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Multi-objective optimization for green-grey infrastructures in response to external uncertainties

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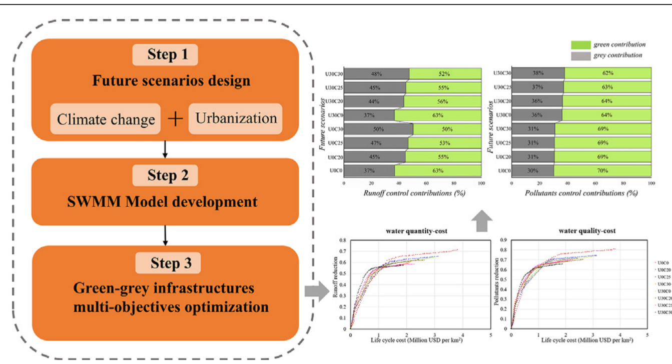
HIGHLIGHTS

- A multi-objective optimization framework is proposed.
- Optimization is conducted under uncertainties of climate change and urbanization.
- The synergistic benefits of green-grey infrastructures are verified.
- Green infrastructures have more environmental contributions.

GRAPHICAL ABSTRACT



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ABSTRACT

The optimized green-grey infrastructures are promising solutions to combat the urban flood and water quality problems which have been severe owe to the increasing urbanization and climate change. However, the focusses in existing researches have been either on finding the best strategy by scenario analysis method or optimal design of LID practices under the hypothesis of unchanged grey infrastructures. Little is known regarding the synergistic effect of synchronous optimization design of both green and grey infrastructures. In the study, we conduct green-grey infrastructures synchronous optimization by modifying the decision variables of traditional simulation-optimization frameworks and investigate how external uncertainties will affect their performance. The methodology was applied to a case study in Suzhou, China. The results showed that although the cost of green-grey synchronous optimized scenarios is lower than that of green optimized only scenarios by 1.69–4.19 thousand USD per km^2, the runoff/pollutants reductions of green-grey synchronous optimized scenarios are 0.11%–5.24% higher than that of green optimized only scenarios. In the green-grey synchronous optimized scenarios, green infrastructures can contribute to runoff/pollutants control by 50%–63%/62%–70%, while grey infrastructures can contribute to the remaining part by 37%–50%/30%–38%.

1. Introduction

Studies have identified that rapid urbanization and climate change are the two most influential factors that lead to uncertainties of urban water systems management (Luan et al., 2019; Manocha and Babovic, 2018). Meanwhile, they resulted in severe issues, including urban

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flooding, water pollution, groundwater depletion, etc. (Jenkins et al., 2017; Wang et al., 2016).

Traditional stormwater management solutions are based on the efficient collection and fast conveyance of runoff and pollutants through grey infrastructures (we mainly consider pipe networks as grey infrastructures) (Hood et al., 2007). However, the fixed capacity of grey infrastructures has limited their abilities to cope with upcoming challenges in a changing environment (Lucas and Sample, 2015). The implementation of sustainable stormwater management, including Low Impact Development (LID) practices, Sustainable urban Drainage Systems (SuDS), and Sponge Cities has been regarded as a promising strategy (Dong et al., 2017). They emphasized the use of green infrastructures which adopt a range of environmental engineering techniques to promote the drainage, storage, and evaporation of natural rainwater so that it can recover the natural circulation of urban water systems (Autixier et al., 2014; Tzoulas et al., 2007).

Despite their benefits, green infrastructures cannot fully replace grey infrastructures due to the limited capacity during large storm events (Xu et al., 2019a). A new tendency suggested that green infrastructures should be coupled with grey infrastructures in conjunction with the reliability and acceptability of grey infrastructures as well as multi-functionality, sustainability, and adaptability of green infrastructures (Alves et al., 2018; Damodaram and Zechman, 2013). However, how to achieve the optimized green-grey infrastructures are the main concerns.

To date, a few simulation-optimization frameworks that couple the hydrological models and multi-objective optimization algorithms have been developed for decision-making of green infrastructures implementations. Liu et al. (2019) coupled a physically-based model, the Markov chain, with the multi-objective shuffled frog leaping algorithm (MOSFLA) to provide the optimal design of LID practices. Eckart et al. (2018) developed a coupled model by linking the Stormwater Management Model (SWMM) to the Borg multi-objective evolutionary algorithm (Borg MOEA) to evaluate LID strategies. Macro et al. (2018) developed an open-source multi-objective SWMM optimization tool by connecting SWMM with the Optimization Software Toolkit for Research Involving Computational Heuristics (OSTRICH). Researchers have made efforts to either improving the algorithm (Chen et al., 2015; Torres et al., 2019; Xu et al., 2018) or developing surrogate models to reduce the complexity of the hydrological model (Beh et al., 2017; Latifi et al., 2019). However, most of the work focused on the optimal design of LID practices under the hypothesis of unchanged grey infrastructures.

Many studies have demonstrated that the green-grey infrastructures are more cost-effective than the grey-only option (Alves et al., 2016, Bakhshipour et al., 2019, Sun et al. 2020). Nevertheless, the focus in existing researches has always been to find the best strategy through the scenario analysis method (Alves et al. 2019, Gong et al. 2019). Although a few researchers have attempted to present multi-objective optimization frameworks to implement different green-grey infrastructures, only storage tanks were comprised as grey infrastructures to couple with green infrastructures (Alves et al., 2016; Damodaram and Zechman, 2013). Little is known regarding the synergistic effect of synchronous optimization design of green infrastructures and pipe networks. Nonetheless, the respective contribution of green and grey infrastructures to the environment is still unknown. Additionally, optimizations are always operated on a stable basis to achieve required targets, while the long-term performance of green-grey infrastructures solutions should be evaluated to test its resilience to climate change and urbanization (Casal-Campos et al. 2015, Wang et al., 2016).

Accordingly, the novelty of this study is: (1) to conduct green-grey infrastructures synchronous optimization by modifying the decision variables of the traditional simulation-optimization framework (adding pipe diameter as decision variables of grey infrastructures); (2) to explore the respective contributions of green and grey infrastructures to water quantity control and water quality improvement under synchronous optimization; (3) to understand the green-grey infrastructures optimization response to future interference by analyzing the differences among optimization solutions under different future scenarios.

To achieve the above goals, most-commonly used SWMM and Non-dominated Sorting Genetic Algorithm II (NSGA-II) were coupled to obtain the cost-effectiveness curves in green-grey infrastructures synchronous optimization. Future climate scenarios are predicted using the Global Climate Models (GCMs), downscaled by a change factor methodology. Then, a case study was designed in Suzhou, China.

