Predictive Modeling of Storm-Water Runoff Quantity and Quality for a Large Urban Watershed

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Abstract: A predictive model for storm-water runoff was implemented on a GIS platform based on the unit area loading method and Browne's empirical relation for soil characteristics for the Upper Ballona Creek Watershed in Los Angeles. The heterogeneity of the watershed was quantified by dividing it into many small subareas and applying lumped parameters for each. Characterization of total pollutant load by land-use types to total loads was achieved through zeroth-order regularization and limited memory Broyden–Fletcher–Goldfarb–Shanno bound constrained optimization techniques. Relative form was used in the objective function to compensate for strong contributions of high magnitude variables. Model predictions showed reasonable agreement with pollutant loadings, using Zn as an example, measured at the mass emission site at watershed mouth. The predicted runoff volumes using the developed quantity model were in good agreement with the data and had R^2 of 0.86. The RMS error of the quality model was 9 kg, which is low compared to the mean discharge of 77 kg/event.

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CE Database subject headings: Predictions; Stormwater management; Quality control; Urban areas; Watersheds; Optimization.

Introduction

Over the past 10 years, storm-water management has become the major priority for water pollution control. This has occurred in part because of the completion of wastewater treatment plants and in part because of the recognition of contaminant contributions from storm water. Storm-water management is intrinsically more challenging than wastewater treatment because of the distributed nature of storm water and because "ownership" of storm-water problems has not been clear. Various approaches are being taken to mitigate storm-water impacts and these include individual actions, such as industrial storm-water management permits as well as agency- or citywide actions, such as Los Angeles' recent passage of Proposition O, which provided $500 million for storm-water management.

In 1987, Congress amended the Clean Water Act to require implementation of a comprehensive national program for addressing storm-water discharge. The program required national pollutant discharge elimination system (NPDES) permits for storm-water discharge. More recently, total maximum daily loads (TMDLs) are being developed. The concept of the TMDL is to obtain the maximum allowable or permissible discharge rate by optimally minimizing all sources. In this way, a more economical design can be obtained by reducing the easily controlled sources and minimizing controls for small sources or sources that cannot be effectively treated. One approach to deal with this complex nonpoint source (NPS) pollutant problem is through modeling and information management using GIS.

Among the many urban storm-water pollution modeling programs, the USEPA Storm Water Management Model (SWMM) continues to be widely used throughout the world since its development in 1971. This model simulates NPS pollution in as much detail as possible; however, this approach requires that many parameters be measured. These parameters are influenced by many temporal and aerial factors that are related to the heterogeneous characteristics of the subcatchments. The measurements required by this type of model are costly and time consuming, especially for a large watershed. If there are insufficient measured data available, inaccurate predictions can be expected (Donigian and Huber 1991).

The other approach to this inherently complex problem is to adopt a unit area model where all runoff is assumed to have a constant concentration for a given pollutant. The changes in pollutant concentration over a large watershed during a storm event tend to have a small impact on the receiving waters due to their relative insensitivity to rapid changes (Donigian and Huber 1991). The insensitivity may be due in part to averaging of the dispersed load because of differing conditions over the large area, or to the large dilution that can occur in receiving water. Additionally, the time of travel of the runoff for a large watershed tends to average out first flush impacts (Kang et al. 2008). This insensitivity makes the assumption of time invariant concentrations a viable option for receiving water quality analysis. This method has been used to estimate oil and grease in an urban catchment (Stenstrom et al. 1984; Fam et al. 1987), loads of a number of pollutants from the Santa Monica watershed (Wong et al. 1997), larger areas in Southern California (Ackerman and Schiff 2003; McPherson et al. 2005), and many other areas (Wu et al. 1998; Shinya et al. 2000; Choe et al. 2002).

In order to better understand storm-water management and to create a tool for TMDL development, a GIS-based model was developed. The model was implemented in Visual Basic for Ap-

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plication (VBA), which is included with ArcGIS Desktop Version 9.1 (Redlands, Calif.) to incorporate inherent heterogeneity of urban watershed surfaces and climatic conditions. The model contains several layers which characterize land use, rainfall, slope, elevation, and hydrologic soil group. An empirical runoff model, based largely on the unit area loading or rational method, is used to estimate pollutant loads. The model can be used to estimate pollutant loads and compare contributions from different land-use types. In this way, costly and time-consuming field surveys can be avoided.

The objectives of this research are (1) to develop a model to predict storm-water runoff quantities for a large watershed taking into account the spatial variability of watersheds with minimal data requirements; (2) to develop a methodology for predicting storm-water runoff quality; and (3) to validate the method for predicting loads for one or more pollutants using existing monitoring data. The specific procedures and methodologies can serve as a guide for a general approach to modeling and developing strategies to meet TMDLs for large watersheds. To illustrate the effectiveness of the developed models, total Zn was chosen as an example, as there is a TMDL for total Zn and also because it was well represented in the monitoring data (more observations and fewer nondetects). TMDLs have been issued for other pollutants such as litter and indicator organisms and are in development or being evaluated for conventional pollutants, other metals, and nutrients.

