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A Multi-Objective Decision Making System (MDMS) for a Small Agricultural Watershed Based on Meta-Heuristic Optimization Coupling Simulation

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Abstract: [Background] The key to integrated watershed management is to take simultaneous account of environmental, economic, and social development goals; hence, a multi-objective decision making approach is required. However, our understanding and application of multi-objective decision making in watershed management remains limited. [Objective] The objective of this study was to develop a multi-objective decision making system (MDMS) that could simultaneously handle multiple problems and objectives in a small watershed based on the relationships among land, water and economy. [Methods] The MDMS was coupled with the watershed hydrological model and economic benefit evaluation model to comprehensively simulate the watershed operational process, and established a multi-objective function to minimize sediment, nitrogen, and phosphorus outputs, while maximizing the economic benefits for integrated watershed management. The MDMS also utilized an improved meta-heuristic algorithm to optimize the agricultural land use structure of the small watershed to obtain the best integrated management plan at the small watershed scale. [Results] We found that the MDMS achieved seamless connections between automatic updating, analysis, and the optimization of land use structures in the iterative process, and successfully obtained an optimal scheme from a large number of agricultural land use structure alternatives, with particularly high time efficiencies. [Conclusions] Overall, the MDMS effectively controlled the negative impacts of crop planting on the environment, and simultaneously considered the economic benefits, which might assist managers in arriving at efficient scientific decisions toward the integrated management of small agricultural watersheds.

Keywords: small agricultural watershed; land use structure; multi-objective; Tabu Search; optimization

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1. Introduction

With rapid anthropogenic development and proliferation, our heavy dependence on natural resources has significantly disrupted the balance of watershed ecosystems, which endangers the survival of humanity [1–5]. Precipitous population growth, coupled with global scale increases in agricultural activities and the development of agricultural science and technology, in agricultural watersheds have exacerbated already serious water resource issues and associated environmental pressures [6–8]. Non-point source pollution and soil erosion in watersheds have emerged as serious environmental challenges worldwide that have severely increased environmental degradation [9–13], which has been of serious concern and under intense study over the last two decades [14–19]. In the Yangtze River of China, agricultural non-point source pollution and soil erosion comprise the key issues that have been troubling watershed management [20,21]. According to an estimation of cultivated land area in 2018, the average fertilizer application amount per hectare was ~419 kg, which is far higher than the world average of 120 kg per hectare [22]. The area of soil erosion in the Yangtze River basin is 3.47×10^5 km^2, which accounts for 19.36% of the total area of the watershed, and 17% of the annual sediment transport in China (8.31×10^7 t) [23,24]. However, the decision making systems that could effectively balance and optimize the development goals of various elements within the watershed need to be further studied,, particularly those suitable for the small agricultural watershed in Yangtze River Delta region of China [25–29].

Watersheds are complex systems with multiple components including natural, economic, demographic, and political factors [30–32]. These subsystems are connected and interact with each other, forming four main characteristics: integrated, multi-objective, dynamic, and uncertain [33–35]. To address these multiple objectives, integrated watershed management (IWM) was first proposed by the U.S. National Water Commission in 1968 [36]. IWM was defined as "a method to encompass and coordinate all of a watershed's potential uses, services, and values in management decisions and regulatory activities rather than attempting to maximize selected resources or regulate individual pollutants." [37]. IWM dealt with human activities in watersheds, driven by multiple goals or constraints, such as increased agricultural income and soil and water conservation, which could be utilized for multi-objective decision making (MODM) [38–43].

Previous researchers have investigated multi-objective decision making for watershed management in many ways using various strategies. Research on the application of multi-objective decision-making in the IWM process primarily involves the optimization of water resource allocation [44–47], water resource quality management [48–51], land use planning [40,52,53], best management practices [54–56], and other aspects [57,58]. Additionally, the rapid development of computer performance and mathematical optimization technologies have opened up new pathways for the efficient optimization of alternative IWM schemes. These techniques can improve the quality of the decision-making process in various areas with different management options. Meta-heuristic algorithms (genetic algorithms and harmony search) and their applications in hydrological science have been discussed and are considered to be an effective tool for the development of hydrological models and watershed management [59]. Mousavi et al. [60] presented a framework that linked the water evaluation and planning system simulation module, which benefited from rapid, single-period linear programming, to the multi-objective particle swarm optimization for multiperiod optimization. Some researchers have combined mathematical optimization algorithms with hydrological models and applied these to resolve multi-objective IWM decision making problems. Xu et al. [52] developed a spatially explicit integrated modeling approach based on the SWAT model and mixed integer programming to compare the effectiveness and economic efficiency of alternative spatially optimized land-use and -management strategies. Through an integrating of export coefficient model (ECM), interval parameter programming (IPP) and fuzzy parameter programming (FPP), a multi-objective model was developed to effectively address the multiple uncertainties expressed as discrete intervals and fuzzy membership functions [53]. Geng et al. [54] proposed an optimization methodology that employed a multi-objective sorting genetic algorithm combined with a SWAT model, which served as the nonpoint source pollution watershed model. Qi et al. [55] combined the AnnAGNPS model, CCHE1D model, and tabu search heuristic to optimize land use combinations at the watershed scale to improve the tradeoffs between watershed outputs and economic benefits. Therefore, the integration of watershed and economic models, and the optimization algorithm has been proven to be a feasible strategy toward the development of an improved multi-objective decision making solution.

This study employed the Peiqiao River watershed as the research area, which is a typical small watershed dominated by traditional agriculture, which spans the middle and lower reaches of the Yangtze River. We hypothesized that it might be possible to create an innovative strategy to effectively balance and optimize the environmental quality and economic benefits of this small agricultural watershed. Subsequently, we developed a multi-objective decision system (MDMS) for the coordination and optimization of multiple objectives to facilitate the integrated management process for the Peiqiao River watershed. The MDMS was established by coupling the hydrological model (AnnAGNPS), economic model (EBEM), and the improved tabu search algorithm (TS).

2. Materials and Methods

2.1. Description of MDMS

Multi-objective decision making methods can effectively coordinate a diverse set of issues and objectives that must be concomitantly attended to for efficient watershed management, including soil and water conservation, land planning, water quality safety, and economic benefits, etc., so as to build a balanced "bridge" between various issues and objectives. For this study, a multi-objective decision making system (MDMS) was developed to assist with the management and optimization of agricultural watershed in the Yangtze River Delta region. Different stakeholders can adjust or add objective functions and constraints according to their concerns, including those related to land erosion, water quality in rivers, agricultural practices, and economic development.

MDMS is a coupling system based on watershed process simulations and the evaluation of economic benefits, encompassing a hydrological model (employed for the simulation of watershed sediment yields and pollutant loads of key exports), an economic model (used to assess costs and benefits), and an improved meta-heuristic search algorithm (used to optimize the structure of land use) (Figure 1).

