The Evaluation of the RGB and Multispectral Camera on the Unmanned Aerial Vehicle (UAV) for the Machine Learning Classification of Maize

Analiza RGB i multispektralne kamere na bespilotnome zrakoplovu za klasifikaciju kukuruza strojnim učenjem

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THE EVALUATION OF THE RGB AND MULTISPECTRAL CAMERA ON THE UNMANNED AERIAL VEHICLE (UAV) FOR THE MACHINE LEARNING CLASSIFICATION OF MAIZE

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SUMMARY

This study investigated a crop and soil classification applying the Random Forest machine learning algorithm based on the red-green-blue (RGB) and multispectral sensor imaging deploying an unmanned aerial vehicle (UAV). The study area covered two 10 x 10 m subsets of a maize-sown agricultural parcel near Koška. The highest overall accuracy was obtained in the combination of the red edge (RE), near-infrared (NIR), and normalized difference vegetation index (NDVI) in both subsets, with a 99.8% and 91.8% overall accuracy, respectively. The conducted analysis proved that the RGB camera obtained sufficient accuracy and was an acceptable solution to the soil and vegetation classification. Additionally, a multispectral camera and spectral analysis allowed for a more detailed analysis, primarily of the spectrally similar areas. Thus, this procedure represents a basis for both the crop density calculation and weed detection while deploying an unmanned aerial vehicle. To ensure crop classification effectiveness in practical application, it is necessary to further integrate the weed classes in the current vegetation class and separate them into crop and weed classes.

Keywords: crop density, Random Forest, supervised classification, spectral analysis, normalized difference vegetation index (NDVI)

INTRODUCTION

Due to their rapid development, the unmanned aerial vehicles (UAVs) are increasingly influencing the changes in the economic and social sectors. They are increasingly deployed in agricultural production because of their affordable price and the benefits of agricultural land management. Thanks to the possibility of their deployment at low altitudes, by means of which they achieve a high imaging spatial resolution, they demonstrate a very high potential for their deployment in precision agriculture (Malamiri et al., 2021; Rodríguez et al., 2021). The UAVs facilitate data collection, with the aim of increasing the agricultural products' competitiveness and reducing a negative impact on the environment (Michels et al., 2020). Furthermore, they enable the obtainment of data with a high temporal resolution, which is extremely important for an early detection of crop diseases. Monitoring the crop condition in the early phenological stages may indicate the possible issues during crop development (Jurišić et al., 2021). Precision agriculture retrieves the data collected by remote sensing from various sources, thus empowering a farmer to make decisions about the necessary agrotechnical operations in the shortest possible time (Candiago et al., 2015). Despite these advantages, the deployment of UAVs in agricultural production still lags behind (Bramley and Ouzman, 2019). The conventional and most common procedure for determining crop density is performed by counting the plants per unit area on an agricultural parcel. The deployment of UAVs has a high potential to devise the automated methods that

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may cover an entire parcel, with the high-resolution photographs used to determine the exact crop location.

A basic RGB camera captures a standard form of photography in three channels for each pixel (red, green, and blue) and is very applicable in agriculture due to its affordability. A successful detection of vegetation and the determination of canopy cover height while using the photographs taken with an RGB camera was performed by Surový et al. (2018). A number of previous studies (Chang et al., 2017; Surový et al., 2018; Torres-Sánchez et al., 2018) used an RGB camera for the creation of 3D crop models. With this type of camera, the assessment of biomass on the agricultural parcels was also successfully determined (Viljanen et al., 2018; Roth et al., 2017; Grüner et al., 2019). Weed mapping in the early stages of development using a UAV was investigated by Castro et al. (2018), emphasizing that a high spatial resolution is required for a successful detection. In order to further improve classification accuracy, multispectral cameras were introduced, which, in addition to the visible spectral channels, commonly have a red edge and the near-infrared bands. Multispectral cameras are used to determine various vegetation indices, which primarily use these two additional spectral bands.

