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Plastic gear loss estimates from remote observation of industrial fishing activity

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Abstract

Derelict fishing gear is a highly visible source of marine plastic pollution, causing mortality and ecosystem degradation with uncertain long-term consequences. The quantity of derelict gear entering the oceans remains unknown because of heterogeneity in fishing gear and effort, as well as inadequate monitoring. Prior studies have been limited in scope to specific fisheries and regions, and large-scale estimates lack an empirical basis. It is critically important for decision makers to have credible information in order to design effective remediation efforts. We estimated the amount of industrial fishing effort and the associated plastic debris entering the ocean globally each year from lost fishing gear. Using remote observations of fishing vessel activity paired with technical fishing gear models, we generated a bounding estimate for gear operation and loss worldwide in 2018. We estimate that industrial trawl, purse-seine and pelagic longline fisheries operated 2.1 Mt of plastic gear over 2018 to obtain 49.7 Mt of retained and discarded catch, representing 74% of industrial marine capture globally. The median estimate for plastic gear lost during the use of these gear types was 48.4 kt (95% confidence interval: 28.4–99.5 kt). This estimate excludes abandoned and discarded gear. Improved observation, especially of small-scale fisheries, is needed to better understand the sources of derelict gear. These findings serve as a benchmark for future monitoring and management efforts to reduce derelict gear in the global ocean.

KEYWORDS
derelict fishing gear, fishing effort, industrial fisheries, marine plastic debris, material flow analysis, vessel monitoring systems

1 | INTRODUCTION

The amount and distribution of marine debris have been substantially increasing over recent decades, causing immense ecological and socioeconomic problems (Amon et al., 2020; Galloway et al., 2017; Li et al., 2016). Abandoned, lost or discarded fishing gear (ALDFG), otherwise known as derelict gear, from the world's estimated 4.6 million marine fishing vessels is particularly a harmful component of marine litter (FAO, 2000; Li et al., 2016). Because of the expansion of fishing effort in the last decade and the transition to synthetic and more durable materials for fishing gear, the quantity, distribution and adverse effects of ALDFG have likely increased (Derraik, 2002;

Gilman, 2015). Designed to capture marine organisms, ALDFG can retain ghost fishing efficiency for both target and incidental catch for decades (Al-Masroori et al., 2004; DelBene et al., 2019; Macfadyen et al., 2009; Scheld et al., 2016; Wilcox et al., 2016). Derelict gear can harm marine habitats, including seagrass beds, mangroves and coral reefs (Arthur et al., 2014; Consoli et al., 2019; NOAA, 2016; Valderrama Ballesteros et al., 2018). ALDFG damages in-use fishing gear, causing more gear loss, poses navigational hazards and creates safety risks at sea (Gilman, 2015; Macfadyen et al., 2009; Scheld et al., 2016).

Although there has been increasing international attention to the problem of ALDFG (FAO, 2019), little is known about the magnitude of the problem (Gilman, 2015; Gilman et al., 2016; Macfadyen et al., 2009). While Goal 14.1 of the United Nations 2030 Agenda for Sustainable Development calls for significant reductions in marine pollution by 2025 (UN General Assembly, 2015; UNSDG, 2018), the lack of robust estimates of marine debris, including ALDFG, prevents measuring progress towards meeting this goal. There are several fishery- or area-specific estimates of the quantity of ALDFG production (Deshpande et al., 2020; Havens et al., 2008; Kim et al., 2014; Szulc et al., 2015), yet there remains a critically important gap in robust global gear-specific estimates. Past studies estimating gear loss rates had large uncertainty, covered a small proportion of global fishing gears and regions, and/or relied on outdated records (Breen, 1990; Gilman et al., 2016; Macfadyen et al., 2009; MacMullen et al., 2003; Richardson et al., 2019). A figure that has been repeatedly referenced, for example, (FAO, 2018; Löhr et al., 2017; UNEP, 2016; World Animal Protection, 2018) is of spurious origin, derived from applying a rough generalization of "less than 10%" of global marine litter (Macfadyen et al., 2009) to an estimate of 6.4 Mt of marine litter. The basis for that figure is in fact an elementary generalization about marine shipping wastes (US National Academy of Sciences, 1975) that was misreported (Richardson et al., 2021). A more robust and contemporary estimate is needed.

The total industrial market for "fishing net fabrics" was estimated to be 1.3 Mt in 2017, dominated by polyamide, high-density polyethylene and polyester, with "synthetic ropes" for marine and fishing applications adding another 0.2 Mt (Persistence Market Research, 2019). This provides an upper bound for the eventual mass flow of plastic to the ocean resulting from the year's production of fishing gear, but would exclude non-net materials like floats, as well as non-plastic gear components.

While landings are reported worldwide according to an assumed approximately consistent statistical framework, there exists no such consistency for estimates of fishing effort (Anticamara et al., 2011). Synthesis estimates of fishing effort must rely on extrapolation to fill substantial data gaps (Bell et al., 2016). Moreover, the relationship between effort and catch is highly variable, depending on the temporal and spatial distribution of fishing effort, fishing technology, gear designs, target species, stock abundance, practitioner expertise, sea conditions, management measures, and many other explanatory factors (Anticamara et al., 2011; Maunder & Punt, 2004; McCluskey & Lewison, 2008).

