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A web-based urban hydrology model for municipal scale applications

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ABSTRACT

Extensive data and computational requirements limit the application of existing urban hydrology models at municipal scales. Community-enabled Lifecycle Analysis of Stormwater Infrastructure Costs (CLASIC) is a web-based deployment of the SWMM model with decoupled hydrologic and hydraulic components to enable hydrologic assessment at the municipal and larger scales. This study comprehensively evaluates the performance validity of CLASIC for characterization of hydrologic responses against SWMM and observed data. Furthermore, global sensitivity analysis is used to explore the significance of hydrologic and hydraulic model parameters across spatial and temporal scales. CLASIC reliably represents the urban hydrological processes and accurately quantifies stream discharge at the municipal scale and temporal scales greater than the catchment's time of concentration. Notably, the computational requirements of CLASIC are substantially lower than those of SWMM as the catchment drainage area increases. The application of CLASIC for flood assessment may be conducted with careful examination of the estimated peak discharge at sub-daily timescales.

1. Introduction

Urbanization can substantially alter hydrologic budgets in urban catchments, leading to changes in the natural water cycle and increasing the risk of flooding and water pollution (C. Li et al., 2018; Locatelli et al., 2017; Miller et al., 2014; Wang et al., 2022). Urban hydrological models are important tools in stormwater management, flood resilience, and urban planning. These tools are increasingly used to inform stormwater decisions, such as planning, design, and implementation of gray, green, and hybrid stormwater infrastructure (Ahiablame et al., 2012; Moral-es-Torres et al., 2016). However, their applications for comprehensive hydrologic assessments at the larger municipal scale are hampered by cumbersome computational requirements, numerical convergence, and model parameterization challenges (Hamouz and Muthanna, 2019; R. L. Pachaly et al., 2020; Shahed et al., 2020).

The US Environmental Protection Agency (EPA) Storm Water Management Model (SWMM) (Rossman, 2015) is one of the most used tools for representation of hydrological processes in urban areas. The model enables evaluation of the efficiency of stormwater control measures (SCMs), including green stormwater infrastructure (GSI), in reducing the consequences of increased imperviousness from urban development (Cipolla et al., 2016; Hamouz and Muthanna, 2019; Haris et al., 2016; Jang et al., 2007; Shahed et al., 2020). However, modeling large-scale urban watersheds with SWMM may be hampered by extensive data requirements for site-specific parameters and drainage structure, which may not be broadly available (Ha and Stenstrom, 2008; Shahed et al., 2020). Furthermore, providing the input data related to the study area can be challenging and time-consuming due to the lack of direct GIS linkage in the model (Xiao et al., 2019). Moreover, the simulation runtime and numerical convergence exacerbate as the drainage area and the number of computational elements of the model increase (Niazi et al., 2017; R. Pachaly et al., 2019). SWMM is also typically applied for stormwater and flood management at the sewershed scale (Babaei et al., 2018; Hidayat and Soekarno, 2020; Rai et al., 2017).

Several tools incorporate SWMM as the simulation engine for representation of hydrological process to enable assessment of the effects of climate change, land use, and stormwater practices, such as green stormwater infrastructure (GSI) (Baek et al., 2020; Rai et al., 2017; Zeng et al., 2021). For instance, the EPA's Storm Water Calculator (Rossman and Bernagros, 2019) estimates runoff at site scale planning units (less than 5 ha) for alternative land use and stormwater control scenarios. The web-based tool is desirable because it does not require considerable user input and parameterization. However, its simulation has been shown to be highly uncertain at large scale areas (Dell et al., 2021). Moreover, the tool does not have options for representation of the co-benefits and water quality effects of the stormwater control measures. Another

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decision support tool, called System for Urban Stormwater Treatment and Analysis INtegration (SUSTAIN), offers a public domain tool for determining the optimal location, type, and construction cost of stormwater practices (Shoemaker et al., 2009). SUSTAIN utilizes algorithms from SWMM to simulate the flow and pollutant routing (Lee et al., 2012). Therefore, modeling a large-scale watershed using SUSTAIN is as complex as SWMM and demands extensive data and a thorough understanding of watershed and GSI modeling processes. While focusing primarily on water quality outcomes, SUSTAIN does not include the additional benefits from implementing stormwater control measures (e.g., social, economic, and environmental) or lifecycle costs (LCC). Other tools not based on SWMM are also available for the assessment of stormwater control infrastructure, including the Center for Neighborhood Technology (CNT) Green Values Calculator (CNT, 2022), RECARGA (Severson and Atchison, 2004), and E2STORMED Decision Support Tool (Morales-Torres et al., 2016). The major shortcoming of these tools is their simplistic methodology for simulation of hydrologic and water quality processes. Moreover, these tools do not include lifecycle cost and benefit assessment capacities.

With the increasing complexity of the existing urban hydrology models, increasing interactions between hydrological and hydraulic processes at large spatial scales tend to govern model convergence and computational costs (Chen et al., 2022; Muñoz-Carpena et al., 2023; R. L. Pachaly et al., 2020). While representation of these interactions may be important for characterization of sub-hourly flood responses, they may not substantially influence model performance for characterization of hydrological processes at larger temporal and spatial applications that focus on the effects of stormwater control measures on the daily, monthly, or annual water budgets and water quality. Selecting an appropriate level of model complexity must incorporate the specific purposes of the study, available data, and desired level of accuracy (Birhanu et al., 2018; Devia et al., 2015; Gui et al., 2021; Pechlivanidis et al., 2011).

The Community-enabled Lifecycle Analysis of Stormwater Infrastructure Costs tool (CLASIC, 2020) uses SWMM for urban hydrological simulations. However, it remedies challenges with municipal or regional applications of SWMM by disaggregating hydraulic components from hydrological simulations without compromising performance validity for hydrologic assessments (Dell et al., 2021). The web-based CLASIC tool supports stormwater planning and decision-making by characterizing lifecycle costs (LCC), runoff volume reduction, and pollutant removal, as well as triple-bottom-line (TBL) co-benefits (i.e., social, economic, and environmental co-benefits) of the SCMs. The tool enables users to assess different scenarios of stormwater infrastructure using different designs and combinations of practices and to compare them in terms of their costs, co-benefits, and performance in evaluating the extent and combination of green, hybrid green-gray, and gray infrastructure practices (WRF, 2019). The integration of hydrologic and water quality performance, TBL co-benefits, and LCC of gray and green stormwater practices in CLASIC provides a unique web-based data analysis and modeling software for comprehensive planning and decision-making.

The hydrologic components of CLASIC provides acceptable performance in estimating the total volume of water cycle components (i.e., runoff, evaporation, and infiltration) and evaluating the performance of stormwater control measures (SCM) compared to the full SWMM simulations (Dell et al., 2021). However, the effects of disaggregating hydrologic and hydraulic components on hydrologic and water fluxes at different temporal and spatial scales have not been previously investigated. The municipal scale holds a significant interest for city planners and decision-makers, and different temporal scales are appropriate for different applications, depending on the study's objectives (Moriasi et al., 2015). Furthermore, the computational requirements of hydrologic models increase as the drainage area of the study catchment increases. However, the potential improvements in simulation time by using CLASIC compared to SWMM has not been sufficiently characterized.

This study aims to examine the performance validity and computational requirements of the CLASIC tool for municipal scale characterization of urban water cycle and hydrologic fluxes. Specifically, the objectives of this study are to: 1) assess the performance validity of the CLASIC model in simulating runoff volume, evaporation, infiltration, and full discharge statistics at hourly to annual time steps compared with SWMM model and observed discharge; 2) investigate the importance of interconnected hydrologic and hydraulic parameters and their associated processes for simulated stream discharge at different temporal and spatial scales; and 3) examine the computational time of the CLASIC and SWMM models at varying spatial scales. The findings of the study support appropriate applications of the CLASIC tool for evaluations of SCMs (e.g., GSI) and climate and land use change assessment at neighborhood to municipal scales.

2. Methods

To examine the study objectives, the SWMM and CLASIC models are developed for the urban Spring Creek catchment in northern Colorado. Model development incorporates detailed information about hydrologic and hydraulic characteristics of the system. The hydrologic performance of the models is evaluated at two stream discharge gauging stations within the study catchment over the 2008–2018 period. The Sobol global sensitivity analysis technique is conducted to examine the importance of hydrologic and hydraulic model parameters, individually and in combination, at hourly to annual time steps. Furthermore, the computational requirements of the SWMM and CLASIC models are assessed in terms of time of simulation as a function of contributing drainage area and the number of hydrologic and hydraulic elements.

2.1. SWMM and CLASIC urban hydrology models

The Storm Water Management Model (SWMM) is a widely used tool for urban watershed drainage system design and management (Haris et al., 2016; Shahed et al., 2020). The model is utilized in hydrological studies to simulate the hydrologic effects of urbanization and flood analysis (Babaei et al., 2018; Jang et al., 2007). With the integration of Low Impact Development (LID) controls in 2010 and further enhancements in 2015, SWMM evolved to support green infrastructure performance evaluation, notably in runoff reduction via various LID controls like green roofs and porous pavements (Rossman, 2015). Several studies corroborate SWMM's efficacy in evaluating LID controls, highlighting its reliable simulation of runoff from SCMs including GSI and LID controls (Cipolla et al., 2016; Hamouz and Muthanna, 2019; Kong et al., 2017). The important parameters of the SWMM model that are used in this study are provided in Table 1. There are also other infiltration methods that can be applied to a model in SWMM (e.g., Green-Ampt) which are

Table 1
SWMM model parameters that are used in this study.

Parameter	Unit	Description
Width	m	Width of overland flow path
Slope	%	Average surface slope
%Imperv	%	Percent of impervious area
DstoreImperv	mm	Depth of depression storage on impervious area
DstorePerv	mm	Depth of depression storage on pervious area
%ZeroImperv	%	Percent of impervious area with no depression storage
Max infiltration rate	cm/hr	Horton maximum infiltration rate
Min infiltration rate	cm/hr	Horton minimum infiltration rate
Decay Constant rate	1/hr	Horton decay rate
Manning's N	–	Channel's Manning's roughness
N-Imperv	–	Manning's N for impervious area
N-Perv	–	Manning's N for pervious area

not included in this study.

Despite the widespread application of SWMM, modeling a large-scale watershed with this model is impeded by issues such as numerical convergence, simulation time, and extensive data required due to the detailed flow routing methods, including kinematic wave routing model that is based on solving the continuity equation, and the dynamic wave routing model that solves the full Saint Venant equations for conservation of mass and momentum (Niazi et al., 2017; Rossman, 2010).

