Chapter 4 Predicting Stormwater Quality Resulting from Traffic Generated Pollutants

Abstract Accurate stormwater quality prediction is essential for effective stormwater quality mitigation. The knowledge created in the previous chapters was applied for predicting stormwater quality using mathematical models. This chapter presents a detailed discussion of the outcomes of the modelling study including model selection, input parameter determination and model setup. The model setup procedure consisted of model schematisation, determination of boundary conditions and replication of pollutants build-up and wash-off processes. Eventually, the estimation results using the modelling approach developed are given and a series of predictive equations based on traffic and land use characteristics were developed. These outcomes are expected to contribute to the translation of research outcomes into practical recommendations for model developers, decision-makers and stormwater treatment system designers.

Keywords Mathematical modelling • Stormwater quality estimation • Pollutants build-up • Pollutants wash-off • Predictive equations • Stormwater quality • Stormwater pollutant processes

4.1 Background

Accurate stormwater quality prediction is essential for effective stormwater pollution mitigation. Accuracy strongly relies on the in-depth understanding of pollutant processes and transport pathways. Chap. 3 presents the in-depth knowledge created in relation to atmospheric pollutants build-up, atmospheric pollutant deposition and pollutants build-up on road surfaces. This formed the fundamental platform for developing modelling approaches to accurately estimate stormwater quality. This chapter presents the development of a modelling approach to predict stormwater quality for targeted pollutants (heavy metals and PAHs), incorporating knowledge presented in Chap. 3 into a commonly available modelling tool.

This chapter firstly discusses model selection and approach adopted to determine model input parameters, model setup including model schematisation, determination of boundary conditions and the numerical equations adopted to replicate pollutants build-up and wash-off processes. Outcomes of the modelling approach are then presented with necessary justifications. Model outcomes and implications discussed are expected to provide practical suggestions and recommendations to model developers, decision-makers and stormwater treatment system designers.

4.2 Model Setup

4.2.1 Model Selection

As stormwater treatment design is commonly based on long-term pollutant characteristics, the modelling approach was formulated to estimate annual pollutant loads (Liu et al. 2016a). However, due to the need for accurate estimation of a range of pollutant types with varied process and pathway characteristics, a state-of-the-art modelling tool capable of simulating pollutant processes on an event-by-event basis was required.

Three stormwater quality models, EPA SWMM (Stormwater Water Management Model), MIKE URBAN and MUSIC (Model for Urban Stormwater Improvement Conceptualization), are commonly used in industry practice in Australia. EPA SWMM is a fully dynamic stormwater and wastewater modelling package developed by the United States Environmental Protection Agency and is a physically based discrete-time simulation model that employs the principles of conservation of mass, energy and momentum (Huber and Dichinson 1988). MIKE URBAN is a Geographic Information System (GIS)-based integrated urban modelling system developed by the Danish Hydraulic Institute (DHI). This model includes a collection system (CS) and water distribution (WD) system, data management, stormwater modelling, wastewater modelling and water distribution network modelling (MIKEURBAN 2008). MUSIC which was developed by the Cooperative Research Centre (CRC) for Catchment Hydrology in Australia, requires longterm continuous rainfall input rather than event-based rainfall data (Lloyd et al. 2002).

Both EPA SWMM and MIKE URBAN were considered suitable for the envisaged modelling as they are capable of simulating pollutants build-up and wash-off processes on an event-by-event basis. However, EPA SWMM has the ability to incorporate user defined pollutant process equations into the modelling structure. Therefore, EPA SWMM was selected as the most appropriate modelling tool for the study. This selection was also supported by the better performance of EPA SWMM in trial simulations, giving consistent output.

4.2.2 Determination of Input Parameters

In typical modelling studies, model calibration and validation play an important role in assessing the accuracy of model outcomes (Henriksen et al. 2003; White and

Chaubey 2005). This is the process of adjusting model input parameters to suit actual field conditions. However, this procedure was not undertaken in this study. Instead, model parameters to suit actual field conditions were determined from the outcomes of the detailed field investigation discussed in Chap. 3. This approach was recommended by Egodawatta (2007). He noted that small-plot pollutant processes can be extrapolated to catchment scale, and this procedure is particularly appropriate for the condition where stormwater quantity and quality data required for calibration and validation are not available for the study areas. In this context, fundamental knowledge generated in Chap. 3 regarding atmospheric build-up, atmospheric deposition and build-up on road surfaces as well as knowledge on pollutants wash-off obtained from previous research studies (Herngren 2005; Egodawatta et al. 2007; Mahbub et al. 2010) were employed to determine the model parameters.

