Simulation-Optimization Approach to Design Low Impact Development for Managing Peak Flow Alterations in Urbanizing Watersheds

Chandana Damodaram[1] and Emily M. Zechman, M.ASCE[2]

Abstract: The process of urbanization transforms natural landscape into impervious land cover, affecting the ecosystem health of receiving water bodies and downstream communities by changing the timing and volumes of the natural flow regime. Best management practices (BMP) and low impact development (LID) are a set of mitigating measures that can be considered for watershed management to mitigate the hydrologic consequences of urbanization. This research develops a methodology to select sites for placing LID technologies, namely rainwater harvesting and permeable pavements, to reduce hydrologic impacts, measured as alterations to the peak flow while meeting a prespecified budget. A simulation-optimization methodology couples a genetic algorithm with a hydrologic model, a hydraulic model, and curve number-based models of LID technologies. The trade-off between costs and peak flow alteration is explored by optimizing LID placement under varying budget constraints. Strategies that combine a detention pond and LID are explored and optimized for a spectrum of design storms, including 2-, 10-, and 100-year events. Trade-offs among management strategies that are designed to control storms of different sizes are analyzed. The simulation-optimization framework and methodology is applied for a small watershed on the Texas A&M University campus. **DOI: 10.1061/(ASCE)WR.1943-5452.0000251.** © *2013 American Society of Civil Engineers.*

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Introduction

As watersheds become increasingly urbanized, the in-stream flow regimes of receiving surface water bodies are altered through large storm water volumes that reach the watershed outlet quickly. High runoff volumes associated with flooding events and increased velocities of small, frequent storms may erode stream banks and create an altered long-term comprehensive flow regime. Storm water management has conventionally focused on flood control through the use of detention ponds, which are designed to store and slowly release large volumes of runoff. Detention ponds, however, are not designed to mitigate alterations to the long-term flow regime. Detention ponds reduce peak flows, but significantly change the timing and shape of storm hydrographs because they release high flows for a long duration as the stored runoff passes to the downstream reach. Smaller storms may pass through ponds without attenuation, and because these storms occur more frequently, they can cause a significant amount of streambank erosion (Roesner et al. 2001). Low impact development (LID) is an alternative approach for storm water management that may more effectively sustain the natural flow regime (USEPA 2000; Coffman 2000; Chang 2010). Low impact development includes technologies and practices that are designed to actively prevent runoff at its source, such as rooftops, parking lots, and sidewalks. Low impact development aims to replicate the natural hydrologic landscape by mimicking the characteristics of predevelopment catchment-level processes, including small-scale storage, high rates of infiltration, and longer flow paths and runoff time.

Developing watershed management plans is a process of selecting best management practices (BMP), LID, and ponds to mitigate the impacts of urbanization. Budget constraints and limitations of the topology increase the complexity of identifying feasible and cost-effective watershed management plans. Simulation-optimization methodologies have been developed and applied to design detention ponds (Yeh and Labadie 1997; Harrell and Ranjithan 2003; Zhen et al. 2004) and allocate infiltration-based LID technologies (Perez-Pedini et al. 2005; Zhang 2009) based on the reduction of the peak flow at the watershed outlet. The performance of ponds and LID designs depends on the size of the design storm. Ponds reduce peak flows for infrequent intense storms more effectively than LID strategies, whereas LID technologies reduce peak flows for frequent, less intense storms (Hood et al. 2007; Dietz and Clausen 2008; Holman-Dodds et al. 2003; Brander et al. 2004; Damodaram et al. 2010).

Simulation-optimization frameworks applied in previous studies explored LID and pond design separately and developed plans for a single design storm. Damodaram et al. (2010) demonstrated that a combination of LID and ponds was able to most closely match the predevelopment hydrograph in both timing and magnitude of flows compared to LID or ponds alone. The research presented here develops a simulation-optimization framework that integrates a genetic algorithm with hydrologic and hydraulic models to design

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combined LID and pond designs for minimizing the alteration of peak flows for urbanized areas. This study explores watershed development plans for storm water control of a wide range of storms to better match a comprehensive predevelopment flow regime, including both frequent, less intense storm events (2-year) and intense storm events (10- and 100-year). This methodology is applied for an illustrative case study for a watershed on the Texas A&M University campus to study the trade-off between the costs of storm water management strategies and their efficiency in reducing hydrological impacts.

Simulation-Optimization Methodology

Storm water management may specify mitigation measures such as LID and BMP, land use allocation, and infrastructure designs to achieve a specified reduction in the hydrologic impacts of development. This study simulates and optimizes the placement of two LID strategies, including permeable pavements and rainwater harvesting. Permeable pavements are simulated as porous concrete that can be used in place of conventional asphalt or concrete for covering roads, parking lots, and sidewalks. Permeable pavements increase on-site storage by storing water within a highly permeable matrix as it slowly infiltrates into the underlying soil (Schluter and Jefferies 2002; Bean et al. 2007; Scholz and Grabowiecki 2007; Collins et al. 2008). Porous concrete systems consist of an aggregate overlaid on a well-draining soil. A simple system without an underdrain is simulated in this study. A rainwater harvesting system is also simulated in the integrated framework as a system to collect storm water from a rooftop and store it in a storage tank for irrigation purposes after the rain event (Gould and Nissen-Petersen 1999). The following optimization model [Eqs. (1)–(3)] is used to identify watershed management plans that would maximize the reduction of peak flow for a limited budget by implementing rainwater harvesting systems and permeable pavement systems.

