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A Multi-Objective Optimization Approach to Layout Planning of Bio-Retention Facilities Based on Digital Elevation Models

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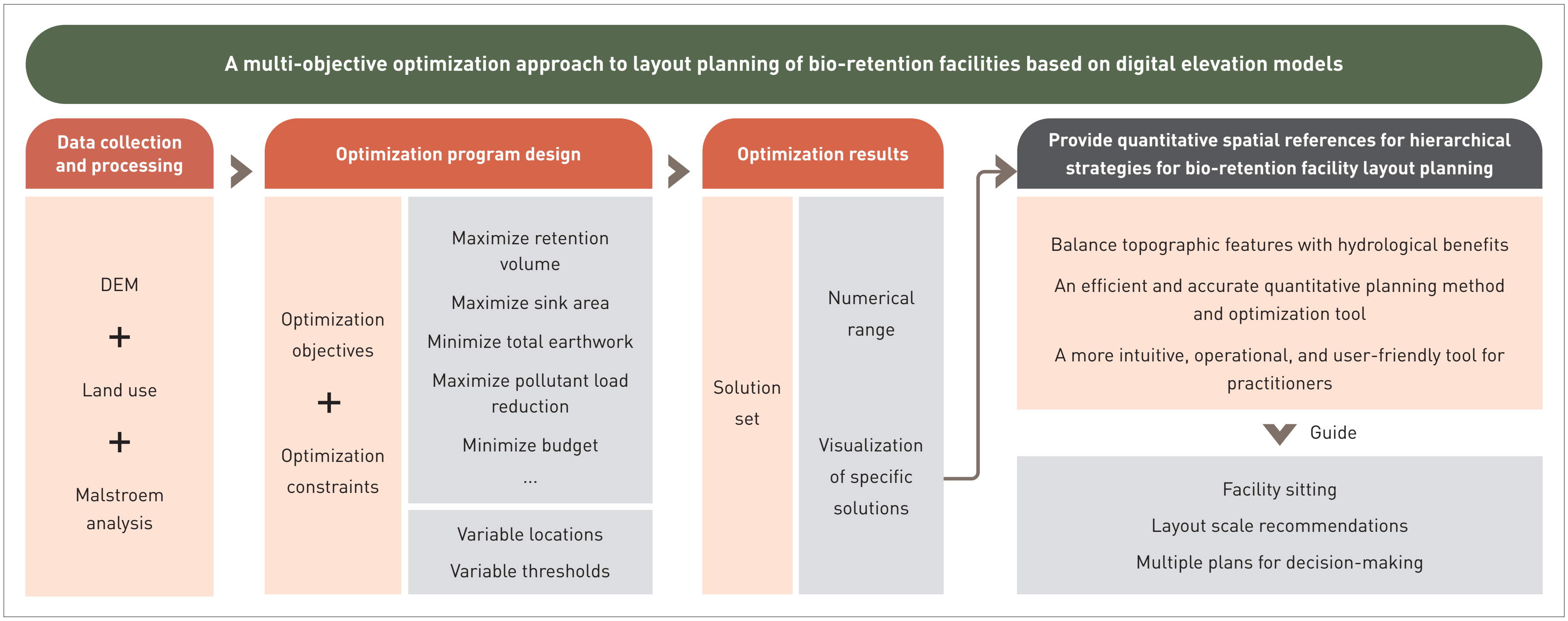
GRAPHICAL ABSTRACT



ABSTRACT

Under the trends of global urbanization and climate change, urban stormwater management has become increasingly critical in addressing urban flooding and water scarcity issues. Bio-retention facilities play a key role in stormwater management systems by reducing runoff volume and peak flow. Surface elevation is directly related to the layout of facilities by influencing their sink areas, runoff paths, and retention capacity. This study treats the raster cells of the digital elevation model as optimization variables to establish the linkage between surface elevation modification and layout objectives, and employs the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to solve for retention space and facility layout. At a demonstration site in Copenhagen, the method was tested under different constraint scenarios and proved capable of rapidly generating solution sets based on three objectives: maximizing retention volume, maximizing sink area, and minimizing total earthwork. The resulting surface elevation changes in the solution sets exhibited clear spatial differences and a gradient of retention benefits. Furthermore, this paper discussed optimization efficiency, solution set probability visualization, and layout strategies, providing feasible roadmaps and insights for identifying potential stormwater retention spaces and improving blue–green infrastructure planning.

KEYWORDS

Multi-Objective Optimization; Bio-Retention Facilities; Digital Elevation Model; Terrain Modification; Stormwater Management; Genetic Algorithm

HIGHLIGHTS

- Proposes a layout planning approach to bio-retention facilities that integrates DEMs with the genetic algorithm
- Achieves multi-objective optimization of retention volume, sink area, and earthwork objectives
- Applying a multi-objective optimization approach to rapidly optimizing terrain design and facility layout strategies

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1 Research Background

Under the background of global climate change and rapid urbanization, the increasing frequency of extreme rainfall events and the expansion of impervious surfaces have become major drivers of urban flood risk[1–2]. To mitigate the negative impacts of conventional gray infrastructure, modern stormwater management has introduced a variety of new paradigms and technical measures[3]. Among these, bio-retention facilities have emerged as common measures for intercepting, infiltrating, and attenuating runoff while reducing pollutant loads[4–5]. Bio-retention facilities generally refer to localized depressed areas composed of soil matrix and vegetation, designed to mimic natural hydrological processes in order to reduce surface runoff and delay peak flows. Their primary functions include stormwater storage, runoff regulation, and pollutant load reduction[6–8].

In the layout planning of bio-retention facilities, terrain factors play a critical role. The surface elevation directly determines the form and distribution of depression zones within sub-catchments, thereby influencing sink areas, retention volume, and runoff path[9–10]. In addition, since changes in surface elevation are associated with earthwork in practice, designers should balance hydrological benefits with the complexity of terrain modification. Previous studies mostly utilize digital terrain and related analytical tools to identify depressions, delineate catchment boundaries, and simulate runoff processes, thus providing a foundation for the layout planning of bio-retention facilities[11–13]. However, these approaches tend to focus on static planar identification and lack a systematic consideration of trade-offs among multiple hydrological benefits under complex terrain conditions. Thus, efficient and accurate quantitative planning methods and optimization tools are needed.

This study aims to propose a novel method for layout planning of bio-retention facilities based on the principle of multi-objective optimization. Building upon a preliminary analysis of surface runoff networks, it integrates digital elevation models (DEM) with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to quantitatively assess the impacts of surface elevation modification on multiple layout objectives, thereby supporting rapid identification and optimization of facility layout planning. Using a catchment in Copenhagen, Denmark as the demonstration site, this research 1) investigates how to balance topographic features with hydrological benefits in the layout planning of bio-retention facilities; and 2) provides an operational framework for identifying potential stormwater retention spaces and informing blue–green infrastructure planning.

2 Research Review

2.1 Stormwater Management and Layout Planning of Bio-Retention Facilities

Traditional stormwater management began with the development of urban sewer systems in Europe in the mid-20th century, where curbs, drainage pipes, and other gray infrastructure were employed to achieve centralized pipe-based drainage in order to meet public health and wastewater discharge needs[2]. Contemporary stormwater management emphasizes climate adaptation and urban resilience, developing concepts and practices such as Low Impact Development and Sustainable Drainage Systems by mimicking natural hydrological processes through diversified stormwater facilities[3]. Nowadays, many countries and regions are actively promoting stormwater management measures. For instance, the Danish government has advanced climate-adaptive planning pathways for stormwater management and, under the guidance of the EU Water Framework Directive, established municipal stormwater discharge permits and local governance rules, which have driven the demand for layout planning of bio-retention facilities[14–16]. In addition, unofficial guidelines such as Sustainable Urban Drainage Systems and Nature-based Solutions provide practical instructions for localized construction practices, though site selection and layout planning of facilities require continuous exploration[17–18].

Bio-retention facilities include types of sunken green spaces, bio-retention cells, infiltration trenches, etc. During rainfall events, surface runoff flows along convergence lines toward low-lying area and accumulates in depressions before ultimately spilling over. Therefore, low-lying areas within the natural or built environments are supposed to be suitable sites for implementing bio-retention facilities. How to rationally matching facilities and sites thus becomes one of the essential issues when considering site selection and layout. Previous studies have focused on the type, size, and layout pattern of bio-retention facilities[19–20]: 1) the facility type focuses on the compatibility of structural layers and their configuration, such as matrix composition, layer thickness, and vegetation combination; 2) the facility size focuses on the relationship among geometric dimensions, retention capacity, and layout effectiveness; and 3) the layout pattern concentrates on the connectivity among facilities and upstream–downstream linkages[21–23]. Among these, facility size is the core factor determining retention capacity and is strongly dependent on the depth and area characteristics of depressions. Therefore, this study takes facility size as the entry point, focusing on the interactions between scale and surface elevation change, in order to support layout planning of facilities.

