Optimal Location of Infiltration-Based Best Management Practices for Storm Water Management

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Abstract: A distributed hydrologic model of an urban watershed in the northeast United States was developed and combined with a genetic algorithm to determine the optimal location of infiltration-based best management practices (BMPs) for storm water management. The distributed, event-based hydrologic model integrates the curve number method with a distributed hydrologic network model of the catchment using a system of 4,533 hydrologic response units (HRUs). The infiltration-based BMP was conceptualized as an element that alters the infiltration/runoff partitioning of the HRUs in which it was applied. The results indicate that the optimal location and number of BMPs is a complex function of watershed network connectivity, flow travel time, land use, distance to channel, and contributing area, requiring an optimization approach of the type introduced here. A Pareto frontier describing the trade-off between the number of BMPs, representing project cost, and watershed flooding was developed.

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Introduction

Management of storm water is a common concern in urbanizing watersheds where development-related increases in impervious areas result in increases of flood flows. Floods occur in urbanized watersheds with greater magnitude and frequency than they did previously, presenting greater challenges for mitigating flood damage and water quality impacts. The concept of best management practices (BMPs) encompasses a wide variety of appropriate technologies and activities intended to minimize the effect of watershed development on flow regimes without altering riparian morphology. Examples of BMPs that achieve storm flow peak reduction include infiltration trenches, pervious pavement, grass swales, buffer strips, detention, retention, and bioretention basins.

Traditional engineering approaches to storm water management have tended to focus on structural BMPs such as detention and retention basins, and over the past several decades, flood detention/retention facilities have become the most common engineering approach to controlling the impacts of storm water runoff (Yeh and Labadie 1997). There is now extensive literature on the design, operation, and optimization of individual detention ponds (Behera et al. 1999) as well as the optimization of systems of detention ponds (Yeh and Labadie 1997; Behera et al. 1999; Harrell and Ranjithan 2003). The idea of determining the optimal number and location of detention basins in a watershed for storm water management (Mays and Bedient 1982; Zhen et al. 2004) is analogous to this study; however, this study focuses on infiltration-based BMPs rather than storage-based BMPs.

Detention-based storm water basins are often highly effective in controlling peak flow rates, but are relatively expensive to construct and maintain, and can even negatively impact a watershed when there is no systematic basin-wide approach to their implementation (Ferguson 1991). In contrast to storage-based BMPs such as detention ponds, there is increasing interest in infiltration approaches for storm water management (Holman-Dodds et al. 2003; Potter 2004) ranging from infiltration basins, rain gardens, and pervious pavements, to the use of swales and curb cuts to direct runoff from impervious surfaces to nearby pervious surfaces and depressions. While infiltration approaches reduce runoff volumes, they are not a substitute for storage-based approaches (Brander et al. 2004) and the two methods could be used effectively in combination with each other. The strategic integration of a wide variety of distributed storage and infiltration storm water controls is one example of a group of management techniques now referred to collectively as low impact development (LID). LID offers a new approach to urban storm water management by proposing the integration of storm water controls throughout an urban landscape in a more distributed manner than conventional structural BMP systems, such as detention pond networks. One intent of LID is to create a hydrologically functional landscape that mimics a basin's natural hydrologic regime. (Prince Georges County 1999).

The goal of this study is to introduce a methodology to determine the optimal number and location of infiltration-based BMPs on a watershed to reduce peak flood flows at the watershed outlet. Since the interest here is in management of storm water quantity, we ignore the expanding literature relating to the optimal management of nonpoint source water quality. While there is a rela-

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tively large amount of literature addressing the optimal network of detention pond storm water control structures on a watershed, to our knowledge there are only a few previous attempts to determine the optimal number and location of infiltration-based BMPs at the watershed scale (Elliott 1998; Srivastava et al. 2002, 2003; Veith et al. 2003). To allocate infiltration-based BMPs on a watershed, a fully distributed hydrologic model is needed to account for the complex hydrologic, topographic, and network flow processes involved, and to reflect the greater location flexibility offered by LID BMPs. Elliott (1998) employed a quasidistributed optimization/simulation approach by separating a catchment into 43 subcatchments with 27 potential pond locations and 8 potential infiltration sites. By comparison, this study modeled a watershed as a network of 4,533 hydrologic response units (HRU), each of which had potential to contain an infiltration-based BMP. HRUs were modeled as square cells with side lengths of 120 m, which is large compared to more detailed analyses such as Lee and Heaney (2003), who measured directly connected impervious area at the roof-top scale for land parcel scale studies in areas of less than 10 ha. Lee and Heaney's approach could be used to refine the results from the watershed scale analysis introduced here, which targets areas for BMP application on 1.4-ha plots.

