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

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Key Points:

- Proposed a novel idea to optimize implementation orders of watershed best management practices (BMPs) under stepwise investment
- Introduced net present value to compare net costs of BMP scenarios and BMP's time-varying effectiveness to assess environmental effects
- The basic idea of extending BMP optimization to the spatio-temporal level is demonstrated through an agricultural watershed case study

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 BMP type-selection and location-allocation but neglect the BMP implementation time or orders in a management scenario, which is most likely restricted by investments. This study proposes a new optimization framework for the implementation orders of BMPs by introducing the net present value to calculate the economic costs of BMP scenarios, and the process of taking effect of BMPs to evaluate the environmental effectiveness of multistage BMP scenarios. The proposed framework was implemented based on a spatially explicit integrated modeling system (SEIMS) and demonstrated using a small agricultural watershed case study of controlling soil erosion under a 5-year stepwise investment. Experiments focused on optimizing the implementation time of four representative agricultural BMPs in a specific spatial configuration scenario. The results demonstrated 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. Time-varying BMP effectiveness should be adopted extensively to better model the effect of BMPs on improving the environment over time. The proposed framework was sufficiently flexible to be transplanted to other technical chains 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 the spatio-temporal level by considering a stepwise investment. It emphasized the value of integrating physical geographic processes and anthropogenic influences.

Plain Language Summary

"When and where to implement which types of best management practices (BMPs) across the watershed to control which environmental issues" are common but complex questions faced by comprehensive watershed management. Multi-objective BMP optimization based on watershed modeling can provide scientific and effective decision support. Existing approaches primarily focus on optimizing the spatial dimension but neglect the temporal dimension, including the optimization of BMP implementation orders to pursue trade-offs between high environmental effectiveness and low economic burden during the implementation period. This study proposed a novel spatio-temporal optimization framework considering two significant factors: stepwise investment and time-varying effectiveness of BMPs. The framework was implemented and demonstrated in an agricultural watershed to optimize BMP implementation plans for controlling soil erosion. Comparative experiments demonstrate that if a small portion of environmental effectiveness can be sacrificed temporarily, optimizations considering the stepwise investment can provide more feasible implementation plans with less financial pressure, especially in the first year of implementation. This study emphasizes the value of integrating physical geographic processes (i.e., the response of the watershed to various spatio-temporal distributions of BMPs) and anthropogenic influences (i.e., stepwise investment) to design, implement, and apply more flexible, robust, and feasible geospatial analysis methods.

1 Introduction

The scientific and reasonable spatial configuration and optimization of diverse 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). 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 key watershed areas such as the 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 areas are common priority areas for implementing BMPs to control eco-environmental problems, including non-point source pollution and soil erosion (Chen et al., 2016; White et al., 2009; Rana & Suryanarayana, 2020). Therefore, after key areas are identified and ranked as priorities, the implementation orders of suitable BMPs in these areas 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 step by step during the implementation period. Consequently, such approaches cannot generate optimized BMP implementation orders 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 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 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 diverse 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 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 the optimization: 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 comprises 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 next optimization problem occupying the remaining spatial units in the study area. The stepwise optimized BMP scenarios were 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 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 the optimization, which is the implementation orders of BMPs. The few studies assessing the optimization of the implementation orders of BMPs have failed to optimize the BMP implementation orders 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) 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 soil erosion reduction rate and minimizing the net cost.

2 Methods

2.1 Basic idea

The critical issue in optimizing BMP implementation orders under stepwise investment is the reasonable quantification of the optimization objective, such as the most frequently used economic cost of BMP scenarios and the 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 as these methods assume that each BMP has a fixed effectiveness, which is often optimum 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, 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 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 can achieve the desired optimal environmental effectiveness once implemented. Generally, environmental efficiency of BMPs can be quantified from two perspectives. The first is measuring the direct effect of BMP on its governance objective, such as the reduction rate of pollutant concentration in the surface flow out of the vegetation filter strip. The other is measuring the effect of BMP on its related geographic variables whose changes indirectly affect the governance objective. For example, measuring improvements in soil properties resulting from returning farmland to forests can be utilized in simulating the increased infiltration and then 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 BMP can be used as an effective supplement to a few measured data over time. It is now accepted that the environmental efficiency of BMPs usually changes over time and gradually increases to the optimum in the process of its taking effect in the first stage of life cycle of the BMP (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 BMP and evaluate the environmental effectiveness of BMP scenarios.

