Automatic Calibration of the U.S. EPA SWMM Model for a Large Urban Catchment

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Abstract: The Storm Water Management Model was adapted and calibrated to the Ballona Creek Watershed, a large urban catchment in Southern California. A geographic information system (GIS) was used to process the input data and generate the spatial distribution of precipitation. An optimization procedure using the complex method was incorporated to estimate runoff parameters, and ten storms were used for calibration and validation. The calibrated model predicted the observed outputs with reasonable accuracy. A sensitivity analysis showed the impact of the model parameters, and results were most sensitive to imperviousness and impervious depression storage and least sensitive to Manning roughness for surface flow. Optimized imperviousness was greater than imperviousness predicted from land-use information. The results demonstrate that this methodology of integrating GIS and stormwater model with a constrained optimization technique can be applied to large watersheds.

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Introduction

Major metropolitan areas are characterized by continuous increases in imperviousness due to urban development. Increasing imperviousness increases runoff volume, and maximum rates of runoff, with possible negative consequences for natural systems. To avoid environmental degradation, new development standards often prohibit increases in total runoff volume and may limit maximum flow rates. Methods to reduce runoff volume and maximum runoff rate are required, and solutions to the problems may benefit from the use of advanced models. Developing management strategies for large urban watersheds is especially difficult when the flow network is large or complex, such as the Ballona Creek Watershed located in west Los Angeles, and is the subject of the present study. Designers and managers are now using mathematical models to address the problems of such a large and complex watershed.

Various models are available to manage urban runoff, including HEC-1 (U.S. Army Corps of Engineers 1985), TR-20 and TR-55 (Soil Conservation Service 1983, 1986), MOUSE (Danish Hydraulic Institute 1995), HydroWorks (HR Wallingford Ltd. 1997), and storm water management model (SWMM) (Huber and Dickinson 1988). The Environmental Protection Agency's (EPA) SWMM is a dynamic rainfall-runoff model for simulation of quantity and quality problems associated with runoff from urban areas (Huber and Dickinson 1988). The model simulates aspects of urban hydrologic and water quality cycles, including rainfall, snow melt, surface runoff, transport through the drainage network, storage and treatment, and receiving water effects. Both single event and continuous simulation can be performed on catchments having storm drains, or combined sewers and natural drainage.

In this study SWMM was modified and adapted for the upper Ballona Creek Watershed. The drainage system and subcatchments were defined using records from the City and County of Los Angeles, and a ground survey of the undefined areas. Imperviousness was obtained from land-use data and the spatial distribution of precipitation was developed using the geographic information system (GIS) and isohyetal map. Calibration was performed using a constrained optimization procedure, and a total of ten storms were used for calibration and validation. The calibrated model was able to predict the observed outputs with reasonable accuracy.

Background

SWMM, developed for the EPA, has been applied on numerous watersheds in United States cities and other part of the world (Selvalingam et al. 1987; Warwick and Tadepalli 1991; Bhaduri et al. 2001). It has been applied to all types of storm water management from urban drainage (Zaghloul 1998; Campbell and Sullivan 2002) to flood routing (Hsu et al. 2000). An alternative approach to commercial packages with graphical user interfaces is to couple SWMM or a suitable model to a GIS. Martin et al. (2005) presented a state-of-the-art critical review of current trends in interfacing GIS with predictive water resources models.

Physically based deterministic rainfall-runoff models require initial estimates of one or more parameters. Manual calibration is

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labor intensive, especially when the catchment is large and complex. Automatic parameter estimation and calibration methods have been implemented to overcome this difficulty. Maalel and Huber (1984) proposed a calibration procedure for SWMM using multiple, single events, and continuous simulation. Baffaut and Delleur (1989) described an automated parameter estimation and calibration procedure that used expert system technology. Liong et al. (1991) described a knowledge-based system for automating the calibration of the SWMM's runoff block. Methodologies for estimating global optimum sets of calibration parameters have been presented by Ibrahim and Liong (1992, 1993), and Liong and Ibrahim (1994) and Liong et al. (1995). The proposed methods consist of two operations. The first derives functional relationships using the response surface method and the second estimates the optimal set of parameters using a probabilistic approach. Liong et al. (1995) and Balascio et al. (1998) have described genetic algorithms for calibrating SWMM. Zaghloul and Abu Kiefa (2001) used an artificial neural network for sensitivity calibration of the SWMM model.

Box (1965) developed a pattern-search optimization method called the complex method, which has been applied to many problems. The method uses a set of parameter values, called vertexes, which are successively created, evaluated, and eliminated to locate the optimum solution. Advantages of the complex method are that it can be applied to any cost function, does not require the calculation of any derivatives, both explicit constraints (upper and lower bounds of the parameters) and implicit constraints (limits on properties of the resulting solution) can be used, and the number of vertexes can be increased to better manage problems with local optima. The complex method has been used by many researchers for different problems and with stable calibration results. Yuan et al. (1993) applied this method on the high-purity oxygen-activated sludge process and found the algorithm to be very robust, converging to the same optimal values for a wide range of starting points and constrains, and concluding that if the model has only random errors (no systematic errors), the algorithm is capable of estimating the parameters to any acceptable precision. Haque (1996) used the method for structural optimization, and Subramanian et al. (2005) used it for warpage analysis for an optimal housing of compact disks. The complex method was used in this problem because the Ballona Creek Watershed is far too complicated for manual calibration, and anticipated future uses of the calibrated model need to incorporate implicit constraints.

Another technical problem in developing an SWMM model for a large watershed is defining precipitation data. Rainfall data drive the model and produce runoff, which means that an accurate estimation of rainfall data determines the success of the modeling effort. Singh and Chowdhury (1986) reviewed 13 different methods for computing mean, areal rainfall, including the inverse distance-squared method (IDSM). The result of their investigation showed that all 13 methods yielded comparable estimates.

