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Highlights

- A “Microplastic Concentration Standardization model” is formulated.
- The average microplastic concentration in North America is the highest.
- Excessive microplastics are found in the Yangtze River and North American coasts.
- On a global scale, the main driving factor is the Human Development Index.
- Only in North America, the main driving factor is Mismanagement Plastic Waste.
Standardization of Monitoring Data Reassesses Spatial Distribution of Aquatic Microplastics Concentrations Worldwide

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Abstract

Microplastics are found in continental and oceanic waters worldwide, but their spatial distribution shows an intricate pattern. Their driving factors remain difficult to identify and
widely discussed due to insufficient and unstandardized monitoring data. Here, based on in situ experiments and hundreds of river samples from the Qinghai-Tibet Plateau, we formulate a model to standardize aquatic microplastic measurements. The model was applied to existing data on a global scale. These data are standardized to a 20 µm mesh size, resulting in a new spatial distribution of aquatic microplastic densities, with average concentrations of $554.93 \pm 1352.42$ items/m$^3$ in Europe, $2558.90 \pm 4799.62$ in North America and $1741.94 \pm 3225.09$ in Asia. Excessive contaminations (microplastic concentration $> 10^4$ items/m$^3$) are in the Yangtze River, the Charleston Harbor Estuary, the Bodega Bay and the Winyah Bay. We show that, based on these standardized concentrations, new driving factors could be used to predict the global or regional microplastic distribution in continental waters, such as the Human Development Index with a correlation of $75.86\%$ on a global scale, the nighttime lights with a correlation of $37.26 \pm 0.30\%$ in Europe and $39.02 \pm 0.54\%$ in Asia, and the Mismanagement Plastic Waste with a correlation of $61.21 \pm 19.86\%$ in North America. Mapping standardized concentrations of aquatic microplastics enables a better comparison of contamination levels between regions and reveals more accurate hotspots to better adapt remediation efforts and future plastic pollution scenarios.

**Keywords**

Microplastics; Standardized data; Spatial distribution; Driving factors; Excessive contaminations.

1 **Introduction**

Microplastics are plastic particles smaller than 5 mm. They have been observed in continental and oceanic waters worldwide. The first evidence of microplastics was found in the Northeast Atlantic [1], followed by numerous studies reporting their presence up to the highest
latitudes of the Arctic Ocean, but also in continental waters, such as rivers, lakes and reservoirs.

An intricate pattern of spatial variability was reported, ranging from more than $10^5$ items/m$^3$ in the WangYu River to less than $10^2$ items/m$^3$ in the Antarctic Ocean. Even considering similar water bodies, the concentrations of aquatic microplastics can vary by 2 to 6 orders of magnitude worldwide. Due to complex causal links, the driving factors of the spatial distribution of aquatic microplastics are still not understood. In 2015, Jambeck, et al. developed a concept of Mismanagement Plastic Waste (MPW), which was then identified as the main driving factor forcing aquatic microplastic and macroplastic flux estimations from rivers to the sea.

However, recent studies claimed that the use of MPW in statistical models is questionable, leading to an overestimation of predicted microplastic fluxes, and have preferred the use of other anthropogenic factors such as population density or the Human Development Index (HDI).

Unstandardized monitoring data used by the previous studies might be the main obstacle to establishing robust relationships between microplastic concentrations and driving factors. We identify at least two methodological sampling issues that cause this high diversity in monitoring data. On the one hand, observations in rivers, lakes and oceans are expressed in many different units measured by various sampling tools. Microplastics in oceans, lakes and rivers are commonly detected by plankton nets in area-based units (items/km$^2$). However, numerous studies in rivers and lakes also use filtering pumps, net, and stainless-steel sieves with volume-based units (items/L). On the other hand, there is a large amount of unstandardized data in term of particle size distribution at a same location caused by diverse mesh sizes used for water filtration. The mesh size variability (from 0.45 to 2000 µm) can cause potential bias (± $10^5$ items/m$^3$) in aquatic microplastic concentrations. The potential bias was even equal to the extreme
microplastic concentration in the urban water body of the WangYu River (i.e., $1.05 \times 10^5$ items/m$^3$). The scientific community is now calling for high-quality standardized global data 13, 21, 22.

A possible solution for compiling standardized data is to build a standardization model that can convert existing monitoring data from various sampling approaches to a homogeneous global dataset. In this study, we attempt to formulate such a model based on in situ experiments and statistical analysis. Rivers on the Qinghai-Tibet Plateau and Northern China were selected to integrate various microplastic measurements collected in different natural and anthropogenic environments. The low concentration of aquatic microplastic on the Qinghai-Tibet Plateau guarantees sufficient precision of microplastic measurement (microplastic concentration $\geq 3$ items/m$^3$) 23. In contrast, the high concentration in Northern China provides various microplastic forms and compositions with high spatial heterogeneity.

