

Sensitivity Analysis of the SWMM Model for Runoff Simulation in an Arid Urban Catchment

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ABSTRACT

Objective: Hydrological models' performance is highly dependent on the accurate calibration of multiple parameters. Sensitivity analysis can play a key role in optimizing this process by identifying the most influential parameters. The present study investigates the sensitivity of the Storm Water Management Model (SWMM) in simulating urban runoff in Shahrood, a city located in an arid region of Iran.

Methods: The sensitivity of the SWMM to changes in seven key calibration parameters, including the Width factor of the subcatchment, Curve Number (CN), Manning's roughness coefficients for pervious (N-Perv) and impervious (N-Imperv) areas, the percentage of impervious areas (Imperv factor), and depression storage depth for both pervious (Des-Perv) and impervious (Des-Imperv) areas, was quantified using the Sensitivity Factor (S) proposed by Morris. The study area was divided into 18 relatively homogeneous sub-catchments, with runoff from these areas drained through two outlets. During the sensitivity analysis process, peak discharge and runoff volume responses to these parameters were examined across seven rainfall events characterized by different intensities and durations.

Results: The results showed that peak discharge (Qp) and runoff volume (RV) are sensitive to the Imperv factor (S= 0.64 and 0.93, respectively). Qp is generally sensitive to the Width factor (S=0.17) and N-Imperv (S=0.13), while showing no sensitivity to other parameters (S<0.05). Longer rainfall durations increased the sensitivity of Qp to both CN and the Imperv factor, while sensitivity to other parameters decreased. CN significantly affected both RV and Qp only during long-duration events.

Conclusions: Longer rainfall durations increased the sensitivity of Qp to both CN and the Imperv factor, while sensitivity to other parameters decreased. CN significantly affected both RV and Qp only during long-duration events.

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1. Introduction

Hydrological models play a crucial role in various areas, including flood forecasting, flood management, drought monitoring, building design, and reservoir management (Samiei et al., 2024). The extensive range of applications for hydrological models, combined with the diverse climatic and physiographic regions, contributes to an overall increase in the complexity of these models (Mai et al., 2022; Zahiri et al., 2024). Hence, hydrological models inherently involve simplifying the complex reality within watersheds. This simplification is achieved through the use of mathematical equations and assumptions, primarily relying on the conceptual representation of physical processes that influence runoff at the basin level. The parameters in these models typically pertain to soil characteristics, vegetation features, topography, river properties, crops, weather, and atmospheric conditions (Ranatunga et al., 2017).

The incomplete representation of real-world hydrological processes often introduces uncertainties in the outputs of hydrological models. These uncertainties arise from various sources, including measurement error, model structural error, and parameter uncertainty (Van Zelm & Huijbregts, 2013). Many parameters associated with hydrological processes are typically unknown and require calibration to align model outputs with measured data sets (Bajracharya et al., 2020; Rezvani et al., 2024). Understanding the most influential parameters during model calibration is crucial and can significantly aid model users in the evaluation stage (Madrado-Uribeetxebarria et al., 2021).

One valuable approach to gaining this understanding is sensitivity analysis. Sensitivity analysis assesses the hydrological effects of various parameters on simulation results, enabling the modeler to identify the relative influence of each parameter on the model outputs (Ranatunga et al., 2017). Therefore, sensitivity analysis helps prioritize the calibration of parameters with the greatest impact on simulation results (Gu et al., 2017). This information is then utilized by the modeler to streamline the calibration process by limiting the number of parameters involved, thereby enhancing the efficiency of calculations (Höllering et al., 2018). In practice, parameters with minimal effect on model output can be set to default values and not recalibrated. Performing sensitivity analysis before initiating the calibration of a hydrological model is strongly recommended. This proactive step allows for a more focused and efficient calibration process, contributing to the overall reliability of the model (Bajracharya et al., 2020).