Unit Area Loading Method

This study is based on the conventional unit area loading method, sometimes called the rational method, and event mean concentrations (EMCs) for all land-use categories. However, to account for the spatial heterogeneity of a watershed, a distributed approach was taken. A watershed is divided into many small subareas to account for the heterogeneity and lumped parameters were applied to each of them. Thus, the unit area loading method can be rewritten as follows:

$$L = c\sum_{j} \mathrm{EMC}_j \left(\sum_{i} A_i P_i \mathrm{RC}_i \right)_j \tag{1}$$

where L=pollutant loading (kg); j=land-use type (–); EMC_j=EMC of land-use type j (μg/L); A_i=homogeneous subarea (ha); P_i=precipitation in the subarea A_i (mm); RC_i=runoff coefficient of the subarea A_i (–); and c=units conversion factor, 0.01 for the given units.

The division of a watershed depends on the availability of data that can be applied to each of the divided subareas. The watershed information must be sufficiently detailed so that each subarea can have unique parameters. In this way, heterogeneity of a watershed is accounted for up to available data sets.

Storm-Water Runoff Quantity Analyses

The developed GIS model is used to calculate runoff quantities from each land-use type. Total runoff quantity is then calculated by adding these quantities for a storm event. In the following, procedures for calculating watershed area, rainfall, and runoff coefficients are described. Data needed for these calculations are the digital elevation model (DEM), hydrologic soil groups, land-use types, rainfall data for rain gauge stations in or near the watershed, and locations of the gauge stations. The calculated storm-water runoff volumes were compared to the measured volumes at the emission site of the Upper Ballona Creek Watershed.

Watershed Area

The top eight land-use types based on total area were selected by the Los Angeles County Department of Public Works [(LADPW), http://ladpw.org/] through the field survey conducted in 1996 (Woodward Clyde 1996). They are: educational facilities, high density single family residential, light industrial, multi-family residential, mixed residential, retail/commercial, transportation, and vacant land uses. Each county in the United States, including Los Angeles County, is required by the NPDES program to monitor pollutant loadings to its receiving water body. LADPW monitored four drainage areas near their ocean discharges to comply with their 1990 and 1996 NPDES permits. These four sites, called mass emission sites, are the Los Angeles River, San Gabriel River, Ballona Creek, and Malibu Creek. The Ballona Creek site drains a highly urbanized watershed, which is the ideal subject for this research project. It was chosen for this study because it has been the subject of previous studies conducted by UCLA investigators (Wong et al. 1997; Kayhanian et al. 2008; McPherson et al. 2005; Park and Stenstrom 2006; Lee et al. 2007).

Most of the previously collected data and the county's monitoring program used a mass emission monitoring station located on Ballona Creek between Sawtelle and Sepulveda Boulevards in the City of Los Angeles. This station was chosen to avoid tidal influences and has a USGS gauge. The upstream tributaries of Ballona Creek, which is called the Upper Ballona Creek Watershed, drain 23,211 ha (89.6 sq m). This research project utilizes these accumulated data to estimate total pollutant loadings in a new, automated fashion. To apply EMCs monitored by LADPW [see Eq. (1)], the Southern California Association of Governments' land-use types were reclassified to LADPW's eight land-use types.

Runoff Coefficients

Spatial variability of runoff coefficients in a watershed is incorporated using Browne's relation (1990), which relates runoff coefficient with hydrologic soil group, percent land slope, and land-use type. Soils are classified by the Natural Resource Conservation Service into four hydrologic soil groups based on the soil's runoff potential, which are A, B, C and D. Group A has generally the smallest runoff potential and Group D has the greatest. The Upper Ballona Creek is made up of entirely Group D soils, which have very low infiltration rates and consist chiefly of clay soils.

The Browne relation uses three categories of percent slopes, 0–2, 2–6, and 6+%. A DEM raster downloaded from USGS seamless data distribution system was used to calculate a percent slope raster. The percent slope raster was then reclassified into three categories defined in the Browne relation.

The land-use category polygons were overlaid with a hydrologic soil group layer and a percent slope layer created from the DEM. The resulting polygons are internally homogeneous in terms of runoff coefficients. However, the layer does not yet contain runoff coefficient values. To create a runoff coefficient field in the overlaid layer, runoff coefficient calculation module was implemented in VBA. This module identifies three fields in the overlaid layer, land-use category, hydrologic soil group, and re-

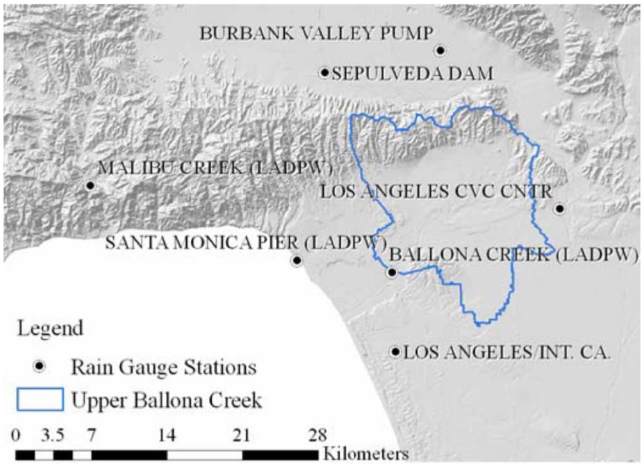

Fig. 1. Rain gauge station locations

classified percent slope fields. The module then creates a new runoff coefficient field using the Browne relation.

