OBJECT-BASED ANALYSIS AND MULTISPECTRAL LOW-ALTITUDE REMOTE SENSING FOR LOW-COST MAPPING OF CHALK STREAM MACROPHYTES

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ABSTRACT:

Their small size and high biodiversity have until now made UK chalk streams unsuitable subjects for study with remote sensing techniques. Future technological developments are however likely to change this. The study described in this paper shows how high resolution multispectral images taken with an off-the-shelve, infrared sensitive digital camera, can give a first insight into future opportunities for mapping and monitoring of submerged chalk stream environments. The high resolution multispectral images have been used in combination with Object Based Image Analysis (OBIA) techniques to map submerged vegetation. Preliminary results show that the Near Infrared Red information recorded by the camera greatly improves the classification of individual macrophyte species. The benefit of the object-based image analysis approach is at the presented stage only limited, but a first attempt at creating a robust rule set has been applied to photos taken at two different field sites with some success. The analysis also showed how texture features are useful for the separability between macrophyte classes. Overall the results are promising for further applications of remote sensing techniques to chalk streams as well as for application of the low cost sensor set-up.

1. INTRODUCTION

1.1 Chalk stream vegetation mapping

UK lowland chalks streams are internationally rare environments with high biodiversity. Unfortunately they are under increasing pressure from human activities such as groundwater abstraction. Since most of the flow in chalk streams is derived from groundwater, these practices can significantly reduce water levels and affect stream biota. Regular mapping/monitoring of the stream biodiversity is essential to understand the true impacts, but this remains difficult because it relies on slow and costly field investigations. Remote sensing could provide a useful tool, to help monitoring chalk streams, but so far this tool has rarely been applied to aquatic river environments. Certainly compared to marine environments this field of applications is in need of a catch-up (Gilvear et al., 2007).

In a recently published project by Hill et al. (2009) airborne hyperspectral data was used to assess the distribution of Water Crowfoot (Ranunculus pseudofluitans) in the River Frome, Dorset. The image data had a 1m resolution, which was suitable for this particular purpose, but does not allow any more detailed characterization of the distribution of macrophyte species, which usually involves a sub-meter scale. Some of the latest commercially available satellite sensors such as GeoEye can achieve higher resolutions, but only record wavelengths in the visible light (VIS).

The above underlines the spatial and spectral limitation of most data, which are main reasons for the lack of remote sensing applications in river environments. Two further limitations are the often limited transparency of river water due to suspended sediment concentrations and the fact that water strongly absorbs the Near Infra Red (NIR) wavelengths, which are normally essential for vegetation mapping.

Due to the shallow depth and high clarity of water in chalk streams, the latter two problems may not affect remote sensing applications so much (Visser and Smolar-Žvanut, 2009). However their size and vegetation diversity would still require image data of a spatial and spectral resolution that isn't yet available at an affordable price.

1.2 Low altitude remote sensing and OBIA

The most promising direction for remote sensing of chalk streams is the use of Unmanned Aerial Vehicles (UAVs). However, in combination with a sufficiently light multispectral sensor, such equipment is currently beyond the financial reach of most interested parties. Still, despite fully calibrated multi resolution sensors not being readily available, there may be an off-the-shelve option in the form of an infrared sensitive digital DSLR. The set-up would be small enough for application on smaller and cheaper types of UAV or other low altitude remote sensing platforms. This paper presents results obtained with such a set-up.

Further improvements in the mapping of chalk streams may also be achieved by making use of current developments in Object Based Image Analysis (OBIA). This image analysis technique not only makes use of spectral information from image bands, but can also include textural, structural and relational information on image objects. It has been successfully applied in a wide range of fields including ecology (e.g. Addink et al., 2004). Some of the greatest benefits are experienced with analysis of high spatial resolution image data.

The combination of multispectral digital photography from a low-altitude platform and object based image analysis, could turn out to be a very (cost) effective tool to monitor chalk streams. The current paper describes a first attempt at combining the two techniques and aims to provide an evaluation its potential benefits.

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2. METHODS

2.1 Study Area

Multispectral photographs were taken of stretches of two different chalk streams. One site was located near Wool in the River Frome in Dorset (A); a second site was located in the River Wylye, at Langford Trust Nature Reserve in Wiltshire (B). Both sites where chosen for their comparable size and vegetation composition.