Although there is extensive literature on the application of BMPs for storm water management, the application of systems analysis for determining an optimal approach to watershed scale LID, such as distributed, infiltration-based storm water controls, or both infiltration and storage-based storm water controls, is in its infancy. The conceptual approach presented here ignores storage-based BMPs, and instead, we envision the storm water management problem as locating BMPs that maximize the reduction in peak storm flows at the basin outlet for a fixed storm water management budget.

A fully distributed event-based hydrologic/optimization model is introduced, which is based on the well-known curve number (CN) approach (SCS 1986). This method is attractive because it uses readily available soil and land use information and is easily adapted to determine the influence of infiltration-based BMPs. The model was applied to the Aberjona River watershed shown in Fig. 1, a small highly urban catchment, located northwest of Boston, Massachusetts. The model was programmed in a spreadsheet and optimized using a genetic algorithm (GA) to determine areas within the watershed where the application of infiltration-based BMPs would be most effective in decreasing flood flows at the catchment outlet. Repeated optimization for differing numbers of BMPs resulted in the equivalent of a Pareto frontier illustrating the trade-off between the storm water control program budget and flood flow reduction.

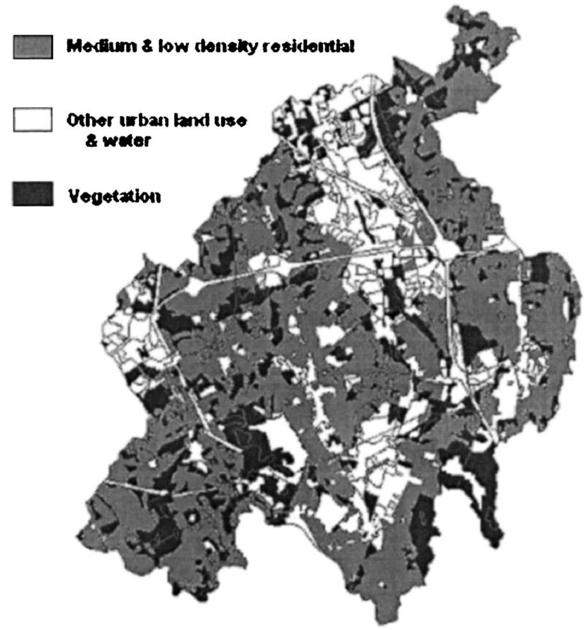

Fig. 1. Primary land uses within the Aberjona River watershed, Massachusetts

Methods

Distributed Hydrologic Model Development

Over the past decade, there has been a tremendous surge in the development of distributed hydrologic rainfall-runoff models due in large part to recent advances in computational tools and digital databases (Beven 2001; Abbott and Refsgaard 2002). There are now dozens of distributed rainfall-runoff models, all differing primarily in their approaches to watershed discretization and in the mathematical expressions used to model various hydrologic processes. The Soil Conservation Service (SCS) runoff curve number method is an attractive option for studying the impacts of land use modifications and BMPs on resulting streamflow, because unlike many other rainfall-runoff models, it can be easily modified to represent watershed land use changes and the effects of BMP implementation. A brief summary of the distributed hydrologic model is provided below, and greater detail is provided by Perez-Pedini (2004). It is important to mention at the outset that the primary contribution of this paper involves the formulation of the overall watershed system planning problem of choosing upslope watershed BMP locations that will yield the most downstream flood protection. Therefore, our distributed hydrologic model was developed to enable the solution of this particular systems optimization problem, and as a result, lacks many features of more general distributed hydrologic models.

The event-based distributed rainfall-runoff model discussed here was programmed using Microsoft Excel and Visual Basic for Applications, and consists of a system of 4,533 square HRUs that have a side length of 120 m. Watershed topography dictated system connectivity by routing runoff in the direction of the most negative slope using the D8 algorithm developed by O'Callaghan and Mark (1984). Each HRU drains to a single adjacent downslope HRU, and may receive inflow from a maximum of seven adjacent upslope HRUs, although most HRUs in the model receive runoff from only one or two adjacent upslope HRUs.

The flow of water through two adjacent HRUs is illustrated in Fig. 2. Rainfall is partitioned between infiltration, which enters the soil storage compartment, and excess runoff is routed to the adjacent downslope HRU. Water infiltrates into groundwater storage and then may move into groundwater storage of the adjacent downslope HRU. Flow continues downslope at a rate of one HRU per time step until it enters an HRU connected to a stream network cell. The stream network cell collects water from its contributing HRU and routes the water to the watershed outlet with a time lag to represent stream travel time. Spatial characterization of the HRUs (position, CN, and elevation) was developed using ArcGIS© and imported into Excel, and the model's cell-to-cell connectivity was built from flow direction information using the D8 algorithm developed by O'Callaghan and Mark (1984). Perez-Pedini (2004) reviews the advantages and disadvantages associ-

