Session D4: Hydrology

Investigating micropollutant dynamics in urban catchment using stormwater management model (SWMM) and low impact development (LID)

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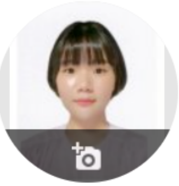
1. Introduction

My research background



Daeun Yun

Ulsan National Institute of Science and Technology
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Hydrologic modeling   Water quality modeling   Micropollutant   Deep neural network

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Developing a deep learning model for the simulation of micro-pollutants in a watershed

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ABSTRACT

In recent years, as agricultural activities and types of crops have become diverse, the occurrence of micro-pollutants has been reported more frequently in rural areas. These pollutants have detrimental effects on human health and ecological systems; thus, it is important to manage and monitor their presence in the environment. The modeling approach could be an effective way to understand and manage these pollutants. This study predicts the concentrations of micro-pollutants (MPs) using deep learning (DL) models, and the results are then compared with simulation results obtained from the soil water assessment tool (SWAT) model. The SWAT model showed an unacceptable performance owing to the resulting negative Nash–Sutcliffe efficiency (NSE) values for the simulations. This may be caused by the limitations of SWAT, which pertains to adopting simplified equations to simulate micro-pollutants. In addition, the ambiguous plan of pesticide application increased the model uncertainty, thereby deteriorating the model result. Here, we developed two different DL models: long short-term memory (LSTM) and convolutional neural network (CNN). LSTM exhibited the highest model performance, with NSE values of 0.99 and 0.75 for the training and validation steps, respectively. In the multi-target MP model, the error decreased as the number of simulated pollutants increased. The simulation of the four pollutants had the highest error, while the six-target simulation had the lowest error. In conclusion, this study demonstrated that the LSTM model has the potential to improve the prediction of MPs in aquatic systems.

Process-based VS Data-driven model

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A novel method for micropollutant quantification using deep learning and multi-objective optimization

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ABSTRACT

Micropollutants (MPs) released into aquatic ecosystems have adverse effects on public health. Hence, monitoring and managing MPs in aquatic systems are imperative. MPs can be quantified by high-resolution mass spectrometry (HRMS) with stable isotope-labeled (SIL) standards. However, high cost of SIL solutions is a significant issue. This study aims to develop a rapid and cost-effective analytical approach to estimate MP concentrations in aquatic systems based on deep learning (DL) and multi-objective optimization. We hypothesized that internal standards could quantify the MP concentrations other than the target substance. Our approach considered the precision of intra-/inter-day repeatability and natural organic matter information to reduce instrumental error and matrix effect. We selected standard solutions to estimate the concentrations of 18 MPs. Among the optimal DL models, DarkNet-53 using nine standard solutions yielded the highest performance, while ResNet-50 yielded the lowest. Overall, this study demonstrated the capability of DL models for estimating MP concentrations.

LC-HRMS data-based deep learning model to estimate MP

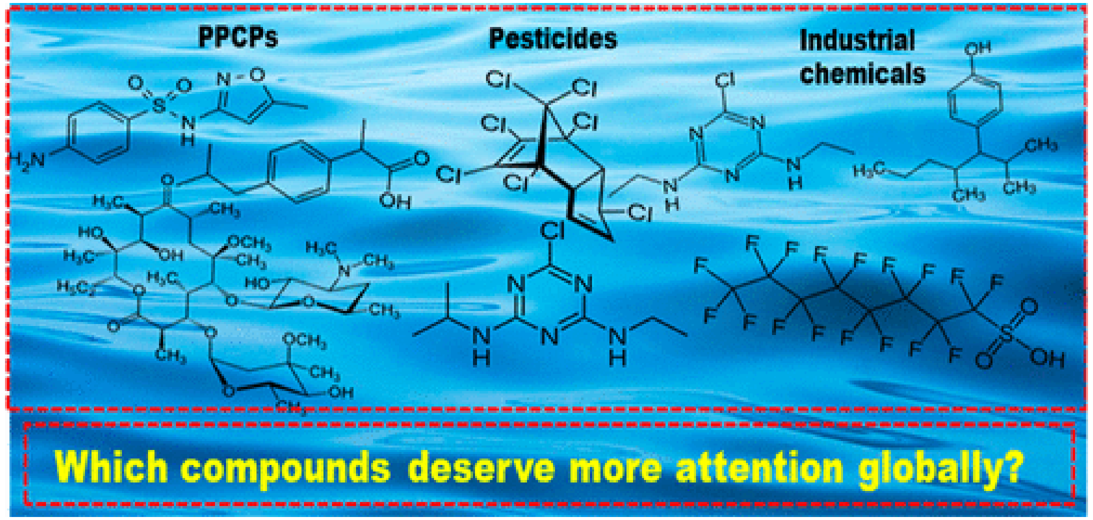
Micropollutant modeling in high temporal resolution for rainfall events

Requirement of micropollutant simulation using process-based model !

Micropollutants and Challenges

Micropollutant (MP)

- A large number of organic chemicals are termed as "micropollutants" due to their low concentrations (ng/L to μg/L).
- It is also referred to as **emerging pollutants**, and **emerging contaminants**.



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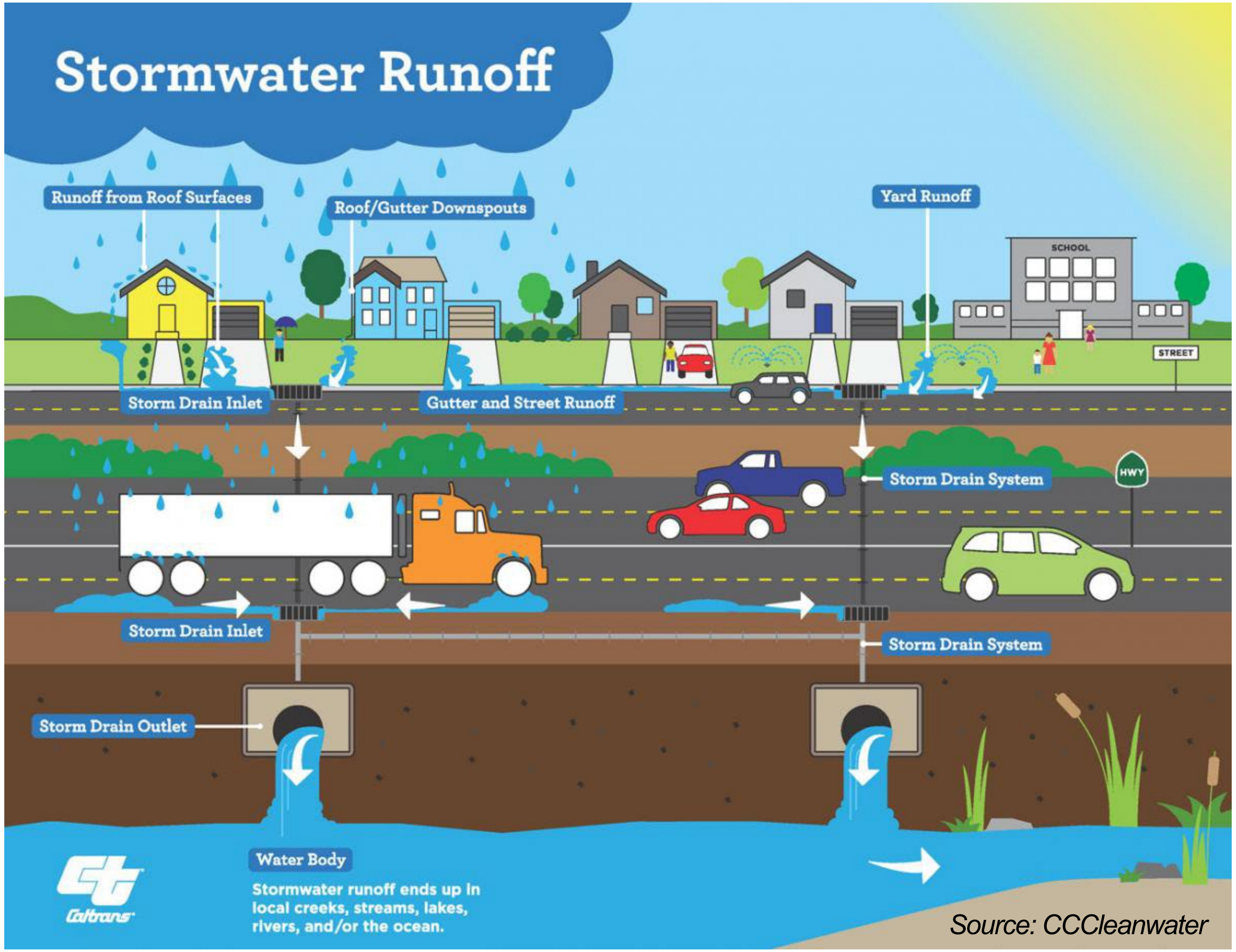
Challenges of MPs in aquatic systems

- Some of MPs have high persistence, bioaccumulation, and biomagnification.
- Long-term exposure to MPs can cause immunological disorders and ecosystem disturbances.
- Unregulated and unregistered MPs remain challenging.
- It is necessary to monitor and analyze MPs to prevent damage to ecosystem.