Based on hundreds of samples from the rivers on the Qinghai-Tibet Plateau and Northern China, we first developed a Microplastic Concentration Standardization (MCS) model. Then, we used this model to standardize existing monitoring data at a global scale, revealing a new spatial distribution of microplastic concentration at a global scale. The relationship between standardized aquatic microplastic concentrations and widely accepted driving factors (e.g., MPW, population and HDI) is re-examined worldwide and regionally with an assertion of their relative prevalence per region. This study remaps global aquatic microplastic distribution, establishes a new homogeneous database and new driving factors for modeling future scenario of pollutions, and provides insights for future global plastic treaty.

2 Material and methods

2.1 Study area.
The in situ experiments occurred in the Wenyu River and the Upper Yellow River. They were expected to reflect the microplastic pollution in a high and low anthropized region, respectively. A total of 164 samples from the Qinghai-Tibet Plateau were collected to validate the relation established by the in situ experiments between microplastic concentrations and mesh sizes.

The Wenyu River is about 47.5 km long, taking its source in south Jundu Mountain and flowing through Beijing to the North Canal River 24. More than 70% of Beijing’s population and 80% of its economic aggregate are in the Wenyu River basin. The wastewater from this part of Beijing is treated and discharged into the Wenyu River. Sewage entering the Wenyu River accounts for 76% of Beijing’s total sewage 25. Considering the inefficient filtration of microplastics by wastewater treatment plants, the outflow is highly loaded with particles, polluting directly the Wenyu River 26.

The Upper Yellow River is about 1694 km, taking its source in Gyaring Lake and Ngoring Lake and flowing out of the Qinghai province in Sigou Gorge 27, 28. Strict protected area management policies fully protect the Upper Yellow River. For instance, the Upper Yellow River basin runs through two of China’s ten national parks. In addition, human activities are low in the Upper Yellow River basin, with population density about 33.6 people/km² in 2020.

The samples from the Chinese part of the Qinghai-Tibet Plateau covered mostly water bodies and regions with diversified human activities (Fig. S 1). It has an area of $2.58 \times 10^6$ km² with an average altitude of 4400 m 29. It is the head source of the Yellow River, the Yangtze River, the Brahmaputra River and the Lancang River, also called the Mekong River. The area of lakes in the Qinghai-Tibet Plateau exceeds $5 \times 10^4$ km² 30. The Qinghai-Tibet Plateau contains regions with a diversity of human activities. Except for some regions like the Upper Yellow River basin, the western and northwestern of Plateau shows low population densities ($\leq 10$ people/km²). Lhasa
and Xining are the two provincial capitals in the Plateau with high population density in their urban area (915 and 3203 people/km², respectively). Their attractiveness is reflected in the passage of 26 and 28 million tourists each year.

2.2 **Sampling and analysis methods.**

The in situ experiments aimed to determine a relation between mesh size and aquatic microplastic concentration. We considered 6 sampling stations in the Upper Yellow River and 5 sampling stations in the Wenyu River (Fig. S 2 and Fig. S 3). In each sampling station, we used five stainless-steel sieves, with mesh sizes of 355, 200, 100, 50 and 20 µm, to collect 5 independent samples of microplastics. Each stainless-steel sieve filtered 20 L of water, which was collected by a bulk sampling approach. For each different sieve, a 2 L stainless steel bottle was filled with surface water (top 0–10 cm) by a 5 m long pole, and a total of 10 buckets of water (20 L) were sampled. Then, we flushed all retained materials into a clean 250 mL blue wide-mouth glass bottle.

To increase the representativeness of in situ experiments, sampling stations were uniformly distributed in the study catchments and were chosen based on the environmental characteristics around the stations. For the Upper Yellow River, the sampling stations covered a lake, a reservoir, a straight river, a branched river, a meandering river and a braided river (Fig. S 2). For the Wenyu River, most sampling stations were on the upstream side of sluice gates of the river (Fig. S 3). The microplastic concentrations on the upstream side of sluice gates were higher than on the downstream side, because the sluice gates opened from the bottom and most microplastics floated on the surface. In situ experiments on the upstream side can get more representative results of highly anthropized regions.

Then microplastic samples were analyzed. In the extraction step, samples were treated with 0.05 M Fe (II) solution and 30% H₂O₂ to degrade organic matter. Then, they were filtered through
a GF/C filter (0.45 µm pore size, 47 mm diameter) using a vacuum system. All filter papers with samples were stored in a glass Petri dish for identification. The sample filters were observed visually under a Stereomicroscope (Chongqing COIC Industrial Co., Ltd. UB100-CV320, Chongqing, China) to identify and count all the plastic-like particles. The polymer types of those particles were confirmed based on a micro-Raman spectroscopy (Wotton-under-Edge, Bristol, Gloucestershire, UK). In addition, utmost precautions were taken to avoid possible sample contamination throughout the whole laboratory process. More details of microplastic detection and quality control are described by Feng, et al. 32.

