A quantitative assessment of the reliability and feasibility of process-based urban stormwater quality models: Towards new evaluation criteria

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Abstract

Hydrologic models have been increasingly used as a numerical tool to support urban stormwater management. Evaluation of modeling approaches helps identify the strength and weakness of a model to meet end-user requirements. However, traditional model evaluations only focus on the technical performance of a model, whereas very few studies have been conducted to quantitatively evaluate practical constraints for model applications. Therefore, this study proposed a quantitative model evaluation framework, to analyze tradeoffs between scientific reliability and practical feasibility of four process-based urban stormwater quality models. These models were based on different levels of spatial discretization, including lumped, sub-catchment, UHE and grid based approaches; test simulations were applied to an urban catchment near Paris. Six criteria were introduced to quantitatively assess the characteristics of modeling approaches, including (1) match to observation, (2) forecast accuracy, (3) forecast variability, (4) data accessibility, (5) computational costs, and (6) model reusability. The results showed that the lumped model was the best tradeoff between scientific reliability and practical feasibility for the study case. Moreover, the greater spatially distributed exponential build-up/wash-off processes from the lumped to sub-catchment based model could only improve the numerical approximation of simulations to observations at the outlet, but performed much less well in other scientific reliability aspects. Which implies that these processes may not properly represent mechanisms for stormwater quality dynamics at the catchment scale. In addition, it was suggested that complex grid based models should work together with advanced parameter calibration approaches, in order to achieve good scientific reliability for research purposes. In perspective, quantitative evaluation of the stakeholder participation throughout the modeling processes could help to improve model-based outcomes with more adaptive stakeholder engagement.

Keywords

Urban stormwater quality management; Process-based modeling; Reliability and Feasibility; Quantitative evaluation; SWMM; Stake-holder engagement

1 Introduction

Hydrological models are increasingly being relied upon to support urban stormwater management, including flood protection, pollution control, infrastructural construction and operations (Fletcher et al., 2013; Salvadore et al., 2015). In a context of water management, these modeling practices are incorporating a broader range of disciplines and sometimes confront people without strong modeling backgrounds (e.g., stake holders, students, etc.). Therefore, success in model development and application – particularly for challenging interdisciplinary issues – requires not only getting the science and engineering right, but also engaging with scientists, decision makers, stake holders, and wider public towards achieving intended research and management outcomes (Bach et al., 2020; Hamilton et al., 2022; Jakeman et al., 2006). Both scientific reliability and practical feasibility should be considered to meet end-user needs.

Evaluation of different modeling approaches could discover the strength and weakness of these models, hence helps identify appropriate models to meet user requirements for specific research and management projects. However, the traditional paradigm of modeling evaluations only focuses on the technical performance of a model, including the fit between observations and simulations, uncertainty analysis, and forecast accuracy (Moriasi et al., 2007). Recent publications underline the importance of involving social complexity in model evaluation process (Badham et al., 2019; Hamilton et al., 2019), such as data accessibility, computational cost, model reusability, etc. A number of existing studies have evaluated technical performance of various urban stormwater models (Bonhomme and Petrucci, 2017; Freni et al., 2009; Hong et al., 2019), but very few research works has been conducted to quantitatively evaluate practical constraints for model applications. In this perspective, this paper aims to assess the scientific reliability, and practical feasibility of different process-based urban stormwater quality models, by introducing new measurable criteria. The outcomes of this research could provide new insights into the good practice in development and application of process-based models for urban stormwater management. Moreover, the evaluation criteria for quantitative assessment of model reliability and feasibility could be further applied for other model evaluation analysis.

During the past six decades, process-based modeling approaches have attracted a great attention of research communities, for their possibility to improve the understanding of hydrological processes, with debates around issues of the model adequacy, uncertainty, and computational constraints (Clark et al., 2017; Hong et al., 2016a). Depending on spatial discretization levels, process-based urban stormwater models can be categorized as (i) lumped, (ii) sub-catchment based, (iii) urban hydrological element (UHE) based and (iv) two-dimensional grid based (Salvadore et al., 2015). Lumped models use spatially averaged information to represent the overall behavior of an urban catchment. Sub-catchment based models consider sub-regions in the urban catchment as uniform with respect to the hydrological processes. UHE based models are based on the identification of an object or a unit of calculation small enough to be considered as homogenous regarding the urban hydrological processes. Two-dimensional grid based models apply small scale equations for each grid cell, and adopt a spatially distributed representation of catchments.

Theoretically, more detailed process description at finer spatial scales would lead to more accurate model simulations. Nevertheless, this hypothesis is increasingly questioned by researchers and engineers. Recent studies progressively reveal that modeling performance is not always advantageous with complex process-based models (Bonhomme and Petrucci, 2017; Tang et al., 2021). As more complex models usually imply higher costs of computational and human resources, comprehensive evaluations are required to assess tradeoffs between societal costs and gains in technical performance for better management outcomes.

To this end, this paper proposed an original model evaluation approach to quantitatively analyze scientific reliability and practical feasibility of four process-based stormwater quality models with different spatial discretization. Scientific reliability was assessed by criteria including match to observation, forecast accuracy, and forecast variability. Practical feasibility was measured by criteria such as data accessibility, computational costs, and model reusability. This study intends to expand modeling evaluation from technical performance, towards new criteria considering more holistic outcomes that recognizes good practice in urban stormwater modeling, that should always under an application perspective of wider social implications. Moreover, results of model evaluation in this paper can serve as a preliminary guideline for researchers and practitioners to select appropriate urban stormwater quality models for future analysis.

2 Methods and Materials

2.1 Study site and data collection

The study site is a 12-ha urban catchment located in the eastern suburb of Paris (Le-Perreux-sur-Marne, Val-de-Marne, France). The area is mainly residential with small commercial shops and is crossed by the highly trafficked boulevard "Alsace Lorraine" (more than 30,000 vehicles per day). The impervious surfaces account for 70%. The Western section has a higher slope than the Eastern side, with an average slope $\leq$ 2% (Fig. 1).

