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The comparison of pixel-based image analysis for detection of weeds in winter wheat from UAV imagery

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***Abstract*—Creating weed maps directly by growers is becoming increasingly common. In this study, an unmanned aerial vehicle (UAV) imaged a field infested by field thistle (*Cirsium arvense*). This paper compares four detection methods that can be used concerning agricultural practice. Two algorithms are supervised classification methods - Maximum Likelihood (ML) and Supported Vector Machine (SVM). The Pix4Dfields (Magic Tool) classification algorithm and the thresholding method are other methods used. The Kappa coefficient and the overall accuracy determined the accuracy of the individual algorithms. The highest accuracy was achieved by the thresholding method, and the lowest by the Pix4Dfields algorithm. Among the supervised classification methods, SVM achieved higher accuracy than the ML algorithm. In terms of using the methods in practice, the thresholding method proved more effective than supervised classification methods.**

***Index Terms*— Precision agriculture, SSWM, Pix4D, Remote sensing**

I. Introduction

OPTIMISING the use of herbicides is a primary goal and is crucial for maintaining the competitiveness of farms and decreasing the consumption of agrochemicals in crop management. Effective site-specific weed management (SSWM) requires knowledge of the spatial variability of the weed plants in the field. UAVs capable of capturing images with high spatial and spectral resolution have proven effective for this purpose [1], [2]. RTK modules, which accurately locate both the UAV and the photos taken, are now a standard feature. Some UAVs have the advantage of carrying multiple interchangeable or integrated sensors simultaneously. Sensors that capture in the visible spectrum (RGB) and multispectral cameras that acquire data from red-edge (RE) or near-infrared (NIR) bands are commonly used for weed detection [3], [4].

Confidence in accurate weed management is bolstered by modern application technology of sprayers that allows section-by-section or individual nozzle control based on the prescription map. This map typically consists of polygons outlining the application area [5], where nozzles are turned on. The accuracy of the application is ensured by the RTK guidance systems mounted on the machinery [6].

The technique for detecting weed plants from acquired images depends on the sensor type, the computing technology's performance, and the spraying technique. The modern sprayers with individual nozzle control require higher accuracy of prescription maps than older sprayers with section application swath control [5]. Besides the section control, the sprayer terminal's computing technology is crucial to processing the large data sets of the detailed prescription map. Weed detection in realistic conditions uses images combined into a single orthorectified mosaic (orthomosaic) representing the entire area of interest. Commercial software like Pix4D fields, Agisoft Metashape, Drone Deploy, or open-source options like OpenDroneMap are commonly used for this purpose [7], [8].

In addition to site-specific applications using a prescription map derived from UAV imagery, real-time detection and application techniques are also used. Techniques for detecting green vegetation on bare soil based on spectral features have existed since the last century [9]. Currently, sensor systems on application technology can detect weeds in broad-row crops like corn and soybeans. These systems save the cost of field surveys by UAV imaging but are usually more expensive than section control sprayers and can only be used in specific cases [10].

Application drones capable of applying solid and liquid products are increasingly becoming an alternative to traditional boom sprayers. The drone system automatically suggests a flight path and the optimal flight level for the application. This allows pesticide application in conditions where conventional machinery sprayers cannot enter the field, such as in unsuitable soil conditions, to avoid soil destruction and compaction [11]. Application drones are considerably cheaper than conventional sprayers, making them an attractive option for some growers. However, their weakest link is the batteries, which allow flight times of around 10 minutes, with excessive heating during charging slowing down the process [10], [12].

Identification of weed infestation based on the UAV data

There are two main categories of weed detection from UAV image data: object-based image analysis (OBIA) and pixel-based image analysis (PBIA). Supervised classification on high spatial resolution images taken by UAVs has promising results [13]. Supervised PBIA classifiers leverage prior knowledge to identify spectral similarities in raster data, assigning each pixel to the most appropriate class. In PBIA for supervised weed classification, each pixel may contain a mix of soil, plant leaves, residue, and shadow. This mixture can introduce variability in the target's spectral reflectance, limiting classification accuracy. In high-resolution PBIA, the heterogeneity of spectral values within a single class further restricts its effectiveness [14]. Compared to these two approaches, OBIA usually achieves better results than PBIA. Each classifier has its limitations, and the choice of the classifier depends on many factors, such as the data's spectral and spatial resolution, classification accuracy, algorithm performance, and computational resources [13; 15].

The study aimed to validate weed detection techniques on images taken by UAVs and concerning agricultural practices. Four classifiers were chosen for verification: two basic classifiers based on machine learning: Maximum Likelihood (ML), which works best when class samples are normally distributed, and Supported Vector Machine (SVM), which is commonly used in the research community and can handle standard images as well as segmented images, with less susceptible to noise, correlated bands [16]. The other two classifiers used in this study are a Pix4Dfields (Magic Tool) classification tool and a pixel extraction procedure based on vegetation index threshold setting. All classifiers were chosen for their versatility and simple hyperparameter adjustment, which are important elements in agronomic practice.