Data Screening

LADPW measured total runoff volumes and their EMCs for mass emission sites starting from 1998, which are available from their website. Among the available 49 storm events from the 1998 to 2003 storm seasons, four storm events without flow measurement data were excluded. For the rest of the 45 storm events, nine storm events were filtered according to the following filtering criteria:

1. Implausibly high or low total runoff volume compared to rainfall records, suggesting an error in the data (three cases).
2. Rainfall patterns which were unusually irregular across the rain gauge stations (five cases), with some gauges reporting zero rainfall, suggesting rain gauge failures at specific locations.
3. Large, atypical storm events corresponding to approximately a one in 50 year storm event (one case).

The main reason for filtering storms is to exclude the possibility of perturbation errors, such as measurement errors, approximation errors, or equipment malfunction errors. Therefore, storm events with extremely irregular rainfall patterns were filtered. LADPW uses a previously established rating table to calculate flow rate by measuring water elevation in a storm drain or calculated with an equation such as Manning's. But their storm-water flow measurement efforts indicated that all stations required multiple storm events to gather the data necessary for calibration of the measurement devices. Thus, filtering relatively large storm events is reasonable, as those cases are rare.

Interpolation of Precipitation Data

Hourly precipitation data from the seven rain gauge stations located around the Upper Ballona Creek were used. Fig. 1 shows the gauge station locations. The precipitation data were gathered from National Climate Data Center (NCDC) and LADPW.

Interpolation of the precipitation data gathered from the gauge stations is important because precipitation is one of the most influential parameters in the calculation of total pollutant loads. Among many interpolation techniques, Kriging was chosen for the first attempt. Unlike the other interpolation techniques, Kriging assumes that the spatial variation is statistically homogeneous throughout the surface. For example, inverse distance weighted (IDW) interpolation is based on the weighted distance of each data point from a point being estimated. The disadvantage of the IDW interpolation is that it treats all points the same way regardless of their geographic orientations. Kriging uses different weighting functions depending on the distance to each data point and spatial relationships among these points. This was done by creating a empirical semivariogram, which is computed from an input data set.

Zimmerman et al. (1999) conducted an investigation to compare the spatial interpolation accuracy of Kriging and IDW. Their result showed that Kriging interpolation outperformed the IDW interpolation. The relative superiority was greatest when the surface was most regular, noise was low, and spatial correlation was high. However, as Kriging is based on the assumption that the spatial variation in the phenomenon is statistically homogeneous throughout the surface, data sets that have rapidly changing values are not appropriate for Kriging interpolation and IDW interpolation was used for these events (approximately 15% of the events).

Implementation of a GIS Model

A GIS model to predict the total storm-water runoff volume of storm events is implemented in VBA. The main objective of this model is to account for the heterogeneity of a watershed up to available data sets. Reclassified land-use layer and the runoff coefficient layer were overlaid to get internally homogeneous polygons in terms of runoff coefficients and EMCs. This overlay created approximately 33,000 polygons for the Upper Ballona Creek Watershed as shown in Fig. 2. Runoff volumes for the eight land-use types were calculated by spatially referencing the isohyets layer, which was created from the seven rain gauge stations' rainfall data, from each polygon of the overlaid layer.

Storm-Water Runoff Quantity

The total number of storm events available from the LADPW after the data screening was 36 from the 1998 to 2003 storm seasons. The GIS model was used to predict storm-water runoff quantities for the 36 storm events. The results were compared with the measured runoff quantities at the Upper Ballona Creek Emission Site, which is shown in Fig. 3. For the heterogeneity of such a large watershed (23,211 ha) and the variability of rainfall, the predicted runoff volumes were in good agreement with the measured data having an R^2 of 0.86, and generally were within $+184/-54\%$ percent of the measured runoff.

The implemented model showed improved runoff prediction (-8% of the measured runoff) over the model defined by land-use definitions [+54%; Wong et al. (1997)] for a sample analysis of the Dec. 2, 2001 storm event. The model overpredicted runoff from small storms and underpredicted runoff from large storms, which is a well-known characteristic of the rational method. The model has the advantage of reduced data needs, when compared to a runoff model such as SWMM. For example, Barco et al. (2008) required approximately 30,000 input data points for the characteristics of drain network and about 2,500 subcatchments to model the Upper Ballona Creek Watershed. The new model required only four GIS layers—DEM, hydrologic soil group, land-use type, and isohyets layers. More important, only the fourth layer needed to be developed for the modeling activity.

