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Evaluating the Use of Very High-Resolution RGB Imagery from UAV for Vegetation Classification

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Abstract— The article explores using very high-resolution RGB data from unmanned aerial vehicles (UAVs) to explore the possibilities of utilizing data to monitor vegetation. The Baroch nature reserve, located in the Pardubice region of the Czech Republic, is used as an area of interest. Data is collected using the UAV DJI Mavic 2 DUAL Enterprise. The reserve is overgrown mainly with reed and cattail and is used as a pasture. The paper aims to determine the effectiveness of utilizing UAV technology and very high-resolution RGB data to identify, monitor, and classify vegetation types in this grassy habitat and to provide insights into the practicality of using such data for ecological research and landscape management purposes.

Keywords—UAV, Data Processing, Supervised Classification, Unsupervised Classification, RGB Data

I. INTRODUCTION

Currently, the utilization of remote sensing data for monitoring changes in protected areas has great potential and importance [1]. Modern technologies, like satellites or drones, allow us to obtain large amounts of high-quality data. These technologies provide an easy and efficient way to get information about the state of the landscape and monitor its development over time [2]. In particular, grassland habitats are very valuable in terms of biodiversity because they provide a suitable environment for many plant and animal species. Changes in these habitats can impact the entire ecosystem, so monitoring their development and taking measures to maintain and protect them is crucial. [3,4]

With the help of remote sensing data, we can monitor many different characteristics, such as vegetation density, land cover, water regime, temperature and humidity of the environment [5,6]. This information allows us to evaluate the state of the landscape and assess what changes are happening in it. One option to monitor these characteristics is to classify data from remote sensing.

During the classification process, the measured radiometric values of pixels in an image are replaced with information values corresponding to specific classes. The type and content of information values used in classification depend on the nature of the problem being addressed. For example, in land cover classification, the information values may correspond to different land cover types, such as forests, urban areas, or water bodies. Classifiers are used in the classification process to assign pixels to specific classes based on their information values. A classifier is a mathematical algorithm that maps the measured radiometric values of a pixel to a specific class label. There are various types of classifiers. The classification accuracy depends on several factors, including the quality and quantity of training data used

to develop the classifier, the suitability of the classifier for the specific problem at hand, and the complexity of the image and the classes being classified. [7]

There are two main types of classification, namely, supervised classification and unsupervised classification.

In supervised classification, cells are classified based on pre-trained training sets. These sets are chosen from the classified image. They should correspond to the information category. As part of the supervised classification process, detecting classification errors when exploring training data is possible. Inaccurate classification of training data presents problems in classifying or selecting training areas. [8]

Supervised classification is based on the knowledge and experience of the user who performs this method and his knowledge of the area of interest. The result of the classification may be distorted by the user's subjective view or misleading due to incomplete knowledge or ignorance of the field. [9]

On the other hand, in unsupervised classification, there is minimal possibility of human error, as the human factor only decides the number of classification classes. Unsupervised classification is based on data and is automatically optimized according to clustering statistics, where each cell is clustered and labelled with the same symbol or colour. Knowledge of the area of interest is optional for performing unsupervised classification, but this knowledge is necessary for interpreting the results. [10]

The article [11] deals with the classification of grasslands using various methods. The study uses automatic and semi-automatic classification methods to classify several grasslands from RGB images captured by unmanned aerial vehicles (UAVs) in the Western Italian Alps. The manual photo interpretation was the most accurate method, followed by the pixel-based approach. These data and methods were limited because they struggled to classify shadows accurately.

Study [12] evaluated using RGB imagery from a DJI Mavic Pro drone for wetland vegetation classification at the species level in Honghu. Object-based image analysis and machine learning algorithms were used, with random forest performing the best overall accuracy. The study found that multi-feature combinations and feature selection improved classification accuracy. Despite limited spectral information, the author's results indicate that using UAV-based RGB imagery and the OBIA approach is a powerful and straightforward method for wetland vegetation classification.

Paper [13] compares RGB and Multispectral sensors from UAVs for monitoring vegetation, bare soil, and dead matter in landslide areas. The Multispectral UAV had high accuracy (> 95 %) for identifying all land cover types, while the RGB UAV had lower overall accuracy. The RGB UAV was reliable

for vegetation monitoring and had high accuracy for the vegetation class over time. Both UAVs showed similar patterns of vegetation and bare soil. The study states that an increase in vegetation corresponds with a decrease in bare soil.