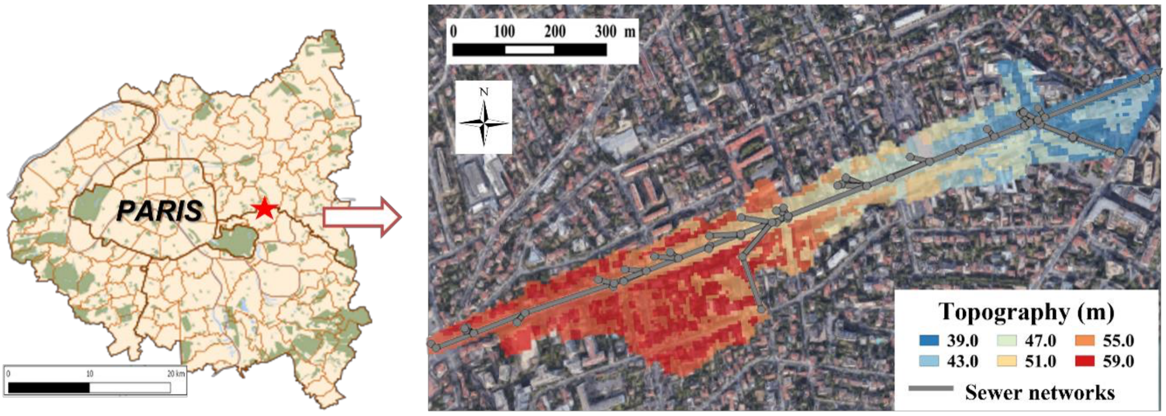


Fig. 1 Study site at Eastern Paris (12 ha, Le-Perreux-sur-Marne, France).

The catchment is drained with a separated sewer network. The sewage outlet is located at the North-Eastern edge of the catchment, where the flow is continuously monitored by a Nivus Flowmeter with 2 minutes time interval, and the turbidity is consistently measured by a multi-parameter probe (mini-probe OTT) at 1 minute time step. The turbidity measurements are transformed into total suspended solids (TSS) concentrations following the linear regression TSS (mg/L) = 0.8533 × Turbidity (NTU) (R^2 = 0.97) derived from laboratory analysis (Hong et al., 2017). In collaboration with the National Institute of Geography of France (IGN), the department council (Conseil Départemental du Val-de-Marne, CD94) and the municipality of Le-Perreux-sur-Marne, the studied urban catchment has been well monitored and investigated to acquire the necessary input data for model implementation. Including 25 m resolution DEM (Digital Elevation Model), 20 cm resolution Lidar topography, landuse generated from multiple data sources (aerial ortho-photos, LiDAR, etc.), IGN's cadastral map, and precise sewer networks derived from departmental and municipal sewer networks plans.

As the study area is quite small, rainfall is considered homogeneous within the basin. By analyzing 56 recorded rainfall events, six representative rains were selected for model evaluations, that encompass the diverse characteristics (rain depth, intensity, duration, antecedent dry days) of rainfall events of this region. Characteristics of the selected rains are summarized in Table S1.

2.2 Process-based models based on different spatial discretization

Four process-based stormwater quality models based on different spatial discretization were investigated in this study, including lumped, sub-catchment based, UHE based and grid-based approaches.

In the context of model application, water quality parameters were optimized by applying conventional approaches which were widely used and fully tested, to ensure that there were no technical barriers for people without strong modeling backgrounds. As the lumped and sub-catchment based models used in this study were commonly used and a number of packages and software were available for parameter optimization, the genetic algorithm (GA) were applied for these models. On the contrary, relatively less sophisticated methods, such as random parameter sampling and trial-and-error, were used for parameter optimization of the UHE-based and grid-based models, respectively. Input data, water quantity/quality processes, and parameter optimization methods were summarized in Table 1:

Table 1 Input data, water quantity/quality processes, and parameter optimization methods used for lumped, sub-catchment based, UHE based and grid based models.

Model Type	Input data	Water flow Processes	Water quality Processes	Parameter optimization

				method
Lumped	DEM	Non-linear reservoir	Exponential build-up/wash-off	Genetic algorithm
Sub-catchment based	DEM; Landuse; Sewer networks	Non-linear reservoir; 1D-SW equation	Exponential build-up/wash-off; Pipe transport	Genetic algorithm
UHE based	DEM; Landuse; Sewer networks; Cadastral parcels	Travel time routing; 1D-SW equation	Dynamic mass conservation; Exponential wash-off; Pipe transport	Random parameter sampling
Grid-based	DEM; Landuse; Sewer networks; LiDAR	2D-SW equation; 1D-SW equation	H-R erosion equations; Pipe transport	Trial-and-error

2.2.1 Lumped model

In this approach, the surface compartment of SWMM model (Rossman, 2010) was applied without considering any spatial variability within the catchment. The entire catchment was thus conceptualized as a rectangular surface with a uniform slope and a pre-defined width that drains into a single outlet. The water flow was generated by modelling the catchment as a nonlinear reservoir.

The quality module in this approach was represented by the commonly used exponential build-up/wash-off models (Bonhomme and Petrucci, 2017). In this approach, the hydrological and the water quality parameters were homogeneous over the whole urban catchment. One set of parameters was calibrated for the entire surface where no distinction between the processes over different land use was made.

Four build-up/wash-off parameters were optimized by using the genetic algorithm (GA). The optimized parameters were obtained following a procedure that mimics the processes observed in the natural evolution. First, an initial random population was generated from the predefined samples, the best members of the population survived to the next generation based on their goodness of fit estimated by the Root Mean Square Error (RMSE) objective function. This process was repeated for 200 generations of 20 parameter sets in this study, a total of 4000 simulations were performed for one rainfall event. Please refer to (Bonhomme and Petrucci, 2017) for details of the GA method.

