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Optimizing Agricultural Production to Mitigate Groundwater Nitrate Pollution: An Irrigation–Fertilization–Economy Framework

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Abstract

To address the challenge of balancing food production, groundwater protection, and economic sustainability in agricultural systems, this study developed a novel multi-objective optimization framework integrating an Extreme Learning Machine (ELM)-based surrogate model. An irrigation–fertilization–economy (IFE) model was established to evaluate region-specific agricultural adjustment strategies under four scenarios: baseline adjustment, flexible restructuring, production reduction and profit-oriented expansion scenarios. The optimization results were subsequently used to assess the impacts of agricultural production regulation on groundwater nitrate concentrations in the study area. The results showed that the IFE model consistently favored the conversion from wheat to maize cultivation across all regions, because maize requires less irrigation and fertilizer inputs while maintaining relatively high net profits. However, the optimal strategies varied among regions: Pingdu and Jiaozhou showed greater economic potential for production expansion, whereas regions with lower economic potential were more suitable for reducing high-input crop cultivation. During the 2020–2030 prediction period, nitrate concentrations exhibited substantial interannual variations. Reducing the overall production scale shifted nitrate concentrations approximately 6% closer to the 30–50 mg/L range over the decade, but this limited environmental benefit was accompanied by substantial short-term economic losses. Considering both environmental impacts and economic viability, the optimization results suggest that moderate agricultural expansion could be acceptable provided that environmental burdens are effectively managed.



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1. Introduction

Groundwater is an essential source of irrigation water for agricultural systems [1]. Global demand for food and water is projected to increase by 50% and 30%, respectively, by 2030 [2,3], thereby placing increasing pressure on groundwater resources. This emerging

water shortage not only poses risks to food production in China but also threatens global food security [4]. Meanwhile, fertilizer use remains a key driver of crop yield improvement in China [5,6]. However, excessive fertilization, particularly in regions such as North China [7], increases the risk of soil nitrate leaching, leading to groundwater contamination and other environmental problems [8,9]. Recent global syntheses have shown that coordinated nutrient, crop, and soil management can substantially reduce nitrogen losses while maintaining or improving agricultural productivity [10,11]. Consequently, expanding food production may require irrigation water and fertilizer inputs beyond the optimum levels, intensifying the conflict between food security and groundwater protection [12]. This conflict is especially pronounced in semi-arid and arid regions, where groundwater accounts for approximately 70% of agricultural water use [13].

Therefore, establishing effective regulatory frameworks to protect groundwater and reduce the adverse impacts of agricultural development is essential for achieving sustainable agricultural production [14,15]. However, focusing solely on agricultural control or water treatment alone has proven insufficient. Implementing irrigation allocation, fertilizer management, and crop-area adjustment strategies requires coordinated actions among water management agencies, environmental authorities, agricultural sectors, and farmers [1]. Such coordination is necessary because these stakeholders often pursue different objectives, and unbalanced strategies may intensify trade-offs among water conservation, pollution control, agricultural production, and farmers' income [16]. Recent irrigation network and farm-scale studies have likewise shown that crop pattern, irrigation, and fertilizer decisions jointly affect groundwater recovery, nitrate leaching, and agricultural net returns [17,18]. Accordingly, the water–food–energy–environment–land nexus has received increasing attention in recent years [1,2,19–21], highlighting the increasing complexity of groundwater management. Thus, developing a systematic approach to balance hydrological, economic, and environmental objectives is crucial [22].

One of the primary goals of groundwater management is to reduce contaminant concentrations. However, solute transport in aquifers is often difficult to observe directly and may exhibit strong spatial and temporal variability, making groundwater quality difficult to assess and predict [21,22]. By coupling hydrogeological simulations with multi-objective algorithms, simulation–optimization (S-O) frameworks show promise for managing complex trade-offs and have been widely applied in groundwater management studies [21,23–26]. However, the computational burden of numerical simulation models remains a major challenge for optimization [27], especially when multiple decision variables, interacting agricultural–hydrological features, and repeated scenario evaluations are involved. Recent studies on multi-feature computation and complex decision modeling further indicate that computational efficiency becomes increasingly important as model dimensionality and scenario complexity increase [28,29]. Therefore, machine-learning surrogate models have been widely used to replace computationally intensive numerical simulations in simulation–optimization (S-O) frameworks [28–30]. Among these methods, artificial neural networks (ANNs) are widely used because of their ability to approximate nonlinear relationships among aquifer conditions, management variables, and groundwater responses. The Extreme Learning Machine (ELM), a single-hidden-layer feedforward neural network, has the advantages of rapid training and simple implementation, making it suitable for repeated model evaluations in multi-objective optimization.

Recent research has further expanded agricultural optimization from single-factor management to integrated water–land–crop management. Spatial multi-objective frameworks now integrate water quantity and quality, food production, ecological outcomes, and allocation costs, while field-based optimization in winter wheat–summer maize systems explicitly balances crop yield, irrigation water productivity, and production costs [31,32].

Meanwhile, groundwater nitrogen legacy can delay water-quality improvement for years or decades after current nitrogen inputs decline, indicating that short-term agricultural optimization should be evaluated in conjunction with long-term groundwater responses [33]. These advances motivate an integrated framework that jointly evaluates irrigation, fertilization, crop structure, economic returns, and groundwater nitrate dynamics.

The aim of this study was to develop a regional-scale irrigation–fertilization–economy (IFE) optimization framework to evaluate how agricultural production adjustment can alleviate groundwater nitrate pollution while maintaining economic viability. Specifically, this study aimed to: (1) optimize irrigation demand, nitrogen inputs, and agricultural profits by adjusting the production scale of four major crops in four counties surrounding the Dagū River groundwater reservoir; (2) predict groundwater nitrate responses associated with different crop-structure adjustment scenarios using an Extreme Learning Machine (ELM)-based surrogate model; and (3) assess the trade-offs among groundwater protection, agricultural production, and economic returns under different management scenarios. By integrating agricultural production adjustment with groundwater quality prediction, this study provides a scenario-based assessment framework for balancing food production, economic benefits, and groundwater protection in the Dagū River basin.

2. Materials and Methods

2.1. Data Sources

2.1.1. Agricultural, Meteorological and Economic Data

In this study, the data sources included the Qingdao Yearbook (sown area, crop output value, and fertilization amount), the National Meteorological Information Center (temperature, effective precipitation, ground radiation, soil heat flux, wind speed at 2 m high, saturated and actual vapor pressure, and average air pressure), the National Agricultural Product Cost Benefit Data (crop price, crop cost, and fertilizer requirement), and the Qingdao Agriculture and Rural Bureau (crop's growth coefficient, soil nutrient content and fertilizer absorption rate).

Meteorological data collected from the National Meteorological Information Center are used to calculate reference evapotranspiration. Similarly, data from the Qingdao Agriculture and Rural Bureau and the National Agricultural Product Cost Benefit Data are used to calculate fertilizer amount and crop profit.

2.1.2. Groundwater Nitrate Monitoring Data

The groundwater nitrate concentration data were collected from 38 monitoring wells. The data included six monitoring sessions from October 2018 to November 2019. According to the spatial relationship between the monitoring wells and the sections monitored, the monitoring points are divided into three parts: northern (5 wells), central (25 wells), and southern (8 wells). The spatial distribution of monitoring wells is shown in Figure 1a.

The monitoring data were first used to verify the predictive performance of the ELM model and were treated as initial concentrations to serve as inputs for the ELM model in order to predict changes in nitrate concentrations in 2021 and beyond.

2.2. Study Area

The Dagū River basin is located in northwestern Qingdao, Shandong Province, China. Its groundwater resources provide an important and stable water supply for urban use and agricultural production, especially in the main farming area in Qingdao City [34]. The Dagū River groundwater reservoir ($120^{\circ}04'48'' \sim 120^{\circ}21'00''$ E, $36^{\circ}18'00'' \sim 36^{\circ}45'45''$ N) is surrounded by four farming counties: Pingdu, Laixi, Jimo and Jiaozhou (Figure 1a). These counties produce large quantities of wheat, maize, peanut, vegetables and fruits,

and contribute a major share of Qingdao's agricultural output value (Figure 1c). Local cropping systems included winter wheat–summer maize rotation, maize–vegetable rotation, peanut–vegetable rotation, and continuous vegetable cropping.

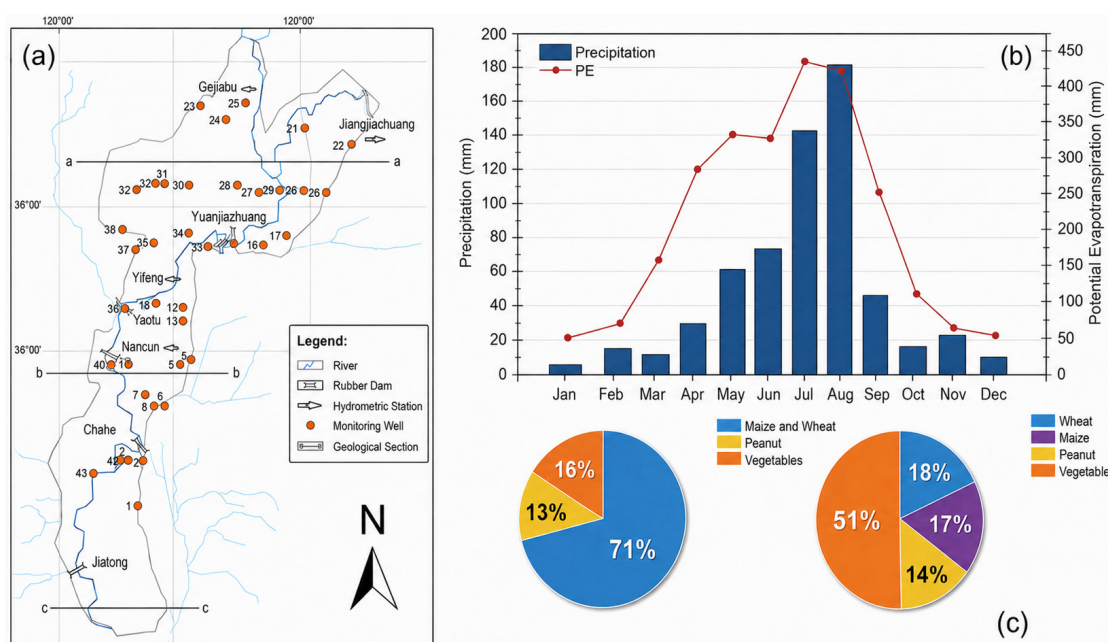


Figure 1. Overview of hydrogeological and agricultural conditions in the study area: (a) study area and locations of monitoring wells; (b) monthly precipitation and evapotranspiration (ET); (c) average proportions of planting area and annual output value of the four representative crops (wheat, maize, peanut, and vegetables). Other crops are cultivated in the study area but were not included in this analysis.

