Over 1,000 rivers accountable for 80% of global riverine plastic emissions into the ocean

Short title: Global distribution of riverine plastic emissions

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Abstract

Plastic waste increasingly accumulates in the marine environment, but data on the distribution and quantification of riverine sources, required for development of effective mitigation, are limited. Our new model approach includes geographical distributed data on plastic waste, landuse, wind, precipitation and rivers and calculates the probability for plastic waste to reach a river and subsequently the ocean. This probabilistic approach highlights regions which are likely to emit plastic into the ocean. We calibrated our model using recent field observations and show that emissions are distributed over up to two orders of magnitude more rivers than previously thought. We estimate that over 1,000 rivers are accountable for 80% of global annual emissions which range between 0.8 – 2.7 million metric tons per year, with small urban rivers amongst the most polluting. This high-resolution data allows for focused development of mitigation strategies and technologies to reduce riverine plastic emissions.

Introduction

Ocean plastic pollution is an emerging environmental hazard *(1)* and accumulation on coastlines *(2)* and the ocean surface *(3)* is rapidly increasing. Off all the plastics ever made to date, 60% has been discarded in landfills or in the natural environment *(4)*. Plastic pollution imposes threats on aquatic life, ecosystems and human health *(5,6)*. Plastic litter also results in severe economic losses through damage to vessels and fishing gear, negative effects on the tourism industry and increased shoreline cleaning efforts *(7)*. Work on the origin and fate of plastic pollution in aquatic environments suggests that land-based plastics are one of the main sources of marine plastic pollution *(8)*, either by direct emission from coastal zones *(9)* or transport through rivers *(10,11)*. Riverine plastic transport remains understudied, especially in areas that are expected to contribute most to global plastic emission into the ocean *(12)*. Better understanding of the global distribution of riverine plastic emissions into the ocean are a prerequisite to developing effective prevention and collection strategies.

Previous attempts to estimate the distribution of global riverine emissions of plastic into the ocean (*10,11*) relied on empirical indicators representative of waste generation inside a river basin. These assessments demonstrated a significant correlation between (micro)plastic concentration data collected by surface trawls in rivers and national statistics on mismanaged plastic waste (MPW) generation and population density. For both studies, an empirical formulation was presented based on this correlation, which was extrapolated to other rivers where data was not available. With predicted emissions of 1.15 - 2.41 million metric tons per year (*10*) and 0.41 – 4 million metric tons per year (*11*). These studies did not account for spatial distribution of plastic waste in a river basin or climatological or geographical differences between river basins. According to these studies, the ten largest emitting rivers contribute 50 - 61% and 88 - 94% to the total river emissions. Both models agreed on a disproportional contribution of Asian rivers to global plastic emissions. While these modeling efforts have provided a first approximation of the magnitude and spatial distribution of global riverine plastic emissions, they emphasized the scarcity of data on macroplastic contamination in freshwater ecosystems. Available measurements used for calibration of emission predictions were not always collected directly at the river mouths and studies reported data on plastic contamination using variable units and methods, including surface trawling from boats or bridges (*13-15*).

Sampling methods, using surface net trawls for freshwater contamination by plastic may be well suited for monitoring microplastic concentrations (size < 0.5cm). However, insufficient sampled volumes limited by net opening width or pump outlet dimensions may result in underestimation of macroplastics (several cm in size) *(16)* that account for most of the mass of plastic emissions *(17)*. Instead, visual observations from bridges provide more consistent results for the quantification of floating macroplastic in rivers *(18)*. In recent years, results from long term visual counting campaigns for the quantification of floating macroplastic emissions from rivers of different continents have been made available *(19)*. At global scale, these studies provided observational evidences for the disproportional contribution of Asian rivers in plastic emissions predicted by numerical models (*20-24*). However, at local scale, the studies reported discrepancies between observations and theoretical formulation *(23)* emphasizing the limitation of current models and the need for a revised formulation accounting for basin-scale geography, land use and climate to more accurately estimate floating macroplastic emissions.

Here, we present a revised estimate of global riverine plastic emissions into the ocean using most recent field observations on macroplastics and a newly developed, distributed probabilistic model to more accurately represent driving mechanisms of plastic transport (e.g. wind, runoff, river discharge), differentiating between areas with different land use and terrain slope, and including plastic retention on land and within rivers. We derived probabilities for plastic waste to be transported from land to river and from river to sea from six different geographical indicators and generated a high resolution (3 x 3 arcsecond cells) global map of the probability for waste discarded on land to reach the ocean within a given year. This information combined with the most recent estimates of mismanaged plastic waste generation on land *(25)*, allowed us to estimate annual emissions of plastic from rivers into the ocean. We validated our model against recent field observations (n=52) of monthly riverine plastic transport from over 16 rivers in 11 countries. We show how the consideration of transport probability for plastic within a river basin can highly increase or decrease the estimated emission of the corresponding river into the ocean. At global scale, this results in a considerably wider distribution of source points with large rivers contributing less to the total than expected while urban rivers in South East Asia and West Africa are identified as the main hotspots for plastic emissions. We classified plastic emitting rivers according to size, providing insight in which river class contains the highest number of rivers and the largest accumulative emission. The classification and distribution of emission points provides a basis for development of mitigation strategies and technologies as well as a roadmap for upscaling existing mitigation technologies.

Results

Global distribution of riverine plastic emissions

Out of the total 100,887 outlets of rivers and streams included in our model, we found that 31,913 locations emit plastic waste into the ocean, leaking in 1.2 (0.8-2.7) million metric tons into the marine environment in 2015. Rivers are included in the model if the annual average discharge is over 0.1 m^3s^{-1} and counted as plastic emitting river if the annual plastic emission is over 0.1 metric tons $year^{-1}$. Our model reveals that emissions are more widely distributed between contributing rivers with 1,378 (range 1,348 – 1,668) rivers accountable for 80% of the global emission against previously reported 47 and 5 rivers *(10,11)* (Fig. 1A). In this study, we calculated a high-resolution distribution (3 x 3 arcseconds) of probability P(E) for waste discarded on land to reach the ocean. P(E), with a global average of 0.4%, varied considerably between 0% for land-locked regions and up to 80% for coastal urban centers located near a river. When combined with distribution of waste generation on land, emission probabilities greatly increased the number of estimated riverine emission locations. This resulted in a considerably different ranking of the largest contributing rivers compared with previous assessments (top 50 rivers presented in Table S1), from which can be concluded that small rivers emerged in the top ranking, for example the Klang river in Malaysia.

Based on recent field observations and by considering probabilities of transport of plastic waste on land at high resolution within a river basin, we showed that land use, distance from waste generation to nearest river and coastline, play a more important role than the size of the river basin itself. As such, coastal cities associated with urban drainage and paved surfaces presented the highest emission probabilities, particularly in regions with high precipitation rates. On average, river basins with the dominant landuse 'artificial surfaces' are calculated to have a larger probability to emit plastic into the ocean than river basins with predominantly 'cultivated land', (13% and 2% respectively) and are observed and modeled to emit larger fractions of plastic waste into the ocean (15% and 3% respectively), see Table S2. To illustrate this, we compare the Ciliwung River, Indonesia and the Rhine River, Western Europe. The Ciliwung River basin on Java, covers a much smaller surface area than the Rhine river basin (respectively 591 km^2 versus 163,000 km^2), and with less total generation of plastic waste (respectively 19,590 metric tons year-1 versus 34,440 metric tons $year^{-1}$), emits substantially more floating plastic waste into the ocean with two orders of magnitude difference in emissions between the two river basins (308 metric tons year-1 observed and 377 metric tons $year^{-1}$ modeled for the Ciliwung River, and 3 metric tons year-1 observed and 6 metric tons $year^{-1}$ modeled for the Rhine River). This difference may mostly be explained by the spatial distribution of waste generation; in the Ciliwung River basin, waste is generated at 1 km from the river network on average, and 29 km from the ocean. Waste generation in the Rhine River occurs, on average, at a much greater distance from the river network and the ocean with an average of 5 km and 1,021 km from the river network and the ocean, respectively. Moreover, the annual precipitation *(26)* in the Ciliwung River basin is over 2.5 times larger than for the Rhine river basin (2,445 mm year-1 against 950 mm year^{-1}), further increasing mobilization of plastic waste. The resulting average probability of emission for the Ciliwung River basin was 15.7% versus 0.04% for the Rhine.

We divided the 1,378 rivers accountable for 80% of emissions over five river discharge classes (Fig. 1B, Fig. 2A). We found that the 683 rivers in the first class ($Q < 10\ m^3s^{-1}$) combined account for 30% of global emissions, while middle sized rivers (479 and 174 in class two ($10\ m^3s^{-1} < Q < 100\ m^3s^{-1}$) and three ($100\ m^3s^{-1} < Q < 1{,}000\ m^3s^{-1}$) respectively) combined account for 47%. Both in numbers (22 and 5 rivers in class four ($1{,}000\ m^3/s < Q < 10{,}000\ m^3s^{-1}$) and five ($Q > 10{,}000\ m^3s^{-1}$) respectively) and in combined emissions (2% and 1% respectively) the large rivers account for a relatively small fraction. The remaining 20% of emissions is divided over 30,535 rivers of varying size and low (< 124 metric tons year^{-1}) emission per river. Our results therefore suggest that focusing on implementing mitigation measures such as barriers and trash racks on small and medium sized rivers already could considerably reduce plastic emissions.

Predicting national emissions and potential for plastic waste leakage into the ocean

We estimated that 1.8% (range 1.2 – 4.0%) of the 67.5 million metric tons *(24)* of total globally generated mismanaged plastic waste (MPW) enters the ocean within a year. However, on a national level, the fraction of discarded waste entering the ocean differs considerably between countries (Fig. 2B). Our results indicate that countries with a relatively small landmass compared to the length of their coastline and with high precipitation rates are more likely to emit ocean plastics (Table S3). Particularly, for areas in the Caribbean such as the Dominican Republic and tropical archipelagos like Indonesia or the Philippines this results in a higher ratio of discarded plastic waste leaking into the ocean, respectively 3.8%, 7.8% and 10.8%. The plastic emission of these countries is therefore disproportionally higher compared to countries with similar MPW concentrations but different geographical and climatological conditions. For example, Malaysia generates over ten times less MPW than China (0.8 million metric tons year^{-1} in Malaysia against 12.8 million metric tons year^{-1} in China) however the fraction of total plastic waste reaching the ocean is 9.9% for Malaysia and only 0.7% for China. The largest contributing country estimated by our model was the Philippines with 4,826 rivers emitting 435,202 metric tons year-1 (10.8% of the total generated MPW in the country), followed by India with 151,385 metric tons year-1 (1.2% of total generated MPW through 1,170 rivers) and China with 87,942 metric tons year-1 (0.7% of total generated MPW through 1,310 rivers), see Table 1 and Fig. 2C.

