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Prediction of Microplastic Emissions in River Basins Based on Mathematical Models

Qiuyi Qian[1*], Jinsong Huang[2†], Xikai Wang[3†], Haotian Yan[4]

[1]*School of Civil and Architectural Engineering, Beijing University of Technology, Beijing, China*
[2]*College of Resources and Environment, Northwest Agriculture and Forestry University, Xianyang, China*
[3]*Beijing Haidian Kaiwen Academy, Beijing, China*
[4]*College of Science, Xi'an Jiaotong-Liverpool University, Suzhou, China*
**Corresponding Author. Email: 3226378578@qq.com*
[†]*These authors contributed equally to this work and should be considered as co-second author.*

Abstract. Microplastics have become a globally concerning persistent pollutant in aquatic environments, with rivers acting as critical pathways for their transport from land to oceans. This study developed a mathematical model to predict microplastic emissions in the Guangzhou section of the Pearl River Basin—a typical urban river area in the Pearl River Delta. The model integrated "multivariate linear regression" and "stepwise regression". The annual average microplastic abundance (item/L) served as the dependent variable. The updated model was used to predict the 2025 annual average microplastic abundance in the study area, yielding a value of 2730.64 item/L. This study provides a cost-effective, reliable tool for predicting riverine microplastic emissions and offers scientific support for microplastic pollution prevention and control in the Pearl River Basin and similar urban river systems.

Keywords: Microplastics, Pearl River Basin, Mathematical Model, Multivariate Linear Regression, Stepwise Regression, Emission Prediction

1. Introduction

Microplastics, defined as plastic particles less than 5 millimeters in diameter, have become as a widespread and persistent pollutant in aquatic environments [1]. Originally introduced in a 2004 study to describe the accumulation of these microscopic plastics in marine environment, the term now refers to a wide range of plastic fragments, fibers, films, and pellets from both intentionally manufactured plastics and fragments from larger plastic items [2]. These two origins are known as primary and secondary microplastics respectively. More recently, frameworks, such as the one mentioned in a 2019 study, offers more refined definition and criteria in defining microplastics by considering factors such as chemical composition, solid state, solubility, size, shape and structure, color, and origin [3]. These particles can be traced to have originated from a wide variety of products including personal care products, textiles, industrial and commercial applications, tire wear, and many other origins. Rivers, which serve as a major media for transporting microplastics between land-based sources and the oceans, are undoubtedly recognized as critical pathways for microplastics moving into marine ecosystems as identified by the authors of a 2017 study [4]. However, with those findings indicating river being the

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major transporter of microplastics, the dynamics of microplastic behavior in river systems; in other words, the dynamic emissions of microplastics in rivers, remain understudied.

When talking about where the microplastics in river originate, it is known that they generally come from both point sources, such as wastewater treatment plants and non-point sources, such as surface runoff, disposal, and atmospheric deposition [5]. Wastewater treatment plants, although having an efficient removal rate and being able to successfully remove a considerable amount of microplastics through processes such as filtrations and other sedimentation processes, still are suspected to be a significant contributor of microplastics to the nearby environment, leaving significant outcomes [6].

Due to their small sizes and persistent existence in the environment, microplastics are easy to be ingested by aquatic organisms, accumulate in the food web, and potentially reach humans through different food chains. Current studies suggest that microplastics may be related to possible health effects such as oxidative stress, inflammation, and exposure to toxic additives [7]. The widespread distribution and potential ecological and human health implications have made microplastics an emerging, urgent pollutant that raise global concerns recent years.

In response to the growing amount of microplastic pollution, various international and national measures have been introduced. Many countries, including China, have banned microbeads in personal care products. China's 5-year Plan to Control Plastic Pollution outlines bans and reductions in single-use plastics, aiming to take control of both primary and secondary microplastic inputs [8]. However, while such regulatory policies aim to take effective control on sources, assessing whether they effectively reduce microplastic emissions remains a challenge.

Direct monitoring in river ecosystems could be costly and difficult to implement, which was often limited to scattering datasets in some non-consecutive months, making it hard to trace trends of microplastic emissions over time. Field sampling of microplastics is time-consuming, expensive, and often constrained by weather and labor resources. In this case, Mathematical modeling offers a cost-effective way by allowing researchers to integrate diverse datasets, such as hydrology, population density, seasonality, and infrastructure, to estimate emissions across different times and scenarios [9,10].