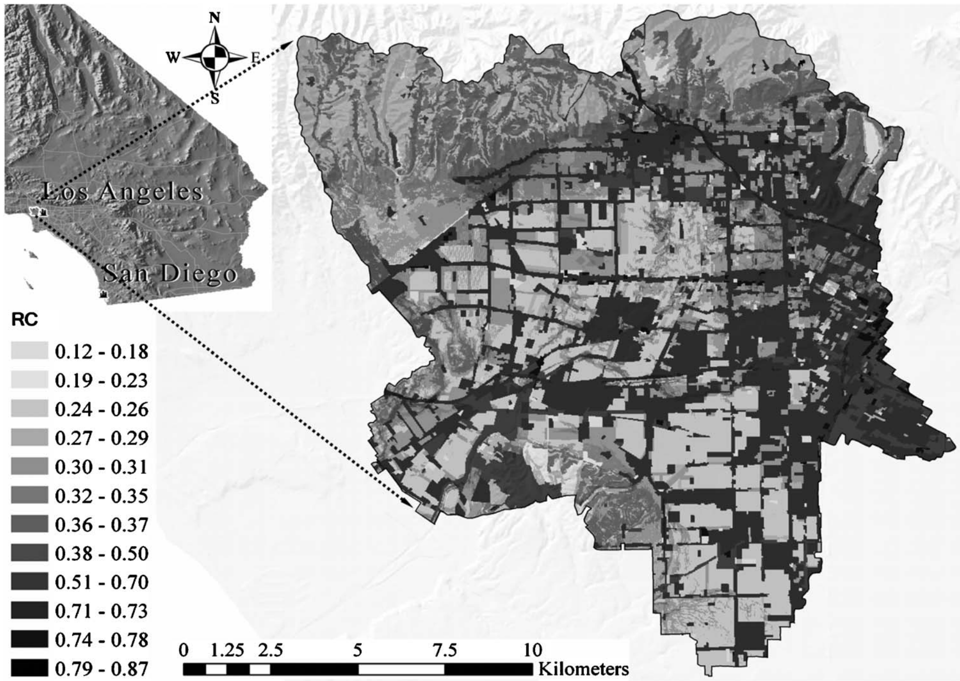

Fig. 2. Runoff coefficient distributions in the Upper Ballona Creek

Storm-Water Runoff Quality Analyses

Among the trace metals that have toxic effects on aquatic plants and animals, total Zn was chosen for quality analyses. A TMDL was set for total Zn for the Ballona Creek Watershed by the Los Angeles Regional Water Quality Control Board and USEPA Region 9 in 2005 (LARWQCB and USEPA 9 2005). LADPW under their 1990 NPDES Permit sampled representative areas that were predominantly of a single land-use type. The experimental catchments chosen by the LADPW were scattered around Los Angeles County.

In the following sections, sampling results of the experimental catchments and the calculated runoff quantities of the GIS model were used to predict the total Zn loads at the mass emission site of the Upper Ballona Creek Watershed. The model was initially calibrated using monitoring data from eight experimental land-use catchments. Total Zn EMCs were determined by regression of event mean concentrations ($\mu g/L$) reported in a large monitoring program for 13 to 33 storms per catchment (LADPW; http://ladpw.org/). Using these EMCs, the model was used to predict the total loads of the Upper Ballona Creek Watershed for 32 storm events from the 1998 to 2003 storm seasons. An optimization routine using weighting factors and regularization was used to improve the estimates. The RMS error of the optimized model without regularization was 24 kg and only 9 kg with regularization, which is low compared to the mean discharge of 77 kg/storm event.

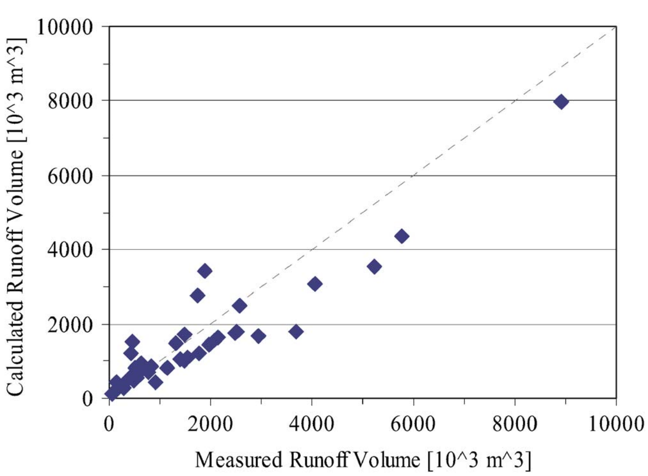

Fig. 3. Calculated versus measured storm-water runoff quantities (1998–2003 storm seasons). The diagonal line shows one-to-one correspondence.

LADPW Experimental Catchments

The sampling protocol required that EMCs be measured, which are obtained from flow-weighted composite samples. Automatic samplers with flow meters were used over the duration of each storm event. The permit required continued sampling until one of two provisions were met: achieving an EMC at an error rate of 25% or less or detecting a constituent less than 25% of the time for ten consecutive samples. Sampling was discontinued for constituents that meet either criterion. Otherwise, 200 station samples are required.

Data Screening

Outlier detection is important for effective modeling. If all the available data are included in the model fitting, the fitted model may be poor. Outliers can be attributable to equipment errors and human errors. For example, rain gauge, automatic sampler, or stage monitoring equipment may malfunction and this can be especially important for storm-water monitoring, as storm water may contain debris and other material that can foul or plug sensors. Also, a measurement might be correct but represents a rare event. There may also be unusual human or animal activities

Table 1. Ranges of Storm Characteristics of the Sampled Storm Events for Land-Use Type Monitoring Catchments

Land-use types	ADD (days)	Rainfall (mm)	Duration (h)	Intensity (mm/h)[a]	N[b]
Vacant	0.3–158.1	2.5–74.7	1–35	0.5–12.2	22
Light industrial	0.3–122.8	1.5–50.3	2–26	1.0–18.3	31
Mixed residential	0.4–157.8	2.5–66.0	1–37	2.5–17.8	25
Transportation	0.3–175.8	2.0–46.7	3–33	1.0–17.3	33
Retail/commercial	1.2–179.0	5.1–35.6	1–45	[c]	14
Educational facilities	0.3–157.0	3.3–132.3	1–77	1.0–12.2	21
High density single family residential	0.4–157.8	2.5–66.0	1–37	2.5–12.7	13
Multi-family residential	0.3–158.1	1.3–74.7	2–35	0.5–11.7	25

[a]Peak 1 h intensity of a storm event in mm/h calculated from the NCDC hourly rainfall data.

