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Trade-offs Between Discretization Approaches in Urban Stormwater Modeling: Accuracy, Interpretability, and Practical Implications

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Abstract

Stormwater models are important tools for urban drainage design, planning, and analysis, but their performance and interpretation depend heavily on how spatial discretization is handled. This study evaluates the influence of two common discretization strategies – topography- and sewer geometry-based – on hydrological representation and simulation accuracy in the Storm Water Management Model (SWMM), using a mixed urban and peri-urban watershed in London, ON, Canada. Leveraging long-term flow data from multiple monitoring locations across the watershed, we systematically evaluated the effects of discretization strategy across different rainfall conditions and land use settings (e.g., urban vs. peri-urban) using continuous and event-based simulations, as well as a fixed-effects regression model. The two models with different discretization approaches showed no significant differences in simulating outlet flows (mean NSE = 0.88 for the topography-based model and 0.85 for the sewer geometry-based model). However, the topography-based model yielded parameter values with greater hydrological interpretability and, accordingly, performed better at simulating flows at locations within the watershed (NSE = 0.74–0.86) compared to the geometry-based model (NSE = 0.55–0.83). In addition, model performance was strongly influenced by rainfall depth and land use characteristics, with significantly improved results observed during larger storm events and in the urban watershed. Ultimately, the study demonstrates that discretization choice can significantly influence model structure, parameter interpretation, and spatial simulation accuracy. While the topography-based approach enhances hydrological representation, the sewer geometry-based model remains a practical and efficient alternative particularly in data-limited areas.

Keywords

Stormwater modeling; discretization; hydrological representation; SWMM; spatial data processing; urban and peri-urban watersheds

1. Introduction

Urban stormwater management is a major challenge as urbanization increases impervious surface cover, resulting in higher stormwater flow volumes and peak flow rates (Hopkins et al., 2014, Jefferson et al., 2017). To support stormwater regulation and planning, hydrologic-hydraulic stormwater models – such as the U.S. EPA Storm Water Management Model (SWMM) – are widely used to simulate flow responses of urban drainage systems to precipitation events (Niazi et al., 2017). These models help planners and practitioners assess existing drainage infrastructure networks, evaluate and design stormwater control measures, and evaluate alternative land use scenarios (Tamm et al., 2023 Javan et al., 2025 Khatooni et al., 2025).

Spatial discretization of the watershed is an essential step in constructing stormwater models whereby the boundaries of subcatchments (fundamental drainage areas) that direct local runoff to sewer systems are determined (Rossman and Huber, 2016). In urban settings, this task is challenging as runoff pathways are influenced by both the engineered drainage infrastructure (e.g., sewer inlets and pipes) and complex human-modified surface topography (Gironás et al., 2010, Dong et al., 2022). At high spatial resolution, small urban parcels (e.g., buildings) can be modeled as individual subcatchments, routing overland flow to a nearby sewer inlet, which closely reflects actual drainage behavior. While effective at the block scale, such fine-scale mapping is time-intensive and often not practical for larger watersheds or scenario-based planning (Dong et al., 2022, Si et al., 2024). Hence, model discretization approaches that can provide physically based representation of stormwater drainage behavior but with reduced spatial complexity are favored for larger-scale models (greater than a few blocks) (Dobson et al., 2022).

Two simplification strategies are commonly used for discretization of large watersheds. The first is a topography-based approach, which uses digital elevation models (DEMs) to determine subcatchment boundaries and outlets. Since drainage infrastructure is not represented in DEMs, sewer network data is often integrated with the subcatchment delineation to manually define surface-subsurface flow paths (i.e., connecting subcatchment outlets to sewer inlets) (Si et al., 2024). To improve efficiency, “burning” techniques have also been used to improve representation of engineered drainage pathways by lowering DEM elevations along known sewer alignments such as sewer inlets or pipes (Gironás et al., 2010 Sokolovskaya et al., 2023 Si et al., 2024). However, discretization outcomes (e.g., drainage boundaries) are sensitive to the quality and resolution of DEM data (Leitão et al., 2009, Salvadore et al., 2015). For example, Sokolovskaya et al. (2023) found that DEMs, with a resolution coarser than approximately 1.5 m, may not be able to capture relevant urban microtopographic features as needed to derive realistic drainage areas. Similarly, Zhou et al. (2021) highlighted that a fine-resolution DEM (~0.2 m) is necessary to delineate reliable drainage areas in flat urban terrains. Despite the increasing availability of freely available high-resolution DEMs (e.g., LiDAR-derived datasets), their spatial coverage remains patchy across cities, particularly in developing regions. As a result, modelers continue to rely on coarser global DEM products (e.g., SRTM) in many areas, which can hinder accurate delineation of drainage boundaries (Hawker et al., 2019).

The second strategy is a sewer geometry-based approach, where watersheds are discretized by drawing Thiessen polygons around the sewer inlets. This method directs surface runoff within each polygon to its nearest inlet, thereby simplifying the physical definition of drainage boundaries and their connection to the sewer system. Recently, the sewer geometry-based approach has gained popularity due to its ease of use and efficient integration with available infrastructure datasets (Dong et al., 2022, Li et al., 2024, Ni et al., 2025, Qi et al., 2025). However, the lack of consideration for topographic characteristics may result in less accurate representation of terrain-driven flow patterns, such as runoff along roads to drains. This limitation may reduce the accuracy of the model in simulating flow accumulation within the watershed, potentially leading to misclassification of areas vulnerable to localized flooding.

Despite their distinct strengths and limitations, the topography-based (e.g., Warsta et al., 2017, Swathi et al., 2019) and geometry-based (e.g., Dong et al., 2022, Li et al., 2024) discretization approaches have both been successfully applied to develop stormwater models. Yet, the performance of these models has largely been evaluated using data collected from single monitoring locations, often at the watershed outlet. As a result, it remains unclear whether alternative discretization approaches lead to differences in the representation of hydrological processes within a watershed, such as subcatchment-scale parameter estimates and simulated flows. More specifically, it is unknown whether the increased complexity of topography-based discretization improves flow simulations within the watershed compared to the simpler geometry-based discretization approach. This question is particularly important in urban areas where calibration and validation are often constrained by limited rainfall-flow data, typically available only at the watershed outlet (Broekhuizen et al., 2020). A few studies have qualitatively compared the two discretization approaches. For example, Li et al. (2024) recently conducted scenario-based simulations to compare node surcharge responses from models developed using the two discretization approaches. They reported comparable total overflow volumes between the two models (absolute difference < 5%), although discrepancies increased with increasing storm magnitudes. Dong et al. (2022) compared flow simulations between topography- and geometry-based models at the outlet of a small urban watershed and found that the two models produced comparable peak flows relative to observations. However, the analyses of Li et al. (2024) and Dong et al. (2022) were limited to scenario-based or uncalibrated simulations and neither study examined how the discretization approach influences parameter calibration, flow simulations within the watershed, or the consistency of model performance across different storm events.

In urban-rural transitional (peri-urban) areas, natural drainage and engineered stormwater infrastructure (e.g., sewer systems) both exist (Niazi et al., 2017), often resulting in a combination of fast and slow hydrological responses to storm events (Braud et al., 2013). In such settings, different discretization methods may yield distinct representations of dominant drainage processes, given their different underlying assumptions (i.e., topography-driven versus sewer-network-driven), potentially making one approach more suitable than another depending on the degree of urbanization and drainage characteristics. With urban areas rapidly expanding worldwide, understanding how spatial discretization choices influence model performance across watersheds with varying land use and drainage configurations is important for developing robust stormwater models that balance complexity and applicability for planning and design purposes. To fill these gaps, this study systematically evaluates the influence of discretization approach on model structure, parameter interpretation, and performance under varying rainfall and land use conditions.

