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Review Article

A systematic review of state-of-the-art technologies for monitoring plastic seafloor litter

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ABSTRACT

Plastic litter has been widely documented in our oceans, leading to growing worldwide concerns regarding its potential impact on the marine environment. A large proportion of this plastic accumulates at the bottom of the ocean, resulting in a need to monitor and quantify seafloor litter. Seafloor litter monitoring is mostly performed using benthic beam trawls, which have several limitations and environmental implications. New innovative ways to document and address seafloor litter are therefore necessary and requested by the United Nations Sustainable Development Goal 14 (SDG 14.1.1b), the Oslo Paris Convention (OSPAR) and the International Council for the Exploration of the Sea (ICES). This systematic review gives an overview of the state-of-the-art of 14 current underwater technologies that are eligible for future in situ detection of plastic litter on the seafloor based on 101 publications. A set of objectives and a Technology Readiness Level (TRL) scale were used to benchmark the technologies and revealed that the most suitable system is often very scenario-specific and, therefore, demands investments in more than one specific group of technologies. A decision tool was established to determine the most suitable technique for a range of different situations. This review indicates that most of these technologies are currently at low-middle TRLs, requiring several more development, testing and commercialization steps before they can be applied effectively in marine field conditions. However, these technologies, alone or in combination, have the potential to contribute to the establishment of more robust global environmental indicators and monitoring programs for plastic pollution.

Abbreviations: AI, Artificial Intelligence; ALDFG, Abandoned, Lost or Discarded Fishing Gear; AMAP, Arctic Monitoring and Assessment Programme; AUV, Autonomous underwater vehicle; BTS, Beam Trawl Survey; CNN, Conventional Neural Network; EEZ, Exclusive Economic Zone; FLS, Forward-Looking Sonar; FTIR, Fourier-Transform Infrared Spectroscopy; GESAMP, Joint Group of Experts on the Scientific Aspects of Marine Environmental Protection; GPR, Ground Penetrating Radar; HDPE, High Density Polyethyleen; HI, Hyperspectral Imaging; IBTS, Internation Bottom Trawl Survey; ICES, International Council for the Exploration of the Sea; ICES, WGML International Council for the Exploration of the Sea Working Group on Marine Litter; ILVO, Flanders Research Institute for Agriculture, Fisheries and Food; LDPE, Low Density Polyethyleen; LIDAR, Light Detection and Ranging of Laser Imaging Detection and Ranging; MBSS, Multibeam Sonar System; MSFD, European Union Marine Strategy Framework Directive; NIR, Near-Infrared Spectroscopy; NIVA, Norwegian Institute for Water Research; NOAA, US National Oceanic and Atmospheric Administration; OSPAR, Oslo Paris Convention; PA, Polyamide; PAME, Protection of the Arctic Marine Environment; PBMA, Polybutyl methacrylate; PC, Polycarbonate; PET, Polyethylene Terephthalate; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; PP, Polypropyleen; PPG, Photoplethysmograms; PS, Polystyrene; PTFE, Polytetrafluoroethylene; PUR, Polyurethane; PVC, Polyvinylchloride; QA/QC, Quality Assurance/Quality Control; ROV, Remotely Operated Vehicle; SAS, Synthetic Aperature Sonar; SDG, Sustainable Development Goals; SSS, Side Scan Sonar; SVM, Support Vector Machine; TRL, Technology Readiness Level; UN, United Nations; USV, Unmanned Surface Vehicle; VIS, Visible Spectroscopy; VLIZ, Flanders Marine Institute; WoS, Web of Science.

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1. Introduction

In recent decades, the increasing levels of plastic in the World's oceans has drawn significant public attention and raised concerns about the impacts this might be having on the marine environment, marine organisms and human health (e.g. [1,2]). This has resulted in marine litter, and especially plastic litter, being high on the political agenda [3–5]. Litter assessments are currently performed within the framework of both monitoring programs and fundamental scientific research. An increasing amount of knowledge on the behavior of plastic in marine environments, the settling velocities, the sinking behavior and the role of external factors such as biofouling provide clear insights into how plastic litter is transported to the seafloor (e.g. [6–10]). Several efforts have been made to characterize seafloor litter and assess its spatiotemporal dynamics (e.g. [11–13]). To do so, a large suite of technologies and approaches has been applied ranging from in situ sampling to remote observations. Imagery, for example, has been used in several studies to quantify seafloor litter [14]. There is a need to monitor seafloor litter and its impacts, to locate accumulation zones (hotspots), and, to define strategies for supporting long-term evaluation of plastic accumulation (e.g. fishing grounds) [15]. Effect assessment of seafloor plastic litter is necessary to understand which species are most exposed, impacted and sensitive [16,17]. For example, cross mapping the distribution of litter and benthic species, especially commercial fish, supports a good evaluation of the exposure and risk of ingestion [18]. A 2021 global analysis of litter data observations showed that the proportion of plastic in total litter increased progressively from 49% on riverbeds to 64% on nearshore bottoms (<100 m depth, <100 km from shoreline) and 77% on deep seafloors (>100 m depth, >100 km from shoreline) [19]. This trend is mainly documented along canyons, which act as deep conduits of litter. The diffuse vertical input from floating loads and sea-based sources is also suggested as a major cause of deep-sea littering [19]. A number of studies have identified the shelf and deep-sea environments as long-term net sinks for plastic litter of all sizes, including microplastic [20,21].

The monitoring of litter in marine environments is a fundamental part of the wider state of environmental reporting, and a key component of ecological risk assessments, which are ideally based on realistic exposure conditions [22–24]. Marine litter is a transboundary problem and international cooperation and coordination are crucial to monitor and reduce marine pollution. On a global level, marine litter is included under the UN Sustainable Development Goal 14 'Life Below Water' (14.1.1b Plastic debris density) and Challenge 1 of the UN Decade of Ocean Science for Sustainable Development 'Understand and beat marine pollution'. Since the 2010s, frameworks such as the International Council for the Exploration of the Sea (ICES), the Regional Seas Conventions (e.g. Oslo Paris Convention; OSPAR) and the European Union Marine Strategy Framework Directive (MSFD) have been quantifying and monitoring seafloor litter using beam trawl hauls, revealing the first insights into the prevalence distribution patterns, transport routes and accumulation zones of plastic litter [24–27]. Benthic trawl surveys are a practical way to monitor seafloor litter because they are already coordinated by ICES for fish stock assessments [28]. These surveys cover a large proportion of the European marine regions [26,28], attempt to standardize methods [26–28] and, in practice, appear to sample sufficient litter for analysis [25].

Unfortunately, bottom trawling is a destructive sampling technique that has been subject to discussion and criticism for many years. In line with the Biodiversity Strategy 2030, the European Commission has the intention of implementing restrictions to limit bottom trawling in EU waters, supporting the transition to more selective and less damaging fishing techniques. It has subsequently put forward a legislative proposal to phase out bottom trawling by 2030 [23]. In addition, a catch-based assessment of seafloor litter comes with a number of other drawbacks [26]. The trawls are limited to locations relevant for the fish stock surveys on which they piggyback, rather than focusing specifically on areas that might be particularly relevant for seafloor litter monitoring [26]. Hence, mostly shallow waters are examined by benthic trawling [26,28]. In addition, trawling is not permitted in regions such as marine protected areas, which may be important to monitor. As litter items are collected after a tow or trawl track is completed, there is also no precise information on the location of each litter item. Seafloor litter monitoring using bottom trawls is not applicable in all marine environments, for example, deep areas with complex topography (rocky substrates, canyons, coral reefs, etc.) cannot be included [14,29,30]. However, Pham et al. [31] showed that bottom trawling, in rare cases, can be used to document litter down to a depth of 3000 m. Trawling surveys will miss small items due to the mesh size of the net [32]. Different litter types have different catchabilities, which is also affected by the size of the catch and sediment type [33,34]. The most important drawback, however, is the variation in catchability of different nets, which creates an uncertainty when comparing areas [24,26]. Some trawls appear to capture <5% of seafloor litter items by number, meaning that actual litter numbers could be substantially higher than what is caught in nets [35]. In light of all these drawbacks, scientists have been seeking new and innovative ways to detect and quantify plastic litter present on the seafloor and in the lower layer of the water column [14,29,36,37]. These approaches include elements of autonomous detection (in situ detection without human interference), which can enable swift observations of marine litter, allowing the quick analysis of evolutionary patterns of litter distribution, as well as better policy alignment [37].

With the increased interest and desire to efficiently and effectively sample and monitor seafloor litter, it is necessary to compare the different available approaches to allow researchers and regulators to identify the most suitable techniques for use in research or monitoring. One important decision making tool for selecting the approach is the use of a Technological Readiness Level (TRL) scale to group technologies and approaches into basic research, applied research, development and implementation. A TRL scale for application in litter and plastic pollution monitoring was recently put forward by Aliani et al. [38]. The TRL scale enables systematic validation and global harmonization of plastic pollution monitoring methods by ranking them from 1 to 9 (Fig. A1, Appendix A) [38].

Currently, there is no off-the-shelf in situ detection technique that is operational (TRL 7–9) for systematic seafloor monitoring of plastic litter in diverse marine environments that provides sufficient details to meet the required objectives for exposure, effects, and risks assessment of seafloor plastic litter. Therefore, this study evaluates which existing technologies are eligible for future in situ meso– and macroplastic litter (>5 mm) detection on the seafloor and the hyperbenthic area (<1 m above seafloor). Two design processes of detection systems are assessed: (i) methods from other sectors (e.g. food industry) that have already proven themselves to be useful for plastic detection and that have been published as a possible technique in an underwater setting and (ii) established underwater technologies for new applications such as plastic litter detection.

