


Article

A Quantity–Quality Model to Assess the Effects of Source Control Stormwater Management on Hydrology and Water Quality at the Catchment Scale

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Abstract: The vast development of urban areas has resulted in the increase of stormwater peak runoff and volume. Water quality has also been adversely affected. The best management practices (BMPs) and low impact development (LID) techniques could be applied to urban areas to mitigate these effects. A quantity–quality model was developed to simulate LID practices at the catchment scale using the US Environmental Protection Agency Storm Water Management Model (US EPA SWMM). The purpose of the study was to investigate the impacts of LID techniques on hydrology and water quality. The study was performed in BUNUS catchment in Kuala Lumpur, Malaysia. This study applied vegetated swale and rain garden to assess the model performance at a catchment scale using real field data. The selected LIDs occupied 7% of each subcatchment (of which 40% was swale and 30% was rain garden). The LID removal efficiency was up to 40% and 62% for TN and TSS, respectively. The peak runoff reduction was up to 27% for the rainfall of up to 70 mm, and up to 19% for the rainfall of between 70 and 90 mm, respectively. For the longer storm events of higher than 90 mm the results were not as satisfactory as expected. The model was more effective in peak runoff reduction during the shorter rainfall events. As for the water quality, it was satisfactory in all selected rainfall scenarios.

Keywords: urbanization; runoff; water quality; best management practices; low impact development

1. Introduction

Urbanization is increasing vastly all over the world [1,2]. This massive increase in urbanization coupled with the increasing rate of climate change are the two main factors contributing to urban stormwater runoff that could not be handled properly by applying conventional stormwater management [3,4]. Many urban areas are undergoing rapid development around the world and the urbanization process is gaining more interest. This has profoundly modified the natural environment in urban areas [2].

Urbanization results in the modification of natural landscapes, with pervious vegetated surfaces being replaced with impervious surfaces [5]. Human activities are the main reasons for this modification of natural surfaces and the growth of impervious surfaces in urban areas. Construction of structures such as roofs, parking lots, and roads are some examples of impervious surfaces in urban areas.

The growth of impervious surfaces decreases infiltration capacity, increases runoff generation and direct runoff, improves the connectivity of flow and leads to the reduction of groundwater recharge [5]. These changes in natural surfaces will ultimately result in the modification of magnitude and duration of urban catchment floods [6]. Some other factors, such as climate change and population growth will also intensify the consequences of urbanization [7]. The increased imperviousness and the resultant contaminated stormwater will also deteriorate the water quality in urban areas [8–10]. Different types of pollutants could be found in stormwater, such as sediments, nutrients, heavy metals, trace elements, and pathogens [11–13]. These pollutants will be built up on impervious surfaces during dry period and will be washed off by surface runoff during rainfall events to the waterbodies [14].

The impacts of urbanization on runoff process also depend on the extent of urban catchment development. The small-sized and highly urbanized river basins suffer more from urban runoff rather than large river watersheds. In the large-sized river catchments, the runoff peaks constitute only a small portion of flow [15].

Urbanization can also have adverse impact on sewage systems, as urban development increases the volume of runoff discharged to sewerage networks. This might lead to hydraulic overloading or sewage backflows [16].

With regard to this, urban stormwater management should be an integral part of any urban development. It has significant effects on both the economy and the ecology of the society [4]. The conventional approach for stormwater management use gutters and a system of sewers and canals to convey the stormwater out of the city as fast as possible. This traditional approach could not contribute to the sustainable urban development [3,17].

There are different types of Best Management Practices (BMPs) used to manage urban stormwater, namely constructed wetlands, ponds, buffer strips, and bioretention systems, which are the most popular types [18–20].

Some newer types of BMPs have been developed to control the urban stormwater at the source such as vegetated swales, rain gardens (or bioretention systems), permeable pavements, and green roofs. These newer techniques are generally known as Low Impact Development (LID) [21]. LID refers to distributed small-scale treatment systems located at the sources of runoff generation, such as roofs and streets [22,23]. The LID techniques are capable of mitigating the impact of imperviousness on both hydrology and water quality of urban stormwater runoff. Particularly, the LID techniques have been developed to mimic the predevelopment hydrologic conditions and promote the storage, infiltration, and evapotranspiration processes [24]. In other words, the key principle of LID measures is to ensure that new urban developments do not make the existing hydrologic regime flashier and increase flooding in the catchment. The capabilities of BMPs and LID in urban runoff reduction and water quality improvement have been well documented in numerous studies [25–31]. In comparison with the traditional stormwater management approaches, LID techniques have the advantage of returning the natural hydrological cycle in urban areas if the development is on a greenfield site, such as runoff volume reduction [25] infiltration improvement [24], peak flow reduction [32], extending the lag time, pollutant loads reduction [33], and baseflow increase [4].

Studies conducted to assess the performance of LID on runoff control, reported that LID perform significantly differently in storms with different intensities. Hood et al. [34] studied the runoff volume, peak discharge, and runoff coefficients of low impact residential development and compared them with traditional approaches. They found that the effects of LID on runoff reduction were more significant for smaller storms with shorter durations. Damodaram, Giacomoni, Prakash Khedun, Holmes, Ryan, Saour, and Zechman [27] used a hydrologic model to evaluate the impacts of LID on the stream flow. Their study showed that LID is able to control stormwater for smaller storms, while it is not as effective as conventional detention ponds in case of flooding events. Thus, although LID practices are quite essential to control urban stormwater runoff, the conventional urban drainage systems could not be completely ignored.

The main purpose of this study was to assess the effects of LID techniques on hydrology and water quality at a catchment scale using EPA SWMM and collected field data. In this study, vegetated swale and rain garden, among all types of LIDs, were selected to be applied to impervious areas to reduce the effect of imperviousness on hydrology and water quality at the catchment scale. These two LIDs have the advantage of controlling the stormwater quantity and quality at the source, and are able to reduce the flow volume, and thus delay the hydrologic response and reduce the pollutant load washed-off from urban surfaces [4].

Rain garden (bioretention) is relatively highly efficient for both runoff and pollutant reduction [35]. For example, bioretention cells reduced the average peak flows by at least 45% in Maryland and North Carolina during a series of rainfall events [36]. It has also been proved that bioretention are capable of reducing sediment and nutrient from 0% to 99% [35]. Swales have also been shown to have an average retention of 14% to 98% for nutrients and TSS, and up to 93% for metals [24].

Previous studies also investigated the impact of other types of LID controls on urban runoff, flooding, and water quality. Jackisch and Weiler [37] carried out a study on the hydrological performance of LIDs. They used some LIDs, such as permeable pavement, vegetated roofs, and bioretention. They found out that LIDs were able to capture 73% of rainfalls and the runoff volume was also reduced by 66–87%. The results confirmed that LID could replace the conventional stormwater management systems. Wilson, et al. [38] compared the water quality performance of commercial LID with the conventional development. The results showed that LID control water quality performance was much better than the conventional systems. There are many more similar researches investigating the hydrological or water quality performance of LIDs [39–44].

Based on this, the main aim of this study was to investigate the impacts of LID practices to manage stormwater runoff and water quality in urban areas by developing a quantity–quality model at the catchment scale. The first specific objective was to assess the impact of the two types of LIDs: vegetated swale and rain garden on the hydrologic response and water quality of an urban catchment. This objective aims to assess the performance of the selected LIDs to reduce peak runoff and pollutants in the case of stormwater. The purpose was to investigate how much the peak runoff and selected pollutants would be reduced by applying vegetated swale and rain garden to the catchment. The second objective of the study was to evaluate the hydrologic response and water quality improvement of the selected LIDs in different rainfall scenarios with different intensities. The purpose was to investigate the hydrological and water quality performance of the selected LIDs in higher intensities and longer duration rainfall events. In other words, the specific aim of the study was to investigate the efficiency of the selected LIDs in reducing the stormwater runoff and its pollutants in various rainfall intensities and durations. For this purpose, nine different rainfall scenarios were achieved using the intensity–duration–frequency (IDF) curves, which were already developed for the study area. Three different return periods, T , namely 5, 10, and 20 years, with three different durations, D , namely 1, 1.5, and 2 h, were selected accordingly, nine rainfalls with different intensities were achieved from IDF curves to be simulated in the developed model. The developed model was tested with these nine rainfalls to evaluate the model performance with LID in peak runoff and pollutant reduction. Total suspended sediments (TSS) and total nitrogen (TN) were selected as available pollutants to evaluate the model performance in pollutants reduction. To achieve the best results, samples were collected from a real rainfall event of the catchment on the 20 September 2018. The samples were analyzed in the environmental laboratory to achieve the selected pollutants, namely TSS and TN. The rainfall and amount and the respective flow were also collected from the automated hydrological station at the site. After that the model was carefully calibrated and validated for both quantity and quality using the 20 September 2018 data. Historical rainfall–flow data were also collected from the on-site automated rain gauge for model validation. Other required data were collected via site inspection and GIS maps. A sensitivity analysis and goodness-of-fit test were also carried out to find out the most sensitive parameters of the model and to check the reliability of the developed model. The significance of the study was to support the idea that LID application in urban areas

can remarkably reduce peak run off, enhance water quality, and can also replace the conventional stormwater management systems.

