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An empirical modeling approach to predicting pollutant loads and developing cost-effective stormwater treatment strategies for a large urban watershed

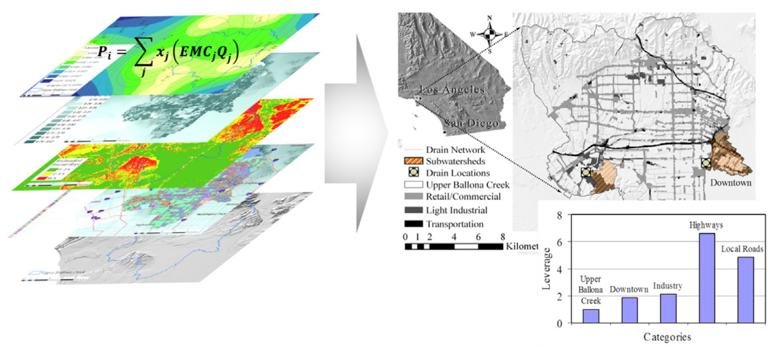
Joo-Hyon Kang [a], Mi-Hyun Park [b,*], Simon J. Ha [b], Michael K. Stenstrom [b]

[a] Dept. of Civil and Environmental Engineering, Dongguk University-Seoul, Seoul 04620, South Korea
[b] Dept. of Civil and Environmental Engineering, University of California-Los Angeles, Los Angeles, CA 90095, USA

HIGHLIGHTS

- Empirical stormwater quantity and quality models were developed and validated.
- Zeroth-order regularization with a L-BFGS-B algorithm was used in the models.
- Two subwatersheds with high leverages were identified in a large urban watershed.
- Transportation landuse was revealed as a high leverage pollutant emitter.
- Using an optimal strategy, the Zn water quality goal can be achieved at 75% less cost.

GRAPHICAL ABSTRACT



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ABSTRACT

Stormwater treatment strategies were evaluated for the upper Ballona Creek Watershed in Los Angeles, CA using an empirical model of stormwater runoff quantity and quality with zeroth-order regularization and a limited memory Broyden-Fletcher-Goldfarb-Shanno Bound constrained optimization routine. The model used landuse based estimation on the runoff volume, event mean concentration (EMC) and pollutant load employing ten different landuses, including highways and local roads. The model was validated by showing that its predictions were in reasonable agreement (r^2 ~0.6 to 0.8) with total zinc (Zn), Total Kjeldahl Nitrogen (TKN), and Total Suspended Solids (TSS) loadings measured at the monitoring site at the bottom of the watershed. The developed model was used to demonstrate and quantify the benefits of the stormwater treatment practices (STPs) prioritized at specific landuses with high pollutant mass emission rates. For this demonstration, total Zn was selected as it is one of the most concerning pollutants in an extremely urbanized area such as the Ballona Creek Watershed. Transportation landuse including local roads and highways was found to be the best candidate for the STP applications due to their high percent load contribution per percent area. By focusing STPs for transportation landuse, the water quality goal of total Zn in the study watershed was expected be achieved at approximately 75% less cost.

1. Introduction

Since the 1972 Clean Water Act in the United States (US), point source pollution has been addressed to protect the nation's surface waters but many of the waters are still impaired. For example, the United

* Corresponding author.
E-mail address: parkmh@ucla.edu (M.-H. Park).

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States Environmental Protection Agency (US EPA)'s national water quality inventory (2017) reveals that 46% of rivers/streams, 21% of lakes/ponds/reservoirs, and 18% of coastal waters were reported as impaired due primarily to nonpoint source pollution. Urban runoff and storm drains were found to be the largest and the third largest source of water quality impairment for the surveyed estuaries and lakes, respectively (US EPA, 2003, 2017). Hence, the management of stormwater pollution has become important for water pollution control.

In 1987, the US Congress amended the Clean Water Act to regulate stormwater discharges and issued permits similar to point source permits (NRC, 2009). As a result, stormwater dischargers were issued National Pollutant Discharge Elimination System Permits (NPDES) in two phases: 1990 and 1999. During the 1990s, the concept of the Total Maximum Daily Load (TMDL) was established to create discharge water quality requirements for all permittees within a watershed in order to regulate the total mass discharges. However, the large number of permittees within a watershed makes the assessment of stormwater pollution complex and expensive.

Modeling inherently complex stormwater pollution is not an easy task. A process-based model typically requires too many unknown parameters to be measured or calibrated (Lee et al., 2020; Yin et al., 2020). Ideally the model parameters obtained from calibrating in a subwatershed should be transferable to a nesting watershed or other subwatersheds without additional data or recalibration; otherwise the models have limited usability and robustness (Heuvelmans et al., 2004; Demeritt and Wainwrite, 2009; Jackson-Blake et al., 2017). The accumulated error from these parameters may result in poor estimation. Alternatively, stormwater pollution can be addressed using a simple modeling approach: the unit area model based on rational method. In the rational model, all runoff is assumed to have a constant concentration for a given pollutant from a landuse (Ha and Stenstrom, 2008), which is also known as unit load. Unit loading rates are represented by mass per area per time. The method has been used to estimate loads of a number of pollutants from the Santa Monica watershed (Stenstrom et al., 1984; Wong et al., 1997; Park and Stenstrom, 2008), larger areas in Southern California (Ackerman and Schiff, 2003; McPherson et al., 2005), and many other areas (Fam et al., 1987; Wu et al., 1998; Shinya et al., 2000; Choe et al., 2002). Unit loading rates are extremely variable and difficult to apply over shorter periods of time, and the approach is best suited to estimation of long term loads, such as seasonal or annual loads. Simple prediction methods generally perform better over a long averaging time than a single storm event.

A geographic information system (GIS)-based model has been applied to stormwater runoff modeling and TMDL development (Adamus and Bergman, 1995; Wong et al., 1997; Seiker and Klein, 1998; Vitro et al., 2017). A GIS has been proven to be efficient for data preparation, model parameter extraction, and model results visualization. Wong et al. (1997) developed landuse runoff model using a GIS coupled with an empirical runoff model. They stated that the integration of a nonpoint source model and a GIS offered a powerful tool to assist watershed managers in developing control strategies to improve water quality within local drainage systems. Brun and Band (2000) coupled the Hydrological Simulation Program – FORTRAN (HSPF) and a GIS to assess the effects of landuse change and imperviousness on the stormwater runoff ratio.

