Remote Sensing Data in Mapping Plastics at Surface Water Bodies

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Key words: plastics, surface water bodies, geospatial technologies, Remote Sensing

SUMMARY

The millions of tons of plastics ending up in the ocean every year. Marine plastic litter is a global environmental problem with significant economic, ecological, public health and aesthetic impacts. In order to reduce those impacts and reduce plastics abundance, source of litter and they pathways need to be identified. Land based litter, transported by rivers to oceans, is estimated to be a major contributor but there is not comprehensive methodologies for providing quantitative data for assessment of riverine as well as ocean plastics. Currently, there are only regional assessments of plastics at on beaches and water columns. Beach surveys, is usually conducted by volunteer community groups, are highly accurate but are very constrained both spatially and temporally.

Plastic litter is mostly concentrated at banks, coastlines and in upper layer of surface water bodies. Therefore, remote sensing from space and airborne platforms, available in different spatial, spectral and temporal resolution, has the potential to be a reliable source of long-term qualitative and quantitative information on large geographic areas. The distinguish plastics from surrounding classes, and assessment of it spatial extent and temporal variability, is possible due to unique spectral signature of polymers in near-infrared part of electromagnetic spectrum.

In this paper, the object-pixel based algorithm for mapping plastic distribution at surface water is presente. High resolution WorldView-2 images are used to investigate optical properties of wet and dry plastics and asset the possibility of multispectral images in detection of floating plastic at freshwater bodies. Those data represents useful information for determine priority sites for mitigating adverse impacts across broad areas and increasing water quality.

Remote sensing data in mapping plastics at surface water bodies

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1. INTRODUCTION

Our planet facing one of the biggest treats in human history. Global plastic production increases annually, reaching 335 million metric tonnes just in 2016. Only nine per cent of the nine billion tonnes of plastic the world has ever produced has been recycled (UNEPa, 2019). More than 8 million tonnes of plastics end up to the ocean each year which is equal to dumping a garbage track of plastic every minute (UNEPb, 2019). Most plastics is not biodegrade and during the time it just breaks down to smaller fragments known as microplastics. Microplastics becomes even larger thath because it is more difficult to remove it from ocean. Wide variety of marine organisms become entangled or ingest in these plastic product with direct and often deadly effects. In that way plastic and related toxic materials rising through the food chain onto our dinner tables. According to some estimates, at the rate we are dumping items such as plastic bottles, bags and cups after a single use, by 2050 oceans will carry more plastic than fish and an estimated 99 per cent of seabirds will have ingested plastic (UNEPa, 2019). But how much do we exactly know about sources, pathways, and trends in abundance of marine plastic litter, its harmful impacts on human and marine life? Unfortunately, a knowledge gap exists in terms of the temporal and spatial distribution of plastics. Although large concentrations of floating or suspended plastic debris are being observed or modeled those estimations are generally based on regional assessments of plastics on beaches and shipboard observation of large debris patches. This methods are time consuming both in collecting as well as the subsequent quantification and also spatially limited.

Therefore, a compressive analysis of the spatial and temporal extent and abundance of debris at regional or global level and the monitoring tools are missing. Remote sensing technologies with moderate to high temporal, spectral and spatial resolution is one of the most promising methods and has the potential to be a reliable source of quantitative and qualitative information on a wide geographical scale. Applications of satellite and airborne remote sensing tools for assessing ocean plastic pollution is challenging duo to many different types and size of plastics. Areal images seem to be capable of mapping plastic pollution due to their high geospatial resolution. Moy et al. (2018), was created hot spot map of debris at Hawaii Island beaches by visual interpretation of orthorectified imagery mosaics at 2 cm ground sample distance. Karaoka, et al. (2018) was extracted the debris pixels form the aerial photographs by using color references on a CIELUV color space. In addition, optical properties of both micro and macro plastic have been investigated along with case studies showing potential of remote sensing data in detection of plastics on water and land. Goddijn Murphy et al. (2018), suggested that fraction of plastic surface area can be mapped from air if reflectance of the clear sea surface and of the plastic are known. Garaba et all. (2018), investigated the SWIR spectral signatures of large plastic items detected in the ocean. Their results confirmed unique spectral feature common to plastic especially that ∼1215 and ∼1732

nm absorption features have potential applications in detecting ocean plastics from spectral information.
Aoyama (2016), used high resolution satellite images WordView-3 and Spectral Angle Mapper for extraction of marine debris in the Sea of Japan, while Ge et al., (2016) was developed semi-automatic recognition of marine debris on beaches based on LiDAR data and Supported Vector Machine algorithm.
The scale of the ocean problem is global, involving many countries and many stakeholders therefore the collaborative effort should be used to intercept ocean plastics on the land before they reach the sea. Land based sources are considered to be the dominant input of plastics into oceans, especially rivers draining areas with high population density and industrial development, represte key enter point of plastics debris to the ocean. Ten big rivers are source of more than 80 % of ocean plastic, eight of them is located in Southeast Asia. Collecting land sourced ocean plastic prior to entering the sea is relatively easy, requiring little energy and no skilled workforce, and are one of better short terms solutions (Campbell et al., 2017).
The aim of this paper is to develop algorithm for detection of floating plastic at freshwater bodies based on high resolution remote sensing data. Additional, optical properties of wet and dry plastics will be investigate.