2.2 Layout Planning of Bio-Retention Facilities Based on Multi-Objective Optimization Algorithms

Multi-objective optimization has been used for addressing engineering problems that involve multiple conflicting objectives. Since different objectives usually cannot be optimized simultaneously, the results are typically expressed as a set of trade-off solutions, referred to as the Pareto Front Solution Set ("solution set" hereafter)[24–25]. The solution set demonstrates the trade-offs among multiple objectives, allowing decision-makers to comprehensively observe and compare results, thereby supporting decision-making. In recent years, multi-objective optimization has been widely applied in research on stormwater facility layout planning, and the combination of optimization algorithms with simulation models has become one of the mainstream approaches[20]. For instance, studies have constructed various optimization frameworks for facility layout planning using multi-objective algorithms and solved problems of facility configuration under hydrological, ecological, and economic objectives such as runoff volume control, budget constraints, and runoff pollution reduction[26–28].

Multi-objective optimization algorithms mainly include simulated annealing, ant colony optimization, strength Pareto evolutionary algorithm, and genetic algorithms[24,29]. Among them, simulated annealing is effective at avoiding local extrema but has relatively lower computational efficiency; ant colony optimization is suitable for discrete search spaces; and the strength Pareto evolutionary algorithm can effectively maintain diversity in the solution set, but its computational complexity increases substantially in high-dimensional problems[24–25,30–31]. By contrast, genetic algorithms represented by NSGA-II, owing to their non-dominated sorting strategy and crowding distance calculation mechanism, perform well in terms of convergence speed, diversity, and balance of solutions, and are therefore widely employed[32–36].

Multi-objective optimization algorithms are typically combined with hydrological simulation or facility layout tools. Models are primarily implemented through platforms such as SWMM, SWAT, SUSTAIN, and UrbanBEATS, or via secondary development built upon these platforms[37–44]. Such studies have revealed the quantitative relationships between bio-retention facility size and evaluation benefits. However, issues such as how facility scale is constrained by terrain conditions and how it matches with surface space remain insufficiently represented in existing models. Meanwhile, DEM-based hydrological analysis methods (e.g., runoff path analysis, depression identification) have already been widely applied[13,45–47]. Using DEM as the analytical object and solving layout problems with multi-objective optimization algorithms provide a more intuitive and operational tool for practitioners in determining facility locations and scale during the planning stage. Nevertheless, few studies have attempted to carry out optimization modeling upon DEM-based hydrological analysis. In summary, this study proposes a DEM-based multi-objective optimization method for the layout planning of bio-retention facilities, in which DEM raster cells are treated as optimization variables for multi-objective operations, thereby providing generative terrain schemes and determining facility size and layout strategies.

3 DEM-Based Multi-Objective Optimization Method for the Layout Planning of Bio-Retention Facilities

3.1 Establishment of the Multi-Objective Optimization Framework

The DEM-based multi-objective optimization for bio-retention facility layout is established by decomposing, abstracting, and refining terrain features and layout problems into optimization variables, objectives, and constraints in a mathematically logic (Fig. 1). First, in the initialization stage, DEMs are encoded to define optimization variables, objectives, and constraints according to the specific problem. Second, in the optimization stage, the solving process is carried out to test the stability under different scenarios. Finally, in the result stage, the solution set is decoded into corresponding schemes, which are presented in visual forms to assist the final decision-making.

3.2 Defining Optimization Variables, Objectives, and Constraints

Optimization variables broadly refer to the adjustable parameters that define the search scope of the problem, i.e., all possible solutions. In this study, the elevation values of DEM raster cells are treated as optimization variables, and data recognition and conversion between DEM and the optimization procedure are achieved through stepwise encoding and decoding.

Optimization objectives refer to the outcome indicators that are improved by changing the optimization variables. There is a linkage between the modified surface elevation and the objectives of bio-retention facility layout (Fig. 2). Layout objectives usually include retention volume, sink area, pollutant reduction, earthwork volume, and facility cost[5,10].

Optimization constraints refer to restrictions imposed on the range of values for optimization variables or objectives. For example, constraints can be applied to the locations of DEM raster cells that are allowed to vary, or to the thresholds of permissible elevation changes—both of which limit the spatial extent and depth of terrain modification. It can be anticipated that looser constraints yield higher upper limits for optimization results. Therefore, to produce more practical and targeted optimization results, constraints should be set based on specific factors such as existing sink areas, land-use types, or cut-and-fill limitations of the terrain.

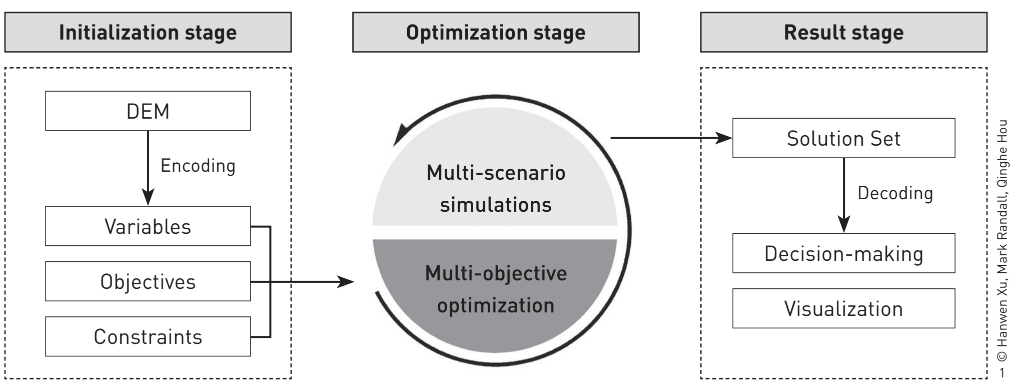
3.3 Data Preprocessing

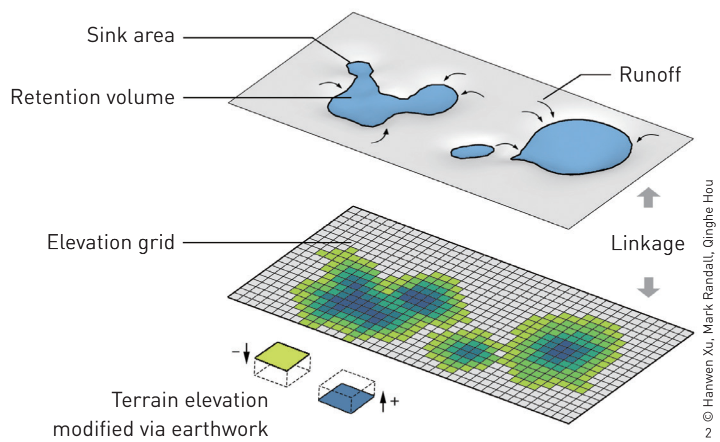
The DEM provides essential spatial and hydrological information of the given site and forms the data basis for the optimization procedure. Data preprocessing mainly focuses on the basic attributes and characteristics of the DEM, including resolution, catchment delineation, runoff path, overflow volume, and the initial values of layout objectives. It is worth noting that, since the DEM generalizes terrain into a matrix of raster cells, the total number of raster cells directly affects optimization efficiency. Too low a resolution will lose terrain details and reduce result reliability, whereas too high a resolution will produce excessive raster counts and lower computational efficiency. Therefore, the input DEM resolution should be reasonably determined based on site scale and the precision requirements of optimization.

4 Demonstration Site and Results

To verify the DEM-based multi-objective optimization for bio-retention facility layout planning proposed in this study, an area in Copenhagen, Denmark, was selected as the demonstration site.

Fig. 1 The framework of DEM-based multi-objective optimization.
Fig. 2 The linkage between optimization variables of DEM and objectives.