2. Materials and Methods

2.1. Study Area

The study has been carried out in the Bunus River Subcatchment located in Kuala Lumpur City, Malaysia. The Bunus Subcatchment is part of the bigger catchment: Klang River Catchment. The Bunus catchment area is $\sim 18 \text{ km}^2$ in terms of total size, with the main river stretching 9.5 km originating from Wangsa Maju (3.212° N and 101.735° E) and joining Klang river next to Jalan Munshi Abdullah (3.153° N and 101.698° E). The catchment has two hydrological monitoring points (S1 and S2 in Figure 1) and one automated streamflow gauge (S2) run by the SMART (Stormwater Management and Road Tunnel) control center which is under the Malaysian Department of Irrigation and Drainage (DID).

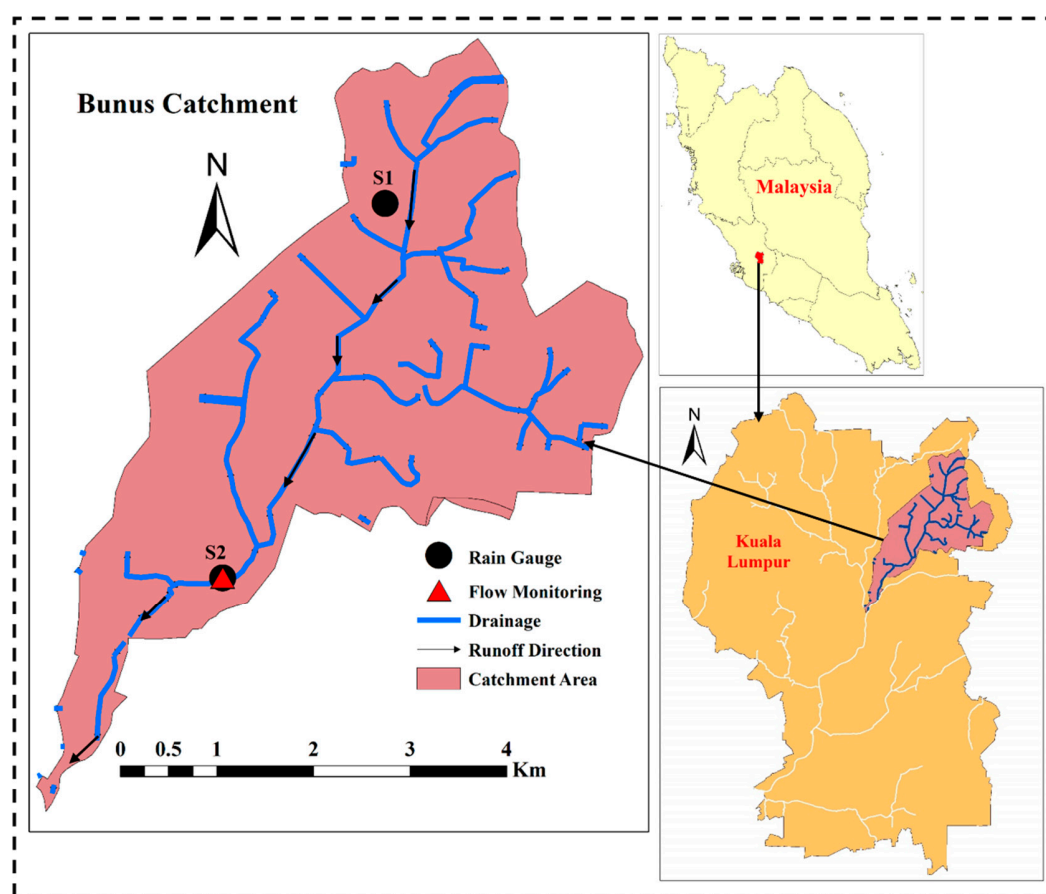


Figure 1. Study area location within Kuala Lumpur, Malaysia.

The city of Kuala Lumpur has undergone a remarkable development in the past few decades which has widely resulted in the vast urbanization and urban runoff. As the Bunus River subcatchment is one of the most densely populated areas within Kuala Lumpur, the urban runoff quantity and quality is a major issue in the area. Figure 1 shows the Bunus River subcatchment within Kuala Lumpur city in Malaysia. The arrows depict the direction of drainage in the catchment which is from the upper right to the lower left.

2.2. SWMM Model

The US EPA Storm Water Management Model (SWMM) [45] (has been selected to evaluate the effects of LID on runoff reduction and water quality improvement in the study area. A dynamic

rainfall–runoff module and a hydraulic module are included in SWMM for piped systems. SWMM is used to simulate runoff quantity and quality mostly from urban areas. An LID control module has been provided to the model from version (5.1.010), which can precisely model the hydrologic performance of LID controls in urban areas. In SWMM, LID controls are depicted by a combination of vertical layers and their properties (such as thickness, void volume, hydraulic conductivity, underdrain characteristics, etc.) are defined on a per unit area basis. The defined LID controls can be assigned within the selected subcatchments with different designed sizes (or areal coverage). The SWMM model has been successfully used in numerous studies to investigate the impacts of stormwater management based on traditional drainage systems [46] or LID designs [22]. The SWMM model has been used in many studies related to urban stormwater, and the capabilities of this model have been well proved in all these studies [17,19,21,43,47–50].

SWMM is a deterministic and spatially distributed hydrological model, which is able to simulate the hydrological cycle mainly within urban areas [45,51]. SWMM uses the continuity equation along with the Manning's equation to simulate hydrological outflows [51].

To apply SWMM in urban areas, hourly, or subhourly, rainfall data, topographic slope and elevation, soil, land use data, sewer system network map, and storm sewer discharge data are required for calibration and validation of the model [52]. Input parameters required by the SWMM model to simulate stormwater runoff include rainfall and climatology data (for continuous modeling), parameters for hydrologic components (subcatchments, pipes, storage units, etc.), and run time controls (time step, starting and ending time, etc.).

2.3. Input Data

The historical rainfall and the relevant flow data were collected from the SMART control center which is part of the DID. There are two hydrological monitoring points within the Bunus catchment located at Jalan (Street) Genting Klang (S1) and Jalan Tun Razak (S2) area. The S2 is an automated streamflow gauge as well. All rainfall and flow data used for quantity and quality modeling were collected from S2 automated hydrological monitoring station located at Jalan Tun Razak. The DID office also provided us with relevant GIS maps of the Klang catchment and Bunus subcatchment consisted of the main Klang River and the tributaries.

For the purpose of calibration and validation of the model, we collected runoff samples during one rainfall event at Jalan Tun Razaq Hydrological station (S2) on 20 September 2018. Later, the rainfall data of the same event was collected from the SMART control center to calibrate the model. A total of 17 samples were collected from the rainfall event and were analyzed in the Environmental Laboratory at the University of Malaya for the quality parameters. We used the water quality parameters to calibrate the quality model. Among the analyzed pollutants from the collected samples, total suspended sediments (TSS) and total nitrogen (TN) were selected to be used for the stormwater quality modeling. TSS and TN are among the most widespread Pollutants in urban areas [53].

2.4. Modeling Procedure

To set up the SWMM model, different types of data are required. The data required to set-up the model consist of rainfall and flow data, topographic data of the study area, river characteristics, catchment drainage networks, catchment slope, land use of the study area, and soil type. The rainfall and flow data were provided by the SMART control center, while GIS maps were provided by DID. Topographic data, such as elevation and slopes were delineated from GIS maps. The catchment drainage networks were also provided by DID. The land use and soil type in the study area were achieved through GIS maps, site inspection and Google Earth. The study area is a heavily populated residential part of Kuala Lumpur consisted of 70% residential and 30% commercial, which consist of mostly food outlets and shops. The soil type in the area is mostly clay loam. The river characteristics were achieved through site inspection. The most important characteristics of the river used for modeling are river width, depth, and shape. The river length was also delineated from the GIS maps.