4.2.3 Model Schematisation

Sites investigated in road surface pollutants build-up in Sect. 3.4 were considered as catchments for the modelling exercise. Existing maps and aerial photographs were used to calculate the baseline parameters related to road characteristics such as road width. However, Hope Island road site was removed from the modelling study due to the unavailability of baseline road characteristics. Accordingly, a total of 10 road sites were included in the modelling study.

A 100 m long road section with typical road geometry and drainage characteristics was selected as the schematised model catchment for each road site. The selected model catchment was further divided into two sub-catchments draining to either side of the road (see Fig. 4.1). Road kerb drains were modelled as a triangular open channel section with roughness equivalent to concrete. Relevant geometric data was obtained from maps and aerial photographs provided by the Gold Coast City Council (GCCC).

4.2.4 Boundary Conditions

Stormwater models commonly require two types of boundary conditions, namely, water quantity and water quality. The water quantity is primarily related to rainfall data used in the modelling exercise while rainwater quality was used as the water quality boundary condition, which is associated with wet deposition as discussed in Chap. 3.



Fig. 4.1 Model schematisation (a): road cross section; (b): road in model (*RG* raingauge, S_x slope)

4.2.4.1 Rainfall Data

The appropriate selection of rainfall boundary conditions was critical for the accurate estimation of stormwater quality. The rainfall data recorded at the Gold Coast Seaway Station (Bureau of Meteorology station no: 040764) was used as the rainfall boundary condition due to its close proximity to the study sites and the availability of fine resolution rainfall data (6-min rainfall data).

As treatment design is commonly conducted based on an annual pollutant load, representative years should be selected for modelling. After investigating the rainfall data over the period of 2000–2010 (see Fig. 4.2), three representative years were selected. They were the year with minimum annual rainfall depth (2001), the year with average rainfall depth (2004) and the year with the maximum rainfall depth (2010). This was to account for the variability in annual pollutant load due to the variations in annual rainfall characteristics.

4.2.4.2 Wet Deposition

Atmospheric wet deposition was used as one of the water quality boundary conditions in the modelling study. As noted in Sect. 3.3.1, areas with intense anthropogenic activities have a high concentration of pollutants in the atmospheric deposition samples and wet deposition varies with rainfall depth. However, EPA SWMM model is not capable of incorporating variations in rainwater quality with



Fig. 4.2 Rainfall data over the period of 2000-2010 at study sites

time. Therefore, average concentrations of solids and heavy metals in wet depositions were used. As PAH concentrations in wet deposition were below the limit of detection, only solids and heavy metals were considered as the quality boundary conditions.

4.2.5 Replication of Pollutants Build-Up and Wash-Off

EPA SWMM model simulates water quantity and quality together by replicating pollutants build-up and wash-off processes on catchment surfaces. For this, appropriate replication equations are needed to be selected according to the pollutants build-up and wash-off characteristics of the given catchment. This section discusses the selection of build-up and wash-off equations as well as the determination of their coefficients.

4.2.5.1 Pollutants Build-Up

Pollutants build-up is a dynamic process and at any given time, the process may undergo change based on the state of deposition and removal characteristics (Liu et al. 2016a, b; Wijesiri et al. 2016). Egodawatta (2007) recommended a power function to replicate pollutants build-up on road surfaces, and his study was undertaken at the same study areas as this study. Consequently, the power equation was selected for the study (as shown in Eq. 4.1). In Eq. (4.1), C_1 is the upper limit of pollutants build-up on a catchment surface. According to the results obtained by Egodawatta (2007), pollutants build-up approaches its maximum possible value after 21 antecedent dry days. C_2 is the build-up rate and is dependent on sitespecific parameters such as population density. It was determined based on actual measured build-up values for seven antecedent dry days. C_3 depends only on the road surface type. As all road surfaces are paved with asphalt, C_3 was set as 0.16 to represent a typical asphalt road surface (Egodawatta 2007). All of these coefficients were calculated based on total solids build-up loads since other pollutants such as heavy metals and PAHs can be obtained by determining pollutants–solids

