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# Determination of the number of storm events representing the pollutant mean concentration in urban runoff

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ABSTRACT

Urban storm water quality monitoring is usually limited due to time and cost constraints, and thus, the determination of the minimum number of storm events that should be sampled necessary to estimate the pollutant mean concentration relative to the landuse is valuable. In this research, the minimum number of storm events was derived by considering both the variability of event mean concentration (EMC) values and the associated degree of uncertainty for a given set of measured storm events using monitored storm event data during a three-year period from 2009 to 2011 on five urban sites. Based on the findings, the required number of storm events could be determined using the propose method but representing only the 99 and 95% confidence limits of the site mean concentration (SMC) and differed depending on the pollutant. Results showed that a minimum of six to eight storm events were adequate to estimate the SMC of total suspended solids at low levels of uncertainties with relative standard error of less than 20%. The storm event sampling was preferable to be conducted five to six times during spring and summer when most of rainfall occurs while only once or twice during the fall and winter season.

*Keywords:* Event mean concentration; Minimum number of storm events; Monitoring scheme; Site mean concentration; Urban runoff

## 1. Introduction

It is a common knowledge that urbanization can lead to significant water quantity and quality impacts [1–4]. Consequently, the management of water quality impacts in urban areas has been proven to be a difficult task. Hence, the quantification of nonpoint sources (NPS) of pollution from urban stormwater runoff in impervious areas is necessary in order to select measures for impact assessment and water quality protection [5]. Compared with urban point source pollution, stormwater runoff shows very different and specific characteristics, concerning quality and discharge mode in the environment [6–9]. Storm water runoff occurs depending on rainfall events and

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concentrations of pollutants change very much both within and between events [10–11]. Additionally, a large variability between different sites is observed [12–13]. Although the type of pollutants should be the same as found elsewhere, concentrations, accumulation and removal processes may vary, and specific climate conditions are an important factor controlling these mechanisms [11,14]. In general, receiving water bodies respond relatively slowly to storm inflows compared with the rate at which constituent concentrations change during a runoff event. Thus, a representative value of the distribution of the event mean concentrations (EMCs) during a given period of time is necessary.

The most commonly used catchment based approach to estimate the central value of the EMC distribution is the site-specific mean concentration (SMC) calculated as the simple arithmetic mean of the EMC values. The SMC value should be representative of the distribution of the EMCs to be encountered during a given period of time. The pollutant unit load is then calculated by the product of runoff volume and SMC value [13]. The estimation of the EMC value as a weighted mean value is affected by uncertainties due to the variability of EMCs and the number of events used [15]. Accordingly, the uncertainty is necessary to have an overview of the range of possible values of the estimated load.

Due to the expense involved in obtaining NPS pollution data, it is important to determine the minimum number of storm events that represent the pollutant mean concentration or SMC within a given level of uncertainty. Reference [16] derived the optimum number of storms by considering both the cost and uncertainty, whereby the minimum number of storms producing a relatively accurate estimate of SMC was accepted. The study suggested that a minimum of five to seven storms were sufficient to derive a relatively accurate estimate of SMC. However, they concluded that the number of storms varied slightly depending upon catchment and the error measure analyzed. Reference [17] concluded that the most efficient method for attaining small confidence interval (CI) width for annual concentration was sampling at least seven storm events. In addition, their study estimated that sampling three storms for each year could allow a 20% trend to be detected in mass emissions or concentration over five years. It was observed that in most studies, suspended solids (SS) was often used as the predominant pollutant monitored in determining the errors associated with the number of sampled storms [17–19]. The analysis of reference [18,19] proved that the validation error CI associated with SS concentration and load predictions could be decreased if more than 10 storm events were monitored. However, when using other pollutant parameters such as biological oxygen demand (BOD) and chemical oxygen demand (COD), more storm events were required for proper estimation of SMC [15,20].

The objective of this research was to determine the minimum number of storm events representing the pollutant SMC of urban stormwater runoff using the storm event data collected during a three-year monitoring period (MP) on five sampling sites inside a university campus. Guidance on the optimum sampling scheme was provided considering both the SMC and the corresponding level of uncertainties.