The Storm Water Management Model (SWMM) is widely employed in hydrological modeling, particularly in urban basins. This model serves various purposes, including runoff management, drainage network design, and runoff disposal, especially in identifying flood-prone areas like the Arvand region (Arvand et al., 2020). Numerous studies have utilized the SWMM model for urban runoff management. For instance, Arvand et al. (2023) evaluated the effectiveness of low-impact development methods in mitigating runoff in Neishabur. (Lai et al., 2022) applied SWMM to assess different scenarios of low-impact development methods for flood control in China. Behrouz et al. (2020) simulated floods in New York, utilizing the SWMM model. Zhuang et al. (2023) employed SWMM to implement low-impact development methods for runoff control in Hong Kong. Ma et al. (2022) conducted a study on simulating urban runoff in the central area of Zhengzhou using the SWMM model. The versatility of the SWMM model makes it a valuable tool in addressing various urban hydrological challenges across different geographical locations.

Sensitivity analysis is a crucial step in the calibration and evaluation of hydrological models like SWMM. Several studies have been conducted to analyze the sensitivity of the SWMM model, shedding light on key parameters. In the northern part of Tehran, Badizadegan et al. (2021) studied sensitive parameters influencing peak discharge and flow volume in the watershed. (Omidi Arjenaki et al., 2021) conducted a study in Shahrekord, analyzing parameters sensitive to peak discharge and runoff volume. Peng et al. (2023) determined the

most effective parameters influencing peak flow rate and peak occurrence time using the Morris method. Kheshti Azar et al. (2025) introduced an event-based calibration method for urban drainage models in EPA-SWMM, improving accuracy and efficiency through sensitivity analysis and a genetic algorithm. Yang et al. (2025) developed an intelligent method for improving SWMM calibration by combining unsupervised clustering and sensitivity analysis. Their findings revealed that when the impervious area is less than 10%, there are no significantly sensitive parameters. Peng et al. (2024) combined SWMM, GIS, and Python to analyze parameter sensitivity for airport flood modeling. The results indicated that no parameters were highly sensitive, and the nonlinear correlation between the parameters and total inflow was weak.

In numerous hydrological studies, sensitivity analysis is typically performed within a single watershed. However, to better understand the complex interrelations of hydrological processes under diverse environmental conditions, there is a growing need to compare the sensitivity of parameters across multiple watersheds and under different flow regimes (Ranatunga et al., 2017). This consideration forms the primary motivation of the present research. The city of Shahroud, located in Iran, experiences seasonal rainfall events that frequently lead to urban flooding. Accordingly, it is essential to evaluate the performance of the SWMM model within this urban catchment. Once validated, the model can be used to propose improvements to the city's urban drainage system. In this context, conducting a sensitivity analysis of the SWMM model with respect to its calibration parameters can provide substantial benefits for researchers working in the Shahroud urban watershed. This approach not only enhances model understanding but also significantly reduces the time and effort required for model calibration and validation. Therefore, the main objective of this study is to perform a comprehensive sensitivity analysis of the SWMM model.

2. Materials And Methods

2.1. The study Area

The study area covers a large portion of the city of Shahroud (Figure 1), and urban runoff is drained from the region through two outlets. The Shahroud synoptic station, located at an altitude of approximately 1380 meters, reports that the average minimum, maximum, and annual temperatures are 8.6°C, 20.6°C, and 14.6°C, respectively. January is typically the coldest month, while July is the hottest. The region receives an average annual rainfall of around 150 mm. The monthly mean of meteorological data over the last 30 years is summarized in Table 1.

