

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

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13 **Running head:** The ocean floor reservoir of plastic pollution

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20 **Significance Statement**

21 Novelty and Significant Advancement in Science: Researchers are trying to solve the problem of
22 the missing plastic. To solve the puzzle, global estimates are needed for major plastic reservoirs
23 – e.g., surface waters, bottom. Here, we provide one of the first global estimates of plastic on the
24 ocean floor and predict its global distribution, thereby providing another piece of the puzzle of
25 the missing plastic. Our methods are not purely theoretical; our model synthesizes and
26 incorporates empirical data allowing for more reliable and insightful predictions. Overall, we
27 show that plastic clusters around continental shelves, closer to human populations. Moreover, the
28 size of our reservoir suggests that plastic on the ocean floor is not increasing at the same pace as
29 plastic production. Our finding challenges the prevailing estimate of how much plastic enters the
30 ocean annually. Finally, our study shows numerous gaps in sampling effort and we discuss how
31 researchers can fill these gaps to improve future models.

32 Breadth of interest of science and appropriateness of L&O: Our research will be of interest to the
33 multidisciplinary audience of L&O, including oceanographers who are interested in the global
34 distribution of plastics, biogeochemists and earth scientists who are interested in how plastics are
35 changing the composition of the Earth, ecologists and conservationists who are interested in how
36 plastics are affecting benthic organisms and ecosystems, and policymakers who are working on
37 global environmental issues such as this one.

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41 *Author Contribution Statement*

42 **Xia Zhu:** conceptualization (lead); data curation (lead); formal analysis (lead); methodology
43 (lead); project administration (lead); visualization (lead); writing – original draft preparation
44 (lead); writing – review & editing (equal). **Chelsea Rochman:** formal analysis (supporting);
45 methodology (supporting); resources (lead); supervision (equal); writing – review & editing
46 (equal). **Britta Denise Hardesty:** formal analysis (supporting); methodology (supporting);
47 resources (lead); supervision (equal); writing – review & editing (equal). **Chris Wilcox:** formal
48 analysis (supporting); methodology (supporting); resources (lead); supervision (equal); writing –
49 review & editing (equal).

50

51 **Abstract**

52 The exponential increase in plastic production coupled with variable global waste management
53 system efficiencies has resulted in large amounts of plastic waste entering the ocean every year.
54 Although we know millions of tonnes of plastic have entered the oceans, we do not yet
55 understand the patterns of its accumulation across space nor the drivers of these patterns. The
56 deep ocean is expected to be a resting place, or reservoir, for plastic pollution. Here, we
57 conducted a rigorous, systematic review of previously published datasets to synthesize our
58 understanding of macroplastic pollution (> 5 mm) on the ocean floor. Using extracted data, we
59 built predictive additive models to estimate the amount and distribution of plastic on the ocean
60 floor. We built two models: one using data from remote operated vehicles (ROVs) and another
61 using data from bottom trawls. Using the model built with ROV data, which was better-
62 constrained, we estimate that 3 to 11 million metric tonnes (MMT) of plastic pollution resides on

63 the ocean floor as of 2020. This is of similar magnitude to annual inputs from land and one to
64 two orders of magnitude greater than what is predicted to be floating on the ocean surface. To
65 improve future estimates and our understanding of global patterns, we provide recommendations
66 for ocean floor monitoring of plastic pollution.

67 **Introduction**

68 The production of plastic has increased exponentially over time, such that by 2050 we are
69 predicted to have generated a total of 26,000 million metric tonnes (MMT) of virgin resin¹.
70 Approximately half of this plastic is projected to become waste¹. Plastic waste that escapes
71 management systems or is shed from plastic during use (e.g., tire wear particles) enter the
72 environment as emissions of plastic pollution²⁻⁴ and cycle through environmental reservoirs
73 much like carbon and nitrogen^{5,6}. Millions of tonnes of plastic pollution, estimated at 4 - 23
74 MMT per year^{7,8}, enter the ocean as part of the Global Plastic Cycle^{5,9}.

75 *Fate of plastic pollution is poorly understood*

76 Physical forcing via wind¹⁰⁻¹³ and currents^{14,15}, biological forcing via the movement of marine
77 life, and the incorporation of plastic into organic particles (e.g., marine snow and fecal material)
78 ¹⁶⁻¹⁹ transport plastic pollution throughout the ocean. The amount and spatial distribution of
79 plastic pollution in all major marine reservoirs, including the ocean surface, ocean column, ocean
80 floor, marine sediments, coastlines, and marine animals have not yet been quantified^{5,20}.
81 Although there are estimates of the amount of plastic floating on the surface of the global
82 ocean^{14,21,22}, global estimates for the other reservoirs are lacking. Moreover, due to a lack of
83 broad-scale empirical data across reservoirs, including the ocean's surface, models to date are
84 poorly constrained²³. The risks that plastic pollution may pose to marine life^{24,25} is motivation for

85 better understanding the spatial extent of plastic pollution to inform the exposure landscape for
86 organisms more holistically.

