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Remote Sensing for Monitoring Macroplastics in Rivers: A Review

Ashenafi Tadesse Marye[1,2] | Cristina Caramiello[3] | Dario De Nardi[4] | Domenico Miglino[3] | Gaia Proietti[5] | Khim Cathleen Saddi[3,6,7] | Chiara Biscarini[5] | Salvatore Manfreda[3] | Matteo Poggi[4] | Flavia Tauro[8]

[1]Department of Economics, Engineering, Society, and Business Organization, University of Tuscia, Viterbo, Italy | [2]Department of Natural Resources Management, College of Agriculture and Environmental Sciences, University of Gondar, Gondar, Ethiopia | [3]Department of Civil, Architectural and Environmental Engineering, University of Naples Federico II, Naples, Italy | [4]Department of Computer Science and Engineering, University of Bologna, Bologna, Italy | [5]UNESCO Chair in Water Resources Management and Culture, University for Foreigners of Perugia, Perugia, Italy | [6]Istituto Universitario di Studi Superiori IUSS Pavia, Pavia, Italy | [7]Department of Civil Engineering and Architecture, Ateneo de Naga University, Naga, Philippines | [8]Department for Innovation in Biological, Agro-Food and Forest Systems, University of Tuscia, Viterbo, Italy

Correspondence: Flavia Tauro (flavia.tauro@unitus.it)

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ABSTRACT

Given the exponential rise in global plastic production and its significant ecological and socio-economic impacts, monitoring macroplastics in rivers has become a central focus of water management efforts. However, standardized monitoring methodologies are lagging behind the rate of plastic waste currently entering aquatic systems on a global scale. This translates into a shortage of spatially and temporally refined data on the macroplastic pollution circulating in inland waters. Recent advancements in remote sensing techniques, primarily satellites, UASs, fixed and handheld cameras combined with crowd-sourced data and automated macroplastic detection using machine and deep learning, offer promising opportunities for versatile monitoring solutions. Thus, this paper reviews state-of-the-art approaches and emerging methods for macroplastic identification in rivers to provide researchers with a comprehensive inventory of techniques and to encourage the scientific community to harmonize monitoring methods and define standard protocols. According to our investigation, addressing the challenges of remote sensing-based river macroplastics monitoring mandates further efforts to enhance and integrate multiple platforms with an emphasis on long-term monitoring.

1 | Introduction

Since the 1950s, over 8000 million tonnes (Mt) of plastics have been produced globally (OECD 2022). Over the past two decades, production nearly doubled from 234 to over 400 Mt (OECD 2022; Europe-Plastic 2024), and is expected to double again by 2050 (Stegmann et al. 2022). In 2019 alone, over 18% of plastic resulted in mismanaged waste, with 6.1 Mt ended up in rivers, lakes, and oceans, exceeding prior annual discharge estimates (0.41–4 Mt per year) (Jambeck et al. 2015; Lebreton et al. 2017;

Schmidt et al. 2017; Meijer et al. 2021; Gallitelli and Scalici 2022). Rivers also act as reservoirs or sinks for plastics (Tramoy, Gasperi, Colasse, Silvestre, et al. 2020; van Emmerik, Mellink, et al. 2022; Mennekes et al. 2024; Oswald et al. 2025). Plastic pollution poses a major threat to our planet's health (MacLeod et al. 2021; Fletcher et al. 2023). The implications of recently escalating plastic pollution are alarming not only for the marine and freshwater ecosystems (Bucci et al. 2020; Azevedo-Santos et al. 2021; González-Fernández et al. 2021; Battisti et al. 2023; MacAfee and Löhr 2024) but also for the socioeconomic well-being of global communities. Besides the direct dumping into water bodies, mismanagement of terrestrial plastics feeds such debris to rivers (Liro et al. 2020; Tramoy et al. 2020), a process further exacerbated during flash floods (Roebroek et al. 2021; van Emmerik, Kirschke, et al. 2023; MacAfee and Löhr 2024; Cózar et al. 2024). Furthermore, in urban areas, plastic debris clogs drainage systems, increasing the risk of flooding (Lebreton and Andrady 2019; Honingh et al. 2020; Nepal and Bharadwaj 2022). Altogether, these phenomena are expected to increase with climate change (MacAfee and Löhr 2024).

Internationally, stakeholders are working to reduce plastic pollution in aquatic and terrestrial ecosystems (Da Costa et al. 2020; Knoblauch and Mederake 2021; Dauvergne 2023). However, global monitoring efforts, particularly in freshwater systems, remain limited (Winton et al. 2020; Earn et al. 2021; Kirschke et al. 2023; Nava et al. 2023). Despite the lack of consensus in the literature, three broad plastic categories are typically defined based on size: microplastics (< 5mm) (Browne 2015; Andrady 2017; Lusher et al. 2017), macroplastics (≥ 5mm) (Kawecki and Nowack 2019), and megaplastics (> 1000mm) (Lusher et al. 2017; GESAMP 2019). In some instances, the additional category of mesoplastics is adopted to refer to materials ranging from 5 to 25 mm (Lusher et al. 2017; GESAMP 2019; Nihei et al. 2024). As illustrated in Figure 1, research on freshwater plastic pollution has increased in recent years; however, much of the scientific focus remains on microplastics (Blettler et al. 2018; Gallitelli and Scalici 2022; Zhao et al. 2024). Most likely, this attention is related to detection advancements as well as increased awareness of their ecological and human health implications, including ecotoxicology, risk assessment and total environmental health (Lusher et al. 2021; Rochman 2018).

Monitoring plastic dynamics is vital for informed decision-making and assessing mitigation efforts. Yet, a lack of standardized methods for macroplastic monitoring is the bottleneck to draw concrete indications on river plastic movement (Hurley et al. 2023). This leads to limited data with insufficient spatial and temporal coverage. According to recent studies, macroplastics that leak into rivers persist for decades or even centuries (van Emmerik, Mellink, et al. 2022; Mennekes et al. 2024). They are often transformed into microplastics due to fragmentation and photodegradation (European-Parliament 2018; Tursi et al. 2022; Liro et al. 2023; Huang and Xia 2024). Once converted into

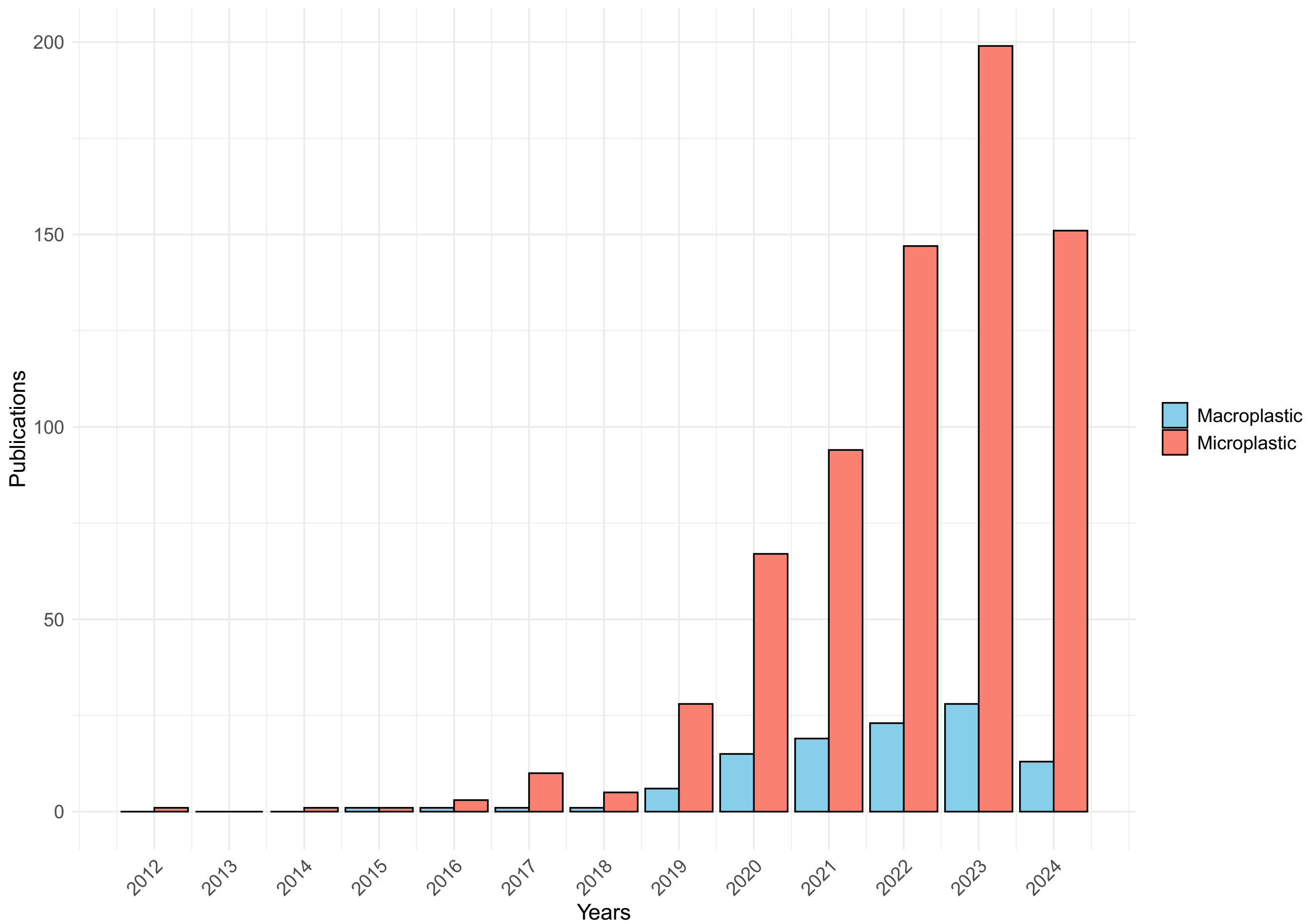

FIGURE 1 | Number of studies on micro- and macro-plastics in freshwater (June 2024, Web of Science).

smaller particles, plastics are extremely difficult to track and remove. On the other hand, macroplastics can be monitored through several techniques, including visual observation, physical interception, remote sensing, and underwater sensing (Gallitelli, Girard, et al. 2024). However, many of these methods remain in the early stages of development (van Emmerik and Schwarz 2020). Environmental practice largely relies on either visual observations or physical interception. In visual observations, operators directly assess floating and partially submerged plastics, providing insight into their types, sizes, and loads (González-Fernández and Hanke 2017; Castro-Jiménez et al. 2019; González-Fernández et al. 2021; Pinto et al. 2024). Although cost-effective, this method can be resource-intensive for long-term monitoring and susceptible to detection biases. In contrast, physical interception actively traps plastic debris using nets or passive barriers like booms (Cowger et al. 2022; Vriend et al. 2020; Blettler et al. 2023). The effectiveness of these methods depends on factors like deployment location, net and mesh dimensions, and flow conditions (Wendt-Potthoff et al. 2020; Hurley et al. 2023). Although physical interception provides tangible data on plastic pollution, it requires multiple points in larger rivers and faces challenges for frequent application due to operational costs, possible risks and logistical difficulties.

