COVER PAGE

Assessing Remote Sensing Approaches to Map Invasive *Phragmites australis* at Multiple Spatial Scales

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TITLE: Assessing Remote Sensing Approaches to Map Invasive *Phragmites australis* at Multiple Spatial Scales

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Lay Abstract

Invasive common reed, *Phragmites australis* subsp. *australis*, is one of the most aggressive and problematic invasive species in North America. This species rapidly expanded in the late 1900s and now occupies large patches of our critical wetland habitats as monocultures, especially in the northeastern states and the Great Lakes basin. My thesis presents new methods to identify where invasive common reed is present at a landscape level so that it can be targeted for large-scale control and removal. With colleagues in Michigan we created the first basin-wide map of invasive common reed for the Great Lakes region using satellite image data. Within Ontario, I used imagery from satellites and planes to determine the extent of invasive common reed along our road networks. At a site-specific scale, I used drones or unmanned aerial vehicles to map a protected wetland with high precision and accuracy. I used many of these approaches in combination to determine how effective current invasive common reed removal efforts are along roadway corridors. I compare all of these mapping processes and techniques to showcase the strengths and weaknesses of each approach and to help managers decide which approach is most suitable for their unique case. With all of these data, I have created new mapping techniques that can show the rapid spread of invasive common reed and how effective current management plans have been in combatting this aggressive invader.

General Abstract

Phragmites australis (Cav.) Trin. ex Steud., the invasive common reed, is a perennial grass with a cosmopolitan distribution. Unlike the native subspecies (*Phragmites australis* subsp. *americanus*) in North America, this invasive haplotype is an aggressive competitor and has firmly established itself throughout the Great Lakes basin by dominating wetlands and wet habitat, forcing out native plants and creating monocultures of little use to native fauna. Growing clonally and from seed, invasive *Phragmites* can quickly dominate wet areas throughout North America. It has also become a prominent feature in roadside habitats, where native plants are subject to increased disturbance under which invasive *Phragmites* will thrive competitively. In order to effectively manage this aggressive invader, we must be able to accurately map its distribution at multiple spatial scales, understand its invasion ecology, and determine efficacy of current removal efforts.

In this thesis, I evaluated multiple remote sensing methods to determine the extent of invasive *Phragmites*. The basin-wide wetland mapping project based on satellite image data was a collaborative effort between U.S. and Canadian scientists to document the current and potential distribution of invasive *Phragmites* throughout 10-km of the shoreline of the Great Lakes, including all coastal marshes. To elucidate its distribution through road networks, I used provincial orthophotography databases to map changes in the distribution of *Phragmites* in road corridors between 2006 and 2010. Based on these data, I created a conceptual model to show the relationships among the main factors that govern the establishment of invasive *Phragmites* in roadsides within Ontario. These factors included habitat quality, habitat availability, and propagule dispersal. I also showed how unmanned aerial vehicles can be used with very high accuracy to map the distribution of very small stands of *Phragmites* at the beginning of an invasion, and to determine short-term changes in habitat availability in smaller wetlands. Using various remote sensing approaches, I was able to determine the efficacy of treatment programs implemented by provincial agencies on roadway corridors at the scale of the entire southwestern, southcentral and central regions of Ontario. This is the first quantitative evidence of invasive *Phragmites* removal along roads and one of the largest spatial and temporal time scales used to evaluate these processes. Finally, I synthesized the capabilities and limitations of these remote sensing methods to create an evaluative framework that outlines how to best map invasive *Phragmites* across varying landscapes. This research integrates geography and biology to create novel mapping techniques for invasive *Phragmites* and has furthered our understanding of this aggressive plant and how its invasion can be controlled.

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I am grateful to my supervisory committee, Dr. Jon Stone and Dr. Darren Scott, for their insights and comments throughout this period. You have helped shaped my thesis into what it is today. I also greatly appreciate the comments and engaging questions from my external committee member, Dr. Yuhong He.

There were quite a few PCF lab members over my time here, and I'm so glad to have met you all. I think I made a lot of people hate Phrag and go cross-eyed looking at computer screens all year, but I am thankful for all your work and I am proud of what we have accomplished together. A special thanks to the crew of grad students who have helped me so much through these past years: Dallas, Amanda, Chris, Chantel, Julia, J.P., Dan, Stuart, Lindsey, Nick, Prabha, Morgan, Alana, Sawsan, Danielle, and Steve*; and former lab members who I've had the pleasure of meeting and learning from: Jon, Dan, Rachel, Maya, , Mel, Lyndsay, & Anhua (*honorary degree). We've had some great experiences, stories, and lessons come out of our time together in the lab. I would like to especially thank Chantel for convincing me to stay here and being an awesome co-author, Julia for your contributions to 'Grand River 2.0', Steve for being so qualified and an amazing friend, Nick for keeping me up-to-date on internet things, and Dan for your continued guidance and help throughout our tenure together (even if you left me four months early).

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Finally, I have to give immense thanks and appreciation to the residents of 20 York. Lewis, you have been a wonderful (if somewhat annoying) roommate that can be so demanding, but I appreciate your nonsense anyways. You’re basically a financial parasite, but I guess that’s what I get for bringing a cat into my life. To the wonderful Cayleih Robertson, you’ve been the best partner I could ask for through this time. Your love and support have made this all possible, and I am forever grateful.

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List of All Abbreviations and Symbols

AADT: Average Annual Daily Traffic

AOI: Area of interest

ASF: Alaska Satllite Facility

C-CAP: Coastal Change and Analysis Program

CAD: Canadian dollar

cm: centimetre

COOP: Central Ontario Orthophototgraphy Project

CPU: Central processing unit

ELC: Ecological Land Classification System

EM: Emergent vegetation

EPA: Environmental Protection Agency

FBD: Fine beam dual

FBS: Fine beam single

FL: Floating aquatic vegetation

FPV: First person view

GB: gigabyte

GE: Geo-Eye

GLCWC: Great Lakes Coastal Wetland Consortium

GLIC: Great Lakes Instrumentory Collaboratory

GLM: Generalized linear model

GLNPO: Great Lakes National Program Office

GLRI: Great Lakes Restoration Initiative

GPS: Global Positioning System

ha: hectare

HIIFP: Highway Infrastructure Innovation Funding Program

Hwy: Highway

JERS-1: Japanese Earth Resources Satellite 1

km: kilometre

km/h: kilometres per hour

L-HH: L-band horizontal send, horizontal receive

L-HV: L-band horizontal send, horizontal receive

L: Litre

LEDPAS: Landsat ecosystem disturbance adaptive processing system

LULC: Land-use, land-cover

m: metres

m/s: metres per second

MTO: Ministry of Transportation, Ontario

NDVI: Normalized difference vegetation index

NIR: Near-infrared

NOAA: National Oceanic and Atmospheric Administration

NWI: National Wetland Inventory

OBIA: Object-based image analysis

OFAH: Ontario Federation of Anglers and Hunters

OMNRF: Ontario Ministry of Natural Resources and Forestry

PALSAR: Phase-array L-type Synthetic Aperture Radar

RAM: Random access memory

S2: Sentinel-2

SAOCOM: Satéllite Argentino de Observación Con Microondas

SAR: Synthetic aperture radar

SAV: Submerged aquatic vegetation

sbsp: subspecies

SCOOP: Southcentral Ontario Orthophotography Project

SE: Standard error

SOLRIS: Southern Ontario Land Resource Information System

spp.: species

SWOOP: Southwestern Ontario Orthophototgraphy Project

TOA: Top of atmosphere

U.S., U.S.A.: United States of America

UAV: Unmanned aerial vehicles

USFWS: U.S. Fish and Wildlife Service

USGS: U.S. Geologic Survey

WV3: Worldview-3

Declaration of Academic Achievement

This thesis is comprised of a general introduction, 5 chapters, and 3 appendices. Chapters 1 and 3 have been published in peer-review scientific journals, and chapter 5 is published in a conference proceedings. Chapter 2 is prepared for submission to a scientific journal and chapter 4 is being prepared for submission; both are subject to approval from the Ministry of Transportation of Ontario. Appendix 1 is published as an internal report for the Ministry of Natural Resources and Forestry of Ontario. Appendices 2 and 3 are published as an internal report for the Ministry of Transportation of Ontario.

Chapter 1: General Introduction

Author: James V Marcaccio

Chapter 2: Development of a bi-national Great Lakes coastal wetland and land use map using three season PALSAR and Landsat imagery

Authors: Laura Bourgeau-Chavez, Sarah Endres, Michael Battaglia, Mary Ellen Miller, Elizabeth Banda, Zachary Laubach, Phyllis Higman, Pat Chow-Fraser, & James Marcaccio

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Chapter 3: Mapping invasive *Phragmites australis* in highway corridors of Ontario.

Authors: James V Marcaccio & Patricia Chow-Fraser

Journal: Presented in manuscript format and awaiting review from funding agency before submission.

Comments: J.V.M. collected and analyzed all data and wrote the manuscript under the supervision of P.C-F.

Chapter 4: Use of fixed-wing and multi-rotor unmanned aerial vehicles to map dynamic changes in a freshwater marsh.

Authors: James V. Marcaccio, Chantel E. Markle, & Patricia Chow-Fraser

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Chapter 5: Assessing efficacy of invasive *Phragmites* removal in highway corridors with orthophotography & satellite image data: The Ontario case study

Authors: James V. Marcaccio & Patricia Chow-Fraser

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Chapter 6: Mapping options to track invasive *Phragmites australis* in the Great Lakes basin in Canada

Authors: James V. Marcaccio & Patricia Chow-Fraser

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Editors: Petre Gâstescu, Petre Bretcan.

Comments: J.V.M. collected and analyzed all data and wrote the manuscript under the supervision of P.C-F.

Chapter 7: General Conclusion

Author: James V. Marcaccio

Chapter 8 / Appendix A: Comparison of remote sensing approaches to map invasive *Phragmites* in coastal areas of southern Ontario

Authors: James V. Marcaccio, Laura Bourgeau-Chavez, & Patricia Chow-Fraser

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Chapter 9 / Appendix B: Mapping invasive *Phragmites australis* in highway corridors using provincial orthophoto databases in Ontario

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Chapter 10 / Appendix C: Assessing efficacy of treatment programs to control invasive *Phragmites* highway corridors of southern Ontario

Authors: Patricia Chow-Fraser & James V. Marcaccio

Date Accepted: November 2018

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Chapter 1: General Introduction

Remote Sensing:

The field work required to accurately map multiple features of interest in a study area would require a significant investment of time, resources, and travel which may not be feasible. By using remote sensing and modern technologies, detailed and accurate maps of land cover and a feature of interest can be made rapidly with minimal site visits. Many different sensors can be mounted on airborne imaging systems to suit the unique needs of researchers and agencies looking to identify and map features of interest.

Using remote sensing can be critically important for ecological research. Using these data, we can describe habitat complexity, changes in habitat over time, and species' use and distribution throughout a landscape (Rose et al. 2014). In especially dynamic systems like wetlands, it is important to have both high resolution and up-to-date image data to properly interpret landscape processes and species' use of these habitats (Gallant 2015). Untimely data can skew our understanding of the landscape (Marcaccio et al. 2016) which can lead to incorrect conclusions on how species utilize their habitat (Markle & Chow-Fraser 2014). If image data have insufficient resolution, small-scale processes are not visible (Ishihama et al. 2012, Chabot & Bird 2013). Coastal wetlands can be very small in size and they represent an important crossover point between aquatic and terrestrial ecosystems and must be mapped appropriately (Midwood 2012, Gallant 2015). Similarly, anthropogenically modified wet habitats can take many irregular shapes and be very difficult to collect data for with traditional remote sensing techniques (Maheu-

Giroux & de Blois 2005, Brisson et al. 2010). Researchers must determine and use the correct techniques in order to best assess wetland habtat.

Invasive Common Reed :

Phragmites australis (Cav.) Trin ex. Steudel, the invasive common reed, is a perennial grass found worldwide in wet habitats. A native subspecies (*americanus*) exists in North America, but it is the invasive *Phragmites* from Eurasia that has become most dominant in wet habitats (Saltonstall 2003, Price et al. 2013). Invasive *Phragmites* is competitively superior to many other semi-aquatic and terrestrial species (Uddin et al. 2017): it is tolerant of high disturbance (Chambers et al. 1999) and can grow clonally from suitable habitat into poor quality areas (Armstrong et al. 1999, Amsberry et al. 2013). It is extremely efficient at taking up nutrients from the environment (Ge et al. 2017) and can even displace other vegetation by injecting volatile compounds into the surrounding soil (Armstrong & Armstrong 2001).

Invasive *Phragmites* landed in eastern North America and has rapidly spread throughout the Atlantic states, Great Lakes basin, and beyond (Meyerson et al. 2000, Catling & Mitrow 2011). In Canada, the invasion started in the maritime provinces and Quebec with rapid expansion taking place in the latter following highway construction in the Montreal area (Lelong et al. 2007, Catling & Mitrow 2011). Multiple invasion events are predicted to have occurred in Ontario leading to a unique genetic population compared to the rest of the country (Kirk et al. 2011). It has rapidly expanded through road networks in the St. Lawrence region (Jodoin et al. 2008, Brisson et al. 2010) and heavily invaded Great Lakes coastal wetlands (Tulbure et al. 2007, Jung et al. 2017).

From a remote sensing perspective, invasive *Phragmites* offers unique challenges to work through. As a whole, wetlands are incredibly dynamic systems that can undergo large inter- and intra-annual fluctuations (Gallant 2015). In the Great Lakes, an abundance of species are often present within a single wetland which can make differentiation between unique classes difficult. While we currently do not offer a means to delineate between species of *Phragmites*, the native subtypes do not grow with such vigor and abundance as the invasive (Saltonstall 2003). Compared to other emergent wetland species commonly found in the Great Lakes (specifically *Typha* and *Schoenplectus*) invasive *Phragmites* is much taller and due to its clonal growth often appears in circular patterns when unrestricted by habitat. Unlike many other wetland plants, invasive *Phragmites* also remains standing throughout winter; while the colour turns from green/blue to beige/yellow, invasive *Phragmites* still acts as a significant barrier and is easily observed.

Wetland Management:

To effectively manage our current and future wetland habitats, we must take control of the spread of invasive *Phragmites* throughout the Great Lakes basin. Millions of dollars have been spent on management and management outcomes have not always been achieved (Martin & Blossey 2013). Furthermore, insufficient monitoring has not allowed for tracking of management outcomes after initial eradication, such as regrowth of native vegetation (Hazelton et al. 2014). More money will not solve the problem if we cannot accurately report results and determine better solutions (Martin & Blossey 2013). By using novel remote sensing techniques consistently, we can obtain the necessary data for proper management at multiple spatial scales. When we obtain these data, we can assess current trends and create new hypotheses on the expansion and necessary eradication of invasive *Phragmites*.

Thesis Objectives:

The goal of my thesis is to introduce novel remote sensing techniques to map invasive *Phragmites* so that we may further understand the species' invasion and ecology. In order to effectively manage invasive *Phragmites*, we must be able to map it at multiple spatial scales throughout the Great Lakes basin. International, regional, and site-specific monitoring is necessary to fully understand how invasive *Phragmites* is distributed and how it is advancing in these areas. These data can be used by agencies and groups that are involved in wetland monitoring and invasive *Phragmites* control to give them the best chances of eliminating this species from their landscape.

To accomplish international monitoring, chapter 1 defines a novel remote sensing methodology using sensor fusion and multi-seasonal image data. This method is described within the context of coastal wetlands but can be applied to any temperate zone near the Laurentian Great Lakes. Chapter 2 addresses regional mapping throughout roadside habitat in southern Ontario. Using a provincial orthophotography database, we delineate the distribution of invasive *Phragmites* over multiple years. We investigate the use of unmanned aerial vehicles (UAVs) in Chapter 3 to deliver very high-resolution site-specific data which can be optimized by a team in order to provide the best possible end product. To address these approaches in unison and provide a framework for invasive

Phragmites mapping, chapter 5 compares each approach and shows the benefits of each approach and how multiple solutions may be required to successfully complete a project.

In chapters 2 and 4, we address the expansion of invasive *Phragmites* in roadside habitat and associated removal efforts. A conceptual model of invasion is assessed in chapter 2 that synthesizes research and our outcomes from multiple years of mapping invasive *Phragmites*. Chapter 4 describes removal efforts by the Ontario Ministry of Transportation and their effectiveness over time. Using our mapping approach from chapter 2 and additional high-resolution satellite data, we show that invasive *Phragmites* expansion can outpace removal efforts even when they are highly effective in their targeted area. Combined, these two chapters present an image of the aggressive colonization of invasive *Phragmites* in roadsides and how this must also be treated similarly to its invasion in our Great Lakes wetlands.

This thesis has three additional appendices which highlight additional work that has been undertaken. The first provides a direct comparison of the methods from chapter 1 with a unique approach created by the Ontario Ministry of Natural Resources and Forestry. Appendix 2 provides more information on the creation of the roadside invasive *Phragmites* mapping protocol and relevant statistics for the Ministry of Transportation of Ontario. Appendix 3 looks at the efficacy of invasive *Phragmites* removal efforts in southwestern Ontario. Each appendix is presented as a document prepared for their respective Ministry (Appendix 1: Ontario Ministry of Natural Resources and Forestry; Appendix 2 & 3: Ontario Ministry of Transportation) and are targeted for this audience.

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Chapter 2: Development of a Bi-National Great Lakes Coastal Wetland and Land Use Map Using Three-Season PALSAR and Landstat Imagery

Laura Bourgeau-Chavez, Sarah Endres, Michael Battaglia, Mary Ellen Miller, Elizabeth Banda, Zachary Laubach, Phyllis Higman, Pat Chow-Fraser and James Marcaccio

Bourgeau-Chavez, L., Endres, S., Battaglia, M., Miller, M., Banda, E., Laubach, Z., … Marcaccio, J. (2015). Development of a Bi-National Great Lakes Coastal Wetland and Land Use Map Using Three-Season PALSAR and Landsat Imagery. *Remote Sensing*, *7*(7), 8655–8682. http://doi.org/10.3390/rs70708655

Abstract:

Methods using extensive field data and three-season Landsat TM and PALSAR imagery were developed to map wetland type and identify potential wetland stressors (*i.e.*, adjacent land use) for the United States and Canadian Laurentian coastal Great Lakes. The mapped area included the coastline to 10 km inland to capture the region hydrologically connected to the Great Lakes. Maps were developed in cooperation with the overarching Great Lakes Consortium plan to provide a comprehensive regional baseline map suitable for coastal wetland assessment and management by agencies at the local, tribal, state, and federal levels. The goal was to provide not only land use and land cover (LULC) baseline data at moderate spatial resolution (20–30 m), but a repeatable methodology to monitor change into the future. The prime focus was on mapping wetland ecosystem types, such as emergent wetland and forested wetland, as well as to delineate wetland monocultures (*Typha*, *Phragmites*, *Schoenoplectus*) and differentiate peatlands (fens and bogs) from other wetland types. The overall accuracy for the coastal Great Lakes map of all five lake basins was 94%, with a range of 86% to 96% by individual lake basin (Huron, Ontario, Michigan, Erie and Superior).

Introduction:

As the link between land and water, coastal wetlands of the Great Lakes serve major ecologic and economic roles contributing to the overall health and maintenance of the Great Lakes. These coastal wetlands provide habitat, sources of food, and breeding grounds for many common and regionally rare bird, mammal, herptile, and invertebrate species (Albert et al 2005). They also provide many other ecosystem services including water filtration, flood control, shoreline protection, and recreation. Managing such an important resource requires periodic mapping of the extent, type, and location of the wetlands and adjacent land use and land cover (LULC), as well as field monitoring of indicator variables such as water chemistry, water levels, and biodiversity of flora and fauna. Wetlands are highly vulnerable to both climatic (Bates et al 2008) and anthropogenic changes such as drainage, dredging, filling, shoreline modification, water-level regulation, nutrient enrichment, introduction of non-native species, and road development. Historically, more than two-thirds of wetlands in the Great Lakes region have been drained for agriculture and other development (Dahl et al 1990), making the management of the remaining wetlands essential. Monitoring at a regional scale is necessary for effective coastal land and water management to understand and mitigate the increasing risk posed to the Great Lakes from LULC change and climatic influences.

The Great Lakes Coastal Wetland Consortium (GLCWC) developed a monitoring plan that is designed to not only assess the health and quality of the ecosystems, but also to provide a baseline for assessing effects of climate change and to provide key inputs to decision support for coastal management (Great Lakes Coastal Wetlands 2008). The monitoring plan requires a baseline map of wetland type and areal extent and adjacent land, as well as periodic updates. Such a map has been lacking in comprehensive form for the basin. In the past, mapping efforts have stopped at political boundaries. On the United States (U.S.) side there are the U.S. Fish and Wildlife Service's (USFWS) National Wetlands Inventory (NWI), National Oceanic and Atmospheric Administration's Coastal Change and Analysis Program (NOAA C-CAP), and a host of state-based maps such as the Ohio Wetland Inventory and Michigan's Integrated Forest Monitoring Assessment and Prescription. On the Canadian side, there are the Ontario Great Lakes Coastal Wetlands Atlas and the Canadian Wetland Inventory. To date, the best map of both the U.S. and Canada coastline has been the Great Lakes Coastal Wetland Inventory (Ingram et al 2004), which used a hydrogeomorphic classification scheme and integrated existing databases including the NWI, the Ohio Wetland Inventory, USFWS reports and hardcopy maps, and the Ontario Great Lakes Coastal Wetland Atlas. The Great Lakes Coastal Wetland Inventory includes the U.S. and Canada coastline and extends inland 1 km, but lacks information on wetland stressors (e.g., LULC categories such as agriculture and urban) and is outdated (circa 1970s–80s). The mapping methods were mixed and the accuracy varied among the sources.

In 2010, under the Great Lakes Restoration Initiative, the U.S. Environmental Protection Agency (EPA) solicited the production of a map of the entire U.S. and Canadian coastal basin using a consistent methodology, such as the hybrid radar and optical satellite based approaches that had been demonstrated in a pilot study under the Great Lakes Coastal Wetlands Consortium (Bourgeau Chavez et al 2008). That 2008 pilot study focused on archival Japanese Earth Resources Satellite 1 (JERS-1), Radarsat-1, and Landsat data and relied on existing maps and expert knowledge for training, rather than field data. The method included: (1) creating a categorical map from multi-date Landsat data; (2) creating a separate categorical map from multi-date JERS-1 and Radarsat-1 data; and (3) merging the two maps. A maximum likelihood classifier was used to create categorical maps for three 70 km × 70 km regions of the Great Lakes. The merged SAR-optical maps were found to have greater detectability of wetlands and reduced commission and omission errors, particularly for the wetland classes (Bourgeau Chavez et al 2008). This pilot effort demonstrated the importance of using both optical and SAR data for mapping Great Lakes wetlands for three small areas of the Great Lakes and, thus, provided the basis for a complete mapping of the entire coastal basin. Since 2008, there have been many advances in remote sensing technology and software, as well as computing capability, which allow for such a large mapping effort with multiple datasets to be efficiently implemented.

The goal of the mapping effort presented in this article was to create a high accuracy map of not only wetlands, but also adjacent LULC for the Coastal Great Lakes basin such that the map could be used for management purposes to better understand the wetland distribution and wetland health through indicators of wetland stressors (*i.e.*, land use). The objective was to develop a mapping approach that utilized the fusion of moderate resolution (20–30 m) SAR and optical data from multiple seasons and integrated air photo interpretation and field data for training and validation to: (1) map broad land cover classes, with a focus on the wetland ecosystem classes (e.g., emergent, shrub wetland, forested wetland); (2) distinguish forested bog, open, shrubby and treed fen *versus* inundated shrub and forested wetlands (non-peat, swamps); (3) delineate monocultures of wetland plant species including invasive (*Typha spp*. and *Phragmites australis*) and non-invasive (*Schoenoplectus spp*.) species; and (4) target overall map accuracies greater than 90% and individual class accuracies greater than 70%. In this article, the approach and methods are detailed and the map results are presented and tested through accuracy assessments of independent datasets.

Background:

Image fusion has long been used both to increase spatial resolution and classification accuracy by gaining additional spectral information (Wang et al 2010). Whereas several researchers have evaluated the use of optical or SAR data alone for mapping wetlands, until more recently few had evaluated SAR and optical fusion for wetland mapping (Bourgeau Chavez et al 2008; Loranzo Garcia et al 1993; Bourgeau Chavez et al 2004; Grenier et al 2007; Augustenijn et al 1998; Corcoran et al 2012; Fournier et al 2007; Margono et al 2014) and most ignored the coarser-resolution thermal bands.

It has been well documented that multispectral data that include near-infrared (NIR) and shortwave infrared bands allow improved wetland detection and mapping over visible sensors alone because the near-infrared portion of the electromagnetic spectrum allows identification of plant and hydrologic wetland conditions (Ozesmi et al 2002). Similarly, the thermal wavelengths, although often neglected in mapping efforts due to the coarse spatial resolution on satellite systems (e.g., Landsat 5 TM band 6 at 120-m resolution), are of high utility for mapping wetlands. The fact that water has a high thermal inertia results in temperature differences between uplands and wetlands, thus allowing them to be distinguished. Despite these advantages of infrared and thermal data, optical sensors have limitations in dense vegetation settings, particularly for detection of inundation beneath a dense shrub or forest cover.

Synthetic Aperture Radar (SAR) data are capable of detecting flooding beneath a vegetation canopy, monitoring water levels and soil moisture, and distinguishing other biophysical vegetation characteristics such as biomass and structure. Several researchers have evaluated the utility of SAR for wetland mapping using single and multi-date single channel SAR data (Whitcomb et al 2009; Arzandeh and Wang 2002; Rao et al 1999) , and others have evaluated polarimetric SAR (Hess et al 1990; Bourgeau Chavez et al 2001; Pope et al 1991; Touzi et al 2007). The horizontal send and horizontal receive (HH) polarization of SAR systems have long been known to improve distinction of swamp from other wetland classes and uplands (Bourgeau Chavez et al 2004; Grenier et al 2007; Hess et al 1990; Lang et al 2008; Grenier et al 2007) due to an enhanced double bounce effect from the water surface to the tree trunks and back to the sensor (or vice versa). Non-flooded forests have more diffuse scatter from the ground surface, and less energy is returned to the SAR sensor than for flooded forests. If the vegetation in a non-forested wetland is of great enough biomass relative to the L-band wavelength (~24 cm), then a strong return due to some double bounce scattering will occur in that case, as well, although the strength of the return is typically less than in a flooded forest. This allows for the detection of the large invasive *Phragmites australis* (*Phragmites*), for example, which tends to dominate large patches of wetlands with tall (up to 5 m), dense stems (Baghdadi et al 2001).

In addition to multi-sensor datasets, there are advantages to using multi-temporal imagery datasets, which capture differences in vegetation and flood condition over the course of a growing season (Bourgeau Chavez et al 2013; Fujimura et al 1999). A multi-temporal and multi-sensor image fusion approach was applied in the work presented here using Landsat 5 TM and PALSAR imagery. The impetus for using this combination was based on the need for the detection of the presence of surface water, both in open areas and beneath canopies, as well as for improved detection of vegetation type. Previous research has noted that in practice it is difficult to accurately classify wetland species types based solely on optical spectral characteristics (Shang et al 2008; Schmidt and Skidmore 2003). However, fusion with a complementary sensor type, such as SAR, should allow for a larger set of wetland characteristics to be detected. Further, by using spring, summer, and fall imagery the phenological and hydrological characteristics that define different wetland types should be captured, allowing for improved mapping (**Figures 2.1 and 2.2**). As an example, much of the variation within the wetland landscape is confused when observing the region only at a particular time of year, such as in the summer Landsat 5 TM image of the St. Clair river delta (**Figure 2.1** top center). However, when considering the phenological changes through the seasons (**Figure 2.1** top row) better distinction of various wetland types in this river delta are revealed. The L-HH three-season false-color composite of this area (**Figure 2.1** bottom center) shows variations in hydroperiod during spring, summer, and fall; and L-HV (horizontal send, vertical receive) composite shows variations in biomass in the different seasons (**Figure 2.1** bottom right). The thermal channel of Landsat TM (band 6; Figure 1 bottom left and **Figure 2.2**) aids in distinguishing wetland (darker regions) from upland, but the specific wetland type classes are confused. The spectral signatures from Landsat 5 for the various wetland classes of the St. Clair River Delta show the importance of the NIR band (band 4) and the seasonal patterns of reflectance for the wetland types (**Figure 2.2**). The reflectance signatures are based on the mean of a minimum area of 500 ha for each class. For *Schoenoplectus*, band 4 reflectance is much lower than all other wetland types and it peaks in the fall (**Figure 2.2**) whereas all other wetland types peak in mid-summer. There is a similar trend for L-band HV backscatter for *Schoenoplectus*, with a peak in the fall. *Typha*, on the other hand, peaks mid-summer in L-HV and L-HH backscatter, when most of the other wetland classes (except aquatic bed) are somewhat constant in backscatter between summer and fall. When using three seasons of data, each sensor appears to provide a unique set of information, which when used in combinations should provide a powerful means to distinguish different types of LULC, and in particular, different wetland types.

<u>Methods:</u>

Study Area

The study area spans the United States and Canada coastline and the land within 10 km of the shoreline for lakes Ontario, Erie, Huron, Michigan, and Superior. In addition, included in the study area are the connecting waterways, consisting of Lake St. Clair and the St. Mary's, St. Lawrence, Detroit, and St. Clair rivers. The 10-km shoreline buffer provides coverage of coastal wetlands and additionally encompasses areas of hydrologic, biological, and geophysical transition between the interface of upland land cover and the deep-water boundary of the Great Lakes. Furthermore, a 10-km spatial extent captures the dynamics of anthropogenic influence, as land use interacts in a "downstream model" with surrounding land cover types. In total, the study area covers 9,056,410 ha inland in the U.S. and Canada, as well as captures all large offshore islands lying within the Great Lakes. Although the entire Great Lakes watershed affects the health of the coastal wetlands and the quality of water entering the lakes, mapping of areas further inland than the 10-km shoreline buffer was beyond the mapping goals and budget constraints.

Field Data

Field data on wetland ecosystem types were collected specifically for Great Lakes Restoration Initiative (GLRI) funded mapping projects and supplemented by other sources from independent projects throughout the 2007–2014 timeframe (**Table 2.1**). These supplemental datasets were systematically included or excluded, depending on their ability to assist image analysts. GPS locations had to have been collected within the wetland ecosystem for the field data to be usable, and the field data had to define an area that was at least the minimum mapping unit of the map to be produced (0.2 ha).

The main source of training and validation data came from extensive field campaigns in 2010–2011 under GLRI cooperative agreements with the USGS Great Lakes Science Center and USFWS for mapping areas of the problematic invasive species, *Phragmites*.

That project was focused on mapping large stands of the invasive plant along the U.S. coastline; a detailed description of this methodology is outlined in Bourgeau-Chavez *et al.* (Baghdadi 2001). From May–October in 2010 and 2011 field data were collected by regionally located teams at 1191 locations. Field-visited locations represented a pool of randomly selected data points primarily within the emergent wetland category of the NWI and additional observer-selected points of interest (see Baghdadi 2001 for details). However, many of the field sites turned out to be forested or shrub wetlands. Field crews were instructed to supplement pre-selected random field points with additional opportunistic field points. The goal of additional observer-selected field points was to characterize and delineate areas of vegetative transition, possible unique spectral signals, and areas of likely classification confusion. At all field locations, data collections followed a standardized protocol. Field crews used a hand held GPS, a GPS camera, laminated maps of aerial photographs (30-cm to 1-m resolution), density grids, and tape measurers. At each location a vegetative index was constructed; wetland type was assigned, species diversity noted, dominant species composition assigned, water level measured, vegetation life stage recorded, and for *Phragmites* and *Typha spp.*, height and density measures were collected. Additionally, hand drawn maps and delineations of laminated aerial photograph maps distinguished unique vegetation types and species transition areas within wetland complexes. Finally, geolocated photographs were taken in the four cardinal directions at a centralized location providing an additional layer of validation and ground truth for each data location. The *Phragmites* map product, as well as the data characterizing other LULC features, was used in the coastal wetland and upland mapping.

The field data collection methodology used as a part of the *Phragmites* mapping project provided the foundation on which subsequent field data collects were organized. During 2012–2014, the field campaign was extended to inform the basin-wide bi-national map on not only emergent wetland types, but also shrub, forest, and peatland classes, and to gather additional field data for the Canadian side of the basin. For this field effort, the locations of the field sampling were not random, but specifically selected to target those areas within the study region that were data-poor and/or for wetland classes that were unrepresented. An additional 560 field data locations were sampled in 2012–2014, with 70 locations provided by McMaster University with their 2013 collections along lakes Erie, Ontario, and Huron using the project field collection protocol. Additionally, McMaster had collected 249 field locations in 2007–2008 in Georgian Bay that provided ancillary information. Another source of field data was the vegetation species dominance metrics from the Fish and Invert database of the Great Lakes Instrumentation Collaboratory (GLIC) project, also funded by the GLRI. These data were not included in classification training or validation, but provided ancillary information to inform the image analysts for specific wetland classes. Upland areas were not field visited because the identification and delineation of upland classes were conducted using air photo interpretation techniques.

The wetland field data collection resulted in a total of 1751 sampled sites. All wetland field sites in the database were checked for quality by comparing the location and information input to the database against the original field sheet, site description, field photos, and GPS location from both the GPS camera and the Garmin GPS unit. The breakdown of field sites by dominant cover type (**Figure 2.3**) shows a fairly good distribution of field samples, however, there were some regions along northern lakes Superior and Huron that were inaccessible due to lack of roads and/or rough terrain. Only those field collections that were sampled with the project-designated sampling design, as described above, are shown on the map. There were additional locations (GLIC and 2007–2008 McMaster) used to aid the image interpreters in defining training polygons, as noted above.

Image Area

Satellite imagery from both Landsat 5 TM and PALSAR that were collected in three seasonal time frames (spring, summer, and fall) were used for the mapping. Most imagery was collected in 2010 for PALSAR, but additional years (2007–2011) were needed to fill gaps to obtain the triplicate datasets from the three seasons. Similarly, for Landsat 5 TM, due to cloud cover, multiple years of data were aggregated to obtain complete coverage of the entire coastline. Thus, the seasonal triplicates of Landsat 5 TM data spanned the time frame between the years of 2007 and 2011. Note that only spring data were available from PALSAR for 2011, as it went out of commission thereafter. Seasonal date cutoffs for imagery were based on an approximation of early growth after leaf flush (spring: April–May), peak growth (summer: June–August), and early senescence (fall: September–October). These dates were adjusted based on latitude within the basin; for example, spring was later in the northernmost reaches of the basin.

Both Landsat 5 TM and SAR sensors required independent pre-processing procedures before the data were suitable for building a classified map. These steps are detailed in the sections below. After pre-processing, the images were combined into image stacks before being classified. The number of seasonal PALSAR scenes required to obtain the spatial and temporal coverage of the study area was 520 and the number of Landsat scenes needed was 159 (**Table 2.2**).

Landstat Data Selection and Processing

Image interpreters used EarthExplorer to identify and download clear Landsat 5 TM scenes acquired between the years of 2007–2011. When possible, the seasonal dataset for each area of interest (AOI; a PALSAR frame area) was created using scenes from the same year, and efforts were made to use the most recent imagery possible. For lakes Ontario, Erie, Huron, and Michigan the spring scenes were acquired in April and May, summer scenes were from June, July, August, and fall scenes were from September and October. Lake Superior is farther north and green up typically occurs later, so the month of June was included in the spring scenes. Cloud-free imagery was not always available for the specified time frames; therefore, for some AOIs it was necessary to composite Landsat scenes from multiple dates. Julian day was included in each image stack to keep track of image sources. Multispectral Landsat TM data used in mapping coastal areas included bands 1–7 from spring, summer, and fall scenes. Optical bands were converted to radiance values, then to top-of-atmosphere (TOA) reflectance to normalize differences in illumination due to temporal changes in sun angle and earth-sun distance. The thermal bands were converted to TOA temperature brightness in degrees C assuming all pixels had an emissivity of water (Becker et al 2005). This assumption resulted in a relatively small underestimation of land surface temperature. Typically, in the warmer months the thermal difference between land and water is greater than the underestimation, making such an assumption suitable for mapping purposes.

Atmospheric correction using the latest Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) software to convert Landsat digital counts to surface reflectance (Rebelo 2010) is considered by many to be the best correction; however, we found TOA to produce comparable results with less computational burden. The effects of atmospheric correction were tested by comparing classification results using TOA reflectance and surface reflectance. Image classification and error analysis was then carried out using both TOA reflectance and LEDAPS surface reflectance. Atmospheric correction did not improve classification accuracy, but added considerable computational burden to each scene. Other previous large-scale mapping projects have found that using TOA reflectance values for image classification yielded more accurate results than using atmospherically corrected data (Rebelo et al 2010; Masek et al 2006; Homer et al 2007).

Normalized Difference Vegetation Index (NDVI) images created from the visible-red (band 3) and NIR (band 4) bands (Wulder et al 2003) were also produced for inclusion in the map classification. This ratio works well for mapping green vegetation, as the reflectance in the red band is low due to absorption by chlorophyll and high in the near infrared band due to chlorophyll reflectance. The thermal and spectral indices allow for improved wetland detection and mapping over the optical sensors alone. All Landsat TM data and NDVI products were resampled using nearest neighbor to match the PALSAR Fine Beam Dual mode pixel size of 12.5 m and output as 32-bit data.

SAR Processing

SAR data for the study area were acquired from the Japanese ALOS PALSAR satellite, which has an L-band (~24 cm wavelength) SAR sensor. PALSAR data are collected in various modes, and for this project the single channel and dual channel modes were used. In Fine Beam Single mode (FBS), the sensor transmits and receives horizontally polarized signals (HH) with 10 m spatial resolution. In Fine Beam Dual mode (FBD), the sensor transmits horizontally polarized signals and receives horizontally and vertically polarized signals (HH and HV) with 20 m spatial resolution. PALSAR imagery used for this project was processed at the Alaska Satellite Facility (ASF) via a service contract. ASF downloaded the data from the ALOS satellite, processed, terrain corrected, and georeferenced it to within 1.5 PALSAR pixels (12.5 m), and delivered the 32-bit data with 12.5 m pixel spacing for the FBD data and 6.25 m pixel spacing for the FBS. Upon receipt, the FBS data were resampled using bilinear interpolation to match the FBD PALSAR pixel size of 12.5 m.

Once received from ASF, the data were checked to ensure geographic accuracy. Images that shared the same spatial extent were required to be within one pixel (12.5 m) of each other for mapping. If images did not meet this accuracy requirement they were processed through a co-registration algorithm. The SAR images were checked for alignment using Landsat TM images. If the SAR images were found to be misaligned they were georeferenced to a corresponding cloud-free Landsat 5 TM image. Spatial accuracy was calculated for each image using the root mean square error (RMSE). Lastly, a 3 × 3 median filter was applied to the PALSAR images to reduce speckle. Speckle is the coherent addition of backscatter from multiple scatterers in the same resolution cell. The result is random constructive and destructive interference, manifesting itself in bright and dark neighboring pixels, a "salt and pepper" effect. Because of speckle, a single pixel in SAR imagery cannot be used to measure features on the ground. Filtering of the data must be applied to reduce inherent speckle when producing a map.

Mapping Technique

Several image classification methods were evaluated, including hierarchical classification, object based image analysis (OBIA with eCognition), maximum likelihood (Erdas Imagine) classification of optical and SAR data separately and then recombination of the classes (Bourgeau Chavez et al 2008), and Random Forests (in R). Each of these approaches has advantages and disadvantages, and was evaluated for accuracy, consistency (between scenes and image analysts), and time consumption. These approaches were assessed in three experimental study areas with varying amounts of developed land (Northern Lake Michigan coastal wetland, Lake St. Clair coastal wetland, and Lake Huron coastal wetland). Random Forests (Rouse et al 2001) provided the best combination of high classification accuracy and time efficiency and was selected for our study. As a machine learning algorithm, Random Forests is an ensemble classifier consisting of multiple decision trees generated from a random subset of training data sites and bands from a stack of all data. Once the forest of decision trees is created, an individual pixel's classification is determined by which class receives the most "votes" across all decision trees. Random Forests is able to handle datasets with a small number of observations and a large number of attributes, is well suited to parallel processing, and is relatively insensitive to non-predictive inputs (Brieman 2001). Additionally, the algorithm can easily handle missing attributes, such as cloud obscured pixels, as decision trees built without the missing attributes can be used to classify the compromised data.

A minimum mapping unit of 0.2 ha was used for the project. This unit was determined by application needs and limitations of the SAR imagery. Although the original multi-looked SAR imagery has 10–20 m resolution in the ground plane, due to inherent SAR image speckle the effective mapping unit must be a multiple of the resolution cell. Based on field data comparison with the fused Landsat-PALSAR map products and in reference to the coarsest SAR spatial resolution used (20 m), 0.2 ha, or 2 × 2.5 resolution cells, was the minimum size that could be confidently mapped (Bourgeau Chavez et al 2008).

The classification scheme applied to the datasets consisted of a combination of Anderson Level I upland classes (Liaw and Weiner 2002), USFWS NWI classes, additional specific wetland classes (peatlands, invasive monotypic vegetation types including *Phragmites*, *Typha spp*., and *Schoenoplectus spp*.), and other upland classes that aided in improving map accuracy by reducing confusion (e.g., urban grass, fallow field). All upland and wetland classes are defined in **Table 2.3**.

The mapping process was iterative (**Figure 2.4**). First, wetland vegetation types were identified using field data and air photo interpretation. Next, polygons were drawn in ESRI ArcMap to spatially expand the field sampled locations and avoid edges of transitions between covertypes or land categories. These polygons were used as training and validation data, with a reserved priority of the field sampled sites for validation. Training data for uplands were created by image interpretation of current aerial photographs and were not field visited. Homeland Security Border 2009 Flight Imagery collected at 30-cm resolution was used for assessment of the coastlines of lakes Ontario, Erie, Huron, and Superior. The Border Flight data were not collected for Lake Michigan or Georgian Bay in Lake Huron, so a combination of publicly available satellite and aerial imagery was used. USDA National Agricultural Imagery Program (NAIP) 1-m data from 2009 to 2010 were used for Lake Michigan. For Georgian Bay, ESRI's World Imagery and Google Earth were used. These upland and wetland polygons provided the supervised training data and validation data (**Figure 2.4**). The supervised data were input to Random Forests with the three-date Landsat TM-PALSAR image stack that included all Landsat TM bands (21) and PALSAR bands (6), as well as an NDVI layer for each Landsat TM date (3), for a total of 30 input remote sensing bands. Post-classification, the classified images were filtered to eliminate isolated pixels and reduce the errors introduced by mixed pixels. Each classified pixel's value was replaced by the majority class of its eight neighbors using the ESRI majority filter. This resulted in the reduction of some errors at the expense of some correctly classified small linear features.

The mapping process (**Figure 2.4**) was applied individually to AOIs nominally defined by each 70 km × 70 km PALSAR frame area (**Figure 2.5**). This approach was required because even small differences in adjacent PALSAR scene collection dates can result in great differences in SAR backscatter, depending on moisture conditions. The study area also covered a transition in ecoregions from southern boreal in the north to temperate conditions in the south, and a range in LULC from primarily rural in the north to highly urban in the south. An effort was made to collect field data within each 70 km × 70 km frame area for training. Note that there were small areas of the map that did not have PALSAR imagery available. These were generally slivers of the map where overlapping PALSAR coverage was unavailable for the seasons used in mapping. In these cases the maps were produced solely from Landsat 5 TM data. Once all of the AOIs were completely mapped, they were mosaicked to the extent of each of the five lake basins and accuracy was assessed.

Accuracy Assessment

To ensure a robust set of validation data (polygons) for the Great Lakes coastal wetland maps, a percentage of the input training polygons was reserved for validation. Specifically, this was carried out by setting aside 20% of the training polygons as validation for each class. Whole polygons, not partial polygons, were set aside. The validation data were prioritized to include polygons derived from field verified sites. If less than 20% of a class's training polygons included field sites, then polygons derived from photo interpretation were also reserved. When more than 20% of the polygons were field verified, then validation polygons were randomly selected to be included in the training data. The average number of validation polygons per class was 328, exceeding the 75–100 recommended by Congalton and Green 2008 for large areas (Anderson et al 1976).

The Random Forests algorithm generates an "out of bag" estimate of classification accuracy using the random subset of training data not used in generating each tree. However, these data are used to generate other trees within Random Forests and, thus, they are not independent. The "out of bag" accuracy was typically inflated compared to the independent assessment. Therefore, to ensure a robust and independent validation set, all accuracies presented in this article are based on the twenty percent of the training data that were reserved for validation.

Results:

The mapping was completed in the summer of 2014 for all five lake basins (**Figure 2.6**). The results are presented below for the whole Great Lakes Basin and can be viewed on a webpage and requested for download (Congalton et al 2008). The area of wetland mapped by class type in each lake basin is shown in Table 4. A total of 2,200,631 ha of wetlands were mapped in the bi-national Great Lakes coastal region to within 10 km of the coastline. This represents 24% of the total land area within the study extent (9,056,410 ha mapped). Of these coastal wetlands, a majority were forested or shrubby wetlands (18.2% of mapped area), with 3.7% of the mapped area representing emergent wetland types. Within the emergent wetland class, 24% of the area mapped was dominated by *Typha spp*. and 11% was dominated by invasive *Phragmites*.

The targeted goal for overall accuracy was 90% and the goal for individual classes was 70% accuracy. The overall accuracy of the entire basin map is 94% (**Table 2.5**), and for individual lakes it is greater than 90% for all lakes except Ontario, which is 86% (**Table**

2.6). If water is excluded, then overall accuracy reduces to 85%–87% and when all the wetland classes are lumped, overall wetland class accuracy is 75%–82%.

The producer's accuracy represents how well the reference pixels are classified, whereas the user's accuracy represents the probability that a classified pixel actually represents that class on the ground. For individual classes for the entire basin, all of the producer's class accuracies are greater than 69% and all of the user's accuracies are greater than 61% except for one class, *Schoenoplectus* (35%; **Table 2.5**).

A single AOI covering the St. Clair Flats area provides an example of the details of the map (**Figure 2.7**). The St. Clair Flats is home to a large river delta wetland complex with a variety of herbaceous and woody wetlands, including large expanses of the invasive *Phragmites* and *Typha spp*., as well as large areas of *Schoenoplectus spp*. along the coastline. For this AOI, most of the producer's class accuracies are greater than 70%, except wetland, which is 65%, and all of the user's accuracies are greater than 70%, except wetland (38%), *Schoenoplectus* (59%), and forested wetland (60%; Table 7).

One of the outputs of Random Forests is a plot of band importance (mean decrease in accuracy). The mean decrease in accuracy is computed by permuting the out-of-bag data (Liaw and Weiner 2002). For each tree, the prediction error on the out-of-bag portion of the data is recorded and then the calculation is repeated after permuting each predictor (input band) variable. The difference between the two are then averaged over all the trees, and normalized by the standard deviation of the differences. The band importance from the mean decrease in accuracy plot for the St. Clair Flats AOI, which is dominated by wetlands (**Figure 2.8**), was very different than the plot for all 40 AOIs over Lake Michigan, of which a majority of the landscape was upland classes (Figure 9). For the wetland dominated AOI (Figure 8), the three most important bands were spring Landsat TM NDVI, spring Landsat TM thermal, and spring L-HH, followed by L-HV from summer and L-HH from fall. In contrast, for the upland dominated landscape (Figure 9) the three most important bands were the Landsat TM thermal (band 6) from spring, NIR (band 4) from spring, and NIR from fall. PALSAR L-HV from spring was 12th in band importance, with the other two HV bands at 14th and 15th, and the HH bands at 17–19th in importance.

Discussion:

Accuracy and Confusion Classes

The overall accuracy for the coastal Great Lakes maps was 94%, with a range from 86% to 96% overall accuracy by lake basin (Huron, Ontario, Michigan, Erie, Superior). This overall accuracy is slightly higher than the rates of 80%–89% achieved in other large-area mapping projects around the world (Margono et al 2014; Fujimura et al 1999; Becket et al 2005; Bourgeau Chavez et al 2015; Draper et al 2014) and comparable with the rate of 95% achieved for Alaska (Whitcomb et al 2009) For the coastal Great Lakes maps, a few wetland classes had individual accuracies below the targeted 70% producer's and user's accuracies. For example, *Schoenoplectus spp.* had a producer's accuracy of 83% and a user's accuracy of only 35% for all the Great Lakes (**Table 2.5**). The low user's accuracy suggests only 35% of all *Schoenoplectus spp.* pixels are indeed

Schoenoplectus spp. on the ground. *Schoenoplectus spp.* proved difficult to map because the plants often grow in narrow, patchy stands along the coast. *Schoenoplectus* stands are also much less prevalent than the more common large monotypic stands of *Typha spp.* or *Phragmites*. *Schoenoplectus spp.* are often seen mixed with other vegetation and patches of open water or floating aquatics which can explain the confusion with the generic wetland class, aquatic bed, and open water classes. In areas dominated by wetlands, such as the St. Clair Flats AOI, the accuracy of *Schoenoplectus spp.* improves, with a producer's accuracy of 98% and a user's accuracy of 59% (**Table 2.7**). The specific dominant cover wetland classes could be collapsed into a higher-order class (e.g., *Typha* and *Phragmites* could be collapsed into "wetland" (NWI emergent wetland class; see **Tables 2.4 and 2.6**) to increase the map accuracy. However, in many cases the major confusion is with similar or higher-order wetland classes, and lower accuracy of a specific cover type is compensated by the general ability to distinguish differences among classes. *Schoenoplectus* may be better collapsed with open water in many regions. For this genus a shorter wavelength SAR, such as C-band (~5.7 cm), would likely improve mapping.

In some regions of the map, specifically those areas that are more developed, accuracies are slightly lower because of the higher variability in LULC over small spatial extents. In these areas, there are some noticeable classification discrepancies because of mixed pixel effects. For example, an area that transitions from urban to emergent wetland may show false instances of other classes in pixels where the transition occurs. Another example is fallow fields along woodlots, which result in false identification of *Phragmites* in a linear patch along the treeline. These errors were reduced as much as possible by clumping and sieving, but further filtering would actually remove true classes.

There is some confusion of agriculture with many of the LULC classes (**Table 2.5**). Agricultural land often borders many of these LULC types and, depending on the crop planted, it can look spectrally similar to various LULC types. In addition, many of the agricultural lands are former wetlands and therefore may exhibit hydrological changes similar to intact wetlands, thus appearing "wet" in the PALSAR data.

Due to the high confusion of *Schoenoplectus* with open water, the maps were adjusted post-classification to correct the problem. Using all available field data, a spatial query was conducted to retain areas mapped as *Schoenoplectus* that were field verified and relabel all other areas mapped as *Schoenoplectus* to open water. Unfortunately, using all field data to make the correction did not allow for an independent assessment of the new *Schoenoplectus* class accuracy. In making this adjustment some true *Schoenoplectus* areas are likely lost, but with the high errors from the unadjusted map it was justifiable.

Importance of SAR-Optical Fusion in Wetland Mapping

The plot of band importance for the St. Clair Flats AOI (**Figure 2.8**) shows that the most important bands for wetland type mapping when using three-season Landsat TM and PALSAR data were spring Landsat TM NDVI, spring Landsat TM thermal, and spring L-HH, followed by L-HV from summer and L-HH from fall. The PALSAR L-HH band (which is sensitive to moisture/inundation), along with the spring Landsat TM NDVI and thermal band, are particularly important to the classification, and that importance was consistent across AOIs with large regions of wetland cover. However, for classifications generated in areas with a greater percentage of urban and suburban coverage (**Figure 2.9**), the output maps relied more heavily on the visible Landsat TM bands, and the PALSAR L-HV bands were ranked 12th, 13th and 14th, slightly above the L-HH bands (ranked 17–19th). L-HV is more sensitive to biomass than moisture and Landsat TM bands are most useful for distinguishing upland cover types. It is for the wetland classes that PALSAR L-HH is of such high utility, as seen in Figure 8. However, the L-HV band, with its sensitivity to structure and biomass, aids in distinguishing shrub from forest from herbaceous wetland. It is notable that the thermal channel is of high importance (ranking 1st or 2nd) for both wetland-dominated AOIs and urban/suburban-dominated AOIs. The thermal band, in conjunction with NDVI, has been shown to be effective for LULC classification (Evans et al 2014; Baker et al 2006; Melesse 2003). Water has a high thermal inertia, therefore the temperature of water and wetlands changes more slowly than for surrounding uplands. In the summer, water is generally cooler than the land, and in the winter, it is warmer. Additionally, evapotranspiration from vegetation results in cooler temperatures than from barren or sparsely vegetated LULC classes (Baker et al 2006). Urban environments are also typically warmer due to solar heating of paved surfaces and heat generated from anthropogenic sources (Melesse et al 2003).

Other researchers have noted the importance of L-band in detection of woody wetlands (in particular Hess et al 1995; Lang et al 2008; Southworth 2004) and for detection of the large, dense forming invasive wetland grass *Phragmites* in the coastal Great Lakes (Baghdadi et al 2001). L-band fused with optical data has been helpful in overall wetland mapping, such as for tropical peatland types in Peru (Bourgeau-Chavez et al 2015), and when combined with C-band dual-band/dual-season data for distinguishing and mapping a diverse set of ecosystems in the vast wetland complexes of the Pantanal in South America (Draper et al 2014). Whereas most researchers find the L-HH band to be of greatest utility for wetland mapping due to its ability to detect inundation, others note the usefulness of the L-HV band for differentiating vegetation structure in wetlands (e.g., Bourgeau-Chavez et al 2015).

For the coastal Great Lakes map presented here, both L-HH and L-HV were found to be of high importance in wetland mapping. The methods developed for mapping coastal wetlands of the Great Lakes are unique in fusing three season Landsat 5 TM, including the thermal band, and three-season PALSAR L-HH/L-HV data over a large region. Whereas others have investigated multi-sensor fusion, and some have used dual-season multi-sensor fusion, few have used three-season datasets and most remove the Landsat 5 TM thermal band. The three-season data are crucial because they capture the phenologic differences in the vegetation and the seasonal variation in the hydrology. For example, *Typha* stands are typically fallen over in the spring with high water; in summer they are at peak vegetation height and density with lower water tables and less distinguishable from other wetland types. In contrast, stands of *Phragmites* have significant standing dead biomass in the spring that remains in the summer as new shoots sprout up. Using summer data alone makes distinguishing these two genera difficult, but using the phenology of the vegetation aids in distinguishing them, and the patterns of hydroperiod distinguish the wetlands from the uplands. Some of the wetlands are wet in spring and fall, such as the forested wetlands, and that provides two chances to detect the inundation, depending on the timing of the satellite collections.

The SAR-optical technique for mapping Great Lakes wetlands was demonstrated as a repeatable, high accuracy, and timely method (3.5 years including development of mapping methodology) that can be applied to large regional areas while integrating high accuracy image interpretation, field data and moderate spatial resolution remote sensing in a sophisticated machine-learning approach. Such an approach has wide applicability beyond the coastal wetlands of the Great Lakes. This approach to wetland mapping has been applied to non-coastal temperate regions, including the state of Michigan and the state of Maine, as well as to boreal peatlands of Alberta (Townsend 2002) and is currently being applied to map tropical peatlands of Peru.

Summary and Significance:

The Great Lakes bi-national coastal wetland product represents a current, circa 2010, comprehensive basin-wide inventory of coastal wetlands, as defined by USFWS NWI types with additional classes for dominant plant species *Phragmites*, *Schoenoplectus spp*. and *Typha spp* and adjacent LULC classes as defined in the GLCWC Monitoring Plan protocol (Bourgeau-Chavez et al 2008). This effort represents the first comprehensive wetland delineation of the bi-national coastal Great Lakes using a consistent mapping technique. The map provides information not only on wetland extent and type, but also contemporary information on potential wetland stressors (e.g., invasive plant species and level and type of development surrounding the wetlands). More specifically, the map is designed to assist in identifying indicators of wetland health defined through the State of the Lakes Ecosystem Conference, including: (1) land cover adjacent to coastal wetlands; (2) land cover/land conversion; (3) urban density; (4) non-native terrestrial species, and (5) wetland extent and composition [48]. It was also developed to provide reference and input for the GLIC, which has a five-year plan for collection of biologic and other field-based indicators of wetland health throughout the Great Lakes (Bourgeau-Chavez et al 2008).

Although the map produced represents a static point in time depicting the distribution of wetlands by type across the basin, it serves as a baseline for future mapping of change. The mapping methodology used is reproducible, allowing for the continual development of future maps for monitoring and detecting change in the Great Lakes Basin. With the launch of Landsat 8 in 2013 and PALSAR-2 in 2014, map updates and changes can be made in the next few years. The German Aerospace Center (DLR) has plans to launch L-band satellites (Tandem-L), as do NASA, India with NISAR (L-band and S-band SAR sensors), and Argentina with SAOCOM–1, thus extending the mapping capability into the longer-term future. In addition, mapping past conditions circa 1997 is possible with JERS-1 (predecessor to PALSAR) and Landsat 5 TM. A change mapping technique, such as is conducted by NOAA for C-CAP, could be applied to the hybrid PALSAR-Landsat methodology for efficiency.