The study [14] evaluated articles dealing with grassland ecosystems using remote sensing. In this case, the evaluation was based on 253 articles that used satellite data to assess grassland production and support grassland management. More automatized workflow is needed, according to the authors.

II. DATA AND METHODS

This paper explores the possibilities of utilizing very high-resolution RGB data from unmanned aerial vehicles.

A. Area of Interest

The area of interest of this paper is the Baroch nature reserve, located in the Pardubice region of the Czech Republic. The reserve is located near the municipality of Hrobice, north of the regional city of Pardubice. It is situated at an altitude of 225 meters and covers an area of approximately 31 hectares. The nature reserve is located on the site of the former Baroch Pond and is formed by lagoons connected by canals and wetlands. The pond has no inflow and therefore depends on rainfall. The large area is overgrown, mainly with reed and cattail.

Since 2020, this area has been used as a pasture for Exmoor ponies [15]. These horses help maintain grassy habitats. [16]

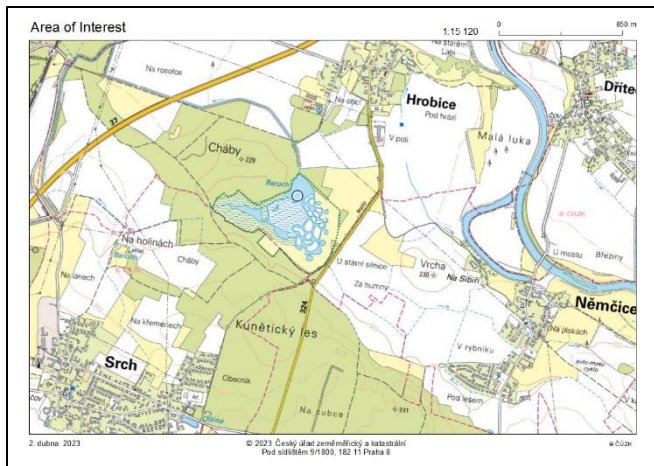


Figure 1 Area of Interest

B. Data Collection

The data was collected as part of regular monthly imaging of the area of interest in 2022 using the UAV DJI Mavic 2 DUAL Enterprise. It is a commercial quad-rotor system from DJI weighing up to 900 g and with a flight time of up to 30 minutes. The drone is equipped with an RGB spectrum imaging sensor, a 1/2.3" CMOS sensor with effective pixels of 12M and a FOV of 85°. It captures outputs in JPEG format with a resolution of 4056x3040 (4:3) or 4056x2280 (16:9). The second sensor is an Uncooled VOx Microbolometer thermal camera with a FOV of 57° and a resolution of 640x480 (4:3) or 640x360 (16:9). The thermal sensor images were not used in this study. [17]

A standalone flight was conducted based on a pre-planned route in Pix4D mapper software with a front and side overlap of 60%. In total, 128 images were captured during the flight. The data collected this way were used to create a mosaic of the area of interest. Images obtained by UAV have very high spatial resolution, specifically 2 cm per pixel. The data was captured on June 26, 2022, between 12 am and 12:30 am. The mosaic of the area of interest was created from that data in Tiff format [18]. A preview of the mosaic is shown in Figure 2.



Figure 2 Example of a mosaic of the area of interest - June 2022

C. Data Processing

A smaller area of interest with an area of 35 m by 35 m was selected to reduce computational complexity.

In this area, which serves as pasture, trees, bushes, tall grasses, and low vegetation, such as trampled and grazed vegetation, can be observed. Additionally, paths and bare soil are visible.



Figure 3 Cropped area of interest

Four land cover classes were selected for classification in the chosen area: high vegetation, low vegetation, bare soil, and shadows. These elements are present in the area of interest. High vegetation is represented by trees, bushes, and tall grasses, which cast shadows. Low vegetation is represented by grasses, grazed vegetation, and trampled vegetation. Bare soil class is present in the areas of paths and dry patches of ground.

Shadows were selected as the final class because, even though the optimal time around noon was used for capturing the images, trees, bushes, and tall vegetation still cast shadows. Although these helped determine the training set for supervised classification of the high vegetation class, it is impossible to estimate where a particular element ends and whether it casts a shadow on another element, as shown in Figure 4.



Figure 4 Tree shade

ArcGIS Desktop 10.5.1 was used as a software tool for data processing. Three methods were used for classification in ArcMap. These are the unsupervised classification IsoCluster and supervised classifications Maximum Likelihood and Support Vector Machine.

