TYPE Review
PUBLISHED 16 November 2023
DOI 10.3389/frsen.2023.1302384

OPEN ACCESS

EDITED BY
Zenghui Zhang,
Shanghai Jiao Tong University, China

REVIEWED BY
Samantha Jane Lavender,
Pixalytics Ltd., United Kingdom
Andrea Buono,
University of Naples Parthenope, Italy

*CORRESPONDENCE
Oktay Karakuş,
✉ karakuso@cardiff.ac.uk

RECEIVED 26 September 2023
ACCEPTED 08 November 2023
PUBLISHED 16 November 2023

CITATION
Karakuş O (2023), On advances, challenges and potentials of remote sensing image analysis in marine debris and suspected plastics monitoring. *Front. Remote Sens.* 4:1302384. doi: 10.3389/frsen.2023.1302384

On advances, challenges and potentials of remote sensing image analysis in marine debris and suspected plastics monitoring

Oktay Karakuş*

School of Computer Science and Informatics, Cardiff University, Cardiff, United Kingdom

Marine plastic pollution is an emerging environmental problem since it pollutes the ocean, air and food whilst endangering the ocean wildlife via the ingestion and entanglements. During the last decade, an enormous effort has been spent on finding possible solutions to marine plastic pollution. Remote sensing imagery sits in a crucial place for these efforts since it provides informative earth observation products, and the current technology offers further essential development. Despite the advances in the last decade, there is still a way to go for marine plastic monitoring research where challenges are rarely highlighted. This paper contributes to the literature with a critical review and aims to highlight literature milestones in marine debris and suspected plastics (MD&SP) monitoring by promoting the computational imaging methodology behind these approaches along with detailed discussions on challenges and potential future research directions.

KEYWORDS

marine debris, suspected plastics, floating plastics, remote sensing, machine learning, image analysis

1 Introduction

The ocean provides a livelihood for more than 3 billion people whilst being the habitat for billions of species and generates more than $3 trillion each year to the global economy (Leape, 2018). Despite this importance, especially in the last decade, plastic pollution and marine debris have become one of the most important reasons for endangering the ocean and marine environment due to the large needs of the human population and the massive production of plastic. Particularly, low-density plastics remain buoyant in the water, while high-density particles descend and settle in the sediment at the bottom of the benthic system (Thushari and Senevirathna, 2020). Microplastics, defined as plastic particles with a diameter of less than 5 mm, present a multifaceted worldwide issue, impacting both the environment and potentially posing a health risk to the public (Farré, 2020). On the other hand, when we consider larger plastic pieces, often referred to as macroplastics (greater than 5 mm), they emerge as a particularly significant subgroup of floating plastics. This subgroup is primarily responsible for entangling and being ingested by marine wildlife. Hence, it is vital to identify and monitor large-scale floating plastic debris to prevent its breakdown into smaller particles at the micro and nano levels, which can pose a threat to wildlife. In addition to the problems caused for human health and marine wildlife, the ocean pollution problem can heavily affect economies, especially for countries whose economy relies on summer tourism (The NOAA, 2022).

For a multitude of maritime environmental applications, exploiting earth observation systems and their products such as active and passive imagery is a long-established approach, to name but a few: oil spill detection (Angelliaume et al., 2017; Fingas and Brown, 2017), algal blooms (Shen et al., 2012; Sagan et al., 2020), vessel-tracking and recognition (Shan et al., 2020; Yasir et al., 2023). Although in the early stages, remote sensing techniques have been invaluable tools for monitoring *marine debris and suspected plastics* (MD&SP), offering unparalleled advantages in comprehensively assessing and managing this critical environmental issue. Unlike traditional ground-based methods, remote sensing provides a holistic view of debris patterns, facilitating the identification of hot spots and accumulation areas. Additionally, the non-intrusive nature of remote sensing minimises disturbances to fragile marine ecosystems during data collection. Thus, the application of remote sensing techniques in monitoring MD&SP holds immense promise in advancing our understanding of the issue and guiding effective conservation strategies.

In this emerging field, the utilisation of machine and deep learning in remote sensing for computational imaging is still in its developing phase. One of the primary factors contributing to this early stage of development is the absence of officially sanctioned datasets for MD&SP. However, in recent years, there has been a surge in academic publications introducing cutting-edge computational imaging techniques and making data-sets available, largely due to the concerted efforts of academic institutions aimed at enhancing MD&SP detection and tracking capabilities (Salgado-Hernanz et al., 2021; Topouzelis et al., 2021; Veettil et al., 2022; Politikos et al., 2023). Yet, the number of open-access data sets to train advanced machine learning methods for pixel-level classification remains limited, resulting in remote sensing imaging research moving slower compared to other computerised image analysis areas. Existing data sets, despite guiding the current MD&SP monitoring research, are however suffering from various other problems such as small amounts of target pixels and highly unbalanced class distributions. On the other hand, due to the small target size of the floating plastics and similar other marine pollutants, the current data set spatial resolutions cause a high number of mixed pixels (i.e., pixels whose values are averaged from multiple classes) in the data sets. The above problems and many others remain challenging and degrade the performance of MD&SP detection and monitoring of the existing remote sensing image analysis techniques.

This article presents a comprehensive review of recent developments in the utilisation of remote sensing imagery to identify and monitor MD&SP whilst highlighting the advanced computational image analysis approaches behind these important works. During the second half of this review, we specifically list and discuss a non-exhaustive list of challenges in MD&SP monitoring research areas. This presents an in-depth critical analysis of the strengths and weaknesses of the published articles with consideration for the validity of the claims made in previous works, as well as consideration for the ongoing scientific debate. Hence, the primary aim of this paper is to enhance the existing body of knowledge by not only summarising key academic findings in the field of monitoring MD&SP but also engaging in a thorough analysis of significant challenges. Noticeably, this primary aim differentiates this review from other relevant surveys (Salgado-Hernanz et al., 2021; Topouzelis et al., 2021; Gnann et al., 2022; Mukonza and Chiang, 2022; Veettil et al., 2022; Vighi et al., 2022; Politikos et al., 2023) as it provides a more comprehensive discussion on ongoing challenges and future research directions. The paper concludes by outlining several crucial directions for potential research as envisioned by the author, intended to provide a guiding framework for future studies. Please note that throughout this paper we use *MD&SP* to refer to *marine debris, floating plastics, marine plastics, plastic litter, plastic debris* and similar definitions for consistency and to provide a clear understanding of the term.

2 MD&SP monitoring applications

Following a general introduction to the importance of MD&SP monitoring research, this section reviews the literature under three sub-sections: 1) Initial/current efforts via spectral arithmetic, 2) Machine learning approaches and 3) important efforts on active remote sensing.

2.1 Promoting spectral arithmetics

Initial efforts to detect and analyse the MD&SP rely on *in situ* approaches via 1) visual surveys (Thiel et al., 2011; Lavers and Bond, 2017), 2) airborne data (Garaba and Dierssen, 2018; Moy et al., 2018; Themistocleous et al., 2020), and 3) satellite-based remote sensing imagery due to its capability to cover large and inaccessible areas. Aoyama (2014), Aoyama (2016) proposes using several candidate MD&SP pixels and making a spectral analysis of whether there is a discrimination between debris and surrounding ocean pixels. The proposed approach works effectively in cases where the size or area of MD&SP is large enough. Matthews et al. (2017) have shown that high spatial resolution satellite tracking reveals faster-than-expected MD&SP motions. A study by Goddijn-Murphy et al. (2018) has shown that plastic litter and seawater develop a reflectance model from their spectral signatures and optical geometry. The authors consider only one type of macro plastic and propose that the fraction of a plastic surface can be estimated from the surface reflectance provided the clear water reflectance.

Reflectance analysis of Goddijn-Murphy et al. (2018) motivated Topouzelis et al. (2019), Topouzelis et al. (2020) for further analysis via both satellite and unmanned aerial imagery. Topouzelis et al. (2019) have created a measurement setup at Tsamakia Beach, Greece, which includes a set of three artificial floating plastic targets. It has been shown that plastic litter such as bottles, bags, and fishing nets, reflect light in the near-infrared (NIR) band where clear water absorbs the light. Moreover, it has been reported that the reflectance intensity is also directly related to the amount of plastic in a single pixel (10 m × 10 m for Sentinel-2). Thus, if water composes more than 50%–70% for a given pixel, the reflection from the plastic pollutant is relatively low in the NIR band. Martínez-Vicente et al. (2019) discuss the requirements of a specifically designed remote sensing monitoring system for plastic pollution, and report that an ideal system would compromise both passive (short-wave infrared (SWIR) band) and active (SAR) satellite modalities, as well as support from UAVs.

TABLE 1 Spectral bands for the Sentinel-2.

#	Sentinel-2 bands	Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)
Band 1	Coastal aerosol	442.7	21	60
Band 2	Blue	492.4	66	10
Band 3	Green	559.8	36	10
Band 4	Red	664.6	31	10
Band 5	Vegetation red edge 1	704.1	15	20
Band 6	Vegetation red edge 2	740.5	15	20
Band 7	Vegetation red edge 3	782.8	20	20
Band 8	Near Infrared	832.8	106	10
Band 8A	Narrow NIR	864.7	21	20
Band 9	Water vapour	945.1	20	60
Band 10	Shortwave Infrared – Cirrus	1,373.5	31	60
Band 11	SWIR 1	1,613.7	91	20
Band 12	SWIR 2	2,202.4	175	20

FIGURE 1
Representation of FDI index in optical imagery. **(A)** An example of Sentinel-2 imagery in RGB. **(B)** FDI representation of imagery in **(A)**. **(C)** Expert labels of MD&SP. The Sentinel-2 imagery was chosen from the MARIDA data set where the labelling steps are specifically explained in Kikaki et al. (2022). Using the corresponding spectral bands and Biermann et al. (2020)'s FDI formulation, we calculated FDI representations in **(B)**. The region of Interest for this Sentinel-2 imagery is Haiti, Northern America and the imagery was acquired on the 20th of March 2020. **(A)** and **(C)** reproduced from MARIDA dataset, licensed under CC-BY 4.0

The very first work on detecting and classifying plastic patches using *solely* optical satellite data has been studied by Biermann et al. (2020) with two joint objectives: demonstrating the capability of Sentinel-2 data on detecting floating macroplastics and classifying macroplastics and other natural materials. The authors propose a novel parameter - the floating debris index (FDI) - to analyse sub-pixel interactions of macroplastics to increase the chance of detection of patches. The FDI is inspired by the floating algae index (FAI) of Hu (2009) by replacing the red band with the red edge band, and the authors leverage the difference between the NIR band and its baseline reflectance (Please refer to Table 1 for Sentinel-2 band characteristics). The

FDI dramatically highlights plastic and has been found useful in identifying floating plastics in water bodies. An example of the visibility of the FDI is depicted in Figure 1. It can be seen from Figure 1 that FDI increases the visibility of MD&SP when comparing the sub-scenes in yellow rectangles. It has also been shown by Biermann et al. (2020) that using FDI in conjunction with the Normalised Vegetation Difference Index (NDVI) (Rouse et al., 1974) makes detecting differences between plastics, vegetation, driftwood, and seafoam possible.

Themistocleous et al. (2020) set up a pilot study consisting of a target of plastic water bottles with the size of 3 m × 10 m in the sea near the Old Port in Limassol, Cyprus. They gathered UAV multi-spectral images during the same time as the Sentinel-2 satellite passed. They propose a new index called the Plastic Index (PI) where their analysis shows that the newly developed PI has been able to identify floating plastics. Kikaki et al. (2020) have conducted research over the Bay Islands in the Caribbean Sea where remarkable amounts of MD&SP have been reported. Satellite imagery for 2014–2019 has been investigated and in situ data collected with vessel and diving expeditions. This work utilises classical spectral analysis approaches to analyse the source of pollution, and concludes that the main source of pollution in the target area is the river discharges from the basins of Honduras and Guatemala, and dynamic sea currents affect plastic patches to travel more than 200 km.

Park et al. (2021), instead of Sentinel-2, utilises very high geospatial resolution 8-waveband WorldView-3 imagery to observe floating plastic litter in the Greater Pacific Garbage Patch (GPGP). They apply various spectral analysis approaches and investigate anomalies to infer the presence of suspected plastic litter. Furthermore, Hu (2022) also suggests that it may not be possible to detect floating material by optical spectra and analysis should be performed over the difference spectra to minimise the impact of variable subpixel coverage. Knaeps et al. (2021) publish a data set of 47 hyperspectral-reflectance of plastic litter in dry and wet conditions from the Port of Antwerp. They highlight water absorption and suspended sediments could allow future research to appropriately select wavelengths. Garaba et al. (2021) propose an analysis of the reflectance measurements collected from virgin and ocean-harvested plastics, and show that wet ocean-harvested plastics (ropes, foam, *etc.*) have lower reflectance compared to virgin plastics (low-density polyethylene, polypropylene) due to their wet nature and the impact of water absorption. Moshtaghi et al. (2021) propose another hyperspectral reflectance analysis in a controlled environment for virgin and natural plastics submerged in water with different sediment conditions and depths. Their findings provide evidence to utilise SWIR and visible spectrum for plastic detection. Arias et al. (2021) present the ESA-funded “Windrows As Proxies” project (WASP) which involves the development of a novel WASP Spectral Index (WSI). Their results indicate that WSI is a robust index for the task, technically simpler than existing alternatives.

