

Identifying Marine Sources of Beached Plastics Through a Bayesian Framework: Application to Southwest Netherlands

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Abstract

Beaches are thought to contain a large part of plastics entering the marine environment. Here, they can cause harm to biota, and can potentially break down into smaller fragments over time. To protect vulnerable beaches, it is advantageous to have information on the sources of this plastic. Here, we develop a universally applicable Bayesian framework to map sources for plastic arriving on a specific beach, applied to a beach in southwest the Netherlands. In this framework, we combine Lagrangian backtracking simulations of drifting particles with data of plastic input from coastlines, rivers and fishing activity. This facilitates spatiotemporal source attribution for plastic arriving at the specified beach. We show that the main sources are the east coast of the UK, the Dutch coast, the English channel (fisheries) and the Thames, Seine, Rhine and Trieux (rivers). We also show that particle age is a major uncertainty in source attribution using backtracking.

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3 **Southwest Netherlands**

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6 **Key Points:**

- 7 • Combined oceanic backtracking and Bayesian statistics supports source attribu-
8 tion of beached plastic
9 • Strong temporal variability in likely sources is found, due to variability in plas-
10 tic input and currents
11 • Particle age remains a major uncertainty in determining the origin of beached plas-
12 tic via backtracking

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Abstract

Beaches are thought to contain a large part of plastics entering the marine environment. Here, they can cause harm to biota, and can potentially break down into smaller fragments over time. To protect vulnerable beaches, it is advantageous to have information on the sources of this plastic. Here, we develop a universally applicable Bayesian framework to map sources for plastic arriving on a specific beach, applied to a beach in southwest the Netherlands. In this framework, we combine Lagrangian backtracking simulations of drifting particles with data of plastic input from coastlines, rivers and fishing activity. This facilitates spatiotemporal source attribution for plastic arriving at the specified beach. We show that the main sources are the east coast of the UK, the Dutch coast, the English channel (fisheries) and the Thames, Seine, Rhine and Trieux (rivers). We also show that particle age is a major uncertainty in source attribution using backtracking.

Plain Language Summary

A large part of plastic in the ocean is located at or near beaches. This plastic can break down into micro-plastics or be ingested by animals. Therefore, it is important to clean up these beaches. The easiest way to do so is to prevent the plastic from entering the oceans initially by interfering at the source. In this study, we develop a framework to find these sources for a given beach. We first simulate the path that plastic has taken to reach this beach. We do this by releasing virtual plastic particles at the beach where they end up. Next, we calculate their paths back in time, computing their trajectories until they reach this beach. We then combine these simulations with data on the sources of plastic: where and when did plastic enter the ocean? We apply this framework to a beach in southwest Netherlands, near the town of Domburg. We quantify seasonal effects, where time-varying currents cause the plastic to come from different sources. Lastly, we study how plastic sources vary with plastic age (the time between the plastic entering the ocean and beaching at its final location).

1 Introduction

Most buoyant marine plastics are either beached or afloat in coastal waters (Onink et al., 2021; Morales-Caselles et al., 2021). Beached macro-plastic can more easily degrade into smaller micro-plastics than floating or submerged plastics, for example due to a higher exposure to solar UV radiation (Andrady, 2011) and mechanical fragmentation (Chubarenko et al., 2020). These micro-plastics can contain high concentrations of pollutants present in the oceans (FronD et al., 2019) and can, due to their small size, easily be ingested by marine biota and thus enter the food web (Andrady, 2011). High concentrations of plastic are already found in many species in the marine environment (Franeker et al., 2011; Coe & Rogers, 1997; Ryan et al., 2009). The importance of cleaning up our beaches is therefore evident (Kataoka & Hinata, 2015). However, it is difficult to do this efficiently when much is unknown about the source and fate of the plastic (van Sebille, 2015; C3zar et al., 2014). By locating and then mitigating at upstream sources (van Gennip et al., 2019; Robinson et al., 2017), it may be possible to prevent this pollution and its consequences. Moreover, knowing the sources of plastic pollution enables ‘naming and blaming’ of the polluters.

Source attribution of beached plastics for specific beaching locations has been done before by for example Neumann et al. (2014) and Strand et al. (2021), who both used Lagrangian particle simulations (van Sebille et al., 2018) to compute virtual particle trajectories back in time. These studies did not take into account where plastic enters the ocean and how much, giving only a rough indication of the general source regions based on hydrodynamics. The combination of source input data and Lagrangian simulations has been used by for example Lebreton et al. (2012, 2018); Liubartseva et al. (2018) and

63 Kaandorp et al. (2020). These studies, however, only make use of forward particle sim-
 64 ulations, which can be used to assess the general fate of plastic coming from certain sources
 65 (van Sebille et al., 2020). To assess the sources of plastic litter ending up on a specific
 66 beaching location, as in this study, backtracking simulations are more efficient.

