Utilization of UAV-Borne RGB Data for Monitoring Horses: Comparison of Classification Methods

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Abstract — **The paper describes utilizing remotely sensed RGB data to support monitoring horses in a natural environment on demand. Data are sensed using an unmanned aerial vehicle (UAV). UAVs provide very high spatial resolution data sensed at a low altitude on demand. Sensing is limited by weather conditions and legal rules only. Terrain does not need to be accessible. The paper provides a comparison of several pixel-based and object-based classification methods, namely Maximum Likelihood, Random Trees, SVM, and K-NN. Manual classification is used as a reference method.**

Keywords – UAV; live animals monitoring; imagery; pixel-based classification; object-based classification

I. INTRODUCTION

Monitoring live animals and their movement in wild nature is a very important issue to support their protection. The natural environment of animals may not be accessible. Direct in-situ monitoring by people entering the environment may undesirably disturb animals, and it is a time-demanding approach. Camera traps require in-field installation and maintenance, which can still cause animal disturbances.

Remote sensing is another available option. It can decrease the level of interaction of humans with the wild environment and the disturbance of wild animals. It allows monitoring in not accessible terrain and can fasten the monitoring. It can decrease the costs of monitoring, especially in the case of large areas. Traditional carriers, i.e. satellites and aeroplanes, provide data with medium spatial resolution only in many cases; they are not available on demand (many satellite systems); they are costly.

UAVs are increasingly understood as the most appropriate carrier for data sensing for smaller areas and in suitable weather conditions. They can provide very-high spatial resolution data sensed at very-low altitudes on demand, of course, with respect to the law and weather limitations.

Monitoring of various mammal species in their natural and wild environment has been conducted by environment protection agencies and natural reserve employees for many various reasons. Large mammals monitoring in nature reserve to support their breeding and enlargement of the population [1]; hippopotamus monitoring [2]; animal monitoring to prevent collisions in areas with high vehicle traffic, including aeroplanes [3]; or monitoring livestock population dynamics [4] can be given as examples.

Various classification techniques can be used to process collected data. Deep learning methods are increasingly used. In study [3], CNN and ResNet provided enough accurate classification results for identifying four animal species. CNN was successfully used to conduct animal census too [2] and to process multispectral aerial imagery to identify mammals in Africa [5].

The main aim of the paper is to compare chosen pixel-based and object-based methods for identification of horses using RGB UAV-borne data. Wild horses are placed in the wild nature (area of interest – see Section II) to support the landscape management of the area and growth of several protected plants. Horses should be remotely observed using medium-class or even low-cost UAV to verify that they are alive. There is no requirement on real time monitoring.

The rest of the paper is organized as follows. Area of interest is described in Section II, data collection and pre-processing in Section III, data analyses in Section IV. Section V provides discussion and Section VI conclusion.

II. AREA OF INTEREST

Area of interest is situated close to Pardubice city in the Pardubický region, the Czechia. Figure 1. shows its location and the surrounding.

The paper is focused on observation of a part of the nature reserve named Baroch, close to the Hrobice municipality. The total area of the nature reserve is 0,314 km2. Occurrence and nesting of rare bird and occurrence of several protected plant species are key reasons for its protection [6]. A small herd of wild horses have been moved to the reserve to support its management two years ago.

