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Geographical features and management strategies for microplastic loads in freshwater lakes

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In recent years, microplastic contamination in freshwater lakes has become a significant environmental concern. Despite this, there remains a lack of comprehensive understanding of the distribution patterns and regional characteristics of microplastic loads in global lacustrine environments under a unified standard. To address this gap, our study utilizes Machine Learning (the random forest algorithm), combined with number-to-mass transformation techniques to generate a global prediction. The results indicate an average microplastic concentration of 0.57 items/m^3 in lakes and reservoirs worldwide, with an accumulated microplastic load of 10167 tons within top 20 m of water—equivalent to 508 million plastic bottles. The primary sources of microplastics are linked to agricultural land use and the proportion of urban areas within watersheds. Notably, the highest microplastic loads are observed in North America, Africa, and Asia, though the contributing factors vary, including concentration-dependent and area-dependent influences, as well as differences in shape composition. These findings provide valuable insights that can guide the development of targeted policies to effectively mitigate microplastic pollution in freshwater ecosystems.

Microplastics have demonstrated a ubiquitous presence across the globe, from remote polar regions[1,2], to the summit of Mount Everest at 8440 meters[3] and the depths of the Mariana Trench[4]. Currently, lakes and reservoirs are increasingly threatened by microplastic pollution. Although lakes and reservoirs account for only 0.4% of global freshwater resources, they serve as critical sources of freshwater for drinking, agriculture and the maintenance of diverse ecosystems. Microplastics in these water bodies can transfer through the food chain, threatening food safety and human health. Additionally, harmful chemicals[5,6] and microorganisms (e.g., bacteria and viruses) that adhere to microplastics pose significant risks to human health[7–9].

It is estimated that approximately 31.9 million tons of mismanaged plastic waste are released into the environment annually[10]. However, the majority of research efforts have focused on understanding microplastic pollution in marine environments. For instance, a 2021 report by the United Nations Environment Programme (UNEP) estimated that 75 to 199 million metric tons of plastic waste have accumulated in the world's oceans, with microplastics making up 85% of the total weight of marine debris[11]. In contrast, the mass loading of microplastics in lakes and reservoirs remains poorly understood. Given that freshwater lakes and reservoirs are in closer proximity to human habitats, understanding the loads and distribution of microplastics in these systems is crucial for assessing their potential health risks[12]. Furthermore, analyzing microplastic loading patterns can provide valuable insights into global plastic waste trends, which are essential for scientific research, policy-making, and evaluating the effectiveness of remediation efforts.

The geographical distribution of microplastics in lakes is influenced by a combination of sources, transport drivers, and ambient environmental conditions[13]. Evidence suggests that microplastic concentrations in water bodies are closely linked to the land use types, social-economic development in surrounding areas, and specific weather conditions within their catchments. In reality, these factors interact in complex and integrated ways, making it challenging to isolate their individual effects. Identifying the key determinants is therefore a prerequisite for understanding microplastic distribution patterns.

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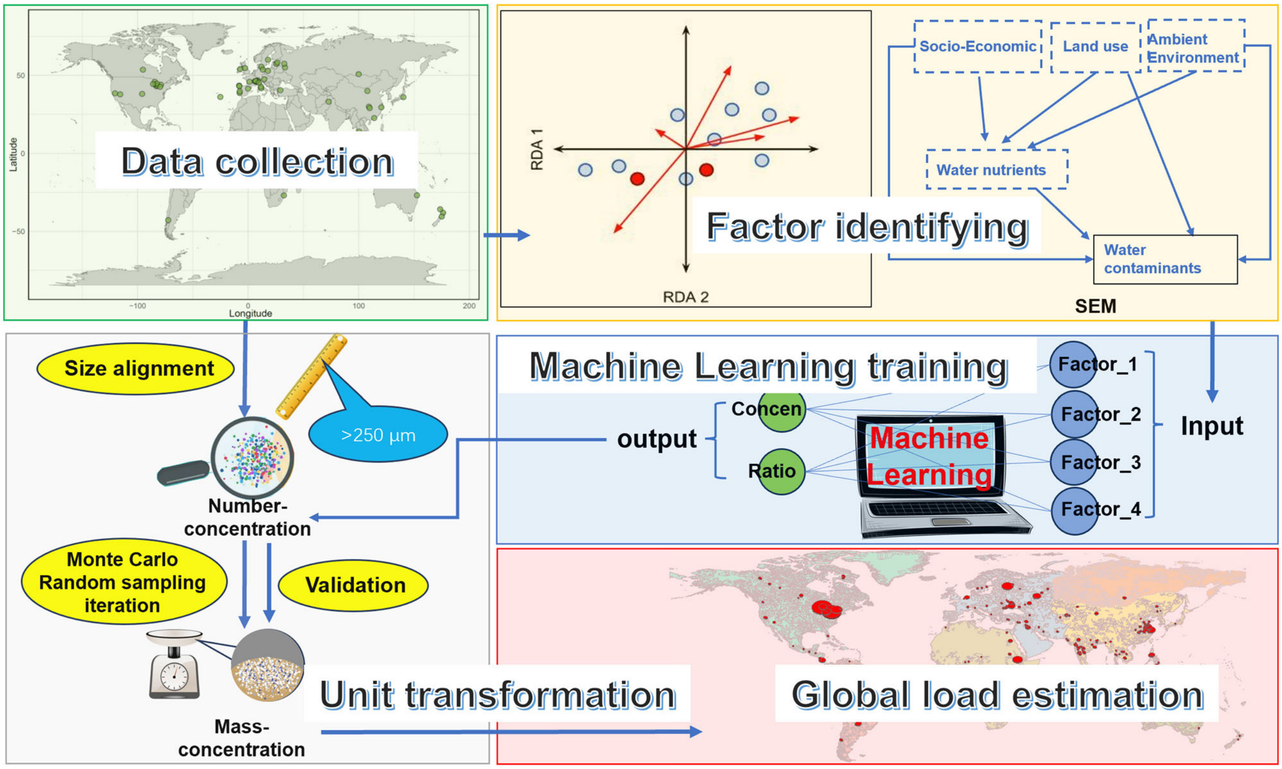

Fig. 1 | Research framework of global estimation of microplastic loads in lakes/reservoirs.

Microplastic concentration levels in some well-known lakes, such as the Laurentian[14], Victoria[15], Baikal[16] and Taihu[17], have been reported to range from 0.25 to 2.46 items/m^3. However, microplastics continuously fragment in the environment, meaning that particle counts alone cannot be considered a conserved or reliable metric. In contrast, mass concentration is unaffected by physicochemical processes such as fragmentation, making it a more robust measure for quantifying environmental microplastic loads. Determining mass concentrations allow for direct comparisons of influencing factors and the development of targeted strategies to address microplastic pollution.

