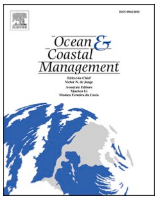
Ocean and Coastal Management 238 (2023) 106555

Contents lists available at ScienceDirect

Ocean and Coastal Management

journal homepage: www.elsevier.com/locate/ocecoaman



Assessing the performance of marine plastics cleanup technologies in Europe and North America

Roy Brouwer[a,b,*], Yichun Huang[a], Tessa Huizenga[b], Sofia Frantzi[b], Trang Le[c], Jared Sandler[a], Hanna Dijkstra[b], Pieter van Beukering[b], Elisa Costa[d], Francesca Garaventa[d], Veronica Piazza[d]

[a] *Department of Economics and Water Institute, University of Waterloo, 200 University Avenue West, Waterloo, Ontario, N2L 3G1, Canada*
[b] *Institute for Environmental Studies, Vrije Universiteit Amsterdam, De Boelelaan 1087, 1081 HV, Amsterdam, the Netherlands*
[c] *School of Environment, Resources and Sustainability, University of Waterloo, 200 University Avenue West, Waterloo, Ontario, N2L 3G1, Canada*
[d] *National Research Council, Institute for the Study of Anthropic Impacts and Sustainability in the Marine Environment (CNR-IAS), Via De Marini 6, 16149, Genova, Italy*

ARTICLE INFO

Keywords:
Plastic litter
Clean-up technology
Cost-effectiveness
Multi-criteria analysis

ABSTRACT

This study fills an important gap in policymaker understanding of the effectiveness and implementation costs of marine plastic cleanup technologies. Previous studies have mainly listed inventories of different plastic litter cleanup technologies, not systematically examined their cost-effectiveness. Through a survey in Europe and North America that asked for cost and cleanup capacity data, per kilogram cost figures were calculated for several categories of cleanup technologies, ranging from fixed-in-place filters in stormwater drainage systems to mobile skimmers on water. Mobile skimmers and dredgers appear to be most cost-effective. Adding performance criteria related to operational conditions and ease of use, such as energy use and economies of scale, dredgers and stormwater filters rank higher. Litter traps in drainage systems are most preferred when furthermore considering weather sensitivity and whether technologies operate standalone, making them an interesting complementary technology to skimmers and dredgers to prevent plastic litter from entering water courses. These results show how sensitive the outcome of the ranking is to the inclusion of additional operational criteria, how different categories of technologies can effectively be combined in the plastic waste supply chain, and what the cost implications are for the future upscaling of plastic litter cleanup technologies.

1. Introduction

Plastic litter has accumulated rapidly and presents serious threats to the marine environment and society (Maes et al., 2021). Plastics are the largest marine litter category, accounting for at least 85% of total marine waste (Maes et al., 2021). Much of the plastic litter (80%) originates from land-based sources and finds its way to seas through a variety of pathways, including river, atmospheric transport, and beach littering. The remaining 20% of marine plastic litter are from water-based sources, i.e. they are produced directly at sea by aquaculture, shipping and fishing activities (Li et al., 2016; Lebreton et al., 2017). Less than 10% of all plastics ever produced have been recycled (Geyer et al., 2017), and plastic production and consumption are expected to continue to grow despite recent bans on, for example, single use plastics worldwide (OECD, 2022). Plastics' persistence in seas makes it a major concern (Lebreton et al., 2017). Due to the complicated and uncertain impacts of plastic use and disposal, plastic pollution has been deemed a 'wicked' problem, i.e., a problem without clear solution (Landon-Lane, 2018). The massive abundance of litter in our natural environment, in particular plastics in our oceans and seas (Ritchie and Roser, 2018), has made it imperative to improve our scientific and technological understanding of how to best address marine plastic litter (Maes et al., 2021).

There has been a rapidly increasing number of studies focusing on marine plastic litter cleanup technologies (e.g. Schmaltz et al., 2020; Winterstetter et al., 2021; Nikiema and Asiedu, 2022). These technologies target a full range of litter, from micro litter that is invisible to the naked eye to visible macro litter. This study presents a new and unique overview of the main characteristics of different types of visible plastics clean-up technologies, including their costs and effectiveness in capturing and removing plastic litter from freshwater and marine water bodies. Technical and cost data were collected through an international survey targeting companies that develop and market plastic litter

---

* Corresponding author. Department of Economics and Water Institute, University of Waterloo, 200 University Avenue West, Waterloo, Ontario, N2L 3G1, Canada.
E-mail address: rbrouwer@uwaterloo.ca (R. Brouwer).

https://doi.org/10.1016/j.ocecoaman.2023.106555
Received 11 November 2022; Received in revised form 28 January 2023; Accepted 28 February 2023

capture and removal devices in Europe and North America. Compared to the existing literature, these data allow us to conduct a more detailed cost-effectiveness and multi-criteria analysis. The results of these analyses inform policy and decision-making not only about the available different types of marine plastic litter cleanup technologies, but more importantly the least cost way to capture and remove plastics at prevention and cleanup points along different plastic litter pathways. The collected data include details that technology owners prefer to keep confidential in order not to undermine their competitiveness, especially when a technology is relatively new and has not yet reached market maturity. Due to the sensitivity of the data, they have been anonymized and aggregated in the analysis so results cannot be traced back to individual technologies.

2. Existing inventories of marine plastic technologies

Inventories of different marine plastic technologies are reported in Schmaltz et al. (2020) and Bellou et al. (2021). Based on a systematic global literature review, the latter identified 177 technologies, most of which (60%) relate to monitoring devices developed primarily by the scientific community, including sampling and detection. Out of the remaining 71 technologies that can either prevent or clean marine litter, only 15 had the highest Technology Readiness Level (TRL 9), which indicates they are ready for full operation. In a similarly extensive and systematic review of internet resources, including news articles and the environmental solutions platform Ubuntoo, Schmaltz et al. (2020) identified 52 technologies, 14 of which prevent the leakage of plastic pollution into waterways and 38 collect plastic waste, mainly macroplastics. Although no TRL information is provided, 9 of the 14 preventive technologies (64%) and 27 of the 38 collection technologies (71%) are "in use".

