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Use of World View 3 (WV 3) satellite imagery for early detection of invasive Phragmites australis in roadway corridors in Ontario

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Abstract	We tested the suitability of high-resolution (80 cm) multi-spectral satellite data from World View 3 (WV 3) to detect small patches of invasive Phragmites within 20-m buffer of the centre-line of the road. We used ENVI 5.5 to classify the image into seven classes: roads, trees, Phragmites, roadsides, ground, grass, and agriculture. We applied the Mixture-Tuned Match Filtering (MTMF) procedure to the image, which is a spectral unmixing method in which the target features could be separated out from the other background features in mixed pixels. The highest confusion with Phragmites were with grasses and agricultural lands. Accuracy of the Phragmites classification was higher for the MTMF image (81.6% producer's and 75.6% user's accuracy) than for the reflectance image (73.7% producer's and 71.4% user's accuracy), while overall accuracy was 84.4% and 74.6%, for the MTMF and the reflectance image, respectively. We conclude that WV 3 can be used in early-detection programs, as long as the procedure is applied to a relatively small area in wetlands (maximum 100 ha) or roadsides (4-km segment) to increase accuracy and publishing requirements necessary to achieve the best possible product.

Keywords Invasive *Phragmites*, early detection, road maintenance, remote sensing

Distribution Unrestricted.

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Use of World View 3 (WV 3) satellite imagery for early detection of invasive Phragmites australis in highway corridors of Ontario

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Executive Summary

Phragmites australis (the common reed) is a taxonomically diverse perennial grass, with 27 genetically distinct groups throughout the world, 11 of which are found in North America. One of the European haplotypes, M, is an aggressive invader in coastal wetlands and roadway corridors and have been growing at the expense of native vegetation in many coastal marshes of the lower Great Lakes. This invasive *Phragmites* has also been invading the roadway corridors in southwestern Ontario over the past decade. Currently, no provincial agencies include an early-detection program as part of their overall control strategy to manage invasive *Phragmites* in wetlands or roadways. An early-detection program would be beneficial since efficacy of herbicide treatment is known to be better when *Phragmites* patches are small and sparse than when they are large and dense.

Some recent studies have explored the use of high-resolution multispectral satellite data such as IKONOS, QuickBird, WorldView 2 and 3 (WV 3) for species-level mapping. Although these multispectral data have relatively low spectral resolution, the images have higher temporal resolution and the image availability is higher. Hence these data are very useful in largescale *Phragmites* mapping and monitoring. In this paper, we tested the suitability of high-resolution (80 cm) multi-spectral satellite data from World View 3 (WV 3) to detect small patches of invasive *Phragmites* in wetlands and roadside corridors. These results should inform MTO of the feasibility of using WV 3 in early detection programs.

We selected Norfolk County for this study because it is situated on the north shore of Lake Erie, where there are several small towns connected by approximately 4,100 kms of roads, of which 83% are in rural areas. There are also several large coastal wetland complexes including the Big Creek National Wildlife Area (BCNWA), where we have ground-truth data of invasive *Phragmites* from an ancillary study. Big Creek wetland is located west of Hwy 59 at the base of Long Point Bay on Lake Erie, in the municipality of Norfolk County.

WV 3, which is operated by DigitalGlobe, is a fourth-generation, optical and commercial earth-observation satellite, with the highest spatial resolution (30 cm panchromatic and 1.24 m multispectral) of all existing optical satellites available for research. A cloud-free WV 3 image was acquired in 07th July 2016. The image covered an area of 437 km^2, which includes Big Creek Marsh and other parts of the Long Point watershed. The training data for image classification and accuracy assessment of invasive *Phragmites* in the BCWNA were manually digitized from an image (8-cm resolution) acquired with an Unmanned Aerial Vehicle (UAV; Sensefly eBee) in late summer 2015. We selected a sample area of 1 × 1 km^2 within the wetland that contained large *Phragmites* patches as well as many of the most common wetland classes. We also selected a 4-km stretch of arterial 2 lane road (Hwy 59) that included six spraying locations to test the usefulness of WV 3 for mapping *Phragmites* in roadsides. These relatively smaller areas were chosen to increase our classification accuracy.

