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Determination of litter accumulations in different rivers using Sentinel-2 and Pleiades data

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Abstract

Following events such as extreme precipitation, floods, storms and hurricanes, litter accumulation in rivers increases. After these events, it is important to identify the areas of litter accumulation in rivers to protect the aquatic ecosystem, prevent secondary disasters from occurring, and prevent this litter from being transported to the seas and oceans. This study aims to determine the areas of litter accumulation in rivers of different lengths after extreme precipitation events in different parts of the world using remote sensing data. Litter accumulations were investigated in the Potpecko River in Serbia in January 2021, the Yangtze River in China in August 2018, the Drina River in Bosnia-Herzegovina in March 2021, and the Ezine River in Türkiye in August 2021. Medium spatial resolution Sentinel-2 and high spatial resolution Pleiades satellite imagery were used. Normalized Difference Water Index (NDWI) and Random Forest (RF) classification algorithms were used to extract information from the images. As a result of the classifications, the overall accuracy was 91.7%, 78.3%, and 95.2% for the Drina, Yangtze, and Potpecko rivers, respectively. In the Ezine River, tree stumps transported by the river were detected with an overall accuracy of 76.9%. Higher resolution Pleiades imagery was more effective in detecting smaller details, while Sentinel-2 imagery was able to detect larger litter accumulations with high accuracy.

1. Introduction

Litter is one of the most important sources of pollution in seas and rivers. It accumulates heavily in water bodies and seriously threatens both ecosystems and aquatic life. This litter can be transported from land to water by natural means such as wind and rain, or it can be caused by litter that is unconsciously thrown directly into the water. It usually accumulates on shorelines, in bays, in river waters, and near river mouths. Not only can litter in rivers have direct impacts on ecosystems, but it can also spread over wider areas and reach seas and oceans. Rivers act as conduits that carry land-based waste to the sea. The seas and oceans, which cover a large area on the Earth's surface, are among the most important factors affecting climate (Tuzcu Kokal et al., 2023). Therefore, tackling pollution in rivers is also critical to preventing pollution in the sea. Litter or debris can pose threats to water quality and blue economy (Garaba and Park, 2024). Especially after events such as rain, storms and cyclones, significant amounts of litter accumulate in rivers. In this context, identifying, monitoring and taking precautions against all kinds of litter in rivers is a very important issue for the healthy continuation of aquatic life.

Today, remote sensing technology plays an important role in the detection of water pollution and floating litter. There are many studies in which the spatial and temporal distribution of pollutants in water bodies are monitored and factors that degrade water quality are detected with the developing satellite imaging systems (Tuzcu Kokal and Musaoğlu, 2021; Hassan and Woo 2021). Satellites are a reliable data source in terms of their spatial and temporal resolution, their ability to detect large areas over time without interference, and their cost. Satellite data is an effective tool for detecting litter in seas and rivers as it covers large areas. Furthermore, satellite imagery such as Sentinel and Landsat is freely and openly available. Papageorgiou et al. (2022), conducted a spectral analysis and comparison of artificial floating targets placed on the sea surface using Sentinel 2 data as part of the Plastic Litter Project 2021. They reported that some floating litter can be detected using significant spectral similarities between artificial targets and other floating litter. According to the literature review by Politikos et al. (2023), it is possible to detect floating litter on the sea surface with classification, semantic segmentation, in-situ detection and similar methods using medium and high spatial resolution satellite imagery, unmanned aerial vehicles and cameras. Themistocleous et al. (2020), used Sentinel-2 satellite imagery to investigate the detectability of plastic litter on the sea surface using remote sensing methods. In this context, plastic water bottles were placed on the sea surface and their spectral signatures were measured using a spectroradiometer. As a result of the analysis, it was determined that plastic litter is most easily distinguished at near-infrared (NIR) wavelengths. They stated that it is easiest to detect plastic litter at NIR wavelengths. Biermann et al. (2020), developed a floating debris index (FDI) using Sentinel-2 satellite imagery to detect floating debris on the ocean surface. This index allows the determination of floating debris using Sentinel-2's Red, Red Edge, NIR and SWIR bands. In a project initiated by VITO has created a comprehensive database of spectral signatures of various types of plastics, including wet, dry and submerged plastics. This database enables the development of machine learning algorithms aimed at detecting plastic waste on the water surface (Url-1). Kikaki et al. (2022), created a dataset called Marine Debris Archive (MARIDA) based on Sentinel-2 satellite data to provide input for machine learning methods to detect marine debris. This dataset distinguishes marine debris from other marine features such as ships, sea foam, turbid water, clouds, and organic matter, making it possible to detect it using machine learning methods. Sannigrahi et al. (2022), analysed Sentinel satellite data with Support Vector Machines (SVM) and Random Forest (RF) algorithms to detect and classify marine litter in different regions of the world. It was found that both algorithms classified marine litter with high accuracy. In addition, using multi-resolution satellite imageries contributes to more accurate detection of floating litter (Kremezi et al., 2022).