Ciappa (2022), for the North Adriatic during the summer of 2020, uses spectra arithmetic to analyse anomalies of the red edge bands, assuming changes of the red edge in pixels where marine litter was mixed with vegetal materials. Papageorgiou et al. (2022) present the Plastic Litter Project 2021 in which artificial floating marine litter (FML) targets are deployed, and a set of 22 Sentinel-2 images are acquired. The detection of FML is performed through a partial unmixing methodology and the study finds that floating substances such as pollen exhibit similar spectral characteristics to FML and are difficult to differentiate. Mikeli et al. (2022) use the Marine Debris Archive (MARIDA) of Kikaki et al. (2022) to investigate various spectral indices and texture features, and conclude that spectral information alone is inadequate to distinguish marine plastic from other floating materials with similar spectral behaviour. The aim of the study by Sakti et al. (2023) is to detect illegal dumping for the first time in the literature in a river area by utilising the adjusted plastic index (API) and Sentinel-2 satellite imagery. The Rancamanyar River in Indonesia was chosen and their results indicate that API successfully improves the accuracy of identifying plastic waste. The most common spectral indices are given in Table 2.

2.2 Computational image analysis meets marine debris research

In this sub-section, we focus on works that promote machine/deep learning-based computational imaging techniques such as feature extraction, segmentation, and classification for MD&SP detection. We start firstly with two non-marine environment studies since both helped other marine environment research by exploiting machine learning approaches despite being based on the beach environment. Acuña-Ruz et al. (2018) promote the utilisation of 8-band very-high resolution WorldView-3 products via testing random forests (RF), support vector machines (SVM) and linear discriminant analysis (LDA) in the classification of beach debris. The results show that SVM is mostly the best with an accuracy of around 85%–90%. Fallati et al. (2019) propose a combined use of a UAV and the deep-learning software of PlasticFinder which consists of several Convolutional Neural Networks (CNN) which are constructed to detect and quantify anthropogenic marine debris (AMD) and reach a sensitivity value of 67% with a positive predictive value of 94%.

The first satellite-only computational image analysis approach has been proposed by Biermann et al. (2020). In fact, their approach has two main steps: manual detection using FDI and NDVI, and using Näive Bayes to classify the types of debris and plastics. Across all five test sites, the proposed approach reaches 86% accuracy of the plastic pixels. Furthermore, Jakovljevic et al. (2020) aim to investigate the applicability of semantic segmentation based on the U-Net architecture with UAV orthophotos. Results show that the ResUNet50 architecture achieved the best performance via detecting plastics with more than 85% precision. van Lieshout et al. (2020) propose an automated plastic pollution monitoring approach for the river surfaces using bridge-mounted camera imagery for five rivers in Jakarta, Indonesia. The proposed deep learning-based approach consists of the so-called Faster R-CNN for segmentation and Inception v2 for object detection stages and reaches the highest 69% precision of plastic detection.

Freitas et al. (2021) propose an ML method with a data set collected with manned/unmanned airborne hyper-spectral sensors. Their results with two supervised methods of RF and SVM show a performance of up to 80% precision (50% recall). Tasseron et al. (2021) present a hyper-spectral laboratory setup to collect spectral

TABLE 2 Frequently utilised spectral indices.

Index	References	Expression
Normalized Difference Vegetation Index (**NDVI**)	$\frac{R_{NIR}-R_{RED}}{R_{NIR}+R_{RED}}$	Rouse et al. (1974)
Floating Debris Index (**FDI**)	$R_{NIR}-\left[R_{RE2}+\left(R_{SWIR1}-R_{RE2}\right)\cdot\frac{\lambda_{NIR}-\lambda_{RED}}{\lambda_{SWIR1}-\lambda_{RED}}\cdot 10\right]$	Biermann et al. (2020)
Plastic Index (**PI**)	$\frac{R_{NIR}}{R_{NIR}+R_{RED}}$	Themistocleous et al. (2020)
Water Ratio Index (**WRI**)	$\frac{R_{GREEN}+R_{RED}}{R_{NIR}+R_{SWIR2}}$	Shen and Li (2010)
Reversed Normalized Difference Vegetation Index (**RNDVI**)	$\frac{R_{RED}-R_{NIR}}{R_{RED}+R_{NIR}}$	Themistocleous et al. (2020)
Automated Water Extraction Index (**AWEI**)	$4\cdot\left(R_{GREEN}-R_{SWIR2}\right)-\left(\frac{R_{NIR}+11\cdot R_{SWIR1}}{4}\right)$	Feyisa et al. (2014)
Modified Normalization Difference Water Index (**MNDWI**)	$\frac{R_{GREEN}-R_{SWIR2}}{R_{RED}+R_{SWIR2}}$	Xu (2006)
Normalization Difference Moisture Index (**NDMI**)	$\frac{R_{NIR}-R_{SWIR}}{R_{NIR}+R_{SWIR}}$	Wilson and Sader (2002)
Normalized Difference Water Index (**NDWI**)	$\frac{R_{GREEN}-R_{NIR}}{R_{GREEN}+R_{NIR}}$	MacFeeters (1995)
Adjusted Plastic Index (**API**)	*IF*(NDVI >0): PI_1 = PI − NDVI, *ELSE*: PI_1 = PI *IF*(MNDBI >0): API = PI_1 − MNDBI, *ELSE*: API = PI_1	Sakti et al. (2023)
Soil adjusted vegetation index (**SAVI**)	$(1+L)\cdot\frac{R_{NIR}-R_{RED}}{R_{NIR}+R_{RED}+L}$	Huete (1988)
Normalised Difference Build-Up Index (**NDBI**)	$\frac{R_{SWIR}-R_{NIR}}{R_{SWIR}+R_{NIR}}$	Zha et al. (2003)
Floating Algae Index (**FAI**)	$R_{NIR}-\left[R_{RED}+\left(R_{SWIR1}-R_{RED}\right)\cdot\frac{\lambda_{NIR}-\lambda_{RED}}{\lambda_{SWIR1}-\lambda_{RED}}\right]$	Hu (2009)

signatures of 40 virgin macroplastic items and vegetation. The experiment setup generates around 2 million pixels that are processed by the LDA method. Their results provide evidence of the gold spectral indices of NDVI and FDI by returning peaks of plastics (1215, 1410 nm) and vegetation (710, 1450 nm). Basu et al. (2021) utilise Sentinel-2 imagery to detect MD&SP in coastal water bodies in Cyprus and Greece. The authors test four machine learning approaches K-means, fuzzy c-means (FCM), support vector regression (SVR), and semi-supervised fuzzy c-means (SFCM). Their results suggest that SVR outperforms all other ML models with around 97% plastic detection accuracy.

Kremezi et al. (2021) leverage *satellite-based* hyper-spectra imagery for the first time in the literature by using the PRISMA data consisting of fine spectra but low spatial resolutions. To increase the spatial resolution, they propose exploiting pansharpening where thirteen different pansharpening methods are tested and the PCA-based substitution method is managed to efficiently discriminate plastic targets from water bodies. Jamali and Mahdianpari (2021) propose a cloud-based framework for large-scale marine pollution detection, integrating Sentinel-2 satellite imagery and machine learning tools. The performance of two shallow machine learning algorithms (RF & SVM) and a deep learning method of the generative adversarial network-random forest (GAN-RF) are evaluated where GAN-RF reaches an overall accuracy of 96% by generating synthetic ocean plastic samples. In a technical report, Mifdal et al. (2021) use a CNN deep learning predictor and highlight the importance of increasing diversity in the dataset and addressing domain shifts between regions and satellite acquisitions.

In their work, Kikaki et al. (2022) present the MARIDA dataset, a benchmark dataset derived from Sentinel-2, which marks a significant improvement in MD&SP detection research. Notably, it stands out as the first comprehensive dataset originating from Sentinel-2, potentially reshaping the landscape of research and development of machine learning algorithms in this domain. The authors have gathered plastic pollution information for 2015–2021 from more than 11 countries and annotations have been done by using high-resolution information from Planet and Google Earth imagery. MARIDA data consists of 837,377 annotated pixels 3,339 of which are MD&SP pixels. Of these, 1,625, 1,235 and 539 are annotated with high, moderate and low confidence, respectively. MARIDA also presents two baseline approaches based on RF (with three versions) and a U-Net architecture. The results indicate that RF outperforms U-Net with an F_1 score of higher than 0.7 whilst U-Net achieves 0.5. Interested readers might refer to the MARIDA data class distributions and Sentinel-2 band-specific reflectance plots in Figure 2.

Kremezi et al. (2022) propose to enhance the capabilities of Sentinel-2 via image fusion with very high-resolution WV3 images. Various image fusion techniques have been tested in terms of preserving spectral and spatial information where the coupled non-negative matrix factorization (CNMF) is the best via producing a fused image with clear edges, no blurring, and favourable spectral characteristics. Utilised Fusion-GAN and Fusion-ResNet approaches have also shown significant performance regarding spectral similarity. The superior performance can be listed as the reduction in the smallest detectable target in the fused image to 0.6 × 0.6 m^2 in size, which is equivalent to 3% pixel coverage of the original Sentinel-2 imagery with 10 m resolution. Taggio et al. (2022) develop a new method based on the combination of unsupervised and supervised ML algorithms using pan-sharpened hyperspectral PRISMA data. The

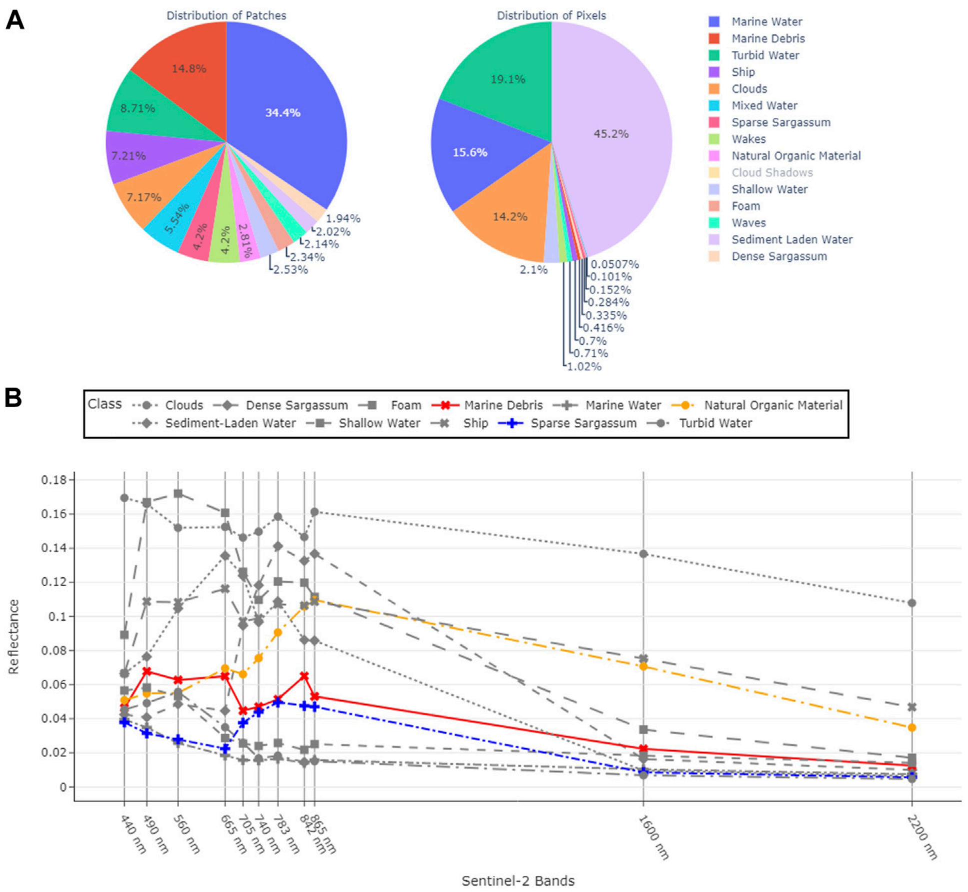

FIGURE 2
(A) MARIDA data set class distributions. **(B)** Sentinel-2 band-specific reflectance plot for each class. Please note this has been created for 11 classes after Mixed Water, Wakes, Cloud Shadows, and Waves classes are aggregated under the Marine Water class (Kikaki et al., 2022).

combined computational imaging approach exploits Light Gradient Boosting Model (LGBM) as its supervised path whilst K-means is for the unsupervised path. Results suggest that the tested approach can effectively recognize plastic targets, and increasing input datasets can help achieve higher-quality results. Lavender (2022) proposes a detection approach using satellite imagery for marine and terrestrial environments. This work produces a data set by manually digitising some land cover classes into plastics, greenhouses, tyres, and waste sites that consist of around 1.3 million pixels (1% of which is labelled as plastics). The proposed detection algorithm is fed by Sentinel-1/2 imagery and consists of an artificial neural network (ANN) where RF is used to compare the ANN performance. Despite having around 95% of aggregate average precision, their plastic detection precision is 91%. Except for the proposed data set, maybe the most important contribution of this paper is to propose a post-ANN decision tree that adds a second classification step to fix errors caused by the ANN.

