Water Research 235 (2023) 119888

Contents lists available at ScienceDirect

Water Research

journal homepage: www.elsevier.com/locate/watres

Water Sensitive Urban Design (WSUD) Spatial Prioritisation through Global Sensitivity Analysis for Effective Urban Pluvial Flood Mitigation

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ARTICLE INFO

Keywords:
LID spatial planning
SuDS sitting strategy
sponge cities
drainage network surcharge
stormwater quantity management
eFAST

ABSTRACT

Water Sensitive Urban Design (WSUD) has attracted growing attention as a sustainable approach for mitigating pluvial flooding (also known as flash flooding), which is expected to increase in frequency and intensity under the impacts of climate change and urbanisation. However, spatial planning of WSUD is not an easy task, not only due to the complex urban environment, but also the fact that not all locations in the catchment are equally effective for flood mitigation. In this study, we developed a new WSUD spatial prioritisation framework that applies global sensitivity analysis (GSA) to identify priority subcatchments where WSUD implementation will be most effective for flood mitigation. For the first time, the complex impact of WSUD locations on catchment flood volume can be assessed, and the GSA in hydrological modelling is adopted for applications in WSUD spatial planning. The framework uses a spatial WSUD planning model, the Urban Biophysical Environments and Technologies Simulator (UrbanBEATS), to generate a grid-based spatial representation of catchment, and an urban drainage model, the U.S. EPA Storm Water Management Model (SWMM), to simulate catchment flooding. The effective imperviousness of all subcatchments was varied simultaneously in the GSA to mimic the effect of WSUD implementation and future developments. Priority subcatchments were identified based on their influence on catchment flooding computed through the GSA. The method was tested for an urbanised catchment in Sydney, Australia. We found that high priority subcatchments were clustering in the upstream and midstream of the main drainage network, with a few distributed close to the catchment outlets. Rainfall frequency, subcatchment characteristics, and pipe network configuration were found to be important factors determining the influence of changes in different subcatchments on catchment flooding. The effectiveness of the framework in identifying influential subcatchments was validated by comparing the effect of removing 6% of the Sydney catchment's effective impervious area under four WSUD spatial distribution scenarios. Our results showed that WSUD implementation in high priority subcatchments consistently achieved the largest flood volume reduction (3.5-31.3% for 1% AEP to 50% AEP storms), followed by medium priority subcatchments (3.1-21.3%) and catchment-wide implementation (2.9-22.1%) under most design storms. Overall, we have demonstrated that the proposed method can be useful for maximising WSUD flood mitigation potential through identifying and targeting the most effective locations.

1. Introduction

Pluvial or rain-related flooding, caused by intense precipitation exceeding the capacity of stormwater drainage systems, is expected to increase in frequency and intensity under climate change and urbanisation (IPCC, 2021). Traditional urban flood management relies on engineered drainage systems such as gutters and pipes to convey stormwater away (Rosenzweig et al., 2018). However, there has been

Abbreviations: AEP, Annual Exceedance Probability; eFAST, Extended Fourier Amplitutde Sensitivity Test; $E_{ffect}I_{nt'}$, Effect of Interaction; EIA, Effective Impervious Area; FOSI, First Order Sensitivity Indices; GSA, Global Sensitivity Analysis; LSA, Local Sensitivity Analysis; SWMM, Storm Water Management Model; TOSI, Total Order Sensitivity Indices; UrbanBEATS, **Urban Biophysical Environments and Technologies Simulator**; WSUD, Water Sensitive Urban Design.

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https://doi.org/10.1016/j.watres.2023.119888
Received 6 October 2022; Received in revised form 16 February 2023; Accepted 16 March 2023
Available online 17 March 2023

growing recognition that such single-purpose systems are becoming increasingly unaffordable to maintain and expand to meet growing demands, urging a paradigm shift to more sustainable approaches (Ashley et al., 2020).

In light of this, Water Sensitive Urban Design (WSUD), alternatively known as Sustainable Urban Drainage Systems, Low Impact Development and Sponge Cities (Fletcher et al., 2015; Yin et al., 2021), has been proposed. With an aim to minimise impacts of urban development on the natural water cycle, WSUD manages stormwater quality and quantity through decentralised infrastructures such as green roofs, permeable pavements, bio-retention cells, constructed wetlands and rainwater tanks (Lloyd et al., 2002). Through retention and detention of surface runoff, these technologies have been found effective in mitigating flooding, especially small and frequent floods (Myers and Pezzaniti, 2019). These diverse infrastructure options offer flexibility in how they can be distributed across the urban environment (Zhang and Chui, 2018). Studies have shown that targeted locations for WSUD implementation led to better performance in flood mitigation than random or homogeneous placement across the catchment (Ercolani et al., 2018; Webber et al., 2019). However, spatial planning of WSUD in the complex urban environment with physical and socio-economic constraints is not an easy task (Zhang and Chui, 2018).

Several spatial WSUD planning support tools and models, such as SUSTAIN (Lee et al., 2012), SUDSLOC (Viavattene and Ellis, 2013) and the Adaptation Support Tool (van De Ven et al., 2016), have been developed to assist decision makers in finding feasible locations for WSUD. Many of these models rely on the users to specify specific WSUD types and designs, which can be time-consuming with limited options explored. A recently developed planning tool, UrbanBEATS (Bach et al., 2020), allows systematic exploration of thousands of combinations of feasible WSUD options and spatial layouts across the urban landscape to meet stormwater harvesting and pollution control objectives in a timely manner. UrbanBEATS has been applied to explore the effect of spatial distribution of rainwater harvesting on water supply networks (Sitzenfrei et al., 2017) and the robustness of WSUD implementation scenarios for stormwater pollution management (Castonguay et al., 2018). However, urban flood mitigation has not been included as an objective in UrbanBEATS. Indeed, installing WSUD wherever possible lacks strategic consideration of the best location for effective flood mitigation (Zhang and Chui, 2018). Identification of priority locations for WSUD implementation is vital for maximising WSUD's potential for flood mitigation, but such spatial prioritisation is currently lacking in WSUD planning support tools.

Various types of locations have been prioritised for WSUD implementation to mitigate flooding. Flood-prone areas are a commonly targeted location to apply WSUD for on-site flood impact reduction (Lu et al., 2019). Alternatively, recognising the need to address flooding at its source, flood source area has attracted growing attention (Singh et al., 2021). As pluvial flooding is caused by excess stormwater runoff, subcatchments with characteristics contributing to high probability of runoff generation are often prioritised. These characteristics include upstream locations (Kapetas and Fenner, 2020), high impervious area ratios (Samouei and Özger, 2020), steep slopes and soils of low infiltration rates (Kaykhosravi et al., 2019). However, there is high uncertainty in the occurrence of pluvial flooding due to influence of rainfall characteristics and performance of existing urban drainage systems (Penning-Rowsell and Korndewal, 2019), which means simple subcatchment characteristics may not be sufficient for identifying influential flood source locations. For example, Vercruysse et al. (2019) reported high contributions to catchment maximum flood depth from downstream subcatchments. This finding was based on results from analysing the sensitivity of catchment flooding to removal of rainfall input in individual subcatchments. Similarly, Zischg et al. (2018) and Rodriguez et al. (2021) identified priority locations for WSUD implementation by successively implementing fixed extent of WSUD in each subcatchment and assessing the corresponding changes in catchment flood volume. A bioretention of 500m^2 was placed in each subcatchment in Zischg et al. (2018)'s study, and the maximum spatial extent for bioretention cells, green roofs and permeable pavements in each subcatchment was modelled in the work of Rodriguez et al. (2021). Simperler et al. (2020) calculated the discharge reduction potential of each subcatchment by disconnecting that subcatchment from the drainage network in each simulation. As there was no correlation between subcatchments' discharge reduction potential and their impervious area size or their distance from the overflow point, the authors stressed the importance of applying sensitivity analysis for WSUD spatial prioritisation.