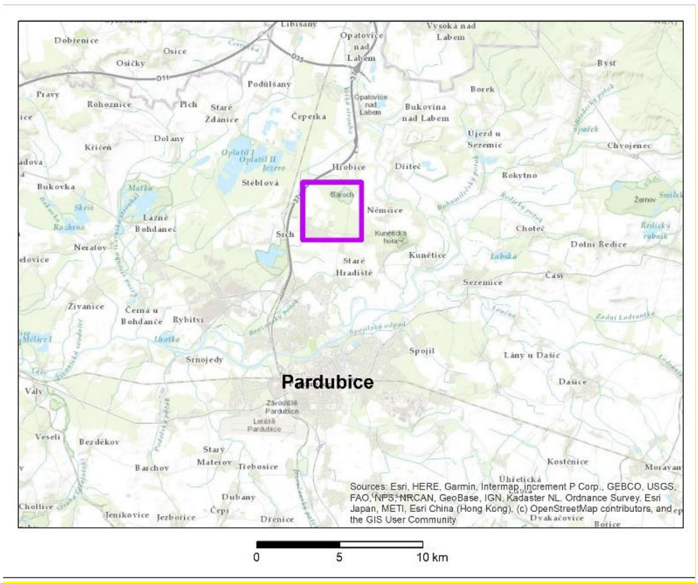


Figure 1. Location of the nature reservation Baroch, source: [8]

III. Data Collection, Pre-Processing, Software

The methodology consisted of the following steps:

- Flight planning
- Data sensing (flights)
- Data pre-processing (building mosaics); no atmospheric corrections were calculated because of the low altitude of the flight
- Manual classification (reference data)
- Classifications by particular classifiers
- Kappa coefficient calculation
- Results visualization and comparison

Pix4Dcapture application (for iOS, version 4.13.1) was used for planning flight and data acquisition. Pix4Dmapper (version 4.7.5) was used for image data pre-processing. Image data pre-processing provides methods for creating a mosaic from individual images. ArcGIS PRO (version 3.0.3) is the most commonly used GIS commerce software. In this paper, it was used for image classification.

DJI Mavic 2 DUAL (Figure 2.) was used as a data acquisition tool. DJI Mavic 2 DUAL [7] has the following characteristics: weight 899 g, maximal takeoff weight 1 100g, 4 motors, max speed 72 km / h, maximal range (CE mode) 5 000 m, maximal flight time 31 minutes. The UAV has wind protection up to 38 km/h and operation temperature from -10 °C to 40 °C. For safety, the UAV use a 4-direction visual protection system and visual and IR from the bottom. The drone has built-in dual camera. The first one is a 1/2,3” RGB camera with 12 Mpx resolution. The second one is an IR camera with 160x120 px sensor resolution. The UAV costs approx. 5000 EUR.

Figure 2. DJI Mavic 2 DUAL, source: authors

The nature reservation was observer on June 28, 2022. For data collection, in advance planned flight was used. The following parameters were set: flight level (altitude) 60 m, total length of the flight was 2752 m, size of observed area was 0,0285 m^2, the flight was planned in 8 lines with 65% overlap from both sides. In total, 128 images, all RGB only, were taken. Flight duration was 21 minutes 40 seconds and it covered area 280x394 m. The UAV provides very high spatial resolution data, in this case the spatial resolution is 2,18 cm/px. Output coordinate system is WGS 84 – UTM zone 33.

The atmospheric correction was not calculated because of the low altitude (60 m) and good weather conditions. The geometric correction was not calculated as well. Coordinates are recorded during the flight by the software itself.

IV. Data Analysis

Before classification begins, the image is segmented. The Figure 3. shows an example of segmentation with the following parameters: spectral detail = 16; spatial detail = 20; minimum segment size in pixels = 200. Due to the use of UAV images, we can afford to set the minimum segments to high values because image data taken from UAVs have a very high spatial resolution.

The following methods were used for data classification: maximum likelihood (ML), random trees (RT), SVM, and K-NN, all as pixel-based and object-based methods. Manual classification was used as a source of reference data.

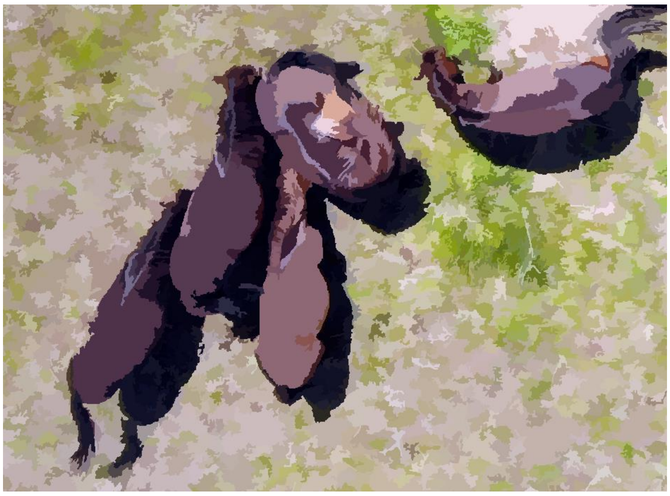


Figure 3. Example of image segmentation, source: authors

There were also errors in the classification because the shadows of the animals were classified in the same class as the animals themselves (see Figures 4., and Figure 5.). However, this is a limitation that is dealt with within RGB images.