The CLASIC tool is a robust cloud-based web tool for the assessment of hydrologic, life costs, and triple bottom line (social, economic, and environmental) co-benefits of gray, green, and hybrid stormwater infrastructure (CLASIC, 2020). The CLASIC tool is deployed as a web analytic using the eRAMS cloud computing platform software (eRAMS, 2024). The eRAMS platform offers powerful cloud-based capabilities for building computationally scalable and platform-independent tools that can be accessed through web browsers on desktop or mobile devices. The software supports content management, geospatial mapping and processing, data analysis and modeling services, and apps (Catena, 2024). Data analysis and modeling services in the eRAMS are deployed using the Cloud Services Implementation Platform (CSIP) (David et al., 2014; W.s Lloyd et al., 2013; W. J. Lloyd et al., 2015) with RESTful web services (Pautasso and Wilde, 2010). Specifically, features presented within the CLASIC tool include (Fig. 1): define study area (selecting project boundaries, land use, soil type, and land slope), climate and geographic information (precipitation, evaporation, and EPA region), model defaults, scenario builder (i.e., develop scenarios of technologies, climate, and land use), co-benefits assessment, targets (i.e., set targets for pollutant reduction, runoff volume reduction, and costs), run tool, and view outputs in the results panel. Fig. 1 illustrates a schematic of the CLASIC web tool, which is publicly available at clasic.erams.com.

Development of a hydrologic model in CLASIC is supported by cloud data and modeling services that obtain data from publicly available climate, land use and land cover, soil, slope, and water quality databases (Table 2). Moreover, the tool leverages data from the International BMP Database (BMPdatabase, 2019) and The National Green Infrastructure Certification Program (NGICP, 2019) to parameterize stormwater technologies. All model parameters can be modified for site-specific parameterization and calibration.

The study area may include a single or multiple subcatchments. CLASIC tool disaggregates the subcatchments based on the specific properties assigned to each subcatchment. The spatial disaggregation scheme in CLASIC is as follows: First the subcatchments are comprised of

Table 2
Publicly available datasets used in the CLASIC tool.

Database	Reference
Climate: precipitation, temperature, evaporation	Climate station data from EPA Better Assessment Science Integrating Point and Non-Point Sources (BASINS) (USEPA, 2023)
Land use and Land cover	The National Land Cover Database (NLCD) (U.S. Geological Survey, 2018)
Soil	Soil Survey Geographic database (SSURGO/STATSGO) (Soil Survey Staff, 2019)
Slope	Digital Elevation Model (U.S. Geological Survey, 2023)
Water quality: pollutant concentration	National Stormwater Quality Database (NSQD) (Pitt et al., 2004) International Stormwater BMP database (BMPdatabase, 2019)

directly connected impervious area (DCIA) and separate pervious area (SPA) based on the percentage of the impervious area. Additionally, SCMs such as GSIs can be explicitly added to subcatchments using the Scenario module. Fig. 2 illustrates an example of a subcatchment with GSI placed in the available surrounding pervious area. The area allocated to the GSI (represented by the receiving pervious area (RPA) in Fig. 2) is taken out from the SPA and will be a standalone subcatchment. The area of the DCIA treated by GSIs is a model parameter. This parameter is set to a default value equal to 10 percent of the total imperviousness and can be modified by the user based on their specific target. The treated area is subsequently taken out from DCIA and becomes the unconnected impervious area (UIA) that flows to RPA. CLASIC starts with a baseline scenario where there is no GSI implemented. Additional scenarios can be created by adding SCMs to the baseline scenario. SCMs that can be explicitly modeled in the Scenario Builder module of CLASIC include Rain Garden/Bioretention, Sand Filter, Infiltration Trench, Vegetative Swale, Extended Detention Basin, Wet Pond, Stormwater Harvesting, Storage Vault/Tunnel, Green Roof, Permeable Pavement, and Rooftop Disconnection (CLASIC, 2020).

The Scenario Builder module of CLASIC includes a component to compute the number of required SCMs based on the treated impervious surface and the design characteristics of SCMs. For volume based SCMs, the volume required to be captured by GSIs is calculated based on the UIA and the design depth. Subsequently, the number of GSI units will be calculated based on the total volume required to be captured and the volume capacity of each GSI unit. The number of area-based GSIs (e.g.,

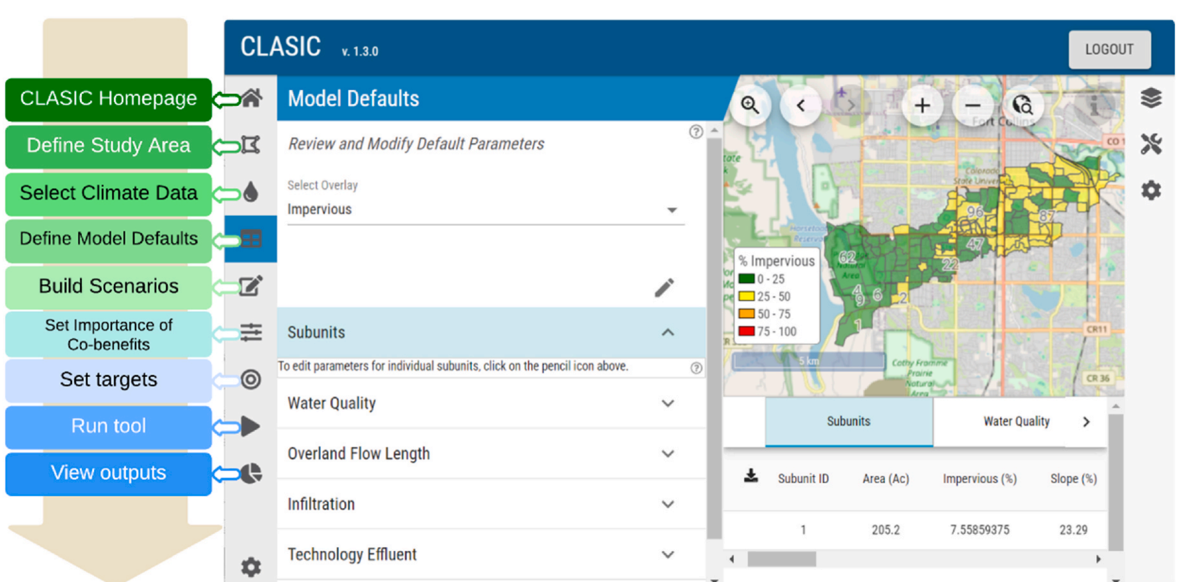

Fig. 1. CLASIC web tool interface.

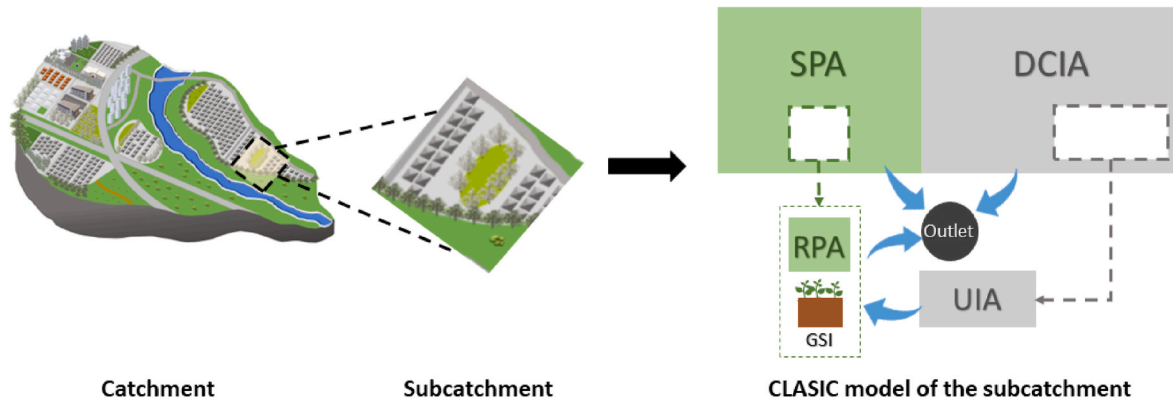

Fig. 2. Illustration of the CLASIC hydrologic model of a subcatchment. The white boxes represent the area of DCIA and SPA that were specified by the user to be used as UIA and RPA, respectively (they are taken out from DCIA and SPA to become standalone subcatchments of UIA and RPA).

permeable pavements) solely depends on the treated impervious area and the area of the GSI unit (CLASIC, 2020). The detailed information and calculations can be found in the CLASIC's user guide at clasic.erams.com.

Finally, CLASIC incorporates a modified SWMM model (Fig. 2) to simulate hydrologic and routing processes. The modified model disaggregates the hydrologic and hydraulic components of SWMM, models the hydraulics within the subcatchments, routes runoff through them, and then employs dummy conduits in SWMM for the linear routing of hydrological responses to the outlet of the watershed. This modeling approach, while reducing the computational burden, may affect the simulated hydrographs at different spatial and temporal scales. In this study, we examine the effects of these changes on the model performance.

2.2. Model evaluation

Model evaluation is often conducted using non-commensurate statistical measures of model performance (Gupta et al., 1997). Specifically, this study employs the coefficient of determination (R^2), root mean square error (RMSE), Nash-Sutcliffe coefficient of efficiency (NSCE), and percent of bias (PBIAS) to examine the performance of the SWMM and CLASIC models. The model's performance is "very good" when NSCE is greater than 0.8, R^2 is greater than 0.85, and PBIAS is less than ±5 percent for daily and monthly simulation time steps (Moriasi et al., 2015). The model performance may be characterized as "good" when NSCE is between 0.7 and 0.8, R^2 is between 0.75 and 0.85, and PBIAS is between 5 and 10 percent. Furthermore, it is recommended that the RMSE value is low enough to be less than the standard deviation of the observed data for good model accuracy (Singh et al., 2005). However, a more robust model performance evaluation may be conducted using hydrologic signatures from the probabilistic characteristics of observed and simulated discharge.

A flow duration curve (FDC) represents the full statistics of discharge conditions and is obtained by plotting the discharge versus exceedance probability of discharge (i.e., the percentage of time that the indicated discharge is equaled or exceeded). Fig. 3 illustrates a schematic of observed and simulated FDCs. The shape of FDCs is influenced by the hydrologic, climatic, and hydrogeologic characteristics of the watershed (Searcy, 1969). FDCs have a wide range of applications in the field of hydrology and water resources planning, such as water quality management, flood frequency analysis, and water resource allocation (Vogel and Fennessey, 1996).

