Optimizing the Implementation Plan of Watershed Best Management Practices with Time-varying Effectiveness under Stepwise Investment

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Abstract

Optimizing the spatial configuration of diverse best management practices (BMPs) can provide valuable decision-making support for comprehensive watershed management. Most existing methods focus on selecting BMP types and locations but neglect their implementation time or order in management scenarios, which are often investment-restricted. This study proposes a new simulation-optimization framework for determining the implementation plan of BMPs by using the net present value to calculate the economic costs of BMP scenarios and the time-varying effectiveness of BMPs to evaluate the environmental effectiveness of BMP scenarios. The proposed framework was implemented based on a Spatially Explicit Integrated Modeling System and demonstrated in an agricultural watershed case study. This case study optimized the implementation time of four erosion control BMPs in a specific spatial configuration scenario under a 5-year stepwise investment process. The proposed method could effectively provide more feasible BMP scenarios with a lower overall investment burden with only a slight loss of environmental effectiveness. Time-varying BMP effectiveness data should be gathered and incorporated into watershed modeling and scenario optimization to better depict the environmental improvement effects of BMPs over time. The proposed framework was sufficiently flexible to be applied to other technical implementations and extensible to more actual application cases with sufficient BMP data. Overall, this study demonstrated the basic idea of extending the spatial optimization of BMPs to a spatiotemporal level by considering stepwise investment, emphasizing the value of integrating physical geographic processes and anthropogenic influences.

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Key Points:

- Proposed a novel idea to optimize the implementation plan of watershed best management practices (BMPs) under stepwise investment
- Introduced the net present value to compare net costs of BMP scenarios and time-varying BMP effectiveness to assess environmental effects
- The proposed BMP optimization approach was demonstrated in an agricultural watershed case study using four erosion control BMPs

Abstract

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Plain Language Summary

Best management practices (BMPs) are a series of structural and nonstructural management practices implemented at different spatial scales in a watershed (e.g., sites, agricultural fields, roads, and streambanks) to reduce the negative environmental impacts of stormwater, soil erosion, nonpoint source pollution, etc. When, where, and which types of BMPs should be implemented across a watershed to control certain environmental issues are common but complex considerations in comprehensive watershed management. Multi-objective BMP optimization based on watershed modeling can provide scientific and effective support for decision-making. Existing approaches primarily focus on optimizing the spatial dimension but neglect the temporal dimension of BMPs, including the optimization of their implementation order to address the trade-offs between the environmental effectiveness and economic burden during the implementation period. This study proposed a novel spatiotemporal optimization framework considering two significant factors: stepwise investment and the time-varying effectiveness of BMPs. The framework was implemented and demonstrated in an agricultural watershed to find near-optimal BMP implementation plans for controlling soil erosion. The comparative experiments demonstrated that if a small portion of environmental effectiveness could be temporarily sacrificed, optimizations considering stepwise investment could provide more feasible implementation plans with lower financial pressure, especially in the first year of implementation.

1 Introduction

The scientific and reasonable spatial configuration and optimization of diverse best management practices (BMPs) in a watershed (a BMP scenario) involve trade-offs between environmental effectiveness and economic benefits. Optimized BMP scenarios can provide valuable decision-making support for comprehensive watershed management, including recommendations for the types and locations of BMPs (Bracmort et al., 2004; Gitau et al., 2006; Veith et al., 2003). Additionally, a feasible watershed management plan often demonstrates "when to implement BMPs" considering available investments and other policy-related factors (Bekele & Nicklow, 2005; Liu et al., 2020). Therefore, how to better select BMP types and where and when to implement them are critical issues in optimizing watershed BMP scenarios.

The existing optimization methods for watershed BMP scenarios can be categorized into two types. The first is based on identifying priority management areas (PMAs) in the watershed (Shen et al., 2015; Wu et al., 2023). A PMA, also known as a critical source area (Pionke et al., 2000; Srinivasan et al., 2005), refers to a small area that produces disproportionately high pollutants. More importantly, it dramatically impacts the water bodies that directly or indirectly receive those pollutants (Wu et al., 2023). These areas are common priority areas for implementing BMPs to control eco-environmental problems, including nonpoint source pollution and soil erosion (Chen et al., 2016; White et al., 2009; Rana & Suryanarayana, 2020). Therefore, after PMAs are identified and prioritized, the implementation order of suitable BMPs in the PMAs can be designed accordingly (Jang et al., 2013; Shen et al., 2015). However, this approach is based only on the evaluation of current watershed conditions. It does not consider watershed responses to previously selected BMPs in a stepwise manner during the implementation period. Consequently, such approaches cannot generate an optimized BMP implementation plan with multiple stages spanning several years.

The second type of optimization method is an intelligent optimization algorithm-based method that simplifies, formulates, and solves the complex optimization problem of selecting and locating BMPs by incorporating watershed modeling (Chen et al., 2016; Srivastava et al., 2002; Veith et al., 2003; Zhu et al., 2021). The optimization problem formulation comprises objectives, geographic decision variables, and constraining conditions (Arabi, Govindaraju, & Hantush, 2006; Zhu et al., 2021). Optimization objectives are often related to multiple and potentially conflicting objectives, including eco-environmental effectiveness and economic investment. A geographic decision variable generally represents the decision to plan, implement, and maintain BMPs in one spatial unit within the study area. A set of decisions determined for all spatial units constitutes a BMP scenario. The constraining conditions refer to the restrictive situations that enable better representation and solving of the optimization problem, including spatial constraints (e.g., suitable spatial locations for implementing BMPs and spatial relationships among BMPs) and nonspatial constraints (e.g., limited budgets) (Zhu et al., 2021).

Most studies on optimization-based methods focus on determining and optimizing the spatial locations of BMPs from two perspectives. The first perspective is to adopt diverse types of spatial units to define decision variables (Zhu, Qin, et al., 2019). In the literature, the spatial units are classified into five types with different levels in the watershed (Zhu, Qin, et al., 2019): subbasins (Liu et al., 2019), slope position units (Qin et al., 2018), hydrologically connected fields (Wu et al., 2018), farms and hydrologic response units (HRUs) (explicitly referring to HRUs in the SWAT [Soil and Water Assessment Tool]) (Gitau et al., 2004; Kalcic et al., 2015), and grid cells (Gaddis et al., 2014). The second perspective introduces diverse spatial constraints to ensure that the optimization results have meaningful geographic interpretations and practicability (Kreig et al., 2019; Wu et al., 2018; Zhu et al., 2021). Existing studies have considered three types of spatial constraints: spatial relationships between BMPs and locations, spatial relationships among adjacent BMPs, and spatial characteristic adjustment of spatial units (e.g., unit boundary; Zhu et al., 2021). These studies have significantly improved the reasonability, practicability, and efficiency of optimization methods for watershed BMP scenarios. However, they still follow the ideal assumption that one BMP scenario can be entirely implemented at one time. This signifies that they ignored one critical, realistic factor during optimization: the implementation plan of BMPs over time that are often restricted by stepwise investment (Hou et al., 2020).

To the best of our knowledge, few studies have been conducted to optimize the BMP implementation plan (Bekele & Nicklow, 2005; Hou et al., 2020). One existing idea is to consider all feasible orders of the selected BMPs during a decision-making period on the same type of spatial units (e.g., HRUs) as options for these corresponding decision variables. Consequently, the optimal order configured at each spatial unit usually comprises multiple BMPs, one per year in the decision period (Bekele & Nicklow, 2005). However, such optimization of an implementation plan is more focused on every single spatial unit than on all the spatial units of one scenario. Another idea is to optimize BMP scenarios under different investment periods as different optimization problems with independent environmental targets and economic constraints (Hou et al., 2020). These problems are solved in turn, that is, an optimization problem under the first investment is first solved using several spatial units, and then the next optimization problem is solved using the remaining spatial units in the study area. The stepwise, optimized BMP scenarios are then combined (Hou et al., 2020). However, this idea only conducts BMP scenario optimization under diverse investment periods separately and then loosely combines the results instead of considering stepwise investment as an overall constraint in a single optimization problem. Therefore, existing methods cannot optimize the BMP implementation orders from a holistic perspective.

In summary, research on optimizing BMP scenarios often emphasizes BMP type-selection and location-allocation but neglects one crucial situation during optimization, which is the implementation order of BMPs. The few studies assessing the optimization of BMP implementation order have failed to optimize the BMP implementation order from a holistic perspective. Therefore, an effective optimization method for the implementation order of BMPs at all spatial units of the study area under a stepwise investment process for one optimization problem is still lacking.

In this study, we proposed a new simulation-optimization framework for the implementation plan of BMPs considering two important, realistic factors: stepwise investment and time-varying BMP effectiveness. This framework extended the existing spatial optimization framework of BMP scenarios (Arabi, Govindaraju, Hantush, et al., 2006; Maringanti et al., 2011; Qin et al., 2018; Zhu et al., 2021) with regard to four aspects: geographic decision variables, BMP scenario cost model, BMP knowledge base, and watershed model. The framework was implemented and exemplified in an agricultural watershed in southeastern China by considering the optimization problem of maximizing the soil erosion reduction rate and minimizing the net cost.

