Monitoring the invasion of *Phragmites australis* in coastal marshes of Louisiana, USA, using multi-source remote sensing data.

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ABSTRACT

Phragmites australis a native marshland species to the North American Atlantic Coast is presently expanding to new habitats at very high rates. To understand the causes and consequences of this invasion, monitoring programs, especially at the Gulf Coast, need to be established. The first step to this is to obtain a method for accurate mapping *Phragmites* distribution. In this study an object oriented classification approach that combines lidar and multispectral imagery is proposed. After segmentation of a dataset of three multispectral bands plus a lidar based digital surface model, two classification methods were explored: a class assignment (CA) and a nearest neighbor classification (NNC). CA requires more involvement and knowledge form the analyst, but the decisions to be made are better understood than in the NNC. Both methods performed similarly, and were able to map most of the *Phragmites* present in the study area. Results show that the use of multi-source data not only can produce accurate distribution maps for future monitoring, but also guide on present day surveys and even help in the interpretation of old data to map past conditions.

Keywords: lidar, multispectral data, object oriented classification, segmentation, coastal marshlands, *Phragmites* invasion

1. INTRODUCTION

Although the wetland grass *Phragmites australis* (common reed) is a native species to North America, it was historically restricted to few areas of the marshes. In the past century, however, it has dramatically expanded along the Atlantic Coast [1]. The rapid spread of *P. australis* has been attributed to a Eurasian genotype that likely arrived in the U.S. in the late 1800s. The invasion of this species is known to have a substantial impact on marsh ecosystem structure and function by affecting nutrient cycles and hydrological regimes, displacing native plant species, and reducing the quality of wetland habitat for migratory waterfowl and wading bird species, and a variety of other species.

Some *P. australis* monitoring programs are well established for along the Atlantic Coast, however this problem has received relatively little attention in the Gulf Coast, and efforts to understand the phenomenon in this region are almost non-existent. Mapping the distribution and monitoring the spatial spread of *P. australis* is a necessary step towards the understanding of the characteristics of the invasion and to determine its causes and consequences.

Multispectral data, such as aerial photography, has been, and continues to be, of great assistance to environmental monitoring, given its widespread accessibility. However, they are of limited use when it is necessary to distinguish between vegetation species with slight spectral differences, especially for species with highly variable appearance in space and/or season. Relatively more recently available instruments such as lidar (light detection and ranging) can provide an additional source of valuable information. Lidar incorporates elevation information at high spatial resolution, which can help in discriminating vegetation types and species. Moreover, it is able to reveal detailed structural properties of canopies, which can be used to study growth patterns [2] or measure plant volume to estimate biomass [3].

Lidar in combination with multispectral data has been already used in urban environments and land use mapping [4,5,6,7], and to study forest properties [8,9,10]. The relatively simple vertical structure of marshlands and the ability of *Phragmites* to produce extraordinarily tall stems constitute an ideal situation to map the distribution of this grass using multispectral and lidar data combined. In this study, two object oriented classification approaches using both sources of data are explored as tools to map *Phragmites*.

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2. METHODS

2.1 Study area

The study area is located at the Rockefeller Wildlife Refuge, Lousiana, U.S.A. (Fig. 1), a protected marsh at the coast of the Gulf of Mexico. It has an area of approximately 90 km^2, centered on 29°41'40" N and 92°48'30" W. Most of the study area is occupied by brackish marsh and, to the south, partially by salt marsh, at both of which *Phragmite australis* has become increasingly prevalent. Due to restrictions in computational processing time and speed, most of the analyses presented here were carried out on a sub-area of approximately 18 km^2.