In this study, we propose a simple approach to derive a cost-effective strategy for stormwater treatment practices (STPs) to comply with TMDL regulations. An empirical modeling approach previously developed by the authors (Ha and Stenstrom, 2008) was used for estimating stormwater runoff quantity and quality. The developed model was used to estimate pollutant mass, evaluate the effectiveness of potential STPs, and explore the feasibility of proposed TMDLs. The approach used in this study is applicable for a wide range of pollutants in other watersheds. In order to produce a manageable problem and data availability, this study focuses on selected common pollutants that are the most concerning pollutants in the study area. Note that development of the empirical model and STPs strategies conducted in this study were based on the publicly available stormwater monitoring data, which can date back to 1998, thus we would like to put our emphasis on the methodology developed rather than the numeric results.

2. Methodology

2.1. Study watershed and landuses

The Ballona Creek Watershed is one of the highly urbanized watersheds in the US and occupies approximately 340 km^2 of in the coastal plain of the Los Angeles basin. The watershed covers several large cities including the City of Los Angeles and is highly developed with 49% of total imperviousness. The watershed has been listed as an impaired water body for the last two decades and is subject to TMDLs for metals and bacteria that require compliance by 2021. A recent collaborative watershed management program, called “enhance watershed management program (EWMP)”, established by responsible agencies in the watershed estimated that approximately 2.7 billion dollars of optimized STPs will be needed to comply with TMDL regulations of total zinc (Zn) and bacteria by 2021 (Ballona Creek Watershed Management Group, 2015). In EWMP, the watershed was divided into a total of 180 subwatersheds, which were independently assessed for their optimal STP installation strategies using process-based models and a multi-objective optimization algorithm.

Land use distribution of the upper Ballona Creek Watershed is shown in Fig. S1. The Southern California Association of Governments (SCAG) landuse types (year 2000) were reclassified into eight landuse types adopted in the landuse -based stormwater monitoring program of Los Angeles Department of Public Works (LADPW) (Woodward Clyde, 1996). The eight landuse types were “Vacant (V)”, “High Density Single-family Residential (HDR)”, “Multi-family Residential (MFR)”, “Mixed Residential (MR)”, “Educational Facilities (EF)”, “Transportation (T)”, “Retail/Commercial (R/C)”, and “Light Industrial (LI)”. The study area was extremely urbanized with 63% of total area occupied by residential areas including HDR (33.8%), MR (16.7%) and MFR (12.5%), followed by R/C (13.8%), V (13.3%), LI (5.2%), EF (2.9%), and T (1.8%). More detailed site description including geographical characteristics and climate conditions of the upper Ballona Creek Watershed can be found in Wong et al. (1997) and Ha and Stenstrom (2008).

2.2. Model description

The model was developed using the measured data of Zn, total Kjeldahl nitrogen (TKN), and total suspended solids (TSS). The model structure is briefly described in this section, and more detailed descriptions on the model development and calibration procedure for the study area can be found in Ha and Stenstrom (2008).

2.2.1. Unit area load estimation

The model was based on the Volume-Concentration method (Park et al., 2009) where the total mass load was calculated from the product of the runoff volume and pollutant concentration for a given area. Both runoff volume and pollutant concentrations were calculated as a function of landuse type. The unit area loading was calculated as follows:

$$L = \sum_j EMC_j Q_j = \sum_j EMC_j \left(\sum_i A_i R_i RC_i \right)_j \tag{1}$$

where L = pollutant loading [M], j = landuse type [−], EMC_j = event mean concentrations (EMCs) of landuse type j [ML^{-3}], Q_j = total runoff volume from landuse type j, A_i = area of each landuse parcel [L^2], R_i = precipitation in the landuse parcel A_i [L], and RC_i = volumetric runoff coefficient of the landuse parcel A_i [−]. EMCs from each landuse were predicted by a multiple regression equation where four storm characteristics, antecedent dry days (ADD), total rainfall, rainfall duration, and maximum hourly rainfall intensity, were used as explanatory variables. The landuse based EMC regression equation (called "EMC prediction model" hereafter) is as follows:

$$EMC_j = C_{1,j} + C_{2,j} \times ADD^k + C_{3,j} \times R^k + C_{4,j} \times D^k + C_{5,j} \times I^k \quad (2)$$

where, EMC_j = EMC of a landuse type j [ML^{-3}], $C_{1.5,j}$ = regression coefficients of the EMC prediction model for a landuse type j [−], ADD = antecedent dry days [T], R = rainfall [L], D = storm duration [T], I = maximum intensity [LT^{-1}], k = superscript for landuse type, which denotes 0 for V, 1 for LI, MR and T, and −1 for the other landuse types (Ha, 2006).

The R_i values in Eq. (1) were site-representative values obtained by a spatial interpolation technique (i.e, ordinary Kriging) using hourly precipitation data from 7 rain gauge stations located around the Ballona Creek Watershed (geographic information on the 7 rain gauge stations is shown in Table S2). RC_i values were estimated based on the Browne's (1990) relation, which relates runoff coefficient with hydrologic soil group, percent land slope, and land-use type. The EMC_j values generated from the Ballona Creek Watershed were simulated based on the LA Civic Center rainfall records as site-representative data, which were best correlated with the total runoff volume measured at the outlet of the watershed.

2.2.2. Parameter optimization

Direct application of Eq. (1) to the total load calculation in a watershed can result in poor correlation between the calculated and measured loads, due partially to the landuse mixture of the monitoring sites, and to uncertainty in the regression model (Ha, 2006). To consider this non-ideal effect, an adjusting factor or weighing factor (x_j) to pollutant load contributions of landuse types to total load from a watershed was introduced to Eq. (1) as follows:

$$P_i = \sum_j x_j \left(EMC_j Q_j\right) \quad (3)$$

where P_i = predicted total loading for storm i [M], and x_j = landuse type adjusting factor or weighing factor to the load contribution of landuse type j [−]. Values of x_j need to be optimized for the model to appropriately reproduce the observation. In order to optimize x_j values, the zeroth-order regularization and a limited memory Broyden-Fletcher-Goldfarb-Shanno Bound (L-BFGS-B) constrained nonlinear optimization technique were used (Zhu et al., 1994). The objective function to be minimized, F, is as follows:

$$F = \sum_i \left(\frac{P_i - M_i}{P_i}\right)^2 + \lambda \sum_j \left(\frac{x_j - x_j^0}{x_j^0}\right)^2 \quad (4)$$

where M_i = measured total loading for storm i [M], λ = regularization parameter [−], x_j^0 = initial value of the optimization parameter x_j [−]. The regularization parameter λ was determined for the optimal solution based on the L-curve, which illustrates relative changes between the residual norm and the solution norm with changing λ values using a log-log scale (Ha and Stenstrom, 2008). A value of λ based on the maximum curvature of the L-curve can be an optimal value for balancing between perturbation errors and regularization errors (Hansen and O'Leary, 1993). Beside the x_j values, regression coefficients (i.e., $C_{1,j} \ldots C_{5,j}$) in Eq. (2) were also optimized when the EMC regression model has a R^2 value less than 0.6. The upper and lower bounds of the regression coefficients for optimization were determined by the standard errors of the regression coefficients. The values of x_j^0 were set to be 1 and their upper and lower bounds were calculated based on the standard error of the regression. As a result, the optimal values of x_j (x_j^*) and optimal regression coefficients were determined.

