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A drainage network-based impact matrix to support targeted blue-green-grey stormwater management solutions

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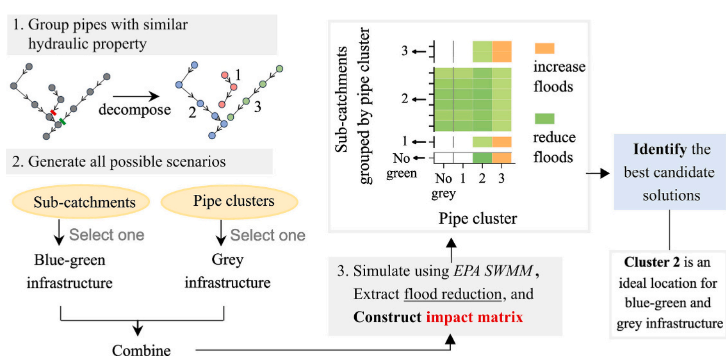
HIGHLIGHTS

- A pipe cluster-based flood impact matrix method is proposed.
- Locations for flood mitigation interventions (blue-green-grey) are identified
- Identified flood locations depend on pipe cluster and connected sub-catchment characteristics
- Flood interventions choice (blue-green or hybrid) depends on the magnitude of flooding
- Grey interventions may shift floods downstream that can be compensated by BGI implementation

GRAPHICAL ABSTRACT



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ABSTRACT

Urban floods will continue to be an alarming issue worldwide due to climate change and urban expansion. The costly and less environmentally friendly grey infrastructure is not always the most adequate solution to resolve urban pluvial flooding issues. The combination of grey and blue-green infrastructures, also called hybrid infrastructure, has been considered a promising solution for urban stormwater management. Existing approaches for identifying suitable hybrid solutions frequently rely on global multi-objective optimization algorithms. We developed a pre-screening method that decomposes a drainage network into clusters of pipes connected to sub-catchments, based on pipe hydraulic characteristic that allows for the impact of infrastructure combinations (blue-green and grey) to be mapped. Four impact matrices are proposed to map the total, local, upstream, and downstream flood reduction of all possible blue-green, grey, and hybrid solutions. Using an urban catchment in Guangzhou (China) as a case study, results showed that such an exercise could identify prime candidate locations for blue-green and grey infrastructure while filtering out ineffective locations for flood reduction. Furthermore, the impact matrices enabled the identification of flood zones where blue-green infrastructure could handle flood mitigation without the need of local grey infrastructure upgrades. As such, they are not only useful for quick screening of suitable interventions for each flooded zone, but can also potentially serve as a priori knowledge

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before diving into the data and computationally expensive process of finding the most effective flood mitigation solutions.

1. Introduction

Floods are among the most prevalent natural hazards in urban areas, due to the replacement of natural vegetation by anthropogenic impervious materials such as concrete and asphalt (Bonneau et al., 2017; Li et al., 2020; Paprotny et al., 2018). These materials reduce stormwater infiltration and alter the natural hydrologic cycle, thereby increasing surface runoff. Concurrently, it is expected that 6.7 billion people will live in cities by 2050 (United Nations Department of Economic and Social Affairs, Population Division, 2018) and urban areas are projected to experience more extreme precipitation events due to climate change. Urban pluvial flood reduction is, therefore, critical to ensure the safety and well-being of urban residents.

Traditionally, grey infrastructures involving structural measures such as drainage pipes, channels, and storage tanks are the primary means of traditional urban drainage management. They are designed to collect surface runoff in a connected drainage system and to drain it away from cities as fast as possible. However, their fixed capacity is gradually showing deficiencies in meeting the additional stresses induced by increasing impervious surfaces associated with rising occurrence of extreme rainfall events due to climate change (Wouters et al., 2016; Marlow et al., 2013). Furthermore, the cost of renovating grey infrastructure is large. In response to these changing circumstances, policymakers are turning to blue-green infrastructures (BGI) (Brears, 2018; Joshi et al., 2021; Bach et al., 2020), also frequently known as Nature-Based Solutions (NBSs) or Low Impact Development (LID) practices (Fletcher et al., 2015). The common goal behind these strategies is the use of nature-inspired solutions such as green roofs, porous pavements, and bio-retention cells to mimic the natural water cycle and attenuate peak discharges by reducing surface runoff water (Chang et al., 2018). BGI systems can also provide additional environmental benefits, such as receiving water bodies pollution mitigation (Fowdar et al., 2021), air quality improvement (Jayasooriya et al., 2017), local microclimate regulation (Gobatti et al., 2023), biodiversity enhancement (Molné et al., 2023), and overall improvements to urban amenity (Hoyer et al., 2011).

BGI are usually not sufficient for flood control during heavy rainfall events (Vineyard et al., 2015). Nevertheless, Jamali et al. (2020) have previously demonstrated that these systems can still deliver significant flood mitigation benefits for smaller, frequent storms that nevertheless cause significant surface ponding and cumulative damage to local infrastructure. Compared to traditional stormwater management approaches that rely solely on BGI or grey infrastructure, some attention has been paid to their combination or so-called ‘hybrid’ solutions (Beloqui, 2020; Browder et al., 2019; Lund et al., 2019; Li et al., 2019; Kapetas and Fenner, 2020). Xu et al. (2019) selected the best hybrid solution from predefined hybrid schemes using the Analytic Hierarchy Process. Chen et al. (2021) compared different flood mitigation strategies (blue-green, grey, or hybrid) using hydraulic models, while Dong et al. (2017) assessed the resilience to climate change. The results of their study consistently showed that hybrid infrastructure systems are generally more effective in managing stormwater and adaptable to external uncertainties compared to systems relying solely on either blue-green or grey infrastructure. Consequently, many researchers have developed simulation-optimization frameworks that integrate the hydraulic models with optimization algorithms in order to maximize the benefits of hybrid solutions while minimizing their costs (Alves et al., 2016; Martínez et al., 2021; Gao et al., 2022). The simulation-optimization frameworks allow for exploring a wide range of solutions, leading to potentially better outcomes compared to scenario-based methods. However, they are computationally demanding and can generate different solutions presenting similar results.

A few researchers have attempted to enhance the efficiency of optimization computations and solutions quality by reducing search space (i.e., the number of decision variables that are being solved). Wang and Shan (2004) successfully obtained multiple noteworthy subspaces by utilizing multiple sampling techniques to map an optimized performance space to a design space. Results showed that optimization with a reduced search space can expedite the process while still capturing the optimal solutions. Ngamalieu-Nengoue et al. (2019) and Bayas-Jiménez et al. (2021) pre-simulated all possible locations in a catchment of storage tanks to identify promising options for optimization, which resulted in improved performance with less computational burden compared to global optimization methods. In the field of layout optimization for hybrid solutions, the question arises: how can we gain prior knowledge about areas where implementing hybrid infrastructures would likely result in significant benefits for stormwater management? Despite research efforts, there is still a lack of a suitable approach that can address this question.