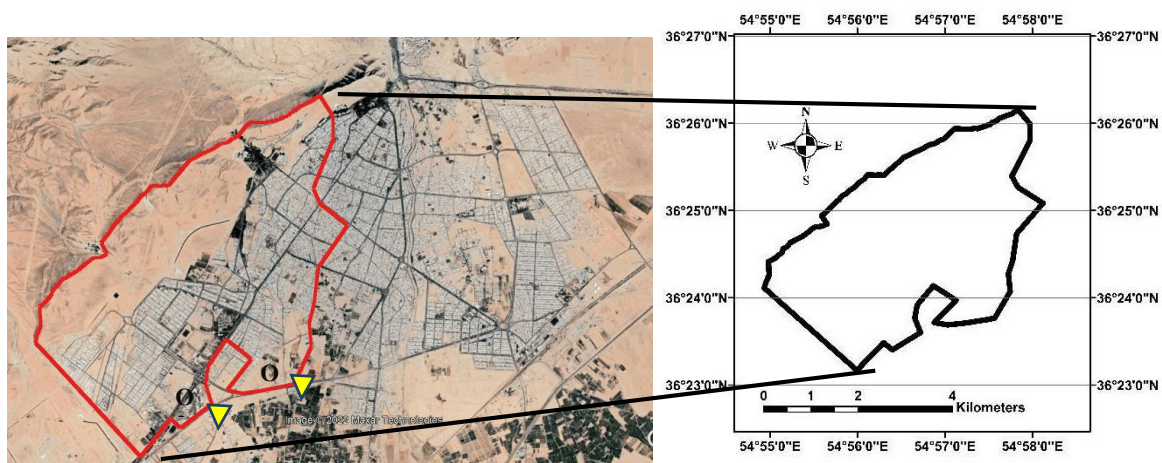


Figure 1- Study area**Table 1- The monthly mean of meteorological data over the past 30 years**

Month	Precipitation (mm)	Min Temperature (°C)	Max Temperature (°C)	Relative Humidity (%)
January	28.1	7.8	19.3	44
February	24.6	13.0	25.3	42
March	7.3	17.6	30.3	36
April	2.1	21.2	33.3	36
May	1.5	21.0	33.2	35
June	4.4	17.8	30.5	39
July	6.8	12.5	25.0	43
August	9.9	6.4	17.0	51
September	14.1	1.0	9.6	61
October	10.4	-1.7	6.7	62
November	20.2	-1.2	7.8	58
December	23.4	2.5	12.9	50

2.2. Hydrological modeling

The EPA Storm Water Management Model (SWMM5.1), which is a powerful rainfall-runoff model, can simulate the runoff quantity and quality of single or long-term rainfall events (D'Ambrosio et al., 2022; Taghizadeh et al., 2021). Among all hydrological models developed for urban watersheds, it has been proven that the SWMM is the most efficient in urban runoff management (D'Ambrosio et al., 2021; Taghizadeh et al., 2021). The input data required to run the SWMM5.1 are physiographic and hydro-meteorological data, including precipitation, flood hydrographs, concentration time, lag time, curve number, percentage of pervious and impervious area, infiltration equation, coefficient of roughness, elevations, sub-catchment area, land-use map, and so on (Zakizadeh et al., 2022). The SWMM includes several computational blocks to simulate the rainfall-runoff process. Runoff is generated from rainfall using a nonlinear reservoir approach, and surface runoff is calculated based on the principle of mass conservation. To route the runoff through urban drainage networks, the model employs kinematic and dynamic wave routing techniques. Infiltration is modeled using the Horton method, the Soil Conservation Service Curve Number (SCS-CN), and the Green-Ampt approach (Rossman & Huber, 2016). In this study, following the recommendations of Arvand et al. (2023). The SCS-CN method and kinematic wave routing were used for infiltration and flow routing, respectively. The SCS-CN approach was selected due to its simple data requirements and its ability to produce reliable results.

A key consideration in urban catchment modeling involves the appropriate delineation of the study area into a suitable number of sub-catchments (Arvand et al., 2023). In this study, a four-step procedure was employed to delineate the boundaries of the main catchment and its sub-catchments. In the first step, the existing drainage network was mapped. In the second step, land-use data and a Digital Elevation Model (DEM) at a scale of 1:500 were utilized to gain a preliminary understanding of the sub-catchment boundaries. Similar to natural catchment delineation, ArcMap and DEM data were used to define the initial boundaries. In the third step, elevation differences between the upstream and downstream points of each street were identified, and Google Earth was used to refine the delineation of each sub-catchment with greater precision. In the final step, a field survey was conducted to validate and revise the delineated maps, including sub-catchment boundaries and the drainage network. The direction of surface water flow and outlet points within each sub-catchment were also identified and

cross-checked with the extracted drainage network to enhance the accuracy and performance of the drainage system. Finally, the study area was divided into 18 sub-catchments, and runoff was measured at two outlets (Figure 2).

