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Assessing uncertainty in stormwater quality modelling

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A B S T R A C T

Designing effective stormwater pollution mitigation strategies is a challenge in urban stormwater management. This is primarily due to the limited reliability of catchment scale stormwater quality modelling tools. As such, assessing the uncertainty associated with the information generated by stormwater quality models is important for informed decision making. Quantitative assessment of build-up and wash-off process uncertainty, which arises from the variability associated with these processes, is a major concern as typical uncertainty assessment approaches do not adequately account for process uncertainty. The research study undertaken found that the variability of build-up and wash-off processes for different particle size ranges leads to processes uncertainty. After variability and resulting process uncertainties are accurately characterised, they can be incorporated into catchment stormwater quality predictions. Accounting of process uncertainty influences the uncertainty limits associated with predicted stormwater quality. The impact of build-up process uncertainty on stormwater quality predictions is greater than that of wash-off process uncertainty. Accordingly, decision making should facilitate the designing of mitigation strategies which specifically addresses variations in load and composition of pollutants accumulated during dry weather periods. Moreover, the study outcomes found that the influence of process uncertainty is different for stormwater quality predictions corresponding to storm events with different intensity, duration and runoff volume generated. These storm events were also found to be significantly different in terms of the Runoff-Catchment Area ratio. As such, the selection of storm events in the context of designing stormwater pollution mitigation strategies needs to take into consideration not only the storm event characteristics, but also the influence of process uncertainty on stormwater quality predictions.

1. Introduction

In urban areas, the transformation of natural environment into residential, commercial and industrial land use leads to the generation of pollutants ranging from particulate solids to toxic particle-bound heavy metals and hydrocarbons (Brown and Peake, 2006; Hvitved-Jacobsen et al., 2010; WWAP, 2015). These pollutants, which accumulate on urban impervious surfaces over dry weather periods are entrained in stormwater runoff during storm events. The urban water quality is degraded once polluted stormwater runoff is discharged into receiving waters (Makepeace et al., 1995; Zhao and Li, 2013). Stormwater pollution is therefore a major concern in urban water management. As such, effective stormwater pollution mitigation is necessary for improving stormwater quality. In this context, informed decision making plays an important role in the design of effective pollution mitigation strategies.

Information on catchment stormwater quality is essential for planning and management decision making. This knowledge (stormwater quality predictions) is commonly generated using stormwater quality models which incorporate mathematical replications of primary pollutant processes, namely, build-up and wash-off (WWAP, 2012; Xu and Tung, 2008). However, it has been highlighted in past studies (e.g. Freni et al., 2009a; Helton and Burmaster, 1996; Métadier and Bertrand-Krajewski, 2011 and Zoppou, 2001) that uncertainties primarily arising from process modelling itself and the variability in pollutant processes significantly influence the interpretation of stormwater quality predictions. Decision making without adequate knowledge of these uncertainties can lead to the design of ineffective stormwater pollution mitigation strategies (Hvitved-Jacobsen et al., 2010; Loucks et al., 2005; Obropta and Kardos, 2007).

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Stormwater quality modelling uncertainty, which arises from sources such as model structure, input and calibration data and model parameters, is generally understood. A number of techniques are available for assessing modelling uncertainty as summarised in Table 1. However, these techniques exhibit significant drawbacks such as the use of user defined likelihood measures in Generalized Likelihood Uncertainty Estimation (GLUE) and the role of prior knowledge in Bayesian techniques in uncertainty assessments.

On the other hand, how inherent process uncertainty stems from process variability is investigated only in a limited number of research studies. Wijesiri et al. (2016) confirmed that process uncertainty can be quantitatively incorporated in build-up and wash-off predictions, which in fact, as highlighted by Zoppou (2001), is essential for informed decision making.

The approach for assessing build-up and wash-off process uncertainty proposed by Wijesiri et al. (2016) is based on mathematical formulations which replicate the temporal variations of the build-up and wash-off loads of particles <150 μm and >150 μm. These temporal variations describe different behaviours to each other during build-up and wash-off, which were found to primarily influence process variability (Herngren et al., 2006; Wijesiri et al., 2015a,b). Therefore, the incorporation of process variability into build-up and wash-off process models can account for the different behaviour of particles of different size fractions, which also result in differences in their association with other pollutants, while undergoing build-up and wash-off. This approach has previously been undertaken using only small-plot scale field data obtained from road surfaces. There is a need to translate this approach to catchment-scale water quality predictions in order to demonstrate the practical application of the study outcomes and to support the interpretation of model outcomes.

The primary objective of the investigation described in this paper was to quantitatively assess process uncertainty in relation to catchment scale stormwater quality predictions focussing on road surfaces, as these are the primary pollutant source to urban stormwater runoff. Accordingly, the research study focused on: (1) the translation of small-plot scale particulate build-up and wash-off data into catchment scale stormwater quality predictions; and (2) the extension of the uncertainty assessment approach proposed by Wijesiri et al. (2016) for small-plot scale pollutant processes models to catchment stormwater quality predictions. The outcomes of this study are expected to facilitate the development of approaches for enhancing stormwater pollution mitigation strategies to improve urban stormwater quality.

2. Materials and methods

2.1. Study design

Accurate model development followed by satisfactory calibration and verification is critical for the accuracy of the modelling outcomes. However, the lack of adequate data sets for calibration often challenges the reliability of most modelling approaches (Bertrand-Krajewski, 2007). As such, Egodawatta (2007) recognised that a modelling approach that utilises field data on pollutant build-up and wash-off for generating necessary model parameters enables the accurate prediction of stormwater quality, without having to perform model calibration. Similarly, the modelling approach developed and the uncertainty assessment undertaken in this investigation also utilised small-plot scale field data collected from urban catchments.

2.2. Study catchments

Three catchments: Gumbeel, Birdlife Park and Highland Park were selected from Gold Coast, South East Queensland, Australia. Gumbeel and Birdlife Park are small catchments located within the larger Highland Park catchment. The field investigations on particulate build-up and wash-off were undertaken at selected road sites located within each catchment. The selection of road sites was based on the fact that roads constitute a significant component of urban impervious surfaces and contribute significant pollutant loads to stormwater runoff. Figs. S1–S3 in the Supplementary Information show the aerial views of the selected catchments and the locations of road sites.

All three catchments are predominantly residential. Gumbeel, which is 1.6 ha in extent, consists of duplex housing. The catchment impervious area due to road surfaces (ratio between area of road surfaces and total catchment land area) is 15%, and has a simple and short drainage network compared to the other two catchments. Birdlife Park (7.5 ha) consists of single detached housing, and road surfaces form 12% of the impervious area. The drainage network in Birdlife Park includes road gutters and side manholes. The largest of the three catchments with an area of 105.2 ha, Highland Park, has fractions of commercial and forestry land uses in addition to the primary residential land use with single detached housing. The road surfaces form 16% impervious area. The drainage network in Highland Park includes pipes and channels which are connected to Bunyip Brook tributary that runs across the catchment.

The catchment area and the impervious area were calculated using Google Earth Pro. The impervious area was assumed to be evenly distributed over the catchment. The details of the drainage network in each catchment were obtained from the maps provided by the Gold Coast City Council. The roads in the sampling sites were found to have slopes varying from 7.2 to 10.8% and texture depth varying from 0.66 to 0.92 mm. Detailed information regarding the characteristics of the sampling sites located within each catchment can be found in Wijesiri et al. (2015a,b).