67 In this study, we provide a Bayesian framework that allows for the combination of
 68 Lagrangian backtracking simulations with plastic input data and the possibility to nor-
 69 malise these results based on observations. Combining the scalability of simulations and
 70 the tangibility of observations allows for source attribution of plastic beaching on a tar-
 71 get location. This framework is laid out in Section 2. We then showcase this framework
 72 for plastic beaching at the coast of the southwestern Dutch province Zeeland, more specif-
 73 ically the beach near Domburg. We perform a general source attribution, study tempo-
 74 ral variability, and assess the influence of assumed particle age on the source attribution
 75 in Section 3. Finally, we provide our conclusions and discussion in Section 4.

76 2 Methods

77 In this study, we propose a Bayesian framework to map sources of plastic arriving
 78 on a given beach. Bayes theorem is a statistical method to calculate conditional prob-
 79 abilities taking prior knowledge into account (Downey, 2013). Here, this theorem is in-
 80 terpreted as follows:

$$P(\text{Source}|\text{Beaching}) = \frac{P(\text{Beaching}|\text{Source})P(\text{Source})}{P(\text{Beaching})}. \quad (1)$$

81 $P(\text{Source} | \text{Beaching})$, the key quantity of interest in our framework, is the pos-
 82 terior probability: the probability that a given location is the source of a plastic parti-
 83 cle, given that this particle ends up at the studied beach. This posterior probability can
 84 not be calculated directly from simulations, but can be found through a combination of
 85 the likelihood and prior probability. $P(\text{Beaching} | \text{Source})$ is the likelihood, the prob-
 86 ability that a particle beaches at the specified location, given that it originates from a
 87 certain source location. This likelihood can be computed through Lagrangian backtrack-
 88 ing simulations. $P(\text{Source})$ is the prior probability, in this case the probability that a
 89 given location is a source of plastics. Here, we will determine $P(\text{Source})$ for three dif-
 90 ferent source types: coastal population, fishing activity and riverine sources, as discussed
 91 in Section 2.2. The likelihood in all locations is multiplied with the prior $P(\text{Source})$ in
 92 the same location. This multiplies the probability that a particle origins from a location
 93 (prior) with the probability that it reaches the beaching location from this same start-
 94 ing location (likelihood). Lastly, we normalize the source probability using $P(\text{Beaching})$,
 95 the total beaching probability per source type. This normalisation is based on estimated
 96 abundances of beached plastic per source type, as described in Section 2.3.

97 2.1 Likelihood and Lagrangian Framework

98 The likelihood $P(\text{Beaching} | \text{Source})$ can be calculated from the Lagrangian back-
 99 tracking simulation. Lagrangian particle trajectories can be described (forwards in time)
 100 using the Fokker-Planck equation (van Sebille et al., 2018), containing a deterministic
 101 drift due to currents acting on scales larger than the grid size as well as a random forc-
 102 ing (Wiener process) due to sub-scale processes (van Sebille et al., 2020). The backwards
 103 in time equivalent of this equation is the Kolmogorov backwards equation, describing the
 104 probability that an observed target state at time s is reached from a different starting
 105 state at time $t < s$. We approach the Kolmogorov backwards equation numerically, by
 106 releasing a large set of passive, floating virtual particles and tracking them back in time
 107 according to:

$$\mathbf{X}(t - \Delta t) = \mathbf{X}(t) - \int_{t-\Delta t}^t \mathbf{v}(\mathbf{x}, \tau) d\tau + R\sqrt{2K\Delta t}, \quad (2)$$

108 where \mathbf{X} is the particle location, $\Delta t = 2$ hours the integration time step, $\mathbf{v}(\mathbf{x}, \tau)$ the
 109 Eulerian velocity field, R a random normally distributed number between -1 and 1 and
 110 $K = 13.39 \text{ m}^2/\text{s}$ the (uniform) eddy diffusivity (Neumann et al., 2014). The diffusion
 111 term has the same sign as when solving the forwards (Fokker-Planck) equation, see e.g.
 112 (Issartel & Bavarel, 2002; Robertson, 2004). We evaluate Eq. (2) using a Runge-Kutta4
 113 integration in the Parcels framework (Delandmeter & van Sebille, 2019) in a combined
 114 currents-Stokes-tides velocity field (see Section 2.4). We use only the surface velocities,
 115 thereby neglecting sinking or upwelling of particles. Moreover, the virtual particles are
 116 infinitesimally small and degradation of floating plastic is neglected. Beaching processes
 117 are not part of the simulation, since the particles are only expected to beach in the fi-
 118 nal location where they are released for backtracking. We use the approach from Delandmeter
 119 and van Sebille (2019) to prevent particles from getting stuck on land.

120 The simulated particle trajectories are stored at daily frequency. Every time a par-
 121 ticle passes through a certain grid cell, there is a certain probability that this cell is the
 122 source cell. The more time a particle spends in a grid cell, the more likely it is that this
 123 is the starting location of that particle. Thus, using this backtracking approach, we find
 124 the likelihood/probability that the target state of plastic beaching in our studied loca-
 125 tion is reached from a certain starting state or source location. The procedure is shown
 126 schematically in Figure S1.

