Effect of storm network simplification on flooding prediction with varying rainfall conditions

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Abstract. In the context of climate change and urban expansion, cities are increasingly vulnerable to floods for increased frequency of rainfall extremes. Timely and accurate flooding prediction is crucial to reduce the losses of life and property. Despite its crucial role in urban hydrologic modelling, storm network, as a key component of urban drainage system, has to be simplified because of both the data availability and computation power. Current literatures have noted the effects of storm network simplification (SNS), while the understanding is limited to certain models and conditions and still far from sufficient. In this study, a grid-based urban hydrologic model was employed to further investigate the effects of SNS on flooding prediction under varying rainfall conditions. The results show that SNS significantly affects both peak flow and total flow volume, while simplification to different degrees may lead to opposite effects. Larger degree of simplification leads to underestimation of flooding magnitude, while smaller degree of simplification results in overestimation of flooding magnitude. More importantly, the simulation bias caused by SNS is further amplified with increased rainfall intensity and peak ratio, especially for higher degree simplifications where the underestimation bias of river discharge can be as large as three times. Through qualitative and quantitative analysis, this study helps to further understand the effects of SNS, and provides some bias estimation for flooding prediction and management in urban areas.

1. Introduction

Storm network, as one of the key drainage facilities [1], can transport runoff to river rapidly [2], playing an important role in urban flooding management. In urban areas, storm network is the dominant factor in controlling runoff volume [3], affecting both peak flow and water quality significantly. Proper storm network planning can not only mitigate waterlogging in the city [4], but also coordinate with the flooding management strategies of downstream city.

For hydrologic modelling and flooding prediction, the density and structure of storm network affect peak discharge even more significantly than land cover types [5]. Given the sensitivity of flooding prediction to the change of storm network, reasonable description of it is crucial to reproduce hydrologic process accurately [6,7]. While, in most cases, simplification of storm network has to be adopted due to the limits of available storm network data and computing power. Hence, in recent decades, extensive studies were conducted to investigate the effects of storm network simplification on hydrologic modelling. Park et al [8] studied simplification effects with the Storm Water Management Model (SWMM) and negligible effects on the simulated runoff volume was found. By constructing both actual and artificial drainage networks, Ghosh et al [9] found that the simplification of storm network leads to dual-scale effect, showing opposite results for larger and smaller rainfall events.
Krebs et al [10] noted that, despite the effects on runoff volume is negligible, simplification of storm network resulted in the overestimation of peak flow due to excessively rapid hydrologic response to storm events. Yang et al [11] examined the simplification effects in three different basins and found that change in the complexity of storm network lead to different influence on total runoff volume, depending on the number of drainage system in the catchment. For the catchment with only one drainage system, the effects are negligible. While significant effects are found in the catchment with multiple drainage systems. In the above studies, different degree of storm network simplifications were usually achieved with alternation of the catchment discretization at the same time, which yields complicated cumulative effects attributed to multiple impact factors instead of the change of storm network alone. Moreover, the variability of rainfall characteristics, induced by climate change and urbanization, is insufficiently taken into account in these studies, e.g. return period of rainfall, peak ratio and the integration of them.

Hence, in the context of climate change and urbanization, with rainfall extremes occurring more frequently [12,13] and rainfall characteristics varying a lot [14], this study is conducted to investigate the effects of storm network simplification on flooding prediction and further understand the affecting mechanism. A grid-based urban hydrologic model (section 3) was applied to study the simplification effects with consistent catchment discretization in a 3.3 km$^2$ urban catchment (section 2). For multiple simplifications of different degree and varying rainfall events (section 3), the effects on flooding prediction were quantitatively evaluated and discussed in section 4, with the introduced indicators (section 3). Consequently, section 5 conclude this study with some main findings.

![Figure 1. Location, land cover composition and spatial distribution of the study area.](image)

2. Study area
The study was conducted at a 3.3 km$^2$ urban catchment located at Haidian District, Beijing, China, as
shown in figure 1. Typical underlying surface features are contained in this catchment, as building, pavement, road, lawn and tree, etc. and the imperviousness coefficient approaches 50%. Artificial lining river channels, road networks and dense storm networks are constructed over the study area as main drainage facilities. Given the existence of the surrounding borders, negligible surface water exchange between this catchment and the adjacent catchments can be assumed, except discharges from river and several main roads.

In order to represent both the complex land cover composition and spatial distribution in urban catchment, we collected multiple sets of high-resolution data, including high-resolution land cover data, detailed surface elevation data, road data and fine drainage network data. Among them, the storm network data was provided by the administration department, including both dimension and storm network spatial distribution. The road networks and the river channels data were derived based on the imagery of Gaofen-2 (GF-2) satellite (made in China and launched in 2014). The land cover data with vector format was extracted from the same imagery as well, which contains 7 types, i.e., building, water, grass, shrub, tree, road and pavement. The data for Digital Elevation Model (DEM) of the catchment was generated from nearly 30,000 elevation points distributed over the study area.