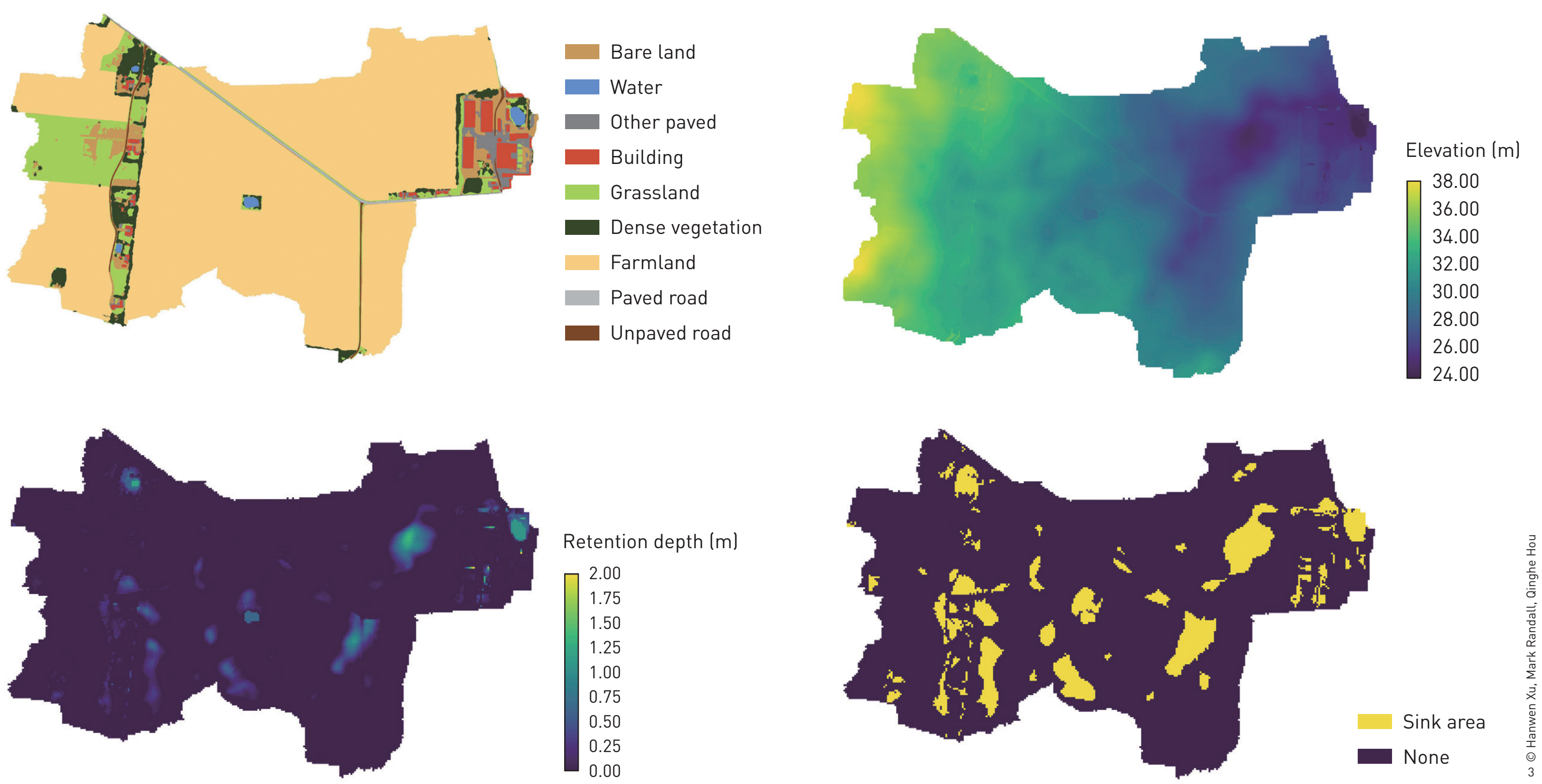
4.1 Demonstration Site

The demonstration site covers approximately 89 hm^2. The overall terrain slopes gently from west to east, with elevations ranging from 24.04 m to 38.19 m (Fig. 3). The reasons for selecting this site include 1) the area lies in an independent upstream catchment within the local watershed, which largely eliminates external inflow during rainfall events; 2) the underlying surface is predominantly farmland and grassland, with only a few buildings and roads, allowing it to be approximated as green space composed of natural pervious soils and minimizing interference from initial soil saturation, hydraulic conductivity, and land-cover heterogeneity; and 3) the area already contains local depressions, providing favorable conditions for facility layout. The DEM of the study area was obtained from the open database of the Danish Agency for Data Supply and Infrastructure, with an original resolution of 0.4 m. Considering the spatial scale of the study, computational efficiency, and the effect of different resolutions on hydrological convergence analysis, the DEM was resampled to 5 m resolution after multiple pre-tests to balance model complexity and result accuracy. After resampling, a total of 33,930 raster cells were obtained; the initial retention volume was 26,270 m^3 and the depression area was 97,400 m^2.

Local government encourages the use of regenerative agriculture and grassland restoration to enhance the retention and detention capacities of agricultural and public green spaces. Accordingly, the optimization objectives were set as follows: 1) maximum retention volume, to increase stormwater storage capacity during extreme rainfall events and reduce flood risk downstream; 2) maximum sink area, to improve spatial capacity for capturing and retaining runoff; and 3) minimum total earthwork, to reduce construction costs and environmental disturbance.

In this case study, the Malstroem bluespot tool was employed to conduct a preliminary runoff network analysis of the demonstration site (Fig. 4). Based on DEM data, this tool identifies surface depressions, pour points, and runoff paths, and simulates spillover processes, thereby quantifying spillover volumes and runoff connectivity between depressions[48]. Preprocessed results indicate that runoff in the study area primarily converges from west to east, successively accumulating in multiple depressions, spilling over, and eventually discharging toward the downstream eastern region. Considering that green spaces and water bodies are easier to modify and already possess relatively higher retention

Fig. 3 Basic information of the demonstration site (data source: Danish Agency for Data Supply and Infrastructure 2024).



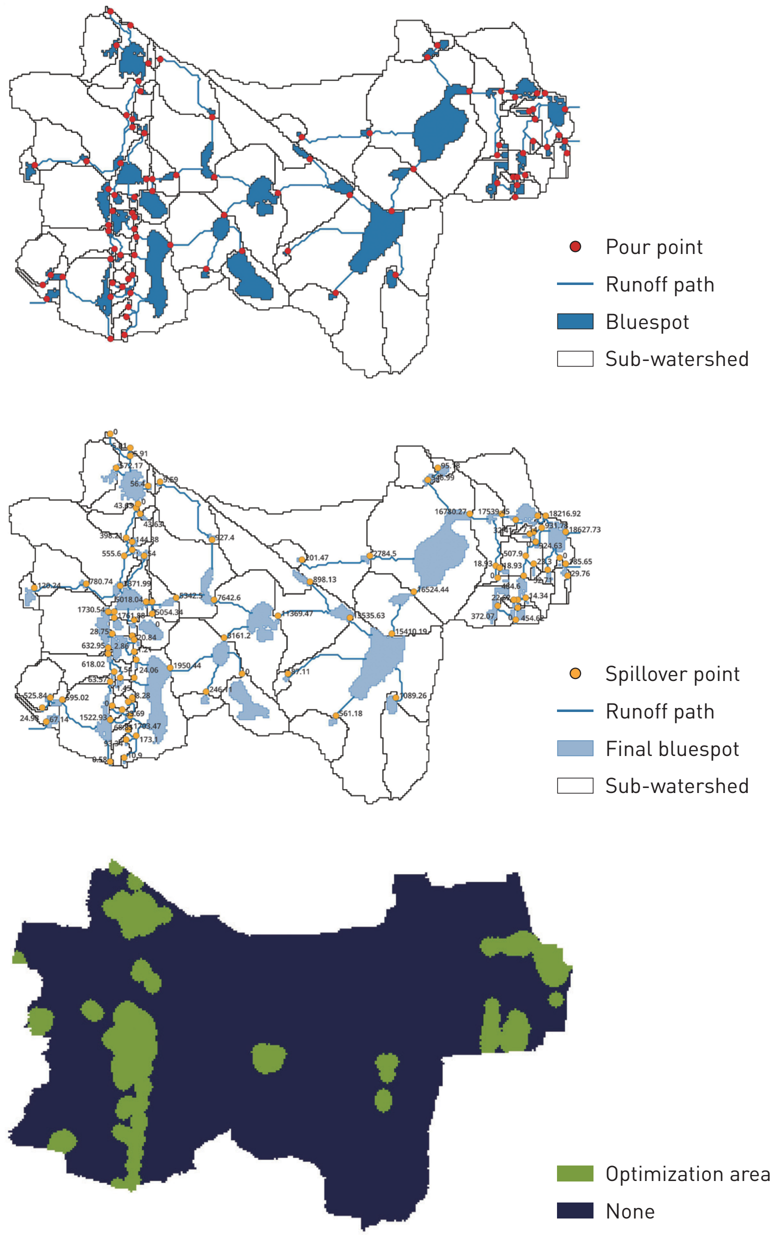


Fig. 4 Runoff network pre-analysis of the demonstration site (data source: Danish Agency for Data Supply and Infrastructure 2024).

potential, these land-cover types were overlaid with depression areas, and a 20 m buffer zone was applied to obtain the optimization area①, comprising a total of 4,386 raster cells. Finally, four scenarios were defined according to different ranges of terrain elevation modification as constraints: 1) Scenario 1: elevation variation ranging from 0 to 0.5 m; 2) Scenario 2: elevation variation ranging from 0 to 1.0 m; 3) Scenario 3: elevation variation ranging from 0 to 1.5 m; and 4) Scenario 4: elevation variation ranging from 0 to 2.0 m. Each scenario was run 10 times to test program stability and average computation time. The specific program settings are provided in Table 1[30–31,49].

4.2 Solution Sets and Visualization Analysis

According to the four scenarios, four groups of solution sets were obtained, all of which exhibited convergence (Table 2, Fig. 5). The average computation time across the four scenarios was

Table 1: Parameter settings for multi-objective optimization

Category	Parameter	Description
Optimization objectives	Maximum retention volume ($V_{\text{retention volume}}$)	$V_{\text{retention volume}} = \sum_{i=1}^{n} d_i \times R$ In the formula, d_i is the depth of the ith depression cell (calculated using the Fill depression tool), R is the area of a single raster cell, and n is the total number of variable raster cells
	Maximum sink area ($A_{\text{sink area}}$)	$A_{\text{sink area}} = \sum_{i=1}^{m} R$ In the formula, m is the number of depression cells (calculated using the Sink tool, excluding depressions with depth less than 0.05 m), and R is the area of a single raster cell
	Minimum total earthwork ($V_{\text{total earthwork}}$)	$V_{\text{total earthwork}} = \sum_{i=1}^{n} \lvert E_i \rvert \times R$ In the formula, E_i is the elevation change value (m), R is the area of a raster cell (m^2), and n is the total number of variable raster cells
Optimization constraints	Elevation modification range (m)	· Scenario 1: [0, 0.5] · Scenario 2: [0, 1.0] · Scenario 3: [0, 1.5] · Scenario 4: [0, 2.0]
Optimization algorithm	NSGA-II	· Population size: 100 · Offspring size: 40 · Generations: 200 · Crossover method: Simulated Binary Crossover (probability = 0.9, eta = 15) · Mutation method: Polynomial Mutation (eta = 20)