2 Methods

2.1 Basic idea

A critical issue in optimizing BMP implementation order under a stepwise investment process is the reasonable quantification of the optimization objective, such as the most frequently used economic cost and environmental effectiveness of BMP scenarios. This is because, according to most quantitative methods in existing research, if one complete BMP scenario is divided into several implementation stages, its economic net cost during the evaluation period (usually defined as the initial construction cost plus the maintenance cost minus the benefit) may either remain the same, increase, or decrease. However, stepwise implementation of the BMP scenario will undoubtedly reduce the overall environmental effectiveness, as these methods assume that each BMP has a fixed effectiveness, which is often optimal during the life cycle of the BMP. Consequently, the comprehensive effectiveness of the BMP scenario is likely to be reduced and cannot reflect a situation in which stepwise investment is less stressful to decision-makers and managers. Thus, if the relative loss of environmental effectiveness is acceptable to them, considering the reduced budget burden, multistage implementation under a stepwise investment process will be more attractive than a one-time investment. Therefore, the basic idea is to reasonably quantify the economic net cost and environmental effectiveness of a BMP scenario that is implemented in multiple stages, considering the actual economic activity and time-varying effectiveness of the BMP.

The net present value (NPV) is a dynamic economic benefit indicator commonly used in capital budgeting and investment planning to evaluate the profitability and feasibility of a multiyear project. Therefore, the NPV can be used to better represent the economic characteristics of a stepwise investment. The core idea of the NPV is that a dollar today is worth more than a dollar tomorrow (Khan & Jain, 1999; Žižlavský, 2014). The NPV calculates the difference between the discounted present value of cash inflows and outflows over time. To quantify net cost (outflow minus inflow), we revised the NPV calculation to the opposite form of its original formula in economics:

$$NPV = \sum_{t=1}^{q} \frac{O_t - F_t}{(1+r)^t} \qquad (1),$$

where O_t and F_t are cash outflows and cash inflows, respectively, during period t; q is the number of periods; and r is the discount rate set by the investor or project manager (e.g., 10%).

For environmental efficiency, adopting the time-varying environmental efficiency of BMPs can overcome the ideal assumption that one BMP can achieve the desired optimal environmental effectiveness once implemented. Generally, the environmental efficiency of BMPs can be quantified from two perspectives. The first is to measure the direct effect of a BMP based on its governing objective, such as its reduction rate of a pollutant concentration in the surface flow out of the vegetation filter strip. The other is to measure the effect of a BMP based on its related geographic variables, whose changes indirectly affect the governing objective. For example, measuring the improvements in soil properties resulting from the return of farmlands to forests can be utilized to simulate increased infiltration and the subsequently reduced surface flow and soil erosion. However, all these ideal measurements based on field-controlled experiments (Wang et al., 2013; Zhu et al., 2020) are often time-consuming, laborious, and expensive, especially for time-varying data. Theoretical analyses based on the mechanisms of a BMP can be used to effectively supplement limited measured data over time. It is now accepted that the environmental efficiency of a BMP usually changes over time and gradually increases to an optimal level in the first stage of its life cycle (Bracmort et al., 2004; Emerson & Traver, 2008; Emerson et al., 2010; Liu et al., 2017). Based on this, Liu et al. (2018) generalized a variety of possible time-varying curves for the average effectiveness of BMPs (Figure 1). Therefore, theoretical curves, combined with sampling data in individual years (if available), can be used to estimate changes in some key BMP parameters characterized in watershed models. In this manner, we can reasonably model the time-varying effectiveness of BMPs and evaluate the environmental effectiveness of BMP scenarios.

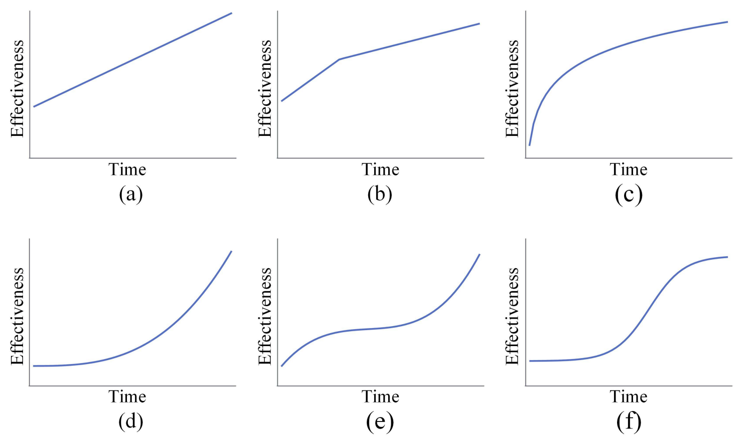

Figure 1. Typical theoretical changes in the effectiveness of a best management practice (BMP) over time for the first stage after implementation [adapted from Liu et al. (2018)]. (a)–(f) represent the linear, piecewise linear, logarithmic, exponential, polynomial, and logistic changes in the BMP effectiveness over time, respectively.

2.2 Overall design

To achieve the basic idea, we adopted a widely used simulation-optimization framework applied to agricultural and urban BMPs (Arabi, Govindaraju, Hantush, et al., 2006; Maringanti et al., 2011; Raei et al., 2019; Qin et al., 2018; Zhu et al., 2021) and improved it with respect to four aspects (Figure 2). The first was to extend the geographic decision variables to represent the implementation time of a BMP in initializing and generating BMP scenarios (label 1, Figure 2). The second improvement was to incorporate the NPV indicator into the BMP scenario cost model (label 2, Figure 2). Thus, the initialized and regenerated scenarios during the optimization process could be constrained by stepwise investment and screened before being evaluated. The third improvement was to support the time-varying effectiveness of BMPs in the BMP knowledge base (label 3, Figure 2). The fourth was to improve the applicability of the watershed model during the simulation (label 4, Figure 2). Subsections 2.3–2.6 of this study present detailed designs for the four improvements with the specific method implementation for a case study of a small agricultural watershed that aimed to control soil erosion. Moreover, the multi-objective optimization algorithm was customized to handle the extended geographic decision variables during optimization (Subsection 2.7). The optimized BMP scenarios based on this framework could provide decision-makers with a reference for including implementation plans for BMPs with multiple stages.

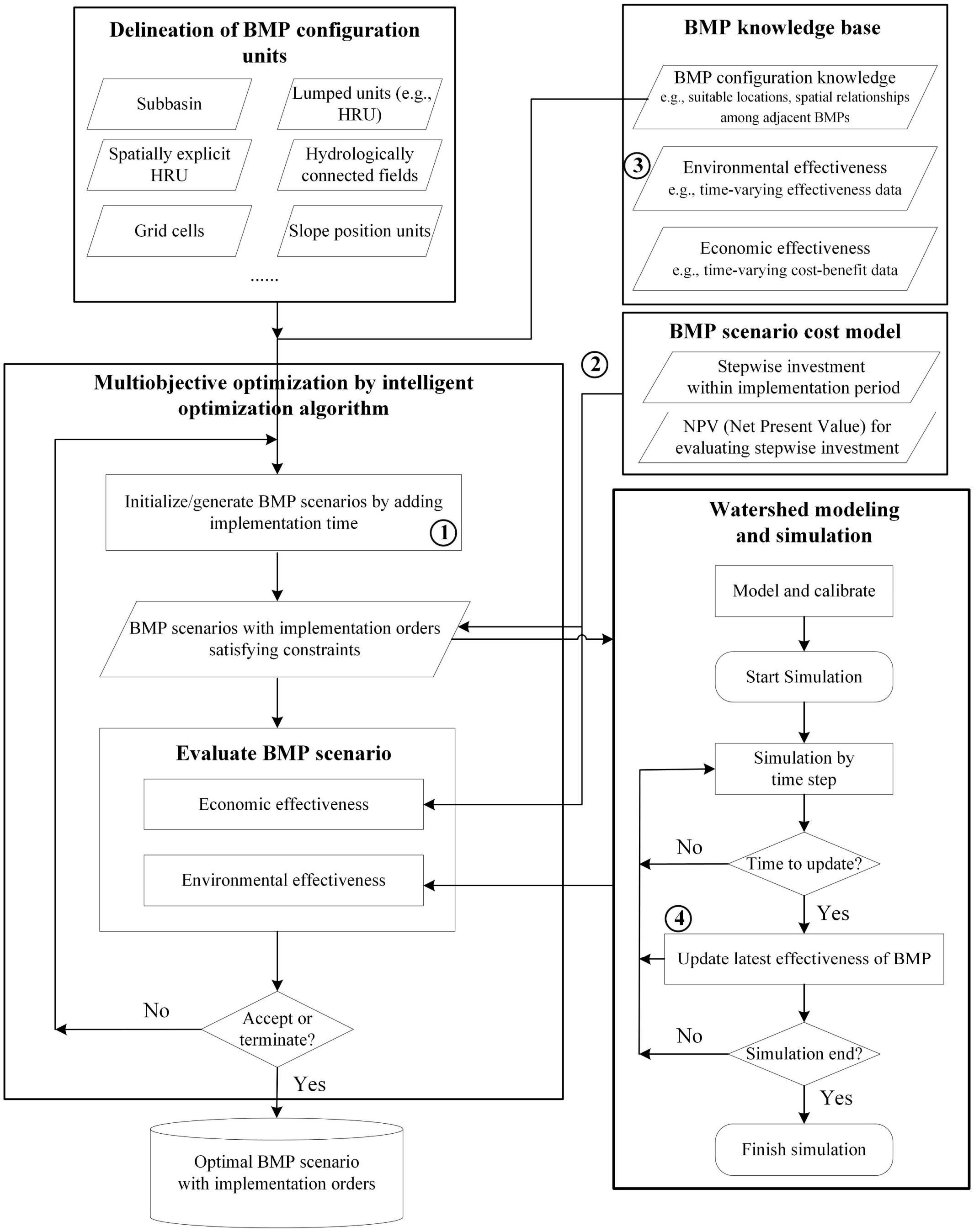

Figure 2. Proposed framework for optimizing the implementation plan of best management practices (BMPs), considering stepwise investment and their time-varying effectiveness. Labels 1–4 represent improvements on the existing and widely-used spatial optimization framework of BMP scenarios.