Due to a large amount of data and the shortening of decision time, the algorithms have been developed that accurately and efficiently perform classification (Rodriguez-Galiano et al., 2012). Several machine learning algorithms have been developed that are used in different classifications depending on the number and the type of the samples to be classified. The most commonly used are the artificial neural networks, decision trees, Random Forest, and support vector machines. The Random Forest (RF) machine learning algorithm is very often used due to its speed and robustness (Du et al., 2015; Radočaj et al., 2021). Du et al. (2015) investigated the sensitivity of the RF classifiers and stated that the number of selected samples in the intervals from 10 to 200 samples does not have a significant impact on the classification results' accuracy. This algorithm is very effective for classifying the UAV image data with a high spatial resolution, making it very suitable for mapping the agricultural parcels (Li et al. 2016; Lottes et al. 2017).

An increasing availability of UAVs having the different types of cameras mounted caused a necessity to determine the extent to which an RGB camera is usable to the farmer, without an additional investment in the expensive multispectral cameras. The aim of the research was to determine the influence of spectral imaging resolution by analyzing the RGB, multispectral camera, and spectral analysis on the accuracy of a machine learning classification on a maize-sown soil.

MATERIAL AND METHODS

The study area involved the two subsets of a maize-sown agricultural parcel having the dimensions of 10 x 10 m in the vicinity of Koška (Fig. 1). These subsets were imaged during different atmospheric conditions and especially regarding insolation, which was higher for the B subset. Topographic parameters of the terrain also affected a higher retention of precipitation on the surface of the A subset, as opposed to the B subset.

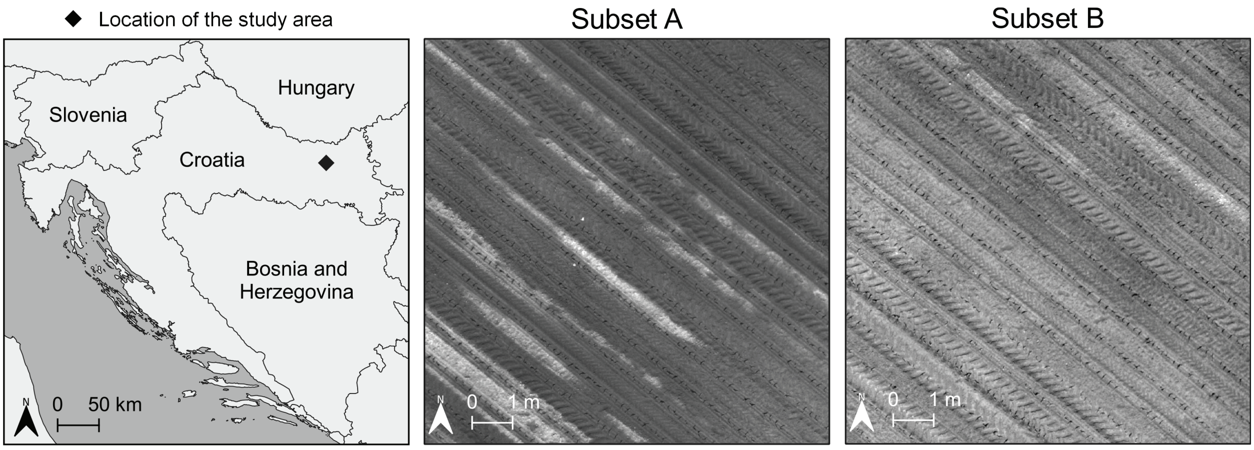

Figure 1. The location of the study area with two 10 x 10 m subsets
Slika 1. Područje istraživanja s dvama podskupovima dimenzija 10 x 10 m

A UAV flight with the DJI P4 Multispectral was performed on 21 May 2021, having started at 12:15 p.m. The multispectral camera used contained the blue (B), green (G), red (R), red edge (RE) and near-infrared bands (NIR). The chosen imaging time was justified by the reduction of an undesirable spectral noise caused by the shadows. The relative altitude of the flight was 30 m, with an 80% front and side overlap during the flight. A digital orthophoto with a spatial resolution of 1.0 cm was created in the *Agisoft Metashape v1.5.2*. The images were georeferenced in the Croatian Terrestrial Reference System (HTRS96/TM).

