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Modeling flow of the major canals of Sylhet city using the EPA SWMM runoff model

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ABSTRACT

Geographically, local canals in Sylhet city, Bangladesh, mostly transport the rainwater to the Surma River as the city lacks typical drainage infrastructure for runoff control. Hence, proper hydraulic and hydrologic models are required to assess the current potential of these canals to withstand significant runoff and enhance the protection of flood problems during a severe storm. In this study, Malni Chara and Goali Chara sub-systems of Sylhet city's major drainage networks were calibrated and verified using the EPA Storm Water Management Model (SWMM), respectively, using the hydrological data from 2016 to 2019 and the meteorological data from 1975 to 2019. The models were suitable for measuring the runoff quantity since the simulated results matched the observed data well. For the Malni Chara sub-system, R^2 of 0.94, Nash–Sutcliffe efficiency (NSE) of 0.92, d of 0.97, percent bias (PBIAS) (%) of 2.96%, and RMSE standard deviation ratio (RSR) of 0.05 have been found and for the Goali Chara sub-system, R^2 of 0.96, NSE of 0.90, d of 0.93, PBIAS (%) of 1.54%, and RSR of 0.08 have been found.

Key words: drainage, Goali Chara, Malni Chara, runoff, SWMM, Sylhet

HIGHLIGHTS

- The innovative SWMM-based flood model for Sylhet, Bangladesh, addresses data scarcity and serves globally.
- Unique sub-system analysis improves drainage capacity accuracy.
- The robust SWMM model calibration and verification ensure reliability.
- Canal response to the 25-year design rainfall informs urban planning.
- Transferable findings benefit data-scarce flood-prone areas worldwide.

GRAPHICAL ABSTRACT

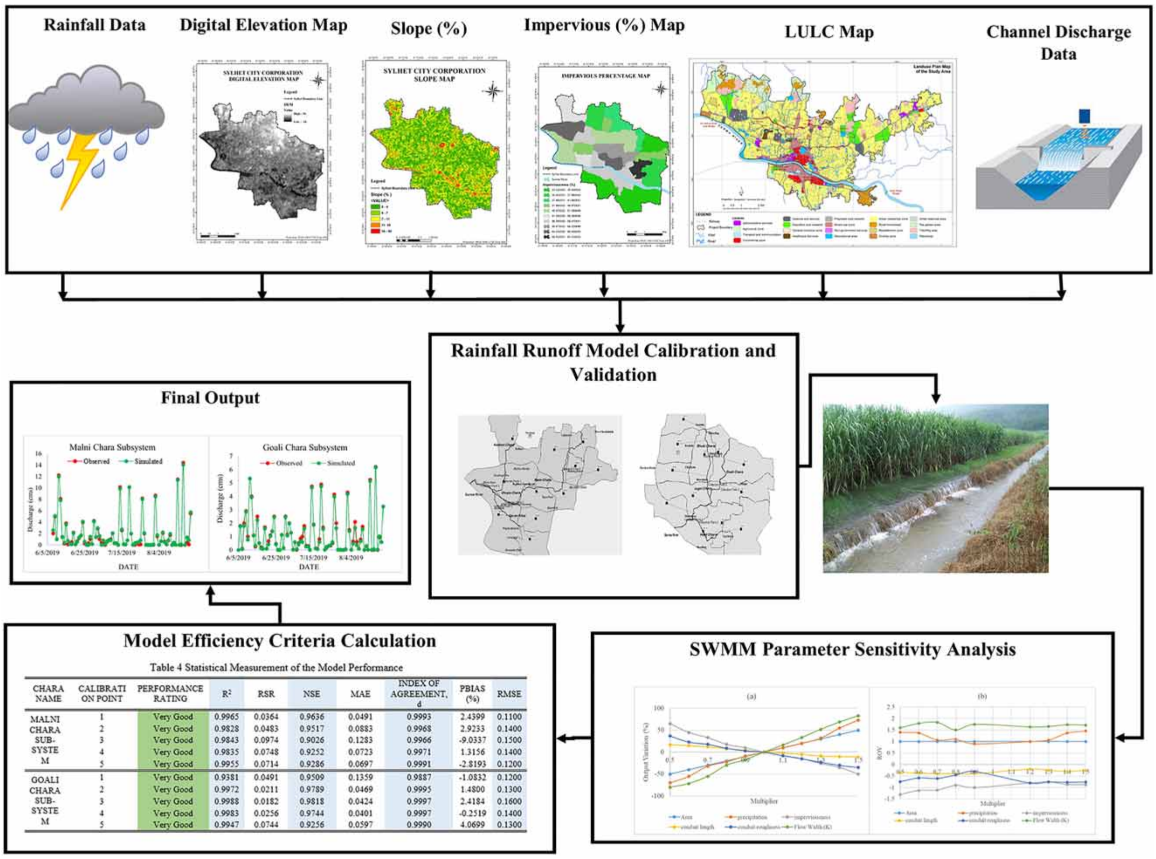

Table 4 Statistical Measurement of the Model Performance

CHARA NAME	CALIBRATION POINT	PERFORMANCE RATING	R^2	RSR	NSE	MAE	INDEX OF AGREEMENT, d	PBIAS (%)	RMSE
MALNI CHARA SUB-SYSTEM	1	Very Good	0.9965	0.0364	0.9636	0.0491	0.9993	2.4399	0.1100
	2	Very Good	0.9828	0.0483	0.9517	0.0883	0.9968	2.9233	0.1400
	3	Very Good	0.9843	0.0974	0.9026	0.1283	0.9966	-9.0337	0.1500
	4	Very Good	0.9835	0.0748	0.9252	0.0723	0.9971	1.3156	0.1400
	5	Very Good	0.9955	0.0714	0.9286	0.0697	0.9991	-2.8193	0.1200
GOALI CHARA SUB-SYSTEM	1	Very Good	0.9381	0.0491	0.9509	0.1359	0.9887	-1.0832	0.1200
	2	Very Good	0.9972	0.0211	0.9789	0.0469	0.9995	1.4800	0.1300
	3	Very Good	0.9988	0.0182	0.9818	0.0424	0.9997	2.4184	0.1600
	4	Very Good	0.9983	0.0256	0.9744	0.0401	0.9997	-0.2519	0.1400
	5	Very Good	0.9947	0.0744	0.9256	0.0597	0.9990	4.0699	0.1300

INTRODUCTION

Bangladesh has a low-lying landscape with more than 230 waterways, making it one of the most vulnerable disaster-prone countries in the world. As the lowest riparian in a huge transboundary river basin, Bangladesh faces an increasing threat of massive flood exposure. Though flood is a natural event and cannot be avoided, the damages can be reduced by responding appropriately and providing necessary drainage channels. However, urbanization and changing demographic features of urban cities have increased the exposure to urban flood hazards (Zhou 2014). Developing countries like it are facing the wrath of this kind of disaster, as the vulnerability level is very high across these regions due to poor socio-economic conditions and haphazard settlements (Khadka & Bhaukajee 2018). The nature of urban flooding is different from riverine flooding due to its hazardous characteristics, including environmental, social, and technical aspects. The flood peaks in urban areas increased from 1.8 to 8 times due to faster flow time (Rangari *et al.* 2016). So, the increasing trend of urban flooding is now drawing the attention of urban planners worldwide.