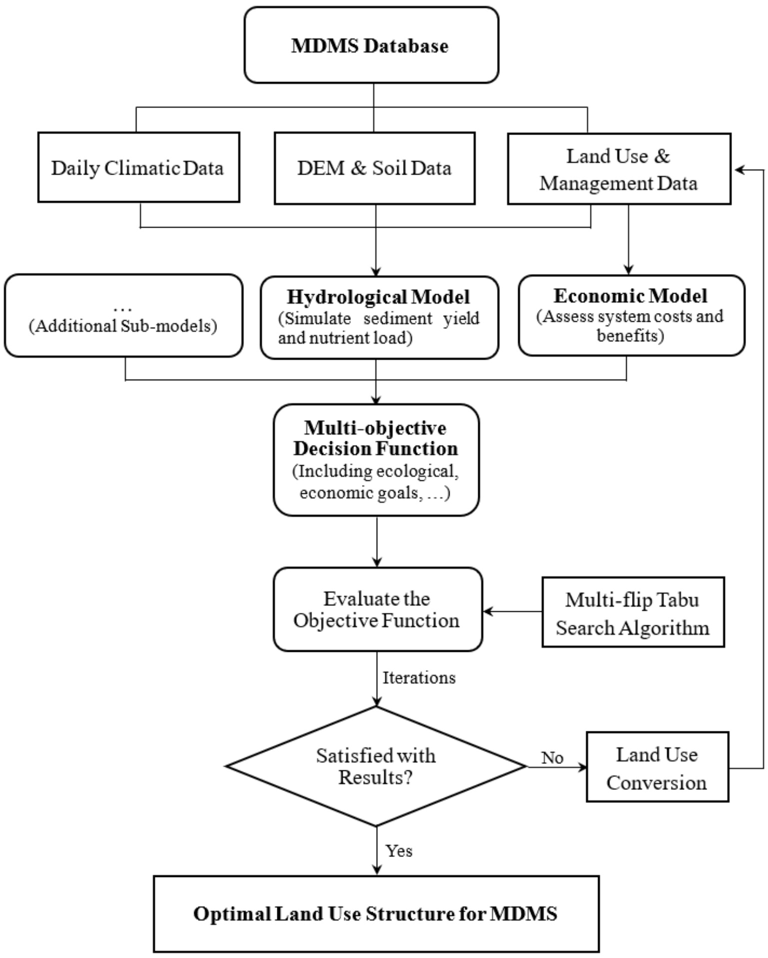
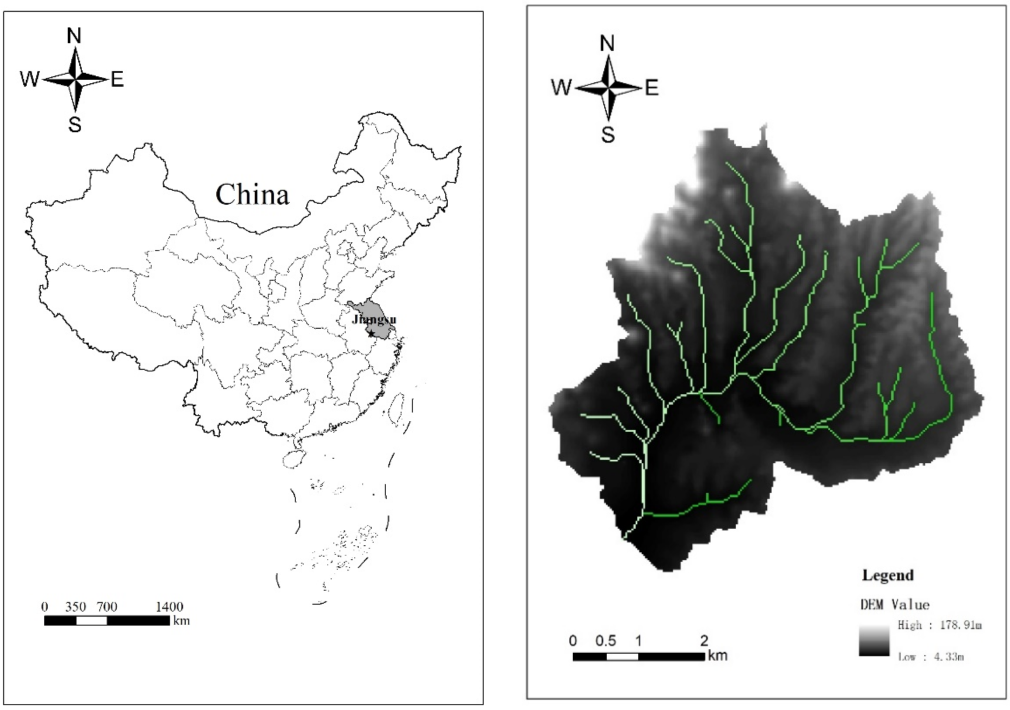


Figure 1. MDMS framework for agricultural land use optimization based on coupling modeling.

2.2. Study Area and Data

The Peiqiao River watershed is a typical crop farming agricultural watershed located in the transitional monsoon climate region between the North and Middle Subtropical regions. It belongs to the Shuiyang River system, with a total area of 34.85 km^2, where paddy fields and dry land areas occupy ~37% and 25%, respectively. The primary soil types include skeletal soil, yellow brown soil, red soil, limestone soil, percogenic paddy soil, and gleyed paddy soil. Influenced by monsoon circulation, this small watershed has four distinct seasons. The average precipitation from 2005–2018 was 1296.10 mm, which occurred mainly from June to September, and accounted for 52.82% of the annual rainfall. As shown in Figure 2, the Peiqiao River watershed is located in Gaochun District, Nanjing, Jiangsu Province, 31°13′~31°26′ N, 118°41′–119°21′ E. The DEM value of Peiqiao River watershed ranges from 4.33 m to 178.91 m.



(**a**) (**b**)

Figure 2. (**a**) Location of Peiqiao River watershed in China; (**b**) DEM feature of Peiqiao River watershed.

The coupling model requires a significant amount of basic data to support the simulation of watershed processes, encompassing topographic, soil, land use, meteorological, and land management data. The precision of the coupling model simulation is closely related to the accuracy of the acquired data. To ensure that the acquired data best reflected the characteristics of the small watershed and optimized the accuracy of the simulation, a considerable quantity of available field and survey data were collected for this study to examine its usability (Table 1).

Table 1. Classification and sources of the data inputs required for the MDMS coupling model.

No.	Model	Input Data Required	Data Source
1	AnnAGNPS	Topographic feature data	Nanjing Planning and Natural Resources Bureau
2		Land use data	Tillage Protection Station of Gaochun district, Nanjing
3		Soil basic data	Nanjing Planning and Natural Resources Bureau
4			Laboratory analysis
5		Soil hydrology grouping	Laboratory analysis
6		Meteorological data	Meteorological Bureau of Gaochun District, Nanjing
7		Agricultural management data	Tillage Protection Station of Gaochun District, Nanjing
8	EBE	Cost and benefit of agricultural land use	Data from Gaochun district yearbooks and Jiangsu Provincial Price Bureau

2.3. Methods

2.3.1. Coupling Simulation Models

Initially, for efficient scientific watershed management decisions, the simultaneous coupling of multiple model simulations that can meet the needs of different management objectives is required to simulate the watershed process for the real world, including a hydrological model "Annualized Agricultural Nonpoint Source (AnnAGNPS)" and an economic model "Economic Benefit Evaluation (EBE)". The two models are then combined to simulate water flow, sediment transport, pollutant loads, and cost benefits in a small watershed under different agricultural land use schemes. These results comprise the basic parameters for the formulation of the objective function. Based on the results of hydrological model calculations, decision-makers with different backgrounds can formulate objective functions to resolve issues of concern. According to the results of the agricultural sector survey, the main concerns of stakeholders involved in watershed management decisions include soil erosion, water quality, crop cultivation practices, and economic development.

(1) AnnAGNPS model

AGNPS is a watershed simulation tool that is employed to simulate and predict runoff, peak flow, as well as sediment and nutrient loads [61]. AnnAGNPS, which is an improved version of AGNPS that supports continuous day-based simulation and improved processing methods, has evolved into a powerful watershed simulation tool [62]. It has been widely used to successfully simulate hydrological, sediment, and nutrient transport at differently scaled watersheds to assist with the determination of BMPs, TMDLs, and risk and cost–benefit analyses [63–65]. Sediment yields calculated based on particle size levels, as well as nutrient (nitrogen, phosphorus, and organic carbon) concentrations, can be utilized to assess response practices to agricultural management in watersheds [66]. Based on the historical data of the study area (2008–2018), we calibrated and verified the AnnAGNPS model [67]. A differential sensitivity analysis (DSA) method was employed for parameter sensitivity analysis, and the applicability of the model was comprehensively evaluated using the correlation coefficient (R^2), efficiency coefficient (E), and relative error (E_R). The results showed that the calibrated AnnAGNPS model presented a credible simulation for the sediment, nitrogen, and phosphorus outputs of the Peiqiao River watershed.

(2) EBE model

Based on the relationships among land, water and economy, cost and benefit factors must be considered in the overall management and development of watersheds. Integrated watershed management implies a focus on the long-term economic returns and costs associated with agricultural production [68–70]. Therefore, watershed cost-effectiveness was assessed based on different land use activities. The EBE model was used to determine the net income of the watershed based on the agricultural activities under different land use structures, as shown in Equation (1). The estimation of total costs and benefits is an important component of the cost–benefit evaluation of integrated watershed management [71–73].

$$EBE = PB - MC \tag{1}$$

where: *EBE* is the net income of the watershed based on the agricultural activities, 10,000 yuan/ha; *PB* is the total revenue from agricultural production, 10,000 yuan/ha; *MC* is the total operating cost, 10,000 yuan/ha.

2.3.2. Multi-Objective Decision Function

(1) Environmental impact assessment function

According to the calculated results of the AnnAGNPS model, the environmental impact assessment function can be defined by the load values of sediments, nitrogen, and phosphorus pollutants. Environmental impacts involve multiple environmental factors of interest, where a weighted average method is employed to combine the values of individual environmental elements.