Koelmans, et al.[18,19] developed a method to convert microplastic number concentrations to mass concentrations based on particle size, shape, and density distributions. However, this approach may underestimate mass if an average particle size (e.g., 20 µm ellipsoid with a density of 1 g/cm^3) is used[19]. Actually, the total weight of microplastics is often dominated by a smaller number of large-sized particles. Models have proven effective in estimating microplastic mass in river networks and predicting their environmental fate[20,21]. However, many models require detailed hydrological data or long-term monitoring, limiting their applicability on a global scale. Therefore, developing accurate unit transformation methods and predictive models using retrievable data is critical for estimating global microplastic mass loads.

In this study, we collected existing lake and reservoir data within aligned size ranges to first identify the major factors influencing microplastic distribution. Using a Machine Learning model, we then predicted microplastic number concentrations in lakes and reservoirs worldwide based on factor datasets to each water body. After converting number concentrations to mass concentrations, we estimated the microplastic mass loads in global freshwater lake system. The framework of this study is illustrated in Fig. 1. The key scientific questions addressed are: (1) what are the microplastic mass loads in global freshwater lakes and reservoirs? (2) where are the hotspot areas for microplastic storage? and (3) what are the corresponding control strategies to mitigate this pollution?

Results

Main factors influencing microplastic concentrations in lakes/reservoirs

To determine the main factors influencing the microplastic concentrations in lakes/reservoirs, data on lake parameters and microplastic concentrations (with size standardized, as described in Methods section under "How to make size alignment?") were collected from 74 lakes. The dataset was analyzed using redundancy analysis (RDA, Fig. 2a) and a structural equation model (SEM, Fig. 2b) to assess the direct and indirect effects of 12 variables, including human activities, land cover types, and lake morphometric characteristics, on microplastic concentration.

The RDA results, based on the nominal variable positions, revealed two distinct categories of lakes with high plastic concentrations. The first category includes lakes influenced by both cropland and urban land cover, which are characterized by fibrous microplastics (Fig. 2a). The second category comprises lakes affected by population density and lake depth, which are associated with fragmented microplastics (Fig. 2a). Notably, cropland, urban land cover, and population density showed the strongest correlations with microplastic concentrations (Fig. 2a).

The SEM results further supported these findings (Fig. 2b). Cropland exhibited a strong, positive, and direct effect on microplastic concentrations (path coefficient $\beta = 0.43$, $p < 0.01$, no mediation). Population density emerged as the second most significant factor, directly influencing microplastic abundance ($\beta = 0.40$, $p < 0.01$). Urban land cover, while significantly correlated with population density, had an indirect effect on microplastic distribution, contributing less ($\beta = 0.24$, indirect impact) compared to cropland ($\beta = 0.43$, direct impact). Among all factors, vegetation coverage ranked third, showing a negative and indirect effect on microplastic abundance ($\beta = -0.30$, $p < 0.01$). This suggests that higher vegetation coverage in the basin reduces the input of microplastics from the terrestrial sources into lakes.

Interestingly, lake depth ($\beta = 0.21$, $p < 0.01$) and lake area ($\beta = -0.17$, $p < 0.05$) had direct but contrasting roles, making it challenging to predict microplastic concentrations based solely on physical lake parameters. Additionally, wastewater treatment plants (WWTPs) had a direct and

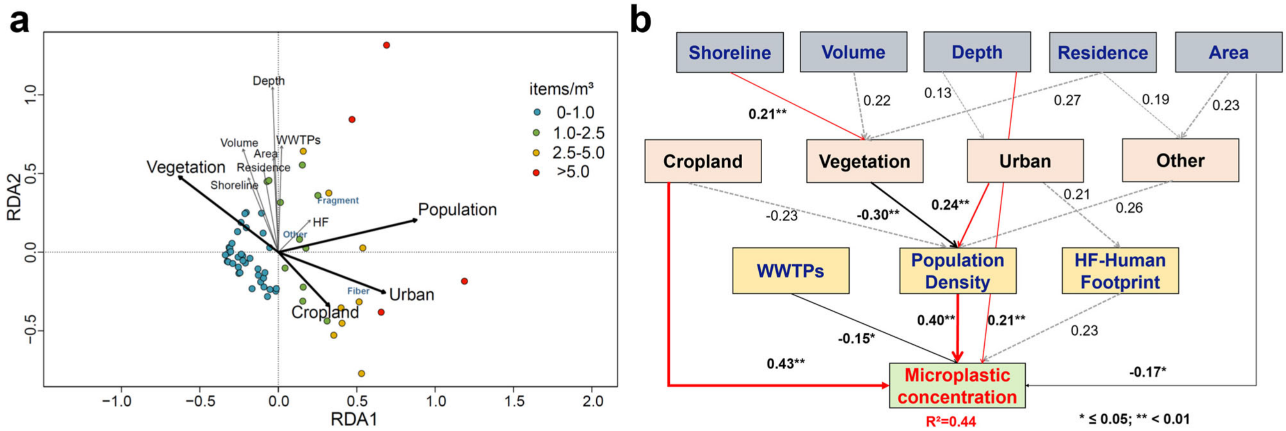

Fig. 2 | Identification of primary factors influencing the microplastic concentrations in lakes and reservoirs. **a** RDA among microplastic concentrations in lakes/reservoirs worldwide, microplastic features and environmental and anthropogenic drivers. **b** SEM modeled direct and indirect effects of 12 variables on microplastic concentrations. The numbers next to the arrows indicate the effect size (path coefficients, β) of the relationship. Solid red arrows represent positive paths ($p < 0.05$), solid black arrows represent negative paths ($p < 0.05$), and dotted grey arrows represent non-significant paths ($p > 0.05$). The width of arrows is proportional to the strength of path coefficients. R^2 indicates the proportion of the explained variance.