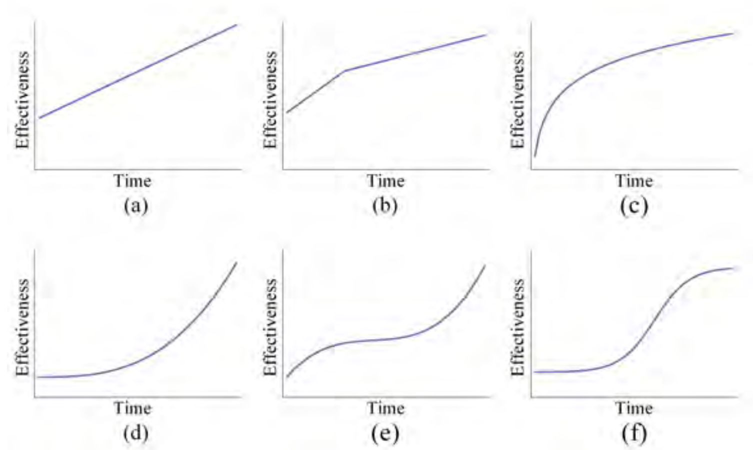

Figure 1. Typical theoretical changes of best management practice (BMP) effectiveness over time for the first stage post implementation [adapted from Liu et al. (2018)]. (a)–(f) represent the linear, piecewise linear, logarithmic, exponential, polynomial, and logistic changes of BMP effectiveness over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

2.2 Overall design

To achieve the basic idea, we adopted a widely used spatial 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 BMP 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 be constrained by stepwise investment and screened before being evaluated. The third improvement supported the time-varying effectiveness of BMPs 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). Subsection 2.3–2.6 of this study present detailed designs of the four improvements with specific implementations for a small agricultural watershed case study that aimed to control soil erosion. Moreover, the multi-objective optimization algorithm should be customized accordingly 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 the option to include implementation plans for BMPs with multiple stages.

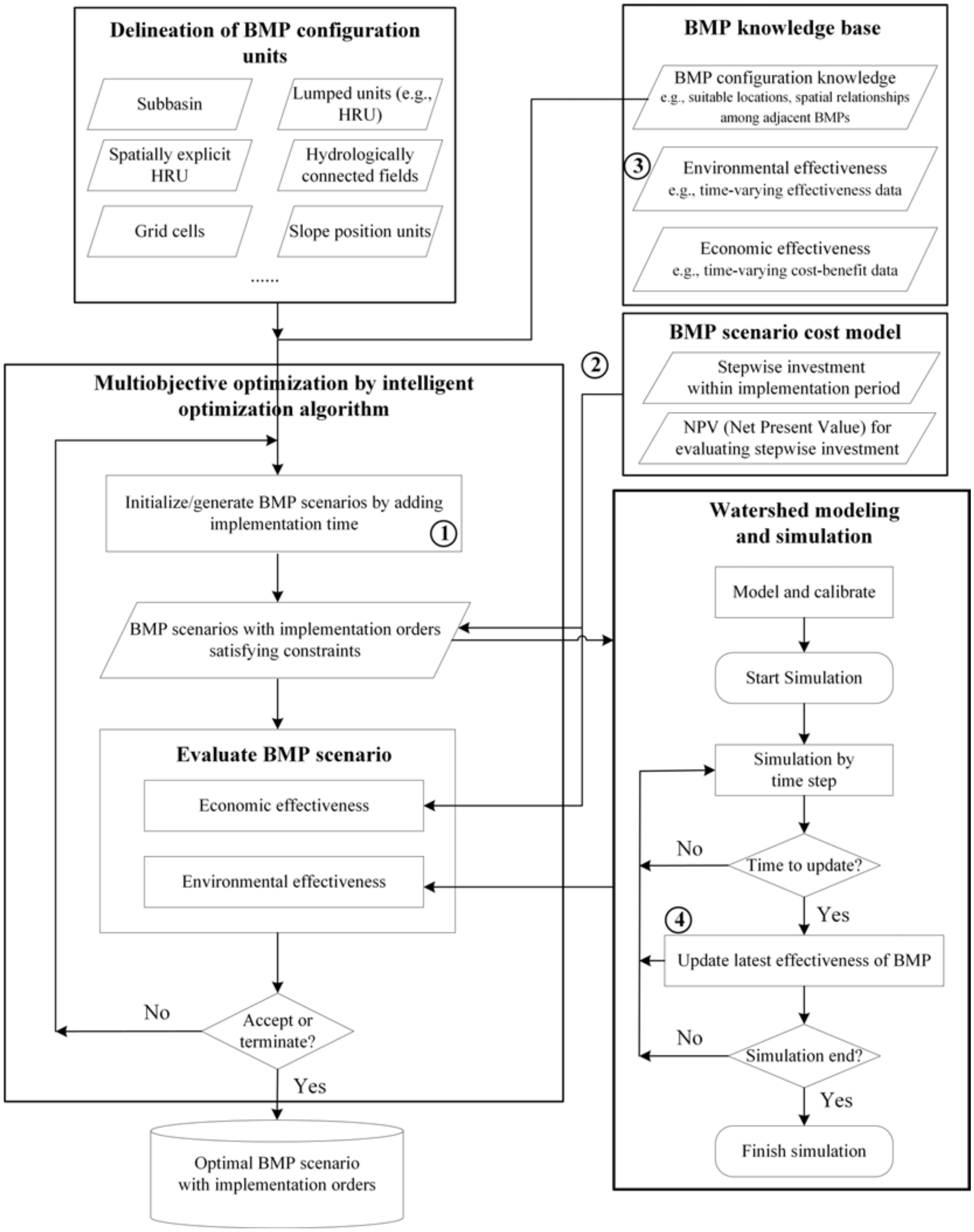

Figure 2. Proposed framework for optimizing implementation orders of best management practices (BMPs) considering their stepwise investment and time-varying effectiveness. Labels 1–4 represent improvements on the already-existing and widely utilized spatial optimization framework of BMP scenarios.

