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

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Key Points:

- Proposed a new optimization framework for implementation orders of BMPs with time-varying effectiveness under stepwise investment
- Introduced net present value to compare net costs of different BMP scenarios
- Exemplified the basic idea of extending BMP optimization to spatio-temporal level

Abstract

Optimizing the spatial configuration of various best management practices (BMPs) can provide valuable decision-making support for comprehensive watershed management. Most existing methods focus on the type selection and location-allocation of BMPs but neglect implementation time or orders of BMPs in a management scenario, which are most likely restricted by investments. Therefore, this study proposes a new optimization framework for implementation orders of BMPs by introducing the net present value to calculate the economic cost of BMP scenarios and the process of taking effect of BMPs to evaluate the environmental effectiveness of multistaged BMP scenarios. A case study was conducted in the Youwuzhen watershed in Fujian, China, with the aim of optimizing BMP implementation orders under a 5-year stepwise investment to control watershed soil erosion. The experiments focused on optimizing the implementation time of four representative BMPs in a specific spatial configuration scenario. The results showed that the proposed method could effectively provide more feasible BMP scenarios with a lower overall investment burden at the cost of a slight loss of environmental effectiveness. In addition, considering time-varying BMP effectiveness can reduce the uncertainty in evaluating the environmental effectiveness of BMP scenarios to some degree. The proposed framework was sufficiently flexible to be transplanted to other technical chains and extensible to more actual application cases. Overall, this study exemplified the basic idea of extending the spatial optimization of BMPs to the spatio-temporal level by considering a stepwise investment. This idea also emphasized the value of integrating physical geographic processes and anthropogenic influences.

1 Introduction

The scientific and reasonable spatial configuration and optimization of various best management practices (BMPs) in the watershed (the BMP scenario) imply a trade-off between environmental effectiveness and economic benefits. Optimized BMP scenarios can provide valuable decision-making support for comprehensive watershed management, including the types and locations of BMPs (Bracmort et al., 2004; Gitau et al., 2006; Veith et al., 2003). In addition, 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 answer questions regarding the type of BMP to select and where and when to implement is a critical issue 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 key areas in the watershed, such as critical source areas (Pionke et al., 2000; Srinivasan et al., 2005) and priority management areas (Dong et al., 2018; Shen et al., 2015). A key area often refers to a small area that produces disproportionately high pollutants. More importantly, it dramatically impacts direct or indirect receiving water bodies. These key areas are common priority areas for implementing BMPs to control eco-environmental problems such as non-point source pollution and soil erosion (Chen et al., 2016; White et al., 2009). Therefore, after key areas are identified and ranked as priorities (Jang et al., 2013; Shen et al., 2015), the implementation orders of suitable BMPs in these areas can be designed accordingly (Shen et al., 2015). However, this method is based only on the evaluation of current conditions of the watershed. It does not consider watershed responses to previously selected BMPs step by step during the implementation period. Consequently, such methods cannot generate optimized implementation orders of BMPs with multiple stages spanning several years.

The second type is intelligent optimization algorithm-based methods that simplify, formulate, and solve 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 consists of 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, such as 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 constitute a BMP scenario. Constraining conditions refer to restrictive situations for better representing and solving the optimization problem, including spatial constraints (e.g., suitable spatial locations for implementing BMPs and spatial relationships among BMPs) and non-spatial 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 is to adopt different types of spatial units to define decision variables (Zhu, Qin, et al., 2019). The spatial units adopted in the literature can be 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 model) (Gitau et al., 2004; Kalcic, Chaubey et al., 2015), and grid cells (Gaddis et al., 2014). The second perspective introduces various 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 (Zhu et al., 2021). These studies have greatly 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 means that they ignored one critical realistic factor during the optimization: the implementation orders of BMPs that are most likely restricted by stepwise investment (Hou et al., 2020).

To the best of our knowledge, few studies have been conducted to optimize BMP implementation orders (Bekele & Nicklow, 2005; Hou et al., 2020). One existing idea is to take 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 on each spatial unit usually consists of multiple BMPs, one per year in the decision period (Bekele & Nicklow, 2005). However, such optimization of an implementation order is more focused on every single spatial unit than on all spatial units of one scenario. Another idea is the optimization of 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, the optimization problem under the first investment is solved first with the result of occupying several spatial units, followed by the following optimization problem starting on the remaining spatial units in the study area. Finally, the stepwise optimized BMP scenarios were combined (Hou et al., 2020).

This idea only conducts optimization of BMP scenarios under different investment periods separately and then loosely combined instead of considering stepwise investments as an overall constraint in a single optimization problem. Therefore, the existing methods cannot optimize the implementation orders of BMPs from a holistic perspective.

In summary, research on optimizing BMP scenarios often emphasizes the type selection and location-allocation of BMPs but neglects one crucial realistic situation during the optimization, which is the implementation order of BMPs (Bekele & Nicklow, 2005; Liu et al., 2020). The few studies on optimizing the implementation orders of BMPs have failed to perform optimization from a holistic perspective. Therefore, an effective optimization method for the implementation orders of BMPs on all spatial units of the study area under stepwise investment in one optimization problem is still lacking.

In this study, we proposed a new optimization framework for the implementation orders 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) in four aspects: geographic decision variables, BMP scenario cost model, BMP knowledge base, and watershed process model. Comparison experiments were designed to verify the validity and rationality of the proposed method in the optimization problem of maximizing the reduction rate of soil erosion and minimizing the net cost in a small erosional watershed in Southeastern China.

2 Methods

2.1 Basic idea

The critical issue in optimizing BMP implementation orders under stepwise investment is reasonably quantifying the optimization objective, for example, the most frequently used economic cost of BMP scenarios and environmental effectiveness. 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 maintenance cost minus benefit) may either remain the same, increase or decrease. However, the stepwise implementation of the BMP scenario will undoubtedly reduce the overall environmental effectiveness because these methods assume that each BMP has a fixed effectiveness, which is often the optimum during the BMP's life cycle. Thus, 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, considering the reduced budget burden, multi-stage implementation under stepwise investment 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 the BMP scenario implemented in multiple stages, considering the actual economic activity and process of taking effect of BMPs.