As the local agricultural production scale has expanded over the past few decades, annual crop profits have steadily increased (Qingdao Yearbook, 2005–2020). However, flood irrigation and excessive fertilization can exacerbate nitrate leaching into groundwater [35,36]. Additionally, the period of intensive precipitation (June to September, Figure 1b) coincides with the fertilization period. Therefore, heavy rainfall during the fertilization period may enhance nitrate leaching [37]. Thus, both cultivation patterns and climatic conditions may pose substantial risks to groundwater quality in the Dagu River basin.

2.3. Simulation–Optimization (S-O) Model

In this research, the S-O model was designed to balance annual irrigation water demand, fertilization amount, and agricultural profit, while proposing regional production adjustment strategies and evaluating effects on groundwater nitrate concentrations. The general optimization workflow is shown in Figure 2. The main decision variable was the sown area (SA), and the optimization objectives included irrigation requirement (IR), planned fertilizer input (PF), and net profit (NP).

2.3.1. Irrigation Requirement

The reference evapotranspiration (ET_0) was used to estimate crop water demand during growth [34]. The equation for irrigation requirement is expressed as follows:

$$IR_{ijk} = (K_C \cdot ET_{0ijk} - EP_{ijk}) \cdot SA_{ijk} \cdot 10^{-1} \quad (1)$$

where i , j , and k represent the i crop, j subregion, and k year in the study area; IR_{ijk} (m^3), ET_{0ijk} (mm), EP_{ijk} (mm) and SA_{ijk} (ha) are the corresponding crop irrigation requirement,

reference evapotranspiration, effective precipitation, and sown area; and K_C is the crop's growth coefficient.

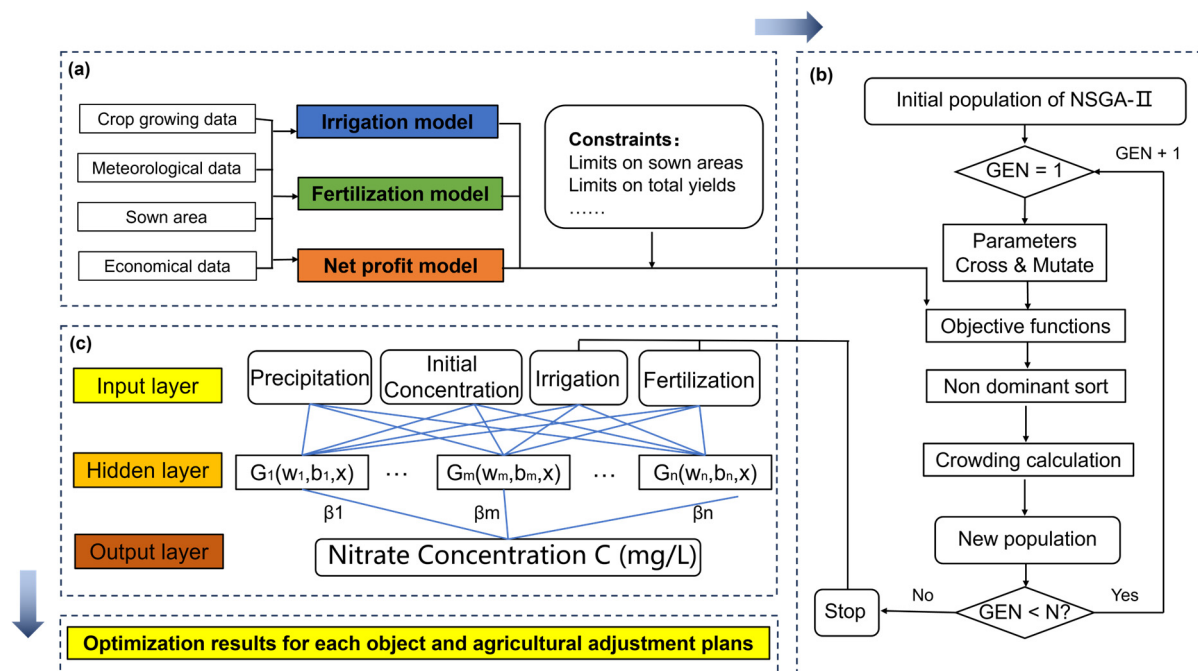


Figure 2. Main flow chart of the S-O process: (a) inputs for sub-models of NSGA-II and constraints; (b) flow chart of NSGA-II; (c) flow chart of ELM model.

The Penman–Monteith equation is widely used to estimate the reference evapotranspiration (ET_0). The formulas for this are as follows:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_{mean} + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (2)$$

where Δ (kPa/°C), R_n (MJ/m²/d), G (MJ/m²/d), γ (kPa/°C), T_{mean} (°C), u_2 (m/s), e_s (kPa), and e_a (kPa) represent the saturated vapor pressure curve slope, net radiation on the canopy surface, soil heat flux, psychrometric constant, average temperature, wind speed at 2 m high, saturated vapor pressure, and actual vapor pressure respectively.

$$\Delta = \frac{2532.564 \exp\left(\frac{17.27T}{T + 237.3}\right)}{(T + 237.3)^2} \quad (3)$$

$$R_n = R_{ns} - R_{nl} \quad (4)$$

Here, R_{ns} (MJ/m²/d) and R_{nl} (MJ/m²/d) represent shortwave radiation and longwave radiation, respectively.

$$\gamma = 0.665 \cdot 10^{-3} P \quad (5)$$

Here, P (kPa) is the average atmospheric pressure in the study area.

2.3.2. Planned Fertilizer Input

Fertilizer applications help improve crop yield and quality. However, the optimal fertilization amount varies with regional environmental and hydrological differences [38]. Thus, predefined fertilization-intensity categories may not adequately represent fertilization demand in the optimization mode [39]. Therefore, the recommended annual total nitrogen

fertilizer amount was calculated using a modified nitrogen-use-efficiency formula to reflect the relationship between fertilizer input and crop yield:

$$PF_{ijk} = SA_{ijk} \cdot F_{ijk} \quad (6)$$

where PF (kg) and F (kg/ha) represent the total planned fertilizer input and fertilizer required per hectare, respectively.

$$F_{ijk} = \frac{0.01FN_{ijk} \cdot y_{ijk} - FE_{ijk}}{\mu} \quad (7)$$

where FN (kg/100 kg), y (kg/ha), FE (mg/kg) and μ (%) are the fertilizer required per 100 kg of crop production (CP), per-unit area yield, and the soil nutrient content and fertilizer absorption rate. The amount of fertilization is the net amount after considering the effective content.

2.3.3. Crop Net Profit

Annual crop net profit was calculated as total yield multiplied by the average market price, minus production costs, following the commonly used input–output accounting approach [40]:

$$NP_{ijk} = SA_{ijk} \cdot (y_{ijk} \cdot P_{ijk} - C_{ijk}) \quad (8)$$

where NP (CNY), P (CNY/kg), and C (CNY/ha) are the total net profit, crop price per unit weight, and crop cost per unit planting area. Crop cost comprises the cost of seed, fertilizer, pesticides, agricultural film, irrigation, mechanical operations, and other tools and materials. The water price is not directly considered but has been expressed as the electricity cost using water pumps. Crop prices and production costs were treated as exogenous economic parameters. The calculation did not include market-price responses, subsidies, crop-conversion costs, or changes in labor demand. Therefore, NP represents the accounting profit under assumed price and cost conditions rather than total regional economic welfare.

2.3.4. Constraints and NSGA-II Implementation

In agricultural production systems, environmental agencies aim to reduce nitrogen leaching and groundwater use, whereas farmers primarily focus on economic returns. To reconcile these competing objectives, the optimization model was designed to (1) minimize total irrigation demand; (2) minimize total fertilizer input; and (3) maximize total net profit (Equation (9)). By adjusting sown areas, the model balanced these three objectives to obtain a Pareto-optimal solution set. In this study, the sown area was the main decision variable. Unit crop yield was constrained within its historically observed range and was not calculated using an explicit water–yield or nitrogen–yield response function. Therefore, the model evaluates regional crop-area reallocation under historically observed productivity conditions rather than field-level yield responses to a deficit in irrigation or reduction in fertilizer use.

$$\begin{cases} \text{MIN } O_1 = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K IR_{ijk} \\ \text{MIN } O_2 = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K PF_{ijk} \\ \text{MAX } O_3 = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K NP_{ijk} \end{cases} \quad (9)$$

Here, O_1 (m^3), O_2 (kg), and O_3 (CNY) are the total irrigation requirement, planned fertilizer input, and net profit; I , J , and K are the total number of i , j and k , set as four crops, four subregions and 16 years in this study.

To avoid unrealistic optimization results caused by unconstrained adjustment ranges, the constraints were defined as follows:

$$\begin{cases} (1 - \alpha)SA_{\min} < SA < (1 + \beta)SA_{\max} \\ F_{ijk} > 0 \\ IR_{ijk} > 0 \end{cases} \quad (10)$$

where SA represents the sown area, $\max$ and $\min$ represent the historical maximum and minimum, and α and β vary from scenario settings.