Comparison with observations

A dataset of monthly averaged plastic transport near the river mouth was constructed from literature case studies and observational reports (Table S4). A selection of published results was made which report on floating macroplastic particle transport. These studies use standardized methods to observe and quantify macroplastic transport according or comparable to published approaches *(18,21,27)*, see Table S5 for details on observational data.

Calibrated model results are compared with field observations and a good order of magnitude relationship is demonstrated (coefficient of determination, $r^2 = 0{,}71$, n = 51). All model predictions are within one order of magnitude from observations (the Pasig River is on the border of one order of magnitude, Fig. 3) except for the Kuantan River. The Kuantan River is considered an outlier, with observed concentrations an order of magnitude lower then estimated by the model, when the Kuantan River is included in the model, the coefficient of determination r^2 is 0.61 (Table S6).

Discussion

Our study shows that riverine plastic emission into the ocean is distributed across a much larger number of rivers than reported in previous studies. The number of rivers responsible for 80% of global emissions (1,378 in this study) is one to two orders of magnitude larger than previously reported (47 rivers *(10)* and 5 rivers *(11)*). An important difference is that in previous studies, mismanaged plastic waste (MPW) was lumped within a river basin, leading to disproportionally high predictions of plastic emissions for large rivers while smaller rivers may have been underestimated. In this study, we considered spatial variability of MPW generation within a river basin and introduced climate and terrain characteristics to differentiate the probability for waste to leak into rivers and subsequently the ocean. Therefore, MPW near a river and near the coast has a relatively high probability of entering the ocean while MPW far upstream in a basin has a lower probability of entering the ocean. By taking into account these parameters, relatively small yet polluted river basins contribute proportionally more compared to equal amounts of MPW spread out over a larger river basin. Cities like Jakarta and Manila are drained by relatively small rivers, yet observations and our model suggest these rivers contribute more than rivers like the Rhine or the Seine, for which the MPW generation is similar yet located further upstream.

The results from this study are important for the prioritization and implementation of mitigation strategies. The large number of emission points estimated by our model calls for a global approach to prevent, reduce and collect plastic waste in aquatic environments instead of focusing on just several rivers. Furthermore, our results suggest that small and medium sized rivers account for a substantial fraction of global emissions. The probability map presented in this study suggests that besides the annual emission of plastic into the ocean, a considerable fraction of plastic waste (98.2%) remains entrapped in terrestrial environments where it accumulates and progressively pollutes inland aquatic systems. As a majority of MPW is generated and remains on land, prevention and mitigation regulations for waste reduction, collection and processing as well as clean-ups will naturally yield the largest impact on reducing the emissions of plastic into the ocean.

Understanding the total annual global riverine emission of plastic into the oceans is an important input for mass balance exercises and mapping the severity and fate of plastic pollution in the ocean. We calculated the annual global emission to be between 0.8 and 2.7 million metric tons. This in the same order of magnitude as previous river emission assessments, which estimated 1.15 – 2.41 million metric tons10 and 0.41 – 4 million metric tons *(11)* for global riverine plastic emissions. However, a wider distribution of emission points in this study led to a new ranking of largest contributing rivers, where the Pasig in the Philippines is now the largest emitter. The Yangtze river, which was previously estimated as the highest contributing river *(10,11)*, is now ranked 50th by our model. The Yangtze catchment is one of the largest river basins, with a very high total amount of MPW generation. However, the distance from MPW generation to the river, and to the ocean is large as well. Therefore, according to our model, only a relatively small fraction of MPW reaches the Yangtze river and subsequently the ocean. It is important to note that we calibrated our model against visual observations of macroplastics (>0.5 cm in size) therefore we are not considering microplastic transport. Global riverine microplastic emissions are estimated to be several orders of magnitude lower (between 20 and 70 thousand metric tons per year, projected for 2050) *(17)* than our macroplastic emission estimate. Although plastic observations are extrapolated to the entire water column, our model does not include riverbed transport of plastic waste. As such, our global riverine emission estimate can be considered conservative. We note that our estimated range for emissions in 2015 is one order of magnitude lower than previous predictions for plastic waste inputs from land into the ocean *(9)* for 2010 (range 4.8 and 12.7 million metric tons per year). This study did not specify a transport mechanism and includes all emissions into the ocean and not only riverine emissions. This emphasizes the uncertainty related to estimating plastic waste generation and emissions, as well as the need for additional ground truth data.

Previous studies *(10,11)* on global river emissions of plastic in the ocean were mainly calibrated against data collected in European and North American rivers. Following the recommendations from these studies, we included more data from South East Asian rivers to refine our model predictions. The difference between observed and modeled emissions is within one order of magnitude for 51 out of 52 observational data points. Given the uncertainty in observational accuracy as well as MPW data, we consider this an acceptable result and a major improvement compared with performance of previous models. This study is limited to monthly average and annual emissions intended for quantification of global riverine plastic transport and river to river comparison. We expect temporal variations in discharge, and especially floods, to have a large impact on macroplastic mobilization and transport, as was found for microplastics *(28)*, therefore future studies should include higher resolution for temporal hydrological variations, aimed at better accounting for extreme events such as floods and quantify their contribution to emissions. The model parameters chosen for this study are based on expert elicitation and calibration on field observations. More research and data are required to improve and validate the established relationships in this study. It is important to note that this study does not differentiate between types and characteristics of plastic waste. Mobilization, transportation likelihood and buoyancy may be influenced by plastic particle properties such as shape, weight and density. Therefore, the transport of plastic of different type and size should be differentiated in future assessments. Our global model does not include changes in local waste management policies as well as the contribution of the informal recovery sector. We also do not consider the presence of regulating structures in rivers such as dams or trash racks, and local extraction efforts. We acknowledge the need for local modeling and observational studies to better address local conditions. The uncertainty in parameter values should be minimized by conducting extensive monitoring campaigns on plastic mobilization and transport behavior rather than extensive calibration. Population densities, waste practices and consumption patterns are subject to change leading to a varying generation of MPW *(25)*. Ongoing efforts to improve global datasets on land cover, precipitation and elevation continue to deliver more accurate input datasets. Our probabilistic modeling approach and framework allows for the inclusion of these improved datasets and benefit from parameterizations derived from local models with high resolution temporal and spatial data on plastic transport and hydrology.

Our results include a global dataset of 31,913 locations representing river mouths and their estimated emissions. This data will be publicly available for researchers, policy makers and citizens to identify and address the nearest polluting river.

Materials and Methods

Study design

In this study, we calculate the probability for mismanaged plastic waste (MPW) generated inside a river basin to leak into aquatic environments. When combined with spatial data on MPW generation *(24)*, our framework (Fig. S1) allows for the accurate prediction of riverine plastic emissions, ME into the ocean. Probabilities are derived from physical and environmental characteristics including precipitation, wind, terrain slope, land use, distance to river, river discharge and distance to the ocean. We conducted an expert elicitation to constrain model parameters. Finally, we calibrated our model against 52 field measurements of monthly emissions of floating macroplastics from 16 different rivers across 3 continents, collected between 2017 and 2019.

Model formulation

The probability P(E) for a plastic waste, discarded on land, to be emitted into the ocean is constructed from the probability of intersection of three events: M (mobilization on land), R (transport from land to a river) and O (transport from the river to the ocean):

$$P(E) = P(M \cap R \cap O) = P(M) * P(R) * P(O) \quad (1)$$

For each 3 x 3 arcsecond grid cell, the amount of plastic waste leaking into the ocean is therefore calculated by multiplying the probability P(E) with the total amount of generated MPW mass (kg year^{-1}) within the cell. The total annual emission ME of plastic into the ocean from a river is then computed by accumulating this product for all n grid cells contained in the river basin:

$$M_E = \sum_n MPW * P(E) \quad (2)$$

Similarly to sediment *(29)* and debris *(30)*, plastic waste may be mobilized during events of rainfall *(31)* where surface runoff is generated. Wind can also transport littered plastic waste on land, particularly from open-air landfills *(32)*. In this framework, we consider that plastic waste can be mobilized through both events of precipitation and wind. As such the probability of mobilization P(M) can be formulated from the union probability of precipitation event P and wind event W:

$$P(M) = P(P \cup W) = P(P) + P(W) \quad (3)$$

Probabilities of mobilization by precipitation and wind are linearly ranging from 0% (respectively no rain or no wind) to 100% corresponding to an upper threshold (see Table 2). For probability of mobilization by wind, we consider the maximum monthly average wind speed (m s^{-1}). The upper threshold for total mobilization was set at 32.7 m s^{-1} which equals to Beaufort 12 (i.e. under hurricane conditions 100% of littered waste is mobilized). The upper threshold for probability of mobilization by rain was determined during the model calibration exercise presented later in the Methods section, considering the annual rainfall. Data for monthly averaged wind speed and annual rainfall were sourced from global 30-arcseconds datasets distributed by WorldClim2 *(26)*.

For the mobilized fraction of plastic waste, we compute the probability to reach the nearest river. The river network in our model contains the annual average discharge [m3 s^{-1}] on a 3 x 3 arcseconds spatial resolution and was derived by accumulating annual average 0.5° x 0.5° runoff between 2005 and 2014 [mm year-1] *(33)* by a nearly global flow direction grid *(34)*. Cells with a discharge higher than 0.1 m^{3}s^{-1} are considered rivers *(35)*. The shortest downslope distance D_{land} (km)from each grid cell to the nearest location in the river network is calculated based on flow direction data.

Similarly to Chezy's formula *(36)* and the Rational Method *(37)* in hydrology, we introduce a roughness coefficient based on land use classification. For example, plastic waste will by more likely transported by wind or rain on paved surface than in dense vegetation *(31,38)*. Furthermore, we also consider the average terrain slope (%), known to increase erosion rates and sediment transport over land *(39)*. As such, the probability of transport to a river will naturally increase with terrain slope. We derive the roughness of each cell from land use and terrain slope and compute the average probability from the initial emitting grid cell to the nearest river cell. As roughness is cumulated on the downslope path, the resulting probability to reach a river is exponentially decreasing with distance to river D_{land}. The landuse data was sourced from 30 x 30 arcseconds classification distributed by GLC2000 *(40)* and the terrain slope was calculated from the 3 x 3 arcseconds Digital Elevation Model (DEM) provided by HydroSHEDS *(34)*. The probability of transport to a river is formulated as follows:

$$P(R) = \left(\frac{\sum_{i=1}^{n} \nu_i*(\varepsilon*s_i+\tau)}{n}\right)^{\mathrm{D_{Land}}} \quad (4)$$

where ν_i is the probability associated to land use (see classification in Table S7) of grid cell i, s_i is the percent slope of cell i, ε and τ are model parameters (Table 2), and n is the number of cells from origin to the nearest river cell.

