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Global Sensitivity Analysis-based Design of Low Impact Development Practices for Urban Runoff Management Under Uncertainty

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Abstract

In this paper, a new methodology is developed for urban runoff management based on global sensitivity analysis of the storm water management model (SWMM) considering uncertainties. The variogram analysis of response surface (VARS) model is utilized for sensitivity analysis of the SWMM parameters by combining the runoff simulation model of the SWMM with VARS. Three model efficiency metrics, namely Nash–Sutcliffe efficiency metric for the runoff, NSE metric for the logarithm of the runoff, and percent bias in simulating runoff are used to evaluate SWMM outputs and rank its parameters. The reliability of the obtained rankings of parameters is evaluated by developing a bootstrapping-based strategy to estimate confidence intervals for the calculated sensitivity values. A multi-objective optimization model is integrated with the calibrated SWMM, to select optimum scenarios of low impact development-best management practice (LID-BMP). To take into account the rainfall uncertainty, design storm hyetograph is stochastically derived using Monte Carlo analysis and Huff curves (Huff in Water Resour Res 3(4):1007–1019, 1967; Time distributions of heavy rainstorms in Illinois, State of Illinois Department of Energy and Natural Resources, Illinois, 1990). Finally, a socially acceptable LID-BMP scenario out of a set of non-dominated solutions is obtained using the Nash bargaining theory. The proposed method is applied to an urban watershed Iran. The resulted LID-BMPs could decrease runoff volume and pollution load by 24% and about 74%, respectively.

1 Introduction

Hydrological pattern of urban flows can drastically alter due to urbanization. These changes mostly include increased peak flows, reduced concentration time of the watershed, change in the intensity and frequency of floods, and ecological degradation resulted from

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increased runoff rates (McGrane 2016; Duan et al. 2016; Chui et al. 2016; Li et al. 2017; Paule-Mercado et al. 2017). Low impact development (LID) practices as sustainable and environment-friendly techniques for management of urban stormwater are meant to reduce the impacts of urbanization (Jia et al. 2015a; Singh et al. 2020; Rezaei et al. 2021; Corrêa et al. 2021; Li et al. 2022). These practices are based on controlling runoff at the source and reducing the total pollutant load in a natural and aesthetic manner (Lee et al. 2012; Liu et al. 2018). Bio-retention cells, detention/retention ponds, green roofs, permeable pavements, infiltration trenches and rain barrels are among LID-BMPs. Over the last decades, several researches were conducted to investigate the efficiency of LID-BMPs for urban runoff management. (Pyke et al. 2011; Karamouz and Nazif 2013; Qin et al. 2013; Gwenzi and Nyamadzawo 2014; Jia et al. 2015a, b; Zahmatkesh et al. 2015; Ghodsi et al. 2016a, b; Huang et al. 2018; Ghodsi et al. 2020; Yang et al. 2020, 2022; Li et al. 2021; Saniei et al. 2021; Tansar et al. 2022). An efficient combination of LID management practices across all sub-catchments in an urban watershed can be obtained considering objectives of reducing runoff quantity, improving runoff quality and decreasing the execution costs of the LID management practices (Cano and Barkdoll 2017). Doing so usually entails urban runoff discharge modelling based on several different scenarios of LID runoff management practices.

Among several urban runoff simulation models, the storm water management model (SWMM) of the U.S. Environmental Protection Agency (EPA) is one of the most widely used (Eckart et al. 2017). In the current paper, the SWMM is selected for simulating urban runoff due to its simple structure, low impact development (LID) module (Zhang and Chui 2018), open source feature and ability to be directly linked with other softwares such as MATLAB.

The SWMM contains several site-specific parameters for adequately considering features and characteristics of urban watershed and its drainage network as well as rainfall-runoff relationship. Complete and detailed information on these properties are often unavailable. Thus, parameter calibration of the simulation model is necessary. The calibration process can be very time-consuming when having a large number of model parameters to be determined. Sensitivity analysis (SA) can decrease the number of parameters that should be calibrated. Changes in model outputs or values of model performance metrics (criteria) in response to the changes of model parameters are investigated in the sensitivity analysis (More studies on sensitivity analysis of model parameters are reviewed in Sect. S1 of the Online Supplementary Material).

Despite the widespread applications of the SWMM for urban runoff simulations, the sensitivity analysis done in the previous works were either local or derivative-based and the impact of parameter perturbation scale to analyze global sensitivity over the entire space of model parameters were not considered. Thus, a comprehensive and robust global sensitivity analysis (GSA) on the SWMM parameters and their impact on model performance has not yet been done. In this paper, the sensitivity of the SWMM outputs to the values of model parameters is evaluated based on different goodness of fit metrics. Each of these metrics is responsible for measuring a distinct feature of the data. Three commonly used model efficiency metrics, namely Nash–Sutcliffe efficiency (NSE) metric for the runoff (NSE(Flow)), NSE metric for the logarithm of the runoff (NSE_{log}(Flow)), and percent bias (PBIAS) in simulating runoff (PBIAS(Flow)) are used. Moreover, the reliability of the obtained rankings of parameters is evaluated by developing a bootstrapping-based strategy to estimate confidence intervals for the values of calculated sensitivity metrics. The calibrated SWMM is integrated with an optimization model for selecting optimum urban runoff management scenarios. The proposed method is applied to a case study of Velenjak urban watershed, located in the north of Tehran,

Iran. The proposed methodology includes the following components: 1) sensitivity analysis of surface runoff simulation model of the SWMM for understanding the importance of its parameters using the VARS framework, 2) general sensitivity analysis of the SWMM parameters using the VARS tool and selecting and ranking the most influential parameters, 3) estimating confidence intervals for the values of calculated sensitivity metrics and evaluating the reliability of the obtained rankings of parameters 4) the automatic calibration of the selected parameters of the SWMM using the non-dominated sorting genetic algorithm (NSGA-II) multi-objective optimization model which is linked with the SWMM 5) stochastically deriving the design storm hyetograph using Huff curves and Monte Carlo analysis 6) developing a multi-objective simulation–optimization model for finding a set of non-dominated scenarios based on LID-BMPs considering rainfall uncertainty and 7) selecting a socially acceptable LID-BMP scenario out of the obtained set of non-dominated solutions using the Nash bargaining theory. In the next sections, details of the proposed methodology and its implementation in the study area are described.

2 Methodology

A flowchart which presents the main steps of the proposed methodology is shown in Fig. 1. Details of the main steps of this flowchart will be discussed in the following sections.

2.1 Data Collection and Catchment Discretization

In this section, the data and information regarding the hydrologic, hydraulic, geomorphologic and socio-economic conditions, stakeholders and their interests, LID-BMPs as well as quantity and quality of the pollution sources of the study area are collected and analyzed. More details on the required data and information can be found in the Sect. S2 of the Online Supplementary Material.

2.2 Urban Runoff Simulation

The Storm Water Management Model (SWMM), developed by the US Environmental Protection Agency (USEPA), is used to simulate urban runoff quantity and quality. The SWMM was first developed in 1971 and has been widely used in design and analysis of storm water runoff drainage systems, sanitary sewer networks, and other drainage systems (Rossman 2010). The SWMM 5.1.013, the most recent version of the SWMM, simulates the hydrologic processes considering both single event and continuous simulations.