87 *Plastic resting on the ocean floor*

88 The ocean floor is predicted to be among the largest reservoirs of plastic pollution^{20,23}, and is
89 suspected to be a long-term reservoir, or sink, due to the lack of removal processes acting upon
90 it. This is further exacerbated by the extremely slow degradation rates of plastic in cold
91 environments lacking in both oxygen and UV radiation²⁶. The deep ocean consists of two major
92 reservoirs of plastic pollution: the ocean floor^{20,23}, which consists of large plastic objects sitting
93 on top of the floor, and bulk ocean sediment²⁷⁻²⁹, which consists of smaller plastic particles
94 mixed into the sediment.

95 Field surveys and sampling campaigns have quantified benthic plastic pollution from seas,
96 estuaries, and deep ocean basins (e.g.,³⁰⁻³⁴). Modelling studies have used empirical data to
97 assess drivers of benthic debris accumulation regionally (e.g.,^{28,35-37}) and data simulations to
98 predict vertical particle transport (e.g.,^{38,39}). Regional studies shed light on plastic accumulation
99 in specific locations, and simulations of vertical transport allow extrapolation to predict benthic
100 contamination. To date, we lack a holistic assessment of the global distribution and overall
101 importance of the ocean floor as a global reservoir.

102 Here, we synthesize empirical data from the peer-reviewed literature to build a predictive model
103 of the extent and spatial distribution of plastic pollution on the ocean floor at a global scale. We
104 also consider the driving forces relevant to the transport and accumulation of plastic in the deep
105 ocean, which informs source-reduction and environmental remediation efforts. Finally, based on

106 our findings, we make specific suggestions for improving sampling and data collection to
107 improve future predictions of the load of plastics in the global ocean.

108 **Materials and Methods**

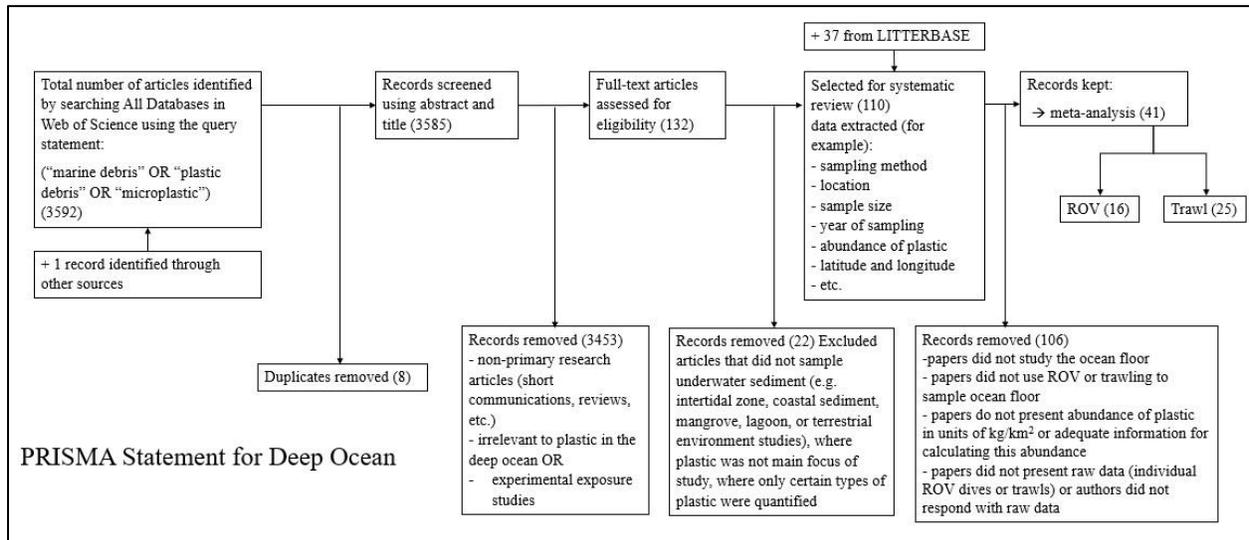
109 *Systematic review*

110 The terms (“marine debris” OR “plastic debris” OR “microplastic”) was included in a literature
111 search query via “All Databases” in Web of Science to find peer reviewed publications that
112 report abundances of plastic pollution in either the ocean floor or the sediment compartment of
113 the deep ocean. We included papers published from September 1976 until January 1st, 2020.
114 Inclusion criteria were used to select papers for the systematic review and meta-analysis (see
115 details in **Figure 1**). Only studies that report abundances of plastic in marine settings that are
116 underwater, or below zero meters with respect to sea level, were included in the analysis. As a
117 result, we excluded studies conducted in intertidal environments (e.g., wetlands, mangroves), on
118 beaches, and in any terrestrial or freshwater environments (e.g., lagoons, terrestrial parks,
119 forests). A quality assurance search through LITTERBASE (<https://litterbase.awi.de/>) was
120 conducted to identify any studies that our search may have missed. To synthesize what we know
121 about plastics in the deep ocean and to retrieve data needed for our predictive modelling, we
122 extracted geographic coordinates, area name, country (if applicable), sampling method, sample
123 size, abundance of plastic pollution, plastic sizes, plastic types, year of sampling, sampling
124 depth, sampling season, and ocean floor topographic feature from each of the included studies.