Booth et al. (2023) propose a high-precision MD&SP mapping algorithm by utilising the MARIDA data set for training an ML algorithm. It is the first time, this approach focuses on improving the precision of the MD&SP detection algorithms by keeping recall values high enough to produce a reliable algorithm. Booth et al. (2023) facilitate semi-automated monitoring of MD&SP via a data pipeline named MAP-Mapper that enables inputting coordinates of the region of interest and the examination period so that Sentinel-2 data could be downloaded, pre-processed and individual pixels could then be classified. At the output, a plastic density map is produced and enables users to identify areas of high plastic density in the investigated area. The authors also proposed a novel index called the Marine Debris Map (MDM) in which the average probability of a pixel is positively weighted. This gives a better picture of measuring the MD density maps on a global time scale. Their approach promotes utilising the MARIDA data within a U-Net-inspired machine learning approach. The MAP-Mapper reaches 95% precision of MD&SP in the MARIDA data whilst the original U-net-based baseline of Kikaki et al. (2022) do only 30%. In Figure 3, an example of an MD&SP density map generated by open-access MAP-Mapper software are depicted.

Olyaei et al. (2022) promote the utilisation of Deep Knockoff and use a generative model to learn the high-dimensional distribution of reflectance in visible to NIR wavelengths. The authors conclude that the NIR and Red bands are the most important bands. Furthermore, they also indicate that in the presence of dense Sargassum macroalgae, their deep knockoff-based technique isolates the green band. The study of Nagy et al. (2022) provides a comprehensive framework that includes a large

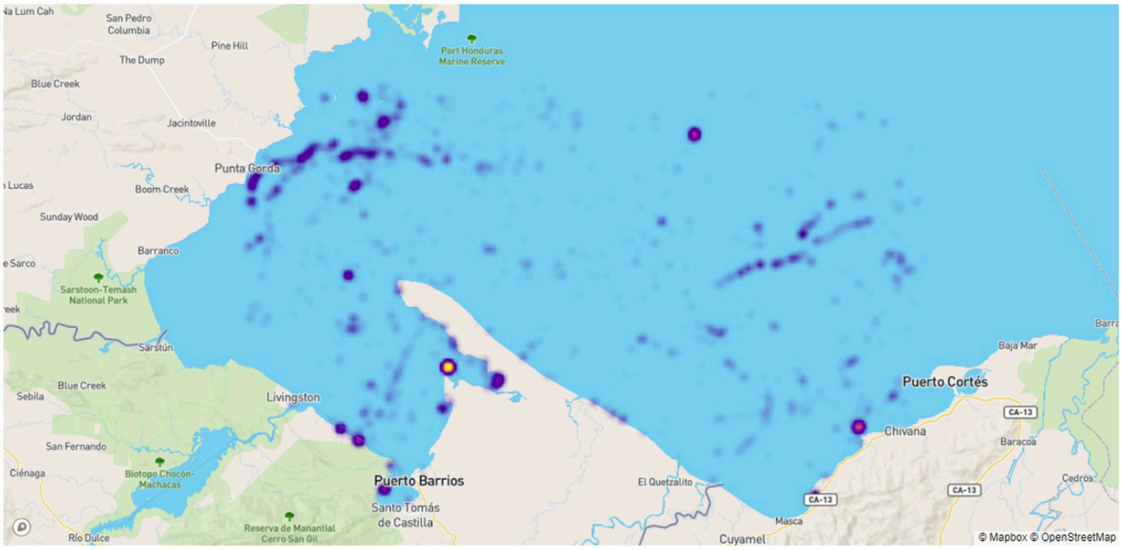

FIGURE 3
MD&SP Density Map of the Gulf of Honduras generated via MAP-Mapper software of Booth et al. (2023). After giving the above region coordinates and the time interval for the analysis (Jan-September 2022) to MAP-Mapper Software, it returns the above density map in terms of MDM metric.

simulated dataset of over 16,000 pixels of marine debris, plastic, and wood. The RF classifier is tested on actual satellite images and successfully distinguishes marine litter from seawater. Sannigrahi et al. (2022) aim to detect and classify MD&SP in Greece, Cyprus, Italy and Lebanon and utilise SVM and RF models. The newly developed kernel Normalized Difference Vegetation Index (kNDVI) is found effective and increases model performances. The developed automated system achieves 80%–90% accuracy for the test locations of Calabria and Beirut. The study suggests that the FDI is the most important variable for detecting marine plastic.

Gómez et al. (2022) detects MD&SP in rivers with high precision with an approach based on image segmentation architectures of U-Net and DeeplabV3+. The results show that the approach can identify MD&SP and suggest that a more extensive labelled dataset is needed to generalise the approach. In their recent preprint, Magyar et al. (2023) analyse illegal waste dumps and identification of water-surface river blockages. The authors use medium to high-resolution multispectral satellite imagery, especially focusing on the Tisza River as the study area. Their RF classifier works well mainly with images taken in spring and summer. Gupta et al. (2023) present a novel approach named multi-feature pyramid network (MFPN), which consists of three subnetworks: feature extractor, feature pyramid, and pooling block. These subnetworks are concatenated to form an end-to-end network and are evaluated on the MARIDA dataset by achieving a pixel accuracy of 84%.

2.3 Leveraging active remote sensing sensors

Apart from the hyper-/multi-spectral remote sensing-based approaches discussed above, the literature also accommodates recently published active-sensor-promoting research. In Topouzelis et al. (2019), Sentinel-1 SAR imagery has also been analysed for the same measurement setup and it has, however, not concluded notable results. Conversely, Savastano et al. (2021) provide one of the first successful applications of SAR to MD&SP detection. Nevertheless, it is important to approach this success with a degree of caution since the authors utilise a spectral optical index [FDI of Biermann et al. (2020)] to establish connections between spectrally classified pixels and SAR data. This process is aimed at training an SVM algorithm capable of converting optical signals into SAR signals, ultimately enabling detection using SAR. They advocate for the use of Gaussian Naive Bayes and RF in conjunction with SVM, and through this approach, they achieve an accuracy level of up to 86%. Serafino and Bianco (2021) use a ground-located X-band radar sensor to identify, discriminate, characterise and follow small floating aggregations of marine litter. They conclude that in calm sea conditions, X-band radar is capable of distinguishing targets on the sea surface. Giusti et al. (2022) propose a drone-based multi-sensor system and present the main results of the POSEIDON project. This work promotes utilising an image fusion approach to exploit the advantages of both radar and multi-spectral imagery where the proposed algorithm leverages the use of a CNN with a multi-resolution feature pyramid network (FPN) backbone. For SAR data, a constant false alarm (CFAR) based detection mechanism is proposed.

The capacity of radar backscattering to identify floating plastics has been investigated by Simpson et al. (2023). The authors present the results of a rigorous microwave multi-frequency investigation conducted at Deltares facilities in the Netherlands. They exploit C- and X-band radar to detect floating plastic in controlled conditions and find that there are differences in backscattering between the reference water and water that contains MD&SP. The X-band radar is found to perform significantly better than the C-, with backscattering differences being detected in 48 out of 68 test cases. In addition, Evans and Ruf (2021) propose a technique to detect and image microplastics with a spaceborne bistatic radar that

TABLE 3 Literature summary on proposed/utilised computational image analysis methods. ***WV3: Worldview-3, S1: Sentinel-1, S2: Sentinel-2, UAV: unmanned air vehicle, HSI: Hyperspectral, MSI: Multispectral.***

References	Proposed method(s) (based on)	Other utilised methods	Data
Acuña-Ruz et al. (2018)	-	RF, SVM and LDA	WV3
Fallati et al. (2019)	CNN	-	UAV
Biermann et al. (2020)	Naïve Bayes	-	S2
Jakovljevic et al. (2020)	Unet	ResUNet50, ResUNext50, XceptionUNet, InceptionUResNetv2	UAV
van Lieshout et al. (2020)	CNN	Faster R-CNN, Inception v2	Mounted Camera
Freitas et al. (2021)	-	RF, SVM	HSI
Tasseron et al. (2021)	-	LDA	HSI
Basu et al. (2021)	-	K-means, FCM, SVR and SFCM	S2
Kremezi et al. (2021)	Pansharpening & PCA	13 other pansharpening methods	HSI - PRISMA
Jamali and Mahdianpari (2021)	-	RF, SVM and GAN-RF	S2
Mifdal et al. (2021)	Unet	RF, SVM and Naïve Bayes	S2
Kikaki et al. (2022)	-	Unet, RF	S2 - MARIDA
Kremezi et al. (2022)	Image Fusion	CNMF, Fusion-PNN, Fusion-PNN-Siamese, Fusion-ResNet, Fusion-GAN, SRGAN, RCAN	S2 & WV3
Taggio et al. (2022)	K-means + LGBM	-	HSI - PRISMA
Lavender (2022)	ANN + post-detection decision tree	RF	S1 & S2
Booth et al. (2023)	Unet (MAP-Mapper-HP)	MAP-Mapper-Opt, Unet	S2 - MARIDA
Olyaei et al. (2022)	Deep Generative Models - Deep Knockoff	RF, SVM	S2 - MARIDA
Nagy et al. (2022)	Simulated Data Exploitation	RF	Sim & S2
Sannigrahi et al. (2022)	Spectral Feature Selection	RF, SVM	S2
Gómez et al. (2022)	U-Net3DE	U-Net and DeeplabV3+	S2
Magyar et al. (2023)	-	RF	S2 & Planetscope
Gupta et al. (2023)	MFPN	RF and Unet	S2 - MARIDA
Serafino and Bianco (2021)		RF, SVM and Naïve Bayes	S1 & S2
Giusti et al. (2022)	Image Fusion, FPN and CNN	-	SAR & MSI

measures ocean surface roughness to estimate the reduction in responsiveness. The efforts utilising meteorological radar systems to detect and map marine litter have been motivated by Van Sebille et al. (2015). The authors promote using a statistical framework for MD&SP measurements and use surface-trawling plankton nets and couple this with three different ocean circulation models to spatially interpolate the observations. The findings in this paper construct the basis of some other works (Van Sebille et al., 2020; Evans and Ruf, 2021; van Duinen et al., 2022).

Another important active remote sensing technique - light detection and ranging (LiDAR) - provides a vector dataset which has relatively higher spatial resolution thanks to the gathered point cloud data. In a seminal work by Ge et al. (2016), a semiautomatic recognition of MD&SP on a beach has been studied and revealed that LiDAR is a useful tool for the classification of MD&SP into plastic, paper, cloth and metal. In addition, the utilisation of LiDAR gives the capability to 3D model different types of debris on a beach with a high validity of debris revivification. Furthermore, Yang et al. (2023) utilises terrestrial laser scanning to detect and extract marine litter in a coastal environment.

Table 3 provides a summary of the academic achievements discussed in this section alongside the computational image analysis models utilised. While some of these studies introduce specific techniques for monitoring MD&SP, others showcase the effectiveness of various techniques through comparative analyses. Upon reviewing the models in Table 3, it is evident that generic machine learning techniques like RF and SVM have emerged as the most commonly employed methods among these studies. Furthermore, when it comes to deep learning model development, the U-net technique stands out as the preferred choice, demonstrating acceptable performance across the majority of the studies that implemented it. Regarding data sources, Sentinel-2 (S2) has established itself as the succeeding standard in this domain, with particular thanks directed toward the recently introduced open-access MARIDA dataset by Kikaki et al. (2022).

3 Challenges & limitations

In the previous section, we discussed some technical and application details of the advances in the literature on MD&SP monitoring. Some of the cited papers above claim to have achieved spectral floating plastic detection, especially by using Sentinel-2/MSI data. However, there are also several studies and an ongoing academic debate on the satellite remote sensing applicability for this problem. The following references, in particular, raise serious concerns about Sentinel 2's ability to distinguish plastics from other floating matters (Hu, 2021; Hu, 2022; Hu et al., 2022; Papageorgiou et al., 2022). Considering the concerns raised by the academic community on this topic, in this section, we reflect on our understanding and experience of challenges in MD&SP research and please note that the challenges reported below are not exhaustive.

3.1 Multi-spectral imagery limitations

The aforementioned literature mostly focuses on optical multi-/hyper-spectral imagery, which provides a great amount of information whilst having serious disadvantages at the same time. To name but a few.

1. Nevertheless providing 13 different spectral bands, Sentinel-2 has up to 10 m of spatial resolution that significantly influences the detection capability of methods since the amount of plastic in a single pixel determines the light intensity. This lower reflectance limits detection capability considering the ocean generally has various pollutants combined in a single patch. The sub-pixel indexes like the FDI (Biermann et al., 2020) can be thought of as a solution, but it is still open to improvements.
2. Optical images are prone to cloud cover and incapable of night-time data generation as well as suffering from long revisiting times that limit their capability to collect continuous data, specifically for plastic patch tracking applications. To the best of our knowledge, in the literature, a limited number of works have studied tracking plastic patches. There are several but non-exhaustive reasons behind this:
    a. Due to atmospheric limitations of the optical sensors, the low spatial resolution also causes a risk in tracking individuals of plastic bits.
    b. Considering that floating plastics are drifting due to winds, sea waves, and currents, developing a robust tracking approach requires modelling these hydrological variables. Since optical sensor wavelengths are not capable of covering the Bragg scattering mechanism, imaging hydrological features such as gravity waves, swell waves, and ocean currents cannot be possible.
3. The limitations of satellite optical imagery have led the research somehow to UAV-based approaches. Despite important outcomes for the understanding of imaging of plastic patches (Garaba and Dierssen, 2018; Moy et al., 2018; Topouzelis et al., 2019), they are operator- and location-dependant whilst having high costs and lack of standardisation.