2. Materials and methods

2.1. Description of optimization framework

The framework for determining the optimal layout of green-grey infrastructures under future scenarios is described in the flowchart shown in Fig. 1. The SWMM model is established to quantify the performance of various green-grey infrastructures solutions (Section 2.3). The NSGA-II algorithm is integrated with SWMM so that it can (a) perturb SWMM parameters, (b) run the SWMM executable, and (c) compute the objective function using SWMM outputs (Section 2.4). Furthermore, future scenarios are developed based on predicted land use and rainfall data (Section 2.5).

2.2. Study site description

The study site is in the north of Suzhou city, China with an area of 120 ha (Fig. 2). This site has a subtropical monsoon climate and the rainy season lasting from April to September with an annual average rainfall of 1100 mm, which has increased by 18% in the last three decades due to climate change (Xu et al., 2019b). The land uses in the region in 2017/2030 are presented in Fig. 2(c). Land use in 2017 was obtained from the analysis of the Institute of Urban Environment, Chinese Academy of Sciences using satellite images. Land use in 2030 was based on the Regulatory Detailed Planning of Suzhou Central District (2030). In the following years, the study area has experienced a certain level of land use change due to regional socio-economic development. Surface water pollution has been an on-going concern in recent years with most of the water samples not meeting the Class III standard for surface water quality (GB3838-2002). Therefore, the region is selected as the case study to demonstrate how the proposed framework supports local stormwater management.

2.3. SWMM model development

2.3.1. Model setup

According to ground elevation and land use, the study area was divided into 48 sub-catchments (Fig. 2(d)). The infiltration of water into the soil was calculated using Horton's equation (Osman Akan, 1992). In the water quality module, the exponential function was selected for both the build-up model and wash-off model of COD (Chemical Oxygen Demand), TN (Total Nitrogen), TP (Total Phosphorus) pollutants. Pollutants' build-up and wash-off processes vary according to different land use, so the pollutant-generating land use was further divided into three types: roof, road, and green space. Detailed information of model setup is provided in Supplementary Material (Section 1).

2.3.2. Calibration and validation

Since there is no rainfall runoff data monitored in the study area, monitored data for model calibration and validation has been obtained from Shantang street outfall in Suzhou urban district, which is the nearest monitoring point to the study area (see Fig. 2(b)). They are both located in the Suzhou area which means the climate, soil conditions and underlying surface features are similar. So, there is little effect on the site identification of uncertain parameters. In this study, the rainfall event on the 8th May 2015 was used for model calibration while

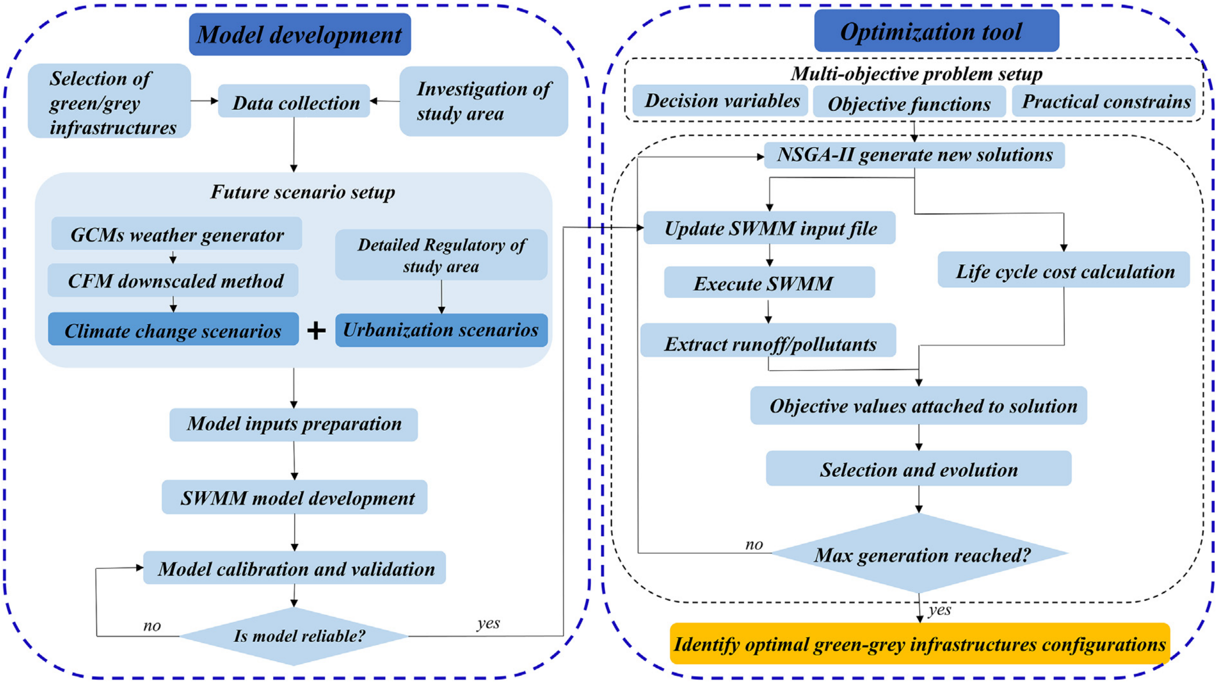

Fig. 1. Optimization framework for green-grey infrastructures layout.

rainfall events on the 28th May 2015/15th June 2015/23rd July 2015 were used for model validation. The Nash–Sutcliffe efficiency (NSE) was chosen to evaluate the simulation results for model calibration and validation (Nash and Sutcliffe, 1970). According to the current assessment standard for sponge city effects, the NSE of the model calibration and validation should not be less than 0.5 (MHURD, 2019). The NSE