Additionally, the current state of the different technologies is benchmarked against the envisaged final product to determine the main steps toward innovation. Therefore, a set of objectives to describe the final product were introduced and a TRL was defined for each technique in the context of plastic litter detection based on the suggested scale by Aliani et al. [38]. As detection methods are region-specific in terms of applicability, a decision tool to define the most suitable method for different scenarios is demonstrated. It is anticipated that the compilation of information in

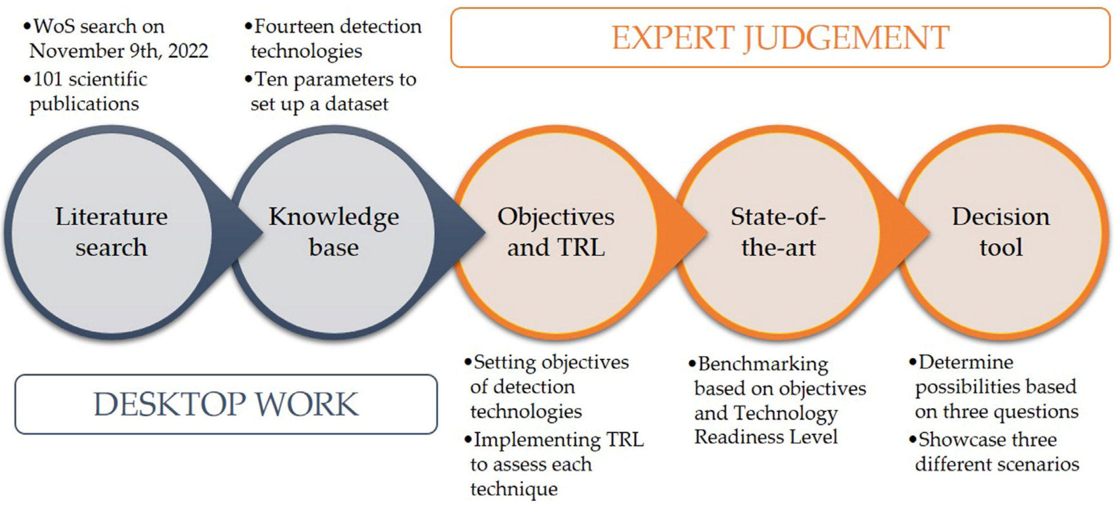

Fig. 1. Illustration of the process implemented to determine the state-of-the-art of detection technologies and to create a decision tool.

this study, in combination with the proposed decision framework would be helpful in identifying the optimal monitoring system design worldwide for seafloor litter [39]. While a TRL scale has many advantages, there is an additional need for a comparability assessment between the different technologies to ensure that the resulting monitoring data is fit for purpose and sufficiently comparable across studies utilizing different analysis approaches.

The motivation for this study is rooted in the need for innovation in monitoring and observation activities for seafloor litter, which was raised by the ICES Working Group on Marine Litter (ICES WGML) [26] and explicitly mentioned in the OSPAR Quality Status Report [24]. The latter is endorsed by 15 Governments and the EU, and is considered the overarching environmental assessment for the Northeast Atlantic, supported by the marine research landscape. Furthermore, a clear gap in the available literature and current knowledge has been identified for sustainably and accurately monitoring plastic seafloor litter at an international level.

The objective of this systematic review is to contribute to the current knowledge regarding in situ detection methodologies for plastic seafloor litter by providing an overview of the state-of-the-art underwater technologies based on a comprehensive literature study. This systematic review is a unique first step towards a supported monitoring program for plastic seafloor litter and combines for the first time literature on existing detection techniques from different research disciplines and sectors with the newly developed TRL scale for plastic pollution monitoring methods of Aliani et al. [38].

2. Materials and methods

An overview of technologies eligible for underwater detection of plastic on the seafloor was generated by a systematic literature study (Fig. 1). This comprehensive search was performed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [40]. Scientific peer-reviewed publications were collected by multiple Web of Science (WoS) searches on November 9, 2022. This electronic platform was screened for the presence of ‘underwater detection’ or ‘underwater observation’ in combination with ‘plastic’, ‘debris’ or ‘litter’ in all searchable fields of a publication. A primary selection of the resulting list of publications was made based on the abstract, and a secondary selection was performed based on the content. Publications without any reference to underwater applications or object detection were excluded. Only publications describing technologies and approaches that have the ability to perform in underwater conditions were included. Furthermore, a quality assurance and quality control (QA/QC) procedure was conducted by comparing the reference list to the EUROqCHARM systematic review for macrolitter/seafloor [41].

Existing techniques that only consider floating litter (e.g. remote sensing) were not included. In addition, this review focuses on plastic objects or particles >5 mm, actively excluding micro- and nanoplastics that need alternative methods and separate monitoring programs. Following the recommendations of GESAMP experts [42], we use the size definitions of microplastic (<5 mm), mesoplastic (5 mm - 2.5 cm), macroplastic (2.5 cm - 1 m) and megaplastic (>1 m). This set of inclusion criteria is clear and unambiguous, eliminating the risk of bias. The resulting publications generated a list of described technologies with the potential for seafloor plastic litter detection. A second screening for publications in WoS was performed with the resulting technologies in combination with ‘plastic detection’, ‘debris detection’, ‘litter detection’ or ‘underwater detection’, and ‘plastic observation’, ‘debris observation’, ‘litter observation’ or ‘underwater observation’. For completeness, other publications of the respective authors were reviewed to collect more information on the different technologies. In total, information about 14 different technologies was gathered from 101 scientific publications.

Each technology was characterized based on ten characteristics which gave a structure to an underlying dataset. These characteristics include; frequency/wavelength, detected materials, compatible platform, method resolution, detection size range, spatial coverage, processing algorithms, projects and publications (Table B.1, Appendix B). The established dataset forms a knowledge base to identify the different gaps between the current state of each technology’s development process/level and the envisaged final product.

For each technique, a different approach is required to reach an optimal technology level for in situ seafloor plastic litter detection given that these techniques have their roots in other scientific disciplines. For example, 2D imaging sonar can generate high-quality forward-looking sonar imagery, regardless of carrier speed. This allows for seamless follow-on actions like visual identification, sampling or recovery. However, the narrow field of view means that the number of transects needed to cover an area equivalent to that of a side looking sonar can be substantial and therefore time-consuming [36]. Depending on the expected outcome, there will likely be a trade-off between the spatial coverage and the minimum detected object size. Side looking sonar systems, such as side scan sonar (SSS) and synthetic aperture sonar (SAS), can cover vast areas, but need a stable platform with precise navigation and a constant, relatively low, speed (<5 knots) to generate the highest resolution. Furthermore, there are often several trade-offs within the same class of detection techniques. For example, a Sound Metrics ARIS sonar (2D imaging sonar) has a very good resolution but a narrow field of view (40°), while the Teledyne Blueview has a wider field of view (130°) but a lower resolution [36].

To benchmark the different techniques, four objectives (each with their own criteria, Section 3.1), underpinned by the expert judgment of the ICES WGML, were set up that matched the expectations of the desired technology for seafloor plastic litter detection:

1. Identification and differentiation of plastic litter
2. Spatial coverage of detection techniques
3. Detection size range of detection techniques
4. Artificial intelligence for plastic detection

The implementation of the objectives by the different techniques was subsequently examined based on the established knowledge base, and, in the absence of literature-based information, assessed by expert judgment. This allowed determination and comparison of the different state-of-the-art detection techniques. A color code was allocated for each technique in combination with a specific platform (e.g. remotely operated vehicle [ROV], unmanned surface vehicle [USV], autonomous underwater vehicle [AUV], ship, etc.) to represent the implementation of the objective. This was also conducted for the technique in general without it being linked to a specific platform. The same color code was used for all objectives with green indicating a complete implementation of the objective, orange representing a strong implementation of the objective and red indicating that only a small part of an objective is covered.

In addition to the objectives, the plastic monitoring TRL scale published by Aliani et al. [38] was used to assess each detection technique. The TRL indicates in which phase a technology is situated in the framework of plastic monitoring. The exact TRLs are listed below and illustrated in Fig. A.1 of Appendix A [38]:

Basic research (TRL 1–3)

1. Basic principles presented
2. Concept and application formulation
3. Proof of concept / Feasibility

Applied research (TRL 4–5)

4. Method validation in the laboratory / Experimental pilot
5. Method validation in relevant environment / Demonstration pilot

Development (TRL 6–7)

6. Demonstration in relevant environment / Record(s) of successful monitoring
7. Operational in environment / Widely applied in field studies

Implementation (TRL 8–9)

8. Method complete and qualified / Records of successful monitoring
9. Standard protocol enforced and applied / Widely used for monitoring operations

Lastly, a decision tool was established to determine the most suitable technique for a range of different situations. The decision tool is a scheme based on three questions, and their possible answers, which correspond with the first three objectives of this review paper.

1. What differentiation level of plastic litter is needed? (Objective 1)
   a. Material level
   b. Polymer level
2. What area should be covered? (Objective 2)
   a. <1 km²
   b. >1 km²
3. What plastic object sizes do you want to detect? (Objective 3)
   a. Microplastics
   b. Mesoplastics
   c. Macroplastics
   d. Widest possible size range

For each combination of answers the suitable techniques were verified based on the established dataset. The implementation of the objectives was then used as a step-by-step process to exclude unsuitable techniques. The remaining techniques were subsequently placed in the respective boxes of the scheme to provide the different possibilities. In several scenarios multiple techniques can be put forward. However, the decision tool does not convey preferences. Depending on the region or situation, a different detection technique may be identified as most favorable. To enhance the use of the tool, three example scenarios (i.e. Southern North Sea region, the Azores and Central Arctic Ocean) are used as demonstration regions, with each being completed by experts from Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), University of the Azores (OKEANOS) and Norwegian Institute for Water Research (NIVA), respectively.