The unit flood response (UFR), achieved by iteratively run model omitting rainfall in individual sub-catchment, was widely used to identify source areas significantly contributing to flood risk (Singh et al., 2021). Vercruysse et al. (2019) and Dawson et al. (2020) linked UFR method with existing urban infrastructure systems to prioritise BGI intervention locations for flood management. Furthermore, Zeng et al. (2019) developed three siting strategies for BGI, distributing BGI at the upstream, midstream, and downstream locations of their study area. The purpose was to investigate the impact of BGI location on flood mitigation, and the results highlighted the critical role of BGI placement in enhancing the effectiveness of flood control. To determine the precise location where BGI can achieve high flood reduction, Zischg et al. (2018) implemented BGI in each sub-catchment individually. Wu et al. (2023) pointed out that this method did not account for the interaction between BGIs across various sub-catchments. They utilized the extended Fourier Amplitude Sensitivity Test for global sensitivity analysis to identify priority locations. Notably, this alternative method introduces additional complexity and a much higher computational burden. Although these methods effectively identify priority locations for BGI implementation, they do not encompass the potential location identification of grey infrastructure or hybrid solutions. Singh et al. (2023) tested different rainfall removal rates for a more realistic representation of the real system drainage capacity, but they did not prioritise the grey infrastructure that contributes more in flood control. Comparative analysis conducted by Cheng et al. (2022) revealed that optimal intervention (BGI, grey, or hybrid) vary across different flood-prone regions, depending on the underlying causes of flooding. Their approach involved enlarging the diameters of all pipes in the study area but does not allow for the precise identification of the optimal location for implementing grey solutions for flood control. Conducting a sensitivity analysis of grey infrastructure, as such, is not as straightforward as BGI sensitivity analysis in each sub-catchment, as it is not possible to treat each pipe as an individual unit since changing the diameter of one has implications for the diameters of its neighbouring pipes located downstream.

To the best of our knowledge, there is still a lack of understanding on how to prioritise grey and blue-green flood mitigation interventions based on hydraulic characteristics of the drainage system and its contributing catchments. This understanding can provide valuable insights into determining the most suitable flood mitigation intervention for each specific area of the system. This study proposes an exploratory approach that constructs so-called impact matrices to identify which type of flood mitigation solutions (blue-green, grey, or hybrid) should best be considered spatially across a catchment. This study addresses two specific objectives: i) how do we best decompose a centralized drainage network into clusters for targeted grey infrastructure upgrades (our primary criterion is based on surcharge conditions), and ii) how do we map the extent to which BGI, grey and hybrid solutions can reduce flooding overall, locally, upstream and downstream. Our proposed methodology can serve as a blueprint for planners in assessing potential flood reduction or as a priori input to current approaches in multi-objective global optimization algorithms (e.g., narrowing down search space for genetic algorithms).

2. Methodology

Our proposed workflow is illustrated in Fig. 1. A drainage network with its connected sub-catchments is first partitioned using the Louvain algorithm (Blondel et al., 2008). After an initial pre-simulation of baseline scenario without any solutions (here, we use EPA SWMM (Rossman et al., 2010) to obtain key performance indicators), the drainage network is converted to an undirected graph in which edge weights are represented as surcharge hours of each node (Section 2.1). Then, based on graph decomposition results, a One-Factor-At-a-Time method (Czitrom, 1999) is used to construct a matrix of sub-catchments vs. pipe clusters to analyze the interaction between grey and blue-green infrastructures and identify vulnerable areas (Section 2.2). The total computation time depends on the multiplication of the time taken for each individual simulation and the number of scenarios, which is the product of (the number of sub-catchments +1) and (the number of pipe clusters +1). The one refers to the scenario without any BGI or grey infrastructure. This method provides a transferable and comparable approach for an urban catchment with drainage network to identify optimal locations for BGI and grey infrastructure for flood management.

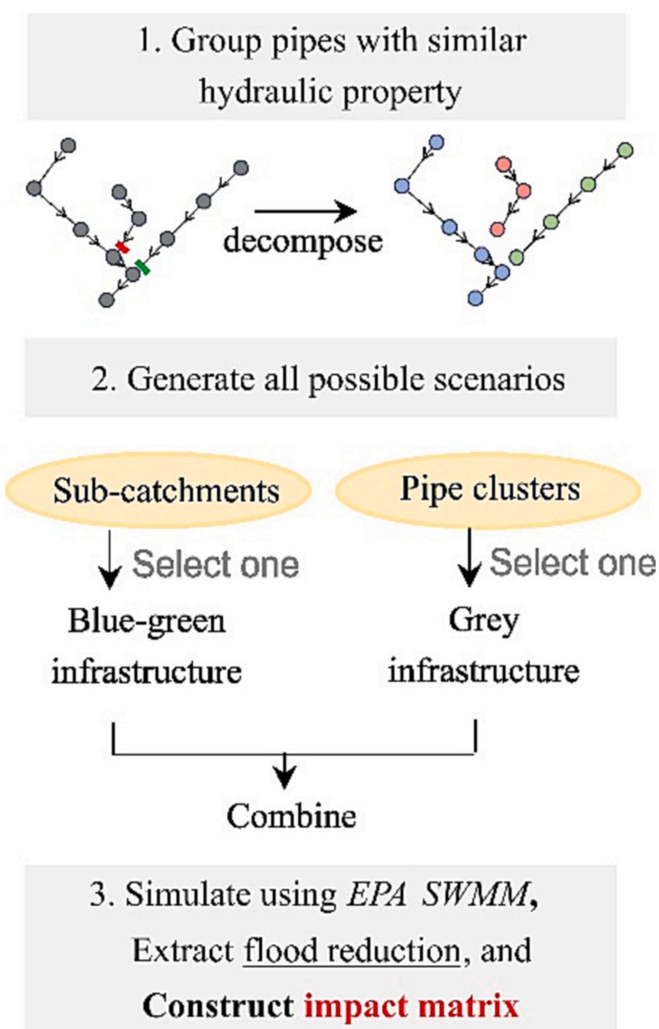

Fig. 1. Workflow to generate a flood mitigation impact matrix for blue-green, grey and hybrid solutions.

In this study, we represented changes to grey infrastructure as the increase in pipe diameter to that of its immediately adjacent downstream pipe cluster. BGI options are numerous in SWMM, but in this study we represent a BGI implementation in a sub-catchment by setting the sub-catchment impervious area to zero. This would simulate conditions of natural catchment hydrology. Apart from these modifications, other factors such as slope and drainage connection remained unchanged.

2.1. Identifying pipe clusters

The layout of urban drainage system is often represented as a graph G consisting of a set of vertices V (manholes) that are interconnected through a set of links or edges E (conduits) (Hesarkazzazi et al., 2022). In this study, our goal is to partition the system to identify pipe clusters with similar hydraulic characteristics and performance associated between them. To achieve this, we abstracted the network into a relational graph where conduits are represented as vertices rather than edges, which are defined by the performance occurring between them. Thus, we assigned surcharge hours of the nodes as edge weights to then allow the algorithm to group the pipes. The greater the value of surcharge hours, the higher the probability of flooding. Quality of the partitioning is measured by modularity Q (Newman, 2004), defined as Eq. (1).

$$Q = \frac{1}{2m}\sum_{i,j}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j) \tag{1}$$

$$m = \frac{1}{2}\sum A_{ij} \tag{2}$$

where A_{ij} denotes the weight of connection between nodes i and j, m denotes the sum of the weights of all the edges in the network, $\delta(c_i, c_j)$ is 1 if vertices i and j are in the same partition and 0 otherwise, $k_i = \sum_j A_{ij}$ and $k_j = \sum_i A_{ij}$ represent the sum of the weights of the links attached to i and j, respectively.

The Louvain algorithm proposed by Blondel et al. (2008) has been widely used in many application domains for community detection. It can find high modularity partitions efficiently by greedily maximizing the modularity gain ΔQ when moving an isolated node i into community c, defined by Eq. (3). Two steps are applied for modularity partition, as follows.

Step 1: Generate pipe clusters.