By analogy to the transport of leaves *(41)* and wooden debris *(42)* by rivers, the probability in our model for plastic introduced in rivers, to reach the ocean, increases with river discharge and decreases with distance to ocean. Rivers with a higher Strahler *(43)* stream order (SO) have a larger cross section *(44)* and therefore on average less friction *(45)*, decreasing the likelihood for floating macroplastic to be intercepted. Therefore, for each river grid cell, we compute the distance D_{River} to the ocean, the Strahler stream order and the annual river discharge ($m^3\ s^{-1}$). The probability for transport into the ocean is calculated as follows:

$$P(O) = \left(\frac{\sum_{i=1}^{n} (\theta*SO_i+\iota)*(\kappa*Q_i+\mu)}{n}\right)^{\mathrm{D_{River}}} \quad (5)$$

where θ_i is the probability related to Strahler stream order for cell i, Q_i is the river discharge at cell i, ι,κ and μ are model parameters (Table 2) and n is the number of cells from river entry point to the ocean. An example of the different steps leading to the calculation of probability of emission P(E) is provided in Fig. 4.

Expert elicitation

To constrain our model parameters, an expert survey was conducted during the EGU General Assembly, April 2019, in Vienna, with a panel of 24 geoscientists. The advantage of benefitting from the intuitive experience of experts to assess complex modeling problems has been reported for hydrology *(46)* and ecology *(47)*. Here, a series of 7 questions related to the probability of plastic waste transport over land and through rivers were asked to individual experts. The questions are presented in Table S8, while the individual responses are given in Table S9. From this elicitation exercise we calculated the average and standard deviation of returned values for each question (Table S10). This data determined a bandwidth for our parameter during the model calibration (i.e. while varying our model parameters when comparing with measurements, the resulting probability should remain in the range determined by experts elicited for this study, avoiding unreasonable parameter values).

Model calibration

To calibrate our model, we used newly available datapoints measuring the monthly averaged emissions of floating macroplastics (> 0.5 cm in size) measured from visual observations near river mouths between 2016 and 2019 (Table S4) and extrapolated these measurements over the water column. Data were collected using visual counting measurements of floating macroplastic litter from bridges *(18,27)*. This was converted into mass flux (M T^{-1}) using the following equation:

$$M_{obs} = p * m_p * c \quad (6)$$

With observed floating plastic transport p (items T^{-1}), m_p mean mass per plastic item [kg/item], and conversion factor *c* to account for plastics at deeper layers. We use both monthly and annual estimations in the comparison with the model results. Variables m_p and c were measured at each river through net sampling at the same location as the visual counting measurements. In case these were not available we used the global or regional average values. These published field observations covered 16 rivers on three different continents. These rivers have different characteristics regarding total basin area, average landuse, rainfall and MPW generation (Table S2).

Our model calculates annual plastic emissions which are scaled by monthly average discharge to distribute annual emissions over 12 months. First, we ran a version of the model to match with the average values reported by the expert elicitation exercise. Our model predicts total annual plastic load which is distributed over the months by scaling with river discharge. We evaluated the model performance by calculating the regression coefficient r^2 between the logarithm of measured and modeled monthly averaged emissions. Under these conditions, the model estimated emissions appeared higher than observations. We initially decreased the probability for plastic waste to be transported from land to a river cell P(R) by progressively increasing the roughness related to land use, as introduced in Equation (4). Second, the model overestimated emissions of rivers where precipitation was relatively higher than other rivers, when compared to observations. We improved our model results by decreasing the probability of mobilization P(M) induced by precipitation, as introduced in Equation (3). Third, the emissions of river basins in which the generation of MPW occurring further away from the mouth, were underestimated (e.g. the Motagua in Guatemala and the Seine in France). Therefore, we improved our model predictions by increasing the probability of transport from river entry to ocean P(O), as presented in equation (5). This model calibration exercise resulted in 8 iterations which are presented in Table S6, showing the score model versus measurement per iteration, for the different parameters considered by our model. Our best calibrated scenario returned a regression coefficient of determination r2 = 0.71 between modeled and measured logarithm of monthly average emissions per rivers, and with 51 datapoints modeled within one order of magnitude from measurements.

H2: Supplementary Materials

Materials and Methods
Fig. S1. Model framework
Table S1. Top 50 plastic emitting rivers.
Table S2. Characteristics of observed river basins
Table S3. Country Statistics.
Table S4. Observation locations
Table S5. Observed and modeled plastic fluxes.
Table S6. Model calibration and metrics for performance.
Table S7. Land use classification and P[landuse].
Table S8. Expert elicitation questions
Table S9. Individual expert responses.
Table S10. Model and expert panel parameters.

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Author contributions: L.J.J.M , T.v.E and R.v.d.E. designed the study. T.v.E. and L.J.J.M. conducted field expeditions to collect data. L.J.J.M developed the model and T.v.E. and L.C.M.L reviewed the model. L.J.J.M. T.v.E. and L.C.M.L wrote the manuscript. L.J.J.M. and L.C.M.L. prepared the figures. All authors reviewed the manuscript.

Competing interests: L.J.J.M. and L.C.M.L. are employed by The Ocean Cleanup. T.v.E. was employed by The Ocean Cleanup. All other authors declare no competing interests.

Data and materials availability: Data will be made available on Figshare.

Figures and Tables

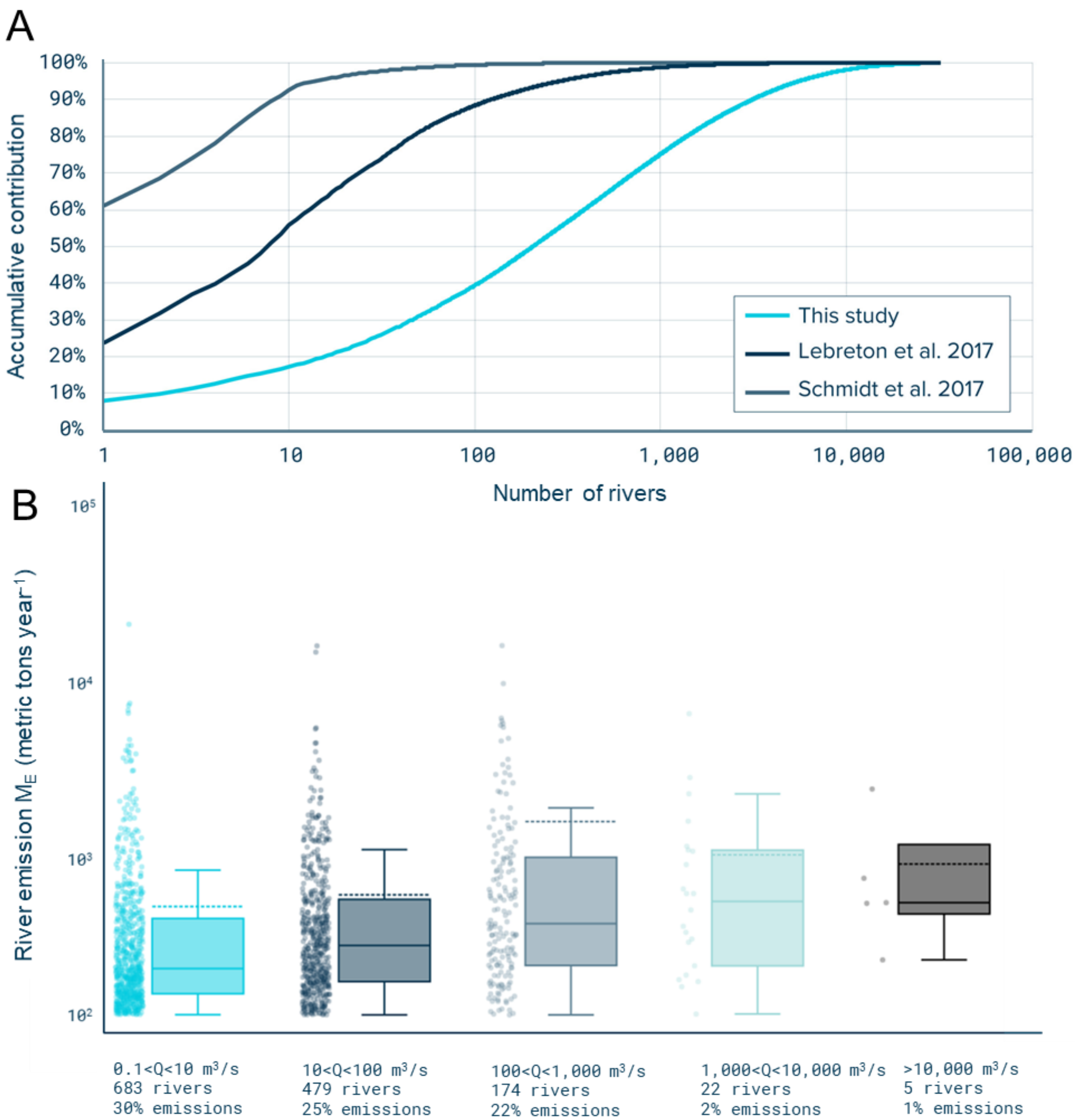

Fig. 1| Global distribution of riverine plastic emission into the ocean. (a) Contribution of plastic emission to the ocean (ME) (y-axis) is plotted against the logarithm of the number of rivers accountable for that contribution (x-axis), for previous studies and this study. **(b)** Distribution of 1,378 rivers accountable for 80% of emissions over five discharge classes, each river is represented by a dot.