2.3. Small-plot scale field sampling and laboratory analysis

Particulate build-up and wash-off sampling were undertaken on small road surface plots (3 m^2) using a portable wet vacuum system and a rainfall simulator. The use of the rainfall simulator was to simulate storm events with different intensities and durations, and also to avoid the constraints associated with sampling under natural storm events. The performance of both sampling tools was validated under field conditions similar to the road surfaces in the study sites prior to being used in the field experiments. The

Table 1
Commonly used techniques for assessing stormwater quality modelling uncertainty.

Technique	References
Generalized Likelihood Uncertainty Estimation (GLUE)	Beven and Binley (1992), Freni et al. (2008), Freni et al. (2009a)
Shuffled Complex Evolution Metropolis Algorithm (SCEM-UM)	Vrugt et al. (2003)
Multi-algorithm Genetically Adaptive Multi-objective method (AMALGAM)	Vrugt and Robinson (2007)
Classical Bayesian Approach based on Markov Chain Monte Carlo (MCMC) method and the Metropolis-Hastings Sampler	Beven (2009), Doherty (2003), Freni et al. (2009b)

validation procedure discussed in detail in Herngren et al. (2006) and Egodawatta et al. (2007) was adopted.

In the build-up experiments, particulate build-up samples (road deposited solids) were collected for antecedent dry periods of 1, 2, 3, 7, 14 and 23 days at Gumbeel Court (refer to Fig. S1) and Lauder Court (refer to Fig. S3) road sites, while sampling was undertaken for antecedent dry periods of 1, 2, 7, 14 and 21 days at Piccadilly Place (refer to Fig. S2). Road deposited solids are a composite of several sources such as soil, vehicular emissions, vegetation and traffic related abrasion products (Mummullage et al., 2016a, 2016b). For wash-off sampling, storm events with intensities of 20, 40, 65, 86, 115 and 133 mm/h were simulated at Gumbeel Court and Piccadilly Place, while at Lauder Court, 40, 65, 86, 115 and 133 mm/h storm events were simulated. The selection of storm event durations took into consideration the fact that the development of sheet flow over time decreases the impact of raindrop kinetic energy in the mobilisation of particles adhering to the road surface (Egodawatta et al., 2007; Vaze and Chiew, 2000). As such, the durations beyond which particulate wash-off load becomes insignificant were selected for the simulation of the storm events. Accordingly, the durations corresponding to storm event intensities were 20 mm/h – 40 min, 40 mm/h – 35 min, 65 mm/h – 30 min, 86 mm/h – 25 min and 115 and 133 mm/h – 20 min. Further, samples of initial particulate build-up available on road surfaces prior to the simulation of storm events were also collected from a road surface plot just beyond the wash-off sampling area.

The build-up and wash-off samples were analysed for two parameters: total particulate solids load and particle size distribution. Standard methods 2540C and 2540D (APHA, 2012) were used to determine particulate solids load in each sample. Particle size distributions were determined using a Malvern Mastersizer S instrument which can analyse a particle size range of 0.05–900 μm. The quality audit standards QAS3002 and QAS3001-B were used to verify the instrument performance (Malvern Instrument Ltd., 1997).

2.4. Catchment model set-up and runoff simulation

The SWMM (US Environmental Protection Agency's Stormwater Management Model) module in Mike URBAN software developed by the Danish Hydraulics Institute (MikeUrban, 2014) was selected for setting up the catchment models. Hydrologic modelling by Mike URBAN – SWMM module was based on the non-linear reservoir method (MikeUrban, 2014). The criterion for hydrologic modelling software selection was primarily based on the fact that the process replications are physically based and catchment-specific hydrologic parameters can be determined using field data. Additionally, ability to set up catchment models to account for the spatial variability of hydrologic processes and to perform runoff simulations for individual storm events were considered as necessary capabilities that should be available in the software.

In setting up the catchment models, the spatial variability of hydrologic processes in the catchment was accounted for by dividing the catchment into several sub-catchments conforming to the drainage network. Accordingly, the catchment models developed are shown in Figs. S4–S6 in the Supplementary Information which also give the details of the number of sub-catchments, nodes and conduits allowed in each catchment model. The runoff generated by each sub-catchment is drained into a 'load point' which is typically a node or an adjacent sub-catchment. Nodes are hydrological components of a drainage network such as junctions (manholes) and outfalls (terminal node of network). The water accumulating at nodes is transported through conduits such as pipes and channels (MikeUrban, 2014). A sample set of input data consisting of sub-catchments, nodes and conduits for Mike URBAN – SWMM for setting up the catchment models are given in Fig. S7 in the Supplementary Information.

2.5. Selection of storm events for runoff simulation

In order to simulate stormwater runoff generated from a catchment, the primary boundary condition required is the rainfall records. It was important to obtain records of storm events with different characteristics (i.e. intensity and duration) that typically occur in the study area. Therefore, the rainfall records from the Hinze Dam weather station (Station ID: 040584), which is the nearest to all three study catchments, for the period 2004–2014 were analysed. These rainfall records were provided as rainfall depths in 1 min time steps by the Australian Bureau of Meteorology.

For model simulation, it was necessary to select individual storm events from the rainfall records. In order to select representative years, the variation of annual rainfall depth over the period 2004–2014 was analysed. Fig. S8 in the Supplementary Information shows the variation of annual rainfall depth with respect to the average annual rainfall depth for the selected period. The average annual rainfall depth was 1436.3 mm. As evident from Fig. S8, annual rainfall depths for five years are less than the average annual rainfall depth, while annual rainfall depths for six years are greater than the average annual rainfall depth. Therefore, it was decided to select two representative years (i.e. 2005 and 2008) with the annual rainfall depth below and above the average annual rainfall depth for model simulations. The selection of these representative years also reduced the number of storm events to be used for model simulation.

The rainfall records for the selected two years were further analysed to select the storm events where the event rainfall depth is greater than the depression storage for road surfaces. Depression storage is the surface storage of water resulting from processes such as ponding, surface wetting and interception at the beginning of a storm event. This was to ensure all selected storm events generate runoff. The depression storage for the road surfaces was calculated as the difference between the rainfall depth and the runoff depth corresponding to the initial period of the storm events simulated at each road site. The simulated storm events used to calculate the depression storage are given in Table S1 in the Supplementary Information. The average depression storage for the road surfaces in the three catchments was found to be 2.87 mm.

In selecting storm events, continuous and longest storm events were first selected. Further, where such events had continued to the next day, it was considered as a single event. The selected events were further assessed to ensure that the rainfall depth of each event was greater than 2.87 mm. Accordingly, 27 storm events from the year 2005 and 38 storm events from the year 2008 were selected for model simulation. Further, the average intensity of each selected storm event was also calculated. Given the time series of intensities for the selected storm events, the runoff volume generated from the road surfaces was simulated using the three catchment models. The intensities and durations of storm events and the runoff volume simulated at each catchment are given in Tables S2 and S3 in the Supplementary Information.