2.3 Extending geographic decision variables to represent BMP implementation time

Geographic decision variables are normally organized as a one-dimensional array to encode the spatial configuration information of BMPs, which is conveniently used as a chromosome in genetic optimization algorithms. Each geographic decision variable uses an integer value to record a decision on a spatial unit without a BMP (i.e., equals 0) or a type of BMP (Qin et al., 2018). A reversible and easily extensible encoding approach was proposed and implemented to represent the BMP type and implementation time as one decision variable (Figure 3).

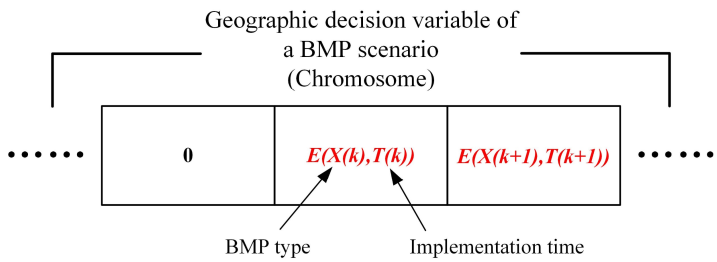

Figure 3. Schematic of the extended geographic decision variable of a best management practice (BMP) scenario. For spatial unit k in BMP scenario S, $X(k)$ and $T(k)$ denote the BMP type and implementation time, respectively. E is the reversible encoding method; for example, if $E = X(k) \times 10 + T(k)$, and if $X(k) = 4$, and $T(k) = 3$, the encoded value is 43. The multiplier 10 can be scaled up or down in multiples of 10, depending on the number of implementation periods. The decision variable equals 0 if the spatial unit is not configured with BMP.

Therefore, the extended geographic decision variables of a BMP scenario S can be expressed as follows:

$$S(k) = \begin{cases} E\big(X(k), T(k)\big) = X(k) \times 10 + T(k), unit\ k\ configure\ a\ BMP \\ 0, otherwise \end{cases} \quad (2),$$

where $k \in [1,n]$, $X(k) \in [1,p]$, $T(k) \in [1,q]$, n is the chromosome length (the number of spatial units in the study area), p is the number of BMP types, and q is the number of investment periods (typically in years) for implementing the BMPs.

With the extended geographic decision variables, the spatial distribution and implementation time of BMPs can be separately optimized in the solution spaces of $(p+1)^n$ and q^n, respectively, and simultaneously optimized in an enlarged $(p*q+1)^n$ solution space. Stepwise investment can be used as a nonspatial constraint to limit the solution space by setting the minimum and maximum allowable investment amount for each period.

2.4 Extending the BMP scenario cost model to calculate NPV

As stated above, once the geographic decision variable supports the BMP implementation time, the classical cost calculation of the BMP scenario using simple cost accumulation is no longer applicable but is still retained for compatibility with the previous framework. We extended the BMP scenario cost model using Equation (1) to support the calculation of the NPV of the BMP scenario with implementation orders. The annual cost (e.g., the abovementioned net cost) is first summarized as a discrete numerical series $O = \{o_1, o_2, \ldots, o_q\}$. The NPV can then be derived by discounting all costs to the first year of the implementation period, allowing comparison of the net costs of BMP scenarios with different implementation orders.

2.5 Extending the BMP knowledge base to represent time-varying effectiveness

The spatial optimization framework utilized three main types of knowledge (Figure 2): spatial configuration, environmental effectiveness, and economic effectiveness (Zhu, Qin, et al., 2019). The latter two types of knowledge are time related. Environmental effectiveness can be expressed as changes in overall effectiveness corresponding to some specific environmental indices (e.g., total nitrogen reduction rate by vegetated filter strips) or changes in BMP modeling parameters, such as improvements in soil properties (e.g., increased soil conductivity by returning farmlands to forests). Economic effectiveness includes cash outflow (e.g., initial implementation and maintenance costs) and inflow (e.g., direct and indirect income).

Generally, time-varying data can be represented in two forms: time-related formulas (Liu et al., 2018) and enumerated values. The former is suitable for ideal situations, such as when the mechanism of the BMP effect is clearly understandable and the formula is derived from long-term environmental observation data. The latter method is relatively simple, flexible, adaptable, and easy to implement. The form of enumerated effectiveness values over time is appropriate when little observational data are available, and the BMP mechanism can be reasonably estimated using theoretical curves (Figure 1). Therefore, the form of enumerated values for environmental and economic effectiveness was implemented in this study as an example to verify the proposed framework. All time-related effectiveness data were prepared as arrays with user-defined time intervals and periods.

2.6 Extending the watershed model to apply the time-varying environmental effectiveness of BMPs

Unlike the updating of watershed parameters related to the fixed effectiveness of BMPs (e.g., soil hydraulic properties) at the beginning of a watershed simulation, which is performed in most existing watershed models, the environmental evaluation of BMP scenarios considering the implementation order requires an iterative updating process during the simulation (Figure 2). When an incremental simulation time, the model verifies whether it is time to update the subsequent BMP effectiveness data: if the simulation time meets the preset update time, the model updates the relevant parameters and conducts subsequent simulations with the updated parameters until the next update time is reached or the entire simulation period ends (Figure 2).

To support the iterative updating of time-varying environmental effectiveness data of the BMP, source code-level improvement for the watershed models is needed. The Spatially Explicit Integrated Modeling System (SEIMS), which has been developed over the past few years (Liu et al., 2014; Liu et al., 2016; Zhu, Liu, et al., 2019), was used as the watershed modeling framework to implement this improvement (Shen & Zhu, 2022). SEIMS has been successfully utilized in the spatial optimization of BMP scenarios with diverse types of spatial units and spatial configuration knowledge (Qin et al., 2018; Zhu et al., 2021; Zhu, Qin, et al., 2019).

2.7 Customizing a multi-objective optimization algorithm to handle the extended geographic decision variables

The nondominated sorting genetic algorithm (NSGA-II) (Deb et al., 2002) is one of the most efficient algorithms for multi-objective optimization problems, and it has been extensively employed in the spatial optimization of BMP scenarios (Babbar-Sebens et al., 2013; Kalcic et al., 2015; Maringanti et al., 2011; Qin et al., 2018; Wu et al., 2018). This study adopted the NSGA-II as the intelligent optimization algorithm, customizing its crossover and mutation operators to support the regeneration process of BMP scenarios considering implementation time (Figure 2).

Because the extended geographic decision variables included information on both the BMP type and implementation time, crossover and mutation operations that were accordingly designed could be separately and simultaneously performed. For example, Figure 4 depicts a two-point crossover operation on implementation time only, that is, the second number in the genes of the two-parent individuals, S_a and S_b, between two randomly selected cross points, m_1 and m_2, were swapped.

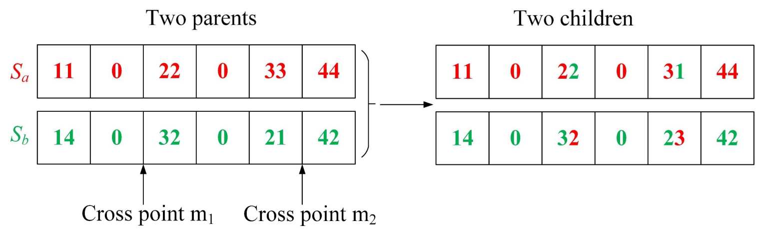

Figure 4. Example of the two-point crossover operation of two parents, S_a and S_b, on implementation time only. To facilitate this demonstration, the first number of each gene denotes the best management practice (BMP) type, and the second number represents the implementation time.

The mutation operator iterates over each gene value of the new individual child and mutates (i.e., changes the original value to one of the applicable values) according to a small probability ρ. If a randomly generated number between 0 and 1 is less than ρ, mutation occurs. The proposed framework allows users to determine whether the mutation object is the BMP type, implementation time, or both, according to the application.

