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MAPPING OPTIONS TO TRACK INVASIVE *PHRAGMITES AUSTRALIS* IN THE GREAT LAKES BASIN IN CANADA

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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.

Keywords: Remote sensing, Landsat, PALSAR, orthophotography, UAV, *Phragmites australis*, Great Lakes.

1 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. Recent literature has shown that it has rapidly colonized wetlands along the St. Lawrence River and has become firmly established in wetlands of Lakes Erie, Ontario and Huron over the past two decades (Bourgeau-Chavez et al. 2015; Saltonstall 2003; Lelong et al. 2007). 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.

2 METHODS
2.1 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.

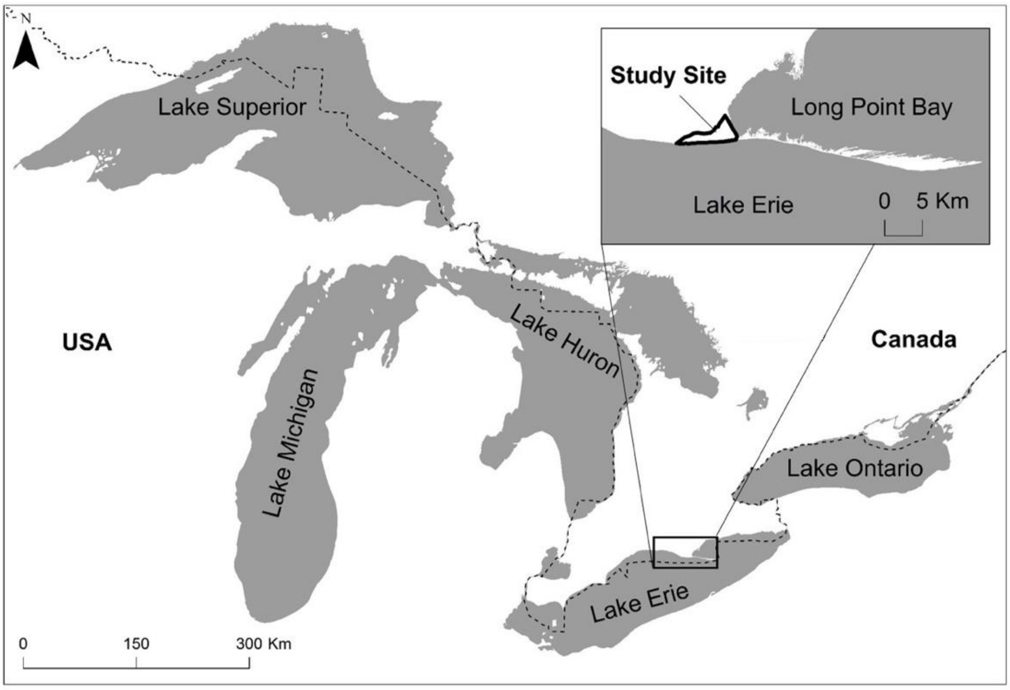

Figure 1. Research area located on the north shore of Lake Erie, Canada

2.2 Remote sensing methodologies

We will refer to the four methods in this study as the Landsat, PALSAR, SWOOP and UAV methods (Table 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 1). The last method used the 'eBee' UAV to capture image data for a subsection of the study area which was then manually classified.

2.3 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 were 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.

Table 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

2.4 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 et al. 2015).

2.5 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.

2.6 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 were 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.

2.7 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.

3 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.

3.1 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 (Fig. 2).

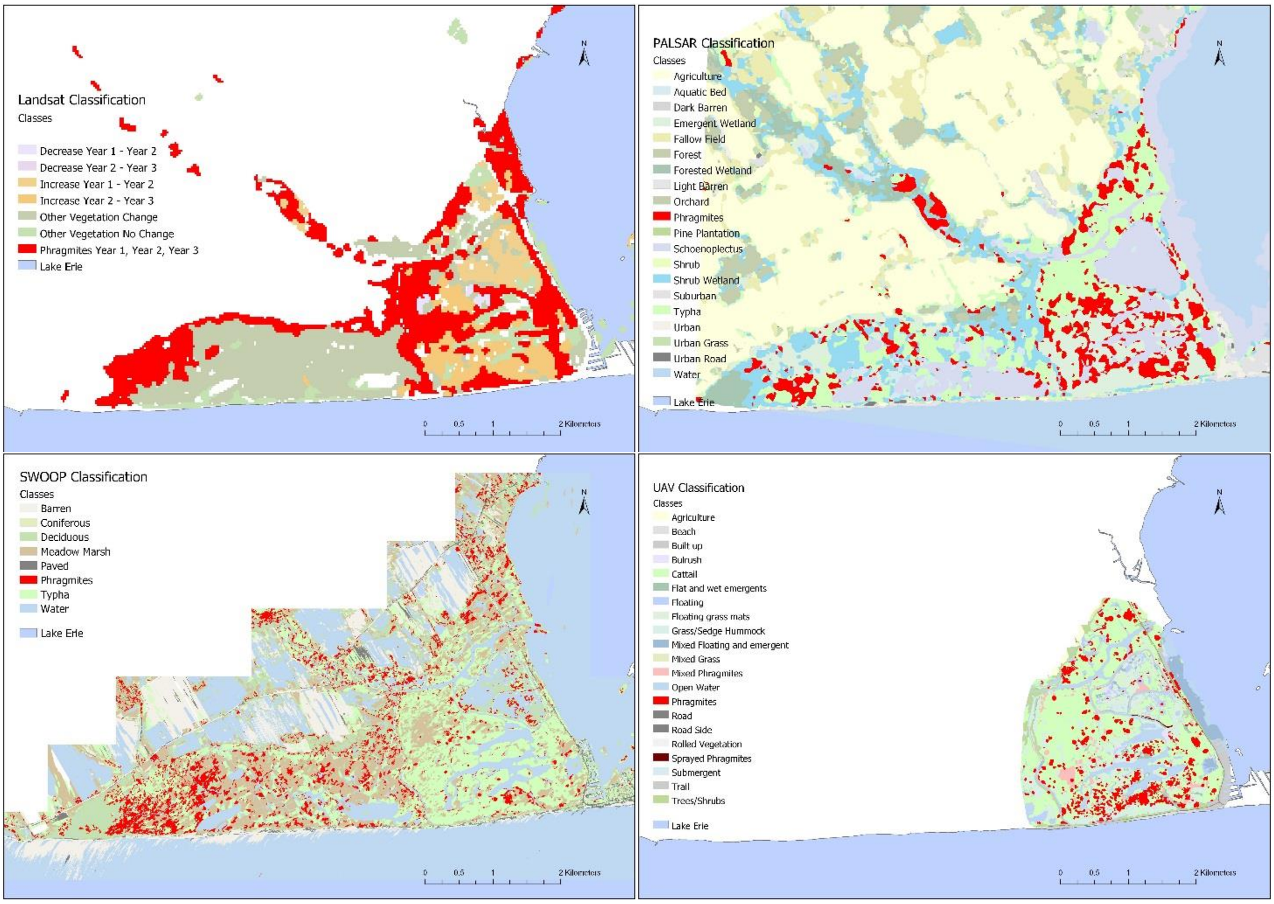

Figure 2. Remote sensing classification outputs. Invasive *Phragmites* appears in red on each map

3.2 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.

Table 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%**
Kappa Score			0.466				

3.3 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.

Table 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

4 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 of the SWOOP method 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.

5 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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