3.2 Atmospheric correction & pre-processing

Atmospheric correction techniques serve to minimize the detrimental influence of atmospheric interferences, such as aerosols and water vapour, on optical imagery. This, in turn, yields improved image quality and greater clarity, enabling more precise detection and classification of floating debris against the backdrop of water bodies. Furthermore, the application of pre-processing techniques, including radiometric calibration and geometric correction, significantly enhances the contrast and visibility of objects within the imagery, further facilitating the identification of floating debris. Accurate spectral information is crucial for distinguishing and characterizing various types of floating debris based on their unique optical properties. The importance of these steps lies in their contribution to the acquisition of dependable data for decision-making in environmental conservation and resource management domains. With trustworthy data at their disposal, authorities and organizations can develop more effective strategies for addressing floating debris issues and implementing sustainable policies. Moreover, the consistent application of atmospheric correction and pre-processing techniques allows for long-term monitoring of floating debris trends, aiding in the assessment of mitigation efforts and policy efficacy. These reliable datasets also play a vital role in scientific research, where they are employed to investigate the impact of floating debris on aquatic ecosystems and wildlife.

However, while the benefits of atmospheric correction and pre-processing are evident, challenges persist in their implementation. The availability of suitable data for atmospheric correction can be limited, and acquiring high-quality satellite imagery with necessary data can be a costly endeavour. Moreover, choosing the appropriate atmospheric correction and pre-processing algorithms presents a complex task, as these selections must align with specific imaging sensors, environmental conditions, and study objectives. Additionally, the processing of substantial datasets for these purposes may require substantial computational resources, posing a challenge for researchers with limited access to high-performance computing facilities. Furthermore, the validation of the accuracy of atmospheric correction and pre-processing results necessitates ground truth data, which can be challenging to obtain, particularly in remote or inaccessible areas. Despite these challenges, the continued advancement of technology and data accessibility are helping to address these obstacles, solidifying remote sensing as an indispensable tool in the comprehensive effort to combat the issue of floating debris in aquatic ecosystems.

3.3 Uncertainty of spectral reflectance of floating plastics

The spectral reflectance of floating plastics measured via multi-spectral imaging sensors can introduce uncertainties due to several factors. These uncertainties may arise from variations in plastic composition, shape, surface texture, and environmental conditions, such as water quality, lighting conditions, and wave-induced distortions. Additionally, the presence of other materials in the water, such as algae, debris or driftwood, can further complicate spectral measurements. Accurate quantification of floating plastic pollution requires accounting for these uncertainties and implementing appropriate calibration and data processing techniques to improve the reliability of spectral reflectance measurements.

This matter is connected to the ongoing debate regarding the appropriate remote sensing principles to apply for machine learning-based detection and characterisation. Several of the studies mentioned rely on a scarce amount of ground-truth data, such as the MARIDA database or artificial targets in Lesbos Island (Greece). These limitations substantially challenge the assessment of the effectiveness of the different algorithms proposed, prompting us to question the true nature of the information they are extracting.

In Hu (2022), the author highlights that Sentinel-2 data exhibit spectral distortions due to variations in spatial resolution among its bands, which range from 10 to 60 m when they are adjusted to the same spatial resolution. Additionally, these distortions are compounded by pixel misalignment between different bands. Consequently, these spectral distortions give rise to a misleading spectral peak at approximately 842nm, which has been commonly utilised within the research community for identifying MD&SP in Sentinel-2 data. This peak's significance is evident, for instance, please see Figure 2B. Hu (2022) demonstrates that after eliminating the distortions, the spectral signature closely resembles that of driftwood rather than plastic. These concerns form the basis of the hypothesis proposed by Arias et al. (2021), aligning with Hu's assertion that distinguishing floating materials is considerably more straightforward than identifying floating plastics. We refrain from providing conclusive evidence in this regard and suggest that researchers in this field consider the possibility that the previously mentioned discoveries may not be influenced by these spectral distortions.

3.4 Importance & challenges in addressing the mixed pixel problem in MD&SP

Precisely addressing the mixed pixel problem in the context of MD&SP holds profound importance for a range of important reasons. Above all, it generates a direct influence on the accurate quantification of marine debris and plastics within aquatic environments. The capacity to discriminate among the diverse materials coexisting within mixed pixels is key for estimating the volume and distribution of debris. This, in turn, plays a pivotal role in facilitating comprehensive environmental impact assessments and the formulation of effective strategies for mitigating pollution. Furthermore, the varied origins of marine debris and plastics, each with its level of ecological and environmental threat, underline the significance of successfully resolving the mixed pixel issue. This achievement empowers researchers to identify the sources of pollution, thereby aiding regulatory bodies and environmental organizations in implementing precise measures to address the root causes of marine debris and plastics. Additionally, the accurate identification of mixed pixels is crucial for assessing the ecological impact of MD&SP on marine ecosystems, providing valuable insights into how different materials interact with marine life, including issues related to entanglement and ingestion.

Nonetheless, despite its essential importance, the challenge of dealing with the mixed pixel problem in MD&SP poses a formidable set of challenges. The heterogeneity of debris, characterised by materials with distinct properties, origins, and various degrees of weathering and biofouling, complicates the task of distinguishing and segregating mixed pixels due to significant spectral overlap. The limitations in the spatial and spectral resolution of remote sensing data occasionally restrict the ability to accurately discriminate fine-scale differences within MD&SP, particularly when closely situated objects or materials coexist. Moreover, the temporal variability of marine debris and plastics, influenced by factors such as ocean currents, tides, and changing weather conditions, further complicates efforts to resolve the mixed pixel problem, as the same location may exhibit different materials at different times. Coastal environments, characterised by the coexistence of diverse land and water features, boost these challenges by making it difficult to differentiate terrestrial objects from marine debris, particularly in nearshore regions. The interference from natural elements, such as algal blooms and floating vegetation, can mimic the spectral characteristics of plastics and debris, leading to misclassification and the misidentification of mixed pixels. Furthermore, the complexity of developing algorithms to manage mixed pixel issues can be significant. Finally, validating the accuracy of remote sensing results when dealing with mixed pixel problems is complex, primarily due to the challenges of acquiring ground truth data for the various types of marine debris and plastics, especially in remote or offshore areas.

3.5 Remote sensor related challenges: sensitivity, noise and coverage

Another aspect that would require consideration is a view of the sensitivity of the various proposed sensors to plastic content. The sensitivity analysis of satellite remote sensing techniques concerning their observational capabilities for detecting floating plastics has been notably limited. While these techniques have shown promise in monitoring marine pollution, however, up to date, no proper sensitivity analysis has been done with them to address their observational capabilities for floating plastic. Factors such as plastic size, shape, colour, and concentration in the water, as well as environmental conditions like sunlight, water turbidity, and wind-induced surface roughness, can all influence the effectiveness of satellite-based plastic detection. A thorough sensitivity analysis is imperative to quantify the reliability and limitations of these methods under different scenarios, ultimately enhancing the accuracy and utility of satellite remote sensing for tracking and addressing the global issue of plastic pollution in our oceans.

The primary research in this field is the study conducted by Papageorgiou et al. (2022), which establishes the detection threshold for Sentinel-2/MSI at 20% of the pixel area. In contrast, Garaba et al. (2021) have determined a limit of 1% based on laboratory measurements with an ideal sensor. Nevertheless, it is worth noting that there currently exists no sensor specifically designed for this particular task. To gain a more comprehensive understanding of their capabilities, there is a need to expand the number of analytical studies conducted not only for Sentinel-2 sensors but also for other commonly used sensors such as Landsat-8 and WV-3. This broader assessment will enable a more thorough evaluation of their performance.

Furthermore, in MD\&SP monitoring, In optical remote sensors, the signal-to-noise ratio (SNR) is crucial for data quality, offering reduced noise, enhanced precision, and reduced uncertainties in data products. However, the purpose of higher SNR entails trade-offs as it requires greater instrument sensitivity, potentially narrowing the dynamic range and increasing the risk of signal saturation in the presence of very bright targets. Achieving a higher SNR may also involve coarser spatial and lower spectral resolutions to gather an adequate number of photons. Beyond a certain SNR threshold, other factors contributing to data uncertainties may eclipse the benefits of further SNR improvement. Therefore, optimising SNR in optical remote sensors necessitates careful consideration of sensitivity, dynamic range, spatial and spectral resolutions, and the delicate balance among these elements to ensure the highest quality and accuracy of data products (Qi et al., 2017). On the other hand, Noise Equivalent Sigma-Nought (NESZ) challenges for SAR involve speckle noise, which can obscure small or low-contrast marine debris. The incident angle of the radar beam also plays a role, as varying angles can produce different NESZ levels, necessitating consideration of specific angles for each data acquisition. Furthermore, SAR signals can interact with natural features like vegetation, potentially leading to false positives and misinterpretations in MD&SP monitoring.

Simultaneously, medium to high-resolution missions face systematic global coverage limitations in MD&SP monitoring. These missions often prioritise spatial and temporal resolution, leading to detailed data collection in specific areas of interest, leaving gaps in systematic global coverage. The high costs associated with acquiring high-resolution data over extensive ocean areas can be prohibitive, leading to concentrated data collection in specific regions. Mission lifespans are finite, and when a mission ends, data acquisition stops, causing gaps in long-term monitoring efforts and restricting the ability to track changes in MD&SP distribution over time. Moreover, managing and storing resource-intensive high-resolution data can pose significant challenges, particularly for systematic global coverage.

3.6 On spectral indices

The utilization of spectral indices for investigating and detecting marine plastic from remote sensing imagery is a promising avenue, but it is not without its challenges and limitations. While spectral indices have been successfully applied in various environmental monitoring tasks, their efficacy in the context of plastic detection remains uncertain. The spectral signature of marine plastics can be highly variable, influenced by factors like plastic type, weathering, and the presence of other materials in the water. This variability can make it challenging to develop a one-size-fits-all spectral index that reliably identifies MD&SP across diverse marine environments. Furthermore, spectral indices often rely on empirical relationships between spectral bands and specific materials, and these relationships may not hold consistently for plastic detection due to the wide diversity of plastic types and conditions. Additionally, the accuracy of these indices can be affected by atmospheric conditions, water quality, and sensor characteristics, introducing sources of uncertainty that must be carefully considered. Therefore, while spectral indices offer a valuable tool in the quest to address plastic pollution in our oceans, their application should be approached with a critical awareness of the complexities and limitations inherent to the task.

Despite being the first-ever developed and widely used spectral index, doubts persist regarding the effectiveness of Biermann's FDI for its intended purpose. As previously highlighted in the preceding sections, issues with Sentinel-2 data raise questions about its ability to distinguish plastics from other floating materials. Biermann et al. (2020) Figure 2C unmistakably demonstrates that when comparing FDI and NDVI, the latter appears to be significantly more adept at distinguishing floating litter from other spectral categories. FDI exhibits noticeable signal overlap and range convergence with the other considered spectral categories. The same concern has also been experimentally shown in Papageorgiou et al. (2022) (pg. 15, Figure 9) that using FDI alone to discriminate floating plastics is not possible, since there is considerable overlap between the FDI values of the different classes. While these uncertainties are cause for concern, it is important to note that FDI remains the predominant spectral index in the literature for detecting floating plastics. Nevertheless, it necessitates a comprehensive supplementary analysis to establish its reliability definitively.

An alternative index designed for discriminating floating plastics is the PI introduced by Themistocleous et al. (2020). Alongside the PI, practical indices like NDVI have also been employed to differentiate artificial plastic from the sea surface. Initial findings demonstrate the successful detection of plastic targets using most of these indices, with authors subsequently incorporating a statistical validation step to bolster the credibility of their proposed method. However, while the inclusion of statistical validation is a positive step, its applicability may still be considered limited since it was tested specifically with one type of artificial plastic target and excludes other potential floating materials originating from sources like vegetation and land. Sakti et al. (2023) have made further enhancements by combining PI with NDVI and MNDBI to identify floating plastic litter in watersheds, particularly in complex scenarios where plastic waste is mixed with various land covers. Their primary objective was to rectify land cover discrepancies around rivers, especially those that might interfere with the PI results. Despite achieving satisfactory outcomes in their study, the developed index remains reliant on spectral indices that may not be tailored for MD&SP analysis, and the authors themselves acknowledge this limitation. It is certain that certain river types exhibit unique characteristics, such as substantial riverbank activities, transportation-related disturbances, wave patterns, rock distributions, and diverse water quality parameters like sedimentation and vegetation, necessitating further investigation. In light of these characteristics, spectral indices for both riverine aqua systems and open waters require an advanced and validated approach by also exploiting other water-related alternative index corrections such as NDWI, turbidity index (Tasseron et al., 2021), and bare soil index (BSI) (Nguyen et al., 2021).