Image pre-processing and processing was conducted with the software ENVI 5.5

(Harris Geospatial). Radiometric correction and atmospheric correction (ENVI QUAC correction) were performed for the image data to obtain surface reflectance values. Minimum Noise Fraction (MNF) transformation was performed for the pre-processed WV 3 image to reduce image dimensionality. Then Mixture-Tuned Match Filtering (MTMF) was applied to the image. MTMF is a partial un-mixing algorithm for the mixed pixels so that the relative fraction of the reflectance of the target feature can be separated out from the background. MTMF reduces the image classification errors (especially omission errors) when detecting *Phragmites* and makes it possible to detect smaller, less dense patches. After MTMF transformation, we classified the image using maximum likelihood classification. The reflectance image was also classified with the maximum likelihood classification and was compared against the classification with MTMF transformation. For roadsides, we created a 20-m buffer around the center-line of the road to avoid having to classify complex features in the image such as built-up areas. Ground-truthing data were obtained as described above. Random points that were not used as training data for the classification were used for the accuracy assessment.

Using ENVI 5.5, we classified the wetland image into seven classes: Cattail Organic Shallow Marsh, Floating Leaved Sallow Aquatic Marsh, Meadow Marsh, Mixed Organic Shallow Marsh, Open water, invasive *Phragmites*, and roads with overall accuracy of 87.4% for the MTMF image and 89.8% for the reflectance image. We also classified the road image into seven classes: roads, trees, *Phragmites,* roadsides, ground, grass, and agriculture. The highest confusion with *Phragmites* were with grasses and agricultural lands. Accuracy of the *Phragmites* classification was higher for the MTMF image (81.6% producer's and 75.6% user's accuracy) than for the reflectance image (73.7% producer's and 71.4% user's accuracy), while overall accuracy was 84.4% and 74.6%, for the MTMF and the reflectance image, respectively.

One challenge we experienced with WV 3 was the considerable time and skill required to pre-process the image initially. After determining the exact mapping protocol, however, the processing time was significantly reduced; nevertheless, some knowledge and expertise in remote sensing and ecology would still be required for anyone considering using our approach. Furthermore, we emphasize that ground-truth data collected at the appropriate time is essential for accurate estimation of *Phragmites* in both wetlands and roadsides. We conclude that WV 3 can be used in early-detection programs, as long as the procedure is applied to a relatively small area in wetlands (maximum 100 ha) or roadsides (4-km segment) to increase accuracy.

Introduction

Phragmites australis (Cav.) Trin. ex Steudel (the common reed) is a perennial grass that grows in aquatic, semi-aquatic, and terrestrial habitats throughout the world. Saltonstall (2002) identified 27 genetically distinct groups (haplotypes) worldwide, of which 11 have been found in North America. Over the past 2 decades, the European haplotype M began to make rapid incursions into Canada and the U.S., especially into coastal wetlands of the Laurentian Great Lakes (Wilcox et al. 2003; Tulbure et al. 2007; Wilcox 2012; Bourgeau-Chavez et al. 2015), and along highway corridors (Saltonstall 2002; Lelong et al. 2007). This haplotype exhibits invasive characteristics, including its ability to aggressively colonize exposed mud flats sexually (through seeds), and then expand asexually (through rhizomes) to form dense monocultures that inhibit biodiversity of other plants and wildlife (Meyerson et al. 2000a; Markle and Chow-Fraser 2018). 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) (McNabb & Batterson,1991; Marks et al.,1994; Chambers et al. 1999; Saltonstall 2002).

Roadsides provide suitable conditions for invasive *Phragmites* to establish. Most roadsides are bordered by drainage ditches that form a linear network of 'wetlands' (Jodoin et al. 2008). Over the past 50 years, *Phragmites* has expanded in these roadside ditches in both Canada and the U.S. (Meyerson et al. 2000b). Studies have documented a dramatic expansion of invasive *Phragmites* throughout Quebec following the construction of a road network (Jodoin et al. 2008; Brisson et al. 2010). Even though these ditches can facilitate the spread of *Phragmites* into nearby ecosystems, only a few studies have been conducted to investigate how infested roadways influence the invasion pattern of *Phragmites* in adjacent wetlands (Richburg et al. 2001; Maheu-Giroux & de Blois 2007).