2.2.2 Sub-catchment based model

In this approach, the spatial variability of the processes was accounted for through the discretization of the urban surface into sub-catchments. The basin was divided into three parts that represent the upstream, central, and downstream areas. Each part was also divided into three sub-catchments that represent three types of landuses (road, roof, and vegetation). The water flow and quality processes were simulated at the scale of each of the nine sub-catchments based on the same principles as the lumped model, where a different set of parameters was calibrated for every sub-catchment.

The surface runoff and suspended solids (SS) generated from the sub-catchments with this approach flow into the sewer networks via junction nodes. Flow routing in pipes from one junction node to another was computed by the one-dimensional (1D) kinematic wave approximation of the Shallow Water (SW) equations. Water quality routing considers that the sewer pipes were represented as completely mixed reactors connected at junction nodes.

Using the GA approach, build-up/wash-off parameters were optimized for different land-use types.

2.2.3 UHE based model

The Urban Runoff Branching Structure (URBS) model was used in this study to represent the UHE based modelling approach (Rodriguez et al., 2008). The surface was divided into Urban Hydrological Elements (UHE) consisting of the cadastral parcels and their adjacent street. Each UHE includes three land use types: street, roof, and uncovered soil. For each UHE, the areas of the entire parcel, the buildings, the adjacent street, the alleys, the parking lots, and the vegetation were calculated. The coordinates of the UHE centroids and of the ends of the hydrological network segments were used to determine the connection point of the UHE to the sewer. In total, the studied urban catchment encompasses 274 UHEs.

Water flow at each UHE outlet was simulated by modelling the hydrological processes such as interception, infiltration, surface runoff, evapotranspiration, and soil water drainage (Rodriguez et al., 2008). Water quality simulations at the UHE scale were based on the exponential washoff equation. The initial available mass of particles at the surface prior to a rainfall event was determined based on the assumption of mass conservation (Al Ali et al., 2016). After the calculations of surface runoff and water quality processes of every UHE, water and pollutants were drained into the closest manhole of the sewer through a flow path using a travel time function. Then they were routed in the sewer networks to the outlet using the Muskingum-Cunge scheme.

Water quality parameters were randomly sampled for each UHE within predefined intervals for parameter optimization. These predefined intervals were obtained by analyzing field measurement data. In total, 274×6 parameters were randomly selected for one rainfall events, with 10 repeated simulations. Optimized parameter sets were hence obtained by considering the disagreement between simulations and observations. Please refer to (Al Ali et al., 2016) for more details.

2.2.4 Grid based two-dimensional (2D) modelling

In this paper, LISEM-SWMM model (Hong et al., 2017) was used for the grid based 2D modelling. Within LISEM-SWMM, the catchment surface was divided into 224 × 85 rectangular meshes. Grids were then categorized into several classes according to the landuse information. Different parameters were attributed to each grid point in accordance with the landuse type. Interception, infiltration, water runoff and pollutant transfer processes were calculated at the grid scale. Diffusive wave approximation of SW equations was applied for simulating the surface runoff, which was able to represent the spatial and temporal variations of the water flow at the grid level.

Regarding sediment transport on the urban surface, the detachment and deposition processes were simulated at steady state. Within each time-step, particles eroded by the rainfall splash detachment were firstly added to the concentration of suspended solids; the updated concentration was then compared with the transport capacity of the water flow, which was calculated by the Hairsine and Rose (1992) (H-R) equations. The flow-driven detachment takes place when the updated concentration falls below the transport capacity, while the deposition occurs when the transport capacity was exceeded. In this approach, the simulation of flow routing and SS transport in sewer networks relies on the sewer network compartment of the SWMM model.

Only one parameter of the H-R equations was analyzed for water quality simulations, the trial-and-error approach was applied for parameter optimization. In this approach, 8 parameter values were uniformly sampled from a predefined interval based on literature research, the optimized value could hence be determined after 8 simulation runs by selecting the simulation which has the least bias comparing to observations. Please refer to (Hong et al., 2017) for more details.

2.3 Evaluation criteria

Under the perspective of good practice in urban stormwater quality modeling, we proposed six quantitative criteria, including (1) match to observation, (2) forecast accuracy, (3) forecast variability, (4) data accessibility, (5) computational costs, and (6) model reusability, all of which are presented in detail below. The former three criteria aim to evaluate the scientific reliability regarding technical performance, the latter three intent to assess the practical feasibility considering societal costs. Moreover, as described in (Al Ali et al., 2016; Bonhomme and Petrucci, 2017; Clayton, 2017; Hong et al., 2017), all modeling approaches were proven accurate to replicate water flow, the focus was hence presently placed on water quality modeling

2.3.1 Scientific reliability criteria

The RMSE-observations Standard deviation Ratio (RSR, Eq. 1), and the coefficient of determination r^2 (Eq. 2) were used to assess the technical performance of a model over different rainfall events. RSR incorporates the benefits of error index statistics and includes a scaling/normalization factor, so that the resulting values can be applied to various rains. RSR varies from the optimal value of 0, which indicates perfect match between simulations and observations, to unlimited positive values. As a complement to RSR, r^2 was applied to calculate the bias and the collinearity between simulated and observed values. The range of r^2 lies between 0 and 1, a value of 1 means that simulated values perfectly co-fluctuate with the observed ones, whereas a value of 0 indicates no correlation between simulations and observations.