Micropollutants and Challenges

Stormwater Quality



Source: CCCleanwater

Urban Stormwater Pollution

- Referring to the contamination of water bodies, such as rivers, lakes, and streams, as a result of rainfall and runoff in urban areas.
- It occurs when rainwater flows over impervious surfaces, picking up pollutants and carrying them into waterways.

Sources of Urban Stormwater Pollution

a. Point Sources

- Industrial discharges, municipal sewage systems, illicit connections

b. Non-Point Sources:

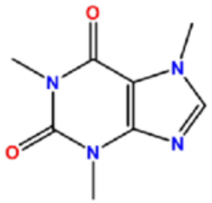
- Runoff from roads, highways, residential areas, construction sites, etc.

Micropollutant in urban stormwater

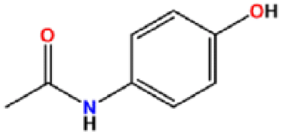
Untreated MPs

Dominant MPs in Gwangpyeong-stream, Korea (Yun et al., 2023)

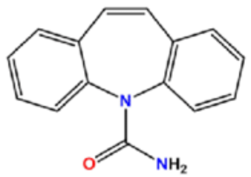
Anthropogenic indicators



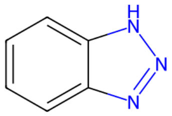
Caffeine



Acetaminophen

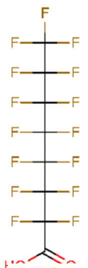


Carbamazepine

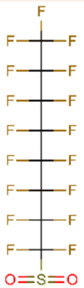


Benzotriazole

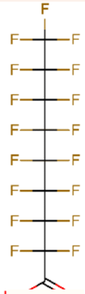
Hazard MPs with low degradation



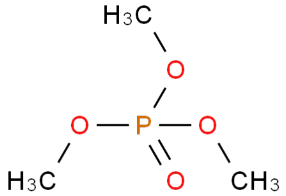
PFOA



PFOS



PFNA



Trimethyl phosphate

MPs from Non-point source

- Diffuse pollution from multiple sources, making it challenging to pinpoint specific origins.
- **Common non-point sources are:**

a. **Agricultural runoff**
Pesticides, fertilizers, and veterinary pharmaceuticals from crop fields and livestock operations.

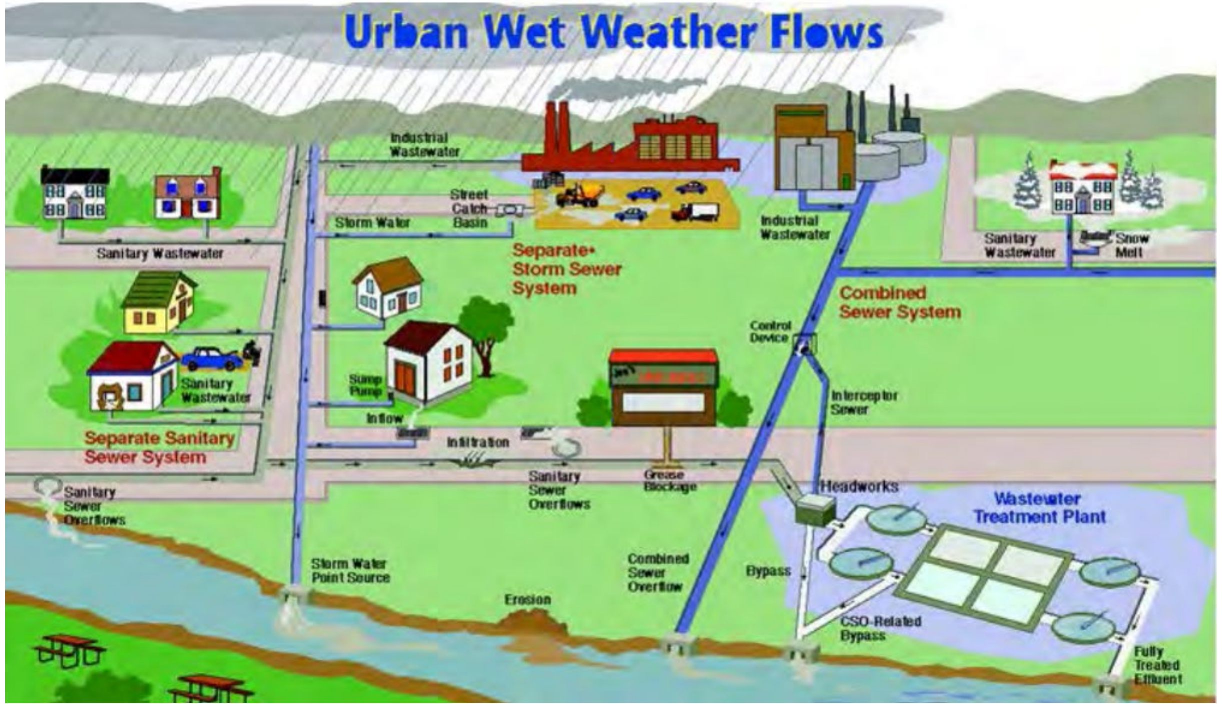
b. **Urban runoff**
Chemicals from road surfaces, parking lots, and residential areas.

Potential strategies for treating and managing MPs in urban stormwater

1. **Stormwater treatment systems**: Constructing treatment facilities to remove micropollutants before discharge into water bodies.
2. **Green infrastructure**: Vegetated swales, constructed wetlands, and biofiltration systems that help filter and retain micropollutants.
3. **Implementing stricter regulations and monitoring programs** to control micropollutant discharges from industrial and municipal sources.
4. **Establishing watershed management plans** to address non-point source pollution and promote best management practices.

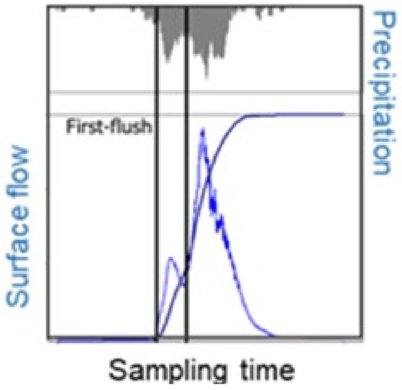
Management strategies

Water quality modeling in urban area



- **The Stormwater Management Model (SWMM)** developed by the Environmental Protection Agency (EPA) is a widely used software tool for analyzing and managing stormwater runoff.
- SWMM helps simulate **the hydrologic and hydraulic processes** associated with stormwater runoff, allowing for the evaluation of various stormwater management strategies.