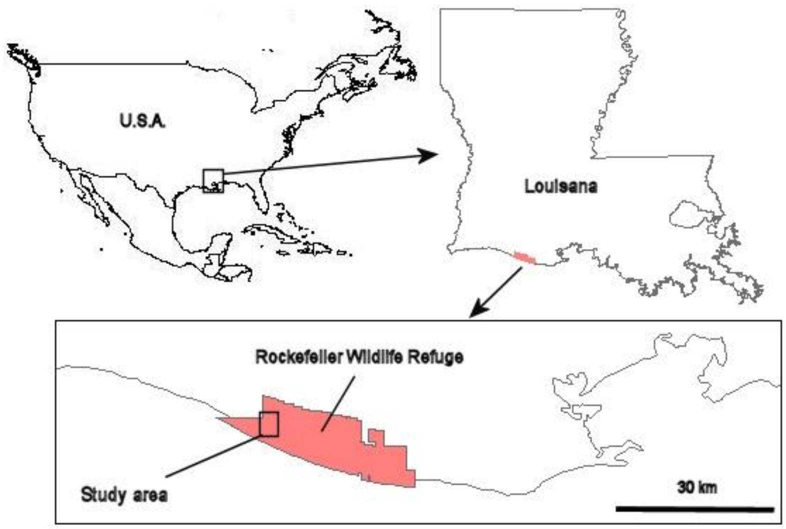

Fig 1. Study area

2.2 Data characteristics and processing

The main source of multispectral data was a digital orthophoto quadrangle (DOQQ) from 2005, available at the Louisiana Statewide GIS Atlas (http://atlas.lsu.edu/), at a spatial resolution of approximately 1m on the ground, which has been georeferenced to the UTM system (Zone 15, NAD 1983). Lidar data was also obtained from the same source in the form of raw, xyz points, obtained in March 2003, with a point density of approximately 1 point/6.11 m^2. Additional DOQQs and aerial photographs from previous years were used to explore past conditions of Phragmites growth and distribution.

Based on previous studies and after trying several possible resolutions, lidar point data were interpolated to a 2m pixel resolution raster to produce a digital surface model (DSM). An Inverse Distance Weighted approach was used, with a maximum of 3 points at each interpolated grid cell to preserve local variability (Rosso et al. 2006). To maximize the spatial matching between the DSM and the DOQQ, a rubbersheeting resampling procedure was applied to the DSM, based on sampling points extracted from the DOQQ.

2.3 Analyses

2.3.1 Marsh topography

One of the most important features to be used in the analyses was the difference in tallness between *Phragmites* and the other plant species. It was expected that actual plant height could not be calculated because most canopies in the study area would not let lidar reach the ground [2] in order to generate a digital terrain model (DTM) to be subtracted from the

DSM. Therefore, a relevant question was whether the absolute elevation of the DSM could be directly used for that purpose. That is, whether the ground elevation across the study site was uniform enough for the absolute elevation to be used. Otherwise, a short plant species on higher terrain could have the same elevation average than a tall canopy on low terrain. The lidar point database was systematically sampled at different vegetation types and other landscape features to obtain the corresponding elevation values. Descriptive statistics and plots were used to detect possible elevation patterns or slopes across the study area.