3. Methodology

3.1. gUHM model

In light of the high complexity of both underlying composition and drainage system in urban catchment, a grid-based distributed urban hydrological model (gUHM) was constructed to capture the spatial heterogeneity in this study. Taking advantage of both the multi-level urban flooding model [15] and the distributed urban hydrological model [16,17], gUHM adopts a four-layer structure, i.e. surface, road network, storm network, and river network. Each grid is further subdivided into impervious and pervious areas, direct runoff is then calculated by subtracting infiltration and interception from the rainfall. If the grid contains road, the generated runoff will be routed into road network. Otherwise, it will be routed onto adjacent grid, according to the overland flow direction calculated by the D8 algorithm [18,19] based on the detailed elevation data. After flowing into the road network, the water will be further routed into the storm network through neighbouring manholes and finally flows into the river. According to this calculation flowchart, the urban hydrological process can be realistically described. The model contains three calculated components, i.e. surface runoff, overland flow, sewer and river flow. Among them, the Green-Ampt equation [20,21] is used to calculate the infiltration process at every grid and the one dimensional dynamic wave approach is utilized to simulate the flowing process in sewer and river systems. Overland flow calculation is a two-step process, including flowing inside the grid and routing between neighbour grids. The nonlinear reservoir algorithm [22] is used to simulate the overland flow inside the grid with slope and proper feature width, and then the routed flow is distributed uniformly over the downstream grid. The reliability and rationality of gUHM has been verified by a few studies [16], and hydrologic parameters are derived based on the related research in the same area. Among them, key parameters for urban hydrologic modelling were summarized in table 1, including the parameter of soil infiltration and the roughness of drainage system.

| Parameters                  | Calibration value |
|-----------------------------|-------------------|
| Suction Head (m)            | 210               |
| Conductivity (mm/h)         | 1                 |
| Initial Deficit (frac.)     | 0.15              |
| Roughness (Road)            | 0.011             |
| Roughness (Sewer)           | 0.012             |
| Roughness (River)           | 0.013             |
3.2. Simplification design

In order to investigate the effects of SNS on hydrologic modelling, simplifications of different degrees were designed based on the sewer diameter [11]. Figure 2 shows the distribution of both sewer number and sewer length of different diameter ranges, indicating the sewer diameters mainly concentrated in three intervals, i.e. 0-0.2 m, 0.2-0.4 m and 0.4-2 m. Hence, simplification degrees were set to be three levels, with the 1st degree of simplification removing the sewers with the diameter smaller than 0.2 m and the 2nd degree of simplification removing the sewers with diameters smaller than 0.4 m. For the 3rd degree of simplification, only road networks and the river channel were maintained with the whole storm network disconnected, as shown in figure 3. Among them, sub-figure (a) presents the base case, i.e. the storm network without simplification, while sub-figure (b), (c) and (d) present the simplified scenarios with 1st, 2nd and 3rd degree of simplification respectively. To maintain the same catchment discretization with varying storm network conditions, the study area was discretized into about 1,000 regular grids. In addition, the impervious properties of every grid are kept consistent among different scenarios, avoiding the simulation difference in runoff process.

![Figure 2](image)

**Figure 2.** The distribution of sewer diameters: (a) distribution of total number of different diameters; (b) distribution of total length of different diameters. PD_n and PD_d denote the probability density of different diameter ranges of total number and total length respectively.
3.3. Rainfall design

In the context of climate change and urban expansion, there exhibit a tendency that both the extremes of rainfall event and the complexity of rainfall characteristic increase simultaneously. Moreover, given the inherent characteristics of urban catchment with high impervious rate and fast hydrologic response, thereby easily facilitating the transferring from rainfall to runoff to even floods, hydrological response shows significant sensitivity to variations in rainfall conditions. Hence, taking into account the variation of rainfall characteristics, e.g., the variation of rainfall intensity and peak ratio, is necessary. In this study, the input rainfall data was derived from the regional storm intensity formula (SIF) in Beijing, China [23,24], which represents an Intensity-Duration-Frequency (IDF) relationship as follows:

\[
p = 12.004 \times \frac{(1 + 0.81 \times \log P)}{(t + 8)^{0.711}}
\]

where \( p \) denotes the rainfall intensity (mm/min), \( t \) denotes rainfall duration (min), and \( P \) equals to the return period (year). Among them, the return period of rainfall was set as 1 year, 10 years and 100 years to consider the varying rainfall intensity. The rainfall duration was set as 2 hours according to the diurnal characteristics of summer rainfall over Beijing city [25], where rainfall events with 1-3 h
duration make a considerable contribution to both amount and frequency of summer rainfall. Subsequently, the Chicago Storm Profile [26-28] was used to generate the rainfall hyetograph with different rainfall peak ratios \( r \). i.e., with different relative location of rainfall peak during the total rainfall duration. Considering peak ratio \( r \) is a coefficient ranging from 0 to 1, 0.2, 0.5 and 0.8 were adopted to cover the variation of rainfall pattern. Thereby, 9 types of rainfall events were designated in this study (as in figure 4), with varying return period and peak ratio of rainfall.