3.7 On capabilities of SAR imagery

All the efforts in the last decade led to the development of the pioneering works mentioned above. However, optical imagery that displays the earth as the human eye sees it, is at the mercy of the clouds and the amount of sunshine. On the other hand, the SAR system constitutes an active sensor, which emits microwaves towards the Earth and receives back-scattered signals from the surface. Since SAR utilises larger wavelengths (1 cm to 1 m), it can image day/night and in almost all-weather conditions through clouds and storms. SAR imagery provides us with useful information about forest biomass, and crop cover types. Furthermore, SAR also provides useful information on ocean state, including wind speed/direction, gravity waves, swells, currents, and sea-ice structures. Hence, SAR imagery is recognised as superior to optical imagery in applications such as detecting/tracking oil spills (Li and Li, 2010; Shirvany et al., 2012; Zhao et al., 2019), assessment of sea surface signatures (Graziano et al., 2016; Karakus et al., 2019; Rizaev et al., 2022), ship detection/tracking (Pappas et al., 2018; Kartal and Duman, 2019; Liang et al., 2019), and ice sheets tracking (Lemos et al., 2018; Gomez et al., 2019; Barbat et al., 2021).

Despite this widespread usage and advantages, its usage in MD&SP monitoring works has been limited up to now. As discussed in Section 2.3, we have explored several SAR-based studies primarily aimed at complementing surface spectral information. While some of these studies did not yield positive contributions to the detection of MD&SP (Papageorgiou et al., 2022), others have shown promising and encouraging results for future research (Savastano et al., 2021; Giusti et al., 2022; Simpson et al., 2023). However, it is important to exercise caution when applying SAR imagery, despite these encouraging outcomes. For instance, the first successful use of SAR in plastic detection, as demonstrated by Savastano et al. (2021), relies on SAR data findings that are conditional on spectral information obtained through the FDI metric. This connection has been further extended through machine learning algorithms, introducing an additional layer of uncertainty [*epistemic* within the context of Kendall and Gal (2017)]. Conversely, while Simpson et al. (2023) have identified distinguishable features between different frequency bands for detecting floating plastic under controlled conditions, a closer examination of Tables 4 and Table 5 in their study reveals that the majority of results were non-significant, particularly when scenarios resembled real-world events at sea. Furthermore, the work of Serafino and Bianco (2021) suggests the suitability of X-band radar, but this is contingent on mild weather and calm sea surface conditions, which may not always align with the realities of open ocean scenarios.

All the studies mentioned above represent significant achievements in exploring the potential of SAR in this field, underscoring the pivotal need for enhancing SAR technology to support machine learning methods. This does not mean that SAR usage is not viable, but rather underscores the necessity for further research efforts to thoroughly establish its capabilities, which have yet to be comprehensively documented or published.

3.8 Data related challenges

In addition to the sensor-related challenges mentioned above, there is also another important problem causing this research area to move slower compared to other computational imaging areas; that is *the data availability and other data-related problems.*

3.8.1 Open-access MD&SP data

Before 2022, there was only one source of data set from Plastic Litter Projects (PLP) of (Themistocleous et al., 2020; Topouzelis et al., 2020) consisting of artificial plastic targets. Despite providing a great source of information for future studies, the shared data sets consist of a couple of Sentinel-2 images with a handful of annotated plastic pixels. Thus, their applicability in advanced computational imaging approaches naturally remained limited. Thanks to the efforts in this area, during 2022 two important data sets have been published (Kikaki et al., 2022; Lavender, 2022). These data sets, even though still suffering from the number of annotated plastic pixels, provide a basis and some chances for the applicability of the advanced deep-machine learning approaches. The International Ocean Colour Coordinating Group (IOCCG) is listing all available data in this research area in a database bibliography. Interested readers may refer to this exhaustive list of databases by The IOCCG (2022). In addition, Politikos et al. (2023) set a primary objective to explore a wide range of subjects to recognize the multifaceted impact of artificial intelligence in this domain and create a valuable point of reference for researchers in the field of MD&SP. To accomplish this goal, the authors have introduced an internet-based repository[1], wherein users have the capability to search for publications categorized under various topics and tagged accordingly. For those seeking more information on open-access resources and public datasets, we encourage them to refer to these sources.

3.8.2 Limitted annotation

Machine learning algorithms possess significant potential for enhancing detection and classification tasks, as they excel at labelling complex datasets. However, the effectiveness of these technologies is unpredictable on the quality of the training data. Even in the case of one of the largest existing databases, MARIDA Kikaki et al. (2022), the number of pixels considered to have "high confidence" in terms of plastic pollution is relatively limited. Training ML algorithms with only 1,625 "high confidence" pixels (constituting 0.4% of all pixels) out of nearly a million others elevates the risk of training errors. We contend that this limitation is a major factor contributing to the prevalent issue of low precision (resulting in a high number of false detections) observed in most of the proposed methods documented in the literature.

3.8.3 Non-applicability of advanced approaches

The utilisation of advanced computer vision algorithms for the detection of MD&SP has been hindered by several factors. These include the aforementioned reasons for the limited availability of datasets and a scarcity of highly reliable annotated pixels for training purposes. Another contributing factor is the unfortunate lack of collaboration between machine learning experts and marine scientists/field researchers. Consequently, most research efforts in this field rely on conventional approaches such as RF, Naive Bayes, or relatively straightforward deep learning architectures. In contrast, computer vision research in fields like medical imaging or other challenging domains often produces groundbreaking algorithms

1 https://dimpolitik-ai-marine-litter-app-zd7cow.streamlit.app/

that make innovative use of minimal or unsupervised learning methods.

4 Future research directions

4.1 Applicability of new generation satellites

The advent of new-generation satellite imagery has brought about significant advancements in the realm of marine floating plastics detection. However, it is essential to recognise that, even with these technological strides, challenges persist. While Sentinel-2 represents the current state of the art, it does come with certain limitations, such as its spatial resolution and spectral capabilities. The applicability of new-generation satellite imagery, therefore, holds promise for improved plastic detection due to enhanced spatial and spectral characteristics, allowing for more precise identification and monitoring of MD&SP in marine environments. Nevertheless, the efficacy of these new tools hinges on addressing the remaining limitations and the development of innovative algorithms and analysis techniques, which can better exploit the potential of these advanced satellite systems for comprehensive and accurate plastic pollution detection and assessment.

In the last decade, new technology satellites for optical imagery have been launched. Worldview-3 is a super-spectral, high-resolution commercial satellite sensor from Maxar launched on 13 August 2014, and can be named among those technologies. WV3 collects images at 0.31 m panchromatic, 1.24 m in VNIR, and 3.7 m in SWIR bands whilst having enhanced multi-spectral analysis bands (coastal blue, yellow, red edge, NIR2) designed for land and aquatic applications. Since WV3 products started to be delivered by the ESA, their applicability has increased (refer to (ESA, 2023c) for the WorldView ESA archive).

In addition to Maxar's WV3, Planet Space's SkySat is a constellation of high-resolution Earth-observing satellites owned and operated by the commercial company Planet Labs where the first SkySAT-1 launched in 2013 whilst the latest SkySat-21 in 2020. It is known for capturing highly detailed images of the Earth's surface, with spatial resolutions as fine as 50 cm. SkySat offers frequent revisits (up to 12 times a day) for dynamic event monitoring. PlanetScope, another satellite constellation by Planet Space consists of multiple launches ("flocks") of Dove satellites and provides medium-resolution optical imagery with spatial resolutions between 3 and 5 m. It is ideal for daily revisits, making it valuable for tracking changes like crop growth and urban development but at a coarser resolution compared to SkySat. Both constellations have ESA data archives with limited coverage. Interested readers might refer to (ESA, 2023a; ESA, 2023b) for SkySat and Planetscope data archives of ESA.

We believe satellite products like WV3, SkySat and PlanetScope will direct the following years of research for MD&SP monitoring by filling the gaps in a low spatiotemporal resolution of Sentinel-2. On the other hand, we should note that the pressing need for a dedicated satellite constellation tailored to monitor MD&SP has become increasingly evident. Existing satellite systems primarily designed for broader Earth observation purposes lack the specialised capabilities required for precise and comprehensive detection and tracking of these pollutants across the world's oceans. A specifically developed constellation would offer the advantage of optimised spectral bands (mitigating the effects of the aforementioned spectral distortion), spatial resolution, and revisit frequencies, precisely tuned to the unique characteristics of MD&SP. Such a constellation could enhance our ability to monitor the global distribution, movement, and accumulation of plastic waste, providing critical data for informed decision-making, pollution mitigation efforts, and policy formulation aimed at addressing this urgent environmental crisis. By focusing our resources and technology on a constellation designed explicitly for this purpose, we can significantly improve our capacity to understand and combat the pervasive problem of marine plastic pollution.

4.2 Solutions via computational image analysis

To sum up our discussion on the computational imaging methods mentioned earlier, it is worth mentioning that these methods predominantly depend on traditional machine learning techniques. Nonetheless, it is crucial to recognise that one of the most dynamically evolving fields in artificial intelligence is computer vision, where new and sophisticated approaches are emerging almost daily. Interestingly, the remote sensing image analysis domain, despite being a part of computer vision research, has not kept pace with these recent advancements and still mostly relies on older methodologies developed several years ago.

4.2.1 Multi-modal AI and fusion

Various environmental applications have benefited from multi-modal image fusion by exploiting complementary features provided by different remote sensors. Specifically, for active-passive data fusion, passive sensors play the role of feeding the system with high spectral information whilst active sensors usually provide sufficient textural and structural information (Zhang et al., 2022). Some example remote sensing applications can be listed as land use/cover classification (Ma et al., 2022; Roy et al., 2023), air pollution detection (Scheibenreif et al., 2022; Rowley and Karakuş, 2023), building footprint extraction (Shermeyer et al., 2020), and maritime vessel detection (Farahnakian and Heikkonen, 2020).

4.2.2 Minimal supervision

The low amount of annotated data has been a great driving force for the development of semi-, weakly-, and self-supervised learning computational imaging approaches especially in the medical imaging area, which has the same annotated data problem as in remote sensing. Along with the advances in multi-modal fusion approaches, developing minimal supervision techniques for MD&SP monitoring is a crucial step, and we believe academic literature will gradually get involved in this area to leverage unlabelled data simultaneously with the limited amount of high-confidence pixels. The weakly supervised approach proposed by Kikaki et al. (2022) is a good starting point for this, but of course not enough for high-precision MD&SP monitoring software development tools. Ma et al. (2022), in their land cover mapping paper, have shown that without losing much performance accuracy, multi-modal usage in a parallel manner can reduce the amount of required labelled training data down to 1/20, whilst Ma et al. (2023) also further demonstrate the capability of the semi supervision techniques in which the authors reach better performance metrics compared to the state-of-the-art techniques utilising several times higher number of labelled data sets.

4.3 Employability of spectral unmixing techniques

As a natural outcome of the conversation regarding the uncertainty surrounding spectral reflections from floating plastics in Section 3.2, particularly within the current marine optics research community, a consensus emerged. This consensus acknowledged that the application of one-to-one spectral classification through machine learning using existing sensors requires the incorporation of spectral unmixing. This approach becomes essential due to the current absence of ground-truth data and serves as a means to evaluate the effectiveness of proposed algorithms.

In general terms, spectral or pixel unmixing can be described as follows: In remote sensing, a common challenge arises due to the inherent limitation of spatial resolution in remote sensors (or relatively small target class sizes even when high spatial resolution exists), resulting in "mixed" pixels near the boundaries of different classes. In essence, individual pixels often encompass more than one type of material, causing the pixel's spectral response to represent a combination of underlying pure classes known as "endmembers." When conventional single-class per pixel classification is applied, the best-case scenario involves compromised accuracy, as a portion of the pixel is inaccurately categorised. In the worst-case scenario, mixing can create a perplexing spectral blend, leading to entirely incorrect pixel classifications. A more effective approach, which mitigates both of these error sources, is to model the spectral mixture and, at each pixel, determine the proportions of the endmember classes for classification Rosin (2001).

One of the most important spectral unmixing analyses has been implemented by Papageorgiou et al. (2022). In their work, the authors have reported that biofouling primarily impacts the spectral response of floating marine litter concentrations in the RGB part of the spectrum, affecting signal intensity and shape, while the NIR bands remain relatively unaffected. The accumulation of biofouling notably alters the shape of high-density polyethylene's (HDPE) spectral response. This observation corresponds with chlorophyll absorption features, although stable reflectance in the green part of the spectrum is not consistently observed. Further research is necessary to gain a comprehensive understanding and quantification of biofouling effects, as well as the characteristics of the organisms involved. Submerging the HDPE mesh target to depths between 20 and 30 cm below the water surface leads to a 30%–40% signal decay across the visible range of the MSI's sensor, with a greater impact on NIR bands. This decrease in signal could potentially impede the detection of submerged or partially submerged floating marine litter, which is often encountered in real-world scenarios. However, partial unmixing methodologies have demonstrated the ability to detect partially submerged target pixels. Additionally, the spectral features of floating materials like pollen, sea snot, wakes, foam, and vessels closely resemble those of floating marine litter, making their discrimination challenging and presenting a significant constraint in pixel classification [also reported in Kikaki et al. (2022) and Booth et al. (2023)]. In practical terms, the detection of floating marine litter using partial unmixing methodologies with atmospherically corrected Sentinel-2 data is feasible under reasonable conditions, typically requiring an estimated abundance fraction of less than 20% for successful detection. Discriminating other floating features, such as pollen, vessels, and vessel wakes, remains problematic due to their similar spectral characteristics to floating marine litter in the proposed model.