Using the same global online platform (Ubuntoo), Winterstetter et al. (2021) asked 13 anonymous experts to identify available plastics prevention and cleanup technologies for deployment specifically in developing countries, based on information provided by technology owners. Only 55% of the technologies had TRL 9 and 51% consisted of marine litter cleanup technologies (the rest focused on plastic processing and treatment, digital solutions like citizen's apps, remote sensing or integrated waste management solutions), of which 23% was land-based (mainly beaches) and the other 77% were either employed in rivers and streams or in the sea. Most sea-based solutions furthermore focused on the recovery of fishing gear. For each intervention point from land to sea two examples are highlighted. Winterstetter et al. (2021) conclude that the most cost-effective solutions tackle land-based sources of marine litter, which they defined as technologies that recover plastics from harbors, lakes and areas of the ocean within easy reach of land. They estimated that the average costs of these solutions are roughly USD 400 per ton of collected plastic waste. Ocean cleanup is not considered a first-choice solution, because the overall amount of floating plastic and the concentration of litter in oceans is considered relatively low. The important role of the presence of litter is highlighted in Falk-Andersson et al. (2020), who discuss the various factors that influence the cost-effectiveness of marine litter clean-up technologies based on the fisheries literature. They identify litter density and accessibility as a key factor, pointing out that density may vary spatially and over time, giving acute spills such as through ship wrecking, container loss and storm events as an example.

Besides technical background descriptions and geographical focus, also the costs per ton of captured litter is presented in Winterstetter et al. (2021), but in half of the cases (for 3 of the 6 technologies) part of the cost data are missing, mainly because of corporate confidentiality of investment and operation costs. Helinski et al. (2021) similarly reviewed solutions that can be deployed in rivers, including booms, watercraft vehicles and receptacles and found only 35% reported capacity or efficiency. Costs were also context dependent and not always publicly available, which led the researchers to create categories of cost estimates, i.e. low (≤\$10,000), medium (>\$10,000 and ≤\$100,000) and high (>\$100,000). Most devices were categorized as medium cost, but this was not tied to their effectiveness.

Dijkstra et al. (2021) identified 105 companies active in marine plastic management and reviewed their business models using publicly available information. The companies rarely publish data on the effectiveness of their litter management strategies, and the study concluded that more comprehensive sustainability reporting is needed in the industry. Murphy et al. (2022) identified the lack of consistent cost accounting as a major gap in the literature and present a conceptual framework for the identification of different types of economic, social and ecological costs and benefits of plastic pollution interventions for different sectors and stakeholders. They illustrate their framework with the help of two examples, a solid waste management project in the Philippines and the Clearwater Mills Trash Wheel in the inner harbor of Baltimore, also included in the reviews by Schmaltz et al. (2020) and Winterstetter et al., 2021. Although Murphy et al. (2022) provided a detailed overview of the various cost items related to the Trash Wheel, no indication is given of its cost-effectiveness.

Winterstetter et al. (2021) estimate that the cost of operation (including transport and disposal of waste) and maintenance for the Trash Wheel amounts to approximately USD 750 per ton of waste, excluding installation costs, which were estimated at USD 382 to 895 thousand depending on the location. Using a 10-year time frame (the time period over which the Trash Wheel was evaluated in Murphy et al. 2022) and an interest rate of 5%, the total cost per kg of waste for the Trash Wheel including the mentioned installation costs would be between USD 1.00 and 1.30 (own calculation).

This is on the lower end of the range of unit costs presented in Nikiema and Asiedu (2022) for three in-stream plastic capture technologies, i.e. sea bins, booms and trash racks. Sea bins are floating trash bins installed like the trash wheel in ports or marinas that skim the surface of the water by pumping water into the device which allows it to intercept floating debris, including plastics. A boom is a floating barrier designed to prevent litter from continuing to float downstream, while trash racks are structures with bars that block and guide litter into a set trap before it flows downstream. Although no information is provided about the TRL of the technologies, most seem to be applied already. Cost data originate mainly from the Seabin project (http://seabinproject.com/), the company Elastec in the USA for booms and the UK Government costing tool of a wide range of flood and coastal risk management measures for trash racks. In their cost calculations, Nikiema and Asiedu (2022) estimated that trash racks are orders of magnitude more expensive (USD 4.87–8.46 per kg of plastic) than sea bins (USD 1.24–1.55 per kg of plastic), while booms are the most expensive technology to capture 1 kg of plastic (USD 22.5–30.1).

3. Methodology

3.1. Data collection

Existing inventories and reviews of technologies (e.g. Schmaltz et al., 2020; Winterstetter et al., 2021) were used as a starting point for the identification of companies that develop marine plastic litter capture and removal technologies. The focus here was on companies in Europe and North America (Canada and the USA). Company websites with technologies that were already in the market were screened. Digital platforms such as Google, Facebook and LinkedIn were used to search and obtain contact information. Thirty-seven companies were identified for which contact information was available, including 2 companies that participated in the Horizon2020 project CLAIM (https://www.claim-h2020project.eu/).

An online survey was created and set up using Qualtrics, with technical questions about the technologies and their costs and effectiveness in capturing and removing plastic litter. Technology companies were contacted via a standardized email that included a link to the online survey. The survey consisted of thirty questions and is reproduced in the supplementary information (SI) to this article. The questions aimed at improving the understanding of the functioning and operation of the various technologies, in particular their costs and clean-up performance. The survey participants were guaranteed that their responses would be treated confidential and the information they provided would only be used for this study and not for commercial purposes.

A total of 53 survey links were sent to 37 technology companies across Europe and North America between May 13 and May 17, 2021. The number of links is greater than the number of companies, because some companies developed and market more than one technology. Out of these 53 links, 27 are for technologies developed by 20 European companies, 20 for technologies from 12 American companies, and 6 for technologies from 5 Canadian companies. To encourage survey participation, reminder emails were sent to 12 companies that had not clicked on their survey links or left the survey incomplete two weeks later. After this first reminder, more questionnaires were completed. Ten days later, a second reminder email was sent, but this did not result in any more completed surveys.

We also offered companies the opportunity to do an online interview instead of the online written survey. Three companies preferred to provide the information during a Zoom call. These interviews took place between May 20 and June 3, 2021, and data was collected in this way for five plastic litter cleanup technologies. Feedback was ultimately received from 20 of the 37 companies, yielding a response rate of 59%, for 25 of the 53 technologies.