## 2. Materials and methods

### 2.1. Site description and monitoring method

This research used the storm event data from a total of 48 storm events monitored from a three-year period (2009–2011) on five urban sites such as roads and parking lots inside the Kongju National University campus in Cheonan, South Korea (36°51′1.11″N, 127°9′0.23″E). The characteristics of the monitoring sites were provided in Table 1.

Runoff sampling was undertaken during storm events. Manual grab sampling was utilized following the typical sample collection method practiced similarly in most NPS studies in Korea and globally [11,21–23]. The sampling frequency was matched to

Table 1
Monitoring site characteristics

| Characterization | Unit | Site 1 | Site 2 | Site 3 | Site 4 | Site 5 |
|---|---|---|---|---|---|---|
| Landuse/runoff source | – | Road | Parking lot | | Road/parking lot | |
| Catchment area | $m^2$ | 520 | 880 | 450 | 597 | 457 |
| Imperviousness[a] | % | 100 | 100 | 100 | 100 | 100 |
| Ground slope[b] | % | $2.5 \pm 1.5$ | $1.3 \pm 0.7$ | $0.5 \pm 0.5$ | $1.5 \pm 0.8$ | $1.9 \pm 1.5$ |

[a]All sites were asphalt-paved.

[b]Indicates mean ± standard deviation.

the hydrograph, with more intensive sampling during the first part on an event. The short interval time during the first hour was selected since the initial runoff is normally highly polluted. Four samples were taken every five minutes for the first 15 min with the first sample collected as soon as runoff was evident, and two samples after 30 min and one hour, and more samples hourly thereafter until a maximum of 12 samples. For most of the shorter events, the scheme was modified by adjusting the number of samples until the runoff flow ended. The concentrations of six typical water quality parameters such as total suspended solids (TSS), BOD, COD, dissolved organic carbon (DOC), total nitrogen (TN), and total phosphorous (TP) were measured for each collected water sample following the standard test methods for the examination of water and wastewater [24].

### 2.2. Calculations and data analyses

EMC was calculated using Eq. (1) to represent water quality characteristics of runoff by means of the quotient of the total pollutant mass and the total volume discharged during a storm event [8,11]. The $\mathrm{EMC}_n$ values were calculated as the average of EMCs depending on the number of storm events. The SMC refers to the arithmetic mean of EMC using all storm event data as shown in Eq. (2).

$$\mathrm{EMC\ (mg/L)} = \frac{M}{V} = \frac{\int_0^T C(t) \times q_{\mathrm{run}}(t)dt}{\int_0^T q_{\mathrm{run}}(t)dt} \approx \frac{\sum_0^{t=T} C(t) \times q_{\mathrm{run}}(t)}{\sum_0^{t=T} q_{\mathrm{run}}(t)} \tag{1}$$

where $M$ (g) is the total mass of a pollutant transported during a storm event; $V$ ($\mathrm{m}^3$) is the total volume of runoff; $C(t)$ (mg/L) is concentration at time $t$; $q_{\mathrm{run}}(t)$ is the runoff flow rate discharged at time $t$. The limits of integration $t = 0$ and $t = T$ refer to the time associated with the initiation and cessation of runoff, respectively.

$$\mathrm{SMC}(mg/L) = \frac{\mathrm{EMC}_1 + \cdots + \mathrm{EMC}_n}{n} = \frac{\sum_{i=1}^{n} \mathrm{EMC}_i}{n} \tag{2}$$

Table 2
Summary calculation of the required number of storm events to be monitored representing the SMC. Values inside the parenthesis correspond to values using the upper 95% confidence limit of SMC