Moreover, we used aquatic microplastic concentrations from 164 samples collected on the Qinghai-Tibet Plateau in the past 3 years to validate the MCS model. The aforementioned samples were collected by a 20 µm stainless-steel sieve. Associated with each sampling station, two parallel sub-stations 20 m apart in different directions were sampled for quality control, leading to a total of 3 replicates per site. Other sampling steps and the microplastic detection steps are the same as the ones described for the Wenyu and Yellow rivers. Further information regarding the validation of the MCS model can be found in section 2.6.

2.3 The Microplastic Concentration Standardization model step 1: conversions.

The first step of the MCS model (MCS-1) is a converter to transform area-based units to volume-based ones (Fig. S 4). MCS-1 aims to standardize the units of aquatic microplastic concentrations. We first convert all length units to meters, such as the area-based units (items/km² to 10⁶ items/m²). Then, area-based units (items/m²) are converted into volume-based units (items/m³) using the net immersion depths 15-33. The average net immersion depths during trawling are 68.5% of the net mouth height.

2.4 The Microplastic Concentration Standardization model step 2: regression analysis.
The second step of the MCS model (MCS-2) is based on regression analysis to establish a relation between microplastic concentrations measured during the in situ experiments in the Yellow and Wenyu rivers (Fig. 1a-b) and the mesh size used to filter the corresponding sample (Fig. S 4). This statistical analysis led to the MCS equation (Eq.(1)), obtained with the nonlinear fitting method of Origin 2018.

\[ C(S) = MPI * S^{ad} \]  

Where \( C(S) \) is the microplastic concentration (items/m\(^3\)); \( S \) is the sieve mesh size (µm); \( ad \) is the ability of the sampling tool to detect microplastics, \( ad \leq 0 \); \( MPI \) is the microplastic intensity around the sample location, \( MPI \geq 0 \). When \( S \) is equal to the minimum size (1 µm) of microplastics 34, \( C(1) = MPI \), which is equal to the theoretical total concentration of microplastics and can also be called ‘the microplastic intensity’.

In MCS-2, the MCS equation would be used twice. First, it is fitted to obtain the fitting \( MPI \) by the raw microplastic concentration and the sieve mesh size from literature as well as a unique \( ad \). In this study, the unique \( ad \) was set to the average (-0.288) of two in situ experiments and two validations of the MCS model (samples from the Qinghai-Tibet Plateau and parameters of the Conditional Fragmentation microplastic Distribution (CFD) model from ref. 4). Second, the MCS equation is fitted to obtain the standard concentration of aquatic microplastics by the raw microplastic concentration, a standard mesh size (20 µm), the unique \( ad \) and the fitting \( MPI \).

2.5 The Conditional Fragmentation microplastic Distribution model.

The CFD model was established by Wang, et al. 35 to study the relation between microplastic concentration and particle sizes in the soil environment. It was also used to identify potential sources of microplastics in function of their size distribution in the Yangtze River 4. In our study, we use the key equation (Eq.(2)) of the CFD model to validate the physical significance.
of the MCS equation's parameters and the possibility to define a unique value for the coefficient \( ad \) in the MCS equation independently of the type of environment. Eq.(2) describes the size distribution of microplastics as:

\[
F(x) = 1 - e^{-\lambda x^\alpha} \quad (x \geq 0)
\]

where \( F(x) \) is the cumulative percentage of microplastics; \( x \) is the sizes of microplastics (\( \mu m \)); \( \lambda \) is range parameter; \( \alpha \) is fragmentation parameter.

### 2.6 Validation of the Microplastic Concentration Standardization model.

The validation is divided into two parts: (a) the validation of the physical significance of \( MPI \) and \( ad \), and (b) the validation of a unique value for the coefficient \( ad \) using the CFD model and samples from the Qinghai-Tibet Plateau.

Considering its physical significance, \( F(x) \) can also be calculated as the ratio of the concentration of microplastics of size < \( x \) \( \mu m \) to the total concentration of all microplastics (Fig. S 5):

\[
F(x) = \frac{C_x}{C_{tot}}
\]

where \( C_x \) the concentration of microplastics smaller than \( x \) \( \mu m \) in items/m\(^3\); \( C_{tot} \) is the total microplastic concentration in items/m\(^3\). Then, assuming that a sample tool can only catch microplastics larger than its mesh size, we used Eq.(1) to express \( C_x \) and \( C_{tot} \) as a function of \( C(S) \). \( C(S) \) is then considered as the concentration of microplastics larger or equal to \( S \) (Fig. S 5). Thus, \( C_x \) can be expressed as:

\[
C_x = C(S_{min}) - C(S) - \frac{dC(S)}{dS}, S = x
\]

where \( S_{min} \) is the minimum mesh size equal to the minimum size of a microplastic based on its definition, i.e., 1 \( \mu m \) by ref. 34. The differential coefficient of \( C(S) \) can be calculated as:
\[
\frac{dC(S)}{dS} = MPI \times ad \times S^{ad-1} \tag{5}
\]

The maximum value that \( S \) can take is equal to the maximum size of a microplastic based on its definition, i.e., 5000 \( \mu \)m ref. 34. So, the differential coefficient of \( C(5000) \) is supposed to be 0.