2.3. Model calibration and validation

The EMC prediction model was initially calibrated using the monitored LADPW data from 1998 to 2003 for eight experimental catchments ("LADPW landuse sites"), which ranged from 34 to 1342 ha, respectively, representing the eight aforementioned landuse types (see Table S1). For the calibration of the EMC prediction model, the explanatory variables were calculated based on the hourly precipitation data at nearby National Climate Data Center (NCDC) rain gauges of the LADPW landuse sites located across the Los Angeles basin (Fig. S2).

The model (Eq. (3)) was calibrated and validated using the data of the LADPW mass emission site located at the outlet of the Ballona Creek Watershed (Fig. S2). The developed model was calibrated using 24–25 storm events from the 1998 to 2000 storm seasons and validated with 4–7 additional storm events from the 2001 to 2003 storm seasons for the three pollutants: total Zn, TKN and TSS. Information on the total rainfall recorded at each of the seven rain gauges and total runoff volume measured at the LADPW mass emission site of the upper Ballona Creek Watershed was provided in Supplementary material (Table S3). Calibration and validation were performed by comparing model predictions to measurements from the LADPW mass emission sites. All spatial data processing and programming were conducted using ArcGIS Desktop Version 9.1 (Redlands, CA).

Multiple linear regression analyses were performed for EMCs and mass loads (preliminary) using storm characteristics (i.e., ADD, total rainfall, rainfall duration, and maximum hourly rainfall intensity) in the upper Ballona Creek Watershed. Storm characteristics were calculated from the LA Civic Center rainfall records because rainfall data from the rain gauge station showed the best correlation with the runoff volume observed at the outlet of the watershed. Peak hourly intensity of a stormwater event was calculated from the NCDC hourly rainfall data.

2.4. Evaluation of stormwater treatment strategies

The evaluation of STP strategies was focused on total Zn, one of the most concerning pollutants in the study area (LARWQCB and USEPA 9, 2005).

2.4.1. TMDL estimation

The total Zn TMDL was developed by the Los Angeles Regional Water Quality Control Board and US EPA Region 9 (LARWQCB and USEPA 9, 2005) and is defined by the following equation:

$$\text{Total Zn TMDL [g/day]} = \left(1.18 \times 10^{-4}\right) \times \text{Daily storm volume [L]} \quad (5)$$

For effectiveness calculations of STPs, rainfall records at the LA Civic Center gauge (Table S2) for the 1998–2003 were used, which is closest to the upper Ballona Creek Watershed and showed best correlation to the total runoff volume of upper Ballona Creek watershed among the seven rain gauge stations in the extent of the upper Ballona Creek Watershed (Ha, 2006).

2.4.2. Land use contribution to total pollution load

Landuse contributions to the total Zn loads were investigated for Dec. 2, 2001 storm event. The storm event had 3 mm of total precipitation and thus was chosen as an "example storm event" to investigate the landuse contributions in the earlier part of runoff for a typical storm, which generally has higher concentration or load emission in urban catchments (i.e., first flush; Berndtsson, 2013).

Percent contributions from eight landuses to the upper Ballona Creek watershed were calculated using the optimized model (Eq. (3)). Besides the eight landuses, two additional landuses, i.e., highways and local roads, were separately studied. The average values of EMCs for six California Department of Transportation (Caltrans) sampling sites around the upper Ballona Creek watershed were used for load

Table 1
EMC regression models for upper Ballona Creek watershed.

	Landuse types	Regression coefficients					$R^{2(1)}$	No. storm events	Model[(2)]
		Intercept	ADD [days]	Rainfall [cm]	Duration (h)	Intensity (cm/h)			
Zn	Vacant[(3)]	25.00						22	Constant
	Light industrial	202.66	24.60**	−1.44	−1.25	−0.39	0.84	31	Linear
	Mixed residential	123.29**	3.51**	−5.75	1.30	−36.73	0.85	25	Linear
	Transportation	241.51**	7.34**	−77.95	−3.61	189.25	0.88	33	Linear
	Retail/commercial	218.45**		108.66	−309.64		0.27	14	Inverse
	Educational facilities	64.81**		14.35			0.10	21	Inverse
	High density single family residential	24.53*		−12.79*		13.57*	0.39	13	Inverse
	Multi-family residential	56.96**				5.09**	0.37	25	Inverse
TKN	Vacant	1.00**	0.08	0.60	−3.32	−0.18	0.25	22	Inverse
	Light industrial	2.45**	0.06**	−0.87	0.01	1.31	0.62	32	Linear
	Mixed residential	3.19**	0.03**	0.42	−0.07	−2.30*	0.71	24	Linear
	Transportation	2.01**	0.04**	−1.09*	0.05	1.19	0.75	35	Linear
	Retail/commercial	8.65**	0.01	−2.12	0.01	–[(4)]	0.42	14	Linear
	Educational facilities	1.49**	0.05**	0.12	−0.02	−0.19	0.85	21	Linear
	High density single family residential	3.59**	0.06**	0.14	−0.04	−2.46	0.80	13	Linear
	Multi-family residential	1.89**	−0.31	0.82	−2.79	−0.19	0.48	22	Inverse
TSS	Vacant	232.70*	23.33	32.19	−1299.81	−8.23	0.26	24	Inverse
	Light industrial	156.18**	5.68**	−50.14	−1.34	100.78	0.50	30	Linear
	Mixed residential	73.05*	2.22**	3.17	−2.23	−15.57	0.44	22	Linear
	Transportation	59.87	1.57**	−18.60	1.51	28.28	0.38	35	Linear
	Retail/commercial	90.71**	−150.35	7.48*	−153.81*	–[(4)]	0.44	13	Inverse
	Educational facilities	127.60**	−0.35	38.14	−4.33	−34.13	0.19	20	Linear
	High density single family residential	76.36	−10.55	−67.64*	1684.44*	2.58	0.58	12	Inverse
	Multi-family residential	−20.18	12.43	3.26	514.02	−1.05	0.45	21	Inverse

Note: n coefficients are marked with one asterisk (*) if p $p < 0.05$ and two (**) if $p < 0.01$.
(1) Regression coefficients for landuses with low R^2 values ($R^2 < 0.6$, table lines grayed for identification) were not used, and the optimization technique was used for parameter estimation.
(2) Best fit regression models for each landuse types.
(3) 21 out of 22 events were below detection limit, 50$\mu g/L$.
(4) Data not available (LADPW does not measure maximum intensity and NCDC rain gauge station is not available near this site)

Table 2
Multiple linear regression models of total pollutant loads for upper Ballona Creek watershed.