For each vertex i, repeat the following steps until no further increase in ΔQ for each vertex i is detected.

a. Assign vertex i to its neighbouring clusters and calculate ΔQ, respectively;
b. Join the cluster that yields the largest ΔQ.

$$\Delta Q = \left[\frac{\sum_{in}^{c} + 2k_{i,\text{in}}}{2m} - \left(\frac{\sum_{tot}^{c} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{in}^{c}}{2m} - \left(\frac{\sum_{tot}^{c}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right] \tag{3}$$

where Σ_{in}^{c} denotes the sum of the weights of the edges inside cluster c, Σ_{tot}^{c} denotes the sum of the weights of the links incident to vertices in cluster c, k_i is the sum of the weights of the links incident to vertex i, and $k_{i,\text{in}}$ is the sum of the weights of the links from node i to nodes in cluster c.

Step 2: Reconstruct a new network

a. Compress the clusters detected during the Step 1 to a new set of vertices
b. Calculate the self-loop weights of new vertices by summing edge weights within the same clusters
c. Calculate edge weights between new vertices by summing the edge weights between vertices in the corresponding two clusters
d. Re-apply Step 1 until there is no further improvement.

2.2. Construct impact matrix

To identify the effective upgrade options for grey infrastructures in each pipe cluster, priority areas for blue-green infrastructures in each sub-catchment, and suitable locations for a hybrid approach, an impact matrix is constructed based on flood mitigation performance under various grey-green combination scenarios. These scenarios are generated by One-Factor-At-a-Time method (Saltelli et al., 2008) in which only one variation changes between continuously simulations (see Fig. 1). The process can be represented in a matrix form as follows.

$$S = \begin{bmatrix} s_0 \\ s_1 \\ s_2 \\ \vdots \\ s_m \end{bmatrix} \begin{bmatrix} c_0 & c_1 & c_2 & \cdots & c_n \end{bmatrix} = \begin{bmatrix} s_0c_0 & s_0c_1 & \cdots & s_0c_n \\ s_1c_0 & s_1c_1 & \cdots & s_1c_n \\ s_2c_0 & s_2c_1 & \cdots & s_2c_n \\ \vdots & \ddots & \vdots & \\ s_mc_0 & s_mc_1 & \cdots & s_mc_n \end{bmatrix} \quad (4)$$

where $s_i(i \in \{1, 2, \dots, m\})$ represents a scenario in which the impervious fraction of sub-catchment i is set to 0 (to represent BGI implementation), $c_j(j \in \{1, 2, \dots, n\})$ refers to a scenario in which the diameters of pipes in sub-network j will be enlarged to be the same as the diameter of bordered pipe belonging to another downstream sub-network, and the subscript 0 means that no BGI or grey infrastructure (pipes enlargement) is applied. The element $s_ic_0(i \neq 0)$ in the first column of matrix S represents the BGI scenarios without grey infrastructures (BGI-only scenarios). Similarly, the element $s_0c_j(j \neq 0)$ in the first row of matrix S represents the grey scenario without BGI (grey-only scenarios), and $s_ic_j(i \neq 0 \; and \; j \neq 0)$ refers to the hybrid scenarios. They were simulated with EPA SWMM model (Rossman et al., 2010) one at a time for the whole catchment where node surcharge information for each node was extracted from model outputs.

For each hybrid scenario s_ic_j, the inundation nodes in the study area are classified into three categories (upstream, local, downstream) based on their locations relative to the pipe cluster j. For example, if there are six flooded nodes $\{f_1, f_2, f_3, f_4, f_5, f_6\}$ in the study area, f_1 and f_2 belong to *local* as they are inside a pipe cluster j, f_3 and f_4 belong to *upstream* as they are located upstream of the cluster j, and f_5 and f_6 belong to *downstream* as they are located downstream of the cluster j. For BGI-only scenario s_ic_0, *local* flooding nodes refer to those nodes that are located in the pipe cluster that sub-catchment i directly drains into, and *upstream* and *downstream* flooding nodes can be found based on this. As such, the BGI-only scenarios linked to the same pipe cluster are always grouped together to simplify the matrix and the subsequent data analysis. Eq. (5) is applied to calculate increase in flood volume $\Delta v_{t,s_ic_j}$ of each category and $\Delta v_{total,s_ic_j}$ of the entire drainage system. The value of $\Delta v_{t,s_ic_j}$ for each scenario in matrix S form a hybrid matrix $\Delta \boldsymbol{V_t}$, expressed as Eq. (6).

$$\Delta v_{t,s_ic_j} = v_{t,s_ic_j} - v_{t,s_0c_0} \quad (5)$$

$$\Delta \boldsymbol{V_t} = \begin{bmatrix} \Delta v_{t,s_0c_0} & \Delta v_{t,s_0c_1} & \cdots & \Delta v_{t,s_0c_n} \\ \Delta v_{t,s_1c_0} & \Delta v_{t,s_1c_1} & \cdots & \Delta v_{t,s_1c_n} \\ \Delta v_{t,s_2c_0} & \Delta v_{t,s_2c_1} & \cdots & \Delta v_{t,s_2c_n} \\ \vdots & \ddots & \vdots & \\ \Delta v_{t,s_mc_0} & \Delta v_{t,s_mc_1} & \cdots & \Delta v_{t,s_mc_n} \end{bmatrix}, t \in \{upstream, local, downstream\} \quad (6)$$

where v_{t,s_ic_j} refers to the sum of flood volume of nodes in category t for combined scenario s_ic_j, v_{t,s_0c_0} represents total flood volume of category t for the baseline scenario $s_ic_0(i \neq 0)$ without BGI and grey infrastructures. From this methodology, we can establish four matrices relating to total, local, upstream and downstream conditions.

3. Application

3.1. Study area

The case study was based on a catchment located in Changban district, Guangzhou city, Guangdong Province, China, covering a total drainage area of 15.7 ha (Fig. 2a). The area has a subtropical monsoon climate, and the annual average rainfall is approximately 1800 mm, mainly from April to September (approx. 80 % of annual rainfall). The north of the catchment is mountainous, and the urban area situated in the south presents a relatively flat slope. The main conduits in Fig. 2a, primarily consisting of culverts and channels, transport water from the north to the south, while branch pipes drain runoff from sub-catchments into the main conduits. During intense rainfall events, excessive runoff flows southward from the mountains, always causing floods in the downstream urban areas due to the low capacity of the drainage network. BGI can be placed in southern urban areas to retain detain rainfall and relieve drainage network pressure. To prioritise the location of BGI with high flood control, each sub-catchment was turned into natural land with 100 % pervious areas at each simulation. However, doubt remains about its capacity to withstand floods. Besides, it can be seen in Fig. 2b that flooding nodes are distributed in various locations. This presents an opportunity to categorize flood zones and investigate the optimal options between BGI and grey infrastructure for various flooded zones, utilizing the proposed flood impact matrix method.

