Mukonza and Chiang. *Water Emerg Contam Nanoplastics* 2022;1:17
DOI: 10.20517/wecn.2022.12

Water Emerging Contaminants & Nanoplastics

Review

Open Access

Check for updates

Satellite sensors as an emerging technique for monitoring macro- and microplastics in aquatic ecosystems

Sabastian Simbarashe Mukonza[1], **Jie-Lun Chiang**[2]

[1]Department of Civil Engineering, National Pingtung University of Science & Technology, Neipu, Pingtung 91201, Taiwan.
[2]Department of Soil and Water Conservation, National Pingtung University of Science & Technology, Neipu, Pingtung 91201, Taiwan.

Correspondence to: Dr. Jie-Lun Chiang, Department of Soil and Water Conservation, National Pingtung University of Science & Technology, No. 1, Shuefu Rd., Neipu, Pingtung 91201, Taiwan. E-mail: jlchiang@mail.npust.edu.tw

How to cite this article: Mukonza SS, Chiang JL. Satellite sensors as an emerging technique for monitoring macro- and microplastics in aquatic ecosystems. *Water Emerg Contam Nanoplastics* 2022;1:17. https://dx.doi.org/10.20517/wecn.2022.12

Received: 24 Jul 2022 **First Decision:** 29 Aug 2022 **Revised:** 10 Sep 2022 **Accepted:** 20 Sep 2022 **Published:** 30 Sep 2022

Academic Editor: Antonio Ginebreda **Copy Editor:** Peng-Juan Wen **Production Editor:** Peng-Juan Wen

Abstract

Plastic pollution in aquatic ecosystems has been identified as a growing global water pollution threat that is negatively impacting water quality and, as a result, affecting the health of humans, aquatic animals, and wildlife. Therefore, it presents a global environmental catastrophe that requires immediate attention. Plastics in water (in their different forms, macro-, meso-, micro-, and nanoplastics) are contaminants of emerging concerns that have since evolved to be a global environmental threat. Despite increasing levels of pollution in aquatic ecosystems, there are insufficient monitoring data to evaluate the extent of the catastrophe. Traditional methods of monitoring plastics in water are constrained by high sampling costs, intensive labor, and limited temporal and spatial coverage, which results in limited monitoring data. Thus, insufficient monitoring data limit our understanding of the true quantities and persistence of plastic particles in aquatic ecosystems, as well as the extent to which they impact the aquatic environment. There is increasing availability of free big geospatial data (amounting to petabytes/day) from satellite sensors for potentially monitoring plastics. This provides a possible solution to these challenges by minimizing the fieldwork required and therefore reducing the costs and sampling time. The study purpose of this review is to analyze advances in emerging technology such as the use of satellite sensors to monitor the occurrence of macro- and microplastics in freshwater, ultimately aimed at creating new operational monitoring solutions. This review: (1) examines the literature to identify trends, accomplishments, and limitations of using satellite data to monitor plastics in water; (2) identifies and compares traditional, and machine and deep learning satellite image classification methods for monitoring plastics in water; and (3) identifies research gaps and summarizes future perspectives and recommendations to improve monitoring methods.

Keywords: Plastic contaminants, satellite, machine learning, deep learning, classification, aquatic ecosystems

INTRODUCTION

Several studies demonstrate the ubiquitous occurrence of plastic debris as a worldwide contaminant or pollutant in water ecosystems[1-6]. The United Nations Environment Program 2017 (UNEP 2017) estimated that plastic waste constitutes approximately 80% of the total waste deposited in the oceans; this translates to 80 million tons per annum[7-9]. The negative global economic impact of plastic pollution on downstream industries such as aquaculture, tourism, wildlife, and the cost of cleanup has been calculated to be 6-16 billion USD annually[1,7,8]. Aquatic species get trapped and entangled in plastic webs, which hinders their mobility, and all forms of plastics in seafood and drinking water are ingested by wildlife[7,10]. Additionally, most plastic products, including those certified as bisphenol A-free plastics that find their way into the aquatic bodies, pose potential risks. The effects of leaching chemical components of plastic can have estrogenic activity (EA)[11]. Therefore, plastic pollution in water is a source of endocrine-disrupting activity chemicals that are hazardous to human health[12,13]. Most researchers have highlighted plastic pollution in water as a twenty-first-century problem of contaminants of emerging concerns (CECs) in the coastal zones, terrestrial, riverine, and oceanic ecosystems[14-17].

Plastic waste emissions into aquatic ecosystems are predicted to increase three-fold by 2040 if there are no significant interventions put in place[18]. Despite these increasing trends of plastic pollution in water, water quality monitoring data on plastic pollution are insufficient[19,20]. Most aquatic plastic pollution monitoring data are obtained through numerical modeling and in situ sampling laboratory-based methods (e.g., micro Fourier transform infrared (μ-FTIR) spectroscopy, attenuated total reflection-Fourier transform infrared (ATR-FTIR) spectroscopy, μ-Raman imaging microscope, microscope, energy-dispersive X-ray spectroscopy (EDS), and scanning electron microscope (SEM))[21,22]. Numerical modeling[23] has the advantage of high spatial coverage, although its drawbacks include low sampling frequency and design faults that may result in under- or overestimation of the true values of plastic concentrations[24]. Traditional laboratory approaches are precise and accurate; however, they are constrained by manual sampling, which is laborious, time-consuming, and costly[25]. Additionally, sampling only provides discrete units of information with limited coverage of the space-time continuum, which is not ideal for monitoring quantities such as microplastics with highly dynamic concentration distributions; geolocations in close proximity can have concentration variances of greater than three orders of magnitude within a short period of time[26]. The highlighted weaknesses of these methods due to the effects of complex plastic transport mechanisms create a fundamental knowledge gap, which renders these methods inadequate to resolve global plastic pollution in aquatic systems[26-28]. Satellite remote sensing for the detection of plastic litter in water is still at the research and development stage, albeit there is huge promising potential to offset the drawbacks highlighted for the other methods[29].

Satellite sensors, including optical, synthetic aperture radar (SAR), hyperspectral, and thermal infrared (TIR) sensors, can either monitor plastics directly or simulate plastic concentrations based on proxy measurements[24]. Satellite observations provide high spatial resolution and long time series data that fill in missing values in all pixels, thus bridging data gaps between sparse sampling points and providing a uniform survey[30-32]. Furthermore, satellites acquire images over physically inaccessible sampling sites due to physical barriers, and sampling is not interrupted by hazardous or extreme weather conditions such as typhoons[30-32]. Due to their design, satellite sensors generate large volumes of complex and high-dimensional spectral data because of long time series and high spatial/spectral/radiometric/temporal resolutions tailor-made for their application[33,34]. As a result, it is challenging or impossible for human brains and traditional statistical methods to perform pattern analysis on satellite data in order to establish relationships between variables of interest. Accordingly, machine and deep learning (ML/DL) techniques have found useful applications in monitoring plastic pollution in aquatic systems[35-43]. Artificial intelligence (AI)-processed satellites are transforming the manner in which experts study plastic pollution in global aquatic ecosystems, and they are proving to be a new powerful tool in the fight to protect water systems from pollution.

THE SCOPE OF THE STUDY

This review article adopts the traditional critical literature review approach to analyze theories and hypotheses through critical evaluation of results obtained from different methodologies for research conducted in different studies[44]. In addition to the traditional approach, a bibliometric approach that statistically analyzes the performance of the selected journal articles using different citation metrics is also applied[45]. No previous studies using bibliometric analysis to explore research activity and trends of plastic pollution monitoring in aquatic ecosystems using satellites have been published. Micro- and nanoplastics are considered contaminants of emerging concern (CECs)[46]. Mechanical abrasion and solar ultraviolet radiation (UV) frequently act on the surface of large plastic particles floating in water, causing deterioration and the release of micro- and nanoplastics into the environment[47,48]. Therefore, plastics in water exist in different shapes and sizes and are made of different polymeric compositions[49]. It is critical to monitor all plastics in their various shapes and sizes because they are byproducts of macro- and mesoplastic degradation. There is a real possibility that satellite sensors can identify all forms of plastics in their aggregated forms, even though their sizes are not distinguishable using the same method. As a result, the scope and focus of this study are to review the literature on using satellites to monitor macro-, meso-, micro-, and nanoplastics in water. Furthermore, hyperspectral, thermal imaging, and multispectral sensors have been successfully applied to monitoring macroplastic debris[15,16,29,35-42], and researchers recently discovered that SAR can be used for monitoring microplastics, a research domain still in its infancy[24]. The significance of monitoring global plastic regardless of size, occurrence, source, and location is emphasized by many researchers[42,50].

CONTRIBUTIONS AND PREVIOUS REVIEWS OF RELATED WORK

The purpose of this review is to develop and test hypotheses that answer the following abstract questions:

-What factors affect the performance of ML/DL classifiers applied to identify plastics in water using satellite data by evaluating the different methodologies used to achieve certain results? This particular question is formulated to close the evidence gap arising from contradictory evidence-results highlighting model performance inconsistencies in different studies. Hypothesized factors in this review include satellite type and classifier model. Notwithstanding the fact that image prepossessing such as geometric, radiometric, and atmospheric correction methods also improve and affect the accuracy of predictions, it is difficult to establish how they contribute to model performance because they are not consistently reported in literature. Therefore, this review does not consider the analysis of pre-processing methods towards model performances.

-Given the fact that this research territory is still in its infancy, how impactful has it been within the scientific research community? Bibliometric measures such as journal impact factor (IF), citation index, and research funding attraction are used to measure the quality of scholarship in this field.

-A broader and general research question is also posed. Since this is an emerging and novel field, what social impact is the research having in different communities?

Comparable reviews were published in this field by Maxemenko *et al.* (2019)[29], Martinez-Vicente *et al.* (2020)[51], Farré (2020)[52], Mace (2012)[53], and Topouzelis (2021)[54]. Maxemenko *et al.* (2019)[29] reviewed an integration of various remote sensing and in situ observations with the objective of optimizing and designing integrated marine debris observing system (IMDOS). Martinez-Vicente *et al.* (2020)[51] evaluated theories and methodologies to develop a generic protocol useful in observations and formulation of design specifications for satellite sensors of the same observation requirements. Farré *et al.* (2020)[52] compared different remote and in situ devices (biosensors, sampling and laboratory analysis, sensors, satellite, and aerial observations) for monitoring CECs. Mace (2012)[53] reviewed technologies, processes, issues, and options in marine debris monitoring with a specific interest in multistage modeling, particularly the improvement of the Ghost Net procedures. The scope and orientation of all these reviews followed a similar traditional way of literature reviewing for analyzing multi-source remote sensing techniques and aimed to achieve a similar objective of improving data quality through multi-sensor data fusion. Although the review by Topouzelis *et al.* (2021)[54] follows a similar approach to the other studies, its scope was confined to optical remote sensors only. Our research used a detailed PRISMA-compliant literature review and a bibliometric approach focusing on spaceborne sensors for monitoring plastic pollution in diverse water ecosystems. Such a deep evaluation allows more deductions to be made with some degree of statistical measure, and this marks the uniqueness of our research from the previous reviews.

METHODOLOGY

Data source

A comprehensive literature search was performed online in three different databases: Scopus, Web of Science (WOS), and Knovel. The key search terms were "satellite remote sensing", "plastic pollution in water", and "satellite data for water quality classification". A detailed search strategy is presented in Figure 1. The search conducted was not time filtered to allow an optimized retrieval of all the literature available in the specific databases. A one-day search was performed on each database to avoid bias due to daily database updates. Only original research, review, conference and credible scientific report articles which were published in peer-reviewed journals were considered for selection.