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 multi-year project. Therefore, NPV can be introduced to better represent the economic characteristics of stepwise investment; that is, 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 the 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 time-varying environmental efficiency of BMPs can overcome the ideal assumption that one BMP scenario can achieve the designed optimal environmental effectiveness once implemented. According to field sampling experiments (Wang et al., 2013; Zhu et al., 2020) and theoretical analyses (Liu et al., 2018), the environmental efficiency of BMP usually changes over time and gradually increases to the optimum in the process of taking effect in the first several years (Bracmort et al., 2004; Emerson & Traver, 2008; Emerson et al., 2010; Liu et al., 2018; Liu et al., 2017). For example, Liu et al. (2018) generalized a variety of possible time-varying curves for the average effectiveness of BMP in the first stage after its implementation (Figure 1). The 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. Therefore, we can reasonably model the time-varying effectiveness of BMP and evaluate the environmental effectiveness of the BMP scenarios.

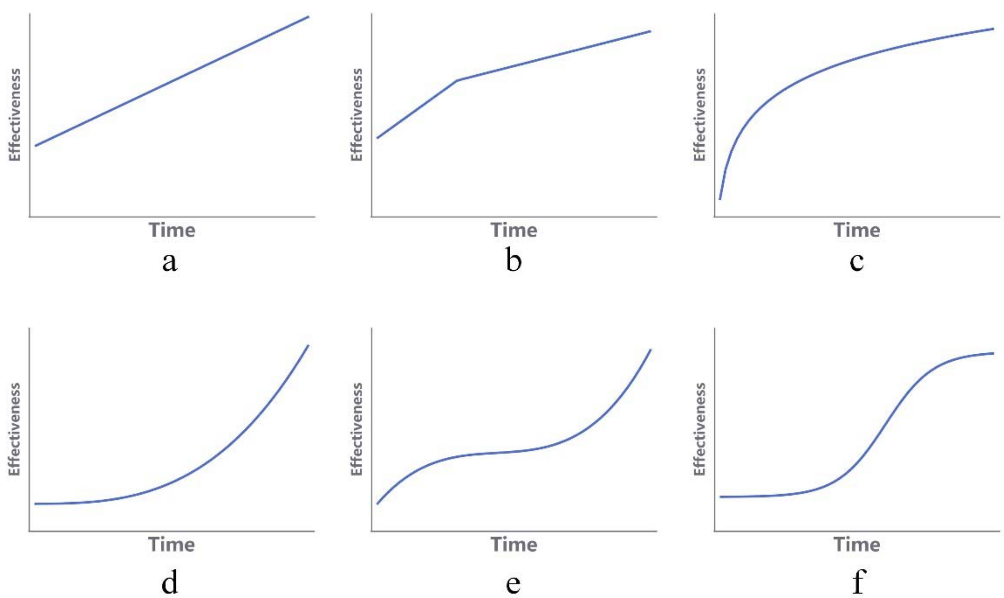

Figure 1. Typical theoretical changes of best management practice (BMP) effectiveness over time for the first stage after implementation [adapted from Liu et al. (2018)]

2.2 Overall design

To achieve the basic idea, a widely used spatial optimization framework of BMP scenarios (Arabi, Govindaraju, Hantush, et al., 2006; Maringanti et al., 2011; Qin et al., 2018;

Zhu et al., 2021) was adopted and improved in four aspects (Figure 2). The first was to extend the geographic decision variables to represent the BMP's implementation time in initializing and generating BMP scenarios (label 1, Figure 2). The second improvement was incorporating the NPV indicator into the BMP scenario cost model (label 2, Figure 2). Thus, the initialized and regenerated scenarios during the optimization process could first be constrained by stepwise investment and screened before being evaluated. The third improvement supported the time-varying effectiveness of BMP in the BMP knowledge base (label 3, Figure 2). The fourth was to improve the watershed model for application during the simulation (label 4, Figure 2). The optimized BMP scenarios of this framework could provide decision-makers with implementation plans for BMPs in multiple stages.