The catchment map was imported into the SWMM model and the subcatchments were drawn following the contour lines. The system of nodes and conduits were also added to the model, likewise. Figure 2 illustrates the drainage system in SWMM in the base case with all subcatchments, nodes and conduits network. Totally, we came up with 35 subcatchments and 10 junctions in the model. Some of the principal input parameters for each subcatchment in SWMM include assigned rain gage, outlet node for each subcatchment, assigned land uses, tributary surface area, imperviousness, slope, characteristic width of overland flow, Manning's n for overland flow on both pervious and impervious areas, depression storage in both pervious and impervious areas, and percent of impervious area with no depression storage. Some of these parameters are assigned by the user, like rain gage, and some of them were assigned by site inspection and using ArcGIS and google earth, such as land uses and imperviousness, and some of them were calculated mathematically, such as slope and width. SWMM offers three main choices for modeling infiltration, namely Horton, Green-Ampt, and Curve Number methods. In the hydrologic module of SWMM, the Green-Ampt model was employed in the infiltration model, which calculates the amount of rainfalls infiltrated into the unsaturated upper soil zone of a pervious surface area, whereas Manning's equation was used to compute the surface runoff [54]. Based on Green-Ampt and on-site soil type, the pertinent parameters to the infiltration model were adjusted in SWMM. The main parameters are hydraulic conductivity, suction head, and initial deficit. Having set-up the required parameters, the model was ready to operate by employing the rainfall data series.

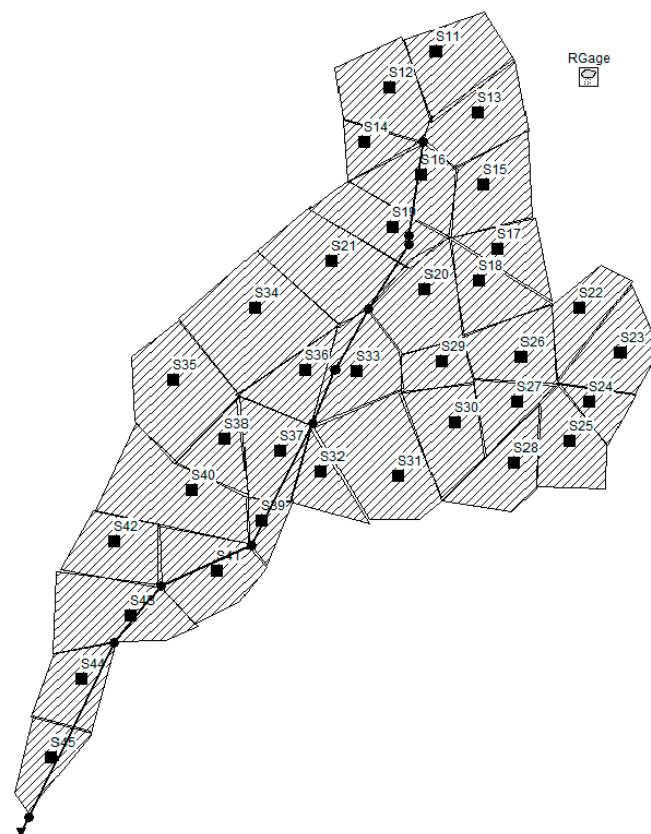


Figure 2. Drainage system in the base case in the Storm Water Management Model (SWMM) with subcatchments.

2.5. Sensitivity Analysis

Different parameters, such as Manning's roughness coefficient, depression storage depth, infiltration parameters (e.g., curve number), subcatchments percent imperviousness, subcatchment slope, percentage of impervious surfaces with no depression storage, and channel roughness values

have been used in previous studies as calibration parameters [39,48,55–57]. Before conducting the model calibration in this study, the sensitivity of the model to different parameters was analyzed to figure out what parameters are more sensitive to the model. In order to achieve the best match between the observed and modeled flow, these parameters were adjusted in the model. To carry out sensitivity analysis, the parameters were checked one by one. For each parameter to be analyzed, different amounts of the parameter were used in the model, while keeping all other parameters fixed. The model was run and the results of the simulated outflow hydrograph was compared with the observed one each time. The process was repeated several times to figure out the most sensitive parameters to the model.

2.6. Calibration and Validation

In the model calibration and validation approach, the predicted (modeled) and the observed outflow hydrographs were compared with each other. Particularly, two values, namely the discharge volume and the peak flow rate were assessed for an event. The calibration was conducted using the data of 20 September 2018 event. In order to calibrate the model more accurately, we collected samples of a real rainfall event on 20 September 2018 from the monitoring station at Jalan Tun Razak. The rainfall and the respective flow were also collected from the automated hydrological station run by the SMART control center. The collected data was used for both quantity and quality calibration of the model. As some of the historical data might not be accurate, collecting data from a real event was very important to make sure the calibration is precise and accurate. The historical rainfall and flow data were also collected from SMART control center to be used for model validation. For the validation purpose, the data on 1 August 2017 was used. For a good validation result, it is required that the general shape of both hydrographs follow each other, and the results of goodness-of-fit test are satisfactory. With regard to this, to evaluate the model calibration and validation performance, the goodness-of-fit test was performed to compare the modeled discharge volume against the observed discharge volume for a specific analysis period [43].

Modeling of stormwater quantity usually aims for the prediction of stormwater runoff volumes, hydrographs and peak discharge rates to mitigate the runoff peak and volume in urban areas. Modeling of urban stormwater quality normally focuses on the pollution prevention and impact assessment resulting from stormwater.

Several mechanisms determine stormwater quality, with build-up and wash-off being the most important ones. It is generally assumed that a supply of contaminants is built up on the land surface during dry weather in an impervious urban area. The buildup of pollutants may or may not be related to time, traffic flow, dry fallout and street sweeping [14]. When the storm occurs, the built-up pollutants are washed off into the drainage system. Wash-off is the process of erosion or solution of pollutants from an impervious surface during the period of runoff in urban areas.

The calibration of stormwater quality models is normally more difficult than quantity models. Modeling is used to predict, analyze and manage urban water quality and pollution, as urban runoff quality monitoring needs substantial resources [58]. In SWMM, the stormwater quality is modeled using different build-up and wash-off equations, such as exponential function, power function, or saturation equation [59]. There is usually a wide range of variation in urban stormwater quality data between rainfall events. The buildup and wash-off equations consist of many parameters which make the stormwater quality difficult to calibrate without on-site data [23]. The spatial and temporal variation of the quality modeling process also make it difficult to use the buildup and wash-off equations on a catchment scale [60,61]. Moreover, the urban stormwater quantity model is usually calibrated first, followed by calibrating the quality module [62].

For the quality calibration of the model, total suspended sediments (TSS) and (NO_x+NH₃) (referred to as TN) were selected. We used nitrate, nitrite (NO_x), and ammonia-N (NH₃) as the total nitrogen. Dissolved inorganic nitrogen (DIN) includes ammonia (NH₃), nitrite (NO₂), and nitrate (NO₃). The waterbodies are greatly affected by these constituents because they are easily available to be

taken up by simple organisms [63], and may result in eutrophication, hypoxia, and loss of biodiversity and habitat [64]. As TSS and TN are widespread pollutants in residential areas [53], they were selected for the model quality calibration.

2.7. Goodness-of-Fit Test

Different evaluation methods are often used for measuring the accuracy of the predicted stormwater runoff against the observed values. Three main methods selected to be used for the current research model evaluation are root mean square error (RMSE), Nash–Sutcliffe coefficient (NSC), and the regression method. The Normalized Objective Function (NOF) can be used for the root mean square error. The RMSE and NOF are explained as follows

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2} \quad (1)$$

$$NOF = \frac{RMSE}{O} \quad (2)$$

where P_i and O_i are the predicted and observed values at time step i , respectively, and N is the number of observations during the flow period. O is the mean of observed values. The ideal value for NOF is 0, however, it cannot be expected to occur; otherwise it would be a perfect model. So, values between 0.0 and 1.0 are acceptable for NOF when field specific data are available for calibration [65].

Nash–Sutcliffe coefficient (NSC) is explained as follows [66]

$$NSC = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - O)^2} \quad (3)$$

where P_i is the predicted value, and O_i is the observed value for the n observations, and O is the mean of observed values. The optimal condition for the model occurs when the NSC is 1.

Regression method:

In the regression method, the linear regression line is fitted between the modeled and observed values. Generally, the best calibration requires that r^2 be as close to 1.0 as possible [67].

