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OBIA Classification of Riverine Vegetation in a Small Open Channel Using RGB Drone Imagery

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A b s t r a c t

In temperate areas, small watercourses, especially agricultural ditches, are typically surrounded by seasonally changing vegetation, which significantly influences hydrodynamic and ecological processes within and around the channel. However, research on how different vegetation maintenance practices affect flow and mixing processes at the reach scale remains limited. Addressing this knowledge gap requires a series of field experiments conducted under varying flow and vegetation conditions, along with a simple and accessible method for vegetation characterisation. This study evaluates the efficiency of RGB drone imagery in mapping riverine vegetation using OBIA classifiers. For low vegetation coverage, SVM combined with Haralick textural features provided the best results, while for high vegetation, SVM combined with DEM delivered the best classification outcomes.

1. INTRODUCTION

Fluvial vegetation plays a crucial role in the wellbeing of lotic ecosystems by creating habitats for aquatic fauna, reducing pollutant and nutrients loads, and, importantly, influencing hydrodynamics. Fluvial vegetation includes both riparian and riverine vegetation. However, most studies focus primarily on riparian vegetation, while riverine vegetation, especially in small channels, plays a key role in modifying flow dynamics. Regular mowing of vegetation for flood prevention remains common, yet its impact on fluvial ecosystems is poorly studied. Although the need for alternative solutions is often emphasised, it has not been thoroughly investigated. (Kalinowska et al. 2023). To fill the gap, a series of field experiments are planned to investigate the impact of riverine vegetation on flow and mixing processes in small watercourses with natural vegetation. Assessing seasonal changes in vegetation coverage (V_C) will be essential. Therefore, developing an efficient, objective, and reproducible method for evaluating aquatic vegetation coverage is crucial. The primary objective of this study is to explore the feasibility of using RGB drone imagery alone for river vegetation assessment in small rivers.

2. METHODS

The images were captured using a DJI Phantom 4 UAV equipped with an RGB camera in Warszawicki Channel, located within the Vistula Basin in eastern Poland (Kalinowska et al. 2023). The mission was conducted twice: firstly under full vegetation conditions (high V_C) and after mowing (low V_C). The collected images were processed in Agisoft Metashape using the Structure from Motion technique to generate orthomosaics and Digital Elevation Models (DEMs). The orthomosaics for both low and high V_C were then segmented using the Mean Shift algorithm. Training sample layers were generated with a relatively small number of samples to maintain a similar number of polygons (20–30 per class) and comparable area for both classes in two vegetation cases.

The segmented images and training layers were then used to perform supervised classification using all four supervised object-based image classification (OBIA) algorithms available in ArcGIS Pro: Maximum Likelihood (ML), Random Trees (RT), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). OBIA was chosen because, in contrast to pixel-based image classification, it groups adjacent pixels into meaningful objects and classifies them based on spectral, shape, texture, and spatial characteristics.

In order to calculate accuracy of the classification results, 250 points were generated randomly and manually labeled as either water or vegetation. Moreover, the F1 score (a metric useful when there is an imbalance between classes due to its emphasis on misclassifications) and Cohen's kappa (assesses the agreement between two classifiers, correcting for the agreement that could happen by chance) were calculated.

In this study, the use of DEM and Haralick Texture Extraction (HTE) (Haralick et al. 1973) in addition to RGB data was also investigated. HTE was performed using the Orfeo Toolbox (OTB) plugin in QGIS. Three Haralick texture features were selected: Entropy (distinguishes heterogeneous vegetation from homogeneous water surfaces), IDM (measures texture homogeneity), and Inertia (highlights local intensity variations, particularly at edges and boundaries).

3. RESULTS AND CONCLUSIONS

KNN and RT produced inconsistent results due to the inherent randomness in the algorithms. RT's randomness could not be controlled in ArcPy, preventing reproducibility. The minimum accuracy for KNN ranged from 0.62 to 0.92, and for RT, it ranged from 0.47 to 0.88 in case of 60 layers for both vegetation coverages. These variations suggest that such inconsistency is unacceptable in regular field studies, where stable and reproducible results are crucial.