Methodologies

In its standard form, SWMM version 4.3 has ten processes and is able to simulate 500 subcatchments and 500 channels/pipes. For the current study, seven processes (or blocks) were removed; Process 2—Statistics, Process 3—Graph, Process 4—Combine, Process 5—Rain, Process 6—Temperature, Process 9—Extran, Process 10—Storage/Treatment. A new process was added which uses an optimization technique for calibration. The executive

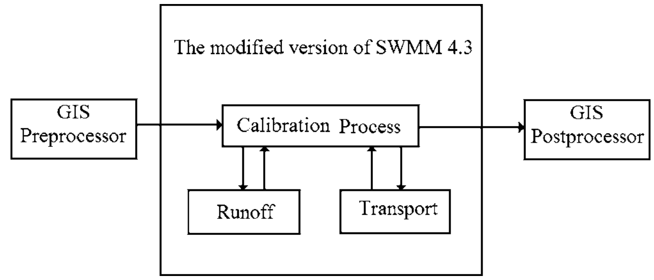

Fig. 1. Modified GIS/SWMM for urban stormwater processes

block (Process 1) was replaced by a new main block to accommodate the addition of the calibration process. The runoff and transport processes were used for routing in lieu of Extran, and were modified to handle the larger watershed, with its greater number of subcatchments and channels/pipes. The runoff process was also modified to incorporate the rainfall weighting factor for each subcatchment, which was based upon an isohyetal map, described later. The modified SWMM code had three processes and the maximum number of subcatchments and channels/pipes was increased to 1,580 and 4,300, respectively. The modified version GIS/SWMM is illustrated in Fig. 1.

The GIS used in this study was Environmental System Research Institute ARC/INFO (ESRI, Redlands, Calif.) and Compaq Visual FORTRAN 6.5 was used to compile the SWMM code.

Catchment Description

Ballona Creek, which has become a concrete lined channel to facilitate flood routing, drains the entire watershed and enters Santa Monica Bay at Marina del Rey. There is a USGS gauging station and a Los Angeles County Department of Public Works (Alhambra, Calif.) monitoring station near the intersection of the Creek and the IS 405 Freeway. The area upstream the gauging station, called the upper Ballona Creek Watershed, was modeled in this study because of the availability of monitoring data. The total contributing area of the catchment above the gauging station is to 217 km^2, and 65% of the total area is residential land use and over 19% is either commercial or public/industrial land use. A total of 1,579 subcatchments are delineated within the watershed. Rainfall in each subcatchment becomes overland surface runoff and flows are assumed to exit each subwatershed through a single outlet (i.e., catch basin). Surface runoff flow entering the inlet is then routed through the connected channel or pipe (open or closed, depending on the location). Finally, all surface flow is summed up at the watershed outlet after routing through 2,648 channels and pipes, and the total length of all channels and pipes is over 283 km. The slope of the channels/pipes averages 2.6% and ranges from 0.005 and 47%. Fig. 2 shows the watershed with subcatchments, channels/pipes, and the flow gauge at the watershed outlet. Land-use data for the watershed were obtained from the Southern California Association of Governments (SCAG) Database, which contains land-use records based on Anderson level II (Anderson et al. 1976) that were reduced to eight types based upon environmentally similar characteristics (Park and Stenstrom 2006).

J. Hydraul. Eng., 2008, 134(4): 466-474

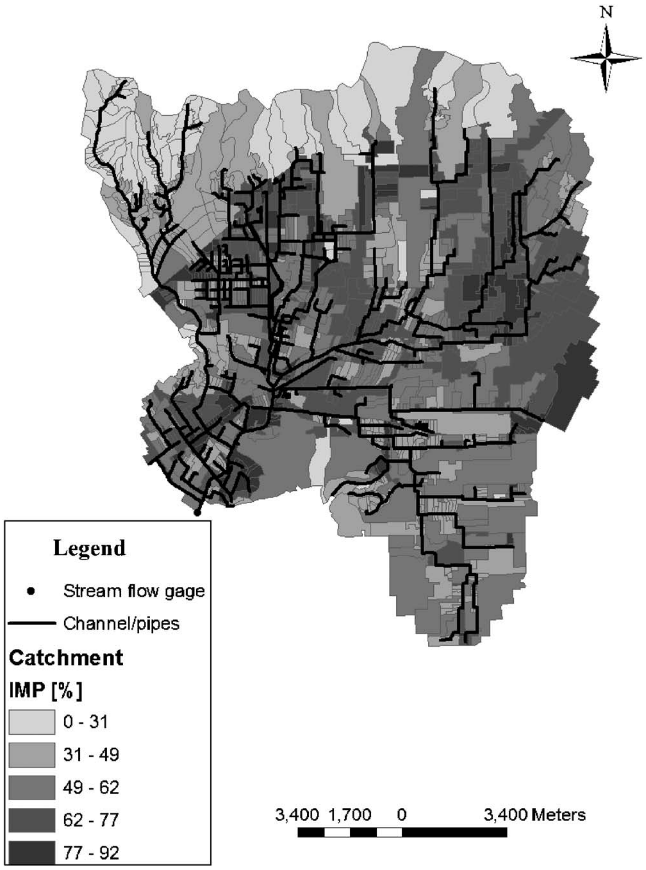

Fig. 2. Catchments, imperviousness, and channels for upper Ballona Creek Watershed (method of calculating imperviousness from Wong et al. 1997, based on landuse data)

Data

The precipitation data were obtained from the 1997 Edition of EarthInfo, Inc. (Boulder, Colo. 80301-2846) NCDC hourly precipitation CDROM to obtain the average rainfall for each storm. Ten rain gauges were available. Precipitation in each subcatchment was calculated from the average rainfall using weighting factors from an isohyetal map based upon 50-year record rainfall events (Stenstrom and Strecker 1993). The GIS was used to create the rainfall weighting factor corresponding to the rainfall in each subcatchment, which was read by the SWMM runoff process. Hourly flow data were obtained from the Los Angeles County Department of Public Works (Alhambra, Calif.). Ten representative storms from the 1994 to 1996 wet seasons were selected and Table 1 shows the dates, rainfall, and duration.