The flow duration curve is obtained by plotting discharge values (Q) sorted in the order of largest to smallest values versus their corresponding exceedance probability (p). Exceedance probability of observed discharge may be obtained from the plotting position formulas in Eq. (1) (Cunnane, 1979):

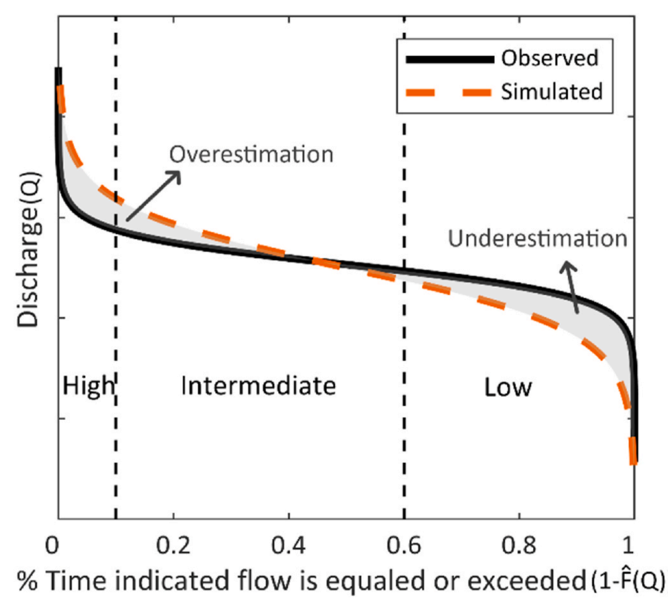

Fig. 3. Illustration of a flow duration curve (FDC) for model evaluation. The shaded region represents the difference between the areas under the observed and simulated FDCs. The black dashed lines divide FDC into three segments of high flow (p<10%), intermediate flow (10%<p<60%), and low flow (p>60%). The area under FDC may be referred to as the probability-weighted discharge.

$$p = 1 - \widehat{F}(Q) = \frac{j - \alpha}{N + 1 - 2\alpha} \tag{1}$$

where $\widehat{F}(Q)$ denotes the empirical cumulative probability distribution function of discharge, j is the rank of observed discharge in descending order of magnitude, N denotes sample size, α is the constant that is defined based on the underlying probability distribution of discharge. In this study, α is set at 0.

Several studies have used FDC as a measure of model performance to simulate observed stream discharge (Hughes and Smakhtin, 1996; Ley et al., 2016; Müller and Thompson, 2016; Matthias Pfannerstill et al., 2014; Rauf and Ghumman, 2018). Hydrologic signature indices derived from FDC's different meaningful regions (i.e., high-flow, intermediate-flow, and low-flow) have been used to compare simulated and observed discharge from specific segments of FDCs (Yilmaz et al., 2008). Other studies used the difference in discharge at various exceedance probability evaluation points (Coxon et al., 2014; Westerberg et al., 2011). An example of these indices is the maximum difference in discharge between observed and simulated FDCs (Q_{max}). The maximum difference in exceedance probability between observed and simulated (FDCs) represents the test statistic for the commonly used Kolmogorov-Smirnov test of the hypothesis that observed and simulated data come from the same underlying probability distribution.

The area under the FDC represents the probability-weighted discharge (PWQ), which is an aggregate measure of discharge that incorporates the full range of discharge conditions. For example, (Vogel et al. (2007) suggest using the area under annual FDCs to assess eco-surplus and eco-deficit hydrologic conditions. Here, we use the area under the FDC to assess the performance validity of the SWMM and CLASIC models against observations using a probability-weighted discharge index (*FDCA*):

$$FDCA = \frac{(PWQ_O - PWQ_S)}{PWQ_O} = \left(\int_0^1 \widehat{F}^{-1}(p)dp - \int_0^1 F^{-1}(p)dp \right) \Big/ \left(\int_0^1 \widehat{F}^{-1}(p)dp \right) \tag{2}$$

where PWQ_O and PWQ_S represent the area under the observed and simulated FDCs, respectively, and $\widehat{F}^{-1}(.)$ and $F^{-1}(.)$ denote the inverse cumulative distribution function (i.e., quantile estimation function) of observed and simulated discharge.

Additionally, we use the normalized maximum difference between ranked simulated and observed discharge ($FDCQ_{max}$):

$$FDCQ_{max} = \max\left[\frac{(Q_O - Q_s)}{Q_O}\right] = \max_p\left[\frac{\left(\widehat{F}^{-1}(p) - F^{-1}(p)\right)}{\widehat{F}^{-1}(p)}\right] \tag{3}$$

and the maximum difference between observed and simulated exceedance probability ($FDCP_{max}$) for the full range of discharge values:

$$FDCP_{max} = \max[|p_O - p_S|] = \max_Q[|\widehat{F}(Q) - F(Q)|] \tag{4}$$

The closer values of the FDC signature indices in Equations (2)–(4) to zero indicate better model performance.

2.3. Identification of influential model parameters

SWMM simulation of hydrologic responses is influenced by model uncertainties from inputs, model structure, and parameter uncertainty (Fassman-Beck and Saleh, 2021; Gorgoglione et al., 2019; Renard et al., 2010; Song et al., 2015; Sun et al., 2014; Vrugt, 2016; Zhang et al., 2022). Thus, disaggregating hydraulic components of the model may influence hydrological simulations. We employ a global sensitivity analysis (GSA) technique to examine the effects of disaggregating hydraulic parameters from the SWMM model on sub-daily to annual time steps.

Global Sensitivity Analysis (SA) is used to determine how the output of a model is sensitive to the uncertainty of the inputs, and it plays an essential role in any hydrological research. Global SA techniques explore the whole feasible range of uncertain parameters and evaluate the interactions between the parameters; they are suitable for nonlinear and non-monotonic models (Saltelli et al., 2008; Song et al., 2015). Considering the wide range of advantages and capabilities of global sensitivity analysis compared to other sensitivity approaches (e.g., local methods), modelers have used this method for many different purposes in hydrological and hydraulic modeling (J. Li et al., 2013; Nossent et al., 2011; M Pfannerstill et al., 2015; Sanadhya et al., 2014). Among various global sensitivity analysis techniques, the method of Sobol (1990) is a well-known and widely used approach. Studies have found this method very successful in factor fixing and factor prioritization for discharge simulations as well as finding controlling factors on salinity in soil, groundwater, and river water (Cibin et al., 2014; Hosseini and Bailey, 2022; Nossent et al., 2011). Leimgruber et al. also found this method proper to evaluate the sensitivity of water balance components to SCM parameters using a SWMM model (Leimgruber et al., 2018).

The method of Sobol was developed in 1990 based on the Fourier Haar series (1969) for nonlinear models. Sobol used Monte Carlo methods to evaluate multidimensional integrals to estimate sensitivity measures (Archer et al., 1997). First-order sensitivity measures will be calculated as below:

$$S_i = \frac{V_i}{V(Y)} = \frac{V(E(Y|X_i))}{V(Y)} \tag{5}$$

S_i^T , as the total-order sensitivity measure, indicates the contribution to the output variance from X_i including both its main effect and all its interactions with other factors:

$$ST_i = 1 - \frac{V(E(Y|X_{\sim i}))}{V(Y)} \tag{6}$$

where $X_{\sim i}$ represents all input factors except X_i.

The larger the S_i and ST_i, the more sensitive the output model is to the parameter X_i. The smallest sample size in this method is n(2k+2). The term "n" is the minimum model evaluation for estimating one individual effect, taking a value of 16, or 32, 64, 128, …, and the term k is the number of input factors (Koo et al., 2020; Nguyen and Reiter, 2015; Saltelli et al., 2008).

2.4. Comparing computational runtime of the CLASIC and SWMM models

To compare the computational time between CLASIC and SWMM models, the study area was divided into eight segments. First, only one subcatchment was considered, and the simulation time was recorded. Then, in each subsequent run, an additional segment was included, continuing this pattern until the final run covered the entire watershed. This approach allowed for a detailed comparison of the computational times for both CLASIC and SWMM across varying scales of the study area.

2.5. Study area: the Spring Creek watershed

To compare the performance of the CLASIC and SWMM models, the Spring Creek watershed (Fig. 4), with a 23 square kilometer surface area in northern Colorado, was selected as the study area consisting of 134 subcatchments. Spring Creek originates in western Fort Collins, north of Horsetooth Mountain. After passing through the Horsetooth Reservoir, it flows eastward to its confluence with the Cache La Poudre River. It also has two gauged locations to observe the creek's discharge. Hourly discharge, provided by the City of Fort Collins, was observed and collected from these two locations from 2006 to 2018. The gauged locations are the intersections of the creek with Center Avenue and Timberline Road, as shown in Fig. 4.

2.5.1. SWMM urban hydrology model of Spring Creek watershed

Division of the study area into subcatchments can have significant effects on the modeled responses (Arabi et al., 2006). The detailed SWMM model for the watershed was built in SWMM 5 with 134 subcatchments and more than 200 hydraulic elements, including pipes, channels, and storage units. The required data for each subcatchment and the drainage network were collected from the City of Fort Collins and the Google Earth measuring tool. The selected settings for this model are the Horton infiltration method, dynamic wave method, and continuous simulation. Furthermore, hourly precipitation data (2006–2018) and average monthly evaporation data were collected for the Fort Collins climate station from Colorado Agricultural Meteorology Network Database (CoAgMet, 2019) and EPA climate stations (USEPA, 2023), respectively. The soil characteristics beneath the storage units were collected from SSURGO data (Soil Survey Staff, 2019), and the imperviousness characteristics were extracted from the NLCD 2016 (U.S. Geological Survey, 2018).

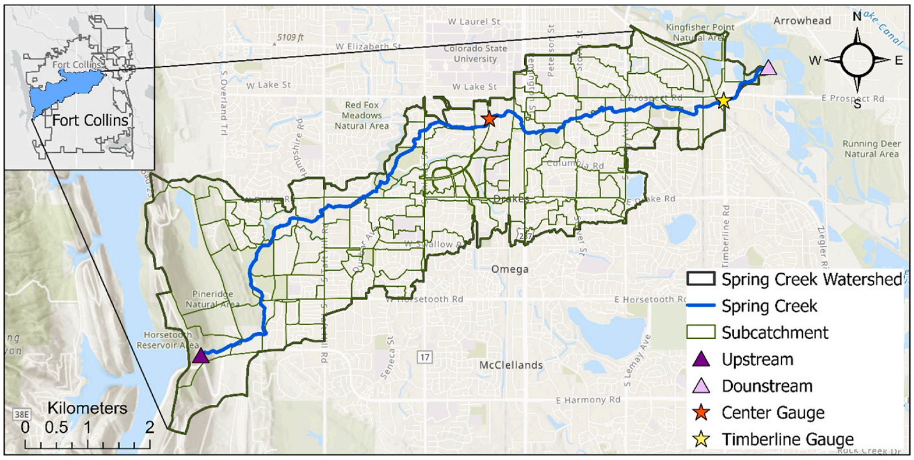

Fig. 4. Spring Creek watershed (drainage area: 23 square kilometers) and stream gauge locations.

2.5.2. *CLASIC urban hydrology model of Spring Creek watershed*

After calibrating the SWMM model, three models were built in the CLASIC tool. Since there are two gauged locations within the watershed, two models were created to simulate the outflow of each of these two locations: one model for the upstream drainage area of the Center Avenue gauge and another for the upstream drainage area of the Timberline Road gauge. A third model was also provided from the entire watershed to simulate the hydrologic components of the entire study area (i.e., runoff, evaporation, and infiltration).

The stormwater control measures (SCM) in the study area are detention basins and retention basins; however, they were modeled as storage units in the SWMM model. Thus, the storage units needed to be converted to comparable SCMs in the CLASIC models. The main factors must remain consistent in converting the storage units in SWMM to the SCMs in CLASIC. These factors are total drainage area, total technology area, total captured volume, seepage rate, and total percentage of imperviousness. Since detention ponds and retention ponds are volume-based technologies, the most important factor to be consistent in the SCMs between the models is the total captured volume (Dell et al., 2021).