Since its evaluation involves multiple factors that affect the ecological environment, such as sediment, nitrogen, and phosphorus, the value of the overall ecological environment impact assessment function is shown in Equation (2).

$$f_p = \sum_{i=1}^{N_I} \omega_i \frac{p_i}{p_{i,\max}} \tag{2}$$

where: I: reference number of the involved environmental element, p_i: load of environmental element i, ω_i: weighting factor, which defines the relative importance of each environmental element in the overall environmental value ($\sum_i \omega_i = 1$), $p_{i,max}$: maximum output of environmental element i at the watershed outlet, f_p: environmental impact assessment value $0 < f_p \leq 1$.

(2) Economic benefit evaluation function

An economic module was employed to assess the cost-effectiveness of agricultural production on all agricultural land use types within the watershed. According to the *EBE* model (Equation (1)) and the current land use structure of the study area, the economic benefit evaluation function was constructed, as shown in Equation (3). The total operating cost (MC_x) and product benefit ($B_x Y_x$) of different agricultural land use types are shown in Table 2.

$$f_b = \sum_{f=1}^{N_f} A_f B_x Y_x - \sum_{f=1}^{N_f} A_f (MC_x) \tag{3}$$

where: f_b: economic income of the current land use structure of the watershed, 10,000 yuan; f: cell (land unit) number, f = 1,2,3..., N_f; x, y: land use type number. (x, y = 1,2,3, . . . ,X); A_f: area of cell f, ha; B_x: benefit from production of land use type x, 10,000 yuan/t; Y_x: crop yield of land use type x, t/ha; MC_x: total operating cost of land use type x, 10,000 yuan/ha.

Table 2. Costs and benefits of different crop planting methods in different cultivated land types.

Types of Agricultural Land Use			Cost (¥10^4/ha)	Production Benefit (¥10^4/ha)
paddy field	LU_1	rice (summer), wheat (winter)	2.18	3.92
	LU_2	rice (summer), rape (winter)	2.06	3.98
	LU_3	rice (summer), corn (spring)	1.95	4.70
	LU_4	soybean (summer), wheat (winter)	1.46	2.55
	LU_5	soybean (summer), rape (winter)	1.33	2.60
	LU_6	soybean (summer), corn (spring)	1.22	3.32
dry land	LU_7	corn (autumn), wheat (winter)	1.79	2.88
	LU_8	corn (autumn), rape (winter)	1.67	2.93
	LU_9	soybean (summer), wheat (winter)	1.52	2.16
	LU_10	soybean (summer), rape (winter)	1.39	2.21
	LU_11	sweet potato (spring), rape (winter)	2.93	5.01
	LU_12	sweet potato (spring), wheat (winter)	3.05	4.96

Following the change of land use structure in the small watershed, the economic benefit evaluation function value f_e was calculated based on a group of binary variables (Equation (4)).

$$f_e = f_b + \sum_{f=1}^{N_f} V_{f,x,y} A_f [(B_y Y_y - B_x Y_y) - (MC_y - MC_x)] \tag{4}$$

where, the change of binary variable indicated whether the land use in cell f changed from type x to y, and only one type could be selected by transformation. Therefore, $V_{f,x,y} \in$ [1], $x \neq y$ needed to be satisfied. In the above equation, only non-zero $V_{f,x,y}$ were considered (Equation (5)).

$$\sum_{\substack{x=1 \\ x \neq y}}^{X} V_{f,x,y} \leq 1,\ f = 1, 2, \ldots, N_f \tag{5}$$

where, the land use type of any cell changed from x to y, $V_{f,x,y}$ = 1; or if the cell did not change, then $V_{f,x,y}$ = 0.

(3) Total objective function

As shown in Equation (6), the multi-objective function F was constructed by combining the environmental impact assessment and economic benefit evaluation functions using the exponential weighting method, which was proposed by Zadeh [74] to overcome the inability of the weighted sum method to capture points on the nonconvex portions of the Pareto optimal surface. The exponential weighting method was verified to be an effective method to construct the objective function in the multi-objective decision management of the watershed [75].

$$Max\ F = (1 - f_p) \exp[S_e(f_e - f_b)] \tag{6}$$

where: S_e is the constant to measure the cost constraint strength. In this test case, S_e = 1×10^{-2} was the most appropriate value. If ($f_e - f_b$) was positive (net economic benefit was profitable, which was favorable for such land use structure), then $\exp[S_e(f_e - f_b)]$ was slightly more than 1. If ($f_e - f_b$) was negative (net economic benefit was a loss, which was rejective for such land use structure), then $\exp[S_e(f_e - f_b)]$ was slightly less than 1.

2.3.3. Improved Meta-Heuristic Search Algorithm

A multi-flip Tabu Search algorithm (MTSA) based on C++ was designed to optimize the structure of agricultural land in the study area. Following the TOPAGNPS treatment of the DEM data in AnnAGNPS, 88 cells were obtained in the study area. The land use options of the paddy field and the dry land in the agricultural land were LU_1–6 and

LU_7–12, respectively. There were $6^{88} \times 6^{88}$ potential alternatives of land use structure in the study area.

First, a set of binary variables (0/1) was used to model the land use structure change. MTSA guided a local heuristic search process to explore the solution space, which is a search that uses an operation called "move" to define any given solution neighborhood. MTSA guided a local heuristic search process to explore the solution space, which defined the search in any given solution neighborhood via an operation called "move". For example, in the process of optimizing the current land use structure, "move" could be defined as the transformation of the cell's land use type, then the binary variable $V_{f,x,y}$ was transformed from 0 to 1 (or back from 1 to 0), which indicated that cell f (f = 1, 2, 3..., N_f) changed from type x to y.

If the current land use type x = 4 for cell was 1 (f = 1), and there were five future land use options (y = 1, 2, 3, 5, 6), then there would be five binary land change variables, named $V_{1,4,1}$, $V_{1,4,2}$, $V_{1,4,3}$, $V_{1,4,5}$, and $V_{1,1,6}$. If the future land use type y = 2 was selected, $V_{1,4,2}$ would be transformed to 1, then $V_{1,4,1}$, $V_{1,4,3}$, $V_{1,4,5}$, and $V_{1,1,6}$ were all equal to 0 (Figure 3). All land use type transformations of the remaining cells were defined in this way.

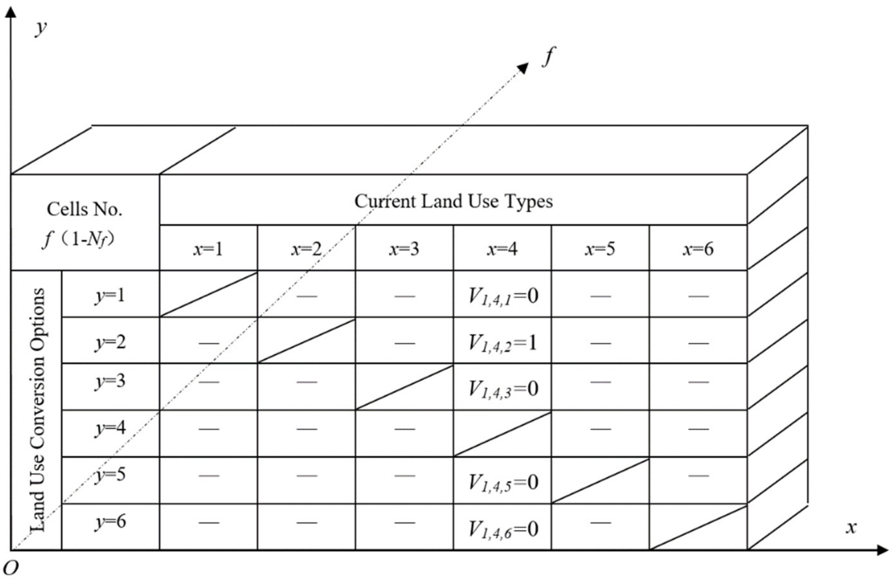


Figure 3. Binary transformation for land use type of cell f.