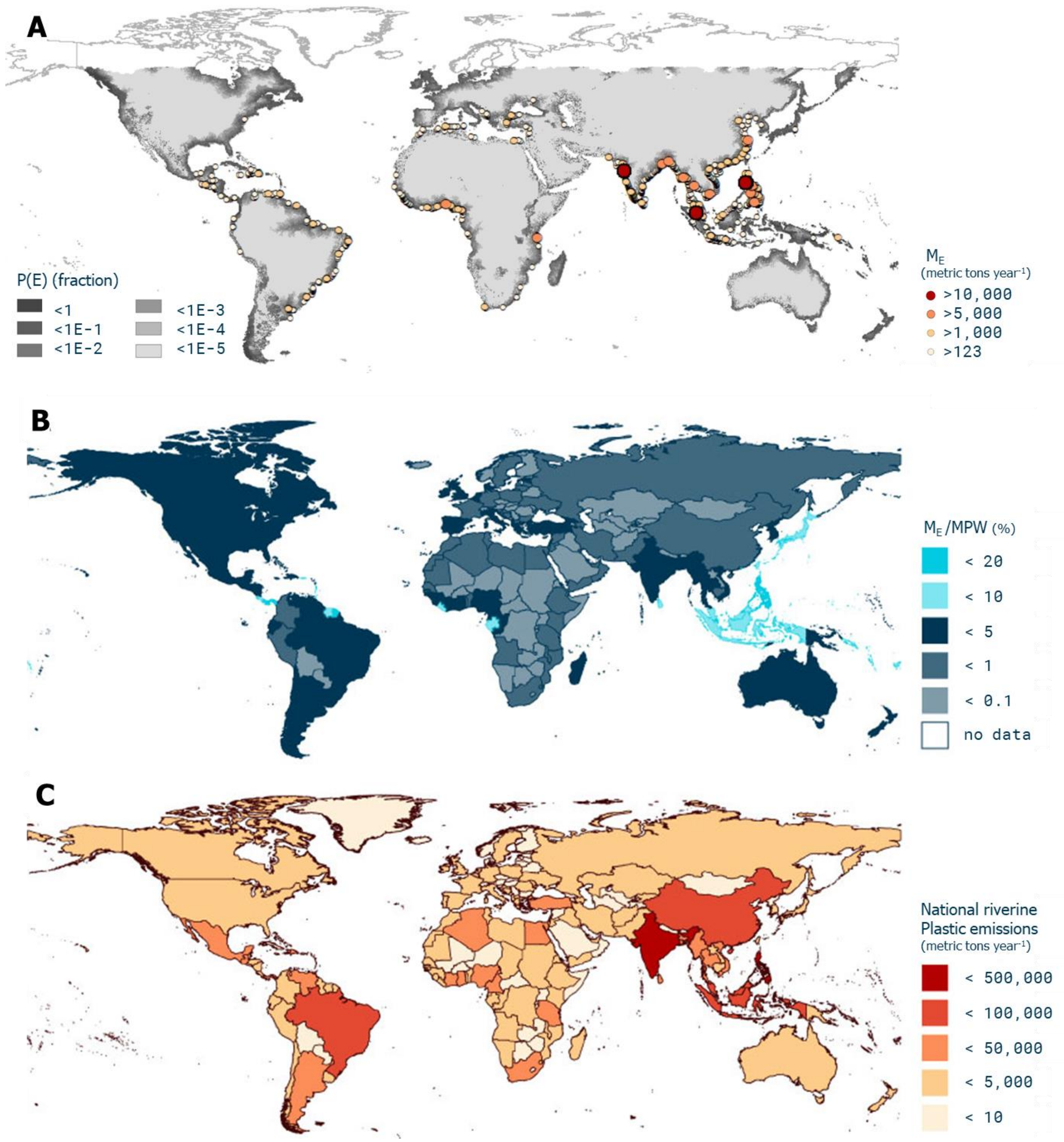

Fig. 2 | National emissions of plastic into the ocean. (a) The geospatial distribution of plastic entering the ocean through rivers. The 1,378 rivers accountable for 80% of the total influx are presented. The grey shading indicates the probability for plastic entering the ocean (P[E]) on a 10 x 10 km resolution. **(b)** Total emitted plastic into the ocean ME per country divided by the national generation of mismanaged plastic waste (MPW), globally ranging between 0% and 18%. **(c)** Total emitted plastic into the ocean ME (metric tons year^{-1}) per country.

Fig. 3 | Observations compared with modeled data for floating macro-litter monthly emissions per rivers. Regression analysis carried out with 52 records from 16 different rivers of different sizes spread across the globe. Dots indicate midpoints of extrapolated measurements [metric tons month^{-1}], where the river name is represented by a letter which can be found in the table, and the number is the month of the year [1-12]. The logarithm of both the measurements and the model results is presented here. The dotted black lines represent one order of magnitude deviation from the x=y line in the middle. Only the Kuantan river (considered an outlier) is more than 1 order of magnitude different compared with observational results.

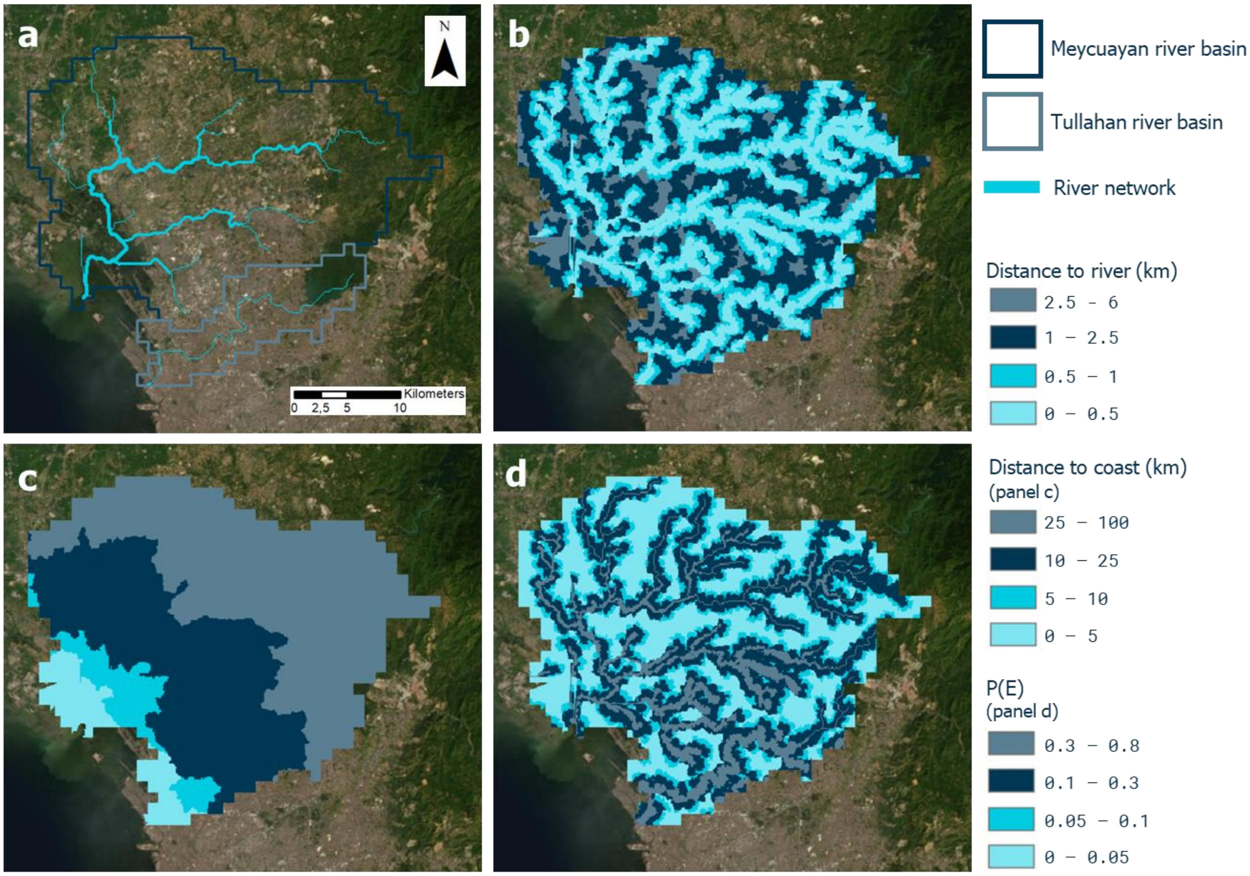

Fig. 4 | Probability maps. (a) The Meycuayan and Tullahan river basins and river network in Manila, the Philippines. **(b)** The distance (km) from a 3 x 3 arcsecond grid cell toward the nearest river. **(c)** The distance (km) from each grid cell to the ocean, trough the river network. (d) The probability for a grid cell to emit plastic waste into the ocean P(E), equation (1), for a given year, ranging from 0% – 5% for areas further away from a river up to 0.8% for areas near a river and near the coast.

Country	*M_E [metric tons year^{-1}]*	*MPW [ton year^{-1}]*	*Ratio MPW to Ocean [MPW/M_E]*	*Average emission probability P(E) [%]*	*Number of rivers contributing to 100% M_E*	*Number of rivers contributing to 80% M_E*
Global	**1.2E+06**	**6.8E+07**	**1.8%**	**0.4%**	**31,913**	**1,378**
Philippines	4.4E+05	4.0E+06	10.8%	7.3%	4,826	377
India	1.5E+05	1.3E+07	1.2%	0.5%	1,170	191
China	8.8E+04	1.2E+07	0.7%	0.2%	1,310	118
Malaysia	7.8E+04	8.1E+05	9.6%	4.4%	1,071	91
Indonesia	6.4E+04	8.2E+05	7.8%	4.5%	5,547	83
Brazil	5.2E+04	3.3E+06	1.6%	0.2%	1,240	69
Myanmar	4.3E+04	9.9E+05	4.3%	1.7%	1,596	63
Vietnam	3.1E+04	1.1E+06	2.8%	1.6%	490	52
Bangladesh	2.7E+03	1.0E+06	2.7%	2.4%	588	28
Thailand	2.6E+04	1.3E+06	1.9%	0.9%	624	34
Nigeria	2.1E+03	1.9E+06	1.1%	0.4%	303	22
Turkey	2.0E+04	1.7E+06	1.2%	0.4%	661	23
Cameroon	1.1E+04	5.8E+05	1.9%	0.5%	176	12
Sri Lanka	1.1E+04	1.6E+05	6.9%	3.5%	147	16
Tanzania	9.8E+03	1.7E+06	0.6%	0.2%	102	5
Haiti	8.5E+03	2.4E+05	3.6%	3.0%	233	17
Dominican Republic	7.3E+03	1.9E+05	3.8%	2.6%	186	8
Guatemala	7.0E+03	3.1E+05	2.2%	1.8%	75	15
Algeria	6.7E+03	7.6E+05	0.9%	0.1%	94	15
Venezuela	6.5E+02	6.7E+05	1.0%	0.4%	224	10

Table 1 | Country statistics. Top 20 countries ranked according to annual plastic emission M_E into the ocean as calculated in this study. The third column contains the annual mismanaged plastic waste (MPW) generated in each country. The fourth column contains the fraction (%) of MPW reaching the ocean (calculated by dividing national M_E by MPW) within a year. The fifth column contains the country averaged probability for a plastic particle to reach the ocean within a year, P(E). This sixth column contains the number of rivers accountable for national emission M_E and the last column holds the number of rivers for a country that are contribute to the global 80% riverine plastic emission (emitted by 1,378 rivers in total).