Systematic literature review-based process search strategy

A systematic search for peer-reviewed literature published in English for journals and conference proceedings indexed in Scopus (http://www.scopus.com/ accessed May 2022), web of science (WOS) (https://www.webofscience.com/wos/alldb/basic-search accessed May 2022), and Knovel (Knovel, guest accessed May 2022) was performed. The selection process was based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)[22] guiding principle method that details the eligibility for the selection of literature and is laid out and explained in Figure 1. The following Boolean string search query was used: TITLE-ABS-KEY (Plastics) AND TITLE-ABS-KEY (Microplastic) AND TITLE-ABS-KEY (Satellite) OR TITLE-ABS-KEY (Water pollutants) OR TITLE-ABS-KEY (Machine learning) or TITLE-ABS-KEY (Water quality).

RESULTS

An unfiltered preliminary search based on the Boolean string search query yielding 3249 peer-reviewed publications was conducted, which showed that no significant literature was published before 2009.

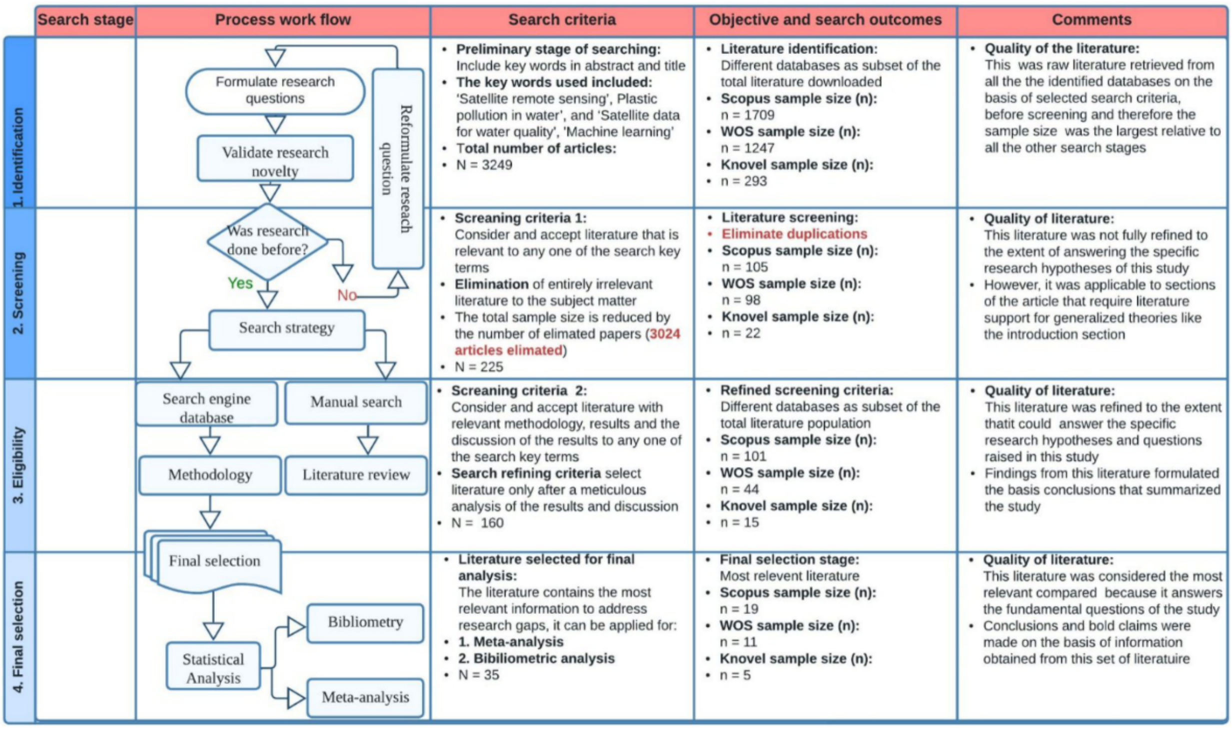

Figure 1. Detailed step-wise process for illustrating the implementation of PRISMA as conducted in this study[22].

Afterwards, there was a moderate increase in the number of published articles across all three databases. In total, 3249 articles were retrieved from all three databases; Scopus, WOS, and Knovel contributed 1709, 1247 and 293 articles, respectively [Figure 2]. The results visualized by the stacked bar charts illustrate a gentle increase in the research trends, with a significant number of publications being noted since 2010. The increasing trend can be attributed to a solid supporting policy framework being offered to researchers through the launch of Sustainable Development Goals (SDG) by the United Nations (UN) Conference in Rio De Genero, Brazil, in 2012[55]. Additionally, the increasing availability of geospatial big data from sensors stored and accessible in free open access portals provides a cheap and convenient way to conduct research[56].

To complement the initial stage of literature search, a word cloud image visualization for texts used in the 35 important references was generated, in which the individual word size indicates the frequency of its appearance in the selected references. The following words appeared frequently and were visualized in various colors and bigger font sizes (in no specific order): marine plastic debris, plastic polymers, Sentinel-2, World View (WV), machine learning, and deep learning [Figure 3]. The word cloud technique was applied for quick identification of research themes in different papers and made the literature selection process simple for the reviewing process.

The geospatial distribution of study locations

After the final selection of literature in Stage 4 [Figure 1], the geospatial distribution [Figure 4] pattern of the various study areas in the selected published peer-reviewed journals is displayed to visualize how frequently satellite data have been used to monitor plastic pollution in different parts of the world. Through a bibliometric analysis of author affiliation and research study area, a biased geospatial distribution of research is observed, showing that much of the research is being conducted around the European Union (EU) relative to other regions. Such a bias may result in knowledge gaps and inconsistencies; the causes of

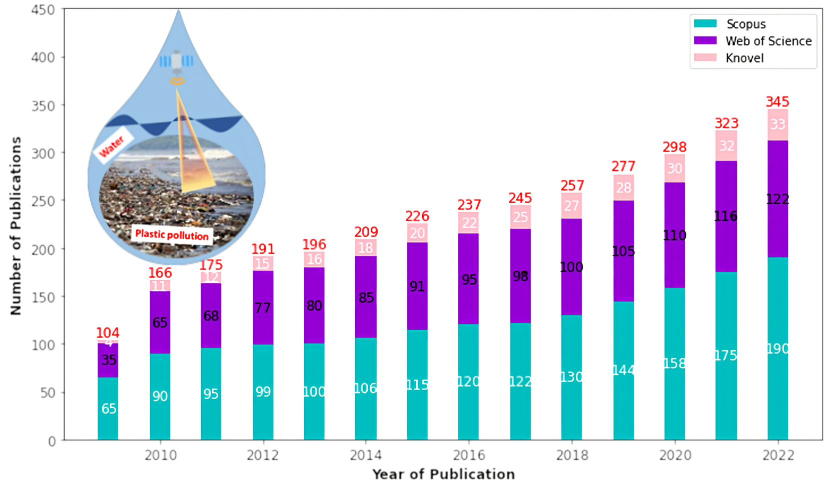

Figure 2. Stacked column charts showing the trends of publications retrieved from the three citation and abstract databases.

Figure 3. Word-cloud visualization presentation of research keywords that appear in 35 scientific papers relevant to the review topic.

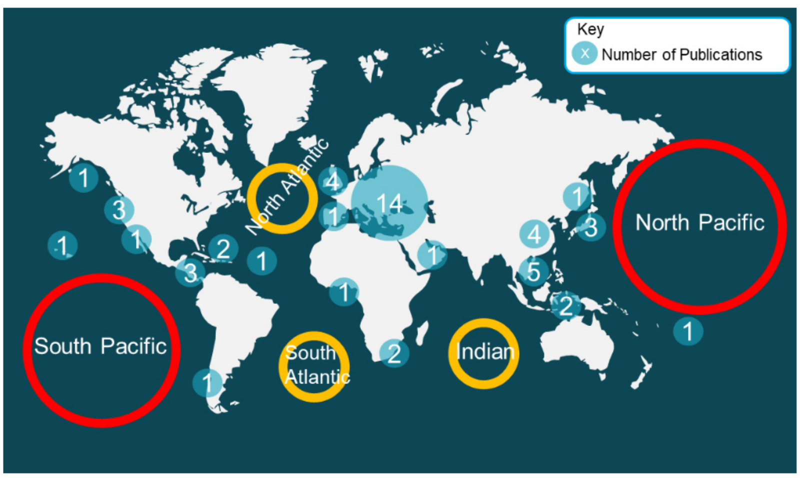

Figure 4. Map of study locations and estimated accumulation of the five major plastic gyres encircled in red- and yellow-colored circles[59] and the geospatial distribution of the number of publications involving satellites and artificial intelligence.

this might be because of funding deficiencies and/or technological gaps in areas with limited reporting. This finding is corroborated by research carried out by Evans and Ruf (2021), who highlighted the fact that there is plastic under-sampling in the global south[24]. The global distribution pattern of plastic accumulation shows higher levels deposited in the North Pacific and the South Atlantic Gyres, as well as the Mediterranean Seas[57-59].

LEACHING AND SORPTION OF SECONDARY POLLUTANTS BETWEEN PLASTICS AND WATER

Plastic litter is a product of polymers mixed with additives; these are chemicals added to improve quality in terms of their performance, functionality, and durability. The term additives refer to antioxidants, anti-static agents, colorants, coupling agents, curing agents, flame retardants, foaming/blowing agents, heat stabilizers, impact modifiers, lubricants, nucleating agents, plasticizers, preservatives, processing aids, and UV stabilizers[60]. The process of thermo-oxidative degradation of plastic debris in water significantly contributes to high levels of dissolved organic carbon (DOC) in water systems[61], along with plastic additive contaminants. On the one hand, plastics resident in water can represent a solid-liquid leaching system[62] of plastic additives such as phthalates (PAEs), organophosphate esters (OPEs), and Bisphenols (BPs)[63]. The bulk of these plastic additives leached into water systems are endocrine disruptors with potential carcinogenic effects in human beings[63,64].

On the other hand, plastic debris in different zones of the water column enables a solid-phase extraction (SPE), resulting in the sorption of contaminants out of the water column and concentration of them onto the plastics surface. For example, pollutants in water from diffuse and point source pollution, such as polychlorinated biphenyls (PCBs), organochlorine pesticides, and polycyclic aromatic hydrocarbons (PAHs), were detected in plastic samples collected from the North Pacific Gyre[65]. The contaminants concentrated on the surface of plastics (i.e., PCBs, PAHs, organochlorine pesticides, and nonylphenol) are classified as persistent organic pollutants (POPs) and hydrophobic organic compounds (HOCs)[66,67]. These are molecules with higher hydrophobicity; therefore, their affinity for hydrophobic plastic is greater relative to their affinity for sediments and water. This favors their diffusion from the water column onto the plastic surface, stimulating the sorption of HOCs and POPs by plastics[66,67]. After the sorption process, the solid phase plastic sorbent is likely to float on the water surface and will be easily mistaken for food by aquatic species. This means that the subsequent links in the food web ultimately expose humans to similar hazardous HOCs when they consume seafood. Therefore, the two ways in which plastics in aquatic systems can transport pollutants are leaching and sorption of contaminants.