Figure 4. Horse and its shadow classification, source: authors

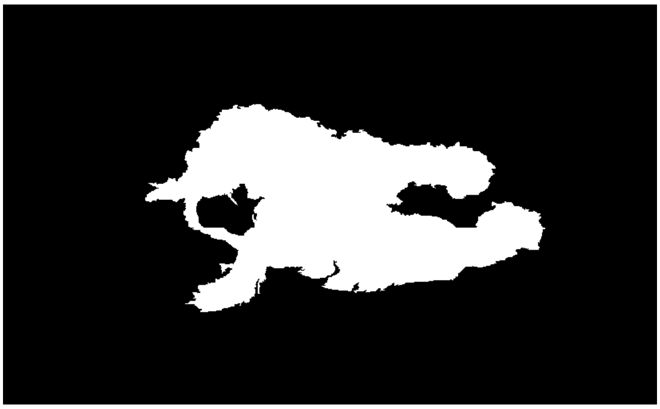


Figure 5. Horse and its shadow classification, reclassification emphasizing horses, source: authors

Data for further verification was obtained using a thermal camera placed in the UAV body. When compared with the RGB image, taken from the same location, it can be seen that the animals are feeding from a bright spot that has accumulated heat and appears as animals in the thermal image (see Figure 6.).

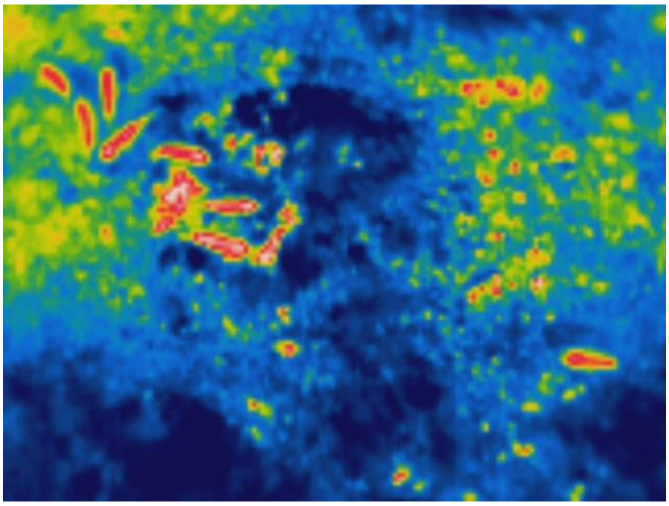
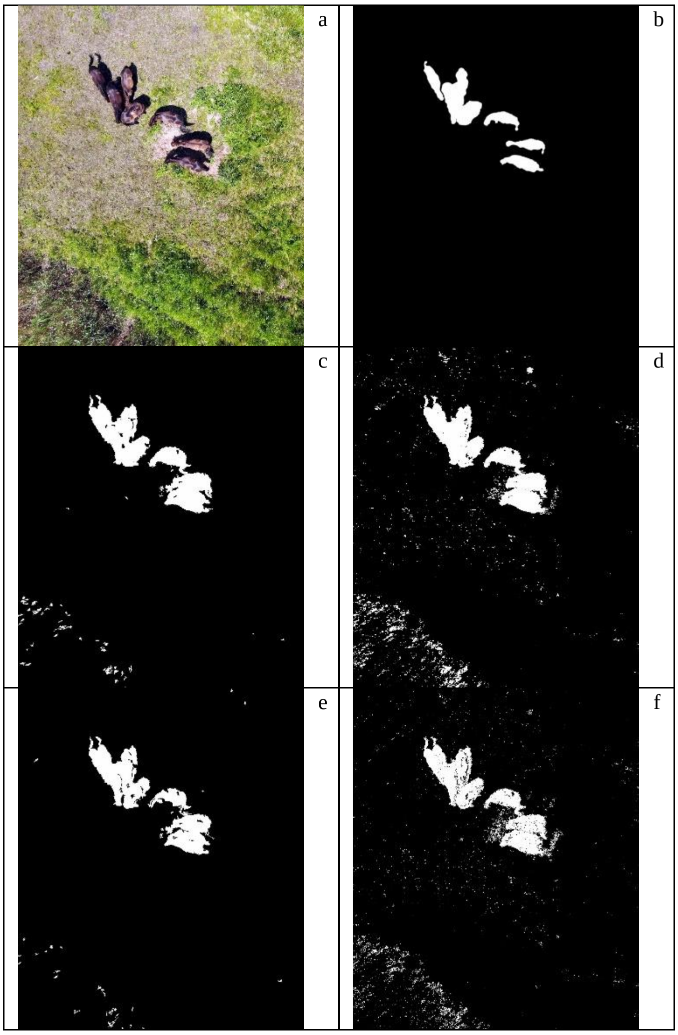