Table 4.1 Co	efficients for	· build-up replica	tion equation							
Coefficients	Shipper Drive	Towncenter Drive	Abraham Road	Linfield Road	Beattie Road	Billinghurst Crescent	Peanba Park	Dalley Park Drive	Discovery Drive	Reserve Road
<i>C</i> ₁	2.21	0.78	2.52	0.60	0.74	5.60	0.68	13.09	0.80	7.68
C_2	1.36	0.48	1.55	0.37	0.46	3.44	0.42	8.04	1.81	0.49
C_3	0.16									

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co-fraction coefficients (representing the percentage of pollutants attached to solids). Table 4.1 gives these coefficients for build-up on each road site.

$$L = Min(C_1, C_2 d^{C_3}) \tag{4.1}$$

Where

L—Build-up load (kg/ha) C_1 —Maximum possible build-up load (kg/ha) C_2 —Build-up rate constant (kg/ha/day) d—antecedent dry days C_3 —Time exponent

4.2.5.2 Pollutants Wash-Off

There are a number of replication methods available for wash-off process simulations including exponential equation, rating curve and event mean concentrations. In this study, wash-off data obtained from Mahbub (2011), which was undertaken at exactly same road sites, was plotted to assess the most suitable mathematical replication equation. The equation format with the least data scatter was selected. As such, it was found that an exponential form of mathematical replication is the most suitable to replicate solids wash-off. The equation format is shown in Eq. (4.2).

$$W = D_1 q^{D_2} L \tag{4.2}$$

Where

W—Wash-off load in units of mass per hour D_1 —Wash-off coefficient D_2 —Wash-off exponent q—Runoff rate per unit area (mm/h) L—Pollutants build-up in mass units given in Eq. (4.1)

Wash-off primarily depends on the build-up load (pollutant loads availability prior to rainfall) and rainfall characteristics rather than site-specific characteristics. Therefore, in order to determine the coefficients for the wash-off equation, Eq. (4.2) was expressed as wash-off per unit build-up (W/L), which can be referred to as the wash-off fraction (Egodawatta 2007). W and L are the actual wash-off (obtained from Mahbub 2011) and build-up mass (obtained from this study as discussed in Sect. 3.4) collected at seven antecedent dry days. The wash-off coefficient (D_1) and the wash-off exponent (D_2) were estimated by plotting the wash-off fraction against runoff rate as shown in Fig. 4.3. As shown in Fig. 4.3, the coefficients D_1 and D_2 were determined as 80.409 and -0.875, respectively.



Fig. 4.3 Variation of wash-off fraction with runoff rate for total solids

4.2.5.3 Heavy Metals

As recommended by EPA SWMM, co-fraction wash-off approach was applied to investigate heavy metals co-fractions in the modelling study. In this approach, heavy metals are modelled as a co-fraction of total solids, which was calculated by dividing the heavy metal concentration by the corresponding total solids concentration. In order to determine the co-fraction coefficient for each heavy metal species, variation of co-fractions of heavy metals with rainfall duration was plotted as shown in Fig. 4.4. It can be noted that except for Zn, other heavy metals have consistent co-fractions. Although Zn co-fraction is highly variable, it has a reasonable consistency before 120 min rainfall duration. As rainfall events with duration longer than 120 min is relatively rare, use of co-fractions were 0.113, 0.010, 0.001, 0.002, 0.001, 0.008 and 0.004 for Zn, Cu, Mn, Ni, Cr, Cd and Pb, respectively.

4.2.5.4 PAHs

Same as for heavy metals, the co-fraction approach was used for simulating PAH loads. For this purpose, data from Herngren (2005) was used to generate co-fractions for each PAH species. Herngren (2005) undertook his research study in the Gold Coast region, which is the same study area as this study. Therefore, the use of data from Herngren (2005) was considered appropriate. However, only nine PAHs were investigated by Herngren (2005), and hence the modelling was performed for these nine PAHs only. The variation of co-fractions for the nine PAHs with rainfall duration is plotted in Fig. 4.5. It is evident that all PAHs investigated have appreciably consistent co-fractions. Accordingly, the resulting



Fig. 4.4 Variation of heavy metal co-fractions with rainfall durations

co-fractions were 0.0018, 0.0012, 0.0019, 0.0009, 0.0027, 0.0027, 0.0024, 0.0014 and 0.0020 for ACE, FLU, PHE, ANT, FLA, PYR, BaA, CHR and BaP.

