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Optimizing Rice Field Yield with Deficit Irrigation to Support Fish Populations in River Ecosystems

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Abstract: This study presents a simulation–optimization framework that integrates deficit irrigation strategies with ecological considerations to mitigate the impact of water abstraction on potential fish populations in river ecosystems. The framework addresses two primary objectives: minimizing fish population loss, an ecological index reflecting environmental impacts, and minimizing the yield reduction of rice crops caused by deficit irrigation. Regression models and adaptive neuro-fuzzy inference systems were employed to simulate the physical and water quality parameters of the river. Additionally, a multivariate linear regression model was developed to estimate potential fish populations using combined physical and water quality indices as inputs. Multi-objective particle swarm optimization was applied to achieve the defined objectives. Results from the case study demonstrate the model's ability to balance ecological requirements with rice production through deficit irrigation. The ecological degradation of river ecosystems was found to be comparable during dry and normal years, while rice yield decreased by approximately 10% in dry years. Comparisons with unsustainable practices, where ecological flow was disregarded, revealed that significant reductions in rice production are inevitable to sustain river ecosystems. The proposed method provides a practical approach for achieving a fair balance between agricultural benefits and environmental sustainability in river basins, making it a valuable tool for water resource management.

Keywords: rice yield; ecological degradations; river ecosystems; data-driven model; multi-objective optimization

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1. Introduction

The increasing global population is a primary driver of rising agricultural production in many countries. Among the critical inputs for farming, water often represents a significant constraint to enhancing food production, particularly in regions experiencing recurrent droughts. Climate change further intensifies water scarcity by amplifying extreme events, such as severe droughts. On one hand, stakeholders advocate for increased water abstraction from surface water sources like rivers to boost food production. On the other hand, this practice reduces the availability of water in rivers, potentially disrupting the ecological status of these vital ecosystems. As critical components of inland water ecosystems, river ecosystems have increasingly faced environmental degradation over recent decades, as emphasized by previous studies [1].

To address these challenges, the concept of environmental flow regimes has been introduced to mitigate environmental degradation in rivers. These regimes aim to maintain or restore a suitable ecological status [2]. A wide range of methods has been developed to assess environmental flow regimes, including hydrologic methods, hydraulic rating methods, habitat-based methods, and holistic approaches [3]. Among these, the Instream Flow Incremental Methodology (IFIM) is recognized as a robust process that incorporates integrated habitat simulation for evaluating environmental flows [4]. IFIM is officially endorsed in the U.S. and has been widely adopted globally due to its reliability. This method enables the simultaneous assessment of water quality and quantity, offering a comprehensive evaluation of river ecosystem health. Complementary approaches, such as univariate and multivariate methods, have also been employed to assess the ecological status of river ecosystems [5].

Achieving sustainable food production requires balancing the environmental requirements of water resources with agricultural productivity. In essence, optimizing the food–environment nexus is vital to ensuring the sustainability of food systems, particularly for strategic crops like rice, which significantly contribute to community food security. Given its potential to manage agricultural water demand during shortages, deficit irrigation has been identified as a practical strategy [6]. While the strategy often leads to a reduction in yield [7], it also enhances water use efficiency. Despite the increasing recognition of deficit irrigation's benefits, its role in mitigating the environmental impacts of irrigation supply on river ecosystems remains underexplored in the existing literature.

Optimization methods, a cornerstone of water resource engineering and management, have long been applied to achieve sustainable solutions. Linear programming, a foundational method, has been extensively utilized for optimizing water resource systems [8]. More advanced techniques, including non-linear programming and dynamic programming, have been adopted to address the non-linear performance of water resource systems [9]. Over recent decades, the complexity of many water management problems has led to the widespread use of computational approaches like evolutionary algorithms, which offer efficient solutions for single-objective and multi-objective optimization problems. Such methods include classical and new-generation algorithms as well as animal- and non-animal-inspired algorithms (e.g., [10–13]). Evolutionary optimization techniques are now recognized as powerful tools for tackling complex challenges in water resource management.