Current research on WSUD spatial prioritisation has seen popular applications of local sensitivity analysis (LSA), in which the response of the model output (i.e., catchment flooding) to variations in the model parameters (i.e., changes in subcatchments) is evaluated based on changing the value of a single model parameter (e.g., rainfall input or runoff volume in a single subcatchment) around a nominal value one at a time, whilst keeping all other parameters fixed (Saltelli and Annoni, 2010). Despite its popularity, there are numerous issues with the application of LSA in WSUD spatial prioritisation. First, traditional LSA has been criticised for their limited applicability to non-linear models and inability to consider interactions between parameters (Saltelli and Annoni, 2010; Song et al., 2015). However, studies have reported non-linear changes in catchment flooding as WSUD implementation level increased (Zeng et al., 2019). In addition, the effect of interactions, i.e., the compounding effect of implementing WSUD in two or more subcatchments at the same time on catchment flooding, is not considered in LSA. Furthermore, studies often only simulated limited possible scenarios in each subcatchment, either complete removal of runoff (Simperler et al., 2020), or maximum possible WSUD implementation based on current land use (Rodriguez et al., 2021). Given uncertainty in the nature of future urban development, it is critical to understand the catchment's response to a wide range of WSUD implementation scenarios across the catchment for identifying futureproof, effective locations for flood mitigation.

In this paper, we present a novel WSUD spatial prioritisation framework for pluvial flood mitigation, using Global Sensitivity Analysis (GSA) to identify effective subcatchments where WSUD implementation would lead to optimum flood volume reduction under a range of design storms. GSA explores the entire range of possible values of all input parameters and their interactions, making it well suited for analysing non-linear models and assessing effects of parameter interactions (Song et al., 2015). It has been useful for identifying influential parameters in hydrological models (Wang and Solomatine, 2019) and urban drainage models (Vanrolleghem et al., 2015). To our knowledge, this is the first framework for WSUD spatial prioritisation for pluvial flood mitigation using GSA. By coupling UrbanBEATS and SWMM, and then applying GSA, we introduce a simple approach to simulate all possible extents of WSUD implementation and future development scenarios through changes in effective impervious area (EIA) ratio of subcatchments, as a proxy for WSUD's effect in reducing runoff by converting impervious area to pervious. This enables assessment of the complex impact of WSUD implementation in different locations on catchment flooding for the first time. Based on the influence of subcatchments on flooding under all design storms, priority subcatchments that are futureproof for achieving effective flood mitigation can be identified. This work also provides the basis for setting a simple and quantifiable target for the selection of WSUD design and types at subcatchment scale to meet catchment-wide flood mitigation targets, which is an essential part of WSUD planning for pluvial flood mitigation.

2. Methodology

2.1. Proposed WSUD Spatial Prioritisation Framework

The proposed framework consists of four modules (M1-4, Fig. 1).

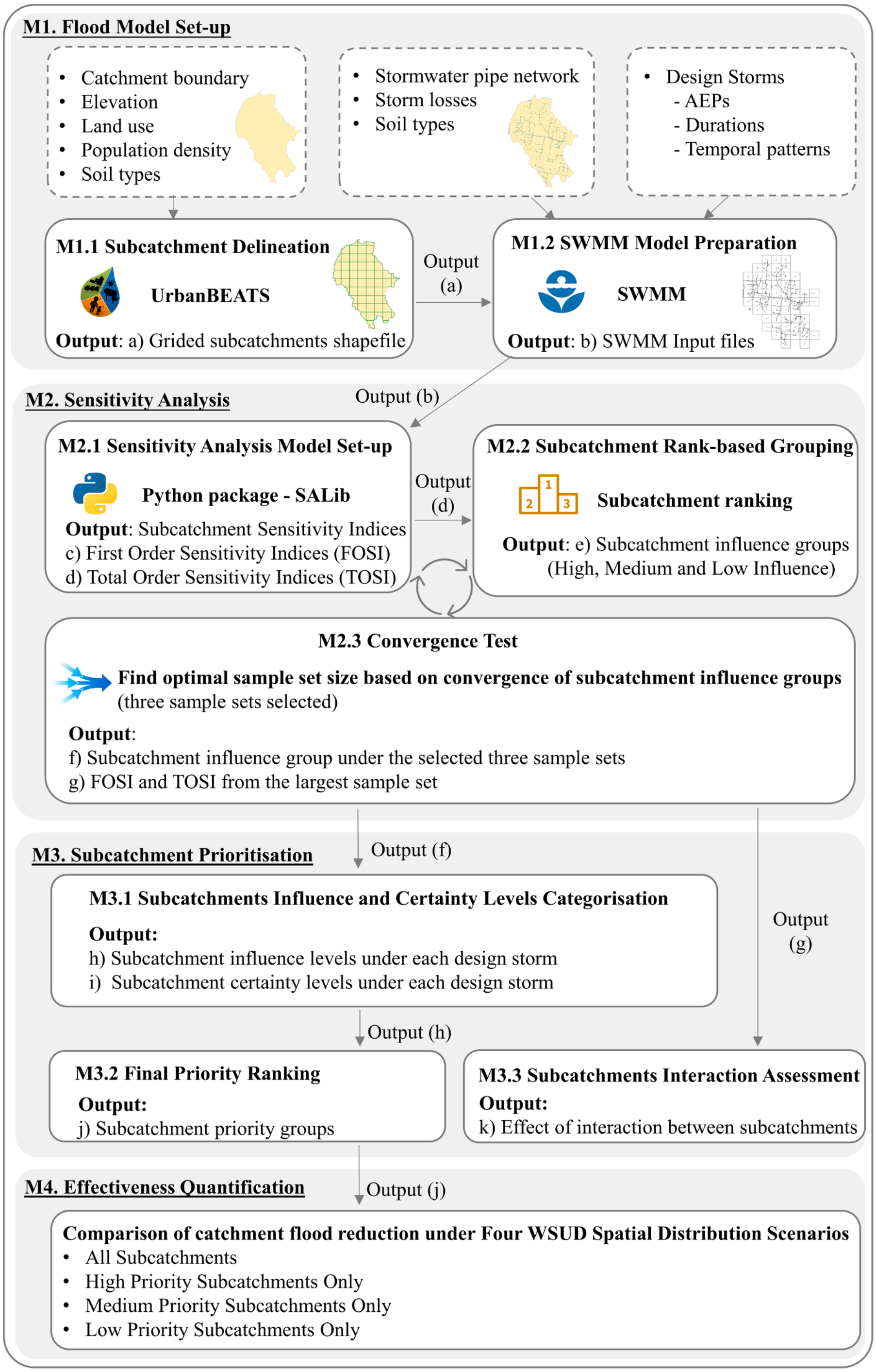

Fig. 1. Overview of WSUD spatial prioritisation framework for pluvial flood mitigation. Module M1 prepares a flood model for the study area, with subcatchments delineated into grid-shape in UrbanBEATS (M1.1) and connected to stormwater pipe networks in SWMM (M1.2). Module M2 applies a global sensitivity analysis (GSA) algorithm to assess the influence of changes in the effective impervious area (EIA) ratio of different subcatchments on catchment flooding (M2.1). Subcatchments are ranked based on their total order sensitivity indices (TOSI) and are grouped into High, Medium and Low Influence Groups (M2.2). Convergence of subcatchment influence groups is conducted to select three sample sizes in the GSA for robust results (M2.3). In Module M3, subcatchment influence groups under the selected sample sets are used to determine subcatchment influence levels under each design storm, and their final priority ranking (M3.1-3.2). The effect of interactions between subcatchments on catchment flooding is also assessed (M3.3). Finally, the effectiveness of prioritised subcatchments for flood reduction is validated in Module M4 by comparing four WSUD spatial distribution scenarios. Dashed line boundary indicates input data.

Module M1 involves setting up a flood model to simulate pluvial flooding. A GSA algorithm is applied in Module M2 using inputs and outputs of the flood model to assess the sensitivity of catchment flooding to changes in the effective impervious area (EIA) ratio of different subcatchments. The results from the GSA are used to prioritise subcatchments in Module M3. Finally, the effectiveness of the prioritised subcatchments for flood reduction is validated in Module M4.

M1. Flood Model Set-up

M1.1. Subcatchment Delineation. A spatial representation of the catchment is produced using UrbanBEATS (Bach et al., 2020), with input data including the catchment boundary, elevation, land use types, population density, and soil types generated through ArcMap. Subcatchments are delineated into scalable grid-cells, known as “blocks”, using UrbanBEATS’ GIS-based automated block delineation. Each “block” contains aggregated spatial information from the input data, including key characteristics such as imperviousness which is essential for runoff estimation (Bach et al., 2018). Such uniform, block-based subcatchment delineation has been applied in previous flood source identification studies (Saghafian et al., 2010; Vercruysse et al., 2019). It reduces the influence of subcatchment size on flood contribution and offers simplicity in communicating with stakeholders for WSUD planning. It also provides matching spatial scales for future coupling with UrbanBEATS to select optimal WSUD options for flood mitigation.

