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Integrating Bayesian Belief Networks in a toolbox for decision support on plastic clean-up technologies in rivers and estuaries☆

Giulia Leone [a,b,e,*], Ana I. Catarino [a], Ine Pauwels [b], Thomas Mani [c], Michelle Tishler [c], Matthias Egger [c,d], Marie Anne Eurie Forio [e], Peter L.M. Goethals [e], Gert Everaert [a]

[a] *Flanders Marine Institute, Ostend, Belgium*
[b] *Research Institute for Nature and Forest, Aquatic Management, Brussels, Belgium*
[c] *The Ocean Cleanup, Rotterdam, The Netherlands*
[d] *Egger Research and Consulting, St. Gallen, Switzerland*
[e] *Ghent University, Research Group Aquatic Ecology, Ghent, Belgium*

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A B S T R A C T

Current mitigation strategies to offset marine plastic pollution, a global concern, typically rely on preventing floating debris from reaching coastal ecosystems. Specifically, clean-up technologies are designed to collect plastics by removing debris from the aquatic environment such as rivers and estuaries. However, to date, there is little published data on their potential impact on riverine and estuarine organisms and ecosystems. Multiple parameters might play a role in the chances of biota and organic debris being unintentionally caught within a mechanical clean-up system, but their exact contribution to a potential impact is unknown. Here, we identified four clusters of parameters that can potentially determine the bycatch: (i) the environmental conditions in which the clean-up system is deployed, (ii) the traits of the biota the system interacts with, (iii) the traits of plastic items present in the system, and, (iv) the design and operation of the clean-up mechanism itself. To efficiently quantify and assess the influence of each of the clusters on bycatch, we suggest the use of transparent and objective tools. In particular, we discuss the use of Bayesian Belief Networks (BBNs) as a promising probabilistic modelling method for an evidence-based trade-off between removal efficiency and bycatch. We argue that BBN probabilistic models are a valuable tool to assist stakeholders, prior to the deployment of any clean-up technology, in selecting the best-suited mechanism to collect floating plastic debris while managing potential adverse effects on the ecosystem.

1. Introduction

Plastic pollution is a widespread issue of global concern. Therefore, there is an increasing effort to mitigate the presence of plastic debris in the environment. Since the beginning of plastic mass production in the 1950s, discards have led to plastic debris being found everywhere in the environment (Fahrenkamp-Uppenbrink, 2018), from mountain tops (Napper et al., 2020) to the deep sea (Barnes et al., 2009). The plastic pollution issue is highly relevant for marine ecosystems due to its impact on marine life (Lusher et al., 2018). Plastics that accumulate in marine environments originate from various sources. For instance, abandoned or lost fishing gears are a significant source of plastic pollution (Richardson et al., 2019). However, it is estimated that the majority of ocean plastics have a land-based origin (Li et al., 2016). To reach the marine ecosystem, terrestrially originated plastic fluxes are majorly transported via riverine systems. Current model estimates indicate that about 1000 rivers account for almost 80% of the annual global riverine plastic emissions into the ocean, ranging between 0.8 million and 2.7 million metric tons per year (Meijer et al., 2021). The flow of these plastic items towards the marine environment could remain significant for the upcoming decades due to societal lifestyles and human behaviours that became highly dependent on plastics (Parker, 2018), and the fact that plastics can persist in the environment for several years to decades (Ryan et al., 2009). Thus, "legacy" plastic pollution that has already accumulated in riverine environments may gradually get washed out into the marine domain. In this context, Borrelle et al.

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* Corresponding author. Flanders Marine Institute, Ostend, Belgium.
E-mail address: giulia.leone@vliz.be (G. Leone).

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(2020) and Lau et al. (2020) calculated that substantial reductions in plastic waste emission can only be achieved by immediate and concrete actions, with major technological intervention playing an imperative role. However, preventive measures to reduce the input of plastic debris to marine ecosystems have only been recently implemented, with 'circular economy' principles still in their infancy (European Commission, 2020, 2019a; Ministry of Environment and Forestry, 2020). Currently, one of the best approaches to mitigate marine plastic pollution is to prevent debris from entering the ocean in the first place. Once in the ocean, floating plastic debris can rapidly spread due to a "dilution" effect, and its removal becomes difficult and more costly (Helinski et al., 2021; Hohn et al., 2020). End-of-pipe and in-situ solutions, such as plastic clean-up technologies, are currently being developed to actively or passively remove buoyant plastics from aquatic systems such as rivers and estuaries (Schmaltz et al., 2020). Manifold are the mechanisms used in the plastic clean-up technologies that are currently deployed in freshwater environments. Water-wheels, litter boom equipped with conveyor belts or curtains of air bubbles are examples of different mechanisms. With the development of more legislative targets to minimize and remediate plastic pollution (European Commission, 2008, 2019b) the design and deployment of new plastic clean-up technologies is likely to increase in the coming years.

