Influences of rainfall variables and antecedent discharge on urban effluent concentrations and loads in wet weather

Zuxin Xu, Lijun Xiong, Huaizheng Li, Zhengliang Liao, Hailong Yin, Jun Wu, Jin Xu and Hao Chen

ABSTRACT

For storm drainages inappropriately connected with sewage, wet weather discharge is a major factor that adversely affects receiving waters. A study of the wet weather influences of rainfall-discharge variables on storm drainages connected with sewage was conducted in the downtown Shanghai area (374 ha). Two indicators, event mean concentration (EMC) and event pollutant load per unit area (EPL), were used to describe the pollution discharge during 20 rain events. The study showed that the total rainfall and discharge volume were important factors that affect the EMCs and EPLs of the chemical oxygen demand, total phosphorus, and especially those of NH_4^+-N. The pollutant concentrations at the beginning of the discharge and the discharge period were also major factors that influence the EMCs of these three pollutants. Regression relationships between the rainfall-discharge variables and discharge volume/ EPLs ($R^2 = 0.824$–0.981) were stronger than the relationships between the rainfall-discharge variables and EMCs. These regression equations can be considered reliable in the system, with a relative validation error of less than ±10% for the discharge volume, and less than ±20% for the EPLs. The results presented in this paper provide guidance for effectively controlling pollution in similar storm drainages.

Key words | correlation coefficients, event mean concentration (EMC), event pollution load per unit area (EPL), multiple linear regression equation, urban wet weather discharge (UWWD)

Zuxin Xu
Lijun Xiong (corresponding author)
Huaizheng Li
Zhengliang Liao
Hailong Yin
Jun Wu
Jin Xu
Hao Chen
Key Laboratory of Yangtze River Water Environment, Ministry of Education,
Tongji University,
Shanghai 200092,
China
E-mail: *xionglj@saes.sh.cn*

INTRODUCTION

For reasons such as planning, construction and management, the erroneous flow of sewage in storm drainages has become a widespread problem in some urban storm drainages (Xu & Zhang 2010; Morihama *et al.* 2012; Li *et al.* 2014; Xu *et al.* 2014). In some regions, sewage during dry periods is intercepted and transported to wastewater treatment plants (WWTPs); however, some excess sewage can still be discharged into receiving waters (i.e., rivers) due to a limited interception capacity. In wet weather, stormwater and sewage are both discharged into receiving waters, which is referred to as urban wet weather discharge (UWWD) (Bi *et al.* 2015a). Three main pollution sources contribute to UWWD: sanitary and industrial sewage, nonpoint-source pollution from urban surfaces, and sediment that has accumulated in storm drainages during dry periods (Bertrand-Krajewski *et al.* 1998; Soonthornnonda & Christensen 2008; Gasperi *et al.* 2010; Zgheib *et al.* 2012). As cities develop, the percentage of impervious area increases, thereby increasing the amount of runoff, altering the original runoff processes under natural conditions, decreasing the natural storage capacity of the soil, accelerating the time of the runoff peak appearance and increasing the peak flow (Lee & Bang 2000; Zhang *et al.* 2012; Chow *et al.* 2013). According to some previous studies, global climate change is increasing the frequency and intensity of rainfall; hence, surface runoff into storm drainages will significantly increase, consequently washing more sediment into receiving waters (Jalliffier-Verne *et al.* 2015). The growth of urban populations also increases the quantity of sewage that ends up in storm drainages. Therefore, the pollution discharged into receiving waters through urban storm drainages in wet weather seriously threatens the hydrologic environment. Furthermore, pollution in the early stage of

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discharge contains many pathogenic microorganisms, nutrients (nitrogen and phosphorus) and toxic substances (Casadio *et al.* 2010; Bi *et al.* 2015b; Thorndahl *et al.* 2015). If the discharge is not treated or intercepted effectively, these pollutants will directly enter receiving waters, threatening both the urban hydro-ecological environment and human health (Gromaire *et al.* 1997; Chebbo & Gromaire 2004). Thus, to control UWWD effectively, it is important to study the influences of rainfall variables and antecedent discharge on urban effluent concentrations and loads in wet weather.

The factors that influence UWWD are complex. Some researchers have suggested that UWWD is related to the catchment surface area, type of land use, proportions of impervious surfaces, local meteorology, connected sewage, rainfall characteristics, etc. (Li *et al.* 2010; Sun *et al.* 2011; Feng & Wu 2012). In different regions, the event mean concentration (EMC) and event pollutant load per unit area (EPL) are different (Kafi *et al.* 2008; Becouze 2010; Bi *et al.* 2015a). In a specific area, rainfall characteristics are important factors; however, in storm drainages connected inappropriately with sewage, the previous discharges are also important. The influence of rainfall on pollution discharge has been previously studied (Bertrand-Krajewski *et al.* 1998; Gromaire-Mertz 2000; Kafi *et al.* 2008; Gasperi *et al.* 2010; Park *et al.* 2010; Bi *et al.* 2015a). However, studies of the influences of both rainfall and previous discharges on the pollution discharge have not yet been carried out in detail, especially for storm drainages connected inappropriately with sewage.

Quantitative research on effluent concentrations and loads in wet weather has generally been performed based on two approaches. The first approach is numerical simulation based on the understanding of physical models (Tsihrintzis & Hamid 1998; Choi & Ball 2002; Krebs *et al.* 2013; Madarang & Kang 2014; Mancipe-Munoz *et al.* 2014). This approach has the advantage of requiring less pollutant monitoring data; however, it requires numerous characteristic parameters. The second approach involves building a statistical regression equation. This approach is operationally simple, and it includes fast calculations that require fewer input variables. The major disadvantage of this approach is that it requires a large amount of monitoring data. Additionally, regression equations cannot be extrapolated to other regions. In a data-rich area, a statistical regression equation can reflect the relationship between a dependent variable and independent variables, easily predict research factors and be applied to studies of pollution discharge (Lewis 1996; Irish *et al.* 1998; Brezonik & Stadelmann 2002; Schilling & Wolter 2005; Wang & Linker 2008; Nason *et al.* 2012; Chow *et al.* 2013). For example, Madarang & Kang (2014) built linear regression equations of antecedent dry days for both total suspended solids (TSS) loads and the EMCs of rainfall variables (Madarang & Kang 2014). Chen and Chang constructed a multiple linear regression of antecedent precipitation, TSS and temperature for *Escherichia coli* prediction (Chen & Chang 2014). Ellison *et al.* built a simple linear regression of stream discharge and suspended sediment concentrations (Ellison *et al.* 2006). All of these studies focused more on the relationship between discharge pollution and rainfall and less on the relationships between discharge pollution, rainfall and antecedent discharge. Different drainage systems, regional population densities and land use structures produce different relationships among discharge pollution, rainfall and antecedent discharge. Therefore, regions with high population densities, high degrees of urbanization and combined sewage should build individual regression equations between discharge pollution, rainfall and antecedent discharge. Understanding these relationships and quantifying discharge concentrations and loads in wet weather can improve design criteria and optimize interception, thereby controlling pollution associated with UWWD. Thus, the concentrations and loads of pollutants in these types of storm drainages should be examined and analyzed to determine their correlations with rainfall and antecedent discharge and improve the water quality of receiving waters.