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 an 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 approach was proposed and implemented to represent BMP type and implementation time in one decision variable (Figure 3).

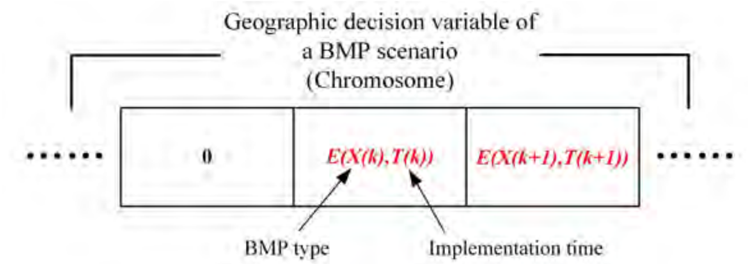

Figure 3. Schematic of the extended geographic decision variable of a best management practice (BMP) scenario. For the spatial unit k in a BMP scenario S, $X(k)$ and $T(k)$ denote the BMP type and implementation time, respectively. E is the reversible encoding method; for example, if $E = X(k) \times 10 + T(k)$, 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:

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

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 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 $(p*q+1)^n$ solution space. 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 BMP implementation time, 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 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 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, such as when the mechanism of the effect of BMP 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 knowledge of 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 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 environmental evaluation of BMP scenarios considering implementation orders requires an iteration updating process during the simulation (Figure 2). When the simulation time step is incremented, the model verifies 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 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 update of time-varying environmental effectiveness data of the BMP, a source code-level improvement for the watershed models is required. 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 utilized in the spatial optimization of BMP scenarios with diverse types of spatial units and 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 non-dominated sorting genetic algorithm (NSGA-II) (Deb et al., 2002) is as one of the most efficient algorithms for multi-objective optimization problems and 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 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 time (Figure 2).

Because the extended geographic decision variables include both BMP type and implementation time information, crossover and mutation operators designed accordingly can be conducted on them separately and simultaneously. 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 are swapped.

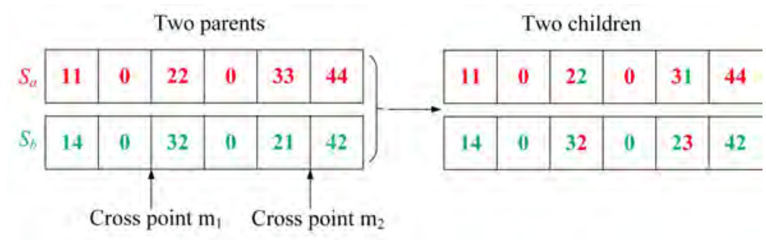

Figure 4. Example of the two-point crossover operator of two parents S_a and S_b on implementation time only. To facilitate the demonstration, the first number of each gene denotes best management practice (BMP) type, and the second number represents implementation time.

The mutation operator iterates over each gene value of the new child individual to conduct 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 allows users to determine whether the mutation object is the BMP type, implementation time, or both, according to the application.

3 Experimental designs

To verify the rationality and validity of the proposed optimization framework for BMP implementation orders, we implemented a new optimization tool. It is based on our former distributed watershed modeling and BMP optimization studies on slope position units, as introduced in the last section. The follow-up case study aimed at optimizing BMP implementation plans for controlling soil erosion under a 5-year stepwise investment 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 Hetian Town, 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. It 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, the study area is dominated by secondary or human-made forests with low coverage owing to the destruction of vegetation 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* as per the US Soil Taxonomy, respectively (Shi et al., 2010). Red soil is predominantly distributed in hilly regions, while paddy soil is distributed primarily in broad alluvial valleys with a similar spatial pattern as that of the land use of paddy rice. The study area is one of the counties with the most severe soil erosion in the Southern China. The soil erosion type was majorly severe and moderate water erosion, which is typical and representative.