Due to the climatic and geological conditions, Sylhet city faces a large amount of rainfall each year (Hasnat *et al.* 2019). This heavy rainfall generates a large amount of runoff flow, which is evacuated through the channels (locally termed 'charas') linked to the Surma River (Munna *et al.* 2018). These natural channels act as the main drainage network system of the city. However, due to rapid urbanization, improper management, and siltation, these drainage canals within the catchment no longer could convey as much water as they formerly did within their active domain (Ghosh & Mistri 2015). Since the subsidiary natural channels are the main media to carry out the runoff to the river, it is necessary to know whether the existing cross-sections of these channels can carry out heavy runoff and mitigating the flood problem at the time of a heavy shower. This results in the inefficiency of drainage systems and canals and increases the risk of flooding and waterlogging (Ten Veldhuis 2010). In addition, the sewage is disposed of directly to these charas, which reduces the depth and deteriorates the water quality. Such inadequacy in the drainage systems spreads several types of diseases and increases the mortality rate. A defective stormwater management system contaminates the limited freshwater resources and pollutes the environment, whereas a sound management system can minimize the losses if the priorities and the choices are set up.

Watershed development and increased impervious surface development led to decreased infiltration capacity and increased runoff velocity. These circumstances effectively improve the efficiency of water transport to rivers. As rainfall and stormwater runoff from urban areas cause river pollution and watershed impairment, it is essential to integrate drainage system routing into these single and multiple storm event models (Tsihrintzis & Hamid 1998). Many hydrological models are used, such as Storage Treatment Overflow and Runoff Model (STORM), Technical Release Model (TR - 20/55), Hydrologic Engineering Centers River Analysis System (HEC-RAS), Storm Water Management Model (SWMM) and many more. However, studies on urban flood modeling in Bangladesh are limited. Rahman *et al.* (2014) assessed the drainage system of Chalna city, considering the city's response to hydrology analytically. They included a digital elevation map, satellite picture, and land use for comprehending the city's drainage network (Rahman *et al.* 2014). Khan (2015) developed a guideline for urban flooding and stormwater drainage for Mymensingh. Afrin *et al.* (2021) applied Hydrologic Engineering Centers River Analysis System (HEC-RAS) to find the peak runoff considering catchment delineation and the future land use of Dhaka. Kumar & Bhagavanulu (2007) studied an inundation map for a city on the Adyar River's bank. Hossain *et al.* (2016) performed a study that focused on designing a stormwater drainage system specifically for Sylhet Agricultural University, considering the frequent waterlogging caused by blockages in the existing drainage system, often resulting from sediment and solid waste accumulation (Hossain *et al.* 2016).

Previous studies have not addressed the development of a rainfall–runoff model specifically for the local canals (charas) within the Sylhet City Corporation (SCC) area. This gap is significant for performing capacity analysis of the major charas, which are crucial in managing most of the stormwater. Furthermore, there is a lack of understanding of the current conditions under various storm scenarios and existing land-use patterns. Notably, no prior research has simultaneously modeled two of the most critical sub-systems: the Malni Chara and Goali Chara sub-systems. These canal sub-systems are pivotal in the urban flooding crisis, often exceeding their capacity in many parts of the City Corporation area, thereby contributing significantly to the havoc caused by urban flooding.

Although many hydrologic and hydraulic models available can predict the effects of watershed changes and characterize stormwater runoff peaks and volumes (Yan *et al.* 2013), SWMM has been used in the study. SWMM has the key advantage of running the model using a dynamic routing system and is more user-friendly than the others. Though SWMM is developed to model urban drainage network settings, it can be well suited to model natural watersheds (Jang *et al.* 2007). In addition, the wide acceptance by the scientific society and engineers, user-friendly interface, and technological advancement make SWMM better suited for use. So, after properly calibrating and validating to provide realistic scenarios of runoff generation, hydrological models may be used to comprehend and assess these channel reactions to future land-use changes and climate changes (Du *et al.* 2012).

The specific objective of this research has been multi-fold. Firstly, rainfall–runoff models were developed for the significant canals (charas) of Sylhet city. Then, calibration and validation of the formulated hydrologic models were carried out respectively to assess the model performance. However, this study focuses only on the calibration and validation of the wide ranges of charas within different storm conditions and to find the sensitivity of different parameters in developing a rainfall–runoff model for the two significant sub-catchments within the area. Also, the study provides a comprehensive understanding of the stormwater management needs in this rapidly urbanizing region, offering significant insights for urban planners, stakeholders, and policymakers.

MATERIALS AND METHODS

Modeling input data

The required input data were collected from different public institutions or websites. All the inputted datasets that have been used are summarized in Table 1.

Study area description

Sylhet and its neighboring areas are geologically located in the Sylhet Trough. Physio-graphically, it falls underneath the category of tertiary hills and comprises a tropical climate having an annual average highest temperature of 23 °C (August to October) and an average lowest temperature of 7 °C (January) and the mean annual rainfall is around 3,963 mm (Roy *et al.* 2014; Bari *et al.* 2015).

Table 1 | Datasets used for the study

Data type	Source of the data	Location/Websites	Period of data
Sentinel 2A image	United States Geological Survey	www.earthexplorer.usgs.gov	2017
Rainfall data	Bangladesh Meteorological Department	Sylhet	1975–2019
Chara discharge data	BWDB	Sylhet	Water Development Board
Soil map	Soil Resource Development Institute	www.srdi.gov.bd	2018
Cross-section and elevation data of the canals (Charas)	SCC	Sylhet	2018
Land-use data	UDD	http://www.udd.gov.bd/	2018

Drainage of sewers and stormwater to the Surma River relies solely on nine canals that cross the city from different parts of the city (Munna *et al.* 2018). These canals include Malni Chara, Kalibari Chara, Dhupa Chara, Gavier Khal, Goali Chara, Bhubi Chara, Jugni Chara, and Holdi Chara. Among these charas, the Goali Chara and the Malni Chara directly join with the Surma River. The Kalibari, Dhupa, and Gavier Khal join with the Malni Chara, whereas the Jugni Chara, Bhubi Chara, and Holdi Chara join with the Goali Chara and fall into the river Surma. In this study, the total drainage system of this local canal (charas) has been separated into two sub-systems named 'Malni Chara sub-system' (canals that are connected to the Malni Chara) and 'Goali Chara sub-system' (canals that are connected to Goali Chara). Furthermore, the Malni Chara sub-system was segmented into 11 sub-catchments, while the Goali Chara sub-system was broken down into 12 sub-catchments following the contour map. The sub-systems, including the sub-catchments are illustrated in Figure 1.