NSGA-II was selected because the optimization problem contained three conflicting objectives and multiple scenario constraints. Unlike a weighted-sum method, NSGA-II generates a diverse Pareto-optimal solution set without requiring the objectives to be converted into a common unit or assigned fixed weights before optimization. The crossover and mutation probabilities were set to 0.8 and 0.2, respectively, and the population size was set to 300. The maximum number of generations was 500 and was used as the stopping condition; no additional tolerance-based termination criterion was applied. Accordingly, each optimization run involved approximately 150,000 candidate-solution evaluations. Because the three objective functions were evaluated using algebraic equations, the computational cost of an individual evaluation was relatively low.

2.3.5. ELM Model

ELM was selected for its simple structure, fast training speed, and suitability for repeated evaluations in simulation–optimization frameworks. Although other machine-learning models, such as random forest, support vector regression, and gradient boosting models, may also be used as surrogate models, the present study focused on using ELM to provide an efficient predictive link between agricultural production indicators and groundwater nitrate responses.

The Extreme Learning Machine (ELM) consists of an input layer, a hidden layer, and an output layer (Figure 3c). ELM randomly generates the input layer weights and the hidden layer biases, and it minimizes the loss function of the output layer [41]. For M samples (x_j, y_j) , the ELM model with L additive hidden nodes and activation function $G(x)$ can be expressed as follows:

$$\sum_i^L \beta_i \cdot G(w_i x_j + b_i) = t_j, j \in [1, M] \quad (11)$$

where w_i is the connection weight between the input and hidden layer; b_i is the bias of the hidden node; β_i is the connection weight between the hidden layer and output layer; and t_i is the predicted outcome. When $L \geq M$, the ELM predicted outcomes can be seen as having zero error (Equation (12)).

$$\sum_{j=1}^M \|t_j - y_j\| = 0 \quad (12)$$

Equation (11) can be abbreviated as the following matrix calculation equation:

$$\beta = H^+ Y \quad (13)$$

where H is the hidden layer output matrix, and H^+ is the Moore–Penrose inverse of matrix H . The connection weight β for the output and hidden layer can be calculated by solving the least squares problem.

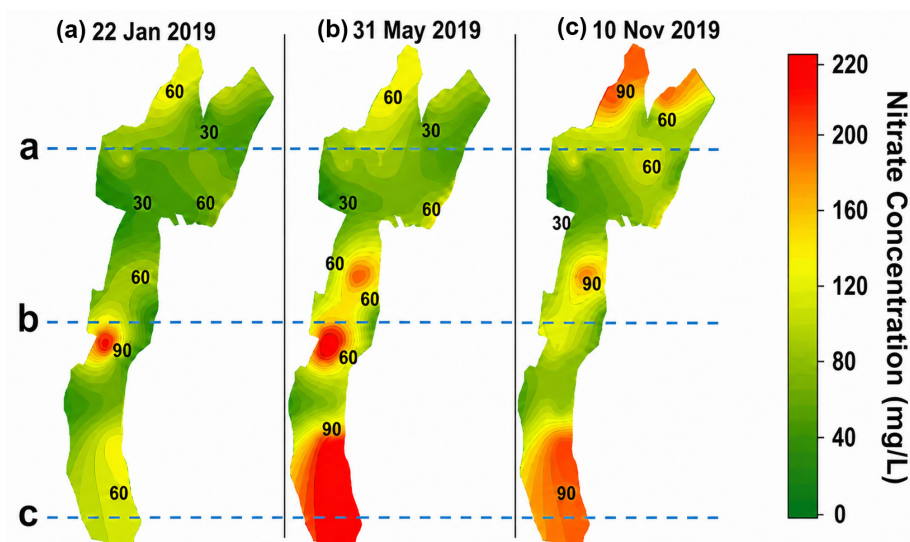


Figure 3. Contour maps of nitrate concentrations in 2019: (a) 22 January; (b) 31 May; (c) 10 November.

After obtaining the value of β , the output function of ELM can be expressed as follows:

$$f(x) = h(x) \cdot \beta \quad (14)$$

where

$$h(x) = [G(w_1x + b_1), \dots, G(w_lx + b_l)] \quad (15)$$

In this study, the input layer of ELM included precipitation, initial nitrate concentration, irrigation requirement (IR), and planned fertilizer input (PF). The output layer contained the predicted nitrate concentration only. The ELM was used as a statistical surrogate model and did not explicitly simulate nitrogen transformation, unsaturated-zone transport, or groundwater flow. Compared with traditional neural network models, ELM provides advantages including a simple training process, fast learning speed, and good nonlinear approximation capability due to the random assignment of hidden-layer parameters and analytical determination of output weights [42–44]. It assumes that the statistical relationships learned from the monitoring data remain applicable under the scenario conditions. Therefore, the predictions represent relative nitrate responses among scenarios rather than mechanistic estimates of nitrate mass transport.

2.4. Optimization Scenario Design and Solution Selection

2.4.1. Optimization Scenario

In this study, optimization scenarios were designed to represent different regional production adjustment strategies, with specific ranges assigned for the sown area (SA), unit yield (UY), irrigation requirement (IR), net profit (NP), and planned fertilizer input (PF). The detailed constraints are summarized in Table 1. Given the limitation of total SA, changes in the planting scale of various crops mainly reflect adjustments within existing crop rotation systems. To reflect realistic field conditions, fertilizer and irrigation water requirements were allocated on a monthly basis according to local farming practices.

Scenario 1 (S1), the baseline adjustment scenario, was designed to maximize profit while minimizing irrigation requirements and planned fertilizer inputs under wet, normal and dry years under a relatively small adjustment range. The results of S1 were used as the baseline for evaluating the remaining scenarios. Thus, the ranges of SA and UY were defined (Table 2) using the historical maximum (his_{max}) and minimum (his_{min}) values.

Table 1. Constraints on total production and sown area under different scenarios.

Scenario	Total Production		Total-SA		Sub-SA	
	Min	Max	Min	Max	Min	Max
Scenario 1	his _{min}	his _{max}	his _{min}	his _{max}	his _{min}	his _{max}
Scenario 2	80% his _{min}	inf	95% his _{min}	105% his _{max}	80% his _{min}	120% his _{max}
Scenario 3	50% his _{min}	75% his _{max}	50% his _{min}	his _{max}	50% his _{min}	his _{max}
Scenario 4	110% his _{max}	inf	his _{max}	110% his _{max}	50% his _{min}	150% his _{max}

Table 2. Monitoring data of groundwater in the Dagu River basin in October 2018.

Section (Number of Wells)	Beyond Class V (%)	NO ₃ [−] Concentration (mg/L)		
		Max	Min	Average
North (5)	60.0	134.2	0.2	57.1
Middle (25)	68.0	120.0	0.2	49.3
South (8)	75.0	169.0	1.1	77.6

Scenario 2 (S2), referred to as the flexible restructuring scenario, allowed greater adjustment in SA while maintaining the total planting area. In S2, the SA of crops in each subregion could be adjusted within a broader range (80% of his_{min} to 120% of his_{max}) while total SA remained constrained within a historical range. Total crop production was not strictly constrained in this scenario.

Scenario 3 (S3), referred to as the production-shrinkage scenario, was designed to evaluate the effects of reducing agricultural production on groundwater nitrate mitigation. In this scenario, total production was strictly limited to 50% of his_{min} and 75% of his_{max} to represent production shrinkage, and only reductions in SA were allowed.

Scenario 4 (S4), referred to as the profit-oriented expansion scenario, was designed to increase agricultural profit. Thus, the lower bound of SA was set 10% above the historical maximum value, whereas the upper bound was determined according to actual production constraints.

2.4.2. VIKOR Solution Selection

The output of the NSGA—II model is a set of Pareto-optimal solutions containing multiple solutions, which are distributed as surfaces in three-dimensional space. To select a compromise solution from the Pareto-optimal solution set, the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [45] decision scheme was then applied, with the highest-ranked compromise candidate based on the minimum Q_i, the specific calculation method of VIKOR:

1. Determine the positive ideal solution y_j^+ and the negative ideal solution y_j^- for each objective.

$$y_j^+ = \max(y_{ij}) \quad (16)$$

$$y_j^- = \min(y_{ij}) \quad (17)$$

2. Calculate the group benefits S_i and individual regret value R_i for each individual in the Pareto-optimal solution set:

$$S_i = \sum_{j=1}^n \omega_j (y_j^+ - y_{ij}) / (y_j^+ - y_j^-) \quad (18)$$

$$R_i = \max\left(\frac{\omega_j (y_j^+ - y_{ij})}{y_j^+ - y_j^-}\right) \quad (19)$$

where ω_j represents the weight of each indicator. In this study, the weights of IR, NP, and PF are set to 0.3, 0.3, and 0.4, respectively.

3. Determine the benefit ratio value Q_i for each solution:

$$Q_i = \nu \left(\frac{S_i - \min S_i}{\max S_i - \min S_i} \right) + (1 - \nu) \left(\frac{R_i - \min R_i}{\max R_i - \min R_i} \right) \quad (20)$$

where ν is the decision coefficient; in this study, it was set to 0.5 to assign equal importance to the two decision strategies [46].

4. Sort by Q_i , where a lower Q_i indicates a solution closer to the ideal compromise.

2.5. Post-Optimization Analyses

2.5.1. Precipitation-Year Classification

Since IR is also determined by effective precipitation (Equation (1)), differences in annual rainfall may lead to different optimization strategies. To further explain production variation patterns under different optimization scenarios and summarize strategy preferences under varying precipitation conditions, the optimized years were categorized based on the percentage deviation of annual rainfall from the long-term average into dry years (with precipitation 10% below the average), wet years (with precipitation 10% above the average), and normal years (other cases).

In this study, dry years included 2006, 2009, 2012, 2013, 2014, and 2015; wet years included 2007, 2008, 2011, 2018, and 2020; and normal years included 2005, 2010, 2016, 2017, and 2019.