The objective of this study is to evaluate and compare the performance, sensitivity, and interpretability of stormwater models developed using topography- and sewer geometry-based discretization approaches. To address this, we develop two SWMM models of a highly monitored watershed in London, Canada using topography-based and sewer geometry-based discretization approaches. Using continuous and event-based simulations, along with fixed-effects regression, we evaluate how discretization strategy affects model performance across different land use types, storm event sizes, and monitoring locations at the outlets and within the watershed. This quantitative comparison is used to clarify the tradeoffs in selecting a discretization strategy including model physical realism, simplicity of implementation, and model performance. Overall, this study provides new insights to support discretization strategy selection for efficient, reliable stormwater scenario simulations.

2. Methods

2.1 Study site and data

The study area is the Thornicroft Drain watershed, located in London, ON, Canada (Figure 1A and Figure S1 Supplementary Material (SM)). The watershed area is approximately 580 ha. The upper watershed (~210 ha) is highly urbanized, with 94% of the area consisting of urban land uses, including residential, commercial, industrial, and transportation. Runoff is collected and conveyed through a separated sewer system and discharged to the Thornicroft Drain open channel at the upper outlet. The lower watershed (~370 ha) is a peri-urban area comprising 50% rural land uses, including agricultural land and forest. Most runoff in the lower watershed drains directly to the Thornicroft Drain, except for one residential neighborhood (~100 ha) that is serviced by a separated sewer system that ultimately discharges into the Thornicroft Drain. The primary soil type in urban land use areas is silty clay, while silty sand is the primary soil type in rural land use areas. Hereafter, we refer to the upper watershed as the upper urban watershed and the lower watershed as the lower peri-urban watershed, based on their distinct land use characteristics and stormwater drainage infrastructure.

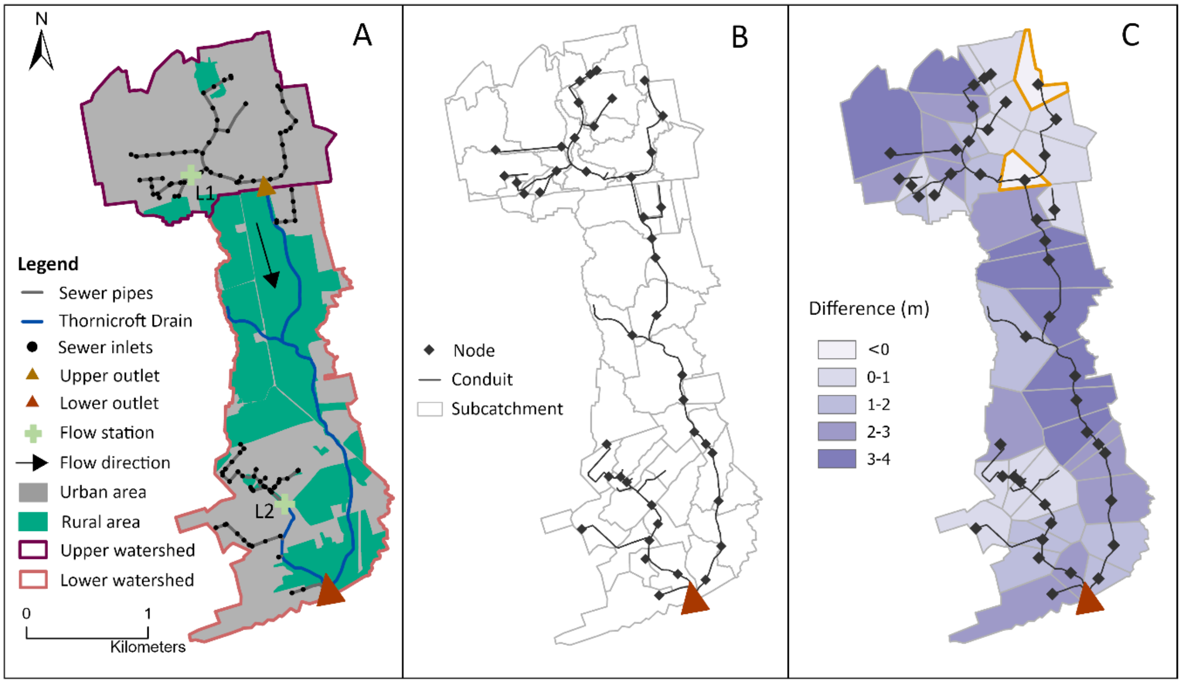

Figure 1. (A) major land use within upper watershed and lower watershed areas, stormwater drainage pathways, and flow monitoring stations at the outlets of the upper and lower watersheds and at two locations within the watershed (L1 and L2). Model configurations developed based on (B) topography-based discretization and (C) sewer geometry-based discretization. Elevation difference between subcatchment average elevation and corresponding node elevation for sewer geometry-based discretization model is shown in panel (C). Subcatchments for which the average surface elevation is less than the node elevation are marked with orange border.

Stormwater flow monitoring was conducted from August 2021 to November 2023 at the outlets of the upper urban watershed and the lower peri-urban watershed. At these locations water levels in Thornicroft Drain were continuously measured at 15-minute intervals using a pressure transducer (TD/CTD Diver, Van Essen Instruments). Measured water levels were converted to flow rates by developing rating curves for each location. These rating curves were based on flow rate measurements performed using a portable flow meter (HACH FH950) across a wide range of flow conditions. Over the same monitoring period, flows were also measured at two locations within the watershed – L1 (a storm drain) within the upper urban watershed and L2 (an open drain) within the lower peri-urban watershed. These locations were selected because they are accessible for continuous flow monitoring and represent flows from distinct land uses within the upper (urban) and lower (peri-urban) portions of the watershed. However, even with regular site visits and equipment maintenance, sediment build-up and sewer backwater in these drains occasionally affected flow measurements. Therefore, flow data for some individual events needed to be excluded from the simulations. Further details of the monitoring program and dataset are available in Vyn (2023). As snowmelt data during the monitoring period are not available, this study focuses on simulating stormwater flows during the warm season (June to October).

Rainfall data with 5-minute resolution were obtained from two City of London rain gauges located 0.6 km southwest and 1.7 km northeast of the watershed boundary (Figure S1). Sewer infrastructure data, including spatial layout and pipe geometry, were provided by the City of London. Spatial datasets were obtained from the Ontario Ministry of Natural Resources and Forestry (OMNRF, 2019), including a 2-m LiDAR-derived digital elevation model (DEM) and 0.5-m resolution aerial imagery. Daily climate data, including minimum and maximum temperatures, were collected from Environment and Climate Change Canada (EMCC, 2024). A summary of all datasets used in this study is provided in SM Table S1.

2.2 Model development

The U.S. EPA Storm Water Management Model (SWMM) was used to simulate stormwater flows in the study watershed. SWMM is a widely used for urban stormwater simulations

(Rossman and Huber, 2016). It simulates runoff generation from subcatchments (the basic hydrological units) and routes the resulting flow through sewer networks to an outfall. Watershed discretization, a fundamental step in model development, involves delineating subcatchment boundaries and specifying the direction of runoff toward sewer inlets. In this study, two SWMM models were developed using the same precipitation input and sewer data (Table S1), but with the watershed discretized using topography- and sewer geometry-based methods, respectively.

For the topography-based model, subcatchment boundaries were delineated using ArcGIS hydrologic analysis tools applied to raw DEM data. These included sink filling, flow direction and accumulation, and watershed basin delineation (Bibi, 2022). In urban areas, the resulting subcatchments were overlaid with sewer network data to refine boundaries and assign subcatchment outlets to sewer inlets. This task was completed with additional input from City of London municipal engineers to ensure that the assigned subcatchment-sewer connections were consistent with the actual drainage conditions, with adjustments made where discrepancies were identified. For subcatchments without nearby sewer infrastructure, runoff was routed to adjacent downstream subcatchments or directly to Thornicroft Drain.