[b]Number of storm events used (LADPW storm-water runoff monitoring data from 1998 to 2001).

[c]Data not available.

which cause abnormal quality peaks. For example, wildfires in Southern California may cause episodic high loads. To determine the potential impacts of outliers caused by possible error sources, Cook's distance versus leverage plot was used (Cook 1977; Cook and Weisheg 1982).

Cook's distance is a measure of the influence of a case. It measures the effect of deleting a given observation. Cook's distance for *i*th observation is based on the differences between the predicted responses from the model constructed from all of the data and the predicted responses from the model constructed by deleting the *i*th observation. Leverage values are the measures of the influence of a point on the fit of regression.

High leverage gives an extra weight in the computation of regression line. A high Cook's distance indicates that the case affects the slope of the regression line. Thus, cases with high leverage and high Cook's distance were identified as outliers in a preliminary test. If the residual frequency distribution does not follow a normal curve, Cook's distance versus leverage plot needs to be reconstructed from the data set without identified outliers. The procedure should continue until all outliers are removed.

Storm Characteristics of Experimental Catchments

Experimental catchments for eight land-use types are scattered around Los Angeles County. To apply analysis results of land-use types to the Upper Ballona Creek Watershed as a function of site-specific conditions, four types of storm characteristics were used as independent variables: antecedent dry days (ADD), total rainfall, rainfall duration, and maximum hourly rainfall intensity. Site-specific characteristics that may influence pollutant loads such as subcatchment impervious fraction, depression storage, infiltration, and roughness coefficient were not used in the analyses to simplify inputs to the model and to avoid expensive and time-consuming field surveys. Simple correlation tests were conducted with the rainfall records of the seven gauge stations shown in Fig. 1. LA Civic Center rainfall records showed best correlation to the total runoff volume of Upper Ballona Creek Watershed. Thus, the storm characteristics are calculated from LA Civic Center hourly rainfall records using a procedure written in VBA. Two parameters affect the storm characteristic calculations:

1. Minimum rainfall that can be considered a storm event.
2. Minimum dry period between two consecutive rainfall events to make these two events separate storm events.

Effects of minimum rainfall parameter on total rainfall and ADD calculations were minimal until 1 mm of rainfall. For some events, total rainfall and ADD showed large changes when the minimum rainfall parameter became greater than 1. Also, runoff usually starts with 1 mm of rainfall from our field experience. Thus, 1 mm (0.04 in.) of rainfall was chosen for the first parameter. For the second parameter, 6 h was chosen. This parameter does not significantly affect the calculated results.

Table 1 summarizes storm characteristics of the sampled storm events from 1998 to 2001 for the eight experimental catchments, which are available from the LADPW website. LADPW reported average storm intensities and NCDC rain gauge is not available around the Retail/Commercial monitoring catchments. Thus, maximum intensity data for this land-use type is not available. For the other sites, nearby NCDC rainfall data were used to calculate storm characteristics, including hourly maximum intensities.

Multiple Linear Regression Models of the Monitored Land-Use EMCs

Multiple linear regression analyses were performed to develop correlations between Total Zn land-use EMCs and the storm characteristics discussed previously. The results are shown in Table 2. Total Zn EMCs of the light industrial, mixed residential, and transportation land-use types showed high correlations with storm characteristics ($R^2 > 0.8$), whereas retail/commercial, educational facilities, high density single family residential, and multi-family residential land-use types showed low correlations ($R^2 < 0.4$). Regression coefficients of the land-use types that showed low correlations were used as part of the optimization parameters as EMCs calculated with these coefficients may not represent the EMCs of the corresponding land-use types. Total Zn EMCs for the vacant land-use were mostly below detection limit. Thus, half of the detection limit ($25\ \mu g/L$) was used as a constant for the total load prediction of a storm event for the Upper Ballona Creek Watershed.

Optimization Technique

The percent of each representative land-use type for the LADPW eight experimental catchments ranged from 54% (retail/commercial) to 100% (high density single family residential). As a result, the regression models developed from these eight land-use types do not represent a single land-use type. In contrast, total runoff volumes calculated for each land-use type by the GIS model discussed in the previous section represent runoff volumes

Table 2. Multiple Linear Regression Models of Total Zn EMCs (μg/L) for LADPW Land-Use Monitoring Catchments

	Coefficients												
Land-use types	Intercept	P[a]	ADD (days)	P	Rainfall (cm)	P	Duration (h)	P	Intensity (cm/h)[b]	P	R^{2c}	N[d]	Models[e]
Vacant[f]	25.00											22	Constant
Light industrial	**202.66**	**0.08**	**24.60**	**0.00**	*−1.44*	*0.99*	*−1.25*	*0.89*	*−0.39*	*0.99*	0.84	31	Linear
Mixed residential	**123.29**	**0.00**	**3.51**	**0.00**	*−5.75*	*0.78*	*1.30*	*0.69*	*−36.73*	*0.48*	0.85	25	Linear
Transportation	**241.51**	**0.00**	**7.34**	**0.00**	*−77.95*	*0.26*	*−3.61*	*0.53*	**189.25**	**0.22**	0.88	33	Linear
Retail/commercial	218.45	0.00			108.66	0.10	−309.64	0.07			0.27	14	Inverse
Educational facilities	64.81	0.00			14.35	0.17					0.10	21	Inverse
High density single family residential	24.53	0.05			−12.79	0.03			13.57	0.05	0.39	13	Inverse
Multi-family residential	56.96	0.00							5.09	0.00	0.37	25	Inverse

[a]Significance of independent variables.