2.5.2. Regional Marginal-Return Analysis

Marginal-return (MR) indicators were calculated to evaluate the economic responses to changes in SA, IR, and planned PF in each region [47,48]. Taking S1 as the reference scenario, the indicators were calculated as follows [48,49]:

$$MRSA = \frac{dNP}{dSA} = \frac{NP_{s4} - NP_{s1,2,3}}{SA_{s4} - SA_{s1,2,3}}, \quad MRIR = \frac{dNP}{dIR}, \quad MRPF = \frac{dNP}{dPF} \quad (21)$$

where MRSA, MRIR, and MRPF represent the marginal changes associated with changes in SA, IR, and PF. Because these indicators have different units, they were evaluated separately rather than being combined into a single index.

2.5.3. Nitrate Simulation and Scenario Comparison

The ELM model was used to evaluate both short-term and long-term groundwater nitrate responses under the optimized agricultural scenarios. Short-term spatial and temporal variations were analyzed using the 2019–2020 simulation results. For the long-term assessment, the agricultural production conditions of 2020 and average annual precipitation were used to simulate nitrate concentrations from 2020 to 2030. The results were evaluated separately for the northern, central, and southern sections, as well as for the entire study area.

In addition to directly comparing the temporal and spatial distribution characteristics of nitrate concentrations under various scenarios, the scenarios were also compared based on the proportion of monitoring wells within selected concentration ranges. For each year and concentration range, the dominant scenario was defined as the scenario with the largest proportion of monitoring wells within the corresponding range. The 30–50 mg/L and 50–100 mg/L concentration ranges were used to distinguish scenario effects, whereas the <30 mg/L range was excluded because its proportion varied little among scenarios.

3. Results

3.1. Observed Nitrate Concentrations

By 2020, groundwater quality in the Dagu River basin had generally deteriorated, and shallow groundwater had largely become unsuitable as a drinking water source [34,50,51]. Previous studies have identified agricultural non-point sources, particularly fertilizer and manure inputs, as the dominant contributors to nitrate pollution [52]. According to the Chinese Groundwater Quality Standard (GB/T 14848-93) [53], Class V represents the lowest groundwater quality category and indicates groundwater that is unsuitable for drinking purposes. Analysis of data from 38 local monitoring wells revealed that 68% of samples exceeded the Class V nitrate threshold (>30 mg/L), indicating severe nitrate pollution, with nitrate concentrations ranging from 0.2 to 168.9 mg/L (Table 2). In addition, the results (Figure 3) indicated higher nitrate concentrations in the southern part of the basin and a circular high-concentration zone in the central region, consistent with previous studies [21]. Temporally, nitrate concentrations in the central and southern sections increased during the first half of the year and then decreased during the second half, whereas concentrations in the northern section showed a continuous increasing trend throughout the year.

3.2. Model Evaluation

The observed groundwater nitrate concentrations were first summarized to characterize the baseline nitrate pollution status of the study area. Nitrate concentrations from the 38 monitoring wells showed substantial spatial variability, with observed values ranging from 0.1 to 174.9 mg/L and an average value of 67.2 mg/L. These observations indicate that groundwater nitrate pollution was widespread and spatially heterogeneous, providing the basis for subsequent ELM training and IFE scenario evaluation.

The ELM model was then trained and evaluated using the observed nitrate concentration data. The model performance was assessed using the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), and root mean square error (RMSE) (Table 3). The predicted nitrate concentrations were compared with the observed values using scatterplots and spatial contour maps (Figure 4a,b). The average R^2 and NSE values were both 0.7, indicating acceptable predictive performance. In addition, the simulated spatial distribution was generally consistent with the observed nitrate distribution, suggesting that the ELM model was suitable for representing annual and long-term variations in groundwater nitrate concentrations.

Table 3. Comparison between observed and calculated nitrate concentrations.

	Max	Min	Average	Median
Obs NO_3^- (mg/L)	174.9	0.1	67.2	53.0
Cal NO_3^- (mg/L)	211.1	0.3	65.5	50.8
R^2	0.7	0.8	0.9	0.9
NSE	0.7	0.6	0.7	0.7
RMSE	32.6	27.7	30.3	30.3

Note: Obs, observed; Cal, calculated; NO_3^- , nitrate; R^2 , coefficient of determination; NSE, Nash–Sutcliffe efficiency; RMSE, root mean square error.

After evaluating the ELM model, the IFE optimization results were analyzed. The IFE model generated 300 candidate solutions for each scenario. For Scenario 1 (S1) in 2005, the optimized solution set showed a clear trade-off among irrigation demand, fertilizer input, and crop net profit (Figure 4c). Lower irrigation and fertilizer inputs were generally associated with lower crop profit. The two-dimensional projections of NP–IR and NP–PF (Figure 4d,e) also showed convergence toward the optimization direction, indicating continuous improvement of the objectives during model iterations [50].

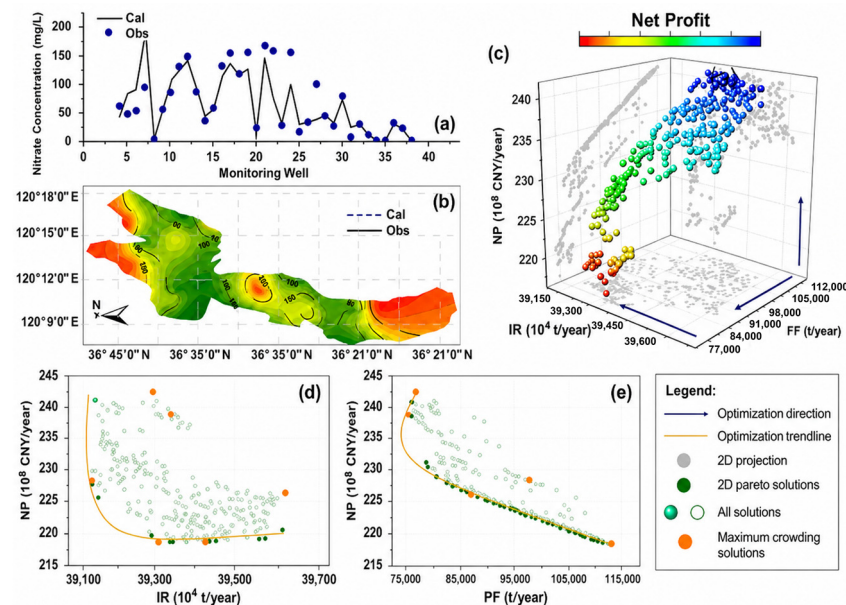


Figure 4. (a) Observed and ELM-predicted nitrate concentrations; (b) contour maps of ELM-predicted and observed nitrate concentrations; (c) 3D projection of optimization solution sets; (d) 2D projection of NP–IR; (e) 2D projection of NP–PF.

3.3. Agricultural Optimization Results Analysis

In the strictly constrained scenario (S1), the average optimized crop composition consisted of 35.6% wheat, 35.6% maize, 11.7% peanut, and 17.1% vegetables. The contributions of different crops to the optimization objectives were compared to evaluate their relative contributions. Table 4 shows that vegetables had the highest economic performance (190,000 CNY/ha), accounting for more than half of the total NP (57.3%). In contrast, grain crops contributed only 32.3% of the total profit, although they accounted for 71.1% of total production. In terms of input demand, peanut and vegetables required relatively high inputs: vegetables accounted for 25.1% of total IR, and peanuts accounted for 38.9% of total PF, both exceeding their respective SA proportions (17.1% for vegetables and 11.7% for peanuts). The results per unit area showed a similar pattern: peanuts had the highest PF demand per unit area, whereas vegetables had the highest IR demand per unit area. The unit-area PF demand of peanuts was 4.1–7.3 times higher than that of the other crops. In addition, maize showed higher input-use efficiency than wheat: it required only 58.9% of the IR and 64.8% of the PF required by wheat, while producing 90.7% of the NP of wheat NP. Overall, these results indicate that the optimization was driven not by crop profitability alone, but by the combined balance among irrigation demand, nitrogen input, and economic returns.

Table 4. Contribution of each crop to each optimization objective in S1.

Crop Types	Crop Proportions				Per Unit Area (/ha)		
	SA	IR	NP	PF	IR (t)	NP (CNY)	PF (kg)
Wheat	35.6%	39.8%	16.9%	31.9%	602.8	26,226.9	119.8
Maize	35.6%	23.5%	15.4%	21.9%	355.3	23,779.1	77.6
Peanut	11.7%	11.6%	10.4%	38.9%	534.6	49,524.0	491.1
Vegetable	17.1%	25.1%	57.3%	7.3%	792.4	192,123.8	67.2

Note: SA, sown area; IR, irrigation requirement; NP, net profit; PF, planned fertilizer input.

3.3.1. Interannual Changes in Crop Structure and Production

The results of S1 were used as the benchmark scenario for comparison with the other scenarios. First, Figure 5 illustrates the interannual differences in sown area (SA) and crop production (CP). Overall, the optimization trajectories were consistent with the scenario settings: SA and CP fluctuated slightly in the flexible restructuring scenario (S2), declined in the production shrinkage scenario (S3), and increased markedly in the profit-oriented expansion scenario (S4). However, different crops exhibited distinct response patterns. Wheat planting area decreased in both S2 and S4, thereby releasing SA to the more profitable peanut and vegetable crops and increasing NP. In contrast, under S4, maize showed the largest increase in SA (5.27×10^4 ha, averaging 22.1%) and the second-largest increase in CP (6.36×10^5 t, averaging 38.76%), whereas peanut production increased only slightly in S2 (10.5% in SA) and S4 (8.5% in SA). These differences in change patterns may be attributed to the fact that maize is not only more profitable than wheat but also requires substantially lower IR and PF inputs than vegetables and peanut (Table 4). Similarly, in S3, wheat (38.3% in SA and 37.1% in CP) and vegetables (30.9% in SA and 33.4% in CP) showed the greatest declines, whereas maize was less affected despite being subject to the same lower-bound constraint (50% of $h_{\min}$). Thus, maize production was consistently favored across scenarios, and its planting scale was more likely to be maintained or expanded. In contrast, the planting areas of peanuts and vegetables changed within a relatively narrow range, whereas wheat more readily ceded the area to other crops.