3.2. Data analysis

3.2.1. Cost-effectiveness analysis

The purpose of a cost-effectiveness analysis is to find out how an objective, for example a predetermined target of resource recovery or removing a certain amount of plastics from water, can be achieved at the lowest cost possible (e.g. Brouwer, 2022). Various possible marine plastic cleanup technologies are ranked in increasing order of their marginal costs, i.e. the costs (€) to capture and remove one extra unit (kg) of plastic waste. Besides a different marginal cost, each technology usually also has a specific cleanup capacity. The least-cost technology is the one that is able to remove 1 kg of plastic litter at the lowest unit cost. Typically, marginal costs are hard if not impossible to find in practice unless a detailed cost function can be specified, and the analysis for cost-effective solutions therefore often relies on the average costs to remove one unit of waste. This also applies to the cost information provided in the survey in this study. These costs are based on the companies' expert judgment of the average capital, operation and maintenance costs of their specific technologies in the year 2021 to capture and remove plastic litter.

Using the information provided by the technology developers, a first step was to harmonize the measurement units across all technologies, e.g. kilograms in Europe and Canada, pounds in the US; US dollars in the US, Canadian dollars in Canada and Euros in Europe. All values are expressed in Euros and kilograms. Then one-off capital expenditures (CAPEX) were annualized to make them comparable with the annual operation and maintenance expenditures (OPEX). To this end, we amortized the one-off costs of the technologies equally over their lifetime using a 5% annual interest rate. By combining the annualized one-off costs, annual operation and maintenance costs and the technologies' clean-up capacity, the total annual costs per unit of litter capture and clean-up can be calculated.

Table 1
Design of the multicriteria analysis (MCA).

Criterion	Description	Criteria set			MCA method	
		1	2	3	SAW	TOPSIS
1	Technical lifetime	✓	✓	✓	✓	✓
2	Annualized costs (€/year)	✓	✓	✓	✓	✓
3	Clean-up capacity (kg/year)	✓	✓	✓	✓	✓
4	Number of people	✓	✓	✓	✓	✓
5	Energy use (kWh)		✓	✓	✓	✓
6	Economies of scale (%)		✓	✓	✓	✓
7	Standalone/automated (yes/no)			✓	✓	✓
8	Training needed (yes/no)			✓	✓	✓
9	Weather sensitive (yes/no)			✓	✓	✓
Number of evaluation criteria		4	6	9		
Number of plastic cleanup technologies		14	11	11		

3.2.2. Multi-criteria analysis

Additionally, we extend the cost-effectiveness analysis to a multi-criteria analysis (MCA). We include various other evaluation criteria, such as technical lifetime, labour input, energy use, and weather sensitivity. As not all questions were answered for all technologies, we utilize three criteria sets containing 4, 6 and 9 criteria to minimize the dropout of technologies. The overview of MCAs conducted in this study is shown in Table 1.

Because the outcome of an MCA is often not just sensitive to the selection of criteria, but also the method of analysis, we use two different methods: simple additive weighting (SAW) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Kaliszewski and Podkopaev, 2016). For simplicity reasons and because we are particularly interested in the possible change in ranking of technologies due to the addition of new evaluation criteria, we weigh each criterion equally.

As the number of evaluation criteria increases, the number of plastic litter cleanup technologies decreases due to missing information for specific criteria. We start with the 14 technologies for which we have both cost and effectiveness data, but we include the annualized costs and cleanup capacity as separate criteria. Beyond costs and effectiveness, the decision to implement a cleanup device faces other considerations such as operational conditions and ease of use (Helinski et al., 2021). We therefore construct three MCAs with additional relevant criteria. The first includes technical lifetime of the technologies and the number of people needed to operate the technologies (criteria set 1). We then extend this with the criteria energy use and economies of scale (criteria set 2), and finally several binary criteria related to whether the technology can be operated as an automated standalone technology, whether specialized training is needed, and whether the technology is vulnerable to stormy weather conditions (criteria set 3).

The normalization procedure to make the effect scores of each technology comparable across criteria is slightly different when using SAW and TOPSIS (see Eq. (1)- Eq. (4)). The main difference between the two methods lies in how the integrated performance score, which is the basis for the ranking of the technologies, is derived. SAW ranks based on weighted averages (see Eq. (5)), whereas TOPSIS ranks technologies based on their similarity to the positive ideal solution (see Eq. (6)). Based on these two different normalization procedures and assuming equal weights for each evaluation criterion, the different marine plastics cleanup technologies can be ranked.

$$V_{RAW}^{i,b} = \frac{\textit{performance score of a specific alternative} - \textit{minimum performance score}}{\textit{maximum performance score} - \textit{minimum performance score}} \quad \text{Eq. (1)}$$

$$V_{RAW}^{i,c} = \frac{\textit{maximum performance score} - \textit{performance score of a specific alternative}}{\textit{maximum performance score} - \textit{minimum performance score}} \quad \text{Eq. (2)}$$

$$V^{i,b}_{TOPSIS}=\frac{performance\ score\ of\ a\ specific\ alternative}{\sqrt{\sum each\ single\ alternative's\ performance\ score^2}} \qquad \text{Eq. (3)}$$

$$V^{i,c}_{TOPSIS}=1-\frac{performance\ score\ of\ a\ specific\ alternative}{\sqrt{\sum each\ single\ alternative's\ performance\ score^2}} \qquad \text{Eq. (4)}$$

where V is the normalized performance score of an alternative (i.e. a technology) on each criterion, superscript i denotes the index of each criterion, superscript c and b means that the i-th criterion measures the cost or benefit of a technology respectively, and the subscript shows the specific methods for MCA.

$$Score_{SAW}=\sum_{i=n}^{N}\omega_i \bullet V^i_{RAW} \qquad \text{Eq. (5)}$$

$$Score_{TOPSIS}=\frac{\sqrt{\sum_{i=n}^{N}\left[\omega_i \bullet V^i_{TOPSIS}-\min_i\left(\omega_i \bullet V^i_{TOPSIS}\right)\right]^2}}{\sqrt{\sum_{i=n}^{N}\left[\omega_i \bullet V^i_{TOPSIS}-\min_i\left(\omega_i \bullet V^i_{TOPSIS}\right)\right]^2}+\sqrt{\sum_{i=n}^{N}\left[\omega_i \bullet V^i_{TOPSIS}-\max_i\left(\omega_i \bullet V^i_{TOPSIS}\right)\right]^2}} \qquad \text{Eq. (6)}$$

where N is the number of criteria, ω_i denotes the i th criterion's weight, and superscript c or b is removed because we do not consider whether a criterion is cost or benefit in this final step.

