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# Multi-objective Optimisation Framework for Assessment of Trade-Offs between Benefits and Co-benefits of Nature-based Solutions

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## Abstract

Urbanization and climate change are producing an escalation in the prevalence of urban problems, particularly those connected to flooding, prompting authorities and stakeholders to recognize the need for sustainable solutions. Nature-Based Solutions are progressively replacing traditional engineering solutions as an alternative since they are more eco-friendly. By re-activating the urban hydrological cycle processes, NBS intends to increase the natural water storage capacity to help decrease urban flooding. The work described here outlines a framework for optimising the efficacy of NBS for flood risk reduction and its co-benefits, as well as defining the trade-offs among these co-benefits. The framework integrates 1D hydrodynamic models with multi-objective optimisation techniques. To demonstrate the applicability of the framework and its methods it has been used in Sint Maarten, which is an island located in the Caribbean Sea. Four NBS measure were identified as having good potential to be applied in the case study, namely: green roof, permeable pavement, bio-retention pond, and open detention basin. The results showed that the developed framework has the ability to represent the link between benefits and costs when evaluating various NBS, hence aiding the decision-making process to select and implement NBS.

**Keywords** Nature-based solution · Flood risk reduction · SWMM model · Multi-objective optimisation · NSGA-II · NBS benefits

## 1 Introduction

Traditional grey infrastructures for stormwater collection, conveyance, and discharge are favoured for flood risk control. However, they often offer little or none benefits for maintaining habitat and ecosystem services as well as reducing the effects of climate change. On the other hand, nature-based solutions (NBS) that depend on natural hydrological processes to mitigate urban flood risks by intercepting, storing, and infiltrating urban runoff have emerged as viable alternatives (Vojinović and Abbott 2012).

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High-porosity medium (e.g., permeable pavements) and vegetation are utilized in the development of NBS to promote rainwater infiltration and storage. It also employs structural components to temporarily store rainwater and runoff, which eventually evaporate or flow into the drainage system, so lowering peak flows and prolonging the length of the flow hydrographs (Jato-Espino et al. 2018). The additional benefits offered by NBS, which are referred to as "co-benefits," might increase the competitiveness of NBS in addition to help reducing flooding risks (Alves et al. 2019). NBS can be used as a replacement for infrastructure performing a crucial function (i.e. drainage) while at the same time improve the performance of natural and social processes (Brillinger et al. 2020). Therefore, it is anticipated that research on co-benefits would play a central role in designing an NBS strategy, ultimately optimising and realizing all the potential benefits that NBS have to offer (Pagano et al. 2019).

Many existing co-benefits analyses choose to examine the benefits and impacts for one particular NBS, but not for the entire NBS strategy. Furthermore, often the analysis consider the valuation of NBS co-benefits expressed in monetary units (for example, Alves et al. 2018; Vojinovic et al. 2017). Although the tool that illustrates the monetary benefits of NBS can help visualize the economics of decision-making, it is susceptible to overlooking some intangible co-benefits (Ruangpan et al. 2020). Introducing qualitative and quantitative analyses simultaneously and within the same framework helps compensate for each other's limitations (Alves et al. 2020). Therefore, different researchers have attempted to establish a conceptual framework for assessing the co-benefits of NBS in various sectors (Lafortezza and Sanesi 2019).

When a conflict of interest arises, finding a trade-off between benefits and co-benefits is vital, but few research have examined the changing trend of each form of co-benefit and how they affect each other under the NBS approach of the optimal solution set (Hoang et al. 2018). Multi-objective evolutionary algorithms have been developed and applied to identify Pareto optimal solutions to water resources planning problems (Mala-Jetmarova et al. 2015). Even if every optimal result point is irreplaceable, it is unlikely to simultaneously optimise all objectives in multi-objective optimisation. Thus, trade-offs are generated between these objectives, thereby helping with allocating limited resources to more essential objectives.

In response to the outlined limitations here above, this study evaluates the efficacy of Nature-Based Solutions in reducing urban flooding and at the same time identify trade-offs among co-benefits in order to develop an optimal strategy. To evaluate the performance of NBS, first the primary benefit and co-benefits of the different NBS measures is identified. Second, objective functions are defined considering different performance indicators to be able to compare various NBS or the NBS combination, allowing decision-maker to define trade-offs between co-benefits. Finally, this study addresses how the incorporation of various benefits/co-benefits generates an impact in the type of solutions that can be found in the case study. Incorporating both main benefits and co-benefits into a multi-objective optimisation framework for assessing the influence of NBS on water, nature and people, in order to identify the trade-off between multi-benefits without sacrificing flood risk mitigation efficiency is a novelty aspect of this paper.

## 2 Background

### 2.1 Trade-off of NBS

The purpose of trade-offs is to distribute the different co-benefits perceived by the relevant beneficiaries/users in order to maximize the overall benefits, and this typically occurs in two or more areas of mutual competition (Sharifi 2020). For instance, when the implementation of adaptation measures negatively affects mitigation activities, there may be trade-offs (Berry et al. 2015).

The benefits of NBS can be classified into three categories water, nature and people. The water-related benefits include water purification, water recycling, groundwater recharge, drought mitigation, and enhanced flood resilience. (Granados-Olivas et al. 2016). The nature-associated benefits include urban heat island effect mitigation, enhance biodiversity, improvement of air and soil quality, and even reducing light and noise pollution (Francis and Jensen 2017). People-related benefits include improved mental and physical health, social cohesion, recreation and communication, and urban aesthetic value and enhanced urban landscape (Calfapietra and Cherubini 2019).

Different beneficiaries of NBS co-benefits may experience both synergy and competition. Thus, flood control strategies should recognize their interconnection and strike the appropriate balance between two or more benefit representatives in order to maximize synergy and prevent potential trade-off risks (Shrestha and Dhakal 2019).

### 2.2 Multi-objective Optimisation Analysis

In multi-objective optimisation, improving any objective function based on a non-dominant solution will inevitably weaken at least one other objective function due to conflict between objectives (Ngatchou et al. 2005). Consequently, the outcome of multi-objective optimisation is the coexistence of multiple benefit combinations derived from various parameters. Numerous studies have linked optimisation-based tools and algorithms with modeling techniques, and the use of a genetic algorithm (GA) to solve multi-objective equations has attracted wide attention (Jayasooriya and Ng 2014).