2. SYUDY AREA

The Drina River is located in east Republic of Srpska and its lower flow represent natural border between Serbia and Bosnia and Herzegovina. Drina is longest tributary of the Sava River and belongs to the Danube river watershed. It’s ordinate from the merging of the Tara and Piva rivers at Šćepan polje in Montenegro. The Drina is a very fast river with cold and greenish water, its average depth is 3 to 5 m while wide vary between 15 to up to 200 m. Power of river has been tamed by lakes and dams. Three hydroelectric power plants have been built on the Drina, which turned lower part of river course into a peaceful lake area. The river is not navigable, but together with the Tara it represents the main kayaking and rafting attraction in this part of Europe.

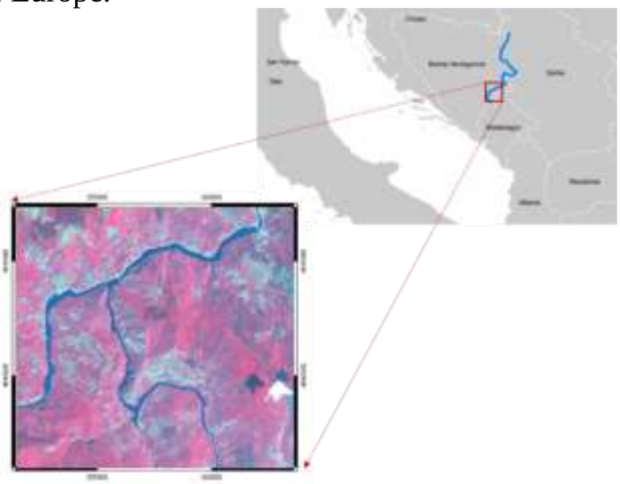

Figure 1. Study area

Drina River is considered as one of the most beautiful rivers in the former Yugoslavia but when plastic debris enter in environment all those beautiful landscapes despaired.

Unfortunately, Drine is one of the best examples for that. The tonnes of litter, plastic bottles, begs etc. floating in the Drina. More than 80 % of that litter is carried by Lim River, the longest Drina tributary and in same time the biggest polluter. The major source of litter are thousands of wild landfills located at river banks. During the raining period when water level increase the Lim wash away garbage from banks and carry it intro Drina.

Figure 2. (a) upper flow (b) lower Drina flow (source: http://www.rts.rs/page/tv/sr/story/22/rts-svet/3300539/sasvim-prirodno-dva-lica-reke-drine-4-deo.html)

Although, there are several wood floater which collect and prevent plastic from flowing over the problem need to be resolved systematically. First of all, the landfill site management system and humans awareness need to be improved. Also, the plastic collected from river should be recycled.

3. MATERIALS

WorldView-2, launched October 2009, is the first high-resolution 8-band multispectral commercial satellite. Operating at an altitude of 770 kilometers, WorldView-2 provides 46 cm panchromatic resolution and 1.85 meter multispectral resolution. It has an average revisit time of 1.1 days and is capable of collecting up to 1 million square kilometers of 8-band imagery per day (Digital Globe, 2019). The WorldView-2 images supply detail and geospatial accuracy, further expanding the applications of satellite images in both commercial and government usage including spectral analysis, mapping and monitoring, disaster management, exploration etc. List of WorldView-2 bands used in the plastic detection is showed at Table 1.

Table 1. List of WorldView-2 bands used in this study

Band	W1 [µm]	R1 [m]
Blue	0.45-0.51	0.46
Green	0.51-0.58	0.46
Red	0.63-0.69	0.46
NIR	0.77-0.895	0.46

In this study, one standard satellite (level 2A) image captured at 15.08.2016, was used. Level 2A apply radiometric, sensor and geometric correction. Standard product is mapped to a WGS84/ UTM zone 34 (EPGS 32634) cartographic projection.

3.2. Light reflectance of natural water

Remote-sensing reflectance Rrs (λ) is a widely used parameter to express the spectral reflectance signature of a water body and is defined as (1):

$$R_{rs}(\lambda) = \frac{L_w(\lambda)}{E_d(\lambda)} \quad (1)$$

Where $L_w(\lambda)$ is a water leveling radiance, and $E_d(\lambda)$is downwelling irradiance just above the water surface.