2.2 Equipment

The photographs were taken with a Fujifilm IS-Pro infrared sensitive digital DSLR camera (up to 1000nm) and a set of lens filters. A CC1 Infrared blocking filter (MaxMax.com) was used to obtain VIS RGB wavelength bands. A R72 VIS blocking filter (Hoya) was used to record a broad band of infrared light and two further band pass filters were used to obtain three specific NIR wavelength bands. Specifications of the filters are as follows:

- R72 (Hoya R72) VIS (<720nm) blocking filter
- BP1 (MaxMax XNiteBPB) 650nm to 787nm (5% low cut – 5% high cut) band pass filter
- BP2 (MaxMax XNiteBPB) 735nm to 935nm (5% low cut – 5% high cut) band pass filter

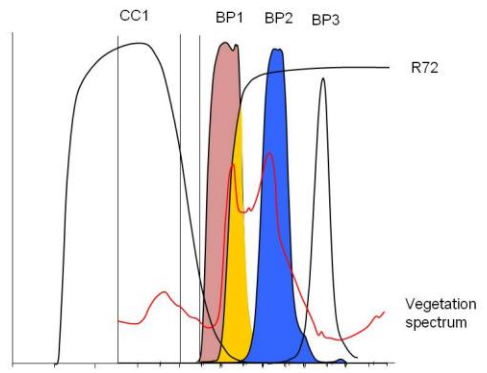

Figure 1. The combined transmission spectra of CC1, BP1, BP2 and R72 band pass and blocking filters based on manufacturers specifications.

The combined effect of the transmission spectra for the three filters is illustrated in Figure 1. The application of the various individual filters and one filter combination to the infrared sensitive DSLR camera resulted in a 6-7 band multispectral image.

A low altitude aerial platform was created by attaching the camera onto a telescopic camera mount. Photos were taken from 6.5m elevation with the camera at nadir. The set-up resulted in photos with sub-cm ground resolution.

2.3 Image preprocessing

The basic filter – camera – pole setup has the disadvantage that image bands are recorded separately and therefore require intensive image preprocessing. Lengths of white tape were fixed to metal pegs and located in the stream as ground control points (GCPs). The images were rubbersheeted using ground control points only. Not all points were visible in all image layers, which will have reduced the accuracy of the image rectification. The RGB bands were used as base image onto which the other images have been warped using 6-8 tiepoints and 1st order polynomial resampling.

2.4 Ground reference data

Reflectance spectra were obtained from all vegetation species in the image with more than 10x10cm ground cover, using a GER1500 field spectroradiometer. 5 different macrophyte/algae species were found at site one, 4 species at site B (Table 1). The species showed spectral variation in both the VIS and NIR wavelengths, although the absolute differences were small (Figure 2). Further information on the spectral discrimination between the species can be found in Visser and Smolar-Žvanut (2009) and in future publications by Visser and Wallis (in prep.)

	Site A	Site B
Brooklime (Veronica Beccabunga)	x	x
Spiked water milfoil (Myrlophylum spicatum)	x	x
Pondweed (Potamogeton)	x	x
Water crowfoot (Ranunculus Fluitans)	x	-
Blanket weed	x	x

Table 1. Species composition of the significant vegetation cover at field sites

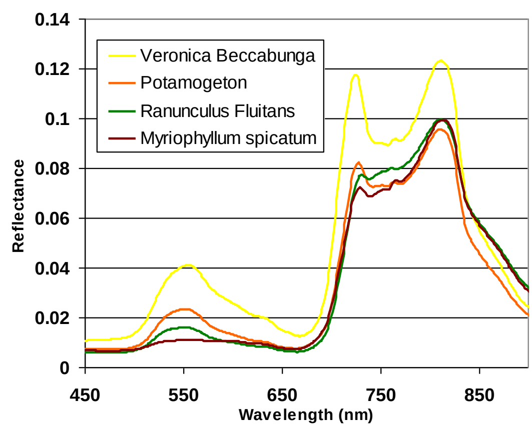

Figure 2. Average reflectance spectra for four of the vegetation species present at field sites A and B.

Field sketches with locations of all significant vegetation patches were used to manually delineate classes in both photos. These digitized classes were used for accuracy assessment.