[b]Peak 1 h intensity of a storm event in centimeters-per hour calculated from the NCDC hourly rainfall data.

[c]Regression coefficients for land uses with low R-square values ($R^2 < 0.6$, underlined number for emphasis) were not used, and the optimization technique was used for parameter estimation. Italic fonts indicates that the parameters have no impact on the final solution due to low significance. Bold denotes significant parameters.

[d]Number of storm events used for each land-use site (LADPW storm-water runoff monitoring data from 1998 to 2001).

[e]Best fit regression models for each land use type.

[f]Twenty one out of 22 events were below detection limit, 50 μg/L.

from single land-use types. Thus, to apply the regression models to the total loading calculations of the Upper Ballona Creek Watershed, optimization techniques are needed.

The limited memory Broyden–Fletcher–Goldfarb–Shanno Bound (L-BFGS-B) constrained nonlinear optimization technique was used for this study (Zhu et al. 1994). The algorithm is a quasi-Newton algorithm good for a limited memory large scale bound constrained optimization problem. The user is required to calculate the objective function value and its gradient. The cost of the iteration is low but on highly ill-conditioned problems, it may fail to converge. Detailed algorithm is described by Byrd (1994). The ending criteria is based on the change of the objective function F or projected gradient, which is the projection of the gradient vector onto the space tangent to the active bounds. The program terminates when changes of objective function F or the norm of the projected gradient becomes sufficiently small. The projected gradient is zero at a local minimum of the bound constrained problem.

Objective Function

Solutions of ill-posed inverse problems inevitably end up with active bounds. The active bounds problem can be avoided with the zeroth-order regularization method (Press et al. 1986). The objective function shown in Eq. (2) is to minimize both the residual norm (first term) and the solution norm (second term). The regularization parameter λ in the equation acts as a weight between these two norms and is often acquired empirically. Increasing λ pulls the solution away from minimizing residual norm in favor of minimizing solution norm, which means that the initial values of optimization parameters are weighted high. Also, relative least-square form is used in the objective function to compensate for strong contributions of high magnitude state variables (Saez and Rittmann 1992).

Objective function

$$F = \sum_i \left(\frac{P_i - M_i}{P_i}\right)^2 + \lambda \sum_n \left(\frac{x_n - x_n^*}{x_n^*}\right)^2 \tag{2}$$

$$P_i = \sum_j x_j(\mathrm{EMC}_j Q_j) \tag{3}$$

$$\mathrm{EMC}_j = C_{1,j} + C_{2,j}\mathrm{ADD}^k + C_{3,j}R^k + C_{4,j}D^k + C_{5,j}I^k \tag{4}$$

where subscript i=storm events; P_i=predicted total loadings using regression equations for land-use types; M_i=measured total loadings; λ=regularization parameter; subscript n=optimization parameters; x_n, x_j=optimization parameters; x_n^*=initial values of optimization parameters; subscript j=land-use types; EMC_j=event mean concentration for each land-use type; Q_j=total runoff volume from each land-use type; and $C_{1..5,j}$=constants from regression equations. These constants also serve as optimization parameters for the Retail/Commercial, Educational Facilities, High Density Single Family Residential, Multi-Family Residential land-use types. These constants become initial values when used as optimization parameters; superscript $K=0$ for Vacant land-use type, 1 for Light Industrial, Mixed Residential, and Transportation landuse types, −1 for the other land-use types; ADD=antecedent dry days; R=total rainfall; D=storm duration; and I=maximum hourly rainfall intensity.

The optimization parameters x_j in Eq. (3) behave as weighting factors. Contributions of each land-use type to the total loadings of the Upper Ballona Creek Watershed will be adjusted by the weighting factors x_j. This is to account for the variability of the percent of each representative land-use type for the experimental catchments, which ranged from 54 to 100%.

Initial values of the optimization parameters x_n were given with the underlined coefficients of the regression equations shown in Table 2. Standard deviations of regressions were used as bound constraints for these parameters. Also, the initial values of the optimization parameters x_j were given all ones. The upper and lower bounds were 1.7 and 0.3, respectively.

L Curve

A graphical tool for the analysis of ill-posed problems is called an L curve, which is shown in Fig. 4. This figure was constructed by

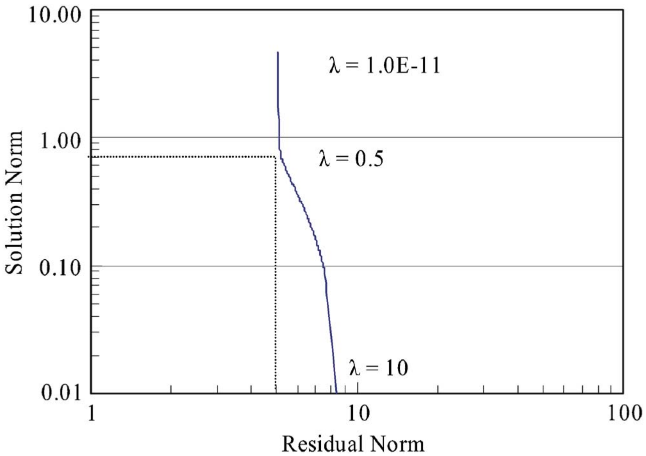

Fig. 4. L Curve for total Zn with λ values as data labels

trying many different λ values in the L-BFGS-B optimization program and plotting calculated solution and residual norms in terms of λ values.