Input factor	*Symbol*	*Unit*	*Data Range*	*Probability range [%]*	*Equations*
Precipitation	*P*	*mm year-1*	*0-11,256*	*0-100*	$min(P*\alpha, 1)$
Wind	W	m s-1 (maximum monthly average)	0-36	0-100	$min(W*\beta,1)$
Landuse	*L*	*class*	*0-1*	*10 - 100*	*Classification* *(Table S7)*
Slope	S	%	0-1,117	η - 100	$min(\varepsilon*S + \zeta, \eta)$
StreamOrder	*SO*	*class (Strahler)*	*1-10*	ι – 100	$min(\theta* SO +\iota, 1)$
Discharge	Q	m3 s-1 (annual average)	0,.1-190,000	μ – 100	$min(\kappa *Q +\mu ,1)$

Table 2 | Overview input factors. Overview of mobilizing, resistance and transportation forces and the range of their values distrusted across the globe. The parametrized relation between the input value and the probability is presented in the right column. All input values are available on or constructed on a 3” spatial resolution.

SUPPLEMENTARY MATERIALS

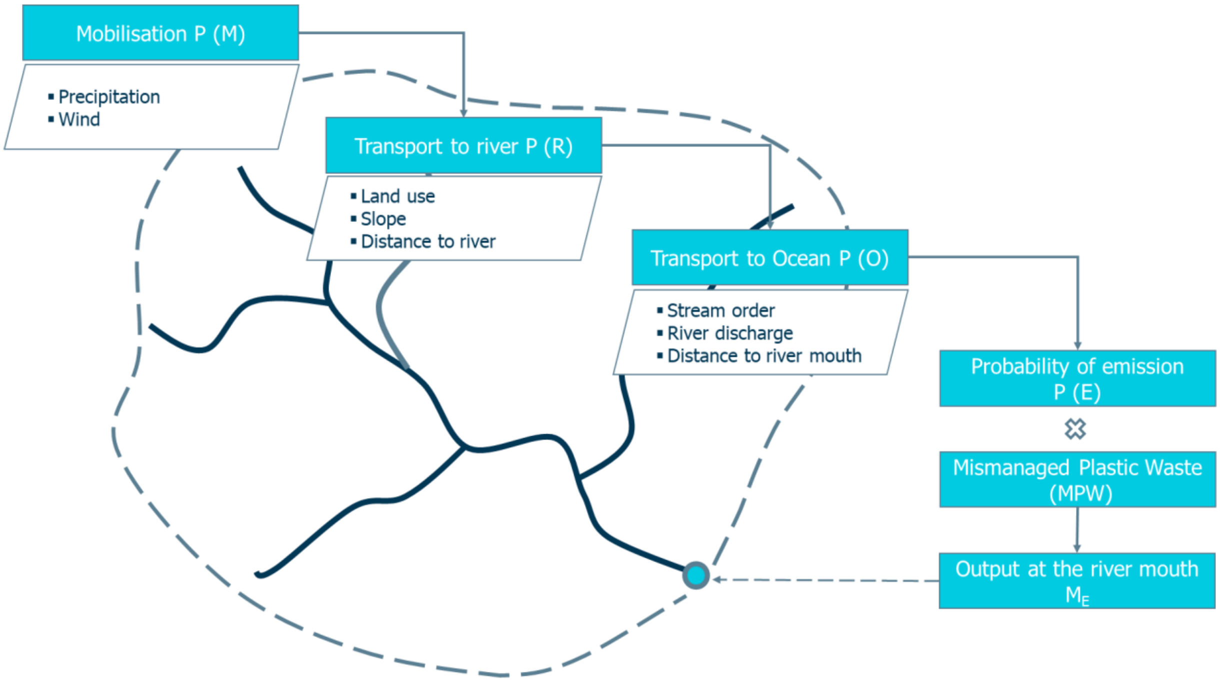

Fig. S1 | Model framework. Plastic emission in a river mouth ME is computed by accumulating of mismanaged plastic waste (MPW) multiplied with the probability of waste leaking into the ocean, P(E) within a river basin. P(E) is constructed with P(M), P(R) and P(O) which contain physical processes accountable for MPW transport.

Ranking	*Catchment*	*Country*	*Plastic mass emissiont M_E (metric tons year^{-1})*	*Average plastic output (gram s^{-1})*
1	Pasig	Philippines	9.7E+04	*3,070*
2	Tullahan	Philippines	2.2E+04	703
3	Ulhas	India	1.7E+04	529
4	Meycauayan	Philippines	1.7E+04	527
5	Klang	Malaysia	1.5E+04	485
6	Pampanga	Philippines	1.0E+04	320
7	Libmanan	Philippines	7.7E+03	246
8	Ganges	Bangladesh	7.5E+03	239
9	Ciliwung	Indonesia	7.1E+03	225
10	Paranaque	Philippines	7.1E+03	225
11	Chao Phraya	Thailand	6.7E+03	215
12	Huangpu	China	6.4E+03	202
13	Soài Rạp	Vietnam	5.9E+02	188
14	Rio Grande de Mindanao	Philippines	5.8E+03	184
15	Hugli	India	5.6E+03	179
16	Iloilo	Philippines	5.6E+03	178
17	Pazundaung Creek	Myanmar	5.5E+03	175
18	Agno	Philippines	4.9E+03	155
19	Malad Creek	India	4.8E+03	152
20	Agusan	Philippines	4.7E+03	149
21	Ébrié Lagoon/Komoé	Ivory Coast	4.6E+03	146
22	Zapote	Philippines	4.4E+03	141
23	Rio Pavuna (Rio de Janeiro)	Brazil	4.4E+03	140
24	Imus	Philippines	4.2E+03	132
25	Panvel Creek	India	4.1E+03	131
26	Zhujiang/Canton	China	4.1E+03	129
27	Storm drain (Tambo, Pasay)	Philippines	4.0E+03	128
28	Nile	Egypt	4.0E+03	126
29	Mithi	India	3.9E+03	123
30	Bharathappuzha	India	3.7E+03	117
31	City Drain Black Bay (Mumbai)	India	3.6E+03	116
32	Cagayan de Oro	Philippines	3.6E+03	116
33	City Drain Versova Beach (Mumbai)	India	3.6E+03	114
34	Shenzhen River	China, Hong Kong	3.6E+03	114
35	Sarawak	Malaysia	3.3E+02	105
36	Kelani	Sri Lanka	3.3E+03	104
37	Las Piñas	Philippines	3.2E+03	101
38	The Golden Horn	Turkey	3.2E+03	100
39	Langat	Malaysia	3.1E+03	100
40	Rio Sarapuí/Rio Iguaçu (Rio de Janeiro)	Brazil	3.1E+03	100
41	Yangon	Myanmar	3.1E+03	98
42	Karnaphuli	Bangladesh	3.0E+03	96
43	Wouri River	Cameroon	3.0E+03	95
44	Rio Ozama	Dominican Republic	2.9E+03	93
45	Minjiang/Wulong	China	2.9E+03	92
46	Malaking Tubig	Philippines	2.9E+03	92
47	Hijo	Philippines	2.7E+03	87
48	Kelantan	Malaysia	2.7E+03	86
49	Tributary of Wouri Estuary (Southern Douala)	Cameroon	2.5E+02	79
50	Yangtze	China	2.5E+03	79

Table S1 | Top 50 plastic emitting rivers. The top 50 plastic emitting rivers are presented, ranked on annual amount of metric tons plastic waste ME. The average emission in the last column is converted to average number of grams per second.

ID	*Name*	*Surface area [km2]*	*MPW [metric tons year-1]*	*Average rainfall [mm year-1]*	*Average distance to river mouth [km]*	*Average distance to coast [km]*	*Dominant landuse type [class]*	*P(E) [%]*	*ME [metric tons year-1]*
A	Can Tho	10	1,587	1,548	92	3	Cultivated land	2.23%	131
B	Chauo Phraya	144,380	442,535	1,132	655	6	Cultivated land	0.05%	3,864
C	Ciliwung	591	19,590	2,445	29	1	Artificial surface	15.67%	3,606
D	Jones Falls	156	323	1,131	20	4	Artificial surface	4.78%	21
E	Rach Cai Khe	100	2,530	1,550	80	3	Cultivated land	0.17%	3
F	Kuantan	1,654	2,510	2,990	51	2	Tree cover	7.65%	624
G	Meycuayan	542	100,759	2,657	27	2	Cultivated land	12.92%	1,6587
H	Motagua	16,328	78,527	1,582	133	4	Cultivated land	0.72%	244
I	Pahang	28,833	30,679	2,435	288	3	Tree cover	1.00%	556
J	Pasig	4,068	550,339	2,215	66	2	Mixed cropland/tree cover	6.30%	96,631
K	Pesanggrahan	54	6,530	1,951	9	3	Artificial surface	14.52%	1,202
L	Rhine	163,029	34,440	950	1,021	5	Cultivated land	0.04%	36
M	Rhone	96,016	5,384	1,037	513	4	Cultivated land	0.12%	10
N	Seine	73,090	7,518	707	619	7	Cultivated land	0.06%	8
O	Tiber	16,664	3,021	700	257	5	Cultivated land	0.29%	14
P	Tullahan	101	95,981	2,586	19	1	Artificial surface	18.79%	14,771

Table S2 | Characteristics of observed river basins. The surface area (column three), generated amount of mismanaged plastic waste (MPW) (column four) and the average precipitation (column five) are sourced from input data. The average distance to the river mouth (column six), the average distance to the river network (column 7), dominant (most abundant) landuse class (column 8), probability for MPW to reach to ocean P(E) (column nine) and the plastic emission into the ocean ME were calculated.