2.3. Calibration and Validation

Hydrological models require the estimation of multiple parameters by the user (Imani et al., 2023). These parameters are iteratively modified to minimize the discrepancy between simulated outputs and observed data. The SWMM hydrological model had previously been calibrated and validated for the Shahroud region using six rainfall–runoff events (Rahimi et al., 2023). The present research aims to evaluate the model's sensitivity to key calibration parameters. To this end, three events from the earlier dataset, along with four newly observed rainfall events, were selected (Table 2). This selection was intended to cover a wide range of rainfall intensities, from low to high. Since hydrological models respond differently under diverse rainfall conditions due to their dependence on surface and subsurface interactions, incorporating a range of rainfall intensities is essential for a more comprehensive evaluation. Under low-intensity rainfall, surface runoff may be minimal, and processes such as soil infiltration and evaporation may dominate, whereas high-intensity events emphasize drainage capacity and rapid runoff generation. Therefore, analyzing model sensitivity under diverse rainfall conditions is essential to ensure model robustness and the generalizability of its results across different hydrological scenarios.

Since there was no hydrometric station in the study basin to measure the hydrograph, runoff discharge was measured at 10-minute intervals at the outlets of the sub-basins (two outlets). For this purpose, a microcurrent meter was used to measure flow velocity, and a Water level staff gauge was used to measure flow depth. Given the rectangular shape of both outlets, the flow cross-sectional area was calculated. Flow velocity was measured at various points across the cross-section (based on a rectangular grid). By determining the average velocity and the cross-sectional area of the flow at different times, the runoff discharge at different times (urban runoff hydrograph) was calculated.

Table 2-Characteristics of rainfall events.

Rainfall Event No	Rainfall Date (Gregorian)	Rainfall Intensity (mm/hr)	Cumulative rainfall (mm)	Rainfall Duration (hh:mm)
1	2022-01-05	0.57	2	3:30
2	2021-03-12*	2.1	23.2	11:10
3	2020-05-03*	2.4	3.9	1:40
4	2023-03-16	3.2	11.2	3:40
5	2021-05-03	4.5	13.7	3:10
6	2020-04-11*	4.7	3.1	0:40
7	2020-04-27	10.7	7.1	0:40

*Data were obtained from the study conducted by Rahimi et al. (2023).

2.4. Parameter sensitivity analysis

In this study, sensitivity analysis of the SWMM model was conducted using seven parameters, including the Width factor (m) of the subcatchment, CN, N-Perv, N-Imperv, Imperv factor, Des-Perv, Des-Imperv. The Morris method (Francos et al., 2003) was employed for parameter sensitivity analysis. The sensitivity of the selected parameters was evaluated by assessing the degree of influence of single-parameter variations on the simulation results. For

this analysis, one parameter was altered at a fixed perturbation while the other parameters were unchanged. The mean values of the sensitivity factor (S) under multiple perturbations were calculated as follows:

$$S = \frac{1}{n} \sum_{i=0}^{n-1} \frac{(Y_{i+1} - Y_i)/Y_0}{(P_{i+1} - P_i)/100} \quad (1)$$

In which S is Sensitivity factor; Y_0 is initial simulation output (baseline result); n is number of perturbations applied to the parameter; Y_i is simulation output corresponding to the i -th perturbation; Y_{i+1} is simulation output corresponding to the $(i+1)$ -th perturbation; P_i is percentage value of the parameter at perturbation i , relative to the initial value; and P_{i+1} is percentage value of the parameter at perturbation $i+1$, relative to the initial value (Xu et al., 2019). In this study, during the sensitivity analysis of peak discharge, Y represents the peak discharge, while in the sensitivity analysis of runoff volume, Y refers to the runoff volume.

The sensitivity factor (S) is computed to evaluate how changes in a given input parameter affect the simulation results. The magnitude of $|S|$ is then used to classify the sensitivity of the parameter, following the criteria (Xu et al., 2019):

- $|S| < 0.05$: The parameter is not sensitive
- $0.05 \leq |S| < 0.2$: The parameter is generally sensitive
- $0.2 \leq |S| < 1.0$: The parameter is sensitive
- $|S| \geq 1.0$: The parameter is very sensitive

This classification helps to identify which parameters have the most significant impact on the model output and should therefore be prioritized in calibration and uncertainty analysis.