Water provides a semi-transparent medium for the electromagnetic radiation therefore downwelling irradiance partly reflects directly at water surface and partly penetrates in water body. In water body, light is absorbed and scattered in all direction. If the water is optically depth, the fraction of light that scatters back upwards and passes through water-air interface contain the information about optically active components (Goddijn-Murphy et. al, 2018).

According to bio-optical theory the $R_{rs}(\lambda)$ observed immediately above the water surface sub surface can be expressed as (Gordon et al., 1975)(2):

$$R_{rs}(\lambda) = \frac{b_b(\lambda)}{[a(\lambda) + b_b(\lambda)]}$$

Where $b_b(\lambda)$ represents total backscattering coefficient and $a(\lambda)$ is total absorption coefficient.

The main backscattering and absorption are function of optical active water components such as phytoplankton's, suspending sediments etc. Natural water shows high reflectance in visible region while absorbs radiation in near infrared (NIR) wavelength and beyond. In the SWIR part of the spectrum, the pure water absorption is very high, and at very long SWIR wavelengths (λ > 1600 nm) even extremely turbid waters are effectively black (Shi and Wang 2009) (the radiation completely absorbed by the water body).

Buoyant floating ocean plastic is concentrated in the upper layer of oceans, mostly within the first 0.5 m (Kooi, et al., 2016). Plastic objects floating on the water surface change $R_{rs}(\lambda)$ duo to following characteristics: plastics reflects downwelling light differently than water, transmittance of downwelling light through plastic is different from transmittance through the air-water interface, and subsurface upwelling light transmits through plastic differently than through the water-air interface (Goddijn-Murphy et. al, 2018). Therefore in the case of the floating plastic on the water surface total $L_t(\lambda)$ is defined as (3):

$$L_t(\lambda) = fL_w(\lambda) + fL_p(\lambda) \quad (3)$$

Where $L_w(\lambda)$ is water leaving light, $L_p(\lambda)$ is plastic leveling light. For transparent plastic $L_p(\lambda)$ also include the subsurface upwelling light that is transmitted through the plastic.

Equation (1) and (3) led to estimation of *f* (Eq.4)

$$f(\lambda) = \frac{R_t - R_w}{R_w - R_p} \quad (4)$$

According to (4) the best option for plastic detection using single band algorithm would be wavelength where $R_w(\lambda)$ is near to zero and where $R_p(\lambda)$ is high. Regarding the band radio the best option would be wavelengths where $R_w(\lambda_1) \approx R_w(\lambda_2)$ and $R_p(\lambda_1) \neq R_p(\lambda_2)$.

Plastic have characteristic absorbance and reflectance spectra in the near-infrared domain (~750–2500 nm) (Masoumi et al., 2012) but significant limitation for the direct detection using NIR spectral range is the strong absorption by water.

Feature more, using remote sensing data for mapping plastic is complicated due to different types, size, color, shape and level of degradation. Size and level of degradation plays important role in optical properties since physical and chemical properties: surface type, shape and transparency can change as plastic breakdown (Filella, 2015). Also, floating and submerged parts have a different spectral characteristics.

4. METHODOLOGY

In this paper, pixel –object model for mapping floating plastic litter based on high resolution optical satellite images was proposed. The proposed workflow is presented at figure 3. Its consists of algorithm for automatic water body extraction and algorithm for detection of plastic litter.

The water body extraction is carried out by using Object Based Image Analysis (OBIA). OBIA approaches are commonly used on high spatial resolution data with limited spectral bands (e.g., red, blue, and green) and where image features are composed of more than one pixel. Grouping of those pixels into segments provides additional properties such as additional spectral information compared to pixels (mean band value, median values, minimum and maximum values, mean ratios, variance) but also spatial dimension like shape, size, distance, neighborhood, topologies etc. Segmentation algorithm aggregates the pixels into an object according to the one or more criteria of homogeneity and provides building blocks of object-based image analysis. In this study Simple Non-Iterative Clustering (SNIC) algorithm is used for image segmentation. The SNIC algorithm begins with the centroids initialization, which is completed by sampling the pixels on a regular grid in the image plane. The affinity of a pixel to centroid is measured using distance in five dimensional space of color and spatial coordinates (Achanta & Susstrunk, 2017). In order to preform segmentation using SNIC, three parameters need to be defined: size, compactness and connectivity. Size represents the object's seed location spacing in pixels. For image with N pixels, each of the K object is expected to contain N/K pixels. Assuming a square shape of object, the value of size parameter can be computed as $\sqrt{\frac{N}{K}}$. High value of compactness factor results in more compact objects at the cost of poorer boundaries (squared). SNIC enforcing connectivity from the start i.e. adjustment of initial object is defined according to the distances between those objects and their 4- or 8- connected pixel.