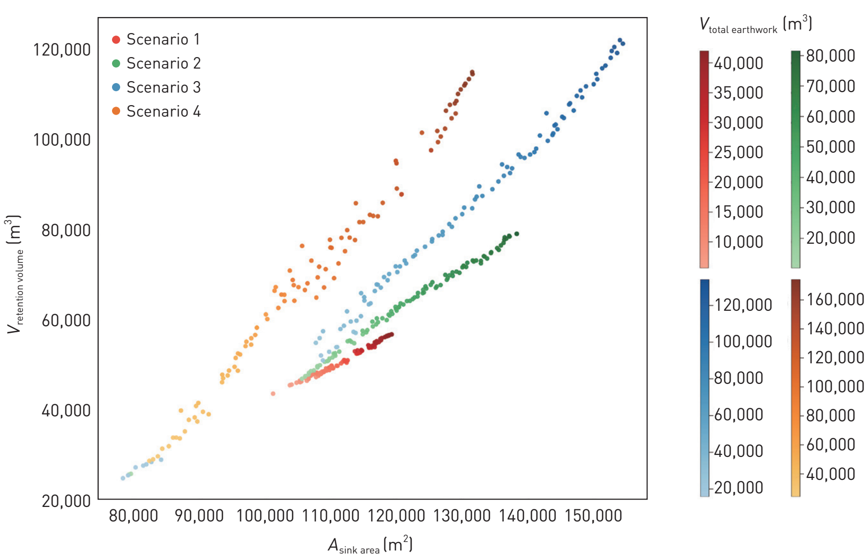
NOTE
The settings of the optimization algorithm are based on Refs. [30–31,49].

① Adding the 20 m (four-cell) buffer was accounted for the reasonable expansion and adjustment during terrain modification. This value may be adjusted according to the specific conditions of the given site.

Table 2: Function value intervals of Solution Sets

Scenario	$V_{\text{retention volume}}$ (m^3)	$A_{\text{sink area}}$ (m^2)	$V_{\text{total earthwork}}$ (m^3)	Average operation time (min)
Existing	26,270	97,400	—	—
Scenario 1	44,188 ~ 57,264	101,225 ~ 119,325	5,631 ~ 42,016	20.5
Scenario 2	26,379 ~ 79,445	79,275 ~ 138,400	10,250 ~ 81,563	21.6
Scenario 3	25,542 ~ 122,154	78,325 ~ 154,575	16,473 ~ 134,027	22.4
Scenario 4	29,373 ~ 115,113	82,350 ~ 131,650	24,326 ~ 173,925	21.8

Fig. 5 2D scatter plot of Solution Sets under four scenarios.



around 20 min, with constraints having little effect on calculation speed, indicating overall high computational efficiency. The results show that 1) under different scenarios, the optimization results consistently produced solution sets, proving the feasibility and stability of the proposed framework; 2) as the elevation modification threshold increased, the distribution ranges of the three optimization objectives expanded, with maximum retention volume and maximum sink area corresponding to larger earthwork volume and showing a simultaneous growth; and 3) under conditions of similar maximum sink area, higher-threshold scenarios could achieve greater retention volume at the cost of larger earthwork, and vice versa for similar maximum retention volume. Decision-makers are able to thus select suitable solution sets according to specific engineering requirements.

Each of the four solution sets contained 100 solutions, and any solution could be decoded to generate corresponding DEMs. It is impossible to present all solutions individually in this study; instead, Fig. 6 shows the mean DEM results of the solution sets under the four scenarios—average retention depth map and sink probability map. The former was obtained by averaging the retention depths across all DEM raster cells, while the latter was calculated by overlaying all sink area maps of DEM solutions and counting the frequency at which each raster was identified as a sink.

Spatial distribution patterns indicate that, in all four scenarios, continuous depression areas formed along the north–south drainage route on the western side of the site and in the northeast. This suggests that these locations have a higher probability of being selected for implementing bio-retention facilities. As the constraint threshold increased, these high-probability areas generally expand and connect on the basis of the existing depressions, exhibiting a more "aggressive" areal pattern. However, in Scenario 4, the depressions around certain locations in the northeastern part shrunk. This is because the enlarged threshold broadened the feasible solution space and altered the objective trade-offs. The nonlinear response of the local terrain structure consequently led to a decline in local connectivity. Changes in retention depth were reflected mainly in two aspects: 1) as constraints increased, average retention depth of depressions rose from 1.2 m to about 2 m, while local peaks increased from 2 m to 3 m, indicating larger scales of terrain excavation; and 2) high-depth areas strongly overlapped with high-probability sink areas, whereas low-depth areas were markedly reduced in Scenarios 3 and 4, reflecting that the additional earthwork operations were concentrated in existing sink areas rather than randomly dispersed.

The visualization of optimization results provides quantitative spatial references for hierarchical strategies for bio-retention facility layout planning. Specific strategies include 1) if terrain modification is limited, Scenarios 1 and 2 may be preferred, as depressions are more concentrated and depths moderate, making them suitable for embedding bio-retention facilities in a "point–strip" pattern with minimal disturbance to existing land-cover texture; and 2) if the goal is to substantially increase retention capacity and expand sink areas, Scenarios 3 and 4 offer larger and more spatially continuous potential depressions, allowing for an "areal" systematic layout of bio-retention facility networks. Overall, high-probability areas may be defined as priority terrain modification units, while medium- and low-probability areas can be regarded as alternatives.

It should be noted that in all four scenarios, some solutions

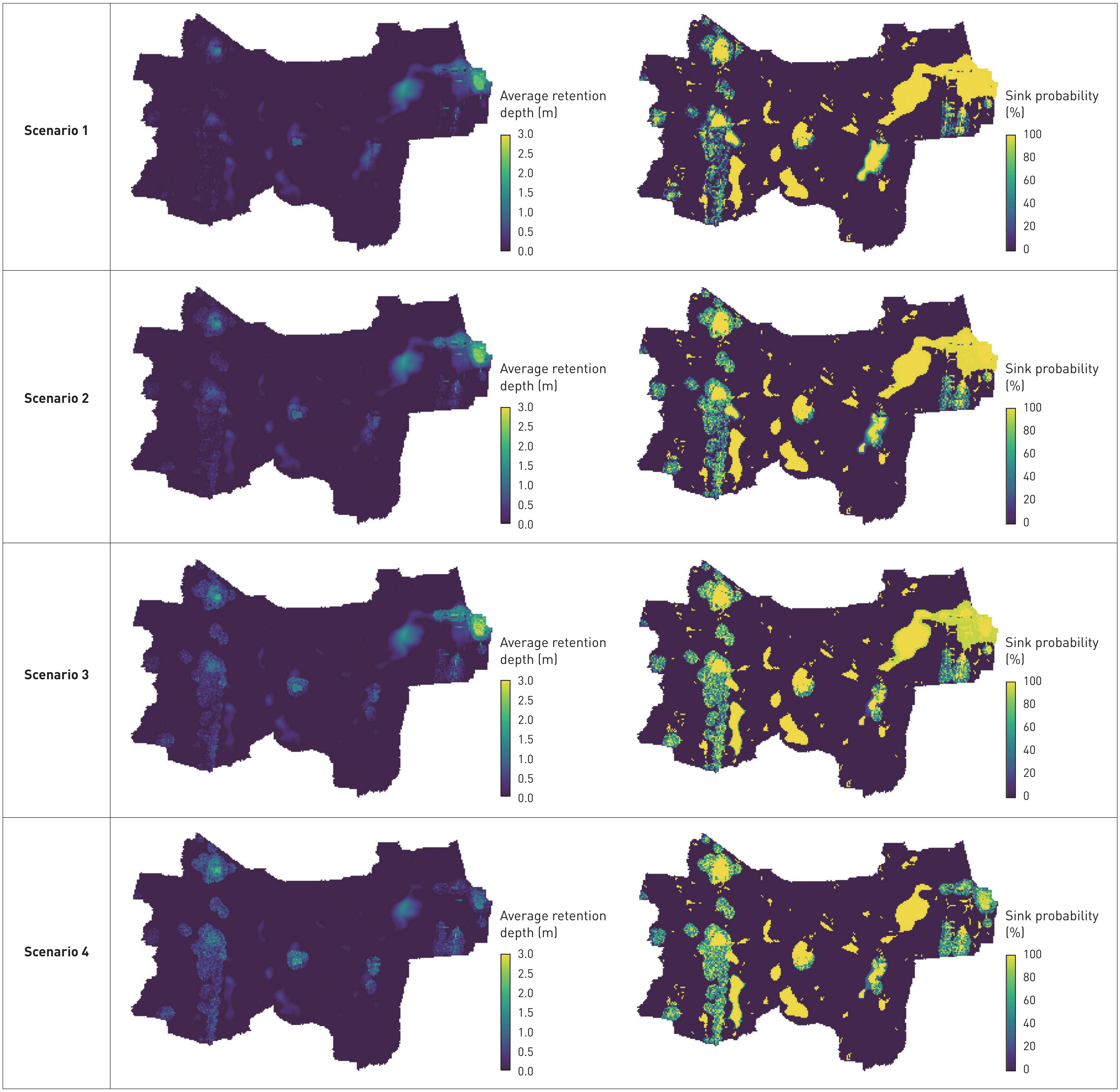
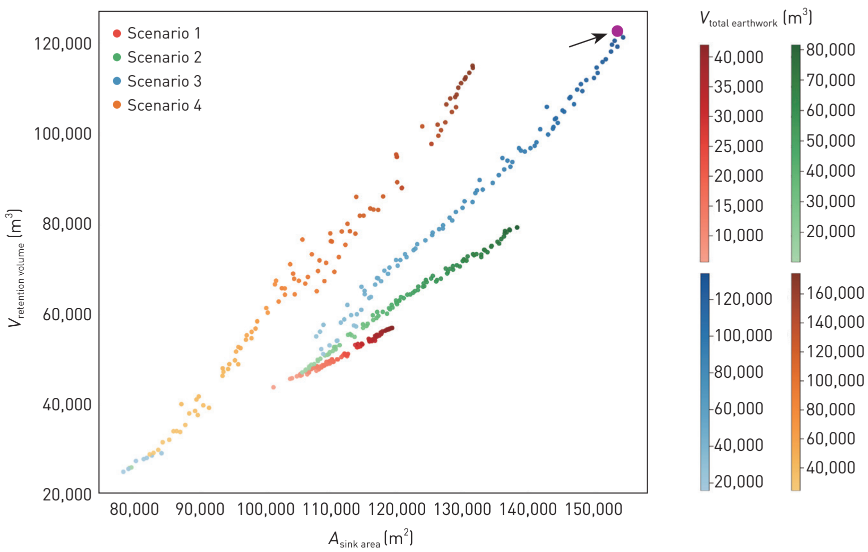