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{t=1}^{n}(Sim_t - Obs_t)^2}}{\sqrt{\sum_{t=1}^{n}\left(Obs_t - \overline{Obs}\right)^2}} \quad (1)$$

$$r^2 = \left(\frac{\sum_{t=1}^{n}(Sim_t - \overline{Sim})(Obs_t - \overline{Obs})}{\sqrt{\sum_{t=1}^{n}(Sim_t - \overline{Sim})^2}\sqrt{\sum_{t=1}^{n}(Obs_t - \overline{Obs})^2}}\right)^2 \quad (2)$$

where $STDEV_{obs}$ is the standard deviation of the observed data, n is the number of time steps for the simulated rainfall event, Sim_t and Obs_t are the simulated and observed TSS concentrations at t^{th} time step, $\overline{Sim}$ and $\overline{Obs}$ are the averaged simulated and observed TSS concentrations at the event scale (event mean concentrations). The diagram for calculation of the three scientific reliability criteria (SRC) are presented in Fig. 2:

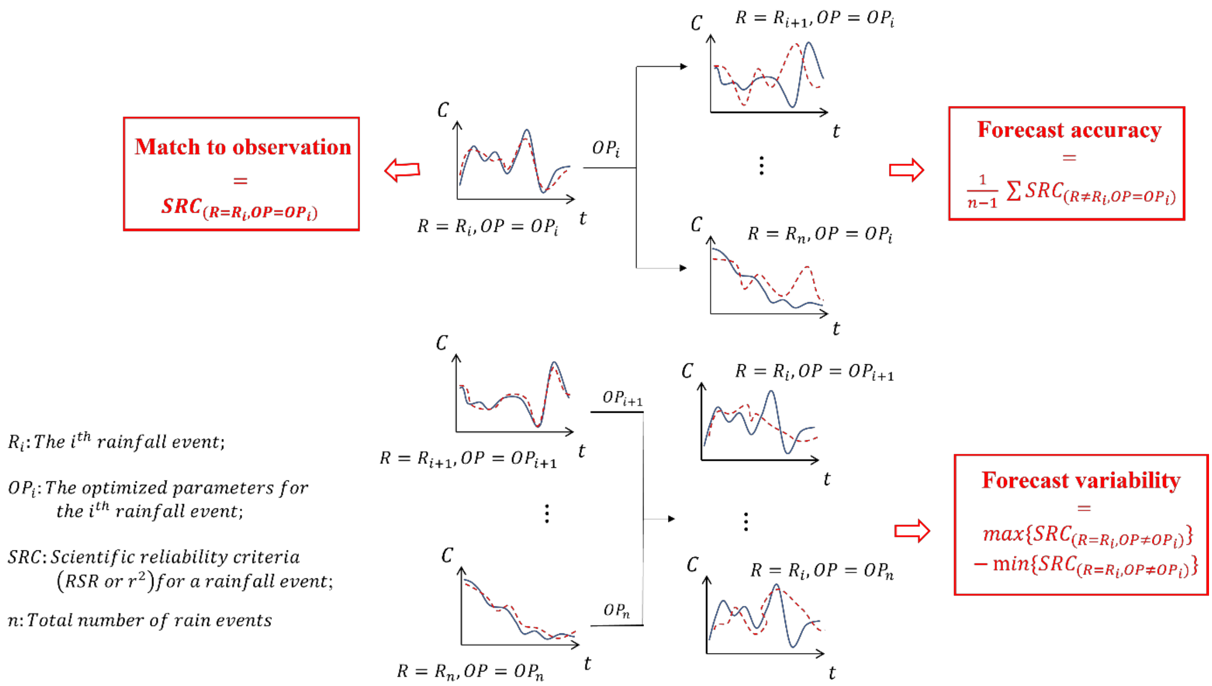


Fig. 2 Diagram for calculation of the three scientific reliability criteria (SRC) for a rain event. Including match to observation, forecast accuracy, and forecast variability.

Match to observation

Using the parameter optimization methods described in the above section, the "best-fit" water quality parameters of every model could be determined for each of the six studied rainfall events. RSR and r^2 were applied to quantify the consistency between observed and simulated TSS concentration. The averaged RSR and r^2 over six rains was then calculated to represent the "match to observation" for different modeling approaches.

Forecast accuracy

The "forecast accuracy" of a modeling approach was computed by applying the optimized parameter values of one event, to other five rains. This corresponds to mimics the process in which one event was used for model calibration, and observations of other independent events were then used to verify the accuracy of predictions. These procedures were repeated five times for every rainfall event, RSR and r^2 were used to describe the bias between observations and predictions. Values of this criterion for one event were hence represented by averaging the computed RSR and r^2 by using optimized parameter values of other five rains.

Forecast Variability

Following a similar approach as described above to quantify "forecast accuracy", the "forecast variability" was calculated by rating the fluctuation range of predictions, instead of the average values of RSR and r^2. Specifically, the value for this criterion for one event was equal to the difference between the max and minimum values of RSR or r^2, obtained for this rainfall event, using the optimized parameters of other rains.

2.3.2 Practical feasibility criteria

This section describes methods to quantify the practical feasibility considering required data, computational, and human resources for different modeling approaches.

Data accessibility

Here we proposed a concept of "Input Element" (IE) to quantify the required input data for modeling approaches. An IE was defined as an input digital number (float/integer), which occupies a certain space of the computer memory (RAM) when running simulations. For instance, the topographic data for a catchment in the lumped model indicates 1 IE, while that data for the grid-based model with 10 × 10 grids implies 100 IEs. The required IEs for the four different models were summarized in Table 2.