3 Experimental design

To verify the rationality and validity of the proposed simulation-optimization framework for the BMP implementation order, we implemented a new optimization tool based on our previous distributed watershed modeling and BMP optimization studies on slope position units, as introduced in the last section. The follow-up case study aimed to find the near-optimal BMP implementation plans for controlling soil erosion under a 5-year stepwise investment process in a representative agricultural watershed in the red-soil region of southeastern China.

3.1 Study area and data

The study area was the Youwuzhen watershed (approximately 5.39 km^2) in the town of Hetian, Changting County, Fujian Province, China (Figure 5). This small watershed belongs to the Zhuxi River watershed, a first-level tributary of the Tingjiang River, and is located between 25° 40′ 13″ N, 116° 26′ 35″ E and 25° 41′ 29″ N, 116° 28′ 40″ E. The primary geomorphological characteristics are low mountains and hills. The elevation ranges from 295.0 to 556.5 m, with an average slope of 16.8°. The topographic trend inclines from northeast to southwest, and the riverbanks are relatively flat and wide. The area has a mid-subtropical monsoon moist climate, with an annual average temperature of 18.3 °C and precipitation of 1697 mm (Chen et al., 2013). Precipitation is characterized by concentrated and intense thunderstorm events, and the total rainfall from March to August accounts for 75.4% of the rainfall of the entire year. The main land-use types are forests, paddy fields, and orchards, with proportional areas of 59.8%, 20.6%, and 12.8%, respectively. Additionally, the study area is dominated by secondary or planted forests with a low coverage owing to vegetation destruction due to soil erosion and economic development (Chen et al., 2013). The soil types in the study area are red soil (78.4%) and paddy soil (21.6%), which can be classified as *Ultisols* and *Inceptisols*, respectively, per the US Soil Taxonomy (Shi et al., 2010). The red soil is predominantly distributed in hilly regions, while the paddy soil is primarily distributed in broad alluvial valleys with a similar spatial pattern as that of the paddy rice agricultural land. The study area is within one of the counties with the most severe soil erosion in southern China. The soil erosion type is severe water erosion, which is typical and representative of Changting County.

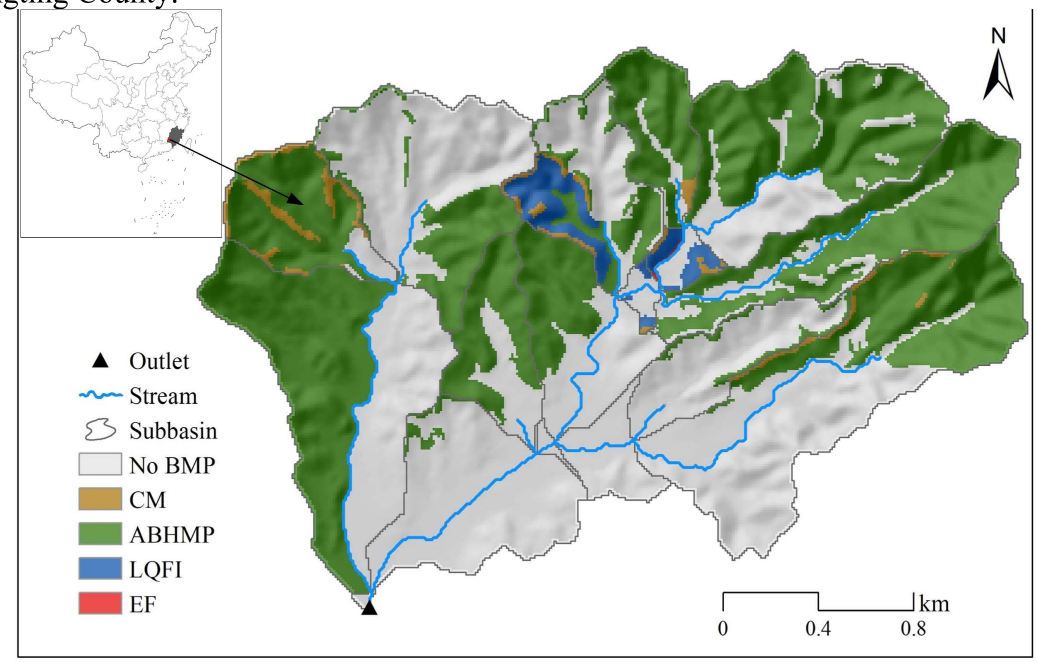

Figure 5. Spatial location of the Youwuzhen watershed in Changting County, Fujian Province, China and the spatial distribution of the fundamental scenario of best management practices (BMPs) based on slope position units derived from Zhu et al. (2019b). Four BMPs are included: closing measures (CM), arbor–bush–herb mixed plantation (ABHMP), low-quality forest improvement (LQFI), and economic fruit (EF).

The basic spatial data collected for the watershed modeling of the Youwuzhen watershed included a gridded digital elevation model, soil type map, and land-use type map, all of which were unified to a 10 m resolution (Qin et al., 2018). Soil properties of each soil type (e.g., organic matter and mechanical composition) were measured by field sampling (Chen et al., 2013) and derived from the Soil–Plant–Air–Water (SPAW) model (e.g., field capacity and soil hydraulic conductivity; Saxton and Rawls, 2006). Land use or land cover-related parameters were referenced from the SWAT database (e.g., Manning's roughness coefficient; Arnold et al., 2012) and relevant literature (e.g., cover management factor for the universal soil loss equation [USLE]; Chen et al., 2019). Daily climate data from the nearest national weather station, including temperature, relative moisture, wind speed, and sunshine duration hours from 2011 to 2017, were derived from the National Meteorological Information Center of the China Meteorological Administration. Moreover, daily precipitation data from a local monitoring station were also collected. The periodic site monitoring streamflow and sediment discharge data of the watershed outlet from 2011 to 2017 were provided by the Soil and Water Conservation Bureau of Changting County. Due to limited data quality, the streamflow and sediment discharge data were screened by searching for complete rainstorm records with more than three consecutive days for watershed modeling (Qin et al., 2018).

3.2 BMP knowledge base

We selected four representative BMPs that have been widely implemented for soil and water conservation in Changting County: closing measures (CM), arbor–bush–herb mixed plantations (ABHMP), low-quality forest improvement (LQFI), and economic fruit (EF). Table 1 lists brief descriptions for these BMPs, which mainly include their spatial configuration knowledge (Figure 2).

Table 1. Brief description of the four best management practices (BMPs) considered in this study [adapted from (Qin et al., 2018)]

BMP	Brief description
Closing measures (CM)	Closing off the ridge areas and/or upslope positions from human disturbance (e.g., tree felling and forbidding grazing) to facilitate afforestation.
Arbor–bush–herb mixed plantation (ABHMP)	Planting trees (e.g., *Schima superba* and *Liquidambar formosana*), bushes (e.g., *Lespedeza bicolor*), and herbs (e.g., *Paspalum wettsteinii*) in level trenches on hillslopes.
Low-quality forest improvement (LQFI)	Improving infertile forests on upslopes and steep backslopes by applying compound fertilizer on fish-scale pits.
Economic fruit (EF)	Building new orchards on mid-slopes and downslopes or improving them under superior water and fertilizer conditions by constructing level terraces, drainage ditches, storage ditches, irrigation facilities and roads; planting economic fruit (e.g., chestnut, waxberry); and interplanting grasses and Fabaceae (*Leguminosae*) plants.

The environmental effectiveness of BMPs in controlling soil erosion can be reflected by their improvements of soil properties, including organic matter, bulk density, texture, and hydraulic conductivity. The Soil and Water Conservation Bureau of Changting County examined 50 sample plots in the study area in 2000, including the four BMP types mentioned above. Intensively eroded plots with similar basic conditions, including soil type, landform, and parent material, were selected as control plots. The physical and chemical properties of all the plots were measured in 2005. The change ratio of the soil properties compared to the control plot over five years under each BMP was considered its environmental effectiveness. By combining these measured data and the soil stable infiltration rate data from Lin (2005), this study assumed that key soil parameters reasonably fluctuate in certain years after BMP implementation. The time-varying changes in BMP effectiveness can be predominantly characterized by one of the functions depicted in Figure 1, including linear functions, first fast and then slow functions, and first slow and then fast functions. Other derived properties and parameters utilized in the SEIMS model, including the total porosity and soil erodibility factor, were prepared accordingly.

The annual data on the environmental effectiveness and cost–benefit knowledge of the four BMPs are depicted in Table 2. For example, in the first, second, third, fourth, and fifth year after implementing CM, organic matter (OM) increased by 1.50, 1.62, 1.69, 1.74, and 1.77, respectively. The relative changes in the USLE_P conservation practice factor of the USLE in Table 2 were adopted from a calibrated SWAT model for this area (Chen et al., 2013), which maintained the same value over five years.