2.3.2 Segmentation and classification

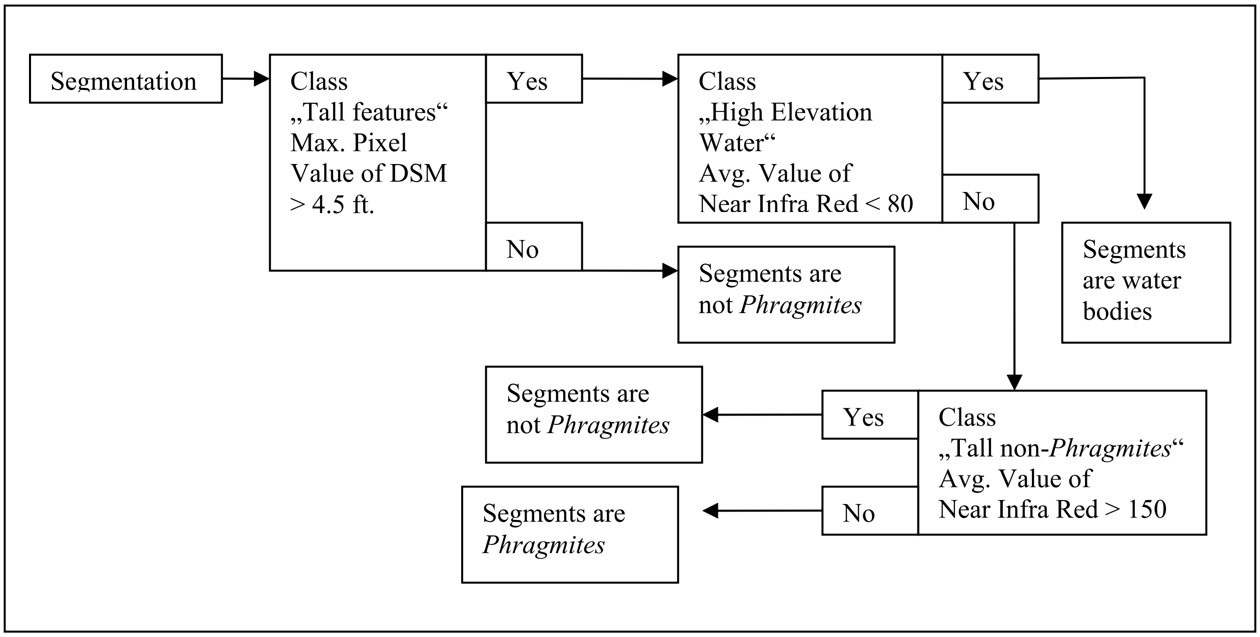

Fig.2. Assign class (AC) process.

A segmentation-classification approach was carried out to map *Phragmites* combining the multispectral and lidar data using Definiens Developer 7 (Definiens AG, München, Germany). A combination of four layers (DOQQ's near infrared, NIR, red and green; and the DSM), all with equal weight, was used. The algorithm selected for segmentation was Multiresolution Segmentation. Required parameters were set to: Shape=0.1 and Compactness=0.5. A series of different Scale parameter values, ranging from 10 to 100, were applied to find the most adequate segmentation scale. For example, a value of 10 resulted in extremely small segments and at 100, segments were too large to separate key terrain features. Finally, a scale of 50 was chosen.

Two alternative approaches were used and compared for the classification of segments.

1) a Class Assignment (CA) method, which requires more input from the analyst and knowledge of the system, based on the assumption that the main terrain features can be discriminated in a stepwise manner using their intrinsic properties.

2) a Nearest Neighbor Classification (NNC) method, in which the classification is guided by a selective sampling of segments of known identity, but with no need of any other previous knowledge.

For the CA, after segments enclosing different features were carefully analyzed and compared, some variables and their threshold values were selected to dichotomously separate the segments in the study area. The variables chosen were: Maximum pixel value of the DSM and average value of NIR (Fig. 2). To this end, the Assign Class algorithm was used, which was applied hierarchically until *Phragmites* was successfully identified.

For the NNC, three classes were created: *Phragmites*, non-*Phragmites* and water. The criterion to choose these classes was based on the assumption that the analyzer has relatively little knowledge of the actual number of species present in the area, and that the number of classes to be used can be simply visually determined, according to the variability observed in the data. Ten segments of each class were selected based on appearance, and used to inform the Nearest Neighbor classification algorithm.

Results of both methods were exported to raster formats to assess their accuracy and to be compared with the available information.

2.3.3 Accuracy assessment

A ground survey of 80 points with samples of the location of *Phragmites*, water, and other three dominant plant species was used to assess the accuracy of the classification methods.

3. RESULTS AND DISCUSSION

3.1 Analyses

An analysis of the lidar points and the lidar generated DSM, permitted to conclude that baseline differences in elevation across the study area were not substantially large, indicating that the coastal marsh in this region is basically flat. To show this, a linear sample of the DSM running south-north is shown in Fig. 3. There it can be observed that portions of the transect that correspond to ground or very short vegetation have very similar elevation values (all around 1 ft.). Moreover, the profile does not show evidences of elevation gradients or trends.