2.6. Prediction of stormwater quality and quantification of associated uncertainty

Prediction of catchment stormwater quality and quantification of associated uncertainty were undertaken based on two scenarios: (1) using the primary build-up and wash-off models where build-up and wash-off process variability is poorly characterised (Ball et al., 1998; Sartor and Boyd, 1972); and (2) using the revised build-up and wash-off models which were derived by incorporating process variability into the primary models (Wijesiri et al., 2016). Equations (1) and (2) given below define the primary build-up and wash-off models which were adapted from Ball et al. (1998) and Sartor and Boyd (1972), respectively. In this regard, it is important to note that the validation of these simplest forms of build-up and wash-off models was not undertaken as they were used only for implementing the approach to assess process uncertainty, and thereby to guide the uncertainty assessment in relation to the revised models. Equations (3) and (4), which define the revised build-up and wash-off models were adapted from Wijesiri et al. (2016). The derivation of revised models (details are given in the Supplementary Information) were based on the fact that the differences in behaviour of particles <150 μm and >150 μm during build-up and wash-off predominantly influences process variability (Gnecco et al., 2005; Gobel et al., 2007; Wijesiri et al., 2015a,b).

$$B_{primary} = \alpha t^{\beta} \tag{1}$$

$$W_{primary} = (W_o \equiv B_{primary})(1 - \exp(-kIt)) \tag{2}$$

$$B_{revised} = \left\{B_{(<150)} = \alpha_{<150} t^{-\beta_{<150}}\right\} + \left\{B_{(>150)} = \alpha_{>150} t^{\beta_{>150}}\right\} \tag{3}$$

$$W_{revised} = B_{(<150)}(1 - \exp(-k_{<150}It)) + B_{(>150)} \times (1 - \exp(-k_{>150}It)) \tag{4}$$

where: B – particulate build-up load

W – amount of particulates washed-off
W_o – amount of particulates available at the beginning of storm event
t – antecedent dry period/storm event duration
I – storm event intensity
α, β, k – build-up and wash-off coefficients (subscripts indicate corresponding particle size fraction)

Although Mike URBAN – SWMM is capable of simulating build-up and wash-off, the software does not allow the incorporation of user-defined mathematical models of build-up and wash-off. Therefore, numerical computing software was required to predict catchment scale particulate build-up and wash-off using Equations

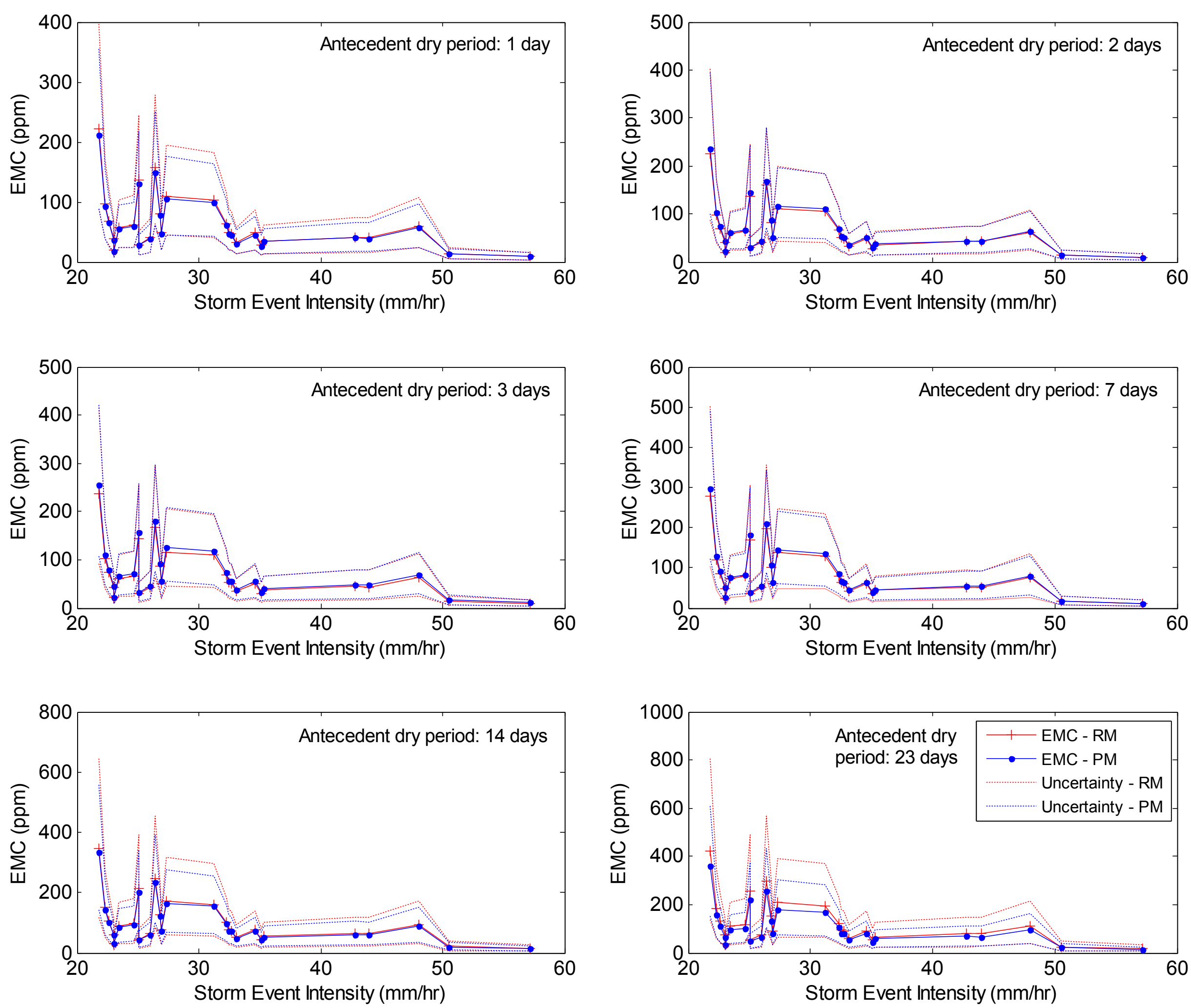

Fig. 1. Predicted Event Mean Concentration (EMC) of particulate solids and associated uncertainty limits for primary and revised models – Gumbeel, year 2005 storm events; Note: PM – primary models, and RM – revised models. Results for 2008 storm events are given in the Supplementary Information.

(1)–(4). Consequently, MATLAB in-built non-linear regression tools that include the function *nlinfit* (MathWorks, 2013) were used for the prediction of particulate build-up and wash-off from road surfaces, and thereby to translate the predictions into catchment stormwater quality and also for quantifying uncertainty.

Firstly, parameters of build-up and wash-off models were estimated for each catchment using the small-plot scale field data. In regard to wash-off model parameters, it was necessary to estimate a common value for the wash-off coefficient (k) which can be used for predicting wash-off for the selected storm events. In fact, adoption of this approach was supported by the fact that the wash-off coefficient is approximately similar for storm events with different intensities (Avellaneda et al., 2009; Wijesiri et al., 2015a). As such, a common value for 'k' was estimated for the range of intensities of the selected storm events which varied from 13.8 mm/h to 74.2 mm/h. Accordingly, the common 'k' value was estimated using the wash-off data corresponding to 20, 40, 65 and 86 mm/h storm events, which were simulated in the field investigation. Estimated build-up and wash-off parameters are given in Table S4 in the Supplementary Information.

