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# Mapping the invasive species *Phragmites australis* in linear wetland corridors

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**Abstract**

The detection and monitoring of invasive species at the initial stage of invasion is often critical to control/eradication efforts. In the case of *Phragmites australis*, anthropogenic linear wetlands such as roadside and agricultural ditches are believed to play a key role in invasion patterns. Accurate remote sensing of an aquatic macrophyte in such narrow habitats, however, remains a challenge. We used large-scale (1/8000) panchromatic and color aerial photographs to produce different distribution maps of *P. australis* in a network of linear wetlands. Accuracy assessments were conducted to compare the two classifications and sources of errors were identified using logistic regressions. Different thresholds of stem abundance (1%, 5%, 20%, and 40%) were used in the error matrices to determine the stem abundance at which our classification is optimized. Results show that color images are much better in enabling the detection of *P. australis*. Producer's accuracy ranges from 44% to 71% (depending on the selected threshold of stem abundance) for color images and from 16% to 28% for panchromatic images. User's accuracy ranges from 84% to 55% for color photographs and from 51% to 28% for panchromatic photographs. Generally, the mapping of vigorous populations is more accurate. The presence of *Typha* sp. is the main source of commission errors. Landscape context also affects the mapping accuracy. We discuss the relevance of our results for mapping invasion patterns in narrow linear wetlands.


*Keywords:* Common reed; Biological invasion; Linear habitat; Agricultural weed; Accuracy assessment; Road ecology

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## 1. Introduction

In the context of plant invasion, scientists and land managers need efficient methods to detect and appraise the severity and progression of infestations (Byers et al., 2002). In spite of recent promising advances in the use of remote sensing tools such as hyperspectral imagery (Underwood et al., 2003), large-scale photographs, because of their availability for time-series analysis and relative low cost, are still largely used for mapping wetland vegetation changes (Shay et al., 1999). Best classification accuracies using this type of data, however, are achieved usually by categorizing vegetation according to life-forms and not species (Valta-Hulkkonen et al., 2003). Another significant problem arises when invasive species, especially herbaceous ones, are confined to narrow linear habitats such as drainage ditches or riparian corridors. Linear habitats may act as dispersal corridors and invasion foci into the land that they intersect (Bart and Hartman, 2000), but their spatial structure makes accurate mapping of invasion patterns particularly challenging compared to natural wetlands.

This study reports on the feasibility of mapping populations of *Phragmites australis* (common reed), an emergent macrophyte, in narrow linear wetlands of Eastern Canada using aerial photographs. We define linear wetlands as linear, highly connected features of the landscape such as roadside, railroad, or agricultural drainage ditches that can support permanent or transient populations of hydrophytic plant species. Common reed has been expanding rapidly in wetlands of North-Eastern America following the introduction of a competitive non-native strain (Saltonstall, 2002). Evidence from field survey (Catling et al., 2003) and examination of herbarium records (Delisle et al., 2003) also show an extensive colonization of linear anthropogenic wetlands, especially along highways and agricultural lowlands. Although several studies have quantified common reed invasion patterns in natural wetlands using remote sensing (Havens et al., 1997; Kotschy et al., 2000; Krumscheid et al., 1989; Rice et al., 2000; Weisser and Parsons, 1981; Wilcox et al., 2003), the potential of aerial photographs to map common reed in narrow linear habitats has never been assessed to our knowledge. Errors in photo-interpretation and classification are potentially high in these habitats and must be rigorously assessed. We therefore conducted an accuracy assessment of maps obtained from large-scale aerial photographs, comparing the results for panchromatic and color photographs at the same spatial resolution. The sources of mapping errors were identified and analyzed by logistic regression.

## 2. Methods

### 2.1. Study area

We focused our investigation on periurban/agricultural landscapes with heterogeneous land-covers, and where *P. australis* is growing in a complex network of linear wetlands. The study site was chosen primarily according to the availability of large-scale aerial photographs. The selected site is situated in Saint-Bruno-de-Montarville (45°30′N, 73°19′W) on the South shore of Montréal (Que., Canada) and encompasses an area of 1162 ha. It is primarily composed of agricultural fields, residential zones, forests, old-fields, and commercial/industrial zones. Small rivers, highways, and railroads pass through it.