In light of all these studies, the importance of detecting litter at its source before it reaches the sea is significant. In this context, determination of litter in rivers that flow into the sea allows for intervention before the litter enters marine environments. Furthermore, detecting litter accumulation after natural disasters such as floods helps prevent secondary disasters. For instance, large tree stump carried after a flood can cause significant damage to buildings and roads in residential areas. In this study, the RF method was applied to Sentinel-2 and Pleiades imagery to detect litter accumulation in rivers following extreme rainfall. The method was tested on rivers of varying sizes in different regions of the world. The selection of these rivers in different parts of the world is intended to assess the applicability of the method to rivers with different environmental conditions and characteristics.

2. Data and Methodology

The study focused on the examination of litter accumulation following extreme precipitation events in several significant river systems, including the Potpecko River in Serbia in January 2021, the Yangtze River in China in August 2018, the Drina River in Bosnia and Herzegovina in March 2021, and the Ezine River in Türkiye in August 2021 (Figure 1). In this context, determination of litter accumulation with satellite images in different rivers, following extreme precipitation events, contributes to assessing the effectiveness and usefulness of a globally applicable method.

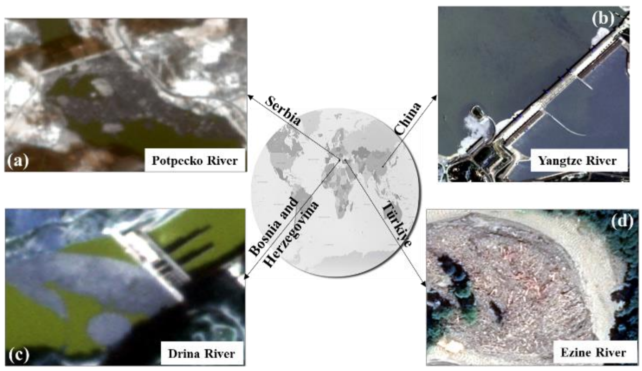

Figure 1. The location of the study area (a) Potpecko River, Serbia b)Yangtze River, China (c) Drina River, Bosnia and Herzegovina (d) Ezine River, Türkiye

2.1 Data Used

This study utilized Sentinel-2 and Pleiades, imagery to assess litter accumulation in different river systems. Sentinel-2 imagery was used to detect litter accumulations in the Potpecko, Yangtze, and Drina rivers. In the Ezine River, the accumulation of tree stumps following flooding in the region was examined. These tree stumps were distinguishable in the Pleiades imagery, which offers a higher spatial resolution, but was not identifiable in the Sentinel-2 images. Therefore, the Pleiades imagery was selected for analysis in the Ezine River. Planetscope satellite data was only used in the accuracy assessment. The Sentinel-2 image was downloaded from the Copernicus website (https://dataspace.copernicus.eu/) (Url-2). Pléiades data are commercially available. Planetscope data was downloaded from the Planet website (https://www.planet.com/explorer/) (Url-3). The technical specifications of the images used in the study are given in Table 1 (Url-4, Url-5, Url-6).

Sentinel-2			
Band Number	Band	Wavelength (µm)	Spatial resolution (m)
1	Coastal and Aerosol	0.433 – 0.453	60
2	Blue	0.458 – 0.523	10
3	Green	0.543 – 0.578	10
4	Red	0.650 – 0.680	10
5	Red Edge	0.698 – 0.713	20
6	Red Edge	0.733 – 0.748	20
7	Red Edge	0.773 – 0.793	20
8	NIR	0.785 – 0.900	10
8A	Red Edge	0.855 – 0.875	20
9	Water vapour	0.935 – 0.955	60
10	Cirrus	1.360 – 1.390	60
11	SWIR	1.565 – 1.655	20
12	SWIR	2.100 – 2.280	20
Radiometric Resolution = 12 bit			
Temporal Resolution = 5 days			
Pleiades			
1	Blue	0.450 – 0.530	2
2	Green	0.510 – 0.590	2
3	Red	0.620 – 0.700	2
4	NIR	0.775 – 0.915	2
5	Pankromatic	0.480 – 0.820	0.5
Radiometric Resolution = 12 bit			
Temporal Resolution = daily			
Planetscope			
1	Blue	0.455 – 0.515	3
2	Green	0.500 – 0.590	3
3	Red	0.590 – 0.670	3
4	NIR	0.780 – 0.860	3
Radiometric Resolution = 12 bit			
Temporal Resolution = daily			

Table 1.Technical specifications of the data used in the study

2.2 Methodology

In order to determine litter accumulations, Normalized Difference Water Index (NDWI) was applied to the images to distinguish water and litter. In the literature, FDI is one of the most commonly used indices to determine litter on the water surface. However, the FDI requires Red, Red Edge, NIR and SWIR bands. Since the Red Edge and SWIR bands are not available in the Pleiades images, the NDWI was used instead of FDI in this study. NDWI was then added as input to the RF classification algorithm. Classification accuracy analysis was performed with Planetscope and Pleiades images. The flow chart of the study is shown in Figure 2.