A big challenge to those trying to study the effects of roadside *Phragmites* invasions on ecosystems is lack of an efficient method to map *Phragmites* accurately in the narrow linear wetlands along road sides or highway medians. In past studies, investigators relied on visual surveys while driving on roads to map *Phragmites* distributions (Lelong et al. 2007; Jodoin et al. 2008). Such an approach necessarily limits the geographic coverage of the study area. Remote sensing is the most appropriate approach to use for mapping *Phragmites* along roadsides, especially for areas that are difficult to survey safely (Davranche et al. 2009), such as sides and medians of busy highways and roads. Since herbicide treatments are more effective when *Phragmites* stands are small, it would be beneficial to have an early detection system that could identify and eradicate new patches in a timely manner before they can spread and become dense. Fortunately, a number of remote sensing options are now available both for routine monitoring and for early detection purposes.

Airborne sensors such as AVIRIS, CASI, HyMap, and PROBE-1 have been used successfully in species level mapping (Schmidt and Skidmore, 2001). These approaches are however limited by the relatively small geographic coverage, and the low temporal resolution of image acquisition. Some recent studies have explored the use of high-resolution multispectral satellite data such as IKONOS, QuickBird, WorldView 2 and 3 (WV 3) for species-level mapping (Adam et al. 2010; Li et al. 2015; Mustafa & Habeeb, 2014). Although these multispectral data have lower spectral resolution, the images have higher temporal resolution and the image availability is higher. Hence these data are very useful in large-scale *Phragmites* mapping and monitoring.

Objectives

The goal of this study is to test the feasibility of using WV 3 satellite data to detect young, less dense and small Phragmites patches occurring in both wetland complexes and along roadsides of Norfolk County.

Methodology

Study Sites

We selected Norfolk County for this study because it is situated on the north shore of Lake Erie, where there are several small towns and numerous recreational destinations (Niewójt, 2007) as well as several large coastal wetland complexes including the Big Creek National Wildlife Area (BCNWA), where we have ground-truth data of invasive *Phragmites* from an ancillary study (Marcaccio et al. 2016). Approximately 4,100 km of roads currently exist in Norfolk County, of which 83% percent are in rural areas ("Asset-Management-Plan-Roads.pdf," n.d.). Big Creek wetland is located west of Hwy 59 at the base of Long Point Bay on Lake Erie, in the municipality of Norfolk county (Ashley & Robinson 1996). In 1982, the Long Point wetlands were declared to be "Wetlands of International Importance" and was designated a "World Biosphere Reserve" by the Man and the Biosphere Program of UNESCO.

