

Global mass of buoyant marine plastics dominated by large long-lived debris

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The fate of plastics that enter the ocean is a longstanding puzzle. Recent estimates of the oceanic input of plastic are one to two orders of magnitude larger than the amount measured floating at the surface. This discrepancy could be due to overestimation of input estimates, processes removing plastic from the surface ocean or fragmentation and degradation. Here we present a 3D global marine mass budget of buoyant plastics that resolves this discrepancy. We assimilate observational data from different marine reservoirs, including coastlines, the ocean surface, and the deep ocean, into a numerical model, considering particle sizes of 0.1–1,600.0 mm. We find that larger plastics (>25 mm) contribute to more than 95% of the initially buoyant marine plastic mass: 3,100 out of 3,200 kilotonnes for the year 2020. Our model estimates an ocean plastic input of about 500 kilotonnes per year, less than previous estimates. Together, our estimated total amount and annual input of buoyant marine plastic litter suggest there is no missing sink of marine plastic pollution. The results support higher residence times of plastics in the marine environment compared with previous model studies, in line with observational evidence. Long-lived plastic pollution in the world's oceans, which our model suggests is continuing to increase, could negatively impact ecosystems without countermeasures and prevention strategies.

An estimated 250 metric kilotonnes (250 million kilograms) of plastic pollution floats on the surface of the global ocean^{1,2}. A much larger amount of plastic pollution is estimated to enter the ocean every year, on the order of 800–2,400 kilotonnes from rivers³ and 4,800–23,000 kilotonnes from coastal regions^{4,5} (see Extended Data Fig. 1). We assess what causes the misalignment between the estimated plastic input and the total floating plastic mass by assimilating unprecedented amounts of observational data into a state-of-the-art three-dimensional (3D) global transport model for marine plastics, considering timescales on the order of decades (1980–2020). Our dataset includes concentrations in terms of both number (in $n\text{ m}^{-3}$ in the ocean and $n\text{ m}^{-1}$ on beaches) and mass (in g m^{-3} in the ocean and g m^{-1} on beaches). In total, we use 14,977 measurements from the surface water, 7,114 from beaches and 120 from the deep ocean (for an overview, see Extended Data Fig. 2 and Extended

Data Table 1). From 2,303 beach measurements, we additionally use the fraction of fishing-related items such as fishing nets. We expand on previous mass budget studies⁶ by increasing the model complexity, incorporating numerous recently developed models for different processes affecting marine plastic transport: sinking via biofouling, beaching, turbulent vertical mixing and fragmentation. By using a Bayesian framework, our model results match well with both observed plastic concentrations across different marine reservoirs and different size classes (Extended Data Fig. 3) and the latest understanding of processes removing plastic from the surface ocean.

Sinking of plastic particles probably plays an important role in removing plastic mass from the surface water^{6–8}. Initially buoyant items can start sinking due to the growth of biofilm on their surface, on timescales of weeks to months^{9–11}. We consider various biofouling

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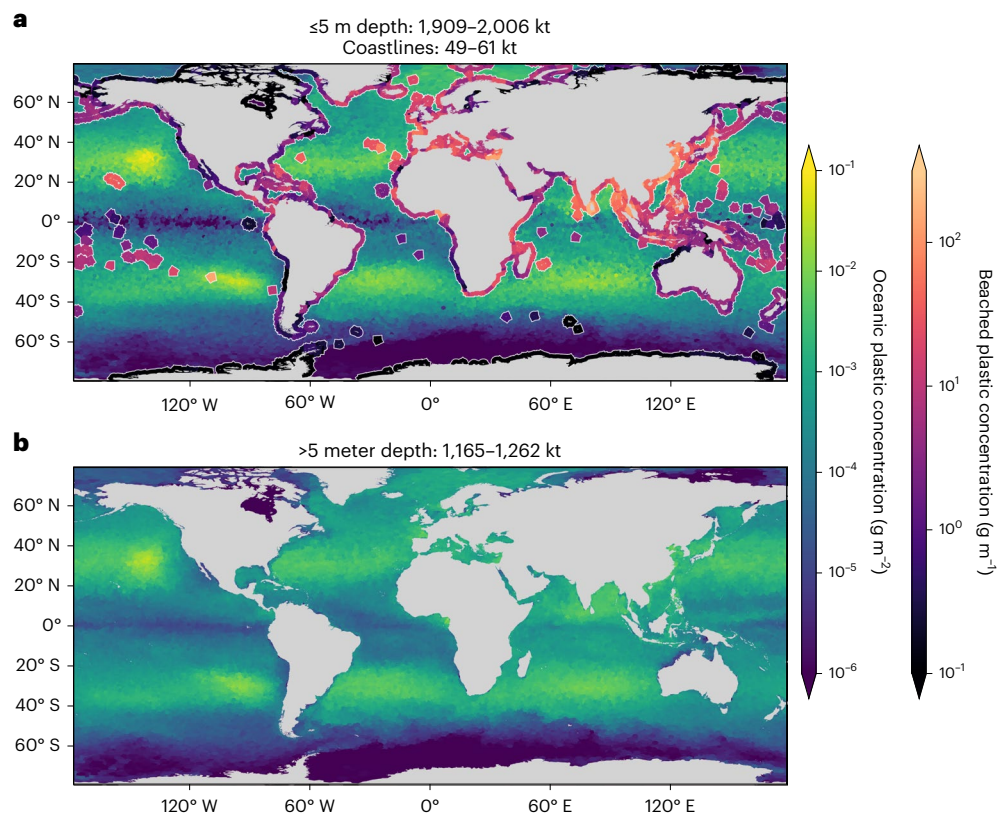


Fig. 1 | A map of the predicted plastic concentrations in the marine environment. a,b, The predicted concentrations (g m^{-2}) of plastic items (0.1–1,600.0 mm) are shown for the most likely parameter estimates in the ocean

surface (0–5 m depth) (a) and below the ocean surface (b). Predicted plastic concentrations on beaches (in purple to red in a, white delineation) are shown in terms of g m^{-1} . The estimated concentrations are shown for the year 2020.

scenarios, including fouling–defouling cycles^{12,13}. Model studies^{14,15} have suggested that the majority (67–77%) of plastics reside on beaches or in coastal waters up to 10 km offshore. We therefore include models for beaching and resuspension of plastics back to the ocean¹⁶. Surface measurements are currently the only large global observational datasets available in the ocean. Mixing of plastic particles in the water column is hypothesized to be an explanation for the relatively low estimates of plastic mass found in surface net trawls^{13,17}. We account for this by resolving plastic transport three dimensionally, including the modelling of vertical turbulent mixing in the water column¹⁸.