Table 2 Summary of required Input Elements (IE) for lumped, sub-catchment based, UHE based and grid based models

Model Type	Spatial Unit	IE per spatial unit	IE counting	Total IE
Lumped	1 Catchment	Area, Slope, Flow length, Imperviousness	1×4	4
Sub-catchment based	9 Sub-catchments	Area, Slope, Flow length, Landuse, Connected sewer node ID	9×5	114
	23 Sewer sections	Node Depth, Section length, Sewer diameter	23×3	
UHE based	274 UHEs	Gravity center Lat/Lon/Elevation, Outlet Lat/Lon/Elevation, Area of Street/Soil/Roof, Connected sewer node ID	274×10	3049
	103 Sewer sections	Node Depth, Section length, Sewer diameter	103×3	
Grid-based	224×85 grids	Lat/Lon, Topography, Landuse	224×85×4	76465

	61 Sewer sections	Node Depth, Connected grid ID, Section length, Sewer diameter	61×5

Computational cost

The computational cost of a model was analyzed by counting the computational time for simulating a 4-hour rainfall event. Simulations were performed with a computer of 2.7 GHz Intel Core i7 processor and 16G RAM. Computational time for parameter optimization (see section 2.2) was also considered. In summary, the estimated computational time for lumped model was 3 minutes, for subcatchment based model was 15 minutes, for UHE based model was 30 minutes, and that for grid based model was 200 minutes.

Model reusability

Model reusability refers to the understanding of the basic concepts, set-up and running the model for a new study case. It depends on the complexity of modeling processes, and technical implementation details. For estimating this criterion, we analyzed the required working time of four graduate students, each student was intended to apply one modeling approach to simulate dynamics of stormwater quality of the studied urban catchment. Finally, it took one week for setting up the lumped model, two weeks for the sub-catchment based model, six weeks for the UHE based model, and five weeks for the grid based model.

2.3.3 Scaling for model criteria

This paper proposed a scaling function to rate the above criteria to a value between 0 and 100 (Eq. 3). For each criterion, the scale of a model can be calculated as:

$$S_i = 100 \times \frac{MAX\{\log C_i : i = 1,2,3,4\} - \log C_i}{MAX\{\log C_i : i = 1,2,3,4\} - MIN\{\log C_i : i = 1,2,3,4\}} \qquad (3)$$

Where S_i is the score of the i_{th} model for the given criterion; C_i is the quantitative value of that criterion for the model. For scientific reliability criteria such as "Match to observation", "Forecast accuracy", and "Forecast variability", C_i was calculated by averaging RSR values for all the six rainfall events. Whereas, for practical feasibility criteria including "Data accessibility", "Computational cost", and "Model reusability", C_i was evaluated by the required IE, computational time, and model implementation time, respectively. For each criterion, a score of 100 points was given to the "best" model, on the contrary, a 0-point score was for the "worst" model. Finally, a radar chart and the total score of each model for all the six criteria were calculated to explicitly display tradeoffs between model reliability and feasibility.

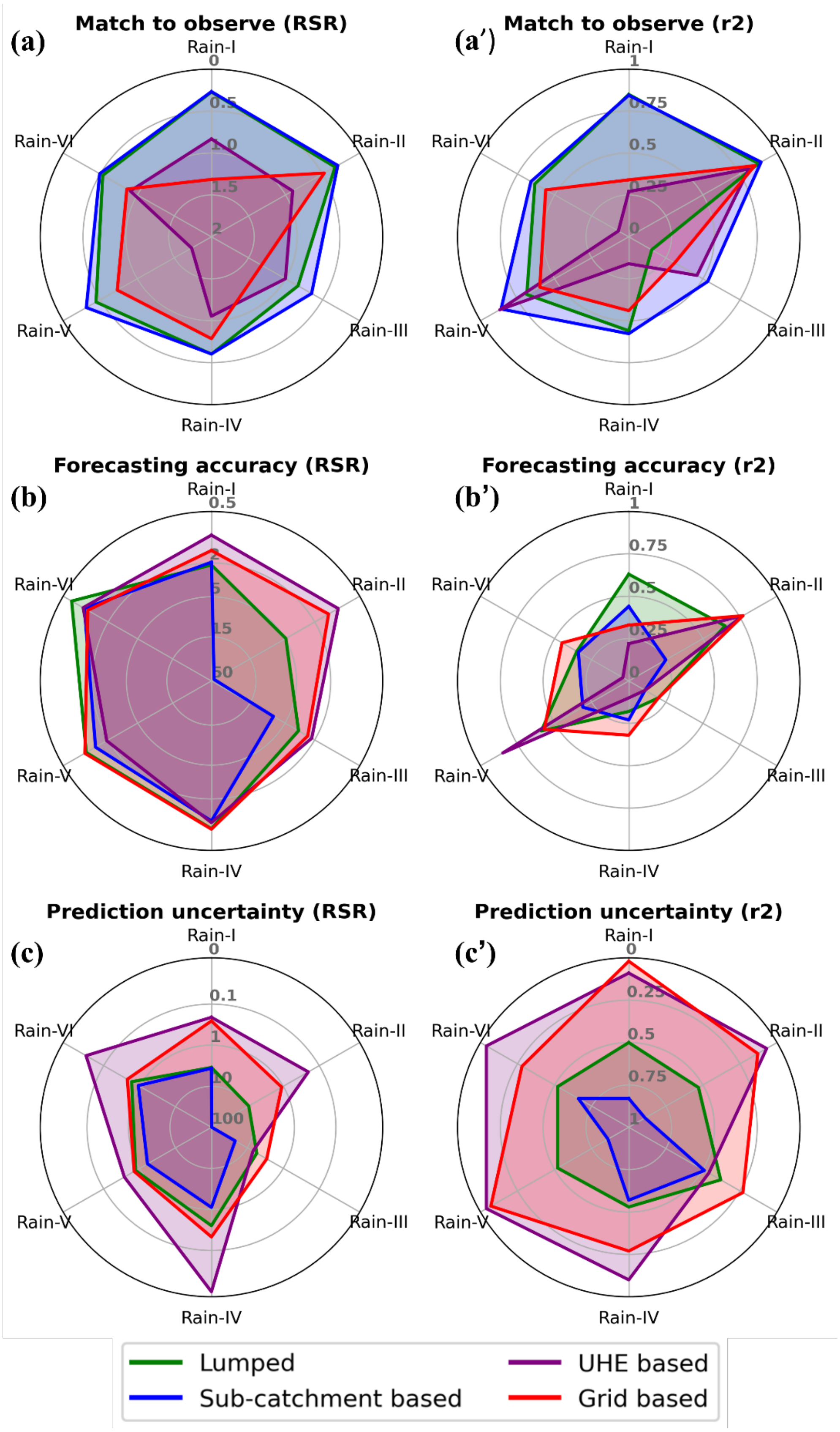
3 Results

Measured and simulated concentrations of TSS were compared for evaluating the scientific reliability of each model.