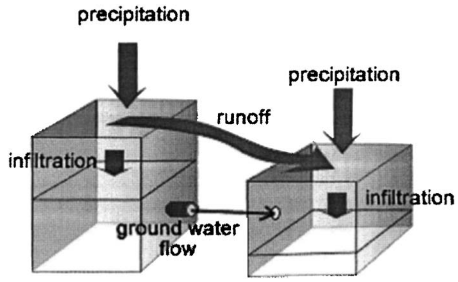

Fig. 2. Conceptualization of the distributed hydrologic model for two hydrologic response units

ated with a number of flow-direction algorithms. The D8 algorithm was employed in this study due to its simplicity; however, Perez-Pedini (2004) and others recommend the algorithm introduced by Tarboton (1997) as having several advantages over the D8 and other algorithms.

A BMP is introduced as a binary integer decision variable that decreases the CN of an HRU by five units if implemented. While a 5-unit reduction in CN is a highly stylized representation of an infiltration-based BMP, it seams reasonable and provides a simple representation for use in the screening-level optimization discussed here. One could easily imagine different representations of BMPs, such as 2-unit or 10-unit reductions in CN, or perhaps a percentage reduction based on the original CN; however, the exact form of BMP representation is not critical to our discussion. The idea is that after using our methodology to locate those HRUs that have the greatest impact on watershed peak flow reduction, a hydrologist would then need to determine what particular BMPs to apply to each HRU, which would lead to a 2-, 5-, 10-, or other unit reduction in CN for those HRUs. Thus, our methodology really only deals with the overall watershed system planning problem and not the particular BMP design problem(s) associated with each HRU.

Sample et al. (2001) introduced an optimization algorithm to determine the optimal suite of BMPs to achieve a certain reduction in CN for a particular HRU, but our approach is more general, because it deals with the entire watershed system. The advantage of limiting our analysis to a single BMP type is that the number of BMPs implemented then serves as a surrogate for total project cost, under the assumption that implementation costs are the same regardless of HRU land use and surface conditions. Fewer BMPs implemented would always result in lower overall project costs, which would not necessarily hold if different BMP types were considered.

The hydrologic model follows closely from the procedure of Chow et al. (1988) to account for the time distribution of the CN method's initial abstraction, infiltration, and runoff generation within a storm event. We modified the approach to allow for water contributions from upslope HRUs and excess groundwater. We begin by defining cumulative water $WC_{i,j,t}$ at $HRU_{i,j}$ at time t that is available to runoff or infiltrate

$$WC_{i,j,t} = \sum_{n=1}^{t} \left(P_n + GE_{i,j,n-1} + \sum_{i,j} R_{i,j,n-1}^{\text{upslope}} \right) - AC_{i,j,t} \tag{1}$$

where the subscripts i and j=cartesian coordinates associated with each HRU; P_n=incremental precipitation (cm) on the HRU in time step $n \leq t$; $GE_{i,j,n-1}$=HRU's excess groundwater (cm) in the previous time step; and $\Sigma_{i,j} R_{i,j,t-1}^{\text{upslope}}$=sum of previous time step incremental runoff from all adjacent upslope HRUs. The bracketed quantity in Eq. (1) represents incremental water inflow, and the time sum represents cumulative available water. The term $AC_{i,j,t}$ represents cumulative initial abstraction (cm) and takes values according to

$$AC_{i,j,t} = \begin{cases} WC_{i,j,t} & \text{for } WC_{i,j,t} \leq Ab_{i,j} \\ Ab_{i,j} & \text{otherwise} \end{cases} \tag{2}$$

where $Ab_{i,j}$=initial abstraction associated with the CN method, which is defined as a fraction λ_2 of soil storage capacity $S_{\max,i,j}$

$$Ab_{i,j} = \lambda_2 \cdot S_{\max,i,j} \tag{3}$$

Similarly, soil storage capacity (cm) is defined by the CN method as

$$S_{\max,i,j} = \lambda_1 \left(\frac{2540}{CN_{i,j}} - 25.4 \right) \tag{4}$$

where $S_{\max,i,j}$ is in centimeters. The scaling term λ_1 is used here to account for differing antecedent moisture conditions analogous to the CN method's selection of type I, II, or III curve numbers. The term λ_1 takes a value between zero and one, with smaller values representing wetter conditions.