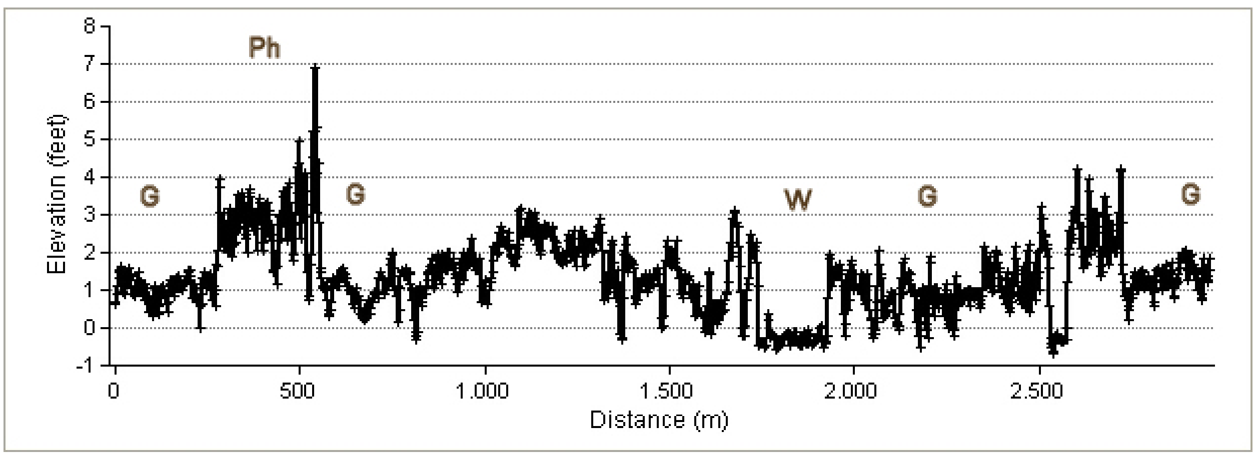

Fig 3. Profile of the lidar DSM along a south-north transect stretching across the entire study area. G: ground or very short vegetation; Ph: *Phragmites patch*; and W: water body.

Both, the CA and the NNC provided satisfactory results when compared to the ground survey. Out of a total of 80 points CA had one (1.25%) omission and one (1.25%) commission errors. The NNC had 5 (6.25%) omission and no (0%) commission errors.

The CA omission error was on a very small *Phragmites* patch surrounded by water, which due to scale issues was too small to be exclusively considered in a segment, and as a result, the segment also included portions of water. However, this patch was considerably smaller (~15 m in its maximum length) than any other isolated patch, and thus, was the only case in the entire image. The commission error consisted of identifying a levee as a *Phragmites* patch. This has to do with the difficulty this approach had to separate tall *Phragmites* from high elevation human made structures that had a relatively low NIR reflectance (Fig. 2, last step). Even though levees and roads tend to have high NIR reflectance, these structures are usually relatively narrow, and thus they can easily be included in segments together with surrounding vegetation.