3. Results

Several acoustic and electromagnetic techniques may be eligible for plastic detection in the marine environment (Fig. 2). These techniques can be divided into two different approaches: (i) existing marine monitoring equipment (e.g. sonar systems) that might need some modifications to meet the requirements for plastic detection, and (ii) less elaborated techniques that have a documented capacity to differentiate plastic under laboratory conditions, but might need adjustments to be deployable in the marine environment (e.g. spectral imaging techniques). In both cases, the key characteristics of these techniques, from the perspective of usability for this study, were collated and listed in Table B.1 of Appendix B.

3.1. Objectives and criteria toward innovation

Establishing a robust and accurate technique for plastic litter detection on the seafloor is a step-by-step process that must meet several requirements. To work toward this innovation, several approaches are possible, with each having their own advantages and limitations. An overview of the intended objectives, based on the application requirements and assessment criteria, as well as their implementation through the current detection techniques is therefore provided. The objectives represent crucial aspects of a monitoring method and are therefore stepping-stones toward innovation.

3.1.1. Objective 1. Identification and differentiation of plastic litter in the marine environment

- Criteria 1.1. Differentiation between object and environment

To be eligible for seafloor detection, a technique or a combination of techniques needs to be capable of differentiating plastic

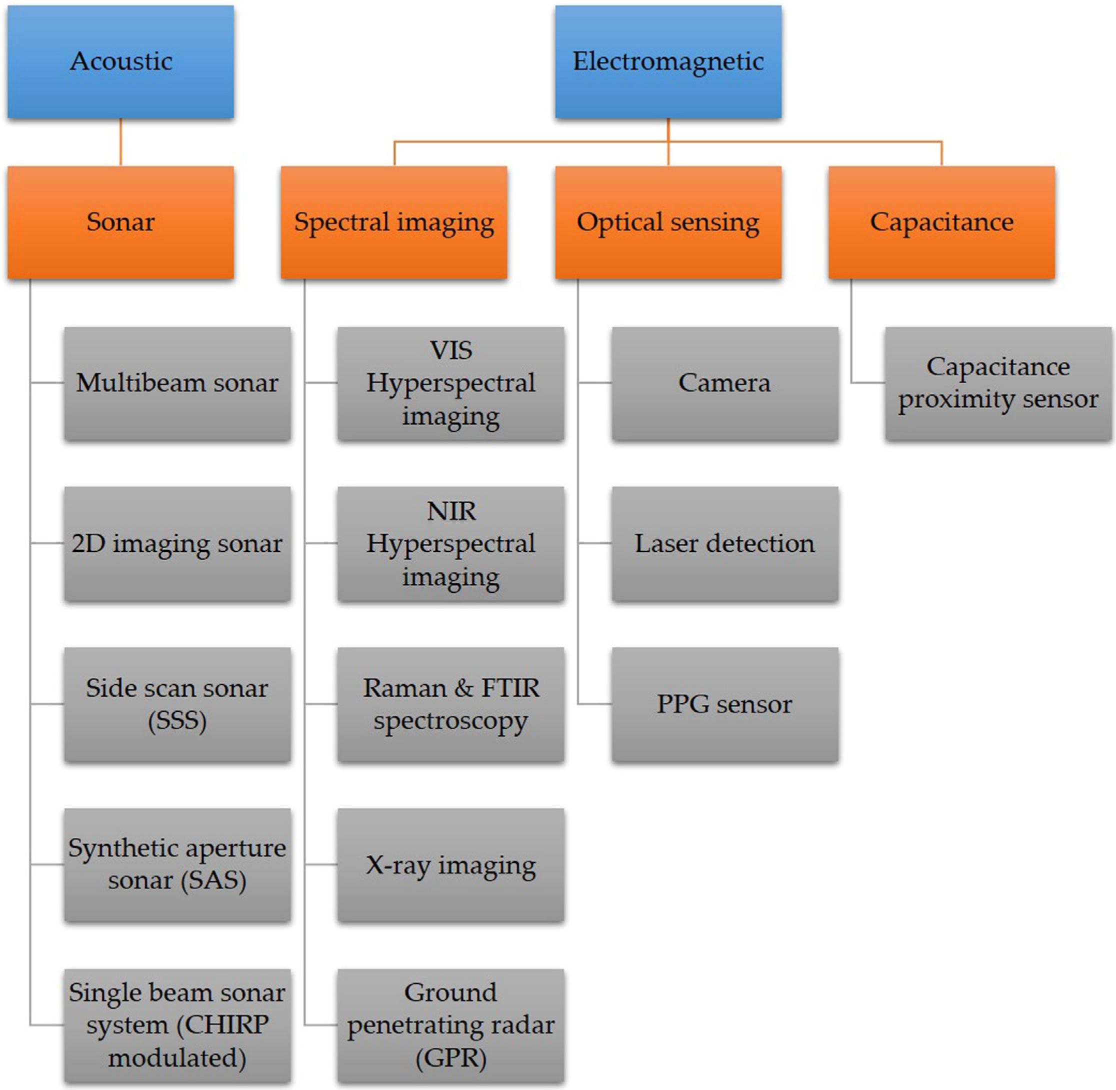

Fig. 2. Conceptual overview of the different technologies that are suitable or have potential to detect plastic on the seafloor.

items (e.g. tires, plastic bottles, fishing nets, etc.) from natural features present in the environment (e.g. rocks, sediment, fish, etc.). Sonar systems generate an image based on the reflection of sound waves. These images show different shapes along the seafloor that can be identified as objects and classified by processing algorithms [43,44]. Spectral imaging systems collect a wide spectrum of reflected light to obtain both imaging and spectroscopic data for their surroundings. Given that these spectroscopic data directly correspond to the material type of an object, a more precise classification is possible (e.g. [45–47]). Capacitive proximity sensors use a different method than the ones above. This type of sensor detects a target based on the permittivity of each material and is widely used in the food industry [48].

- Criteria 1.2. Differentiation between plastic and other litter objects

In marine litter monitoring, the differentiation of plastic objects from other materials (e.g. glass or metal objects) is required (Fig. 3). This material classification can be directly for the generated outcome (e.g. hyperspectral imaging, [45,47]) or indirectly by processing the generated image with artificial intelligence (AI) (e.g. sonar images, [43,44]). Generating data that are directly linked to the chemical composition of an object may enable a more accurate classification. Techniques where the outcome needs additional processing by AI may miss certain objects or even count/include incorrect objects (e.g. biota or rocks), which will result in a lower success rate. Furthermore, algorithms that classify objects based on their shape may not consider fragmented objects that lack the characteristic features associated with pristine consumer products. Additional challenges, such as biofouling, partial burial and accumulation, may also influence the success rate of detection systems [49].

- Criteria 1.3. Differentiation between synthetic polymer types

Some spectral imaging technologies can identify individual synthetic polymer types (i.e. PET, PVC, PP, etc.) (Fig. 3) [45–47,50]. Until now, testing of these methods has only been performed under laboratory conditions [45,47,50]. Furthermore, these detailed classification levels are not yet mandatory, which has implications for monitoring and reporting obligations [27,51].

3.1.2. Objective 2. Spatial coverage

When reflecting over future monitoring and research needs, it is important to consider the spatial coverage of detection systems (Fig. 4), where the extent of spatial coverage is subject to a combination of the method's display resolution and the distance to the target [43]. The display resolution defines the dimensions of a pixel in an obtained image and therefore the precision of an individ-

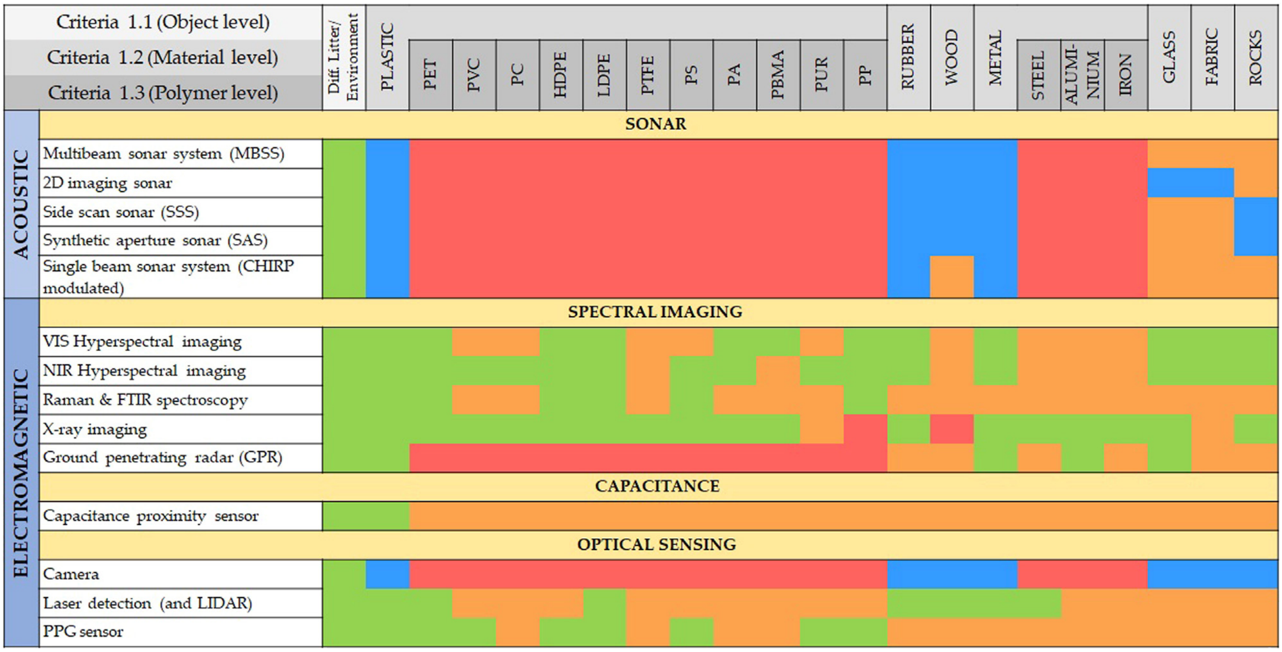

Fig. 3. Material differentiation capacity for each seafloor detection technique. (Green: positive differentiation, Blue: differentiation only based on the shape of target, Orange: not tested, Red: no differentiation).