![Figure 4](image-url)  
**Figure 4.** Rainfall input with varying return period (1yr, 10yr and 100yr) and peak ratio (0.2, 0.5 and 0.8). The yr denotes year, e.g., 1yr represents the return period of a rainfall event is one year.

### 3.4. Evaluation indicators

Both dimensionless and dimension indicators (in table 2) were used to quantitatively evaluate the effects of SNS on flooding prediction [29,30]. Given peak flow and total flow volume are key descriptors of flooding magnitude in river and an important induce to waterlogging, both were considered in this study. In addition, both absolute error and relative error were taken into account due to the varying rainfall intensity. In the indicator equations, the subscript \( s \) denotes simplification scenarios, while the subscript \( i \) denotes the initial scenario without storm network simplification, e.g., \( PR_s \) and \( PR_i \) are the simulated peak flow of river under simplification scenarios and initial scenario respectively, and \( TR_s \) and \( TR_i \) are the simulated total outflow volume of river under simplification scenarios and initial scenario respectively. In order to evaluate comprehensively the effects and to further understand the affecting mechanism, the total runoff and the total outflow volume from the whole catchment (i.e. considering the water volume flowing out by several main roads) were focused on as well, which might affect the flooding prediction of a larger spatial scale. Among them, \( R \) denotes the total runoff generated in the catchment, and \( TC \) denotes the total outflow volume flowing out by both the river and roads.
Table 2. Indicators used to quantify the effects of storm network simplification on flooding prediction.

| Indicator | Description | Unit | Equation | Equation number |
|-----------|-------------|------|----------|----------------|
| PE        | Absolute error in the peak flow of river | m³/s | PE = PR_s - PR_i | (2) |
| RPE       | Relative error in the peak flow of river | - | RPE = PR_s - PR_i | (3) |
| TE        | Absolute error in the total outflow volume of river | 10^4 m³/s | TE = TR_s - TR_i | (4) |
| RTE       | Relative error in the total outflow volume of river | - | RTE = TR_s - TR_i | (5) |
| TE_c      | Absolute error in the total outflow volume of all outlets in the catchment | 10^4 m³/s | TE_c = TC_s - TC_i | (6) |
| RTE_c     | Relative error in the total outflow volume of all outlets in the catchment | - | RTE_c = TC_s - TC_i | (7) |
| RE        | Absolute error in the total runoff of catchment | mm | RE = Rs - Ri | (8) |
| RRE       | Relative error in the total runoff of catchment | - | RRE = Rs - Ri | (9) |

Figure 5. Effects caused by storm network simplification on flooding hydrograph at the river outlet under varying rainfall conditions. BC denotes base case, i.e. the initial scenario without storm network simplification; S1, S2 and S3 denote 1st, 2nd and 3rd degree simplification scenarios respectively.
4. Results and discussion

4.1. Effects on flooding hydrograph at the outlet

Figure 5 shows that the effects of SNS on flooding prediction are varied with both varying simplification degrees and varying rainfall characteristics. Although the effects on the shape of flooding hydrograph and the occurring time of peak flow are negligible, it may lead to enormous difference in both total outflow volume and peak flow at the river outlet. Among them, higher degree simplification (e.g. S2 and S3) of storm network leads to more water transported to other directions by the road system, and then leads to decreased peak flow and total outflow volume at the river outlet. However, the effects for lower degree simplification (e.g. S1) are dramatically opposite, where SNS leads to overestimation of both the peak flow and the total outflow volume, especially under intensive rainfall conditions. The reason for this antinomy is that denser storm network has a dual effects on flooding prediction. On the one hand, denser storm network can significantly promote drainage capacity and rapidly transport more runoff to the river. On the other hand, it also leads to more overflow from the storm network due to the excessively captured runoff from the total study area.