Alternatively, recent advancements in remote monitoring, artificial intelligence, citizen science, and crowd-sourced data offer significant potential for improving river systems monitoring (Tauro et al. 2018; Manfreda et al. 2024). Particularly, remote sensing-based monitoring (through satellite, Unmanned Aerial Systems [UASs], and fixed or handheld camera-based systems) provides a scalable solution for frequent and objective observations. Remote sensing methods can be integrated with data-driven algorithms such as machine learning (ML) and deep learning (DL), hold promise in unsupervised identification of floating macroplastics types, and can enhance reliability in detection and quantification over time (Jakovljevic et al. 2020; Wendt-Potthoff et al. 2020; Wolf et al. 2020; Iordache et al. 2022; Solé Gómez et al. 2022; Tasseron et al. 2022; Jia et al. 2023; Mohsen et al. 2023; Sakti et al. 2023). However, despite these advantages, such methods are relatively unexplored in river systems (Geraeds et al. 2019; Solé Gómez et al. 2022) compared to their use in marine environments (Waqas et al. 2023).

Towards improving monitoring practices, this paper offers a systematic review of emerging remote sensing methods and tools to tackle macroplastic identification in riverine environments. This review specifically focuses on buoyant macroplastics within river systems, excluding underwater and other environments such as marine and terrestrial ecosystems. It emphasizes image acquisition methodologies, detailing the platforms used, including satellites, UAS, and fixed or handheld cameras. In addition, we examine data collection processes and image analysis methods. Our objectives are twofold: from one perspective we aim to provide researchers and practitioners with a comprehensive inventory of techniques applicable to diverse experimental settings; and from another perspective given the urgent need for reliable and consistent methodologies, this review aims to support the development of effective and comparable monitoring strategies.

This review is organized as follows. In Section 2, we present routinely adopted techniques for assaying macroplastics in rivers; in Section 3, we focus on remote image-based methods as well as on the analytical tools currently available to sense plastics in images; in Section 4, we critically point out advantages and limitations of the reviewed methods, and in Section 5, we provide a conclusion and outlook.

2 | The State of the Art

2.1 | Visual Observations

Visual observations entail inspection, quantification, and categorization of floating and slightly submerged macroplastics in rivers by operators. This method allows to directly assess the type, dimensions, and characteristics of plastic pollution (González-Fernández and Hanke 2017; Castro-Jiménez et al. 2019; González-Fernández et al. 2021; Pinto et al. 2024). It is relatively inexpensive since it does not require special equipment. However, producing fine-scale, long-term data with this method can become both cost- and labor-intensive. As demonstrated by the RIMMEL project and census by the Italian Ministry for Ecological Transition and SNPA (Vighi et al. 2022; JRC 2016), in spite of their simplicity, visual observations have proven effective for large-scale and long-term monitoring. However, the efficacy of this approach relies on several aspects associated with the configuration of the monitoring site and sampling timing. First, it is essential to conduct the observations from a monitoring location that accurately captures most of the river section while guaranteeing that even small objects are seen. For instance, surveys are frequently performed from an elevated position like a bridge or along the riverside (Pinto et al. 2024). The choice of the river section also affects the results: selecting a spot near the river mouth could be ideal for transport studies (van Emmerik, van Klaveren, et al. 2020; Kuizenga et al. 2023). The height of the observation point controls the smallest detectable plastic size (Castro-Jiménez et al. 2019), while the bridge's dimensions determine the width of the observable section. Second, since flow velocity variations (along with the river section morphology) influence plastic waste accumulation and transport, the sampling duration and frequency of visual observations should adapt to flow changes. While the duration of monitoring surveys also depends on the plastic load (van Emmerik, van Klaveren, et al. 2020), it is usually recommended that observations are performed at least hourly for rivers with significant flow changes. Ideally, the number of surveys should be proportional to the number of monitored sections. For high plastic load rivers (>1000 items/h), sampling duration typically ranges from 1 to 2 min per section, while for lower loads (100 items/h), it ranges up to 15 min per section (Wendt-Potthoff et al. 2020). Bias and errors may arise from missing or misidentifying plastics, especially small or transparent objects (Castro-Jiménez et al. 2019), and accuracy may decrease due to water turbidity, sun glare, as well as during periods of high plastic loads and extended observation times (van Emmerik, de Lange, et al. 2022; Kuizenga et al. 2023). Towards mitigating such errors, it is usually preferred to conduct surveys in teams (including at least an observer and a recorder) (Pinto et al. 2024), and to use binoculars (Cesarini et al. 2023). To minimize subjectivity and improve accuracy, however, adopting alternative methods, such as cameras for passive counting or DL (van Lieshout et al. 2020) as well as combining observations with physical interception methods

(Kuizenga et al. 2023), is recommended. Citizen science has proven an effective approach to acquiring larger visual observation datasets of river channels and riversides (Rech et al. 2015; Kiessling et al. 2019; van Emmerik, Roebroek, et al. 2020; van Emmerik, Seibert, et al. 2020; Honorato-Zimmer et al. 2021; Kiessling et al. 2021; Liro, Zielonka, Hajdukiewicz, et al. 2023). Various riverside macroplastic monitoring protocols have been developed. Some adopt procedures originally designed for marine plastic monitoring, such as OSPAR Beach and NOAA Beach Litter (OSPAR 2010; Lippiatt et al. 2013; van Emmerik, Vriend, et al. 2020), while others rely on newly developed approaches, including Plastic Pirates, CrowdWater (Kiessling et al. 2019; van Emmerik, Seibert, et al. 2020), and harmonized techniques particularly designed for riparian environments (Gallitelli, Cutini, et al. 2024). It is important to note that balancing between imprecise measurements or human biases and citizen participation is crucial.

2.2 | Physical Interception

Unlike noninvasive visual observations, physical interception involves trapping and removing plastic debris from rivers using physical barriers. Physical interception can be classified as active sampling, which uses equipment such as nets (Cowger et al. 2022), and passive sampling, which relies on existing infrastructure such as booms (Vriend et al. 2020; Blettler et al. 2023). Nets, which are meshed screens or bags, can be fixed at bridges (van Emmerik et al. 2019; Cowger et al. 2022) or deployed from riverbanks (Moore et al. 2011; Munari et al. 2021) and boats (Karpova et al. 2022; Oswald et al. 2023), and positioned at different depths to capture various plastic transport pathways. Additionally, they can be deployed in fleets to sample different parts of the water column (Blondel and Buschman 2022; Hurley et al. 2023; Oswald et al. 2023). The quantity of macroplastics intercepted by nets relies on variables such as net dimensions, mesh size, deployment site, and water flow conditions (Wendt-Potthoff et al. 2020; Hurley et al. 2023). A flow velocity greater than 1 m/s can be powerful, while lower flow velocities may not be sufficient to keep the net properly positioned, thus hindering effective plastic collection (van Emmerik and Schwarz 2020). Booms are floating barriers designed to gather natural and non-natural materials across sections of a river channel. While they are primarily used for clean-up and pollution prevention, a few studies have explored their use for sampling purposes and evaluated their effectiveness in controlling macroplastic pollution (Blettler et al. 2023; Hurley et al. 2023). These studies involve isolating, counting, categorizing, and weighing the collected plastic material (Malik et al. 2020; Vriend et al. 2020; Sari et al. 2022; Blettler et al. 2023). Booms can also include a mesh or screen to catch debris just below the water's surface (Sari et al. 2022). River macroplastic monitoring using physical interception involves diverse duration, frequencies, deployment locations, and depth. For instance, monitoring is different for large rivers compared to small streams. Large rivers may need several monitoring spots across their width, while small streams can often be sampled from the bank or by wading.

The duration may vary within short intervals lasting minutes or less (Moore et al. 2011; Weideman et al. 2020), to extended periods lasting up to a few days (Morritt et al. 2014), with frequency guided by monitoring objectives and resource constraints. Similarly, it may be possible to select multiple monitoring sites at the same river cross-section depending on the specific purpose of the campaign, that is, if the survey aims to collect comprehensive data or evaluate cross-sectional variability. Rivers with deltas and intermittent streams require flexible and ad hoc designed monitoring approaches (Wendt-Potthoff et al. 2020). Among the advantages of physical interception, the possibility to provide direct and tangible data on plastic pollution is certainly a valuable asset. However, practical difficulties, costs, and possible risks to operators may hamper frequent implementations.

3 | Remote Sensing

Image-based monitoring in freshwater settings can provide large scale spatial coverage at potentially frequent temporal resolutions. A bibliographic search was conducted using Web of Science and Google Scholar with various keyword combinations, including "river litter," "river debris," "plastic debris," "macroplastics," "remote sensing," "drones," "Unmanned Aerial Vehicles," "cameras," "machine learning," and "deep learning." After removing duplicates and excluding studies outside the scope of this review (e.g., those focusing on marine, soil, biota or other plastic size categories), research articles specifically addressing the use of remote sensing for monitoring buoyant macroplastics in river systems were selected. Upon careful evaluation of the identified studies, only peer-review articles providing sufficient methodological details for accurate interpretation were included. As a result, a total of 16 studies were retrieved. Most of the literature emerged between 2022 and 2023, indicating a recent surge in research interest in this field.