In this paper, 20 rain events were surveyed in the storm drainage of Xuhui District, Shanghai, China, in 2011 and 2015. The rainfall variables and discharge variables in antecedent dry or wet weather conditions were considered to assess the characteristics of pollution discharge at the event scale. The main objectives of this study are as follows: (1) identify the main factors that influence the EMCs and EPLs of major pollutants during rainfall events; (2) identify the correlations between the EMCs and EPLs of major pollutants, rainfall variables and discharge variables; and (3) construct equations to estimate the discharge volume and pollution discharge in wet weather.

MATERIALS AND METHODS

Study area

This study was conducted in the Caohejing catchment area (Figure 1), which is a typical high-density urbanized area (approximately 270 population/ha) in Shanghai's downtown area, comprising 374 ha. The land consists of residential (41%); commercial, physical and institutional (27%); industrial (25%); and park (7%) areas. The storm recurrence interval in the Caohejing catchment area is 1 year, and the

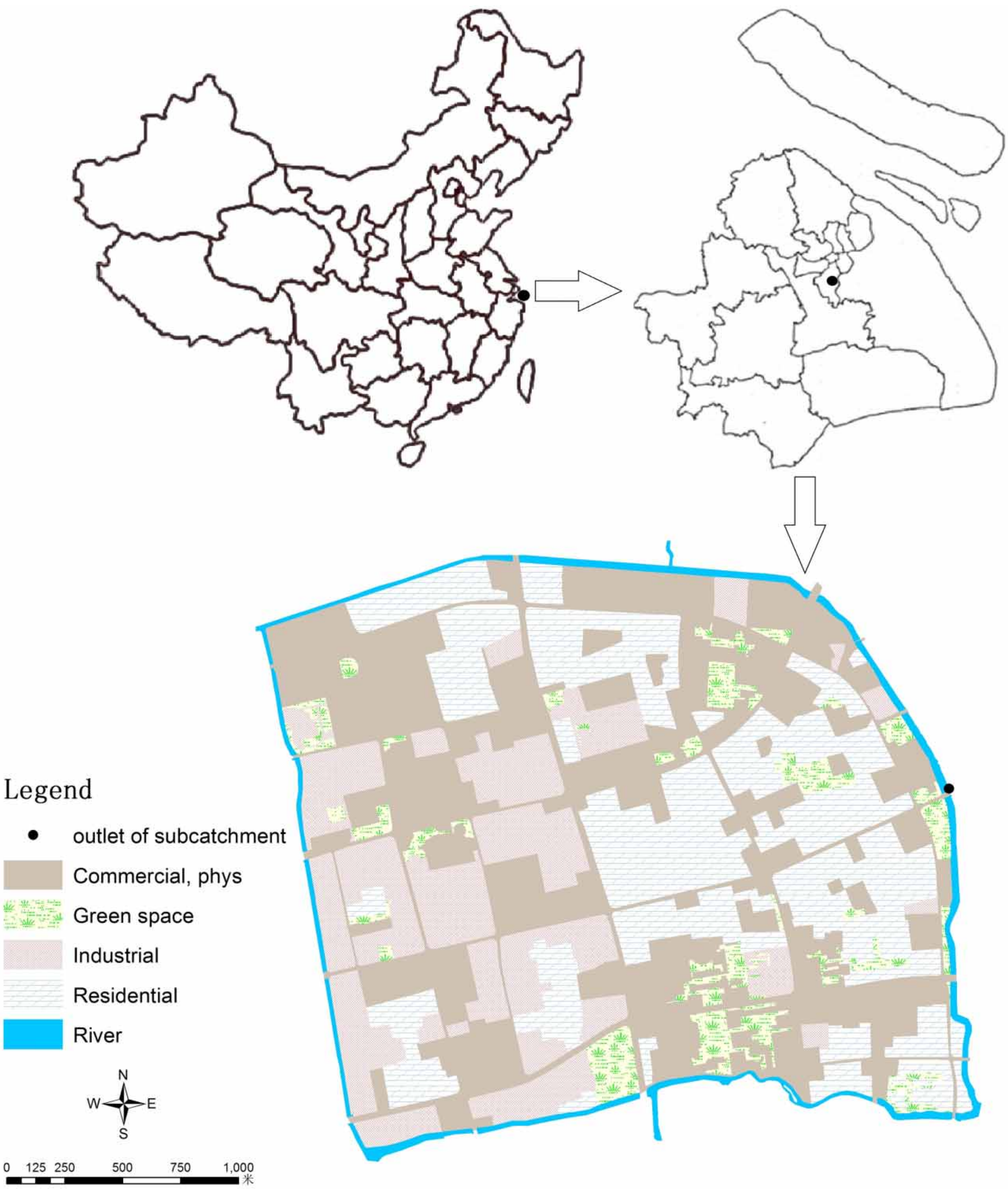

Figure 1 | Location and land use of the Caohejing catchment.

total runoff coefficient is 0.7. The Puhui River receives discharge from the storm drainage in the catchment. The pumping station in the Caohejing catchment area is a flood control pumping station equipped with six axial flow pumps (2.3 m^3/s per pump) that discharge stormwater to the Puhui River. In the area, there are 200 pollution sources inappropriately connected to the storm drainage. In dry weather, the station is equipped with two additional sewage interception pumps (0.25 m^3/s per pump) that run 24-hours, and 21,600 m^3/d of sewage is transported to WWTPs. However, due to groundwater infiltration and river water backflow into the storm drainage, some excess sewage is still discharged into the Puhui River (Xu *et al.* 2014). Moreover, during rainfall events, the intercepting pumps are usually closed to reduce the pressure associated with peak flows at WWTPs; thus, stormwater and sewage are mixed and discharged into the Puhui

River. This information was provided by the Shanghai Municipal Sewerage Co., Ltd and the Shanghai Academy of Environmental Sciences.

Sampling and analysis

Samples were collected using an Isco 6712 autosampler at the pumping station forebay in the Caohejing storm drainage. The autosampler was fitted with a data-logging system to record measurements at 15, 30 or 60 min intervals based on the rainfall characteristics. The autosampler started sampling when the axial flow pumps started and continued until the discharge ceased. When the discharge duration was longer than the time required to fill 24 1 L bottles in the autosampler, the bottles were replaced manually with new bottles for continuous sampling. All the samples were stored in HDPE bottles at 4 °C and were analyzed within 8 h. Three identical water samples were collected during each sampling to ensure precision and accuracy.