GA is a computational model that is based on the principles of biological evolution process of natural selection and the genetic mechanism of Darwin's biological evolution theory. Thus, GA is a technique for searching the optimal solution by simulating the natural evolution process. It has a global search capability that prevents the conventional multi-objective optimisation method (i.e. mathematical or gradient techniques) from settling on the optimal local solution during the optimisation process (Maier et al. 2014). Moreover, the Non-Dominated Sorting Genetic Algorithm (NSGA-II) is one of the most popular multi-objective genetic algorithms at present. It reduces the complexity of non-inferior ranking genetic algorithms and offers fast running speed and good solution set convergence (Deb et al. 2002).

**Fig. 1** Cul de Sac, Sint Maarten location, source: (Medina et al. 2019)

# 3 Case Study

The study area used in the present work is the Cul De Sac area on Sint Maarten Island presented in Fig. 1. It is a Caribbean island nation in the Kingdom of the Netherlands, where tourism drives its development and population growth (Vojinovic et al. 2014; Vojinović and Abbott 2012). The basin encompasses a total area of 509 hectares, the majority of which is residential land with scattered commercial areas and urban roads. The urban area's location in the central low-lying area and the surrounding steep terrain that causes runoff to converge on urban areas are the primary causes of flooding, while the residential areas have higher imperviousness.

The existing river channel-based drainage system lacks the capacity to prevent flooding during high intensity rainfall events. Additionally, the majority of streets are narrow, restricting the expansion of these drainage channels (Vojinovic and Teeffelen 2007).

In the event of light precipitation, traffic interruption, travel delays and other issues, are common. Heavy rainfall results in widespread flooding, which destroyed residential and commercial structures in the past. The application of the developed framework in this study area envisions spatial development with NBS to enhance connectivity and foster positive interactions between environmental and social progress.

# 4 Methodology

## 4.1 Overall Multi-objective Optimisation Framework

The overall framework for multi-objective optimisation using Python and SWMM as the fundamental tools is presented in Fig. 2. The NSGA-II algorithm is used to optimise

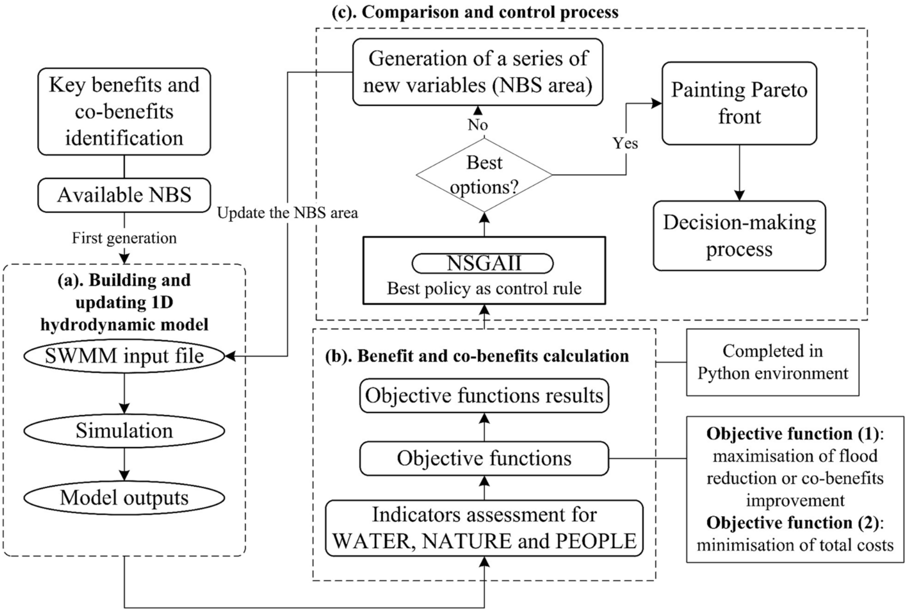


**Fig. 2** Multi-objective Optimisation framework

solutions based on the performance assessment of an urban drainage system model. The proposed framework is applied primarily on the principle of quantitative assessment for flood reduction, while concurrent qualitative analysis compensates for the limitations of assessing specific co-benefits. The optimisation procedure is comprised of three major aspects: (a). Building and updating the 1D-hydrodynamic model, (b). benefits and co-benefits calculation, and (c). comparison and control process.

As presented in Fig. 2, some pre-process steps are required as key benefits and co-benefits from the case study area need to be identified to reflect local stakeholders' preferences. The local preferences are required to set the search space (upper and lower limits of the decision variables) as the basis for the optimisation objects. The key benefits used in the work described here are based on the EU-funded HORIZON2020 RECONECT project indicator framework. The indicators are classified into three groups, which are WATER, NATURE, and PEOPLE (Ruangpan et al. 2021). As part of the indicator framework of RECONECT, Ruangpan et al. (2021) developed a questionnaire to identify stakeholder's preferences for NBS measures. This questionnaire was used to identify the local benefits in the study area. Information regarding each part of the optimisation framework is provided below.

## 4.2 1D-hydrodynamic Model

### 4.2.1 Building and Updating 1D-hydrodynamic Model

The 1D-Hydrodynamic model was based on a 1D-1D model of the drainage system in the selected catchment area. The model is described in detail in Alves et al. (2020). The entire study area is divided into 12 sub-catchments with distinct soil characteristics and land uses.

Each sub-catchment is further subdivided into two areas, residential and the region where the NBS are planned, in accordance with the planning function.

### 4.2.2 Measure Selection and Scenarios Building

For the optimisation process four NBS were selected: 1. green roof (GR), 2. permeable pavement (PP), 3. bioretention pond (BR), and 4. open detention basin (ODB). These measures were selected considering factors such as geographical conditions and local demands. The efficacy of the selected measures can be assessed by developing various scenarios that combine multiple NBS. Table 1 shows the chosen four scenarios that combine two to four NBS from the set of options. Each of the NBS has a different size or potential area of implementation in each sub-catchment. Therefore, the decision variables depend on the sub-catchment size and the combination of NBS measures.

