Deep–Sea Research I 206 (2024) 104266

Contents lists available at ScienceDirect

Deep-Sea Research Part I

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

Plastics in the deep sea – A global estimate of the ocean floor reservoir

Xia Zhu [a,*], Chelsea M. Rochman [b], Britta Denise Hardesty [c], Chris Wilcox [d]

[a] Department of Physical and Environmental Sciences, University of Toronto Scarborough, Toronto, Ontario, Canada
[b] Department of Ecology and Evolutionary Biology, University of Toronto, Toronto, Ontario, Canada
[c] Commonwealth Scientific and Industrial Research Organisation – Environment, Tasmania, Australia
[d] Centre for Marine Sociology, University of Tasmania, Hobart, Australia

ARTICLE INFO

Keywords:
Plastic pollution
Ocean floor
Reservoirs
Global plastic cycle
Environmental contaminants

ABSTRACT

The exponential increase in plastic production coupled with variable global waste management system efficiencies has resulted in large amounts of plastic waste entering the ocean every year. Although we know millions of tonnes of plastic have entered the oceans, we do not yet understand the patterns of its accumulation across space nor the drivers of these patterns. The deep ocean is expected to be a resting place, or reservoir, for most plastic pollution. Here, we conducted a rigorous, systematic review of previously published datasets to synthesize our understanding of macroplastic pollution (>5 mm) on the ocean floor. Using extracted data, we built predictive additive models to estimate the amount and distribution of plastic on the ocean floor. We built two models: one using data from remote operated vehicles (ROVs) and another using data from bottom trawls. Using the model built with ROV data, which was better-constrained, we estimate that 3 to 11 million metric tonnes (MMT) of plastic pollution resides on the ocean floor as of 2020. This is of similar magnitude to annual inputs from land and one to two orders of magnitude greater than what is predicted to be floating on the ocean surface. To improve future estimates and our understanding of global patterns, we provide recommendations for ocean floor monitoring of plastic pollution.

1. Introduction

The production of plastic has increased exponentially over time, such that by 2050 we are predicted to have generated a total of 26,000 million metric tonnes (MMT) of virgin resin (Geyer et al., 2017). Approximately half of this plastic is projected to become waste (Geyer et al., 2017). Plastic waste that escapes management systems or is shed from plastic during use (e.g., tire wear particles) enter the environment as emissions of plastic pollution (Zhu and Rochman, 2022; Hann et al., 2018; Boucher and Friot) and cycle through environmental reservoirs much like carbon and nitrogen (Zhu, 2021; Stubbins et al., 2021). Millions of tonnes of plastic pollution, estimated at 4–23 MMT per year (Borrelle et al., 2020; Jambeck et al., 2015), enter the ocean as part of the Global Plastic Cycle (Zhu, 2021; Rochman and Hoellein, 2020).

1.1. *Fate of plastic pollution is poorly understood*

Physical forcing via wind (Lebreton et al., 2018; Olivelli et al., 2020; Alsina et al., 2020; Van Emmerik et al., 2019) and currents (Van Sebille et al., 2015; Maximenko et al., 2012), biological forcing via the movement of marine life, and the incorporation of plastic into organic particles (e.g., marine snow and fecal material) (Kooi et al., 2017; Katija et al., 2017; Lobelle et al., 2021; Galgani et al., 2022) transport plastic pollution throughout the ocean. The amount and spatial distribution of plastic pollution in major marine reservoirs, including the ocean column, ocean floor, marine sediments, coastlines, and marine animals have not yet been quantified (Zhu, 2021; Law, 2017). Although there are estimates of the amount of plastic floating on the surface of the global ocean (Van Sebille et al., 2015; Eriksen et al., 2014, 2023), the discrepancies between the estimates are large, spanning many orders of magnitude. Due to a lack of broad-scale empirical data across reservoirs, including the ocean's surface, models to date are poorly constrained (Canals et al., 2021). The risks that plastic pollution may pose to marine life (Mehinto et al., 2022; Bucci et al., 2020) is motivation for better understanding the spatial extent of plastic pollution to inform the exposure landscape for organisms more holistically.

* Corresponding author.
E-mail addresses: alicexia.zhu@mail.utoronto.ca (X. Zhu), chelsea.rochman@utoronto.ca (C.M. Rochman), denise.hardesty@csiro.au (B.D. Hardesty), chris.v.wilcox@gmail.com (C. Wilcox).

https://doi.org/10.1016/j.dsr.2024.104266
Received 3 November 2023; Received in revised form 27 January 2024; Accepted 22 February 2024
Available online 2 March 2024

1.2. Plastic resting on the ocean floor

The ocean floor is predicted to be among the largest reservoirs of plastic pollution (Law, 2017; Canals et al., 2021), and is suspected to be a long-term reservoir, or sink, due to the lack of removal processes acting upon it. This is further exacerbated by the extremely slow degradation rates of plastic in cold environments lacking in both oxygen and UV radiation (Chamas et al., 2020). The deep ocean consists of two major reservoirs of plastic pollution: the ocean floor (Law, 2017; Canals et al., 2021), which consists of large plastic objects sitting on top of the floor, and bulk ocean sediment (Martin et al., 2022; Barrett et al., 2020; Woodall et al., 2014), which consists of smaller plastic particles mixed into the sediment.

Plastic is the dominant form of marine litter found in the deep ocean, and derelict fishing gear is predominantly made of plastic (Canals et al., 2021; Lopez-Lopez et al., 2017; Cau et al., 2017; Buhl-Mortensen and Buhl-Mortensen, 2017). Field surveys and sampling campaigns have quantified benthic plastic pollution from seas, estuaries, and deep ocean basins (e.g. (Cau et al., 2017; Maes et al., 2018; Galgani et al., 1996; Topçu and Öztürk, 2010; Bergmann et al., 2017),). Modelling studies have used empirical data to assess drivers of benthic debris accumulation regionally (e.g. (Barrett et al., 2020; Lopez-Lopez et al., 2017; Spedicato et al., 2019; Moriarty et al., 2016),) and data simulations to predict vertical particle transport (e.g. (Mountford and Morales, 2019; Wu et al., 2021),). Regional studies shed light on plastic accumulation in specific locations, and simulations of vertical transport allow extrapolation to predict benthic contamination. To date, we lack a holistic assessment of the global distribution and overall importance of the ocean floor as a global reservoir.

Here, we synthesize empirical data from the peer-reviewed literature to build a predictive model of the extent and spatial distribution of plastic pollution on the ocean floor at a global scale. We also consider the driving forces relevant to the transport and accumulation of plastic in the deep ocean, which informs source-reduction and environmental remediation efforts. Finally, based on our findings, we make specific suggestions for improving sampling and data collection to improve future predictions of the load of plastics in the global ocean.

2. Materials and methods

2.1. Systematic review

The terms "marine debris" OR "plastic debris" OR "microplastic" were included in a literature search query via "All Databases" in Web of Science to find peer reviewed publications that report abundances of plastic pollution in either the ocean floor or the sediment compartment of the deep ocean. We included papers published from September 1976 until January 1st, 2020. Inclusion criteria were used to select papers for the systematic review and meta-analysis (see details in Fig. 1). Only studies that report abundances of plastic in marine settings that are underwater, or below zero meters with respect to sea level, were included in the analysis. As a result, we excluded studies conducted in intertidal environments (e.g., wetlands, mangroves), on beaches, and in any terrestrial or freshwater environments (e.g., lagoons, terrestrial parks, forests). A quality assurance search through other relevant databases (Alfred Wegener Institute for Polar and Marine Research) was conducted to identify any studies that our search may have missed. To synthesize what we know about plastics in the deep ocean and to retrieve data needed for our predictive modelling, we extracted geographic coordinates, area name, country (if applicable), sampling method, sample size, abundance of plastic pollution, plastic sizes, plastic types, year of sampling, sampling depth, sampling season, and ocean floor topographic feature from each of the included studies.