Fig. 6 Average retention depth map and the sink probability map under the four scenarios.

produced maximum retention volume or maximum depression area values lower than the existing baseline. Theoretically, these solutions are mathematically valid within the optimization process; but in this study, such solutions do not provide practical improvement and can be regarded as invalid solutions.

Finally, the solution with the largest retention volume was selected for an example of decoding and visualization (Figs. 7, 8). In this solution, the three objective values were maximum retention volume of 122,153 m^3, maximum sink area of 154,125 m^2, and minimum total earthwork volume of 134,027 m^3. Compared with the baseline, new depressions were mainly located within existing green spaces and open areas, with local depths reaching up to 3 m. Retention volume was significantly improved, and spillover analysis revealed that overflow at 5 typical pour points decreased by 63% ~ 100% (Fig. 9). This solution represents a high-cost extreme case under benefit-prioritized conditions, illustrating the upper limit of retention potential and the spatial configuration characteristics in an extreme scenario.



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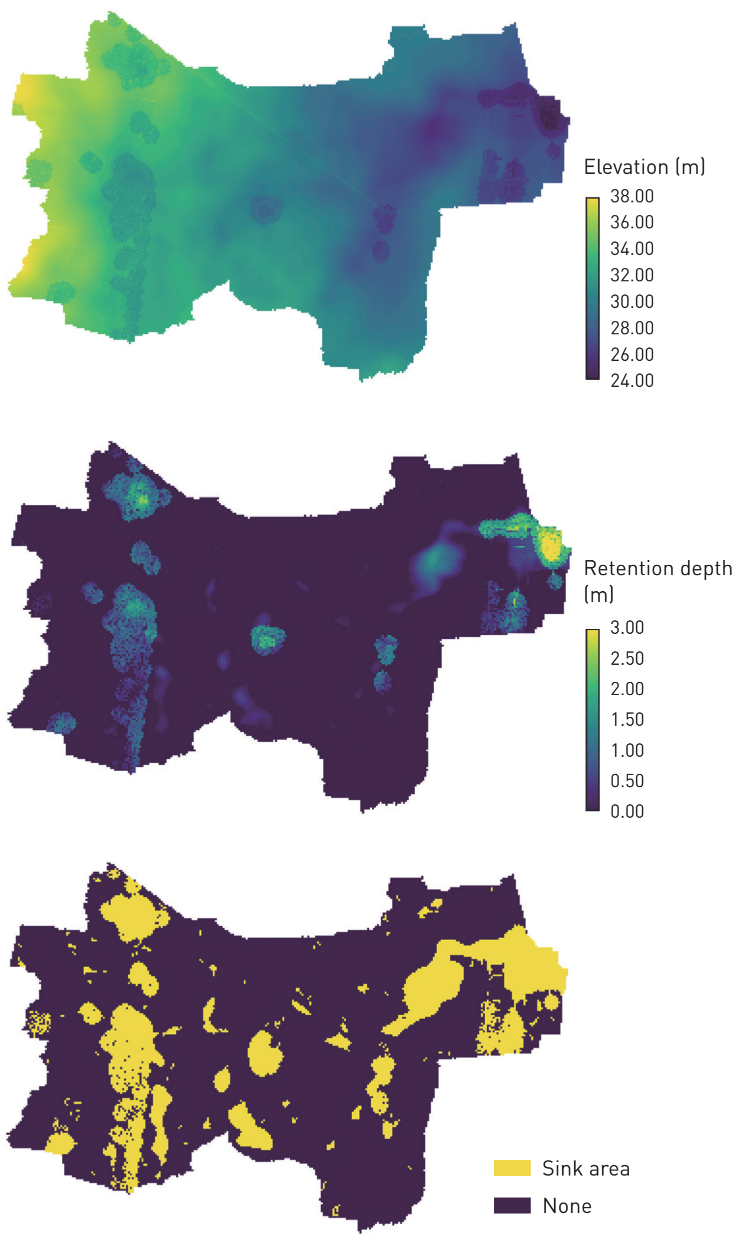

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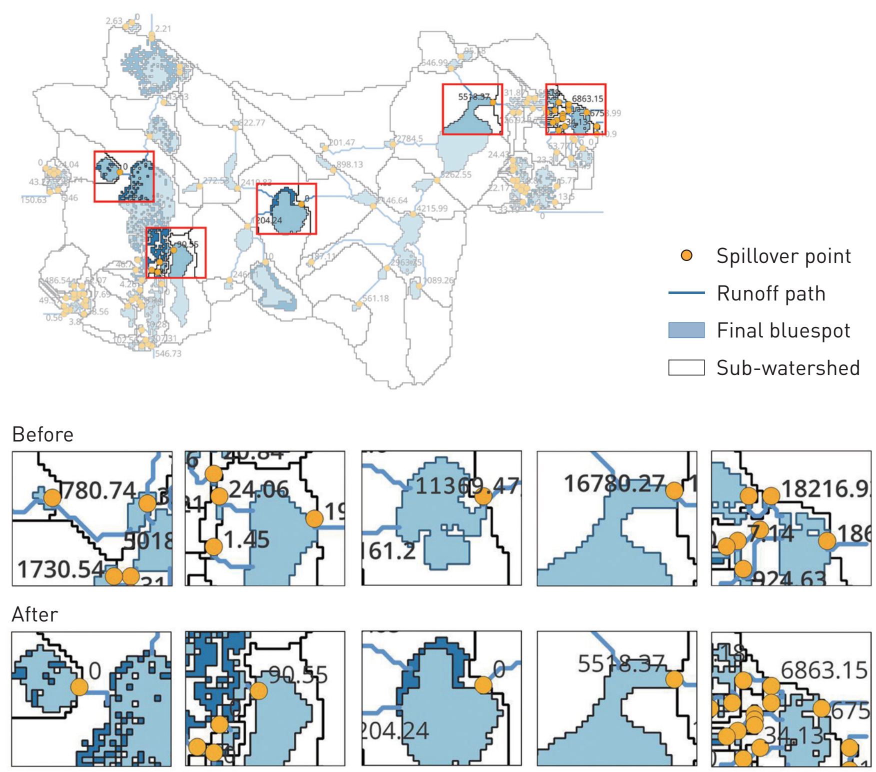
Fig. 7 The decoding and visualization of the solution: 2D scatter plot.
Fig. 8 The decoding and visualization of the solution: the retention depth map and the sink area map.
Fig. 9 Comparison analysis of simulated spillover volume of the selected solution in local areas. The numeric labels next to spillover points represent the simulated spillover volume at each point (unit: m^3).



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5 Discussion and Conclusions

This study proposed a DEM-based multi-objective optimization method for the layout planning of bio-retention facilities, achieving optimization objectives of maximum retention volume, maximum sink area, and minimum total earthwork. The method demonstrates rapid operability, flexible scalability, and application potential. It is applicable to nature-based terrain modification practices and has shown feasibility and stability in framework construction and solution set generation. However, due to the high uncertainty of terrain variables, further validation under different conditions is required to refine parameter settings and evaluate application effects. The limitations of this study include 1) constrained by computing hardware, the upper limits for the scale of optimization variables and objectives that can be processed are not yet fully clear; 2) facility parameters such as initial saturation, hydraulic conductivity, and vegetation type were not incorporated into this study; 3) the terrain-modification-based approach to enhancing retention volume and area is limited in applicability to sites with complex hydrological connectivity; and 4) the demonstration site selected in this paper contains relatively abundant green and open spaces, which differ substantially from high-density built environments, making it inappropriate to directly apply the optimization parameters and technical pathways presented herein.

To advance research and practice in the layout planning of bio-retention facilities, this study proposes the following recommendations.