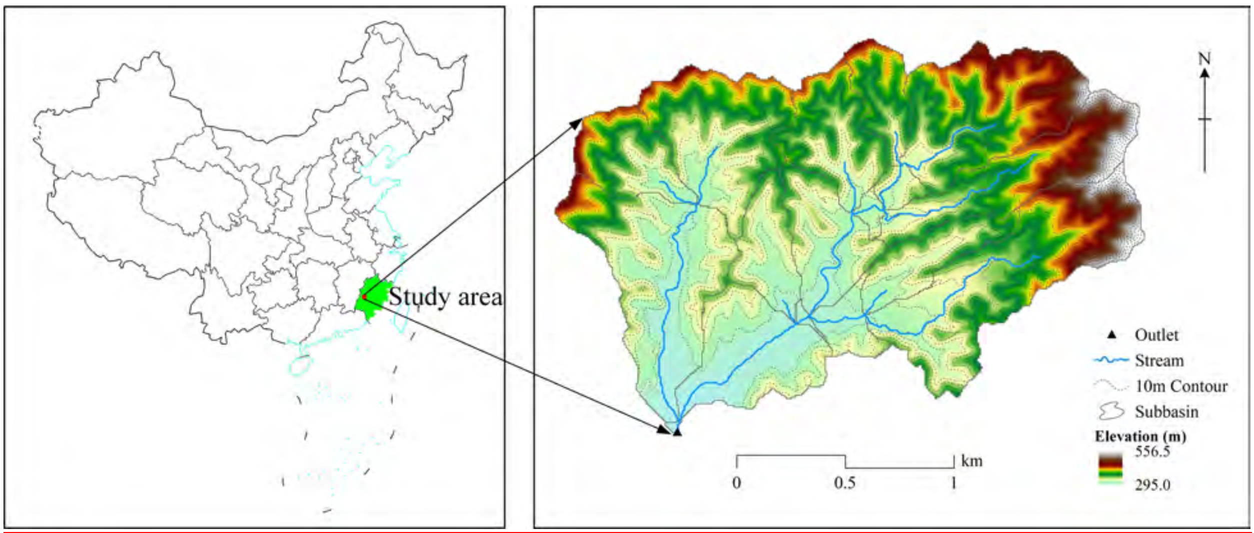

Figure 5. Map of Youwuzhen watershed in Changting County, Fujian Province, China

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 10 m resolution (Qin et al., 2018). Each soil type properties were measured from field samplings (e.g., organic matter and mechanical composition; 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 one local monitoring station were also collected. 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 rainstorms records with more than three consecutive days for watershed modeling due to limited data quality (Qin et al., 2018).

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 include the spatial configuration knowledge (Figure 2).

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 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 forest located in the upslope and steep backslope positions by applying compound fertilizer on fish-scale pits.
Economic fruit (EF)	Building new orchards on the middle and down slope positions 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 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 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 under each BMP to the control plot was considered as environmental effectiveness over five years. Combining these measured data and determining 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 predominantly by one of the functions depicted in Figure 1, including linear functions, first fast and then slow functions, first slow and then fast functions, and so on. Other derived properties and parameters utilized in the SEIMS model were prepared accordingly, including total porosity and soil erodibility factor.

The annual data on environmental effectiveness and cost–benefit knowledge of the four BMPs are depicted 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 five 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 five years.

Table 2. Environmental effectiveness and cost–benefit knowledge of the four best management practices (BMPs) within five years post 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 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 (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 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 directs economic benefits of the four BMPs; for example, fruit production growth and forest stock volume are generally calculated from the third (e.g., CM, ABHMP, and LQFI) or fifth year (e.g., EF) post implementation.

3.3 Calibrated watershed model and selected BMP scenario from 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 calibration and validation of watershed outlet streamflow and sediment discharge can be found in Zhu, Qin, et al. (2019).

To perform the optimization on the temporal dimension and evaluate the impact of stepwise investment and time-varying effectiveness of BMPs on the BMP implementation plans, we selected an optimized BMP scenario (Figure 6) from Zhu, Qin, et al. (2019) as the fundamental spatial scenario. The selected BMP scenario considers 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 the previous studies undertaken by us (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.

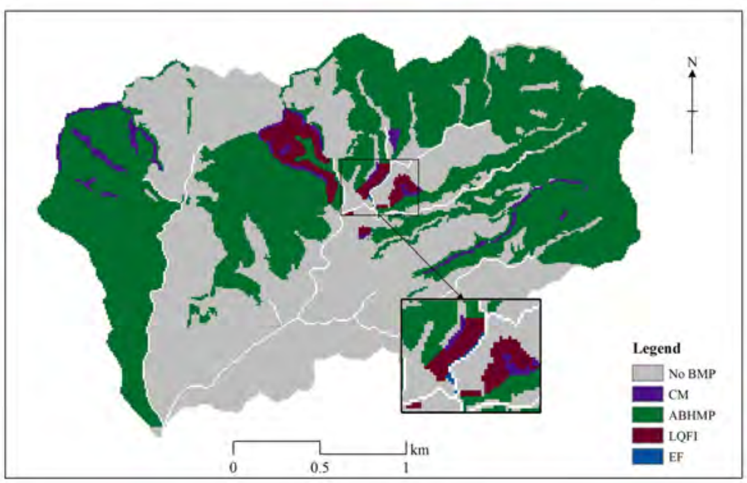

Figure 6. Spatial distribution of the selected BMP scenario based on slope position units from Zhu, Qin, et al. (2019). Partially enlarged details of the configured economic fruit (EF) practice along the river have also been depicted (white lines).