The water index and threshold-based approach have been widely used for rapid and automatic water body mapping in large-scale regions (Yang and Chen, 2017; Tetteh and Schonert, 2015). According to the water absorption/transmission characteristics the largest difference between the spectral signatures of water and the other land covers takes place in the SWIR region, so most water indexes use this band. Dou to limited spectral resolution, Normalized Difference Water Index (NDWI) defined by McFeeters (1996) is only choice for most high resolution images. Therefore NDWI, which maximizes the reflectance properties of water by minimizing the low reflectance of near infrared (NIR) and maximizing the reflectance in the green wavelength, is used in this study. To avoid subjectivity in the choice of the threshold and to maximize the level of automation, we utilized a histogram thresholding approach using the Otsu algorithm. Otsu algorithm determine a threshold under assumption that the digital image contain bimodal histogram, one which is correspondent to water class and another correspondent for other classes. Its maximize variance between water class and background noise, minimizing the probability of misclassification. One of the main problems with application of NDWI to high-resolution images for extraction of water body are shadows. Since the water bodies and dark shadows cannot be easily separated by this spectra additional object based characteristics are used. Identified polygons of water bodies represent mask for satellite images. Masked water pixels represent input data for plastic detection algorithm. Supervised pixel-based image analysis was carried out to identify two classes, plastic and non-plastic. The ground trough samples (training data) were located following a stratified random sampling design, according to visual interpretation of satellite images. After overlaying the training points onto layer stack, each bands spectral reflectance were extracted and indexes are calculated.

The variables input to the neural network were standardized to the rang of the logistic sigmoid function (activation function), namely (0,1). The equation used for standardization was (5):

$$X = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{5}$$

Where x_i represent the value of the raw input variable for the *ith* training case; x_{max} is the maximum value of a training case; and x_{min} is minimum value of a training case in the dataset. The standardized reflectance value, band ratios and spectral indices were used as inputs to train neural network.

In this study, supervised neural network, where there is known target of criteria, was used for mapping floating plastic. ANNs are pattern-recognition algorithms that capture salient features from a set of inputs and map them to outputs. The main advantage of ANN, comparing with statistical classification methods, consist of learning complex patterns with help of non-linear complex relationship between dependent and independent variables, generalization in presence of noisy environment, which makes ANNs robust even in case of incomplete or imprecise data, incorporate different types of datasets and physical constraints into analysis (Gonçalves Mendes & Porfírio Dal Poz, 2018; Fareed and Thuan, 2017). The architecture of ANN is defined by input, one or more hidden layers and output layer. Each layer comprises a predetermined number of highly interconnected computational elements, known as neurons. The input layers consists the set of neurons that represents predictor or independent variables (in this case radiance measurement of different wavelengths) i.e. the number of neurons in this layer correspondents to the dimensionality of the input data. Hidden layers consists of varying number neurons where input data are multiplied by its connections weights parameter, summed and passed through the nonlinear sigmoid function. The number of nodes in the hidden layer depend on the complexity of the approximated function and sample numbers. Usually, the number of hidden layers and neurons is experimentally determined. The output layer is represented by number of classes.

The input data to this network is the feature vector extracted from the data to be classified. The Jefferies Matusita (JM) distance was calculated for different combination of input layers (band ratios such as NIR/R, NIR/G, NIR/B, R/G, R/B, spectral indexes including NDWI and NDVI and spectral bands R, G, B. NIR) to determine the best combination for mapping plastic litter at river Drina. The JM distance is widely used statistical separability criterion. Its tends to suppress high separability values, whilst overemphasizing low separability values. JM separability criterion (J) between two classes $\boldsymbol{w_i}$ and $\boldsymbol{w_j}$ has been defined as follows (5) (Swain and Davis 1978):

$$J_{ij} = 2\left(1 - e^{-d_{ij}}\right) \tag{5}$$

Where d_{ij} is the is the Bhattacharyya distance between the classes w_i and w_j, defined as (6)(Swain and Davis 1978):

$$d_{ij} = -ln\left\{\int \sqrt{P(x/w_i)P(x/w_j)}\, dx\right\} \tag{6}$$

Where $P(x/w_i)$ **and** $P(x/w_j)$are the conditional probability density functions of random variable *x*, given the data classes w_i and w_j, respectively.