3.2. Model setup

Data required for modelling included land-use type as well as a digital elevation model (DEM) with a resolution of 5 m and a drainage network layer (last updated 2010), all of which were provided by the local Land and Resources Bureau and Water Supplies Bureau. The drainage network was first cross-checked in EPA SWMM and corrected for some errors in the pipe invert levels. This produced a hydraulically correct network. The study area was divided into 86 sub-catchments that drain into 175 junctions connected by 175 conduits (see Fig. 2a). An input to the model is a measured event with a total rainfall of approximately 284 mm, which caused significant flooding (i.e., node surcharges). This event is equivalent to a 10-year return period rainfall event with a duration of approximately 42 h. Furthermore, two types of parameters, namely, measured and empirical parameters, in the EPA SWMM were set. Measured parameters included area, width, slope, and impervious percentage of each sub-catchment determined by the topography and land cover type. As for the empirical parameters, the Manning value of the surface, storage depth, and Horton-based infiltration indicators were initially established by referring to the adjacent catchment areas and the EPA SWMM manual. Soil in Guangzhou is notably moist during the rainy season (June to October) so the depth of depression storage on impervious/pervious area and maximum/minimum infiltration rate are relatively small. Parameter values were set as

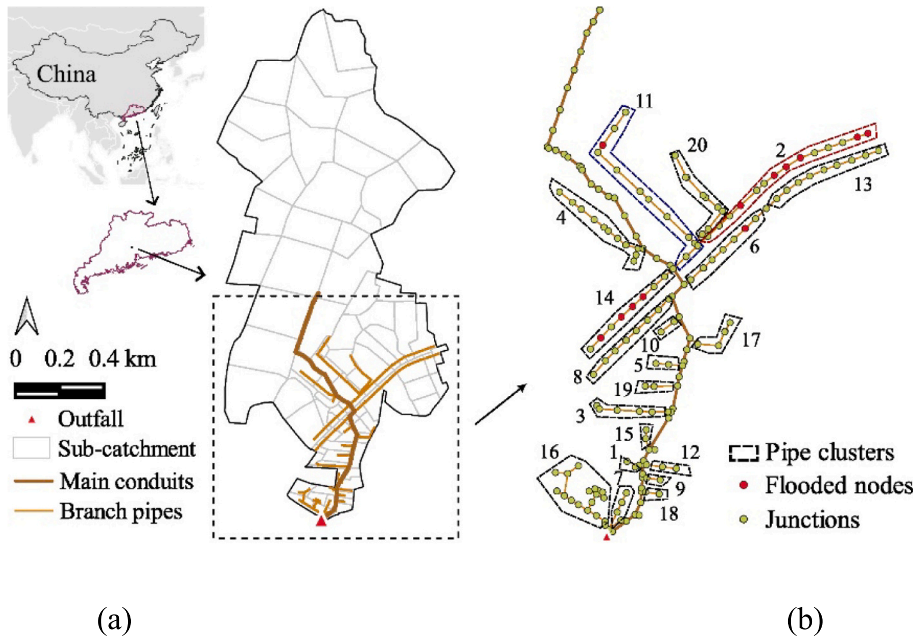

Fig. 2. (a) location of study area and the delineation of sub-catchments; (b) the distribution of pipe clusters (2, 6, 11, and 14 are the flooding clusters).

follows: i) Impervious areas: Manning's value set to 0.011, depression storage depth at 0.5 mm. ii) Pervious sections: Manning's value at 0.24, depression storage depth at 1 mm. iii) Infiltration: Maximum rate set at 10 mm/h, minimum rate at 1.25 mm/h, with a decay constant of 4. iv) Channel: Manning's value ranged from 0.01 to 0.012. Despite the lack of available calibration data, our model setup was aligned as closely to known information about the case study. Since the impact matrix is constructed based on difference in flood volume under various scenarios compared with a baseline scenario, we assessed the model results based on our understanding of the catchment's behaviour and based on previous studies within the catchment (Li et al., 2022), thereby judging the model's quality as adequate for its purpose.

Fig. 2b illustrates the partition results of pipe network using the Louvain algorithm. Grey infrastructure solutions, i.e., enlarging pipe diameter, were implemented exclusively on branch pipes, therefore clustering was performed only considering the branch pipes in the network. The branch pipes were decomposed into 21 pipe clusters, among which Clusters 2, 6, 11, and 14 contained flooding nodes.

4. Results

Calculated impact matrices of *total*, *local*, *upstream*, and *downstream* flood reduction are shown in Fig. 3. The x-axis depicts each pipe cluster where pipe upgrades were performed, while the y-axis depicts sub-catchments where BGI was implemented. Additionally, sub-catchments on the y-axis were grouped by its directly connected pipe clusters to provide a more organized and insightful analysis of the results. Each value in the matrix refers to the flood volume reduction under a hybrid scenario (including a full BGI and a full grey infrastructure along the 'No' column and row, respectively). Each other position in the matrix represents a combination of specific BGI implementation along the y-axis and specific pipe enlargement along the x-axis (Section 2.2). As can be seen, not all BGI and grey infrastructures are beneficial in flood mitigation and most solutions that work are located in or connected to a flooded area (clusters 2, 6, 11, and 14). Their primary function is to reduce local floods, with only minor to no flood impacts on upstream and downstream areas.

4.1. *Local flood reduction*

Fig. 3b shows that increasing the pipes diameter in pipe clusters with flooding issues (2, 6, 11, and 14) and implementing BGI in the area that contribute to these pipe clusters significantly reduced local flooding. Table 1 shows the local impact of these various scenarios. Considering that multiple sub-catchments belong to a single pipe cluster, there are several BGI-only scenarios associated with that cluster and thus the minimum, maximum, and mean flood reductions for these scenarios were calculated.

Results showed that grey-only scenarios can completely address local flooding problems at an efficiency equivalent to the hybrid scenario. This demonstrates the dominant role of grey infrastructure in mitigating flooding. In contrast, BGI-only scenarios could only provide partial flood reduction due to the limited implementation space as well as resulting retention and detention capacity of BGI. Significant variations between the minimum and maximum flood reduction within the same cluster under different BGI-only scenarios suggest that BGI location has a significant impact on flood reduction, but, admittedly requires a location-specific understanding to fully leverage its impact. For the most severely flooded cluster 14, mean and maximum local flood reduction of BGI-only scenarios were only 0.255×10^3 m^3 and 0.857×10^3 m^3, representing 8.9 % and 29.8 % of the flood volume under the baseline scenario, respectively. Mildly flooded cluster 2 showed a maximum flood reduction rate of 46.8 %, but for slightly flooded clusters 6 and 11, the maximum flood reduction rates were 92.5 % and 100 %, respectively. These results imply that BGI-only scenarios are more likely to solve local flood issues in mildly and slightly flooded areas, whereas grey infrastructure appears more effective in severely flooded areas.

4.2. *Upstream and downstream flood reduction*

Fig. 3c illustrates the impact of various flood mitigation solutions on mitigating flooding in their upstream area. It was observed that solutions related to pipe cluster 11, including BGI-only, grey-only, and hybrid solutions at cluster 11, had a minor effect on reducing flooding in the upstream flooded area (cluster 2). Enlarged pipes in cluster 11 enabled a larger discharge from the upstream part of the network. BGI implemented in pipe cluster 11 also contributed to releasing additional capacity for water from its upstream area by retaining and detaining

