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Research papers

Event-based calibration of build-up parameters in conceptual water quality models using turbidity data

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A R T I C L E I N F O

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A B S T R A C T

Build-up/wash-off water quality models are frequently used to assess stormwater runoff quality. In this work, we explore the possibility of using continuous turbidity data to calibrate and validate such models under realistic conditions in two case studies located in Flanders, Belgium. By using such rich continuous data, a much larger number of rainfall events can be used for calibration than it is feasible with grab samples. The approach shows that the build-up rate used in these conceptual models varies widely during different rainfall events between 100 and 1350 kg/ha/y in the first case study and between 100 and 1750 kg/ha/y in the second case study. The time dependence of the build-up rates from different catchment types and its correlations with site-specific information/external conditions, such as wind speed, temperature and traffic volume are investigated. The modelled build-up rates are lower during storm events in weekend days compared to week days, consistent with traffic measurements. Furthermore, emission factors for different vehicle types previously published in literature can be used to estimate the build-up rate for streets. In one case study a strong negative correlation between wind speed and build-up rate was observed ($r = -0.89$). Overall, our study shows that continuous turbidity data can be used to study the impact of external conditions on the build-up rate in conceptual water quality models.

1. Introduction

In recent years, urban runoff has gained attention as a significant pollutant of European waterways (Björklund et al., 2018; Müller et al., 2020; Lee et al., 2007). Pistocchi (2020) estimates that organic pollution from surface runoff at the European level is equivalent to untreated wastewater of about 31 million population equivalents (PE) for BOD_5. In this context, the recently adopted recast of the European Urban Wastewater Treatment Directive (UWWTD) (2024/3019) addresses storm water overflows as one of the main priority issues. In fact, it sets an indicative non-binding target that storm water overflows should represent a small percentage, not exceeding 2 % of the annual collected urban wastewater load calculated under dry weather conditions.

Water quality modeling is a crucial tool to understand this pollution source and implement effective measures to protect receiving waters. Different approaches have been used to model urban runoff quality, with varying levels of success (Bonhomme and Petrucci, 2017; Egodawatta and Goonetilleke, 2006; Egodawatta et al., 2009; Hossain et al., 2010; Liu et al. 2015; Wicke et al., 2012; Zakizadeh et al., 2022). For decision-making purposes, a water quality (WQ) model with a limited number of input parameters is needed, such as a statistical or conceptual model.

The limitation of statistical models is that many measurements are needed to include site-specific information such as traffic volume, vehicle type, and road type, which are known to affect runoff concentrations. Similarly, conceptual build-up/wash-off models do not directly incorporate site-specific information, although many researchers have noted that the build-up rate in these models is influenced by such data. In a previous publication, we showed that this issue with conceptual models can be addressed by calculating the build-up rate using established emission factors for various pollutant sources, including

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atmospheric deposition, traffic, and building materials (Vinck et al., 2023). Using this approach, differences in runoff concentrations from similar catchments, related to site-specific characteristics such as building types, could be estimated. However, the initial validation of this modelling approach relied on a limited number of grab samples, which only allowed for the quantification and comparison of site mean concentrations. To comprehensively evaluate model performance, validation against dynamic water quality data is necessary. Furthermore, while the relationship between the build-up parameter and emission factors was hypothesized and found to be consistent with the calculated site mean concentrations, a more detailed analysis directly linking build-up factors to site-specific characteristics remained to be conducted, which is one of the objectives of the present work.

Many previous studies have already tried to estimate the build-up and wash-off dynamics for different types of surfaces, at both small and larger catchment scales (e.g. Bonhomme and Petrucci, 2017). Some studies have collected grab samples from urban runoff during rainfall events to calibrate these models (Zakizadeh et al., 2022); however, because this approach is expensive and time-consuming, only a limited number of rainfall events can be sampled. As an alternative, vacuum systems have often been used to establish the build-up parameter (Egodawatta and Goonetilleke, 2006), whereas lab-scale setups and artificial rainfall simulators are frequently used to determine the wash-off parameters (Egodawatta et al., 2009; Hossain et al., 2010). Again, the expensive lab analyses set a limit to the number of samples that can be analyzed. With the rapid advancement of continuous water quality sensors, new opportunities are emerging to determine the model parameters under realistic conditions, with an adequate amount of representative data.

In this work, as a main objective we explore the option of using continuous turbidity data to calibrate and validate a build-up/wash-off model for total suspended solids (TSS) at two case studies (CS) in Flanders (Belgium), in the framework of the Horizon European project "Protecting the Aquatic Environment from Urban Runoff Pollution" (StopUP). Utilizing continuous data leads to a better model validation and allows investigating the temporal evolution of the model parameters and their relationship with site-specific information, such as the wind speed during the antecedent dry period, the temperature and the traffic volume. Moreover, specific objectives of the study are: (i) determining field values of the three most influential parameters of the water quality model, the wash-off parameters K_W and N_W and the build-up rate K_B, evaluating their variability among rainfall events, and comparing them with literature values from previous studies; (ii) evaluating the reliability of existing approaches for determining the build-up rate from traffic measurements; (iii) finding qualitative correlations, if any, of the build-up rate with the aforementioned site-specific information.

2. Materials and methods

2.1. Case studies

The water quality model was calibrated using continuous turbidity data collected at two case studies, depicted respectively in Figs. 1 and 2

Fig. 1. Location of CS1 and CS2 in Flanders.

and of characteristics summarized in Table 1. Both case studies are small catchments with a drainage area of less than one hectare and stormwater sewers. The first case study (CS1 − Wetteren) consists of a commercial area with a parking lot (0.16 ha) and roofs from commercial buildings (0.39 ha). The second case study (CS2 − Wolvenberg) drains the runoff from a busy ring road. In CS1, potential sources for TSS pollution are atmospheric deposition and the gradual accumulation of particles from building materials and vehicle activity in the parking area. In contrast, CS2 is expected to have significantly higher TSS loads due to traffic-related sources. Road surfaces exposed to frequent vehicle movement contribute to the build-up of particulates such as tire and brake wear debris, road dust, and sediment resuspension. The intensity and frequency of traffic in CS2 thus make it a more likely hotspot for TSS pollution.

At both sites, turbidity data was collected with NTU turbidity sensors by Aqualabo supplied by Fluves (0–4000 NTU, accuracy < 5 %). A large set of continuous turbidity data is available, covering the period from the 23rd of May 2023 to the 13th of September 2024 (18 months) for CS1 and the period from the 4th of March to the 18th of November 2024 (8 months) for CS2, with a temporal resolution of 15 min.

Turbidity (Turb) measurements were converted to TSS with eq. (1), based on previous literature studies (He et al., 2010), to enable the modelling and the comparison with other studies.

$$TSS = 0.5 \cdot \mathrm{Turb}^{1.32} \tag{1}$$

It is important to note that such conversion equations are often site-specific.

To check the validity of formula (1), grab samples were collected at both case studies. The grab samples did not allow for a site-specific calibration, but verify the plausibility and order of magnitude of TSS values derived from turbidity, as discussed in Appendix A.

At both sites, also flow and/or level sensor data are available for calibration of the hydraulic model. The flow was measured with an electromagnetic Bjong flow meter supplied by BM Tecnologie Industriali, with a temporal resolution of 5 min. The level in the sewer pipes was measured with Sensor Technik Sirnach AG (STS) relative pressure sensors supplied by Fluves (range 0–5 m, accuracy 0.1 %), with a temporal resolution of 15 min. In CS1, a rain gauge (Ijinus Pluvio RG 20–3) is positioned on– site. The data from this local rain gauge showed very good agreement with that from a nearby public rain gauge located approximately 14 km away, indicating that rainfall patterns and timing were consistent over this distance. For CS2, data from a public rain gauge situated 6.5 km from the case study area were used. Given this relatively short distance and the consistency observed between gauges in CS1, it is reasonable to assume that the public rain gauge used for CS2 provides a reliable representation of local rainfall conditions.

The Flemish agency of roads and traffic (AWV) counted daily traffic during approximately two weeks in 2021, 2022 and 2023 (49 days in total) at several locations in the area of CS2 of three classes of vehicle types: light (cars and motors), medium (vans and busses) and heavy (trucks).

This data was utilized to investigate possible correlations with the calibrated parameters of the water quality model. The histogram of the traffic data collected at CS2 reveals that data globally lie in the interval between 0 and 14,000 vehicles per day, but the most frequent data by far lie in the interval 8,000–14,000 vehicles/day, confirming the definition of busy road; the highest number of counts is in the range 10,000–12,000 vehicles/day, see Fig. 3.

The traffic measurements were performed during several days in different years, but at a different time than the turbidity measurements. As the traffic data showed limited variability, it was considered representative of the period during which the turbidity measurements were collected. This is confirmed by more recent (limited) countings of traffic volume in the area (https://www.straatvinken.be).

Moreover, weather data was collected for both CS1 and CS2 to

Fig. 2. Top: overview of case study 1 (CS1) – Wetteren – Latitude and longitude [50.99 N, 3.88E]. Bottom: case study 2 (CS2) – Wolvenberg – Latitude and longitude [51.19 N, 4.42E].

Table 1
Details of the catchments.

Case study	Drainage area (ha)	Land use
CS1 Wetteren	0.55	Parking + roof
CS2 Wolvenberg	0.72	Ring road

investigate possible correlations with the calibrated parameters of the water quality model. These data included wind speed and air temperature and were collected from public weather stations in the area of the case studies, available from https://www.waterinfo.be.

2.2. Hydrological model

A simplified hydrological model was developed for both case studies, in order to minimize computation time without losing accuracy. This approach is particularly justified given the limited size of the catchment areas, where detailed hydraulic routing through pipe networks has minimal impact on overall runoff dynamics. Consequently, flow through pipes was excluded from the model, a simplification that proved to be valid and effective.