First flush effect (FFE) of MPs



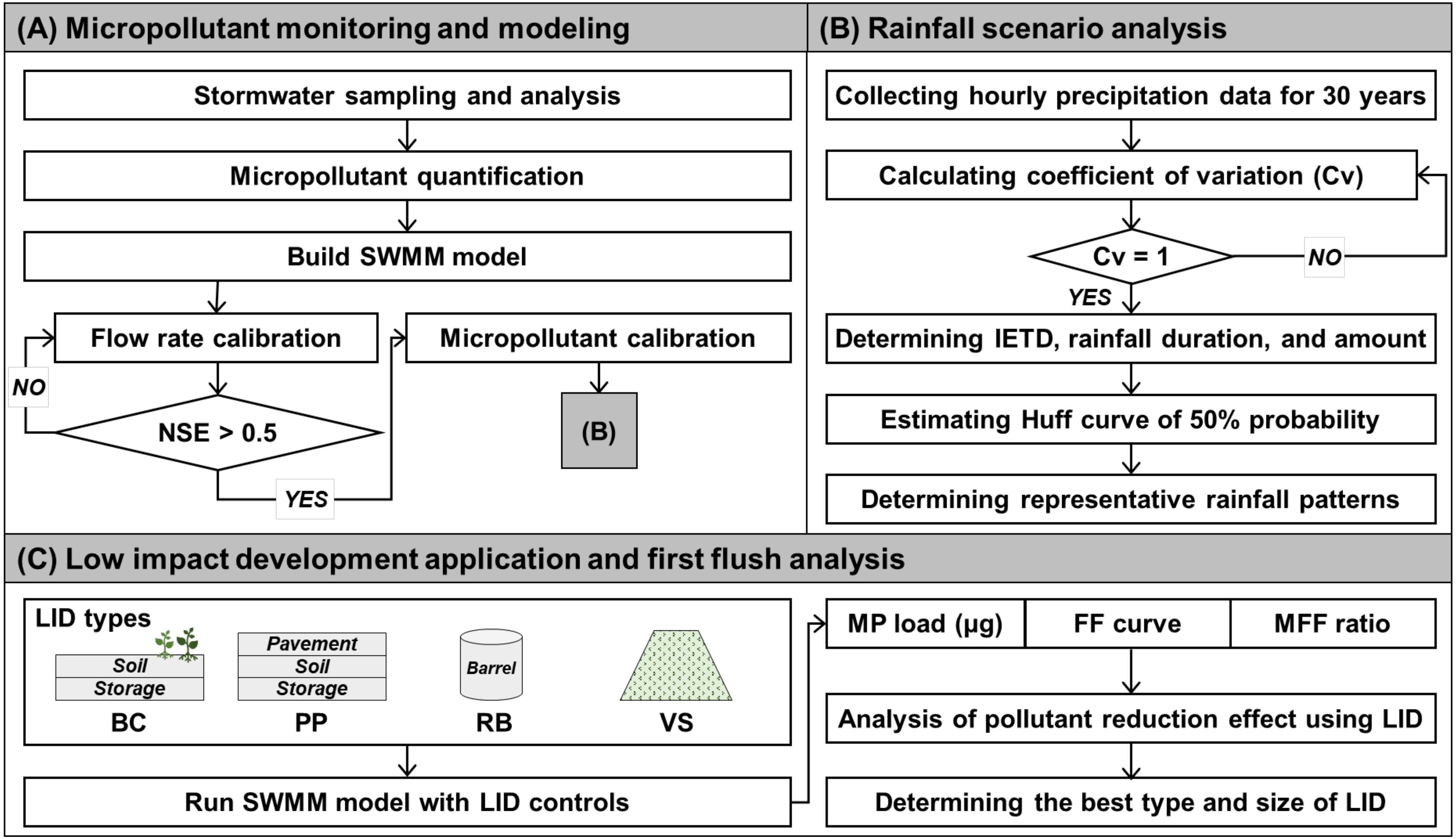
- The FFE refers to **the initial runoff from a rainfall event that contains a higher concentration of pollutants** compared to subsequent runoff.
- During dry periods, pollutants accumulate on impervious surfaces, such as roads and rooftops.
- When it rains, the first flush carries these accumulated pollutants into storm drains and water bodies.

Low Impact Development (LID)

- An approach to land development and stormwater management that aims to **mimic natural hydrological processes** and **minimize the impact of urbanization on the environment**.
- LID emphasizes the use of decentralized, small-scale practices to manage stormwater at its source, promoting infiltration, evapotranspiration, and pollutant removal.

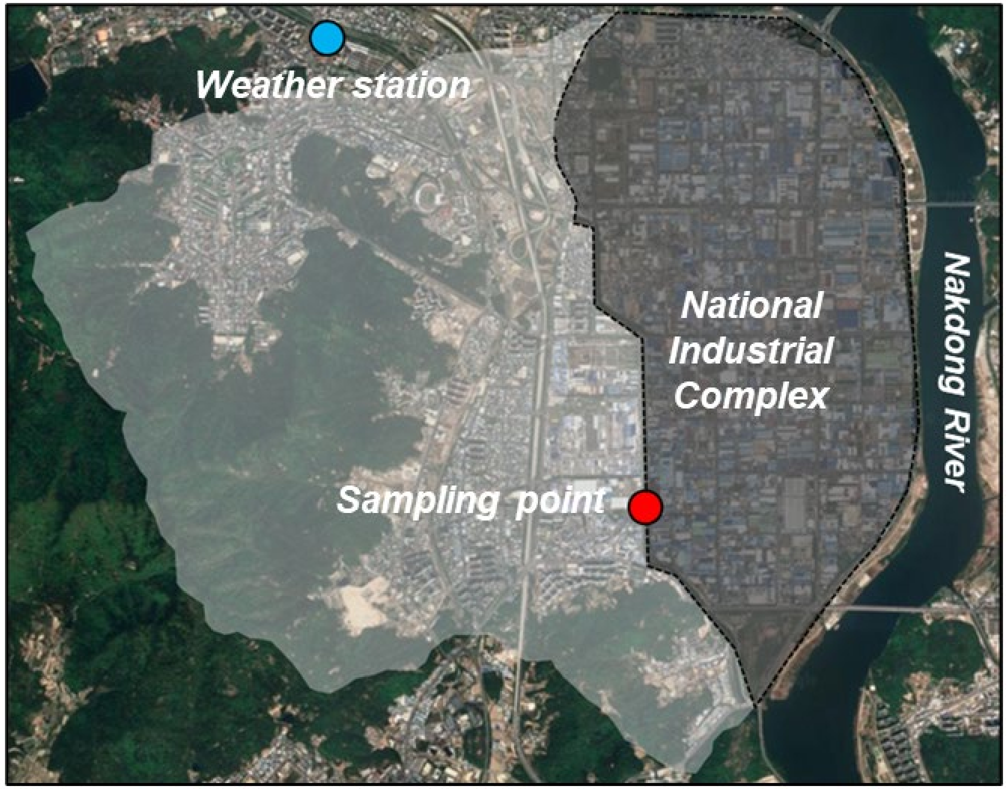
2. Methods and Materials

Research overview



Study area

Gwang-Pyeong catchment in Gumi, South Korea



Imperv.	Industrial (30%)	Residential (18%)
Perv.	Agriculture (10%)	Forest, grassland (42%)

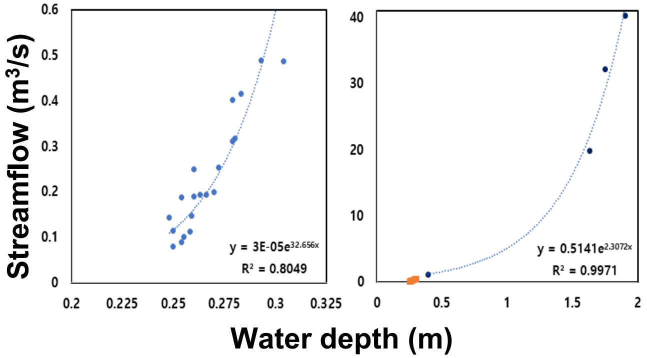
Gwang-Pyeong Stream

- Drinking water source for millions of people.
- Faces significant pollution from manufacturers and large population.

- Electronics manufacturing involves chemicals like PFASs.
- Pharmaceutical pollutants like metformin and acetaminophen are also present.
- Chemicals discharged through surface runoff and diffusion.