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Table 2.1: Sources of field data collection used to aid in image interpretation. The top four sources were used for the development of training and validation data for the coastal Great Lakes map. The bottom two sources provided ancillary information.

Source	Region	Years of Collection	No. of Sites
MTU [1] (USGS [2]/USFWS funded)	USA: All 5 Lakes	2010–2011	1191
MTU (EPA funded)	USA and Canada: Lakes Huron, Superior, Erie, Michigan	2011–2014	147
McMaster University	Canada: Lakes Huron, Erie Ontario	2013	70
Michigan State University (EPA funded)	Canada: Lakes Superior, Huron, USA: Lake Michigan	2012–2013	343
Great Lakes Instrumentation Collaboratory (GLIC)	USA and Canada: All Lakes	2011–2013	--
McMaster University	Canada: Georgian Bay	2007–2009	249

[1] Michigan Technological University; [2] U.S. Geological Survey.

Table 2.2: Number of scene footprints required from each satellite sensor to map the coastal Great Lakes. Note that scenes covering Lake St. Clair are included in Huron.

Lake Basin	Number of PALSAR Scenes	Number of Landsat 5 TM Scenes
Erie	57	27
Huron	117	27
Michigan	107	26
Ontario	66	12
Superior	173	67

Table 2.3: Description of each class mapped

Class	Description
Urban	Residential areas, cites, towns, industrial areas, utilities, commercial services where the manmade structures have >75% coverage.
Suburban	Primarily residential areas where manmade structures (*i.e.*, buildings, farm equipment) are present, with more than or equal to 25% vegetation (trees, shrubs, grass) interspersed.
Urban Grass	Lawns, golf courses, athletic fields, urban parks, and mowed transitional zones such as medians or airfields.
Urban Road	Linear transportation routes, large driveways, and parking areas. Transportation routes can include highways, small two-lane roads, railroad beds, airfield landing areas, parking lots, and off- and on-ramps.
Agriculture	Hay fields and croplands where row crops such as corn, beans, and grains are in production. Land used for production of food or fiber; land use distinguishes agricultural land from similar natural ecosystem types (*i.e.*, wetlands and rice paddies).
Fallow Field	Agriculture fields not in row crop production, such as areas of native grasses or meadows and pastures.
Orchard	Orchards, vineyards, and ornamental plants/trees.
Forest	Broadleaf and needle leaf deciduous and evergreen trees and dead forests. Characterized by woody vegetation with a height >6 m. Crown closure percentage (*i.e.*, aerial view) >75%.
Pine Plantation	Needle leaved deciduous and evergreen trees with distinct row structure and typically planted in defined geometric plot. Crown closure percentage (*i.e.*, aerial view) >75%.
Shrub	True shrubs, immature trees, or stunted growth trees/shrubs. Characterized by woody vegetation with a height <6 m. May represent a successional growth stage that has not yet matured to forest, or stable communities of shrubs and stunted growth trees. Crown closure percentage (*i.e.*, aerial view) >50%.
Barren Light	Salt flats, beaches, sandy areas, bare rock, strip mines, quarries, gravel pits, and transitional areas (on gray scale >50% white). Land with limited ability to support life. Contains less than 33% vegetative cover. May include thinly dispersed scrubby vegetation.
Barren Dark	Salt flats, beaches, sandy areas, bare rock, strip mines, quarries, gravel pits, and transitional areas (on gray scale ≥50% black). Land with limited ability to support life. Contains less than 33% vegetative cover. May include thinly dispersed scrubby vegetation.
Water	Streams, canals, rivers, lakes, estuaries, reservoirs, impoundments, and bays. Areas persistently inundated by water that do not typically show annual drying out or vegetation growth at or above the water's surface. Depth of water column is >2 m, such that light attenuation increases significantly and surface and subsurface aquatic vegetation persistence declines or is less detectable.

Table 2.3: cont'd

Class	Description
Aquatic Bed	Algal beds, aquatic mosses, rooted vascular plants (e.g., eelgrasses and sea grasses, pond weeds, lily pads, milfoil) and floating vascular plants (e.g., lemna, water hyacinth, coontails, and bladderwarts). Inundated wetlands or water <2 m (excluding deep water zones). Habitats dominated by plants that grow principally on or just below the water's surface.
Wetland	Emergent wetland and wet meadow vegetation not represented by other classes. These are areas where the water table is at or near the Earth's surface. Seasonal inundation and/or drying are common. Vegetative species distributions are strong indicators of wetland condition. Does not include cultivated wetlands, such as rice paddies or cranberry farms.
Schoenoplectus	Dominate species is *Schoenoplectus spp.* and crown closure percentage (*i.e.*, aerial view) >50%.
Typha	Dominate species is *Typha spp*. and crown closure percentage (*i.e.*, aerial view) >50%.
Phragmites	Dominate species is *Phragmites australis* and crown closure percentage (*i.e.*, aerial view) >50%.
Open Peatland	Brown and graminoid moss dominated with >30 cm peat. Connected ground and surface water flow; minerotrophic. Crown closure percentage (*i.e.*, aerial view) >75%.
Shrub Peatland	Brown and graminoid moss dominated with >30 cm peat. Connected ground and surface water flow; minerotrophic. May represent a successional stage growth that has not yet matured to forest, or stable communities of shrubs and stunted growth trees. Crown closure percentage (*i.e.*, aerial view) >50%.
Treed Peatland	Brown and graminoid moss dominated with >30 cm peat. Connected ground and surface water flow; minerotrophic. Characterized by woody vegetation with a height >2 m. May represent a successional growth stage that has not yet matured to forest, or stable communities of shrubs and stunted growth trees. Crown closure percentage (*i.e.*, aerial view) >75%.
Wetland Shrub	Wetlands dominated by shrubs <6 m in height. Crown closure percentage (*i.e.*, aerial view) >50%.
Forested Wetland	Wetlands dominated by woody vegetation (dead or alive) >6 m in height. Includes seasonally flooded forests. Crown closure percentage (*i.e.*, aerial view) >50%.

Table 2.4. Summary of area mapped by wetland class type (ha) and percentage of each class type mapped within the study area.

Wetland Type	**Lakes Erie and St. Clair**	**Lake Ontario**	**Lake Michigan**	**Lake Huron**	**Lake Superior**
Emergent (including *Typha* and *Phragmites*)	63,216	53,800	54,921	97,201	63,166
Typha	18,707	19,552	15,190	18,906	6509
Phragmites	20,129	2036	8851	6266	0
Woody Wetlands (Ha: Shrub and Forest)	111,049	108,738	361,307	525,446	539,624
Peatland (Bogs and Fens—open and woody)	0	0	11,522	33,439	46,635
Total Wetlands	194,527	179,570	447,005	708,647	670,882
Total Mapped Area	1,280,800	1,224,930	1,746,030	2,508,840	2,295,810
% Area Mapped as Wetland	15.2%	14.7%	25.6%	28.2%	29.2%
% Area Mapped as Emergent Wetland	4.9%	4.4%	3.1%	3.9%	2.8%
% Area Mapped as Woody Wetland	8.7%	8.9%	20.7%	20.9%	23.5%

Table 2.5. Error matrix for all coastal Great Lakes. Numbers represent pixels. Some classes have been collapsed to higher-order classes for display purposes.

Classified	Ground Truthed Values															
	Urban	**Agriculture**	**Forest**	**Shrub**	**Barren**	**Water**	**Aquatic Bed**	**Wetland**	***Schoeno-plectus***	***Typha***	***Phragmites***	**Peatland**	**Shrub Wetland**	**Forested Wetland**	**Sum**	**Comm-ission**	**User Acc.**
Urban	55,555	7257	315	519	4222	204	26	31	0	139	64	11	94	9	68,446	19%	81%
Agriculture	1575	650,640	452	3051	1149	65	82	585	0	121	61	13	394	43	658,231	1%	99%
Forest	88	1714	108,758	3027	39	15	14	145	3	12	14	173	1174	5069	120,245	10%	90%
Shrub	381	5625	3034	123,911	290	44	32	470	8	78	34	351	2775	3097	140,130	12%	88%
Barren	534	1979	7	80	43,168	566	0	38	0	63	1	0	24	0	46,460	7%	93%
Water	0	0	0	20	363	184,5154	324	1	96	7	0	15	4	8	1,845,992	0%	100%
Aquatic Bed	40	1034	0	31	64	7597	17,777	534	233	144	103	92	153	157	27,959	36%	64%
Wetland	165	3232	37	372	83	70	362	13,083	99	848	226	319	2359	92	21,347	39%	61%
Schoenoplectus	2	2	0	2	1313	2065	375	290	2256	52	12	32	22	0	6423	65%	35%
Typha	15	1514	16	175	38	43	423	1143	22	17,631	333	44	207	70	21,674	19%	81%
Phragmites	52	2360	47	26	10	114	99	667	1	694	7775	0	210	77	12,132	36%	64%
Peatland	19	427	236	878	28	13	45	168	1	83	0	14,945	1475	165	18,483	19%	81%
Shrub Wetland	209	1676	1595	3454	33	7	105	1432	8	250	84	828	27,942	3910	41,533	33%	67%
Forested Wetland	30	183	4261	4523	8	42	36	52	2	13	1	353	3804	63,097	76,405	17%	83%
Sum	58,665	67,7643	118,758	140,069	50,808	1,855,999	19,700	18,639	2729	20,135	8708	17,176	40,637	75,794			
Omission	5%	4%	9%	13%	15%	1%	10%	30%	17%	14%	11%	13%	31%	17%			
Prod. Acc.	95%	96%	92%	88%	85%	99%	90%	70%	83%	88%	89%	87%	69%	83%			94%

Table 2.6: Summary of classification accuracy by lake basin. Included is the accuracy for wetland classes with water removed.

Lake Basin	Overall Accuracy	All Classes Except Water	Wetlands Classes Only
Erie	**92%**	85%	82%
Ontario	**86%**	85%	81%
Huron	**93%**	85%	75%
Michigan	**96%**	87%	82%
Superior	**95%**	86%	82%

Table 2.7. Error Matrix for the St.Clair Flats AOI. Numbers represent pixels. Some classes have been collapsed into higher-order classes for display purposes.

Classified	Ground Truthed Values														
	Urban	**Agriculture**	**Forest**	**Shrub**	**Barren**	**Water**	**Aquatic Bed**	**Wetland**	***Schoeno-plectus***	***Typha***	***Phragmites***	**Shrub Wetland**	**Forested Wetland**	**Sum**	**Comm-ission**
Urban	1744	46	0	0	175	0	0	0	0	0	8	0	0	1973	12%
Agriculture	5	30,197	5	147	0	0	2	19	0	0	13	43	0	30,431	1%
Forest	0	1	214	11	0	0	0	0	0	0	0	52	0	278	23%
Shrub	0	44	0	2700	0	0	0	4	0	0	0	153	0	2901	7%
Barren	123	89	0	0	860	0	0	0	0	0	0	0	0	1072	20%
Water	0	0	0	0	0	80,981	0	0	5	2	0	0	0	80,988	0%
Aquatic Bed	0	0	0	0	0	15	347	0	0	0	0	0	0	362	4%
Wetland	0	56	0	0	0	0	0	53	0	0	23	9	0	141	62%
Schoenoplectus	0	0	0	0	0	166	1	0	283	27	0	0	0	477	41%
Typha	0	2	0	0	0	0	25	0	0	1000	0	1	0	1028	3%
Phragmites	0	76	0	0	0	4	17	5	0	100	1170	13	0	1385	16%
Shrub Wetland	0	0	0	17	0	0	0	0	0	1	32	733	0	783	6%
Forested Wetland	0	2	45	0	0	0	1	0	0	0	0	22	106	176	40%
Sum	1872	30,513	264	2875	1035	81,166	393	81	288	1130	1246	1026	106		
Omission	7%	1%	19%	6%	17%	0%	12%	35%	2%	12%	6%	29%	0%		
Prod. Acc.	93%	99%	81%	94%	83%	100%	88%	65%	98%	88%	94%	71%	100%		97.5%

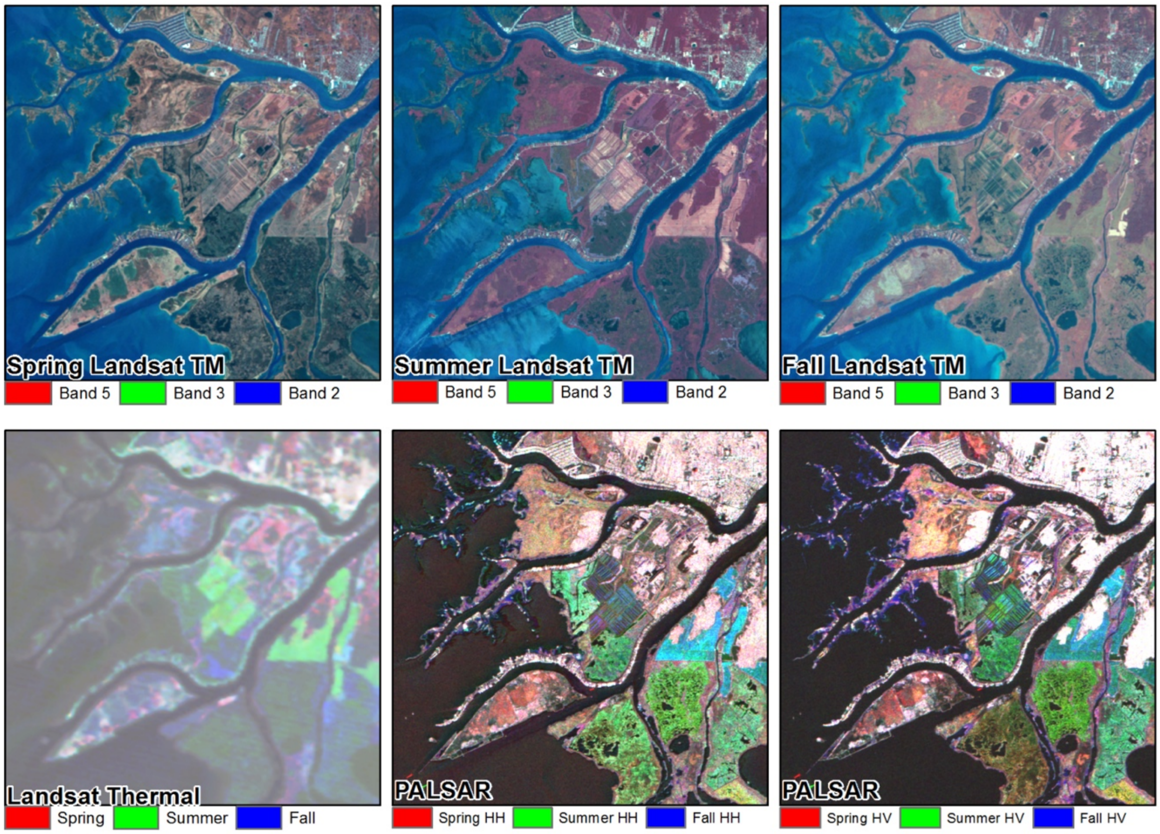

Figure 2.1. Multi-temporal and multi-sensor depiction of a large wetland complex on the St. Clair River Delta bordering the U.S. and Canada. Top row of images show spring, summer, and fall Landsat 5 TM imagery (bands 5, 3, 2). Bottom row shows Landsat 5 TM thermal false-color composite (spring, summer, and fall); PALSAR spring, summer, and fall HH false-color composite; and PALSAR spring, summer, and fall HV false-color composite. Image dates: Landsat spring = 5 May 2011, summer = 8 July 2011, fall = 9 October 2010; PALSAR spring = 26 May 2008, summer = 17 July 2010, fall = 17 October 2010.

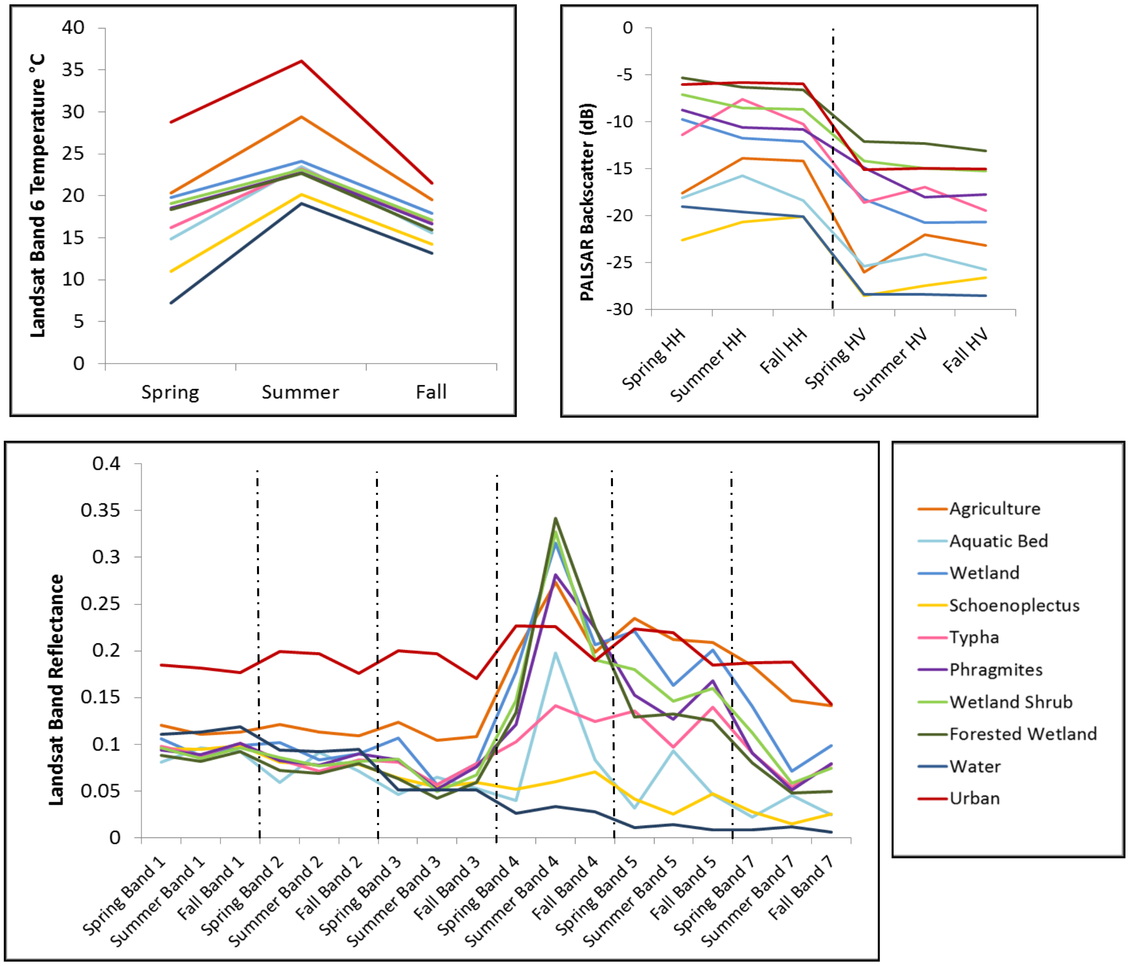

Figure 2.2: Plots showing spring, summer, and fall signatures for different land cover types: Landsat 5 TM band 6 temperature (top left), PALSAR L-band backscatter for HH and HV polarizations (top right), and Landsat 5 TM bands 1–5 and 7 for wetland classes and urban, water, and agriculture. Image dates are listed in Figure 1.

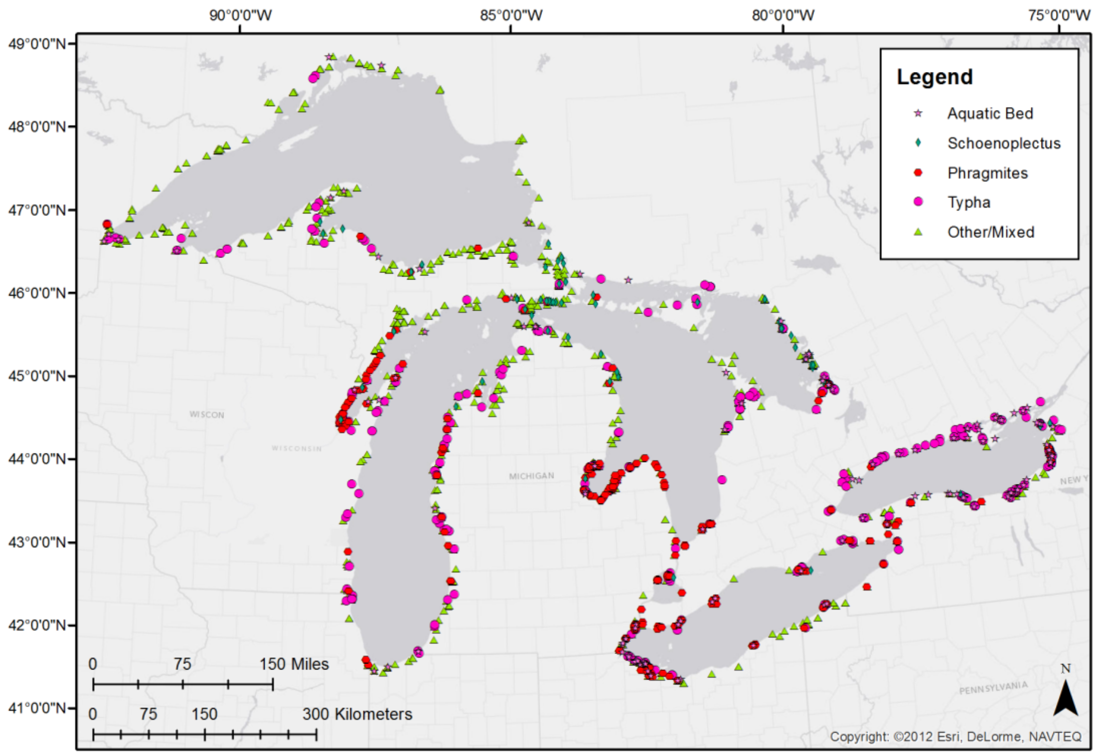

Figure 2.3: Map of field data locations, color-coded by dominant cover type. "Other/mixed" green triangles include all peatland, shrub, and forested wetland, as well as mixed emergent and wet-meadow wetlands.

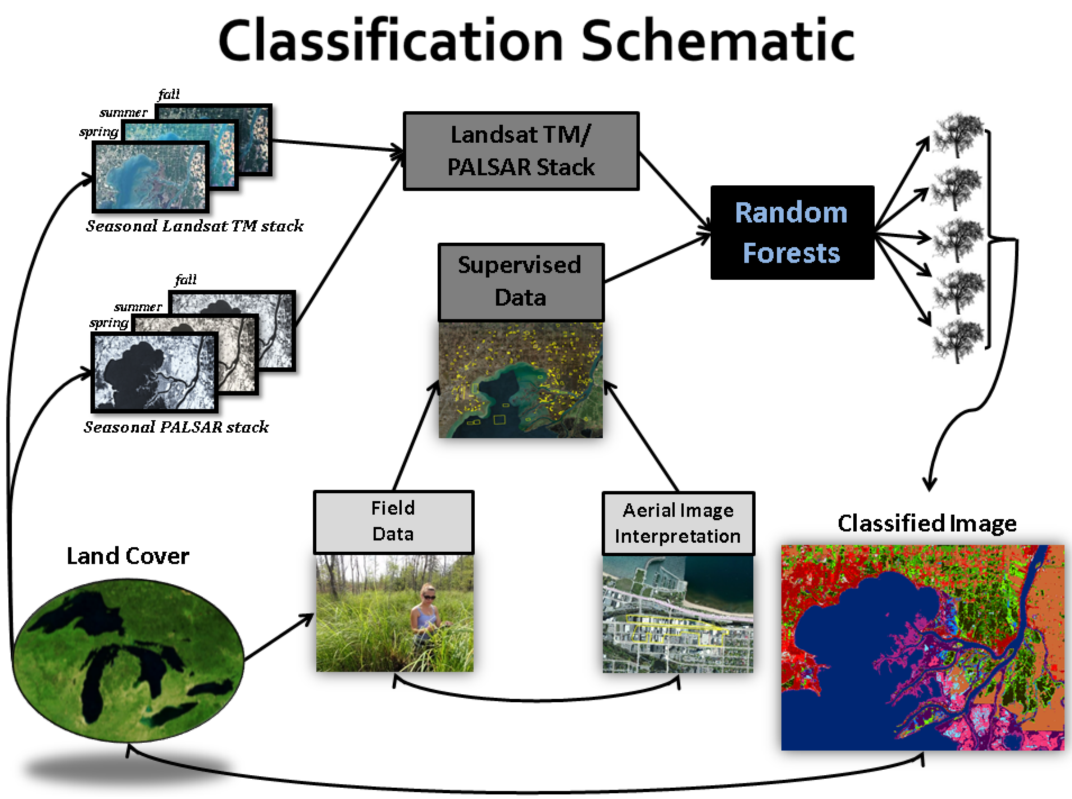

Figure 2.4: Schematic showing the mapping methodology from field data, aerial image interpretation, and satellite imagery to classified map.

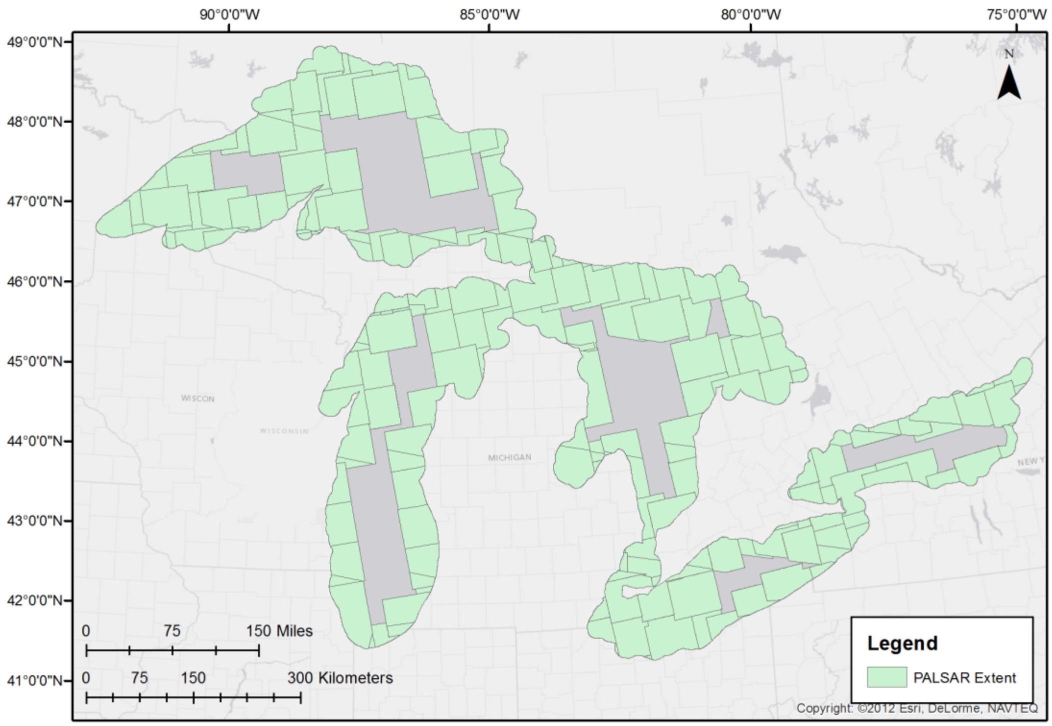

Figure 2.5: Map of extent of each area of interest (AOI) mapped. The AOIs are based on PALSAR image extents within the 10 km coastline buffer. Due to overlap of scenes, some AOIs are smaller than the full 70 km × 70 km PALSAR extent.

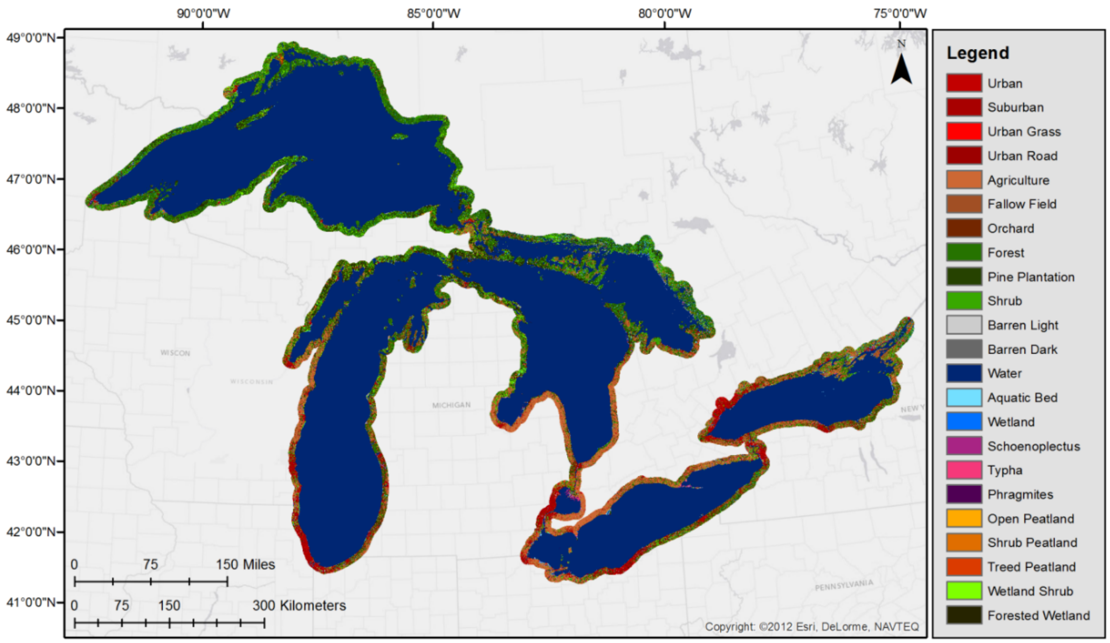

Figure 2.6: LULC map of the coastal Great Lakes, with a total accuracy of 94%.

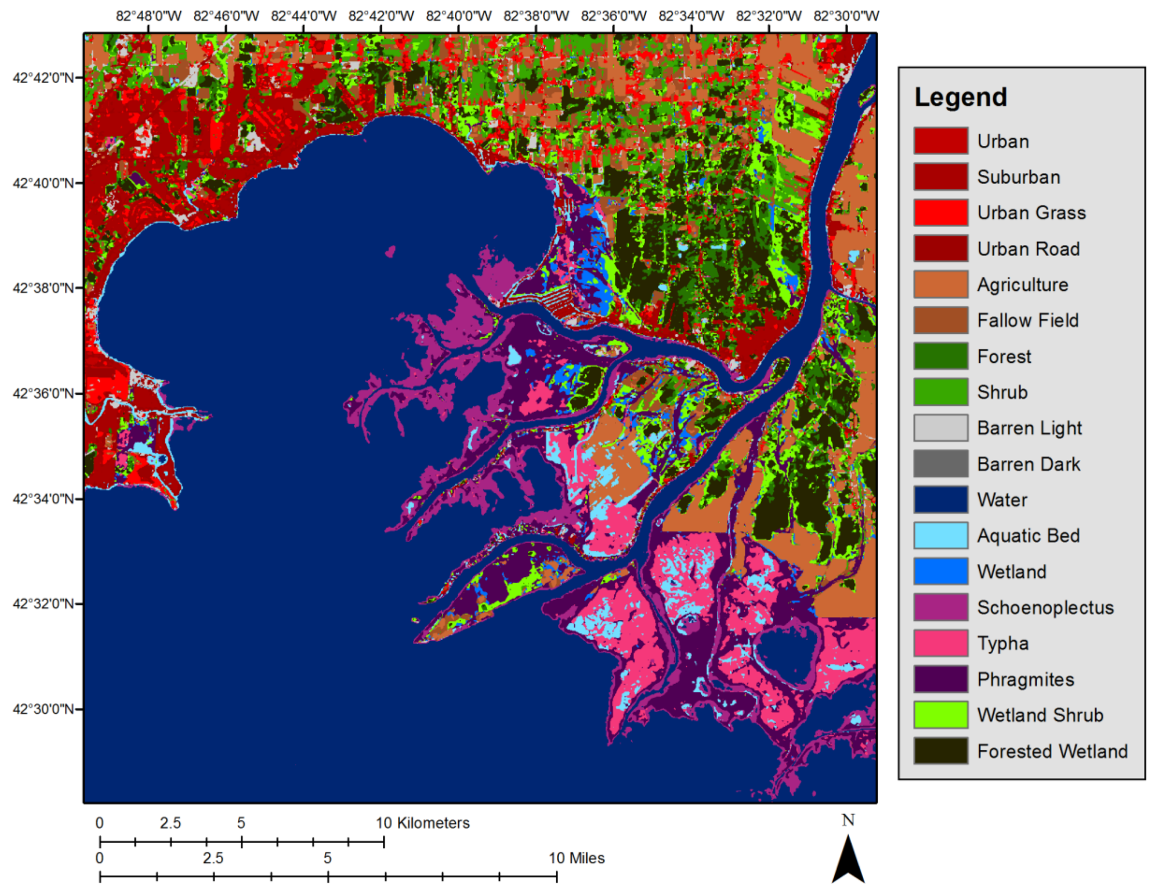

Figure 2.7: Map of wetland type and LULC for the St. Clair Flats AOI. Overall accuracy is 97.5%.

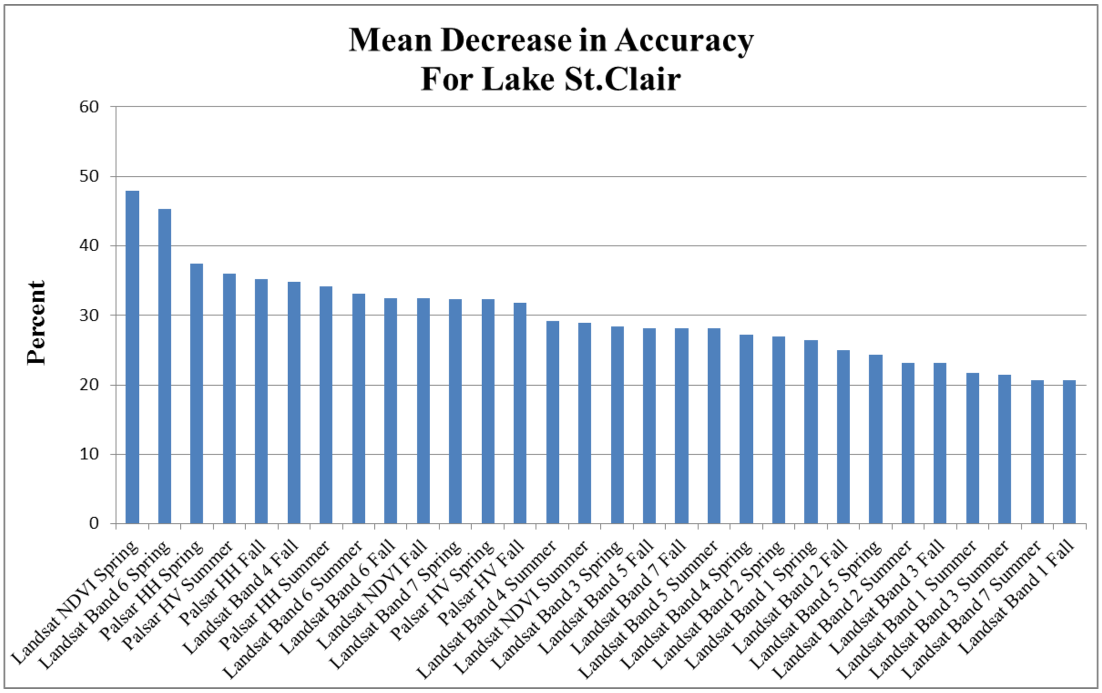

Figure 2.8: Band importance for the wetland dominated Lake St. Clair Flats computed from Random Forests.

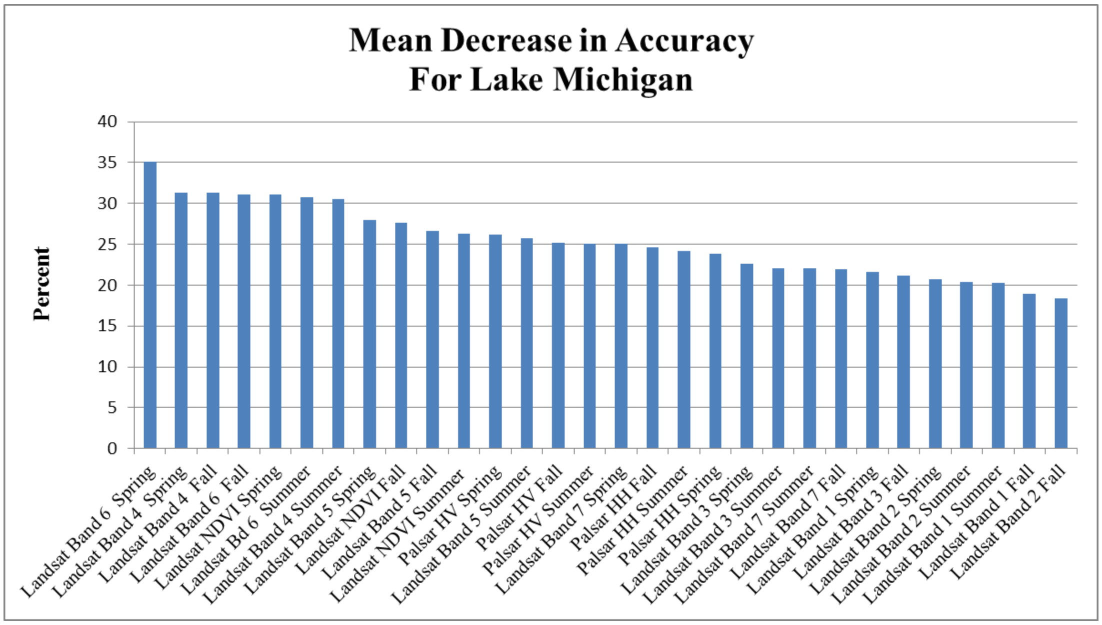

Figure 2.9: Average band importance for 40 AOIs in the upland dominated Lake Michigan Basin computed from Random Forests.

Chapter 3: Mapping Invasive *Phragmites australis* in Highway Corridors of Ontario

By

James V. Marcaccio* and Patricia Chow-Fraser

Abstract:

Invasive *Phragmites australis* is a highly aggressive grass that has become firmly established in wetlands throughout the Great Lakes basin, displacing native plant biodiversity and diminishing wildlife habitat. Roads have been implicated in their rapid dispersal but no study has yet documented the expansion rate at a large regional scale. In this study, we mapped *Phragmites* in corridors of 16,869 km roads with posted speed limits over 60 km/h within 7.04 million ha across southwestern Ontario in both 2006 and 2010. We also mapped *Phragmites* in provincially managed highways in southcentral (3.8 million ha; 2,586km) and central Ontario (13.7 million ha; 4,738 km). Using high-resolution aerial photography and an automated image classification protocol, we determined that *Phragmites* increased by over 700% from 80 ha in 2006 to 569 ha in 2010, with majority of the new growth centered around roadways with large rights-of-way/habitat. The most common land-cover class to change into *Phragmites* is low-lying grasses, with nearly 60% of *Phragmites* in 2010 coming from this class. As expected, approximately half of the areal cover of *Phragmites* was associated with three major highways in southwestern Ontario which were associated with significantly higher traffic volume than other road types; however, in southcentral Ontario, with similarly high traffic volume, these roads only accounted for 20% of the areal cover of *Phragmites*, while several highways that served large seasonal residences had relatively high areal cover. Results of this comprehensive mapping of highway corridors in one of the most populated provinces in Canada are interpreted according to a conceptual model relating

areal cover of invasive *Phragmites* to habitat characteristics, habitat availability and dispersal potential within road corridors.

Introduction:

Phragmites australis (Cav.) Trin. ex Steudel (the common reed) is a perennial grass that grows in many habitat types throughout the world. There are 27 genetically distinct haplotypes worldwide, of which 11 have been found in North America (Saltonstall 2002). Over the past two decades, Haplotype M, which originated from Europe, invaded coastal and inland wetlands throughout southern Ontario, replacing native vegetation and generally reducing biodiversity (Chambers et al. 1999; Markle and Chow-Fraser 2018). This invasive haplotype aggressively colonizes exposed mud flats sexually (through seeds), and then expand asexually (through rhizomes) to form dense monocultures. Its rapid spread has been attributed to it being a superior competitor against other emergent vegetation (Rickey and Anderson 2004; Uddin et al. 2017) and to being more tolerant of disturbances (e.g. road maintenance and changes in hydrologic regimes) and stress (Chambers et al. 1999; Saltonstall 2002).

Past studies have shown that transportation corridors provide excellent invasion pathways for species such as invasive *Phragmites* (Saltonstall 2002, Lelong et al. 2007, Jodoin et al. 2008, Kirk et al. 2011, Brisson, de Blois, & Lavoie 2010; Kettenring, de Blois, & Hauber 2012). Linear ditches along roadsides or in the median can be readily colonized by invasive *Phragmites* (Leong et al. 2007; Brisson et al. 2010) as they have abundant seed dispersal through wind (Brisson, Paradis, & Bellavance 2008, Kirk et al. 2011, Albert et al. 2015, Kettenring et al. 2016). In addition, Medeiros et al. (2013) has hypothesised that this haplotype can tolerate high salinity from road salts and require little moisture in comparison to other aquatic vegetation in the environment. Because roadside environments are highly disturbed (by traffic, maintenance, and construction activities), it is likely that any available habitat would be rapidly colonized by seeds of invasive *Phragmites* (Kettenring et al. 2016). Since the primary role of these habitats is water drainage, constant flooding and drying would likely cause increased stress to many common terrestrial plants while providing ideal 'mudflat' habitat for invasive *Phragmites* (Chambers et al. 2003, Baldwin et al. 2010). It is likely that the rapid spread of invasive *Phragmites* throughout wetlands of eastern North America (and now much of the rest of the continent) has been hastened by roadways and their associated 'linear wetlands' (Maheu-Giroux & de Blois 2006, Lelong et al. 2007, Brisson, de Blois, & Lavoie 2010, Kettenring, de Blois, & Hauber 2012, Albert et al. 2015)

Previously, invasive *Phragmites* has been mapped on a large scale with satellite-based imaging sensors in true colour, near-infrared, radar, and combinations thereof (Bourgeau-Chavez et al. 2015; CH2; Pengra, Johnston, & Loveland 2007, Samiappan et al. 2016, Deakin et al. 2016). These large-scale projects use satellite-based sensors that have a ground-based resolution of 10 to 30 m per pixel with repeat image times of two to four weeks. Although they provide us with important baseline data on the historic, current, and potential spread of invasive *Phragmites* in coastal and inland wetlands in large regions such as states, provinces, or watershed basins, these projects are typically unable to identify the extent of invasions in roadsides that are long linear wetlands, extending over hundreds of kilometers and that are known to be an important vector of dispersal. This is primarily because the resolution of these sensors often exceeds the dimension of the average highway ditch (<20 m on large highways), which for these sensors is too narrow to be appropriately mapped. By comparison, orthophotography can provide a much smaller minimum mapping unit (<1m). The trade-off for this high resolution however, is the requirement for costly flights to be flown with acquisition of many thousands of images to cover large spatial scales and the associated problems with managing such large databases.

Based on the literature, the three main drivers that influence the distribution of invasive *Phragmites* in road networks are habitat characteristics, habitat availability and dispersal potential (**Figure 3.1**). Habitat characteristics are large landscape-level factors that provide optimal growth conditions for invasive *Phragmites*. Since this semi-aquatic plant thrives in high nutrient environments and is competitive in highly saline environments (Chambers et al. 2003; Rickey & Anderson 2004, Bellavance & Brisson 2010; Medeiros et al. 2013; Mozdzer et al. 2013), the topography, geology (substrate), and land use can influence the habitat's suitability. In addition to providing moisture (Jodoin et al. 2008; Brisson et al. 2010), highway ditches can select for invasive *Phragmites* when they receive additional runoff from adjacent agricultural and urban land with high nutrient and ionic content (Lelong et al. 2007). Therefore, habitat availability will be a function of the type of plants that already exist within roadside habitats prior to colonization; for instance, grass species that have typically been planted by transportation authorities would not be competitive against invasive *Phragmites* (Rickey & Anderson 2004; Jodoin et al. 2008; Albert et al. 2015), while woody plants (such as shrubs and trees) would be more resilient land cover that could inhibit colonization by invasive *Phragmites* (Albert et al. 2013). Finally sources of dispersal of invasive *Phragmites* along roadways will be dependent on 1) source populations from other roads and wetlands (Lelong et al. 2007; Kettenring et al. 2012), 2) increased traffic volume that directly provide physical movement and indirectly create artificial wind patterns for dispersal (Gelbard & Belnap 2003; Catling & Mitrow 2011), and 3) direct seeding of invasive *Phragmites* from propagules attached to infected vehicles used in road construction and maintenance projects (see **Figure 3.1**).

This research project was initiated to assist the Ministry of Transportation in Ontario (MTO) to control and possibly eradicate invasive *Phragmites* in the most populous provincial jurisdiction in Canada, with over 20,000 km of roads. Our challenge was to design a protocol to efficiently map the distribution of invasive *Phragmites* across large portions of the provincial road network at regular intervals. Using existing provincial orthophoto databases that spanned 10 years, we performed object-based image classification and manual digitization to delineate the extent of invasive *Phragmites* in southern and central Ontario roadsides in 2006, 2010, 2013, 2015 and 2016. By conducting a change-detection analysis between 2006 and 2010 for southwestern Ontario, we were able to determine roads associated with the highest rate of expansion in a highly developed (both agricultural and urban) region of Ontario and use data from this early stage of colonization to test hypotheses proposed in our conceptual model (**Figure 3.1**). Our results will clarify the relative importance of factors such as land-cover, land uses and traffic volume on the colonization pattern of invasive *Phragmites* in road networks.

Methods:

Orthophotography datasets

In this project, we used images from multiple provincial orthophotography databases which are organized and funded cooperatively by multiple government agencies (municipal, provincial and federal) to obtain seamless aerial photos of the province at regular intervals (approximately every 5 years). In the Southwestern Ontario Orthophototgraphy Project (SWOOP), the dataset covers an area from Windsor east to Brantford/Niagara (2006; 2010 & 2015) and north to Tobermory (**Figure 3.2**). In addition, we analyzed roads managed by the provincial authority (Ministry of Transportation of Ontario; MTO) within areas covered by the SWOOP 2015, SCOOP 2013 (Southcentral Ontario) and COOP 2016 (Central Ontario) databases.

Because these projects were developed primarily for government planning purposes, the image data were acquired during spring when leaf-off conditions allowed for unobscured view of buildings and roads (April-May, weather dependent). These images are freely available to participating stakeholders and to research agencies and universities. The data are true-colour images with red, green, and blue bands and had a spatial resolution of 20 cm per pixel. Such high-resolution imagery would allow for a minimum mapping unit of <1m and is therefore suitable for mapping invasive *Phragmites* stands within roadway and/or highway ditches.

In this study, we analyzed over 20,000 km of roads within the province of Ontario, covering a period from 2006 to 2016 (**Figures 3.2 & 3.3**). Roads in these datasets included arterial roads, city streets, collector roads, highways, highway ramps, recreational roads, and suburban streets (**Figure 3.3**). Arterial roads are high capacity roads that are used to distribute traffic to highways or between municipalities. City streets and suburban streets are roads within these municipalities which are connected to arterial roads via collector roads (low to medium capacity). Highways are very high-capacity roads designed to move traffic between large urban centres; in Ontario the largest highways are designated as 400-series roads. Recreational roads can be used by vehicular or non-vehicular traffic and include gravel and cycling paths.

Automated Image Classification

To process the large amount of high-resolution data, we used eCognition, an object-based classification software (Trimble Navigation Limited, Colorado, USA). Object-based approaches avoid problems associated with high-resolution data and very small pixels, by first splitting the image into segments that are spectrally similar and/or have a consistent parameter (e.g. shape, length, volume) associated with them. We created a base classification using 5% randomly selected images within a particular image subset. We conducted multiple accuracy assessments for these images until our base classification met or exceeded our accuracy threshold of 70% for total accuracy and minimum 80% for invasive *Phragmites*. We then applied this base classification to remaining images in the subset. The literature has shown that classifications created in one image can be transferred to another with a small decrease in total accuracy (Rokitnicki-Wojcik et al. 2011). While other studies have completed accuracy assessments for every image used, this was not logistically feasible given the large number of images we had in our dataset. To improve total accuracy of the classification when the dates of image acquisition were not similar, we started with our previous base classification and then modified it to incrementally improve the accuracy until an acceptable level could be attained. The base classification was created to primarily identify invasive *Phragmites* but also included other land-cover types (**see Table 3.1**). These classes were subsequently used in our change-detection analyses to determine the land-cover type that invasive *Phragmites* were more likely to colonize. No field data were used in this classification as this project was not started until 2015 and no historic field data were available. Because of the very high resolution of the image data (i.e. 20 cm/pixel), lack of field data would not have affected the accuracy of the base classifications. Image data were extracted from a unique buffer for each road type, with larger roads getting a larger buffer (Highways 120m; arterial roads 80m; city streets 60m)

Manual digitization of invasive Phragmites

Following creation of the 2010 SWOOP database, another post-processing method was used to build the 2015 SWOOP database, and this resulted in image data that were too compressed for automated image classification (Ontario Ministry of Natural Resources and Forestry, pers. comm.). Two trained technicians digitized all of the invasive *Phragmites* within MTO-operated roadways only in the SWOOP 2015, SCOOP 2013 and COOP 2016 datasets. All technicians had been trained to identify invasive *Phragmites* as part of the eCognition classification procedure. To minimize differences in digitization between the two technicians, every road segment was digitized by both individuals and the overlap between the two was output to the final product. A typical accuracy report could not be generated for this protocol because we did not have any independently classified image with which to compare. As a measure of precision, we noted that there was greater than 80% overlap in the digitization by the two technicians. Most of the mismatch corresponded to small differences in boundary delineation. In general, manual digitization tended to produce fewer but larger polygons whereas eCognition was able to pick out many of the smaller stands. These differences combined with invasive *Phragmites* removal efforts by MTO had a large influence on changes between the 2010 and 2015 SWOOP datasets. Knowing these biases, we refrained from conducting a large-scale change detection between these two periods. Even with these differences, however, we were able to assess large-scale changes in the distribution of invasive *Phragmites* between time periods and the three sub-regions within the province.

All statistical analyses were conducted in JMP (SAS Institute, North Carolina, USA; v.13). The data were extracted as database files from ArcPro (v. 2.1; ESRI, California, USA) and analyzed in JMP. Relevant spatial statistics (i.e. area, location) were applied in ArcPro before data export. To appropriately analyze the data and reduce error associated with automated classification, the data were split into 1-km segment for each road, and the data were aggregated at this level. In this way, each road had multiple (>30) data 'points' with areal cover of each land-cover class.

Traffic Volume Data

Traffic volume data were provided by MTO and only included data on highways managed by the agency. The 2016 Average Annual Daily Traffic (AADT) was defined as the average twenty-four hour, two-way traffic per year. This statistic was measured empirically for a portion of time and then estimated for each highway segment occurring between two exit ramps and was applied to 1,831 segments across the province.

Results:

2006 and 2010 road datasets

In southwestern Ontario, we conducted automated image classification with 2006 and 2010 image data on 16,270 km of roads (**Figure 3.4**). These data included all road types with speeds above 60 km/h to make the data analyses tractable. Excluded roads were likely to be in residential zones and we have verified (from Google Earth images) that most residential streets lacked available habitat for growth of invasive *Phragmites.* Even if habitat existed, we believe that homeowners would likely have cut down this weed bordering their properties. We did not include roads within the municipality of London (Ontario) in our analyses because the City had implemented an invasive *Phragmites* removal program prior to 2010, and this municipality is one of the largest cities in the study area with many residential streets. In summary, the distribution of roads in the dataset we analyzed had a similar distribution to the whole road dataset within southwestern Ontario, excluding the large proportion of city streets with posted speed limits below our 60 km/h threshold (**Figure 3.3a**).

Automated Image Classification of SWOOP

Based on our automated classification, the amount of invasive *Phragmites* grew from 275 ha in 2006 to 634 ha in 2010, representing an increase of 235% over the four-year period, with a growth of nearly 60% per year. The distribution of invasive *Phragmites* in road types also differed between the two time periods (**Figure 3.5**). During

2006, invasive *Phragmites* were distributed disproportionately on arterial roads compared with highways (54% vs 12% respectively). By 2010, however, this dropped to 45% and 8.4%, respectively. Most of the difference in distribution of invasive *Phragmites* came from collector roads, which grew from 17% in 2006 to 30%% in 2010. While representing a small total area, highway ramps had the largest percent increase between years, growing from 0.05% to 0.25%. The areal cover of invasive *Phragmites* per 1-km segment also increased from 3.073 ± 0.005 (maximum size 243.08 m^2) to 4.269 ± 0.006 m^2 (maximum size 306.78 m^2). The mean areal cover per kilometre of road in both years was associated with highway ramps, and these more than doubled in size from 2.957 ± 0.229 in 2006 to 7.732 ± 0.286 in 2010; by comparison, dimensions of invasive *Phragmites* stands on most other road types were constant throughout these time periods.

A change detection indicated that almost 60% of the invasive *Phragmites* in 2010 had been classified as grasses in 2006 (**Figure 3.6a**). This rate of conversion was four times higher than that of any other cover class. Only 0.5% of invasive *Phragmites* in 2010 had been mapped as invasive *Phragmites* stands in 2006 (32 ha). The most resilient classes were the forests (deciduous and coniferous), which were least likely to be invaded. We also assessed which habitat category eventually took over areas occupied by invasive *Phragmites* in 2006. The dominant change of land cover was to coniferous trees, which is likely indicative of their growth between 2006 and 2010. Grasses was the next most abundant class; this may be the result of maintenance projects (such as ditching, where the topsoil and plants had been removed to restore proper drainage) for which we do not have comprehensive records. A change to built-up environments may also have been due to construction projects or road maintenance projects between 2006 and 2010, during which new asphalt or concrete had replaced *Phragmites* stands.

The areal cover of invasive *Phragmites* had been widely distributed in the study area in both 2006 and 2010. We analyzed only road segments containing invasive *Phragmites,* and found that in 2006, invasive *Phragmites* occupied 3.07 m^2/km of roads in southwestern Ontario; by 2010, this invader occupied a higher areal cover of 4.27 m^2/km of road and was distributed more widely within the road network. Assuming that invasive *Phragmites* had grown exponentially between 2006 and 2010, the exponential growth equation $N = N_0e^{rt}$ would predict a growth rate of 0.178. If we apply this growth rate to the 634 ha in 2010, the total areal cover of invasive *Phragmites* by 2015 would have expanded to 1,544 ha within the study area associated with our automated image classification (i.e. as defined in **Figure 3.4**).

We analyzed the amount of available space in corridors of different road types that had been colonized by invasive *Phragmites* in southwestern Ontario using the 2010 SWOOP images (Figure 7). Although there was 1.6 times more habitat associated with arterial roads than with collectors, the proportion of this space that had been colonized by invasive *Phragmites* was only 61% for arterial roads compared with 67% for collectors. Approximately 15% of the available habitat in ramps had been colonized compared with less than 12% of available habitat in expressways.

Manual Digitization

Due to the heavy investment of time and labour required for manual digitizations, we had to restrict our analyses to only roads managed by MTO within the most recent orthophotography datasets (i.e. SWOOP 2015 (after treatment); SCOOP 2013 and COOP 2016). We analyzed 2,624 km of roads in the 2015 SWOOP dataset, and mapped 331.47 ha of invasive *Phragmites* (**Figure 3.8a**). Within the SCOOP 2013 dataset, we mapped 151.95 ha of invasive *Phragmites* on 2,586 km of roads (**Figure 3.8b**). By comparison, the total areal cover of invasive *Phragmites* in the COOP 2016 dataset was very low, with only 7.78 ha over 4,738 km of roads (**Figure 3.8c**). Similar to what we observed for the 2010 SWOOP dataset, most of the areal cover of invasive *Phragmites* in 2015 occurred within corridors of the 400-series highways (**Figure 3.9**). When we analyzed the 2013 SCOOP dataset, we found the greatest areal cover on Highway 400, although it was comparatively lower than the amount of invasive *Phragmites* found on Hwy 612 and 632. Currently, there are no major roads such as the 400-series highways within the 2016 COOP dataset. In this central Ontario region, Hwy 539A had the highest density of invasive *Phragmites*, but only 2km of this road had been available for this study.