OVERVIEW OF MONITORING METHODS FOR PLASTICS IN THE WATER TRANSPORTATION PATHWAY

Research on plastic pollution in water systems is expeditiously developing, as are the methods used in monitoring this type of pollution. The methods to characterize and quantify plastics in the aquatic environment include visual inspection[68-72], harmonized sampling and analytical laboratory techniques[22,73,74], modeling[75-78], and remote sensing[35-43,79]. Laboratory methods cover a wide range of techniques that include simple and rapid procedures such as the use of physical characteristics, i.e. specific density and color[70]. More complex analyses include imaging spectroscopy from optical microscopy, scanning electron microscopy, and fluorescence microscopy[80-82]. Spectral analyses are additional complex analytical techniques that include Fourier transform infrared spectroscopy (FT-IR), Raman spectroscopy, pyrolysis gas chromatography-mass spectrometry, laser-induced breakdown spectroscopy (LIBS), and energy dispersive X-ray spectroscopy[68,83,84]. Numerical modeling is one of the quantitative methods for the evaluation of fluxes and concentrations of microplastics based on field data. Fluid mechanics/sediment transport/process-based dynamic models include the INCA microplastics model[85-87], Delft3D-FLOW[85-87], and Full Multi[85-87]. Remote sensing approaches include hyperspectral cameras[88,89], hyperspectral radiometry[90,91], thermal infrared imaging (TIR) imaging[92], aerial and underwater vehicles[52,93], video imaging[94,95], and satellites[36,39,51,54,96-98].

Satellites application for monitoring aquatic macroplastic debris

The major component of plastic debris in water is a mixture of multiple polymer sources that include polyethylene (PE), polypropylene (PP), polystyrene (PS), polyesters (PEST), polyamide (PA), acrylics, polyvinyl alcohol (PVA), polyvinyl chloride (PVC), polyethylene terephthalates (PET), synthetic rubber (SR), and polyacrylonitrile (PAN)[98-101]. These polymers have unique spectroscopic features defined by their chemical composition. Generally, hydrocarbon-based plastic polymers exhibit high absorption characteristics in the infrared channel as a result of the hydrogen-carbon bonds (C-H) of specific overtone vibrational frequency observable in the IR region[101]. Therefore, researchers have taken advantage of plastic polymers' optical activity in the IR region to map and quantify plastic litter using NIR[102], SWIR[103], and TIR[92] bands from satellite images. These spectral characteristics are distinct from the spectral features of other debris components such as vegetation, sediments, and metals, making it possible to discriminate plastic particles from other debris; for example, researchers have recently been able to identify plastics entangled in hyacinth plants[78]. Pre-processing methods such as atmospheric correction (AC) and sun glint removal play an important role in improving the quality of reflectance data for plastic signals and therefore help return higher identification accuracy[104,105]. ACOLITE and Sen2Cor[105,106] AC methods are commonly applied in the pre-processing of most Sentinel-2 MSI water surface reflectance products in various studies. In aquatic plastic waste monitoring, Sentinel-2 and WV are the most commonly used satellites, and the most applied pre-processing algorithms are those that are tailor-made for these two satellites[35,36,38,40,41,107-115]. Although applied in rare cases, the neural network (NN)-based Case 2 Regional Coast Color processor (C2RCC) was applied to pre-process Sentinel-2 MSI for the detection of plastic debris[35]. Some studies used analysis ready data (ARD) products pre-processed at Levels 1, 2, and 3[23,42,116,117]. Themistocleous *et al.* (2020)[96] declared not to have used any pre-processed data, while other studies did not disclose their image pre-processing methodologies[37,43,93,104,118-120]. There is evidence that AC pre-processing of images improves the quality of water surface reflectance products[118]; given this background of inconsistent application of AC in image preprocessing, it is difficult to compare how the different AC processing algorithms applied in the various studies affect the retrieval of plastic debris in aquatic ecosystems.

Sentinel-2 MSI is the most frequently used satellite sensor for monitoring plastic debris in water[35-38,40,41,43,96,103,104,107-114,118,119,121], followed by WV[39,42,43,114,115,120,122,123] and SAR[24,107,116,118,121,124] used in 20, 9, and 6 studies, respectively [Figure 5]. Landsat-8 OLI is in fourth place, tied with PRecursore IperSpettrale della Missione Applicativa (PRISMA), which have both been used twice[41,116,125,126], while the remaining satellites were only used once[41,94,121,123,124]. Multispectral imager (MSI) sensors on board the Sentinel-2 satellite platform (ESA Copernicus), a constellation of twin satellites (S2A and S2B), provides high spatial and temporary resolution products, with a significant number of cloud-free satellite images per year. Researchers prefer Sentinel-2 because of its 13 bands [ultra-violet (UV) to near-infrared (NIR)] with different band-dependent spatial resolution (10-60 m)[118,119]. Very high resolution (VHR) WorldView-2 and -3 satellites sensors with four new spectral channels [coastal blue, yellow, red edge (RE), and NIR-2] are proving to be effective in aquatic plastic waste monitoring[39,42,43,114,120,121,123]. Some studies used different sensor combinations: Kikaki *et al.*[41], Tasseron *et al.*[43], Topouzelis *et al.*[107], Atwood *et al.*[125], Mathews *et al.*[121], and Davaasuren *et al.*[124] used a combination of more than two satellite sensors. Kremezi *et al.*[116] applied 13 pansharpening techniques to fuse PRISMA hyperspectral band with PRISMA panchromatic band for spectral discrimination of plastics from water[116]. In addition, some researchers, including Topouzelis *et al.*[109] and Aoyama *et al.*[123], combined unmanned aerial vehicles and satellite sensors to monitor plastic

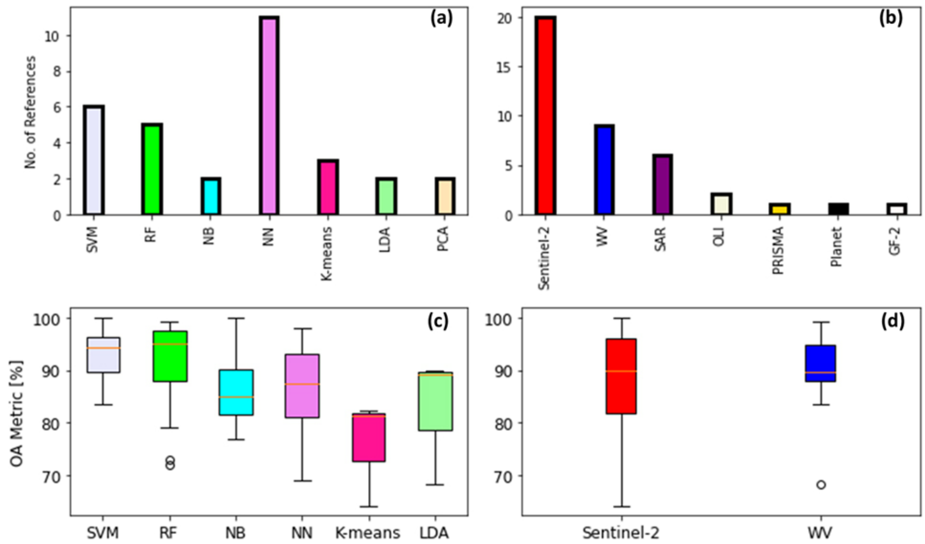

Figure 5. Bar charts representing the frequency of references that utilized (A) different classifiers and (B) sensors on different satellite platforms used for identifying plastics. Boxplots comparing performances of (C) the different ML/DL classifiers and (D) sensors on various satellite platforms used in different studies.

debris in water. Sensor combination/data fusion was applied in several studies to improve satellites image quality through optimization of the different sensor characteristics, i.e. spectral, radiometric, spatial, and temporal resolutions. With the exception of the listed sensor combinations, the rest of the studies applied single sensors. A comparison of sensor performance based on the commonly applied predictive accuracy evaluation metric called overall accuracy (OA) shows a comparable median OA performance of both Sentinel-2 and WV of around 90% OA, albeit with higher variability in the classification accuracy for Sentinel-2 images.

The source of ML/DL model performance variation is influenced by several factors: study area complexity, the type of remote sensing data, quality of training samples, input features, classifier, and hyperparameter optimization[127]. Several performance evaluation metric approaches such as overall accuracy[35-40,109,119], F1 score[35,37,38,42,108], Kappa coefficient (k)[35,39,42], intersection over union (IoU)[40], recall[35,37], precision[35,37], McNemer p-value[35,108], similarity measure (SS)[116], and correlation coefficient (r)[116] were normally used for evaluating the performances of plastic debris classifiers. The OA measure is a good measure for the purposes of cross comparison of ML/DL performance for algorithms applied in the same research, in different studies of similar research areas, or in different study areas because it is the commonly applied evaluation metric in most classification problems.

ML/DL classifiers are gaining popularity over traditional methods such as spectral unmixing and pixel matching. Learning approaches based on conventional ML algorithms, including support vector machine (SVM)[35-39], random forest and tree-based[35,37,39,42,108], Naïve Bayes (NB)[36,116], K-means[38,126], principal component analysis (PCA)[116], linear discriminant analysis (LDA)[39,43], and light gradient boosting model (LGBM)[126] have found useful applications in monitoring plastic debris in aquatic ecosystems. In addition to the conventional ML methods, simple and deep-neural architectures (NN)[37,40,108,116,119,120] were the dominantly applied classifiers. SVM, RF, and NN outperform other plastic debris classifiers based on assessing the OA performance evaluation metric [Figure 5]. NN research continues to advance, particularly deep NN (DNN), which comprises the common classifiers in the identification of marine plastic debris [Figure 5]. Despite all the gains achieved by neural networks (NN) in the field of remote sensing classification, aquatic plastic debris monitoring in water is a novel research area, and researchers have reported a common drawback of limited training data for building acceptable models[35-43,96,102,103,106-113,116,118-127]. Since SVM and RF are superior classifiers under the conditions of limited data[127-130], in most cases, they outperform other classifiers [Figure 5]. Additionally, RF classifiers are well suited for remote sensing image classification because of their ability to manipulate high-dimensional tabular datasets[127-131]; this is beneficial for hyperspectral data[130,131] and object-oriented methods[132]. On the contrary, NN performance is constrained by data limitations due to overfitting problems on smaller training datasets[133,134]. However, it is important to highlight that their performance is scalable. In the case of insufficient labeled data, semi-supervised classification, data augmentation, and synthetic training data are potential solutions[129,135]. The OA of K-means, NB, and LDA models were typically less than those of SVM, RF, and NN classifiers.

REMOTE SENSING (R_{rs}) FLOATING PLASTIC DEBRIS SPECTRAL INDICES

In plastic detection, multispectral- or hyperspectral-band (as single bands, different band combinations, or all-band combination/spectral signature) derived band ratios and indices are utilized as classifier input features. The indices can be categorized into vegetation, water, soil, and floating object indices. Indices input features tend to increase the plastic selectivity (ability to discriminate the plastic class from other classes including water, foam, metal, and wooden debris) so that the plastic debris can be determined in simple or complex mixtures or matrices under a set of given conditions without the matrix effect impacting on classification accuracy[136,137]. Therefore, spectral indices play a huge role in improving classifier performance for the identification of plastic debris. This section outlines the theories of different indices used and their formulae:

i. Vegetation feature spectral indices: Vegetation indices are based on the red and near-infrared reflections of electromagnetic light, and, theoretically, they are correlated to green vegetation color pigmentation[138-140]. Therefore, normalized difference vegetation index (NDVI) is often applied to monitor blue-green algae and aquatic weeds floating on the upper layer of the water surface[140,141]. Besides vegetation monitoring, NDVI combined with other indices such as floating debris index (FDI) has been applied to distinguish marine plastic litter that possibly consists of accumulated macroalgae (e.g., cyanobacteria and floating invasive macrophyte species)[16,36]. In aggregation, microplastics promote the growth of algae and later allow them to aggregate and co-precipitate through adsorption and adhesion processes[141]. This makes NDVI an important spectral feature in distinguishing aquatic plastic from vegetative debris material, and it is calculated by measuring the difference between infrared- and red-light reflectance and normalizing it[142], as shown in Equation 1:

$$NDVI = \frac{R_{NIR}-R_{RED}}{R_{NIR}+R_{RED}} \quad \text{Equation 1}$$

Sannigrahi *et al.*[35] introduced a novel kernel-normalized difference index (k-NDVI) to eliminate problems related to the presumption of linearity in NDVI computations. This is a radial basis function (RBF) nonlinear kernel (k)[143,144] for mapping linear NDVI spectral band features into nonlinear ones through Hilbert spaces to a high-dimensional feature map[143,144]. The k-NDVI is calculated as follows:

$$k - NDVI = \frac{k(n,n)-k(R_{rs},NIR,\ R_{rs},RED)}{k(n,n)+k(R_{rs},NIR,\ R_{rs}RED)} \quad \text{Equation 2}$$

where n, R_{rs}, *NIR*, and $R_{rs}RED$ refer to the remote sensing reflectance in NIR and red channels, respectively. k is the kernel function that measures the similarity between the two bands, i.e. NIR and red in the case of