## 4.3 Benefits and Co-benefits Calculation

The benefit and co-benefits calculation are based on the indicator assessment from the RECONECT project. Each indicator expresses the degree of benefits, which is intended to be quantified using a specific formula. This process requires the establishment of reasonable objective functions that are related to the indicator assessment. When multiple benefits are selected to be optimized, each must be quantified with a unique value to indicate its magnitude.

### 4.3.1 Indicator Assessment for WATER

Indicators used for the category WATER include the assessment of flooding and water quality decline. Reduction of flooding can be illustrated by decreasing runoff volume and peak flow, and postponing the time to peak flow (Majidi et al. 2019). In terms of water quality, the current SWMM model calculates the reduction of pollutants by simulating the reduction of runoff pollutant mass load, rather than directly through the pollutant quality itself (Morgan et al. 2020).

In this research, the flood reduction is expressed by the percentage of flood volume reduction compared with the original situation. The flood reduction percentage (%) can be calculated by using the Eq. (1):

$$\text{Flood reduction(FR)}\% = \frac{(FV_{baseline} - FV_{nbs})}{FV_{baseline}} \tag{1}$$

**Table 1** Evaluated scenarios and amount of decision variables

| ` | Measures | Decision variables |
|---|---|---|
| Scenario 1 | GR + PP + BR + ODB | 48 |
| Scenario 2 | GR + PP | 24 |
| Scenario 3 | GR + ODB | 24 |
| Scenario 4 | PP + BR + ODB | 36 |

where: $FV_{baseline}$ is the flood volume before NBS was implemented, $FV_{nbs}$ is the flood volume after NBS implementation.

The decrease in the concentration of total suspended solids (TSS) will represent the efficacy of NBS in improving water quality. In this indicator calculation, surface runoff is the formula's independent variable, and its value is determined by the type and area of NBS. The original pollutant concentration of each sub-catchment is used as a constant parameter (Liu et al. 2016; Tuomela et al. 2019). The event means concentration (EMC) wash-off functions were chosen for simulating TSS reduction percentage. The EMC wash-off function for TSS is expressed in Eq. (2):

$$\mathrm{W} = K_w * R_{gi} \tag{2}$$

where: W: is the concentration of TSS in mg/l; $K_w$ refers to the EMC with the unit of mg/L in a sub-catchment; $R_{gi}$ is the fraction of the total runoff rate after the selected NBS implementation in the sub-catchment.

Therefore, TSS reduction percentage can be calculated by using Eq. (3):

$$\text{TSS reduction (TSSR)\%} = \sum\nolimits_{i=1}^{n} \frac{W_{max} - W_i}{W_{max} - W_{min}} \tag{3}$$

where: $W_{max}$ and $W_{min}$ are the TSS wash-off concentration in the whole watershed before and after NBS implementation in sub-catchments; $W_i$ is TSS wash-off concentration when implementing a set of variables generated by NSGAII in sub-catchments; n is the total number of sub-catchments.

### 4.3.2 Indicator Assessment for NATURE

The indicators used for the category NATURE are biodiversity and ecology improvement and urban heat island mitigation. The general term for biodiversity improvement refers to the variety and number of local species. Species richness is the number of different species in an area, and species composition refers to all the living things within that environment. Therefore, obtaining and simulating the biodiversity situation is not only difficult, data is scarce and there not simulation models to approach this.

To assess the impact score of various NBS on the degree of biodiversity and ecology improvement a scoring system was used. The score is represented by a number ranging from 0 to 5. The higher score indicates a more positive impact of NBS on the benefit. It is also assumed that green infrastructure has no negative effects on nature. The impact of green roofs, permeable pavement, bioretention filters, and detention basins on the improvement of biodiversity and ecology is 4, 1, 4, 2, respectively as it is also described in the work of Alves et al. 2018.

Thus, the expression of the percentage of biodiversity and ecology improvement (BIOI %) is shown in Eq. (4):

$$BIOI\% = \frac{4 * A_{gr} + 1 * A_{pp} + 4 * A_{br} + 2 * A_{bd}}{4 * A_{gr\_avai} + 1 * A_{pp\_avai} + 4 * A_{br\_avai} + 2 * A_{db\_avai}} \tag{4}$$

where: $A_{gr}$ is the area of a green roof; $A_{gr\_avai}$ is all available green roof in the field; $A_{pp}$ is the area of permeable pavement; $A_{pp\_avai}$ is all available permeable pavement; $A_{br}$ is the area of bio-retention pond; $A_{br\_avai}$ is all available of bio-retention pond; $A_{db}$ is the area of detention basin; $A_{db\_avai}$ is all available detention basin in the field.

The urban heat island effect refers to the "high temperature" of the city due to a large amount of artificial heating, the increase of high heat storage bodies, and the reduction of green space. The performance of NBS in lowering surface temperature is an indicator for calculating the percentage of UHIM (Gómez 2016). According with the Teeb-Stad tool's description and built-in parameter, the temperature in urban areas can decreases by 0.1 degrees for every 1% increase in green (http://www.teebstad.nl).

The calculation for the percentage of urban heat island mitigation (UHIM %) is shown in Eqs. (5) and (6):

$$\mathrm{UHIM}\% = \frac{\Delta T_i}{\Delta T_{max}} \tag{5}$$

$$\Delta T_i = \frac{\sum_{s=1}^{n} A_{gs\_s}}{A_{tot} * 1\%} * 0.1\ {}^\circ\mathrm{C} \tag{6}$$

where: n is the number of sub-catchments; $A_{gs\_s}$ is the green space implemented in sub-catchments; $A_{tot}$ is the total area of the field; $\Delta T_i$ is the change of temperature when the specific area of NBS implementation, and the unit is ℃; $\Delta T_{max}$ is the change of temperature when all available area of NBS are implemented, and the unit is ℃.

### 4.3.3 Indicator Assessment for PEOPLE

People-related indicators involve improvements in population health and social cohesion. In the study presented in Maas et al. 2009, the number of hospital patients is negatively correlated with the number of green plants within a one-kilometer radius of the living environment, and the increase in the green area can decrease the number of hospital patients. According with the Teeb-Stad tool's description and built-in parameter there can be 0.835 fewer patients per 1000 inhabitants on 1% more green spaces.