The runoff from the catchment area was calculated by convolution of

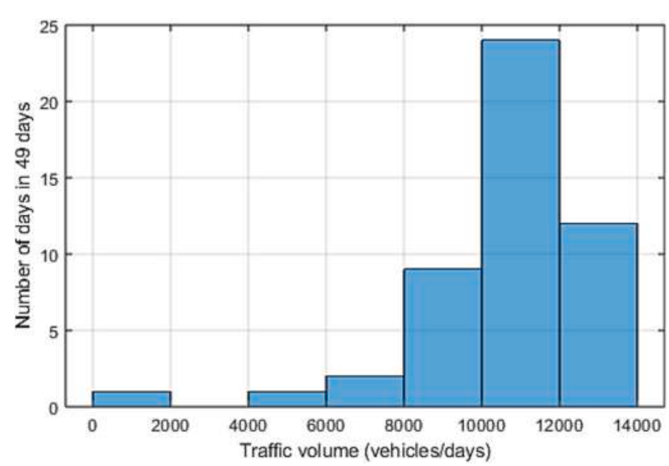

Fig. 3. Traffic data collected at CS2.

the data from the rain gauge with a unit hydrograph, consisting of a triangle function. The triangle function is defined by the following parameters: T_p – time of peak flow, T_b – total runoff time and Q_{max} –

maximum flow.

The parameters of the unit hydrograph were calibrated by least mean squares fitting of the model to the data from the flow meter, and are shown in Table 2.

To assess the performance of the simplified model, simulations were compared with results from two widely used hydraulic modeling platforms: InfoWorks ICM and SWMM. Appendix E first shows the NNSE values obtained for the three hydrological models, by comparing the measured flow rate with the flow rate obtained from the three models for three representative rain events. Appendix E then extends the comparison to the range of NNSE values for all rainfall events. These results demonstrate that the simplified model not only captures the essential hydrological response of the catchment but also performs comparably to more complex models.

The strong agreement between the simplified model and established hydraulic models confirms its suitability for small urban catchments, especially in studies focused on pollutant build-up and wash-off processes. By reducing computational demands without compromising accuracy, this approach enables a calibration that is more efficient and allows scenario analysis, making it a practical alternative for urban water quality (WQ) modeling.

2.3. Water quality model

The build-up/wash-off model was applied to both CS1 and CS2; it was implemented in MATLAB and includes linear pollutant build-up during dry weather and exponential wash-off during rain events, according to the procedure outlined in Hossain et al. (2010). Sediment transport through pipes is ignored, which is acceptable for the limited areas covered by the case studies.

The model calculates the build-up rate during dry periods (i.e., periods with zero runoff rate) by the following formula (Hossain et al., 2010):

$$b = \min(B_{\max}, K_{\mathrm{B}} t) \tag{2}$$

with b the build-up (g), t the build-up time interval (i.e., the number of antecedent dry days), $B_{\max}$ the maximum build-up (kg) and K_{B} the build-up rate (kg/h). For reporting purposes, the build-up rate K_{B} is often expressed per year and divided by the connected impervious area to compare different catchments (yielding a value in kg/ha/y).

During rain events (i.e., events with runoff rate larger than zero), the model calculates the wash-off (w). Two equations to express the wash-off are used and compared; the first one is source- limited, i.e. the amount of pollutant washed off is limited by the availability of the pollutant on the surface (m_{B}). Even if there is a lot of runoff, only a limited amount of pollutant can be washed off because the source is finite or has already been depleted, hence

$$w = K_{\mathrm{W}} q^{N_{\mathrm{W}}} m_{\mathrm{B}} \tag{3}$$

The second model is transport-limited, i.e. the amount of pollutant washed off is limited by the capacity of the runoff to transport it. There is plenty of pollutants available on the surface but the runoff is not strong or voluminous enough to carry all of it away, therefore

$$w = K_{\mathrm{W}} Q^{N_{\mathrm{W}}} \tag{4}$$

In Eqs. (3)-(4), w is the wash-off (kg/h), K_{W} the wash-off coefficient (mm^{-1}), N_{W} the wash-off exponent (−), q the runoff rate over the sub catchment (mm/h), Q the volumetric runoff rate (m^3/h) and m_{B} the total quantity of pollutant remaining at the surface (g). The runoff rates (q and Q) are calculated for each time step from the hydraulic model (section 2.2). The total quantity of pollutant m_B at the surface at time step t is calculated from equation (2).

The build-up rate K_{B} can also be calculated from traffic data combining them with Emission Factors (EF), which have been published in the literature for different vehicle types and road types (Baensch-Baltruschat et al., 2021; DELTARES and TNO, 2016); the typical formulation for K_{B} is

$$K_{\mathrm{B}} = \sum_i (EF_i \cdot V_i) \cdot L \tag{5}$$

with EF_i being the emission factor (g km^{-1}) and V_i the traffic volume (number·h^{-1}) for vehicle type i, and L the length of the connected street (km).

Table 2
Parameters of the hydrological model.

Case study	T_{p} (min)	T_{b} (min)	$Q_{\max}$ (m^3/h)
CS1 Wetteren	12	23	0.29
CS2 Wolvenberg	15	24	0.22

2.4. Selection of calibration events

During the data collection period, approximately 500 and 370 rainfall events took place in CS1 and CS2, respectively. The statistics of the rainfall events are shown and discussed in Appendix B; summarizing, the typical duration falls in the 0–80 h range for CS1 and in the 0–30 h range for CS2; the number of dry days before a rain event lies in the 0–10 range for CS1 and 0–2 range for CS2, and the peak intensity is in the 0–20 mm/h range for both CS1 and CS2.

The calibration of the WQ model was performed on an event basis. An event starts when the flow in the sewer system (induced by rain) is larger than zero. Only events with a minimum of three data points (corresponding to a duration of 30 min) are considered for calibration of the model. Events with a time interval in between of less than 30 min were considered as the same event.

Fig. 4 shows a representative slice of the high-resolution flow and turbidity data collected at CS1. Rainfall events, as defined earlier, are marked with a red bar. This visualization highlights the richness of the dataset and the temporal resolution achieved through continuous monitoring.

However, it also reveals a key challenge: several turbidity peaks do not coincide with rainfall events. Further, some peaks show very high turbidity values, which seem not realistic in the context of the hydrological model. These anomalies are likely due to non-hydrological disturbances, such as biological activity (e.g., mosquito larvae) or sediment resuspension in stagnant water. Such noise introduces uncertainty and underscores the importance of rigorous data screening prior to model calibration. These non-rainfall-related turbidity fluctuations are not representative of wash-off processes and must be excluded from the modeling dataset. To assess the suitability of each rainfall event for model calibration, the Pearson correlation coefficient between flow and turbidity was computed. This correlation varies widely across events, as shown in the histograms in Appendix C, and is also apparent from Fig. 4. This variability is consistent with findings from previous studies (e.g. Cheng et al., 2025; Jensen et al., 2021). Indeed, on one hand, a larger flow rate favors advective transport and a larger concentration; on the other hand, a larger flow rate is associated with a dilution effect.

In contrast, conceptual water quality models assume that turbidity closely follows the flow pattern. Therefore, only events with a positive correlation between flow and turbidity are suitable for calibration.

To proceed with model calibration, events were selected based on the following criteria:

- a minimum Pearson correlation coefficient between turbidity and flow of 0.6, which corresponds to a moderate correlation. This threshold represents a compromise between retaining a sufficient number of events and ensuring that turbidity dynamics are

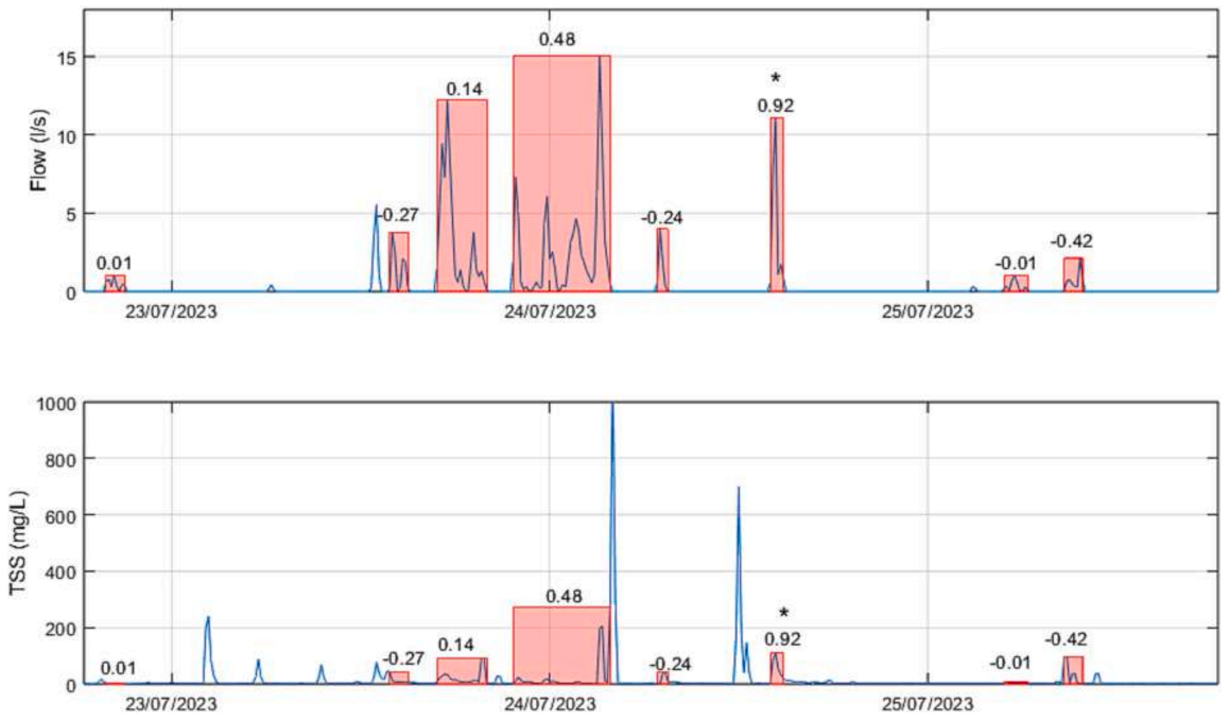

Fig. 4. Slice of high resolution flow and turbidity data collected at CS1. Rain events, as defined at the beginning of Section 2.4, are shown by the red bars (two events are not marked because their duration is less than 30 min). The Pearson correlation coefficient between turbidity and flow is displayed on top of the bars. One event, marked by an asterisk, was selected for calibration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

consistently linked to runoff dynamics, as assumed in conceptual build-up/wash-off models.

