DEVELOPMENT OF A KNOWLEDGE DRIVEN RULE SET FOR CLASSIFICATION OF SUBMERGED AQUATIC VEGETATION (SAV) IN A CLEAR WATER STREAM: WHERE DO YOU DRAW THE BOUNDARIES...?

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SUMMARY

A recent attempt at mapping submerged aquatic vegetation (SAV) species composition of a clear water stream in Belgium from ultra-high resolution, multispectral photographs, using object based image analysis (OBIA), resulted in a low, but consistent overall classification accuracy (53-61%). Since the results were obtained with a single rule set they show promise for the development of an automated tool to map SAV despite the challenges of its submerged environment. This extended abstract investigates to what extent difficulties with species delineation in the validation data may have influenced the results. We compare class boundaries, as drawn by experts along image segmentation outlines, with the results from the expert knowledge driven classification rules. A comparison for 'pure' objects, where the expert is certain about the assigned object class, resulted in a moderately good overall similarity (68%), while inclusion of ambiguous objects reduces the results to 59%. Under ideal circumstances the rule set seems capable of 74% similarity with expert validation data.

1. INTRODUCTION

1.1 Introduction

The mapping of submerged aquatic vegetation (SAV) using remote sensing techniques has not been attempted much until quite recently. The detailed scale required to study SAV and the absorption of light in water have been major barriers to the effective use of remote sensing techniques. Very High or Ultra High Resolution (VHR) image data in combination with Object Based Image Analysis (OBIA) has brought some change to this situation, as it reduces the reliance on spectral information for vegetation species detection.
Although species can show very subtle differences that even experts find difficult to detect when observing the plants up close, they also display considerable differences in their morphology that allow for broad mapping of SAV species cover by eye from the bank side of a river. For this reason we expected that expert driven OBIA could be a useful tool to provide some form of automation to this mapping process.
An initial attempt at developing a ruleset for the mapping of SAV in the Desselse Nete, a clearwater stream in Flanders, Belgium has been presented in Visser et al. (accepted). The classification accuracies that we achieved in this study were however not as good as we hoped. We are currently in the process of improving our methods in a number of ways. Adjustments of the ruleset for effects of water depth and variable illumination conditions are two things that we expect may improve the work. Another issue, which may have influenced the results is the complexity of delineating the species class boundaries.

The canopy morphology of the species in our target river varies from very dense with sometimes fuzzy edges (e.g. Blunt-fruited Water Starwort: *Callitriche obtusangula* Le Gall) to very open groups of narrow, but well defined leaves (e.g. European Bur-reed: *Sparganium emersum* L.). Other species included in this study were Water Crowfoot (*Ranunculus aquatilis* L.), Curly-leaf Pondweed (*Potamogeton crispus* L.) and Broad-Leaved Pondweed (*Potamogeton natans* L.). In many cases it is difficult, if not impossible to identify where one species cover starts and another ends. However, the only means to check the classifications we produced was by manually delineating class boundaries in images of our study area. We soon realized that hand-drawn boundaries could not achieve the same detail as automated classification and would therefore not necessarily provide a fair assessment of mapping accuracy. To overcome this problem we decided on a slightly different approach to obtain validation data. Instead we asked our experts to use the Level 1 OBIA image segmentation as basis for their validation map and assign each object to what they think would be its appropriate class.
This still resulted in a number of notable issues. Firstly, although the segmentation applied to the image was to our knowledge the most appropriate, it certainly was not perfect and the experts noted various under-segmented objects, where an additional boundary would have been beneficial in order to assign the object a distinct class. Similarly for the more open canopies where only one or two leaves fall within an object, covering a relatively small part of the object surface area, decisions on how to classify that object are debatable. Where the vegetation of the more open canopies varied in submergence depth another difficulty was caused by the visibility of the target. At some point it becomes difficult to judge from the image whether slight spectral variation is part of the bottom surface texture or presence of vegetation a greater depth.

This extended abstract further describes and discusses how the validation data was created and how effective it was at assessing the performance of the knowledge-driven classification ruleset.

2. METHODS

2.1 Image data acquisition

Images used for this project were collected from the Desselse Nete, a lowland River in Flanders, Belgium, during the spring/summer of 2012. The Fujifilm IS-Pro NIR sensitive DSLR camera was used in combination with a radio controlled shutter to produce 3024x2016 pixels photos in 8-bit GEOTIFF format from a telescopic pole fixed in position with guy ropes at approximately 4.5 m at nadir over the centre line of the river.