Country or administrative area	*Area [km2]*	*Coast length [km]*	*Rainfall [mm year^{-1}]*	*Factor L/A [-]*	*Factor L/A *P [-]*	*P[E] [%]*	*MPW (metric tons year^{-1})*	*M[E] (metric tons year^{-1})*	*Ratio M[E]/MPW*
Global Median	**110,292**	**646**	**1,068**	**9.0E-03**	**8**	**0.005**	**21,293**	**280**	**1.80%**
Albania	28,486	362	1,117	1.0E-02	14	1.56%	69,833	1,867	2,67%
Algeria	2,316,559	998	80	4.0E-04	0	0.09%	764,578	7,004	0,96%
Angola	1,247,357	1,600	1,025	1.0E-03	1	0.09%	236,946	1,032	0,14%
Antigua and Barbuda	443	153	996	3.0E-01	344	3.10%	627	2	0,29%
Argentina	2,779,705	4,989	567	2.0E-03	1	0.26%	465,808	5,411	1,28%
Australia	7,687,219	25,760	480	3.0E-03	2	0.18%	5,266	35	2,03%
Bahamas	13,336	3,542	1,006	3.0E-01	267	2.04%	2,212	22	1,01%
Bahrain	673	161	73	2.0E-01	17	0.00%	1,043	0	0,00%
Bangladesh	136,478	2,320	2,249	2.0E-02	38	2.38%	1,021,990	27,410	2,53%
Barbados	439	97	1,512	2.0E-01	334	4.53%	872	48	5,51%
Belgium	30,671	67	844	2.0E-03	2	0.73%	2,284	38	1,46%
Belize	22,217	386	2,003	2.0E-02	35	3.49%	6,021	382	4,50%
Benin	115,542	121	1,035	1.0E-03	1	0.14%	133,335	2,067	0,00%
Bosnia and Herzegovina	50,993	20	1,031	4.0E-04	0	0.95%	55,551	6	0,59%
Brazil	8,484,839	7,491	1,746	9.0E-04	2	0.24%	3,296,700	51,989	1,57%
Brunei	5,880	161	3,392	3.0E-02	93	9.92%	692	522	16,81%
Bulgaria	111,300	354	590	3.0E-03	2	0.13%	3,117	7	0,14%
Burkina Faso	273,367	354	752	1.0E-03	1	0.00%	317,298	0	0,00%
Myanmar	667,871	1,930	2,015	3.0E-03	6	1.70%	986,948	42,838	4,21%
Cambodia	181,380	443	1,787	2.0E-03	4	0.63%	247,495	1,131	0,53%
Cameroon	466,295	402	1,612	9.0E-04	1	0.45%	578,798	11,205	1,94%
Canada	9,924,777	202,080	468	2.0E-02	10	0.55%	23,587	257	1,18%
Cape Verde	4,058	965	204	2.0E-01	49	0.00%	3,568	0	0,00%
Chile	754,237	6,435	957	9.0E-03	8	2.57%	30,767	345	1,12%
China	9,373,898	14,500	561	2.0E-03	1	0.20%	12,272,200	87,942	0,72%
Colombia	1,137,921	3,208	2,632	3.0E-03	7	0.62%	85,454	442	0,52%
Comoros	1,671	340	1,993	2.0E-01	405	0.00%	59,158	0	0,00%
Congo	341,574	169	1,644	5.0E-04	1	0.08%	65,291	787	1,24%
Congo (Democratic Republic of the)	2,327,986	37	1,575	2.0E-05	0	0.01%	1,369,730	584	0,05%
Costa Rica	51,222	1,290	2,856	3.0E-02	72	6.25%	5,751	482	7,47%
Côte d'Ivoire	321,882	515	1,274	2.0E-03	2	0.39%	291,614	6,101	7,47%
Croatia	56,377	5,835	966	1.0E-01	100	1.16%	17,544	230	0,80%
Cyprus	9,013	648	482	7.0E-02	35	0.66%	837	3	0,47%
Denmark	44,441	7,314	673	2.0E-01	111	2.34%	390	10	2,26%
Djibouti	21,679	314	169	1.0E-02	2	0.22%	10,289	4	0,08%
Dominica	767	148	1,827	2.0E-01	353	7.75%	1,082	53	5,11%
Dominican Republic	48,183	1,288	1,366	3.0E-02	37	2.63%	194,018	7,317	3,67%
Ecuador	256,212	2,237	1,985	9.0E-03	17	0.57%	108,797	1,203	1,12%
Egypt	982,443	2,900	20	3.0E-03	0	0.04%	1,435,510	6,278	0,41%
El Salvador	20,580	307	1,803	1.0E-02	27	2.73%	21,693	783	2,35%
Equatorial Guinea	26,987	296	2,223	1.0E-02	24	2.92%	9,403	411	2,90%
Eritrea	122,099	2,234	361	2.0E-02	7	0.13%	84,088	49	0,06%
Estonia	45,438	3,794	644	8.0E-02	54	0.75%	600	12	1,54%
Federated States of Micronesia	692	1,117	3,821	2.0E+00	6164	5.01%	447	37	7,72%

Fiji	18,298	1,129	2,570	6.0E-02	159	7.56%	3,858	379	9,62%
Finland	335,647	125	580	4.0E-04	0	0.00%	2,621	0	0,00%
France	548,780	4,668	847	9.0E-03	7	0.56%	27,780	257	0,94%
French Guiana	83,267	459	2,704	6.0E-03	15	2.16%	126	45	11,68%
Gabon	264,716	885	1,838	3.0E-03	6	0.69%	5,991	471	7,39%
Gambia	10,797	80	789	7.0E-03	6	0.65%	35,095	533	1,45%
Georgia	69,798	310	1,090	4.0E-03	5	1.21%	307	118	1,96%
Germany	357,242	2,389	778	7.0E-03	5	0.26%	50,676	142	0,29%
Ghana	238,761	539	1,211	2.0E-03	3	0.29%	520,002	5,527	1,05%
Greece	132,559	13,676	655	1.0E-01	68	0.92%	4,506	244	0,00%
Grenada	366	121	1,701	3.0E-01	563	6.07%	1,357	131	1,68%
Guadeloupe	1,673	306	1,411	2.0E-01	258	4.40%	162	4	9,67%
Guatemala	109,283	400	2,270	4.0E-03	8	1.74%	311,003	6,994	3,13%
Guinea	244,872	320	1,807	1.0E-03	2	0.76%	147,997	2,493	2,46%
Guinea-Bissau	33,973	350	1,614	1.0E-02	17	2.35%	20,465	249	1,75%
Guyana	210,025	459	1,938	2.0E-03	4	0.88%	27,565	1,321	1,19%
Haiti	27,069	1,771	1,456	7.0E-02	95	3.02%	237,968	8,505	4,60%
Honduras	113,032	820	1,697	7.0E-03	12	1.49%	145,995	2,623	3,50%
Hong Kong	1,046	1,189	1,863	1.0E+00	2118	5.55%	5,781	4,540	1,57%
Iceland	102,566	497	1,026	5.0E-03	5	0.00%	151	0	10,14%
India	3,153,013	7,517	1,128	2.0E-03	3	0.47%	12,994,100	151,385	0,00%
Indonesia	1,888,924	54,716	2,703	3.0E-02	78	4.48%	824,234	63,965	1,18%
Iran	1,621,476	244	235	2.0E-04	0	0.08%	495,965	953	7,66%
Iraq	437,114	58	212	1.0E-04	0	0.02%	491,771	70	0,28%
Ireland	69,809	1,448	1,237	2.0E-02	26	2.99%	2,675	127	0,01%
Israel	21,981	273	300	1.0E-02	4	0.31%	6,060	44	4,84%
Italy	301,631	7,600	792	3.0E-02	20	0.89%	38,803	452	0,71%
Jamaica	11,025	1,022	1,713	9.0E-02	159	5.13%	49,673	2,421	1,20%
Japan	373,665	29,751	1,606	8.0E-02	128	3.64%	35,684	2,159	4,97%
Jordan	89,066	26	108	3.0E-04	0	0.07%	124,425	1	6,16%
Kazakhstan	2,704,399	26	247	1.0E-05	0	0.10%	54,242	13	0,10%
Kenya	582,253	536	601	9.0E-04	1	0.17%	289,917	288	0,07%
Kiribati	930	1,143	1,211	1.0E+00	1488	0.00%	74	0	0,23%
Kuwait	17,323	499	116	3.0E-02	3	0.21%	2,640	9	0,00%
Latvia	64,563	498	670	8.0E-03	5	0.49%	955	9	0,24%
Lebanon	10,133	225	812	2.0E-02	18	1.28%	46,622	1,031	0,99%
Lesotho	30,454	225	758	7.0E-03	6	0.00%	30,391	0	2,19%
Liberia	95,878	579	2,639	6.0E-03	16	3.66%	39,930	2,758	0,00%
Libya	1,616,873	177	32	1.0E-04	0	0.06%	188,535	931	6,44%
Lithuania	64,945	90	656	1.0E-03	1	0.21%	1,037	8	0,51%
Macau	19	41	1,750	2.0E+00	3771	0.00%	14,749	517	0,44%
Madagascar	591,575	4,828	1,384	8.0E-03	11	1.59%	25,250	778	0,01%
Malaysia	329,721	4,675	2,865	1.0E-02	41	4.41%	814,454	78,476	2,42%
Maldives	183	644	129	4.0E+00	455	0.00%	60	0	9,46%
Malta	314	197	490	6.0E-01	308	0.00%	259	0	0,00%
Marshall Islands	199	370	859	2.0E+00	1595	0.00%	16	0	0,00%
Martinique	1,142	350	1,840	3.0E-01	564	10.27%	139	23	0,00%
Mauritania	1,040,736	754	84	7.0E-04	0	0.10%	20,796	183	17,97%