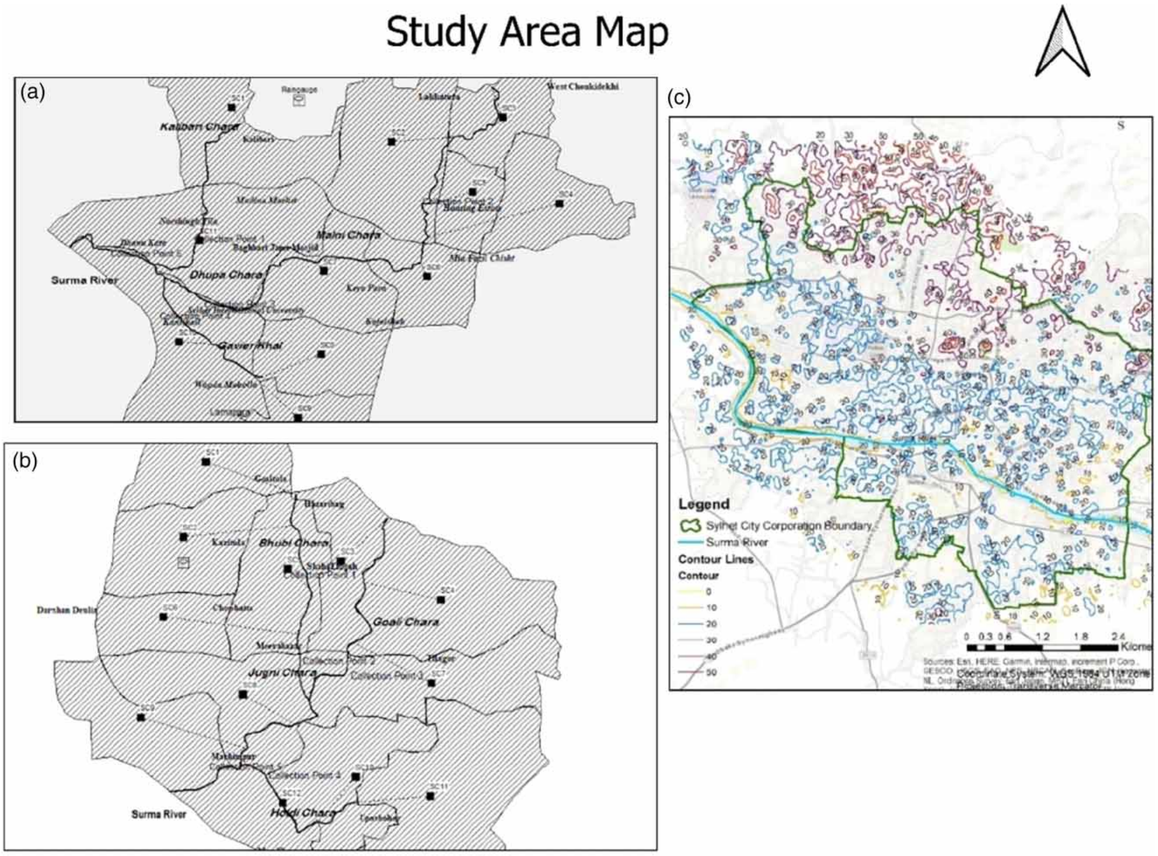

Figure 1 | Study area map. (a) Malni Chara sub-system, (b) Goali Chara sub-system, and (c) Contour map of the area.

Approach and modeling

In SWMM, the user must select the infiltration process as well as the flood routing method. For channel flow routing in SWMM, three different types of routing techniques can be used: steady flow routing, kinematic routing, and dynamic routing (Rossman *et al.* 2008). By modeling the pressured and backwater effects brought on by downstream flow constraints, the dynamic wave routing approach entirely solves the Saint-Venant equations (Rossman *et al.* 2008; Greenberg 2015). For this reason, we used the dynamic wave routing method (Greenberg 2015). Also, for the infiltration process, the Green-Ampt method was selected.

Model parameterization

EPA SWMM requires three major parameter categories for runoff quantity modeling including the physical catchment characteristics, rainfall, and infiltration data (Niyonkuru *et al.* 2018). The physical characteristics include sub-catchment area, percentage of impervious area, sub-catchment width, average slope, surface depression storage, and surface roughness (Paterne 2019a). This information has been derived by processing the topographic data using the ArcMAP and drainage data collected from the local authority.

However, the soil map for Sylhet city or the specific soil characteristics for Malni and Goali sub-systems were unavailable. Hence, the default value of Type C soil has been used.

Percentage of the impervious area has been calculated using the existing land-use data provided by the Urban Development Directorate (UDD). The land-use map was georeferenced and imperviousness (%) for every sub-catchment within the study area was calculated. The impervious area was divided by the total area to determine the percentage of imperviousness for each sub-catchment.

For conduit properties, 'irregular' shapes for the conduits were inputted using the cross-section editor. The cross-section map collected from the SCC provided the length, station distance, and elevations for the section concerned.

Manning's roughness value (n) was selected from the ASCE manual of practice for gravity sanitary sewer design and construction. As the charas are natural channels with an irregular section, the value 0.07 represents the channel roughness (ASCE 1982; Bizier 1982). Other input parameters are mentioned in Table 2.

Table 2 | Input parameter for the sub-catchments

Parameters	Value	Description	Source
N-imperviousness	0.015	Manning's roughness coefficient for the impervious areas of the sub-catchments	McCuen *et al.* (1996)
N-perviousness	0.40	Manning's roughness coefficient for the pervious area of the sub-catchments	
D-store-imperviousness	1.533 mm	Depth of depression storage on the impervious portion of the sub-catchments	ASCE (1992)
D-store-perviousness	5.08 mm	Depth of depression storage on the pervious portion of the sub-catchments	

Model calibration

By contrasting the actual field-measured data with the simulated data, the SWMM model was calibrated (Zaghloul & Abu Kiefa 2001). In this study, the surface discharge data were collected from the Bangladesh Water Development Board (BWDB) at five locations (Figure 2) for individual charas to evaluate the performances of the models. The developed model has been calibrated against these discharge data by matching generated runoff patterns against actual rainfall events for a 3-month period from June to August 2016 (Figure 3), as the heaviest rainfall in the area generally occurs within this timeline. The most sensitive parameters for the rainfall–runoff model of the area for both sub-catchments have been identified through a sensitive analysis. A realistic range for each parameter was defined based on literature and local expert knowledge (Wu *et al.* 2017) (Table 3). After that, the parameters were varied according to the defined range, and the simulations were run. After that, the best fit between the simulated discharge and the actual discharge was achieved using the iterative adjustments of the parameters (Wu *et al.* 2017; Wu *et al.* 2021). Finally, the validation was checked for the runoff for the rainfall events of 2019 for the period of July to August.