Pollutants reach conduits and sewers via surface runoff. The types of pollutants in urban runoff can vary with characteristics of the surfaces of a catchment. In the SWMM, the pollutant transport model which is integrated with the runoff model considers two main stages: (1) formation of the pollutant on the catchment surfaces before a heavy rainfall, (2) washing off the pollutants during rainfall.

The amount of build-up is a function of elapsed time preceding a rainfall and critical conditions such as traffic flow, dry fallout and street sweeping (Rossman 2010) and is calculated as follows:
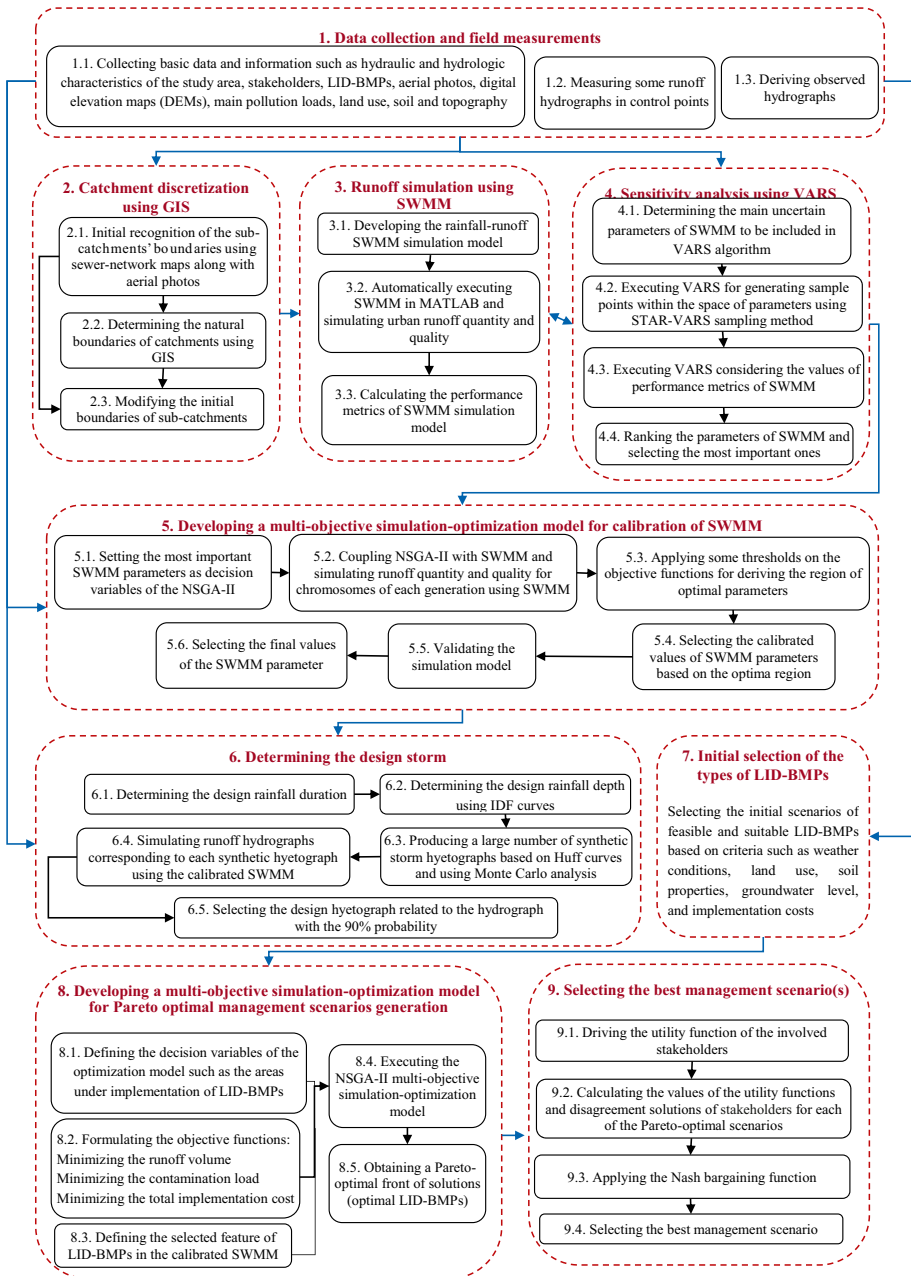
$$B = \text{Min}(C_1, C_2 t^{C_3}) \tag{1}$$

Fig. 1 The flowchart of the proposed methodology

where, B is mass per unit length of pollutant build-up and C_1 and C_2 are respectively maximum possible mass per curb length and build-up rate constant. The term t denotes elapsed time from the end of the preceding rain and C_3 is a constant time exponent.

The rate at which pollutants are washed off into the drainage system is calculated using an exponential function (Rossman 2010):

$$W = D_1 \times q^{D_2} \times B \tag{2}$$

where, W is mass of wash-off load per hour. The terms D_1 and D_2 respectively stand for wash-off coefficient and wash-off exponent. The term q is runoff discharge per unit area in mm/hour and B denoted the total mass of contaminants.

The runoff quantity and quality is simulated for all sub-catchments. These runoffs and wastewater loads (if any) are added when joined in receiving nodes. Then runoff discharge routing through pipes, channels, storage/treatment devices, pumps, and hydraulic regulators such as weirs, orifices, and other outlet types can be carried out using kinematic or dynamic wave methods. Complicating hydraulic conditions such as backwater effects, flow reversal, and flows under pressure, can also be considered in runoff simulations. In addition, the commonly used LID-BMPs for controlling runoff quantity and quality, such as porous pavements, rain barrels, infiltration trenches, bio-retention cells, and vegetative swales are simulated using the SWMM 5. Each sub-catchment in the SWMM is represented by a number of parameters that should be estimated in the calibration phase. Initial values for model parameters in each sub-catchment are derived based on the information related to soil characteristics, imperviousness, land use and topography using a Geographic Information System (GIS) software. The parameters are considered as random variables with uniform distributions within a predefined range. The possible ranges for the values of parameters are selected based on sub-catchment characteristics and previous recommendations along with engineering judgment. Calibrating the values of all of the parameters related to all sub-catchments is not feasible. Therefore, sensitivity analysis is carried out to choose the most important parameters for runoff calculations.