2.8. Assigning LID Controls to the Model

Having calibrated and validated the model, the selected LIDs were assigned into the model. The LIDs are assigned to each subcatchment through the LID control editor of the subcatchment. The LID Control editor is used to define a low impact development control in each subcatchment which can be placed throughout a catchment to store, infiltrate, and evaporate subcatchment runoff. The design of the LID control is made on a per unit area basis so that it can be placed in any number of subcatchments at different sizes or number of replicates.

The common types of LID being defined in SWMM include bioretention cell, rain garden, green roof, infiltration trench, permeable pavement, vegetative swale, and rain barrel. Vegetated Swale and Rain Garden have been the selected LIDs to be assigned in the final model. According to the literature, the two LIDs have a high capacity of runoff reduction and pollutants removal in the urban areas. The rain garden and vegetated swale are able to reduce TSS and TN in urban runoff up to 89% and 58%, respectively [68]. In this study, the selected LIDs occupy 7% of each subcatchment. Swale and Rain Garden treats 40% and 30% of the impervious area of each subcatchment, respectively. The final model was tested by the calibrated rainfall as well as the TSS and TN to check the model efficiency. After that the model was executed using the selected rainfall scenarios to check efficiency of the developed model for different rainfall intensities.

2.9. Selecting Rainfall Scenarios

In order to test the final model with different rainfall scenarios, nine sets of rainfall were selected as follow. The intensity–duration–frequency (IDF) curves for the area had already been prepared by DID and published in the Urban Stormwater Management Manual for Malaysia [69]. These curves have been developed based on 100-year hydrological data for the return periods of 2, 5, 10, 20, 50, and 100 years. They have been particularly developed to be used by researchers working on the respective study areas. In IDF curves, the rainfall durations are depicted on the “X” axis and the intensities are depicted on the “Y” axis. The rainfall frequencies are illustrated in the form of diagonal curves. The return periods of 5 years, 10 years, and 20 years were selected for the three selected durations, namely 1, 1.5, and 2 h. For instance, to achieve the first rainfall intensity, the 1-h duration is found on the “X” axis and the intersection of the vertical line with the return period of 5 is found. Then the intersection of the horizontal line with the “Y” axis of this point will be the respective rainfall intensity of that return period and duration. Likewise, the process was repeated for other durations and with other return periods. Therefore, for each return period, three durations were applied to find the corresponding rainfalls. Thus, total nine different rainfalls were achieved. The achieved rainfalls are depicted in Table 1 and Figure 3.

Table 1. Rainfall scenarios for three return periods and three durations.

Return Period	Duration (h)	Rainfall (mm)
5	1	72
5	1.5	81
5	2	90
10	1	80
10	1.5	90
10	2	96
20	1	90
20	1.5	99
20	2	110

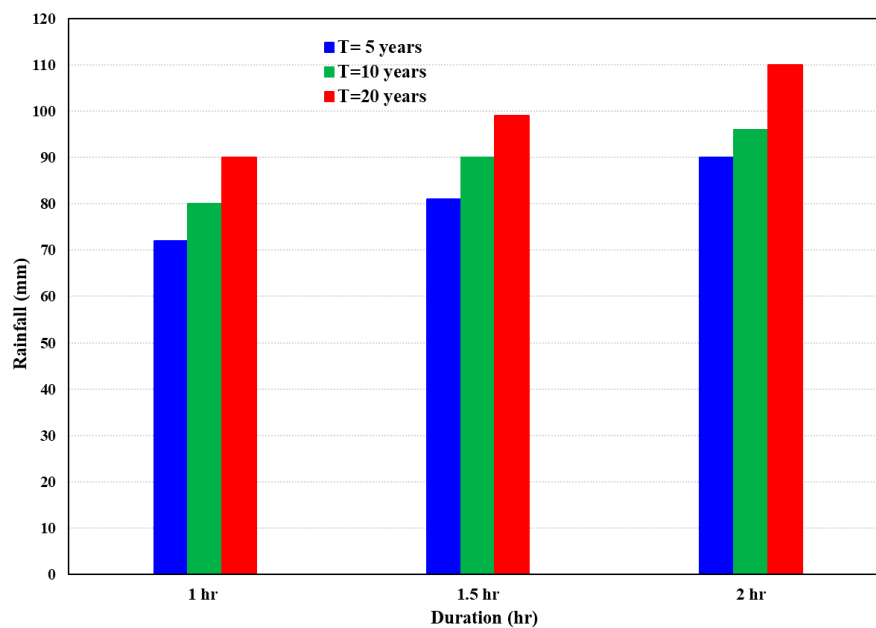


Figure 3. Rainfall scenarios for three return periods, namely 5, 10, and 20 years.

3. Results

3.1. Sensitivity Analysis

Before conducting calibration and validation, the sensitivity analysis was performed. Figure 4 depicts the results of sensitivity analysis. As can be observed, the most sensitive parameters for the model calibration are % imperviousness (Percent of the land area which is impervious), % zero imperviousness (Percent of the impervious area with no depression storage), Dstore-impervious (Depth of depression storage on the impervious portion of the subcatchment), and Dstore-pervious (Depth of depression storage on the pervious portion of the subcatchment) which have been shortened as D-Store impervious-pervious. This means that the model is mostly sensitive to these three parameters and they need to be adjusted accordingly to get a good calibration. However, care should be taken that the sensitivity of the model to the three parameters is not the same. The peak runoff is directly proportional to the changes in imperviousness and zero imperviousness, whereas it is inversely proportional to the D-Store impervious-pervious. This means that the peak runoff will increase with the increase of % imperviousness and % zero imperviousness. Likewise, the peak runoff will decline with the reduction of the two parameters. On the other hand, the peak runoff will decline with the increase of D-Store impervious-pervious, while it will increase with the D-Store impervious-pervious reduction. It should also be noted that the peak runoff is more sensitive to the reduction of the D-Store impervious-pervious than the increase. In other words, the peak runoff will only decrease 5% with the 30% increase in the D-Store impervious-pervious, whereas it will increase 12% with the 30% reduction of D-Store impervious-pervious.

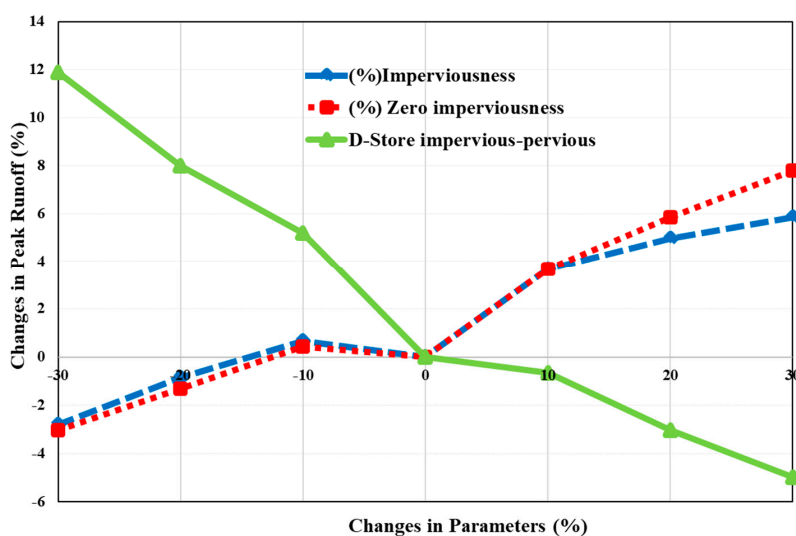


Figure 4. Sensitivity analysis results for SWMM model.

3.2. Calibration and Validation

To calibrate the model, the quantity and quality data collected on 20 September 2018 was used. Based on the sensitivity analysis performed and the goodness-of-fit test, the best result was achieved after running the model for many times. To calibrate the model, the data series was applied to the model and the respective parameters were set accordingly. The modeled values are compared with the observed ones. Then, the model evaluation criteria (goodness-of-fit test) is applied to the results. If the error between the modeled and observed values is in the acceptable range, the model is calibrated, otherwise the process is repeated. Figure 5 illustrates the result of model calibration. As it is obvious from Figure 5, there is a discrepancy between the modeled and the observed values at the beginning of the hydrograph which could be due to some uncertainties in modeling. The modeled and observed values are in good match before the hydrograph peak, at which point the model starts underestimating the flow a little bit. This trend continues up to the middle of the hydrograph falling

limb. From this point onward, the model overestimates the flow a little bit. Nevertheless, it is obvious from Figure 5 that, overall, the modeled and observed hydrographs are a very good match. This could also be confirmed by the results of goodness-of-fit test. As it is obvious from the goodness-of-fit test, the evaluation parameters, namely NOF, NSC, and r^2 are 0.05, 0.93, and 0.93, respectively, which show a very good match between the modeled and observed values.