2.2. Meta-analysis – predicting global estimates

Although we present the state of the knowledge of plastic pollution in both the ocean floor (macroplastic) and bulk sediment (microplastic) reservoirs, we only modelled the distribution of plastic on the ocean floor. Studies on plastic pollution in sediment were not included due to the inherent differences in plastic morphologies and sizes between the ocean floor and bulk sediment reservoirs, and because preliminary estimates of the size of the bulk sediment reservoir already exist (Martin et al., 2022; Barrett et al., 2020). Studies included in the meta-analysis were used to build a generalized additive model (Wood, 2017) (Supplementary Information Table S1). The chosen studies must have reported adequate quantitative information that enables the calculation of an abundance measure for plastic pollution on the ocean floor - specifically, they need to either provide a mass of plastic per area measurement, or a count of plastic per area measurement along with a physical

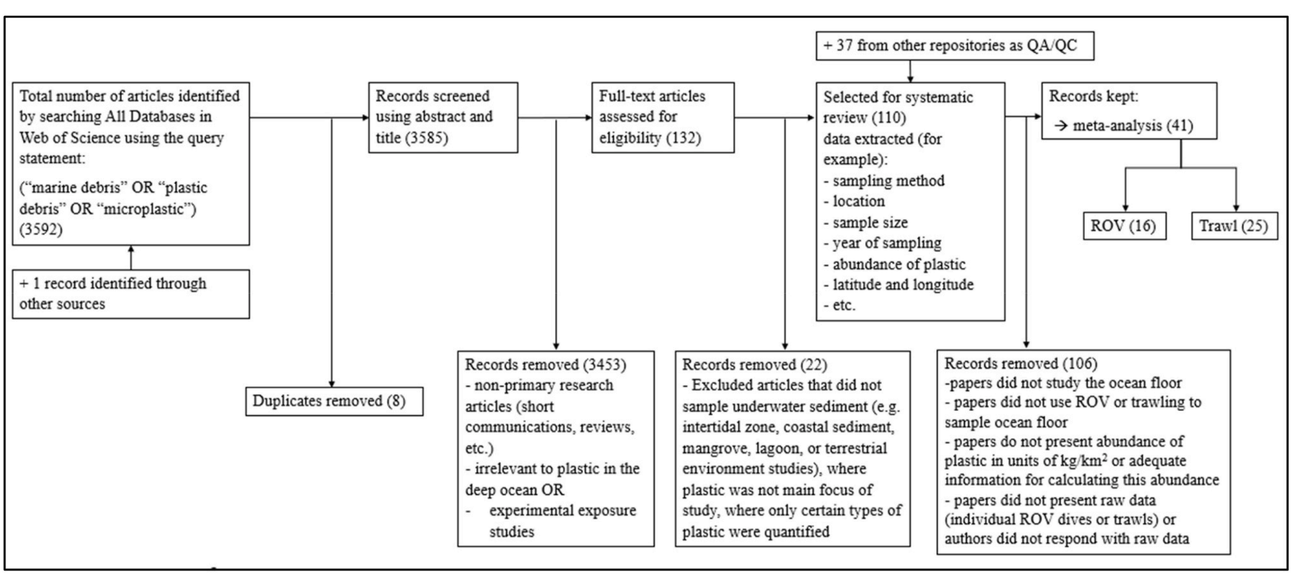

Fig. 1. PRISMA statement showing how studies for the systematic review and meta-analysis were sequentially filtered. The numbers in parentheses represent the number of papers relevant to each step in the process.

description of the plastic items retrieved. We chose to only focus on studies that used remote operated vehicles (ROV) or trawling methodology because they are the most commonly deployed methods for sampling plastic pollution on the ocean floor.

Our literature search generated a total of 3592 studies. After filtering out articles using exclusion criteria at every step, and adding articles we missed from other repositories as a quality check, we were left with 41 studies (16 ROV and 25 Trawl studies) for the meta-analysis or modelling component of this paper (Fig. 1).

We asked authors of the 41 studies chosen for the ocean floor meta-analysis (Supplementary Information Table S1) to provide raw data when raw data was not presented in their manuscript or corresponding Supplementary Materials (please see Acknowledgements section). Our meta-analysis originally consisted of all studies that contained quantitative abundances of plastic pollution (raw or average), but because we needed raw data to build our model via a Generalized Additive Model (GAM) approach, we only included studies where raw data was available or ultimately provided by the authors. Authors were asked to provide geographic coordinates and a mass of plastic per area measurement for each of the ROV dives or trawls (Fig. 2). Where only count of plastic per area information was provided (and not mass), mass was calculated (Supplementary Information Text 1).

We fitted two generalized additive models, using masses of plastic pollution from ROV imagery and trawl samples, in R 3.4.3 (Barton, 2023) using the *mgcv* package (Simon Wood, 2022). After evaluation, we found these two sampling methodologies to be too divergent to be combined and used to fit a single model. For both of our models, covariates were checked for collinearity. The parent models are fit to their respective data using the *Tweedie* distribution (The Comprehensive R Archive Network). The *dredge* function in the *MuMIn* package (R Core Team. R, 2023) was used to search through all possible permutations of covariates and select the model with the most parsimonious fit to the data, measured using Akaike's Information Criterion (AIC) score (Wood, 2017; Burnham and Anderson). The AIC score uses a model's maximum likelihood estimation as a relative measure of goodness-of-fit, and penalizes for complexity. The model with the lowest AIC score was considered the best model, and any model that is within two points of the best model is considered equivalent as it falls within the 95% confidence interval around the best model. More details on the modelling process can be found in the supplementary text (Supplementary Information Text 2).

The covariates we included in the GAMs were depth, slope, shipping intensity, fishing effort, distance to shore, and distance-weighted population. Area sampled and median year were control variables for the ROV model. Area sampled, median year, and net mesh acted as control variables for the trawl model.