Mathematical models can simulate conditions that are hard to record in actual practices, such as long-term seasonal trends or extreme weathers, and can be updated as soon as new data become available. These features make mathematical modeling especially useful when predicting future microplastic pollution trends.

Several environmental and infrastructural factors influence the amount of microplastic emissions from the rivers to downstream waters. First, seasonality plays an important role in influencing microplastic concentration in water downstream. For example, a 2020 study mentioned the Qing River in Beijing, which receives effluent from four wastewater treatment plants and multiple small dams. Sampling in both July (wet season) and November (dry season) indicated higher concentrations of microplastics in November than in July, possibly due to the dilution caused by rainfall in July [11]. Second, tidal variability also has influence on microplastic emissions. A 2023 study investigated the eight major outlets of the Pearl River Estuary using full-tidal-cycle sampling at each outlet. While the dataset did not provide precisely monthly or seasonal time series, its high spatial resolution enabled authors to estimate an annual export of around 304 trillion particles to the South China Sea [12]. By investigating tidal variation, the study offers valuable references for modeling large-scale microplastic transport under real-world circumstances.

These examples show that river flow patterns, seasonality, tidal fluctuations, and infrastructure all play significant and indispensable role in controlling microplastic emissions. These factors could also be beneficial when integrated into the mathematical model.

Despite the scarcity of long-term, high-frequency data for microplastics in riverine systems, most studies are either limited to short-term sampling or focused on few seasonal snapshots. This gap in data collection hinders the ability to assess regulatory effectiveness or predict emission trends.

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This study aims to address this issue by developing a mathematical model to predict riverine microplastic emissions, using available seasonal datasets. Referencing from both the Qing River and Pearl River Estuary studies, the model will integrate environmental and infrastructural factors to produce more reliable estimations of future microplastic emissions to help with future policymaking.

2. Theoretical basis and model framework

2.1. The multivariate linear regression model

The foundation of our predictive framework is the multivariate linear regression model. This model serves as the core "calculation engine," designed to capture the relationship between a single outcome and multiple influencing factors. In the context of our study, the outcome, or dependent variable (y), is the annual microplastic abundance. The factors, or independent variables (x_1, x_2, ..., x_k), are the socioeconomic and environmental indicators we have identified, such as GDP and population density. The model postulates a linear relationship, expressed by the equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \tag{1}$$

Here, β_0 is the intercept, representing the baseline value of y when all independent variables are zero. Each coefficient (β_i) quantifies the effect of its corresponding variable (x_i) on y, while ε is the random error term. This model is particularly suitable for our research because the link between many microplastic sources and their emission levels is often direct and can be approximated linearly. For example, as regional economic activity increases, so too might the generation of plastic waste, leading to a proportional rise in microplastic pollution. The model excels at translating such real-world relationships into a clear, predictable formula.

2.2. The stepwise regression method

The stepwise regression method can be understood as adding a "filter" to our model, helping us to select the most important variables from a large number of candidates. Its core function is to identify the independent variables that have the greatest impact on the predicted outcome through repeated testing. As we all know, if too many irrelevant or redundant independent variables are included in a model, it is prone to the problem of "overfitting," which means the model performs well on the training data but its predictive ability for new data decreases. To avoid this situation, stepwise regression can help us remove unimportant variables, ensuring the accuracy and stability of the model.

In other words, stepwise regression is a process of selecting the most appropriate combination of independent variables one by one through a sequence of statistical tests. At the beginning, we may have many candidate variables. Stepwise regression tests the contribution of each candidate variable to the accuracy of the model one by one. If the certain independent variable does not bring about an improvement in the model accuracy, it will be deleted; otherwise, it will be reserved. It’s like finding out the best variables from many candidates for predicting the microplastic emission, making the model more concise.

The advantage of stepwise regression is that it ensures every independent variable included in the model is an important variable that has been selected by the screening process. In this way, we can avoid making the model become too complex, and focus more on the factors that have an impact on the microplastic emission. By this way, the model becomes more accurate and has a stronger ability to predict. So that the model does not fall into the “overfitting” but can reflect the true situation of microplastic emission.