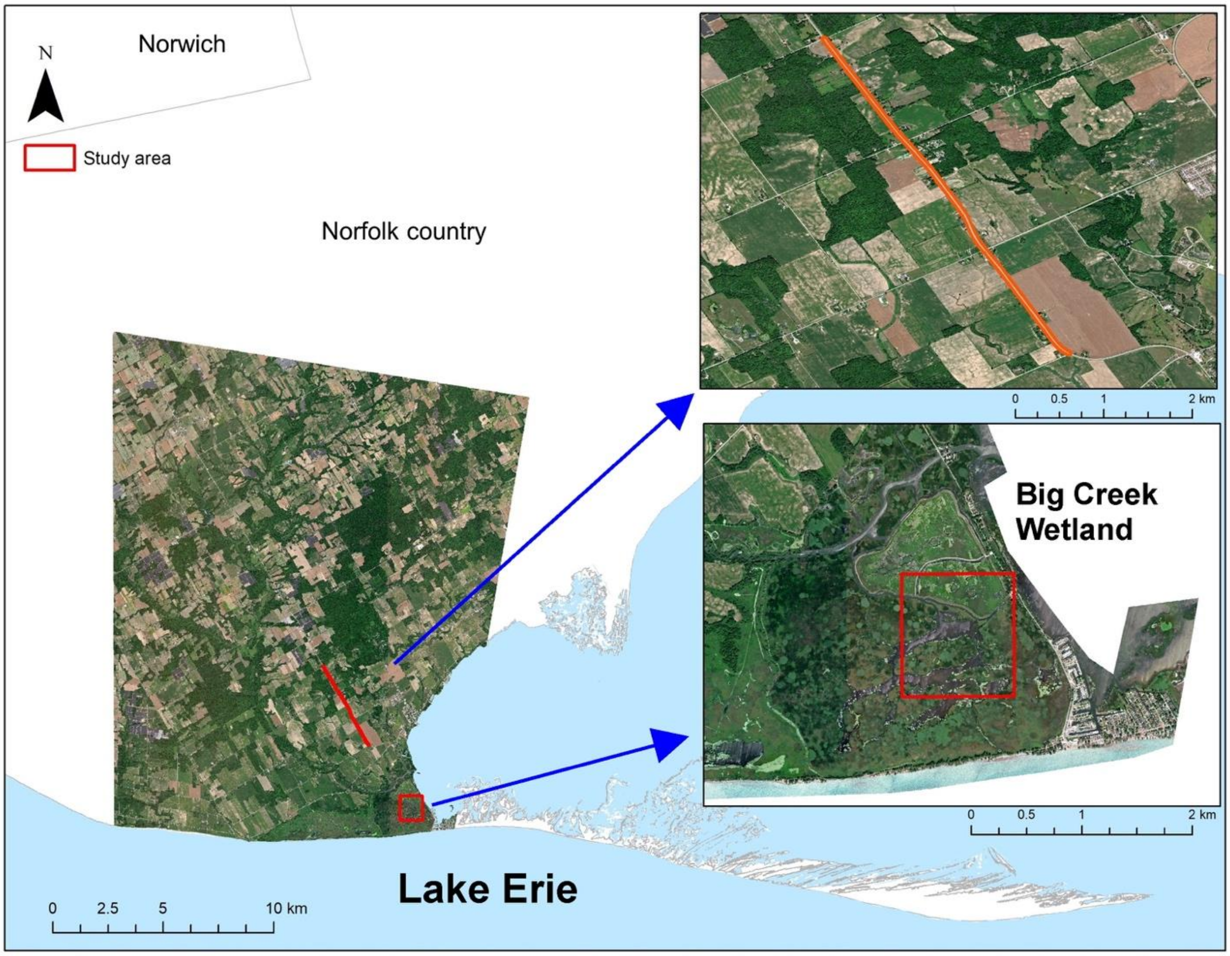

Figure 1. Footprint of the WV 3 image used in this study showing Big Creek Wetland (bottom right inset) and the road segment (top right inset) that was classified.

Remote sensing data

WV 3, which is operated by DigitalGlobe, is a fourth-generation, optical and commercial earth-observation satellite, with the highest spatial resolution (30 cm panchromatic) of all existing optical satellites available for research. A cloud-free WV 3 image was acquired in 07th July 2016. The image covers an area of 437 km^2, which includes Big Creek Marsh and other parts of the Long Point watershed (Figure 1). The image consists of one panchromatic band (445-808 nm spectral resolution and 30 cm spatial resolution) and eight multispectral bands (80 cm spatial resolution), including the coastal blue (397-454 m), blue (445-517 nm), green (507-586 nm), yellow (580-629 nm), red (626-696 nm), red edge (698-749 nm), Near InfraRed 1 (NIR 1; 765-899 nm) and NIR 2 (857-1039 nm) bands. The range of available spectral bands and high spatial resolution makes WV3 suitable for a wide range of applications including vegetation monitoring, coastal monitoring, mineral exploration and species-level mapping (Kruse & Perry, 2013; Wang, Zhang, Lin, & Fang, 2015).

Ground Truth Data

The training data for image classification and accuracy assessment of invasive *Phragmites* in the BCWNA were manually digitized from an image (8-cm resolution) acquired with an Unmanned Aerial Vehicle (UAV; Sensefly eBee) in late summer 2015 (Marcaccio et al. 2016). We selected a sample area of 1 × 1 km^2 within the wetland that contained large *Phragmites* patches as well as many of the most common wetland classes. We selected a 4-km stretch of arterial 2 lane road (Hwy 59) that included six spraying locations to test the usefulness of WV 3 for mapping *Phragmites* in roadsides. (Figure 1). These relatively smaller areas were chosen to increase our classification accuracy. Training data for image classification and accuracy assessment of invasive *Phragmites* in roadsides of Norfolk County were geographic coordinates corresponding to *Phragmites* stands that had been sprayed during the summer of 2017 (E. Clelland, Nature Conservancy Canada, unpub. data). We also consulted Google street View to determine accuracy of *Phragmites* being classified on these roads.