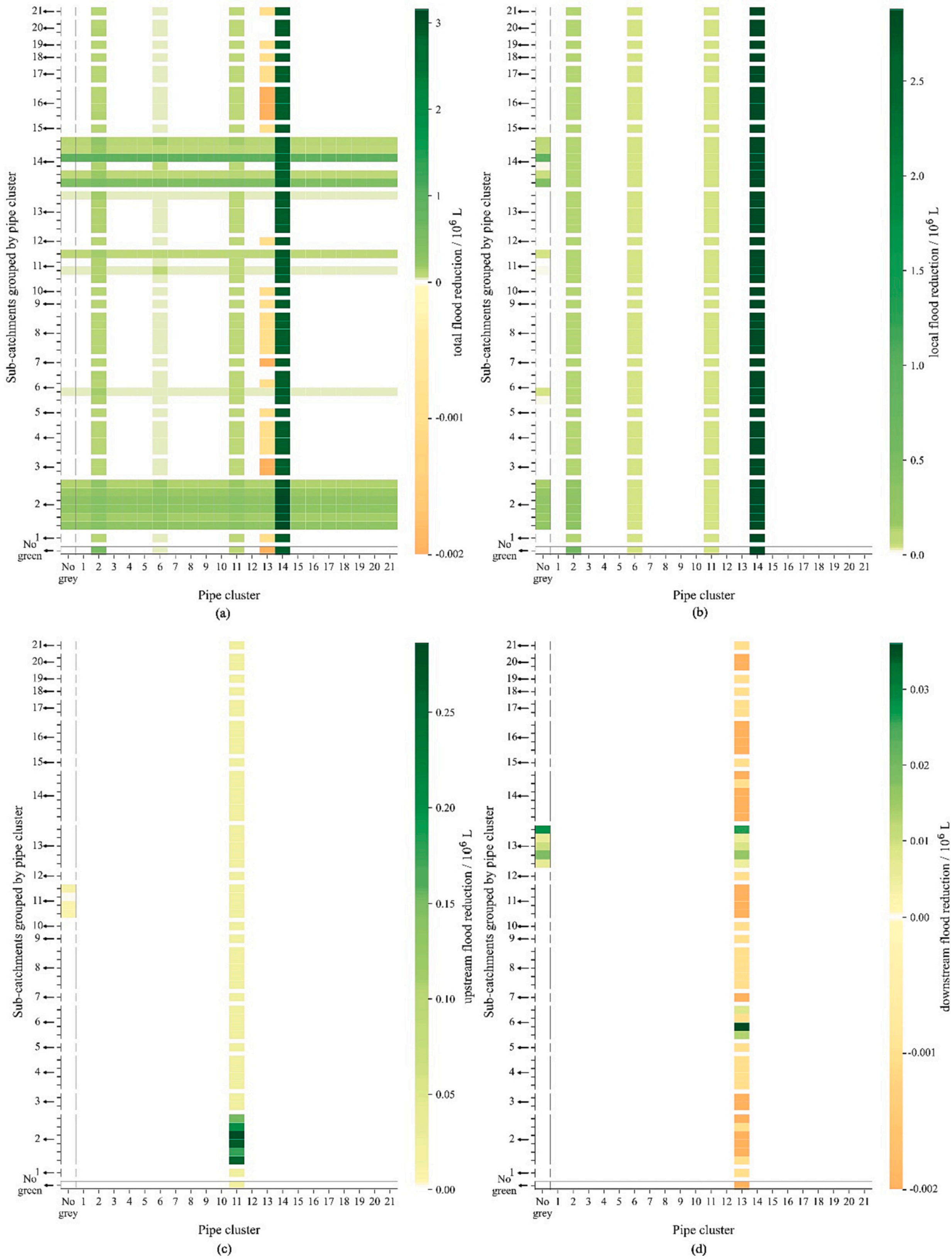

Fig. 3. Impact matrices of (a) total, (b) local, (c) upstream, and (d) downstream flood reduction. The x-axis represents pipe clusters where pipe upgrades were performed, while the y-axis represents the sub-catchments where BGI was implemented. Each value in the matrix refers to the flood volume reduction under baseline (left-bottom), grey-only (first column), BGI-only (first row), or hybrid scenario.

Table 1
Comparison of flood reduction under various scenarios.

Pipe cluster ID	Flood volume under baseline scenario (10^3 m^3)	Local flood reduction (10^3 m^3)				
		Grey-only scenarios	BGI-only scenarios			Hybrid scenarios
			Min	Max	Mean	
2	0.585	0.573	0.142	0.274	0.211	0.585
6	0.04	0.04	0.001	0.037	0.016	0.04
11	0.043	0.043	0.001	0.043	0.018	0.043
14	2.876	2.876	0.02	0.857	0.255	2.876

water on-site. This indicates that the flooding in cluster 2 was also caused by the insufficient capacity of its downstream pipes in cluster 11. Hybrid solutions, which involve both pipe upgrades in cluster 11 and BGI implementation in cluster 2, yielded superior flood mitigation performance. This was not unexpected, considering that cluster 2 is the upstream flooded area of cluster 11 and BGI linked with cluster 2 played an important role in its local flood mitigation.

In Fig. 3d the results show that scenarios involving pipe upgrades in pipe cluster 13 caused a slight increase in downstream floods in cluster 6. The reason is that after increasing pipes diameter in cluster 13, more water is drained downstream, thereby increasing and shifting the flooding problem elsewhere. BGI in cluster 13, however, could greatly alleviate these downstream floods by 66.7 %. This indicates that too much runoff from upstream clusters could increase the risk of downstream floods and that in such situations, adopting BGI can be the preferable choice to control floods. These examples emphasize the usefulness of our pre-screening approach and further emphasizes the need for proper planning and analysis when implementing hybrid solutions to ensure overall benefits.

4.3. Total flood reduction

Table 2 presents the total flood reductions under various hybrid scenarios. Considering that multiple sub-catchments belong to a single pipe cluster, there are several BGI-only scenarios associated with that cluster. The BGI solution with the best performance and its corresponding hybrid solution were selected for analysis. Comparing the results presented in Tables 1 and 2, it can be seen that total flood reduction achieved by the grey-only scenario (0.573×10^3 m^3) and the hybrid scenario (0.578×10^3 m^3) in cluster 2 was slightly smaller than local flood reduction (0.585×10^3 m^3). This can be explained by the increase of flooding in its downstream cluster 11, an interaction discussed in the previous section. It can be seen in Fig. 2 that flooded nodes in cluster 11 are not downstream of cluster 2, but rather linked to its downstream pipe. This suggests that water flow converted from floods by grey infrastructure may indirectly lead to an increase in floods associated with its downstream pipes. In such cases, BGI can alleviate this negative effect. In contrast, as grey-only and hybrid solutions in cluster 11 could reduce its upstream floods (Section 4.2), their performance in total flood reduction (0.054×10^3 m^3) are better than the local flood reduction results (0.043×10^3 m^3). For clusters 2 and 11, there is no difference between local and total flood reduction, possibly due to the capacity of their downstream pipes being sufficient to handle additional discharge.

In conclusion, grey infrastructure and BGI play complementary roles in flood reduction and seem to be best considered in conjunction. Grey-only solutions can effectively address local flooding issues but may result in shifting floods to other areas. In such situations, BGI implementation in potentially affected or flood-prone areas can offset adverse effects of grey infrastructure to achieve more favourable flood mitigation outcomes.

Table 2
Comparison of total flood reduction under various scenarios based on BGI and grey infrastructure implementation in different pipe clusters (2, 6, 11 and 14) [10^3 m^3].

BGI / Grey	2	6	11	14	No BGI
2	0.578	0.61	0.628	1.43	0.573
6	0.314	0.04	0.094	0.897	0.04
11	0.329	0.095	0.058	0.915	0.058
14	3.15	2.913	2.93	2.876	2.876
No Grey	0.274	0.037	0.054	0.857	0

4.4. Influences on outlet hydrograph

As mentioned in the previous sections, flooding volume will be converted into outflow through the implementation of grey infrastructure, which can increase floods downstream. It is therefore important to analyze the differences in outlet hydrographs under the various scenarios. Since both BGI and grey infrastructure performed well in reducing flood in pipe cluster 2, this cluster was selected as a representative example for comparison of the outlet hydrographs (Fig. 4) and the corresponding BGI option in sub-catchment 47 of cluster 2, which had the best performance. The representative hybrid solution shown is the combination between BGI in sub-catchment 47 and grey infrastructure in pipe cluster 2.