### 2.2. Remotely sensed data sources

Preliminary examinations of color aerial photographs have shown that images acquired in early spring (late April–early May) have the greatest potential of distinguishing *P. australis* populations. At that time of the year, the vegetation is turning green again while *P. australis* populations from the previous growing season appear beige, young shoots not being visible yet. The most recent coverage available was flown in spring 2002 in color photographs at a scale of 1:8000. To also evaluate the accuracy of panchromatic photographs, we converted the color 2002 photographs to panchromatic format.

### 2.3. Construction of the photo-map

The aerial photographs were first scanned at a resolution of 600 dpi and saved in Tagged Image File Format (TIFF). The images where then rectified with ArcGIS 9 (Environmental Systems Research Institute Inc., Redlands, CA, USA), using an average of 16 Ground Control Points (GCPs) per photograph. This procedure is necessary before the images can be used as geo-referenced photo-maps (Bolstad, 1992; De-Leeuw et al., 1988). GCPs were taken with an Alto-G12$^{TM}$ global positioning system (GPS), in Universal Tranverse Mercator (UTM, NAD 1983), which registers geographical coordinates with a sub-meter precision. In order to avoid distortions occurring at the edge of each photograph, we cropped the overlapping part of each image prior to mosaicking. We did not ortho-rectify the images because the study site is situated on a flat terrain. After the rectification and geo-referencing procedure, we imported the images in ENVI 4.0 (Research Systems Inc., Boulder, CO, USA) to mosaic them. The resulting pixels have a corresponding ground resolution of 0.33 m. We calculated the root mean square error (RMSE) resulting from the geo-referencing and rectification procedure, digitizing phase, and subjectivity of polygons boundaries as described in Green and Hartley (2000). The resulting RMSE is equivalent to 1.66 m.

Training sites were established on a small but representative portion of the mosaic in a preliminary study. An independent observer conducted the photo-interpretation of the two mosaics to minimize biases in the interpretation. The panchromatic mosaic contains less spectral information than the color mosaic and was thus classified first. *P. australis* polygons, all linear wetlands (roadsides ditches, railroad ditches, and agricultural ditches), and other potential *P. australis* habitats (wet patches and river banks) were manually digitized on-screen (Fig. 1).

### 2.4. Field sampling and accuracy assessment

We conducted an accuracy assessment of our two classifications using a stratified random sampling scheme to allocate the samples. The stratification was made using two categories of interest: *P. australis* polygons and all other habitats (linear wetlands, wet patches, and river banks). Each point was located at least 1.66 m inside the *P. australis* polygons to avoid bias associated with positional errors. Points falling in the training area

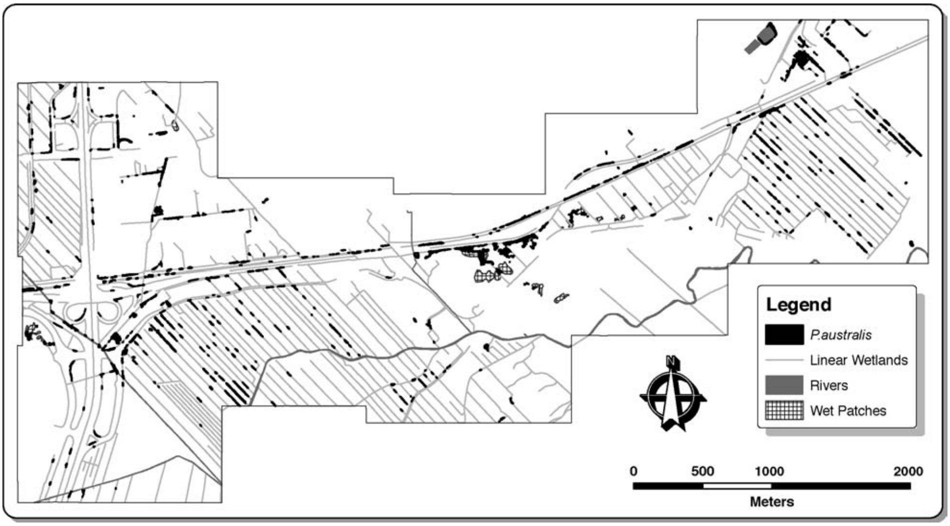


Fig. 1. Distribution map of *P. australis* populations in linear wetlands and other potential habitats (from color aerial photographs) of Saint-Bruno-de-Montarville, Que., Canada (45°30′N, 73°19′W).