NDVI. The kernel function k is calculated using the RBF kernel as follows:

$$k = (a, b) = exp(-(a-b)^2/(2\sigma^2)) \quad \text{Equation 3}$$

where a and b are the two bands in the case of NDVI and σ parameter determines the distance between NIR and Red bands. The kernelization is further simplified as:

$$k - NDVI = \frac{1-k(R_{rs}NIR,\ R_{rs}RED)}{1+k(R_{rs}NIR,\ R_{rs}RED)} = \tanh\left(\left(\frac{R_{rs}NIR - R_{rs}RED}{2\sigma}\right)^2\right) \quad \text{Equation 4}$$

The fixing of σ parameter is done as follows: σ = 0.15(R_{rs}, NIR, $R_{rs}RED$). The σ parameter fixing further simplifies the kernelization as follows[35]:

$$k - NDVI = tanh(NDVI^2) \quad \text{Equation 5}$$

A modified NDVI formulated by reciprocally exchanging Sentinel-2 NIR with the red band remote sensing values in the original NDVI formula, termed reversed normalized difference vegetation index (RNDVI), was also applied to identify plastic litter in water, and its performance was compared to a customized Plastic Index (PI)[96]. The formula for RNDVI is:

$$RNDVI = \frac{R_{RED} - R_{NIR}}{R_{RED} + R_{NIR}} \quad \text{Equation 6}$$

Floating algae index (FAI) is an ocean color index based on subtracting a linear base line reflectance interpolation of red (645 nm) and SWIR (1240 or 1640 nm) from the reflectance observed at 859 nm (vegetation RE)[144]. Researchers have reported the strengths of FAI over the traditional NDVI or EVI (enhanced vegetation index) because of its lower sensitivity to changes in observation conditions related to atmospheric and geometric properties. This can be calculated using Equation 7:

$$FAI = R_{rc,NIR} - R'_{rc,\,NIR} \quad \text{Equation 7}$$

$$R'_{rc,\,NIR} = R_{rs,RED} + \left(R_{rc,\,SWIR} - R_{rc,\,RED}\right) \times \frac{(\lambda_{NIR} - \lambda_{RED})}{(\lambda_{SWIR} - \lambda_{RED})} \quad \text{Equation 8}$$

$R'_{rc,\,NIR}$ is the baseline reflectance of NIR.

ii. Water feature extraction spectral indices: The applicability of different water feature extraction indices derived from satellites in plastic identification is based on the fact that clear water absorbs and reflects light in the NIR and green channels of the electromagnetic spectrum, respectively[36,145]. Clear and colored plastic matter displays contrasting spectral characteristics to clear water. For example, clear and white plastic matter displays higher light reflectance in the NIR region of the electromagnetic spectrum while often reflecting flat signals in the RGB channels[54,92,94,106,107,109]. These differing spectral characteristics make plastic discernable from clear water using water features extraction indices such as normalized difference water index (NDWI)[146], modified NDWI (MNDWI)[147], normalized difference moisture index (NDMI)[148], water ratio index (WRI)[149], and automated water extraction index (AWEI)[150], which were investigated for the extraction of surface water from Landsat data. The respective equations are reported as Equations 9-13:

$$NDWI = \frac{R_{GREEN} - R_{NIR}}{R_{GREEN} + R_{NIR}} \quad \text{Equation 9}$$

$$MNDWI = \frac{R_{GREEN} - R_{MIR}}{R_{GREEN} + R_{MIR}} \quad \text{Equation 10}$$

$$NDMI = \frac{R_{NIR} - R_{MIR}}{R_{NIR} + R_{MIR}} \quad \text{Equation 11}$$

$$WRI = \frac{R_{GREEN} + R_{RED}}{R_{NIR} + R_{MIR}} \quad \text{Equation 12}$$

$$AWEI = 4 \times (Green - MIR) - (0.25 \times NIR + 2.75 \times SWIR) \quad \text{Equation 13}$$

In Sentinel-2 imagery, green = Band 3, red = Band 4, NIR (near-infrared) = Band 8, MIR (middle-infrared) = Band 12, and SWIR (shortwave-infrared) = Band 11.

iii. Plastic debris designed spectral indices: Sentinel-2 MSI-based floating debris index (FDI) algorithm was designed to identify floating matter on water surface[35]. The basic principle of operation for the FDI algorithm leverages the numerical difference existing between NIR and the baseline reflectance of NIR at a subpixel level; the baseline is a linear interpolation fitted to NIR-flanking MSI Red Edge 2 (RE2) and SWIR1 bands. FDI is a modification of the floating algae index (FAI) based on Landsat, Medium Resolution Imaging Spectrometer (MERIS), and Moderate Resolution Imaging Spectroradiometer (MODIS)[144,151,152]. In the FDI algorithm, the chlorophyll sensitive red band is replaced by the MSI red edge (RE) band positioned around 740 nm. This novel index has proved efficient at identifying floating objects relative to NDVI, PI, and single band approach[35,36,114]:

$$FDI = R_{rs,NIR} - R'_{rs,\,NIR} \quad \text{Equation 14}$$

$$R'_{rs,\,NIR} = R_{rs,RE2} + \left(R_{rs,\,SWIR1} - R_{rs,\,RE2}\right) \times \frac{(\lambda_{NIR} - \lambda_{RED})}{(\lambda_{SWIR1} - \lambda_{RED})} \times 10 \quad \text{Equation 15}$$

where FDI is the floating debris index, $R'_{rc,\,NIR}$ is the baseline reflectance of NIR, and $R_{rs,\,RE2}$ and $R_{rs,\,SWIR1}$ are the remote sensing reflectance of NIR, Red Edge 2, and SWIR 1 bands, respectively.

The plastic index (PI) is another debris identification tailored index applied to model and classify floating plastic debris in water[35,96]. PI is a plastic feature extraction input established on the basis of the R_{rs} in the red and NIR spectral regions, which can be calculated as follows:

$$PI = \frac{R_{rs,\,NIR}}{R_{rs,\,NIR} + R_{rs,\,RED}} \quad \text{Equation 16}$$

NIR and red refer to the pixel's reflectance in the NIR and red spectrum.

Kremezi *et al.*[116] proposed three new plastic litter indices centered on the radiance differences between the maximum peak height (MPH) of the spectrum and troughs in the VNIR region.

$$Index_1 = R_i^2 - R_j \quad \text{Equation 17}$$

$$Index_2 = R_i^2 - R_j^2 \quad \text{Equation 18}$$

$$Index_3 = R_i - R_j \quad \text{Equation 19}$$

$R_i \in$ [749.8, 781, 866, 988.4, 1088.6] nm are the plastic spectra MPHs and $R_j \in$ [951].

iv. Hydrocarbon designed spectral indices: These are indices based on user-friendly algorithms for the detection of hydrocarbons centered on their noticeable absorption features at 1730 and 2310 nm[153]. Plastics are largely hydrocarbons; therefore, hydrocarbon indices in combination with others have been successfully applied for the detection of plastic litter in water using hyperspectral images[42]. The following formula can be used to calculate the hydrocarbon index (HI)[153]:

$$HI = (\lambda_B - \lambda_A)\frac{R_C - R_A}{\lambda_C - \lambda_A} + R_A - R_B \quad \text{Equation 20}$$

Zhou *et al.*[42] formulated a normalized hydrocarbon index (NHI) on the basis of the HI proposed by Kühn *et al.*[153]. The NHI tends to provide a pronounced curvature at the point λ_B. Equation 21 shows how the NHI is calculated:

$$NHI = 1 - \frac{R_B}{R_A + (\lambda_B - \lambda_A)\frac{R_C - R_A}{\lambda_C - \lambda_A}} \quad \text{Equation 21}$$

R_A and λ_A, R_B and λ_B, and R_C and λ_C are radiance/wavelength pairs for each "index point", respectively.

All the indices described in this section are tabulated in Table 1, indicating how they were applied in different studies.

APPLICATION OF SATELLITES FOR MONITORING AQUATIC MICROPLASTIC CONTAMINANTS

Cutting-edge research on global monitoring of microplastic concentration in marine and riverine systems was first reported by Davaasuren *et al.*[124], followed by another groundbreaking research co-authored by Evans and Ruf (2022)[24]. Both studies used SAR data to measure surface water fluid mechanics properties such as changes in viscosity (μ), surface tension (T), and sea surface roughness (SSR). SAR is an active satellite remote sensing system for environmental monitoring, and recently, a few studies confirmed the benefit of using SAR for the estimation of water surface parameters, such as surface roughness[24,118,121,124]. Many sensor design configurations regarding wavelength, polarization, and incidence angle facilitate the discrimination of various water characteristics, e.g. surface roughness, water dielectric constant, and plastic waste in water systems[24,118,124]. The manipulation of X-, L-, or C-band for surface water roughness retrieval was reported in four studies: from X-band[24,118,121,124] to C-band[24,120,121,124] and L-band[24,118,124]. Plastic debris in water experiences microbial disintegration and degradation processes which discharge metabolic

Table 1. Studies focusing on the identification of plastic debris in water bodies based on the classification of satellite imagery

Research title	Satellite sensor or platform	Classifying features	Classifier(s)	AC method(s)	Cite score	Journal IF
Development of automated marine floating plastic detection system using Sentinel-2 imagery and machine learning models[35]	MSI	FDI, NDVI, PI, k-NDVI	SVM and RF	ACOLITE and Case 2 Regional Coast Color (C2RCC)	-	7.001
Finding plastic patches in coastal waters using optical satellite data[36]	MSI	NDVI, FDI	Naïve Bayes	DSF, POLYMER and Sen2Cor	59	4.996
Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018)[106]	MSI & SAR	R/G/B/NIR	Spectral unmixing	Sen2Cor and ACOLITE	76	7.672
Remote sensing of sea surface artificial floating plastic targets with Sentinel-2 and unmanned aerial systems (Plastic Litter Project 2019)[107]	MSI	Single band	Spectral unmixing and matched filtering	ACOLITE (DSF)	20	5.349
A cloud-based framework for large-scale monitoring of ocean plastics using multi-spectral satellite imagery and generative adversarial network[37]	MSI	B, G, R, RE-2, NIR, SWIR1, NDVI & FDI	RF, SVM & GAN-RF	-	1	3.530
Development of novel classification algorithms for detection of floating plastic debris in coastal waterbodies using multispectral Sentinel-2 remote sensing imagery[38]	MSI	B, G, R, RE2, NIR, SWIR1, FDI & NDVI	K-means, fuzzy c-means (FCM), SFCM & SVR	ACOLITE (DSF)	4	5.349
Investigating detection of floating plastic litter from space using Sentinel-2 imagery[96]	MSI	NDWI, WRI, NDVI, AWEI, MNDWI, NDMI, SR, PI & RNDVI		N/A	28	5.349
Remotely sensing the source and transport of marine plastic debris in bay islands of honduras (Caribbean Sea)[41]	MSI, OLI, Planet	Spectral signature, pixel tiles	Pixel matching, weighted calculations	ACOLITE	22	5.349
Anthropogenic marine debris over beaches: Spectral characterization for remote sensing applications[39]	World View-3	Spectral signature	Polynomial, linear and radial SVM, RF and LDA	Atmospheric Compensation algorithm from DigitalGlobe (AComp)	45	13.85
Coastal accumulation of microplastic particles emitted from the Po River, Northern Italy: Comparing remote sensing and hydrodynamic modelling with in situ sample collections[125]	MSI, OLI	Spectral signature	Dekker's SPM calibrated algorithm	hierarchical object-based image analysis (OBIA)	63	7.001
Applicability of SAR to marine debris surveillance after the great east Japan earthquake[118]	SAR	X- and L-bands total, diffusive disappearance rate; vector velocity; local damage assessment	Two-dimensional constant false alarm rate (2D-CFAR)	-	14	4.715
A learning approach for river debris detection[40]	MSI	FDI, NDVI, NDWI	U-Net, U-Net3DE, DeeplabV3+	Sen2Cor	1	7.672
Remote sensing data in mapping plastics at surface water bodies[120]	World View-2	NDWI, NDVI, NIR/R, NIR/G, NIR/B, R/G, R/B	ANN	-	5	