M1.2. SWMM Model Preparation. Catchment flood simulation is performed using the U.S. EPA Storm Water Management Model (SWMM) (Rossman, 2010), one of the most commonly used models in urban drainage flood simulation (Jamali et al., 2020; Niazi et al., 2017). Subcatchment properties such as subcatchment area, imperviousness, and slope in SWMM are set based on M1.1's output catchment shapefile from UrbanBEATS. Each subcatchment's outlet is set to the nearest inlet node in the pipe network in SWMM following slope gradients. Ten design storms of 1-50% annual exceedance probabilities (AEPs) under short and long durations are simulated to assess the catchment response. The rainfall temporal pattern that resembles the average peak runoff in ten temporal patterns for a given AEP and duration is selected to reflect natural storm variability (Ball et al., 2019).

M2. Sensitivity Analysis

A popular GSA algorithm known as the extended Fourier Amplitude Sensitivity Test (eFAST) (Saltelli et al., 1999) is applied to assess the sensitivity of catchment flooding to changes in the EIA ratio in subcatchments. The eFAST algorithm is a variance-based method, which quantifies the variability in the model output caused by variability of individual model parameters and parameter interactions (Norton, 2015). It is capable of generating accurate and robust results at higher computational efficiency than other variance-based methods (Saltelli et al., 1999; Song et al., 2015).

An open-source Python package called SALib (Herman and Usher, 2017) is deployed to perform eFAST, generating two outputs: the First Order Sensitivity Indices (FOSI) and the Total Order Sensitivity Indices (TOSI). FOSI quantifies what proportion of variations in the model output is caused by varying a single parameter; TOSI accounts for additional variations in the model output caused by that parameter's interactions with others. The effect of a parameter's interactions with others on the model output can be quantified by the arithmetic difference between its TOSI and FOSI.

M2.1. Sensitivity Analysis Model Set-up. Using SALib, four steps are involved to compute FOSI and TOSI for each subcatchment. In Step 1, the EIA ratio of each individual subcatchment in the catchment is set as an input parameter in the eFAST algorithm, with a value range of 0-100%. This value range allows consideration of all possible extent of EIA in the subcatchment, representing possible scenarios of future development (increase in EIA) and effects of WSUD implementation in converting EIA into pervious area, thus reducing the amount of runoff generated in EIA from entering drainage networks (reduction in EIA). Previous studies have introduced concepts to quantify and represent the effectiveness of WSUD for stormwater quality control in relation to imperviousness. Walsh et al. (2009) used an index called "retention capacity" to quantify the degree of disconnection between effective impervious area and its receiving waters. Zhang et al. (2020) introduced an indicator called "impervious area offset" to provide a straight-forward representation of how much additional impervious area can be left untreated due to implementation of stormwater harvesting measures to meet a set pollution control objective. Similar practice of simulating the effect of WSUD for stormwater quantity management through changes in imperviousness has also been applied in the work of Löwe et al. (2017), where the effect of rainwater harvesting tanks on runoff and flood risk reduction was computed by converting the roof area of buildings from impervious area to pervious area when rainwater tanks were installed in the building. A key merit of this approach is that it provides simplicity in simulating possible runoff reduction scenarios in each subcatchment without the burden of exploring and setting up countless possible WSUD types, designs and sizes in each subcatchment in SWMM model. It also provides the basis for setting runoff volume reduction targets at subcatchment levels, calculated by changes in runoff due to reduction in EIA, to select appropriate sizes of WSUD design to meet flood mitigation objectives at catchment scale.

In Step (2), a sample set containing all input parameters' values within the defined value ranges is generated using the eFAST sampling algorithm in SALib. The size of the sample set is determined by Eq. (1):

$$N = n \times D \tag{1}$$

where N is the size of the sample set (i.e., total number of SWMM model simulations), n is the size of base samples (user-defined), and D is the number of model input parameters (i.e., number of subcatchments each with a corresponding EIA). As N is a function of n, the chosen value of n determines the size of N required to obtain reliable results for the sensitivity analysis and its computational cost (Pianosi et al., 2016). The process of deciding an optimal value of n is given in M2.3.

In Step (3), the SWMM model is run with new EIA ratio values from the generated sample set. The resulting catchment flood volume (i.e., total node flooding in the unit of 10ˆ6 litre) and peak flow rates (litre per second) are recorded and processed in Step (4) using SALib's eFAST analysis algorithm to compute FOSI and TOSI for each subcatchment.

In Step (4), a simple summation of catchment flood volume values and peak flow rate values is used to represent catchment flooding. While catchment flood volume is the primary performance indicator in our study, preliminary analysis showed that using peak flow rate accelerated the process of identifying influential subcatchments when there was no or limited node overflowing. As catchment flood volume values are usually significantly larger than peak flow, adding peak flow rate is expected to have limited impact on the prioritisation results.

Step (1)-(4) is repeated using SWMM models with ten design storms created in M1.2. They are of 1%, 5%, 10%, 20%, and 50% AEPs under short and long durations, with varying rainfall temporal patterns.

M2.2. Subcatchment Rank-based Grouping. The TOSI value of each subcatchment from M2.1 is used to determine the subcatchment's ranking in terms of its influence on catchment flooding. TOSI is used instead of FOSI, because a larger TOSI value indicates a stronger influence of a subcatchment on flood volume both by itself and through its interactions with others. As it would take more than a handful of subcatchments to implement WSUD to achieve substantial reduction in flooding, subcatchments are further categorised into three influence groups based on their ranking: High Influence (top third), Medium Influence (median third) and Low Influence (bottom third).

M2.3. Convergence Test. To ensure robustness of the sensitivity analysis results, an appropriate base sample size n is pivotal. If n is too small, it does not generate enough samples to explore the entire range of the input parameters values for quantifying their impacts on model output; if n is too big, it results in unnecessarily large sample set (N). Therefore, a convergence test is necessary for identifying the minimum n that balances result robustness and computational expense.

The size of n depends on several factors including the number of input parameters, the level of model complexity, and the type of convergence of interest (e.g., convergence of sensitivity indices or ranking order of parameters based on the sensitivity indices) (Sarrazin et al., 2016; Wang and Solomatine, 2019). For the purpose of our study, convergence of subcatchment ranking orders is adopted because it is well-suited for identifying top ranking influential subcatchments and is more computationally economic, requiring fewer samples than convergence of TOSI values (Sarrazin et al., 2016). To further reduce the computational cost, convergence is consider reached when a subcatchment' ranking stays in the same influence group as n increases. The convergence test is carried out by repeatedly running Step (2) to (4) in M2.1, and M2.2 with increasing value of n, at an interval of 2000 until there is no change in the subcatchments' influence groups based on their rankings. When over 80% of the subcatchments in the catchment has reached convergence under all design storms, the three largest n are considered sufficient and the three sample sets created using these three

n values are selected. The resulting subcatchment TOSI values, ranking orders, and influence groups from these three sample sets are used in M3.

M3. Subcatchment Prioritisation

Results from M2.3 are processed to decide subcatchments' final influence levels under each design storm, assess effect of interactions between subcatchments on catchment flooding and determine subcatchment priorities.

M3.1. Subcatchments Influence and Certainty Levels Categorisation. A final influence level (High, Medium, and Low) of each subcatchment is determined according to its influence group results based on TOSI values from the sensitivity analysis using the largest sample set, because the largest sample set is believed to provide the most robust results among the three sample sets. Subcatchments that are in the same influence groups under all three sample sets have high certainty in their influence level; those with fluctuations in their influence groups over the three sample sets are marked with low certainty. The influence levels and certainty levels of each subcatchment under all design storms are compared and analysed.

M3.2. Subcatchments Interaction Assessment. Under each design storm, the effect of each subcatchment's interactions with other subcatchments on catchment flooding (known as $\mathrm{E_{ffect}I_{nt'}}$) is quantified by the arithmetic difference between the subcatchment's TOSI and FOSI values from the sensitivity analysis with the largest sample set.