Each subcatchment and all channel/pipe in Ballona Watershed were manually digitized and converted into GIS databases based on the information provided by the drainage maps from the Los Angeles County Department of Public Works and the Bureau of Engineering, City of Los Angeles (LADWP) (Los Angeles). Each subcatchment was delineated based on the location of inlets (catch basins) and the flow direction of each street provided by the drainage maps. Fig. 2 shows the imperviousness which are based on the ground surveys by LADWP. The Horton (1942) equation was used for estimating infiltration in the pervious areas all soil was assumed to be highly permeable (ASCE 1996). The USGS 7.5 min digital elevation model (DEM) spatial data transfer system (SDTS) combined with the GRID module of

Table 1. Description of Ten Storms Used in This Study

Storm number	Precipitation depth (mm)	Duration of the precipitation (h)
1	2.8	4.0
2	8.5	4.0
3	24.4	8.0
4	10.5	14.0
5	3.3	9.0
6	12.2	10.0
7	17.1	11.0
8	2.5	6.0
9	5.5	5.0
10	10.3	8.0

ARCINFO GIS were used to compute the subcatchment and channels/pipes slopes. The slopes were then used to compute the impervious depression storage coefficients based on methods by Kidd (1978) and Viessman et al. (1989). These parameter values were used as the initial estimates or starting values for the optimization, which is described later. More information on the methodology is available (Wong et al. 1997).

Calibration Strategy

The complex method was used for calibration and was incorporated into the modified GIS/SWMM as illustrated in Fig. 1. Calibration begins by generating at least $m+1$ sets of parameters, called vertexes, where m=number of parameters being identified. In this case the vertexes were calculated from the upper and lower constraints using random numbers as follows

$$X_{i,j} = L_i + r_{i,j}(U_i - L_i) \tag{1}$$

where $X_{i,j}$=value of the ith parameter in the jth set of parameters; U_i=upper bound of the ith parameter; L_i=lower bound of the ith parameter; r_{ij}=random real number ranging between 0 and 1; i is ith parameter; and j=jth vertex. It is also possible to manually select one or more of the initial vertexes, and the first vertex was manually entered in this study. The parameters for the first vertex were based on their most probable values. It is also possible to test for local optima by selecting different initial vertexes, different constraint intervals, or a different series of random numbers used in calculating the parameters for the remaining vertexes. The objective function, F, for each vertex is evaluated and the X_k vertex having the greatest function value F is selected (rejected). The centroid of the remaining points (in the case of Cartesian coordinates, the average value of the coordinates of the remaining vertexes), is then computed. The set X_k is projected toward the centroid using a projection factor γ (Box recommended the use of γ = 1.3). This creates a new vertex X_g that replaces the rejected vertex if and only if the error of the new vertex is less than the rejected vertex. Conversely, if the new set has an error greater than or equal to the error of the rejected set, the projection distance, γ, is reduced by 50%, and another vertex is projected. The projection factor is decreased until a new vertex with a lower error than the rejected vertex is obtained. The technique is repeated by selecting the next vertex with the largest error for replacement. The whole process continues until the termination criterion assigned by the user is satisfied. The termination criteria can be the maximum number of iterations, the minimum size of γ, or a relative improvement criterion of F. Constraints are

J. Hydraul. Eng., 2008, 134(4): 466-474

handled by reducing the value of γ. If a vertex is projected outside of the feasible region, defined by the upper and lower bounds on the parameters, the value of γ is reduced until a feasible vertex is obtained. A violation of an implicit constraint is handled in the same way.

The procedure is not guaranteed to obtain a global optimum and can fail if the initial set of vertexes surrounds a nonconvex area, but is robust and rarely failed to find the global optimum, even when repeating an optimization many times using different initial vertexes, and a wide range of explicit constraints. Increasing the number of vertexes relative to the number of parameters generally improves the likelihood of obtaining a global optimum, but requires more iterations. To ensure that a global optimum is obtained, the problem can be solved multiple times with different starting points. The most likely difficulty a user might have in implementing this method for complicated problems with many constraints is the creation of a suitable, initial set of vertexes.

The maximum number of iterations depends upon the number of parameters and the complexity of the problem. The average number of iterations for this problem was 60 and rarely was the required number of iterations greater than 200 iterations. Yuan et al. (1993), when simulating the activated sludge process using 3–7 parameters, found that 2,000 iterations were always sufficient. The large number of required iterations means that the complex method will be useful for problems which have easily evaluated objective functions and implicit or explicit constraints. It is not necessary to calculate derivatives of the model with respect to the parameters, which can sometimes be difficult. For problems with more computationally intensive objective functions, other approaches may be justified (Becker and Yeh 1972; Tzeng et al. 2003).

The objective function used in this study is

$$F = w_1\left(\frac{Q^* - Q}{Q^*}\right)^2 + w_2\left(\frac{P^* - P}{P^*}\right)^2 + w_3\sum_{i=1}^{n}\left(\frac{f^* - f}{f^*}\right)_i^2 \qquad (2)$$

where Q=total flow volume; P=peak flow rate; f=instantaneous flow rate at the outlet hydrograph; the superscript * denotes the ith predicted value, the subscript i denotes the ith observation of the outlet hydrograph; w_1, w_2, and w_3=weights; and n=total number of observed data points in the outlet hydrograph. The division by the predicted value normalizes the objective function and the three terms have equal weights for equal values of w_i. Other objective functions and methods of weighting are possible, such as a function to locate the peak flow as a function of time. For the initial calibrations, weights of 1.0 were used for w_1 and w_2 and zero for w_3.