Multi-spectral image composites were created by adding different filters to the Tamron AF Aspherical 28-80 mm f/3.5-5.6 lens. Red, Green and Blue image bands were obtained by adding a NIR blocking filter (model XNite CC1, LDP LLC, Carlstadt, USA, formerly 'maxmax.com', here referred to as 'CC1'). A single band covering most of the NIR spectrum (NIR(R72)) was obtained by adding a Hoya R72 VIS blocking filter and a further two bandpass filters (XNite Bandpass IR Filters, LDP LLC, Carlstadt, USA), were used to obtain one narrow NIR wavelength band around 710 nm (model XNite BPB, here referred to as 'NIR(BP1)') and one around 828 nm (model XNite BPG, here referred to as 'NIR(BP2')).

2.2 Image pre-processing and mage segmentation

The use of a low-cost image data collection approach meant that image data layers could not be collected simultaneously and needed co-registration before they could be combined in an image composite. A significant error is introduced at this stage, more so because the submerged vegetation target is highly dynamic. This meant that plant elements such as leaves were not located in exactly the same position in each image data layer and would not show up as distinct objects during a segmentation based on multiple image layers.

To minimize the effect of this on the further classification we decided to use a segmentation based on a single data layer. For this purpose the NIR(BP1) band was used. This relatively narrow band of the NIR spectrum was noted by the experts involved to show SAV species most clearly, allowing for the most relevant object delineation.

Several issues affected the image quality, for example sun and sky glint at the river water surface. However, no radiometric pre-processing of the data was undertaken, as it was not expected to significantly improve further analysis for reasons described in Visser et al. 2015.

2.3 Image classification

The result from this project are based on a ruleset, which was created based on two 'development' images and a validation image, results of which have been published in Visser et al. (accepted). The ruleset has however been modified to enable classifications of one species at a time. We also checked that each included rule related to an identification step undertaken by the experts involved. Examples of this are given in the Results section.

The classification rule set makes use of two segmentation levels. The first level (Level 1) outlines patches of different vegetation species, while objects at the second level (Level 2) delineated distinct plant morphological elements (e.g. individual leaves and stem segments). The parameter settings used for each segmentation level were based on a trial and error approach.

2.4 Classification validation

In pixel-based classification studies a sample of cells is generally used to assess the accuracy of a classification. For OBIA classifications the sampling units should consist of polygons rather than pixels (Radoux et al., 2011). However, a universal method that can deal with objects varying both in size and class definition has not yet been devised. Due to the difference in the way automatic classifications and manual delineation of polygons work, they can produce maps with significantly differ ranges in shape and size of polygons. It actually makes the selection of a random sample of polygons to estimate the accuracy of the full classification impossible.

Rather than manually outlining each patch we used the Level 1 segmentation polygons and manually classified all those into one of the available classes, using all six data layers and a field sketch, for confirmation. The validation dataset then consisted of polygons with the same shape and size as the automatic classification. This approach would allow an accuracy assessment based on probability sampling. However, this study is a bit exceptional since there is full validation cover for the classified image, so a direct comparison can be made between the maps without the need to rely on statistical inference.

In the original study of Visser et al. (accepted) similarity values were still relatively low despite the use of Level 1 polygons to create the validation data, with 61% the best overall accuracy levels obtained. These poor results could be due to inadequate classification rules. However the 'accuracy' of the validation data may also be questioned. The submerged environment is notoriously difficult to map even when done by hand from the bank of a river. Overlap between vegetation species and variation in visibility make it difficult to draw boundaries between SAV species as as well as determine vegetation and substrate boundaries.

Issues with image object composition, as those mentioned in the Introduction made it impossible to assign all objects to an appropriate SAV class. In order to assess the effect of these ambiguous objects, a number of additional combination classes were defined. Where an object would for example consist of mostly river bottom with a few *S. emersum* elements, it could be assigned to *S. emersum/*bottom combination class.

Running rulesets separately for each class resulted in overlap where individual objects fitted the rules of more than one class. All possible classes were noted for each object and compared with the expert classification result to assess how well each class was represented by the set of rules.

3. RESULTS

Figure 1 shows the classification of SAV for section of the Desselse Nete river based on a knowledge-driven ruleset.