were disregarded. A total of 347 points were sampled (*P. australis* = 237, potential habitats = 110) for the color mosaic and 297 points (*P. australis* = 181, potential habitats = 116) for the panchromatic mosaic. This discrepancy occurs because the interpretation of the color mosaic resulted in more *P. australis* polygons being digitized. Field sampling was performed in mid-July 2004, before full bloom. We located the sampling points with a MobileMapper$^{TM}$ GPS (1 m accuracy) and a circular plot (radius = 1 m) was used as the sampling unit. In order to characterize the digitized *P. australis* polygons, we measured the height, stem abundance (%cover), and inflorescence abundance of *P. australis* (%cover), as well as abundance of other plant species using semi-quantitative cover classes.

We constructed several error matrices to compare our classifications with information obtained by ground-truthing. Those matrices were used to compute overall accuracies, producer's accuracies, and user's accuracies. Overall accuracy is the sum of the correctly classified samples divided by the total of samples and is a measure of agreement. For a specific category, producer's accuracy is a measure of omission error (population present in the field at the time of sampling but omitted on the map), whereas user's accuracy is a measure of commission error (population identified as *P. australis* on the map but not present in the field at the time of sampling). *P. australis* has been reported to grow as much as 2.6 m per growing season in linear wetlands of Southern Québec (C. Lavoie, unpublished data). For that reason and to acknowledge the existence of a two year lag between photo-acquisition and field sampling, we used different stem abundance thresholds (1%, 5%, 20%, and 40%) in the accuracy assessment for a population to be recorded as present in the field. For instance, in the case of a 5% threshold, only sampling units that had $\geq$5% stem cover and that had been classified as *P. australis* population during photo-interpretation were considered as correctly classified on our map. Using these thresholds allows us to identify the stem cover abundance at which our classification accuracy is optimized. However, the way those thresholds are defined will also affect producer's and user's accuracies. Proportional allocation was not used in the design of our sampling scheme which resulted in unequal inclusion probabilities. In the perspective of finite population sampling, we corrected the estimates of the different parameters using the equations given in Stehman (1995) and Stehman and Czaplewski (1998). Confidence intervals were derived from the formulas in Singh and Mangat (1996) for overall accuracy. Stehman (1995) advocates the use of the Taylor linearization technique to calculate confidence intervals for the producer's and user's accuracy. Nevertheless, this method is cumbersome to implement because of the theoretical calculation needed to program the derivatives (Sitter, 1992). The bootstrap percentile method (Efron, 1979) is known to give equivalent results as the Taylor linearization technique and is thus preferred (Li and Maddala, 1999). The confidence intervals were estimated using MatLab 7.0 (MathWorks Inc., Natick, MA, USA) with 4000 bootstrap replications.

### *2.5. Data analysis*

We used logistic regression to identify which variables could best predict omission errors and commission errors. Two logistic regressions (one modeling omission errors and the other modeling commission errors) were performed for each data set. We decided to analyze separately the two types of errors because some variables measured on the reed population, such as stem abundance, could not be included in the analysis of commission errors. Logistic regression was used to test the occurrence of an omission error with respect to the following variables: stem abundance and the presence of other dominant plant species. Only plant species with a relative cover of more than 5% were included: *Lythrum salicaria*, *Typha* sp., *Salix* sp., *Fraxinus* sp., and *Solidago* sp. We also included one contextual variable with four classes to characterize the landscape position of sampling points. They were: right-of-way (highway, roads, and railroad), agricultural fields, urbanized areas (residential, commercial, and industrial zones), and old-fields. Theses classes are related to the habitat structure and management practices that can both influence the detection of *P. australis*. To facilitate interpretation of the results, we recoded the classes of the contextual variable that were found significant in preliminary analysis as binary variables and excluded the non-significant ones. The height and the inflorescence abundance of a population were not included because they were exhibiting strong collinearity with the stem abundance.