2.5 Analysis overview

The object based analysis described in this paper is preliminary work that explores the possibilities of the technique in combination with the low-cost camera-setup. The analysis of the image data so far consisted of three stages:

- Supervised classifications of the visible light bands using a pixel and an object based approach.
- Supervised classification of all image bands as above
- A manually developed rule-based classification

The first stages of analysis are performed on the Frome image only (site A). The rule-based classification is tested on both the Frome and Wylye image.

2.6 Segmentation

The Definiens Developer 8 multi-resolution segmentation algorithm was used to generate image objects. An initial segmentation was applied to all of the following bands:

- Red
- Green
- Blue
- Pan
- Median Pan
- R72 (All NIR)
- BP1 (narrow NIR band 1)
- R72+BP1 (narrow NIR band 2)
- BP2 (narrow NIR band 3)

The Median Pan band was obtained by applying a 11x11 cell median filter on the panchromatic band. The filtered layer as suggested by Jarlath O'Neil-Dunne (online comm.) seemed to improve the delineation of objects. The segmentation scale factor was set to 50 with a shape factor of 0.2 (to increase the influence of the spectral information on the segmentation) and a compactness factor of 0.5.

2.7 Supervised classification

First a pixel-based supervised classification was performed to obtain a classification standard with which other results could be compared. The ENVI Maximum Likelihood classification algorithm was used for this purpose. A training dataset was prepared based on the manually delineated map. It contained 4-5 training areas per vegetation/bottom class. Training objects at similar locations were chosen from the segmentation result in order to perform a second supervised classification based on the image objects. The Nearest Neighbor algorithm included in the Definiens software was used for this. The above two classifications were repeated for a band composite that only contained three VIS bands.

2.8 Observations on texture features

Murray et al. (2010) successfully applied Grey Level Co-occurrence Matrices (GLCM) to improve their multispectral classification of sub-Antarctic vegetation. Some of the image bands of the chalk stream photos show distinct texture differences between vegetation species. At current scale it was therefore expected that texture features would be able to improve classification results. Laliberte et al. (2007) found that while applying a decision tree analysis to develop a rule-based classification for mapping of arid rangelands, GLCM texture also improved their results. The texture features were mainly used lower down the classification tree, while initial separation in the data was based on NIR spectral information. For the current study the Feature Space Optimization Tool in Definiens Developer 8 was used to identify the significance of texture features for vegetation classification.

2.9 Rule-based classification

Ideally the mapping of chalk streams should happen over much longer stretches of river and is frequently repeated. It is therefore important to try developing a robust transferable rule set that can be applied to different rivers under varying conditions, without requiring much adjustment. The abovementioned texture features could form an important element of such a rule sets, because they may be less sensitive to illumination variation in the photos. A first attempt was made to manually create a rule set using some of the features previously identified as significant. The rule set is subsequently applied to both field sites.

3. RESULTS

Figure 3 shows the RGB composite of the VIS layers of the River Frome photograph. The white square in the bottom left is a PTFE reference panel. The results of the first stage of the analysis are shown in figures 6 to 8. These are the results of supervised classifications, applying an object-based and a pixel-based approach to all available bands respectively. To obtain the result of Figure 7 only the RGB bands were used in the classification. Based on this the significance of the additional image bands could be evaluated. Figure 5 shows the manual delineation of the vegetation classes for ground reference.

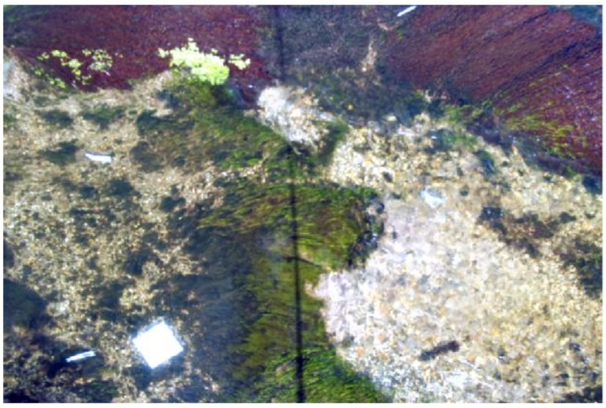

Figure 3. RGB composite of the VIS layers of the River Frome photograph (location A).