127 In the simulation, we perform a daily release between 01-01-2015 and 01-01-2020
 128 of 100 particles homogeneously spread over the coastal cell adjacent to the studied beach-
 129 ing location (see Section 2.4). Every particle is backtracked for maximum two years.

130 2.2 Prior

131 The likelihood only contains information on how particles have moved through the
 132 environment and is in itself nothing but a backtracking simulation. The value of Bayes'
 133 theorem lies in combining this likelihood with prior knowledge, in this case knowledge
 134 about plastic input, as a map of plastic input quantities for every possible cell in the do-
 135 main. We distinguish fisheries, rivers and coastal population as sources, following the
 136 approach used by Kaandorp et al. (2020). An overview of plastic input per source can
 137 be seen in Figure 1a. Plastic sources located outside of this domain are not considered.
 138 Note that different source types can not be compared to each other due to different units.

139 Coastal plastic sources are defined as plastic input coming from coastal population
 140 (population living within 50 km of the coast). These values are estimated by combin-
 141 ing population density data (SEDAC et al., 2015) with data of mismanaged plastic waste
 142 per capita in the same region (Jambeck et al., 2015). Population density data from 2020
 143 are used. Plastic input from coastal population is assumed to be constant over the year.

144 River sources are defined as plastic coming from inland population, entering the
 145 ocean through river transport. River inputs are specified based on a study by Meijer et
 146 al. (2021). River inputs are reported in tonnes of discharged plastic per year and are thus
 147 assumed to be constant over time.

148 Fishery sources are defined as plastic litter coming from fisheries, e.g. nets, ropes
 149 and fluff (used to protect nets when bottom trawling). Fishery inputs are based on spa-
 150 tiotemporal fishing intensity data by Kroodsmas et al. (2018), assuming that a higher fish-
 151 ing intensity corresponds to a proportionally higher amount of plastic litter input from
 152 these fisheries. To take seasonal variability in fishing intensity into account, the fishing
 153 intensity is averaged per calendar week. This averaging is done over a period of 7 years,

154 from 01-01-2013 up until 01-01-2020, matching the simulation period. The fishing inten-
 155 sity is gridded on the $1/9^\circ \times 1/15^\circ$ grid of the simulation.

156 In order to facilitate the analysis, we aggregate grid cells belonging to the same ge-
 157 ographical area. This geographical division is done separately for coastal & river sources
 158 and fishery sources (Figures 1b and 1c).

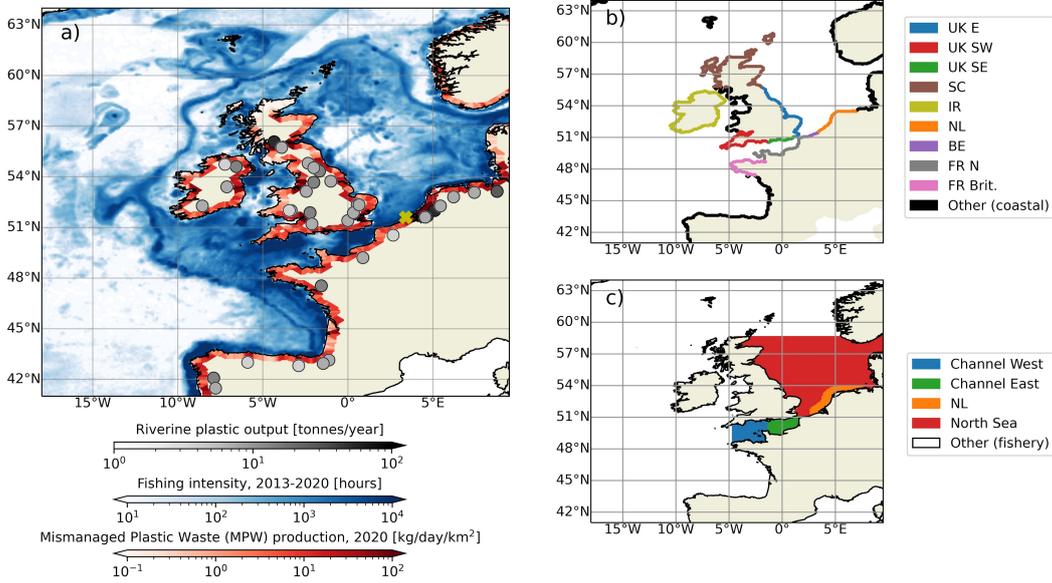


Figure 1. a) Overview of relative contribution of coastal, river and fishery plastic sources. Yellow marker: beaching location. Rivers with a plastic output below 5 tonnes/year are not shown to prevent cluttering. The total fishing intensity over the whole simulation period is shown. b) Division of coastal & riverine source regions, used for aggregation. c) Division of fishery source regions, used for aggregation.