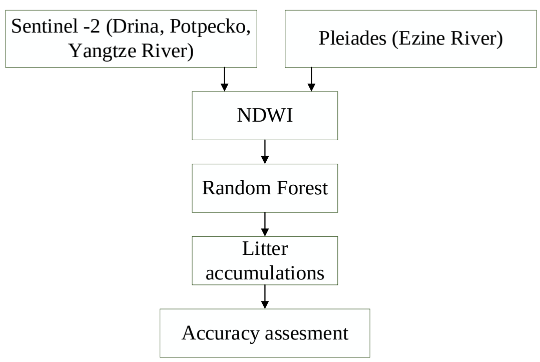

Figure 2. Flow chart of the study

2.2.1 Normalized Difference Water Index and Random Forest Algorithm

Indices used in remote sensing are frequently applied in various fields. These are values obtained as a result of the processing of remote sensing data, quantitatively expressing a certain surface feature or environmental condition. It is created by combining reflectance values from different spectral bands of satellite images with mathematical operations. In this study, NDWI, one of the most commonly used indices for water discrimination, was used (McFeeters, 1996). The formula for this index is shown below (Eq. 1).

$$NDWI = (Green - NIR)/ (Green + NIR) \quad (1)$$

After NDWI was applied to the images, this index was used as input for RF Classification.

Classification is an image processing method that is frequently used to extract information from satellite images. The purpose of classification is to group objects with similar characteristics. In many image classification processes performed in remote sensing studies, it is seen that machine learning and deep learning methods give better results than classical methods. Machine learning and deep learning methods can save time and cost in image classification, reduce human influence as much as possible, perform various analyzes and processes automatically and obtain high accuracy information. Decision trees, one of the machine learning methods, are frequently used in the literature and high accuracy results are obtained from the studies conducted with this method. There are many classification methods based on decision trees, and RF Method (Breiman, 2001), one of these methods, is used in this study. RF is a collective learning approach developed to solve classification and regression problems. In this approach, multiple models are integrated to solve the same problem, creating a scheme that improves accuracy (Sheykhmousa et al., 2020). Each tree in the RF algorithm is built based on prediction through controlled learning. This algorithm basically consists of nodes, branches and leaves. This method combines a large number of decision trees together to create a more powerful and consistent prediction model. After the training, decision trees classify the data by branching. In each branch, only a randomly selected group of features is considered, which allows the models to diversify. In the final stage, the results of all decision trees are combined. For the classification problem, the result is determined by majority vote (Figure 3).

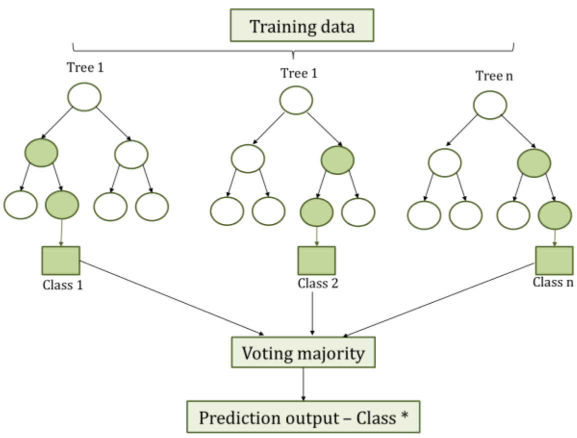

Figure 3. Schematic diagram of Random Forest algorithm

3. Results and Conclusion

As a result of the RF method, 3 classes were created in the Drina, Yangtze and Potpecko rivers: Litter, water and other. Other class includes roads, buildings, dam bodies, snow, etc. The area of the Ezine River is densely forested and only tree stumps are available as litter. Tree stumps could not be identified with Sentinel-2 image due to the spatial resolution. Therefore, the RF method was applied to the Pleiades image in this region. In these four rivers with different sizes, litter accumulations could be identified by RF classification. In the Drina, Yangtze and Potpecko rivers, all of the litter accumulated on the river surface could be identified. In some areas outside rivers, classes that do not belong to the litter class were classified as litter. Upon a comprehensive examination of the images, it is evident that the RF method effectively classifies litter, as illustrated in Figure 4.