A significant gap in the existing research lies in integrating environmental models of water resources with irrigation strategies to manage the ecological impacts of agricultural water use in river basins. Recognizing the potential of deficit irrigation to optimize water consumption in agriculture, the present study introduces a novel multi-objective optimization framework. This framework links hydrological analysis, environmental modeling of river ecosystems, and deficit irrigation functions to achieve a balance between rice production and the ecological impacts of water abstraction through diversion projects. The proposed method was implemented in the Talar River Basin in Iran, a region renowned for rice cultivation. By addressing this critical nexus, the study offers a transformative perspective on the integration of irrigation strategies and hydro-environmental modeling. This approach aims to promote sustainable food production while mitigating environmental degradation, addressing a pressing global need in the face of growing ecological challenges.

2. Application and Methodology

2.1. Overview of the Method and Study Area

Figure 1 illustrates the workflow of the proposed method, which consists of three key components. The first component is the deficit irrigation model, which can be developed based on regional agricultural data from local farms. The second component is the ecological impact assessment model, which utilizes several models to evaluate the ecological degradation in the study area. The fish population was selected as the environmental index for assessing the ecological impact in the case study. The outputs from these models are then integrated within a multi-objective optimization framework, where two primary objectives are defined: (1) minimizing the difference in fish population between the natural flow and the optimal water abstraction (from the water diversion project), and (2) minimizing the gap between the potential and actual yield of rice. More detailed explanations of each component are provided in the following sections.