3. Results and discussion

Accurate determination of the physical characteristics of subcatchments, including area, width factor, percentage of impervious areas, slope, and depression storage, is essential for effective rainfall-runoff simulation. The study area was divided into 18 relatively homogeneous subcatchments to enhance the precision of parameter estimation. Based on land use maps and field surveys, the main channels within each subcatchment were identified and their characteristics recorded. These features included the channels' location, length, shape, and dimensions. Fig. 2) illustrates a schematic representation of the subcatchments, the connecting conduits, and the outlets.

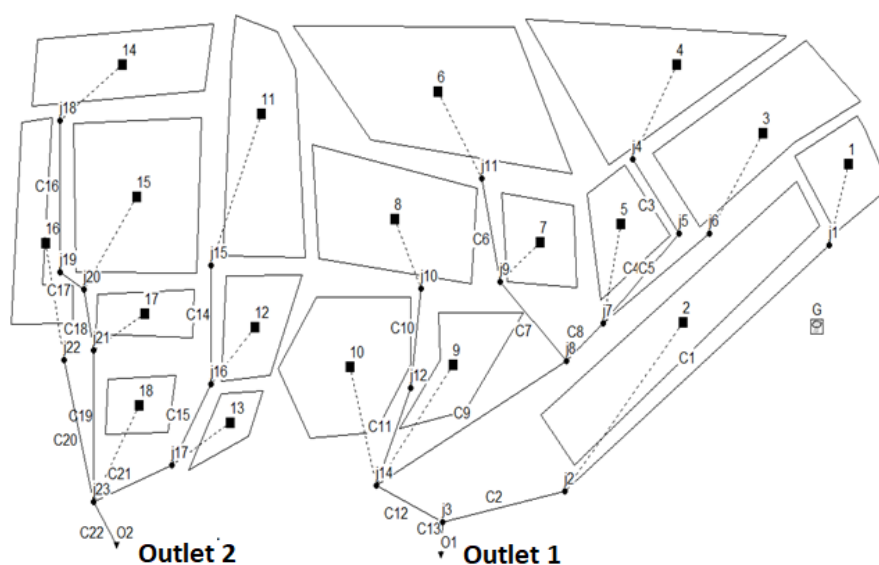


Figure 2- Subcatchments, conduits, outlets and junctions of the drainage network system

3.1. Sensitivity analysis

As previously mentioned, the model employed in this study had already been evaluated for the study area by Rahimi et al. (2023). Accordingly, the calibrated parameters reported in their study were adopted to define the increments used in the sensitivity analysis. However, to enhance the robustness of the sensitivity assessment, in addition to the three rainfall-runoff events considered by Rahimi et al. (2023), four additional rainfall events observed in the present study were also incorporated (Table 2).

The sensitivity analysis was conducted on seven calibration parameters, each examined across seven increments. These increments were determined based on the allowable ranges of variation and the corresponding calibrated values (Table 3). The simulated Qp and RV based on the calibrated parameters, along with the observed values, are presented in Table 4. For the Width factor, the baseline value was increased and decreased by 10%, 20%, and 30%, respectively. For the Curve Number (CN), adjustments of ± 3 , ± 6 , and ± 9 units were considered. Regarding the Imperv factor, considering an allowable variation of up to 15%, values of $\pm 5\%$, $\pm 10\%$, and $\pm 15\%$ relative to the calibrated value were used. Four additional parameters, whose calibrated values were close to the lower bounds of their allowable ranges during the calibration process, were examined using only incremental increases. Specifically, the increment for the N-Perv was set at 0.003 units, while for the N-Imperv, increments of 0.1 units were used. Incremental increases of 0.35 mm for Des-Imperv and 0.40 mm for Des-Perv were applied in the analysis (Table 5).

Table 3- Calibrated values and allowable ranges of the SWMM model calibration parameters

Calibration Parameter	Allowable Ranges Of Variation (Arvand et al., 2020)	Calibrated Value
Width factor (m)	$\pm 30\%$	*
Imperv factor(%)	$\pm 15\%$	*
N-Imperv	0.011-0.033	0.01
N-Perv	0.02-0.8	0.03
Des-Perv (mm)	2.48-5.08	2.5
Des-Imperv (mm)	0.25-2.48	0.35
CN	$\pm 60\%$	*

* different for each sub-catchment.