In the sewer geometry-based model, watershed discretization was completed by drawing Thiessen polygons around nodes (e.g., sewer inlets), such that any point within a polygon is closer to its corresponding node than to any other node (i.e., representing the shortest flow path). This approach assumes that each node is located at a minimum local elevation, allowing runoff from the surrounding area to be routed to that node (Dong et al., 2022). Although Dong et al. (2022) showed that the location of nodes used to generate polygons does not significantly impact outlet flow simulations, identical node locations were used in both the topography-based and sewer geometry-based models to ensure consistent comparisons of inflows at each node.

Specifically, subcatchment outlets from the topography-based model were used to generate polygons.

The slope and imperviousness parameters for each subcatchment were first determined using DEM data and aerial imagery (Figure S2). As SWMM assumes spatial-uniform characteristics within each subcatchment, area-weighted averages were assigned to each subcatchment. Subcatchment width, representing the stormwater overland flow width, was inferred from spatial data. In the topography-based model, the subcatchment width was initially calculated by dividing the subcatchment area by the flow path length determined from the DEM, with outlets typically located at the downslope edge of the subcatchment (Figure S2A). In the sewer geometry-based model, subcatchment width was estimated by dividing the subcatchment area by a two-sided symmetrical flow length (Rossman and Huber, 2016). The one-side flow length (i.e., half of the two-sided symmetrical length) was calculated as the longest distance from any point within the subcatchment to its corresponding sewer inlet (Dong et al., 2022).

Other parameters were obtained from literature, including Manning's roughness, depression storage, and pipe roughness (Krebs et al., 2014 Bisht et al., 2016 Lee et al., 2018 Macro et al., 2019 Perin et al., 2020 Behrouz et al., 2020 Dong et al., 2022 Zhuang et al., 2023 Wu et al., 2024). In both models, infiltration was simulated using the Green-Ampt method, which requires specification of soil parameters including saturated hydraulic conductivity, suction head, and initial moisture deficit. This method was applied because it provides a physically based representation of infiltration processes, with parameters that can be approximated using literature values that are based on extensive measurements for different soil classes (Rossman and Huber, 2016). Subsurface flow was simulated using the SWMM groundwater module, which represents surface runoff-groundwater interactions by simulating water movement between an upper unsaturated soil zone and a lower saturated soil zone. Parameters estimated for this module include aquifer porosity, field capacity, and saturated hydraulic conductivity. Parameter values related to infiltration and groundwater modules were adopted from a previous study by Jivani (2024), who calibrated these parameters using flow data measured within the watershed. Further information on estimation of these parameters and values used is provided in Table S2.

2.3 Model calibration and evaluation

Model calibration was performed using continuous flow data from August to October 2021. Given the distinct land use characteristics between the upper and lower watersheds, the parameters for subcatchments in the upper urban watershed were first calibrated using the upper outlet flow data. Following this, the parameters for subcatchments in the lower peri-urban watershed were calibrated using lower outlet flow data, while keeping the parameters calibrated for the upper subcatchments fixed. This stepwise calibration helped reduce the influence of parameterization in the upper watershed on simulations in the lower watershed. A warm-up period of 15 days was used to stabilize initial conditions. Parameters for calibration included subcatchment width, Manning's roughness, depression storage, and pipe roughness. The Nash-Sutcliffe Efficiency (NSE, Equation 1) (Nash and Sutcliffe, 1970) was used as the primary performance evaluation metric (both for calibration and validation), with this metric supplemented by runoff volume error (Equation 2), peak flow error (Equation 3), and time-to-peak error (Equation 4), and flow residuals (Equation 5). Model calibration was conducted using Monte Carlo simulations (Dong et al., 2022), in which parameters were randomly sampled from the ranges provided in Table S2. For each model, 1,000 simulation runs were executed, and the parameter set from the best-performing run which yielded the highest NSE value was selected for validation.

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Q_{o,i} - Q_{s,i})^2}{\sum_{i=1}^{n}(Q_{o,i} - \overline{Q_O})^2} \quad \text{Equation 1}$$

$$\text{Volume error} = \frac{\sum_{i=1}^{n}(Q_{o,i} - Q_{s,i})}{\sum_{i=1}^{n}(Q_{o,i})} \times 100\% \quad \text{Equation 2}$$

$$\text{Peak flow error} = \frac{(P_{o,i} - P_{s,i})}{P_{o,i}} \times 100\% \quad \text{Equation 3}$$

$$\text{Time-to-peak error} = (t_{o,i} - t_{s,i}) \quad \text{Equation 4}$$

$$\text{Flow residual} = Q_{s,i} - Q_{o,i} \quad \text{Equation 5}$$

where $Q_{o,i}$ and $Q_{s,i}$ are the observed and simulated flow rates (m^3/s), respectively, $\overline{Q_O}$ is the observed mean flow (m^3/s); $P_{o,i}$ and $P_{s,i}$ are the observed and simulated peak flow rates (m^3/s), respectively, and $t_{o,i}$ and $t_{s,i}$ are the time corresponding to the observed and simulated peak flow rates (min), respectively. An NSE value closer to 1 indicates better model performance.

Validation was conducted using continuous flow data from June to October for 2022 and 2023 at the upper and lower watershed outlets, along with two monitoring locations that are within the upper urban watershed (L1) and lower peri-urban watershed (L2), receptively (flow data from 2021-2023). In addition to calibrating and validating the model based on continuous flow simulations, model performance was also evaluated at the event scale. To define individual storm events, we tested dry inter-event periods of four hours (Alivio et al., 2024) and six hours (Dong et al., 2024a), both of which are commonly used to divide continuous datasets into individual events. In our preliminary analysis, applying a four-hour threshold resulted in 5–8 more annual events (warm-season only) than the six-hour threshold over the study period; however, most of these additional events corresponded to the falling limbs of hydrographs during larger storms.

Therefore, a six-hour inter-event dry period was adopted to divide the continuous data into individual storm events. To capture delayed flow responses, the corresponding flow data were extended by an additional six hours, without overlapping with subsequent events (Dong et al., 2024a). The same performance metrics used for the continuous flow models were applied to evaluate the performance of the event-based models.

To assess the influence of discretization method on the performance of the models across different rainfall depths and land use characteristics (urban versus peri-urban), a linear fixed-effects model was applied. This statistical approach evaluates how specific factors affect an outcome (i.e., response variable; Equation 6) (Fox, 2015).

$y_i = \sum \beta_j \cdot x_{i,j} + \alpha_j + \varepsilon_{i,j}$ Equation 6

here β_j is a coefficient describing the influence of the jth predictor $x_{i,j}$ on performance metric y_i in the ith event, α_j is the unobserved event-invariant effect (e.g., the distinct effects of upper and lower watershed land uses) $\varepsilon_{i,j}$ is a stochastic error term with an expected value of zero $E\left[\varepsilon_{i,j}\right] = 0$, and constant variance $E\left[\varepsilon_{ij}^2\right] = \sigma^2$.

Model performance metrics, including NSE, peak error, volume error, and time-to-peak error, were used as response variables (y_i). Discretization method, rainfall depth, and watershed land use characteristics were treated as fixed effects (predictors) to test whether variations in model performance could be attributed to these factors. Events with rainfall depths less than 1 mm were excluded to reduce noise from low-intensity events that do not generate runoff. Categorical predictors were modeled as binary: sewer-based discretization and lower outlet were assigned as 0, while topography-based discretization and upper outlet were assigned as 1.

Finally, the hydrological interpretability of parameter values, defined as the extent to which the calibrated model parameters physically reflect watershed characteristics and can be used to interpret underlying hydrological processes, was assessed. For this, Spearman's correlation analysis was used to examine the relationships between discretization-related parameters (including imperviousness, slope, drainage area, and width) and subcatchment outputs (e.g., runoff volume and peak runoff rate) across all subcatchments, with stronger correlations indicating greater physical relevance.