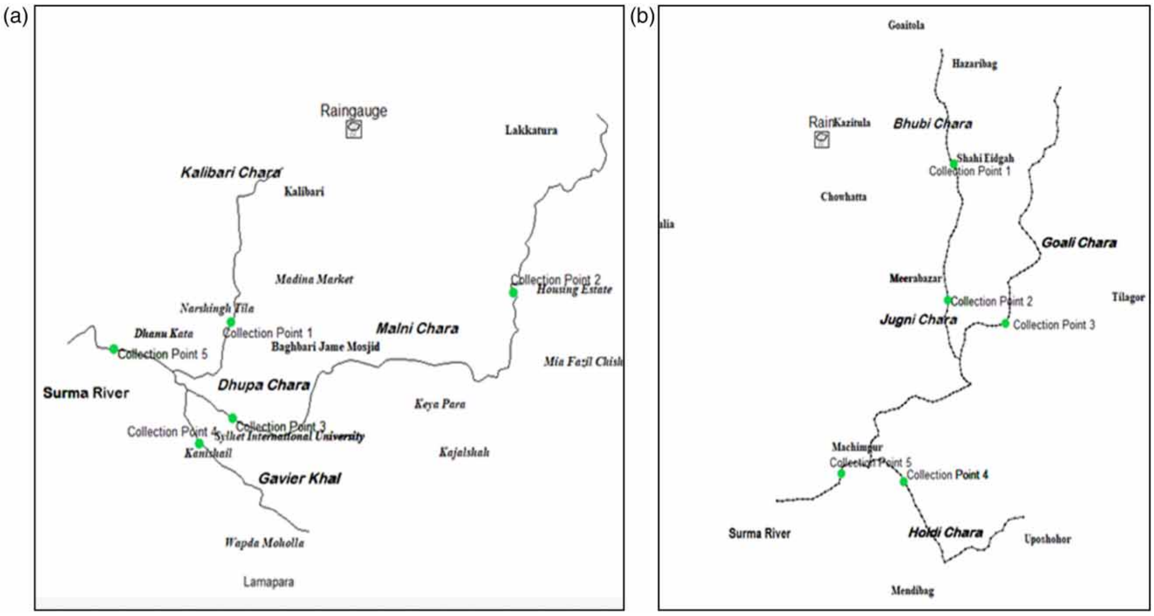

Figure 2 | Runoff data collection for the sub-systems (a) Malni Chara sub-system and (b) Goali Chara sub-system.

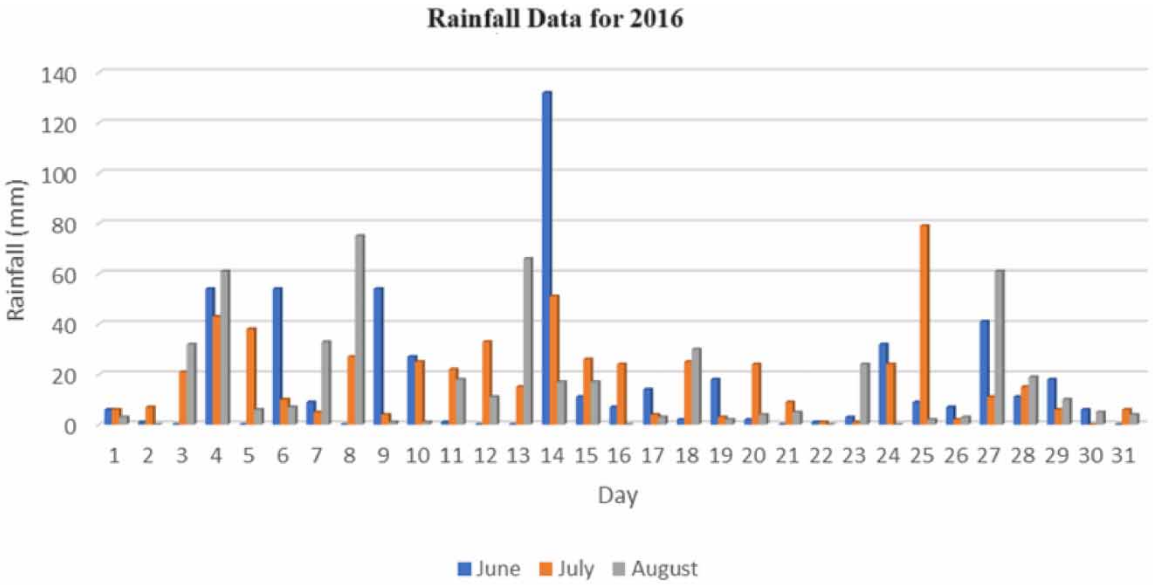

Figure 3 | Rainfal data for June, July and August of 2016.

Table 3 | Ranges used for adjusted parameters for calibration

Parameters adjusted	**Range**	**References**
Sub-catchment width	0–30 m	Local experts
Depression storage	1.27–5.08 mm	ASCE (1992)
Imperviousness (%)	35–50	Urban Development Directorate (2015)
Roughness coefficient of banks	0.010–0.015	ASCE (1992)
Saturated hydraulic conductivity (mm/hr)	0.06–0.57	Mockus (1964)
Manning's 'n' for main channel	0.04–0.10	ASCE (1982)

Parameter sensitivity analysis

Model outputs for the year 2016 are observed when the values of each chosen factors are adjusted in 10% additions within a scale of 100%, starting from −50% to +50% (Akdoğan & Güven 2016). By changing the value of one input parameter while keeping the other factors constant during the simulation, the sensitivity analysis was carried out (Niyonkuru *et al.* 2018). The model output variations resulting from changes in input parameters, the relative sensitivity of the outcomes to the various model parameters is identified, and the ratio of variations is calculated using Equation (1) (Akdoğan & Güven 2016):

$$\mathrm{ROV} = \left(\frac{I_{\mathrm{BC}}}{O_{\mathrm{BC}}}\right)\frac{(O - O_{\mathrm{BC}})}{(I - I_{\mathrm{BC}})} \tag{1}$$

where I is the value of the input parameter, I_{BC} is the value of the input parameter for the base-case scenario, O is the value of the output variable, and O_{BC} is the value of output variable for the base-case scenario (Dubus *et al.* 2003).

Model efficiency criteria estimation

Nash–Sutcliffe efficiency

The Nash–Sutcliffe efficiency (NSE) (Equation (2)) is calculated as one minus the ratio of the error variance of the modeled time-series divided by the variance of the observed time-series:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Q_{\mathrm{si}} - Q_{\mathrm{oi}})^2}{\sum_{i=1}^{n}(Q_{\mathrm{oi}} - \bar{Q}_{\mathrm{oi}})^2} \tag{2}$$

where Q_{si} is the model simulated output; Q_{oi} is the observed hydrologic variable; $\bar{Q}_{\mathrm{oi}}$ is the mean of the data, which the NSE utilizes as a standard to measure the hydrologic model's performance; and n is the total number of observations (Muleta 2012). NSE values range from 0.5 to 1, where 1 shows a perfect model and 0.5 indicates a poor performance from the model.