Thus, \( C_{tot} \) can be calculated as:

\[
C_{tot} = C(1) - C(5000) \tag{6}
\]

The solution to Eq.(3) can be expressed as Eq.(7) by substituting Eq.(1), (2), (4), (5) and (6). For \( S = x \), considering Eq.(3), we substitute the term on the left with Eq.(2) and the term on the right with Eq.(4) and (5) in the numerator and Eq.(6) in the denominator, we thus obtain:

\[
1 - e^{-\lambda(x)^a} = \left(1 - x^{ad} - ad \times x^{ad-1}\right) / (1 - 5000^{ad}) \tag{7}
\]

Eq.(7) is thus free of \( MPI \) and \( ad \) become the only constant coefficient affected by the parameters of the CFD model. The parameters of the CFD model reflect the size distribution of microplastics, not their concentration. Thus, \( ad \) rather than \( MPI \) was affected by the size distribution of microplastics. Moreover, the sensitivity analysis (Fig. S 6) showed that \( MPI \) could affect both theoretically maximum (mesh size = 1 \( \mu \)m) and detected concentration of microplastics and \( ad \) could affect only detected concentration. Therefore, the physical significance of \( ad \) is the ability of sample tool to detect aquatic microplastics of various size distributions, and the physical significance of \( MPI \) is the microplastic intensity around sample location.

To validate the possibility of relying on a unique value for \( ad \), we obtained \( ad \) from ref. 4 by fitting Eq.(7) and \( ad \) of the Qinghai-Tibet Plateau by fitting the MCS equation. Eq.(7) was fitted by parameters (\( \lambda \) and \( \alpha \)) of the CFD model from ref. 4. The MCS equation (Eq.(1)) was fitted using 164 samples from the Qinghai-Tibet Plateau and a sliding algorithm. The sliding algorithm ensured each fitting of the MCS equation (Eq.(1)) used 30 microplastic concentrations (\( C(S) \)) from
6 consecutive samples ranked by their increasing concentrations. Each consecutive sample shows 5 different microplastic concentrations for different mesh sizes (20, 50, 100, 200 and 355 µm) converted from the raw measurements of each sample. The microplastic concentrations for a particular mesh size, such as 20 µm, can be obtained by summing the concentrations of microplastics larger than 20 µm, i.e., in size ranges of 20-50 µm, 50-100 µm, 100-200 µm, 200-355 µm and larger than 355 µm, sampled on the Qinghai-Tibet Plateau. Thus, we obtained the microplastic concentration for 5 different mesh sizes using:

\[ MP_{i,j} = \sum_{i}^{5} mp_i / V_j * 1000 \]  

where \( MP_{i,j} \) is the microplastic concentration sampled by a mesh size \( i \) in a sample \( j \) (item/m³); \( mp_i \) is the raw microplastic concentration from size \( i \) to size \( i + 1 \) (item/L); \( V_j \) is the water volume of sample \( j \) (L); \( i \) is the mesh size. When \( i = 1 \), the mesh size is 20 µm. As \( i \) increases, mesh size would increase to 50, 100, 200 and 355 µm.

2.7 Standardization of the global dataset.

The global dataset of aquatic microplastic was built in three steps. First, we performed a literature search of aquatic microplastic studies published prior to December 2019, in lake, river and ocean environments. We elected only the studies that provided raw data on microplastic concentrations, leading to a database containing 1051 data from 97 articles. For each measure, we reported the sampling coordinates, the microplastic concentration, the unit, the height of the net mouth and the mesh size of the sampling tool. Second, we added our data from the Qinghai-Tibet Plateau to the database, that contained 1262 measures of microplastic concentrations from 100 previous articles and this current study. Finally, we checked the consistency and the normality of the database using the Shapiro–Wilk normality test. A total of 1091 microplastic concentrations passed the tests.
The microplastic concentrations from the global dataset were standardized and categorized using the MCS model and ArcGIS 10.2. First, the microplastic concentrations were converted from various units to a unique volume-based unit (items/m$^3$) by MCS-1. Then, the microplastic concentrations were adjusted by MCS-2 to convert the data sampled with different mesh sizes into homogenized data based on the lower mesh size of 20 µm considered in this study. Finally, the hot and cold spots of microplastic concentrations were categorized thanks to the tool *Optimized Hot Spot Analysis of ArcGIS 10.2* 36. This tool allowed us to identify the clusters of high (hot spots) and low (cold spots) concentrations according to the sample coordinates and the corresponding standardized microplastic concentrations. When a concentration has been identified as non-significant, it can't form a statistical cluster with other concentrations around, even though the concentration may be extremely high or low at that location.