The percentage of people health improvement (PHI %) can be calculated by using Eqs. (7) and (8):

$$PHI\% = \frac{\Delta PH}{\Delta PH_{max}} \tag{7}$$

$$\Delta PH = \frac{\sum_{s=1}^{n} (A_{gs\_s} * P_s)}{\sum_{s=1}^{n} A_{tot\_s} * 1\%} * \frac{0.835}{1000} \tag{8}$$

where: n is the number of sub-catchment; $A_{gs\_s}$ is the green area implemented in sub-catchments; $A_{tot\_s}$ is the total area of the field in sub-catchments; $P_s$ is the population in sub-catchments; $A_{tot}$ is the total area of the field; $\Delta$PH is the number of fewer patients when the specific area of NBS implementation; $\Delta PH_{max}$ is the number of fewer patients when all available area of NBS are implemented.

Regarding the improvement in social cohesion, the Teeb-Stad tool indicates that a 1% increase in surface water area results in a 0.37% improvement in social cohesion. The water area consists of a green roof, bioretention ponds, and detention ponds.

The percentage of social cohesion improvement (SOCO %) can be calculated by suing Eqs. (9) and (10):

$$\mathrm{SOCO}\% = \frac{\Delta SC_i}{\Delta SC_{max}} \tag{9}$$

$$\Delta SC_i = \frac{\sum_{s=1}^{n} A_{wa\_s}}{A_{tot} * 1\%} * 0.37\% \tag{10}$$

where: n is the number of sub-catchment; $A_{wa\_s}$ is the increased water area in sub-catchments; $A_{tot}$ is the total area of the field; ΔSC is the percentage of social cohesion improvement when a specific area of NBS implementation and the unit is %; $\Delta SC_{max}$ is the percentage of social cohesion improvement when all available area of NBS are implemented, and the unit is %.

### 4.3.4 Objective Functions

For the formulation of the optimisation problem the decision variables, constraints, and objective functions need to be established. In this study, the decision variables were the application area of each selected NBS for a particular scenario in the study area, while the constraint of the optimisation process was the minimum and maximum implementation areas of each NBS that were available in each sub-catchment. Appendix 1 details the area coverage of each NBS availably per each sub-catchment.

Within the modelling tool, in this case the EPA SWMM engine the term "LID usage" refers to the ratio of the implemented area of each NBS to its maximum implementable area in a given sub-catchment. When the LID utilization of all NBS reaches 100 percent, the performance of each benefit enhancement should achieve its maximum effect.

To analyse the proportional relationship between costs and benefits, the objective functions must be normalized. Therefore, the cost must be expressed as a percentage that represents the ratio of the actual cost to the cost when LID usage is at 100 percent (maximum costs). The cost used in the optimisation process includes investment costs and annual operation and maintenance (O&M) costs in the future; therefore, the present value of O&M expenditure throughout the NBS life cycle should be calculated. The discount rate in the Cul De Sac district is 0.05, assuming a 30-year life cycle for each measure. Appendix 2 contains the investment and annual O&M costs for the selected NBS measures.

Three objectives were studied for the multi-objective optimisation of NBS, namely maximisation of urban flood reduction (Eq. (11)), maximisation of total benefits (Eq. (12)), and minimisation of the cost of NBS implementation (Eq. (13)).

The objective function of maximisation of urban flood reduction is presented in Eq. (11):

$$\text{Max FR} = \frac{F_b - F_i}{F_b} \times 100 \tag{11}$$

where FR is flood reduction, $F_b$ flooding volume of baseline (doing nothing), $F_i$ is flooding volume when simulating each combination of NBS measures generated by NSGA II.

The objective function of maximisation of total benefits is presented in Eq. (12):

$$\text{Max TB} = \sum_{n=1}^{j} G_n \tag{12}$$

where TB is total benefits, j means that the amount of indicator is selected, $G_n$ is the contribution of NBS on the corresponding benefits, which is calculated by each indicator equation, and it is expressed as each normalised benefit of NBS combination.

The cost objective function described by Eq. (13) is normalized by the total costs of the maximum number of GI possible to be constructed on each sub-catchment.

$$\text{Min Cost} = \sum_{X=1}^{N}\left[\left(C_{Inv_x} + \sum_{y=1}^{LT}\frac{C_{O\&M\_x}}{\left(1+\frac{i}{100}\right)^{y}}\right) * \sum_{j=1}^{SC} S_{xj}\right] \tag{13}$$

where: $C_{\text{Inv-x}}$ is the investment cost for the measure x; $C_{\text{O\&M\_x}}$ is the operation and maintenance cost of the measure x; LT is the lifetime of each measure x; i is the discount rate; $S_{xj}$ is the application size of the measure x in the sub-catchment j.

## 4.4 Comparison and Control Process

### 4.4.1 Comparison Process

The decision variables are encoded with integer values as the GA chromosomes. These values represent the area covered by the applied NBS measure as described in Alves et al. 2020. The NSGA-II algorithm requires a stopping criterion which is related to the population size and number of generations. In this study, a population of 100 individuals and 40 generations were proved to be enough combinations to test this optimisation framework.

### 4.4.2 Control Process

The control process refers to the computer code written to launch the 1D-hydrodynamic model and it is also able to compute the different objective functions. Therefore, this code is in charge of integrating the hydrodynamic computational engine with the NSGA-II algorithm. This code was developed in Python environment taking adavantage of the existing Pyswmm libraries to simulate the 1D-hydrodynamic model, (McDonnell et al. 2020; Sadler et al. 2019). Since the entire optimisation process is completed using python programming, Pyswmm makes it easier to obtain simulation results without explicitly calling SWMM engine and avoiding interfacing with output files.

# 5 Results

## 5.1 Optimisation Results of Various Scenarios

When simulating flood control using the original drainage system, the baseline model without optimisation, the simulated rainfall event with a return period of 20 years causes a flooding volume of 15,432 $m^3$. The flood volume can be reduced 1,766 $m^3$ if all the selected NBS are fully developed the available space, meaning the maximum flood reduction that can be achieved is 89% and it will be the most expensive solution. Hence, the need to formulate different scenarios for the optimisation process.