159 2.3 Normalisation

160 The normalisation $P(Beaching)$ is constructed such that the accumulated prob-
 161 abilities per source type match the observed relative source abundances of plastic beach-
 162 ing in the Netherlands (Section 2.4 for more information), based on 20 years of beach
 163 cleanup observations by Boonstra et al. (2021). According to their observations, 42% of
 164 the beached plastic along the Dutch coast originates from fishery sources. Since we only
 165 assume two other source categories, riverine and coastal sources (ignoring for example
 166 shipping and aquaculture), we extrapolate that 58% of the plastic waste must come from
 167 these two sources. A study by Lebreton et al. (2018) estimates that globally, 59.8% of
 168 plastic originates from coastal population, 12.1% from riverine sources, 17.9% from fish-
 169 eries, 8.9% from shipping and 1.3% from aquaculture. This gives a ratio of roughly 5/1
 170 for coastal/riverine sources. Applying this ratio to the specific source percentages of Zee-
 171 land, we assume that roughly 50% of the beached plastic comes from coastal population,
 172 10% from river transport and 40% from fisheries. Note that these values have been rounded
 173 to the nearest ten to give a more appropriate representation in terms of significant fig-
 174 ures. This means that the summed source probability of all fishery sources should be 40%,
 175 the summed source probability of all riverine sources should be 10%, and the summed
 176 source probability of all coastal sources should be 50%. The normalisation is performed
 177 over the whole simulation period. This means, for example, that some periods can have

178 a higher total fishery source probability, if those particles experience a higher than av-
 179 erage fishing activity and thus are more likely from fishery sources. Normalisation of coastal
 180 & riverine sources is then adapted such that the total source probability sums to 100%
 181 and the 5/1 ratio of coastal/riverine plastic is maintained.

182 2.4 Study area and data description

183 We apply our framework to plastic beaching at the coast of the southwestern Dutch
 184 province Zeeland. More specifically the beach near Domburg (51.57 °N, 3.49 °E). This
 185 beach is often visited by local beach cleanups and is adjacent to the North Sea, which
 186 is part of the European northwest shelf (Northern Hemisphere). A detailed overview of
 187 the general circulation pattern in the study area can be found in for example Ricker and
 188 Stanev (2020) or Holt and Proctor (2008).

189 The surface current reanalysis data are provided by E.U. Copernicus Marine Ser-
 190 vice Information (2020a) at a $1/15^\circ \times 1/9^\circ$ resolution in latitudinal and longitudinal di-
 191 rections, respectively. These data are available on the European northwest shelf, limit-
 192 ing the simulation domain but compensating for this flaw by their relatively high res-
 193 olution. Stokes drift reanalysis data are provided by E.U. Copernicus Marine Service In-
 194 formation (2020b) on a global scale with a $1/5^\circ$ resolution in both directions. The $M_2, S_2, K_1,$
 195 O_1 (linear) and M_4, S_4 and MS_4 (non-linear) barotropic tidal velocity constituents from
 196 FES2014 data (Lyard et al., 2021) are taken into account using the approach from Sterl
 197 et al. (2020).

198 3 Results

199 First, we present a general overview of plastic sources, averaged over the whole sim-
 200 ulation period, and making no assumptions on the particle age (i.e. every age between
 201 0 and 2 years is just as likely). This averaged result is the most representative for the
 202 sources of plastic on an uncleaned beach at a random time. Next, to study seasonal ef-
 203 fects in source locations, we analyse the source probability as a function of beaching week,
 204 taking a climatological average over 5 years. Lastly, we assess the influence of assumed
 205 particle age on the source attribution. If this age is known, for example from observing
 206 the state of degradation of beached plastic, a much more specific source attribution can
 207 be done.

208 3.1 Averaged sources

209 A general overview of plastic sources is shown in Figure 2. From this Figure, sev-
 210 eral source hot spots are clear: predominantly the eastern and western part of the En-
 211 glish Channel, and in the North Sea along the Dutch coast (fishery sources). In terms
 212 of coastal plastic, the east coast of the UK near London, Edinburgh, the coast of Nor-
 213 mandy near Caen and the Dutch coast near Amsterdam are important sources (coastal
 214 population). Furthermore, the Rhine, the Seine, the Trieux and the Forth belong to the
 215 most important riverine sources. It stands out that semi-enclosed regions often show a
 216 high (coastal) source probability, for example near Caen, London, Edinburgh and The
 217 Wash estuary (east coast UK).

218 3.2 Temporal Variability

219 Source probability as a function of beaching week is shown in Figure 3. Strong sea-
 220 sonal variation is clear, mostly in the source probability of the Dutch coast & rivers and
 221 fisheries. The lower source probability of Dutch plastic in winter months can be explained
 222 due to increased stratification starting in spring causing currents to be more southward
 223 along the Dutch coast (Holt & Proctor, 2008). This generally causes Dutch plastic to