As can be seen in Fig. 4a, the shape of the outflow hydrographs of various scenarios is similar, with the largest differences occurring around the peaks. Fig. 4b shows the differences between the outflows for the BGI-only, grey-only, hybrid scenarios and the baseline scenario; it shows that grey-only scenario greatly increased outflow, especially during the peak, whereas the BGI-only scenario in contrast performed best in terms of reducing outflow, but not always below that of the baseline scenario (an increase was always followed by a decrease). Moreover, performance of BGI deteriorated as rainfall continued, with a sharp contrast between the first flow peak (zoom in Fig. 4c) and the last flow peak (zoom in Fig. 4d). In both cases, peak flow rates were similar (~2 m^3/s). When the first peak arrived, BGI reduced outflows more, followed by the hybrid solution. However, during the last peak, BGI only reduced outflow for around two minutes, while the hybrid solution increased outflow as seen in the grey-only case. This can be explained by the fact that soil became saturated with an increase in rainfall duration and can no longer store more water, leading to a decline in outflow reduction performance of BGI-only scenario.

5. Discussion

5.1. Study implications and novelty

The impact matrices approach highlights the effectiveness of BGI in addressing local floods without any side effects (increasing downstream floods) in slightly flooded areas. However, BGI alone cannot achieve complete flood reduction in severely flooded areas. These findings align with previous research conducted by Cheng et al. (2022), indicating that the effectiveness of BGI in flood reduction is dependent on the severity of flooding in the specific pipe cluster it is linked to, especially during intense rainfall events. As such, constructing a cluster-based impact matrix, such as the ones we propose in this study, can help map out the performance of various interventions for each flooded area.

In addition to the sensitivity analysis of BGI location conducted earlier by Zischg et al. (2018) and Wu et al. (2023), the impact matrices introduced in this study also considered the impact of grey and hybrid solutions location on flood control. The Louvain algorithm was strategically applied to decompose drainage networks based on hydraulic characteristics, enabling the treatment of each pipe cluster as an individual unit for pipe upgrades. This clustering approach allows for an effective classification of the flooded nodes into different pipe clusters, enabling a spatial analysis of the impact of each intervention on flood reduction, i.e., its upstream, local, downstream, and total flood reduction. The impact matrices provide clear insights into the complementary

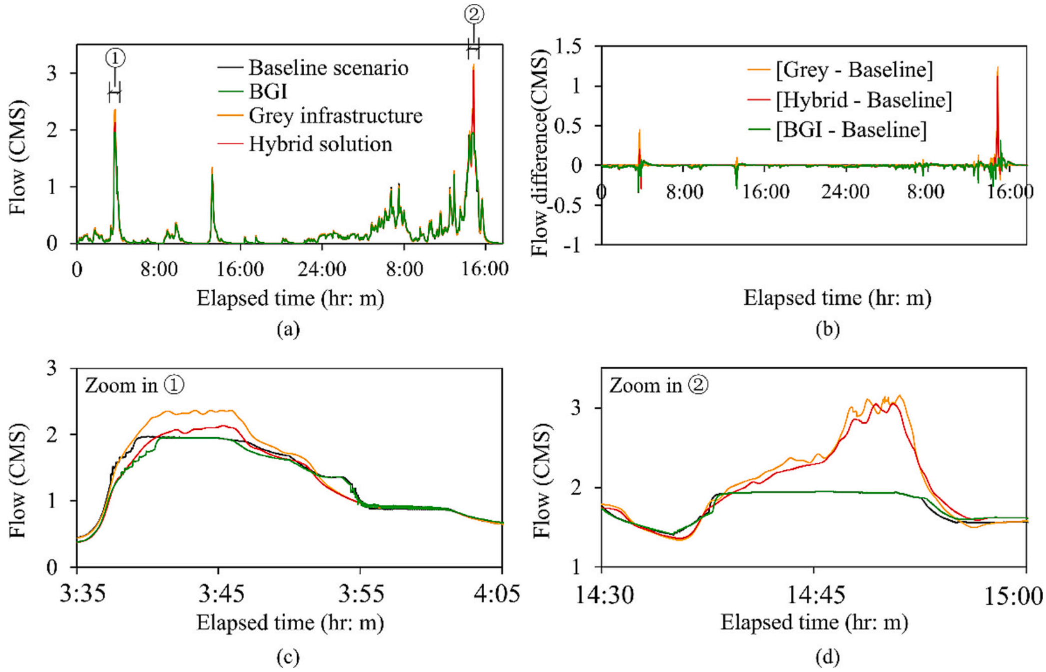

Fig. 4. The comparison of outflow hydrographs of pipe cluster 2 under baseline, BGI-only, grey-only, and hybrid solutions. (Note that in panel a, the hydrograph of the baseline scenario is almost overlapped by the hydrograph of BGI-only scenario.)

nature of grey and BGI and their interactions across different pipe clusters. For instance, in cluster 14, enlarging pipes' diameter can greatly reduce local flooding without increasing flooding in other clusters; meanwhile, only BGI directly linked to cluster 14 will have an impact in reducing flooding. This indicates that it is efficient to separately run the layout optimization for cluster 14, since the scheme that minimizes local floods is also the one that contributes most to reducing total floods. However, grey infrastructure within one cluster may redirect floods downstream as it can drain more runoff outward. Conversely, floods downstream can be alleviated by BGI located in the upstream cluster, which assists in detaining and retaining rainfall, consequently reducing outflow volume from the upstream clusters. In such cases, it is advisable to optimize all factors that concurrently contribute to alleviate flooding, as presented in this study. This development represents a significant improvement compared to what was presented in Zeng et al. (2019), where the study area was artificially divided into upstream, midstream, and downstream sections for spatial analysis.

Previous studies (Alves et al., 2020; Leng et al., 2020; Martínez et al., 2021) have developed simulation-optimization frameworks to find optimal hybrid solutions through extensive simulations of various combinations across the study area. However, not all combinations of blue-green and grey infrastructure are effective, as shown in Fig. 3. Without pre-screening or guidance, applying optimization algorithms can waste time on invalid schemes (Wang and Shan, 2004). The proposed impact matrices in this study can serve as an effective tool for locating valid blue-green and grey infrastructure solutions that positively contributes to flood reduction. Through such a preliminary identification before optimization, optimization schemes can focus on searching for the most efficient solution in less time.

5.2. Limitations and future developments

Despite the advantages discussed above, this study presents some limitations. Since the main purpose of this study is to provide a new approach to support the selection between blue-green and grey infrastructure, only one rainfall event was used to evaluate the value of the impact matrices. Numerous studies have demonstrated that the shape, intensity, and duration of rainfall events impact the performance of BGI (Lewellyn et al., 2016; Mei et al., 2018; Mobilia and Longobardi, 2020). In order to check the impact of the rainfall event on the impact matrix, a simple study was conducted by inverting the original rainfall event (Fig. S1 and Fig. S2 in the supplementary material). The original rainfall event selected in this study is bimodal, and the intensity of the last peak is stronger than the first peak. Inverting the rainfall event resulted in a total flood volume of 3410m^3, less than the original 3655m^3. It should be noted that maximum flooding always occurs at the strongest peak, i.e., the last peak for original rainfall event and the first peak for inverted rainfall event. Local floods in each flooding area (see Table S1) also changed: floods in clusters 6, 11, and 14 decrease while floods in cluster 2 increase. The most significant result we gain from the impact matrices under inverted rainfall events is similar to that under original rainfall events: the preference for blue-green, grey, and hybrid solutions for each pipe cluster. A more detailed analysis provided in Table S1 shows that under the inverted rainfall event, BGI-only scenarios can further reduce flooding in clusters 2 and 14 and address flood issues in clusters 6 and 11. Moreover, a different measured rainfall event lasting around 25.5 h and with a total volume of 112 mm (see Fig. S3) was used to create the flood impact matrix. The results in Table S2 and Fig. S4 consistently indicated persistent occurrences of flooding within identical clusters, despite alterations in the flood volume. The minor differences in impact matrices emphasize the small influence of different rainfall events on BGI performance. Future work should focus on refining the approach to incorporate diverse rainfall scenarios for a comprehensive understanding of the performance of BGI, grey, and hybrid solutions for the catchment.