2. Presentation of the concern

Together with improved waste management efforts and the use of sustainable materials, the deployment of clean-up technologies in riverine and estuarine environments is a required solution to reduce environmental plastic pollution (Schmaltz et al., 2020). However, to date, there is a lack of empirical data concerning their efficiency and potential environmental impact (Bellou et al., 2021; Helinski et al., 2021), and a lack of integrated models to analyze both the impacts of plastics in the environment and potential responses in the context of sustainable development (Forio and Goethals, 2020).

Estuarine and riverine environments are amongst the world's most productive biomes, providing fundamental life support systems for humans (Costanza et al., 1997). Estuarine sheltered waters support unique communities of native and endemic plants and animals, specially adapted for life at the seas margins and are often serving as important spawning or nursing grounds to commercially relevant as well as to endangered species (Maes et al., 2005; Vasconcelos et al., 2011). Protecting these habitats is imperative from an ecological and economic point of view (Kennish, 2003). Therefore, the deployment of human-made infrastructures, including plastic clean-up technologies, requires careful consideration as not to negatively impact the habitats around them. To date, externally sourced environmental impact assessments are performed by some of the clean-up technologies companies. These assessments are important tools to establish an initial understanding of potential environmental impacts of the technologies for a specific location, project type, and used for permits and regulatory decision making.

However, an independent and objective tool to support stakeholders and river managers in deploying these clean-up technologies to prevent and reduce the unintentional bycatch is currently not available yet.

Overall, the following knowledge is scarce or missing in published scientific literature:

- Objective and standardised quantification of the potential bycatch by plastic clean-up technologies common to all companies performing these operations;
- Insight into the probability of specific biota getting caught;
- Information on how environmental parameters can influence the chance of bycatch;
- An off-the-shelf tool to support a decision framework to assist stakeholders in selecting the adequate technology and optimize the operation to minimize impacts under specific environmental settings.

3. Way forward: Bayesian Belief Network models to support the selection of suitable plastic pollution solutions

Multiple criteria and related parameters might play a role on the likelihood of potential bycatch of clean-up devices, making it a multidimensional knowledge gap. Here, we identified four main clusters that could contribute to the probabilities of bycatch occurring. These are: (i) the **environmental conditions** in which the clean-up system is deployed, (ii) the **traits of the biota** the system interacts with, (iii) the **traits of plastic** items present in the river system, and (iv) the **mechanism** behind the remediation technology itself (Fig. 1).

The first cluster (i) relates to the local river conditions. The transport of plastic debris in rivers is highly influenced by hydrological conditions, such as flow velocity, water level and river discharge (van Emmerik and Schwarz, 2019), as well as the presence of organic debris such as reed or other biological material (van Emmerik et al., 2019). The second cluster (ii) is related to all aspects of the unintentional bycatch. Typical factors describing the unintentional bycatch are the size of the biota, shape, density, buoyancy, as well as adhesiveness and mobility. The unique physical characteristics of the biota might influence their chances of being caught by the clean-up systems. For instance, adhesiveness – a typical characteristic of certain fish eggs (Rottmann et al., 1991) – could increase their likelihood to be unintentionally caught as a secondary bycatch, while sticking to floating plastic items or organic debris. However, other traits of biota could reduce the chances of them becoming bycatch, such as smaller size or swimming capacity linked to avoidance potential (Coutant and Whitney, 2000). The third cluster (iii) integrates all aspects of the targeted anthropogenic debris (i.e. shape, size, volume, buoyancy and its degree of weathering and biofouling). Environmental plastics, due to their various degrees of weathering or biofouling, alongside their various sizes, shapes and densities, are complex and diverse. Therefore, their characteristics cannot be limited to a set of discrete values, but they rather cover a continuous parameter space (Kooi and Koelmans, 2019). A possible approach to account for the continuous nature of plastic debris is to work with probability density distributions on the primary characteristics of the plastic items. A recent