### 2.8 Regression analysis.

To process the statistical analysis and identify regional driving factors, we used the *Ordinary Least Squares* and *Geographical Weighted Regression* from *ArcGIS 10.2*. The multiple regression used to identify global driving factors of aquatic microplastic concentrations comes from *IBM SPSS Statistics 22*. The coefficient of determination $R^2$ is calculated as:

$$
R^2 = 1 - \frac{\sum_{m=1}^{n}(C(20,m) - \overline{C(20)})^2}{\sum_{m=1}^{n}(C(20,m) - \overline{C(20)})^2}
$$

where $C(20,m)$ is the standardized microplastic concentration (based on 20 µm mesh size) from the sample $m$ (items/m$^3$); $\overline{C(20)}$ is the average of $C(20)$ in all samples; $\overline{C(20,m)}$ is the predicted value of $C(20,m)$ calculated by the geographical weighted regression or the multiple regression.

A total of 9 potential driving factors were utilized in the geographical weighted regression and the multiple regression. These factors included biome types, climate types, HDI, nighttime
lights, population, Gross Domestic Product (GDP), solid waste, plastics waste, and MPW. In addition, mesh size was also used in the geographical weighted regression and in the multiple regression to demonstrate the effect of the MCS model.

In the geographical weighted regression, potential factors, mesh size, and aquatic microplastic concentration were first processed by zero-mean normalization. This is to gain the standardized coefficients ($\gamma_k$) and relative importance ($I_k$) of factors and mesh size. Then, potential factors and mesh size, which showed non-multicollinearity and significant relationships with aquatic microplastic concentration, were collected by the ordinary least squares. In the end, the collected potential factors and mesh size were used in the geographical weighted regression.

The multiple regression used 9 potential factors and mesh size differently from the geographical weighted regression. $I_k$ can be calculated by $\gamma_k$ in results of multiple regression (Eq.(10)). Thus, there is no need to process potential factors by zero-mean normalization in the multiple regression. However, because biome types and climate types aren't continuous data, they were converted to dummy variables before being used by multiple regression. In addition, before applying multiple regression, we checked the multicollinearity among 9 potential factors and mesh size and confirmed that the results of the multiple regression were not affected by the multicollinearity.

$$I_k = \frac{\gamma_k}{\sum_{k=1}^{n} \gamma_k} \quad (10)$$

Where $k$ is the serial number of potential factors and mesh size.

The data source of potential factors can be found in the section ‘Data availability’. Potential factors were extracted by establishing 100 km buffers around sample locations. For some ocean samples, 100 km buffers may not extract the valid value of potential factors. We used the nearest grid, of which the value was valid, to establish 100 km buffers and extract potential factors of those
ocean samples. When extracting the potential factors, we used the mode values for the biome types and climate types, the average value for the HDI, and the summation values for the remaining potential factors. The original data for GDP, solid waste, plastics waste, and MPW were obtained at the national level and were expressed on a per capita basis. To gain potential factors corresponding to every sample, we rasterized them by population density data. More details of the extraction process of potential factors can be seen in Fig. S 7.

3 Results

3.1 The Microplastic Concentration Standardization model.

To standardize existing monitoring data on microplastics, the first step of the MCS model (MCS-1) consists in homogenizing the measurement units (Fig. S 4) from literature studies 15-33 and in situ experiments. The second step of the MCS model (MCS-2) is based on in situ experiments in the Upper Yellow River and the Wenyu River (Fig. S 2 and Fig. S 3). The measures of microplastic concentrations in those two rivers were used to fit the MCS equation in both rivers, respectively ($p < 0.05$, F-test, Fig. 1a-b). The microplastic intensity $MPI$ in the Upper Yellow River (Fig. 1a, $MPI = 1686.16$) is smaller than in the Wenyu River (Fig. 1b, $MPI = 37743.49$), reflecting the difference in the level of anthropization between the two rivers. Interestingly, both $ad$ parameters representing the ability of sampling tools to detect aquatic microplastics are close for the two rivers (-0.319 and -0.348).

To validate the MCS model, we first used the key equation (Eq.2) of the CFD model 35 and validated the physical significance of the MCS equation's parameters (see ‘2.6 Validation of the MCS model’). Second, we obtained $ad$ from ref. 4 by fitting Eq.(7) and parameters of the CFD model. The average $ads$ from ref. 4 are $-0.389 \pm 0.545$ (mean $\pm$ standard deviation) for specific microplastics and $-0.177 \pm 0.238$ for general microplastics (Fig. S 8). Though the results of fitting
Eq. (7) are not very accurate, the average $a_d$s are still close to $a_d$s in the in situ experiments. This may reveal the possibility to consider feasibility of a unique $a_d$, independent of the environment and sampling tool, in the MCS equation. Finally, we fit the MCS equation based on 164 samples from the Qinghai-Tibet Plateau (Fig. S 1). As shown in Fig. 1c, the $a_d$s (with mean $a_d \sim -0.301 \pm 0.078$) are closed to $a_d$s in the in situ experiments. This further reveal that it is coherent to determine a unique $a_d$ in the MCS equation for aquatic microplastic concentrations. However, the other parameter of the MCS equation, $MPI$s, varies from 353.3 to 4047.5 in Fig. 1c and shows a positive correlation with aquatic microplastic concentration for every mesh size.