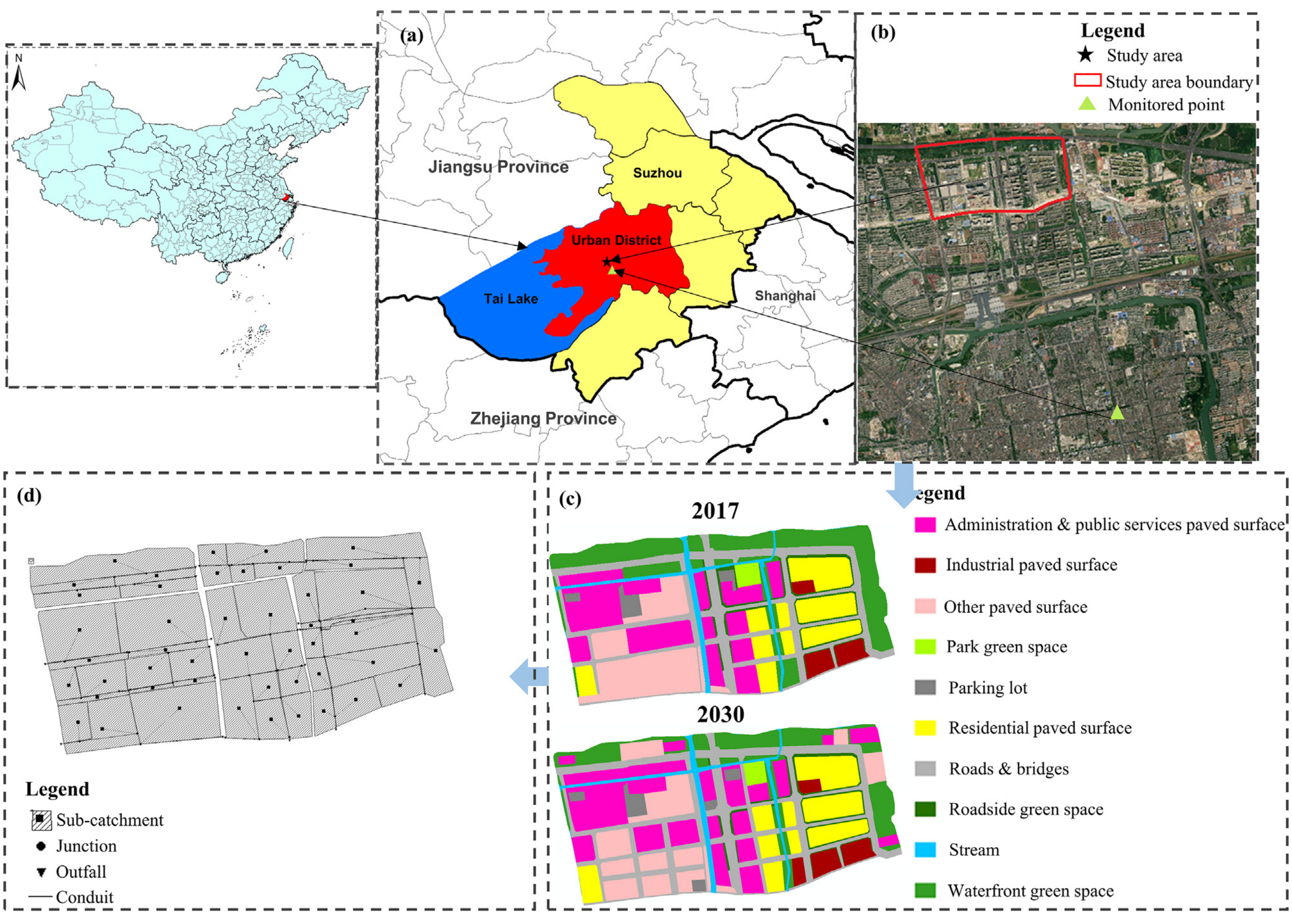

Fig. 2. (a) Location of Suzhou in China; (b) location of study area and monitored point of runoff and pollutants; (c) the associate land use of study area (2017/2030); (d) schematic representation of sub-catchments of the study area in SWMM.

values were ranged from 0.52 to 0.93, which indicates an acceptable prediction accuracy. Detailed information of model calibration and validation is provided in Supplementary Material (Section 2).

2.3.3. Grey-green infrastructures solutions

In the optimization process, many solutions representing different combinations of the green and grey infrastructures will be generated. Considering the requirements of regulation in the study area, bio-retention and permeable pavement are adopted as green infrastructure options. As the efficiency of green infrastructures would be more obvious when multiple green infrastructures are combined, a linked pattern as depicted in Fig. 3(b) for each sub-catchment was designed. The design parameters of LID practices are set according to their construction drawing. To estimate the life cycle cost for the green-grey infrastructures, the detailed price information is provided in Supplementary Material (Section 3).

2.4. Optimization tool

2.4.1. Mathematical definition of a multi-objective problem (MOP)

2.4.1.1. Decision variables. The scale of infrastructure is typically the most important parameter affecting the cost and performance of green and grey infrastructures (Di Matteo et al., 2017). More precisely, the decision variables for green infrastructures are the area ratios of LID practice in certain types of land surface covers, including the permeable pavement area ratios in road area (y_1) and the bio-retention area ratios in green space (y_2) (see Fig. 3(b)). The decision variables for grey infrastructures are the percentage enlarge or decrease of a certain class of pipe diameter. According to the National Guidance for Design of Outdoor Wastewater Engineering (GB50014-2006), the enlarging or decreasing of pipe diameter is generally using 100 mm or 50 mm as one level. Therefore, the pipe diameter specification is discrete. Meanwhile, the existing pipeline design basically meets the local drainage requirements, and the adjacent pipe diameters are selected for upgrading or downgrading options of a certain class pipe. For pipe k (k represents the index of pipe class, and the pipes are arranged in ascending order from class 1 to class 7 in diameter), x_{k3} of L_k becomes pipe $k+1$, x_{k1} of L_k becomes pipe $k-1$, and x_{k2} of L_k remains unchanged (L_k is the actual total length of pipe k in the study area; x_{ki} represent the changed percentage of pipe k) (see Fig. 3(a)). As there are seven classes of pipe and two kinds of LID facilities, there are 23 decision variables in the optimization problem.

2.4.1.2. Objective functions. In order to measure environmental benefits, the reductions of runoff volume and pollutant loads are the most intuitive indicators. Furthermore, life cycle cost (LCC) was used to determine the economic costs of green-grey infrastructures which considers the construction cost, and the operation & maintenance (O&M) cost (ISO, 2008). It is usually calculated by the discounted cash flow model which is a discounted sum of expected future cost and has been used as an economic indicator by many researchers (Bakhshipour et al., 2019; Xu et al., 2019a).

