Mapping plastic based on multispectral UAV images

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Key words: UAV, deep learning, plastic detection, PET, OPS, Nylon

SUMMARY

Plastic pollution in water ecosystems has been a razing problem since the mid-1970s and it is becoming one of the biggest global environmental problems. Today, plastic litter is presented everywhere from river banks, coastal areas, and seafloor to the most remote points in the ocean. However, there is still a lack of exact data on the amount and spatial distribution of plastic. Currently, most of the available data represents the results of empirical estimates or beach surveys which are time and money consuming and limited to small areas. Remote sensing data, artificial intelligence, and GIS tools have a great potential to overcome current limitations and provide the long-term, resource-effective, monitoring of floating plastics. However, the knowledge gap in the fundamental understanding of the spectral signatures of floating plastic represents the major challenge in the application of remote sensing data in this area. Therefore, we created the set of three artificial floating plastic targets equipped with different types (Oriented Polystyrene, Nylon, and Polyethylene terephthalate) and sizes of plastics (squares from 1 to 10 cm) to analyze spectral signatures of floating and submerged plastic. The UAV equipped with a multispectral camera, covering the range from 450 nm to 840 nm, was used for capturing ultrahigh-resolution images. Moreover, the relationship between the spatial resolution of the image and detectable plastic size was presented. Our results indicated that multispectral data can be effectively used for the detection and quantification of floating plastics. The findings can be used to enhance the existing methodology for monitoring plastic pollution.

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1. INTRODUCTION

Plastic debris has become a major global threat to the environment and human health since plastic affects the whole environment from terrestrial to aquatic ecosystems. Plastic can be found in almost every area of our lives including food, medical equipment, clothes, furniture, cars, etc. Due to that, plastics are the third most-produced material by industries worldwide after steel and concrete (Lavars & Bond, 2017). Since the beginning of its mass manufacture in the 1950s production of plastic has increased from 1.7 million tons in 1954 to 367 million tons in 2020 (PlasticsEurope, 2021). Plastic litter can be classified into three categories based on size: macroplastic (>5 mm), microplastics (5 mm – 0.1 µm), and nano plastics (0.1 – 0.001 µm) (Bråte, 2017)
Marine debris pollution is no longer a regional problem affecting all water bodies, especially water surfaces in coastal areas. Plastics are the most common marine litter, estimated to contribute from 60% to 80% of the total amount of marine debris (Martínez-Vicente, Clark, & et, 2019). Plastic is a durable material and it remains in the ocean for a long time representing a serious threat not only to flora and fauna but also to human health. In addition to environmental and health effects, marine debris impact economic system such as tourism and fishing. Fragments of microplastic produce microplastics, through UV radiation, the mechanical force of wind and waves, chemical and biological processes becoming even more harmful to the aquatic ecosystem. The key challenge for better understanding and addressing the plastic impacts are quantifying the volume of plastic, locating and understanding plastic paths and accumulation locations. It is estimated that 4.8 to 12.7 million tons of plastic debris entered the ocean in 2010 (Jambeck, i drugi, 2015) while Meijer et. al. (Meijer, van Emmerik, van der Ent, Schmidt, & Lebreton, 2021) estimated that more than 1000 rivers account for 80% of global annual emission, which ranges between 0.8-2.7 million tons per year. Although, the results of such global model estimation which were based on reliable observational data differ significantly currently it is not possible to estimate the concentration of marine plastic more precisely. Therefore, there is an urgent need to define a monitoring tool for a comprehensive analysis of the spatial extent and abundance of plastic in aquatic ecosystems on a global scale.
Remote sensing technologies with moderate to high spatial, spectral, and temporal resolution has great potential to become effective monitoring method for the identification of plastic waste in the aquatic environment. In particular, earth observation data from public and commercial satellite missions, unmanned aerial vehicles (UAV) as well as bridge-mounted cameras have been employed for the detection of plastic debris.
Sannigrahi et. al. used open Sentinel 2 data and advanced machine learning algorithms (Support Vector Machine and Random Forest) resulting in 80%-90% accuracy (Sannigrahi, Basu, Sarkar Basu, & Pilla, 2022). Kikaki et.al. combined Sentinel 2 images and RF