Traffic Volume Data

An advantage of using MTO roads was the additional opportunity to compare the influence of traffic volumes on the distribution of invasive *Phragmites* on road rights-of-way. We grouped roads in this portion of our study according to road name/route (i.e. 400-series or Trans-Canada vs others) and excluded highways where less than 25 km were analyzed within our dataset. In the 2015 southwestern dataset, the abundance of invasive *Phragmites* was much higher on roads that had more habitat available (i.e. larger roadside rights-of-way in the Hwy 400 series highways) (Figure 9a). Accordingly, approximately 50% of all invasive *Phragmites* mapped in this footprint of our study occurred on the 400-series freeways. In the same areas in 2010, this number had been slightly lower at 45%. Traffic volume varied along and among roads, though without exception, traffic volume on major highways (i.e. 400-series) were significantly higher than that on any other road type (t-test, $p>0.001$; Figure 10). Regardless of the region, when we regressed invasive *Phragmites* areal cover against traffic volume, we found a significant effect ($P<0.0001$), albeit the amount of explained variation was low (R^2 = 0.001, 0.022, and 0.057 for SWOOP 2010, SCOOP 2013, & COOP 2016 respectively). This effect was stronger on non-major highway types but still explained less than 10% of the overall variation in areal cover of invasive *Phragmites*.

Discussion:

Previous studies have noted that land cover and geography may influence the presence of invasive *Phragmites* on roadsides (Lelong et al. 2007, Maheu-Giroux et al. 2005, Brisson et al. 2010). These studies were conducted in Quebec where invasive *Phragmites* had been established for a long time, whereas in roadway corridors of southwestern Ontario, the invasion occurred relatively recently, having been established initially in the late 1940s (Wilcox et al. 2003; Catling & Mitrow 2011). Although invasive *Phragmites* has been spreading via a major highway from Quebec to Ontario since the 1970s (Lelong et al. 2007; Maheu-Giroux & de Blois 2005), our 2006 mapping results included many small invasive *Phragmites* patches on spatially restricted roadsides, suggesting that the invasion was at an early stage of invasion. We did not see evidence of rapid growth and expanded distribution of invasive *Phragmites* in roadway corridors until 2010. Given that the expanded growth of invasive *Phragmites* had already been documented in wetlands as early as 1988 (Wilcox et al. 2012), there may have been a lag from 2000 to 2006, before growth exploded on road sides during the subsequent decade (Crooks 2005).

The extremely large size of our database (tens of thousands of image tiles) severely limited our ability to conduct automated image classification and accuracy assessments on most of our images. We were also limited by lack of field data to conduct accuracy assessments, and the timing of the image acquisition (during spring) also led to problems associated with accurate classification of vegetation other than invasive *Phragmites.* This is because invasive *Phragmites* overwinter with their stems and ramets in upright position and their clonal growth gives stands a characteristic round shape that are easy to identify when they are surrounded by senescent vegetation or bare ground.

While transferal of a classification scheme from image to image in eCognition has been carried out successfully by Rokitnicki-Wojcik et al. (2011), this protocol could contribute an additional source of error when tiles used for calibration do not contain all of the land-cover classes. These errors may have been greater in the 2006 mapping because there had been fewer stands of invasive *Phragmites* that were of smaller size and that had not been uniformly distributed among the image tiles. Under these circumstances, transfer of a classification scheme developed with tiles that did not contain invasive *Phragmites* could lead to errors when applied to tiles containing invasive *Phragmites*, and vice versa. Although we cannot estimate the extent of this error, we feel that our use of randomly chosen tiles for calibration should minimize this error.

In some portions of the dataset, the buffer we applied around the centreline included adjacent forests. Since it is difficult to spectrally distinguish between invasive *Phragmites* and shadows cast by trees in forested areas, forests that fell within the buffer could artificially inflate the areal cover of invasive *Phragmites* on these road sides. This may explain the artifact we observed when some of the forested land in the 2006 image was transformed to invasive *Phragmites* in the 2010 image, since it is unlikely that a grass could displace mature trees. The large change from deciduous trees is likely due to poorer accuracy of identifying that particular land-cover class due to leaf-off conditions and abundant shadows. The 400-series highways have very large roadside rights-of-way but limited forest cover; therefore, this issue likely applies to collector and arterial roads where forested landscapes are more common. In general, southwestern Ontario is an agriculturally dominated landscape and we believe our results are still indicative of general trends in the landscape.

While invasive *Phragmites* can damage road infrastructure and directly replace it, changes in land cover from built-up land to invasive *Phragmites* are likely due to construction projects. Over the four years from 2006 and 2010, many constructions projects were carried out along roadsides in southern Ontario. We were unable to find all possible locations where road work could have altered the landscape to make more habitat available for invasive *Phragmites*. These plants can grow very tall (> 4.5 m) and their canopy may appear over top of roads from an aerial perspective if they sag towards built up surfaces (such as sidewalks, roads, and parking lots) from their habitat in roadway rights-of-way.

Our conceptual model predicted that we should observe high replacement rate of grass-covered areas by invasive *Phragmites*, and this was borne out by our data. In such roadside habitats, governments tend to seed with fast-growing short grasses and sedges. It is very likely that the higher salinity and physical disturbance in these highway ditches offer a competitive advantage to invasive *Phragmites*. Future research should identify the mix of native seeds that are likely to compete effectively against invasive *Phragmites*. Re-seeding with an appropriate mix of road-side plants may be an important follow-up action following herbicide application (Kettenring & Adams 2011)

During 2006, the highest areal cover of invasive *Phragmites* occurred on arterial roads and the size of stands were generally small; by 2010, dominance by invasive *Phragmites* occurred in collector roads, and the size of stands had grown considerably in size. This trajectory may be the result of higher volume of vehicular traffic on arterial roads initially which distributed seeds and plant fragments over long distances and eventually reaching adjacent roads that are used less frequently. Over time, the collectors would become invaded as seed dispersal continue to expand (Brisson et al. 2008; Albert et al. 2015). Our results suggest that there is at least three or four years between road invasion when stands are small and distributed more locally until they become large and are distributed widely. Since smaller stands of invasive *Phragmites* are more effectively treated than are larger stands (Marcaccio and Chow-Fraser 2019; CH 4), we recommend that arterial roads be preferentially targeted for eradication to prevent further spread of propagules and seeds within road networks.

Southwestern Ontario is the most densely populated subregion in Ontario and may have facilitated the rapid expansion of invasive *Phragmites* due to increased anthropogenic disturbance between 2006 and 2010. As defined in our conceptual model (Figure 1), high nutrient loading for agriculture and urban areas combined with a high density of roads would benefit invasive *Phragmites*. The areal cover we mapped for this region across only MTO-operated roads in 2015 was 331.5 ha. This amount of invasive *Phragmites* is only half of what would have been expected (632.4 ha) if it had been allowed to grow exponentially (growth rate of 0.568 calculated for highways in this study area). The lower growth reflects the results of a large-scale removal program implemented by MTO in southwestern Ontario beginning in 2012. It is sobering to think that if no treatment program had taken place at all, the amount of invasive *Phragmites* in MTO-operated roadways might expand to 4,445.0 ha by 2020.

The SCOOP dataset had two major highways that accounted for approximately 20% of all invasive *Phragmites* within the dataset, even though they occurred in a region with relatively low population densities. Nevertheless, these highways are corridors to northern communities and have moderately high traffic volumes. Unlike the 400-series highway segments in southwestern Ontario, those in southcentral Ontario did not support invasive *Phragmites* to the extent expected based solely on traffic volume. To facilitate valid comparisons, we calculated the 2015 theoretical areal cover of invasive *Phragmites* using the instantaneous growth rate of 0.568 and the 2010 SWOOP and 2013 SCOOP data for southwestern and southcentral regions, respectively. The predicted areal cover of 632.4 ha for southwestern Ontario was 33% higher than that of 473.2 ha calculated for southcentral Ontario. This discrepancy between regions may be due to differences in bedrock geology between southwestern and southcentral Ontario. Southwestern Ontario is underlain by glacial till (luvisolic), which supports rich farm lands, whereas southcentral Ontario is forested and is underlain by nutrient-poor granitic rock that would not have given a competitive advantage to invasive *Phragmites*, given its requirement for a high-nutrient environment (Mozdzer et al. 2013, Holdredge et al. 2010). This comparison illustrates the complex factors that must be considered when modelling the rate of expansion and colonization pattern of invasive *Phragmites* across different landscapes and the relative importance of various landscape and site-specific factors (**Figure 3.1**).

There were no major highways (i.e. 400-series) associated with the COOP dataset, but it is noteworthy that most of the invasive *Phragmites* were found on two roads, Hwy 11 and 17, though admittedly, their total areal cover were relatively low compared with those in the southwest and southcentral regions (**Figure 3.9c**). Hwy 11 connects southern Ontario with Minnesota and was recently twinned in the study area while Hwy 17 passes east-west through nearly all of Ontario. Both are part of the Trans-Canada highway system, so while they are not as wide as the 400-series highways, they play a major role in cross-country movements. Given the high traffic volume and their juxtaposition between two infected regions, successful invasion would have happened even with a few invasive *Phragmites* propagules per vehicle. For these reasons, it is incredibly important to control invasion levels even if roads are located in remote regions.

Even with an active eradication program, southwestern Ontario had the largest areal cover of invasive *Phragmites* by a large margin compared with the other two regions. Based on our conceptual model (**Figure 3.1**), we suggest that the invasion rate had been decreased in eastern and central Ontario compared with southwestern Ontario because of lower agricultural development. The southwest is also home to many of Ontario's largest coastal wetlands (e.g. Walpole Island Wetland Complex, Rondeau Bay Wetland Complex and Long Point Bay Wetland Complex) that are known to support a large population of invasive *Phragmites* (see CH 2; Borgeau-Chavez et al. 2015) and would therefore provide a constant source of propagules. Partial support for this hypothesis is the observation that between 2006 and 2010, the distribution of invasive *Phragmites* on roadsides changed dramatically: the cover in arterial roads decreased while those in collector roads, highway ramps and suburban roads showed a corresponding increase. Many of the arterial roads that were initially colonized were located close to wetland sites, and it would have taken more time before propagules could have spread to collectors, ramps, and other suburban roads.

Previous studies have proposed traffic volume as being important for propagule distribution over road networks (Gelbard & Belnap 2003; Catling & Mitrow 2011). Although we found a statistically significant effect of traffic volume on the areal cover of invasive *Phragmites*, it alone did not have much resolving power. In our conceptual model (Figure 1), traffic volume was predicted to be only one of three variables that may influence the colonization pattern of invasive *Phragmites.* We speculate that even if traffic volume were high, invasive *Phragmites* would not establish dense stands unless habitat was available and suitable. Our findings support this speculation since the density of invasive *Phragmites* in Hwy 400 in southcentral Ontario was low, even though there was high traffic volume.

As we did not analyze roads other than highways in the SCOOP and COOP datasets, we cannot conduct the same analysis to determine the distribution of invasive *Phragmites* in different road types. Since both southcentral and central Ontario regions have many more kilometres of arterial roads than does southwestern Ontario, the possibility of invasive *Phragmites* invasion is high, and we believe that both southcentral and central Ontario will become infested with invasive *Phragmites* unless immediate coordinated management actions are taken to restrict their spread.

Invasive *Phragmites* is present on nearly all roads in southern Ontario, and it continues to expand throughout these road networks. Divided highways with medians offer more habitat than other road types, which typically leads to greater areal cover of invasive *Phragmites* but not necessarily to the highest mean areal cover per km of road (see **Figure 3.9 d-f**). The greatest amount of invasive *Phragmites* currently occurs in the southern portion of the province, where there are both major highways and large wetland complexes. We are aware that small populations of the less aggressive native haplotype exist within southern Ontario, and do not exhibit invasive behaviours and therefore do not need to be treated or removed. The current remote-sensing techniques, however, cannot differentiate between native and invasive haplotypes.

We speculate that invasive *Phragmites* is still at an early stage of invasion and will likely continue to expand into any and all available habitat unless they are treated with suitable herbicides (see Chow-Fraser & Marcaccio 2018; CH 4). This is necessary to prevent the roughly ten-fold expansion that occurred between 2006 and 2010 in southwestern Ontario. While the growth rates between southwestern Ontario and the rest of the province are likely not the same due to other landscape factors, using our determined growth rate and manually digitized roads we could see 806 ha, 528 ha, and 8 ha of invasive *Phragmites* in southwestern, southcentral, and central Ontario, respectively, as of 2016, when the last image data (Central Ontario) had been acquired. Our data serve as an important historical assessment of roadways in Ontario that could not have been achieved with other data sources. In the future, newer technologies and sensors should be explored for image classification along roadway corridors (see Rupasinghe & Chow-Fraser 2018). As defined in our conceptual model (**Figure 3.1**), any areas that have suitable habitat (high moisture, no existing woody plants) are likely to be colonized in short order, and existing stands will continue to expand until they meet a physical barrier. Results of this study, the first comprehensive time-lapse mapping of *Phragmites* in highway corridors of Ontario, illustrates how quickly and far-reaching this invader can expand over four short years if it is allowed to grow unchecked, and should be a stark warning to other jurisdictions not to be complacent.

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Table 3.1: Classes included in the image classification process.

Classes	**Explanation**
Phragmites	Class of interest
Grasses	Small ground-covering plants that occupy majority of land cover
Shrubs	Small plants that are woody/more robust than grass
Deciduous Trees	Bare leafless tree, generally indicating it is deciduous
Coniferous Trees	Conifers; still green in early spring orthophoto
Paved	Any built-up surface, such as road, building, sidewalk, etc.
Water	Streams near roads
Shadow	Land cover obscured by shadow, resulting in dark/black area

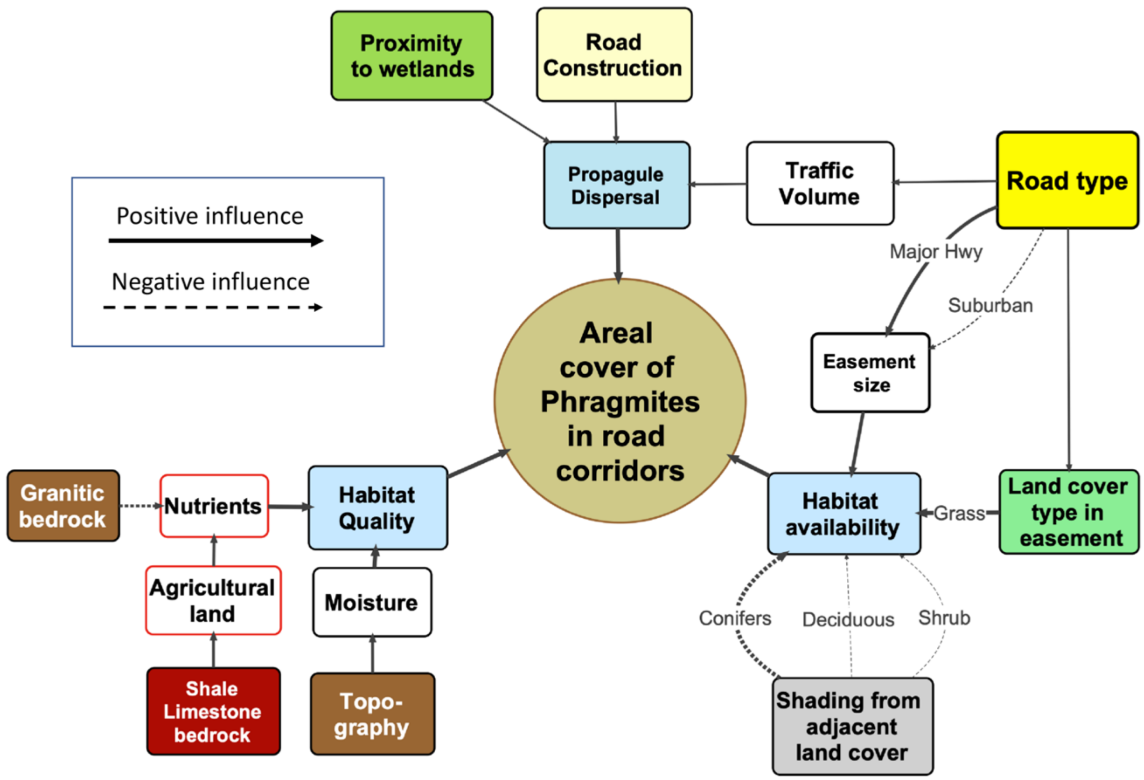


Figure 3.1: Conceptual model to show the relationship among three main factors and associated variables that influence the distribution of invasive *Phragmites* within corridors of road networks.

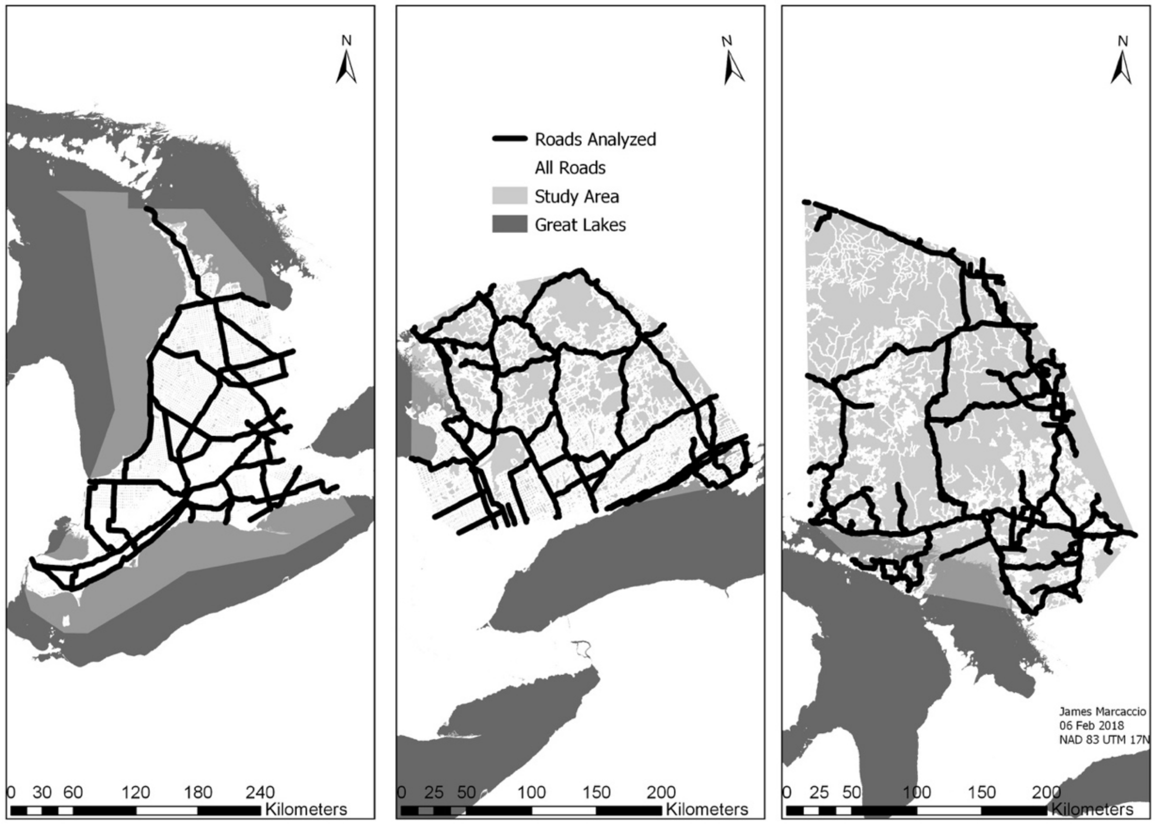
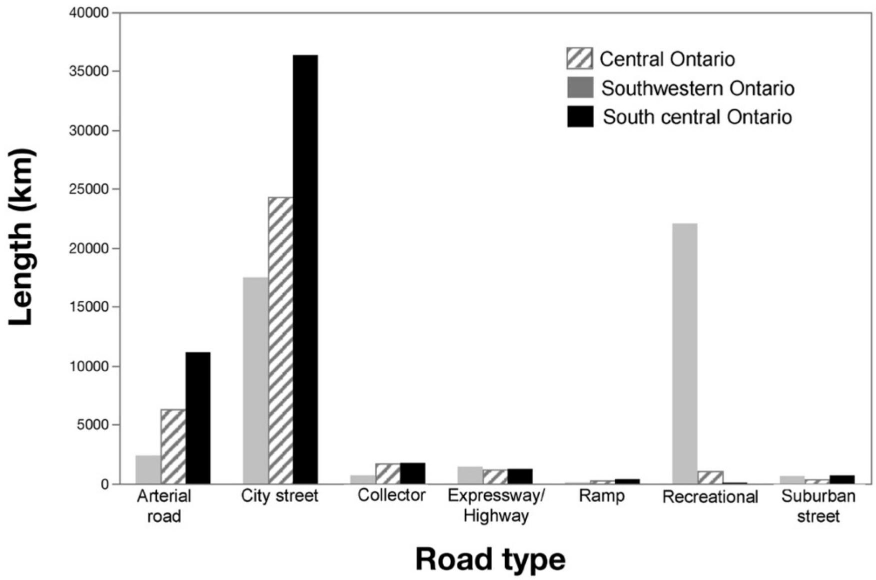


Figure 3.2: Area covered by various Ontario orthophotography project databases. The area covered by SWOOP for 2015 and 2010 is the same but that for 2006 did not include portions around Hamilton and Niagara. SCOOP was completed in 2013 while COOP was completed in 2016.

a)



b)

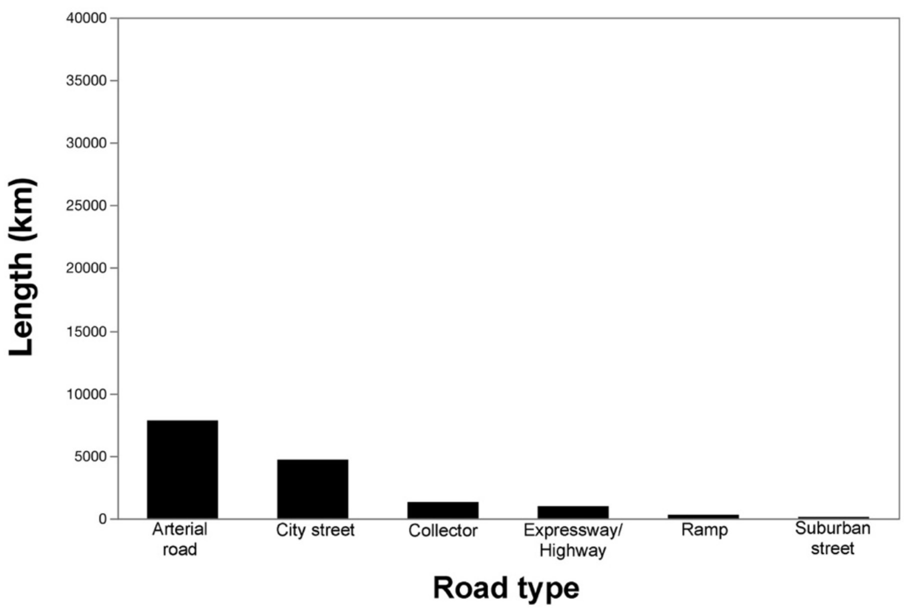


Figure 3.3: Total length by road type for a) southwestern Ontario, south central Ontario and central Ontario, calculated from SWOOP, SCOOP and COOP image data, respectively and b) total length by road type for subset of SWOOP data used in change detection (see Figure 3).

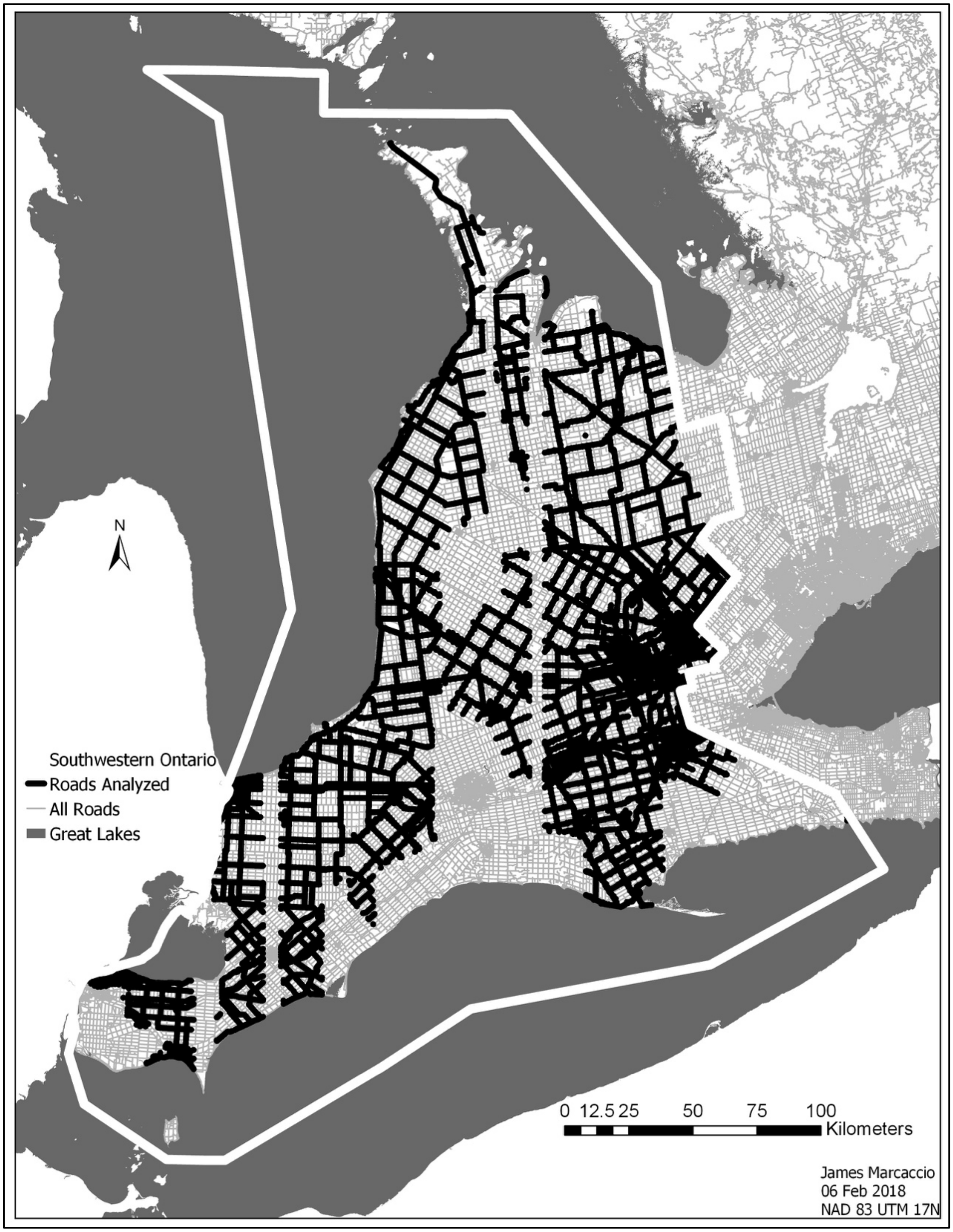


Figure 3.4: Roads in southwestern Ontario that were included in the 2006 and 2010 automated classification analyses (black). See text for explanation of excluded road segments (light grey).

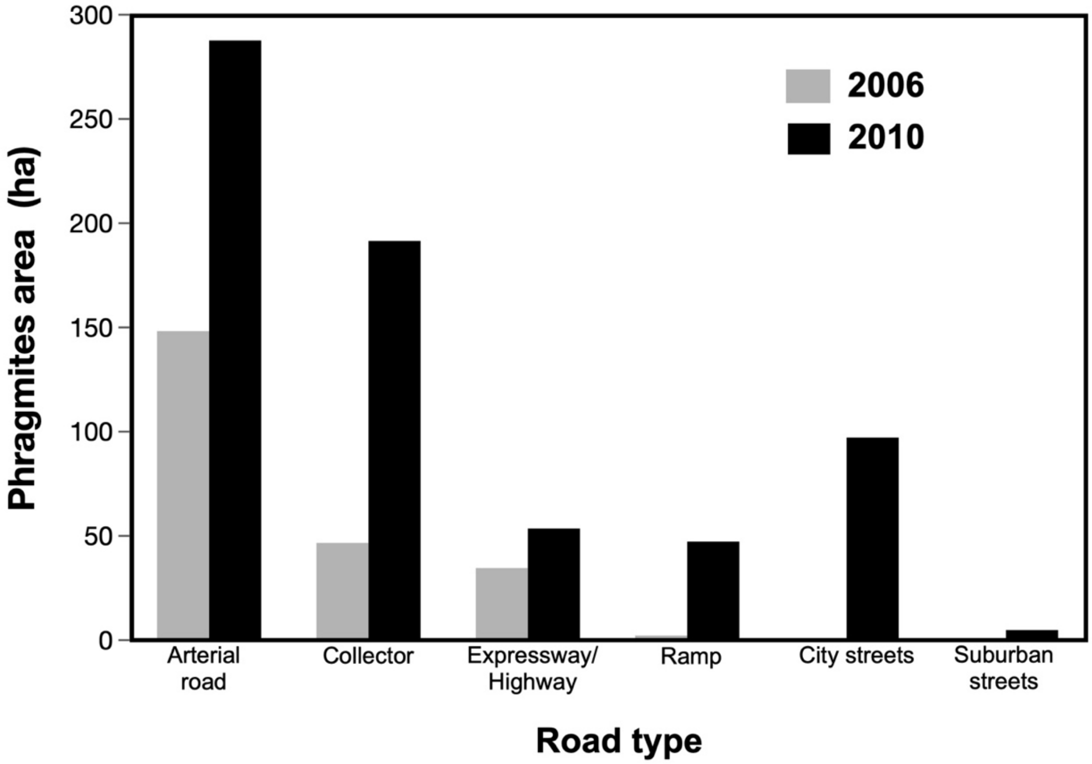
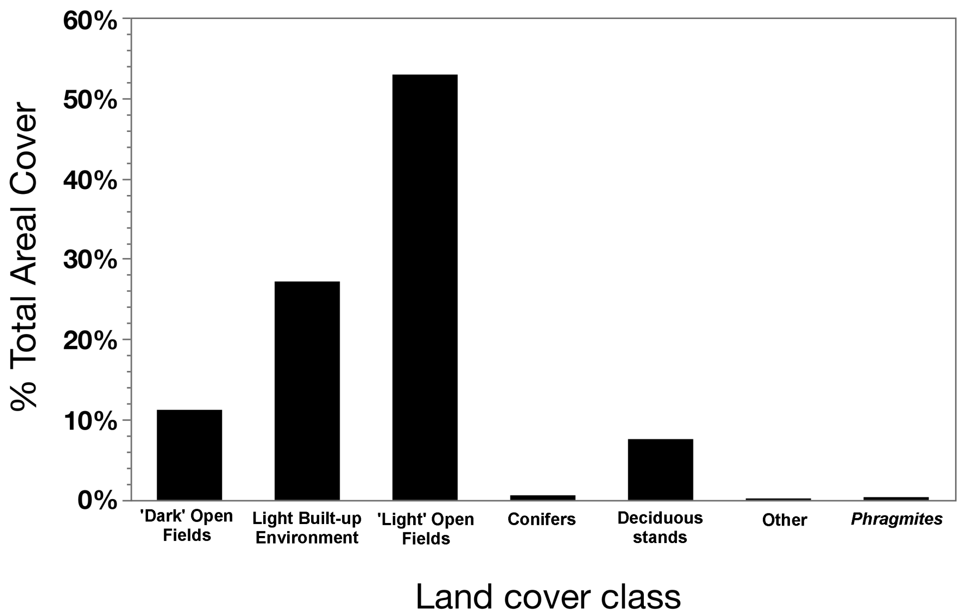


Figure 3.5: Total areal cover of invasive *Phragmites* (ha) calculated for each road type in 2006 and 2010 within southwestern Ontario. Calculations are based on automated classification of SWOOP images.

a)



b)

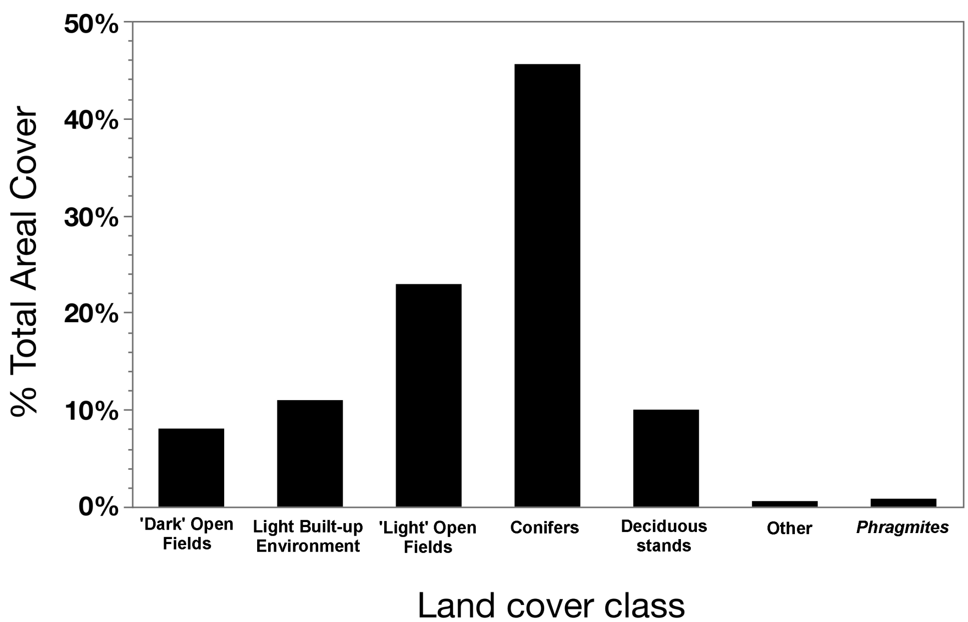


Figure 3.6: a) Percentage of 2006 land-use land-cover classes by areal extent that was colonized by invasive *Phragmites* in 2010 in southwestern Ontario and b) percentage of 2010 land-use land-cover classes by areal extent that had been occupied by invasive *Phragmites* in 2006 in southwestern Ontario.

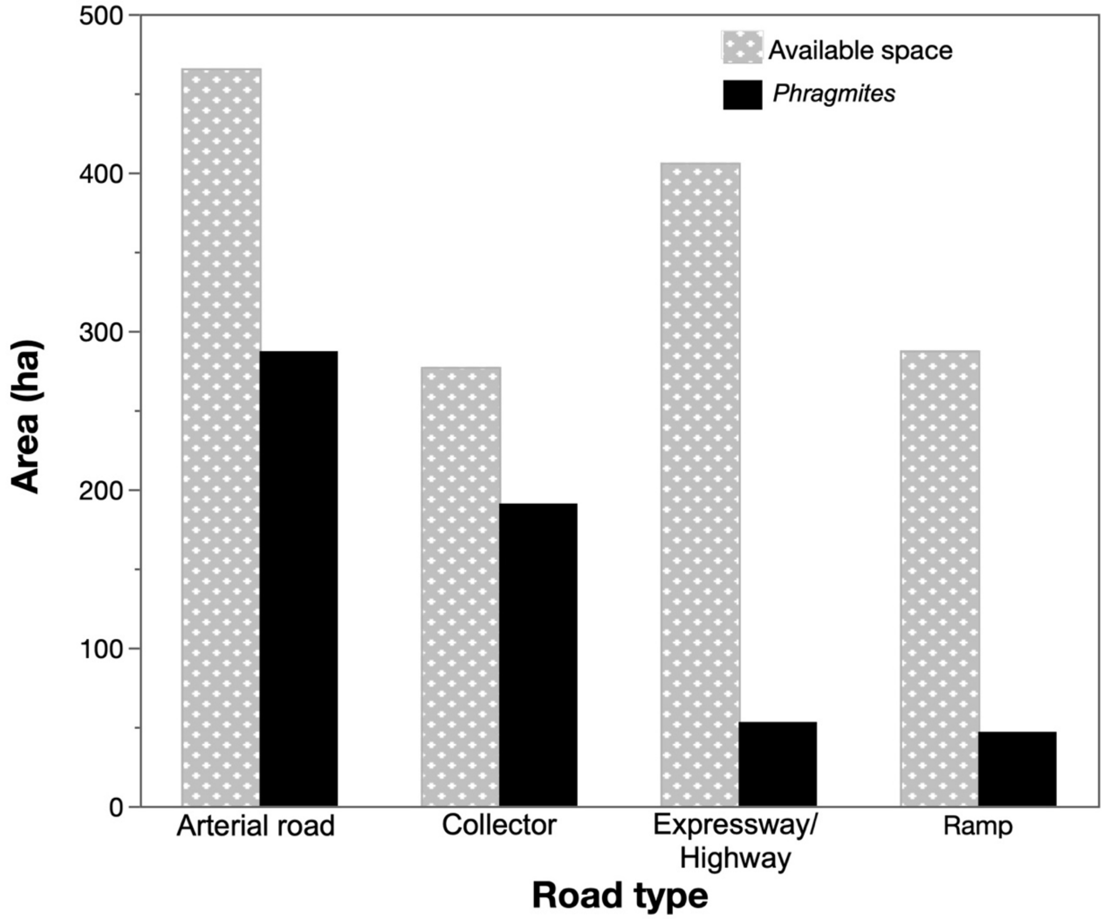


Figure 3.7: Comparison of total area occupied by invasive *Phragmites* and available space in corridors of different road types within southwestern Ontario. Automated classification was used to map *Invasive Phragmites* in the 2010 SWOOP images.

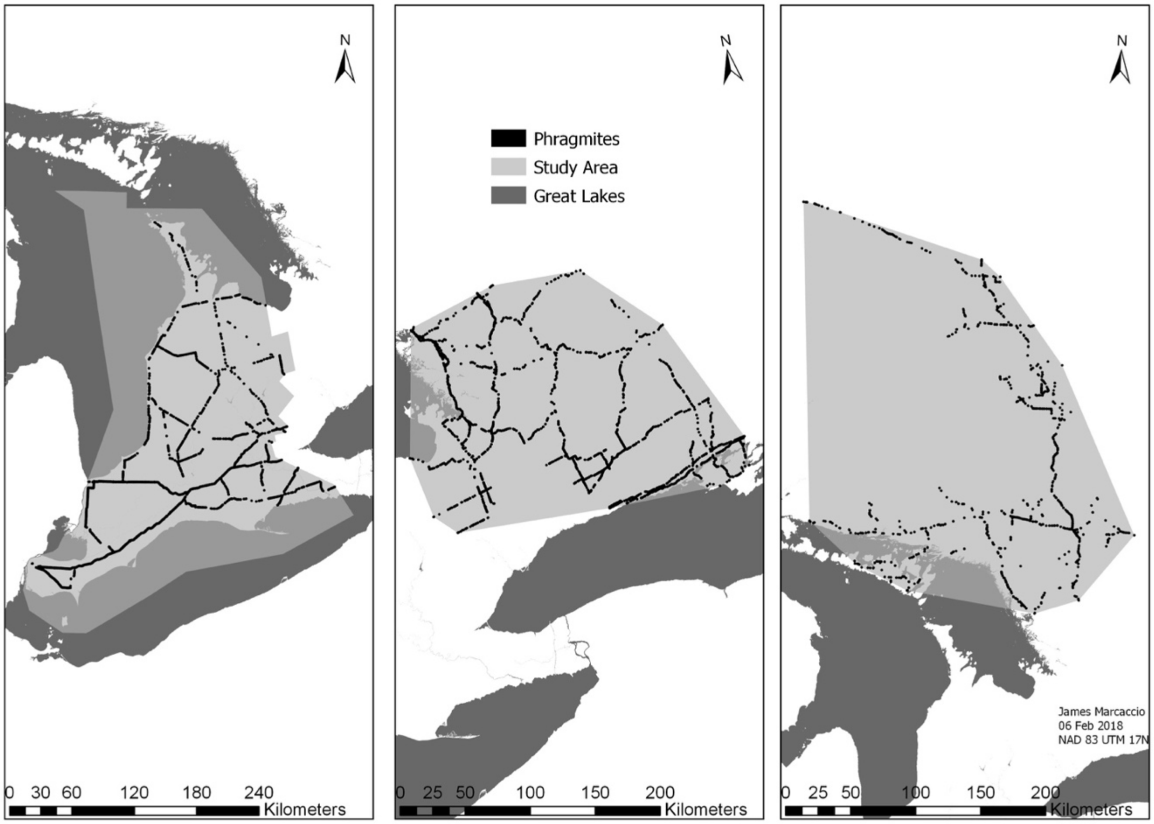


Figure 3.8: Distribution of invasive *Phragmites* in corridors of provincial highways in a) south western Ontario in 2015 b) south central Ontario in 2013 and c) central Ontario in 2016. *Phragmites* were mapped digitally. Outlines of polygons have been thickened to allow them to be visible at this scale.

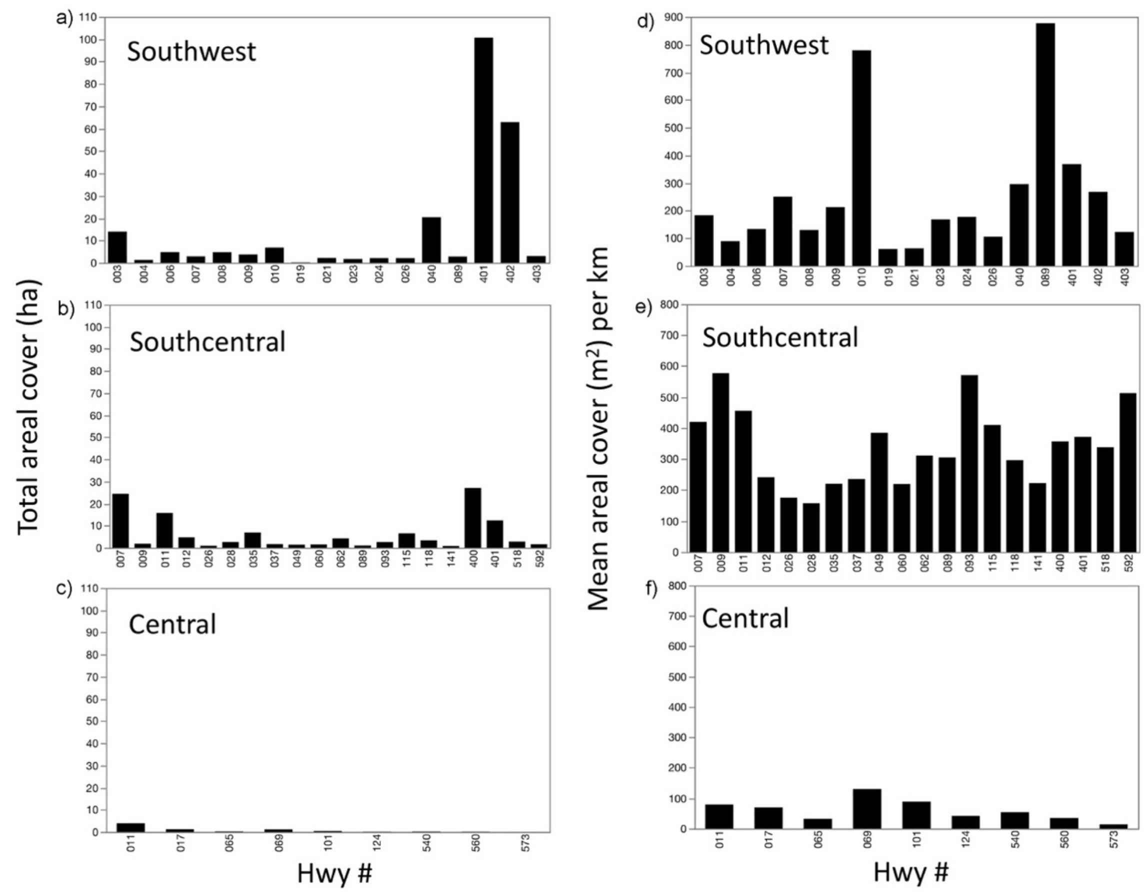


Figure 3.9: a-c) Total areal cover (ha) of invasive *Phragmites* calculated for each Hwy # in three named regions d-f). Mean areal cover of invasive *Phragmites* per km of highway in three named regions. Roads included in this graph had a minimum of 25 km of highways analyzed.

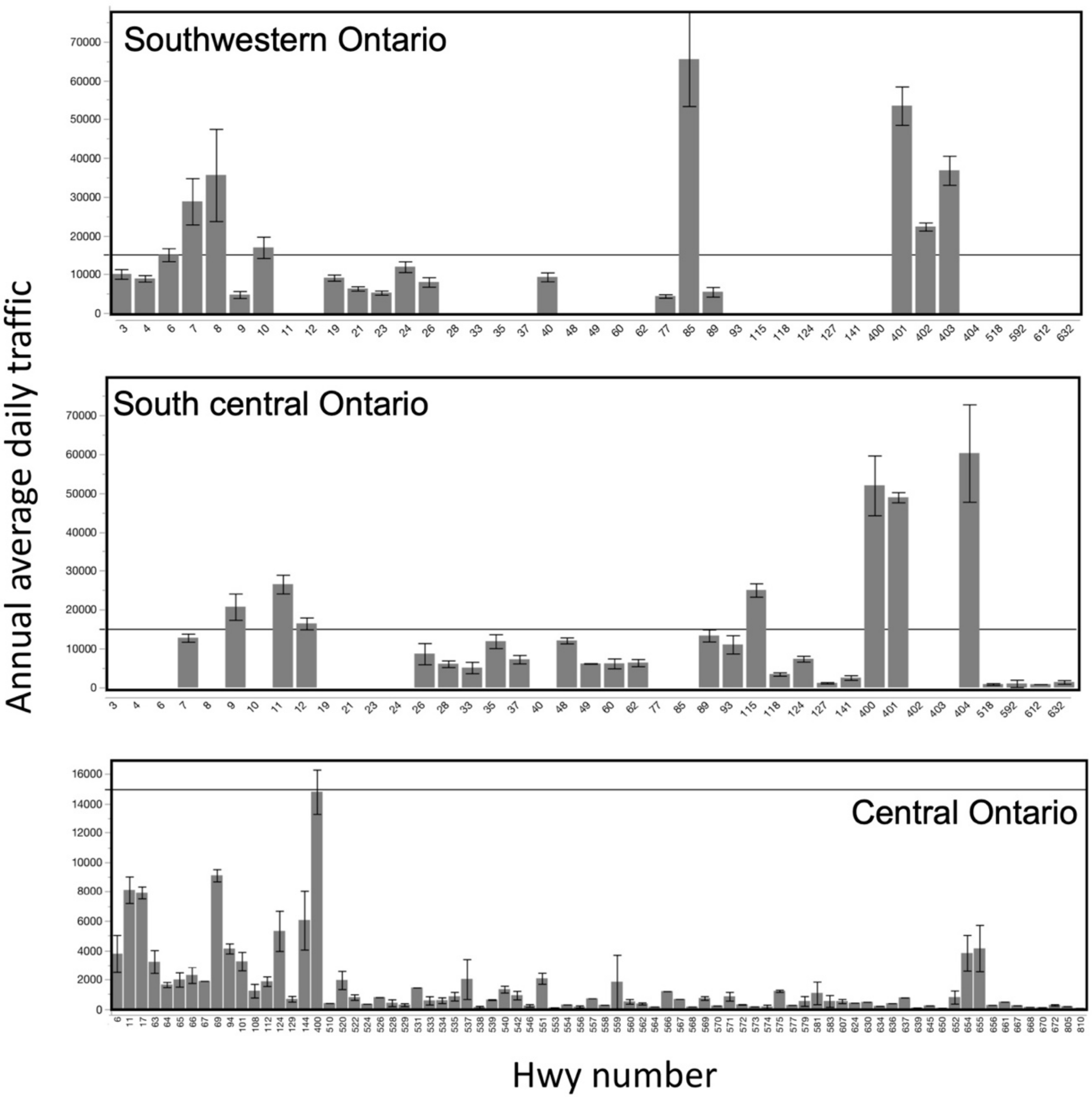


Figure 3.10: 2012 mean$\pm$SE daily traffic (number of vehicles enumerated) calculated for provincial highways in Ontario for three named regions. The reference line in each panel corresponds to 15,000 vehicles/day

Chapter 4: Use of fixed-wing and multi-rotor unmanned aerial vehicles to map dynamic changes in a freshwater marsh

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Marcaccio, J. V., Markle, C. E., & Chow-Fraser, P. (2016). Use of fixed-wing and multi-rotor unmanned aerial vehicles to map dynamic changes in a freshwater marsh. *Journal of Unmanned Vehicle Systems*, *4*, 193–202. http://doi.org/10.1139/juvs-2015-0016

Abstract:

We used a multi-rotor (Phantom 2 Vision+, DJI) and a fixed-wing (eBee, senseFly) unmanned aerial vehicle (UAV) to acquire high spatial-resolution composite photos of an impounded freshwater marsh during late summer in 2014 and 2015. Dominant type and percent cover of three vegetation classes (submerged aquatic, floating or emergent vegetation) were identified and compared against field data collected in 176 (2m x 2m) quadrats during summer 2014. We also compared these data against the most recently available digital aerial true colour, high-resolution photographs provided by the government of Ontario (Southwestern Ontario Orthophotography Project (SWOOP), May 2010), which are free to researchers but taken every five years in leaf-off spring conditions. The eBee system produced the most effective data for determining percent cover of floating and emergent vegetation (58% and 64% overall accuracy, respectively). Both the eBee and the Phantom were comparable in their ability to determine dominant habitat types (moderate Kappa agreement) and were superior to SWOOP in this respect (poor Kappa agreement). UAVs can provide a time-sensitive, flexible and affordable option to capture dynamic seasonal changes in wetlands that ecologists often require to study how species at risk use their habitat.

Introduction:

In ecological research, especially in the field of conservation, aerial images are a prerequisite to creating effective management plans for ecosystems and species-at-risk. Without accurate knowledge of what habitat is present and how it is changing, it is difficult to form a management or recovery strategy for endangered species and places. The conventional method of image acquisition, using sensors mounted on planes or satellites, can collect image data for large areas at a time, but can cost tens or hundreds of thousands of dollars depending on the region of interest (Anderson & Gaston, 2013). Although these methods can acquire image data for large areas, it can be difficult to use these to obtain data for a specific time period of interest (e.g. year, season or day). For instance, satellites can only obtain photos on days when the image sensor is in line with the study area, and then these photos take time to come to market. Air photos require detailed planning and can be limited by weather and flight regulations. Desired image data may never be obtained for a study site, and consequently researchers and management agencies often have to settle for whatever image data are available. For example, timing of aerial image data collection can limit ability of investigators to study movement patterns and habitat use of migratory animals (Markle and Chow-Fraser, 2014), carry out change-detection analyses (Singh, 1989), or monitor the spread of invasive species (Wan et al., 2014).

Recent advancements in technology have opened up a new source for aerial image data: unmanned aerial vehicles (UAVs), commonly referred to as drones. These systems fly without an onboard operator and are controlled remotely from the ground. The proliferation of the ‘flying camera’ market for recreational users has permitted lower prices with consistent improvement in quality of all small-scale UAVs. One of the most important additions to UAVs has been global positioning systems (GPS), with live-feeds of video (first person view; FPV) and base stations that can determine the UAV’s location. Equipped with these, a UAV can know its own location in three-dimensional space and apply this to its image data to allow operators to view the landscape from the UAVs point of view during flight.

Many potential uses of this new technology in the field of ecology are being explored, although not all have yet been attempted or brought to their full realization, especially for time-sensitive research (Rose et al., 2014). Martin et al. (2012) have brought this to light, using an artificial study identifying randomly placed and randomly covered tennis balls in the hopes that it can provide a crucial positive application to conservation. Researchers have attempted to quantify the accuracy (e.g. Chabot & Bird, 2013; Gómez-Candón et al., 2013) and savings (e.g. Brekenridge et al., 2012) of a UAV-based mapping approach. Breckenridge et al. (2012) found that using a helicopter-style UAV for determining vegetation cover was 45% faster compared to in-field identification. In addition to faster surveys, they found no difference in vegetation cover interpretation between these techniques (Breckenridge et al., 2012), which could be due to the higher degree of texture seen in UAV image data as compared to traditional image data sources like satellites (Laliberte & Rango, 2009). An approach with fixed-wing, plane-style UAVs has also been used, which yielded highly accurate images (Koh & Wich, 2012; Chabot & Bird, 2013). Gómez-Candón et al. (2013) used a quad-copter to produce image data suitable for monitoring agricultural crops, and Wan et al. (2014) monitored growth of invasive species in salt marshes of China. Moreover, they determined that flight paths 30 metres above ground only required a few ground-control points to maintain spatial accuracy of these images.

The purpose of our study is to compare the ability of recently available multi-rotor and fixed-wing UAVs to produce image data that permits accurate mapping of wetland vegetation when compared to field-collected vegetation data. We will also compare UAV image data with the most recently available digital aerial photographs provided by a consortium of governments in Ontario (Southwestern Ontario Orthophotography Project (SWOOP), May 2010). These orthophotos are true colour and have been acquired during spring (vegetation in leaf-off conditions) at 4-year intervals since 2002. They are commonly used in Ontario research projects because they are provided at no cost to researchers and cover almost all of southwestern Ontario. While many studies have assessed the merits of these technologies with respect to object-based image classification (Laliberte et al., 2011; Laliberte et al., 2012; Knoth et al., 2013), we present a comparison directly between image data and field data.

Study Site

Our study took place in a 90-ha impounded wetland located within a larger wetland complex along the northern shore of Lake Erie, Ontario (**Figure 4.1**). The owner of the dyked wetland regulates water levels within the impounded area to discourage establishment of invasive emergent species like the non-native *Phragmites australis spp. australis* and consequently only a few of these are found within the impoundment. This is in striking contrast to the edge of the impoundment, which is covered with this invasive subtype. Overall, the most common emergent vegetation (EM) in this area is cattail (*Typha* spp.) and swamp loosestrife (*Decodon verticillatus*), along with a variety of floating aquatic vegetation (FL) (e.g. *Nymphaea odorata, Nymphoides peltata*) and submerged aquatic vegetation (SAV) (e.g. *Ultricularia* spp., *Potamogeton* spp.). This diverse and dynamic vegetation community provides habitat for many at-risk turtles, snakes, and birds (Environment Canada, 2015).

Materials and Methods:

Piloted aircraft image acquisition

Image data from piloted aircraft used in this study were obtained from the Southwestern Ontario Orthophotography Project, herein referred to as SWOOP (SWOOP, 2010). Various levels of governments provide funds to acquire images (leaf-off conditions) every 4 years for a large portion of southwestern Ontario. We use these image data from piloted aircraft because they are commonly used in Ontario for research and planning purposes, and are similar to aerial image data from piloted aircraft utilized in many countries. We use the most recent image data available, which were captured in spring (April/May) 2010 using a Leica geosystems ADS80 SH82 sensor. These image data have 20 cm resolution with 50 cm horizontal accuracy (see **Table 4.1**).

Multi-rotor image acquisition

The multi-rotor UAV used in this study was a DJI Phantom 2 Vision+ (DJI, Nanshan district, Shenzen, China), herein referred to as Phantom, is a low-cost unit that is extremely popular amongst recreational UAV pilots. This was operated with a Samsung

Galaxy S3 (running Android 4.3 “Jelly Bean”) and the DJI Vision application. The total weight of the system is 1242 g with a DJI 5200mAh LiPo battery. We kept the remote control at factory settings and flew the UAV with both S1 and S2 levers in the upright position. The S1 lever in this position indicates it is in GPS hold configuration. That is, if the UAV is not given a command it will hold its position regardless of external factors such as wind effects. The S2 lever in the upright position turns off intelligent orientation control. This means that the directional input is always relative to the UAV. For example, pushing the lever forwards will make the drone move forward from its current position, whereas with intelligent orientation control on, pushing the lever forward will move the drone forward with respect to the controller’s position.

The UAV was operated with the lens in the 90-degree position (NADIR) for the duration of the imaging process, and all images were acquired with a DJI FC200 sensor (110-degree field of view, 1/2.3” sensor, 14 megapixel, true colour) from a height of 120 m. This flight height was chosen to balance spatial resolution with the amount of flight time required to collect image data for the study area, with a goal of achieving spatial resolution < 10 cm and capturing all image data in a single day. We opted to fly the UAV manually rather than use the built-in autopilot system because otherwise we would be limited to a flight distance of 5 km, travelling no further than 500 m from the operator. When autopilot is engaged, the flight speed is 10 m/s which would only allow for an 8-minute flight plan and resulting in only 2 flights per battery. Since this severely limits the area of image data we can collect, we opted for manual operation, which allows us to fly a longer period and thereby capture the majority of the study site. We set the camera on the Phantom 2 Vision+ to take photos every 3 seconds (time lapse mode), and set the camera to auto white balance and auto exposure with no exposure compensation. Flight speeds were maintained between 10 and 15 km/h to allow for 60% overlap in post-processing (i.e. image stitching).