MARIDA: A benchmark for Marine Debris detection from Sentinel-2 remote sensing data[108]	MSI	Spectral signature, NDVI, NDWI, FAI, FDI, shadow index (SI), normalized difference moisture index (NDMI), bare soil index (BSI) and NRD, gray-level co-occurrence matrix (GLCM)	RF, U-Net	ACOLITE Dark Spectrum Fitting (DSF)	3	3.752
Detecting floating plastic marine debris using Sentinel-2 Data via modified infrared NDVI[102]	MSI	NDVI				N/A
Plastic Litter Project 2019: Exploring the detection of floating plastic litter using drones and Sentinel 2 satellite images[109]	MSI-UAV	R/G/B/NIR	Reversed linear spectral unmixing	ACOLITE	1	N/A
Marine litter survey at the major sea turtle nesting islands in the Arabian Gulf using in-situ and remote sensing methods[121]	MSI	FDI, PI	-	N/A		N/A
Big plastic masses detection using Sentinel 2 images[119]	MSI	Spectral signature, NDVI, FDI	MPL	-		N/A
Can we quantify the aquatic environmental plastic load from aquaculture?[123]	World View-2 and GF-2 satellite and UAV		Supervised classifier in ENVI 5.3		2	13.4
Marine plastic litter detection offshore Hawai'i by Sentinel-2[110]	MSI	NDVI and FDI	-	ACOLITE Dark Spectrum Fitting (DSF) algorithm	2	7.001
Spectral reflectance of marine macroplastics in the VNIR and SWIR measured in a controlled environment[103]	Analytical Spectral Devices (ASD) FieldSpec resampled to Sentinel-2 MSI	NDVI, FDI	-	-	17	4.996
On thermal infrared remote sensing of plastic pollution in natural waters[92]	ECMWF reanalysis v5 (ERA5)	TIR	-	-	14	5.349
A knowledge-based, validated classifier for the identification of aliphatic and aromatic plastics by WorldView-3 satellite data[42]	WV-3	NHI, spectral signature and SWIR bands	Decision tree style, knowledge-based classifier	L2 level, radiometrically and atmospherically corrected	2	13.85
Advancing floating macroplastic detection from space using experimental hyperspectral imagery[43]	MSI and WV-3	NDVI and FDI	Linear discriminant analyses (LDA)	-	7	5.349
Toward the detection and imaging of ocean microplastics with a spaceborne radar[24]	Delay doppler mapping instrument on board the cyclone global navigation satellite system (CYGNSS/DDMI)	Wind speed (m/s) and mean square slope (MSS), L-Band MSS	Global ocean CYGNSS model	L2 level, corrected products	6	8.125
GhostNet marine debris survey in the Gulf of Alaska - Satellite guidance and aircraft observations[115]	Multistage oceanographic data	Multivariate inputs	Manual identification and tracking of eddies through altimeter, chlorophyll and SST satellite products	N/A, analysis ready data (ARD)	41	7.001
Extraction of marine debris in the Sea of Japan using high-spatial-resolution satellite images[123]	WV-2, WV-3		Spectral angle mapper (SAM)	Spectrally anomalous pixels	9	N/A
CleanAtlantic - tackling marine litter in the atlantic area[111]	MSI	B8-B12 band difference		Sen2Cor AC	-	-
Optical methods for marine	MSI and UAV	FAI, NDVI and NDHI	-	Sen2Cor,	N/A	N/A

litter detection (OPTIMAL) - final report. zenodo[112]				generation of spectral signatures		
Pansharpening PRISMA data for marine plastic litter detection using plastic indexes[116]	PRISMA	HI, Sentinel-2 based index, FDI, three novel indices	CS, MRA, hybrid, Bayesian, and DL methods	Fine co-registration of data (L1 and L2D products)	4	3.476
Report on detailed processing model, EO tracking of marine debris in the mediterranean sea from public satellites project[113]	MSI	Contrast enhancement, red band values, indices (NDVI, NSI, FAI)	-	Sen2Cor AC, cloud and shadow masking, glint correction	N/A	N/A
Dynamics and early post-tsunami evolution of floating marine debris near Fukushima Daiichi[122]	WV-2, ASTER, and SAR	Single bands	-	-	20	16.908
Finding riverine plastics in floating plant patches using WorldView-3 satellite imagery[114]	VW-3			ACOLITE	N/A	N/A
Detecting Microplastics pollution in world oceans using SAR remote sensing[12]	Sentinel-1A and COSMO-SkyMed	L-, C-, and X- band		VV-polarized	8	N/A
A combination of machine learning algorithms for marine plastic litter detection exploiting hyperspectral PRISMA data[126]	PRISMA	Spectral bands	LGBM, K-Means	L1 products image fusion and PCA pan-sharpening	-	5.349

byproducts during energy synthesis. The byproducts of the disintegration and degradation chemical reactions include simple chains and more complex organic molecules called surfactants. The presence of these surfactants reduces the responsiveness of water surface morphology or roughness to surface wind velocity. In view of this hypothesis, surfactants can therefore act as microplastic tracers. SAR is capable of measuring water surface roughness and surface wind speed; these parameters are then used to estimate the concentration of microplastics. The studies showed seasonal dynamics in the garbage patches in all the plastic gyres due to changing vertical mixing at lower temperatures. Evans and Ruf (2020)[24] also analyzed time series visualization of major world rivers and spotted huge concentrations of microplastics in the Yangtze and Ganges Rivers. This is an innovative methodology with huge potential to offset the drawbacks of physical sampling and laboratory analyses.

BIBLIOMETRIC ANALYSIS

Bibliometric studies help to illustrate the significance of the problems posed by plastic waste in water on a global scale and highlight significant gaps with respect to monitoring and standardizing new satellite monitoring methods[154]. A basic Interquartile Range (IQR) visualization tool is developed to easily analyze two important bibliometric measures, citation score and journal impact factor (IF), for the 35 research articles (all listed in Table 1) that strictly satisfied the following criteria: the study used satellite sensors to monitor any form of plastics presence in any aquatic ecosystem. The IQR for citation score and IF are 18 and 2.78, respectively [Figure 6]. Articles and journals that have extremely high scores are visualized as outliers. Citation hierarchy, as highlighted by citation score (in brackets), showed that the studies by Topouzelis *et al.*[106] (76), Atwood *et al.*[125] (63), Biermann *et al.*[36] (59), and Acuña-Ruz *et al.*[39] (45) were the highest cited papers in descending order. Out of the 35 publications, three articles were published in journals with IF much greater than the normal IF, those by Matthews *et al.*[121] (Nature Geoscience, IF = 16.908), Acuña-Ruz *et al.*[39] (Remote Sensing of The Environment, IF = 13.85), and Zhou *et al.*[42] (Remote Sensing of The Environment, IF = 13.85).

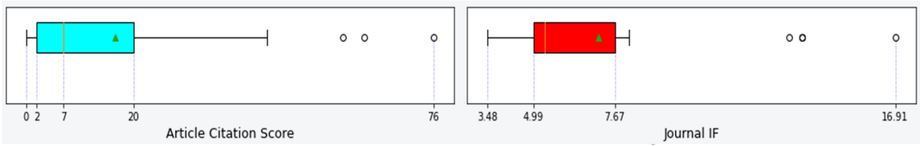

Figure 6. Boxplots for visualizing IQR measures for citation score and journal impact factor.

PRINCIPAL FINDINGS, PROSPECTS, AND CONCLUSIONS

Many researchers who have conducted studies on monitoring aquatic plastics using satellites mainly focused on macroplastics compared to microplastics. Most of these scientists have reported a lack of training data as a major limitation in achieving higher accuracy and consistent results[126]. The lack of training data also limits the extent of spatial coverage and constrains the choice of classifiers to be used, i.e. some classifiers perform poorly when trained with inadequate data. This review identifies the need for a comprehensive strategy to have a wider research area coverage to harness more training data. More knowledge can be gained by studying how EU researchers are conducting their work because they are leading in this research. Alternatively, the SAR satellites approach, which relies on in situ sampling data and therefore does not require manual preparation of training datasets, provides a possible solution to augment monitoring methods[155]. The major advantage of SAR is its ability to apply a model that monitors plastics at a global level, including simultaneously covering inland and ocean areas. Given that it is the only method thus far that has shown potential to monitor plastics at a microscopic level, it presents researchers with an added advantage. Although the SAR method has only been applied to microplastics, the principle behind it can potentially monitor plastics at all size levels (macro- to nanoplastics).

Many different kinds of spectral indices have been used as input features to help classifiers discriminate plastic from other debris. However, no single research has applied turbidity indices such as normalized difference turbidity index (NDTI)[156] as an input feature for classifying plastics. This is important to highlight because NDTI can be a useful feature for discriminating plastic matter in highly turbid water. Furthermore, there is evidence for the physiochemical interactions of plastics and sediments in water systems, which can help to establish a numerical relationship between plastics and sediments in terms of concentration[157]. Plastics and sediment concentration is normally high during the rainy season due to transportation by erosion surface run-off, and at the same time, turbidity is also high. Therefore, it is important to understand the effects of sediment-driven turbidity on plastic identification using optical satellites. We, therefore, note that turbidity should be a useful input feature for discriminating plastic waste submerged in highly turbid water.

We note that technologies essential for leveraging geospatial big data such as satellites and artificial intelligence (AI) for application in the domain of monitoring CECs are still developing, although some significant progress can be noted, especially using the branch of AI called machine learning and its deep learning subset, but all these studies have focused on only one type of AI computer vision (CV) referred to as image classification CV. Additional CV-based AI methods for image processing could add more to progress in this domain. Some of the CV-based AI techniques applicable to satellite images include object detection (OD) (one of the most popular OD models is you only look once (YOLOv5), semantic segmentation, instance segmentation, and panoptic segmentation. The advantages of these methods include their ability to execute pixel-level classification and the ability to separate different instances of classes.

Using satellites to monitor plastic pollution in water is an emerging research area, and the results from our preliminary studies indicate a bias in the geospatial distribution of plastic waste monitoring which is concentrated around the European Union (EU) area, which is confirmed in similar research[155,158]. However, while our results indicate this bias, there is a need to collect more evidence as peer-reviewed research is conducted to further validate this hypothesis. For instance, the global south suffers greater pollution but is the least sampled and monitored. The fact that there are fewer studies conducted thus far in this area was a limitation because we had to rely on a relatively smaller number of papers to make our findings.