The total influx of gear into the ocean during industrial fishing is an example of an industrial material flow (Baccini & Brunner, 2012)—an analytic result that cannot be directly observed, but whose estimation can inform efforts to assess and mitigate the environmental impacts of industrial activity. Material flow analysis (MFA) based on a priori modelling and statistical reports is commonly used to evaluate the sustainability of material extraction, manufacturing and recycling systems (Allesch & Brunner, 2015; Graedel, 2019; Guyonnet et al., 2015) and to estimate stocks-in-use of industrial materials (Pauliuk et al., 2017; Song et al., 2019). However, a lack of empirical data leads to a fundamental uncertainty in MFA results that is difficult to quantify (Laner et al., 2014; Meylan et al., 2017). Researchers must resort to inferences made from economic statistics and technical models, often paired with probabilistic methods, to estimate flow magnitudes (Rajkovic et al., 2020; Schiller et al., 2020; Sun et al., 2017; Zhu et al., 2019). None of these methods measure industrial activity directly.

However, in the case of fisheries, direct observations of industrial fishing activity are available at the global scale in the form of vessel telemetry data collected via satellite and other remote-sensing technologies (Kroodsma et al., 2018). Our objective for this study was to pair these observations of fishing effort with technical models of gear used in order to develop a bounding estimate for the quantity of gear that is lost into the sea during the course of industrial fishing operations. Aside from reducing the fundamental uncertainty about the generation of derelict gear, our results establish a set of benchmarks, quantitative performance indicators that can guide organizations to improved outcomes in both centralized and decentralized management and governance activities (Bogetoft, 2012; Grafton et al., 2007). Our findings can be used by fishery managers and policymakers to evaluate the gear loss performance of individual fisheries, both industrial and small-scale and to prioritize interventions to mitigate ALDFG.

2 | MATERIALS AND METHODS

Using a corpus of vessel telemetry data maintained by Global Fishing Watch (GFW), we correlated observations of fishing activity with statistical reports of the Food and Agriculture Organization of the United Nations (FAO) of landed catch (FAO, 2020) in order to estimate the aggregate intensity of fishing effort. Then, assuming that the corpus of observations is incomplete, we created a model to describe the upper quantiles of observed effort intensity and applied it uniformly to industrial fisheries to estimate an upper bound for total fishing effort. We applied stochastic models of gear utilization and gear loss for the industrial purse seine, trawl and longline sectors to estimate gear use and gear loss for each fishery.

2.1 | Vessel telemetry data

GFW maintains a database of fishing vessel activity from satellite and terrestrial radio transmissions (Kroodsma et al., 2018). They use machine learning techniques to identify fishing vessels and to distinguish between different types of fishing (Natale et al., 2015; de Souza et al., 2016). They provided a vessel activity dataset that reported observed operating time for each unique vessel observed to operate in a given year and oceanic region according to FAO statistics (known as FAO regions). Each record included the vessel ID, flag state, FAO region, number of days observed operating, and total duration of time at sea (operating hours). The machine learning algorithm outputs for each record included the total duration that the vessel was indicated to be conducting fishing operations (fishing hours), days on which fishing was observed (fishing days), most likely fishing gear type from a set of 17 vessel types, and three descriptive parameters: vessel length overall (LOA), gross tonnage (GT) and engine power in kilowatts, obtained from a mix of reporting and predictive algorithms. Fishing effort was measured by weighting fishing hours by each descriptive parameter. Data for 2017 and 2018 were used in the analysis.

To protect the confidentiality, the GFW dataset is provided in aggregated form, grouped by year, flag state, FAO region and gear type. Total operating hours and fishing hours and days are reported, as well as sums over each metric of fishing effort.

2.2 | Fishery landings

To estimate catch and discards, we utilized the annual series of global fishery production provided by the FAO (FAO, 2020) along with a recent research effort to characterize the global catch in terms of approximately 2,100 sub-national fisheries (Pérez Roda et al., 2019). We allocated catch from the current study years to those fisheries on the basis of their share of catch from 2010 to 2014. We increased the reported retained catch by a fishery-specific discard rate (Pérez Roda et al., 2019) and refer to the total landings plus discards as capture.

We then grouped the fisheries by nation, FAO region and gear type to join with the GFW dataset and computed effort intensity as a ratio of total observed effort to total capture. Quantile regressions were run against the set of log-adjusted effort intensity to produce the effort-intensity models used to generate the results.

2.3 | Unit gear models

Gear intensity and dissipation were modelled according to the framework described in Kuczenski et al. (2021). We considered fishing effort to be a composite measurement, comprising the product of a gear scaling parameter and an operating time. For a given fishery f, we defined the quantity of gear P lost to sea over a year as:

$$P_f = F_f \cdot u_f \cdot g_f \cdot d_f \quad (1)$$

where F is the total capture of fish by the fishery, including landed catch and discards, u is the effort intensity of the fishery (effort per unit catch), g is the gear intensity of effort (mass of gear per scaling parameter), and d is the rate at which gear is dissipated into the ocean, having units of fractional mass dissipated per operating time. The effort intensity was computed from regression models as described above. The gear intensity was estimated from vessel size using probabilistic models derived from literature reports (Isman, 2016; Laissane, 2011; Marçalo et al., 2019; Pravin & Meenakumari, 2016; Sala et al., 2019; Zhou et al., 2019) for trawlers and seiners, and for longliners from a survey of longline fishing vessels (n = 14) conducted by the authors. Proxy estimates of effort intensity for set gillnets were drawn from (Dalzell, 1996) and paired with a technical gillnet model. Effort and gear intensity of dFADs was estimated from Banks & Zaharia, 2020; Schaefer et al. (2021). Detailed descriptions of the gear intensity models can be found in the Appendix S1 and software.