M3.3. Final Priority Grouping. A scoring system is applied to decide the priority order of subcatchments based on their final influence levels (from M3.1) across all design storms. For each design storm, each subcatchment is awarded 10 points for having high influence, 5 for medium and 0 for low. The total score for each subcatchment is then used to rank their priority and decide their priority groups. Three priority groups (High, Medium, Low Priority Subcatchments) containing equal number of subcatchments are created.

M4. Validation of Spatial Prioritisation's Effectiveness for Flood Mitigation

We apply a validation method adopted from published studies (Zeng et al., 2019; Zischg et al., 2018) to assess the effectiveness of the proposed framework in identifying priority subcatchments. WSUD is assumed to be implemented (1) catchment-wide (evenly in every subcatchment); (2) in High Priority Subcatchments only; (3) in Medium Priority Subcatchments only; (4) in Low Priority Subcatchments only. Under each scenario, the same total amount of EIA in the catchment is reduced to represent WSUD implementation (i.e., the connected impervious area is converted to pervious area, reducing runoff to the receiving drainage system). The total EIA to be reduced is calculated as:

$$EIA_{Total} = EIA_{Min} \times X_{PG} \tag{2}$$

where EIA_{Total} is the total amount of effective impervious area (EIA) to be reduced in the catchment, EIA_{Min} is the numerical size of EIA in the smallest subcatchment and X_{PG} is the number of subcatchments in each priority group.

Under Scenario (1) catchment-wide implementation, EIA_{Total} is evenly distributed across the catchment, and the amount of EIA to be reduced in each subcatchment, EIA_{CW}, is calculated as:

$$EIA_{CW} = EIA_{Total} \div X_{Total} \tag{3}$$

where X_{Total} is the total number of subcatchments in the catchment.

Under Scenario (2)-(4) with targeted-implementation in High, Medium and Low Priority Subcatchments only, EIA_{Total} is only distributed to the subcatchments in the priority group considered in the scenario. Thus, Eq. (3) is modified to:

$$EIA_{TI} = EIA_{Total} \div X_{PG} \tag{4}$$

where EIA_{TI} is the amount of EIA to be reduced in each subcatchment in the priority group, and X_{PG} is the number of subcatchments in the priority group.

The effectiveness of each scenario under each design storm is then assessed by:

$$V_{reduction\%} = \frac{V_{baseline} - V_{scenario}}{V_{baseline}} \tag{5}$$

where $V_{reduction\%}$ is the percentage reduction in catchment flood volume, $V_{baseline}$ is the baseline catchment flood volume under current land use, and $V_{scenario}$ is the catchment flood volume under each WSUD distribution scenario.

2.2. Case study application

The proposed framework was applied in Coogee catchment in Sydney, Australia; a highly urbanised and steep catchment draining eastward into the sea (Fig. 2). Approximately 80% of the catchment is connected to a large stormwater pipe network, and the Southern part of the catchment is drained by smaller local pipe networks (Williams, 2013) (Fig. 2b). Most of the pipe networks were designed to cope with rainfalls of 20% AEP to 10% AEP (Williams, 2013). Previous floodplain risk assessment commissioned by Randwick City Council has revealed significant impact of flooding on the catchment, with nearly $2.1 million annual average damage on properties (Griffin, 2016).

A spatial representation of the catchment was created using UrbanBEATS with subcatchments delineated into blocks of 250 × 250m (6.25 ha), a subcatchment size that has been tested and validated in Bach et al. (2018) (see Appendix A1 for input data source). This size resulted in a manageable number of subcatchments and produced similar runoff volume to a finer block size of 200 × 200m. A total of 57 subcatchments with a total area of 286.89 ha were set up in SWMM (see Appendix A2 for SWMM data preparation). Note that due to limited data available, the SWMM model in this study was not calibrated. Future applications of the framework should be used with a calibrated model if feasible.

Ten design storms were created using local rainfall data, covering design storms of 1%, 5%, 10%, 20%, and 50% AEPs under short (90min) and long (360min) durations (see Appendix A3 for rainfall intensity and rainfall distribution).

Convergence tests showed that sample sets created with base sample size $n = 6000$, 8000, and 10,000 were sufficient to reach convergence for over 80% of the subcatchments under all ten design storms, except under the 50% AEP 360min duration rainfall (see Appendix A5 for details). Only 77% of subcatchments reached convergence under this 50% AEP event with no signs of increase in convergence even with $n = 14000$. This is likely a result of limited flooding under low intensity rainfall of long duration. The ranking order of subcatchments from the largest sample set (created with $n = 10{,}000$) was used to decide the final influence level of subcatchment for prioritisation. Given 57 subcatchments in total, each influence group had 19 subcatchments, as did each priority group.

With the total number of subcatchments in Coogee and the number of subcatchments in each priority group, $X_{Total} = 57$ and $X_{PG} = 19$. The smallest size of EIA in subcatchments, EIA_{Min}, was 0.6 ha. According to Eq. (2), this resulted in $EIA_{Total} = 11.4$ ha, which is approximately 4% of total catchment area and 6% of total catchment EIA. Using Eq. (3) and (4), EIA_{CW} and EIA_{TI} were calculated to be 0.2 ha and 0.6 ha, respectively.

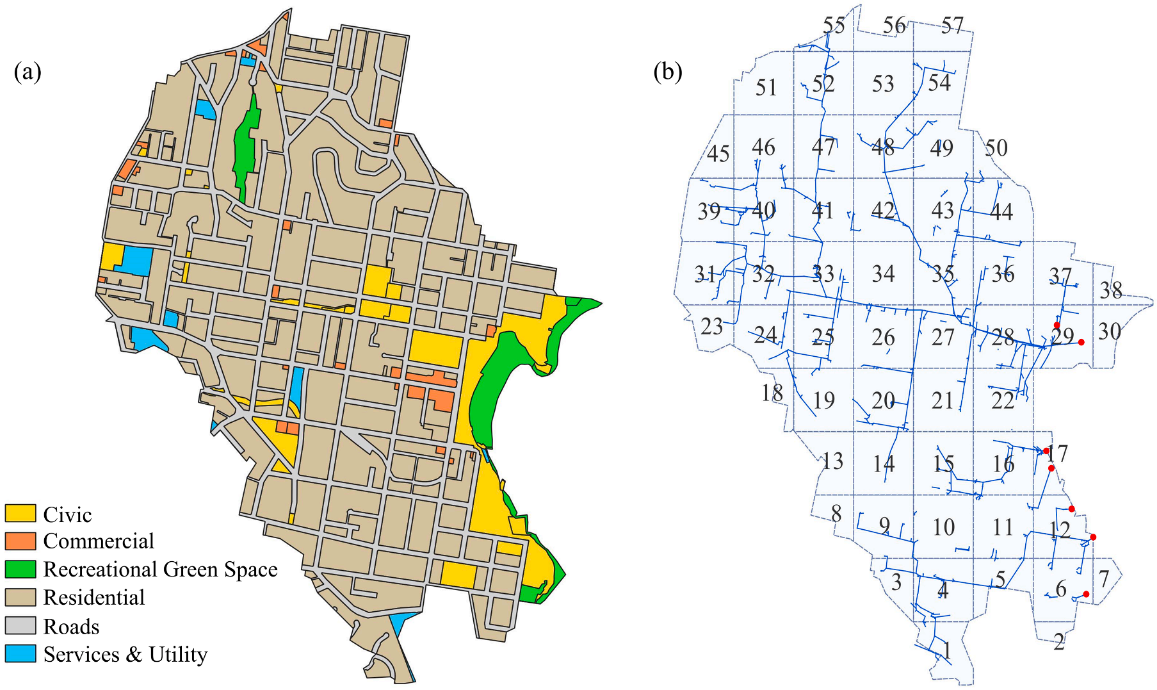

Fig. 2. Maps of Coogee (a) land use (classified by URBANBEATS), and (b) subcatchment boundaries and stormwater pipe networks (represented by blue lines). Drain outlets are indicated by red dots. Numbers in subcatchments represent subcatchment IDs.