2.5.3. *Global sensitivity analysis for urban hydrologic modeling in the Spring Creek watershed*

The method of Sobol global sensitivity analysis in SIMLAB 2.2.1 tool (Saltelli et al., 2004) was used to evaluate the importance of the model's parameters. Specifically, the analysis examines the significance of open channel or pipe hydraulic parameters individually and in combination with other hydrologic parameters at various temporal and spatial scales. SWMM is a distributed hydrological model, i.e., the value of model parameters can vary by land use, soils, terrain, and other physiographic characteristics of the catchment. It is impractical and inappropriate to alter the values of model parameters for each computational subunit individually. To account for the spatial variability of the model parameters and their relative values across subcatchments or hydraulic components, default values of each parameter were adjusted by a scaling factor that is applied to all values. The initial values of the model were obtained from an initial manual calibration of the model. Using Sobol technique, 3328 random samples were generated for 12 scaling factors corresponding to each model parameter in Table 3. The scaling factors were assumed to be uniformly distributed. A range of scale factors was selected for each parameter based on the parameters' feasible range (Table 3) and their initial values. The SWMM was run using the 3328 random samples to simulate discharge at the gauged locations along the Spring Creek catchment (Fig. 4) over the 2008–2018 period. Finally, the sensitivity of different hydrological responses (i.e., total flow, peak flow, total runoff, evaporation, and infiltration) to the selected parameters and their interactions with each other were evaluated at different temporal and spatial scales.

Table 3
Range of values of the SWMM parameters for the sensitivity analysis in the Spring Creek watershed.

Parameter	Units	Range
Width	m	107–6346
Slope	%	0.25–43.8
%Imperv	%	4–99
DstoreImperv	mm	0–2.54
DstorePerv	mm	2.54–7.62
%ZeroImperv	%	1–5
Max infiltration rate	cm/hr	2.54–25.4
Min infiltration rate	cm/hr	0.025–1.27
Decay Constant rate	1/hr	2–12
Manning's N	–	0.01–0.4
N-Imperv	–	0.011–0.024
N-Perv	–	0.014–0.8

2.5.4. *Model parameterization, calibration, and testing in the Spring Creek watershed*

The SWMM model was calibrated for total flow at the hourly time scale and at both gauged locations using only the catchment's parameters that could be modified in both SWMM and CLASIC tools. The roughness of the impervious and pervious area (N-Imperv, and N-Perv) were excluded from the calibration as they were found not sensitive. Since the groundwater was not modeled in this study, baseflow was extracted from the observed discharge using the Web-based Hydrograph Analysis Tool (WHAT) baseflow separation tool (Lim et al., 2006) based on the digital filter method by Lyne and Hollick (Lyne and Hollick, 1979) and was added to the models. The method of Sobol was utilized to generate 2560 parameter samples using SIMLAB 2.2 (Saltelli et al., 2004). The period of available observed discharge (2006–2018) was divided into two parts for the calibration and testing the calibrated model's performance. The first nine years of the data (2006–2014) were used for the calibration of the SWMM model, considering the first two years (2006–2007) for the model's warm-up period. During the calibration process, the model performance metrics were calculated, and the best sample set based on the closest value of NSCE to one was selected, and other performance metrics were also checked to meet the acceptance criteria (Moriasi et al., 2015). The calibrated model was then tested against the observed data from 2015 to 2018.

3. Results and discussion

The results of the study indicate that the CLASIC tool is appropriate for urban stormwater modeling and assessment of SCMs including GSIs at municipal scale. Specifically, the model reliably characterized the annual water budget, daily FDCs, and daily to monthly stream discharge time series at different spatial scales. The hydraulic parameters gain more importance in hydrologic responses of the catchment at smaller time steps, and thus, must be carefully incorporated for flood assessments at the hourly or sub-hourly time steps. The CLASIC tool demonstrates notably faster simulation runtime compared to SWMM. The gains in computational efficiency grow superlinearly as the drainage area and the number of computational elements increase, capability that makes it suitable for municipal scale characterization of hydrologic responses.

3.1. Model performance for hydrologic responses at different temporal scales

The parameter set with the highest NSCE over the calibration period 2008–2014, referred to as the calibrated parameters, was selected for the SWMM and CLASIC model assessment. The selected set of scale factors assigned to the initial values of the parameters was 0.73 for width, 1.94 for slope, 0.50 for %Imperv, 0.79 for depression storage of impervious area (DstoreImperv), 0.76 for depression storage of pervious area (DstorePerv), 2.78 for percent impervious area with no depression storage (%ZeroImperv), 13.06 for max infiltration rate, 0.76 for min infiltration rate, and 0.63 for decay rate.

The performances of the models for simulation of hourly, daily, and monthly discharge using the calibrated parameters for the two stream discharge gauging stations are provided in Table 4 for both the calibration and testing periods. Overall, the evaluation statistics indicated a very good fit between the SWMM model and observed responses with NSCE greater than 0.7 and PBIAS less than 10 percent at all time steps and both gauging locations. In the Spring Creek watershed, the observed standard deviations of hourly, daily, and monthly discharges are 0.72, 0.56, and 0.47 (m^3/s) at the Center location and 0.62, 0.36, and 0.29 (m^3/s) at the Timberline location. Thus, the results indicate that RMSE values are low enough for all the temporal scales and in both locations, indicating good model accuracy.

The CLASIC model with the calibrated parameters provides a very good fit with observed monthly discharge at both gauging locations. At the Center gauging location, the model performs very well for daily discharge simulations over both the calibration and testing period. However, the simulated daily discharge seems to inadequately represent observed values at the Timberline location over the calibration period. Although NSCE values from the Timberline model are not satisfactory for small temporal scales (hourly and daily), CLASIC's performance is good for the monthly temporal scales. In the Center model, the hourly results are not "Good" but still acceptable; however, daily and monthly results are "Very Good". Thus, the CLASIC tool is more accurate in estimating the total discharge at the Center location than at the Timberline location, which has a bigger drainage area.

The time of concentration for the Center's and Timberline's catchments is about 7 and 10 h, respectively, based on the SCS method (USDA-NRCS, 2010). As shown in the results, for the Timberline location, although the CLASIC model does not show good R^2 and NSCE on the daily scale, it has a "Good" PBIAS (Table 4). Thus, it can be concluded that in both locations, the CLASIC tool shows acceptable performance for time scales larger than the time of concentration.

The FDC indices were derived from both simulated and observed daily FDCs (Table 4). A negative sign for the normalized maximum difference in discharge ($FDCQ_{max,}$) indicates that the model has underestimated the observed values, while a positive sign indicates overestimation in the model. In the Center stream gauge location, which has a smaller drainage area, both models consistently underestimate the discharge across all segments of the FDCs (low-flow, intermediate-flow, and high-flow) at the selected evaluation points (Table 4). Thus, the

Table 4
Model performance metrics and FDC indices.

Model Evaluation Metric		Time Step	*Center*		*Timberline*	
			SWMM	CLASIC	SWMM	CLASIC
Over the calibration period (2008–2014)	*PBIAS (%)*	Hourly	8.70	4.70	−0.06	−12.28
		Daily	7.22	4.90	4.95	−5.00
		Monthly	8.15	4.50	1.22	−10.68
	RMSE (m3/s)	Hourly	0.28	0.49	0.34	1.10
		Daily	0.15	0.23	0.16	0.49
		Monthly	0.11	0.09	0.07	0.14
	R^2	Hourly	0.87	0.64	0.86	0.36
		Daily	0.94	0.85	0.89	0.50
		Monthly	0.98	0.97	0.95	0.88
	NSCE	Hourly	0.85	0.54	0.70	−2.21
		Daily	0.93	0.83	0.81	−0.94
		Monthly	0.95	0.96	0.94	0.76
Over the testing period (2015–2018)	*PBIAS (%)*	Hourly	9.03	3.89	6.51	−0.75
		Daily	8.30	4.68	8.10	3.41
		Monthly	8.80	3.97	9.74	2.21
	RMSE (m3/s)	Hourly	0.14	0.19	0.22	0.50
		Daily	0.07	0.08	0.11	0.14
		Monthly	0.05	0.04	0.08	0.07
	R^2	Hourly	0.90	0.79	0.87	0.59
		Daily	0.96	0.92	0.92	0.88
		Monthly	0.99	0.98	0.95	0.94
	NSCE	Hourly	0.89	0.79	0.83	0.15
		Daily	0.94	0.92	0.91	0.85
		Monthly	0.96	0.95	0.94	0.94
Daily FDC (2008–2018)	FDCA *(%)*		3.80	2.60	5.20	4.60
	$FDCA_{under}$ *(%)*		7.66	5.20	5.81	3.83
	$FDCA_{over}$ *(%)*		0.00	0.00	1.90	5.28
	$FDCQ_{max,high}$		−0.19	−0.07	−0.01	0.09
	$FDCQ_{max,mid}$		−0.12	−0.08	0.55	0.52
	$FDCQ_{max,low}$		1.73	0.10	0.11	0.05
	$FDCP_{max}$ *(%)*		4.21	3.70	6.90	5.97

Note: The negative values of $FDCQ_{max}$ in the table show underestimation of the observed discharge in the simulation.

normalized difference between *PWQs* (*FDCA*) arise only from underestimation.

Conversely, at the Timberline location with a larger catchment, the $FDCA_{over}$ for the CLASIC model is roughly three times the one for SWMM, and the $FDCQ_{max,\text{high}}$ for CLASIC is nine times the one for SWMM (Table 4). Thus, when both models overestimate the observed discharge, particularly at higher flows, CLASIC is more prone to overestimating observed discharge than SWMM. However, it's important to note that despite these differences in estimation, both models display a strong alignment with the observed data. The daily FDCs from both locations confirm this alignment (Fig. 5). Extremely high flows, which have the possibility of being equaled or exceeded by less than 0.001 (1000-year return period), produce the biggest overestimation in the CLASIC tool at both locations. However, these discharge values are not considered in the FDC indices in this study as they have been rarely exceeded (Alaya et al., 2018; Johnson and Smithers, 2020). Therefore, unlike the performance metrics, the indices based on FDCs are not extracted based on all the discharge values, emphasizing the more frequent ones (0.001–0.99). At the Timberline location, the CLASIC model tends to overestimate discharge with an exceedance probability below 5% (return periods greater than 20 years), while the SWMM model overestimates discharge with an exceedance probability below 1.5%. This variation in overestimation between the two models is highlighted by $FDCA_{over}$, derived from the difference in the overestimated area under FDCs.