Solutions of real world problems are always contaminated by various types of perturbation errors. The L curve shows the compromise between minimization of perturbation error and the error caused by regularization. For the horizontal part of the curve, the solution changes little with the regularization parameter, which means that the error caused by regularization dominates. In contrast, the vertical part of the curve corresponds to solutions that are dominated by the perturbation error, where the solution norm undergoes large changes with the regularization parameter and residual norm undergoes very small change.

Hansen (1992) showed that the optimal regularization parameter is not far from the regularization parameter that corresponds to the L curve's corner. Thus, by selecting $\lambda = 0.5$, we can compute the regularized solution with optimal balance between perturbation errors and regularization errors.

Storm-Water Runoff Quality

Preliminary regression analysis was performed with the available 36 storm events and storm characteristics calculated with LA Civic Center rainfall records for the total Zn measured at the emission site of the Upper Ballona Creek Watershed. Two outliers were dropped by this preliminary test. For two storm events, no rainfall records were available from the LA Civic Center rainfall gauge station. Among the remaining 32 storm events, 25 events from 1998 to 2001 were used for optimization and 7 events from 2001 to 2003 were used for validation.

The 18 optimized parameters are shown in Table 3. The percent of representative land use for each experimental catchment is shown for comparison. Optimized weighting factors increased in value for the land uses where the defining experimental catchment had a high fraction of the representative land use. For example, the weighting factor of the Retail/Commercial land use, which has the lowest percent representative land use (54%), had the lowest weighting factor. Also, the weighting factors did not show any relationships to the size of experimental catchments.

Total Zn loadings of the Upper Ballona Creek Watershed for the 32 storm events calculated using the optimized regression coefficients and weighting factors along with the storm characteristics calculated from the LA Civic Center rainfall records were plotted against the measured loadings at the top of Fig. 5(a). The diamonds indicate 25 storm events used in the optimization and the triangles indicate 7 storm events used to validate the optimized quality prediction model. Predicted and measured loadings showed a reasonably good agreement without any site-specific information. Further, this model can be applied to LA County as the experimental catchments are scattered over LA County.

To illustrate the effectiveness of the regularization method, ten regression coefficients of the land-use types for R-square values less than 0.4 were used in the optimization without regularization. In this analysis, all of the 32 storm events were used in the optimization process. Nevertheless, the predictions of total Zn loadings generally overestimate the corresponding measured ones, which are shown at the top of Fig. 5(b). The RMS error of the optimized model without regularization for total Zn was 24 kg and only 9 kg with regularization, which is low compared to the mean discharge of 77 kg/storm event.

To check the validity of the optimized regression coefficients, the EMCs of Retail/Commercial experimental catchment were calculated using the coefficients optimized with regularization and the results are shown at the bottom of Fig. 5(a). For the same land-use type, EMCs were calculated using the coefficients optimized without regularization and the results are shown at the bottom of Fig. 5(b). Again, calculated EMCs using optimization with regularization show better predictions overall than the calculated EMCs using optimization alone.

Table 3. Optimized Parameters and Regression Coefficients

Land-use types	Coefficients					x_j	Representative land use (%)	Drainage area (ha)
	Intercept	ADD (days)	Rainfall (cm)	Duration (h)	Intensity (cm/h)			
Vacant	25.00					*0.96*	98	1,341.6
Light industrial	202.66	24.60	−1.44	−1.25	−0.39	*0.63*	74	277.1
Mixed residential	123.29	3.51	−5.75	1.30	−36.73	*0.68*	77	51.8
Transportation	241.51	7.34	−77.95	−3.61	189.25	*0.94*	73	349.7
Retail/commercial	*167.42*		*104.75*	*−309.40*		*0.32*	54	33.7
Educational facilities	*62.13*		*14.33*			*0.96*	90	106.2
High density single family residential	*22.21*		−12.95		*13.54*	*0.92*	100	67.3
Multi-family residential	*52.13*				*5.08*	0.92	74	88.1

Note: Italics indicate optimized parameters.