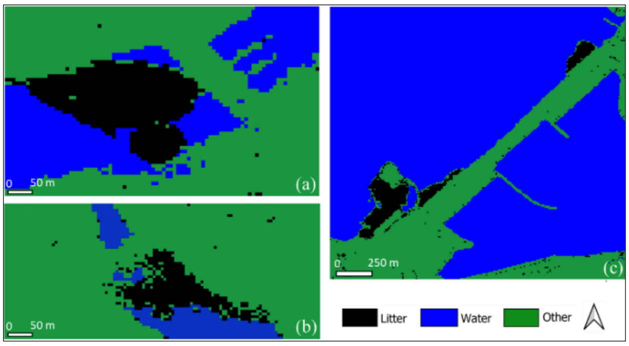

Figure 4. RF Classification Results (a) Drina River (b) Potpecko River, (c) Yangtze River

The region surrounding the Ezine River is characterized by dense forestation, with only tree stumps present as litter. Additionally, settlements are located along the riverbank. Following the flooding of the Ezine River, the floodwaters transported these tree stumps, which could not be distinctly identified in the Sentinel-2 imagery due to the limitations of its resolution. Consequently, the RF method was applied to high-resolution Pleiades imagery, which allowed for the effective differentiation of tree stumps from the floodwater and mud. (Figure 5).

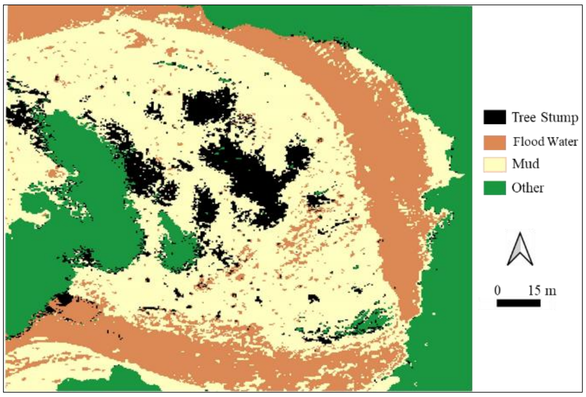

Figure 5. Ezine River RF Classification Result

The error matrix was used to determine the classification accuracy. It was created by combining the reference data, the data that is known exactly to which class it belongs, and the classified data in rows and columns. The overall accuracy across all rivers exceeded 70%, indicating a high level of classification performance for litter. However, the accuracies in the Yangtze and Ezine rivers were comparatively lower. This is because the spectral reflectance in the artificial areas around the Yangtze River is similar to the spectral reflectance in the litter. In the case of the Ezine River, the accuracy was lower than in the other rivers due to confusion in the spectral reflectance of mud and flood water (Table 2).

	Overall Accuracy (%)
Drina	91.7
Yangtze	78.3
Potpecko	95.2
Ezine	76.9

Table 2. The overall accuracies of the classification results

After extreme precipitation, floods and storms, litter accumulation in rivers increases. Detection of these accumulations is very important in terms of preventing the transportation of litter to the sea, preventing secondary disasters and taking appropriate measures. With remote sensing, it is possible to identify these litter in large areas. In this study, images with different spatial resolutions were used to detect litter in rivers in different parts of the world where litter accumulation occurs after extreme precipitation. NDWI was used to distinguish between water and litter on the water surface and this index was used as input for the RF classification method. The medium spatial resolution Sentinel- 2 image used in the study was able to detect large litter accumulations, while smaller litter accumulations were detected in the Pleiades image. The RF method gave high accuracy results in all four rivers. As a result of the study, it was observed that litter on the river surface can be detected from satellite images with remote sensing. It is clear that the Sentinel- 2 image is a successful tool for the detection of large litter accumulations. For the detection of smaller details, high resolution images give better results.

It should be further investigated whether different classification methods and indices can be applied to different satellite imagery to detect litter in larger areas, such as seas and larger rivers. Remote sensing has good global and long-term potential for monitoring marine and river litter. Remote sensing of litter in rivers is a relatively new area and research on the ability of satellite imagery to detect and track litter is generally limited; the various interactions and mechanisms are largely unknown. Therefore, such research in this area will shed light on future work. Combining machine learning algorithms with remote sensing data can enable the creation of real-time litter monitoring and detection systems. These systems can send instant alerts to authorities, speeding up emergency responses and helping to prevent litter accumulation before it reaches the seas. It will also be an important tool to prevent secondary environmental impacts such as reduced water quality, degradation of ecosystems and the spread of microplastics that harm marine life. With higher resolution imagery, it may become possible not only to detect accumulations of litter, but also to identify the types of litter. In particular, more detailed classification can be made by taking into account the spectral characteristics of pollutants such as plastics, organic wastes, etc. In addition, temporal variations of litter accumulation can be monitored by using images of the same region taken at different time periods, and thus, it can be analyzed which seasons or weather events result in more litter accumulation. Such studies will contribute to the improvement of waste management strategies and more effective implementation of response plans in the relevant regions.

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