Secondly, the parameter setting of MTSA were set as follows:

(1) Selection of the initial solution: current land use structure. This step is the initialization running of integrated model system. Set all land change variables $V_{f,x,y}$ to 0, initialize the tabu list, and run the integrated model to obtain the objective function value for the base line scenario;

(2) Way to explore the solution domain: randomly start to explore the solution domain with multiple structures, diversified movement modes such as "select move"(Equation (7)), "cancel move" (Equation (8)) and "switch move" (Equation (9)) were adopted.

$$V_{f,x,y} : [0 \to 1], f = 1, 2, \cdots, N_f, y \in (1, X) \textit{ and } y \neq x \tag{7}$$

$$V_{f,x,y} : [1 \to 0], f = 1, 2, \cdots, N_f, y \in (1, X) \textit{ and } y \neq x \tag{8}$$

$$\begin{gathered} V_{f,x,y} : [0 \to 1], f = 1, 2, \cdots, N_f, y \in (1, X) \textit{ and } y \neq x \\ V_{f,x,y'} : [1 \to 0], f = 1, 2, \cdots, N_f, y' \in (1, X) \textit{ and } y' \neq x, y' \neq y \end{gathered} \tag{9}$$

(3) Length of the candidate list: 30;

(4) Number of iterations: 600;

(5) Optimal solution of the candidate set and the global optimal solution, etc.

3. Results

3.1. Objective Function Value and Iterations

Based on the MinGW5.3.0 component in QT-OpenSource-Windows-x86-5.11.1, this study used C++ to implement MTSA, and performed a six-year (2013–2018) simulation on the computer with Intel(R) Core(TM) I7-4700MQ CPU@2.40GHz, Win 7 64 bit and 16 GB of memory. The entire simulation process required ~7.99 h, where most of the computation time was occupied by AnnAGNPS, and the time consumed by optimization was negligible.

The initial value, optimal value, and change rate of each objective function changed in different directions and amplitude in the overall iteration process (Table 3). The optimal value of sediment yield per unit area (SYU), nitrogen yield per unit area (NYU), and phosphorus yield per unit area (PYU) and f_p (overall ecological environment impact assessment function value), were all reduced by 6.68%, 4.74%, 7.03%, and 6.13%, respectively. Both the economic benefit evaluation function value (f_e) and total objective function value (F) increased by 15.28% and 27.56%, respectively, which were significantly higher than the decreased amplitude of the environment impact factors. The optimizing amplitude of the optimal values of f_e and F were 2.5 and 4.5 times that of f_p, respectively. Further, the improvement in economic benefits were obvious under this scenario with a small reduction in environmental pollution. In addition, with the introduction of a more cost-effective land use optimization scheme in the watershed, the total objective function value F tended to increase.

Table 3. Initial, optimal value, and variation of each objective function.

Objective Function Value	SYU	NYU	PYU	f_p	f_e (¥10^4)	F
Initial value	0.7781	0.894	0.7345	0.7998	3275.38	0.2003
Optimal value	0.7261	0.8516	0.6829	0.7508	3775.78	0.2555
Variation (%)	−6.68	−4.74	−7.03	−6.13	15.28	27.56

With the continuation of the iteration, the search process of MTSA converged rapidly, and the optimal solution was obtained at the 388th iteration (Figure 4). As a function of the iteration numbers of the search process SYU, NYU, PYU, f_p, f_e, and F continuously cooperated with each other according to the setting during the iteration process to seek the maximum value (optimal solution) of the total objective function. In this process, the individual environmental impact factors (SYU, NYU, PYU) and overall ecological environment impact assessment function (f_p) showed a downward oscillation trend.

After 318 iterations, f_p began to move near the optimal value and no longer decreased, and the trends of SYU, NYU, and PYU were similar to f_p. This revealed that with the iterative optimization of the algorithm, the output of sediment, total nitrogen and phosphorus loads of the small watershed presented a decreasing trend, but not unlimited decline. This was aligned with the optimization design of the overall objective function. Conversely, the economic benefit evaluation function value (f_e) demonstrated an overall rising oscillation rise trend, where f_e attained a maximum value at the 343rd iteration. Subsequently, to maximize the common goal between the economic benefit evaluation function and the environmental impact assessment function, f_e continued to seek optimization, and weighed to the value of 34.16 million yuan at the 437th iteration.

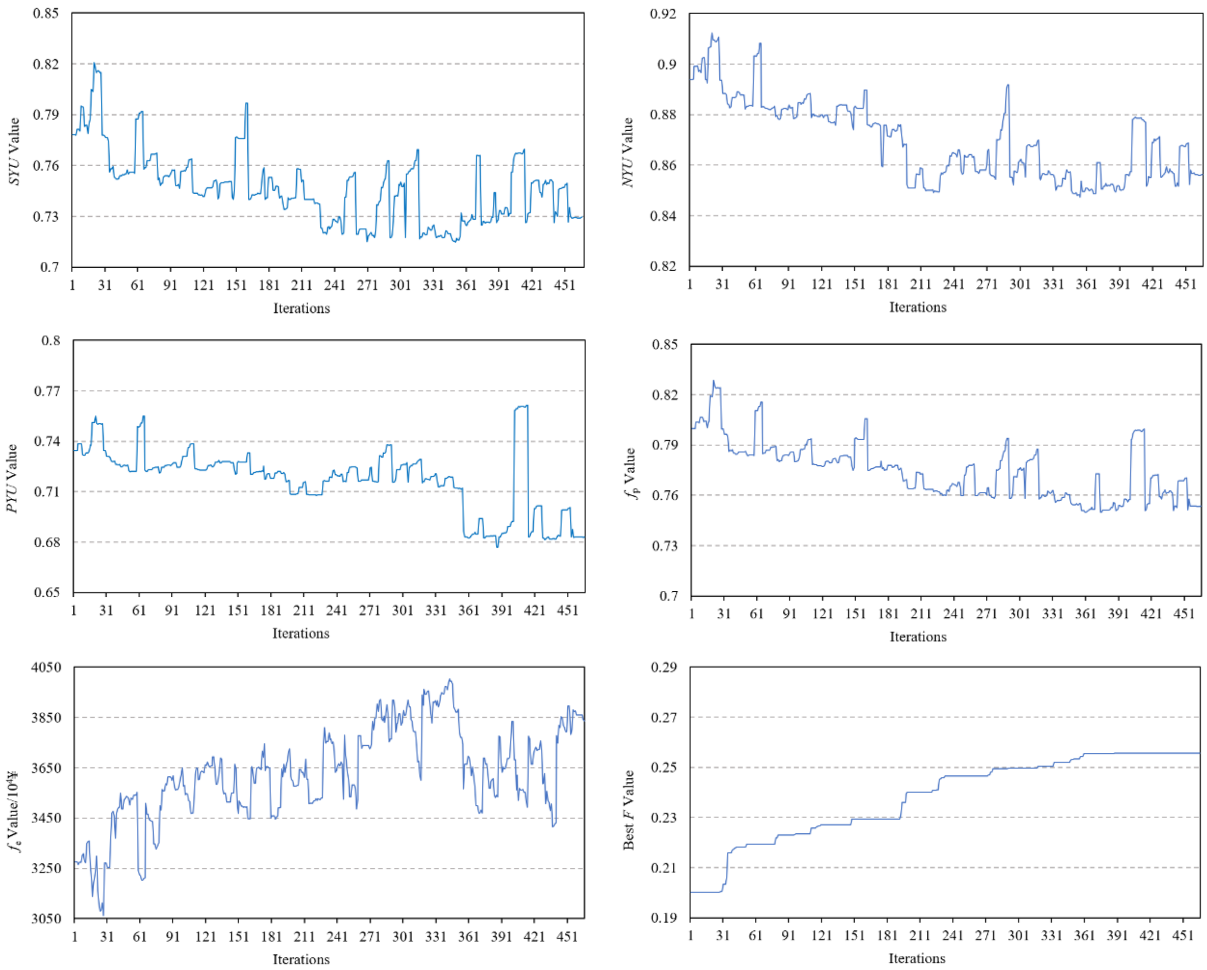


Figure 4. The value of each objective function changed with the MTSA iteration.

3.2. Variation of Land Use Area after Optimization

Following the MTSA optimization, the 12 types of agricultural land utilization areas varied differently (Table 4). The agricultural land types with enlarged areas following optimization included four land use types (LU_12 > LU_6 > LU_1 > LU_3). LU_12 in the dry land increased the most, from 0 to 312.21 ha, followed by LU_6 with 123.02%. LU_1 and LU_3 also increased by 89.92% and 56.30%, respectively. On the other hand, agricultural land types with decreased areas following optimization included eight land use types (LU_10 > LU_5 > LU_2 > LU_11 > LU_9 > LU_8 > LU_4 > LU_7).