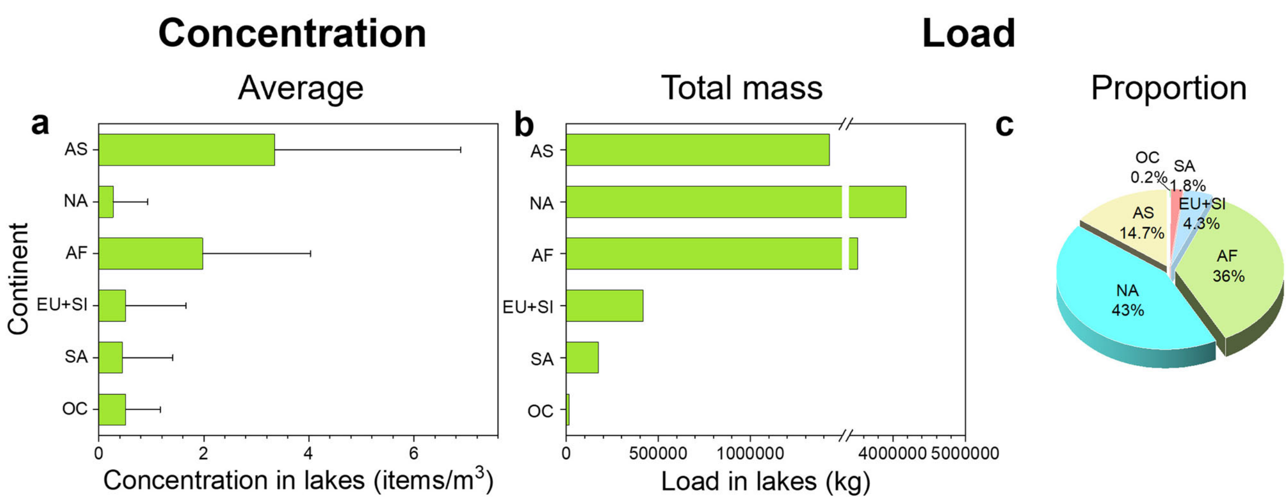

Fig. 3 | The continent-specific statistics of Machine Learning-predicted microplastic data in lakes. The predicted microplastic concentrations (**a**), loads (**b**), and load proportion (**c**) in lakes for each continent. The abbreviations in the plots: AS Asia, NA North America, EU Europe, SI Siberia, AF Africa, SA South America, OC Oceania.

negative effect on microplastic loading (β = −0.15, $p < 0.05$, Fig. 2b), as they remove significant amounts of microplastics, thereby reducing their concentrations[22]. In summary, the primary factors influencing microplastic concentrations in lakes and reservoirs include cropland, population density, vegetation coverage, urban land use proportions, WWTPs, and lake depth.

Microplastic pollution levels in global lakes

Using a Machine Learning approach (random forest), microplastic concentrations in lakes were predicted based on input parameters. The global distribution of microplastic pollution, divided by continents, is illustrated in Fig. 3 (excluding Antarctic). Figure 3a shows that lakes in Asia (3.4 ± 3.5 items/m^3) and African (2 ± 2.1 items/m^3, Table S1 in Supplementary Information) exhibit the highest microplastic concentrations, while North America has the lowest average concentration.

Supplementary Fig. S1 displays the global distribution of microplastic concentrations in lakes. Hotspots of microplastic contamination in freshwater environments are identified in East China, India, Indonesia, the Philippines, Ukraine, Nicaragua and Ethiopia. These lakes are predominantly located between the equator and 60°N latitude. As latitude increases, microplastic concentrations in lakes tend to decrease. For example, remote lakes in the Canadian Arctic and Russian Siberia show relatively low microplastic levels, averaging only about 0.2 items/m^3. These findings align with the distribution patterns summarized by Yang et al.[23], validating the accuracy of our prediction method.

Microplastic mass burden in global lakes

In contrast to concentration levels, North America has the highest total microplastic mass load in its lakes, exceeding 4000 tons (Table 1 and Fig. 3b). Africa ranks second, with a microplastic load of approximately 3500 tons (Table 1 and Fig. 3b), closely approaching that of North America. Despite being the largest producer of plastics, Asia contributes only 1429 tons of microplastic load (~15% of the global total), significantly less than North America and Africa (Fig. 3c), Europe and Russian Siberia account for just 416 tons, representing 4.3% of the global share (Table 1 and Fig. 3c). South America and Oceania have the lowest microplastic loads, at 175 and 15 tons, respectively (Table 1 and Fig. 3c).

The total microplastic load in freshwater lakes and reservoirs on the planet is estimated at 10167 tons (Table 1). Using a standard plastic bottle (500 mL volume, 20 g weight) as a reference, this equates to approximately 508 million plastic bottles stored in lakes and reservoirs worldwide.

Table 1 | Microplastic loads in lakes/reservoirs categorized by continents

Continent	Lakes/ Reservoirs number	Load (kg)			Prediction range		Mass range		Weiss's method	Chen's method
		Lakes	Reservoirs	Sum	Upper limit	Lower limit	High	Low		
AS	24632	1429254	85438	1514692	7030576	99657	2224192	300600	590698	422871
NA	227686	4184510	29738	4214249	19558303	277234	6190229	832973	1643199	1174317
AF	5152	3516639	113621	3630260	16850175	238847	5332522	717364	1415478	1011467
EU + SI	93999	416134	142475	558609	2527458	35826	820158	111048	217861	156076
SA	17147	175115	59163	234278	1087423	15414	344043	46449	91360	65376
OC	5181	14928	302	15229	70688	1002	22351	3043	5941	4265
Total	373797	9736580	430737	10167317	47124624	667979	14933497	2011477	3964536	2834373
Measured by tons		9737	431	10167	47125	668	14933	2011	3965	2834

AS Asia, *NA* North America, *AF* Africa, *EU* Europe, *SI* Siberia, *SA* South America, *OC* Oceania.