2.3 Global Sensitivity Analysis

To reduce the computational burden of calibrating the runoff simulation model, global sensitivity analysis (GSA) is done to identify, prioritize, and screen the dominant parameters of the SWMM. These parameters highly affect the simulated runoff in response to a given rainfall. The spatial dependence structure and variability of the simulated runoff, within the domain of n parameters of the SWMM ($\boldsymbol{x} = \{x_1, x_2, \ldots, x_n\}$) is identified using variogram analysis. Thus, for any two points on the response surface of the simulated runoffs within the domain of parameters, the multidimensional variogram can be written as $\gamma(\boldsymbol{h})$ (Cressie 1993; more details can be found in Online Supplementary Material (Sect. S3). If the variogram is calculated along one of the n dimensions (corresponding to ith parameter of the SWMM), the calculated variogram is one-dimensional. The sensitivity of the simulated runoff to any parameter i of the SWMM, across a wide range of perturbation scales (h_i), is denoted by $\gamma(h_i)$. To combine the mentioned one-dimensional variograms and form a global sensitivity measure, these variograms are integrated across their range of scale (between o and H_i) and $\Gamma(\boldsymbol{H_i})$ is derived (Razavi and Gupta 2016):

$$\Gamma(\boldsymbol{H_i}) = \int_0^{H_i} \gamma(\boldsymbol{h_i}) d\boldsymbol{h_i} \tag{3}$$

More details of the global sensitivity analysis (GSA) used in this paper is given in the Online Supplementary Material (Sect. S3). In this paper, based on the bootstrapping technique, the degrees of uncertainty in the results of the sensitivity analysis is evaluated based on 90% confidence intervals (CIs) of the sensitivity indices. To comprehensively analyze the sensitivity of the runoff simulation results to the SWMM parameters, multiple sensitivity analysis using VARS and considering different metrics (criteria) is done. These criteria are approximately uncorrelated metrics, each responsible for measuring a distinct feature of the data. These metrics are based on commonly used model efficiency criterion of Nash–Sutcliffe, namely Nash–Sutcliffe efficiency (NSE) criterion for the runoff (NSE(Flow)), NSE criterion for the logarithm of the runoff (NSE_{log}(Flow)), and percent bias (PBIAS) in simulating runoff (PBIAS(Flow)) (Table 1).

Using these metrics, one can assess model performance in reproducing hydrograph characteristics, (i.e. high flows (runoff peak), low flows, and total volume of runoff (Table S1). Generally, the NSE metric shows more sensitivity to high flows, which can be attributed to squaring. On the other hand, NSE_{log}(Flow), which considers logarithmic transformation of the runoff discharge, accentuates the effect of low flows and decreases the effect of high flows (Krause et al. 2005). PBIAS is a measure of deviations of runoff data over the simulation period collectively. Therefore, this metric can represent model performance in predicting the total volume of the observed runoff (Moriasi et al. 2007). In this paper, $IVARS_{50}$, which represents an integrated variogram over 50% of the parameter range, is used for parameter ranking.

2.4 Calibration of the Runoff Simulation Model

After determining the most effective parameters of the runoff simulation model using the sensitivity analysis, the optimum values of these parameters are determined. The aim of calibration is to determine the values of the effective parameters so that simulated hydrograph is fitted to the observed hydrograph as possibly as it can be. More details can be found in Online Supplementary Material (Sect. S4).

Table 1 Definition of the used metrics for evaluating model performance[*]

Nash–Sutcliffe coefficient of efficiency:

$$NSE = 1 - \frac{\sum (Q_{obs} - Q_{sim})^2}{\sum \left(Q_{obs} - \overline{Q_{obs}}\right)^2} \tag{4}$$

Nash–Sutcliffe for the logarithm of flows:

$$NSE_{log} = 1 - \frac{\sum (\log(Q_{obs}) - log(Q_{sim}))^2}{\sum \left(\log(Q_{obs}) - log\left(\overline{Q_{obs}}\right)\right)^2} \tag{5}$$

Percent Bias:

$$PBIAS = \frac{\sum (Q_{obs} - Q_{sim})}{\sum (Q_{obs})} \times 100 \tag{6}$$

[*]Q_{obs}: Observed flow, Q_{sim}: Simulated flow, $\overline{Q_{obs}}$: Mean of observed flows

2.5 Determination of the Design Storm

To determine the design storm, duration, depth and spatial and temporal patterns of rainfall are needed. Details of this section have been provided in the Online Supplementary Material (Sect. S5).

2.6 Defining and Initial Selection of the LID–BMP Scenarios by Developing a Multi-Objective Optimization Model

Different scenarios of LID-BMPs are defined for urban runoff quantity and quality management in the study area, considering technical and socio-economic factors. These factors include landuse, natural hydrology and soil hydrologic group, groundwater level, the required space for executing the LID-BMPs, the slope of the region under devepoment, and the desired effects of development. Public acceptability is also an important consideration. These factors can be obtained based on field observations and the physcial and hydrological characteristics of the urban watershed.

The SWMM.5 is used to simulate the impacts of LID-BMPs on the quantity and quality of runoff. In addition, hydrologic impacts of implementing different types of LID-BMPs such as bio-retention cells, rain gardens, green roofs, infiltration trenches, permeable pavements, rain barrels and vegetative swales are modelled using SWMM.5. In this paper, the proposed initial LID-BMPs, consist of bio-retention cells, vegetative swales, permeable pavements and infiltration trenches.

Using bio-retention cells, urban runoff water is stored through vegetative surfaces, or soil mixture and a gravel beds, and then infiltrates into the soil or evaporates. By the use of vegetative swales, which are vegetated channels with steep sides, transportation of urban runoff is slowed down and as a result, more infiltration to the soil can occur. Permeable pavements are pavements with high porosity that enable stormwater runoff to infiltrate into the ground through their porous media. Their surfaces can consist of pervious concrete, plastic grids, recycled glass, porous asphalt, resin-bound paving, paving stones, porous turf and interlocking concrete pavers. Infiltration trenches known also as percolation trenches are ditches or shallow excavations filled with gravel, rubble or stone. They provide temporary subsurface storage of runoff, and enhance the ground capacity for storing and draining water and increase the time needed for collected water to infiltrate into the soil through the trenches' bottom and sides.

In this step, an optimization model is developed to obtain a set of non-dominated scenarios to determine the best LID-BMPs in each sub-catchment of the study area. First, different scenarios each containing a set of LID-BMPs are considered. These scenarios are defined based on physical and hydrological characteristics of sub-catchments including catchment area, slope imperviousness and land use. The type of LID-BMPs and the area of every sub-catchment, where the LID-BMPs are undertaken, are considered as the decision variables of a multi-objective optimization model. In this paper, LID-BMPs are implemented in sub-catchments with high runoff volume and pollution loads.

The objectives of the optimization model are minimizing the runoff volume, total pollution load and the total cost of LID-BMPs. The decision variables include characteristics, locations and areas under implementation of LID-BMPs. The minimum and maximum values of the areas under each scenario of LID-BMPs constitute the

constraints of the optimization model. In this paper, the multi-objective optimization algorithm of the NSGA-II (Deb et al. 2002), is used to find the non-dominated Pareto optimal scenarios for the urban runoff management problem. These scenarios are used in the next step for selecting the final urban runoff management scenarios. More details on the NSGA-II section have been provided in the Online Supplementary Material (Sect. S6).