Figure 6. Example of image segmentation, source: authors

The results of the classification by all methods are shown in Figure 7.



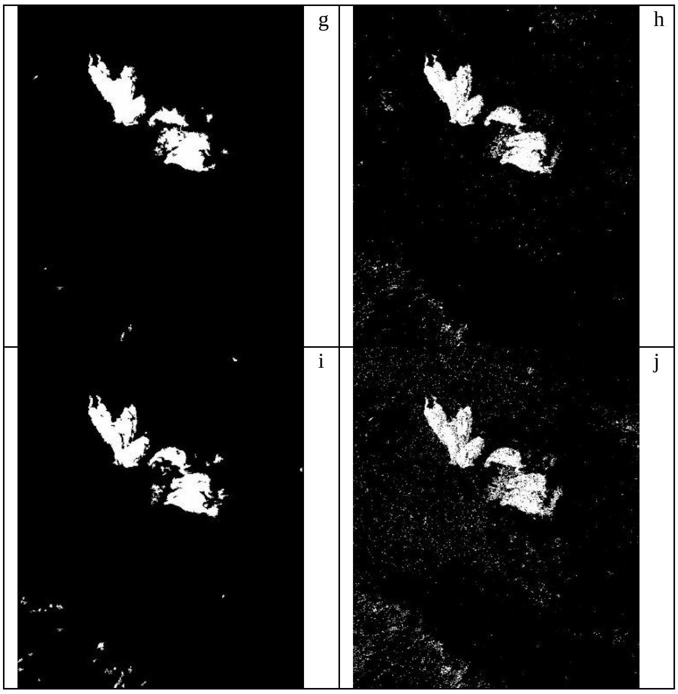


Figure 7. Results of classification: a) source data; b) manual classification; c) object-based maximum likelihood; d) pixel-based maximum likelihood; e) object-based random trees; f) pixel-based trees; g) object-based SVM; h) pixel-based SVM; i) object-based K-NN; j) pixel-based K-NN, source: authors

Kappa coefficient was calculated based on the random placement of 100 points to verify the precision of classification (see Table I and Figure 8.).

TABLE I. RESULTING KAPPA COEFFICIENT (100 POINTS – RANDOMLY GENERATED)

Method	Kappa
Ref. Data	1
Pixel_ML	0,586
Pixel_RT	0,555
Pixel_SVM	0,713
Pixel_KNN	0,462
Object_ML	0,645
Object_RT	0,689
Object_SVM	0,739
Object_KNN	0,603