3. Results and Discussion

3.1 Model configurations

Model configurations derived from the two discretization approaches are shown in Figure 1B-C. The sewer geometry-based model comprised 44 subcatchments, with 19 of these subcatchments located in the upper urban watershed. All subcatchments except two have average elevations higher than their outlet node elevations (Figure 1C). The two subcatchments with average elevations slightly lower than those of their corresponding outlet nodes had elevation differences less than 0.1%. This suggests the "naive" surface-to-node flow assumption (i.e., routing runoff toward the nearest node) is generally acceptable, as this modest elevation difference could result from data processing processes or limitations in DEM resolution (Dong et al., 2022). This aligns with the findings of Dong et al. (2022), who showed that most subcatchments in their modeled sewershed satisfied the surface-to-node assumption. In comparison to the sewer geometry-based model, the topography-based model has 52 subcatchments, with 22 located in the upper urban watershed. Due to incomplete infrastructure documentation in the lower peri-urban watershed, particularly around a newly developed residential neighborhood (near Location L2 in Figure

1A), subcatchment boundaries and flow routing were primarily determined using known major trunk sewers and input from municipal stormwater engineers. These data limitations may contribute to uncertainty in parameter estimation and calibration for the lower watershed. Further details are discussed in the sections below.

3.2 Comparison of discretization-related parameters

A comparison of the discretization-related subcatchment physical parameters between the topography- and sewer geometry-based models is shown in Figure 2. For both models, subcatchment areas in the lower peri-urban watershed were generally larger than those in the upper urban watershed. In the sewer geometry-based model, the area of the subcatchments varies from 3.1–17.2 ha (mean = 11.6 ha) in the upper urban watershed and from 3.9–28.8 ha (mean =14.7 ha) in the lower peri-urban watershed, while in the topography-based model, the area varies from 1.9–28.7 ha (mean = 10.3 ha) in the upper watershed and from 3.1–29.9 ha (mean =13.4 ha) in the lower watershed. In the sewer geometry-based model, the delineation resolution (shape) depends on the spatial distribution of nodes (e.g., sewer inlets), resulting in finer subcatchments in the upper watershed where nodes were more densely distributed. In contrast, topography-based delineation was determined based on terrain variation and flow paths. In the upper urban watershed, anthropogenic modifications to the terrain, such as road crowns and lot grading, could alter natural flow paths, thereby producing relatively smaller drainage areas.

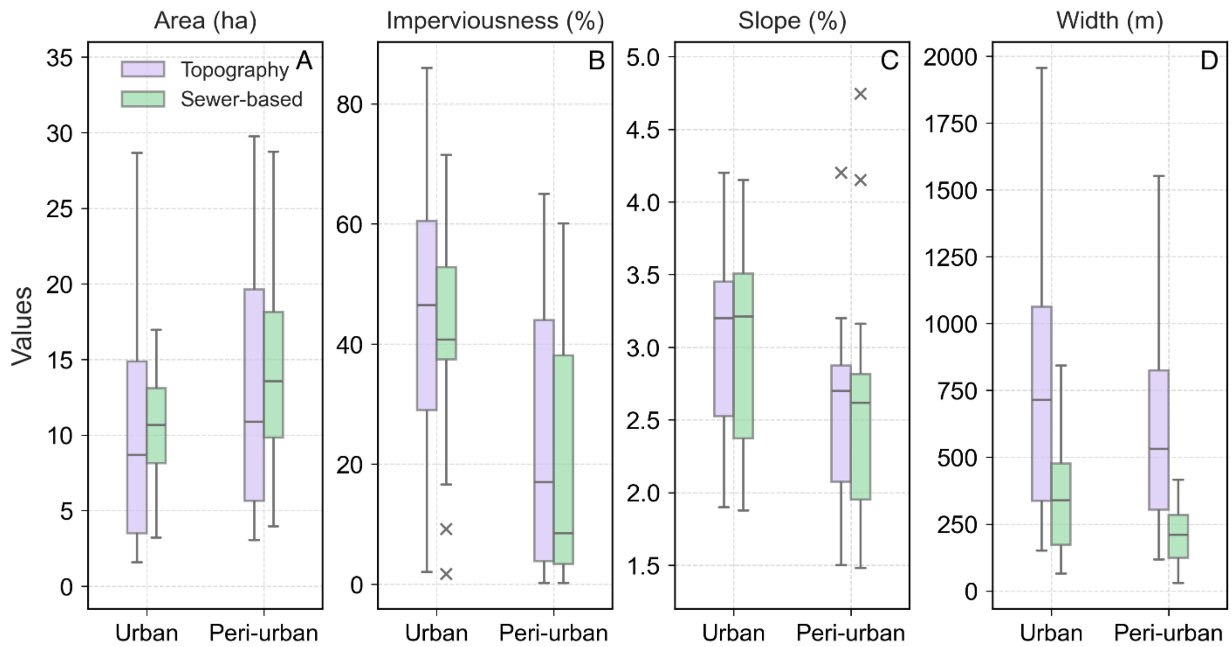

Figure 2. Comparison of discretization-related physical parameters (A) area, (B) imperviousness, (C) slope, and (D) width for the subcatchments in the two models. The horizontal lines within the boxes show the median value. The bottom and top of the box show the 25th and 75th quantiles. The whiskers extend 1.5 times the interquartile range (IQR; 25th and 75th quantiles).

In the urban watershed, the subcatchments in the topography-based model had greater variability in imperviousness compared to the sewer geometry-based model (Figure 2B). This may be due to the drainage areas (i.e., subcatchments) produced by the topography-based delineation aggregating less heterogeneous land cover within individual subcatchments. In contrast, the sewer geometry-based delineation, which does not account for topography, resulted in subcatchments with more mixed land cover (varying degrees of imperviousness), ultimately resulting in a narrower range of imperviousness. In the lower peri-urban watershed, the imperviousness generated by the two models was comparable, likely due to the lower degree of urbanization in the lower watershed. Subcatchment slopes showed limited difference between the models, with both having steeper slopes in the upper watershed compared to the lower watershed (Figure 2C and Figure S2C). However, it should be noted that parameter estimates of imperviousness and slope derived from area-weighted averaging may mask surface heterogeneity and reduce the variability in parameter estimates. In areas with limited high-resolution spatial data, parameter homogeneity assumptions within subcatchments can further weaken the representation of spatial variability, potentially reducing the physical interpretability of model parameters and overall model performance.

Subcatchment width, after calibration, varied considerably between the two models (Figure 2D). In general, the width values for subcatchments in the topography-based model were larger compared to the sewer geometry-based model. This suggests that polygon-based subcatchments created in the sewer geometry-based model tend to generate narrow overland flow paths (or channels). Considering that the flow paths derived based on terrain variation in the topography-based model aligned well with the road distributions (Figure S2A), topography-derived subcatchment width may better reflect the actual overland flow width.

Correlation analysis showed that, in both the upper and lower watersheds, the topography-based model exhibited stronger relationships between the discretization-related physical parameters and subcatchment hydrological outputs (i.e., surface runoff volume and peak runoff rate) (Figure 3). While the strength of correlation between subcatchment parameter values and model outputs does not directly influence model performance, it provides a useful means to assess whether these parameters physically represent hydrological processes, based on current understanding of their influence on runoff generation and flow dynamics. Two strong, positive correlations, reflecting key input-output relationships, have been consistently observed and are wellestablished: (1) between imperviousness and runoff volume, and (2) between subcatchment width and peak flow (Behrouz et al., 2020, Dong et al., 2022). If model parameters are better estimated in one model, we would expect stronger correlation strengths between these two input-output pairs. Impervious was more strongly correlated with runoff volume in the topography-based model (mean ρ across the upper and lower watersheds = 0.81) than in the sewer geometry-based model (mean ρ = 0.61) (Figure 3). Similarly, peak flow was more strongly correlated with subcatchment width in the topography-based model (mean ρ = 0.71) compared to the sewer geometry-based model (mean ρ = 0.39). These results indicate that the parameter values from the topography-based model may have greater hydrological interpretability. In addition, stronger inter-parameter correlations were observed in the topography-based model. For instance, in the upper urban watershed, subcatchment area was highly correlated with width in the topography-based model (ρ = 0.96), compared to a weaker correlation in the sewer geometry-based model (ρ = 0.34). For an ideal discretization, minor changes in drainage area boundaries should not substantially alter the estimation of actual flow paths (e.g., runoff traveling along roads before entering a sewer inlet), although changes in the boundaries may influence the volume of runoff entering the sewer inlet. The stronger correlation strength between subcatchment area and width observed in the topography-based model suggests that this discretization approach may produce more consistent estimates of flow path lengths. Overall, the comparison of parameter values and the results of correlation analysis suggest that the topography-based discretization approach may yield more physically meaningful parameter values than the sewer geometry-based discretization approach.