3.1 Scientific reliability

RSR and r^2 were used to represent the scientific reliability criteria of models based on different spatial discretization (lumped, sub-catchment based, UHE based, grid based) for every studied rainfall event (Fig. 2). As lower RSR values imply better "Match to observation", "Forecast accuracy", and "Forecast variability" for a model, reversed scale radar charts were applied. In addition, logarithmic scale was used in Fig. 2b, c for a better representation. As for the r^2, values close to 1 indicate better performance for the first two criteria (Fig. 2a', b'), while reversed scale was used in Fig. 2c' since higher differences between maximum and minimum r^2 values suggest unsatisfactory forecast variability.

347



348 **Fig. 2** Radar charts of RSR (a, b, c) and r^2 (a', b', c') to represent the (a) Match to observation,

349 (b) Forecast accuracy, and (c) Forecast variability of Lumped (green), Sub-catchment based

(blue), UHE based (purple), and Grid based (red) models over the six studied rainfall events (Rain I - VI).

Fig. 2 clearly indicates that lumped and sub-catchment based models performs better in "Match to observation", UHE and grid based models are advantageous in "Forecast variability", while the "Forecast accuracy" of different models is varied over different rains.

Specifically, RSR values with the optimized parameters (Fig. 2a) for lumped and sub-catchment based models were around 0.5 for all the studied rains. Those values for UHE and grid based models were ranged from 0.5 to 1.7 for different rains, and mostly have lower performance than the previous two types of model. However, these RSR values for lumped and sub-catchment based models declines largely when using optimized parameters of other rains (Fig. 2b), with RSR > 2 for most events. Yet that for UHE and grid based models remains between 1 to 2, which was much less varied than the other two models. Results of r^2 (Fig. 2a', b') demonstrate similar patterns of these four models, that lumped and sub-catchment based models perform better in "Match to observation", but considerably decrease in "Forecast accuracy", whereas values of these criteria for UHE and grid based models were less varied. This phenomenon also explains the better performance in "Forecast variability" (Fig. 2c, c') for the latter two models.

3.2 Tradeoffs between scientific reliability and practical feasibility

Using the Eq. 3, a score between 0 and 100 was calculated for the six evaluation criteria for all the studied models. Scores for each model were listed in Table 3, the radar chart plot was used to represent tradeoffs between model reliability and feasibility (Fig. 3).

Table 3. Scores of model performance evaluation criteria including scientific reliability (Match to observation, Forecast accuracy, Forecast variability), and practical feasibility (Data accessibility, Computational costs, Model reusability) for lumped, sub-catchment, UHE and grid based models. Highest scores for each criterion were underlined.

Model Type	Lumped	Sub-catchment based	UHE based	Grid-based
Match to observation	84.3	100	0	17.6
Forecast accuracy	76.0	0	100	99.2
Forecast variability	59.7	0	89.1	100
Data accessibility	100	66.7	34.7	0
Computational costs	100	61.8	45.2	0
Model reusability	100	66.7	0	13.9
Total Score	520.0	295.2	269.0	230.7

According to Table 3, it is surprising to see that the total score of the lumped model is much higher than the other modeling approaches. This result is mainly due to its outstanding scores in practical feasibility, together with its relatively good performance in scientific reliability. In addition, it can be noticed that the practical feasibility declines with the increase in modeling complexity, however, the scientific reliability is not always improved with more detailed spatial discretization, particularly for "Match to observation". This is mainly related to the used parameter optimization methods, and the correctness of applied modeling processes at different spatial scales. This phenomenon will be further discussed in the next section.