We processed the images in Adobe Photoshop Lightroom 5.0 (Adobe Systems Incorporated, San Jose, California, USA) using the lens-correction algorithm provided by DJI for the Vision camera. We cropped images to squares in order to remove the distortion inherent in the 140-degree fisheye Vision+ lens. No other modifications were made to the photos. We then used Microsoft ICE (Image Composite Editor; Microsoft Corporation, Redmond, Washington, USA) to stitch together the suite of photos and used the planar motion 1 option to avoid skewing and distortion. This treatment assumes that all of the photos were taken at the same angle, but may have differences in orientation or height above the ground. The mosaic was visually assessed for accuracy stitching before it was used in a GIS.

We manually geo-referenced the stitched image in ArcMap 10.2 (ESRI, Redlands, California, USA) and imported the available SWOOP image data into ArcMap as a base layer. At first, we attempted to use the GPS coordinates directly from the image metadata for geo-referencing, but the accuracy was too low for this purpose. We had to use this method of processing because the GPS information in the geotagged image is not sufficiently accurate to be used in a software such as Pix4D or photoscan. While the GPS itself has an accuracy of 2.5 m (DJI, 2015), this is not stored in the image data. Even though the coordinates are recorded in degrees, minutes, seconds, no decimal places are recorded in the geotagged image, and this results in a grid-like orientation with 20 m accuracy. For example, if you have two images with different coordinates (43°15’40.19”, 79°55’4.11” and 43°15’40.45”, 79°55’4.49”), only the rounded coordinates are stored with the image (both geotagged images are now located at 43°15’40.00”, 79°55’4.00”); hence, both images would be placed in the same location even though it is not necessarily the correct location for either image. This is an inherent data reporting issue with Phantom 2 Vision+ models and below, but has been rectified in the Phantom 3 Pro/Advanced models.

In total, we recorded and stitched over 800 images in the Microsoft ICE software. All computations were performed on a Lenovo desktop computer (equipped with Windows 7 64-bit, Intel Core i7-4770 CPU, 12.0 GB RAM, Intel HD Graphics 4600, and a 1TB hard drive), and the entire process took approximately 6-8 hours to create a TIFF file (4.02 GB).

Fixed-wing image acquisition

The fixed-wing UAV used in this study was a senseFly eBee (Parrot, Cheseaux-Lausanne, Switzerland), herein referred to as eBee, with a 96 cm wingspan, 0.25 m^2 wing area, and electric brushless motor. Including the sensor (Canon ELPH 110 HS, true colour) the total weight was 800 g (Styrofoam body). The eBee is powered by a 3-cell Lithium-Polymer battery with each flight lasting approximately 50 minutes and is hand launched and cruises at about 27 – 31 knots, with a landing speed of 2 – 17 knots for either straight in or circular landing options. The flight plans are pre-programmed in eMotion 2.9 (Parrot, Cheseaux-Lausanne, Switzerland) and the image collection is controlled by autopilot. Onboard, the eBee is equipped with a GPS, barometric pressure sensor and wind speed sensor. The flight paths were pre-programmed to ensure that complete coverage of the study area is obtained. We conducted all post-processing in PostFlight Terra 3D (Parrot, Cheseaux-Lausanne, Switzerland) which downloads the image data and flight plan from the eBee to create a georeferenced orthomosaic. The eBee is aimed at commercial/industrial users and is the first ‘compliant UAV’ in Canada, meaning government authorities have approved its airworthiness. This also makes flight applications (called Special Flight Operating Certificates) easier and allows for a longer or broader scope of flight areas.

Image data from the eBee were collected on 4 September 2015 during clear-sky conditions and a wind speed of 5 km/hr. A total of 3 flights were completed between 1000 hrs to 1300 hrs, totalling 30 passes, and taking off and landing occurred in the same spot each flight (**Figure 4.3**). The fixed-wing UAV collected 1319 images and were all pre-processed in PostFlight Terra 3D 3.2 (**Figure 4.2b**). All computation was performed on a custom-built desktop (Intel Core i7-4790K CPU, 32GB RAM, EVGA GeForce GT 730 (2GB GDDR5), Samsung 850 Pro 256GB SSD), and the entire process took approximately 24 hours to create a TIFF file (6.38 GB).

Field validation data

As part of a separate study on habitat use by several species at risk, we had conducted vegetation surveys of the impounded wetland between 14 July and 14 August 2014. Using a quadrat (2m x 2m), we estimated the percent cover of each of the three aquatic vegetation groups (i.e. emergent, submergent, and floating). Separately, each vegetation group was assigned to one of the 6 categories: 0-10%, 11-20%, 21-40%, 41-60%, 61-80%, 81-100%. If any vegetation was present within the quadrat, we determined the dominant vegetation as that with the highest cover. In total, we collected vegetation information in this way for 176 quadrats. To permit comparisons, we converted the data to three relative percent cover categories: none, < 50% cover, or > 50% cover. When percent cover was recorded as 41-60%, the result was counted as >50% if only that class existed, or another species of the same class (e.g. *Typha* and grasses are both emergent) was present in another category other than 0-10% so that total cover would be over 50%.

To determine dominant vegetation and percent cover from the collected image data, points from the field were plotted in ArcMap 10.2 (ESRI, Redlands, California, USA). A quadrat (2m x 2m) was placed around the points to represent area surveyed in the field. These individual points were manually identified by remote sensing of each type of image data (i.e. SWOOP, Phantom, eBee). To calculate dominant vegetation type, the entire quadrat was considered and whichever vegetation (grasses, cattail, submergent, floating) occupied the greatest area was given this class. To calculate percent cover, the relative area which each vegetation type (emergent, submergent, floating) occupied was determined and then directly translated into one of the three classes (i.e. 0, >50%, <50%).

Accuracy analyses

We created 3 x 3 matrices to compare image data (SWOOP, Phantom, eBee) to the field classification separately for percent cover of emergent, submergent, and floating and dominant vegetation type. For each 3 x 3 matrix, we calculated producer and user accuracy in addition to overall identification accuracy. Producer's accuracy provides an estimate of precision, and is the proportion of plots correctly identified compared to all plots that contains the particular class, whereas user's accuracy, or reliability, is the probability that a plot identified as one class actually belongs to that class. These accuracy measurements were calculated for each class (percent cover: none, up to 50%, over 50%; dominant vegetation: grass, cattail, submerged, floating/open water). Finally, we provide the kappa estimate to provide a unitless measure of agreement between the image data and field data (Viera & Garrett 2005). It is reported on a scale of no agreement, poor, fair, moderate, good, to very good agreement.

Results:

Image data

Using the multi-rotor DJI Phantom Vision 2+, we began flights at 0900 hrs on 8 August 2014 and ended at 1200 hrs. The UAV was operated from a small grassy patch located on the east side of the impoundment. We completed four flights, 19 passes in total, in favourable weather conditions with wind speeds below 15 km/h and limited cloud cover, with each flight lasting approximately 22 minutes in length. Although manual operation was required in order to achieve desired spatial resolution (< 10 cm) and temporal resolution (all image data collected on a single day), image data for a section of the wetland were missing (**Figure 4.2a**). We were unable to obtain comprehensive coverage of the entire dyked impoundment because after changing the batteries and re-launching the UAV, it was difficult to ascertain where the previous flight path had stopped, and this led to missing data in the final mosaic. The UAV itself does not record its flight path and therefore we were unable to download this to view previously flown areas. This is a trade-off between manual operation and automatic operation for this multi-rotor platform. While manual operation permits longer flying times and further flying distances to maximize area of capture, it can result in sections of missing data as was the case in our study.

The total root mean square error (of the georectification process) for the completed image from the multi-rotor UAV was below 5.0 m, and visual observations confirmed a good fit of the UAV-acquired image to the SWOOP dataset. The image had a resolution of 8.0 cm/pixel as defined in ArcGIS (**Table 4.1**). The final image data from the fixed-wing UAV had a spatial resolution of 4 cm/pixel as defined in ArcGIS (**Table 4.1**). In addition, a digital elevation model was created by PostFlight Terra 3D in areas where sufficient image overlap existed, although this data was not used in this study.

Accuracy Analyses

Both the Phantom and eBee were comparable when used to identify dominant vegetation, with an accuracy of 62 – 65% (**Table 4.2**). Both image data sources were in moderate agreement with field data, with the lowest identification accuracies for floating vegetation. The Phantom and eBee were both able to identify grass and cattail as the dominant habitat class with accuracies ranging from 60 – 80 % (Table 2). In comparison, the SWOOP image data were in poor agreement with the field data due to the difference in timing between the field survey and image data capture and had an overall identification accuracy of 35% (**Figure 4.2c; Table 4.2**). This source of image data failed to accurately identify any of the dominant vegetation classes.

Identification accuracies varied among image data collection method when used to determine the percent cover of emergent, submerged, and floating vegetation. When determining percent cover of emergent vegetation, the eBee produced a 64% accurate identification and was a fair match with the field data (**Table 4.3**). The majority of the confusion occurred when identifying an area with less than 50% cover. The Phantom had a similar problem with this class which resulted in a slightly lower overall accuracy of 55%, but was still a fair match to the field data (**Table 4.3**). The SWOOP image data were only able to identify percent cover of emergent vegetation with an accuracy of 39%, and had the poorest agreement with ground truth data of the three methods evaluated (**Table 4.3**).

All methods had high overall accuracy when used to identify submerged vegetation; however, we must interpret these cautiously because none of the field plots had over 50% submergent vegetation cover, and this meant that only two classes (no submergent vegetation and less than 50% submergent vegetation) had been identified. Between these two remaining classes, user accuracy was quite low for the below 50% cover class (Phantom = 0.52; SWOOP = 0; eBee = 0.44; **Table 4.3**). This indicates that image data were very good at interpreting locations with no submergent vegetation, but not as good at identifying the amount of cover. For example, SWOOP was unable to identify the cover of submerged vegetation, had 0% reliability and 0% precision, and consequently no agreement with the field data (**Table 4.3**). In comparison, the Phantom and eBee methods had moderate to fair agreement, respectively, with the field data (**Table 4.3**).

The identification accuracy of floating vegetation cover ranged from 18% for SWOOP, 35% for the Phantom and 58% for the eBee (**Table 4.3**). The SWOOP image data were completely unable to identify floating vegetation, and yielded 0% producer and user accuracy for both cover classes (**Table 4.3**). Both the Phantom and SWOOP image data had poor agreement with field data, whereas the eBee was in fair agreement (**Table 4.3**).

Discussion:

Use of a multi-rotor or fixed-wing UAV is of particular interest for mapping coastal wetlands because these ecosystems are dynamic, and experience seasonal and interannual fluctuations in water levels that greatly influence the vegetation community (Midwood and Chow-Fraser, 2012). As a result, during the growing season, coastal wetlands can often appear as large open bodies of water in the spring, and undergo seasonal succession to a completely vegetated habitat towards late summer (See **Figure 4.4**). This characteristic is one of the main reasons why coastal wetlands can support high biodiversity, and provide unique, sometimes critical habitat for many species at risk. This dynamic nature of coastal marshes means that a single image acquired at the beginning of the season (such as SWOOP) is inappropriate for mapping habitat that is used by species later in the season. This situation is challenging for most researchers who lack funds to acquire their own image data at the most appropriate time of the season, and who must use publically available orthophotoimagery. This may also explain the lightning speed at which UAVs have become adopted by wetland ecologists over the past year.

We found that the eBee system produced the most effective data for determining percent cover of floating and emergent vegetation compared to the SWOOP and Phantom image data. For submergent vegetation identification, all methods had high accuracy (75 – 83%), although this is likely inflated because plots with no submergent vegetation are almost impossible to identify incorrectly. Logically, when determining percent cover of emergent and floating vegetation, image data in the summer season with high spatial accuracy is best. But, if the goal is to determine where submergent vegetation will or will not colonize, publically available spring images were able to identify this just as well as the UAV acquired image data. For both UAV platforms, percent cover of vegetation was identified with 55 – 83 % accuracy (eBee 58 – 75%; Phantom 55 – 83%) and dominant vegetation type with 62 – 65% accuracy. This large range underscores how image data can vary in a dynamic ecosystem. Even though the two UAV images were acquired at roughly the same time of year over two consecutive years, there were marked differences between them (**Figure 4.2; Figure 4.4**).

Both multi-rotor and fixed-wing platforms can allow researchers to acquire aerial images of their study sites at a time in the year that is most relevant to their study objectives. When compared to aerial image data acquired by mounting cameras on an airplane, the Phantom and eBee were much more cost-effective. For example, for a wetland of the size in this study (approximately 90 ha), it would have taken two researchers six to eight days to complete all of the field work in order to generate a habitat map. By comparison, acquiring images with the UAV only took 6 - 24 hours (**Table 4.1**). While up to $5,000 CAD would be required to map even a small area by plane, the DJI Phantom 2 Vision+, with extra batteries, case, and a tablet or phone for viewing, would cost less than $3,000 CAD. If the desire mapping area is a few hundred hectares in size, the eBee would be more effective, but involve a higher cost of $30,000 CAD. The benefit in both cases, however, is that these are one-time costs, and maintenance/operation costs are relatively low (Phantom spare propellers, the most frequently broken part, can be obtained for $5 CAD each).

While the Phantom can be useful for mapping small areas (< 100 ha), restrictions in data reporting (coordinates, flight plans) capabilities limited its functionality. For instance, we attempted automatic geo-rectification to reduce the time required, but the GPS accuracy on the DJI Phantom 2 Vision+ was too low for this purpose. Recently, Pix4D have released an Android application to improve mapping and geo-rectification called Pix4DMapper (Pix4D, Xuhui District, Shanghai, China), but it requires the use of their own software and can only map relatively small areas at one time (maximum 200 m by 120 m; 2.4 hectares) compared to manual flight (with 60% overlap, approximately 20 hectares). In total, using autopilot would have garnered less than 20% of the area obtained during our 3 flights (65 ha; **Table 4.1**). This being said, the Phantom Vision 3 Series does provide the GPS coordinate accuracy required to overcome these challenges.

Even though we found SWOOP to be inferior to the UAV-acquired image data, it is freely available for research and are ideal for other research applications (e.g. planning and agriculture). Limitations discussed in this study are more of a reflection of the image data being collected in the spring, long before floating and submerged vegetation are fully established (**Figure 4.4**). Overall, our comparison highlights how technological advances can improve our ability to map dynamic systems like coastal wetlands.

Conclusion:

The flexibility of UAVs for research and monitoring will revolutionize the way we address and solve ecological problems, especially in dynamic coastal wetlands. The resulting high spatial and temporal resolution image data will permit investigators to ask questions previously limited by traditional imaging technologies. We confirmed that the UAV-acquired images could be used to estimate the percent cover of three broad classes of wetland vegetation (submerged aquatic vegetation, floating aquatic vegetation, and emergent vegetation) with fair to moderate agreement with field data. To achieve a more exact picture of vegetation communities, we recommend using a UAV platform to acquire image data precisely when desired. By comparison, image data from SWOOP was unable to determine dominant vegetation type and percent cover for emergent and floating aquatic vegetation, which comprise a large portion of the study site in the summer season.

As demonstrated, the timing of aerial image acquisition can limit the extent of our research. Seasonal image data can greatly improve our mapping of dynamic wetland ecosystems and allow managers to develop more effective recovery strategies for species at risk. Acquiring images multiple times during a single season would have been prohibitively expensive with traditional large plane or satellite platforms, but with low-cost UAVs, this is no longer an obstacle. Researchers no longer need to use commercially available image data that are out-of-date or taken at the wrong season, and instead, learn to create their own. We hope that this study will affirm the use of UAVs in ecological coastal wetland research while encouraging more research into this emerging and inexpensive remote sensing platform.

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Table 4.1: Comparison of 3 methods for image data collection. *Southern Ontario Orthophotography Project (spring 2010 edition).

Parameter	**Multi-rotor: DJI Phantom 2 Vision+**	**Fixed-wing: sensefly eBee**	**Piloted Aircraft: (SWOOP*)**
Time of data acquisition	User determined This study: Aug 2014	User determined This study: Sept 2015	Spring only every 4-5 years This study: spring 2010
Sensor	DJI FC200 sensor	Canon ELPH 110 HS	Leica geosystems ADS80 SH82 sensor
Spatial resolution	8 cm	4 cm	20 cm
Cost to researcher	$1,500 CAD	$30,000 CAD	No cost to university researchers under existing data-sharing agreement
Coverage	65 ha 16 ha/flight	281 ha 94 ha/flight	4,500,000 ha (throughout Southwestern Ontario)
Operator	User Manual or automated	User Automated	---
Post-processing type and duration	Manual (6-8 hours)	Automated (24 hours)	---
Lag time	---	---	1 to 1.5 years after image acquisition

Table 4.2: Accuracy values calculated for each method when image data are compared to field data for respective types of dominant vegetation.

Method	Accuracy Type	Class Grass	Cattail	Submerged	Floating	Kappa Assessment	Overall Accuracy
Phantom	Producer	0.693	0.565	0.910	0.465	moderate	**62%**
	User	0.658	0.667	0.910	0.435		
eBee	Producer	0.813	0.630	0.910	0.302	moderate	**65%**
	User	0.656	0.690	1.000	0.433		
SWOOP	Producer	0.750	0.475	0.002	0	poor	**35%**
	User	0.300	0.463	0.334	n/a		

Table 4.3: Accuracy values calculated for each method when image data are compared to field data. n/a indicates that no field plots exist for this class.

Vegetation Type	Method	Accuracy Type	Class (Percent Cover)			Kappa Assessment	Overall Accuracy
			None	Up to 50% cover	Over 50% cover		
Emergent	Phantom	Producer	0.733	0.226	0.8	Fair	**55%**
		User	0.379	0.459	0.623		
	eBee	Producer	0.666	0.387	0.869	Fair	**64%**
		User	0.625	0.690	0.624		
	SWOOP	Producer	0.666	0.480	0.259	Poor	**39%**
		User	0.172	0.444	0.611		
Submerged	Phantom	Producer	0.786	0.833	n/a	Moderate	**83%**
		User	0.983	0.521	n/a		
	eBee	Producer	0.765	0.667	n/a	Fair	**75%**
		User	0.941	0.444	n/a		
	SWOOP	Producer	0.979	0	n/a	No agreement	**81%**
		User	0.826	0	n/a		
Floating	Phantom	Producer	0.677	0.316	0.148	Poor	**35%**
		User	0.236	0.649	0.138		
	eBee	Producer	0.581	0.675	0.148	Fair	**58%**
		User	0.327	0.693	0.667		
	SWOOP	Producer	1.000	0	0	Poor	**18%**
		User	0.177	0	0		

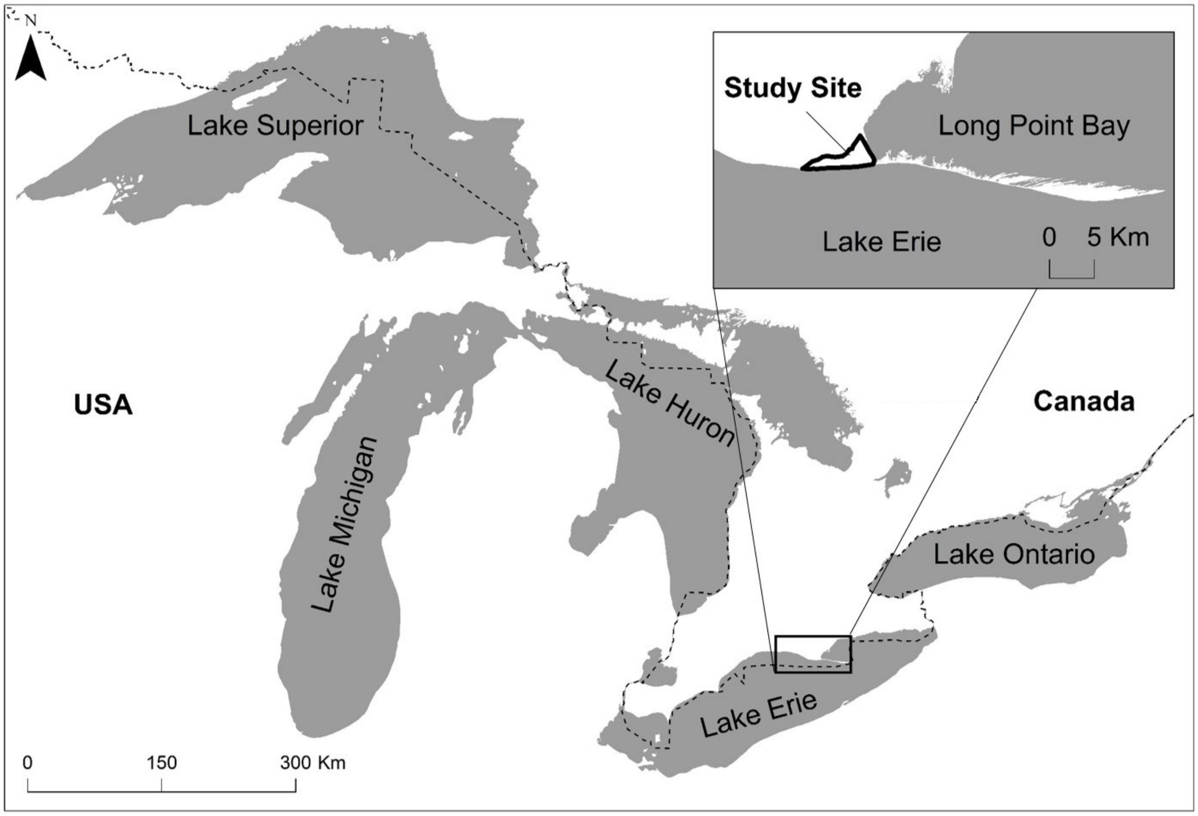

Figure 4.1: Location of study site: impoundment along the northern shore of Lake Erie.

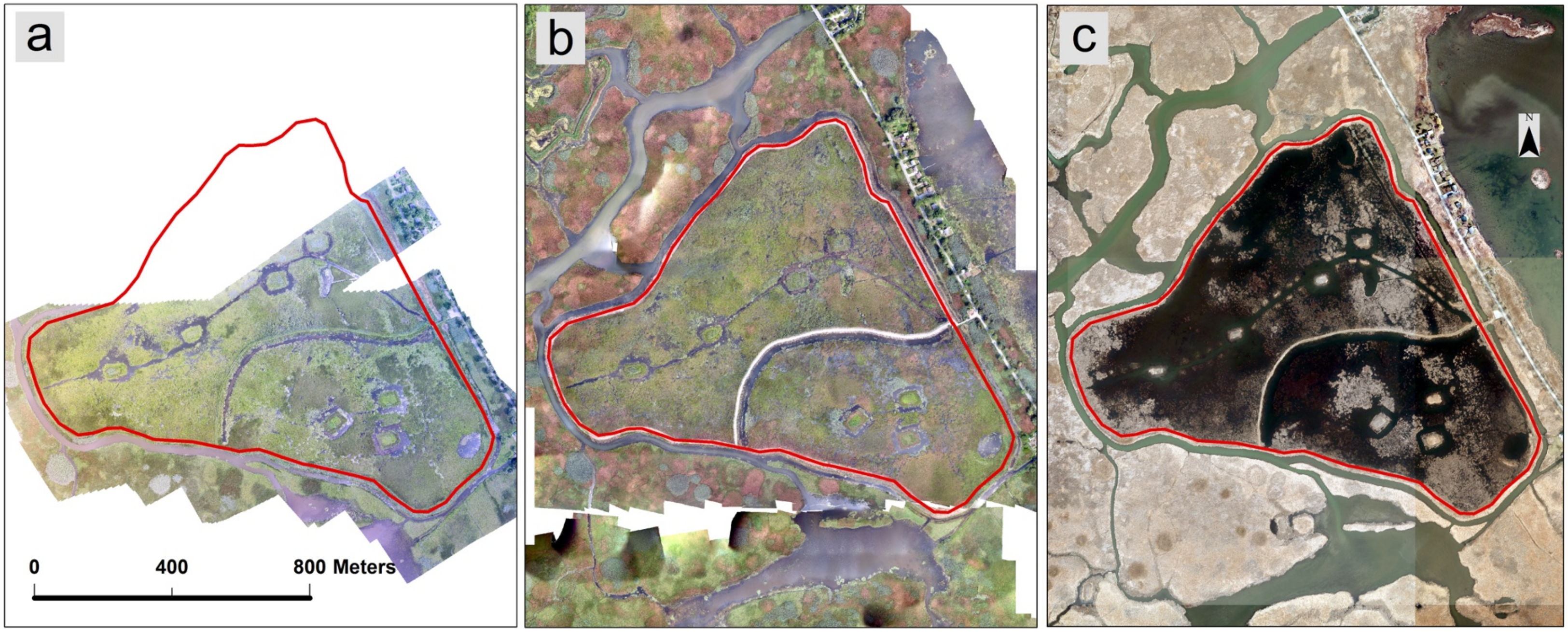

Figure 4.2: Comparison of (a) mosaic image acquired with multi-rotor UAV (b) mosaic image acquired with the fixed-wing UAV and (c) SWOOP image. The red line indicates the boundary of the impoundment and survey site.

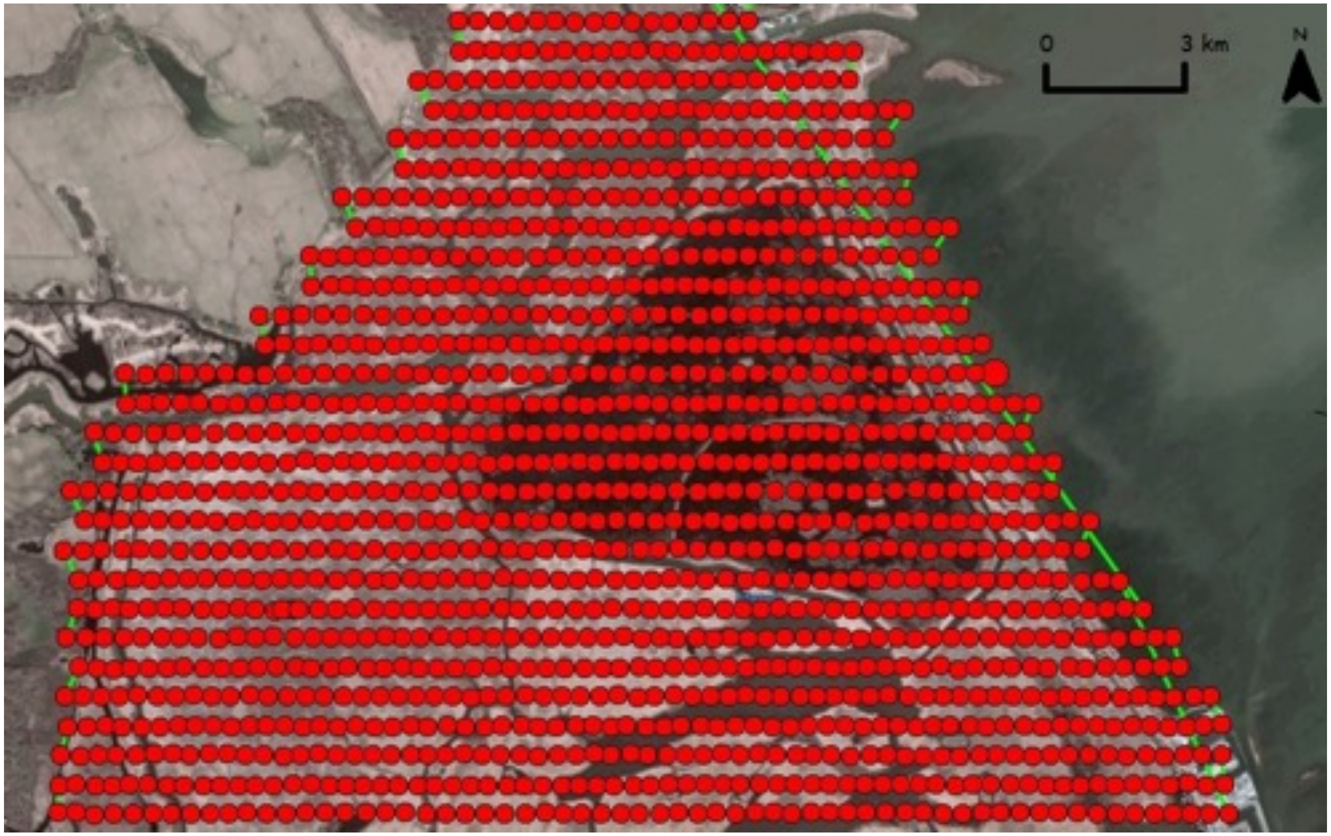

Figure 4.3: Flight path taken by the senseFly eBee. Each red dot represents the location of a photo and green lines show the connecting flight path.

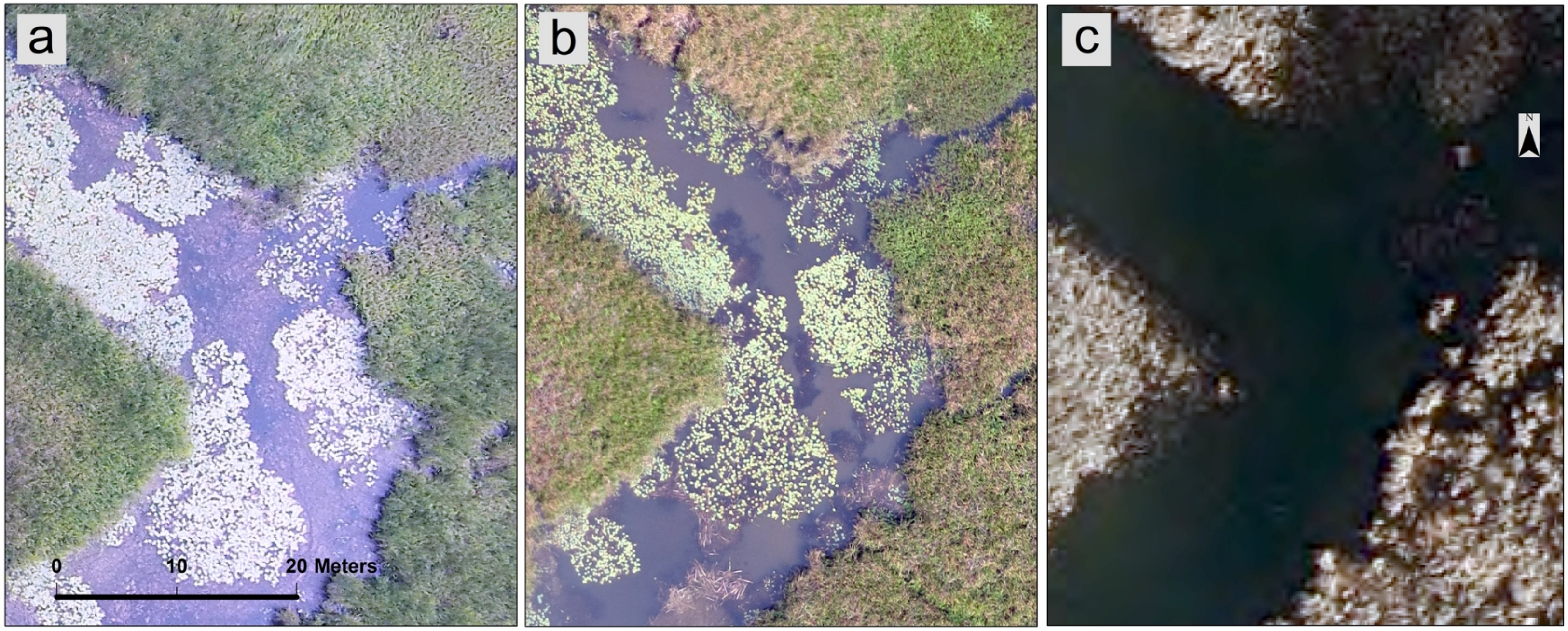

Figure 4.4: Comparison of (a) mosaic image acquired with multi-rotor UAV (b) mosaic image acquired with the fixed-wing UAV and (c) SWOOP image. Details associated with the floating and submersed aquatic vegetation in (a) and (b) are absent in (c).

Chapter 5: Assessing Efficacy of Invasive *Phragmites* Removal in Highway Corridors with Orthophotography & Satellite Image Data: The Ontario Case Study

By

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Abstract:

Roadside rights-of-way are a unique linear habitat that can be easily invaded by invasive *Phragmites australis.* While many North American jurisdictions have initiated control programs, few have established associated effectiveness monitoring programs. Here, we propose and apply three methods to determine effectiveness of a regional treatment program undertaken by the Ministry of Transportation of Ontario (MTO) in southwestern Ontario. We utilized 1) high-resolution spring orthophotography, 2) medium resolution multi-seasonal satellite image data and 3) high-resolution multispectral satellite image data to assess the effectiveness of MTO's treatment program. Using digitization and image classification, we deduced effectiveness of treatment programs in over 3,900km of roadside habitat between 2010-2015 (orthophotography) and 2016-2018 (satellite data). Net decreases in areal cover of *Phragmites* were over 95% for all road types other than for major expressways, which saw decreases between 80-95% between 2010 and 2015 but only 20-55% between 2016 and 2018. The areal cover of *Phragmites* also increased more rapidly within untreated expressway habitat compared with other road types over the same time period. Although orthophotography (20-cm resolution) acquired in spring yielded good results for identification of invasive *Phragmites*, it is only available once every five years on a provincial scale. By comparison, medium resolution satellite data (Sentinel-2) provided good results within large expressways (with larger and wider rights-of-way/habitat area) but was poor for all other road types (<2 lanes). These data miss small patches which are confirmed through high-resolution satellite data (Worldview 3; <1.5m). We advocate for use of medium-

resolution satellite data for annual baseline information on expressways, and high-resolution satellite data before and after treatment programs to directly assess effectiveness at smaller spatial scales.

Introduction:

Phragmites australis (Cav.) Trin. ex Steudel (invasive common reed) is a perennial grass that grows in many habitat types throughout the world. There are 27 genetically distinct groups (haplotypes) worldwide, of which 11 have been found in North America (Saltonstall 2002). One sub-species known as *Phragmites australis americanus* is native to North America and the rest are from Eurasia (Saltonstall 2003). Over the past two decades, Haplotype M (hereafter referred to as invasive *Phragmites*), which originated from Europe, invaded North American wetlands along the Atlantic and Great Lakes coastlines, replacing native vegetation and generally reducing biodiversity (Meyerson et al. 2000; Markle and Chow-Fraser 2018). In Canada, this haplotype was relatively confined to the St. Lawrence river until a population explosion in the 1970s, which coincided with highway construction in Montreal, Quebec (Lelong et al. 2007). Using genetic analyses, Catling & Corbyn (2006) confirmed that the *Phragmites* in road networks is the invasive rather than the native subtype.

There are only a few documented studies of the distribution of invasive *Phragmites* in highway corridors within Canada, but these have confirmed the explosive nature of this weed in road networks. Individual patches of *Phragmites* in roadsides have been observed to expand by 1.0 – 5.6 metres per year (Brisson et al. 2010). Jodoin et al. (2008) reported that 67% of 1-kilometre segments of road in Quebec had been colonized by invasive *Phragmites* in 2003. Recently, Marcaccio and Chow-Fraser (CH 2) found that within all road types in southwestern Ontario (covering nearly 17,000 km of roads), growth of *Phragmites* increased from 275 ha to 634 ha between 2006 and 2010, an overall expansion of 230% or 58% per year. Within well-travelled highways over the same time period, there was an increased expansion rate of 969% (26.8 ha to 259.7 ha). The density of invasive *Phragmites* per kilometer of road was also over two orders of magnitude higher in highways than any other road type. With such substantial areal cover and growth, it is vital to control invasive *Phragmites* along Ontario highways to successfully manage and eradicate this species within the province.

Much more is known about the traits that have led to the successful invasion of invasive *Phragmites* in wetlands and roadside habitats. First, it is a superior competitor against other emergent vegetation (Rickey and Anderson 2004; Uddin et al. 2014) because it is more tolerant of disturbances (e.g. road maintenance and changes in hydrologic regimes) and stress (e.g. increased salinity due to road de-icing salts) (Chambers et al. 1999; Saltonstall 2002). Secondly, high nutrient loading (especially in agricultural landscapes) can disproportionately benefit invasive *Phragmites* compared with other species because of its superior ability to sequester nitrogen and phosphorus (Rickey & Anderson 2004; Ge et al. 2017). It can also increase its range through secretion of allelopathic chemicals (volatile monocarboxylic acids) from its roots and rhizomes that prevent other vegetation from growing near it (Armstrong & Armstrong 2001). Finally, its ability to colonize sexually through thousands of wind-dispersed seeds (Gervais et al. 1993; Kettenring & Whigham 2009; Meyerson et al 2000), and grow clonally along linear networks (Brisson, de Blois & Lavoie 2010) allows it to aggressively colonize exposed wet habitat and then quickly expand to form dense monocultures that can extend into deep water (Armstrong et al. 1999). Taken together, increased salts, nutrients, and disturbance put other wetland plants at a competitive disadvantage compared with invasive *Phragmites* in brackish marshes (Minchinton & Bertness, 2003) and road ditches (Chambers et al. 1999; Bart et al. 2006; Brisson et al. 2010).

Environmental agencies throughout North America have used various strategies to eradicate/control invasive *Phragmites* (see **Table 5.1**). Besides mechanical treatment such as cutting, drowning, rolling, burning and covering them to prevent access to light, almost all agencies have used herbicides alone or with other mechanical control. The herbicide used most often is glyphosate, a broad spectrum herbicide sold commercially as Roundup, Weathermax, Rodeo or Aquamaster. Effectiveness of glyphosate in controlling invasive *Phragmites* populations in greenhouse experiments (Derr 2008) and experimental plots have been reported (e.g. Reimer 1976), but these are relatively small artificial settings that do not necessarily reflect the many kilometers of invasions occurring along the linear wetlands in highway corridors. Due to the high cost (both economically and socially) associated with diverting traffic in order to safely service roadways, the only option available is to use herbicides alone. Without knowing how invasive *Phragmites* responds to glyphosate applications administered as part of routine road maintenance programs, managers cannot justify the relatively high cost of implementing such treatment programs given competing demands on dwindling budgets.

The primary objective of this study is to investigate approaches to quantify the effectiveness of treatment programs for invasive *Phragmites* occurring in highway corridors. Since these habitats are long and narrow, and occur for many kilometers, conventional remote sensing methods that have been used to map invasive *Phragmites* do not apply. For instance, large-scale mapping of common reed in the Great Lakes basin has been successful with satellite-based imaging sensors in true colour, near-infrared, radar, and combinations thereof (Pengra, Johnston, & Loveland 2007; Young et al. 2011; Bourgeau-Chavez et al. 2015;). These sensors typically have a ground-based resolution of 20-30 m per pixel and can often return their orbit to a specific location within two weeks. Due to the nature of these sensors, any feature (e.g. *Phragmites*) that is to mapped must be approximately four times the size of the pixel to ensure that, regardless of orientation, the feature would fall completely within one pixel. This exceeds the dimension of the average highway ditch which precludes mapping any feature of interest within their boundary. By comparison, new medium resolution (10 m) and high resolution (>1.5m) satellite sensors and orthophotography (imagery taken from an airplane) can provide a much smaller minimum mapping unit. With these capabilities we can accurately assess the distribution and cover of invasive *Phragmites* throughout roadsides habitats.

Invasive *Phragmites* has been present within Ontario for many decades and the Ministry of Transportation of Ontario (MTO) has acknowledged the destructiveness of invasive *Phragmites*, both with respect to integrity of road infrastructure and to the health of adjacent ecosystems. Given the reported success of glyphosate in controlling invasive *Phragmites* populations in wetland habitats (Reimer 1976), MTO, like other agencies in North America (see **Table 5.1**) has sprayed highway corridors with this broad-spectrum herbicide to control *Phragmites* and other weeds in the West Region since 2012 (**Figure 5.1**). Since then, treatment has been ongoing on an annual basis but is limited by budget and timing with other construction projects taking precedence.

Here, we propose and apply three methods to determine effectiveness of a regional treatment program undertaken by the Ministry of Transportation of Ontario (MTO) in southwestern Ontario. We utilized 1) high-resolution spring orthophotography, 2) medium resolution multi-seasonal satellite image data and 3) high-resolution multispectral satellite image data to assess the effectiveness of MTO's treatment program. This study is the first large-scale multi-year assessment of the effectiveness of repeated glyphosate applications to control invasive *Phragmites* in highway corridors, and should yield important insights on how best to implement future effectiveness monitoring programs for Ontario and other jurisdictions in the Great Lakes basin.

Methods:

Ontario's southwestern region encompasses over 100,000 kilometres of roadways of varying size, construction type and management. In this paper, we examined the 16,900 kilometres of highways managed by the provincial Ministry of Transportation of Ontario's (MTO's) West Region which includes two-lane highways, divided highways, and large divided expressways. All of these roads have some right-of-way associated with them that often includes a vegetated depression (ditch) which is primarily designed for hydrological reason (efficiently removing water from the roads' surface). These rights-of-way are of different sizes depending on the road (and portion within) and some expressways also have vegetated medians (as opposed to concrete/barriers).

Highways in this large study area are of two basic types, the 400-series highways (401, 402, and 403) which are expressways with multiple lanes and speed limits of 100 km/h, and the non-400 series highways that are primarily two-lane roads although some have four-lanes segments or passing lanes and are 60-80 km/h. The lengths of each road also vary greatly with Highway 6 running north-south for 472 km while Highway 77 is very short at 22.6 km. The 400-series highways are associated with much higher traffic volumes than the non-400 series highways (Marcaccio & Chow-Fraser 2019; CH 2).

Treatment data were obtained from the Ontario Ministry of Transportation (MTO) from a GIS database. These treatments were conducted by private contractors using glyphosate (concentration: 5%, spray rate: 8L/ha) on boom arms from vehicles. All treatments were completed with one application between August and October of the year indicated and included both sides of the roadway as well as the median if present. Since direct GPS data of sprayed areas were not available, we have assumed that all stands of *Phragmites* within the area delineated by the contractors were treated. In some instances, ditching may have also occurred, a process wherein a segment of the topsoil is removed to re-establish appropriate hydrological patterns to ensure proper flow of water within the right-of-way. In these instances, all plants including *Phragmites* would be completely removed from the landscape and replaced with barren soil. Additionally, occasional cutting treatments have been conducted throughout the study area but the focus of these were for road safety and drainage maintenance rather than removal. As the amount of mechanical treatment was low compared to herbicide treatment (<40 km), these were not considered as a separate treatment group within the dataset.

An automated image classification was conducted for the 2010 Southwestern Ontario Orthophotography Project (SWOOP) image data (see Marcaccio & Chow-Fraser, 2019; CH3 for details), and manual digitization was employed for the 2015 SWOOP image data. All 2015 data were digitized by two technicians and only polygons that were within agreement between both technicians were included. In lieu of field data, a third technician compared the digitization against Google Earth and Google Streetview data from the same time periods to ensure accuracy. These data only include *Phragmites* as a land cover class as delineating other classes was too time consuming. Although these datasets had the same resolution, we could not directly compare individual polygons as each method of identifying invasive *Phragmites* (image classification in 2010 versus manual digitization in 2015) produced similar areas but different polygon sizes.

For the 2016 and 2018 comparison, Sentinel-2 (10 metre resolution) image data were processed in ENVI (v. 5; Harris Geospatial, Colorado, USA) with the multi-temporal support vector machine (SVM) tool. For each year, three images were acquired in spring, summer, and fall and these were combined to enhance our ability to distinguish *Phragmites* from other land-cover classes. Worldview-3 (1.25 metre resolution) data were also acquired from the summer (August) of 2016 and GeoEye (1.25 metre resolution) from summer 2018 and were manually digitized to determine the accuracy of the Sentinel-2 classification (**Figure 5.2**). Due to the difference in pixel size between products, we assessed the level of agreement between datasets based on the *proportion* of patches in the high-resolution datasets that were successfully identified in the medium-resolution datasets, rather than the absolute areas. Additional comparisons between these datasets were conducted to determine the geometric differences in patches from medium-resolution data versus the patches from high-resolution data. Within each dataset, a change detection was conducted by splitting each road into 1-km segments and determining changes within these segments to standardize units of measure and to account for errors and misaligned pixels between years (which would result in false changes in boundaries for each invasive *Phragmites* patch). Areal cover in the earlier year that decreased (was no longer visible) in the later year was interpreted as having been successfully treated, while a stable (remained) or increasing areal cover was deemed to have been unsuccessful. We only report increases and decreases by road within the area that was treated and not the entire length of the road due to the differences in geographic distribution and length of some roads.

Details on the results of the 2010 image classification with spring orthophotography have been documented elsewhere (Marcaccio & Chow-Fraser 2019; CH3). The 2015 image data had been manually digitized due to use of a different sensor and pre-processing method that resulted in compressed data that were no longer suitable for automated image classification. For our comparison between 2010 and 2015, 16,900 km of roads and their habitat were mapped (**Figure 5.3**). This represented all roads that MTO currently manage, along with additional portions of roads where data on completion of treatment had been provided by MTO for use in this project. Although the 2010 and 2015 image data were from spring, we were able to clearly identify invasive *Phragmites* stands because they do not senesce and collapse like other vegetation, but remain tall and visible throughout the winter and spring. Since the 2015 data represent growth through 2014 (and not 2015), we only considered treatments conducted in 2012, 2013, and 2014.

Results:

In total, between 2010 and 2015, MTO treated 2,331 km of unique road segments (Figure 3), and removed 213 ha of invasive *Phragmites* (**Figure 5.4**). Despite this, the total area of invasive *Phragmites* still increased by 18 ha, presumably because of growth and expansion of *Phragmites* that had not been effectively treated. While treatments were effective for all roads, lower efficacy was observed for Hwy 401, 402, and Hwy 40 (a bypass road between the western portion of Hwy 401 and 402; **Figure 5.5**). While the 403 had a high removal rate, the total length of roadway within this study area was quite short (only 48 km) compared to Hwy 401 and 402 (255 km and 94 km, respectively). Compared with the 400-series highways, removal rates for all other highways were significantly higher (t-test, $P<0.001$; **Figure 5.6**). Timing of treatment also appeared to affect efficacy; road segments that had been treated more recently were associated with higher removal rates. In this study, repeat treatments did not have a significant effect on the outcome of removal because of confounding effects of road type (i.e. only 400-series highways were treated twice). A major driver of the expansion of invasive *Phragmites* was the total areal cover that had been present in 2010 (**Figure 5.7a**). Similarly, resistance to treatment was also a function of historic areal cover (**Figure 5.7b**).

Between 2016 and 2018, only the 400-series highways and a short length of smaller roads were treated and as such we conducted our analyses on only the 400-series highways (**Figure 5.8**). Using Sentinel-2, we found many areas of net decrease where treatments had taken place, but these did little to diminish the total expansion of invasive *Phragmites* across the entirety of the roadways (**Table 5.2**). Repeated treatment over two years on Highway 401 led to the best results for removal within these areas, but they did not approach those levels seen in our earlier analysis (Figure 8a). According to previous analyses (2010-2015), smaller patches of *Phragmites* responded best to treatment. Given we used the Sentinel 2 image for the 2016-2018 analysis, the 10-metre pixel resolution could not be used to accurately identify patches larger than 100m^2 (**Figure 5.9**), which is much larger than the 1 m^2 patches identified in orthophotos (20 cm pixel, with minimum object size in eCognition equal to 4 pixels) and manual digitization of 1.5 m image data (**Table 5.3**).

By comparison, our high-resolution satellite data (WorldView-3 & GeoEye) could be used to identify much smaller patches similar to that obtained through orthophotography (**Table 5.3**). Of the 163ha in 2016 and 138 ha in 2018 of study area mapped, 90 ha of these overlapped spatially and all of the invasive *Phragmites* in this area had been treated. In addition to the inherent difference between manual digitization and automated image classification with respect to polygon size, these products were also different in terms of areal cover. Sentinel-2 overestimated by 142% in 2016 and 213% in 2018 (**Table 5.3**). Treatment effectiveness in this study area as determined by Sentinel-2 showed only a 27% decrease. With high-resolution data, however, treatment effectiveness showed a 51% decrease, which is closer but still lower than that obtained in the 2010-2015 analyses (>80%). This confirms our earlier finding that smaller stands of *Phragmites* are more easily eradicated with glyphosate treatment. If patches < 100m^2 (smallest size of Sentinel-2 patch) are removed from the high-resolution data, the change in invasive *Phragmites* areal cover is small. These findings indicate that the Sentinel-2 data had overestimated areal cover of *Phragmites* because of its coarser pixel size.

Discussion:

Roads have been hypothesized to be a major long-distance transporter of invasive *Phragmites* (Lelong et al. 2007), and Marcaccio and Chow-Fraser (2019; CH3) have shown how rapidly it can expand within southwestern Ontario from 2006 to 2010 when they are left untreated. From road ways, they can also expand quickly to other adjacent disturbed habitats (Ailstock, Norman, & Bushman 2001). Therefore, the unchecked growth of invasive *Phragmites* is a problem not only for the integrity of road infrastructure, but also for biodiversity conservation in natural ecosystems.

Due to management constraints and logistics, all treatment programs took take place in late summer, when efficacy was typically lower for glyphosate applications (Mozdzer et al. 2008). Because there had been no baseline mapping of invasive *Phragmites* prior to 2015, MTO carried out their treatment program without knowing the full extent and distribution of infected corridors. Even with these constraints, we have found good rates of removal across the study area. Due to the extent of the invasion in 2012 and lack of previous management, any removal efforts were likely to produce positive results in the short-term. The uniform recommendation by all agencies to repeat treatment (see **Table 5.1**), which are well supported by the literature (Riemer 1976, Turner & Warren 2003, Derr 2008, Lombard, Tomassi & Ebersole 2012) means that appropriate and consistent mapping must also be carried out to ensure that management actions are appropriately allocated and continue to be effective.

Overall, the results of our 2010-2015 analyses were acceptable in terms of invasive *Phragmites* removal; however, despite the effectiveness, we found an increase in distribution of *Phragmites* in 2015 that was primarily from new growth and regrowth from treated stands that varied from <1 to 27%. Both new growth and regrowth were more prolific on the 400-series highways. We also found that patch size of *Phragmites* had a significant influence on both efficacy of glyphosate treatment and the colonization rate, and that the 400-series highways tended to have larger patch size than other road types. We had no evidence of complete eradication, and this may be due to the large size of patches in particular road types, and the low frequency of invasive *Phragmites* treatment between years.

We have also found that smaller stands on the fringes of the invasion front (north in this study) are more easily removed than dense stands on invaded highways (**Figure 5.4**). Removing these fringing stands can help limit the spread of *Phragmites* into novel habitat as this plant can reproduce effectively over large distances by seed (Fér & Hroudová 2009; Kirk et al. 2011). Since these small stands are difficult to identify with traditional satellite-based remote sensing products, more effort should be focused on finding an effective strategy for early detection. Future studies can and should consider developing a landscape-level model for *Phragmites* expansion and management in roadsides similar to what Duncan et al. (2017) and Long, Kettenring & Toth (2017) created for wetland systems; the unique spatial attributes of roadsides may require different parameters and considerations for a successful modelling approach to be created.

We found a reduction in effectiveness on large freeways with larger rights-of-way and greater habitat availability. These roads often have much larger patches of *Phragmites*; we cannot determine through remote sensing methods whether these come from one clonal stand or convergence of multiple unique genetic individuals. Larger *Phragmites* patches are extremely difficult to fully eradicate and thus may limit the apparent effectiveness of any control program along well colonized roadsides when viewed on shorter (< decadal) time scales (Quirion et al. 2017). While a decrease in total areal extent is possible, it is likely that roads such as the 400-series highways will need to be managed for decades longer before they are fully eradicated. In addition, these roads were only treated once in 2012 compared to others which had been treated closer to 2015 and/or treated multiple times.

The 400-series highways are associated with higher traffic speeds (100 km/h vs <=80km/h) and much higher traffic volumes than other road types (Marcaccio and Chow-Fraser 2019; CH 2). These roads also have large on/off-ramp complexes that are difficult to manage due to their depth and width (limiting the area possibly treated by roadside vehicles) and the creation of artificial wind vortexes which affects the distribution of airborne particles of glyphosate (MTO, personal communication). The combination of these factors has been hypothesized to lead to increased frequency and distance of seed-borne dispersal through artificial winds and direct attachment to vehicles (Ailstock et al.

2001). This would make repeat treatments an absolute necessity as even small patches of invasive *Phragmites* left behind could easily repopulate long stretches of these roads.

A notable anomaly in our dataset was Hwy 40, which had similarly low efficacy to those reported for Highways 401 and 402, but is a two-lane highway (**Figure 5.5**). The invasion pattern on this road was similar to those of other non-400 series highways and was also constructed in a similar fashion to other highways (two lanes with no divided median). We speculate that high volume of traffic on this road and source populations of invasive *Phragmites* may explain this anomaly. Hwy 40 was constructed as a west-end link between two very busy highways (Hwy 401 and 402) before they crossed two international border crossings near Sarnia and Windsor, Ontario. It is also located east of and in close proximity to the St. Clair river, Lake St. Clair, and the Walpole Island wetlands, which is currently densely populated with invasive *Phragmites* (Wilcox 2012). With the predominant winds being westerly in this area and a flat, agricultural landscape, it is possible that the wetlands act as a source of invasive *Phragmites* seeds that continuously invade Hwy 40 and the western ends of Hwy 401 and 402. Genetic analyses could help test this hypothesis and elucidate the underlying causality.

As mentioned earlier, the 2010-2015 comparison did not bear out the merit of repeated treatments on these highways. We were, however, able to support this using the 2016-2018 comparison (**Table 5.2**). Our data also showed that regrowth of invasive *Phragmites* can outpace the efficacy of treatment programs, especially if viewed on a road-by-road (not kilometre-by-kilometre) basis. Care must be taken to consider smaller units of roadway to accurately assess impacts especially when roads are relatively long and only a small subset of the road is actually treated.

The degree of expansion in 2015 appears to be directly related to the amount that had been present in 2010, and this is consistent with observations that *Phragmites* expands clonally **(Figure 5.7a**, Jodoin et al. 2008, Bellavance & Brisson 2010). While we cannot directly compare individual patches due to the differences in how the data were processed, our data are consistent with clonal expansion of invasive *Phragmites* that had existed historically. We do not believe that seed-based dispersal had occurred over these small distances, since high winds generated by traffic across these landscapes are expected to be associated with longer seed dispersal distances. Similarly, our finding that degree of resistance to treatment (amount of *Phragmites* that remained unchanged following treatment) was directly related to the amount that had been present in 2010 (**Figure 5.7b**) again points to difficulties in eradicating more heavily infested landscapes.

We emphasize the importance of using the same type of image data to permit valid comparisons. This was the most challenging aspect of monitoring across different time periods in this study. The only way to use SWOOP image data (scheduled to be acquired in 2020) for future comparisons would involve labour-intensive and tedious manual digitizations, and we do not recommend this approach. Instead, we recommend using multi-season image classification of Sentinel 2 or 3 satellite data on large highways (such as the 400-series highways) for periodic updates. Unfortunately, the relatively narrow and linear nature of roads mean that even 10-metre resolution is simply too coarse in most circumstances. Along a typical highway in southwestern Ontario the rights-of-way can be 5 metres, which results in an abundance of mixed pixels.

Although effectiveness monitoring was acknowledged as a necessary component of treatment programs by all agencies that we surveyed (see **Table 5.1**), none of the agencies documented how to accomplish this using either remote sensing or field surveys. Of the three approaches used in this study, those involving satellite image data are directly transferable to other jurisdictions. Nevertheless, we only recommend using the high-resolution satellite data (e.g. Worldview 2, 3 or Geo-Eye) to map individual *Phragmites* stands for a select number of smaller highways. As these high-resolution data are not freely available, their use will be limited to agencies with available budgets and expertise. By conducting image classifications before and after treatment, areas in need of repeat treatment can be identified and efficacy can be determined. As we and others have noted, repeat spot treatments are extremely effective in reducing *Phragmites* cover throughout the landscape and only manual field work or high-resolution data will suffice for this purpose.

Our results are reported solely as areal cover and give no indication of biomass or density of invasive *Phragmites* present within each patch. The density of patches is known to have a significant influence on treatment efficacy because patches with higher stem counts are less responsive to treatment (Quirion et al. 2017). This may account for some variability in treatment effects in this study. Preliminary data suggest that *Phragmites* stands on the 400-series corridors are not only larger, but also much denser (DeBoer and Chow-Fraser, unpub. data). Although biomass/density determinations may require multi-spectral image data, the results would prove especially useful for managers to estimate amount of glyphosate that is required to effectively treat the amount of *Phragmites*.