Four parameters were chosen for calibration: subcatchment imperviousness, width, impervious depression storage coefficient, and channel Manning's roughness coefficient. The parameters were varied uniformly across the watershed and the constraints on the four parameters were selected based on the physical meaning of the parameters (i.e., physically plausible values, see Table 2), and trial runs of the calibration algorithm. Only explicit constraints were needed in this problem, and were generally set to 50 and 150% of most probable parameter values. Reducing the range of constraints will increase the speed of convergence, but may exclude appropriate parameter values, if the initial vertex is poorly estimated.

Table 2. Parameter Values Constraints

Parameter	Range of expected values	Upper and lower constraints (percentage of initial value) Lower (%)	Upper (%)
Imp	0–92 (%)	50	180
Wid	10–2,228 (m)	80	180
Stor	0–127 (mm)	50	190
Roug	0.013–0.027	50	230

Results and Discussion

Calibration

Three types of simulations and parameter identifications were performed. Each was designed to show the robustness of the parameter identification methodology. The first group of simulations, called "Pred/Cal storm by storm," identified the optimal parameters for each storm by running the optimization program for each storm. In the second simulation, called "Pred/Cal average all," the mean values of the parameters identified in the Pred/Cal storm by storm simulations were used in a new SWMM simulation, and the error for each storm was recalculated. In the third simulation, called "Pred/Valid," the mean values of the parameters identified for five of the storms were used to simulate the other five storms. The five storms used for calibration were chosen by ranking the storms in descending order by rain depth and selecting every other storm. The remaining storms were used for validation. The hyetograph, observed hydrograph, and predicted hydrograph, using Pred/Cal storm by storm, for Storms 2 and 4 are shown in Fig. 3. The hydrographs for Storms 5–8 are shown in Fig. 4. Table 3 shows the total flow volume and the peak flow rate for the observed storms and for the different types of simulations. The relative errors are shown in Table 4.

Fig. 5 shows the optimized imperviousness of the subcatchment. The value is an average of the optimal values obtained from the Pred/Cal storm by storm simulations. Based on the observation of model outputs illustrated in Figs. 3 and 4, and Tables 3 and 4, the three types of simulations were able to capture the shape, total volume, peak flow, and peak time of the observed outlet hydrograph (Obs) with reasonable accuracy.

Table 4 shows the parameters optimized for each storm (Pred/Cal storm by storm), and the errors are generally small. Only two storms have errors in either volume or peak flow greater than 16% and one of these (Storm 8) had the least rainfall of all storms. The errors using the mean optimized parameter values (Pred/Cal average all) are larger than the errors using the optimized parameters for each storm. This is expected because in the storm-by-storm method, the specific parameters were calibrated from only one set of precipitation and observed flow data, and the optimization can adjust the parameters for the unique aspects of each storm. Storms 3 and 4 have the largest error, and both are large storms, with Storm 3 being the largest. This suggests that the calibration for the average storms is not as appropriate for the larger storms. The result for the simulations using five storms for calibration produced errors similar to the errors observed using the mean values from all ten storms. Storms 2 and 5 produced the smallest relative error in the total flow volume, peak flow, and peak time in the calibration storm-by-storm and there appears to be no pattern or reason to account for the low error.

The results of this study show that the complex method can be

J. Hydraul. Eng., 2008, 134(4): 466-474

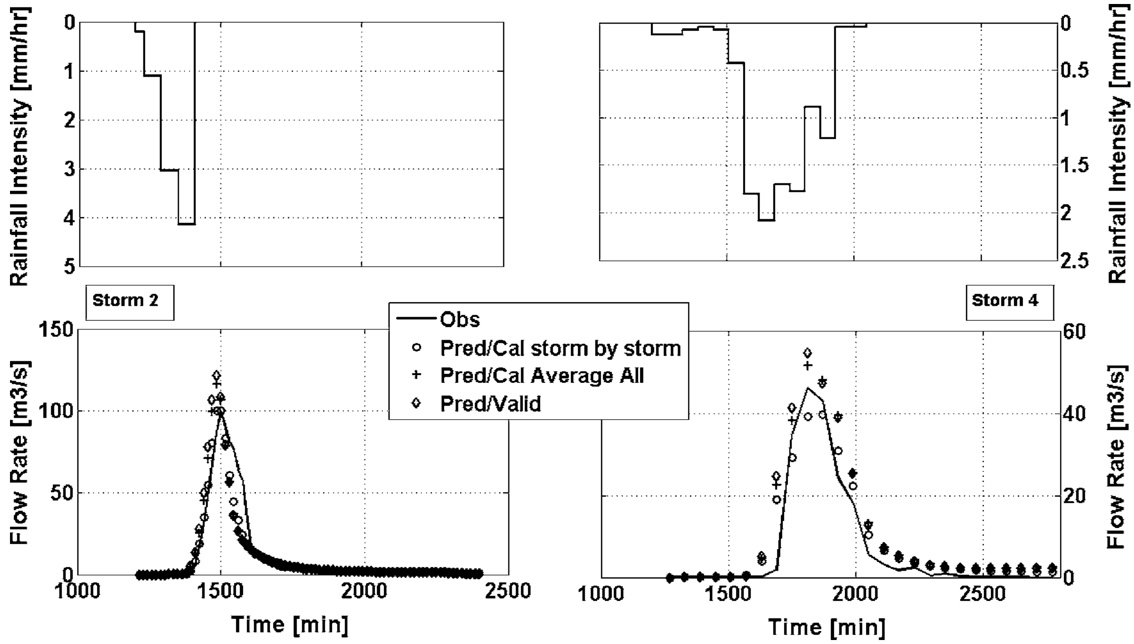

Fig. 3. Hydrographs and rainfall for Storms 2 and 4

a valuable optimization tool for calibration of rainfall-runoff models. The time savings can be significant because it is an automatic search method that reduces the time required by the modeler. The required time for an optimization for a single storm on a fast computer is also low (less than 5 min on a 2.8 GHz Intel Pentium dual-core processor).