Combining Eqs. (1), (2), and (4), cumulative runoff is defined, as it is in the CN method, by

$$RC_{i,j,t} = \frac{(WC_{i,j,t} - AC_{i,j,t})^2}{WC_{i,j,t} - AC_{i,j,t} + S_{\max,i,j}} \tag{5}$$

Cumulative infiltration (cm) is then quantified as the difference between available water and losses due to runoff and initial abstraction

$$IC_{i,j,t} = WC_{i,j,t} - RC_{i,j,t} - AC_{i,j,t} \tag{6}$$

Having accounted for initial abstraction using the cumulative water balance we now convert to incremental quantification. Incremental runoff and infiltration are defined as

$$R_{i,j,t} = RC_{i,j,t} - RC_{i,j,t-1} \tag{7}$$

and

$$I_{i,j,t} = IC_{i,j,t} - IC_{i,j,t-1} \tag{8}$$

The groundwater storage (cm) in each HRU is

$$S_{i,j,t} = S_{i,j,t-1} + I_{i,j,t} + \sum_{i,j} BF_{i,j,t-1}^{\text{upslope}} \tag{9}$$

where $\Sigma_{i,j} BF_{i,j,t-1}^{\text{upslope}}$=sum of previous time step baseflow (cm) from adjacent upslope HRUs, and incremental infiltration $I_{i,j,t}$ is computed in Eq. (8). Baseflow $BF_{i,j,t}$(cm) from an upslope HRU enters an adjacent downslope HRU at a rate proportional to groundwater storage by the constant r

$$BF_{i,j,t} = \begin{cases} r(S_{i,j,t} - hS_{\max,i,j}) & \text{if } S_{i,j,t} > hS_{\max,i,j} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where h=fraction of groundwater storage capacity that is held as inactive groundwater and does not contribute to groundwater outflow. In Eq. (10) groundwater outflow occurs only after inactive storage capacity $hS_{\max,i,j}$(cm) is satisfied. The initial storage condition $S_{i,j,0}$ is assumed to be a fraction S_0 of the storage capacity of each HRU

$$S_{i,j,0} = S_0 \cdot S_{\max,i,j} \tag{11}$$

If $S_{i,j,t}$ is greater than $S_{\max\, i,j}$, there is excess groundwater, and $GE_{i,j,t}$ in Eq. (1) is taken as the difference of $S_{i,j,t}$ and $S_{\max\, i,j}$.

Excess groundwater becomes available to runoff.

Overland runoff continues downslope in the model until flow reaches an HRU that is connected to a stream network cell. Incremental outflow volume $VQ_{k,t}$(m^3) from a stream connected HRU$_{i,j}$ to its corresponding stream network cell, k, is the sum of baseflow and surface runoff

$$VQ_{k,t} = \frac{A}{100}(R_{i,j,t} + BF_{i,j,t}) \tag{12}$$

with A representing HRU area (m^2).

Stream channel routing of water is considered to occur more quickly than overland routing of water from HRUs on the watershed. The stream network is modeled as a sequence of one-dimensional cells of length 120 m. A stream cell k accepts runoff and baseflow from its connected HRU, and routes water directly to the watershed outlet with a time lag

$$\phi(k) = \frac{d_k}{2} \tag{13}$$

rounded down to an integer, where d_k=number of stream cells between cell k and the watershed outlet. Thus, the in-stream velocity is taken as twice overland flow velocity. Finally, observed flow rate (m^3/s) at the watershed outlet in time step t is

$$Q_t = \frac{1}{T}\sum_k VQ_{k,t-\phi(k)} \tag{14}$$

with T representing time step length in s. While the overland flow and stream routing methods are highly stylized, they serve as computationally simple representations of these processes, which enable the efficient solution of the overall watershed system optimization problem. Another disadvantage of our model formulation is that the time step exerts a great deal of control on model behavior; hence, time step is a model calibration parameter that is adjusted to match time to peak and to capture basin time of concentration.

Hydrologic Model Calibration and Validation

The model was applied to the Aberjona River watershed, a 6,400 ha (24.7 sq m) urban catchment located northwest of Boston, Massachusetts. Estimates of CN values were obtained using digital soil and land use maps in combination with tables available in SCS (1986). The hydrologic model was calibrated for a storm event using 15-min precipitation data from two rain gauges within the watershed; one located at the USGS gauging station on the Aberjona River (USGS 01102500 at Winchester, Mass.) and the NOAA-NCDC rain gauge in Reading, Mass. The modeled hydrograph was compared to observed hydrograph data, recorded by USGS gauge at the catchment outlet.

The calibration process involved finding values of the time step, initial conditions of λ_1 and S_0; and basin parameters λ_2, r, and h that could reproduce the observed hydrograph for the calibration event. Fig. 3(a) illustrates the model calibration for a storm that occurred on October 15, 2003, during which 2.69 cm (1.06 in.) of rain fell in 5 h. A time step of 3 min was selected, and the basin parameters of initial abstraction fraction λ_2=0.4, groundwater outflow rate constant r=0.0088, and inactive groundwater storage fraction h=0.2 were found using manual calibration.