Four parameters of water quality pollutants were measured, including TSS, chemical oxygen demand (COD), ammonia nitrogen (NH_4^+-N) and total phosphorus (TP). COD is strongly correlated to TSS in these events, with a correlation coefficient ranging from 0.83–0.92, and a high correlation between TSS and COD has been noted in previous studies (He & Tian 2006; Gasperi *et al.* 2010; Bi *et al.* 2015a). In addition, COD is a good indicator of organic pollution and eutrophication in aquatic environments. Therefore, COD is selected to analyze the relationship between the discharged pollution and rainfall-discharge variables in this study. TP is another indicator of eutrophication in aquatic environments, and NH_4^+-N is soluble and mainly associated with sewage (Soonthornnonda & Christensen 2008; Gasperi *et al.* 2010; Li *et al.* 2013). Therefore, indicators of COD, NH_4^+-N and TP were selected to analyze the relationships between the discharged pollution and rainfall-discharge variables in this study. These parameters and their respective analytical limits of detection (LOD) fell within the national standard guidelines of China.

Rainfall events

The annual average rainfall in Shanghai was 1,133 mm from 1971 to 2010, with a minimum rainfall of 667 mm in 1978 and a maximum rainfall of 1,729 mm in 1977. Most of the rainfall occurred during the summer and autumn, corresponding to the southeast monsoon season in Shanghai. A rain gauge was placed at the Caohejing pump station, and rain and discharge data were obtained from the comprehensive drainage application system of the Shanghai Municipal Sewerage Company, Ltd (see http://www.smsc.sh.cn/oa_index/).

According to the classification standard of the Shanghai Municipal Sewerage Co., Ltd, a total rainfall of less than 10 mm in 24 h was classified as light rain, 10–25 mm was classified as moderate rain, 25–50 mm was classified as large rain and more than 50 mm was classified as heavy rain. Of the 235 rainfall events with 0.2–173.2 mm of rainfall that occurred from 2009 to 2011, 156 were light rains, accounting for 66.4% of all rainfall events. Additionally, 41 were moderate rains, 26 were large rains and 12 were heavy rains, accounting for 17.4%, 11.1%, 5.1% of all events, respectively, as shown in Figure 2.

Generally, the pollutant concentrations in discharge are higher during light and moderate rains; however, the pollutant concentrations in the early stage of discharge are high during heavy rains, but then decrease due to rainwater dilution. To better describe the characteristics of the pollution discharge, light to moderate rain events are the focus of this study. Twenty typical rainfall events were selected in 2011 and 2015 (Table 1). Among these events, four were less than 10 mm (light rain), nine were between 10 and 25 mm (moderate rain), three were between 25 and 50 mm (large rain) and four were more than 50 mm (heavy rain). Five rainfall variables were selected to describe the rainfall characteristics: total rainfall (R_{total}), rainfall duration ($R_{duration}$), mean rainfall intensity ($R_{intensity}$), peak rainfall (R_{peak}) and dry antecedent time (D_{dry}). Because the storm drainages are connected with sewage, the discharge pollution is not only related to the volume of discharge ($V_{discharge}$) but also to the pollutant concentrations at the beginning of the rainfall event (i.e., the initial concentrations and pollutant concentrations of the first sample). The initial concentrations are affected by sediments that accumulate due to sanitary and industrial sewage inputs during dry periods. Xu *et al.* showed that sediment accumulation is an important factor that affects the pollution load at the

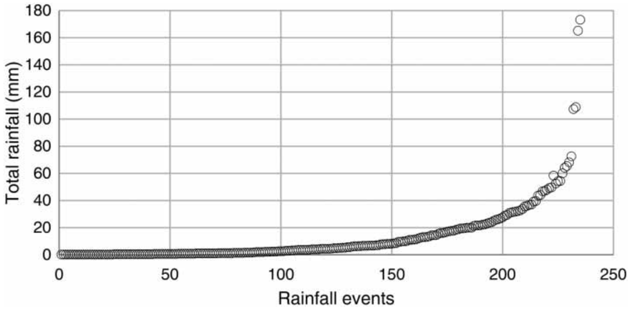

Figure 2 | The total rainfall in 235 events from 2009 to 2011.

Table 1 | Primary characteristics of the 20 rainfall events

Event number	Event date (2011)	R_{total} (mm)	$R_{duration}$(h)	$R_{intensity}$ (mm/h)	R_{peak} (mm/h)	D_{dry} (h)	$V_{discharge}$ (m^3)	$T_{ant\ discharge}$ (h)	$V_{ant\ discharge}$ (m^3)	Sample number
E1	2011/5/22	28.8	30.0	1.0	5.3	18.3	68,300	84	2,070	26
E2	2011/6/4	19.1	20.5	0.9	6.9	270.3	60,030	96	2,070	20
E3	2011/6/10	46.0	49.3	0.9	27.7	8.5	190,440	12	45,540	24
E4	2011/6/17	158.3	49.8	3.2	34.5	29.0	892,170	8	53,820	57
E5	2011/9/29	15.3	19.8	0.8	8.5	208.0	45,540	264	24,840	17
E6	2011/10/20	0.5	3.8	0.1	0.3	157.3	28,980	41	12,420	11
E7	2011/10/24	11.2	11.8	1.0	2.2	70.3	66,240	72	28,980	23
E8	2011/11/2	21.8	14.5	1.5	5.3	75.8	99,360	108	24,840	24
E9	2011/12/6	28.7	41.5	0.7	2.2	134.8	91,080	12	44,140	34
E10	2015/4/28	21.8	10.9	2.0	16.9	203.7	86,940	180	3,864	6
E11	2015/5/2	9.7	10.2	1.0	6.5	73.8	36,708	82	86,940	9
E12	2015/5/8	6.5	5.4	1.2	3.6	112.1	59,064	55	4,140	18
E13	2015/5/11	9.1	20.7	0.4	4.0	41.3	47,886	61	59,064	14
E14	2015/5/15	27.9	16.1	1.7	6.1	82.1	97,704	93	47,886	20
E15	2015/5/18	15.8	6.1	2.6	10.0	47.1	71,622	66	97,704	15
E16	2015/5/27	18.7	4.8	3.9	13.4	83.4	101,982	31	2,622	20
E17	2015/6/2	59.9	21.4	2.8	19.1	90.5	323,058	127	101,982	32
E18	2015/6/15	115.5	18.5	6.3	14.4	153.3	804,402	172	57,960	48
E19	2015/7/1	21.8	10.9	2.0	10.1	17.2	85,284	36	37,536	11
E20	2015/7/10	75.0	36.6	2.0	4.5	16.7	429,870	14	35,190	39

outlet (Xu *et al.* 2014). Antecedent discharge carries away some of the sediments and decreases the amount of sediment present during the next rainfall event. More sediment will accumulate if the interval between the antecedent discharge and next discharge event is large. Therefore, two discharge variables were selected to describe the antecedent discharge characteristics and study the effect of antecedent discharge on current discharge pollution: the antecedent discharge volume ($V_{ant\ discharge}$) and the time interval between the two adjacent discharges ($T_{ant\ discharge}$).