Fragmentation plays an important role in explaining the increasing number of plastic particles for smaller particle sizes^{19,20} and can furthermore affect mass budget analyses by breaking down plastic items into particles smaller than typically measured sizes²¹. We therefore use a recently developed fragmentation model²¹, including a size spectrum of plastic particles (0.1–1,600.0 mm). This allows us to assimilate different types of observations such as net trawls that capture mainly microplastics (<5 mm, with a typical mesh size of 0.2 mm (ref. 22)), as well as measurements of larger plastics (>25 mm) from shipboard observations and beach clean-up campaigns. With this size spectrum, we can also more accurately link concentrations in terms of number of plastic particles to concentrations in terms of plastic mass, as a biased conversion between the two has been shown to have a big impact on mass budget estimates²³.

We focus on plastics that are initially buoyant when entering the marine environment, such as polyethylene, polypropylene and polystyrene. These polymers have been shown to make up the majority of items in the ocean's surface²⁴, deeper layers²⁵ and beaches^{26–28}. This means we do not consider polymers denser than seawater such as polyvinyl chloride and polyethylene terephthalate, which are estimated to make up about 35–40% of the plastic mass entering the marine environment^{6,29,30}.

A 3D map of marine plastic litter

We estimate a total amount of initially buoyant plastics in the 3D global ocean of 3,200 kilotonnes (95% confidence interval: 3,000–3,400 kilotonnes) for the year 2020 on the basis of our assimilated model. A 3D global map of the estimated marine plastic pollution for the complete modelled particle size spectrum (0.1–1,600.0 mm) is shown in Fig. 1. The largest fraction of plastic mass is located at the ocean surface: 59–62%. More than a third of the mass resides deeper in the ocean (36–39%) and the remainder is located on beaches (1.5–1.9%).

These results, as well as the the estimated fluxes into and out of the marine environment, are summarized in the schematic overview in Fig. 2. We calculate a total marine plastic input of 500 kilotonnes per year (95% confidence interval: 470–540 kilotonnes for the reference year 2020), originating from coastlines (39–42%), from fishing activity (45–48%) and from rivers (12–13%). The total input we predict increases by about 4% per year, which is consistent with the estimated increase in global plastic waste generation of about 5% per year (ref. 31) and with the observed increase of plastic concentrations in the Pacific Ocean³⁰ and the North Atlantic Ocean³². Our calculated global riverine input of 57–69 kilotonnes per year is lower than previous estimates (800–2,700 kilotonnes per year (ref. 3)). The 190–220 kilotonnes of input from coastlines is furthermore at least an order of magnitude smaller than previous estimates (4,800–12,700 kilotonnes per year (ref. 4)). These much lower input estimates for rivers and coastlines are consistent with recent modelling and observational studies^{6,23,33,34}. The estimated input of 220–260 kilotonnes from fishing activity is somewhat lower than previous estimates of 640 kilotonnes per year³⁵. Our modelled concentrations of fishing-related plastics are consistent with the observed amount of items on beaches (Supplementary Information section 1.2) and match qualitatively with review studies showing that the majority of plastic litter in the

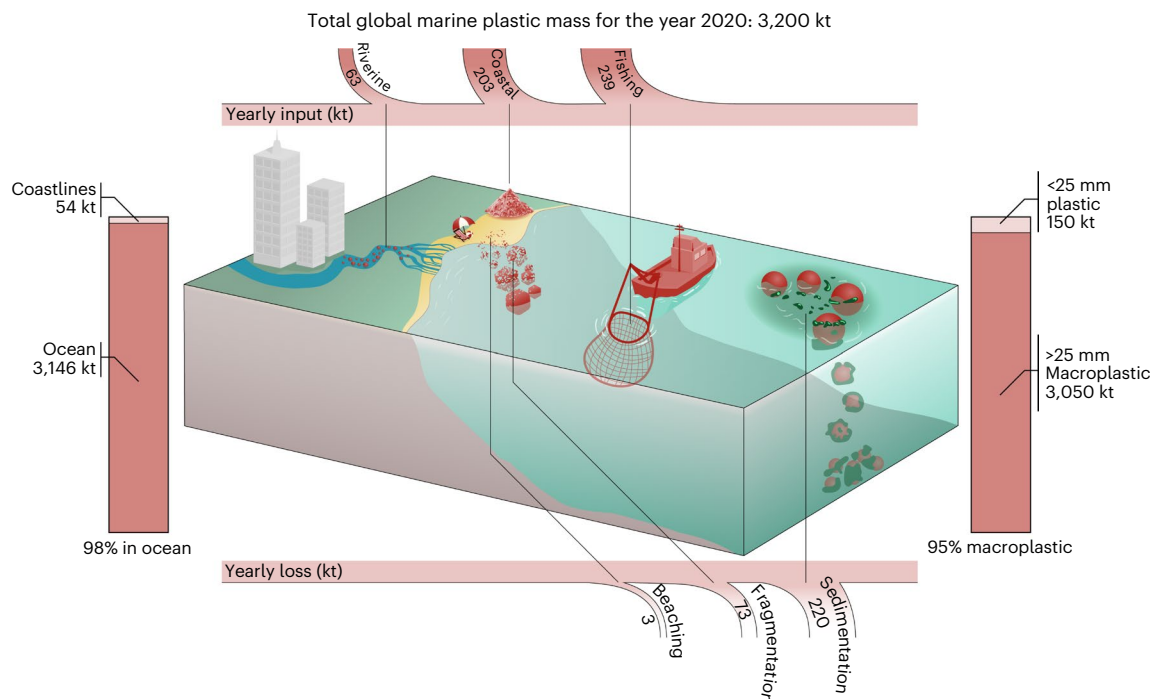


Fig. 2 | Schematic overview of the estimated marine plastic fluxes and standing stocks. Fluxes (top and bottom) are given in kilotonnes per year; standing stocks (left and right) are given in kilotonnes. Sizes of objects are not to scale. Fragmentation loss is defined as particles becoming smaller than 0.1 mm. Credit: thisillustrations.com.

open ocean originates from the ocean³⁶ (for example, items such as nets, ropes and buoys).