MP monitoring

Hydrologic Monitoring



Estimation of streamflow

- $Q_h = 0.5141^{e2.3072D}$ (D > 0.321 m)
- $Q_l = 0.00003^{e32.656D}$ (D ≤ 0.321 m)

Stormwater sampling

- A composite sampler, the AS950 (HACH Lange GmbH, Colorado, USA) was implemented to obtain stormwater sample
- Wet (rainfall > 1.0/day) weather: 15min interval
- Dry weather: 1h – 3h interval
- 1L collection in PE bottles

SWMM model – Flow rate simulation

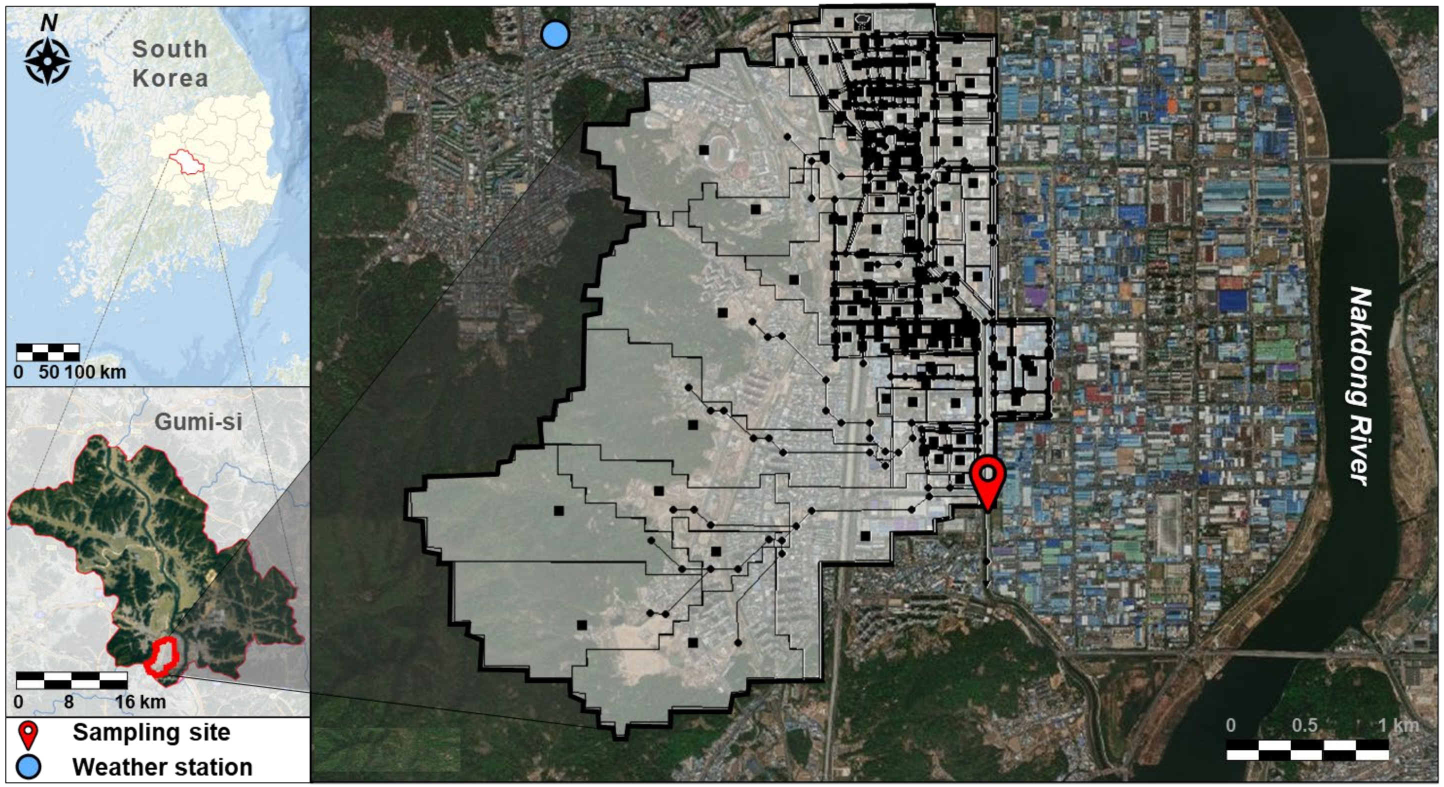


Figure. Along the Gwang-pyeong stream, the sampling site is located downstream (red marker), surrounded by residential and industrial areas. The weather station is located in upstream of the study area.

Hydrologic Component

- To estimate rainfall-runoff processes, **the modified Green-Ampt infiltration method** was applied.
- SWMM simulates runoff from rainfall, infiltration, evaporation, and depression storage.

Hydraulic Component

- **The dynamic wave method** was selected to consider flow routing, pipe capacities, flow velocities, and the interaction between different components of the stormwater system.
- SWMM also simulates the flow of stormwater through drainage systems, including pipes, channels, and storage facilities.

Water quality component

- SWMM incorporates water quality simulations to assess the impacts of stormwater runoff on receiving water bodies.
- It can model **pollutant build-up on surfaces, wash-off processes**, and pollutant transport through the stormwater system.

SWMM model – MP simulation

Rainfall events for simulation

	Event 1	Event 2	Event 3	Event 4
Start	07/05/2021 12:00	08/01/2021 12:00	08/31/2021 13:00	09/06/2021 12:00
End	07/06/2021 23:59	08/02/2021 01:59	09/01/2021 16:59	09/07/2021 05:59
Rainfall duration (hours)	15	8	9	5
Rainfall volume (mm)	66.8	47.5	37.1	9.5
Mean intensity (mm/h)	4.5	5.6	4.1	1.9
Antecedent dry days	0.87	11.67	1.50	2.60

MP simulation processes

Build-up process

$$b_{pow} = \mathrm{Min}(B_{max}, K_B t^{N_B}) \quad \textit{Power} \quad (1)$$

$$b_{exp} = B_{max}(1 - e^{-K_B t}) \quad \textit{Exponential} \quad (2)$$

$$b_{sat} = B_{max}\mathrm{t}/(K_B + \mathrm{t}) \quad \textit{Saturation} \quad (3)$$

- ***t***: the build-up time interval (days)
- $\boldsymbol{B_{max}}$: possible maximum build-up of the pollutant
- $\boldsymbol{K_B}$: the build-up rate constant
- $\boldsymbol{N_B}$: the build-up time exponent

Wash-off process

$$w_{exp} = K_W q^{N_W} m_B \quad \textit{Exponential} \quad (4)$$

$$w_{rc} = K_W Q^{N_W} \quad \textit{Rating curve} \quad (5)$$

$$w_{emc} = K_W q f_{LU} A \quad \textit{EMC} \quad (6)$$

- ***Q***: the flow rate (cfs)
- ***q***: the runoff rate over the subcatchment (in/hr).
- $\boldsymbol{K_W}$: the wash-off coefficient
- $\boldsymbol{N_W}$: the wash-off exponent
- $\boldsymbol{m_B}$: the initial mass of the constituent on the surface at time (exponential).

MP management strategy: Rainfall scenario analysis

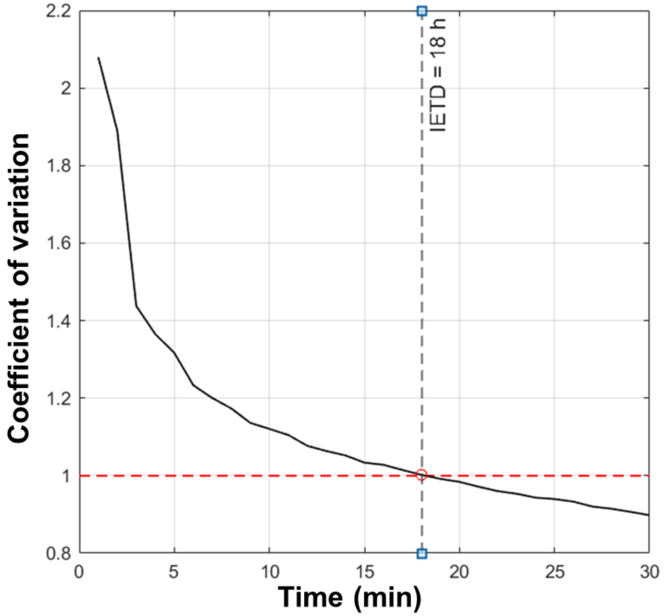
Representative rainfall

Inter-Event Time Definition (IETD):

- IETD determines the minimum duration between two consecutive rainfall events, which plays a significant role in analyzing rainfall patterns (Driscoll et al., 1989).

Coefficient of Variation (CV) Analysis:

- CV analysis is utilized to select appropriate IETD.
- This statistical method is based on probability density and resembles the exponential distribution (Dolšak et al., 2016).