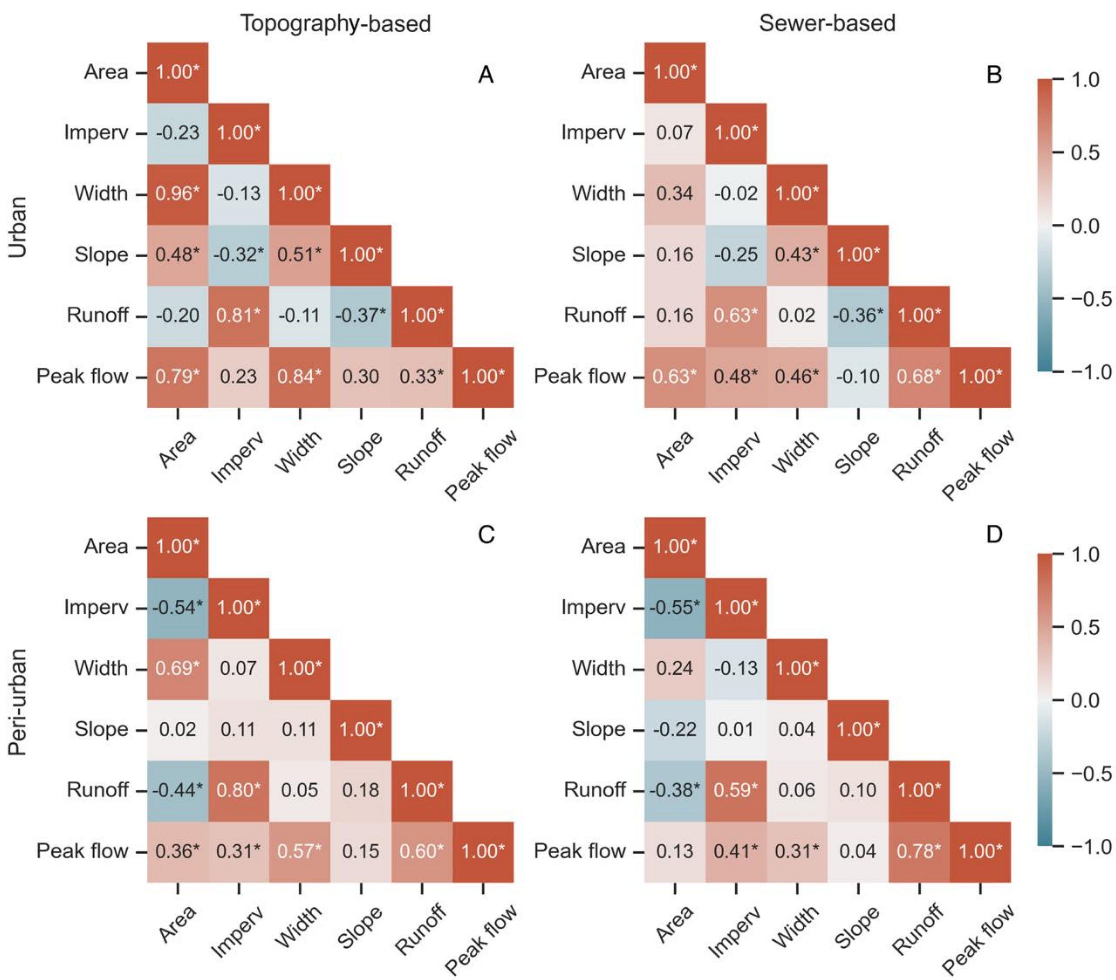

Figure 3. Spearman correlation coefficients across discretization-related subcatchment physical parameters (area, width, imperviousness, and slope) and model outcomes (subcatchment runoff volume, represented by runoff in the figure, and peak flow): (A) topography-based model for the upper urban watershed, (B) sewer geometry-based model for the upper urban watershed, (C) topography-based model for the lower peri-urban watershed, and (D) sewer geometry-based model for the lower peri-urban watershed. An asterisk (*) indicates values with $p < 0.01$.

3.3 Model performance evaluation

3.3.1 Overall model performance for continuous simulations

Continuous model calibration and validation results are provided in Figure 4 and Table S3. Both models achieved high NSE values (> 0.9) during calibration using 2021 flow data at the lower and upper watershed outlets, indicating good agreement between simulated and observed flows. At the upper outlet, NSE values were 0.96 for the topography-based model and 0.93 for the sewer geometry-based model. At the lower outlet, NSE values were 0.95 and 0.91, respectively. Validation using 2022-2023 data suggests slightly reduced model performance for both models, but the simulated flows still matched well with the observations, with all NSE values > 0.8 except for the sewer geometry-based model at the lower outlet in 2022 (0.64). In addition, at the upper outlet, the topography-based model produced smaller absolute runoff volume errors (-6.5% and -13.2% for 2022 and 2023, respectively) and peak flow errors (2.6% and -8.1%) compared to the sewer geometry-based model, which had volume errors of -28.1% and -22.6%, and peak flow errors of 2.6% and -19.5% for 2022 and 2023, respectively (Table S3 and Figure S3). Similar differences in runoff volume and peak flow errors between the models were observed at the lower outlet, except in 2023, when the absolute runoff volume error for the topography-based model (25.1%) was higher than that of the sewer geometry-based model (-8.1%).