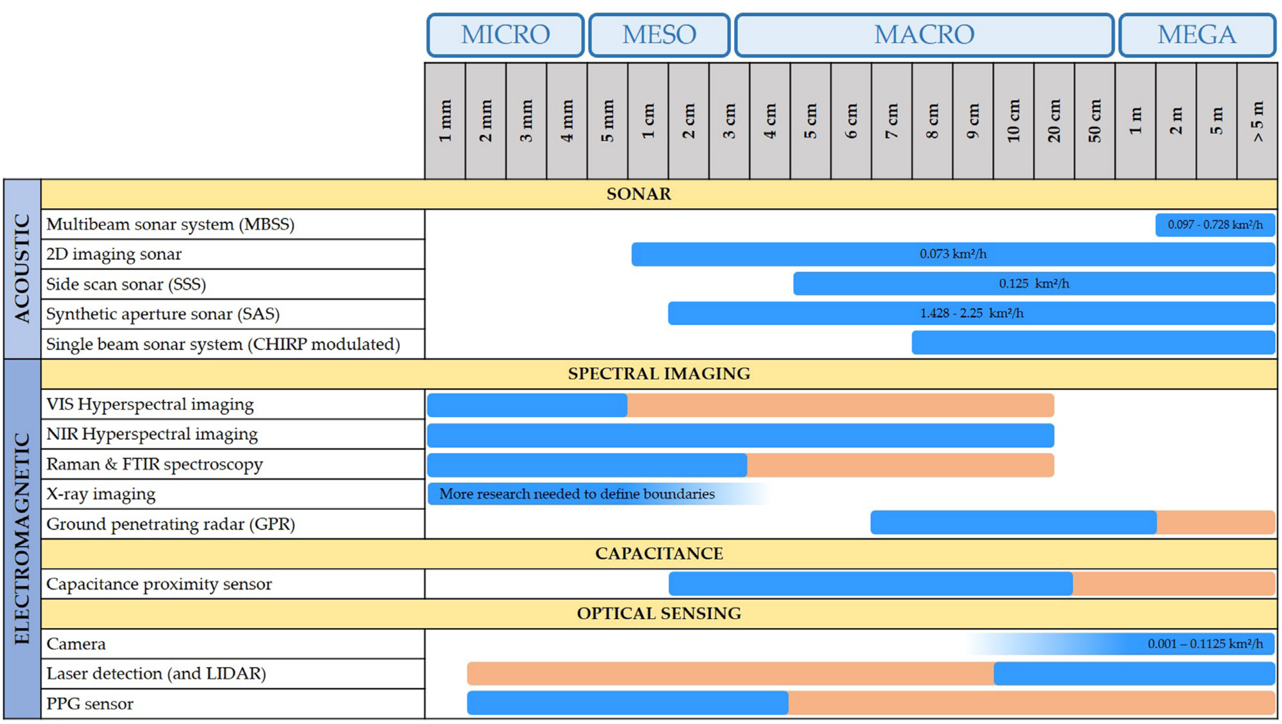

Fig. 4. Detection size range and spatial coverage (in km²/h) by seafloor detection technique. Blue bars show the detection range reported in literature to date. Orange bars show the possible extension of size range based on expert judgement of the co-authors.

ual technique. Techniques that can operate further away from a target (e.g. sonar systems, [29]), will generally cover larger areas than short-range technologies (e.g. hyperspectral imaging, [45,47]). Furthermore, the method's display resolution will commonly be higher for systems operating close to the target. The synthetic aperture sonar (SAS), however, represents an exception, as it combines a high spatial coverage due to its ability to operate further from the target with a high resolution by virtue of a strong processing capacity [29,52–55].

An additional factor that affects the spatial coverage of a sensor is the platform it operates from. This platform can be ROVs, USVs, AUVs, ships, towed systems, etc. However, not all sensors can be integrated in every platform (Fig. 5), resulting in various coverage ranges for different combinations of detection techniques

		Cost of purchase	ROV	USV	AUV	Ship	Hand-held	Towed	
ACOUSTIC	**SONAR**								
	Multibeam sonar system (MBSS)	€€€	✓	✓	✓	✓		✓	Shallow
			✓		✓				Deep
	2D imaging sonar	€€	✓	✓	✓		✓		Shallow
			✓		✓				Deep
	Side scan sonar (SSS)	€€	✓	✓	✓			✓	Shallow
			✓		✓			✓	Deep
	Synthetic aperture sonar (SAS)	€€€			✓			✓	Shallow
					✓			✓	Deep
	Single beam sonar system (CHIRP modulated)	€	✓	✓		✓			Shallow
			✓						Deep
ELECTROMAGNETIC	**SPECTRAL IMAGING**								
	VIS Hyperspectral imaging	€€€	✓				✓		Shallow
			✓						Deep
	NIR Hyperspectral imaging	€€€	✓				✓		Shallow
			✓						Deep
	Raman & FTIR spectroscopy	€€	✓				✓		Shallow
			✓						Deep
	X-ray imaging	€€€	✓						Shallow
			✓						Deep
	Ground penetrating radar (GPR)	€€	✓						Shallow
			✓						Deep
	CAPACITANCE								
	Capacitance proximity sensor	€	✓						Shallow
			✓						Deep
	OPTICAL SENSING								
	Camera	€€	✓	✓	✓	✓	✓	✓	Shallow
			✓		✓			✓	Deep
	Laser detection (and LIDAR)	€€	✓		✓		✓		Shallow
			✓		✓				Deep
	PPG sensor	€	✓		✓		✓		Shallow
			✓		✓				Deep

Fig. 5. Cost of purchase and compatibility of detection techniques with marine platforms based on literature data and expert judgement. (€: <10.000 euro, €€: 10.000–100.000 euro, €€€: >100.000 euro; and shallow waters: <200 m, deep waters: >200 m).

and platforms. Finally, the coverage area also depends on the costs of operation, the monitoring budget, and the logistics of a specific deployment.

3.1.3. *Objective 3. Detection size range*

The detection size range of a technique is a decisive objective in selecting the right system for monitoring plastic litter. Unlike the display resolution, the detection size range describes the minimum and maximum size of an object that can be detected and identified. The detection size range is, therefore, commonly larger than the display resolution. Depending on the size range of plastic items targeted in an individual study or monitoring campaign, a particular technique or a combination of techniques may be required for detection. In Fig. 4, the reported sizes of the detected objects of each reviewed study (Table B.1, Appendix B) are plotted separately for each detection system (blue bars). In addition, the theoretical extension of the detection size range was added (orange bars) based on literature findings and expert judgment.

For each technique, different object sizes can be detected with the correct adjustment of the sensor [29], acknowledging that the entire size range of plastic objects may not always be detected with one specific adjustment. This also means that the additional theoretical range (Fig. 4, orange bars) may require a certain adjustment or modification. It is important to note that the size frequency distribution approach proposed by Kooi and Koelmans [56] is not yet clarified for seafloor plastics. Based on such distributions, one could focus on a specific/defined size range, and then extrapolate towards larger or smaller plastic objects to provide an estimate of the entire size distribution. However, this requires an existing understanding of the average frequency with which plastic objects from specific size classes occur in the environment.

As for spatial coverage, the method's display resolution is an important factor for the detection size range of a technique. The higher the resolution of the sensor, the more detailed the developed images will be and the easier (small) objects can be detected or even identified. However, a higher resolution typically implies an increase in the time required for data collection and analysis, which increases the overall cost of the operation. Furthermore, the distance to the target and the visibility in the water column also have an influence on the detection size range.

3.1.4. *Objective 4. Artificial intelligence for plastic detection*

Innovation in the field of seafloor plastic detection is often driven by the need for more labor- and cost-efficient methodologies. Therefore, investments in autonomous in situ detection techniques and even autonomous platforms are essential [37]. The use of smart devices may enable immediate and remote identification of plastics [57], allowing fast state-of-the-art assessments and swift action against plastic accumulation on the seafloor. Automatic object recognition and/or material identification by the system is therefore desirable. Besides generating an image or data outcome by using a sensor, the detection systems need to process and analyze the data. In general, this can be done by various machine learning algorithms (i.e. support vector machine (SVM), conventional neural network (CNN), etc.) and several studies have already tested the feasibility of these algorithms for seafloor plastic detection (Table B.2, Appendix B). For example, Valdenegro [43] concluded that Deep Neural Networks are a sufficiently thorough technique to survey and detect marine litter on the bottom of water bodies from Forward-Looking Sonar (FLS) images. Aleem et al. [44] even achieved a success rate of 96% with their proposed deep learning algorithm for FLS images. Furthermore, such algorithms have also been demonstrated to be applicable for images from a towed camera, showing similar success rates (e.g. [58,59]). However, there remains a degree of uncertainty about whether these algorithms are sufficiently capable of detecting fragmented objects. Fragments of 'known' objects (e.g. bottles, tires etc.) that retain sufficient characteristics of the original object can be more readily detected, but this reduces as the fragments become smaller and/or contain fewer diagnostic characteristics.