| Parameter | TSS | BOD | COD | DOC | TN | TP |
|---|---|---|---|---|---|---|
| TME[a] | 46 | 37 | 46 | 46 | 46 | 46 |
| MP[b] | 3 | 3 | 3 | 3 | 3 | 3 |
| TME/MP[c] | 16 | 13 | 16 | 16 | 16 | 16 |
| $E$[d] | 23(25) | 7(11) | 21(22) | 18(20) | 7(12) | 20(22) |
| $E$/TME[e] | 50% (54%) | 19% (30%) | 46% (48%) | 39% (43%) | 15% (26%) | 43% (48%) |
| RME[f] | 8(9) | 3(4) | 7(8) | 6(7) | 3(4) | 7(8) |
| MP:S/S[g] | 6(7) | 2(3) | 6(6) | 5(6) | 2(3) | 6(6) |
| MP:F/W[h] | 2(2) | 1(1) | 1(2) | 1(1) | 1(1) | 1(2) |
| RSE[i] | 18% (17%) | 67% (57%) | 31% (24%) | 18% (18%) | 15% (14%) | 7% (6%) |
| RME at $\mathrm{RSE}_{10–15\%}$ | 10 | 24 | 14 | 9 | 3 | 3 |
| RME at $\mathrm{RSE}_{<20\%}$ | 8 | 18 | 10 | 6 | –[j] | 2 |
| RME at $\mathrm{RSE}_{<30\%}$ | 6 | 10 | 6 | – | – | – |

[a]Total number of monitored storm events.
[b]MP (yr).
[c]Ratio of TME to MP rounded off to the next whole number event.
[d]Number of average storm events beyond the upper 99% confidence limit of the SMC.
[e]Ratio of $E$ to TME (%).
[f]Minimum number of storm events to be monitored within a year to represent until the upper 99 or 95% CI of the SMC rounded off to the next whole number event.
[g]Number of storm events that should be monitored during Spring/Summer season between April and September.
[h]Number of storm events that should be monitored during Fall/Winter season between October and March.
[i]Relative standard error (%).
[j]Indicates that the value was either unavailable or undetected.

where $EMC_i$ is the EMC at event $i$; and $n$ is the total number of storm events.

The SMC of each pollutant was plotted by means of cumulative moving average of the EMC ($y$-axis) with the corresponding number of monitored storm events ($x$-axis). The upper 99 and 95% confidence limits of SMC were estimated using the total number of storm events. For each water quality parameter, the number of monitored storm events that reached the upper 99 or 95% confidence limits of SMC were counted and labeled as $E_{99}$ and $E_{95}$, respectively (see Table 2). The number of storm events represented by $E_{99}$ and $E_{95}$ were divided by the total MP (i.e. three years) to determine the number of storm events that should be monitored for a given year to estimate the SMC value. This was done to give account to the occurrence of storms and availability in sampling of storm events for a given period. The 99 and 95% CI, standard errors of the mean (SE), and relative standard errors (RSE) were also calculated to define the levels of uncertainties of the SMC values using Eqs. (3)–(6).

$$95\%\ \mathrm{CI(mg/L)} = 1.96 \times \frac{\sigma_{\mathrm{EMC}}}{\sqrt{n}} \tag{3}$$

$$99\%\ \mathrm{CI(mg/L)} = 2.575 \times \frac{\sigma_{\mathrm{EMC}}}{\sqrt{n}} \tag{4}$$

$$\mathrm{SE\ (mg/L)} = \frac{\sigma_{\mathrm{EMC}}}{\sqrt{n}} = \frac{\sum_{i=1}^{n} \mathrm{EMC}_i}{n} \tag{5}$$

$$\mathrm{RSE(\%)} = \frac{\mathrm{SE}}{\mathrm{SMC}} = \frac{\frac{\sigma_{\mathrm{EMC}}}{\sqrt{n}}}{\mathrm{SMC}} \tag{6}$$

where $\sigma_{\mathrm{EMC}}$ is the standard deviation of EMC; $n$ is the total number of storm events.

## 3. Results and discussion

### 3.1. Characteristics of monitored storm events

In Fig. 1, it can be seen that the majority of the sampled storm events were conducted during the spring/summer season when most of rainfall usually occurs (i.e. between April and September). On the contrary, fewer events were sampled during the fall/winter season (between October and March) after the end of wet weather period. The ratio of storm events monitored during spring/summer to fall/winter season was 4:1. Significant differences was also observed in the coefficient of variations (CVs) (i.e. equal to the standard deviation divided by the mean) of various routinely monitored water quality parameters on Fig. 2 depending on season. During spring/summer, the CV of runoff EMC ranges between 0.6 and 1.1, while between 0.3 and 0.7 during the fall/winter season. The high variations in pollutant EMC was attributed to the rainfall events since it was during the spring/summer season when most rainfall occurs that resulted to increase in runoff and pollutant concentrations. Based on the results, the optimum monitoring scheme also considered the time when to perform the sampling of storm events by accounting the percentage of storms occurring during a season within a year. For instance, more events need to be sampled during the spring/summer season than fall/winter season.