In conclusion, this research acknowledges the developments that have been made in the domain of plastic monitoring using multispectral, hyperspectral, and radar satellites despite the fact that the initial research was published recently in 2014[118]. This review leads to the following deductions: (1) The top three commonly applied classifiers are SVM, RF, and NN, and they generally tend to outperform the other classifiers. (2) This research is proving to be highly impactful because reputable highly cited researchers are publishing high-quality work in high impact factor journals, and their research is being highly cited, demonstrating that this type of research is having a significant impact on the scientific community. (3) This research has a high potential to benefit society and contribute to creating plastic-free water ecosystems. The median scores for citation index and IF are 7 and 5.349, respectively. Although little research has focused on satellite thermal imaging despite its potential, thermal imaging is used in monitoring other water-related parameters such as global sea surface temperature (SST) coverage products which can potentially be useful for plastic monitoring. New spectral indices designed for plastics have been developed, but still more could be achieved with respect to turbidity indices for plastic monitoring-tailored input features.

DECLARATIONS

Authors' contributions

Conceptualization, methodology, writing - original draft preparation, formal analysis, data curation, visualization, investigation: Mukonza SS
Software, validation, writing - review & editing: Mukonza SS, Chiang JL
Resources, supervision, project administration, funding acquisition: Chiang JL

Availability of data and materials

Not applicable.

Financial support and sponsorship

Taiwan's Ministry of Science and Technology funded this research through the National Science and Technology Council of Taiwan, ROC grant number MOST 111-2221-E-002-164. The funders had no involvement in the study's design, data collection, analysis, or interpretation, manuscript writing, or decision to publish the results.

Conflicts of interest

Both authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

REFERENCES

1. Avio CG, Gorbi S, Regoli F. Plastics and microplastics in the oceans: From emerging pollutants to emerged threat. *Mar Environ Res* 2017;128:2-11. DOI PubMed
2. Duhec AV, Jeanne RF, Maximenko N, Hafner J. Composition and potential origin of marine debris stranded in the Western Indian Ocean on remote Alphonse Island, Seychelles. *Mar Pollut Bull* 2015;96:76-86. DOI PubMed
3. Galgani F, Hanke G, Maes T. Global distribution, composition and abundance of marine litter. In: Bergmann M, Gutow L, Klages M, editors. Marine anthropogenic litter. Cham: Springer International Publishing; 2015. p. 29-56. DOI
4. Terzi Y, Erüz C, Özşeker K. Marine litter composition and sources on coasts of south-eastern Black Sea: a long-term case study. *Waste Manag* 2020;105:139-47. DOI PubMed
5. Chassignet EP, Xu X, Zavala-romero O. Tracking marine litter with a global ocean model: where does it go? *Front Mar Sci* 2021;8:667591. DOI
6. Selvam K, Xavier KAM, Shivakrishna A, Bhutia TP, Kamat S, Shenoy L. Abundance, composition and sources of marine debris trawled-up in the fishing grounds along the north-east Arabian coast. *Sci Total Environ* 2021;751:141771. DOI PubMed
7. United Nations Environment Programme. UN declares war on ocean plastic. Available from: https://www.unenvironment.org/news-and-stories/press-release/un-declares-war-ocean-plastic [Last accessed on 29 Sep 2022].
8. Deloitte (2019). The price tag of plastic pollution: an economic assessment of river plastic. Available from: https://www2.deloitte.com/content/dam/Deloitte/nl/Documents/strategy-analytics-and-ma/deloitte-nl-strategy-analytics-and-ma-the-price-tag-of-plastic-pollution.pdf [Last accessed on 29 Sep 2022].
9. Zhao H, Zhou Y, Han Y, et al. Pollution status of microplastics in the freshwater environment of China: a mini review. *WECN* 2022. DOI
10. Savoca MS, McInturf AG, Hazen EL. Plastic ingestion by marine fish is widespread and increasing. *Glob Chang Biol* 2021;27:2188-99. DOI PubMed PMC
11. Yang CZ, Yaniger SI, Jordan VC, Klein DJ, Bittner GD. Most plastic products release estrogenic chemicals: a potential health problem that can be solved. *Environ Health Perspect* 2011;119:989-96. DOI PubMed PMC
12. Völker J, Ashcroft F, Vedøy Å, Zimmermann L, Wagner M. Adipogenic activity of chemicals used in plastic consumer products. *Environ Sci Technol* 2022;56:2487-96. DOI PubMed PMC
13. Agathokleous E, Barceló D, Fatta-kassinos D, Moore MN, Calabrese EJ. Contaminants of emerging concern and aquatic organisms: the need to consider hormetic responses in effect evaluations. *WECN* 2021. DOI
14. Goldberg ED. Emerging problems in the coastal zone for the twenty-first century. *Marine Pollution Bulletin* 1995;31:152-8. DOI
15. Hafeez S, Sing Wong M, Abbas S, et al. Detection and monitoring of marine pollution using remote sensing technologies. In: Bachari Fouzia H, editor. Monitoring of marine pollution. IntechOpen; 2019. DOI
16. Emmerik T, González-fernández D, Mendrik F, Biermann L, Drummond J, Liedermann M. Editorial: early career scientists' contributions to river plastic monitoring across scales. *Front Earth Sci* 2022;10:861531. DOI
17. Wang T, Hu M, Song L, et al. Coastal zone use influences the spatial distribution of microplastics in Hangzhou Bay, China. *Environ Pollut* 2020;266:115137. DOI PubMed
18. United Nations Environment Programme (UNEP). From pollution to solution: a global assessment of marine litter and plastic pollution. Available from: https://www.unep.org/resources/pollution-solution-global-assessment-marine-litter-and-plastic-pollution [Last accessed on 29 Sep 2022].
19. Kirschke S, Avellán T, Bärlund I, et al. Capacity challenges in water quality monitoring: understanding the role of human development. *Environ Monit Assess* 2020;192:298. DOI PubMed PMC
20. Richard D, Sébastien D, Aude-Sophie R, Jason R, Esha Z. Quality unknown: the invisible water crisis. World Bank Group; 2019. Available from: https://openknowledge.worldbank.org/handle/10986/32245 [Last accessed on 29 Sep 2022].
21. Cowger W, Gray A, Christiansen SH, et al. Critical review of processing and classification techniques for images and spectra in microplastic research. *Appl Spectrosc* 2020;74:989-1010. DOI PubMed
22. Kumar P, Inamura Y, Bao PN, Abeynayaka A, Dasgupta R, Abeynayaka HDL. Microplastics in freshwater environment in asia: a systematic scientific review. *Water* 2022;14:1737. DOI
23. Meijer LJJ, van Emmerik T, van der Ent R, Schmidt C, Lebreton L. More than 1000 rivers account for 80% of global riverine plastic emissions into the ocean. *Sci Adv* 2021;7:eaaz5803. DOI PubMed PMC
24. Evans MC, Ruf CS. Toward the detection and imaging of ocean microplastics with a spaceborne radar. *IEEE Trans Geosci Remote Sensing* 2022;60:1-9. DOI
25. Hafeez S, Wong MS, Abbas S, Asim M. Evaluating Landsat-8 and Sentinel-2 data consistency for high spatiotemporal inland and coastal water quality monitoring. *Remote Sensing* 2022;14:3155. DOI
26. Law KL, Morét-Ferguson SE, Goodwin DS, et al. Distribution of surface plastic debris in the eastern Pacific Ocean from an 11-year data set. *Environ Sci Technol* 2014;48:4732-8. DOI PubMed
27. Kukulka T, Proskurowski G, Morét-ferguson S, Meyer DW, Law KL. The effect of wind mixing on the vertical distribution of buoyant plastic debris: wind effects on plastic marine debris. *Geophys Res Lett* 2012;39:n/a-n/a. DOI
28. van Sebille E, Aliani S, Law KL, et al. The physical oceanography of the transport of floating marine debris. *Environ Res Lett* 2020;15:023003. DOI
29. Maximenko N, Corradi P, Law KL, et al. Toward the integrated marine debris observing system. *Front Mar Sci* 2019;6:447. DOI

30. Tan Z, Cao Z, Shen M, Chen J, Song Q, Duan H. Remote estimation of water clarity and suspended particulate matter in qinghai lake from 2001 to 2020 using MODIS images. *Remote Sensing* 2022;14:3094. DOI
31. Zhang L, Zhang L, Cen Y, et al. Prediction of total phosphorus concentration in macrophytic lakes using chlorophyll-sensitive bands: a case study of lake baiyangdian. *Remote Sensing* 2022;14:3077. DOI
32. Du C, Li Y, Lyu H, et al. Characteristics of the total suspended matter concentration in the hongze lake during 1984-2019 based on landsat data. *Remote Sensing* 2022;14:2919. DOI
33. Yang L, Driscol J, Sarigai S, Wu Q, Chen H, Lippitt CD. Google earth engine and artificial intelligence (ai): a comprehensive review. *Remote Sensing* 2022;14:3253. DOI
34. Liu P. A survey of remote-sensing big data. *Front Environ Sci* 2015:3. DOI
35. Sannigrahi S, Basu B, Basu AS, Pilla F. Development of automated marine floating plastic detection system using Sentinel-2 imagery and machine learning models. *Mar Pollut Bull* 2022;178:113527. DOI PubMed
36. Biermann L, Clewley D, Martinez-Vicente V, Topouzelis K. Finding plastic patches in coastal waters using optical satellite data. *Sci Rep* 2020;10:5364. DOI PubMed PMC
37. Jamali A, Mahdianpari M. A cloud-based framework for large-scale monitoring of ocean plastics using multi-spectral satellite imagery and generative adversarial network. *Water* 2021;13:2553. DOI
38. Basu B, Sannigrahi S, Sarkar Basu A, Pilla F. Development of novel classification algorithms for detection of floating plastic debris in coastal waterbodies using multispectral Sentinel-2 remote sensing imagery. *Remote Sensing* 2021;13:1598. DOI
39. Acuña-ruz T, Uribe D, Taylor R, et al. Anthropogenic marine debris over beaches: spectral characterization for remote sensing applications. *Remote Sensing of Environment* 2018;217:309-22. DOI
40. Gómez À, Scandolo L, Eisemann E. A learning approach for river debris detection. *Int J Appl Earth Obs Geoinf* 2022;107:102682. DOI
41. Kikaki A, Karantzalos K, Power CA, Raitsos DE. Remotely sensing the source and transport of marine plastic debris in bay islands of honduras (Caribbean Sea). *Remote Sensing* 2020;12:1727. DOI
42. Zhou S, Kuester T, Bochow M, Bohn N, Brell M, Kaufmann H. A knowledge-based, validated classifier for the identification of aliphatic and aromatic plastics by WorldView-3 satellite data. *Remote Sens Environ* 2021;264:112598. DOI
43. Tasseron P, van Emmerik T, Peller J, Schreyers L, Biermann L. Advancing floating macroplastic detection from space using experimental hyperspectral imagery. *Remote Sensing* 2021;13:2335. DOI
44. Whelan MJ, Linstead C, Worrall F, et al. Is water quality in British rivers "better than at any time since the end of the Industrial Revolution"? *Sci Total Environ* 2022;843:157014. DOI PubMed
45. Ogashawara I. Determination of phycocyanin from space - a bibliometric analysis. *Remote Sensing* 2020;12:567. DOI
46. Enfrin M, Lee J, Gibert Y, Basheer F, Kong L, Dumée LF. Release of hazardous nanoplastic contaminants due to microplastics fragmentation under shear stress forces. *J Hazard Mater* 2020;384:121393. DOI PubMed
47. Ter Halle A, Ladirat L, Gendre X, et al. Understanding the fragmentation pattern of marine plastic debris. *Environ Sci Technol* 2016;50:5668-75. DOI PubMed
48. Song YK, Hong SH, Eo S, Han GM, Shim WJ. Rapid production of micro- and nanoplastics by fragmentation of expanded polystyrene exposed to sunlight. *Environ Sci Technol* 2020;54:11191-200. DOI PubMed
49. Hu C. Remote detection of marine debris using satellite observations in the visible and near infrared spectral range: challenges and potentials. *Remote Sens Environ* 2021;259:112414. DOI
50. Dasgupta S, Sarraf M, Wheeler D. Plastic waste cleanup priorities to reduce marine pollution: a spatiotemporal analysis for Accra and Lagos with satellite data. *Sci Total Environ* 2022;839:156319. DOI PubMed
51. Martínez-vicente V, Clark JR, Corradi P, et al. Measuring marine plastic debris from space: initial assessment of observation requirements. *Remote Sensing* 2019;11:2443. DOI
52. Farré M. Remote and in situ devices for the assessment of marine contaminants of emerging concern and plastic debris detection. *Current Opinion in Environ Sci Health* 2020;18:79-94. DOI
53. Mace TH. At-sea detection of marine debris: overview of technologies, processes, issues, and options. *Mar Pollut Bull* 2012;65:23-7. DOI PubMed
54. Topouzelis K, Papageorgiou D, Suaria G, Aliani S. Floating marine litter detection algorithms and techniques using optical remote sensing data: A review. *Mar Pollut Bull* 2021;170:112675. DOI PubMed
55. Andries A, Morse S, Murphy RJ, Lynch J, Woolliams ER. Using data from earth observation to support sustainable development indicators: an analysis of the literature and challenges for the future. *Sustainability* 2022;14:1191. DOI
56. Bachmann N, Tripathi S, Brunner M, Jodlbauer H. The contribution of data-driven technologies in achieving the sustainable development goals. *Sustainability* 2022;14:2497. DOI
57. Cózar A, Echevarría F, González-Gordillo JI, et al. Plastic debris in the open ocean. *Proc Natl Acad Sci U S A* 2014;111:10239-44. DOI PubMed PMC
58. Cózar A, Sanz-Martín M, Martí E, et al. Plastic accumulation in the Mediterranean sea. *PLoS One* 2015;10:e0121762. DOI PubMed PMC
59. Viatte C, Clerbaux C, Maes C, et al. Air pollution and sea pollution seen from space. *Surv Geophys* 2020;41:1583-609. DOI
60. Hahladakis JN, Velis CA, Weber R, Iacovidou E, Purnell P. An overview of chemical additives present in plastics: migration, release, fate and environmental impact during their use, disposal and recycling. *J Hazard Mater* 2018;344:179-99. DOI PubMed