algorithm for detection of marine debris with average F1-score of 0.79 (Kikaki, Kakogeorgiou, Mikeli, Raitsos, & Karantzalos, 2022). Jakovljevic et. al. developed an algorithm for the detection of floating plastic in freshwater, based on Artificial Neural Networks and high-resolution multispectral WorldView-2 images, reporting a Root Mean Square Error (RMSE) of 0.03 during the test phases (Jakovljevic, Govedarica, & Alvarez Taboada, 2019). Aoyama used high-resolution WordView-3 satellite images and the Spectral Angle Mapper algorithm for the extraction of marine debris in the Sea of Japan (Aoyama, 2016).
In addition to satellite images, ultra-high-resolution UAV data have been used for the detection of floating plastic in inland water bodies. (Han, Luo, Jin, & Zhu, 2021) combined EfficientNet classification algorithm, Yolov5 target detection algorithm, and UAV data for automatic floating plastic waste identification with high accuracy (up to 95%) while (Jakovljevic, Govedarica, & Alvarez-Taboada, 2020) used UAV data and U-Net algorithm for automatic plastic detection and localization with similar accuracy (up to 92%).
Detection of any type of aquatic and land remote sensing application is generally dependent on the distinct spectral characteristics of objects.
The aim of this study is to (1) analyze spectral characteristics of different floating plastics materials in real case scenarios, (2) to investigate the applicability of previously identified plastic spectral characteristics for detecting floating plastic.

2. MATERIALS AND METHODS

In this section, the materials and methods used in this study are described. The workflow is presented in figure 1.

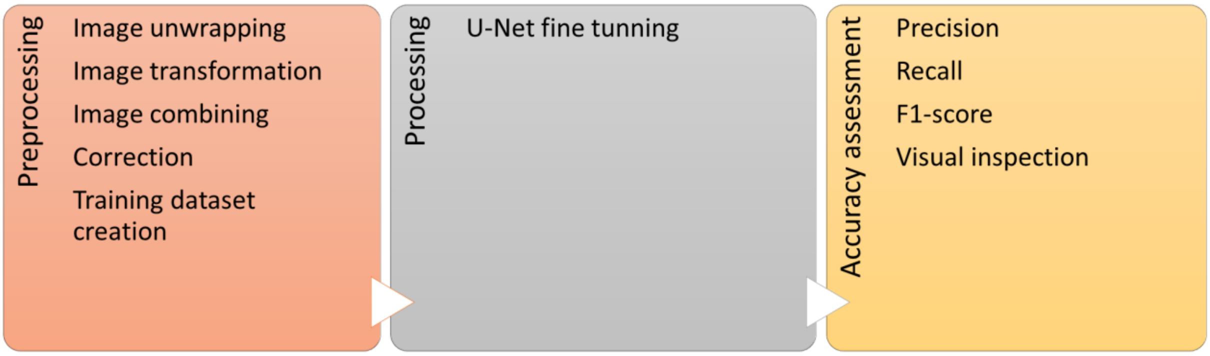

Figure 1. Workflow

2.1 Study area

The study area is lake Balkana near Mrkonjić Grad in the western part of the Republic of Srpska and Bosnia and Herzegovina. The Balkana is located on the slopes of Lisina Mountain at 700 m above sea level, surrounded by coniferous forests and pastures. It consists of two artificial lakes (Small and Big) with a total area of 56000 m^2. The big lake is rich with several species of fish and it is created by two mountain streams Cjepalo and Skakvac. The small lake hasn't tributaries and it gets water from Big Lake via the small underground canal.