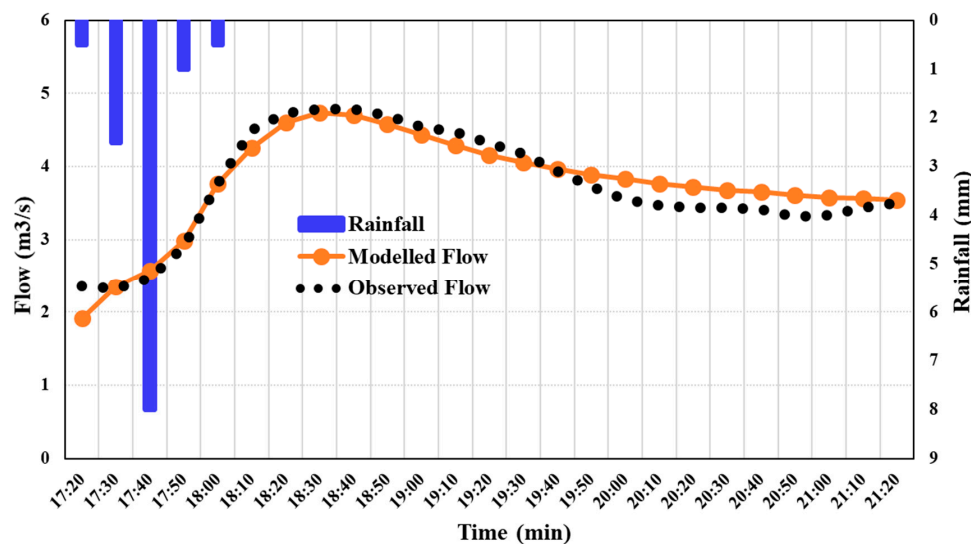


Figure 5. Calibration of the model for the rainfall on 20 September 2018 event.

For the model validation, the data on 1 August 2017 was used. This data was selected from the historical data collected from the SMART control center. Figure 6 depicts the result of model validation. As can be seen, the modeled and observed values are in good match from the starting point up to the middle of the rising limb. However, the model overestimates the flow at the peak. This might be due to some uncertainties in the observed data. After this, the modeled and observed hydrographs follow each other, although there is a little bit underestimation in the falling limb. Overall, the modeled and observed hydrographs follow each other throughout the validation process and the validation is acceptable. The goodness-of-fit test also shows that the validation result is quite acceptable, and the two hydrographs satisfactorily match each other. As can be seen, the evaluation parameters (goodness-of-fit test), namely NOF, NSC, and r^2 are 0.08, 0.74, and 0.77, respectively, which show an acceptable match between the modeled and observed values.

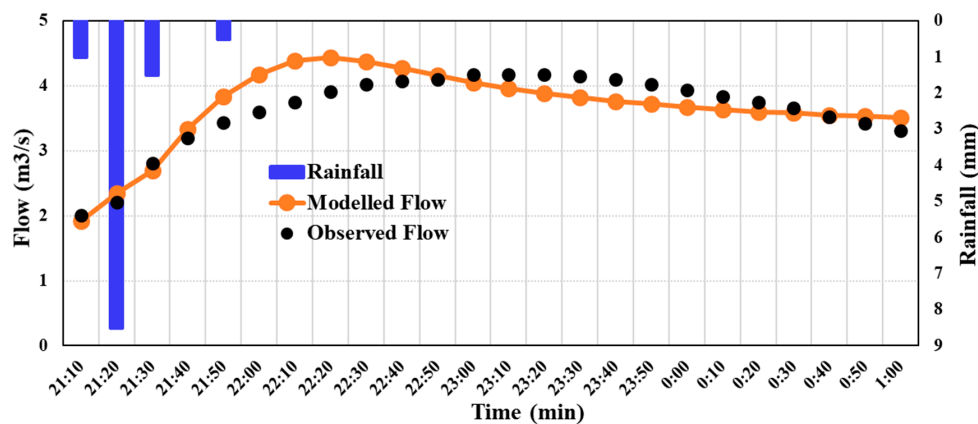


Figure 6. Validation of the model for the rainfall on 1 August 2017 event.

In order to calibrate the quality model for TSS and TN parameters derived from the 20 September 2018 event sampling, the catchment was divided into two categories—residential and commercial—consisting of

70% and 30% of the catchment, respectively. The residential and commercial percentage of the study area were derived through site inspection and google earth.

Similarly, there are influential parameters to be adjusted to calibrate the quality model as well. The most important parameters affecting the model calibration are the buildup and wash-off functions and the input parameters (C_1 , C_2 , C_3 , and C_4). Pollutant accumulation can be represented by different types of buildup functions on an urban catchment, including power function, exponential function, or saturation equation, while the wash-off is simulated using exponential function, rating curve equation or event mean concentration (EMC). Among various types of pollutant buildup and wash-off functions, the exponential function was selected for both buildup and wash-off after testing the model for different functions. The exponential functions for buildup and wash-off in SWMM are explained as follows.

Buildup follows an exponential growth curve that approaches a maximum limit asymptotically,

$$B = C_1(1 - e^{-C_2t}) \quad (4)$$

where C_1 = maximum buildup possible (mass per unit of area or curb length), C_2 = buildup rate constant (1/days), and t is the time.

The wash-off load (W) in units of mass per hour is proportional to the product of runoff raised to some power and to the amount of buildup remaining, i.e.,

$$W = C_3q^{C_4}B \quad (5)$$

where C_3 = wash-off coefficient, C_4 = wash-off exponent, q = runoff rate per unit area (inches/hour or mm/hour), and B = pollutant buildup in mass units. The buildup here is the total mass (not per area or per curb length) and both buildup and wash-off mass units are the same as used to express the pollutant's concentration. The input parameters (C_1 – C_4) for quality modeling are depicted in Table 2.

Table 2. Results of buildup and wash-off input parameters to calibrate the quality model.

Land Use	Pollutant	Build-Up		Wash-Off	
		C1	C2	C3	C4
Residential	TSS	1.5	0.3	0.4	0.9
	TN	0.002	0.05	12	1.7
Commercial	TSS	12	0.3	1.5	0.6
	TN	0.1	0.7	0.3	3.5

Having adjusted the parameters (C_1 – C_4) after many runs, a satisfactory match between the observed and calibrated values for TSS was achieved, as shown in Figure 7. As can be seen, there is a good match between the modeled and the observed values in the rising limb. However, there is an inconsistency at the peak, in which one observed point is higher than the modeled peak. This might be due mainly to the uncertainty in sampling, data collection, or the model itself. In contrast, the model overestimates the TSS a little bit in the falling limb, although the modeled and observed graphs converge at the end. As the quality modeling is always more challenging than quantity one, these discrepancies are quite normal. The evaluation parameters in Table 3, namely NOF, NSC, and r^2 for TSS, are 0.14, 0.81, and 0.84, respectively, which show a satisfactory match between the modeled and observed values. Overall, it is clear from the calibrated model and the result of test in Table 3 that the modeled TSS graph follows the observed TSS graph and the calibration is satisfactory.

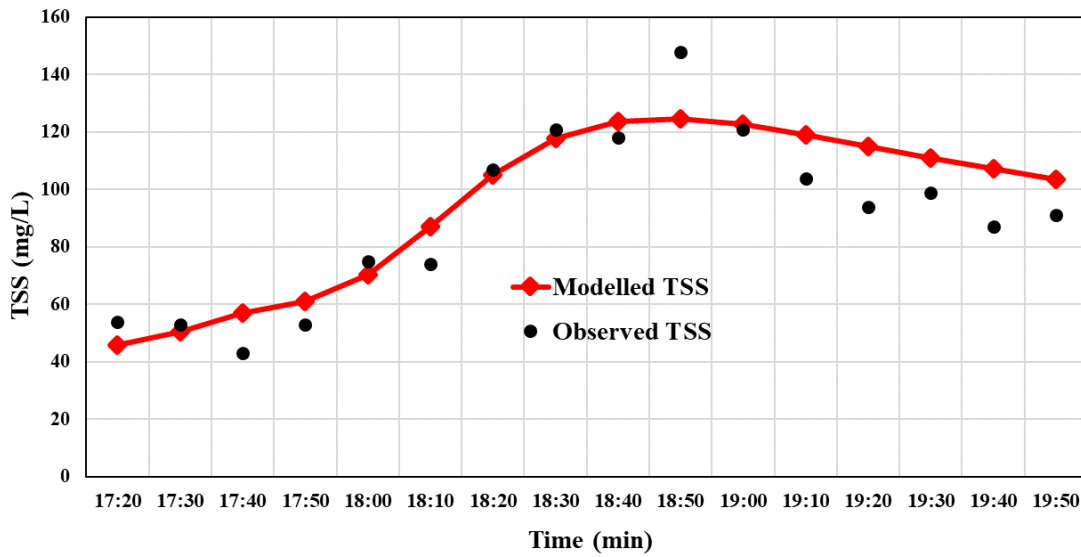


Figure 7. Total suspended sediments (TSS) calibration result.