The ground-truth polygon samples were created, based on a field identification of land cover classes, containing 20 samples for the vegetation (maize) and 20 soil samples per subset. These samples were overlayed with the five spectral bands used, determining the mean value of the sample per band. Subsequently, the normalized difference vegetation index (NDVI) was determined as one of the most frequently used vegetation indices, given the reliable possibility of distinguishing between the vegetation and the soil (López-Granados et al., 2016). Based on these samples, a spectral analysis was performed per subset to determine the bands that made a reliable difference in the spectral values between the vegetation and the soil. Statistical analysis of spectral values from the vegetation and the soil indicated a spectral diversity of subsets to test the robustness of the method, comparing the classification accuracy under different imaging conditions. The *SAS Enterprise Guide 7.15* was used for the LSD0.05 statistical test, as a basis for spectral analysis.

The training and test data were created from the ground-truth data by a stratified random splitting in a 50:50 ratio. Based on the camera and complexity processing levels, three classification variants were evaluated by using the spectral bands from the following sources: 1) an RGB sensor, 2) a multispectral sensor, and 3) a spectral analysis in bands that had produced a reliable distinction between the vegetation and the soil. The RF algorithm of a supervised machine learning classification was used due to its computational efficiency and superior classification accuracy when compared with the similar algorithms (Breiman, 2001; Belgiu and Dragut, 2016). The *SAGA GIS software v7.9.1* was used to evaluate the accuracy of classification results based on the overall accuracy (OA) and the Kappa coefficient, while data visualization was rendered by the *QGIS v3.8* software.

RESULTS AND DISCUSSION

Spectral analysis by subset was performed on the selected samples, determining the spectral bands in which there was a reliable difference in values between the vegetation and the soil. Figure 2 represents the values of spectral analysis by individual spectral bands for the subsets A and B. The results for subset A manifested a significant difference in the spectral values between the soil and the crops in the RE, NIR,and NDVI values, while the highest spectral-value congruence was expressed in the G spectral channel. For the subset B, the largest differences were detected concerning the spectral values in the same spectral bands (RE, NIR, and NDVI, respectively), while the highest match was calculated for the R band. The spectral values distinguishing the weeds and crops on an agricultural land were also successfully applied by Che'Ya et al. (2021) and Norasma et al. (2020), emphasizing that the spectral values can detect the weeds in a shorter period than the conventional methods.