4. Results

4.1. Plastic litter cleanup technologies

Most of the surveyed technologies (32%) are implemented in the USA, followed by Canada and the UK (16% each), and most have a TRL of 9 (68%). The list of companies and a brief description of each technology is provided in the SI. Twelve of the 25 technologies are also included in the inventories of previous studies, in particular Schmaltz et al. (2020). Hence, just over 50% of the technologies in our database are not covered anywhere else and therefore presented for the first time in this study. The Clearwater Mills Trash Wheel in Baltimore, USA is by far the most highlighted plastic cleanup technology, followed by the WasteShark developed in the Netherlands by RanMarine Technology, and the Bandalong Litter Trap sold by Storm Water Systems in Cleveland, USA. For an overview of the extent to which the technologies overlap across studies, see the SI.

Despite targeting technologies that are already on the market, one technology is just an idea (TRL 1), 5 technologies are between TRL 5 and TRL 7, which means that the technologies have been validated in their operational environment, and two technologies are in TRL stage 8, which means that they are complete and qualified. The two technologies focusing on microplastics in wastewater treatment both have a TRL of 6. One of the two TRL5 technologies is merely described as treating and reducing the volume of a variety of waste materials at the source and reuse of waste by-products and aggregates.

The variety of marine litter capture and removal technologies in the database is illustrated in Fig. 1. Participating companies focus on plastic litter cleanup on the land, like a beach, and in the water. Most of the technologies (68%) operate on the water and try to capture and remove litter from surface waters. This includes booms, which are typically located near river mouths preventing litter transported by rivers to enter lakes, seas or oceans; skimmers that either actively (mobile) or passively (immobile) suck up litter, and dredgers that remove litter from the surface or bottom of a water body, or accumulated litter in smaller water bodies such as channels and ditches.

Unfortunately, not all 25 information sets included sufficient data to conduct a cost-effectiveness analysis, including the two microplastics technologies and the unknown technology treating waste materials at source. Out of 25 sets of information, only 14 were complete to conduct a full cost-effectiveness analysis.

4.2. Ranking of technologies based on their cost-effectiveness

The average one-off CAPEX and annual OPEX for the different plastic litter cleanup technologies are presented in Fig. 2. All categories listed in Fig. 1 are included except microplastics removal in wastewater treatment. In the case of CAPEX, the costs mainly consist of materials and installation costs, while labor and energy are the main underlying drivers of OPEX. For the labor component, the litter capture devices in stormwater drainage systems, booms, and immobile skimmers only require labor input for installing the technologies and removing the captured litter from the site where the technologies are implemented.

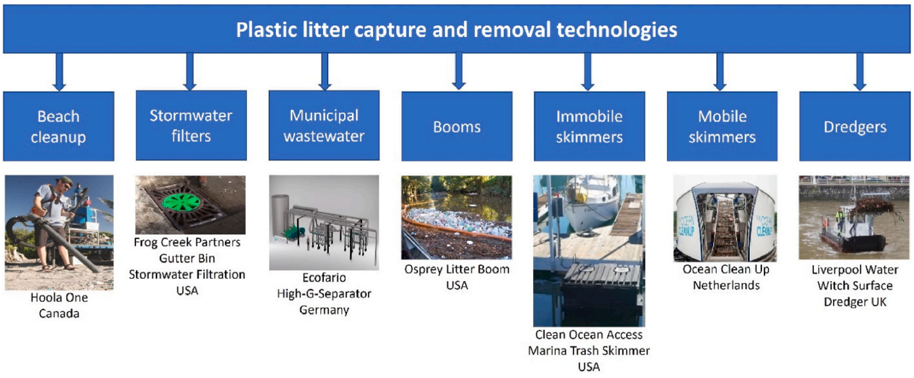


Fig. 1. Examples of the various types of plastic litter collection and removal technologies from around the world included in the database (pictures are downloaded from the companies' public websites).

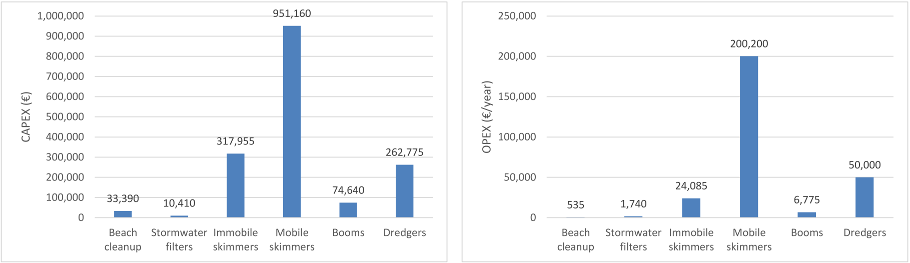


Fig. 2. Average capital expenditures (CAPEX) (left) and operation expenditures (OPEX) (right) per plastic litter cleanup technology category.
Note: values have been rounded.

The technologies are otherwise stand-alone and need no labor between litter removals. Especially immobile skimmers require specialized operational skills. Often the organization hiring or purchasing the immobile skimmer is trained on site during installation, with maintenance services offered by the company marketing the skimmers. Similarly, booms and other litter capture devices in stormwater systems are installed by experts working for the companies that sell them, and their services are usually hired prior to technology implementation to identify where to best install them, and once installed to remove the captured litter off-site and regularly maintain the devices.

Booms need to be checked approximately every fortnight, while immobile skimmers and beach cleanup technologies need monthly maintenance. The maintenance of filters in stormwater drainage systems occurs approximately quarterly. The booms and stormwater filters do not use energy during operation, while energy use is considerable for the mobile and immobile skimmers and dredgers. Only three technologies indicated that they operate on solar energy.