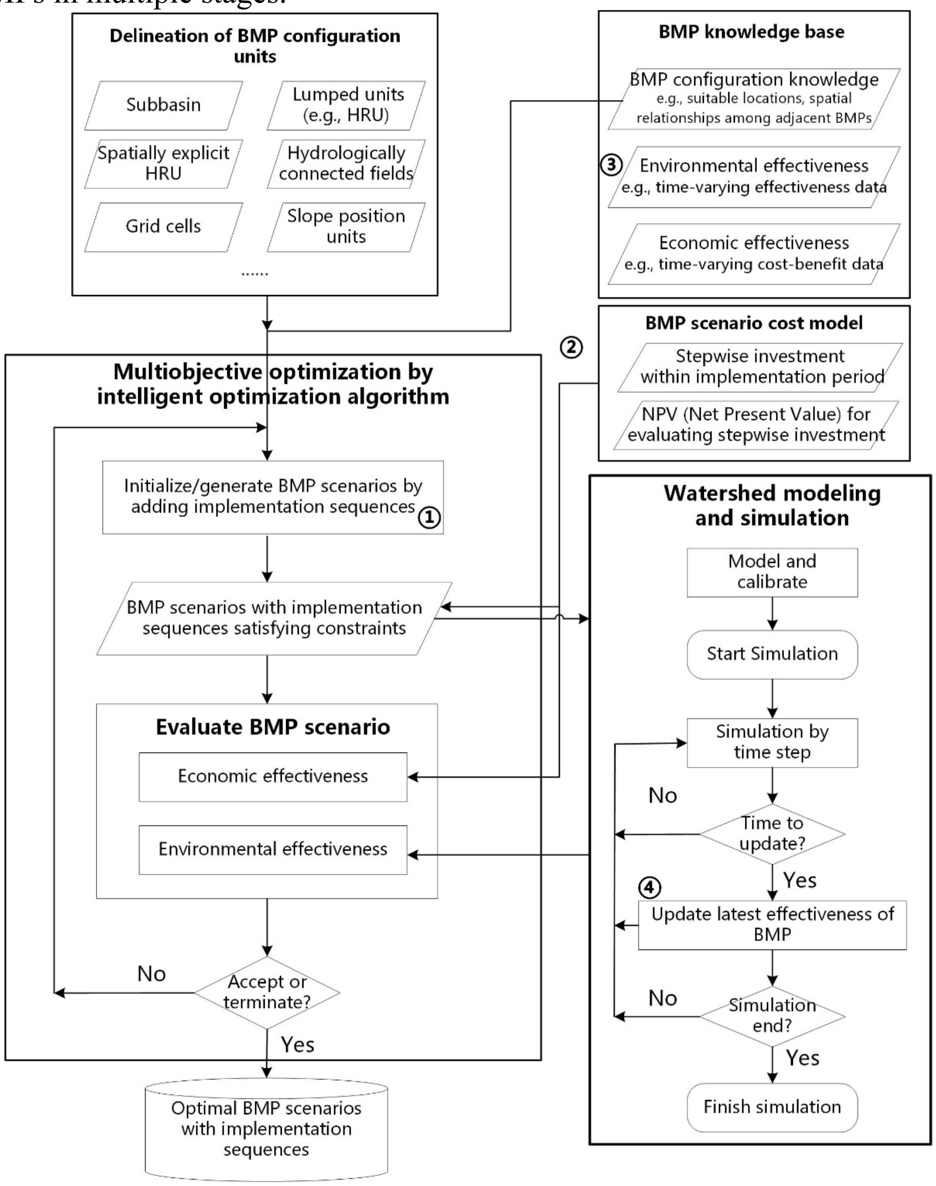

Figure 2. Proposed framework for optimizing implementation orders of best management practices (BMPs) considering stepwise investment and time-varying effectiveness of BMP. Labels 1–4 represent improvements in a widely used spatial optimization framework of BMP scenarios.

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 convenient for use as a chromosome in genetic optimization algorithms. Each geographic decision variable uses a integer value to record the decision on the spatial unit without a BMP (i.e., equals 0) or the type of BMP (Qin et al., 2018). A reversible and easily extensible encoding method was proposed to represent BMP type and implementation time in one decision variable (Figure 3).

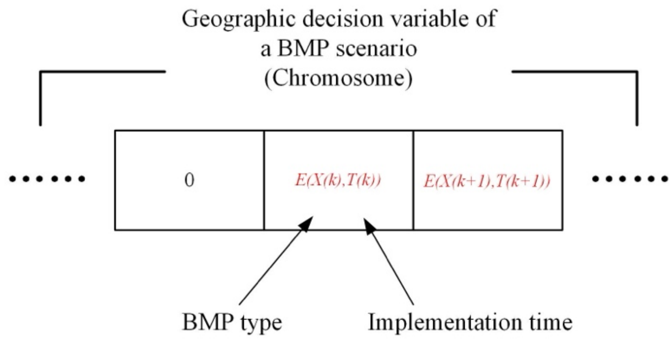

Figure 3. Schematic of the extended geographic decision variable of a best management practice (BMP) scenario. For the spatial unit k in a BMP scenario S, $X(k)$ and $T(k)$ denote the BMP type and implementation time, respectively. E is the reversible encoding method such as $X(k) \times 1000 + T(k)$. 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

$$S(k) = \begin{cases} E\big(X(k), T(k)\big) = X(k) \times 1000 + T(k), unit\ k\ configure\ a\ BMP \\ 0, otherwise \end{cases} \quad (2),$$

where $k \in [1,n]$, $X(k) \in [1,p]$, $T(k) \in [1,q]$, n is the length of the chromosome (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 BMPs.

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

2.4 Extending BMP scenario cost model to calculate NPV

As stated in the basic idea, once the geographic decision variable supports the implementation time of the BMP, the classical cost calculation of the BMP scenario by simple cost accumulation is no longer applicable but is still retained for compatibility with the previous framework. Therefore, 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 net cost explained earlier) was 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 beginning year of the implementation period, making the net cost of BMP scenarios with different implementation orders comparable.

2.5 Extending BMP knowledge base to represent time-varying effectiveness

The BMP knowledge utilized in the spatial optimization framework of BMP scenarios included 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., the reduction rate of total nitrogen by vegetated filter strips) or changes in modeling parameters of the BMP, such as improvements in soil properties (e.g., increased soil conductivity by returning farmland 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 formulae (Liu et al., 2018) and enumerated values. The former is suitable for ideal situations, for example, the mechanism of the effect of BMP is clearly understood, 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 discrete effectiveness values over time is appropriate when little observational data are available, and the mechanism of BMP can be reasonably estimated by theoretical curves (Figure 1). Therefore, the form of enumerated values for both knowledge of environmental and economic effectiveness was implemented in this study as an example to verify the proposed framework. That is, all time-related effectiveness data were prepared as arrays with a user-defined time interval and period.

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

Unlike updating watershed parameters related to the fixed effectiveness of BMPs (e.g., soil hydraulic properties) at the beginning of watershed simulation in most existing watershed models, the BMP scenario environmental evaluation considering implementation orders requires an iteration updating process during the simulation (Figure 2). When the simulation time step is incremented, the model confirms whether it is time to update the following BMP effectiveness data: if the simulation time meets the preset update time, the model updates the relevant parameters and performs 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 update of time-varying environmental effectiveness data of the BMP, a source code-level improvement is required for watershed models. 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 adopted as the watershed modeling framework to implement this improvement. SEIMS has been successfully applied to BMP scenario spatial optimization using different 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 for BMP implementation orders

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

Because the extended geographic decision variables include both BMP type and implementation time information, crossover and mutation operators designed accordingly can be performed on BMP type and implementation time separately and simultaneously. For example, Figure 4 shows 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 are swapped.