Based on the model performance metrics SWMM and CLASIC models, both models performed better in the testing period (2015–2018) than the calibration period (2008–2014). Furthermore, it was understood from the FDCs that the primary discrepancy in the performance of SWMM and CLASIC is related to their ability to predict peak discharge. To gain deeper insights into these findings, the peak daily discharge extracted from the time series of CLASIC and SWMM models for the period of 2008–2018 is compared to the observed daily discharge (Fig. 6). The comparative analysis between these two models at both gauged locations shows that CLASIC tends to overestimate the extreme peak discharge values more than SWMM, while in lower peak discharge values, the models show more agreement. A notable observation is a single instance where CLASIC significantly overestimated observed flows. Further investigation revealed its connection to a severe storm event in July 2009 (within the calibration period), during which the study area experienced approximately 50 mm of rainfall within an hour, as recorded by the rain gauges. This event appears to be a key factor in the observed discrepancy in the models predictions.

3.2. Estimation of annual hydrologic budgets

The average annual hydrologic components (runoff, infiltration, and evaporation) were also extracted and compared with those from the calibrated SWMM model (Fig. 7). Results revealed that both CLASIC and SWMM models provide closely aligned estimates of each hydrologic component with a maximum difference of 2% in evaporation. These results suggest that the CLASIC is an appropriate tool to estimate the urban hydrologic balance for assessing urban green stormwater infrastructure at the municipal scale.

3.3. Importance of model parameters at different temporal and spatial scales

Table 5 and Fig. 8 represent the results of Sobol sensitivity analysis for different outputs of the SWMM model, including average annual runoff, evaporation, and infiltration of the Spring Creek watershed, as well as the total and peak flow volume at the gauged locations at different temporal scales. The first-order indices (S_i) and total order indices (ST_i) are displayed, representing the individual effects of each parameter on model outputs and their influence when interacting with other parameters, respectively.

Table 5 highlights the importance of the percentage of impervious area (%Imperv) in simulating the water cycle components (i.e., hydrologic budgets), particularly infiltration. The depression storage in the impervious area (DstoreImperv) is the next most influential parameter, followed by the minimum infiltration rate regarding both the individual effect and the interactions with other parameters. These parameters have also been found important in previous studies (Barco et al., 2008; Dell et al., 2021). Therefore, for research topics primarily focusing on water cycle components, such as hydrological modeling and water resource management, incorporating only these critical parameters for water cycle components may be sufficient to provide accurate results.

Fig. 8 demonstrates the average and standard deviation of sensitivities of total flow and peak flow at different temporal scales (i.e., hourly, daily, weekly, monthly, and annual) to each input parameter. As observed for the water cycle components, the percentage of imperviousness (%Imperv) is the most influential parameter for the discharge outputs at both gauged locations. This parameter has also been reported as the most influential parameter for hydrological responses by many studies (Barco et al., 2008; Dotto et al., 2011; Gamerith et al., 2013; Guanipa Rivero et al., 2019; Hidayat and Soekarno, 2020; Zaghloul, 1983). In contrast to the average total flow, all the input parameters have some level of importance when simulating peak flow, and their

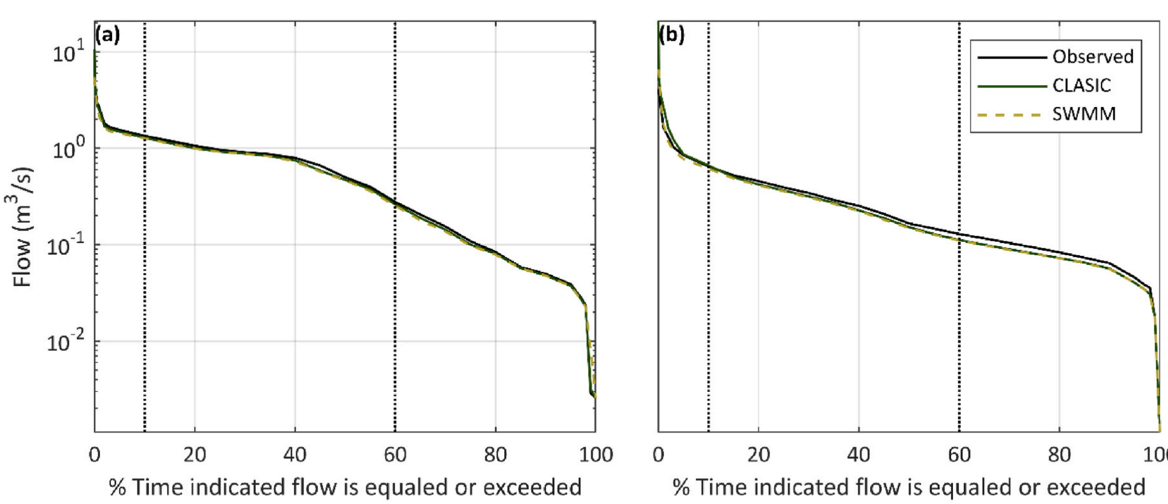

Fig. 5. Flow duration curves (FDC) of observed average daily discharge against the CLASIC and SWMM models: (a) Center stream gauge (drainage area: 11 square kilometers), (b) Timberline stream gauge (drainage area: 21.5 square kilometers).

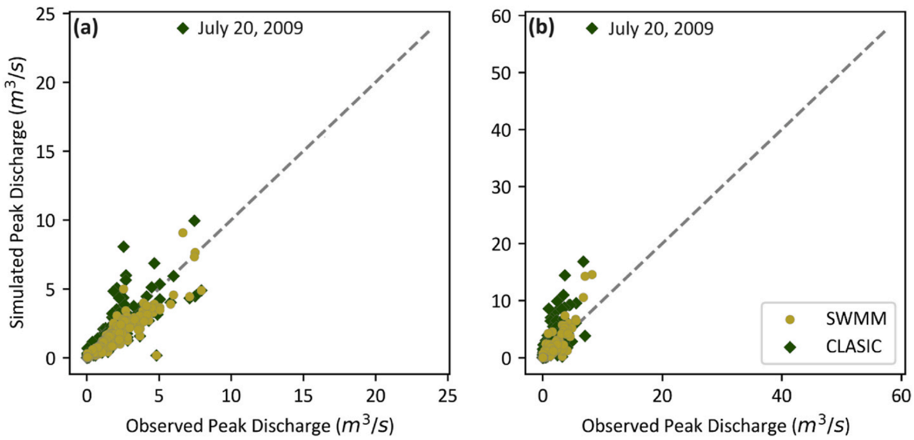

Fig. 6. Comparative analysis of the SWMM and CLASIC model in simulating the peak daily discharge. (a) at Center stream gauge location, (b) at Timberline stream gauge location.

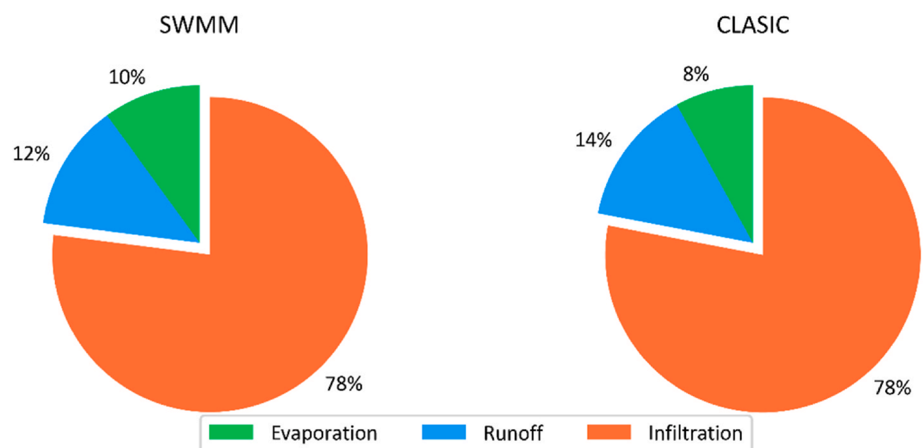

Fig. 7. CLASIC vs SWMM in computing the proportion of each hydrologic component in the total average annual rainfall from 2008 to 2018 (432.56 mm).

Table 5
Most important parameters of the watershed for simulating the water cycle components (hydrological budgets).

Parameter	First order index (*S*)			Total order index (***ST***)		
	Runoff	Evaporation	Infiltration	Runoff	Evaporation	Infiltration
%Imperv	0.60	0.47	0.88	0.60	0.48	0.88
DstoreImperv	0.31	0.42	0	0.31	0.43	0
Min Infiltration rate	0.04	0.08	0.07	0.06	0.12	0.11

sensitivity varies substantially across different temporal scales, especially at the Timberline location with a larger drainage area. This suggests that for studies related to peak flows, such as flood management, a comprehensive understanding and careful calibration of these input parameters are essential, and simplified models that ignore some of them may not be a suitable choice.

3.4. The sensitivity of peak flow to the Channel's parameter across different temporal and spatial scales

Given the observed variation in the influence of input parameters on discharge across various temporal scales and the enhanced accuracy of CLASIC to simulate discharge at larger temporal scales considering its decoupled hydrologic and hydraulic components, the focus of sensitivity analysis was narrowed to examine the peak flow's sensitivity to the channel's Manning's N coefficient. The channel's roughness shows higher importance to peak flow at smaller time scales and in the Timberline location with a bigger drainage area (Fig. 9).

Overall, global sensitivity analysis showed that as the temporal scale gets smaller and the size of the watershed increases, the peak flow becomes more sensitive to the roughness of the channel. This observation can be corroborated by the performance metrics of the CLASIC tool, which indicated that sub-daily discharge simulations, particularly at the larger drainage area (upstream of the Timberline location), were not as accurate. These findings emphasize the critical role of channel characteristics when smaller temporal scales are crucial for the study, such as in research topics focused on flood events, flood modeling and forecasting, flood risk analysis, etc., where the CLASIC tool may not be applicable.