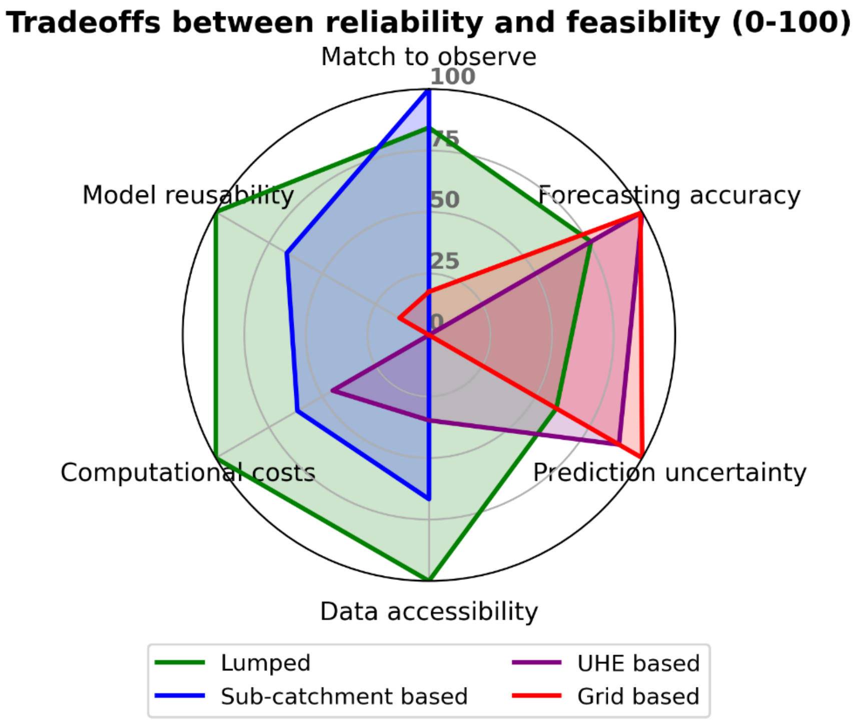


Fig. 3 Radar chart of scores of evaluation criteria including scientific reliability (Match to observation, Forecast accuracy, Forecast variability), and practical feasibility (Data accessibility, Computational costs, Model reusability) for Lumped (green), Sub-catchment based (blue), UHE based (purple), and Grid based (red) models

Fig. 3 explicitly represents tradeoffs between the scientific reliability and practical feasibility of different models. The lumped model (green) occupies the largest area of the radar chart, which implies the most efficient modeling tool considering the six evaluation criteria of this study. On the other hand, other models have distinct strengths and weaknesses. For example, UHE and grid based models are highlighted by their good performance in

Forecast accuracy and Forecast variability, however, these models are also underlined by their unsatisfactory performance in other criteria.

4 Discussion

4.1 Calibration of process-based models in the context of urban stormwater management

Although process-based models intend to describe hydrological processes with mathematical equations, understanding of these processes is still limited, particularly for urban stormwater quality dynamics (Hong et al., 2016b; Refsgaard et al., 2022). Therefore, all these models require some degree of calibration. In the context of urban stormwater management, it is quite common that model end-users do not have a strong modeling background, the ease of application for tested model calibration methods hence should be considered in this study. Conventional parameter calibration methods, such as regression based (e.g., Saltelli et al., 2008) and variance based (e.g., Sobol, 1993) methods, are usually combined with high computational costs, which restricts their applications for complex models. In this study, the genetic algorithm (GA) requires 4000 simulation runs for one rainfall event, that was not feasible for UHE and grid based models. Instead, "easy-to-run" methods including stochastic sampling, and trial-and-errors were applied for these two types of models, respectively. This circumstance also corresponds with numerous actual model applications. Since lumped and sub-catchment based models are widely used and tested in existing studies, a number of model calibration tools are available for practical applications of these models (Salvadore et al., 2015). On the contrary, calibration of UHE and grid based models are much less discussed by scientific and engineering communities, moreover, most existing researches only focus on specific case studies.

According to (Moriasi et al., 2007), model simulation can be judged as satisfactory if RSR < 0.70, and $r^2 > 0.50$. Following these standards, the UHE and grid based models were not well calibrated yet in this study, that explains the low performance of these models in "Match to observation" (Fig. 2). Regarding their good performance in "Forecast accuracy" and "Forecast variability", improving the calibration of these complex models could make them much better in scientific reliability and great tools for research applications. This result suggests that complex models with detailed spatial discretization should work together with advanced parameter calibration approaches (e.g., Hong et al., 2019), in order to achieve good scientific reliability for research purposes. On the other hand, it can be noticed that although UHE and grid based model could improve "Match to observe", their low scores in practical feasibility aspects make them not the best choices for management practices, especially regarding that the lumped model has acceptable performance in scientific reliability with the conventional GA calibration method.

4.2 Spatial complexity and scientific reliability of process-based models

Four modelling approaches based on different spatial discretization were investigated in this study. One of the major obstacles for comparing multiple modelling approaches for urban catchments is the difficulty of ensuring consistency between different types of models. In this study, this is encountered with respect to the modelling of the sewer network. To overcome this issue, the processes in sewer network such as deposition, erosion and reaction are neglected, as these mechanisms are not included in the lumped and UHE based models. The sewer network module of the used models only calculates the transport of water flow and suspended solids. This modeling setting allows comparisons of these models focus on the effects of different spatial complexity.

It may be thought that more detailed spatial complexity described in a model would lead to more accurate model simulations, but a growing number of research tests showed that this is very often not the case (Orth et al., 2015; Refsgaard et al., 2022). In this study, lumped and sub-catchment based models were on the basis of the same SWMM model, using the same GA calibration approach, only with different spatial discretization. Results showed that the more complex sub-catchment based model only slightly better in "Match to observation", but performed much less well in other scientific reliability aspects than the lumped model. As these models both applied exponential equations to describe build-up/wash-off processes, this phenomenon implies that a more heterogeneous distribution of these exponential build-up/wash-off processes could only improve the numerical approximation of a model to observations at the outlet, it might not be the "real" mechanisms for stormwater quality dynamics. If not, more distributed configurations of these processes should enhance all the criteria for scientific reliability. This finding is in line with (Bonhomme and Petrucci, 2017), that exponential build-up/wash-off process is actually a black-box model at the catchment scale.

On the other hand, simulations using UHE and grid based models are more stable over different rains (Fig. 2). This phenomenon might because of that many parameter values of these models were pre-defined according to measurements, as they have physical meanings. On the one hand, those pre-defined parameters could help to reduce the number of parameters for calibration, and hence increase the model reliability for simulating different rains. On the other hand, the measured parameter values might not be optimal for numerically approximating to TSS observations. Moreover, considering the available data, the model calibration in this study only tried to minimize the RMSE between measured and simulated TSS concentration at the catchment outlet, advanced observation and calibration techniques that consider spatially distributed information could make full use of the potential of spatially complex models.

4.3 Practical applications and future developments of process-based urban stormwater quality models based on different spatial discretization

Benefitting from the quantitative information of the radar chart (Fig. 3) which clearly illustrates the strengths and weaknesses of each modeling approach, we could make suggestions for their proper application cases, as well as future developments for overcoming current disadvantages.