### 3.2 Spatial variability of microplastic concentrations

We compiled 1262 aquatic microplastic concentrations from 100 literature and 164 samples from the Qinghai-Tibet Plateau, and standardized them by the MCS model. A high spatial variability is observed worldwide (Fig. 2) with average standardized microplastic concentrations of $554.93 \pm 1352.42$ items/m$^3$ in Europe, $2558.90 \pm 4799.62$ in North America and $1741.94 \pm 3225.09$ in Asia. However, standardized concentrations differ less between continental waters and oceans, with $1766.43 \pm 3464.92$ and $1477.02 \pm 9314.50$ items/m$^3$, respectively, with high concentration in the Yangtze River and along the Pacific coast of North America and East Asia. The only open-ocean region where standardized microplastic concentrations are high is the South China Sea. Finally, within a given area, concentrations can vary widely by several orders of magnitude, for example, ranging from 1.76 to 11618.00 items/m$^3$ in middle Yangtze River (30°N, 115°E). A high variability is also detected in north Germany and western America.

The MCS model results in an increase in the average aquatic microplastics concentration of $73.33 \pm 62.77 \%$, and up to $101.27 \pm 49.61 \%$ in oceans, compared to unstandardized aquatic microplastic concentrations. Inland, the average aquatic microplastic concentration is also
increasing by several orders of magnitude: up to 108.74 ± 37.64 % in Europe, 68.94 ± 54.28 in North America and 32.31 ± 37.64 in Asia.

To improve the spatial distribution of aquatic microplastics, we identified the hot and cold spots before and after the standardization process. The samples identified as "hot spots" are considered to be clusters of high standardized concentrations, whereas the samples identified as "cold spots" are considered to be clusters of low standardized concentrations. There is also a difference between standardized concentrations on land and at sea (Fig. 2). 118 significant hot spots ($p < 0.01$, U-test) are located in North America and Canada, and 279 significant cold spots ($p < 0.01$, U-test) in the Qinghai-Tibet Plateau and at sea around continental Europe. The significant cold spots are consistent with the low microplastic concentrations in Qinghai-Tibet Plateau and ocean around continental Europe, most of which are lower than 1000 items/m$^3$. The hot spots are induced by the extreme high microplastic concentrations (42800 - 122400 items/m$^3$) in the Bodega Bay (38°N, 123°W) 37 and the Winyah Bay (32°N, 79°W) 38 and high microplastic concentrations (the Charleston Harbor Estuary 39, > 10000 items/m$^3$) near (< 100 km) the Winyah Bay. The extreme high microplastic concentrations (82800 - 106200 items/m$^3$) are also found in the Sanggou Bay (37°N, 122°E) 40 and the Xisha Island (16°N, 112°E) 41. However, they aren’t identified as hot spots because of the deficiency of high microplastic concentrations (> 10000 items/m$^3$) near them. In addition, the reason why hot spots ($p < 0.1$, U-test) don’t show in the Yangtze River is that extreme high microplastic concentrations (i.e., >30000 items/m$^3$) don’t appear in it, though there are some high microplastic concentrations (>10000 items/m$^3$) in it.

After the standardization, the statistic significance (U-test) of 25 cold spots and 18 hot spots decreases, while 133 cold spots and 1 hot spot turn to non-significant values; there are also 3 non-significant points changing to hot spots. Note that, all changed hot spots occur in oceans and coasts,
and most of the changed cold spots are detected in the eastern Qinghai-Tibet Plateau. This suggests that the standardization tends to relatively increase the concentration in eastern Qinghai-Tibet Plateau and relatively decrease the concentration sampled in coastal and open-ocean zones, comparing to other areas.

3.3 Driving factors of inland microplastic concentrations.

We performed statistical regression tests to identify the best global and regional factors to explain the spatial variability of inland microplastic concentrations (before and after the standardization). This section focuses on driving factors of inland microplastic concentrations because of the high coefficient of determination ($R^2$) of continental water samples (Table. S 1, Table. S 2 and Table. S 3) and the difference of driving factors between continental and ocean waters samples. The 9 factors we considered are biome types, climate types, HDI, nighttime lights, population, GDP, solid waste, plastics waste and MPW. To show the effect of the MCS model, the mesh size was also used in this section. We used geographical weighted regression for the regional factors and multiple regression for the global factors.

Standardization increases the performance of geographical weighted regression and changes the relative importance of the different regional driving factors of inland microplastic concentrations. It decreases the Akaike information criterion (520.07 to 276.57), a lower which indicates that the model is brief and accurate \[42\], and increases the $R^2$ (0.21 to 0.23). Also, it decreases the relative importance of mesh size (14.05 % to non-significant) and increases the relative importance of nighttime lights (28.14 % to 35.96 %) and biome types (18.85 % to 24.93 %). The impacts on the Akaike information criterion, $R^2$, and relative importance from the standardization also varies in Asia, Europe and North America (Table. S 4).
The main regional driving factors with the highest relative importance for microplastic concentrations in continental waters are illustrated in Fig. 3. Among 512 inland samples, 83.79% are driven by nighttime lights, particularly in Asia, Europe and Australia, which is entirely different from the unstandardized data. For the unstandardized data, MPW predominates in 94.92% inland samples and occurs in Europe, Asia and North America (Fig. S9). After the standardization, MPW is only prevalent in North America. Nighttime lights alternatively substitute MPW as the main driving factor in Europe and Asia, with the relative importance being 37.26 ± 0.30% and 39.02 ± 0.54%, respectively.