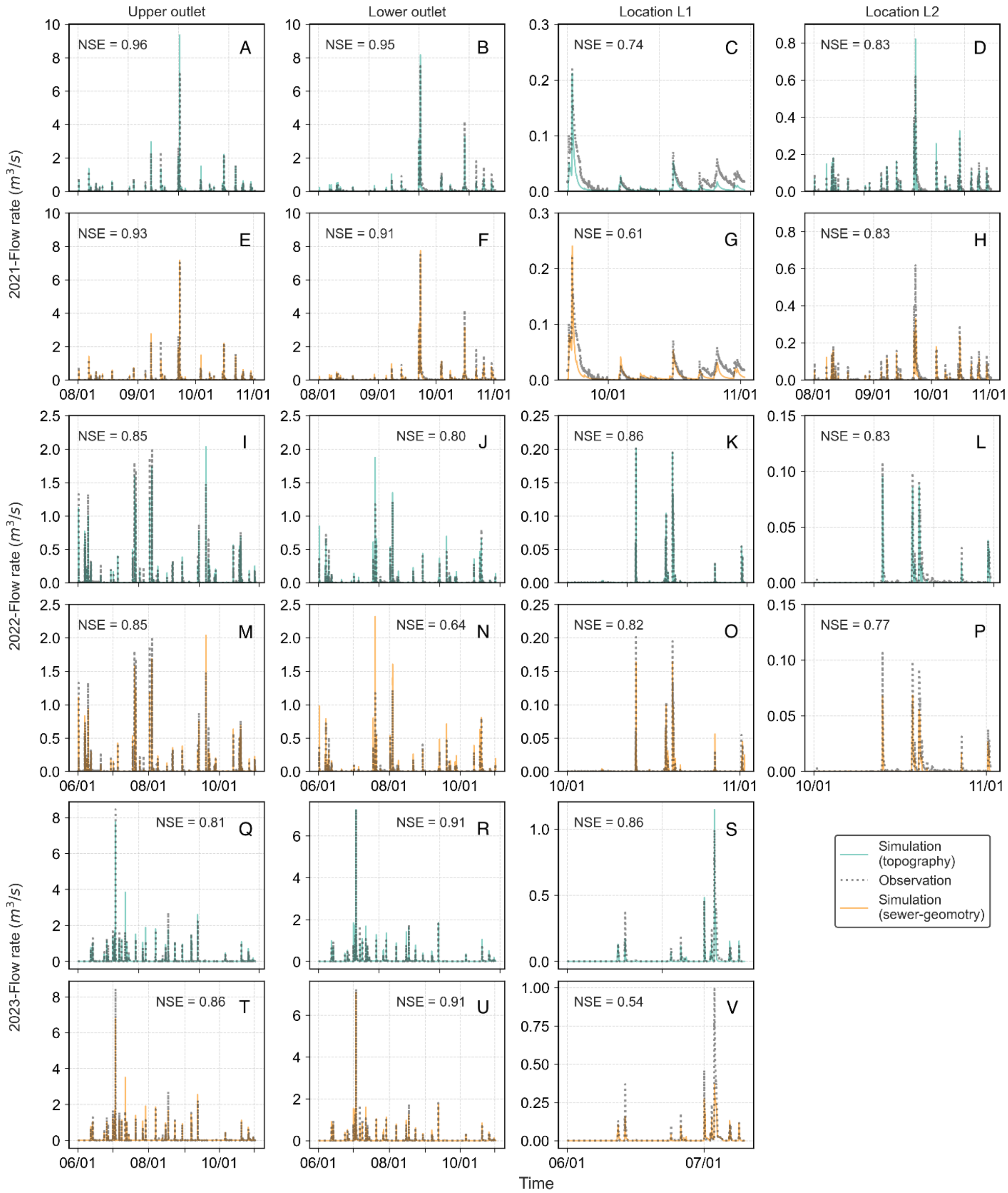

Figure 4. Simulation results at the upper and lower outlets and at the two flow monitoring locations within the upper (L1) and lower (L2) watersheds. Data from 2021 at the two outlets

were used for model calibration (A–H), while the remaining data were used for model validation (I–P for 2022 and Q–V for 2023).

Flow residuals at the upper outlet from the two models were similar and tightly clustered around the 1:1 line ($R^2 = 0.92$, Figure 5A). These results suggest that the discretization approach used had limited influence on error structure at the outlet of the urban watershed. In contrast, residuals between the two models diverged substantially at the lower outlet ($R^2 = 0.48$, Figure 5B). This indicates increased sensitivity to discretization approach used in peri-urban areas. In addition, for both models, residuals decreased as rainfall intensity increased (Figure 5C-D). This may be because infiltration, evapotranspiration, and groundwater processes become more important for smaller rainfall events particularly in the peri-urban area and it is possible that these processes may be less accurately represented (Dong et al., 2024b, Irvine et al., 2024, Vrugt et al., 2024). The lower model performance for the 2022 validation period could therefore be due to the relatively dry weather and the resulting low-flow conditions during that year. These findings indicate that the faster, simpler sewer geometry-based discretization approach may be sufficient for simulating outlet flows in urban watersheds. However, in peri-urban areas with more complex, terrain-driven runoff pathways, even though both models were able to capture the observed overall flow processes at the lower outlet, the topography-based model generally performed better than the sewer geometry-based model, as indicated by its relatively higher NSE values.

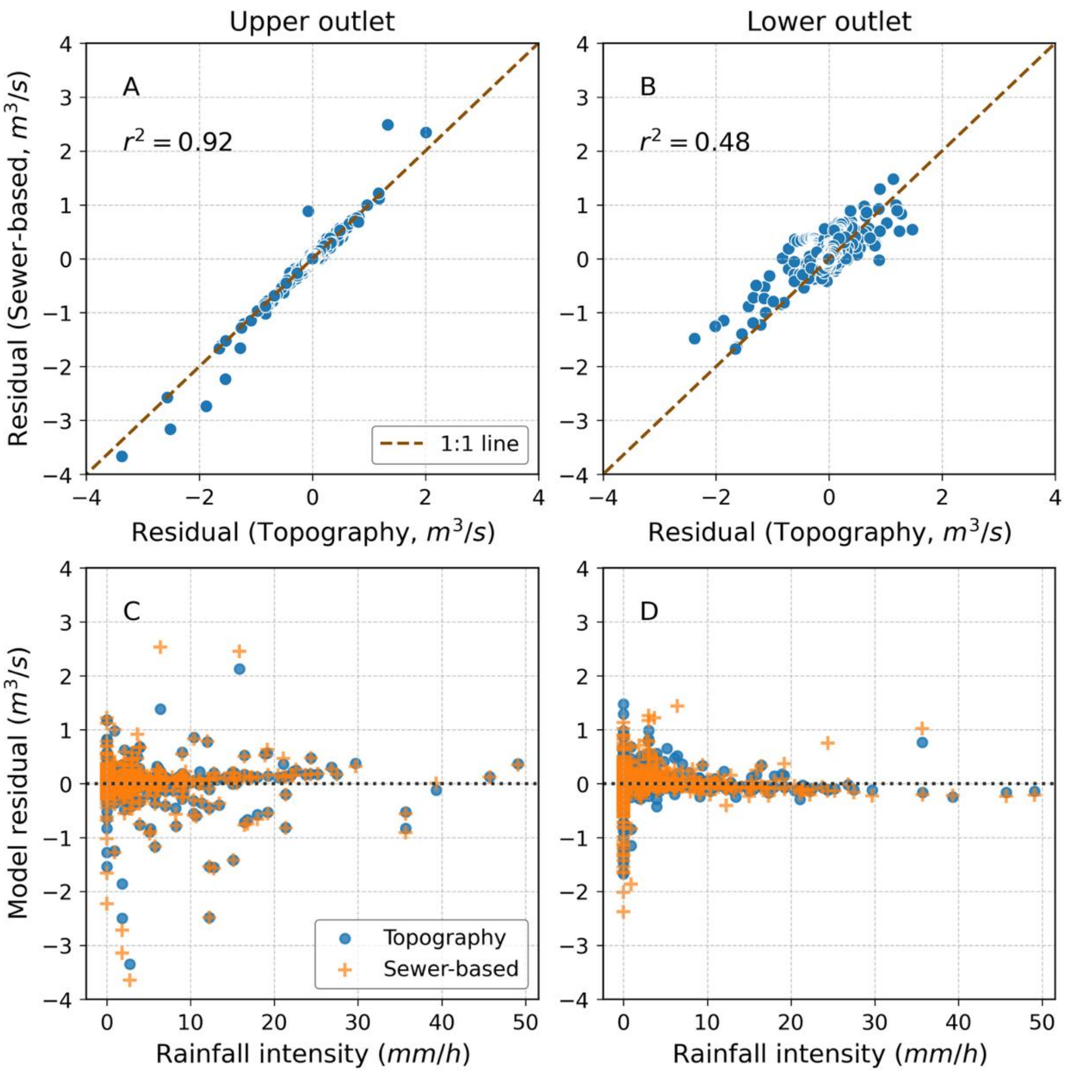

Figure 5. Comparisons of flow residuals (difference between simulated and observed flows) between the topography- and sewer geometry-based model at the (A) upper outlet and (B) lower outlet, and relationships between residuals and rainfall intensity at the (C) upper outlet and (D) lower outlet.