Data processing

EMC is an important analytical parameter that refers to the discharge-weighted average concentration of a pollutant based on the entire discharge volume in wet weather (Smullen *et al.* 1999). The EMC value was determined as follows:

$$EMC = \frac{\sum_{t=1}^{n} C_t Q_t \Delta t}{\sum_{t=1}^{n} Q_t \Delta t} \text{ in mg/l} \quad (1)$$

where C_t (mg/l) is the pollutant concentration at time t, Q_t (m^3/s) is the discharge flow rate at sampling time t, n is the total number of times that the discharge was sampled and Δt (min) is the sampling time interval.

EPL reflects the load density of each pollutant (Li *et al.* 2015), which is the load per active surface area for a specific event. Values of EPL are obtained using the following formula:

$$EPL = \frac{EMC \cdot V_{discharge}}{A} \text{in g/ha} \quad (2)$$

where A is the active surface area in the catchment that effectively contributes to runoff (ha).

The EMC and EPL values of the pollutants were calculated to describe the characteristics of discharge for each event. The experimental data were analyzed using a statistical approach. In this paper, the statistical analysis software package IBM SPSS Statistics 19.0 was used to compute the Pearson's correlation coefficient (r) and determine the correlations between the EMC and EPL values of the pollutants and the rainfall-discharge variables. The variables are fully correlated if values of −1 (negative correlation) or 1 (positive correlation) are obtained. A weak correlation was defined as values between 0 and 0.3, and a low correlation was defined as values between 0.3 and 0.5. Furthermore, values between 0.5 and 0.8 indicated a significant correlation, and values between 0.8 and 1 indicated a highly significant correlation. The statistical significance of each correlation coefficient was assessed using Student's t-test, and critical values were obtained from Pearson's table for n = 2 degrees of freedom (where n is the observed sample size) at different statistical risk levels ($P = 0.05$ or 0.01).

A multiple linear regression equation was used to estimate the discharge volume, EMC and EPL, which are affected by multiple factors. IBM SPSS 19.0 was used to build the equation. To avoid multiple collinearity between some variables, a group of variables with high correlation (correlation coefficients higher than 0.8 and lower than 1) was selected according to a bivariate correlation analysis. Then, the variables with large correlation coefficients based on the discharge volume, EMC and EPL were selected in the regression analysis. According to the F statistic values, the stepwise regression method was used to build regression equations for the discharge volume, EMC and EPL. In each step, the independent variables in the regression equation were considered until no variables could be removed from the regression equation and no independent variables could be added, resulting in an equation with the lowest F statistic. The equations of multiple linear regression are expressed as follows:

$$V^*_{\text{discharge}} = a_0 + a_1x_1 + , \cdots , a_ix_i + , \cdots , + a_nx_n \text{ in } m^3 \quad (3)$$

$$EMC^* = b_0 + b_1x_1 + , \cdots , b_ix_i + , \cdots , + b_nx_n \text{ in mg/L} \quad (4)$$

$$EPL^* = c_0 + c_1x_1 + , \cdots , + c_ix_i + , \cdots , + c_nx_n \text{ in g/ha} \quad (5)$$

where x_i ($i = 1$…..n) are independent variables that include rainfall and discharge variables; $V^*_{\text{discharge}}$, EMC^* and EPL^* are the estimated values of discharge volume, EMC and EPL, respectively, according to the independent variables of x_i; and a_i, b_i and c_i ($i = 1$…..n) are the partial regression coefficients of the independent variables. A partial regression coefficient is the ratio of a dependent variable to the change in a single independent variable when the remaining independent variables are fixed.

RESULTS AND DISCUSSION

Inter-event pollutant concentrations and pollutant loads for different rainfall events

Table 2 shows the EMCs and EPLs obtained from Equations (1) and (2) for each monitored pollutant during 20 rain

Table 2 | Basic statistics of pollutant EMCs and EPLs based on 20 events

Statistics	Event	COD	NH_4^+-N	TP	Statistics	Event	COD	NH_4^+-N	TP
EMC (mg/l)	E1	451.7	21.31	4.753	EPL (g/ha)	E1	78,363	3,801	819
	E2	512.9	26.54	5.105		E2	93,234	4,458	846
	E3	175.5	13.22	2.390		E3	111,677	8,493	1,209
	E4	176.9	9.68	1.543		E4	357,877	18,500	3,107
	E5	361.8	18.08	3.942		E5	43,946	2,199	480
	E6	369.7	21.75	4.630		E6	30,872	1,844	391
	E7	256.3	23.37	3.784		E7	42,636	3,869	629
	E8	419.1	18.62	2.226		E8	106,496	4,805	589
	E9	104.8	19.09	2.940		E9	25,663	4,655	719
	E10	880.9	28.25	7.270		E10	204,780	6,568	1,690
	E11	295.8	21.32	3.546		E11	29,032	2,092	348
	E12	519.5	25.49	6.762		E12	82,044	4,025	1,068
	E13	251.2	19.18	3.272		E13	32,166	2,456	419
	E14	274.5	16.71	5.189		E14	71,699	4,365	1,356
	E15	186.6	18.12	2.615		E15	35,739	3,469	501
	E16	440.8	21.81	6.783		E16	120,209	5,948	1,849
	E17	97.7	15.83	2.016		E17	84,369	13,670	1,741
	E18	184.5	9.97	1.621		E18	396,830	21,444	3,487
	E19	99.5	14.57	2.804		E19	22,685	3,323	639
	E20	101.4	13.95	2.138		E20	116,515	16,031	2,458

events. As described in previous studies, the EMC and EPL values varied significantly between wet weather events (Bi et al. 2015a).

In the 20 events, the EMCs of COD, NH_4^+-N and TP ranged from 97.7–880.9 mg/l, 9.68–28.25 mg/l and 1.543–7.270 mg/l, respectively. The ranges of COD and TP were similar to the values reported by Bi et al. (2015a) in CSO Longueuil, Canada (41–830 mg/l for COD and 0.36–5.20 mg/l for TP), and Bertrand-Krajewski et al. (1998) for a combined system of discharge in France (42–900 mg/l for COD). However, the ranges of COD and TP in this study were much higher than the values reported by the United States Environmental Protection Agency (1983) (0.42–0.88 mg/l for TP) and Bi et al. (2015a) (39–58 mg/l for COD and 0.13–0.48 mg/l for TP) for storm sewer water in Boucherville, Canada. The COD EPLs in the discharge ranged from 22,685 to 396,830 g/ha, which was almost more than the 3,000 to 48,000 g/ha in discharge from a combined sewer site in Lyon, France (Becouze 2010), the 26,000 to 57,000 g/ha in discharge from six combined sewer overflows (CSO) in Paris, France (Kafi et al. 2008) and the 65.6 to 15,000 g/ha in discharge from the combined sewer overflow (CSO) in Longueuil, Canada (Bi et al. 2015a). The TP EPLs in the discharge were 348 to 3,487 g/ha greater than that in discharge from the CSO in Longueuil, Canada, which ranged from 0.4 to 79.8 g/ha (Bi et al. 2015a). High population density, connected sewage, street cleaning methods, rainfall patterns and high urbanization likely resulted in the high values observed in the Caohejing catchment area.