For instance, lumped models could be used for Real Time Control system with good tradeoff between scientific reliability and practical feasibility, it would work correctly for different case studies with dedicated auto-calibration systems. Sub-catchment based models are attractive tools for management practices with well agreement with observations and acceptable practical feasibility, but uncertainty analysis should be performed to enable more confident modeling applications. UHE based models can be considered as an alternative solution of the sub-catchment based models, while it works better when more detailed measurements are available for the study case. At last, grid based models are more suitable for research purposes, particularly for simulating impacts of extreme events under climate change, nevertheless, the development of efficient calibration approach, user-friendly modeling interface and training would make this type of models a valuable tool for solving water hazard and risk management issues.

4.4 Towards new evaluation criteria for good modeling practice

The benefit of a model in practical water management depends on both the technical performance and the credibility of the model as perceived by stakeholders and policy makers.

To effectively bridge science and management, Hamilton et al. (2022) and Jakeman et al. (2006) proposed practical frameworks that consider fit-for-purpose modeling as the intersection of addressing the needs of end users, obtaining an adequate level of certainty, and within practical constraints of the project. In addition, Hamilton et al. (2019) have listed 32 evaluation criteria covering a multi-dimensional and multi-perspective concept to characterize the efficiency of an modeling approach. These studies have provided a theoretical base for identifying the effectiveness of modeling in stormwater management. Quantitative assessment of these new criteria is an important step to guide good practice for different types of modeling approaches.

One major barrier to the quantitative assessment of practical feasibility of a model is the lack of standard procedures for interpreting model characteristics into relevant quantitative indicators. In this study, we have introduced concepts such as Input Element (IE), simulation time, and required model set-up time for graduate students, to quantify criteria including data accessibility, computational cost, and model reusability, respectively. However, it should be noticed that subjective biases may be involved in the calculation of these indicators. For instance, the ease of accessing input data sources was not considered in the IE concept, experiences of different students were not described when calculating the model reusability. To reduce these subjective biases, more comprehensive analysis could be done in combining with teaching/training activities. For example, we could assign modeling projects to a large group of students and then record the required time for different modeling steps (e.g., understanding of the concepts, getting input data, setting up models, analyzing outputs, etc.), when using different types of models. Despite these shortcomings, this study was one the first attempts to quantitatively assess tradeoffs between scientific reliability and practical feasibility. The proposed model evaluation procedures could be used in other studies to improve model-based outcomes in the context of urban stormwater management.

In addition to the proposed evaluation criteria, future studies could attempt to introduce criteria to quantitatively evaluate the degree of stakeholder participation throughout the modeling processes. Stakeholder participation is a key requirement of good modeling practice, particularly when models are to address management questions. For urban stormwater quality issues, decision makers and public could participate from the model concept design phase to the social learning of simulation outcomes. Innovative indicators could be proposed to quantify exchanges between producers and users of knowledge, including scientists, decision makers, and public. For example, criteria such as frequency of feedbacks between scientists and decision makers during model development, number of page views to the website containing simulation results, economic benefits by adopting suggestions derived from modeling outcomes, etc., could be analyzed to evaluate the effectiveness of a modeling approach.

5 Conclusion

In this study, we proposed a quantitative model evaluation approach, to analyze tradeoffs between technical performance gains and societal costs of four process-based urban stormwater quality models. These models were based on different spatial discretization, including lumped, sub-catchment, UHE and grid based approaches. The proposed approach emphasized the importance of integrating new criteria into model evaluation procedures, that focus on good modeling practice in the context of water management.

Six criteria were introduced to quantitatively assess the scientific reliability and practical feasibility of a model, such as (1) match to observation, (2) forecast accuracy, (3) forecast variability, (4) data accessibility, (5) computational costs, and (6) model reusability.

Reasonable assumptions and equations were presented to calculate these criteria, radar chart plots were then applied to explicitly display characteristics of different models.

The results showed that the lumped model was the best tradeoff between scientific reliability and practical feasibility, for its outstanding performance in practical feasibility, together with its acceptable achievement in scientific reliability. Moreover, the practical feasibility of a model declined with more detailed spatial discretization, however, the scientific reliability was not always improved, particularly for "Match to observation". Detailed analysis revealed that more heterogeneous distribution of the exponential build-up/wash-off processes from lumped to sub-catchment based models could only improve the numerical approximation of simulations to observations at the outlet, it could not correctly represent stormwater quality mechanisms at the urban catchment scale. In addition, it was suggested that complex grid based models should work together with advanced parameter calibration approaches, in order to achieve good scientific reliability for research purposes. In perspective, quantitative evaluation of the stakeholder participation throughout the modeling processes could help to improve model-based outcomes with more adaptive stakeholder engagement.

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Appendix

Table S1 Summary of the studied rainfall events.

Rainfall event	Begin date; time	Rainfall depth (mm)	Mean intensity (mm/h)	Maximum intensity (mm/h)	Duration (hour)	Antecedent dry days (day)
Rain-I	10/08/2014; 04:53	9.4	1.67	6.89	5.64	0.4
Rain-II	10/08/2014; 17:30	7.5	2.06	10.1	3.63	0.3
Rain-III	10/09/2014; 20:17	4.5	7.76	42	0.58	1.23
Rain-IV	10/12/2014; 13:24	3.6	1.68	6.9	2.14	1.8
Rain-V	11/15/2014; 00:16	9.3	2.1	5.54	4.41	0.5
Rain-VI	11/26/2014; 00:42	2.9	1.1	4.99	2.6	9
Summary of 56	D10	1.6	0.5	2.57	0.70	0.24

rainfall events	D50	3.4	2.27	7.15	3.29	1.82
	D90	8.7	16.36	56	7.51	10.18