4.3 Model Results

The modelling was performed for 2001, 2004 and 2010 rainfall events, which are the 3 years with minimum, average and maximum annual rainfall depths. The simulation results were extracted for the ten road sites corresponding to the 3 years. Furthermore, in order to identify the most polluted sites in terms of heavy metal and PAH loads, the modelling results were further analysed using PROMETHEE ranking method. Detailed information on PROMETHEE ranking method can be found in Liu et al. (2015).

In addition, predictive equations were developed based on the modelling results in order to estimate the annual solids loads in stormwater runoff generated by a 100 m long road section. These predictive equations were developed based on traffic and land use characteristics. As heavy metals and PAHs were considered as co-fractions of solids, the predictive equations were developed for solids only.

4.3.1 Heavy Metal and PAH Loads

The simulated heavy metal and PAH annual loads were extracted from the model outputs, and summary of results for heavy metals and PAHs are given in Tables 4.2 and 4.3, respectively. These simulation data were used to undertake PROMETHEE



Fig. 4.5 Variation of PAH co-fractions with rainfall durations

analysis. Although the annual heavy metal and PAH loads were predicted for 2001, 2004 and 2010 rainfall events, the PROMETHEE rankings were carried out only for modelling results generated for 2004. This was because the annual rainfall depth in 2004 represents the average rainfall observed during the period of 2001–2010, while the outcomes obtained based on 2001 and 2010 were to understand the limits of variability. Therefore, using modelling results in 2004 gives the most accurate estimation of average annual pollutant loads.

Table 4.4 gives the PROMETHEE ranking results for heavy metals and PAHs, respectively. The five road sites, namely, Da_r, Sh_i, Bi_r, Li_C and Re_r are ranked as the most polluted roads in terms of both heavy metals and PAHs. Most of these roads are within commercial and residential land uses. The results obtained can be attributed to their relatively high traffic volumes. The ranking results can provide useful insights into identifying road areas where stormwater runoff is highly polluted with toxic pollutants such as heavy metals and PAHs and hence need to be provided with appropriate stormwater treatment measures.

4.3.2 Development of Predictive Equations

The purpose of developing predictive equations was to estimate the annual pollutant load generated from roads based on traffic and land use characteristics. This is essential for the implementation of appropriate stormwater treatment strategies.

Multiple liner regression analysis was undertaken to develop the predictive equations to estimate the annual total solids loads based on the model outcomes generated for 2001 (minimum), 2004 (average) and 2010 (maximum) rainfall events. It was assumed that the variability of total solids loads among different sites could be predicted as a linear combination of land use and traffic parameters. Selecting linear regression was because it is the simplest model to investigate the

		Total solids	Pb	Cr	Cd	Zn	Mn	Ni	Cu
Road	Year	(mg)	(mg)	(mg)	(mg)	(mg)	(mg)	(mg)	(mg)
Ab_c	2001	11,167	31	26	41	699	30	14	59
	2004	13,167	34	33	41	734	39	15	61
	2010	16,707	42	44	47	874	51	18	71
Be_i	2001	10,373	23	30	19	424	36	9	33
	2004	13,317	29	40	21	506	48	11	39
	2010	17,858	39	54	27	665	64	15	51
Bi_r	2001	14,781	47	28	74	1156	32	22	100
	2004	17,983	55	36	85	1346	42	26	115
	2010	19,688	57	44	79	1310	51	25	111
Da_r	2001	33,160	122	45	227	3295	49	59	289
	2004	47,713	176	65	328	4765	69	86	418
	2010	49,116	176	71	321	4713	78	85	412
Di_r	2001	16,404	45	39	60	1017	45	20	74
	2004	20,348	54	51	66	1172	59	23	82
	2010	26,977	71	68	85	1527	79	31	106
Li_c	2001	19,574	52	48	65	1139	56	70	95
	2004	24,794	64	63	75	1356	74	83	111
	2010	30,508	75	82	79	1522	95	93	123
Pe_r	2001	6774	35	19	14	298	23	6	24
	2004	8294	41	25	14	325	29	7	25
	2010	10,568	46	33	14	377	38	9	29
Re_r	2001	19,455	62	44	77	1275	51	25	108
	2004	23,282	77	57	80	1393	66	27	116
	2010	27,531	77	72	79	1466	84	30	120
Sh_i	2001	21,254	46	38	113	1737	44	32	150
	2004	28,252	60	52	149	2295	59	43	198
	2010	28,277	62	60	124	2002	69	38	170
To_c	2001	10,474	12	30	20	436	36	9	34
	2004	13,428	15	41	22	518	48	12	40
	2010	18,000	20	54	28	681	64	15	52