Pollutant loads	Coefficients										R^2	No. of storm events
	Intercept	P	ADD	P	Rainfall [cm]	P	Duration [h]	P	Intensity [cm/h]	P		
Zn [kg]	25.61	0.22	0.35	0.60	45.21	0.00	−0.76	0.46	−9.58	0.83	0.75	32
TKN [ton]	−0.17	0.91	−0.02	0.40	1.71	0.03	−0.07	0.39	6.18	0.09	0.63	34
TSS [ton]	−92.26	0.26	0.99	0.67	18.94	0.75	7.71	0.08	448.61	0.05	0.44	30

calculations for highway runoff within the watershed (Table S4). For the load calculation for local roads, EMCs of LADPW Transportation landuse were used.

To better compare the pollution contributions as a function of landuse and area, the concept of "leverage" was used (Stenstrom et al., 1984). Leverage of a specific landuse is defined as the percent load divided by percent area. Leverage is a good indicator of the relative contribution to pollution load. If the watershed is uniformly polluted, the leverage for all landuse types is equal to one; so called "hot spots" will have a high leverage. If the cost of applying STPs is proportional to land area, landuses with higher leverages are better candidates for further STP considerations.

2.4.3. Removal efficiency and cost of STPs

For the STPs performance measure, typical percent removal (concentration) was adopted because of limited data availability. Although effluent quality distribution is a more robust measure of STP performance (Strecker et al., 2001). Using removal efficiencies is the best available method with the limited data. For the STPs construction cost calculations, Caltrans (2004) costs per cubic meter of stormwater runoff to be treated were used because they were calculated from smaller STP unit constructions. The average installation costs per cubic meter of stormwater runoff to be treated are highly variable between jurisdictions and are relatively higher for smaller units. Smaller STPs may be better for highly urbanized areas, where large areas for installing STPs may not be available. In this study two contradicting filtration/infiltration type STPs-sand filter and infiltration trench-were assessed against the TMDLs.

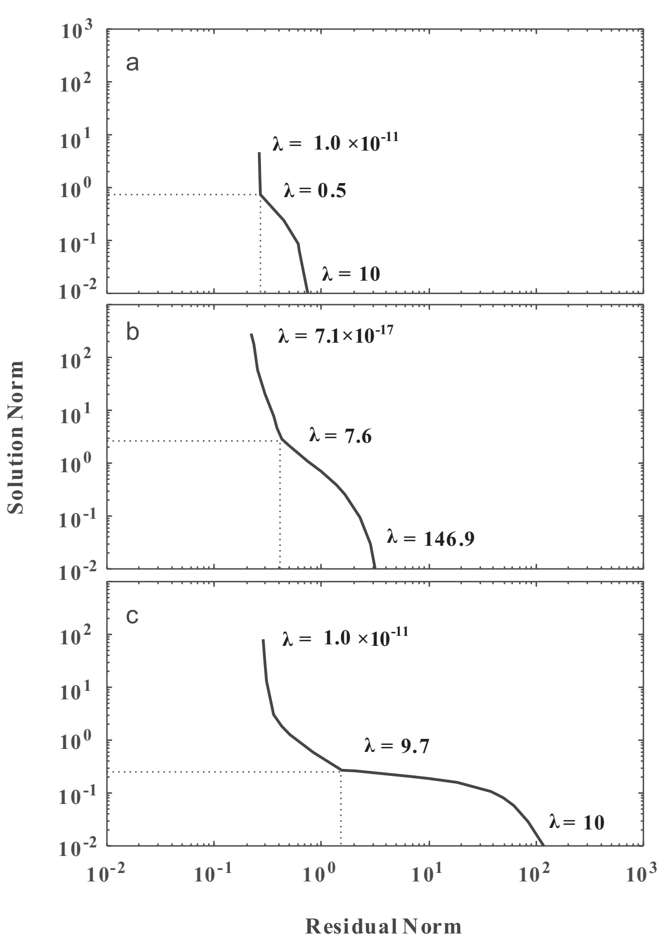

Fig. 1. L-curve for (a) Zn, (b) TKN and (c) TSS.

3. Results and discussion

3.1. Regression models for EMCs

The EMC prediction models calibrated for total Zn, TKN and TSS are shown in Table 1. The regression explained more than 80% of the variability in total Zn EMCs for LI, MR, and T landuses, which had high percent representative land uses (>70%; Table S1) and relatively large numbers of data sets used for the regression analysis. In spite of high land use representativeness, the variabilities of Zn EMCs for EF and HDR were poorly explained by the regression. The poor accuracy is due to the high non-ideal effects likely resulting from variability and uncertainty in data sets, site-specific drainage conditions, and the inherent nonlinearity in the transport behavior. In particular, the non-ideal effect of the transport behavior was more pronounced in the TSS regression results (all R^2 values were <0.6) as suspended solids include particles with a wide range of sizes and densities introducing heterogeneous transport behaviors in water.

The coefficient of determination for TKN EMC ($R^2 > 0.8$) better explained the variability for all land use types other than for Zn and TSS EMCs. R^2 values for the R/C and MFR landuses were below 0.5 for all of the three pollutants. The poor accuracy for R/C might be the best example to show how the low land use representativeness of the monitoring site (54%; Table S1) and relatively small numbers of data sets ($n = 14$) deteriorate the regression accuracy.

In general, ADD was the most significant explanatory variable for the three pollutant EMCs considering their p values. Total rainfall was the next significant variable while the maximum hourly rainfall intensity was the least significant.