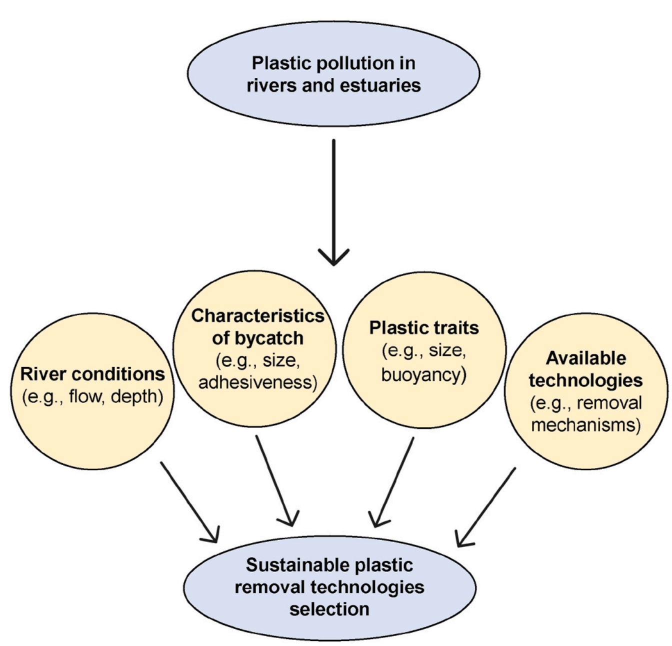

Fig. 1. Parameters that play a role in the selection of sustainable plastic removal technologies.

and relevant example of such approach is the work conducted by Kooi and Koelmans (2019) in which the complexity of environmental microplastics is simplified by the use of continuous probability distribution for size, shape and density. This parametrization ensures an approximate yet representative depiction of environmental microplastics capturing the variability of plastics and ensuring a more representative characterization. The fourth cluster (iv) relates to the envisaged clean-up technology itself, including its design and operation. Each plastic remediation technology, based on its mechanical and physical function, has the potential to collect more or less debris in the categories of plastics, as target, as well as organics, and biota as bycatch. Thus, it is fundamental to individually address the technological approaches behind the clean-up devices (e.g., water wheels, booms or nets with conveyor belts, curtain of air bubble etc.).

Alongside these four clusters, which are essential in creating a decision framework to support stakeholders in their choices of clean-up devices, other externalities such as available budget and relevant legislations can be important when choosing a clean-up remediation technology over another. However, these additional externalities will not be discussed further in this paper since they do not directly influence the potential collateral bycatch of the clean-up technologies. In fact, the proposed approach is an environmental based decision framework. All other aspects, such as costs and legislation are non-environmental externalities.

To create such a decision support framework, we suggest the use of Bayesian Belief Networks (BBNs), probabilistic graphical models that have demonstrated efficiency and utility in supporting river management decisions. The BBN models consist of an oriented acyclic graph in which the nodes are discrete variables and the arrows causal relationships (Van Echelpoel et al., 2015). These models differ from other modelling techniques as most methods focus on accurately quantifying the response variable while BBNs provide probabilistic predictions of all considered variables. With uncertainty accounted for in the model itself, BBNs are particularly suitable as a decision support tool for managing systems where quantifying uncertainty is paramount. Bayesian Belief Networks are also implemented in a causal graphical structure, which can be easily understood by non-technical stakeholders (Chen and Pollino, 2012). Furthermore, BBNs are very useful for cases where diverse sources of data and knowledge need to be integrated, because the method can combine information from literature and experts in addition to data from field and lab experiments. Bayesian Belief Networks work with discrete variables and/or categorized variables. Continuous variables can be included in a BBN. However, in this case, discretization is needed (Landuyt et al., 2013). For BBNs to be successful, it is of paramount importance to find an appropriate balance between the model complexity and model fit with realistic development and simulation times (Goethals and Forio, 2018). This balance can be achieved by focusing on key processes in the system and its management, and by using simplified methods for the description of relations among variables (such as probabilistic methods). Models based on BBNs have been widely applied for river management purposes (Marcot et al., 2001; Piffady et al., 2021) and often been used as computational background for risk-based adaptive environmental management (Barton et al., 2020). The BBN technique has often been used in trade-off analyses, since it allows for the clear probabilistic description of systems and processes (Forio et al., 2020). The earlier success of BBNs in supporting river management decisions, and the advantages described above indicate that this type of models can potentially serve as decision support tools for the implementation of riverine and estuarine plastic clean-up technologies.