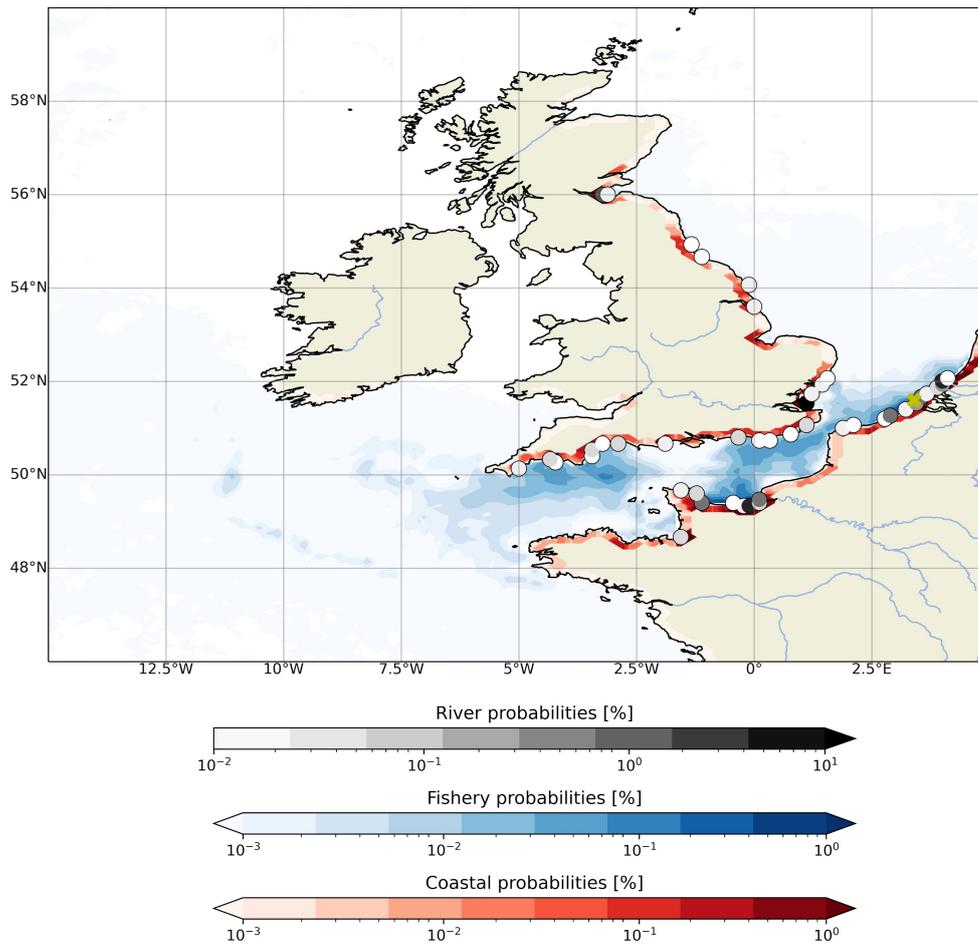


Figure 2. Source probabilities for particles beaching near marker between 2015 and 2020.

224 be transported northward in winter and consequently not reaching the studied beach-
 225 ing location.

226 Another interesting result is that Dutch coastal & riverine plastic has the highest
 227 source probability in June, whereas plastic from fisheries along the Dutch coast peaks
 228 in August. This can be explained due to temporal variability in the fishery prior. This
 229 prior is higher in Dutch waters for particles beaching in August than in other months
 230 (shown in Figure S2). Furthermore, fishing intensity is relatively high over the whole do-
 231 main in the months up to August, causing a relatively high proportion of plastic to be
 232 attributed to fishery sources.

233 3.3 Age variability

234 To investigate the effect of particle age (defined as the time the plastic has spent
 235 in the ocean from source to final destination), we have analysed source probabilities as
 236 a function of particle age for any age between 0 and 24 months. The Figure is not cu-

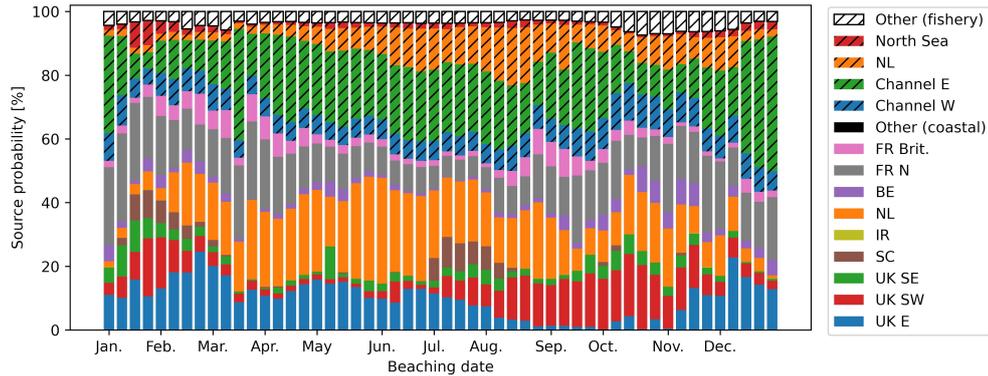


Figure 3. Source probabilities for particle beaching as a function of week of the year. Non-hatched: Coastal & riverine sources. Hatched: Fishery sources. Note that source probabilities of Other (coastal) and Ireland (IR) are too small to be visible.

237 mulative, i.e. for an age of t months, we only study the part of the trajectory between
238 t and $t + 1$ months before beaching.

