



# Integrated SUSTAIN-SWMM-MCDM Approach for Optimal Selection of LID Practices in Urban Stormwater Systems

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## Abstract

Rapid urbanization has increased impervious areas, leading to a higher flood hazard across cities worldwide. Low Impact Development (LID) practices have shown efficacy in reducing urban runoff; nevertheless, choosing the best combinations in terms of implementation cost and performance is of great importance. The present study introduces a framework based on green infrastructure, multi-objective optimization, and decision support tools to determine the most cost-effective LID solutions. The Storm Water Management Model (SWMM) was employed for rainfall-runoff and hydraulic modeling in Region 1, District 11 of Tehran, Iran. Six scenarios of different combinations of LID practices were developed. The system for Urban Stormwater Treatment and Analysis Integration (SUSTAIN) was used to optimize and evaluate each scenario. The selected solutions were imported to the SWMM to evaluate the stormwater system performance. Then, two multi criteria decision making (MCDM) models, including TOPSIS and COPRAS, were employed to rank the scenarios based on four technical and economic criteria. Results showed that scenario 4, consisting of rain barrels, porous pavements, and vegetated swales, had the best performance under TOPSIS with a 7.68 million USD and reduced the runoff volume and peak flow by 20.77% and 19.2%, respectively. However, Under the COPRAS method, Scenario 2 with a combination of rain barrels, bio-retention cells, and vegetated swales showed higher performance than the other scenarios with 3.25 million USD and led to a 15% reduction in the runoff volume and 4.30% in the peak flow. The COPRAS method was more sensitive to cost weights and chose the most economical scenario as the ideal. However, Scenario 4 concluded to be more feasible due to spatial limitations in the study area. The proposed SWMM—SUSTAIN—MCDM framework could be helpful to decision-makers in the design, performance evaluation, cost estimation, and selection of optimal scenarios.

**Keywords** Urban stormwater management · Low impact development (LID) · SUSTAIN · SWMM · MCDM

## 1 Introduction

In recent decades, rapid urbanization has dramatically changed land uses worldwide, and the ratio of impervious areas has been raised subsequently (Guan et al. 2015; Yao et al. 2016). Hence, declines in watersheds' permeability have led to 1) an increase in runoff

volume and peak flow rate, 2) ineffective aquifer recharge, and 3) water quality reduction (Yang et al. 2011; Du et al. 2012; Valtanen et al. 2014; Li et al. 2016; Bell et al. 2016; Chen et al. 2017). Consequently, stormwater management has become a challenge in numerous cities across the world (Sundermann et al. 2014; Schubert et al. 2017). In order to cope with these challenges, many cities seek more sustainable approaches to implement balanced development, focusing on monitoring and controlling the water cycle (Van Roon 2007; Barbosa et al. 2012; Kim et al. 2017). For the control and management of urban stormwater systems, it is essential to consider not only technical but also social, economic, and environmental aspects (Tingsanchali 2012; Shariat et al. 2019). In order to minimize the adverse effects of urbanization, it has been recommended to impose limitations on the construction of traditional stormwater systems by replacing Low Impact Development (LID) techniques (Rezazadeh et al. 2019).

LID solutions are generally designed to capture stormwater at the source to minimize runoff transport, leading to a decrease in stormwater contamination and providing positive environmental contributions (Dietz 2007; Barbosa et al. 2012; Eckart et al. 2018). The benefits of low impact development in urban runoff management have been demonstrated by several studies (You et al. 2019; Macro et al. 2019; Raei et al. 2019; Yin et al. 2020; Taghizadeh et al. 2021; Ferrans and Temprano 2022; Tansar et al. 2022). Some of the most popular LID solutions include green roofs, rain barrels, bio-retention cells, porous pavements, and vegetated swales (Liu et al. 2021).

The Storm Water Management Model (SWMM) has been widely used to evaluate and simulate urban stormwater systems. Kong et al. (2017) employed SWMM and analyzed the hydrological response of an urban watershed under land-use change scenarios. Roobahani et al. (2020) utilized SWMM to simulate the urban stormwater system of Region 1 of District 11 of the Tehran Municipality and The performance of the stormwater system was evaluated based on the reliability, resilience, vulnerability, and sustainability indices. Platz et al. (2020) evaluated SWMM through the quantitative comparison of observed data and modeling results using a multi-event multi-objective calibration. Zhang et al. (2022) used the Monte Carlo method to quantify the uncertainty associated with SWMM performance in modeling five LID facilities.

Coupling SWMM with other models has been studied for optimizing LID scenarios. De Paola et al. (2018) and Pugliese et al. (2022) exploited an optimization model based on the harmony search (HS) optimization algorithm and SWMM for urban stormwater management of a study area in Naples. Eckart et al. (2018) developed a coupled optimization-simulation model by linking SWMM to the Borg Multi-Objective Evolutionary Algorithm (Borg MOEA). Lu and Qin (2019) developed a simulation-optimization model with uncertainty analysis to evaluate the performance of different LID solutions, including green roofs, bio-retention cells, and porous pavements. In another study, Taghizadeh et al. (2021) used SWMM-MOPSO combination to optimize three LID practices, including infiltration trenches, bio-retention, and permeable pavements in an urban drainage network.

The System for Urban Stormwater Treatment and Analysis Integration (SUSTAIN) model was developed by the United States Environmental Protection Agency (USEPA 2009). It could simulate the rainfall-runoff process in watersheds and implement cost-effectiveness evaluation and LID scenario optimization. Some studies utilized the SUSTAIN model to perform cost-effectiveness and optimization of LID scenarios (Chen et al. 2017; Jia et al. 2015; Mao et al. 2017) and Li et al. (2018) employed SUSTAIN and SWMM to optimize the sponge city construction scheme and reduce stormwater based on cost minimization and performance maximization in China.

It is necessary to implement effective risk management methods to diminish urban stormwater. However, it is difficult to select the most efficient strategies as it would require complex interactions between natural, social, and constructed urban environments. Also, the complexities in urban drainage systems, the implementation cost of such strategies, and uncertainty in future conditions add to the difficulty and complexity of decisions (Jha et al. 2012; Simonovic 2012; Alves et al. 2018). Hence, some studies have utilized Multi-Criteria Decision Making (MCDM) models to rank LID scenarios. Song and Chung (2017) adopted TOPSIS to prioritize locations and LID solutions. Social, hydrological, and geometrical criteria were weighted using the entropy weight method (EWM) and the Delphi method. Jayasooriya et al. (2018) used TOPSIS as an MCDM technique to identify the optimal green infrastructure configuration in an industrial site in Melbourne, Australia. Sheikh and Izanloo (2021) evaluated six LID scenarios based on hydrological, social, and economic criteria. Then, six MCDM techniques were employed to rank the decision alternatives, including TOPSIS, VICOR, SAW, MEW, ELECTRE III, and NFM.

A review of previous research shows that several studies have coupled simulation models such as SWMM with other optimization algorithms to generate cost-effective solutions. Also, a few studies used MCDM models alone to prioritize scenarios without optimizing LID combinations.

This study used the integrated SUSTAIN-SWMM-MCDM framework for the first time to not only optimize LID features, costs, and effectiveness but also prioritize the most feasible scenarios concerning flow reduction, drainage network performance, and implementation costs.

After the cost-effectiveness analysis and optimization using SUSTAIN model, the TOPSIS and COPRAS methods were used to rank six scenarios of various LIDs combinations, namely Green Roofs, Rain Barrels, Bioretention Cell, Porous Pavements, Vegetated Swales, and Dry Ponds based on four technical and economic decision criteria including: 1) runoff volume reduction, 2) runoff peak flow reduction, 3) Reduction of channels with insufficient capacities, and 4) Implementation costs. Also, three weighting methods were used, including AHP, Entropy, and combined AHP-Entropy, to make robust weights for each criterion. In order to evaluate the performance of the proposed framework, a high-density district of the Tehran Municipality with high traffic, social, and environmental challenges was selected as the study area.

## 2 Materials and Methods

This study employed SWMM to simulate the rainfall-runoff process. Rainfall data from a baseline period of 1988–2018 were used (Roozbahani et al. 2020). Then, the simulated hydrograph was imported into the SUSTAIN model, evaluating the costs and performance of the designed LID scenarios through its built-in simulation module. The optimal solutions of each scenario were identified based on the optimization module and NSGA-II algorithm. The optimized solutions were imported to SWMM to evaluate the performance of the urban stormwater system. Finally, the scenarios were ranked based on technical and economic criteria and MCDM techniques. Figure 1 depicts the flowchart of the proposed methodology.

## 2.1 Study Area

In the present study, the existing stormwater system located in Region 1, District 11 of Tehran municipality was selected as the study area. It occupies an area of 2.7 km<sup>2</sup> in Central Tehran. The highest and lowest elevations of the region are 1207 m and 1153 m above sea level, respectively (Roozbahani et al. 2020). The current urban stormwater system includes 321 channels, approximately 46.5 km, to drain stormwater. The system ended in one of the three major outlets of Khayyam, Sezavar, or Firouzabadi. In addition, 325 sub-watersheds with soil hydrological groups of B and C existed in the region. The watershed curve number variation was above 90, suggesting low permeability due to excessive urbanization and non-adherence to sustainable urban development standards (Zistab Consulting Engineers 2015). It should be noted that the region is of great importance in light of its political, commercial, and military centers. Intense rainfall events, insufficient channel capacities, and urban waste accumulation impose frequent flooding and disturbance in the urban stormwater system (Shariat et al. 2019). Figure 2 illustrates the location of the study area.