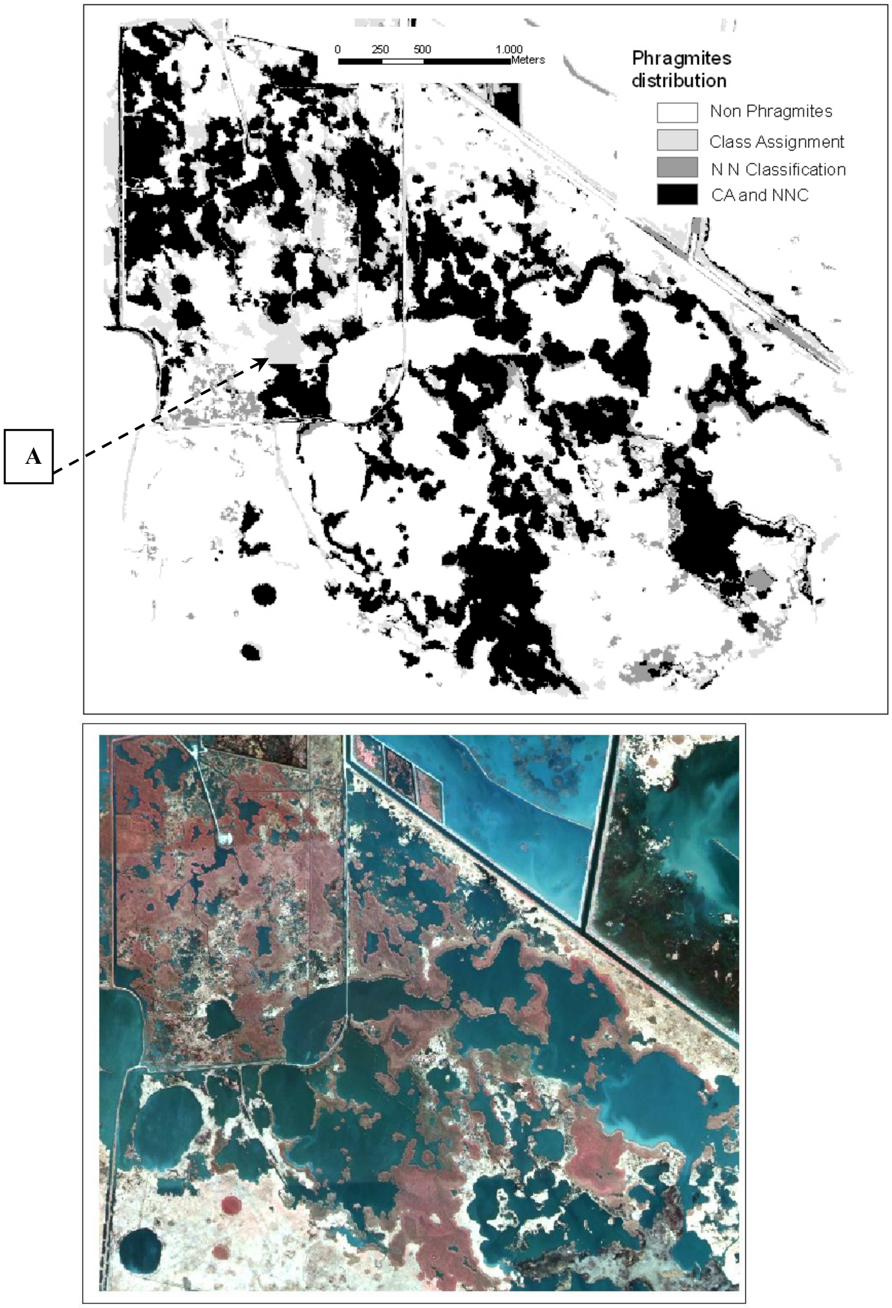

Fig 4. Map of Phragmites distribution produced by the CA and NNC methods, and aerial photograph of the study area. A: See text for explanation.

The causes of NNC omission errors are more difficult to establish due to the uncontrolled characteristics of the approach itself. It is evident however, that the NNC did not consider some patches to be similar enough to other *Phragmites* segments when comparing the mean values of all layers in segments as a whole. In contrast, the CA does not take all layers into account, and when the threshold is clear enough there is no possibility of confusion.

As it is often the case, the ground survey provided a very accurate source of terrain feature identification, but it was not sufficient in terms of area coverage, in order to extensively assess the performance of the classification approaches. For this reason, we carried out an extensive qualitative assessment of the results based mostly on visual clues and analyst expertise. Both methods coincided in assigning most of the study area to *Phragmites* distribution (Fig. 4). Discrepancies between the CA and the NNC were restricted to relatively small areas.

On the NW section of the study area there was a region where the NNC failed to identify *Phragmites* (Fig. 4, letter A) where it is evident that the species is present. The straight, horizontal line that can be seen in that area corresponds to an artificial channeling with an abrupt drop in elevation of about 60 cm between both sides. The resulting contrast in average elevation values of segments at either side of the channel was enough to be interpreted by the NNC method as belonging to two different cover types. The sensitivity of the NNC to slight differences in reflectance can also be exemplified in other areas. NNC also failed to identify other - most likely -*Phragmites* patches (Fig. 5, A), which seemed to have been correctly classified by the CA (Fig. 5, light gray color). These patches, as can be seen in the aerial image, have noticeable higher values of NIR reflectance.