To test the occurrence of a commission error, we used the same variables as for the occurrence of omission errors excluding the stem abundance variable because it is always equal to 0 in the case of a commission error. To select the best model among alternative ones, we compared the Akaike Information Criterion (AIC) (Akaike, 1973) and the Schwarz Criterion (SC) (Schwarz, 1978) for the full model, and the ones resulting from forward selection, backward selection, and stepwise selection. The forward selection procedure consistently produces the smallest AIC and SC for the four analyses. Following the principle of parsimony, we excluded from the models selected by the forward procedure any variable that had marginal influence. Logistic regressions were performed using SAS 9.1 (SAS Institute Inc., Cary, NC, USA). Our four analyses exhibited a separation of data points; consequently, the maximum likelihood estimates may not exist and are not reliable

(Albert and Anderson, 1984; Santner and Duffy, 1986). To circumvent that particularity, we used exact conditional logistic regressions to obtain the true estimates (Cox, 1970). The Wald statistic was used to test the significance of the regression criterion. Note that for exact conditional logistic regression, this statistic is conditional on the other parameters of the model, including the intercept.

For our error models, we used a lower threshold stem abundance of 5% measured in the field to record *P. australis* as present. This takes into account the time lag between photo-acquisition and field sampling and can be considered conservative.

## 3. Results

### 3.1. Accuracy assessment: panchromatic images

Overall accuracy ranged from 71% (1% stem abundance) to 87% (40% stem abundance) but no statistically significant differences ($\alpha = 0.05$) were found across the range of stem abundances for overall accuracy (Fig. 2). Omission and commission errors are fairly high. For producer's accuracy, we report accuracy ranging from 16% (1% stem abundance) to 28% (40% stem abundance). A non-significant trend is observed between the producer's accuracy and the stem abundance threshold. User's accuracy ranges from 51% (1% stem abundance) to 28% (40% stem abundance). The trend suggesting that user's accuracy decreases as the stem abundance increases is here significant. This decrease is mostly due to the fact that 72% of *P. australis* polygons on the map have a stem abundance in the field below the maximum threshold (40%). Thus, they were considered misclassified at this particular threshold, even when common reed was present.

### 3.2. Accuracy assessment: color images

Overall accuracy ranged from 77% (1% stem abundance) to 88% (40% stem abundance) but those differences are not statistically significant (Fig. 2). Moreover, when

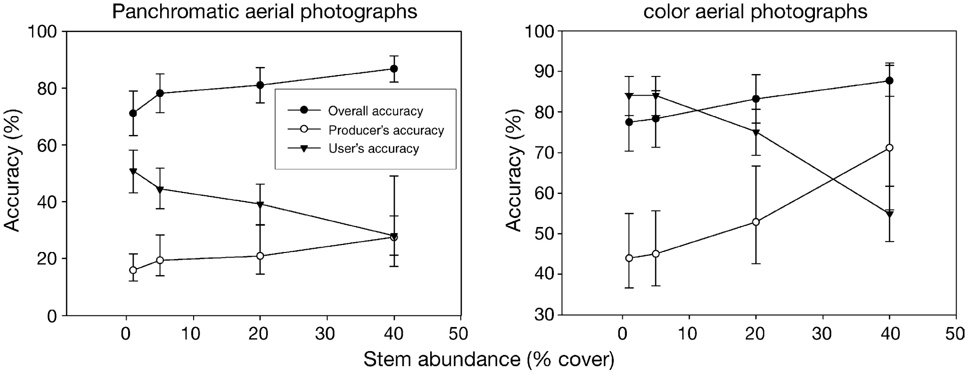


Fig. 2. Accuracy assessment results for the panchromatic and color images at different thresholds of stem abundance.