The initial concentrations of pollutants are closely related to the sediments in the storm drainage before rainfall events, especially the COD. Previous studies showed that approximately 50–70% of COD pollution from a combined system was associated with sediment from sewage during rainfall events, and the remaining percentage was from surface runoff (Chebbo & Gromaire 2004; Lei et al. 2008). Therefore, it is important for the initial concentration to study the EMCs and EPLs of pollutants in different events. The initial pollutant concentration of the first sample and final pollutant concentration of the last sample of discharge are also summarized in Figure 3. The initial pollutant concentrations, especially COD and TP, are mainly affected by the antecedent discharge volume and the time interval between the two adjacent discharges. For those events with low initial pollutant concentrations, generally they either have a large antecedent discharge volume or a short time interval between the two adjacent discharges. For instance, E17 has the largest antecedent discharge volume, and E19, E9 and E20 have short time intervals in between the two adjacent discharges (12–36 h) as well as relatively large antecedent discharge volumes (35,190–44,140 m^3) (Table 1). For those events with high initial pollutant concentrations, they have a small antecedent discharge volume and a long time interval between the two adjacent discharges (i.e., E1 with 84 h and 2,070 m^3; E10 with 180 h and 3,864 m^3) (Table 1). The final pollutant concentrations are mainly affected by the volume of discharge and the initial pollutant concentrations. Larger discharges will produce lower final pollutant concentrations such as in E8, E3, E17, E20, E18 and E4 (discharge range from 99,360 m^3 to 892,170 m^3) (Table 1). Also, the lower initial pollutant concentrations are likely to have lower final pollutant concentrations, such as in E19 and E9.

Inter-event EMC variability

The EMCs of COD, NH_4^+-N and TP and discharge volumes for 20 events are compared in Figure 4. Of the 20 events, eight exhibited COD EMCs below 200 mg/l (E3, E4, E9,

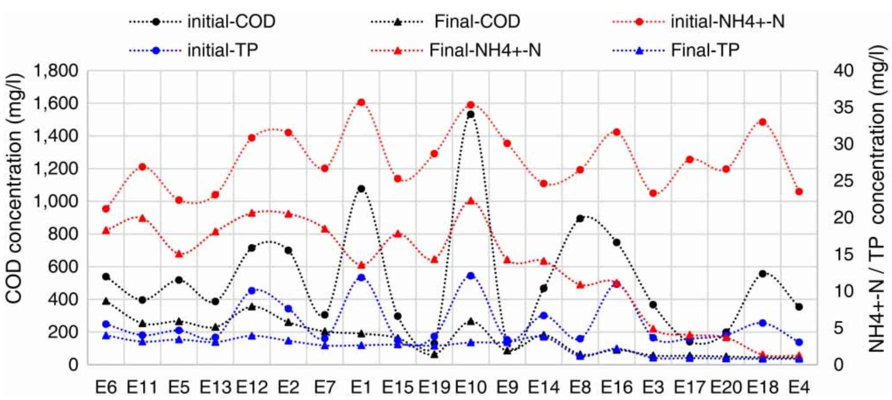

Figure 3 | The initial pollutant concentration and final pollutant concentration of discharge for 20 events (listed in order of increasing discharge volume).

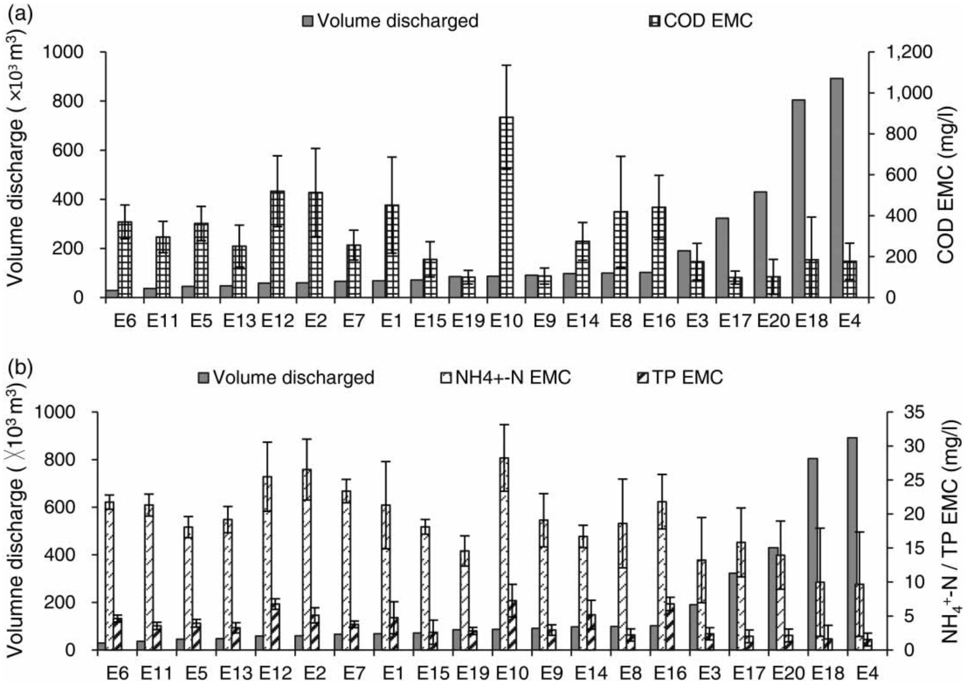

Figure 4 | Comparison of the EMCs of COD, NH_4^+-N and TP and discharge volume for 20 events (listed in order of increasing discharge volume).

E15 and E17-E20), mainly including those with low initial concentrations (E9, E17, E15 and E19, with low initial concentrations ranging from 131.2 to 297.6 mg/l; Figure 3) and large discharge volumes (E3, E4, E18, E17 and E20, with high discharges ranging from 190,440 to 892,170 m^3; Table 1). E4 and E18 had considerably lower values of NH_4^+-N EMC ($\leq$9.97 mg/L) and TP EMC ($\leq$1.621 mg/L) than the other events. This result is mainly because these events had the largest discharge volumes. The E10 event had the largest COD, NH_4^+-N and TP EMCs, mainly due to maximum initial concentrations and moderate rainfall. This result indicates that the COD, NH_4^+-N and TP EMCs are affected by the discharge volume and initial pollutant concentration.