Sensitivity Analysis

A sensitivity analysis was performed to assess the importance of the various parameters by showing how the solutions change with the parameters. The analysis was performed around the optimal calibrated parameters in order to show impact for probable parameter values. Fig. 6 shows the sensitivity of runoff volume, peak flow, and peak time to changes in the calibrated parameters for imperviousness (Imp), width (Wid), impervious depression storage (Stor1), channel Manning's roughness coefficient (Roug), pervious depression storage (Stor2), subcatchment impervious Manning's coefficient (Imp-n), and subcatchment pervious Manning's coefficient (Per-n). The sensitivity analysis was performed by changing each parameter while keeping all others constant and observing the changes in model output. The percent changes in runoff volume are most sensitive to changes in Imp and Stor1.

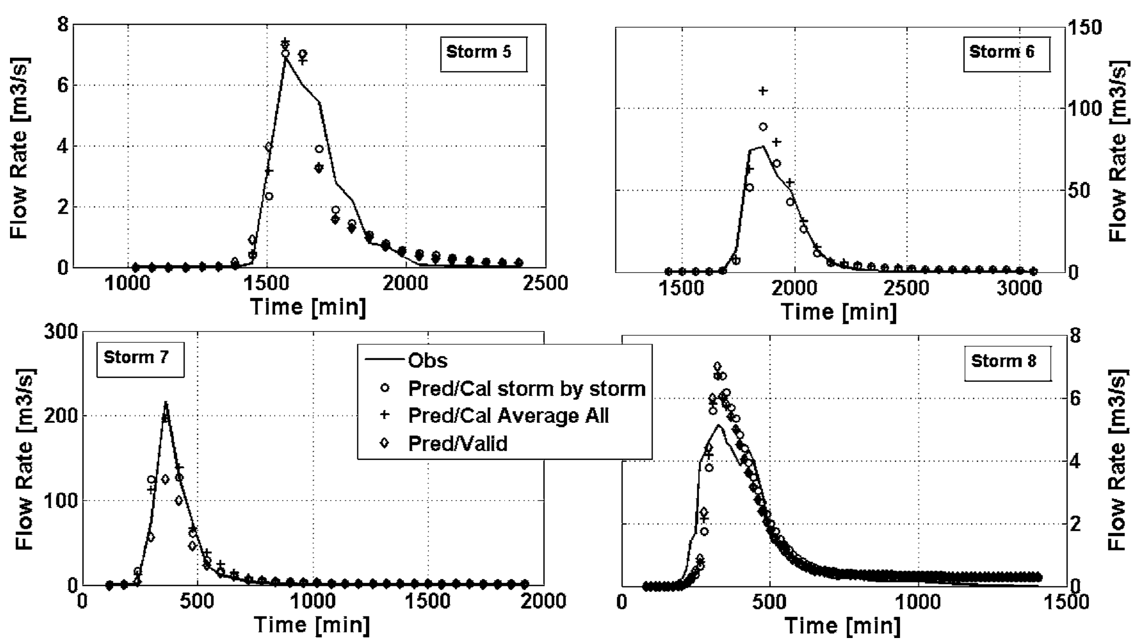

Fig. 4. Hydrographs for Storms 5–8

J. Hydraul. Eng., 2008, 134(4): 466-474

Table 3. Model Outputs Using the Three Different Types of Simulations

Storm number	Observed V (m^3)	Observed P (m^3/s)	Pred/Cal[a] storm by storm V^* (m^3)	Pred/Cal[a] storm by storm P^* (m^3/s)	Pred/Cal average all V^* (m^3)	Pred/Cal average all P^* (m^3/s)	Pred/Val[b] V^* (m^3)	Pred/Val[b] P^* (m^3/s)
1	1.15E+05	13	1.23E+05	13	9.46E+04	10	Calibration	
2	7.67E+05	100	7.59E+05	100	8.04E+05	116	8.32E+05	121
3	1.66E+06	192	1.87E+06	180	3.33E+06	290	Calibration	
4	6.58E+05	46	8.12E+05	40	1.01E+06	51	1.04E+06	55
5	1.04E+05	7	1.02E+05	7	1.01E+05	7	1.05E+05	7
6	1.18E+06	77	1.19E+06	89	1.45E+06	111	Calibration	
7	1.98E+06	217	2.27E+06	197	2.35E+06	196	2.35E+06	196
8	1.05E+05	5	8.88E+04	7	8.40E+04	7	8.43E+04	7
9	2.32E+05	17	2.21E+05	18	2.69E+05	22	Calibration	
10	1.47E+06	163	1.65E+06	145	1.07E+06	100	Calibration	

Note: V=total flow volume; P=peak flow rate; *=superscript, denotes the model predictions.

[a]Prediction/calibration.

[b]Prediction/validation.

Changes in all other parameters were small by comparison and sometimes insignificant. Modifying the width (Wid) parameter must be done with care, since the SWMM assumes that the depth of the overland surface flow is very small compared to the width of the subcatchment. If the width of the subcatchment is decreased and the assumption is no longer valid, errors in flow rate calculation will occur.

Fig. 6 shows a similar trend with percent changes in runoff peak flow versus changes in model parameters. Stor2 and Per-n also play a minor role in terms of its effect on percent changes in runoff peak flow. Imp and Stor1 cause greater changes in runoff peak flow. Fig. 6 also shows the percent changes in time of peak flow versus changes in model parameters. The roughness coefficient causes the greatest changes in time of peak flow. Changes in all other parameters caused insignificant changes in the timing of the peak flow.

Multiple Objective Functions

In order to evaluate the solution's sensitivity to each factor in the objective function, weights were applied to the errors in total flow volume and peak flow [see Eq. (2)]. These weights, w_1, w_2, and w_3, can be chosen depending on the purpose of the calibration. If the total flow volume is most critical, then it can be weighted higher. If the peak flow is more important, it can be weighted higher. In this way, a calibration that favors the users' purposes can be obtained. For example, a user interested in avoiding floods, or washout of sensitive environmental areas might want to more accurately quantify the peak flow rather than the total runoff volume. Other priorities are also possible.