3.4 Multi-objective BMP scenarios optimization

The multi-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:

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

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, as follows:

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

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 yields from hillslope routed into 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:

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

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

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 scenario: a net cost of 300 (CNY 10,000) and a soil erosion reduction rate 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 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 executing four SEIMS models per node simultaneously.

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 fixed BMP effectiveness used the stable environmental effectiveness data of BMPs in this case study, that is, data in the fifth year post 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 as Pareto fronts).

The experimental design followed three assumptions for implementing 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 subsequent evaluation periods.
- The number of BMPs that could be implemented within a year was unlimited, ranging from zero to the total number of spatial units *n*.
- Each BMP type could be implemented on any spatial unit within one 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 7). The environmental effectiveness and cost–benefit data of the four BMPs listed in Table 2 were input within the model 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 BMPs (i.e., soil properties of spatial units with BMPs; Table 2) would be updated (red dots in Figure 7), including the newly and previously implemented ones. Therefore, the period of BMPs taking effect in this study lasted from 2013 to 2017.

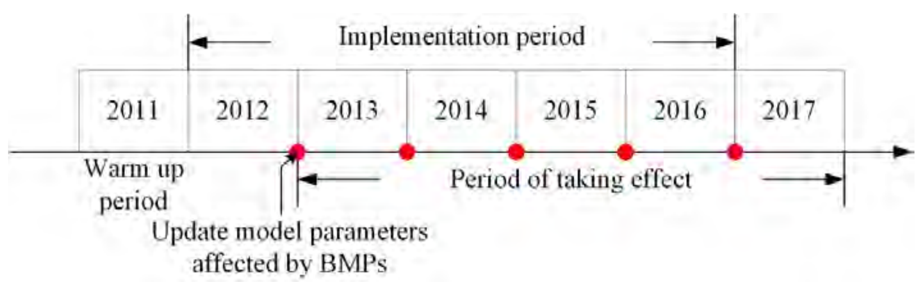

Figure 7. Schematic diagram of the watershed model simulation periods for evaluating a best management practice (BMP) scenario.

The selected BMP scenario required 207.35 (CNY 10,000) for the initial construction and subsequent maintenance costs before making a profit (the first two years) (Zhu et al., 2019b). To conduct experiments with stepwise investment, 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).

3.6 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 the qualitative perspective, we analyzed characteristics of selected solutions considering BMP implementation orders.

In this case study, two aspects were considered in the numerical evaluation of BMP scenarios under the two objectives. One is intuitive comparison by plotting Pareto fronts from stepwise investment experiments and BMP scenarios from one-time investment experiments as scattered plots. The other is using quantitative index to measure the overall quality of the Pareto fronts, such as, the commonly used hypervolume index (Zitzler et al., 2003). In this study, the larger the hypervolume, the better the Pareto front. Additionally, 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 evaluate the BMP implementation orders 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 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 soil erosion reduction rate as axes (Figure 8a). 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) 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 8a) required the greatest NPV (163, the unit is 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 took dominant positions. Figure 8b 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 ONE-1 scenarios saving about 7.7 NPV and about 0.4% higher than those of ONE-2 scenarios requiring similar NPVs. In general, the proposed optimization method of BMP implementation orders considering stepwise investment could effectively provide more choices with less investment burden at the cost of a slight loss of environmental effectiveness.