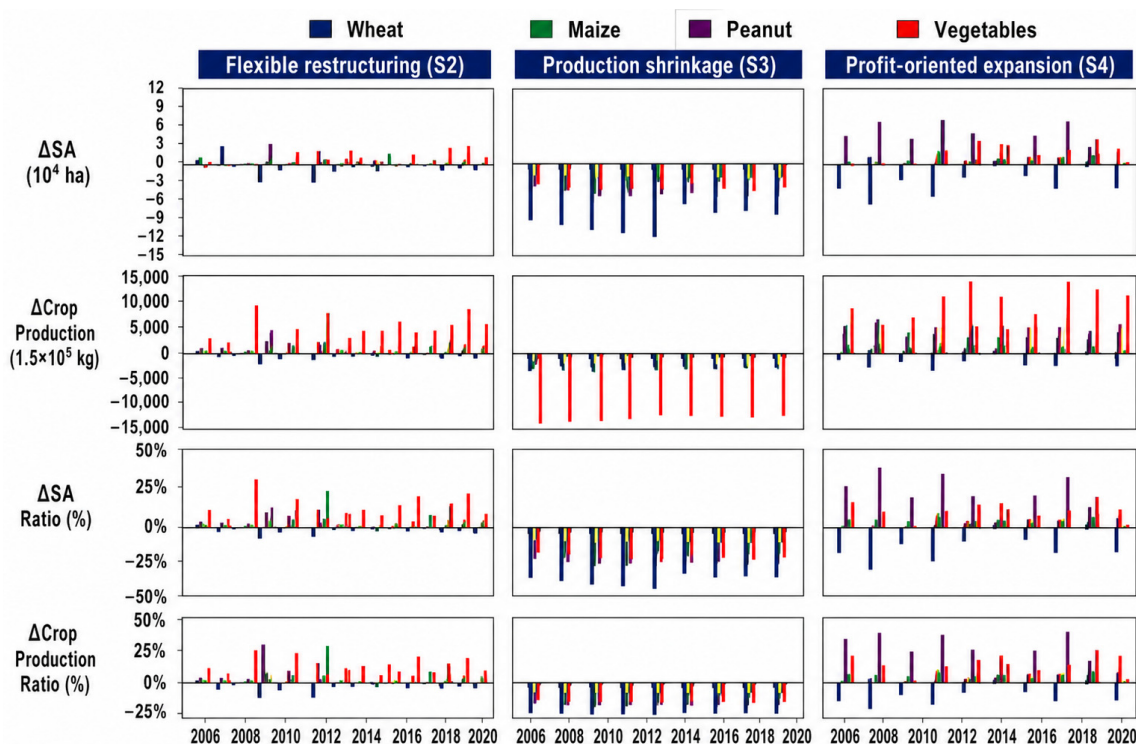


Figure 5. Interannual changes in sown area and crop production relative to S1.

However, not all years followed the same pattern. Wheat planting in S2 increased in 2006 and 2013, whereas in S3, maize SA and CP declined more than wheat SA and CP in 2010, 2013, 2014, and 2016. Similar deviations were observed in S4, where wheat production did not decline in wet years (2011, 2018) or dry years (2012, 2015). A comparison of the average ΔSA and ΔCP ratios among the three groups (Figure 6) showed that when greater adjustment flexibility was allowed (S3 and S4), wheat SA and CP decreased markedly, whereas increases occurred only under S2 during dry and normal years. This pattern helps

explain the anomalous increase in wheat planting in 2006 and 2013. Maize planting was strongly favored in both wet and dry years: its SA showed the smallest decrease in S3 (20%) and largest increase in S4 (24%). By contrast, this preference was less evident in normal years, when SA decreased by 27% in S3 and increased by 19% in S4. This may be because lower precipitation in dry years increases irrigation demand (Equation (1)), whereas in wet years, a greater proportion of low-demand crops further reduces total irrigation demand; both conditions facilitate achieving the IR objective. Peanut and vegetable production was higher in normal years than in wet years. These findings suggest that, in wet years, wheat area was converted to maize to the greatest extent, likely because this conversion reduced both IR and PF. Therefore, conversion from wheat to maize provided greater optimization benefits in dry and wet years, whereas vegetable and peanut production were more favorable in normal years. These patterns indicate that precipitation variability altered the relative resource advantages of different crops but did not fundamentally change the model preference for maintaining maize production under wider adjustment ranges.

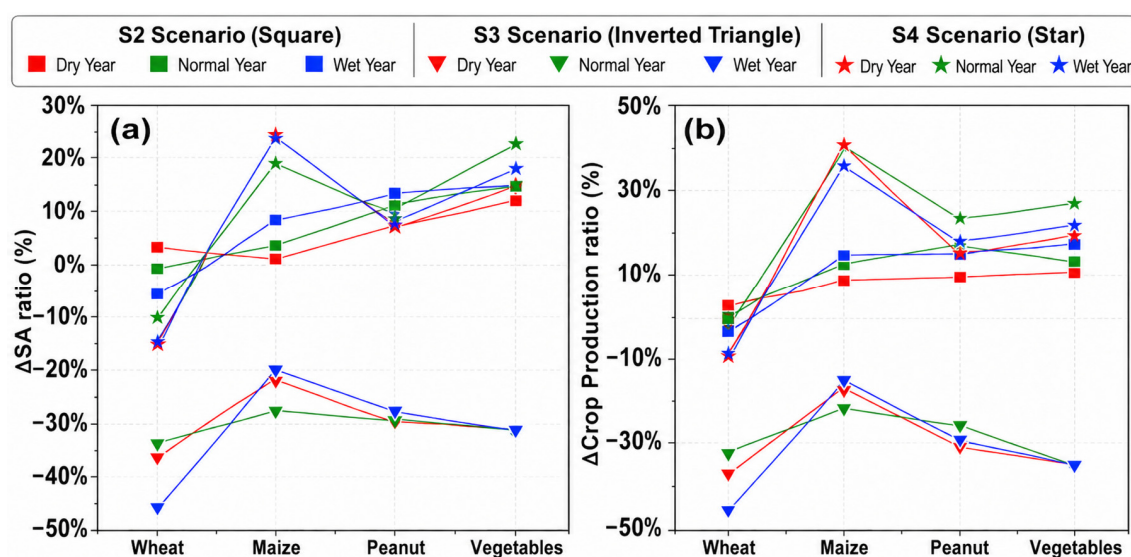


Figure 6. Changes in SA and CP ratios for each crop under different annual precipitation conditions: (a) SA ratios; (b) CP ratios.

3.3.2. Production Regulation Strategies in Different Subregions

Subregional comparisons were conducted to identify region-specific agricultural production adjustment strategies. Figure 7(a1–a4) shows the average regional optimization results and marginal returns (MRs) from 2005 to 2020. The production scale ranking (Pingdu > Laixi > Jimo > Jiaozhou) and scenario-based outputs (S4 > S2 > S1 > S3) were generally consistent with actual regional conditions and the predefined scenario settings. However, Jiaozhou generated 40.6% of Pingdu's NP despite accounting for only 18.6% of Pingdu's PF (7.03×10^9 CNY). Furthermore, Jiaozhou had a higher NP than Jimo across all scenarios, despite having a smaller SA. Table 5 explains this: a significant proportion of Jiaozhou's agricultural output was derived from vegetable cultivation, which generated substantial profits while requiring relatively low IR and PF inputs. This finding highlights that regional optimization outcomes were controlled not only by planting scale but also by crop-specific economic and resource-use characteristics.

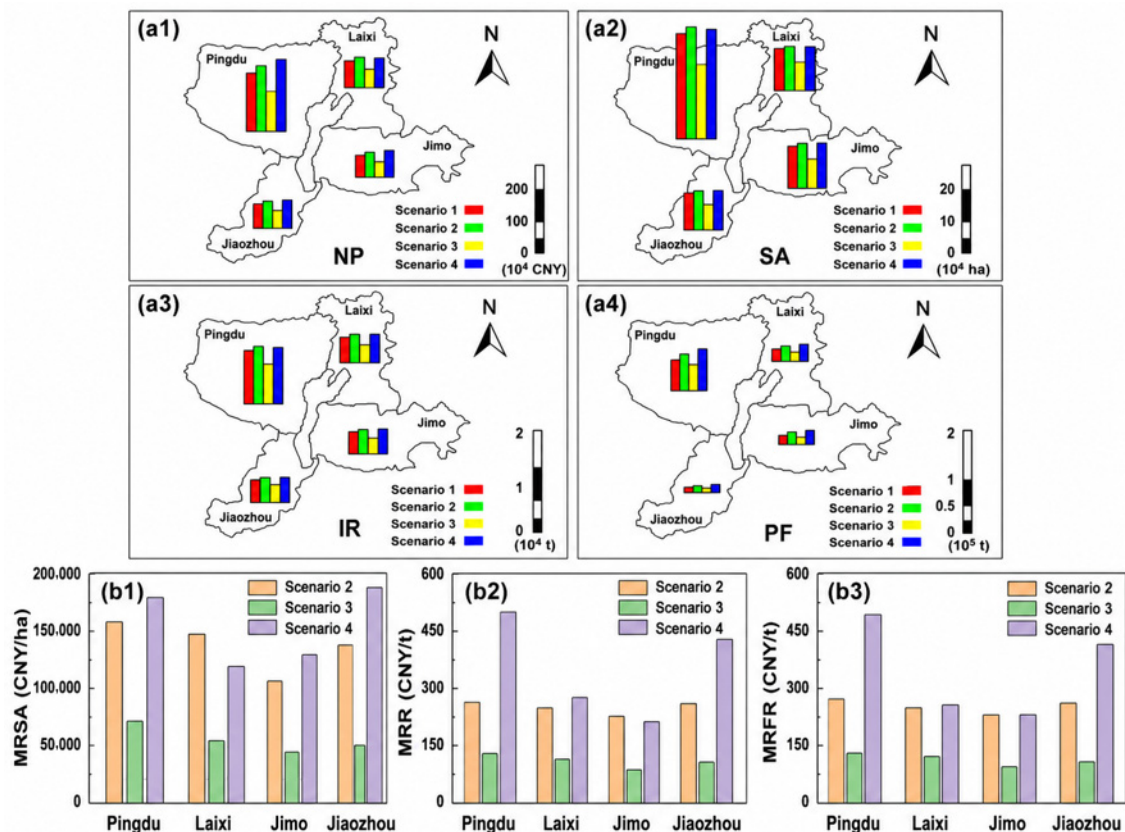


Figure 7. Spatial distribution of scenario-based optimization results and marginal-return indicators: (a1) net profit (NP); (a2) sown area (SA); (a3) irrigation requirement (IR); (a4) planned fertilizer input (PF); (b1) marginal return of sown area (MRSA); (b2) marginal return of irrigation requirement (MRIR); and (b3) marginal return of planned fertilizer input (MRPF).