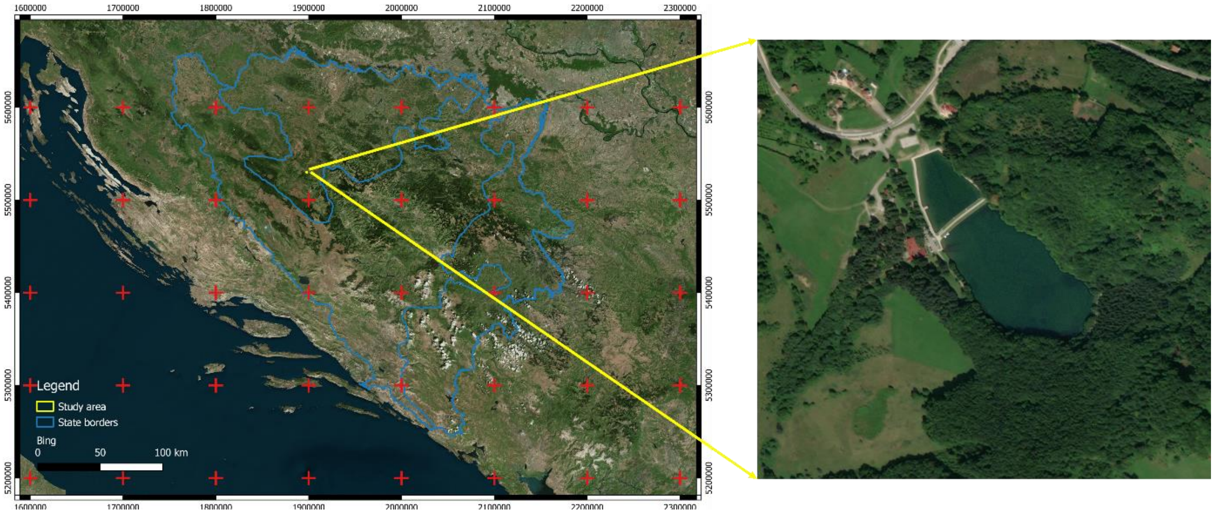

Figure 2. Study area (EPSG:3857)

2.2 Data

Specialy targets were designed to exemin the spectral characteristics of different plastic materials including Polyethylene terephthalate (PET), Oriented polystyrene (OPS) and Nylon. The targets consisted of (i) a wooden frame (100 cm × 80 cm) with thin and transparent gauze and plastic squares, with side lengths from 1 to 16 cm (ii) a wooden frame (100 cm × 80 cm) attached to a metal frame located 20 cm below it, with thin and transparent gauze and plastic squares, with sides from 1 to 10 cm, and (iii) plastic bottles of different sizes and colors (iv) rope with a diameter of 4 mm was used to keep the frames in the area of interest during the surveys. In order to reflect from the lake bottom, targets were realized in the deep part of Small Lake.
The UAV survey was conducted in March 2022, using DJI Phantom 4 Multispectral. DJI Phantom 4 Multispectral includes one RGB sensor for visible light imaging and a multispectral camera array with five monochrome sensors imaging (Table 1) and an RTK module. To maximize the accuracy and consistency of data collected through different times of day and weather conditions, dron integrates a spectral sunlight sensor. The spatial resolution of created images was 21 mm.

Table 1. Bands and corresponding wavelengths (Dji, 2022)

Band	Wavelength
Blue (B)	450 nm ± 16 nm
Green (G)	560 nm ± 16 nm
Red (R)	650 nm ± 16 nm
Red Edge (RE)	730 nm ± 16 nm
Near-Infrared (NIR)	840 nm ± 26 nm

2.3 Preprocessing

The image collected during surveys were preprocessed using the open-source library developed by Micasense (MicaSense, 2020) in order to calibrate the raw pixel intensity value into reflectance and to remove the optical and imager effect. The library is implemented in the Python programming language. The influence of the solar radiation intensity was removed by using the spectral sunlight sensor's data.
Each band of the multispectral image was collected from a slightly different position therefore to create meaningful data the bands must be aligned to each other. Image alignment allows using multiple bands in classification, calculation of indices, and well as for display and management uses. The alignment consists of a three-step process: image unwrapping using the built-in lens calibration, transformation to align band to a common band, and image combining and cropping. After that, images were exported as .geotiff and stored.
The labels were created by visual inspection of images. To reduce errors caused by the manual delineation of plastic pieces, the pixels were merged to obtain non-overlapping polygons. The parameters of the segmentation algorithm were defined through a trial-and-error process. Each polygon was manually labeled using QGIS software, based on a visual inspection. Plastic was classified into three classes: PET (plastic bottles), OPS (plastic squares), and Naylon (rope).
After that spectral characteristics of different materials (plastic, water, wood), different plastic types different colors were analyzed.