Particulate build-up load per unit area was then predicted for different antecedent dry periods using the estimated build-up models. Then, particulate wash-off load per unit area was predicted for each predicted build-up value and for each storm event selected from the two representative years. Given the catchment area and the volume of stormwater runoff simulated using the catchment models, the predicted particulate wash-off load per unit area was then converted to catchment scale Event Mean Concentration (EMC) values. The EMC values for particulate solids are presented in Tables S5 and S6 in the Supplementary Information.

For the quantification of uncertainty associated with predicted stormwater quality, the procedure followed in the study described in Wijesiri et al. (2016) was adopted. Accordingly, 10,000 simulations of the EMCs of particulate solids were performed primarily accounting for residual errors and parameter estimation errors that correspond to the prediction of build-up and wash-off. In regard to accounting for these errors, the *proportional error model structure* (MathWorks, 2013) as defined by Equation (5) was assigned. As such, the residual errors were accounted for in terms of the variance of 'y' given the build-up and wash-off model parameters 'δ' and predictor variable 't'. The variance of 'y' can be written as shown by Equation (6). The parameter estimation errors were accounted for in terms of the standard error of each estimated parameter value which was obtained from the observed Fisher Information Matrix generated by the *nlinfit* function. Thus, using the simulated EMCs of particulate solids, lower (2.5th percentile) and upper (97.5th percentile) uncertainty limits could be determined, accounting for 95% uncertainty interval.

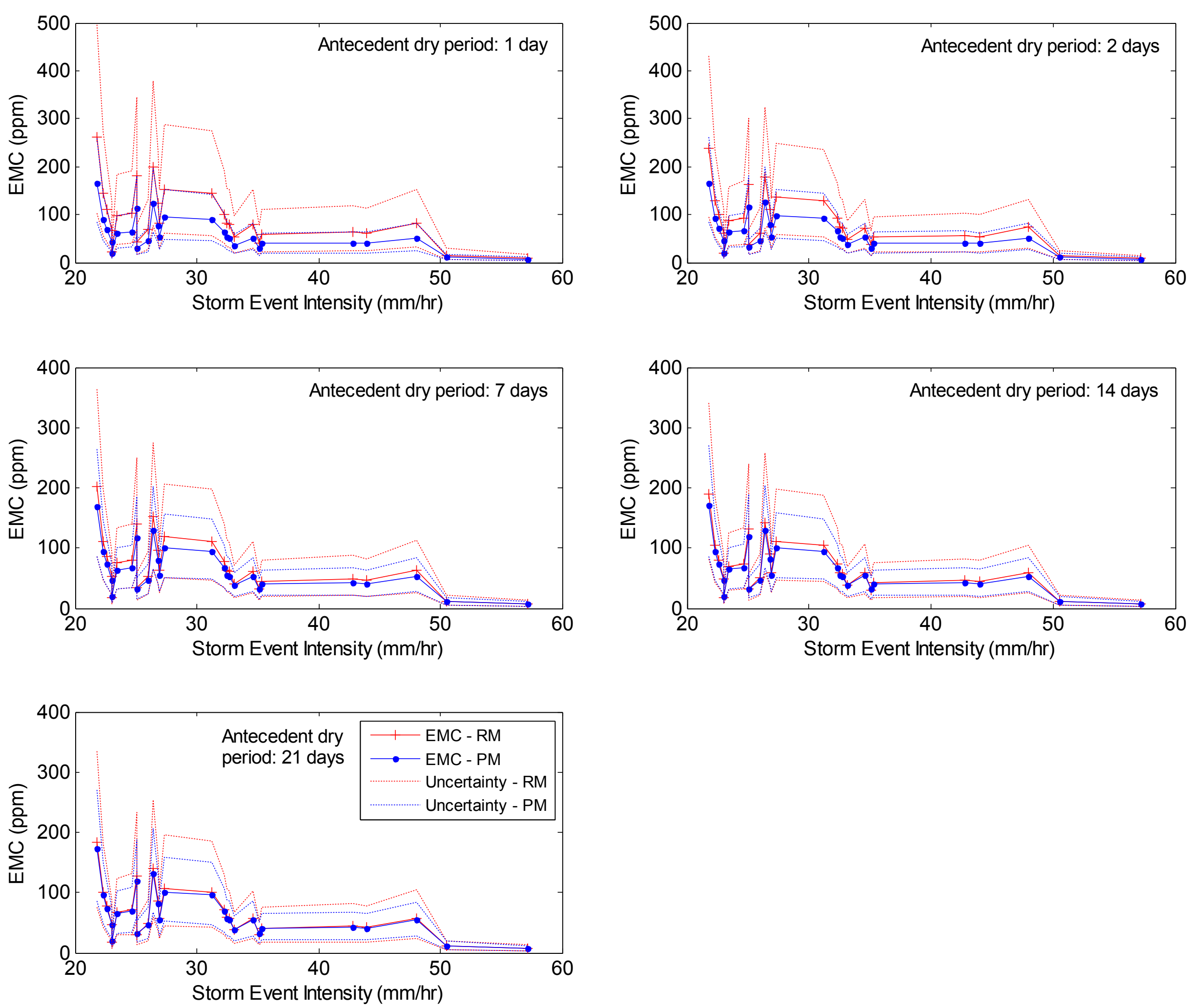

Fig. 2. Predicted Event Mean Concentration (EMC) of particulate solids and associated uncertainty limits for primary and revised models – Birdlife Park, year 2005 storm events; Note: PM – primary models, and RM – revised models. Results for 2008 storm events are given in the Supplementary Information.

$$y = f + \theta_1 f \varepsilon \tag{5}$$

$$var[y|\delta, t] = \theta_1^2 f(t, \delta)^2 \tag{6}$$

where: y – response variable

f – function value
θ_1 – error parameters
$\varepsilon \sim N(0, 1)$
t – predictor variable
δ – build-up and wash-off model parameters

Further, when simulating EMCs, the error parameter θ_1 was set to 1 (default value) similar to the study in Wijesiri et al. (2016). However, it is important to note that the uncertainty is a function of both θ_1 and the predicted response. As the predicted response is a function of δ, the uncertainty associated with δ is also considered in the uncertainty assessment. Moreover, θ_1 is a proportionality parameter which shows that when the predicted response is relatively large, the variance is relatively large (similarly when θ_1 is relatively small, the variance is relatively small). In practice, θ_1 could be a range of values. However, the impact in terms of uncertainty will be a function of the predicted response, and similar trends of different magnitudes will be observed. Hence, setting θ_1 to a reasonable value allows assessing this impact in terms of uncertainty.

3. Results and discussion

3.1. Accounting of process uncertainty

As discussed in Wijesiri et al. (2016), the quantitative accounting of process uncertainty was related to the difference in uncertainty associated with the build-up and wash-off predictions between primary and revised models, noting that this was done using small plot data. Therefore, the uncertainty associated with catchment stormwater quality predicted in terms of EMC was compared between primary and revised models. As evident in Figs. 1–3 (storm events for 2005) and Figs. S9–S11 (storm events for 2008), the uncertainty bandwidth incorporated into the predicted EMCs using revised build-up and wash-off models shows an increase.