2.7 Selecting the Best Management Scenario(s)

In this paper, to select a final solution out of a set of non-dominated solutions, the negotiation process among stakeholders is simulated using the Nash bargaining theory (Nash 1950). This theory considers the stakeholders' preferences through using their utility functions, dissatisfaction points and relative powers in the negotiation. In this paper, the utility functions are obtained based on consulting the experts and engineering judgment. In the Nash bargaining function, the disagreement point for a stakeholder equals the value of their utility function when no LID-BMPs have been implemented. The values of relative weights are assigned to the stakeholders by the analyst according to the stakeholders' relative importance or power. The Nash bargaining theory as follows. Suppose $f_i()$ is the utility function of the stakeholder i and $\bar{d} = (d_1, \ldots, d_n)$ is the vector of disagreement points. The unique solution to this conflict-resolution problem is determined by solving the following optimization problem:

$$\text{Maximize } Z = (d_1 - f_1)^{w_1}(d_2 - f_2)^{w_2} \ldots (d_n - f_n)^{w_n} \tag{7}$$

$$\text{Subject to :} \qquad f_i \leq d_i \qquad i = 1, 2, \ldots, n \tag{8}$$

where, Z is called the Nash product, f_i stands for the utility function of the ith stakeholder, d_i represents the disagreement point for the ith stakeholder, n denotes the total number of stakeholders and w_i stands for the relative weight of the ith stakeholder which shows this stakeholder's relative power.

3 Case Study

The study area is the Velenjak urban watershed located between the suburban and mountainous areas in the north of Tehran and the suburban and agricultural regions in the northeast of Tehran which suffers from the aforementioned environmental problems. The drainage system of the Velenjak watershed includes one major conduit, called Velenjak Channel. The service area of Velenjak Channel in runoff drainage is 22.13 km^2, 7.35 km^2 and 14.78 km^2 of which are respectively, undeveloped mountainous area and urban area. The catchment is divided into 27 sub-catchments based on the method described in Sect. 2.2. Figure S1 (Online Supplementary Material) shows the location of the study area as well as the sub-catchments and the layout of the drainage system. More details on the study area can be found in the Online Supplementary Material (Sect. S7).

4 Results and discussion

In this section, we present the results of applying the proposed methodology to the case study. The global sensitivity analysis of the SWMM is conducted based on the observed runoff and rainfall data related to storm events occurred in 2017. The computational time of the sensitivity analysis using a 2.50 GHz Intel(R) Core(TM) i5-3210 M processor is 46 min. In this model, a perturbation resolution (Δh) of 0.1, number of star centers (Razavi and Gupta 2016) of 100 and bootstrap size (number of sampling iterations with replacement) of 1000 results in a total of 13,600 executions of the SWMM.

The derived variograms of VARS for the SWMM parameters are demonstrated in Fig. 2 (as well as Figs. S2 and S3 in the Online Supplementary Material). In these figures, plots (a) and (c) illustrate the directional ($\gamma(h)$) and integrated ($\Gamma(H)$) variograms, respectively. Plots (b) and (d) display zoom-in images of plots (a) and (c), respectively. As shown in Fig. 2 (as well as Figs. S2 and S3 in the Online Supplementary Material), for most of the parameters, the response surfaces of the SWMM considering small perturbation scales (h), exhibit linear and monotonic behavior, while it exhibits non-linear and monotonic behavior considering larger perturbation scales. As an exception, based on $NSE_{log}(Flow)$, the response surfaces of the SWMM exhibits non-linear and non-monotonic behavior for parameter U-Width (see Fig. S2 in the Online Supplementary Material). Meanwhile, based on NSE(Flow) and $NSE_{log}(Flow)$ criteria, the response surfaces of the SWMM corresponding to changes in parameter U-% Imperv (as the most influential parameter) show linear and monotonic behavior over all perturbation scales (see Figs. S2a and S3a in the Online Supplementary Material). Also, based on NSE(Flow), $NSE_{log}(Flow)$ and PBIAS(Flow) metrics, for less important parameters such as Decay and MaxRate, the response surfaces of the SWMM show linear and monotonic behavior over all perturbation scales. Not only do these directional variograms demonstrate how the model response changes with the perturbation scale of a certain parameter in the multi-dimensional space, but also they show the relative importance and ranking of all parameters at any particular perturbation scale.

According to Fig. 2, and Figs. S2 and S3 in the Online Supplementary Material, in some cases, the values of $\gamma(h)$ and $\Gamma(H)$ for two or more parameters are similar considering low perturbation scales. However, considering larger perturbation scales, the value of $\gamma(h)$ and $\Gamma(H)$ for some of the parameters are different and even in some cases the values of $\gamma(h)$ and $\Gamma(H)$ related to some of these parameters increase significantly. For instance, based on NSE(Flow), the values of $\gamma(h)$ and $\Gamma(H)$ for parameters of N-Conduit, U-Slope and S-Imperv, considering h (and H) ~< 0.2, are similar (Figs. 3b, d). However, considering h (and H) ~> 0.2, the values of $\gamma(h)$ and $\Gamma(H)$ are different for these parameters and the values of $\gamma(h)$ and $\Gamma(H)$ for S-Imperv is significantly larger than those of the parameters N-Conduit and U-Slope. The same behavior can be seen for N-Imperv and U-%Imperv, based on $NSE_{log}(Flow)$ (see Fig. S2a in the Online Supplementary Material), S-Imperv, U-Width and PctZero, based on PBIAS(Flow) (see Fig. S3b, d in the Online Supplementary Material). Based on these figures, the relative rankings of parameters are also derived. For example, as seen in Fig. S1a, based on $NSE_{log}(Flow)$, the values of $\gamma(h)$ for U-%Imperv considering h~< 0.35 is larger than those of the parameter S-Imperv, while the values of $\gamma(h)$ for U-%Imperv considering h~> 0.35 is smaller than those of S-Imperv.

Similar behavior can be seen between parameters N-Imperv and U-%Imperv and also parameters PctZero and U-%Imperv, based on $NSE_{log}(Flow)$. These results confirm that unlike most traditional methods for sensitivity analysis of the model response surface,

a) NSE(Flow)