- a pronounced turbidity peak (increase in turbidity by at least a factor of two): during small rainfall events, the turbidity sensor often shows a nearly flat response, which is not suitable for model calibration even if the correlation with flow is high. This criterion ensures a meaningful turbidity response while still retaining events with relatively low turbidity peaks (~20 mg/L), particularly in CS1, where background TSS levels are intrinsically low due to limited traffic-related sources.

Applying these criteria resulted in 41 and 34 rain events for CS1 and CS2, respectively. The selected events are shown in Fig. 5a for CS1 and Fig. 5b for CS2.

This event selection strategy ensures that the model is calibrated using high quality, representative data, thereby enhancing its predictive capability. It also highlights the importance of combining automated data collection with robust quality control procedures, particularly when working with high-frequency environmental datasets.

2.5. Calibration procedure

Next, to obtain the optimum parameter set for the water quality model, 50,000,000 model runs were performed, varying each parameter between a minimum and a maximum with a given step. The parameters and ranges that are adopted in the model runs are shown in Table 3.

For each model run, the Normalized Nash-Sutcliffe Efficiency (*NNSE*) between the modelled and measured TSS during the selected rainfall events was determined by the following equations:

$$NSE = 1 - \frac{\sum_t (TSS_0(t) - TSS_m(t))^2}{\sum_t (TSS_0(t) - \overline{TSS_0}(t))^2}, \tag{6}$$

$$NNSE = \frac{1}{2 - NSE}, \tag{7}$$

where *NSE* is the Nash-Sutcliffe Efficiency, Σ_t is the summation over time, TSS_0 is the measured flow rate, TSS_m is the modelled flow rate, and $\overline{TSS_0}$ is the mean of the measured flow rate.

Note that *NNSE* is a measure of the performance of the water quality model. A unit value corresponds with a perfect model fit, whereas a zero-value indicates that the model predictions are as accurate as simply using the mean of the observed data.

This procedure yields a set of (N)NSE values for each rainfall event and each combination of parameter values. This set allows us to calibrate the model, by selecting the parameters corresponding to the highest NNSE values for each event. While many studies report a single parameter set obtained from calibration/validation of conceptual WQ models against measured pollutant data, this approach resulted in unsatisfactory low NNSE values for our data set. This may be related to the much more limited data sets used in previous studies for calibration, often obtained under artificial and more constant conditions. Therefore, we adopted a different calibration approach, in which part of the model parameters (build-up rate) are calibrated on an event-basis, while the remaining model parameters (wash-off parameters) are determined globally (i.e. as a single optimum value for all rainfall events). As all events are used for calibration, no separate validation step is performed; however, an independent assessment of model performance is provided in Appendix E. The application of the procedure is described in detail in the Results and discussion section.

3. Results and discussion

3.1. Calibration of the WQ model

To gain insight on the impact of the four model parameters in equations (2)-(4), the results of their local variation are first discussed. The starting values of the WQ model parameters were taken from Wicke et al. (2012), and are shown in Table 4. Fig. 6 shows the impact of the four model parameters on the NNSE coefficient between modelled TSS

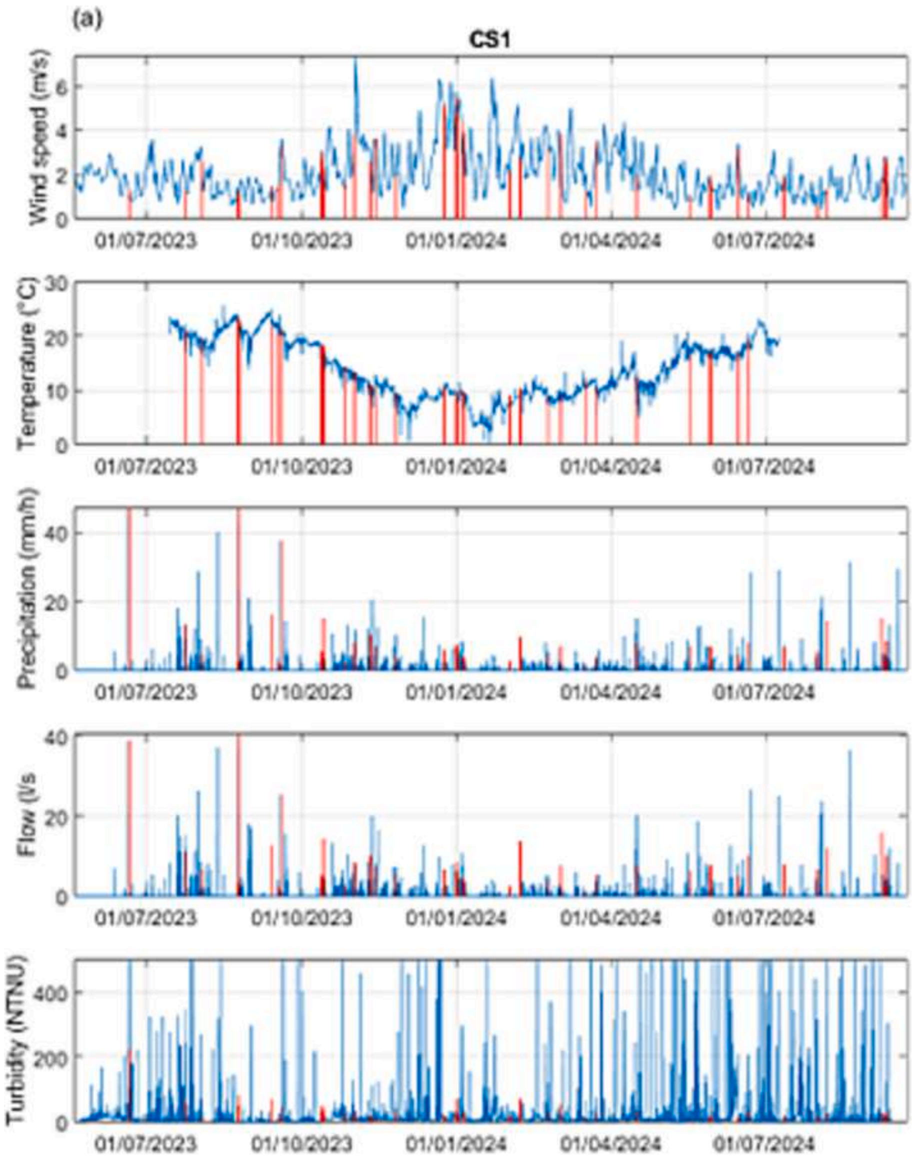

Fig. 5. Meteorological and continuous turbidity data monitored at (a) CS1 and (b) CS2. The red lines indicate the events that were used in the calibration procedure. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and TSS derived from turbidity measurements during two selected rainfall events for CS1.

For the maximum build-up (B_{max}) only a minimum value could be determined (Fig. 6), because the maximum of antecedent dry days before a rainfall event was six days, which did not allow for a good estimation of this model parameter. When the transport-limited wash-off equation is used (eq. (4)), only a minimum build-up rate can be determined, as the build-up on the surface is non-limited. For the other parameters, a clear optimum value can be derived, see Fig. 6.

Similar findings were obtained for CS2, see Appendix D.

The model with source-limited wash-off performs slightly better than the model with transport-limited wash-off; the former is indeed most frequently used to model urban catchments (Hossain et al., 2010; EPA, 2016).

The source-limited wash-off was then selected as being more representative; for this model, sets of the build-up rate and wash-off-parameters, corresponding to the highest NNSE values, were determined. A tolerance of 0.01 from the maximum NNSE value was selected. These maximum NNSE values lie between 0.53 and 0.95 (median 0.74) for CS1 and between 0.40 and 0.97 (median 0.57) for CS2.The corresponding optimal parameter values are shown in Fig. 7 for both case studies in the three-dimensional space (K_B, K_W, N_W) with different colors for each rainfall event.

The maximum build-up rate B_{max} is not shown in these figures, as our analysis shows that this parameter does not have much impact on the goodness of fit for the selected rainfall events, as discussed earlier. It is clearly seen that: i) for some events, there is a large spread in the optimal build-up parameter K_B, which is most pronounced in CS2. However, it is also clear that the optimal K_B is strongly event dependent; ii) the optimal wash-off parameter N_W clusters around 1.5 for most rain events, with the exception of one event in CS1 for which the optimal N_W is between 2.5 and 3.5; iii) the optimal wash-off parameter K_W lies around 0.01–0.05.

The optimal values of the wash-off parameters K_W and N_W, that correspond to the majority of the calibration events for CS1 and CS2, are reported in Table 4 and compared with values for generic surfaces as derived from the scientific literature; it is seen that results of the same order of magnitude are obtained. This suggests that the selected parameter set is representative and robust. This is in line with previous