The mobile skimmers have by far the highest CAPEX and OPEX. The CAPEX of mobile skimmers are, on average, three times higher than those of immobile skimmers or dredgers, while their OPEX are a factor 4 to 8 higher. The average CAPEX of devices in stormwater drainage systems are lowest and merely a fraction (1%) of those of mobile skimmers. Preventing floatable plastics from entering the water through drainage systems therefore is a much cheaper solution than trying to capture and remove them afterwards using skimmers, dredgers or booms.

Beach cleanup is also a relatively cheaper solution, both in terms of CAPEX and OPEX. This technology targets a different source, i.e. litter either left behind by beach visitors or washed ashore, but also seems to confirm, as also concluded by Winterstetter et al. (2021), that litter capture and removal on the land is cheaper than litter capture and removal from the water. Interestingly, beach clean-up has the lowest OPEX to CAPEX ratio (less than 2%), followed by immobile skimmers and booms (7–9%). Dredgers and mobile skimmers have equally higher ratio's (19–21%), while stormwater filters have a similar but slightly lower OPEX to CAPEX ratio (16–17%).

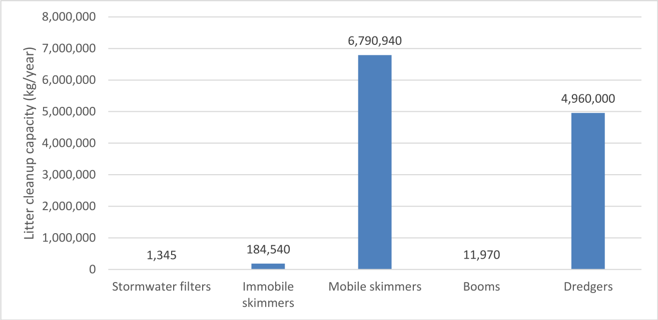


Fig. 3. Average cleanup capacity of plastic litter per cleanup technology category.
Note: values have been rounded.

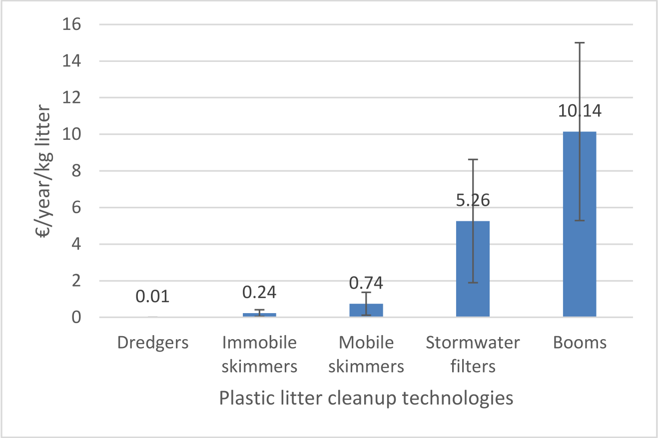


Fig. 4. Average unit costs per plastic litter cleanup technology category.
Note: The unit costs consist of CAPEX and OPEX. Error bars reflect the average unit costs' standard errors.

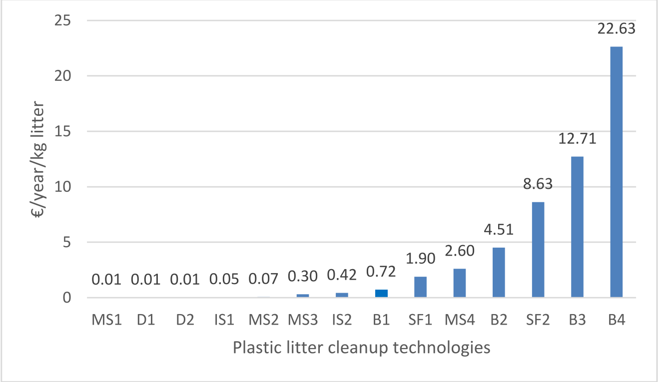


Fig. 5. Unit costs per plastic litter cleanup technology.
Notes: The unit costs consist of CAPEX and OPEX. MS: mobile skimmer. D: dredger. IS: immobile skimmer. B: boom. SF: stormwater filter. The numbers refer to the individual technologies within each technology category in the database.

While the most expensive, mobile skimmers also collect and clean up the most floatable plastic litter. This is shown in Fig. 3. Mobile skimmers and dredgers can remove between 5 and 7 thousand tons of plastic waste annually. The devices installed in stormwater drainage systems remove just over a ton per year, which is around 10% of the amount of plastics removed by booms from rivers. An important reason for this is that the filters installed in stormwater drainage systems are mainly effective when it rains, allowing water flows to transport the plastic litter, whereas rivers typically flow constantly and have been shown to be an important source of plastics and thus capture overall more litter than filters in drainage systems. No information is available about the cleanup capacity of the beach technology.

There exists a lot of variation in litter capture for both stormwater filters and booms, most likely because their performance is highly dependent on the presence of litter at the locations where they are implemented. The estimated annual amount of litter captured by the filters in stormwater drainage systems varies between 110 and 3800 kg per year, while for booms this is between 135 and 46,000 kg.

The average annual unit costs (consisting of CAPEX and OPEX) to capture and remove one kg of plastic waste across the various cleanup technology categories are presented in Fig. 4, and the ranking of the anonymized individual technologies in terms of their increasing unit cleanup costs per kg of plastic litter in Fig. 5. As in Fig. 3, beach cleanup is not shown in Fig. 4 or 5 because it lacked information about its cleanup capacity.

Fig. 4 shows a gradually declining increase of average annual cleanup costs when moving from the cheapest cleanup technology (dredgers) to the most expensive cleanup technology (booms). It also shows, as can be seen from the standard error bars, that there is considerable unit cost variation within each category of cleanup technology. Overall, Figs. 4 and 5 tell a similar story. The water-based dredgers and immobile and mobile skimmers are the most cost-effective plastic waste cleanup technologies. In the case of dredgers, the average unit cost is just €0.01 per kg of litter, whereas this is €0.24 per kg for immobile skimmers and €0.74 per kg in the case of mobile skimmers. The unit costs go up considerably to over €5 per kg when moving to the land-based technologies installed upstream in stormwater drainage systems, while the booms are, on average, the most expensive plastic litter capture technologies as also shown in Nikiema and Asiedu (2022).