3.2. Compatible platforms for detection techniques

In situ identification and quantification of marine plastics requires the sensor array or instrument to operate under marine conditions [42], often in combination with a dedicated platform (e.g. USV, AUV, ROV, ships, and towed systems). A first overview on existing methods, specifically to locate derelict pot items, was completed as part of a dedicated workshop in 2009 organized by the US National Oceanic and Atmospheric Administration (NOAA) [60].

Subject to the scale, region and budget of a monitoring or research activity, a certain platform may be favored, but not always compatible with the intended detection technique. Based on the analyzed studies in this review and the expert judgement of the co-authors, Fig. 5 provides an overview of the platforms that can be used for each detection technique. Depending on the distance needed between the system and the target – and therefore the water depth of the sampling site – a sensor can operate from a ROV or AUV for short-range detection systems (i.e. 2D imaging sonars, hyperspectral imaging systems), and from a ship, USV, AUV or towed system for long-range systems (i.e. multibeam sonar system (MBSS), SSS, SAS). In shallow waters (<200 m), it might even be possible to use surface vessels for short-range sensors, i.e. 2D imaging sonar on a USV [57]. In deep waters (>200 m), a ROV, AUV or towed system is required to map the seafloor in sufficient detail [61]. Consequently, there are fewer detection possibilities in deep waters as not all techniques are suited for these platforms (Fig. 5).

In addition, some platforms (i.e. AUV and USV) provide a certain level of autonomy and can therefore reduce the labor-intensity of the sampling process. Furthermore, the cost of the different platforms is of importance. In its guidance, the EU MSFD Technical Group on Marine Litter analyzed the costs of monitoring the different compartments of the environment through diving, trawling and ROVs [22]. Finally, the use of multiple, complementary monitoring systems in a synergistic approach implemented at sufficient spatial and temporal scales could contribute to a better understanding of the scale of the problem.

3.3. Cost of purchase

Besides the intrinsic objectives and requirements, financial factors can also influence the choice of a particular detection technique. Both operating and non-operating expenses (e.g. maintenance) should be considered when an overall cost is estimated [62]. Given the complexity of a cost-effectiveness analysis and the scope of this review, however, only the cost of purchasing a specific detection technique is reviewed. To increase the interpretability of the deployment possibilities of the techniques, three categories for cost of purchase were determined and added to Fig. 5; i.e. low (€, <10.000 euro), medium (€€, 10.000 - 100.000 euro) and high (€€€, >100.000 euro) cost.

3.4. State-of-the-art detection techniques

Examining the current state of each detection technique for responding to the different objectives allows for benchmarking and defining the required innovation pathways. Each technique can fulfill these objectives differently, showing its strengths and weaknesses, as well as its suitability for plastic monitoring in a marine environment (Fig. 6). Fig. 6 uses a specific color for each objective, with green indicating a complete implementation of the objective, orange representing an almost complete realization of the objective and red indicating that only a small part of an objective is covered. As a result, whenever a technique is awarded 'green' for a certain objective, it will be applicable in diverse cases (e.g. differentiation at the polymer level and material level, capable of covering both small and large areas, or detecting both micro- and macroplastics). In contrast to monitoring data produced by trawling, these digital analysis techniques will allow a revision of data if any improvements in software processing tools for data analysis are developed in the future.

4. Discussion

4.1. Potential detection techniques for the future monitoring of plastic seafloor litter

4.1.1. Sonar systems

Acoustic sonar systems are typically capable of differentiating litter objects from the general natural environment, but cannot classify objects based on their material type (Objective 1, Fig. 3). However, studies have shown that the use of AI (Objective 4, Table B.2, Appendix B) offers the possibility to classify certain litter objects based on their shape [29,43,44,63–67]. Nonetheless, this indirect classification does not consider fragmented litter objects. Hence, there is a high probability that a large proportion of litter objects would be ignored or misclassified using this technique. In addition, trying to decrease the number of missed targets will increase the false alarm rate. To minimize this effect, considerable training datasets would be needed to improve the accuracy and reliability of the AI for litter detection based on acoustic sonar systems.

The actual detection size range of acoustic techniques is relatively large compared to other methods (Objective 3, Fig. 4), ranging from a lower limit of 1–2 cm for 2D imaging sonars and SAS, to an upper limit of several meters. To reach these lower limits, however, ideal circumstances are required. In the case of a 2D imaging sonar, this requires the use of a high-resolution model (e.g. Blueprint Oculus, Teledyne Blueview or Sound Metrics ARIS), a short distance to the target (0.1 - 1 m), and a down angle of 15° [36,68]. For a SAS system, a stable platform (towed system or AUV), precise micro-navigation, a relatively low speed (<5 knots) and a long transducer are required to reach the lower limit. However, micro- and mesoplastics are untraceable with sonar systems. In addition, the maximum distance to the target, and therefore the spatial coverage range, decreases when the detection of smaller objects is desired [43]. Nonetheless, these methods are highly suited to the identification of larger objects and cover larger areas (Objective 2, Fig. 4) compared to electromagnetic techniques, thus allowing large-scale monitoring activities. The 2D imaging

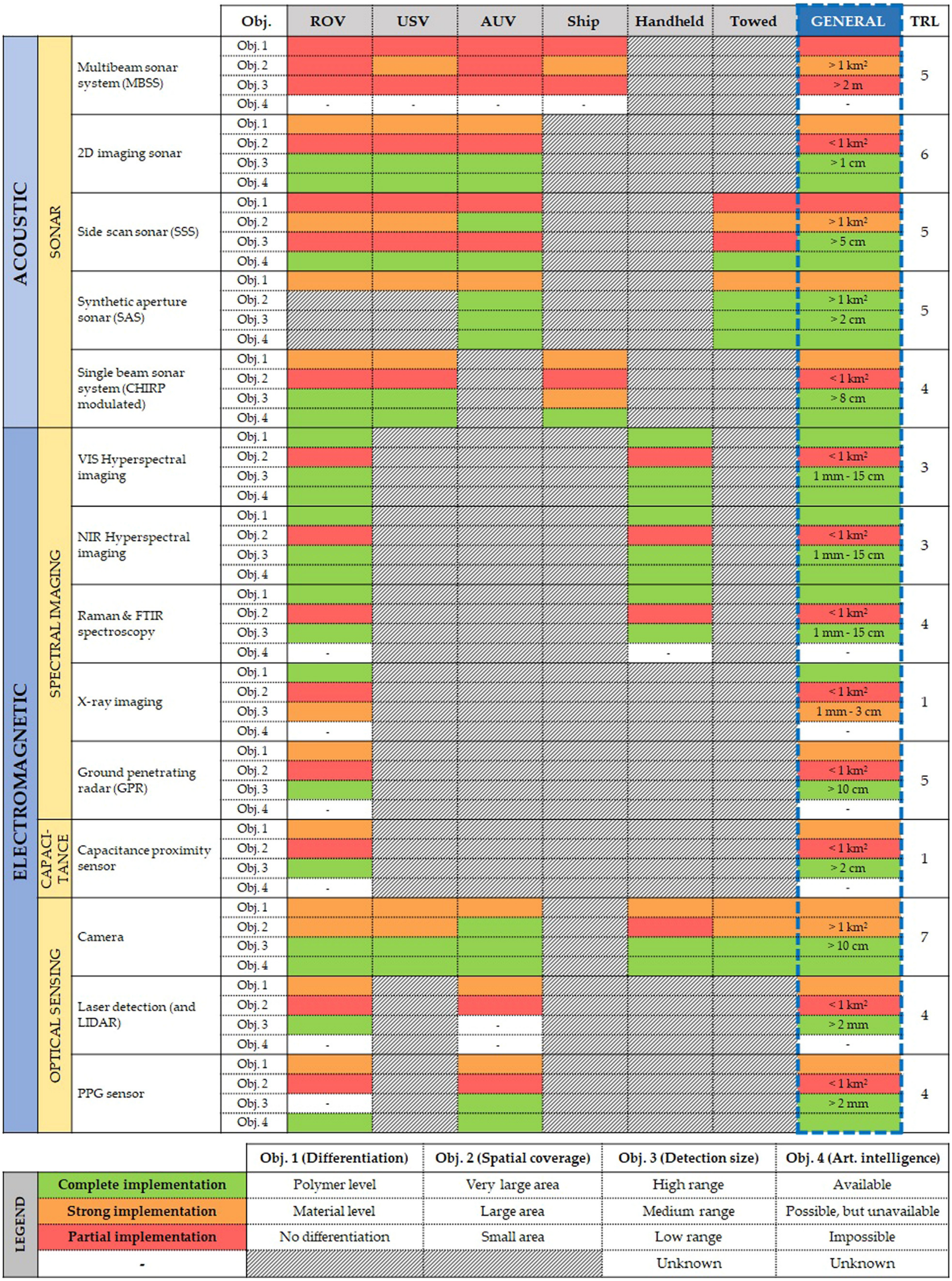

Fig. 6. The implementation of objectives and Technology Readiness Level (TRL) of the different detection techniques based on literature and expert judgement, with the objectives being 1) Identification and differentiation of plastic litter in a marine environment, 2) Spatial coverage of detection techniques, 3) Detection size range of detection techniques, and 4) Artificial intelligence for plastic detection; with green indicating a complete implementation of the objective, orange representing an almost complete realization of the objective and red indicating that only a small part of an objective is covered. Definitions of each TRL level are presented in Fig. A.1 of Appendix A [38].