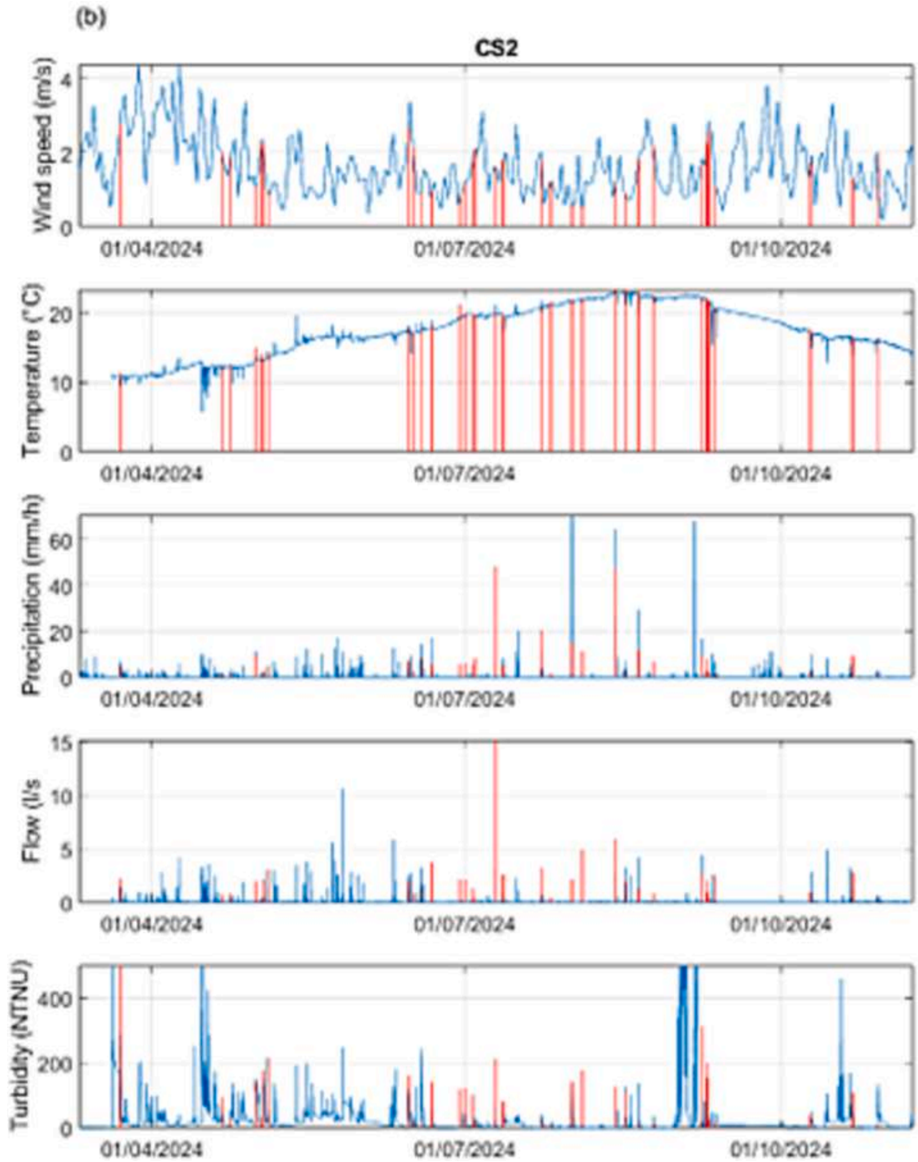

Fig. 5. (*continued*).

Table 3
Parameters and ranges included in the model runs.

Parameter	Min value	Max value	Step	Unit
K_B	50	1500	25	kg/ha/y
B_{max}	1	100	2	kg
K_W	0.0001	5	0.005	mm^{-1}
	0.5	1	0.1	
	1.5	5	0.5	
N_W	0.1	10	0.1	

Table 4
TSS wash-off parameters for different catchment types.

Catchment type	K_W	N_W	Reference
Commercial	0.01	1.59	CS1 (calibrated)
Transport	0.01	1.76	CS2 (calibrated)
Concrete	0.008	1	(Wicke et al., 2012)
Asphalt	0.01	1	(Wicke et al., 2012)
Transport	2.48E-5	3.588	(Zakizadeh et al., 2022)
Commercial	0.0661	0.855	(Zakizadeh et al., 2022)

studies (Egodawatta et al., 2009; Egodawatta and Goonetilleke, 2006) who pointed out that the wash-off depends primarily on the rainfall intensity (conform with equations (3) and (4)). Consequently, this calibrated set of wash-off parameters K_W and N_W, applied consistently across all rainfall events, was adopted for all subsequent model simulations.

Next, we give a closer look at the variability of the optimal build-up rate K_B (associated with the highest NNSE values) of the WQ model. Since the build-up rate influences the magnitude of the TSS peak, its variability indicates that using a single global parameter can lead to both overestimation and underestimation of TSS loads across different events. This variability likely reflects underlying physical differences in catchment conditions or temporal changes in pollutant accumulation processes, suggesting that some model parameters may not remain constant over time or across events. Indeed, while the wash-off rate primarily depends on the rainfall intensity, the build-up rate is not only determined by the antecedent dry period, but also depends on external factors such as traffic intensity and weather conditions (wind speed, temperature, humidity) during the preceding dry period (Zheng et al., 2014). A simplified correlation analysis with wind speed and traffic is investigated in the next Section.

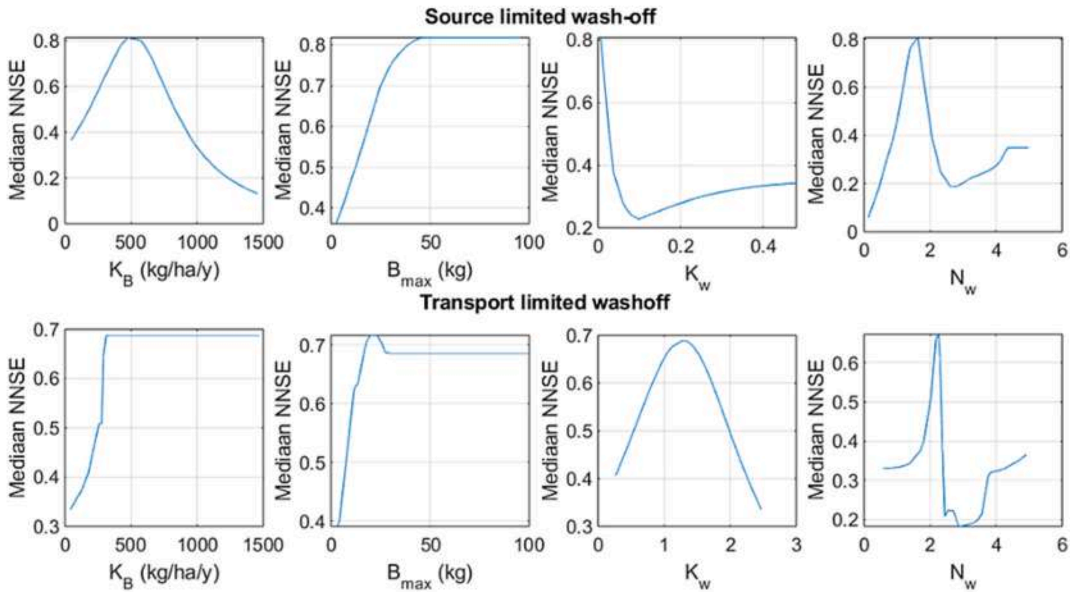

Fig. 6. Normalized NSE coefficient between TSS derived from the turbidity sensor and the modelled TSS with source-limited (upper graphs) or transport- limited (lower graphs) wash-off equation as a function of the value of the four model parameters for the rainfall events of June 20th and July 24th at CS1.

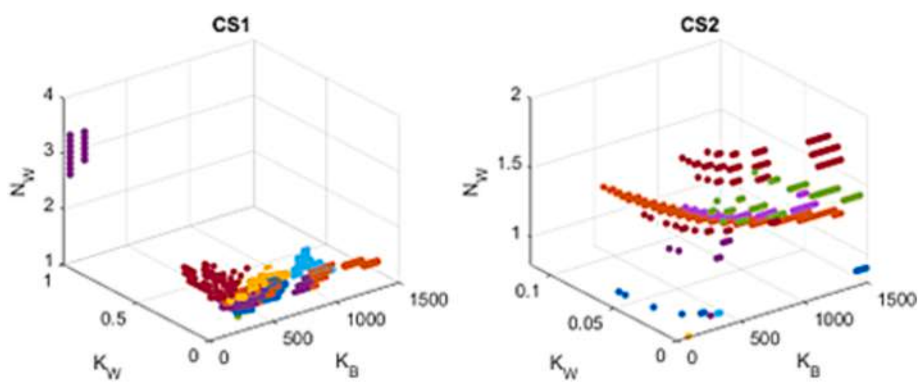

Fig. 7. Clusters of parameter sets of the build-up rate and wash-off parameters with a high NNSE value for both case studies and the model with source-limited wash-off. The colors of the dots represent the different rainfall events used in the calibration procedure.

The time evolution of the optimal build-up rate K_B corresponding to the wash-off parameters listed in Table 4 for CS1 and CS2 is shown in Fig. 8. For CS1, the build-up rate fluctuates mostly around 200 kg/ha/y, while there is one clear outlier of $\sim$ 1400 kg/ha/y and a few other outliers around 400–800 kg/ha/y. For CS2, the variability is larger, which might be related to higher variations in traffic volume compared to CS1, which is expected for a busy road compared to a parking lot. Two further outliers (around 1500 kg/ha/y) are observed in CS2 at the same period in time. Perhaps these outliers are related to incidents, such as car accidents or spills or the construction works at this time occurring on-

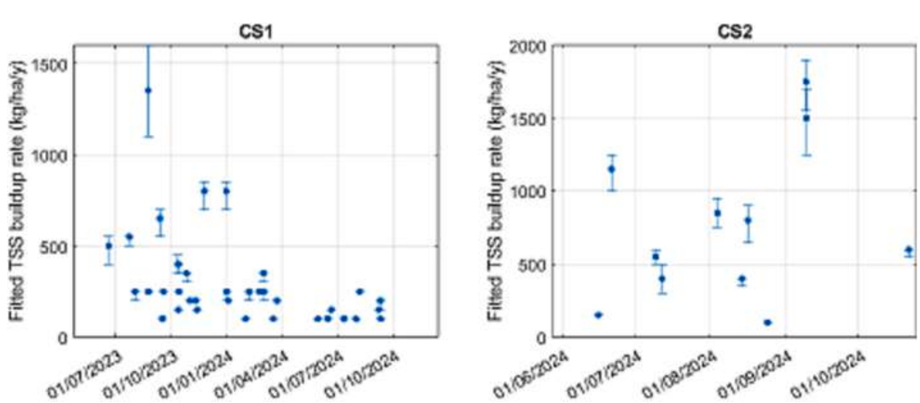

Fig. 8. Time evolution of the optimal build-up rate for CS1 (left) and CS2 (right). The error bars indicate the tolerance of 0.01 on the maximum NNSE value that was used to determine the optimum value.

site.

Finally, Figs. 9 and 10 compare the measured and modelled TSS concentrations using the event-dependent optimal build-up value and the wash-off parameters listed in Table 4 for three rainfall events in CS1 and CS2 respectively; the corresponding rainfall events are also shown. For CS1, results from a global model using a fixed build-up rate of 500 kg/ha/y across all events are also shown. The comparison clearly illustrates the improved model performance when applying an event-based build-up rate, particularly in capturing the variability in TSS peaks across different rainfall events. The performance of the event-based model is very good, especially at peaks, with NNSE values between 0.41 and 0.91 (median 0.67) for CS1. Note that the NNSE values are positively correlated with the correlation coefficient between turbidity and flow. In Appendix E, our event-based model is compared with simulations in ICM/SWMM, again confirming its validity.