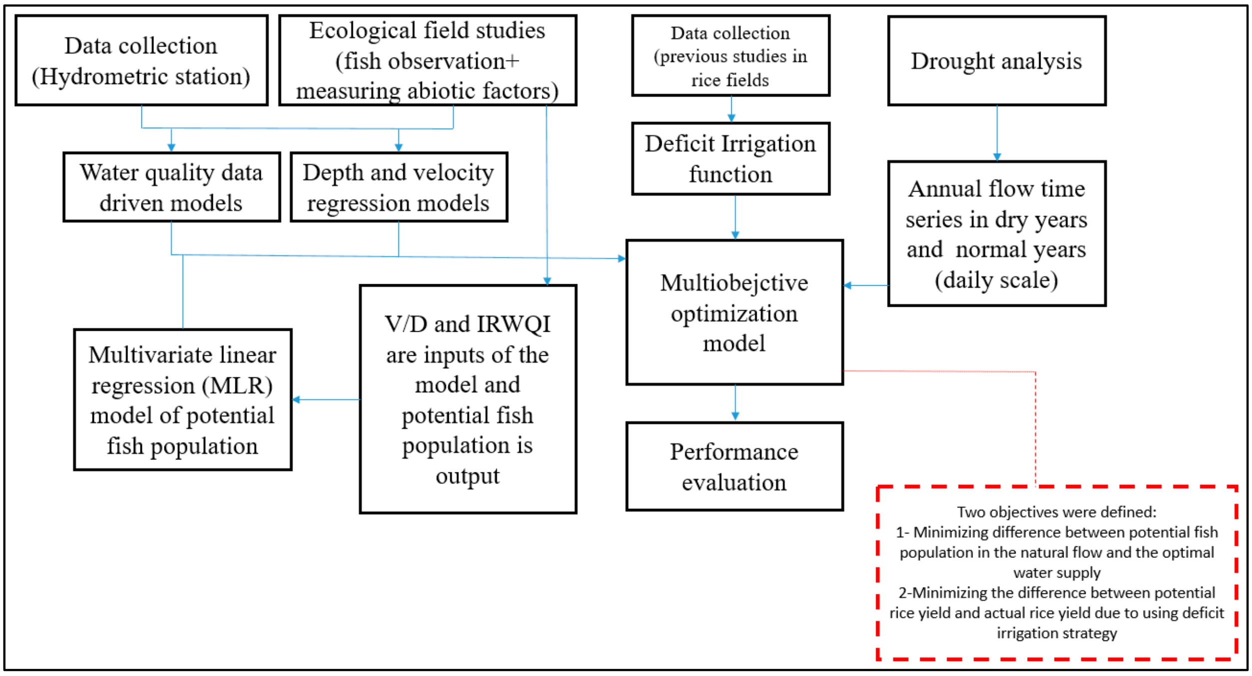

Figure 1. Workflow of the proposed method (in this workflow, V/D means flow velocity to depth, and IRWQI is a combined water quality index).

The proposed simulation–optimization method was applied in the Talar River Basin, located in Mazandaran Province, Iran. Rice cultivation is of significant importance to the local farmers, both economically and strategically, due to the limited available land for this crop in the country. The Talar River is the primary source for meeting the irrigation demands in this region, making water abstraction from the river a key factor for irrigating rice fields. However, increasing droughts and population pressures in the river basin present considerable challenges for both farmers and environmental managers. On the one hand, farmers aim to maximize water abstraction to enhance economic returns. On the other hand, environmental agencies are deeply concerned about ecological degradation in the river's aquatic habitats caused by reduced instream flows. Regional environmental engineers have identified deficit irrigation as a potential solution to reduce agricultural water use while protecting river ecosystems. However, farmers are reluctant to adopt deficit irrigation due to the associated decrease in yield and total rice production. Thus, a balanced approach that meets both irrigation and environmental needs is essential for this river basin. An optimization framework appears to be an effective tool for reconciling irrigation demands with environmental considerations to sustain rice production while mitigating ecological impacts on the river ecosystem. Figure 2 shows the Talar River Basin, highlighting the locations of the farms and the diversion dam responsible for supplying water to the downstream rice fields. It is important to note that the optimization model was applied under two different hydrological scenarios—dry years and normal years—ensuring the sustainability of rice production across varying hydrological conditions.