Table 5 shows the residuals and relative errors in the simulations using weights in the total runoff volume (w_1) and in the peak flow (w_2). The results show how increasing the weight in the peak flow and keeping constant weight for the total flow volume changes the residuals and relative errors. When the peak flow is weighted higher, the errors in peak flow decrease. Fig. 7 shows the differences between the simulations for the same storm and using the same range of weighting factors used in Table 5.

The weighting factor for the discharge flow (w_3) in the objective function [Eq. (2)] was not useful in these simulations, because the error in discharge flow rate is related to the timing of the flow. Identical hydrographs for the measured and calculated results can produce large errors if there is a small time lag between the hydrographs. The sensitivity analysis showed that none of the selected parameters strongly influences the timing of the peak flow or the lag between calculated and measured hydrographs. Only Manning's n affected peak timing and the effect was

Table 4. Relative Errors between Observed Data and Predictions Using Three Different Types of Simulations

Storm number	Pred/Cal storm by storm E_V^* (%)	Pred/Cal storm by storm E_P^* (%)	Pred/Cal average all E_V^* (%)	Pred/Cal average all E_P^* (%)	Pred/Val E_V^* (%)	Pred/Val E_P^* (%)
1	7	3	18	25	Calibration	
2	1	0	5	17	8	6
3	12	6	100	51	Calibration	
4	23	14	54	12	59	13
5	2	2	3	8	11	4
6	1	16	23	44	Calibration	
7	15	10	19	10	20	15
8	16	30	20	32	28	10
9	5	8	16	27	Calibration	
10	7	11	27	38	Calibration	

Note: E_V^*=relative error in the total volume; E_P^*=relative error in the peak flow.

J. Hydraul. Eng., 2008, 134(4): 466-474

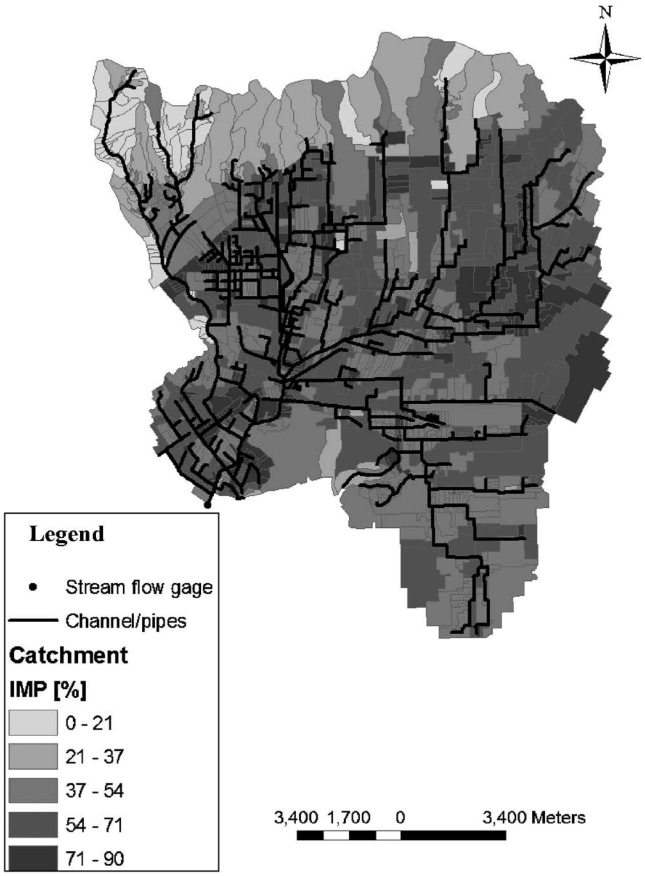

Fig. 5. Imperviousness based upon averaged optimal SWMM parameters for ten storms

not large. Therefore, a lag difference between measured and calculated hydrographs produces a large error in the flow part of the objective function, which is independent of the optimization parameters and overwhelms improvements made in the other two error functions. The use of the flow error in the objective function will only be useful when optimization parameters are chosen that can affect the timing of the calculated hydrograph.

Table 5. Residuals and Relative Errors in Simulation Results Using Weighting Factors for Storm No. 4

	Residuals		Relative error (%)	
Weight	Flow volume (m^3)	Peak flow (m^3)	Flow volume	Peak flow
$w_1=1$ $w_2=0$	16,990	12	−3	−25
$w_1=1$ $w_2=1$	−155,744	6	23	−14
$w_1=1$ $w_2=2$	−175,565	6	26	−13
$w_1=1$ $w_2=5$	−249,190	2	37	−4

Note: The negative values in the residuals refer to overestimations and positive values refer to underestimation.

The calibration of the model and choice of weighting factors can be selected to maximize the utility of the results for each user. More information and a general discussion of multiobjective functions are available (Yan and Haan 1991).

Unfortunately, only one runoff gauge station existed in the entire watershed. If additional gauges had been available, the objective function [Eq. (2)] could have been expanded to include the addition runoff data. An additional weighting factor could be used, and the values set based on the relative importance of the additional flow rates, or on the confidence of the measurements. An advantage of the complex method is that the additional objective function can be included without changing the optimization procedure or code. Also, it is relatively easy to increase the number of parameters in order to include additional parameters that influence the new terms of the objective function, and the speed of convergence will still be reasonable.