The following are examples of plant spectral and morphological characteristics for *C. Obtusangula*, as used by an expert to identify the species:

- Bright overall, but especially in NIR and green with little spectral variation =>

Mean NIR(BP1) > 70

Mean NIR(BP2) > 25
- ‘Fluffy’ appearance due to rosette shaped leaves/canopy =>
Relative area of sub-object ‘Rosettes’ > 0.23
- Rosettes shaped leaves or ‘Rosettes’ => Level 2 objects with:
Length/Width < 2

Similarly rules for *S. emersum* were as follows:

- Bright narrow and elongated leaves => Level 2 objects with:
Length/Width > 4
Mean NIR(BP1) > 60
Relative border with brighter objects BP1 < 0.5
Width (18 pxl)
- A certain density of *S. emersum* leaves and absence of *P. natans* leaves =>
Number of sub-objects *S. emersum* >= 1
Relative area of sub-objects .*S emersum* > 0.1
Number of sub-objects *P. natans* <= 1

The chosen parameter values and settings for each of the two segmentation levels are as follows:

Level 1: Multiresolution segmentation: Scale parameter 100; Shape 0.2 Compactness 0.2: NIR(BP1) data layer only.
Level 2: Multiresolution segmentation: Scale parameter 20; Shape 0.2 Compactness 0.2: NIR(BP1) data layer only.

Figure 1 shows the full classification of the river section.

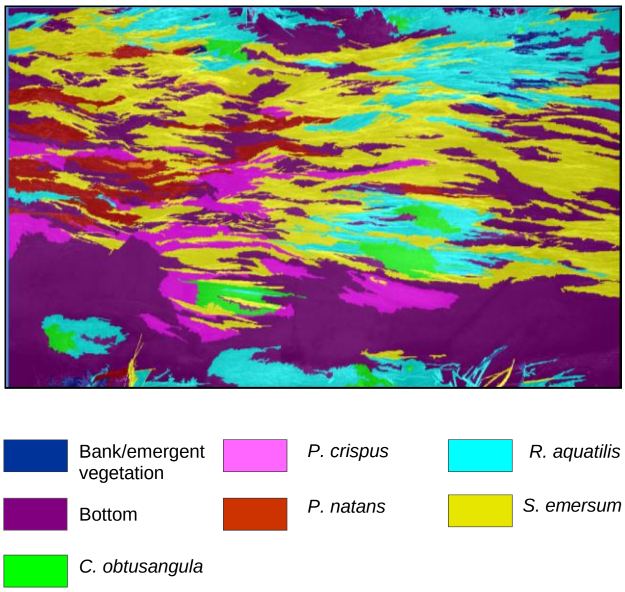

Figure 1. Original classification of the river section.

Figures 3a-d provide examples of the classification vs. validation results for four of the 8 classes defined for this project. The figures show areas where the classifications are identical and where they differ for both the automatic classification and the manual validation data.

Table 1 shows percentage similarities of the comparisons of the classification result and the manual validation data.
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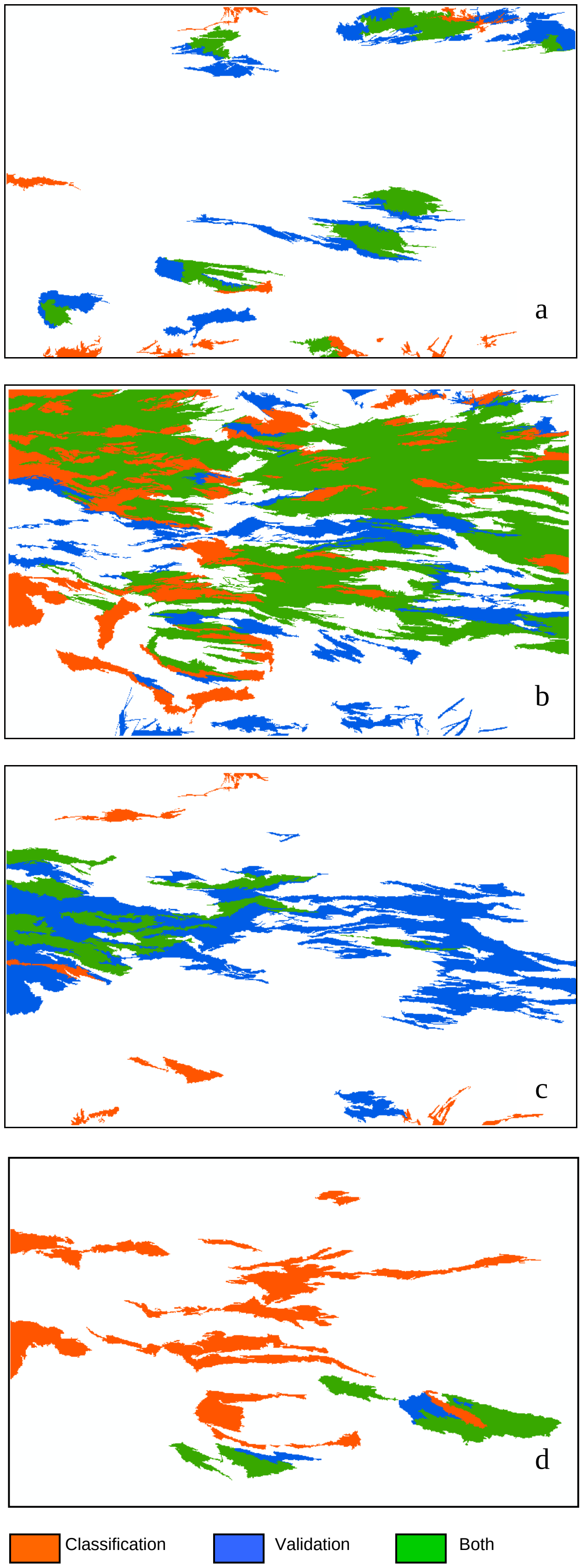