In addition, the time of occurrence of the discharge period is also an important factor that affects the COD, NH_4^+-N and TP EMCs. For example, events E3 and E4 had similar initial concentrations of COD, NH_4^+-N and TP (Figure 3) but different total rainfalls (a difference of 100 mm; Table 1); however, the EMC and final concentration of COD were approximately the same. The NH_4^+-N and TP EMCs of E4 were 27% and 21% lower, respectively, than the EMCs of E3, and the final concentrations of E4 were 74% and 15% lower than the concentrations of E3. The final concentrations of COD, NH_4^+-N and TP were 57.1, 4.91 and 0.96 mg/l, respectively, in E3, with a discharge volume of 190,440 m^3; however, the concentrations of COD, NH_4^+-N and TP were 212.9, 21.48 and 2.37 mg/l, respectively, at the same discharge volume in E4. The concentrations of the two events were different, mainly because a discharge of 190,440 m^3 was observed at 23:40 in E3 (corresponding to the period when most people are sleeping and less sewage is produced) compared to the same volume discharge observed at 12:25 in E4 (corresponding to a period of higher human activity and higher sewage production). This result also suggests that sewage waters were an important source of COD, NH_4^+-N and TP during the later stage of discharge in E4. The EMCs of NH_4^+-N and TP are affected by total rainfall more than is the EMC of COD.

Inter-event EPL variability

The EPLs of COD, NH_4^+-N and TP and discharge volumes for 20 events are compared in Figure 5. The EPL trends of the three pollutants generally correspond to the discharge volume. The discharge volume is an important impact factor that affects the EPLs of the three pollutants. However, the initial concentration is another factor that affects EPLs. For example, the discharge volume was largest in E4, while the EPLs of COD, NH_4^+-N and TP were second largest due to their lower initial concentrations compared to that of E18. The EPLs of COD, NH_4^+-N and TP in E18 were the largest, and the event exhibited

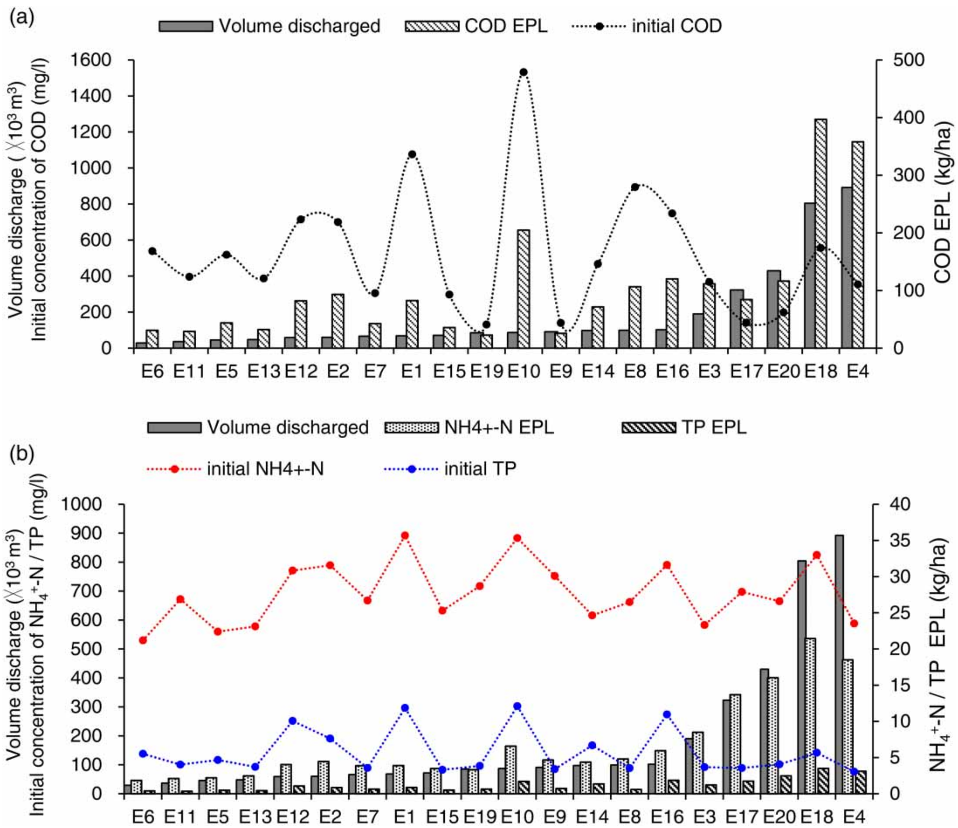

Figure 5 | Comparison of the EPLs of COD, NH_4^+-N and TP and discharge volume for 20 events (listed in order of increasing discharge volume).

the second largest discharge volume. Additionally, E18 had the seventh, third and sixth largest initial concentrations of COD, NH_4^+-N and TP, respectively. The COD EPLs of five events (E2, E12, E1, E10 and E8), the NH_4^+-N EPLs of three events (E12, E2 and E10) and the TP EPLs of one event (E10) were larger than the EPLs of other events with similar discharge volumes (Figure 5). This trend is also related to their high initial concentrations. Therefore, the initial concentration is an impact factor that cannot be ignored.

Correlations between rainfall and discharge variables based on EMC and EPL values

Table 3 shows the correlations between the pollutant EMCs and EPLs (COD, NH_4^+-N and TP), rainfall variables and

Table 3 | Analysis of the Pearson correlation values between rainfall and discharge variables based on EMCs and EPLs

Parameter		Rainfall variables					Discharge variables		
		R_{total}	$R_{duration}$	$R_{intensity}$	R_{peak}	D_{dry}	$T_{ant\ discharge}$	$V_{ant\ discharge}$	$V_{discharge}$
EMCs	COD	−0.383	−0.416	−0.167	−0.118	0.542*	0.400	−0.661**	−0.372
	NH_4^+-N	−0.744**	−0.546*	−0.492*	−0.506*	0.503*	0.162	−0.527*	−0.728**
	TP	−0.562**	−0.517*	−0.230	−0.290	0.429	0.153	−0.663**	−0.549*
EPLs	COD	0.849**	0.317	0.762**	0.640**	0.081	0.146	−0.003	0.881**
	NH_4^+-N	0.928**	0.485*	0.752**	0.597**	−0.133	−0.022	0.264	0.949**
	TP	0.878**	0.370	0.813**	0.593**	−0.058	−0.003	0.074	0.903**
$V_{discharge}$		0.982**	0.498*	0.722**	0.632**	−0.161	–	–	1.000

*Significant at the 0.05 level ($P < 0.05$).

**Significant at the 0.01 level ($P < 0.01$).

discharge variables. The main objective of this study was to analyze the influences of rainfall and discharge variables on the concentrations and loads of pollutants in 20 events.

Correlations between the rainfall variables and the EMCs and EPLs

Based on the analysis of the correlation matrix, a negative correlation was found between the COD, NH_4^+-N and TP EMCs and all of the rain variables, except the dry antecedent time, which was positively correlated with the EPLs of the three pollutants.

The negative correlations between the EMC values of the three pollutants and four rainfall variables (R_{total}, $R_{duration}$, $R_{intensity}$ and R_{peak}) suggest that higher rainfall amounts, intensities and durations increase the amount of rainwater in the storm drainage and dilute the sewage and sediment, resulting in lower EMCs. High rainfall intensities result in considerable sediment flushing, increasing pollutant concentrations (COD and TP). However, high rainfall intensities are also associated with large rainfall amounts, resulting in dilution that decreases the EMC values.