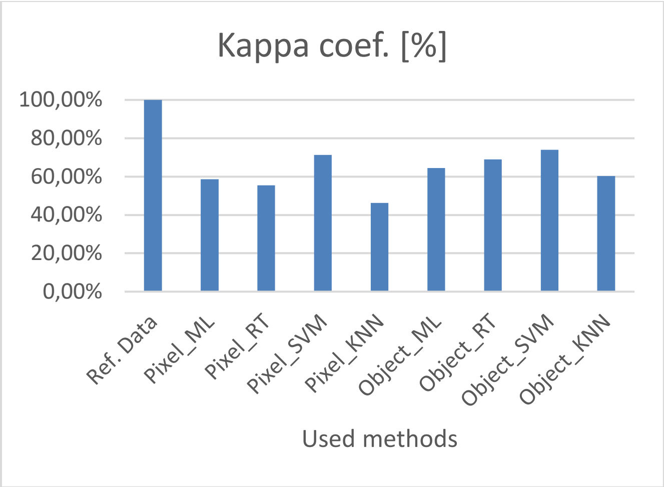


Figure 8. Comparison of methods – resulting kappa, source: authors

Data from different parts of the preserve and with lower spatial resolution were used to verify the results of the methods. For this image, the segmentation settings had to be reduced to 50px (because of the lower spatial resolution, but still higher than the aerial images). Figure 9. shows the input image, and Figure 10. reference data obtained by manual classification.

Figure 9. Input image, source: authors

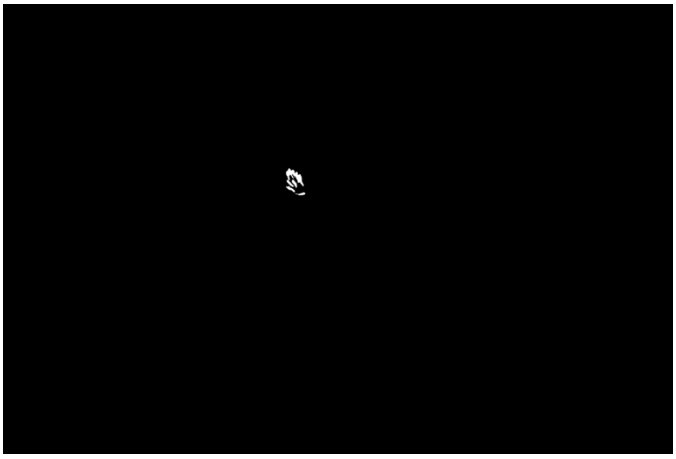


Figure 10. Reference data – the result of manual classification, source: authors

Again, Kappa coefficient was calculated based on random placement of 100 points to verify the precision of classification (see Table II and Figure 11. Figure 8.).

TABLE II. RESULTING KAPPA COEFFICIENT (100 POINTS – RANDOMLY GENERATED)

Method	**Kappa**
Ref. Data	1
Pixel_ML	0,094
Pixel_RT	0,116
Pixel_SVM	0,118
Pixel_KNN	0,062
Object_ML	0,121
Object_RT	0,349
Object_SVM	0,212
Object_KNN	0,233

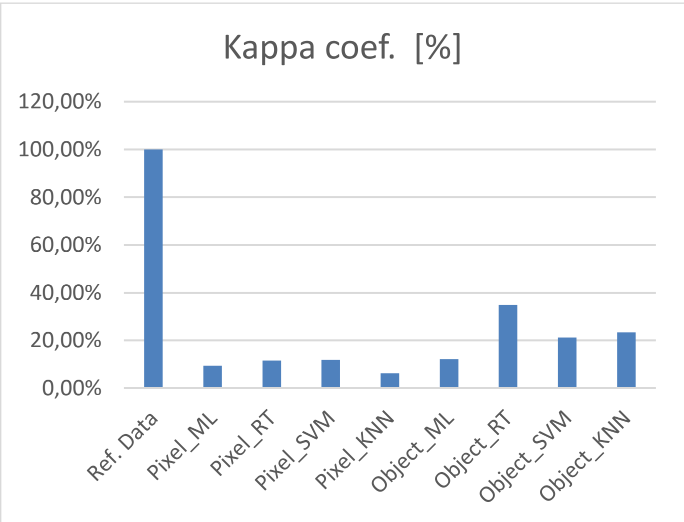


Figure 11. Comparison of methods – resulting kappa, source: authors

Such low results are achieved because the animals take up very little space in the image. Next, there is a spectral limitation of RGB images – the same or very similar colour may represent both horses and bare land.