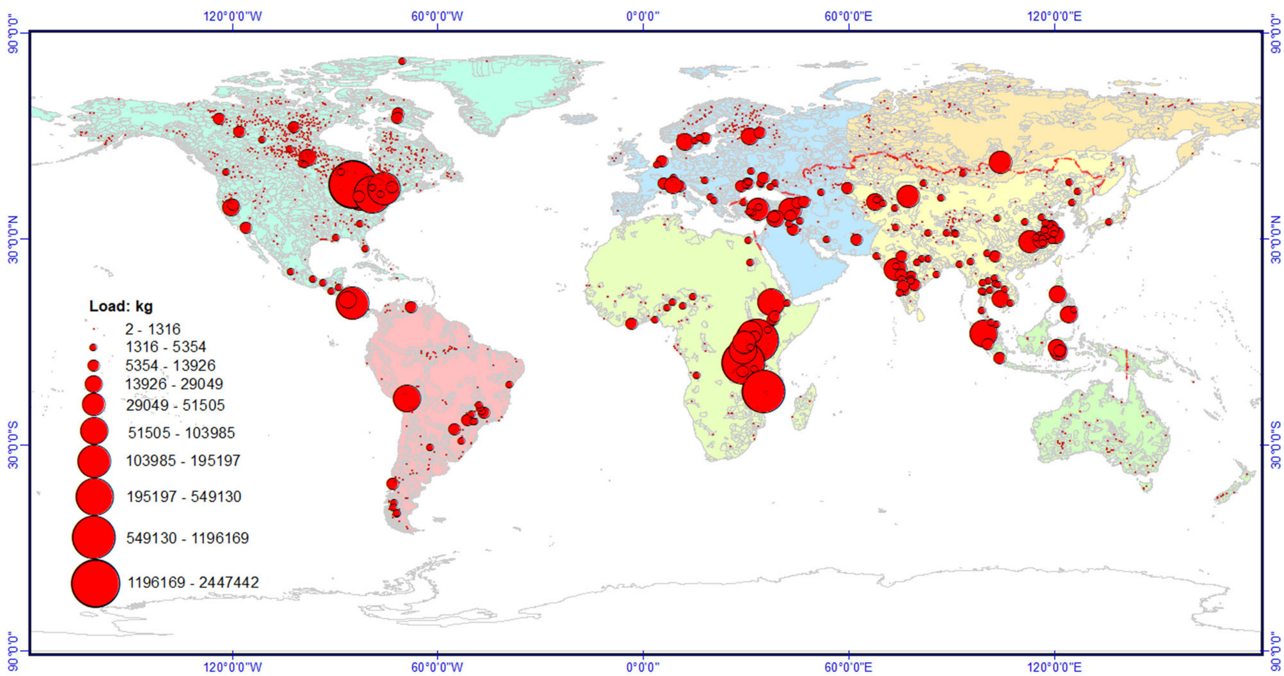

Fig. 4 | The predicted microplastic loads in lakes worldwide (lake area>100 km^2). The red dotted lines are boundary lines of continents in the present study.

Lakes with high priority and their microplastic load patterns

There are notable differences in microplastic number concentrations and mass burdens across continents. The distribution of microplastic loads in lakes is illustrated in Fig. 4, with higher loads observed in the Laurentian Great Lakes, African Great Lakes, East China, India, Southeast Asia, Central America, and the Black Sea region. Microplastic mass loads in lakes exhibit regional clustering, with higher loads typically associated with the following characteristics: large lake areas, high microplastic concentrations, and a high ratio of non-fiber to fiber (nf/f) particles. This ratio significantly influences the lake's load, as non-fiber particles are considerably heavier than fibers[24–26]. Supplementary Fig. S2 reveals that lakes with higher proportions of non-fiber microplastics are predominantly located in the world's major industrial and agricultural zones. To further explore these distribution patterns, we selected hotspot regions across various continents and analyzed the relationships between microplastic loads and the aforementioned indices.

The Laurentian Great Lakes are highlighted as a region with a particularly high microplastic burden (Fig. 4). In North America, the microplastic load in these large lakes appears to be primarily area-dependent and shape-dependent (Fig. 5). For instance, Lake Superior, which has the largest surface area (81,844 km^2), exhibits a microplastic load of 5199 kg (Fig. 5b and Supplementary Table S2). Non-fiber microplastics are generally predominant in large lakes (nf/f ratio> 1, Fig. 5a). Lake Michigan, with a moderate concentration of 4.6 items/m^3 (Fig. 5b and Supplementary Table S2), but a high nf/f ratio of approximately 4, as reported by Mason, et al.[27] displays a substantial microplastic mass load of 122,372 kg (Fig. 5a, b). However, in smaller lakes with surface areas under 150 km^2 (indicated by the blue dash line in Fig. 5b), the microplastic load shifts to a concentration-dependent pattern.

A similar trend is observed in the African Great Lakes of the Rift Valley (Supplementary Fig. S3). The vast surface areas of these lakes make them ideal sinks for microplastic storage. Higher concentrations also contribute to increased loads. For example, with a concentration of 4.7 items/m^3, the microplastic load in Lake Malawi reaches 57,605 kg (Supplementary Fig. S3b and Table S2), slightly lower than that of Lake Victoria (59,808 kg, Supplementary Table S2).

Figure 4 highlights that China and India are heavily affected by microplastic contamination. In Central and East China, a series of large freshwater lakes are distributed along the Yangtze River. The microplastic

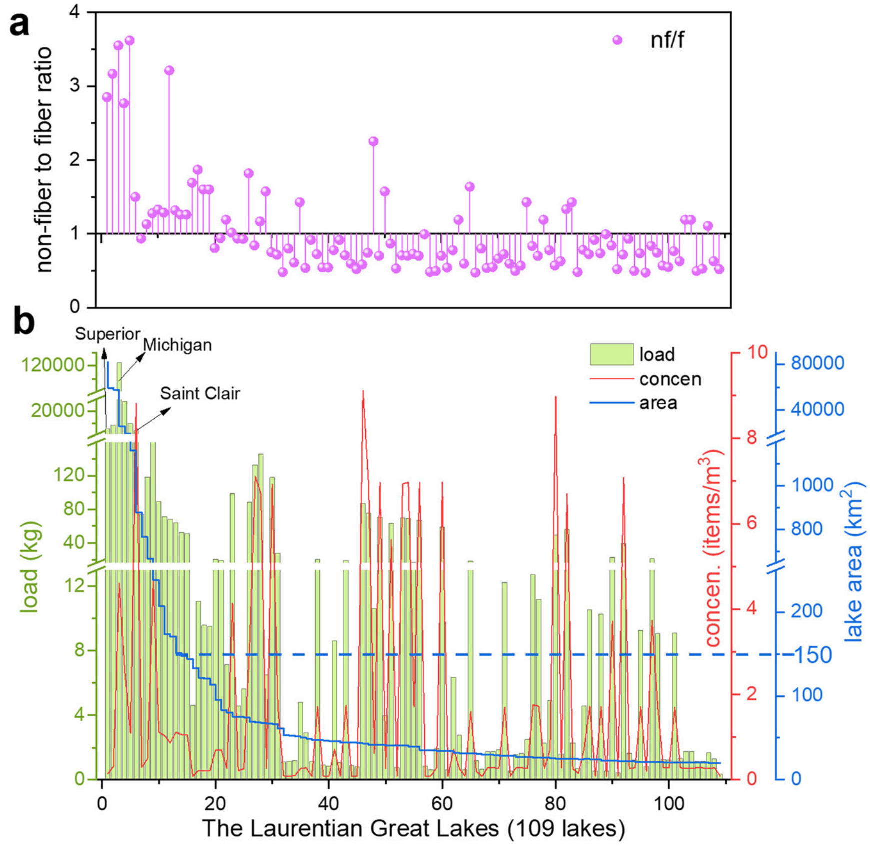

Fig. 5 | Multivariate analysis of microplastic load determinants in lakes of the Laurentian Great Lakes region. The relationships between microplastic loads (adjusted by depth) and non-fiber to fiber ratios (nf/f) (**a**), microplastic concentrations and lake areas (**b**). The horizontal axis represents lake number in a descending order of lake areas. Loads, concentrations and lake areas are plotted as green bars, red dog-leg lines, and blue stepped lines, respectively.

loads in these shallow lakes are influenced by both area and concentration (Supplementary Fig. S4). For instance, Dongting Lake (2579 km^2), Poyang Lake (2398 km^2), and Taihu Lake (2329 km^2) exhibit both large surface areas and high concentrations (8.8 items/m^3, 3.7 items/m^3, and 9.3 items/m^3, respectively), resulting in significant microplastic loads (Supplementary Table S2). In contrast, in India and Southeast Asia, microplastic loads in lakes are primarily concentration-dependent (Supplementary Figs. S5 and S6).