However, as the predicted EMCs of primary and revised models were found to be slightly different, the relative uncertainty bandwidth (ratio between uncertainty bandwidth and predicted EMC) was also compared. This allowed for an unbiased comparison of uncertainty between primary and revised models. Accordingly, Figs. 4–6 confirm the increase in uncertainty in relation to the revised model. The change in uncertainty associated with predicted

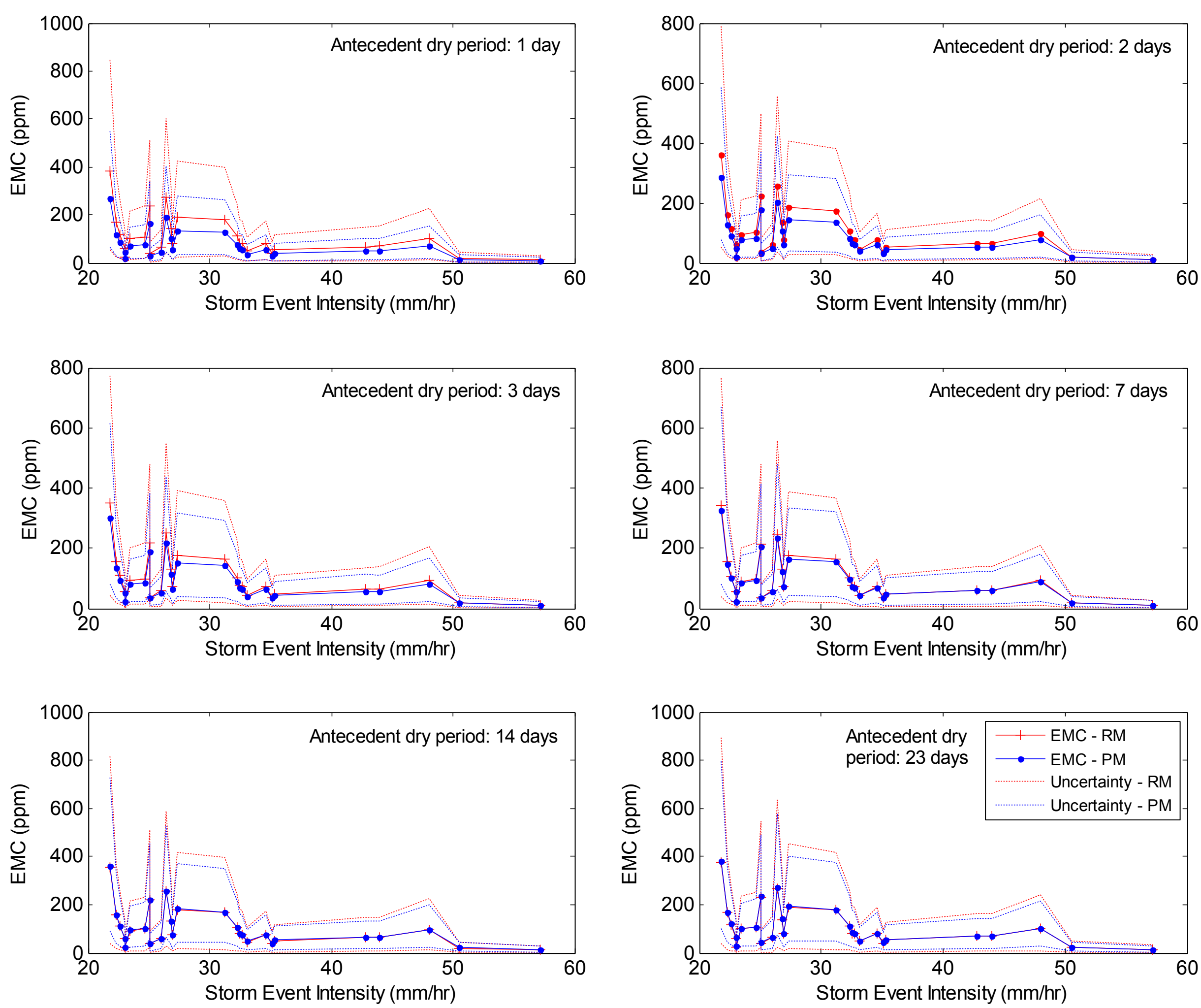

Fig. 3. Predicted Event Mean Concentration (EMC) of particulate solids and associated uncertainty limits for primary and revised models – Highland Park, year 2005 storm events; Note: PM – primary models, and RM – revised models. Results for 2008 storm events are given in the Supplementary Information.

EMCs between primary and revised models can be due to changes in the mathematical form of the primary models which result from the incorporation of process variability. Similar fact was noted by Wijesiri et al. (2016) in the case of the small plot scale pollutant processes modelling study.

Accordingly, it could be concluded that accurate characterisation of build-up and wash-off process variability in the respective models enables process uncertainty to be accounted for as an integral part of the uncertainty associated with catchment stormwater quality predictions. Furthermore, it has been highlighted in past studies (e.g. Haddad et al., 2013; Lee et al., 2012; Sun et al., 2012; Zoppou, 2001) that uncertainty associated with stormwater quality predictions plays an important role in the interpretation of these predictions. This makes it essential to understand how build-up and wash-off process uncertainty could translate to uncertainties in catchment stormwater quality predictions and thereby support the interpretation of modelling outcomes.

3.2. Characterisation of the influence of process uncertainty

It is evident from Figs. 1–3 and Figs. S9–S11 that the change in uncertainty is significantly influenced by the change in the upper uncertainty limit, which is consistently greater than that of the lower uncertainty limit. This applies to the change in the limits within which predicted stormwater quality varies. On the other hand, this change in uncertainty reflects the influence of variability in build-up and wash-off on pollutant loads released into stormwater runoff. As such, in the case where process uncertainty is not accounted for, it may not be possible to correctly interpret the predicted catchment stormwater quality. This can lead to ineffective decision making in relation to the formulation of stormwater pollution mitigation strategies.