1) Explore computational efficiency limits and effective constraint conditions. The number of optimization variables determines the dimensionality of the algorithm's population, thereby affecting resource consumption in encoding/decoding, objective function calculation, and memory allocation. During testing, it was observed that increasing DEM resolution or the number of variables led to a significant decline in computational efficiency. Therefore, for high-resolution DEMs or larger-scale applications, users should improve computational efficiency by enhancing computing resources or splitting data objects.

2) Adopt more diverse optimization objectives. The number of optimization variables and objectives in this study still has room for improvement. The approximately linear distribution of solutions suggests that some objective functions may be strongly correlated or coupled in optimization trends. Future research should consider incorporating objectives with stronger independence or broader representativeness to enhance the diversity of solutions and the scientific validity of optimization dimensions. Moreover, recent advances in many-objective optimization algorithms make it increasingly feasible to simultaneously address a larger number of objectives while further improving computational efficiency[50].

3) Expand the scale and hierarchy of research objects. By generalizing the depression characteristics of lakes, ponds, and constructed wetlands as large-scale blue–green infrastructure, this optimization framework has the potential to be extended to the city or watershed scale. Designing urban runoff conveyance through DEMs and strategically embedding retention spaces can enhance spatial retention capacity and improve the city's overall resilience to extreme rainfall events.

4) Consider multiple impacts of terrain optimization. Large-scale terrain modifications may lead to localized surface damage, soil structure disturbance, and rainfall-induced erosion, thereby affecting vegetation cover and ecological stability. Future studies could incorporate surface stability models, water pollution diffusion models, and vegetation restoration strategies to conduct integrated optimization under multi-dimensional constraints, ensuring the site's ecological sustainability.

Admittedly, interpretable multi-objective optimization methods provide a foundation of instrumental rationality② for the layout planning practice of bio-retention facilities. However, beyond engineering and technical considerations, urban stormwater management also involves multiple social and cultural factors. Future research should deepen the understanding of the "chaotic" nature and "pain points" in planning and design, thereby offering valuable guidance for practical decision-making.

② "Instrumental rationality" is a concept proposed by sociologist Max Weber, also known as "efficiency rationality" or "purposive rationality." It refers to the use of precise calculations to select the most effective means for achieving predetermined goals, focusing on minimizing costs, maximizing benefits, and realizing utilitarian purposes in the most optimal way. In contrast, "value rationality" emphasizes choices guided by values or beliefs rather than utility (source: Ref. [51]).

Competing interests | The authors declare that they have no competing interests.

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基于数字高程模型多目标优化的生物滞留设施规划布局方法

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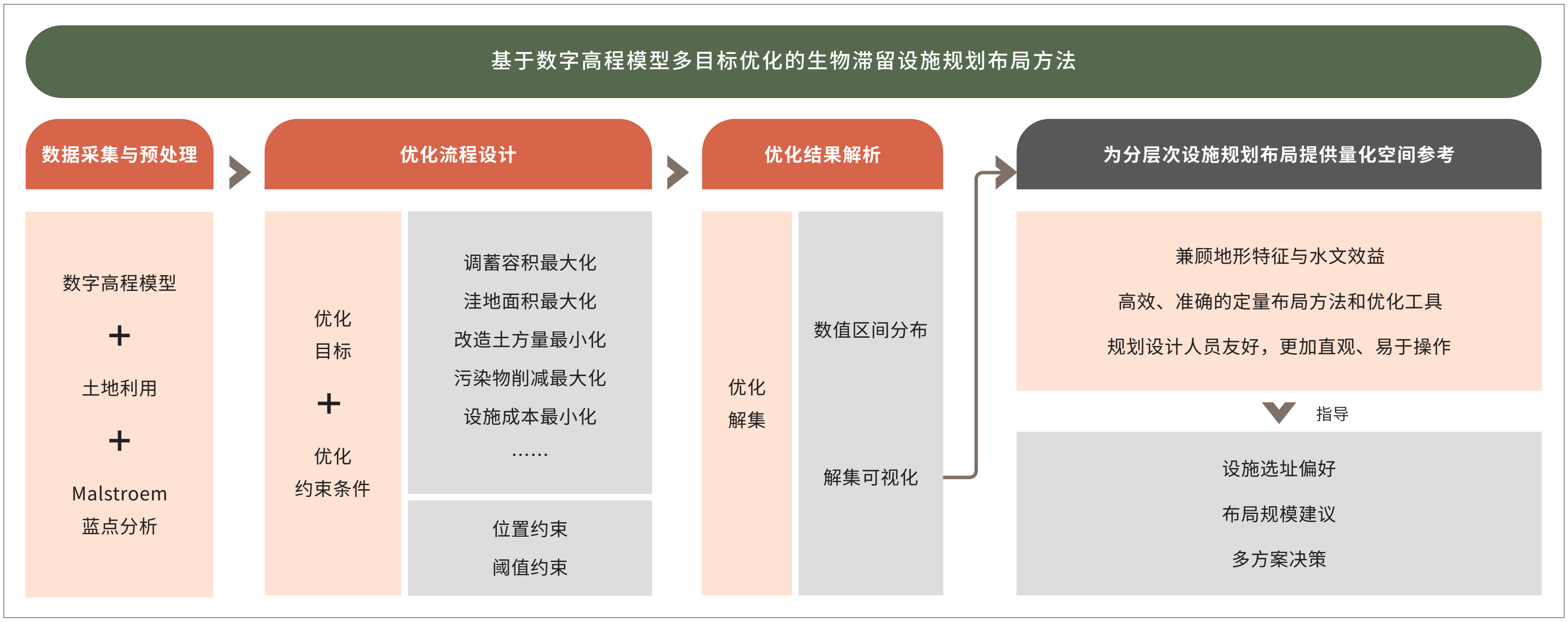
图文摘要



摘要

全球城市化与气候变化背景下，为应对城市洪涝灾害与水资源短缺等问题，城市雨洪管理的重要性愈发凸显。生物滞留设施通过径流存蓄、峰值削减等功能在雨洪调蓄管理系统中发挥着关键作用。其中，地表高程通过影响洼地区域、径流路径和调蓄容积，直接关系到设施选址与布局。本研究将数字高程模型（DEM）栅格单元视作优化变量，构建地表高程与布局目标之间的联动关系，采用非支配性排序遗传算法-II（NSGA-II）实现调蓄空间与设施布局求解。以哥本哈根某地块为例，设置不同的约束情景对优化方法进行测试，结果表明该方法可基于调蓄容积最大化、洼地面积最大化、改造土方量最小化3个目标快速生成解集。解集的地表高程变化呈现明显的空间差异与调蓄效益梯度。本文进一步探讨了优化计算效率、解集概率可视化和生物滞留设施布局策略，为识别潜在雨洪调蓄空间及蓝绿基础设施规划提供了可行思路与方法参考。

关键词

多目标优化；生物滞留设施；数字高程模型；地形改造；雨洪管理；遗传算法

文章亮点

- 提出一种结合数字高程模型和遗传算法的生物滞留设施布局方法
- 实现了调蓄容积、洼地面积和土方工程量的多目标优化
- 运用多目标优化方法快速优化地形设计与设施布局策略

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1 研究背景

全球气候变化和城市化背景下，极端降雨事件频发、不透水下垫面激增已成为加剧城市洪涝风险的主要诱因[1–2]。为缓解传统灰色基础设施的负面影响，当代雨洪管理相继涌现出诸多新范式及技术措施[3]。其中，生物滞留设施已成为一种截留、渗蓄、缓释雨水径流，削减污染物负荷的常见设施类型[4–5]。生物滞留设施主要指由土壤基质和植被层构成的局部洼地空间，旨在通过模拟自然水文过程削减地表径流，延缓径流峰值，其主要功能包括存蓄雨水、调节径流、减少污染物负荷[6–8]。

在生物滞留设施的规划布局中，地形要素扮演着关键角色。地表高程直接决定了子汇水区内下凹空间的形态与分布，从而影响洼地区域、调蓄容积和径流路径等[9–10]。此外，由于地表高程变化涉及实践中的土方工程，设计者需在布局时考虑水文效益和复杂地形设计之间的平衡。现有研究多利用数字化地形及相关分析工具识别洼地、分析汇水边界并模拟径流过程，为设施选址提供了基础支撑[11–13]。然而，这些方法多集中于静态平面识别层面，缺少对复杂地形条件下多重水文效益之间权衡的系统考虑。因此，亟待扩展高效、准确的定量规划布局方法和优化技术工具。

本研究旨在提出一种基于多目标优化原理的生物滞留设施规划布局新方法：在地表径流网络预分析的基础上，耦合数字高程模型（DEM）和非支配性排序遗传算法-II（NSGA-II），定量评估地表高程变化对多个布局目标的影响，进而支持快速识别和优化设施布局规划。本文以丹麦哥本哈根某汇水区为例，尝试解答如何在生物滞留设施规划布局中兼顾地形特征与水文效益，并为识别潜在雨洪调蓄空间和蓝绿基础设施规划提供操作框架。