Biological processes (such as biofouling) play an important role in the dynamics and export of plastic waste from the ocean surface. We estimate that 220 kilotonnes of plastics are exported to marine sediments per year, of which 6 kilotonnes are microplastics (<5 mm), which is close to the 7–420 kilotonnes of microplastics per year from previous modelling studies⁷. We estimate that 6,200 kilotonnes of initially buoyant plastics have ended up in marine sediments since 1950, which is less than a recent estimate of 25,000–900,000 kilotonnes (ref. 8) for all plastic (buoyant and non-buoyant). Plastic items with densities higher than seawater are not accounted for in our model, and hence sedimentation fluxes near source regions may be underestimated considerably. Our model shows that about half of the initially buoyant plastic particles in the marine environment experience so much biofouling that they start sinking or become neutrally buoyant. The large quantity of plastic particles in the deep ocean²⁵, for a large part consisting of low-density polymers such as polyethylene and polypropylene, cannot be explained without this fouling.

We estimate a plastic sink of three kilotonnes per year at coastlines due to processes such as burial, clean-up efforts and direct ultraviolet degradation. In addition, a substantial amount of plastics are fragmented into particles smaller than 0.1 mm—about 73 kilotonnes per year. We estimate that 2.2% of plastics larger than 5 mm fragment into particles smaller than 5 mm per year, which is very close to previous model estimates of about 3% per year (ref. 14).

Dominant contribution of large plastic items

One of our key results is that the majority of plastic mass is contained in the large plastic items (>25 mm): 90–98% (2,800–3,300 kilotonnes). Microplastics (<5 mm) and plastics between 5 and 25 mm form the small remainder at 49–53 kilotonnes and 150–170 kilotonnes, respectively, which is on the same order of magnitude as previous estimates for small (0.3–200.0 mm) floating plastics (93–236 kilotonnes²). These findings

are also consistent with an analysis of the Great Pacific Garbage Patch³⁰, where it was found that microplastics (<5 mm) make up only 8% of the total plastic mass at the ocean surface.

Particle size distributions (Fig. 3a) reveal an increase in the total plastic mass with particle size according to a power law, up to an estimated dominant particle size of about 0.4 metres. Few particles above this length scale are expected to enter the marine environment. The model results indicate that most of the plastic mass for particles smaller than 0.8 mm is below the ocean surface. The total plastic mass on coastlines is about an order of magnitude less compared with the surface and deep ocean for all particle sizes. The number of particles increases for decreasing particle size (Fig. 3b) according to a power law, as has been shown in previous observational studies^{19,37}.

Our estimate of the total buoyant plastic mass for particles smaller than 5 mm (51 kilotonnes) is similar to previous studies (35.5 kilotonnes¹). However, our mass estimate for particles between 5 and 200 mm, 700 kilotonnes, is much higher than previously estimated (30.6 kilotonnes (ref. 1)). This is even more so for particles larger than 200 mm, where our estimate of 2,500 kilotonnes vastly exceeds the previously estimated 202.8 kilotonnes (ref. 1). This difference can be explained largely by the very broad size intervals used previously¹.

As an example, it can be seen in Fig. 3 (left panel) that the larger particles around 200 mm by far dominate the total mass in the size range 4.76–200.00 mm, whereas these particles are very sparse in terms of total number (right panel). These large particles are therefore likely to be undersampled, causing an underestimation of the total mass. Biases in mass budget estimates due to incorrect usage of mean particle masses were also observed for riverine plastic studies²³. The large differences in total mass estimates underline the importance of treating different particle sizes very carefully in mass budget studies: preferably a (semi-) continuous size spectrum should be used.

We recommend that future plastic measurement campaigns and mass budget studies treat number and mass measurements more carefully. The amount of plastic particles increases exponentially for

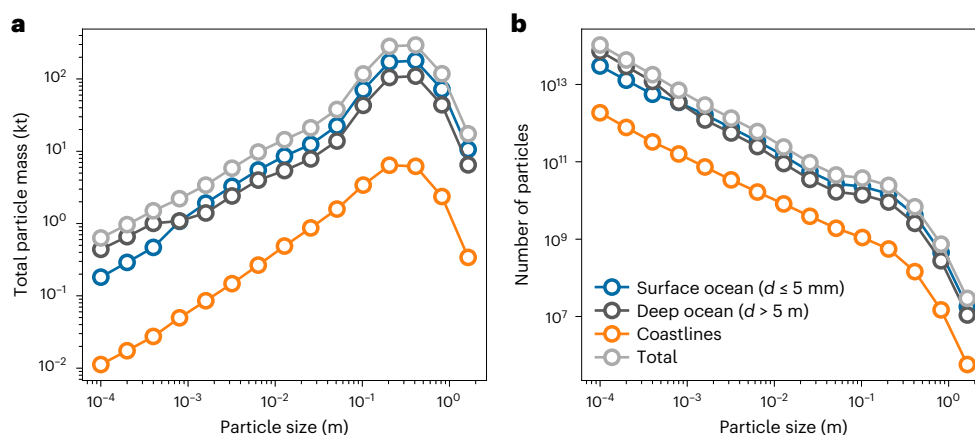


Fig. 3 | Particle size distributions of marine plastics. a,b, The total mass in kilotonnes (a) and number of particles (b) for different size classes (from 0.1 to 1,600.0 mm diameter). Note the logarithmic axes.