3.2. Correlations of optimal build-up rate with wind speed, temperature and traffic intensity

The time dependency of the optimal build-up rate K_B prompted an analysis of its possible correlations with external factors, such as wind speed, temperature and traffic intensity. First, potential correlation with wind speed was investigated for both CS1 and CS2, as shown in Fig. 11. Prior to the analysis, outliers were detected using a combination of (1) visual inspection of scatterplots, and (2) the statistical median absolute deviation (MAD) method. While visual inspection suggested the presence of two potential outliers, the statistical MAD-based approach identified only one.

The Pearson correlation coefficient between wind speed and build-up rate was

- CS1: r = -0.09 (n = 36, p = 0.58);
- CS2:
  - o with visual outlier removal: r = -0.89 (n = 9, p = 0.0014);
  - o with MAD outlier removal: r = -0.24 (n = 10, p = 0.50).

This implies no correlation for CS1, while the build-up rate parameter seems to decrease with the average wind speed in the dry period before the rain event in CS2, when potential outliers are removed (Fig. 11). This indicates that higher wind speeds during the antecedent dry period may inhibit the accumulation of total suspended solids (TSS) on impervious surfaces, possibly due to enhanced resuspension or dispersion of particulate matter. However, this relationship should be interpreted with caution. The limited dataset, uncertainty about outliers and the potential influence of other site-specific factors, such as surface roughness, may confound the observed trend. Moreover, the strong correlation observed at CS2 could be partially attributed to the site's proximity to high-traffic roads, where wind-induced resuspension may be more pronounced. Additional data collection across a broader range of meteorological conditions and urban morphologies is necessary to validate this finding.

No significant correlation was found between temperature and build-up rate, as the corresponding Pearson correlation coefficient was:

- r = 0.22 (n = 29, p = 0.24) for CS1;
- r = 0.22 (n = 11, p = 0.52) for CS2.

This suggests that temperature alone does not play a dominant role in influencing the rate of TSS accumulation during dry periods. It is possible that temperature effects are more indirect, potentially modulating other processes such as biological activity or evaporation rates, which in turn could influence pollutant build-up. However, these secondary effects may be too subtle to detect within the current dataset.

As for traffic, daily measurements of different vehicle types are available for the drainage catchment of CS2 from the Flemish Agency of Roads and Traffic (AWV). From this data, the build-up rate can be calculated using Equation (5).

The traffic volume and corresponding build-up rates (from eq. (5)) are compared in Fig. 12 with build-up rates derived from the model, i.e. by fitting the turbidity data. Build-up rates from the model are on the first row, build-up rates from traffic are on the second, while the results for weekdays and weekends are reported separately in the first and second columns. It is seen that although the amount of data is limited, the build-up rates from traffic are in good agreement with those obtained from fitting the turbidity data. This consistency supports the hypothesis that vehicular activity is a key driver of TSS accumulation in urban catchments. Notably, both methods yield build-up rates of the same order of magnitude, reinforcing the reliability of the model-based estimates.

Furthermore, the observed reduction in build-up rates during

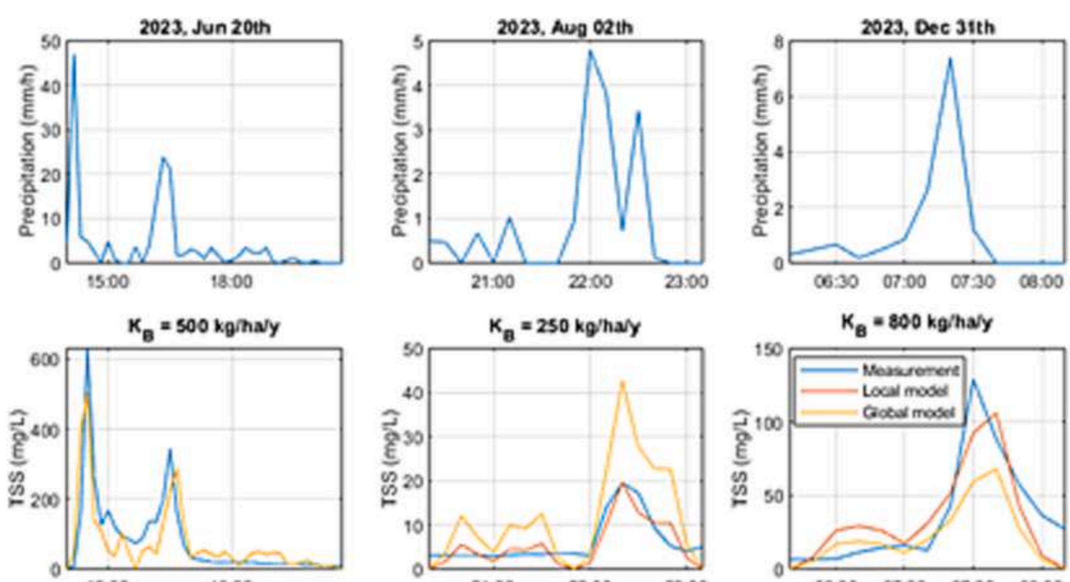

Fig. 9. Comparison between measured and modelled TSS (second row) for three rainfall events at CS1 (first row). The model was run with the wash-off parameters listed in Table 4 and an event-dependent optimum build-up rate, which is mentioned in the figure heading. A comparison with the results from a global model with a fixed build-up rate of 500 kg/ha/y is also shown in the second row figures.

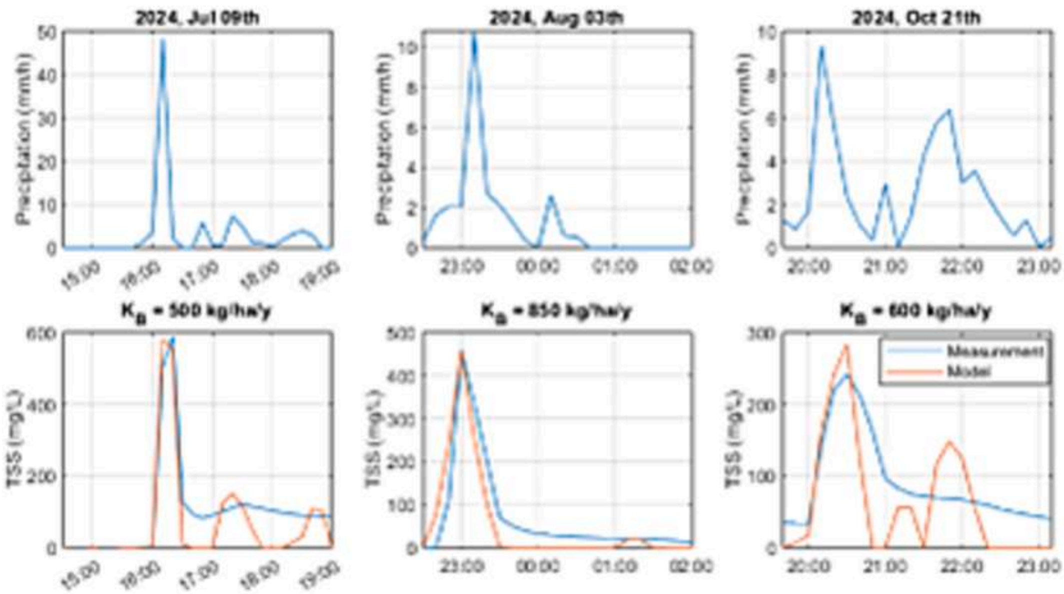

Fig. 10. Comparison between measured and modelled TSS (second row) for three rainfall events in CS2 (first row). The model was run with the wash-off parameters listed in Table 4 and an event-dependent optimum build-up rate, which is mentioned in the figure heading.

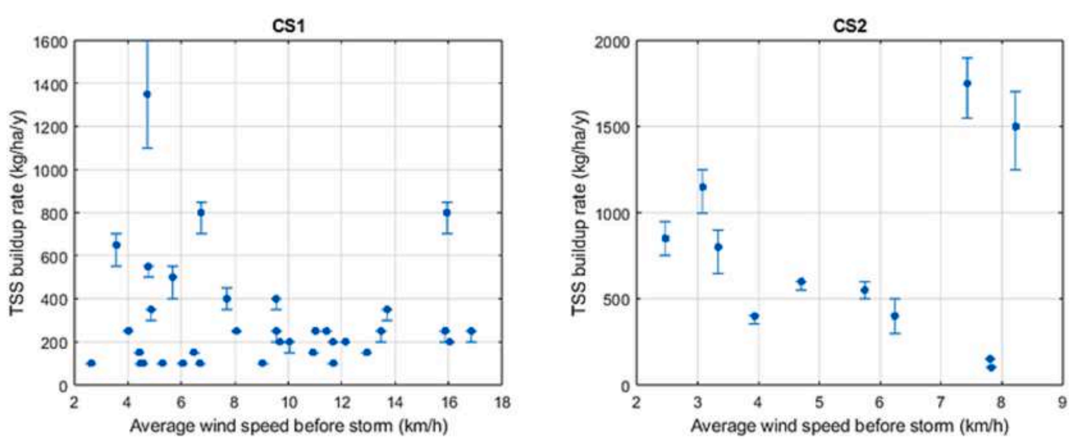

Fig. 11. Relation between the average wind speed during the antecedent dry period and the fitted TSS build-up rate for each rainfall event. The error bars indicate the tolerance of 0.01 on the maximum NNSE value that was used to determine the optimum value.

weekends compared to weekdays aligns with lower traffic volumes, highlighting the temporal variability of pollutant accumulation linked to human activity patterns (Fig. 12).

These findings underscore the multifactorial nature of TSS build-up processes, where meteorological conditions, anthropogenic activity, and site-specific characteristics interact in complex ways. While traffic appears to be a dominant factor at CS2, the influence of wind speed—particularly under certain conditions—warrants further investigation. Expanding the dataset to include more rainfall events, diverse urban settings, and additional environmental variables (e.g., land use, surface material, street cleaning frequency) would enhance the robustness of the analysis.