For TN, it was even more difficult to calibrate the model as TN is more sensitive to the model parameters. Hard effort was made to adjust the parameters in many runs to get the best result. Figure 8 illustrates the result of TN calibration. As is obvious, there is an incompatibility at the beginning and in the middle of the graphs. For the rest of the calibration, the modeled graph follows the observed one and the two graphs converge very well at the end, although there is an overestimation just before the last point. The evaluation parameters in Table 3, namely NOF, NSC, and r^2 for TN, are 0.14, 0.74, and 0.74, respectively, which are in the acceptable range and show a good match between the modeled and observed values. Overall, Figure 8 and Table 3 show that the result of calibration was quite satisfactory.

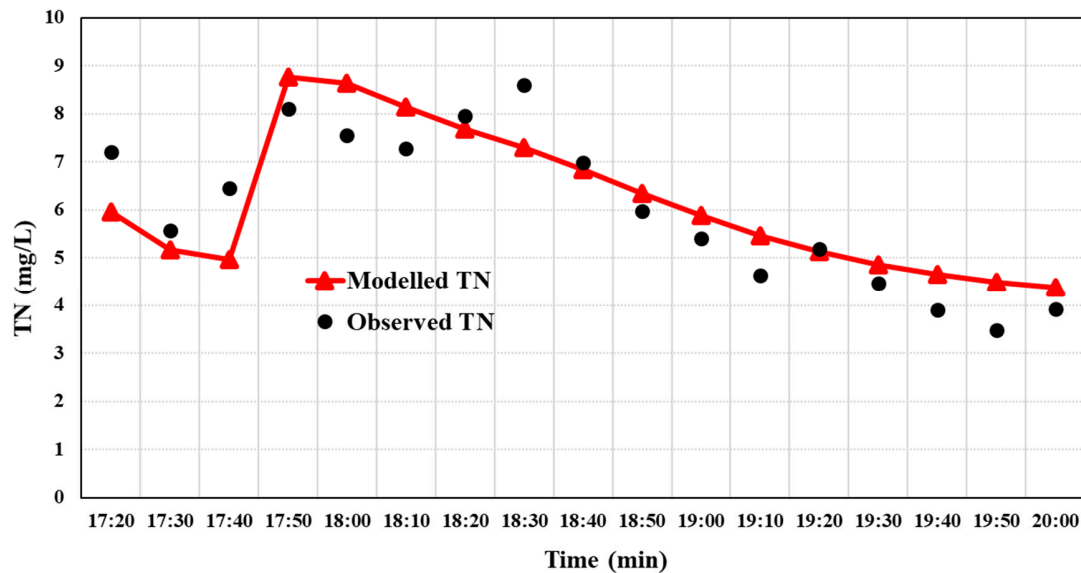


Figure 8. Total nitrogen (TN) calibration result.

3.3. Goodness-of-Fit Test Results

The goodness-of-fit test results for the quantity and quality calibration and validation are depicted in Table 3.

As shown in Table 3, the results of quantity calibration are quite satisfactory. Although for TSS and TN, the results are not the same as quantity calibration, the three evaluated parameters still show

a good match between the predicted and the observed values in both TSS and TN, based on the criteria for the goodness-of-fit test.

Table 3. The goodness-of-fit test results to evaluate the reliability of the model.

Parameter	Flow Calibration	Flow Validation	TSS Calibration	TN Calibration
NOF	0.05	0.08	0.14	0.14
NSC	0.93	0.74	0.81	0.74
r^2	0.93	0.77	0.84	0.74

3.4. The Results of Assigning LIDs to the Model

Having finished the calibration and validation of the model, the selected LIDs were assigned to the model. Then, the model was executed for the same rainfall event that was calibrated (20 September 2018). The aim was to check the performance of the model after assigning the LIDs. The results of the model with the applied LIDs are shown in Table 4 and Figures 9 and 10.

Table 4. Best management practices (BMP) removal and peak runoff reduction after assigning low impact developments (LIDs) to the model.

Rainfall on 20 September 2018 (mm)	LID Removal (%)		Peak Runoff Reduction (%)
	TN (%)	TSS (%)	
12.50	29	41	23

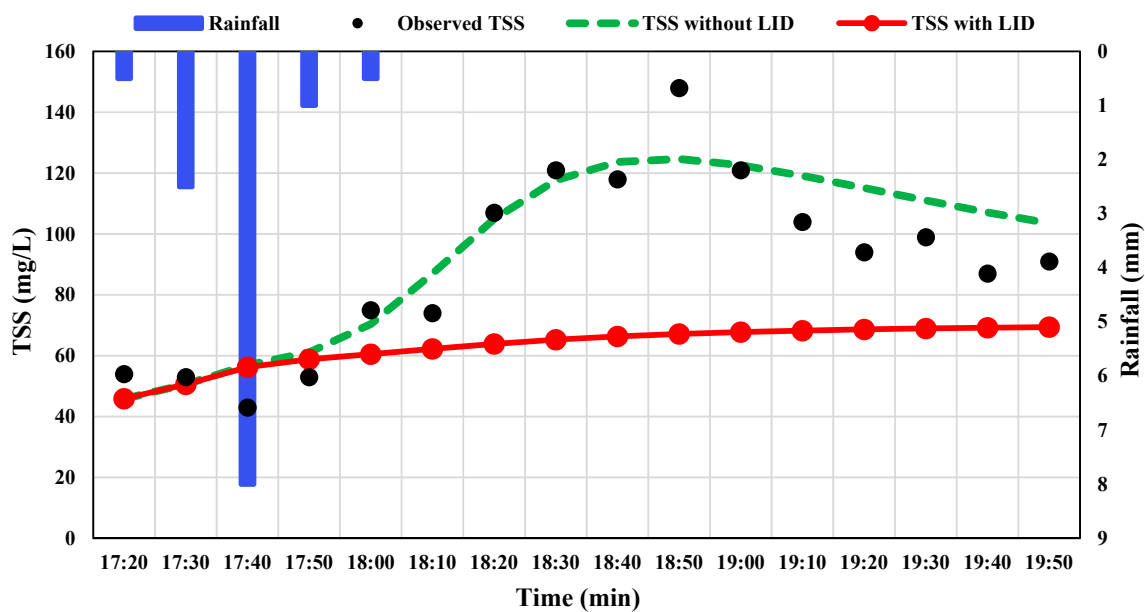


Figure 9. TSS reduction after assigning LIDs to the model.

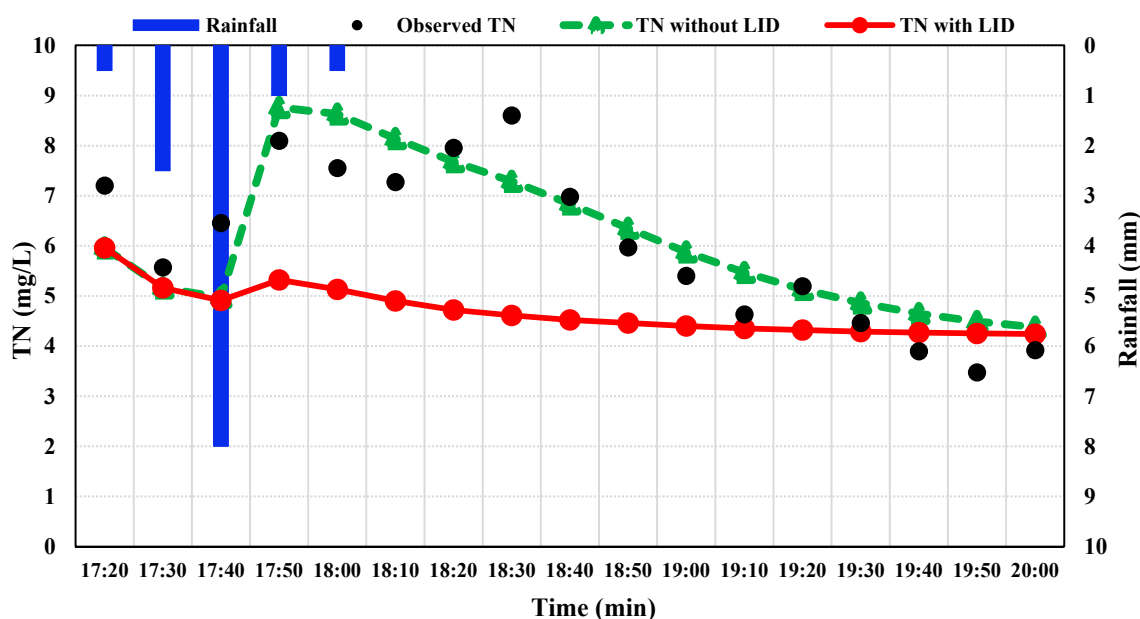


Figure 10. TN reduction after assigning LIDs to the model.