![Figure 5](image_url)

**Figure 6.** Effects of storm network simplification on flooding prediction under varying rainfall intensity. Different lines refer to different scenarios and the black vertical lines refer to the range of simulation bias compared to base case under specific rainfall intensity. BC denotes the base case, i.e. the initial scenario without storm network simplification; S1, S2 and S3 denote 1st, 2nd and 3rd degree simplification scenarios respectively.
4.2. Effects under varying rainfall intensity

Given the high impervious rate and perfect drainage system in urban catchment, urban hydrologic modelling is significantly sensitive to the change in rainfall characteristics, especially rainfall intensity [31]. Figure 6 indicates that increased rainfall intensity significantly increases the simulation errors in both the peak flow and total flow volume at the river outlet, despite basically unchanged relative errors. Among them, increased rainfall intensity contributes to the overestimation and underestimation of river flooding in lower and higher degree simplification scenarios respectively. In addition, SNS leads to decreased runoff from the catchment due to the limited storm network, which decreases the directly connected impervious area [32,33] and in turn causes runoff generated from impervious areas to infiltrate more. More importantly, the underestimation is aggravated by increased rainfall intensity as shown in sub-figure (g) of figure 6. Considering the decreased runoff from the catchment and increased ponding on the road due to the limited storm network under simplification scenarios, higher degree simplification of storm network reduced the total outflow volume from the catchment (in sub-figure (e) and (f) of figure 6). However, more overflow occurs under the initial scenario with increased rainfall intensity, leading to larger overestimation under S1 scenario but smaller underestimation under S2 and S3 scenario.

![Figure 7](image)

**Figure 7.** Effects of storm network simplification on flooding prediction under varying peak ratios. Different line refers to different scenarios and the black vertical lines refer to the range of simulation bias compared to base case under specific rainfall peak ratio. BC denotes base case, i.e. the initial scenario without storm network simplification; S1, S2 and S3 denote 1st, 2nd and 3rd degree simplification scenarios respectively.
4.3. Effects under varying peak ratio

Peak ratio is another important characteristic of rainfall event, except rainfall intensity, to which sufficient attention should be paid [34]. Although increased peak ratio causes negligible influence on the simulation errors in the total outflow volume at the river outlet, it significantly contributes to the simulation errors in peak flow (in sub-figure (a), (b), (c) and (d) of figure 7), where larger peak ratio lead to increased peak flow errors, i.e. simplified storm network can mitigate the increment of peak flow induced by larger peak ratio. In addition, increased peak ratio reduces the sensitivity of simulated river discharge to the varying rainfall to a certain extent, but higher degree simplification tends to yield increased sensitivity to the change in rainfall intensity (as shown by the black vertical line in sub-figure (a), (b), (c) and (d) of figure 7). Overall, the change in simulation errors of runoff caused by varying peak ratio can be disregarded (in sub-figure (g) and (h)), while both large and small peak ratio lead to decreased simulation errors in the total outflow volume from the whole catchment, especially in the scenarios of higher degree simplification, where different peak ratio alters the degree of both the overflow from storm network and the ponding water volume on the roads. Among them, storm network simplification leads to more ponding water on the road, and the bias increases with increased peak ratio. While increased peak ratio also leads to larger increment of overflow under the initial scenario compared to higher simplification scenarios, which plays a dominant role under the large peak ratio condition and yields the non-monotonic effects on flooding prediction with increased peak ratio.

5. Conclusion

The effects of storm network simplification (SNS) on hydrologic modelling is studied by applying gUHM to a 3.3 km² urban area with designed rainfall events of varying characteristics. The results revealed the followings.

SNS significantly affect flooding prediction by altering the ponding water on the road, overflow from the storm network and runoff generation, and simplifications of different degree yield opposite results. Simplifications of lower degree lead to the overestimation of the flooding magnitude at the river outlet due to underestimated overflow, while simplifications of higher degree result in underestimation of that due to both more ponding water volume on the road and less runoff captured by the simplified storm network. Under the most simplified storm network (scenario S3), the underestimation bias in peak flow and total flow volume of river are as high as 30 m³/s and 200,000 m³ respectively.

In addition, the effects of SNS on flooding prediction at the river outlet is further amplified with increased rainfall intensity and peak ratio, especially under higher simplification conditions where underestimation bias of river flooding magnitude can be trebled. It is noteworthy that decreased peak ratio increases the sensitivity of simulated results to the change of rainfall intensity, despite reducing the simulation bias. Evaluating the effects of SNS on flooding prediction from a larger spatial scale, i.e. focusing on the runoff and total outflow volume from the whole catchment, the results present more sensitivity to the change of rainfall intensity compared to the change of peak ratio. A opposite variation tendency of the effects of SNS with increased rainfall intensity was noted between high degree and low degree simplification, where simplification of high degree yields reduced underestimation in total flow with increased rainfall intensity, but simplification of low degree yields increased the overestimation.

This study improved the understanding of the effects of SNS especially under varying rainfall conditions, and provided urban planners and policy makers with estimation of bias caused by limited storm network data. Future research will be done to explore the effects of storm network generalization instead of simplification.

Acknowledgments

This work was funded by National Natural Science Foundation of China (51679119) and the National Key Research and Development Program of China (2018YFA0606002). The authors thank Tsinghua
University for providing pipe data.

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