Control variables need to be considered in the model because they may confound the true relationships between plastic mass and the predictor variables. Covariates were chosen based on previous studies or their suspected influence on plastic abundances on the ocean floor (Lopez-Lopez et al., 2017; Moriarty et al., 2016; Kaandorp et al., 2020; Duinen et al., 2022; Naranjo-Elizondo and Cortés, 2018; Richardson et al., 2019). We summarize the covariates included in our model below and the reason for including them:

- While our response variable, plastic mass (kg/km^2), is already standardized by area, area sampled (km^2) is important to include as a control variable because as area sampled increases, the likelihood of detecting rare items with huge masses also increases (Roman et al., 2019a).
- Median year is the central value of the year range during which samples were collected. It was included to control for the effects of time.
- Net mesh is only considered in the Trawl model and controls for the different sizes of mesh that are used in trawl nets.
- Depth of ocean floor is measured from zero meters at the surface and becomes more negative with increasing depth (International Hydrographic Organization, 2020). Depth has previously been found to be correlated with plastic litter abundance (Barrett et al., 2020; Spedicato et al., 2019; Eryaşar et al., 2014)

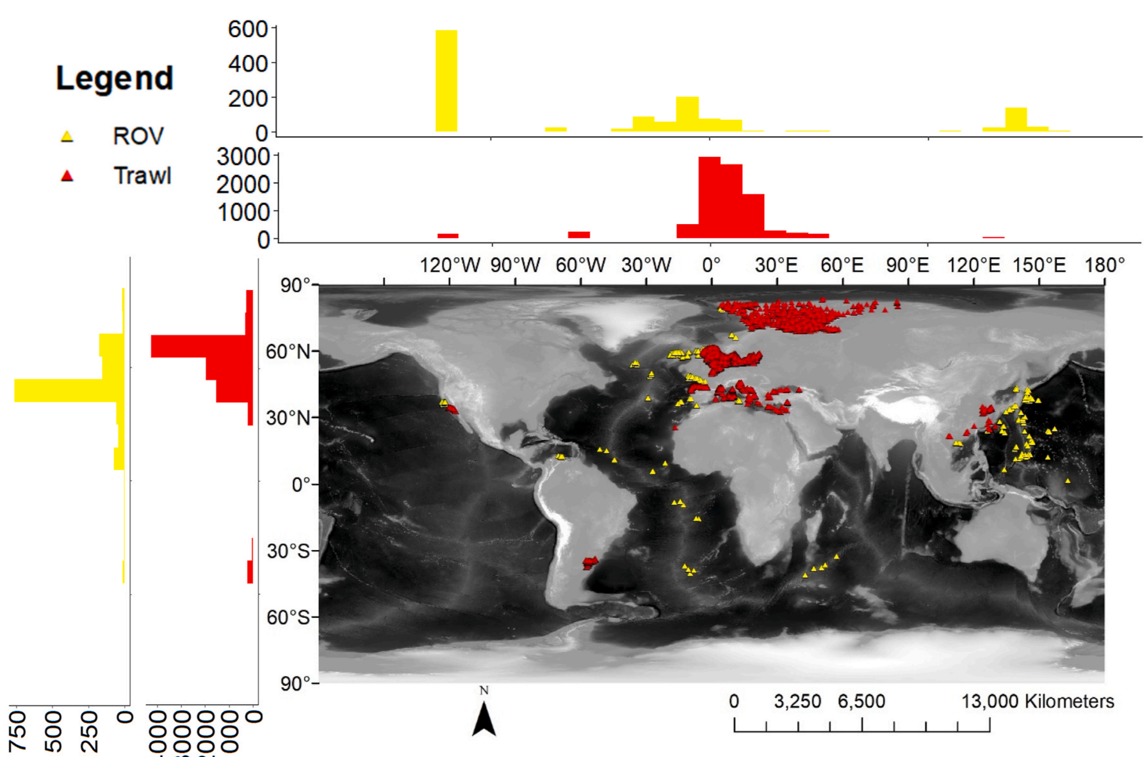

Fig. 2. Raw ROV (n = 1306) and trawl (n = 8878) samples used to train each model from surveys taking place 1988–2018 and 1993–2017, respectively. Histograms show number of ROV (yellow) and trawl (red) samples by 10° latitudinal and longitudinal bins. Basemap shows ocean floor bathymetry (source: GEBCO, 2020).

- Slope of ocean floor is measured in degrees. Flatter areas tend to accumulate more debris than sloped areas (Barrett et al., 2020; Spedicato et al., 2019)
- Shipping intensity is represented by the density of major shipping routes within a 1° x 1° grid cell (Ocean Health Index). Increased litter abundance on the Mediterranean seafloor has been linked to increased marine traffic (Spedicato et al., 2019).
- Fishing effort is represented by the product of a vessel's engine power (kiloWatts) and its length of deployment in the ocean (hours), and has units of kiloWatt-hours (Institute for Marine and Antarctic Studies, 2022). Fishing intensity has been correlated with high plastic debris abundance on the ocean bottom[32.]
- Distance to shore is the distance in kilometers of the sampling location to the nearest coast. It is a representation of a location's susceptibility to influence from anthropogenic activity (Cau et al., 2017).
- Population density is another source-related covariate, and is included as a smooth in our model and corrected for the effect of distance. We fitted the "population by distance" effect as a smooth term, which is a non-parametric approach using a set of approximating basis functions to build a complex functional relationship. Here, we used signal regression or a variable coefficient model, which allows coefficients to vary with different values of the covariate. The collective integration of the effect of distance on population over a given interval is represented by the p-value of the smooth, or the overall significance of the fit. Essentially, we fit a population-to-distance relationship before fitting this in the broader model, to account for how population changes with distance.

Data sources for all covariates are described and links provided, if applicable (Supplementary Information - Text 3). We also considered latitude, longitude, and their smooths as predictor variables, but discarded them from our model due to the limited spatial coverage of our ROV and trawl samples. Covariates were standardized by subtracting the average from each value and dividing by the standard deviation.

Both models were used to predict the mass of plastic (in kg/km^2) for every 1° x 1° grid cell of the ocean floor for the year 2020 to match the lowest resolution of spatial covariate data. The total mass of plastic (kg) in each grid cell was determined by multiplying the predicted mass/area from our fitted models by the total area of the grid cell (km^2). The ocean floor reservoir was estimated by summing the masses of plastic pollution predicted across all ocean floor grid cells. Upper and lower bounds on the reservoir estimated were derived by summing the "prediction ± model standard error" across all ocean floor grid cells.

3. Results

3.1. Summary of sampling effort in the deep ocean

Our systematic review shows that for both the ocean floor and bulk ocean sediment, plastic pollution sampling efforts are concentrated in coastal marine environments (Figs. 2 and 3a, Supplementary Information Fig. S1a). For macroplastics on the ocean floor, 73 out of 95 (77%) independent sampling campaigns took place in coastal marine environments including inland and coastal seas, bay-estuary systems, bights, reef habitats, continental shelves, and canyons (Fig. 3a). The Atlantic and Pacific ocean basins had the highest number of sampling campaigns overall (Fig. 3a). For microplastics embedded within bulk ocean sediment, 42 out of 50 (84%) independent sampling efforts took place in coastal marine environments (Supplementary Information Fig. S1a). The Arctic Ocean had the most sampling campaigns across all ocean basins. Plastic pollution sampling efforts on the ocean floor are dominated by ROV and trawl sampling; in fact, 80 of 96 studies (83%) used ROV or trawling to sample the ocean floor (Fig. 3b). For bulk ocean sediment, just over half (51%) of all sampling campaigns deployed the grab sampling technique to sample microplastic pollution embedded within deep ocean sediment (Supplementary Information Fig. S1b).