Root mean square error

The evaluation criteria of root mean square error (RMSE) were used to compare the simulated model output with the observed data (Ghazavi *et al.* 2017). RMSE is calculated using Equation (3):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[Q_{\mathrm{oi}} - Q_{\mathrm{si}}]^2}{n}} \tag{3}$$

where Q_{oi} and Q_{si}, respectively, are the observed and simulated data and 'n' is the number of observations.

Index of agreement

Willmott (1981) proposed the index of agreement (d) (Equation (4)) to overcome the limitation of R^2 described previously (Muleta 2012):

$$d = 1 - \frac{\sum_{i=1}^{n}(Q_{\mathrm{oi}} - Q_{\mathrm{si}})^2}{\sum_{i=1}^{n}(|Q_{\mathrm{si}} - \bar{Q}_{\mathrm{oi}}| + |Q_{\mathrm{obs}} - \bar{Q}_{\mathrm{oi}}|)^2} \tag{4}$$

where Q_{si} is the modeled output; Q_{oi} is the observed parameter; and $\bar{Q}_{\mathrm{oi}}$ is the average of the total observations (Muleta 2012).

The standard range is defined between 0 and 1 for the index of agreement where a value of zero means no correlation at all and a value of 1 means that the dispersion of the prediction is equal to that of the observation (Paterne 2019a).

Percent bias

In 2007, Moriasi *et al.* recommended percent bias (PBIAS) (Equation (5)) as one of the measures that should be included in model performance reports (Moriasi *et al.* 2007). PBIAS describes whether the model simulations overestimate or underestimate the observations:

$$\text{PBIAS} = \frac{\sum_{i=1}^{n} (Q_{\text{oi}} - Q_{\text{si}}) * 100}{\sum_{i=1}^{n} Q_{\text{oi}}} \tag{5}$$

RMSE standard deviation ratio

The RMSE standard deviation ratio (RSR) is calculated as the ratio of the RMSE and the standard deviation of measured data (Golmohammadi *et al.* 2014) (Equation (6)). The performance of the model simulation improves with decreasing RSR, RMSE, and NSE:

$$\text{RSR} = \sqrt{\frac{\sum_{i=1}^{n} (Q_{\text{oi}} - Q_{\text{si}})^2}{\sum_{i=1}^{n} (Q_{\text{oi}} - \bar{Q}_{\text{oi}})^2}} \tag{6}$$

Mean absolute error

Mean absolute error (MAE) is a measure of errors between paired observations expressing the same phenomenon (Nasirtafreshi 2022) (Equation (7)). It is thus an arithmetic average of the absolute errors, where Q_{si} is the prediction and Q_{oi} is the true value. MAE is expected to be less sensitive to high flows and more sensitive to low flows than NSE and RMS and is expected to describe model performance more evenly (Muleta 2012):

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |Q_{\text{oi}} - Q_{\text{si}}| \tag{7}$$

RESULTS AND DISCUSSION

Sensitivity analysis

In hydrological modeling, understanding the high sensitivity to small environmental changes is crucial for effectively managing water resources. This is evident in Figure 4(a), which demonstrates the variation in runoff estimates in response to changes in different parameters. Notably, flow width (K), imperviousness, and precipitation significantly influence the model's output, highlighting their importance in calibration.

Figure 4(b) illustrates the ratio of variations for different outputs which represents the sensitivity to changes in various parameters. The roughness of conduit has an average sensitivity of 0.55 for runoff while flow width (K)

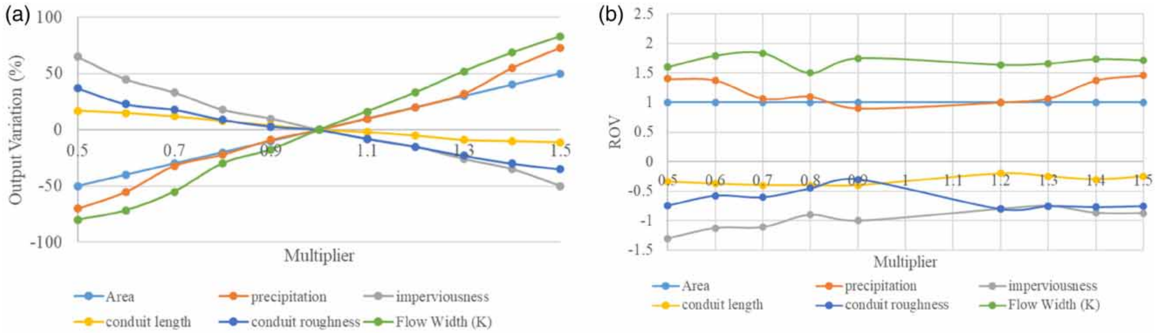

Figure 4 | Influences of the parameters in the runoff estimation: (a) output variation vs multiplier and (b) ratio of variation vs multiplier.

has an influence with 0.83. Imperviousness, conduit roughness, and conduit length have negative coefficients, which means that lowering this input parameter will lead to higher output values (Niyonkuru *et al.* 2018). From this figure it is clear that the imperviousness percentage, flow width (K), and roughness are the most vital parameters in the Goali Chara sub-catchments and Malni Chara sub-catchments.

Both figures collectively emphasize the substantial impact of impervious percentage and flow width on peak flow during simulations of tropical urban catchment runoff, both in terms of quantity and quality, as per SWMM modeling (Chow *et al.* 2012; Paterne 2019b). This is in line with Li *et al.* (2016), who found that conduit roughness and imperviousness percentage greatly affect runoff components, a conclusion also supported by our analysis. Table 4 shows the correlation and the sensitivity class for different parameters that have been used in this study.

Table 4 | Correlation and classification of the sensitive parameters

Parameter	Sensitivity class	Correlation
Area	High	Direct
Precipitation	High	Direct
Flow width (K)	High	Direct
Imperviousness (%)	Medium	Direct
Conduit roughness	Medium	Inverse
Conduit length	Low	Inverse

Model calibration

The model was evaluated for proving its competencies with different performance markers using Equations (2)–(7). The results show that all the performance indicators are within the well-accepted ranges for all events denoting a good fit between the modeled and actual runoff. Figures 5 and 6 indicate the calibration curve for the Malni Chara and Goali Chara sub-systems. Moreover, Table 5 shows the statistical measurement for the model performance indicators, while Table 6 illustrates the standard ranges for the efficiency parameters.