## 2.2 SWMM

EPA’s SWMM is a dynamic rainfall-runoff simulation model for both single-event and long-term rainfalls in urban watersheds for runoff’s quantitative and qualitative simulation. It has been widely used for planning, analyzing, and designing urban stormwater systems (Rossman 2015; Hashemi and Mahjouri 2022). Sub-watershed runoff, pipe/channel flow rates, and stormwater runoff quality are simulated at the predefined time steps. Also, SWMM has modules that can simulate LID methods (Roozbahani et al. 2020; Baek et al. 2020). A single-event six-hour rainfall from the base period of 1988–2018 was imported to

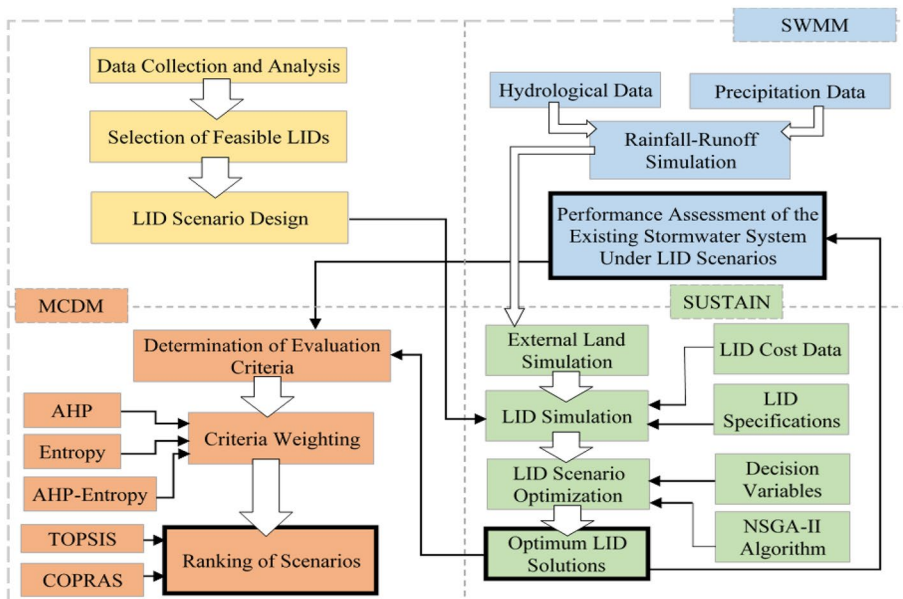
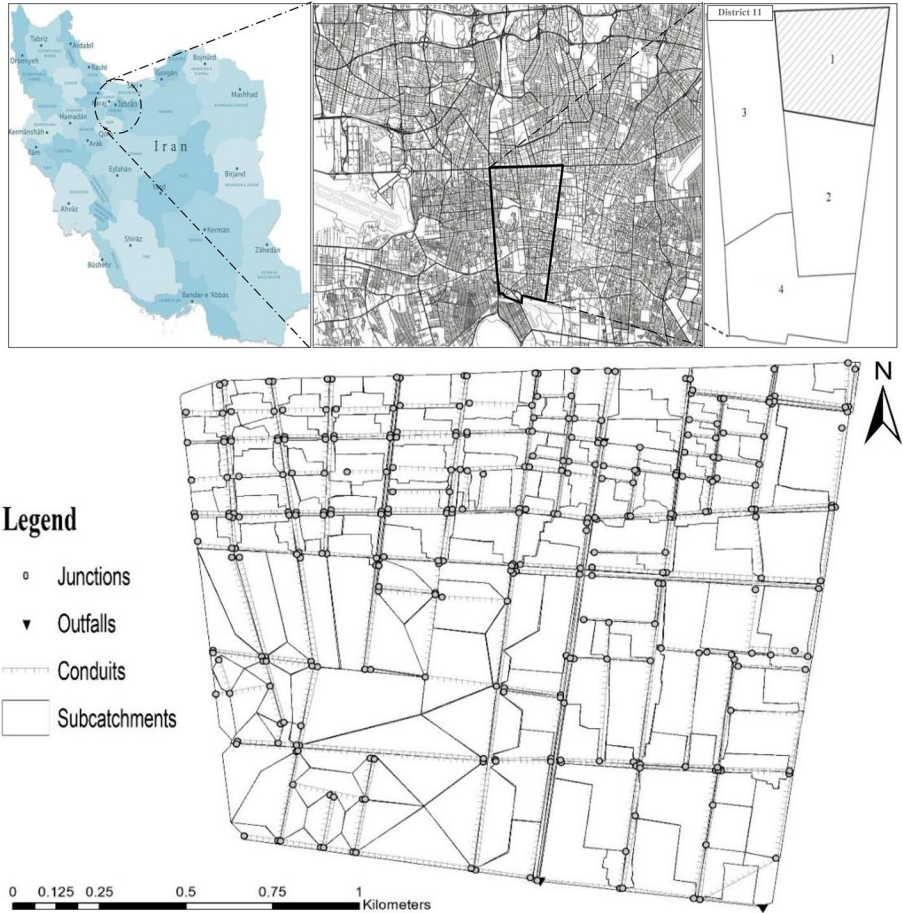


Fig. 1 Flowchart of the proposed methodology

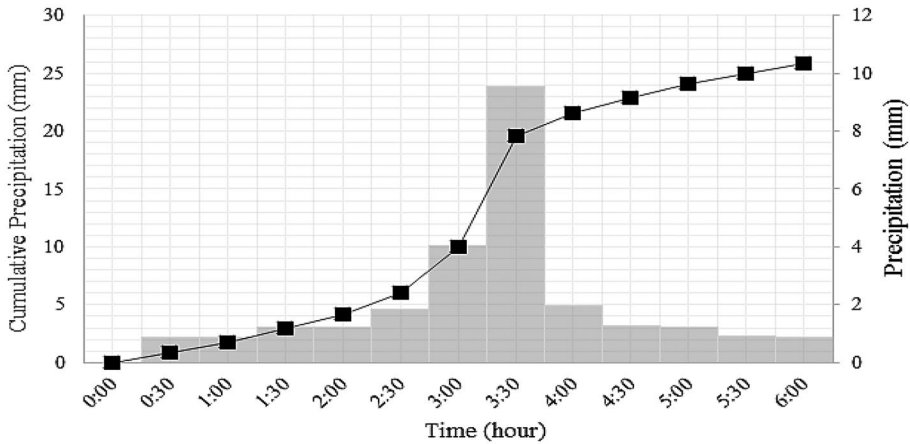


**Fig. 2** Position of the study area and the existing stormwater system in Tehran

SWMM. Precipitation data was taken from Mehrabad synoptic station located in the vicinity of the study area. As the sub-channels of the region have been designed for a return period of ten years, the present work used a ten-year return period to evaluate the stormwater system and LID scenarios. Figure 3 presents the hyetograph used in the rainfall-runoff simulation. The Soil Conservation Service (SOS) curve number method was exploited for infiltration calculations.

### 2.3 SUSTAIN

The SUSTAIN model is an ArcGIS tool developed by the USEPA, capable of analyzing and managing urban stormwater flow and its contamination (USEPA 2009). SUSTAIN may be used at small local and larger scales, such as watersheds. It can be used to simulate single-event and continuous rainfalls (Lee et al. 2012). It is a pack of algorithms that are accurate in technical and theoretical calculations and enable cost and performance analyses



**Fig. 3** Hyetograph of the rainfall-runoff simulation (Rozebani et al. 2020)

with effective results in real-life operations (USEPA 2009). The SUSTAIN model has an optimization module that could be exploited to optimize and compare LID scenarios (Chen et al. 2014). Table 1 provides the required input data of SUSTAIN.

### 2.3.1 Land Simulation Module

Stormwater runoff and pollution load can be simulated using the land simulation module in two ways. The module uses the SWMM simulation algorithms to calculate the hydrograph and pollutograph. It is referred to as internal simulation in SUSTAIN. The rainfall-runoff process can be simulated in SUSTAIN at the same accuracy level as the original model (USEPA 2009).

It is also possible to import the results of other models to SUSTAIN, known as external simulation, which is used in this study. This option can be implemented using pre-calibrated models such as SWMM and HSPF to generate the hydrograph of the region and

**Table 1** Input data of SUSTAIN (USEPA 2009)

Data	Format	Description
Land use	Raster	For the analysis and description of the hydrological characteristics of the watershed and the suitability of the site for LID usage
Digital elevation model (DEM)	Raster	For the calculation of the watershed drainage slope and the outlets detection
Soil	Vector (polygon)	For the detection of soil characteristics, soil hydrological groups, and permeability characteristics
Urban infrastructure	Vector (polyline points, polygon)	For the detection of suitable sites for LID implementation
Urban stormwater system	Vector	For the development of the urban stormwater system in modeling
Watersheds and sub-watersheds	Vector (polygon)	Watershed delineation

import flood times-series data (USEPA 2009). The required parameters used for external simulation using SWMM model are presented in the Table 2.