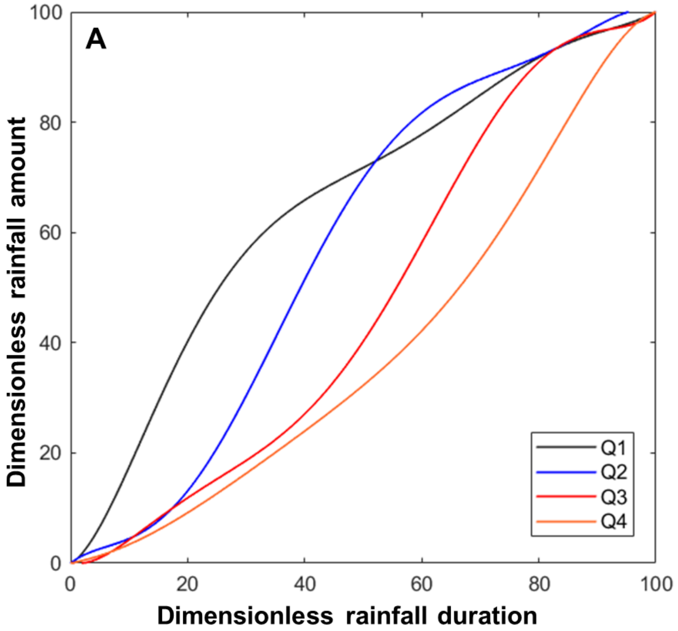


Huff Curve:

- The Huff curve, introduced by Huff in 1967, was applied to obtain representative rainfall patterns.
- It helps determine the quartiles of 50% probability of cumulative rainfal (Park et al., 2018).

Data Collection and Analysis:

- Hourly rainfall data from 30 years (1992-2021) in Gumi-si (KMA) was collected.



MP management strategy: First flush analysis

First flush (FF) analysis

Definition

- The FFE of a pollutant is defined by the pollutant load discharged during the initial part of the rainfall period, in which the cumulative pollutant mass is larger than the cumulative rainfall runoff.
- For urban and industrial areas, **FFE analysis is required to understand build-up and wash-off processes.**

Mass first flush (MFF)

$$L' = \int_0^t C(t) \times Q(t)dt\,/M$$

$$V' = \int_0^t Q(t)dt\,/V$$

$$MFF_n = L'/V'$$

- L': the normalized cumulative pollutant mass for each time t
- V': the normalized cumulative runoff volume at each time t
- C(t): the MPs concentration
- Q(t): the runoff volume at time t
- M and V: the total chemical mass and total runoff volume

MFF from observed MPs

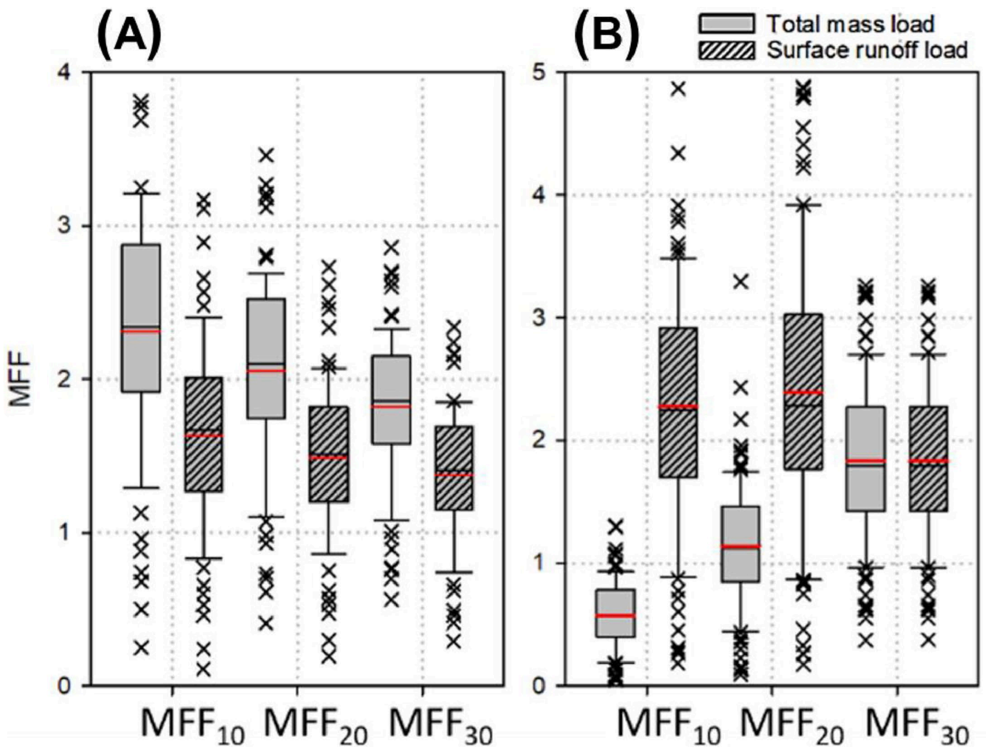
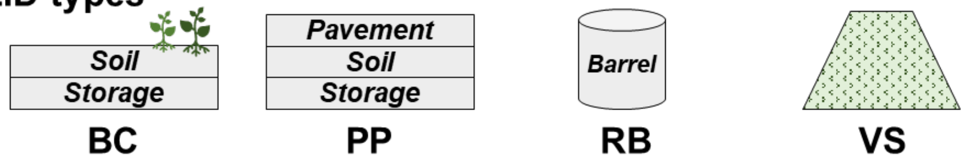


Figure. Calculated MFF10, MFF20, and MFF30 values for (A) event 1 and (B) event 3. In event 3, the FFE pattern of each chemical usage group (i.e., pharmaceutical, industrial, and pesticide) differed significantly from that of event 1.

MP management strategy: LID

LID modules in SWMM

LID types



Bioretention Cell (BC) capture and treat stormwater through filtration, infiltration, and biological processes.

- Shallow depressions with engineered soil and vegetation.
- Remove pollutants and recharge groundwater.

Pervious Pavement (PP) allows stormwater infiltration through the pavement.

- Reduces surface runoff and encourages groundwater recharge.
- Filters pollutants through permeable layers.

Rain Barrel (RB) collects and stores rooftop rainwater.

- Reduces stormwater runoff and demand on municipal water supplies.
- Alleviates pressure on stormwater infrastructure.

Vegetative Swale (VS) promotes infiltration and filtration.

- Shallow, vegetated channels for stormwater conveyance and treatment.
- Vegetation removes pollutants and reduces runoff volume.

	LID Parameters	BC	PP	RB	VS
Surface	Berm Height (in)	5	0	-	0.077
	Vegetation Volume Fraction	0	0	-	0
	Surface Roughness (n)	0.1	0.1	-	0.24
	Surface Slope (percent)	0	1	-	2
	Swale side slope	-	-	-	2
Pavement	Thickness (in)	-	5	-	-
	Void Ratio (Voids/Solids)	-	0.12	-	-
	Imperv.Fraction	-	0	-	-
	Permeability (in/hr)	-	19.7	-	-
	Clogging Factor	-	9179	-	-
	Regeneration Interval	-	0	-	-
	Regeneration fraction	-	0	-	-
Soil	Thickness (in)	27.5	18	-	-
	Porosity	0.5	0.5	-	-
	Field Capacity	0.2	0.2	-	-
	Wilting Point	0.1	0.1	-	-
	Conductivity (in/hr)	0.5	0.5	-	-
	Conductivity Slope	10	10	-	-
	Suction Head (in)	3.5	3.5	-	-
Storage	Thickness (in)	11.8	11.8	29.52	-
	Void Ratio (Voids/Solids)	0.6	0.625	-	-
	Seepage Rate (in/hr)	0.04	0.04	-	-
	Clogging Factor	7042	7042	-	-
Drain	Flow Coefficient	0	0	0	-
	Flow Exponent	0.5	0.5	0.5	-
	Offset (in)	0	0	0	-
	Drain Delay (hr)	-	-	6	-
	Open Level (in)	-	-	-	-
	Closed Level (in)	-	-	-	-

Sensitivity analysis and model evaluation criteria

LH-OAT method

LH-OAT = Latin Hypercube (LH) sampling

+ One-factor-At-a-Time (OAT)

Combination of One-factor-At-a-Time (OAT) design and Latin Hypercube (LH) sampling by taking LH samples as initial points for an OAT design.

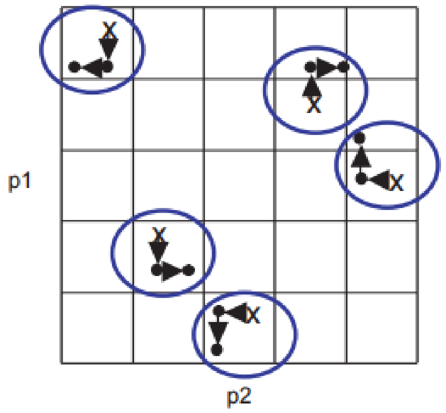


Figure 3 Illustration of LH-OAT sampling of values for a two parameters model where X represent the Monte-Carlo points and • the OAT points (van Griensven *et al.*, 2004).