$$\text{Maximize } Q_o = PF_{\text{EXIST}} - PF_{\text{DEV}} \tag{1}$$

$$\text{subject to } C_{PP} \times \left[\sum_{i=1}^{NP} P_i \times AP_i\right] + C_{\text{RHS}} \times \left[\sum_{i=1}^{NR} R_i \times AR_i\right] \leq C_{\text{Budget}} \tag{2}$$

$$PF_{\text{DEV}} = f(AP_1, AP_2, \ldots, AP_{NP}, AR_1, AR_2, \ldots, AR_{NR}) \tag{3}$$

where Q_o = change in peak flow associated with a design storm event; PF_{EXISTING} = peak flow for existing conditions for a design storm event; PF_{DEV} = peak flow for a solution, which is calculated using a hydrologic/hydraulic modeling system; $P_i = 0/1$ decision to retrofit parking lot i with permeable pavement; $R_j = 0/1$ decision to retrofit the rooftop j with rainwater harvesting; NP = total number of parking lots in the watershed; NR = total number of rooftops in the watershed; AP_i = area of parking lot i; AR_j = area of rooftop j; C_{PP} = cost per unit area of permeable pavement; and C_{RHS} = cost per unit area of rainwater harvesting system.

Eq. (1) represents the reduction of peak flow produced by a solution or LID design strategy based on existing or predevelopment conditions. Eq. (2) represents the constraint on the total implementation cost of the watershed management strategies, which is calculated based on the percentage of area that should be retrofitted with LID technologies. Eq. (3) demonstrates that calculation of the peak flow for any solution depends on the values of the decision variables, which are the area and placement of permeable pavements and rainwater harvesting, and is completed using a hydrologic and hydraulic simulation system. Decision variables include whether or not to convert each parking lot and rooftop to permeable pavement or a rainwater harvesting system, respectively.

The peak flow (PF_{DEV}) for a management strategy or solution is calculated using hydrologic and hydraulic models to simulate the rainfall-runoff process and routing of runoff through a receiving water body or open channel. Whereas the hydrologic and hydraulic simulation of watershed runoff and detention pond functions has been demonstrated through many existing software systems, the simulation of the hydrologic performance of LID technologies has been developed through only a limited set of studies. Perez-Pedini et al. (2005) modeled the watershed as individual hydrologic response units and simulated LID placement as a reduction of five points in the curve number value. Zhang (2009) represented a parking lot or rooftop that is retrofitted using LID as a storage unit, with storage capacity provided by green roofs, bioretention, or permeable pavements. The model simulated generation of runoff, which is routed to the storm drainage network when the rainfall rate exceeds the LID infiltration rate. For rainfall rates that do not exceed the LID infiltration rate, the runoff is routed to either storage in natural soil or to the drainage system only after LID storage is completely utilized. Damodaram et al. (2010) developed the S-storage and Ia-storage curve number approaches to simulate permeable pavement and rainwater harvesting systems, respectively, based on a procedure suggested by HydroCAD Software Solutions (2006). These approaches are based on the curve number approach, which simulates runoff using the following equations (USDA 1986):

$$S = \frac{25{,}400}{CN} - 254 \tag{4}$$

$$Ia = 0.2S \tag{5}$$

$$R = \frac{(P - Ia)^2}{P + S - Ia} \tag{6}$$

where CN = curve number, which represents the rainfall-runoff characteristics of a watershed; Ia = initial abstraction; S = maximum potential retention; R = depth of runoff; and P = precipitation. All units are in mm.

The S-storage curve number method calculates runoff for permeable pavement. The maximum potential retention is set equal to the effective storage (s_e), which is the depth of rain stored by the permeable pavement, as determined by the depth (d) and porosity (n) of the pavement:

$$S = s_e = d \times n \tag{7}$$

The value of CN is calculated as a function of S, using Eq. (4); Ia is calculated using Eq. (5); and Eq. (6) is used to calculate runoff for a precipitation event. The units are in mm. Damodaram et al. (2010) validated the S-storage curve number approach using a set of data for three different sites and historic rainfall events up to 100 mm in depth. For the three sets of data, using the S-storage curve number approach predicted runoff volumes accurately.

The Ia-storage curve number approach calculates runoff for rainwater harvesting systems. The initial abstraction, Ia, is set equal to the effective depth (s_e) of the rainwater harvesting system by using Eq. (8) in place of Eq. (5)

$$Ia = s_e = \frac{V}{A} \tag{8}$$

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where V = volume of storage provided by the rainwater harvesting system; and A = area of the rooftop. The units are in mm. Once the rainwater harvesting system is full, or the depth of precipitation is equal to Ia, the runoff is calculated as runoff from an impermeable surface using a CN value of 98. The maximum potential, S, is calculated using Eq. (4) as 2.1 mm, and Eq. (6) is used to calculate the runoff for a precipitation event.

When the hydrologic modeling system that is used to simulate the watershed hydrology is based on the curve number approach, the modeling techniques represented by Eqs. (4)–(8) can be readily integrated within the model. Rooftops and paved areas are discretized as subbasins that are represented using a CN value, which is reduced using either the Ia-storage or S-storage approach when permeable pavements or rainwater harvesting systems are implemented. Runoff hydrographs are calculated for precipitation events using a modeling system that converts runoff volume to a hydrograph using the unit hydrograph approach, such as the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) (US Army Corps of Engineers 2008).