125 *Meta-analysis – predicting global estimates*

126 Although we present the state of the knowledge of plastic pollution in both the ocean floor and
127 bulk sediment reservoirs, we only modelled the distribution of plastic on the ocean floor. Studies

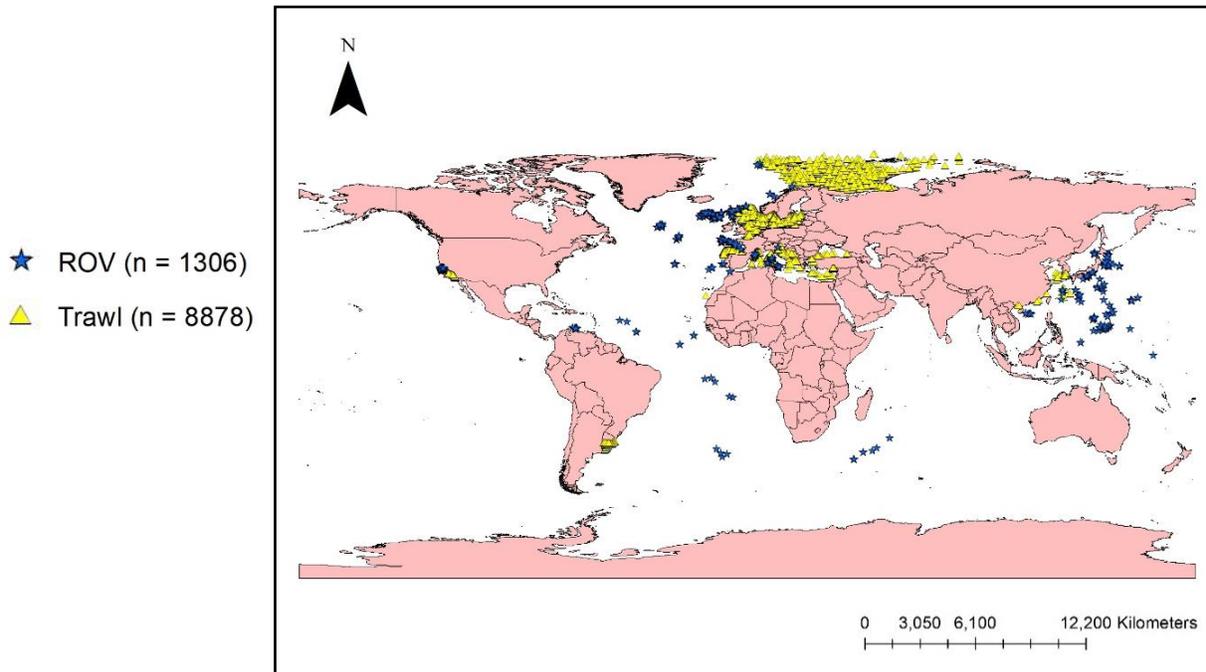
128 on plastic pollution in sediment were not included due to the inherent differences in plastic
129 morphologies and sizes between the ocean floor and bulk sediment reservoirs, and because
130 preliminary estimates of the size of the bulk sediment reservoir already exist^{27,28}. Studies
131 included in the meta-analysis were used to build a generalized additive model⁴⁰ (**Supplementary**
132 **Information Table S1**). The chosen studies must have reported adequate quantitative
133 information that enables the calculation of an abundance measure for plastic pollution on the
134 ocean floor - specifically, they need to either provide a mass of plastic per area measurement, or
135 a count of plastic per area measurement along with a physical description of the plastic items
136 retrieved. We chose to only focus on studies that used remote operated vehicles (ROV) or
137 trawling methodology because they are the most commonly deployed methods for sampling
138 plastic pollution on the ocean floor.



139
140 **Figure 1.** PRISMA statement showing how studies for the systematic review and meta-analysis
141 were sequentially filtered. The numbers in parentheses represent the number of papers relevant to
142 each step in the process.

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

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



157

158 **Figure 2.** Raw ROV (n = 1306) and trawl (n = 8878) samples used to train their respective
159 models from surveys taking place 1988-2018 and 1993-2017, respectively.

160 We fitted two generalized additive models, one using masses of plastic pollution from ROV
161 imagery and the other using trawl samples, in RStudio using the *mgcv* package⁴¹. After
162 evaluation, we found these two sampling methodologies to be too divergent to be combined and
163 used to fit a single model. For both of our models, covariates were first checked for collinearity.
164 The parent models are fit to their respective data using the *Tweedie* distribution⁴². The *dredge*
165 function in the *MuMIn* package was used to search through all possible permutation of covariates
166 and select the model with the most parsimonious fit to the data, measured using Akaike's
167 Information Criterion (AIC) score^{40,43}. The AIC score uses a model's maximum likelihood
168 estimation as a relative measure of goodness-of-fit, and penalizes for complexity. The model
169 with the lowest AIC score was considered the best model, and any model that is within two
170 points of the best model is considered equivalent as it falls within the 95% confidence interval

171 around the best model. More details on the modelling process can be found in the supplementary
172 text (**Supplementary Information Text 2**).

173 The covariates we included in the GAMs were depth, slope, shipping intensity, fishing effort,
174 distance to shore, and distance-weighted population. Area sampled and median year were control
175 variables for the ROV model, while area sampled, median year, and net mesh acted as control
176 variables for the model built using trawl samples. Covariates were standardized by subtracting
177 the average from each value and dividing by the standard deviation. The covariates were chosen
178 based on their consideration in previous studies or their suspected influence on the mass and/or
179 distribution of plastic pollution on the ocean floor (please see supplementary text for more
180 information, **Supplementary Information Text 2**).