II. MATERIAL AND METHODS

A. Study area

The study was realized in 2023 in the form of field trial with the area 15.85 located at Rataje site (Kromeriz, Czech Republic; 49.254° N, 17.332° E). The main investigation was focused on the detection of occurrence of weed "field thistle" (*Cirsium arvense*) in winter wheat in the early stage of crop growth (BBCH 10-13).

Fig. 1 Position of the field of study in the Czech Republic.

B. Data acquisition

The UAV imagery was carried out on October 12, 2023, by the quadrocopter DJI Matrice 300 RTK. The drone was equipped with two sensors: RGB sensor DJI Zenmuse P1 and multispectral sensor MicaSense RedEdge-P. The flying altitude was 120 m above the ground, with GSD 13 mm (RGB camera) and 40 mm per pixel (RedEdge-P). Flying speed was set to 8.2 m/s. Both sensors were positioned in a nadir view of the canopy. The image overlap ratio was set at 70 % side and 80 % frontal. The RGB sensor exposure time was set at 1/2000 s, and the ISO and aperture were set to auto with timed interval shot. On multispectral sensors, images were taken every 1.5 s. After the flight mission was completed, a calibration reflection panel was photographed. The final orthomosaic from UAV imagery was processed using Pix4Dfields software.

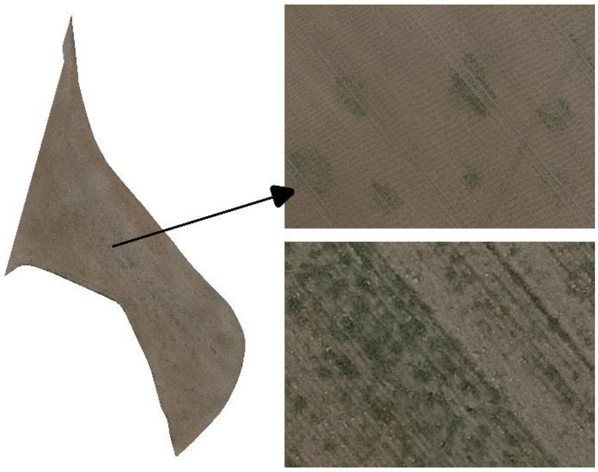

Fig. 2 Stitched images and a sample of resolution.

C. Classification approach

Classification algorithms based on ML and SVM were triggered in the ESRI ArcGIS Pro software. The classification was performed on RGB imagery. Due to the crop's early phenological stage and low spatial resolution of orthomosaic the detection of winter wheat plants was limited. Thus, only two classes were identified - bare soil (mixed with winter wheat plants) and weeds (as full vegetation cover). The OBIA method was not used in this case, and the classification was made using PBIA techniques [17]. The PBIA classifications were performed on the original image. Algorithms ML and SVM were trained using samples created by an expert based on ground truth identification. The training dataset included 50 samples for each category.

The Pix4Dfields mapping software includes a "Magic tool" classification tool. It is a simple and user-friendly multipurpose classification tool based on machine learning, which can detect weed patches or plant damage. The algorithm uses a grid over the field and the user labels grids that should be treated and untreated. The recommended number of labelled grids per class is 20; the minimum is three. In our case, the size of the grid over the field was set to 1 m and rotated in the driving direction. Subsequently, 40 grids (20 per class) were selected as the training samples.

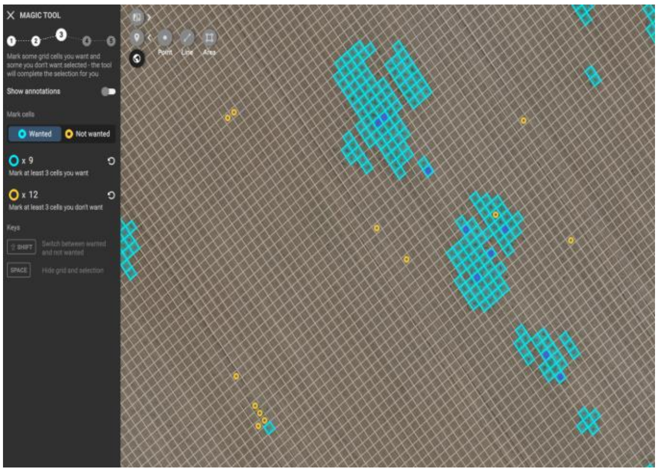

Fig. 3 Example of grid labelling using Pix4Dfields classification tool.