Fig. 3(b) illustrates the model validation for another storm that occurred on October 26, 2002, during which 3.66 cm (1.44 in.) of rain fell in 13 h. The time step and three basin parameters selected during model calibration were retained, and only the initial conditions, λ_1 and S_0, were adjusted. For the calibration λ_1=0.64, and for the validation, λ_1=0.95. Initial groundwater storage fraction S_0=0.044 for the calibration period and S_0=0.01 for the validation period. The model appears to perform fairly well in reproducing time to peak, peak flow rate, and short-term recession, indicating that our highly stylized representation of hydrologic partitioning and flow routing provide an adequate representation of basin hydrology for the purpose of the system-wide optimization of BMP location. The model is unable to reproduce observed longer term recession, indicating potential problems with groundwater storage and outflow characteristics in the formulation. However, since peak flow rate reduction was the chosen objective of the BMP implementation scheme discussed here, the model appears to be useful for this application.

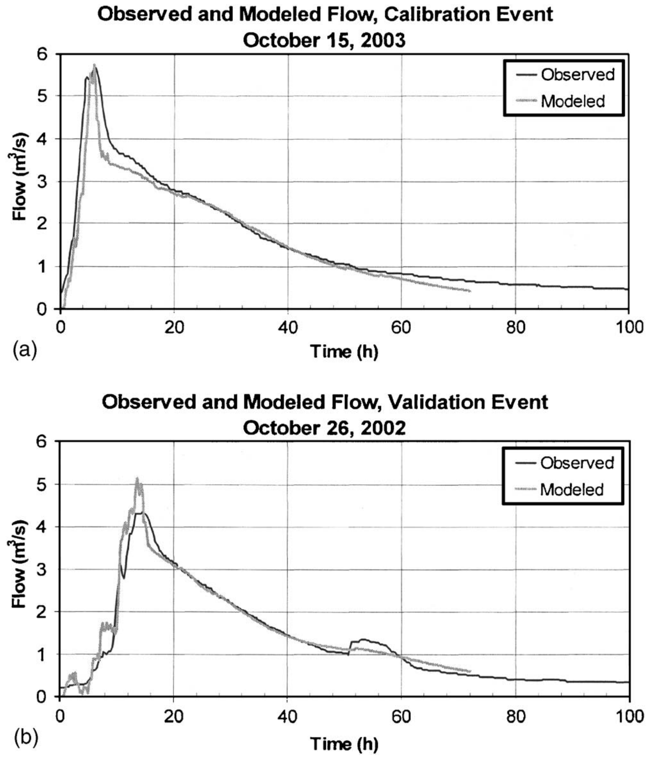

Fig. 3. Comparison between observed and modeled flow for the (a) calibration event on October 15, 2003; and the (b) validation event on October 16, 2002

Optimization Approach

The overall goal of our optimization model is to locate those HRUs which, if BMPs were applied, would lead to a maximum reduction in peak streamflow at the watershed outlet. Because only one type of BMP is considered, and equal cost of implementation is assumed, the total number of BMPs is proportional to project cost. By repeatedly solving the optimization over a range of project costs (numbers of BMPs applied), we obtain the trade-off or Pareto frontier between peak flow reduction and project cost.

This optimization problem is quite large, requiring a very efficient and robust algorithm to provide any assurance that the resulting solutions converge to the global optimal solution. Srivastava et al. (2002) reviews the reasoning behind the need for employing a GA for this type of BMP selection problem. GAs are optimization tools based on the principles of natural selection that consider the decision variables as genes, which taken together, form a vector representing a single solution alternative, or chromosome. A GA begins by generating a random set of alternate solutions (population of chromosomes) and evaluates their fitness (values of objective function), then selects the best alternatives to carry forward in the next round of optimization. A group of the best alternatives are combined (crossed over) and randomly shuffled (mutated) according to preselected rules to form new alternative solutions, and as this process proceeds, the better-performing decision variable values are carried forward, analogous to biological evolution, and are intended to eventually converge on the global optimal solution.