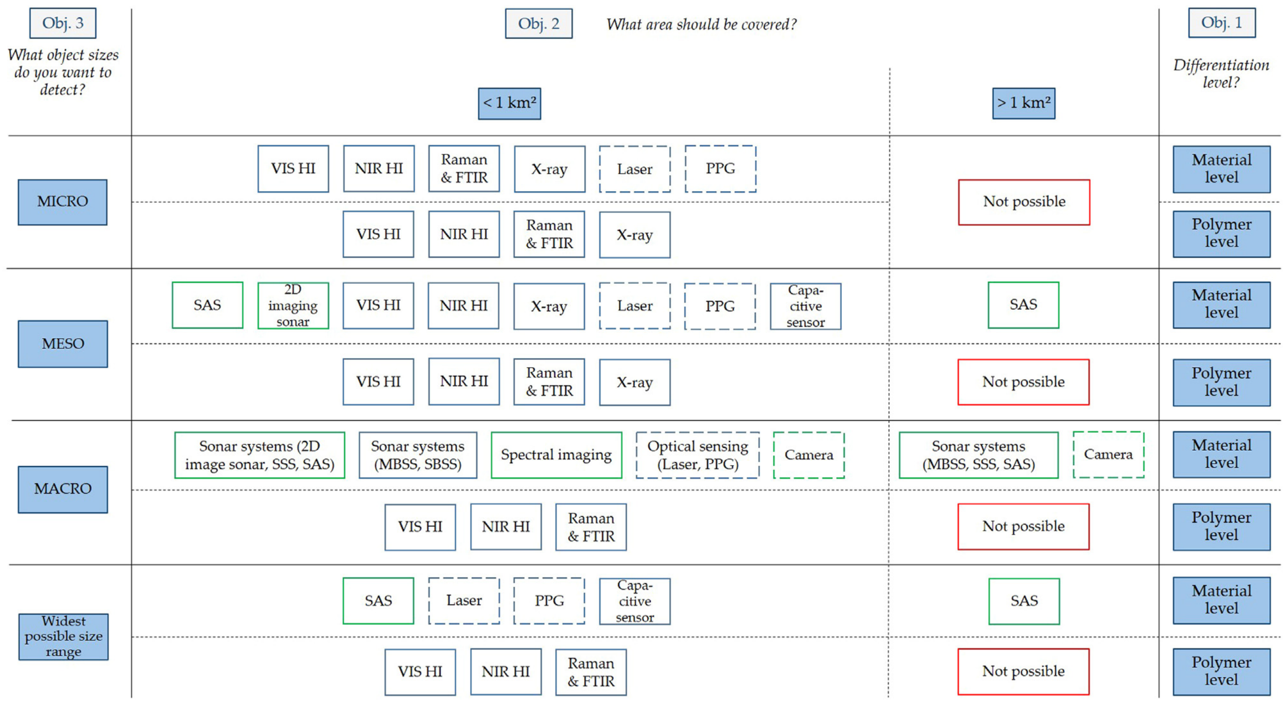

Fig. 7. Decision tool: suitable detection techniques for seafloor litter assessments in different scenarios. Green border: classification of items possible based on Artificial Intelligence (Objective 4), blue border: material or polymer level, red border: combination not possible, dashed border: not applicable in turbid waters.

sonars achieved the largest detection size range (objects greater than 1 cm) of the sonar systems, while the SAS demonstrated the highest spatial coverage with 2.25 km²/h. Given that SAS also has a large detection size range (objects greater than 2 cm), it makes it the most promising sonar system for seafloor plastic detection (Fig. 4) [29,52,55].

Sonar systems are easily compatible with different platforms (Fig. 5), providing a wide range of possibilities for in situ detection. Given their high TRL, sonar systems are easily deployable in several scenarios. Based on the available resources and the dispersed importance of the different objectives in a given scenario (Figs. 6 and 7), different sonar systems may be eligible for plastic monitoring on the seafloor. Currently, SAS has been demonstrated to be the most promising technique for monitoring plastic seafloor litter, followed by side scan sonars, 2D imaging sonars and single beam sonars. For mapping marine plastic litter in sufficient detail in deep areas with a rocky, rough, or steep seabed, a 2D imaging sonar mounted on a ROV may be preferable.

4.1.2. Spectral imaging systems

Hyperspectral and X-ray imaging techniques can differentiate and identify objects on a synthetic polymer level, but currently lack development for in situ applications underwater (Objective 1, Fig. 3). While, Huang et al. [47] have shown the potential of underwater hyperspectral imaging for in situ detection of small plastic particles, further research must determine the suitability of these imaging techniques in marine environments. Pakhomova et al. [69] demonstrated the possibility of using a miniaturized handheld near-infrared spectrometer (MicroNIR) for on-site identification of different plastic polymers. Nonetheless, when analyzing plastic items from the seafloor a preliminary extraction step from the sample matrix is still required owing to the presence of biofouling on the surface of the plastic object that will interfere with the analysis. Furthermore, the short distance required between the system and the target (20–30 cm) means that the spatial coverage is low compared to other detection methods (Objective 2, Fig. 4) [47]. Therefore, these systems are only applicable with platforms that can come within less than 0.5 m of the seafloor (i.e. ROVs). Hyperspectral imaging techniques have a high detection size range (Objective 3, Fig. 4) but are mainly focused on the smaller objects (1 mm – 15 cm). In contrast, the broad detection size range of ground penetrating radar (GPR), which has already been tested in the marine environment [70], is more suited to the identification of larger-sized objects (7 – 100 cm). However, the differentiation of GPR is less accurate than hyperspectral imaging techniques (Fig. 3). Finally, portable Raman and FTIR spectroscopy instruments have been shown to meet the objectives at a comparable level to the hyperspectral imaging techniques, but are less suitable for in situ monitoring because water absorbs IR and measurements require the separation and clean-up of microplastics from the matrix prior to analysis [46]. Nonetheless, Iri et al. [71] have reported the first steps in the development of a portable Raman sensor capable of detecting microplastics in a water-filled quartz cuvette. Moreover, a recent study developed an in situ underwater Raman system compatible with a ROV that could be used for the detection of seafloor objects [72].

Based on their characteristics, hyperspectral imaging techniques are complementary to sonar systems (Figs. 4 and 6). Hence, the most complete approach to monitor the seafloor may be the combination of a sonar system (i.e. SAS or 2D imaging sonars) and hyperspectral imaging. For example, a 2D imaging sonar deployed on a ROV can scavenge the seafloor, and subsequently, hyperspectral imaging can be conducted to gain more detail once an object is detected to gain more detail. Alternatively, an area can first be screened by a SAS-equipped AUV, allowing an area of interest to be selected based on the outcome and then subsequently screened using hyperspectral imaging.

4.1.3. Capacitance systems

Capacitive proximity sensors are widely used in the food processing industry to detect dielectric materials like liquids, glass or plastics [73]. Although this sensor is applicable to underwater conditions, little is known about the possibilities of these sensors in terms of underwater plastic detection [74,75]. This review indicates that capacitive sensors can classify objects based on their material type, if they are larger than 2 cm (Fig. 6). Given the short distance required between the sensor and the object, however, capacitance systems would only be able to document smaller marine areas when operated from a ROV. Further research is recommended to determine the exact boundaries of such systems and their potential future applications. Similarly, examining the possibilities of other detection techniques from terrestrial food or waste treatment industries may create new opportunities for the monitoring of plastic seafloor litter.

4.1.4. Optical sensing systems

Conventional camera systems are widely used as a detection method in the framework of plastic monitoring (e.g. [12,14,58,76–78]). This optical sensing system is affordable, easy to deploy and usable in rough terrains and remote areas when installed on a ROV, AUV or towed system. However, this system is highly dependent on water turbidity [78], only being usable in clear waters. To date, image analysis is predominantly conducted manually, but more recent automation of image annotation using machine learning algorithms has proved successful for classifying objects (Objectives 1 and 4, Fig. 3 and Table B.2, Appendix B) and is therefore capable of differentiating some plastic objects from other objects. In addition, camera systems can detect objects starting from just a couple of centimeters and, when deployed on a USV, AUV or towed mechanism, can cover a relatively large area of up to 0.1125 km²/h (Objectives 2 and 3, Fig. 4) [58]. In the LIFE DEBAG project, for example, a seafloor area of 83 km² was covered with a towed underwater camera [13]. It is important to note that visual detection can provide additional information about the local environmental and biological setting. In this sense, optical systems can provide valuable supporting information that can be used to help determine the impact of marine litter on biota [79]. Recently, underwater polarization camera systems have been put forward to maximize object detection [80,81]. Polarization differences allow better distinction between objects and enhance image quality in turbid waters [81]. This image restoration technique can therefore be relevant in some cases as an additional step between imaging and image processing.