3.2. Summary of ROV and trawl models, and derived predictions

The best model built using ROV samples, henceforth referred to as the "ROV model", explained 37.1% of the variability in the mass of plastic pollution on the ocean floor and included area sampled, median year, depth, shipping intensity, fishing effort, and distance to shore (Table 1). All variables were significantly correlated with mass of plastic pollution except for area sampled (p = 0.056) and fishing effort (p =

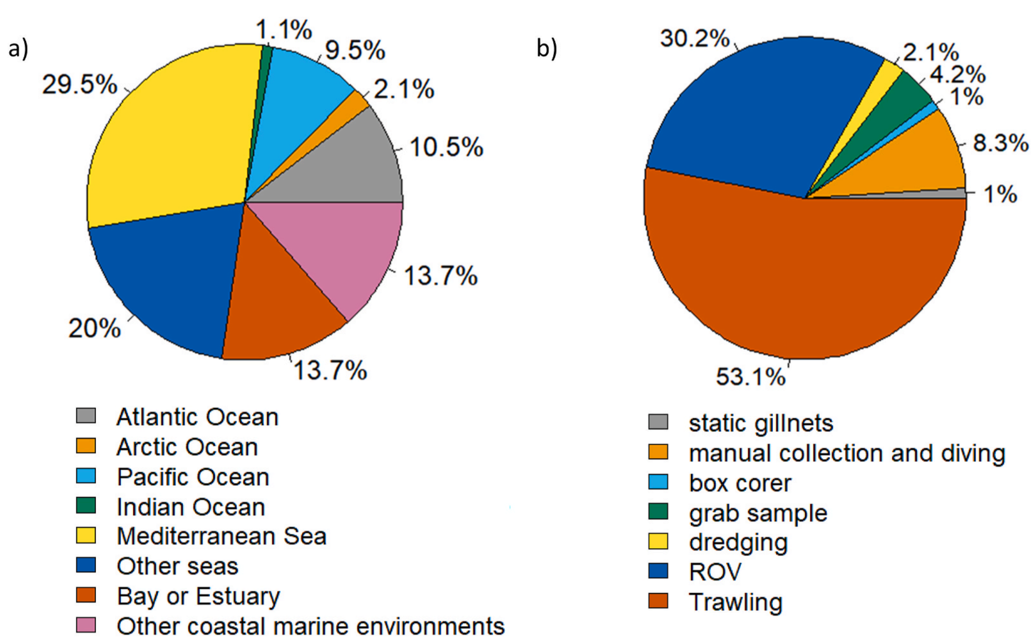

Fig. 3. a) Sampling locations of plastic pollution on the ocean floor are displayed as percentage of total sampling campaigns conducted up until January 1, 2020. b) Sampling methodologies for large plastic objects on the ocean floor are also displayed as percentage of total sampling campaigns conducted globally up until January 1, 2020. Examples of other coastal marine environments include gulfs, canyons, reefs, marine sanctuaries, harbours, bights, fjords, and coves.

Table 1
Summary of parametric variables in the best ROV and trawl models. Coefficients/effect estimates are directly comparable because covariates were standardized by subtracting their mean and dividing by the standard deviation.

ROV			
Variable	Coefficient/estimate	Standard Error	p-value
area sampled	0.11	0.055	0.056
median year	1.46	0.090	$<2{*}10^{-16}$
depth	0.93	0.086	$<2{*}10^{-16}$
shipping intensity	0.66	0.096	$1.4{*}10^{-11}$
fishing effort	−0.18	0.10	0.087
distance to shore	−0.22	0.088	0.015
Trawl			
Variable	Coefficient/estimate	Standard Error	p-value
area sampled	6.9	1.2	$3.2{*}10^{-8}$
median year	−0.15	0.050	0.0027
net mesh	−1.1	0.056	$<2{*}10^{-16}$
depth	−0.45	0.031	$<2{*}10^{-16}$
slope	−0.36	0.040	$<2{*}10^{-16}$
shipping intensity	−0.25	0.046	$4.6{*}10^{-8}$
fishing effort	−0.15	0.040	0.00011
distance to shore	−0.52	0.044	$<2{*}10^{-16}$

0.087). The ROV model has a much lower AIC score than the null model, which is an indication that the ROV model has greater goodness-of-fit to the data than the null model (Supplementary Information Table S2). The best model built using trawl samples, henceforth referred to as the "Trawl model", explained 21.8% of the variability in mass of plastic pollution on the ocean floor and included area sampled, median year, net mesh, depth, slope, shipping intensity, fishing effort, and distance to shore (Table 1). All variables in the Trawl model were significantly correlated with mass of plastic pollution found on the ocean floor. As with the ROV model, the Trawl model also has greater goodness-of-fit to the data than the null model, as indicated by its lower AIC score (Supplementary Information Table S3). Model diagnostics were performed for both models (Supplementary Information Figs. S2, S3).

For both the ROV and the Trawl model, distance-weighted population density was significantly correlated with plastic mass on the ocean floor (Supplementary Information Fig. S4). For both models, the general trend is that large distant human populations have the largest impact on plastic densities at sampling locations. This finding may suggest a combination of limited mixing and settling out of material at short distances, as well as the importance of distant sources such as large cities that are delivering large amounts of inputs (Supplementary Information Fig. S4).

The prediction heat map for ROV shows densities of macroplastic pollution ranging from 0 to 1719.30 kg/km^2, with the highest predicted density in the Baltic Sea (Fig. 4). From the Trawl predictions, we find that the highest predicted densities are clustered in the Western Pacific Ocean basin (Supplementary Information Fig. S5). We focus on the ROV results due to reasons detailed in the sections below.

3.3. *The ocean floor reservoir*

We estimate the size of the ocean floor reservoir to be 3 to 11 MMT (middle estimate of 7 MMT) using the ROV model. The estimate using the Trawl model is 5–571 MMT (middle estimate of 255 MMT). We did not combine the two model prediction maps together due to the inherent differences in the two sampling techniques, the spatial distributions of the samples, and the differences between the models. We used the ROV predictions to inform the ocean floor reservoir estimate because we had greater confidence in the ROV model.

4. Discussion

We begin with a detailed comparison of the reliability of the ROV and Trawl models. Then we discuss the important drivers of plastic pollution accumulation on the ocean floor identified by each model, analyze spatial trends in the predicted masses, compare our results to those of other studies, and finally end with recommendations for sampling efforts to improve future models.

Although we have estimates of the ocean floor reservoir from both models, we focus on the ROV model due to the better spatial coverage of its raw data, and therefore the greater reliability of its predictions. The distribution of plastic mass with respect to size for the objects collected by both ROV and trawl methods are surprisingly similar, in that both distributions are bimodal near zero and near their upper size cutoff (Supplementary Information Text 4, Fig. S6). Their agreeable mass frequency distributions initially supported the use of both prediction maps to inform the ocean floor reservoir. However, the ROV and trawl data differ in important ways. There is a strong bias in the trawl sampling data as trawls are limited to deployment in shallow, relatively flat regions of the ocean floor. Consequently, the coverage of the ocean floor by trawling is poor (Fig. 2), meaning global predictions encounter