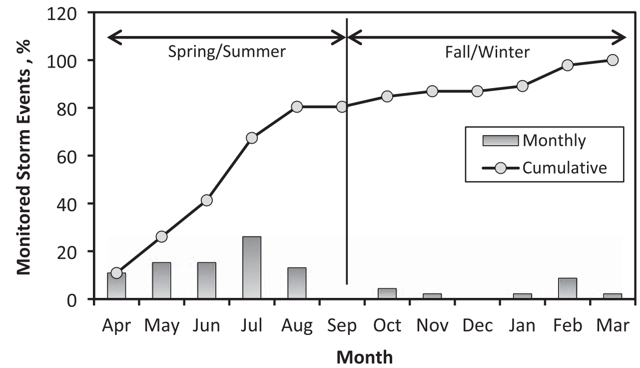


Fig. 1. Proportion of storm events monitored for each month (data is based from 2009 to 2011 MP).

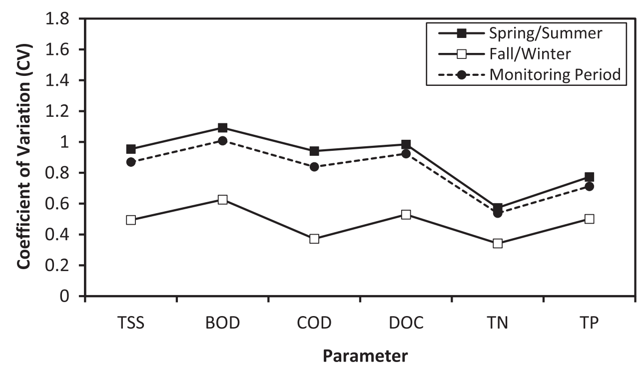


Fig. 2. Seasonal coefficient of variation of runoff EMC.

### 3.2. Determination of minimum number of storm events

The determination of the minimum number of storm events needed to represent the runoff pollutant SMC using the new approach includes the graphical and analytical plots of the number of monitored storm events with the corresponding $EMC_n$ values shown in Fig. 3. A typical trend was observed for all the plots that follow an indistinct decreasing trend at the first