Table 2. Environmental effectiveness and cost–benefit knowledge of the four best management practices (BMPs) in the five years after their implementation

BMP	Year	Environmental effectiveness [a]						Cost–benefit (CNY 10,000/km^2)		
		OM	BD	PORO	SOL_K	USLE_K	USLE_P	Initial	Maintain	Benefits
CM	1	1.50	0.98	1.02	2.21	0.78	0.90	15.50	1.50	0.00
	2	1.62	0.97	1.03	4.00	0.99	0.90	0.00	1.50	0.00
	3	1.69	0.95	1.05	3.35	0.70	0.90	0.00	1.50	2.00
	4	1.74	0.94	1.06	3.60	0.60	0.90	0.00	1.50	2.00
	5	1.77	0.92	1.08	5.24	0.26	0.90	0.00	1.50	2.00
ABHMP	1	1.30	0.99	1.01	1.39	0.71	0.50	87.50	1.50	0.00
	2	1.36	0.98	1.02	1.38	0.89	0.50	0.00	1.50	0.00
	3	1.40	0.97	1.03	1.26	0.76	0.50	0.00	1.50	6.90
	4	1.42	0.96	1.04	1.15	0.75	0.50	0.00	1.50	6.90
	5	1.42	0.95	1.05	1.07	0.80	0.50	0.00	1.50	6.90
LQFI	1	2.80	0.98	1.02	1.54	0.88	0.50	45.50	1.50	0.00
	2	3.22	0.96	1.04	2.00	0.80	0.50	0.00	1.50	0.00
	3	3.47	0.94	1.07	2.76	0.60	0.50	0.00	1.50	3.90
	4	3.66	0.92	1.09	2.53	0.69	0.50	0.00	1.50	3.90
	5	3.80	0.90	1.11	2.38	0.73	0.50	0.00	1.50	3.90
EF	1	1.20	0.99	1.01	0.90	1.10	0.75	420.00	20.00	0.00
	2	1.23	0.98	1.02	1.16	1.06	0.75	0.00	20.00	0.00
	3	1.25	0.96	1.04	0.95	0.70	0.75	0.00	20.00	0.00
	4	1.26	0.95	1.05	1.60	0.65	0.75	0.00	20.00	0.00
	5	1.30	0.94	1.06	1.81	0.76	0.75	0.00	20.00	60.30

Note. [a] Environmental effectiveness of BMPs as indicated by soil property parameters [organic matter (OM), bulk density (BD), total porosity (PORO), and soil hydraulic conductivity (SOL_K)] and universal soil loss equation (USLE) factors [soil erodibility (USLE_K) and conservation practice factor (USLE_P)]. The values in each column represent relative changes (multiplying) and thus have no units.

CM, closing measures; ABHMP, arbor–bush–herb mixed plantation; LQFI, low-quality forest improvement; EF, economic fruit.

The economic data for these BMPs were estimated by Wang (2008) according to the price standard adopted 15 years ago. Although this is no longer applicable to the current price standards, it is still suitable for evaluating the relative net cost among the BMP scenarios. Owing to the long estimation cycle of the economic benefits of soil and water conservation projects, the direct economic benefits of the four BMPs (e.g., fruit production growth and forest stock volume) were generally calculated from the third (e.g., CM, ABHMP, and LQFI) or fifth year (e.g., EF) after implementation.

3.3 Calibrated watershed model and selected BMP scenario from a former study

To simulate daily soil erosion in the Youwuzhen watershed, we adopted the SEIMS-based watershed model that considers gridded cells as the basic simulation unit constructed and calibrated by Zhu, Qin, et al. (2019). The details of the selected watershed process and the calibration and validation processes of the watershed outlet streamflow and sediment discharge can be found in Zhu, Qin, et al. (2019).

To optimize the temporal dimension and evaluate the impact of stepwise investment and the time-varying effectiveness of BMPs on the BMP implementation plans, we selected an optimized BMP scenario (Figure 5) from Zhu, Qin, et al. (2019) as the fundamental spatial scenario. The selected BMP scenario considered a simple system of three types of slope positions (ridge, backslope, and valley) as the BMP configuration units, which have been proven to be effective in our previous studies (Qin et al., 2018; Zhu, Qin, et al., 2019). In this scenario, ABHMP occupied the most prominent area, with large clumps distributed over the west, central, and northeast ridge, backslope, and valley. LQFI was concentrated on the backslope in the middle region. CM was scattered on the west, central, and east ridges and backslope. EF occupied the smallest area in the central valley.

3.4 Multi-objective BMP scenario optimization

The objective of this case study was to maximize the soil erosion reduction rate and minimize the net cost of a BMP scenario. The optimization problem can be formulated as follows:

$$min\{-f(S), g(S)\} \quad (4),$$

where $f(S)$ and $g(S)$ denote the reduction rate of soil erosion and net cost of BMP scenario S, respectively. $f(S)$ is calculated by the average soil erosion reduction rate after implementing scenario S with an implementation order, as follows:

$$f(S) = \sum_{t=1}^{q} f(S,t)/q = \sum_{t=1}^{q} \frac{V(0)-V(S,t)}{V(0)} \times 100\%/q \quad (5),$$

where t is the implementation period, q is the total number of time periods, $f(S, t)$ represents the reduction rate of soil erosion within period t, and $V(0)$ and $V(S, t)$ are the total amounts of sediment yield from hillslopes that are routed to the channel (kg) under the baseline scenario and S scenario, respectively, in period t.

$g(S)$ can be calculated by the net cost of implementing scenario S with implementation order scheme T using the NPV defined in Equation (1). The cash outflow O_t and inflow F_t of S at time t were calculated using Equations (6) and (7), respectively：

$$O_t = \sum_{k=1}^{n} O(S,k,t) = \sum_{k=1}^{n} \begin{cases} A(X(k),t) * \{C(X(k)) + M(X(k),t)\}, if\ t \geq T(k) \\ 0, if\ t < T(k) \end{cases} \quad (6),$$

$$F_t = \sum_{k=1}^{n} F(S,k,t) = \sum_{k=1}^{n} \begin{cases} A(X(k),t) * B(X(k),t), if\ t > T(k) \\ 0, if\ t \leq T(k) \end{cases} \quad (7),$$

where $A(X(k), t)$ is the configured BMP area on the kth spatial unit in time t; $C(X(k))$, $M(X(k), t)$, and $B(X(k), t)$ are the initial construction cost, annual maintenance cost, and annual benefit per unit area, respectively (Table 2).

The parameter settings for the NSGA-II algorithm included an evolutionary generation of 100, a population number of 100, a crossover rate of 0.8 for the two-point crossover operator, a mutation rate of 0.1, and a selection probability of 0.8. The reference point for calculating the hypervolume index was set to (300, 0), which denotes the worst-case scenario: a net cost of 300 (CNY 10,000) and a soil erosion reduction rate of zero. To improve the computational efficiency of numerous executions of the SEIMS model, as required by the optimization algorithm, the Tianhe-2 supercomputer (Liao et al., 2014), one of the fastest supercomputers in the world, was utilized to take full advantage of the parallelizability of the SEIMS (Zhu, Liu, et al., 2019), that is, occupying a maximum of 10 nodes and simultaneously executing four SEIMS models per node.

3.5 Comparative experiments

Based on the selected spatial distribution of BMPs from the former study, we designed four comparative experiments to evaluate the effects of stepwise investment and the time-varying effectiveness of BMPs on the optimized implementation plans:

- Stepwise investment and fixed BMP effectiveness (STEP + FIXED)
- One-time investment and fixed BMP effectiveness (ONE + FIXED)
- Stepwise investment and time-varying BMP effectiveness (STEP + VARY)
- One-time investment and time-varying BMP effectiveness (ONE + VARY)

Experiments with a fixed BMP effectiveness used the stable environmental effectiveness data of the BMPs in this case study, that is, data in the fifth year after implementation (Table 2). For the one-time investment, we assumed that all funds would be available at the beginning of a specific year in the implementation period and that all BMPs would be implemented within the same year. Therefore, each experiment with one-time investment had only five solutions. Simultaneously, experiments with a stepwise investment needed to be optimized, resulting in near-optimal Pareto solutions (also termed Pareto fronts).

The experimental design followed three assumptions for implementing a target BMP scenario:

- Once a spatial unit was configured with a BMP in a certain year, the BMP type would not change in subsequent evaluation periods.
- An unlimited number of BMPs, ranging from zero to the total number of spatial units n, could be implemented within a year.
- Each BMP type could be implemented on any spatial unit within a year and would start to take effect in the subsequent year.

The simulation period for each SEIMS-based model was from 2011 to 2017 (Figure 6). The environmental effectiveness and cost–benefit data of the four BMPs listed in Table 2 were used as model inputs with a one-year update interval. The implementation period for the BMP scenario was from 2012 to 2016. At the end of each year, the model parameters affected by the BMPs (i.e., soil properties for the spatial units of the BMPs; Table 2) would be updated (red dots in Figure 6), including the newly and previously implemented BMPs. Therefore, the effect period of BMPs in this study lasted from 2013 to 2017.