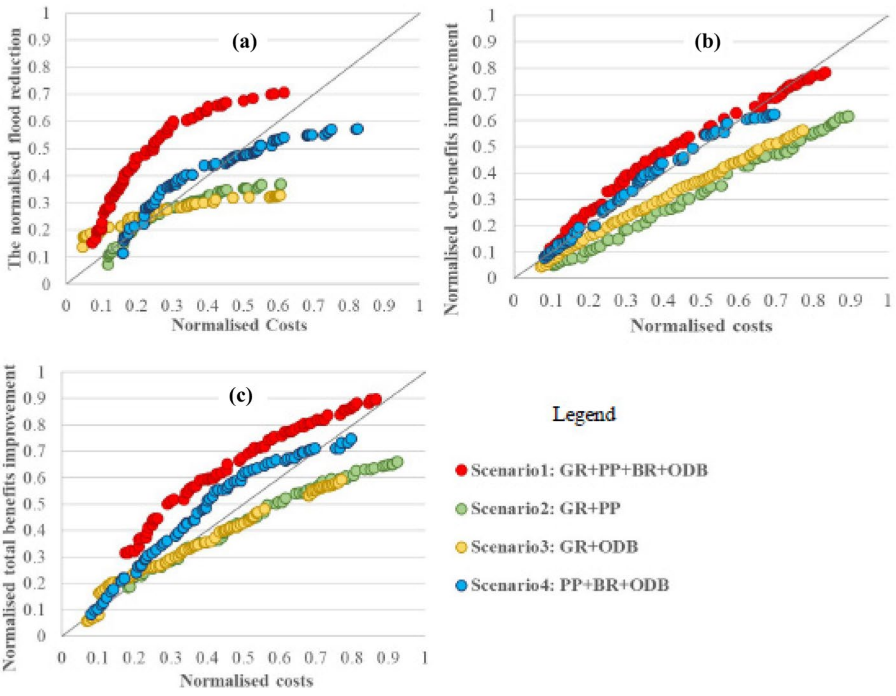


**Fig. 3** Performance of the four scenarios on **a** flood reduction, **b** co-benefits improvement, **c** total benefits improvement

Using the optimisation framework four scenarios were evaluated. As expected, they all perform differently due to the different characteristics of the NBS and their combination in terms of flood reduction maximisation, co-benefits maximisation, and cost minimisation as it can be expected. In Fig. 3 the performance for each scenario is presented and the approximation to the pareto front or best population obtained by the NSGA II.

In Fig. 3 it can be observed that if the same cost is considered the scenario 1 (GR + PP + BR + ODB) outperforms the other three, while scenario 4 (PP + BR + ODB) ranks second. As the normalized cost increases, they do not receive the same proportion of benefits, as it can be observed in the changes of slope of their scatter plots. Figure 3a illustrates that when the cost exceeds approximately 0.46 percent of the maximum cost, the rate of flood reduction is less than the normalized cost value for Scenario 4.

The efficiency of the three objectives ((a) flood reduction, (b) co-benefits improvement, (c) total benefits improvement) is lower in scenarios 2 and 3. The proportion of benefits will be less than the proportion of costs if the normalized cost is greater than 28%. As the normalized cost is less than 10%, scenario 3 performs better than the other scenarios for flood mitigation, which may be triggered by the storage capacity and saturation time of the open detention basin.

The optimisation results for all simulated scenarios show that zero flooding cannot be achieved under the simulated rainfall event as it was expected. However, this study investigates the most optimal number of NBS and its combinations that can reduce flooding and gain co-benefits at the best possible investment cost.

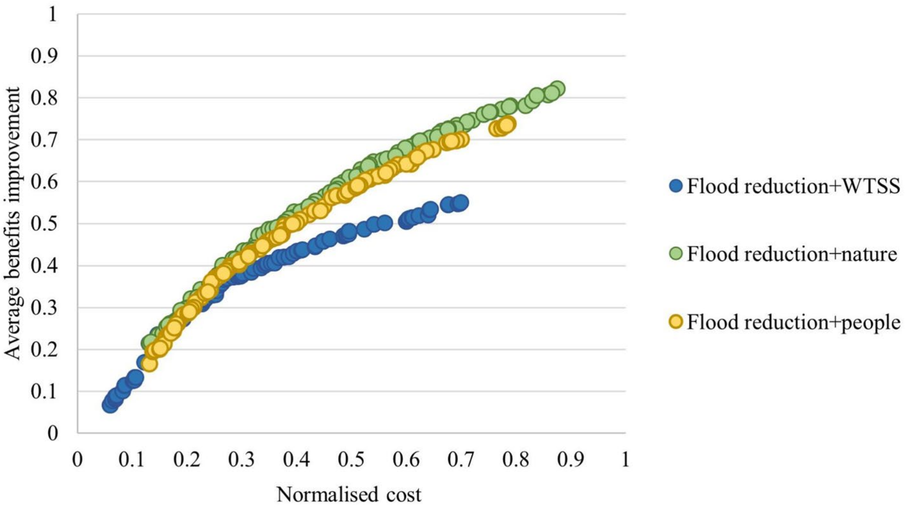


**Fig. 4** The trade-off among the different co-benefits

## 5.2 Trade-offs Among the Co-benefits

To explore the trade-offs among co-benefits, Fig. 4 shows the relationship between the normalized cost and the average benefits improvement percentage for scenario 1, which is the best performing scenario as discussed in the previous section. The three scatter plots depict three types of flood reduction and co-benefit combinations. Nature-related co-benefits, such as biodiversity enhancement and urban heat island mitigation, are associated with the optimisation objectives of the “flood reduction + nature” trend. For the optimization objectives for people-related co-benefits, s the improvement of people’s health and social cohesion were included.