Model evaluation

Coefficient of determination (R^2)

$$R^2 = \left(\frac{\sum_{i=1}^{N}(P_i - P_{mean})^2 (O_i - O_{mean})^2}{\sqrt{\sum_{i=1}^{n}(P_i - P_{mean})^2} \sqrt{\sum_{i=1}^{n}(O_i - O_{mean})^2}} \right)^2 \quad (8)$$

Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - P_i)^2}{N}} \quad (9)$$

Nash-Sutcliffe efficiency (NSE)

$$NSE = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(O_i - O_{mean})^2} \quad (10)$$

- O_i and P_i are the observed and predicted value at time step i.
- O_{mean} and P_{mean} are the mean of observation and prediction, respectively. N is the number of samples.
- These criteria have been used for comparing the predicted and observed values (Nash and Sutcliffe, 1970; Ritter and Munoz-Carpena, 2013).

3. Results and Discussion

MP monitoring

Characteristics of micropollutants in stormwater

MP name	Class	Min (ng/L)	Mean (ng/L)	Max (ng/L)	DF (%)
Caffeine	Pharmaceutical	59.6	1015.6	3369.8	100
9H_PFNA	PFCs	106.0	523.0	2707.6	100
Trimethyl phosphate	OPFRs	20.1	123.1	20115.0	100
Carbamazepine	Pharmaceutical	16.1	124.3	385.3	100
PFOS	PFCs	3.3	10.1	74.2	100
Acetaminophen	Pharmaceutical	150.7	695.0	3051.7	100
PFOA	PFCs	4.4	11.4	18.7	100
Benzotriazole	Industrial chemical	272.2	1350.0	5156.3	100

- BTR (Benzotriazole): High mean concentration (1350.04 ng/L), indicating urban anthropogenic activities (Tran et al., 2019).
- PFOS (Perfluorooctane sulfonate): Lowest mean concentration (10.11 ng/L), environmental concerns due to persistence (Kim and Kannan, 2007; Xiao et al., 2012; Zushi and Masunaga, 2009).
- 9H-PFNA (Nonanoic acid perfluorononylethyl ester): Highest mean concentration (523 ng/L) observed in a street sweep study (Ahmadireskety et al., 2021).
- ACT, CFN, and CBZ: Mean concentrations of 695.03 ng/L, 1015.61 ng/L, and 124.30 ng/L, respectively, detected in the Nakdong river, indicating wastewater contamination (Park and Jeon, 2021; Yun et al., 2022).
- Persistence and dominance of micropollutants confirmed in the catchment (MFF30 values > 1) (Yun et al., 2023).

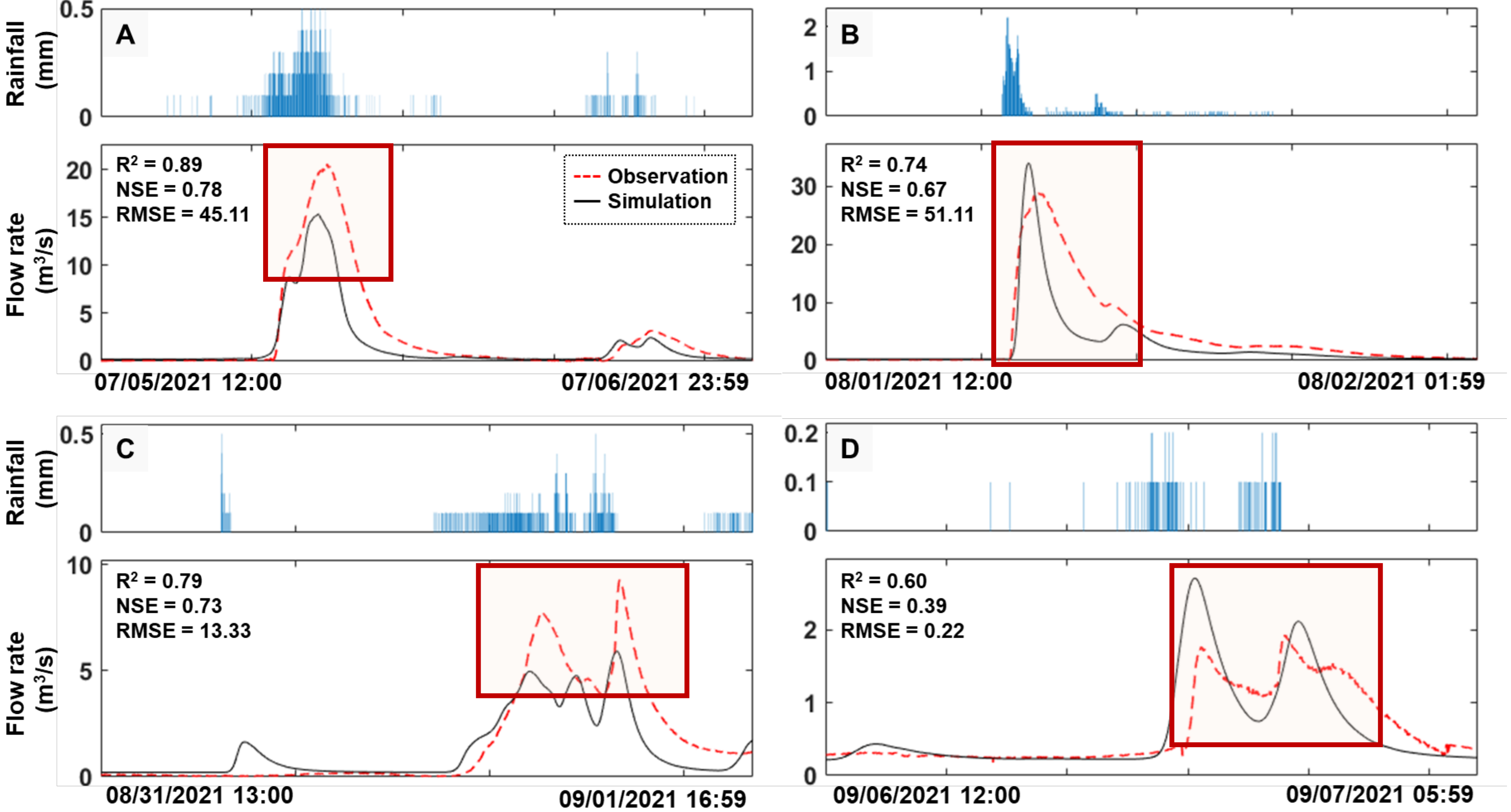
Sensitivity analysis for water quantity and quality simulation

Table 4. Range of hydrologic and micropollutant parameters during the sensitivity analysis, and calibrated parameter values.

	Variable	Parameters	[min, max]	Calibrated value	Rank
Hydrologic module	N-Imperv	Manning's n of impervious area	[0.001, 0.05]	0.015	1
	N-Perv	Manning's n of pervious area	[0.005, 0.5]	0.40	6
	S-Imperv	Depth of depression storage on impervious area (mm)	[0.01, 1]	0.098	4
	S-Perv	Depth of depression storage on pervious area (mm)	[0.01, 1]	0.16	8
	Pct-Zero	Percent of the impervious area with no depression storage (%)	[10, 100]	98.85	3
	Suction	Average capillary suction	[0.1, 10]	1.87	9
	Hycon	Saturated hydraulic conductivity	[0.01, 5]	3.09	5
	IMDmax	Maximum infiltration rate	[0.001, 0.2]	0.13	7
	ConduitN	Conduit Manning's n (concrete)	[0.001, 0.05]	0.013	2

- Most sensitive parameter: **N-Imperv** (Manning's roughness coefficient of impervious subareas), followed by ConduitN (Manning's roughness coefficient of pipelines), **PctZero** (percentage of impervious area without depression storage), and S-Imperv (depression storage in impervious surfaces).
- **N-Imperv** and **ConduitN** affect flow routing, while **PctZero** and **S-Imperv** relate to depression storage, influencing the hydrograph shape and exhibit inverse effects on runoff volume (Rossman, 2010a).
- Other parameters (Ksat, N-Perv, IMD, S-Perv, Suction) had lower ranks but adjusted for their importance in infiltration calculations.
- **Impervious surface parameters have a significant impact on the model's output.**

Flow rate simulation



Underestimated flow rate and the faster time of simulated discharge than the observation.