b) NSE(Flow)
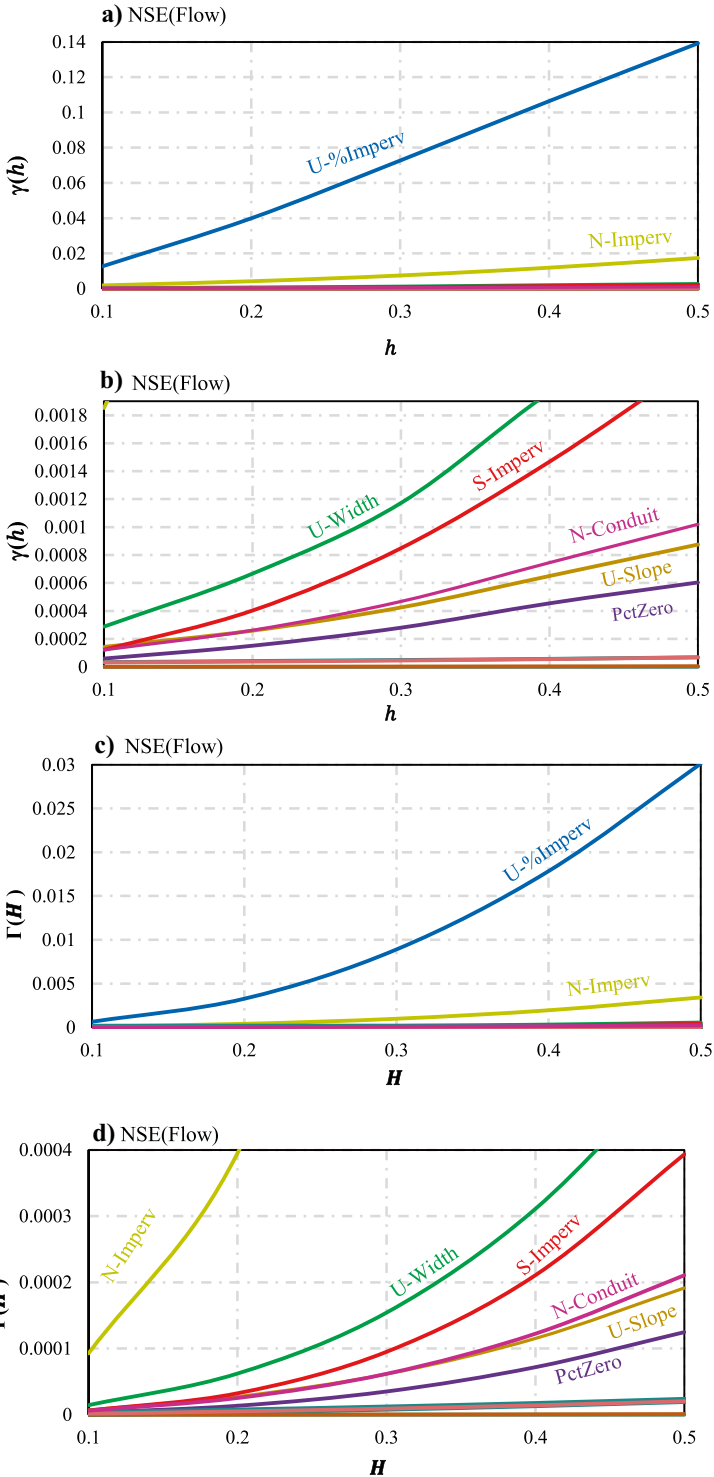
c) NSE(Flow)

d) NSE(Flow)

◄ **Fig. 2** Resulted variograms based on the sensitivity analysis on the SWMM parameters considering NSE(Flow) criterion (Plots (**a**) and (**b**) are directional variograms; plots (**c**) and (**d**) are integrated variograms (IVARS). Plots (**b**) and (**d**) are respectively zoom-in plots of plots (**a**) and (**c**), to illustrate very small values on the vertical axis. Note that for variograms to remain meaningful, the distance between any two points within a given parameter range should not exceed half of its range, i.e., H ≤ 50%)

VARS is able to characterize dependency to perturbation scale by giving different sensitivity rankings at different perturbation scales.

In order to further investigate the sensitivity of the SWMM to perturbation scale, IVARS indices of 10%, 30% and 50% are calculated based on metrics of NSE, NSE_{log}, and PBIAS; and their corresponding parameter rankings are shown in Fig. 3a–c. In these figures, a ranking of 1 represents the least influential and a ranking of 15 represents the most influential parameter. To better interpret the resulted values of IVARS in term of parameter importance and enable a more consistent comparison, the calculated values of IVARS are normalized such that the resulted ratios of sensitivity for all parameters add up to 100%.

$IVARS_{50}$ is the most comprehensive global sensitivity index in VARS, which encapsulates the SA information of all the perturbation scales (Razavi and Gupta 2016). On the other hand, $IVARS_{10}$ and $IVARS_{30}$ provide assessments considering smaller perturbation scales. Based on Fig. 3a–c, usually the ratio of sensitivity and rankings of parameters change with perturbation scale of the parameters. For example, based on NSE_{log}(Flow) metric, parameter S-Imperv is ranked respectively as "4", "3" and "1" using $IVARS_{10}$, $IVARS_{30}$ and $IVARS_{50}$ (Fig. 3b). Also, the rank of U-%Imperv based on the same metric using $IVARS_{10}$, $IVARS_{30}$ and $IVARS_{50}$, is estimated as 1, 2 and 3, respectively. Similar behavior is also seen for parameter U-Slope (Fig. 3a) and parameters U-%Imperv and PctZero (Fig. 3c). Therefore, it is clear that perturbation scale of parameters has a significant impact on determining the degree of importance of the parameters and their impacts on the SWMM performance.

In general, there is more similarity between the results of SA in identifying the most influential parameters using NSE (used mainly for high flow predictions) and PBIAS (used mainly for prediction of total flow volume). The parameter U-%Imperv, which represents the percentage of impervious urban area of the catchment, such as roofs and roadways, is by far the most important parameter. This parameter contributes to 80% to 95% of the sensitivity, considering all sensitivity indices, based on NSE and PBIAS metrics. These high values can be partly caused by a relatively large range considered for this parameter. The next important parameter based on NSE(Flow) and PBIAS(Flow) considering different perturbation scales is N-Imperv, which represents Manning's roughness coefficient for impervious areas. This parameter is related to the amount of resistance that overland flow encounters as it runs off the sub-catchment surface. The next important parameter is U-width, which is defined as the sub-catchment's area divided by the length of the longest overland flow path. Parameter S-Imperv, which is depression storage in impervious surfaces, is the next suggested important parameter. This depression storage is filled prior to the occurrence of any runoff and represents initial abstractions such as surface ponding, interception by flat roofs and vegetation, and surface wetting.