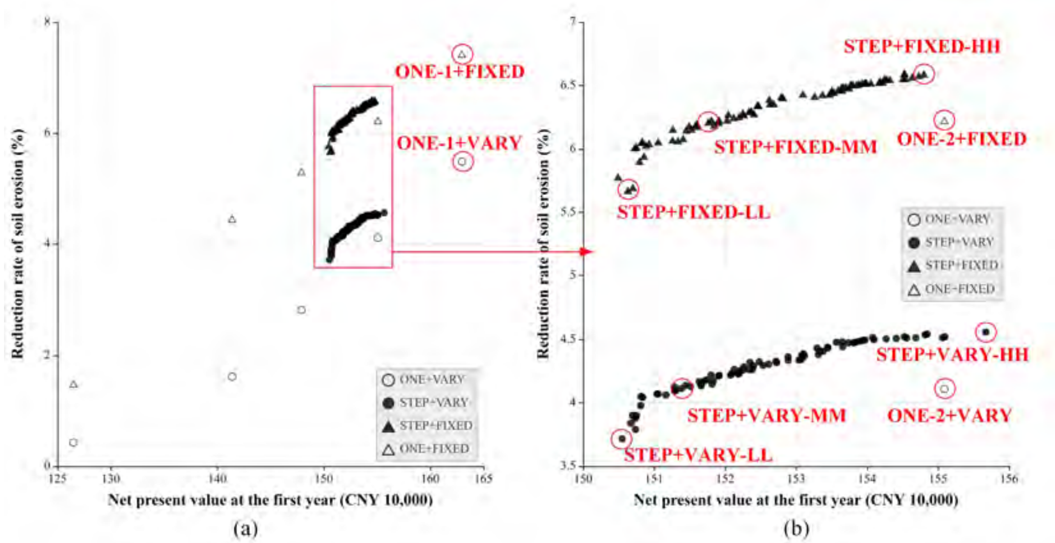

Figure 8. Comparison of best management practice (BMP) scenarios derived from the four comparative experiments: (a) overall comparison; (b) zoomed in area at approximately 150–156 NPV (CNY 10,000) with a soil erosion reduction rate of 3.5–7.0%. STEP: stepwise investment; ONE-*n*: one-time investment 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 make more specific comparisons with the two ONE-2 scenarios, as depicted in Figure 8b (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, LL scenario was set as the one with the lowest NPV and reduction rate and HH scenario as the highest NPV and reduction rate. Table 3 enlists 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 changes in the hypervolume index with generations for the two optimization experiments also demonstrated similar changing trends (Figure 9). 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, which considered the time-varying effectiveness of BMP, was the cause of the overall high hypervolume index of STEP + FIXED, as depicted in Figure 9. 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 (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
1st investment (CNY 10,000)	0.00	55.31	72.80	85.53	0.00	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	31.87	25.53	29.68	3.60	31.86	32.31	33.07
4th investment	3.60	27.42	28.23	14.56	3.60	28.81	29.32	10.83
5th investment	3.60	30.63	29.39	17.23	3.60	31.16	30.64	12.80

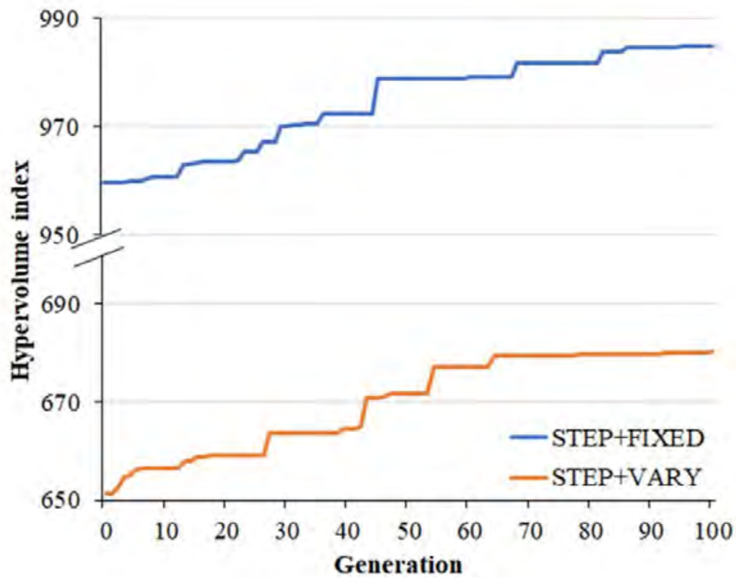

Figure 9. Changes in the hypervolume index with generations for two optimization experiments under stepwise investment (STEP + VARY denotes the optimization using time-varying effectiveness of best management practices [BMPs] and STEP + FIXED using fixed effectiveness)

4.2 Impact of stepwise investment on BMP implementation plans

In our case study, 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 project's start-up fund (i.e., money 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 that 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.

From Table 3, we learn that the start-up fund has a positive correlation with overall environmental effectiveness. The cumulative investments over time decreased from the HH to MM, and then to the LL scenario. This phenomenon is precisely in accordance with the processes of environmental effectiveness and investment trade-offs. The more and earlier BMPs implemented, the higher the environmental effectiveness. The less and later BMPs implemented, the lower the NPV will be. Further, from Figure 8b, we can observe obvious inflection points at an NPV of approximately 151, that is, as the NPV of Pareto fronts decreases, the soil erosion reduction rate gradually decreases and declines rapidly after the inflection point. This phenomenon may be caused by low investment in the first year (e.g., the 1st investment is less than the 2nd in the two LL scenarios; Table 3), and most BMPs implemented in and after the second year.

Therefore, by considering stepwise investments for optimizing BMP implementation plans, the significantly reduced burden on start-up funds would undoubtedly improve the flexibility in funding during the entire implementation period. In the meantime, the 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 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 in VARY scenarios decreased by approximately 1.6–2.8% (Figure 8a). The apparent results are attributed to the representation of BMP effectiveness data. Inaccurate representation may over- or under-estimate the overall effectiveness of BMP scenarios, especially in long-term evaluations. Figure 10 depicts a comparison between BMP scenarios under one-time investments using fixed effectiveness in the first (ONE+FIXED (1)) and the fifth year (ONE+FIXED (5)) and time-varying effectiveness (Table 2). Figure 10 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 measure precisely. Therefore, to minimize this bias or error as much as possible, researchers are suggested to monitor BMP effectiveness data periodically and thoroughly. Modelers are meanwhile suggested to reasonably quantify time-varying BMP data and utilize it in watershed models.