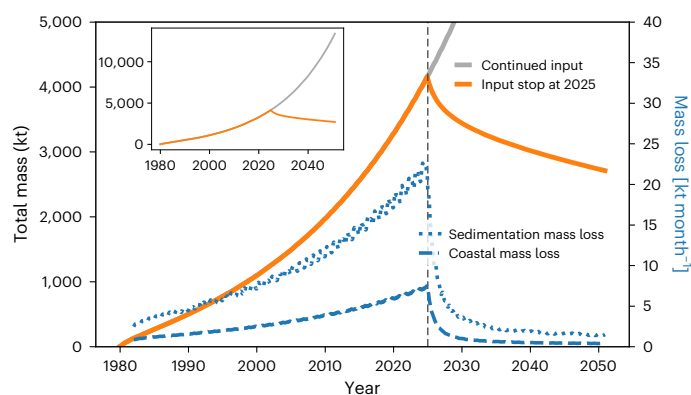


Fig. 4 | Scenarios for the future marine plastic mass budget. A scenario for a sudden stop of new plastics introduced into the marine environment in 2025 is shown in orange, a business-as-usual scenario with an exponentially increasing input in grey. The inset presents a zoom out of both scenarios. Also shown are the expected marine plastic mass losses along coastlines (dashed blue line) and due to sedimentation (dotted blue line), showing that the mass loss after a sudden input stop is expected to decrease rapidly.

decreasing particle sizes. Reporting the number of particles in observational studies can be unreliable when no strict lower limit of the particle size is used. This is especially true for visual observations (the main source of data for beaches^{38,39}) as the lower detection limit probably varies per person. Measuring the total mass of items is more reliable in those cases as most of the plastic mass in the marine environment is contained in the larger particle sizes, which are more easily observed.

Implications of residence times for future projections

In summary, we find that the total amount of buoyant marine plastic litter, 3,000–3,400 kilotonnes, is much higher than previous estimates¹, which for a large part can be explained by better representing large plastic object masses. We also find a plastic input into the marine environment of 470–540 kilotonnes per year, at least an order of magnitude less than previous estimates^{3–5}. The decreased input and increased standing stock suggest that there is no ‘missing sink’ for marine plastic pollution, which has been the focus of many recent papers^{7,23,33,40}. Our mass budget estimate is consistent with observed plastic concentrations in different marine reservoirs and with our latest understanding

of processes removing plastic particles from the surface ocean, such as biofouling and sedimentation, beaching, fragmentation and mixing.

Our finding of a lower plastic input into the marine environment and a higher standing stock means that the residence time of plastics in the marine environment is much higher than previously estimated. For example, some studies⁴¹ predicted that given an instantaneous stop of plastic emissions, more than 95% of the plastic mass would be removed from the ocean surface within 1–2 years due to fragmentation and sinking. We show a similar analysis for a sudden stop of new plastics introduced into the marine environment in 2025 in Fig. 4 using our data-assimilated model. We expect that in this scenario only 10% of the plastic mass would be removed from the marine environment within 2 years (orange line). The removal rate is expected to decrease rapidly over time as plastics move from coastal regions to the subtropical gyres. As there is no beaching and little sinking of marine plastics in these low algal areas compared with coastal waters^{11,13}, the plastic particles become highly persistent (Supplementary Information section 1.3).

We estimate that the plastic input into the marine environment is probably still growing around 4% per year. Previous studies⁴² found no conclusive temporal trends regarding the amount of plastic litter in the marine environment. Establishing temporal trends is difficult due to the high variance in measured plastic concentrations⁴³. Our estimated growth rate of 4% per year gives the best match with observational data over the past decades (Supplementary Information section 1.5) but might change in the future under the influence of mitigation strategies and clean-up efforts. Without further mitigation strategies and clean-up efforts, our estimated growth rate of 4% per year has the potential to double the plastic standing stock within two decades, as shown in the inset in Fig. 4. The combination of a projected exponentially increasing input and long persistence of marine plastics means a likely increasing negative impact of marine plastic pollution on ecosystems in the future.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41561-023-01216-0>.

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Methods

We use a hybrid Lagrangian–Eulerian model to efficiently advect a virtual plastic tracer through the global ocean, under various environmental forcings. First, we use Lagrangian simulations to advect a globally dense set of virtual plastic particles over a time span of one month. We run simulations for different particle sizes, different biofouling scenarios and different months. We then use each of these simulations to construct transition matrices: linear systems that define the probability that plastic particles move from one grid cell of the ocean to another^{44,45}. Parameterized sources and sinks for marine plastic pollution are then directly added into the transition matrix model. This allows us to efficiently evaluate different source and sink scenarios, which is necessary during the data assimilation step where we calibrate the set of unknown parameters to optimally match the observational data. For a more detailed explanation, see Supplementary Information (section 2.4). With the hybrid Lagrangian–Eulerian approach, we have a parsimonious model that can explain the sparse observed data with as few parameters as possible (16 in total; Supplementary Fig. 5).

Data assimilation

Parameters defining sources, transport and sinks of plastic pollution are given a plausible range (the Bayesian ‘prior’) in accordance with current understanding of these processes as discussed in the next sections. Gaussian probability density functions are used to define the ranges, where the 95% confidence intervals define the lower and upper parameter estimates. Measurements contain an error due to both instrument errors (for example, differences between campaigns in sampling) and representation errors (for example, due to unresolved scales and processes⁴⁶). Measurement error is estimated by calculating variograms of the observational data^{6,47}. We use an ensemble smoother with multiple data assimilation to update the model parameter values with the observational data⁴⁸. An ensemble of 55 members (iterated 8 times) is used to estimate the most likely posterior parameter values and confidence intervals. The ensemble members are furthermore used to quantify uncertainty ranges for the estimated plastic concentrations and fluxes. The modelled plastic concentrations represent a mean state, where subgrid-scale variability is not captured. We estimate the subgrid-scale variability from the model–observation mismatch after the data assimilation procedure. The subgrid-scale variability is accounted for in the uncertainty ranges by performing a Monte Carlo analysis⁶, where the plastic concentrations in each ensemble member are perturbed 100 times.