In this study, we consider optimally place green-grey infrastructures by applying three objective functions: (1) maximizing the reduction of runoff volume (Eq. (1)); (2) maximizing the reduction of pollutant loads which considered the geometric average of COD, TN, TP loads (Eq. (2)); (3) minimizing the LCC of green-grey infrastructures (Eqs. (3)–(7)).

$$F_1 = max\left(1 - \frac{Runoff}{Runoff'}\right) \tag{1}$$

$$F_2 = max\left(1 - \sqrt[2]{\frac{1}{3}\left(\frac{COD}{COD'}\right)^2 + \frac{1}{3}\left(\frac{TN}{TN'}\right)^2 + \frac{1}{3}\left(\frac{TP}{TP'}\right)^2}\right) \tag{2}$$

$$\begin{aligned} F_3 &= \min(LCC) \\ &= \min\left(Construction_{green} + PV_{O\&M\ green} + Construction_{grey} + PV_{O\&M\ grey}\right) \end{aligned} \tag{3}$$

$$Construction_{green} = \sum_{i=1}^{n}\sum_{j=1}^{m}\left(A_{sc_i} * R_{ad_{ij}} * c_{green_j} * y_j\right) \tag{4}$$

$$\begin{aligned} &Construction_{grey} \\ &= \sum_{k=1}^{q}\left[c_{grey_k} \times \left(length_k x_{k2} + length_{k+1} x_{(k+1)1} + length_{k-1} x_{(k-1)3}\right)\right] \end{aligned} \tag{5}$$

$$PV_{O\&M\ green} = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{t=1}^{T_{green_j}}\left(A_{sc_i} * R_{ad_{ij}} * y_j * c_{O\&M\_green_j}\frac{1}{(1+r)^t}\right) \tag{6}$$

$$PV_{O\&M\ grey} = \sum_{k=1}^{q}\sum_{t=1}^{T_{grey_k}}\left[\left(length_k x_{k2} + length_{k+1} x_{(k+1)1} + length_{k-1} x_{(k-1)3}\right) * c_{O\&M\_grey_k}\frac{1}{(1+r)^t}\right] \tag{7}$$

The objective functions are subject to the following constraints:

$$R_{ad_{ij}}, y_j, x_{k1}, x_{k2}, x_{k3} \in [0, 1] \tag{8}$$

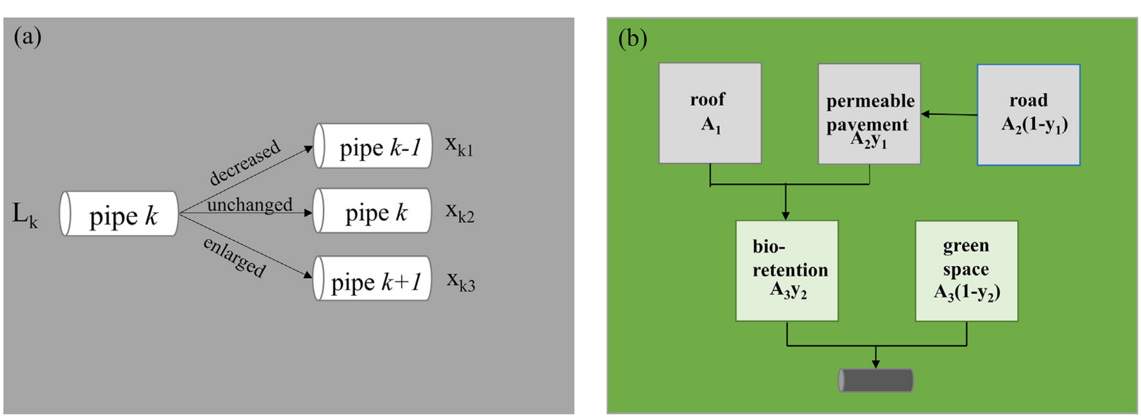

Fig. 3. Schematic of decision variables for green and grey infrastructures: (a) decision variables for grey infrastructures; (b) decision variables for green infrastructures. Where, A_1 is the area of roof in a sub-catchment; A_2 is the area of road in a sub-catchment; A_3 is the area of green space in a sub-catchment; y_1 is the area ratio of permeable pavement in the road; y_2 is the area ratio of bio-retention in green space.

$$\sum_{k=1}^{q} length_k = length_{total} \tag{9}$$

$$x_{k1} + x_{k2} + x_{k3} = 1 \tag{10}$$

where, $Runoff'$ and $Runoff$ are the runoff volume before and after placing green-grey infrastructures, respectively. $pollutant'$ and $pollutant$ are pollutant loads before and after placing green-grey infrastructures, respectively. $Construction_{green}$ and $Construction_{grey}$ are the construction cost of green and grey infrastructures; i is the index of a sub-catchment; j is the index of a LID practice; A_{SCi} is the area of sub-catchment i; $R_{ad_{ij}}$ is the maximum area ratio of LID j in sub-catchment i; y_j is the area ratio of LID j; c_{green_j} is the construction cost per unit of the LID j (USD/m^2); d_k is the diameter of pipe class k; $length_k$ is the total length of pipe class k; x_{k2} is the percentage of unchanged pipe k; x_{k1} is the percentage of decreased pipe k; x_{k3} is the percentage of enlarged pipe k; c_{grey_k} is the construction cost per unit of the pipe k (USD/m); $PV_{O\&M}$ is the present value of green or grey infrastructures O&M cost; $c_{O\&M\_green_j}$ is the O&M cost per unit of the LID j (USD/m^2); $c_{O\&M\_grey_k}$ is the O&M cost per unit of the pipe k (USD/m); r is the discount rate; T_{green_j} is the lifetime considered for the LID j; T_{grey_k} is the lifetime considered for the pipe class k.

2.4.2. Optimization algorithm

NSGA-II was selected as the optimization engine in this study for its wide use in green infrastructures optimal design and efficiency when dealing with complex, high nonlinearity, discrete optimization problems (Oraei Zare et al., 2012). Based on the principles of “natural selection” and “survival of the fittest”, the population quality is improved through evolution until the convergence reaches a near-global optimum, which also includes, escaping local optimum traps through the preservation of diversity in the offspring population via iterative mutation and crossover. Compared with the early genetic algorithm, NSGA-II utilises fast non-dominated sorting and ranking selection with the elitist crowded comparison operator to speed up the optimization process and improve the solution quality. The entire optimization procedure was automatically set up and run in the integrated platform of SWMM and Python.

2.5. Future scenarios setup

Considering the joint pressure from both climate change and urbanization, eight combined scenarios (U0C0, U0C20, U0C25, U0C30, U30C0, U30C20, U30C25, U30C30) were designed.

The urbanization scenarios include baseline scenario in (U0) 2017 and future scenario (U30) in 2030. Further details of land use changes in each time period are summarized in Supplementary Material (Table S6). The urbanization trend in the study area increases the paved surface, street & transportation by 13.7% and 19.39% while decreasing the green space by 46.35% from 2017 to 2030.