3.5. The computational time of the CLASIC tool and the SWMM model for simulating hydrologic response at different spatial scales

A comparative analysis was conducted between the computational

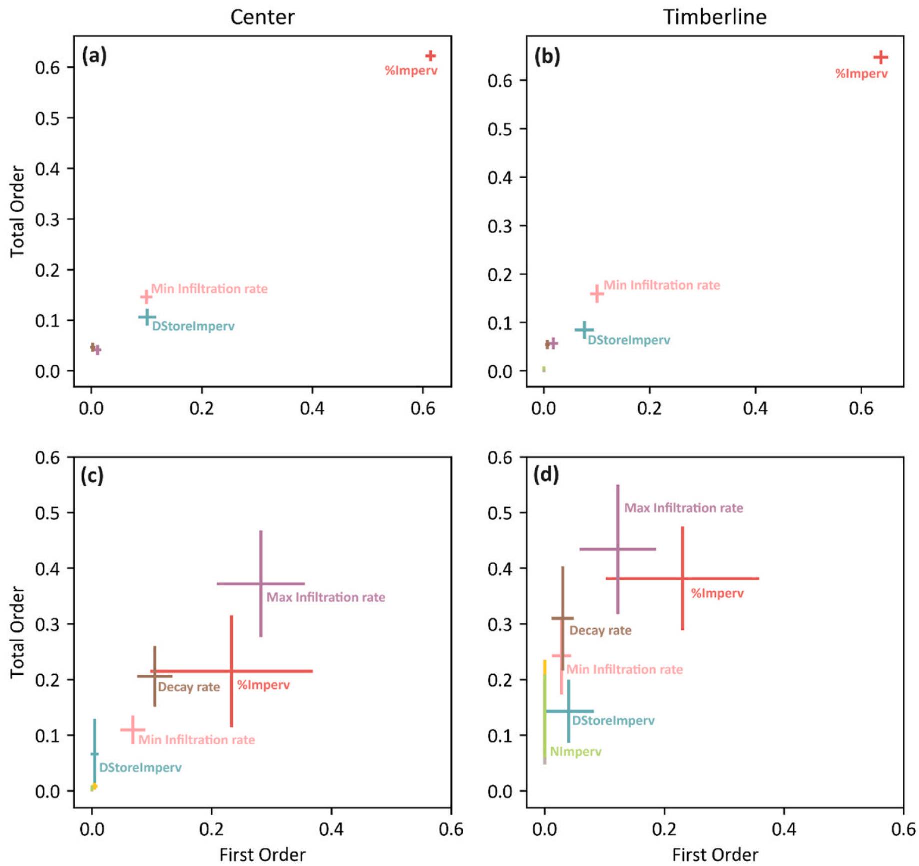

Fig. 8. Average effect of each input parameter on the streamflow. The vertical and horizontal bars represent the variability (standard deviation) of each parameter's total and first sensitivity indices, respectively, at various temporal scales: (a) Average total flow at Center stream gauge, (b) Average total flow at Timberline stream gauge, (c) Peak flow at Center stream gauge, (d) Peak flow at Timberline stream gauge.

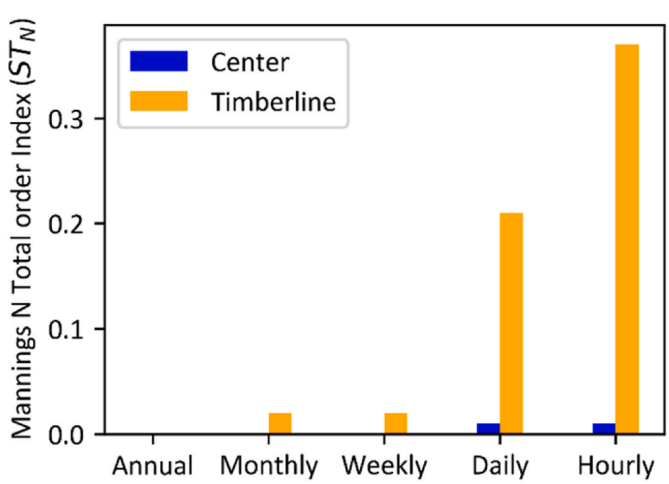

Fig. 9. Variation in the sensitivity of peak flow to channel's roughness (Manning's N) at different temporal scales. The time of concentration at Center and Timberline stream gauges are 7 and 10 h, respectively.

time of the SWMM and CLASIC models for assessing the hydrologic responses across varying spatial scales (Fig. 10). The expanding area corresponds to a more complex model and subsequently, an increase in the number of elements. With a greater number of elements, especially hydraulic elements, SWMM requires considerably more time to simulate the processes. The computational time for both models increases as the drainage area expands (Fig. 10(a)). Specifically, the SWMM model's computational time shows a superlinear growth from approximately 95 s at five sq. km to nearly 1900 s at 23 sq. km. As shown by the trendline, the superlinear growth is quantitatively expressed by the R^2 value of 0.998, indicating a strong relationship between the SWMM model's computational time and the drainage area size. Conversely, the computational time of the CLASIC tool increases at a relatively constant rate with expanding drainage area. The trendline shows the linear behavior of the CLASIC model with an R^2 value of 0.977. Furthermore, the difference between the computational time of SWMM and CLASIC models indicates a superlinear relationship with the expansion of the drainage area with R^2 value of 0.96 (Fig. 10(b)). This comparative analysis demonstrates the enhanced efficiency of the cloud-based CLASIC web tool compared to the complex SWMM model in assessing the hydrologic responses at larger scale study areas, especially at the municipal scale.

4. Conclusion

CLASIC tool's performance and efficiency in simulating the hydrological responses were evaluated and compared to the complex SWMM model and observed data at the Spring Creek watershed. Sobol global sensitivity analysis was also conducted to investigate the significance of interconnected hydrologic and hydraulic parameters and their associated processes on hydrologic responses. These analyses allowed for assessing the effect of decoupling hydrology and hydraulic components on the water cycle and the stream discharge at various temporal and spatial scales. The flow analysis results suggested that the performance of the CLASIC tool is acceptable to evaluate the total volume of the discharge at the temporal scales greater than the time of concentration of the watershed. Furthermore, the CLASIC tool performed well at municipal scale simulation of the urban water cycle, suggesting that it is

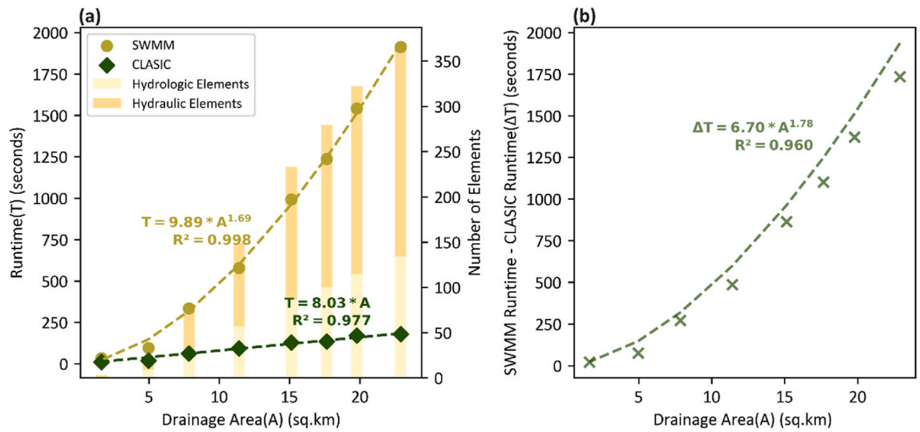

Fig. 10. Computational time of CLASIC tool versus SWMM model. (a) The relationship between models' computational time and drainage area. Stacked bars show the number of hydrologic and hydraulic elements of full SWMM model at various scales of the drainage area. (b) Computational time difference between CLASIC and SWMM models at various scales of drainage area.

well suited for urban stormwater management applications, such as evaluating the performance of green and gray infrastructures, where the primarily focus is on the total runoff volume.

The global sensitivity analysis results emphasized the importance of effective imperviousness (or directly connected impervious area) in urban watershed models, which is sometimes overlooked by modelers who rely on total imperviousness. Furthermore, it underscores the importance of channel parameters in hydrologic responses for studies, such as flood analysis, where smaller temporal scales (i.e., hourly and sub-hourly) are crucial. In such cases, the models that provide more detailed insights into hydrographs are preferable.

CLASIC significantly enhances efficiency in urban hydrology studies by automating parameterization using national datasets, thereby reducing the need for extensive user input. Additionally, its faster simulation capabilities become particularly advantageous for larger study areas, such as municipal scale, while the SWMM model's simulation time tends to grow superlinearly with the expansion of the drainage area.

This study helps researchers and engineers select appropriate models for future studies based on specific objectives, data availability, and time limitations. Specifically, it underscores the effective use of the CLASIC tool for evaluations of SCMs (e.g., GSI) and climate and land use change assessment at neighborhood to municipal scales. However, the cost and co-benefit components of the CLASIC tool are not discussed in this study. Hence, future work will focus on these components of the tool and the development of optimization components that allow planners to select the technologies most consistent with their desired goals regarding hydrologic effects, co-benefits, and life cycle costs.

5. Software availability

Web tool URL: https://clasic.erams.com/

Documentation URL: https://erams.com/catena/tools/urban-planning/clasic/

CRediT authorship contribution statement

Mahshid Mohammad Zadeh: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Mazdak Arabi:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Tyler Dell:** Writing – review & editing, Resources, Methodology. **Sybil Sharvelle:** Writing – review & editing, Project administration, Conceptualization.

Declaration of competing interest

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

The authors don't have utilities' permission to share the data publicly. The software is available at https://clasic.erams.com/

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References

Ahiablame, L.M., Engel, B.A., Chaubey, I., 2012. Effectiveness of low impact development practices: literature review and suggestions for future research. Water Air Soil Pollut. 223 (7), 4253–4273. https://doi.org/10.1007/s11270-012-1189-2.

Alaya, M.A.B., Zwiers, F., Zhang, X., 2018. Probable maximum precipitation: its estimation and uncertainty quantification using bivariate extreme value analysis. J. Hydrometeorol. 19 (4), 679–694. https://doi.org/10.1175/JHM-D-17-0110.1.

Arabi, M., Govindaraju, R.S., Hantush, M.M., Engel, B.A., 2006. Role of watershed subdivision on modeling the effectiveness of best management practices with SWAT. J. Am. Water Resour. Assoc. 42 (2), 513–528. https://doi.org/10.1111/j.1752-1688.2006.tb03854.x.

Archer, G.E.B., Saltelli, A., Sobol, I.M., 1997. Sensitivity measures, anova-like techniques and the use of bootstrap. J. Stat. Comput. Simulat. 58 (2), 99–120. https://doi.org/10.1080/00949659708811825.

Babaei, S., Ghazavi, R., Erfanian, M., 2018. Urban flood simulation and prioritization of critical urban sub-catchments using SWMM model and PROMETHEE II approach. Phys. Chem. Earth 105 (February), 3–11. https://doi.org/10.1016/j.pce.2018.02.002.

Baek, S., Ligaray, M., Pachepsky, Y., Ahn, J., Yoon, K., 2020. Assessment of a green roof practice using the coupled SWMM and HYDRUS models. J. Environ. Manag. 261 (March 2019), 109920 https://doi.org/10.1016/j.jenvman.2019.109920.

Barco, J., Wong, K.M., Stenstrom, M.K., Asce, F., 2008. Automatic Calibration of the U . S . EPA SWMM Model for a Large Urban Catchment, vol. 134, pp. 466–474. https://doi.org/10.1061/(ASCE)0733-9429(2008)134:4(466, 4.

Birhanu, D., Kim, H., Jang, C., Park, S., 2018. Does the complexity of evapotranspiration and hydrological models enhance robustness? Sustainability 10 (8). https://doi.org/10.3390/su10082837.

BMPdatabase, 2019. International Stormwater BMP Database. https://bmpdatabase.org/home.

Catena, 2024. Catena Analytics. https://erams.com/catena/.