3.2. Total pollutant load analysis

3.2.1. Preliminary regression of total pollutant loads using storm characteristics

Table 2 shows the results of multiple regression using storm characteristics for total loads for the three pollutants. The R^2 value of total Zn loading was the highest (0.75) among the three pollutants but less than 50% of the variance in loadings was explained for TSS by the storm characteristics. Like the EMC regression, the poor TSS load prediction might be due to the high nonlinearity in the solid transport behavior and site-specific drainage conditions that can affect the solid delivery efficiency. Total rainfall was a significant variable for total Zn and TKN loadings, while peak hourly rainfall intensity was significant for TSS loadings (p value <0.05).

Table 3
Optimized parameters and regression coefficients.

	Landuse types	Intercept	ADD [days]	Rainfall [cm]	Duration [h]	Intensity [cm/h]	X_j^*
Zn	Vacant	25.00					0.96
	Light industrial	202.66	24.60	−1.44	−1.25	−0.39	0.63
	Mixed residential	123.29	3.51	−5.75	1.30	−36.73	0.68
	Transportation	241.51	7.34	−77.95	−3.61	189.25	0.94
	Retail/commercial	167.42		104.75	−309.40		0.32
	Educational facilities	62.13		14.33			0.96
	High density single family residential	22.21		−12.95		13.54	0.92
	Multi-family residential	52.13				5.08	0.92
TKN	Vacant	1.01	0.08	0.60	−3.33	−0.18	1.00
	Light Industrial	2.45	0.06	−2.21	0.01	3.31	1.01
	Mixed residential	3.19	0.03	1.06	−0.07	−5.85	0.99
	Transportation	2.01	0.04	−2.77	0.05	3.03	1.01
	Retail/commercial	10.21	0.01	−1.74	0.01	n/a	1.14
	Educational facilities	1.49	0.05	0.30	−0.02	−0.48	1.00
	High density single family residential	3.59	0.06	0.36	−0.04	−6.25	1.01
	Multi-family residential	1.93	−0.31	0.82	−2.81	−0.18	1.00
TSS	Vacant	285.91	23.63	224.89	−1205.52	−40.53	1.12
	Light industrial	176.91	5.77	−46.65	−1.31	103.82	1.10
	Mixed residential	87.50	2.26	3.21	−1.96	−15.34	1.13
	Transportation	61.07	1.57	−18.41	1.53	28.38	1.03
	Retail/commercial	111.68	−118.51	49.39	−150.96	n/a	1.12
	Educational facilities	135.54	−0.35	39.31	−4.15	−33.92	1.08
	High density single family residential	97.13	−10.34	−289.21	2152.11	21.08	1.52
	Multi-family residential	−19.80	12.51	21.11	526.07	−6.55	0.99

Note: grayed table cells indicate optimized parameters; n/a: data not available.

3.2.2. Parameter optimization

Fig. 1 shows and the selected λ values from the L Curve for total Zn, TKN, and TSS, which were 0.5, 7.6, and 9.7, respectively. Table 3 shows optimized landuse type weighing factors, $x_j^*{}'$ for total Zn, TKN, and TSS. Regression coefficients of the EMC regression models with R^2 values lower than 0.6 were used as optimization parameters for all pollutants. That is, regression coefficients of R/C, EF, HDR, MFR landuses for total Zn, regression coefficients of V, R/C, MFR landuses for TKN, and all regression coefficients for TSS were used as optimization parameters. The calculated residual norms for total Zn, TKN, and TSS were 5.1, 6.5, and 13.6, respectively. Thus, TSS regression is expected to be worse than for the other pollutants. The values of x_j^* for Zn and TKN showed a similar tendency (i.e., degree of deviation of x_j values from 1) with each other. That is, the weighting factor (x_j^*) of the R/C landuse, which has the lowest percent representative landuse, and relatively smaller drainage area, had the greatest deviation from 1. A smaller drainage area where the data were obtained can be less accurate in representing the characteristics of the entire watershed area. However, weighting factors for TSS did not show such tendency of deviation from 1 and most of the landuses had weighing factors largely deviated from 1, suggesting that accuracy in TSS load prediction can be more affected by the non-ideal transport behavior of solid materials (i.e., nonlinearity in solid discharge) than the site representativeness.

3.2.3. Prediction of total pollutant loads

Total Zn, TKN and TSS loadings calculated for the upper Ballona Creek watershed using the optimized regression coefficients and weighting factors were plotted against the measured loadings in Fig. 2. The empty circles indicate storm events used in optimization and the solid circles indicate storm events used to validate the optimized

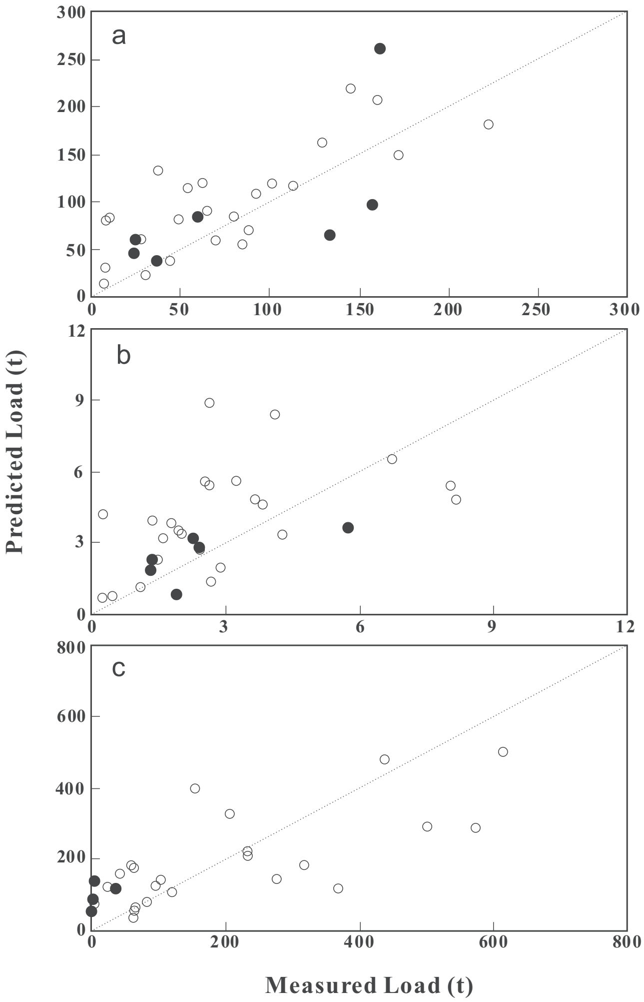

Fig. 2. Comparisons of predicted and measured loads for the upper Ballona Creek watershed using regularization: (a) Zn; (b) TKN; (c) TSS. ○: storm events used for optimization (1998–2000 storm seasons). ●: storm events used for validation (2001–2003 storm seasons).

prediction model. The predicted and measured loadings for Zn and TKN showed reasonable agreement without using site specific information. The root mean square (RMS) errors and mean discharges for total Zn and TKN were 9 kg/storm and 0.5 t/storm, respectively, which were only 11.7% and 17.2% of their mean discharges (77 kg/storm, and 2.9 t/storm for Zn and TKN, respectively).