The climate change scenarios including baseline scenario (C0), future scenario 1 (C20), future scenario 2 (C25), future scenario 3 (C30) in 2015, 2020, 2025, 2030, respectively. They were developed based on the change factor methodology (CFM) and GCMs' precipitation products. GCMs is a weather generator for future climate estimation by downscaling results from 17 GCMs (Jones and Thornton, 2013) for the four Representative Concentration Pathway (RCP) scenarios (i.e., RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) (IPCC, 2007). Given specific longitude and latitude coordinates, it can establish a random series of local daily precipitation in the future. 17 GCMs were applied to obtain the ensemble average, and RCP 6.0 was used because it is an intermediate scenario with the greatest possibility of happening (Liu et al., 2016a, 2016b). CFM incorporates the future climate change predicted by GCMs model to provide future rainfall data at local scale. The development process of future rainfall events is described as follows:

(1) The present-day 2-hr rainfall event with return period (1-yr) was designed based on the Chicago approach and the intensity-duration-frequency curve in Suzhou, as follows:

$$q = \frac{3306.63(1 + 0.8201 lgP)}{(t + 18.99)^{0.7735}} \tag{11}$$

where q is rainfall intensity (L/s·ha); P is return period (year); t is rainfall duration (min); return period was set according to Suzhou's rainfall and drainage system design guidelines.

(2) Daily precipitations (including 2015, 2020, 2025, 2030) were obtained by GCMs weather generator.
(3) Change factors were calculated based on the ratios of the historical and future daily precipitations of GCMs projections (Eq. (12)).
(4) 2-hr future rainfall events with 5-minute intervals were determined using multiplicative relationships to scale the present-day 2-hr design rainfall with change factors (Eq. (13)).

$$CF_i = P_i^{Fut} / P_i^{His} \tag{12}$$

$$LP_i^{Fut} = CF_i \times LP_i^{Bas} \tag{13}$$

where CF_i is the change factor for future climate scenario (i); P_i^{Fut} and P_i^{His} are the future and baseline values of annual average precipitation for scenario (i); LP_i^{Fut} and LP_i^{Bas} are local-scaled future value and corresponding baseline value of rainfall events. The change factors were 1.15, 1.17, 1.23 in 2020, 2025 and 2030, respectively.

3. Results and discussion

In this section, we firstly explore the climate change and urbanization impact on hydrology and water quality in the study site without considering green-grey infrastructures implementation (Section 3.1). Then, we analyze the cost-effectiveness curves of multi-objective optimization under different future scenarios (Section 3.2.1) and detailed solutions which maintain the water quantity/quality of the U0C0 in future scenarios (U0C20-U30C30) (Section 3.2.2). To explore the synergistic benefits of green-grey infrastructures synchronous optimization, runoff optimized solutions are further discussed (Section 3.3). At last, the contributions of green and grey infrastructures to the runoff and pollutants control are analyzed based on the optimized solutions with maximum runoff/pollutants reductions (Section 3.4).

3.1. Impact of external uncertainties: climate change and urbanization

The results of climate change and urbanization impacts on runoff volume and pollutant loads are summarized in Supplementary Material (Table S7). For all climate scenarios (C0/C20/C25/C30), runoff volume and COD, TN, TP pollutant loads under U30 increase by 3.07%–5.87%, 2.27%–4.15%, 3.17%–3.72%, 2.50%–3.12%, respectively, compared to those of U0. The increasing urban construction area in 2030, compared to 2017, will result in more impervious areas and have a negative impact on runoff quantity and quality, where similar findings were concluded in previous research (Liu et al., 2016a, 2016b; Wang et al., 2014). When we compare the results of different climate scenarios under the same urbanization scenario, we can also find increasing runoff volume and pollutant loads with higher rainfall. The finding is consistent with other related studies (Pruski and Nearing, 2002, Wang and Kalin, 2017).

Regarding the joint consequence of climate change and urbanization, the impact on runoff and pollutants would be aggravated under U30C30 which leads to the biggest challenge in achieving management plan goals. The results present the nonlinear response of the relations among climate change, urbanization, and hydrology/water quality performance.

Climate change tends to induce more dramatic changes in runoff/pollutants than urbanization. The impact on runoff volume and pollutant loads is more sensitive to the changes of rainfall intensity than that of impervious surfaces. This finding is consistent with previous studies on stormwater management (Fan and Shibata, 2015, Liu et al., 2017). In the meantime, the average runoff growth rate in future scenarios is lower than that of pollutant loads, indicating that the external uncertainties lead to greater impacts on water quality than hydrology. This could be attributed to the increase of both runoff volume and pollutant concentration resulting in the increase of pollutant loads, which has been justified by other studies (Liu et al., 2016a, 2016b; Wang et al., 2016).

3.2. Optimization results

3.2.1. Analysis of cost-effectiveness curves

The cost-effectiveness curves (i.e., runoff volume reduction versus cost, pollutant loads reduction versus cost) under U0C0-U0C30 are shown in Fig. 4. Each point represents a compromise solution between the selected objectives. Decision-makers could choose one optimal solution from a range of potential solutions as well as include their preferences in the design process. Additionally, the Pareto front provides a better understanding of all the objectives and visualizes the effectiveness of each investment level.

By observing the trade-off curves, we find a convex trend that the curve slopes transform from steeper to flatter. An obvious improvement in runoff/pollutants reduction is observed in the beginning with an increased cost. However, when the cost further increases after the turning point, no considerable change in runoff/pollutants reduction occurs, which can be explained by the limitation treatment capabilities of green-grey infrastructure. The finding is similar to other studies on the optimal placement of green infrastructures (Jia et al., 2012; Lee et al., 2012; Xu et al., 2018). The trade-off curves provide valuable information for decision-makers when identifying where investment in green-grey infrastructures will begin to offer diminishing returns.

The results indicate that optimized green-grey infrastructures solutions could result in potential reductions of 57.2%–71.3% and 65.7%–80.5% in runoff volume and pollutant loads, respectively, and the corresponding cost is 1.84–3.81 million USD per km^2. The results elucidate that optimal solutions are sensitive to future scenarios. The maximum runoff volume/pollutant load reduction decreases with the increase of rainfall intensity and impervious area. For the same amount of runoff volume and pollutant loads reduction, more expenditures will be spent on green-grey infrastructures in future scenarios. Additionally, urbanization has a greater influence on optimization results.

It should be noted that in all future scenarios, runoff volume reduction is less than pollutant load reductions for the same cost. One reason is that pollutants reduction contributed from green-grey infrastructures is dependent on both runoff volume reduction and pollutant concentration reduction (Liu et al., 2016a, 2016b). Another reason is that runoff volume reduction is severely limited by the poor hydraulic conditions of soils.