Among the three pollutants (COD, NH_4^+-N and TP), the negative correlations between the NH_4^+-N EMC and the four rain variables were almost the most significant, with correlation coefficients ranging from −0.492 to −0.744 (at $P < 0.05$ or $P < 0.01$), followed by the TP and COD EMCs. The main reason for this result is that sewage waters are the main contributor of NH_4^+-N. The dilution factor is larger during events with higher rainfall, decreasing the NH_4^+-N concentration. By contrast, the EMCs of COD and TP are controlled by the sediment at the beginning of discharge, as well as the sewage waters, which reduce the dilution effect of rainfall.

Strong correlations were found between the EPLs of COD, NH_4^+-N and TP and the total rainfall (R_{total}), with correlation coefficients greater than 0.849 (at $P < 0.01$). The mean rainfall intensity ($R_{intensity}$) and peak rainfall (R_{peak}) were significantly correlated with the EPLs of the three pollutants, with correlation coefficients ranging from 0.752 to 0.813 and 0.593 to 0.640, respectively (at $P < 0.01$ significance levels). These results suggest that the total rainfall, mean rainfall intensity and peak rainfall affect the COD, NH_4^+-N and TP EPLs because large rainfall events generally have high mean intensities and peak rainfalls, in which more sediment is flushed and more sewage waters are transported into receiving waters from the storm drainage. Among the three pollutant EPLs (COD, NH_4^+-N and TP EPLs), the correlation between the NH_4^+-N EPL and total rainfall (R_{volume}) is highest.

In terms of the dry antecedent time, positive correlations were observed between the EMCs of COD, NH_4^+-N and TP (from 0.429 to 0.542), and these correlations were larger than those with EPLs. The correlation between the EPLs of COD, NH_4^+-N and TP and the dry antecedent time is weak, because EPLs are mainly affected by the total rainfall (R_{total}). This result indicates that the dry antecedent time influences the EMC values, mainly because it reflects the effects of antecedent rainfall, which flushes a certain amount of sediment in the storm drainage, on the EMCs of the subsequent discharge. Generally, more sediment accumulates in the storm drainage during longer dry antecedent time. Although the previous discharge during dry times also flushes sediment, the discharge due to antecedent rainfall has a dilution effect on the sewage; thus, the dry antecedent time has a certain effect on the EMCs of the next event.

However, the influence of the dry antecedent time on the discharge volume is weak ($r = -0.161$) and is associated with the high percentage of impermeable area (72%) in Caohejing. Generally, the soil moisture content varies at different dry antecedent times. However, because the percentage of permeable area is low, the influence of the dry antecedent time is not significant.

Correlations between discharge variables and the EMCs and EPLs

The EMCs of COD, NH_4^+-N and TP are positively correlated with the time interval between two adjacent discharges ($T_{ant\ discharge}$) at low or weak correlation levels (Table 3); however, they are negatively correlated with the antecedent discharge volume ($V_{pre\ discharge}$), with significant correlation coefficients ranging from R values of −0.513 to −0.659 (at $P < 0.05$ or $P < 0.01$). These results indicate that the antecedent discharge volume has a greater impact on EMCs than does $T_{ant\ discharge}$ because a higher antecedent discharge transports more sediment from the storm drainage, which decreases the initial concentrations of the pollutants in the current discharge event. For example, the $T_{ant\ discharge}$ values in E1 and E5 are 84 h and 264 h, respectively, but the initial COD in E1 (1,076.5 mg/l) is larger than that in E5 (518 mg/l) because $V_{pre\ discharge}$ in E5 is 24,840 m^3, which is 12 times that in E1 (Table 1; Figure 3).

The EMCs of COD, NH_4^+-N and TP are negatively correlated with the discharge volume. Among these correlations, the correlation coefficient of NH_4^+-N is the largest (−0.728 at a $P < 0.01$ significance level), followed by those of TP and COD. These results indicate that the sediment in storm drainages at the beginning of a discharge event will significantly increase the COD, followed by that of TP. NH_4^+-N is affected minimally by the sediment in the system. The EPLs of COD, NH_4^+-N and TP are positively correlated with the discharge volume, with high correlation coefficients ranging from 0.881 to 0.949 (at the $P < 0.01$), indicating that the discharge volume and total rainfall are key factors that influence EPLs. This result is not surprising, given that the discharge volume and total rainfall are highly and positively correlated ($r = 0.982$), which is consistent with the findings of Bi *et al.* (2015a) and Sabin *et al.* (2005).

Multiple regression analyses of the discharge volume, EMCs and EPLs

Independent variable screening

The discharge volume is only associated with five rainfall variables and is not related to the discharge variables. The EMCs and EPLs of the pollutants are related to rainfall and discharge variables. Therefore, five rainfall variables were included in the regression analysis of the discharge volume, and eight variables were included in the regression analyses of the EMCs and EPLs. To avoid multiple collinearity issues, the correlation coefficients between these variables were analyzed, as shown in Table 4. There are two highly correlated variables, total rainfall and discharge volume, with a correlation coefficient of 0.982. The correlation coefficients between the groups of variables and dependent variables (EMCs and EPLs) are compared (Table 3). Variables with larger correlation coefficients are selected and included in the regression equation, and variables with smaller correlation coefficients are eliminated (Table 4).

The multiple regression analysis equation

After eliminating some variables, the regression equations between the discharge volume, EMCs, EPLs, rainfall variables and discharge variables were established using a stepwise regression analysis method that met the T-test requirements ($P < 0.05$), as shown in Table 5. The regression equation of the discharge volume was established using two variables, total rainfall and rain duration, with an adjusted R-square value of 0.981. The partial regression coefficients of the other rainfall variables (mean rainfall intensity, peak rainfall and dry antecedent time) did not meet the T-test requirements ($P < 0.05$) and were consequently eliminated from the equations. Seven variables were used in the EMC regression equations, excluding the discharge volume; however, no variables could describe the EMCs of COD and TP and meet the T-test requirements ($P < 0.05$). This result suggests that the data from the selected events cannot be used to estimate the COD EMC. Only two variables, total rainfall and the time interval between two adjacent discharges, satisfied the T-test requirements ($P < 0.05$) in the regression analysis of the NH_4^+-N EMC. However, the adjusted R-square value of the equation was 0.641, which is less than 0.8, indicating that the equation established based on the 20 events cannot be effectively used to calculate the EMC of NH_4^+-N. Seven variables were used in the EPL regression equations, excluding total rainfall. Three

Table 4 | Pearson correlation analysis of the rainfall and discharge variables

Variable		R_{total}	$R_{duration}$	$R_{intensity}$	R_{peak}	D_{dry}	$T_{ant\ discharge}$	$V_{ant\ discharge}$	$V_{discharge}$
R_{total}		1					ns	ns	0.982**
$R_{duration}$		0.617**	1				ns	ns	0.498*
$R_{intensity}$		0.653**	−0.031	1			ns	ns	0.722**
R_{peak}		0.695**	0.507*	0.459*	1		ns	ns	0.632**
D_{dry}		−0.210	−0.300	−0.040	−0.198	1	0.601**	ns	−0.161
$V_{discharge}$ equation		y	y	y	y	y	ns	ns	ns
EMCs equation	COD	y	y	y	y	y	y	y	n
	NH_4^+-N	y	y	y	y	y	y	y	n
	TP	y	y	y	y	y	y	y	n
EPLs equation	COD	n	y	y	y	y	y	y	y
	NH_4^+-N	n	y	y	y	y	y	y	y
	TP	n	y	y	y	y	y	y	y

ns, non-significant; *significant at the 0.05 level ($P < 0.05$); **significant at the 0.01 level ($P < 0.01$); y, the variable with the larger correlation coefficient is included in the regression equation; n, the variable with the smaller correlation coefficient is eliminated.