- Simulating the arrival of peak flows and their instantaneous timing poses challenges due to hidden factors like sewer inlets and buried pipelines (Fassman-Beck and Saleh, 2021).

MP simulation

Sensitivity analysis

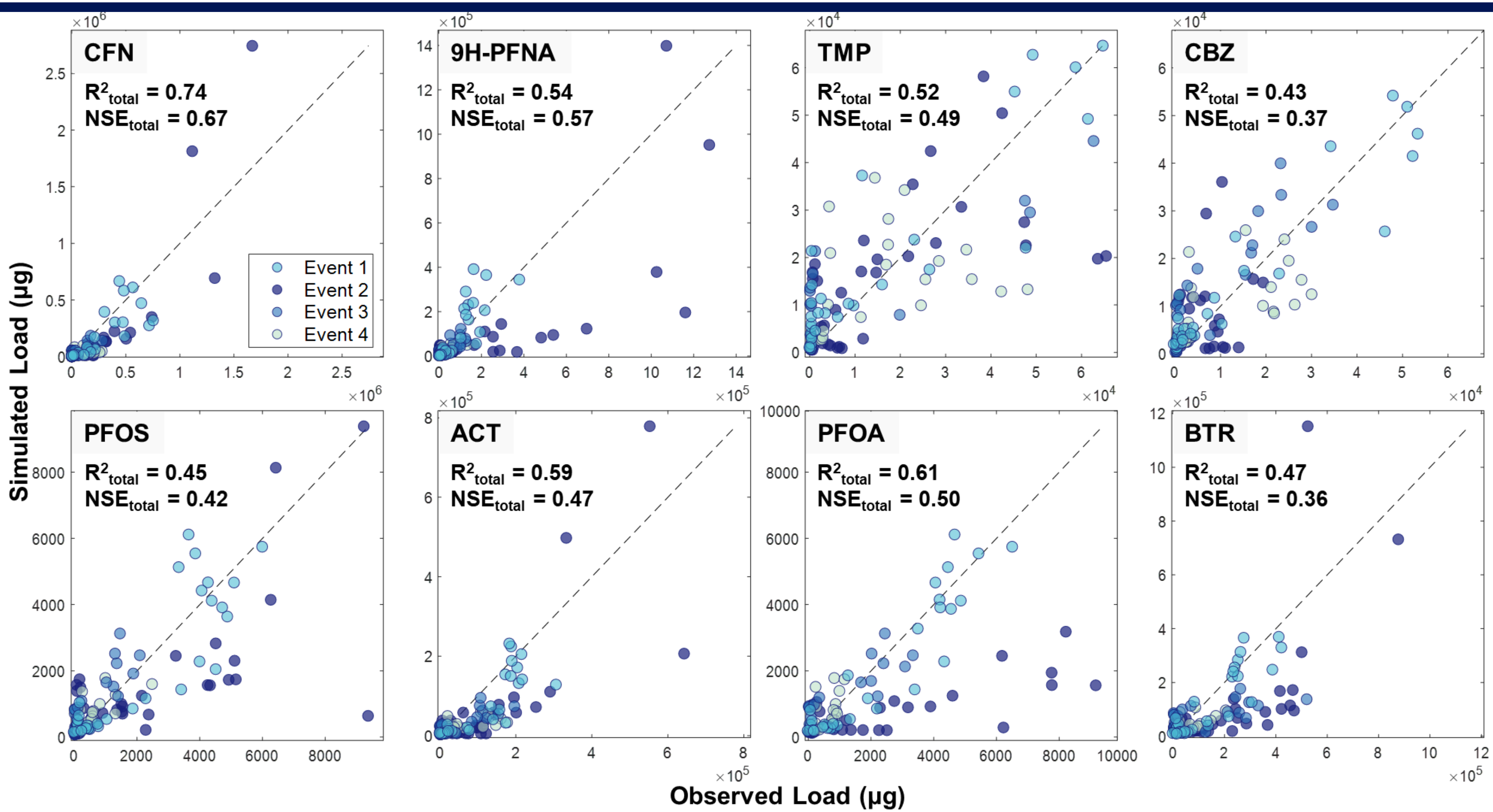
	Variable	Parameters	[min, max]	Calibrated value	Rank
Pollutant build-up/wash-off	Build-up	Build-up function	-	EXP, SAT	4
	C1(B)	Maximum build-up possible	[0, 30]	1.08-4.05	3
	C2(B)	Half saturation constant	[0, 1]	0.3-0.68	6
	Wash-off	Wash-off function	-	RC	1
	C1(W)	Wash-off coefficient	[0, 30]	0.64-26.51	5
	C2(W)	Wash-off exponent	[0, 10]	0.49-1.24	2

Build-up/Wash-off parameters for each MP

MP name	Build-up Function	C1(B)	C2(B)	Wash-off Function	C1(W)	C2(W)
Caffeine	SAT	2.05	0.3	RC	24.51	0.99
9H-PFNA	SAT	2.05	0.3	RC	9.51	1.24
Carbamazepine	SAT	2.05	0.55	RC	7.89	0.77
Acetaminophen	SAT	2.05	0.30	RC	26.51	0.49
Trimethyl phosphate	SAT	4.05	0.55	RC	13.51	0.49
PFOS	SAT	2.05	0.30	RC	26.51	0.49
PFOA	EXP	1.08	0.34	RC	0.64	0.71
Benzotriazole	SAT	2.05	0.68	RC	25.76	0.86

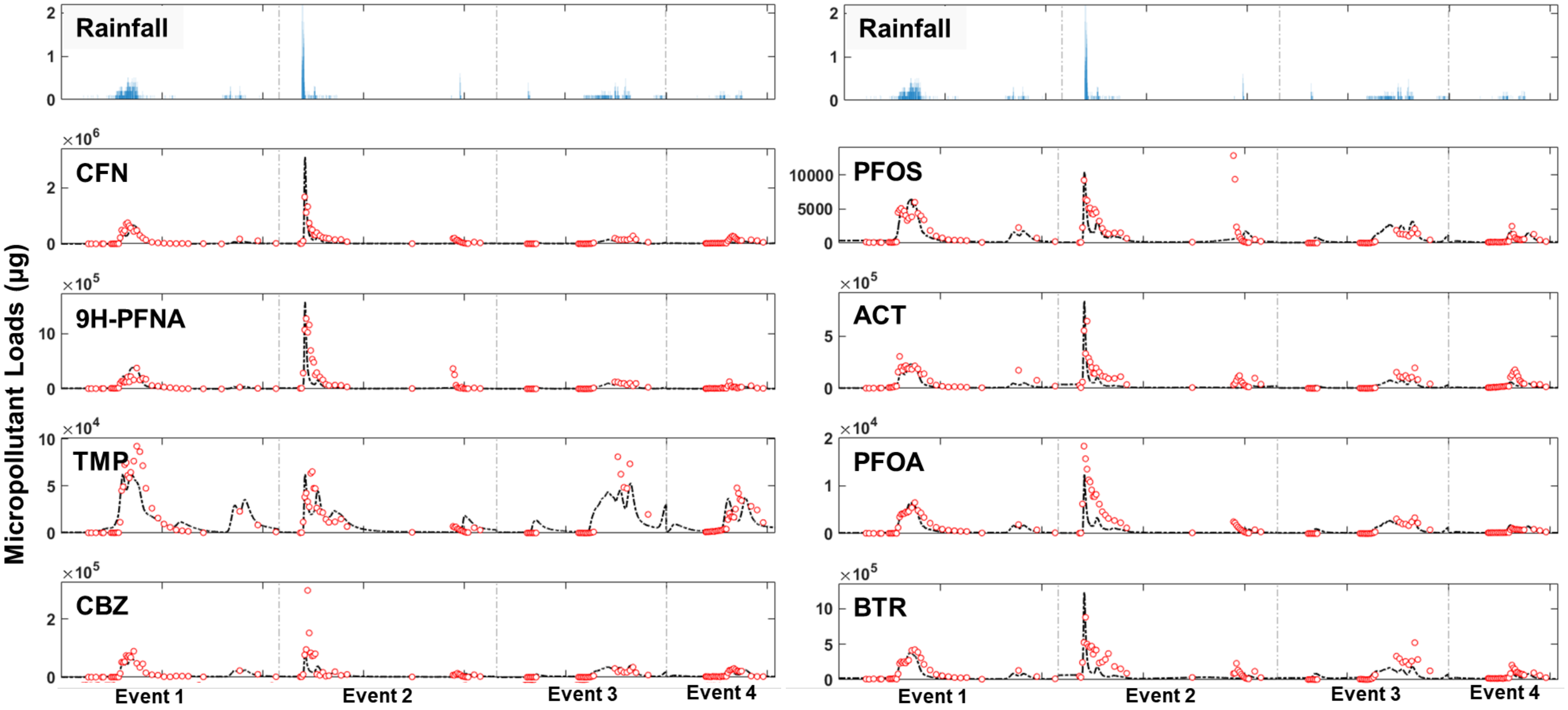
- **Wash-off function** and **C2(W)** were identified as the most sensitive parameters for micropollutant output.
- **C2(B)** showed the least sensitivity among the parameters analyzed.
- **Rating curve wash-off function** was used to estimate pollutant transport, considering the interrelation between pollutant surface runoff and wash-off.
- Each MP has the different coefficient (C1) and exponent (C2) values for **saturation build-up and rating curve wash-off.**
- Previous studies have applied this methods to investigate the behavior of pollutants in impermeable areas (Gülbaz and Kazezyilmaz-Alhan, 2012; Gülbaz et al., 2019; Palli et al., 2021; Wicke et al., 2012), but not MPs.