3. Results and Discussion

3.1. *Subcatchments Influence and Certainty Levels under Different Rainfalls*

There were considerable variations in the subcatchment influence levels under different design storms (Fig. 3). Only 40% of the subcatchments had the same level of influence under all storms. The variations are likely caused by compounded effects of rainfall characteristics, subcatchment locations, and interactions with the pipe networks. The spatial distribution of subcatchments of different influence levels under different design storms and their relative locations to the pipe networks are shown in Fig. 4. Under rare rainfalls (e.g., 1% AEP), the majority of highly influential subcatchments were clustered upstream and midstream of the large pipe network. As reported in the literature (Zeng et al., 2019), this is mainly due to the direct influences these subcatchments had on the amount of runoff entering the entire large pipe network, relieving or aggravating flooding downstream. In addition, since most of the pipe network was designed for managing runoff from rainfalls of up to 10%AEP, catchment flooding is more sensitive to changes in these subcatchments under rare and intense rainfalls because these subcatchments have a dominating effect in

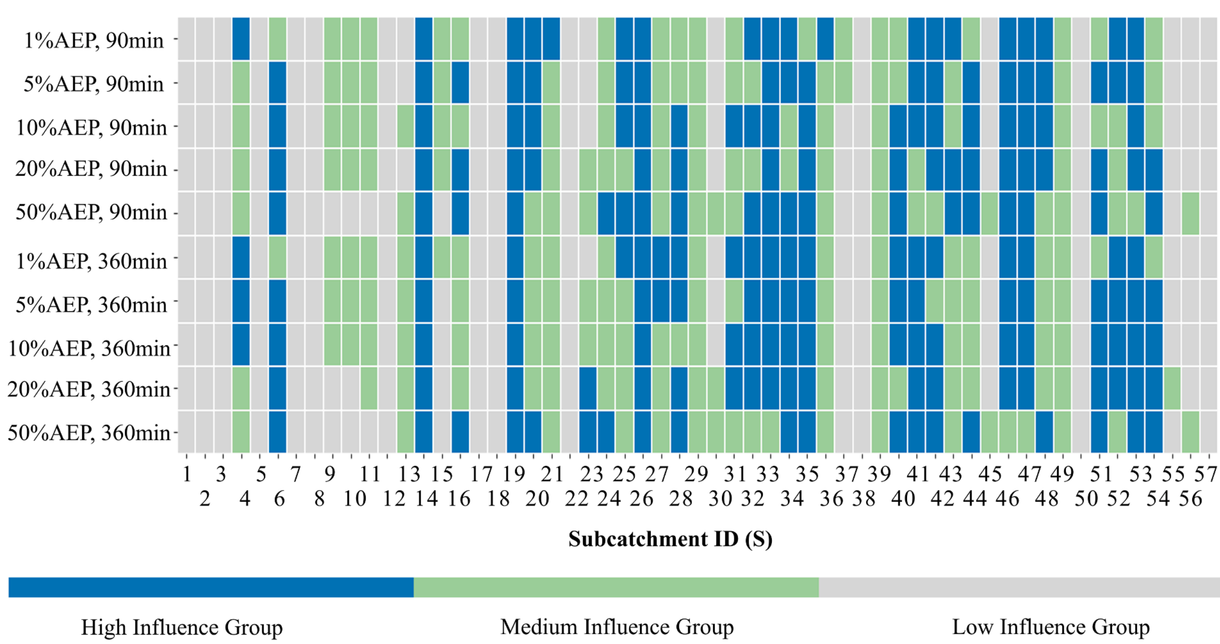

Fig. 3. Subcatchment influence groups under rainfall of short duration (90min) and long duration (360min).

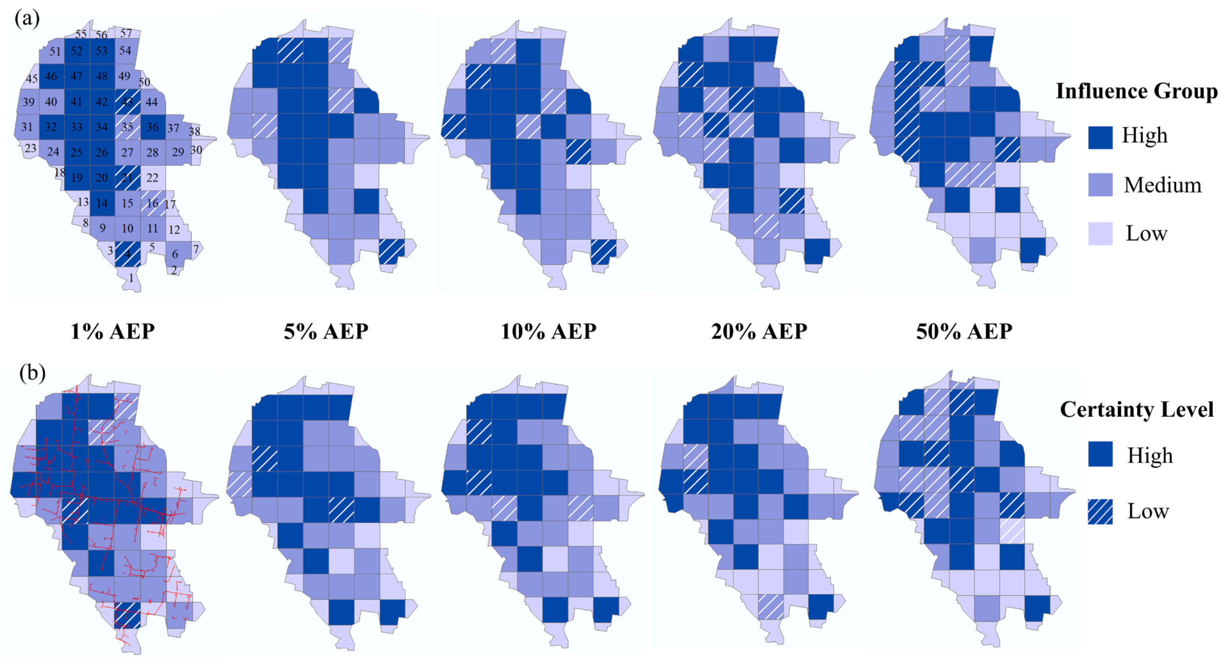

Fig. 4. Influence group and certainty levels of subcatchments under (a) short duration (90min) rainfalls, and (b) long duration (360min) rainfalls. Numbers in the subcatchments represent subcatchment ID number. Red lines represent the pipe networks.

determining whether the pipe's drainage capacity would be exceeded and by how much.

As rainfall frequency increased, highly influential subcatchments became scattered across the catchment, including in downstream areas. The spatial dispersion of highly influential subcatchments can be attributed to reduction in flooding under more frequent rainfall of lower intensity. While changes in the upstream and midstream subcatchments would still impact the amount of runoff going into the pipe network, their effects on catchment flooding were much less pronounced as the pipe network can cope with most of runoff from small rainfalls despite large increase in EIA in these subcatchments. In addition, while the study area is a steep catchment which facilitates rapid flow of runoff and flooding, the impact of catchment slope on flood generation is less significant under frequent, low intensity storms, resulting in localised conditions to be more influential. Catchment flooding thus became more sensitive to localised changes in subcatchments across the catchment. This result highlights the importance of considering pipe network drainage capacity in identifying influential subcatchments under different rainfalls.

The variation in the spatial distribution of influential subcatchments over different rainfall AEPs was observed in both short and long duration rainfalls. No other distinctive patterns were found when comparing subcatchments' influence between short and long duration rainfalls. While some subcatchments (e.g., S6 and S11; Fig. 3) showed a similar increase or decrease in their influence levels under both short and long duration rainfalls, others displayed completely different patterns (e.g., S25, S28 and S48), possibly due to differences in rainfall temporal patterns, local drainage configuration, relative location to the outlets, and uncertainty in the subcatchments' influence levels.

As rainfall frequency increased, there was growing uncertainty in subcatchment influence levels (Fig. 4; see Appendix A5 for data on certainty levels). Under 1%AEP events, there was high certainty in those highly influential subcatchments clustered in the upstream and midstream of the large pipe network, and low certainty in only four subcatchments distributed across the catchment. However, under 50% AEP events, there were over 10 subcatchments with low certainty in their influence levels, all distributed in the areas drained by the large pipe network, especially upstream and midstream. Similar to the changes observed in influence levels, uncertainty in these subcatchments could be due to overall limited flooding in the drainage systems under frequent rainfalls of reduced intensity. Changes in these subcatchments had less deterministic effect on causing substantial changes in flooding as the pipe networks' capacity was not always overwhelmed under such rainfalls. Similar findings have been reported by Zeng et al. (2019) who noted high instability in the effect of WSUD implementation in different locations on flood reduction under low intensity rainfall events due to small flood volume, followed by gradual stabilisation as rainfall intensity increased.