As can be observed in Fig. 4, when the normalized cost is less than 0.30, the improvement percentages in these graphs are comparable. Also, it can be observed that the results for all the co-benefits are part of the Pareto front, as long as flood reduction is involved in the optimisation process. However, once the normalized cost exceeds 0.30, the ’’flood reduction + nature" scatter is marginally greater than "flood reduction + people" scatter and significantly greater than the "flood reduction + WTSS" scatter. The NBS strategy established for the case study can significantly enhance the co-benefits associated with nature and people, but the benefits of improving water quality are not very significant beyond the 0.3 value of normalized costs. In other words, the combination of NBS measures will enhance the other co-benefits better than achieving water quality (represented with TSS concentrations) improvements.

## 5.3 The Effect of the Incorporation of Benefits on Solutions

The effect of incorporating benefits into solutions in order to interoperate the allocation of each screened measure during the optimisation process was study. To investigate whether the optimised NBS strategy of one benefit improvement influences the others. The

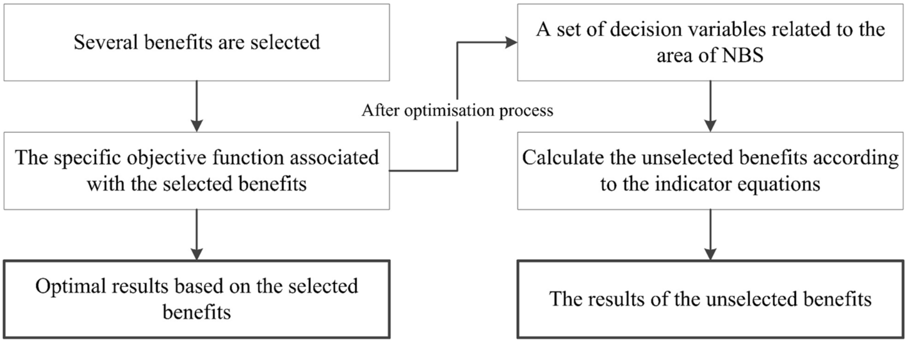


**Fig. 5** The calculation procedure of benefits depended on different optimisation objects

objective function associated with these benefits and co-benefits is formulated by the sum of the indicator equations, which means each benefit value can be calculated regardless of whether it participated in the optimisation process.

The calculation procedure of each benefit based on the different optimisation targets is shown in Fig. 5.

Each objective function is formed from several benefits or co-benefits taking into account the relative indicator equation. After optimisation, the optimal results of the selected benefits can be simulated again individually and the decision variables related to NBS can be generated or calculated. These variables and the indicator equation can calculate the results of the unselected benefits, but the Pareto front values cannot be guaranteed for those indicators. After simulating "maximum flood reduction versus minimum total cost," the values of co-benefits brought by the optimisation process can be recalculated according to the NBS area variables, but the result is less possible to be the best solution for co-benefit improvement. Table 2 presents the optimization experiments and the objective functions and equations used to re-calculate the benefits or co-benefits during post-processing.

Using the results obtained from the scenario 1 optimisation simulation as an example, the effect of incorporating the targeted benefits into solutions is discussed. Figure 6A, B respectively show the impact of these five optimisation processes on flood reduction and total benefits improvement. Figure 6A illustrates the percentage increase in total benefits and all Pareto fronts with a similar and overlapping trend. Due to the synergistic effect of each benefit, when optimising based on a combination of one or more indicators, the generated NBS strategy will still promote objectives that are not involved in the optimisation process.

However, Fig. 6B shows a clear difference of the flood reductions strategies among the other five optimisation processes. The blue scatter graph with "maximum flood reduction VS minimum costs" in Fig. 6B “dominates” all the other solutions found in the other five optimization runs. This also indicates that the other flood reduction percentages are not optimal when used in combination with other benefits and co-benefits. In other words, the flood control measures and other co-benefit enhancement compete for NBS coverage, this is due to the characteristics/properties of different NBS offering emphatically different benefits. The optimisation processes based on co-benefits, nature and people show lower performance on flood reduction (Fig. 6B). Nevertheless, it can be observed that the optimisation objectives based on flood reduction and total benefits (blue and red), have the best flood mitigation efficiency than the others.

**Table 2** Summary of optimisation experiments

| Optimisation run | Optimised objective | Objective function | Re-calculated equations |
|---|---|---|---|
| Based on total benefits | Total benefits | $= \text{Max} \sum \begin{matrix} FR\%, TSSR\%, BIOI\%, \\ UHIM\%, PHI\%, SOCO\% \end{matrix}$ | None |
| Based on co-benefits | All co-benefits | $= \text{Max} \sum \begin{matrix} TSSR\%, BIOI\%, UHIM\%, \\ PHI\%, SOCO\% \end{matrix}$ | FR% |
| Based on flood reduction | Flood | $= \text{Max} \sum FR\%$ | TSSR%, BIOI%, UHIM%, PHI%, SOCO% |
| Based on TSS reduction | TSS | $= \text{Max} \sum TSSR\%$ | FR%, BIOI%, UHIM%, PHI%, SOCO% |
| Based on nature | Nature-related benefits | $= \text{Max} \sum BIOI\%, UHIM\%$ | FR%, TSSR%, PHI%, SOCO% |
| Based on people | People-related benefits | $= \text{Max} \sum PHI\%, SOCO\%$ | FR%, TSSR%, BIOI%, UHIM%, |