The RMS error for TSS was 25 t/storm, which was 11.3% of the mean discharge (220 t/storm). However, measured TSS loads for the validation dataset were much lower than the predicted loads. The maximum hourly rainfall intensity, which was the most significant explanatory variable for TSS loads for the upper Ballona Creek watershed (see Section 3.2.1), had a higher median in the validation dataset than in the optimization dataset (medians were 5.5 in/h and 7.4 in/h for optimization and validation datasets, respectively, as shown in Fig. S3). This means that the measured loads for the validation dataset should be higher than the measured loads for the optimization dataset. This discrepancy might be caused by measurement errors. Also, it might be an indication of other activities in the watershed, which would require further investigation to understand.

3.2.4. Landuse contributions to total pollutant loads

Among the eight landuses, LI and R/C, MR and HDR were four major contributors (>15% each) to the total Zn load for the example storm event (Dec. 2, 2001) in the Ballona Creek Watershed (Fig. S4) whereas T (4.1), and LI (3.4) landuses were identified as high leverage land uses. Fig. 3 shows two subwatersheds with LI clusters, i.e., Industrial and Downtown, for STP considerations with their drain locations.

Percent contributions and leverages for the two subwatersheds, highways, and local roads compared to the entire upper Ballona Creek watershed for the example storm event (Dec. 2, 2001) are shown in Figs. 4 and 5, respectively. Leverages of Downtown and Industry subwatersheds are both about two, which means doubled load reduction could be achieved by treating these two subwatersheds as compared to the average. However, percent load contributions of Downtown and Industry subwatersheds are only 6.3% and 4.3%, respectively. Thus, reduction in total load would be small. Highway areas had the greatest leverage (6.6) and achieve the same percent contribution (4.3%) with much smaller area in the watershed. Local road areas had the greatest percent coverage (54.4%) with the percent area of 10.9%. This makes local roads the best candidate for implementing STPs.

3.3. STP strategies

3.3.1. TMDL

Fig. 6 shows the estimated TMDLs compared with measured total Zn loads for the 1998 to 2003 along with rainfall records. Since TMDLs are defined in terms of EMCs, they are likely to be exceeded during small storm events with high ADD, when rainfall depth is insufficient to dilute pollutant concentrations (Brezonik and Stadelmann, 2002). Among the 32 storm events, two events exceeded TMDLs. Total Zn load of the Feb. 9, 1999 and the Jan. 8, 2001 storm events exceeded the TMDL by 18% and 70%, respectively, with total rainfall of 9.4 and 6.9 mm, respectively. Therefore, STP strategies focusing on the treatment of small storm events or first flush of large storm events are preferred, since the Zn concentration is diluted in very large events. If the total Zn concentration of the Jan. 8, 2001 storm event is uniform over the upper Ballona Creek watershed, and over the duration of the storm event, STPs with pollutant removal efficiencies higher than 44% will be needed to treat the entire runoff to comply with the TMDL requirements. In highways, the most polluted stormwater runoff occurs during the first part of the runoff (Berndtsson, 2013); therefore, if the entire storm runoff volume cannot be treated, it is preferable to treat the early runoff at the expense of not treating the later runoff. Also, the leverages shown in Fig. 5 were higher for highways and local roads. Therefore, strategies utilizing leverage and first flush phenomena are valuable for the management of urban stormwater runoff.

3.3.2. Sand filter for subwatersheds

Table 4 shows the calculated results of total Zn removal for Downtown and Industry subwatersheds before and after the application of Austin sand filters for the January 8, 2001 storm event with typical total Zn removal efficiency of 45% (US EPA, 1999a). Total Zn removal at the mouth of the watershed was 12.4% with the treatment of 5% of the watershed area (or the equivalent of 9% of the runoff volume).

To meet the TMDL requirement, more than 30% load reduction needs to be achieved besides the treatment of the two subwatersheds. If the same leverage and runoff per area are assumed for additional area in the upper Ballona Creek watershed, this would require about four times the construction costs than the costs estimated for the two subwatersheds, which means about 20% of the watershed area (or equivalently about 36% of the runoff volume) would need to be treated.

3.3.3. Infiltration trenches for local roads

If we do not utilize high leverage areas and first flush phenomena, all the stormwater runoff of the Jan. 8, 2001 storm event must be treated with STPs that have 44% or better pollutant reduction rates. Since over 50% of total Zn was estimated to come from local roads for the Dec. 2, 2001 storm event as shown in Fig. 4, infiltration trenches for local roads are considered for assessing total load reduction and STP costs.