Here, the role of the GA was to generate different groups of BMP locations with the objective of maximizing the peak flow reduction for the October 15, 2003, storm event, which had a peak discharge of $5.66\,\mathrm{m}^3/\mathrm{s}$ (200 cfs) [see Fig. 3(a)]. We employed a commercially available GA called Evolver©, which is easily attached to a spreadsheet. Initially we considered possible implementation of a BMP in every HRU; however, this approach proved infeasible. If m denotes the number of BMPs considered, the decision space yields $C_m^{4,533}$ possible solutions or $C_{100}^{4,533}=1.6\cdot 10^{207}$ for $m=100$ BMPs. To reduce the required computational effort, the decision space was restricted so that BMPs were allowed to be applied to only those HRUs meeting either of the criteria: (a) HRU has $\mathrm{CN}\geqslant 89$, or (b) HRU has $\mathrm{CN}\geqslant 70$ and distance to the river is no greater than two downslope HRUs. Criterion (a) targets the most impervious HRUs of the watershed, and criterion (b) targets the HRUs that cause significant runoff with little chance for flow attenuation by infiltration or groundwater storage in downslope areas prior to discharge to the stream. Of the watershed's 4,533 HRUs, 1,904 of them met both criteria, resulting in a reduced decision space of size $C_{100}^{1,904}=7.0\cdot 10^{168}$ for $m=100$. As a check on the adequacy of this reduced decision space, we tested the peak flow reduction for two scenarios. In the first scenario, the application of BMPs was simulated in each of the 1,904 HRUs (the reduced decision space) resulting in a peak flow reduction of 30.8%. In the second scenario, implementation of BMPs in all 4,533 HRUs was simulated with a resulting peak flow reduction of 31.2%. Therefore, application of BMPs in all of the 2,629 HRUs that are excluded by criteria (a) and (b) would result in an additional peak flow reduction of only 0.4% beyond the application of BMPs in the 1,904 HRUs meeting criteria (a) and (b). The excluded 2,629 HRUs appear to have a marginal impact on peak flow reduction, and are reasonably eliminated from consideration during optimization.

The GA was used to find the maximum peak flow reduction, given a budget constraint that the total number of watershed BMPs must be equal to a preselected value. Normally, using a gradient search optimization algorithm, one might constrain the sum of BMPs to be less than or equal to a preselected value; however, we found that this technique was not as effective as an equality constraint when employing a GA. Perez-Pedini (2004) provides a detailed discussion of constraint selection and a comparison of the efficiency of various GA optimization techniques.

Results and Discussion

Fig. 4 illustrates the optimal trade-off between project budget and peak flow reduction. Since both project budget and peak flow reduction can be considered separate objectives, Fig. 4 is essentially a Pareto frontier describing the trade-off between these two objectives, which is obtained by using the constraint method of multiobjective programming. The Pareto frontier in Fig. 4 bounds the feasible region of all pairs of expenditure (number of BMPs) and peak flow reduction located below the curve, and infeasible pairs of expenditure and peak flow reduction located above the curve. The slope of the frontier in Fig. 4 represents the marginal value of BMPs, and the decreasing slope of the frontier indicates diminishing marginal returns associated with an increasing number of BMPs. For example, the effectiveness of the 200th BMP is less than the effectiveness of the 25th BMP applied. Since the slope of the curve in Fig. 4 quantifies the marginal peak flow reduction for BMP application, this type of analysis could be used to determine the optimal number of BMPs that should be applied in the watershed if the costs of flood damage and BMP implementation were made explicit. The reduction in damage costs associated with the reduction in peak flow achieved by applying one more BMP could be compared over a range similar to that shown in Fig. 4, and the number of BMPs for which marginal cost is equal to marginal benefit in damage reduction would represent the optimal allocation of management funds.

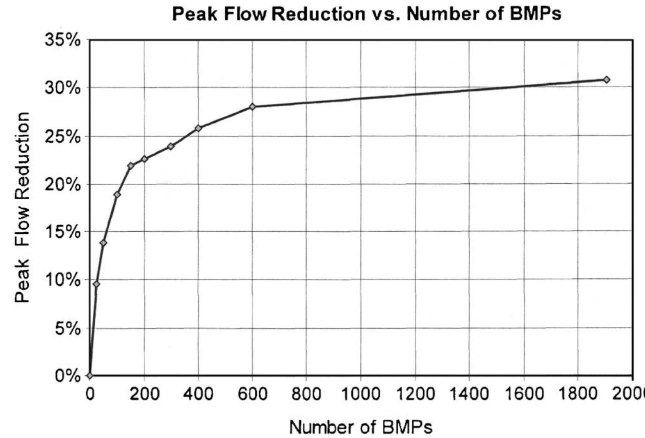

Fig. 4. Trade-off between peak flow reduction and number of best management practices

Fig. 5 illustrates the location of HRUs selected for BMP implementation for budgets increasing from 25 to 400 BMPs. The number of trials used by the GA in finding the four solutions shown in Fig. 5 ranged from 15,200 to 72,900. Four critical regions in the watershed were found where BMPs had the greatest impact. One can observe from Fig. 5 a progression in which BMPs were selected early in those four critical regions and continued to fill when the BMP budget was increased.

Fig. 6 provides another view of the watershed showing that the four regions in which BMPs had the greatest impact coincide with industrial and commercial developments in the vicinity of major highway intersections. Together, Figs. 1, 5, and 6 suggest the optimal solutions were not simply the location of BMPs in HRUs with the greatest impervious areas (urban land use in Fig. 1).