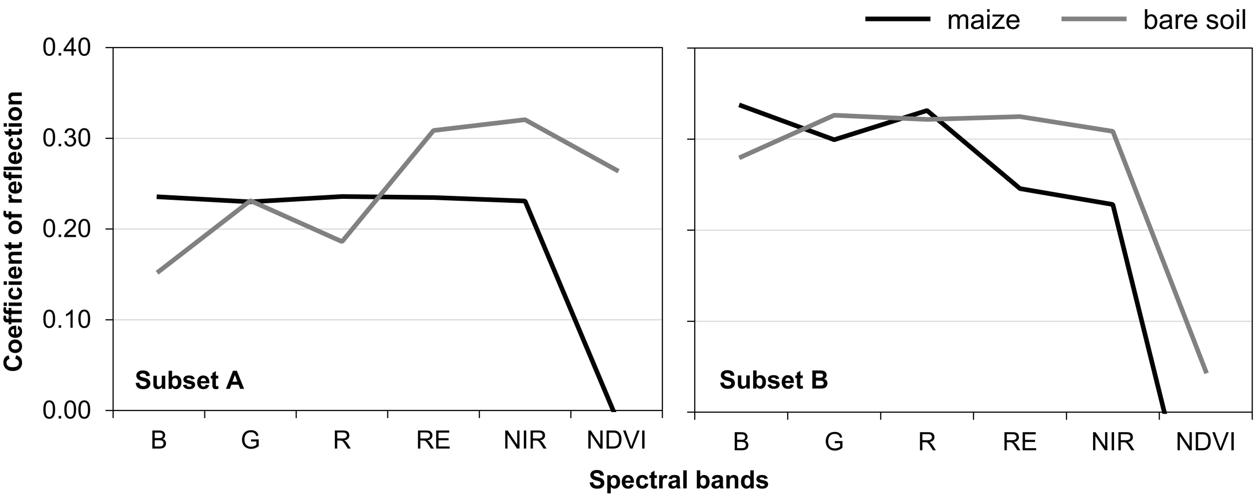

Figure 2. Spectral signatures of the ground-truth data for maize and bare soil
Slika 2. Spektralne krivulje referentnih podataka za kukuruz i golo tlo

The achieved results of the spectral values' LSD 0.05 test indicated a statistical significance between the subsets A and B by individual spectral bands from the crop and soil, except in the case of NIR and RE spectral channel for the soil and NIR for the crops (Table 1). This further indicates that the study objective of evaluating the robustness of the classification method under two different atmospheric and field conditions was attained.

Table 1. The results of the LSD 0.05 statistical test within the spectral analysis

Tablica 1. Rezultat statističkoga testa LSD0.05 unutar spektralne analize

Spectral band / *Spektralni kanal*	Bare soil / *Golo tlo*			Maize / *Kukuruz*		
	Subset A	Subset B	$LSD_{0.05}$	Subset A	Subset B	$LS_{D0.0}5$
B	0.33909[a]	0.23548[b]	0.0521	0.245318[a]	0.153391[b]	0.0168
G	0.29752[a]	0.22994[b]	0.0523	0.321010[a]	0.231317[b]	0.0155
R	0.33676[a]	0.23579[b]	0.0534	0.298606[a]	0.186142[b]	0.0206
RE	0.24093[a]	0.23481[a]	0.0517	0.332439[a]	0.308617[b]	0.0214
NIR	0.23085[a]	0.22291[a]	0.0503	0.325993[a]	0.320525[a]	0.0204
NDVI	-0.00865[a]	-0.20220[b]	0.0231	0.264990[a]	0.044480[b]	0.0377

Table 2 illustrates the results obtained by the RF classification method in the three selected classification variants. The highest achieved classification accuracy for the combination of RE, NIR, and NDVI, selected using the spectral analysis, is observed in both subsets. A notable difference in the results between the A and B subsets is due to the heterogeneity of the soil, caused by different humidity levels at the imaging time. A higher result accuracy pertaining to the conducted classification was obtained on the subset A in relation to the subset B due to the significant spectral differences between the soil and vegetation in the RE, NIR, and especially NDVI values. Due to lack of insolation, the atmospheric conditions negatively affected the results of classification accuracy assessment, which is particularly notable in the subset B.

Table 2. Classification accuracy assessment for evaluated classification variants

Tablica 2. Ocjena točnosti za analizirane varijante klasifikacije

Classification variant / *Varijanta klasifikacije*	Subset A / *Podskup A*		Subset B / *Podskup B*	
	Kappa	OA (%)	Kappa	OA (%)
RGB bands / *RGB kanali*	0.951	97.62	0.772	89.64
Multispectral bands / *Multispektralni kanali*	0.955	97.81	0.786	90.35
Spectral analysis (RE, NIR, NDVI) / *Spektralna analiza (RE, NIR, NDVI)*	0.998	99.81	0.815	91.77