4.3. How does the ranking change when more performance criteria are added?

When considering in addition to the technologies' implementation costs and cleanup capacity also their technical lifetime and the number of people involved in their operations, the ranking of technologies changes, irrespective of the MCA method (Table 2). Instead of mobile skimmer MS1, now the two dredgers are ranked first (D1 and D2). Using SAW, D1 and D2 are ranked first and second, respectively. Using TOPSIS, dredger D2 is ranked first, followed by the two mobile skimmers MS1 and MS2. Both SAW and TOPSIS rank MS2 third, but differ in the next ranked technology. One of the two devices installed in stormwater drainage systems (SF2) is ranked fourth when using SAW, followed by the most cost-effective mobile skimmer MS1, whereas dredger D1 is ranked fourth based on TOPSIS, followed by SF2. Notably, both methods rank the same immobile (IS2) and mobile skimmers (MS4) last.

When adding energy use as a negative criterion and economies of scale as a positive criterion into the MCA under criteria set 2, two of the mobile skimmers (MS1 and MS3) and one of the immobile skimmers (IS2) drop out of the analysis because of missing values. Under this second criteria set, the rankings seem to stabilize, and dredger D1 is ranked first under SAW and TOPSIS. The top two ranking under TOPSIS is the same as under criteria set 1. The litter filter in stormwater drainage systems (SF1) is ranked second and third under SAW and TOPSIS, respectively. The ranking of the second stormwater filter SF2 remains the same as under the first set of criteria. Remarkably, the previously third ranked plastic litter cleanup technology MS2 drops to the second last position under criteria set 2, and the same mobile skimmer (MS4) remains ranked last.

Adding the last three binary criteria, i.e. automated standalone (positive), necessary training (negative) and weather sensitivity (negative), results in the two dredgers D1 and D2 remaining in the top 3 under TOPSIS, but not under SAW. The first stormwater filter SF1 is ranked first when using 9 criteria. The second drainage system device SF2 is ranked second under SAW, while one of the booms (B2) is ranked third this time. As before under the second criteria set, the two mobile skimmers are ranked last. The normalized scores of the various technologies on the 9 criteria are visualized in radar graphs in Fig. 6 for both SAW and TOPSIS. The same graphs for 4 and 6 criteria are available from the authors upon request.

5. Discussion and conclusions

The main objective of this study was to assess the performance of existing plastic litter cleanup technologies in Europe and North America. Compared to previously published reviews of plastic litter cleanup technologies, this is the first assessment that provides a more detailed break-down of the costs and litter removal capacity of different technologies in a cost-effectiveness analysis using the same cost accounting framework. It also presents the first MCA of marine plastic litter cleanup technologies. Previous studies either present an inventory of different types of available technologies (e.g. Bellou et al., 2021; Schmaltz et al., 2020) or a more limited comparative evaluation of selected technologies. The study by Winterstetter et al. (2021) present incomplete unit costs of 4 different marine litter cleanup technologies, while the study by Nikiema and Asiedu (2022) report what they refer to as the 'typical' investment and operation and maintenance costs per kg of plastic for 3 technologies, namely booms, trash racks and sea bins.

In this study, we collect data for 25 plastic litter capture and removal technologies, more than half of which are not covered in any of the previous reviews, and categorize them based on their point of intervention in the plastic litter supply chain. For 14 of these technologies, we manage to collect sufficient data to conduct a more detailed cost-effectiveness analysis and MCA. Although still relatively limited, this is a substantial increase in the number of observations compared to the existing empirical evidence base. Moreover, for each type of technology between two and four data points are available.

Comparing the unit costs from previous studies with the values found in this study, our unit costs are generally lower. For example, converting the unit cost for the Trash Wheel in Winterstetter et al. (2021) into Euros per kg, their estimated value without installation costs is substantially higher than the value derived in our study.[1] Similarly, the midpoint estimate for the range of unit costs reported for booms in Nikiema and Asiedu (2022) is almost a factor two higher than the same midpoint estimate in our study for booms. The highest unit cost for booms in our study overlaps with the lower end of the range presented in Nikiema and Asiedu (2022). Only the unit cost range of the trash racks overlaps in our study and theirs.

What is also remarkable is that the unit cost of the sea bin is a factor two higher in Nikiema and Asiedu (2022) than in Winterstetter et al. (2021). Hence, also across previous studies substantial differences exist between unit cost estimates. These differences are either caused by differences in cost estimates or, more likely, differences in the amount of on-site litter capture and removal. Although companies were asked to consider the technologies' average annual cleanup capacity, many indicated that this is highly dependent on the presence of litter, as also pointed out by Falk-Andersson et al. (2020). The self-reported cleanup estimates within technology categories therefore varied widely, and we had no possibility to independently cross-check the self-reported information from the technology companies. An important recommendation for future cross-validation would be to identify the exact locations where the technologies are implemented. This could provide more background information about how much litter was present on-site. However, even if the locations are known where the technologies are implemented, not many urban watersheds, ports or marinas have such detailed litter monitoring data.

---

[1] The CAPEX for the trash wheel in our study is exactly the same as the total capital asset costs reported in Murphy et al. (2022). The OPEX in our study are, however, lower than in Murphy et al. (2022).

Table 2
Ranking of the plastic litter cleanup technologies applying different criteria sets.

Plastic litter clean-up technology		Cost-effectiveness analysis	Criteria Set 1		Criteria Set 2		Criteria Set 3	
			SAW	TOPSIS	SAW	TOPSIS	SAW	TOPSIS
Stormwater filters	SF2	12	4	5	4	5	2	4
	SF1	9	7	7	2	3	1	1
Immobile skimmers	IS1	4	8	8	5	6	8	8
	IS2	7	13	13	n.a.	n.a.	n.a.	n.a.
Mobile skimmers	MS2	5	3	3	10	10	10	10
	MS1	1	5	2	n.a.	n.a.	n.a.	n.a.
	MS3	6	11	12	n.a.	n.a.	n.a.	n.a.
	MS4	10	14	14	11	11	11	11
Dredgers	D1	2	1	4	1	1	4	3
	D2	3	2	1	8	2	6	2
Booms	B4	14	6	6	3	4	7	7
	B1	8	9	9	7	7	5	5
	B3	13	10	10	9	9	9	9
	B2	11	12	11	6	8	3	6

Explanatory notes: SF: stormwater filter. IS: immobile skimmer. MS: mobile skimmer. D: dredger. B: boom. The numbers refer to the individual technologies within each technology category in the database. n.a.: these technologies drop out because of missing data when adding evaluation criteria.