Based on the multiple criteria and related parameters that might play a role on the likelihood of potential bycatch of clean-up devices, and the advantages that BBNs offer in supporting river management decision, we identified six fundamental steps to the creation and validation of a decision support framework (Fig. 2). This framework could be used as a guideline for the selection of suitable plastic remediation technologies, prior to the deployment of the clean-up system, which could be adapted to users' needs. Each specific user will have to also consider other externalities. For instance, the feasibility of a technology or operation in a specific location based on local regulations, specific partnerships, or costs. Moreover, prior to deploying the device, stakeholders should also assess, as part of an environmental impact assessment, whether rare or endangered species are present in the specific area.

Firstly, data can be collected from experts, scientific and grey literature, and based on a large range of well-designed, quality-controlled experiments, covering the four different clusters introduced earlier. After data collection, results are obtained and probability density distributions can be created. The use of probability density distributions provides quantified information on the chances that the targeted plastic debris and potential bycatch are trapped by a specific plastic pollution removal mechanism, accounting for the local river conditions, and the multiple inherent characteristics of the plastic debris and biota themselves. These results can be integrated in BBNs (Fig. 3), providing a suitable basis to develop the desired decision support framework, which can be evaluated and constantly improved with new data. Once created and validated, the framework can be adapted to different geographical areas, by modifying the input data in accordance with the clusters' information relevant for the study.

4. Conclusions

Innovative techniques are being developed, commercialized and implemented to collect plastic debris from the aquatic environment. However, due to the novelty and cruciality of these technologies, open

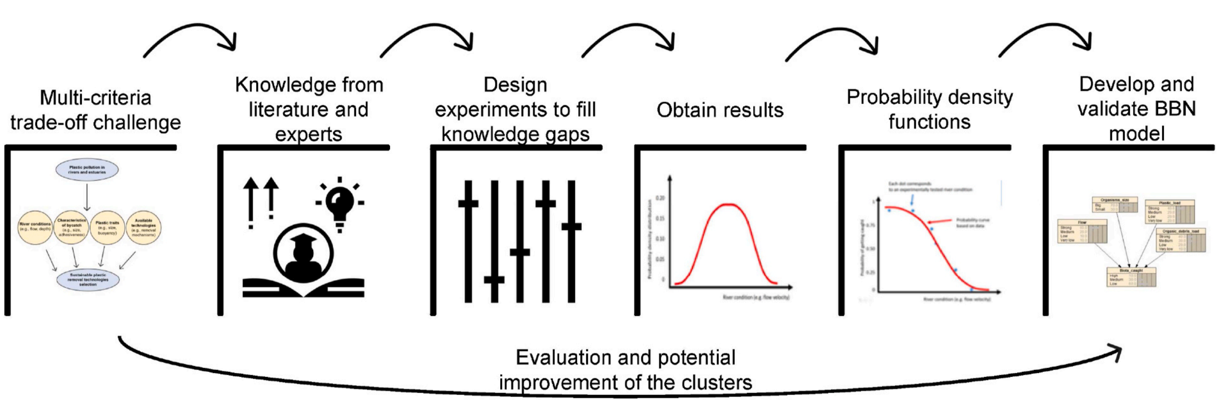

Fig. 2. Pathway towards a decision support framework for the deployment of plastic clean-up technologies in riverine and estuarine environments: from problem identification (multi-criteria trade-off challenge), to the combination of existing data, expert knowledge, and experimental work as the basis for a BBN-trade-off model development and validation.