Based on metrics of NSE(Flow) and PBIAS(Flow) and considering the three indices, the mentioned four parameters contribute to nearly 96 to 99 percent of sensitivity of overland runoff to the simulation model parameters. It is interesting that based on PBIAS(Flow) metric, U-width is identified as an important parameter when considering small perturbation scales. This can be due to small-scale roughness (non-smoothness) in the response surface of the model that may not be easily identified at larger scales (Razavi and Gupta
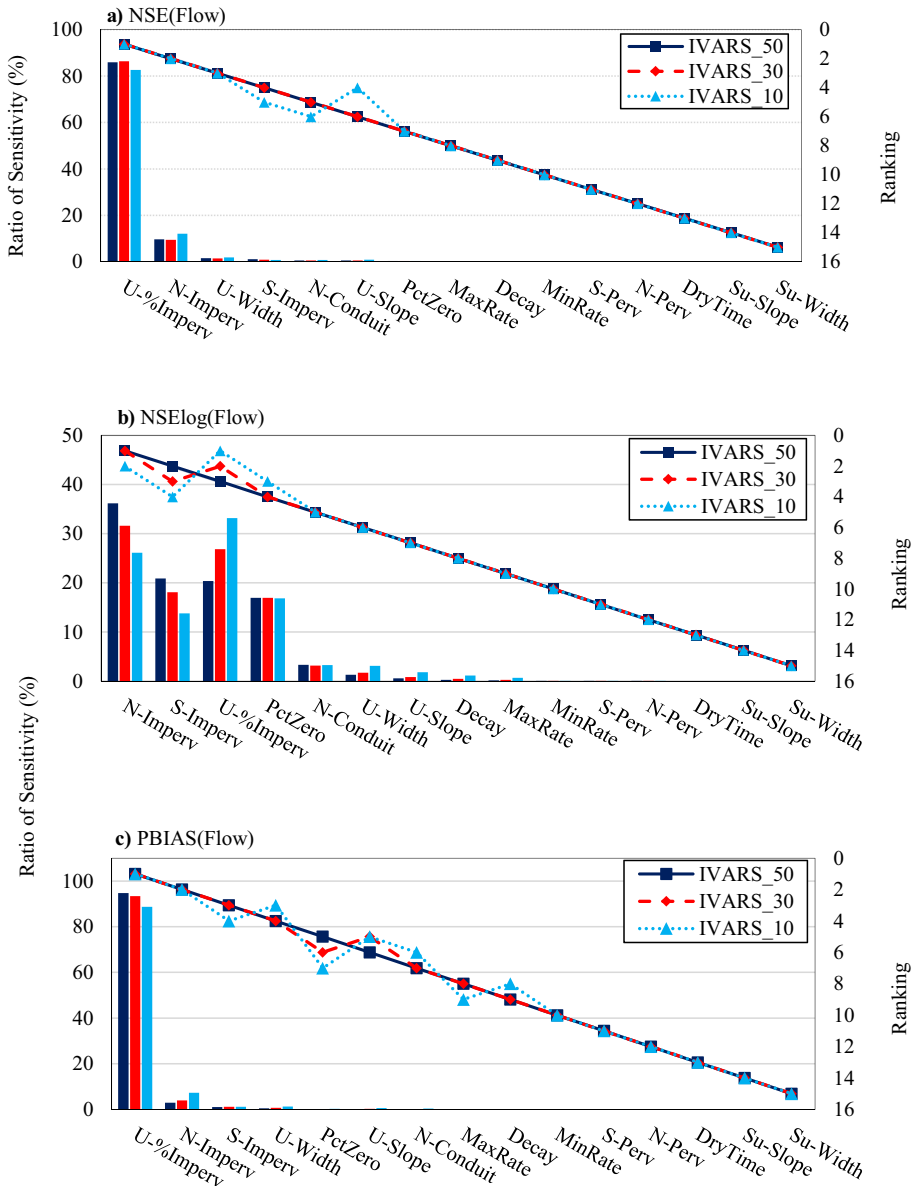
Fig. 3 IVARS indices of 10%, 30% and 50% (bar charts), and corresponding rankings (dotted lines) of parameters of the SWMM based on performance metrics of **a**) NSE, **b**) NSE_{log}, and **c**) PBIAS. The values of IVARS are normalized such that the resulted ratios of sensitivity for all parameters add up to 100%. Parameters are sorted based on $IVARS_{50}$. Rankings are shown in reverse order on a secondary axis on the right

2016). On the other hand, based on NSE(Flow), the importance of this parameter increases considering larger perturbation scales. This happens as a result of relative smoothness and existence of local extreme point(s) in the response surface of the model that may not be easily identified when considering small scales.

As seen in Fig. 3, when using $NSE_{log}(Flow)$, which is mostly used for low flow prediction, the order of importance of parameters differs with the one obtained based on $NSE(Flow)$ and $PBIAS(Flow)$. When using this metric, the most influential parameters for runoff simulation are respectively, N-Imperv, U-%Imperv, S-Imperv, PctZero, N-Conduit, U-width, U-Slope and Decay. These four parameters contribute to nearly 90%-94% of sensitivity based on $NSE_{log}(Flow)$. Parameter PctZero, which is the percentage of impervious area with no depression storage, accounts for runoff that immediately occurs at the beginning of rainfall before depression storage happens. It can represent pavement close to the gutters that has no surface storage, pitched rooftops that drain directly to street gutters and new pavement that may not have surface ponding, etc. This parameter accounts for approximately 17% of sensitivity based on $NSE_{log}(Flow)$. This is perhaps, due to the role it plays in producing immediate low runoff. Parameter N-Conduit, manning's roughness coefficient, as expected, is the next important parameter (~3% of sensitivity), which controls routing (timing) of the low flow in the channel. In low flow prediction, U-width is more important in small perturbation scales and its ratio of sensitivity changes from ~1%, considering $IVARS_{50}$ to ~3%, considering $IVARS_{10}$. Also, based on $NSE_{log}(Flow)$, U-Slope, which is the average surface slope of urban sub-catchments and "Decay", which is the decay constant in the Horton infiltration, becomes more important in small perturbation scales.

Based on the results, the sensitivity of runoff to parameter U-Slope (the average surface slope of urban sub-catchment) is not high expect for $NSE_{log}(Flow)$ when considering small perturbation scales. This can be attributed to the narrow variation bond of this parameter in the study area, since limiting the range of variation of a parameter decreases its impact on the variability of model response. Similarly, the sensitivity of model to parameter "Decay" rate of Horton infiltration is high only when $NSE_{log}(Flow)$ metric and small perturbation scales are considered.

In this paper, the parameters are arranged according to $IVARS_{50}$ index, which is the most comprehensive global sensitivity index in VARS, since it encapsulates the information of SA related to all perturbation scales (Razavi and Gupta 2016). All the important parameters for runoff simulation using the SWMM are listed in Table S4. A parameter is considered to be "important" when its $IVARS_{50}$ ratio of sensitivity is greater than 1% and is marked as "very important" if its $IVARS_{50}$ ratio of sensitivity is larger than 10% (Rosolem et al. 2012). In this paper, parameters that are identified as important with respect to any of the metrics are generally considered to be important. When selecting a subset of important parameters for calibration of the SWMM, it is also important to ensure enough parameters are included. This way, a large range of variability of model response with respect to parameter variations can be taken into consideration. Uncertainty analysis and estimating the confidence intervals (CIs) of the sensitivity indices have been estimated using Bootstrap method. The results of this section are provided in the Online Supplementary Material (Sect. S8).