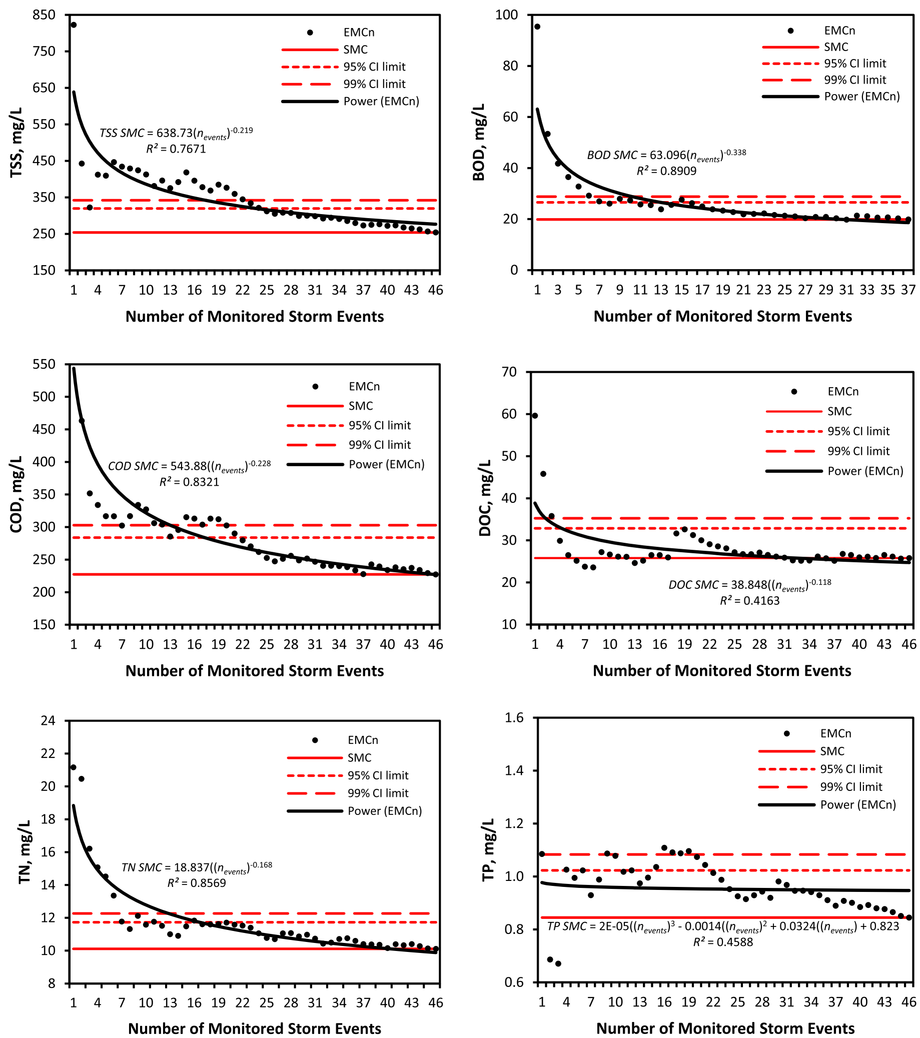

Fig. 3. EMC, SMC and corresponding limits of the SMC with respect to the number of storm events.

three to five storm events. The curves exhibited a gradual decrease approaching the SMC value with an asymptotic trend as the number of storm events increased. Apparently, the results indicate the higher variability of SMC values when using small datasets. The SMC distribution with respect to the number of monitored storm events fit a power regression for all the six parameters. BOD, TN, COD and TSS had higher coefficients of determination ($R^2 > 0.77$) compared with DOC and TP ($R^2 < 0.5$). Using the random EMC data, the variations in TP and DOC concentrations were not consistent with regards to the number of monitored events. It is possible that the low detection on TP concentration (mean, 0.85 mg/L) might affect the SMC distribution. In addition, the standard deviations have relatively wide range of between 1 and 128% of the mean concentrations.

Based on the plots, the number of storm events that reached the upper 99% ($E_{99}$) and 95% ($E_{95}$) confidence limits vary for each water quality parameter. The highest number was observed for TSS, COD, DOC, and TP, while least for BOD and TN. The minimum number of storm events to be monitored within a year to represent the upper 99% ($RME_{99}$) and 95% ($RME_{95}$) confidence limits of SMC values was determined as follows: TSS, 8–9; BOD, 3–4; COD, 7–8; DOC, 6–7; TN, 3–4; and TP, 7–8. Based on the results, no consistent number of storm events resulted for each water quality parameter making it difficult to determine the minimum number of storm events that represent the SMC values.

### 3.3. Uncertainties associated with the number of monitored storm events

The uncertainty in the SMC value vary very significantly with respect to the number of monitored storm events as depicted in the 99 and 95% CI plots of each water quality parameter shown in Fig. 4. Larger CI correspond to higher EMC variability which is detected for relatively small number of monitored storm events (e.g. less than three). The results confirm that SMC values based on few events are affected by very significant uncertainties. Among the water quality parameters, the most significant discrepancies in CI were observed for TSS, BOD, COD, and TP. The CI of the four parameters were significantly reduced to 45% in the first three to five storm events and did not proportionately decreased after monitoring ten storm events. However, in the case of TN and DOC, it needs more than 10 storm events to reduce the uncertainty to at least half. Based on the CI, the determination of an optimal number of storm events is still subjective.