Table 4- Observed (Obs) and simulated (Sim) of Qp and RV based on calibrated parameters.

Event No	Outlet1				Outlet2			
	Qp		RV		QP		RV	
	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
1	0.21	0.24	2310	2475	0.14	0.15	1656	1503
2	12	12.55	43418	41550	11.56	11.9	35394	33159
3	1.07	1.04	6515	6564	0.69	0.64	3742	3903
4	3.15	3.44	27921	26202	2.01	2.14	15230	16071
5	3.46	3.97	30214	32808	2.36	2.52	18526	20127
6	1.15	1.17	5049	4377	0.69	0.72	2246	2547
7	11.46	12.53	42125	41613	10.74	11.9	36125	33378

Table 5- Adjusting range for SWMM calibration parameters

Parameter	Outlet	Adjusting range						
		1	2	3	4	5	6	7
Width factor (m)	1	402.3	459.7	517.2	574.7	632.1	689.6	747.1
	2	416.6	476.2	535.7	595.2	654.7	714.2	773.8
Imperv factor (%)	1	33.1	35.0	37.0	38.9	40.8	42.8	44.7
	2	29.8	31.5	33.3	35.0	36.8	38.5	40.3
CN	1	64.4	67.4	70.4	73.4	76.4	79.4	82.4
	2	61	64	67	70	73	76	79
N-Imperv	1 & 2	0.01	0.013	0.016	0.019	0.022	0.025	0.028
N-Perv	1 & 2	0.03	0.13	0.23	0.33	0.43	0.53	0.63
Des-Perv (mm)	1 & 2	2.5	2.9	3.3	3.7	4.1	4.5	4.9
Des-Imperv (mm)	1 & 2	0.35	0.7	1.05	1.4	1.75	2.1	2.45

The sensitivity factor (S) for peak discharge (Qp) and runoff volume (RV) was calculated for various rainfall-runoff events at two outlets, O1 and O2 (Tables 6 and 7). The results indicate that the sensitivity of peak discharge to calibration parameters is very similar at both outlets. Accordingly, to gain a more comprehensive understanding of Qp and RV sensitivity, the average sensitivity factors across all rainfall-runoff events were calculated for both outlets (Fig. 3). Fig. 3 reveals that among the seven parameters examined, Qp exhibited the highest sensitivity to the Imperv factor, with a sensitivity factor of $S = 0.64$, which falls into the sensitive category. The Width factor and N-Imperv were identified as the next most influential parameters, to which Qp was generally sensitive. In contrast, Qp showed no sensitivity to the rest calibration parameters. Consequently, four parameters, particularly N-Perv and Des-Perv, can be excluded from the Qp calibration process. To enhance the agreement between simulated and observed Qp values, greater emphasis should be placed on the three most effective parameters. The results of Peng et al. (2024) indicated that Qp is not highly sensitive to any of the model parameters, which aligns with the results of the present study. It is worth noting that the Imperv factor, identified in this study as a relatively influential parameter on Qp, was not examined by Peng et al. (2024). Furthermore, Width factor and N-Imperv were categorized as insensitive in the study by Peng et al. (2024), whereas in the current research, Qp showed general sensitivity to both parameters.

The average sensitivity factor (S) of RV to variations in calibration parameters (Fig. 3) indicates that, among the seven parameters, Imperv factor exhibited the highest influence on runoff volume ($S=0.93$), categorizing it as sensitive. The Curve Number (CN) showed a general sensitivity ($S = 0.10$). The remaining five parameters showed no significant influence on runoff volume. Jiang et al. (2024) evaluated the sensitivity of the SWMM model to eight different parameters, including Des-Imperv, N-Perv, and N-Imperv. Their findings were broadly in agreement with those of the current research. More specifically, RV showed no sensitivity to

N-Perv and N-Imperv, and its sensitivity to Des-Imperv closely matched the values identified in this study. Qp, their analysis indicated that it was generally sensitive to changes in N-Perv and N-Imperv, whereas no sensitivity was observed in relation to Des-Imperv.