Figure 3. Overview of objects that are part of the classification, validation and of both validation and classification, for *C. obtusangula*, (a) *S. emersum*, (b) *P. natans* (c) and *P. Crispus* (d).

	Per class				All classes	
	Correctly classified / total in pure class	%	Correctly classified / total in class+ boundary cases	%	Correctly classified / total	%
Bank/emergent vegetation	11 / 45	24	11 / 45	24	11 / 45	24
C. obtusangula	22 / 39	56	24 / 53	45	32 / 53	60
P. crispus	8/10		8/11	73	8 / 10	80
S. emersum	259 / 299	87	301 / 381	79	343 / 375	91
R. aquatilis	10 / 16	63	10 / 16	63	10 / 16	63
P. natans	13 / 69	19	16/118	14	51 / 113	45
Total		68		59		74

Table 1. Percentages of objects that have the correct class assigned out of 1 or more 'fitting' classes

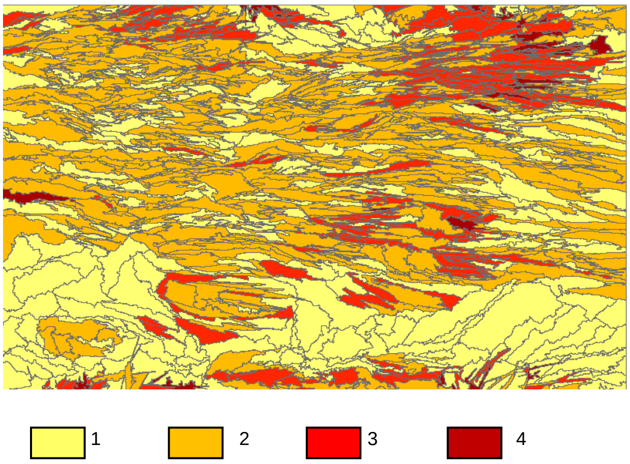

Figure 4. Class membership numbers for each object polygon

When only objects are considered that were manually assigned to one of the six cover classes the classification rules correctly classified 68% of the objects. The best performing class was *S. emersum* with 87% of the object correctly classified. *P. natans* preformed least well with only 19% of objects correctly classified. When also objects were considered that could not be classed unambiguously by the expert the percentage correctly classified objects is reduced to 59%, with the same best and worst performing classes. However, because there is overlap between the rules of the different classes, this means some objects are part of more than one class (membership numbers are shown in Figure 4). This means in a best case scenario when the best fitting class is chosen for an object a 74% accuracy could be achieved with the current ruleset.

4. DISCUSSION

Table 1 shows that when pure class objects are considered our rules perform moderately well to classify certain plant species with a 68% overall 'accuracy'. However, the results deteriorate when objects are included that could not be classified unambiguously by the expert, often because they clearly included elements of more than one class. This raises the question exactly how/where the validation class boundaries should be drawn or whether rules should be rewritten.

To some extent problems were created by basing the validation data on image objects, as the object boundaries often did not follow the boundaries the expert would have liked to draw. However, it would be an impossible task to draw boundaries around for example individual *S. emersum* leaves to create the perfect validation dataset.

Alternatively the expert could be requested to assign class membership values to each object, however memberships are difficult to estimate by the expert in the validation data set and also difficult to quantify in an object based environment, where the membership of a polygon to a particular class may be dependent on a combination object features such as the number of leave-shaped sub-object present.

An important consideration is that where an expert will make mistakes and inconsistent decisions on class definitions/content, a digitally applied OBIA ruleset will be able to provide much more objective classification results. This is great strength of the remote sensing approach and should be developed further. However, one does need to bear in mind that the expert-driven ruleset development is also a result of human understanding and perception of class definitions and boundaries, which is a weakness of the approach that requires further work (Arvor et al., 2013).

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