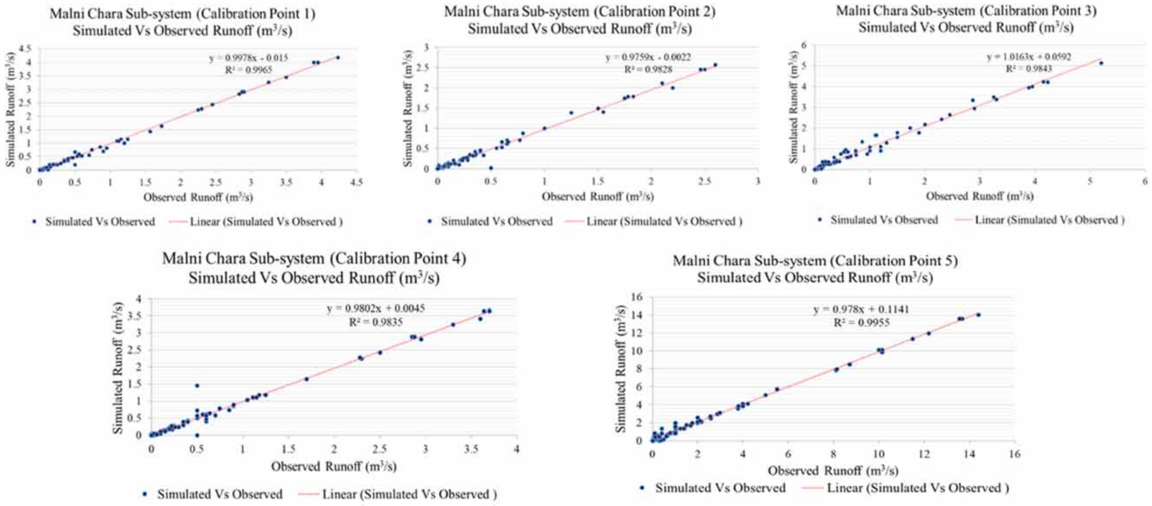

Figure 5 | Calibration curve for the Malni Chara sub-system.

Continuity error of the models

The continuity error is a critical metric used to evaluate the accuracy and reliability of the SWMM simulation. It represents the difference between the total inflow (including rainfall, runoff, external inflows, etc.) and total outflow (including outflow to downstream system, infiltration, evapotranspiration, etc.) from the system, plus any

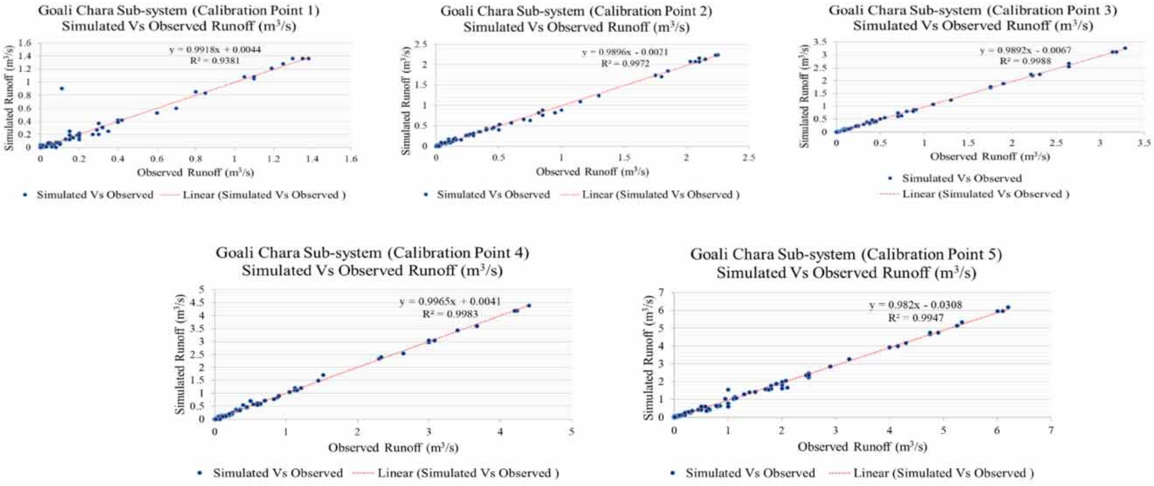

Figure 6 | Calibration curve for the Goali Chara sub-system.

Table 5 | Statistical measurement of the model performance

Chara name	**Calibration point**	**Performance rating**	***R*²**	**RSR**	**NSE**	**MAE**	**Index of agreement, *d***	**PBIAS (%)**	**RMSE**
Malni Chara sub-system	1	Very good	0.996	0.036	0.963	0.049	0.999	2.439	0.11
	2	Very good	0.982	0.048	0.951	0.088	0.996	2.923	0.14
	3	Very good	0.984	0.097	0.902	0.128	0.996	−9.033	0.15
	4	Very good	0.983	0.074	0.925	0.072	0.997	1.315	0.14
	5	Very good	0.995	0.071	0.928	0.069	0.999	−2.819	0.12
Goali Chara sub-system	1	Very good	0.938	0.049	0.950	0.135	0.988	−1.083	0.12
	2	Very good	0.997	0.021	0.978	0.046	0.999	1.480	0.13
	3	Very good	0.998	0.018	0.981	0.042	0.999	2.418	0.16
	4	Very good	0.998	0.025	0.974	0.040	0.999	−0.251	0.14
	5	Very good	0.994	0.074	0.925	0.059	0.999	4.069	0.13

Table 6 | Standard range and performance rating for different parameters

Performance Rating	**Ranges RSR**	**NSE**	**PBIAS (%)**	**RMSE**	**MAE**	**Index of agreement**
Very good	0 ~ 0.5	0.75 ~ 1	< ±10	0.1 ~ 0.25	0	1
Good	0.5 ~ 0.6	0.65 ~ 0.75	± 10 ~ ±15	0.25 ~ 0.5	Not defined	Not defined
Satisfactory	0.6 ~ 0.7	0.5 ~ 0.65	± 15 ~ ±25	0.5 ~ 0.75	Not defined	Not defined
Unsatisfactory	> 0.7	< 0.5	> ±25	0.75 ~ 1.0	1	0

change in storage within the system over a given period. The continuity error can be calculated with the following formula in Equation (8):

$$\text{Continuity error (\%)} = [(\text{Total inflows} - \text{Total outflows} - \Delta\ \text{Storage})/\text{Total inflows}] \times 100 \tag{8}$$

Continuity errors verify the accuracy of the SWMM's calculations. Two different kinds of continuity errors are calculated: one for flow routing and the other for runoff modeling (Greenberg 2015). These errors are calculated for the system by summing the final storage and total outflow and then subtracting it from the sum of the initial storage and total inflow (Rossman *et al.* 2008; Greenberg 2015). For maintaining the validity of the model and the system, the continuity error should not exceed 5% (Rossman *et al.* 2008). The runoff and routing continuity error found for the Malni Chara sub-system is −0.13 and 1.18%, whereas for the Goali Chara sub-system it is −0.15 and 1.49%.

Model validation

The model was validated using the input parameters produced during the calibration procedure. Figure 7 illustrates the observed and simulated runoff values for the two sub-systems. For the Malni Chara sub-system R^2 of 0.94 which is close to 1; NSE of 0.92 which is between 0 and 1; d of 0.97 which is close to 1, PBIAS (%) of 2.96%, and RSR of 0.05. For the Goali Chara sub-system, R^2 of 0.96 which is close to 1; NSE of 0.90 which is between 0 and 1; d of 0.93 which is close to 1, PBIAS (%) of 1.54%, and RSR of 0.08. The findings demonstrate that all performance metrics are within the permissible range for the events, demonstrating a solid match between the predicted and measured runoff. Research on using low-impact development techniques for canal restoration in urban catchments was carried out using the EPA SWMM, and both the R^2 and NSE indices were employed for the model performance evaluation (Paterne 2019a). The R^2 values varied from 0.89 to 0.99 for peak runoff, while the NSE values fluctuated from 0.79 to 0.99 (Paterne 2019a). Hence, the models were determined to be suitable for runoff quantity modeling for both Malni and Goali Chara sub-systems.