2.4 | Dissipation models

Dissipation of gear into the ocean was modelled probabilistically according to the best-available statistics from recent publications (Deshpande et al., 2020; Gilman et al., 2021; Richardson et al., 2019), expert knowledge and personal communications from observers.

Dissipation rates, given in terms of fraction of gear mass per year of use, were applied to gear usage estimates developed from the regression models and catch statistics. Effort metrics (given as scaling parameter * hours) were converted to years of use according to average fishing hours per vessel indicated by the GFW dataset, as reported in Table 2. A complete specification of probabilistic dissipation models used in the study can be found in Table S3.

3 | RESULTS

3.1 | Observed effort and catch

The GFW dataset included observation of 52,413 distinct vessels in 2017 and 57,117 vessels in 2018. Roughly, 16,000 vessels in each year were small trawlers operating under the Chinese flag, making up the largest cohort of vessels in each year. A total of 1.13×10^8 operating hours and 4.52×10^7 fishing hours were observed in 2018. Total capture, including both reported retained catch and estimated discards, was estimated to be 91.9 Mt in 2018, of which 67.0 Mt was industrial. Out of the industrial amount, trawlers accounted for 40.1%, seiners for 37.0% and drifting longlines for 2.1% in 2018. Table 1 shows the allocation of catch and capture to gear type and productive sector. Additional statistics about the effort dataset can be found in the Appendix S1 and in our software repository.

TABLE 1 Total reported catch by sector and gear type used in the study

	2017		2018	
Observation	Mt	Per cent	Mt	Per cent
Reported landings	82.347		85.376	
Landings matched to fishery				
Total	79.042	95.99	81.876	95.90
Fishery sector				
Industrial	56.126	71.01	59.549	72.73
Non-Industrial	22.916	28.99	22.326	27.27
Capture (landings plus discards)				
Total	88.947		91.818	
Industrial	63.441	71.32	66.952	72.92
Non-Industrial	25.506	28.68	24.866	27.08
Industrial capture by gear				
Trawlers	27.270	42.98	27.022	40.36
Seiners	21.345	33.65	24.776	37.01
Tuna Purse Seine	2.615		2.813	
Set Gillnets	2.668	4.21	2.734	4.08
Drifting Longlines	1.380	2.17	1.411	2.11
Other/not assessed	10.779	16.99	11.009	16.44

Source: FAO (2020), Pérez Roda et al. (2019).

3.2 | Shares of total effort and catch

We measured the effort intensity of each fishery as the ratio of total observed fishing activity to total attributed capture. Fishing hours were weighted by the size of the vessel according to three parameters provided by the GFW model: gross tonnage (GT), length overall (LOA) and engine power (kw).

The observed effort was matched to capture by fisheries on the basis of year, flag state, gear type, and FAO area. Because the linkage between observations and fishery models was imprecise, some capture was left un-matched to effort, and some observed effort was un-matched to capture. The fraction of capture and effort that were matched to a logical fishery is reported in Table 2 (see also Table S1). In total, 44.925 Mt of capture was matched to effort observations in 2017, representing 70.8% of worldwide industrial capture and 50.5% of total capture in that year. In 2018, the equivalent figure was 49.651 Mt, representing 74.1% of worldwide industrial capture and 54.1% of total capture. Table 2 also reports the average fishing hours per vessel per year observed in the GFW dataset.

We then computed quantile regression models for each gear-and-effort tandem. Inspecting the plot and the regression results reveals a wide dynamic range in effort intensity, and also distinct trends depending on the effort metric used. Figure 1 (see also Figure S2) shows the effort intensity of fisheries by scaling factor for each of the three studied gear types.

The different gear types show distinct scattering patterns, with longline vessels showing the smallest distribution of vessel characteristics and also the tightest concentration of regression slopes. The maximum effort moments for longlines were 1,600 kW, about 55 m LOA and 800 GT, whereas the maximum figures for trawlers were over 10,000 kW, 150 m LOA and 14,000 GT. These trawl figures were all set by the same two logical fisheries, trawlers in FAO area 87 operated by the Netherlands and Lithuania. Outliers at low and high effort intensities can be seen for all three gear types, for all three effort metrics.

Seiner vessels appear to show two distinct clusters of vessel size, with one cluster of smaller vessels (up to 1,000 kW; 50 m LOA; 750 GT) showing relatively lower effort intensity, and a second cluster (around 2000–3000 kW, 60–80 m LOA; 1000–2000 GT) having notably higher effort intensity. It is possible these clusters correspond to non-tuna and tuna purse-seine vessels, but that hypothesis is difficult to test because GFW data do not distinguish by target species.