239 During a backtracking simulation of 2 years, many particles leave the simulation
240 domain, as shown in Figure S3. The first particles leave the domain after backtracking
241 for 5 months and after 24 months more than 80% of particles have left the domain. In
242 this analysis, we will only consider the particles that are within the simulation domain
243 for the assumed age, since we neglect sources located out of the domain. Particles al-
244 most exclusively leave the simulation domain at the Atlantic Ocean, west of the English
245 Channel. No land is nearby at this region. Plastic originating from, for example, New-
246 foundland, Canada has less than 5% probability to reach the North Sea in under 2 years
247 according to PlasticAdrift (van Sebille et al., 2012). It is therefore safe to assume that
248 plastic coming from the Atlantic within 2 years of simulation is almost exclusively from
249 fishery sources. We justify neglecting these out-of-bounds sources by the fact that fish-
250 ing intensity is much lower in the Atlantic Ocean compared to the European northwest
251 shelf (Kroodsma et al., 2018), so there is low probability that these areas are sources of
252 plastic in the prior.

253 Figure 4 shows that for low particle age, there is a high probability that the plas-
254 tic originates from fishery sources, likely because fishing intensity is relatively high near
255 southwest NL (see Figure 1). With increasing age, the North Sea and fisheries along the
256 Dutch coast become less likely sources and fishery plastic will most likely come from the
257 English Channel. For coastal plastic, the most important sources are the east coast of
258 the UK initially, then the north of France and Scotland for plastic of ages over 18 months.
259 Since the coast of Scotland (near Edinburgh) is an enclosed region, particles circulate
260 here for a longer time, causing high source probabilities.

261 It is interesting that, for high age, coastal sources are mainly located in Scotland,
262 but fishery sources are located in the English Channel and the Atlantic Ocean (also shown
263 on a map in Figure S4). This seems contradictory at first, as these regions are far apart,
264 but can be explained based on plastic input data. While many particles reach the At-
265 lantic (high likelihood), this area contains little possible sources of plastics such as fish-
266 ing activity or coastlines (low prior). On the other hand, the coast of Scotland has a lower
267 likelihood, but a high plastic input from coastal population (high prior).

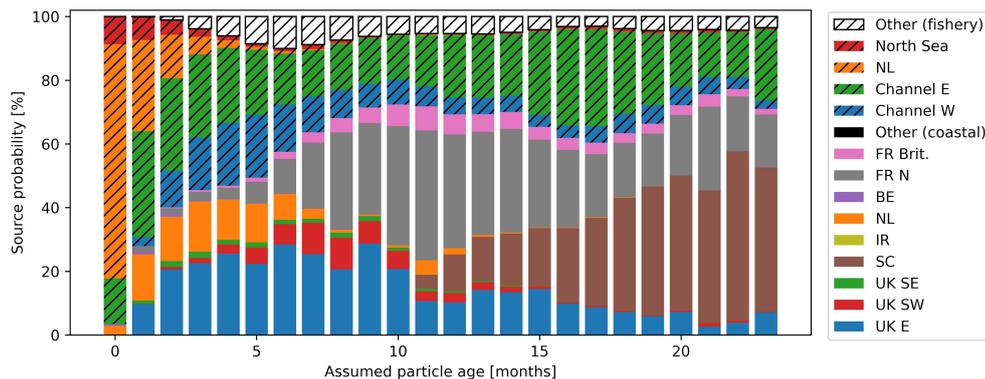


Figure 4. Source probabilities for different particle ages. Non-hatched: Coastal & riverine sources. Hatched: Fishery sources. Note that source probabilities of Other (coastal) and Ireland (IR) are too small to be visible.

268 4 Conclusions and discussion

269 In this study, we provided a new framework to identify sources for beached plastic,
 270 using backwards Lagrangian particle simulations combined with estimated plastic
 271 input data for coastal, riverine and fishery sources. To showcase this framework, we iden-
 272 tified the sources for plastic beaching in Domburg, southwest Netherlands. Furthermore,
 273 we assessed how source locations depend on the time spent at sea, which facilitates a more
 274 refined source attribution when particle age is known.

275 Our framework can seamlessly be extended to more complex flows and larger do-
 276 mains, which would support source attribution for higher particle ages. In this study,
 277 the fine-resolution northwest European shelf hydrodynamic data meant that sources lo-
 278 cated out of the simulation domain could not be incorporated. On the other hand, the
 279 hydrodynamic data are too coarse for solving complex coastal dynamics accurately. Sim-
 280 ulation results can therefore be improved if hydrodynamic data with a higher resolution
 281 becomes available. Moreover, particle transport was currently only modeled in 2D, ne-
 282 glecting upwelling and sinking. Also, windage, particle degradation and resuspension of
 283 beached particles were not explicitly included.

284 In our showcase, we assumed a constant flux of beached particles, since 100 par-
 285 ticles were released daily. The Bayesian framework can be extended by releasing parti-
 286 cles proportional to the amount of observed beached plastic in the corresponding period,
 287 if these data are available.