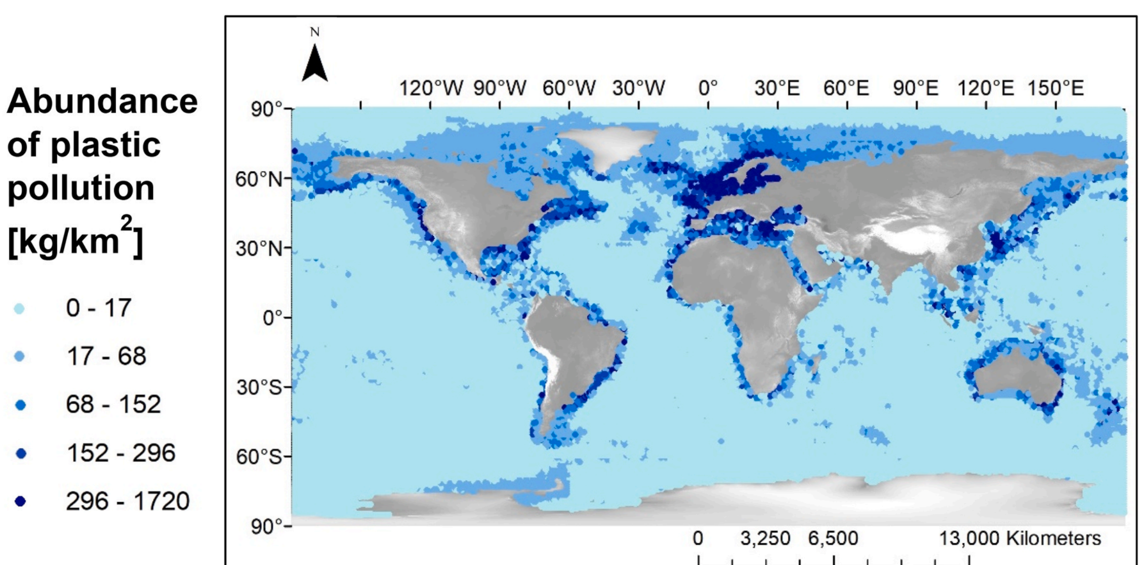

Fig. 4. Heat map showing predictions of the mass [kg/km^2] of plastic pollution for 1° x 1° grid cells of the ocean floor using the best ROV model (Table 1).

conditions well outside of the covariate ranges covered by our observation data (Supplementary Information Fig. S7). It is evident from the histograms in Fig. 1 that ROV samples cover a greater range of latitudes and longitudes, and there is less clustering of samples within regions. For instance, 88% percent of trawl samples were collected between 30°W and 30°E longitude, as opposed to only 36% for ROV (Fig. 1). As a consequence, predictions of plastic abundance by the ROV and Trawl models in regions with a similar set of values for covariates sometimes differ substantially (Supplementary Information Fig. S8). This is shown in Fig. S8, where the covariate values associated with each sample, or the set of conditions under which the sample was taken, were used to plot the samples in multivariate space, with each point representing the difference in mass of plastic for a ROV-Trawl pair. Even for samples that are taken under very similar conditions (depth, slope, shipping intensity, fishing effort, latitude, longitude), the difference in masses of plastic pollution measured by ROV and trawls sometimes spanned as much as six orders of magnitude (Supplementary Information Fig. S8). As the difference between sampling contexts (measured by Euclidean distance) increases, it also seems that Trawl tends to be biased high, suggesting that trawling often occurs in places with higher plastic accumulations. Considering this, we have higher confidence in the results obtained from the ROV model.

4.1. What predicts patterns of accumulation?

Here, we provide an overview of the significant variables that were retained in each model. For both models, plastic abundance increased as more area was sampled. The positive correlation between plastic abundance and sampling effort found here could be the result of the increased probability of detecting an outlier as area sampled increases (Roman et al., 2020). When the outliers are orders of magnitude higher in plastic mass than the rest of the observations, they generate a significant effect on the plastic mass-area relationship, as is represented here by the large coefficient for the area sampled covariate for the Trawl model (Table 1).

The variables of area sampled, median year, depth, shipping intensity, fishing effort, and distance-to-shore were retained in the best fit ROV model. Median year has a positive coefficient. Over time, it is expected that macroplastic abundance will increase on the ocean floor because the ocean floor is expected to be a permanent reservoir, i.e. a sink. It is not a surprise that as depth becomes less negative (towards surface), we find more plastics because shallower waters are closer to land, where effects of terrestrial inputs are felt most greatly (Pham et al., 2014). In areas with greater shipping intensity, we expect to find more plastic on the ocean bottom. Although MARPOL Annex V prohibits the dumping of plastic waste from ships, this is not easily enforceable. It is surprising that fishing effort is not positively correlated with macroplastic mass on the ocean floor, since fishing gear is often found in the marine environment (Cau et al., 2017; Maes et al., 2018; Woodall et al., 2015; Lee et al., 2006). Slope was not retained in the final model ($p > 0.05$).

For the trawl model, the variables of area sampled, median year, net mesh, depth, slope, shipping intensity, fishing effort, and distance-to-shore were retained in the best-fit model. The signs of median year, depth, and shipping intensity are reversed compared to the ROV model. This shows that the sampling methodology differs from ROV, to the point where the relationships between litter detected and predictor variables were reversed. The limited distribution of trawl samples across all of its covariates may have also resulted in a different model structure. Distance to shore was not retained in the final model ($p > 0.05$). Furthermore, there is a strong negative correlation between the masses of plastic sampled using trawls and mesh size of the trawl net. This correlation is expected because as net mesh increases, the mass of plastic found in trawls is expected to decrease due to the loss of smaller-sized plastic objects.

4.2. Predicted global spatial distribution

Below, we explore the spatial distribution of predictions from the ROV model and the Trawl model, and what covariates drive these patterns. Subsequently, we analyze the relative distribution of plastic mass predicted by the ROV model by ocean floor bathymetry, ocean floor topography, and ocean basin. The ROV model predicted large amounts of plastic pollution clustered along continental shelves. This is likely driven by distance to shore and depth (Table 1). The high predictions in the Mediterranean Sea, the Arctic Ocean, and in coastal seas along the northern border of continents in the Northern Hemisphere including the North Sea, Barents Sea, and Norwegian Sea are likely driven by a high density of shipping traffic (Fig. 4; Table 1). There is also a strong correlation between the masses of plastic pollution detected using ROV and median year of sampling, which would result in higher predictions for the year 2020 relative to previous years (Table 1). This positive correlation between plastic mass and median year could be the result of increasing plastic concentrations on the ocean floor, or the increasing attention paid to plastic in ROV surveys. Most likely, it reflects both.

The Trawl model predicted large pools of plastic in ocean basins, particularly in the Western Pacific Ocean. This trend seems to be driven by a combination of depth, slope, and distance to shore: e.g., deep, flat areas offshore contain high quantities of plastic. The bias in where trawls operate, i.e. on relatively flat, shallow areas along the continental shelf, is likely what resulted in these predictions: the concept of "deep" for trawling is different from how deep the ocean truly extends. For trawls, the limit of their operation is around 200 m, or roughly where the continental shelf ends and the continental slope begins. The Trawl model is calibrated against depth observations that only span 0–200 m, so when predicting for the rest of the ocean (i.e. deeper than 200 m), this results in high, extrapolated plastic abundances in the centers of ocean basins that are absent from the ROV heat map.

Analysis of ROV results reveals that approximately half (46%) of the predicted plastic mass on the global ocean floor resides above 200 m depth, which is often used as the contour for continental shelves. The remainder of the ocean, from 200 m to as deep as 11,000 m contains the remainder of predicted plastic mass (54%). Although inland and coastal seas cover much less surface area than do oceans (11% vs 56% out of the entire Earth's area), the bottom of these areas is predicted to hold as much plastic mass as does the rest of the ocean floor (44% vs 41%). Underwater features such as trenches and submarine canyons hold relatively little plastic mass (0.6% and 0.2%, respectively), which is in contrast to the previous suspected notion that deep ocean features are repositories for plastic (Pham et al., 2014; Miyake and Shibata, 2011; Peng et al., 2019; Bergmann and Klages, 2012; Bergmann et al., 2015). This result, however, is consistent with what Martin et al. (2022) found for bulk ocean sediment globally – that abundance of non-fibrous microplastics decreases with depth. The three ocean basins that hold the most plastic mass on the ocean floor are the North Atlantic Ocean (14%), North Pacific Ocean (7%), and South Atlantic Ocean (6%) basins.