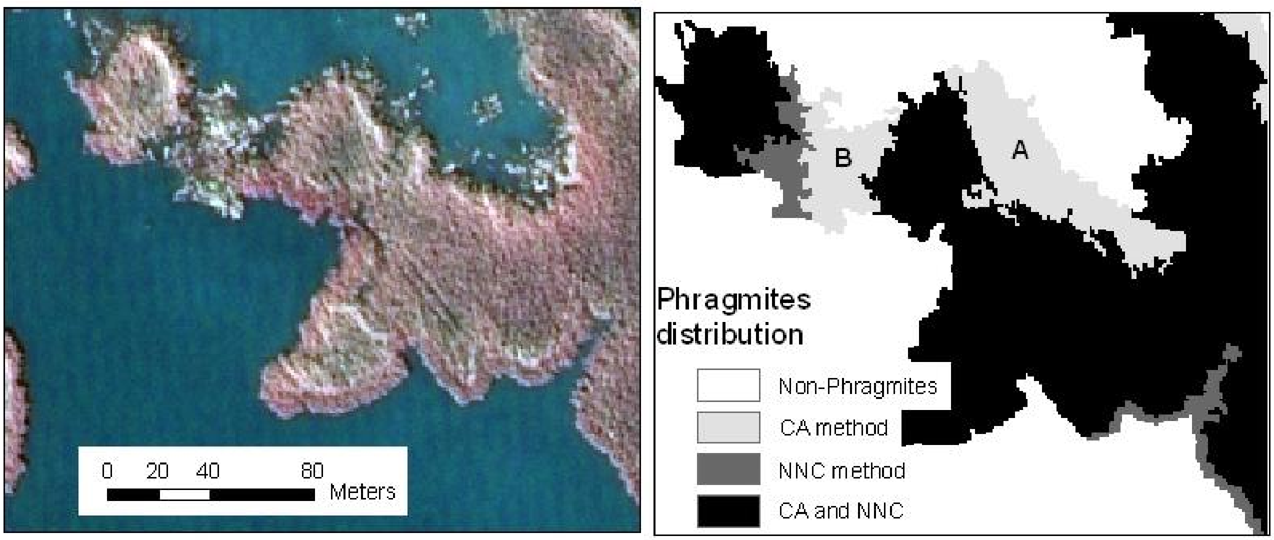

Fig 5. Map of Phragmites distribution produced by the CA and NNC methods, and aerial photograph of the area. A and B: See text for explanation.

Other patches (Fig. 5, B), which seem to be partially covered by *Phragmites* and partially by something else, appeared as *Phragmites* in the CA and as non-*Phragmites* in the NNC. Some segments classified as *Phragmites* by the NNC and as non-*Phragmites* by tha CA (Fig. 5, dark gray areas) appear dominated by water and have few pixels with higher reflectance, which in average might have had resulted similar to a typical *Phragmites* patch for the NNC approach.

Segments corresponding to small water bodies that had an average NIR value higher than 80 were erroneously classified as *Phragmites* by the CA method (Fig. 6, center of the image). Fig. 6, as commented above, shows more examples of coastline water classified as *Phragmites* by the NNC approach.

One of the advantages of the NNC is that it is a fuzzy classification, in which segments are not univocally assigned to a certain class but only to a degree. This aspect could be further explored as a way to refine the final classification.