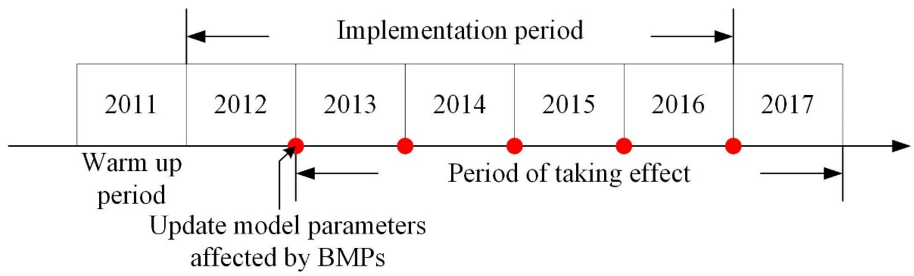

Figure 6. Schematic diagram of the watershed model simulation periods for evaluating a best management practice (BMP) scenario.

The selected BMP scenario required 207.35 (CNY 10,000) for the initial construction and subsequent maintenance costs before making a profit (in the first two years) (Zhu, Qin, et al., 2019). To conduct experiments with stepwise investment, investments were designed to gradually decrease within the 5-year implementation period, specifically, from 90 to 70 to 30 to 20 and finally to 20 (CNY 10,000). The maximum available investment was set to increase by 10% to more quickly generate possible scenarios. The discount rate was set to 0.1. All cash flows during the implementation period were discounted to values in the first year of the implementation period (2012).

3.6 Evaluation methods

We compared and discussed the four comparative experiments from two perspectives. From the numerical perspective, we evaluated all solutions under two objectives. From a qualitative perspective, we analyzed the characteristics of the selected solutions considering the BMP implementation order.

In this case study, two aspects were considered in the numerical evaluation of BMP scenarios under the two objectives. One was an intuitive comparison conducted by plotting Pareto fronts from stepwise investment experiments and BMP scenarios from one-time investment experiments as scattered plots. The other used a quantitative index, such as the commonly used hypervolume index, to measure the overall quality of the Pareto fronts (Zitzler et al., 2003). In this study, the larger the hypervolume was, the better the Pareto front. Additionally, changes in the hypervolume index with evolutionary generations could provide a qualitative reference for optimizing the efficiency. In an ideal optimization process, the hypervolume initially rapidly increases, then gradually slows, and finally stabilizes. The faster the hypervolume becomes stable, the higher the optimization efficiency (Zhu, Qin, et al., 2019).

To qualitatively evaluate the BMP implementation order characteristics under the impacts of stepwise investment and time-varying BMP effectiveness, typical scenarios were selected and compared based on their temporal distributions. Three selection criteria were designed: high NPV with a high soil erosion reduction rate (HH), low NPV with a low soil erosion reduction rate (LL), and moderate NPV with a moderate soil erosion reduction rate (MM).

4 Experimental results and discussion

4.1 Numerical evaluation of BMP scenarios under two objectives

The BMP scenarios derived from the four experiments were plotted as scatter points with the NPV and soil erosion reduction rate as axes (Figure 7a). Two comparisons between stepwise and one-time investments (STEP + FIXED vs. ONE + FIXED and STEP + VARY vs. ONE + VARY) demonstrated the same distribution patterns. The NPV and reduction rate of soil erosion of the one-time investment solutions (ONE + VARY and ONE + FIXED) synchronously declined from the top right (ONE-1) to the bottom left (ONE-5, which denotes investment in the fifth year). The ONE + FIXED scenario with the first year investment (the existing method, labeled ONE-1 + FIXED in Figure 7a) required the greatest NPV (163, in CNY 10,000) to achieve the most significant soil erosion reduction rate (7.42%). The Pareto fronts under stepwise investment were densely distributed near the ONE-2 solutions and had dominant positions. Figure 7b depicts an enlarged area of 150–156 NPV with a reduction rate of soil erosion at 3.5–7.0% to highlight this pattern. The best soil erosion reduction rates under stepwise investment were approximately 0.8–0.9% lower than those under the ONE-1 scenarios, with savings of approximately 7.7 NPV and soil erosion reduction rates that were approximately 0.4% higher than those of the ONE-2 scenarios requiring similar NPVs. In general, the proposed optimization method of the BMP implementation order considering stepwise investment could effectively provide more choices with a lower investment burden with only a slight loss in environmental effectiveness.

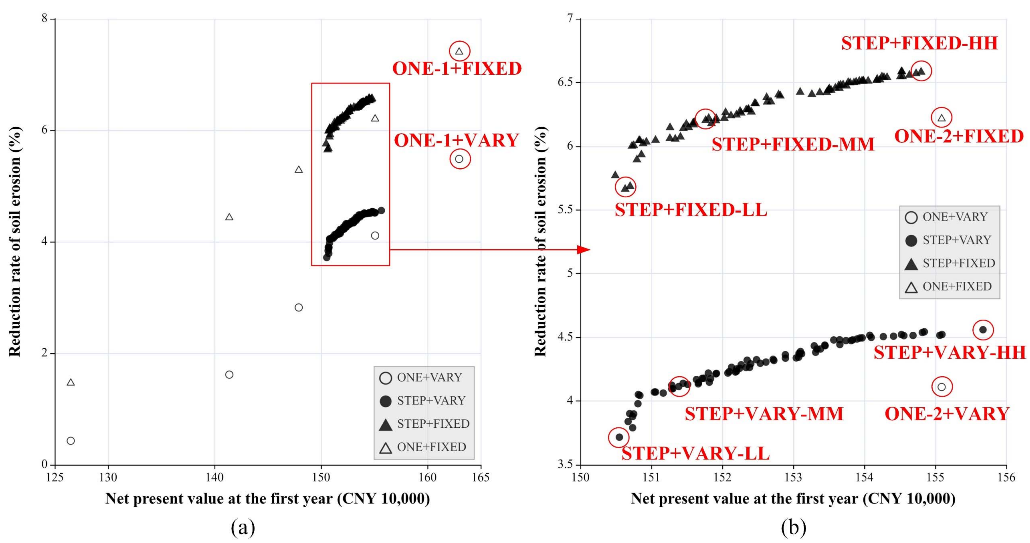

Figure 7. Comparison of best management practice (BMP) scenarios derived from the four comparative experiments: (a) overall comparison; (b) zoomed-in area at approximately 150–156 NPV (CNY 10,000) with a soil erosion reduction rate of 3.5–7.0%. STEP: stepwise investment; ONE-n: one-time investment in the n^{th} year; FIXED: fixed effectiveness of BMP; VARY: time-varying effectiveness of BMP; LL: low NPV and low soil erosion reduction rate; MM: moderate-moderate; HH: high-high.

Six representative scenarios were selected from the two STEP Pareto fronts to more specifically compare the two ONE-2 scenarios, as depicted in Figure 7b (e.g., STEP + VARY-HH, STEP + VARY-MM, STEP + VARY-LL, and ONE-2 + VARY). One scenario with the same soil erosion reduction rate as the ONE-2 scenario was selected as the MM scenario. Conversely, the LL scenario was the scenario with the lowest NPV and reduction rate, and the HH scenario had the highest NPV and reduction rate. Table 3 lists the NPV in the first year and the detailed investments (including initial and maintenance investments, i.e., the cash outflow of the NPV) in different years for the selected scenarios.

In addition to the similar pattern of the two Pareto fronts under stepwise investment (STEP + VARY and STEP + FIXED), the generational changes in the hypervolume index for the two optimization experiments also demonstrated similar changing trends (Figure 8). Although the STEP + VARY hypervolume seemed to first attain stability in the 65th generation, while STEP + FIXED demonstrated a slowly increasing trend, we believed that they both had similar evolution characteristics without significant differences in optimization efficiency under the current experimental settings of the NSGA-II algorithm. The only difference between the two experiments that considered the time-varying effectiveness of a BMP was the cause of the overall high hypervolume index of STEP + FIXED, as depicted in Figure 8. This result could be expected because the experiments with a fixed BMP effectiveness used data from the fifth year (Table 2), which had the optimal effectiveness values during the evaluation period of this study. The hypervolume index proved that optimization under stepwise investment could enlarge the solution space and derive better BMP scenarios.