The area-dependent pattern and high proportions of non-fiber microplastics are also evident in Lake Baikal and large lakes in Northern Europe (Supplementary Fig. S7). Similarly, lakes in Central America align well with the area-dependent pattern (Supplementary Fig. S8). Another heavy loaded region is located near the Black Sea, where microplastic loads in lakes are concentration-dependent (Supplementary Fig. S9).

Microplastic load patterns in reservoirs

Based on our estimates, reservoirs generally exhibit higher microplastic concentrations compared to lakes (Fig. 3, Supplementary Fig. S10 and Table S1). In the present study, Supplementary Figs. S10a and S11 show that Asia has higher microplastic concentrations in reservoirs than other continents. However, the highest total microplastic mass loads in reservoirs are found in Eastern Europe and Siberia (~140 tons, Supplementary Fig. S10b), followed by Eastern Africa, Brazil, India and China (Supplementary Fig. S12). North America has the lowest microplastic mass load in reservoirs (~30 tons, Supplementary Fig. S10b). Additionally, higher nf/f ratios are observed in reservoir regions with dense populations or extensive irrigated agricultural activities (Supplementary Fig. S13).

In most cases, microplastic loads in reservoirs within hotspot regions are concentration-dependent. For example, in Eastern Europe, higher microplastic concentrations in Ukrainian reservoirs, such as the Kakhovka Reservoir (~6 items/m^3), contribute to high microplastic loads (Supplementary Fig. S14 and Table S3). In contrast, reservoirs in Russian Siberia, which have very low microplastic concentrations, exhibit an area-dependent pattern of load (Supplementary Fig. S14). For instance, the Kuybyshev Reservoir, due to its large area, has a microplastic load exceeding 5000 kg (Supplementary Fig. S14b).

A similar pattern is observed in Africa, where the Nasser Reservoir (famous for the Aswan Dam) has a relatively low concentration but a high microplastic load due to its large size (Supplementary Fig. S15). In Brazil, the Itaipu Reservoir and adjacent reservoirs also follow this trend (Supplementary Fig. S16).

In India, reservoirs are characterized by the highest average microplastic concentrations (6.9 items/m^3), resulting in significant greater microplastic loads compared to reservoirs of similar size in other regions (Supplementary Fig. S17 and Table S3). In China, microplastic loads in reservoirs are influenced by both concentration and area. For example, the Three Gorges Reservoir (853 km^2) has a microplastic load of 320 kg, with a concentration of 0.82 items/m^3 (Supplementary Fig. S18 and Table S3).

Discussion

The role of cropland in microplastic abundance within lakes has often been overlooked in previous studies. However, as indicated by the highest path coefficient in the SEM (Fig. 2b), cropland emerges as a critical factor influencing microplastic distribution in lakes and reservoirs. This finding is well-founded, as cropland soils are recognized as significant sinks for microplastics, primarily due to the release of plastics from agricultural practices such as plastic mulching, irrigation, sewage sludge application, and fertilizer use[28]. Simultaneously, croplands also act as emission sources, transporting microplastics into lakes and rivers through artificial drainage systems, runoff, soil erosion, and wind dispersal[29]. For instance, mulching films, can undergo mechanical fragmentation or microbial degradation, breaking down into microplastics that are subsequently carried away by runoff[30].

Globally, Supplementary Fig. S1 demonstrates a linkage between agricultural land and microplastic pollution. The main agricultural land worldwide are also coincident with regions with notably high microplastic concentrations in lakes. Consistent with this, Li, et al.[31] reported higher contributions of agricultural land in relation to microplastic pollution in Asia. Regarding a specific lake, large plastic consumption combined with densely inhabited rural areas generally leads to the high microplastic concentrations in lakes[32]. For example, Dongting Lake in Central China, as surrounded by farmland and usage of plastic-containing fertilizers[33], has a measured microplastic concentration of 8.6 items/m^3 [34]. Notably, in Africa, Lake Tana, which lies entirely within an agricultural catchment, exhibits significantly higher concentration (8.3 items/m^3, Supplementary Fig. S1 and Table S2).

Moreover, intense agricultural activities can also produce microplastics. In Europe, the application of sewage sludge introduces microplastics into the environment, which can then be released into water bodies via agricultural drainage systems[35,36]. Farmland along Ain River in France has been closely linked to polyester concentrations[37]. In central agricultural regions of United States and Canada, certain lakes (e.g., Devils Lake, 0.9 items/m^3; Quill Lake, 0.8 items/m^3; Beaverhill Lake, 1.7 items/m^3) are predicted to have higher microplastic concentrations than those in non-agricultural areas (Northern Canada, usually < 0.2 items/m^3, Supplementary Fig. S1). This is largely attributed to the use of wastewater for irrigation and the application of biosolids to agricultural fields[38]. All these evidences indicate that microplastic pollution is closely linked to local agricultural practices.

Our results also highlight the role of vegetation in trapping microplastics and reducing their transport. Similar findings have been reported by Yuan et al.[29] and Wang, et al.[39], suggesting that increasing vegetation coverage in upstream areas could be an effective strategy to mitigate plastic pollution in freshwater lakes.

With respect to lake parameters, their contribution to microplastic distribution is relatively minor compared to surrounding environments such as cropland, urban areas, and vegetation, as indicated by the path coefficients in Fig. 2b. However, lake parameters suggest that small and deep lakes are more prone to accumulating microplastics, while large and shallow lakes tend to have stronger water exchange, which dilutes microplastic concentrations[22].

WWTPs are highly effective in mitigating microplastic pollution by removing over 90% of microplastics from influent water[22]. However, it is important to note that WWTPs sludge, which often contains high concentrations of microplastics, is frequently repurposed as agricultural fertilizer[40]. This practice inadvertently facilitates the transfer of microplastics from WWTPs to lakes through agricultural runoff. Despite this challenge, the findings of this study emphasize the overall positive impact of WWTPs in reducing microplastic contamination in lakes, particularly when evaluated from a broad watershed perspective. For instance, the extensive network of WWTPs along the coast of the Laurentian Great Lakes[41] has contributed to relatively lower microplastic concentration levels (1.7 tems/m^3, Supplementary Table S2) in this region.