2.4 Processing

In order to provide pixel-level semantic segmentation of floating plastic the deep learning algorithm based on U-Net architecture was proposed.
The U-Net has a symmetrical encoder-decoder architecture (Ronneberger, Fischer, & Brox, 2015). Encoder side converts input image into feature representation at multiple different levels. reduces the image dimensionality and encreasing the image depth. It consists of the repeated convolution filters of fixed size (3x3) followed by a rectified linear unit (ReLU) and 2x2 max-pooling operation. EaIn each block the number of feature maps (number of channels) is doubled, while spatial dimensionality (height and width of the image) is reduced to half by the max-pooling operator. In this case, the pre-trained classification network ResNet 34 was used as the encoder. ResNet is constructed by multiple bottleneck blocks called residual blocks consisting of three layers of 1x1, 3x3 and 1x1 convolutions followed by batch normalization and ReLU activation function (He, Zhang, Ren, & Sun, 2016).
The second part of the network is the decoder. The encoder and decoder architecture are fully symmetrical meaning that for each encoder there is a corresponding decoder. The decoder blocks aim to upsample feature maps (low resolution) learned by the encoder onto the pixel space (higher resolution) to get semantic segmentation of the input image at the pixel level. The decoder consists of 2x2 upsampling operators followed by 3x3 convolutions and the ReLU activation function. The encoder and corresponding decoder are connected via skip connection.

2.5 Accuracy assessment

The performance of the suggested workflow was tested by using three standard parameters: precision, recall, and F1-score.
Precision quantifies the number of positive class predictions that belong to the positive class (i.e. of all labeled plastic pixel how many is actually plastic). High precision indicates a low false-positive ratio.
Recall quantifies the number of all truly positive class that are labeled (i.e. of all plastic pixel how many is labeled). High recall indicates a low false-negative ratio.
F1-score is the weighted average of Precision and Recall. The higher value of the F1-score indicates a better model performance.

3. RESULTS AND DISCUSSION

In this section, the main findings are presented and discussed. First, the spectral signatures are analyzed in order to better understand the optical characteristics of floating plastic and their contributions to visible and infrared wavelengths in a real case scenario.
Water, wood, and plastic showed unique spectral signatures (Figure 3). The wood shows significantly higher reflectance compared to the other classes. The spectral reflectance curve of plastic and water has a similar shape. The reflectance peak for plastic was in NIR and G band. The largest difference between them is noticed in the NIR part of the spectrum since the water is strongly absorbed in the NIR region and beyond. Moreover, plastics show the unique inherent optical characteristic in the NIR and SWIR part of the electromagnetic spectrum that has been used in automated optical sorting of waste in the industry (Moroni, 2015).

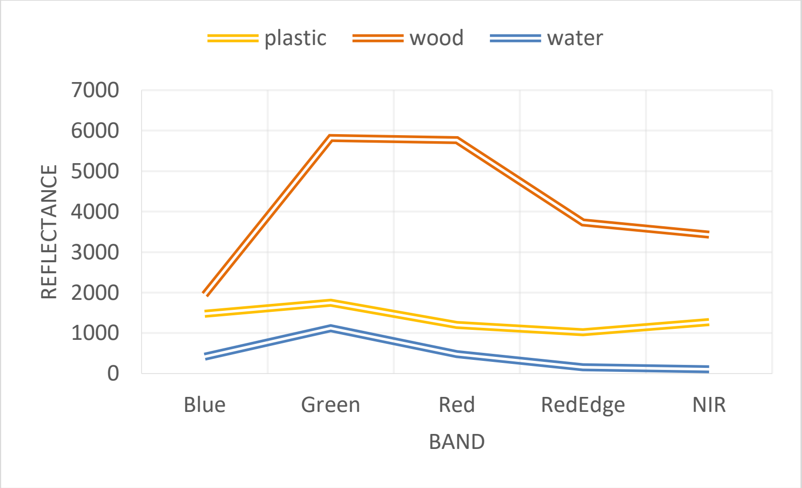

Figure 3. Mean spectral reflectance of different materials

However identification of the floating plastic is aquatic environment is highly chalanging due to several factors including plastic type, color, size, orientation, and surface features such as sun glint and chemical characteristics of water (suspended solids)
In an aquatic environment, plastic can be wer, slightly or fully submerged. Figure 4 shows the OPS plastic reflectance in wet and fully submerged conditions (20 cm bellow water level). As

expected, the submerged reflectance is lower compared to the reflectance of the wet sample due to the strong absorption of the water. The reflectance value falls sharply with an increase in wavelength. The value reduction in the RGB part of the spectrum is 10-20 %, in RE 45 % while in NIR is 67 %. This indicates that the visible part of the spectrum is most suitable for the detection of submerged plastic.