Table 5. Average planting structure in different counties from 2005 to 2020.

	Scenario 2				Scenario 3				Scenario 4			
	Wheat	Maize	Peanut	Vege	Wheat	Maize	Peanut	Vege	Wheat	Maize	Peanut	Vege
Pingdu	33.6%	36.3%	10.9%	19.2%	31.8%	43.3%	10.3%	14.7%	27.6%	41.9%	11.0%	19.6%
Laixi	33.8%	34.0%	14.6%	17.6%	31.7%	35.5%	15.1%	17.7%	33.5%	35.4%	14.8%	16.4%
Jimo	35.2%	35.9%	17.6%	11.3%	33.4%	39.7%	15.6%	11.3%	28.6%	44.5%	14.6%	12.4%
Jiaozhou	31.8%	34.0%	7.5%	26.8%	28.4%	32.8%	9.0%	29.8%	25.9%	39.1%	7.4%	27.6%

Table 5 also provides important insights into region-specific production adjustment strategies. First, differences among scenarios indicate that when greater adjustment flexibility was allowed in S3 and S4, a large proportion of wheat area was converted to maize. This structural adjustment, characterized by wheat-to-maize conversion and constraints on peanut and vegetable cultivation, was particularly evident in Pingdu and Jimo. In contrast, Laixi and Jiaozhou exhibited only minor changes in crop structure across the different scenarios.

The results provide further insights into region-specific adjustment strategies (Figure 7(b1–b3)). Although the optimized patterns showed a broadly similar direction among the four regions, the magnitude of adjustment and the associated economic responses differed because of variations in existing crop structure, rotation practices, irrigation demand, and production profitability. These differences indicate that the IFE model does not simply provide a uniform adjustment strategy for the whole basin but can identify region-specific optimization intensities based on local agricultural production conditions. Overall, marginal returns (MRs) were higher in Pingdu and Jiaozhou than in Laixi and Jimo,

indicating lower economic returns from production expansion in the latter two regions. Furthermore, marginal returns from planned fertilizer input (MRPF) and sown area (MRSA) were substantially greater than marginal returns from irrigation requirement (MRIR). A 1 ha increase in SA or a 1 t increase in PF increased profits by approximately 400–1200 times, which is as much as a 1 t increase in IR, indicating that changes in irrigation had a negligible effect on crop profit. MRSA and MRPF peaked in S4 and S3, respectively, indicating that the additional profit generated by expanding SA remained substantial. However, the trend of MRPF under S4 also suggested a marked decline in the efficiency of additional fertilizer input for generating income. Consequently, production expansion was not universally optimal, highlighting the need to prioritize crops with lower input requirements and higher resource-use efficiency.

In summary, the IFE optimization favored maize and vegetable cultivation, while restricting peanut cultivation and reducing wheat area. However, the adjustment strategies varied among regions. Under S3 and S4, Pingdu and Jimo experienced substantial conversion from wheat to maize, together with strict limitations on peanut expansion. In contrast, Laixi and Jiaozhou showed relatively minor changes in crop proportions across scenarios. An expansion strategy showed greater potential in Pingdu and Jiaozhou. However, the declining marginal return of PF suggests that expansion of high-performing crops should still be moderated to maintain overall efficiency. These regional differences show that the same basin-wide objective may require different crop-adjustment intensities, depending on existing crop structure and the economic returns generated by additional water, fertilizer, and land inputs.

3.4. Groundwater Nitrate Responses

3.4.1. Spatiotemporal Distribution of ELM-Simulated Results from 2019 to 2020

To characterize the spatiotemporal variations in ELM-simulated nitrate concentrations, predictions were made for the period of 2019–2020. Monitoring wells were classified into northern (above a–a), central (between a–a and b–b), and southern (below b–b) sections based on the spatial divisions shown in Figure 8. Figure 8c indicates that average concentrations were generally higher in the northern section than in the southern section. However, the concentration differences among scenarios were small, ranging from 0.026 to 4.8 mg/L (0.04–5.8% relative to S1) relative to S1 (Figure 8a,c). Therefore, S1 was selected as a representative scenario for analyzing spatiotemporal concentration changes (Figure 8a,b).

Figure 8a shows a generally consistent spatial distribution pattern of nitrate concentrations. High-concentration areas (>100 mg/L) occurred in the central and southernmost regions, whereas concentrations in the northern section were relatively lower and more uniform. An additional high-concentration zone also appeared in the northernmost region. From 2019 to 2020, overall concentrations increased slightly (Figure 8b), with the average and median concentrations in 2020 being 4.4 and 0.3 mg/L higher, respectively, than those in 2019. However, marked seasonal variations were observed (Figure 8a). Concentrations in the northern and central sections increased markedly from June to August, coinciding with the peanut and maize growing seasons (April to September). The increasing trend in the northern section continued until December, after which concentrations returned to a lower level in the following June. In contrast, concentrations in the southern section remained high throughout the year, whereas those in the central section steadily declined from August to the following June.

These concentration patterns can be attributed to a combination of geographical characteristics, agricultural inputs, and crop conditions. A regional comparison based on marginal returns was used to explain differences in economic responses to the optimization strategies. In contrast, the comparison based on production scale and geographical location

was used to interpret the spatial distribution of groundwater nitrate pollution. Pingdu and Laixi had relatively large agricultural production scales and are located in areas where agricultural inputs may more strongly influence nitrate transport to groundwater. First, Pingdu and Laixi, which had relatively large agricultural production scales, required more water and fertilizer inputs (Figure 7), potentially leading to enhanced nitrate leaching and the formation of high-concentration areas in the north. Nitrate may have accumulated along downstream flow paths in the southern section, forming a high-concentration zone. Second, the timing of fertilizer application was closely associated with periods of increasing nitrate concentrations. For instance, fertilizer application during the maize and peanut growing period (April to August) could have contributed to the observed nitrate concentration increase in the central section from June to August. Similarly, the application of basal fertilizer to wheat in September may also have influenced nitrate concentration changes in the northern section.

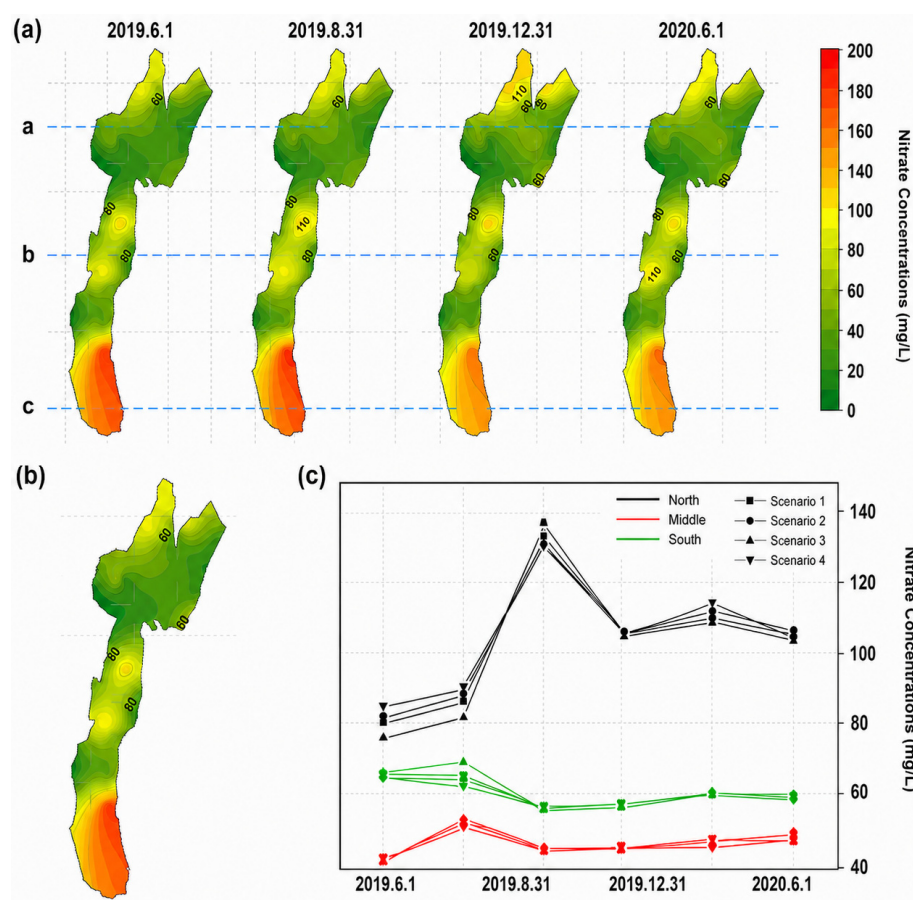


Figure 8. Simulated nitrate concentrations: (a) from 1 June 2019 to 1 June 2020; (b) on 31 December 2020; and (c) median concentrations.

3.4.2. Decadal Nitrate Dynamics from 2021 to 2030

To assess the long-term impacts of adjustment strategies on nitrate concentrations, the production conditions of 2020 and average annual rainfall were used to predict nitrate concentrations from 2021 to 2030. The following sections present the corresponding prediction results and interpretations.