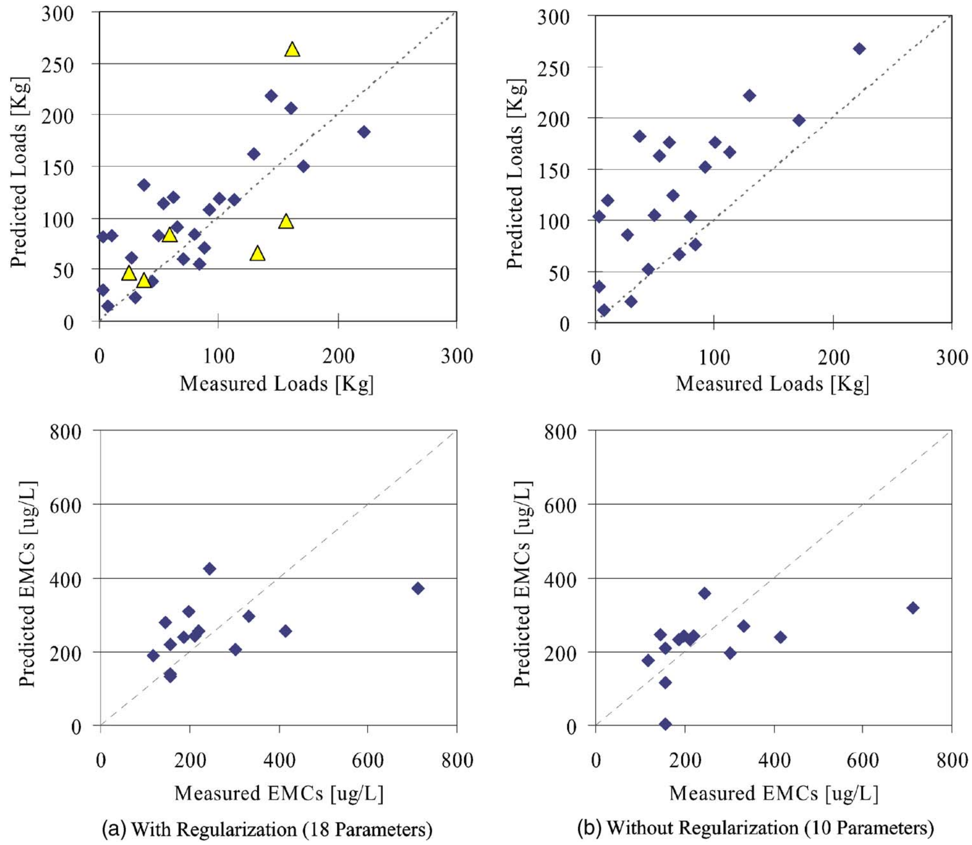

Fig. 5. Comparisons of predicted and measured total Zn loads for the Upper Ballona Creek Watershed and EMCs for retail/commercial land-use: (a) 25 events (diamonds) were used for optimization (1998–2000 storm seasons), and 7 events (triangles) were used for validation (2001–2003 storm seasons); (b) 32 events were used for optimization (1998–2003 storm seasons)

Conclusions

A storm-water quantity and quality model was developed to estimate runoff volumes and pollutant loads for a large urban watershed with many smaller subwatersheds. The model was based on the unit area loading method and land-use types but used improvements to account for build up between storm events, ground slope, hydrologic soil group, and storm characteristics. The models were integrated with a GIS to manage subcatchments (~33,000; Fig. 2) and optimization techniques were used for calibration. The model successfully predicted storm-water volumes and pollutant loads for total zinc. The water quality model was calibrated using 24 storm events from the 1998 to 2000 storm seasons and validated with 7 additional storm events from the 2001 to 2003 storm seasons for the Upper Ballona Creek Watershed (23,211 ha). Calibration and validation were performed by comparing model predictions to measurements from the Los Angeles County Department of Public Works' mass emission site at intersection of Sawtelle Blvd. and Ballona Creek (34°00′, 118°24′). The following specific conclusions are made:

1. The unit area loading method, Browne's empirical relation from DEM, land-use type, hydrologic soil group, and isohyets layers were integrated into a GIS platform with Visual Basic to calculate runoff. The implemented model showed improved runoff prediction when compared to models defined by land-use definitions [average of −8% difference compared to +54% average difference using land-use-only models; Wong et al. (1997)].
2. The predicted runoff volumes using the new model were in good agreement with the measured data (Fig. 3) and had R^2 of 0.86, and generally were within +184/−54% of the measured runoff. The correlation with antecedent dry days partially overcomes the well-known tendency of the rational method but the model still overpredicts small storm runoff.
3. The new model has the advantage of reduced data needs, when compared to a runoff model such as SWMM. For example, Barco et al. (2006) required approximately 30,000 input data points for the characteristics of the drain network and about 2,500 subcatchments to model the Upper Ballona Creek Watershed. The new model required only four GIS layers—DEM, hydrologic soil group, land-use type, and isohyets layers.
4. Four types of storm characteristics were used as independent variables in multiple linear regression analyses to derive correlations between the pollutants' land-use EMCs and the storm characteristics. In general, antecedent dry days were the most significant explanatory variable in predicting pollutant concentration, with total rainfall, rainfall duration, and the maximum hourly rainfall intensity being of descending importance. The regression explained more than 80% of the variability in total Zn EMCs for light industrial, mixed residential, and transportation land uses. The regressions poorly explained ($R^2 < 0.4$) the variability in total Zn for retail/commercial, educational facilities, high density single family residential, and multi-family residential land uses.
5. Zeroth-order regularization and L-BFGS-B optimization technique were used to improve the model predictions of pollutant load contributions from various land-use types to

total loads of the Upper Ballona Creek Watershed. Optimized weighting factors increased in value for the land uses where the defining experimental catchment had a high fraction of the representative land use. For example, the weighting factor of the retail/commercial land use, which has the lowest percent representative land use (54%), had the lowest weighting factor. Also, the weighting factors did not show any relationships to the size of experimental catchments.

6. Model predictions showed reasonable agreement with measured loadings for total Zn without using site-specific information. The RMS error of the optimized model without regularization for total Zn was 24 kg and only 9 kg with regularization, which is low compared to the mean discharge of 77 kg/storm event. Although this paper concentrates on Zn, the approach is applicable for other pollutants and results are forthcoming (S. J. Ha et al., private communication, 2007).

This paper illustrates the development and validation of a conceptually simple model, based on existing data sets (land use, rainfall, monitoring) that was able to predict mass emissions to within 8% measured loads. The model should be useful to not only rank best management practices but also to develop initial designs for long-term programs to comply with TMDLs at minimum cost. The model was validated only for a large watershed and its application to smaller watersheds will require validation.

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