Chen, L., Šimůnek, J., Bradford, S.A., Ajami, H., Meles, M.B., 2022. A computationally efficient hydrologic modeling framework to simulate surface-subsurface

hydrological processes at the hillslope scale. J. Hydrol. 614 (November) https://doi.org/10.1016/j.jhydrol.2022.128539.
Cibin, R., Athira, P., Sudheer, K.P., Chaubey, I., 2014. Application of Distributed Hydrological Models for Predictions in Ungauged Basins : a Method to Quantify Predictive Uncertainty, vol. 2045, pp. 2033–2045. https://doi.org/10.1002/hyp.9721. March 2013.
Cipolla, S.S., Maglionico, M., Stojkov, I., 2016. A long-term hydrological modelling of an extensive green roof by means of SWMM. Ecol. Eng. 95, 876–887. https://doi.org/10.1016/j.ecoleng.2016.07.009.
CLASIC, 2020. User guide user guide. https://clasic.erams.com/docs/?token=%5BobjectObject%5D.
CNT, 2022. Tools | Center for Neighborhood Technology. https://www.cnt.org/tools.
CoAgMet, 2019. CoAgMet hourly data access. https://coagmet.colostate.edu/hourlysum_form.php.
Coxon, G., Freer, J., Wagener, T., Odoni, N.A., Clark, M., 2014. Diagnostic evaluation of multiple hypotheses of hydrological behaviour in a limits-of-acceptability framework for 24 UK catchments. Hydrol. Process. 28 (25), 6135–6150. https://doi.org/10.1002/hyp.10096.
Cunnane, C., 1979. Unbiased plotting positions - a review - comments. J. Hydrol. 41 (1–2), 183–185. https://doi.org/10.1016/0022-1694(79)90120-3.
David, O., Lloyd, W., Rojas, K., Arabi, M., Geter, F., Ascough, J., Green, T., Leavesley, G., Carlson, J., 2014. Model-as-a-service (MaaS) using the cloud services innovation platform (CSIP). Proceedings - 7th International Congress on Environmental Modelling and Software: Bold Visions for Environmental Modeling, IEMSs 2014, 1, 243–250.
Dell, T., Razzaghmanesh, M., Sharvelle, S., Arabi, M., 2021. Development and application of a SWMM-based simulation model for municipal scale hydrologic assessments. Water 13 (12), 1644. https://doi.org/10.3390/w13121644.
Devia, G.K., Ganasri, B.P., Dwarakish, G.S., 2015. A review on hydrological models. Aquatic Procedia 4 (Icwrcoe), 1001–1007. https://doi.org/10.1016/j.aqpro.2015.02.126.
Dotto, C.B.S., Kleidorfer, M., Deletic, A., Rauch, W., McCarthy, D.T., Fletcher, T.D., 2011. Performance and sensitivity analysis of stormwater models using a Bayesian approach and long-term high resolution data. Environ. Model. Software 26 (10), 1225–1239. https://doi.org/10.1016/j.envsoft.2011.03.013.
eRAMS, 2024. Community-enabled Life-Cycle Analysis of Stormwater Infrastructure Costs. https://erams.com/catena/tools/urban-planning/clasic/.
Fassman-Beck, E., Saleh, F., 2021. Sources and impacts of uncertainty in uncalibrated bioretention models using SWMM 5.1.012. Journal of Sustainable Water in the Built Environment 7 (3), 1–10. https://doi.org/10.1061/jswbay.0000944.
Gamerith, V., Neumann, M.B., Muschalla, D., 2013. Applying global sensitivity analysis to the modelling of flow and water quality in sewers. Water Res. 47 (13), 4600–4611. https://doi.org/10.1016/j.watres.2013.04.054.
Geological Survey, U.S., 2018. National Land Cover Database. U.S. Geological Survey. https://www.usgs.gov/centers/eros/science/national-land-cover-database.
Geological Survey, U.S., 2023. Digital Elevation Models (DEMs). U.S. Geological Survey. https://www.usgs.gov/faqs/what-digital-elevation-model-dem.
Gorgoglione, A., Bombardelli, F.A., Pitton, B.J.L., Oki, L.R., Haver, D.L., Young, T.M., 2019. Uncertainty in the parameterization of sediment build-up and wash-off processes in the simulation of sediment transport in urban areas. Environ. Model. Software 111, 170–181. https://doi.org/10.1016/j.envsoft.2018.09.022. July 2017.
Guanipa Rivero, K.J., Lugo Aguilar, A.L., Rincón Ortiz, J.C., 2019. Sensitivity Analysis of the Hydrological and Hydraulic Parameters of the Swmm Model and its Application in Urban Drainage Systems, vol. 21, pp. 44–64. https://doi.org/10.13140/RG.2.2.26994.66248, 1.
Gui, H., Wu, Z., Zhang, C., 2021. Comparative study of different types of hydrological models applied to hydrological simulation. Clean 49 (8), 1–10. https://doi.org/10.1002/clen.202000381.
Ha, S.J., Stenstrom, M.K., 2008. Predictive modeling of storm-water runoff quantity and quality for a large urban watershed. J. Environ. Eng. 134 (9), 703–711. https://doi.org/10.1061/(asce)0733-9372(2008)134:9(703.
Hamouz, V., Muthanna, T.M., 2019. Hydrological modelling of green and grey roofs in cold climate with the SWMM model. J. Environ. Manag. 249 (July), 109350 https://doi.org/10.1016/j.jenvman.2019.109350.
Haris, H., Chow, M.F., Usman, F., Sidek, L.M., Roseli, Z.A., Norlida, M.D., 2016. Urban stormwater management model and tools for designing stormwater management of green infrastructure practices. IOP Conf. Ser. Earth Environ. Sci. 32 (1) https://doi.org/10.1088/1755-1315/32/1/012022.
Hidayat, S., Soekarno, S., 2020. Sensitivity analysis of surface runoff parameters towards peak discharge and flood volume. IOP Conf. Ser. Earth Environ. Sci. 451 (1) https://doi.org/10.1088/1755-1315/451/1/012083.
Hosseini, P., Bailey, R.T., 2022. Investigating the controlling factors on salinity in soil, groundwater, and river water in a semi-arid agricultural watershed using SWAT-Salt. Sci. Total Environ. 810, 152293 https://doi.org/10.1016/j.scitotenv.2021.152293.
Hughes, D.A., Smakhtin, V., 1996. Complètement ou extension de séries chronologiques de débits journaliers: Une approche par interpolation spatiale basée sur les courbes de valeurs classées. Hydrol. Sci. J. 41 (6), 851–871. https://doi.org/10.1080/02626669609491555.
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. https://doi.org/10.1016/j.desal.2007.05.005.
Johnson, K.A., Smithers, J.C., 2020. Updating the estimation of 1-day probable maximum precipitation in South Africa. J. Hydrol.: Reg. Stud. 32 (August), 100736 https://doi.org/10.1016/j.ejrh.2020.100736.
Kong, F., Ban, Y., Yin, H., James, P., Dronova, I., 2017. Modeling stormwater management at the city district level in response to changes in land use and low impact development. Environ. Model. Software 95, 132–142. https://doi.org/10.1016/j.envsoft.2017.06.021.
Koo, H., Chen, M., Jakeman, A.J., Zhang, F., 2020. A global sensitivity analysis approach for identifying critical sources of uncertainty in non-identifiable , spatially distributed environmental models : a holistic analysis applied to SWAT for input datasets and model parameters. Environ. Model. Software 127 (February), 104676. https://doi.org/10.1016/j.envsoft.2020.104676.
Lee, J.G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J.X., Shoemaker, L., Lai, F., 2012. A watershed-scale design optimization model for stormwater best management practices. Environ. Model. Software 37, 6–18. https://doi.org/10.1016/j.envsoft.2012.04.011.
Leimgruber, J., Krebs, G., Camhy, D., Muschalla, D., 2018. Sensitivity of model-based water balance to low impact development parameters. https://doi.org/10.3390/w10121838.
Ley, R., Hellebrand, H., Casper, M.C., Fenicia, F., 2016. Comparing classical performance measures with signature indices derived from flow duration curves to assess model structures as tools for catchment classification. Nord. Hydrol 47 (1), 1–14. https://doi.org/10.2166/nh.2015.221.
Li, J., Duan, Q., Gong, W., 2013. Assessing parameter importance of the Common Land Model based on Assessing parameter importance of the Common Land Model based on qualitative and quantitative sensitivity analysis. June 2016. https://doi.org/10.5194/hess-17-3279-2013.
Li, C., Liu, M., Hu, Y., Shi, T., Zong, M., Walter, M.T., 2018. Assessing the impact of urbanization on direct runoff using improved composite CN method in a large urban area. Int. J. Environ. Res. Publ. Health 15 (4). https://doi.org/10.3390/ijerph15040775.
Lim, K.J., Engel, B.A., Tang, Z., Choi, J., 2006. AUTOMATED WEB GIS BASED HYDROGRAPH ANALYSIS TOOL , WHAT 1. 1397, 1407–1416.
Lloyd, W., Pallickara, S., David, O., Lyon, J., Arabi, M., Rojas, K., 2013. Performance implications of multi-tier application deployments on Infrastructure-as-a-Service clouds: towards performance modeling. Future Generat. Comput. Syst. 29 (5), 1254–1264. https://doi.org/10.1016/j.future.2012.12.007.
Lloyd, W.J., Pallickara, S., David, O., Arabi, M., Wible, T., Ditty, J., Rojas, K., 2015. Demystifying the clouds: harnessing resource utilization models for cost effective infrastructure alternatives. IEEE Transactions on Cloud Computing 5 (4), 667–680. https://doi.org/10.1109/tcc.2015.2430339.
Locatelli, L., Mark, O., Mikkelsen, P.S., Arnbjerg-Nielsen, K., Deletic, A., Roldin, M., Binning, P.J., 2017. Hydrologic impact of urbanization with extensive stormwater infiltration. J. Hydrol. 544, 524–537. https://doi.org/10.1016/j.jhydrol.2016.11.030.
Lyne, V., Hollick, M., 1979. Stochastic time-variable rainfall-runoff modeling. Institute of Engineers Australia National Conference 79 (10), 89–93.
Miller, J.D., Kim, H., Kjeldsen, T.R., Packman, J., Grebby, S., Dearden, R., 2014. Assessing the impact of urbanization on storm runoff in a peri-urban catchment using historical change in impervious cover. J. Hydrol. 515, 59–70. https://doi.org/10.1016/j.jhydrol.2014.04.011.
Morales-Torres, A., Escuder-Bueno, I., Andrés-Doménech, I., Perales-Momparler, S., 2016. Decision Support Tool for energy-efficient, sustainable and integrated urban stormwater management. Environ. Model. Software 84, 518–528. https://doi.org/10.1016/j.envsoft.2016.07.019.
Moriasi, D.N., Gitau, M.W., Pai, N., Daggupati, P., 2015. Hydrologic and water quality models: performance measures and evaluation criteria. Transactions of the ASABE 58 (6), 1763–1785. https://doi.org/10.13031/trans.58.10715.
Müller, M.F., Thompson, S.E., 2016. Comparing statistical and process-based flow duration curve models in ungauged basins and changing rain regimes. Hydrol. Earth Syst. Sci. 20 (2), 669–683. https://doi.org/10.5194/hess-20-669-2016.
Muñoz-Carpena, R., Carmona-Cabrero, A., Yu, Z., Fox, G., Batelaan, O., 2023. Convergence of mechanistic modeling and artificial intelligence in hydrologic science and engineering. PLOS Water 2 (8), e0000059. https://doi.org/10.1371/journal.pwat.0000059.
NGICP, 2019. National Green Infrastructure Certification Program. https://envirocert.org/ngicp/.
Nguyen, A.T., Reiter, S., 2015. A performance comparison of sensitivity analysis methods for building energy models. Build. Simulat. 8 (6), 651–664. https://doi.org/10.1007/s12273-015-0245-4.
Niazi, M., Nietch, C., Maghrebi, M., Jackson, N., Bennett, B.R., Tryby, M., Massoudieh, A., 2017. Storm water management model: performance review and gap analysis. Journal of Sustainable Water in the Built Environment 3 (Issue 2). https://doi.org/10.1061/jswbay.0000817.
Nossent, J., Elsen, P., Bauwens, W., 2011. Environmental Modelling & Software Sobol ' sensitivity analysis of a complex environmental model. Environ. Model. Software 26 (12), 1515–1525. https://doi.org/10.1016/j.envsoft.2011.08.010.
Pachaly, R., Vasconcelos, J., Allasia, D., Minetto, B., 2019. Field evaluation of discretized model setups for the storm water management model. Journal of Water Management Modeling 2019, 1–10. https://doi.org/10.14796/JWMM.C463.
Pachaly, R.L., Vasconcelos, J.G., Allasia, D.G., Tassi, R., Bocchi, J.P.P., 2020. Comparing SWMM 5.1 calculation alternatives to represent unsteady stormwater sewer flows. J. Hydraul. Eng. 146 (7), 1–16. https://doi.org/10.1061/(asce)hy.1943-7900.0001762.
Pautasso, C., Wilde, E., 2010. RESTful Web Services, pp. 1359–1360. https://doi.org/10.1145/1772690.1772929. November.
Pechlivanidis, I.G., Jackson, B.M., Mcintyre, N.R., Wheater, H.S., 2011. Catchment scale hydrological modelling: a review of model types, calibration approaches and uncertainty analysis methods in the context of recent developments in technology and applications. Global Nest Journal 13 (3), 193–214. https://doi.org/10.30955/gnj.000778.