Figure 3 displays the classification results of subsets A and B according to different classification variants, including the RGB, multispectral imaging, and spectral analysis. Similar observations were recorded in a number of scientific studies, in which it was proven that the use of vegetation indices significantly increases spectral differences between the observed classes (Gašparović et al., 2020; Solano et al., 2019; Villoslada et al., 2020). Regarding the observation of the OA values, the highest values in the same combination of spectral bands in both subsets were also achieved. RGB and multispectral bands did not allow for a reliable separation of the overall heterogeneity of soil from vegetation. It was observed that the RGB and multispectral classification resulted in a substantial amount of noise, which is primarily related to the topographic properties of permanent tractor traces, leading to the difficulties in the detection of spectral differences between the soil and the crops. This phenomenon is particularly pronounced in the southwestern and northeastern part of the subset A. With regard to the observation of classification with the RE, NIR, and NDVI spectral channels, which ensured a large spectral difference, the noise in the form of permanent tractor traces is minimized, which emphasizes the importance of using additional spectral analysis to obtain greater accuracy.

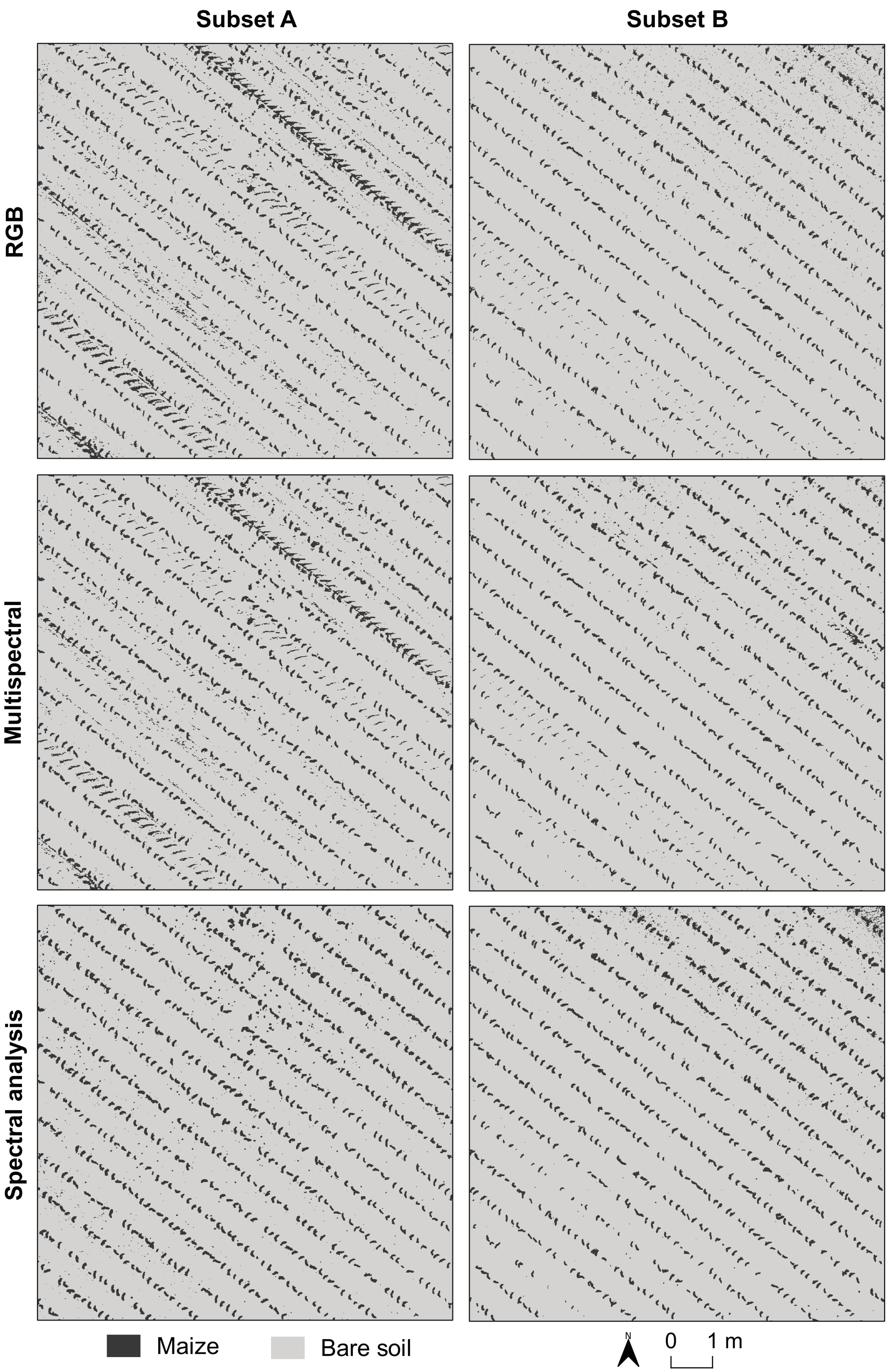

Figure 3. Classification results by three evaluated classification variants

Slika 3. Rezultati klasifikacije dobiveni iz triju testiranih varijanata klasifikacije

CONCLUSION

The results obtained in this study indicate that the RGB camera provides a satisfactory accuracy and is an acceptable solution to the soil and vegetation classification. Meanwhile, a multispectral camera and spectral analysis allowed for a more accurate and detailed analysis. This was primarily observed concerning the more sensitive areas subjected to the moderate atmospheric and topography conditions, in the cases in which a maximum accuracy is required and in which there are more than two classes required for classification. RGB and