Table 3. Net present value (NPV) in the first year and detailed investments (including initial and maintenance investments, i.e., the cash outflow part of the NPV) in different years of selected scenarios (STEP: stepwise investment; ONE-*n*: one-time investment in the n^{th} year; FIXED: fixed effectiveness of best management practice [BMP]; VARY: time-varying effectiveness of BMP; LL: low NPV and low reduction rate of soil erosion; MM: moderate-moderate; HH: high-high)

	ONE-2 + FIXED	STEP + FIXED			ONE-2 + VARY	STEP + VARY		
		LL	MM	HH		LL	MM	HH
NPV (CNY 10,000)	155.09	150.63	151.77	154.80	155.09	150.55	151.39	155.67
Soil erosion reduction rate (%)	6.22	5.67	6.20	6.59	4.11	3.72	4.11	4.56
1^{st} investment (CNY 10,000)	0.00	55.31	72.80	85.53	0.00	57.94	76.28	88.40
2^{nd} investment	203.75	67.36	57.35	67.57	203.75	62.77	44.56	69.82
3^{rd} investment	3.60	31.87	25.53	29.68	3.60	31.86	32.31	33.07
4^{th} investment	3.60	27.42	28.23	14.56	3.60	28.81	29.32	10.83
5^{th} investment	3.60	30.63	29.39	17.23	3.60	31.16	30.64	12.80

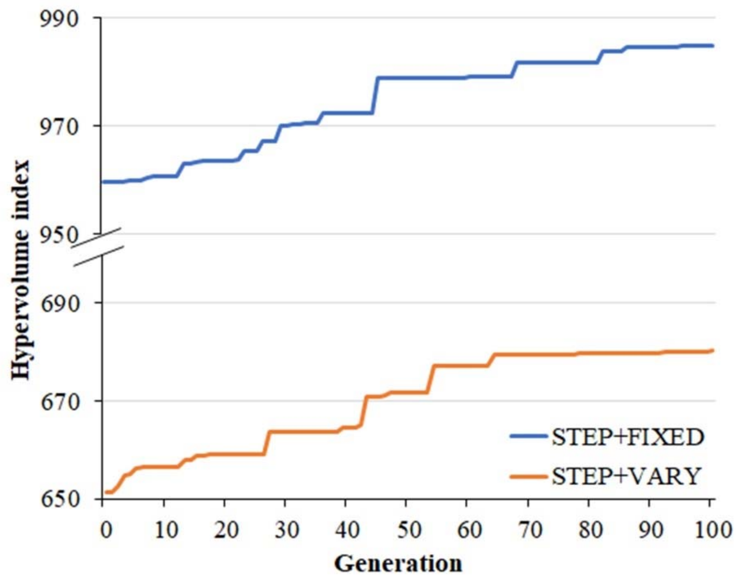

Figure 8. Generational changes in the hypervolume index for two optimization experiments with stepwise investment (STEP + VARY denotes the optimization using time-varying effectiveness of best management practices [BMPs] and STEP + FIXED using fixed effectiveness).

4.2 Impact of stepwise investment on BMP implementation plans

In our case study, the NPVs of the STEP scenarios did not seem to be significantly lower than the ONE-2 scenario (e.g., 151.39 in STEP + VARY-MM compared to 155.09 in ONE-2 + VARY). However, from the perspective of a project's start-up fund (i.e., money invested in the first year), the STEP scenarios had apparent advantages. For example, the start-up fund of scenario ONE-1 + VARY was 203.75 (CNY 10,000), while those of scenarios STEP + VARY-HH and STEP + VARY-LL were only 88.40 and 57.94 (CNY 10,000), with reductions of 56.61% and 71.56%, respectively.

Table 3 shows that the start-up fund is positively correlated with the overall environmental effectiveness. The cumulative investments over time decreased from the HH to the MM to the LL scenarios. This phenomenon is consistent with the processes of environmental effectiveness and investment trade-offs. The more and the earlier BMPs are implemented, the higher their environmental effectiveness. The fewer and the later BMPs are implemented, the lower the NPV will be. Furthermore, from Figure 7b, we can observe obvious inflection points at an NPV of approximately 151; that is, as the NPV of the Pareto fronts decreases, the soil erosion reduction rate gradually decreases and rapidly declines after the inflection point. This phenomenon may be caused by low investment in the first year (e.g., the 1st investment is lower than the 2nd investment in the two LL scenarios; Table 3), as most BMPs are implemented in and after the second year.

Therefore, by considering stepwise investments to optimize BMP implementation plans, the significantly reduced burden of start-up funds would undoubtedly improve the flexibility in funding during the entire implementation period. In the meantime, investments should be made extensively in the first few years (e.g., two or three years in this case study) to achieve higher environmental effectiveness.

4.3 Impact of time-varying effectiveness on BMP implementation plans

Two comparisons of the time-varying and fixed effectiveness of BMPs (i.e., STEP + FIXED vs. STEP + VARY and ONE + FIXED vs. ONE + VARY) demonstrated that under the same NPV, the reduction rates of soil erosion decreased by approximately 1.6–2.8% in the VARY scenarios (Figure 7a). The apparent results are attributed to the representation of BMP effectiveness data. Inaccurate representation may over- or underestimate the overall effectiveness of BMP scenarios, especially in long-term evaluations. Figure 9 depicts a comparison between BMP scenarios under one-time investment using a fixed effectiveness in the first (ONE+FIXED (1)) and fifth year (ONE+FIXED (5)) and time-varying effectiveness (Table 2). Figure 9 indicates that using reasonable time-varying effectiveness can appropriately reduce the bias in evaluating the overall effectiveness of the BMP scenario since the "true" effectiveness of BMPs over time is difficult to precisely measure. Therefore, to minimize this bias or error as much as possible, researchers should periodically and thoroughly monitor BMP effectiveness data. Furthermore, modelers should reasonably quantify time-varying BMP data and utilize it in watershed models.

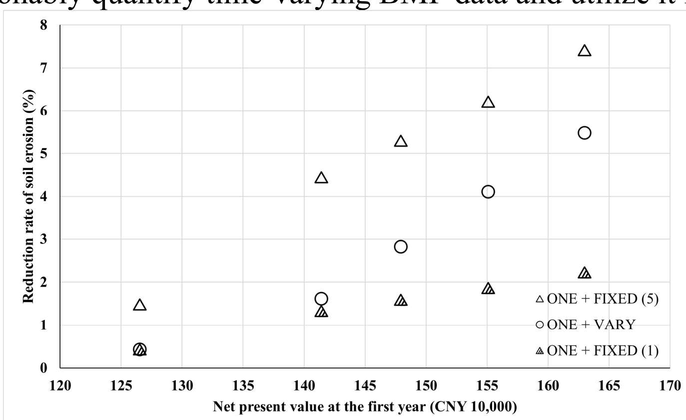

Figure 9. Comparison of best management practice (BMP) scenarios under one-time investment using diverse BMP environmental effectiveness data. ONE + VARY represents a BMP scenario with a one-time investment using time-varying effectiveness. ONE + FIXED (1) and ONE + FIXED (5) represent BMP scenarios with one-time investments using a fixed effectiveness in the first and fifth years, respectively.

4.4 Qualitative analysis of the spatiotemporal distribution of selected BMP scenarios

Figure 10 presents the spatiotemporal distributions of the six selected representative scenarios from two STEP Pareto fronts and two ONE-2 scenarios. All scenarios have the same BMP spatial distribution but different implementation times. With the same NPV and implementation time, the two ONE-2 scenarios achieved a 6.22% soil erosion reduction rate based on a fixed effectiveness of BMPs (155.09 NPV, 6.22%) and a soil reduction rate of 4.11% based on a time-varying effectiveness (Table 3). Figures 10a–c demonstrate three representative scenarios based on a time-varying effectiveness of BMPs, including STEP + VARY-LL (150.55 NPV, 3.72%), STEP + VARY-MM (151.39 NPV, 4.11%), and STEP + VARY-HH (155.67 NPV, 4.56%). Figures 10d–f demonstrate three other scenarios based on a fixed effectiveness of BMPs, including STEP + FIXED-LL (150.63 NPV, 5.67%), STEP + FIXED-MM (151.77 NPV, 6.20%), and STEP + FIXED-HH (154.80 NPV, 6.59%).