While previous studies have considered a range of rainfall events in identifying influential subcatchments (Rodriguez et al., 2021; Simperler et al., 2020), our results provide new insights into how the spatial distribution of influential subcatchments varied under different rainfall frequencies. Considering the notable variations in subcatchment influence and certainty levels under different rainfall intensities, flood mitigation targets set based on rainfall AEPs will have implications on the optimum spatial distribution of priority subcatchments for WSUD implementation. Rainfall temporal patterns may have contributed to the variations in subcatchments' influence but no distinctive effect of rainfall duration on subcatchments' influence was found. The choice of design storms should be given careful consideration to ensure confidence in the prioritised locations. If the main objective is to implement WSUD to mitigate flooding from more frequent rainfalls in this catchment, the priority locations for its implementation would be more scattered in the catchment.

Apart from the impact of rainfall, the high uncertainty in subcatchments' influence levels under frequent rainfalls could be due to strong non-linearity in the catchment's response to variations in these subcatchments. While a larger sensitivity analysis sample set size may help reach better convergence of these subcatchments' influence groups, there has been reported increase in instability in sensitivity analysis results due to high model complexity (Wang and Solomatine, 2019). It is possible that because of the complex hydrological and hydraulic responses of the catchment to variations in subcatchments' EIA ratio, complete stabilisation of these subcatchments' effect on catchment flooding may not be reached even with substantial computational effort. More future applications of this framework on flood models for other catchments with different levels of complexity would help build a better understanding of such uncertainty in the model.

3.2. Subcatchment Prioritisation

Based the subcatchments' influence levels under ten design storms, almost 90% of the high priority subcatchments were found clustered in the upstream and midstream of the large stormwater pipe network, with a few placed closed to the network outlets (Fig. 5). Among the high priority subcatchments, three subcatchments, S14, S19 and S26, were highly influential under all design storms (i.e., priority score 100). One key factor that contributed to such high influence of S19 is slope. Across the catchment, the subcatchments' slope ranged from 0.11 to 10.15%, with a median slope of 5.34%. S19, with a slope of 8.03%, was among the steepest subcatchments in the area (for slope map, see Appendix A4). Similarly, S47 (priority score 95) had a slope of 7.53%, creating a steep gradient for runoff generation, resulting in large influx of runoff at fast speed to cause flooding in the receiving conduit. While strong influences of catchment slope on flood generation have been observed in absence of modelling underground drainage networks (Gao et al., 2018), our study further shows that slope is influential for subcatchments' contribution to pluvial flooding. In addition to slope, drainage system configuration also plays an important role in subcatchment influence. For example, the other two subcatchments with priority score of 100, S14 and S26, have a gentler slope (6.14% and 5.4%, respectively) but were both drained by a small conduit (0.3m in diameter). In particular, the small conduit receiving runoff from S26 was connected to a downstream conduit with less steep slope, which acts as a bottleneck to restrict flows from going downstream. An increase in the amount of runoff from S26 could easily overload this part of the network and cause node flooding. Furthermore, the pipe networks configuration can also create compounding effects with slope together. For example, S6, one of the high priority subcatchments, had the steepest slope (10.15%) in the catchment and was drained by a small conduit (0.225m in diameter). Despite its spatial proximity to a catchment outlet, this subcatchment was highly influential on catchment flooding when its EIA ratio was varied. While our results confirm the strong influences of upstream subcatchments as noted in previous studies (Rodriguez et al., 2021; Zeng et al., 2019), our results also show that subcatchments in other parts of the catchment could be influential due to local subcatchments characteristics and drainage networks configuration. In addition to prioritising WSUD implementation in these influential subcatchments, future developments in these subcatchments should also be given careful consideration as an increase in EIA in these locations will likely lead to more flooding than other locations.

Thirteen subcatchments were of low influence under all design storms (priority score 0), mostly due to their marginalised location at the catchment boundary with irregular subcatchment shapes (i.e., smaller sizes) (Fig. 5). The only exception was Subcatchment S22, which had a standard 250 × 250m catchment area drained by a large conduit (0.75m in diameter) to a catchment outlet, so changes in this subcatchment did not have significant effects on flooding.

It is worth noting that in our case study application, the priority scores and grouping were based on subcatchment influence levels only, i.e., their certainty levels, discussed in section 3.1, were not taken into account. To ensure consideration of uncertainty, subcatchments with fluctuating influence on catchment flooding can be given weighted scores in the prioritisation process. The scoring system is arbitrary depending on the level of risk aversion. Since there were only three priority groups in our case study and the majority of uncertainties occurred under design storms of 20% and 50%AEP which were of relatively low flood risk, we expected minimum changes in the subcatchments' overall grouping even if each subcatchment with low certainty was given additional weights. Another aspect to consider is that if certain rainfall frequencies were of interest, for instance 20% and 50% AEP, then the priority scoring system should be modified to prioritise subcatchments that have higher influence levels under these rainfall frequencies, and those with high uncertainty in their influence levels should also be carefully considered.

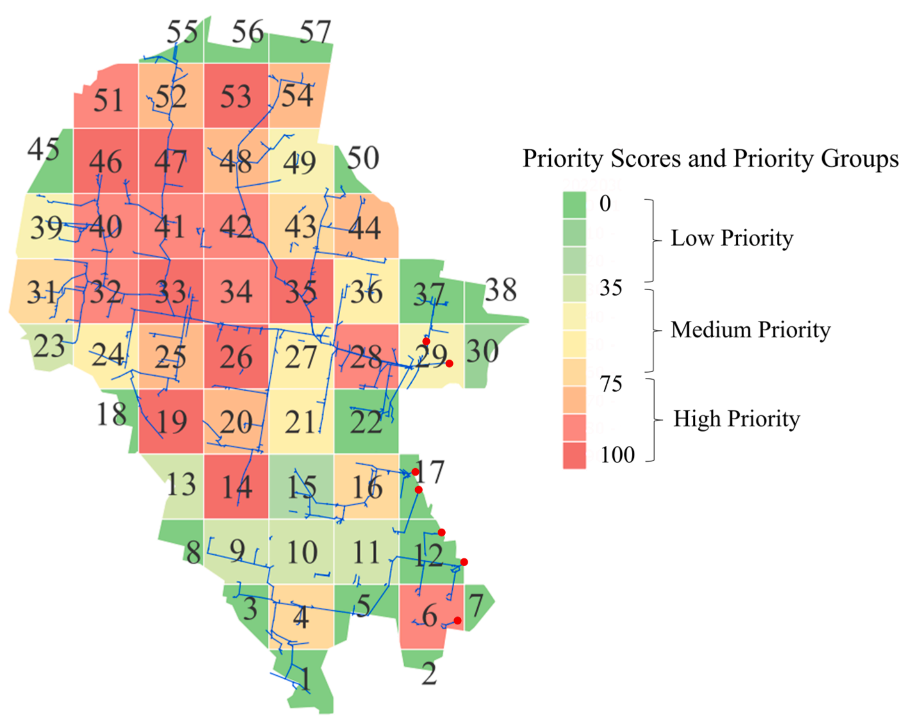

Fig. 5. Priority scores and priority groups of subcatchments based on their influence level under ten design storms. Blue lines represent the pipe networks. Numbers in subcatchments represent subcatchment IDs. Drain outlets are denoted by red dots.