In this paper, hydrographs resulted from different rainfall events are measured and used to calibrate the parameters of the rainfall-runoff simulation model based on the SWMM. The SWMM simulation model is calibrated using several independent rainfall events occurred in 2017. Some simulated and observed hydrographs used in the calibration phase are presented in Fig. S4 of the Online Supplementary Material. Then, the model is validated using two independent rainfall events occurred on February 13th, 2017 and March 11th, 2017. The simulated and observed hydrographs in the validation phase are presented in Fig. 4. Rainfall data related to these events were recorded in the Shomal-e-Tehran synoptic station (34°48′N and 51°29′E and elevation of 1548.2 m
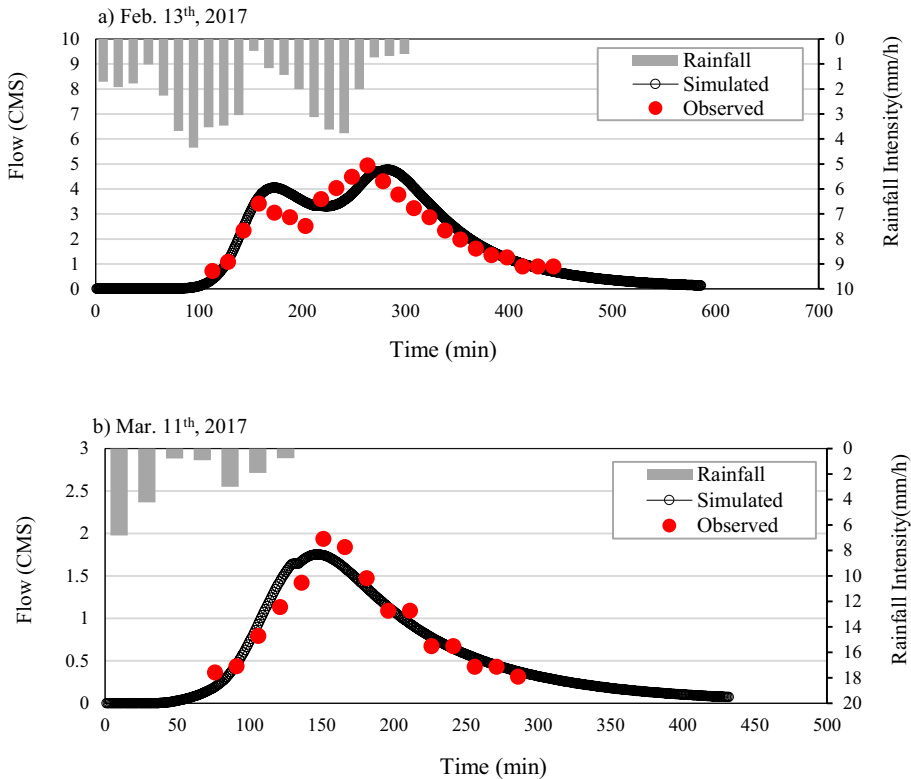
Fig. 4 The simulated and observed hydrographs in the validation phase

from the sea level) of Iran Meteorological Organization (IRIMO). The location of the Shomal-e-Tehran synoptic station is shown in Fig. S1.

In this paper, six parameters of U-%Imperv, N-Imperv, S-Imperv, PctZero, U-Width and N-conduit which their related sensitivity indices were high have been selected for calibrating the SWMM. The identified important parameters are only related to the urban sub-catchments (not sub-urban or undeveloped sub-catchments) and their connected conduits (see Fig. S1). Since, there is 16 urban sub-catchments with 16 connected conduits, each having a different value for each of the six parameters, the number of model parameters for calibration is 96 (16×6).

Three performance metrics of $(NSE)_{modified}$, $(NSE_{log})_{modified}$ and $(PBIAS)_{modified}$ are used as the objective functions for calibrating rainfall-runoff simulation model of the SWMM. A three-objective optimization model with mentioned objective functions and 96 decision variables is solved. The NSGA-II-based optimization model is linked with the SWMM rainfall-runoff simulation model. The developed simulation–optimization model is executed for each of the calibration events, and the corresponding Pareto front of non-dominated solutions is shown in Fig. 5.

The solutions corresponding to the largest values of metrics NSE(Flow) and NSE(logFlow) (close to 1), and the smallest value of the metric PBIAS(Flow) (close to zero), which represent a good accordance between the predicted and observed time series, are selected. Considering some thresholds for each of the three objective

Fig. 5 Pareto fronts of non-dominated solutions obtained using the multi-objective simulation–optimization model for calibrating the important parameters of the SWMM
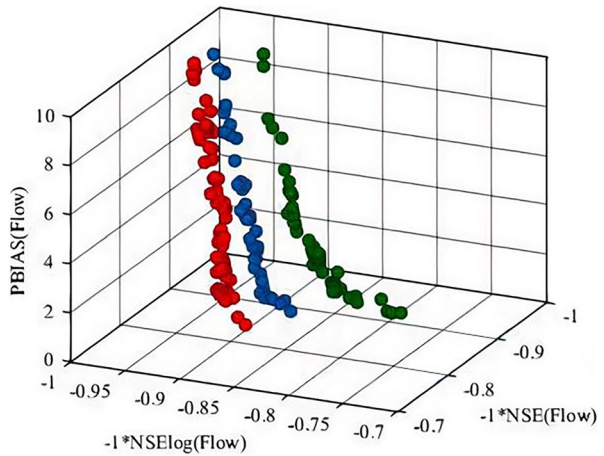
functions in the Pareto front of non-dominated solutions, values for the parameter sets corresponding to the region of acceptable solutions are obtained based on the engineering judgment.

The values of NSE(Flow), NSE(logFlow) and PBIAS(Flow) performance metrics are also calculated to assess the validity of the calibrated SWMM. The values of model performance metrics for the validation phase along with the rainfall characteristics of each event are also summarized in Table 2. The runoff hydrograph at the outlet of the Velenjak urban watershed based on different observed events is simulated using the selected values for parameter sets.

Since the optimal values of parameter sets obtained in the calibration process are almost similar, in order to validate the calibrated simulation model, arithmetic mean of the optimal values of the three parameter sets obtained in the validation phase is used. The observed and simulated hydrographs in the validation phase are shown and compared in Fig. 6a, b. As seen in these figures, the simulated hydrographs are in accordance with the observed ones. Based on the results of validating the SWMM, the best values for the three metrics are 0.98, 0.97, and 1.

The design rainfall duration is considered equal to the concentration time of the catchment. Since, the Velenjak catchment consists of two urban and non-urban (undeveloped) regions, the time of concentration of these two regions are separately calculated and then, the summation is considered as the overall time of concentration of the catchment. More details on the selected design rainfall have been provided in Sect. S8 of the Online Supplementary Material.

Table 2 Selected rainfall events and the values of model performance metrics in the validation phase of the SWMM

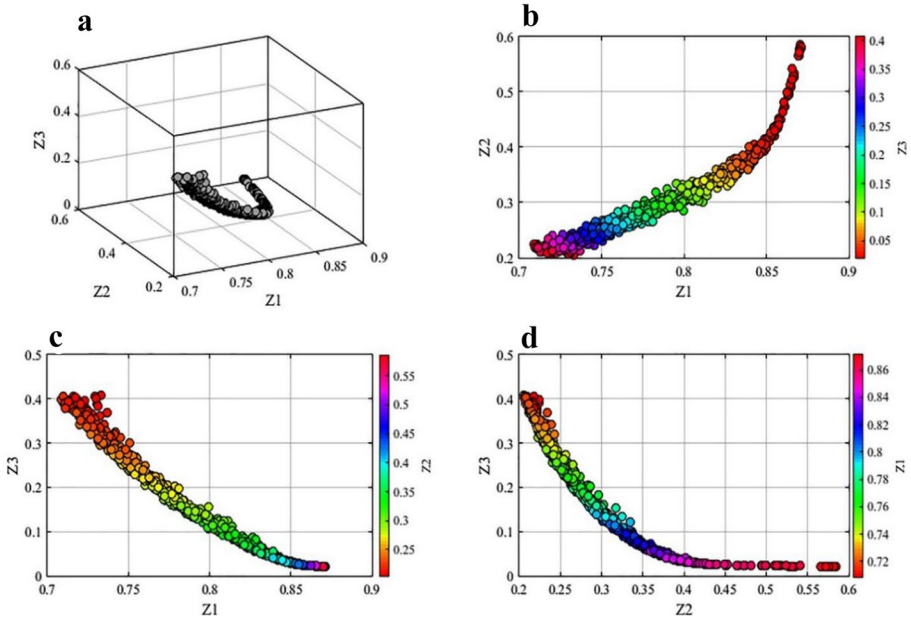| Event	Rainfall Duration (min)	Rainfall Depth (mm)	Variable	NSE	NSE_{log}	PBIAS
13 Feb 2017	315	11.6	Flow discharge	0.86	0.95	8.2
11 Mar 2017	105	4.6	Flow discharge	0.90	0.87	1