In East China, high production and usage of plastics are the primary drivers of elevated microplastic concentrations in freshwaters[42]. China accounted for 32% of global plastic production in 2023[43] and has become the largest plastic producer and consumer over the past decade, which has likely fueled the rapid generation of microplastics. The predicted microplastic concentrations in lakes across East China range from 1.1 to 13.8 items/m^3 (Supplementary Table S2), which align with the high concentrations measured in Taihu Lake (2.5 items/m^3)[17] and Dongting Lake (8.6 items/m^3)[34]. In India, a highly dense population, massive plastic waste generation, and unrestricted sewage discharge contribute to significant microplastic pollution[44]. Additionally, frequent flood events during rainy seasons effectively transport microplastics into freshwater lakes[45,46]. In Southeast Asian countries such as Indonesia and the Philippines, high levels of mismanaged plastic waste are the main causes of microplastic pollution[47]. For example, the microplastic concentration in the Surabaya River on Java Island, Indonesia, reaches as high as 1.5 to 43 items/m^3 [48], which is consistent with the predicted concentrations for Danau Ranau Lake (8.5 items/m^3, Supplementary Table S2) and Danau Singkarak (9.0 items/m^3, Supplementary Table S2).

In Ukraine, large areas of diffuse agricultural non-point source pollution, combined with limited wastewater treatment systems, result in high microplastic levels in lakes[49,50]. Similarly, in Africa, low recycling efficiency and poor plastic waste management contribute to high microplastic concentrations[51]. For example, Nyaga et al.[52] highlighted the widespread presence of extremely high microplastic concentrations in rivers across Nigeria, which matches the high-concentration scenarios predicted for lakes such as Lagos Lagoon (6.4 items/m^3, Supplementary Fig. S1).

When considering mass load, North America, characterized by numerous large and interconnected lakes, benefits from stronger water flow, which dilutes microplastic concentrations. However, the sheer number of lakes in North America counteracts this advantage, leading to high overall microplastic loads. Indeed, statistical analysis reveals that the total microplastic load in a continent's lakes is often dominated by a few giant lakes. For instance, the Laurentian Great Lakes alone account for approximately 83% of the microplastic load in North America (Table 1 and Supplementary Table S2). Consequently, regional priorities for microplastic pollution control can begin with addressing these major lakes.

In other regions, Strokal et al.[53] noted that Asia and Africa are the regions most affected by mismanaged plastic waste. While Asia faces severe microplastic pollution, it has relative few giant freshwater lakes compared to other regions[23]. The widespread distribution of highly polluted lakes across Asia underscores the urgent need for global pollution control efforts. In contrast, high microplastic loads in Africa are concentrated in the African Great Lakes region, mirroring the situation in North America. This regional concentration provides a focal point for targeted mitigation strategies.

In general, the large areas of lakes in Laurentian Great Lakes and African Great Lakes regions lead to higher microplastic loads. In contrast, the high microplastic burdens in lakes in China, India, and Southeast Asia are primarily due to heavy pollution levels, driven by large-scale plastic production, usage, and poor management. In African countries, Ukraine and some European nations—regions known for extensive agricultural activity but insufficient wastewater treatment and waste management—higher microplastic mass loads are observed[54,55]. Additionally, tourism contributes to relatively high microplastic concentrations (~6 items/m^3, Supplementary Fig. S8 and Table S2) and mass loads in Lake Nicaragua and Lake Managua (Supplementary Fig. S8b). Therefore, regulating agricultural activities and tourism is essential to control plastic pollution.

Reservoirs, as critical man-made structures for drinking water supply[56], are highly susceptible to becoming sinks for microplastics, posing significant risks to aquatic organisms and humans[13]. When surrounding human activity intensity is similar, the nf/f ratio serves as an important indicator of microplastic loads in reservoirs. Large reservoirs in Africa, as well as most reservoirs in Brazil, China, and India, are characterized by higher proportions of non-fiber particles (nf/f ratio> 1, Supplementary Fig. S13), indicating multiple sources of microplastic input.

Reservoirs often have different operational cycles compared to natural lakes, which can lead to discrepancies in microplastic accumulation (Supplementary Text S1 and Fig. S19). On one hand, reservoirs are characterized with higher microplastic concentrations than lakes (Supplementary Table S1), likely due to longer residence times and reduced water flowability[57]. On the other hand, reservoirs primarily function as irrigation water storage, making them more susceptible to microplastics contamination from agricultural activities. That is likely the reason for the high microplastic loads observed in reservoirs around the Black Sea (Supplementary Fig. S12). Despite this variability, the storage of microplastics in reservoir serves as an indicator of local aquatic characteristics and the impact of urban and agricultural activities.

Compared to rivers, the water in lakes and reservoirs is relatively calmer, providing favorable conditions for the deposition of microplastics. Under the influence of gravity and biofouling, microplastics settle, making lakebed sediments a significant sink for microplastics[58]. The accumulation of microplastics in sediments can impact the nutrient dynamics and habitats of lakes, as well as release adsorbed harmful substances such as persistent organic pollutants, pharmaceuticals, and heavy metals. Additionally, microplastics in lake water are easily ingested by aquatic organisms, including plankton, benthic organisms, and fish, leading to a range of biotoxic effects such as intestinal blockages, oxidative stress, and cellular damage[59]. In lake/reservoir environments, physical and chemical conditions such as hydrology, light, and oxygen levels, as well as the activities of aquatic organisms and sediment-dwelling microorganisms, all play a role in the degradation of microplastics[60].

Since lakes and reservoirs often serve as sources of drinking water, it is crucial to mitigate microplastic pollution in these water bodies. Drinking water and consuming aquatic products are the primary pathways through which microplastics in water enter the human body. The ingestion of microplastics can lead to respiratory and intestinal diseases, as well as cellular damage. Additionally, the release of additives and adsorbed pollutants from microplastics can cause allergies, reproductive and immune toxicity, and in severe cases, even cancer[61]. Although the trophic levels of organisms in freshwater lakes are not particularly high, the widespread ingestion of microplastics by aquatic organisms can still result in trophic transfer, leading to biomagnification within food webs and posing risks to human health[62].

Although the estimation of mass loads involves gaps and uncertainties, decision-making and consensus-building can be guided by the precautionary principle. This approach enables the development of more effective strategies to control freshwater microplastic pollution. Key measures include reducing pollution at its source, establishing regular monitoring and quantification of pollution loads, and implementing context-specific integrated management policies (see below).

1. To control pollution at its source, it is essential to promote the adoption of more sustainable agricultural practices, reduce the use of plastic mulching films and sewage sludge fertilizers, and strengthen plastic recycling initiatives at the national level. To prevent the transport of microplastics, establishing vegetative buffer zones between farmland/urban areas and lakes can significantly reduce microplastic release.
2. Region-specific measures are essential. In the Laurentian Great Lakes of North America, focus on agricultural and urban microplastic control. In African Great Lakes, improve wastewater treatment infrastructure. In major plastic-producing countries like China and India, reduce factory emissions, promote biodegradable materials, enhance recycling, and raise public awareness. In tourist areas, enforce strict environmental policies and implement waste sorting and recycling.
3. Effective reservoir management requires controlling pollution sources by establishing a watershed pollution inventory and targeting primary plastic inputs. Regular water quality monitoring and sediment cleaning, especially for microplastic removal at the bottom, are essential. Public involvement in cleanup activities and promoting proper waste recycling and disposal should also be encouraged.
4. To minimize the health risks posed by microplastics in lake water, it is essential to adopt more advanced water purification technologies. On a societal level, efforts should be made to reduce the consumption of plastic products, raise public awareness of environmental protection, and enhance the recycling and reuse of waste plastics.