3.3. Effect of Interactions between Subcatchments

There was evidence of interactions between varying EIA ratio in different subcatchments, but this was marginal compared to the subcatchments' independent influence. Quantified by $E_{ffect}I_{nt'}$ values, the effect of interaction accounted for, on average, only 0.11% of variations in catchment flooding across all design storms (see Appendix A6 for detailed $E_{ffect}I_{nt'}$ values). This means that a subcatchment's overall influence on catchment flooding is predominantly caused by changes in its own EIA ratios, with low dependency on simultaneous changes in other subcatchments' EIA ratio, thus limited effect of interactions. Such limited effect is likely a result of homogenous behaviour of the subcatchments due to catchment characteristics, subcatchment size and rainfall intensity. The catchment overall is steep and highly urbanised, so similar hydrological response across the catchment is expected. The typical size of subcatchments is 250 × 250m. Although this is smaller than the 500 × 500m subcatchment size used in Vercruysse et al. (2019), the inclusion of pipe networks in our study means that the inlets of drainage networks could easily experience surcharge because the inlets were originally designed to drain much smaller subcatchments. Furthermore, under heavy rainfalls, the runoff generated from individual subcatchments was enough to overload or reduce flooding in the

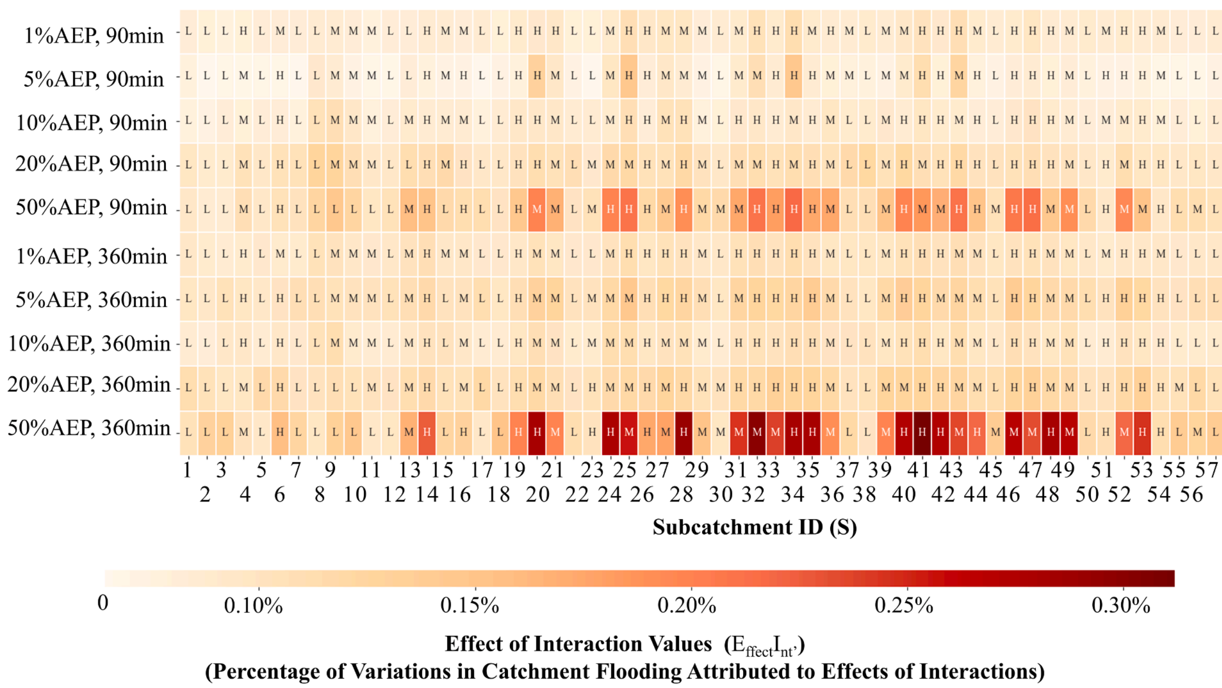

Fig. 6. Effects of individual subcatchment's interactions with other subcatchments quantified by $E_{ffect}I_{nt'}$ values. Annotation in individual cells indicates the subcatchment's influence group: H for High Influence, M for Medium Influence, and L for Low Influence. Under each design storm (shown on the Y axis), darker colour cell means the subcatchment had relatively stronger effects of interaction than other subcatchments.

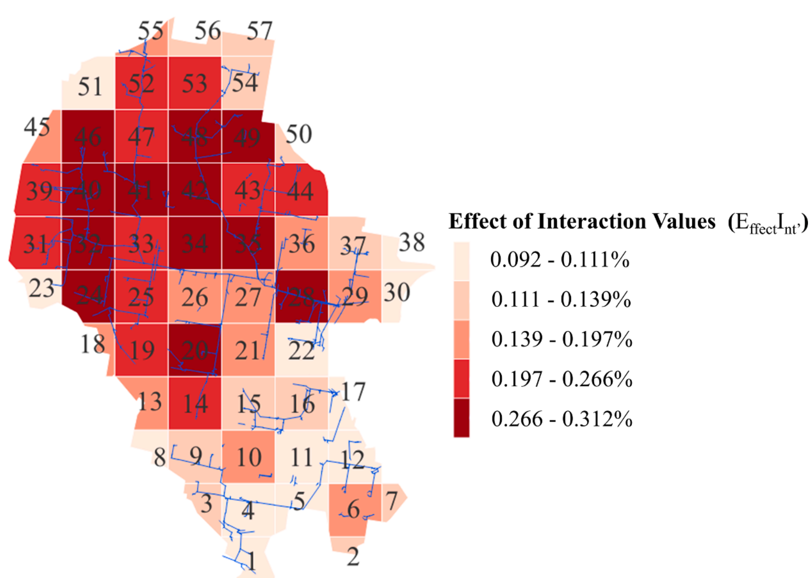

Fig. 7. Subcatchments' effect of interaction ($E_{ffect}I_{nt'}$) values under long duration rainfall of 50%AEP. Blue lines represent the pipe networks. Numbers in subcatchments represent subcatchment IDs.

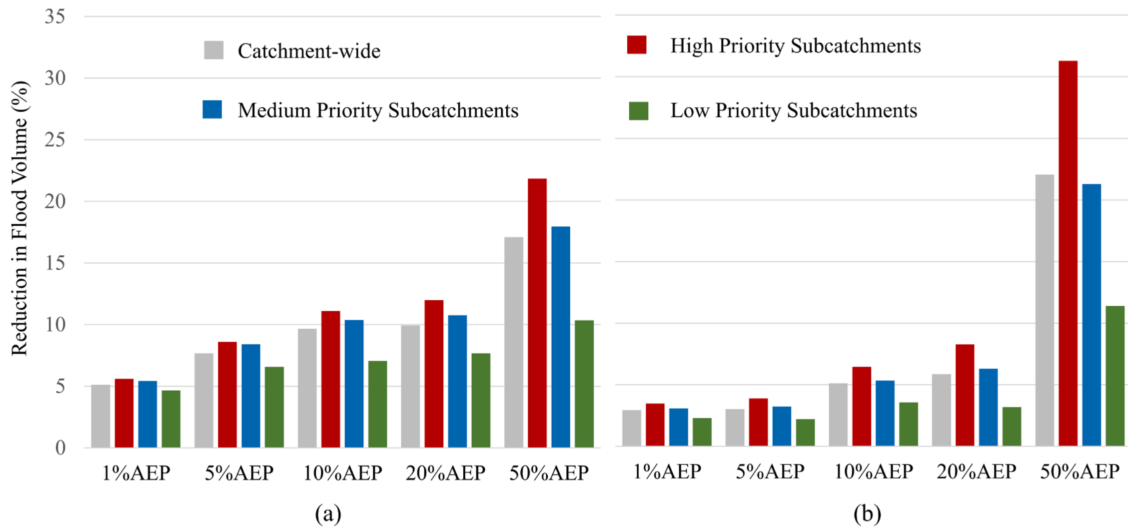

Fig. 8. Reduction in baseline catchment flood volume ($V_{reduction\%}$) under four WSUD spatial distribution scenarios where WSUD were implemented (1) Catchment-wide, (2) in High Priority Subcatchments, (3) Medium Priority Subcatchments and (4) Low Priority Subcatchments only, under (a) short duration (90min) rainfalls, and (b) long duration (360min) rainfalls. For data details, see Appendix A7.

pipe networks, leaving limited room for influence from other subcatchments. Under 1% and 5%AEP rainfalls, all subcatchments had similar and low $E_{ffect}I_{nt'}$ values (range between 0.06% and 0.14%) (Fig. 6). Slightly higher $E_{ffect}I_{nt'}$ values (range between 0.09-0.31%) were found under rainfalls of 50%AEP, especially under long duration where the strongest effect of interaction between subcatchments (0.31%) was observed in subcatchments drained by the large pipe networks (Fig. 7). This illustrates that with reduced amount of runoff under small rainfalls, changes in the EIA ratio of multiple subcatchments connected by the same drainage network could have marginally more compounded effects on catchment flooding.