Table 4.2 Annual total solid and heavy metal loads simulated

relationship between independent parameters and a dependent variable (Mahbub et al. 2011). In this context, it was assumed that the total solids loads generated by a 100 m road section can be expressed as a linear combination of independent variables as shown in Eq. (4.3).

Solid loads =
$$f(C, I, R, DTV, V/C, HDTV)$$
 (4.3)

Where

C, *I*, *R*—Percentages of commercial, industrial and residential areas within 1 km radius from each sampling site, obtained by initially demarcating the area in an

		ACE	FUI	DHE	ANT	FLA	DVD	BaA	СНВ	BaD
Road	Year	(mg)	(mg)	(mg)	(mg)	(mg)	(mg)	(mg)	(mg)	(mg)
Ab c	2001	9.1	6.2	9.7	4.6	13.8	13.8	12.2	7.1	10.1
	2004	9.1	6.0	9.7	4.5	13.7	13.7	12.2	7.0	10.2
	2010	10.4	7.0	11.0	5.1	15.6	15.6	13.9	8.2	11.6
Be_i	2001	4.0	2.7	4.2	2.0	6.3	6.3	5.6	3.1	4.5
	2004	4.6	2.9	4.8	2.2	6.9	6.9	6.2	3.5	5.0
	2010	5.8	3.7	6.2	2.8	8.7	8.7	7.8	4.5	6.5
Bi_r	2001	16.7	11.0	17.6	8.2	24.9	24.9	22.2	12.9	18.5
	2004	19.0	12.7	20.0	9.6	28.6	28.6	25.4	14.9	21.1
	2010	17.6	11.7	18.6	8.9	26.6	26.6	23.6	13.8	19.6
Da_r	2001	50.9	34.0	53.7	25.5	76.4	76.4	67.9	39.5	56.6
	2004	73.7	49.1	77.8	36.9	110.6	110.6	98.2	57.3	81.8
	2010	72.2	48.1	76.1	36.1	108.2	108.2	96.2	56.2	80.1
Di_r	2001	13.4	8.6	14.2	6.5	19.9	19.9	17.8	10.3	14.9
	2004	14.7	9.8	15.6	7.4	22.1	22.1	19.7	11.3	16.5
	2010	19.0	12.6	20.0	9.4	28.6	28.6	25.3	14.7	21.1
Li_c	2001	14.2	9.5	15.0	7.1	21.6	21.6	19.1	11.1	15.8
	2004	16.4	10.9	17.4	8.3	24.9	24.9	22.1	12.8	18.4
	2010	17.5	11.5	18.5	8.7	26.4	26.4	23.5	13.4	19.4
Pe_r	2001	3.0	2.0	3.2	1.5	4.7	4.7	4.1	2.3	3.3
	2004	3.0	1.9	3.2	1.5	4.6	4.6	4.1	2.3	3.3
	2010	3.1	2.0	3.2	1.5	4.7	4.7	4.2	2.4	3.5
Re_r	2001	16.9	11.3	17.9	8.5	25.7	25.7	22.9	13.1	18.9
	2004	17.9	11.8	18.9	8.8	26.7	26.7	23.9	13.8	19.8
	2010	17.6	11.6	18.6	8.7	26.3	26.3	23.4	13.6	19.6
Sh_i	2001	12.5	8.3	13.2	6.3	18.8	18.8	16.7	9.8	13.9
	2004	16.2	10.8	17.1	8.1	24.4	24.4	21.7	12.6	18.1
	2010	17.8	11.8	18.7	8.7	26.5	26.5	23.7	13.8	19.8
To_c	2001	4.1	2.8	4.4	2.1	6.5	6.5	5.9	3.3	4.7
	2004	4.8	3.1	5.0	2.3	7.1	7.1	6.5	3.7	5.3
	2010	6.1	4.0	6.5	2.9	9.1	9.1	8.1	4.7	6.8

Table 4.3 Annual PAH loads simulated

aerial photograph from Google Earth and then calculating each land use area fraction using ArcMap.