Object-based random trees provided the best classification results by the Kappa calculation (see Figure 12.

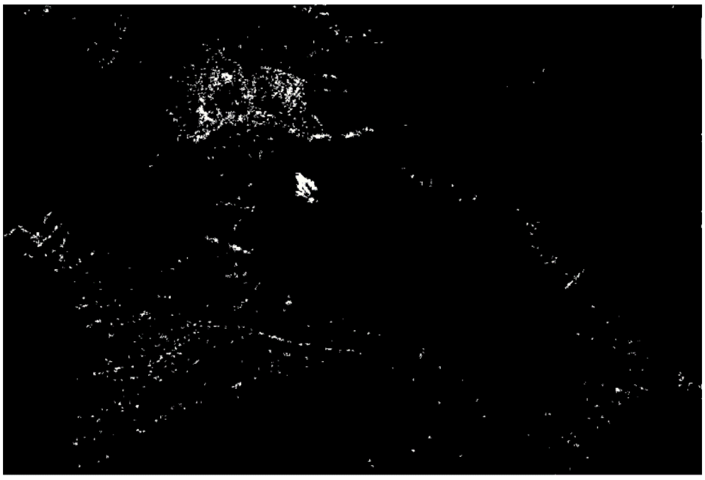


Figure 12. Classification results – object-based random trees, source: authors

The majority filter was applied six times to the best classification results. Unfortunately, utilization of the very high spatial resolution data leads to low improvement (see Figure 13.).

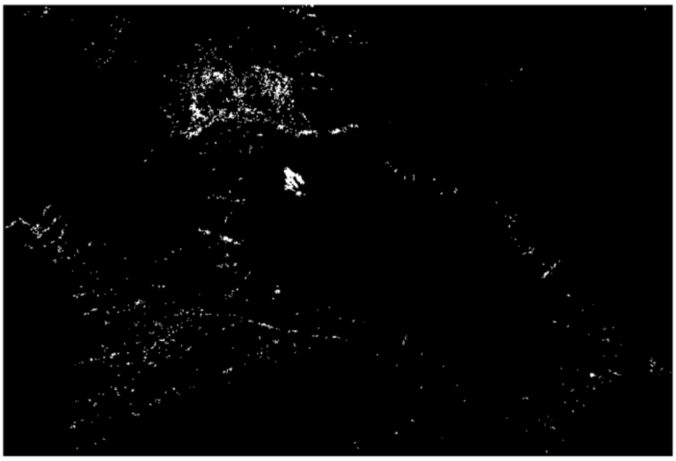


Figure 13. The output of application of majority filter to the result of object-based random trees classification, source: authors

V. DISCUSSION

Obtained results demonstrate that large mammals can be successfully identified by automatic classification of UAV-borne data, as shown by other authors [1], [2]. Our results show that even RGB data (visible bands of electromagnetic spectrum) can be successfully used.

Of course, RGB bands also represent the key limitation of large mammals. Classification results depend on the colours in the visible spectrum only. It, among others, leads to lower classification precision and decreases the ability to distinguish between the animal and its shadow.

VI. Conclusions

Mammals monitoring can significantly support and ease their protection in wild environment. UAVs can provide very detailed data on demand. Low and middle-class UAVs are usually equipped with a standard RGB camera. The paper shows that it is possible to monitor mammals even using data collected by these UAVs.

Various object-based and pixel-based classification methods were used, namely maximum likelihood, random trees, SVM, and K-NN. In general, object-based methods provided better results. Imagery with a higher spatial resolution led to better results in our case.

For future work, it is planned to use deep learning classification and YOLO and compare new results to already obtained results. Additionally, the identification of shadows of big mammals should be addressed.

Acknowledgment

The authors thank the University of Pardubice, Students grant competition, SGS_2023_13 project for the support.

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