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2.3. Integrated framework and model evaluation

In addition, integrated framework integrates multiple linear regression and stepwise regression. Multiple linear regression gives us a predictive framework. Stepwise regression can make the framework become more concise. Therefore, we can find out the clear pattern from the messy data and establish an efficient model.

In order to validate the efficiency of integrated framework, we also select some important statistical indicators to validate the model. First, the determination coefficient is R^2. The determination coefficient is an important indicator to validate the goodness of fit of the model. The determination coefficient shows the proportion of the variation of dependent variables which is explained by the independent variables. The closer to 1, the stronger explanatory power of independent variables to the dependent variable. For example, the closer to 1, the stronger predictive ability of model is, and the model can reflect the variation of data very well. Furthermore, we also use F-test to validate the model. The purpose of F-test is to test the significance of regression coefficients, that is, test whether all regression coefficients are significantly different from zero. If the p-value < 0.05, it means that the model is significant and the model can reflect a true relationship. In addition, we also do residual analysis to validate the model. If the residual is randomly distributed, it means that the model can capture the data pattern and there is no bias and no important variable is omitted.

Finally, we calculated relative error, that compares the model obtained values directly with the values (i.e. was calculated for practical application). It is the relative error of the model is less than 30%, the model is applicable. The relative error of our model was 13%, so, it corresponds to the above condition and the model is applicable.

3. Study area and data processing

This study focuses on the Guangzhou section of the Pearl River Basin. The Guangzhou section of the Pearl River Basin is roughly located between 22°26′N - 23°56′N and 112°57′E - 114°03′E. It is situated in the core area of the northern part of the Pearl River Delta and is an important transitional section where the three rivers converge and flow into the estuary network area. It connects the inland and the ocean, playing a pivotal role in the ecological and hydrological system of the Pearl River. Its hydrology and ecology are influenced by the characteristics of the basin and urban development, making it a typical area for microplastic pollution research [13].

Based on this, we chose to construct a mathematical model to assist in predicting the content of microplastics in water bodies. We use multiple linear regression combined with stepwise regression to construct it: first, unify the calculation units of all the data; next, fit the data based on the multiple linear regression framework to explore the linear relationship between the dependent variable (microplastic abundance) and multiple independent variables (industry, population, precipitation, and so on); then, use stepwise regression, and based on the significance tests, sequentially include or exclude variables to simplify the model. This accurately identifies the driving factors that significantly affect microplastic abundance, and provides data and model support for pollution prevention and control.

In terms of data, the “annual average abundance (item/L)” is selected as the dependent variable to characterize the microplastic concentration in water bodies. After the data collection process, the team found that in the selected river basin, the Guangzhou section of the Pearl River, relatively systematic records of microplastics only appeared from 2016 to the present. Moreover, the data for 2022 from different journals and websites varied greatly, and we can’t find reliable data at that time, so they were eliminated. As a result, there were only seven sets of data in the final independent variable data group.

In the process of variable selection, it is necessary to ensure that the sample size is larger than the number of model parameters to avoid the problem of overfitting. Given that this study ultimately only obtained 7 valid samples, and according to the equation of the multiple linear regression model

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($Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$) [14], its parameters include 1 intercept term and several slope terms corresponding to the independent variables. The total number of parameters in the model needs to be strictly controlled to be 7 or fewer. Based on this, after excluding the 1 intercept term, the model can include a maximum of 6 independent variables (corresponding to 6 slope terms). After group discussion, we use the "stepwise regression" method to select variables, and finally choose six independent variables that have a strong logical relationship with the abundance of microplastics in the river, they include: GDP, industrial activity intensity/output value, per capital plastic waste generation, Guangzhou's population density, recycling rate of plastic waste, and annual average precipitation.

This table systematically summarizes the annual data of microplastics and related impact indicators in the Guangzhou section of the Pearl River Basin from 2017 to 2024. It covers the core dependent variable "annual average abundance of microplastics" and 6 key independent variables.