As Figs. 4–6 reveal, the influence of process uncertainty on catchment stormwater quality predictions can be distinguished between build-up and wash-off processes. As such, in relation to the revised models, the relative uncertainty bandwidths show greater variation over different build-up events compared to the variation in relative uncertainty bandwidths over different storm events (wash-off events). The influence of build-up process uncertainty on stormwater quality predictions implies that the variability in pollutant build-up plays a relatively more important role in influencing catchment stormwater quality predictions. This conclusion is further supported by the fact that build-up process uncertainty propagates to the wash-off process (Wijesiri et al., 2016), resulting in significant variations in the load and composition of pollutants entrained in stormwater runoff, and thereby, the stormwater quality predictions. Moreover, the significance of the build-up process variability in the context of the prediction of catchment stormwater quality can be considered to be a generic finding as the revised build-up model shows similar behaviour in

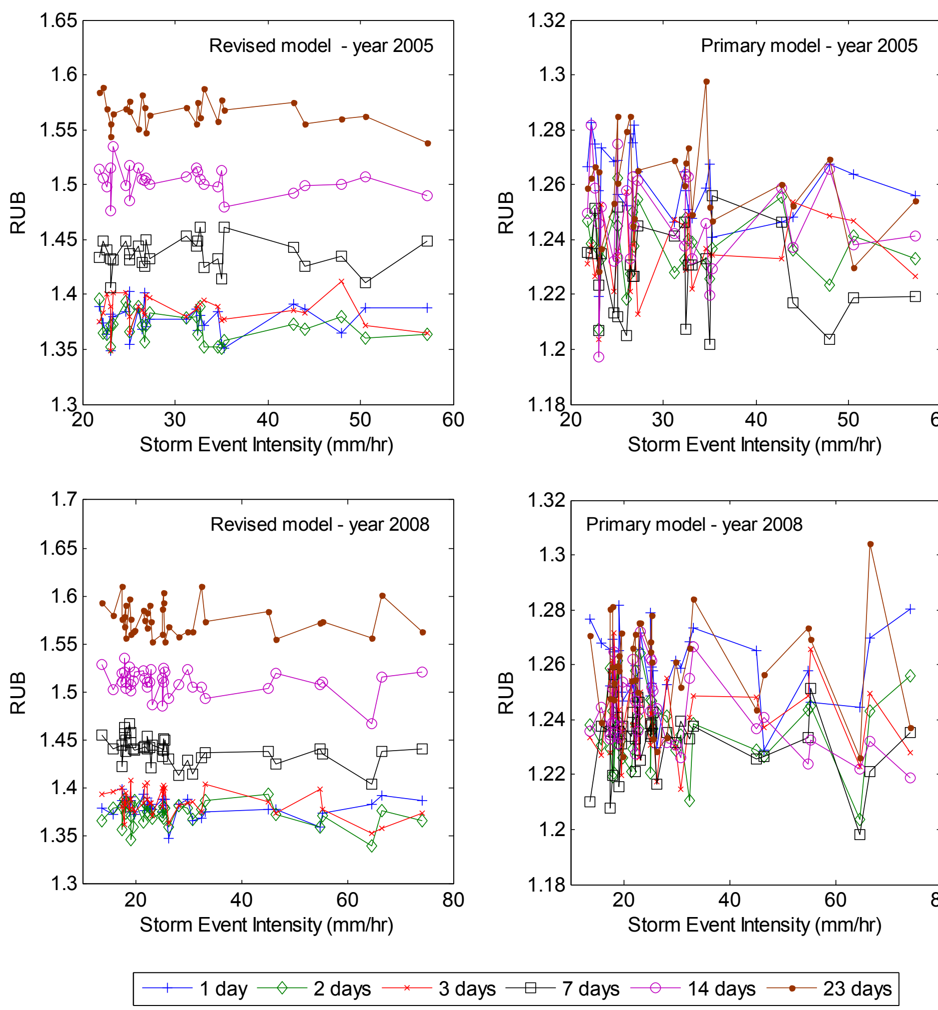

Fig. 4. Relative uncertainty bandwidth (RUB) for primary and revised models – Gumbeel.

relation to small plot scale predictions (Wijesiri et al., 2015b).

Furthermore, in the context of designing stormwater pollution mitigation strategies, Liu et al. (2012) highlighted the need to focus on specific storm events based on the pollutant loads present in stormwater runoff. Therefore, investigating the influence of process uncertainty on stormwater quality predictions specifically in relation to such storm events would also facilitate the formulation of effective pollution mitigation strategies. Liu et al. (2012) adopted an approach primarily based on storm event intensity and duration in order to classify the storm events occurring in the same geographical area as this study.

Accordingly, the Intensity-Frequency-Duration distributions of the storm events selected from the years, 2005 and 2008 were developed as shown in Fig. 7. Evidently, four types of storm events could be identified as shown. In this classification, the storm events with intensities less than 30 mm/h and durations less than 0.5hr were considered as low intensity-short duration storm events (Type 1), while Type 2 storm events were identified as low intensity-long duration (>0.5hr) storm events. Similarly, Type 3 and 4 storm events were identified as high intensity (>30 mm/h)-short duration and high intensity-long duration events, respectively. As can be seen in Fig. 7, Type 1 storm events have occurred most frequently in both 2005 (11 events) and 2008 (21 events). However, this observation differs slightly from the results reported by Liu et al. (2012), where low intensity (<20 mm/h)-long duration (>2hr) events were found to occur more frequently. This could be due to the fact that the classification in the current study is relatively broader (four types of storm events) than the classification by Liu et al. (2012) (three types of storm events) could influence the difference in the characteristics of the most frequent storm events. In effect, the criteria for selection and classification of storm events can influence the design of effective stormwater pollution mitigation strategies.

In addition to the storm event intensity and duration, runoff volume is also critical for designing effective stormwater pollution mitigation strategies. Specifically, pollutants contained in smaller volumes of stormwater runoff can be effectively treated (Guo and Urbonas, 1996; Liu et al., 2013). As such, it was important to consider the runoff volume generated by the different types of storm events, and investigate the influence of process uncertainty on stormwater quality predictions that correspond to each type of storm event. Fig. 8 (for 2005) and Fig. S12 (for 2008) in the Supplementary Information show the Intensity-Runoff-Duration distributions for the storm events selected from the two representative years. It is evident that both Type 1 and Type 3 events generate significantly smaller volume of runoff compared to Type 2 and Type 4 events. Figs. S13 and S14 in the Supplementary Information show the distributions of Runoff-Area ratio (ratio between runoff volume and total catchment area) for the selected storm events, which is a useful index in the context of the