3.2.2. Detailed optimization solutions considering environmental goals

Table 1 shows the results of maintaining the water quantity/quality of U0C0 in future scenarios (U0C20-U30C30). If the reduction of the pareto set is equal to the corresponding reduction in Table 1, it means that the green-grey infrastructures solution can offset the effect of climate change and urbanization in the future. It implies that investing 45.03–102.69/17.97–78.73 thousand USD per km^2 can help the site maintain the current hydrological/water quality conditions under U0C20-U30C30. Such investment can be termed as “opportunity cost” of robustness.

To maintain runoff volume/pollutant loads at the U0C0 level, further reductions need to be attained with the increase of rainfall intensity and impervious area. Thus, the corresponding costs are higher due to additional green-grey infrastructures being needed. The reductions needed to be attained under U0C20 are lower than that under U30C0, which can be concluded that the challenge of rainfall intensity increases 15% is bigger than the land-use change from 2017 to 2030 on water quantity/quality. This result reflects the need to consider the influence of external uncertainties on optimization progress.

Under the same future scenario, an optimization solution that can both achieve runoff volume and pollutant loads levels of U0C0 and save the cost does not exist. For instance, to attain the runoff volume and pollutant loads of U0C0 under U30C30, the pollutant loads optimized solution cost less compared to runoff optimized solution. However, when applying pollutant loads optimized solution to the study area, runoff volume is reduced by 9.06%, where 12.01% reduction is needed. This is due to the reduction of pollutants needed to attain U0C0 level being lower than that of runoff volume. However, this is different from the results in Liu et al. (2017), which found that runoff volume optimized solutions can also reduce all pollutants to baseline scenario level. This is mainly because the external uncertainties affecting optimization varies from the land-use and climate conditions in different sites. This result demonstrates that the consideration of individual runoff and pollutant goals during operating the multi-objective optimization is important in order to obtain optimized solutions for each goal.

The changes in the composition of optimized solutions when the pursued environmental goal is switched are analyzed. The optimal area ratios of green infrastructures to attain runoff volume and pollutant

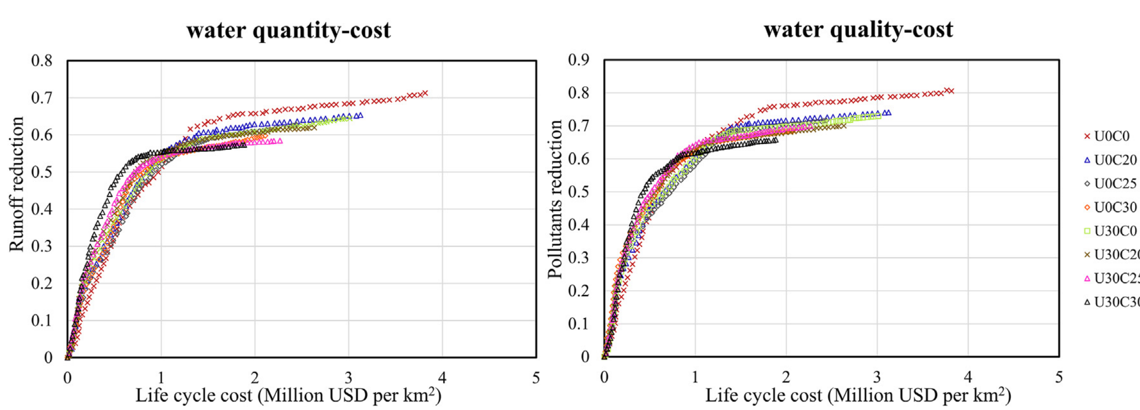

Fig. 4. Water quantity-cost trade-off and water quality-cost trade-off curves under future scenarios.

Table 1
Results of maintaining water quantity/quality of U0C0 in U0C20-U30C30.

Concerns	Reductions needed to attain U0C0 level (%)							Corresponding cost (based on optimization results) thousand USD per km^2						
	U0C20	U0C25	U0C30	U30C0	U30C20	U30C25	U30C30	U0C20	U0C25	U0C30	U30C0	U30C20	U30C25	U30C30
Runoff volume	1.94%	4.92%	5.80%	3.07%	5.44%	10.05%	12.01%	45.03	57.31	70.52	53.25	59.83	83.14	102.69
Pollutant loads	1.68%	2.45%	3.18%	2.29%	4.54%	6.04%	7.46%	17.97	19.73	23.58	38.72	46.94	57.31	78.73

loads of U0C0 in U0C20-U30C30 are shown in Fig. 5. The optimal solutions for runoff/pollutants reductions can be achieved before the significant point of diminishing returns is reached. Permeable pavement is implemented the most for all runoff optimized solutions because it is the most cost-effective alternative to reduce runoff volume compared to other alternatives. Besides, bio-retention is implemented the most for pollutants optimized solutions because it is the most cost-effective alternative to reduce pollutant loads. These results are compatible with other recent studies, which found that permeable pavement is the most cost-effective practice for runoff reduction, followed by bio-retention (Chui et al., 2016). The area ratios of selected infrastructures in each optimized solution are higher with increasing rainfall intensity and impervious area due to the larger reductions of runoff volume and pollutant loads that need to be attained.

The explanation of the ranking difference of most implemented infrastructures in different optimized solutions can be found in the different cost-effectiveness of alternatives regarding the different environmental goals. As a result, optimization operated individually for each environmental goal is preferable. Liu et al. (2016a, 2016b) found similar results that the optimal application of green infrastructures varied with different environmental goals. In multi-objective optimization progress, optimization operators will identify the most cost-effective alternative as the first option for implementation. Meanwhile, its area ratio continues to increase until it reaches a maximum. Then, the most cost-effective solution among the residual alternatives becomes favourable until its maximum area ratio is reached.