Table 1. Annual data of microplastics and associated indicators in the Guangzhou section of the Pearl River Basin

Year	Abundance(item/L)	GDP	Population Density	Industrial Output Value	Per Capita Plastic Waste Generation	Annual Precipitation	Plastic Waste Recycling Rate
2017 [15]	890	21503.15	1950.2	17858.56	109.6	1857.7	25
2018 [16]	1364	22859.35	2004.8	18595.11	92	1821	20
2019 [17]	1990	23629	2058.8	19554.91	97.6	2306.3	28
2020 [18]	1280	25019	2512.2	20310.16	89.8	1820.5	32
2021 [19]	2640	28231.97	2530.2	23121	112.3	1435.5	24.3
2022	Excluded	Excluded	Excluded	Excluded	Excluded	Excluded	Excluded
2023 [20]	2070	30356	2532.4	24246.36	92.3	1933.6	44
2024 [21]	2331	31032.5	2552.7	22675.18	92.2	2536.7	36.3

Table 1 shows the annual data of microplastic abundance and associated socioeconomic and environmental indicators in the Guangzhou section of the Pearl River Basin from 2017 to 2024.

In the table, the sample size is slightly larger than the number of variables, and the selection of the variables is also very appropriate. It not only meets the basic data requirements of the model calculation, but also ensures the reliability and practical application value of the analysis results, avoiding the model from becoming one that merely fits the data but has no practical significance.

4. Model construction and result verification

After collecting all relevant data within the studied river basin, the research team developed a corresponding mathematical model using MATLAB software to accurately predict the microplastic content in the basin. In the model setup, the annual average microplastic content of the basin was defined as the dependent variable y, while six types of key data that might have a huge impact on microplastic content were selected as independent variables X. By establishing a mathematical relationship between the dependent variable and independent variables, the study aims to reveal the comprehensive mechanism of action of various social-economic and natural environmental factors on

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the microplastic content in the river basin, and provide scientific data support and model reference for subsequent microplastic pollution prevention and control in the basin.

4.1. Variable screening based on stepwise regression

Before conducting the fitting calculation of the mathematical model, the research team found that the number of initially set model parameters was relatively close to the sample size. This situation may lead to overfitting of the model, meaning that although the model can well fit the existing sample data, its ability to predict new data will decrease significantly, and it will also be difficult to accurately determine the true impact of each variable on the dependent variable. To solve this problem and ensure the stability and accuracy of the model, the research team adopted the stepwise regression method for variable screening.

With the gradual addition of variables, the coefficient of determination R^2 of the model showed a gradual upward trend, and the specific changes are shown in Figure 1. The horizontal axis of Figure 1 represents the codes of the six

independent variables X1-X6, and the vertical axis represents the coefficient of determination R^2 of the model. It can be clearly seen from the data in the figure that when X1 was added, R^2 was 0.66801; after adding X2, X3, X4, X5, X6, the R^2 consistently climbed to 0.91656.

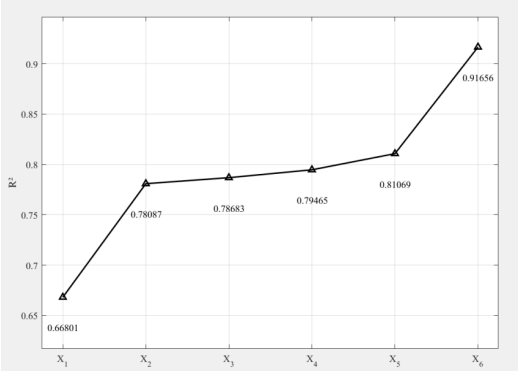

Figure 1. The changes in R^2 during stepwise regression

As shown in Figure 1, the coefficient of determination (R^2) increased steadily with the inclusion of more independent variables, indicating that each variable contributed positively to improving the model's explanatory power.

The specific meanings of each variable are as follows: X_1 represents Gross Domestic Product (GDP), X_2 represents population density, X_3 represents industrial output value, X_4 represents per capita plastic waste generation, X_5 represents annual precipitation, and X_6 represents plastic waste recycling rate.

The continuous increase of R^2 during this variable screening process means that each newly added independent variable can bring additional explanatory power to the model, effectively improving the fitting accuracy of the model for the annual average microplastic content in the river basin. Therefore, the research team decided to retain all these six independent variables for the subsequent model fitting calculation.