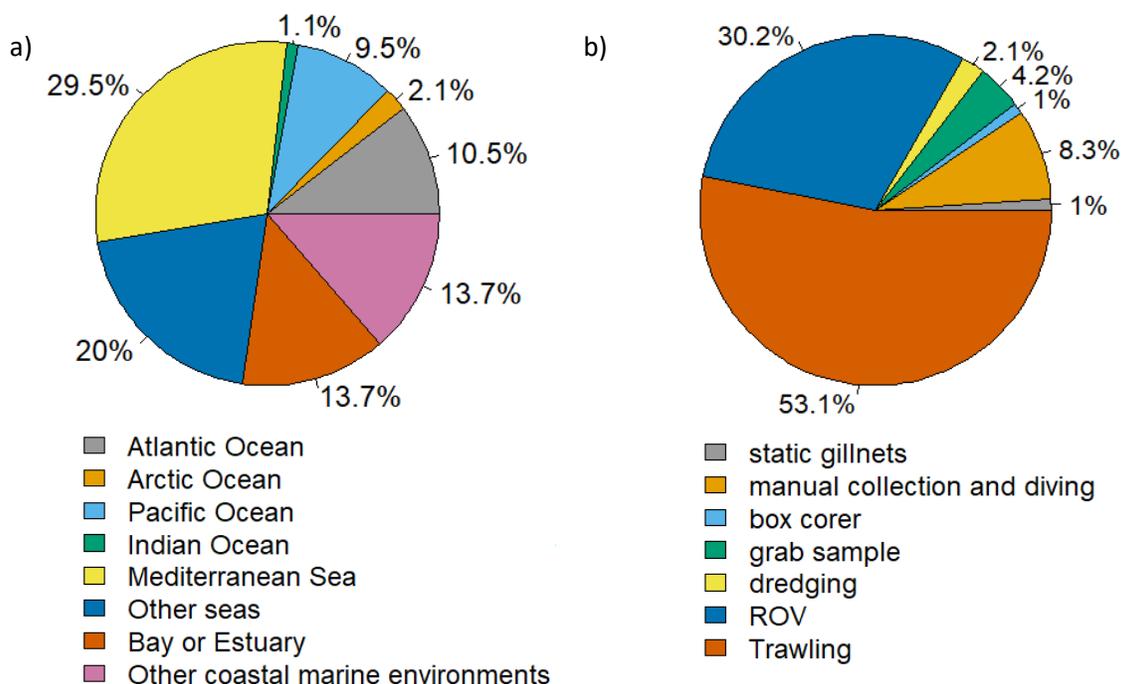
181 Both models were used to predict the mass of plastic (in kg/km²) for every 1° x 1° grid cell of the
182 ocean floor. The total mass of plastic (kg) in each grid cell was determined by multiplying the
183 predicted mass/area from our fitted models by the total area of the grid cell (km²). The ocean
184 floor reservoir was estimated by summing the masses of plastic pollution predicted by a model
185 across all ocean floor grid cells.

186 **Results**

187 *Summary of sampling effort in the deep ocean*

188 For both the ocean floor and bulk ocean sediment, plastic pollution sampling efforts are
189 concentrated in coastal marine environments (**Figures 2, 3a, Supplementary Information**
190 **Figure S1a**). These sampling campaigns have not been decomposed into individual raw points.
191 For macroplastics on the ocean floor, 73 out of 95 (77%) independent sampling campaigns took
192 place in coastal marine environments including inland and coastal seas, bay-estuary systems,

193 bights, reef habitats, continental shelves, and canyons (**Figure 3a**). The Atlantic and Pacific
 194 Oceans were the ocean basins with the highest number of sampling campaigns overall (**Figure**
 195 **3a**). For microplastics embedded within bulk ocean sediment, 42 out of 50 (84%) independent
 196 sampling efforts took place in coastal marine environments (**Figure S1a**). The Arctic Ocean had
 197 the most sampling campaigns across all ocean basins. Plastic pollution sampling efforts on the
 198 ocean floor are dominated by ROV and trawl sampling; in fact, 80 of 96 studies (83%) used
 199 ROV or trawling to sample the ocean floor (**Figure 3b, Supplementary Information Figure**
 200 **S1b**). For bulk ocean sediment, just over half (51%) of all sampling campaigns deployed the
 201 grab sampling technique to sample microplastic pollution embedded within deep ocean sediment.



202
 203 **Figure 3.** a) Sampling locations of plastic pollution on the ocean floor are displayed as
 204 percentage of total sampling campaigns conducted up until January 1, 2020. b) Sampling
 205 methodologies for large plastic objects on the ocean floor are also displayed as percentage of
 206 total sampling campaigns conducted globally up until January 1, 2020. Examples of other coastal

207 marine environments include gulfs, canyons, reefs, marine sanctuaries, harbours, bights, fjords,
208 and coves.