Maximum Likelihood classification is one of the most common supervised classification methods in remote sensing. The principle is statistical pattern recognition, where the probability of a pixel being assigned to predefined classification classes is calculated. Then, based on the calculated probability, the pixels are assigned to their respective classification classes according to the highest probability. [8] In the Maximum Likelihood classifier, the reject fraction attribute was set to 0, which means that every cell was classified. Another setting was the prior probabilities attribute, where Equal was chosen. This means that all classified classes have the same prior probabilities.

The SVM (Support Vector Machine) classifier is a supervised learning method that classifies data into two groups separated by a hyperplane. The algorithm aims to find a hyperplane that maximizes the distance between the classes. The advantage of the supervised classification SVM is that it is less prone to noise and unbalanced training set sizes. [19] The attribute max samples per class in the SVM classifier settings was changed to a value of 0, which means that the classifier will use all the elements from the training sites to train the classifier.

The IsoCluster classification method is based on the K-mean method. In this case, it is necessary to define the number of classification classes and the number of algorithm iterations. This method assigns pixels to clusters divided according to their standard deviation. Clusters close to each other are merged, and classes containing a small number of pixels are eliminated. Their contained pixels are reclassified into the nearest clusters. [20]

The classifier IsoCluster was configured by setting the number of iterations of the clustering process to 20 and the minimum number of cells in a valid class to 20. The interval for sampling was set to 10. The last parameter that was changed was the number of classes. Several variants were tested within this parameter, usually multiples of 3 or 4. The best result was achieved by classifying 24 classes, which were then reclassified into bare soil, low vegetation, and high vegetation.

The Kappa coefficient was calculated for one thousand generated accuracy assessment points in ArcMap software, where the points were randomly distributed over the area to compare the classification. Then, one of the classified categories was manually assigned to them. The Kappa coefficient represents an accuracy indicator that compares classification accuracy with the accuracy of random pixel assignment, i.e., the agreement of pixel assignment between the selected classifications. [21]

III. RESULTS AND DISCUSSION

The Kappa coefficient was calculated for each classification with values of 0.58 for the IsoCluster method, 0.89 for the Maximum Likelihood method, and 0.85 for the Support Vector Machine method. It reveals that Maximum Likelihood and SVM provided good classification results, while IsoCluster did not.

Table 1 shows the area in square meters of particular land cover types obtained by each classification method.

TABLE I. AREA OF LAND COVER CLASSES

Classifier	The land covers area [m ²]				Kappa
	Bare soil	Low vegetation	High vegetation	Shadow	
IsoCluster	253.589	484.763	489.820	0	0.58
Maximum Likelihood	294.007	562.032	366.240	5.894	0.89
SVM	238,956	529,047	451,805	8.365	0.85

Figure 5 represents a visualization of all the classification methods performed in the area of interest from June 2022.

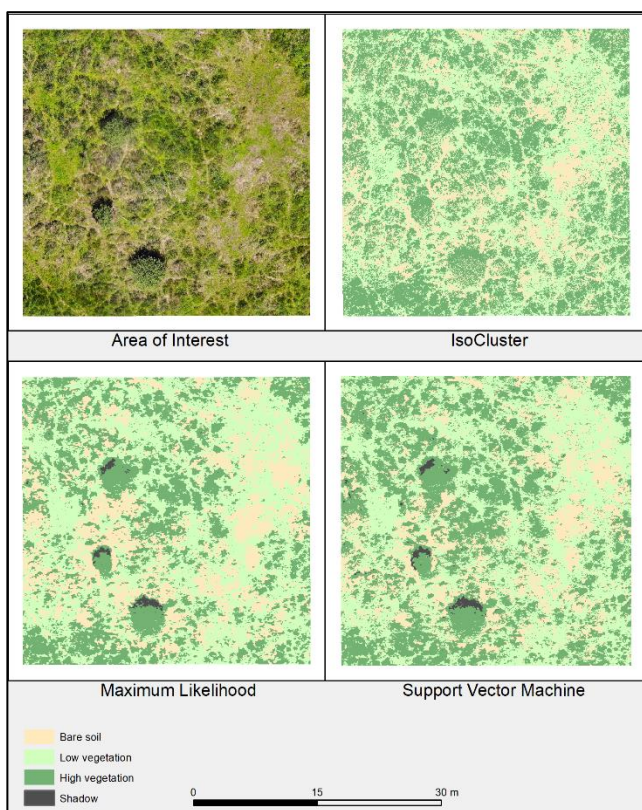


Figure 5 Results of Classifications

The Maximum Likelihood and Support Vector Machine classification methods have demonstrated their effectiveness in classifying bare soil and low vegetation in the image taken in June. However, these methods encountered difficulties in correctly identifying shadows cast by tall vegetation and areas with dry vegetation, often classified as bare soil.