At the two monitoring sites located within the upper and lower watersheds (L1 and L2), although both models showed decreased performance compared to simulating flows at the watershed outlets, simulated flows from the topography-based model showed stronger agreement with observed flows compared with the sewer geometry-based model (Figure 4 and Table S3). The mean NSE values during the validation period were 0.82 and 0.83 at L1 and L2, respectively, for the topography-based model compared with 0.66 at L1 and 0.80 at L2, respectively, for the sewer-based model. At location L1, within the upper urban watershed, the lower performance of the sewer geometry-based model may be due to the less representative subcatchment boundaries generated using Thiessen polygons, as discussed in Section 3.2. In contrast, both models yielded similar NSE values at location L2, within the peri-urban area, where the relatively flat terrain and sparsely distributed drainage infrastructure potentially reduced differences caused by the varying drainage boundaries between the two models. However, when comparing runoff volume and peak flow errors (Table S3), the topography-based model still outperformed the sewer geometry-based model at location L2. Overall, these results indicate that while both models can effectively replicate observed flows at the outlets of urban and peri-urban watersheds (with comparable NSE values), the topography-based model was more consistent in simulating observed flows at the monitoring sites located within the watershed. Therefore, to further compare model performance in simulating outlet flows, the next section focuses on evaluating event-based model performance at watershed outlets.

3.3.2 Model performance across individual events

The total number of individual events ranged from 36 to 42, with a mean of 39 events over the simulation period (2021-2023). Model performance was evaluated at the event scale to examine the influence of rainfall characteristics on simulation accuracy (Figure 6). In general, better model performance was observed during larger rainfall events for the two models. At the upper outlet, the mean NSE values increased from 0.24 to 0.83 for the topography-based model and from 0.17 to 0.89 for the sewer geometry-based model as event depth increased from <10 mm to >40 mm. Correspondingly, the absolute mean runoff volume error decreased from 25% to 13% for the topography-based model and from 30% to 19% for the sewer geometry-based model. Further, the absolute mean peak flow error was reduced from 18% to 12% and from 30% to 12%, respectively, as the event depth increased from <10 mm to >40 mm. Although the reduction in mean time-to-peak errors was relatively small (~15 min) for both models as rainfall depth increased from <10 mm to >40 mm, the range of these errors decreased by more than fivefold. Similar trends in the performance metrics were observed for the lower outlet; however, the performance metrics exhibited greater variability at the lower outlet compared to the upper outlet, suggesting that accurately simulating stormwater flow in peri-urban areas, where natural and urban hydrological processes occur concurrently, is more challenging than in highly urbanized areas.

Overall, consistent trends in performance metrics across storm magnitudes and between the two models suggest that model performance was sensitive to event rainfall depth. Smaller storms (<10 mm) exhibited greater variability and lower accuracy, likely because the simplified formulations of infiltration and evaporation (e.g., the assumption of soil saturation in the Green-Ampt infiltration equation) may not fully represent the spatial and temporal heterogeneity of initial soil moisture conditions across subcatchments. Consequently, greater attention may be needed to improve the parameterization of these hydrological processes beyond the selection of an appropriate discretization method. It is possible that the observed influence of rainfall depth on model performance may be biased by the uneven distribution of events across rainfall categories (e.g., 61 events with rainfall depth <10 mm compared with 9 events with depth >30 mm). A more robust evaluation of model performance requires additional rainfall-runoff data to enable more balanced comparisons among rainfall depth categories.

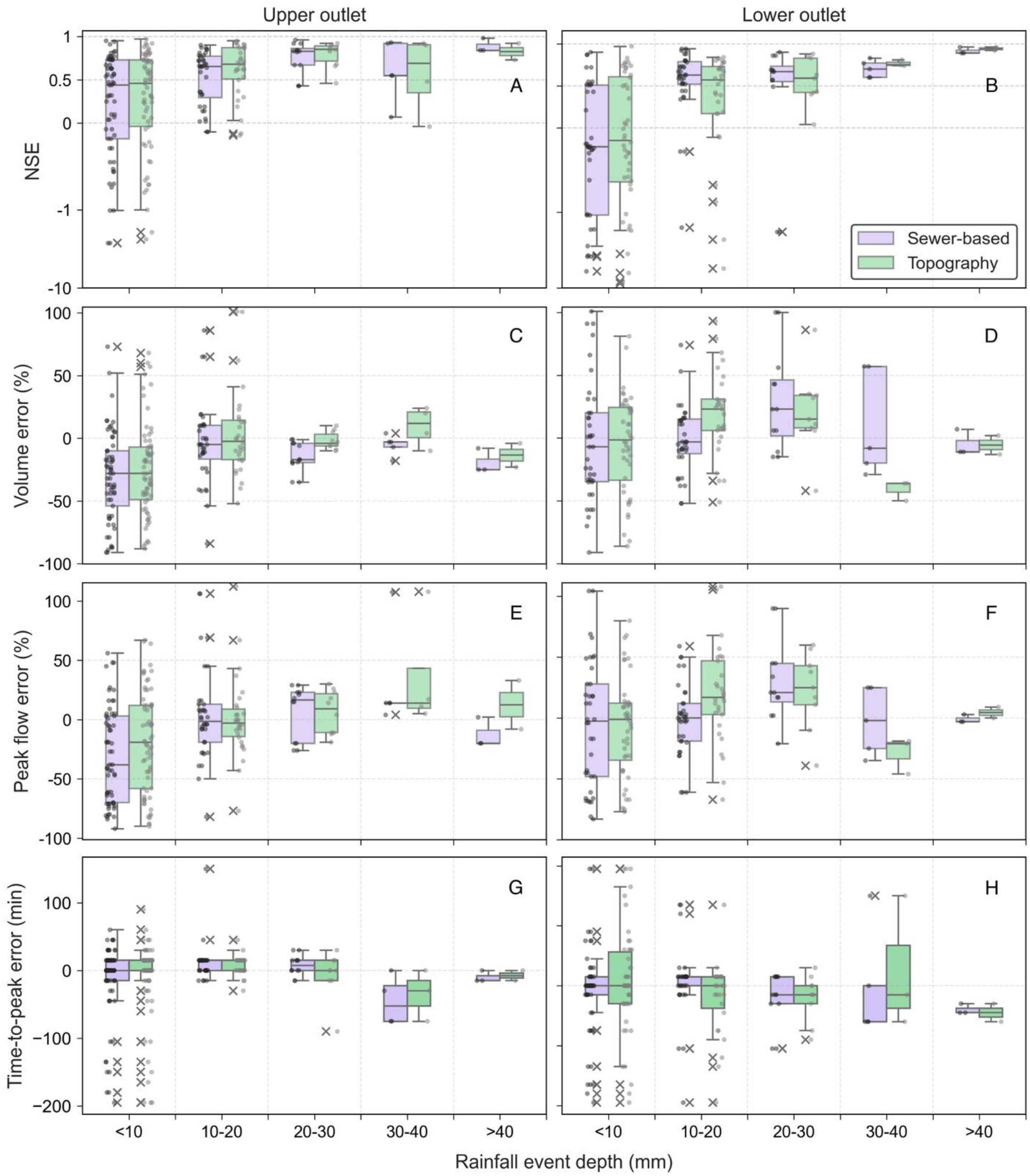

Figure 6. Comparison of (A-B) NSE values, (C-D) runoff volume errors (%), (E-F) peak flow errors (%), and (G-H) time-to-peak error (min) between the topography-based and sewer-based models for individual events. Comparison between events is presented in five event depth

classes: < 10mm, 10-20mm, 20-30mm, 30-40mm, and >40mm. Gray dots indicate the performance of individual events. For readability, NSE values between -1 and 1 are presented on a linear scale, while values outside this range are shown on a log scale.