A genetic algorithm (GA) approach (Goldberg 1989) is used to solve the optimization model in Eqs. (1)–(3). A GA uses a population of solutions that converge to a near-optimal solution after several iterations, or generations, of the algorithm. Each solution is represented as an array of integers that represent the indices corresponding to parking lots and rooftops that are chosen for retrofit through a LID technology. For different budget levels, the number of roofs and parking lots that can be retrofitted is specified by the size of the array of decision variables. At each generation, a new population of solutions is generated using genetic operators such as crossover, which combines decision characteristics of highly fit solutions, and mutation, which randomly changes a few decision variable values in a population of solutions. Genetic algorithm-based approaches have been demonstrated for planning BMP and LID strategies for managing urban watersheds [e.g., Yeh and Labadie (1997); Harrell and Ranjithan (2003); Perez-Pedini et al. (2005)]. The modeling methodology coupling a GA and the hydrologic modeling system is shown in Fig. 1, as implemented for the case study described subsequently.

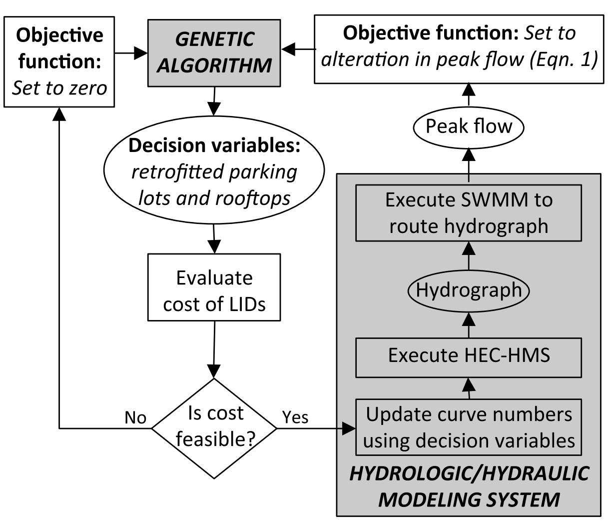

Fig. 1. Computational framework to couple genetic algorithm and hydrologic/hydraulic modeling system

Illustrative Case Study: Texas A&M University Campus Watershed

An illustrative case study is used to demonstrate optimization of planning LID and pond BMP strategies within a watershed for storm water control. The Texas A&M University campus is located in College Station, Texas (Fig. 2), and covers an area of 21.37 km^2 (5,280 acres). The campus is divided into two sections, Main Campus (3.03 km^2) and West Campus (4.4 km^2). West Campus has witnessed unprecedented development over the past 50 years, increasing the impervious land cover, and the new development has increased the volume of runoff that drains southwest through Tributary D, shown in Fig. 2. The hydrologic system and watersheds of the Texas A&M University campus are described in the campus master plan (Texas A&M University 2004), and a study was conducted to document erosion at critical locations in Tributary D (JF Thompson Inc. 2005). The study also developed a hydrologic and hydraulic simulation system to model runoff and streamflow in Watershed D and Tributary D (AECOM 2008). The hydrologic simulation was implemented using HEC-HMS, and the storm water management model (SWMM) (Rossman 2008) was used for hydraulic simulation of the storm water sewer network and receiving stream. For modeling purposes, Watershed D is delineated as 444 subbasins based on the storm water infrastructure, which is composed of storm sewer manholes, culverts, channel junctions, buildings, parking lots, and streets. The drainage area of Watershed D is 3.18 km^2, with a total of 41% impervious land cover. A combination of links and nodes represent the storm water infrastructure, composed of box and circular storm sewers, open

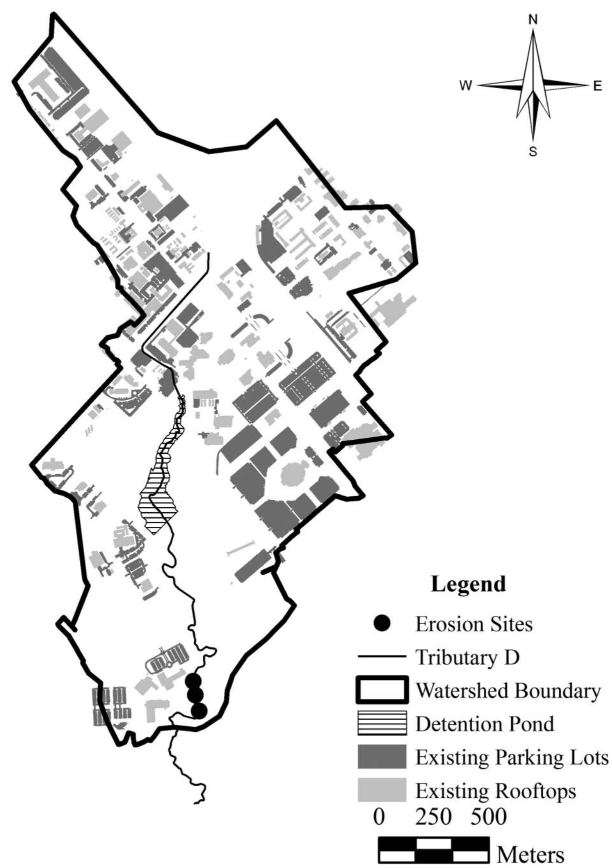

Fig. 2. Location of potential detention pond, rooftops, parking lots, and sites of erosion in Watershed D

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channels, and a natural waterway. The hydrologic model for Watershed D was calibrated and validated for two historic storms. Streamflow and precipitation data were collected in 5-min intervals for the two storms, and the coupled HEC-HMS/SWMM modeling system was calibrated and validated to accurately predict the runoff and timing of the hydrograph (Damodaram et al. 2010).