Figure 9 illustrates the interannual variations in nitrate concentrations in each section over the prediction period. In both the northern and southern sections, median concentrations generally peaked in June and reached their minimum in December each year (Figure 9a–c), although some interannual fluctuations were observed. The relatively small seasonal differences indicate that groundwater nitrate concentrations respond slowly

to agricultural management changes because of the delayed response characteristics of groundwater systems. This pattern suggests that nitrate concentrations in these two sections exhibited a seasonal decline within each year, even in the absence of additional external interventions. At the basin scale, nitrate concentrations generally showed a decreasing tendency from summer to winter (Figure 9d) and increased again during the first half of the following year. However, both intra-annual and interannual variations in nitrate concentrations were limited after 2020. The maximum differences in the northern and southern sections were 5.3 and 3.1 mg/L, respectively, accounting for approximately 5% of the observed nitrate concentrations. These findings highlight the difficulty of reducing groundwater nitrate concentrations to drinking water standards in regions dominated by intensive agricultural activities. Therefore, supplementary measures, such as drip irrigation [36] and slow-release fertilizers [52], are needed to mitigate fertilizer-induced nitrate leaching losses [21].

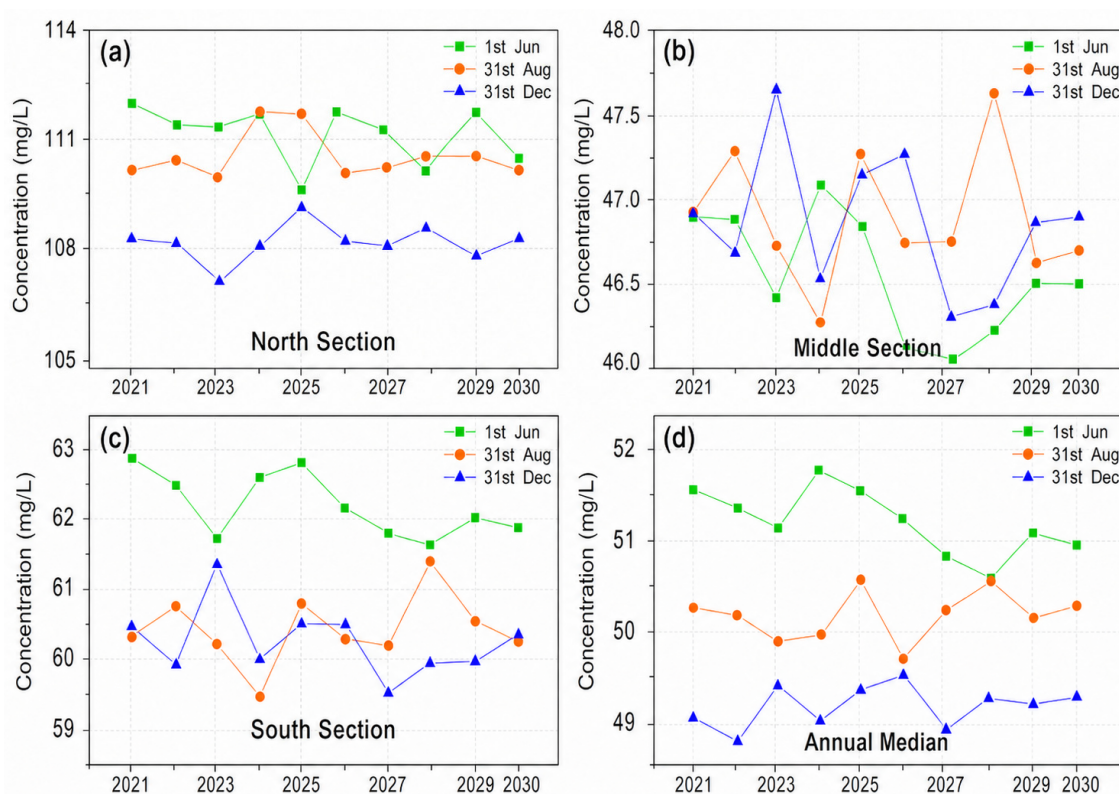


Figure 9. Interannual variations in ELM-predicted nitrate concentrations from 2021 to 2030 in the (a) northern section; (b) central section; (c) southern section; and (d) entire study area.

Thus, under stable production scales, groundwater nitrate concentrations exhibited predictable seasonal cycles of increase and decline. Both agricultural production activities and intense precipitation events influenced these concentrations, typically resulting in relatively lower levels (median nitrate concentrations < 50 mg/L) by the end of each prediction year. The small interannual differences are consistent with delayed groundwater responses and suggest that changing annual agricultural inputs alone is unlikely to produce rapid water-quality recovery.

3.4.3. Scenario Effects on Nitrate Distributions

To assess the impacts of different scenarios on nitrate concentrations, scenario dominance was compared for both maximum and minimum nitrate concentrations. The 30–50 mg/L and 50–100 mg/L nitrate concentration ranges were selected for analysis,

as depicted in Figure 10. The <30 mg/L range was excluded from the comparison because its proportion showed little variation among scenarios.

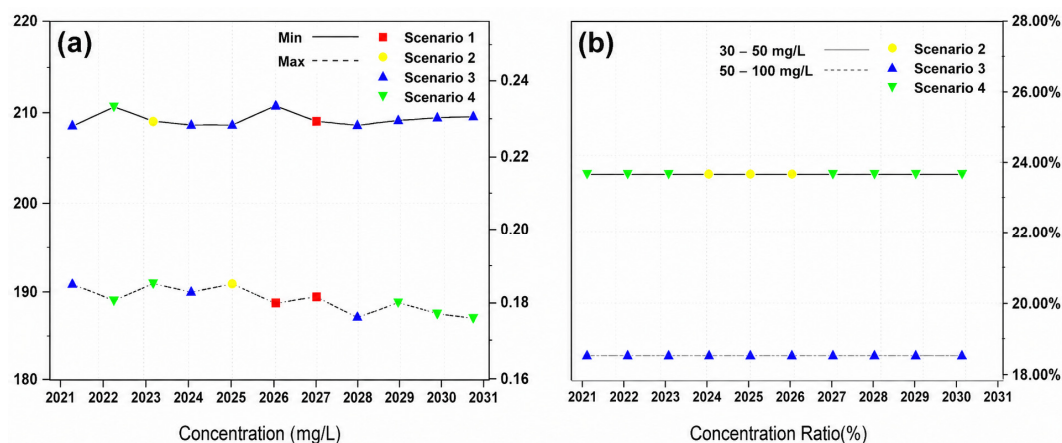


Figure 10. Dominant scenarios for (a) minimum and maximum concentrations; (b) dominant scenario and the proportion of monitoring wells within selected nitrate concentration ranges.

For maximum concentrations, all scenarios exhibited scenario dominance in certain years. Consistent with the previous predictions, the dominant maximum concentrations changed only marginally after 2020. This suggests that the relationship between maximum concentrations and scenario settings was weak, implying that production adjustments had limited impacts on peak nitrate concentrations.

However, the distribution of monitoring wells among concentration ranges differed more clearly between scenarios (Figure 10b). The production-shrinkage scenario (S3) more frequently resulted in the largest proportion of wells within the lower concentration range of 30–50 mg/L, whereas the profit-oriented expansion scenario (S4) more frequently resulted in the largest proportion of wells within the higher concentration range of 50–100 mg/L. In addition, S3 produced the lowest annual minimum nitrate concentration after 2022 (Figure 10a). These results suggest that reducing agricultural production can shift more wells toward lower nitrate concentration ranges, whereas production expansion may slow this improvement. However, the magnitude of this effect remained limited, indicating that production adjustment alone is unlikely to fully restore groundwater nitrate conditions.

Beyond environmental impacts, reducing agricultural production has significant negative economic consequences. Compared with S1, S3 reduced IR and PF by 32% and 22%, respectively, on average over the study period. This led to a substantial 31% decrease in net profit (NP), equivalent to 116.63×10^8 CNY/year. Conversely, S4 increased IR and PF by 5% and 44%, respectively, resulting in a 20% increase in NP (78.05×10^8 CNY/year). From a development perspective, the economic loss over a 10-year period would be difficult to accept [3,19], given that reducing agricultural production had only a limited short-term effect on nitrate concentration reduction while substantially constraining local agricultural and economic development. From another perspective, the IFE model optimized production structure to reduce resource consumption and environmental impacts while maintaining economic benefits without requiring reductions in overall agricultural scale, which may represent a more acceptable strategy. Thus, the main distinction among the scenarios was not whether nitrate pollution was eliminated, but whether limited groundwater quality improvement could be achieved without imposing disproportionate losses in agricultural income.

4. Discussion

The results demonstrate that agricultural production adjustment can influence groundwater nitrate concentrations, but the magnitude and timing of these responses vary spatially and remain limited over the decadal prediction period. This finding indicates that groundwater nitrate mitigation cannot be achieved solely by changing the overall agricultural production scale. Instead, effective management requires joint consideration of crop structure, irrigation and fertilizer inputs, economic returns, and delayed groundwater responses. This implies that groundwater nitrate mitigation in intensive agricultural regions requires an integrated strategy. Economic viability, crop production stability, and nitrogen-leaching control should be considered simultaneously. The proposed IFE framework can help screen alternative production-adjustment scenarios, but its outputs should be further evaluated with local agronomic constraints and more detailed soil nitrogen processes before implementation.

4.1. Impact on Spatial and Seasonal Nitrate Distribution

The observed and ELM-predicted nitrate distributions showed substantial spatial heterogeneity across the Dagou River basin. The persistent high-concentration zones in the middle and southern sections may reflect the combined effects of agricultural nitrogen inputs, groundwater flow pathways, and nitrate transport from upstream agricultural areas. However, because the present model does not explicitly simulate groundwater flow and solute transport, these spatial relationships should be interpreted as plausible explanations rather than direct process attribution.

The seasonal variation in nitrate concentrations was broadly consistent with the timing of crop fertilization and concentrated precipitation. Fertilization during the growth periods of maize and peanuts may increase the amount of leachable mineral nitrogen, particularly when heavy rainfall occurs shortly after fertilizer application. Similarly, the application of basal fertilizer for winter wheat may also contribute to nitrate accumulation during the subsequent recharge period. These processes may explain why nitrate concentrations increase during certain periods and decrease during others, as well as why optimization strategies differ under dry, normal, and wet years.