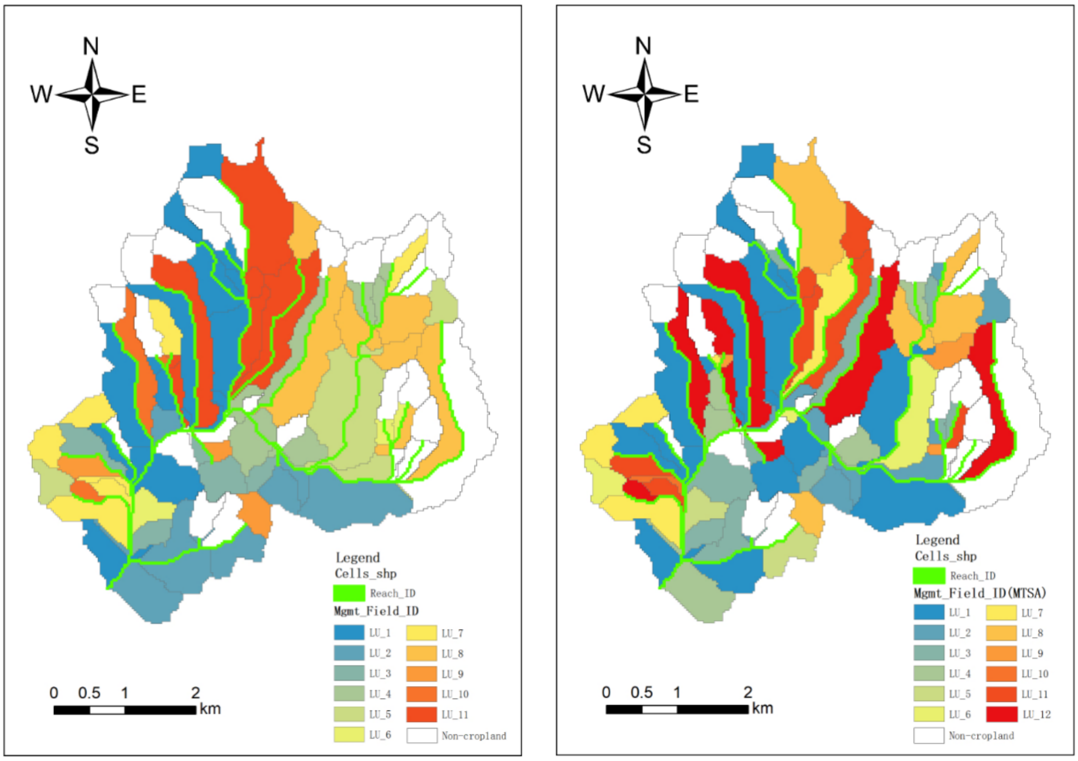
Table 4. Variation of each agricultural land type area following optimization.

Types of Agricultural Land Use			Initial Area (ha)	Optimal Area (ha)	Rate (%)	Ratio (%)
paddy field	LU_1	rice (summer), wheat (winter)	395.46	618.12	56.30	52.85
	LU_2	rice (summer), rape (winter)	297.18	115.20	−61.24	9.85
	LU_3	rice (summer), corn (spring)	92.88	176.40	89.92	15.08
	LU_4	soybean (summer), wheat (winter)	143.82	122.76	−14.64	10.50
	LU_5	soybean (summer), rape (winter)	202.77	53.46	−73.64	4.57
	LU_6	soybean (summer), corn (spring)	37.53	83.70	123.02	7.16
dry land	LU_7	corn (autumn), wheat (winter)	146.70	139.59	−4.85	16.28
	LU_8	corn (autumn), rape (winter)	279.63	219.15	−21.63	25.56
	LU_9	soybean (summer), wheat (winter)	53.55	28.17	−47.39	3.29
	LU_10	soybean (summer), rape (winter)	53.82	6.12	−88.63	0.71
	LU_11	sweet potato (spring), rape (winter)	323.73	152.19	−52.99	17.75
	LU_12	sweet potato (spring), wheat (winter)	0	312.21	-	36.41

In particular, all of the LU_7-LU_11 areas in the dry land decreased, where LU_10 decreased the most, followed by LU_11 and LU_9, and all decreased areas were converted to LU_12. However, LU_5, LU_2, and LU_4 had the largest decreases in the paddy fields. The decreased areas were converted to the other three types in paddy fields, respectively, where the largest increase after the area conversion was LU_1, followed by LU_3.

After transitioning to the optimal solution, the proportion of the land type area in the dryland was ranked from large to small as LU_12 > LU_8 > LU_11 > LU_7 > LU_9 > LU_10. That is, LU_12 occupied the largest proportion of the dry land area, reaching 36.41%, and LU_10 occupied the smallest proportion, at only 0.71%. The proportion of land type areas in the paddy fields, from large to small was LU_1 > LU_3 > LU_2 > LU_4 > LU_6 > LU_5. That is, LU_1 occupied the largest proportion of the paddy fields, reaching 36.41%, whereas LU_5 occupied the smallest proportion, at only 4.57%.

The initial and optimal land use structures of agricultural land are shown in Figure 3. Compared with the initial land use structure, 54 cells changed their land use type, while the remaining 34 cells remained unchanged. LU_12 was a new land use type that was not used previously in the dry land of the Peiqiao River watershed. The introduction of this new land use type not only helped to reduce water quality degradation, but also added ~5.95 million yuan of economic benefits to the watershed. Furthermore, by comparing the agricultural land use structure prior to and following optimization (Figure 5), decision-makers could identify the 54 cells in the small watershed that played important roles in the total cost effectiveness. This assisted in the realization of the optimal agricultural land use structure for the integrated water and soil conservation management of the Peiqiao River watershed.



(**a**) (**b**)

Figure 5. Initial (**a**) and optimal (**b**) land use structure for the Peiqiao River watershed.

4. Discussion

The current environmental situation in China strongly demands the accelerated development of watershed management technologies, particularly to effectively enhance the overall benefits of integrated management [28]. To meet these technical requirements, the proposed approach was tested using a hypothetical land-use management study for the Peiqiao River watershed. We developed a multi-objective decision system (MDMS) based on the optimization of land use structures, which could simultaneously deal with the multiple issues and objectives involved in the integrated management of small watersheds, such as sediment yields, nutrient loads, costs, and benefits.

Based on different research objectives and available data, researchers can select different watershed models, economic models and optimization algorithms. Geng et al. [54] also selected the SWAT model as the watershed model to help develop and utilize a BMP database that included BMP reduction efficiencies and costs, and the optimization algorithm combined with the SWAT model is a multi-objective sorting genetic algorithm (NSGA-II). Liu et al. [56] combined the SWAT model with the shuffled frog leaping algorithm (SFLA) for recommending the BMP maintenance-replacement strategies and optimizing the BMP configuration. However, some studies selected AnnAGNPS as the watershed model. Altinakar et al. [76] proposed a multi-objective optimization method of agricultural land use-management, based on the AnnAGNPS watershed model. Qi et al. [40] combined the AnnAGNPS with CCHE1D model to manage the agriculture-induced water quality problems based on the design of vegetation buffer strips. Srivastava et al. [75] also selected AnnAGNPS as a watershed model to help optimize the selection of best management practices on a field-by-field basis for an entire watershed. In MDMS, we selected AnnAGNPS to simulate sediment transport, nitrogen, and phosphorus loads in a small watershed under different management schemes. With the development of spatially distributed hydrological watershed models, such as AnnAGNPS, SWAT, and InVEST, many studies have focused on simulating the impacts of changes in land use structures during different periods of runoff, sediment transport, and nutrient loading [40,66]. Although these models employed similar datasets to compute runoff, soil erosion, and nutrient loads, such as rainfall, soil, elevation data, and land use maps, there were differences in the methodologies of how these data were utilized in these models. For the AnnAGNPS model, all cells modeled in the watershed possessed unique properties, where sediments and the nutrients deposited within them, or transported out the channel system, began from each cell. Their respective loads were identified at source and tracked as they passed through the watershed system [62]. The SWAT model has a good physics-based BMPs simulation module that is employed to predict the pollutant reduction and removal process, where the hydrological response unit (HRU) in SWAT is only a branch unit under the image. However, the spatial location of HRU cannot be recognized; thus, runoff, sediments, and nutrients cannot be transported between HRUs [66]. The InVEST model is relatively simple, with low resolution data demands, and is primarily employed to simulate large-scale watersheds [77]. Conversely, the AnnAGNPS model is superior to the SWAT model in efficacy, primarily because the SWAT model needs to work with ArcGIS, and the run time of each land use flip iteration calculation is much longer than that of the AnnAGNPS model.