Figure 4. Legend for all subsequent classification results

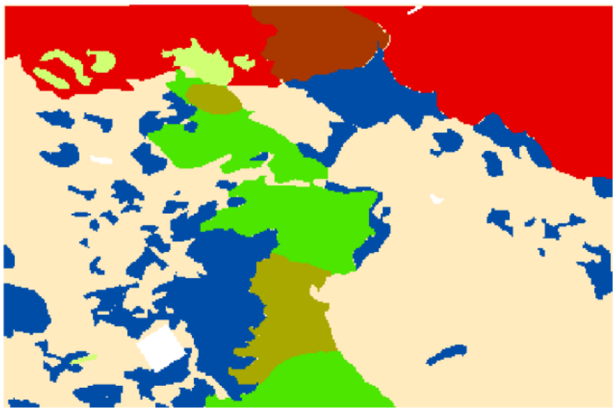

Figure 5. Results of the manual delineation of vegetation classes (location A).

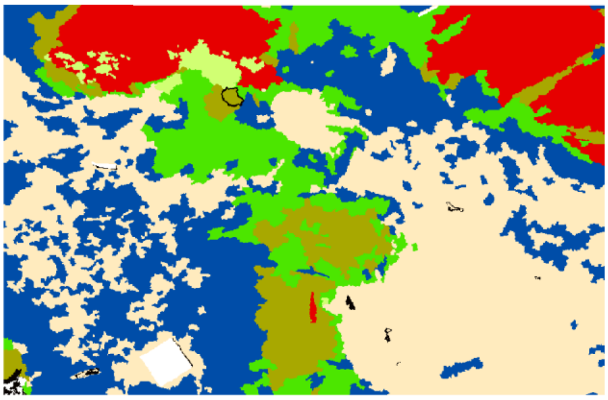

Figure 6. Results of the object-based nearest neighbour classification using all bands (location A).

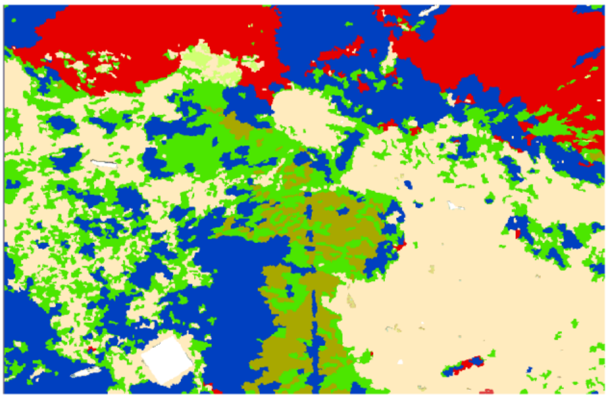

Figure 7. Results of the object-based nearest neighbour classification using VIS bands only (location A).

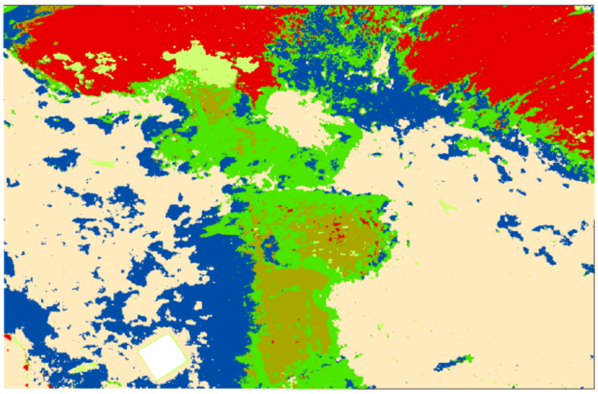

Figure 8. Results of the pixel-based Maximum Likelihood analysis using all bands (location A).

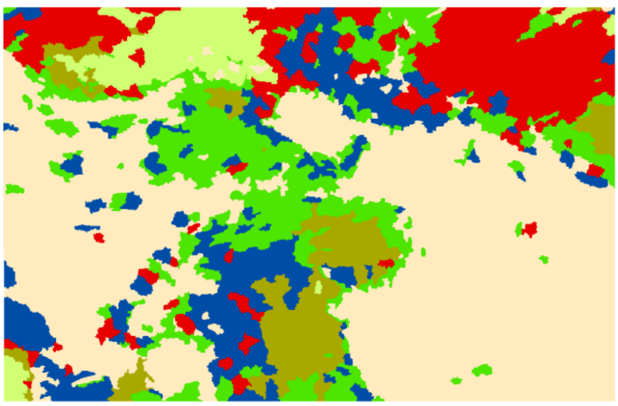

Figure 9. Results of the rule-based classification (location A).