Nevertheless, the limited interannual changes after 2020 suggest that groundwater nitrate concentrations are not controlled solely by current-year fertilizer application. Nitrate remaining in the soil profile or unsaturated zone may continue to migrate downward after fertilizer inputs are reduced. Such legacy effects can delay groundwater quality responses to changes in agricultural management. Similar delayed and spatially heterogeneous nitrate responses have been reported in other intensively cultivated aquifers, where current fertilizer inputs interact with legacy nitrogen stored in soils and the unsaturated zone [54]. Regional transport studies have also shown that reductions in agricultural nitrogen loading may not lead to immediate groundwater-quality improvement because nitrate migration is controlled by recharge conditions, groundwater-flow paths, and travel times [33]. Therefore, the limited short-term response identified in the Dagou River basin is not necessarily unique to this site but reflects a broader challenge in agricultural aquifers with long nitrate residence times.

These results indicate that measures aimed only at reducing annual fertilizer input may be insufficient to rapidly improve groundwater quality. Production adjustment should therefore be combined with management practices that reduce nitrate accumulation and leaching, including improved fertilizer timing, drip irrigation, slow-release fertilizers, and soil nitrate monitoring [36].

4.2. Agronomic Interpretation of Crop-Structure Adjustment

The optimization results generally favored maize because it provided a relatively favorable balance among irrigation requirement, fertilizer input, and net profit. Compared with wheat, maize required less irrigation and fertilizer while maintaining a similar level of economic returns. This explains why the optimized crop structure tended to maintain or expand maize cultivation, especially under scenarios with greater adjustment flexibility.

However, the model's preference for maize should not be interpreted as a direct recommendation to replace wheat with maize at the farm scale. In the study area, wheat and maize may occur within the same winter wheat–summer maize cropping system. Therefore, changes in their optimized sown areas represent regional adjustments in annual crop composition and the relative extent of existing cropping systems, rather than the unrestricted replacement of one crop with another. Practical implementation would require consideration of crop calendars, land suitability, food-security objectives, irrigation infrastructure, market demand, and farmers' willingness to adjust production.

The region-specific results further demonstrate that a uniform crop adjustment strategy would be inappropriate. Pingdu and Jiaozhou showed greater economic potential for production adjustment, whereas Laixi and Jimo showed lower returns from expansion. These differences may arise from existing crop composition, regional production scale, irrigation demand, and the relative profitability of dominant crops. The IFE model should therefore be regarded as a regional decision-support tool that identifies the direction and intensity of possible adjustments, rather than a field-level crop prescription.

The use of crop-structure adjustment to reconcile agricultural production with environmental or resource constraints is not unique to the Dagu River basin. Hydro-economic studies in North China and the Indus River basin have shown that crop pattern optimization can help balance groundwater or irrigation-water use, food production, and agricultural income [1,2]. Spatial optimization studies in the Yellow River and Heihe River basins further demonstrate that preferred crop composition depends on regional water availability, crop profitability, and existing production conditions [55]. Accordingly, the generalizable finding of the present study is not that maize should universally replace wheat, but that crop composition should be adjusted according to locally specific resource–profit trade-offs.

4.3. Environmental–Economic Trade-Offs

The comparison of scenarios revealed a clear trade-off between environmental improvement and economic cost. Reducing agricultural production decreased irrigation demand and fertilizer inputs. However, the corresponding improvement in groundwater nitrate concentrations remained modest over the prediction period, while the reduction in agricultural net profit was substantial. This result suggests that strict production reduction may not be an efficient or socially acceptable nitrate-control strategy. The economic effects of production reduction may occur immediately, whereas environmental benefits may emerge only gradually. Therefore, reducing agricultural production alone may impose high short-term costs without producing proportional improvements in groundwater quality.

By contrast, crop structure adjustment and input optimization may provide a more practical management pathway. Maintaining a reasonable production scale while reallocating planting areas toward crops with lower irrigation and fertilizer requirements can reduce environmental pressure without causing the same level of economic loss. The management implication is not that agricultural production should simply be expanded or reduced. Rather, agricultural production should be reorganized according to local resource conditions and combined with improved nitrogen management practices. Suitable measures include synchronizing fertilizer application with crop uptake, replacing flood irrigation

with water-saving irrigation where feasible, using slow-release fertilizers, and monitoring residual soil nitrate before subsequent fertilizer applications.

The results also support differentiated regional management. Areas with stronger economic responses to crop adjustment may be able to maintain agricultural income through structural optimization, whereas areas with lower marginal returns may require stricter control of high-input crops. Regional authorities should therefore avoid applying uniform reduction targets across the basin. Instead, crop structure, fertilizer efficiency, irrigation demand, groundwater vulnerability, and local economic dependence on agriculture should be considered simultaneously.

From an economic perspective, the estimated net profit represents the balance between crop revenue and production costs, including seed, fertilizer, pesticides, agricultural film, irrigation, mechanical operations, and other material inputs. Therefore, agricultural adjustment strategies should consider not only environmental benefits but also changes in farmers' production costs and income stability. In practice, policies that promote water-saving irrigation, efficient fertilizer management, and suitable crop restructuring may provide a more feasible pathway compared to direct production reduction. Economic incentives, technical support, and region-specific agricultural policies may further facilitate the transition toward groundwater-compatible agricultural management.

4.4. Limitations and Future Work

Several limitations should be considered when interpreting the results. First, the ELM model represents statistical relationships between agricultural production indicators and groundwater nitrate concentrations. It does not explicitly simulate nitrogen transformation, soil water movement, unsaturated-zone transport, or groundwater flow. Therefore, the model can identify statistical responses and scenario differences, but it cannot fully explain the physical pathways through which agricultural nitrogen reaches individual monitoring wells. In addition, this study focused on irrigation demand, planned nitrogen input, agricultural profit, and groundwater nitrate responses. These indicators do not represent a complete assessment of agricultural production performance. Water-use efficiency and nitrogen-use efficiency were not calculated because the model does not explicitly simulate crop uptake or nonlinear yield responses to water and nitrogen inputs. Greenhouse gas emissions and long-term soil health were also outside the present system boundary because emission factors, soil organic carbon, salinity, nutrient balance, and soil biological indicators were unavailable. Although the robustness of the optimization results was examined under different years, precipitation conditions, and management scenarios, a comprehensive probabilistic uncertainty analysis was not conducted in this study. In addition, groundwater recharge and nitrate leaching coefficients were not included as sensitivity parameters because the ELM-based surrogate model does not explicitly simulate groundwater flow and nitrogen transport processes. Future extensions could incorporate these indicators as additional objectives, but their inclusion would require additional process data and model components.

Second, model performance was constrained by the number of monitoring wells, temporal coverage of observations, and the limited set of explanatory variables. Other factors, including soil texture, groundwater depth, hydraulic conductivity, land-use history, pumping intensity, and local recharge conditions, may also influence nitrate concentrations. Incorporating these variables may improve the spatial transferability and predictive robustness of the model.

Finally, the optimization was conducted at the county administrative scale using annual agricultural statistics. The resulting strategies therefore represent regional adjustment directions rather than field-scale management prescriptions. Future studies should

integrate the IFE framework with process-based soil nitrogen and groundwater transport models, higher-frequency monitoring data, and field-scale agronomic information. Such integration would allow the feasibility and environmental effectiveness of individual crop rotations, fertilizer practices, and irrigation strategies to be evaluated more directly. Accordingly, the framework is most suitable for comparing regional agricultural adjustment strategies and identifying environmental–economic trade-offs. Application to field-scale management or other regions requires recalibration using local crop response, irrigation efficiency, nitrogen cycling, hydrogeological, and economic data. Therefore, the practical value of the proposed framework lies in supporting regional-scale agricultural planning and identifying feasible management directions, rather than providing direct field-scale recommendations for individual farmers.

5. Conclusions

The irrigation–fertilization–economy (IFE) optimization model linked crop production requirements with geographical and meteorological conditions to achieve multiple objectives by adjusting agricultural production scale. The model results were generally consistent with actual production conditions and addressed multiple management objectives. Under the flexible restructuring scenario (S2), the model increased crop profit by 12% while maintaining moderate increases in IR and PF.

The optimization results showed a clear preference for shifting cultivation from wheat to maize, because maize generated higher economic returns with lower irrigation and fertilizer requirements. This preference was more pronounced in dry and wet years, helping to balance environmental and economic objectives. In contrast, the expansion of high-input vegetable cultivation was constrained because of its potential impact on groundwater quality. However, this restriction was balanced against the substantial economic value of vegetables during normal years. In addition, expanding the planting scale in Pingdu and Jiaozhou showed greater economic potential than in Laixi and Jimo, whereas Pingdu and Jimo exhibited greater flexibility in crop structure adjustment. Reducing the proportion of peanut cultivation was also beneficial under the model objectives across all regions, especially in Laixi County. Therefore, the IFE model provided region-specific agricultural production adjustment strategies that accounted for local production conditions and balanced the diverse needs of regional stakeholders.

The ELM model established a statistical relationship between IFE outputs and groundwater nitrate concentrations, indicating that adjustments in agricultural production affected groundwater nitrate dynamics. However, reducing the overall production scale moved nitrate concentrations only about 6% closer to the 30–50 mg/L range over the 10-year prediction period. These results suggest that moderate production adjustment, rather than simple production reduction, may provide a more acceptable regional management strategy when economic impacts are considered. Such adjustment should be implemented together with feasible crop rotation planning, improved fertilizer timing, manure management, and measures to reduce residual soil nitrate accumulation. Therefore, further analysis of nitrate concentration change patterns will require process-based simulations and more detailed monitoring data.

However, some limitations should be acknowledged. The optimization results are influenced by the availability of regional agricultural, hydrogeological, and economic data, and uncertainties associated with model parameters may affect the robustness of the solutions. Future research should incorporate more dynamic environmental and socioeconomic factors, as well as additional field observations, to further improve the applicability and transferability of the proposed framework.

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