2 研究现状

2.1 雨洪管理与生物滞留设施规划布局

传统的雨洪管理始于欧洲20世纪中期开发的城市下水道系统，使用路缘、排水管道等灰色基础设施完成集中式快速排水，以满足公共卫生及雨污排放需求[2]。当代雨洪管理强调气候适应性和城市韧性，通过多样化的雨洪设施模拟自然水文过程，进而发展演变出“低影响开发”“可持续排水系统”等理念和实施方法[3]。目前许多国家及地区积极发展雨洪管理措施，例如，丹麦政府积极推进以气候适宜性规划为基础的雨洪管理路径，在欧盟《水框架指令》指导下制定市政雨水排放许可和地方治理规则，从而推动了生物滞留设施的规划布局需求[14–16]；《可持续都市排水系统》《基于自然的解决方案》等非官方资料也为在地化施工案例做法提供了具体指导，但对设施的选址和布局规划仍处于持续探索阶段[17–18]。

生物滞留设施的形式包括下沉式绿地、生物滞留池、渗沟等。降雨过程中，地表径流沿汇水线流向地势低洼处，并在洼地蓄集后满溢。自然环境中的低洼地带或建成环境中的下凹空间往往是布局生物滞留设施的适宜地点，而如何合理匹配设施是其选址和布局的核心问题之一。过往研究普遍关注设施类型、规模和布局模式[19–20]，具体而言：1）设施类型主要关注自身结构层级与配置的匹配程度，如基质类型、层级厚度、植被配置等设计参数；2）设施规模主要考虑几何尺寸、调蓄容积与布局效益间的关联；3）布局模式主要关注设施之间的连通方式和上下游衔接关系[21–23]。其中，设施规模是决定其调蓄能力的核心因素，同时又高度依赖洼地的深度与面积特征。因此，本文以设施规模作为切入点，聚焦规模与地形高程变化间的联动关系，从而辅助该类设施的规划布局。

2.2 基于多目标优化算法的生物滞留设施规划布局

多目标优化可解决涉及多个互斥目标的工程优化问题。由于不同目标往往无法同时实现最优，其结果通常表现为一组相互权衡的最优解，称为“帕累托前沿解集”（以下简称“解集”）[24–25]。解集能直观地展示多个目标之间的权衡关系，通过相互比较，决策者可以全面观察解集结果，进而辅助制定决策。近年来，多目标优化被广泛运用于雨洪设施规划布局研究，结合多目标优化算法与仿真模型模拟已成为主流思路之一[20]。例如，已有研究基于多目标优化算法构建了多种雨洪设施布局优化框架，以解决在径流控制、成本预算、径流污染削减等诸多水文—生态—经济效益目标下的设施组合优化问题[26–28]。

常见的多目标优化算法包括模拟退火算法、蚁群算法、强度帕累托进化算法、遗传算法等[24,29]。其中，模拟退火算法能有效避免陷入局部极值，但计算效率相对较低；蚁群算法多适用于离散空间搜索；强度帕累托进化算法则能够有效保持解集的多样性，但在高维问题中的计算复杂

度较大[24–25,30–31]。相比之下，以NSGA-II为代表的遗传算法凭借其非支配性排序策略和拥挤距离计算机制，在收敛速度、解集多样性、平衡性方面表现突出，广受青睐[32–36]。

多目标优化算法通常与水文模拟或设施规划布局工具联合使用，模型主要通过SWMM、SWAT、SUSTAIN、UrbanBEATS等平台，或在平台基础上搭建二次开发工具[37–44]。此类研究结果揭示了生物滞留设施规模与评估效益之间的定量关系，但设施规模如何受到地形条件制约、如何与地表空间相匹配等问题尚缺乏明确建模表达。与此同时，基于DEM的水文分析方法（如径流路径分析、洼地识别等）已经被广泛应用[13,45–47]。以DEM为对象，运用多目标优化算法求解对规划设计人员而言更加直观和易于操作，有助于在规划设计阶段明确设施的空间位置和规模布局。然而，鲜有研究尝试在基于DEM的水文分析基础上开展优化建模。综上，本研究提出基于DEM多目标优化的生物滞留设施规划布局方法，以DEM栅格单元作为优化变量实施多目标优化操作，提供生成式地形方案，确定设施规模及布局策略。

3 基于DEM多目标优化的生物滞留设施规划布局方法

3.1 多目标优化框架构建

基于DEM多目标优化的生物滞留设施规划布局通过拆解、抽象和提炼地形特征与布局问题中的优化变量、目标和约束条件，构建基于数理逻辑的优化框架（图1）。首先，在优化初始化阶段，通过对DEM编码，根据具体优化问题确立优化变量、目标和约束条件。随后，在优化程序阶段，完成求解过程，通过多情景模拟实现不同情景条件下的稳定性测试。最后，在优化结果阶段，解集通过解码得到对应方案，并以可视化形式呈现，辅助最终决策。

3.2 确定优化变量、目标与约束条件

优化变量广义上是指可以被调整的模型参数，它们定义了问题的搜索空间——即所有可能的解决方案。本研究将DEM栅格单元高程值视为优化变量，并通过逐一编码、解码实现变量在DEM和优化程序之间的数据识别和转换。

优化目标是指通过改变优化变量以达到改善的结果指标。改造前后的地表高程与生物滞留设施规划布局目标之间存在联动关系（图2）。布局目标通常包括调蓄容积、洼地面积、污染物削减、改造土方量、设施成本等[5,10]。

优化约束条件是指对优化变量或目标的取值范围进行限制。例如，限制DEM栅格单元的可变位置或数值可变阈值，两者也是限制地形高程变化的平面范围和高度。可以预见的是，更宽松的约束条件通常会生成上限更高的优化结果。合理的约束条件有助于得到更为实际、聚焦的优化结果，因此需要依据场地已有洼地范围、土地利用类型或地形挖填限制等具体因素设定优化约束条件。

3.3 数据预处理

DEM提供了地形空间和水文过程分析信息，是开展优化程序的数据基础。数据预处理主要关注DEM的基本属性和特征，包括分辨率、汇水区划分、径流路线、溢流量、布局目标的初始值等。值得注意的是，由于DEM将地形概化为行列式的栅格单元，其栅格总数将直接影响后续优化效率。精度过低将丢失地形细节，降低结果的可信度；精度过高会导致栅格总数过大，降低优化运算效率。因此，应根据场地的尺度大小和优化精度需求合理确定输入的DEM分辨率。

4 案例应用与结果

为验证本文提出的基于DEM多目标优化的生物滞留设施规划布局方法，本研究选取丹麦哥本哈根市某地块作为研究区域。

4.1 研究区域

研究区域面积约89 hm^2，整体地势西高东低，地形坡度平缓，海拔高程范围24.04～38.19 m（图3）。选择该场地作为研究区域的原因包括：1）区域位于当地流域内的上游独立汇水区，可基本排除降雨期间外部入流的干扰；2）区域内下垫面绝大部分为田野或草地，仅包含少量建筑物及内部道路，可将其近似视为自然下渗土壤组成的绿地空间，减少土壤初始饱和度、水力传导率及下垫面类型等因素干扰；3）区域内已存在局部洼地，具备布局设施的有利条件。研究区域的DEM从丹麦数据供应和基础设施局开源数据库下载获取，初始数据分辨率为0.4 m。考虑到本研究的空间尺度、计算效率及不同分辨率在水文汇流分析中对整体趋势的影响，经多次预测试后将分辨率重采样为5 m，以兼顾模型计算量与结果精度。重采样后共获得总栅格数33 930个；初始调蓄容积为26 270 m^3，洼地面积为97 400 m^2。

当地政府鼓励借助再生农业与草地修复的天然滞蓄作用，提升农业用地与公共绿地周边的雨水渗蓄与滞留能力。因此，研究将优化目标设定为：1）最大调蓄容积，以增加暴雨期间场地雨水存蓄能力，降低下游地区的洪涝风险；2）最大洼地面积，以增加空间平面上对径流的捕获与滞留能力；3）最小改造土方量，以降低施工成本与环境扰动。

本案例采用Malstroem蓝点工具对研究区域进行径流网络预分析（图4）。该工具可基于DEM识别地表洼地、倾泻点、径流路径并模拟溢流过程，得到不同洼地之间的径流传递关系及其溢流量测算[48]。从数据预处理结果可见，研究区域内的径流主要自西向东逐步汇集，途经多处洼地蓄集并满溢后传导至东部下游区域。考虑到绿地或水体的改造难

度较低且已具备较高的调蓄潜力，本研究将这两类下垫面类型同洼地区域进行叠合处理，并计算20 m缓冲区得到待优化区域①，共计4 386个栅格单元。最后，根据约束条件设定4类情景，即4种不同的地形高程变化幅度：1）情景一：高程变化范围0～0.5 m；2）情景二：高程变化范围0～1.0 m；3）：情景三高程变化范围0～1.5 m；4）情景四：高程变化范围0～2 m。每类情景重复运算10次以测试程序稳定性及平均运算时长。具体程序设定见表1[30–31,49]。

4.2 解集与可视化分析

根据4种情景，案例得到4组解集，且解集均已呈现收敛态（表2，图5）。这4种情景的平均运算时长约20 min，约束条件对计算速度影响较小，整体运算效率高。结果表明：1）不同情景下，运算结果均可形成解集，证明该优化框架具有操作可行性和稳定性；2）随着高程变化阈值的增加，3个优化目标的数值分布区间整体呈现扩大趋势，最大调蓄容积和最大洼地面积对应更大的改造土方量，呈现同时增长结果；3）最大洼地面积相近条件下，高阈值情景可通过更大的改造土方量获得调蓄容积更高的解集；最大调蓄容积相近条件下亦同此。决策者可以根据具体工程需求选择适合的解集。