3.1 Rule-based classification results

Figure 9 shows the results of a rule-based classification that was developed using Definiens software. A single level rule set was manually developed using knowledge on the separating features that were obtained from the Feature Space Optimization Tool. The features that were identified as most discriminating were considered in the rule set development. Most of these were texture features.

The original rule set was created for the Frome image (site A) and then applied to the Wylye image. Most of the rules applied to both rivers with none or only slight adjustments. Only on two occasions a new feature was chosen. The following list shows the features and coefficients used for each site:

Wylye
[GLCM Mean Red (all dir.)]/[GLCM Mean R72 (all dir.)] < 0.85
Max. Diff. >1.6
[GLCM Mean (quick 8/11) R72 (all dir.)] > 200
[GLCM Mean (quick 8/11) Red (all dir.)] < 97
[GLCM Contrast (quick 8/11) Red (135º)] > 15

Frome
[GLCM Mean (quick 8/11) Red (all dir.)]/[GLCM Mean (quick 8/11) R72 (all dir.)] < 0.9
Max. Diff. >1.25
[GLCM Mean (quick 8/11) R72 (all dir.)] > 200
[GLCM Mean (quick 8/11) Red (all dir.)] < 97
[GLCM Mean (quick 8/11) Blue (all dir.)] < 60
[GLCM Mean (quick 8/11) Green (all dir.)] > 106
([GLCM Contrast (quick 8/11) Red (135º)] > 15)

A particularly useful custom feature was created (GLCM Mean Red (all dir.)]/[GLCM Mean R72 (all dir.)), which provided a clear initial distinction between areas with and without vegetation cover.

Figure 10 shows the RGB composite of the River Wylye photograph. Figure 11 shows the result of the rule-based classification of this image.

3.2 Supervised classification Accuracy

A manual delineation of the vegetation in the photos based on the field sketch was used to assess the accuracy of the classifications. This delineation is certainly not error free itself, as not all boundaries between species could be clearly identified from the photo. Smaller clumps of vegetation (e.g. blanket weed) may have been excluded from the ground reference map, while still being picked up by the classification.

The results of an accuracy assessment for the different classification methods are shown in table 2. Both the object and pixel based multispectral approaches perform similarly well, with kappa values of 0.77 and 0.76. The object-based method using only VIS bands and the rule-based method perform less well, with a Kappa value of 0.64 for both.
The lesser performance of the VIS only classification, suggests that even though the sensor set-up has not been calibrated in any way, the contribution of relative NIR information significantly improves the classification. Also the effect of

absorption by water does not eliminate the application of this wavelength region.

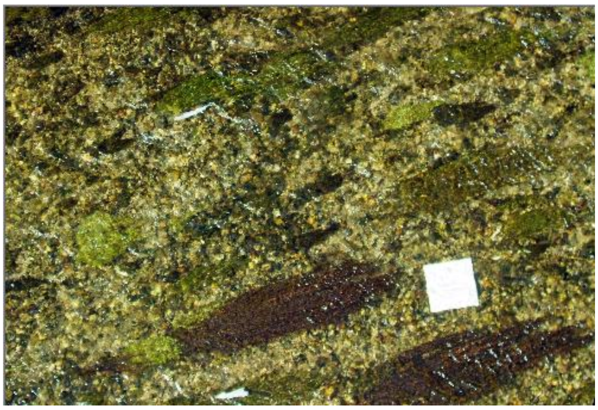

Figure 10. RGB composite of the VIS layers of the River Wylye photograph.

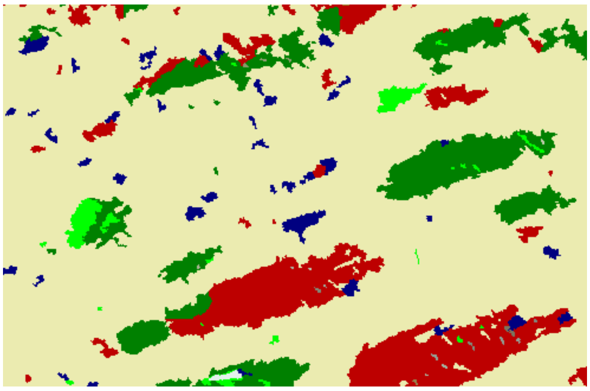

Figure 11. Results of the rule-based classification (location B, note: the colour scheme used is slightly different).