comparing the overall accuracy, for each stem abundance thresholds, between the panchromatic images and the color images, no significant differences are found. Producer's accuracies range from 44% (1% stem abundance) to 71% (40% stem abundance). Significant differences between the stem abundance thresholds are only found between the 40% threshold and the 1% and 5% thresholds, but not with the 20% threshold. User's accuracy scores range from 84% (1% stem abundance) to 55% (40% stem abundance) and only the 40% threshold is statistically different from the other thresholds. Significant differences are found between the classification based on the panchromatic images and the classification based on the color images for both the producer's and user's accuracies at each density thresholds.

### 3.3. Logistic regression

#### 3.3.1. Panchromatic images: omission errors

The forward procedure of the logistic regression produced a non-significant model with three variables included (stem abundance, *Solidago* sp., and the contextual variable). Only the stem abundance variable was found significant and we therefore excluded the other variables from the model. The result of the exact conditional logistic regression has shown that the stem abundance has marginal influence (score $X^2 = 3.51$, $p = 0.0607$) on the detection of *P. australis*. The fitted model is:

$$\text{OMISSION ERRORS} = \text{INTERCEPT} - 1.91 \times (\text{STEM ABUNDANCE})$$

According to the logistic regression model, the probability ($p = \log(\text{CCP}/(1 - \text{CCP}))$) of committing an omission error decreases as stem abundance increases. Confidence intervals for the odds/ratio parameter are 0.92–60.48 (95% C.I.) which indicates that the positive effect of this variable on the detection of a population is not significant even though this effect is likely to occur. This model predicts accurately 53.2% of all samples.

#### 3.3.2. Panchromatic images: commission errors

No samples being located in old-fields, the contextual variable has only three classes in this analysis. One variable (*Fraxinus* sp.) originally retained by the forward selection procedure was omitted since it had only marginal influence and was not significant. The final model is composed of the following variables: *Typha* sp. (score $X^2 = 17.29$, $p \leq 0.0001$), agricultural fields (score $X^2 = 14.23$, $p = 0.0002$), *L. salicaria* (score $X^2 = 8.16$, $p = 0.0043$), and *Solidago* sp. (score $X^2 = 6.97$, $p = 0.0083$). The fitted model is:

$$\begin{aligned}&\text{COMMISSION ERRORS}\\&\quad = \text{INTERCEPT} + 9.57 \times (\text{TYPHA SP.}) + 2.41\\&\qquad \times (\text{AGRICULTURAL FIELDS}) + 11.65 \times (\text{LYTHRUM SALICARIA})\\&\qquad + 10.64 \times (\text{SOLIDAGO SP.})\end{aligned}$$

The probability of doing a commission error thus increases with the presence of other macrophytes (mainly *Typha* sp., but also *L. salicaria* and *Solidago* sp.) and when the sample is situated in an agricultural field. This model accurately predicts 91.3% of the samples. (No separation of data points occurred with this model.)

#### 3.3.3. Color images: omission errors

The model retained is composed of two variables: stem abundance (score $X^2 = 35.41$, $p \leq 0.0001$) and old-field (score $X^2 = 18.41$, $p \leq 0.0005$). A preliminary forward procedure included stem abundance, contextual, and *Solidago* sp. but the last variable was disregarded because it was not significant. The significant class of the categorical variable is the one indicating that the sample is located in an old-field.

$$\text{OMISSION ERRORS} = \text{INTERCEPT} - 5.34 \times (\text{STEM ABUNDANCE}) + 3.50 \times (\text{OLD-FIELD})$$

The probability of an omission error decreases with stem abundance and increases when the reed population is situated in an old-field. This model predicts accurately 80.3% of the samples. Note that only 20 omissions errors were recorded for a total of 180 samples for this analysis.