Fig. 6 The Pareto front of non-dominated solutions obtained using the NSGA-II in 3-D and 2-D displays (Z_1, Z_2 and Z_3 are defined in Eqs. S10, S11, and S12)

Details on the structure of the developed optimization model used for runoff quantity and quality management have been provided in the Sect. S8 of the Online Supplementary Material. The optimization model provides 678 non-dominated solutions that represent the area of each LID-BMP in each sub-catchment (Fig. 6). These solutions are considered as the final candidate runoff management practices and will be further used in the conflict resolution model to select a set of LID-BMPs that the stakeholders mostly agree upon.

In order to propose a final scenario of LID-BMP, firstly, the goodness of each of the non-dominated solutions obtained in the previous section with respect to the stakeholders' utilities is determined. The utility functions are defined based on the stakeholders' priorities and preferences. These functions are standardized into the scale of zero to one. The main stakeholders in the study area which are mostly affected by the urban runoff management along with their utility functions are described in Sect. S8 of the Online Supplementary Material.

Table 3 The proposed areas (m^2) for implementing each type of the candidate LID-BMPs (scenario 361)

| LID type | Sub-catchment | | | | | | | | | |
	12	13	14	15	17	18	20	22	25	27
Bioretention cell	570	478	750	509	382	455	421	827	845	425
Infiltration trench	1224	1208	2347	1692	1216	1138	1550	2994	1936	1689
Grassed swale	630	2262	1583	2120	1542	976	1935	4633	5297	4826
Porous pavement	1168	2060	1010	3450	1208	910	1646	1510	5473	2775

Based on the results of the Nash bargaining model, the stakeholders can reach an agreement on scenario 361. The values of utility functions for TM, TRWC, TPWWC, AS equal 0.45, 0.60, 0.76, 0.24, respectively. Implementing the management scenario 361 with the cost of 26.10 billion Rials, leads to more than 24% decrease in runoff volume and about 74% decrease in runoff TSS load in the Velenjak urban watershed outlet. The characteristics of the candidate management scenarios are given in Table 3.

5 Summary and Conclusion

In this paper, a new methodology was developed for finding best urban runoff management scenarios under uncertainty. Using IVARS indices based on directional variograms, a comprehensive assessment of sensitivity of the SWMM to its parameters across a full spectrum of perturbation scales was made. The uncertainty related to the ranking of the parameters was incorporated based on a bootstrapping technique. A comprehensive evaluation of the effectiveness and reliability of the variogram-based global sensitivity analysis of VARS on the SWMM parameters was conducted. In the GSA, important parameters of the SWMM were identified with respect to three metrics of NSE, NSE_{log}, and PBIAS. These metrics were used to measure the SWMM performance in reproducing high flows, low flows and total flow volumes, respectively. An NSGAII-based optimization model with three objectives was developed for automatic calibration of the SWMM. The model was calibrated and validated using different rainfall events. Also, the uncertainty regarding the design rainfall hyetograph was taken into account by developing the Huff curves and using Mont Carlo analysis. Different scenarios of LID-BMPs regarding combinations of the type, area and location of runoff management practices in the sub-catchments were proposed to improve surface runoff quantity and quality. A Pareto front of solutions were obtained by developing an NSGA-II-based optimization model which was coupled with the calibrated SWMM. The objectives of the optimization model were minimizing the runoff volume, total pollution load and the total cost of the LID-BMPs. Based on the obtained results, the following remarks have been concluded:

1. Directional variograms and integrated variograms of the response surface of the SWMM were mostly non-linear and monotonic. The linear and monotonic variograms were observed only in few cases.
2. The choice of perturbation scale of the SWMM parameters has a significant impact on the performance of the SWMM in sensitivity analysis, particularly on the values of sensitivity indices and the SWMM parameter rankings.
3. The metric used for model performance significantly influences the assessment of the SWMM sensitivity to its parameters. Therefore, the use of multiple metrics that capture various distinct characteristics of the SWMM can be considered as a more comprehensive sensitivity analysis approach. Generally, for the results of SA to be more effective, the type of the selected criteria or their relative weights in sensitivity analysis are better to be in line with the purpose of the modeling.
4. The use of the sensitivity analysis for finding the most influential parameters of the SWMM, resulted in reducing the number of calibration parameters and prediction uncertainty and consequently decreasing the computational cost. In this paper, six parameters of the SWMM were identified based on the chosen metrics and IVARS index. These parameters included urban percent imperviousness, Manning's roughness coefficient,

depression storage of impervious surfaces, percentage of impervious areas with no depression storage, width of urban sub-catchments and Manning's roughness coefficient of conduits which were used in the calibration phase.

5. The uncertainty analysis on the results of ranking the SWMM parameters using the bootstrapping procedure showed high reliability of VARS in sensitivity analysis of the SWMM parameters.

6. The results of validating the SWMM using different criteria such as Nash–Sutcliffe efficiency showed the good performance of the calibrated SWMM in runoff simulation.

7. Deriving the design rainfall hyetograph by developing Huff curves and using Monte Carlo uncertainty analysis, wide ranges of variation in rainfall depth, duration and pattern were taken into account.

8. The results of the NSGA-II-based optimization model, developed for obtaining optimum scenarios of LID-BMPs, showed that the Pareto optimal solutions could significantly reduce the runoff volume and improve runoff quality at the Velenjak watershed outlet.

9. Using the Nash bargaining function, the utility functions of the four major stakeholders in the study area (TM, TRWC, TPWWC and AS) were considered and the most desirable scenario of LID-BMP was selected.

In future studies, it is suggested to perform the sensitivity analysis on the parameters related to runoff quality such as built-up and wash-off parameters in the SWMM. In addition, built-up and wash-off parameters can be used as decision variables of the optimization model developed for calibrating the SWMM. In future works, for deriving the design rainfall, time series of rainfall can be used instead of individual rainfall events.

Author Contribution Contribution of the authors are detailed as: Majid Hashemi: Conceptualization, Methodology, Writing, Original draft preparation, Software. Najmeh Mahjouri: Supervision, Methodology, Validation, Writing, Reviewing and Editing. All authors read and approved the final manuscript.

Declarations

Conflicts of Interests The authors declare that they have no known competing interests and relevant financial or non-financial interests to disclose.

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