trying to locate the *Phragmites* along the river using NAIP imagery. The classified NAIP images resulted in having the MS site *Phragmites* spreading at 1,011 m²/year.

After the analysis, the best season to separate between *Phragmites* from cattails based on their spectral properties was in the fall. Landowners or resource management groups in Saginaw Bay Michigan can use satellite imagery acquired in the fall around September 15th. One
implementation that could be done better for better results was finding a study area that was not
affected by human manipulations, such as the mowing done at the MS site for aesthetic purposes
of the park. An undisturbed site would offer a natural dispersal pattern that can be measured for
spread rate.

The focus on the Saginaw River Phragmites came to the researcher’s attention after the
study done by Soomers et al. (2013). They found that seeds disperse farther by water than by
wind. With the Phragmites established along the Saginaw River, this became a significant site
for identifying Phragmites. Resource management groups should focus on eradication efforts
upstream, which prevents Phragmites’ seeds from dispersing into the Saginaw Bay. Mapping
the Phragmites along rivers and tributaries are essential to identify where eradication is needed
for Saginaw Bay’s current and future Phragmites problems. This technique would suggest
focusing on where the Phragmites is coming from and how they spread, instead of focusing on
where they are now. If the eradication process does not focus on Saginaw Bay’s rivers and
tributaries, then conservation groups will continue to fight the Phragmites battle in Saginaw Bay
because seeds will continue to be dispersed downstream.

If adequately removed, conservation methods of cutting back and managing the spread
rate may influence other native vegetation to continue their growth, which would maintain some
biological diversity in the wetlands. Michigan’s DEQ has many guidelines online about how to
remove the Phragmites and when to remove them (DEQ, 2017). There are also brochures online
to educate people on which Phragmites are native versus non-native. The conservation
guidelines from the DEQ influences can slow down, and possibly, intercept the dispersal of the
non-native Phragmites.
Although there are management plans available to remove *Phragmites*, it might be too late to remove them all. There is a large population of *Phragmites* already in the Great Lakes, such as Lake Huron shorelines. These large populations are suitable to manage, but all that work can become useless because of the way *Phragmites* disperse. Conservation groups spend too much time focusing on eliminating the *Phragmites* from the Great Lakes shoreline and the Saginaw Bay rather than the rivers. Seeds dispersing by water become a problem when trying to manage the invasive reed on the Great Lakes shoreline. In theory, conservation groups should eradicate the *Phragmites* that are thriving along rivers and tributaries on Saginaw Bay as well.

Eradicating all the *Phragmites* along the rivers and tributaries could be time extensive and show little to no improvements, which could lead to another long-term solution, such as, learning how to live with *Phragmites*. *Phragmites* are aggressive so multiple applications of an herbicide may be needed. If eradication is too expensive, then options for managing and thinning out current portions are still a suitable decision. Trying to create a seed trap in rivers that discharge into the Saginaw Bay can help prevent the spread of *Phragmites*. These seed traps can be done by predicting the most suitable time for seed dispersal and apply a dam to collect the floating seeds. Mapping invasive species will allow researchers to spatially determine, not where invasive species are, but where they are coming from.

**Considerations for Future Research**

Some future suggestions come to mind after listing the research limitations. The first suggestion is measuring the canopy of the vegetation. Measuring the canopy would eliminate the possibilities of having a large shadow and water noise on the spectral readings. One solution for this would be to buy a new spectroradiometer, which is also the more expensive solution. A different way to adapt to this suggestion is to find an adaptor for the HandHeld 2 that would
reach above the *Phragmites*. If an adaptor is unavailable, then try to make an extension with an easy extraction and retraction method to calibrate the spectroradiometer every 10 minutes.

Another suggestion for future use with the HandHeld 2 Spectroradiometer measuring tall reeds is to try to angle the spectroradiometer to measure the plant leaves at the sun’s relative angle. The angled spectroradiometer would give better reflectance values since the sun’s angle reflects perpendicular to the plant. If the spectroradiometer is angled too much, there will be noise in the background from open space. To prevent the atmospheric distortion in the background, try bending the plant down so the spectroradiometer can measure perpendicular to the upper half of the plant. The bent *Phragmites* stands would have reflectance closer to the canopy which can reduce the shadow noise.