4.3. Comparisons with other studies

Here, we place the deviance explained of our model, the significant covariates retained in our model, and our reservoir estimate in the context of the scientific literature.

4.3.1. Deviance explained

Deviance explained is defined as one minus the deviance, and is a measure of goodness-of-fit of the regression model to the data (Wood, 2017). The greater the deviance explained, the greater the model's ability to explain patterns in the response variable. Regression models are commonly used to assess the importance of various factors affecting litter accumulation in environmental reservoirs and to make predictions for locations where people have not sampled previously (Barrett et al., 2020; Lopez-Lopez et al., 2017; Spedicato et al., 2019; Roman et al., 2019b). Regression models with deviance explained of 10–30% are commonly reported in the literature, because plastic litter is a complex environmental phenomenon and such phenomena are typically affected by numerous factors. The model of litter densities on the Mediterranean seafloor by Spedicato et al. (2019) explained an overall 20.5% of variability. Another model of marine litter densities on the bottom of the Bay of Biscay in the North Atlantic Ocean explained 14.8% of total variability (Lopez-Lopez et al., 2017). Compared to these studies, our ROV model (deviance explained = 37.1%), which was ultimately used to inform the global ocean floor reservoir, was able to explain a considerable fraction of variability in our plastic abundance data.

4.3.2. Drivers of debris accumulation

The significance and direction of the relationship between plastic abundance on the ocean floor and certain covariates (e.g. shipping intensity) were expected. However, some of the covariate relationships were not anticipated, and we offer reasons as to why. Pham et al. (2014) and Miyake and Shibata (2011) found that debris accumulated in underwater geographic features with depressions such as oceanic trenches, i.e. at the intersection of negative depth values and flat slopes ($\sim 0^\circ$). Our Trawl model agrees with this: deeper depths and smaller slopes are correlated with greater densities of plastic mass found in trawl samples (depth coefficient = −0.45, slope coefficient = −0.36). In ROV samples, the opposite trend is found: plastic densities decrease with increasing depth (more negative depths), and slope was not found to be a significant predictor. Keeping in mind that trawls typically cannot operate beyond 200 m, this seemingly contradictory finding may be plausible. Cau et al. (2017) and Spedicato et al. (2019) found that plastic litter densities increase closer to shore and closer to harbours, respectively – this result agrees with both the ROV model and the Trawl model: distance to shore is negatively correlated with plastic densities (distance-to-shore coefficient is −0.22 and −0.52, respectively). Buhl-Mortensen and Buhl-Mortensen (2017) found that the largest densities of litter in the Barents and Norwegian Seas coincided with areas of intense maritime activity, i.e. fishing effort and shipping intensity. Our ROV model also identified shipping traffic as having a positive influence on plastic densities on the ocean floor (coefficient = 0.66); however, fishing intensity in both the ROV and Trawl models were negatively correlated with plastic density. This result was not expected, and may be related to the sampling methodologies. Adequate documentation of debris on the ocean floor by ROVs requires clear visibility of the ocean floor. If there is high turbidity in the water column, or if the objects are buried, it may be difficult to quantify plastic abundances accurately using ROVs. Reliable trawl estimates of plastic abundances require that the ocean floor topography be relatively flat; if the terrain is rugged or sloped, it can be difficult for trawl nets to be dragged across the ocean floor and satisfactorily capture all of the debris in the area. The limitations of these sampling methodologies may play a role in confounding the true relationships between drivers and plastic abundances. Another explanation for why debris densities are negatively correlated with fishing effort may be due to the behaviour of fishers: fishing operations have been noted to dump by-catch litter in their fishing nets along with discarded fish elsewhere after fishing operations are completed, essentially delocalizing the litter and masking the true relationship between plastic litter densities and fishing effort (Lopez-Lopez et al., 2017; Neves et al., 2015).

4.3.3. Magnitude of reservoir estimate

The difference between the lower bound and upper bound of our estimate are within the same order of magnitude, and this uncertainty range is small relative to other reservoir estimates (e.g. Martin et al. (2022)). While we took uncertainty from our model into consideration, we acknowledge that there may exist other sources of uncertainty that could impact the reservoir estimates including variability in the exact conditions of deployment of ROV and trawl sampling equipment by study authors, and uncertainty in the spatial data of the covariates.

Our estimate for the ocean floor reservoir is, to the best of our knowledge, the first global estimate. This estimate is similar in magnitude to the two other estimates of deep sea reservoirs of plastic pollution that exist – 14 MMT for microplastics in bulk ocean sediment by Barrett et al. (2020), and 25–905 MMT for micro- and meso-plastics in bulk ocean sediment by Martin et al. (2022).

To groundtruth our model and to improve future modelling efforts, it helps to collect more samples using harmonized methods. We discuss next steps in sample collection in the section below.

4.4. Shortcomings and recommendations

We used data that was available to us from the scientific literature to inform the first global estimate of the ocean floor reservoir of plastic pollution. We provide recommendations from this exercise of building models using empirical data to improve future modelling efforts. We encourage this approach rather than the approach of building entirely theoretical models that are not grounded in empirical data.

First, we suggest that not all data is good data. Researchers should not feel the need to always use all of the data that is at their disposal, especially if the quality of a dataset precludes it from being useful for a given purpose. In the case of Trawl measurements of plastic pollution, its limited spatial distribution precludes it from informing an understanding of the global distribution of plastic pollution on the ocean floor. Secondly, we recommend not combining ROV and trawl samples in the same model, because there are differing biases in the sampling methodologies which in turn create bias in the observations. For instance, trawls can only operate on flat, hard substrate. There are some plastic objects detected using ROVs that trawls are not seeing, and vice versa, and more work is needed to reconcile these measurements. The noisiness of the underlying observational data and the significant variation within, as well as the complexity of the system we are trying to model, are the major limitations of our study.

The third recommendation is that we need more sampling of the ocean floor: sampling that covers a greater diversity of ocean floor topographies and habitats, replicate sampling, and paired sampling. Most sampling efforts to date have been concentrated in nearshore marine environments. In order to obtain equivalent or relatively consistent probability of detection, there is a need for some experiments to understand how much detection probabilities vary from sample to sample. This requires replicate sampling attempts in the same location, and in an ideal world, ROV and trawl samples are both taken in the same area – a process referred to as "paired sampling" – so that we can begin to better understand the differences between them. The lack of paired sampling efforts to date prevented us from combining the data.

Finally, the prohibitively expensive nature of deploying such sampling devices can be a major barrier to the recommendation of greater sampling effort. However, this barrier can be surmounted through co-monitoring of plastic with other variables of interest such as biology, and with help from automation.