Besides, the construction of the impact matrices in this study currently only considers flood reduction. In the prioritization of BGI intervention locations, Vercruysse et al. (2019) and Dawson et al. (2020) also incorporated land use and exposure data. This additional information can assist flood management practitioners in devising more effective flood alleviation strategies. In the future, it is worthwhile to explore the possibility of linking exposure data with the existing flood matrices. In addition, while results can be used to optimize hybrid solutions in terms of urban flood control, it will also be interesting to consider water quality and cost during the optimization process (Zhang and Chui, 2019). Grey solutions have clearly contributed to higher flood reduction but show often higher costs and no or limited additional benefits. Compared with grey infrastructure, BGI can provide multiple environmental benefits like pollution control and at a lower cost. If such impact matrices can be constructed based on the reduction of pollution, results may not only be different in highlighting areas that contribute the greatest improvement in water quality, but also provide potentially crucial a priori information for speeding up multi-objective optimization algorithms. Our ultimate goal is to achieve layout optimization of hybrid solutions with multi-objective, i.e., minimizing the budget while maximizing flood and water pollution mitigation. As such, assessing how such impact matrices can support the speed-up of optimization algorithms, particularly in the case of multiple objectives, is very much a subject of future work.

6. Conclusions

In this study, we applied the Louvain algorithm to decompose a drainage network into various pipe clusters, and used EPA SWMM model to simulate the hydrological response of BGI-only, grey-only, and hybrid solutions. Four impact matrices, which represented total, local, upstream, and downstream flood reduction for all possible combinations of interventions, were constructed to examine the spatial effects and suitable locations of BGI, grey, and hybrid infrastructure on flood mitigation. Each value in these impact matrices represented flood reduction for the entire study area, and the flood reduction for the flooded nodes located inside, upstream, and downstream of the pipe cluster under a hybrid solution, respectively. Key findings from this study include:

- The proposed flood impact matrices are useful to identify the best candidate locations for blue-green and grey infrastructure for flood reduction.
- BGI cannot address flood issues on its own in areas with highly inadequate drainage capacity. Creating impact matrices can help identifying these areas and support the development of flood mitigation solutions.
- Grey infrastructure may occasionally shift flooding problems downstream, with BGI being able to provide a marginal benefit when implemented in complementary locations.
- BGI can store more water at the beginning of a rainfall event, so it performs less effectively in flood control for events with a stronger or late peak.

Our approach provides an effective tool for identifying best flood reduction solutions that can be used to improve layout optimization of hybrid solutions to mitigate pluvial flooding and support the understanding of possible options in planning such solutions. Sensitivity to the choice of rainfall event(s), how the proposed approach could also perform on other stormwater management objectives such as water quality control and cost, and its potential utility as a priori knowledge for spatial optimization, are subject of future research.

CRediT authorship contribution statement

Shanshan Li: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization.
João P. Leitão: Conceptualization, Methodology, Formal analysis, Validation, Writing-Review & Editing, Supervision.
Zhaoli Wang: Data collection, Methodology, Formal analysis, Validation, Writing-Review & Editing, Funding acquisition, Supervision.
Peter M. Bach: Conceptualization, Methodology, Formal analysis, Validation, Writing-Review & Editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The code is provided open access.

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Appendix A. Supplementary data

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References

Alves, A., Sanchez, A., Vojinovic, Z., Seyoum, S., Babel, M., Brdjanovic, D., 2016. Evolutionary and holistic assessment of green-grey infrastructure for CSI reduction. Water 8, 402.
Alves, A., Vojinovic, Z., Kapelan, Z., Sanchez, A., Gersonius, B., 2020. Exploring trade-offs among the multiple benefits of green-blue-grey infrastructure for urban flood mitigation. Sci. Total Environ. 703, 134980.
Bach, P.M., Kuller, M., McCarthy, D.T., Deletic, A., 2020. A spatial planning-support system for generating decentralised urban stormwater management schemes. Sci. Total Environ. 726, 138282.
Bayas-Jiménez, L., Martínez-Solano, F.J., Iglesias-Rey, P.L., Mora-Meliá, D., 2021. Search space reduction for genetic algorithms applied to drainage network optimization problems. Water 13 (15), 2008.
Beloqui, A.A., 2020. Combining Green-Blue-Grey Infrastructure for Flood Mitigation and Enhancement of Co-Benfits. CRC Press.
Blondel, V.D., Guillaume, J.L., Lambiotte, R., Lefebvre, E., 2008. Fast unfolding of communities in large networks. J. Stat. Mech. Theory Exp. 2008, P10008.
Bonneau, J., Fletcher, T.D., Costelloe, J.F., Burns, M.J., 2017. Stormwater infiltration and the 'urban karstâ'–a review. J. Hydrol. 552, 141–150.
Brears, R.C., 2018. Blue and Green Cities: The Role of Blue-Green Infrastructure in Managing Urban Water Resources. Springer.
Browder, G., Ozment, S., Rehberger Bescos, I., Gartner, T., Lange, G.M., 2019. Integrating Green and Gray. World Bank and World Resources Institute, Washington, DC.
Chang, N.B., Lu, J.W., Chui, T.F.M., Hartshorn, N., 2018. Global policy analysis of low impact development for stormwater management in urban regions. Land Use Policy 70, 368–383.
Chen, W., Wang, W., Huang, G., Wang, Z., Lai, C., Yang, Z., 2021. The capacity of grey infrastructure in urban flood management: a comprehensive analysis of grey infrastructure and the green-grey approach. Int. J. Disaster Risk Reduction 54, 102045.
Cheng, T., Huang, B., Yang, Z., Qiu, J., Zhao, B., Xu, Z., 2022. On the effects of flood reduction for green and grey sponge city measures and their synergistic relationship-case study in jinan sponge city pilot area. Urban Clim. 42, 101058.
Czitrom, V., 1999. One-factor-at-a-time versus designed experiments. Am. Stat. 53, 126–131.
Dawson, D.A., Vercruysse, K., Wright, N., 2020. A spatial framework to explore needs and opportunities for interoperable urban flood management. Phil. Trans. R. Soc. A 378, 20190205.
Dong, X., Guo, H., Zeng, S., 2017. Enhancing future resilience in urban drainage system: green versus grey infrastructure. Water Res. 124, 280–289.
Fletcher, T.D., Shuster, W., Hunt, W.F., Ashley, R., Butler, D., Arthur, S., Trowsdale, S., Barraud, S., Semadeni-Davies, A., Bertrand-Krajewski, J.L., et al., 2015. SUDS, LID, BMPs, WSUD and more–the evolution and application of terminology surrounding urban drainage. Urban Water J. 12, 525–542.
Fowdar, H., Payne, E., Schang, C., Zhang, K., Deletic, A., McCarthy, D., 2021. How well do stormwater green infrastructure respond to changing climatic conditions? J. Hydrol. 603, 126887.
Gao, Z., Zhang, Q., Xie, Y., Wang, Q., Dzakpasu, M., Xiong, J., Wang, X., 2022. A novel multi-objective optimization framework for urban green-gray infrastructure implementation under impacts of climate change. Sci. Total Environ. 825, 153954.
Gobatti, L., Bach, P.M., Scheidegger, A., Leitão, J.P., 2023. Using satellite imagery to investigate blue-green infrastructure establishment time for urban cooling. Sustain. Cities Soc. 104768.
Hesarkazzazi, S., Hajibabaei, M., Bakhshipour, A.E., Dittmer, U., Haghighi, A., Sitzenfrei, R., 2022. Generation of optimal (de)centralized layouts for urban drainage systems: a graph-theory-based combinatorial multi-objective optimization framework. Sustain. Cities Soc. 81, 103827.