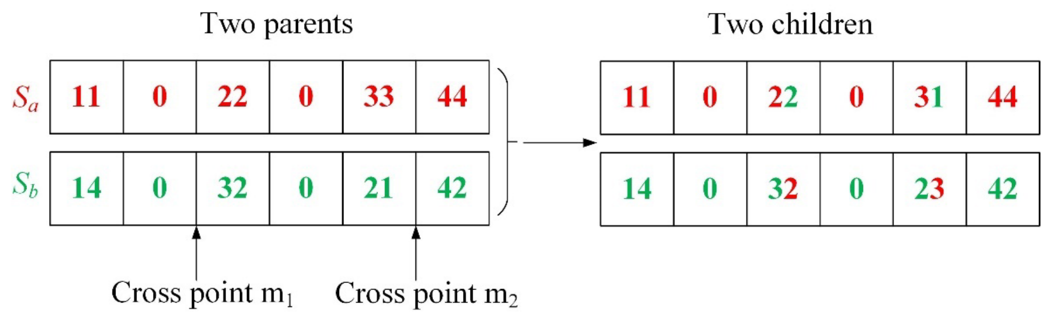

Figure 4. Example of the two-point crossover operator of two parents S_a and S_b on implementation time only. To facilitate the demonstration, the first number of each gene denotes best management practice (BMP) type, and the second number represents implementation time.

The mutation operator iterates over each gene value of the new child individual to perform mutation (i.e., change 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 supports users to determine whether the mutation object is the BMP type, implementation time, or both, according to actual applications.

3 Case study

3.1 Study area and data

The study area was the Youwuzhen watershed (approximately 5.39 km2) in Hetian Town, Changting County, Fujian Province, China (Zhu et al., 2021) (Figure 5). This small watershed belongs to the watershed of Zhuxi River, 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 the low mountains and hills. The elevation ranges from 295.0 m 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 climate 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 entire year. The main land-use types are forests, paddy fields, and orchards, with area ratios of 59.8%, 20.6%, and 12.8%, respectively. Additionally, forests in the study area are dominated by secondary or human-made forests with low coverage owing to the destruction of vegetation caused by 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 in the US Soil Taxonomy, respectively (Shi et al., 2010). Red soil is mainly distributed in hilly regions, while paddy soil is distributed primarily in broad alluvial valleys with a similar spatial pattern of paddy rice land use. The study area is one of the counties with the most severe soil erosion in the granite red-soil region of southern China. The soil erosion type was mainly severe and moderate water erosion, which is typical and representative.

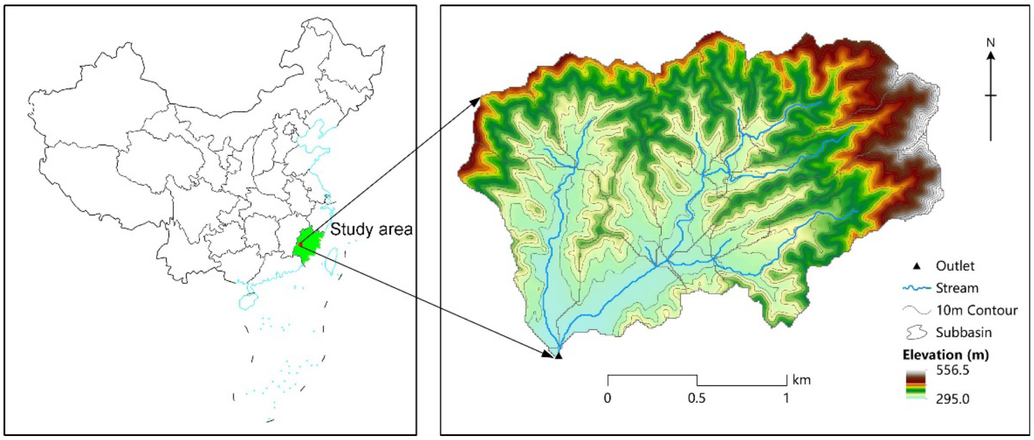

Figure 5. Map of Youwuzhen watershed in Changting County, Fujian Province, China

The basic spatial data collected for 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 resolution of 10 m (Qin et al., 2018). Soil properties were derived from field sampling data (Chen et al., 2013). Land use/land cover-related parameters were referenced from the SWAT database (Arnold et al., 2012) and relevant literature (Chen et al., 2019). Climate data, including daily meteorological and precipitation data from 2011 to 2017, were derived from the National Meteorological Information Center of the China Meteorological Administration and local monitoring stations, respectively. The watershed outlet periodic site monitoring streamflow and sediment discharge data from 2011 to 2017 were provided by the Soil and Water Conservation Bureau of Changting County. The streamflow and sediment discharge data were screened by a rule that required complete records of rainstorms with more than three consecutive days for watershed modeling because of limited data quality (Qin et al., 2018).

Slope position units have been proposed and proven to be effective in our previous studies (Qin et al., 2018; Zhu, Qin, et al., 2019). The same slope position units with a simple system of three types of slope positions (ridge, backslope, and valley) were also utilized in this study.

A daily SEIMS-based watershed model was constructed and calibrated to simulate soil erosion in the Youwuzhen watershed. The details of the selected modules of watershed processes, results of calibration, and validation of watershed outlet streamflow and sediment discharge can be found in Zhu, Qin, et al. (2019).