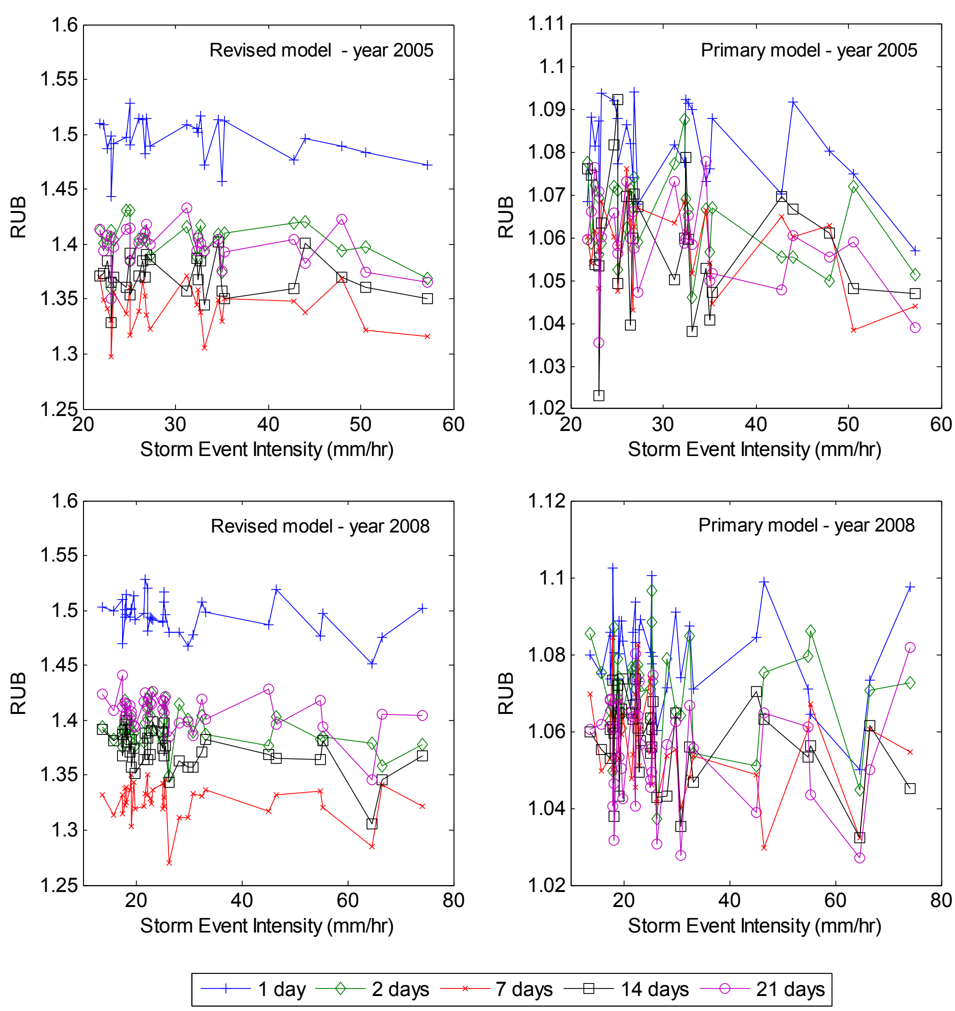

Fig. 5. Relative uncertainty bandwidth (RUB) for primary and revised models – Birdlife Park.

development of stormwater management strategies. It is further evident that Type 1 and Type 3 events can be clearly distinguished from Type 2 and Type 4 events.

In fact, Type 1 and Type 3 storm events together account for more than 70% of the total events that have an average intensity of 30 mm/h. On the other hand, Figs. 1–3 and Figs. S9–S11 and data presented in Tables S5 and S6 reveal that storm events with average intensity around 30 mm/h and duration less than 0.5hr are responsible for generating the highest EMCs for particulate solids. Interestingly, the proportionately wider uncertainty limits associated with these predictions of high EMCs show that the solids concentrations could vary over a relatively wider range compared to the EMCs predicted for Type 2 and Type 4 storm events.

Specifically, in relation to Type 1 and Type 3 storm events, the change in the uncertainty limits corresponding to the revised build-up and wash-off models also shows greater variation than the change in uncertainty limits for Type 2 and Type 4 events. The uncertainty associated with predicted EMCs for Type 1 and Type 3 and Type 2 and Type 4 storm events are shown separately in Figs. S15 and S16 in the Supplementary Information. This implies that the influence of process uncertainty on stormwater quality predictions for Type 1 and Type 3 events is relatively more significant compared to the predictions for Type 2 and Type 4 events. The significance of the influence of process uncertainty on stormwater quality predictions for each type of storm events can be further highlighted by considering the relationship between storm event characteristics and Runoff-Area ratios (by comparing Figs. S13 and S14 with Figs. S15 and S16). Further, the influence of process uncertainty on predictions of particulate solids loadings would be similar to the influence of process uncertainty on EMCs. This is due to the fact that uncertainty is a function of the predicted response (discussed in Section 2.6). Therefore, it is important that the design of stormwater pollution mitigation strategies should specifically focus on accurate interpretation of stormwater quality predictions for Type 1 and Type 3 storm events in order to enhance the effectiveness of such strategies. Liu et al. (2012) also identified the importance of focussing on storm events with characteristics similar to Type 1 and Type 3 events (i.e. intensity >20 mm/h and duration <2hr) in the design of stormwater pollution mitigation strategies.

4. Conclusions

This paper has presented an approach to quantitatively assess the build-up and wash-off process uncertainty as an integral part of the uncertainty associated with stormwater quality predictions. Process uncertainty was found to influence the upper limit of the uncertainty associated with predicted particulate solids event mean concentration values. This illustrates the changes in the limits within which predicted stormwater quality varies, particularly

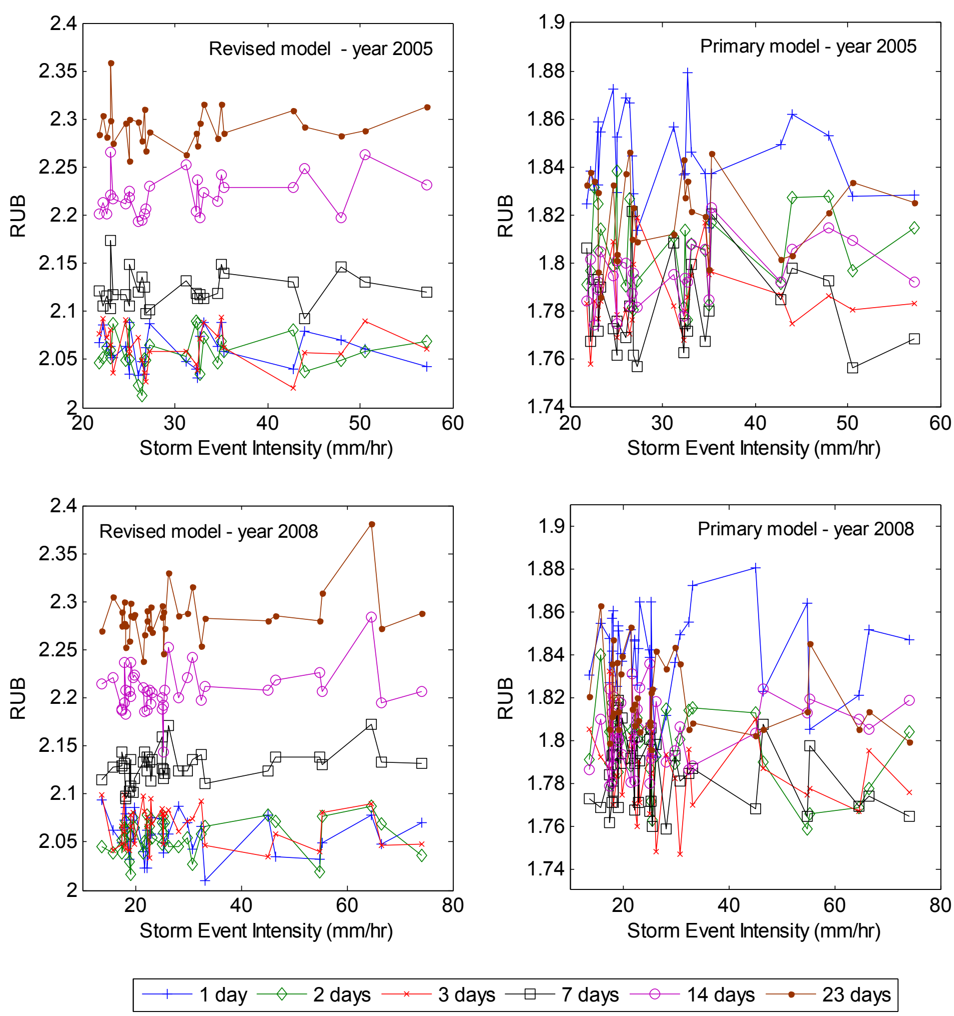

Fig. 6. Relative uncertainty bandwidth (RUB) for primary and revised models – Highland Park.