Methods

Data collection

We collected investigation data on microplastics in typical freshwater lakes/reservoirs around the world (74 lakes/reservoirs in total). To maintain unified conditions and serve the Machine Learning prediction, only manta trawl sampling investigations were selected. This data includes microplastic concentrations, morphological compositions (e.g., fiber, fragment and other shape proportions) of the lakes/reservoirs. Additionally, we collected 12 parameters from three aspects for these 74 lakes/reservoirs (as shown in the Supplementary Data). The hydro-morphometric parameters of the lakes/reservoirs include lake depth, area, volume, shoreline length and residence time of water. The composition of land use types in lake basins includes vegetation, cropland, urban and other land. The anthropological parameters in the lake basins include population density, the number of WWTPs discharging into the lake/reservoir and human footprint.

How to make size alignment?

The manta trawl method has been used as a standard method to investigate the microplastics in open waters or lacustrine environments[63,64]. Manta trawl sampling was usually conducted with trawl nets of 100–333 μm[14,64–67]. Due to the fact that the weight of small-sized microplastics is far less than that of larger ones, the missing small microplastics (smaller than mesh size) was neglected. Thus, we aligned the microplastic sizes to 250–5000 μm to create a unified context for microplastic size ranges from different studies. The size range is consistent with the sizes from Nava, et al.[64].

In specific, the different sizes can be converted to a default range of 250–5000 μm using the method proposed by Koelmans et al.[18]. Firstly, the concentration unit items/km^2 sampled by manta trawl is usually converted to items/m^3 with a descriptive or experimental immersion depth for the trawl net. Secondly, a correction factor (*CF*) is introduced to establish a relationship between the measured size range and the default size range. The equation is shown below. Lastly, the final microplastic concentrations are restricted to items/m^3 in size of 250–5000 μm.

$$CF = \frac{\int_{x_{1D}}^{x_{2D}} bx^{-a}}{\int_{x_{1M}}^{x_{2M}} bx^{-a}} = \frac{x_{2D}^{1-a} - x_{1D}^{1-a}}{x_{2M}^{1-a} - x_{1M}^{1-a}} \tag{1}$$

Here, D and M denote default and measured ranges, the x_{2D} and x_{1D} correspond to the default sizes 5000 μm and 250 μm, and the x_{2M} and x_{1M} correspond to the measured sizes. The "a" and "b" are derived from the relationship between relative microplastic abundance and size, of which "a" can be assigned with an empirical value of 1.6[18].

How to screen the main influencing parameters?

In order to identify the main influencing parameters affecting the microplastic concentrations in lakes/reservoirs, RDA and SEM were combined for analysis. RDA is a method based on multiple linear regression and clustering analysis to reveal the correlation between explanatory variables and dependent variables. Here, RDA was performed and imaged using R (v.4.3.1). The input parameters included hydro-morphometric variables (i.e., lake depth, area, volume, shoreline length, and residence time of water), land cover type variables (i.e., vegetation land, cropland, urban, and other land), human activity variables (i.e., population density, WWTPs, and human footprint), microplastic concentrations, and morphological proportions (i.e., fiber and non-fiber). The results are displayed in Fig. 2a. The RDA double-sequence diagram differentiates microplastic concentrations using the color of the dots. The explanatory variable is represented as a vector (black arrow), with the bolded portion highlighting the key influencing factor. The small blue letters in the figure denote the nominal target variables, indicating the main morphological characteristics of the microplastics.

SEM is also a useful tool for clarifying the relationships between parameters and microplastics. Its introduction can be found in Supplementary Text S2. Compared with RDA, SEM can not only clarify the relationships between observed and latent variables, but also show the significance. In the present case, the SEM model was run by the software AMOS 24.0 (IBM SPSS). The examined key variables include lake hydromorphometric variables, land cover type variables, human activity variables and plastic concentrations. The specific explanation of variables, SEM fitness parameters and descriptions are exhibited in Supplementary Text S2.

Machine learning and algorithms

Machine Learning was applied to train the model for predicting the microplastic concentrations in freshwater lakes and reservoirs. Machine

Learning is a "black box" model that integrates multiple algorithms. Under a certain algorithm, Machine Learning model can be trained and in turn makes predictions on dependent variables (e.g. concentrations) by inputting some independent parameters (e.g. influencing parameters) (Supplementary Text S3). In the present case, many algorithms were compared and picked (Supplementary Text S3). Then, the random forest algorithm was invoked, and the whole codes were accomplished using R-language software (v.4.3.1). The main parameters (x1-population density, x2-vegetation proportion, x3-cropland proportion, x4-urban proportion, x5-WWTPs, x6-depth) and the measured microplastic concentration for each lake/reservoir (the 74 lakes/reservoirs) were set as input variables. All the input data were converted to logarithmic values to conduct the random forest prediction. The model training process used 80% of the input data for training and the remaining 20% of data for testing. After cross-validation, we compared the measured data with the predicted data, and the results of the linear fitting were satisfactory ($r^2 = 0.56$), which was very close to the 1:1 diagonal as showed in Supplementary Fig. S20.

As the mass of non-fiber microplastic particle is remarkably heavier than fiber particle (with same size), the non-fiber's proportion probably strongly affects the mass concentration. Thus, fiber and non-fiber was separated as two main shapes in the present study. The fiber ratios (%, η_{fiber}) can be predicted with random forest algorithm ($r^2 = 0.51$) as well. The non-fiber proportions (%, $\eta_{non\text{-}fiber}$) were obtained by 100 subtracting η_{fiber}.

When predicting the microplastic concentrations or shape composition features in unknown lakes/reservoirs (do not have measured values) around the world, the above trained models were directly invoked.

How to make number to mass conversion?