Sixty-five parking lots cover 14% of the watershed area, and 62 rooftops cover 7% of the watershed in Watershed D. For the design problem that is solved here, each rooftop can be retrofitted with a rainwater harvesting system that can store up to 102 mm (4 in.) of rainfall before releasing overflow to the storm sewer system. Using the Ia-storage curve number approach to simulate a rainwater harvesting system, the initial abstraction is set as 102 mm. The permeable pavement is simulated using the S-storage curve number approach with an effective storage, or maximum potential retention, of 102 mm (4 in.), which results in a curve number of 71.

Optimization Scenarios

A set of scenarios was explored to optimize placement of LID strategies and combined LID and pond BMP (LID/BMP) strategies for various rainfall events and budget constraints for the Texas A&M University campus watershed. Three design storms include a 2-year rainfall event (114 mm or 4.42 in.), a 10-year 24-h rainfall event (185 mm or 7.44 in.), and a 100-year 24-h rainfall event (279 mm or 11.35 in.) (AECOM 2008). Rainfall distributions for the design storms are based on the Soil Conservation Service (SCS) center-weighted distribution method.

The analysis explores varying limitations of a budget that would be available for storm water controls. Costs for implementing LID technologies vary considerably based on the system specifications, soil type, and location of implementation. This study uses a representative cost for installing both permeable pavements and rainwater harvesting at $24.22/m^2$ ($2.25/ft^2$). The implementation cost for permeable pavement is the average cost for different types of permeable pavements, as provided by the National Association of Homebuilders (2001), and the implementation costs of rainwater harvesting for construction in Texas is published by the Texas Water and Development Board (2005). Three budget levels are considered, based on the costs for retrofitting 10, 25, and 50% of the total parking lots and rooftop areas with LID technologies. Based on these figures, three LID scenarios, low LID, medium LID, and high LID, were constructed with budget allowances of $2.75, $6.75, and $13.5 million, respectively. To solve each model, the budget value was used as C_{Budget} in Eq. (2). As the budget increases, the maximum number of LIDs that can be placed also increases through enlarging the size of the array of integers that represent the parking lots and rooftops that are chosen for LID retrofitting. For the low LID scenario, up to seven parking lots out of 65 lots in the watershed were selected for LID retrofitting, and up to six rooftops out of 62 buildings in the watershed were selected for retrofitting. For higher budgets, the number of sites that are retrofit with LID increases, and the representation allows a larger selection of parking lots and rooftops. For the medium LID scenarios, up to 16 parking lots and 16 rooftops can be replaced, and for the high LID scenario, up to 32 parking lots and 31 rooftops can be replaced. Each decision has a cost associated with it based on the area of the roof or parking lot. Representing the solution as a limited number of locations where LIDs may be placed constrains the number of configurations that can be identified. This representation, however, enhances convergence, because very few infeasible solutions (those exceeding the allowed budget) are considered. Execution of the hydrologic/hydraulic simulation model requires 10 min for an Intel Core2 CPU computer (2.66 GHz) host with 2.0 GB of random-access memory operating on a Windows XP SP3 system. A GA-based approach requires thousands of model executions, and by limiting the representation, the time to convergence is kept in a practical range.

Table 1. Problem Parameters Varied to Create 18 Optimization Scenarios

Parameter	Setting
Budget	Low (13 decision variables)
	Mid (32 decision variables)
	High (63 decision variables)
Design storm	2-year
	10-year
	100-year
Development	LID
	LID/BMP

A detention pond is modeled at a central node in the watershed (Fig. 2) to create a combined LID/BMP scenario. A representative construction cost for the detention pond is adopted from a major BMP and LID study conducted for an impaired river in Michigan (Rouge River National Wet Weather Demonstration Project 2001) at $26.49/m^3$ ($0.75/ft^3$). Preliminary simulations explored depths and outlet structures for the pond design and found that because of the physical constraints of the location, there was little variation in the hydrologic flows for different detention pond designs. A final value for the depth of the pond was chosen as 3 m, resulting in a total construction cost of $0.78 million, and corresponding to a LID area of 0.03 km^2. The optimization model does not allow any variation in the detention pond parameters. The same budget constraints, low, medium, and high, are used for optimizing LID placement for the LID/BMP scenario. The LID/BMP scenarios allowed a smaller area for LID retrofitting, because a portion of the budget is allocated to constructing the detention pond. In total, 18 scenarios are simulated (Table 1), representing three storm events, three budget scenarios, and both LID and LID/BMP strategies.

Results

Placement of LID in the watershed was first explored without consideration of a detention pond. Optimization using a GA-based approach uses a random component, and as a result, initializing a population using a pseudorandom number generator can produce different solutions in the final generation. To test the robustness of the final solution, five random trials were executed for each scenario. The settings for the GA were tested in preliminary studies, and the GA was executed using a population size of 50, a maximum number of 50 generations, a crossover rate of 75%, and a mutation rate of 1%. The convergence of the GA for a high LID scenario is shown in Fig. 3. As the GA iterates through generations, the solutions improve in objective values, or peak flow reduction (Q_o), and meet the budget constraint or $13.5 million. Solutions that exceed the cost constraint are considered infeasible and assigned a value for Q_o of zero (as shown in Fig. 1). These solutions occur more often early in the search (Fig. 3), but as the GA converges, only a few infeasible solutions are explored.