Table 6- The sensitivity factor(S) for peak discharge (Qp) and runoff volume RV at outlet 1

Runoff Parameter	Event No	Width factor	CN	Imperv factor	N-Imperv	N-Perv	Des-Imperv	Des-Perv
Qp	1	0.16	0.00	0.81	-0.14	0.00	-0.08	0.00
	2	0.07	0.19	0.85	-0.07	0.00	0.00	-0.01
	3	0.20	0.00	0.78	-0.16	0.00	-0.06	0.00
	4	0.09	0.00	0.86	-0.09	0.00	-0.03	0.00
	5	0.21	0.00	0.68	-0.13	0.00	-0.02	0.00
	6	0.37	0.00	0.65	-0.25	0.00	-0.07	0.00
	7	0.06	0.00	0.17	-0.11	0.00	0.00	0.00
RV	1	0.07	0.00	0.93	-0.08	0.00	-0.07	0.00
	2	0.01	0.45	0.95	-0.01	0.00	-0.01	-0.02
	3	0.04	0.00	0.93	-0.06	0.00	-0.05	0.00
	4	0.01	0.00	0.98	-0.02	0.00	-0.02	0.00
	5	0.01	0.02	0.98	-0.01	0.00	-0.01	0.00
	6	0.07	0.00	0.93	-0.08	0.00	-0.06	0.00
	7	-0.06	0.46	0.91	0.06	0.00	0.00	-0.05

Table 7- The sensitivity factor(S) for peak discharge (Qp) and runoff volume RV at outlet 1

Runoff Parameter	Event No	Width factor	CN	Imperv factor	N-Imperv	N-Perv	Des-Imperv	Des-Perv
Qp	1	0.17	0.00	0.87	-0.12	0.00	-0.08	0.00
	2	0.08	0.13	0.90	-0.08	0.00	0.00	0.00
	3	0.18	0.00	0.76	-0.16	0.00	-0.06	0.00
	4	0.17	0.17	0.89	-0.09	0.00	-0.03	0.00
	5	0.21	0.00	0.74	-0.14	0.00	-0.02	0.00
	6	0.42	0.00	0.06	-0.24	0.00	-0.16	0.00
	7	0.00	0.00	0.00	-0.08	0.00	0.00	0.00
RV	1	0.08	0.00	0.91	-0.08	0.00	-0.08	0.00
	2	0.01	0.23	0.97	-0.01	0.00	-0.01	-0.01
	3	0.04	0.00	0.96	-0.06	0.00	-0.05	0.00
	4	0.01	0.00	0.99	-0.02	0.00	-0.02	0.00
	5	0.01	0.01	0.99	-0.02	0.00	-0.01	0.00
	6	0.07	0.00	0.93	-0.07	0.00	-0.06	0.00
	7	-0.05	0.19	0.68	0.04	0.00	-0.01	-0.02

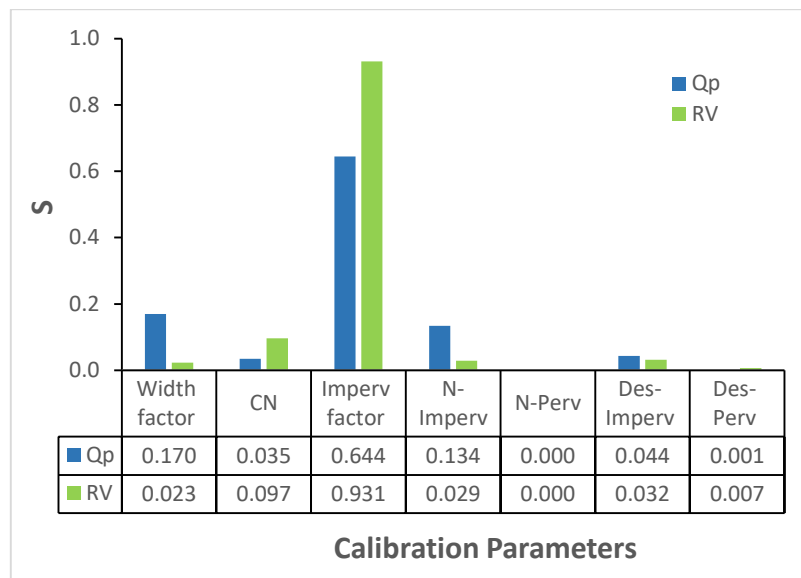


Figure 3- The mean sensitivity factor (S) of peak discharge (Qp) and runoff volume (RV) for both outlets.