3.3 | Plastic gear intensity and dissipation

The gear intensity of each type of fishing vessel was modelled probabilistically according to literature reports and technical models. The components of each gear type that scale with the size of the gear and are made of plastic were included in the models. The modelling

TABLE 2 Matching capture and effort

Gear type	Vessels number	Fishing hours per vessel	Capture, Mt	Capture, per cent	LOA * h, per cent	GT * h, per cent	kw * h, per cent
2017							
Trawlers	23,492	842	24.876	91.2	96.1	95.7	96.0
Seiners	2,920	453	18.927	88.7	89.5	93.5	93.0
Longlines	4,898	1526	1.122	81.3	87.7	88.7	88.4
Total	31,310		44.925	50.5			
2018							
Trawlers	24,909	834	25.533	94.5	94.7	95.7	95.4
Seiners	3,183	438	22.956	92.7	88.4	91.4	91.4
Longlines	5,585	1562	1.162	82.3	87.5	89.0	88.1
Total	33,677		49.651	54.1			

Note: Matching of catch to effort on the basis of logical fisheries defined by flag country, gear type and FAO area. Effort measurements report a weighted sum of fishing hours by vessel parameters of LOA, GT, and kw.

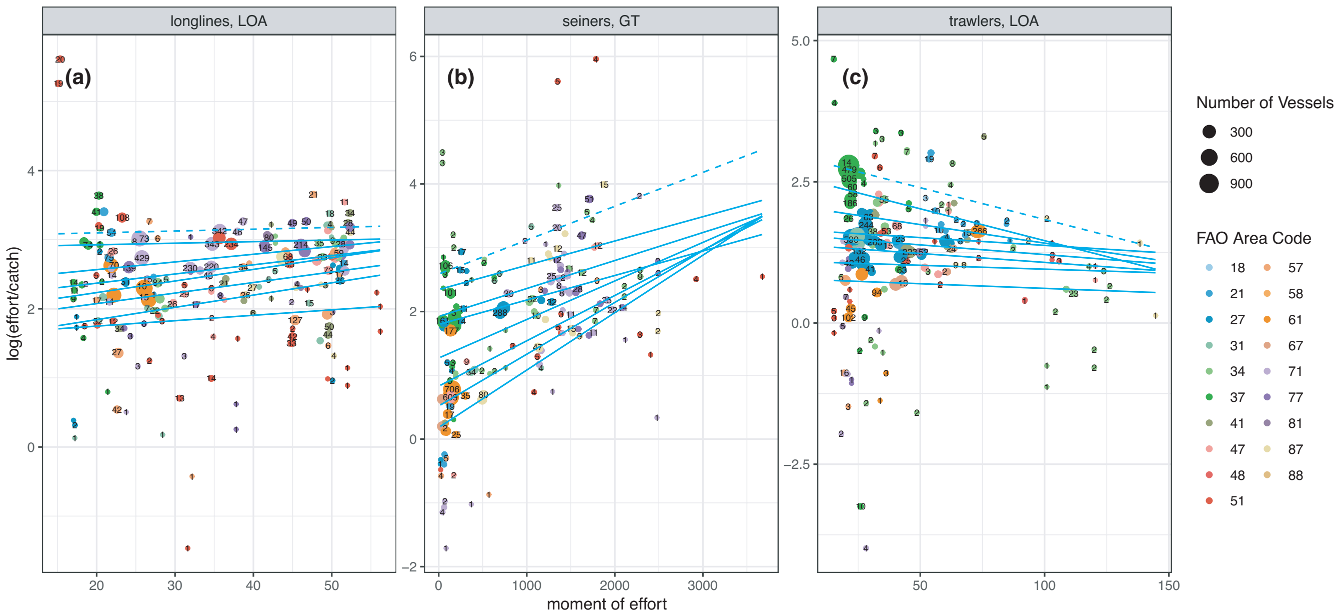

FIGURE 1 Observed effort intensity by gear type. (a) Longline fisheries, scaled by LOA; (b) seiners, scaled by GT; (c) trawlers, scaled by LOA. Points represent logical fisheries, with point diameter indicating number of vessels and colour indicating FAO area. The *x*-coordinate indicates the average scaling characteristic for the fishery; the y-coordinate indicates effort per unit catch on a log scale. Quantile regression lines from $\tau = 0.2$ to $\tau = 0.8$ (solid) and $\tau = 0.9$ (dashed) are shown in blue

framework is described separately (Kuczenski et al., 2021). The gear usage intensity parameter measures the quantity of plastic gear component in service for a year to produce a tonne of catch. This value is the product of the effort intensity, based on the regression model, and the gear intensity. Thus, the gear usage intensity depends on the regression parameter τ. Model results are shown in Table 3 and range from 0.4 to 5 kg*year/tonne for trawlers, 3 to 53 kg*year/tonne for seiners and 7 to 38 kg*year/tonne for longliners.

The loss rates of gear types were also estimated probabilistically based on published studies and modelling (Table S3). The resulting distributions are shown in Figure 2.

Also shown are proxy measurements for two passive gear types that are prominent sources of derelict gear: set gillnets and drifting fish-aggregating devices (dFADs) used in tuna purse-seine fisheries. Because the catch-effort relationship for these gear types was not based on observations of vessel activity, we had to develop independent models of effort intensity, which we then paired with technical models of gear intensity.