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Table 5.1: Targeted survey of current control programs for invasive *Phragmites* in roadways and wetlands throughout N. America

Authors/Agencies	Type of habitat	Herbicide Used/Options	Mechanical Treatment Used or Recommended	All Treatments Used	Recommendation for spraying in consecutive years	Disposal Methods	Post Treatment Monitoring	Results of Effectiveness After Year 1	Results of Effectiveness After Year > 2
BMPs from Canada									
Kincardine (2013)	**Wetlands and shoreline**	Glyphosate 4-5% (Weathermax)	Burning	ATV spraying, backpack spraying, hand-wicking, prescribed burns	Yes	Rolling/Burning	Yes	Speaks of U.S. combining Glyphosate and Imazypyr for 80-100% kill	N/A
Ontario Ministry of Natural Resources and Forestry (2011)	**Generic habitats**	Glyphosate	Cutting, tarping, solarization, drowning, rolling,	Spraying, cutting, tarping, solarization, drowning, rolling	Yes	Bagged in thick plastic, then dried out in the sun. Once dry can be burned or disposed of	Yes	N/A	N/A
Ontario Phragmites Working Group. (2015)	**Roadways**	Glyphosate 4-5%	Rolling, cutting,	Spraying, wicking, wet blade, rolling, cutting, burning,	Yes	Burying, covering (3m deep), covering with heavy plastic, burning, or dispose in an open agricultural field where emerging plants can be treated	Yes	70-95%	For most cells, complete control can be expected after two treatments

Table 5.1: cont'd.

BMPs from USA									
Brigham City, Utah (2007)	**Wetlands**	Glyphosate 2%	N/A	Spraying and Burning	Yes	Burning	Yes	N/A	N/A
King County (2010)	**Roadways and generic habitats**	Glyphosate (Rodeo and Aquamaster) and Imazapyr (Habitat)	Spading young plants, repeated cutting before tasseling	Spading, cutting, wick wiping, herbicide spraying, burning	Yes	Place roots, rhyzomes, and seed heads in sturdy plastic bags and dispose. Stems left on site for compost or burning	Yes	N/A	N/A
Michigan State and Partners n.d.	**Roadways and generic habitats**	Glyphosate (six pints per acre), Imazapyr (six pints per acre), or even mix	Hand tools, weed whips, small mower	Spraying, burning, flooding, mechnical treatments,	Annual maintenance	N/A	Yes	N/A	Annual spot treatments of pioneer colonies 100%
New York State DOT Adirondack Park (2014)	**Roadways**	No specific mention in the BMP	Spading young plants, pulling, digging	Spraying, cutting, pulling, digging	Yes	Drying/liquefying, Brush Piles, Burying, Herbicide	Yes	N/A*	N/A*
Janice Gilbert for Lake Huron Centre for Coastal Conservation (2016)	**Roadways and generic habitats**	Glyphosate	Covering, smothering, rolling, drowning, cutting, spading	Spraying, hand wicking, burning mechanical control	Yes	N/A	Yes	N/A	N/A

N/A = not available *In a webinar (October 2017), reported that probability of eradicating (i.e. no growth after 3 y) decreased drastically with treatment area; 83% for 0.36 sq. m vs 26% for 45 sq. m vs 1% for >3000 sq. m. Also noted that 60% returned after one year of treatment; minimum 20% returned after 2 consecutive years of treatment and <5% after 3 consecutive years.

Table 5.2: Changes in areal cover (ha) of invasive *Phragmites* for 400-series highways based on automated image classification of Sentinel-2 satellite image data. Highways were classified as either "Treated" or "Untreated", depending on whether they received glyphosate or not, respectively during 2016.

Hwy series	Type	Total area analyzed	Area in 2016	Area in 2018	% change from 2016
401	Untreated portion	1200	137.5	172.6	+25.5
	Treated portion	875	63.0	28.9	-54.1
	Entire highway	2075	210.5	201.5	-4.3
402	Untreated portion	606	57.2	74.0	+29.3
	Treated portion	616	41.0	33.3	-18.8
	Entire highway	1222	98.2	107.3	+9.3
403	Untreated portion	195	6.4	7.0	+9.4
	Treated portion	450	11.3	8.2	-27.4
	Entire highway	645	17.8	15.2	-14.6

Table 5.3: Comparison of spatial attributes of invasive *Phragmites* patches identified with Sentinel-2 (S2), Worldview-3 (WV3), and GeoEye (GE) data.

	Medium resolution (S2)		High resolution (WV3 and GE)	
Total Study Area in 2016 (ha)	163.3		163.3	
Total Study Area in 2018 (ha)	138.0		138.0	
Intersected Study Area (ha)	90.4		90.4	
Phragmites 2016 (Total ha)	16.2		10.8	
Phragmites 2018 (Total ha)	9.1		3.5	
Phragmites 2016 (Intersected/Treated ha)	9.5		6.7	
Phragmites 2018 (Intersected/Treated ha)	6.93		3.3	
All Change 2016 - 2018 (Intersected, ha)	2.57		3.4	
Mean polygon size (2016) (Intersected, ha)	0.052		0.050	
Standard Deviation (2016)(Intersected, ha)	0.084		0.104	
Mean Polygon size (2018)(Intersected, ha)	0.029		0.042	
Standard deviation (2018)(Intersected, ha)	0.035		0.067	
Minimum Polygon size (Intersected, ha)	0.0100		(WV3) 0.000927	(GE) 0.001897
Area from (<minimum polygon size of S2) (Intersected, ha)	0		(WV3) 0.2738	(GE) 0.1143
Area from (>min size S2)(Intersected, ha)	(2016)9.5	(2018) 6.93	(WV3) 6.3767	(GE) 3.1451

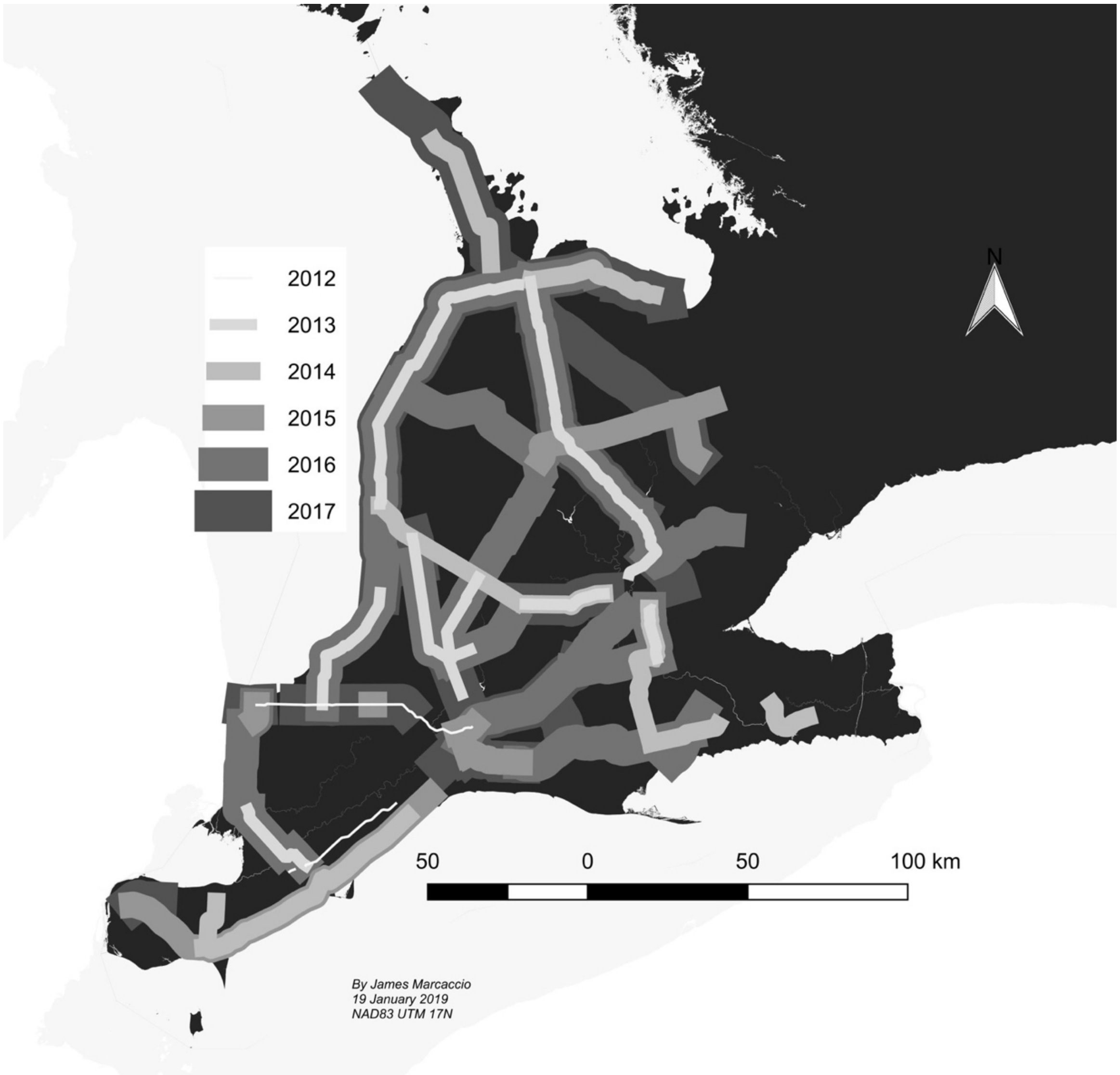


Figure 5.1: Roads in West Region that had been treated with glyphosate between 2012 to 2017.

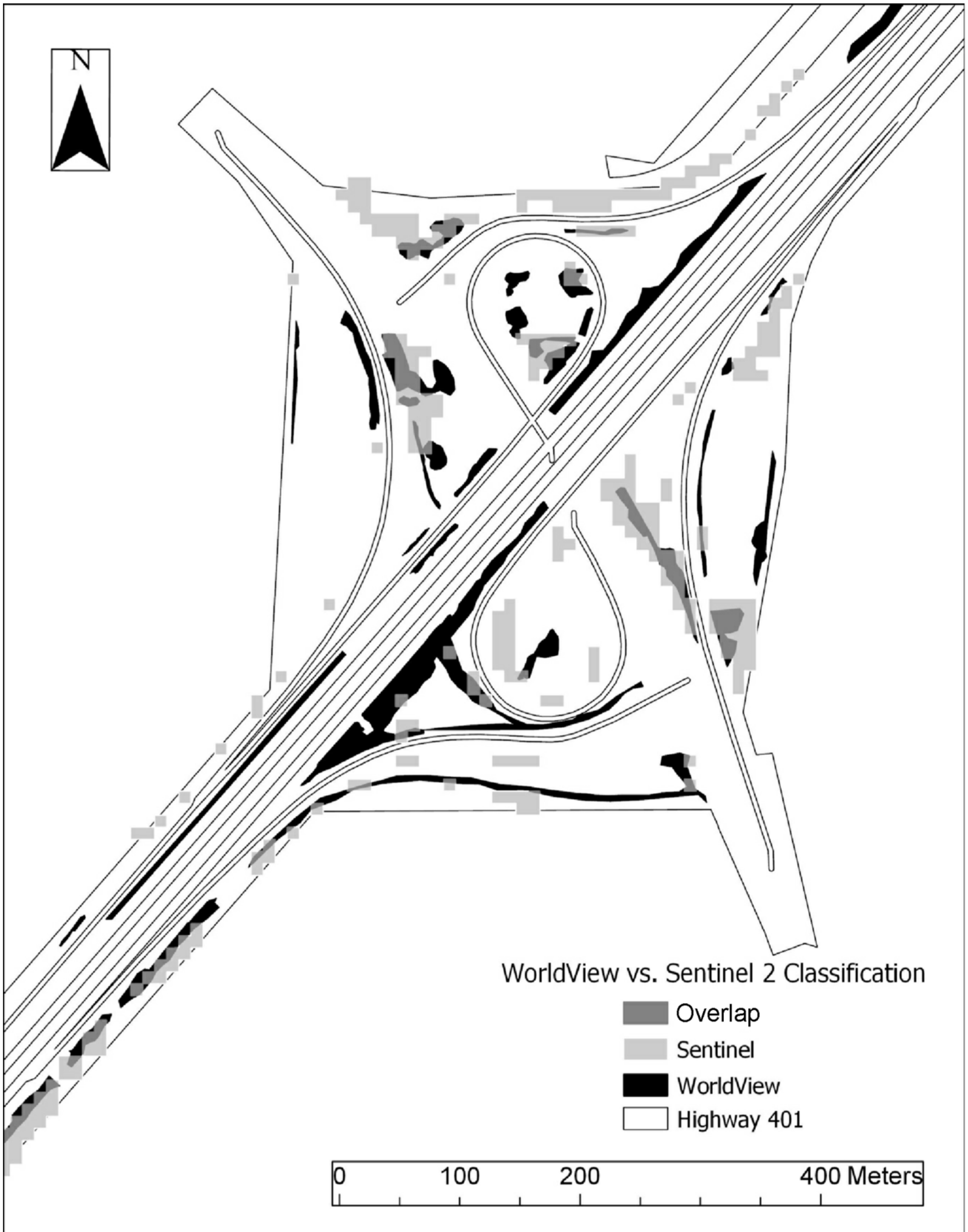


Figure 5.2: Automated image classification identifying invasive *Phragmites* (light grey) compared to manual digitization of invasive *Phragmites* (black).

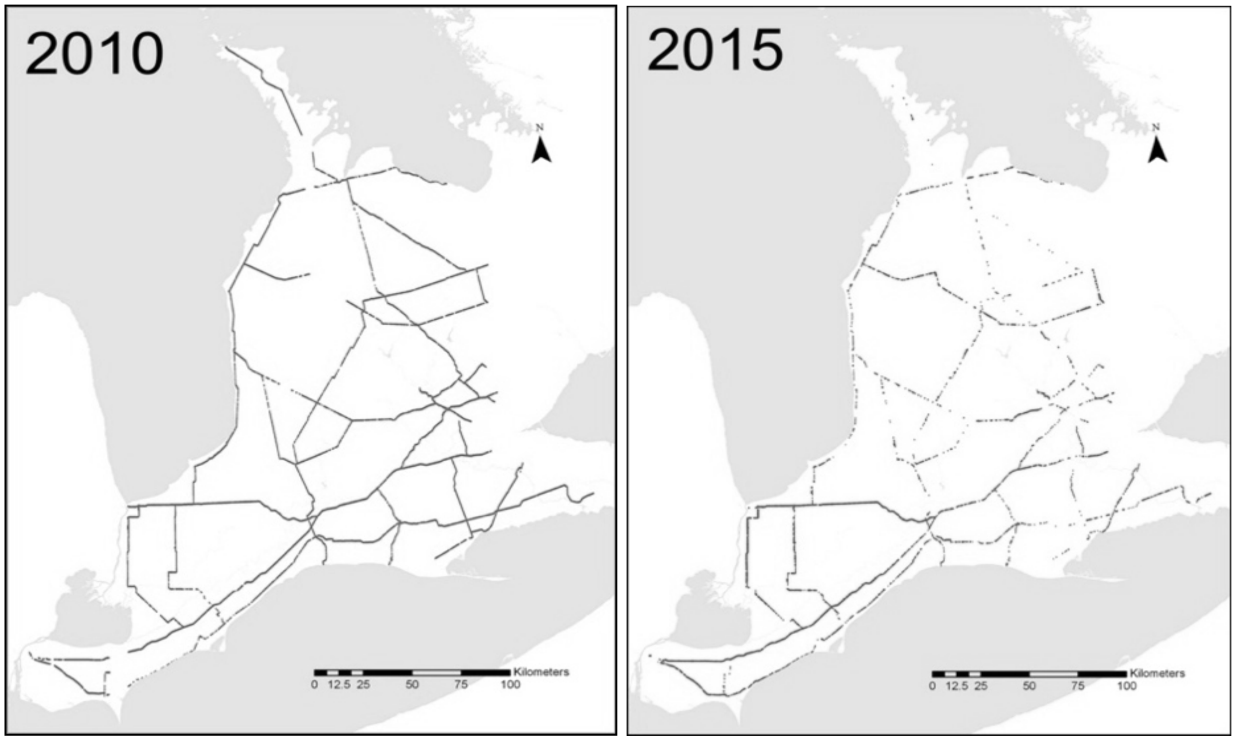


Figure 5.3: Comparison of 2010 and 2015 distribution of invasive *Phragmites* (black) in highway corridors.

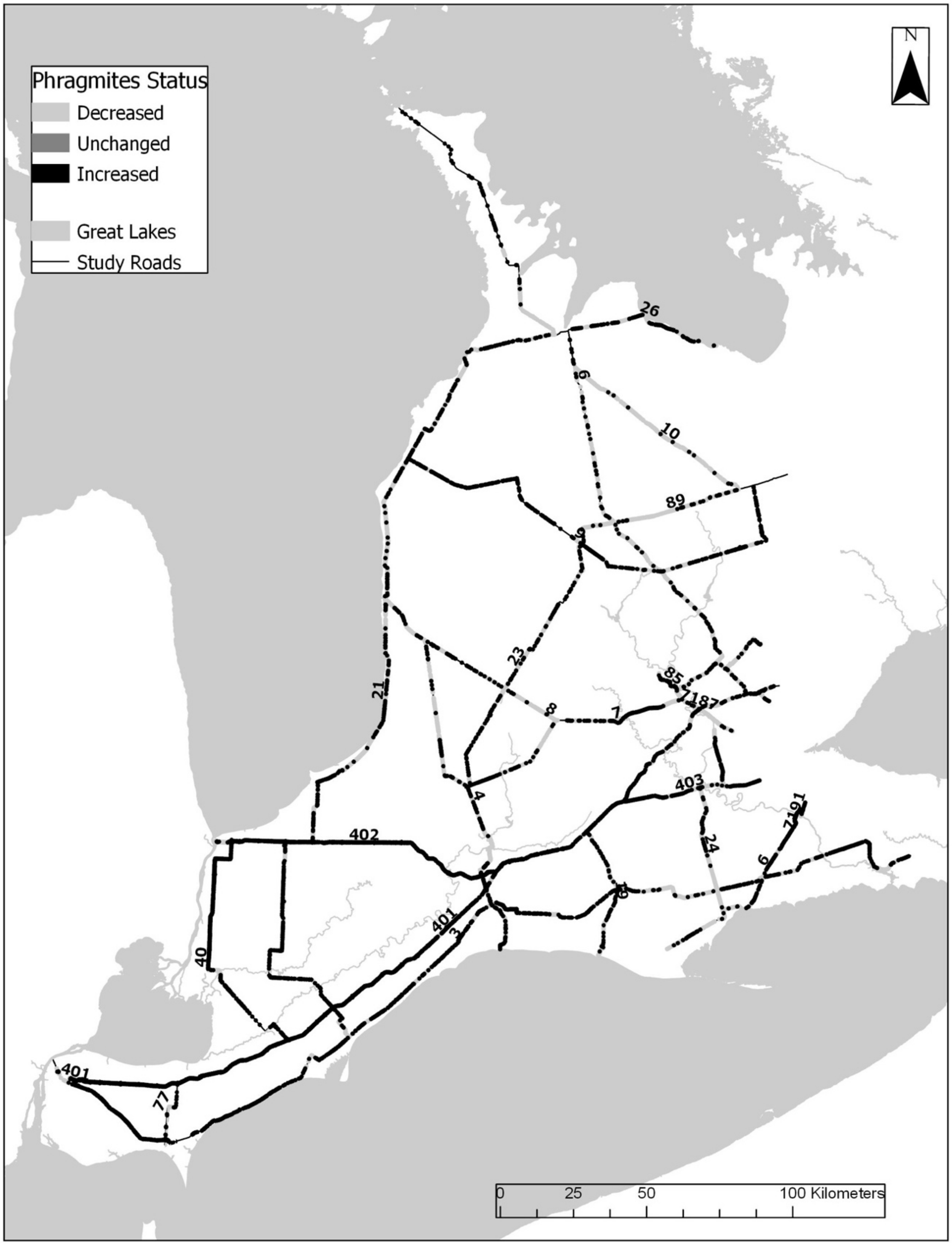


Figure 5.4: Results of a change detection of invasive *Phragmites* occurring in highway corridors of southwestern Ontario between 2010 and 2015, based on SWOOP image data only.

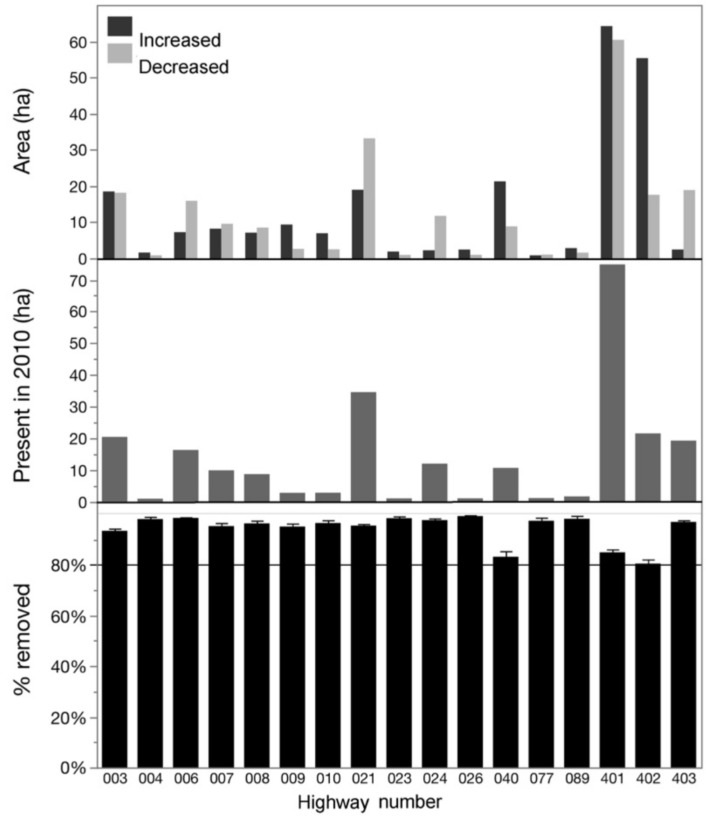
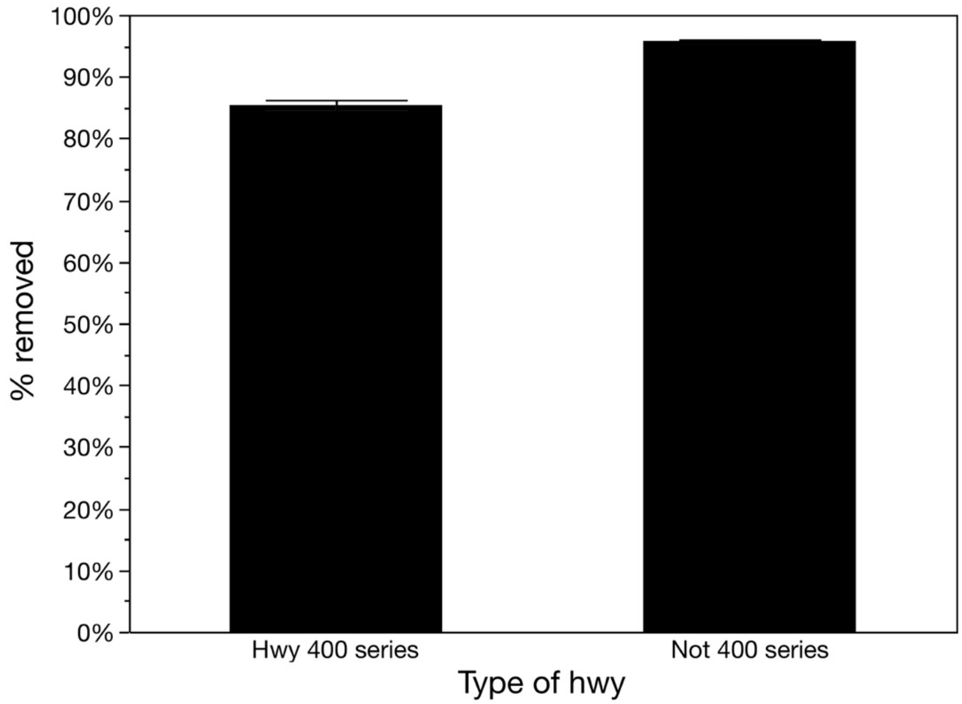


Figure 5.5: Top: Invasive *Phragmites* areal cover that had increased/grown (black) and decreased/removed(grey) between 2010 and 2015, by road. Middle: Invasive *Phragmites* present in 2010 by road. Bottom: Invasive *Phragmites* removed by road. The black line corresponds to an 80% removal rate.

a)



b)

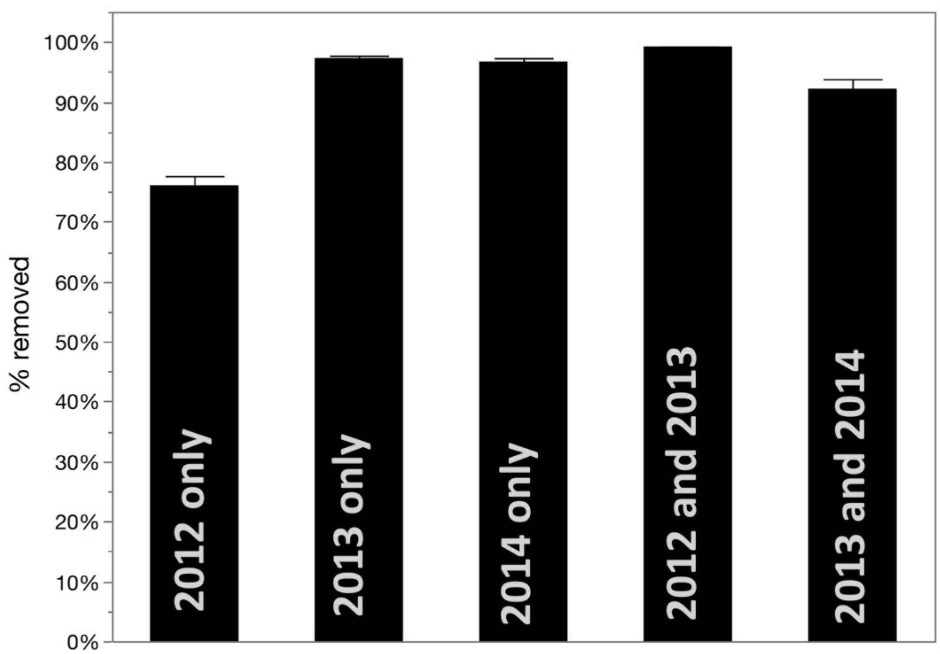
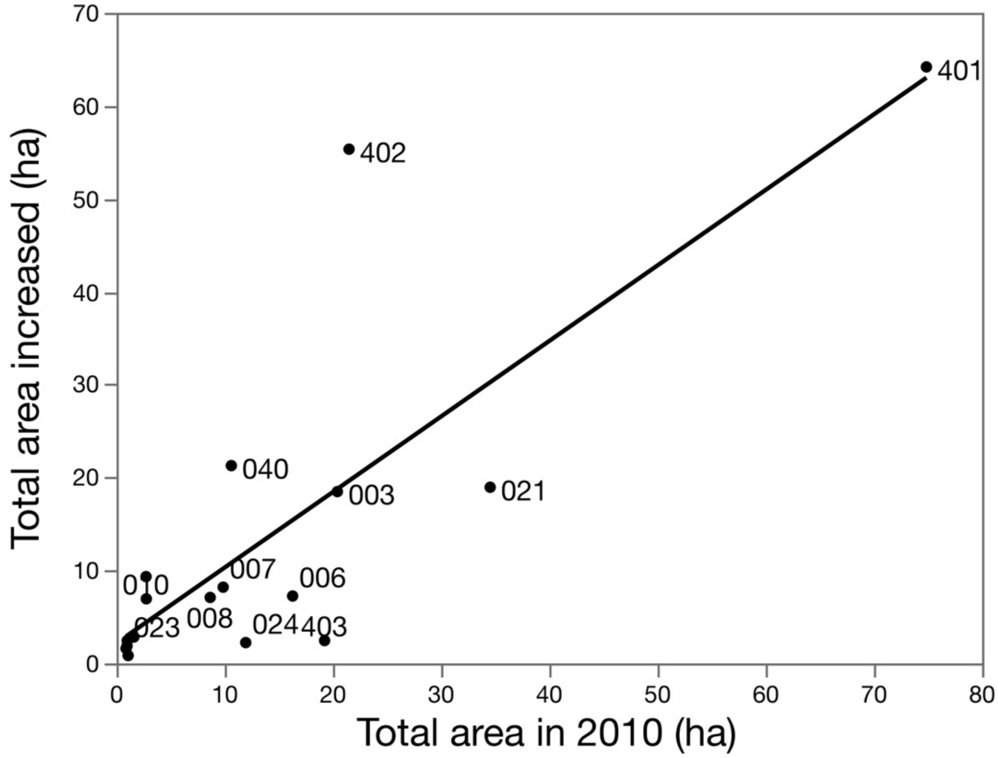


Figure 5.6: Percentage *Phragmites* removed for a) 400-series and non-400 series highways and b) roads grouped according to when they had been treated.



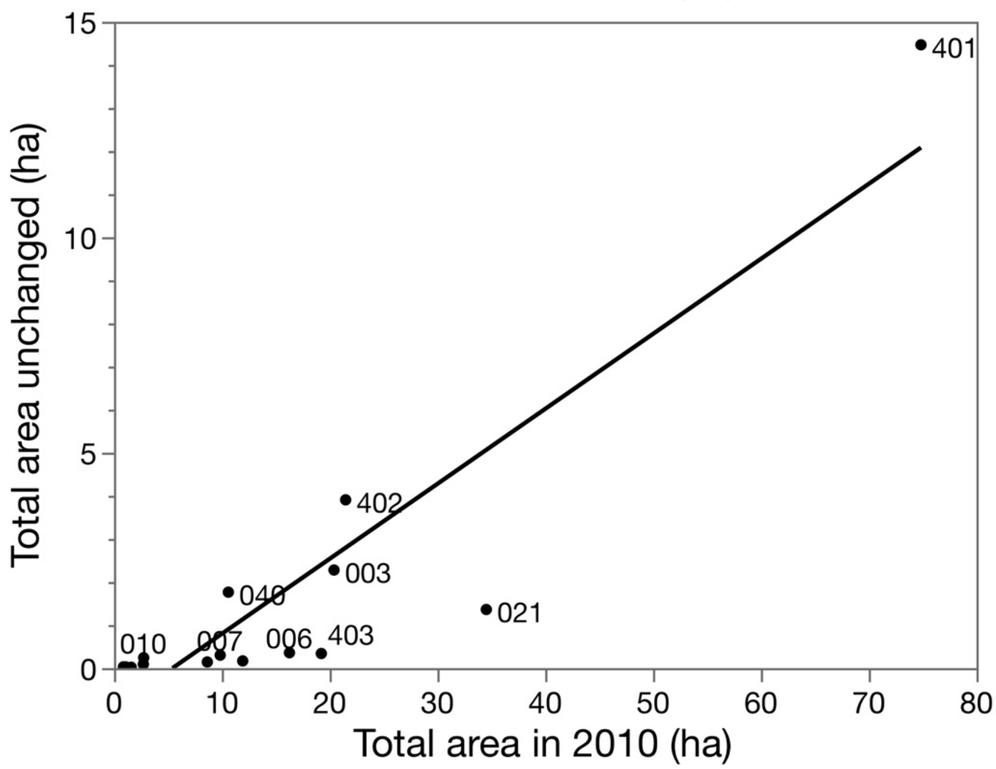


Figure 5.7: a) Total area that had changed as a function of original area in 2010 and b) Total area that remained unchanged as a function of original area in 2010.

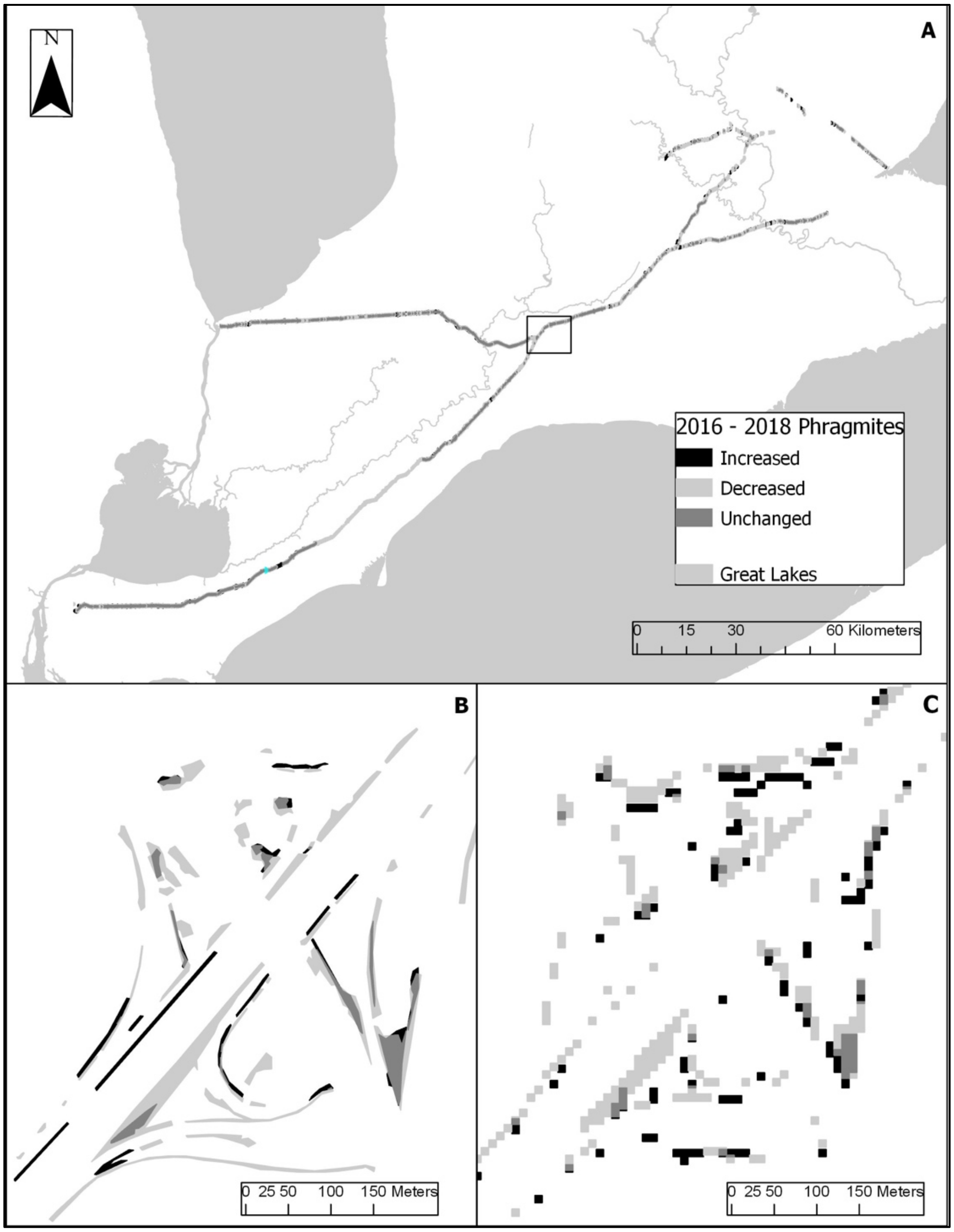


Figure 5.8: a) Results of a change detection of invasive *Phragmites* occurring in large highway corridors between 2016 and 2018, based on Sentinel-2 image classification. Shown in insets, b) enlargement of the above; c) showing the results of a change detection of invasive *Phragmites* between 2016 and 2018 based on manually digitized high resolution satellite data (2016: WV3; 2018: GE)

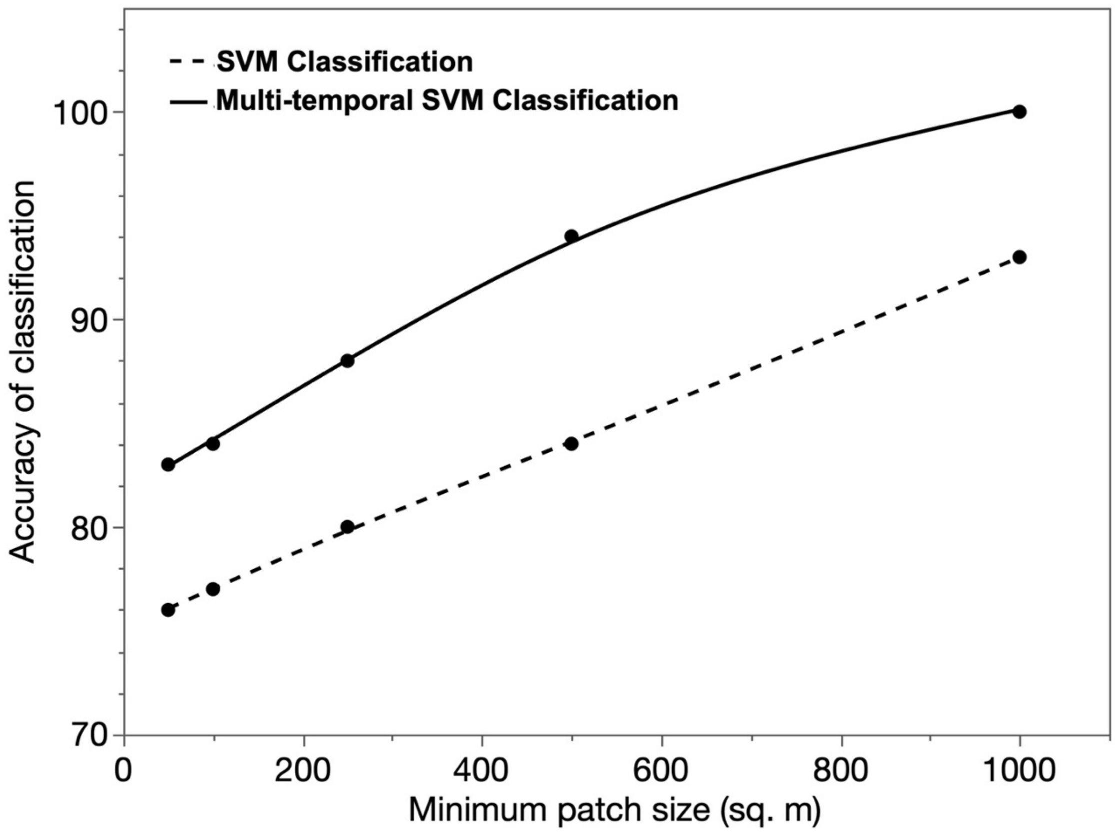


Figure 5.9: Dependency of Sentinel-2 accuracy on minimum patch size along highway corridors for two classification protocols.

Chapter 6: MAPPING OPTIONS TO TRACK INVASIVE PHRAGMITES AUSTRALIS IN THE GREAT LAKES BASIN IN CANADA

James V. Marcaccio & Patricia Chow-Fraser

Maraccio, J. V., & Chow-Fraser, P. (2016). Mapping options to track distribution of invasive Phragmites australis in the Great Lakes basin in Canada. In P. Gatescu & P. Bretcan (Eds.), *3rd International Conference - Water resources and wetlands* (pp. 75–82). Tulcea, Romania. http://doi.org/2285-7923

Abstract:

We directly compared the performance of four remote-sensing methods for mapping invasive *Phragmites* in coastal wetlands of Long Point Bay, Lake Erie, Canada. We refer to the first method as Landsat, which uses Landsat images and NDVI (Normalized Difference Vegetation Index) responses from images acquired in multiple years to determine areal cover of *Phragmites* and other dominant vegetation classes. The second method, which we will call PALSAR (Phase array type L-band Synthetic Aperture Radar) uses radar to aid detection of water level and biomass of *Phragmites* and other wetland classes. We refer to the third method as SWOOP (Southwestern Ontario Orthophotography Project), which uses spring-time orthophotos and object-based image classification to map *Phragmites* and other features in a defined region of interest. Our last method is called UAV (unmanned aerial vehicle) which involves manually delineating *Phragmites* in image data acquired by a UAV. The UAV method was most accurate at identifying *Phragmites* but could only be used to map a small area. The PALSAR approach provided a more accurate view of invasive *Phragmites* than did Landsat, and exceeded the SWOOP in terms of accuracy but not in terms of spatial resolution. The best choice of method to use will depend on the scope of the mapping project and available funding. Landsat and PALSAR may be most appropriate for mapping *Phragmites* at the regional scale, while SWOOP and AUV may be most appropriate for finer-scale updates. To fully interpret the invasion pattern of *Phragmites* at the scale of the Great Lakes basin, a combination of these methods may be required.

Introduction:

Within the Laurentian Great Lakes (N. America), almost 70% of wetlands that existed in southern Ontario prior to European settlement have been lost or degraded (Snell 1987). Most existing coastal wetlands (occurring within 2 km of the shoreline) have macrophyte assemblages and water quality that reflect degraded conditions (Croft & Chow-Fraser 2007; Cvetkovic & Chow-Fraser 2011). Whereas historically, changes in water level (Mortsch 1998) and human development (Niemi et al. 2007) were responsible for this decline, more recently, invasive non-native species have been more problematic. Known as the common reed, *Phragmites australis* is a high-marsh, emergent plant that exists as two sub-species in North America (Saltonstall 2003). The subspecies *americanus* is the native haplotype, whereas the subspecies *australis* is non-native, having arrived from Eurasia during the mid-19th century via shipping ports along the St. Lawrence River (Lelong et al. 2007). Within the Great Lakes basin, it remained relatively isolated in distribution until the late 20th century when invasive *Phragmites* established in large monocultures around the Upper St. Lawrence River. After rapidly colonizing wetlands along the St. Lawrence River, it has become firmly established in wetlands of Lakes Erie, Ontario and Huron over the past two decades. Such monocultures of invasive *Phragmites* have greatly reduced the quality of critical habitat for many native marsh-obligate birds, amphibians, reptiles, and fish (Lazaran et al. 2013; Bolton & Brooks 2010; Kolos & Banaszuk 2013).

Accurate maps of wetlands can be difficult to produce, but the constant need for these have spurred on explorations for better and cheaper methods (Wright & Gallant

2007; Gallant 2015). Relatively good results have been achieved through a variety of traditional remote-sensing methods (e.g. Midwood & Chow-Fraser 2010; Bourgeau-Chavez et al. 2013; Kloiber et al. 2015), and more recently through the use of unmanned aerial vehicles (UAVs; Chabot & Bird 2013; Marcaccio et al. 2016). Given so many available options, it is difficult for the unfamiliar ecologist to choose the most appropriate method for a particular mapping project. The purpose of our study is to conduct a direct comparison of the performance of four remote sensing methods that have been used to map invasive *Phragmites* in a region of the Laurentian Great Lakes (Long Point Bay, Lake Erie, Canada). By summarizing the strengths and weaknesses, and assessing the relative accuracy of each method, we will offer our recommendation for the most appropriate option given specific project goals and objectives.

Methods:

Study area

The study area is a 90-ha impounded wetland located in Long Point, Ontario, Canada (Figure 1), in which water levels are managed to prevent the colonization of invasive species such as *Phragmites australis* sp. *australis*. Therefore, outside the impoundment are large monocultures of invasive *Phragmites* whereas inside this the habitat is dominated by *Typha* spp. Meadow marsh vegetation (e.g. *Decodon verticilatus*) is also present in abundance throughout the basin. The perimeter of the study area is predominantly deciduous trees, with agriculture behind this thin barrier to the north, sandy beaches to the south, and water to the east

Remote sensing methodologies

We will refer to the four methods in this study as the Landsat, PALSAR, SWOOP and UAV methods (**Table 6.1**). The Landsat method was developed by the provincial ministry and identified the location of *Phragmites* using Landsat images acquired in multiple years. The PALSAR method was developed by Bourgeau-Chavez et al. (2015) who used fusion of sensors from both Landsat and the PALSAR (Phase-array type L-band Synthetic Aperture Radar) satellites to map the entire Great Lakes basin within 10 kilometres of the shoreline. The SWOOP method used image data from the Southwestern Ontario Orthophotography Project and object-based image classification of the study site (see **Figure 6.1**). The last method used the 'eBee' UAV to capture image data for a subsection of the study area which was then manually classified.

Landsat

Given that Landsat image data are now freely available to government agencies, the Ontario Ministry of Natural Resources and Forest (OMNRF) developed the Landsat method as a cost-effective way to monitor invasive *Phragmites* populations in the province of Ontario (Young et al. 2011). In addition to mapping the presence of *Phragmites*, they further classified stands as "stable", "expanding" or "diminishing" (based on images acquired over two or more years). All other wetland vegetation was classified as 'other vegetation', with the same three classes (stable, expanding or diminishing). The Landsat images had a spatial resolution of 30 m, and the data were processed with NDVI (Normalized Difference Vegetation Index), which required green, red, and near-infrared bands from the satellite. Each year of data was processed and then combined; if the response of the NDVI increased throughout years, then the patch was said to be increasing. To reduce the processing time, the Southern Ontario Land Resource Information Systems (SOLRIS) data were used to filter out areas from further consideration that were extremely unlikely to support invasive *Phragmites* (e.g. urban areas, pavement). No field-truthing data were used to assist in classification; thus, all polygons from the supervised classification were remotely sensed. The hierarchical portion of the classification built one class at a time and calculated the degree of confusion for that class. This allowed for removal of extraneous portions prior to classification in order to further reduce processing times. To allow accuracy assessment, the classification was compared against prior mapping efforts.

PALSAR

In the PALSAR project, all land use and land cover within 10 km of the Great Lakes shoreline were classified (Bourgeau-Chavez et al. 2015). Although multiple land use and vegetation types were classified, invasive *Phragmites* was the main plant species identified throughout the study area. Areas dominated by *Typha* sp. and *Schoenoplectus* sp. were also noted, as were more diverse wetland systems (compiled under ‘wetlands’). Other wetland classes included fens (with or without trees and shrubs), forested or shrubby wetlands, and aquatic vegetation. Non-wetland (e.g. forest) and types of urban land cover were also identified. The PALSAR satellite captured data at 20-m resolution in two information channels: a horizontal send and receive (L-HH; for estimating water below vegetation) and a horizontal send and vertical receive (L-HV; for estimating biomass). Where dual-polarization was unavailable, a single L-HH band was used with 10-m resolution. Images from each season (spring, summer, fall) acquired between 2008 and 2011 were used to differentiate and classify vegetation that appeared earlier or later in the season. Cloud-free Landsat images that coincided closely with the date of PALSAR acquisition were primarily used to delineate landscape features (e.g. roads, agriculture, grass). Field-truthed data were used to guide the classification and to conduct accuracy assessment. The field plots were at least 0.2 ha (size of mapping unit) with only one habitat feature present. These were superimposed on the image to derive supervised data that were fed into a proprietary Random Forest classifier written in R. As part of the classifier and to simplify processing, an unsupervised classification grouped similar pixels together. Areas of spectral confusion were classified with the supervised maximum likelihood scheme. The accuracy was reported in confusion matrices for each Great Lake and for the basin as a whole (Bourgeau-Chavez 2015).

SWOOP

The SWOOP (Southwestern Ontario Orthophotography Project) was funded by multiple agencies (municipal, provincial and federal) who wanted to obtain seamless aerial photos of the southwestern portion of the province at regular intervals (2006, 2010 and 2015 so far). Because the project was developed primarily for planning purposes, the image data were acquired during spring when leaf-off conditions allowed for unobscured view of buildings and roads. SWOOP images are freely available to participating stakeholders and research institutes. Marcaccio & Chow-Fraser (unpub. data) developed a method to use the SWOOP image data to map invasive *Phragmites* along all major highways of Ontario in southern and central Ontario. Since SWOOP data are captured from a plane rather than from a satellite, the surface of the earth is much closer to the sensor, and the true colour image had a spatial resolution of 20 cm with red, green, and blue bands. Therefore, although the area of interest is very large (half of the province), some of features being mapped can be very small (small *Phragmites* patch). Marcaccio & Chow-Fraser classified the features using an object-oriented approach (eCognition; Trimble Navigation, California, U.S.A.) that allowed for better interpretation of high-resolution data since similar pixels are grouped into 'image objects'. These image objects can be processed quickly and more accurately because they contain more information (shape, texture, geometry) than pixel values do on their own. No field data were needed to supervise this classification because of the high resolution. A confusion matrix was generated from 200 random points which were also remotely sensed from the image data.

UAV

The UAV used for this study was a senseFly eBee (Parrot, Cheseaux-Lausanne, Switzerland) equipped with a Canon ELPH 110 HS digital camera. This method was the most time-consuming of all four methods considered on a per-unit area basis. For only a subset of the study area, Marcaccio et al. (2016) spent 6 hours to acquire image data (30 passes with the UAV) in the field, and then spent an additional 24 hours to post-process the images to create a georeferenced map. The spatial resolution of the resultant image data was 8 cm per pixel. All of the *Phragmites* stands was delineated manually by field researchers who had surveyed habitat features in the study area for over 2 months. The extremely high resolution of the image data and the manual delineation of habitat classes did not necessitate ground truthing in this method.

Independent accuracy analysis

To independently verify the accuracy of all products, we created 90 control points using high-resolution data from Google Earth (Alphabet Inc., Mountain View, California, U.S.A.) that had been acquired as close as possible to the dates of the other image data used in this study (i.e. 2013). We placed 31 control points in invasive *Phragmites* stands, 15 in *Typha* sp., and 15 in other homogeneous areas such as meadow marsh, forests, and open water. To minimize effects of growth or dieback of these land cover types, each point was placed centrally within a large patch (>0.2 hectares where possible) of a single vegetation type. For each remote sensing method, a confusion matrix was generated and a kappa score was calculated. Since the Landsat and UAV methods were not continuous (that is, not every feature is given a value within the classification scheme) these had a smaller number of control points associated with them.

Results:

Comparison of results can be achieved visually (area of *Phragmites* mapped), via individual accuracy assessment, or as part of the independent accuracy analysis. Although it could be difficult to differentiate between native and invasive *Phragmites* through image data, only the invasive type was found in sufficiently high density to be captured by remote sensing methods. This is because native *Phragmites* is often found interspersed with other vegetation and does not contribute to a homogeneous monoculture patch.

Mapped invasive Phragmites

Classifications produced by the different remote sensing methods were relatively unique (Figure 2). The Landsat method classified 622 ha of land covered as *Phragmites*. This can further be broken down chronologically: 428 ha originated from the 1993 image data, with 72 and 122 additional ha from the 1999 and 2010 images. respectively. By comparison, 199 ha were classified as *Phragmites* by the PALSAR method and only 149 ha by the SWOOP method. Logistical constraints only allowed us to classify a small portion of the study area using the UAV. For a direct comparison of the 4 methods, we obtained estimates for the portion of the study site classified by the UAV method; for this same land parcel, the Landsat, PALSAR, SWOOP and UAV methods estimated 452, 135, 41 and 74 ha of invasive *Phragmites*, respectively (see **Figure 6.2**).

Individual accuracy assessments

Since there was no confusion matrix associated with the LANDSAT method, it was impossible to directly compare its results with those of the other remote sensing methods. Therefore, results had to be compared against those of a previous mapping in a different study area, and we found a 57% match with data from 7 years earlier (Young et al. 2011). The majority of the mismatched classification was attributed to invasion by *Phragmites* compared to the earlier study, but it is not possible to verify this assumption. While the UAV method did not have an associated confusion matrix, each habitat feature was created manually (similar to 'truthed' data from the same image data) and therefore, we have assumed these to be very accurate. The PALSAR approach had an overall accuracy of 92% for Lake Erie, with 94% producer accuracy and 82% user accuracy for

Phragmites (full Great Lakes confusion matrix can be found in Table 4 of Bourgeau-Chavez et al. 2015). In comparison, the SWOOP approach had an overall accuracy of 61% and a producer accuracy of 71% and a user accuracy of 85% for *Phragmites* (Table 2). The PALSAR approach was best in terms of overall and individual accuracy for *Phragmites*. The SWOOP data offered more detail due to its ten-fold increase in resolution over PALSAR.

Independent Accuracy Analysis

We were able to directly compare results of the *Phragmites* classification produced by the four methods using the Google Earth image (Table 3). The UAV method had the highest overall accuracy/kappa score and was best at identifying invasive *Phragmites*. The SWOOP method had the next highest producer accuracy, indicating that errors of commission were low. The PALSAR and Landsat methods had the same user accuracy (i.e. similarly low errors of omission). The lowest accuracy was associated with the Landsat method, while overall accuracy and kappa scores were moderate for both the PALSAR and SWOOP methods.

Discussion:

The four remote-sensing methods produced very different results for the same study area. If we accept that the UAV approach produced the most accurate classification of invasive *Phragmites*, the Landsat approach produced the highest overestimates. Both the PALSAR and SWOOP methods produced moderate accuracy, but the SWOOP method classified a greater proportion of the marsh vegetation as being *Phragmites* in the western portion of the study area compared to the PALSAR method. The confusion matrix for the SWOOP method indicated that a high percentage of the confusion was due to meadow marsh being incorrectly identified as *Phragmites*, and a large portion of this land cover occurred in the southeastern portion of the map. The PALSAR method classified major portions in the western portion of the marsh as ‘aquatic bed’ habitat, but in reality, high-resolution image data showed this area to consist of small wetland patches surrounded by water, and this could have led to spectral confusion given the larger pixels of the PALSAR satellite (i.e. both water and small wetland patches combined in a pixel).

The Google Earth image provided an objective means to compare the classification products of the four remote-sensing methods. Overall, the Landsat method had the poorest accuracy, and greatly overestimated the amount of *Phragmites* present; on the other hand, it had very low errors of omission. Since data from this method only included ‘other vegetation’, the confusion matrix was also downscaled (no categories of *Typha,* etc). No field data were used as ground truth inputs prior to (or after) classification. The major advantage of this method is that Landsat data are all freely available to researchers, and it is the only continuously available historical option for many areas in the world. Processing times for this method are relatively rapid because of the low resolution and masking from previous land-use layers; however, it is not well suited for mapping *Phragmites* if the goal is to obtain an accurate distribution of *Phragmites*.

Among the automatically classified systems, the PALSAR method yielded the highest overall accuracy and kappa score; it was only second to the SWOOP method with respect to its user accuracy. This method requires a proprietary R script and radar image data which may not be freely available in the future (a new PALSAR satellite was recently launched to replace the original damaged unit). In addition, processing times were long although the scope of the project was very large. On a basin-wide and even regional basis, this approach appears to be the most suitable method for delineating large stands of *Phragmites*. Spring-time orthophotos were very high resolution but could not be used to map most of the wetland classes because of the timing in the year of image acquisition. Fortunately, invasive *Phragmites* overwinter with their reeds intact and are usually the only vegetation that can be identified during spring time. Nevertheless, the overall accuracy of this approach was diminished by confusion between deciduous trees and water as well as *Phragmites* and meadow marsh. This indicates that some *Phragmites* stands have been misclassified as meadow marsh, although errors of commission are low. SWOOP data are freely available to most researchers in Ontario and the object-based image analysis provided a good alternative to Landsat and PALSAR methods. As well, the province of Ontario is committed to repeating the acquisition of the image data every five years, and this provides an efficient way to to obtain regular updates. If the objective is to have an accurate map of *Phragmites*, the SWOOP method is the most suitable for local scales where finer detail (sub-metre resolution) is required.

Unmanned aerial vehicles are now being used by ecologists to acquire appropriate imagery for small-scale projects that cannot be delivered via satellites or piloted aircraft

(Chabot & bird 2013; Marcaccio et al. 2016). UAVs are much more cost-effective to operate than a plane, and can be deployed multiple times during a single season. Their high resolution means that images can be accurately classified without the need for field-truth data. This method is limited, however, by the large amount of time required to acquire and process the images; consequently, only a portion of the entire study area could be mapped with this method. There is also modest initial investment of the UAV and fees to train the pilots. Although it was shown to be most accurate for mapping *Phragmites*, the spatial and processing limitations mean that this method should be restricted to projects with smaller spatial scales where other appropriate image data cannot be obtained.

Conclusion:

Methods and solutions in remote sensing have made substantial progress in recent years, fueled by innovations in satellite technology, image sensors and unmanned aerial vehicles. We showed that each of the four methods had both strengths and weaknesses for classifying invasive wetland plants in North America. In many regions of the world, Landsat is the best option for continuous and historical monitoring of land cover. Regional maps of aquatic vegetation were accurately produced with PALSAR images while SWOOP image data were best for projects that had a large regional scope but that also required small mapping units to be classified accurately. Unmanned aerial vehicles require the greatest processing times but also produce very accurate results. This method should only be used at smaller spatial scales (in this study, <1,000 hectares) unless extremely high resolution or specific, consistent monitoring is required. Novel satellite sensors are accurate for regional classification, and upon verification of *Phragmites* near one's region of interest, orthophotography and image object-based analyses can be used to minimize errors of omission.

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Table 6.1: Comparison of remote sensing approaches used in this study.