The platforms used by these studies so far can be categorized into three types: space-borne, airborne (UAS), and ground-based (fixed and handheld cameras). All the reviewed studies utilized passive sensors, relying on naturally available energy, across various platform types, except one study that used an active sensor that generates its own illumination, from a spaceborne platform (Simpson et al. 2022). Within the reviewed studies, 20% utilized only satellite or space-borne platforms (Solé Gómez et al. 2022; Simpson et al. 2022; Mohsen et al. 2023; Sakti et al. 2023). 40% used airborne platforms, such as UASs at different elevations and resolutions (Geraeds et al. 2019; Jakovljevic et al. 2020; Wolf et al. 2020; Cortesi et al. 2022; Maharjan et al. 2022; Schreyers et al. 2021). These studies predominantly used the visible spectral range. Only one study integrated data from both satellites (Sentinel-2 and Pleiades) and UASs (Sakti et al. 2023). Ground-based cameras mounted on a fixed location, such as bridges (van Lieshout et al. 2020; Iordache et al. 2022), masts, or handheld (De Giglio et al. 2020), accounted for 33% of the analyzed papers. Approximately half of the studies with ground-based platforms also used a combination of fixed and handheld or UAS data; and were conducted in different image-capturing settings, such as natural environment (van Lieshout et al. 2020), semi-controlled experiments in a natural environment (De Giglio et al. 2020; Iordache et al. 2022; Tasseron et al. 2022; Jia et al. 2023) and lab-based (Tasseron et al. 2022). While all spaceborne-based studies utilized multispectral images, ground-based efforts also demonstrated the use of hyperspectral images in detecting river macroplastics (Tasseron et al. 2022). All studies were conducted across various regions globally, reflecting a diverse geographical distribution of research efforts and underscoring the growing recognition of the urgency to address plastic pollution.

3.1 | Satellite- and UASs-Based Monitoring

Sensing macroplastics through satellites and drones has involved diverse sensors, experimental setups and data acquisition and processing settings. Table 1 summarizes key studies, focusing on: (i) the platform adopted for data acquisition; (ii) the sensor mounted on the platform; (iii) altitude of data collection; sensor features, such as (iv) spatial resolution and (v) spectral range; (vi) eventual image preprocessing procedures; (vii) area of interest; (viii) targeted plastics class(es); (ix) detection methods; (x) and accuracy assessment.

Satellite-based research demonstrated the feasibility of detecting and quantifying plastic debris accumulation along rivers, river shores, lakes, and reservoirs. As reported in Table 1, the spatial resolution of the satellite versus UASs data varied across the studies. Mainly, moderate-resolution sensors (10 m) of Sentinel 2 were commonly used due to their unique spectral bands in the VIS, NIR, and SWIR ranges, though they struggled in precisely identifying small and dispersed plastic particles in rivers (Solé Gómez et al. 2022; Simpson et al. 2022; Mohsen et al. 2023; Sakti et al. 2023). Higher-resolution yet commercial satellites, such as Pleiades (50 cm) and WorldView-3 (31 cm), provide finer detail, enhancing detection accuracy. For instance, (Sakti et al. 2023) validated Sentinel-2 detection performance using Pleiades imagery.

Complementary to the large-scale monitoring capabilities enabled by satellites, UASs-based studies leverage detailed spatial data and precise detection algorithms (Geraeds et al. 2019; Jakovljevic et al. 2020; Wolf et al. 2020; Cortesi et al. 2022; Maharjan et al. 2022). UASs achieved resolutions often < 2 cm with 2–5 cm range, depending on altitude and sensor type. At low altitudes (≤ 90 m), they also allowed detailed categorization, morphological attributes (e.g., size) and quantification of plastic items. The varying altitudes and multi-altitude data acquisition mainly depended on the specific objective of the experiment. For instance, in the pioneering UAS-based river plastic monitoring study by Geraeds et al. (2019), multi-altitude data acquisition was employed that balanced spatial coverage and detection detail by capturing images at various heights (5, 15, and 63 m for plastic counting, identifying transport hotspots and broader flow analysis and riverbank plastic detection, respectively). Similar approaches were adopted by Schreyers et al. (2021) to unravel the influence of water hyacinths on the transport and accumulation of plastic debris within river ecosystems. It is worth noting that the spatial resolution from such platforms depends not only on altitude but also on camera quality, sensor type and focal length, which can significantly influence the spatial resolution (see Figure 2).

Capturing plastic-specific absorption or reflection traits with high spectral resolution is key to advancing remote sensing-based plastic monitoring. Spaceborne- and airborne-based studies mainly use multispectral and RGB (visible) imagery, respectively. The effectiveness of UAS-based RGB imaging primarily depended on the plastic's size, distinctive color, and favorable weather conditions (Maharjan et al. 2022). RGB imaging lacks data from other wavelengths essential for effective plastic detection. To address this limitation, many UAS-based studies relied on high spatial resolution. However, this approach involved a trade-off in spatial coverage, as images were captured at lower altitudes to achieve higher resolution (Jakovljevic et al. 2020; Wolf et al. 2020). In contrast, multispectral sensors on UAS (RGB, Violet, Red Edge1, Red Edge2, NIR1 [Near-Infrared-1], NIR2, and NIR3) effectively distinguished floating plastics from water at 80 m altitude (Cortesi et al. 2022).

The wavelengths between 1215 and 1732 nm were identified as particularly effective in the detection of plastics (Garaba et al. 2018; Garaba and Dierssen 2018). Consistently, a hyperspectral study (400–1700 nm) in laboratory settings revealed distinct reflectance and absorption traits for plastics and vegetation in the 950–1700 m range, while water showed almost no reflectance (Tasseron et al. 2021). Similarly, various plastic polymers showed high absorption at wavelengths of 1150, 1210, 1215, 1400, 1430, and 1460 nm while vegetation absorption peaks at 1450 nm. This enables differentiation from water and vegetation (Tasseron et al. 2021). The analysis was also compared to Sentinel-2 and Worldview-3 satellite bands, previously used for river plastic monitoring. (Solé Gómez et al. 2022; Simpson et al. 2022; Mohsen et al. 2023; Sakti et al. 2023). According to Tasseron et al. (2021), Sentinel-2 bands B5–B8 (705–842 nm) and B10 (1375 nm) were crucial for distinguishing plastics from water and vegetation, and B6 (740 nm) and B8 (842 nm), are fundamental for computing the FDI and detecting floating plastics.

Building on these spectral characteristics of plastics, Solé Gómez et al. (2022) utilized Sentinel-2 imagery to detect plastics in rivers and reservoirs. Their findings align with previous studies: plastics exhibited maximum spectral signatures around B8, B8a (865 nm), and B11 (1610 nm), with a minimum at B9 (940 nm) (see fig. 3 of Solé Gómez et al. (2022) and fig. 4 of Mohsen et al. (2023)). Solé Gómez et al. (2022) also observed a sharp rise in reflectance at 705 nm (B5) in areas with high vegetation cover, which helped differentiate plastics from vegetation. However, rivers near urban areas presented challenges in distinguishing plastics, as construction materials and their surroundings exhibited high reflectance values similar to those of plastics, thus complicating the differentiation (Sakti et al. 2023). A similar approach by Mohsen et al. (2023), reported that artificial barriers shared a similar spectral signature with plastic materials, particularly in the SWIR and NIR bands of Sentinel-2. To distinguish them, inspecting the 842 and 1610 nm wavelengths, was beneficial since barriers and plastics show opposite spectral signatures.

Despite advances in spaceborne- and UAS-based imaging, plastic detection can still be improved. Hyperspectral imaging, with its detailed spectral capture, enhances plastic identification by leveraging unique absorption and reflection traits. Corbari et al. (2020) characterized the spectral signatures of common polymers found in the Mediterranean Sea, showing that WorldView-3 and PRISMA hyperspectral images outperform other alternative satellites for such applications. This capability is critical for identifying different types of plastics and

TABLE 1 | Summary of satellite and UASs image-based studies.

Sources	Platform	Sensor	Altitude	Spectral range	Spatial resolution	Image preprocessing	Area of study	Target class(es)	Detection and analysis	Accuracy
Solé Gómez et al. (2022)	Satellite	Sentinel-2	786 km	13 bands: VIS, VNIR, SWIR and Ultra Blue	10–60 m	Use of ready products	River shores	Man-made debris	Manual labeling, spectral checking, FDI, NDVI, NDWI, U-Net, U-Net3DE, and Deeplab V3+	IoU and confusion matrices
Simpson et al. (2022)	Satellite	Sentinel-1 SAR	~700 km	Center frequency: 5.405 GHz and Bandwidth: 0–100 MHz	20×5 m	Calibration, deblurring, subset creation, multi-looking, ellipsoid correction and co-registration	River, lake and reservoir	Macroplastic	VV, VH intensity, and the Ratio of all pixels, Change detection systems	ROC
Sakti et al. (2023)	Satellite & UAS	Sentinel-2	786 km	13 bands: VIS, VNIR, SWIR and Ultra Blue	10–60 m	Use of ready products	Riverbanks	Plastic debris	RF, Mahalanobis distance and adjusted PI	Confusion matrix and Kappa coefficient
		Pleiades	620 km	Panchromatic, VIS, Deep Blue, Red Edge and NIR	5×10^{-1} m	Use of ready products	—	—	—	Used to validate the Sentinel-2A analysis
		DJI Phantom 4 Pro	75×10^{-3} km	VIS	5×10^{-2} m	NA	—	—	—	Used to validate the Sentinel-2A analysis
Mohsen et al. (2023)	Satellite	Sentinel-2	786 km	13 bands: VIS, VNIR, SWIR and Ultra Blue	10–60 m	Atmospheric correction; nearest neighbor resampling	River and reservoir	Riverine litter	PI, FDI, NDVI, NDWI, ANN, SVM, RF, NB and DT	Overall accuracy, precision, recall, *F*1-score, and Cohen kappa score (K-hat)

(Continues)

TABLE 1 | (Continued)