The solutions generated by the GA for larger BMP budgets were not strictly inclusive of smaller budget solutions, meaning, for instance, the optimal 25-BMP solution is not strictly a subset of the optimal 50-BMP solution, although it is nearly so. Though the GA did not find strictly inclusive solutions, they were nearly inclusive, and we tested the effect of rearranging the GA generated solutions by manually relocating the few BMPs' locations from the smaller budget solutions that did not coincide with those found in the larger BMP budget solutions. The question of whether larger sets include the same locations for BMPs as for the

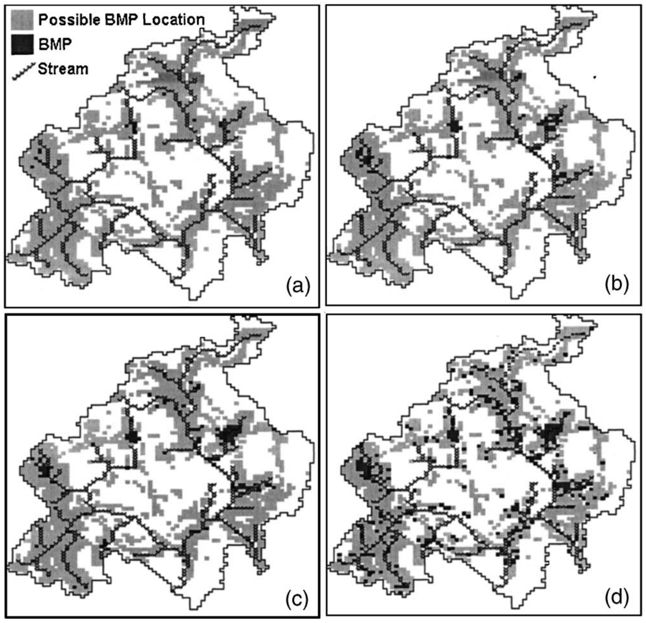

Fig. 5. Quasioptimal locations of (a) 25 best management practices; (b) 100 best management practices; (c) 150 best management practices; and (d) 400 best management practices

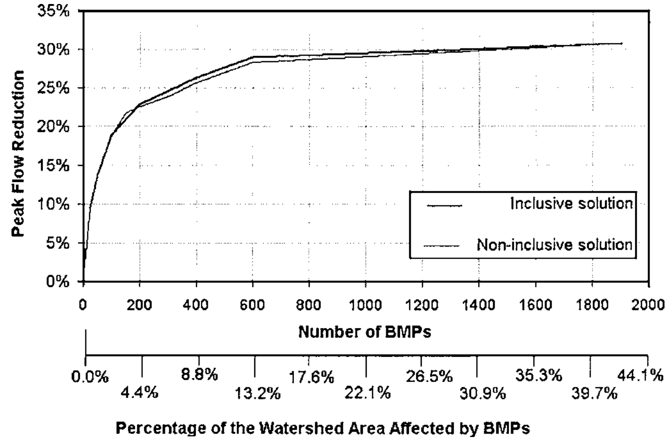

Fig. 7. Comparison of peak flow reduction for the noninclusive set of solutions found using the genetic algorithm, and the inclusive set created by manually relocating the few noncoincident best management practices (best management practice coverage is alternatively represented as percentage of watershed area affected by best management practice implementation)

smaller sets is important, since it has implications as to whether a stepwise or incremental approach to watershed management is sensible or not, as is discussed below.

Fig. 7 compares the peak flow reduction corresponding to the noninclusive solution sets generated automatically by the GA and the solutions, which were manually adjusted to create inclusive sets. Also shown is the percentage of the watershed area on which BMPs are applied for various BMP budgets. The manually rearranged inclusive solutions generally provide larger reductions in watershed peak flow than the noninclusive solutions generated automatically by the GA, confirming that the GA did not find the global optimal solution, though for practical purposes, the two sets of solutions are nearly identical. Although manual rearrangement of automatically generated solutions yielded slightly larger flood peak reductions than the GA, the GA provides indispensable assistance in locating a wide range of near-optimal solutions.

The question of whether successive BMP solutions are inclusive of one another is an important one from the standpoint of watershed management planning. If a larger BMP budget solution includes all of the smaller budget solutions, than a phased approach to BMP implementation is still optimal, since in one year a municipality could find the most effective areas for management action without considering the effects of the larger BMP implementation program. Noninclusive solutions would indicate that master planning is necessary, since one could not arrive at the best 50-BMP solution by first implementing the best 25-BMP solution and then by placing an additional 25 BMPs. In that case the optimal strategy would be to initially consider the location of the final number of BMPs, and then implement the program according to the final master plan. In this study we found that solutions could be considered inclusive, thus master planning for BMP implementation would not be necessary in this particular case.