Aspect compared	Landsat	PALSAR	SWOOP	UAV
Image data	Landsat (optical); land cover data (vector shapefile)	PALSAR (radar) & Landsat (optical)	Orthophotography via Leica geosystems ADS80 SH82 (optical)	Unmanned aerial vehicle (UAV) equipped with Canon ELPH 110 HS (optical)
Extent of classification	Lake St. Clair, Detroit River, & Lake Erie (Canada)	10 kilometre of Great Lakes shoreline (Canada & U.S.A.)	Long Point (study area)	Big Creek National Wildlife Area (subset of study area)
Resolution (per pixel)	30 metres	20 metres	20 centimetres	8 centimetres
Timing of imagery acquisition	Summer; 1993, 1999, & 2010	Spring, summer, fall; 2008-2011	Spring; 2010	Summer; 2015
Classification method	NDVI –based hierarchical image object-oriented decision tree	Random forests isodata unsupervised/supervised maximum likelihood	Image object-oriented classification	Manual delineation
Developed by	Ontario Ministry of Natural Resources and Forestry	Bourgeau-Chavez et al., Michigan Technological University, U.S.A.	Marcaccio & Chow-Fraser, McMaster University, Canada	Markle & Chow-Fraser, McMaster University, Canada (2016)
Classified results	Invasive *Phragmites* (stable; expanding; diminishing), other vegetation (5 types of land cover)	Invasive *Phragmites*, multiple wetland types, urban land cover, agriculture (24 types of land cover)	Invasive *Phragmites*, *Typha*, Meadow Marsh (6 land cover types)	Invasive *Phragmites* (stable; rolled; not monoculture), *Typha*, aquatic habitats (20 types of land cover)
Verification	No field truthing; compared against prior mapping efforts	1751 field truthing sites (30 in study area); confusion matrix for each basin (Great Lake)	No field truthing; confusion matrix for study area (200 random points)	Used field data to guide delineation

Table 6.2: SWOOP method confusion matrix

	Barren Land	Deciduous	Meadow Marsh	*Typha*	*Phragmites*	Water	**Producer Accuracy**
Barren Land	**7**	0	0	3	0	0	70%
Deciduous	1	**6**	7	2	0	8	26%
Meadow Marsh	0	7	**38**	29	3	0	49%
Typha	1	1	7	**48**	0	1	84%
Phragmites	0	2	4	1	**17**	0	71%
Water	0	1	1	0	0	**5**	71%
User Accuracy	78%	35%	67%	58	85%	36%	**61%**

Table 6.3: Results of the confusion matrix associated with external validation of remote sensing products; producer and user accuracy are for *Phragmites* classification only

	Landsat	**PALSAR**	**SWOOP**	**UAV**
Producer Accuracy	56	86	90	100
User Accuracy	77	77	58	100
Overall Accuracy	57	77	62	87
Kappa score	0.125	0.638	0.436	0.780

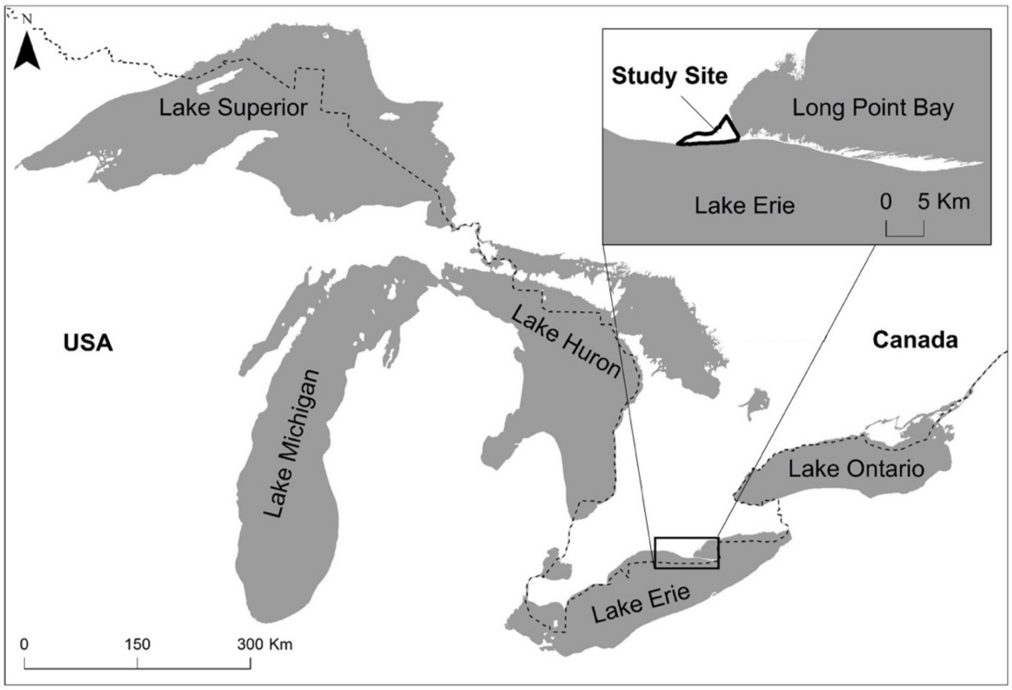

Figure 6.1: Research area located on the north shore of Lake Erie, Canada.

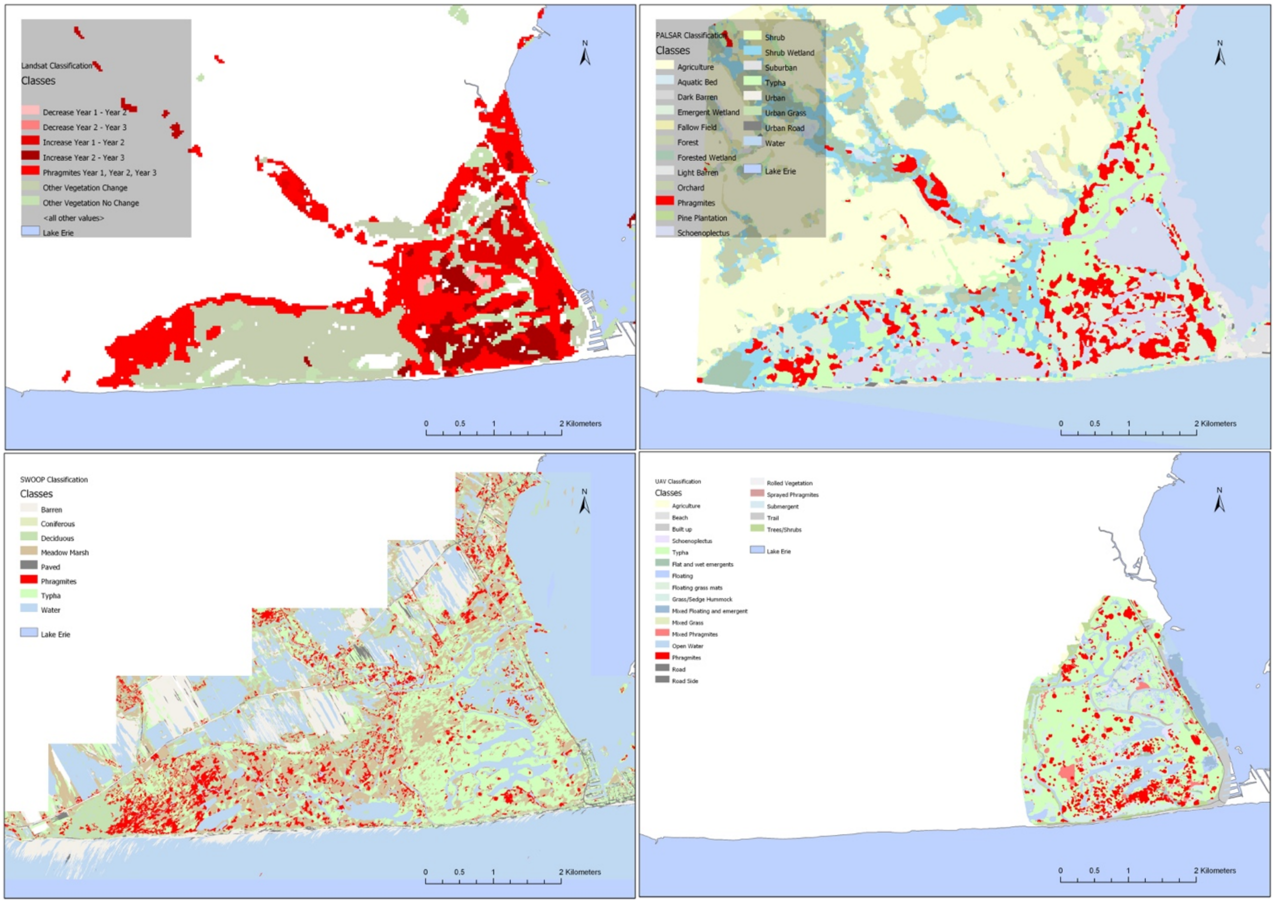

Figure 6.2: Remote sensing classification outputs. Invasive *Phragmites* appears in pink on each map

Chapter 7: General Conclusion

Summary:

In order to effectively manage populations of invasive *Phragmites*, we must understand its geographic distribution. In Chapter 2, we created the first comprehensive basin-wide map of wetlands in the Great Lakes including invasive *Phragmites*. Using a combination of sensors and timepoints, we produced an accurate and consistent mapping effort that includes both natural and anthropogenically modified land cover. It is important that both optical and SAR be combined to obtain the best possible accuracy across the suite of land use classes that were derived. These data serve as an important baseline for mapping future changes in the distribution of all wetlands and especially invasive *Phragmites*. This method is flexible and can also be used to map non-coastal temperate zones such as southern Ontario and Michigan.

In order to map invasive *Phragmites* along smaller roadside habitats in Chapter 3, we used provincial orthophotography databases with a higher resolution than commercially available satellites can provide. With these data, we were able to create the largest comprehensive map of invasive *Phragmites* along a road network with multiple years of data. We synthesized our findings into a conceptual model of the distribution of invasive *Phragmites* throughout road networks. Invasive *Phragmites* was found to consistently take over pre-existing grasses found within the road network, which may indicate a need for more resistant grass species to be seeded in roadside embankments. We found that traffic volume was a significant predictor of invasive *Phragmites* but this was not a strong relationship. While representing a large portion of total areal cover in the dataset expressways and highways were not the most invaded road type by habitat available, and this may point to them being a 'sink' of invasive *Phragmites* in the landscape. While other habitat variables may preclude the establishment of large populations throughout central and northern Ontario, it is possible that invasive *Phragmites* could become an even more dominant and widespread problem throughout all of Ontario in a relatively short period of time.

Using traditional remote sensing data as described above can prohibit mapping of very small or newly establishing patches of invasive *Phragmites,* which are important to eradicate to manage their continued spread. In Chapter 4, we describe a methodology for acquiring images from unmanned aerial vehicles (UAVs) to obtain sub-decimetre image data. Using both multi-rotor and fixed-wing vehicles in wetland ecosystems, we show that very high accuracy can be obtained with only optical image data. These results were the first to compare different types of UAVs against publicly available image data within wetland systems. Using UAVs, researchers, managers, and agencies can obtain timely data for their chosen site of interest. These tools can be considered a low-cost investment when weighed against the acquisition of annual/seasonal high-resolution commercial image data. We believe that the flexibility of UAVs can revolutionize data capture and what ecological questions can be asked especially in dynamic ecosystems such as wetlands.

Using our novel remote sensing methodologies, we conducted a review of an invasive *Phragmites* removal program along highways of southern Ontario in Chapter 5. While many control programs have been induced in the Great Lakes basin, we found that most do not follow up with any form of effectiveness monitoring. Even though this was conducted across an extensive scale, total areal cover of invasive *Phragmites* increased throughout the study period analyzed. We noted that removal efforts on large stands and those on large highways were the most ineffective likely due to complexities in successfully applying herbicides. Resistance to eradication along a given road was directly related to the historic invasive *Phragmites* areal cover. Our comparison with high resolution satellite data showed that repeat treatments were more effective than treatments at single time points. These data have and will continue to assist future efforts in invasive *Phragmites* removal in novel roadside habitats.

Put together, these new methods and insights can have a clear benefit to any involved in invasive *Phragmites* control efforts in North America. In order to determine the best methods to use for a given study we review each and provide suitable use cases in Chapter 6. We identified that the historic and spatial capacities of the Landsat imaging system can provide the only continuous historic coverage throughout the world. New satellite sensors can improve these results but are not available historically and may have high costs associated with them. Orthophotography has been steadily used for decades and can provide excellent spatial coverage with much higher resolution than satellite data but must be scheduled and acquired by the interested party. Finally, unmanned aerial vehicles can provide incredible detail and repetition at a site-specific scale, but their short flight times and regulatory hurdles preclude their use for larger projects.

Recommendations:

With new knowledge obtained during this thesis, I make the following recommendations for management of invasive *Phragmites.*

1. Herbicide suitable for use over aquatic environments must be regulated and introduced in Canada. Without this tool, removal of invasive *Phragmites* will be hampered.
2. A consistent and accurate mapping methodology must be developed and continually used to assess the progression of invasive *Phragmites* in the Great Lakes basin. Without appropriate reference data and continual updates, we will not have any indication as to its current extent or the effectiveness of our eradication strategies. Governments particularly in the Great Lakes basin need to make this a priority in order to appropriately manage this aggressive invader.
3. Future work on invasive *Phragmites* must include regular monitoring post-treatment in order to help guide any future works. Without these data, treatments may become ineffective and invasive *Phragmites* cover could continue to expand instead of diminish.
4. Large scale removal efforts must involve participation and coordination of all adjacent land owners. Even very small patches of invasive *Phragmites* can lead to its continued presence along the landscape. Without the action of all parties, invasive *Phragmites* will continue to be a problem in our wetland and roadside ecosystems.

5. We recommend that unmanned aerial vehicles be used at the site level to obtain the best possible data of invasive *Phragmites* distribution. Since even small patches can continue to disperse and propagate, it is important to know where these are and eliminate them during removal.
6. Removal efforts must be targeted and have a clear plan of action. While one can choose to focus on the large spatial distribution of invasive *Phragmites* within highways of Ontario, these often have large patches and are very difficult to eradicate. If funds are limited, it may be best to focus on smaller roads that have smaller patches which will be more easily eliminated. While it leaves large patches as an 'eyesore', This approach may limit the spread of invasive *Phragmites* to novel habitats.
7. An alternative seed mix for roadside habitats should be investigate. At present, there appears to be little competition against invasive *Phragmites* in roadside habitats but this could change with different native plant species.
8. Unmanned aerial vehicles are excellent for mapping small site-specific areas, but they are not a solution or alternative to traditional remote sensing data. These data will allow us to ask novel answers and acquire interesting data, but they do not replace satellites and orthophotography.

<u>Future Work</u>

During the completion of this thesis, we found many additional projects and questions that could further our understanding of invasive *Phragmites* geography and ecology.

1. While we now have comprehensive methods for determining the areal cover of invasive *Phragmites*, we cannot currently determine its density. It is very likely that removal efforts for and propagation of this invader is impacted by density as well as areal cover.
2. Further validation of our conceptual model from Chapter 5 is necessary. In particular, future efforts can focus on:
    a. If wetlands are a sink or source of invasive *Phragmites* propagules. Future studies should observe the distribution of stands and expansion over time far from and adjacent to wetlands, such as Long Point and Point Pelee.
    b. If road construction assists in the spread of invasive *Phragmites*. With a comprehensive construction database between 2006 and 2010, we could determine if sites near construction (where vehicles and people are disturbing the environment and potentially distributing seeds) are more quickly invaded than sites far from it.
    c. If soil type has a significant influence on invasive *Phragmites* distribution. Southwestern Ontario is all underlain by one soil type, but central Ontario contains unique soil types. With new image data from central Ontario, we could determine if expansion is slower in areas with similar traffic volume but unique soil types.
    d. If the construction or morphometry of roadside habitats influences invasive *Phragmites* distribution. Not all roadside habitat is constructed with the same dimensions and some methods and geometries may be more

or less conducive to invasion. This would require comprehensive and geographic data on the qualities of roadsides in Ontario.

    e. Determining the significance of these variables and how they combine to permit the expansion of invasive *Phragmites*. With data from the above questions and advanced statistical modelling, it may be possible to determine the likelihood of invasive *Phragmites* distribution in the future which would be beneficial when planning removal efforts.

3. A direct comparison of expansion and removal efficacy in wetland and roadsides should be undertaken. These are two unique habitat types and invasive *Phragmites* may not respond to both in the same manner.
4. The expansion pathway of invasive *Phragmites* into Ontario is still elusive. With our remote sensing methods and new novel approaches, we could determine where and when invasive *Phragmites* first began its rapid expansion and how it has spread over time. These results would be important to help stop future expansion throughout the Great Lakes basin.
    a. Using genetic tools, we can observe the number of unique individuals within wetlands and whether these are highly correlated to adjacent roadside habitats.
    b. Similar to the above, historic herbarium samples can also be analyzed if appropriate geographic data were collected along with each sample.
    c. In current areas dominated by invasive *Phragmites*, we can use historic air photos to determine the beginning of invasions.

5. Continued monitoring of treated invasive *Phragmites* patches should be undertaken to determine the regeneration of natural habitat. Specifically, research should determine not just the regeneration of native flora but also the reintroduction of native fauna that were displaced due to invasive *Phragmites* monocultures.
6. Future efforts could determine the unique spectral signature of invasive *Phragmites* from native *Phragmites* and other wetland species. While these values could differ depending on the sensor array and distance from subject, these data would allow for more accurate and definitive mapping products.
7. With data from above, a system can be developed to automatically distribute herbicide over invasive *Phragmites* from unmanned aerial vehicles. Even without automated image classification or automated flights, this tool could lead to a revolution in how we manage this species at the site scale.

Chapter 8/Appendix A: Comparison of remote sensing approaches to map *Phragmites* in coastal areas of southern Ontario

By

Marcaccio, James, Bourgeau-Chavez, Laura, and Chow-Fraser, Patricia

Marcaccio, J.V., Bourgeau-Chavez, L., & Chow-Fraser, P. (2015). Comparison of remote sensing approaches to map *Phragmites* in coastal areas of southern Ontario. Report prepared for the Ontario Ministry of Natural Resources and Forestry, Inventory Monitoring and Assessment, Peterborough, ON. 53 pages

Background:

Invasive species can cause a multitude of ecological, social, and economic problems, and none have been as problematic as invasive *Phragmites australis* (common reed). Different remote sensing approaches have been used to map the *Phragmites* distribution within the Great Lakes basin. In Canada, the Ontario Ministry of Natural Resources and Forestry (OMNRF) uses Landsat images with NDVI bands from three different growing seasons and years to classify and delineate *Phragmites*. After training polygons are created, a hierarchical image object-based decision tree is used to differentiate among vegetation classes. By contrast, in the U.S., Michigan Technological University (MTU; Bourgeau-Chavez et al. 2015) uses PALSAR (Phase Array type L-band Synthetic Aperture Radar) imagery together with Landsat NDVI, with three images taken in different seasons throughout one year (spring, summer & fall). This approach uses a combination of unsupervised and supervised pixel-based classification to differentiate among all class types. The purpose of this document is 1) to directly compare the results of both approaches 2) consider the merits and limitations of using radar and 3) to discuss the benefit of using field data for supervised classification.

Objective:

This document explores the similarities and differences of two remote-sensing approaches, one involving PALSAR + Landsat NDVI (Bourgeau-Chavez et al. 2015), and another involving only Landsat NDVI (Young, Young & Hogg 2011). Independent accuracy assessments for each product as well as a comparison of spatial disparities between the results will be presented. Possible reasons for inaccuracies and mismatches are also discussed. For remainder of this document, we will use the terms "PALSAR+" and "NDVI" to distinguish between the two approaches.

Methods:

Study Area

In the PALSAR+ project, all land use and land cover within 10 km of the Great Lakes shoreline were classified (**Table 8.1; Table S8.1**). Although multiple land use and vegetation types were classified, *Phragmites* was the main plant species identified throughout the study area. Areas dominated by *Typha* sp. and *Schoenoplectus* sp. were also noted, as were more diverse wetland systems (compiled under ‘wetlands’). Other wetland classes included fens (with or without trees and shrubs), forested or shrubby wetlands, and aquatic vegetation.

The NDVI project was designed to map coastal wetlands on the Canadian shoreline of Lake Erie and southern Lake Huron. The Southern Ontario Land Resource Information System (SOLRIS) was first used to identify potential wetland areas and to exclude areas where *Phragmites* was unlikely to occur (e.g. built-up areas). All land use types within each potential area were classified, although the emphasis was on delineating *Phragmites* stands.

Imagery

The PALSAR+ approach used both PALSAR and Landsat imagery . PALSAR was acquired at 20-m resolution that supported two information channels: a horizontal send and receive (L-HH; for estimating water below vegetation) and a horizontal send and vertical receive (L-HV; for estimating biomass). In cases where the dual channel data were unavailable, a single polarization dataset consisting of only L-HH was used, which had a 10-m resolution. Each frame was 70 km x 70 km regardless of the number of channels used, and all three time periods were stacked together to create a single file per area. Cloud-free Landsat 7 images acquired close to the dates of the PALSAR acquisitions were used to classify landscape features (e.g. roads, buildings, fields). If available, other high-resolution aerial photographs were also used for this purpose.

When possible, both PALSAR and LANDSAT imagery were acquired in 2010, with one image each for spring, summer, and fall for each frame area (three seasonal images per year). If imagery for 2010 were unavailable, imagery from 2007 to 2011 were obtained; this may have resulted in some disparities in adjacent areas but possible inaccuracies associated with this is unknown. Multiple seasons were used to better differentiate among classes, as some plant species may grow more quickly during spring while others would become prevalent later in the season.

The NDVI approach used three years of NDVI band information from Landsat from 1993 to 2010. This facilitated analysis of stand growth over multiple years since *Phragmites* has been noted to expand rapidly and this information yielded spectral signatures that can distinguish them from *Typha*.

Field Data

The minimum mapping unit for PALSAR imagery has been determined to be 0.2 ha (2 x 2.5 pixels in this case), as noise in the imagery can reduce the usefulness of the results (Bourgeau-Chavez et al., 2009). Because of this, all sites sampled are at a minimum 0.2 ha in size. All sites were randomly selected from a database of all known emergent wetland locations. Sources included the National Wetland Inventory, the McMaster Coastal Wetland Inventory, and the Great Lakes Coastal Wetland Consortium. Field data were collected from 2010 to 2013 (May to October in each year) in both U.S. and Canada. Initially 100 sites were drawn for the Canadian portion, but there was only sufficient time during 2013 for McMaster researchers to visit 69 that were road accessible. Data collection followed a standardized protocol. Within each site, a homogeneous area (at least 0.2 ha in size) was used as the basis of the training polygon. Handheld Garmin ETrex GPS units were used to record location (accuracy approximately 5 m), and where appropriate photographs were taken for plant identification. The wetland type was assigned, the species diversity and dominant species were noted, the depth of standing water as well as the vegetative life stage was recorded, and the height and density of *Phragmites* and *Typha spp.* were measured. Photographs were also taken in four cardinal directions at the plot centroid to provide additional information to ground truth each data point (see **Table S8.2** for list of all variables).

The NDVI method did not use field information to classify their images. Although members of the Ontario Federation of Anglers and Hunters (OFAH) collected field data for this project, they collected point data rather than polygon areas, and these were not suitable for classification.

Classification

The comprehensive description of the classification and mapping procedures are documented in Bourgeau-Chavez et al. (2015). We will only provide a simplified version of the procedure here. Field data and air photo interpretation were first used to identify the wetland vegetation types. A group of trained individuals performed the photo interpretation to generate two unique sets of data that were then combined. To ensure an accurate classification, we aimed to include 50 polygons for each class. Each PALSAR frame (70km x 70 km) has its own set of field data and remote sensing data, for a total of over 100 frames in Canada (Lake Erie had approximately 15 frames).

All of the shorelines for Lakes Ontario, Erie, Huron and Superior were at 30 cm resolution, except for Georgian Bay, which were based on ESRI's World Imagery and Google Earth. The supervised data were input to "Random Forests" with the three date Landsat-PALSAR image stack which included all Landsat bands (21) and PALSAR bands (6) as well as an NDVI layer for each Landsat date (3), for a total of 30 input remote sensing bands. Random Forests is a proprietary R script developed by researchers at MTU to streamline the process of classification and accuracy assessment. An isodata unsupervised classification is used to group pixels with similar spectral properties together, and this is iterated until each class is classified. For areas of spectral confusion, a supervised maximum likelihood classification is used in conjunction with field data as the supervised cells. Areas identified as having *Phragmites* are then filtered so that areas below 0.2 ha in size are removed. Manual filtration is also used to eliminate any other erroneous areas. We preferred errors of commission rather than omission for *Phragmites* in order to generate a comprehensive distribution of all stands in Canada.

The NDVI approach used training polygons derived by remote sensing within areas identified by SOLRIS. A hierarchical image object-oriented decision tree classification was used, which builds one class at a time and identifies the confusion associated with it. This also allows extraneous portions to be identified and excluded prior to classification. All areas below the minimum mapping unit (0.81 ha) were then eliminated before the final product was created.

Results:

The PALSAR+ approach provided a much larger geographical coverage than did the NDVI approach, and achieved this at a higher resolution. The PALSAR+ approach used images from one calendar year for the most part, compared with the near 20-year span for images in the NDVI approach. While the OFAH had visited more locations than did the McMaster field crew, their data were not suitable for use in classification because they collected point data instead of an area occupied by a pixel. Although both approaches are technically sound, the NDVI protocol was a simpler method, with fewer steps. The accuracy table for the NDVI approach, which compares its results against prior mapping can be seen in **Table 8.2**; the error matrix for the PALSAR+ approach is in the Appendix.

Accuracy Assessment

On a basin-wide scale, the PALSAR+ approach had relatively low errors of omission (11%) for *Phragmites* while commission errors were higher (36%). User accuracy was 64% with a producer accuracy of 89%. In Lake Erie specifically, accuracies for *Phragmites* were very high, with very low errors (82% user accuracy, 18% commission error, 94% producer accuracy, 6% omission error). In contrast, accuracies were low for both Lakes Huron and Michigan and errors were high for *Phragmites*. There were no *Phragmites* identified in Lake Superior within its 10 km shoreline buffer.

The NDVI approach had a qualitative assessment against previous mapping efforts obtained by Arzandeh & Wang (2003), but the validity of the comparison is limited by the 10-y time lag between image acquisitions. There was a good visual fit between both products when taking into consideration the expansion of *Phragmites* throughout the region over the elapsed time. A numeric analysis showed that there was a good match between products, and that discrepancies could be due to a difference in the approaches' intentions (i.e. importance of Type 2 error or commission error) and the time lag (see **Table 8.2**). The approach used by Arzandeh & Wang (2003) as well as the PALSAR+ approach over-predicted the presence of *Phragmites* compared with the more conservative NDVI approach. No error matrix was available for the NDVI approach, as field training data were not used.

Field Verification

During the summer of 2014, McMaster researchers carried out additional field work and we will use these data to assess the accuracy of *Phragmites* mapping by both approaches. Three areas with various densities of *Phragmites* as well as other wetland classes were targeted for data collection: two in Lake Ontario (the western end of Lake Ontario near Hamilton and Presqu'ile Provincial Park and surrounding wetlands) and one in Lake Erie (Big Creek National Wildlife area and north of it within Long Point Marsh Complex). A limited number of sampling locations were visited in Georgian Bay, but there were insufficient information for any conclusive analysis. More work in the area is planned for the summer of 2015.

Altogether, 18 sites were visited in Long Point Bay, a region that had been mapped by both mapping approaches. Using the PALSAR+ approach, over 70% of *Phragmites* sites were correctly identified and 90% of non-*Phragmites* sites were correctly identified (**Table 8.3**). With the NDVI approach, 43% of *Phragmites* field sites were correctly identified and 64% of non-*Phragmites* sites were correctly identified (**Table 8.4**). Two *Phragmites* presence sites indicated by the field validation were not within any classification area in the NDVI approach, and this may have been because the subject land were located too far from the shoreline. The PALSAR+ approach classified the entirety of each frame, and thus no pixels remained unclassified.

We also used training data obtained in 2013 to assess the accuracy of the NDVI approach; unfortunately, training sites cannot be used to assess the accuracy of the PALSAR+ approach, as these had been used in the classification process. Within the region of interest, there were 30 sites, 19 of which contained *Phragmites*. 53% of these were correctly classified by the NDVI approach while 16% were not classified (**Table 8.5**). Points containing other vegetation were classified with 18% accuracy, with the rest being classified as *Phragmites.*

NDVI and PALSAR+ comparison

We used a minimum convex hull around the polygons associated with the NDVI approach to delineate a study area that could be used to directly compare the NDVI and PALSAR+ approaches since the PALSAR+ approach covered a greater total area (**Figure**

8.1). By overlaying mapped areas produced by both approaches, we can calculate the degree of agreement between approaches. There was moderate agreement between approaches; however, the NDVI approach classified a larger amount of the area but achieved a higher amount of mismatched areas compared with the PALSAR+ approach (**Table 8.6**). The disparities between approaches varied among regions. For instance, in the Walpole Island area, the PALSAR+ approach produced a map with greater coverage of *Phragmites* than did the NDVI approach, and therefore resulted in a worse match between the two approaches (**Figure 8.2; Table 8.6**). By comparison, if we focus on the Long Point Bay region, we observe an opposite trend (**Figure 8.3**). Here, the PALSAR+ approach classified less than 50% of the area achieved by the NDVI approach (**Table 8.6**). In the eastern end of the basin in southern Grand River, where the landscape was not dominated by wetlands, the differences become even more striking, and the % match declined drastically (**Figure 8.4, Table 8.6**).

Discussion:

When considering the accuracies reported by both approaches in their respective documentations, there is no evidence that the PALSAR+ approach produced a more accurate classification for *Phragmites* than the NDVI approach; however, when we used field data collected in 2014 to directly compare the accuracy of the two mapping approaches within the study area, differences do emerge (**Figure 8.1**). Although the 2014 data with the PALSAR+ protocol, they were not used in the training and classification, and are therefore suitable to be used for accuracy assessment. Based on the 2014 field data, there was a higher accuracy (5/7; **Table 8.3**) for *Phragmites* using the PALSAR+

method compared to the NDVI approach (3/7; **Table 8.4**). The reason for these differences may be due to the additional field-verified training polygons used during classification in the PALSAR+ approach, whereas the NDVI approach did not include any training data. It is important that the field data be collected for polygons or centroids rather than just points as these do not reveal the spatial distribution of the recorded subject. As the points are likely to be captured at a time when current imagery is not available, remote sensing cannot be used to determine where the subject extends to. With polygons or centroids that match the minimum mapping unit, researchers can know that the entire area is composed of the subject and that the area will be included in a pixel of the imagery used.

For the above comparison, there is a certain amount of error due to the time elapsed between the date of field work and the date of acquisitions (i.e. 4 growing seasons), but this limitation is applied equally to both approaches. Because the 2008 SOLRIS layer was used to isolate potential areas for *Phragmites* classification, the NDVI approach may have inadvertently excluded areas in the landscape where *Phragmites* had expanded between the image acquisition and the field collection, and this might have hindered its ability to detect *Phragmites* in the study area; consequently, two *Phragmites* sites in the field validation were left unclassified. Although only 7 *Phragmites* sites were used in this comparison, the PALSAR+ approach was able to accurately identify all *Phragmites* stands and did not have any false classifications. When field data obtained for the PALSAR+ classification study were used to assess the accuracy of the NDVI approach, we found that accuracy improved but there were similar problems with general confusion between *Phragmites* and other vegetation (**Table 8.5**). Even with a limited data set for the Lake Erie basin, the results showed that the PALSAR+ approach was more accurate than the NDVI approach.

The large amount of mismatch between both approaches underscores an underlying difference in how each approach performs the classification. Whereas the PALSAR+ approach tended to identify many small patches of *Phragmites*, the NDVI approach tended to classify large contiguous areas of *Phragmites*. This could be due to the ability of radar to detect biomass and water depth. *Phragmites* is known to grow in shallower waters and in high density, which can help distinguish it from *Typha* and other wetland vegetation. A radar image like PALSAR will be able to better define areas where *Phragmites* exists based off of these parameters. The NDVI measures are relatively unique for each species, but in areas where multiple species grow spectral confusion could lead to the area being identified as more closely resembling *Phragmites* instead of a mixed wetland.

There was not great a disparity between maps for the Walpole Island (**Figure 8.2**), and the numerical comparison is similar to that of the entire study area. The difference between approaches was especially evident in the southern Grand River, where the NDVI approach classified large wetland areas within the river as *Phragmites* while the PALSAR+ approach identified many smaller areas around the periphery. Based on analysis with SWOOP 2010 imagery, there does not appear to be large patches of *Phragmites* as shown in the NDVI imagery. In the Long Point Bay region, the NDVI approach correctly classified *Phragmites* stands but in most cases over-extended the boundaries of the stands. The reason for this error is unclear, but may be linked to possible confusion between *Typha* and *Phragmites* as there was an abundance of *Typha* in Big Creek National Wildlife Area and the adjacent wetlands (located in the western portion of **Figure 8.3**). Using imagery provided by Google Earth, it can be seen that the impounded wetland within the Big Creek National Wildlife Area has little *Phragmites* present (**Figure 8.5**). The wetlands in the surrounding area do have stands of *Phragmites*, but none are very expansive and are often small and sparse. This error could have been remedied by using field training points in the area to assist with remote sensing.

It is difficult to say how much the NDVI classification could improve with proper field training data, but this is most likely the source of error in certain regions (e.g. Long Point). The NDVI approach is also limited in its reach because only coastal areas were considered. Even if the coverage extended to within 10-km of the shoreline, the NDVI approach would still only classify a small portion of the image due to the SOLRIS boundary, whereas the PALSAR+ approach would classify the entire image.

Conclusion:

We showed that the PALSAR+ approach can identify *Phragmites* patches more accurately than can NDVI approach for the area they share in common. There are more factors to consider than just the accuracy for both approaches, including the cost, amount of time required to perform field collection and the classification process, and the size of the areas being mapped. The sources of imagery pose a problem for both approaches: PALSAR is expensive to acquire, and the NDVI approach uses imagery spanning over almost 20 years (with a minimum 6-y gap). The PALSAR+ approach could be cost-prohibitive for some agencies. As well, the original PALSAR satellite is no longer operational, although a new satellite is now currently in orbit. The time lag required for the NDVI approach means that any mapping products will be dated when it becomes available for use by managers, as the classification work will also add to the delay. Although smaller time spans could be used, they have yet to be tested for *Phragmites* mapping. The extent of the NDVI approach is also limited to what is identified by SOLRIS which does not include central/northern Ontario. Other products could be used as a substitute to SOLRIS above southern Ontario but these have not been tested. The final decision as to which method to use may be a result of the agency's financial situation and whether the NDVI approach could be repeated with relatively high frequency across the entire coast of the Great Lakes.

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Table 8.1: Comparison of the PALSAR+ approach and the NDVI approach to mapping *Phragmites*

	PALSAR+	NDVI
Extent	10 km of Great Lakes shoreline	Coastal wetlands on Lake Erie, Detroit River & Lake St. Clair, as identified in SOLRIS
Imagery Source	PALSAR & Landsat; active radar and passive optical	Landsat; passive optical
Resolution	20 m	30 m
Timing of imagery acquisition	2008 - 2011; spring, summer, fall	Summer of 1993, 1999, 2010
Field Data	1751 sites in total (*30 within NDVI area visited by McMaster University*)	OFAH GPS locations (not used for accuracy assessment)
Classification Methods	Random Forests isodata unsupervised/ supervised maximum likelihood	NDVI-based hierarchical image object-oriented decision tree

Table 8.2: Comparison of *Phragmites* mapping between Arzandeh & Wang (2003) and the NDVI approach (all units in ha) in the Walpole Island region. % Match is calculated by observing the overlap divided by the total area mapped. (Taken from Young & Hog (2011).

	Total	Mismatch	Overlap	% Match
Arzandeh & Wang	1600	577	1022	64
NDVI approach	1794	771	1022	57

Table 8.3: Accuracy comparison of the PALSAR+ mapping of *Phragmites* with field data collected in the Long Point Bay region in 2014.

		PALSAR+ Classification	
		Phragmites	Other
Field observations	*Phragmites*	5	2
	Other	1	10

Table 8.4: Accuracy comparison of the NDVI mapping of *Phragmites* with field data collected in the Long Point Bay region in 2014.

		NDVI Classification		
		Phragmites	Other vegetation	Not classified
Field observations	*Phragmites*	3	2	2
	Other	4	1	6

Table 8.5: Accuracy comparison of the NDVI *Phragmites* mapping with field training sites used in the original PALSAR+ classification (2013).

		NDVI Classification		
		Phragmites	Other vegetation	Not classified
Field observations	*Phragmites*	10	6	3
	Other	9	2	0

Table 8.6: Comparison of areas (ha) classified as *Phragmites* in the total study area.

Region	Approach	Total	Mismatch	Overlap	% Match
Entire	NDVI	8003	5127	2876	36
	PALSAR+	6799	3902	2876	42
Walpole Island	NDVI	2922	989	1933	66
	PALSAR+	3722	1778	1933	52
Long Point Bay	NDVI	1676	1335	340	20
	PALSAR+	764	419	340	44
Southern Grand River	NDVI	631	566	65	10
	PALSAR+	226	159	65	29

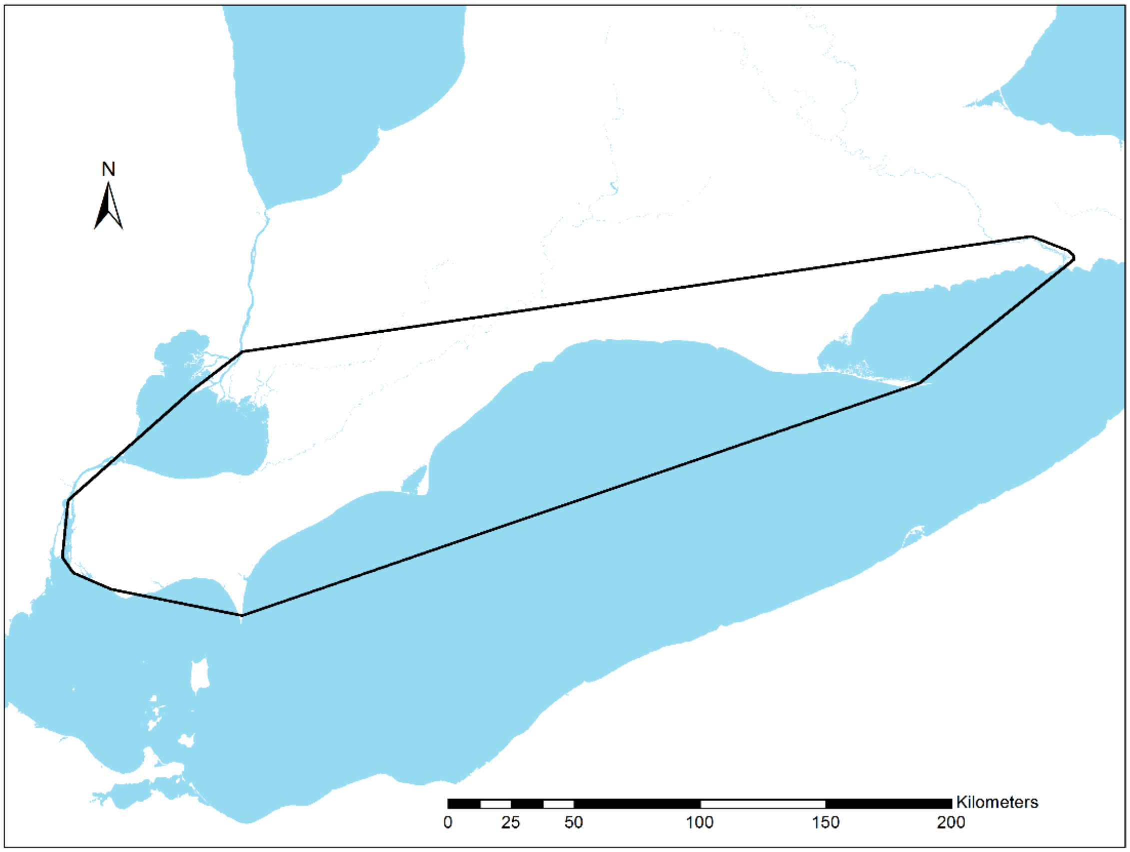

Figure 8.1: Outline of the study area (in black) for accuracy assessment of both.

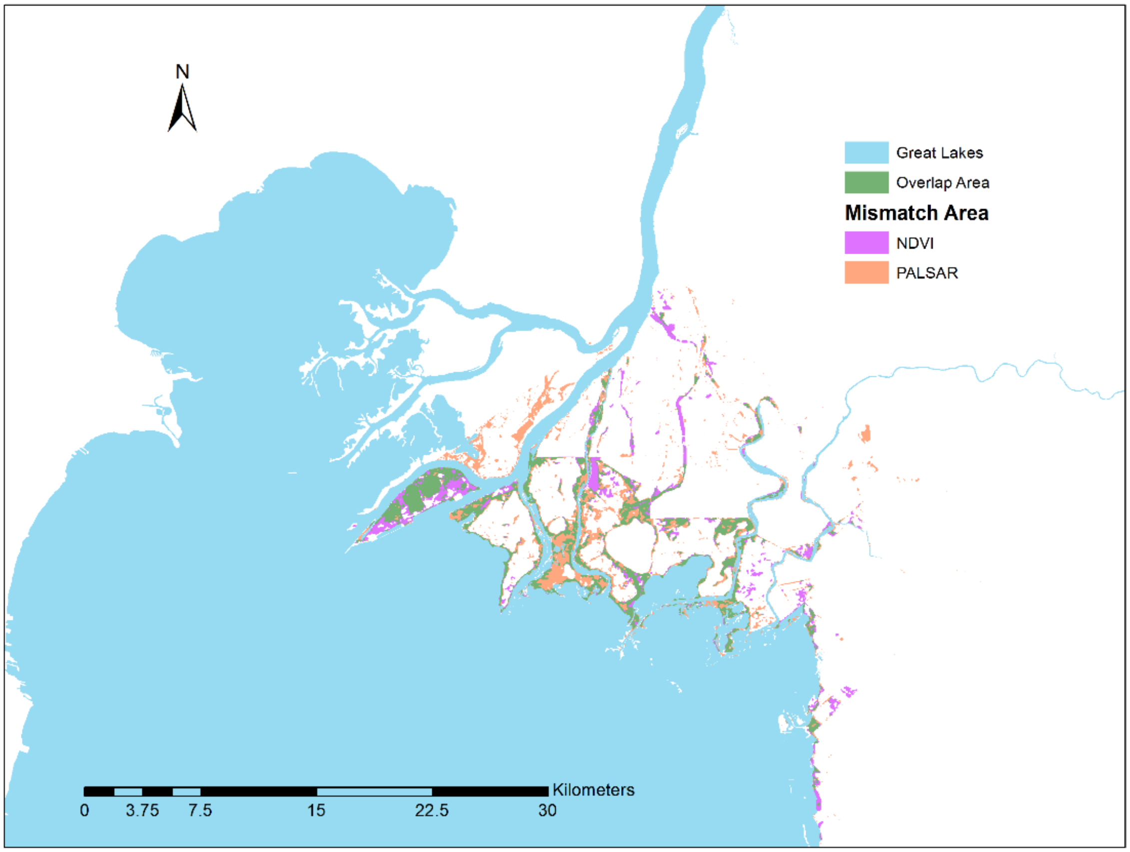

Figure 8.2: Map showing areas of overlap in areas with Visual comparison of overlap and mismatched areas with *Phragmites* that were mapped and classified with both approaches for the Walpole Island region.

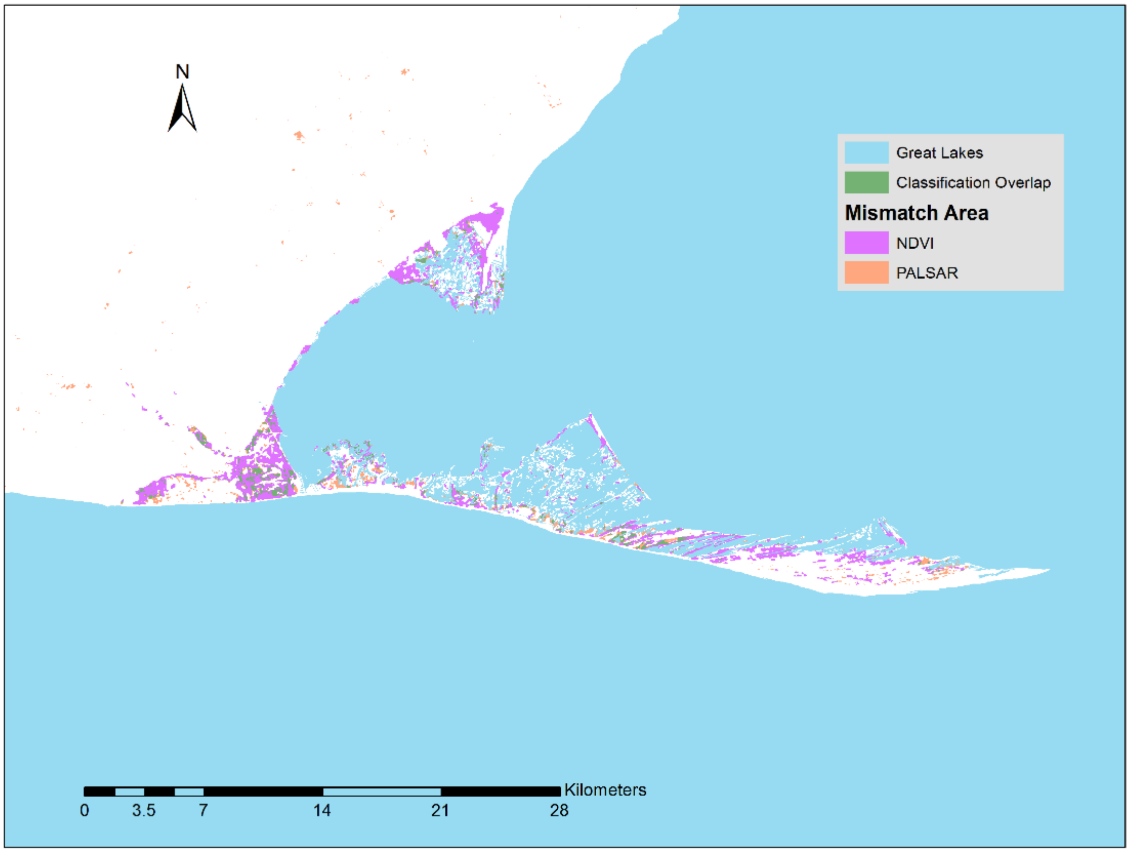

Figure 8.3: Visual comparison of overlap and mismatched *Phragmites* area classified between both approaches in the Long Point region.

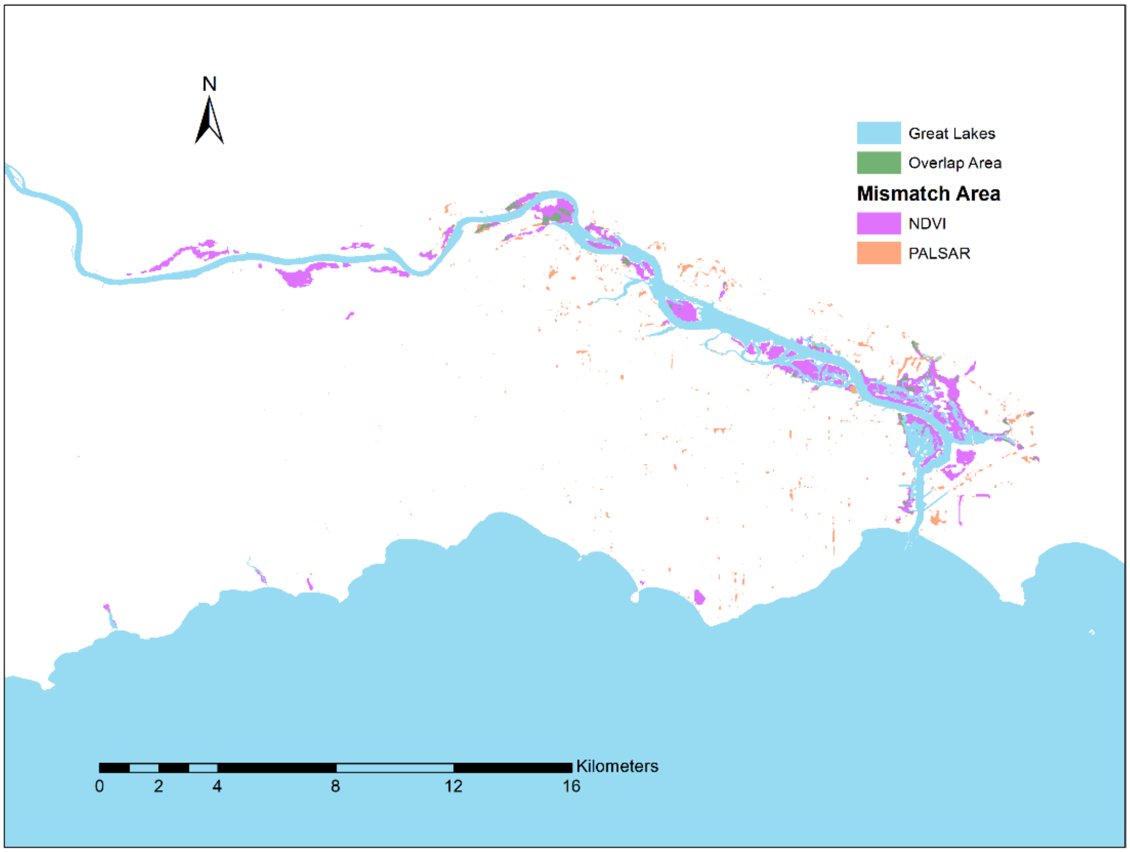

Figure 8.4: Visual comparison of overlap and mismatched *Phragmites* area classified between both approaches near the southern Grand River.

Figure 8.5: Big Creek National Wildlife Area, 2013 (Google Earth). Note the presence of small, sparse *Phragmites* stands throughout. The inset shows the NDVI and PALSAR+ comparison overlaid (image not to scale).

Chapter 9/Appendix B: Mapping Invasive *Phragmites australis* in Highway Corridors Using Provincial Orthophoto Databases in Ontario

By
James V Marcaccio and Patricia Chow Fraser

Marcaccio, J.V., & Chow-Fraser, P. (2018). Mapping invasive *Phragmites australis* in Highway Corridors Using Provincial Orthophoto Databases in Ontario. Report prepared for the Ontario Ministry of Transportation, St. Catharine's, ON. 42 pages

Abstract:

We mapped the distribution of invasive *Phragmites australis* (Eurpoean common reed) in MTO-operated roadways of southern Ontario using airphotos from a provincial databse, the Southwestern Ontario Orthophotography Project (SWOOP), which covers all highways from Windsor east to Norfolk/Niagara and north to Tobermory. We mapped all available SWOOP images acquired in 2006, 2010, and 2015. In addition, we delineated invasive *Phragmites* along MTO-operated roadways within the footprint of Southcentral Ontario Orthophotography Project (SCOOP acquired in 2013) and the Central Ontario Orthophotography Project (COOP acquired in 2016); the mapping excludes the Greater Toronto Area but includes Prince Edward county, roads through the city of Barrie, and north to Parry Sound. Based on available orthophotos for SWOOP only, total areal cover of invasive *Phragmites* expanded an order of magnitude between 2006 and 2010 (26.8 to 259.7 ha, respectively); between 2010 and 2015, there was only an increase of 7.2% (278.7 ha), presumably because of ongoing herbicide treatments that began on selected roads beginning in 2012. Expansion rates differed between road types, with 400-series highways having significantly greater expansion rates than non-400 highways (24.5 vs 6 times, respectively). Areas covered by SCOOP images had an areal cover of 152 ha in 2013, while that for COOP images had an areal cover of 7.8 ha in 2016. This inventory is freely available for anyone to update using provincial orthophotos or medium to high-resolution satellite imagery such as Sentinel 2.

<u>Executive Summary:</u>

We have successfully mapped the distribution of invasive *Phragmites australis* (European common reed) in roadways of southern Ontario using airphotos from a provincial database, the Southwestern Ontario Orthophotography Project (SWOOP), which covers all highways managed by West Region of MTO (Windsor east to Norfolk/Niagara and north to Tobermory). This is the first time a project of this scale has been conducted to map the presence of *Phragmites* in roadway corridors, and the first time the airphoto dataset has been used for remote sensing. No other dataset provided the scale and resolution (20cm/pixel) necessary for identifying historic distributions of *Phragmites*. This study includes all available SWOOP images acquired in 2006, 2010 and 2015. In addition, we delineated *Phragmites* along MTO-operated roadways within the footprints of the Southcentral Ontario Orthphotography Project (SCOOP acquired in 2013) and the Central Ontario Orthophotography Project (COOP acquired in 2016). This study area excludes the Greater Toronto Area but includes Prince Edward county, roads through the city of Barrie, and north to Parry Sound.

Using eCognition software (Trimble), we conducted an automated image classification with the 2006 and 2010 datasets to map *Phragmites* (and 7 other land-cover classes) within an 80-m buffer of the centre-line of all MTO roads. We used this approach to map *Phragmites* in county roads within the West Region to increase our dataset for more robust analyses. For automated image classification, we ensured that a minimum total accuracy of 80% was achieved for *Phragmites*, with minimum total scene accuracy of 75%. Accuracy was assessed by comparing classified features to those that were

manually digitized from airphotos. We were unable to use the automated classification approach to map *Phragmites* in photos acquired after 2010; therefore, *Phragmites* stands in the 2015 SWOOP, 2013 SCOOP and 2016 COOP images were manually digitized. For manual digitization, two technicians were trained to digitize the same road segments until they achieved minimum 80% accuracy. No other land cover classes were classified, and accuracy assessments were made by confirming the presence of delineated stands by comparing against Google Streetview, since no field data were available for this purpose. To preserve consistency in manual delineations, all images were digitized by these two technicians.

Based on amount of *Phragmites* mapped in the SWOOP airphotos, *Phragmites* expanded greatly between 2006 (26.8 ha) and 2010 (259.7 ha); the rate of increase was reduced between 2010 and 2015 (331.47 ha), presumably because of extensive herbicide treatments on selected roads that commenced in 2012 (see Chow-Fraser & Marcaccio 2018). Most of the change between years occurred when *Phragmites* expanded into areas occupied by "grasses", that are essentially low-lying vegetation in road corridors (species could not be further distinguished beyond this category). We saw a statistically significant but weak influence of surrounding land cover (e.g. agriculture, urban, forest) on the expansion rate of *Phragmites* between 2006 and 2010; the only significant predictors were agriculture, grass, and traffic volume (all positive but explained very little of the overall variation). This may mean that *Phragmites* invasion is still in its early stages, and that the only limiting factor is available habitat. There were differences in expansion rate between road types, with 400-series highways having significantly greater expansion rates than did non-400 series highways, especially those with low traffic volume. Between 2006 and 2010, the 400-series highways expanded 24.5 times (from 5.4 ha to 132.7 ha) compared to only 6 times for all other highway categories combined (from 21.4 ha to 127.1 ha). This may be related to the presence of medians in the 400-highways that provided more habitat for *Phragmites* to colonize than on two-lane highways.

Presence of *Phragmites* in the 2013 SCOOP dataset (152 ha) was lower than that for the 2010 SWOOP dataset; however, this is expected to increase since the demand for recreational property is increasing rapidly northward from Barrie to Parry Sound. Not surprisingly, the total mapped area covered by the 2016 COOP images was relatively low (7.8 ha); however, given that treatment is more successful when stands are small and sparsely distributed, we strongly recommend that MTO implement a treatment program as soon as possible to prevent *Phragmites* from expanding further westward and northward within Ontario. The *Phragmites* inventory that we have created should be updated at regular intervals, either with airphotos from future acquisitions of SWOOP and SCOOP, or with medium to high-resolution satellite image data such as Sentinel 2.

Introduction:

Invasive Phragmites

Phragmites australis (Cav.) Trin. ex Steudel (the common reed) is a perennial grass that grows in many habitat types throughout the world. There are 27 genetically distinct groups (haplotypes) worldwide, of which 11 have been found in North America (Saltonstall 2002). Over the past two decades, Haplotype M, which originated from Europe, invaded coastal and inland wetlands throughout southern Ontario, replacing native vegetation and generally reducing biodiversity (Chambers et al. 1999; Markle and Chow-Fraser 2018). This invasive haplotype aggressively colonizes exposed mud flats sexually (through seeds), and then expand asexually (through rhizomes) to form dense monocultures. Its rapid spread has been attributed to it being a superior competitor against other emergent vegetation (Rickey and Anderson 2004; Uddin et al. 2014) and to being more tolerant of disturbances (e.g. road maintenance and changes in hydrologic regimes) and stress (e.g. increased salinity due to road de-icing salts) (Marks et al.,1994; Chambers et al. 1999; Saltonstall 2002).

Past studies have shown that transportation corridors provide excellent invasion pathways for species such as invasive *Phragmites*. Linear ditches along roadsides or in the median can be readily colonized by invasive *Phragmites* (Leong et al. 2007; Brisson et al. 2010), because they are able to tolerate high salinity from road salts and require little moisture in comparison to other aquatic vegetation (Medeiros et al. 2013). Ministry of Transportation of Ontario (MTO) has acknowledged the destructiveness of invasive *Phragmites*, both with respect to the road infrastructure, as well as to adjacent ecosystems, and has been developing a control strategy. Since 2012, MTO has sprayed highway corridors with glyphosate, a broad-spectrum herbicide used to control the growth of *Phragmites* and other weeds (**Figure 9.1**).