Sources	Platform	Sensor	Altitude	Spectral range	Spatial resolution	Image preprocessing	Area of study	Target class(es)	Detection and analysis	Accuracy
Geraeds et al. (2019)	UAS	DJI Phantom 4 Advanced	5×10^{-3} km	VIS	$1–2\times10^{-3}$ m	Image categorization	River	Macroplastic particles (> 2.5 cm) (floating plastic with partially submerged)	Visual interpretation and manual labeling using Zooniverse Project Builder	NA
Jakovljevic et al. (2020)	UAS	DJI Mavic pro	$12–90\times10^{-3}$ km	VIS	4×10^{-3} m	Generate high-resolution orthophoto using SfM algorithm, manual labeling, multiresolution segmentation using eCognition	River and reservoir	Floating and underwater plastic	U-Net	Precision, recall, and *F*-score
Wolf et al. (2020)	UAS	DJI 4 Phantom Pro photography UAS	6×10^{-3} km	VIS	$\sim2\times10^{-3}$ m	Geo-referencing and mosaicking, automated point cloud densification, 3D mesh generation, digital surface modeling and orthomosaic	Rivers, waterways and beaches	Floating and washed ashore macroplastic (diameter > 25 mm)	PLD-CNN, PLQ-CNN, SVM and RF	Precision, Recall and *F*1-score
Maharjan et al. (2022)	UAS	DJI Phantom 4	30×10^{-3} km	VIS	$\sim1\times10^{-2}$ m	Mosaicking (creating grid patches)	River and canal	Floating plastics	Manual labeling and YOLO: v2, v3, v4 and v5	Mean Average Precision and *F*1-Score
Cortesi et al. (2022)	UAS	DJI Matrice 300	$20–80\times10^{-3}$ km	VIS and NIR	1.6 & 4.2×10^{-2} m	Geometric corrections & co-registration	River	Floating plastics	Multi-step RF	Precision, recall, accuracy and *F*1-score
Schreyers et al. (2021)	UAS	DJI Phantom 4 Pro	$5–10\times10^{-3}$ km	VIS	2×10^{-3} m	Image categorization	River	Floating plastics & Aquatic vegetation	Manual labeling & Color filtering	NA

Note: Refer to text for acronyms.

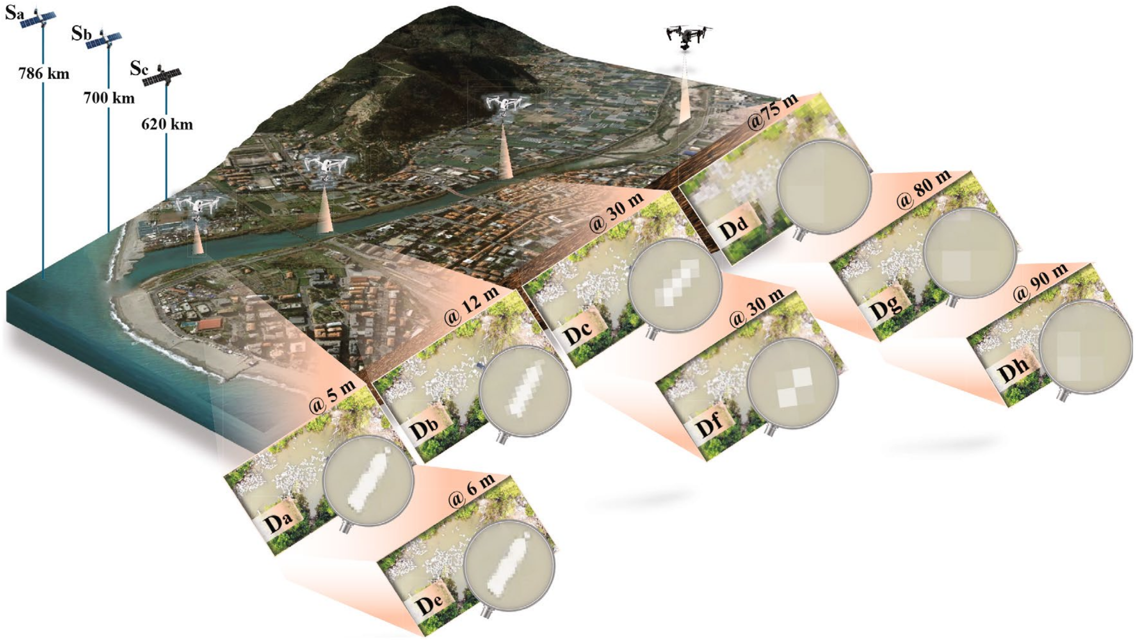

FIGURE 2 | Remote sensing of the riverine environment: Illustrating altitude versus resolution in drone (D) and satellite (S) platforms: (Sa) Sentinel-2 (Solé Gómez et al. 2022; Sakti et al. 2023; Mohsen et al. 2023); (Sb) Sentinel-1 SAR (Simpson et al. 2022); (Sc) Pleiades (Sakti et al. 2023); (Da) (Geraeds et al. 2019; Schreyers et al. 2021); (Db) (Jakovljevic et al. 2020); (Dc) (Maharjan et al. 2022); (Dd) (Sakti et al. 2023); (De) (Wolf et al. 2020); (Df, Dg) (Cortesi et al. 2022); (Dh) (Jakovljevic et al. 2020). The elevation for both types of platforms is not scaled and images illustrating resolutions were pixelized.

differentiating them from other materials in complex environments such as rivers.

Remote sensing raw data often contains errors and noise from device defects and environmental conditions. Image preprocessing corrects these issues to enhance data quality. It includes atmospheric correction, masking, cloud detection, spotting white caps, glare correction, geo-referencing, mosaicking, and orthophoto generation. These measures are crucial for preparing images for better classification and effective subsequent analysis. Although most of the satellite-based studies examined did not perform image pre-processing, instead relying on pre-existing products, Mohsen et al. (2023) applied atmospheric correction and nearest-neighbor resampling techniques on Sentinel-2 imagery. Additionally, Simpson et al. (2022) undertook calibration, deblurring, subset creation, polarimetric matrices establishment through multi-looking, ellipsoid correction and co-registration for single look complex (SLC) acquisitions of Synthetic Aperture Radar (SAR) data. UAS-based imagery required various preprocessing techniques such as image categorization (Geraeds et al. 2019; Schreyers et al. 2021), mosaicking (Wolf et al. 2020; Maharjan et al. 2022), geometric corrections, co-registration and area-based object selection to avoid false positives from sunlight-induced glare (Cortesi et al. 2022). Wolf et al. (2020) further performed geo-referencing, point cloud densification, 3D mesh generation, digital surface modeling, and orthomosaic creation to generate geometrically corrected images and elevation. Similarly, Jakovljevic et al. (2020) applied the Structure from Motion (SfM) algorithm for high-resolution orthophotos generation. Additionally, Schreyers et al. (2021) used color filtering to isolate features of interest.

After preprocessing, river plastic monitoring from airborne and spaceborne platforms involves identification through manual counting (image interpretation), statistical methods, indices-based approaches, ML, and DL. Visual image interpretation, used in UAS-based studies, inspects images to detect and classify plastic debris based on visual traits like shape, color, and texture. While straightforward, it is labor-intensive, prone to human error, and requires high spatial resolution. For instance, Geraeds et al. (2019) used visual image interpretation and compared it with visual observations and trawl-net sampling. The comparison showed a strong alignment between plastic density profiles from image interpretation and other methods. However, discrepancies arose in plastic transport distribution because visual surveys were conducted for longer periods and at substantial distances (500 m) from UASs surveys, plastic pathways changed during tidal cycles, and potential counting errors were introduced. Similarly, in Schreyers et al. (2021), the UASs survey method designed by Geraeds et al. (2019) was used. Therein, plastic items were detected, their size and category determined, and their distribution across the river width and vegetation area assessed. The areas of vegetation and plastic were estimated based on flying elevation, image width in pixels, sensor width, and camera focal length. Findings highlighted that vegetation contributed 78% of plastic transportation in the highly plastic-polluted Saigon River (Vietnam).

Traditional statistical methods were also applied by Simpson et al. (2022) to analyze Sentinel-SAR imagery for detecting floating plastic debris and mapping its distribution via heat-maps in Potpecko Lake (Serbia) and the Drina River (Bosnia and Herzegovina). The area of interest (AOI) was classified as plastic or no plastic based on visual evidence of photographs from news sources. Following preprocessing, they employed traditional incoherent detectors such as the difference, normalized difference, and ratio detectors in co-polarization intensity

(VV) and cross-polarization intensity (VH), as well as coherent detectors, specifically, the power difference, power ratio, and Hotelling–Lawley trace detectors. The study achieved a true positive detection rate of 95% with only 0.1% false alarms using coherent detectors from SLC acquisitions, outperforming those using incoherent detectors from Ground Range-Detected acquisitions. Additionally, it reported that VH signals are more effective at identifying floating plastic accumulation in water than VV signals.

In addition to visual interpretation and statistical methods, several studies applied ML algorithms for imagery analysis. These algorithms can be classified based on their learning approach into supervised, unsupervised, semi-supervised, and reinforcement learning algorithms (Omia et al. 2023). Some of the reviewed studies used supervised learning algorithms, which rely on labeled data to train a model for both classifying and predicting new data. Within this set of approaches, methods such as Random Forest (RF) (Cortesi et al. 2022; Mohsen et al. 2023; Sakti et al. 2023), Mahalanobis distance (MD) (Sakti et al. 2023), Support Vector Machines (SVM), Naïve Bayes (NB), Decision Tree (DT), and Artificial Neural Network (ANN) (Mohsen et al. 2023) were applied to classify plastics based on their spectral characteristics. For instance, as shown in Table 1, RF and MD were combined with indices such as the Plastic Index (PI), Adjusted Plastic Index (API), and Normalized Difference Vegetation Index (NDVI) to detect illegal plastic dumping along the Citarum River (Indonesia) (Sakti et al. 2023). Using Sentinel-2, Pleiades 1a/1b, and UAS images, both RF and MD classifiers detected plastic waste along the riverbanks but had difficulty distinguishing it from ground and buildings due to similar spectral signatures (Sakti et al. 2023). Similarly, the spectral similarity between sun-glare and plastics posed a challenge for the RF classifier in a UAS-based study by Cortesi et al. (2022), resulting in false positives. To address this, the study employed area-based object selection, retaining only objects with an area above a set threshold, which significantly improved detection precision from 3.1% to 89.7% for high-resolution images. Additionally, Mohsen et al. (2023) conducted a comprehensive investigation integrating indices such as PI, Floating Debris Index (FDI), Normalized Difference Water Index (NDWI), and NDVI with ANN, SVM, RF, NB, and DT using Sentinel-2 and Google Earth database images. According to their analysis, better detection performance was achieved using SVM, RF, and ANN. However, due to the spatial resolution constraint of Sentinel-2 images, the study was only able to detect litter hotspots greater than $100\ \text{m}^2$ (Mohsen et al. 2023).