4.2. Model accuracy test: 2024 prediction verification

To verify the prediction accuracy and reliability of the constructed model, the research team selected the relevant data from 2016, 2017, 2018, 2019, 2020, 2021, 2023, 7 years in total, as the training set of the model. After calibrating and training the model parameters using the training set data, the model was used to predict the microplastic abundance in the studied river basin in 2024.

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Through the fitting analysis of the training set data, the fitting equation for microplastic content was obtained as follows:

$$y = -5066.0656 - 0.17857 \times X_1 + 1.9313 \times X_2 + 0.44423 \times X_3 - 18.6559 \times X_4 + 1.2209 \times X_5 - 85.072 \times X_4 \quad (2)$$

To obtain the 2024 prediction result, the research team collected the actual statistical data of X_1-X_6 the river basin in 2024, and substituted these data into the above fitting equation for calculation. After the calculation, the predicted value of microplastic abundance in the studied river basin in 2024 was 2638.99 item/L.

To test the accuracy of the prediction result, the research team obtained the actual value of microplastic abundance in the river basin in 2024 the actual value was 2331 item/L. The relative error was calculated to evaluate the prediction accuracy of the model, with the formula for relative error being:

$$Relative\ Error = |Predicted\ Value - Actual\ Value| / Actual\ Value \times 100\% \quad (3)$$

Substituting the predicted value and actual value into the formula, the relative error of this prediction was approximately

$$|2638.99 - 2331| / 2331 \times 100\% \approx 13\% \quad (4)$$

Generally speaking, for prediction models in the field of environmental science, a relative error within 30% indicates that the model has good reliability and prediction accuracy. The relative error of this model prediction is approximately 13%, which is within the acceptable error range. This shows that the constructed mathematical model can relatively accurately reflect the relationship between the microplastic content in the studied river basin and various influencing factors, the reliability of the model has been effectively verified, and it can be used for subsequent research on microplastic content prediction.

4.3. Model update and 2025 prediction

With the acquisition of relevant data in 2024, to further improve the fitting accuracy and prediction ability of the model, the research team supplemented the latest 2024 data to the model's training set, forming a new training set with 8 sets of data from 2016 to 2024. (excluding the data of 2022) Based on the new training set data, the original mathematical model was re-fitted and its parameters were optimized to complete the model update. The updated model was then used to predict the annual average microplastic abundance in the Guangzhou section of the Pearl River Basin in 2025.

4.3.1. Comparative analysis of actual and predicted values

To intuitively demonstrate the fitting effect of the updated model, the research team plotted a comparison chart (Figure 2) of the actual microplastic abundance values and the model's predicted values in the studied river basin from 2016 to 2024 (excluding 2022), the horizontal axis represents years from 2016 to 2024 and the vertical axis represents the microplastic abundance (unit: item/L). The blue solid line represents the actual value, and the red dashed line represents the predicted value.

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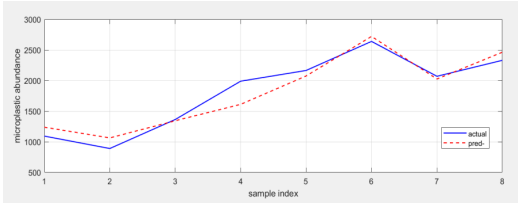

Figure 2. Line chart of actual values vs. predicted values

Figure 2 compares the actual observed values of microplastic abundance with the predicted values generated by the updated model. The close alignment between the two curves demonstrates the high accuracy and strong fitting ability of the model.

It can be observed from the figure that the gap between the microplastic abundance values predicted by the updated model and the actual detected values for each year is small, the data points are relatively close in distribution, and an overall similar variation trend is presented. For example, at the two time points of Sample Number 3 (2018), umber 6 (2020) and Sample Number 7 (2021), the deviation between the actual values and predicted values is the smallest, and they almost overlap; even at Sample Number 5 (2020) where the deviation is relatively larger, the difference between the two is still controlled within a reasonable range. This good consistency fully indicates that after updating the model by adding the latest 2024 data, the fitting effect of the model has been further improved, and it can more accurately reflect the actual variation law of microplastic content in the studied river basin.