One suggestion for NAIP imagery radiometric calibration would be to collect spectral reflectance during July 2018, and every other year during the leaf-on season. The researcher could not collect data during July 2017, due to other spectroradiometer projects. NAIP’s temporal pattern over Michigan is biannual during the leaf-on season, which tends to be early to mid-July. Measurements during the leaf-on season would provide reflectance values that could potentially extrapolate NAIP imagery and create a regression model to calibrate digital numbers. Measuring multiple dates in July provides a better probability of matching the same date as the acquired NAIP image. For best results, spectral readings would have to match the acquisition time the image was collected. A possibility of getting the best time and day to do this is to coordinate with the company that flies for the USDA, which in 2014 and 2016 this company was Quantum Spatial. A more efficient way to calibrate NAIP imagery would be to purchase the original files.
Another suggestion for future consideration is using the historical imagery from Google Earth. After reviewing the historical images, one of the dates that separated the *Phragmites* from cattails was September, which coincides with MS’s most separable date. The September image discriminates *Phragmites* from cattails by displaying them greener. Further investigation upstream the Saginaw River, the *Phragmites* were visibly distinguishable on the September image and showed circular distribution patterns in large wetlands. For future studies, the researcher could use Google Earth September historical imagery to map *Phragmites* along the rivers and identify the circular dispersal patterns.
APPENDIX A

Spectral Reflectance Integrated to NAIP Multispectral Bands
<table>
<thead>
<tr>
<th>Location</th>
<th>Vegetation</th>
<th>May 3, 2017</th>
<th>May 30, 2017</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Band 1</td>
<td>Band 2</td>
</tr>
<tr>
<td>MS</td>
<td>cattails</td>
<td>0.0700</td>
<td>0.0900</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0833</td>
<td>0.1133</td>
</tr>
<tr>
<td>SVSU</td>
<td>cattails</td>
<td>0.0583</td>
<td>0.0700</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0283</td>
<td>0.0417</td>
</tr>
<tr>
<td>MS</td>
<td>cattails</td>
<td>0.0150</td>
<td>0.0250</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0100</td>
<td>0.0250</td>
</tr>
<tr>
<td>SVSU</td>
<td>cattails</td>
<td>0.0167</td>
<td>0.0350</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0200</td>
<td>0.0417</td>
</tr>
<tr>
<td>MS</td>
<td>cattails</td>
<td>0.0133</td>
<td>0.0233</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0250</td>
<td>0.0483</td>
</tr>
<tr>
<td>SVSU</td>
<td>cattails</td>
<td>0.0183</td>
<td>0.0417</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0150</td>
<td>0.0300</td>
</tr>
<tr>
<td>MS</td>
<td>cattails</td>
<td>0.0683</td>
<td>0.1000</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0867</td>
<td>0.1317</td>
</tr>
<tr>
<td>SVSU</td>
<td>cattails</td>
<td>0.0717</td>
<td>0.0967</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.0467</td>
<td>0.0683</td>
</tr>
</tbody>
</table>
Appendix B

Averaged Location’s Multispectral Reflectance Values
<table>
<thead>
<tr>
<th>Vegetation</th>
<th>May 3, 2017</th>
<th>May 30, 2017</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Band 1</td>
<td>Band 2</td>
</tr>
<tr>
<td>cattails</td>
<td>0.0642</td>
<td>0.0800</td>
</tr>
<tr>
<td><em>Phragmites</em></td>
<td>0.0558</td>
<td>0.0775</td>
</tr>
<tr>
<td>June 21, 2017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cattails</td>
<td>0.0158</td>
<td>0.0300</td>
</tr>
<tr>
<td><em>Phragmites</em></td>
<td>0.0150</td>
<td>0.0333</td>
</tr>
<tr>
<td>September 15, 2017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cattails</td>
<td>0.0158</td>
<td>0.0325</td>
</tr>
<tr>
<td><em>Phragmites</em></td>
<td>0.0200</td>
<td>0.0392</td>
</tr>
<tr>
<td>November 29, 2017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cattails</td>
<td>0.0700</td>
<td>0.0983</td>
</tr>
<tr>
<td><em>Phragmites</em></td>
<td>0.0667</td>
<td>0.1000</td>
</tr>
</tbody>
</table>
Appendix C

Euclidean Distances
Euclidean distance for hyperspectral spectroradiometer data.