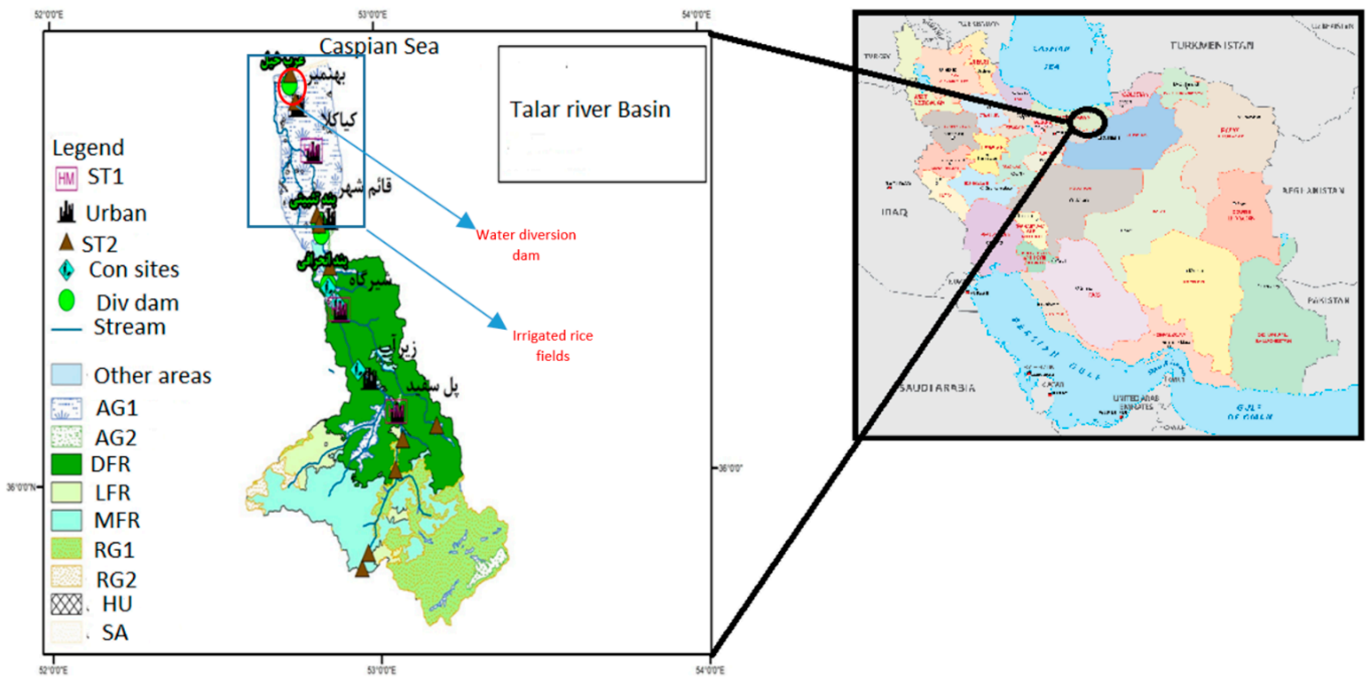

Figure 2. Location of the water diversion project and rice fields, stream network, and land use (ST means hydrometric stations, Urban means urban point, Con sites means construction sites, Div dam means diversion dam, AG1 means agricultural area 1, AG2 means agricultural area 2, DFR means dense forests, LFR means low-density forests, MFR means medium-density forests, RG1 means potential grazing areas 1, GR2 means potential grazing areas 2, HU means lands related to residential areas). The name of non-translated region from upstream to downstream are Polsefid, Zirab, Shirgah, Ghameshahr, Kiakola, Behshahr and Arabkhil.

2.2. *Deficit Irrigation Function*

The deficit irrigation function was developed based on the recorded data in the previous regional studies in which the yield of the rice at different levels of irrigation was observed. Due to many experimental works in this region, enough data were available to generate the deficit irrigation function. The developed function is displayed in Figure 3, which was used in the optimization function directly. According to previous studies and the local varieties of rice, the potential yield is 4200 tons, which is achievable with annual irrigation equal to 8270 m^3/Ha.

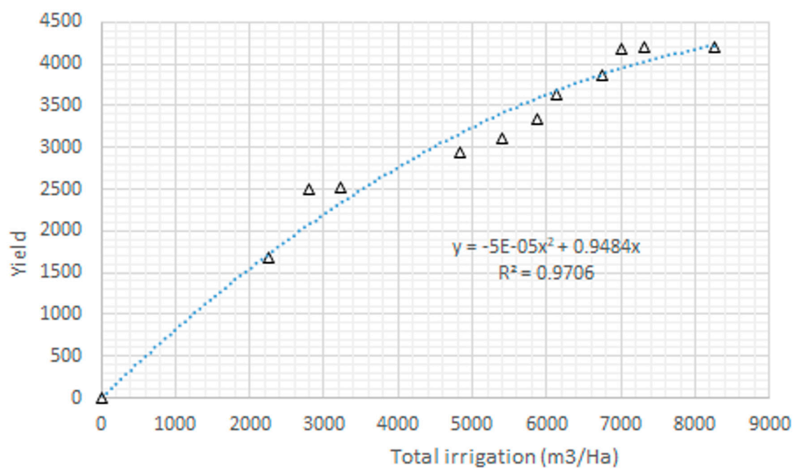

Figure 3. Deficit irrigation function in the study area—yield (Kg/Ha). Triangles are observed/estimated irrigation/yield in practice.