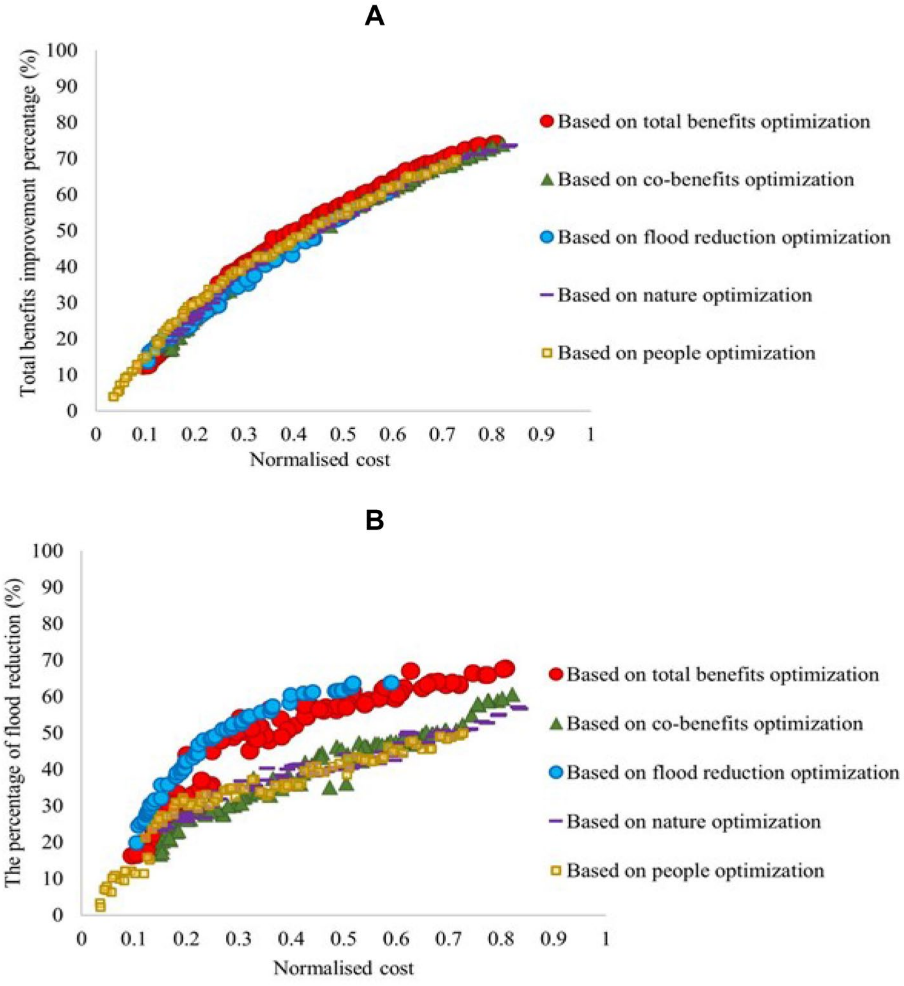
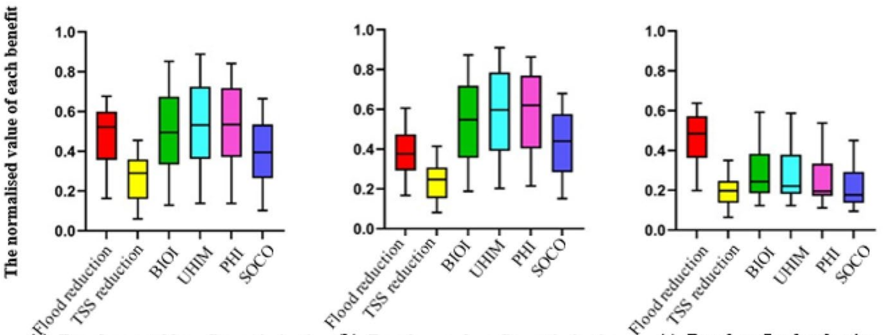


**Fig. 6** Simulation of Scenario1 (GR + PP + BR + ODB) on Total benefits (**A**) and flood reductions (**B**) for different optimisation objectives

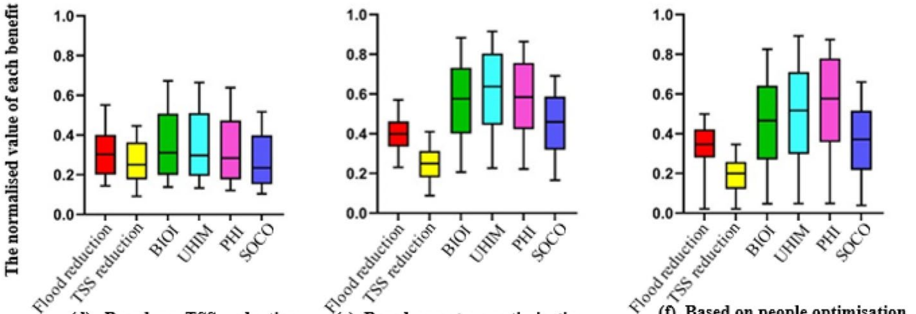
Given the different efficiency of the same measure for different objectives or performance indicators, the optimisation of the total benefits cannot be the sum of each optimised objective. Consequently, the allocation ratio of these five optimisation strategies to each objective must be analysed.

To demonstrate the distribution mechanism, the following section will further investigate the values that each benefit and co-benefits received based on various optimisation runs.

In Fig. 7 the box plots display the maximum, minimum, and median values of the six indicators based on different optimisation objectives as presented in Table 2. The box plot graph shows how the optimisation algorithm technique guide the allocation of measures as it can be seen in the ratio between various benefits or co-benefits while facing different objectives pursued in the optimisation runs or experiments.



(a). Based on total benefits optimisation (b). Based on co-benefits optimisation (c). Based on flood reduction optimisation



(d). Based on TSS reduction optimisation (e). Based on nature optimisation (f). Based on people optimisation

**Fig. 7** Values of each benefit obtained from the optimization processes based on different objectives

Figure 7 shows that int the trend of the box plots graphs the value of each benefit will fluctuate when the optimisation objectives are modified. For instance, the indicator of flood reduction "Based on flood reduction optimisation" (shown in Fig. 7c) achieves the higher values than it does in other optimisation processes, and also the nature-related benefits (i.e. biodiversity and urban heat island mitigation) obtain bigger values in " Based on nature optimisation" than where they are not simulated as optimisation objectives. In addition, the four indicators related to nature and people seems obtain higher value than flood or TSS reduction in every optimisation experiment which can be explained by the related indicator equations.

When analysing the influence between these benefits, it can be found that the increasing water-related benefits (flood and TSS reduction) result in lower value of people and nature-related indicators. What is more, comparing Fig. 7e, f, there is slight competition between nature-related benefits (BIOI and UHIM) and people-related benefits (PHI and SOCO). Figure 7c, d demonstrate that the value of flood and TSS reduction cannot simultaneously rise or decrease, despite the fact that they are related to water. But the main trade-off mainly occurs between water-related benefits and the other two aspects of co-benefits.