61. Romera-Castillo C, Pinto M, Langer TM, Álvarez-Salgado XA, Herndl GJ. Dissolved organic carbon leaching from plastics stimulates microbial activity in the ocean. *Nat Commun* 2018;9:1430. DOI PubMed PMC
62. Chang C, Chou C, Lee M. Determining leaching of bisphenol A from plastic containers by solid-phase microextraction and gas chromatography-mass spectrometry. *Analytica Chimica Acta* 2005;539:41-7. DOI
63. Fauvelle V, Garel M, Tamburini C, et al. Organic additive release from plastic to seawater is lower under deep-sea conditions. *Nat Commun* 2021;12:4426. DOI PubMed PMC
64. Chaukura N, Kefeni KK, Chikurunhe I, et al. Microplastics in the aquatic environment - the occurrence, sources, ecological impacts, fate, and remediation challenges. *Pollutants* 2021;1:95-118. DOI
65. Rios LM, Jones PR, Moore C, Narayan UV. Quantitation of persistent organic pollutants adsorbed on plastic debris from the Northern Pacific Gyre's "eastern garbage patch". *J Environ Monit* 2010;12:2226-36. DOI PubMed
66. Lee H, Shim WJ, Kwon JH. Sorption capacity of plastic debris for hydrophobic organic chemicals. *Sci Total Environ* 2014;470-471:1545-52. DOI PubMed
67. Hirai H, Takada H, Ogata Y, et al. Organic micropollutants in marine plastics debris from the open ocean and remote and urban beaches. *Mar Pollut Bull* 2011;62:1683-92. DOI PubMed
68. Xiang S, Xie Y, Sun X, Du H, Wang J. Identification and quantification of microplastics in aquaculture environment. *Front Mar Sci* 2022;8:804208. DOI
69. Miliute-Plepiene J, Fråne A, Haikonen K, Youhanan L. Overview of available methods to monitor marine plastic litter Incl. method for riverine litter monitoring developed within BLASTIC. Stockholm, Sweden, IVL Swedish Environmental Research Institute, 47pp. DOI
70. Garello R, Plag HP, Shapiro A, Martinez S, Pearlman J, Pendleton L. Technologies for observing and monitoring plastics in the oceans. OCEANS 2019 - Marseille; 2019. DOI
71. Hidalgo-Ruz V, Gutow L, Thompson RC, Thiel M. Microplastics in the marine environment: a review of the methods used for identification and quantification. *Environ Sci Technol* 2012;46:3060-75. DOI PubMed
72. Ginebreda A. Emerging contaminants and nanoplastics in the water environment: a matter of rising concern. *WECN* 2021. DOI
73. Luo X, Wang Z, Yang L, Gao T, Zhang Y. A review of analytical methods and models used in atmospheric microplastic research. *Sci Total Environ* 2022;828:154487. DOI PubMed
74. Whitehead PG, Bussi G, Hughes JMR, et al. Modelling microplastics in the river thames: sources, sinks and policy implications. *Water* 2021;13:861. DOI
75. Ginebreda A, Barceló D. Data-based interpretation of emerging contaminants occurrence in rivers using a simple advection-reaction model. *Water Emerg Contam Nanoplastics* 2022;1:12. DOI
76. Liubartseva S, Coppini G, Lecci R, Creti S. Regional approach to modeling the transport of floating plastic debris in the Adriatic Sea. *Mar Pollut Bull* 2016;103:115-27. DOI PubMed
77. Balas C, Williams A, Simmons S, Ergin A. A statistical riverine litter propagation model. *Mar Pollut Bull* 2001;42:1169-76. DOI PubMed
78. Wright C. Remote sensing tracks down "plastic plants" in rivers. *Eos* 2022:103. DOI
79. Pivokonsky M, Cermakova L, Novotna K, Peer P, Cajthaml T, Janda V. Occurrence of microplastics in raw and treated drinking water. *Sci Total Environ* 2018;643:1644-51. DOI PubMed
80. Cole M, Lindeque P, Halsband C, Galloway TS. Microplastics as contaminants in the marine environment: a review. *Mar Pollut Bull* 2011;62:2588-97. DOI PubMed
81. Driedger AG, Dürr HH, Mitchell K, Van Cappellen P. Plastic debris in the Laurentian Great Lakes: a review. *J Great Lakes Res* 2015;41:9-19. DOI
82. Lee H, Kunz A, Shim WJ, Walther BA. Microplastic contamination of table salts from Taiwan, including a global review. *Sci Rep* 2019;9:10145. DOI PubMed PMC
83. Ripken C, Kotsifaki DG, Nic Chormaic S. Analysis of small microplastics in coastal surface water samples of the subtropical island of Okinawa, Japan. *Sci Total Environ* 2021;760:143927. DOI PubMed
84. L F, I PP, J M, et al. A semi-automated Raman micro-spectroscopy method for morphological and chemical characterizations of microplastic litter. *Mar Pollut Bull* 2016;113:461-8. DOI PubMed
85. Nizzetto L, Bussi G, Futter MN, Butterfield D, Whitehead PG. A theoretical assessment of microplastic transport in river catchments and their retention by soils and river sediments. *Environ Sci Process Impacts* 2016;18:1050-9. DOI PubMed
86. Sousa MC, deCastro M, Gago J, et al. Modelling the distribution of microplastics released by wastewater treatment plants in Ria de Vigo (NW Iberian Peninsula). *Mar Pollut Bull* 2021;166:112227. DOI PubMed
87. Domercq P, Praetorius A, Macleod M. The full multi: an open-source framework for modelling the transport and fate of nano- and microplastics in aquatic systems. *Environ Modell Softw* 2022;148:105291. DOI
88. Zhu C, Kanaya Y, Nakajima R, et al. Characterization of microplastics on filter substrates based on hyperspectral imaging: laboratory assessments. *Environ Pollut* 2020;263:114296. DOI PubMed
89. Serranti S, Palmieri R, Bonifazi G, Cózar A. Characterization of microplastic litter from oceans by an innovative approach based on hyperspectral imaging. *Waste Manag* 2018;76:117-25. DOI PubMed
90. Guffogg JA, Soto-berelov M, Jones SD, Bellman CJ, Lavers JL, Skidmore AK. Towards the Spectral Mapping of Plastic Debris on Beaches. *Remote Sensing* 2021;13:1850. DOI