上述4组解集结果均含有100个解，任意解通过解码后可得到对应的DEM。受限于文章篇幅，无法对解集逐一展示，图6展示了4种情景下的解集DEM的均值结果——调蓄深度均值和洼地区域概率。将所有DEM栅格的调蓄深度图取平均值，得到调蓄深度均值；将所有DEM解的洼地区域图进行叠加统计，计算每个栅格被识别为洼地的频率，得到洼地区域概率。

从空间分布规律上看，4种情景均在研究区域西侧的南北纵向排水路线及东北部区域形成连续的洼地区域，表明这些位置可被选作生物滞留设施布局点位的概率较高。随着约束条件阈值加大，这些高概率区域总体上表现为在原有洼地范围基础上扩展并连通，显示更“激进”的面状调蓄格局。然而在情景四下，东北区域出现了部分洼地范围缩小现象，其原因为阈值增大导致可行域扩大，目标权衡发生改变，局部地形结构的非线性响应致使局地洼地连通性的下降。调蓄深度的演变主要体现在两个方面：1）约束依次增大时，洼地的平均调蓄深度由1.2 m升至2 m左右；局部峰值从2 m升至3 m，表示更大的地形削挖尺度；2）高深度区域与洼地高概率区域高度重叠，而低深度区域在情景三、四中明显减少，反映出增加的土方操作主要集中在原有的洼地单元，而非随机扩散。

可视化结果为分层次设施规划布局提供了量化的空间参考。具体策略包括：1）若地形改造幅度受限，可优先选择情景一、二中的方案，洼地分布集中且调蓄深度适中，适合以“点状—带状”方式嵌入生物滞留设施，减小对现有下垫面肌理的扰动；2）若目标是显著提升调蓄容量并扩大洼地范围，则情景三、四中的方案能提供更大且空间连续性更强的潜在洼地区域，可采用“面状”方式系统化布局生物滞留设施网络。整体而言，可将高概率区域界定为优先地形改造单元，将中低概率区域视作备选。

需要说明的是，在4种情景中，部分解出现了最大调蓄容积或最大洼地面积低于现状值的情况。理论上，这些解虽然在数学运算上符合优化

① 增加 20 m（4 个栅格）的缓冲区是考虑到地形在改造中的合理扩张和变动，此值可根据研究区域的具体条件酌情设置。

表 1：多目标优化程序设定

类别	参数	描述
优化目标	最大调蓄容积	$V_{\text{retention volume}}=\sum_{i=1}^{n} d_i \times R$ 公式中，d_i 为第 i 个洼地栅格的深度（由 Fill depression 填洼工具计算），R 为单位栅格面积，n 为变量栅格总数，$V_{\text{retention volume}}$ 为最大调蓄容积
	最大洼地面积	$A_{\text{sink area}}=\sum_{i=1}^{m} R$ 公式中，m 为洼地的栅格数（由 Sink 工具计算，深度小于 0.05 m 的洼地不计入），R 为单位栅格面积，$A_{\text{sink area}}$ 为最大洼地面积
	最小改造土方量	$V_{\text{total earthwork}}=\sum_{i=1}^{n} \lvert E_i \rvert \times R$ 公式中，E_i 为高程变化值（m），R 表示栅格单元面积（m^2），n 表示变量栅格总数，$V_{\text{total earthwork}}$ 为最小改造土方量
优化约束条件	高程变化阈值（m）	· 情景一：[0, 0.5] · 情景二：[0, 1.0] · 情景三：[0, 1.5] · 情景四：[0, 2.0]
优化算法	NSGA-II	· 种群大小：100 · 子代数量：40 · 迭代次数：200 · 交叉方法：模拟二进制交叉（概率：0.9，eta：15） · 变异方法：多项式变异（eta：20）

注
优化算法的设定依据为参考文献 [30–31,49]。

表 2：解集数值区间与运算时长

情景	最大调蓄容积（m^3）	最大洼地面积（m^2）	最小改造土方量（m^3）	平均运算时长（min）
初始化	26 270	97 400	—	—
情景一	44 188 ～ 57 264	101 225 ～ 119 325	5 631 ～ 42 016	20.5
情景二	26 379 ～ 79 445	79 275 ～ 138 400	10 250 ～ 81 563	21.6
情景三	25 542 ～ 122 154	78 325 ～ 154 575	16 473 ～ 134 027	22.4
情景四	29 373 ～ 115 113	82 350 ～ 131 650	24 326 ～ 173 925	21.8

逻辑，但在本研究中，若将场地初始值视为基准，这些解在实际意义上并不具备改善价值，可被视作“无效解”。

最后，本研究选取解集中调蓄容积最大的解进行解码可视化分析（图7，8）。优化后3项目标值分别为最大调蓄容积122 153 m^3，最大洼地面积154 125 m^2，最小改造土方量134 027 m^3。相较于现状，新增洼地基本位于现有绿地和空地区域，局部深度达3 m，可调蓄容积大幅提升，溢流分析显示有5处典型倾泻点外溢量下降幅度为63%～100%（图9）。此方案代表一种在效益优先条件下的高成本极限解，展示了优化结果在极端情形下的调蓄潜力上限与空间布局特征。

5 讨论与结语

本文提出了一种基于DEM多目标优化的生物滞留设施规划布局方法，实现了最大调蓄容积、最大洼地面积、最小土方工程量的多目标优化，具备快速操作、灵活扩展的应用潜力。该方法适用于近自然环境地形改造实践，在框架构建和解集生成方面表现出可行性和稳定性。但是，由于地形变量的高度不确定性，该方法仍需在不同条件下进一步验证并完善其参数设置和应用效果。本研究存在以下局限性：1）受限于计算硬件条件，对可处理的优化变量、优化目标的数量级上限尚未有全面清晰的认知；2）初始饱和度、水力传导率、植被种类等生物滞留设施参数未纳入本研究的讨论；3）以地形改造提升调蓄容量和面积为主导的思路在水文连通性复杂的场地环境中适用度受限；4）本文所示的案例研究区域存在相对宽裕的绿地或开放空间，与高密度建成环境下的用地条件差异巨大，因此文中优化参数与技术路径不宜直接套用。

为推进生物滞留设施规划布局研究与设计实践，本文提出以下建议：

1）探究运算效率上限与高效的约束条件。优化变量的数量决定了算法运行中的种群维度，从而影响编码解码、目标函数计算及内存分配时的资源消耗。本研究在测试过程中发现，提高DEM分辨率或增加变量数量会导致运算效率大幅下降。因此，在涉及高分辨率DEM或更大尺度的应用时，使用者有必要通过提高计算资源、拆分数据对象等方法提高运算效率。

2）尝试更为多元的优化目标。本文中建立的优化变量和目标数量仍有拓展空间。案例解集表现出近似线性的分布形态表明部分目标函数之间可能存在较强的相关性或优化趋势耦合。未来研究应考虑引入独立性更强或代表性更广的优化目标，以提升解集多样性与优化维度的科学性。同时，超多目标优化算法也在近年取得了长足的发展，同时处理更多目标并进一步提升计算效率正逐渐成为可能[50]。

3）推广研究对象的尺度层级。通过将湖泊、池塘、人工湿地等城市中大型蓝绿基础设施的洼地特征概化，该优化框架具备推广到城市级或者流域尺度的潜力。通过DEM设计疏导城市径流，合理穿插布局调蓄空间，提升空间调蓄能力，从而提高城市整体的雨洪韧性能力。

4）综合考量地形优化的多重影响。大范围的地形改造可能导致局部地表破坏、土壤结构扰动与雨水侵蚀等问题，影响局部植被覆盖与生态稳定性。未来研究可进一步引入地表稳定性模型、水体污染扩散模型及植被恢复策略，在兼顾生态系统可持续性的前提下开展多维约束条件下的综合优化。

诚然，可解释性多目标优化方法为生物滞留设施规划布局实践提供了工具理性②的支撑。然而，除工程技术因素外，城市雨洪管理实践也需考虑诸多社会人文因素。未来研究需要深入了解规划设计中的“混沌性”与“痛点”，从而为应用实践决策提供有价值的指导依据。

② “工具理性”是由社会学家马克斯 · 韦伯提出的概念，也称为效率理性或功效理性，指通过精确计算的方法，选择最有效的手段以达成既定目标，专注于成本最小化、收益最大化，以及如何以最优化的方式实现预设的功利性目的。与之对应的是“价值理性”（来源：参考文献 [51]）。

图 1. 基于 DEM 的多目标优化框架
图 2. DEM 优化变量与布局目标联动关系示意图
图 3. 研究区域基本信息（数据来源：丹麦数据供应和基础设施局 2024 年数据）
图 4. 研究区域径流网络预分析（数据来源：丹麦数据供应和基础设施局 2024 年数据）
图 5. 不同情景下解集 2D 散点图可视化结果
图 6. 不同情景下的平均调蓄深度均值与洼地区域概率图
图 7. 解码可视化示例：解集 2D 散点图可视化结果。
图 8. 解码可视化示例：调蓄深度图与洼地区域图。
图 9. 特定解在局部区域的模拟溢流情况对比。图中溢流点旁数值为该点的溢流量（单位：m^3）。