### 2.3.2 LID Simulation Module

The LID simulation module is a process-based simulator of stormwater and pollution transport that covers a wide range of LID solutions. Furthermore, all the hydrological processes, including runoff capturing, evaporation, shallow and deep infiltration, and output runoff in stormwater control structures (LID), are simulated using this module. The LID simulation module enables the selection of LID solutions and their combinations to configure and evaluate the systems based on physical characteristics (e.g., size, weir type, and soil parameters). The values for parameters are determined based on the local characteristics and standards for each LID to ensure feasibility of implementation. The following relationship is usually used to simulate the flow in LIDs:

$$\frac{\Delta V}{\Delta t} = I - O \tag{1}$$

where  $\Delta V$  = change in storage,  $\Delta t$  = time interval,  $I$  = inflow to LID unit,  $O$  = outflow.

The inflow to the LID is estimated through the simulation results from the upstream. The outflow also includes overflow from LID, evapotranspiration, and infiltration. A summary of key LID simulation processes included in SUSTAIN can be found in Lee et al. (2012)

### 2.3.3 Cost Module

SUSTAIN supports a dataset in which the cost of each element is collected and can be used. The cost module estimates the total cost based on each LID fundamental construction component (FCC). An FCC refers to the services and elements required to construct a single unit of length, area, or volume for each LID type. The total cost is calculated as (Lee et al. 2012):

**Table 2** The external simulation (SWMM) parameters for simulating the stormwater system

<b>Subcatchments</b>	
Number	325
Area (m <sup>2</sup> )	Min:510, max:189100, Mean:18100
Imperviousness %	25
Curve Number	Min:83, Max:93, Mean: 92
Depression Storage (mm)	1.27
Manning (imp)	0.013
Manning (per)	0.01
<b>Conduits</b>	
Number	321
Length (m)	Min: 4, Max: 926, Mean= 145
Manning	0.013
<b>Junctions</b>	
Number	325



$$\text{Cost} = a + b.(\text{Length})^c + d.(\text{Area})^e + f.(\text{Volume})^g \quad (2)$$

where  $a$ ,  $b$ ,  $c$ ,  $d$ ,  $e$ ,  $f$ , and  $g$  are cost parameters dependent on the preparation costs, length, area, and volume of an FCC. The parameters  $c$ ,  $e$ , and  $g$  are related to exponential costs and are equal to one in the present study. The value for other parameters can be seen in Table 3.

### 2.3.4 Optimization Module

The optimization module of SUSTAIN is intended to find the most cost-effective approaches for the quantitative and qualitative control of stormwater using LID methods. It uses evolutionary optimization techniques to find the optimal combination of LIDs based on predefined decision-making criteria (USEPA 2009). The objective function could be either cost minimization or cost-effectiveness curve development using the scatter search and NSGA-II algorithms, respectively. Unlike the single-objective optimization algorithms, there are sets of solutions in the multi-objective algorithm (Ferdowsi et al. 2021). The present study adopted NSGA-II module in SUSTAIN to evaluate the costs and performance of the designed scenarios, which helps find near-optimal solutions. NSGA-II is an efficient multi-objective optimization algorithm that exploits the elitism approach (Yusoff et al. 2011). The NSGA-II solutions are arranged based on the degree of dominance over the other solutions. Finally, the non-dominated solutions of the Pareto front consist of solutions that do not dominate each other (Deb et al. 2000). However, the selection of solutions from the Pareto front would depend on the decision maker's preferences.

**Table 3** Decision variables and costs of the defined LID methods (USEPA 2009)

LID Type	Decision Variables	Cost Data			
		Linear Cost (USD/m)	Area Cost (USD/m <sup>2</sup> )	Volume Cost (USD /m <sup>3</sup> )	Constant Cost (USD)
Rain Barrel (RB)	Diameter (m)	0	0	654.1	0
	Height (m)				
	Number of Units				
Green Roof (GR)	Length (m)	0	187	63.3	0
	Weir Height (m)				
	Soil Depth (m)				
	Number of Units				
Bio-retention Cell (BC)	Length (m)	24.3	10.5	96.3	9.6
	Weir Height (m)				
	Soil Depth (m)				
	Number of Units				
Porous Pavement (PP)	Length (m)	34.3	38.4	50.8	0.2
	Weir Height (m)				
	Soil Depth (m)				
	Number of Units				
Vegetated Swale (VS)	Number of Units	41	0	0	0
Dry Pond (DP)	Length (m)	0	5.5	119.5	1852
	Soil Depth (m)				



The "cost-effectiveness analysis" option in SUSTAIN aims to identify cost-effective solutions based on the objectives (controlling the runoff volume or peak flow). This multi-objective problem can be formulated as follows (Lee et al. 2012):

$$\begin{aligned} & \text{Minimize } \sum_{i=1}^n \text{Cost}(\text{LID}_i) \\ & \text{Minimize EF} \end{aligned} \quad (3)$$

where  $\text{LID}_i$  is a set of LID decision variables in site  $i$ , while EF represents the evaluation factor (runoff volume in the present work). In general, six decision variables are involved in scenario optimization, including diameter, height, weir height, length, the number of LID methods, and soil depth. The SUSTAIN database was exploited to estimate the unit costs of each LID type. Table 3 reports the decision variables of each LID method along with the unit costs.

## 2.4 LID Scenarios

Selecting effective LID methods for a given region is complex due to various alternatives (Jia et al. 2015). In general, due to spatial limitations, decision-makers have limited alternatives in selecting feasible LIDs in high-density urban areas. According to technical reports for the study area, 56% of the region is covered by roofs, and controlling runoff generated on roofs is essential (Zistab Consulting Engineers 2015). Therefore, green roofs and rain barrels would be suitable for the runoff control of such surfaces and have been adopted in many research and operational projects (Raimondi and Becciu 2021, Ghodsi et al. 2021). The remaining 44% includes vehicle roads, sidewalks, and other urban spaces. Due to the space limitations in the study area, LID practices should not occupy large spaces, have satisfactory performance, and be cost-effective.

Hence, bio-retention cells and porous pavements would be effective in controlling runoff in such areas. Moreover, vegetated swales could be an affordable complementary to bio-retention cells and porous pavements to reduce and control stormwater runoff. Therefore, six scenarios of different combinations of the LID methods, including green roofs, rain barrels, bio-retention cells, porous pavements, vegetated swales, and dry ponds, were developed, as shown in Table 4. Figure 4 depicts the runoff control from the origin to the watershed outlet under the designed scenarios.

S1 included a combination of green roofs, bio-retention cells, and vegetated swales. S2 was the same as S1, except rain barrels replaced green roofs. S3 and S4 were the same as S1 and S2, except that porous pavements were used in place of bio-retention cells. S5 was a combination of all the aforementioned LID methods to evaluate their effects on cost and performance. S6 was the same as S5; as mentioned, S6 is a hypothetical scenario due to the lack of adequate space to implement dry ponds.

**Table 4** Designed LID scenarios

Scenario	LID Combinations
S1	GR + BC + VS
S2	RB + BC + VS
S3	GR + PP + VS
S4	RB + PP + VS
S5	GR + RB + BC + PP + VS
S6	GR + RB + BC + PP + VS + DP

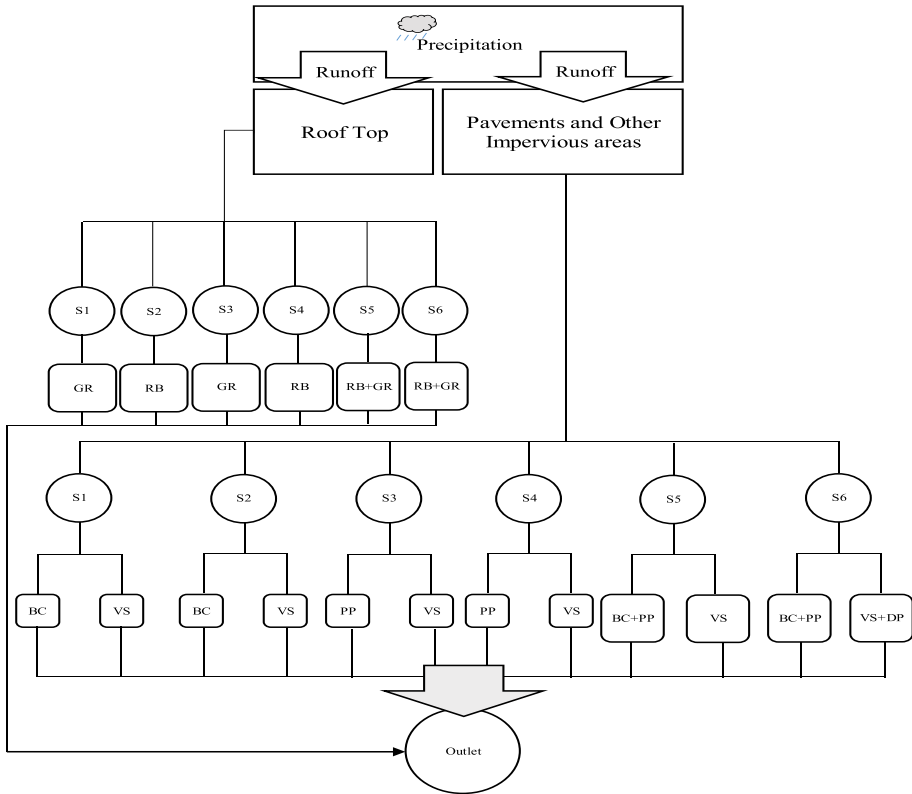


Fig. 4 Schematic of runoff control from the origin to the watershed outlet under the LID scenarios

## 2.5 Ranking of the Scenarios

### 2.5.1 Evaluation Criteria

Four evaluation criteria were employed, including runoff volume reduction, runoff peak flow reduction, the reduction of channels with insufficient capacities, and cost, as shown in Table 5.