3.3. Discussion on the build-up rate

Acquisition of continuous turbidity data allowed to demonstrate that the build-up rate used in conceptual build-up/wash-off models can vary widely between rainfall events. This observation challenges the conventional modeling approach, which often relies on calibrating conceptual build-up/wash-off models using a limited number of events. Such an approach may overlook the dynamic nature of pollutant accumulation, potentially leading to inaccurate predictions under varying environmental and anthropogenic conditions. Therefore, model calibration should be approached with caution, and where possible, supported by high-resolution, event-based monitoring data.

The observed variability in K_B appears to be influenced by external factors, although not uniformly across sites or events. As discussed earlier, wind speed during the antecedent dry period and traffic volume emerged as potential drivers of this variability, while temperature showed no significant correlation. These findings suggest that pollutant build-up is governed by a complex interplay of meteorological and human activity-related factors. Although correlations with traffic incidents were not explored due to data limitations, such events—especially those involving heavy braking, tire wear, or fluid leakage—could plausibly contribute to localized spikes in pollutant accumulation. Future studies incorporating traffic incident data could help elucidate these effects and improve model accuracy.

The mean value (excluding outliers) of the build-up rates K_B obtained from fitting in CS1 and CS2 is shown in Table 5 and compared with previous literature studies on different catchment areas. It is apparent that the WQ parameters for both case studies are of the same order. These parameters also compare well with those found in most previous

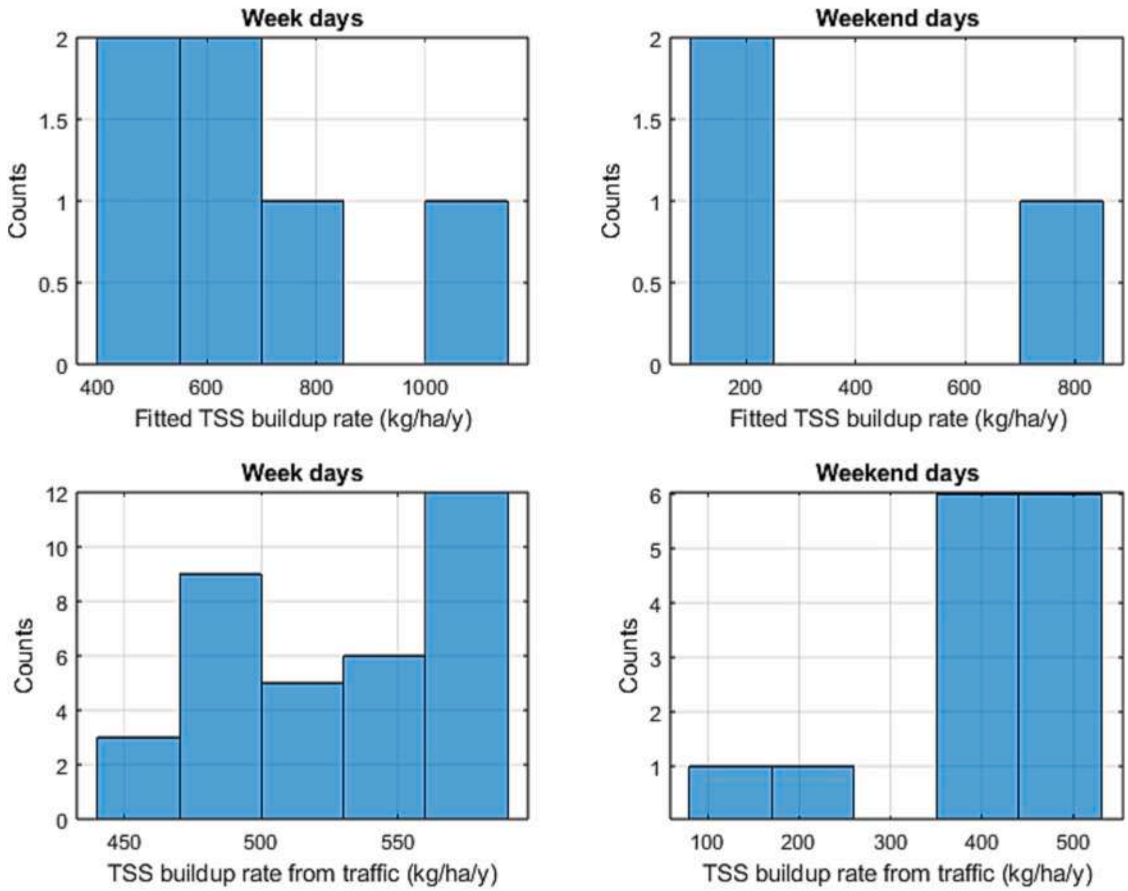

Fig. 12. Fitted TSS build-up rate (first row) during week (first column) and weekend days (second column) at CS2 compared to the build-up rate calculated from traffic measurements (second row).

Table 5
TSS build-up parameters for different catchment types.

Catchment type	K_B (kg/year/ha)	Reference
Commercial area	270	CS1 (calibrated)
Ring road	555	CS2 (calibrated)
parking	448.3	(US EPA, 1983)
Commercial area	1120.9	(US EPA, 1983)
Commercial area	483	(Zakizadeh et al., 2022)

studies (Wicke et al., 2012; Zakizadeh et al., 2022).

The obtained value of the mean build-up rate for TSS in CS1 is lower compared to previous studies. Note that the catchment area in CS1 consists mainly of rooftops from commercial buildings. As rooftops do not emit a lot of TSS, the build-up rate of the parking lot alone will be higher than the mean fitted value of 270 kg/ha/year. When the build-up rate is compared with typical TSS emission factors for vehicles according to Eq. (5), it corresponds to approximately 4800 car equivalents per day, which is not realistic for the small commercial area in CS1. The higher emission factors observed in this study are probably related to low speed and frequent steering at the parking lot, as was also reported in Rienda et al. (2023).

On the other hand, the observed build-up rates for CS2 are in the same order of magnitude as those calculated from the traffic measurements on-site (Fig. 5). This shows that vehicle emission factors can be used to estimate build-up rates from streets, as anticipated in a previous publication (Vinck et al., 2023).

Overall, these results underscore the importance of context-specific data in understanding and modeling urban pollutant dynamics. While generalized emission factors and model parameters provide a useful starting point, site-specific monitoring remains essential for capturing the nuances of local conditions. Future research should aim to expand the dataset across diverse urban typologies and incorporate additional variables such as street cleaning frequency and land use intensity.

4. Conclusions and perspectives for future work

This study demonstrates the value of continuous turbidity data for calibrating stormwater quality models across multiple rainfall events. The build-up rate (K_B) was found to be strongly event-dependent, ranging from 100 to 1500 kg/ha/y, unlike the more stable wash-off parameters (K_W and N_W). A significant negative correlation between build-up rate K_B and average wind speed during the antecedent dry period was observed in CS2 Wolvenberg, suggesting wind may inhibit particle accumulation. No such correlation was found in CS1 Wetteren, indicating that more refined analyses, potentially accounting for wind direction, may be required.

No consistent correlation was found between temperature and build-up rate, while traffic volume showed a clear influence on K_B. Emission factors from literature proved useful for estimating build-up rates in unmonitored basins, offering a promising avenue for model enhancement.

Overall, the novelty of this study lies in the event-based calibration of conceptual build-up/wash-off models using long-term, high-frequency turbidity data, which reveals substantial event-to-event variability in build-up rates and enables independent validation against traffic-derived estimates under real field conditions.

Future work will explore interactions between wind, traffic, and other site-specific factors in modulating pollutant build-up, and will assess the transferability of the proposed approach to other urban catchment types.

CRediT authorship contribution statement

Evi Vinck: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matej Radinja:** Writing – original draft, Supervision, Formal analysis, Conceptualization. **Neil Van den Broeck:** Writing – original draft, Visualization, Investigation, Data curation. **Margherita Evangelisti:** Writing – review & editing, Visualization, Methodology, Investigation, Data curation. **Birgit De Bock:** Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Arnout Roukaerts:** Writing – original draft, Visualization, Validation, Investigation, Data curation. **Stijn Van Hoey:** Writing – original draft, Validation, Investigation, Data curation. **Niels De Vleeschouwer:** Visualization, Validation, Investigation, Data curation. **Sacha Gobeyn:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Dario Frascari:** Writing – review & editing, Writing – original draft, Validation, Methodology. **Vittorio Di Federico:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. – Calibration of turbidity data

For CS1, time dependent grab samples were collected with an automatic sampling device during three rainfall events. The TSS concentration calculated from turbidity using formula (1) is compared with the results of lab analyses on the grab samples in Fig. A1. The TSS concentrations in the grab samples are very low, but their order of magnitude is well predicted by Equation (1). The quality of the data was not sufficient for a site-specific calibration.

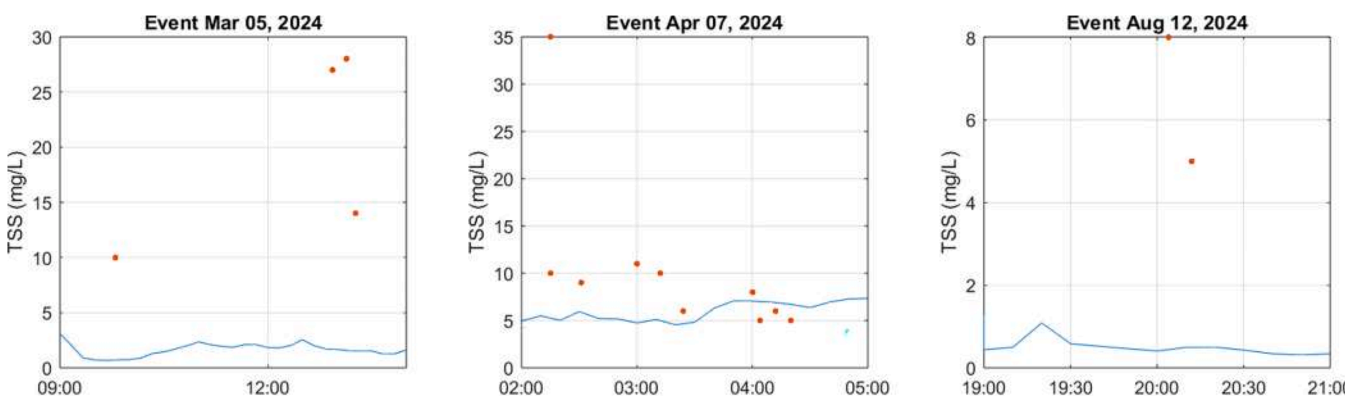

Fig. A1. Comparison of TSS calculated from Equation (1) and lab analyses on grab samples collected at CS1.