288 The framework is universally applicable and has the ability to combine backtrack-
 289 ing simulations with (time-dependent) plastic input data. Normalisation per source type
 290 can be performed to match observations of different litter types from beach clean-ups.
 291 These normalisation constants are currently based on rough estimations, but are easily
 292 adaptable to new information. Knowledge about plastic sources for specific beaching lo-
 293 cations can be used for upstream prevention at the source and can thereby support en-
 294 vironmental protection.

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 302 porarily stored for purposes of review at ([https://github.com/OceanParcels/BayesianAnalysis](https://github.com/OceanParcels/BayesianAnalysis_SW_NL)
 303 [_SW_NL](https://github.com/OceanParcels/BayesianAnalysis_SW_NL)). Permanent storage of data will be at our institutional data management ser-
 304 vice yoda, where it will be publicly available and will be given a doi ([https://www.uu](https://www.uu.nl/en/research/yoda)
 305 [.nl/en/research/yoda](https://www.uu.nl/en/research/yoda)). We thank Marijke Boonstra, Martine van den Heuvel-Greve,
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Supporting Information for "Identifying Marine Sources of Beached Plastics Through a Bayesian Framework: Application to Southwest Netherlands"

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Contents of this file

1. Figures S1 to S4

Introduction

In this document, we provide four Figures to get a more detailed understanding of the framework presented in the main paper.

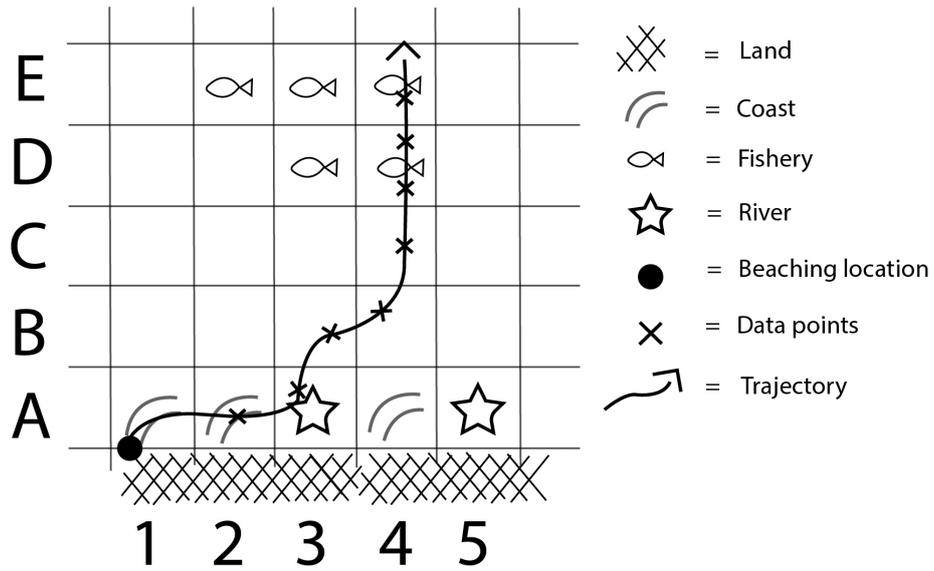


Figure S1. Schematic illustration of backtracking procedure for one particle.

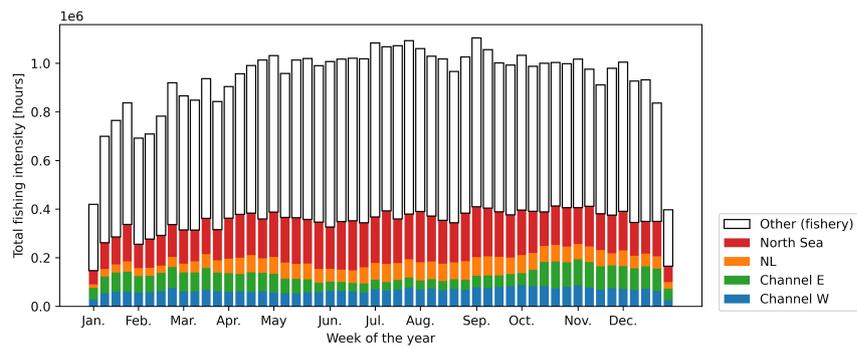


Figure S2. Total fishing intensity per fishery region shown as a function of week of the year.

This is the time-dependent prior $P(Source)$ for fishery sources.