Focusing on the process based on total benefits optimisation (shown in Fig. 7a), each benefit keeps a relative high level, it can be concluded that the indicators involved in the objective function will all attain greater values as a result of the optimisation procedure's distribution of benefits. Therefore, the optimisation process should prioritise the more important preferences and demands on the optimization process, which can maximise the relative benefits.

## 6 Discussion

The objective functions used in the presented methodology for optimisation is based on the sum of the selected indicators; therefore, its value range will vary depending on the number of indicators. The selection of the indicator is determined by local needs and preferences, which also compensates for the limitations of quantitative analysis alone (Alves et al. 2020).

Thus, the indicator equations are important components of the objective function, which influences the value of the final benefits directly. The precise indicator equations also serve as the foundation for determining which benefits play a greater role in allocating a particular solution. Although different indicator equations will produce different results for the same type of benefits, creating the illusion that one benefit can outweigh others. By introducing additional models which can directly assess the relative co-benefits, the indicator equations and more importantly the calculated values can be more precise.

For instance, there is a tool which is used to reveals the percentage of urban heat island effect mitigation brought by NBS, named "THIS". The tool can be simulated with the hydro-dynamic model showing the potential connectivity between these models. (Nakata-Osaki et al. 2018). However, diverse assessment tools generate diverse outcomes, even when analysing the same case study. Incorporating some reliable models to calculate the contribution of NBS on the co-benefits would be a significant way to improve the quantification of benefits and co-benefits, although it has significant consequences in terms of computational time and hardware requirements when those are used in combination with optimisation techniques and methodologies as the one described here.

Another common optimisation strategy is to examine the effects of NBS from an economic standpoint in order to inform decision-making (Alves et al. 2019). In other words, the value of all benefits and co-benefits will be expressed in monetary units. For example, reducing flood risk can prevent economic loss. With the assistance of NBS economic evaluation tools, ecological and social benefits can also be measured as a capital symbolic expression (Van Oijstaeijen et al. 2020). This optimisation model reflects the relationship between costs and benefits more precisely to determine which kind of NBS strategy is more worthy investing in, because the economic analysis is a visualized approach. However, one of the limitations of this model is that it is difficult to quantify certain benefits.

## 7 Conclusion

An integrated evaluation and optimisation framework were developed to assess flood reduction and co-benefits enhancement. Three optimisation objectives were considered which are flood reduction maximisation, total-benefits maximisation, and cost minimisation. It was also defined the trade-offs between flood reduction and water quality, people and nature and the effect of the incorporation of benefits on different solutions.

Four feasible NBS measures have been applied and combined in four scenarios and taking the scenario 1 as an example, the actual implementation area percentage of each measure of them represents that for the same scenario, changing the optimisation objective makes the usage (%) of each measure significantly different. Therefore, it is necessary to analyse the impact of the incorporation of different benefit and co-benefits on the optimisation process. This further demonstrates the effectiveness of the methodology in the selection of different functionalities of each measure in the optimisation process.

Moreover, the value of the benefit or co-benefit whose performance indicators are included in the objective function directly tends to be higher. The performance indicators involved in optimisation are less likely to be negatively impacted. Therefore, the optimisation procedure should actively consider the most essential benefits for each case study area. This also explains how the range of possible solutions may be substantially altered by considering a variety of benefits and co-benefits. Sometimes, there is no obvious competition among the co-benefits but on the contrary synergies can be found. However, the extent to which NBS improves these co-benefits is different. The application of multi-objective optimisation becomes significant in analysing this situation.

The described methodology has the potential to benefit Cul De Sac area through the development of an optimal NBS strategy in multi-objective conditions, with the findings indirectly benefiting other urban areas elsewhere. In order to apply this framework to other cases it is required to re-identifying the key co-benefits, and then formulating the relational indicator equations. Furthermore, changes in geographic conditions may result in implementation variations for the different NBS measures.

## Appendix 1

**Table 3** Value ranges of decision variables in this case: area of GR, area of PP, area of BR, and area of ODB

| Available areas | GR ($m^2$) | | PP ($m^2$) | | BR ($m^2$) | | ODB ($m^2$) | |
|---|---|---|---|---|---|---|---|---|
| | Min | max | Min | max | Min | max | Min | max |
| A1 | 0 | 22000 | 0 | 15000 | 0 | 22000 | 0 | 4000 |
| A5 | 0 | 13000 | 0 | 8000 | 0 | 13000 | 0 | 4000 |
| A10 | 0 | 20000 | 0 | 13000 | 0 | 20000 | 0 | 4500 |
| A15 | 0 | 16000 | 0 | 11000 | 0 | 16000 | 0 | 6000 |
| A20 | 0 | 41000 | 0 | 27000 | 0 | 41000 | 0 | 4000 |
| A25 | 0 | 32000 | 0 | 21000 | 0 | 32000 | 0 | 4000 |
| A30 | 0 | 52000 | 0 | 35000 | 0 | 52000 | 0 | 5000 |
| A40 | 0 | 18000 | 0 | 12000 | 0 | 18000 | 0 | 8000 |
| A45 | 0 | 32000 | 0 | 22000 | 0 | 32000 | 0 | 5000 |
| A50 | 0 | 21000 | 0 | 14000 | 0 | 21000 | 0 | 7000 |
| A55 | 0 | 41000 | 0 | 27000 | 0 | 41000 | 0 | 5000 |
| A60 | 0 | 50000 | 0 | 33000 | 0 | 50000 | 0 | 6000 |

## Appendix 2

**Table 4** Investment cost, O&M costs for the selected NBS (Ashley et al. 2018)

| Solutions | Investment cost | Unit | O&M cost (annual) | Unit |
|---|---|---|---|---|
| Green Roofs | 70 | €/m$^2$ | 55 | €/m$^2$ |
| Permeable Pavement | 60 | €/m$^2$ | 2.5 | €/m$^2$ |
| Bio-retention Cells | 35 | €/m$^2$ | 3 | €/m$^2$ |
| Detention pond | 50 | €/m$^2$ | 2.5 | €/m$^2$ |

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**Availability of Data and Materials** Data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

## Declarations

**Ethical Approval** The authors declare that the manuscript has not been submitted to other journals.

**Consent to Participate** Not applicable.

**Consent to Publish** All authors agree to publish.

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