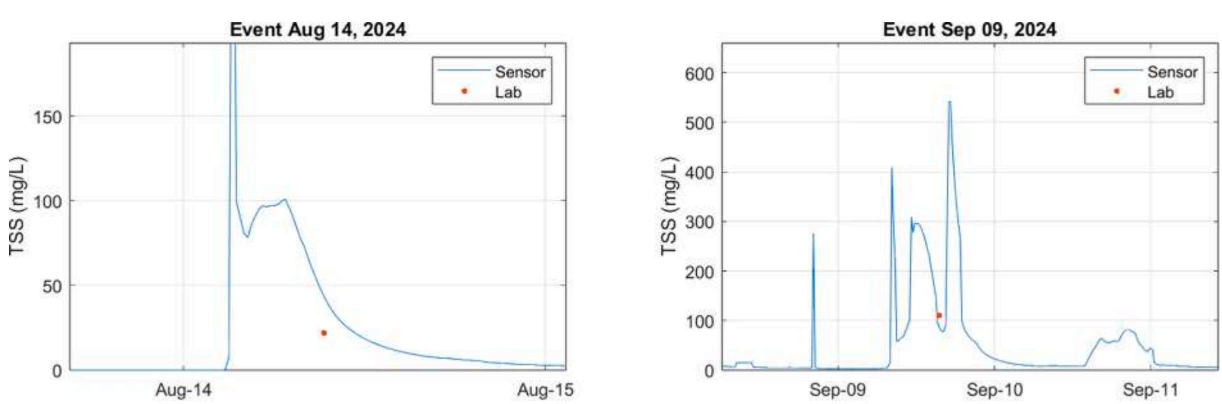

Fig. A2. Comparison of TSS calculated from Equation (1) and lab analyses on grab samples collected at CS2.

CS2 is positioned at a busy ring road, which makes the use of automatic sampling devices unfeasible. At this site, only two grab samples could be collected, but the concentrations in these samples compare well with those calculated from formula (1) – see Fig. A2.

Appendix B. – Rainfall characteristics at CS1-CS2

The rainfall characteristics at CS1 and CS2 are shown in Figs. B1 and Fig. B2, respectively. For CS1, the rainfall duration varies from 0 to 400 h, the peak intensity from 0 to 50 mm/h, and the dry days before rain events from 0 to 30 days. For CS2, the corresponding ranges are 0 to 80 h, 0 to 50 mm/h, and 0 to 6 days. The histograms of rainfall duration, peak intensity and number of dry days before a rain event are highly skewed to the right for both CSs as expected in such statistics; the histograms of CS2 are more skewed hinting at a larger variability though in a different range of rainfall durations and number of dry days before a rain event, while the range of peak intensities is roughly the same. In fact, most durations fall in the 0–80 h range for CS1 and in the 0–30 h range for CS2; the number of dry days before a rain event is typically 0–10 for CS1 and 0–2 for CS2, while the peak intensity falls mostly in the 0–20 mm/h range for both case studies.

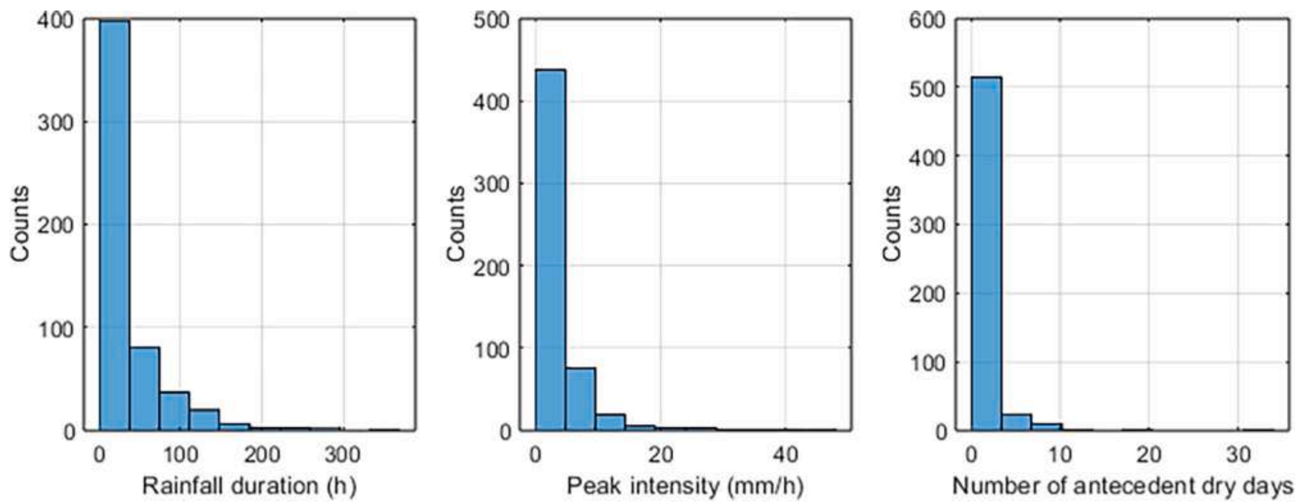

Fig. B1. Rainfall characteristics of CS1.

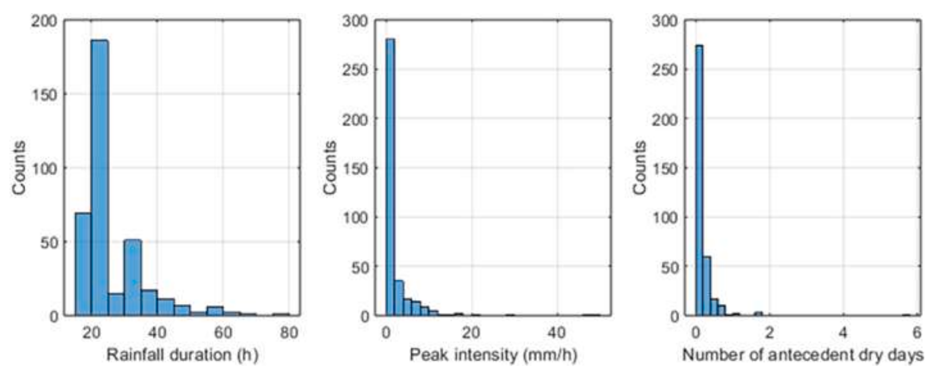

Fig. B2. Rainfall characteristics of CS2.

Appendix C. — Correlation between flow and turbidity

Fig. C1 shows the distribution of the Pearson correlation coefficient between turbidity and flow at both case studies during different storm events. For some events a very high correlation coefficient was observed, but for the majority of the events, (almost) no correlation is seen.

The variability in this correlation is largely unaffected by rainfall characteristics or pollutant concentrations. In some rain events, the absence of correlation can be attributed to peak flow preceding peak turbidity, potentially due to delayed sediment transport. However, for the majority of storm events, the lack of correlation remains unexplained.

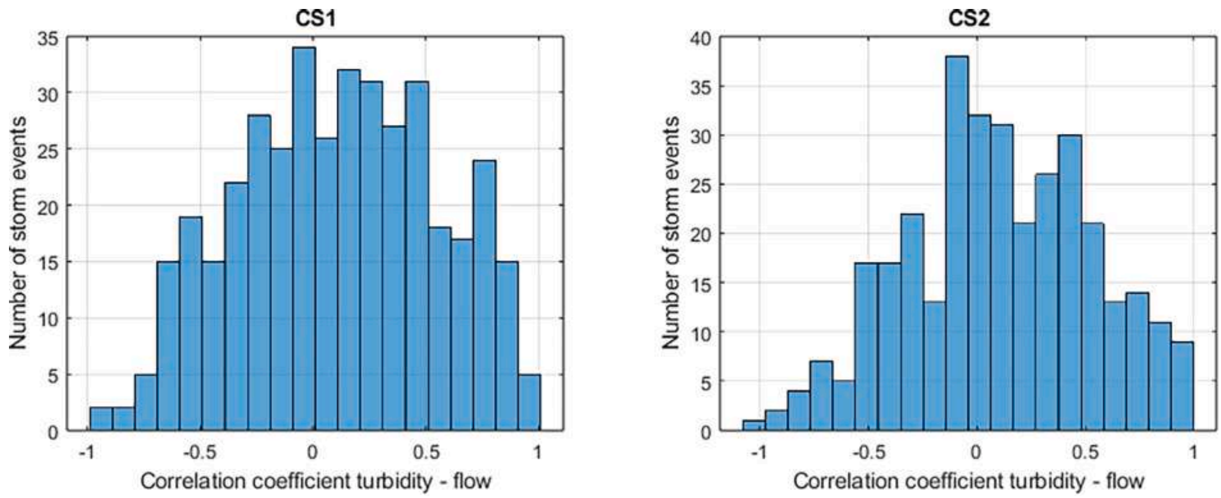

Fig. C1. Pearson correlation coefficient between turbidity and flow for different rainfall events at CS1 and CS2. Rainfall events with a time interval of less than 30 min were considered as the same event. Only rainfall events with a minimum of 30 min were considered.