In the optimization algorithm, Altinakar et al. [76] and Qi et al. [40,78] developed a multi-objective optimization of agricultural land use-management using a Tabu search method based on a coupled simulation of AnnAGNPS watershed model and CCHE1D channel network model, and they obtained a reliable result as verification. Srivastava et al. [75] integrated genetic algorithm (GA) with AnnAGNPS to optimize the selection of best management practices on a field-by-field basis for an entire watershed. Previous studies have tended to select the GA as the primary optimization algorithm, since it provided improved BMPs placement scenarios associated with the reduction in nutrient loadings and operating costs than the random assignment of BMPs [54,75]. Nevertheless, the selection process of GA's emphasizes randomness rather than responsive exploration, as GA is a heuristic search method based on probability, rather than deterministic search rules [79]. As the types of alternative planting and management practices and the number of field plots increased, the definition process became complex and required a large amount of computer time and memory to store the representations. This process was highly problem-specific and could not automatically adapt itself to new problems. However, the tabu list in Tabu Search was helpful toward preventing movement toward non-improvement, such that the continuous scene became increasingly optimized. By accepting a non-improved solution, Tabu Search could move to a neighboring solution and preserve an optimal solution while looking for a better one. Tabu Search could transition from a local optimal solution and search for an improved optimal solution. We used the Tabu Search algorithm to implement the automatic generation, analysis, and iterative optimization of scenarios following land use flips, so as to identify optimal land use structure allocations, while obtaining the maximum comprehensive management benefits of small watershed ecosystems.

Although this study demonstrated a key support for the integrated management decision making of water and soil conservation for a small agricultural watershed by providing a system framework and a programmed decision support tool, there remain several issues to be improved in this study. Due to the limitations in data acquisition, only the DEM data with a resolution of 30 m * 30 m were obtained, which could meet the basic requirements of this study. If conditions permit, the DEM data with a higher resolution would be conducive toward a more accurate hydrological simulation of the small watershed. In addition, due to the limited available data on agricultural economics, only a simple mathematical model could be established for the cost–benefit analysis and evaluation, and the average price of the surveyed years was used in this study. However, for the real evaluation of agricultural production, crop seed prices, fertilizer, agricultural products, and the rental of farm machinery can change according to market dynamics. Future studies might integrate more complex economic models based on dynamic market data to better assist with multi-objective decision making toward the integrated management of water and soil conservation in small agricultural watersheds.

5. Conclusions

This study focused on integrated management technology research and developed MDMS for small agricultural watersheds in the middle and lower reaches of the Yangtze River. Initially, MDMS simulated the changes of environmental and economic factors under different land use structures in a small watershed by coupling AnnAGNPS and EBE models, and then designed MTSA to complete the automatic generation, analysis, and iterative optimization of land use scenarios.

Our results demonstrated that MDMS successfully obtained an optimal scenario from a large number of alternative agricultural land use structures with relatively high time efficiency. The entire simulation process required ~7.99 h of computer time, with an Intel(R) Core(TM) I7-4700MQ CPU@2.40GHz, Win 7 64 bit, and 16 GB of memory. Most of the computation time was occupied by AnnAGNPS, whereas the time consumed by optimization was negligible. The yields of sediments, nitrogen, and phosphorus decreased by 4.74%, 7.03%, and 6.13%, respectively, whereas the economic benefits increased by 15.28%. It was obvious that the MDMS improved the economic benefits of a small agricultural watershed, while effectively controlling the negative impacts of crop cultivation on the environment.

By employing the small watershed as the basic management unit, based on the coupling model simulation combined with an improved meta-heuristic search algorithm, MDMS established a "bridge" between various issues and objectives of a small agricultural watershed model, and integrated multiple objectives and management constraints into an intelligent optimization system. Therefore, the MDMS developed in this study would have the capacity to facilitate multi-objective decision making for the small agricultural watershed in the middle and lower reaches of the Yangtze River.

As a basic strategy for soil and water conservation in China, small watersheds are regarded as units of soil and water loss control, ecological improvement, and economic development [80]. With the rapid development of agriculture in the watershed, humans must face the contradiction between environmental protection and economic development. Intelligent decision making systems, such as MDMS, can be utilized as a problem-solving environment for watershed management. Decision makers can also adjust or add objective functions and related constraints according to the concerns of different stakeholders. Such a decision making system effectively coordinates the multiple problems and objectives that must be paid attention to simultaneously in watershed management, including soil erosion, land use, water quality safety, and economic benefits, etc., and build a "bridge" of trade-offs between the various problems and objectives. Consequently, with the assistance of decision making systems, decision makers can make scientific decisions with multi-tradeoffs in the integrated management of soil and water conservation in small watersheds, rather than adopting traditional and single large watershed planning and evaluation methods, or designing specific optimization strategies according to fixed goals and constraints.

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References

1. Postel, S.L.; Daily, G.C.; Ehrlich, P.R. Human Appropriation of Renewable Fresh Water. *Science* **1996**, *271*, 785–788. [CrossRef]
2. Dorf, R.C. Chapter 1—Sustainability, Economics, and the Environment. In *Technology, Humans, and Society*; Academic Press: San Diego, CA, USA, 2001; pp. 1–37. [CrossRef]
3. Gleick, P.H. Global Freshwater Resources: Soft-Path Solutions for the 21st Century. *Science* **2003**, *302*, 1524–1528. [CrossRef]
4. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global Consequences of Land Use. *Science* **2005**, *309*, 570–574. [CrossRef]
5. Vörösmarty, C.J.; McIntyre, P.B.; Gessner, M.O.; Dudgeon, D.; Prusevich, A.; Green, P.; Glidden, S.; Bunn, S.E.; Sullivan, C.A.; Liermann, C.R.; et al. Global threats to human water security and river biodiversity. *Nature* **2010**, *467*, 555–561. [CrossRef]
6. Hazell, P.B.R.; Wood, S. Drivers of Change in Global Agriculture. *Philos. Trans. R. Soc. B Biol. Sci.* **2007**, *363*, 495–515. [CrossRef] [PubMed]
7. Karki, R.; Tagert, M.L.M.; Paz, J.O.; Bingner, R.L. Application of AnnAGNPS to model an agricultural watershed in East-Central Mississippi for the evaluation of an on-farm water storage (OFWS) system. *Agric. Water Manag.* **2017**, *192*, 103–114. [CrossRef]
8. Li, Y.; Tang, C.; Huang, Z.; Hussain, Z.; Are, K.S.; Abegunrin, T.P.; Qin, Z.; Guo, H. Increase in farm size significantly accelerated stream channel erosion and associated nutrient losses from an intensive agricultural watershed. *Agric. Ecosyst. Environ.* **2020**, *295*, 106900. [CrossRef]
9. Thornton, J.A.; Rast, W.; Holland, M.M.; Jolankai, G.; Ryding, S.-O. *Assessment and Control of Nonpoint Source Pollution of Aquatic Ecosystems: A Practical Approach*, 1st ed.; Informa Healthcare: New York, NY, USA, 1999; pp. 296–299.
10. A Martínez-Casasnovas, J.; Sánchez-Bosch, I. Impact assessment of changes in land use/conservation practices on soil erosion in the Penedès–Anoia vineyard region (NE Spain). *Soil Tillage Res.* **2000**, *57*, 101–106. [CrossRef]
11. Ouyang, W.; Jiao, W.; Li, X.; Giubilato, E.; Critto, A. Long-term agricultural non-point source pollution loading dynamics and correlation with outlet sediment geochemistry. *J. Hydrol.* **2016**, *540*, 379–385. [CrossRef]
12. Alilou, H.; Rahmati, O.; Singh, V.P.; Choubin, B.; Pradhan, B.; Keesstra, S.; Ghiasi, S.S.; Sadeghi, S.H. Evaluation of watershed health using Fuzzy-ANP approach considering geo-environmental and topo-hydrological criteria. *J. Environ. Manag.* **2019**, *232*, 22–36. [CrossRef] [PubMed]
13. Karan, S.K.; Ghosh, S.; Samadder, S.R. Identification of spatially distributed hotspots for soil loss and erosion potential in mining areas of Upper Damodar Basin—India. *Catena* **2019**, *182*, 104144. [CrossRef]
14. Baginska, B.; Milne-Home, W.; Cornish, P. Modelling nutrient transport in Currency Creek, NSW with AnnAGNPS and PEST. *Environ. Model. Softw.* **2003**, *18*, 801–808. [CrossRef]
15. Anctil, F.; Filion, M.; Tournebize, J. A neural network experiment on the simulation of daily nitrate-nitrogen and suspended sediment fluxes from a small agricultural catchment. *Ecol. Model.* **2009**, *220*, 879–887. [CrossRef]