Remote sensing processing

Image pre-processing and processing was conducted with the software ENVI 5.5 (Harris Geospatial). Radiometric correction and atmospheric correction (ENVI QUAC correction) were performed for the image data to obtain surface reflectance values. Minimum Noise Fraction (MNF) transformation was performed for the pre-processed WV 3 image to reduce image dimensionality. Then Mixture-Tuned Match Filtering (MTMF) was applied to the image. MTMF is a partial un-mixing algorithm for the mixed pixels so that the relative fraction of the reflectance of the target feature can be separated out from the background. This technique produces two images that represent percent target feature abundance and a measure of feasibility without prior knowledge of the reflectance of the background features (Lass et al., 2005; Parker Williams & Hunt Jr.2004). MTMF reduces the image classification errors (especially omission errors) when detecting *Phragmites* and makes it possible to detect smaller, less dense patches. The endmembers for the MTMF classification were extracted from the reflectance image. After MTMF transformation, we classified the image using maximum likelihood classification using a separate set of ground truth data. The reflectance image was also classified with the maximum likelihood classification and was compared against the classification with MTMF transformation. For roadsides, we created a 20-m buffer around the center-line of the road to avoid having to classify complex features in the image such as built-up areas. Ground-truth data were obtained as described above. For the accuracy assessment, we used a set of randomly generated points for locations that were not used as training data for the classification.

Results & Discussion

Early detection of Phragmites in wetlands

We classified features in both the reflectance and MTMF transformed images into seven classes (Table 1). Overall accuracy of the reflectance image reached 89.75% and that of the MTMF image was slightly lower at 87.39%.

Table 1. Summary of classification accuracies for wetlands in the BCWNA. Data for *Phragmites* have been bolded for emphasis.

Class	Reflectance image		MTMF image	
	Producer's accuracy (%)	User's Accuracy (%)	Producer's accuracy (%)	User's Accuracy (%)
Cattail Organic Shallow Marsh	98.99	81.59	99.71	73.38
Meadow Marsh	72.60	97.21	62.82	100.00
Mixed Organic Shallow Marsh	91.73	54.96	89.93	56.56
Open Water	100	100.00	100.00	99.53
Phragmites	**80.21**	**99.62**	**77.32**	**95.66**
Roads	100.00	100.00	100.00	100.00
Floating Leaved Shallow Aquatic Marsh	100.00	96.68	99.47	99.21

Both overall accuracy and that for *Phragmites* alone were slightly lower for the MTMF transformed image. Manual digitization of the UAV image only captured the dense, large, and distinct *Phragmites* patches but not the smaller less dense patches that are important for early detection purposes. The MTMF transformation, however, detected smaller, less dense, presumably younger *Phragmites* patches (Figure 2 b and c). Most of the smaller *Phragmites* stands detected by the MTMF transformation occurred in areas classified as meadow marsh by the reflectance image and the manual digitization. These findings indicate that *Phragmites* is likely invading areas initially covered by meadow marsh and cattail.