MP simulation



- The micropollutant modeling **underestimated the observed loadings**, mainly due to similar tendencies in flow rate results, which directly impact pollutant loadings.
- **CFN showed the highest performance** with an R^2 value of 0.74 and NSE value of 0.67, while CBZ and BTR had the lowest R^2 values of 0.43 and 0.47, and NSE values of 0.37 and 0.36, respectively.

MP simulation



- Satisfactory performance was observed in predicting all micropollutants for **events 1 and 3, with NSE values above 0.35.**
- Events 2 and 4 had lower NSE values, indicating limited simulation results due to rapid runoff increase and small rainfall amounts, respectively.

LID simulation

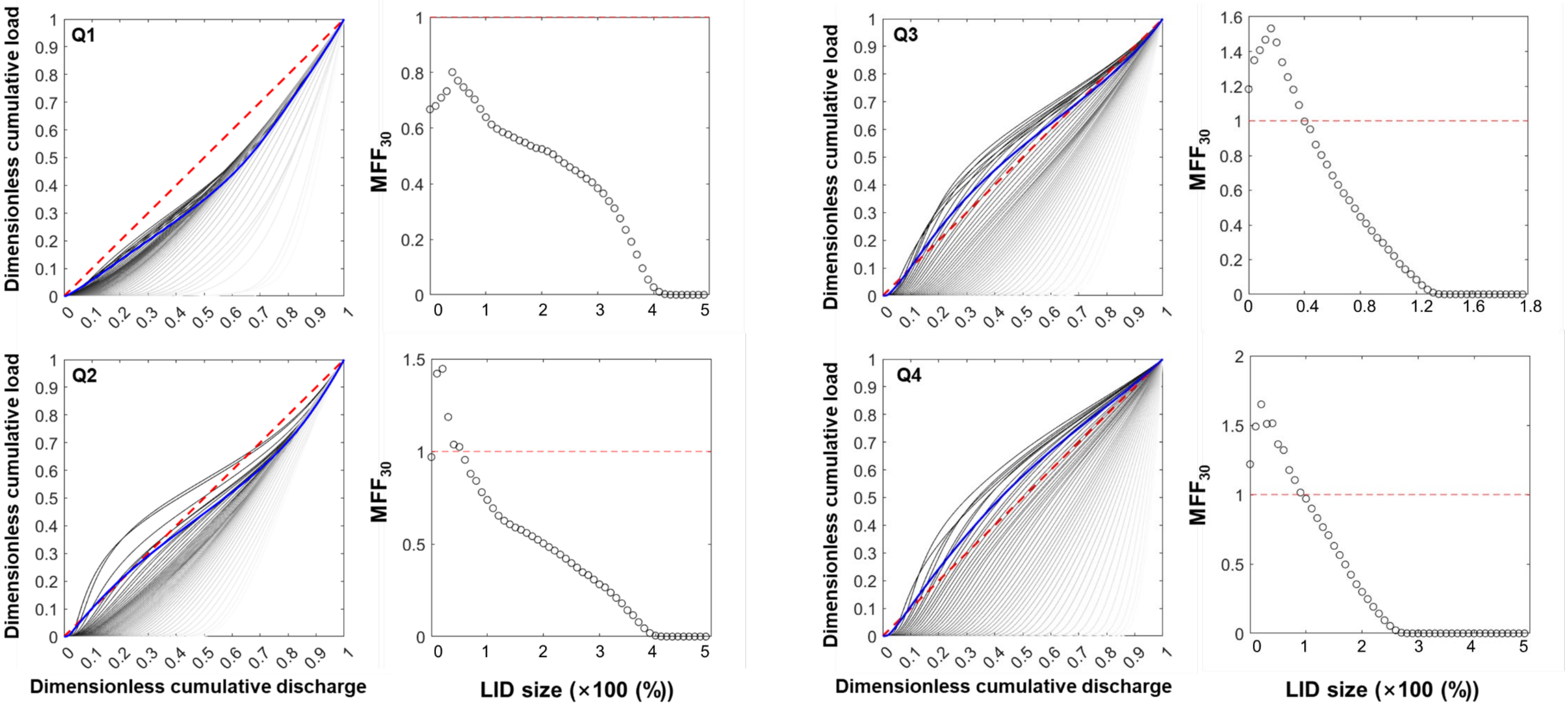
MFF30 for rainfall scenarios

Representative rainfall	Micropollutant	MFF30	LID size (%)			
			BC	PP	RB	VS
Q1	Caffeine	1.114	1.8	2.0	0.64	2.7
	9H-PFNA	1.061	1.6	1.7	0.58	2.2
Q3	Trimethyl phosphate	1.18	1.0	1.1	0.32	1.6
	Carbamazepine	1.07	1.0	1.0	0.30	1.4
Q4	Trimethyl phosphate	1.22	1.0	1.1	0.34	1.4
	Carbamazepine	1.09	0.9	1.0	0.30	1.3

- The initial **MFF30 ratio for TMP** under Q4 was 1.22, indicating that 36.6% of the pollutant mass was transported by the first 30% of runoff volume.
- Increasing the size of LID applications resulted in a decrease in the MFF30 ratio, indicating a reduction in the first flush (FF) effect.
- **Bioretention cells** and **pervious pavement** showed similar decreasing patterns in the FF effect and treated approximately 1.0% to 1.1% of subareas.
- **Rain barrels**, with an application size of 0.34% of subareas, exhibited a decreasing FF effect similar to bioretention cells and pervious pavement.
- **Vegetative swales**, with the largest construction size of 1.4%, had lower effectiveness but the lowest maintenance cost among the LID facilities studied.
- The effectiveness of LID measures depends on factors such as catchment condition, hydraulic properties of the facilities and catchment, and considerations of dispersion, detention, and lag time.

LID simulation

Simulation result of bioretention for TMP



4. Conclusion

Conclusion

Summary

- The SWMM model demonstrated acceptable performance in simulating flow rates and micropollutants in urban stormwater, with **NSE values > 0.5 for three out of four rainfall events.**
- Sensitivity analysis identified key parameters influencing water quantity and quality simulations, highlighting the importance of **roughness coefficients and wash-off functions.**
- **Caffeine** showed the highest simulation performance among micropollutants, while **Carbamazepine** and **Benzotriazole** had lower performance across all rainfall events.
- Representative rainfall patterns with larger FF effects were selected as **4th quartile** for LID design and analysis.
- LID applications demonstrated the potential to mitigate micropollutants, with **larger sizes resulting in lower MFF30 values**.
- The SWMM model provides a valuable tool for predicting MP loadings, estimating FF effects, and assessing the effectiveness of LID measures in reducing MP runoff risks in urban areas.

Challenges

- Further model development is needed to improve accuracy and address uncertainties related to pollutant transport processes such as adsorption, desorption, and resuspension.
- More mathematical solutions are required to enhance the precision of MP estimation in urban stormwater.
- These challenges should be considered for future research and refinement of the SWMM model to enhance its applicability and reliability in assessing and managing micropollutants in urban stormwater systems.

Thank You

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