Trawlers show the lowest gear usage intensity and dissipation intensity per tonne of catch, having a maximum gear usage intensity of 24.5 kg*year per tonne, while purse-seines and set gillnets are the highest. The results suggest that purse seine may be the most gear-intensive fishing technique of those assessed, having lower and upper median gear intensity of 3.0–54 kg*year/tonne and a 95% confidence bound of 630 kg*year/tonne. Previously published life cycle assessments of specific industrial purse-seine fishing have

TABLE 3 Gear use and gear loss simulation results

Gear	Tau	Gear usage intensity, kg*year gear/tonne			Gear operation, kg gear/2018			Total dissipation of plastic, kg dissipated/2018		
		Median	0.05	0.95	Median	0.05	0.95	Median	0.05	0.95
Trawlers	0.5	0.451	0.182	0.919	1.28E+07	1.11E+07	1.47E+07	4.23E+05	3.63E+05	5.03E+05
Trawlers	0.7	1.17	0.284	3.01	3.49E+07	3.06E+07	4.33E+07	1.18E+06	9.95E+05	1.44E+06
Trawlers	0.9	5.55	0.569	24.7	2.10E+08	1.65E+08	2.85E+08	6.97E+06	5.28E+06	9.88E+06
Seiners	0.5	3.04	0.226	37.5	9.47E+07	6.33E+07	1.53E+08	3.18E+06	1.77E+06	6.96E+06
Seiners	0.7	10.4	0.923	82.9	2.97E+08	2.02E+08	4.37E+08	9.98E+06	5.41E+06	2.05E+07
Seiners	0.9	53.5	4.42	632	1.83E+09	1.22E+09	2.57E+09	5.62E+07	3.07E+07	1.28E+08
Longlines	0.5	7.03	2.33	27.1	1.15E+07	9.16E+06	1.71E+07	4.70E+05	3.48E+05	6.46E+05
Longlines	0.7	12.7	4.28	45.2	1.98E+07	1.56E+07	2.63E+07	8.13E+05	6.12E+05	1.25E+06
Longlines	0.9	38.6	15.3	104	5.33E+07	4.18E+07	7.13E+07	2.23E+06	1.72E+06	3.17E+06
Set Gillnets		14.7	0.508	167	6.01E+07	2.97E+07	2.53E+08	3.07E+06	8.93E+05	1.64E+07
Drifting FADs		1.41	0.65	2.29	3.94E+06	3.45E+06	4.58E+06	2.02E+06	1.49E+06	2.62E+06