Mauritius	2,016	177	1,612	9.0E-02	142	0.00%	299	0	0,86%
Mexico	1,957,508	9,330	753	5.0E-03	4	0.47%	430,614	3,888	0,00%
Monaco	8	4	821	5.0E-01	389	0.00%	5	1	1,62%
Montenegro	13,780	294	1,181	2.0E-02	25	2.03%	16	155	0,00%
Morocco	406,318	1,835	295	5.0E-03	1	0.15%	295,488	2,540	1,15%
Mozambique	786,095	2,470	971	3.0E-03	3	0.36%	434,432	2,674	0,86%
Namibia	824,206	1,572	275	2.0E-03	1	0.05%	20,892	3	0,58%
Netherlands	34,968	523	794	1.0E-02	12	1.56%	15,233	293	0,08%
New Zealand	270,409	15,134	1,694	6.0E-02	95	3.79%	1,714	74	1,85%
Nicaragua	129,013	910	2,147	7.0E-03	15	2.09%	110,862	1,332	4,67%
Nigeria	909,482	853	1,158	9.0E-04	1	0.43%	1,948,950	21,390	1,28%
North Korea	122,469	2,495	954	2.0E-02	19	0.70%	322	366	1,22%
Norway	324,286	25,148	1,046	8.0E-02	81	1.03%	1,494	0	1,55%
Oman	307,991	2,092	119	7.0E-03	1	0.11%	1,251	1	0,00%
Pakistan	876,262	1,046	278	1.0E-03	0	0.02%	1,346,460	2,478	0,15%
Palau	460	1,519	2,763	3.0E+00	9129	13.75%	116	7	0,18%
Palestine	12,232	45	2,700	4.0E-03	10	9.29%	2,129	119	5,36%
Panama	75,042	249	2,615	3.0E-03	9	7.11%	36,339	3,636	5,63%
Papua New Guinea	462,196	5,152	2,982	1.0E-02	33	4.40%	119,538	3,072	16,66%
Peru	1,291,445	2,414	1,585	2.0E-03	3	0.06%	140,313	553	4,10%
Philippines	296,017	36,289	2,497	1.0E-01	306	7.27%	4,025,300	435,202	0,39%
Poland	311,947	440	589	1.0E-03	1	0.13%	14,124	31	10,90%
Portugal	91,978	1,793	904	2.0E-02	18	0.85%	3,818	89	0,22%
Puerto Rico	9,018	501	1,698	6.0E-02	94	5.89%	1,293	78	2,22%
Qatar	11,367	563	79	5.0E-02	4	0.07%	1,532	0	6,13%
Reunion	2,541	563	1,504	2.0E-01	333	0.00%	233	0	0,01%
Romania	237,980	225	614	9.0E-04	1	0.04%	52,161	81	0,00%
Russia	16,945,398	37,653	430	2.0E-03	1	0.12%	363,389	569	0,03%
Saint Kitts and Nevis	276	135	1,283	5.0E-01	628	2.57%	97	1	0,14%
Saint Lucia	617	158	2,022	3.0E-01	517	8.01%	4,276	466	0,57%
Saint Martin	55	59	862	1.0E+00	930	0.00%	8	0	11,49%
Saint Vincent and the Grenadines	409	84	1,913	2.0E-01	393	7.25%	1,235	82	0,00%
Samoa	2,877	403	3,323	1.0E-01	465	0.00%	1,738	0	6,67%
Sao Tome and Principe	1,009	209	2,327	2.0E-01	482	3.71%	2,069	93	0,00%
Saudi Arabia	1,959,676	2,640	103	1.0E-03	0	0.06%	7,176	4	4,47%
Senegal	196,761	531	651	3.0E-03	2	0.21%	65,660	173	0,07%
Seychelles	476	491	1,146	1.0E+00	1183	0.00%	33	0	0,27%
Sierra Leone	72,322	402	2,715	6.0E-03	15	3.07%	91,239	4,116	0,00%
Singapore	594	193	2,212	3.0E-01	719	14.23%	2,468	5,284	4,66%
Sint Maarten	41	80	1,027	2.0E+00	1985	0.00%	3	0	0,00%
Slovakia	49,029	193	735	4.0E-03	3	0.00%	1,719	0	0,00%
Slovenia	20,683	47	1,426	2.0E-03	3	1.12%	844	12	0,00%
Solomon Islands	28,724	5,313	2,931	2.0E-01	542	10.35%	3,520	4,049	0,91%
Somalia	633,217	3,025	272	5.0E-03	1	0.14%	42	2	8,73%
South Africa	1,220,394	2,798	482	2.0E-03	1	0.12%	708,467	5,076	0,02%
South Korea	99,085	2,413	1,277	2.0E-02	31	1.65%	12,156	542	0,72%
Spain	505,752	4,964	626	1.0E-02	6	0.36%	20,350	271	4,51%
Sri Lanka	66,533	1,340	1,857	2.0E-02	37	3.49%	155,466	10,712	1,29%

Sudan	2,503,825	853	405	3.0E-04	0	0.01%	781,625	115	6,87%
Suriname	146,101	386	2,177	3.0E-03	6	0.86%	22,933	1,787	0,02%
Sweden	449,206	3,218	649	7.0E-03	5	1.03%	4,255	38	7,73%
Syria	185,757	193	251	1.0E-03	0	0.13%	502	45	0,97%
Taiwan	36,313	1,566	2,514	4.0E-02	108	5.83%	7,502	661	0,61%
Tanzania	941,757	1,424	965	2.0E-03	1	0.23%	1,716,400	9,828	9,53%
Thailand	515,107	3,219	1,404	6.0E-03	9	0.91%	1,361,690	26,172	0,63%
Timor-Leste	14,913	706	1,625	5.0E-02	77	3.84%	17,244	755	1,85%
Togo	57,038	56	1,186	1.0E-03	1	0.18%	121,783	449	4,42%
Tonga	672	419	1,669	6.0E-01	1040	0.00%	666	0	0,56%
Trinidad and Tobago	5,181	362	1,927	7.0E-02	135	5.11%	73,139	3,689	0,00%
Tunisia	155,177	1,148	233	7.0E-03	2	0.18%	289,538	727	5,03%
Turkey	781,152	7,200	594	9.0E-03	5	0.38%	1,656,110	19,514	0,27%
Ukraine	600,353	2,782	575	5.0E-03	3	0.10%	393,777	911	1,27%
United Arab Emirates	70,904	1,318	93	2.0E-02	2	0.18%	5,135	16	0,18%
United Kingdom	244,575	12,429	1,098	5.0E-02	56	3.05%	29,914	808	0,29%
United States	9,325,599	19,924	689	2.0E-03	1	0.35%	267,469	2,917	2,74%
Uruguay	178,158	660	1,262	4.0E-03	5	0.52%	92,620	1,185	1,05%
Venezuela	912,557	2,800	1,875	3.0E-03	6	0.39%	671,431	6,450	1,25%
Vietnam	327,732	3,444	1,772	1.0E-02	19	1.62%	1,112,790	31,472	1,22%
Western Sahara	266,830	111	35	4.0E-04	0	0.11%	4,114	38	2,78%
Yemen	419,900	1,906	112	5.0E-03	1	0.07%	291,737	263	0,92%
Zimbabwe	390,648	1,906	665	5.0E-03	3	0.00%	524,865	0	0,11%

Table S3 | Country Statistics. Alphabetically ranked countries and their corresponding surface area, length of coastline and annual precipitation. The fifth and column provides the ratios of coast length divided by landmass (L/A) and in the sixth column this ratio is multiplied by the annual precipitation (L/A*P). The ratio (L/A) indicates the average distance to the coast and is correlated with the length of rivers. The ratio (L/A*P) is an indicator for both the length of rivers and the density of the river network. The national average probability of plastic emission into the ocean P(E) is presented in the seventh column. The eight column contains the amount of generated mismanaged plastic waste (MPW) and the ninth column the amount of MPW that is emitted into the ocean ME per country. Finally, the tenth column presents the ratio ME/MPW.

ID	River	Location	Country	Period	Observed (metric tons month-1)	Modeled (metric tons month-1)	Source
A	Can Tho	Quang Trung	Vietnam	July 2018	12	29	van Calcar et al. *(19)*
B	Chao Praya	Ratchawithi	Thailand	November 2018	283	97	van Calcar et al. *(19)*
C	Ciliwung	BKB-Angke	Indonesia	May 2018	337	308	van Emmerik et al. *(21)*
D	Jones Falls	Baltimore Harbour	USA	2018; full year	21	49	Lindquist (2014) *(48)*
E	Kuantan	Kuantan	Malaysia	November 2018	63	1	van Calcar et al. *(19)*
F	Meycuayan	Obando	Philippines	March 2019	215	392	van Klaveren et al. *(49)*
G	Motagua	Hopi	Guatemala	January 2019	12.9	39	Meijer et al. *(49)*
H	Pahang	Pekan	Malaysia	November 2018	68	10	van Calcar et al. *(19)*
I	Pasig	Manila	Philippines	March 2019	839	85	van Klaveren et al. *(49)*
J	Pesanggrahan	Cengkareng Kapuk	Indonesia	May 2018; December 2018	212	294	van Emmerik et al. *(20)*
K	Rach Cai Khe	Cau Di Bo Ben Ninh Kieu	Vietnam	July 2018	0.3	1.8	van Calcar et al. *(19)*
L	Rhine	Rotterdam	Netherlands	November 2018; April 2019	6	3.2	Vriend et al. *(16)*
M	Rhône	Arles	France	September 2016 – August 2017	9.9	9.6	Castro-Jiménez et al, *(23)*
N	Seine	Rouen	France	September 2018; March 2019	2.1	9.3	van Emmerik et al. *(24)*
O	Tiber	Fiumicino	Italy	September 2016 – September 2017	14.4	11.4	Crosti et al, *(22)*
P	Tullahan	Malabon	Philippines	March 2019	97	21.6	van Klaveren et al. *(48)*

Table S4 | Observation locations. Listed studies reported macroplastic fluxes, either from visible observations or sampled in the upper water column. Typically, the upper 50 cm with a size larger than 2 cm. Measurements were corrected for depth and scaled for discharge. Average particle mass is derived from debris sampling, used to calculate monthly total plastic transport in metric tons per month. A harmonized dataset of 52 observations from 16 different rivers across 3 continents is presented here.