Due to variations in rainfall characteristics, including intensity, duration, and depth across the seven events, individual sensitivity analysis for each event provided more detailed insights. A comparison between Events 6 and 7, which had the same duration but different intensities, revealed that increasing rainfall intensity led to a general decrease in the sensitivity of Qp to all calibration parameters (Tables 6 and 7). Furthermore, the sensitivity of RV and Qp to changes in Imperv factor decreased with increasing rainfall intensity. Under high-intensity rainfall, infiltration opportunities are reduced, resulting in higher runoff. Therefore, both impervious and pervious areas behave similarly in generating runoff, reducing the model sensitivity to changes in the Imperv factor.

Comparison of Events 2 and 3, which had similar intensities but different durations, showed that longer rainfall duration increased the sensitivity of Qp to CN and Imperv factor, while sensitivity to other parameters declined. Notably, CN affected RV and Qp only during long-duration events. For instance, in Event 2 (duration \approx 11 hours), Imperv factor and RV were generally sensitive and sensitive to changes in CN, respectively. In contrast, for all other events with durations less than 4 hours, no sensitivity to CN was observed. This may be attributed to the fact that, during short-duration and low-intensity rainfall events, soils in pervious areas typically remain unsaturated, allowing most of the rainfall to infiltrate and thus minimizing the influence of CN variations. As the duration of rainfall increases, soil saturation in pervious areas leads to increased surface runoff. Under these conditions, variations in CN significantly affect both RV and Qp.

In summary, the sensitivity of RV and Qp to calibration parameters is highly dependent on rainfall characteristics, particularly intensity and duration. This dependency complicates the calibration and validation processes of rainfall–runoff models. Since these models are typically calibrated and validated using multiple rainfall events with different characteristics, deriving a set of calibration parameters that can accurately simulate flood hydrographs across diverse rainfall events is inherently challenging. Therefore, it is advisable to avoid using rainfall events with identical characteristics in the calibration process, allowing the resulting parameters to represent an average response across different rainfall conditions. Nevertheless, a rainfall–runoff model that performs well during the evaluation process may still fail to produce reliable results when applied to rainfall events that differ significantly from those used in the calibration process.

4. Conclusions

Sensitivity analysis is crucial for optimizing this calibration by identifying the most influential parameters. This study examines the sensitivity of the SWMM model in simulating urban runoff in Shahroud, an arid city in Iran, by quantifying the model's response to changes in seven key calibration parameters across a large area of the city. The sensitivity analysis revealed that both peak discharge (Q_p) and runoff volume (RV) are most influenced by the Imperv factor, while Q_p also shows general sensitivity to the Width factor and N-Imperv. In contrast, parameters such as N-Perv and Des-Perv had negligible effects and can be excluded from the Q_p calibration process. Additionally, the sensitivity of Q_p and RV varies notably with rainfall characteristics. High-intensity rainfall reduced model sensitivity to calibration parameters, particularly the Imperv factor, due to limited infiltration. Conversely, longer rainfall durations increased sensitivity to CN and Imperv factor, highlighting the significant role of soil saturation in runoff generation. Generally, the sensitivity of runoff volume (RV) and peak discharge (Q_p) to calibration parameters is strongly influenced by rainfall characteristics, especially intensity and duration. This dependency poses challenges for calibrating and validating rainfall–runoff models, as it is difficult to determine a single parameter set that performs well across diverse events. To improve model reliability, it is recommended to use a range of rainfall events with varying characteristics during calibration, ensuring that the derived parameters capture an average hydrological response. However, even well-calibrated models may produce unreliable results when applied to events that differ significantly from those used in calibration.

Author Contributions

Mahdi Delghandi: Conceptualization, methodology, supervision, data analysis, writing: original draft preparation, writing: review and editing. Mohammad Ali Rahimi: Data collection, data curation, software. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

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Ethical Considerations

The authors avoided data fabrication, falsification, plagiarism, and misconduct.

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Conflict of Interest

The authors declare no conflict of interest.

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