Standardization also increases the performance of multiple regression and changes the relative importance of the different global driving factors of inland microplastic concentrations (Error! Reference source not found.). The regression performance for continental samples shows a slight increase of $R^2$ after the standardization, especially in equation 2 (0.295 to 0.333). However, the relative importance of mesh size shows a rapid decrease with the standardization, becoming non-significant in equations 1 and 3.

Moreover, the multiple regression reflects that HDI has tremendous potential to become the global driving factor of microplastic concentrations in continental waters. Among 7 human anthropogenic factors and 2 environmental factors used in the multiple regression analysis, only 2 anthropogenic factors (i.e., HDI and MPW) and 2 environmental factors (i.e., climate zones and ecology zones) show significant relationships with standardized microplastic concentrations in continental waters. Although the environmental factors show significant relationships and their relative importance is 25.31 ± 14.37%, they are not directly connected to microplastic pollution. The environmental factors may indirectly affect microplastic concentrations by regulating the degradation process of plastics and the transport process of microplastics. Still, they can't directly
change plastic and microplastic emissions, which is crucial to identify global driving factors. Thus, the relationship between environmental factors and standardized microplastic concentrations can't prove that environmental factors have the potential to become global driving factors. As for the two anthropogenic factors, the relative importance of HDI is over 75 %, and MPW is less than 50 %. Therefore, the HDI has tremendous potential to become the global driving factor of standardized aquatic microplastics.

4 Discussion

With assistance of the MCS model, global aquatic microplastic concentrations were mapped by standardizing various units caused by sample tools and filling the large gap caused by mesh sizes. The MCS model unifies area-based and volume-based units, and makes it possible to compare aquatic microplastic concentrations sampled by different tools. After the standardization, global aquatic microplastic concentrations are highly increased (73.33 ± 62.77 %, all samples). With the standardization, the mesh sizes are no longer determinant to explain the spatial variability of microplastic concentration, showing that our MCS model is efficient. The relative importance of mesh sizes decreases from 14.05 % to non-significant in geographical weighted regression and from 24.56 ± 6.85 % to non-significant for multiple regressions, based on continental water samples.

According to the standardized microplastic distribution (Fig. 2), excessive microplastic contaminations (microplastic concentration > 10^4 items/m^3) occur on land rather than in oceans. The excessive contaminations are mainly located in the Yangtze River 43-44, the Charleston Harbor Estuary 39, the Bodega Bay 37 and the Winyah Bay 38. Considering the deficiency of microplastic regulation and treatment 45, excessive contaminations will continuously exist on land. Then, microplastics of those excessive contaminations may release excessive contamination of
additives, constitutive oligomers and monomers 46 that could present a long-term hazard to ecosystems. Aquatic animals would ingest more microplastics on land, especially above regions, than in oceans 47. More ingested microplastics would cause more damage to the digestive system of aquatic animals and enter the inland food web 48. Microplastics of those excessive contaminations would also serve as overmuch substrates for microbial community, eventually altering microbial community structure and nitrogen cycling processes 49 at a faster clip on land.

The excessive contaminations on land, especially in the above regions, are supposed to be an essential issue for microplastic parts of future research and the global plastic treaty 50. Future research's primary precondition of the global plastic treaty should be clarifying the main processes that microplastics enter the terrestrial ecosystem in the above regions. In the clarification, the life cycle and simulation of microplastics will play a critical role 46. Once found, the main processes, such as wastewater treatment, will define the orientation of microplastic monitoring, regulation and treatment 21-51. Moreover, it is necessary to propel research on microplastic toxicology in the above regions 45-52. Microplastic toxicology can obtain specific indicators and further make details of microplastic monitoring, regulation and treatment.

The global driving factors of inland standardized aquatic microplastic concentrations we have explored suggests that it is inaccurate to consider a single human activity factor as the main factor. HDI has the tremendous potential to become the global driving factor of continental water samples, but R^2 of multiple regression is still low (less than 0.35) using HDI. The low R^2 suggests that it is inaccurate to simulate aquatic microplastics by a single widely accepted driving factor, even by the factor showing the highest relative importance. The inaccuracy from those human activity factors is also reported by Weiss, et al. 13 and Mai, et al. 12. However, those factors are already used in previous studies and play a critical role in their conclusions. For instance, Guerrini,
et al. 53 used MPW as the main factor in establishing the model for assessing the role of microplastics as vectors of plastic-related organic pollutants. Peng, et al. 54 also used MPW as the main factor in the simulation of plastic and microplastic release caused by COVID-19, and concluded that 12.3 thousand tons of pandemic associated microplastics entered the global ocean.