Conclusions

The US EPA SWMM model and a raster-based GIS were applied to a large urban catchment in west Los Angeles. The GIS was used to manage and process input and output data from the model. The model included more than 2,500 nodes. The complex method of Box was used to calibrate the model for ten storms using several strategies and weighting functions. The following specific conclusions were made:

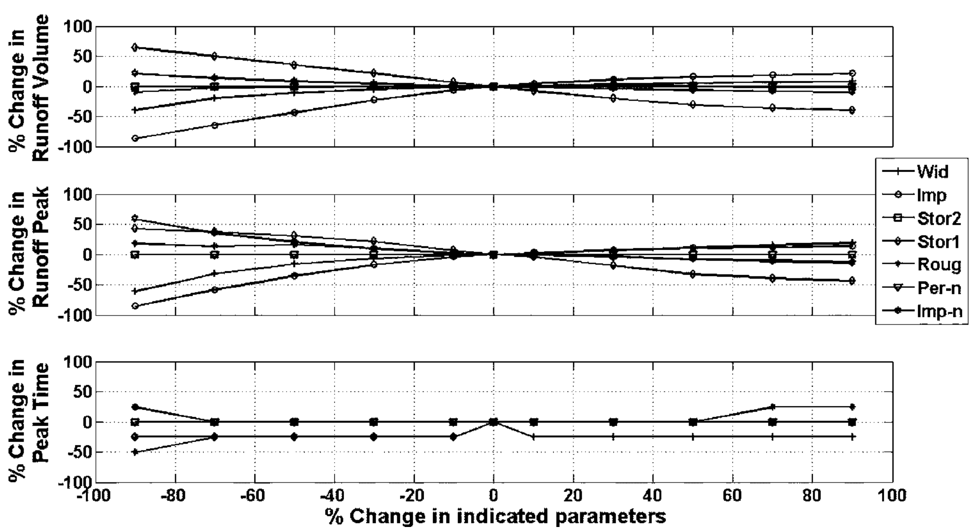

Fig. 6. Sensitivity analysis of Ballona Creek Watershed

J. Hydraul. Eng., 2008, 134(4): 466-474

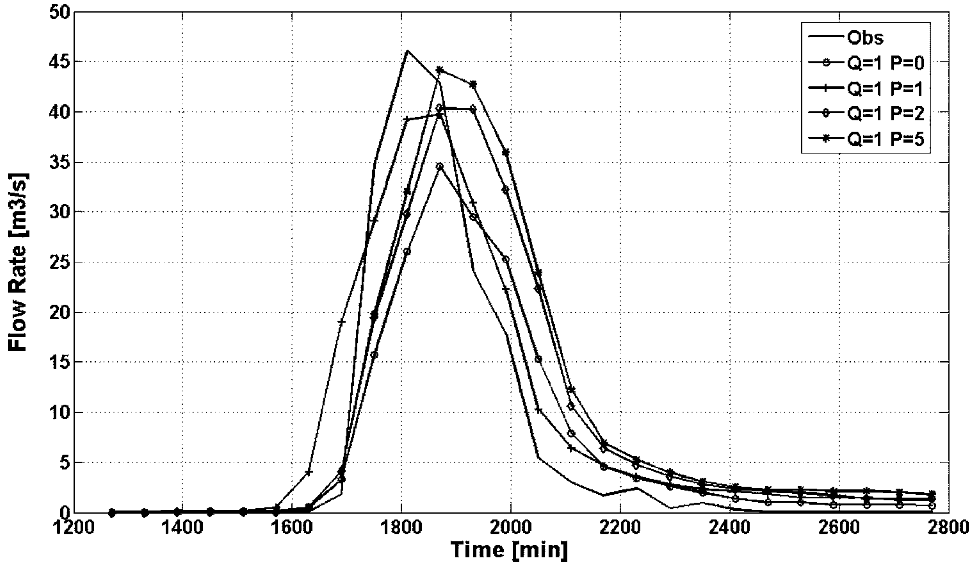

Fig. 7. Differences between predictions using weighting factors

1. The complex method was successful in all cases and global optima were obtained and verified by repeated application of the procedure using different starting points or constraints. Local optima are possible but were rarely obtained and could be identified by repeating the procedure with different starting points;
2. Four SWMM parameters were used for calibration: imperviousness, depression storage, width, and channel Manning coefficient. A sensitivity analysis was performed that showed that imperviousness and depression storage are the most sensitive parameters affecting total runoff and peak flow. The timing of the peak flow was affected only by the Manning coefficient and the effect was small;
3. A multivalued objective function with weights was used which allowed calibrations to be performed to improve the calibration for peak flow at the expense of total runoff or vice versa;
4. The imperviousness estimated from land-use data and ground surveys was not sufficiently high to generate the observed runoff volume, which suggests that land-use data systematically underestimated imperviousness; and
5. The coupling of the GIS, SWMM, and the optimization procedure create a useful modeling tool that can be used for extremely large watersheds. The time required for data management and calibration is dramatically reduced by the GIS and optimization procedure.

References

Anderson, J. R., Hardy, E. T., Roach, J. T., and Witmer, R. E. (1976). "A land use and land cover classification system for use with remote sensor data." *U.S. Geol. Surv. Prof. Pap.*, USGS, Reston, Va.

ASCE. (1996). "Handbook of hydrology." *Manual and Report on Engineering Practice No. 28*, ASCE, New York.

Baffaut, C., and Delleur, J. W. (1989). "Expert system for calibrating SWMM." *J. Water Resour. Plann. Manage.*, 115(3), 278–298.

Balascio, C. C., Palmeri, D. J., and Gao, H. (1998). "Use of a genetic algorithm and multiobjective programming for calibration of a hydrologic model." *Transactions of the American Agricultural Engineers*, 41(3), 615–619.

Becker, L., and Yeh, W. W. G. (1972). "Identification of parameters in unsteady open channel flows." *Water Resour. Res.*, 8(4), 956–965.

Bhaduri, B., Minner, M., Tatalovich, S., and Harbor, J. (2001). "Long-term hydrologic impact of urbanization: A tale of two models." *J. Water Resour. Plann. Manage.*, 127(1), 13–19.

Box, M. J. (1965). "A new method of constrained optimization and comparison with other methods." *Computer*, 8(1), 42–52.