4.3.2. Residual distribution analysis

Residuals refer to the differences between the model's predicted values and the actual observed values, and the distribution of residuals is an important basis for evaluating the reliability and rationality of the model. If the residuals exhibit the characteristics of a random normal distribution and there is no obvious systematic deviation, it indicates that the model can well capture the inherent laws in the data, and there are no issues such as omitted important influencing factors or model setup errors.

The research team calculated the residual values for each year based on the predicted results of the updated model and the actual observed values, and plotted a residual distribution chart (Figure 3). It can be seen from Figure 3 that all residual values fluctuate randomly around zero, with no obvious trend changes or periodic patterns. Most residual values are concentrated within a small numerical range, and only a few residual values are relatively larger, but they still do not exceed the range of reasonable statistical fluctuations.

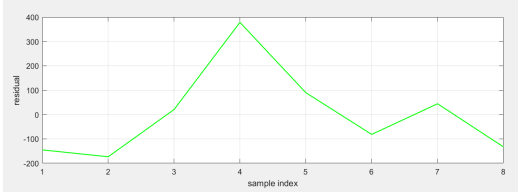

Figure 3. Residual line chart

As shown in Figure 3, the residuals are randomly distributed around zero without any apparent pattern, confirming that the model captures the true relationship between variables without systematic bias.

This random normal distribution characteristic of residuals fully proves that the updated model has no systematic errors, the model setup is reasonable, and the selected independent variables X1-X6 can fully reflect the main factors affecting the microplastic content in the studied river basin. No key

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variables are omitted, and there are no issues such as multicollinearity between variables, indicating that the model has good stability and reliability.

4.3.3. Fitting equation and 2025 prediction result

After re-fitting the new training set data from 2016 to 2024, the research team obtained the updated fitting equation for microplastic content:

$$y = -3846.7854 - 0.035554 \times X_1 + 1.7224 \times X_2 + 0.20245 \times X_3 - 5.7891 \times X_4 + 0.4592 \times X_5 - 60.7346 \times X_6 \quad (5)$$

By comparing the fitting equations before and after the update, it can be found that the coefficients of each variable have changed to a certain extent. This is because after adding the new 2024 data, the model's estimation of the relationship between each variable and microplastic content has changed in order to fit the newly updated data set.

The coefficient of determination R^2 of the updated model is 0.91656. Since R^2 is close to 1, it indicates that the model can explain approximately over 91% of the changes in microplastic content, and the fitting accuracy of the model is at a high level, far exceeding the fitting standard of general environmental prediction models (usually, a fitting effect is considered good when ($R^2 > 0.8$).

To ensure the statistical significance of the prediction results, the research team used the updated model to predict the annual average microplastic abundance in the Guangzhou section of the Pearl River Basin in 2025 at a significance level of 0.05 (i.e., with a 95% confidence level). First, by integrating various factors such as the regional social-economic development plan, population growth trend, industrial development layout, environmental protection policies, and climate prediction data, the research team made a scientific and reasonable estimation of the values of the six independent variables in 2025. Subsequently, the estimated values of each variable in 2025 were substituted into the updated fitting equation for calculation, and finally, the predicted value of the annual average microplastic abundance in the Guangzhou section of the Pearl River Basin in 2025 was obtained as 2730.64 item/L.

To sum up, through variable screening, 2024 verification, and model updating, we built a reliable, high-accuracy microplastic prediction model. This model not only reveals key influencing factors but also provides a practical tool for future pollution control and prediction in the basin.

5. Conclusion

This study focuses on the Guangzhou section of the Pearl River Basin, a typical urban river area, and constructs a reliable mathematical model for predicting microplastic emissions by integrating multivariate linear regression and stepwise regression. And providing an effective tool for cost-effective and accurate prediction of riverine microplastic abundance.

This study has certain limitations: the sample size is relatively small (8 valid sets of data), and the model only considers linear relationships between variables, ignoring potential non-linear effects. In future research, more long-term and high-frequency monitoring data should be collected to expand the sample size. Additionally, non-linear modeling methods can be introduced to optimize the model structure, and more influencing factors (such as tidal fluctuations and land use types) can be integrated to further improve prediction accuracy. Meanwhile, the model can be promoted to other river basins after localization adjustment, contributing to global river microplastic pollution prevention and control.

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