Other optical sensing techniques rely on laser light and photoplethysmograms (PPG) to detect underwater objects [37,82–87]. Both technologies can classify objects based on their material and hence differentiate plastic objects from non-plastic objects (Objective 1, Fig. 3). In addition, the detection size range is large (2 mm to multiple meters) compared to other detection methods (Objective 3, Fig. 4). However, additional scientific evidence is needed to confirm the complete range in both cases. Given the short distance required between these optics and the target, the spatial coverage of these systems is small (Objective 2, Fig. 6). Nonetheless, these systems demonstrate great potential for further examination considering their low-cost (i.e. PPG sensor [87]) and efficiency (i.e. laser system [86]).

4.2. Decision tool and scenarios

To integrate all information gathered on the detection technologies and to increase the applicability of this data, a decision tool has been created (Fig. 7). This decision tool enables easier identification of the most appropriate detection techniques for a certain region or scenario. To clarify its methodology, three different seafloor litter assessment scenarios are demonstrated: (i) Southern North Sea, (ii) Arctic area, and (iii) the Azores. The decision tool is based on the findings from the state-of-the-art (Fig. 6).

Scenario 1: The Southern North Sea is typified by shallow (<40 m) and turbid waters, with currents dominated by semi-diurnal (double) tides. The seabed relief is characterized by a complex system of gullies and sandbanks. Currently, seafloor litter in the North Sea is intensively monitored by registering marine litter collected as bycatch in the net during scientific fisheries surveys, especially the International Bottom Trawl Survey (IBTS) and the Beam Trawl Survey (BTS) coordinated by ICES. Given the drawbacks associated with this way of collecting meso– and macrolitter (>2.5 cm), underwater technologies might provide a promising alternative. In this scenario, litter registration should optimally follow the categorization as described in the ICES Times protocol [27] and enable identification of the material type of the litter objects. A trawl track covers on average 1.47 ha with 5 to 10 tows being conducted on an average sampling day. The covered surface area during a monitoring campaign day is therefore between 15 and 30 ha. As a full monitoring campaign requires several days, techniques with a large spatial coverage are considered necessary. Based on this information, the decision tool recommends the use of SAS for this seafloor litter assessment. This system is compatible with an AUV or can be towed behind a surface vehicle. If the available budget does not allow for the purchase of an expensive SAS system (Fig. 5), a SSS can be considered a good alternative, with the small trade-off that only objects greater than 5 cm will be detected (Fig. 4). A camera system is not applicable because of the high level of turbidity in this area, and a MBSS is as expensive as a SAS (Fig. 5), but less suitable for plastic detection (Fig. 6).

Scenario 2: The Azores is a group of volcanic islands emerging from the mid-Atlantic ridge. The Azorean Exclusive Economic Zone (EEZ) comprises an area of approximately 1 million km^2 with an average depth of about 3000 m. The seafloor topography is very irregular with narrow island shelves and steep slopes made of hard substrates, as well as other features such as seamounts and banks. The seafloor communities within the Azores EEZ are rich in biodiversity and consist of complex deep-sea habitats which include hydrothermal vents, coral gardens and sponge grounds. In this scenario, the aim is to develop a monitoring program of seafloor litter on selected marine litter hotspots (<1 km²) along the island shelves and on offshore seamounts at a depth of 50–800 m. Given the seafloor topography, macroplastic monitoring activities (>10 cm) can only be performed with a ROV, AUV or a towed system. To perform this litter assessment, the decision tool indicates that most detection techniques would be suitable. Based on Fig. 6, the most developed technologies are the camera, 2D imaging sonar, SAS, SSS and GPR. When operating on rough terrain, a camera or 2D imaging sonar operating from a ROV will be most suitable, while monitoring areas with a flatter seabed will be faster with a towed camera or sonar system.

Scenario 3: The Central Arctic Ocean ecoregion encompasses the area of the “Central Arctic and Canadian High Arctic–North Greenland” according to the Large Marine Ecosystems [88,89]. This is mostly a high seas area, remote from landmasses. The Arctic region has a large depth range, consisting of two principle deep basins (Eurasian Basin and Amerasian Basin, between 3800 and 4500 m deep), divided by the Lomonosov Ridge (1300 m deep which rises 3000 m above the seafloor), as well as slopes at 500 m, and shallower shelf areas which boarder the Beaufort/Chukchi and East Siberian/Laptev seas. Reports from both AMAP (Arctic Monitoring and Assessment Programme) and PAME (Protection of the Arctic Marine Environment) called for work to address the transport, pathways, fate and effect of litter and plastics [90,91]. AMAP recommends that methods should be refined for future source and surveillance monitoring as sampling and measurement development is needed. Furthermore, the remoteness and climate of the Arctic poses challenges for establishing monitoring programs [92]. As suggested by PAME [91], this type of monitoring should be employed in regions where abandoned, lost or discarded fishing gear (ALDFG) that is >10 cm may be concentrated (>1 km²). Based on this, the decision tool recommends the use of a camera or a sonar system (SAS, SSS or MBSS) for a seafloor litter assessment targeting

ALDFG (>10 cm). Given the depth range and surface area in the selected region, an SAS or SSS would be the most advantageous choice. As the monitoring area is large and deep, a towed system or an AUV would be the most convenient platforms.

5. Conclusions

The current review has identified 14 technologies that are potentially suitable for in situ plastic detection in marine environments. However, most of these technologies are currently at low-middle TRLs, requiring several more development, testing and commercialization steps before they can be applied effectively in marine field conditions and achieve a level of identification and quantification that is comparable to the existing seafloor litter monitoring programs. Although each technique has advantages and disadvantages when applied for detecting plastic litter on the seafloor, all provide a level of information that can be relevant for environmental status assessments and for guiding management actions to tackle plastic pollution. Several objectives were defined in this study to determine the TRL of each technology and subsequently which would represent the most suitable for different scenarios or regions.

For technologies targeting micro- and mesoplastics, further research is urgently needed. In general, sonar systems (e.g. 2D imaging sonars) and optical sensing systems (e.g. camera) have the highest TRL for in situ meso– and macroplastic detection. SAS has been shown to be the most promising for seafloor plastic detection given its differentiation possibilities, along with the broad detection size range and spatial coverage. Spectral imaging and capacitance systems look promising at the proof-of-concept level, but currently lack validation in an operational environment.

Nonetheless, there is an urgent need to move away from current seafloor litter monitoring approaches based on trawls linked to fish stock assessments. New, less invasive, and environmentally damaging methods must form the basis of this shift. This review indicates that the most suitable system is often very scenario-specific and, therefore, demands investment in more than one specific group of technologies. Given that current environmental monitoring programs do not focus on polymer specific plastics, several technologies (e.g. spectral imaging techniques) may be of less interest as a stand-alone technique. To enable the comparison of data generated by these different technologies as they develop further, there is a need for harmonization of the categories of seafloor litter items and units. These technologies, alone or in combination, have the potential to contribute to the establishment of more robust global environmental indicators and monitoring programs for plastic pollution. The monitoring, research and regulatory communities need to view such technologies as the future for marine litter monitoring and already start to develop a road map for their harmonization, validation, approval and inclusion in official monitoring programs.

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Declaration of Competing Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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Appendix A

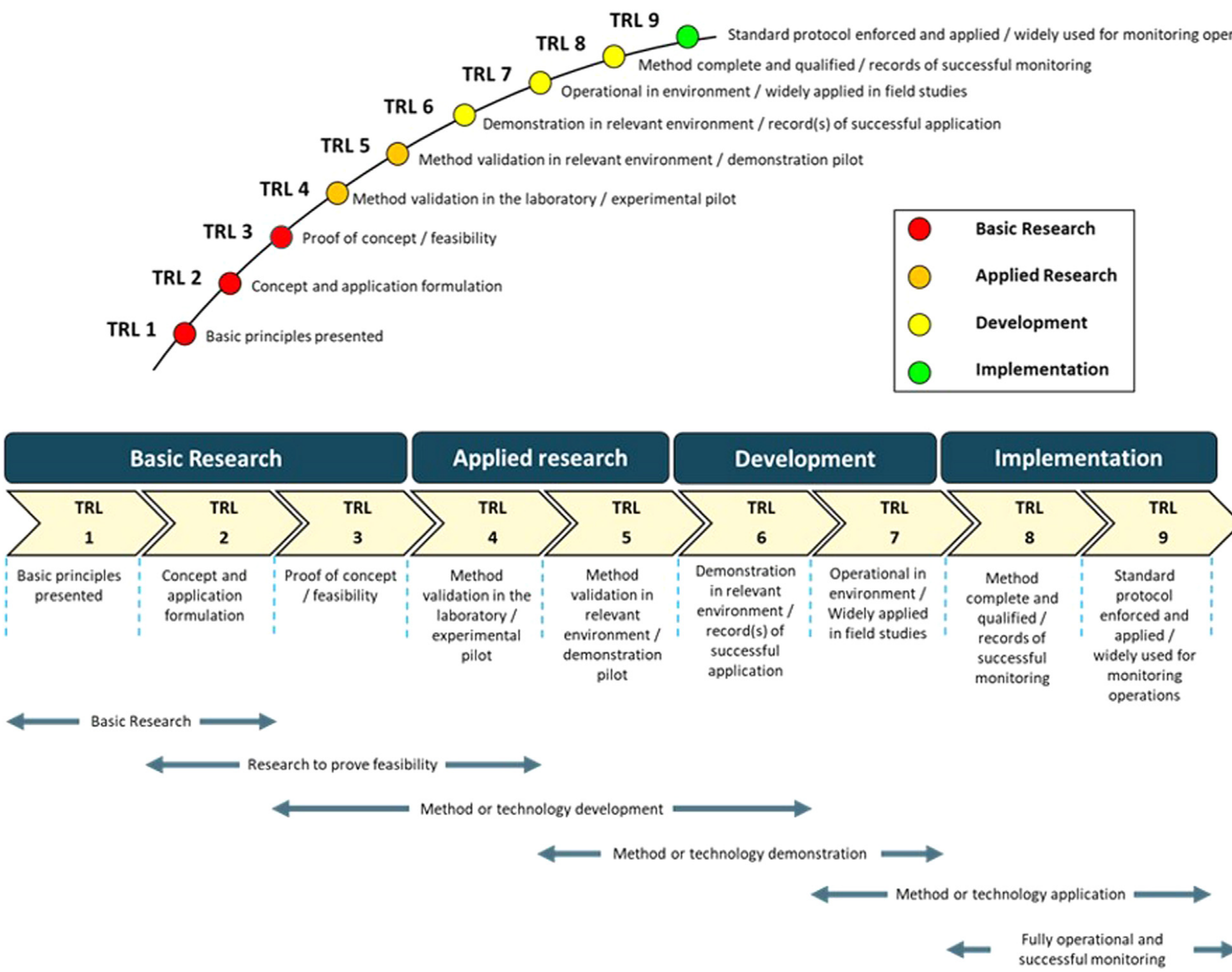

Fig. A1. Technology Readiness Level (TRL) for evaluation of plastic analysis procedures for use in monitoring [38].