5. Conclusion

Using the best available data, we estimate that 3 to 11 MMT of plastic pollution reside on the ocean floor, thereby providing one of the first estimates of the ocean floor reservoir of plastic pollution. This robust estimate fills a longstanding knowledge gap and can be used to better understand the behaviour of plastic in the marine environment. We show how greatly the abundances of plastic measured by two very common ocean floor sampling methodologies differ, raising the question of how we can reconcile measurements across datasets. In this respect, future work that focuses on comparing the size classes, mass, and count abundances of plastic pollution captured by these two sampling methodologies would undoubtedly prove useful. To improve quality assurance and quality control, replicate samples would allow one to better quantify the precision of each methodology or survey approach. Our decision to exclude the predictions by our Trawl model from further consideration shows that not all data should be used just because they exist, and our finding of how incredibly limited the spatial coverage is of deep ocean plastic sampling - to date - calls for renewed efforts to further monitor the contamination of the deep ocean by plastic pollution. The key to large scale monitoring of ocean floor macroplastics likely lies in automation of the process to cut down costs, and the ability to monitor plastic pollution in the context of other activities.

Funding

X.Z. was supported by a Vanier Canada Graduate Scholarship from the Natural Sciences and Engineering Research Council of the Government of Canada.

CRediT authorship contribution statement

Xia Zhu: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. **Chelsea M. Rochman:** Formal analysis, Methodology, Resources, Supervision, Writing – review & editing. **Britta Denise Hardesty:** Formal analysis, Methodology, Resources, Supervision, Writing – review & editing. **Chris Wilcox:** Formal analysis, Methodology, Resources, Supervision, Writing – review & editing.

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

All data used in this study can be accessed free of charge at https://doi.org/10.5683/SP3/MTELIM.

Acknowledgements

Thank you to Kara Lavender Law for discussing the initial idea of global reservoirs with X.Z. and C.R. at the Sixth International Marine Debris Conference in March 2018. Thank you to Ocean Conservancy staff and Marine Debris Tracker staff for sharing their databases of masses of common litter items found during cleanups. Thank you to Marcelo Acha, Alessandro Cau, Michela Angiolillo, David Barnes, Melanie Bergmann, Jennifer Lynch, Sanae Chiba, Patrizia Perzia, Dolfi Debrot, Ahmet Raif Eryaşar, Tomaso Fortibuoni, Francois Galgani, Onur Gönülal, Bjørn Einar Grøsvik, Sedat Gundogdu, Lars Gutow, Ulrike Kammann, Lucia Lopez-Lopez, Thomas Maes, Jake Martin, Shelly Moore, Shamik Dasgupta, Christopher Kim Pham, Kyra Schlining, Nur Eda Topçu, Barbara Urban-Malinga, Inge Van Den Beld, Lucy Woodall, Yury Zablotski, and Sarah Kraak, for providing data to build the systematic review map. Thank you to Michela Angiolillo, David Barnes, Melanie Bergmann, Alessandro Cau, Sanae Chiba, Patrizia Perzia, Dolfi Debrot, Tomaso Fortibuoni, Shamik Dasgupta, Christopher Kim Pham, Kyra Schlining, Inge Van Den Beld, Lucy Woodall, Marcelo Acha, Alessandro Cau, Ahmet Raif Eryaşar, Francois Galgani, Bjørn Einar Grøsvik, Sedat Gundogdu, Lars Gutow, Lucia Lopez-Lopez, Thomas Maes, Shelly Moore, Nur Eda Topçu, Barbara Urban-Malinga, Yury Zablotski, Sarah Kraak, and Christopher Kim Pham for providing raw ROV or trawl data for building the generalized additive model.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.dsr.2024.104266.

References

Alfred Wegener Institute for Polar and Marine Research. LITTERBASE. https://litterbase.awi.de.

Alsina, J.M., Jongedijk, C.E., van Sebille, E., 2020. Laboratory measurements of the wave-induced motion of plastic particles: influence of wave period, plastic size and plastic density. J Geophys Res Oceans 125, e2020JC016294.

Barrett, J., et al., 2020. Microplastic pollution in deep-sea sediments from the great Australian bight. Front. Mar. Sci. 0, 808.

Barton, K., 2023. MuMIn: Multi-Model Inference. https://cran.r-project.org/web/packages/MuMIn/index.html.

Bergmann, M., Klages, M., 2012. Increase of litter at the Arctic deep-sea observatory HAUSGARTEN. Mar. Pollut. Bull. 64, 2734–2741.

Bergmann, M., Gutow, L., Klages, M., 2015. Marine Anthropogenic Litter.

Bergmann, M., et al., 2017. High quantities of microplastic in arctic deep-sea sediments from the HAUSGARTEN observatory. Environ. Sci. Technol. 51, 11000–11010.

Borrelle, S.B., et al., 2020. Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution. Science 369, 1515–1518.

Boucher, J. & Friot, D. International Union for Conservation of Nature: A Global Evaluation of Sources Primary Microplastics in the Oceans. https://portals.iucn.org/library/sites/library/files/documents/2017-002-En.pdf.

Bucci, K., Tulio, M., Rochman, C.M., 2020. What is known and unknown about the effects of plastic pollution: a meta-analysis and systematic review. Ecol. Appl. 30, e02044.

Buhl-Mortensen, L., Buhl-Mortensen, P., 2017. Marine litter in the nordic seas: distribution composition and abundance. Mar. Pollut. Bull. 125, 260–270.

Burnham, K. P. & Anderson, D. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach.

Canals, M., et al., 2021. The quest for seafloor macrolitter: a critical review of background knowledge, current methods and future prospects. Environ. Res. Lett. 16, 023001.

Cau, A., et al., 2017. Submarine canyons along the upper Sardinian slope (Central Western Mediterranean) as repositories for derelict fishing gears. Mar. Pollut. Bull. 123, 357–364.

Chamas, A., et al., 2020. Degradation rates of plastics in the environment. ACS Sustain. Chem. Eng. 8, 3494–3511.

Duinen, B. van, Kaandorp, M.L.A., Sebille, E. van, 2022. Identifying marine sources of beached plastics through a bayesian framework: application to southwest Netherlands. Geophys. Res. Lett. 49, e2021GL097214.

Eriksen, M., et al., 2014. Plastic pollution in the world ' s oceans: more than 5 trillion plastic pieces weighing over 250,000 tons afloat at sea. PLoS One 9, e111913.

Eriksen, M., et al., 2023. A growing plastic smog, now estimated to be over 170 trillion plastic particles afloat in the world's oceans—urgent solutions required. PLoS One 18, e0281596.

Eryaşar, A.R., Özbilgin, H., Gücü, A.C., Sakinan, S., 2014. Marine debris in bottom trawl catches and their effects on the selectivity grids in the north eastern Mediterranean. Mar. Pollut. Bull. 81, 80–84.

Galgani, F., Souplet, A., Cadiou, Y., 1996. Accumulation of debris on the deep sea floor off the French Mediterranean coast. Mar. Ecol. Prog. Ser. 142, 225–234.

Galgani, L., et al., 2022. Hitchhiking into the deep: how microplastic particles are exported through the biological carbon pump in the North Atlantic ocean. Cite This: Environ. Sci. Technol. 2022, 15638–15649.

Geyer, R., Jambeck, J.R., Law, K.L., 2017. Production, use, and fate of all plastics ever made. Sci. Adv. 3, e1700782.

Hann, S., et al., 2018. Investigating Options for Reducing Releases in the Aquatic Environment of Microplastics Emitted by (But Not Intentionally Added in) Products - Eunomia Report. https://www.eunomia.co.uk/reports-tools/investigating-options-for-reducing-releases-in-the-aquatic-environment-of-microplastics-emitted-by-products/.

Institute for Marine and Antarctic Studies, 2022. Global Fishing Effort. https://metadata.imas.utas.edu.au/geonetwork/srv/eng/catalog.search#/metadata/1241a51d-c8c2-4432-aa68-3d2bae142794.