Spectral unmixing methods, while valuable for extracting information from mixed pixels in remote sensing imagery, do have their limitations. One key constraint lies in the assumption of linear mixing, which may not always hold in complex natural environments where interactions between different materials can be nonlinear. Additionally, these methods often rely on prior knowledge of endmember spectra, which can be challenging to obtain accurately, especially in heterogeneous landscapes. Atmospheric effects, such as scattering and absorption, can introduce uncertainties and affect the reliability of unmixing results. Furthermore, spectral unmixing assumes that the number of endmembers is known *a priori*, and determining the appropriate number can be a non-trivial task. Lastly, variations in lighting conditions, sensor calibration, and noise levels can also impact the accuracy of spectral unmixing outcomes. Thus, while spectral unmixing methods are powerful tools, their successful application requires careful consideration of these limitations in real-world scenarios.

4.4 Support from radar backscattering

Upon completing the earlier section concerning the potential of SAR imagery, it became evident that for SAR to play a more active role in this domain, there is a necessity for significant advancements in research to substantiate its capabilities. Here, we enumerate several advantages of SAR in comparison to passive remote sensing methods, alongside potential areas of future research interest as perceived by the authors.

1. Several European missions (e.g., COSMO/SkyMed, TerraSAR-X, NovaSAR-1, ICEYE) have developed a new generation of satellites exploiting SAR to provide spatial resolutions previously unavailable (up to 0.25 m). Investigating the cm scale is crucially important to detect/classify plastic pollutants since these spatial resolutions have recently been available for optical remote sensing (Planet-SkySat, WV3). High-resolution SAR data is continuously obtained for some other monitoring applications and taking these high-potential, yet less-demanded, sources into play supportive information to high-resolution spectral imagery for plastic detection yields crucial importance.
2. Due to its day and night imaging capabilities, synthetic aperture radar (SAR) offers more frequent revisits compared to optical imagery, such as Sentinel-2, which revisits approximately every 5 days. Furthermore, SAR's ability to collect data in all weather conditions and despite cloud cover enables it to provide uninterrupted information, particularly in regions where

optical sensors often lack data due to severe cloud cover and adverse weather conditions. A continuous stream of data with shorter time intervals is essential for monitoring and understanding the behaviour of plastic patches in the open ocean. Leveraging SAR data can help shed light on why certain areas, like Henderson Island, serve as gathering points for ocean plastics (Lavers and Bond, 2017).

3. SAR sensors operate with various frequency bands (P-S-L-C-X) each of which has various advantages compared to the others. Since (i) different frequency bands will therefore develop different interactions between the plastic pollutant and the sea surface waters, and (ii) different penetrable frequency bands such as S (NovaSAR-1), L (ALOS2) and X (TerraSAR-X, ICEYE, *etc.*) have not yet been utilised in the analysis, SAR imagery research is still open to exploration regarding its plastic detection capability. A key fact shared by Papageorgiou et al. (2022) for optical imagery reception of the floating pixels states that if we contemplate submerging the target at a depth of approximately 20–30 cm below the water surface, we observe a notable decline in signal strength, ranging from 30% to 40% across the visible spectrum with a more pronounced effect on the NIR bands. This important observation is supportive evidence of the need for SAR penetration capability exploration for this problem which could offer valuable insights and data for mitigating the effects of this natural phenomenon.

4.4.1 Drawbacks

An important problem degrading statistical inference from SAR imagery is the presence of multiplicative speckle noise. The received back-scattered signals sum up coherently and then undergo nonlinear transformations which causes a granular look in the resulting images. This is referred to as speckle noise (Kuruoglu and Zerubia, 2004) and may lead to the loss of details in SAR and cause problems for feature detection, segmentation, or classification. However, speckle noise has been a well-studied problem for decades and can be removed by precisely determining the statistical characteristics of images (Kuruoglu and Zerubia, 2004; Achim et al., 2006; Karakuş et al., 2018; Karakuş and Achim, 2020; Karakuş et al., 2021).

4.5 Tracking the source of pollution

The literature for marine plastic pollution monitoring does not yet have a complete tracking method due to the incapability of continuous data flow and resolution limitations. Detecting where marine plastics are accommodated and tracking where they are heading are of crucial importance, however, there is another important aspect: the detection of the sources of the plastic. Detecting and acting to clean plastic pollution from the oceans requires repetitive efforts as soon as we do not stop the source of the pollution. Hence, the effort by Lavender (2022) via proposing a date set for plastic pollutants both on the land and coastal areas can be seen as one of the starting points since analysing the source of the pollution requires discriminating the pollutants not only on land/ocean but also in small inland waters such as rivers. Similarly, the work by Sasaki et al. (2022) exploiting coastal debris detection via machine learning approaches and utilising Maxar WV-3 imagery accommodates the same importance to clearly discriminate the debris on the sea surface and on Land. It is also important to note that Bosi et al. (2021) propose two different particle tracking models (PTM-SD and PTM-REF) to investigate the timescales of dispersal from the ocean surface and onto coastal accumulation areas. Their models suggest that the coastal regions of Central America and Western Europe will be most affected by floating plastic particles.

As mentioned in the above sections, floating plastics' trajectory in the ocean has been affected by surface signatures and currents. Combining SAR and optical imagery information with the ground-breaking statistical samplers (Corenflos et al., 2021; Wu et al., 2022; Hao et al., 2023a; Hao et al., 2023b) for tracking approaches will make analysing ocean currents, and wave structures possible, which can lead to developing back-tracking approaches to predict the sources of plastic pollution. Lastly, In order to mitigate the drawbacks of small-sized plastic bits and relatively low spatial resolution remote sensing data, group (or, namely, cloud) tracking-based approaches (Mihaylova et al., 2014) are of great importance.

4.6 Need for consensus

Different from the aforementioned future research directions, the authors would like to finalise the paper with a general but considerably important future direction. Due to its multi-/cross-disciplinary nature, MD&SP monitoring research requires an improved understanding and consistent steps in agreement with academia, decision/policymakers and industry. Thus, a consensus among academia, governments, policymakers, and industry is crucial for effective MD&SP detection/monitoring research. This collaboration is necessary due to several compelling reasons.

1. MD&SP is a complex and multifaceted problem that requires a multidisciplinary approach. Academia contributes scientific expertise and research, governments enforce regulations and policies, industry provides resources and innovation, and policymakers drive effective decision-making. A consensus ensures a holistic understanding of the issue, combining diverse perspectives and knowledge.
2. Efficient allocation of resources is essential to address the scale of MD&SP. A consensus helps prevent duplication of efforts and ensures that funding, technology, and human resources are directed toward the most pressing research areas, leading to impactful outcomes.
3. Collaboration between policymakers, governments, and academia ensures that research findings directly inform policy formulation and implementation. Consensus-driven policies are more likely to be based on accurate, up-to-date information, resulting in effective strategies to reduce, manage, and prevent MD&SP.
4. A unified stance from academia, governments, policymakers, and industry enhances public awareness and engagement. When these entities collaborate, they can communicate findings, goals, and solutions more effectively to the public, generating support and encouraging responsible behaviour.

5. MD&SP is also a global issue that transcends borders. A consensus is essential for international cooperation, facilitating the sharing of data, best practices, and technologies. This enables a coordinated effort to address MD&SP that travels across oceans and affects multiple regions.
6. A shared understanding and coordinated effort are necessary for the long-term sustainability of research initiatives. Consensus-driven research is more likely to have a lasting impact and adapt to evolving challenges over time.
7. Industry involvement is crucial for driving innovation in detection and monitoring technologies. Collaboration with academia and governments ensures that technological advancements are aligned with research needs and regulatory requirements. There is an improved activity on this point thanks to ESA's Open Space Innovation Platform (OSIP) activities. ESA Discovery started (since 2019) sourcing ideas for new activities from industry, academia and the general public through the OSIP. Some example projects can be seen in (ESA, 2019).
8. Collaboration among various stakeholders helps mitigate potential conflicts of interest. It ensures that research outcomes and policies are not unduly influenced by any single group's agenda.

In conclusion, when academia, governments, policymakers, and industry stakeholders reach a common understanding, it promotes a collaborative strategy for the detection and monitoring of MD&SP. This collaborative effort enhances the potential for more efficient, knowledgeable, and environmentally responsible solutions.

5 Summary and final remarks

This paper was concerned with one of the most important nature-related problems of marine plastic pollution. Considering the recent technological developments in remote sensing, machine learning and artificial intelligence areas, this paper aimed to highlight academic efforts that concern MD&SP detection problems. Particularly, we presented a thorough review of the academic efforts and highlighted developed computational remote sensing imaging approaches for detecting MD&SP. Furthermore, a critical discussion was presented to clearly show the challenges and limitations of the reviewed academic outcomes. Finally, depending on the author's experience and research on marine-related remote sensing computational imaging approaches, various potential future research directions have been listed.

Our literature review in the above sections clearly shows that MD&SP monitoring research has had a great interest, especially after 2019. This can be seen as a natural increase in interest due to the vast amount of approaches developed in computer vision research, and the launching of high-resolution new remote sensing technologies. Challenges caused by the dynamic characteristics of MD&SP on the sea surface and their small-scale target size will be important indicators for future research. Moreover, remote sensing sensor limitation and ground truth data labelling problems will also drive researchers to develop advanced minimal supervision approaches.

Author contributions

OK: Conceptualization, Formal Analysis, Validation, Visualization, Writing–original draft, Writing–review and editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Achim, A., Kuruoglu, E. E., and Zerubia, J. (2006). SAR image filtering based on the heavy-tailed Rayleigh model. *IEEE Trans. Image Process.* 15, 2686–2693. doi:10.1109/tip.2006.877362

Acuña-Ruz, T., Uribe, D., Taylor, R., Amézquita, L., Guzmán, M. C., Merrill, J., et al. (2018). Anthropogenic marine debris over beaches: spectral characterization for remote sensing applications. *Remote Sens. Environ.* 217, 309–322. doi:10.1016/j.rse.2018.08.008

Angelliaume, S., Ceamanos, X., Viallefont-Robinet, F., Baqué, R., Déliot, P., and Miegebielle, V. (2017). Hyperspectral and radar airborne imagery over controlled release of oil at sea. *Sensors* 17, 1772. doi:10.3390/s17081772

Aoyama, T. (2014). Monitoring of marine debris in the Sea of Japan using multi-spectral satellite images. *Ocean Remote Sens. Monit. Space* 9261, 92611E. doi:10.1117/12.2068835

Aoyama, T. (2016). Extraction of marine debris in the Sea of Japan using high-spatial-resolution satellite images. *Remote Sens. Oceans Inland Waters Tech. Appl. Challenges* 9878, 987817. doi:10.1117/12.2220370

Arias, M., Sumerot, R., Delaney, J., Coulibaly, F., Cozar, A., Aliani, S., et al. (2021). Advances on remote sensing of windrows as proxies for marine litter based on sentinel-2/msi datasets. *2021 IEEE Int. Geoscience Remote Sens. Symposium IGARSS*, 1126–1129. doi:10.1109/IGARSS47720.2021.9555139

Barbat, M. M., Rackow, T., Wesche, C., Hellmer, H. H., and Mata, M. M. (2021). Automated iceberg tracking with a machine learning approach applied to SAR imagery: a Weddell sea case study. *ISPRS J. Photogrammetry Remote Sens.* 172, 189–206. doi:10.1016/j.isprsjprs.2020.12.006

Basu, B., Sannigrahi, S., Sarkar Basu, A., and Pilla, F. (2021). Development of novel classification algorithms for detection of floating plastic debris in coastal waterbodies using multispectral Sentinel-2 remote sensing imagery. *Remote Sens.* 13, 1598. doi:10.3390/rs13081598

Biermann, L., Clewley, D., Martinez-Vicente, V., and Topouzelis, K. (2020). Finding plastic patches in coastal waters using optical satellite data. *Sci. Rep.* 10, 5364–5410. doi:10.1038/s41598-020-62298-z

Booth, H., Ma, W., and Karakuş, O. (2023). High-precision density mapping of marine debris and floating plastics via satellite imagery. *Sci. Rep.* 13, 6822. doi:10.1038/s41598-023-33612-2

Bosi, S., Broström, G., and Roquet, F. (2021). The role of Stokes drift in the dispersal of north atlantic surface marine debris. *Front. Mar. Sci.* 8. doi:10.3389/fmars.2021.697430

Ciappa, A. C. (2022). Marine litter detection by sentinel-2: a case study in North Adriatic (summer 2020). *Remote Sens.* 14, 2409. doi:10.3390/rs14102409

Corenflos, A., Thornton, J., Deligiannidis, G., and Doucet, A. (2021). "Differentiable particle filtering via entropy-regularized optimal transport," in International Conference on Machine Learning (PMLR), Baltimore, Maryland USA, July 17-23, 2022, 2100–2111.

ESA (2019). *The discovery campaign on remote sensing of plastic marine litter*. Available at: https://www.esa.int/Enabling_Support/Preparing_for_the_Future/Discovery_and_Preparation/The_Discovery_Campaign_on_Remote_Sensing_of_Plastic_Marine_Litter.

ESA (2023a). *Planetscope esa archive*. Available at: https://earth.esa.int/eogateway/catalog/planetscope-esa-archive.

ESA (2023b). *Skysat esa archive*. Available at: https://earth.esa.int/eogateway/catalog/skysat-esa-archive.

ESA (2023c). *Worldview esa archive*. Available at: https://earth.esa.int/eogateway/catalog/worldview-esa-archive.