2.3. Ecological Impact Model

An initial habitat survey was conducted in the study area to select the target species for environmental modeling. It is important to note that several aquatic species inhabit the downstream area of the diversion dam. However, incorporating all these species into the environmental modeling may not be feasible due to the high costs associated with field studies and computational efforts. As a result, a target species was selected as an appropriate environmental index for modeling ecological suitability in the river. Based on the initial survey, *Copoeta copoeta* was chosen as the target species, as it is a known fish species in the river's habitats. This species is highly dependent on abiotic factors, which can change due to alterations in the available water in the river. Given the influence of water quality and quantity on habitat suitability, two key indices were selected: the ratio of velocity to depth and a combined water quality index that represents the average water quality suitability.

For the combined water quality index, the IRWQI (Iranian River Water Quality Index) was employed, as it can incorporate a broad range of water quality parameters to compute an overall index value. More details about this index are provided in the literature [14], with additional explanations available in Figure 4. Long-term field studies were conducted in the downstream section of the river, focusing on two types of studies. First, a representative reach was selected for fish observations, where electrofishing was used to sample fish. Depth, velocity, and water quality parameters were measured using a metal ruler, propeller, and portable water quality device, respectively. Further details about the ecological field studies in river habitats can be found in the literature [15]. In the second phase of the field studies, average depth, velocity, and water quality parameters were measured at different flow rates over an extended period. It should be noted that multiple points along the downstream river reach were averaged in subsequent applications. To estimate the effective abiotic factors, including depth, velocity, and water quality parameters, two regression models were developed based on the field study data, as shown in Equation (1), in which Q is river flow or discharge in cubic meters per second.

$$\begin{cases} V = -0.00394\left(Q^2\right) + (0.21Q) + 0.041 \\ D = -0.0009\left(Q^2\right) + (0.0782Q) + 0.0342 \end{cases} \tag{1}$$

Additionally, several data-driven models were developed to estimate water quality parameters. Various methods can be used to create a robust data-driven model. Previous studies have shown that the adaptive neuro-fuzzy inference system (ANFIS) is highly effective in simulating water quality parameters in rivers. Therefore, we applied an ANFIS-based model to simulate the necessary water quality parameters; detailed information on the theory and applications of the ANFIS model can be found in the literature [16]. The primary objective of the ecological model is to estimate the fish population within the optimization framework. To achieve this, a model was developed to estimate fish populations as part of the simulation–optimization system. As mentioned earlier, two indices—V/D (the ratio of velocity to depth) and IRWQI (the combined water quality index)—were used to estimate the potential fish population as an environmental index within the optimization model. First, a data bank was created based on field studies conducted in the river habitats, where V/D and IRWQI were computed as inputs to the model. The fish population per 100 m^2, sampled during the field studies, was the output of the model. More details regarding all the developed data-driven models are provided in Table 1.