Obviously, these area ratios may be ideal values which means the facilities can completely eliminate the negative effects of climate change

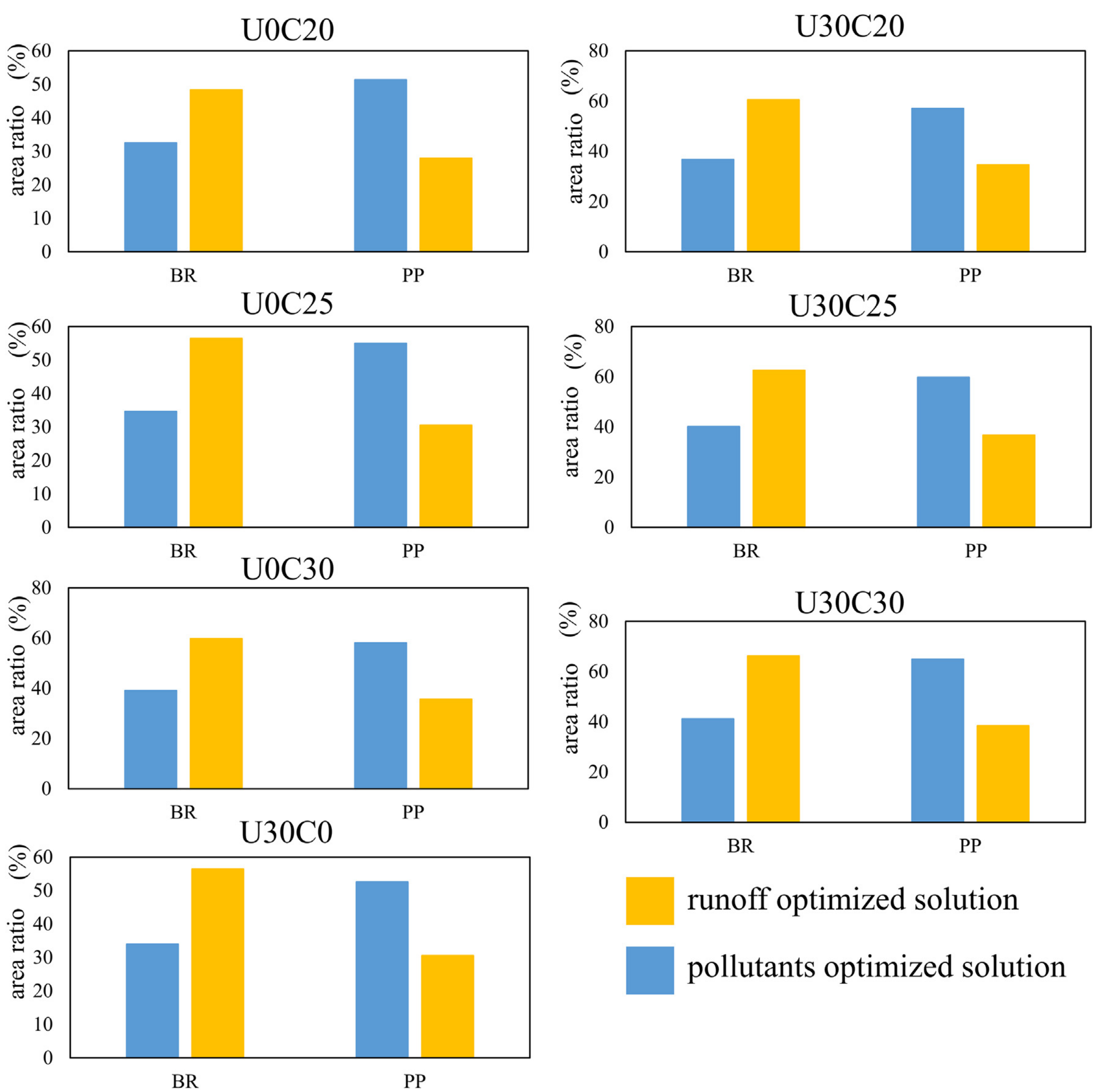

Fig. 5. The green infrastructures area ratios of runoff and pollutants optimized solutions under U0C20-U30C30. (BR represents bio-retention; PP represents permeable pavement.) The X-axis represents green infrastructures considered; Y-axis represents percentages of green infrastructures implemented.

and urbanization when reaching the ratios. However, in actual urban planning, we also need to consider other factors, such as human activity or traffic. The actual implementation rate of facilities often deviates from the ideal values, which is acceptable as we do not expect the runoff/pollutant control rate of green infrastructures to reach 100%.

The original and optimized length of different pipe sizes for attaining runoff volume and pollutant loads of U0C0 in U0C20-U30C30 are summarized in Supplementary Material (Table S8). The optimal design of green-grey infrastructures needs to increase the length of pipe DN300, DN400, DN450, DN500 and DN600 and reduce the length of DN700 and DN800 compared to the original pipe, suggesting that the original pipe size is too large to be cost-effective. DN500 is preferred for short-duration rainfall. As a result, the weighted average pipe diameters will decrease in future scenarios. Improper size of drainage systems for their treatment volume is a general issue in rainfall runoff management (USEPA, 2004).

The increase in rainfall intensity and impervious area will not lead to the decrease of weighted average pipe diameters. It can be concluded that, to some extent, modifying pipe size and implementing additional cost-effective green infrastructures are the “icing on the cake” solutions for rainfall runoff management. However, the non-cost-effective grey infrastructures tend to be necessary with the increase of external uncertainties. It reflects the reliability of grey infrastructures in response to the external uncertainties. Furthermore, urban development tends to result in less reduction of weighted average pipe diameter compared with climate change which elucidates that the resilience of grey infrastructures is more significant to cope with urbanization. Even though it is hard achieved to change the design parameters of the existing pipe networks, the results offer significant rational information for planners when planning green-grey infrastructures in the future.

3.3. Synergistic benefits of green-grey infrastructures synchronous optimization

The simulation results under the baseline scenario, green infrastructures only optimized scenario, grey infrastructures only optimized scenario, and green-grey synchronous optimized scenario under U0C20- U30C30 are summarized in Supplementary Material (Table S9).

Grey optimized scenarios will increase runoff volume and COD, TN, TP pollutant loads by 1.60%–4.02%, 3.50%–5.37%, 1.35%–2.58%, 1.64%–4.29%, respectively, compared with baseline scenarios; While they can reduce total cost by 3.78%–9.67%. The smaller size of grey infrastructures does bring higher runoff and pollutants, but its cost-effectiveness is not lower than the baseline scenarios. The appropriate reduction of pipe size provides more cost-effective solutions for rainfall runoff management as the original grey infrastructures are large and not cost-effective. The importance of grey infrastructures gradually becomes apparent in response to the external uncertainties. As in extreme future scenarios, the maximum conveyance capacity of grey infrastructures is insufficient for rainfall runoff management if the pipe size is reduced too much. In this case, even if slightly higher cost-effectiveness is obtained when pipe size is reduced, the decrease in resilience seems not worth it.