3.2 BMP knowledge base

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

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

BMP	Brief description
Closing measures (CM)	Closing the ridge area and/or upslope positions from human disturbance (e.g., tree felling and grazing forbidden) 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 forest located in the upslope and steep backslope positions by applying compound fertilizer on fish-scale pits.
Economic fruit (EF)	Building new orchards or improving orchards on the middle and down slope positions under better 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 improvements in soil properties, including organic matter, bulk density, texture, and hydraulic conductivity. The Soil and Water Conservation Bureau of Changting County selected 50 sample plots in the study area in 2000, including the four BMP types mentioned above. Intensive eroded plots with similar basic conditions such as 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 under each BMP to the control plot was taken as the environmental effectiveness over 5 years. Combining these measured data and the determination of the soil stable infiltration rate by Lin (2005), this study assumed that key soil parameters fluctuate reasonably in specific years. The time-varying changes in BMP effectiveness can be characterized mainly by a linear function, first fast and then slow function, first slow and then fast function, and other growth methods (Figure 1). In addition to the measured soil properties, other derived properties and parameters used in the SEIMS model were prepared, such as the total porosity and soil erodibility factor USLE_K of the universal soil loss equation (USLE).

The annual data on the environmental effectiveness and cost–benefit knowledge of the four BMPs are shown in Table 2. For example, after implementing CM, the organic matter (OM) would increase in ratios of 1.50, 1.62, 1.69,1.74, and 1.77, respectively, within 5 years. The relative changes in the conservation practice factor USLE_P of the USLE in Table 2 were adopted from one calibrated SWAT model for this area (Chen et al., 2013), which maintained the same value within 5 years.

Table 2. Environmental effectiveness and cost–benefit knowledge of the four best management practices (BMPs) within 5 years after 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	3.8	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 includes 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 factor (USLE_K) and conservation practice factor (USLE_P)]. 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 of these BMPs were estimated by Wang (2008) according to the price standard of 15 years ago. Although this is no longer applicable to today's price standards, it is still suitable for this study to analyze 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; for example, fruit production growth and forest stock volume are generally calculated starting from the third year (e.g., CM, ABHMP, and LQFI) or fifth year (e.g., EF) after implementation.

3.3 Multi-objective optimization of BMP scenarios

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

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

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 implementation orders.

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

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 soil erosion (kg) under the baseline scenario and scenario S, 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 area of the configured BMP 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.

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 scenario: a net cost of 300 (CNY 10,000) and a reduction rate of soil erosion of zero. To improve the computing efficiency of numerous executions of the SEIMS model required by the optimization algorithm, the Tianhe-2 supercomputer (Liao et al., 2014), one of the fastest supercomputers in the world, was used to take full advantage of the parallelizability of the SEIMS (Zhu, Liu, et al., 2019), that is, occupying a maximum of 10 nodes and executing four SEIMS models per node simultaneously.

3.4 Experimental design

To verify the rationality and validity of the proposed optimization framework of BMP implementation orders in this study, we first selected an optimized BMP scenario from Zhu, Qin, et al. (2019). In this scenario, the ABHMP occupied the most prominent area (about 2.55 km^2), with large clumps distributed over the west, central, and northeast ridge, backslope, and valley. The LQFI (approximately 0.11 km^2) was concentrated on the backslope in the middle region. The CM (approximately 0.09 km^2) were scattered on the west, central, and east ridges and backslope. EF occupied the smallest area (approximately 0.002 km^2) in the central valley. Subsequently, on the premise of reducing the solution space and saving computing resources, we designed four combination experiments considering the stepwise investment and time-varying effectiveness of BMPs:

- 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 fixed BMP effectiveness used the stable environmental effectiveness data of BMPs, that is, data in the fifth year after implementation in this study (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, experiments 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 called the Pareto front).

The experimental design followed three assumptions for the implementation of a target BMP scenario:

- Once a spatial unit was configured with a BMP in a certain year, the BMP type would not change throughout the following evaluation periods:
- The number of BMPs that could be implemented within a year was unlimited, ranging from 0 to the total number of spatial units *n*.
- Each type of BMP could be implemented on any spatial unit within one year and would start to take effect in the following year.

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

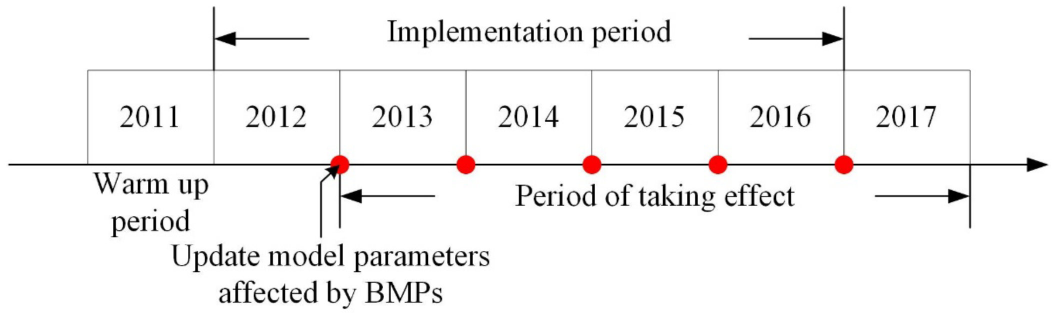

Figure 6. Schematic diagram of simulation periods of the watershed model for evaluating a best management practice (BMP) scenario.

The selected BMP scenario required 207 (CNY 10,000) for the initial construction and subsequent maintenance costs before making a profit (the first two years) (Zhu et al., 2019b). To perform experiments with stepwise investments, gradually decreased investments were designed within the 5-year implementation period, specifically, 90, 70, 30, 20, and 20 (CNY 10,000). The maximum available investment was set to increase by 10% to generate eligible scenarios more quickly. 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).

3.5 Evaluation method

The results of Pareto fronts from two optimization experiments with stepwise investment and discrete BMP scenarios from two experiments with a one-time investment were compared and discussed from the perspectives of the numerical evaluation of all solutions under two objectives and the qualitative characteristics of selected solutions considering BMP implementation orders.

The numerical evaluation of BMP scenarios under the two objectives in this study referred to figures of scattered points with the two objectives as axes and the quantitative index measuring the overall quality of the Pareto fronts. The figures of the scattered points could intuitively compare the BMP scenarios derived from different experiments. The quantitative index was specific to the two optimization experiments considering the convergence and diversity of Pareto fronts, for example, the commonly used hypervolume index (Zitzler et al., 2003). In this study, the larger the hypervolume, the better was the Pareto front. In addition, changes in the hypervolume index with evolutionary generations could provide a qualitative reference for optimization efficiency. In an ideal optimization process, the hypervolume initially rises rapidly, then gradually slows down, and finally stabilizes. The faster the hypervolume becomes stable, the higher the optimization efficiency (Zhu, Qin, et al., 2019).