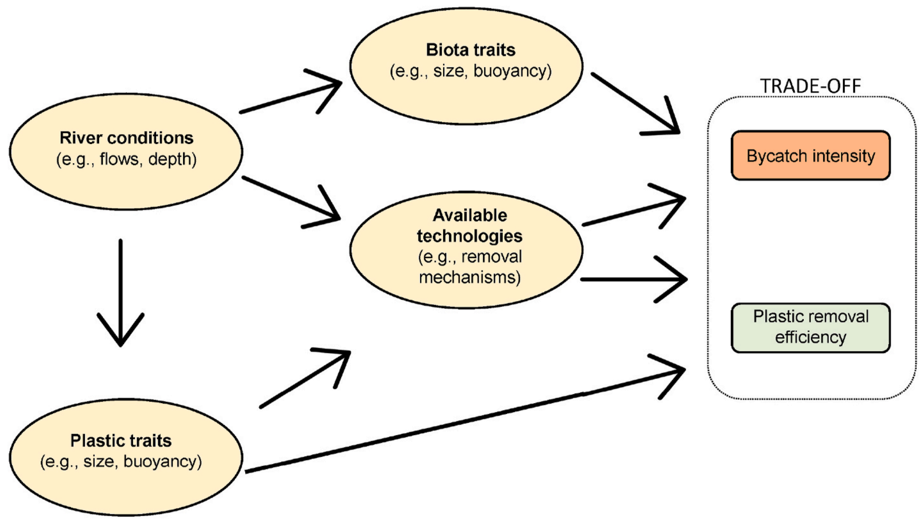

Fig. 3. Information flow for Bayesian Belief Network as a trade-off between bycatch intensity and plastic removal efficiency. The color green is for plastic removal, which is the desired outcome, and red for bycatch. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

access and objective scientific data are necessary to better understand their potential short and long-term environmental impacts. River managers currently lack an objective tool to guide their decision in the selection of a plastic clean-up technology with a minimal impact on the environment. This tool can be used, in conjunction with an environmental impact assessment, to reduce the potential collateral damage of clean-up technologies. Each case will have to be individually evaluated, also addressing local regulations, specific partnerships, feasibility of a technology or operation in a specific location and costs. The final decision regarding the deployment of a system is the stakeholders' responsibility, depending on the outcome of the model and their interpretation.

Considering that multiple criteria and related parameters could influence the bycatch; we have identified four clusters that could influence the chances of bycatch for specific technologies. Here, we propose Bayesian Belief Networks as a good basis for developing such objective decision support framework for plastic clean-up technologies.

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Credit author statement

Giulia Leone: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Visualization. **Ana I. Catarino**: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Ine Pauwels**: Methodology, Writing – review & editing. **Thomas Mani**: Methodology, Writing – review & editing. **Michelle Tishler**: Methodology, Writing – review & editing. **Matthias Egger**: Methodology, Writing – review & editing. **Marie Anne Eurie Forio**: Methodology, Visualization, Writing – review & editing. **Peter L. M. Goethals**: Methodology, Visualization, Writing – review & editing. **Gert Everaert**: Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors Thomas Mani, Michelle Tishler and Matthias Egger are employed by The Ocean Cleanup, a non-profit organization aimed at advancing scientific understanding and developing solutions to rid the oceans of plastic, headquartered in Rotterdam, the Netherlands. The other authors report no conflict of interest.

References

Barnes, D.K.A., Galgani, F., Thompson, R.C., Barlaz, M., 2009. Accumulation and fragmentation of plastic debris in global environments. Philos. Trans. R. Soc. B Biol. Sci. 364, 1985–1998. https://doi.org/10.1098/rstb.2008.0205.

Barton, D.N., Sundt, H., Bustos, A.A., Fjeldstad, H.P., Hedger, R., Forseth, T., Köhler, Berit, Aas, Ø., Alfredsen, K., Madsen, A.L., 2020. Multi-criteria decision analysis in Bayesian networks - diagnosing ecosystem service trade-offs in a hydropower regulated river. Environ. Model. Software 124. https://doi.org/10.1016/j.envsoft.2019.104604.

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

Borrelle, S.B., Ringma, J., Law, K.L., Monnahan, C.C., Lebreton, L., McGivern, A., Murphy, E., Jambeck, J., Leonard, G.H., Hilleary, M.A., Eriksen, M., Possingham, H. P., De Frond, H., Gerber, L.R., Polidoro, B., Tahir, A., Bernard, M., Mallos, N., Barnes, M., Rochman, C.M., 2020. Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution. Science 84 369. https://doi.org/10.1126/science.aba3656, 1515 LP – 1518.

Chen, S.H., Pollino, C.A., 2012. Good practice in Bayesian network modelling. Environ. Model. Software 37, 134–145. https://doi.org/10.1016/j.envsoft.2012.03.012.