DTV-total average daily traffic volume used in Chap. 3

HDTV—total average daily heavy duty vehicle traffic volume, refer to data analysis in Chap. 3

V/C-traffic congestion parameter, refer to data analysis in Chap. 3

The predictive equations developed are given in Table 4.5. It is important to note that all the equations developed are based on a lower number of data points than what is optimally required to attain 95% confidence (Rubinfeld 1998). Furthermore, these equations are capable of predicting solids loads accurately only within the

		Heavy metals		PAHs		
Ranking	Comments		Net ϕ		Net ø	
1	The most polluted site	Da_r	0.7589	Da_r	0.840	
2		Sh_i	0.0869	Bi_r	0.016	
3		Bi_r	0.0111	Re_r	-0.002	
4		Li_c	-0.0612	Li_c	-0.021	
5		Re_r	-0.0764	Sh_i	-0.025	
6		Di_r	-0.1073	Di_r	-0.047	
7		Ab_c	-0.1130	Ab_c	-0.133	
8		Pe_r	-0.1486	To_c	-0.199	
9		Be_i	-0.1719	Be_i	-0.203	
10	The least polluted site	To_c	-0.1786	Pe_r	-0.226	

Table 4.4 PROMETHEE ranking results

Table 4.5 Stormwater quality estimation equations developed for total solids

Equations	R	POT
Solids(minimum) = $11,204.147 - (0.0700 \times DTV) + (74.079 \times HDTV)$	0.978	0.994
$+(136.582 \times V/C) - (52,959.185 \times C) - (7524.183 \times I)$		
Solids(average) = $14,540.746 - (0.285 \times \text{DTV}) + (111.716 \times \text{HDTV})$	0.986	0.999
$+(745.376 \times V/C) - (83,870.577 \times C) - (10,027.701 \times I)$		
$Solids(maximum) = 16,200.682 + (0.137 \times DTV) + (108.813 \times HDTV)$	0.979	0.995
$+(2138.812 \times V/C) - (86,809.775 \times C) - (8180.689 \times I)$		

R regression coefficient, POT power of the test

limits of the data set. These limits are DTV, from 29 to 10,639, HDTV from 4 to 1139, V/C from 0.14 to 1.21, C from 0.01 to 0.44 and I from 0 to 0.82. Outside these limits, predictions may result in greater variations. However, the prediction accuracy and reliability can be improved by undertaking further investigations and following the same modelling and regression approach for further refinement of the equations. Nevertheless, the outcomes from these equations would be satisfactory for preliminary or feasibility studies.

4.4 Conclusions

This chapter presents a modelling approach by incorporating a series of replication equations into a commonly available model tool, EPA SWMM. The input parameters of the model were determined by the knowledge created in Chap. 3 on atmospheric pollutants build-up, atmospheric pollutant deposition and pollutants build-up on road surfaces, as well as wash-off by referring to past studies.

The modelling results estimated the annual loads of traffic generated pollutants including heavy metals and PAHs in stormwater runoff for each road study site. In addition, these road sites were ranked in terms of annual heavy metal and PAH

loads. The ranking can contribute to effective stormwater treatment design based on the identification of the more polluted sites which need to be provided with stormwater treatment systems.

A set of predictive equations for estimating annual total solids loads were developed using traffic and land use related parameters. The equations developed can be used as an urban planning tool not only to estimate solids generation from road sites, but also to identify the required enhancements (such as changes to traffic and land use planning) to improve the resulting stormwater quality. Even though these predictive equations are only applicable within their specified limits, they provide a robust approach to stormwater management. Additionally, it is recommended that the accuracy of the predictive equations can be further improved by including additional sampling sites as part of the further development process.

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