The average peak flow reductions that are identified for each of the nine LID scenarios are shown in Fig. 4, and these results are compared to the peak flow reduction of retrofitting 100% of the parking lots and rooftops. Representative solutions for each LID scenario that are optimized for the 2-year rainfall event are shown in Fig. 5, and the hydrographs for each of these solutions are shown in Fig. 6. For each scenario, the five results from the

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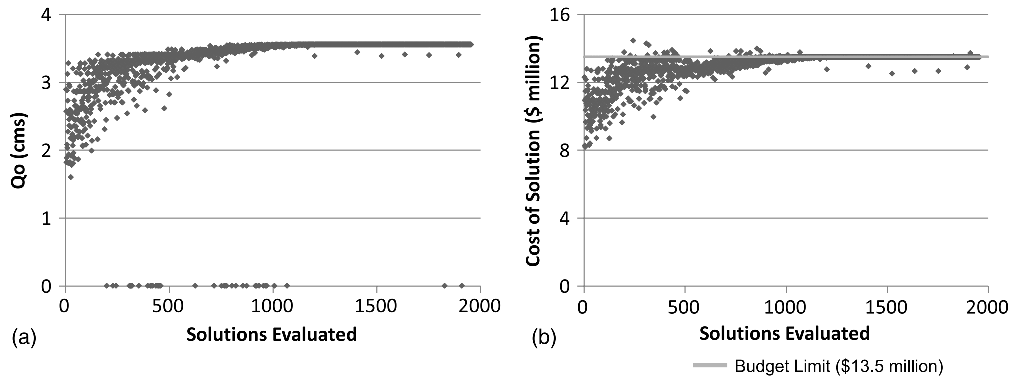

Fig. 3. Convergence of solutions for one GA trial for the high LID scenario, optimized for the 2-year storm, as compared to the budget constraint (a) peak flow reductions of solutions; (b) cost of solutions

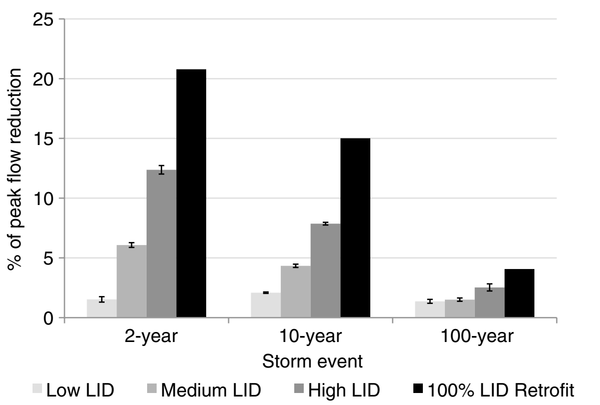

Fig. 4. Average reduction in peak flow compared to existing conditions for LID scenarios and 100% LID retrofit for 2-, 10-, and 100-year rainfall event; error bars show standard deviation over five random trials

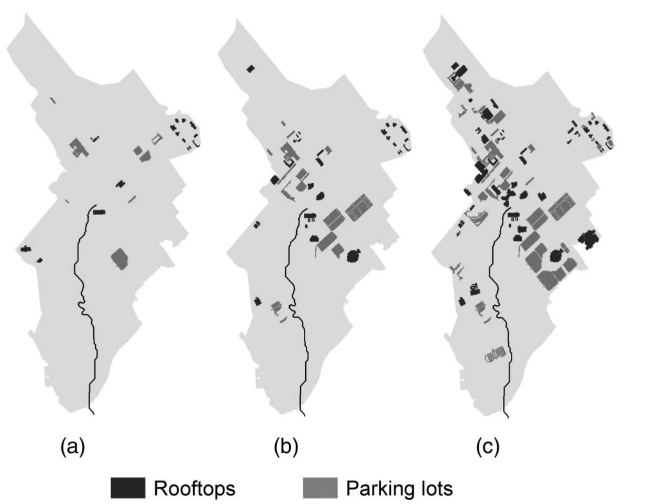

Fig. 5. Representative solutions optimized for the 2-year event under (a) low; (b) medium; (c) high LID scenarios

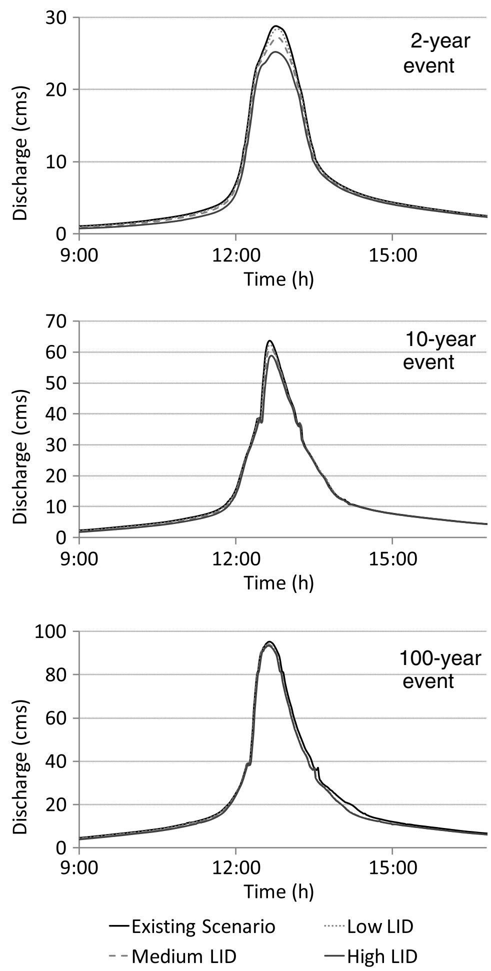

Fig. 6. Hydrographs for the existing conditions and representative solutions for LID scenarios and rainfall events