While our results showed stronger effects of interactions in closely linked subcatchments under small rainfalls than heavy rainfalls, it is surprising to see overall limited effects of interaction between subcatchments in the study area. This implies that for the study area, while GSA is still needed to capture non-linear responses of catchment flooding to changes in different subcatchments, the subcatchments' individual influence on flooding (indicated by FOSI) may be sufficient for prioritising subcatchments for WSUD implementation. Although we did not find significant effect of interactions in the study catchment, application of our framework in other catchments with higher heterogeneity across the catchment or smaller subcatchment sizes may yield different results. This calls for further research applying the proposed framework to other catchments to gain a better understanding of the effect of interactions. Should the effect of interactions be significant, then focusing on a cluster of subcatchments or a subpart of the drainage network would be necessary for achieving effective flood mitigation.

3.4. *Effectiveness of WSUD Spatial Prioritisation for Flood Mitigation*

Applying a validation approach adopted from existing studies (Zischg et al., 2018), our results showed that WSUD implementation (represented by reduction of EIA) in the high priority subcatchments achieved the largest percentage reduction in flood volume across all design storms, ranging between 3.5% to 31.3% for 1%AEP to 50%AEP storms (see Fig. 8 for percentage reduction in flooding and Table 1 for catchment total flood volume under each design storm). This demonstrates the success of our framework using GSA in identifying effective locations, even with high uncertainty under small rainfalls. Implementation in medium priority subcatchments ranked second (3.1-21.3%) and performed slightly better than catchment-wide implementation (2.9-22.1%) under all design storms except in 50%AEP of long duration. Low priority subcatchments produced the least reduction under all rainfall scenarios (2.3-11.4%). Under rainfalls of the same duration, all scenarios achieved more flood reduction as rainfall frequency increased. This confirms the reported effectiveness of WSUD implementation for flood reduction under more frequent rainfalls in existing literature (Myers and Pezzaniti, 2019). The differences in flood reduction achieved by the four scenarios also increased with rainfall frequency, with the biggest difference observed under long-duration rainfall of 50%AEP, where implementation in high priority subcatchments achieved almost tripled the reduction in low priority subcatchments (11.39%). This further highlights the importance of prioritising the most effective subcatchments, especially under frequent and small rainfalls. The reduced differences under rare rainfalls can be explained by the fact that under rare rainfalls, the entire drainage networks

Table 1
Catchment Total Flood Volume (unit: 1,000,000 litre) under Each WSUD Spatial Distribution Scenario

Duration	Distribution Scenario	1%AEP	5%AEP	10%AEP	20%AEP	50%AEP
90min	Baseline (No WSUD)	126.90	72.68	51.97	37.26	15.07
	Catchment-wide	120.49	67.25	47.09	33.64	12.64
	High Priority Subcatchments	119.88	66.55	46.45	32.94	12.03
	Medium Priority Subcatchments	120.12	66.66	46.81	33.36	12.52
	Low Priority Subcatchments	121.09	67.98	48.20	34.38	13.48
360min	Baseline (No WSUD)	198.75	114.96	75.49	43.54	9.81
	Catchment-wide	192.98	111.52	71.80	41.03	8.02
	High Priority Subcatchments	192.03	110.66	70.90	40.10	7.33
	Medium Priority Subcatchments	192.72	111.34	71.62	41.02	8.24
	Low Priority Subcatchments	194.14	112.46	72.82	41.95	8.64

became so overloaded that there were limited differences in the effect of changes in subcatchments at different locations of the catchment on flood reduction. Our finding agrees with the reported decrease in flood reduction differences between different WSUD sitting strategies under high intensity rainfall in the work by Zeng et al. (2019).

Under rainfalls of the same AEP, all scenarios showed higher percentage reduction in flood volume under short duration than long duration, except in the case of 50%AEP, due to the smaller amount of flooding generated under most short duration rainfalls (Table 1). The limited flooding generated under the long-duration rainfall of 50%AEP may help explain the exception where catchment-wide implementation outperformed medium priority subcatchments (Fig. 8). As discussed earlier, under frequent, low intensity rainfalls, catchment flooding became more sensitive to localised, distributed changes across the catchment due to more adequate drainage capacity and less significant impact from steep slopes, so implementation of WSUD homogenously across the catchment may cover more influential subcatchments to deliver better flood reduction than targeting medium priority subcatchments only. This may also explain the reported better performance of catchment-wide implementation than mid-stream subcatchments for flood volume reduction in Zeng et al. (2019)'s work. As Zeng et al. (2019) only simulated one "moderate intensity" design storm for the comparison with catchment-wide implementation, it is unknown whether the same conclusion could be drawn under different rainfalls. In contrast, our results demonstrate that the identified high and medium priority subcatchments achieved more reduction than catchment-wide implementation under nine out of ten design storms, especially in those of higher intensity, providing confidence in the effectiveness of WSUD implementation in the prioritised subcatchments for flood mitigation.

As demonstrated above, our framework has been shown to be effective for assessing complex impact of WSUD spatial distribution on catchment flooding to identify priority locations. The use of changes in EIA ratio in subcatchments in our framework offers simplicity and flexibility in simulating the effect of WSUD implementation. WSUD planners can freely decide the range of reduction in EIA in each subcatchment based on subcatchment characteristics and development plans. In addition, assessing the effect of reduction in subcatchment EIA on catchment flooding provides the basis for setting a simple and quantifiable subcatchment-level WSUD runoff volume reduction performance target for selecting WSUD options to achieve catchment-scale flood mitigation objectives. Our framework can be coupled with WSUD planning models such as UrbanBEATS to rapidly explore effective WSUD options and feasible locations within the prioritised subcatchments to help planners deliver WSUD planning for a set of water management targets to achieve integrated urban water management.

However, it is worth noting that the use of reducing EIA only simulates the effect of WSUD on reducing runoff through converting impervious area to pervious area. Key WSUD performance factors, such as retention capacity limitations (Yao et al., 2020) and antecedent conditions including pre-burst rainfall and storage capacity (Myers and Pezzaniti, 2019) were not considered. Therefore, future work on understanding WSUD performance using continuous rainfall simulation and selecting optimal WSUD options to realise equivalent effects of "impervious area offset" (Zhang et al., 2020) for stormwater quantity management would be instrumental to ensure the robustness of the framework.

Future studies should also consider beyond catchment flood volume, as flood mitigation is not just about reducing flood volume. Due to limitation on data availability, modelling capacity of SWMM and computation cost for running time-consuming flood models for GSA, our framework focuses primarily on flood volume from overflowing nodes. Further research modelling actual flood risk and damage, taking into account flood duration and velocity, would provide a more accurate simulation of the impact of WSUD implementation on flood mitigation. A weighted multi-criteria system and a cost-benefit analysis based on flood damage reduction can be adopted to rank and prioritise subcatchments for their overall influence on flood damage to identify the best WSUD implementation strategies.

4. Conclusion

To the authors' knowledge, our proposed framework is the first application of WSUD spatial prioritisation for pluvial flood mitigation using global sensitivity analysis. Through assessing the sensitivity of catchment flooding to changes in effective impervious area ratio in all subcatchments under multiple design storms, our framework provides a systematic assessment of the complex impact of WSUD locations on catchment flood volume for the first time, enabling identification of WSUD implementation strategies with the best outcome for pluvial flood mitigation. Application of this framework to a highly urbanised, steep catchment in Sydney, Australia demonstrated the usefulness of the framework in identifying priority subcatchments: even targeting medium priority subcatchments can achieve better performance than catchment-wide implementation under most design storms.

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

Python codes and example SWMM file used in this study can be found here: https://github.com/vww-wrc/WSUD-Spatial-Prioritisation-through-GSA-for-Effective-Pluvial-Flood-Mitigatition.

Acknowledgement

This research is funded by Australian Government Research Training Program Scholarship and an Australian Research Council (ARC) Discovery Project (fund number DP210103704). This research includes computations using the computational cluster Katana supported by Research Technology Services at UNSW Sydney. The authors thank Randwick Council for the provision of catchment data. The authors are grateful for the help and support from Dr. Veljko Prodanovic and Dr. Peter M. Bach on UrbanBEATS.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2023.119888.

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