Lagrangian model

To generate the transition matrices, we advect virtual plastic particles three dimensionally in the global ocean using OceanParcels⁴⁹, with the Mercator Ocean PSY4 analysis product at 1/12° resolution as forcing⁵⁰. This forcing product has been assimilated with various data sources (including altimetry, sea surface temperature, salinity and temperature vertical profile data) and includes freshwater fluxes⁵¹. Particles are released horizontally on a hexagonal grid with an average hexagon edge length of 22 km and vertically at 12 logarithmically spaced depth layers between 0.5 m and 5,000 m. This release is repeated every month for five years (2015–2019). Transport is resolved for six different particle sizes (diameter) using an increment of a factor 4 (0.1 mm, 0.4 mm, 1.6 mm, 6.4 mm, 26 mm, 102 mm). These particles experience a varying amount of influence from vertical turbulent mixing, which can affect their horizontal dispersion⁵². Analysis showed that of these sizes, the largest particles (102 mm) experience negligible effect from vertical mixing in the water column due to their high buoyancy. This is therefore the largest particle size for which we calculate the advection in OceanParcels. We assume similar transport for larger particles (up to 1.6 m) when constructing the transition matrices (‘Transition matrix model’ section) since these all remain at the ocean surface. Recent studies have shown that simply adding the Stokes drift velocity⁵³ or a windage term³⁰ to Lagrangian particle simulations representing plastic transport does

not increase the match with observational data, which was verified in a preliminary analysis. These effects are therefore not included in our model. Lagrangian particle simulations usually include a stochastic (diffusive) term⁵⁴ to account for missing subgrid-scale effects (for example, submesoscale eddies). This stochastic term is not included as the transition matrices calculated from the Lagrangian transport (‘Transition matrix model’ section) already introduce diffusion in the dynamics⁴⁵. Transport is resolved for four different vertical transport scenarios under influence of turbulence and biofouling as described in the next section. The total number of particle trajectories across all simulations for the different months, sizes and transport scenarios is 1.7 billion.

Vertical motions. We consider four different scenarios for the vertical behaviour of plastic particles in the ocean. In all four scenarios, vertical diffusion due to turbulence is included, using a Markov-0 random walk model¹⁸ forced by the PSY4 vertical diffusivity fields.

First, we consider plastic particles that remain positively buoyant, with a rise velocity that is dependent on the particle size¹⁷. Spherical particles⁵⁵ with a density of 1,010 kg m⁻³ are used as a baseline, giving the best match with experimentally determined rise velocities of particles found in the marine environment (Supplementary Fig. 9). In reality, environmental plastics have a range of densities and shapes³⁷. For a given particle size in the model, we take a linear combination of the six differently sized baseline particles to model an assemblage of particles with different rise velocities. This linear combination is calibrated during the data assimilation procedure to give an optimal match with the observational data (see the Supplementary Information section 2.3 for further details). Using spherical particles as a baseline keeps the rise velocity model consistent with our biofouling implementation¹³ and keeps the calculation procedure computationally cheap (as opposed to some recent iterative procedures for calculating rise velocities of non-spherical particles^{17,56} that would add extra computational costs).

Second, we include two scenarios for biofouling using a recently developed Lagrangian model¹³. Biochemistry fields from the Mercator Ocean BIOMER4 analysis product are used at 1/4° resolution. Biofilm on plastic particles is gained via collisions and growth with algae in this model and is lost via respiration. Biofilm loss via grazing and viral lysis is neglected to keep the amount of free model parameters limited since this effect is suggested to be minor¹³. Due to the growth and loss of biofilm, plastic particles can oscillate vertically in the water column. This potential oscillatory behaviour has not yet been experimentally observed. We therefore also include a scenario where the fouling of particles is permanent, neglecting the respiration loss term. In our fourth scenario, particles become neutrally buoyant due, for example, to a balance in the fouling and defouling processes or to slightly negatively buoyant particles reaching an equal-density isopycnal surface.

Transition matrix model

The statistics of the Lagrangian particle transport (probabilities that particles move from one grid cell of the ocean to another) are stored in transition matrices, with time windows of 30 days. The Uber H3 grid is used to construct the transition matrix bins horizontally, where each cell has an edge length of approximately 60 km. Each horizontal bin is furthermore divided vertically into four depth bins, with boundaries at 0, 5, 50 and 500 m deep and at the ocean floor. Additional cells are introduced into the transition matrix system representing the coastline segments inside the coastal cells (Supplementary Fig. 11) to model transport between the ocean and beaches. The resulting transition matrices have a size of 121,000 × 121,000.

In the next two sections, we discuss how sources, transport and sinks of marine plastics are parameterized in the transition matrix model. We touch on plausible ranges for each parameter value as these are used to define the prior probability density functions in the Bayesian analysis when assimilating observational data into the model (Supplementary Information section 1.4).

Parameterization of sources. We consider three major types of marine plastic pollution sources in our model: rivers, coastlines and fishing activity³⁰. For a global overview, see Extended Data Fig. 1.

Current estimates of riverine plastic inputs vary widely. Global estimates based on modelling studies calibrated to observational data range from 1,150–2,410 kilotonnes per year (ref. 57) to 800–2,700 kilotonnes per year (ref. 3). However, it was recently argued that these values might be overestimates²³, giving a much lower estimate of about 6.1 kilotonnes per year. Reasons for potential overestimations are (1) biases in conversion from number concentrations to mass concentrations due to too-high particle mass estimates and (2) the mixing of different sampling techniques without accounting for varying lower size detection limits.

We use the most recent global estimate of riverine inputs³, given that they find a reasonable correlation to observational riverine data ($R = 0.86$) and their data are publicly available. We take possible biases into account by scaling the total input with a factor S_{riv} , where the bounds of this prior are chosen to capture both the high-end (2,700 kilotonnes per year (ref. 3)) and low-end (6.1 kilotonnes per year (ref. 23)) estimates.

For coastal mismanaged plastic waste (MPW), we make use of a global MPW dataset per country⁴ in terms of kilotonnes per year per capita. Combined with the estimated population density within 50 kilometres from the coast⁵⁸, this gives us the coastal MPW per unit area per year. A parameter S_{pop} defines the relative input of coastal MPW with respect to the total riverine input.

We estimate plastic loss per fishing hour by scaling a globally estimated fishing hours dataset⁵⁹ with a parameter S_{fis} that defines the relative input of fishing-related plastic with respect to the total riverine input. The prior bounds for S_{pop} and S_{fis} are defined using previously estimated input ranges for different waste categories³⁰. This gives 2.7–7.3 times the riverine input for coastal MPW and 0.2–2.0 times the riverine input for fishing-related plastic.