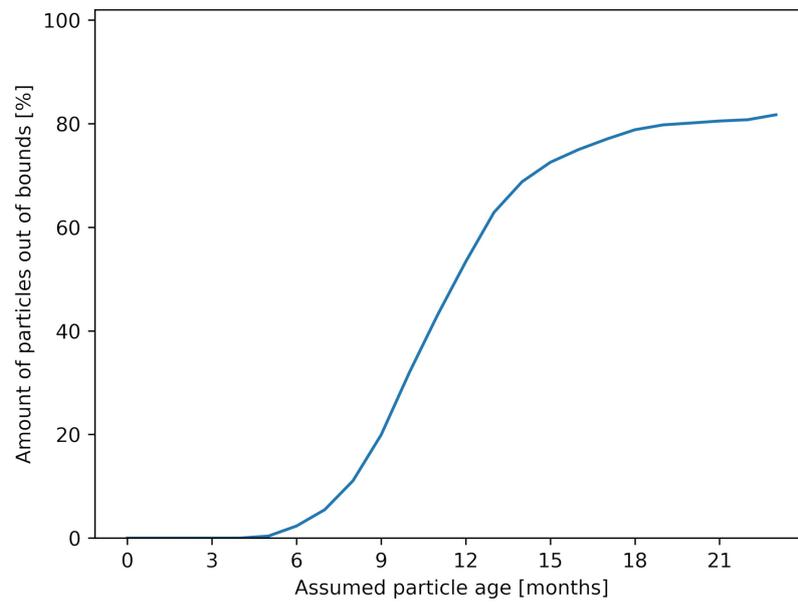


Figure S3. Percentage of particles out of bounds as a function of particle age.

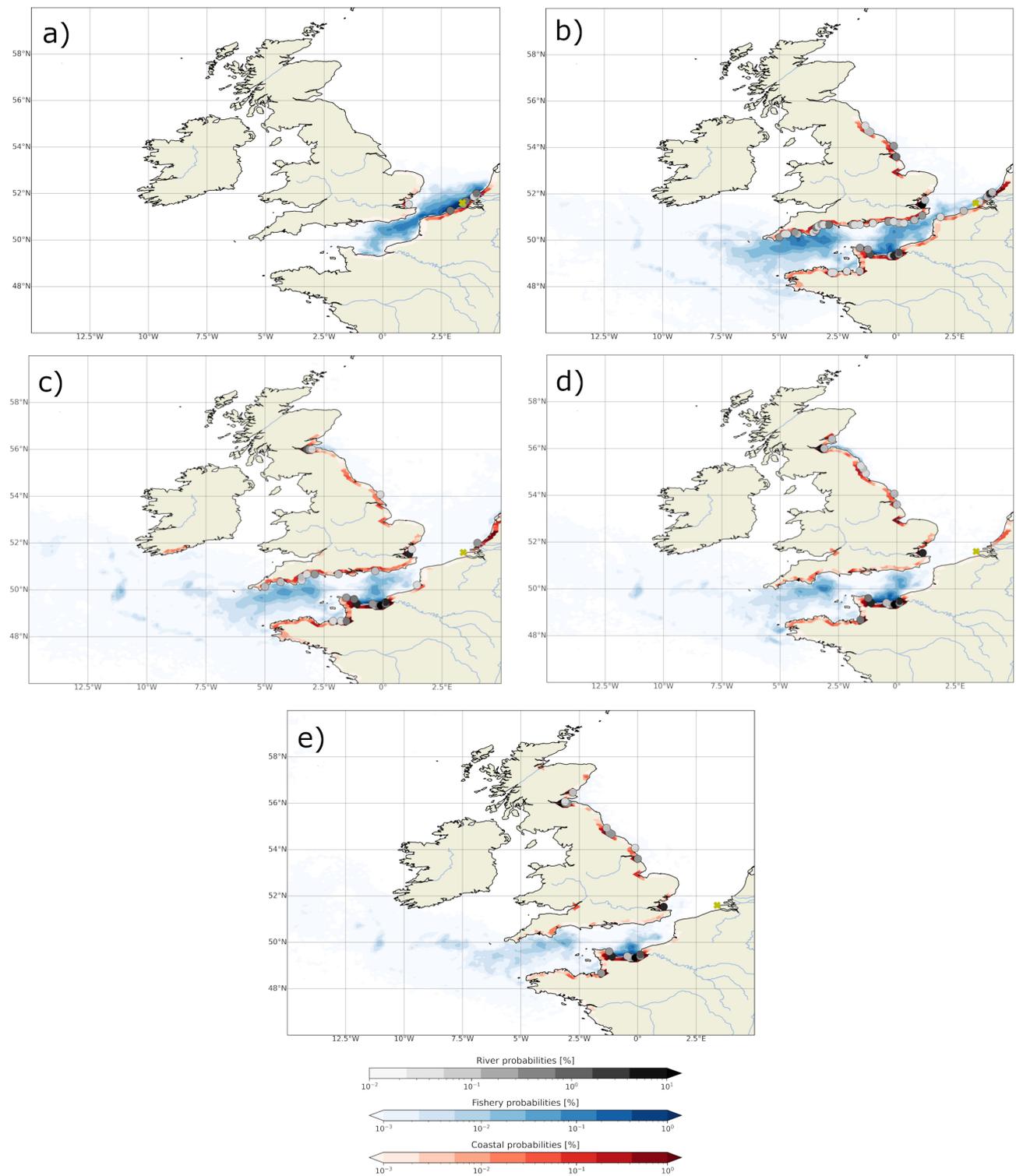


Figure S4. Source probability for different particle ages. a) age = 0-1 month, b) age = 5-6 months, c) age = 11-12 months, d) age = 17-18 months, e) age = 23-24 months.

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