### 2.5.2 Weighting of the Criteria

The analytical hierarchy process (AHP), the entropy method, and the integrated AHP-entropy method were adopted to weigh the criteria. AHP was developed by Saaty (1980) to support MCDM methods. It is based on the views of experts and decision-makers and increases their interaction in the decision-making process (Balali et al. 2014). It helps represent the subjective and objective aspects of a decision by reducing complexities in decision-making, converting them into a set of pairwise comparisons, and combining the results. AHP implements pairwise comparisons of  $n$  criteria in an  $n \times n$  matrix. The matrix represents the weight of each criterion relative to the other criteria. A pairwise comparison in AHP is typically completed by a number of experts. The product of the matrix is calculated using the geometric mean as:

**Table 5** Scenario evaluation criteria

Criterion	Description
Runoff volume reduction (C1)	The ability of LID methods to reduce runoff in the watershed (by comparing the post-LID and the pre-LID total runoff)
Runoff peak flow reduction (C2)	The ability of LID methods to reduce the runoff peak flow in the watershed (by comparing the pre-LID and post-LID peak flows)
Reduction of channels with insufficient capacities (C3)	The ratio of the length of the channels with insufficient capacities in the simulation to the total channel length (reflecting the effect of the LID scenario on stormwater system performance)
Cost (C4)	The total cost of the LID scenario

$$a'_{ij} = \left( \prod_{l=1}^k a_{ij} \right)^{1/k}, \quad 1 = 1, 2, \dots, k; i, j = 1, 2, \dots, n; i \neq j \tag{4}$$

where  $n$  is the number of criteria,  $a_{ij}$  represents the decision matrix elements, and  $k$  is the number of decision-makers. It is also required to normalize the decision matrix as:

$$W_i = \frac{a'_{ij}}{\sum_{i=1}^n a'_{ij}} \tag{5}$$

The consistency index is written as:

$$C.I = \frac{\lambda_{max} - m}{m - 1} \tag{6}$$

Shannon’s (1948) entropy method is a data-based weighting model that has been widely used. Its advantage over several subjective methods (e.g., AHP) is avoiding the interference of human factors with the index weights. The entropy method is based on measuring the distinction of indices. More scattering measured values suggest higher index distinction (Işık and Adalı 2017). The criterion weighting steps include:

Step 1: Normalizing the decision matrix as:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \tag{7}$$

Step 2: Calculating the entropy index as:

$$e_j = -h \sum_{i=1}^m r_{ij} \ln r_{ij} \quad j = 1, 2, \dots, n \tag{8}$$

where  $h = \frac{1}{\ln(m)}$ , and  $m$  is the decision alternatives.

Step 3: Weighting the criteria as:

$$w_j = \frac{1 - e_j}{\sum_{i=1}^n 1 - e_j}, \quad j = 1, 2, \dots, n \tag{9}$$

To simultaneously exploit the advantages of subjective and objective methods in weighting, Eq. (10) can be employed. Since they are different in nature, the AHP and entropy methods can be combined to exploit their advantages at the same time (Al-Aomar 2010; Nyimbili and Erden 2020).

$$W = \frac{w_j^{AHP} \times w_j^e}{\sum_{i=1}^n w_i^{AHP} \times w_i^e} \tag{10}$$

where  $w_j^{AHP}$  stands for the AHP-based weights, whereas  $w_j^e$  denotes the entropy method-based weights. It should be noted that  $W$  represents the final weight obtained from the integrated AHP-entropy weighting method.

### 2.5.3 TOPSIS

TOPSIS is an MDCM method introduced by Hwang and Yoon (1981). It minimizes the Euclidian distance of the decision alternatives from the ideal state and maximizes their Euclidian distance from the non-ideal state (Jayasooriya et al. 2018). It has been widely employed in decision-making problems in light of its simple, comprehensible concept, optimal calculations, and ability to detect the relative performance of the alternatives. The TOPSIS decision-making process includes the following steps:

Step I: Constructing the decision matrix

The general form of a decision matrix is shown as:

$$N = \begin{matrix} & R_1 & R_2 & \dots & R_j \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_p \end{matrix} & \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1j} \\ r_{21} & r_{22} & \dots & r_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ r_{i1} & r_{i2} & \dots & r_{ij} \end{bmatrix} \end{matrix} \tag{11}$$

where elements  $R_1, R_2, \dots, R_q$  represent the criteria,  $A_1, A_2, \dots, A_p$  stand for the decision alternatives, and  $r_{ij}$  denotes the elements of the decision matrix.

Step II: Calculating the normalized decision matrix

The normalized decision matrix is calculated as:

$$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^m r_{ij}^2}} \tag{12}$$

Step III: Finding the weighted normalized matrix

The weighted normalized matrix is obtained by multiplying the weights by each element of each column in the normalized decision matrix:

$$V = N \times W_{n \times n} \tag{13}$$

Step IV: Finding the ideal and non-ideal solutions

Ideal solution  $I^+$  and non-ideal solution  $I^-$  are defined as  $I^- = \{V_1^-, V_2^-, \dots, V_j^-\}$  and  $I^+ = \{V_1^+, V_2^+, \dots, V_j^+\}$ , where

$$\begin{aligned} V_m^- &= \{\min(V_{ij}) \text{ if } m \in J\} \\ V_m^+ &= \{\max(V_{ij}) \text{ if } m \in J'\} \end{aligned} \tag{14}$$

where  $J'$  and  $J$  correspond to non- beneficial and beneficial criteria, respectively.

Step V: Calculating the distance of each criterion from  $I^+$  and  $I^-$

$$S_i^+ = \sqrt{\sum_{j=1}^n (V_j^+ - V_{ij})^2}; i = 1, 2, \dots, m \tag{15}$$

$$S_i^- = \sqrt{\sum_{j=1}^n (V_j^- - V_{ij})^2}; i = 1, 2, \dots, m \tag{16}$$

where  $i$  denotes the alternative number, while  $m$  stands for the criterion number.

Step VI: Determining the relative closeness of  $C_1$  to the ideal solution, which is calculated as Eq. (17):

$$C_1 = \frac{S_1^-}{(S_1^+ + S_1^-)}, 0 \leq C_1 \leq 1 \tag{17}$$

Step VII: Ranking the alternatives

The alternatives are ranked based on  $C_1$ ; a larger  $C_1$  value represents higher performance.

### 2.5.4 COPRAS

To more accurately rank the scenarios, the COPRAS method was also employed apart from TOPSIS. The COPRAS method was developed by Zavadskas and Kaklauskas (1996). The COPRAS ranking steps include:

Step A: Normalizing the decision matrix

The decision matrix is normalized as:

$$r_{ij}^* = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}} \tag{18}$$

where  $r_{ij}^*$  denotes the normalized value of alternative  $i$  from alternative  $j$ .

Step B: Calculating the weighted normalized matrix

The weighted normalized matrix is obtained as:

$$\hat{r}_{ij} = r_{ij}^* \cdot w_j; i = 1, \dots, m, j = 1, \dots, n \tag{19}$$

where  $w_j$  denotes the weight of each criterion.

Step C: Finding the maximizing and minimizing indices

Indices  $S_{+i}$  and  $S_{-i}$  are calculated based on whether the criteria are beneficial:

$$S_{+i} = \sum_{j=1}^g \hat{r}_{ij}; i = 1, \dots, m \tag{20}$$

$$S_{-i} = \sum_{j=g+1}^n \hat{r}_{ij}; \quad i = 1, \dots, m \tag{21}$$

where  $g$  is the number of useful criteria, while  $n-g$  is the number of non-beneficial criteria.

Step D: The relative importance  $Q_i$  can be calculated as:

$$Q_i = S_{+i} + \frac{S_{-min} \sum_{i=1}^m S_{-i}}{S_{-i} \sum_{i=1}^m (S_{-min}/S_{-i})}, \quad (i = 1, 2, \dots, m) \tag{22}$$

The alternative with a higher  $Q_i$  value would have a higher rank.

### 3 Results and Discussion

#### 3.1 Rainfall-runoff Simulation

The hydrograph of a six-hour rainfall event with a return period of ten years in the study area was simulated using SWMM, as shown in Fig. 5. As can be seen, 30-min time steps were implemented in the simulation. The peak hydrograph flow rate was found to be 6.76 m<sup>3</sup>/s. The accumulated precipitation of this six-hour event was 25.8 mm. Finally, the SWMM-generated time-series data was imported to the SUSTAIN model through the land module to simulate the performance of the LID scenarios under the rainfall event.