Although the cost of green-grey synchronous optimized scenarios is lower than that of green optimized only scenarios by 1.69–4.19 thousand USD per km^2, the runoff/pollutants reductions of green-grey synchronous optimized scenarios are 0.11%–5.24% higher than that of green optimized only scenarios. This can be explained as the reductions in pipe size nullified the increase in cost because of the implementation of green infrastructures. The limited capacity of green infrastructures to improve water quantity/quality may also explain the low effectiveness compared to green-grey infrastructures. The performance and technical feasibility of green infrastructures vary under different conditions. Moreover, green infrastructures are more suitable for small, frequent rainfall events and have low effectiveness under heavy rainfall. Green-grey synchronous optimization has proved to have advantages in minimizing runoff volume, pollutant loads, and cost. It reveals the synergistic benefits between green and grey infrastructures for rainfall runoff control. Retrofitting grey infrastructures and green infrastructures optimally is more cost-effective than retrofitting green infrastructure alone.

3.4. The contributions of green and grey infrastructures to water quantity control and water quality improvement

Due to different physical mechanisms, the different parts of runoff are treated separately by green and grey infrastructures. Grey infrastructures capture runoff formed by precipitation but not drainage which can be estimated as the contribution of grey infrastructures to runoff control. When green infrastructures are implemented, they can deal with runoff at the source which can be estimated as the contribution of green infrastructure to runoff control. Regarding pollutant loads, grey infrastructure control the pollutants built up in the initial but not drainage which can be estimated as the contribution of grey infrastructures to pollutants control. When green infrastructures are implemented, they can result in fewer pollutant loads which can be estimated as the contribution of green infrastructures to pollutants control. As shown in Fig. 6, detailed results are calculated by Eqs. (14)–(17).

$$\textit{Runoff control contribution}_{grey}(\%) = \frac{precipitation - runoff'}{precipitation - runoff} \times 100\% \quad (14)$$

$$\textit{Runoff control contribution}_{green}(\%) = \frac{runoff' - runoff}{precipitation - runoff} \times 100\% \quad (15)$$

$$\textit{Pollutants control contribution}_{grey}(\%) = \frac{initial\ pollutants - pollutants'}{initial\ pollutants - pollutant} \times 100\% \quad (16)$$

$$\textit{Pollutants control contribution}_{green}(\%) = \frac{pollutants' - pollutants}{initial\ pollutants - pollutants} \times 100\% \quad (17)$$

where, *Runoff′* and *Runoff* are the runoff volume before and after implementing green-grey infrastructures, respectively. *pollutant′* and *pollutant* are pollutant loads before and after implementing green-grey infrastructure, respectively.

Green infrastructures can contribute to runoff/pollutants control by 50%–63%/62%–70%, while grey infrastructures can contribute to the remaining by 37%–50%/30%–38%. The contribution of green infrastructures to runoff and pollutants control is relatively higher than that of grey infrastructures, which can be explained by the sustainability and adaptability of green infrastructures. Grey infrastructures are expected to have high efficiency in dealing with runoff than pollutants. Green and grey infrastructures should be conducted together to achieve process control and source control.

To handle increasing external uncertainties, however, it is more effective to the increase the contributions of grey infrastructures to runoff and pollutants control. For instance, compared to U0C0 and U0C20, the contributions of grey infrastructures to runoff and pollutants control increase from 37% and 30% to 45% and 31%, respectively, when rainfall intensity is increased by 15%. It demonstrates that the ability to cope with the extreme situation of grey infrastructures gradually appear with the enhancement of external uncertainties.

4. Conclusions

In this study, a framework was proposed to synchronously optimize green-grey infrastructures under future climate change and urbanization scenarios. The main conclusions are as follows:

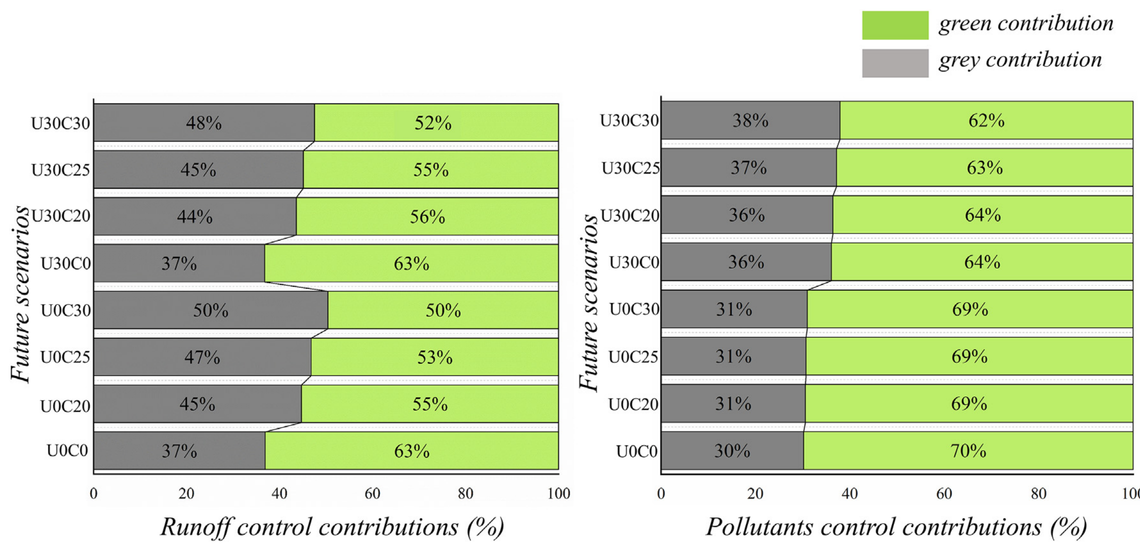

Fig. 6. Runoff and pollutants control contributions of green and grey infrastructures under different urbanization and climate change scenarios.

(1) It is more effective to optimize green-grey infrastructures synchronously than to optimize green infrastructure optimal only.
(2) The external uncertainty will worsen the cost-effectiveness of green-grey infrastructures optimization.
(3) The contributions of green infrastructures to runoff and pollutants control are relatively higher than that of grey infrastructures. The ability to cope with extreme situations of grey infrastructures becomes more and more important in response to external uncertainties.

This research can serve as a guide for the planning of green-grey infrastructures in practical sponge cities projects. For future studies, more types of green infrastructures (e.g., rain garden, green roof) and grey infrastructures (e.g., storage tank) should be considered. Besides, more optimization objectives except for environmental goals and cost, such as social and ecological benefit require future exploration to provide comprehensive information.

CRediT authorship contribution statement

Linyuan Leng: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Haifeng Jia:** Conceptualization, Writing – review & editing, Supervision. **Albert S. Chen:** Writing – review & editing, Funding acquisition. **David Z. Zhu:** Writing – review & editing. **Te Xu:** Software, Resources. **Shen Yu:** Resources.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.145831.

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