random trials demonstrate a relatively robust performance, because the solutions that are identified result in similar values of peak flow reduction. With increasing budget allowances, a greater reduction in peak flow is achieved by the solutions, as expected. By optimizing the location of LID technologies in the watershed, the high LID scenario is able to achieve 13% reduction for the 2-year rainfall event. This compares to replacing all rooftops and parking lots with LID, which achieves 21% reduction of peak flow. The reduction when retrofitting 10% of the potential area (low LID scenario) is relatively insignificant, and though this is the smallest investment, this strategy could be difficult to justify based on the costs that are incurred. The LID strategies also show decreasing impact for more intense storms. This is because of the infiltration-based

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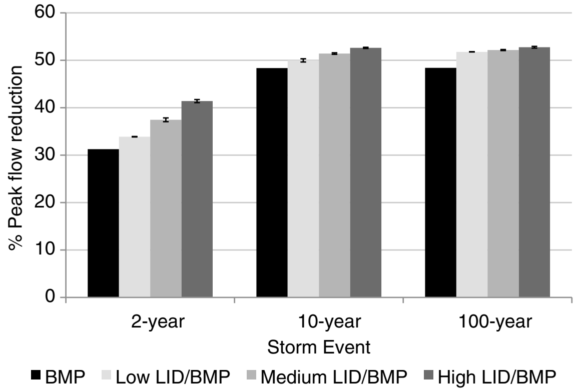

Fig. 7. Average reduction in peak flow for LID/BMP scenarios, compared with a detention pond alone (BMP) for 2-, 10-, and 100-year rainfall event; error bars show standard deviation over five random trials

mechanisms of the LID, which cannot effectively control large storm water volumes.

Solutions were also identified for a set of nine LID/BMP scenarios, corresponding to three LID levels and three rainfall events. The peak flow reduction for all scenarios is shown in Fig. 7, and hydrographs for the LID/BMP scenarios are shown in Fig. 8.

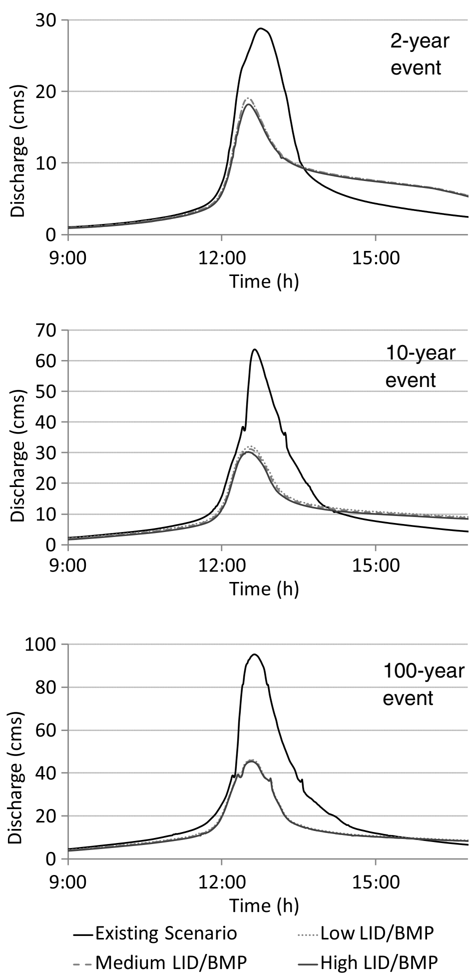

Fig. 8. Hydrographs for the existing conditions and representative solutions for LID/BMP scenarios and rainfall events

For all LID/BMP scenarios, the peak flow reduction is greater than that of LID strategies alone, and the shape of the hydrograph is changed from the existing scenario as the detention pond releases stored water over a longer time period. Whereas increasing levels of LID placement achieves additional reduction in the peak flow for the 2-year storm, for the 100-year storm, additional LID placement reduces the peak flow further by a relatively small value.

Decision Flexibility based on Similarity Analysis among Solutions

For the five solutions that were identified for each of the 18 optimization scenarios, the objective values are similar, demonstrated by small values for the standard deviations in peak flow reductions (Figs. 4 and 7). Though the performances for a set of solutions are similar, the decisions that are specified vary to some degree among the solutions. For example, the five solutions that were identified for the low LID scenario and optimized for the 2-year storm are shown in Fig. 9. For this scenario, 13 rooftops and parking lots are identified for retrofit. Though the five solutions have similar peak flow and cost values, there are only a few parking lots and rooftops that are repeated among these solutions, and as a result, a decision maker may have a significant degree of flexibility when managing this scenario.