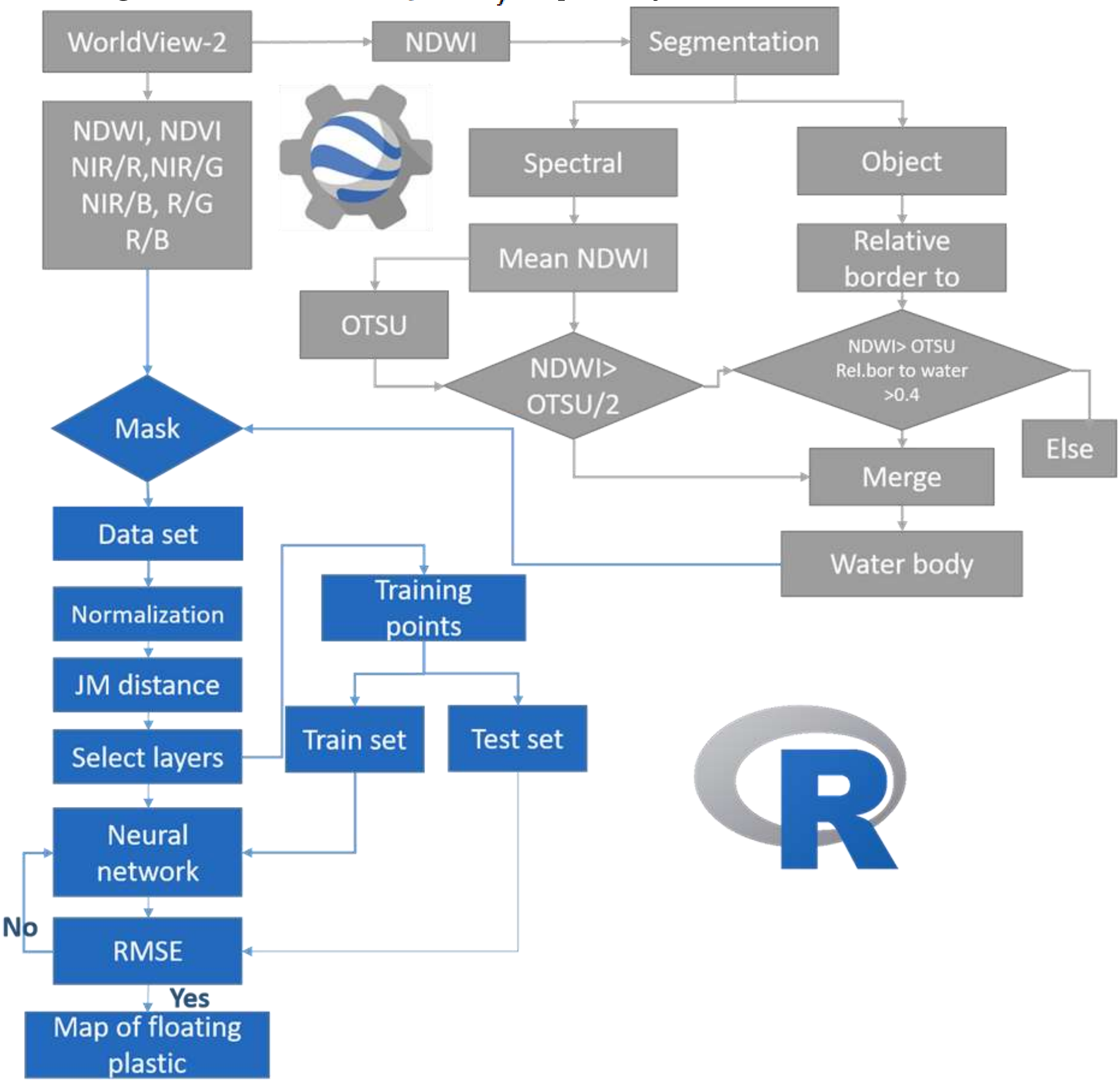

Figure 3. Workflow

The JM distance which ranges between 0 (low separability) and 2 (high separability), provides a general measure of separability between two classes acording to thair probability.

Architecture of neural network was defined by selecting the appropriated number of hidden layers. The number of hidden layers were analyzed by trial and errors in order to minimize root mean square error (RMSE) (7) at the training phase.

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i^{estimated} - x_i^{measured}\right)^2} \tag{7}$$

The ANN technique was applied after splitting the data into 70% for training and 30 % for testing of results. The first, set of weights is randomly initialized and then, the training pixels are propagated forward to estimate the output values for each training pattern set. Each neurons receive the weighted inputs from other neurons, sums these weighted inputs and passed through the nonlinear sigmoid function and send this output to another neuron. In the second phases, the error between known and estimated outputs is fed backward trough network and weights are optimize. The process is iterative, and weights will be updated until the error is minimal. Validation is based on visual inspection of results.