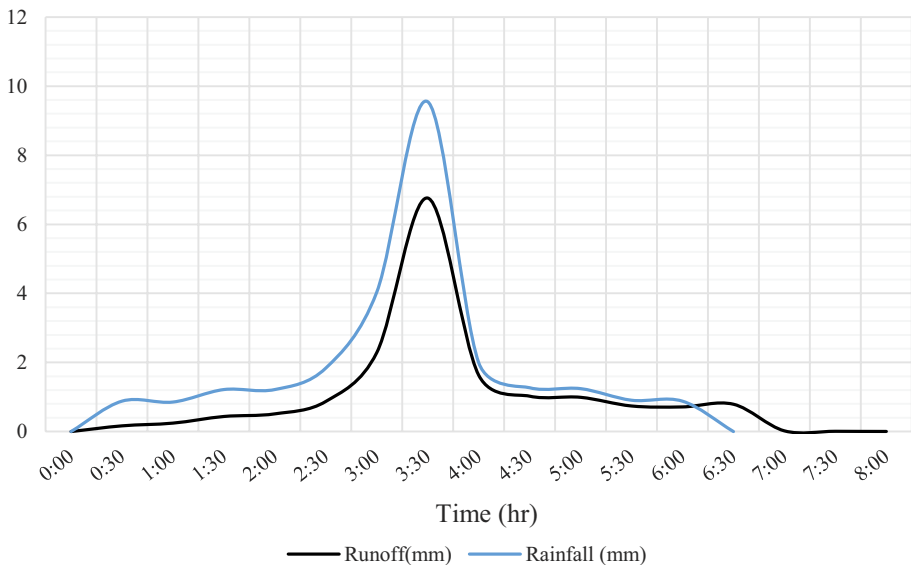


Fig. 5 Simulated hydrograph of the study area in SWMM under the rainfall with a 10-year return period

### 3.2 Cost-effectiveness Evaluation and Optimization of LID Scenarios

The land use, watershed, SWMM rainfall time-series data, and other required data were imported to the SUSTAIN model, implementing the scenarios based on the design parameters and LID. The SUSTAIN model was executed, performing NSGA-II optimization to plot the cost-effectiveness curve of each scenario. The Pareto front would represent the dominant optimal solutions. Figure 6 shows the cost-effectiveness curves obtained from the SUSTAIN model.

The horizontal and vertical axes represent the cost (USD) and runoff volume reduction (%), respectively. The gray spots represent the feasible solutions, while the orange ones stand for the non-dominated solutions of each scenario. The superior solution is selected from the feasible solutions, depending on a number of factors, such as flood reduction, budget, and decision-makers. The criterion for the superior solution (shown in green) is the knee point of the Pareto front; the effectiveness/cost ratio reduces above the superior solution, where the runoff volume slightly declines, despite a higher cost (Jia et al. 2015).

The superior solutions of the Pareto fronts reduced the runoff volume by 59.4%, 15%, 69%, 20.8%, 43.4%, and 44.3% under S1-S6, respectively. Moreover, the cost was estimated to be 196.63, 3.25, 234.66, 7.68, 135.41, and 136.32 million USD under scenarios S1 to S6, respectively. Table 6 illustrates the selected optimal solutions for each scenario.

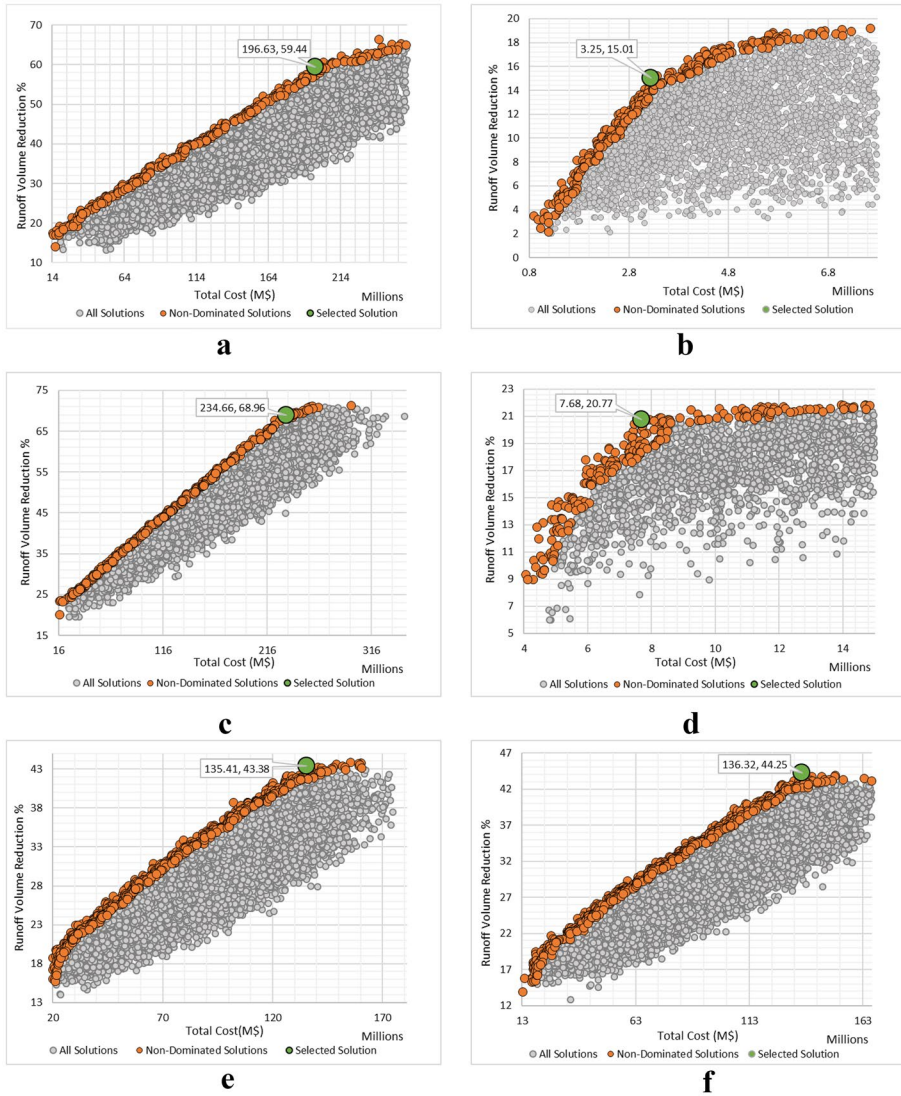
According to Table 6, S3 and S2 had the highest and lowest costs, respectively. Moreover, S3 and S2 had the highest and lowest performance in runoff volume reduction. The peak flow was diminished by 51.3%, 4.30%, 61.3%, 19.2%, 38.2%, and 44.2% in S1-S6, respectively. Likewise, S3 had the highest performance, whereas S2 had the lowest performance. In addition, S1-S6 occupied 35%, 0.8%, 42.1%, 1.4%, 23.2%, and 23% of the total area of the watershed. The lowest and highest area occupied by LID scenarios was obtained to be 21160 and 1147329 m<sup>2</sup> in S2 and S3, respectively. As is clear, the area of LID scenarios has a direct relationship to the total implementation costs. Figure 7 plots the cost distributions of the LID scenarios.

According to Fig. 7, green roofs accounted for over 98% of the total LID cost in S1, while only 2% of the cost (196 million USD) arose from bio-retention cells and vegetated swales. S2 included bio-retention cells, rain barrels, and vegetated swales and was found to be the most affordable scenario, with a total cost of 3.25 million USD. S3 had the highest cost among the scenarios, and green roofs accounted for 92.3% of the total LID cost. Porous pavements and vegetated swales accounted for 7.63% and 0.03% of the total cost in S3. For S4, porous pavements, rain barrels, and vegetated swales consumed 78.15%, 20.51%, and 1.34% of the total cost, respectively. Green roofs accounted for 85.55% and 89.7% of the total costs in S5 and S6, representing the costliest LID methods. Porous pavements, rain barrels, bio-retention cells, and vegetated swales were the second-, third-, fourth-, and fifth-costliest LID methods. The dry ponds accounted for only 0.05% of the total cost in S6.

### 3.3 Contributions of the Optimal Scenarios to the Urban Stormwater System

The contributions of the selected optimal Pareto solutions on the performance of the sub-channels in the study area were evaluated. Once the knee point of the Pareto front had been selected in S1-S6, the SUSTAIN-derived data, including the optimal numbers and sizes of the LID methods, were imported to the SWMM to evaluate the performance of the urban



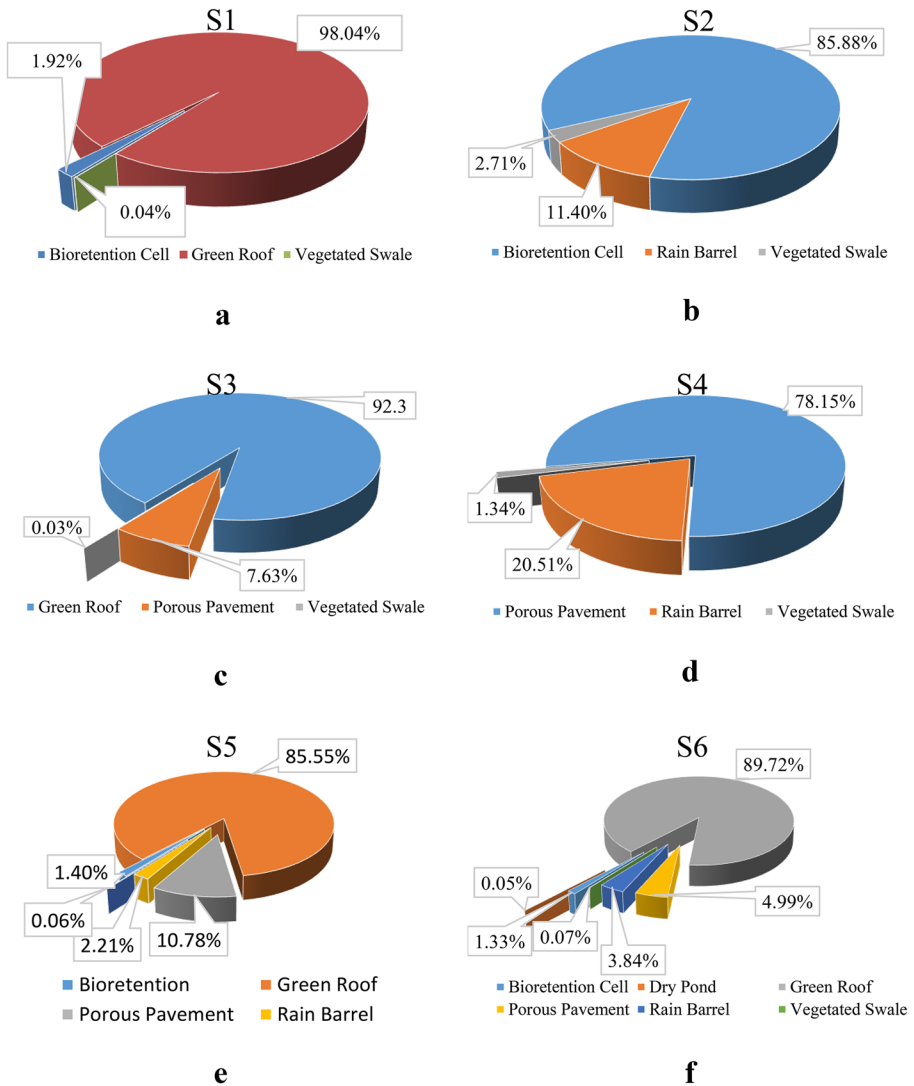


**Fig. 6** Pareto fronts obtained from SUSTAIN for **a** S1, **b** S2, **c** S3, **d** S4, **e** S5, and **f** S6

stormwater system. These data included the optimal number of each LID method, optimal soil depth, weir height, and LID dimensions (i.e., length, width, height, and/or diameter). After importing the LID data and defining scenarios in SWMM, the model was re-executed under the rainfall with a 10-year return period. Then, the performance of the stormwater system was evaluated by comparing the channel capacities in the presence and absence of the LID methods. In the absence of LID scenarios (i.e., the post-development situation) under the rainfall with a return period of ten years, 24% of the channel length (11483 m of 46582 m) had a capacity shortage. Moreover, 62 of the 325 nodes in the system flooded. However, the LID scenarios reduced the channel capacity shortage and flooded nodes, as shown in Table 7.

**Table 6** Cost and effectiveness data of the optimal Pareto solutions

Scenario	LID	Number of Units	Total Area Per LID (m <sup>2</sup> )	LID Coverage Percentage	Cost Per LID (million USD)	Total Cost (million USD)	Peak Flow Rate Reduction (%)	Runoff Volume Reduction (%)
S1	GR	11110	924596	35	192.1584	196	51.3	59.44
	BR	410	26301		0.0784			
	VS	41	457		3.7632			
S2	RB	2653	519	0.8	0.3705	3.25	4.3	15
	BR	289	18802		2.7911			
	VS	165	1839		0.0880			
S3	G.R	12437	1028728	42.1	216.5358	234.6	61.3	68.96
	PP	5478	117888		17.8999			
	V.S	64	713		0.0938			
S4	RB	5751	1698	1.4	6.0019	7.68	19.2	20.77
	P.P	2462	35794		1.5751			
	VS	198	2207		0.1029			
S5	GR	6318	537810	23.2	115.8347	135.4	38.2	43.38
	RB	9681	2793		2.9923			
	BR	151	9149		1.8956			
S6	PP	2807	75768		14.5961			
	VS	486	5418		0.0954			
	GR	6698	535262	23	122.2883	136.3	40.6	44.25
	RB	13480	3593		5.2339			
	BR	143	9029		1.8127			
	PP	1750	73418		6.8013			
	VS	300	5108		0.0954			
	DP	1	297		0.0681			



**Fig. 7** Cost distributions in the LID scenarios: **a** S1, **b** S2, **c** S3, **d** S4, **e** S5, and **f** S6

According to Table 7, S1-S6 reduced the channel capacity shortage by 52.8%, 5.1%, 58.4%, 26.4%, 45.6%, and 46.9%, respectively. Furthermore, the number of flooded nodes declined by 46.7%, 11.3%, 50%, 27.4%, 38.7%, and 41.9%, respectively.

Figure 8 illustrates the urban stormwater system under S0 (non-LID scenario), S1 to S6 at 4:00 when the system experienced the highest overload and maximum rainfall and runoff. Subcatchment runoff, link flows, and flooded nodes due to a disruption or insufficient capacity have shown in the SWMM output map.

According to Fig. 8, it can be inferred that S2 and S4 reduced flooding and improved system performance. The colored lines represent the link flow rate, squares stand for

**Table 7** Contributions of the LID scenarios to the performance of the urban stormwater system

Scenario	Channel Length with a Capacity Shortage (m)	Number of Flooded Nodes
Non-LID	11483	62
S1	5420	33
S2	10897	55
S3	4777	31
S4	8451	45
S5	6247	38
S6	6098	36

subcatchment runoff, and the circles are representative of flooding or link flows due to a channel capacity shortage and disturbed system. The flow amount across the system during the day can be estimated based on the Legend guide.

### 3.4 Ranking of the LID Scenarios

The criteria were weighted through AHP, entropy, and integrated AHP-entropy method. A total of twenty experts provided pairwise comparison matrices in AHP. Table 8 provides the criterion weights in the three weighting methodologies.

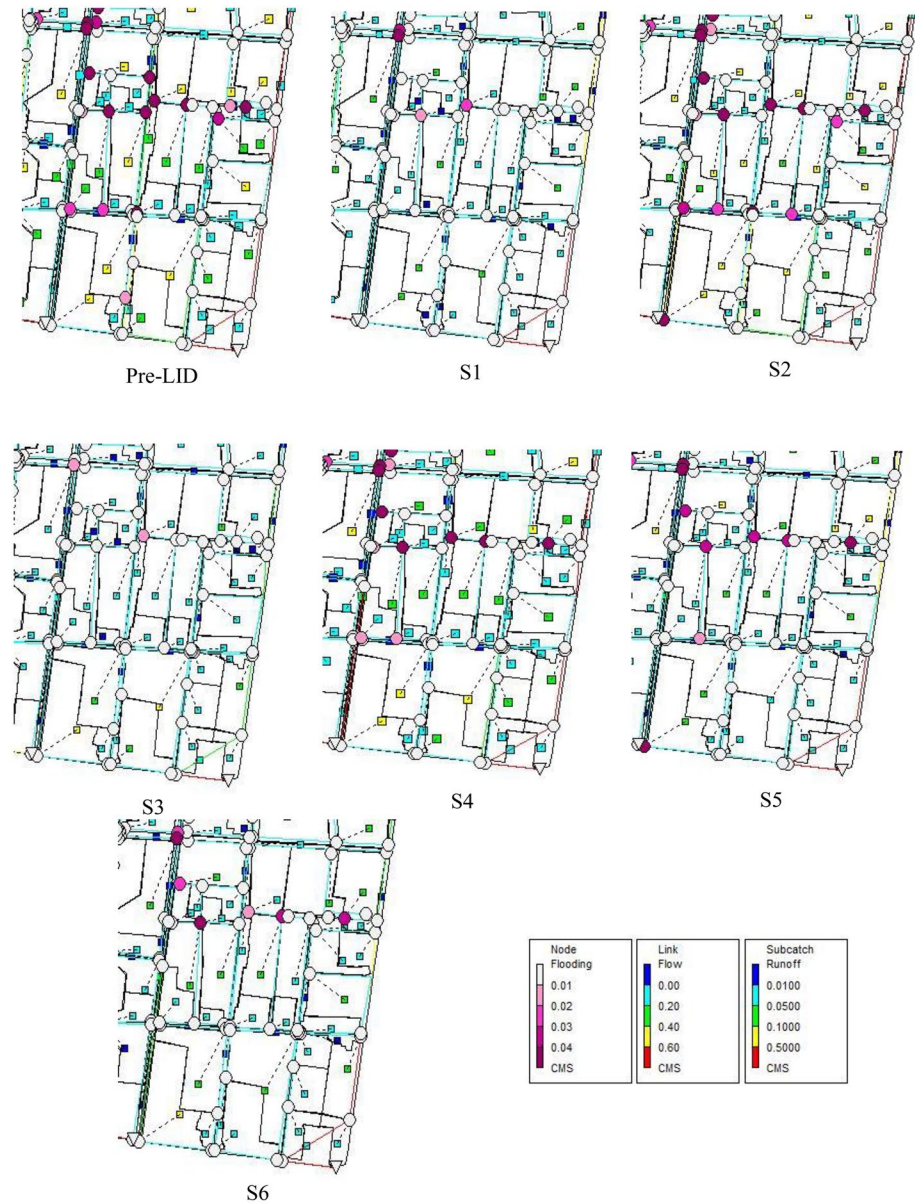
As can be seen, C4 had the highest weights under all three weighting methods. On the other hand, C1 had the lowest weight. The scenarios were ranked using TOPSIS and COPRAS for all three weighting methods, as shown in Table 9.

According to Table 9, S4 ranked first under TOPSIS for all three weighting methods. S2, S6, S5, S1, and S3 had the second, third, fourth, fifth, and sixth ranks under the weighting methods. Despite having the highest runoff volume reduction and improving the stormwater system performance, S3 was very costly due to green roofs used in large areas and had the highest cost criterion weight. Thus, S3 had the sixth rank among the six scenarios. S4 was found to be the most optimal scenario under TOPSIS; it had a cost of 7.68 million USD, a runoff volume reduction of 20.77%, a peak flow reduction of 19.2%, and a channel capacity shortage reduction of 26.4% under a six-hour rainfall event with a return period of ten years.

On the other hand, COPRAS introduced S2 as the most optimal scenario with a cost of 3.25 million USD (the most affordable scenario), a runoff volume reduction of 15%, a peak flow reduction of 4.3%, and a channel capacity shortage reduction of 5.1%. Moreover, S4, S3, S1, S6, and S5 had the second, third, fourth, fifth, and sixth ranks under COPRAS. As can be seen, almost the same ranks were obtained under different weighting methods since the weights had high consistency, and the ranking results were robust.

In this study, three weighting methods were used, and the AHP-Entropy method seems to be more reliable considering that it combines both subjective and objective characteristics.

Both TOPSIS and COPRAS methods differ in nature and relationships, yielding different results. Normalizing the decision matrix, determining the ideal solution (or maximizing the indices in COPRAS), and finding the relative closeness (relative importance) are factors that cause differences in ranking. Nevertheless, both methods chose S4 and S2 as the ideal two scenarios. COPRAS was more sensitive to the cost factor and selected the most economical scenario, while TOPSIS referred to better performance in addition to implementation costs.



**Fig. 8** Urban stormwater system under pre-LID and Scenarios one to six

The selection of the superior scenario between S2 and S4 would depend on various factors, including decision-makers and available financial resources. However, S4 seems to outperform S2 as it has higher suitability at the high construction density in the study area; it uses porous pavements in place of bio-retention cells, and such pavements occupy almost no additional space and do not disturb passage.

**Table 8** Criterion weights in AHP, entropy method, and integrated AHP-entropy method

Weighting Method	Criterion Weight			
	C1	C2	C3	C4
AHP	0.086	0.131	0.332	0.451
Entropy	0.142	0.221	0.178	0.459
AHP-Entropy	0.036	0.09	0.168	0.706

**Table 9** Scenario ranks under TOPSIS and COPRAS and different weighting methods

Method	Rank					
	1	2	3	4	5	6
TOPSIS – AHP	S4	S2	S6	S5	S1	S3
TOPSIS – Entropy	S4	S2	S6	S5	S1	S3
TOPSIS – AHP-Entropy	S4	S2	S6	S5	S1	S3
COPRAS – AHP	S2	S4	S3	S1	S6	S5
COPRAS – Entropy	S2	S4	S3	S1	S6	S5
COPRAS – AHP-Entropy	S2	S4	S3	S1	S6	S5

## 4 Conclusion

This study proposed a framework for managing urban stormwater systems using coupled usage of LID modeling, multi-objective optimization, and decision-making tools and techniques. The proposed framework was implemented in region 1 of District 11 of the Tehran Municipality. Six scenarios were developed, including different combinations of LID types such as Green Roofs, Rain Barrels, Bioretention Cells, Porous Pavements, Vegetated Swales, and Dry Ponds. The optimal solutions of each scenario were then ranked based on technical and economic criteria using MCDM techniques.

SWMM was used to simulate the rainfall-runoff process through the study area. The simulated hydrograph was then imported to SUSTAIN model to find optimal solutions through NSGA-II optimization for each LID scenario. Then, the selected solutions were imported to SWMM in conjunction with the current drainage network to evaluate the performance of the urban stormwater system under the scenarios relative to the pre and post-development situation. Four evaluation criteria were applied, including runoff volume reduction, peak flow, channel capacity shortage reduction, and LID scenario cost, to identify the ideal scenario. TOPSIS and COPRAS were employed to rank the scenarios under the AHP, entropy, and integrated AHP-entropy weighting method. Based on TOPSIS, S4 with a combination of rain barrels, porous pavements, and vegetated swales was selected as the ideal scenario. On the other hand, COPRAS demonstrated that S2 with a combination of rain barrels, bio-retention cells, and vegetated swales would be the preferable scenario.

Despite the higher performance, the other scenarios could not have high ranks since they were much costlier than S2 and S4; the cost criterion had a high weight, and the optimal solution would be selected from more affordable alternatives. The selection of the superior scenario between S2 and S4 depends on decision-makers and financial constraints; however, S4 has higher suitability for the study area as it has relatively higher performance and occupies lower space.

The results could be helpful in comprehensively evaluating urban stormwater systems and developing cost-effective LID solutions. The present work could be helpful to urban decision-makers and managers in the design, optimization, cost estimation, performance evaluation, and selection of the most feasible LID scenarios. However, future works are recommended to use a broader range of criteria (e.g., runoff quality and urban landscape) to rank scenarios. It is suggested that SUSTAIN be integrated with other simulation models, such as ASSA and MIKE URBAN. Also, to achieve more reliable results it is recommended to calibrate and validate the model if sufficient data is available.

**Authors Contributions Amir Hossein Nazari:** Investigation, Methodology, Software, Formal analysis, Writing—original draft. **Abbas Roozbahani:** Conceptualization, Supervision, Validation, Writing—Review & Editing. **Seied Mehdy Hashemy Shahdany:** Supervision, Validation, Writing—Review & Editing.

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## Declarations

**Ethical Approval** Not applicable.

**Consent to Participate** Not applicable.

**Consent to Publish** Not applicable.

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## References

- Al-Aomar R (2010) A combined ahp-entropy method for deriving subjective and objective criteria weights. *Int J Ind Eng Theory Appl Pract* 17:12–24
- Alves A, Gersonius B, Sanchez A, Vojinovic Z, Kapelan Z (2018) Multi-criteria approach for selection of green and grey infrastructure to reduce flood risk and increase co-benefits. *Water Resour Manag* 32:2505–2522
- Baek S, Ligaray M, Pyo J, Park JP, Kang JH, Pachepsky Y, Chun JA, Cho KH (2020) A novel water quality module of the SWMM model for assessing low impact development (LID) in urban watersheds. *J Hydrol*. <https://doi.org/10.1016/j.jhydrol.2020.124886>
- Balali V, Zahraie B, Roozbahani A (2014) A comparison of AHP and PROMETHEE family decision making methods for selection of building structural system. *Am J Civ Eng Archit* 2:149–159
- Barbosa AE, Fernandes JN, David LM (2012) Key issues for sustainable urban stormwater management. *Water Res* 46:6787–6798
- Bell CD, Mcmillan SK, Clinton SM, Jefferson AJ (2016) Hydrologic response to stormwater control measures in urban watersheds. *J Hydrol* 541:1488–1500
- Chen CF, Sheng MY, Chang CL, Kang SF, Lin JY (2014) Application of the SUSTAIN model to a watershed-scale case for water quality management. *Water* 6(12):3575–3589
- Chen J, Theller L, Gitau MW, Engel BA, Harbor JM (2017) Urbanization impacts on surface runoff of the contiguous united states. *J Environ Manag* 187:470–481



- De Paola F, Giugni M, Pugliese F, Romano P (2018) Optimal design of LIDs in urban stormwater systems using a harmony-search decision support system. *Water Resour Manag* 32:4933–4951
- Deb K, Agrawal S, Pratap A, Meyarivan T (2000) A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: *Parallel problem solving from nature PPSN VI*. PPSN 2000. Lecture notes in computer science, vol 1917. Springer, Berlin, Heidelberg. [https://doi.org/10.1007/3-540-45356-3\\_83](https://doi.org/10.1007/3-540-45356-3_83)
- Dietz ME (2007) Low impact development practices: a review of current research and recommendations for future directions. *Wat Air Soil Poll* 186:351–363
- Du J, Qian L, Rui H, Zuo T, Zheng D, Xu Y, Xu CY (2012) Assessing the effects of urbanization on annual runoff and flood events using an integrated hydrological modeling system for Qinghai river basin. *China J Hydrol* 464–465:127–139
- Eckart K, McPhee Z, Bolisetti T (2018) Multi-objective optimization of low impact development stormwater controls. *J Hydrol* 562:564–576
- Ferdowsi A, Valikhan-Anaraki M, Mousavi SF, Farzin S, Mirjalili S (2021) Developing a model for multi-objective optimization of open channels and labyrinth weirs: Theory and application in Isfahan Irrigation Networks. *Flow Meas Instrum* 80:101971
- Ferrans P, Temprano J (2022) Continuous quantity and quality modeling for assessing the effect of SUDS: Application on a conceptual urban drainage basin. *Environ Process* 9(58)
- Ghods SH, Zhu Z, Gheith H et al (2021) Modeling the effectiveness of rain barrels, cisterns, and downspout disconnections for reducing combined sewer overflows in a City-scale watershed. *Water Resour Manag* 35:2895–2908
- Guan M, Sillanpää N, Koivusalo H (2015) Modelling and assessment of hydrological changes in a developing urban catchment. *Hydrol Process* 29:2880–2894
- Hashemi M, Mahjouri N (2022) Global sensitivity analysis-based design of low impact development practices for urban runoff management under uncertainty. *Water Resour Manag* 36:2953–2972
- Hwang CL, Yoon KP (1981) Multiple attribute decision making: Methods and applications. *Lect Notes Econ Math Syst* 186. Springer-Verlag, New York
- Işik AT, Adalı EA (2017) The Decision-making approach based on the combination of Entropy and ROV methods for the apple selection problem. *Eur J Interdiscip Stud* 3(3):80–86
- Jayasooriya VM, Muthukumaran S, Ng AWM, Perera BJC (2018) Multi criteria decision making in selecting stormwater management green infrastructure for industrial areas part 2: a case study with TOPSIS. *Water Resour Manag* 32:4297–4312
- Jha AK, Bloch R, Lamond J (2012) *Cities and Flooding: A guide to integrated urban flood risk management for the 21st century*. The World Bank, Washington
- Jia H, Yao H, Tang Y, Yu SL, Field R, Tafuri AN (2015) LID-BMPs planning for urban runoff control and the case study in china. *J Environ Manag* 149:65–76
- Kim JH, Kim HY, Demarie F (2017) Facilitators and barriers of applying low impact development practices in urban development. *Water Resour Manag* 31:3795–3808
- Kong F, Ban Y, Yin H, James P, Dronova I (2017) Modeling stormwater management at the city district level in response to changes in land use and low impact development. *Environ Model Softw* 95:132–142
- Lee JG, Selvakumar A, Alvi K, Riverson J, Zhen JX, Shoemaker L, LAI FH, (2012) A watershed-scale design optimization model for stormwater best management practices. *Environ Model Softw* 37:6–18
- Li F, Duan HF, Yan H et al (2016) Multi-objective optimal design of detention tanks in the urban stormwater drainage system: LID implementation and analysis. *Water Resour Manag* 30:4635–4648
- Li N, Qin C, Du P (2018) Optimization of China sponge city design: the case of lincang technology innovation park. *Water*. <https://doi.org/10.3390/w10091189>
- Liu T, Lawluy Y, Shi Y, Yap PS (2021) Low impact development (LID) practices: a review on recent developments, challenges and prospects. *Wat Air Soil Poll*. <https://doi.org/10.1007/s11270-021-05262-5>
- Lu W, Qin X (2019) An integrated fuzzy simulation-optimization model for supporting low impact development design. *Water Resour Manag* 33:4351–4365. <https://doi.org/10.1007/s11269-019-02377-7>
- Macro K, Matott LS, Rabideau A, Ghods SH, Zhu Z (2019) Ostrich-SWMM: a new multi-objective optimization tool for green infrastructure planning with SWMM. *Environ Model Softw* 113:42–47
- Mao X, Jia H, Yu SL (2017) Assessing the ecological benefits of aggregate lid-bmps through modelling. *Ecol Modell* 353:139–149
- Nyimbili PK, Erden T (2020) A hybrid approach integrating entropy-ahp and gis or suitability assessment of urban emergency facilities. *ISPRS Int J Geoinf* 9(7):419


- Platz M, Simon M, Tryby M (2020) Testing of the storm water management model low impact development modules. *J Am Water Resour Assoc* 56:283–296
- Pugliese F, Gerundo C, De Paola F et al (2022) Enhancing the urban resilience to flood risk through a decision support tool for the LID-BMPs optimal design. *Water Resour Manag* 36:5633–5654
- Raei E, Alizadeh MR, Nikoo MR, Adamowski J (2019) Multi-objective decision-making for green infrastructure planning (LID-BMPs) in urban storm water management under uncertainty. *J Hydrol* 579:124091
- Raimondi A, Becciu G (2021) Performance of green roofs for rainwater control. *Water Resour Manag* 35:99–111
- Rezazadeh Helmi N, Verbeiren B, Mijic A, Van Griensven A, Bauwens W (2019) Developing a modeling tool to allocate low impact development practices in a cost-optimized method. *J Hydrol* 573:98–108
- Roobzahani A, Behzadi P, Massah bavani A, (2020) Analysis of performance criteria and sustainability index in urban stormwater systems under the impacts of climate change. *J Clean Prod* 271:122727
- Rossmann LA (2015) Storm water management model user's manual version 5.1. EPA- 600/R-14/413b, National Risk Management Research Laboratory, United States Environmental Protection Agency, Cincinnati, Ohio
- Saaty TL (1980) *The analytic hierarcic process*. McGraw Hill, New York
- Schubert JE, Burns MJ, Fletcher TD, Sanders BF (2017) A framework for the case-specific assessment of green infrastructure in mitigating urban flood hazards. *Adv Water Resour* 108:55–68
- Shannon C (1948) A mathematical theory of communication. *Bell Syst Tech J* 27:379–423
- Shariat R, Roobzahani A, Ebrahimi A (2019) Risk analysis of urban stormwater infrastructure systems using fuzzy spatial multi-criteria decision making. *Sci Total Environ* 647:1468–1477
- Sheikh V, Izanloo R (2021) Assessment of low impact development stormwater management alternatives in the city of Bojnord, Iran. *Urban Water J* 18:449–464
- Simonovic SP (2012) *Floods in a changing climate: risk management*. Cambridge University Press, New York
- Song JY, Chung ES (2017) A multi-criteria decision analysis system for prioritizing sites and types of low impact development practices: case of Korea. *Water* 9(4)
- Sundermann L, Schelske O, Hausmann P (2014) *Mind the risk - A global ranking of cities under threat from natural disasters*. Zurich, Switzerland: Swiss Reinsurance Company
- Taghizadeh S, Khani S, Rajaei T (2021) Hybrid SWMM and particle swarm optimization model for urban runoff water quality control by using green infrastructures (LID-BMPs). *Urban for Urban Green* 60:127032
- Tansar H, Duan HF, Mark O (2022) Catchment-scale and local-scale based evaluation of LID effectiveness on urban drainage system performance. *Water Resour Manag* 36:507–526
- Tingsanchali T (2012) Urban flood disaster management. *Procedia Eng* 32:25–37
- U.S Environmental Protection Agency (2009) *SUSTAIN - A framework for placement of best management practices urban watersheds to protect water quality*. Tetra Tech, Fairfax, Virginia
- Valtanen M, Sillanpää N, Setälä H (2014) Effects of land use intensity on stormwater runoff and its temporal occurrence in cold climates. *Hydrol Process* 28:2639–2650
- Van Room M (2007) Water localisation and reclamation: steps towards low impact urban design and development. *J Environ Manag* 83:437–447
- Yang G, Bowling LC, Cherkauer KA, Pijanowski BC (2011) The impact of urban development on hydrologic regime from catchment to basin scales. *Landsc Urban Plan* 103:237–247
- Yao L, Chen L, Wei W (2016) Assessing the effectiveness of imperviousness on stormwater runoff in micro urban catchments by model simulation. *Hydrol Process* 30:1836–1848
- Yin D, Evans B, Wang Q, Chen Z, Jia H, Chen AS, Fu G, Ahmad S, Leng L (2020) Integrated 1D and 2D model for better assessing runoff quantity control of low impact development facilities on community scale. *Sci Total Environ* 720:137630
- You L, Xu T, Mao X, Jia H (2019) Site-scale LID-BMPs planning and optimization in residential areas. *J Sustain Water Built Environ* 5(05018004):1
- Yusoff Y, Ngadiman MS, Zain AM (2011) Overview of NSGA-II for optimizing machining process parameters. *Procedia Eng* 15:3978–3983
- Zavadskas EK, Kaklauskas A (1996) Determination of an efficient contractor by using the new method of multi-criteria assessment. In: Langford, DA and Retik A (eds), *International Symposium for the Organization and Management of Construction. Shaping theory and practice*. Vol. 2: *Managing the Construction project and managing risk*. CIB W 65; London, Weinheim, New York, Tokyo, Melbourne, Madras. London: E and FN SPON, pp. 91–104.

Zhang Z, Hu W, Wang W, Zhou J, Liu D, Qi X, Zhao X (2022) The hydrological effect and uncertainty assessment by runoff indicators based on SWMM for various lid facilities. *J Hydrol* 613:128418. <https://doi.org/10.1016/j.jhydrol.2022.128418>

Zistab Consulting Engineers (2015) A study on operationalizing comprehensive surface waters plan and preparing river streams and channels improvement schemes for the District 11 of the City of Tehran. Basic Studies Report. District 11 of Tehran Municipality, Tehran, Iran (in Farsi)

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