Larger items make up the majority of plastic mass found in the marine environment^{30,33}, while small fragments dominate in terms of the number of particles²². It is not yet well known which particle size dominates new plastic items introduced into the marine environment. We parameterize the plastic input size using a log-normal distribution, capturing the dominant sizes of plastic packaging in municipal solid-waste sorting facilities (about 0.2 m (ref. 60)) and the dominant sizes of plastic items found in rivers (about 0.2–0.3 m (refs. 61,62)) (see Supplementary Information section 2.1 for more details).

Plastic waste generation has increased exponentially the past decades³¹. We use an exponential function to parameterize the possibility that this has led to an increasing amount of waste entering the ocean. The midpoint estimate for the exponential growth rate (GR_{in}) prior is calibrated to plastic waste production estimates³¹, and the lower bound is set to zero to allow for the possibility of no increased input into the ocean (for example, due to more efficient collection and processing of waste).

Parameterization of transport and sinks. The four different vertical transport scenarios ('Vertical motions' section) yield four different transition matrices. We assume particles in the ocean are an assembly of these four scenarios. How much each scenario contributes is parameterized using three fractions— f_{of} (oscillatory fouling/defouling), f_{pf} (permanent fouling) and f_{nb} (neutrally buoyant)—with the remaining fraction being the positively buoyant particles. In the case of permanent fouling, we keep track of particles hitting the ocean floor (which is one of our sinks), in which case they are classified as 'sedimented' and removed from the system. Prior bounds for f_{pf} are set to 1.7–97.0% by comparing previous estimates of plastic seafloor export⁷ with the estimated plastic mass at the ocean surface¹. The remaining fractions are given equal prior probabilities, with the maximum fraction values set to 95%.

The transition matrix contains separate cells for the coastline segments. The probability that plastic particles beach (move from a coastal ocean cell onto the dry land) is parameterized using a beaching timescale τ_{beach} (refs. 6,15). The prior probability density function for τ_{beach} is defined on the $\log_{10}$ of the value to cover a wide range of (positively valued) possibilities. Parameter bounds are based on previous findings⁶, with a midpoint estimate of 100 days and a lower bound set to 25 days. Resuspension timescales determining how quickly differently sized plastics move from the beach to the ocean are based on experimental findings⁶³. A probability $p_{removal}$ is defined for plastics being removed from beaches (for example, due to burial³³, clean-up efforts or direct degradation of plastic material such as oxidation⁶⁴). We use a previously determined removal rate of 0.2% per month as the midpoint estimate²¹ and allow it to vary an order of magnitude, capturing the removal rates from other global mass budget studies⁴⁰ (0.8–4.0% per month). This is the second 'sink' in which particles are permanently removed from our simulations.

The coastline length inside each grid cell, necessary to calculate litter concentrations per unit length of beach, is computed using the natural Earth dataset⁶⁵. Coastlines have a fractal structure, which can lead to different alongshore lengths in beach surveys compared with the discrete map data. We use a correction factor⁴⁰ to account for the 1.27 fractal dimension of coastlines⁶⁶. The typical beach survey resolution is set to 100 m, and the coastline segment resolutions are calculated directly from the natural Earth map data. To account for the fact that less litter might beach in grid cells with only a small amount of coastline, a parameter $l_{beach,min}$ is introduced. Below this value, the beaching probability decreases linearly down to zero.

We assume fragmentation of plastic items is dominant on beaches due to higher temperatures, oxidation, ultraviolet radiation and mechanical abrasion^{20,29,67,68}. Previous studies⁶⁹ show that neglecting ocean fragmentation is justified as long as plastics fragment at the same rate or slower in the ocean compared with on beaches. A fragmentation model²¹ is used here to simulate how plastic items break down into smaller particles over time. Parameters to be estimated are the fragmentation rate λ_f and the shape factor d_N , which is used to represent the dimensionality of plastic items²¹ (2 for flat objects, 3 for cubes and non-integer values for mixtures of differently shaped objects). For plastic items, the fragmentation rate is still not well known. Parameter bounds for λ_f are based on the experimental data²⁰ (up to $1.9 \times 10^{-4} \text{ d}^{-1}$) and previous model results²¹ (down to $2.9 \times 10^{-5} \text{ d}^{-1}$) and are defined on the $\log_{10}$ of the value to cover a wide range of possibilities. Bounds for d_N are based on observational data of plastic particle sizes and masses (Supplementary Information section 2.2). Fragmentation is the third sink for plastic particles in our simulations, where they are removed when reaching a size smaller than 0.1 mm.

In our model, we consider a full size spectrum from 0.1 to 1,600.0 mm, using increments of a factor 2. Lagrangian particle transport is resolved for six sizes (0.1–102.0 mm, 'Lagrangian model' section). For intermediate sizes in the spectrum, the available transition matrices are interpolated linearly. For larger plastics (>0.1 m), similar transport is assumed as these particles remain predominantly at the ocean surface. We model the particle size distribution both in terms of the number of particles and in terms of mass (see ref. 21 for more details). This way, we can quantify which particle size contributes most of the marine plastic pollution. For smaller plastic particles, data are available on typical masses^{70,71}. For bigger items, the particle mass m_p is extrapolated from the particle length l_p using $m_p \propto l_p^{d_N}$, consistent with the fragmentation model. See Supplementary Information section 2.2 for more details.

Data availability

The datasets generated during the current study are available in the Utrecht University Yoda repository with the identifier <https://doi.org/10.24416/UU01-LDAGQN>⁷².

Code availability

Codes used to conduct the experiment are available in the Utrecht University Yoda repository with the identifier <https://doi.org/10.24416/UU01-LDAGQN>⁷².

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Author contributions

M.L.A.K. designed and conducted the study, with steering and supervision from E.v.S. and feedback from H.A.D. D.L. contributed to the methodology. C.K. contributed to the OceanParcels software development. All authors made substantial contributions to the manuscript revisions.

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Competing interests

The authors declare no competing interests.