In addition to the SMC distribution analysis, the standard errors and RSE for each water quality parameter were calculated to assess the uncertainties of the results. Fig. 5 shows the effect of the number of monitored storm events upon the accuracy of results. The magnitude of SE decreased as the number of monitored events increased for all the parameters. Similarly, it is certain that the RES decreased with increasing number of monitored storm events. The trend of SE for TSS, TP, COD, and BOD were similar and not significantly different. However, in the case of

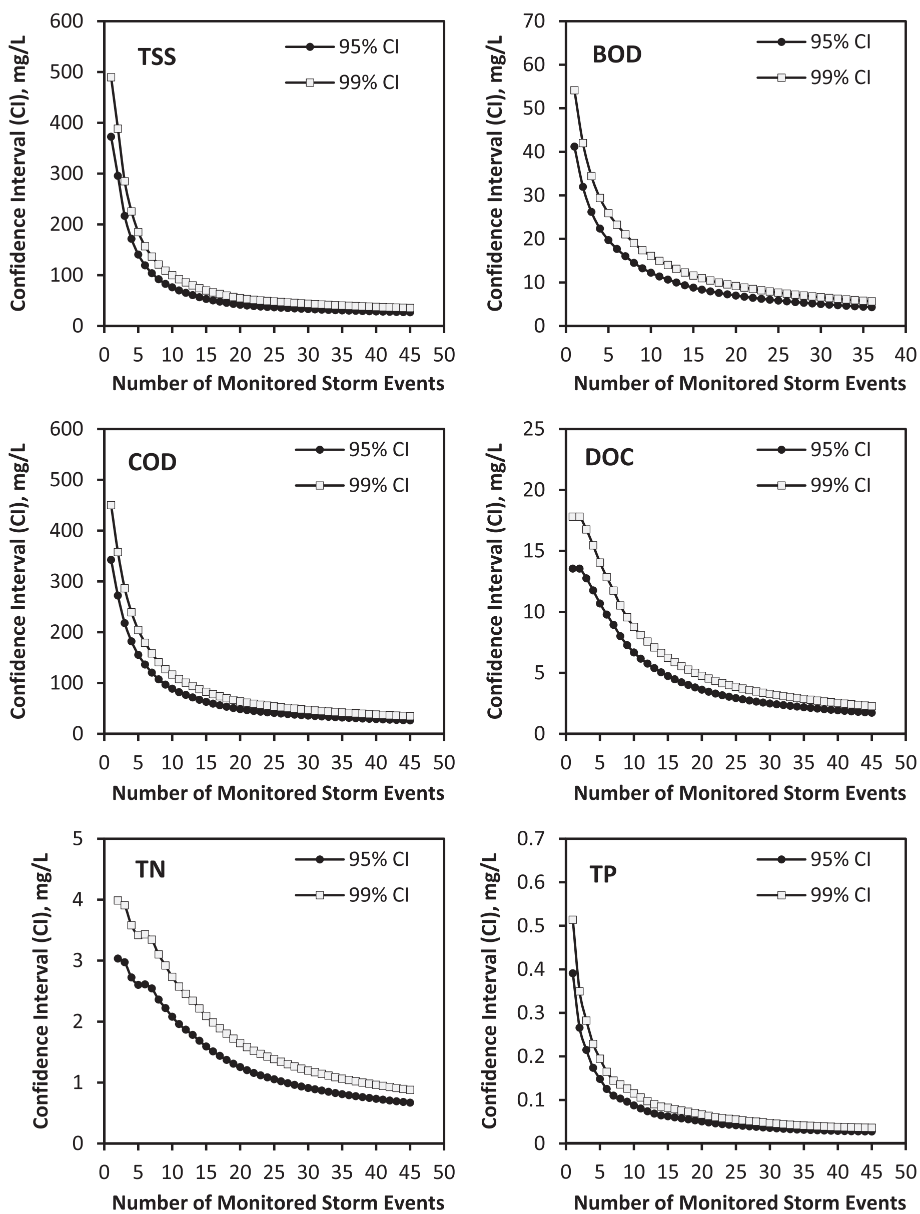


Fig. 4. CI (99 and 95%) of the SMC value with respect to the number of monitored storm events.