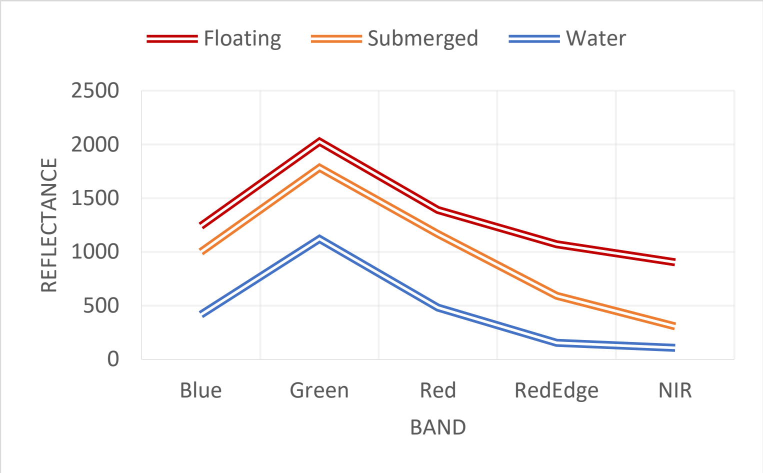

Figure 4. OPS plastic, wet and submerged conditions

Several different types of plastics are produced today, such as PET and OPS. Spectral signatures of different types of plastic with the same color and wetness level are shown at Figure 5. The difference in composition leads to slight optical properties variation in B and NIR while reflectance peaks are common between plastic types. Similar spectral characteristics of marine plastic were presented by (Garaba, et al., 2018) and (Garaba & Dierssen, 2020). Due to spectral similarity, the distinction of different plastic types can be a tedious task.

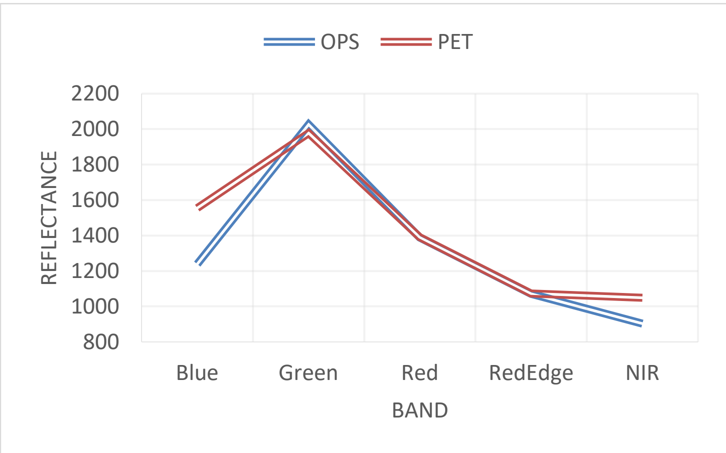

Figure 5. Spectral reflectance of different types of plastic

The color of plastic highly influences the reflectance in the visible part of the spectrum. The transparent plastic reflectance is highly influenced by the spectral properties of water spectral curves have a similar shape but higher reflectance for plastic (Figure 6). The blue plastic reflectance was high in the blue and NIR channels, while it was low in G, R, and RE. Red plastic highly absorbs the B and G part of the spectrum, strongly reflects in R, and slowly decreases reflectance in a longer wavelength.