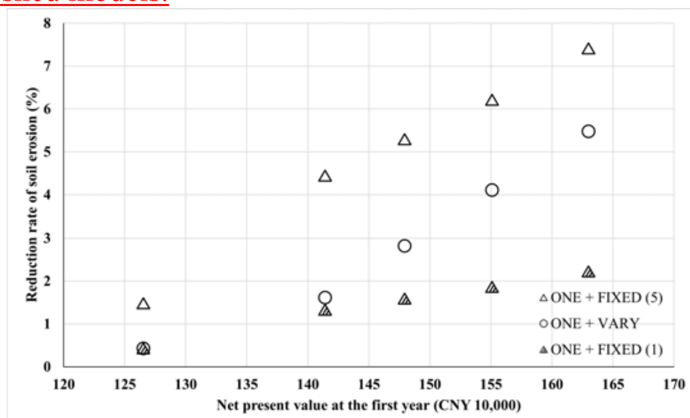

Figure 10. Comparison of best management practice (BMP) scenarios under one-time investments using diverse BMP environmental effectiveness data. ONE + VARY represents the BMP scenarios under one-time investment using time-varying effectiveness. ONE + FIXED (1) and ONE + FIXED (5) represent the BMP scenarios under one-time investments using fixed effectiveness in the first and fifth year, respectively.

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

Figure 11 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 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 the fixed effectiveness of BMPs (155.09 NPV, 6.22%) and 4.11% on time-varying effectiveness (Table 3). Figures 11a–c demonstrated three representative scenarios based on the 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

11d–f demonstrated another three scenarios based on the 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%).

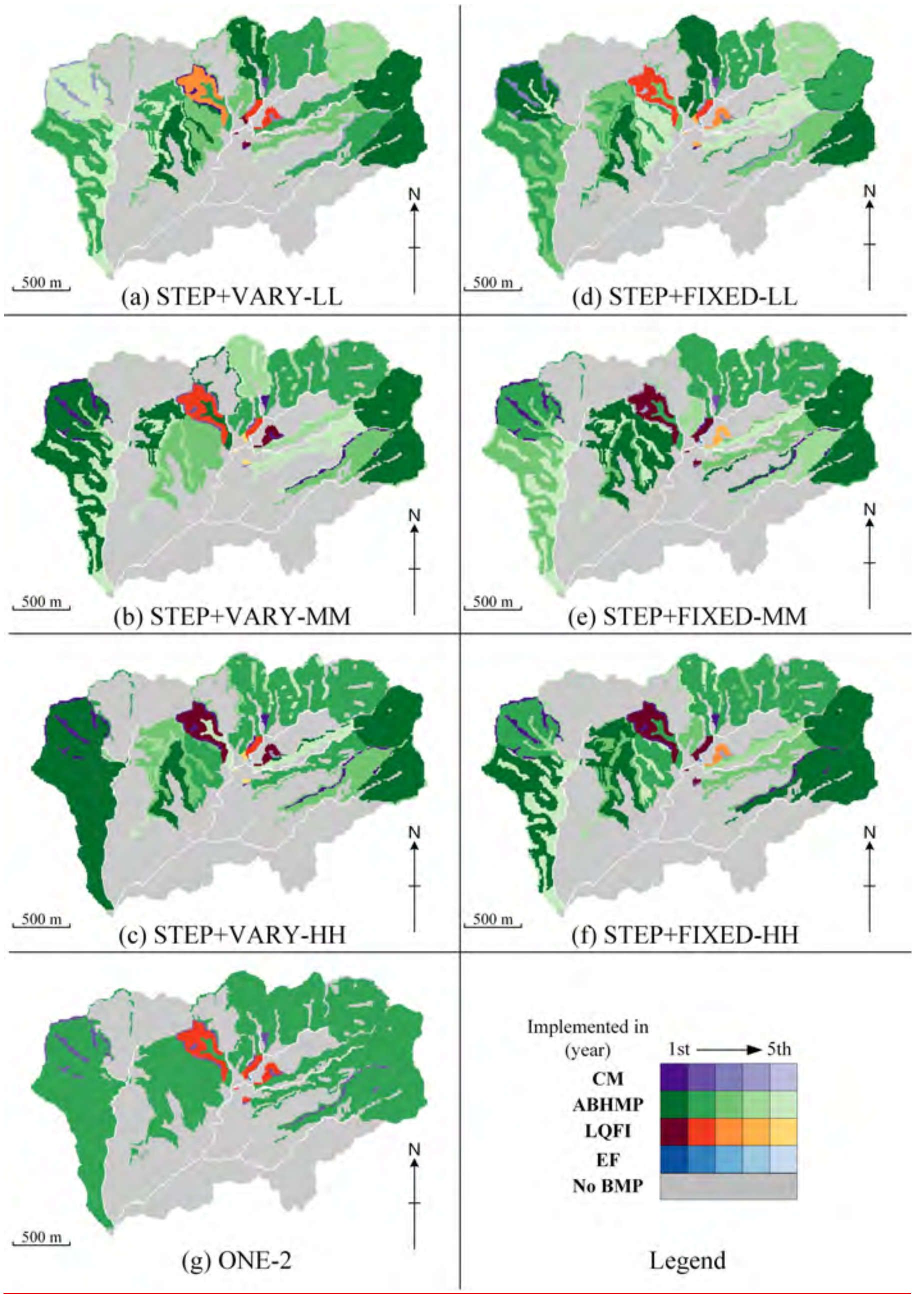

Figure 11. Spatio-temporal distributions of the representative best management practice (BMP) scenarios: (a)–(c) represent scenarios of low net present value (NPV) with low soil erosion reduction rate (LL), moderate NPV with moderate reduction rate (MM), and high NPV with high reduction rate (HH) of 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).