The parking lots and rooftops that are repeated among solutions were analyzed to evaluate the number of similar decisions among solutions. The similarity between two solutions is defined as the number of decisions that are the same, or the number of parking lot and rooftop indices that are repeated between both solutions. The similarity can also be expressed as a percentage, as the number of similar decisions out of the total number of decisions selected (13 for low LID, 32 for medium LID, and 64 for high LID scenarios). When comparing pairs of all possible permutations that could represent a solution, the average similarity across all pairs is 10, 25, and 50% for the low, medium, and high LID scenarios, respectively.

The average similarities between pairs of solutions are shown in Fig. 10 for the LID scenarios. For example, for the set of solutions shown in Fig. 9, an average of 1.4 parking lots and buildings are similar between any pair of solutions. For the three sets of solutions optimized for low LID scenarios (2-, 10-, and 100-year events), the similarity ranges from 1.2–1.8 similar decisions, or 9–14% of the 13 decisions that should be made. The percentage of similar decisions out of the total number of options increases to 23–26% for the medium LID scenario and 33–41% for high LID scenarios. The same analysis was conducted for the LID/BMP scenarios (Fig. 10). The LID/BMP solutions that were optimized for the 2-year rainfall event resulted in similarities of 28, 35, and 46% for the low, medium, and high LID/BMP scenarios, respectively. For the 2-year rainfall event, the use of LID can reduce the peak flow beyond the reduction attributed to the pond, whereas for the 10- and 100-year events, LID cannot further control the storm water volumes significantly beyond the influence of the detention pond (as shown in Fig. 8). Therefore, for the 2-year rainfall event, there may be a smaller number of diverse solutions that best reduce the peak flow. The analysis conducted here is limited, because the set of solutions for each scenario was identified using the GA-based approach for only a small set of random trials. A more systematic approach can be used to identify maximally different alternative solutions and quantify the flexibility for each scenario [e.g., Brill (1979); Reichold et al. (2010)].

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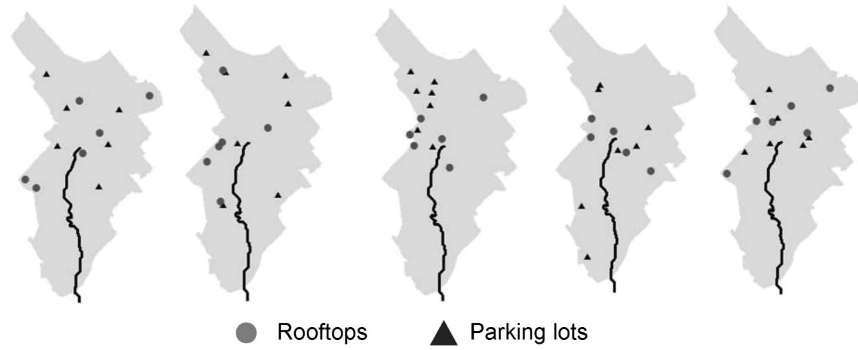

Fig. 9. Five solutions identified for the low LID scenario, optimized for the 2-year rainfall event

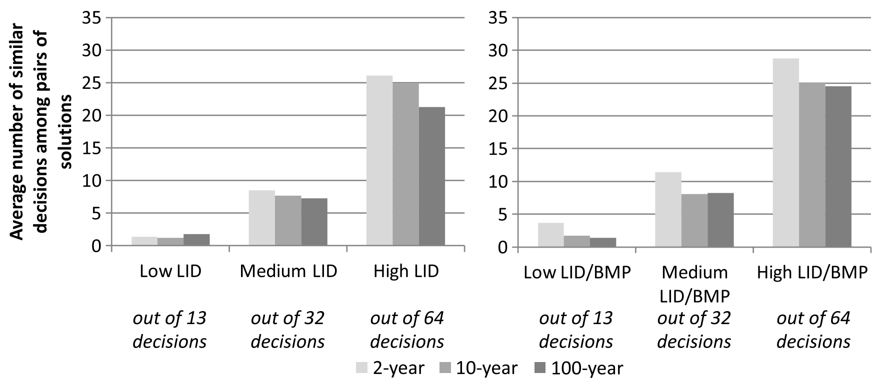

Fig. 10. Similarities in decisions among pairs of solutions; five solutions were identified for each LID scenario and storm event; decisions represent which rooftops and parking lots should be retrofit with LID technologies

Trade-Offs among Design Storms

The solutions identified for the LID and LID/BMP scenarios are analyzed here to determine their efficiency in controlling all storms. One solution is chosen to represent each of the nine LID scenarios, where each solution was optimized for one storm and is evaluated for the remaining two storms that it was not designed to control. For the low LID scenario, for example, the solution that was optimized for the 2-year storm reduces peak flow to a larger degree for the 2-year storm than the solutions that were optimized for the 10- and 100-year storms, but does not perform as well for the 100-year storm as the solution that was optimized for that event. The trade-off between performance for the 2- and 100-year storms for each solution are shown in Fig. 11. The solution optimized for the 10-year storm, located in the compromise region of each trade-off curve, retains some efficiency for both the 10- and 100-year storms.