■ Ranked first ▨ Ranked second □ Ranked third

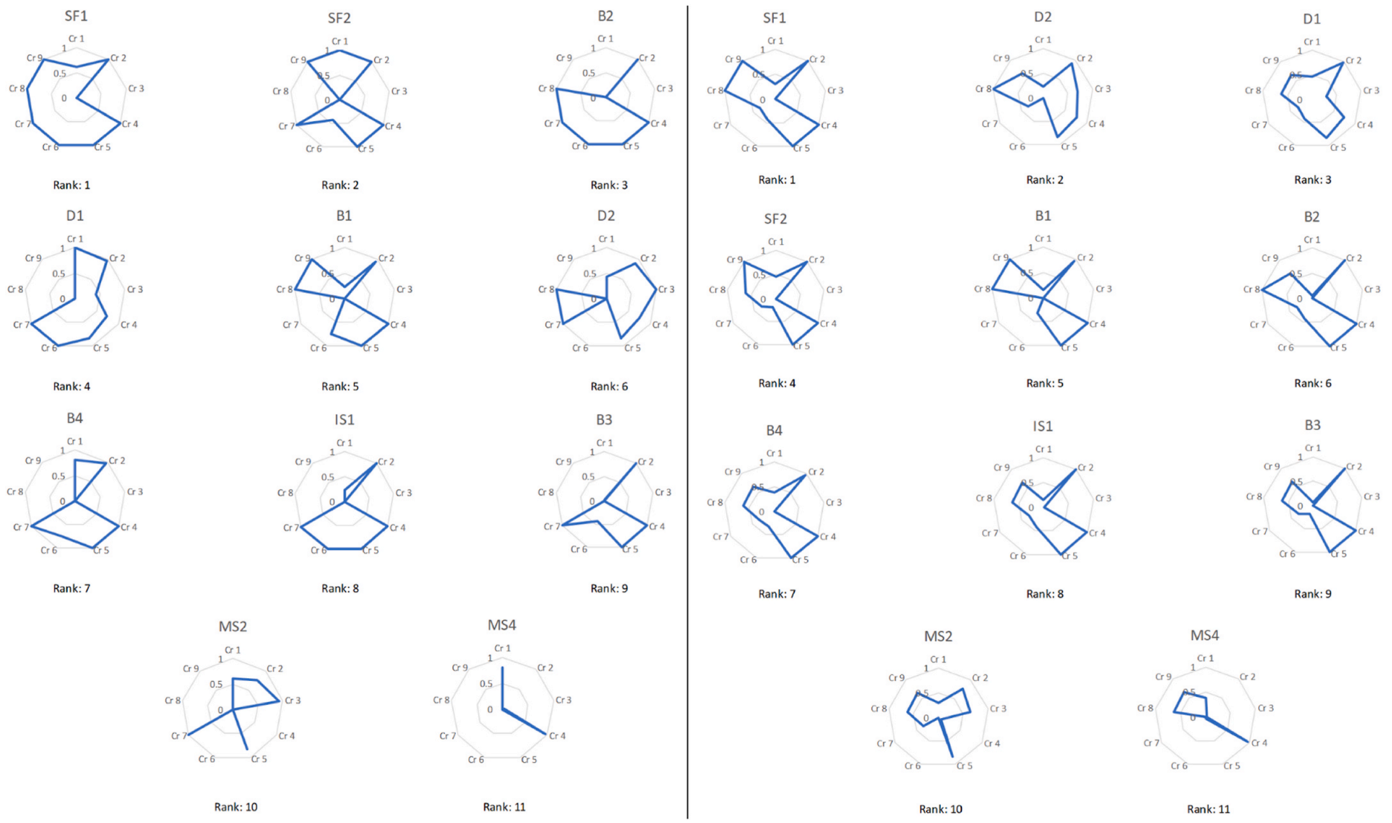


Fig. 6. Example of SAW (left) and TOPSIS (right) normalized performance scores of plastic litter cleanup technologies across 9 evaluation criteria. Explanatory notes: Cr1: technical lifetime (years). Cr2: annualized costs (€/year). Cr3: litter cleaning capacity (kg/year). Cr4: energy use (kWh/day). Cr5: Number of people. Cr6: Economies of scale (%). Cr7: automated standalone (yes/no). Cr8: training needed (yes/no). Cr9: weather sensitive (yes/no).

Similarly, although we asked companies to truthfully share the actual installation, operation and maintenance costs, the reported cost estimates could not be cross-checked. Murphy et al. (2022) present one of the most detailed cost assessments for a particular technology (the Baltimore trash wheel) in the literature. An important reason for this is that the city of Baltimore has been paying for a large share of these costs over the past 10 years and hence has a detailed cost record. The question is whether such detailed cost breakdowns will ever be available for all other technologies. Besides the resources needed to look up the detailed cost data, data confidentiality will play an important role, and data may not be shared as it might undermine the competitiveness of the companies offering the technologies and operation services in this rapidly emerging market of plastic litter cleanup.

We acknowledge that additional criteria could have been included in the MCA that capture important risks associated with the implementation of the technologies. For example, the possible negative effects of the water-based technologies on aquatic habitats or wildlife. Although we asked the technology providers about possible side effects of their technologies, almost nobody answered this question. Some mentioned that organic materials would be captured and removed at the same time, but this did not seem to be considered a negative byproduct. Other risks include congestion of stormwater infrastructure as a result of the installation of stormwater filters, clogging up the pipes that transport excess stormwater and increasing the risk of local flooding. This information will most likely have to be collected from other sources than the technology providers self, for example the municipalities that implement the technologies to hear their experiences.