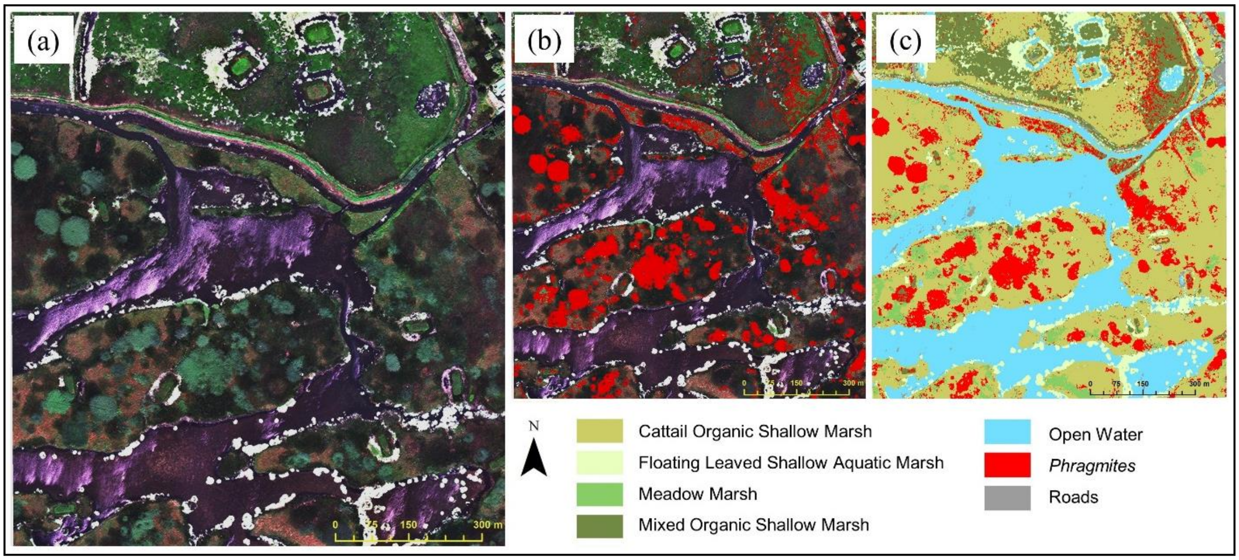

Figure 2. Different views of a segment of the WV3 image of Big Creek National Wildlife Area showing (a) the unclassified true color image in which *Phragmites* appears as distinct blue-green spherical units (b) *Phragmites* detected through MTMF image, (c) *Phragmites* classified in red in the MTMF image. The legend for classification only refers to (b) and (c).

Early detection of Phragmites in roadsides

We classified features in the image of the roadside buffer into seven classes (Table 2). Classification of the reflectance image gave an overall accuracy of 74.6% while that of the MTMF image yielded a higher accuracy of 84.4%. Highest confusion with *Phragmites* were with grasses and agricultural lands. Unlike wetlands, however, accuracy of roadsides was higher for the MTMF than for the reflectance image. Since MTMF reduces the confusion between agricultural lands and *Phragmites*, we obtained higher overall accuracy and *Phragmites* accuracy for the MTMF image than with the reflectance image (Table 2). In a preliminary study, we used a buffer size of 50 m, and obtained a much lower classification accuracy compared to the 20-m buffer we used in this study. Therefore, we recommend using the smallest buffer size possible for the road type of interest, to avoid having to classify additional features such as buildings and paved areas.

Table 2. Summary of classification accuracies for roadsides using WV 3. Data for *Phragmites* are bolded for emphasis.

Class	Reflectance image		MTMF image	
	Producer's accuracy (%)	User's Accuracy (%)	Producer's accuracy (%)	User's Accuracy (%)
Roads	100.00	100.00	100	100
Trees	100.00	57.44	97.00	79.89
Phragmites	**73.73**	**71.43**	**81.57**	**75.64**
Road side	95.45	75.00	100	95.65
Ground	96.09	96.09	99.29	88.36
Grass	73.60	82.09	71.85	85.50
Agriculture	39.89	84.03	80.87	86.82

Figure 3. (a) True color WV3 image showing region of interest that was classified (b) one road segment and 20-m buffer used in the classification (c) classified image for the MTMF image pertaining to (b). The legend only pertains to (c).

Despite the relatively high commission error, five of the six sprayed locations in the selected area had *Phragmites* detected by both the reflectance and MTMF image. Since the spray locations were centroids with no details on the length of the *Phragmites* patch that had been sprayed or which side of the road had been sprayed, we consulted Google Street View to obtain ancillary information to confirm the presence of *Phragmites*. Since the Google Street View image had been collected in August 2013, three years prior to acquisition of the WV 3 image, and four years prior to the herbicide spraying, we were not surprised to see relatively low cover of *Phragmites* on this road segment in the Google Street View. Only three of the sprayed locations in 2017 actually showed *Phragmites* in 2013. We examined all locations where *Phragmites* were eventually sprayed in 2017 and noted that they were either roadside ditches or small ponds that could easily be colonized by *Phragmites* (Figure 4). Some locations had cattail, and some had short grass species and shrubs, making them good candidates to be invaded by *Phragmites* after three growing seasons. There were, however, two sprayed locations that did not show any signs of invasion in 2013 (e.g. Figure 4 c and d). This shows that *Phragmites* can invade suitable habitats relatively quickly. Without more updated field truth, we will not be able to obtain a more valid accuracy assessment. It goes without saying that better results could have been obtained if the timing of image acquisition and field truth had been synchronized.