Appendix B

Table B1
A subset of the collected data during this systematic review.

	Technique	Detected material types	Method resolution	Detection size range	Spatial coverage	Processing algorithms	Number of publications	Literature
ACOUSTIC				SONAR				
	Multibeam sonar system (MBSS)	Large pieces of macro litter (tires, metal plates)	>1 cm	>2 m	0.097 - 0.728 km²/h		4	[29,36,93,94]
	2D imaging sonar	Metal (cans, hooks, pipes, etc.), plastic (bottles, pipes, etc.), rubber (tires), glass (bottles) and cardboard (drink cartons)	0.23 - 10 cm	>1 cm	0.073 km²/h	Faster-RCNN, VGG-16 and ResNet-50, CNN-Softmax, CNN-SVM, RBoxNet, YOLOv2, RCNN, RRPN, MRF-Net, CenterNet-dla, YOLOv3, RFBNet, SSD300, MAFR-TM, MS-1000	20	[29,36,43,44,57, 63–68,95–103]
	Side scan sonar (SSS)	Large pieces of macro litter	>3 cm	>5 cm	0.125 km²/h	Radial Basis Function Neural Network (RBFNN), Spatial variability analysis (SVA), CSS, MRF, kernel classifier, SVM, CNN, unnamed algorithm	14	[29,55,57,68,104–113]
	Synthetic aperture sonar (SAS)	Plastics (pipes, cones, wedges), steel, rocks, macro litter	>1 cm	>2 cm	1.428 - 2.25 km²/h	SURF, NSEM, CNN, unnamed algorithm	11	[29,52–55,57, 64,95,113–115]
	Single beam sonar system (CHIRP modulated)	Plastic (Bottles, cups, wrapper, containers), rubber, metal (cans)	>1 cm	>8 cm		K-Means clustering algorithm	2	[116,117]
ELECTROMAGNETIC				SPECTRAL IMAGING				
	VIS Hyperspectral imaging	Plastics (PS, PET, PA, PBMA, PE, PP), metal, rubber, fabric, rock, glass	>0.2 mm	1 - 5 mm		SVM (e.g. K-PCA), NN, LS-SVM, PLS-DA, Spectral angle mapper (SAM), ML	7	[45,50,69,118–121]
	NIR Hyperspectral imaging	Plastics (PE, PS, PP, PET, PVC, PA, PC, PUR), metals, rubber, fabric, rock, glass	>0.2 mm	1 - 15 cm		SVM (e.g. k-PCA), NN, Partial least squares-discriminant analysis (PLS-DA), Mahalanobis distance (MD), SAM, Maximum likelihood (ML)	7	[45,50,69,118–121]
	Raman & FTIR spectroscopy	Plastics (HDPE, LDPE, PP, PS, PET)	>1 mm	1 mm - 2.5 cm			4	[46,71,72,122]
	X-ray imaging	Plastics (PVC, PTFE, PET,PC, HDPE, LDPE), metals (ferrous and non-ferrous, stainless steel, aluminum), ceramic, glass, stone	>1 mm	>1 mm			3	[123–125]
	Ground penetrating radar (GPR)	Plastic, glass, aluminum	>10 cm	10 - 100 cm			2	[70,126]
ELECTROMAGNETIC				CAPACITANCE				
	Capacitance proximity sensor	Plastics, paper	>1 mm	>2 cm			3	[48,74,75]
ELECTROMAGNETIC				OPTICAL SENSING				
	Camera	Plastics (bottles, bags, cups, etc.), tires, fabric (nets), metal (cans, etc.)		> +- 10 cm	0.001 - 0.1125 km²/h	CNN (Mask R-CNN, YOLOv2, Tiny-YOLO, Faster R-CNN, SSD, CNN, ResNet50-YOLOv3, YOLOv4, InceptionResNetV2), SURF, Iterative Closest Point (ICP), GLCM, DWT, SVM, LR, KNN, RF, NB	29	[13,36,58,59, 76–78,80,81, 127–147]
	Laser detection (and LIDAR)	Plastic (PET, LDPE), metals (steel), rubber, wood		>0.25 mm			9	[36,82–85, 148–151]
	PPG sensor	Plastic (PET, HDPE, PVC, LDPE, PP, PS)	>2 mm	2 mm - 4 cm		KNN, Random forest	2	[37,87]

Table B2
Existing processing algorithms for macroplastic detection by underwater technologies.

	Technique	Processing algorithms	Literature
ACOUSTIC		SONAR	
	Multibeam sonar system (MBSS)		
	2D imaging sonar	Conventional neural networks (CNN) e.g. Fast R-CNN, Faster R-CNN, YOLO, YOLOv2, RBoxNet, RRPN, Mask-RRPN, FireNet-BN, SSD, CNN-Softmax, CNN-SVM, etc.	[43,44,57,64,65,67,95,97–102]
		Multilayer perceptrons (MLP) e.g. combinations of FC10, FC256, FC512, FC1024	[43,65]
		Support vector machines (SVM)	[43,95,100,101]
		Multiple receptive field network (MRF-Net)	[66]
		Multiple-aspect fixed-range template matching (MAFR-TM)	[63]
		Depth-first search (DFS)	[103]
		Markov Random Field (MRF)	[103]
		Otsu algorithm	[103]
		C-means algorithm	[103]
	Side scan sonar (SSS)	Radial basis function neural network (RBFNN)	[111]
		Spatial variability analysis (SVA)	[105]
		Co-operating statistical snake model (CSS)	[110]
		Markov random field model (MRF)	[110]
		Unnamed detection algorithm	[55,113]
		Kernel ridge regression classifier	[106]
		Support vector machines (SVM)	[108]
		Conventional neural networks (CNN)	[107]
	Synthetic aperture sonar (SAS)	Speed up robust feature algorithm (SURF)	[54]
		Unnamed detection algorithm	[55,113]
		Normalized shadow-echo matching (NSEM)	[53]
		Conventional neural networks (CNN)	[114,115]
	Single beam sonar system (CHIRP modulated)	K-Means clustering algorithm	[116,117]
ELECTROMAGNETIC		SPECTRAL IMAGING	
	VIS Hyperspectral imaging	Support vector machines (SVM) e.g. k-PCA	[47,120,121,152]
		Neural networks (NN)	[47,121,153]
		Least squares-support vector machine (LS-SVM)	[47]
		Partial least squares-discriminant analysis (PLS-DA)	[47,118]
		Spectral angle mapper (SAM)	[121,154]
		Gaussian process or maximum likelihood (ML)	[121,155]
	NIR Hyperspectral imaging	Support vector machines (SVM) e.g. k-PCA	[45,120,121,152]
		Neural networks (NN)	[121,153]
		Partial least squares-discriminant analysis (PLS-DA)	[118]
		Mahalanobis distance (MD)	[45]
		Spectral angle mapper (SAM)	[121]
		Gaussian process or maximum likelihood (ML)	[45,121,155]
	Raman & FTIR spectroscopy		
	X-ray imaging		
	Ground penetrating radar (GPR)		
ELECTROMAGNETIC		CAPACITANCE	
	Capacitance proximity sensor		
ELECTROMAGNETIC		OPTICAL SENSING	
	Camera	Conventional neural networks (CNN) e.g. Faster R-CNN, Mask R-CNN, SDD, YOLO, YOLOv2, YOLOv3, YOLOv4, ResNet50-YOLOv3, Tiny-YOLO, VGG, ResNet, InceptionResNetV2, Shuffle-Xception, MobileNet, LeNet, DenseNet, InceptionV3, ConvNet, etc.	[58,59,127–129,131,132,134,135,137,140,143–147]
		Gray level co-occurrence matrix (GLCM)	[136]
		Discrete wavelet transform (DWT)	[136]
		Support vector machine (SVM)	[59]
		Logistic regression (LR)	[59]
		K-nearest neighbor (KNN)	[59]
		Random forest (RF)	[59]
		Naïve bayes (NB)	[59]
		Speed up robust feature algorithm (SURF)	[138]
		Iterative Closest Point (ICP)	[138]
	Laser detection (and LIDAR)		
	PPG sensor	K-nearest neighbor (KNN)	[37,87]
		Random forest (RF)	[37,87]

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