Very good results were achieved for areas with low V_C and good results for areas with high V_C (Fig. 1, Tables 1-2). Note that the F1 score formula does not account for True Negatives, which represent correctly classified negative instances (vegetation). This may lead to underestimation when vegetation is dominant. Calculating the F1 score with vegetation as the

Table 1

Vegetation coverage results*

	RGB [%]	RGB+HTE [%]	RGB+DEM [%]	RGB+HTE+DEM [%]
ML low V_C	6.7	19.2	16.4	16.5
SVM low V_C	22.3	**11.9**	12.5	12.5
ML high V_C	87.1	91.4	96.0	96.7
SVM high V_C	88.0	88.6	**80.7**	82.4

*The best results are bolded

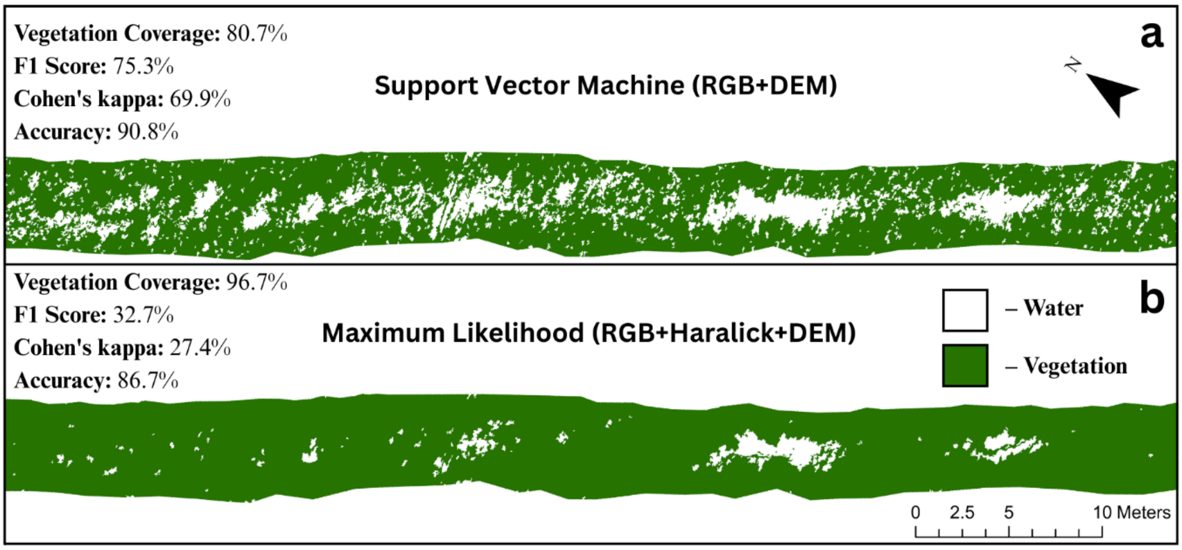

Fig. 1. Classification results showing the best (a) and worst (b) performance for high V_C.

Table 2
F_1 score results*

	RGB [%]	RGB+HTE [%]	RGB+DEM [%]	RGB+HTE+DEM [%]
ML low V_C	96.9	96.3	97.5	97.5
SVM low V_C	90.3	**98.4**	98.0	98.0
ML high V_C	65.7	61.3	36.0	32.7
SVM high V_C	50.7	57.1	**75.3**	74.4

*The best results are bolded

positive class and water as the negative class yielded a score of 94.7%. Overall, SVM performed better than ML in both cases, consistent with the findings of Pande-Chhetri et al. (2017) for wetlands and Szabó et al. (2024) for an oxbow lake.

Based on the results of this study, it can be concluded that using only an RGB camera enables satisfactory classification of aquatic vegetation in small rivers using a drone, with very good results for low vegetation cover and good results for high vegetation coverage.

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