Spatio-temporal distributions of optimized BMP scenarios under stepwise investment exemplified the tacit knowledge that environmental and economic effectiveness of the BMP 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 investment burden alleviation is a priority (Figures 11Figurea and 11d). BMPs which have 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 (Figures 11c and 11f). Additionally, BMPs which have moderate performance in overall effectiveness and take effect efficiently (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 candidates for decision-makers to further screen and reach a consensus, meeting all the stakeholders' interests.

4.5 Applicability of the proposed optimization framework

Although the proposed optimization framework was implemented and demonstrated through an agricultural watershed management problem, it is designed to be a universal framework that is not related to BMP types, watershed models, optimization algorithms, and applied watershed scales. Similar optimization methods and tools (e.g., the System for Urban Stormwater Treatment and Analysis Integration, SUSTAIN; Lee et al., 2012) can be improved according to the proposed idea from the following key points: (1) incorporating BMP implementation time into the construction of BMP scenarios;, that is, for example, updating BMP selection and placement strategies in BMP Optimization of SUSTAIN; (2) considering dynamic economic indicators (e.g., the NPV used in this study) to evaluate the long-term investment; that is, for example, improving the BMP Cost Estimation of SUSTAIN; (3) quantifying time-varying BMP effectiveness data through diverse ways such as integrating sampled data with theoretical analysis; and (4) modifying watershed models to support updating time-varying BMP effectiveness data during the simulation period; that is, for example, the BMP Simulation of SUSTAIN.

The ability to support diverse types of BMPs and watershed scales depends on the specific implementation of the proposed framework, especially the watershed model. The watershed model can represent the time-varying effectiveness of the BMP, which may be quantified by the effect of BMP on its governance 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). The EF 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 significantly different time-varying effectiveness from non-engineering (or non-structural) BMPs. For example, they may take effect immediately after implementation and achieve periodic high effectiveness over time under maintenance operations. Therefore, it will be meaningful to consider structural and non-structural BMPs in practical application cases.

It is worth mentioning that the primary concern of the spatio-temporal optimization of BMPs in a large watershed is the construction of the watershed model and determining the 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 optimization framework for implementation orders 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. This was applied to agricultural and urban BMPs by extending geographic decision variables to represent BMP implementation time and introducing the concept of NPV into the 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. Exemplified framework implementation and experimental results demonstrated 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 those of one-time investments. By accounting for time-varying effectiveness and stepwise investment, the optimized multi-stage BMP scenarios may better reflect the reality of BMP performance and costs over time, providing diverse choices for watershed management decision-making.

The flexibility and extensibility of the proposed framework could make it easy to transplant and implement. The essential components in this framework could be implemented by similar functional techniques to the case study, including multi-objective optimization algorithms and watershed models. Application-specific data and settings could also be extended in this framework, 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). Before implementing a practical application case, the sources of biases or errors in the proposed framework must be known and handled to minimize errors and improve credibility. It is critical to note that the data and modeling method should be highly accurate in its representation for the characteristics of the study area and environmental problems. From this perspective, biases or errors of this proposed framework may be reinduced or avoided by: (1) reasonably describing the time-varying effectiveness of BMPs based on limited observation data and modeling their all-sided effects in watershed models; (2) selecting suitable BMPs and determining the corresponding spatial configuration units and strategies; and (3) reducing the randomness and calculation errors of multi-objective optimization algorithms by incorporating expert knowledge in defining the optimization problem.

As intended to be a universal optimization framework unrelated to BMP types, watershed models, optimization algorithms, and applied watershed scales, there are several issues worth studying in the future, including extensive applications and sensitivity analysis. The wide applications may include: (1) improving other existing optimization frameworks focused on urban BMPs; (2) explicitly considering structural and non-structural BMPs in case studies; (3) solving BMP optimization problems in large watersheds, and so on. The sensitivity analysis of the proposed framework and specific implementation could be conducted on three sets of parameters to provide feasible suggestions for practical applications. The first is related to the evaluation of watershed responses to BMP scenarios, including the proper 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 is 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 the spatio-temporal level by considering the 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 response to various spatio-temporal 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.

Acknowledgments

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Data available statement

The improved SEIMS framework programs and the prepared data are freely available on https://doi.org/10.5281/zenodo.7048969. The Youwuzhen watershed spatio-temporal datasets are located in the /SEIMS/data/youwuzhen/data_prepare folder. These include precipitation and meteorological data, look up 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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