91. Prakash N, Stahl F, Mueller CL, Ferdinand O, Zielinski O. Intelligent marine pollution analysis on spectral data. OCEANS 2021: San Diego - Porto. DOI
92. Goddijn-murphy L, Williamson B. On thermal infrared remote sensing of plastic pollution in natural waters. *Remote Sensing* 2019;11:2159. DOI
93. Valdenegro-Toro M. Deep neural networks for marine debris detection in sonar images. ArXiv; 2019.
94. Goddijn-Murphy L, Peters S, van Sebille E, James NA, Gibb S. Concept for a hyperspectral remote sensing algorithm for floating marine macro plastics. *Mar Pollut Bull* 2018;126:255-62. DOI PubMed
95. Veerasingam S, Chatting M, Asim FS, Al-Khayat J, Vethamony P. Detection and assessment of marine litter in an uninhabited island, Arabian Gulf: a case study with conventional and machine learning approaches. *Sci Total Environ* 2022;838:156064. DOI PubMed
96. Themistocleous K, Papoutsa C, Michaelides S, Hadjimitsis D. Investigating detection of floating plastic litter from space using Sentinel-2 imagery. *Remote Sensing* 2020;12:2648. DOI
97. Erni-Cassola G, Zadjelovic V, Gibson MI, Christie-Oleza JA. Distribution of plastic polymer types in the marine environment: a meta-analysis. *J Hazard Mater* 2019;369:691-8. DOI PubMed
98. Desforges JP, Galbraith M, Dangerfield N, Ross PS. Widespread distribution of microplastics in subsurface seawater in the NE Pacific Ocean. *Mar Pollut Bull* 2014;79:94-9. DOI PubMed
99. Sait STL, Sørensen L, Kubowicz S, et al. Microplastic fibres from synthetic textiles: Environmental degradation and additive chemical content. *Environ Pollut* 2021;268:115745. DOI PubMed
100. Evangeliou N, Grythe H, Klimont Z, et al. Atmospheric transport is a major pathway of microplastics to remote regions. *Nat Commun* 2020;11:3381. DOI PubMed PMC
101. Mecozzi M, Pietroletti M, Monakhova YB. FTIR spectroscopy supported by statistical techniques for the structural characterization of plastic debris in the marine environment: Application to monitoring studies. *Mar Pollut Bull* 2016;106:155-61. DOI PubMed
102. Khetkeeree S, Liangrocapart S. Detecting floating plastic marine debris using Sentinel-2 data via modified infrared NDVI. 2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON). DOI
103. Moshtaghi M, Knaeps E, Sterckx S, Garaba S, Meire D. Spectral reflectance of marine macroplastics in the VNIR and SWIR measured in a controlled environment. *Sci Rep* 2021;11:5436. DOI PubMed PMC
104. Warren M, Simis S, Martinez-Vicente V, et al. Assessment of atmospheric correction algorithms for the Sentinel-2A MultiSpectral Imager over coastal and inland waters. *Remote Sens Environ* 2019;225:267-89. DOI
105. Renosh PR, Doxaran D, Keukelaere LD, Gossn JI. Evaluation of atmospheric correction algorithms for Sentinel-2-MSI and Sentinel-3-OLCI in highly turbid estuarine waters. *Remote Sensing* 2020;12:1285. DOI
106. Topouzelis K, Papakonstantinou A, Garaba SP. Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018). *Int J Appl Earth Obs Geoinf* 2019;79:175-83. DOI
107. Topouzelis K, Papageorgiou D, Karagaitanakis A, Papakonstantinou A, Arias Ballesteros M. Remote sensing of sea surface artificial floating plastic targets with Sentinel-2 and unmanned aerial systems (Plastic Litter Project 2019). *Remote Sensing* 2020;12:2013. DOI
108. Kikaki K, Kakogeorgiou I, Mikeli P, Raitsos DE, Karantzalos K. MARIDA: a benchmark for Marine Debris detection from Sentinel-2 remote sensing data. *PLoS One* 2022;17:e0262247. DOI PubMed PMC
109. Topouzelis K, Papageorgiou D, Karagaitanakis A, Papakonstantinou A, Ballesteros MA. Plastic Litter Project 2019: exploring the detection of floating plastic litter using drones and Sentinel 2 satellite images. IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium. DOI
110. Ciappa AC. Marine plastic litter detection offshore Hawai'i by Sentinel-2. *Mar Pollut Bull* 2021;168:112457. DOI PubMed
111. Le Moigne M, Brun M, Gerigny O, Galgani F. (2021). CLEANATLANTIC. Tackling marine litter in the Atlantic area. Spatial and temporal variability in floating litter in North Sea/English Channel and Bay of Biscay/Celtic Sea-2015-2020. Available from: https://archimer.ifremer.fr/doc/00750/86159/ [Last accessed on 29 Sep 2022].
112. Martinez-Vicente V, Biermann L, Mata Aser. (2020). Optical methods for marine litter detection (OPTIMAL) - final report. Zenodo; 2020. DOI
113. Arias M, Hennen M, Jacobs C. Report on detailed processing model, EO tracking of marine debris in the mediterranean sea from Public satellites Project (2019). Available from: https://eo4society.esa.int/projects/eo-tracking-of-marine-debris-in-the-mediterranean-sea-from-public-satellites/ [Last accessed on 29 Sep 2022].
114. Biermann L, Schreyers L, van Emmerik T, Bui TK, Ling Y, Streett D. (2022) Finding riverine plastics in floating plant patches using Worldview-3 satellite imagery. EGU General Assembly 2022. DOI
115. Pichel WG, Veenstra TS, Churnside JH, et al. GhostNet marine debris survey in the Gulf of Alaska - satellite guidance and aircraft observations. *Mar Pollut Bull* 2012;65:28-41. DOI PubMed
116. Kremezi M, Kristollari V, Karathanassi V, et al. Pansharpening PRISMA data for marine plastic litter detection using plastic indexes. *IEEE Access* 2021;9:61955-71. DOI
117. Martins V, Barbosa C, de Carvalho L, Jorge D, Lobo F, Novo E. Assessment of atmospheric correction methods for sentinel-2 msi images applied to amazon floodplain lakes. *Remote Sensing* 2017;9:322. DOI
118. Arii M, Koiwa M, Aoki Y. Applicability of SAR to marine debris surveillance after the great east japan earthquake. *IEEE J Sel Top Appl Earth Obs Remote Sens* 2014;7:1729-44. DOI

119. Martin-Rodriguez F. Big plastic masses detection using Sentinel 2 images. arXiv;2021. DOI
120. Jakovljević G, Govedarica M, Taboada FÁ. Remote sensing data in mapping plastics at surface water bodies. In Conference: FIG Working Week; 2019. Available from: https://www.researchgate.net/publication/332718025_Remote_Sensing_Data_in_Mapping_Plastics_at_Surface_Water_Bodies [Last accessed on 29 Sep 2022].
121. Matthews JP, Ostrovsky L, Yoshikawa Y, Komori S, Tamura H. Dynamics and early post-tsunami evolution of floating marine debris near Fukushima Daiichi. *Nature Geosci* 2017;10:598-603. DOI
122. Maneja RH, Thomas R, Miller JD, et al. Marine litter survey at the major sea turtle nesting islands in the Arabian Gulf using in-situ and remote sensing methods. 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. DOI
123. Aoyama T. (2016, May). Extraction of marine debris in the Sea of Japan using high spatial-resolution satellite images. In remote sensing of the oceans and inland waters: techniques, applications, and challenges (Vol. 9878, pp. 213-219). SPIE; 2016. DOI
124. Davaasuren N, Marino A, Boardman C, et al. Detecting microplastics pollution in world oceans using SAR remote sensing. In IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium (pp. 938-941). IEEE; 2018. DOI
125. Atwood EC, Falcieri FM, Piehl S, et al. Coastal accumulation of microplastic particles emitted from the Po River, Northern Italy: Comparing remote sensing and hydrodynamic modelling with in situ sample collections. *Mar Pollut Bull* 2019;138:561-74. DOI PubMed
126. Taggio N, Aiello A, Ceriola G, et al. A Combination of machine learning algorithms for marine plastic litter detection exploiting hyperspectral PRISMA data. *Remote Sensing* 2022;14:3606. DOI
127. Ramezan CA, Warner TA, Maxwell AE, Price BS. Effects of training set size on supervised machine-learning land-cover classification of large-area high-resolution remotely sensed data. *Remote Sensing* 2021;13:368. DOI
128. Mountrakis G, Im J, Ogole C. Support vector machines in remote sensing: a review. *ISPRS J Photogramm Remote Sens* 2011;66:247-59. DOI
129. Wang W, Liu X, Mou X. Data augmentation and spectral structure features for limited samples hyperspectral classification. *Remote Sensing* 2021;13:547. DOI
130. Ghamisi P, Plaza J, Chen Y, Li J, Plaza AJ. Advanced spectral classifiers for hyperspectral images: a review. IEEE Geoscience and Remote Sensing Magazine; 2017. Available from: https://www2.umbc.edu/rssipl/people/aplaza/Papers/Journals/2017.GRSM.Spectral.pdf [Last accessed on 29 Sep 2022].
131. Ham J, Yangchi Chen, Crawford M, Ghosh J. Investigation of the random forest framework for classification of hyperspectral data. *IEEE Trans Geosci Remote Sensing* 2005;43:492-501. DOI
132. Maxwell AE, Strager MP, Warner TA, Ramezan CA, Morgan AN, Pauley CE. Large-area, high spatial resolution land cover mapping using random forests, GEOBIA, and NAIP orthophotography: findings and recommendations. *Remote Sensing* 2019;11:1409. DOI
133. Zhu W, Qian C, He N, Kong Y, Zou Z, Li Y. Research on chlorophyll - a concentration retrieval based on bp neural network model-case study of dianshan lake, China. *Sustainability* 2022;14:8894. DOI
134. Sagan V, Peterson KT, Maimaitijiang M, et al. Monitoring inland water quality using remote sensing: potential and limitations of spectral indices, bio-optical simulations, machine learning, and cloud computing. *Earth-Science Reviews* 2020;205:103187. DOI
135. Kravitz J, Matthews M, Lain L, Fawcett S, Bernard S. Potential for high fidelity global mapping of common inland water quality products at high spatial and temporal resolutions based on a synthetic data and machine learning approach. *Front Environ Sci* 2021;9:587660. DOI
136. Andrade H, Glüge J, Herzke D, Ashta NM, Nayagar SM, Scheringer M. Oceanic long-range transport of organic additives present in plastic products: an overview. *Environ Sci Eur* 2021:33. DOI
137. Zhou W, Yang S, Wang PG. Matrix effects and application of matrix effect factor. *Bioanalysis* 2017;9:1839-44. DOI PubMed
138. Carlson TN, Ripley DA. On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sens Environ* 1997;62:241-52. DOI
139. Herrmann SM, Anyamba A, Tucker CJ. Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. *Glob Environ Change* 2005;15:394-404. DOI
140. Guimarães T, Veronez M, Koste E, et al. An alternative method of spatial autocorrelation for chlorophyll detection in water bodies using remote sensing. *Sustainability* 2017;9:416. DOI
141. Liu H, Sun K, Liu X, et al. Spatial and temporal distributions of microplastics and their macroscopic relationship with algal blooms in Chaohu Lake, China. *J Contam Hydrol* 2022;248:104028. DOI PubMed
142. Schell JA, Deering D. Monitoring vegetation systems in the great plains with erts. NASA Special Publication; 1973. Available from: https://ntrs.nasa.gov/citations/19740022614 [Last accessed on 29 Sep 2022].
143. Camps-Valls G, Campos-Taberner M, Moreno-Martínez Á, et al. A unified vegetation index for quantifying the terrestrial biosphere. *Sci Adv* 2021;7:eabc7447. DOI PubMed PMC
144. Hu C. A novel ocean color index to detect floating algae in the global oceans. *Remote Sens Environ* 2009;113:2118-29. DOI
145. Morel A, Prieur L. Analysis of variations in ocean color1: ocean color analysis. *Limnol Oceanogr* 1977;22:709-22. DOI
146. Rokni K, Ahmad A, Selamat A, Hazini S. Water feature extraction and change detection using multitemporal landsat imagery. *Remote Sensing* 2014;6:4173-89. DOI
147. Xu H. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *Int J Remote Sens* 2006;27:3025-33. DOI

148. Wilson EH, Sader SA. Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sens Environ* 2002;80:385-96. DOI
149. Rouse JW, Haas RH, Schell JA, Deering DW. Monitoring vegetation systems in the great plains with ERTS (Earth Resources Technology Satellite). Proceedings of 3rd Earth Resources Technology Satellite Symposium, Greenbelt, 10-14 December, SP-351, 309-317; 1973. Available from: https://www.scirp.org/(S(351jmbntvnsjt1aadkposzje))/reference/referencespapers.aspx?referenceid=1396706 [Last accessed on 29 Sep 2022].
150. Feyisa GL, Meilby H, Fensholt R, Proud SR. Automated water extraction index: a new technique for surface water mapping using landsat imagery. *Remote Sens Environ* 2014;140:23-35. DOI
151. Hu C, Feng L, Hardy RF, Hochberg EJ. Spectral and spatial requirements of remote measurements of pelagic Sargassum macroalgae. *Remote Sens Environ* 2015;167:229-46. DOI
152. Wang M, Hu C. Mapping and quantifying Sargassum distribution and coverage in the Central West Atlantic using MODIS observations. *Remote Sens Environ* 2016;183:350-67. DOI
153. Kühn F, Oppermann K, Hörig B. Hydrocarbon index - an algorithm for hyperspectral detection of hydrocarbons. *Int J Remote Sens* 2004;25:2467-73. DOI
154. Leal Filho W, Dedeoglu C, Dinis MAP, et al. Riverine plastic pollution in Asia: results from a bibliometric assessment. *Land* 2022;11:1117. DOI
155. Campanale F, Savino C, Pojar I, Massarelli IC, Uricchio VF. A practical overview of methodologies for sampling and analysis of microplastics in riverine environments. *Sustainability* 2020;12:6755. MDPI AG. DOI
156. Elhag M, Gitas I, Othman A, Bahrawi J, Gikas P. Assessment of water quality parameters using temporal remote sensing spectral reflectance in arid environments, saudi arabia. *Water* 2019;11:556. DOI
157. Scherer C, Weber A, Stock F, et al. Comparative assessment of microplastics in water and sediment of a large European river. *Sci Total Environ* 2020;738:139866. DOI PubMed
158. Blettler MCM, Abrial E, Khan FR, Sivri N, Espinola LA. Freshwater plastic pollution: recognizing research biases and identifying knowledge gaps. *Water Res* 2018;143:416-24. DOI PubMed