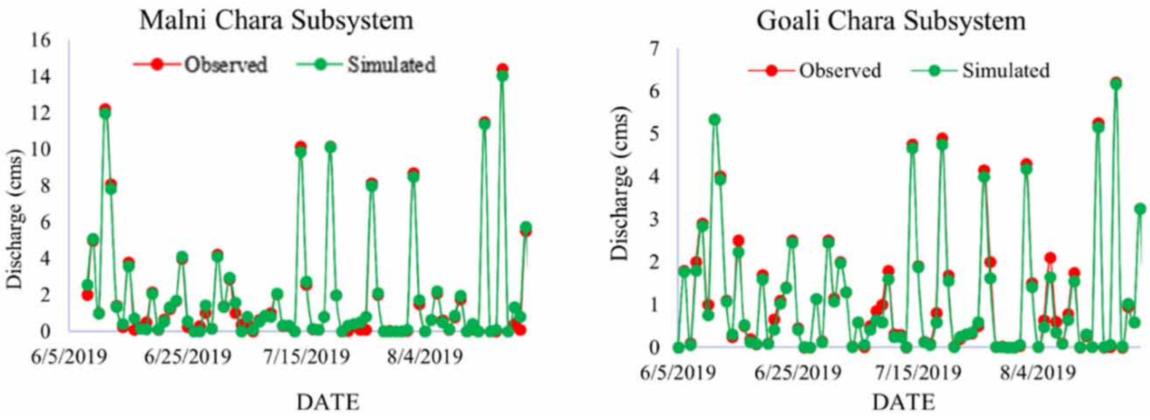

Figure 7 | Observed vs simulated runoff values for the Malni Chara sub-system and the Goali Chara sub-system.

Limitations

To enhance the accuracy of the runoff rainfall model, it is crucial to have access to high-resolution data with shorter intervals. However, the absence of such detailed data in the study area limited our ability to match the peak flow for the catchments precisely. Additionally, the lack of soil data for the canal area also constrained the model's robustness. Access to these data could have significantly improved the precision of runoff and groundwater recharge estimates. Additionally, for calibration, we utilized runoff data from 2016, and for validation, data from 2019 were used. The model's accuracy would have benefited from a broader range of recorded discharge data. We could only collect discharge data corresponding to rainfall for these two years due to data scarcity. Integrating more extensive recorded data would significantly enhance the model's accuracy and predictive capabilities.

CONCLUSIONS

This research focused on calibrating and evaluating the EPA SWMM for stormwater runoff modeling in Sylhet city's main drainage canals. A critical aspect of this study was the division of the total drainage system into two sub-systems and further segmentation into sub-catchments, facilitating precise identification and analysis. The EPA SWMM model parameters were meticulously developed, taking into account the unique characteristics of these sub-catchments, along with the area's topography and drainage network data. A significant part of this study was the parameter sensitivity analysis, which underscored the robustness of the chosen parameters. This robustness was further affirmed by the successful calibration and validation of the model within acceptable performance ranges. The indices used in the study uniformly indicated an excellent fit for the modeled data, reinforcing the model's reliability in simulating the runoff quantity of the city's drainage canals.

The practical implications of this study are significant. The calibrated model is a powerful tool for assessing the performance of drainage systems and crafting flood mitigation strategies. It offers a framework for other urban areas facing similar challenges, highlighting the potential of such models in urban planning and decision-making processes. By applying these findings, urban planners and policymakers can better evaluate the effectiveness of existing drainage systems, identify solutions to flood-related issues, and develop comprehensive stormwater management strategies for the watershed.

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COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

AUTHOR CONTRIBUTIONS

Gulam Md Munna prepared the manuscript. Gulam Md Munna received cooperation from Md Mahmudul Hasan, Ahmed Hasan Nury, and Jahir Bin Alam in performing computation, developing the methodology, and manuscript preparation. Md Misbah Uddin, Mohammad Shahidur Rahman, and Shriful Islam assisted in analysis and draft preparation. Furthermore, the authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Afrin, S., Islam, M. M. & Rahman, M. M. 2021 Adequacy assessment of an urban drainage system considering future land use and climate change scenario. *Journal of Water and Climate Change* **12**(5), 1944–1957.

Akdoğan, Z. & Güven, B. 2016 Assessing the sensitivity of SWMM to variations in hydrological and hydraulic parameters: A case study for the city of Istanbul. *Global Nest Journal* **18**(4), 831–841. doi:10.30955/gnj.001717.

ASCE 1982 *Gravity Sanitary Sewer Design and Construction*. American Society of Civil Engineers, Reston, VA, USA.

ASCE 1992 *Design and Construction of Urban Stormwater Management Systems*. American Society of Civil Engineers and Water Environment Federation, Reston, VA, USA.

Bari, S. H., Rahman, M. T., Hussain, M. M. & Ray, S. 2015 Forecasting monthly precipitation in Sylhet city using ARIMA model. *Civil and Environmental Research* **7**(1), 69–77.

Bizier, P. 1982 *Gravity Sanitary Sewer Design and Construction*. American Society of Civil Engineers, New York (Issues 60, WPCF Manual Practice No. FD-5. Water Environment Foundation (WEF)). doi:10.1061/9780784409008.

Chow, M. F., Yusop, Z. & Toriman, M. E. 2012 Modelling runoff quantity and quality in tropical urban catchments using storm water management model. *International Journal of Environmental Science and Technology* **9**(4), 737–748. doi:10.1007/s13762-012-0092-0.

Du, J., Qian, L., Rui, H., Zuo, T., Zheng, D., Xu, Y. & Xu, C. Y. 2012 Assessing the effects of urbanization on annual runoff and flood events using an integrated hydrological modeling system for Qinhuai River basin, China. *Journal of Hydrology* **464–465**, 127–139. doi:10.1016/j.jhydrol.2012.06.057.

Dubus, I. G., Brown, C. D. & Beulke, S. 2003 Sensitivity analyses for four pesticide leaching models. *Pest Management Science: Formerly Pesticide Science* **59**(9), 962–982.

Ghazavi, R., Rabori, A. M. & Reveshty, M. A. 2017 The effects of rainfall intensity-duration-frequency curves reformation on urban flood characteristics in semi-arid environment. *Ecopersia* **5**(2), 1799–1813.

Ghosh, S. & Mistri, B. 2015 Geographic concerns on flood climate and flood hydrology in Monsoon-Dominated Damodar River Basin, Eastern India. *Geography Journal* **2015**, 1–16. doi:10.1155/2015/486740.