Evans, M. C., and Ruf, C. S. (2021). Toward the detection and imaging of ocean microplastics with a spaceborne radar. *IEEE Trans. Geoscience Remote Sens.* 60, 1–9. doi:10.1109/tgrs.2021.3081691

Fallati, L., Polidori, A., Salvatore, C., Saponari, L., Savini, A., and Galli, P. (2019). Anthropogenic Marine Debris assessment with Unmanned Aerial Vehicle imagery and deep learning: a case study along the beaches of the Republic of Maldives. *Sci. Total Environ.* 693, 133581. doi:10.1016/j.scitotenv.2019.133581

Farahnakian, F., and Heikkonen, J. (2020). Deep learning based multi-modal fusion architectures for maritime vessel detection. *Remote Sens.* 12, 2509. doi:10.3390/rs12162509

Farré, M. (2020). Remote and *in situ* devices for the assessment of marine contaminants of emerging concern and plastic debris detection. *Curr. Opin. Environ. Sci. Health* 18, 79–94. doi:10.1016/j.coesh.2020.10.002

Feyisa, G. L., Meilby, H., Fensholt, R., and Proud, S. R. (2014). Automated Water Extraction Index: a new technique for surface water mapping using Landsat imagery. *Remote Sens. Environ.* 140, 23–35. doi:10.1016/j.rse.2013.08.029

Fingas, M., and Brown, C. E. (2017). A review of oil spill remote sensing. *sensors* 18, 91. doi:10.3390/s18010091

Freitas, S., Silva, H., and Silva, E. (2021). Remote hyperspectral imaging acquisition and characterization for marine litter detection. *Remote Sens.* 13, 2536. doi:10.3390/rs13132536

Garaba, S. P., Arias, M., Corradi, P., Harmel, T., de Vries, R., and Lebreton, L. (2021). Concentration, anisotropic and apparent colour effects on optical reflectance properties of virgin and ocean-harvested plastics. *J. Hazard. Mater.* 406, 124290. doi:10.1016/j.jhazmat.2020.124290

Garaba, S. P., and Dierssen, H. M. (2018). An airborne remote sensing case study of synthetic hydrocarbon detection using short wave infrared absorption features identified from marine-harvested macro-and microplastics. *Remote Sens. Environ.* 205, 224–235. doi:10.1016/j.rse.2017.11.023

Ge, Z., Shi, H., Mei, X., Dai, Z., and Li, D. (2016). Semi-automatic recognition of marine debris on beaches. *Sci. Rep.* 6, 25759. doi:10.1038/srep25759

Giusti, E., Capria, A., Saverino, A., Gelli, S., Muñoz-Castañer, J., Dosil, R., et al. (2022). A drone based multisensory payload for maritime pollutants detections. *IEEE Aerosp. Electron. Syst. Mag.* 38, 4–18. doi:10.1109/maes.2022.3232071

Gnann, N., Baschek, B., and Ternes, T. A. (2022). Close-range remote sensing-based detection and identification of macroplastics on water assisted by artificial intelligence: a review. *Water Res.* 222, 118902. doi:10.1016/j.watres.2022.118902

Goddijn-Murphy, L., Peters, S., Van Sebille, E., James, N. A., and Gibb, S. (2018). Concept for a hyperspectral remote sensing algorithm for floating marine macro plastics. *Mar. Pollut. Bull.* 126, 255–262. doi:10.1016/j.marpolbul.2017.11.011

Gómez, À. S., Scandolo, L., and Eisemann, E. (2022). A learning approach for river debris detection. *Int. J. Appl. Earth Observation Geoinformation* 107, 102682. doi:10.1016/j.jag.2022.102682

Gomez, R., Arigony-Neto, J., De Santis, A., Vijay, S., Jaña, R., and Rivera, A. (2019). Ice dynamics of union glacier from SAR offset tracking. *Glob. Planet. Change* 174, 1–15. doi:10.1016/j.gloplacha.2018.12.012

Graziano, M. D., D'Errico, M., and Rufino, G. (2016). Wake component detection in X-band SAR images for ship heading and velocity estimation. *Remote Sens.* 8, 498. doi:10.3390/rs8060498

Gupta, S., Khurana, Y., Atrey, J., Gupta, S., and Krishnamoorthy, P. (2023). Marine debris detection using a multi-feature pyramid network. *Remote Sens. Lett.*, 231–241. doi:10.1080/2150704x.2023.2183480

Hao, P., Karakuş, O., and Achim, A. (2023a). A hybrid particle-stochastic map filter. *Signal Process.* 207, 108969. doi:10.1016/j.sigpro.2023.108969

Hao, P., Karakuş, O., and Achim, A. (2023b). *Robust kalman filters based on the sub-Gaussian α-stable distribution. arXiv preprint arXiv:2305.07890*.

Hu, C. (2009). A novel ocean color index to detect floating algae in the global oceans. *Remote Sens. Environ.* 113, 2118–2129. doi:10.1016/j.rse.2009.05.012

Hu, C. (2021). Remote detection of marine debris using satellite observations in the visible and near infrared spectral range: challenges and potentials. *Remote Sens. Environ.* 259, 112414. doi:10.1016/j.rse.2021.112414

Hu, C. (2022). Remote detection of marine debris using Sentinel-2 imagery: a cautious note on spectral interpretations. *Mar. Pollut. Bull.* 183, 114082. doi:10.1016/j.marpolbul.2022.114082

Hu, C., Qi, L., Xie, Y., Zhang, S., and Barnes, B. B. (2022). Spectral characteristics of sea snot reflectance observed from satellites: implications for remote sensing of marine debris. *Remote Sens. Environ.* 269, 112842. doi:10.1016/j.rse.2021.112842

Huete, A. R. (1988). A soil-adjusted vegetation index (savi). *Remote Sens. Environ.* 25, 295–309. doi:10.1016/0034-4257(88)90106-x

Jakovljevic, G., Govedarica, M., and Alvarez-Taboada, F. (2020). A deep learning model for automatic plastic mapping using unmanned aerial vehicle (UAV) data. *Remote Sens.* 12, 1515. doi:10.3390/rs12091515

Jamali, A., and Mahdianpari, M. (2021). A cloud-based framework for large-scale monitoring of ocean plastics using multi-spectral satellite imagery and generative adversarial network. *Water* 13, 2553. doi:10.3390/w13182553

Karakuş, O., and Achim, A. (2020). On solving SAR imaging inverse problems using nonconvex regularization with a Cauchy-based penalty. *IEEE Trans. Geoscience Remote Sens.* 59, 5828–5840. doi:10.1109/tgrs.2020.3011631

Karakuş, O., Kuruoğlu, E. E., and Achim, A. (2021). A generalized Gaussian extension to the Rician distribution for SAR image modeling. *IEEE Trans. Geoscience Remote Sens.* 60, 1–15. doi:10.1109/tgrs.2021.3069091

Karakuş, O., Kuruoğlu, E. E., and Altınkaya, M. A. (2018). Generalized Bayesian model selection for speckle on remote sensing images. *IEEE Trans. Image Process.* 28, 1748–1758. doi:10.1109/tip.2018.2878322

Karakus, O., Rizaev, I. G., and Achim, A. M. (2019). Ship wake detection in SAR images via sparse regularization. *IEEE Trans. Geoscience Remote Sens.* 58, 1665–1677. doi:10.1109/tgrs.2019.2947360

Kartal, M., and Duman, O. (2019). "Ship detection from optical satellite images with deep learning." in 2019 9th International Conference on Recent Advances in Space Technologies, 11-14 June 2019, 479–484.

Kendall, A., and Gal, Y. (2017). What uncertainties do we need in bayesian deep learning for computer vision? *Adv. neural Inf. Process. Syst.* 30. doi:10.5555/3295222.3295309

Kikaki, A., Karantzalos, K., Power, C. A., and Raitsos, D. E. (2020). Remotely sensing the source and transport of marine plastic debris in Bay Islands of Honduras (Caribbean Sea). *Remote Sens.* 12, 1727. doi:10.3390/rs12111727

Kikaki, K., Kakogeorgiou, I., Mikeli, P., Raitsos, D. E., and Karantzalos, K. (2022). MARIDA: a benchmark for Marine Debris detection from Sentinel-2 remote sensing data. *PloS one* 17, e0262247. doi:10.1371/journal.pone.0262247

Knaeps, E., Sterckx, S., Strackx, G., Mijnendonckx, J., Moshtaghi, M., Garaba, S. P., et al. (2021). Hyperspectral-reflectance dataset of dry, wet and submerged marine litter. *Earth Syst. Sci. Data* 13, 713–730. doi:10.5194/essd-13-713-2021

Kremezi, M., Kristollari, V., Karathanassi, V., Topouzelis, K., Kolokoussis, P., Taggio, N., et al. (2021). Pansharpening prisma data for marine plastic litter detection using plastic indexes. *IEEE Access* 9, 61955–61971. doi:10.1109/access.2021.3073903

Kremezi, M., Kristollari, V., Karathanassi, V., Topouzelis, K., Kolokoussis, P., Taggio, N., et al. (2022). Increasing the Sentinel-2 potential for marine plastic litter monitoring through image fusion techniques. *Mar. Pollut. Bull.* 182, 113974. doi:10.1016/j.marpolbul.2022.113974

Kuruoglu, E. E., and Zerubia, J. (2004). Modeling SAR images with a generalization of the Rayleigh distribution. *IEEE Trans. Image Process.* 13, 527–533. doi:10.1109/tip.2003.818017

Lavender, S. (2022). Detection of waste plastics in the environment: application of copernicus earth observation data. *Remote Sens.* 14, 4772. doi:10.3390/rs14194772

Lavers, J. L., and Bond, A. L. (2017). Exceptional and rapid accumulation of anthropogenic debris on one of the world's most remote and pristine islands. *Proc. Natl. Acad. Sci.* 114, 6052–6055. doi:10.1073/pnas.1619818114

Leape, J. (2018). "Our oceans are in crisis. Here's how technology could save them," in WEF Annual Meeting, Davos, 23 Jan 2018 – 26 Jan 2018.

Lemos, A., Shepherd, A., McMillan, M., Hogg, A. E., Hatton, E., and Joughin, I. (2018). Ice velocity of jakobshavn isbræ, petermann glacier, nioghalvfjerdsfjorden, and zachariæ isstrøm, 2015–2017, from sentinel 1-a/b SAR imagery. *Cryosphere* 12, 2087–2097. doi:10.5194/tc-12-2087-2018

Li, Y., and Li, J. (2010). Oil spill detection from SAR intensity imagery using a marked point process. *Remote Sens. Environ.* 114, 1590–1601. doi:10.1016/j.rse.2010.02.013

Liang, J., Ahmad, B. I., Gan, R., Langdon, P., Hardy, R., and Godsill, S. (2019). On destination prediction based on Markov bridging distributions. *IEEE Signal Process. Lett.* 26, 1663–1667. doi:10.1109/lsp.2019.2943081

Ma, W., Karakuş, O., and Rosin, P. L. (2022). AMM-FuseNet: attention-based multi-modal image fusion network for land cover mapping. *Remote Sens.* 14, 4458. doi:10.3390/rs14184458

Ma, W., Karakus, O., and Rosin, P. L. (2023). *Confidence-guided semi-supervised learning in land cover classification. arXiv preprint arXiv:2305.10344.*

MacFeeters, S. (1995). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *Int. J. Remote Sens.* 17, 1425–1432. doi:10.1080/01431169608948714

Magyar, D., Cserép, M., Vincellér, Z., and Molnár, A. D. (2023). *Waste detection and change analysis based on multispectral satellite imagery. arXiv preprint arXiv: 2303.14521.*

Martínez-Vicente, V., Clark, J. R., Corradi, P., Aliani, S., Arias, M., Bochow, M., et al. (2019). Measuring marine plastic debris from space: initial assessment of observation requirements. *Remote Sens.* 11, 2443. doi:10.3390/rs11202443

Matthews, J. P., Ostrovsky, L., Yoshikawa, Y., Komori, S., and Tamura, H. (2017). Dynamics and early post-tsunami evolution of floating marine debris near Fukushima Daiichi. *Nat. Geosci.* 10, 598–603. doi:10.1038/ngeo2975

Mifdal, J., Longépé, N., and Rußwurm, M. (2021). Towards detecting floating objects on a global scale with learned spatial features using sentinel 2. *ISPRS Ann. Photogrammetry, Remote Sens. Spatial Inf. Sci.* 3, 285–293. doi:10.5194/isprs-annals-v-3-2021-285-2021

Mihaylova, L., Carmi, A. Y., Septier, F., Gning, A., Pang, S. K., and Godsill, S. (2014). Overview of Bayesian sequential Monte Carlo methods for group and extended object tracking. *Digit. Signal Process.* 25, 1–16. doi:10.1016/j.dsp.2013.11.006

Mikeli, P., Kikaki, K., Kakogeorgiou, I., and Karantzalos, K. (2022). How challenging is the discrimination of floating materials on the sea surface using high-resolution multispectral satellite data? *Int. Archives Photogrammetry, Remote Sens. Spatial Inf. Sci.* 43, 151–157. doi:10.5194/isprs-archives-xliii-b3-2022-151-2022

Moshtaghi, M., Knaeps, E., Sterckx, S., Garaba, S., and Meire, D. (2021). Spectral reflectance of marine macroplastics in the VNIR and SWIR measured in a controlled environment. *Sci. Rep.* 11, 5436. doi:10.1038/s41598-021-84867-6