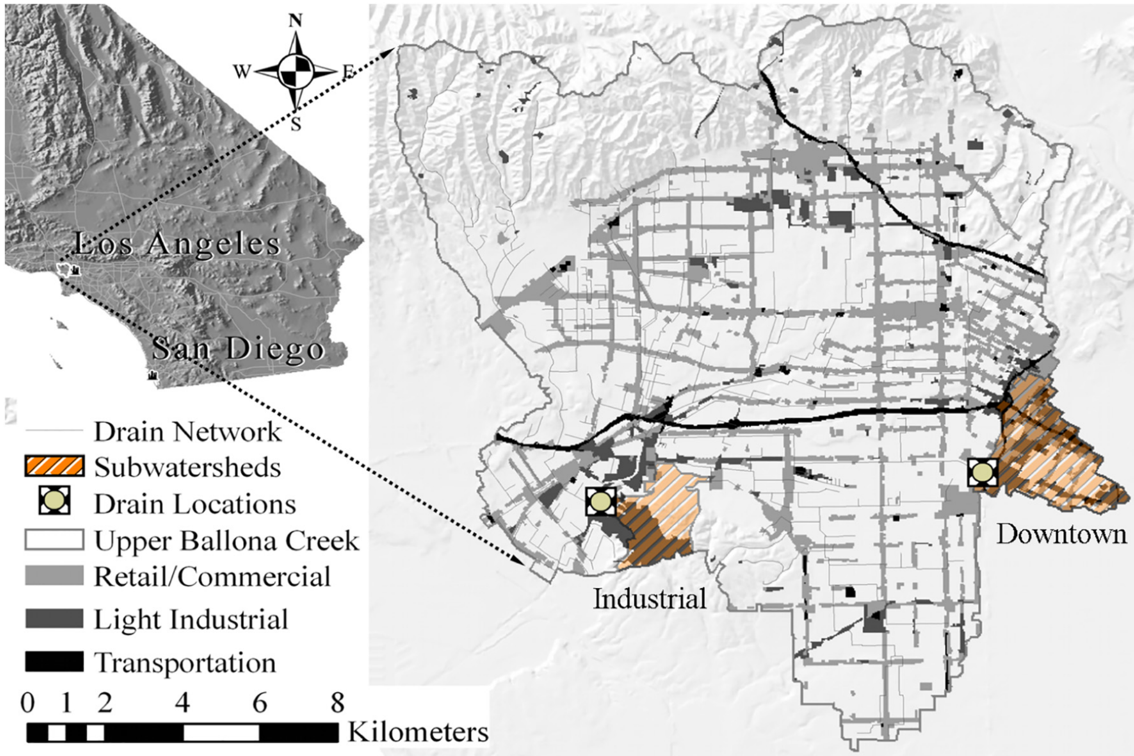

Fig. 3. Distribution of high leverage landuses (Dec. 2, 2001 storm event).

Infiltration trenches are commonly designed to empty prior to the next storm event. This practice is not possible in Ballona Creek watershed because of its low infiltration rate, and the trenches were designed to capture the first flush of a storm event, whose partial EMCs of general pollutants (organics and nutrients) at 30 and 60 min into the storm may be 1.9 to 7.4 times higher than the EMCs (Han et al., 2006; Lau et al., 2009). For example, the ADDs of the two storm events occurring on Feb. 9, 1999 and Jan. 8, 2001 at LA Civic Center gauge station were 5 and 69 days, respectively. Since the ADD of Jan. 8, 2001 storm event was long enough to drain the trenches, the Feb. 9, 1999 storm event (rainfall of 9.4 mm) was considered here. If we assume that the saturated infiltration rate of the upper Ballona Creek watershed is 1.5 mm h^{-1}, trench water level drops about 18 cm prior to the Feb. 9, 1999 storm event. If we further assume that the drainage area is 500 m^2, the runoff coefficient of local roads is 0.9, and the first flush of a storm event occurs within the first 5 mm of rainfall, the infiltration trench area can be calculated as follows:

$$\begin{aligned}\text{Runoff volume of the first flush} &= 500\ \text{m}^2\ (\text{Drainage area}) \times 0.005\ \text{m}\ (\text{Rainfall}) \times 0.9\ (\text{Runoff coefficient}) \\ &= \text{Trench area} \times 0.18\ \text{m}\ (\text{Dropped water level for 5 days}) \times 0.4\ (\text{Void space})\end{aligned}$$

The calculated infiltration trench area for this example was 31 m^2 for the assumed 500 m^2 local road drainage area. Thus, by choosing an appropriate trench area, the first flush of this storm event can be captured (Portland BES, 2004). In turn, this will provide enough coverage to avoid the 18% exceedance with an ADD of 5 days.

For the Jan. 8, 2001 storm event, the load contribution of local roads was calculated to be 77 kg as shown in Table 5. The total Zn load that needs to be removed by infiltration trenches is 52 kg (Total Zn load of the watershed − TMDL), which is 68% of the local road contribution [(52/77)×100%]. Local road runoff and area that needs to be treated by

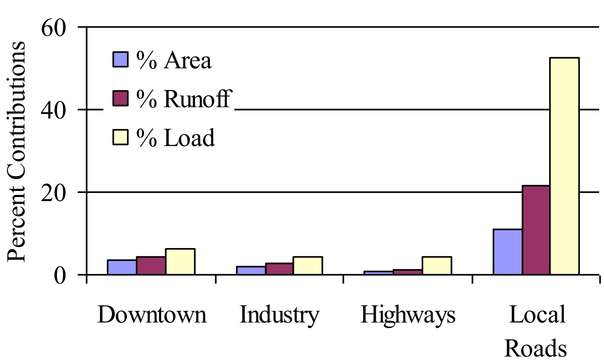

Fig. 4. Percent contributions of total Zn for subwatersheds, highways, and local roads.

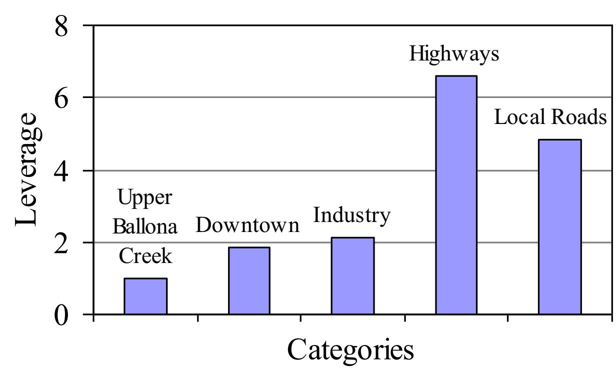

Fig. 5. Total Zn leverage for subwatersheds, highways, and local roads.

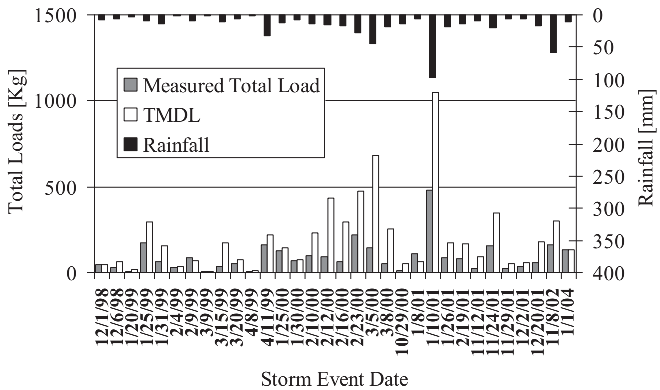

Fig. 6. Total Zn loads, TMDLs, and rainfall data for upper Ballona Creek watershed.

trenches were assumed to be 68%. In the calculation, it was assumed that EMC and runoff generation is homogeneous within local roads. As shown in Table 5, the TMDL was met by treating only 7% of the upper Ballona Creek watershed area (or equivalently about 14% of the runoff volume).