A possible solution for diminishing the inaccuracy of a single human activity factor is that the simulation temporarily uses distributed factors until a correct driving factor is found. According to the distribution of regional main driving factors (Fig. 3), the simulation is recommended to use MPW, which is rasterized by population density, in North America and nighttime lights in the other continents. Nevertheless, a correct driving factor remains to be studied, even simulations using distributed factors may show an accepted performance (e.g., a high R²). The correct driving factor is supposed to fulfill at least two criteria: (1) being accurate in simulation and (2) physically relating to microplastics. Therefore, future studies are recommended to answer the question of how widely accepted driving factors can fulfill the above two criteria. For MPW, verifying MPW by monitoring data in continents except North America may be a possible way to fulfill the first criteria. It has fulfilled the second criteria due to its definition, the amount of plastics entering environments. For the other human activity factors, parts of which have fulfilled the first criteria, the physical relationship between them and microplastics is still unclear. For instance, HDI was calculated by 4 indicators 55 that don't show an apparent physical relationship with microplastics. The high relative importance of HDI may suggest an indirect physical relationship between HDI and microplastics. Only by clarifying the indirect relationship can we figure out the question whether HDI can fulfill the second criteria.

In addition, there are still many unanswered questions about the MCS model. Monitoring data of aquatic microplastics are unstandardized because of not only sample tools and mesh sizes
but also sample volumes, sample numbers and sample depth \textsuperscript{16-19}. The influence mechanism of the above inducements differs even for different aquatic microplastic shapes. For example, as sample volumes increase, fibers caught by sample tools would flush through the tools and further induce underestimate of aquatic microplastic concentration\textsuperscript{56}. On the contrary, aquatic microplastics of other shapes cannot flush through the tools, and the concentration of those microplastics would be stable as sample volumes increase. Therefore, to develop a full picture of aquatic microplastics, additional studies that clarify the relationship between unstandardized monitoring data and inducements are needed.

5 Conclusions

Insufficient and unstandardized monitoring data makes it challenging to clarify the spatial distribution of microplastics in aquatic systems worldwide. This study formulated an MCS model to standardize monitoring data of microplastics. Based on these standardized monitoring data, we reassessed the spatial distribution of aquatic microplastic concentrations worldwide and identified their driving factors. The spatial distribution and new driving factors provide a critical foundation for modeling future scenarios of microplastic pollution and offer new insights for future global plastic treaty.

Our main findings include the following: 1) After the standardization, the global aquatic microplastic concentrations were increased by $73.33 \pm 62.77\%$ and the mesh sizes are no longer determinant to explain the spatial variability of microplastic concentrations. This indicates that the MCS model is efficient in standardizing monitoring data. 2) Excessive microplastic contaminations (microplastic concentration $> 10^4$ items/m$^3$) occur on land rather than in oceans. They are mainly located in the Yangtze River, the Charleston Harbor Estuary, the Bodega Bay, and the Winyah Bay. 3) On a global scale, the Human Development Index showed a high
correlation of 75.86 % with standardized microplastic concentrations. On regional scales, the main
driving factors of standardized microplastic concentrations were different in continents, such as
the nighttime lights with a correlation of 37.26 ± 0.30 % in Europe and 39.02 ± 0.54 % in Asia,
and the MPW with a correlation of 61.21 ± 19.86 % in North America.

Data availability

The authors declare that the main data supporting the findings of this study are available
within the article and its Supplementary Information. The biome data was obtained from terrestrial
climate types were obtained from the Köppen-Geiger Global 1-km climate classification maps on
the GloH2O (http://www.gloh2o.org). The human activity index was obtained from Human
The nighttime lights were obtained from Annual VNL V2 on the Earth Observation Group
(https://eogdata.mines.edu). The population density and GDP per capita were available on
WorldPop (https://hub.worldpop.org) and Department of Economic and Social Affairs, United
Nations(https://unstats.un.org), respectively. Solid waste per capita, proportion of municipal solid
waste composed of plastics and proportion of waste which is inadequately managed was obtained
from published data from ref.57.

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Visualization: Yuxuan Xue, Jiajie Kang, Yanlong Guan
Supervision: Hongwei Lu
Writing—original draft: Yuxuan Xue, Yanlong Guan
Writing—review & editing: Yuxuan Xue, Yanlong Guan, Lisa Weiss, Hongwei Lu

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Ryan, P. G. *et al.* Sampling microfibres at the sea surface: The effects of mesh size, sample...


**Figure caption**

Fig. 1 the MCS equation fitted by (a) in situ experiments in the Upper Yellow River, (b) in situ experiments in the Wenyu River, (c) 164 samples from the Qinghai-Tibet Plateau.
Fig. 2 concentrations, hot spots and cold spots of standardized aquatic microplastic.
Fig. 3 main driving factors of standardized aquatic microplastic concentration.
Table 1: Significant ($p < 0.001$, F-test) results of multiple regression of aquatic microplastic concentration, 9 potential factors, and the mesh size. This table only shows results that were significant both before and after standardization.

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<th>Before or after standardization (20 µm)</th>
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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: