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# Comprehensive Optimization Framework for Low Impact Development Facility Layout Design with Cost−Benefit Analysis: A Case Study in Shenzhen City, China

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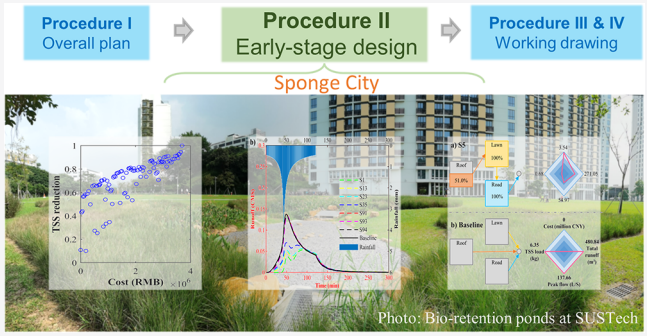
**ABSTRACT:** Sustainable storm water management benefits a lot from low impact development (LID). The early-stage design of LID layout is critical for LID practices. However, the technology gaps still exist for an accurate, flexible, and systematic solution of optimal design. Literature works usually only consider the size and number of LID facilities in a given scenario or even totally empirical, which lacks integration of facility selection, connection, and size with multiple management objectives together. Therefore, this study proposed a generic and comprehensive framework for LID layout design with cost−benefit analysis. Powered by the computer coding scheme for the LID layout and a hybrid optimization algorithm, the framework was successfully verified in Sponge City of Shenzhen, China. The optimization results of genetic algorithm proved the stability of the novel coding scheme for LID layout. The best and worst scenarios are selected from the Pareto front through the entropy weight method. The variable cost weight method revealed the sensitivity from the cost preference of the decision maker. High construction costs and environmental effectiveness can be scientifically balanced in the procedure of early-stage design. The proposed design framework is expected to be widely verified and applied in storm water management practices around the world.




**KEYWORDS:** *cost−benefit analysis, layout design, LID, multi-objective optimization, Sponge City, SWMM*

## 1. INTRODUCTION

To address the urban stream syndrome, urban storm water management practices, e.g., the best management practice, low impact development, and Sponge City, are gaining more attention around the world.[1] Those practices are supported by green infrastructures, which are sustainable but cost more compared with gray infrastructures.[2] The optimal design of spatial allocation for diverse LID facilities is paramount but challenged to some extent. It should be critically considered in the planning process, and the scientific advances made this consideration feasible.[3,4]

Generally, the optimal design of an LID layout is intended to maximize the benefits in terms of storm water quantity and quality control and ecological/social impacts and minimize the cost. The key parameters to be considered include at least the location, connection, size, and type of LID facilities.[5] In practice, an LID-oriented drainage design can be divided into four procedures from a large scale (e.g., city) to a small scale (e.g., parcel or facility). First is selecting a feasible area for LID facilities in a whole developing area. It is impacted by the characteristics of underlying surface and social factors.[6−9] Second is the early-stage design downscaling to sub-catchment. The specific selection, connection, and size of LID are supposed to be considered. This is the most important procedure linking the objective and reality. Third, the working drawing of LID construction in given parcel or sub-catchment is plotted. Finally, the structure LID facilities need to be confirmed.[10] According to our experiences and the literature, procedures I, III, and IV are being largely investigated. The optimal design methods of procedures I and IV tend to be relatively standardized with general approaches such as multiple criteria decision-making (MCDM) methods.[7,11] Oppositely, the methodology of early-stage design of LID layout in the sub-catchment scale (procedure II) is far from systematic and accurate designing although many studies have been reported. Therefore, this paper mainly focuses on this procedure.

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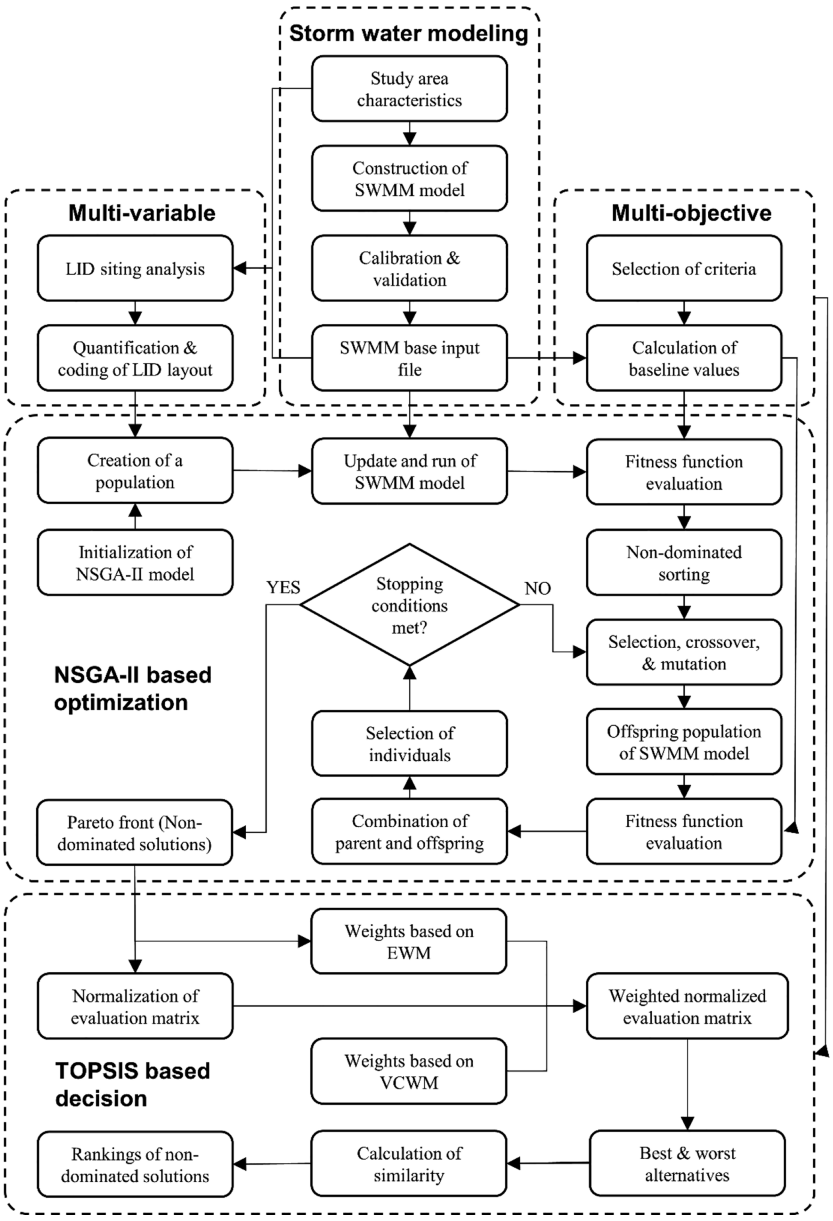


**Figure 1.** Processes of the comprehensive quantitative optimization model as well as their connection.

In this context, optimization frameworks usually combine optimal algorithms with mathematical storm water management models. The most popular model and algorithm are the Storm Water Management Model (SWMM) and the genetic algorithm. Sebti et al.[12] used the linear programming, genetic algorithm, and simulated annealing to optimize the selection and layout of four types of BMP facilities, including rain gardens and green roofs, to obtain the best economical solution under the requirements of storm water quantity and quality control. Giacomoni and Joseph[13] used the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) coupled with the SWMM to find the best location for storm water control measures compatible with obtaining a balance between the effect and cost at the watershed scale. The coupling of particle swarm optimization (PSO) algorithm with the SWMM was proposed by Duan et al.[10] to optimize the location of water tanks and LID devices in urban areas to lower the flood damage risks. Song and Chung[11] used TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) to prioritize various LID scheme types and locations and determined the optimal layout scenario of infiltration ditch and permeable pavement.

Some integrated software packages are also developed to simulate and optimize the LID planning for sub-catchment early-stage design (procedure II) with graphical user interfaces and internal models, such as Structural BMP Prioritization and Analysis Tool (SBPAT), Watershed Management Optimization Support Tool (WMOST), LATIS, SUSTAIN (System for Urban Stormwater Treatment and Analysis IntegratioN), and GreenPlan-IT.[14,15] They also use empirical models to simplify hydrological calculation such as BMP Checker and Opti-Tool.[16] Mao et al.[17] applied SUSTAIN in the cost−benefit analysis of Sponge City construction in Foshan, involving several sponge facilities and multiple environmental indicators. The same approach was also applied in Beijing to optimize the implementation area under a determined LID layout scheme for a more economical planning in line with the environment control requirement of the Sponge City.[18]


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ACS EST Water 2022, 2, 63−74

It shown that most of the existing methods or tools only focused on optimizing the construction planning by determining the spatial coverage of the LID facilities, involving only their numbers and sizes, or only considered the evaluation of predefined LID layout scenarios.[19−25] Such planning with a determined LID layout depends on the practitioners' personal experiences, and/or the general guidelines can be quite subjective and risk producing non-optimal solutions. However, the fine design of Sponge City requires us to bring an overall optimization for the selection, connection, and size of LID, which is hard to realize via existing approaches constrained by the flexibility. Moreover, existing tools for the design of storm water management commonly embody objectives, which reflect the cost, total runoff reduction, and flooding. They pay less attention to the urban water environment and other social/economic impacts,[23,26−29] which are equally vital to for urban storm water management.

To fill the technology gaps and meet goals of accurate, systematic, and standard LID design in early stage, this study proposes a comprehensive quantitative optimization framework with cost−benefit analysis. It makes early-stage LID layout design in sub-catchment (i.e., the facility selection, connection, and size) have the most flexibility when considering different objectives, including the perspective of rainfall runoff, flooding, urban water environment, and construction cost. The study uses the Sponge City demonstration in Shenzhen, China as a case study basis. The study also used the SWMM to obtain the environmental indicator values to support the optimization of the LID layout. Additionally, according to the communication with employees of institutes and corporations, including members of the Sponge City Expert Committee of the Ministry of Housing and Urban−Rural Development of China, we confirmed the necessity and novelty of this study, which is as well expected to be further promoted into the industry for practical design use.

## 2. MATERIALS AND METHODS

Based on a hybrid NSGA-II and TOPSIS algorithm, we introduced a new comprehensive quantitative optimization framework to obtain the best LID layout, aiming at multi-variables and multi-objectives. Figure 1 shows the detailed processes of the whole framework.

**2.1. Storm Water Modeling.** The SWMM developed by the Environmental Protection Agency of United States[30] is employed in this study to assess the effects of LID practices on storm water runoff reduction and water quality improvement because of its remarkable ability for simulation of various hydrological processes such as precipitation, infiltration, surface runoff, pollution transportation, retention of LID practices, and the flow in drainage network. Additionally, as the SWMM is open-source software, it can be further developed and integrated with other tools using tailor-made computer scripts. In this study, we use the R package named *swmmr* developed by Leutnant et al.[31] for the SWMM work used in the present study. The current basic geographic data and monitoring data are used to build and calibrate the baseline SWMM model, which is subsequently used in the comprehensive optimization framework.

**2.2. Multi-variable Optimization.** The multi-variable optimization here means we are computing the best LID layout of selection, connection, and size. First, an LID siting analysis should be carried out using SUSTAIN based on the characteristics of the underlying surface and LID.[9] Then, a novel coding scheme is advanced to realize its quantification. As shown in Figure 2, the proposed coding scheme starts with

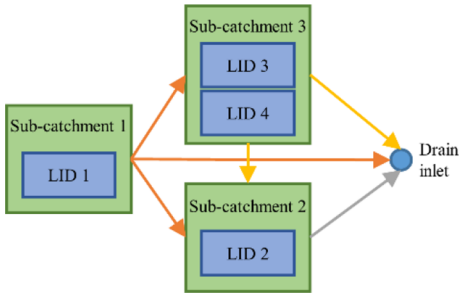


**Figure 2.** Example of the proposed coding scheme for the LID layout.

the following three steps: (a) full allocation based on the availability from the list of the candidates of LID for each sub-catchment. An individual sub-catchment is supposed to have only one kind of LID, and here, LID 3 and LID 4 are candidates for sub-catchment 3; (b) full LID connection involving ordering the potential stream direction of surface runoff from rainfall to a municipal network based on the possible hierarchical structure of sub-catchment and LID. An individual sub-catchment is supposed to have only one outlet for storm water, but we can determine its direction as the mutually exclusive arrows in Figure 2 with the same color; and (c) full coverage that identifies all the suitable area for each LID candidate in sub-catchment. Hence, the three variables of selection, connection, and size are easily linked to the model parameters of the SWMM, which can subsequently be optimized.

**2.3. Multi-objective Optimization.** In general, the Sponge City is considered to be effective in the reduction of the total runoff and peak runoff of storm water and the non-point source pollution of first flush (including emerging pollutants such as microplastics and polycyclic organic hydrocarbons).[32−35] This is very similar to other storm water management concepts such as the LID and BMP.[36] The Sponge City can have more positive roles in alleviating the urban heat island effects and facilitating rainwater reuse. However, these positive roles are difficult to quantify and they are not taken in consideration when designing the Sponge City. The total suspended solid (TSS) is an important index in the Sponge City assessment and acts as a proxy to other closely relevant pollutant indices such as the chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP). The economic index is basically the whole life cycle cost, starting from planning, designing, and construction to the later stages of operation and maintenance. In the context of economic index, the construction cost is the most notable part that affects the decision-making process and extensively weighed in assessment of urban storm water management.[37,38]

Therefore, four indices are selected for optimization of objectives and criteria. These four indices reflect the reduction rate of total runoff, the reduction of peak runoff, the reduction of total TSS load, and the construction cost. They can be calculated by comparing the simulation results of the Sponge City construction scenario to those of the baseline scenario. The construction cost of the four LID facilities used in this work is estimated using the Technical Guidelines for Sponge City Construction in Shanghai (Trial) (issued in 2015 by


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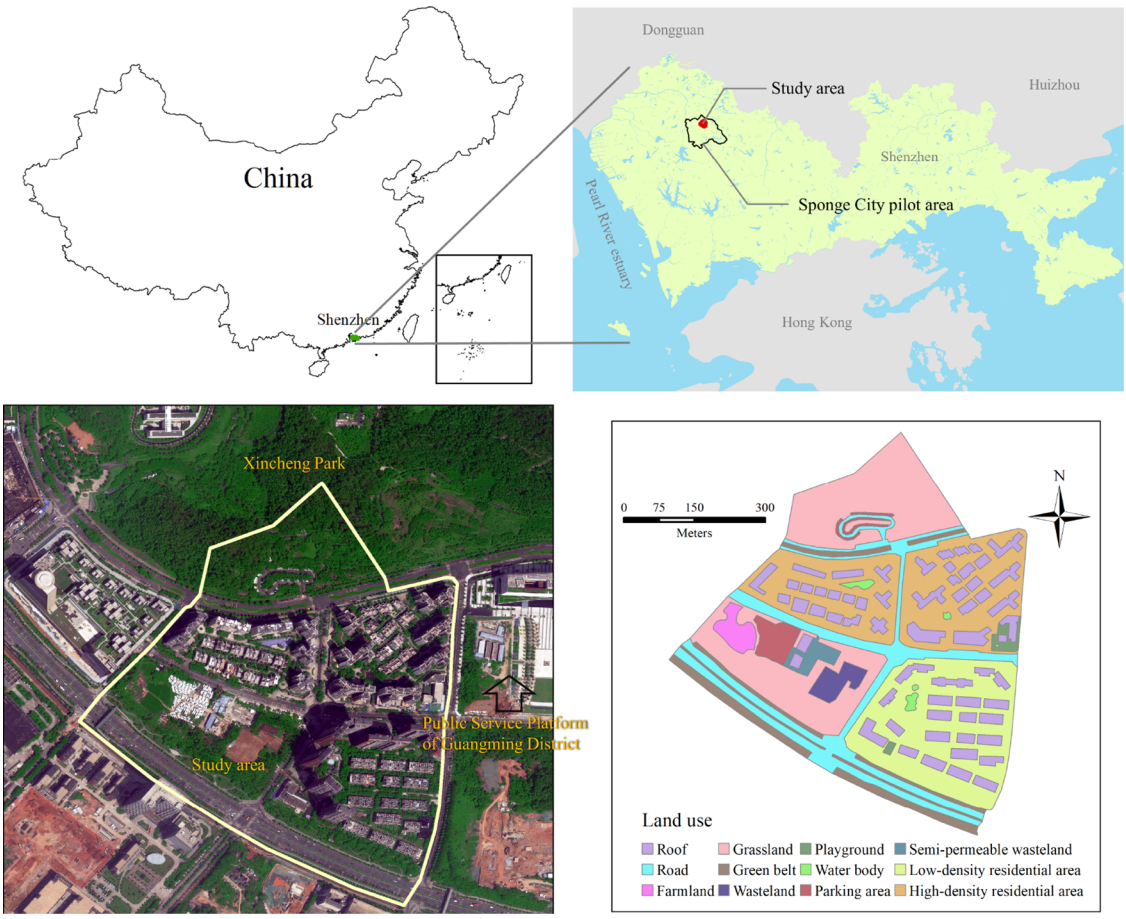


**Figure 3.** Location of study area.

Shanghai where the development level is similar to Shenzhen) and other relevant publications.[39] The construction cost for the bio-retention cell, rain garden, permeable pavement, and green roof are 800, 700, 950, and 800 CNY/m$^2$, respectively.

**2.4. Hybrid Optimization Algorithm.** We advance a hybrid NSGA-II and TOPSIS approach for this study. NSGA-II is a classical but efficient genetic algorithm for multi-objective optimization problems.[40] Two basic concepts of non-dominated sorting and crowding distance are utilized in NSGA-II to generate the desirable Pareto-optimal solutions. Figure 1 shows the general process of NSGA-II used in the present. TOPSIS[41−43] is among the most popular MCDM methods, which is widely applied to ranking problems where alternatives are evaluated based on the Euclidean distance from the best and worst alternative. The operation TOPSIS is governed by the following equations as follows:[44]

$$r_{ij} = x_{ij}/\sqrt{\Sigma_{i=1}^{m} x_{ij}^2} \tag{1}$$

where $x_{ij}$ is the original evaluation matrix with $i$ alternatives and $j$ criteria and $r_{ij}$ is the normalized evaluation matrix. The best alternative $r^+$ and the worst alternative $r^-$ contain the best and worst values for each criterion, respectively. $S_i^+$ and $S_i^-$, the distance between the target alternative $i$ and the best/worst condition, can be calculated as follows:

$$S_i^+ = \sqrt{\Sigma_{j=1}^{n}((r_{ij} - r_j^+)w_j)^2} \tag{2}$$

$$S_i^- = \sqrt{\Sigma_{j-1}^{n}((r_{ij} - r_j^-)w_j)^2} \tag{3}$$

where $w_j$ is the weight of the $j$th criterion. Then, the similarity to the best condition for each alternative can be calculated as follows:

$$C_i = S_i^-/(S_i^+ + S_i^-) \tag{4}$$

where the greater the similarity, the more desirable the alternative.

It should be noted that the weight vector is the key in the evaluation and the decision making. The common approach is the analytic hierarchy process, which requires the comparison of each criterion to get its relative importance by constructing the judgment matrix, subject to the personal experiences and preference. Considering that there are enough alternatives in the Pareto front, in this study, we choose the entropy weight method (EWM) that is based on the principle of information theory. The greater the differentiation degree within each criterion, the greater the amount of information contained, the more important this criterion is, and the higher its weight should be. The weight vector based on the EWM can be calculated as follows:

$$w_j = (1 - e_j)/\Sigma_{j=1}^{n}(1 - e_j) \tag{5}$$

$$e_j = \frac{-1}{\ln(m)}\Sigma_{i=1}^{m} p_{ij}\ln(p_{ij}) \tag{6}$$

$$p_{ij} = r_{ij}/\Sigma_{i=1}^{r} r_{ij} \tag{7}$$

where $e_j$ is the entropy of $j$th criterion. $p_{ij}$ denotes the standardized value of the $j$th criterion in the $i$th alternative.


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ACS EST Water 2022, 2, 63−74

Based on the information abundance derived from the above equations, the quantitative relative importance ranking of criteria can be given, via which the alternatives are evaluated easily in one single dimension. Additionally, a variable cost weight method (VCWM) is proposed in our work to quantify the influence of cost preference of the decision maker on the decision result.[39] The weight of the cost is assigned from 0.05 to 0.95 with an interval of 0.05. If the other criteria except cost have the same important effect on the performance of LID, then the remaining weight value is divided equally.

In this framework, TOPSIS follows NSGA-II, sharing the same objectives/criteria, and ranks the Pareto solutions generated by NSGA-II for the final decision of the construction scenario. All the coding work required in this study was accomplished in the R environment, and the package *caRamel*[45] was used to implement NSGA-II.

## 3. DESCRIPTION OF THE CASE STUDY

**3.1. Study Area.** As shown in Figure 3, the study area selected in this study is located in the Fenghuang Cheng region, a Sponge City pilot area of Shenzhen, which is one of the 30 national demonstration cities for Sponge City. The total area of the study area is approximately 40 ha, and it contains five plots, including the southern part of Xincheng Park, three residential quarters, and one open space to be developed. The southernmost main road is adjacent to Dongkengshui, an upstream tributary of Maozhou River, the largest river in Shenzhen. The catchment storm water runoff enters Dongkengshui through the rainwater pipe network and then flows into the Maozhou River and finally into the Pearl River Estuary. The runoff data in this study was collected at the network outlet by an ultrasonic Doppler flowmeter. There are 12 types of land uses in the study area and are grouped into three categories based on the soil permeability. Table S1 shows the detailed land use information. It should be noted that the land use identification is for hydrological and water quality parameter calculation of sub-catchments. Hence, a simplified classification of land use will hardly affect the property of sub-catchments due to the approximate homogeneity within one land use type. The overall terrain is relatively flat, except for the hill of Xincheng Park in the north of the study area, with an elevation range between 20 and 81 m (Figure S1). According to the Köppen−Geiger climate classification system, the study area has a temperate oceanic climate. The average annual temperature is 22.4 °C, and the mean annual precipitation is 1935.8 mm. Around 86% of rainfall happens in the rainy season during the period April to September. The study area is a typical case of Sponge City construction where LID facilities being built or having been built include but are not limited to permeable pavements, sunken greenbelts, and ecological tree pools. The abundant fundamental data make our case study possible. In addition, the selected area represents a broad part of China due to the typical infrastructures, construction size, and pollution pattern. The results in the study area are expected to provide a benchmark for relevant research.

**3.2. Setup of the SWMM Baseline Model.** In this study, we used SUSTAIN developed by US EPA to visually establish the SWMM baseline model and determine the suitable area for each LID. The data required by SUSTAIN such as terrain and land use were converted into a data format that can be recognized by ArcGIS. The Supporting Information of this paper provide the details of the SWMM model (Figures S1−S5) and LID siting analysis (Figures S6 and S7). After querying the historical rainfall records, we selected nine rainfall events in 4 days during the period 10 to 13 June 2019 to calibrate and validate the baseline model. The first 2 days (five events) were used for calibration and the remaining 2 days (four events) for model validation. The hydrological parameters to be estimated by calibration and their plausible ranges are determined based on previous studies,[46−49] as shown in Table S2. Due to the lack of water quality monitoring data in this area, we used the water quality module parameters of calibrated SWMM models of a previous research in the Fenghuang Cheng region.[50] In this study and in a similar fashion to the previous study of Tang et al.,[50] the calibration algorithm use the Nash−Sutcliffe efficiency coefficient (NSE)[51] for evaluation of model performance and the differential evolution (DE)[52] for optimization.

As shown in Figure S8, the fitness of observation and simulation is relatively high in the calibration period, with an NSE of 0.77 and an $R^2$ of 0.80. In the validation period, the NSE value is 0.52 and the $R^2$ value 0.64 and these values are less than those obtained in the calibration period (Figure S9). Figure S10 shows the scatter plot of the simulated and the monitored flow for both the calibration and the validation periods. The figure shows that the simulated flow underestimates the monitored flow when the monitored flow is high. Likewise, the simulated flow overestimates the monitored flow when the monitored flow is low. The overall NSE is 0.75, and the overall $R^2$ is 0.79, which indicate that the hydrological simulation performance of the SWMM baseline model is reliable.

A single rainfall event with a return period of 10 years and a duration of 2 h was developed to evaluate the performance of LID on peak flow reduction. The Meteorological Bureau of Shenzhen Municipality[53] provides an equation for the rainfall intensity−duration−frequency (IDF) curve for Shenzhen. The IDF curve can be expressed by the following equation:

$$i\frac{8.701(1 + 0.594\lg T)}{(t + 11.13)^{0.555}} \tag{8}$$

where the $i$ is the rainfall intensity in mm/min, $T$ is the return period, and $t$ is the duration. As shown in Figure S11, the Chicago Design Storm[54] was then applied to calculate the intensity hyetograph, with an advancement coefficient $r$ value of 0.35.

**3.3. Initialization of the Optimization Framework.** The proposed framework is logically and theoretically consistent with the general LID layout design process, meaning we only need to consider if it works under the general data condition rather than to pursue a higher accuracy of results. Therefore, a small plot in the southeast corner of the study area was selected to demonstrate the proposed framework, as shown in Figure S12a. There are a total of three sub-catchments. The rectangle inside the figure represents a house with a roof area of 1000 $m^2$, surrounded by a lawn with an area of 4000 $m^2$, and with a 200 $m^2$ hardened pavement on the east side. The drain inlet at the lower right corner receives the rainfall runoff from this area. All the LID candidates and connection between sub-catchments are given based on the LID siting analysis shown in Figure S12b, which are used for the multi-variable optimization. The small plot has four LID devices, namely, the bio-retention cell, rain garden, green roof, and permeable pavement. The design parameters of the selected four LID practices are in Table S3. It should be noted


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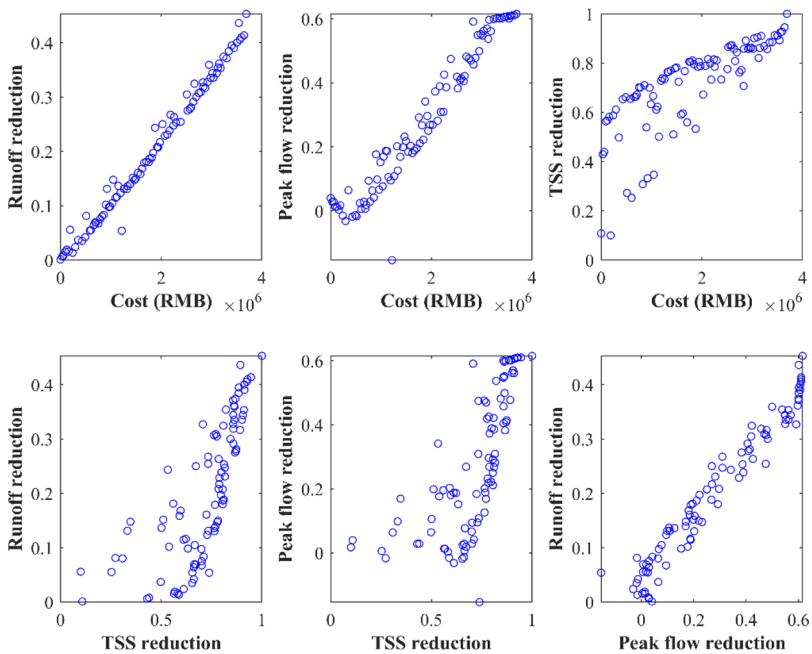


**Figure 4.** Pareto fronts presented by pair-wise objectives whose correlation coefficients are 0.99, 0.97, 0.79, 0.74, 0.71, and 0.97 from left to right and top to bottom ($P < 0.001$).

that for the baseline model, there are no LID devices in the demonstration area and all the rainfall runoff of the three sub-catchments flows directly into the drainage network (Figure 5j).

To minimize the total cost and maximize the environmental benefits, the multi objective framework can be represented as eq 9

$$\begin{cases} \text{minimize } f_1 = \Sigma C_i A_i \\ \text{minimize } f_2 = 1 - V/V_{\text{baseline}} \\ \text{minimize } f_3 = 1 - R/R_{\text{baseline}} \\ \text{minimize } f_4 = 1 - L/L_{\text{baseline}} \end{cases} s.\ t. \begin{cases} [V, R, L] = G_{\text{swmm}}(A_i, LID_{\text{lawn}}, DC_{\text{roof}}, DC_{\text{lawn}}) \\ 0 \le A_i \le A^i_{\max} \\ LID_{\text{lawn}} \in \{\text{BC, PP}\} \\ DC_{\text{roof}} \in \{\text{lawn, road, inlet}\} \\ DC_{\text{lawn}} \in \{\text{road, inlet}\} \end{cases} \quad (9)$$

where $C_i$ and $A_i$ are the cost per m$^2$ (see Section 2.3) and the construction area of LID, respectively. $V$, $R$, and $L$ represent the total runoff volume, peak flow discharge, and TSS load under different states of design, which are compared with the baseline scenario, respectively. On the constraint condition, the feasible set of LID selection for the lawn $LID_{\text{lawn}}$ consists of the bio-retention cell (BC) and permeable pavement (PP). Because other land use types only have one optional LID facility each, we do not list them in the equations. $DC_{\text{roof}}$ and $DC_{\text{lawn}}$ represent the possible downstream connections for the roof and the lawn in the catchment. $A_i$ is the continuous variable with the upper limit size $A^i_{\max}$ of each LID facility. Additionally, the size of unselected LID is 0. $V$, $R$, and $L$ are controlled by the SWMM model-based urban runoff processes, noted by the function $G_{\text{swmm}}$.

## 4. RESULTS AND DISCUSSION

**4.1. Configuration of Optimization Algorithm.** The previously mentioned *swmmr* and *caRamel* packages are used to drive the proposed comprehensive quantitative optimization framework in the R environment. The input of NSGA-II consists of six variables, namely, the size of LID in the three sub-catchments, the two downstream connections of lawn and roof, and the selection of LID in the lawn area. Here, the area of LID denotes its size, which varies from 0 (no LID) to 1 (the full coverage of the sub-catchment extent). The variables of selection and connection are discrete, which are therefore mapped to a continuous range. In the present study, the three objectives of reduction on total runoff, peak flow, and TSS load are maximized, while the objective of construction cost is minimized. The population size of NSGA-II, as well as the number of non-dominated solutions in Pareto front, is set at 100 as recommended.[40] The stopping conditions are a maximum call of 5000 or a loss of $10^{-6}$.

The R script we coded was run with RStudio in the Windows 10 environment (Intel Core i5-7400 3.00 GHz CPU, 8 GB memory). Multi-threaded programing enables us to call all four CPU cores for optimization. The computation ended at 5030 calls, 198 generations, and 94 non-dominated solutions. In the 24.77 min optimization, 8 generations and 203 calls of SWMM were accomplished per minute.

**4.2. Results and Analysis of the Optimization Framework.** The convergence curves of the four objectives during the optimization process are shown in Figure S13. The total runoff reduction rate finally converged at 0.45 and the peak flow reduction rate around 0.616. The TSS load reduction rate reached 100%, while the lowest cost is 0, implying that there is no LID construction.

Figure 4 depicts the Pareto front of the 94 non-dominated solutions, from which the four objectives can be considered as


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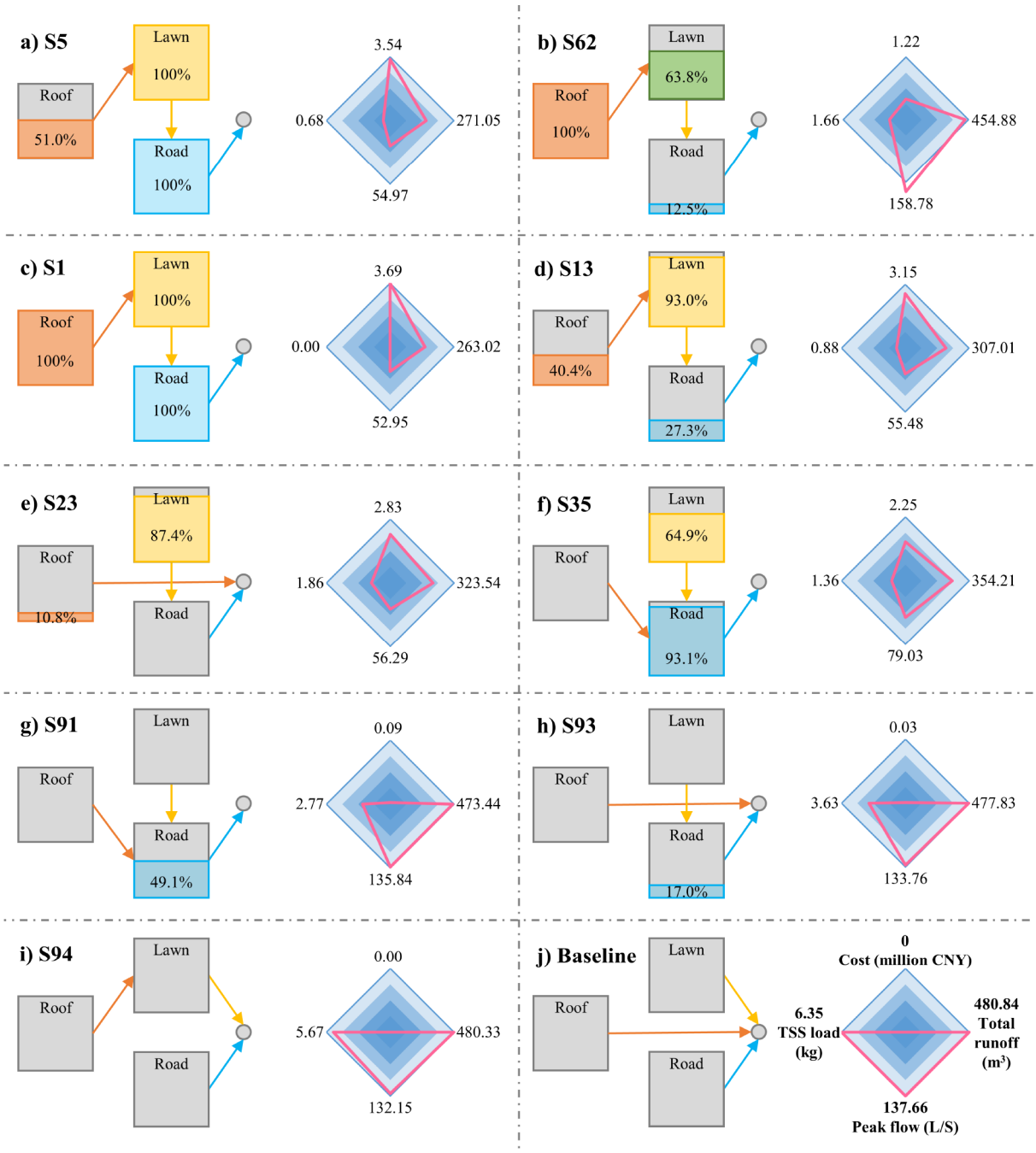


**Figure 5.** Optimization results of multi-variable (LID layout) and multi-objective (decision criteria), with (a, b) EWM-based TOPSIS and (c−i) VCWM-based TOPSIS. Yellow indicates the bio-retention cell in lawn area, and green indicates rain garden.

significantly positively related with each other. The more cost paid in construction, of course, the more effectiveness gained on the storm-runoff quantity and quality control. The correlations involving TSS are relatively weaker than the others, probably due to the more uncertainty of water quality modeling than hydrological modeling with the SWMM[50]. The ranges of the four objectives in the Pareto front are in Figure S14. It is worth noting that the peak flow reduction rate can be negative, which means that some change in the storm water management measure may increase the flooding risk.

**4.3. Multi-criteria Decision Analysis Based on the Entropy Weight Method.** The weight vector derived from the EWM is [0.3650, 0.2216, 0.0014, 0.3169] for the four objectives, respectively. The TSS reduction is considered relatively less important than the other criteria, which is reasonable as most scenarios keep a TSS reduction greater than 80%, while there are some down to 10% still. On the other hand, the two criteria of cost and runoff reduction gain higher weights with their approximate uniform distribution, the maximum entropy distribution among all continuous distributions in a given interval. Figure S15 shows the similarity of 94 scenarios of the Pareto front. The best solution is S5 with a similarity of 0.61, while the worst solution is S62 with a similarity of 0.33. The best and worst scenarios share the same connection pattern between the sub-catchments, i.e., in both scenarios, the storm water runoff flows through the roof, lawn,


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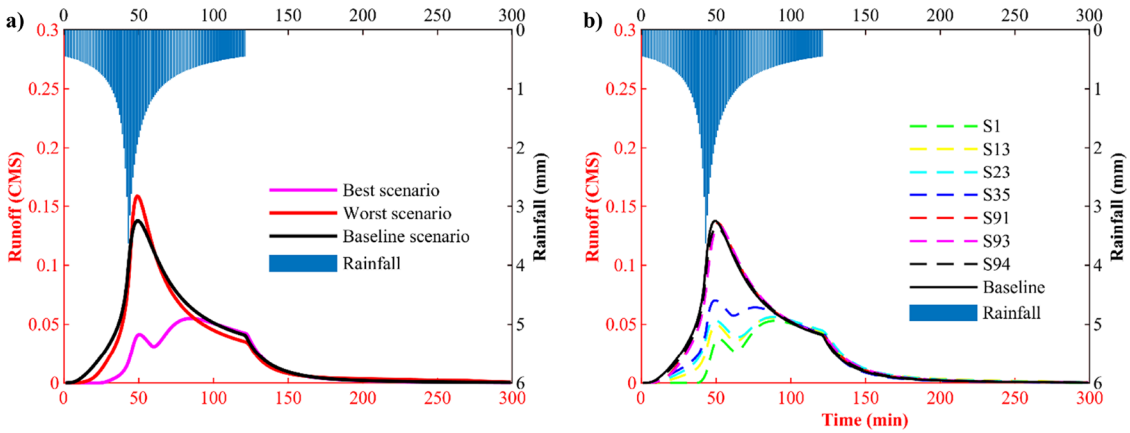


**Figure 6.** Runoff processes of the (a) best, worst, and baseline scenarios based on the EWM and the (b) 7 best scenarios based on the VCWM. (10 year return period, 2 h duration).

road, and finally the drain inlet. They differ on the LID selection of lawn and the specific size of LID devices (Figure 5a,b and Figure S16).

The indicators of the best, worst, and baseline scenario refer to Figure 5 and Table S4. For S5, all four objectives are close to the maximum in the Pareto front, which means high cost and high environmental benefit. The worst scenario pays cost around 1/3 of that of the best scenario, but only performs well in TSS reduction, and even weakens the ability of peak flow reduction. Figure 6a shows that the runoff control is rarely found in the worst scenario. However, the best scenario S5 shows its effectiveness, notably on the peak reduction and the peak delay.

**4.4. Multi-criteria Decision Analysis Based on the Variable Cost Weight Method.** Considering the effect of cost preference on decision making, we sort the 94 non-dominated solutions under variable cost weights. The seven scenarios, S1, S13, S23, S35, S91, S93, and S94, are picked out as the best scenarios successively. Figure 7 illustrates how the final decision alters within the seven scenarios. According to the similarity curve, these seven scenarios can be divided into two types, namely, the effectiveness-type and the cost-type. The similarity of effectiveness-type scenarios (S1, S13, S23, and S35) declines as the cost weight increases, illustrating that the effectiveness-type is more desirable under the low weight constrains. Meanwhile, the similarity of cost-type scenarios (S91, S93, and S94) increases with the cost weight, leading to the preference for the cost-type when the decision maker is sensitive to construction cost. In particular, the ranking has a trend change in the cost weight range of 0.3−0.4 where effectiveness-type is gradually replaced by the cost-type scenarios.

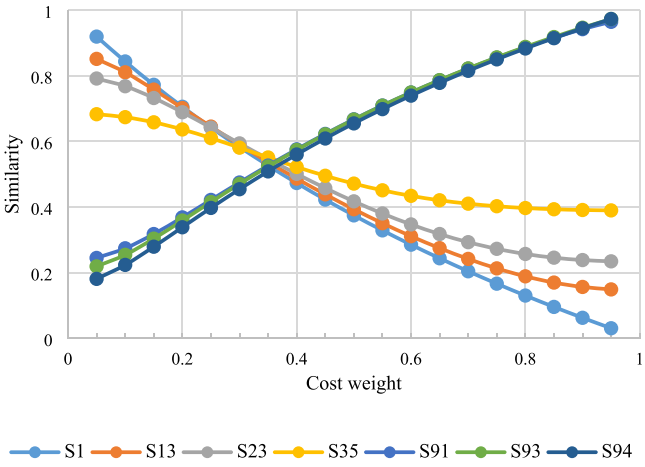


**Figure 7.** Similarity of the best seven scenarios changing with the increase in cost weight.

As presented in Table S5 and Figure 5, scenario S1 requires the 100% implementation of LID practices in all sub-catchments for the most environmental effectiveness, which is also the most expensive scenario with a cost of nearly 3.7 million CNY. The cost of S94 is 0, which means that no additional LID devices are required except for the alteration of runoff direction. Actually, 91 scenarios out of the 94 non-dominated solutions tend to apply the bio-retention cell in the lawn. The rain garden is only selected in three scenarios. The downstream flow direction of runoff from the lawn mostly points to the road rather than the drain inlet directly. The choice of runoff direction from the roof is distributed evenly among the three alternatives. As shown in Figure 6b, the effectiveness-type scenarios have stronger control over the rainfall−runoff transformation. Furthermore, the runoff process curves of cost-type scenarios almost overlap that of the baseline.

In this study, the final decision is not very sensitive to the value of cost weight in most ranges and it is governed by the distinct cost-type or the effectiveness-type scenarios. Only within the cost weight ranges of 0.3 and 0.4 can the decision significantly differ among the 94 scenarios. Furthermore, all of the notable criteria vary up and down sharply, implying that more attention should be paid on the fine evaluation of cost weight, otherwise the negligent cost preference of the decision maker will hardly balance the environmental effectiveness against the construction cost.

**4.5. Practical Implications and Limitation.** The novel coding scheme developed in this study for the selection, connection, and size of LID devices shows its reliability in the optimization process where completely different LID layouts can be generated and selected in the light of evaluation criteria. Within the Pareto front, the outstanding discrimination endowed by the coding scheme makes it rewarding to use the MCDM approach for the final determination of the construction plan.

We finally obtained the desirable construction plan containing the best selection, connection and size of LID,


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ACS EST Water 2022, 2, 63−74

which is more practical for Sponge City design, compared to the optimization under fixed LID layout scenario[23,24] and evaluation for a finite number of LID layout scenarios.[22,28,39] Also, we conducted and compared the previous design approaches[55−57] in our study area. Figure S17 shows the optimization results when we had determined the LID selection and connection in advance via empirical knowledge or official guidelines. The layout scenarios $S_{d1}$ and $S_{d2}$ (Figures S17a,b), which differ in the initial condition of LID type for lawn, give the optimal LID size using EWM-based TOPSIS. Additionally, both two scenarios are dominated by the solutions of the Pareto front of this work as expected, that is, not the optimal scenario under multi-variable conditions. The negative peak runoff reduction (Figures 5b and 6a) also indicates that improper LID selection and connection will lead to worse environmental benefit than doing nothing. Also, Figure 5i also represents that the water volume control can be reached by only adjusting the connection between sub-catchments.

In addition, the flexibility of the multi-objective module will help in developing a comprehensive perspective of the effectiveness of LID, beyond the traditional environmental scope. Hence, more indicators can be added into this evaluation system according to the local requirements. These indicators include flooding risk of peak delay; additional water quality indicators such as COD, TN, and TP; economic indicators of maintenance and operation cost; and social indicators such as water reuse, landscape function, and ecological function.[22] However, it should be noted that there is a considerable disconnect between design and construction, i.e., the indicators are so numerous and high-standard that can hardly be achieved actually. The evaluation system should be built carefully and accurately.

In this study, we verified the ability of the novel coding scheme for LID layout through its stable performance in the quantitative optimization in the demonstration area. However, we may be faced with more potential problems when applying it into a large-scale catchment. The number of optimization variables on the size and selection of LID is linearly related to the number of sub-catchments approximately, while that on the connection of LID may be at most $\left(\frac{1}{2}n^2 - \frac{1}{2}n\right)$ times the number of sub-catchments $n$, even $(n^2 - n)$ times when addressing it a permutation question since bi-directional connection among sub-catchments (without notable hierarchy) is possible. The increasing dimensions of decision space may lead to the failure of optimization by NSGA-II due to the simultaneous increase in computation complexity. Therefore, more efficient multi-objective algorithm should be necessary in a large-scale study with the proposed framework. With regard to cost, our work ignored that for certain LID facilities such as rain gardens, if the original surface is permeable lawn, then the extra cost will be lower than reforming rigid pavements. The considerable difference between replacement and construction is vital to the success of any design. In addition, the data availability is also an important part of design cost accounting. Summarily, the detail of cost is expected to check precisely to ensure the continuity of the project.

The first two procedures of LID early-stage design (see Section 1) are covered by the proposed framework. Although procedure I utilized the established method in SUSTIAN to setup most feasible areas for siting LID facilities, any other established methods for facility siting can be combined here. How to best link the framework to the fine design stage is a good question to be considered in the future. Perhaps, both actual requirements from fine design and objective vision of science are eager to deepen the insight.

## 5. CONCLUSIONS

In this study, we proposed a comprehensive quantitative optimization framework to seek the most desirable LID layout including the selection, connection, and size of LID, with respect to the environmental and economic objectives. The multi-objective module comprehensively involves the reduction of total runoff, peak flow, TSS load, and the construction cost. The novel coding scheme is capable of meeting the need of LID layout quantification, thus composing the multi-variable optimization. In the present study, the framework was tested using a case study in the Sponge City pilot area, Shenzhen. A baseline scenario was first modeled by SWMM and analyzed for the LID siting. Then, the optimization module was established in line with multi-variables and multi-objectives. Finally, the hybrid NSGA-II and TOPSIS algorithm was utilized to search for the optimal LID layout for the Sponge City. Ninety-four non-dominated solutions were generated after over 5,000 calls for SWMM by NSGA-II, which make up the Pareto front. With two ways to determine the weight of evaluation criteria, TOPSIS was then used to find the most outstanding plan among the 94 alternatives and the effect of cost performance on decision.

The following main conclusions were obtained as follows:

(1) The proposed novel coding scheme for LID layout performs well in multi-objective optimization. Despite the small study area, the construction scenarios generated are still distinguishable from each other, which make the fine design of LID layout possible.

(2) Based on the analysis of the 94 alternatives, all the four objectives have pair-wise positive correlations. The total runoff reduction is most related to the cost with a correlation coefficient of 0.99, while the TSS load reduction is distributed a little dispersedly due to the uncertainty of water quality modeling with SWMM.

(3) TOPSIS with the EWM selected scenarios S5 and S62 as the best and worst alternatives, respectively. S5 trades off the high construction cost (3.54 million CNY) against the much environmental effectiveness (runoff reduction rate of 43.63%, peak flow reduction rate of 60.07%, and TSS load reduction rate of 89.32%). As for S62, the relatively low cost (1.21 million CNY) does not gain proportional improvement it deserves but the increase (15.35%) in peak flow instead.

(4) Seven best scenarios were successively picked out with VCWM-based TOPSIS, which are grouped into two categories according to their shapes of similarity curve with the increase in cost weight. The effectiveness-type scenarios (S1, S13, S23, and S35) are the better choice when cost weight is low (<0.3), while cost-type (S91, S93, and S94) stands out above the rest when cost weight is high (>0.4). A slight change on the cost preference of the decision maker may result in a notable difference of scenario selection within the range 0.3−0.4, implying the importance and complexity of LID layout design facing multiple constrains, as well as the potential value of the proposed framework for future needs from the Sponge City or similar concept.


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The proposed comprehensive optimal design frameworks provide a systematic solution of early-stage LID design. With large flexibility, facility types can be freely extended. Hopefully, it can be seamlessly integrated into computer-aided design software as a toolbar or computation engine to effectively empower drainage system designers.

## ■ ASSOCIATED CONTENT

### Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsestwater.1c00235.

Basic information of study area (Figures S1−S5 and Table S1), siting analysis for LID (Figures S6 and S7), setup and initialization of framework (Figures S8−S12), hydrological parameters to be calibrated (Table S2), design parameters of LIDs (Table S3), optimization results from NSGA-II (Figures S13 and S14), results from EWM-based TOPSIS (Figures S15 and S16), statistics of focused scenarios from TOPSIS (Tables S4 and S5), and comparison to a previous approach (Figure S17) (PDF)

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### Notes

The authors declare no competing financial interest.

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