<table>
<thead>
<tr>
<th>Location</th>
<th>May 3</th>
<th>May 30</th>
<th>June 21</th>
<th>August 25</th>
<th>September 15</th>
<th>October 18</th>
<th>November 29</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS</td>
<td>1.2183</td>
<td>1.8539</td>
<td>1.7770</td>
<td>1.6832</td>
<td>2.1499</td>
<td>1.0075</td>
<td>0.7335</td>
</tr>
<tr>
<td>SVSU</td>
<td>1.0135</td>
<td>0.2635</td>
<td>0.3332</td>
<td>1.2578</td>
<td>0.6849</td>
<td>0.9016</td>
<td>0.9231</td>
</tr>
</tbody>
</table>

Euclidean distance for NAIP spectral bandwidths.

<table>
<thead>
<tr>
<th>Location</th>
<th>May 3rd</th>
<th>May 30th</th>
<th>June 21st</th>
<th>August 25th</th>
<th>September 15th</th>
<th>October 18th</th>
<th>November 29th</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS</td>
<td>0.0689</td>
<td>0.0998</td>
<td>0.0988</td>
<td>0.0909</td>
<td>0.1205</td>
<td>0.0524</td>
<td>0.0560</td>
</tr>
<tr>
<td>SVSU</td>
<td>0.0672</td>
<td>0.0161</td>
<td>0.0101</td>
<td>0.0778</td>
<td>0.0394</td>
<td>0.0527</td>
<td>0.0642</td>
</tr>
</tbody>
</table>

Euclidean distance of averaged spectral reflectance of the *Phragmites* and cattails.

<table>
<thead>
<tr>
<th>May 3rd</th>
<th>May 30th</th>
<th>June 21st</th>
<th>August 25th</th>
<th>September 15th</th>
<th>October 18th</th>
<th>November 29th</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0131</td>
<td>0.0563</td>
<td>0.0527</td>
<td>0.0092</td>
<td>0.0416</td>
<td>0.0484</td>
<td>0.0061</td>
</tr>
</tbody>
</table>

Euclidean distance of separated location NDVI.

<table>
<thead>
<tr>
<th>Location</th>
<th>May 3</th>
<th>May 30</th>
<th>June 21</th>
<th>August 25</th>
<th>September 15</th>
<th>October 18</th>
<th>November 29</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS NDVI</td>
<td>0.0105</td>
<td>0.0632</td>
<td>0.0821</td>
<td>0.0696</td>
<td>0.0196</td>
<td>0.0091</td>
<td>0.0417</td>
</tr>
<tr>
<td>SVSU NDVI</td>
<td>0.1174</td>
<td>0.0562</td>
<td>0.0054</td>
<td>0.0138</td>
<td>0.0432</td>
<td>0.2230</td>
<td>0.0577</td>
</tr>
</tbody>
</table>

Euclidean distance of averaged vegetation NDVI.

<table>
<thead>
<tr>
<th>Location</th>
<th>May 5</th>
<th>May 30</th>
<th>June 21</th>
<th>August 25</th>
<th>September 15</th>
<th>October 18</th>
<th>November 29</th>
</tr>
</thead>
<tbody>
<tr>
<td>cattails</td>
<td>0.2226</td>
<td>0.6644</td>
<td>0.8052</td>
<td>0.8011</td>
<td>0.6949</td>
<td>0.4935</td>
<td>0.2931</td>
</tr>
<tr>
<td><em>Phragmites</em></td>
<td>0.2638</td>
<td>0.7355</td>
<td>0.8583</td>
<td>0.8391</td>
<td>0.7434</td>
<td>0.5944</td>
<td>0.2938</td>
</tr>
<tr>
<td>E. distance</td>
<td>0.0412</td>
<td>0.0711</td>
<td>0.0531</td>
<td>0.0381</td>
<td>0.0485</td>
<td>0.1009</td>
<td>0.0008</td>
</tr>
</tbody>
</table>
BIBLIOGRAPHY


Carvalho, S., Schlerf, M., van Der Putten, Wim H., & Skidmore, A. K. (2013). Hyperspectral reflectance of leaves and flowers of an outbreak species discriminates season and


http://www.michigan.gov/deq/0,4561,7-135-3313_3687-178183--,00.html. [February 7, 2018].