Results and Discussion

Among the tested combinations of input layers, the highest value of (JM=1.37) was obtained for B4 and NDWI indicating the moderate separability between plastic and non plastic. In order to verify the capability of ANN in mapping floating plastics, developed model was applied to the water pixel extracted from WorldView-2 image. The network was trained by testing different architectures with two or three hidden layers and varying the number of neurons in each layer. The architecture 2-9-14-2 which produced lowest RMSE (RMSE = 0.03) was selected. The training data are represented by points since size of plastic is smaller than spatial resolution of satellite image. The total number of training points was 2540, from which 956 represents plastic. Validation of results was performed by visual comparison of classification results and original WorldView-2 satellite image. The results of classification are presented at figure 4. Generally, ANN tend to underestimate the surface covered by plastic litter. The classification results are highly correlated with size and level of plastic submerge. The large area covered by plastic i.e. pure plastic pixels are well detected (Figure 4 (a), (c)) but mixed pixels are almost completely omitted (Figure 4 (b),(d)). As expected, the spectral reflectance of pure plastic pixels was higher then water and much more consistent then mixed one (Figure 5). Dou to presence of water in mixed pixel the reflectance is lower comparing with plastic and signature is more similar to non-plastic class. Regarding the separation between wood and plastic ANN performed well since wooden floater isn’t misclassified as plastic. The true ground data are needed to provide deeper insight in the quality of results since some of the omitted pixels can be branches and different kind of wood.

WorldView-2 ANN SVM

(a)

(b)

(c)

(d)