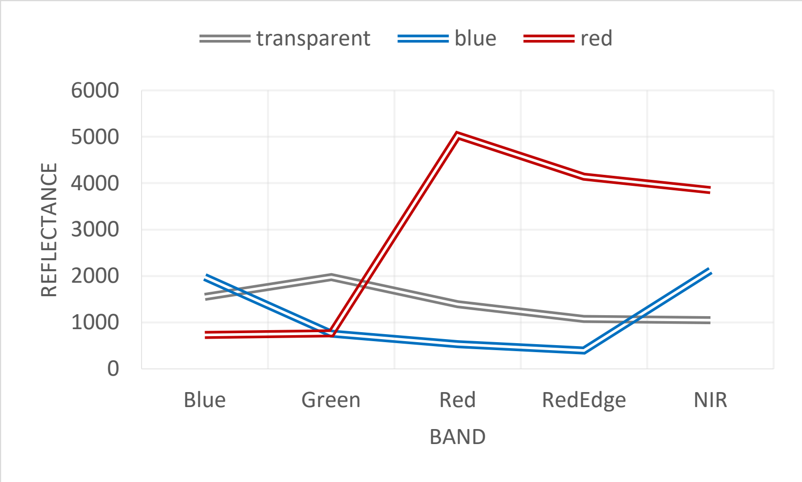

Figure 6. Influence of plastic color on spectral signature

In this paper, the deep learning algorithm based on U-Net architecture was used for semantic segmentation of plastic debris. Table 2. shows the performance of the algorithm for the extraction of different kinds of plastic material. The results of the accuracy assessment show the low number of false-positive meaning can detected all plastic pixels but is highly trustable when it does. Those findings are confirmed by visual inspection The visual inspection of the results is shown in Figure 7.

Table 2. Accuracy assessment

	Precision	Recall	F1
OPS	0.75	0.68	0.71
Nylon	0.91	0.52	0.66
PET	0.80	0.85	0.82

Visual inspection shows that the algorithm detected most OPS squares. The algorithm omitted 1 and 2 cm squares on the water surface while the squares biggest than 6 cm were detected on submerged target. On the other hand, it can be noticed that algorithm overestimates the nylon class.

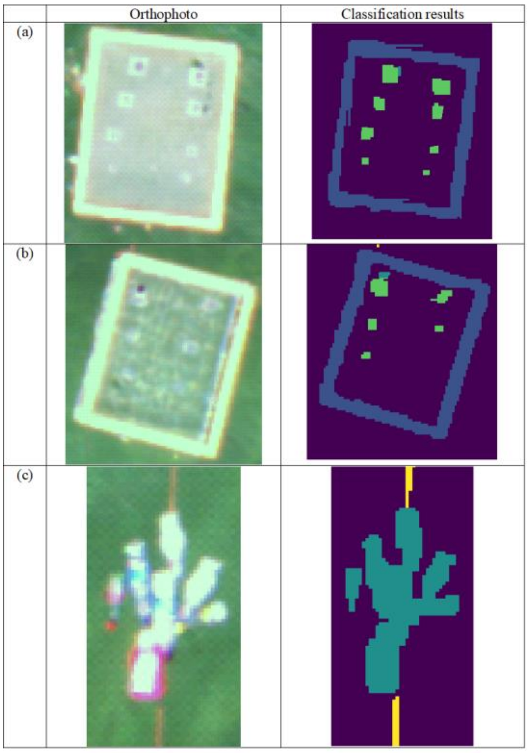

Figure 7. Visual inspection of classification results (a) OPS floating plastic, (b) OPS submerged plastic and (c) PET and Nylon

4. CONCLUSION

The present study utilized high-resolution UAV multispectral image and deep learning algorithm to detect and classify floating plastic. The analysis of spectral signatures show that NIR channel is most suitable for the detection of floating plastics since reflectance is much higher than that of water. On another hand, the visible spectrum is preferable for submerged plastic since the water strongly absorbs the NIR part of the spectrum. It needs to be noted that the color of plastics can be a crucial factor since it significantly varies the spectral reflectance. The results of accuracy assessment and visual inspection show that the deep learning algorithm based on U-Net architecture was able to discriminate different kinds of floating plastics with high accuracy. Despite similar spectral signatures, the mixing between OPS and PET is not significant. Based on the results it can be concluded that the algorithm is not able to detect all plastic pixels but it is highly trustable when it does. In the future, the developed model should be tested in a real case scenario.

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