We were able to use an automated classification protocol in ENVI 5.5 to accurately map very small, sparsely growing patches of *Phragmites* in wetlands and roadsides in a WV 3 satellite image of Norfolk County. Timing of image acquisition and plant phenology play a major role in *Phragmites* mapping (Rupasinghe and Chow-Fraser, unpub. data). *Phragmites* produced the most unique, detectable signal that separated it from other vegetation classes (especially cattail and meadow marsh) during the peak summer period. We believe that the distinct inflorescence, the unique green color due to the high chlorophyll concentration, the leaf arrangement, and the high water-use efficiency of the plant during this period all combine to produce this unique spectral signature. We observed more confusion between *Phragmites* and agricultural lands, especially corn fields when mapping during fall or spring using pixel-based classification methods; however, object-based classification may improve the classification accuracy if fall or spring-time images are used. Several studies reported higher accuracy if images acquired in different months or from different sensors are combined to detect individual species (Hill et al. 2010; Li et al. 2014; Li et al. 2015). Use of Short-Wave IR bands may also improve the classification accuracy. One obvious limitation of WV 3 is the high cost of the images—which makes it less attractive for mapping large invasion areas. Therefore, use of WV 3 images are feasible for early-detection purposes, and other free or low-cost satellite images should be used to map large infested areas.

