

DEVELOPING AN EMPIRICAL RELATIONSHIP BETWEEN RAINFALL CHARACTERISTICS AND MICROPLASTIC EMISSIONS IN AN URBAN RIVER

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Abstract

Rainfall runoff transports microplastics into urban rivers, but concentration responses vary between events. This study analysed a secondary dataset from the Takano River, Kyoto, Japan, to evaluate river flow as a predictor of microplastic concentration. Records for particles between 10 and 300 micrometres were examined using time series, correlations and regression. Light rainfall produced an early concentration peak, moderate rainfall showed coincident flow and concentration peaks, and heavy rainfall produced delayed peaks during flow recession. A power-law model fitted to the light and moderate events explained 84 percent of the variation in log-transformed particle concentration. Leave-one-out cross-validation gave a coefficient of determination of 0.81. River flow therefore provided a useful predictor within the observed event domain. However, the model estimates total concentration at the monitoring site without separating upstream inputs from local rainfall wash-off. Transfer to other catchments requires validation because land use, surface resistance and microplastic sources can alter transport. Heavy rainfall requires consideration of storage, remobilisation and delayed delivery.

Keywords: Environmental pollution, Stormwater runoff, Hydrological modelling, Particle concentration, First flush

1. Introduction

Urban rivers are important pathways for microplastic transport, particularly during rainfall when runoff mobilises particles accumulated on impervious surfaces and within drainage networks. Event-based studies show pronounced first-flush behaviour and substantial intra-event variability, with transport controlled by rainfall and river hydraulics [1], [2]. High-frequency monitoring is therefore needed to capture short concentration pulses that conventional grab sampling can miss.

Process-based transport models can represent complex mechanisms but often require extensive data and parameterisation. Empirical approaches provide a practical alternative when high-frequency hydrological measurements are available [3]. This study examined particle and mass concentration dynamics under different rainfall magnitudes and assessed whether river flow could serve as a parsimonious predictor, while distinguishing direct wash-off from delayed transport during intense storms.

2. Materials and Methods

A secondary rainfall-runoff dataset from Mikage Bridge on the Takano River, Kyoto, Japan, was analysed [1]. The three monitored events represented light rainfall of 6 mm over 5 h, moderate rainfall of 24 mm over 7 h, and heavy rainfall of 52 mm over 7 h. The dataset contained particle-level observations together with rainfall intensity, river flow, particle characteristics, sample volume, and derived concentrations.

The analysis retained small microplastics from 10 to 300 micrometres and aggregated particle records by sampling time, producing 8, 11, and 14 observations for Events 1, 2, and 3. Time-series plots compared river flow with particle and mass concentration, and Pearson correlation matrices were used to evaluate associations among rainfall, flow, particle count, mass, and concentration indicators.

A power-law flow-concentration model was developed from Events 1 and 2 because both showed comparatively direct wash-off behaviour, whereas Event 3 showed delayed peaks and weaker zero-lag association. River flow and particle concentration were transformed using base-10 logarithms and fitted by linear regression. Validation used leave-one-out cross-validation, 5000-replicate bootstrap confidence intervals for the slope, and Cook's distance. Low-flow, high-flow, and mid-range subsets were also tested to determine whether restricting the flow domain improved the fit. All analyses were completed in RStudio. The regression used river flow as its sole predictor; catchment characteristics, source contributions and upstream-downstream background differences were not quantified separately.

3. Results and Discussion

3.1 Event-Specific Transport Behaviour

Under light rainfall, particle concentration peaked before river flow, consistent with first-flush behaviour [2], while mass concentration peaked closer to the rainfall maximum. Moderate rainfall produced synchronous peaks in rainfall, flow and both concentration measures, supporting a close hydrological association consistent with hydraulic influences on transport [4].

During heavy rainfall, mass and particle concentrations peaked approximately three and four hours after peak flow, respectively. These recession-phase peaks suggest delayed delivery, storage and remobilisation [1], supporting exclusion of this event from the zero-lag calibration.

3.2 Empirical Relationship and Model Validation

Combining Events 1 and 2 produced a strong log-log relationship between river flow and particle concentration. The fitted power-law model was:

$$C_p = 1.02 Q^{5.71}$$

Here, C_p is particle concentration in particles m^{-3} and Q is river discharge in $m^3 s^{-1}$. The log-scale coefficient of determination was 0.84. The exponent of 5.71 describes a strongly nonlinear, site-specific response within the observed flow range.

Leave-one-out cross-validation gave a root mean square error of 0.36 and a mean absolute error of 0.26 on the base-10 logarithmic concentration scale, with a cross-validated coefficient of determination of 0.81. The 95 percent bootstrap interval for the slope was 4.848–7.186. Cook's distance flagged influential observations. Independent rainfall events are needed to assess predictive performance beyond this dataset.

Restricting the flow range produced no clear improvement; the complete Event 1 and Event 2 range was retained.