The significant difference in vegetation phases between the main crop and the detected weeds indicates a difference in spectral characteristics, which offers the possibility of using the thresholding method in the image. Thresholding is a technique to segment images by creating binary images based on threshold settings. The input raster was the vegetation index NDVI (1) of the studied field.

$$NDVI = \frac{(\rho_{NIR} - \rho_{Red})}{(\rho_{NIR} + \rho_{Red})} \tag{1}$$

The threshold value was set based on the histogram of the distribution of data values to value 0.385 as the cut-off between crops with soil and weeds. Reclassifying produced a binary image and left the pixels that matched the weeds. Pixels of the raster were converted to vector points, and a weed coverage map was created using a buffer tool with a buffer distance of 0.1 m. The final step was dissolving buffer zones to create a polygon map, which was unified by joining the overlapping polygons.

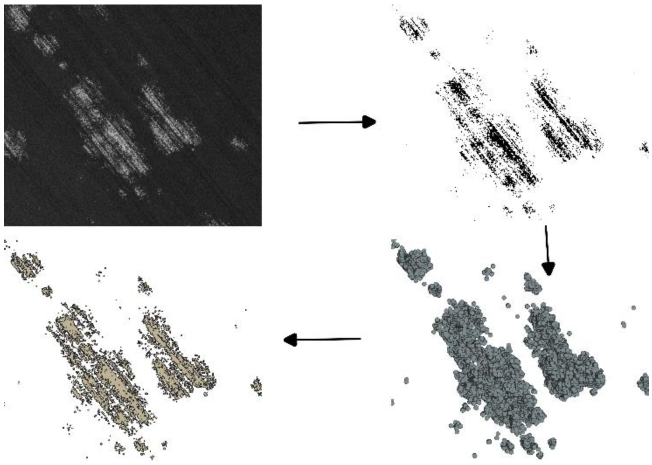

Fig. 4 Example of thresholding NDVI.

The Accuracy Assessment Tool was used with ArcGIS Pro software to estimate the accuracy of classification algorithms. In total, 500 randomly stratified samples. These points contain classified values of all algorithms and the ground truth value based on visual verification. Based on that, a Confusion Matrix was calculated to determine the accuracy of each algorithm. Algorithm accuracy was expressed based on the overall accuracy (OA) and the Kappa coefficient [18]. OA quantifies the level of agreement between two classes (weed and soil), and it is calculated from a number of True positive (TP) samples, which represents classification that matches with the truth and from True negative (TN) samples, which were misclassified. Using (1), the OA was calculated. The percentage ranges from 0-100 %; a higher number indicates a more accurate classification [19].

$$OA = \frac{True\ Positive + True\ Negative}{Number\ of\ samples} \times 100 \tag{2}$$

Meanwhile, the Kappa coefficient represents the level of agreement between two classes corrected by chance. Kappa takes into account the number of samples that are assigned to each class. If the validation points are predominantly represented in one class, the OA will be higher regardless of the number of elements in the other. The level of the Kappa coefficient ranges from 0-1 and provides information if the classifier is better or worse than by random chance. A higher number indicates a more accurate classification. The Kappa coefficient is calculated using (3) from OA and Chance Agreement, which is calculated as the sum of the product of row and column totals for each class [19], [20].

$$Kappa\ Coefficient = \frac{OA + chance\ agreement}{1 - chance\ agreement} \tag{3}$$

III. Result and Discussion

The results of Accuracy Assessment Tool are presented in Table I. The accuracy of the Maximum Likelihood algorithm was 97.8 %, and the Kappa coefficient was 0.633 with an area of 3,643 m^2 as a weed detected. In contrast, the SVM algorithm performed better with an accuracy of 98.2 %, and the Kappa coefficient was 0.792, an area of weed coverage map increase of 5,233 m^2. When comparing those two algorithms, SVM produced more accurate results than ML. In terms of OA, both models performed well. However, the higher Kappa coefficient by SVM indicates a more accurate one. This confirms that SVM performs better in small training sample sizes than other models [19].