The same analysis is conducted for the LID/BMP scenarios. For these scenarios, solutions that are optimized for one storm perform similarly well for other storms, because the detention pond governs a majority of the reduction in peak flow for all of the storms. The trade-off curve (Fig. 12) demonstrates the most significant trade-off

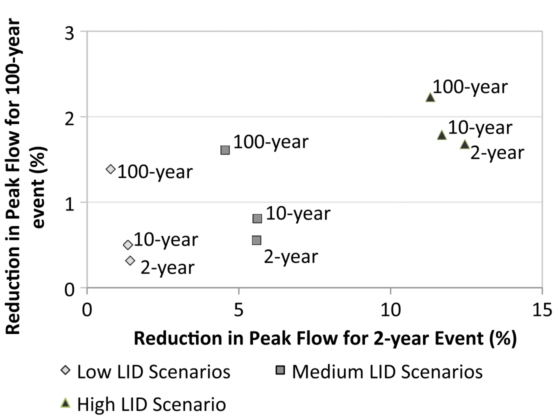

Fig. 11. Trade-off between performance of LID strategies for 2- and 100-year event; label indicates the event that was used to optimize a solution

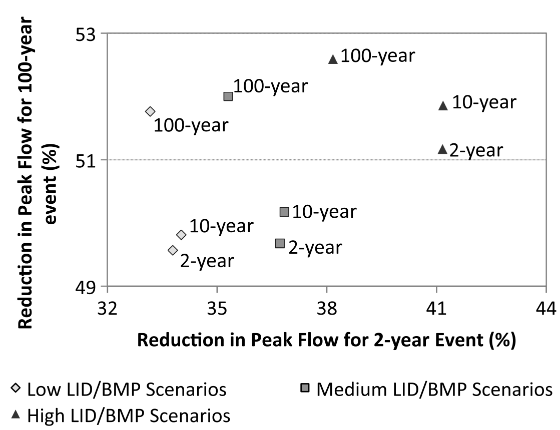

Fig. 12. Trade-off between performance of LID/BMP strategies for 2- and 100-year event; label indicates the event that was used to optimize a solution

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for the high LID scenarios, because the solution that performs best for the 100-year storm reduces the peak flow by 38% for the 2-year storm, compared to a reduction of 41% by the solution optimized for the 2-year storm.

Both the LID and LID/BMP scenarios demonstrate that when managing for one type of storm, it is possible that some performance may be lost for storms of other sizes. For this watershed and the scenarios conducted here, the loss in performance over all scenarios is only a matter of at most a few percentage points, demonstrating that although there is some trade-off among solutions optimized for different storm events, the trade-off is not significant. For other watersheds, there may be a more pronounced trade-off in performance for different depths of rain. The GA-based framework can be applied for new watersheds to evaluate the trade-offs among flood control for infrequent and frequent events.

Conclusions and Discussion

A simulation-optimization framework is developed to identify and explore watershed management plans that utilize LID strategies and combined LID/BMP strategies to reduce hydrologic impacts of urbanization for varying budget levels. By optimizing placement of LIDs, the efficiency of investments in LID can be increased. Results also demonstrate that using LID and detention ponds together can protect the hydrologic regime better than either infrastructure alone. For this watershed, the detention pond design is the same for all storms, and therefore, there is only a small difference between the optimal solutions in peak flow reduction. Further analysis was conducted here to determine any flexibility in decisions and revealed that there is the most flexibility in selecting LID sites for the lowest LID level. The least flexibility is afforded when solutions are found for a combined LID/BMP scenario and optimized for the 2-year storm. The S-storage and Ia-storage methods are used in this study to simulate permeable pavement and rainwater harvesting systems. Although the S-storage approach has been validated to simulate runoff volumes for permeable pavement, it should be validated for accuracy in simulating the shape and timing of runoff hydrographs from permeable pavements. Alternative modeling approaches that capture this timing may reveal more uniqueness in the placement of LIDs within a watershed. The watershed that was studied in this investigation is a relatively small watershed, and all facilities in the watershed are managed centrally by the University; therefore, it is realistic to consider a management strategy that specifies conversion of diverse buildings and paved areas. The simulation-optimization framework can be applied for larger watersheds to explore the effectiveness of decentralized storm water control.

An increasingly significant question in watershed management concerns the sustainability of management plans. Detention ponds are primarily designed to control runoff volumes of flood events, and LID technologies are intended to mimic the natural flow regime by controlling the runoff at the source of generation. Because watershed management aims to meet both goals of flood control and sustainability, a varied spectrum of storm events can be considered for developing storm water management plans for an urban watershed. Implementing these strategies individually or in combination is dependent on their cost effectiveness and their effects on the reduction of hydrological impacts at a watershed level. This analysis simulated each solution for a set of design storms to evaluate the performance of any one solution to preserve the hydrologic flow regime for a spectrum of rainfall events. This study focused on the peak flow of each storm; other metrics have been proposed that may better represent watershed sustainability by representing changes to additional characteristics of the long-term flow regime [e.g., Reichold et al. (2010); Giacomoni et al. (2012)]. These metrics can be incorporated in the simulation-optimization framework described here to optimize LID planning for sustainability. Other sustainability metrics include runoff volume, shape and timing of the hydrograph, and water quality parameters, and these can be included as additional or alternative objective functions.

The analysis shows that for this small watershed, there is a small amount of trade-off between managing for a 2-year rainfall event and managing for flood events. In general, ponds are typically designed for flood control, whereas it has been shown that LID is more effective for smaller, less intense events. In planning watershed development, there may be trade-offs between the goals of flood control, sustainability, and cost-effectiveness. Future research can explore these trade-offs through multiobjective optimization and analysis. The results of this and ongoing research can better advise watershed management in selecting land use allocation, LID technologies and designs, and BMPs.

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