16. Yuan, Y.; Mehaffey, M.H.; Lopez, R.D.; Bingner, R.L.; Bruins, R.; Erickson, C.; Jackson, M.A. AnnAGNPS Model Application for Nitrogen Loading Assessment for the Future Midwest Landscape Study. *Water* **2011**, *3*, 196–216. [CrossRef]
17. Xu, Y.; Chen, Z.; Wu, Y.; Zhu, Y.; Li, P. Advances on Agricultural Non-point Source Pollution and the Control in Regions around Hungtse Lake. *J. Nanjing For. Univ. (Nat. Sci. Ed.)* **2016**, *40*, 1–8. (In Chinese)
18. Gudino-Elizondo, N.; Biggs, T.W.; Bingner, R.L.; Langendoen, E.J.; Kretzschmar, T.; Taguas, E.V.; Taniguchi-Quan, K.T.; Liden, D.; Yuan, Y. Modelling Runoff and Sediment Loads in a Developing Coastal Watershed of the US-Mexico Border. *Water* **2019**, *11*, 1024. [CrossRef]
19. Pulighe, G.; Bonati, G.; Colangeli, M.; Traverso, L.; Lupia, F.; Altobelli, F.; Marta, A.D.; Napoli, M. Predicting Streamflow and Nutrient Loadings in a Semi-Arid Mediterranean Watershed with Ephemeral Streams Using the SWAT Model. *Agronomy* **2019**, *10*, 2. [CrossRef]
20. Hua, W.; Huaiyu, Y.; Fengnian, Z.; Bao, L.; Wei, Z.; Yeye, Y. Dynamics of nutrient export from the Yangtze River to the East China sea. *Estuarine Coast. Shelf Sci.* **2019**, *229*, 106415. [CrossRef]
21. Yan, R.; Li, L.; Gao, J. Framework for quantifying rural NPS pollution of a humid lowland catchment in Taihu Basin, Eastern China. *Sci. Total. Environ.* **2019**, *688*, 983–993. [CrossRef]
22. Jin, S.; Niu, K.; Han, D. The Path of Agricultural Green Development and Its Orientation in the 14th Five-Year Plan Period. *Reform* **2020**, *2*, 30–39. (In Chinese)
23. Ministry of Water Resources. China River Sediment Bulletin 2018. Available online: http://www.mwr.gov.cn/sj/tjgb/zghlnsgb/201906/t20190618-1342326.html (accessed on 25 June 2020).
24. Changjiang Water Resources Commission. Notice on Soil and Water Conservation in the Yangtze River Basin in 2018. Available online: http://www.cjw.gov.cn/zwzc/bmgb/2018gb/ (accessed on 26 June 2020).
25. Yang, G.; Yu, X.; Li, H.; Zhu, J. The Course, Experience and Prospect of Integrated Watersheds Management. *J. Lake Sci.* **2004**, *16*, 1–10. (In Chinese)
26. Yang, G. Water Issues in the Yangtze River and Its formation Causes and Controlling Strategies. Resour. Environ. *Yangtze Basin* **2012**, *21*, 821–830. (In Chinese)
27. Yang, G.; Yu, X.; Li, H.; Gao, J. *Introduction to Integrated Watershed Management*; Science Press: Beijing, China, 2013.
28. Chen, Y.; Wang, Y.; Li, L.; Yu, X. *Research on Integrated Management Strategy of Chinese River Basin*; Science Press: Beijing, China, 2016.
29. Yin, W.; Hu, D.; Fan, P. Analysis and Countermeasure of Existing Problems in River Basin Water Environmental Management in China. *Pollut. Control Technol.* **2017**, *30*, 80–83. (In Chinese)
30. Liu, J.; Dietz, T.; Carpenter, S.R.; Alberti, M.; Folke, C.; Moran, E.; Pell, A.N.; Deadman, P.; Kratz, T.; Lubchenco, J.; et al. Complexity of Coupled Human and Natural Systems. *Science* **2007**, *317*, 1513–1516. [CrossRef]
31. Palmer, M.A. Beyond infrastructure. *Nat. Cell Biol.* **2010**, *467*, 534–535. [CrossRef]
32. Cheng, G.; Li, X. Integrated research methods in watershed science. *Sci. China Earth Sci.* **2015**, *58*, 1159–1168. [CrossRef]
33. Zou, R.; Guo, H.; Chen, B. A Multiobjective Approach for Integrated Environmental Economic Planning Under Uncertainty. *Civ. Eng. Environ. Syst.* **2000**, *17*, 267–291. [CrossRef]
34. Zhang, Z.; Guo, H.; Chen, B.; Zhang, B. An Inexact Multi-objective Economic-environmental Planning Model for Hemoluo Region, Xinjiang. *J. Basic Sci. Eng.* **2001**, *9*, 33–42. (In Chinese)
35. Li, X.; Cheng, G.; Lin, H.; Cai, X.; Fang, M.; Ge, Y.; Hu, X.; Chen, M.; Li, W. Watershed System Model: The Essentials to Model Complex Human-Nature System at the River Basin Scale. *J. Geophys. Res. Atmos.* **2018**, *123*, 3019–3034. [CrossRef]
36. Bulkley, J.W. Integrated Watershed Management: Past, Present, and Future. *J. Contemp. Wat. Res. Edu.* **1995**, *100*, 3–15.
37. Ballweber, J.A. Prospects for Comprehensive, Integrated Watershed Management under Exiting Law. *Water Resour. Update* **1995**, *100*, 19–27.
38. Wang, L.; Meng, W.; Guo, H.; Zhang, Z.; Liu, Y.; Fan, Y. An Interval Fuzzy Multiobjective Watershed Management Model for the Lake Qionghai Watershed, China. *Water Resour. Manag.* **2006**, *20*, 701–721. [CrossRef]
39. Ballweber, J.A. A Critique of Watershed Management Efforts in the Lower Mississippi Alluvial Plain. *JAWRA J. Am. Water Resour. Assoc.* **1999**, *35*, 643–654. [CrossRef]
40. Qi, H.; Altinakar, M.S. Integrated Watershed Management with Multiobjective Land-Use Optimizations under Uncertainty. *J. Irrig. Drain. Eng.* **2013**, *139*, 239–245. [CrossRef]
41. Cobourn, J.; Lewis, S.R. Integrated watershed management and floodplain protection on the carson river in the western usa. *Int. J. Environ. Impacts: Manag. Mitig. Recover.* **2018**, *1*, 221–231. [CrossRef]
42. Brombal, D.; Niu, Y.; Pizzol, L.; Moriggi, A.; Wang, J.; Critto, A.; Jiang, X.; Liu, B.; Marcomini, A. A participatory sustainability assessment for integrated watershed management in urban China. *Environ. Sci. Policy* **2018**, *85*, 54–63. [CrossRef]
43. Gessesse, T.A.; Khamzina, A.; Gebresamuel, G.; Amelung, W. Terrestrial carbon stocks following 15 years of integrated watershed management intervention in semi-arid Ethiopia. *Catena* **2020**, *190*, 104543. [CrossRef]
44. Lee, K.S.; Chung, E.-S.; Chung, E.-S. Development of integrated watershed management schemes for an intensively urbanized region in Korea. *HydroResearch* **2007**, *1*, 95–109. [CrossRef]
45. Ye, Q.; Li, Y.; Zhuo, L.; Zhang, W.; Xiong, W.; Wang, C.; Wang, P. Optimal Allocation of Physical Water Resources Integrated with Virtual Water Trade in Water Scarce Regions: A Case Study for Beijing, China. *Water Res.* **2018**, *129*, 264–276. [CrossRef]