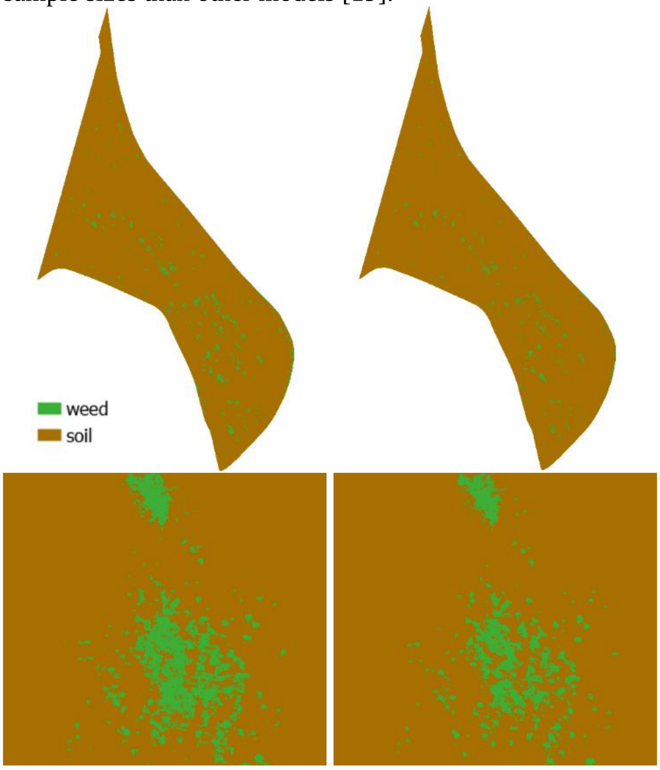

Fig. 5 Classified image by SVM algorithm on the left and ML on the right with the class of weed (green) and mixed bare soil and crop (winter wheat in early stage, brown color)

The detection algorithm by Pix4Dfields software achieved the lowest accuracy; the evaluated accuracy was 96.2 %, but the Kappa index was 0.599. The weed coverage was 5.01 %, representing an area of 7,942 m^2. However, we must remember that the algorithm runs in a square grid (1 m), leading to a higher misleading value. Even though the algorithm achieved the lowest accuracy, the software is applicable in practice and often used by farmers. If a detected weed is even partially in the square, it is marked as a detected weed. This leads to a larger detected area and a higher probability that the algorithm's accuracy based on the point validation data will be lower. After automatic evaluation of the detection, cleaning up the map square by square is possible, which can lead to a good result. Due to the inability to save the training dataset, it is time-consuming to label the grids for each field and then manually clean up the map.

The thresholding method achieved the highest accuracy, with an overall accuracy of 98.6% and a Kappa index of 0.836; the detected area was 8,817 m^2. The accuracy of the vegetation index thresholding method depends on the precise determination of the threshold value, which is determined subjectively based on the distribution of histogram values [21]. This method was the most accurate of the four used in this comparison. The detected area was the highest, and this size can be affected by setting the distance in the buffer tool. Using the buffer tool with dissolve result will simplify the map; the larger the buffer distance, the fewer the polygons and the smaller the map size. However, with a larger buffer distance, the savings from herbicide application are reduced.

TABLE I.
VALUES OF OVERALL ACCURACY, KAPPA COEFFICIENT AND WEED COVERAGE IN THE INVESTIGATED METHODS

Method	Overall accuracy	Kappa coefficient	Weed coverage
ML	97.8 %	0.633	2.29 %
SVM	98.2 %	0.792	3.30 %
Pix4Dfields	96.2 %	0.599	5.01 %
Thresholding	98.6 %	0.836	5.56 %

Creating a weed coverage map for multiple parcels using Pix4Dfields software is time-consuming. Still, the classification tool is intuitive, and even if it does not achieve such accuracy, there is an option to clean up the map. The thresholding method requires basic knowledge of geoinformation software (GIS). It places higher demands on the user's knowledge, but it presents a fast and accurate way of creating weed maps that can be automated to some extent. From the two machine learning-based methods, the SVM is more accurate than ML, but both have a lower detected area than the other methods tested in this paper. However, they require more advanced knowledge of GIS, model parameter settings, and sample collection training. From this perspective, thresholding methods and the Pix4Dfields classifier are more suitable for farmers. However, it also depends on other factors, such as the area of the detected plots, the knowledge of the detection procedures and the software used, and the time possibilities of the grower.

IV. CONCLUSION

The results indicate that the thresholding method achieved the highest accuracy based on the Kappa coefficient and overall accuracy, while Pix4Dfields had the lowest. Among the supervised methods, SVM outperformed ML.

The identification of weed infestation by UAV imagery has shown that only a small part of the field area is covered by weeds (up to 5.56 %). Thus, site-specific spraying can significantly reduce the amount of herbicides. From the four verified weed detection algorithms, the thresholding achieved the highest accuracy (98.6%, Kappa index 0.836). However, the detected area of the weed occurrence was the highest (5.56 %).

Reference [22] confirms that saving herbicides could be more than 90 % in specific scenarios. This offers the opportunity to target herbicides in an environmentally friendly way, with less impact on crops and lower costs.

Further research will be necessary to optimize the parameter settings of the algorithms and to verify their effectiveness under different conditions. This would allow more accurate identification and localization of weeds, thereby increasing the efficiency of herbicide application and minimizing their negative impact on the environment. Future work will also incorporate other different algorithms to further increase the accuracy and reliability of weed detection.

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