The effects of rainfall depth, discretization approach, and watershed land use characteristics on model performance were further assessed using a linear fixed-effects model (Table 1). Results show the linear fixed-effects model significantly explained the variance in NSE, peak error, and volume error (all $p < 0.001$; Table S4), whereas it did not significantly explain the variance in time-to-peak error ($p = 0.21$). Across all performance metrics evaluated, land use characteristics were a statistically significant predictor of model performance. Note that the lower watershed outlet and sewer geometry-based model were designated as the control group (zero values), so the regression coefficients provided in Table 1 represent differences relative to this baseline. Model performance at the upper urban watershed outlet was significantly better than at the lower outlet, with mean runoff volume and peak flow errors 0.1 and 0.2 lower, respectively, and a mean NSE value that was 0.5 higher (Table 1). Rainfall depth was also a strong predictor. For every additional 1 mm of rainfall, the model indicates that the NSE value is expected to increase by 0.02 with all other variables constant. Similar improvements with increasing rainfall depth were observed in volume error (0.4% lower for additional 1 mm of rainfall) and peak error (0.7% lower). However, discretization approach had no significant effect on any performance metric despite the topography-based model showing slightly better performance (e.g., higher NSE values) compared to the sewer geometry-based model at the upper outlet in the continuous simulations (Figure 4). These results suggest that performance of the model at watershed outlets is most influenced by land use characteristics (urban or peri-urban) and rainfall depth, with limited sensitivity to the watershed discretization approach used. In other words, for outlet flow simulations, the influence of spatial discretization could be mitigated through model calibration to achieve an overall water balance across the entire watershed. This was demonstrated in Section 3.2, where the sewer-geometry-based model exhibited weaker relationships between parameters and hydrological outputs, yet was able to replicate the observed outlet flows. Consequently, the effects of spatial discretization are more apparent in simulating flows within the watershed (as shown in Figure 4 and Table S3). That said, despite its reduced accuracy in locations within the watershed, the sewer geometry-based model still generated acceptable results (all NSE values > 0.5). Overall, linear fixed-effects model further indicates that simpler delineation methods, such as the sewer geometry-based approach, may be an acceptable way to reduce model complexity without significantly compromising simulation accuracy at the outlet.

Table 1. Results of the fixed effects model for the four performance metrics (NSE, peak flow error, volume error, and time-to-peak error). The model includes rainfall depth, discretization approach, and watershed land use characteristics as possible explanatory variables. Values are reported as estimated coefficients when the p-value is <0.05. A sign of "-" indicates a coefficient is not statistically significant (p> 0.05), and thus is not reported.

	NSE	Peak flow error	Time-to-peak error	Volume error
Intercept	-0.3	-0.1	-20.8	-
Land use characteristics	0.5	-0.1	21.7	-0.2
Discretization approach	-	-	-	-
Rainfall depth	0.02	0.007	-	0.004

3.4 Implication and trade-offs

Our findings are consistent with previous studies reporting that the two discretization approaches can yield comparable watershed-scale water balance estimates in urban areas (i.e., at the outlet), such as similar peak flow predictions (Dong et al., 2022). However, our results extend this understanding by showing that the similarity in water balance estimates tends to decrease, although not significantly, in peri-urban watersheds, where the topography-based approach is able to better represent actual flow pathways and drainage boundaries, thereby enhancing flow simulations within the watershed. This finding suggests that the topography-based approach may be more appropriate to use across watersheds with varying land-use characteristics. Nevertheless, previous studies have noted that DEM resolution can substantially influence subcatchment delineation outcomes and model performance (Zhou et al., 2021, Sokolovskaya et al., 2023), and that high-resolution DEMs are not uniformly available across urban areas (Hawker et al., 2019). Therefore, the choice of discretization strategy should consider the spatial data availability, modeling objectives, and land use and drainage characteristics of the watershed.

Key considerations distinguishing the two approaches are outlined in Table 2. The topography-based model showed a strong relationship between physical parameters and hydrological responses, making it suitable for simulating flow processes within the watershed and assessing the impacts of land use changes or stormwater management scenarios (e.g., green infrastructure placement), when high-resolution spatial data are available. In contrast, the simplicity and efficiency of the sewer geometry-based discretization approach make it suitable for fast, large-scale applications, particularly when sewer datasets are the primary spatial input and the model objective is on sewer hydraulics at the outlet, such as simulating combined sewer overflows (CSOs). However, this simplicity comes at the cost of reduced hydrological interpretability of parameter values and a lower capability to simulate flows at locations within the watershed. A hybrid discretization approach may also be applied by integrating topography-based surface delineation with geometry-based drainage representation. This approach can be useful in data-limited areas, where low-resolution or incomplete spatial data could introduce substantial uncertainty in defining flow pathways and drainage boundaries. In such cases, hybrid discretization provides means to adjust model configurations to balance the influence of topographic conditions and sewer infrastructure distributions on flow routing, thereby supporting exploratory and preliminary analyses for design and planning purposes.

Table 2. Key differences between topography-based and sewer geometry-based discretization approaches.

Aspect	Topography-Based Approach	Sewer Geometry-Based Approach
Stormwater flow prediction at the outlet	High accuracy	Moderate to high accuracy
Simulation of flows within watershed	High accuracy	Adequate overall but less accurate for peak flow
Hydrological representation	Strong correlation between physical parameters and hydrological processes	Relatively weak correlation
Drainage characteristics	Preserves terrain-driven overland flow paths	Tends to generate long, narrow overland flow paths
Rainfall depth impact	High impact on performance	High impact on performance
Implementation complexity	Requiring high resolution DEM, spatial processing, and expert judgment	Low DEM data requirement and single Thiessen polygon generation
Watershed suitability	Both urban and peri-urban watersheds	Better for urban watersheds
Case suitability	Preferred when surface heterogeneity is an important consideration. Better for scenarios of land use, GI design, flooding detection	Effective when primarily interested in outlet flow responses, suitable for fast drainage planning and scenario testing in areas with reliable sewer data but limited high-resolution DEMs

Finally, it is important to note that while the findings of this study should be transferable for moderately sized mixed watersheds, uncertainties in drainage boundary delineation and parameter estimation may propagate and accumulate through flow routing from smaller to larger scales. That is, when these approaches are applied to larger or more complex systems, the influence of subcatchment delineation on watershed-scale water balance estimates may become more pronounced. Therefore, future research should further assess the scalability of these discretization approaches in larger and more heterogeneous watershed settings.

4. Conclusion

This study evaluated the influence of topography-based and sewer geometry-based discretization strategies on stormwater flow simulations across spatial scales, as well as their effects on model hydrological representation and parameter interpretation in a mixed urban and peri-urban watershed. Simulation results showed that both models were capable of reproducing observed watershed outlet flows (e.g., mean NSE values of 0.88 and 0.85 for the topography-based and sewer geometry-based models, respectively). However, topography-based discretization produced parameter values with greater hydrological interpretability and yielded more consistent model performance in simulating flows at monitoring sites located within the watershed, with NSE values ranging from 0.74–0.86 compared to 0.55–0.83 for the geometry-based model. It is important to note that discretization outcomes from the topography-based approach can be affected by DEM resolution, which will in turn influence parameter estimation and model performance. As a result, in data-limited areas where high-resolution DEMs are unavailable, the sewer geometry-based approach can provide a simplified, yet efficient and practical, alternative for watershed discretization, particularly when the simulation objective is on outlet flows.

It is expected that when these approaches are applied to larger or more complex systems, uncertainties in drainage boundary delineation may propagate from smaller to larger scales, leading to more pronounced effects on watershed-scale water balance. Therefore, future work is needed to evaluate how parameter estimates and model performance vary in larger and more complex watershed settings, and to assess how spatial scale influences model calibration and validation under different rainfall and land-use conditions. Overall, this study highlights the significant influence of discretization strategy choice on model robustness across spatial scales and provides practical guidance for urban stormwater modelers and planners in selecting an appropriate modeling approach based on watershed land-use characteristics and data availability.

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