209 *Summary of ROV and Trawl models, and Derived Predictions*

210 The best model built using ROV samples, henceforth referred to as the “ROV model”, explained
211 37.1% of the deviance in the mass of plastic pollution on the ocean floor and included area
212 sampled, median year, depth, shipping intensity, fishing effort, and distance to shore (**Table 1**).
213 All variables were significantly correlated with mass of plastic pollution except for area sampled
214 ($p = 0.056$) and fishing effort ($p = 0.087$). The ROV model has a much lower AIC score than the
215 null model, which is an indication that the ROV model has greater goodness-of-fit to the data
216 than the null model (**Supplementary Information Table S2**). The best model built using trawl
217 samples, henceforth referred to as the “Trawl model”, explained 21.8% of the variability in mass
218 of plastic pollution on the ocean floor and included area sampled, median year, net mesh, depth,
219 slope, shipping intensity, fishing effort, and distance to shore (**Table 1**). All variables in the
220 Trawl model were significantly correlated with mass of plastic pollution found on the ocean
221 floor. As with the ROV model, the Trawl model also has greater goodness-of-fit to the data than
222 the null model, as indicated by its lower AIC score (**Supplementary Information Table S3**).
223 Model diagnostics were performed for both models (**Supplementary Information Figure S2-**
224 **S3**).

225 Population density was included as a smooth term and not as a parametric term. We fitted
226 population by distance effect as a smooth term, which is a non-parametric approach using a set
227 of approximating basis functions to build a complex functional relationship. Here, we used signal
228 regression or a variable coefficient model, which allows coefficients to vary with different values
229 of the covariate. The collective integration of the effect of distance on population over a given

230 interval is represented by the p-value of the smooth, or the overall significance of the fit. For
 231 both the ROV and the Trawl model, distance-weighted population density was significantly
 232 correlated with plastic mass on the ocean floor (**Supplementary Information Figure S4**). For
 233 both models, the general trend is that large distant human populations have the largest impact on
 234 plastic densities at sampling locations. This finding may suggest a combination of limited mixing
 235 and settling out of material at short distances, as well as the importance of distant sources such as
 236 large cities that are delivering large amounts of inputs (**Supplementary Information Figure**
 237 **S4**).

238 **Table 1.** Summary of parametric variables in the best ROV and trawl models. Coefficients/effect
 239 estimates are directly comparable because covariates were standardized by subtracting their
 240 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	$3.2*10^{-8}$

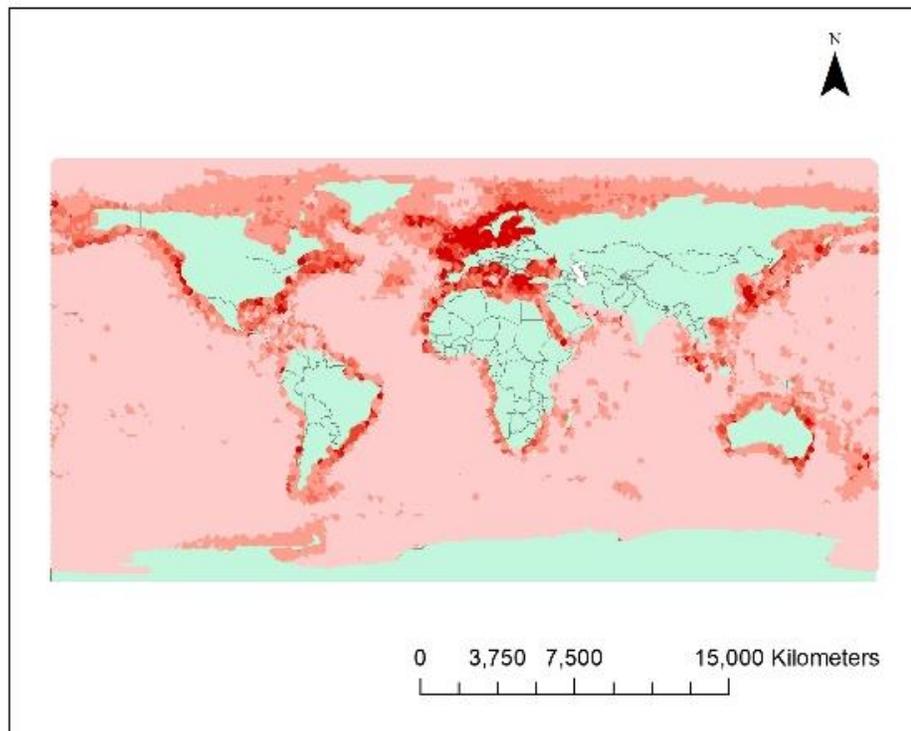
median year	-0.15	0.050	0.0027
net mesh	-1.1	0.056	$<2*10^{-16}$
depth	-0.45	0.031	$<2*10^{-16}$
slope	-0.36	0.040	$<2*10^{-16}$
shipping intensity	-0.25	0.046	$4.6*10^{-8}$
fishing effort	-0.15	0.040	0.00011
distance to shore	-0.52	0.044	$<2*10^{-16}$

241

242 The prediction heat map for ROV shows densities of macroplastic pollution ranging from 0 to
 243 1719.30 kg/km², with the highest predicted density in the Baltic Sea (**Figure 4**). From the Trawl
 244 predictions, we find that the highest predicted densities are clustered in the Western Pacific
 245 Ocean basin (**Supplementary Information Figure S5**).