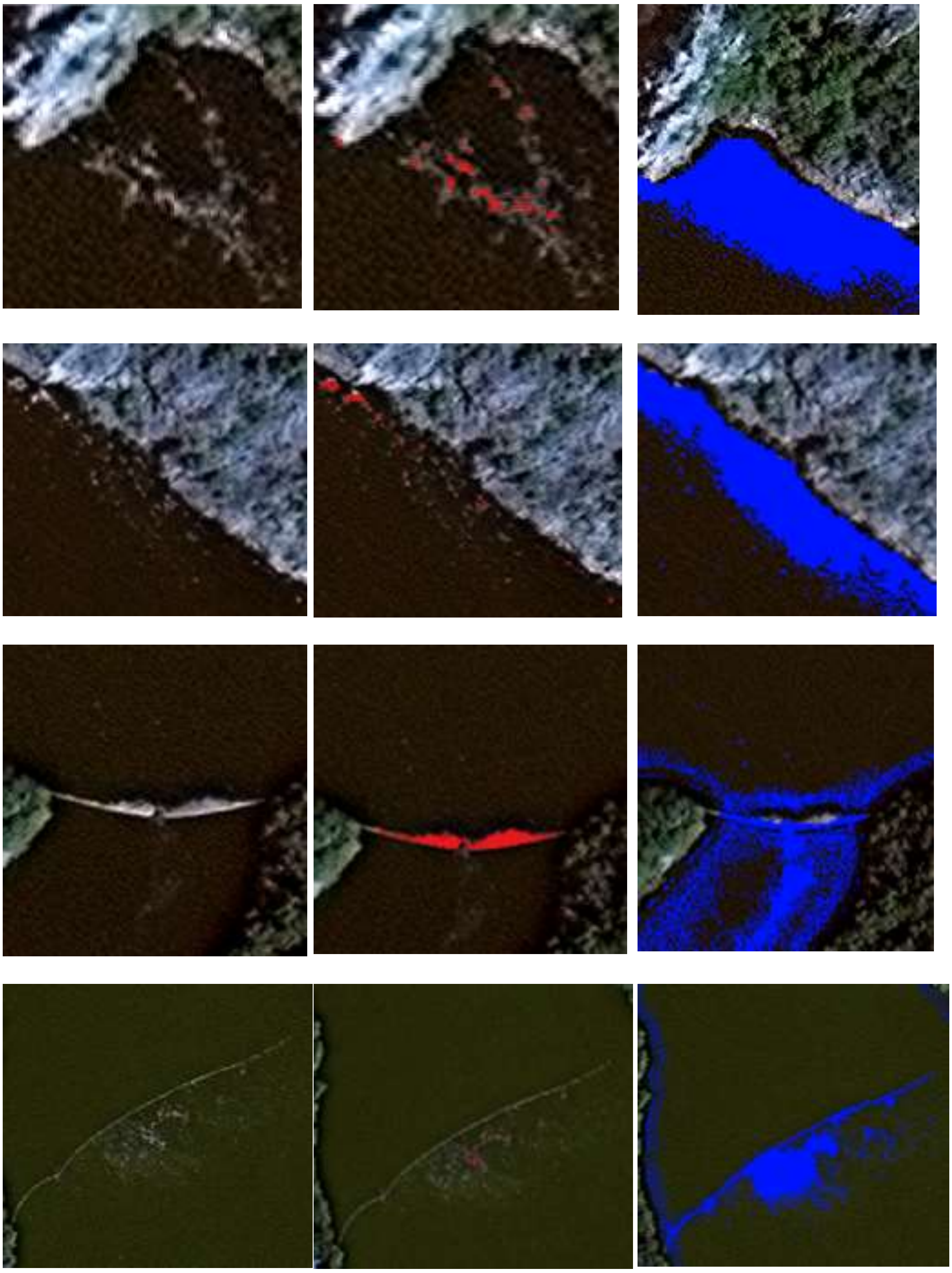

Figure 4. Comparison of classification results and original image

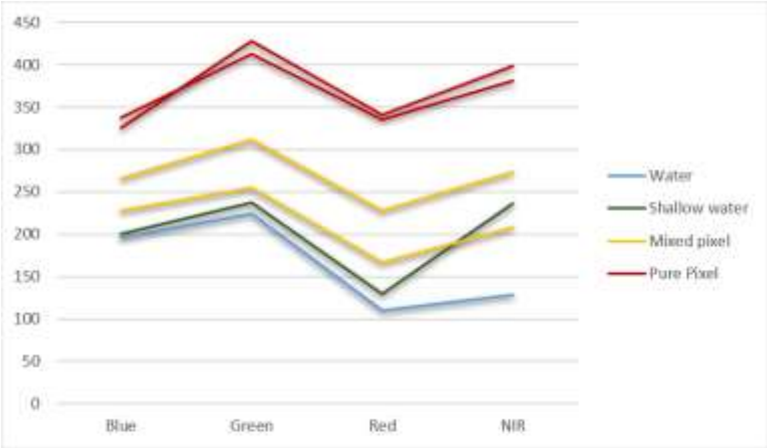

Figure 5. Spectral signatures of subclasses

In addition to ANN, the SVM algorithm was tested at study area. The same training set was used for both algorithms. SVM detect mixed pixel as plastic but also produce large over estimation (Figure 4). Almost all shallow waters are detected as plastic by SVM. Since the water reflectance increase with the presence of river bed, the shallow waters have a similar spectral signature in NIR part of spectrum, which is crucial for plastic detection (Figure 5). In addition, detection of floating plastic is extremely complicated in freshwaters due to the higher subsurface reflectance in the NIR spectrum. The spectral reflectance of water change significant with presence of optical active quality parameters. Elements such turbidity, suspended solid, mud, phytoplankton's increase the reflection resulting to similar spectral characteristic as plastic. Since larger concentrations of plastic in river Drina are highly correlated with raining, same as turbidity and suspended solids, even clear pixels can be omitted. Also, freshwater are more likely to have emerging vegetation interfere with downwelling irradiance. The ocean are larger and generally cleaner than freshwater bodies which eliminated the most of the problems detected in this study. It is expected that developed algorithm will provide better results in mapping floating plastic at Open Ocean.

5. CONCLUSION

This paper describe an experimental study with the main focus on the detection of floating plastic debris in freshwaters based on an ANN classification procedure of high resolution multispectral WorldView-2 images.
The proposed workflow consists of algorithm for automatic water body extraction and algorithm for detection of plastic litter. Due to limited spectral and high spatial resolution the water body extraction was preformed by using object based image analysis and water indexes. In the second algorithm only water pixels are used. The Jefferies Matusita distance is calculated in order to select optimal input layer for neural network. The number of hidden layers is determined by trails and errors. The architecture 2-9-14-2 was produced lowest RMSE (RMSE= 0.03) at testing phase and was selected for detection of plastic. Finally, water pixels are classified into two classes: plastic and non-plastic. Validation of algorithm was performed by visual inspection of results. Generally ANN tends to underestimate floating plastic. The pure plastic pixels are detected. Mixed pixel, duo to presence of water has lower spectral reflectance, are mostly omitted. Additionally, Supported Vector Machine algorithm

tested by using same training data. Produced results suggest the large overestimation. Most of the shallow waters are classified as plastic.

Since freshwater contain large number of mixed pixel and their spectral signature is function of optical active parameters such as mud, turbidity, suspended solids, phytoplankton's etc. It is expected that this algorithm will provide better results in detection of floating plastic in the open ocean.

The limits of presented workflow are the absence of SWIR band in the used WorldView-2 images and absence of true data which would provide deeper insight into results. Our future work will be focused on the optimization of proposed algorithm and application of ultra-high resolution UAV images for plastic detection.

REFERENCES

Achanta, R., Susstrunk, S. 2017. Superpixels and Polygons Using Simple Non-iterative Clustering, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA

Aoyama, T. 2016. Extraction of marine debris in the Sea of Japan using high-spatial-resolution satellite images, SPIE - Remote Sensing of the Oceans and Inland Waters: Techniques, Applications, and Challenges, doi: 10.1117/12.2220370.

Campbell, O., Bushong, A., Gartman, D., Bhargava, S. 2017. IDENTIFYING SOURCES OF OCEAN PLASTICS: A methodology for supply chains, http://i.dell.com/sites/doccontent/corporate/corp-comm/en/Documents/ocean-plastic-white-paper.pdf

DG, Digital Globe, https://www.satimagingcorp.com/satellite-sensors/worldview-2/, [accessed 21.01.2019.]