International Hydrographic Organization, 2020. GEBCO_2020 Grid. https://www.gebco.net/data_and_products/gridded_bathymetry_data/gebco_2020/.

Jambeck, J., et al., 2015. Plastic waste inputs from land into the ocean. Science 347, 768–771.

Kaandorp, M.L.A., Dijkstra, H.A., Van Sebille, E., 2020. Closing the mediterranean marine floating plastic mass budget: inverse modeling of sources and sinks. Environ. Sci. Technol. 54, 11980–11989.

Katija, K., Choy, C.A., Sherlock, R.E., Sherman, A.D., Robison, B.H., 2017. From the surface to the seafloor: how giant larvaceans transport microplastics into the deep sea. Sci. Adv. 3, e1700715.

Kooi, M., Van Nes, E.H., Scheffer, M., Koelmans, A.A., 2017. Ups and downs in the Ocean: effects of biofouling on vertical transport of microplastics. Environ. Sci. Technol. 51, 7963–7971.

Law, K.L., 2017. Plastics in the marine environment. Ann. Rev. Mar. Sci 9, 205–229.

Lebreton, L., et al., 2018. Evidence that the great pacific garbage patch is rapidly accumulating plastic. Sci. Rep. 8, 4666.

Lee, D.I., Cho, H.S., Jeong, S.B., 2006. Distribution characteristics of marine litter on the sea bed of the east China sea and the South sea of Korea. Estuar. Coast Shelf Sci. 70, 187–194.

Lobelle, D., et al., 2021. Global modeled sinking characteristics of biofouled microplastic. J Geophys Res Oceans 126, e2020JC017098.

Lopez-Lopez, L., González-Irusta, J.M., Punzón, A., Serrano, A., 2017. Benthic litter distribution on circalittoral and deep sea bottoms of the southern Bay of Biscay: analysis of potential drivers. Continent. Shelf Res. 144, 112–119.

Maes, T., et al., 2018. Below the surface: twenty-five years of seafloor litter monitoring in coastal seas of North West Europe (1992–2017). Sci. Total Environ. 630, 790–798.
Martin, C., Young, C.A., Valluzzi, L., Duarte, C.M., 2022. Ocean sediments as the global sink for marine micro-and mesoplastics. Limnol Oceanogr Lett 7, 235–243.
Maximenko, N., Hafner, J., Niiler, P., 2012. Pathways of marine debris derived from trajectories of Lagrangian drifters. Mar. Pollut. Bull. 65, 51–62.
Mehinto, A.C., et al., 2022. Risk-based management framework for microplastics in aquatic ecosystems. Microplastics and Nanoplastics 2, 1–10.
Miyake, H., Shibata, H., 2011. Deep-Sea litter study using Deep-Sea observation tools. Interdisciplinary Studies on Environmental Chemistry 261–269.
Moriarty, M., Pedreschi, D., Stokes, D., Dransfeld, L., Reid, D.G., 2016. Spatial and temporal analysis of litter in the celtic sea from groundfish survey data: lessons for monitoring. Mar. Pollut. Bull. 103, 195–205.
Mountford, A., Morales, M.M., 2019. Eulerian Modelling of the Three-Dimensional Distribution of Seven Popular Microplastic Types in the Global Ocean. https://eprints.ncl.ac.uk, 124, 8558–8573.
Naranjo-Elizondo, B., Cortés, J., 2018. Observations of Litter Deposited in the Deep Waters of Isla del Coco National Park, Eastern Tropical Pacific. Front. Mar. Sci. 5, 91.
Neves, D., Sobral, P., Pereira, T., 2015. Marine litter in bottom trawls off the Portuguese coast. Mar. Pollut. Bull. 99, 301–304.
Ocean Health Index. Global OHI assessments - Data. https://ohi-science.org/data/.
Olivelli, A., Hardesty, B.D., Wilcox, C., 2020. Coastal margins and backshores represent a major sink for marine debris: insights from a continental-scale analysis. Environ. Res. Lett. 15, 074037.
Peng, X., et al., 2019. Large debris dumps in the northern South China Sea. Mar. Pollut. Bull. 142, 164–168.
Pham, C.K., et al., 2014. Marine litter distribution and density in European seas, from the shelves to deep basins. PLoS One 9, e95839.
R Core Team. R, 2023. A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.
Richardson, K., Hardesty, B.D., Wilcox, C., 2019. Estimates of fishing gear loss rates at a global scale: a literature review and meta-analysis. Fish Fish. 20, 1218–1231.
Rochman, C.M., Hoellein, T., 2020. The global odyssey of plastic pollution. Science 368, 1184–1185.
Roman, L., Hardesty, B.D., Hindell, M.A., Wilcox, C., 2019a. A quantitative analysis linking seabird mortality and marine debris ingestion. Sci. Rep. 9, 3202.
Roman, L., Bell, E., Wilcox, C., Hardesty, B.D., Hindell, M., 2019b. Ecological drivers of marine debris ingestion in Procellariiform Seabirds. Sci. Rep. 9, 1–8.
Roman, L., et al., 2020. A global assessment of the relationship between anthropogenic debris on land and the seafloor. Environ. Pollut. 264, 114663.
Simon Wood, 2022. Generalized Additive Models Using 'mgcv' Package. https://doi.org/10.1201/9781315370279.
Spedicato, M.T., et al., 2019. Spatial distribution of marine macro-litter on the seafloor in the northern mediterranean sea: the MEDITS initiative. Sci. Mar. 83, 257–270.
Stubbins, A., Law, K.L., Bianchi, T.S., Zhu, L., 2021. Plastics in the Earth system. Science (1979) 5, 1–6.
The Comprehensive R Archive Network. Tweedie Distribution. The Comprehensive R Archive Network.
Topçu, E.N., Öztürk, B., 2010. Abundance and composition of solid waste materials on the western part of the Turkish Black Sea seabed. Aquat. Ecosys. Health Manag. 13, 301–306.
Van Emmerik, T., Strady, E., Kieu-Le, T.C., Nguyen, L., Gratiot, N., 2019. Seasonality of riverine macroplastic transport. Sci. Rep. 9 (1), 1–9. https://doi.org/10.1038/s41598-019-50096-1.
Van Sebille, E., et al., 2015. A global inventory of small floating plastic debris. Environ. Res. Lett. 10, 124006.
Wood, S., 2017. Generalized Additive Models. Boca Raton.
Woodall, L.C., et al., 2014. The deep sea is a major sink for microplastic debris. R. Soc. Open Sci. 1, 140317.
Woodall, L.C., Robinson, L.F., Rogers, A.D., Narayanaswamy, B.E., Paterson, G.L.J., 2015. Deep-sea litter: a comparison of seamounts, banks and a ridge in the Atlantic and Indian Oceans reveals both environmental and anthropogenic factors impact accumulation and composition. Front. Mar. Sci. 2, 1–10.
Wu, P., et al., 2021. Transport and fate of all-time released plastics in the global ocean. Down Earth. https://doi.org/10.31223/X50W58.
Zhu, X., 2021. The plastic cycle – an unknown branch of the carbon cycle. Front. Mar. Sci. 7, 609243.
Zhu, X., Rochman, C., 2022. Emissions inventories of plastic pollution: a critical foundation of an international agreement to inform targets and quantify progress. Environ. Sci. Technol. 56, 3309–3312.