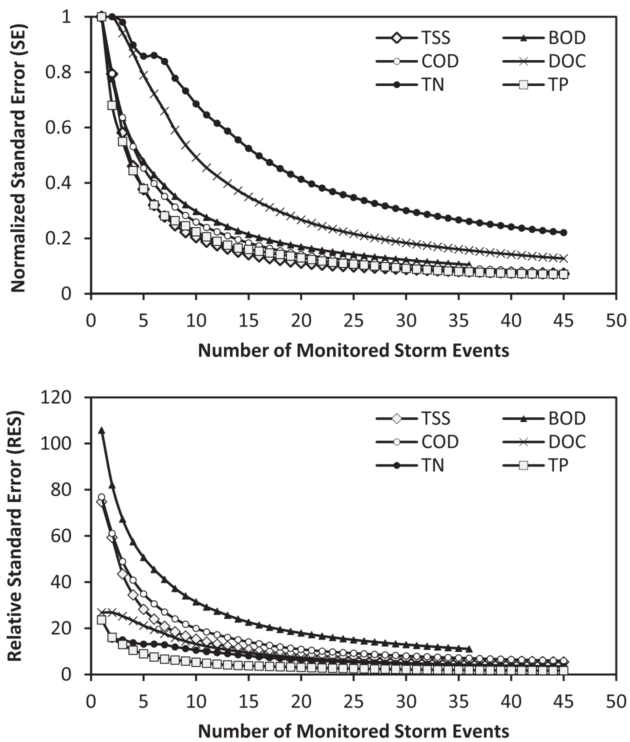


Fig. 5. Uncertainties associated with the EMC based on the number of average storm events.

TN and DOC, the reductions in SE were gradual as the number of storm events increased. The SEs of TSS, TP, COD, and BOD decreased by 35–45% in the first three storm events; 50–60% for five storm events; and 70–80% after ten storm events. On the other hand, it needs eight to ten storm events to reduce the SE of TN and DOC by only 30–40%. In terms of the RSEs, smaller number of monitored storm events resulted in larger RSEs of BOD, COD, and TSS. However, the RSEs also reduced significantly (less than 30%) with at least five monitored storm events.

### *3.4. Summary and implication of results*

Summarized in Table 2 are the results of the approach used in the determination of the optimum number of storm events that represent the pollutant SMC. Based on the findings, the estimated number of events corresponded to low or high RSE values. The minimum number of events was estimated as three for BOD and TN with RSEs of 67 and 18%, respectively; whereas the maximum was eight for TSS with 18% RSE. Due to the inconsistencies in the number of monitored storm events and equivalent RSEs, the propose method is partially subjective and has certain limitations. First, the required number of storm events represents only the upper 99 or 95% confidence limits of the SMC; second, it differs depending on the water quality parameter; and most importantly, it varies based on the measured errors. Despite the limitations, a minimum of six to eight storm events is recommended to adequately estimate the SMC of TSS at low levels of uncertainties (e.g. RSE = 20–30%). The storm event sampling is preferable to be conducted five to six times during spring and summer when most of rainfall occurs while only once or twice during the fall and winter season.

Although some studies assumed and defined a minimum number of storm events enough to derive estimates of SMC [16], the determination of an "optimum" number of storm events that should be measured differed with respect to levels of uncertainties ranging from small to very significant variations depending upon catchment and the error measure analyzed [15–17]. Still, current studies showed that it is not possible to propose a standard minimal number of events to be measured on any catchment in order to evaluate the SMC value with a given uncertainty [15]. This only signifies that the accuracy of SMC estimation could be increased when more storm event data are available. However, due to time and cost constrictions, it is convenient to know the least possible number of storm events representing the wide distribution of EMC values. The study of reference [16] estimated that monitoring six storm events would be approximately 40% cheaper than monitoring 12 events.

## 4. Conclusions

Efforts have been made to developed an optimum monitoring scheme incorporating a detailed guidance on storm event sampling methods; however, due to the inconsistencies in the number of monitored storm events and equivalent RSEs, the propose method was partially subjective and has certain limitations. First, the required number of storm events represents only the upper 99 or 95% confidence limits of the SMC; second, it differs depending on the water quality parameter; and most importantly it varies based on the measured errors. Despite the limitations, a minimum of six to eight storm events was recommended to adequately estimate the SMC of TSS at low levels of uncertainties (e.g. RSE = 20–30%).

The accuracy of SMC estimation could be increased when more storm event data are available. However, due to time and cost constrictions, it is convenient to know the least possible number of storm events representing the wide distribution of EMC values. Although efforts have been made, the possibility of proposing a standard minimal number of storm events to be measured in order to evaluate the SMC value with a given uncertainty is still limited. Continuous monitoring to gather more data is necessary to obtain the desired results.

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