As the mechanism of trench operation is to fill and then bypass, and no treatment of the bypassed flow occurs (US EPA, 1999b), the first flush is always treated and the entire runoff may be treated for small storms (<7 mm rainfall). The simulated storm events were large enough to fill the trench and the load reduction was assumed to be equal to the load reduction shown in Table 5, which was 52 kg per storm event. This assumption is conservative because first flush EMCs for roads and highways may be 1.9 to 7.4 times higher than event EMCs (Han et al., 2006). By the application of infiltration trenches for stormwater runoff from local roads, treatment effectiveness is twice the effectiveness of the Austin sand filters installed in the Industry and Downtown subwatersheds and construction cost is reduced by 75% (Tables 4 and 5).

This example related only to comply with the total Zn TMDL, but other pollutants can also be removed because many pollutants are correlated, such as total metals, COD, and DOC (Han et al., 2006). Additionally, the higher mass loading removals due to the treatment of the first flush will further increase removal rates and treatment effectiveness. Quantification of the additional benefits and the impact of first flush are left to later research, but provide additional incentive to the use of infiltration trenches or other STPs which capture the first flush.

Table 4
Simulation results of Austin sand filters for total Zn load for industry and downtown subwatersheds (January 8, 2001 storm event).

Evaluated Parameters	Downtown		Industry		Entire watershed
Area [hectare]	782	3%	453	2%	23,212
Runoff [m^3]	35,500	7%	9000	2%	549,000
Load without sand filters [kg]	19.9	17%	6.8	6%	117.9
Load with sand filters [kg]	10.9	11%	3.7	4%	103.3
Construction cost [$ million][a]	75.6		19.1		94.7
Treatment effectiveness [kg Zn/$ million][b]	102.0		136.1		129.6

Total calculations are based on model predictions and percentages are based on these totals; TMDL = 66 kg; measured total Zn load = 113 kg; measured total runoff volume = 556,000m^3; LA Civic Center rainfall record = 6.9 mm.

[a] The calculation of the construction costs was adjusted to the year 2017 by considering the average inflation rate from 2000 to 2017 (U.S. DOL., 2018).

[b] Treatment effectiveness is based on the annual average total rainfall (290 mm/year) and 20 years of sand filter lifetime. For example, treatment effectiveness for downtown = (19.9–10.9) kg / 6.9 mm × 290 mm/year × 20 years / 75.6 $ million = 102 kg/$ million.

Table 5
Simulation results of infiltration trench installations for total Zn load for local roads (January 8, 2001 storm event).

Evaluated parameters	Local roads area covered by infiltration trenches		Total local roads		Entire watershed
Area [hectare]	1712	7%	2518	11%	23,212
Runoff [m^3]	79,356	14%	116,700	21%	549,000
Load without trenches [kg]	52.0	44%	77.0	65%	117.9
Load with trenches [kg]	0.0	0%	25.0	38%	66.0
Construction cost [$ million][a]	85.0				85.0
Treatment effectiveness [kg Zn/$ million][b]	220.2				220.2

All calculations are based on model predictions; TMDL = 66 kg; measured total Zn load = 113 kg; measured total runoff volume = 556,000m^3; LA Civic Center rainfall record = 6.9 mm.

[a] The calculation of the construction costs was adjusted to the year 2017 by considering the average inflation rate from 2000 to 2017 (U.S. DOL., 2018).

[b] Treatment effectiveness is based on the average annual rainfall frequency (18 storm events/year) and 20 years of trench lifetime. For example, treatment effectiveness for downtown = 52 kg/storm event × 18 storm event/year × 20 years / 85 $ million = 220 kg/$ million.

4. Conclusions

An empirical modeling approach was used to estimate runoff volumes and pollutant loads for a large urban watershed. The model predicted stormwater runoff volumes and pollutant loads for TSS, TKN, and total Zn with acceptable accuracies. Based on the modeling results, cost-effective STP strategies for compliance with TMDL regulations focusing on total Zn were explored. From this study, the following specific conclusions are made:

1. Performance of the EMC regression model varied depending on landuses and pollutant types showing the highest accuracy ($R^2 > 0.8$) for total Zn EMCs for LI, MR, and T landuses, and relatively poor accuracies ($R^2 < 0.6$) for the other pollutants (TKN and TSS) or landuses. The non-ideal effect of the EMC prediction model caused by the uncertainties of the model and the data could be reduced by adjusting the regression coefficients in the optimization procedure of the subsequent pollutant load estimation.
2. To account for the variability of the percent of each landuse for the catchments, weighting factors were introduced and optimized in the pollutant load estimation. With regularization, model predictions showed reasonable agreement with measured loadings for total Zn, TKN, and TSS: The RMS errors for total Zn, TKN and TSS were respectively only 11.6%, 17.2%, and 11.4% of the corresponding mean discharge load.
3. The contributions of local roads to the total watershed load were significant. In particular, the load contribution from local roads to the total watershed load was 52.4%, even though local road area was only 10.8% of the watershed area. The leverage (% load contribution per % areal contribution) for local roads was 4.8, which makes it the best candidate for STP applications.
4. Two subwatersheds with LI clusters as high leverage area were identified and the implementation of Austin sand filters for treatment of the whole runoff volume were simulated for the storm event. By assuming typical total Zn removal efficiency of 45%, total Zn removal at the mouth of the watershed was 12.4% with the treatment of 5% of the watershed area. If the same leverage and runoff per unit area are assumed for additional locations in the watershed, about 20% of the watershed area (or equivalently 36% of the runoff volume) would need to be treated to meet the TMDL.
5. Infiltration trenches were simulated for treating the first flush from local roads. The TMDL requirement was met with the treatment of 68% of runoff from local roads, which is equivalent to 7% of the

upper Ballona Creek watershed area. By the application of infiltration trenches for stormwater runoff from local roads, treatment effectiveness was twice the effectiveness of Austin sand filters in the two subwatersheds and construction cost was reduced by 75%

CRediT authorship contribution statement

Joo-Hyon Kang: Writing - review & editing, Validation. **Mi-Hyun Park:** Writing - review & editing, Validation. **Simon J. Ha:** Conceptualization, Methodology, Software, Writing - original draft. **Michael K. Stenstrom:** Supervision.

Declaration of competing interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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Appendix A. Supplementary data

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