Golmohammadi, G., Prasher, S., Madani, A. & Rudra, R. 2014 Evaluating three hydrological distributed watershed models: MIKE-SHE, APEX, SWAT. *Hydrology* **1**(1), 20–39. doi:10.3390/hydrology1010020.

Greenberg, S. S. E. 2015 *Urban Hydrological Modeling of the Malden River Using the Storm Water Management Model (SWMM)*. Doctoral dissertation. Massachusetts Institute of Technology, Cambridge, MA, USA.

Hasnat, G. N. T., Kabir, M. A. & Hossain, M. A. 2019 Major environmental issues and Problems of South Asia, Particularly Bangladesh. In: *Handbook of Environmental Materials Management* (Hussain, C., ed.). Springer, Cham, pp. 109–148. doi:10.1007/978-3-319-73645-7_7.

Hossain, M. A., Ishaque, F., Sarker, M. A. R., Ritu, S. P. & Hussain, M. F. 2016 Sustainable storm water drainage system design for sylhet agricultural university. *Journal of the Sylhet Agricultural University* **3**(2), 271–280.

Jang, S., Cho, M., Yoon, J., Yoon, Y., Kim, S., Kim, G., Kim, L. & Aksoy, H. 2007 Using SWMM as a tool for hydrologic impact assessment. *Desalination* **212**(1–3), 344–356.

Khadka, J. & Bhaukajee, J. 2018 *Rainfall-runoff simulation and modelling using HEC-HMS and HEC-RAS models : Case studies from Nepal and Sweden*. TVVR 18/5009. Lund University, Lund, Sweden, pp. 1–69.

Khan, D. M. S. A. 2015 Guidelines for flood risk assessment and storm water drainage plan. Urban Development Directorate, Mymensingh, 300. Available at: https://msdp.gov.bd/reports/report_drainage.pdf.

Kumar, S. V. & Bhagavanulu, D. V. S. 2007 Flood simulation and inundation mapping of Adyar river: A case study using GIS. *Disaster and Development: Journal of the National Institute of Disaster Management* **1**(2), 155–168.

Li, C., Liu, M., Hu, Y., Gong, J. & Xu, Y. 2016 Modeling the quality and quantity of runoff in a highly urbanized catchment using storm water management model. *Polish Journal of Environmental Studies* **25**(4), 1573–1581.

McCuen, R., Johnson, P. & Ragan, R. 1996 *Highway Hydrology, Hydraulic Design Series No.-2, Pub No. FHWA-SA-96-067. September*. US Department of Transportation, Washington, DC.

Mockus, V. 1964 *National Engineering Handbook*. US Soil Conservation Service, Washington, DC, USA, p. 4.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. & Veith, T. L. 2007 Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* **50**(3), 885–900.

Muleta, M. K. 2012 Model performance sensitivity to objective function during automated calibrations. *Journal of Hydrologic Engineering* **17**(6), 756–767.

Munna, G. M., Alam, J. B., Ahmed, J., Al Mamun, A. & Mamun, A. A. 2018 Evaluating discharge capacity of Major Chara's of Sylhet City Using GIS. *Journal of Water Resource and Protection* **10**(02), 167–181. doi:10.4236/jwarp.2018.102010.

Nasirtafreshi, I. 2022 Forecasting cryptocurrency prices using recurrent neural network and long short-term memory. *Data & Knowledge Engineering* **139**, 102009.

Niyonkuru, P., Sang, J. K., Nyadawa, M. O., Munyaneza, O., Nyawada, M. O. & Munyaneza, O. 2018 Calibration and validation of EPA SWMM for stormwater runoff modelling in Nyabugogo catchment, Rwanda. *Journal of Sustainable Research in Engineering* **4**(4), 152–159.

Paterne, N. 2019a *Evaluating Drainage Systems Performance and Infiltration Enhancement Techniques as Flood Mitigation Measures in Nyabugogo Catchment, Rwanda*.

Paterne, N. 2019b *Evaluating Drainage Systems Performance and Infiltration Enhancement Techniques as Flood Mitigation Measures in Nyabugogo Catchment, Rwanda*. Available from: http://hdl.handle.net/123456789/4940

Rahman, M., Saha, R., Haque, M. M. & Hossain, S. 2014 *Storm Water Management for Urban Areas of Bangladesh by Analytical & Modelling Approach: A Case Study of Chalna Municipality. March*.

Rangari, V. A., Umamahesh, N. V. & Patel, A. K. 2016 Development of Different Modeling Strategies for Urban Flooding: a Case Study of Hyderabad City. *Proceedings of National Conference : Civil Engineering Conference Innovation for Sustainability (CEC 2016)*, *5*(Cec), 10th.

Rossman, L. A., Dickinson, R., Schade, T., Chan, C., Sullivan, D. & Burgess, E. 2008 *Storm Water Management Model User's Manual Version 5.0*.

Roy, R., Islam, A., Miah, M. H. N., Uddin, M. S. & Sikdar, A. 2014 Farmers' opinion towards conservation and genetic erosion of citrus species at Jaintapur Upazila of Sylhet District in Bangladesh. *Journal of the Sylhet Agricultural University* **1**, 207–212.

Ten Veldhuis, J. A. E. 2010 *Quantitative Risk Analysis of Urban Flooding in Lowland Areas*.

Tsihrintzis, V. A. & Hamid, R. 1998 Runoff quality prediction from small urban catchments using SWMM. *Hydrological Processes* **12**(2), 311–329.

Urban Development Directorate 2015 *Hydrological Survey Report of the North-Eastern Zone of Bangladesh*.

Willmott, C. J. 1981 On the validation of models. *Physical Geography* **2**(2), 184–194.

Wu, Q., Liu, S., Cai, Y., Li, X. & Jiang, Y. 2017 Improvement of hydrological model calibration by selecting multiple parameter ranges. *Hydrology and Earth System Sciences* **21**(1), 393–407. doi:10.5194/HESS-21-393-2017.

Wu, H., Chen, B., Ye, X., Guo, H., Meng, X. & Zhang, B. 2021 An improved calibration and uncertainty analysis approach using a multicriteria sequential algorithm for hydrological modeling. *Scientific Reports* **11**(1), 16954. doi:10.1038/s41598-021-96250-6.

Yan, B., Fang, N. F., Zhang, P. C. & Shi, Z. H. 2013 Impacts of land use change on watershed streamflow and sediment yield: An assessment using hydrologic modelling and partial least squares regression. *Journal of Hydrology* **484**, 26–37. doi:10.1016/j.jhydrol.2013.01.008.

Zaghloul, N. A. & Abu Kiefa, M. A. 2001 Neural network solution of inverse parameters used in the sensitivity-calibration analyses of the SWMM model simulations. *Advances in Engineering Software* **32**(7), 587–595. doi:10.1016/S0965-9978(00)00072-7.

Zhou, Q. 2014 A review of sustainable urban drainage systems considering the climate change and urbanization impacts. *Water (Switzerland)* **6**(4), 976–992. doi:10.3390/w6040976.

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