**Abundance
 of plastic
 pollution
 [kg/km²]**

- 0 - 17
- 17 - 68
- 68 - 152
- 152 - 296
- 296 - 1720



246

247 **Figure 4.** Heat map showing predictions of the mass [kg/km²] of plastic pollution for 1° x 1° grid
248 cells of the ocean floor using the best ROV model (**Table 1**).

249 *The ocean floor reservoir*

250 We estimate the size of the ocean floor reservoir to be 3 to 11 MMT (middle estimate of 7
251 MMT) using the ROV model. The estimate using the Trawl model is 5 to 571 MMT (middle
252 estimate of 255 MMT).

253 **Discussion**

254 Although we have estimates of the ocean floor reservoir from both models, we focused on the
255 ROV model. The distribution of plastic mass with respect to size for the objects collected by
256 both ROV and trawl methods are surprisingly similar, in that both distributions are bimodal near
257 zero and near their upper size cutoff (**Supplementary Information Text 4, Figure S6**). Their
258 agreeable mass frequency distributions initially supported the use of both prediction maps to
259 inform the ocean floor reservoir. However, the ROV and trawl data differ in important ways.
260 There is a strong bias in the trawl sampling data as trawls are limited to deployment in shallow,
261 relatively flat regions of the ocean floor. Consequently, the coverage of the ocean floor by
262 trawling is poor (**Figure 2**), meaning global predictions encounter conditions well outside of the
263 covariate ranges covered by our observation data (**Supplementary Information Figure S7**). As
264 a consequence, predictions of plastic abundance by the ROV and Trawl models in regions with a
265 similar set of values for covariates sometimes differ substantially (**Supplementary Information**
266 **Figure S8**). This is shown in Figure S8, where the covariate values associated with each sample,
267 or the set of conditions under which the sample was taken, were used to plot the samples in
268 multivariate space, with each point representing the difference in mass of plastic for a ROV-

269 Trawl pair. Even for samples that are taken under very similar conditions (depth, slope, shipping
270 intensity, fishing effort, latitude, longitude), the difference in masses of plastic pollution
271 measured by ROV and trawls sometimes spanned as much as six orders of magnitude
272 (**Supplementary Information Figure S8**). As the difference between sampling contexts
273 (measured by Euclidean distance) increases, it also seems that Trawl tends to be biased high,
274 suggesting that trawling often occurs in dirtier places. Considering this, we have higher
275 confidence in the results obtained from the ROV model.

276 *What predicts patterns of accumulation?*

277 For both models, plastic abundance increased as more area was sampled. The positive correlation
278 between plastic abundance and sampling effort found here could be the result of the increased
279 probability of detecting an outlier as area sampled increases⁴⁴. When the outliers are orders of
280 magnitude higher in plastic mass than the rest of the observations, they generate a significant
281 effect on the plastic mass-area relationship, as is represented here by the large coefficient for the
282 area sampled covariate for the Trawl model (**Table 1**).

283 ROV Model

284 The ROV model predicted large amounts of plastic pollution clustered along continental shelves.
285 The high predictions of plastic mass by the ROV model along continental boundaries are likely
286 driven by the distance to shore and shallowness or depth (**Table 1**). The high predictions in the
287 Mediterranean Sea, the Arctic Ocean, and in coastal seas along the northern border of continents
288 in the Northern Hemisphere including the North Sea, Barents Sea, and Norwegian Sea are likely
289 driven by the high density of shipping traffic in those areas (**Table 1**). In addition, there is also a
290 strong correlation between the masses of plastic pollution detected using ROV and median year

291 of sampling (**Table 2**). This positive correlation between plastic mass and median year could be
292 the result of increasing plastic concentrations on the ocean floor, or the increasing attention to
293 plastic in ROV surveys. Most likely, it reflects both.

294 Trawl Model

295 The Trawl model predicted large pools of plastic in ocean basins, particularly in the Western
296 Pacific Ocean. This seems to be driven by a combination of depth, slope, and distance to shore:
297 e.g., deep, flat areas offshore contain high quantities of plastic. These high predictions may also
298 be a consequence of how trawls operate, because trawling on flat, shallow sediments is much
299 more feasible than trawling on deep, steep, or rocky areas, hence reflecting survey bias.

300 Coincidentally, these are also the areas that are subject to more intense vessel activity
301 (https://knb.ecoinformatics.org/view/resource_map_doi:10.5063/F1NZ85ZN) and are located
302 closer to land-based sources, and this may also contribute to the large abundances of plastic in
303 shallower, flatter areas near the coast. Furthermore, there is also a strong negative correlation
304 between the masses of plastic sampled using trawls and mesh size of the trawl net. This
305 correlation is expected because as net mesh increases, the mass of plastic found in trawls is
306 expected to decrease due to the loss of smaller-sized plastic objects.

307 *Predicted global spatial distribution*

308 Approximately half (46%) of the predicted plastic mass on the global ocean floor resides above
309 200 m depth, which is often used as the contour for continental shelves. The remainder of the
310 ocean, from 200 m to as deep as 11,000 m contains the remainder of plastic mass (54%).