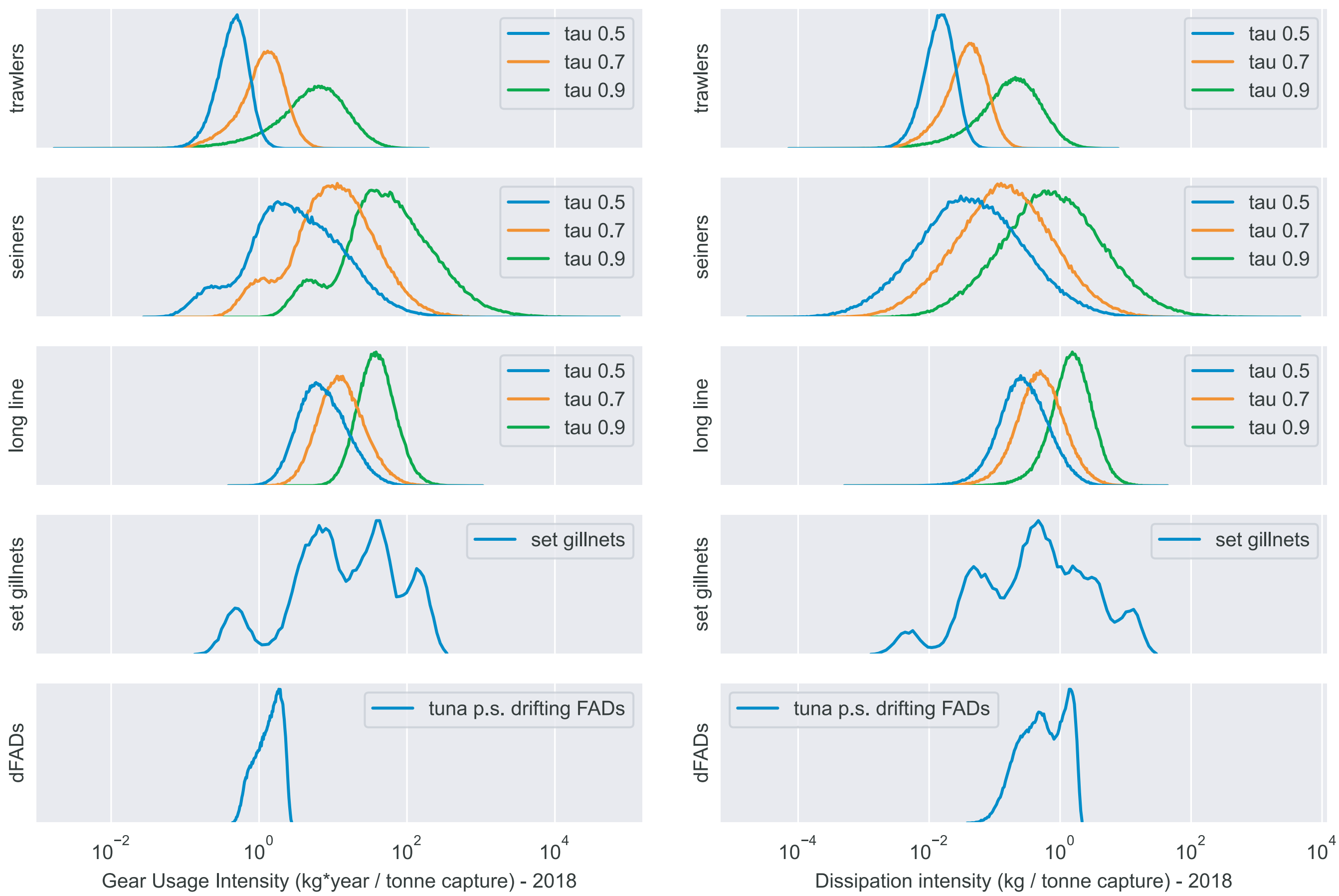

FIGURE 2 Gear usage and dissipation intensity. Apparent gear usage intensity (kg*year per tonne of capture) and dissipation intensity (kg/tonne) of industrial fishing activity, based on unit gear intensity models prepared as described. The graph parameter tau refers to the quantile regression used to predict gear use

reported gear intensities of 0.3–0.5 kg/tonne (Avadí et al., 2014) and 11 ± 2 kg/tonne (Laso et al., 2017). These figures can be converted to kg*year/tonne through multiplication by the gear's expected life, nominally 3 years. These are consistent with the lower median estimates in the current study, but not with the higher probabilistic estimates.

The multimodal gillnet distribution results from the independent sampling of several distinct effort-intensity models. Gillnets appear to span the entire range of gear intensities for other gears, and the more inefficient models exceed all but the highest-quantile results for dissipation intensity. This supports an emerging consensus around the severity of gillnets as a source of derelict gear that poses ecological harm (Huntington, 2017).

Although dFADs are not considered extractive gears, they represent an additive amount of gear associated with industrial tuna purse-seine operations. Though dFADs scarcely affect the overall gear intensity of purse seines, they are abandoned and lost at such high rates that they do potentially affect the dissipation intensity.

3.4 | Total operation and dissipation to ocean

The observed fisheries' catch can then be applied to the intensities from above to estimate total flows of gear into the ocean. The results are shown in Figure 3 and in Table 3. Median (5%–95%) estimates for gear maintained in use totalled 2.09 Mt (1.43–2.93, $\tau = 0.9$) during the year 2018. This figure approximates the total mass of plastic in operable gear on fishing vessels in the scope of the study during 2018. Median (5%–95%) estimates for gear loss total 48.4 kt (28.4–99.5, $\tau = 0.9$). In all cases, the purse-seine figures dominate, making up 62%–85% of the total amount, depending on the value of the regression parameter τ. This is a result of the high gear intensity of the purse-seine models.

Purse seine, despite being a smaller share of catch than trawl, accounts for a much larger dissipative flow, with the 95% confidence interval for the highest-quantile regression approaching 75,000 kt.

The set-gillnet model also indicates a large dissipative flow, despite accounting for only 4%–5% of catch, exceeding the dissipation of longlines and trawlers, modelled at low effort quantiles.

In all, industrial seining, trawling and longline fishing activity as observed in the GFW dataset, plus industrial set-gillnet fishing, accounted for 55.943 Mt of capture in 2018, or 60.9% of total capture. Estimated gear losses from this activity in 2018 according to the regression model, plus gear losses according to the two proxy models, totalled 53.5 kt (31–117 kt with 95% confidence).

4 | DISCUSSION

We have developed a bounding estimate for the quantity of fishing gear that becomes derelict during normal use by industrial marine capture fisheries, based on combined estimates of effort intensity, gear intensity and dissipation rate for various gears. Our findings indicate a total of 2.09 Mt of plastic (less than 2.9 Mt with 95% confidence) was maintained in operation by industrial purse-seine, trawl and longline fisheries in 2018, in the course of harvesting 49.7 Mt of industrial marine capture (74% of the worldwide total for industrial fisheries). Of this amount, a median 48.4 kt (less than 99.5 kt with 95% confidence) of plastic gear was lost into the global ocean. The findings are contingent on the assumptions that (1) gear loss is proportional to operating time, (2) the size of the gear can be predicted from the size of the vessel carrying it, and (3) average effort intensity of large fleets also depends on the mean vessel size. While the study does not include direct observations of gear becoming lost, the gear usage estimation provides a benchmark against which individual fisheries, both industrial and small-scale, can evaluate their own fishing gear use and management.