Campbell, C. W., and Sullivan, S. M. (2002). "Simulating time-varying cave flow and water levels using the storm water management model." *Eng. Geol.*, 65(2), 133–139.

Danish Hydraulic Institute. (1995). *Mouse: User's manual and tutorial*, Horsholm, Denmark.

Haque, M. I. (1996). "Optimal frame design with discrete members using the complex method." *Comput. Struct.*, 59(5), 847–858.

Horton, R. E. (1942) "A simplified method of determining the constants in the infiltration-capacity equation." *Trans., Am. Geophys. Union*, 23(2), 575–577.

HR Wallingford Ltd. (1997). *HydroWorks on-line manual*, Wallingford, U.K.

Hsu, M. H., Chen, S. H., and Chang, T. J. (2000). "Inundation simulation for urban drainage basin with storm sewer system." *J. Hydrol.*, 234(1), 21–37.

Huber, W. C., and Dickinson, R. E. (1988). *Storm water management model user's manual*, *version 4*, *EPA/600/3-88/001a (NTIS PB88-236641/AS)*, Environmental Protection Agency, Athens, Ga.

Ibrahim, Y., and Liong, S. Y. (1992). "Calibration strategy for urban catchment parameters." *J. Hydraul. Eng.*, 118(11), 1550–1570.

Ibrahim, Y., and Liong, S. Y. (1993). "A method of estimating optimal catchment model parameters." *Water Resour. Res.*, 29(9), 3049–3058.

Kidd, C. H. R. (1978). "Rainfall-runoff processes over urban surfaces." *Proc., Int. Workshop Institute of Hydrology*, Wallingford, U.K.

Liong, S. Y., Chan, W. T., and Jaya, S. R. (1995). "Peak-flow forecasting with genetic algorithm and SWMM." *J. Hydraul. Eng.*, 121(8), 613–617.

Liong, S. Y., Chan, W. T., and Lum, L. H. (1991). "Knowledge-based system for SWMM runoff component calibration." *J. Water Resour. Plann. Manage.*, 117(5), 507–524.

Liong, S. Y., and Ibrahim, Y. (1994). "Estimation of peak flow and runoff volume with response surface method." *J. Water Resour. Plann. Manage.*, 120(2), 161–175.

Maalel, K., and Huber, W. C. (1984). "SWMM calibration using continuous and multiple event simulation." *Proc., 3rd Int. Conf. on Urban

J. Hydraul. Eng., 2008, 134(4): 466-474

Storm Drainage, Vol. 4, Chalmers Univ., Gothenburg, Sweden, 1564–1577.

Martin, P. H., LeBoeuf, E. J., Dobbins, J. P., Daniel, E. B., and Abkwitz, M. D. (2005) "Interfacing GIS with water resource models: a state-of-the-art review." *J. Am. Water Resour. Assoc.*, 41(6), 1471–1487.

Park, M. H., and Stenstrom, M. K. (2006). "Spatial estimates of stormwater-pollutant loading using bayesian networks and geographic information systems." *Water Environ. Res.*, 78(4), 421–429.

Selvalingam, S., Liong, S. Y., and Manoharan, P. C. (1987). "Use of RORB and SWMM models to an urban catchment in Singapore." *Adv. Water Resour.*, 10(2), 79–86.

Singh, V. P., and Chowdhury, P. K. (1986). "Comparing some methods of estimating mean areal rainfall." *Water Resour. Bull.*, 22(2), 275–282.

Soil Conservation Service. (1983). "TR-20: Computer programs for projects formulations-hydrology." *Tech. Release 20*, U.S. Department of Agriculture, Washington, D.C.

Soil Conservation Service. (1986). "TR-55: Urban hydrology for small watersheds." *Tech. Release 55*, U.S. Department of Agriculture, Washington, D.C.

Stenstrom, M. K., and Strecker, E. (1993). "Assessment of storm drain sources of contaminants to Santa Monica Bay: Annual pollutants loadings to Santa Monica Bay from stormwater runoff." *Rep. No. UCLA-ENG-93-62*, Vol. I, 1–248, Univ. of California, Los Angeles.

Subramanian, N. R., Tingyu, L., and Seng, Y. A. (2005). "Optimizing warpage analysis for an optimal housing." *Mechatronics*, 15, 111–127.

Tzeng, C. J., Iranpour, R., and Stenstrom, M. K. (2003). "Modeling and control of oxygen transfer in the HPO activated sludge process." *J. Environ. Eng.*, 129(5), 402–411.

U.S. Army Corp. of Engineers. (1985). "HEC-1: Flood hydrograph package." Hydrologic Engineering Center, Davis, Calif.

Viessman, W., Lewis, G. L., and Knapp, J. W. (1989). *Introduction to hydrology*, Harper and Row, New York.

Warwick, J. J., and Tadepalli, P. (1991). "Efficacy of SWMM application." *J. Water Resour. Plann. Manage.*, 117(3), 352–366.

Wong, K. M., Strecker, E. W., and Stenstrom, M. K. (1997). "GIS to estimate storm-water pollutant mass loading." *J. Environ. Eng.*, 123(8) 737–745.

Yan, J., and Haan, C. T. (1991). "Multiobjective parameter estimation for hydrologic model-multiobjective programming." *Trans. ASAE*, 34(3), 848–856.

Yuan, W., Okrent, D., and Stenstrom, M. K. (1993). "Model calibration for the high-purity oxygen activated sludge process—Algorithm development and evaluation." *Water Sci. Technol.*, 28(11–12), 163–171.

Zaghloul, N. A. (1998). "Flow simulation in circular pipes with variable roughness using SWMM-EXTRAN Model." *J. Hydraul. Eng.*, 124(1), 73–76.

Zaghloul, N. A., and Abu Kiefa, M. A. (2001). "Neural network solution of inverse parameters used in the sensitivity-calibration analyses of the SWMM model simulations." *Adv. Eng. Software*, 32(7), 587–595.

J. Hydraul. Eng., 2008, 134(4): 466-474