To qualitatively analyze the characteristics of BMP implementation orders under the impacts of stepwise investment and time-varying BMP effectiveness, typical scenarios were selected and compared based on their spatio-temporal distributions. Three selection criteria were designed: high NPV with high soil erosion reduction rate (HH), low NPV with low soil erosion reduction rate (LL), and moderate NPV with 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 are plotted as scatter points with the NPV and reduction rate of soil erosion as axes (Figure 7a). Two comparisons between stepwise and one-time investments (STEP + FIXED vs. ONE + FIXED and STEP + VARY vs. ONE + VARY) showed the same distribution patterns. The NPV and reduction rate of soil erosion of the one-time investment solutions (ONE + VARY and ONE + FIXED) descended synchronously from the top right (ONE-1) to the bottom left (ONE-5, which denotes investment in the fifth year). The ONE + FIXED scenario that invested in the first year (the existing method, labeled as ONE-1 + FIXED in Figure 7a) required the greatest NPV (163, the unit is CNY 10,000) to achieve the most significant reduction rate of soil erosion (7.42%). The Pareto fronts under stepwise investment were densely distributed near the ONE-2 solutions and took dominant positions. Figure 7b shows an enlarged area of 150–156 NPV and 3.5–7.0% reduction rate of soil erosion to highlight this pattern. The best reduction rates of soil erosion under stepwise investment were approximately 0.8–0.9% lower than those under ONE-1 scenarios saving about 7.7 NPV and about 0.4% higher than ONE-2 scenarios needing similar NPVs. In general, the proposed optimization method of BMP implementation orders considering a stepwise investment could effectively provide more choices with less investment burden at the cost of a slight loss of environmental effectiveness.

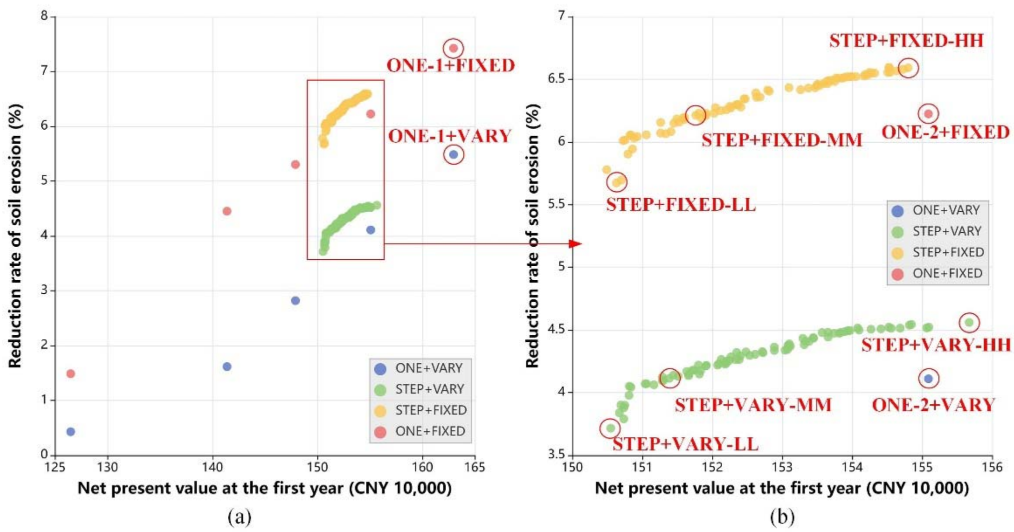

Figure 7. Comparison of best management practice (BMP) scenarios derived from the four experiments: (a) overall comparison; (b) zoomed in area around 150–156 NPV (CNY 10,000) and 3.5–7.0% reduction rate of soil erosion.

Two comparisons of time-varying effectiveness and fixed effectiveness of BMPs (i.e., STEP + FIXED vs. STEP + VARY and ONE + FIXED vs. ONE + VARY) showed that under the same NPV, the reduction rates of soil erosion in scenarios utilizing the time-varying effectiveness decreased by approximately 1.6–2.8% (Figure 7a). This phenomenon confirmed that uncertainties in BMP effectiveness over time may overestimate the long-term environmental efficiency of watershed management scenarios (Liu et al., 2018). Therefore, using the time-varying environmental effectiveness of BMPs was not only reasonable but could also reduce uncertainty to a certain degree.

Six representative scenarios were selected from the two STEP Pareto fronts to make more specific comparisons with the two ONE-2 scenarios, as shown 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. In contrast, the LL scenario was set as the one with the lowest NPV with the lowest reduction rate and the HH scenario as the highest NPV with the highest reduction rate. Table 3 lists the NPV in the first year and the detailed investments in different years for the selected scenarios.

The NPVs of the STEP scenarios did not seem to be significantly reduced compared to that of 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 the start-up fund of the project (money that must be invested in the first year), STEP scenarios had apparent advantages. For example, the start-up fund of scenario ONE-1 + VARY was 203.75 (CNY 10,000), while the start-up funds 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. The significantly reduced burden on start-up funds would undoubtedly improve the flexibility in funding during implementation.