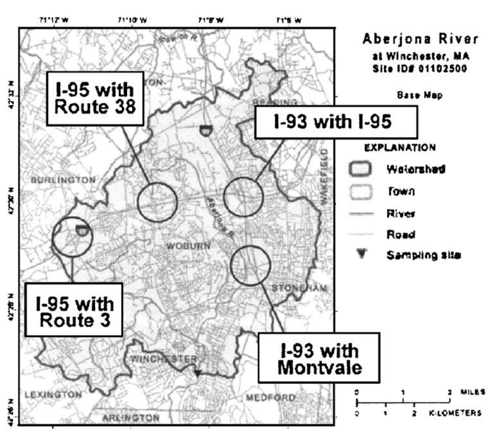

Fig. 6. Map of the Aberjona River watershed with four regions of highest concentration of best management practices chosen by the genetic algorithm (base map source: http://nh.water.usgs.gov/CurrentProjects/nawqa/images/base_ab.gif)

Factors Influencing the Optimal Location of Best Management Practices

We investigated whether it would be possible to determine the optimal location of BMPs without resorting to a distributed hydrologic model and GA optimization. For example, if the optimal location of BMPs always coincided with impervious areas, it would be much simpler to map impervious areas, rather than using the more complex modeling algorithm described here. Multivariate statistical methods were employed to investigate the relationship between watershed peak flow reduction generated by a BMP application to a particular HRU and a variety of HRU characteristics including CN value, upstream contributing area, average CN of the upstream contributing area, time of travel from HRU to watershed outlet, and average CN of downslope connected area, which we define as the area between an HRU and location where its outflow enters the stream channel. The relationship among these factors is quite complex, with none dominating. We conclude that a distributed watershed model is needed to describe the complex temporal and spatial relationships among HRU characteristics and watershed peak flow reduction.

Comparing Figs. 5 and 6, we note the GA suggested the highest concentration of BMPs in areas corresponding to the intersection of a major east–west highway and a generally north–south stream drainage system, making the hydraulic distance to the watershed outlet very similar for these areas. The spatial configuration of the basin results in similar travel times for these contributing areas, which likely combine runoff contributions to produce the watershed hydrograph peak. The GA seldom chose BMPs for areas corresponding with a major north–south trending highway, since the runoff from these cells have arrival times that are not coincident with the hydrograph peak. The topology of HRUs with similar characteristics exhibits enormous influence on the magnitude and timing of the peak flow, thus it is not surprising that multivariate regression fails to adequately explain the resonance of cell contributions at the basin outflow point because the regression approach could not reproduce the spatial connectivity of the HRUs. Our inability to determine a multivariate statistical relationship between the peak flow reduction and HRU characteristics suggests that a distributed physical representation of the basin is needed for the BMP planning analysis.

Conclusions

A distributed rainfall-runoff model was combined with a GA to determine the optimal location of BMPs for reducing the peak storm water discharge at a watershed outlet. A stylized BMP was introduced as a 5-unit reduction in the SCS curve number in a cell where a BMP was applied. For the urban case study presented our results indicate a 20% reduction in the watershed peak flow can be achieved by application of BMPs to fewer than 200 HRUs. Here each HRU represents a 120×120 m plot of watershed land. A Pareto frontier or trade-off curve was developed, which illustrates the marginal benefits of reduced flood damage as a function of the number of additional BMPs that are applied. We observed diminishing returns in terms of watershed peak flow reduction associated with increasing the number of BMPs added to the watershed. Such an analysis could be used to inform policy decisions regarding future storm water management investments.

The factors that influence the ability of BMPs to reduce downstream flood flows include various characteristics associated with the HRU in which the BMP is applied, such as HRU runoff curve number, upstream contributing area, and distance to the stream channel. Multivariate statistical analyses revealed that the relation between the reduction in peak streamflow at the watershed outlet and those HRU characteristics is extremely complex. Analyses suggested that an optimization and distributed hydrologic modeling approach of the type introduced here is necessary to preserve the spatial connectivity among watershed contributing areas and in turn is necessary to determine the optimal location of BMPs.

Interestingly, when only a few BMPs are located, their optimal locations are subsets of the optimal locations of a much larger set of optimal BMPs. This result suggests that an incremental approach to storm water management is possible for the basin considered here. An incremental approach would first implement management practices in the most effective watershed areas as budgets allow, and then target future action in those areas determined to be less critical. This is very similar to the guidelines provided by Haith (2003) for the application of a systems approach to watershed quality management. Haith (2003) suggested that a realistic approach may be to identify the most critical problem areas, and to target resources toward their management, rather than to seek an optimal long-term plan. Our results indicate this philosophy could be applied to storm water management issues, and the approach conceptualized here could provide an effective tool for determining the most critical areas and for ranking their relative importance to target the allocation of limited storm water management funds.

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