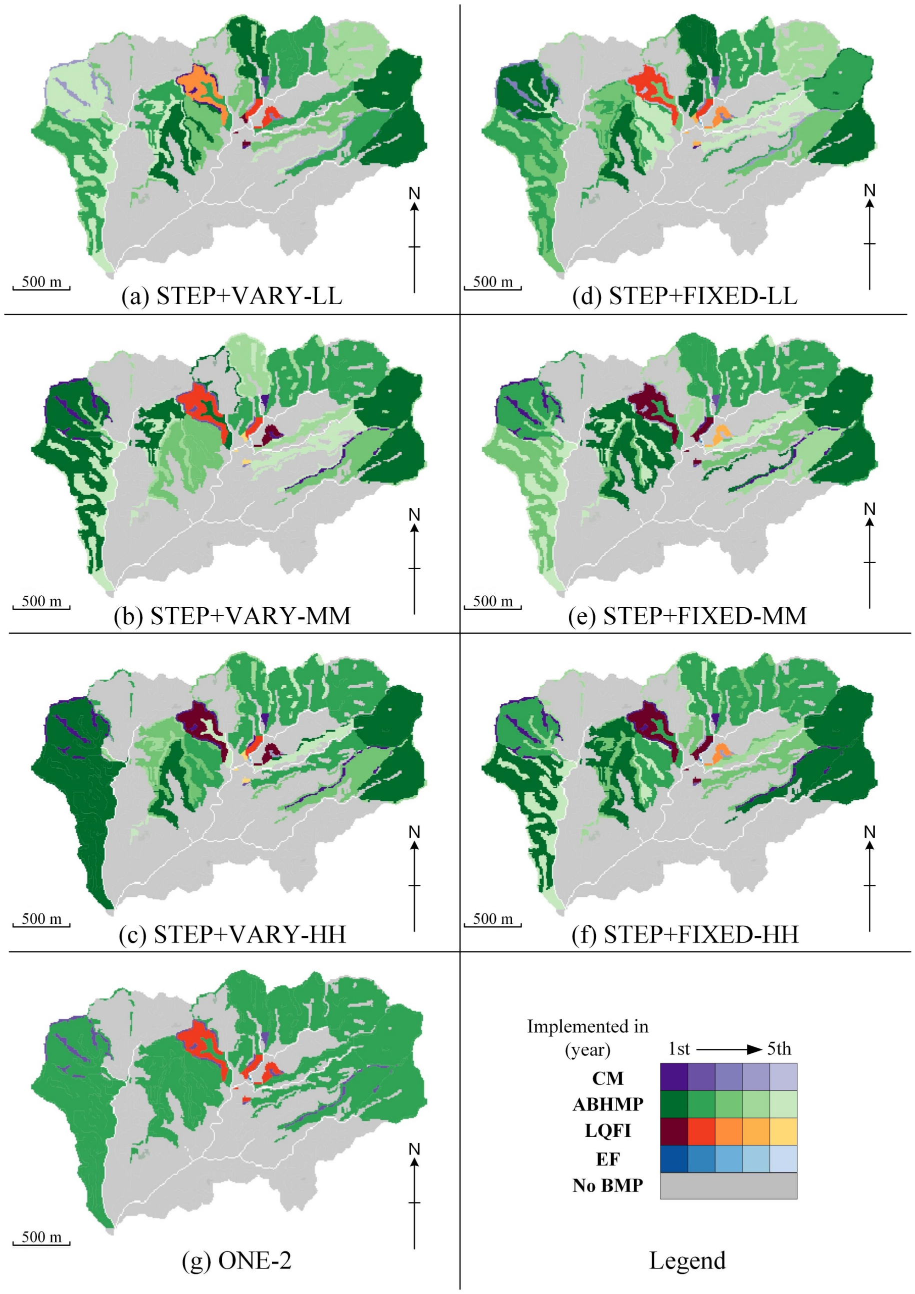

Figure 10. Spatiotemporal distributions of the representative best management practice (BMP) scenarios: (a)–(c) represent scenarios of a low net present value (NPV) with a low soil erosion reduction rate (LL), a moderate NPV with a moderate reduction rate (MM), and a high NPV with a high reduction rate (HH) in optimization experiments with stepwise investment and a fixed BMP effectiveness (STEP + FIXED), respectively; (d)–(f) represent the corresponding scenarios under a time-varying BMP effectiveness (STEP + VARY); (g) represents the scenarios of both fixed and time-varying BMP effectiveness under a one-time investment in the second year (ONE-2).

The spatiotemporal distributions of the optimized BMP scenarios under stepwise investment supported the tacit knowledge that the environmental and economic effectiveness of BMPs affect implementation order decisions under specific investment plans. For example, BMPs that require high initial and maintenance costs but have late returns (e.g., EF) are more likely to be implemented in the mid-to-late stage when investment burden alleviation is a priority (Figures 10a and 10d). BMPs that have high environmental effectiveness and can take effect quickly (e.g., ABHMP) tend to be implemented in large areas in the first stage, which focuses more on eco-environmental governance (Figures 10c and 10f). Additionally, BMPs that have a moderate overall effectiveness performance and take effect quickly (e.g., CM and EF) have more flexibility to be implemented according to diverse investment plans. The proposed framework can provide diverse BMP implementation plans as a reference for decision-makers to further screen and reach a consensus, meeting all stakeholders' interests.

4.5 Applicability of the proposed optimization framework

Although the proposed simulation-optimization framework was implemented and demonstrated through an agricultural watershed management problem, it is designed to be a universal framework that is independent of BMP type, watershed model, optimization algorithm, and applied watershed scale. Similar optimization methods and tools (e.g., the System for Urban Stormwater Treatment and Analysis Integration, SUSTAIN; Lee et al., 2012) can be improved accordingly, referencing the following key points: (1) incorporating BMP implementation time into the construction of BMP scenarios, for example, updating BMP selection and placement strategies in the BMP Optimization program of SUSTAIN; (2) considering dynamic economic indicators (e.g., NPV used in this study) to evaluate long-term investments, for example, improving the BMP Cost Estimation in SUSTAIN; (3) quantifying time-varying BMP effectiveness data in diverse ways, such as by integrating sampled data with theoretical analysis; and (4) modifying watershed models to support updating time-varying BMP effectiveness data during the simulation period, for example, the BMP Simulation in SUSTAIN.

The ability to support diverse types of BMPs and watershed scales depends on the implementation of the proposed framework, especially the watershed model. The watershed model can represent the time-varying effectiveness of a BMP, which may be quantified by the effect of the BMP on its governing objective or BMP-related geographic variables. The four BMPs selected in this case study are representative and successful agricultural BMPs in the study area. Some of them can be regarded as a combination of engineering and non-engineering BMPs, such as the economic fruit (EF) BMP. The EF BMP requires not only the construction of level terraces, drainage ditches, storage ditches, and irrigation facilities but also the plantation of economic fruit, grasses, and Fabaceae plants (Table 1). Engineering BMPs (also known as structural BMPs) may have a significantly different time-varying effectiveness from non-engineering (or nonstructural) BMPs. For example, they may take effect immediately after implementation and achieve periodic high effectiveness values over time under maintenance operations. Therefore, it is meaningful to consider structural and nonstructural BMPs in practical application cases.

It is worth mentioning that the primary issues in the spatiotemporal optimization of BMPs in a large watershed are the construction of a watershed model and the determination of appropriate BMP spatial configuration units. The computational performance of large watershed models may be an important technical issue that can be essentially resolved by utilizing high-performance computing clusters.

5 Conclusions and future work

This study proposed a new simulation-optimization framework for the implementation plan of BMPs by considering two important, realistic factors: the stepwise investment and time-varying effectiveness of BMPs. The framework was designed based on a widely used spatial optimization framework that was applied to agricultural and urban BMPs. The proposed framework extended geographic decision variables to represent the BMP implementation time and introduced the concept of NPV into a BMP scenario cost model. It also customized the BMP knowledge base and watershed model to evaluate the environmental effectiveness of BMP scenarios using the time-varying effectiveness of BMPs. The exemplified framework implementation and experimental results demonstrated that optimizations considering stepwise investment could effectively provide more feasible choices with a lower investment burden with only a slight loss in environmental effectiveness, especially in terms of significantly reducing the pressures on start-up funds versus one-time investments. By accounting for time-varying effectiveness and stepwise investment, the optimized multistage BMP scenarios may better reflect the reality of BMP performances and costs over time, providing diverse choices for decision-making in watershed management.

The flexibility and extensibility of the proposed framework could make it easy to apply to similar simulation-optimization frameworks. The essential components in this framework could be implemented by similar functional techniques as those implemented in the case study, including multi-objective optimization algorithms and watershed models. Application-specific data and settings, including spatial units for BMP configuration, BMP types and knowledge bases for specific watershed problems, and diverse stepwise investment representations (e.g., range constraints, even distribution), could also be extended in this framework. Before undertaking a practical application case, the sources of biases or errors in the proposed framework must be known and addressed to minimize errors and improve credibility. It is critical to note that the data and modeling method should be highly accurate in their representation of the characteristics of the study area and its environmental problems. From this perspective, biases or errors in this proposed framework may be reinduced or avoided by (1) reasonably describing the time-varying effectiveness of BMPs based on observational data and modeling their effects in watershed models from multiple perspectives; (2) selecting suitable BMPs and determining their corresponding spatial configuration units and configuration strategies; and (3) reducing the randomness and calculation errors of multi-objective optimization algorithms by incorporating expert knowledge in defining the optimization problem.

As this framework is intended to be a universal simulation-optimization framework that is independent of BMP type, watershed model, optimization algorithm, and applied watershed scale, there are several issues worth studying in the future, including extensive application and sensitivity analysis. Applications may include (1) improving other existing simulation-optimization frameworks focused on urban BMPs; (2) explicitly considering structural and nonstructural BMPs in case studies; and (3) solving BMP optimization problems in large watersheds. A sensitivity analysis of the proposed framework and specific implementation could be conducted on three sets of parameters to provide feasible suggestions for practical application. The first is related to the evaluation of watershed responses to BMP scenarios, including the appropriate evaluation period length. Correspondingly, the second parameter set concerns the economic calculation of BMP scenarios, including the discount rate for NPV calculation. The last parameter set involves the optimization algorithm settings, including crossover and mutation operators, maximum generation number, and population size.

Overall, this study proposed and demonstrated the novel idea of extending the spatial optimization of BMPs to a spatiotemporal level by considering stepwise investment, which is a realistic constraint that must be taken into account during decision-making. This study also emphasized the value of integrating physical geographic processes (i.e., watershed responses to various spatiotemporal distributions of BMPs) and anthropogenic influences (i.e., stepwise investment) in the design, implementation, and application of more flexible, robust, and feasible geospatial analysis methods.

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Open Research

The improved SEIMS programs and the prepared data are freely available at Shen & Zhu (2022). The Youwuzhen watershed spatio-temporal datasets are located in the /SEIMS/data/youwuzhen/data_prepare folder. These include precipitation and meteorological data, lookup tables, spatial data, and BMP data. Both sets of fixed BMP and time-varying BMP effectiveness used in the case study are included in the BMP data (the scenario subfolder).

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