DL algorithms have advanced plastic monitoring capabilities in rivers by extracting objects directly from raw data, enabling tasks such as classification and detection among others. These algorithms can be categorized as pixel-based or object-based, each offering unique advantages and challenges. Convolutional neural networks (CNNs) are the most commonly used for image-based plastic detection in river environments.

Pixel-based approaches, commonly employed for clustering, have proven effective in segmenting plastics from other environmental elements, such as water and debris. For instance, CNNs applied to satellite and UAS imagery have enabled effective classification (Jakovljevic et al. 2020; Wolf et al. 2020; Solé Gómez et al. 2022). Wolf et al. (2020) developed a dual-CNN system (APLASTIC-Q): the plastic litter detector (PLD-CNN) and plastic litter quantifier (PLQ-CNN). These dual-CNN models achieve classification overall accuracies exceeding 80% (PLD-CNN) and PLQ-CNN with 73% overall accuracies, offering a detailed breakdown of litter types and quantities. Similarly, Jakovljevic et al. (2020) showed strong pixel-wise classification performance using ResNet50, ResNeXt50, Xception, and Inception-ResNet v2 in semi-controlled experiments. Among the tested models, ResUNet50 achieved 0.78 accuracy (*F*1-score) on the Crna Rijeka River dataset. The model also performed well in shallow water, a challenging environment for such classifiers due to the similar spectral signatures of the riverbed and plastic debris. Furthermore, U-Net architectures (U-Net and U-Net3DE) and DeepLab (Deeplab V3+) were also used for satellite images in combination with Floating Debris Index (FDI) (Solé Gómez et al. 2022). This approach enabled accuracy in debris pixel detection; however, the low representation of the debris class in the entire dataset was also thought to affect the results. Among the tested algorithms, the Deeplab V3+Xception backbone performed well in cross-validation, achieving an Intersection over Union (IoU) of approximately 0.5 and debris accuracy of around 80% (Solé Gómez et al. 2022).

In addition to pixel-based DL approaches, object detection frameworks like You Only Look Once (YOLO) have been applied to UAS-based RGB imagery for identifying plastic debris in canals and rivers (Maharjan et al. 2022). Among 12 tested YOLO versions (from YOLOv2 to YOLOv5), the pre-trained YOLOv5s model emerged as the most effective for river plastic detection. Its lightweight nature makes it ideal for limited processing power or storage. In contrast, YOLOv4 achieves higher accuracy but with greater computational demands (Maharjan et al. 2022). However, these algorithms face challenges when applied to diverse environmental conditions. For instance, some CNN-based models struggle to distinguish plastic pixels at the boundaries of other materials, such as water, wood or rocks. Similarly, coarser spatial resolution limits the performance of classifiers (Jakovljevic et al. 2020). Furthermore, PLD-CNN model faced challenges in distinguishing low-density (less than three items per tile) from high-density (three or more items per tile) plastic litter, revealing limitations in their adaptability to certain scenarios Wolf et al. (2020). These factors imply the critical need to leverage datasets that capture a broad range of environmental variability to enhance the generalizability of trained models.

3.2 | Fixed and Handheld Camera-Based Monitoring

Fixed and handheld cameras have become vital tools in addressing the growing issue of plastic pollution. They have provided valuable insights into macroplastic detection through diverse sensors and methodologies (Table 2). Practically, camera-based monitoring has entailed securing a camera on a bridge or a mast located in the banks. Observation periods across studies vary, ranging from a single day to extended campaigns spanning up to 26 days, capturing thousands of images. For instance, in van Lieshout et al. (2020), a bridge-mounted camera setup captured 1272 images over 26 observation days in five locations, while Jia et al. (2023) utilized a combination of GoPro cameras and

TABLE 2 | Summary of fixed and handheld camera-based studies.

Source	**van Lieshout et al. (2020)**	**De Giglio et al. (2020)**	**Lin et al. (2021)**	**Tasseron et al. (2022)**	**Iordache et al. (2022)**	**Jia et al. (2023)**
Platform	Fixed on bridges	Handheld	Handheld	Fixed on a tripod (NE) & fixed on a supporting frame (LB)	UAS & fixed on bridge	Handheld & fixed on bridge
Sensor	Dahua Easy4ip IPC-HDBW1435EP-W	MAIA-WV2	NS	Specim FX17 & Snapscan	MicaSense RedEdge-M	GoPro HERO4 & GoPro MAX 360 & a phone (Huawei P30 Pro)
Observation-days	26	3	NS	NE: 1 and LB: NS	2	10
Number of images	1272	NS	2400	NS	613	9473
Viewing angle (°)	106	NS	NS	NE: NS & LB: 90	NS	0 and 45
Camera height (m)	4.0–8.0	1.7–40	NS	NE: NS and LB: 0.5	Fixed: 7	2.7 and 4.0
Spectral range	RGB	9 bands: VIS–NIR	RGB	74 bands: NIR to SWIR	5 bands: VIS–NIR	RGB
Sensor resolution	4 MP	1.2 MP	NS	LB: HR: 640 pixels/line and VR: NS and NE: 0.77 MP	NS	2.1 MP
Preprocessing	Frame extraction	Geometric & radiometric correction	Data format conversion	Manual reflectance correction & intensity normalization, extracting RoI, Spectral matching	DN to radiance transformation, sky glint correction & removal of saturated pixels	Frame extraction
Area of study	River	River & riverbank	Waterway	River	Land & water	Canal
Classes	Plastic & Organic debris	Plastic, Water, vegetation, & rock	Leaf, plastic bags, grass, branch, bottle, milk boxes, plastic garbage & a ball	Water, vegetation, wood, rock, plastic, & sand	Grass, tree, soil, water, cement, painted surface, metal, plastic, wood	Plastics, metal tins, paper, & cardboard items

(Continues)

TABLE 2 | (Continued)

Source	van Lieshout et al. (2020)	De Giglio et al. (2020)	Lin et al. (2021)	Tasseron et al. (2022)	Iordache et al. (2022)	Jia et al. (2023)
Classifier	Object Detection DL	Unsupervised, Supervised & Hybrid ML	Object detection DL	Supervised & Unsupervised ML	Supervised ML	Pixel-Based DL
Algorithm	Faster R-CNN & Inception v2	K-means, Isodata, Maximum likelihood, & Decision tree	FMA-YOLOv5s, YOLOv2 to YOLOv5, FMA-YOLOv5s	SVM & SAM, SID, & SID-SAM	RF	ResNet50, InceptionV3, DenseNet121, MobileNetV2, & SqueezeNet
Performance evaluation	Average Precision & R^2	Global Accuracy & Kappa Coefficient	mAP	Confusion matrix	Precision, Recall, *F*1-Score, and Accuracy	Overall Accuracy

Abbreviations: HR, horizontal resolution; LB, laboratory; NE, natural environment; NS, not specified; VR, vertical resolution (check the text for other acronyms).

smartphones to collect 9473 images in 10 days. Although smartphone cameras have demonstrated potential for plastic detection and could be integrated into citizen science initiatives, this approach remains under-explored. Fixed camera monitoring techniques operate at varying heights, from as low as 0.5 m in laboratory setups to as high as 40 m in field conditions, providing flexibility to adapt to diverse monitoring scenarios.

Visible (van Lieshout et al. 2020; Lin et al. 2021; Jia et al. 2023), multispectral (De Giglio et al. 2020; Iordache et al. 2022), and hyperspectral (Tasseron et al. 2021, 2022) sensors have been used to detect and classify plastics in rivers offering enhanced identification capabilities. Preprocessing techniques, including frame extraction (van Lieshout et al. 2020; Jia et al. 2023), geometric and radiometric corrections (De Giglio et al. 2020; Tasseron et al. 2022; Iordache et al. 2022), data format conversion (Lin et al. 2021), extracting regions of interest (RoI) and spectral matching (Tasseron et al. 2022) were performed by most of the reviewed studies to ensure accurate detection and classification. These monitoring techniques have been tested in diverse environments, from rivers (De Giglio et al. 2020; van Lieshout et al. 2020; Tasseron et al. 2022) and canals (Jia et al. 2023) to land-water interfaces (De Giglio et al. 2020; Iordache et al. 2022), targeting mainly plastics and vegetation. Supervised, unsupervised and hybrid approaches of ML as well as pixel- and object-based DL algorithms are central to these efforts.

For instance, in De Giglio et al. (2020), supervised, unsupervised, and hybrid ML techniques were employed to detect and classify plastics from images captured with a handheld multispectral camera covering a range from visible to near-infrared (NIR) (akin to the WorldView-2 satellite sensor wavelengths) along the Reno River (Italy). Experiments were executed under different weather conditions (sunny and cloudy), and with diverse experimental setups. Upon preprocessing, images were classified through the ENVI software (NV5 Geospatial 2014) using K-means, isodata, maximum likelihood, and DT, with the latter method resulting in the highest reliability. Importantly, De Giglio et al. (2020) demonstrated that the spectral signature of the sample plastics revealed high radiance levels in the red-edge and NIR bands, with notable fluctuations across the visible bands corresponding to the distinct colors of plastics. Moreover, a supervised ML approach, Linear Discriminant Analysis (LDA), was applied to differentiate floating items from water and to evaluate the contribution of each wavelength in discriminating vegetation and plastics (Tasseron et al. 2021). This lab-based study employed a dual hyperspectral camera setup and highlighted the critical role of bands within the NIR-SWIR range in effectively distinguishing plastics from other debris (Tasseron et al. 2021). Towards further exploration of hyperspectral data in a natural environment, Tasseron et al. (2022) built on experimental findings achieved in the lab to classify images taken in natural settings at the Waal River (Netherlands). Images from both experimental setups (lab and outdoors) were preprocessed to enable spectral matching, and then classified via support vector machines (SVM), Spectral Angle Mapper (SAM), Spectral Information Divergence (SID), and a logarithmic combination of SAM and SID. Lab-based training was instrumental in classifying images in natural settings, where SAM led to the highest accuracy of 96% among all algorithms.