multispectral cameras achieved a very high classification accuracy of over 90% in all three spectral-band combinations. Proportionally, the difference in performance between these cameras arose with regard to two very similar spectral bands between the ground-truth classes. In this study, the determination of crop density using a UAV equipped with an RGB camera is fully justified, given the accuracy of analysis results obtained. In order to ensure the effectiveness of crop classification in practical application, it is necessary to primarily include the weed classes in the current vegetation class and divide them into crops and weeds in further research.

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ANALIZA RGB I MULTISPEKTRALNE KAMERE NA BESPILOTNOME ZRAKOPLOVU ZA KLASIFIKACIJU KUKURUZA STROJNIM UČENJEM

SAŽETAK

U ovoj studiji istražena je klasifikacija usjeva i tla korištenjem algoritma strojnoga učenja* Random Forest*, temeljenoga na crveno-zeleno-plavoj (RGB) i multispektralnoj kameri integriranoj na bespilotnome zrakoplovu. Područje istraživanja obuhvaćalo je dva podskupa poljoprivredne čestice kukuruza dimenzija 10 x 10 m u blizini Koške. Najveća ukupna točnost klasifikacije postignuta je u kombinaciji rubnoga crvenog (RE), bliskoga infracrvenog (NIR) kanala i indeksa normalizirane vegetacijske razlike (NDVI) u oba podskupa, s ukupnom točnošću od 99,8 %, odnosno 91,8 %. Provedena analiza pokazala je da je RGB kamera postigla dovoljnu točnost i da je prihvatljivo rješenje za klasifikaciju tla i vegetacije. Međutim, multispektralna kamera i spektralna analiza omogućile su detaljniju analizu, prvenstveno za spektralno slična područja. Ovaj je postupak temelj i za izračun gustoće usjeva i za otkrivanje korova s pomoću bespilotnih zrakoplova. Kako bi se osigurala učinkovitost klasifikacije usjeva u praktičnoj primjeni, potrebno je dodatno uključiti klase korova u trenutačnu klasu vegetacije i podijeliti ih na klase usjeva i korova.

Ključne riječi: gustoća sklopa, Random Forest, nadzirana klasifikacija, spektralna analiza, indeks normalizirane vegetacijske razlike (NDVI)

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