46. Zhang, X.; Dong, Z.; Song, R.; Han, R.; Xu, B.; Luo, Y. Multi-objective Optimization Model of Water Resource Allocation for Mainstream Channel Segment of Yellow River Basin. *J. Yangtze River Sci. Res. I* **2017**, *34*, 18–22. (In Chinese)
47. Alamanos, A.; Latinopoulos, D.; Loukas, A.; Mylopoulos, N. Comparing Two Hydro-Economic Approaches for Multi-Objective Agricultural Water Resources Planning. *Water Resour. Manag.* **2020**, *34*, 4511–4526. [CrossRef]
48. Behmel, S.; Damour, M.; Ludwig, R.; Rodríguez, M. Participative approach to elicit water quality monitoring needs from stakeholder groups—An application of integrated watershed management. *J. Environ. Manag.* **2018**, *218*, 540–554. [CrossRef] [PubMed]
49. Ye, Z.; Wang, F.; Ji, L.; Yu, J. Agricultural Production Structure Adjustment Based on A Multi-objective Control in the Tiaoxi Watershed. *J. Zhejiang Univ. (Agric. Life Sci.)* **2019**, *45*, 66–74. (In Chinese)
50. Alamdari, N.; Sample, D.J. A Multiobjective Simulation-Optimization Tool for Assisting in Urban Watershed Restoration Planning. *J. Clean. Prod.* **2019**, *213*, 251–261. [CrossRef]
51. Alamanos, A.; Mylopoulos, N.; Loukas, A.; Gaitanaros, D. An Integrated Multicriteria Analysis Tool for Evaluating Water Resource Management Strategies. *Water* **2018**, *10*, 1795. [CrossRef]
52. Xu, H.; Brown, D.G.; Moore, M.R.; Currie, W.S. Optimizing Spatial Land Management to Balance Water Quality and Economic Returns in a Lake Erie Watershed. *Ecol. Econ.* **2018**, *145*, 104–114. [CrossRef]
53. Cai, Y.; Rong, Q.; Yang, Z.; Yue, W.; Tan, Q. An Export Coefficient Based Inexact Fuzzy Bi-level Multi-objective Programming Model for the Management of Agricultural Nonpoint Source Pollution under Uncertainty. *J. Hydrol.* **2018**, *557*, 713–725. [CrossRef]
54. Geng, R.; Yin, P.; Sharpley, A.N. A Coupled Model System to Optimize the Best Management Practices for Nonpoint Source Pollution Control. *J. Clean. Prod.* **2019**, *220*, 581–592. [CrossRef]
55. Qi, H.; Altinakar, M.S. A conceptual framework of agricultural land use planning with BMP for integrated watershed management. *J. Environ. Manag.* **2011**, *92*, 149–155. [CrossRef]
56. Liu, G.; Chen, L.; Wang, W.; Sun, C.; Shen, Z. A water quality management methodology for optimizing best management practices considering changes in long-term efficiency. *Sci. Total. Environ.* **2020**, *725*, 138091. [CrossRef]
57. Alamanos, A.; Rolston, A.; Papaioannou, G. Development of a Decision Support System for Sustainable Environmental Management and Stakeholder Engagement. *Hydrology* **2021**, *8*, 40. [CrossRef]
58. Park, C.H.; Joo, J.G.; Kim, J.H. Integrated washland optimization model for flood mitigation using multi-objective genetic algorithm. *HydroResearch* **2012**, *6*, 119–126. [CrossRef]
59. Yoo, D.G.; Kim, J.H. Meta-heuristic algorithms as tools for hydrological science. *Geosci. Lett.* **2014**, *1*, 4. [CrossRef]
60. Mousavi, S.J.; Anzab, N.R.; Asl-Rousta, B.; Kim, J.H. Multi-Objective Optimization-Simulation for Reliability-Based Inter-Basin Water Allocation. *Water Resour. Manag.* **2017**, *31*, 3445–3464. [CrossRef]
61. Young, R.A.; Onstead, C.A.; Bosch, D.D.; Anderson, W.P. AGNPS: A Nonpoint-Source Pollution Model for Evaluating Agricultural Watersheds. *J. Soil Water Conserv.* **1989**, *44*, 168–173.
62. Bingner, R.L.; Theurer, F.D.; Yuan, Y.P.; Taguas, E.V. *AnnAGNPS Technical Processes Documentation, Version 5.5*; USDA-ARS: Washington, DC, USA, 2018; pp. 1–8.
63. Yuan, Y.; Locke, M.; Bingner, R. Annualized Agricultural Non-Point Source model application for Mississippi Delta Beasley Lake watershed conservation practices assessment. *J. Soil Water Conserv.* **2008**, *63*, 542–551. [CrossRef]
64. Chahor, Y.; Casalí, J.; Giménez, R.; Bingner, R.; Campo, M.; Goñi, M. Evaluation of the AnnAGNPS model for predicting runoff and sediment yield in a small Mediterranean agricultural watershed in Navarre (Spain). *Agric. Water Manag.* **2014**, *134*, 24–37. [CrossRef]
65. Zhang, T.; Yang, Y.; Ni, J.; Xie, D. Best management practices for agricultural non-point source pollution in a small watershed based on the AnnAGNPS model. *Soil Use Manag.* **2019**, *36*, 45–57. [CrossRef]
66. Abdelwahab, O.; Ricci, G.; De Girolamo, A.; Gentile, F. Modelling soil erosion in a Mediterranean watershed: Comparison between SWAT and AnnAGNPS models. *Environ. Res.* **2018**, *166*, 363–376. [CrossRef]
67. Zhang, S.; Zhang, J.; Zhuang, J.; Wang, X.; Zhang, S. Parameters sensitivity and applicability evaluation of AnnAGNPS model in small watershed of Yangtze River Delta. *J. Nanjing For. Univ. (Nat. Sci. Ed.)* **2020**, *45*, 1–13. (In Chinese)
68. Liu, Y.; Wang, R.; Guo, T.; Engel, B.A.; Flanagan, D.C.; Lee, J.G.; Li, S.; Pijanowski, B.C.; Collingsworth, P.D.; Wallace, C.W. Evaluating efficiencies and cost-effectiveness of best management practices in improving agricultural water quality using integrated SWAT and cost evaluation tool. *J. Hydrol.* **2019**, *577*, 123965. [CrossRef]
69. Ghebremichael, L.T.; Veith, T.L.; Hamlett, J.M. Integrated watershed- and farm-scale modeling framework for targeting critical source areas while maintaining farm economic viability. *J. Environ. Manag.* **2013**, *114*, 381–394. [CrossRef] [PubMed]
70. Getahun, E.; Keefer, L. Integrated modeling system for evaluating water quality benefits of agricultural watershed management practices: Case study in the Midwest. *Sustain. Water Qual. Ecol.* **2016**, *8*, 14–29. [CrossRef]
71. Kraff, D.; Steinman, A.D. Integrated watershed management in Michigan: Challenges and proposed solutions. *J. Great Lakes Res.* **2018**, *44*, 197–207. [CrossRef]
72. Hong, B.; Limburg, K.E.; Hall, M.H.; Mountrakis, G.; Groffman, P.M.; Hyde, K.; Luo, L.; Kelly, V.R.; Myers, S.J. An integrated monitoring/modeling framework for assessing human–nature interactions in urbanizing watersheds: Wappinger and Onondaga Creek watersheds, New York, USA. *Environ. Model. Softw.* **2012**, *32*, 1–15. [CrossRef]
73. Teka, K.; Haftu, M.; Ostwald, M.; Cederberg, C. Can integrated watershed management reduce soil erosion and improve livelihoods? A study from northern Ethiopia. *Int. Soil Water Conserv. Res.* **2020**, *8*, 266–276. [CrossRef]

74. Zadeh, L. Optimality and non-scalar-valued performance criteria. *IEEE Trans. Autom. Control.* **1963**, *8*, 59–60. [CrossRef]
75. Srivastava, P.; Hamlett, J.M.; Robillard, P.D.; Day, R.L. Watershed optimization of best management practices using AnnAGNPS and a genetic algorithm. *Water Resour. Res.* **2002**, *38*, 3-1. [CrossRef]
76. Altinakar, M.S.; Qi, H.; Altınakar, M.S. Numerical-Simulation Based Multiobjective Optimization of Agricultural Land-Use with Uncertainty. *World Environ. Water Resour. Congr. 2008* **2008**, 1–10. [CrossRef]
77. Cong, W.; Sun, X.; Guo, H.; Shan, R. Comparison of the SWAT and InVEST models to determine hydrological ecosystem service spatial patterns, priorities and trade-offs in a complex basin. *Ecol. Indic.* **2020**, *112*, 106089. [CrossRef]
78. Qi, H.; Altinakar, M.S.; Altınakar, M.S. Vegetation Buffer Strips Design Using an Optimization Approach for Non-Point Source Pollutant Control of an Agricultural Watershed. *Water Resour. Manag.* **2010**, *25*, 565–578. [CrossRef]
79. "Jenny" Zhen, X.-Y.; Yu, S.L.; Lin, J.-Y. Optimal Location and Sizing of Stormwater Basins at Watershed Scale. *J. Water Resour. Plan. Manag.* **2004**, *130*, 339–347. [CrossRef]
80. Li, H.; Lin, J.; Zhang, J.; Zhang, X.; Zhang, L.; Wang, Z. Spatial Variability of Soil Organic Carbon and Total Nitrogen Based on Small Watershed Scale. *J. Nanjing For. Univ. (Nat. Sci. Ed.)* **2008**, *32*, 38–42. (In Chinese)