Costanza, R., D'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R.V., Paruelo, J., Raskin, R.G., Sutton, P., Van Den Belt, M., 1997. The value of the world's ecosystem services and natural capital. Nature 387, 253–260. https://doi.org/10.1038/387253a0.

Coutant, C.C., Whitney, R.R., 2000. Fish behavior in relation to passage through hydropower turbines: a review. Trans. Am. Fish. Soc. 8487, 37–41. https://doi.org/10.1577/1548-8659(2000)129<0351:FBIRTP>2.0.CO;2.

European Commission, 2020. Turning the Tide on Single-Use Plastics. https://op.europa.eu/en/publication-detail/-/publication/fbc6134e-367f-11ea-ba6e-01aa75ed71a1/language-en/format-PDF/source-112806183. July 12, 2021.

European Commission, 2019a. Single-use Plastics. https://ec.europa.eu/environment/topics/plastics/single-use-plastics_en. July 12, 2021.

European Commission, 2019b. The European Green Deal. https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en. July 9, 2021.

European Commission, 2008. MSFD—Marine Strategy Framework Directive. https://ec.europa.eu/environment/marine/eu-coast-and-marine-policy/marine-strategy-framework-directive/. July 9, 2021.

Fahrenkamp-Uppenbrink, J., 2018. Microplastics everywhere. Science 84 360. https://doi.org/10.1126/science.360.6384.44-q, 44 LP – 46.

Forio, M.A.E., Goethals, P.L.M., 2020. An integrated approach of multi-community monitoring and assessment of aquatic ecosystems to support sustainable development. Sustainability 12, 5603. https://doi.org/10.3390/su12145603.

Forio, M.A.E., Villa-Cox, G., Van Echelpoel, W., Ryckebusch, H., Lock, K., Spanoghe, P., Deknock, A., De Troyer, N., Nolivos-Alvarez, I., Dominguez-Granda, L., Speelman, S., Goethals, P.L.M., 2020. Bayesian belief network models as trade-off tools of ecosystem services in the guayas river basin in Ecuador. Ecosyst. Serv. 44, 101124. https://doi.org/10.1016/j.ecoser.2020.101124.

Goethals, P.L.M., Forio, M.A.E., 2018. Advances in ecological water system modeling: integration and leanification as a basis for application in environmental management. Water (Switzerland) 10. https://doi.org/10.3390/w10091216.

Helinski, Olivia K., Poor, C.J., Wolfand, J.M., 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.

Hohn, S., Acevedo-Trejos, E., Abrams, J.F., Fulgencio de Moura, J., Spranz, R., Merico, A., 2020. The long-term legacy of plastic mass production. Sci. Total Environ. 746, 141115. https://doi.org/10.1016/j.scitotenv.2020.141115.

Kennish, M.J., 2003. Estuarine Research, Monitoring, and Resource Protection. CRC Press.

Kooi, M., Koelmans, A.A., 2019. Simplifying microplastic via continuous probability distributions for size, shape, and density. Environ. Sci. Technol. Lett. 6, 551–557. https://doi.org/10.1021/acs.estlett.9b00379.

Lau, W.W.Y., Shiran, Y., Bailey, R.M., Cook, E., Stuchtey, M.R., Koskella, J., Velis, C.A., Godfrey, L., Boucher, J., Murphy, M.B., Thompson, R.C., Jankowska, E., Castillo, A. C., Pilditch, T.D., Dixon, B., Koerselman, L., Kosior, E., Favoino, E., Gutberlet, J., Baulch, S., Atreya, M.E., Fischer, D., He, K.K., Petit, M.M., Sumaila, U.R., Neil, E., Bernhofen, M.V., Lawrence, K., Palardy, J.E., 2020. Evaluating scenarios toward zero plastic pollution. Science 84 369, 1455–1461. https://doi.org/10.1126/SCIENCE.ABA9475.

Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., Goethals, P.L.M., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environ. Model. Software 46, 1–11. https://doi.org/10.1016/j.envsoft.2013.03.011.

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. 566–567, 333–349. https://doi.org/10.1016/j.scitotenv.2016.05.084.

Lusher, A.L., Hernandez-Milian, G., Berrow, S., Rogan, E., O'Connor, I., 2018. Incidence of marine debris in cetaceans stranded and bycaught in Ireland: recent findings and a review of historical knowledge. Environ. Pollut. 232, 467–476. https://doi.org/10.1016/j.envpol.2017.09.070.