In addition to ML, both pixel- and object-based DL algorithms have also been utilized for advancing river plastic monitoring. Namely, in van Lieshout et al. (2020), plastic pollution across five rivers in Jakarta, Indonesia, was investigated by analyzing footage captured by an outdoor surveillance camera in the visible spectral range. The analysis was performed using Faster R-CNN (Regional-Convolutional Neural Network) and Inception v2 for segmentation and classification, respectively, with results compared to visual observations for validation. Notably, this approach achieved a precision of approximately 69% in estimating plastic density. The automated procedure roughly detected 35% more plastics than visual observations, and it proved even more effective during periods of high plastic transport. Similarly, five DL architectures (ResNet50, InceptionV3, Dense Convolutional Network [DenseNet121], mobile architecture [MobileNetV2], and a smaller CNN architecture called [SqueezeNet]) were employed for similar purposes on images captured from smartphone and fixed cameras on a bridge (Jia et al. 2023). Among these architectures, SqueezeNet and DenseNet121 stood out, achieving overall accuracies of 89.6% and 91.7%, respectively (Jia et al. 2023). Further advancements in DL were demonstrated by Lin et al. (2021), where the YOLOv5s algorithm, enhanced with a feature map attention (FMA) layer, achieved a mean average precision (mAP) of 79.41% for detecting floating plastics.

It is important to note that some studies overlooked crucial details about image collection processes and sensor setups, which are vital for ensuring reproducibility. In fact, evaluating the performance and adaptability of models across diverse environmental conditions, locations, and sensor setups is essential for effective large-scale and long-term monitoring strategies. For instance, van Lieshout et al. (2020) demonstrated model adaptability under varying conditions, including plastic density, water surface conditions (waves), observation altitude, and the presence or absence of organic material. They recommended supplementing training datasets with location-specific data to achieve better generalization to new locations. Similarly, the flexibility of detection algorithms was assessed in Iordache et al. (2022), where a RF algorithm initially tailored to identify land areas (> 88% accuracy) was applied to detect litter in a semi-controlled experiment. In this case, the algorithm was fed multispectral images taken by a MicaSense RedEdge camera mounted on a UAS and fixed on a bridge. However, experimental findings suggested that detection accuracy can be enhanced with algorithms separately trained for land and water areas, whereby distinct spectral properties and litter characteristics are adequately taken into account. Moreover, Tasseron et al. (2022) highlighted that variable weather and light conditions necessitate frequent sensor calibration in hyperspectral imaging. They also noted that low atmospheric transmittance in the 1350–1400 nm range introduces considerable noise, posing additional challenges for accurate plastic detection.

While the efforts thus far are highly valuable, future research should also prioritize long-term monitoring with extended observation periods to encompass a broader range of conditions in natural systems. Most of current studies are confined to controlled or semi-controlled environments, with observation periods typically lasting only a few days. This limitation often necessitates image manipulation to generate additional data for training, testing, and evaluating models.

3.3 | Indices Used in River Macroplastics Detection

Several image-based indices have been introduced to detect floating debris in the visible, NIR, and SWIR bands captured with remote sensing platforms (see Table 3). The FDI was developed by Biermann et al. (2020) from Sentinel-2 bands (4, 6, 8, and 11) in combination with the floating algae index (FAI) (Hu 2009; Hu et al. 2015; Wang and Hu 2016). Instead of the standard red band, this index leverages the red edge band at 740 nm to take advantage of the difference between NIR and baseline reflection of NIR that enables the separation of materials reflecting NIR (like seaweed, wood, and spume) from materials absorbing NIR (like water). In Tasseron et al. (2021), the FDI is computed from hyperspectral images taken in lab-based experiments, whereby this index shows promise in distinguishing between plastics (like LDPE [Low-Density Polyethylene], PP [Polypropylene], and PS [Polystyrene]) and vegetation.

However, limitations were also noted in FDI's sensitivity to submerged debris as it was also highlighted by Moshtaghi et al. (2021).

In Solé Gómez et al. (2022), floating debris accumulation and its seasonal variations in river environments is investigated as in Biermann et al. (2020) using Sentinel-2 images for training classifiers. According to this study though, application of the FDI results into a small IoU score for debris (equal to 0.0023). Similarly, Mohsen et al. (2023) assessed the feasibility of adopting different bands and indices towards river plastic detection, whereby such indicators are used as inputs for training various models (DT, NB, SVM, RF, and ANN). The study found that FDI was the least influential index compared to alternative bands (SWIR and NIR) and indices (PI, NDWI, and NDVI). Such limited performance of FDI could be associated to the turbidity of rivers (Biermann et al. 2020; Moshtaghi et al. 2021).

In Themistocleous et al. (2020), the PI is developed, tested, and compared to alternative established indices for detecting plastic debris on the sea surface using Sentinel-2 images as in Biermann et al. (2020). To provide a sound comparison across platforms, in Themistocleous et al. (2020), a plastic target resembling water bottles was deployed near Limassol, Cyprus, and multispectral images were captured by Sentinel-2 and, simultaneously, with UASs. Experimental findings highlighted the newly developed PI as highly effective in identifying floating plastic objects, surpassing the performance of other indices. Following the introduction of the PI, in Sakti et al. (2023), such an index was adjusted (API) to monitor spatiotemporal variations of illegal dumping, particularly plastics along riverbanks, Table 3. The API included corrections for vegetation using the NDVI, and for land and buildings using the Modified Normalized Difference Built-up Index (MNDBI). The analysis supported that the API enhanced plastic detection in riverine environments compared to the original PI.

4 | Challenges and Opportunities

The inherent heterogeneity of plastics as well as the multi-scale nature of processes involved in their transport are at the basis of monitoring complexity and hamper the use of a single

TABLE 3 | Indices used in river macroplastic detection.

Indices	Equations	Pros and cons	Developed and used
FDI	$\mathrm{FDI}=R_{\mathrm{NIR}}-\left[R_{\mathrm{RE2}}+\left(R_{\mathrm{SWIR1}}-R_{\mathrm{RE2}}\right)\times\frac{(\lambda_{\mathrm{NIR}}+\lambda_{\mathrm{RED}})}{(\lambda_{\mathrm{SWIR1}}-\lambda_{\mathrm{RED}})}\times 10\right]$	*Pros*: alignment with plastic spectral peaks: helps separate plastics from natural materials like vegetation or water. *Cons*: sensitive to turbidity, submerged plastics (due to NIR absorption by water), sun glint and other reflective conditions.	Biermann et al. (2020),[a] Mohsen et al. (2023), Solé Gómez et al. (2022), and Tasseron et al. (2021)
PI	$\mathrm{PI}=\frac{R_{\mathrm{NIR}}}{R_{\mathrm{NIR}}+R_{\mathrm{RED}}}$	*Pros*: simplicity; plastic-water discrimination. *Cons*: limited spectral coverage; potential confusion with vegetation (struggles to distinguish plastics from materials like vegetation that also reflect strongly in NIR); sensitive to turbidity, sun glint and other reflective conditions.	Themistocleous et al. (2020),[a] Sakti et al. (2023), Mohsen et al. (2023) and Tasseron et al. (2021)
API	$\mathrm{IF}(\mathrm{NDVI}>0)\text{: }\mathrm{PI}_1=\mathrm{PI}-\mathrm{NDVI}\text{, ELSE: }\mathrm{PI}_1=\mathrm{PI}$ $\mathrm{IF}(\mathrm{MNDBI}>0)\text{: }\mathrm{PI}_2=\mathrm{PI}_1-\mathrm{MNDBI}\text{, ELSE: }\mathrm{PI}_2=\mathrm{PI}_1$	*Pros*: vegetation and built-up area correction. *Cons*: tested only on riverbanks; sensitive to sun glint and other reflective conditions.	Sakti et al. (2023)[a]
NDVI	$\frac{(R_{\mathrm{NIR}}-R_{\mathrm{RED}})}{(R_{\mathrm{NIR}}+R_{\mathrm{RED}})}$	—	Biermann et al. (2020), Tasseron et al. (2021), and Sakti et al. (2023)
MNDBI	$\frac{(R_{\mathrm{SWIR}}-R_{\mathrm{NIR}})}{(R_{\mathrm{SWIR}}+R_{\mathrm{NIR}})}$	—	Sakti et al. (2023)
NDWI	$\frac{(R_{\mathrm{GREEN}}-R_{\mathrm{NIR}})}{(R_{\mathrm{GREEN}}+R_{\mathrm{NIR}})}$	—	Mohsen et al. (2023)

Note: FDI was developed using Sentinel 2 bands with central wavelength of RED 664.6/665.0; RE2: 740.5/739.1; NIR: 832.8/833, and RSWIR1: 1613.7/1610.4 and PI was also developed using Sentinel 2 without atmospheric correction. Pros and cons are specifically outlined for indices developed for plastic detection.
[a]Index developer.

monitoring technique. For instance, satellite imagery offers extensive coverage, thus being ideal for large-scale plastic pollution monitoring (Table 4). This capability allows for assessing plastic distribution across vast areas, thus providing valuable insights into spatial patterns and seasonal variations (Simpson et al. 2022; Solé Gómez et al. 2022; Mohsen et al. 2023; Sakti et al. 2023). However, satellite imagery frequently encounters challenges related to return periods and spatial resolution, particularly when relying on open-source satellite images that make the accurate detection of small plastic debris especially difficult (Salgado-Hernanz et al. 2021; Solé Gómez et al. 2022). Despite the availability of commercial high-resolution satellite sensors such as WorldView and Pleiades, this challenge persists, particularly in rivers with narrow channels or densely vegetated areas where plastic debris may be concealed (Simpson et al. 2022). In addition, satellite-based monitoring is affected by sun glare, cloud cover, shadows, airborne particles in the atmosphere, and high solar zenith angles, which can impact both the quality and analysis of the data (Salgado-Hernanz et al. 2021).

Besides spatial resolution, spectral resolution also stands out as a critical factor influencing the accuracy of macroplastic classification and detection in river environments. A limited spectral range can hinder the differentiation of plastic debris from surrounding objects and natural features in rivers (Sakti et al. 2023). While open-source satellite imagery offers reasonable spectral resolution, it is still not adequate to monitor macroplastics (Sakti et al. 2023). On the other hand, most satellites with high spatial resolution often lack sufficient spectral resolution, making it challenging to distinguish and classify plastic debris accurately. In addition, cost and accessibility may pose barriers to the widespread use of satellite imagery. Finding a balance between spectral and spatial resolution is thus essential for enhancing accuracy and precision in classification and detection efforts.