Fareed, N., Thuan, L.D., 2017. Land Cover Classification for Satellite Images based on Normalization Technique and Artificial Neural Network, DOI:10.13140/RG.2.2.12071.96163.

Filella, M. 2015. Questions of size and numbers in environmental research on microplastics: methodological and conceptual aspects. Environ. Chem., 12 (5), 527−538.

Garaba, S., Aitken, J., Slat, B., Dierssem, H., Lebreton, L., Zielinski, O, Reisser, J., 2018. Sensing Ocean Plastics with an Airborne Hyperspectral Shortwave Infrared Imager, Environmental Science & Technology.

Ge, Z, Shi, H., Mei, X., Dai, Z, Li, D. 2016. Semi-automatic recognition of marine debris on beaches, Scientific Reports 6, DOI: 10.1038/srep25759.

Goddijn-Murphy, L., Peters, S., van Sebille, E., James, N., Gibb, S., 2018. Concept for a hyperspectral remote sensing algorithm for floating marine macro plastics, Marine Pollution Bulletin 126, 255–262.

Gonçalves Mendes, T.S., Porfírio Dal Poz, A., 2018. Urban road classification in geometrically integrated high-resolution RGB aerial and laser-derived images using the artificial neural network classification method, International journal of image and data fusion, https://doi.org/10.1080/19479832.2018.1469547.

Gordon, H. R., Brown, O. B., & Jacobs, M. M. 1975. Computed Relationships Between the Inherent and Apparent Optical Properties of a Flat Homogeneous Ocean. Applied Optics, 14(2), 417. doi:10.1364/ao.14.000417

Kataoka, T., Clarke Murray, C., Isobe, A. 2018. Quantification of marine macro-debris abundance around Vancouver Island, Canada, based on archived aerial photographs processed by projective transformation, Marine Pollution Bulletin 132, 44–51.

Kooi, M.; Reisser, J.; Slat, B.; Ferrari, F. F.; Schmid, M. S.; Cunsolo, S.; Brambini, R.; Noble, K.; Sirks, L.-A.; Linders, T. E. W.; Schoeneich-Argent, R. I.; Koelmans, A. A. 2016. The effect of particle properties on the depth profile of buoyant plastics in the ocean. Sci. Rep., 6, 33882.

Masoumi, H., Safavi, S.M., Khani, Z., 2012. Identification and classification of plastic resins using near infrared reflectance spectroscopy. Int. J. Mech. Ind. Eng. 6, 213–220

McFeeters, S. 1996. The Use of the Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features. International Journal Remote Sensing 17 (7): 1425–1432. doi:10.1080/ 01431169608948714.

Moy, K., Neilson, B., Chung, A., Meadows, A., Castrence, M., Ambagis, S., Davidson, K. 2018. Mapping coastal marine debris using aerial imagery and spatial analysis, Marine Pollution Bulletin 132, 52-59.

Swain, P. H., and S. M. Davis. 1978. Remote Sensing: The Quantitative Approach. New York: McGraw-Hill.

Tetteh, G., and M. Schonert. 2015. Automatic Generation of Water Masks from RapidEye Images. Journal of Geoscience and Environment Protection 3: 17–23. doi:10.4236/gep.2015.310003.

UNEPa, United Nations Environment Program, http://web.unep.org/unepmap/un-declares-war-ocean-plastic, (accessed 20.01.2019.)

United Nations Environment Program, The state of plastic, https://wedocs.unep.org/bitstream/handle/20.500.11822/25513/state_plastics_WED.pdf?isAllowed=y&sequence=1, (accessed 20.01.2019.)

Wardlow, B. D., Egbert, S. L., & Kastens, J. H. 2007. Analysis of time-series MODIS 250 m vegetation index data for crop classification in the US Central Great Plains. Remote Sensing of Environment, 108(3), 290–310.

Yang, X., and L. Chen. 2017. Evaluation of Automated Urban Surface Water Extraction from Sentinel-2A Imagery Using Different Water Indices. Journal Applications Remote Sensing 11 (2). doi:10.1117/1.JRS.11.026016.

BIOGRAPHICAL NOTES

Gordana Jakoviljević is PhD student on University of Novi Sad and she is emploied at Faculty of Architecture, Civil Engineering and Geodesy in Banja Luka as teaching assisstant in the fileds of cartography and remote sensing. Her practical and theoretical research deals with the application of remote sensing technology in field of environment protect especially in water management. She published several papers in journals and scientific conferences proceedings and she was involved in international and national projects. Also, she is member of FIG (International Federation of Surveyors) commission 4 (Hydrology) and working group 4.3 – mapping plastics.

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