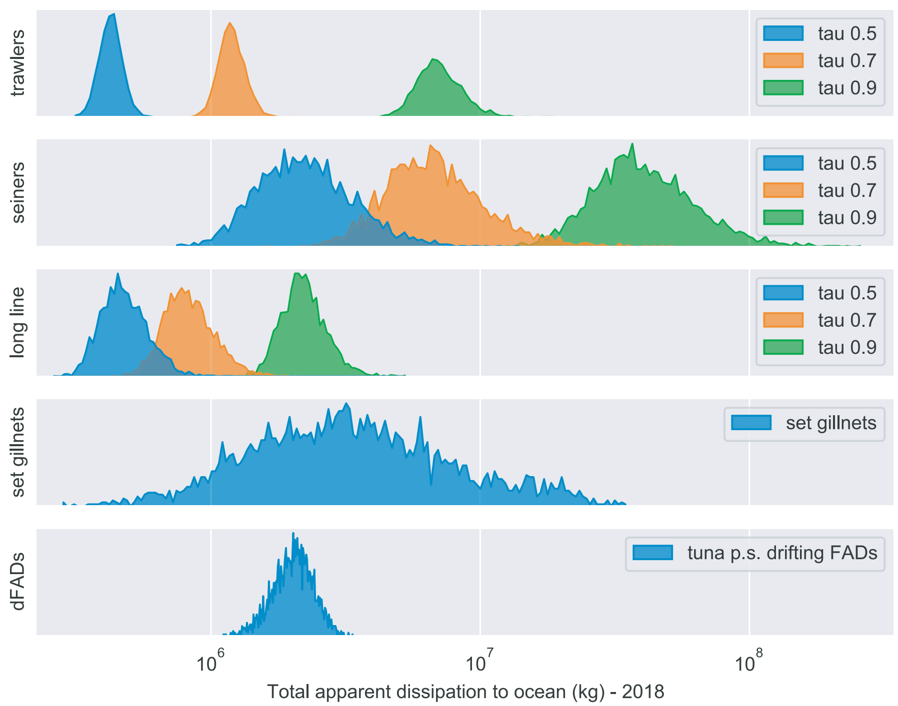

FIGURE 3 Simulated dissipation of plastic fishing gear to the ocean in 2018

4.1 | Scope and limitations

The study uses proxy gear models drawn from literature sources to simulate the gear use of actual fisheries. No fishery-specific modelling was performed, and the results are thus indicative of potential gear loss. The models represent only lost gear and do not include situations of abandoned nor improperly discarded end-of-life gear. The rates at which all gear types are lost during use (see Table S3), abandoned and discarded remain highly uncertain and must continue to be topics of primary and synthesis research.

The study omits small-scale and nearshore fisheries, amounting to 27% of global catch, and also excludes several gear types that may become derelict, including pots and traps, pole and line, driftnets, and others, amounting to 16% of industrial catch (Table 1). This is because the telemetry data for these gear types were not reliable enough to estimate the catch-effort relationship. Many potentially significant sources of derelict gear, including small-scale tropical fisheries, are thus not captured in the study. The estimate may be extended through proxy modelling of these fisheries or fishing gear types, as demonstrated here for industrial set gillnets and dFADs. Of the included catch, 88%–97% of it was mapped to an observed fishery, depending on gear category. The resulting estimate covers just over 50% of global capture (Table 2). Catch was allocated to fisheries on the basis of the period from 2010 to 2014 (Pérez Roda et al., 2019), and changes since then would alter the results.

The effort estimation was based on satellite data with known limitations, mainly that the automatic identification system (AIS) devices used for tracking are installed only on the largest fishing vessels in use, and only when operating far from shore. Thus, it is expected that larger vessels will be better represented in AIS data (Taconet et al., 2019), and thus that plots will be more accurate towards the right-hand side of each panel in Figure 1. Notably, all three gear categories show abundant data for vessel sizes below 300 GT, the legal requirement for AIS use in international waters (Taconet et al., 2019). This is likely due to stricter national and regional requirements for AIS or satellite-based vessel monitoring system use.

4.2 | An upper bound for fishing effort

Gear loss intensity is the product of three factors: effort intensity, gear intensity and dissipation rate. Effort intensity is a ratio of the amount of fishing activity associated with a given logical fishery and the amount of total catch allocated to the same fishery. We augmented landings by a discard rate because the same gear is assumed to be used and degraded for both retained and discarded catch. It is likely that most fisheries include both vessels that were and were not observed by GFW, so in general, the catch will likely be over-allocated to the observed effort. Similarly, errors of omission in the form of non-observation of fishing activity are abundant in the GFW corpus, due to unreliable satellite coverage, uncooperative fishers, and the occurrence of industrial fishing outside of areas where AIS is required or available (Taconet et al., 2019). Therefore, the observed effort is a lower-bound, and any individual effort-intensity value is likely to be an under-estimation. We anticipate that the highest-intensity fisheries are well-observed, and the lower-intensity fisheries are either authentically low-intensity or are poorly observed. By using a high-quantile regression, we apply the characteristics of the highest-intensity fisheries to the whole population, producing an over-estimation.

4.3 | Uncertainty in gear models

Because of the technical complexity and diversity of fishing gear, the zero-order models developed for the study indicate significant knowledge gaps. The current study makes up for a lack of precision in the gear intensity models through stochastic simulation, and so the accuracy of the results is tantamount to whether the actual gear intensity falls within the modelled range. For instance, trammel nets are likely to be far more material-intensive than gillnets having the same area, because they are multi-layered.