#### 3.3.4. Color images: commission errors

The variables retained by the forward selection procedure are: *Typha* sp. (score $X^2 = 75.51$, $p \leq 0.0001$) and *Fraxinus* sp. (score $X^2 = 21.03$, $p = 0.0052$). The model goes as follows:

$$\text{COMMISSION ERRORS} = \text{INTERCEPT} + 5.99 \times (\text{TYPHA SP.}) + 5.36 \times (\text{FRAXINUS SP.})$$

The probability of committing a commission error increases with the abundance of both *Typha* sp. and *Fraxinus* sp. The Wald statistic informs us that the effect of *Typha* sp. is considerably more important than the effect of *Fraxinus* sp. This model accurately predicts 67.3% of our samples.

## 4. Discussion

Color photographs are far superior in enabling the detection of *P. australis* populations, as indicated by the producer's and user's accuracy of this category compared to the panchromatic images. The spectral resolution is therefore a determinant factor in enabling the photo-interpreter to distinguish the populations. Given the thresholds used, our classification is optimized for populations having a stem abundance threshold varying from 20% to 40% on color photographs. This is the threshold at which the best compromise between omission and commission errors is achieved. The large scale (1/8000) of the color photographs is therefore adequate to obtain accurate maps of the distribution of *P. australis* in these linear habitats and provides a reference scale for other studies in similar conditions, especially when other remote sensing approaches such as hyperspectral imagery or airborne videography are not an option. Panchromatic photographs at the same scale

(1/8000) do not have a sufficient spatial resolution to obtain a reliable map, but the lack of spectral resolution could potentially be compensated by using larger scale panchromatic photographs.

A number of factors affect the mapping accuracy of *P. australis* in linear wetlands. On color images, less vigorous populations are the ones that are more often omitted. For panchromatic images, the trend relating vigor and correct classification is only marginally significant. The classification on this data set being inaccurate, errors might be distributed randomly or other factors such as illumination or contrast could be more meaningful in explaining the patterns observed. Regarding landscape context, populations thriving in old-fields are generally omitted compared to other types of habitats when using color images. This could be explained by the lack of contrast between *P. australis* and the dead plants left in these habitats which are not managed. As well, *P. australis* tends to be overestimated in agricultural ditches compared to other habitats when panchromatic images are photo-interpreted, possibly because of the combined effect of poor spectral resolution and the fact that the ditches are narrower in agricultural fields. Because of similar spectral signatures, *P. australis* can be confounded with *Typha* sp. on both panchromatic and color photographs, leading to commission errors. It may be possible to discriminate between the two macrophytes particularly in the case of adjacent populations, using training samples of *Typha* sp., but this remains to be assessed. On color photographs, stems of *Fraxinus* sp., when present at the shrub stage, seem to provide a spectral signature similar to that of *P. australis*, whereas on panchromatic images, other herbaceous species such as *Solidago* sp. and *L. salicaria* also lead to an overestimation of *P. australis*.

Like many suburban areas in North America, our study site is a very dynamic landscape and is constantly threatened by increased urbanization. As much as 12.7% of all points visited were not included in the analysis because of new residential constructions, road or railroad work, etc. Adding to this effect are the management practices to control *P. australis* by land-owners. *P. australis* is cut, sprayed with herbicide, and burned to limit its expansion (personal observation). Those practices result in less vigorous stands or possibly in stands that have disappeared altogether, resulting in an underestimation of the classification accuracy.

Since the exotic strain of *P. australis* shows aggressive behavior, it is especially important to be able to recognize early stages of invasion when control measures may be more efficient. We are currently estimating the rate of progression in linear habitats and historical photographs are often panchromatic ones (Maheu-Giroux and de Blois, in preparation). Compared to panchromatic images, color aerial photographs at the scale used in this study or at larger scale should provide adequate maps of *P. australis* populations in linear wetlands, even at relatively low stem abundance. For these images, accuracy level compares with those considered generally acceptable for remote sensing data. Because color photographs tend to be more recent, photo-interpreting first recent color photographs when available and then older panchromatic ones, when analyzing temporal pattern, could help diminish mapping errors. In any case, because of the potential significant errors associated with mapping macrophytes in linear habitats, we recommend using a methodology similar to ours to provide a measure of map accuracy whenever possible.

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