The primary goal of this project is to create a database (McMaster Invasive *Phragmites* Database; MIPD) to map and update the areal cover of invasive *Phragmites* on MTO-managed roads in Ontario. Using the Southwestern Ontario Orthophotography Project (SWOOP) database, we used object-based image classification software to delineate the extent of *Phragmites* in MTO's western region in 2006 and 2010. We conducted a change detection analysis to determine roads associated with the highest rate of expansion, and to elucidate significant landscape-level factors that may influence *Phragmites* colonization. Additional image data from the Southcentral and Central databases (SCOOP 2013 and COOP 2016 respectively) allowed us to increase our mapping effort of invasive *Phragmites,* although there are no other land cover maps, nor do these data exist for multiple years. We should also mention that our maps do not distinguish between native and invasive haplotypes of *Phragmites*; that said, it is very unlikely that native *Phragmites* would occur in densities as high as what we have been mapping in the present study.

Orthophoto Databases

We used the SWOOP database (Southwestern Ontario Orthophotography Project), which was organized and funded cooperatively by multiple government agencies (municipal, provincial and federal) who wanted to obtain seamless aerial photos of the southwestern portion of the province at regular intervals (approximately every 5 years;

2006, 2010, 2015, 2020, etc). This dataset covers an area from Windsor east to Brantford/Niagara (2006/2010 & 2015) and north to Tobermory (**Figure 9.1**).

We also used the SCOOP database (Southcentral Ontario Orthophotography Project; 2013) which covers an area from Prince Edward county, west to Barrie (excluding the GTA) and north to Parry Sound, as well as the COOP database (Central Ontario Orthophotography Project; 2016), which follows the shoreline of northern Georgian Bay and the North Channel and includes Manitoulin Island (**Figure 9.1**). The Ontario Ministry of Natural Resources and Forestry (OMNRF) has set forth a plan to acquire spring orthophoto image data at regular intervals across the province; eastern and northern regions have also been imaged and are planned to be acquired every five years. Because these projects were developed primarily for planning purposes, the image data were acquired during spring when leaf-off conditions allowed for unobscured view of buildings and roads (April-May, weather dependent). SWOOP, SCOOP and COOP images are freely available to participating stakeholders and to research agencies and universities; the cost would have been prohibitive otherwise. Since SWOOP data are captured from a plane rather than from a satellite, the surface of the earth is much closer to the sensor, and the true colour image had a spatial resolution of 20 cm with red, green, and blue bands. Such high-resolution imagery would allow for a minimum mapping unit of <1m and is therefore suitable for mapping *Phragmites* stands within roadway and/or highway ditches.

Previously, *Phragmites* has been mapped on a large scale with satellite-based imaging sensors in true colour, near-infrared, radar, and combinations thereof (Bourgeau-

Chavez et al. 2015; Pengra, Johnston, & Loveland 2007; Young, Young, & Hogg 2011). These sensors typically have a ground-based resolution of 10-30 m per pixel and can often return their orbit to a specific location within two weeks. Due to the nature of these sensors, any feature (e.g. *Phragmites*) that is to mapped must be approximately four times the size of the pixel to ensure that, regardless of orientation, the feature would fall completely within one pixel. Hence, the satellite-based sensors require a minimum mapping unit of 40x40 to 120x120 m, and this exceeds the dimension of the average highway ditch, which for these sensors is too narrow to be appropriately mapped. By comparison, aerial photos, or orthophotography (imagery taken from an airplane) can provide a much smaller minimum mapping unit (<1m). The trade-off for this high resolution however, is the requirement for costly flights to be flown, and involvement of many thousands of images to cover an area the size of the province of Ontario. In the SWOOP dataset, approximately 50,000 images must be acquired per year, and the SCOOP & COOP datasets are of comparable size.

One of the major challenges of this project was managing the tens of thousands of images acquired over the study period. To save time and money in the classification of these images, we created subsets of images together that had been acquired at approximately the same time of day and during the same time of year within similar geographic locations (e.g. Cambridge, Hamilton). Such aerial images should have similar spectral characteristics and will produce acceptable results when the same classification scheme is developed and applied.

Methods:

Use of eCognition to Map Phragmites

High resolution data such as that found in SWOOP can be difficult to process. Large data files can severely slow processing time for image viewing and even moreso for image classification. High resolution data can also have many mixed pixels, where two abutting objects are found in the same pixel and the signal is a mix of both. In a typical pixel-based method, the unique colour values associated with each pixel is used solely to guide classification. This can often lead to inaccuracies because of variation in the dataset; in addition, it can result in single pixels being misclassified within a group of similar pixels. To process the large amount of high-resolution data, we used eCognition, an object-based classification software (Trimble Navigation Limited, Colorado, USA). Object-based approaches avoid the above problem by first splitting the image into segments that are spectrally similar and/or have a consistent parameter (e.g. shape, length, volume) associated with them. This reduces the number of single pixels that can be misclassified and allows other intrinsic values from remote sensing to be used (e.g. size, shape, perimeter).

To make our task manageable, we first clipped out a small strip of land (buffer) beside each road to be analyzed (**Figure 9.2**) and performed the classification only on these buffer strips. We also included all other roads with posted speed limits above 60km/h in the SWOOP dataset (data obtained from OMNRF shapefile; **Figure 9.3**). This excluded local roads that were usually maintained by property owners and/or have little to no ditch in their right-of-way. The buffer varied according to road speed and road type (e.g. larger buffer was used for 400 series highways compared to two-lane highways). We extracted the image data within the buffer using FME (Safe Software, Surrey, BC, Canada), and inserted them into eCognition for image processing.

We created a base classification for identifying invasive *Phragmites* as well as other land cover-land-use types (see **Table 9.1**). Some classes such as "shadows" have no ecological meaning but are necessary for us to correctly classify the other land cover types without confusion. These classes were subsequently used in our change-detection analyses to determine the land-cover type that invasive *Phragmites* were more likely to colonize.

We created a base classification using 5% randomly selected images within a particular image subset. We conducted multiple accuracy assessments for these images until our base classification met or exceeded our accuracy threshold of 70% for total accuracy and minimum 80% for *Phragmites*. We then applied this base classification to remaining images in the subset. The literature has shown that classifications created in one image can be transferred to another with a small decrease in total accuracy (Rokitnicki-Wojcik et al. 2011). While other studies have completed accuracy assessments for every image used, this was not logistically feasible given the large number of images we had in our dataset. To improve total accuracy of the classification when the dates of image acquisition are not similar, we started with our previous base classification and then modified it to incrementally improve the accuracy until an acceptable level could be attained. No field data were needed to supervise this classification because of the high resolution of the images.

We had difficulty using eCognition to classify habitat classes in the 2015 SWOOP, 2013 SCOOP and 2016 COOP image data. We attribute this to changes in the sensor and/or post-processing that had been employed to produce the 2010 and 2006 SWOOP image data. We found insufficient spectral data to conduct an accurate image classification. The images had a large peak in blue band values that resulted in very low contrast among objects (**Figure 9.4**).

Manual Digitization of Phragmites

Two trained technicians were responsible for digitizing all of the *Phragmites* within MTO-operated roadways in the SWOOP 2015, SCOOP 2013 and COOP 2016 datasets. Both technicians had been trained to identify *Phragmites* as part of the eCognition classification procedure. To minimize differences in digitization between the two technicians, every road segment was digitized by both individuals and the overlap between the two was output to the final product. A typical accuracy report could not be generated for this protocol because all of the data had been manually digitized, and this was the normal method used to assess the accuracy of the automated classification. We compared the overlap to mismatch from each technician and found the 'accuracy' to be acceptably high (80%). Most of the error were due to small differences in boundary delineation, and how carefully technicians followed the outlines of stands with their cursor. In general, manual digitization tended to produce fewer but larger polygons whereas eCognition was able to pick out many of the smaller stands that could easily be missed by the human eye. Knowing this bias, we refrained from conducting a large-scale change detection between methods. The only way to validly compare these dates would have been to manually digitize all road segments in the 2006 and 2010 SWOOP images as well as other land cover classes. This was clearly not feasible given the amount of time we had to complete the project. Even with these differences, we could inspect the classified images to assess large-scale changes in the distribution of invasive *Phragmites* between time periods.

Modelling expansion of Phragmites

With the data obtained from the automated image classification, we conducted stepwise regressions and multiple ANOVAs to determine what landscape factors contributed to the expansion of invasive *Phragmites* between 2006 and 2010. We omitted 2015 data from this analysis because herbicide treatments had been applied to various roadway corridors between 2012 and 2015 and would have altered the outcomes of our modelling (see Chow-Fraser & Marcaccio 2018). SCOOP and COOP data were also omitted because they were only available for a single time period in 2013 and 2016, respectively. We included land-cover data at both the micro- (habitat classes derived for the automated image classification) and the macro-scale (derived from the Southern Ontario Land Resource Information System 2.0 (SOLRIS; 2009-2011, Ontario Ministry of Natural Resources and Forestry). We also added traffic volume as an additional explanatory variable to determine its effect on *Phragmites* distribution.

A description of the landcover classes comprising the micro-habitat scale can be found in Section 2.1 (Methods: Use of eCognition to map invasive *Phragmites*); both 2006 and 2010 data were used as inputs. SOLRIS is a database compiled by the Ontario Ministry of Natural Resources and Forestry (OMNRF) that covers southwestern and southeastern Ontario. The minimum mappable unit (the smallest discernable unit of land cover in the dataset) is 0.5 ha. Land cover classes are based on the Ecological Land Classification System (ELC; Lee et al. 1998). Independent databases created by the OMNRF were used as training data and applied to an image classification using Landsat 8 image data from 2009-2011. Multiple image years were required to ensure proper seasonality and lack of image artifacts (such as cloud cover). A list of complete land cover classes can be found at the source website (www.ontario.ca/data). For our modelling, we grouped multiple layers together to reduce the degrees of freedom, only used ecologically relevant classes, and excluded land cover classes that had very low areal cover in our dataset. Our final class layers consisted of agriculture, wetland, mixed forest, coniferous forest, deciduous forest, built-up area, aggregate extraction and open water. Traffic volume data were obtained from MTO and corresponded to the 2010 dataset.

All statistical modelling was conducted in JMP (SAS Institute, North Carolina, USA; v.13). The data were extracted as database files from ArcGIS (v. 10.4; ESRI, California, USA) and analyzed in JMP. Relevant spatial statistics (i.e. area, location) were applied in ArcGIS before data export. To appropriately analyze the data and reduce error associated with automated classification, the data were split into 1-km segment for each road, and the data were aggregated at this level. In this way, each road had multiple (>30) data 'points' with areal cover of each land cover class. SOLRIS data were extracted from a 2.5-km radius buffer around each 1-km segment; this was deemed an ecologically relevant distance while maintaining a good overview of the surrounding mosaic of landscape.

Results and Discussion

Areal Cover of Invasive Phragmites *in Highway Corridors*

The GIS database assembled in this study includes data that span a decade between 2006 and 2015 for the southwestern region, and to our knowledge, is the only inventory of invasive *Phragmites* in highway corridors within Ontario. It also includes the distribution current to 2013 for MTO-operated roads in south central Ontario, and to 2016 for central Ontario. In most cases, we successfully classified *Phragmites* with eCognition to achieve an accuracy of 80% for the 2006 and 2010 images; however, for reasons that we have explained earlier, we were unable to obtain comparable accuracy for the other sets of image data.

In 2006, total areal cover of *Phragmites* was 26.8 ha (**Figure 9.5**). The greatest amount of *Phragmites* cover was found on Hwy 6 (5 ha) and Hwy 401 (3.4 ha). While there is a pattern of longer roads harbouring more *Phragmites*, Hwy 6 contained more *Phragmites* per kilometre than all other roads in 2006 (0.02 ha/km). While Hwy 403 had the second highest *Phragmites* density per km, Hwy 401 and 402 had closer to average densities during this early period (0.012 ha/km, average 0.011 ha/km). By comparison, Hwy 26, 9, and 40 had much lower densities per kilometre than did other highways (0.003, 0.003, 0.004 ha/km, respectively).

In 2010, total areal cover of *Phragmites* was 259.7 ha (**Figure 9.6**), a substantial increase compared to that in 2006. The average density also increased ten-fold to 0.11

ha/km, although the range of values also increased from 0.02 to 0.40 ha/km. During 2010, Hwy 6 had a median density (0.07 ha/km) while Hwy 403 had the highest density (0.40 ha/km). Hwy 402 and 401 also had high densities (0.22 & 0.29 ha/km), similar to that on Hwy 85 (0.32 ha/km).

By far, the greatest change in areal cover between 2006 and 2010 was associated with Hwy 401 (76.87 ha) which was double that of the next highest increase, Hwy 21 (31.81 ha) (**Figure 9.7**). The largest percent change came from Hwy 40 (2768%) and Hwy 85 (2430%). The largest change in density was seen in Hwy 403 (3.84 ha/km) which was much larger than that in Hwy 85 (3.05 ha/km), Hwy 401 (2.78 ha/km), and Hwy 402 (2.07 ha/km) (**Figure 9.8**).

The total areal cover of *Phragmites* in 2015 was 331.47 ha (Figure 9). The greatest amount of *Phragmites* was found on Hwy 401 (107.22 ha) at a density of 0.04 ha/km. The changes in areal cover and density between 2010 and 2015 had also been impacted by strategic herbicide applications that started in 2012; see Chow-Fraser & Marcaccio 2018 for a more detailed review of these data.

Of all road types, the 400-series highways appeared to be most vulnerable to colonization because of their medians (**Figure 9.10**), which had been become densely colonized by 2010. Hwy 40 connects Hwy 401 and Sarnia at the western terminus of Hwy 402 (**Figure 9.11**). This is a heavily trafficked non-400-series highway that runs close to a heavily invaded marsh in the Walpole Island wetland complex. Hwy 85 is a short collector highway found in the city of Kitchener-Waterloo, and its highway corridors had very high densities throughout both time periods (**Figure 9.12**). This highway runs through a highly populated neighbourhood and serves as a northern corridor into Kitchener-Waterloo. We inspected these highway stretches and found many commission errors that may be attributed to the unique land cover in this region (**Figure 9.13**). For instance, in this stretch of highly urbanized highway, we saw unique habitat classes such as sound barriers and shadows cast by these barriers that had been misclassified as *Phragmites*. The highway was relatively short and had many unique land cover classes that contributed to errors of commission.

Within the SCOOP 2013 database, we mapped 151.95 ha of *Phragmites* (**Figure 9.14**). The greatest areal cover was associated with Hwy 400, Hwy 11 and Hwy 7 (**Figure 9.15)**. The greatest densities were found on Hwy 612 and 632, which are significantly higher than that on any other road in this dataset, but still lower than that found in the SWOOP dataset.

The total *Phragmites* cover within the COOP dataset was very low (7.78 ha; (**Figure 9.16**) and this most likely reflects a very early stage of invasion. Hwy 11 had the greatest areal cover in this dataset (**Figure 9.17**). The very high density reported for Hwy 539A is an artefact, an inflated number due to only 2 kilometres having been analysed for this dataset. Figure 18 shows a better visualization of density, where Hwy 522B, 94, and 639 have the highest densities.

Based on the most recent datasets, we have mapped 491 ha of *Phragmites* across Ontario, of which the northern datasets (SCOOP and COOP) only account for a third (160 ha combined). This lower distribution is due in part to lower traffic volume, and perhaps to more harsh landscapes of the Canadian Shield. Nevertheless, if this area is not managed soon, *Phragmites* may overtake a large portion of available habitat and make it much more difficult to eradicate. Assuming that the rate of expansion (2.14/y) from 2006 to 2010 in southwestern Ontario could be applied throughout the province, the estimated 491 ha of *Phragmites* in the province could grow to 4,283 ha by 2018 and 6,660 ha by 2020 if we do not implement a comprehensive control program.

Modelling Expansion of Invasive Phragmites

Using a stepwise regression, we determined the variables that contributed most to explaining the variation in *Phragmites* abundance in 2010. At the micro-habitat scale, grasses, deciduous stands and *Phragmites* abundance in 2006 had the strongest positive effects while at the macro-habitat scale, agricultural and forested lands, as well as wetlands were the strongest determinants. We excluded *Phragmites* abundance in 2006 since this did not explain any additional variation in the data ($p > 0.05$) after other variables had been accounted for. Because of the large number of observations, all land-cover variables were statistically significant, although the total explained variance was low because of the large geographic area included in this analysis (**Table 9.2**). The strongest effect came from abundance of grasses in 2006. Traffic volume was also a significant predictor of *Phragmites* abundance, but only explained as much as did land cover.

We had to convert roads into 1-km segments in order to standardize the observations since some roads were very long (e.g. Hwy 6), while others were very short (e.g. Hwy 85). We did not experiment with other road lengths, and it is possible that at even smaller spatial scales, some of the variables might have emerged as being more important. Previous studies have noted that land cover and geography may influence the presence of *Phragmites* on roadsides (Lelong et al. 2007, Maheu-Giroux et al. 2005, Brisson et al. 2010). These studies, however, were relatively small in geographic scope, and did not consider the areal cover of *Phragmites*. Another difference is that these other studies had been conducted in Quebec where invasive *Phragmites* had been established for quite some time, whereas it is relatively new to roadway corridors in Ontario.

One interpretation of the outcome of our modelling is that the landscape in Ontario is in an earlier stage of the invasion process compared with the Quebec situation, where roadways have already become saturated. Unfortunately, historical high-resolution image data are not often available to test this hypothesis. Future studies could determine if genotypes of invasive *Phragmites* in highway corridors differ between Quebec and Ontario; we would expect *Phragmites* occurring in close proximity to have the same genotype (spread clonally) while those that are located far apart are more likely to have different genotypes (spread by seed). Based on this information, investigators may be able to develop new control methods that take advantage of gene editing.

Conclusion:

Invasive *Phragmites* is present on all MTO-operated roads in southern Ontario, and it continues to expand throughout these road networks. Divided highways with medians offer more habitat than other road types, which typically leads to greater areal cover of *Phragmites* but not necessarily the densest per kilometre. The greatest amount of *Phragmites* currently occurs in the southern portion of the province, where there are both major highways and large wetland complexes. We are aware that small populations of the less aggressive native haplotype exist within southern Ontario, and do not exhibit invasive behaviours and therefore do not need to be treated or removed. The current remote-sensing techniques, however, cannot differentiate between native and invasive haplotypes. We speculate that invasive *Phragmites* is still at an early stage of invasion and will likely continue to expand into any and all available habitat unless they are treated with suitable herbicides (see Chow-Fraser & Marcaccio 2018). This is necessary to prevent the roughly ten-fold expansion that occurred between 2006 and 2010 in southwestern Ontario.

Recommendations:

Due to the change in post-processing of the Ontario Orthophotography Project databases, we do not recommend using these image data to update the McMaster Invasive *Phragmites* Database in 2020. Our data serves as an important historical assessment of roadways in Ontario that could not have been achieved with other data sources. In the future, newer technologies and sensors should be explored for image classification along roadway corridors (see Rupasinghe & Chow-Fraser 2018). Results of our modeling confirms that *Phragmites* is at an early stage of invasion with respect to roadsides. Any areas that have suitable habitat (high moisture, no existing woody plants) are likely to be colonized in short order, and existing stands will continue to expand until they meet a physical barrier.

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Table 9.1: Classes included in the image classification process.

Classes	**Explanation**
Phragmites	Class of interest
Grasses	Small ground-covering plants that occupy majority of land cover
Shrubs	Small plants that are woody/more robust than grass
Deciduous Trees	Bare leafless tree, generally indicating it is deciduous
Coniferous Trees	Conifers; still green in early spring orthophoto
Paved	Any built-up surface, such as road, building, sidewalk, etc.
Water	Streams near roads
Shadow	Land cover obscured by shadow, resulting in dark/black area

Table 9.2: *Phragmites* invasion habitat modelling. Asteriks (*) indicate significance.

Model	Method	Intercept	Grasses	Conifers	Agriculture	Forests
Grasses	Bivariate	410.30*	0.03*			
Conifers	Bivariate	1439.14*		-0.04		
Agriculture	Bivariate	1651.30*			-1.33e-5*	
Forests	Bivariate	1069.84*				-4.02e-5
All	GLM	-559.62	0.06*	0.09	5e-6	-2e-5*

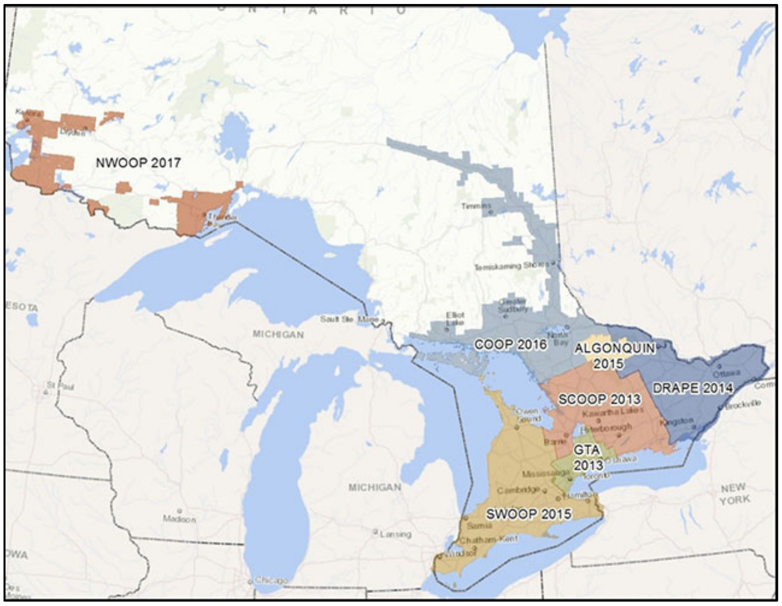

Figure 9.1: Area covered by various Ontario orthophotography project databases. The area covered by SWOOP for 2015 and 2010 is the same; that for 2006 did not include portions around Hamilton and Niagara.

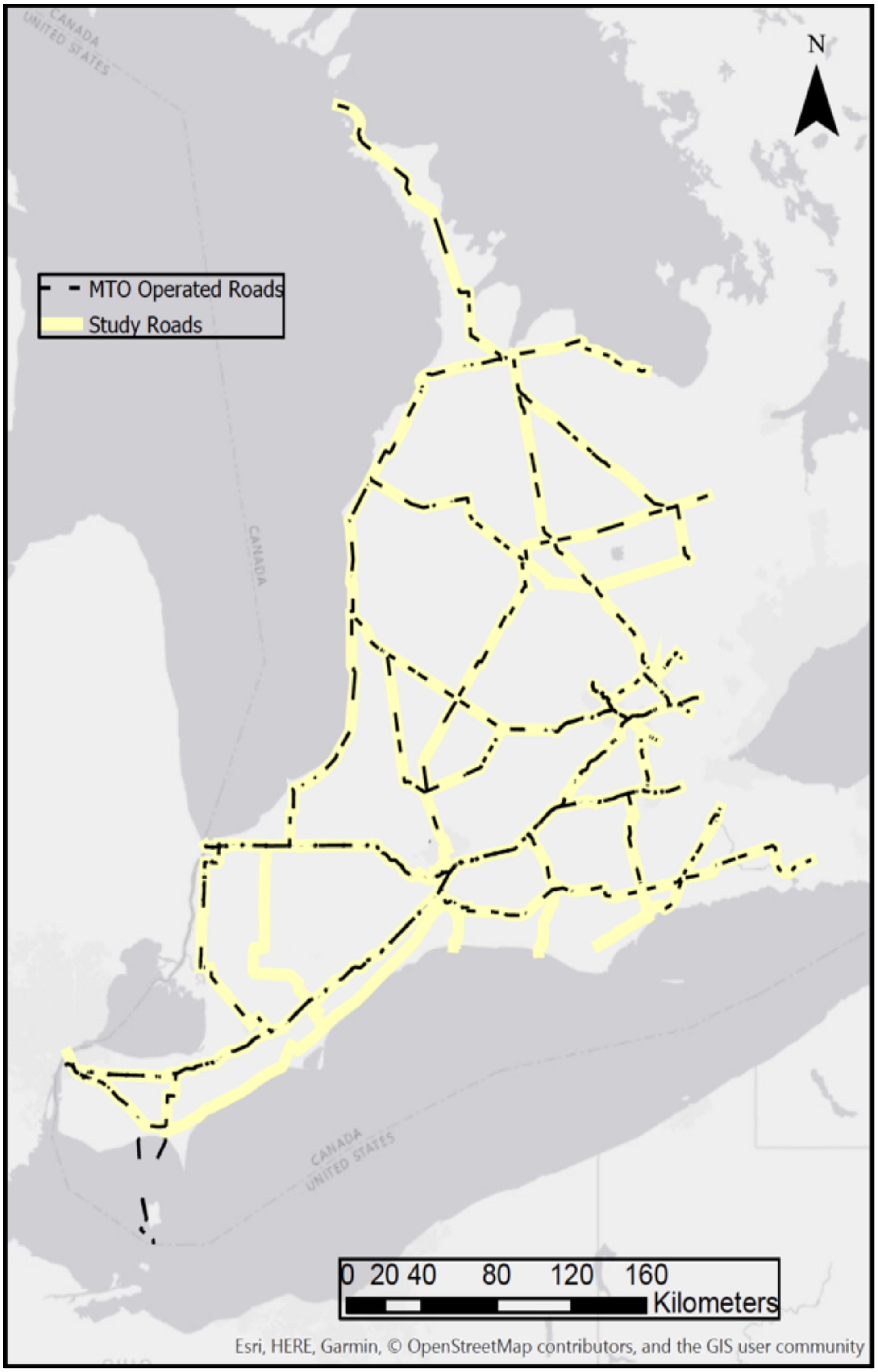

Figure 9.2: Roads analyzed in the MTO Western Region

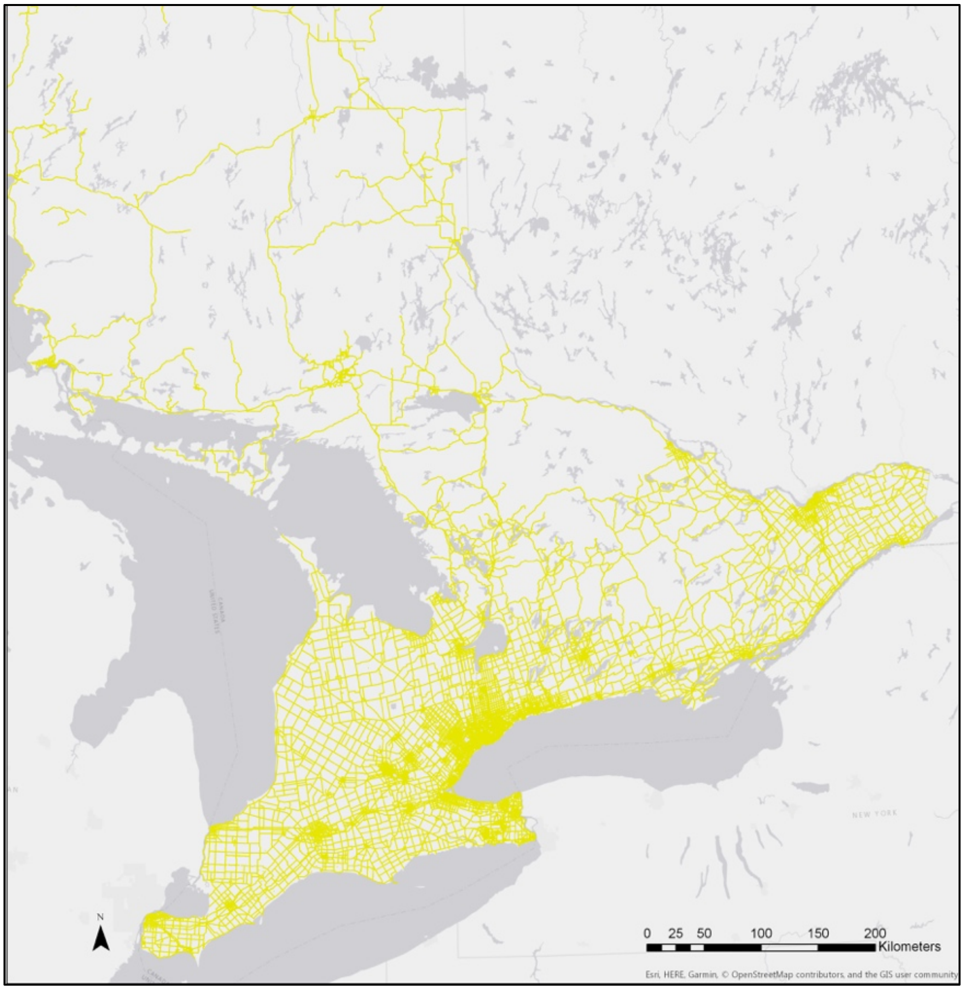

Figure 9.3: Roads over 60 km/h in Ontario.

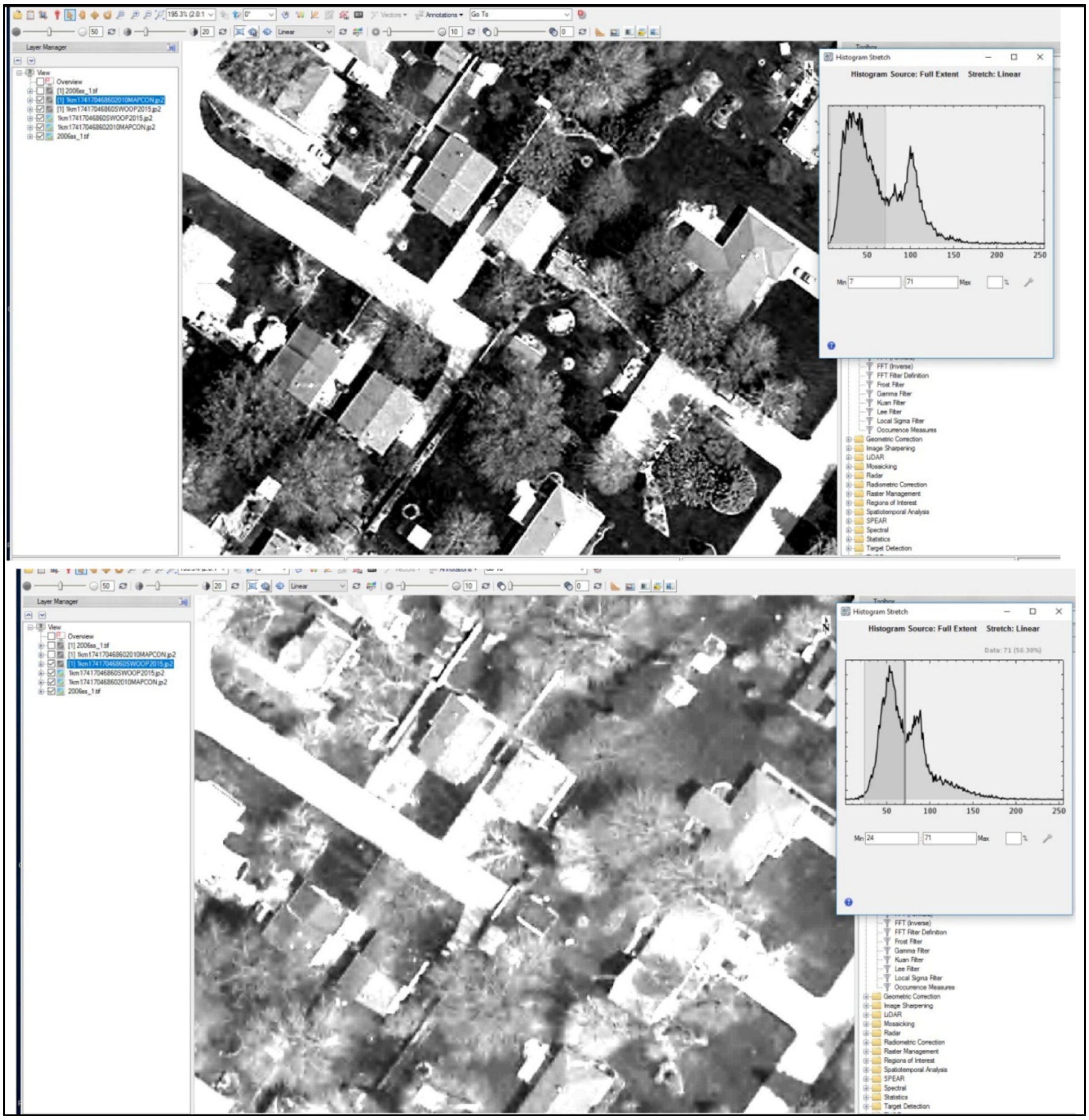

Figure 9.4: Photo of parcel of land taken in 2010 (top) and 2015 (bottom). Note the reduced contrast in the 2015 image and the peaking of values (bottom-right histogram) that led to our inability to perform automated image classification.

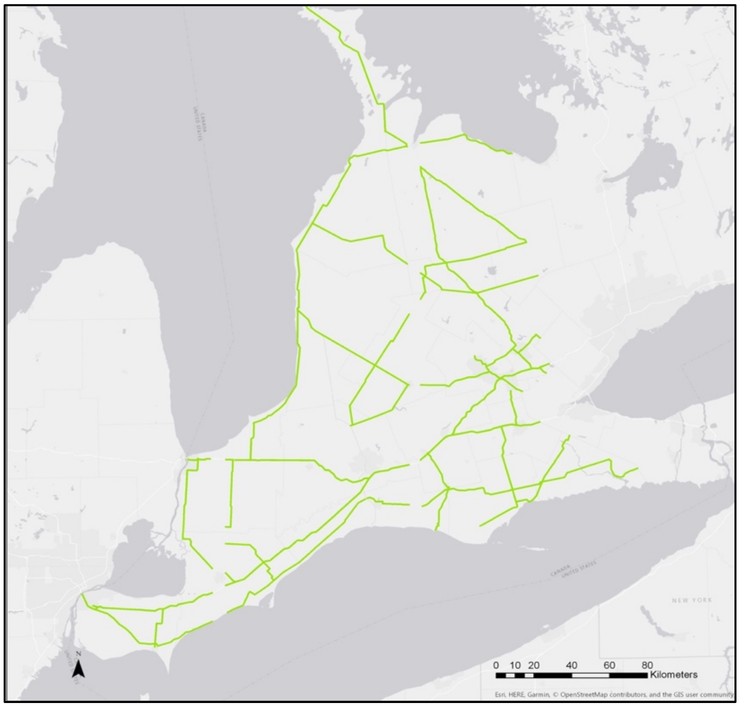

Figure 9.5: 2006 *Phragmites* distribution. The outlines of polygons have been thickened to allow them to be visible at this scale.

Figure 9.6: 2010 *Phragmites* distribution. The outlines of polygons have been thickened to allow them to be visible at this scale.

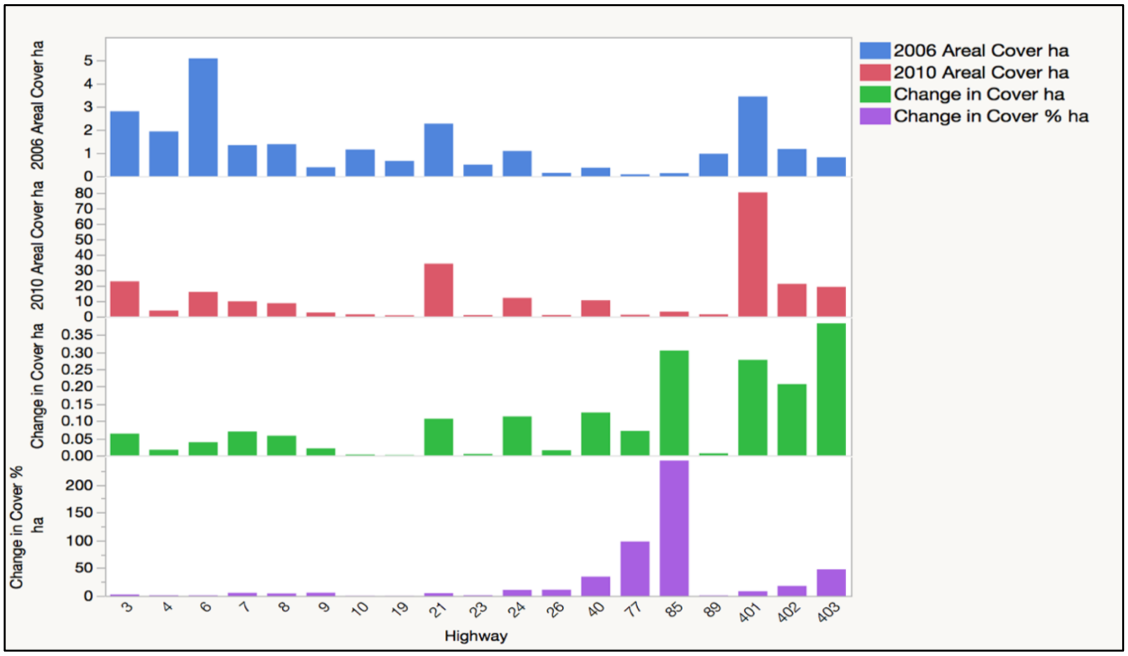

Figure 9.7: Change in *Phragmites* distribution between 2006 and 2010. The total kilometres analyzed may not represent the actual number of roadway kilometres as only segments with *Phragmites* were assessed.

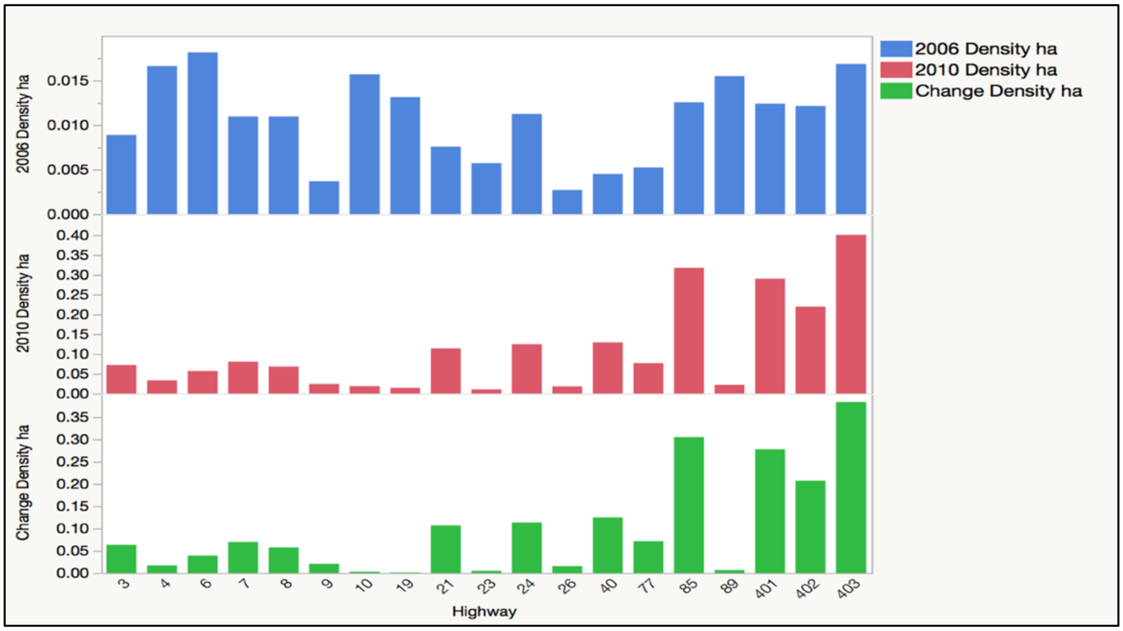

Figure 9.8: Change in *Phragmites* density between 2006 and 2010. The total kilometres analyzed may not represent the actual number of roadway kilometres as only segments with *Phragmites* were assessed.

Figure 9.9: *Phragmites* distribution in 2015. The outlines of polygons have been thickened to allow them to be visible at this scale.

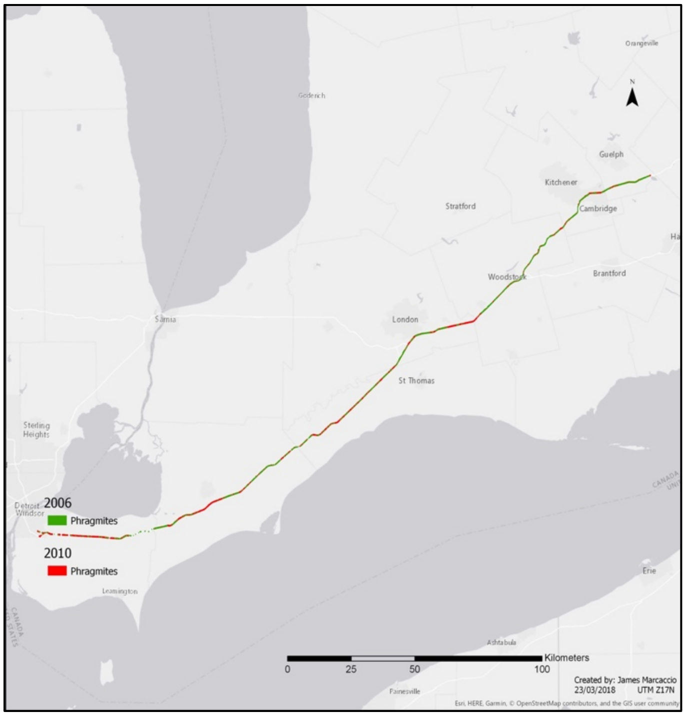

Figure 9.10: *Phragmites* along Hwy 401, which had the largest areal cover of *Phragmites* in our dataset.

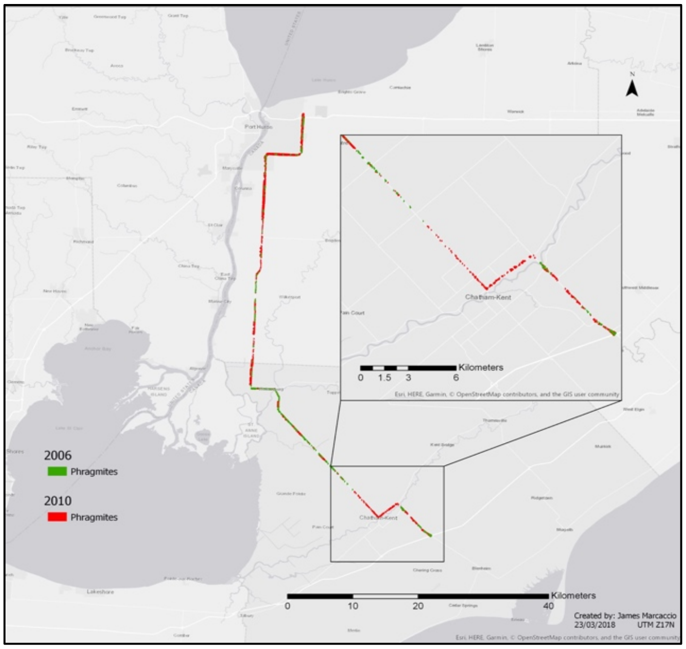

Figure 9.11: *Phragmites* on Hwy 40, one of the most densely populated roads in this dataset.

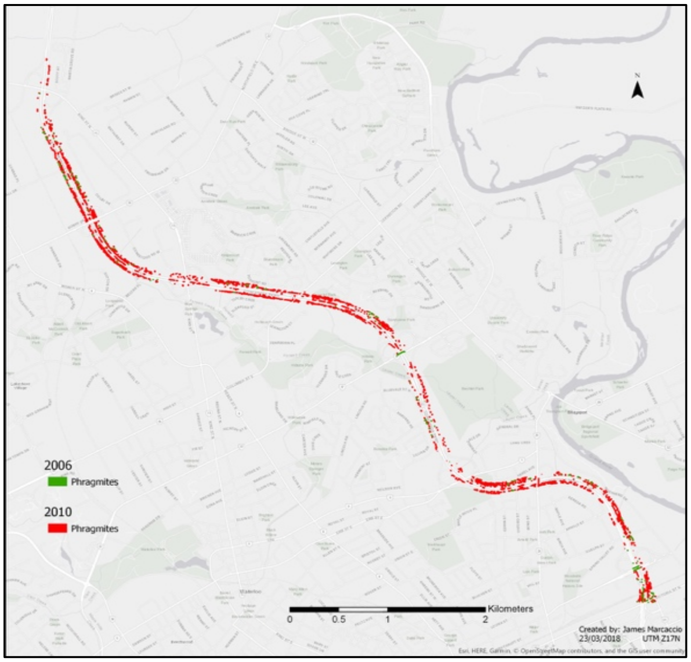

Figure 9.12: Hwy 85 passes through Kitchener-Waterloo and has very unique land cover compared to roadsides of other highways.

Figure 9.13: Sample of orthophoto over Hwy 85 showing *Phragmites* classified in red. Although some error is expected and some *Phragmites* had been accurately classified, the unique configuration of the built-up area led to numerous errors of commission.

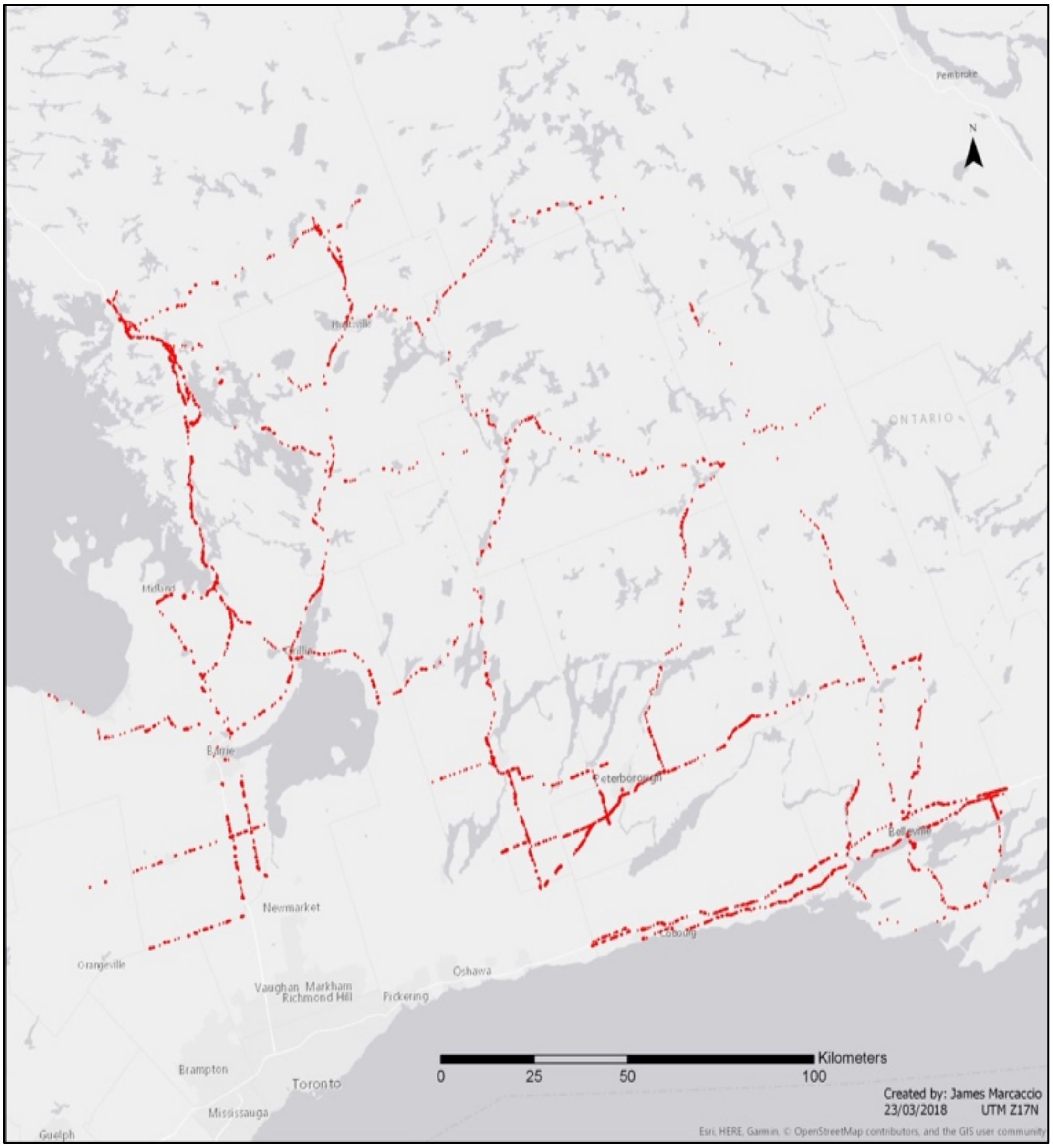

Figure 9.14: *Phragmites* distribution within the SCOOP dataset (2013).

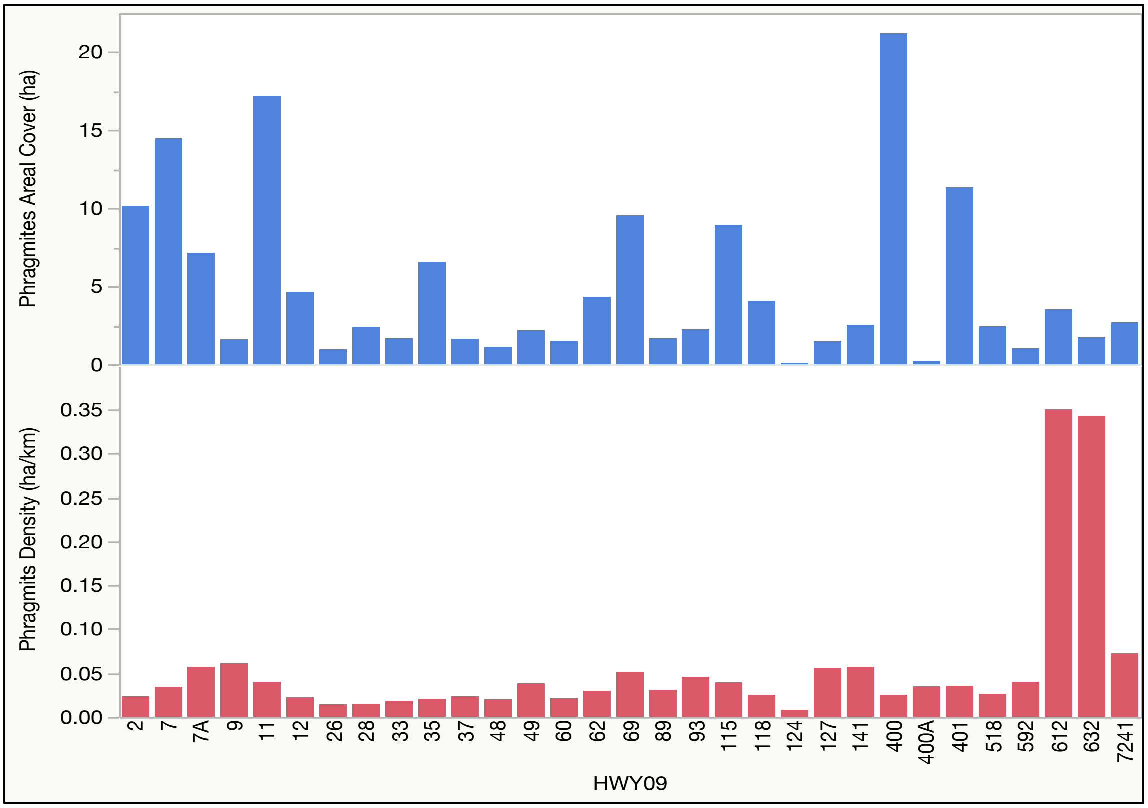

Figure 9.15: Areal cover of *Phragmites* within the SCOOP 2013 dataset.

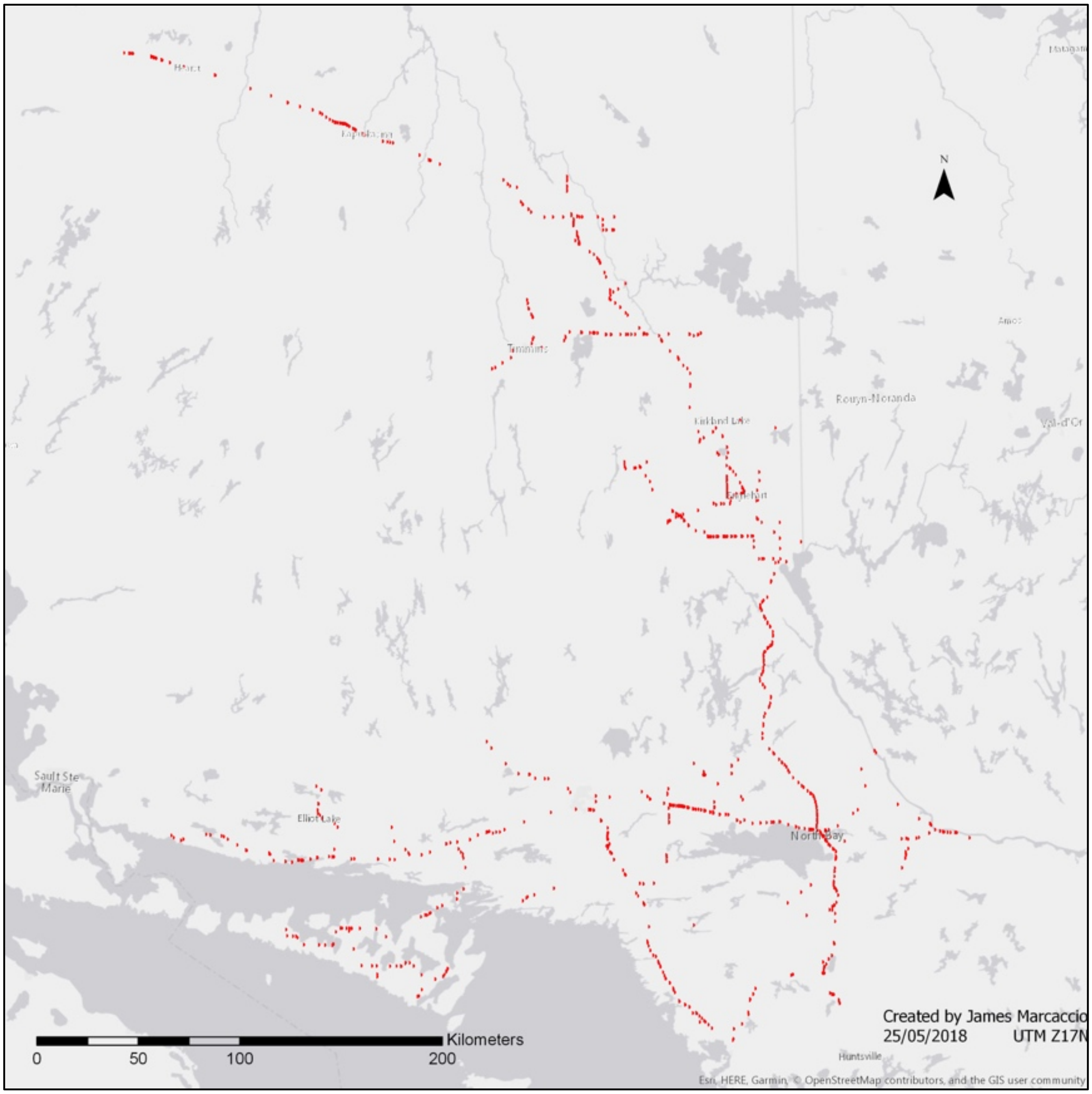

Figure 9.16: *Phragmites* distribution within the COOP dataset (2016).

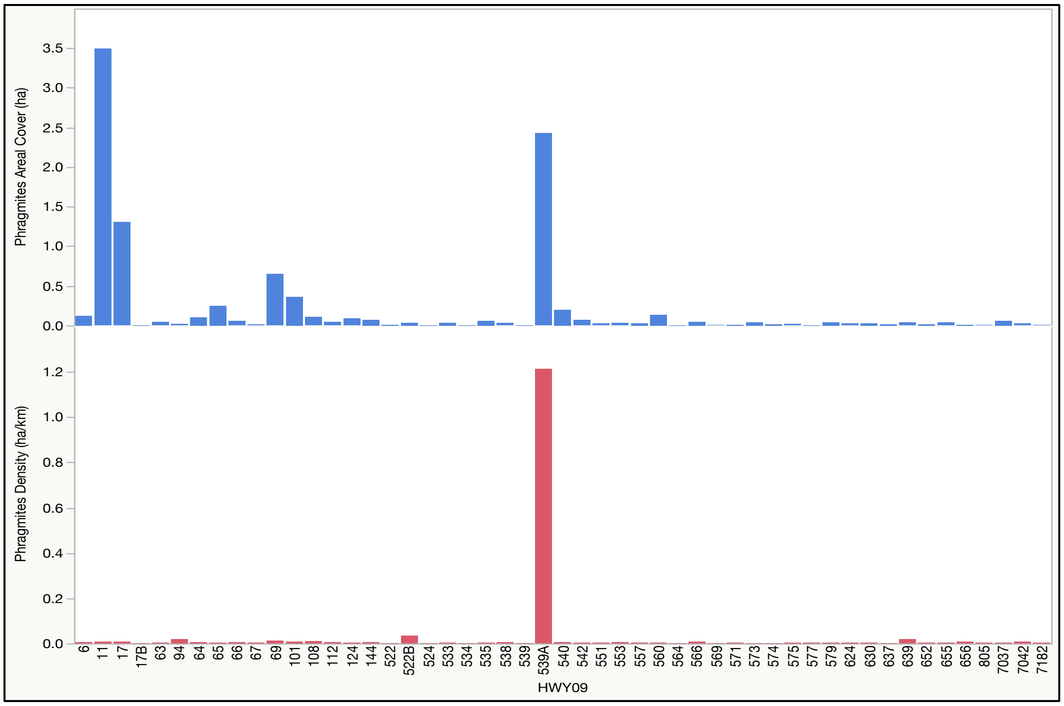

Figure 9.17: Areal cover and density of *Phragmites* within the COOP dataset.