The results depicted in Table 4 show that TN and TSS reduced by 29% and 41%, respectively, after assigning LIDs to the model. The peak runoff also reduced by about 23%. Figures 9 and 10 also clearly show that TSS and TN reductions were satisfactory after assigning the LIDs to the model. As can be seen from the table and figures, LIDs have been more efficient to reduce TSS and TN compared to peak runoff. This means that more LID techniques are required in the study area to effectively control both runoff and pollutants. However, the cost of LID implementation will also be an important issue. In other words, the number and placement of LIDs should be optimized in order to have the maximum runoff and pollutant reduction with the minimum cost. The role of LIDs is to make the impervious surfaces more permeable to reduce runoff and remove pollutants through filtration, chemical, and biological processes. In this study, both the table and the figures confirm that LID practices are of high importance in all developed urban areas to mitigate the effects of imperviousness on both runoff quantity and quality. Thus, it can be concluded that LID techniques could reduce urban runoff and improve stormwater quality substantially.

4. Discussion

4.1. Summary and Findings

Urbanization disturbs the natural landscapes; vegetation covered surfaces are replaced with impervious surfaces. Thus, impervious surfaces such as roof tops, parking lots, and roads, decreases infiltration capacity, and increases runoff generation in urban areas [5]. Low impact development (LID), such as bioretention cells and vegetated swales, are techniques implemented at or near the source of runoff generation to make the ground more permeable and mitigate stormwater runoff and its pollutants [22]. Particularly, the LID techniques have been developed to mimic the predevelopment hydrologic conditions and promote the storage, infiltration and evapotranspiration processes [24]. The main roles of LID practices include runoff reduction (peak and volume), infiltration increase, groundwater recharge, stream protection, and water quality enhancement by removing pollutants through mechanics such as filtration, chemical sorption, and biological processes [70].

The EPA SWMM was used in this study to develop a model to be able to manage stormwater runoff and pollutants at the source using LID controls. To develop SWMM, a wide range of climatic and field data are required to calibrate and validate the model with rainfall and flow being the main one. Based on this, the required data was collected from a rainfall event of the study area. Vegetated

swale and rain garden were selected as LID practices for this purpose. Rain garden and swale are suitable for residential and commercial areas [35,71]. These two LID techniques have been proved to be highly efficient in urban areas for both runoff and pollutant reduction [35,68]. The specific aim of the study was to investigate the efficiency of the selected LIDs in reducing the stormwater runoff and its pollutants in higher intensity and longer duration rainfalls in urban areas.

The model sensitivity to different parameters was first checked to find out the most sensitive parameters for model calibration. Several parameters impact the model calibration. Previous studies have found out that different parameters impact the model calibration. The main parameters affecting the model calibration are subcatchments area, percent impervious area, width, slope, infiltration parameters, Manning's roughness coefficients for pervious and impervious surfaces, depression storage depth for pervious and impervious surfaces, percent zero, and internal routing parameters [48]. In this study, the most sensitive parameters for the model calibration were found out to be % imperviousness (percent of the land area which is impervious), % zero imperviousness (percent of the impervious area with no depression storage), Dstore-impervious (depth of depression storage on the impervious portion of the subcatchment), and Dstore-pervious (depth of depression storage on the pervious portion of the subcatchment).

Appropriate calibration of rainfall–runoff models for urban catchments is necessary to ensure reliable assessment of stormwater modeling results [72]. Rainfall–runoff models can be calibrated over a set of single storm events or continuous storm events. Calibrating the model with a single event provides better time to peak and overall hydrograph shape compared to continuous calibration, but continuous event calibration gives more accurate estimation of the total runoff volume [73]. Single storm event calibration is a rapid process and usually does not require a great deal of observed data [72]. A large number of previous studies can be found in the literature that calibrated their models over a single storm event [43,73,74]. In the current study, the model was also calibrated using a single storm event since the peak runoff was the target of assessment. Moreover, the model is a quantity–quality one, and calibrated was performed for both quantity and quality. There was no continuous quality data available to perform continuous calibration. Therefore, the quantity–quality calibration was conducted over a single-event, collected individually on 20 September 2018.

The results of quantity and quality calibration and validation are depicted in Figures 5–8. Figures 5 and 6 illustrate the flow calibration and validation, respectively. Figures 7 and 8 depict the TSS and TN calibration, respectively. As for the flow, the figures and evaluation test (Table 3) show that there is a good match between the modeled and the observed values. The stormwater quality is generally more difficult than quantity, as urban runoff quality monitoring needs substantial resources [58]. However, in our case, the quality modeling was also satisfactory. As it is obvious from Figures 7 and 8 and Table 3, there is a satisfactory match between the modeled and observed values. The results of goodness-of-fit test in this study have been compared with the results of two previous studies. Chow, Yusop, Toriman, and Technology [67] developed a model and presented the results of SWMM calibration and validation for modeling runoff quantity and quality in tropical areas. Mancipe-Munoz, Buchberger, Suidan, and Lu [72] also presented the calibration and validation of a rainfall–runoff SWMM 5 in their study. The comparison has been presented in Table 5.

Table 5. Comparison of the results of goodness-of-fit test with previous studies.

Parameter	Flow Calibration			Flow Validation			TSS		
	This Study	Chow [67]	Munoz [72]	This Study	Chow [67]	Munoz [72]	This Study	Chow [67]	Munoz [72]
NOF	0.05	0.06	-	0.08	-	-	0.14	0.24	-
NSC	0.93	0.99	0.60	0.74	-	0.62	0.81	0.75	-
r^2	0.93	0.99	-	0.77	-	-	0.84	0.77	-

According to Table 5, the model in this study has outperformed the other two studies in both flow calibration–validation and TSS calibration although the two parameters, namely NSC and r^2 , are a little bit lower than [67] in flow calibration. In terms of TSS, the model in this study has performed much

better than [67] although TSS calibration is more complex than quantity. In other words, the model calibration and validation in this study have been quite satisfactory for both quantity and quality.

Table 4 and Figures 9 and 10 present the results of LID control assigning to the model for the same rainfall that the model was calibrated. The results show a reduction of 23%, 41%, and 29% reduction for the peak runoff, TSS, and TN, respectively. As mentioned in the introduction, rain garden (bioretention) is relatively highly efficient for both runoff and pollutant reduction [35]. Bioretention cells could reduce the average peak flows by at least 45% in Maryland and North Carolina [36]. Bioretentions are also capable of reducing sediment and nutrient from 0% to 99% [35]. Swales have also been shown to have an average retention of 14% to 98% for nutrients and TSS, and up to 93% for metals [24]. According to this, the peak runoff reduction and pollutant removal of LIDs in this study are not compatible with their utmost capabilities. This might be mainly due to the fewer units of LIDs used in this study. In other words, more LIDs are required to be implemented in the study area to improve LID efficiency for both peak runoff reduction and pollutants removal. However, the cost of LID implementation should also be considered in this regard. Optimization methods could be applied to find the optimal number and placement of LIDs for the maximum flow and pollutants reduction with the minimum cost.

The results of model performance for the selected rainfall scenarios have also been depicted in Table 6 and Figure 11. The table shows that the model performance is quite efficient in terms of TSS and TN removal for different rainfall amounts. The LID removal efficiency is up to 40% and 62% for TN and TSS, respectively. The results for TSS and TN show that the LID removal efficiency for TSS and TN is independent of the rainfall amount and the model is highly efficient for TSS and TN removal for both short and long storm events.