Despite these challenges, these classification methods can potentially be used for the annual monitoring of changes in high vegetation, such as those caused by grazing. In particular, very high-resolution RGB images captured by UAVs can be used for this purpose, provided that optimal conditions for classification are met. These conditions include the elimination of shadows and high contrast between vegetation and bare soil, which are most pronounced between the spring and summer seasons. By utilizing these methods, changes in vegetation representation can be monitored over time, enabling land managers to make informed decisions on

grazing management practices and other conservation measures.

Figure 6 shows the Maximum Likelihood classification results.

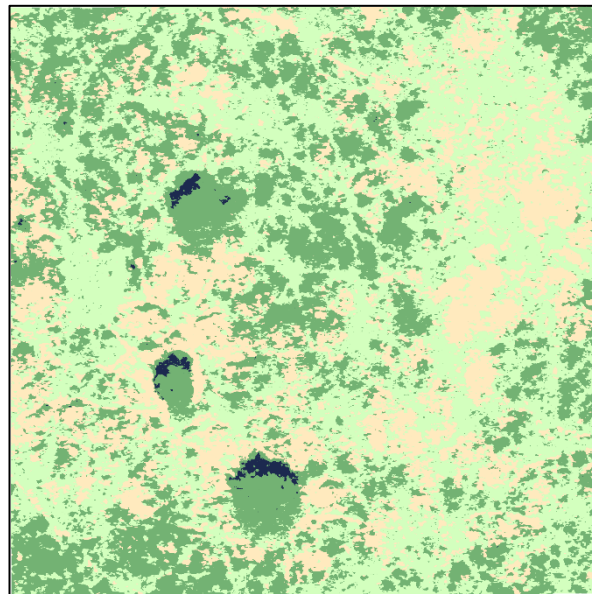


Figure 6 Maximum Likelihood Classification

Figure 7 shows a transparent display of the area of interest and the classification performed using the Maximum Likelihood method.

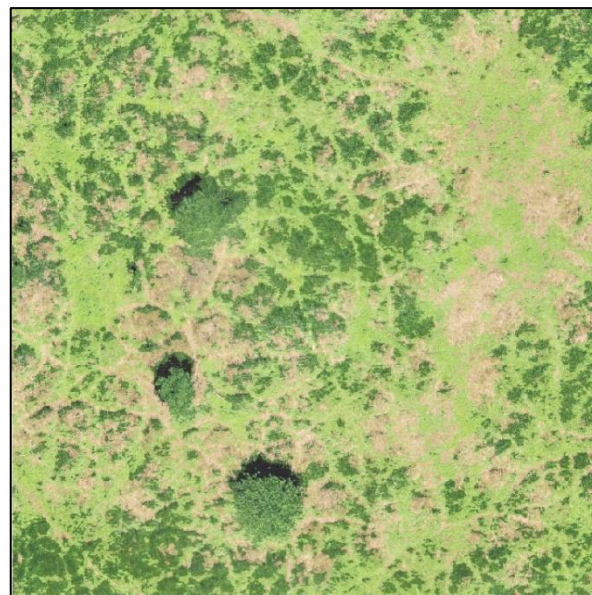


Figure 7 Transparent display of the area of interest and Maximum Likelihood classification

IV. CONCLUSIONS

This study addressed the issue of using very high-resolution data (2 cm per pixel) from UAVs to observe changes in the surface of a pasture where Exmoor ponies are used to maintain grassland habitats. For this purpose,

classification was performed using the classic methods of IsoCluster, Maximum Likelihood, and Support Vector Machine for high vegetation, low vegetation, bare soil, and shadows.

The results show that these methods can be used for RGB data processing under optimal conditions, such as avoiding shadows and requiring a high contrast between the classes in the area of interest.

Furthermore, using UAVs for remote sensing can provide faster, more frequent and cost-effective grassland habitat monitoring than traditional ground-based methods.

Future work will focus on reducing the impact of shadows in the area of interest, which could help improve the quality of classification methods.

ACKNOWLEDGMENT

This paper was supported by SGS University of Pardubice project No. SGS_2023_013.

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