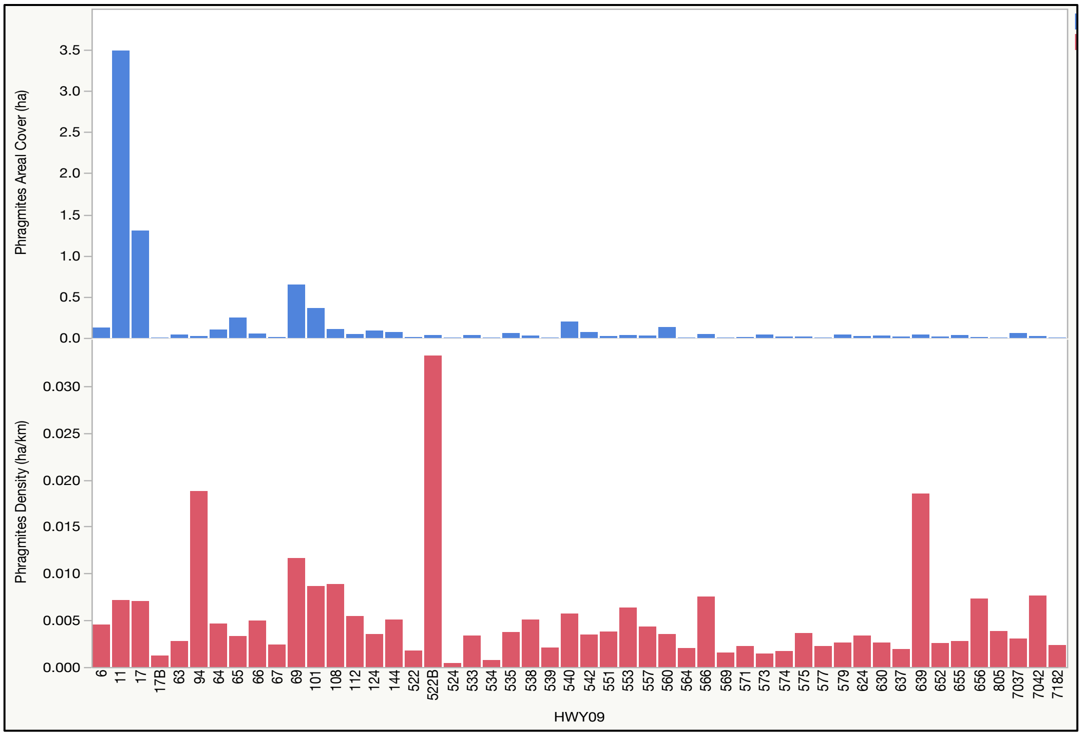

Figure 9.18: Areal cover and density of *Phragmites* within the COOP 2016 dataset, with Highway 539A removed.

Chapter 10/Appendix C: Assessing Efficacy of Treatment Programs to Control Invasive Phragmites in Highways Corridors of Southwestern Ontario

Patricia Chow Fraser, James V Marcaccio and Jordan DeBoer

Chow-Fraser, P., Marcaccio, J.V., & DeBoer, J. (2018). Assessing Efficacy of Treatment Programs to Control Invasive *Phragmites* in Highway Corridors of Southwestern Ontario. Report prepared for the Ontario Ministry of Transportation, St. Catharine's, ON. 34 pages

Abstract:

The invasive haplotype M of *Phragmites australis* originated in Europe and was introduced to the Atlantic coast in the 1800s. It eventually made its way to Southwestern Ontario in the late 1940s. Since 2010, invasive *Phragmites* has greatly expanded into coastal and inland wetlands throughout all Great Lakes states and provinces, and has become firmly established in road corridors. Dense stands of *Phragmites* can be dangerous near roads as they create a fire hazard, block sight lines, and can compromise the structural integrity of roadways and infrastructure. The Ministry of Transportation of Ontario (MTO) developed a control strategy that involves the use of glyphosate, a broad spectrum herbicide, to protect the infrastructure of MTO from this nuisance grass, and also to prevent further spread from highway corridors to adjacent natural heritage areas, watercourses and agricultural fields. Using the McMaster Invasive *Phragmites* Database (MIPD), we conducted a change-detection analysis between 2010 and 2015 GIS data to assess the effectiveness of the weed control program in roadway corridors that has been on-going since 2012. Except for the major expressway (i.e. 400-series highways), most of the treated roads decreased in areal cover by >95%; removal rates associated with the 400-series highways ranges from 80-85%. It is important to note that the amount of new growth on Hwy 401 and 402 equaled or exceeded what had been removed, resulting in a net increase in *Phragmites* in 2016, despite the treatment program.

Executive Summary:

In this report, we present data from the McMaster Invasive *Phragmites* Database (MIPD; see Marcaccio and Chow-Fraser 2018) to show the overall response of *Phragmites* to glyphosate treatment in the southwestern region of the province. We conducted a change-detection analysis between 2010 and 2015 GIS data to assess the effectiveness of the weed control program in roadway corridors that has been on-going since 2012. Except for the major expressway (i.e. 400-series highways), most of the treated roads decreased in areal cover by >95%; removal rates associated with the 400-series highways ranged from 80-85%. Some of the reasons for the difference in response are related to the timing of the treatment relative to the assessment; for example, highway segments in the southern region that had been treated three years earlier in 2012 were associated with lower efficacy than segments in the northern region, which had been treated in 2013 and 2014. To analyze the data at a smaller scale, we divided roads into 1-km segments and conducted a change-detection analysis to determine the effectiveness of treatment for each highway. There was considerable variation in how the road segments responded to treatment, but in general, if roads received minimal or no treatment or if treatment had been applied at least 2-3 years earlier (i.e in 2012 or 2013), we found a net increase in *Phragmites*; conversely, if roads had been treated in 2013 and 2014, they tended to have a net decrease in *Phragmites*. Based on these lines of evidence, we suggest that effectiveness of treatment will vary inversely with length of time since herbicide application; therefore, we support the recommended practice of applying follow-up

treatments every 2 to 3 years to maintain a reduced presence of *Phragmites* until they are eradicated.

On the 400-series highways, *Phragmites* had a faster colonization rate compared with other road types, and this resulted in higher net gains of *Phragmites* over the study period, despite the high effectiveness of glyphosate. We also found that patch size of *Phragmites* had a significant influence on both efficacy of glyphosate treatment and the colonization rate, and that highways tended to have larger patch size than other road types. *Phragmites* along multi-lane divided freeways may be more difficult to control than on two-lane roads, and may require more frequent treatment. We therefore recommend development of different control strategies for each road type, and we warn against developing a single protocol to apply to all roads, sizes and geographic settings. In an appendix, we have also provided the Best Management Practices from jurisdictions throughout the Great Lakes basin, who are responsible for controlling and eradicating invasive *Phragmites* in roadway corridors. The McMaster Invasive *Phragmites* GIS Database, created specifically for MTO (i.e. *Phragmites* mapped in, 2006, 2010 and 2015 for the southwestern region of the province) has been provided to MTO.

Introduction:

Phragmites australis (Cav.) Trin. ex Steudel (the common reed) is a perennial grass that grows in many habitat types throughout the world. There are 27 genetically distinct groups (haplotypes) worldwide, of which 11 have been found in North America (Saltonstall 2002). Over the past two decades, Haplotype M, which originated from Europe, invaded coastal and inland wetlands throughout southern Ontario, replacing native vegetation and generally reducing biodiversity (Meyerson et al. 2000; Markle and Chow-Fraser 2018). This invasive haplotype aggressively colonizes exposed mud flats sexually (through seeds), and then expand asexually (through rhizomes) to form dense monocultures. Its rapid spread has been attributed to it being a superior competitor against other emergent vegetation (Rickey and Anderson 2004; Uddin et al. 2014) and to being more tolerant of disturbances (e.g. road maintenance and changes in hydrologic regimes) and stress such as increased salinity due to road de-icing salts (McNabb & Batterson,1991; Marks et al.,1994; Chambers et al. 1999; Saltonstall 2002).

Past studies have shown that transportation corridors provide excellent invasion pathways for species such as invasive *Phragmites.* Linear ditches along roadsides or in the median can be readily colonized by invasive *Phragmites* (Lelong et al. 2007; Brisson et al. 2010), because they are able to tolerate high salinity from road salts and requires little moisture in comparison to other aquatic vegetation (Medeiros et al. 2013). Ministry of Transportation of Ontario (MTO) has acknowledged the destructiveness of *Phragmites*, both with respect to the road infrastructure, as well as to adjacent ecosystems, and has been developing a control strategy. Since 2012, MTO has sprayed highway corridors with glyphosate, a broad-spectrum herbicide used to control the growth of *Phragmites* and other weeds (**Figure 10.1**).

The primary goal of this project is to use the McMaster Invasive *Phragmites* Database (MIPD; see Marcaccio and Chow-Fraser 2018) to test hypotheses regarding the overall effectiveness of MTO's current treatment program. First, we wanted to document the degree of effectiveness of treatment (i.e. proportion of *Phragmites* removed between 2010 and 2015) on a road-by-road basis throughout West Region. Secondly, we wanted to know if degree of effectiveness varies with 1) the year that herbicide had been applied to highway segments, 2) type of road being treated (400-series highways vs all other highways), and 3) the amount (abundance and areal cover) of *Phragmites* present initially in 2010.

Methods:

McMaster Invasive Phragmites *Database (MIPD)*

The McMaster Invasive *Phragmites* Database (MIPD) is a GIS database that contains maps of the distribution of invasive *Phragmites* within the province of Ontario. It contains *Phragmites* maps of southwestern Ontario corresponding to spring of 2006, 2010 and 2015. These were created by automated classification with eCognition (2006 and 2010) or manual digitizations (2015) (Marcaccio and Chow-Fraser 2018). To determine potential discrepancies in results stemming from the two mapping protocols, we carried out a direct comparison for a subset of 2010 images. For the same stretch of road, we used the eCognition method to obtain 527 polygons of *Phragmites* totalling

0.6947 ha; when we manually digitized the same segment, we only obtained 249 polygons, but these totalled a much larger area of 3.0857 ha. In general, it appears that eCognition tends to produce many more smaller polygons (30% more for our subset), whereas manual digitization tended to produce fewer but larger polygons. The overall effect of this systematic bias is that 2010 maps tended to overestimate *Phragmites* distribution while 2015 maps tended to underestimate areal cover. With respect to assessing effectiveness of treatment, these errors would lead us towards a more conservative estimate of effectiveness, that is, we would be more likely to declare no or lower effectiveness. Given our overall goal, we deemed this to be an acceptable bias.

Assessing Effectiveness of Treatment

We completed a change-detection analysis in ArcGIS 10.3 to track the pattern of change in *Phragmites* between 2010 and 2015. By overlaying 2015 classified polygons on 2010 polygons, we produced a new layer with polygons identified as one of three effectiveness categories: 1) *Phragmites* that remained as *Phragmites* in 2015 (no change), 2) *Phragmites* that had turned into a non-*Phragmites* class in 2015 (decreased) and 3) non-*Phragmites* class that had turned into a *Phragmites* class in 2015 (increased). For example, if a hectare of grass in 2010 became converted to half grass and half *Phragmites* by 2015, then we would have 0.5 ha of a polygon identified as Category 3, indicating *Phragmites* had expanded by 0.5 ha. A new attribute was created for each polygon that identified the associated transformation from one habitat class into another.

To interpret results of the change detection, we have operationally defined roads that had been sprayed with glyphosate between 2012 and 2014 as being “treated” roads.

This information had been conveyed to us by MTO and we did not have the actual areas sprayed by the contractors (see note in Recommendations). Therefore, any *Phragmites* patch that had been present in 2010 on a treated road, and that was no longer present in 2015 was interpreted as having been successfully killed by the herbicide (green=decreased; **Figure 10.2**). By comparison, presence of *Phragmites* on treated roads in both 2010 and 2015 images would indicate that the treatment had been ineffective (blue=unchanged; **Figure 10.2**). Finally, presence of any new *Phragmites* patch in 2015 would indicate that *Phragmites* had expanded (red=increased; **Figure 10.2**). In some instances, *Phragmites* may be regenerated within treated dead stands, and in that case, we would classify the entire stand as having been ineffectively treated (i.e. unchanged) since we were unable to distinguish between living and dead portions within mixed stands (see **Figure 10.3**).

To enable statistical analyses, we divided all roads into 1-km segments so that we had replicate segments by treatment type and highway name. The .dbf file associated with this GIS layer was then imported into JMP 13 (SAS, Cary NC) for further graphical and statistical analyses.

<u>Results and Discussion:</u>

Overall Trends

We used results of the change detection to determine the effectiveness of treatment for each road/highway. As explained in the methods, we have assessed effectiveness by measuring the proportion of *Phragmites* that had disappeared on a treated road between 2010 and 2015. Each highway was converted into 1-km segments prior to change-detection; growth in 2010 that was no longer visible in 2015 was interpreted as having been successfully treated (i.e. removed) while those in 2010 that remained in 2015 was deemed to have been unsuccessfully treated. It is important to note that some highways are very long (e.g. Hwy 6, which runs north-south for 472 km through southwestern Ontario from the Bruce Peninsula to Port Dover, going through many towns and cities) while others are very short (e.g. Hwy 77 running north from Leamington for only 22.6 km). The 400-series highways such as 401, 402 and 403 have multiple lanes and are associated with much larger traffic volumes.

A visual comparison of the 2010 and 2015 distributions of *Phragmites* throughout southern Ontario confirms the efficacy of the treatment program from 2012 to 2014 (**Figure 10.4**). *Phragmites* had been almost eradicated in the Bruce Peninsula in the northern portion of the study area and had been greatly reduced in the central portion of southern Ontario. Overall, relatively high proportions of the original *Phragmites* present in our highways had been removed by 2015, indicating that the treatment program had been highly effective (**Figure 10.5**). The net proportion of *Phragmites* removed on Hwy 40, 401 and 402 were below 85% while most of the other roads were above 95%.

The lower efficacy associated with Hwy 401 and 402 may be because these roads had been treated only once in 2012, compared with other roads that had been treated in 2013, 2014 or in two consecutive years (**Figure 10.6a**). There is growing consensus that *Phragmites* will not be eradicated with a single treatment; in many studies, complete eradication was not achieved without repeated treatments for 2 or 3 years (Reimer 1976, Turner & Warren 2003, Derr 2008, Lombard et al. 2012, Warren et al. 2013). Irrespective of the timing of treatment, effectiveness tended to be lower on freeways (i.e. 400-series highways) than on smaller highways, collectors and arterial roads within highway networks. We therefore re-analyzed the data to determine the influence of road type on the colonization rate of *Phragmites* and found that % *Phragmites* removed from 400-series highways was significantly lower than those on other roads (t-test; $P<0.0001$) (**Figure 10.6b**). This may be due to the larger right-of-way of Hwy 401 and 402, with larger areas to colonize (**Figure 10.7**; middle panel). It may also be due to higher traffic volume on these freeways, redistributing seeds through traffic-generated wind patterns or attachment and transport by vehicle.

> **Repeat applications**
> Based on these results, we conclude that effectiveness of treatment will vary inversely with length of time since herbicide application; therefore, we support the recommend-ed practice of applying follow-up treatments every 2 to 3 years to maintain a reduced presence of *Phragmites* until they are completely eradicated.

It is noteworthy that the efficacy of the treatment program did not necessarily reflect the amount of *Phragmites* present in 2010. For instance, Hwy 40 had less growth compared with Hwy 21 in 2010, but Hwy 40 had a higher rate of removal. There had been greater areal cover of *Phragmites* on Hwy 401 in 2010, and yet, removal rate was higher than that for Hwy 402 (see **Figure 10.7**). The change detection also revealed that all areas that had been sprayed had been effectively treated, and that the reason for the overall lower efficacy for Hwy 401 and 402 was the amount of "new" growth that had occurred—new stands of *Phragmites* that had colonized beside and around the treated stands (top panel; **Figure 10.7**). We verified that very little of the growth observed in 2015 had been re-growth in the treated stands, but were in fact new growth.

The degree of expansion in 2015 appears to be directly related to the amount that had been present in 2010, and this is consistent with observations that *Phragmites* expands clonally (**Figure 10.8a**). Once invasive *Phragmites* colonizes new habitat, it tends to send out rhizomes (Minchinton & Bertness 2003), and the linearity of the highway corridors facilitates easy expansion (rate varied from <1 to 27% in this study). Similarly, we also found degree of resistance to treatment (amount of *Phragmites* that remained unchanged following treatment) was directly related to the amount that had been present in 2010 (**Figure 10.8b**). The implication of this is that *Phragmites* can be more successfully eradicated when they are smaller and fewer in number and is a good reason for implementing an early detection program and treating the sparsely populated areas before they become dense.

> **Road-specific protocols and need for early detection**
> Based on the evidence thus far, we recommend developing different control strategies for each type of highway/road and we warn against developing a single protocol to be applied to all roads types, sizes and geographic settings.
>
> Given that *Phragmites* stands are more effectively eradicated when they are small, implementation of early detection program may be the best way to prevent its expansion throughout the province.

Regional Analysis

The GIS database assembled was used for more in-depth regional analysis. By overlaying the 2010 and 2015 distribution of *Phragmites,* and accounting for the timing of treatment, we produced regional maps of different regions in southern Ontario for visual comparison and assessment.

In all three maps that follow (**Figures 10.9a & b and Figure 10.10**), red represents areal cover of *Phragmites* in 2015, which is essentially the growth at the end of 2014 since the orthophotos had been acquired in spring of 2015. White represents areal cover of *Phragmites* in 2010. Roads treated in 2012 are coloured grey, those treated in 2013 are coloured green and those in 2014 are coloured pink. In the first map (**Figure 10.9a**), Hwy 402 (west of the city of London) appears to be solid red, while Hwy 6 and 8, running north and west of the city of Kitchener had intermittent patches of *Phragmites* in 2015. All roads that had been treated in 2013 appear to have intermittent patches. The second map (**Figure 10.9b**) shows how the 2013 treated road had intermittent patches of *Phragmites* in 2015, while Hwy 401 appeared to have dense *Phragmites* stands throughout. Finally, the third map (**Figure 10.10**) shows that portions of Hwy 24 and 403 that had been treated in 2014 had very few patches of *Phragmites* in 2015, while the eastern segment of 403 (not yet been treated as of 2015) had much more *Phragmites* in 2015.

Conclusion:

This is the first time that high-resolution remotely sensed image data have been used to scientifically assess the effectiveness of the most commonly used methods to control invasive *Phragmites* in highway corridors throughout southern Ontario. We found that regrowth of treated stands varied from <1 to 27% and that increase in distribution of *Phragmites* in 2015 was primarily from new growth. Regrowth and new growth was more prolific on 400-series highways. Our data suggest that freeways may be more difficult to treat than other road types, but we urge that further studies be carried out in which timing of treatment and traffic volume are standardized to allow for direct comparisons. There was considerable variation in how the road segments responded to treatment, but in general, if roads received minimal or no treatment or if treatment had been applied at least 2-3 years earlier (i.e in 2012 or 2013), we found a net increase in *Phragmites*; conversely, if roads had been treated in 2013 and 2014, they tended to have a net decrease in *Phragmites*. We also found that the 400-series highways had lower proportions of *Phragmites* removed overall because there were higher colonization rates, resulting in higher net gains of *Phragmites* compared to other road types. This is likely the reason why *Phragmites* is more difficult to control along multi-lane divided freeways. We also found that patch size of *Phragmites* had a significant influence on both efficacy of glyphosate treatment and the colonization rate, and that the freeways tended to have larger patch size than other road types.

Recommendations:

For a geographic area as large as that of southwestern Ontario, the only cost-effective approach to map the distribution of *Phragmites* over time and space is to use some sort of automated classification system such as eCognition. SWOOP images were the only ones with the required resolution and geographic coverage for this type of large-scale mapping. It is unfortunate, however, that the orthophotos acquired in 2015 could not be used in automated classification with eCognition, and we therefore hope that future acquisitions will rectify this limitation.

The recent pilot study by Rupasinghe & Chow-Fraser (2018) indicated that Sentinel 2 image data may be suitable for regular benchmarking purposes, and that Worldview 3 satellite image data may be used for early detection of sparsely distributed *Phragmites* stands. Using these medium- and high-resolution satellites could circumvent the reliance on Ontario orthophotography datasets, and has the added convenience of faster acquisition times (average revisit times 5 days to <1 day for Sentinel 2 and Worldview 3, respectively). Sentinel 2 can be used to assist in management and determining the initial areal cover of *Phragmites* on roadsides. Very high resolution Worldview 3 data can be used post-treatment to monitor small stands and regrowth in the following years.

Many management agencies within the Great Lakes watershed have produced Best Management Practices (BMP), some specifically targeting roads and others for general wet habitat (Appendix). While effectiveness is rarely documented quantitatively, post-treatment monitoring is conducted to determine the quantity of glyphosate that should occur for complete eradication of *Phragmites*. It is noted in most BMPs that repeat spraying is required to control the population.

We have shown that effectiveness of treatment will vary inversely with length of time since herbicide application; therefore, we support the recommended practice of applying follow-up treatments every 2 to 3 years to maintain a reduced presence of *Phragmites* until they are eradicated. Our evidence thus far leads us to recommend development of different control strategies for each road type, and we warn against developing a single protocol to apply to all roads, sizes and geographic settings.

Knowing the time sensitive nature of treatment efficacy, we recommend that MTO immediately start *Phragmites* treatment in the northern and eastern portions of the province where current *Phragmites* density is still very low. Given the most recent estimates in Marcaccio & Chow-Fraser 2018, areal cover of *Phragmites* in the southwestern and central portion of the province could expand to over 6,000 hectares of *Phragmites* by 2020 if left untreated. Such high densities would prolong eradication efforts and increase the cost of management dramatically. If control programs are started immediately while presence of *Phragmites* is still limited, treatment would be more successful and less costly overall to MTO.

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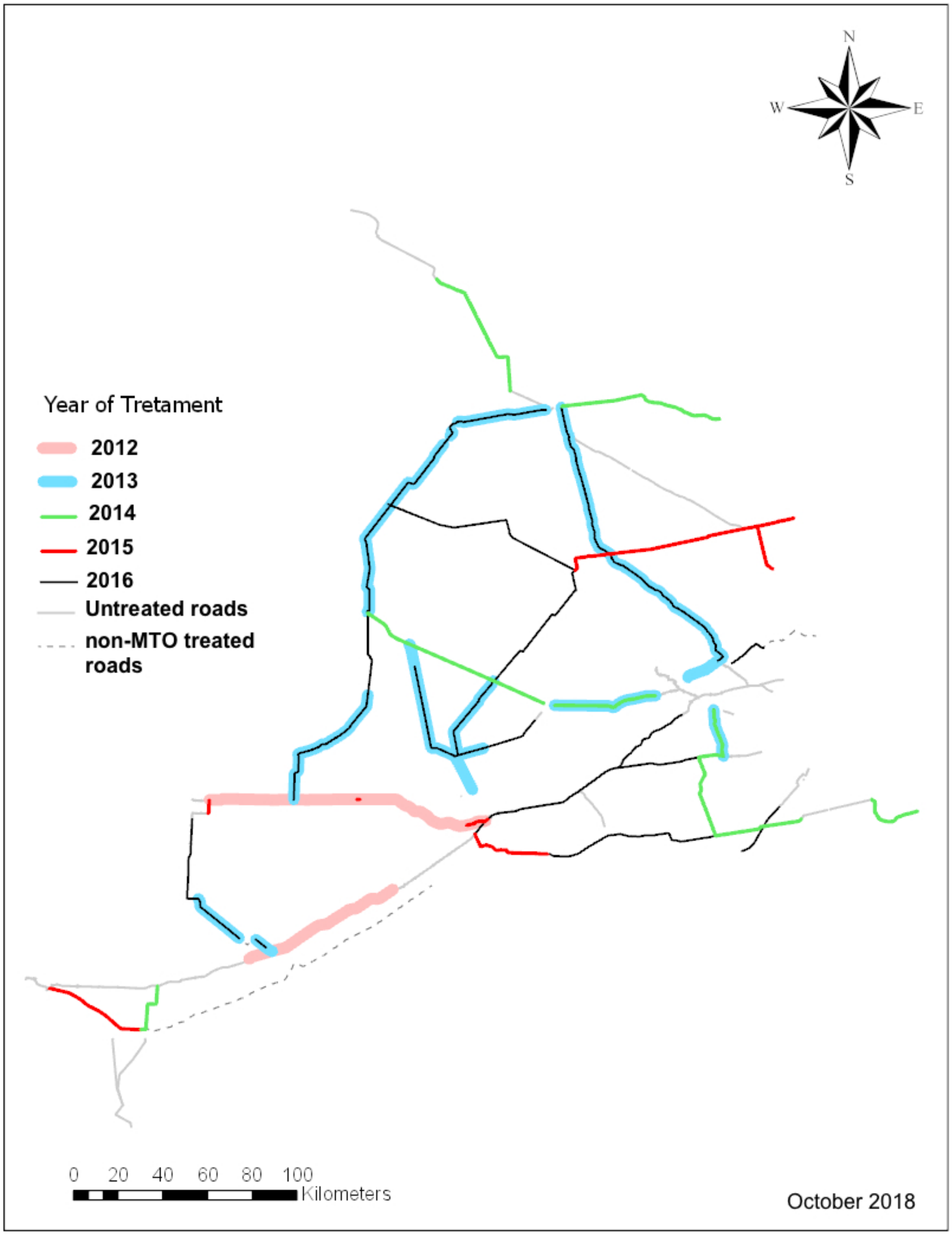


Figure 10.1. Roads in West Region that had been treated with glyphosate between 2012 to 2016. In this study, we included several roads that had been treated but which are not managed by MTO (dotted lines).

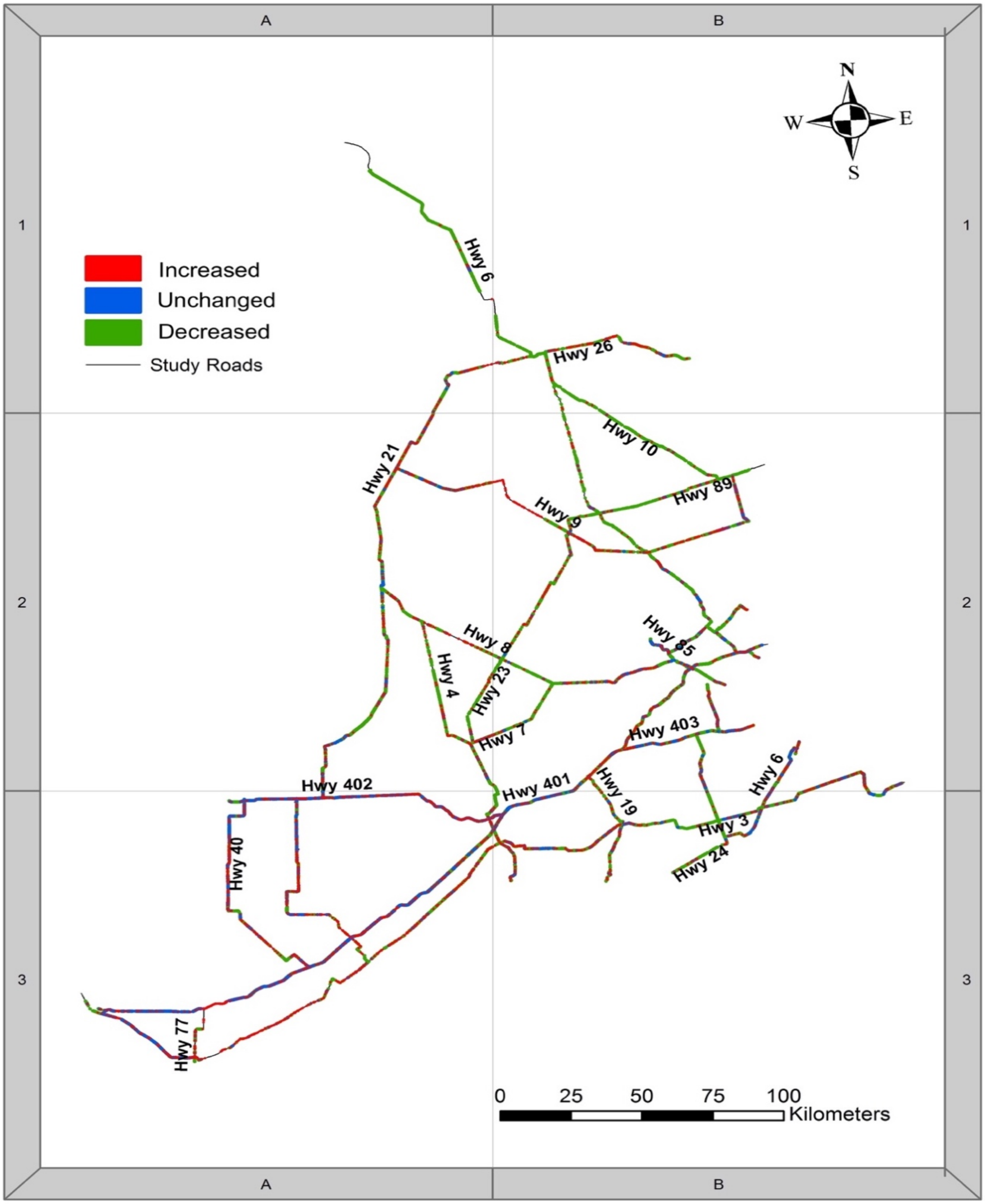


Figure 10.2: Results of a change detection of invasive *Phragmites* occurring in highway corridors of southwestern Ontario between 2010 and 2015, based on SWOOP image data only.

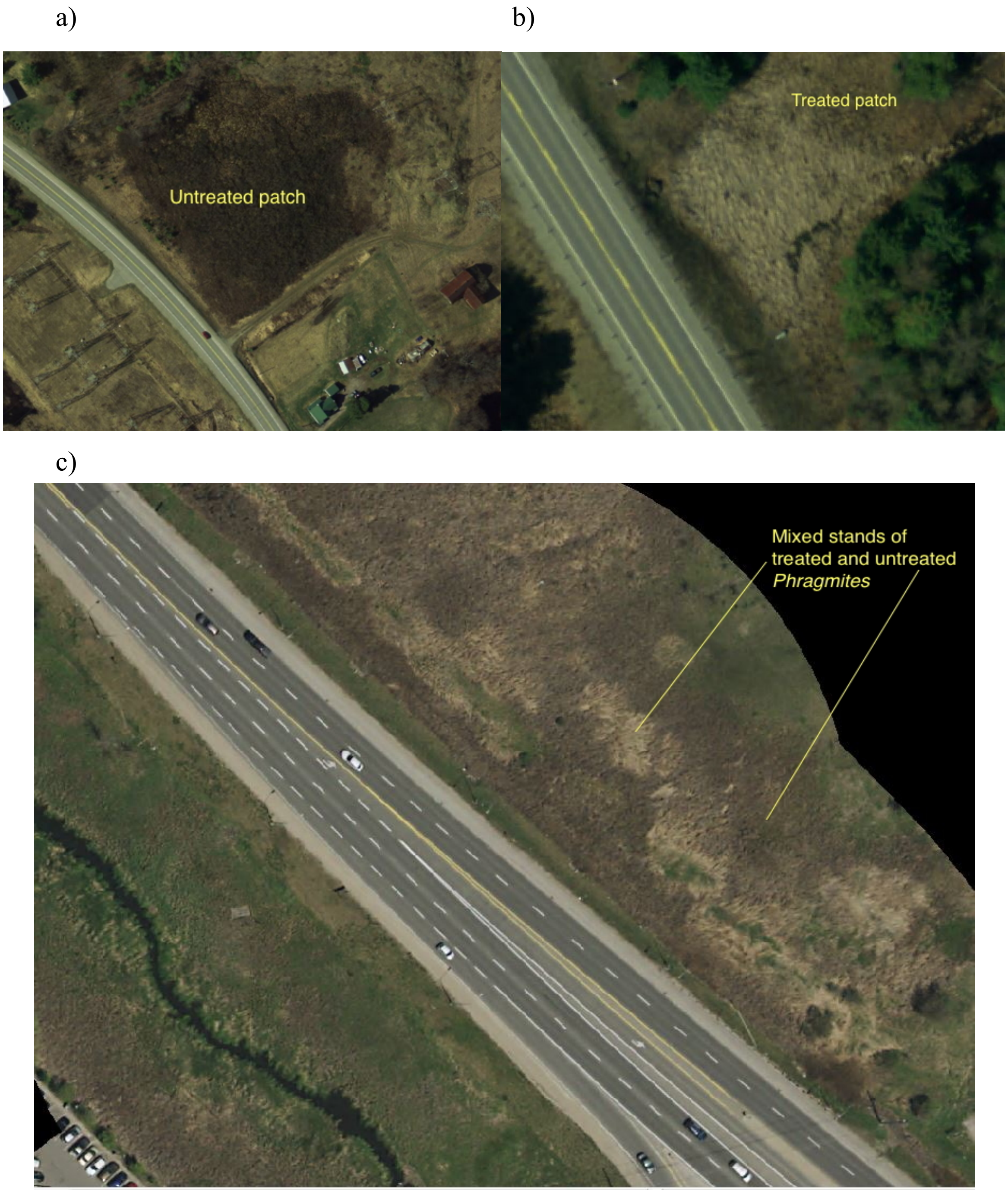


Figure 10.3: Images showing *Phragmites* in highway corridor that had: a) a dark mottled appearance characteristic of living stands, b) a light mottled appearance characteristic of dead stands (presumed to have died from glyphosate treatment). Panel c) shows a mixture of dead and living specimens side by side, which may have resulted from imperfect treatment or regrowth from rhizomes of treated individuals.

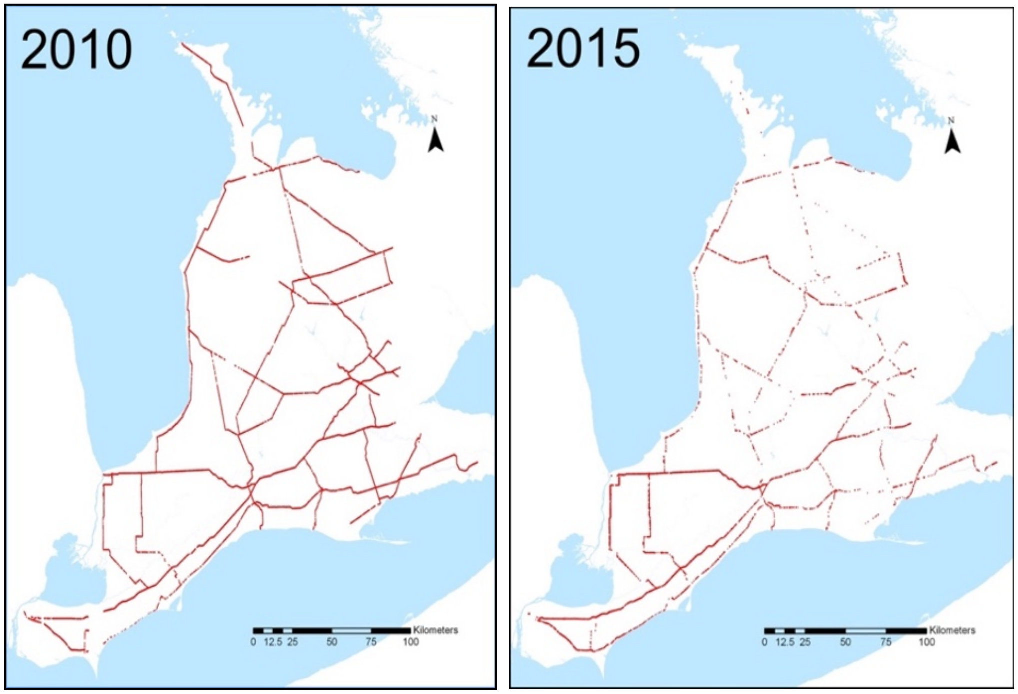


Figure 10.4: *Phragmites* distributions in MTO-managed roads in southwestern Ontario during 2006, 2010 and 2015. Distribution in 2010 was mapped by automated classification whereas that for 2015 was manually digitized.

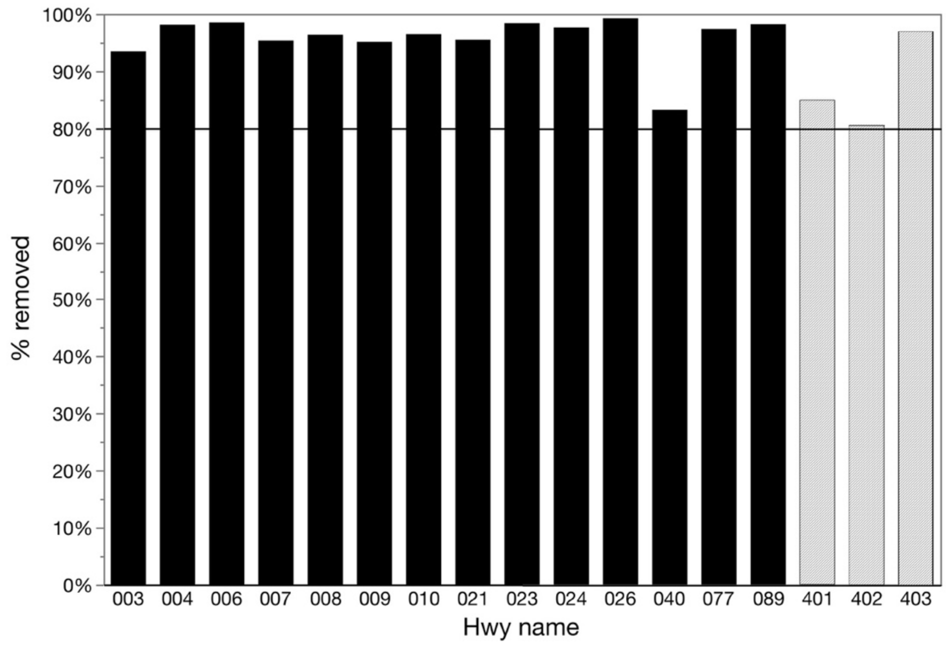
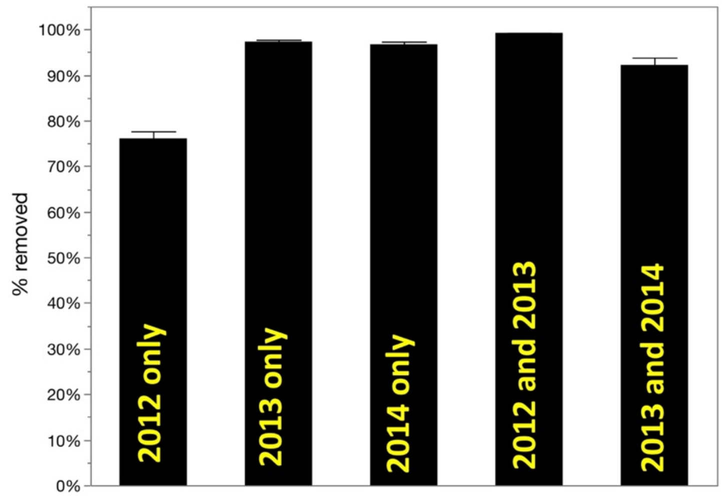


Figure 10.5: Percentage of *Phragmites* that had been removed shown separately by highways. Removal is inferred from decrease in *Phragmites* in 2015 relative to 2010 (see Figure 2). The black line corresponds to 80% removed.

a)



b)

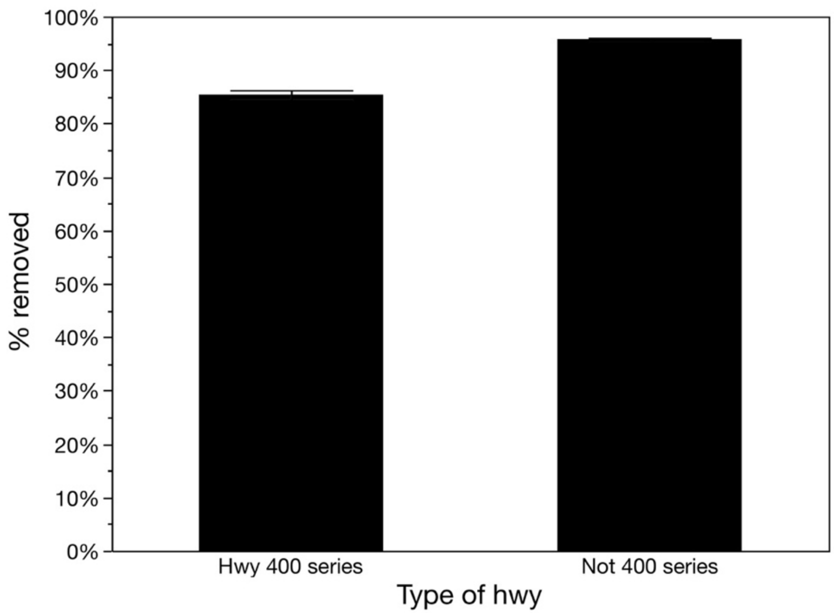


Figure 10.6: % *Phragmites* removed for a) roads grouped according to when they had been treated and b) 400-series and non-400 series highways.

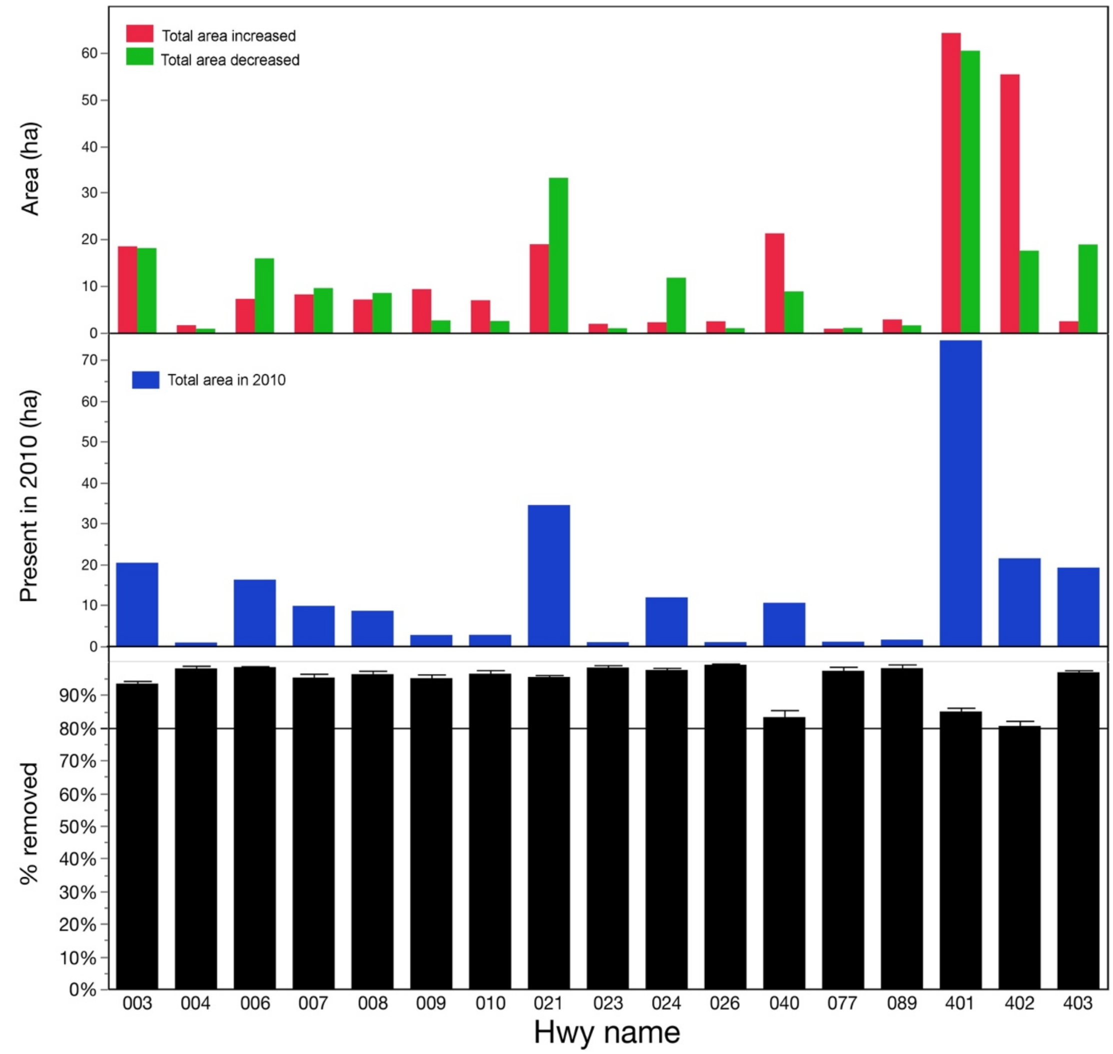
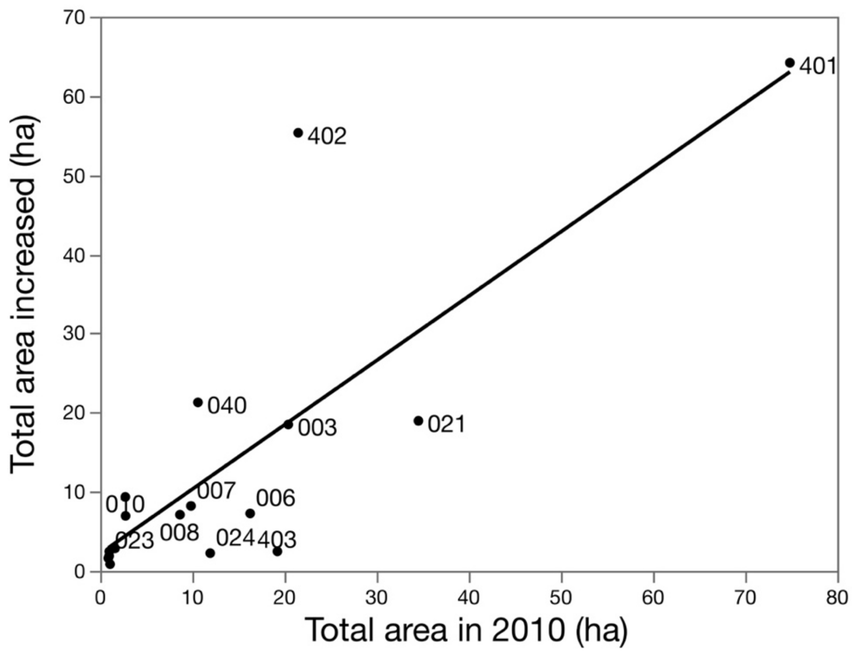


Figure 10.7: Results of a change detection showing amount of *Phragmites* that had decreased, remained unchanged or increased between 2010 and 2015. Top panel: Mean±SE calculated for 1 km-segments for each highway; Middle panel: Total area present in 2010 and Bottom panel: % *Phragmites* removed as of 2015.

a)



b)

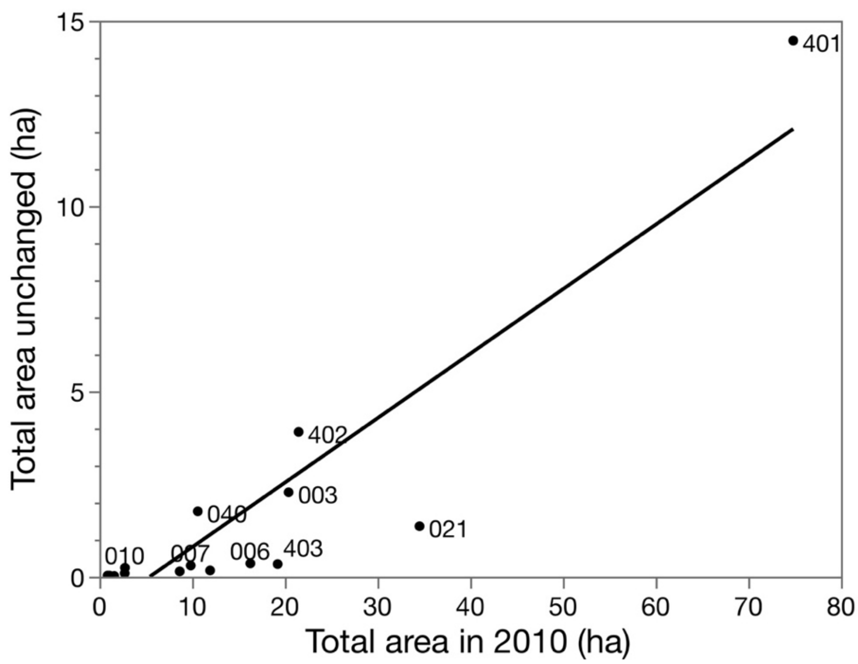
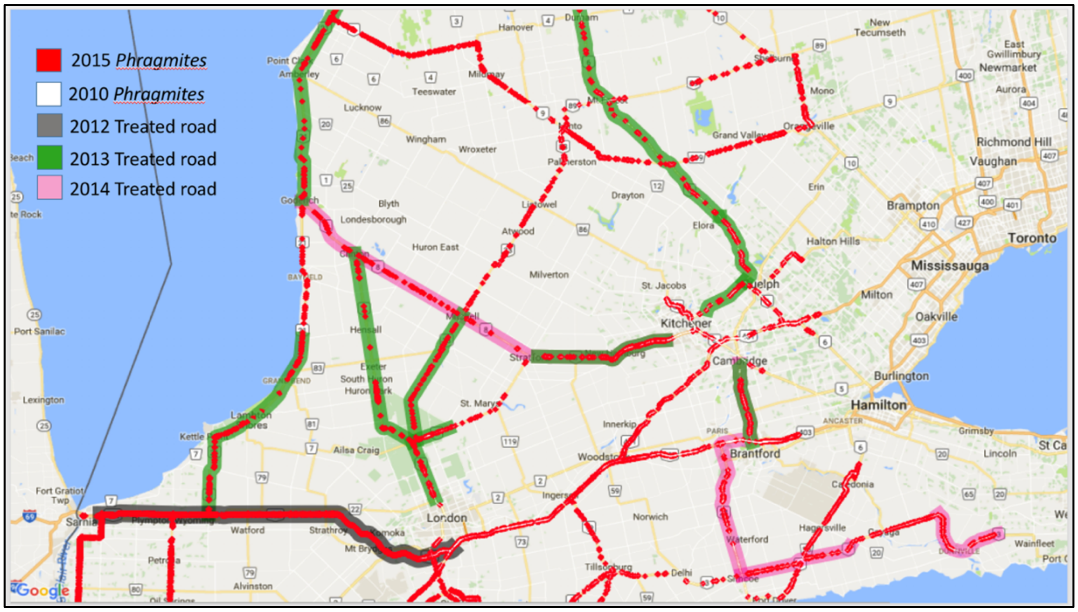


Figure 10.8: a) Total area that had changed as a function of original area in 2010 and b) Total area that remained unchanged as a function of original area in 2010.

a)



b)

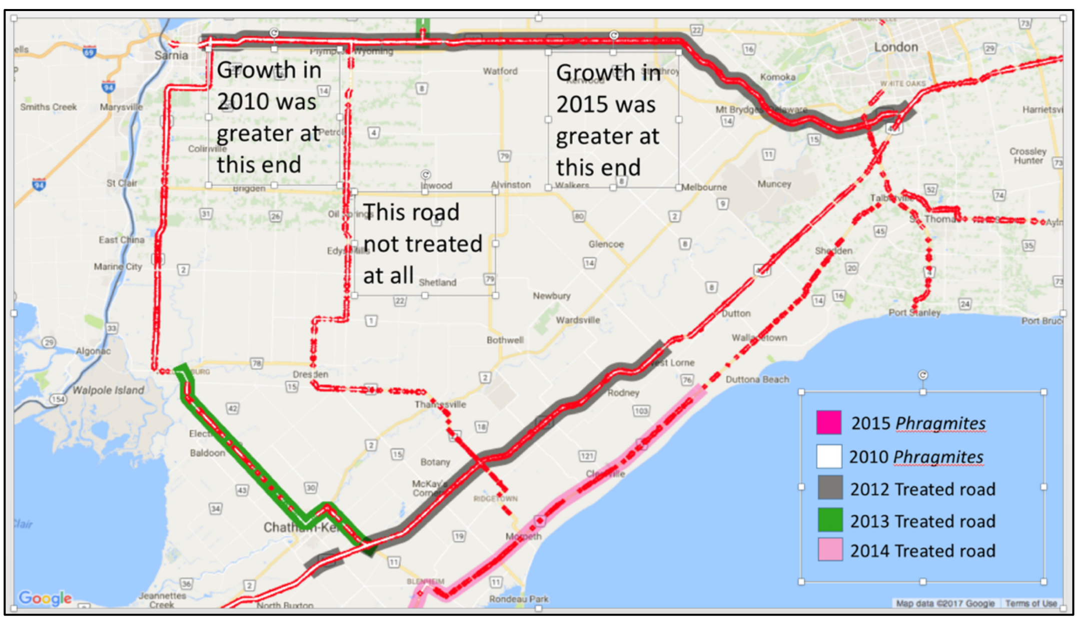


Figure 9: a) Map of *Phragmites* in 2015 (red) and in 2010 (white) superimposed on roads in southwestern Ontario. b) Comparing areal cover of *Phragmites* in highways located between London and Sarnia. Growth of *Phragmites* in 2010 had been greater at the western end of Hwy 402 (near Sarnia) whereas growth in 2015 had been greater in the eastern end (near London).

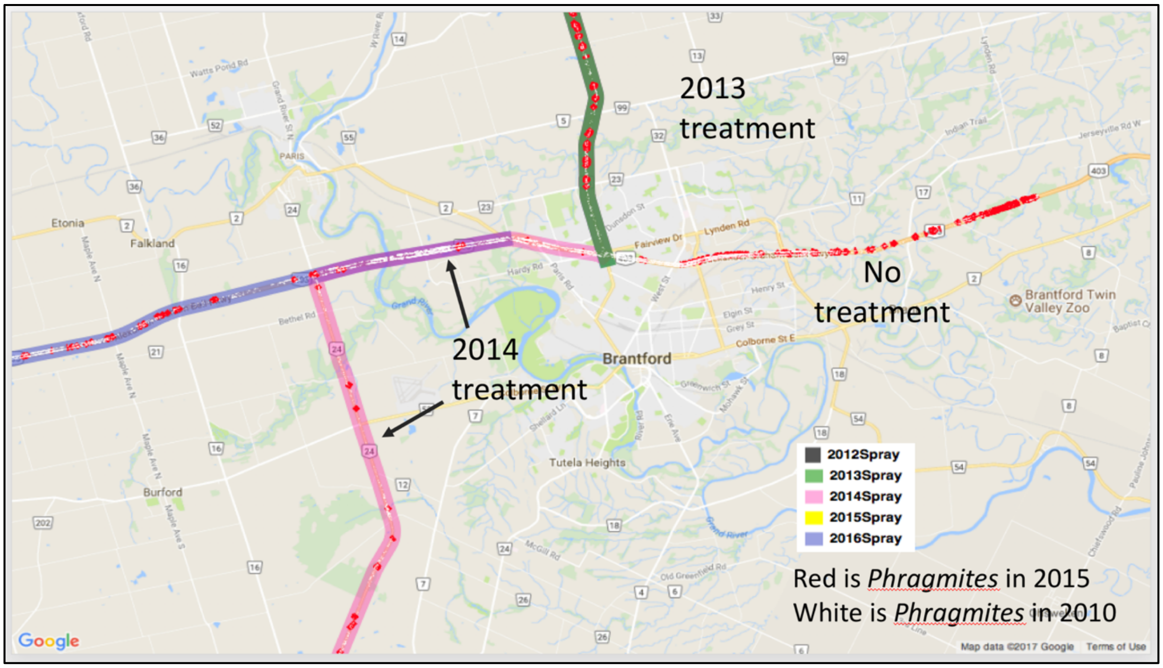


Figure 10.10: Growth of *Phragmites* in 2015 (red) on a segment of Hwy 403 that had not been treated (shown on the right), compared with few patches of *Phragmites* in segments of Hwy 24 and Hwy 403 that had been treated in 2014 (shown towards the left). Also shown are *Phragmites* in 2010 (white) that are no longer evident on these segments.