In addition to the similar pattern of the two Pareto fronts under stepwise investment (STEP + VARY and STEP + FIXED), the changes in the hypervolume index with generations for the two optimization experiments also showed similar changing trends (Figure 8). Although the hypervolume of STEP + VARY seemed to first reach stability in the 65th generation, while STEP + FIXED showed 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, which considered the time-varying effectiveness of BMP, was the cause of the overall high hypervolume index of STEP + FIXED, as shown in Figure 7. This result could be expected because the experiments with fixed BMP effectiveness used data from the fifth year (Table 2), which was the optimum effectiveness 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 detail investments in different years of selected scenarios (STEP: stepwise investment; ONE: one-time investment; 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	154.8	155.09	150.55	151.39	155.67
Reduction rate of soil erosion (%)	6.22	5.67	6.20	6.59	4.11	3.72	4.11	4.56
1st investment (CNY 10,000)	0.00	55.31	72.80	85.53	0	57.94	76.28	88.40
2nd investment	203.75	67.36	57.35	67.57	203.75	62.77	44.56	69.82
3rd investment	3.60	27.58	19.82	22.98	3.60	27.36	26.35	26.15
4th investment	0.00	17.96	18.17	2.75	0.00	19.51	19.98	0.00
5th investment	0.00	18.84	17.54	3.33	0.00	19.53	18.97	0.00

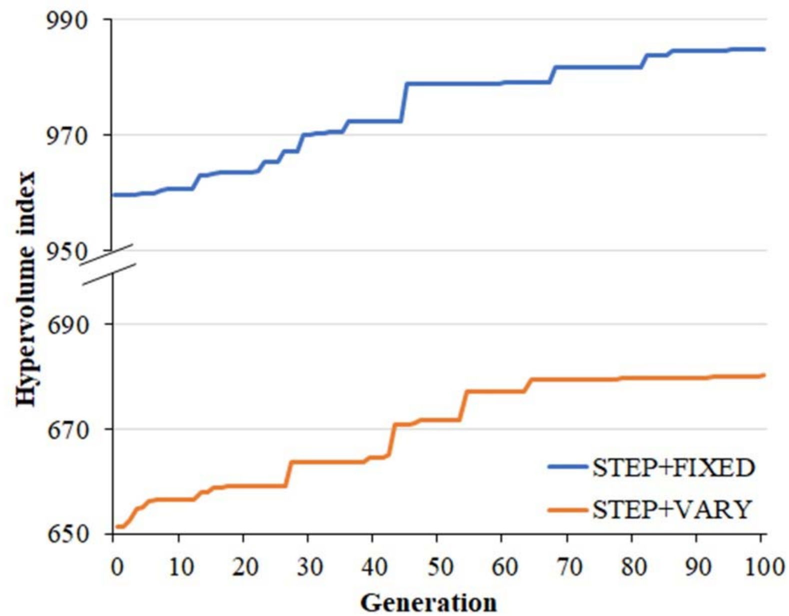

Figure 8. Changes in the hypervolume index with generations for two optimization experiments under stepwise investment (STEP + VARY denotes the optimization using time-varying effectiveness of best management practices [BMPs] and STEP + FIXED using fixed effectiveness)

4.2 Qualitative analysis of spatio-temporal distribution of selected BMP scenarios

Figure 9 presents spatio-temporal distributions of the six selected representative scenarios from two STEP Pareto fronts and two ONE-2 scenarios. All scenarios have the same spatial distribution of BMPs but different implementation times. With the same NPV and same implementation time, the two ONE-2 scenarios achieved a 6.22% reduction rate of soil erosion based on the fixed effectiveness of BMPs (155.09 NPV, 6.22%, for short, similarly hereinafter) and 4.11% on time-varying effectiveness (Table 3). Figure 9a–c demonstrates three representative scenarios based on the time-varying effectiveness of BMPs such as 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%). Figure 9d–f demonstrated another three scenarios based on the fixed effectiveness of BMPs such as 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%).