The high upper-quantile gear usage intensity figures for purse-seiners result from large uncertainties in each of the three intensity terms. Among the three elements of the estimate, effort intensity is most likely to be an overestimate. Because the regression curves shown in Figure 2b are comparatively steep, especially for high quantiles (and noting that the ordinate is logarithmic), the preference within the data for larger vessels could have the effect of significantly overestimating effort from poorly observed and smaller fisheries. Additionally, the distribution of gear intensity data is particularly wide, as it results from a diverse set of fisheries selected at random during the simulation by discrete choice (see Appendix S1). Because the gear intensity of specific fisheries is not random, the inclusion of models with high gear intensity in the discrete simulation would bias upwards the simulation results. Therefore, purse-seine results at the higher end of the probability distribution should be regarded with scepticism. Fishery-specific modelling of gear types would reduce this uncertainty.

4.4 | Comparison to other sources of marine debris

In terms of absolute mass, lost fishing gear appears to be a significantly smaller source of plastic material than the debris of terrestrial origin, which may approach tens of millions of tonnes per year (Jambeck et al., 2015). However, fishing gear is uniquely capable of causing ecological and socioeconomic harm because of its design characteristics (Huntington, 2017). By the same token, some lightweight forms of fishing gear, such as nets, may cause harm that is disproportionate to their mass. Instead of measuring gear dissipation in mass, the same approach could be used to report linear length of line or area of net released. It could also be characterized by other means, such as its relative ability to induce mortality (Uhlmann &

Broadhurst, 2013), or the potentially affected fraction of species (e.g., Klepper et al., 1998; Woods et al., 2019). The same metrics applied to other forms of debris could be used to weigh the relative risks.

4.5 | Fishery benchmarking and knowledge synthesis

The present approach used stochastic simulations to generate bounding estimates for the potential dissipation of plastic gear. The results did not include fishery-specific models of gear use or loss, and, therefore, cannot be used to infer anything about the performance of a specific fishery. Instead, the results establish a credible bound for the quantity of derelict gear generated by industrial fishing. They also have value as a benchmark against which individual fisheries can be compared. Benchmarking as a governance tool provides flexibility to varying conditions, supports a range of incentives and feedback mechanisms and offers transparency to the full range of stakeholders involved in fisheries management, empowering fishers and fishery managers to improve individual and collective performance through a variety of means (Fitzpatrick, 2014; Grafton et al., 2007). The parameters of gear usage intensity and dissipation intensity can be computed for specific fishing operations by direct observation of the quantity of gear in use on a boat, the catch obtained, and the frequency and nature of gear loss events. The resulting observations can be compared with the results published here both to validate the present estimate and to evaluate the fishery's management practices. The gear loss estimates for the South Korean set-gillnet fishery published in Kim et al. (2014) are evaluated as an exemplary case in the Appendix S1.

Fisheries management authorities concerned with derelict gear should prioritize the data collection from fishers under their purview, including the quantity of gear used during normal operations, the rate at which gear is damaged and lost and fishers' practices regarding repair of damaged gear and proper disposal of end-of-life gear. It is straightforward to adapt the method presented to use fishery-specific data when it exists; however, gathering and maintaining fishery-specific knowledge of gear usage intensity and dissipation at a global scale is beyond the capacity of a single research group. The logical fishery model (following Pérez Roda et al., 2019 and as documented in the Appendix S1) could be used as a basis for knowledge synthesis about gear use and losses from the world's fisheries.

5 | CONCLUSION

Our study used direct observations of fishing activity to reduce uncertainty in the amount of derelict gear generated from industrial fishing. The results show that the flow of derelict gear into the ocean from industrial fisheries is in the order of 100 kt per year, while the flow from small-scale fisheries continues to be unknown and uncertain. Although this amount is considerably smaller than contemporary estimates for ocean plastic debris from terrestrial sources (Borrelle et al., 2020), the threats of ghost fishing and other adverse consequences render ALDFG potentially far more lethal than other sources of debris. Fishers and fisheries managers must take steps to understand the generation of derelict gear in their fisheries, potentially adopting our methodology (Kuczenski et al., 2021) to benchmark their own operations. By better identifying and targeting problem areas, those benchmarks can be reviewed and shared with the aim that fishery performance can improve over time. Meanwhile, policymakers must promote a science-based understanding among the public of the many and varied threats to ecosystems from marine debris. These tremendous hazards must be mitigated through individual efforts, collective actions, and policy, directed at consumers and fishers alike.

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CONFLICT OF INTEREST

The authors declare no competing interests.

AUTHOR CONTRIBUTIONS

BK, RG and JW developed the project concept. BK developed the methodology. BK, CVP, ELG and MM conducted the investigation. BK and CVP created the software and visualizations. BK wrote the original manuscript. BK, ELG, MM, RG and JW involved in editing and revision. The project was supervised by RG and JW and administered by JW.

DATA AVAILABILITY STATEMENT

All data, code and materials required to reproduce the results, and analysis reported here can be found online at https://github.com/bkuczenski/scoping-gear-losses. Support in interpreting and using the supplied materials can be provided by the corresponding author. Interactive visualizations of the logical fisheries model and catch-effort plots can also be found online at https://camilavargaspoulsen.shinyapps.io/catch-effort-gear-dashboard/.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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