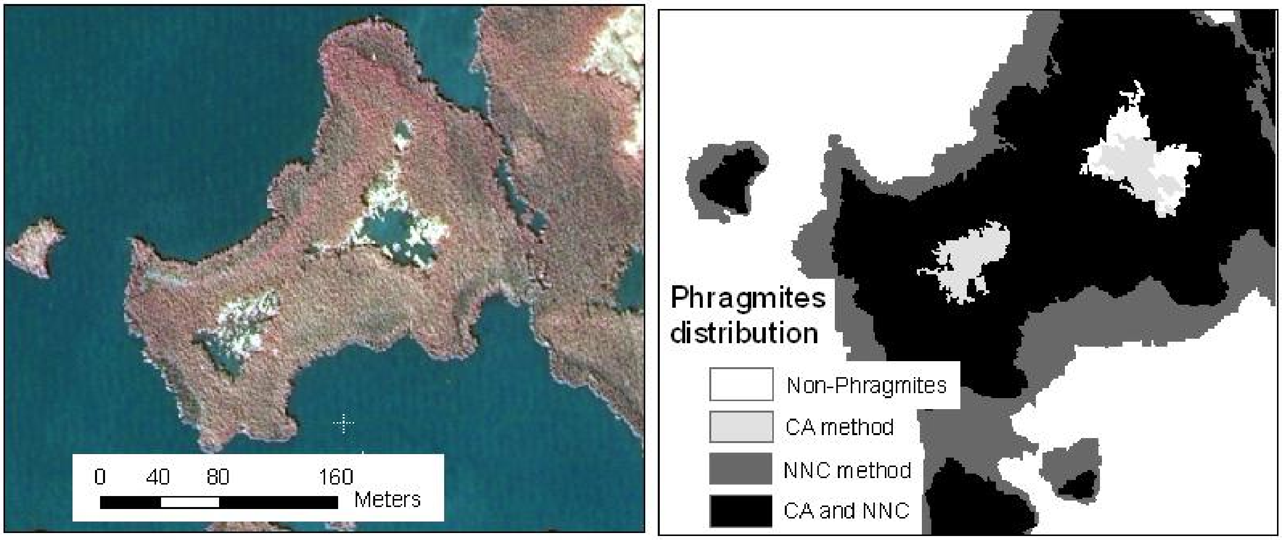

Fig 6. Map of Phragmites distribution produced by the CA and NNC methods, and aerial photograph of the area.

3.2 Monitoring

The combination of lidar and multispectral information has a great potential for future monitoring of *Phragmites* invasion. This approach as such, obviously cannot be applied to the past. However, a better understanding of the structure of the present day *Phragmites* distribution can certainly provide clues to understand the past distribution. For example, when examining a 1995 multispectral image, it was very difficult to determine where *Phragmites* was present and where not. Besides the obvious problems related to image quality and interpretation, coastal marshes are typically subject to varying conditions of water levels due to changes in tide, which hinters its analysis.

A sample of an elevation profile taken on a *Phragmites* patch (Fig. 7) shows that if this species was present in 1995 at a similar extent to what it was present in 2005, even at a high tide levels the plants would not be covered by water. This means that the presence of water in 1995 would not hinter the visual identification of *Phragmites*. Therefore, it is clear that most of the area that was covered by *Phragmites* in 2005 had, at the most, very little *Phragmites* in 1995. A careful inspection of the 1995 image, and based on experience from other photos, some of the patches present at the moment could be individualized (Fig. 7, lower right, arrows). A rough estimate of the average distance between the edges of separate patches, suggests that these patches would have needed to grow in the order of 30m in radius before coalescing, which could have occurred even before 2005. This suggests a very high rate of horizontal expansion.