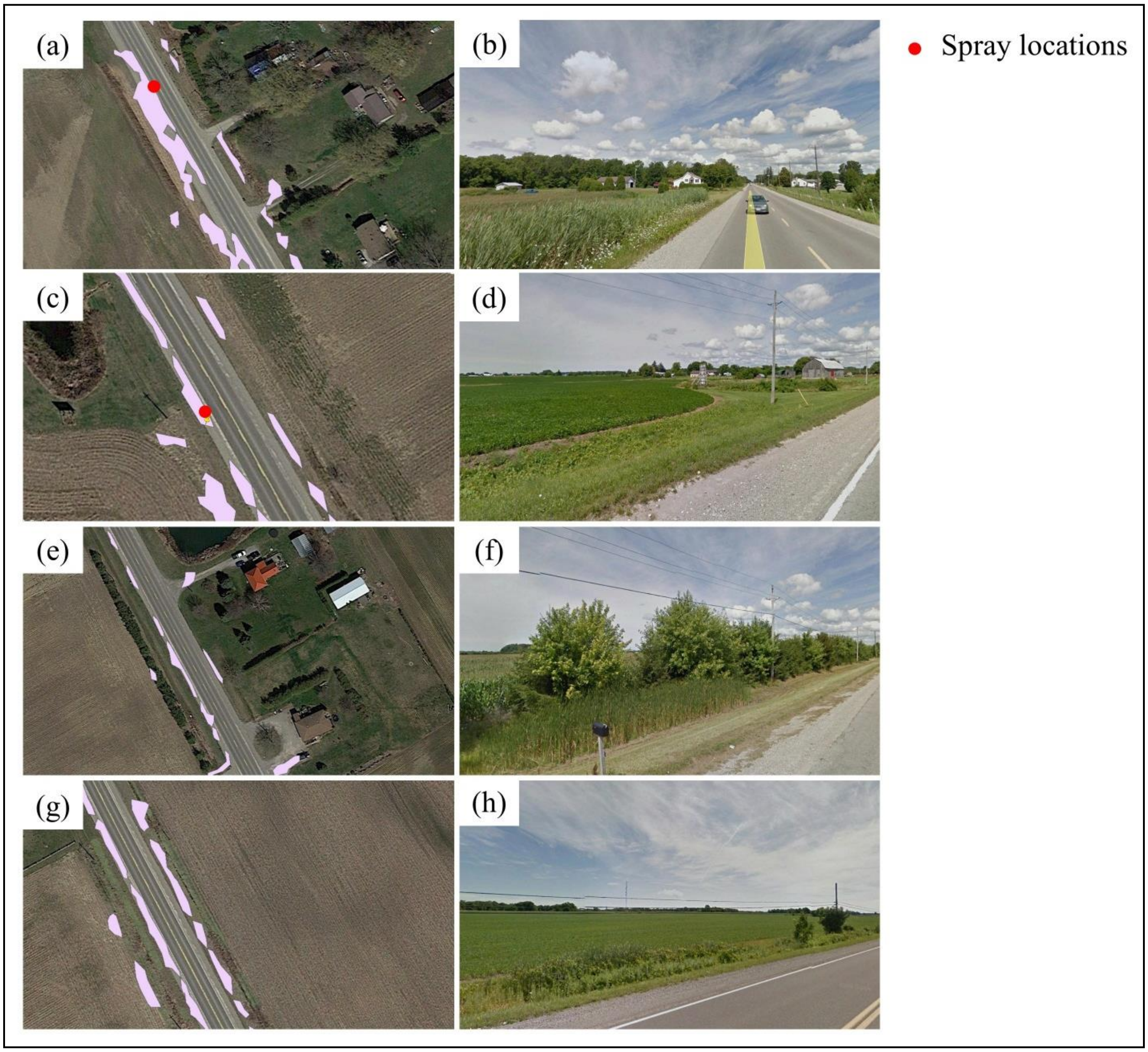

Figure 4. WV3 images of road segments acquired in July 2016 overlain with classified *Phragmites* stands (pink polygons) in the 20-m buffer (left panels) shown with corresponding Google Street View taken in August 2013 at each of these locations (right panels). The red circle indicates locations on the road where herbicide spraying had taken place during July 2017. (a) and (b): Sprayed location where *Phragmites* was confirmed in the 2013 Street View; (c) and (d): Sprayed location where *Phragmites* had not been detected in 2013 Street; (e) and (f): Location of classified *Phragmites* patches in 2016 that showed presence of *Phragmites* in the corresponding 2013 Google Street View; and (g) and (h): Location of classified *Phragmites* patches that did not show *Phragmites* in corresponding Street View, but that had suitable habitat for invasion of *Phragmites* after three seasons.

Airborne, hyperspectral images had been successfully used in species-level mapping in previous studies (Schmidt & Skidmore, 2001). The high spectral resolution of these data provides sufficient details for vegetation mapping, especially for the smaller weed and grass species. However, these data often have limited coverage and are not convenient for frequent monitoring purposes. Soft classification algorithms such as linear spectral unmixing (LSU), MTMF, and Bayesian Probability have been used successfully to detect invasive weed species with hyperspectral imagery (Williams & Hunt Jr 2004; Shafii et al. 2004; Lass et al. 2005). These algorithms separate out defined signatures (endmembers) from the background in the mixed pixels. These mixed reflectance values often produce high omission errors of the target features. Commission errors may also arise if spectrally similar classes occur in the same image. MTMF helps to distinguish smaller, less dense *Phragmites* patches from these mixed pixels and can help to reduce commission error due to occurrence of similar classes such as when corn and *Phragmites* in roadsides occur in the same pixel. Therefore, use of spectral unmixing of WV 3 is a promising method for early detection of *Phragmites* in both wetlands and roadways.

One challenge we experienced with WV 3 was the considerable time and skill required to pre-process the image initially. After determining the exact mapping protocol, however, the processing time was significantly reduced (see Table 3); nevertheless, some knowledge and expertise in remote sensing and ecology would still be required for anyone considering using our approach. Furthermore, we emphasize that ground-truth data and the images collected at the summer time where *Phragmites* stand out from the other wetland classes is essential for accurate estimation of *Phragmites* in both wetlands and roadsides.

Conclusions & Recommendations

Our study shows that the high-resolution multispectral satellite data from WV 3 could be successfully used for early detection. Sub-pixel classification is capable of detecting less dense, smaller *Phragmites* patches in both wetlands and roadsides and reduces the omission error. Moreover, this method resulted in less confusion between *Phragmites* and agricultural lands and built-up areas. Therefore, commission error is also reduced for *Phragmites* detection in roadsides.

Table 3. Overall utility of WV 3 for early detection of *Phragmites* per km^2

Parameter	Details
Cost of imagery (Panchromatic + 8 band multispectral)	$ 23 CAD with minimum area of 25 km^2 (with academic discount)
Time for preprocessing	~ 2 months initially and ~1 hour afterwards
Time for image classification	~ 1.5 month initially and ~5 hours afterwards
Image availability	Temporal resolution is 4.5 days (clear image availability depends on the weather conditions and the cloud cover)
Training data for image classification	At least 5 random locations for each class included in classification. More training locations would provide higher accuracy.
Ground truth for accuracy assessment	At least 5 random locations for each class included in classification. More training locations would provide higher accuracy.
Software	Require specific remote sensing software such as ENVI, PCI Geomatica, ERDAS IMAGINE etc. that may cost >5000 CAD

We recommend using relatively small areas for both wetlands and roadsides. Specifically, we recommend using a smaller buffer size as possible around roads (e.g. 20-m for two-lane) to avoid confusion with complex land-cover classes such as built-up areas. Furthermore, we recommend using as many ground-truth points as possible to increase accuracy. Object-based classification and use of combination of images collected in different months may also increase overall accuracy.

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