Additional information

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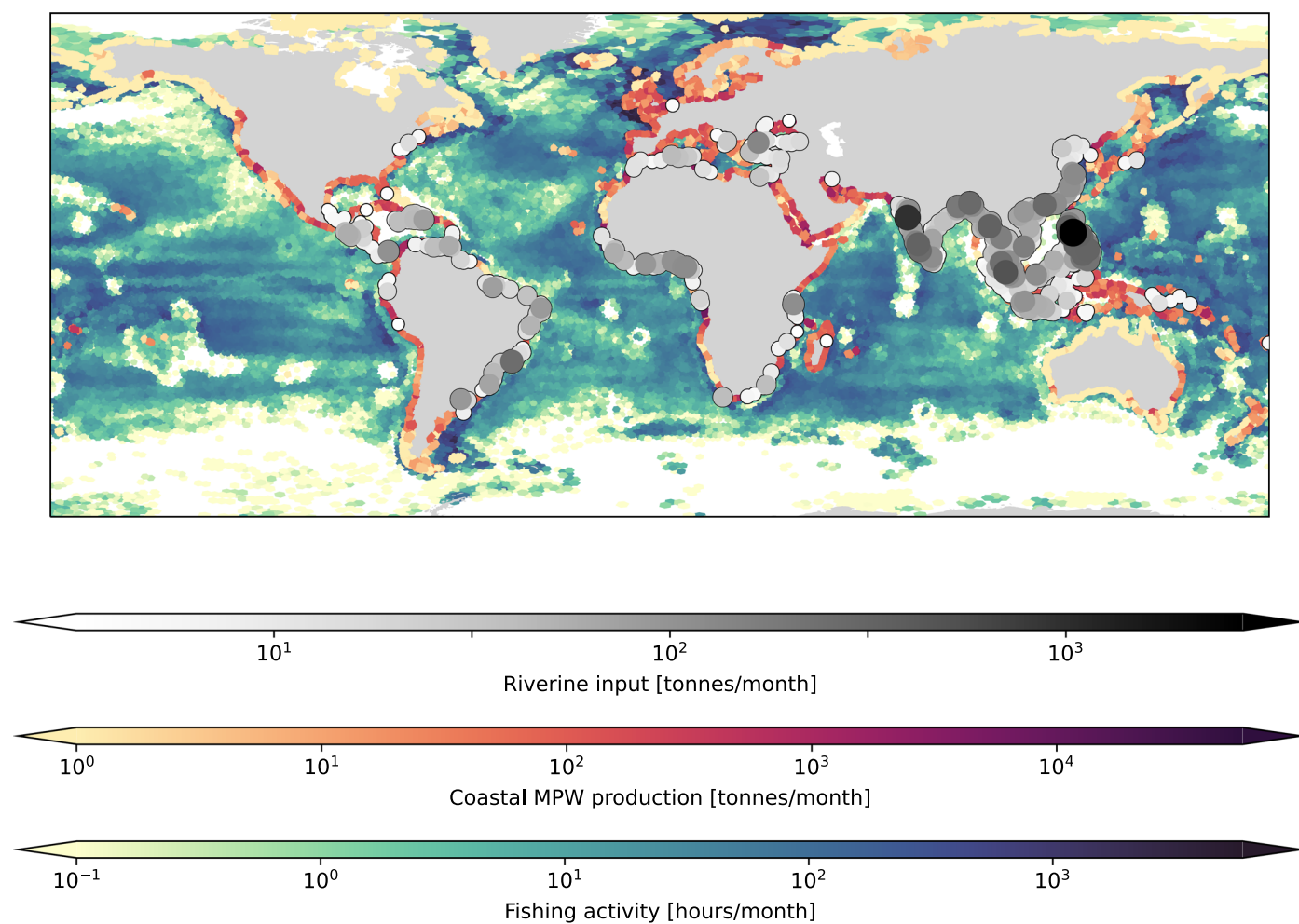
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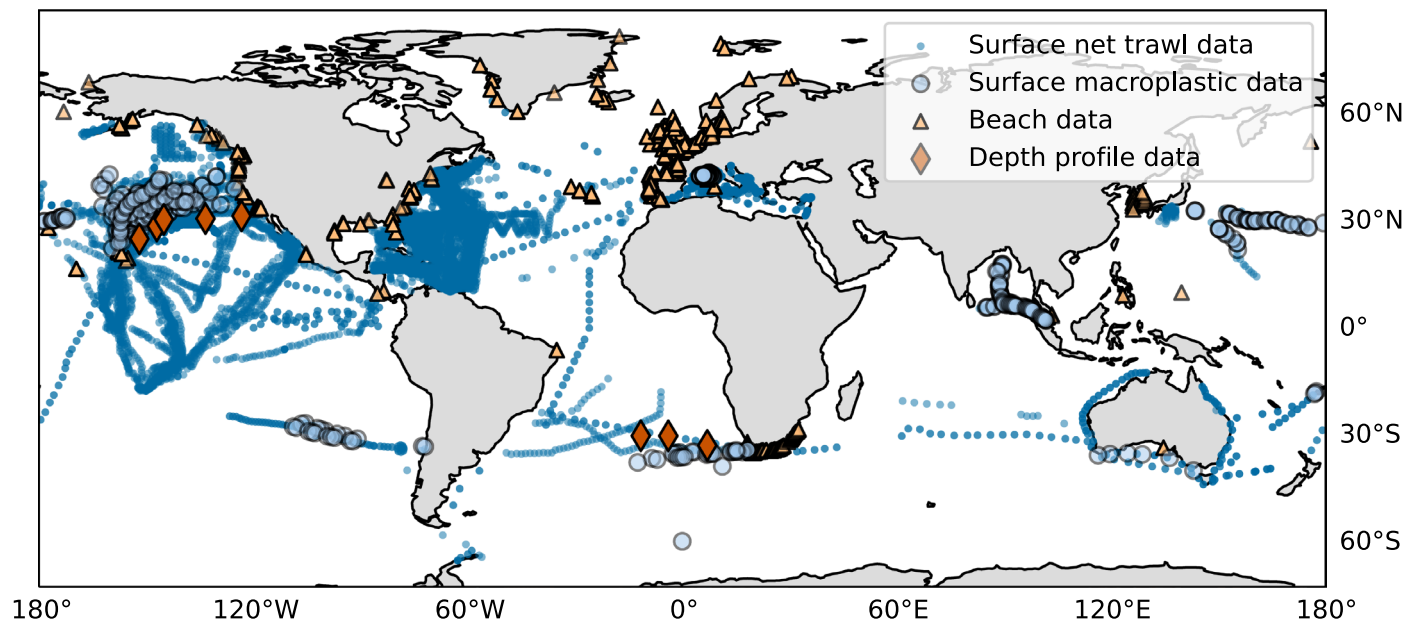
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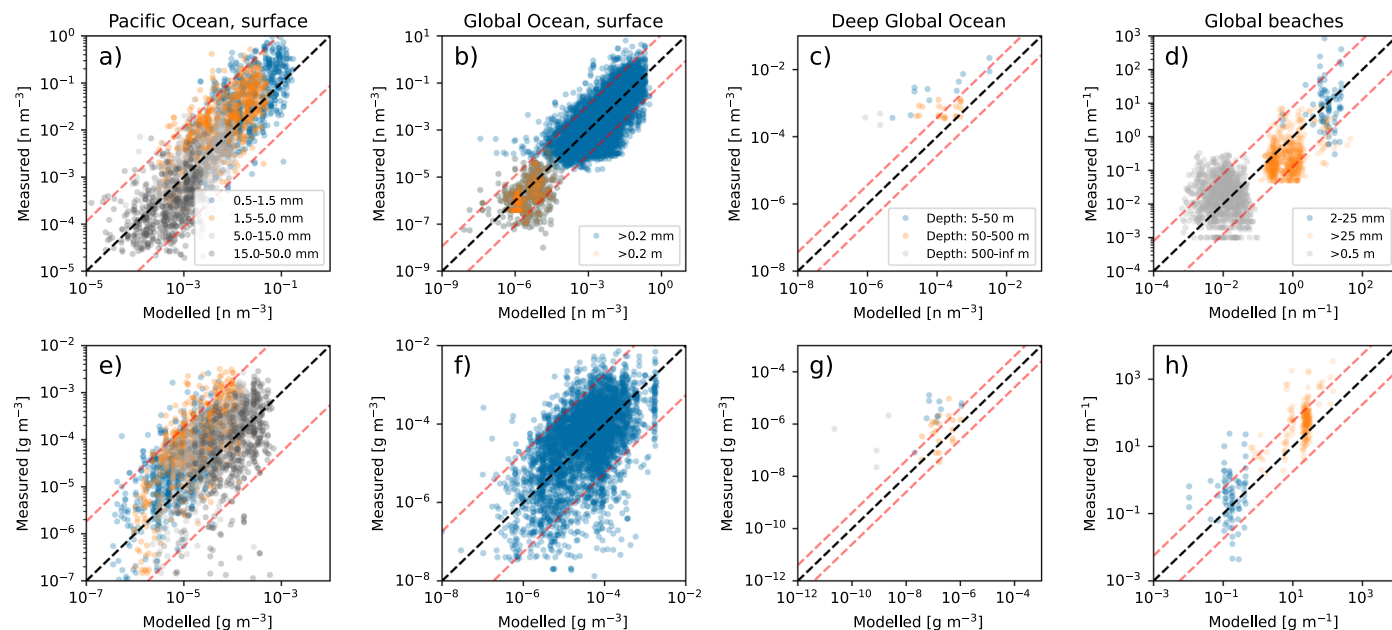
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Extended Data Fig. 1 | Three major sources of marine plastic pollution. Rivers³, shown using grey to black circles; coastal mismanaged plastic waste⁴, shown in red to purple; and fishing activity⁵⁹, shown in blue.