Hoyer, J., Dickhaut, W., Kronawitter, L., Weber, B., 2011. Water Sensitive Urban Design: Principles and Inspiration for Sustainable Stormwater Management in the City of the Future. Jovis Berlin.
Jamali, B., Bach, P.M., Deletic, A., 2020. Rainwater harvesting for urban flood management–an integrated modelling framework. Water Res. 171, 115372.
Jayasooriya, V.M., Ng, A.W.M., Muthukumaran, S., Perera, B.J.C., 2017. Green infrastructure practices for improvement of urban air quality. Urban For. Urban Green. 21, 34–47.
Joshi, P., Leitão, J.P., Maurer, M., Bach, P.M., 2021. Not all suds are created equal: impact of different approaches on combined sewer overflows. Water Res. 191, 116780.
Kapetas, L., Fenner, R., 2020. Integrating blue-green and grey infrastructure through an adaptation pathways approach to surface water flooding. Phil. Trans. R. Soc. A 378 (2168), 20190204.
Leng, L., Mao, X., Jia, H., Xu, T., Chen, A.S., Yin, D., Fu, G., 2020. Performance assessment of coupled green-grey-blue systems for sponge city construction. Sci. Total Environ. 728, 138608.
Lewellyn, C., Lyons, C.E., Traver, R.G., Wadzuk, B.M., 2016. Evaluation of seasonal and large storm runoff capture of an infiltration green infrastructure system. J. Hydrol. Eng. 21, 04015047.
Li, J., Tao, T., Kreidler, M., Burian, S., Yan, H., 2019. Construction cost-based effectiveness analysis of green and grey infrastructure in controlling flood inundation: a case study. J. Water Manag. Model. 27. C466.
Li, S., Wang, Z., Lai, C., Lin, G., 2020. Quantitative assessment of the relative impacts of climate change and human activity on flood susceptibility based on a cloud model. J. Hydrol. 588, 125051.
Li, S., Wang, Z., Wu, X., Zeng, Z., Shen, P., Lai, C., 2022. A novel spatial optimization approach for the cost-effectiveness improvement of LID practices based on SWMM-FTC. J. Environ. Manage. 307, 114574.
Lund, N.S.V., Borup, M., Madsen, H., Mark, O., Arnbjerg-Nielsen, K., Mikkelsen, P.S., 2019. Integrated stormwater inflow control for sewers and green structures in urban landscapes. Nat. Sustain. 2, 1003–1010.
Marlow, D.R., Moglia, M., Cook, S., Beale, D.J., 2013. Towards sustainable urban water management: a critical reassessment. Water Res. 47, 7150–7161.
Martínez, C., Vojinovic, Z., Sanchez, A., 2021. Multi-objective model-based assessment of green-grey infrastructures for urban flood mitigation. Hydrology 8, 110.
Mei, C., Liu, J., Wang, H., Yang, Z., Ding, X., Shao, W., 2018. Integrated assessments of green infrastructure for flood mitigation to support robust decision-making for sponge city construction in an urbanized watershed. Sci. Total Environ. 639, 1394–1407.
Mobilia, M., Longobardi, A., 2020. Impact of rainfall properties on the performance of hydrological models for green roofs simulation. Water Sci. Technol. 81, 1375–1387.
Molné, F., Donati, G.F., Bolliger, J., Fischer, M., Maurer, M., Bach, P.M., 2023. Supporting the planning of urban blue-green infrastructure for biodiversity: a multi-scale prioritisation framework. J. Environ. Manage. 342, 118069.
Newman, M.E., 2004. Analysis of weighted networks. Phys. Rev. E 70 (5), 056131.
Ngamalieu-Nengoue, U.A., Iglesias-Rey, P.L., Martnez-Solano, F.J., 2019. Urban drainage networks rehabilitation using multi-objective model and search space reduction methodology. Infrastructures 4, 35.
Paprotny, D., Sebastian, A., Morales-Nápoles, O., Jonkman, S.N., 2018. Trends in flood losses in Europe over the past 150 years. Nat. Commun. 9, 1–12.
Rossman, L.A., et al., 2010. Storm Water Management Model User's Manual, Version 5.0. Cincinnati: National Risk Management Research Laboratory, Office of Research and Development, US Environmental Protection Agency.
Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global Sensitivity Analysis: The Primer. John Wiley & Sons.
Singh, A., Dawson, D., Trigg, M., Wright, N., 2021. A review of modelling methodologies for flood source area (FSA) identification. Nat. Hazards 107, 1047–1068.
Singh, A., Dawson, D., Trigg, M.A., Wright, N., Seymour, C., Ferriday, L., 2023. Drainage representation in flood models: application and analysis of capacity assessment framework. J. Hydrol. 129718.
United Nations Department of Economic and Social Affairs, Population Division, 2018. World Urbanization Prospects: The 2018 Revision. ST/ESA/SER.A/420, United Nations, New York.
Vercruysse, K., Dawson, D.A., Glenis, V., Bertsch, R., Wright, N., Kilsby, C., 2019. Developing spatial prioritization criteria for integrated urban flood management based on a source-to-impact flood analysis. J. Hydrol. 578, 124038.
Vineyard, D., Ingwersen, W.W., Hawkins, T.R., Xue, X., Demeke, B., Shuster, W., 2015. Comparing green and grey infrastructure using life cycle cost and environmental impact: a rain garden case study in Cincinnati, OH. JAWRA J. Am. Water Resour. Assoc. 51, 1342–1360.
Wang, G.G., Shan, S., 2004. Design space reduction for multi-objective optimization and robust design optimization problems. SAE Trans. 101–110.
Wouters, P., Dreiseitl, H., Wanschura, B., Wörlen, M., Moldaschl, M., Wescoat, J., Novia, K., 2016. Blue-Green Infrastructures as Tools for the Management of Urban Development and the Effects of Climate Change. Ramboll Environ, Madrid.
Wu, W., Jamali, B., Zhang, K., Marshall, L., Deletic, A., 2023. Water sensitive urban design (WSUD) spatial prioritisation through global sensitivity analysis for effective urban pluvial flood mitigation. Water Res. 235, 119888.
Xu, C., Tang, T., Jia, H., Xu, M., Xu, T., Liu, Z., Long, Y., Zhang, R., 2019. Benefits of coupled green and grey infrastructure systems: evidence based on analytic hierarchy process and life cycle costing. Resour. Conserv. Recycl. 151, 104478.
Zeng, S., Guo, H., Dong, X., 2019. Understanding the synergistic effect between lid facility and drainage network: with a comprehensive perspective. J. Environ. Manage. 246, 849–859.
Zhang, K., Chui, T.F.M., 2019. Linking hydrological and bioecological benefits of green infrastructures across spatial scales–a literature review. Sci. Total Environ. 646, 1219–1231.
Zischg, J., Zeisl, P., Winkler, D., Rauch, W., Sitzenfrei, R., 2018. On the sensitivity of geospatial low impact development locations to the centralized sewer network. Water Sci. Technol. 77, 1851–1860.