3.3 Catchment Controls and Model Limitations

Catchment land use, impervious cover and slope influence runoff generation and connectivity, while surface roughness alters flow resistance, particle retention and delivery timing [2], [4].

Rougher surfaces may delay wash-off and retain particles; the response also depends on water depth and particle properties [4]. River flow integrates some catchment effects but does not uniquely describe particle availability or retention. Consequently, the same flow can produce different concentrations under different catchment conditions, and both model parameters may require recalibration elsewhere.

Potential urban sources include tyre and road wear, fragmented litter, industrial plastic losses, atmospheric deposition and wastewater-borne fibres. Their relative importance varies with land use, human activity, wastewater management and antecedent dry periods [2], [5]. Changes in source abundance and particle composition can therefore alter the concentration–flow relationship. These are potential contributors; their proportions were not quantified for the analysed samples.

Downstream concentration combines upstream particle inputs with local wash-off and other discharges, modified by dilution, retention and remobilisation. It therefore need not increase downstream. A high background load can obscure the relative rainfall signal, while dilution can reduce concentration even when particle flux increases. Since particle flux is the product of flow and concentration, concentration differences alone cannot quantify newly washed-off loads. Separating these components requires concurrent flow measurements and upstream–downstream sampling that accounts for travel time. The fitted model predicts total concentration at Mikage Bridge, not the additional load generated solely by rainfall wash-off.

4. Conclusions

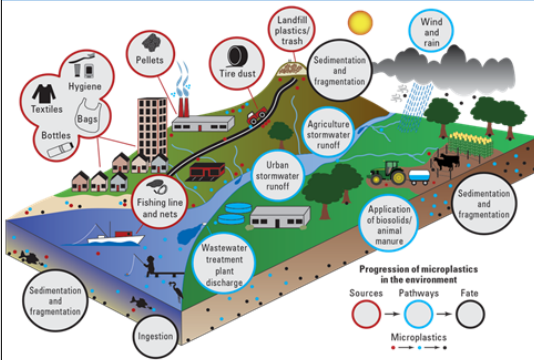
The light and moderate events supported a flow-based model with a log-scale coefficient of determination of 0.84, whereas the heavy event showed delayed concentration peaks. The model predicts total particle concentration under the observed site and event conditions. Catchment properties, source variability and upstream background inputs limit its transferability and the attribution of concentrations to new rainfall wash-off. Further development requires additional events, catchment and source information, and concurrent upstream–downstream monitoring.

References

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Developing an empirical relationship between rainfall characteristics and microplastic emissions in an urban river

MP transport pathways



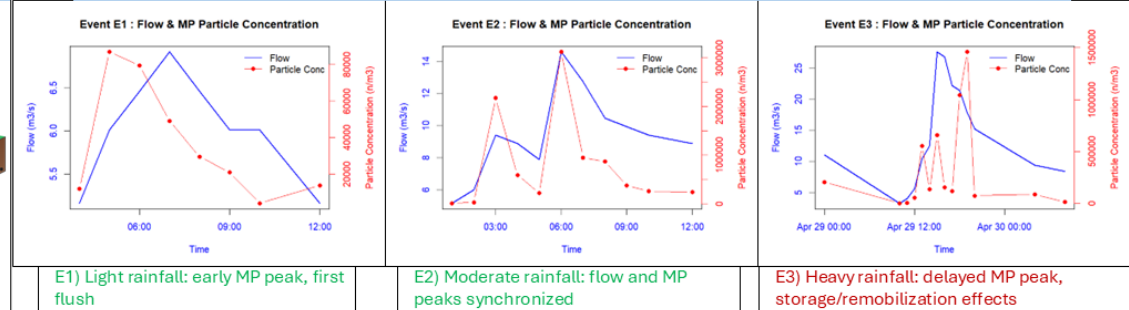
Rainfall mobilizes urban microplastics
Urban surfaces → Stormwater drains → River
MPs enter the river during runoff

Rainfall – MP emissions dataset

Takano River, Kyoto, Japan
3 rainfall events → Light, Moderate, Heavy
Variables: River flow, MP concentration
Analysis using R programming

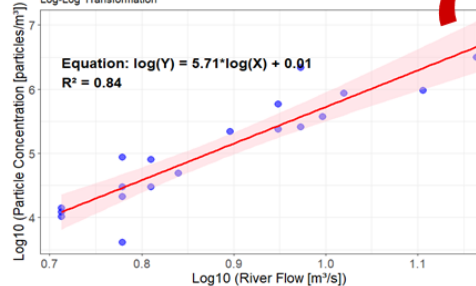


Event specific MP behavior



Empirical prediction model

Flow vs. Mp concentration (Events 1 & 2)
Log-Log Transformation



$$C_p = 1.02Q^{5.71}$$

$R^2 = 0.84$
Events 1 & 2 combined
Event 3 was removed

Validation methods
Leave-one-out cross-validation
Bootstrap confidence interval on the slope
Cook's distance analysis

River flow is a strong predictor under light-to-moderate rainfall
Heavy rainfall requires more complex modelling