Extended Data Fig. 2 | Observational data across different marine reservoirs used to assimilate into the numerical model. The markers show the locations of the available observational data, from neuston net measurements at the ocean surface (blue dots), visual observations of large plastic items (>0.2m, blue circles), the deep ocean (orange diamonds), and beaches (orange triangles).



Extended Data Fig. 3 | Scatter plots for modelled versus measured plastic concentrations. a, e, Measurements for separate size classes at the ocean surface^{25,72}. **b, f,** Measurements for small plastics (>0.2 mm) and large plastics (>0.2 m) at the ocean surface. **c, g,** measurements below 5 m depth. **d, h,** Measurements from beaches. **a–d,** Number concentrations (n m^{-3} in the ocean

and n m^{-1} on beaches). **e–h,** Mass concentrations (g m^{-3} in the ocean and g m^{-1} on beaches). The 1:1 line is shown using the dashed black line, the expected amount of measurement error ($\pm 2\sigma$) is shown using the dashed red lines. The Pearson R correlation coefficients between the modelled and measured concentrations are given in the supplementary information, Table S1.

Extended Data Table 1 | Overview of the observational data used to calibrate the numerical model

Reference	Measurement type	Notes
[2]	Net trawls, surface ocean	Compilation of 37 measurement campaigns for small plastic particles (>0.335 mm) in terms of mass and number, 11,854 data in total
[6]	Net trawls, surface ocean	Compilation of 18 measurement campaigns for small plastic particles in the Mediterranean Sea (>0.335 mm) in terms of mass and number, 1170 data in total
[25, 72]	Net trawls, surface ocean	Data on 4 size classes available in terms of mass and number, 1390 data in total
[25, 77]	Net trawls, deep ocean	Data on 4 size classes available in terms of mass and number, 120 data in total
[1]	Visual observations, surface ocean	Visual detection for large plastics (>0.2 m) in terms of number, 553 data in total
[76]	Visual observations, surface ocean	Automatic floating object detection for large plastics (>0.5 m) in terms of number, 10 data in total
[38]	Beach measurements	OSPAR data (>0.5 m) in terms of number, 1692 data in total
[39]	Beach measurements	MDMAP data (>25 mm) in terms of number, 5022 data in total
[47, 78–80]	Beach measurements	Additional beach measurements in terms of mass, 238 data in total
[81]	Beach measurements	Data on small plastics (2–25 mm) in terms of mass and number, 162 data in total

To account for the fact that net trawl data can be biased due to wind mixing, the Kukulka correction factor⁷⁴ is applied using ERA5 reanalysis wind speeds⁷⁵. Data for large plastic items at the ocean surface (>0.2 m) come from previous studies using visual observations¹⁷⁶. For beach measurements, MDMAP³⁹ and OSPAR³⁸ observations are included in terms of $n\ m^{-1}$, focusing on larger plastic items (>25 mm and >500 m respectively). These datasets contain information on the type of litter items. Plastic litter types containing words such as 'fish', 'rope', or 'net' are categorized as fishing related items, which is used to calculate a minimum percentage of fishing related plastics per measurement location.