Pfannerstill, Matthias, Guse, B., Fohrer, N., 2014. Smart low flow signature metrics for an improved overall performance evaluation of hydrological models. J. Hydrol. 510, 447–458. https://doi.org/10.1016/j.jhydrol.2013.12.044.

Pfannerstill, M., Guse, B., Reusser, D., Fohrer, N., 2015. Process Verification of a Hydrological Model Using a Temporal Parameter Sensitivity Analysis, pp. 4365–4376. https://doi.org/10.5194/hess-19-4365-2015.

Pitt, R., Maestre, A., Morquecho, R., 2004. The National Stormwater Quality Database (NSQD). University, of Alabama, Tuscaloosa, AL, version 1.1.

Rai, P.K., Chahar, B.R., Dhanya, C.T., 2017. GIS-based SWMM model for simulating the catchment response to flood events. Nord. Hydrol 48 (2), 384–394. https://doi.org/10.2166/nh.2016.260.

Rauf, A. ur, Ghumman, A.R., 2018. Impact assessment of rainfall-runoffsimulations on the flow duration curve of the Upper Indus river-a comparison of data-driven and hydrologic models. Water (Switzerland) 10 (7). https://doi.org/10.3390/w10070876.

Renard, B., Kavetski, D., Kuczera, G., Thyer, M., Franks, S.W., 2010. Understanding predictive uncertainty in hydrologic modeling: the challenge of identifying input and structural errors. Water Resour. Res. 46 (5), 1–22. https://doi.org/10.1029/2009WR008328.

Rossman, L.A., 2010. SWMM 5.0 Users Manual.Pdf. July.

Rossman, L.A., 2015. Storm Water Management Model User'S Manuel 5.1. United States Environmental Protection Agency. https://www.epa.gov/water-research/storm-water-management-model-swmm.

Rossman, L.A., Bernagros, J.T., 2019. National Stormwater Calculator User's Guide - Version 2.0.0.1. United States Environmental Protection Agency. https://www.epa.gov/water-research/national-stormwater-calculator.

Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., 2004. Sensitivity analysis in practice: a guide to assessing scientific models (Google eBook). http://books.google.com/books?id=NsAVmohPNpQC&pgis=1.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, 2008. Global sensitivity analysis: the primer. https://doi.org/10.1002/9780470725184.

Sanadhya, P., Gironás, J., Arabi, M., 2014. Global Sensitivity Analysis of Hydrologic Processes in Major Snow-Dominated Mountainous River Basins in Colorado, vol. 3418, pp. 3404–3418. https://doi.org/10.1002/hyp.9896. June 2013.

Searcy, J.K., 1969. Flow duration curve. In: Manual of Hydrology: Part 2. Low-Flow Techniques, pp. 303–326. https://doi.org/10.1201/b19113-16.

Severson, L., Atchison, D., 2004. RECARGA User 's Manual, pp. 1–19. October. http://dnr.wi.gov/topic/stormwater/standards/recarga.html.

Shahed Behrouz, M., Zhu, Z., Matott, L.S., Rabideau, A.J., 2020. A new tool for automatic calibration of the Storm Water Management Model (SWMM). J. Hydrol. 581 (February 2019), 124436 https://doi.org/10.1016/j.jhydrol.2019.124436.

Shahed, M., Zhu, Z., Matott, L.S., Rabideau, A.J., 2020. A new tool for automatic calibration of the Storm Water Management Model. J. Hydrol. 581 (December 2019), 124436 https://doi.org/10.1016/j.jhydrol.2019.124436.

Shoemaker, L., Riverson, J.J., Alvi, K., Zhen, J.X., Paul, S., Rafi, T., 2009. Sustain - a framework for placement of best management practices in urban watersheds to protect water quality. Environmental Protection, September 1–8. http://www.epa.gov/nrmrl/wswrd/wq/models/sustain/.

Singh, J., Knapp, H.V., Arnold, J.G., Demissie, M., 2005. Hydrological modeling of the Iroquois River watershed using HSPF and SWAT. J. Am. Water Resour. Assoc. 41 (2), 343–360. https://doi.org/10.1111/j.1752-1688.2005.tb03740.x.

Sobol, I.M., 1990. On sensitivity estimation for nonlinear mathematical models. Matem. Mod. 2 (1), 112–118. https://doi.org/10.18287/0134-2452-2015-39-4-459-461.

Soil Survey Staff, 2019. Web Soil Survey. Natural Resources Conservation Service, United States Department of Agriculture. http://websoilsurvey.sc.egov.usda.gov/.

Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M., Xu, C., 2015. Global sensitivity analysis in hydrological modeling: review of concepts, methods, theoretical framework, and applications. J. Hydrol. 523 (225), 739–757. https://doi.org/10.1016/j.jhydrol.2015.02.013.

Sun, N., Hall, M., Hong, B., Zhang, L., 2014. Impact of SWMM catchment discretization: case study in syracuse, New York. J. Hydrol. Eng. 19 (1), 223–234. https://doi.org/10.1061/(asce)he.1943-5584.0000777.

USDA-NRCS, 2010. k. Part 630 Hydrology National Engineering Handboo, pp. 1–15 (Chapter 15), Time of Concentration. *National Resource*. https://www.nrcs.usda.gov/conservation-basics/conservation-by-state/north-dakota/nrcs-engineering-manuals-and-handbooks.

USEPA, 2023. BASINS meteorological data. https://www.epa.gov/hydrowq/basins-meteorological-data.

Vogel, R.M., Fennessey, N.M., 1996. Flow duration curves II : a REVIEW OF APPLICATIONS IN WATER RESOURCES PLANNING ' proverb " one picture is worth a thousand words " are used to summarize the results of detailed and ly , streamflow duration curves have been used in sparse . This is the fir. Water Resour. Bull. 31 (6), 1029–1039.

Vogel, R.M., Sieber, J., Archfield, S.A., Smith, M.P., Apse, C.D., Huber-Lee, A., 2007. Relations among storage, yield, and instream flow. Water Resour. Res. 43 (5), 1–12. https://doi.org/10.1029/2006WR005226.

Vrugt, J.A., 2016. Markov chain Monte Carlo simulation using the DREAM software package: theory, concepts, and MATLAB implementation. Environ. Model. Software 75, 273–316. https://doi.org/10.1016/j.envsoft.2015.08.013.

Wang, Y., Zhang, X., Xu, J., Pan, G., Zhao, Y., Liu, Y., Liu, H., Liu, J., 2022. Accumulated impacts of imperviousness on surface and subsurface hydrology—continuous modelling at urban street block scale. J. Hydrol. 608 (August 2021), 127621 https://doi.org/10.1016/j.jhydrol.2022.127621.

Westerberg, I.K., Guerrero, J.L., Younger, P.M., Beven, K.J., Seibert, J., Halldin, S., Freer, J.E., Xu, C.Y., 2011. Calibration of hydrological models using flow-duration curves. Hydrol. Earth Syst. Sci. 15 (7), 2205–2227. https://doi.org/10.5194/hess-15-2205-2011.

WRF, 2019. Rolling out "community-enabled lifecycle analysis of stormwater infrastructure costs" (CLASIC) tool. https://www.waterrf.org/resource/rolling-out-community-enabled-lifecycle-analysis-stormwater-infrastructure-costs-clasic.

Xiao, D., Chen, M., Lu, Y., Yue, S., Hou, T., 2019. Research on the construction method of the service-oriented Web-SWMM system. ISPRS Int. J. Geo-Inf. 8 (6) https://doi.org/10.3390/ijgi8060268.

Yilmaz, K.K., V, G.H., Wagener, T., 2008. A process-based diagnostic approach to model evaluation: application to the NWS distributed hydrologic model. https://doi.org/10.1029/2007WR00716.

Zaghloul, N.A., 1983. Sensitivity Analysis of the SWMM Runoff-Transport Parameters and the Effects of Catchment Discretisation, vol. 6, pp. 214–223, 10.1016/0309-1708(83)90059-3 : Advances in Water Resources | ScienceDirect.com. http://www.sciencedirect.com/science/article/pii/0309170883900593.

Zeng, Z., Yuan, X., Liang, J., Li, Y., 2021. Designing and implementing an SWMM-based web service framework to provide decision support for real-time urban stormwater management. Environ. Model. Software 135 (September 2020), 104887. https://doi.org/10.1016/j.envsoft.2020.104887.

Zhang, Z., Hu, W., Wang, W., Zhou, J., Liu, D., Qi, X., Zhao, X., 2022. The hydrological effect and uncertainty assessment by runoff indicators based on SWMM for various LID facilities. J. Hydrol. 613 (PA), 128418 https://doi.org/10.1016/j.jhydrol.2022.128418.