311 Although inland and coastal seas cover much less surface area than do oceans (11% vs 56% out
312 of the entire Earth's area), the bottom of these areas hold as much plastic mass as does the rest of

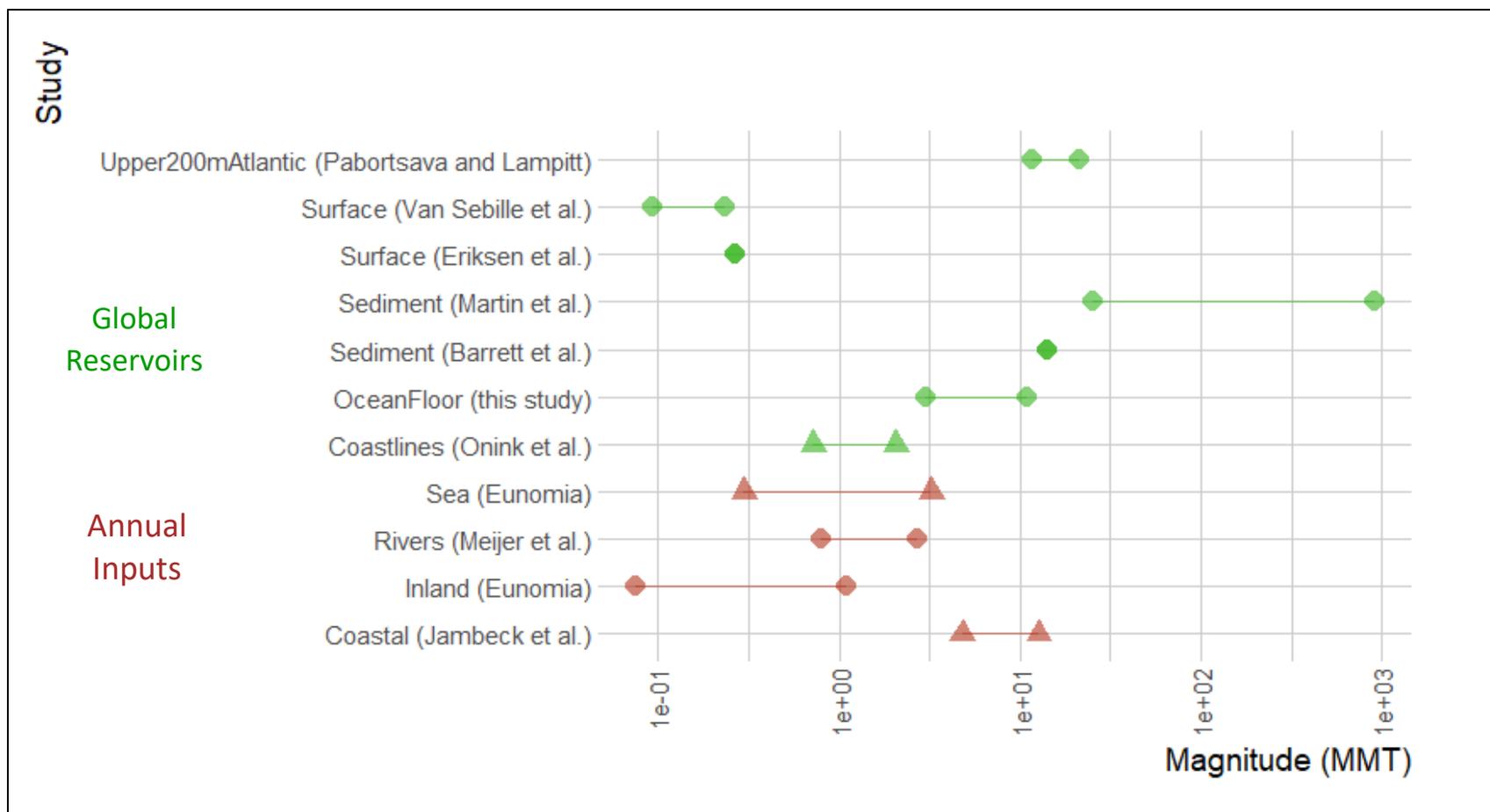
313 the ocean floor (44% vs 41%). Underwater features such as trenches and submarine canyons
314 hold relatively little plastic mass (0.6% and 0.2%, respectively), which is in contrast to the
315 previous suspected notion that deep ocean features are repositories for plastic^{45–49}. This result,
316 however, is consistent with what Martin et al.²⁷ found for bulk ocean sediment globally – that
317 abundance of non-fibrous microplastics decreases with depth. The three ocean basins that hold
318 the most plastic mass on the ocean floor are the North Atlantic Ocean (14%), North Pacific
319 Ocean (7%), and South Atlantic Ocean (6%) basins.

320 *Comparisons with other studies*

321 Our estimate for the ocean floor reservoir is similar in magnitude to preliminary estimates of
322 other marine reservoirs of plastic pollution (**Figure 5**). This observation agrees with the
323 conclusions of Wilcox et al.⁵⁰ The authors looked at temporal trends in ocean surface
324 concentrations of plastic pollution in the western North Atlantic and found that masses of plastic
325 in reservoirs should increase over time, because their long residence times allow reservoirs to
326 reflect increases in global plastic production. However, their estimate of how much the plastic on
327 the ocean surface increased by in 2010 – 506,000 T of plastic or 0.2% of global production – was
328 unexpectedly a whole order of magnitude lower than how much Jambeck et al. estimated entered
329 the global ocean, which was between 2% and 5% of global plastic production. Our findings are
330 consistent with their finding that reservoirs are not increasing in size exponentially, though
331 plastic inputs to the oceans are predicted to be exponentially increasing. There are two possible
332 reasons for this inconsistency: there is a huge missing reservoir we have not accounted for, or the
333 inputs are incorrect, i.e., plastic pollution leaving the coastal area are not actually making its way
334 into the ocean.