Plastic pollution in rivers also exhibits temporal variability, with debris motion influenced by river discharge, flow velocity, water level, precipitation events, extreme weather events, tide patterns, river morphological units, river and riparian vegetation, and engineering structures along with other hydrological and environmental factors (Kurniawan and Imron 2019; van Emmerik and Schwarz 2020; Roebroek et al. 2021; Cowger et al. 2022; Gallitelli and Scalici 2022; Liro et al. 2022; Cesarini et al. 2023; Laverre et al. 2023; van Emmerik, Kirschke, et al. 2023; van Emmerik, Schreyers, et al. 2023; MacAfee and Löhr 2024). Hence, in addition to spatial and spectral resolution, temporal resolution also plays a crucial role in plastic detection and monitoring. Satellite revisits may only roughly allow for tracking changes over time, such as the bulk motion and accumulation of plastic debris in rivers. However, dynamic processes are not accurately captured. Moreover, delays between image acquisition and data availability can hinder near-real-time applications.

To partially mitigate limitations posed by a single monitoring approach, integration from alternative technologies may be promising. For example, a study by Simpson et al. (2022) indicates the applicability of microwave bands via SAR images to detect plastics and other floating debris. Further, data fusion with imagery collected with UASs equipped with high-resolution cameras can complement satellite-based monitoring by providing spatially- and spectrally-refined data in short time frames (Jakovljevic et al. 2020; Wolf et al. 2020; Cortesi et al. 2022; Maharjan et al. 2022). However, it is important to note that data

TABLE 4 | Advantages and limitations of remote sensing methods.

Methods	Advantages	Limitations
Satellite	*Large area coverage*: enables monitoring of extensive regions.	*Coarse spatial resolution*: satellite sensors, especially open-source, often have limited resolution, making small debris detection challenging.
	Cost-effectiveness: open-source data (e.g., Sentinel-2) reduces costs for broad river monitoring.	*Atmospheric interference*: cloud cover, haze, & shadows can limit the visibility of plastics.
	Preprocessed data: simplifies analysis for users.	*Obstruction from riparian vegetation*: riparian vegetation & its shadows may obscure plastics.
	Broad temporal coverage: supports historical analysis with decades of satellite data.	*Update lag*: delays between image capture & availability, which limits near-real-time applications.
	Consistent geographic coverage: enables consistent & comparable data collection.	*Limited spectral resolution*: some satellites may face challenges in distinguishing plastics from other materials due to limited spectral bands.
	Ease of automation: can be integrated with AI for automated detection and analysis.	*Long revisit time*: satellite revisit times of days to weeks limit capturing rapid changes.
	Low operational cost & human effort: mostly no need for field presence; data is accessible remotely.	
UAS	*High spatial resolution*: enables detailed monitoring of small plastics.	*Limited area coverage*: covering extensive areas requires multiple flights or a larger UAS fleet.
	On-demand data collection: can be deployed in response to immediate needs, enabling near-real-time monitoring.	*Operational costs*: operations require pilots, maintenance, & battery charging, adding to monitoring expenses.
	Flexible flight altitudes: enable objective-based assessment & reduce atmospheric distortions by flying at low altitudes.	*Weather dependence*: susceptible to interference from wind, rain, fog, sun glare, & glint.
	Detailed temporal monitoring: can be deployed frequently to track rapid plastic accumulation changes.	*Battery life & storage constraints*: restrict monitoring duration & volume.
	Ability to target specific locations: can focus on hotspots, such as river mouths or urban river sections, where plastics accumulate.	*Regulatory and safety constraints*: subject to regulations & may require permits.
	Capability to access remote or dangerous areas: enhances data collection in challenging terrains.	*Preprocessing requirements*: requires extra time and tools.
	Ease of automation: can be integrated with AI for automated detection and analysis.	*Interference from riparian vegetation*: vegetation interference & shadowing complicate monitoring.
	Potential for hyperspectral & multispectral cameras: enhance precise plastic detection & classification by leveraging unique spectral signatures.	

(Continues)

TABLE 4 | (Continued)

Methods	Advantages	Limitations
Fixed	*Continuous monitoring*: allows long-term data collection at a specific location.	*Static monitoring locations*: limit spatial flexibility.
	Low operational costs: costs limited to installation, maintenance, and retrieval.	*Weather dependence*: susceptible to interference from rain, fog, sun glare, & glint.
	Potential for enhanced multispectral or hyperspectral imaging: enhance precise plastic detection & classification by leveraging unique spectral signatures.	*Power requirements*: often require reliable power sources.
	High spatial resolution: provides high-quality images for detecting small debris.	*Preprocessing requirements*: lead to extra computational time.
	Real-time data collection: supports immediate detection & response to plastic accumulation.	
	Ease of automation: can be integrated with AI for automated detection & analysis.	
Handheld (including smartphones)	*Portability, flexibility, & accessibility*: easy to deploy for on-the-spot observations.	*Manual operation required*: require personnel to capture data, increasing labor costs.
	Cost-effective: widely available & relatively inexpensive.	*Limited area coverage*: it can only capture small areas at a time.
	High image quality: modern smartphones & cameras often feature high-resolution sensors.	*Weather dependence*: susceptible to interference from rain, fog, sun glare, & glint.
	Flexibility: allows targeted monitoring of specific locations.	*Inconsistency in data collection*: manual operation may cause variations in camera setup (e.g., angle), complicating analysis.
	Easy integration with apps & cloud storage: enables direct image uploads to cloud platforms for analysis.	*Battery life & storage constraints*: restrict monitoring duration & volume.
	Ease of automation: can be integrated with AI for automated detection and analysis.	*Lower spectral sensitivity*: smartphones & commercial cameras lack advanced spectral imaging.
	Connectivity: smartphones offer GPS & internet for geotagging & real-time sharing.	*Preprocessing requirements*: require extra computational time.
	Citizen science potential: involves non-specialists in monitoring efforts, increasing dataset, coverage, & awareness.	*Variation in data quality*: citizen science initiatives with varying camera specifications can cause data quality inconsistencies.

fusion presents challenges, such as incompatible data formats and sensors characteristics, temporal misalignment, variations in radiometric calibration, georeferencing accuracy, and significant computational resource requirements. Such factors can complicate the integration process, potentially affecting the quality and reliability of the fused data (Lahat et al. 2015; Ghamisi et al. 2019; Li et al. 2022).

UASs usually fly below 100 m, thus offering a spatial resolution below 1 m. Their low and flexible flight altitudes minimize vulnerability to atmospheric distortions, facilitate objective-based assessments, and improve detection accuracy (Tauro et al. 2015; Tauro et al. 2016; Tauro et al. 2016; Manfreda et al. 2018). Additionally, UASs can be deployed frequently to monitor rapid changes, and target specific areas, including hotspots such as river mouths, urban river sections, and locations inaccessible to personnel. While they tend to be cost-effective and enable near-real-time monitoring, their limited flight range and narrow coverage area pose challenges compared to satellites (Jakovljevic et al. 2020; Cortesi et al. 2022; Maharjan et al. 2022). With regards to spectral resolution, UASs enable hyperspectral imagery acquisition thus opening novel perspectives towards plastics identification (Tasseron et al. 2021; Manfreda and Dor 2023).

However, this advancement is accompanied by increased data processing complexity. Additionally, regulatory requirements, such as flight permits from both civil and military aviation authorities, may be stricter when utilizing sensors with extended spectral capabilities (Salgado-Hernanz et al. 2021; Iordache et al. 2022). Finally, commercial UASs may also present altitude inaccuracies that stem from internal stabilization processes and can significantly impact data quality (Geraeds et al. 2019). These inaccuracies can be alleviated through altitude monitoring using Real-time GPS, employing higher resolution cameras at elevated altitudes, and utilizing custom-made drones as suggested by Geraeds et al. (2019). Furthermore, dynamic weather conditions mandate frequent sensor re-calibration to mitigate issues like cloud-induced shadows (Geraeds et al. 2019; Jakovljevic et al. 2020; Maharjan et al. 2022). Further, atmospheric transmittance issues in specific spectral ranges further complicate accurate analysis of hyperspectral imagery (Tasseron et al. 2022).

Fixed-, handheld-cameras, and smartphones offer unique opportunities for river plastic monitoring, with specific challenges that need to be considered for optimal use in different contexts (Table 4). Fixed cameras excel in continuous, long-term monitoring, making them ideal for persistent surveillance at specific locations and fostering environmental monitoring at the edge (Tosi et al. 2020; Livoroi et al. 2021; Noto et al. 2022; Tauro et al. 2022). They provide high spatial resolution, ensuring high-quality images for detecting small debris. These cameras also hold potential for advanced imaging capabilities like multispectral or hyperspectral analysis, which can significantly enhance plastic identification. However, their limited field of view and static positioning restrict their ability to monitor large and changing river systems. Moreover, fixed cameras require reliable power sources and network connectivity, adding to operational complexity. In contrast, handheld cameras and smartphones offer flexibility and portability, enabling easy deployment for targeted observations of specific locations, such as hotspots like river mouths or urban river sections. This portability makes them highly cost-effective and accessible, especially smartphones, which also feature GPS and real-time connectivity for geotagging and cloud data sharing. These devices allow for rapid response and can involve citizen scientists in monitoring efforts, expanding dataset coverage and raising awareness (Nardi et al. 2021). However, handheld devices require manual operation, which can lead to inconsistencies in data collection, such as variations in image angle, scale, and quality. Their limited area coverage and battery life constraints make them less suitable for extended monitoring, and lower spectral sensitivity limits their ability to capture detailed information compared to fixed or specialized cameras. Furthermore, UASs-, fixed and handheld camera-based imagery tends to be affected by meteorological factors and atmospheric constraints. For instance, variations in brightness, wind speed, river flow rates, water turbidity, shadows, and reflections can influence detection accuracy (Geraeds et al. 2019; Jakovljevic et al. 2020; Tasseron