ID	River	Month	Discharge ($m^3 s^{-1}$)	Modeled [metric tons year^{-1}]	Measured [metric tons year^{-1}]
	Can Tho	Jul	0.9	12.1	29.4
B	Chauo Phraya	Nov	1,133	283.1	97
C	Ciliwung	May	17	337.3	308
D	Jones Falls	Jan	2.5	1.9	1.3
D	Jones Falls	Feb	3.1	2.3	3.2
D	Jones Falls	Mar	4.1	3.1	2.3
D	Jones Falls	Apr	4.5	3.3	9.3
D	Jones Falls	May	2.8	2.1	3.3
D	Jones Falls	Jun	1.8	1.3	7.7
D	Jones Falls	Jul	0.9	0.6	6
D	Jones Falls	Aug	0.9	0.6	4.6
D	Jones Falls	Sep	1.5	1.1	3.2
D	Jones Falls	Oct	1.8	1.3	2.4
D	Jones Falls	Nov	1.71	1.3	3
D	Jones Falls	Dec	2.7	2.0	3
E	Kuantan	Nov	63	63.0	1
F	Meycuayan	Mar	6.8	215.0	392
G	Motagua	Jan	204	12.9	39.7
H	Pahang	Nov	1,704	68.0	10.7
I	Pasig	Mar	71	839.0	85
J	Pesanggrahan	May	8.7	112.4	95.4
J	Pesanggrahan	Dec	7.7	99.6	198.7
K	Rach Cai Khe	Jul	0.1	0.3	1.8
L	Rhine	Jan	2,475	3.3	2.4
L	Rhine	Feb	2	2.7	0.8
M	Rhone	Mar	2,653	1.0	0.9
M	Rhone	Apr	2,542	1.0	1.1
M	Rhone	May	2,643	1.0	1.5
M	Rhone	Jun	2,76	1.1	0.7
M	Rhone	Jul	2,803	1.1	2.2
M	Rhone	Aug	2,065	0.8	0.7
M	Rhone	Sep	1,386	0.5	0.8
M	Rhone	Oct	1,127	0.4	0.4
M	Rhone	Nov	1,026	0.4	0.4
M	Rhone	Dec	1,366	0.5	0.0001
M	Rhone	Jan	2,554	1.0	0.4
M	Rhone	Feb	2,936	1.1	0.5
N	Seine	Mar	1,145	1.8	8.3
N	Seine	Sep	401	0.3	1
O	Tiber	Jan	62	1.5	1.3
O	Tiber	Feb	72	1.8	1.3
O	Tiber	Mar	83	2.1	0.7
O	Tiber	Apr	62	1.5	0.7
O	Tiber	May	71.1	1.8	0.7
O	Tiber	Jun	39	1.0	0.5

O	Tiber	Jul	15	0.4	0.5
O	Tiber	Aug	9	0.2	0.5
O	Tiber	Sep	13	0.3	1.3
O	Tiber	Oct	20	0.5	1.3
O	Tiber	Nov	57	1.4	1.3
O	Tiber	Dec	70	1.8	1.3
P	Tullahan	Mar	1.4	97.0	21.6

Table S5 | Observed and modeled plastic fluxes. The river ID and river name are presented in the first two columns. The monthly average river discharge has been sourced from local measurement stations if available, otherwise the monthly average river discharge has been simulated using HydroSHEDS flow direction data combined with monthly runoff. Exceptions here are the Seine, Pasig, Meycuayan and Tullahan river which were observed during extreme conditions where monthly average discharge was scaled down to daily discharge to better represent scaling flow conditions. For the Rhine and the Tiber, the observed plastic concentrations have been corrected according to the spatial layout of the river because the observation was made in one specific branch while the model simulation represents all branches.

Parameter	*Symbol*	*Run 1*	*Run 2*	*Run 3*	*Run 4*	*Run 5*	*Run 6*	*Run 7*	*Run 8*
Precipitation coefficient	α	5.0E-04	2.5E-04	2.0E-04	2.0E-04	1.5E-04	1.5E-04	1.0E-04	1.5E-04
Wind coefficient	β	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Lower threshold Slope effect	ζ	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4
Upper threshold Slope effect	η	1	1	1	1	1	1	1	1
StreamOrder coefficient	θ	1.0E-03	1.0E-04	1.0E-03	1.0E-04	1.0E-04	1.0E-04	1.0E-04	1.0E-04
Lower threshold StreamOrder effect	ι	0.989	0.999	0.989	0.999	0.999	0.999	0.999	0.995
Discharge coefficient	κ	5.0E-08	5.0E-08	5.0E-08	5.0E-08	5.0E-08	5.0E-09	5.0E-09	5.0E-09
Lower threshold Discharge coefficient	μ	0.99	0.99	0.99	0.99	0.99	0.999	0.99	0.995
Landuse coefficient	ν	1	0.9	0.8	0.85	0.75	0.6	0.5	0.75
Coefficient of determination (n=52)	r^2	0.52	0.56	0.55	0.58	0.61	-0.13	0.02	0.60
Coefficient of determination (n=51)	r^2	0.66	0.68	0.65	0.69	**0.71**	-0.04	0.09	0.69
Ratio M_E -Model / M_E - Observation.	-	2.9	2.3	1.6	1.9	1.6	2.6	1.4	1.6
Difference larger than 1 order of magnitude (excluding Kuantan)	n(>1)	2	2	2	1	**0**	12	10	2

Table S6 | Model calibration and metrics for performance. Variations of model parameters for the last 8 calibration runs. Corresponding metrics for performance; coefficients of determination (r^2, n=52 includes outlier Kuantan River, n=51 is without Kuantan), ratio between the sum of modeled and observed datapoints. In the last row the number or locations with a difference more than 1 order of magnitude between modeled and observed values is indicated.

Description	**Calibrated value (%)**
Tree Cover, broadleaved, evergreen	8%
Tree Cover, broadleaved, deciduous, closed	15%
Tree Cover, broadleaved, deciduous, open	15%
Tree Cover, needle-leaved, evergreen	15%
Tree Cover, needle-leaved, deciduous	15%
Tree Cover, mixed leaf type	15%
Tree Cover, regularly flooded, fresh	60%
Tree Cover, regularly flooded, saline, (daily variation)	68%
Mosaic: Tree cover / Other natural vegetation	15%
Tree Cover, burnt	23%
Shrub Cover, closed-open, evergreen (with or without sparse tree layer)	23%
Shrub Cover, closed-open, deciduous (with or without sparse tree layer)	23%
Herbaceous Cover, closed-open	23%
Sparse Herbaceous or sparse shrub cover	23%
Regularly flooded shrub and/or herbaceous cover	53%
Cultivated and managed areas	45%
Mosaic: Cropland / Tree Cover / Other Natural Vegetation	38%
Mosaic: Cropland / Shrub and/or Herbaceous cover	38%
Bare Areas	45%
Water Bodies (natural & artificial)	75%
Snow and Ice (natural & artificial)	53%
Artificial surfaces and associated areas	60%
No data	0%

Table S7 | Land use classification and P[landuse]. GLC2000 land use classification and corresponding probabilities for mismanaged plastic waste (MPW) transportation per kilometre, derived from rational method. Parameter values determined by calibration confined by a bandwidth determined by expert elicitation.

Question number	*Question*
1	What is the probability of mobile riverine plastic debris traveling 1 km downstream within a year?
2	What is the probability of unsoundly disposed plastic debris traveling 1 km overland through natural drivers (rainfall, surface runoff, wind) in a relatively flat area, such as The Netherlands, within a year?
3	What is the probability of unsoundly disposed plastic debris traveling 1 km overland through natural drivers (rainfall, surface runoff, wind) in a relatively mountainous area, such as New Zealand, within a year?
4	What is the overland transport probability per kilometre for landuse type 'bare land'?
5	What is the overland transport probability per kilometre for landuse type 'urban'?
6	What is the overland transport probability per kilometre for landuse type 'agricultural land'?
7	What is the overland transport probability per kilometre for landuse type 'forest'?

Table S8 | Questions. List of seven questions asked to a panel of 24 experts on the EGU General Assembly 5 – 12 April 2019, Vienna, Austria.

Name	Specialisation	1	2	3	4	5	6	7
Expert 1	Oceanography	0.5	0.1	0.1	-	-	-	-
Expert 2	Physical oceanography	0.1	0.01	0.1	0.9	0.7	0.1	0.1
Expert 3	Microplastic in the Baltic	0.5	0.1	0.5	0.7	0.3	0.1	0
Expert 4	Microplastic river transport	0.99	0.1	0.1	0.99	0.9	0.5	0.001
Expert 5	N/A	0.99	0.5	0.99	-	-	-	-
Expert 6	Hydrology	0.98	0.3	0.35	-	-	-	-
Expert 7	Microplastics	0.99	0.5	0.1	-	-	-	-
Expert 8	Fluvial Geomorphology	0.999	0.5	0.99	1	0.9	0.5	0.1
Expert 9	N/A		0.5	0.1	-	-	-	-
Expert 10	Microplastics in rivers + ecotoxicology	0.99	0.1	0.1	0.9	0.8	0.5	0.5
Expert 11	Hydrology	0.99	0.1	0.5	-	-	-	-
Expert 12	Hydrological modeling	0.99	0.01	0.1	-	-	-	-
Expert 13	N/A	0.99	0.99	0.99	0.99	0.8	0.5	0.1
Expert 14	Hydrological modeling	0.5	0.5	0.5	0.8	0.6	0.5	0.25
Expert 15	Global hydrological modeling	0.99	0.1	0.5	0.75	0.5	0.25	0.1
Expert 16	N/A	0.5	0.99	0.99	-	-	-	-
Expert 17	Hydrology/Geochemistry	0.99	0.99	0.999	-	-	-	-
Expert 18	Isotope hydrologist	0.99	0.1	0.5	-	-	-	-
Expert 19	Coastal Oceanography	0.5	0.1	0.99	0.99	0.7	-	-
Expert 20	Macroplastics in rivers	0.99	0.5	0.99	0.99	0.99	0.99	0.5
Expert 21	Urban climate and hydrology	0.75	0.5	0.8	0.99	0.8	0.65	0.1
Expert 22	Hydrological modeling	0.75	0.5	0.6	0.5	0.45	0.4	0.3
Expert 23	Sensing and global hydrology	0.99	0.1	0.1	0.99	0.5	0.3	0.01
Expert 24	N/A	0.5	0.99	0.1	-	-	-	-

Table S9 |Individual expert responses. Anonymized responses from 24 experts. Questions listed in Table S8.

Probability [per km]	*Location/class*	*Expert Judgement Average*	*Expert standard deviation*	*Bandwidth for calibration*
$P_{[R]}$	Netherlands	0.38	+/- 0.34	0.04 - 0.72
$P_{[R]}$	New Zealand	0.50	+/- 0.38	0.12 - 0.88
$P_{[O]}$	Global	0.80	+/- 0.26	0.54 - 1.00
$P_{[L]}$	Bare areas	0.76	+/- 0.24	0.52 - 1.00
$P_{[L]}$	Urban	0.72	+/- 0.32	0.40 - 1.00
$P_{[L]}$	Cultivated	0.50	+/- 0.27	0.23 - 0.77
$P_{[L]}$	Forrest	0.23	+/- 0.19	0.04 - 0.42

Table S10 | Model and expert panel parameters. Parameter values for MMW transported 1 kilometer (D_{land} and D_{river} = 1 in equation (3) and (4)). Average values for land transport for the Netherlands (flat and cultivated) and New Zealand (hilly and natural) and global average river transport compared to expert panel average and standard deviation. Parameter values for transport probability for four selected main land use classes.