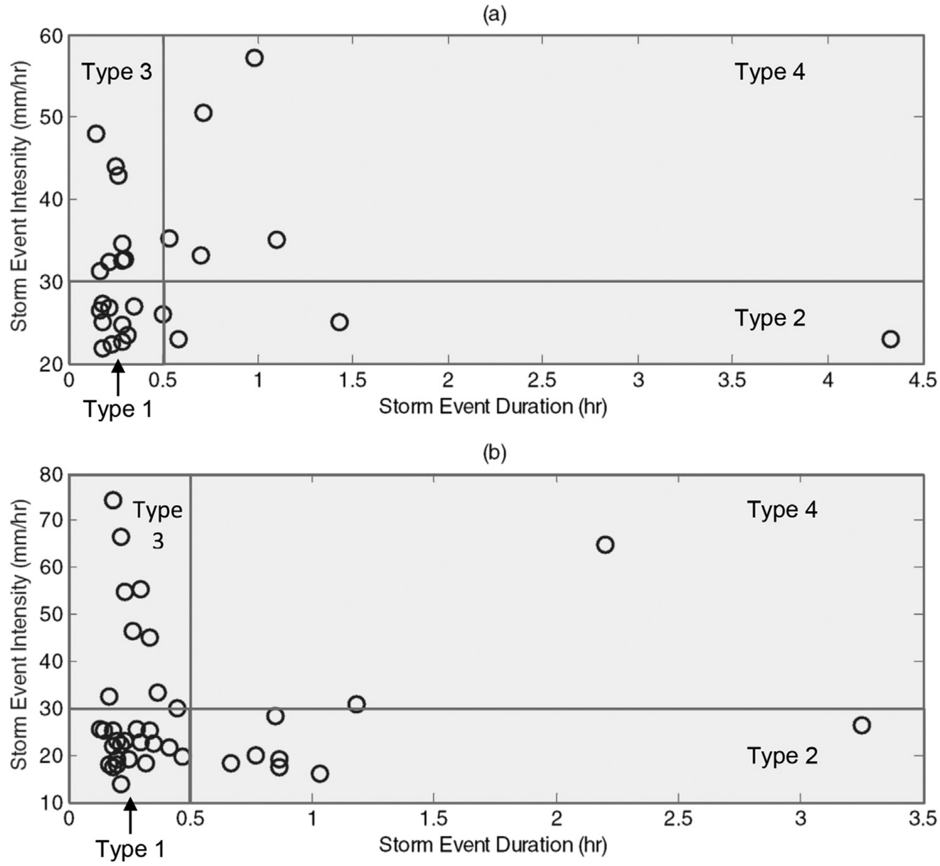

Fig. 7. Intensity-Frequency-Duration distribution of storm events: (a) Year 2005; (b) Year 2008; Note: Type 1 (low intensity-short duration); Type 2 (low intensity-long duration); Type 3 (high intensity-short duration); Type 4 (high intensity-long duration) storm events.

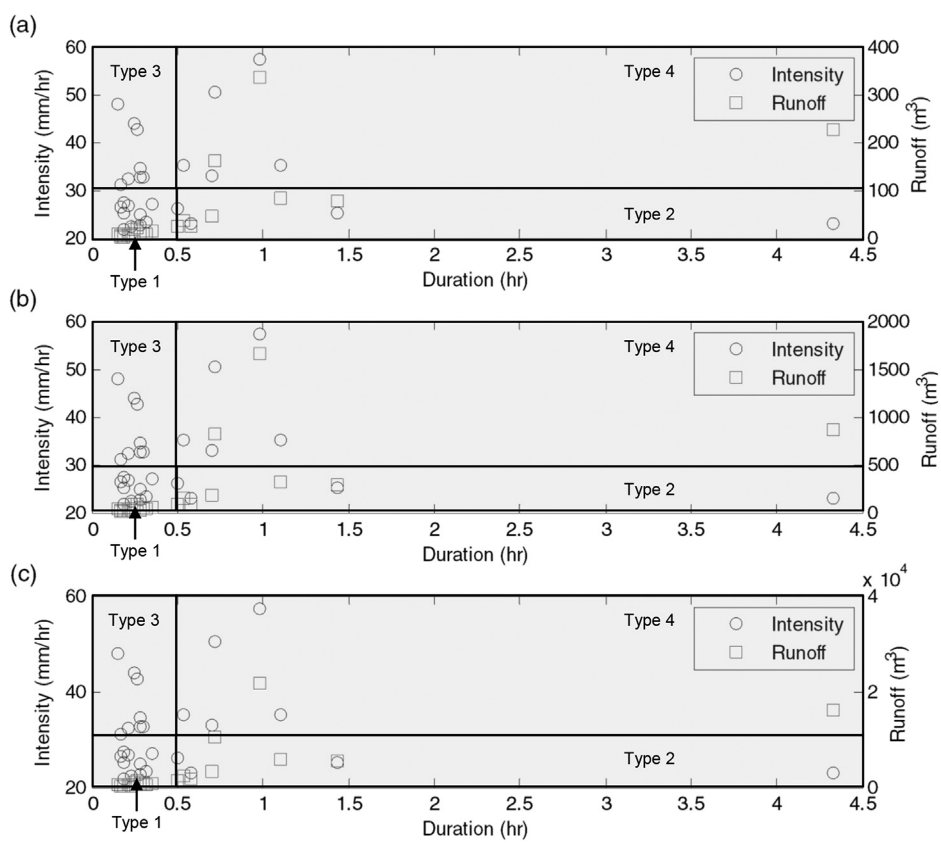

Fig. 8. Intensity-Runoff-Duration distribution of storm events – year 2005: (a) Gumbeel; (b) Birdlife Park; (c) Highland Park; Note: Type 1 (low intensity-short duration); Type 2 (low intensity-long duration); Type 3 (high intensity-short duration); Type 4 (high intensity-long duration) storm events. Results for 2008 storm events are given in the Supplementary Information.

highlighting the influence of process variability on variations in pollutant loads entrained in stormwater runoff. The impact of build-up process uncertainty on stormwater quality predictions was found to be greater than that of wash-off process uncertainty. This implies that the variability in the build-up process contributes significantly to the variations in catchment stormwater quality.

It was also found that the storm events with average intensity around 30 mm/h and duration less than 0.5hr produce the highest concentrations of particulate solids. These storm events could also be distinguished from the events with relatively large average intensity (>30 mm/h) and duration greater than 0.5hr. Further, the storm events (average intensity around 30 mm/h and duration less than 0.5hr) were clearly identified in terms of the Runoff-Catchment Area ratio, which is an important index used for the development of stormwater management strategies. The stormwater quality predictions corresponding to these storm events are significantly influenced by the build-up and wash-off process uncertainty compared to other events. As such, the selection of storm events for the design of stormwater pollution mitigation strategies needs to take into consideration not only the storm event characteristics and runoff volume, but also the influence of build-up and wash-off process uncertainty on stormwater quality predictions.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.watres.2016.07.011.

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