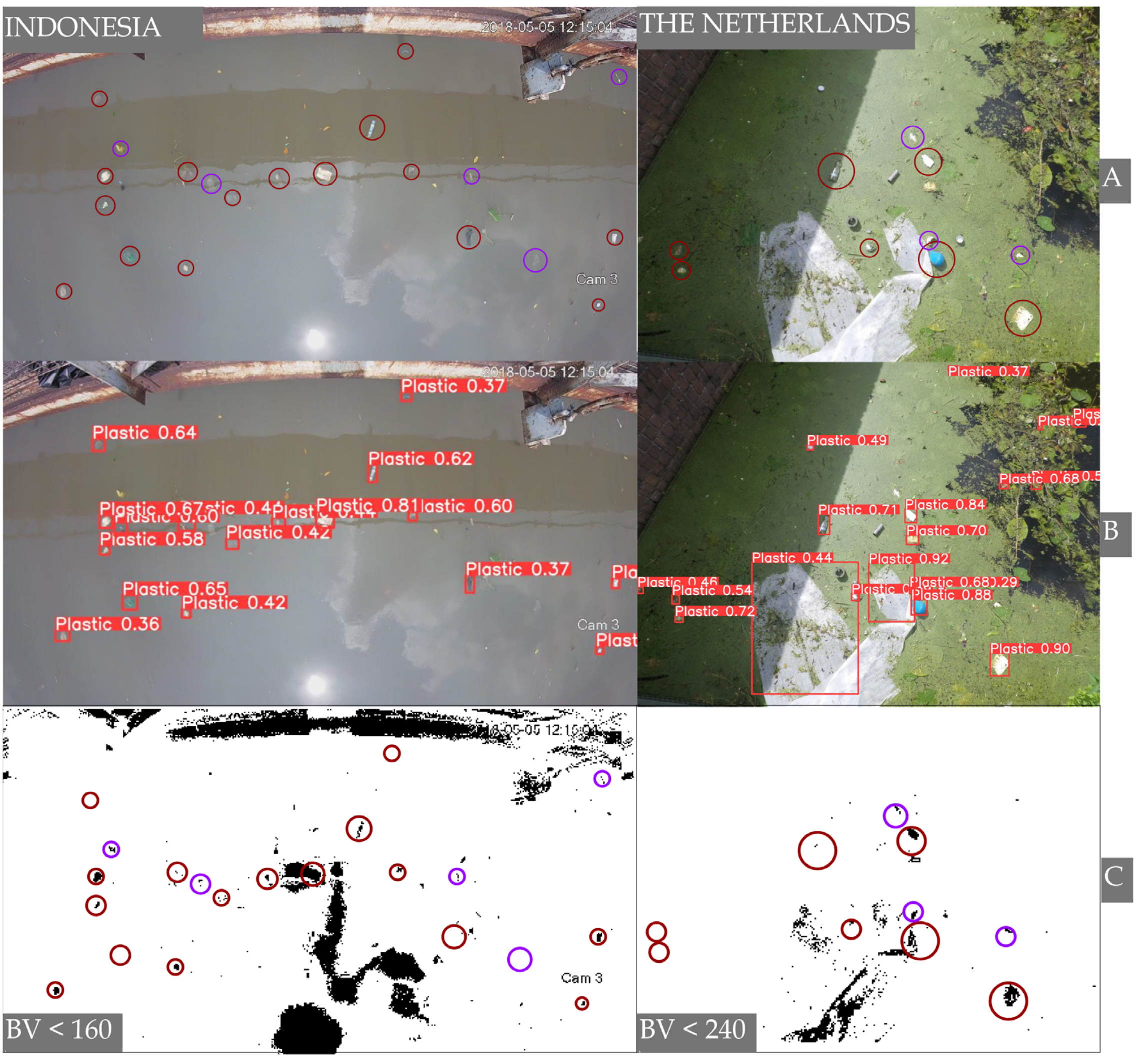

FIGURE 3 | Illustration of the opportunities in data assimilation for detecting river plastic with RGB cameras in two case studies in Indonesia and the Netherlands: (A) raw image with plastic targets, (B) YOLOv8 model detection, and (C) red/green binarized band ratio with varying binarization value (BV). Violet circles in (A) were some of the plastics that YOLO failed to detect, which the binarization aims to discriminate in (C), thus providing an example of detection fusion using spectral RGB data.

et al. 2022). In turn, images also require preprocessing, which increases computational time.

Integrating artificial intelligence with image-based plastic detection automates the process, enabling real-time data collection and facilitating rapid responses to plastic accumulation. This also supports informed, timely management and mitigation strategies. Further, ML and DL approaches for imagery detection and classification could be essential for overcoming image quality challenges and improving the accuracy and efficiency of continuous river plastic monitoring (Waqas et al. 2023). Latest advancements in ML and DL techniques, have indeed demonstrated promising outcomes in detecting and categorizing macroplastics within river environments. These advancements have been further propelled by the rapid evolution of graphics processing unit (GPU) computing, which has significantly enhanced computational capabilities. Leveraging images from various sources, these techniques have been successfully employed in several river macroplastic-focused studies (Jakovljevic et al. 2020; Wolf et al. 2020; Iordache et al. 2022; Solé Gómez et al. 2022; Tasseron et al. 2022; Jia et al. 2023; Mohsen et al. 2023; Sakti et al. 2023). Notably, supervised ML such as RF, SVM, NB, and DT, and unsupervised ML, namely, K-means, Isodata and Maximum Likelihood have been crucial for accurate detection and classification. Additionally, pixel-based DL approaches for both image segmentation and classification such as U-Net and, U-Net3DE, Deeplab V3, ResNet50, InceptionV3, DenseNet121, MobileNetV2, and SqueezeNet, have significantly advanced image segmentation and classification tasks. Object detection DL methods, including Faster R-CNN, and advancements of the YOLO family as well as improvements such as FMA-YOLOv5s, have expanded the capabilities and enabled more precise and efficient plastic detection in various river environments (Lin et al. 2021; Maharjan et al. 2022). Further, this class of algorithms can be complemented with spectral data towards potential detection fusion to improve river plastic detection performance (see Figure 3). However, the effectiveness of these algorithms heavily depends on the availability of extensive datasets for training, validation, and transferability. Unfortunately, macroplastics datasets are often limited, highlighting the need for collaborative efforts to establish open data sources and a shared repository (Solé Gómez et al. 2022; Tasseron et al. 2022; Manfreda et al. 2024).

In this context, the initiative Ocean Scan, recognized by the International Ocean Color Coordinating Group (IOCCG) task force on Remote Sensing of Marine Litter and Debris, serves as a relevant example. It provides a global repository of in situ observations and matching remote-sensing images of marine litter and debris, along with standardized methodologies and tools for accessing, gathering, and categorizing in situ marine litter data. These tools include a user-friendly web portal and a mobile application for easy data access and submission. Creating a similar system for river environments or integrating it with existing databases would significantly mitigate the scarcity of datasets. In fact, citizen science presents a viable option for image collection and labeling by engaging local communities, environmental organizations, schools, and individual volunteers, addressing data scarcity within a single river or across different rivers (Rech et al. 2015; Battisti and Gippoliti 2019; Geraeds et al. 2019; Kiessling et al. 2019; van Emmerik, Roebroek, et al. 2020; van Emmerik, Seibert, et al. 2020; Honorato-Zimmer et al. 2021; Kiessling et al. 2021; Liro, Zielonka, Hajdukiewicz, et al. 2023). An example is the RiverWatch project (RiverWatch 2024), which attempts to involve volunteers to monitor macroplastics in the Sarno River (Italy), one of the most polluted rivers in Europe. Through systematic data collection and image-based documentation, such initiatives have the potential to contribute to a database that can support scientific research, policy decisions, and public awareness campaigns (Popa et al. 2022; Fraisl et al. 2023). This approach may not only expand the available data pool but also facilitate a better understanding on how to advance algorithm transferability in various environmental contexts (van Emmerik, Seibert, et al. 2020; Iordache et al. 2022; Jia et al. 2023; Liro, Zielonka, Hajdukiewicz, et al. 2023). Thus, citizen science not only supplements traditional monitoring methods but also fosters a more inclusive and scalable approach to tackling riverine plastic pollution.

5 | Conclusion and Outlook

While monitoring plastics in river systems is at the forefront of the water management agenda, individual research efforts have been mostly directed towards testing multiple and diverse technologies. We have provided a comprehensive review of the remote sensing approaches for detecting macroplastics in river settings. Since most of the reported methodologies have been just recently introduced, considerable steps are still to be undertaken towards improving and harmonizing plastics monitoring by remote sensing. Plastic monitoring using UASs and fixed and handheld cameras has shown promising potential. In contrast, monitoring through satellite imagery faces challenges due to limitations in spatial, temporal, and spectral resolution. Machine learning and deep learning techniques have greatly enhanced plastic detection by enabling more accurate image processing and analysis. Nevertheless, they are still challenged by transferability and weather-induced distortions such as sun glare. Plastic spectral signatures in river settings remain relatively untapped, and leveraging hyperspectral signals across various platforms could uncover unknown properties of plastic materials in fluvial systems. Besides, adopting and testing indices developed for alternative environments, such as marine, as well as integrating multiple platforms with continuous, long-term monitoring could help overcome the challenges associated with river macroplastics monitoring.

Author Contributions

Ashenafi Tadesse Marye: data curation (lead), investigation (lead), methodology (lead), software (lead), validation (lead), visualization (lead), writing – original draft (lead). **Cristina Caramiello:** writing – review and editing (supporting). **Dario De Nardi:** writing – review and editing (supporting). **Domenico Miglino:** writing – review and editing (supporting). **Gaia Proietti:** writing – review and editing (supporting). **Khim Cathleen Saddi:** visualization (equal), writing – review and editing (equal). **Chiara Biscarini:** funding acquisition (equal), project administration (equal), supervision (equal), writing – review and editing (supporting). **Salvatore Manfreda:** funding acquisition (equal), project administration (equal), supervision (equal), writing – review and editing (supporting). **Matteo Poggi:** funding acquisition (equal), project administration (equal), supervision (equal), writing – review and editing (supporting). **Flavia Tauro:** conceptualization (lead), funding acquisition (lead), methodology (lead), project administration (lead), resources (lead), supervision (lead), writing – review and editing (lead).

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Related WIREs Articles

Plastic debris in rivers

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