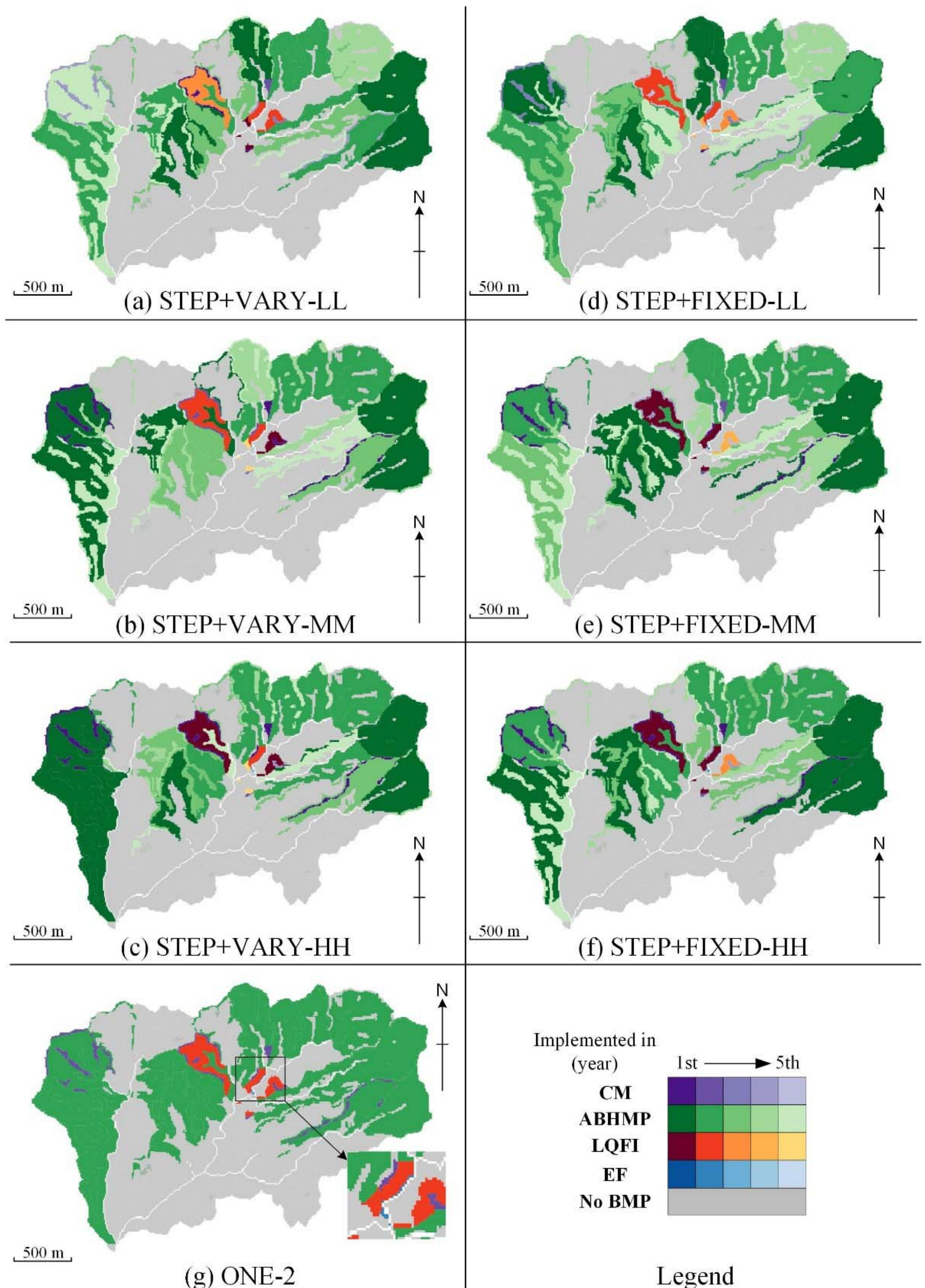

Figure 9. Spatio-temporal distributions of the representative best management practice (BMP) scenarios: (a)–(c) represent scenarios of low net present value (NPV) with low soil erosion reduction rate (LL), moderate NPV with moderate reduction rate (MM), and high NPV with high reduction rate (HH) of optimization experiments under stepwise investment and fixed BMP effectiveness (STEP + FIXED), respectively; (d)–(f) represent the corresponding scenarios under time-varying BMP effectiveness (STEP + VARY); (g) represents the scenarios of both fixed and time-varying BMP effectiveness under one-time investment in the second year (ONE-2), with partially enlarged details of the configured effective fruit (EF) practice along the river (white lines).

Spatio-temporal distributions of optimized BMP scenarios under stepwise investment exemplified the tacit knowledge that BMP's environmental and economic effectiveness affect the decision-making of BMP implementation orders under the specific investment plan. For example, BMPs that require high initial and maintenance costs but late returns (e.g., EF) are more likely to be implemented in the mid-to-late stage when alleviating the investment burden is a priority (Figure 9a and Figure 9d). BMPs with high environmental effectiveness and can take effect quickly (e.g., ABHMP) tend to be implemented in large areas in the first stage when focusing more on eco-environmental governance (Figure 9c and f). In addition, BMPs with moderate performance in overall effectiveness and take effect efficiently (e.g., CM and EF) have more flexibility to be implemented according to different investment plans.

5 Conclusions and future work

This study proposed a new optimization framework for the implementation orders of BMPs considering two important realistic factors: stepwise investment and time-varying effectiveness of BMPs. The optimized multi-stage BMP scenarios were much more practical and attractive for watershed management decision-making, given the reduced budget burden during the multi-year implementation period, once the relative loss of environmental effectiveness in the short term was acceptable. This framework was implemented by extending geographic decision variables to represent BMP implementation time, introducing the concept of NPV into the BMP scenario cost model, and customizing the BMP knowledge base and watershed model to evaluate the environmental effectiveness of BMP scenarios using the time-varying effectiveness of BMPs. Experimental results showed that optimizations considering stepwise investment could effectively provide more feasible choices with less investment burden at the cost of a slight loss of environmental effectiveness, especially the significantly reduced load on start-up funds compared to one-time investments.

The flexibility and extensibility of the proposed framework could make it easy to transplant and implement. The essential components in this framework could be replaced by similar functional techniques, such as multi-objective optimization algorithms and watershed models, which could be modified to iteratively update the BMP effectiveness data during the simulation. Application-specific data and settings could also be extended in this framework, such as spatial units for BMP configuration, BMP types and knowledge bases for specific watershed problems, and various representations of stepwise investment (e.g., range constraints, even distribution).

As a complicated methodology to solve actual management problems, a sensitivity analysis of the proposed framework and implementation should be conducted to provide feasible suggestions for extended applications. Three sets of parameters may affect the optimization results. The first is related to evaluating watershed responses to BMP scenarios, such as the length of the proper evaluation period. Correspondingly, the second parameter set concerns the economic calculation of BMP scenarios, such as the discount rate for NPV calculation. The last parameter set is the optimization algorithm settings, including crossover and mutation operators, maximum generation number, and population size.

Before running a practical application case, the sources of uncertainty in the proposed framework must be known and handled to minimize errors and improve credibility. It is important to note that the data and modeling method should be as accurate as possible to represent the characteristics of the study area and environmental problems. From this perspective, uncertainty research of this proposed framework may include (1) how to reasonably describe the time-varying effectiveness of BMPs based on limited observation data and model their all-sided effects in watershed models; (2) how to select a suitable BMP and determine the corresponding spatial configuration strategy; and (3) how to reduce the randomness and calculation errors of multi-objective optimization algorithms by incorporating expert knowledge.

Overall, this study exemplified the basic idea of extending the spatial optimization of BMPs to the spatio-temporal level by considering stepwise investment, which is an important realistic constraint during decision-making. Although the case study in this paper focused on agricultural watershed management practices, the methodology is also applicable to the spatio-temporal optimization of urban low-impact development practices. This study also emphasized the value of integrating physical geographic processes and anthropogenic influences.

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Data available statement

The modified programs of the SEIMS framework are available from https://github.com/lreis2415/SEIMS/tree/feature/bmps-order-opt/seims. The sptio-temporal datasets of the youwuzhen watershed are available from https://github.com/lreis2415/SEIMS/tree/feature/bmps-order-opt/data/youwuzhen/data_prepare, including precipitation and meteorological data, look up tables, spatial data, and management practices data. Both sets of fixed BMP effectiveness and time-varying BMP effectiveness are included in management practices data.

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