Despite these possible shortcomings, the cost-effectiveness analysis shows unequivocally that mobile skimmers and dredgers are least costly to remove plastic litter from water, with an average unit cost ranging between 1 and 74 Euro cents per kg. Their annual costs can be substantial, but so is their litter reduction capacity. Although there exists some variation in unit costs across dredgers and skimmers, these solutions are largely substitutable. Filters installed in stormwater drainage systems upstream on the land are much cheaper than skimmers and dredgers, but have less litter trapping capacity. Moreover, their cleanup capacity is surrounded by more uncertainty due to the fact that they depend heavily on stormwater flows. This requires careful inspection of the watershed to identify the best locations to install them. However, stormwater filters move up in the ranking quickly and become the first ranked technology when accounting for additional criteria such as energy use, autonomy of application, training and weather extremes, making them an interesting complementary technology to skimmers and dredgers to prevent plastic litter from entering water courses. Filters installed in drainage systems have also been argued to be able to capture a broader spectrum of sinkable pollutants besides floatable plastic, such as sediments and tire treads. Contrary to the above mentioned risk, they have also been argued to have the advantage of avoiding clogging of stormwater drains with debris when emptied regularly. These results show how sensitive the prioritization of specific cleanup technologies is to the inclusion and exclusion of specific selection criteria. Local policy and decision-maker input will therefore be indispensable. Criteria such as necessary manpower and training, autonomy of technology implementation, energy use and economies of scale are expected to play a key role in decision-making related to the future implementation and upscaling of plastic litter cleanup technologies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

This study was funded under the European Horizon 2020 project CLAIM: Cleaning Litter by developing and Applying Innovative Methods in European Seas (grant agreement no. 774586) and the Natural Sciences and Engineering Research Council of Canada (NSERC) funded project Microplastics fingerprinting at the watershed scale: From sources to receivers. We are grateful to the companies and technology developers who agreed to share information about their technologies with us. The authors remain as always responsible for any errors in the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ocecoaman.2023.106555.

References

Bellou, N., Gambardella, C., Karantzalos, K., Gama Monteiro, J., Canning-Clode, J., Kemna, S., Arrieta-Giron, C.A., Lemmen, C., 2021. Global assessment of innovative solutions to tackle marine litter. Nat. Sustain. 4, 516–524. https://doi.org/10.1038/s41893-021-00726-2.

Brouwer, R., 2022. Economic analysis of resource recovery. In: Pikaar, I., Guest, J., Ganigué, R., Jensen, P., Rabaey, K., Seviour, T., Trimmer, J., van der Kolk, O., Vaneeckhaute, C., Verstraete, W. (Eds.), Resource Recovery from Water: Principles and Application. International Water Association (IWA) Publishing, pp. 365–382. https://doi.org/10.2166/9781780409566_0365.

Dijkstra, H., van Beukering, P., Brouwer, R., 2021. In the business of dirty oceans: overview of startups and entrepreneurs managing marine plastic. Mar. Pollut. Bull. 162, 111880 https://doi.org/10.1016/j.marpolbul.2020.111880.

Falk-Andersson, J., Larsen Haarr, M., Havas, V., 2020. Basic principles for development and implementation of plastic clean-up technologies: what can we learn from fisheries management? Sci. Total Environ. 745, 141117 https://doi.org/10.1016/j.scitotenv.2020.141117.

Geyer, R., Jambeck, J.R., Law, K.L., 2017. Production, use, and fate of all plastics ever made. Sci. Adv. 3 (7), e1700782 https://doi.org/10.1126/sciadv.1700782.

Helinski, O.K., Wolfand, J.M., Poor, C.J., 2021. Ridding our rivers of plastic: a framework for plastic pollution capture device selection. Mar. Pollut. Bull. 165, 112095 https://doi.org/10.1016/j.marpolbul.2021.112095.

Kaliszewski, I., Podkopaev, D., 2016. Simple additive weighting - a metamodel for multiple criteria decision analysis methods. Expert Syst. Appl.: Int. J. 54, 155–161. https://doi.org/10.1016/j.eswa.2016.01.042.

Landon-Lane, M., 2018. Corporate social responsibility in marine plastic debris governance. Mar. Pollut. Bull. 127, 310–319. https://doi.org/10.1016/j.marpolbul.2017.11.054.

Lebreton, L.C., Van Der Zwet, J., Damsteeg, J.W., Slat, B., Andrady, A., Reisser, J., 2017. River plastic emissions to the world's oceans. Nat. Commun. 8, 15611 https://doi.org/10.1038/ncomms15611.

Li, W.C., Tse, H.F., Fok, L., 2016. Plastic waste in the marine environment: a review of sources, occurrence and effects. Sci. Total Environ. 566, 333–349. https://doi.org/10.1016/j.scitotenv.2016.05.084.

Maes, T., McGlade, J., Fahim, I.S., Green, D.S., Landrigan, P., Andrady, A.L., Costa, M.F., Geyer, R., Gomes, R., Hwai, A.T.S., Jambeck, J., 2021. From pollution to solution: a global assessment of marine litter and plastic pollution. Published online at unep.org. https://www.unep.org/resources/pollution-solution-global-assessment-marine-litter-and-plastic-pollution.

Murphy, E.L., Bernard, M., Iacona, G., Borrelle, S.B., Barnes, M., McGivern, A., Emmanuel, J., Gerber, L.R., 2022. A decision framework for estimating the cost of marine plastic pollution interventions. Conserv. Biol. 36, e13827 https://doi.org/10.1111/cobi.13827.

Nikiema, J., Asiedu, Z., 2022. A review of the cost and effectiveness of solutions to address plastic pollution. Environ. Sci. Pollut. Res. 29, 24547–24573. https://doi.org/10.1007/s11356-021-18038-5.

OECD, 2022. Global Plastics Outlook: Economic Drivers, Environmental Impacts and Policy Options. OECD Publishing, Paris. https://doi.org/10.1787/de747aef-en.

Ritchie, H., Roser, M., 2018. Plastic Pollution. Published online at OurWorldInData.org. https://ourworldindata.org/plastic-pollution. (Accessed 10 July 2022).

Schmaltz, E., Melvin, E.C., Diana, Z., Gunady, E.F., Rittschof, D., Somarelli, J.A., Virdin, J., Dunphy-Daly, M.M., 2020. Plastic pollution solutions: emerging technologies to prevent and collect marine plastic pollution. Environ. Int. 144, 106067 https://doi.org/10.1016/j.envint.2020.106067.

Winterstetter, A., Grodent, M., Kini, V., Ragaert, K., Vrancken, K.C., 2021. A review of technological solutions to prevent or reduce marine plastic litter in developing countries. Sustainability 13, 4894. https://doi.org/10.3390/su13094894.