Moy, K., Neilson, B., Chung, A., Meadows, A., Castrence, M., Ambagis, S., et al. (2018). Mapping coastal marine debris using aerial imagery and spatial analysis. *Mar. Pollut. Bull.* 132, 52–59. doi:10.1016/j.marpolbul.2017.11.045

Mukonza, S. S., and Chiang, J.-L. (2022). Satellite sensors as an emerging technique for monitoring macro- and microplastics in aquatic ecosystems. *Water Emerg. Contam. Nanoplastics* 1 (4), 17. doi:10.20517/wecn.2022.12

Nagy, M., Istrate, L., Simtinică, M., Travadel, S., and Blanc, P. (2022). Automatic detection of marine litter: a general framework to leverage synthetic data. *Remote Sens.* 14, 6102. doi:10.3390/rs14236102

Nguyen, C. T., Chidthaisong, A., Kieu Diem, P., and Huo, L.-Z. (2021). A modified bare soil index to identify bare land features during agricultural fallow-period in southeast Asia using Landsat 8. *Land* 10, 231. doi:10.3390/land10030231

Olyaei, M., Ebtehaj, A., and Hong, J. (2022). Optical detection of marine debris using deep knockoff. *IEEE Trans. Geoscience Remote Sens.* 60, 1–12. doi:10.1109/tgrs.2022.3228638

Papageorgiou, D., Topouzelis, K., Suaria, G., Aliani, S., and Corradi, P. (2022). Sentinel-2 detection of floating marine litter targets with partial spectral unmixing and spectral comparison with other floating materials (plastic litter project 2021). *Remote Sens.* 14, 5997. doi:10.3390/rs14235997

Pappas, O., Achim, A., and Bull, D. (2018). Superpixel-level CFAR detectors for ship detection in SAR imagery. *IEEE Geoscience Remote Sens. Lett.* 15, 1397–1401. doi:10.1109/lgrs.2018.2838263

Park, Y.-J., Garaba, S. P., and Sainte-Rose, B. (2021). Detecting the Great Pacific Garbage Patch floating plastic litter using WorldView-3 satellite imagery. *Opt. Express* 29, 35288–35298. doi:10.1364/oe.440380

Politikos, D. V., Adamopoulou, A., Petasis, G., and Galgani, F. (2023). Using artificial intelligence to support marine macrolitter research: a content analysis and an online database. *Ocean Coast. Manag.* 233, 106466. doi:10.1016/j.ocecoaman.2022.106466

Qi, L., Lee, Z., Hu, C., and Wang, M. (2017). Requirement of minimal signal-to-noise ratios of ocean color sensors and uncertainties of ocean color products. *J. Geophys. Res. Oceans* 122, 2595–2611. doi:10.1002/2016JC012558

Rizaev, I. G., Karakuş, O., Hogan, S. J., and Achim, A. (2022). Modeling and SAR imaging of the sea surface: a review of the state-of-the-art with simulations. *ISPRS J. Photogrammetry Remote Sens.* 187, 120–140. doi:10.1016/j.isprsjprs.2022.02.017

Rosin, P. L. (2001). Robust pixel unmixing. *IEEE Trans. Geoscience Remote Sens.* 39, 1978–1983. doi:10.1109/36.951088

Rouse, J. W., Haas, R. H., Schell, J. A., Deering, D. W., et al. (1974). Monitoring vegetation systems in the great plains with ERTS. *NASA Spec. Publ.* 351, 309.

Rowley, A., and Karakuş, O. (2023). Predicting air quality via multimodal ai and satellite imagery. *Remote Sens. Environ.* 293, 113609. doi:10.1016/j.rse.2023.113609

Roy, S. K., Deria, A., Hong, D., Rasti, B., Plaza, A., and Chanussot, J. (2023). Multimodal fusion transformer for remote sensing image classification. *IEEE Trans. Geoscience Remote Sens.* 61, 1–20. doi:10.1109/tgrs.2023.3286826

Sagan, V., Peterson, K. T., Maimaitijiang, M., Sidike, P., Sloan, J., Greeling, B. A., et al. (2020). Monitoring inland water quality using remote sensing: potential and limitations of spectral indices, bio-optical simulations, machine learning, and cloud computing. *Earth-Science Rev.* 205, 103187. doi:10.1016/j.earscirev.2020.103187

Sakti, A. D., Sembiring, E., Rohayani, P., Fauzan, K. N., Anggraini, T. S., Santoso, C., et al. (2023). Identification of illegally dumped plastic waste in a highly polluted river in Indonesia using sentinel-2 satellite imagery. *Sci. Rep.* 13, 5039. doi:10.1038/s41598-023-32087-5

Salgado-Hernanz, P. M., Bauzà, J., Alomar, C., Compa, M., Romero, L., and Deudero, S. (2021). Assessment of marine litter through remote sensing: recent approaches and future goals. *Mar. Pollut. Bull.* 168, 112347. doi:10.1016/j.marpolbul.2021.112347

Sannigrahi, S., Basu, B., Basu, A. S., and Pilla, F. (2022). Development of automated marine floating plastic detection system using Sentinel-2 imagery and machine learning models. *Mar. Pollut. Bull.* 178, 113527. doi:10.1016/j.marpolbul.2022.113527

Sasaki, K., Sekine, T., Burtz, L.-J., and Emery, W. J. (2022). Coastal marine debris detection and density mapping with very high resolution satellite imagery. *IEEE J. Sel. Top. Appl. Earth Observations Remote Sens.* 15, 6391–6401. doi:10.1109/jstars.2022.3193993

Savastano, S., Cester, I., Perpinyà, M., and Romero, L. (2021). "A first approach to the automatic detection of marine litter in sar images using artificial intelligence," in 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 11-16 July 2021, 8704. –8707. doi:10.1109/IGARSS47720.2021.9737038

Scheibenreif, L., Mommert, M., and Borth, D. (2022). Toward global estimation of ground-level NO 2 pollution with deep learning and remote sensing. *IEEE Trans. Geoscience Remote Sens.* 60, 1–14. doi:10.1109/tgrs.2022.3160827

Serafino, F., and Bianco, A. (2021). Use of x-band radars to monitor small garbage islands. *Remote Sens.* 13, 3558. doi:10.3390/rs13183558

Shan, Y., Zhou, X., Liu, S., Zhang, Y., and Huang, K. (2020). Siamfpn: a deep learning method for accurate and real-time maritime ship tracking. *IEEE Trans. Circuits Syst. Video Technol.* 31, 315–325. doi:10.1109/tcsvt.2020.2978194

Shen, L., and Li, C. (2010). "Water body extraction from Landsat ETM+ imagery using adaboost algorithm," in 2010 18th International Conference on Geoinformatics (IEEE), 18-20 June 2010.

Shen, L., Xu, H., and Guo, X. (2012). Satellite remote sensing of harmful algal blooms (habs) and a potential synthesized framework. *Sensors* 12, 7778–7803. doi:10.3390/s120607778

Shermeyer, J., Hogan, D., Brown, J., Van Etten, A., Weir, N., Pacifici, F., et al. (2020). "SpaceNet 6: multi-sensor all weather mapping dataset," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, Seattle, WA, USA, June 14-19, 2020, 196–197.

Shirvany, R., Chabert, M., and Tourneret, J.-Y. (2012). Ship and oil-spill detection using the degree of polarization in linear and hybrid/compact dual-pol sar. *IEEE J. Sel. Top. Appl. Earth Observations Remote Sens.* 5, 885–892. doi:10.1109/jstars.2012.2182760

Simpson, M. D., Marino, A., de Maagt, P., Gandini, E., de Fockert, A., Hunter, P., et al. (2023). Investigating the backscatter of marine plastic litter using a C-and X-band ground radar, during a measurement campaign in Deltares. *Remote Sens.* 15, 1654. doi:10.3390/rs15061654

Taggio, N., Aiello, A., Ceriola, G., Kremezi, M., Kristollari, V., Kolokoussis, P., et al. (2022). A combination of machine learning algorithms for marine plastic litter detection exploiting hyperspectral PRISMA data. *Remote Sens.* 14, 3606. doi:10.3390/rs14153606

Tasseron, P., Van Emmerik, T., Peller, J., Schreyers, L., and Biermann, L. (2021). Advancing floating macroplastic detection from space using experimental hyperspectral imagery. *Remote Sens.* 13, 2335. doi:10.3390/rs13122335

The IOCCG (2022). *Datasets – bibliography*. Canada: The International Ocean Colour Coordinating Group.

Themistocleous, K., Papoutsa, C., Michaelides, S., and Hadjimitsis, D. (2020). Investigating detection of floating plastic litter from space using Sentinel-2 imagery. *Remote Sens.* 12, 2648. doi:10.3390/rs12162648

The NOAA (2022). *Discover marine debris*. Canada: The National Oceanic and Atmospheric Administration.

Thiel, M., Hinojosa, I. A., Joschko, T., and Gutow, L. (2011). Spatio-temporal distribution of floating objects in the German bight (north sea). *J. Sea Res.* 65, 368–379. doi:10.1016/j.seares.2011.03.002

Thushari, G., and Senevirathna, J. (2020). Plastic pollution in the marine environment. *Heliyon* 6, e04709. doi:10.1016/j.heliyon.2020.e04709

Topouzelis, K., Papageorgiou, D., Karagaitanakis, A., Papakonstantinou, A., and Arias Ballesteros, M. (2020). Remote sensing of sea surface artificial floating plastic targets with sentinel-2 and unmanned aerial systems (plastic litter project 2019). *Remote Sens.* 12, 2013. doi:10.3390/rs12122013

Topouzelis, K., Papageorgiou, D., Suaria, G., and Aliani, S. (2021). Floating marine litter detection algorithms and techniques using optical remote sensing data: a review. *Mar. Pollut. Bull.* 170, 112675. doi:10.1016/j.marpolbul.2021.112675

Topouzelis, K., Papakonstantinou, A., and Garaba, S. P. (2019). Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018). *Int. J. Appl. Earth Observation Geoinformation* 79, 175–183. doi:10.1016/j.jag.2019.03.011

van Duinen, B., Kaandorp, M. L., and Van Sebille, E. (2022). Identifying marine sources of beached plastics through a bayesian framework: application to southwest Netherlands. *Geophys. Res. Lett.* 49, e2021GL097214. doi:10.1029/2021gl097214

van Lieshout, C., van Oeveren, K., van Emmerik, T., and Postma, E. (2020). Automated river plastic monitoring using deep learning and cameras. *Earth space Sci.* 7, e2019EA000960. doi:10.1029/2019ea000960

Van Sebille, E., Aliani, S., Law, K. L., Maximenko, N., Alsina, J. M., Bagaev, A., et al. (2020). The physical oceanography of the transport of floating marine debris. *Environ. Res. Lett.* 15, 023003. doi:10.1088/1748-9326/ab6d7d

Van Sebille, E., Wilcox, C., Lebreton, L., Maximenko, N., Hardesty, B. D., Van Franeker, J. A., et al. (2015). A global inventory of small floating plastic debris. *Environ. Res. Lett.* 10, 124006. doi:10.1088/1748-9326/10/12/124006

Veettil, B. K., Quan, N. H., Hauser, L. T., Van, D. D., and Quang, N. X. (2022). Coastal and marine plastic litter monitoring using remote sensing: a review. *Estuar. Coast. Shelf Sci.* 279, 108160. doi:10.1016/j.ecss.2022.108160

Vighi, M., Ruiz-Orejón, L., and Hanke, G. (2022). *Monitoring of floating marine macro litter*. Europe: European Commission.

Wilson, E. H., and Sader, S. A. (2002). Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sens. Environ.* 80, 385–396. doi:10.1016/s0034-4257(01)00318-2

Wu, J., Wen, L., Green, P. L., Li, J., and Maskell, S. (2022). Ensemble Kalman filter based sequential Monte Carlo sampler for sequential Bayesian inference. *Statistics Comput.* 32, 20–14. doi:10.1007/s11222-021-10075-x

Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *Int. J. remote Sens.* 27, 3025–3033. doi:10.1080/01431160600589179

Yang, J., Tan, K., Liu, S., Zhang, W., and Tao, P. (2023). Inshore marine litter detection using radiometric and geometric data of terrestrial laser scanners. *Int. J. Appl. Earth Observation Geoinformation* 116, 103149. doi:10.1016/j.jag.2022.103149

Yasir, M., Jianhua, W., Mingming, X., Hui, S., Zhe, Z., Shanwei, L., et al. (2023). Ship detection based on deep learning using sar imagery: a systematic literature review. *Soft Comput.* 27, 63–84. doi:10.1007/s00500-022-07522-w

Zha, Y., Gao, J., and Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from tm imagery. *Int. J. remote Sens.* 24, 583–594. doi:10.1080/01431160304987

Zhang, H., Shen, H., Yuan, Q., and Guan, X. (2022). Multispectral and SAR image fusion based on laplacian pyramid and sparse representation. *Remote Sens.* 14, 870. doi:10.3390/rs14040870

Zhao, Q., Zhang, H., and Li, Y. (2019). Detecting dark spots from SAR intensity images by a point process with irregular geometry marks. *Int. J. Remote Sens.* 40, 774–793. doi:10.1080/01431161.2018.1519278