As for the peak runoff reduction, it could be concluded from Tables 4 and 6 and Figure 11 that in smaller rainfall amounts of up to 70 mm, the model performed well, and the peak runoff reduction reached up to 27%. In rainfall amounts of between 70 and 90 mm, the model performance was moderately good, and the reduction of peak runoff reached up to 19%. In the case of higher intensity rainfalls, when the rainfall was higher than 90 mm, the model performance, in terms of runoff reduction, was poor. That is mainly because in high intensity rainfalls the soil is saturated, and the input and output are equal. In this case, no more runoff infiltrates into the soil and the LIDs and the soil beneath act as filters only to remove pollutants. Generally, the model performed satisfactorily for rainfall of up to 90 mm and for the return period of up to 10 years.

Table 6. Results of model performance for the selected rainfall scenarios.

Return Period (T)	Duration (h)	Rainfall (mm)	LID Removal (%)		Peak Runoff Reduction (%)
			TN (%)	TSS (%)	
5	1	72	40	61	27
5	1.5	81	40	61	19
5	2	90	40	62	18
10	1	80	40	61	18
10	1.5	90	40	61	9
10	2	96	39	60	0
20	1	90	38	58	0
20	1.5	99	38	59	0
20	2	110	39	60	0

Nevertheless, for the return period of more than 10 years and for the rainfall amount of more than 90 mm, the designed LIDs for the catchment cannot handle the surcharge amount of runoff in urban areas, and either we need more LIDs to be installed or a combination of conventional BMPs and LIDs is required to tackle the excess runoff in impervious surfaces to avoid any flooding in urban areas. The results achieved in this study for high intensity rainfalls are well consistent with the findings of previous studies on LID runoff reduction efficiency in urban areas, e.g., Hood, Clausen, and Warner [34], and Damodaram, Giacomoni, Prakash Khedun, Holmes, Ryan, Saour, and Zechman [27].

Based on the results achieved, the final word on the application of this study could be that LID practices (here swale and rain garden) are vital in all developed urban areas and they can

substantially reduce runoff and enhance water quality. They can also replace the conventional stormwater management systems in lower rainfall events (less than 90 mm). However, in higher rainfall events, they need to be coupled with conventional stormwater management systems to tackle the runoff, but for pollutant removal, they maintain good efficiency in high intensity rainfall as well. Furthermore, the cost of implementation is also a concern and should be considered in urban planning.

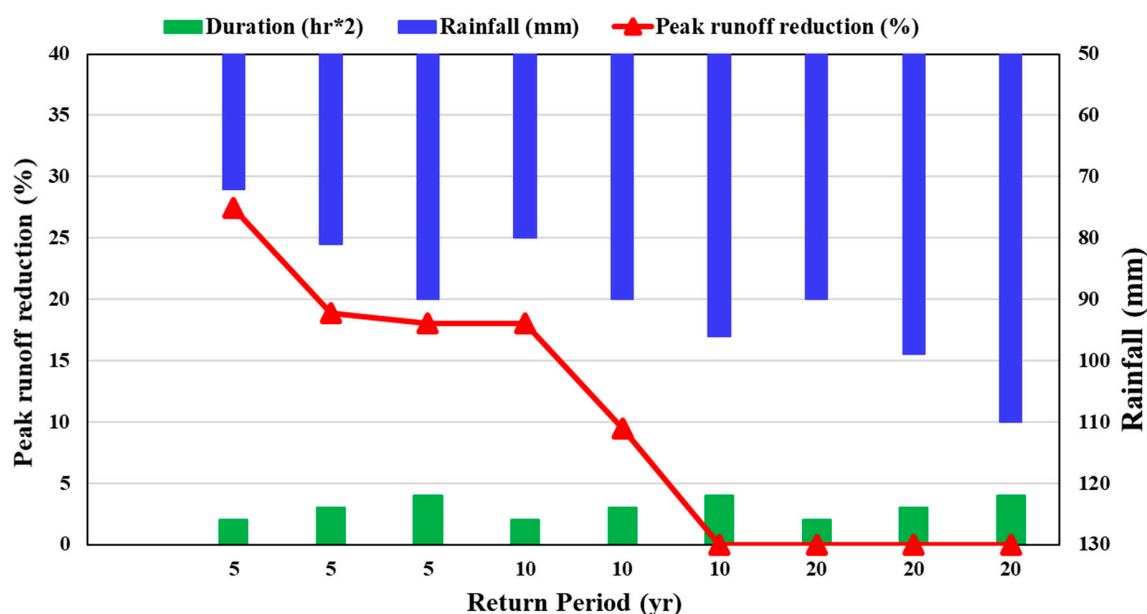


Figure 11. Peak runoff reduction for the selected rainfall scenarios.

4.2. Future Research Directions

Finally, future studies are suggested to consider the following issues in the context of stormwater modeling. Uncertainty reduction is of high importance in modeling. There are various sources of uncertainties to be considered in stormwater runoff modeling from data collection to model calibration. The sources of uncertainties can be classified as input uncertainties, parameter uncertainties, and model structure uncertainties. Therefore, these uncertainties could be addressed in future studies. Another issue to be considered is that other pollutants such as heavy metals and pathogens could be investigated in further researches to study the removal efficiency of LIDs more accurately. It is also suggested that Pilot testing to be carried out in laboratory to investigate the effect of LIDs on hydrology and water quality more precisely. Moreover, the land cover in urban catchments is not homogeneous, which affect the physical processes. Thus, the spatial-temporal distribution of precipitation in urban areas is important and should be addressed in future studies.

5. Conclusions

A quantity–quality model was developed using the US EPA SWMM. The model aimed to assess the impact of LID on stormwater quantity and quality in a subcatchment in Kuala Lumpur, Malaysia. The required rainfall–flow data and quality data were collected in the field from a real event on 20 September 2018. The 18 km² catchment was divided into 35 subcatchments using SWMM model. The model was calibrated and validated both for quantity and quality using the real data from 20 September 2018 event. A sensitivity analysis was also performed beforehand to find out the most sensitive parameters of the model.

The developed model was to simulate LID techniques at the catchment scale by applying vegetated swale and rain garden as efficient practices for urban areas. The impacts of LID practices on water quantity and water quality were evaluated using both the collected field data and the selected rainfall scenarios derived from the IDF curves for the study area.

Based on the model performance and the results achieved, the following conclusions could be made.

- The most sensitive parameters of the model are % imperviousness, % zero imperviousness, and D-Store impervious-pervious. That is to say, a slight change in the imperviousness, the depression storage or the depth of depression storage will significantly change the simulated runoff and the peak flow. However, the model is more sensitive to D-Store impervious-pervious rather than the other two parameters. It was also noted that the peak runoff will be more affected when D-Store impervious-pervious decreased rather than increased. It means that a slight reduction in the depth of depression storage, will substantially increase the peak runoff.
- In terms of water quality, the developed model performed well. The LID removal efficiency reached up to 40% for TN and up to 62% for TSS, respectively. The LID removal efficiency of the model was independent of the rainfall intensity and duration, taking into account the current research rainfall scenarios.
- As for the peak runoff reduction, in smaller rainfall of up to 70 mm the model performed well and the peak runoff reduction reached up to 27%. In rainfall amounts between 70 and 90 mm, the model performance was moderately good, and the reduction of peak runoff reached up to 19%. In the case of higher intensity rainfalls when the rainfall was higher than 90 mm, the model performance in terms of runoff reduction was poor.
- Overall, the model performed satisfactorily for rainfall of up to 90 mm and for the return period of up to 10 years. Nevertheless, for the return period of more than 10 years and for the rainfall amount of more than 90 mm, the designed LIDs for the catchment cannot handle the surcharge amount of runoff in urban areas.
- The LIDs applied for the catchment in this study are more effective in peak runoff reduction during lower intensity rainfall events. Therefore, it would be more efficient to combine the LID techniques with other conventional stormwater management practices to control urban flooding in case of high intensity storm events. However, the LID removal efficiency for TSS and TN was quite satisfactory in all selected rainfall scenarios. The LID applied in this study performed well in improving water quality in both low and high intensity rainfall events.

Thus, the model confirms the significant role of LID in reducing peak runoff and improving water quality in urban stormwater events.

Author Contributions: A.R.R. completed this study as part of his PhD thesis under the supervision of Z.I. and M.H.N. The paper was written by A.R.R., while technical support and revisions were provided by Z.I., M.H.N., and M.A.D. during model development and calibration as well as reviewing the paper final version. A.H.R. assisted in data collection and revision, whereas S.M.S. reviewed and provided feedback.

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Conflicts of Interest: The authors declare no conflicts of interest.

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