Table 5 | Regression equations between the discharge volume, EMCs and EPLs and the rainfall and discharge variables

Dependent variable	Regression analysis equation	R-square	Adjusted R-square	F	P-value (sig.)
Discharge volume	$V^{*}_{\text{discharge}} = 2780.198 + 6824.611R_{\text{total}} - 3042.109R_{\text{duration}}$	0.983	0.981	494.520	0.000
EMCs	$EMC_{NH_4^+-N}{*} = 19.503 - 0.086R_{\text{total}} + 0.025T_{\text{ant discharge}}$	0.679	0.641	17.987	0.000
EPLs	$EPL_{COD}{}^{*} = 44883.907 + 0.314V_{\text{discharge}} - 0.928V_{\text{ant discharge}} + 20838.394R_{\text{intensity}}$	0.882	0.860	39.858	0.000
	$EPL_{NH_4^+-N}{}^{*} = 2701.062 + 0.022V_{\text{discharge}}$	0.900	0.895	162.623	0.000
	$EPL_{TP}{}^{*} = 562.715 + 0.003V_{\text{discharge}} + 227.930R_{\text{intensity}} - 0.006V_{\text{ant discharge}}$	0.908	0.891	52.659	0.000

regression equations were established for EPLs, and all had adjusted R-square values greater than 0.86.

The results of the regression analysis suggest that the discharge volume and EPLs of COD, NH_4^+-N and TP can be better estimated using rainfall variables and discharge variables. However, it is difficult to estimate the EMCs of COD, NH_4^+-N and TP using regression equations with high adjusted R-square values, mainly because the EMCs are influenced more by various factors in a synergistic manner than are the discharge volume and EPLs, including total rainfall, mean rainfall intensity, peak rainfall, dry antecedent time, etc. Additionally, the correlation coefficients between the EMCs and independent variables are small, especially those of COD and TP (Table 3), indicating that these independent variables are not the most influential factors of EMCs. This result is consistent with that of the highway runoff study of Madarang & Kang (2014), which suggested that TSS loads can be predicted better than pollutant EMCs using multiple regression equations (Madarang & Kang 2014).

The validity of each regression equation was verified by the pollution loads and discharge volumes of four rainfall events monitored in 2015, including a light rain, a moderate rain, a large rain and a heavy rain, as shown in Table 6. For different rainfall types, the results show that the maximum relative error in the discharge volume is 7.6% (absolute value), and the minimum error is 4.4%; thus, they are both

Table 6 | Verification of the regression relationships between the discharge volume and EPLs for different rainfall types

Event date	Total rainfall (mm)	Rainfall type	Dependent variables	Simulated value	Monitored value	Relative error (%)
2015/3/30	9.8	light rain	Discharge (m^3)	49,644	53,649	−7.6
			COD EPL (g/ha)	15,159	13,214	6.4
			NH_4^+-N EPL (g/ha)	3,881	3,621	−12.5
			TP EPL (g/ha)	561	691	7.7
2015/3/18	20.6	moderate rain	Discharge (m^3)	122,742	114,039	7.5
			COD EPL (g/ha)	120,058	128,236	−14.7
			NH_4^+-N EPL (g/ha)	5,210	4,632	−7.2
			TP EPL (g/ha)	1,443	1,563	18.8
2015/4/5	45.7	large rain	Discharge (m^3)	221,881	209,994	−5.7
			COD EPL (g/ha)	73,659	83,126	11.4
			NH_4^+-N EPL (g/ha)	7,321	6,952	−5.3
			TP EPL (g/ha)	1,092	1,201	9.1
2015/8/22	144.1	heavy rain	Discharge (m^3)	852,354	816,684	−4.4
			COD EPL (g/ha)	245,218	294,623	16.8
			NH_4^+-N EPL (g/ha)	20,668	24,165	14.5
			TP EPL (g/ha)	2,955	2,861	−3.3

less than ±10%. The maximum relative error in the COD EPL is 16.8%, and the minimum error is 6.4%; the maximum relative error in the NH_4^+-N EPL is 14.5%, and the minimum is 5.3% (absolute value); and the maximum relative error in the TP EPL is 18.8%, and the minimum is 3.3% (absolute value). All of these errors are less than ±20%; therefore, the relative error is not large overall, and these regression equations can be considered reliable in the system.

CONCLUSIONS

Based on the pollutant data collected during 20 rainfall events in a storm drainage inappropriately connected with sewage, the results of this study are as follows:

1. The EMCs of COD, NH_4^+-N and TP were mainly affected by the total rainfall, discharge volume, initial pollutant concentrations and the occurrence time of the discharge period. The discharge volume and total rainfall are important factors that affect the EPLs of the three pollutants. Additionally, the initial concentration is an impact factor that must be considered.
2. The correlations between the EMCs of COD and NH_4^+-N and TP and all of the rainfall variables, except the dry antecedent time, are negative, which is opposite the trend observed for EPLs overall. The absolute values of the correlation coefficients between the EMC and EPL of COD and the rainfall-discharge variables were almost the lowest (the correlation coefficient of the dry antecedent time was lowest), followed by those of TP and NH_4^+-N. The antecedent discharge volume influenced the EMCs of COD, NH_4^+-N and TP more than did the interval of time between two adjacent discharge events. The variables with the largest correlation coefficients between the EPLs and rainfall-discharge variables are the discharge volume and total rainfall, with correlation coefficients greater than 0.849 (at the $P < 0.01$ significance level).
3. The discharge volume and EPLs of COD, NH_4^+-N and TP exhibited better regression relationships with rainfall-discharge variables (the adjusted R-square values of these equations range from 0.824 to 0.981) than did the EMCs of COD, NH_4^+-N and TP, because the EMCs are synergistically influenced more by various rainfall and discharge factors than are the EPLs. The relative validation error of the discharge volume is less than ±10%, and the EPL errors of COD, NH_4^+-N and TP are less than ±20%; thus, these regression equations can be considered reliable in the system.

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