Maes, G.E., Raeymaekers, J.A.M., Pampoulie, C., Seynaeve, A., Goemans, G., Belpaire, C., Volckaert, F.A.M., 2005. The catadromous European eel Anguilla anguilla (L.) as a model for freshwater evolutionary ecotoxicology: relationship between heavy metal bioaccumulation, condition and genetic variability. Aquat. Toxicol. 73, 99–114. https://doi.org/10.1016/j.aquatox.2005.01.010.

Marcot, B.G., Holthausen, R.S., Raphael, M.G., Rowland, M.M., Wisdom, M.J., 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. For. Ecol. Manage. 153, 29–42. https://doi.org/10.1016/S0378-1127(01)00452-2.

Meijer, L.J.J., van Emmerik, T., van der Ent, R., Schmidt, C., Lebreton, L., 2021. More than 1000 rivers account for 80\% of global riverine plastic emissions into the ocean. Sci. Adv. 7 https://doi.org/10.1126/sciadv.aaz5803.

Ministry of Environment and Forestry, 2020. Implementation Plan for the Ban of Single Use Plastics in Protected Areas. http://www.environment.go.ke/wp-content/uploads/2020/03/action-plan.pdf. July 12, 2021.

Napper, I.E., Davies, B.F.R., Clifford, H., Elvin, S., Koldewey, H.J., Mayewski, P.A., Miner, K.R., Potocki, M., Elmore, A.C., Gajurel, A.P., Thompson, R.C., 2020. Reaching new heights in plastic pollution—preliminary findings of microplastics on mount everest. One Earth 3, 621–630. https://doi.org/10.1016/j.oneear.2020.10.020.

Parker, L., 2018. We made plastic. We depend on it. Now we're drowning in it. Natl. Geogr. Mag. 16.

Piffady, J., Carluer, N., Gouy, V., le Henaff, G., Tormos, T., Bougon, N., Adoir, E., Mellac, K., 2021. ARPEGES: a bayesian belief network to assess the risk of pesticide contamination for the river network of France. Integrated Environ. Assess. Manag. 17 https://doi.org/10.1002/ieam.4343.

Richardson, K., Hardesty, B.D., Wilcox, C., 2019. Estimates of Fishing Gear Loss Rates at a Global Scale: A Literature Review and Meta - Analysis, pp. 1–14. https://doi.org/10.1111/faf.12407.

Rottmann, R.W., Shireman, J.V., Chapman, F.A., 1991. Southern Regional Aquaculture Center Techniques for Taking and Fertilizing the Spawn of Fish.

Ryan, P.G., Moore, C.J., van Franeker, J.A., Moloney, C.L., 2009. Monitoring the abundance of plastic debris in the marine environment. Philos. Trans. R. Soc. Lond. B Biol. Sci. 364, 1999–2012. https://doi.org/10.1098/rstb.2008.0207.

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 https://doi.org/10.1016/j.envint.2020.106067.

Van Echelpoel, W., Boets, P., Landuyt, D., Gobeyn, S., Everaert, G., Bennetsen, E., Mouton, A., Goethals, P.L.M., 2015. Chapter 6 - species distribution models for sustainable ecosystem management. E.M.. In: Park, Y.-S., Lek, S., Baehr, C., Jørgensen, S.E.B.T.-D. (Eds.), Advanced Modelling Techniques Studying Global Changes in Environmental Sciences. Elsevier, pp. 115–134. https://doi.org/10.1016/B978-0-444-63536-5.00008-9.

van Emmerik, T., Schwarz, A., 2019. Plastic debris in rivers. WIREs Water 7. https://doi.org/10.1002/wat2.1398.

van Emmerik, T., Strady, E., Kieu-Le, T.C., Nguyen, L., Gratiot, N., 2019. Seasonality of riverine macroplastic transport. Sci. Rep. 9, 1–9. https://doi.org/10.1038/s41598-019-50096-1.

Vasconcelos, R.P., Reis-Santos, P., Costa, M.J., Cabral, H.N., 2011. Connectivity between estuaries and marine environment: integrating metrics to assess estuarine nursery function. Ecol. Indicat. 11, 1123–1133. https://doi.org/10.1016/j.ecolind.2010.12.012.