Classification method	Users Acc.	Producers Acc.	Overall Acc.	Kappa
OBIA VIS only Site A	70.2	66.7	72.8	0.64
OBIA all bands Site A	81.3	84.7	82.2	0.77
Max. Like. all bands Site A	80.8	79.8	82.6	0.76
Rule-based Site A	63.8	68.0	73.8	0.64
Rule-based Site B	74.8	76.2	78.5	0.74

Table 2. Accuracy assessment results of four classification methods applied to the photo of the Frome river stretch.

One of the biggest sources of error in the multispectral object-based supervised classification (and in most other tested approaches) is the overestimation of the area covered by Pondweed (user's accuracy 48%). At one particular location it is consistently confused with Water Crowfoot. Since both macrophytes have a similar green colour separating the two classes, is challenging, but for part of the image texture features seem to make a good distinction between the two classes. This effect will be further investigated for the rule-based classification.

3.3 Rule-based classification accuracy

Comparison of the accuracy assessments for the rule-based classifications of both river sites shows that the accuracy of the site for which the rule set was originally created is lower that that of the site to which the rule set has been transformed. This is an encouraging result, but not completely unexpected. The vegetation patches at site B are mostly clearly separated from each other, which makes accurate delineation and classification easier. There is also more contrast between patches and the surrounding gravel bottom, as there was less blanket weed which tends to blur boundaries at site A.
In the current rule-based classification result for site A particularly the area covered with Brooklime was overestimated. Due to the distinctly different colour of this macrophyte further rules using spectral characteristics should resolve the problem.

3.4 Discussion of image analysis techniques

Both multispectral supervised classification results currently perform better than the rule-base approach. This is probably largely the result of the rule set being only a preliminary version. Various means have been identified that could further improve the classification and additional quantitative approaches can be used (e.g. Laliberte et al., 2007). It remains a disadvantage that developing a suitable rule set is rather time consuming, particularly for inexperienced users. However the potential for automation of the classification process certainly warrants the effort. Since the classification could be repeated on a completely independent image, with little modification of the threshold parameters a correct set-up may enable relatively rapid assessment of longer stretches of river and perhaps even comparisons between rivers. This is less likely to be achieved with the supervised classification approach.
Further work will especially try to assess the added benefit of NIR layer combinations to improve discrimination between vegetation classes.

3.5 Discussion of sensor set-up

Despite the promising results a major weakness of the sensor set-up is the reliability/lack of calibration of the camera + filters. It has not been tested how stable its output is. If the results prove beneficial for a number of applications this is something that should be further studied.
The need to rectify the individual image bands is another weakness of the sensor set-up. The continuously moving submerged environment does not add to the accuracy of the overlays. In the current study mismatches between the image layers did however not prohibited the production of useful results. It is even possible that characteristic underwater movement of vegetation species increases their textural separability.
To make the method suitable for large scale river monitoring, the sensor set-up will have to be transferred to a more mobile platform (e.g. a small UAV). This could further increase the difficulty of image rectification. Also changes in the rule set will be required as the discriminating visual characteristics change with scale. It is possible that the current benefit of textural feature disappears. An additional type of features like shape may on the other hand be introduced as new useful classifiers.

4. CONCLUSION

The study described in this paper aimed to investigate the effectiveness the combined application of a low-cost low-altitude photography and object-based image analysis for the mapping and monitoring of UK lowland chalk streams. The classification results for photos taken at two sites showed that the sensor set-up could potentially lead to methods for rapid mapping of chalk stream environments.

It was possible to create a classification from the photos that distinguishes between a number of macrophytes/algae species with considerable accuracy.

The NIR bands in the sensor set-up significantly improved these classification results. Due to the shallow water depths NIR is not fully absorbed.

The object-based approach to classification of the photos also helped improving the classification of submerged vegetation. A transferable rule set was created, but so far the accuracy of this method remained considerably lower than that of other classification methods.

Further research needs to find out what effect a reduction in resolution will have on the classification rule set, as further development of the method is likely to involve elevation of the sensor platform. It is quite possible that new types of features such as shape become useful classifiers, while the effect of texture will diminish.

5. ACKNOWLEDGEMENTS

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