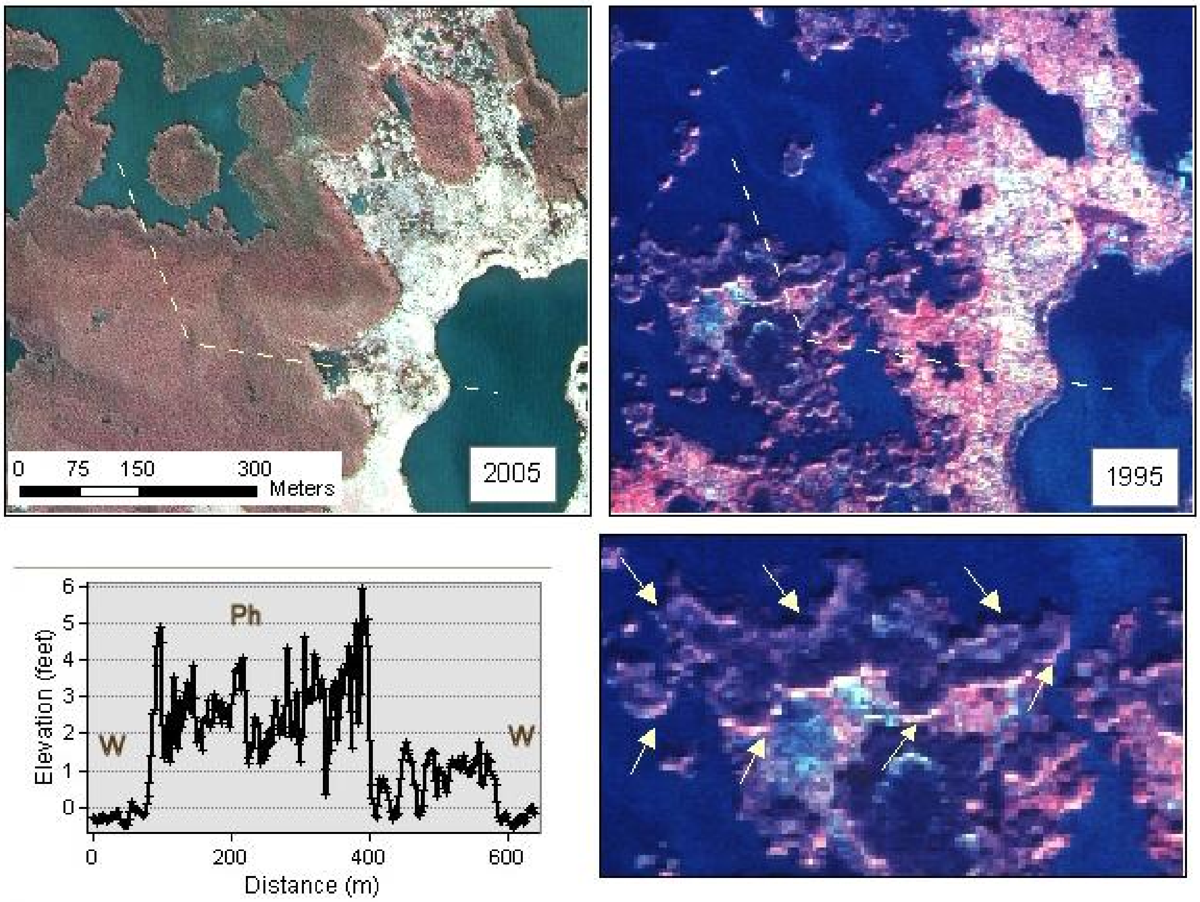

Fig 7. Multispectral images of a portion of the study area at two different dates. Dashed line indicates the sampling of the elevation profile shown on the lower left. Ph: *Phragmites patch*; W: water body. Lower right: a detail of the 1995 image, showing a patch of *Phragmites*. Arrows indicate patch outer margins.

CONCLUSIONS

Lidar in combination with multispectral data can effectively produce valuable maps of *Phragmites* when processed with an object oriented classification approach. CA and NCC performed similarly, both with weaknesses and strengths. In CA the analyst has more control over the classification process and the decision making, but it also needs a better knowledge of the properties of the classes and segments, and it is possible that the specific thresholds could be not applicable to other datasets. Several options need to be further explored. Refinements of the classification results could be done both, through further defining the fuzzy classes in NNC, and through the use of hierarchical classification to improve the accuracy of some classes.

An important achievement of the multi-source remote sensing data of this study is that the mapping could be carried out by analysts with no direct experience on the field, and with the least possible input from local experts. In fact, preliminary maps produced by this approach were able to guide ground based studies to *Phragmites* patches that were previously unknown to the local experts.

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