335 In terms of the first possibility, recent studies have suggested that degradation and fragmentation
336 into micro- and nano-sized plastic particles could be considerable sinks⁵⁰⁻⁵³. However, the rate
337 of disappearance of plastic from global reservoirs must be increasing exponentially at a rate
338 greater than the production rate in order for reservoir sizes to remain constant. This is highly
339 unrealistic, as we know that degradation processes are unlikely to be increasing on a per capita
340 basis adequately to account for an exponential increase in inputs^{53,54}.

341 In terms of the second possible explanation for the similar sizes of inputs and reservoirs, and
342 stemming from the logic of the above argument, it is possible that inputs are not as large as
343 anticipated: the global model by Onink et al.⁵⁵ found that at least 77% of positively buoyant
344 marine plastic debris released by their model did not escape beyond the coastal zone.
345 Chubarenko et al.⁵⁶ also found that large plastic items are continuously trapped in swash waves
346 in the coastal area until they break into small enough pieces to escape into the open ocean.
347 Furthermore, Olivelli et al.¹¹ found that coastal zones, in particular the backshore area of the
348 coast, is a huge sink for plastic pollution. Likewise, numerous simulations have found that
349 negatively buoyant plastics sink immediately upon entering the ocean, forming a ring around
350 coastlines, so a large portion of them remain deposited relatively close to land (e.g.³⁸) – this is
351 consistent with our findings. Overall, more and more studies are suggesting that perhaps a
352 relatively small fraction of terrestrial inputs into the marine environment actually escapes the
353 coastal zone and enters the open ocean. This implies that the Jambeck et al.⁸ is not being
354 interpreted correctly; it is actually measuring the amount of plastic leaving the land at the coastal
355 margin, not the amount of plastic that escapes the coastal zone and enters the open ocean. Future
356 studies that further investigate this mismatch between annual inputs and the amounts of plastic
357 accumulating in reservoirs would be useful.



358

359 **Figure 5.** Lollipop plot comparing the sizes of global marine reservoirs of plastic pollution to one another and to those of annual
 360 inputs globally. The plot shows lower and upper estimates of each input or reservoir in MMT. Data used in plot is from Borrelle et
 361 al.⁷, Eunomia³, Jambeck et al.⁸, Meijer et al.⁵⁷, Onink et al.⁵⁵, Barrett et al.²⁸, Martin et al.²⁷, Eriksen et al.²¹, van Sebille et al.¹⁴, and
 362 Pabortsava and Lampitt⁵⁸. Triangles indicate the study derived its estimate using a simulation approach and did not incorporate actual

363 measurements. Circles indicate the study incorporated empirical measurements in its derivation of the size of the input or reservoir of
364 interest. Data used to make this figure can be found in **Supplementary Information Table S4**.

365 To further reconcile the discrepancy between inputs and reservoirs, it helps to collect more
366 samples using harmonized methods to improve modelling efforts. We discuss next steps in
367 sample collection in the section below.

368 *Shortcomings and recommendations*

369 We used data that was available to us from the scientific literature to inform one of the first
370 global estimates of the ocean floor reservoir of plastic pollution. We provide recommendations
371 from this exercise of building models using empirical data to improve future modelling efforts.
372 We encourage this approach rather than the approach of building entirely theoretical models that
373 are not grounded in empirical data (see **Figure 5**, simulation studies versus empirical studies).

374 First, we suggest that not all data is good data. Researchers should not feel the need to always
375 use all of the data that is at their disposal, especially if the quality of a dataset precludes it from
376 being useful for a given purpose. In the case of Trawl measurements of plastic pollution, its
377 limited spatial distribution precludes it from informing an understanding of the global
378 distribution of plastic pollution on the ocean floor. Secondly, we recommend not combining
379 ROV and trawl samples in the same model, because there are differing biases in the sampling
380 methodologies which in turn create bias in the observations. For instance, trawls can only operate
381 on flat, hard substrate. There are some plastic objects detected using ROVs that trawls are not
382 seeing, and vice versa, and more work is needed to reconcile these measurements. The third
383 recommendation is that we need more sampling of the ocean floor: sampling that covers a
384 greater diversity of ocean floor topographies and habitats, replicate sampling, and paired
385 sampling. Most sampling efforts to date have been concentrated in nearshore marine
386 environments. In order to obtain equivalent or relatively consistent probability of detection, there
387 is a need for some experiments to understand how much detection probabilities vary from sample

388 to sample. This requires replicate sampling attempts in the same location, and in an ideal world,
389 ROV and trawl samples are both taken in the same area – a process referred to as “paired
390 sampling” – so that we can begin to better understand the differences between them. The lack of
391 paired sampling efforts to date prevented us from combining the data.

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

396 **Conclusion**

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

411 macroplastics likely lies in automation of the process to cut down costs, and the ability to
412 monitor plastic pollution in the context of other activities.

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571

572 *Data Availability Statement*

573 All data used in this study can be accessed free of charge at

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