The number concentrations of microplastics (C_{pred}) and fiber proportions (η_{fiber}) were predicted using the above Machine Learning model (code provided in Supplementary Text S3, and results in Table S4). The non-fiber proportions ($\eta_{non\text{-}fiber}$) were then derived (Supplementary Table S4). Regarding the fiber, the fiber sizes (lengths) from the 74 lakes/reservoirs were counted and repeated sampling by 1000000 times using Monte Carlo random sampling iteration via MATLAB (v.R2021a) instruction codes. The mean value of fiber sizes was calculated as 1619 μm. We adopted a weighted average mass of single fiber-shaped particle from the research of Chen et al.[25]. They demonstrated the fiber mass (M_{fiber}) is 1.65×10^{-6} g with a length range of 500–5000 μm. Likewise, the non-fiber sizes could as well be re-sampled (iteration) with mean value calculated as 779 μm. However, the non-fiber microplastic particles comprise of multiple morphologies, of which fragment and pellet are closest related to the particle weight[25,68]. Based on the proportions in literatures[68], we assumed the fragment accounts for 0.6 of the non-fiber mass weight, and pellet contributes the rest 0.4. With the weighed mass obtained by Chen et al.[25] (fragment 221 μg and pellet 1143 μg), the average mass of non-fiber particles was computed as 590×10^{-6} g using the equation below.

$$M_{non-fiber} = 221\mu g \times 0.6 + 1143\mu g \times 0.4 = 590\mu g = 590 \times 10^{-6} g \quad (2)$$

Combined with the η_{fiber} and $\eta_{non\text{-}fiber}$, the average mass of single microplastic particle (M_{av}) could be deduced (Supplementary Text S3). Because of the different η_{fiber} and $\eta_{non\text{-}fiber}$ for different lakes/reservoirs, M_{av} was not the same. Last, the mass concentration (C_m) was calculated as C_{pred} multiplying corresponding M_{av}.

$$\text{Load} = \begin{cases} C_m * d_{real} * S(depth<20m) \\ C_m * d_{20m} * S(depth \geq 20m) \end{cases} \quad (3)$$

The microplastic load in each lake/reservoir surface could be calculated as the product of C_m and V_s (Eq. 3). Where, the C_m of freshwater lakes/reservoirs were expressed as g/m^3. The surface volume (V_s) of each lake/reservoir was obtained by multiplying the depth and surface area (S). We took the surface 20-meter (d_{20m}) depth of the lakes/reservoirs as microplastics could be thoroughly mixed. If the total depth of a lake or reservoir was less than 20 meters, the real depth (d_{real}) was selected. The specific parameters are summarized in Supplementary Table S5. The mass-based load ranges are displayed in Table 1.

How to estimate global load of microplastics in freshwater lakes/reservoirs?

To make global estimation of microplastic load in freshwater lakes/reservoirs, parameters in basin, i.e. population density, vegetation land, cropland and urban proportions, WWTPs discharging into the lake and lake depth should be categorized and summarized. First, the coordinate, geographic and hydromorphometric information (such as lake area, volume, shoreline length, depth and water residence time) of global lakes and reservoirs were acquired from HydroLAKES datasets (https://www.hydrosheds.org/products/hydrolakes), from which we extracted those with area above 0.5 km^2. Also, we excluded the salt lakes (Supplementary Text S4). The total number of lakes/reservoirs is 373797. Next, the lake/reservoir basin boundary database in all continents (i.e., Asia, North America, Europe, Siberia, South America, Africa and Oceania), retrieved from HydroBASINS datasets (https://www.hydrosheds.org/products/hydrobasins), was imported in ArcMap software (v.10.8.1). The lakes or reservoirs were integrated into their corresponding basin. Then, the land use proportions in each lake basin were obtained by clipping the global land use classification map (100 m resolution) from Copernicus Global Land Service (https://lcviewer.vito.be/2019). The population data were obtained from LandScan Global Population Data (https://landscan.ornl.gov/) and computed for different lake basins. Finally, the WWTPs data for the lakes were acquired from HydroWASTE datasets (https://www.hydrosheds.org/products/hydrowaste).

The data collected above were input into the trained machine learning model, the C_{pred}, C_m, and the microplastic load in each lake/reservoir could be predicted and deduced. Therefore, the estimation method for microplastic loads in lakes/reservoirs of different continents is simplified by lakes/reservoirs statistical analyses (sum of area and depth). The global profile of lake/reservoir microplastic loads was then clarified in the present study.

Uncertainties

After comparing various algorithms, we ultimately selected the random forest method to predict global microplastic concentrations in lakes/reservoirs (Please see Supplementary Text S3). The linear relationship between the prediction values from random forest model and measured concentrations is derived in Supplementary Fig. S20. The fitting degree ($r^2 = 0.56$) represents the model error and the root mean square error is 0.36, which depends on the data structure applied in the random forest algorithm and the model settings. The prediction concentrations are first projected to the measured concentrations (C_{meas}) on the regression line (red line in Supplementary Fig. S20). The upper and lower prediction bounds are subsequently representative of model uncertainties. Microplastic load ranges are then computed and displayed in Table 1. In a global context, the microplastic load in freshwater lakes/reservoirs fluctuates from 668 to 47,125 tons. In addition, we calculated the microplastic loads in lakes/reservoirs based on the mass conversion scenarios provided by Weiss et al.[26]. and Chen et al.[25] (Supplementary Text S3). As shown in Table 1, the total computed loads are 3965 and 2834 tons, respectively. These values are lower than the load obtained from the present study, but within the range of model error.

The mass of non-fiber microplastics ($M_{non\text{-}fiber}$) could vary depending on the proportions of fragments and size distributions, leading to significant differences in average mass estimates across studies[23,25,68,69]. In the present study, a mass range was considered to calculate both high and low load scenarios. In the high-load scenario, pellets could account for up to 70% of non-fiber particles, as reported in previous studies[23,68]. Under this assumption, the maximum $M_{non\text{-}fiber}$ was calculated as 867 μg ($221\ \mu g \times 0.3 + 1143\ \mu g \times 0.7$). In the low-load scenario, fragments could represent 100% of the non-fiber category, with the size fraction of 250–500 μm accounting for 70% (and 500–5000 μm for 30%). This results in an average particle size of 779 μm (as described above). Consequently, the minimum $M_{non\text{-}fiber}$ was estimated to be 116 μg (71 μg × 0.7 + 221 μg × 0.3). For fibers, a universal value of 1.65 μg was adopted, as no significant mass differences were observed among fibers. Consequently, the variations resulting from mass conversion can be calculated and are presented in Table 1.

We use the surface to 20 m as the lake depth to calculate the microplastic loads in the present study. Although the microplastics can reach deeper waters, in most cases, the concentration of microplastics descends dramatically with water depth[70,71], 20 m can represent most loads of microplastics in lake, but cause underestimation for the deep freshwater lakes/reservoirs. The data input for WWTPs in random forest estimation model is from HydroWASTE datasets, which is limited in some remote areas. This further weakens the prediction accuracy.

Data availability

No datasets were generated or analysed during the current study.

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Author contributions

X.W. conceived and directed the project. H.D. and R.Z. contributed equally to this article, H.D. performed the prediction work and wrote the manuscript, Z.R. analyzed the results and reviewed the manuscript. L.X. contributed discussion and methodologic directions. L.C. and J.Z. conducted the RDA and SEM analyses. X.N. analyzed the data from the databases. Y.Z., P.G. and Q.Y. reviewed the manuscript. All authors discussed the results and contributed to manuscript writing and editing.

Competing interests

The authors declare no competing interests.

Additional information

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