Appendix D. – Sensitivity analysis for CS2

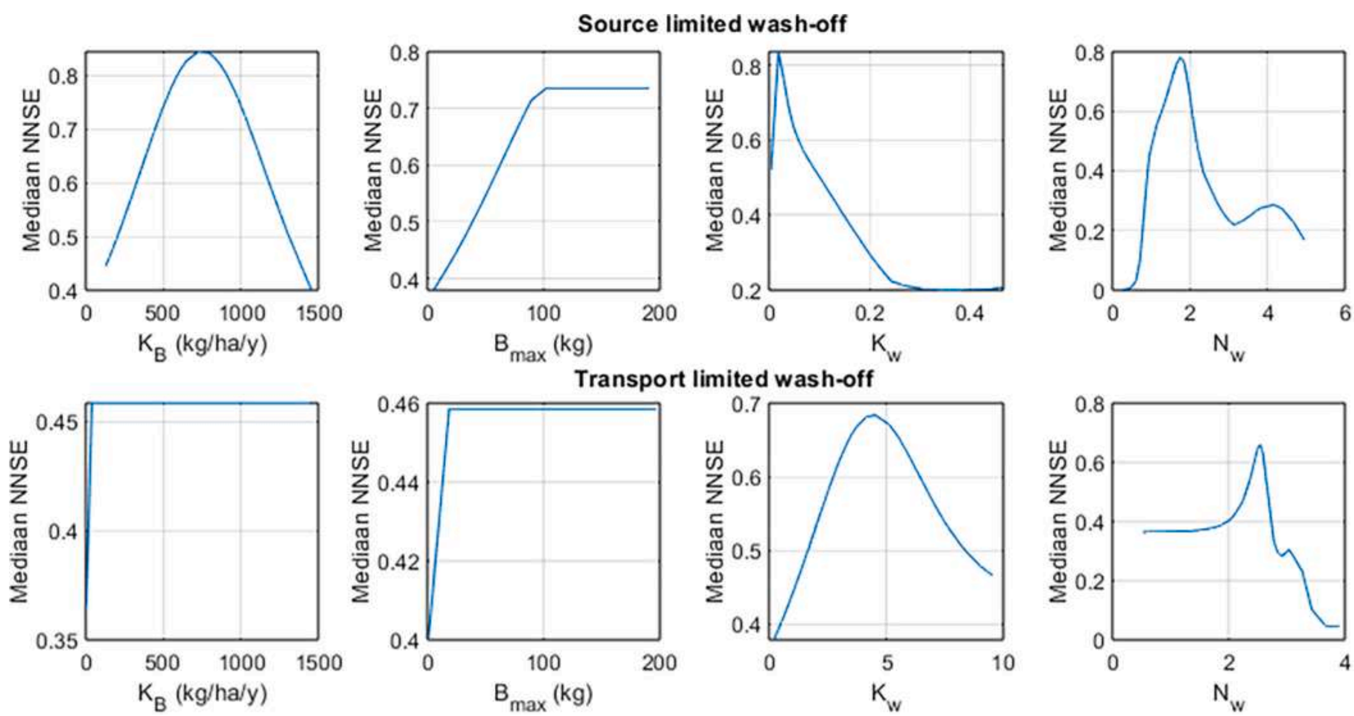

Fig. D1. Normalized NSE coefficient between TSS derived from the turbidity sensor and the modelled TSS with source-limited (upper graphs) or transport- limited (lower graphs) wash-off equation as a function of the value of the four model parameters for two rainfall events at CS2.

Appendix E. — Comparison with ICM/SWMM simulations

E.1. Hydraulic model

For three selected rainfall events spanning a representative range of rainfall characteristics in CS1, the simplified model achieved NNSE values of 0.91, compared to 0.85 and 0.89 for ICM and SWMM respectively (Fig. E1).

Fig. E2 shows in a boxplot the range of NNSE values associated to the simplified hydraulic model, ICM and SWMM for all rainfall events.

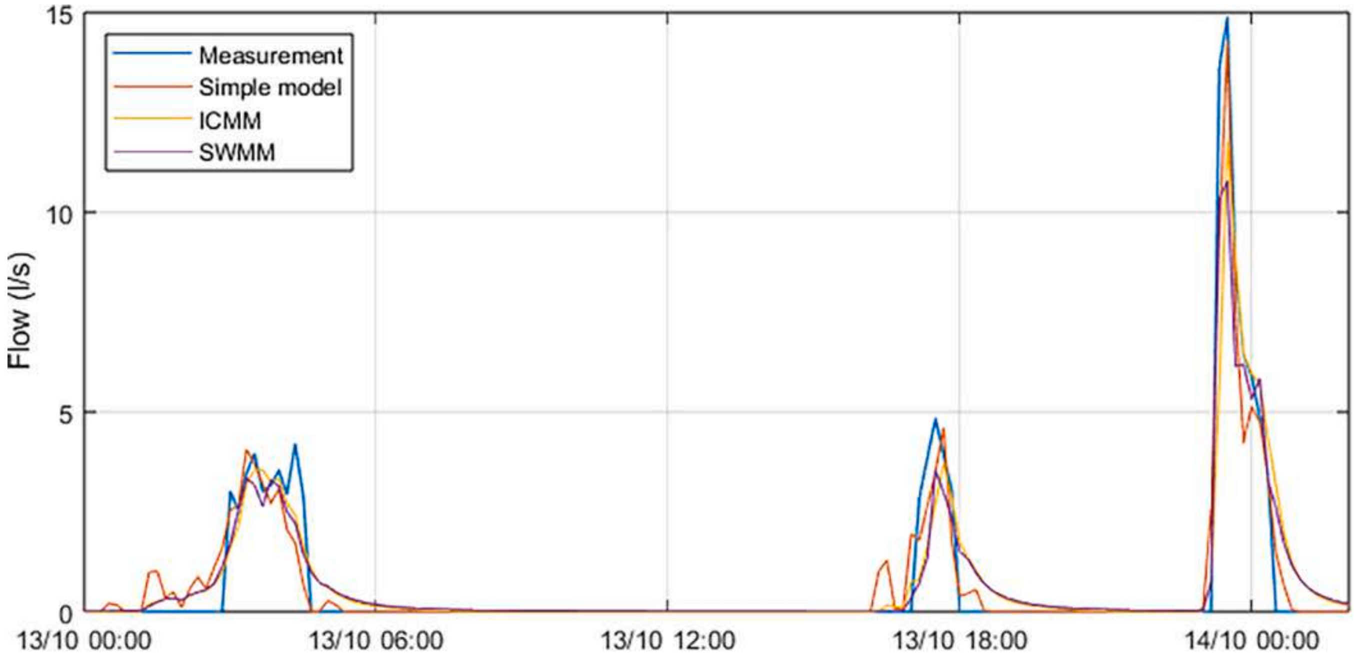

Fig. E1. Comparison of the measured flow rate with the flow rate obtained from our simplified model, ICM and SWMM for three selected rainfall events in CS1.

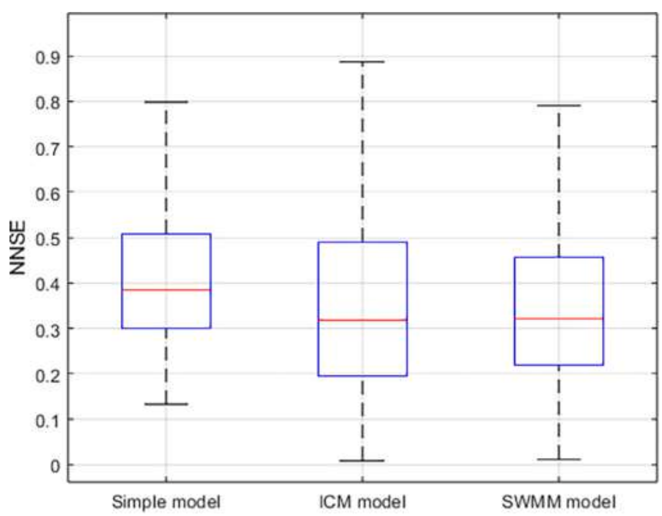

Fig. E2. Range of NNSE values between measured flow rate and the flow rate obtained from the simplified model and the SWMM and ICM models.

E.2. WQ model

Fig. E3 compares the WQ simulations of the simple model with those of the SWMM model for CS1. For the selected rainfall events, the simple model performs better than the SWMM model, likely due to the incorporation of an equilibrium concentration in SWMM. This result confirms that the simple model is a valid alternative to more advanced hydraulic software such as SWMM or Infoworks ICM.

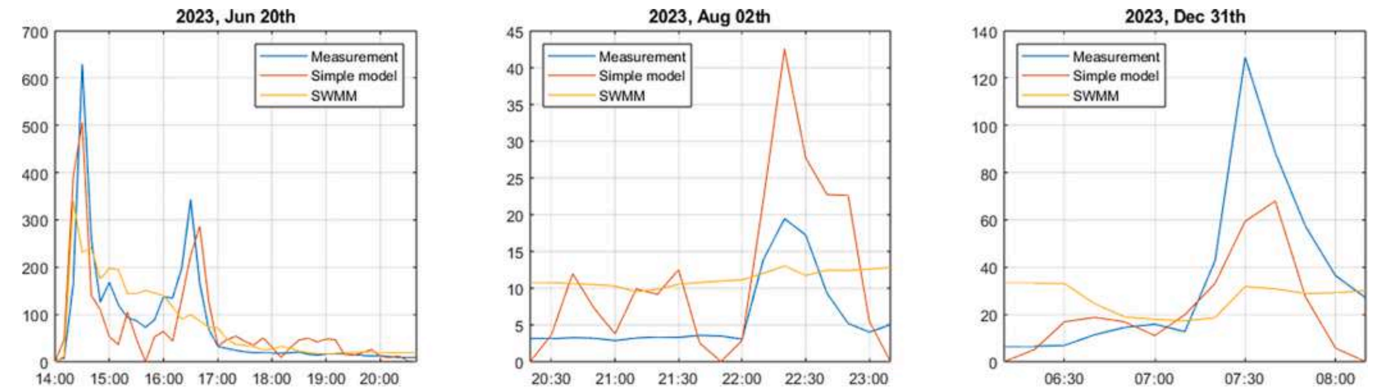

Fig. E3. Comparison of the TSS concentration derived from turbidity with the TSS concentration obtained from the simple model and the SWMM model for three selected rainfall events in CS1. The model was run with a fixed build-up rate of 500 kg/ha/y, so the simulation results deviate somewhat from those in Fig. 9.

Availability of research data

Rainfall and weather data (water wind and temperature) are available at www.waterinfo.be; traffic data were obtained from the Flemish agency of roads and traffic (AWV, personal communication); data for turbidity registered at CS1 and CS2 can be downloaded at https://doi.org/10.5281/zenodo.11280213.

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