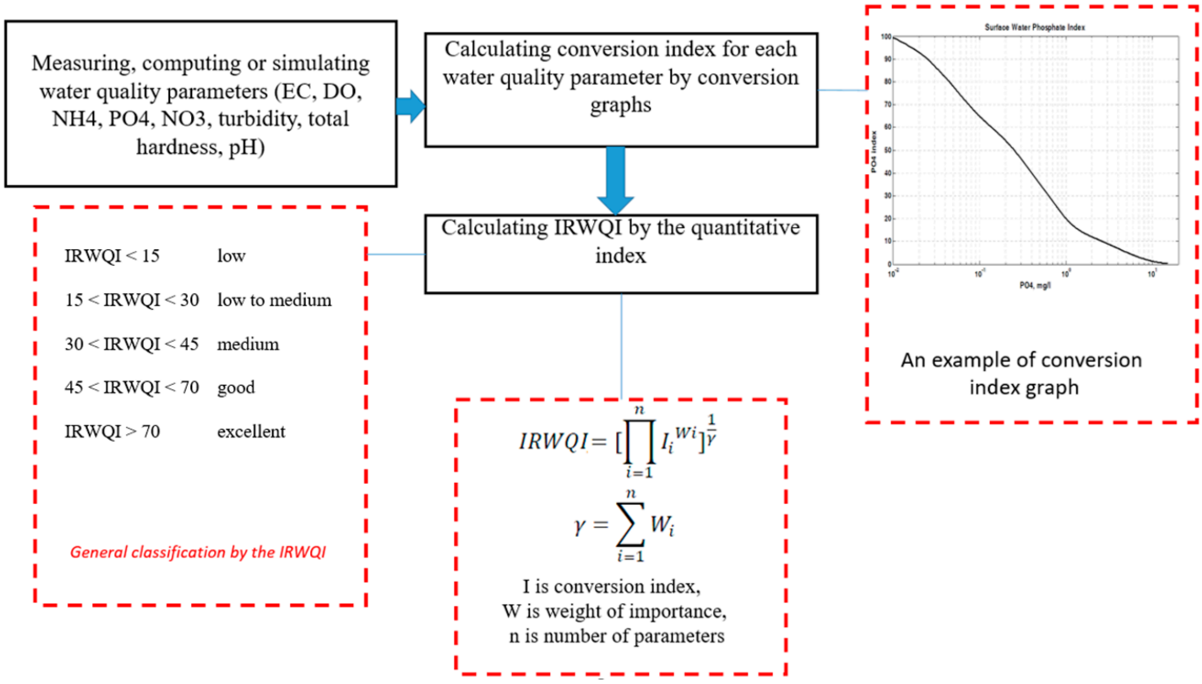

Figure 4. A description of the Iranian River Water Quality Index (IRWQI).

Table 1. Main characteristics of ANFIS-based model for simulating water quality parameters downstream of the hydropower plant.

Inputs	Number of MFs (Inputs)	Type of MFs (Inputs)	Outputs	Number of MFs (Output)	Type of MFs (Output)	Methods
Discharge, distance from the diversion dam, air temperature, top width of the river	10	Gaussian	Water quality parameters as listed in Figure 4	10	Linear	Clustering method: subtractive Training method: hybrid algorithm

Each model might need some indices to evaluate its goodness of fit. In the present study, we applied two known indices to evaluate the robustness of the data-driven models. The Nash–Sutcliffe efficiency index (NSE) and root mean square error (RMSE) were used as displayed in the following equations (more details in [17,18]). M is simulated data, O is observed data, and m means average of the time series.

$$NSE = 1 - \frac{\sum_{t=1}^{I}(M_i - O_i)^2}{\sum_{t=1}^{I}(O_i - O_m)^2} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{I}(M_i - O_i)^2}{I}} \tag{3}$$

2.4. Optimization Model

A multi-objective optimization was developed in which two objective functions were used to obtain the optimal solution. It should be noted that two objectives were considered in the optimization model, including (1) minimizing the difference between the fish population of the river habitats in the natural flow and optimal irrigation supply or minimizing ecological loss and (2) minimizing the difference between the potential yield of rice and actual yield due to using a deficit irrigation strategy or minimizing rice production loss. Equation (4) displays the objective functions developed in the present study where NPI is the potential population in the natural flow, OPI is the potential population in the optimal irrigation supply, PY is the potential yield, and AY is the actual yield due to using deficit irrigation.

$$\begin{cases} Minimize(OF1) = \sum_{t=1}^{T} \left(\frac{NPI_t - OPI_t}{NPI_t} \right)^2 \\ Minimize(OF2) = \left(\frac{PY - AY}{PY} \right)^2 \end{cases} \tag{4}$$

The potential fish population can be estimated using the ecological impact model, as outlined in the previous section. The potential yield of rice was set at 4200 tons/ha, while the actual yield of rice was computed using the deficit irrigation function, as described earlier. The multi-objective particle swarm optimization (MOPSO), a well-known evolutionary algorithm, was employed in the optimization process. Numerous studies support the effectiveness of this algorithm for solving multi-objective problems. Additional details on the theory and applications of MOPSO can be found in the literature [19]. Figure 5 illustrates the flowchart of this algorithm, which is used to find the optimal solutions for the multiple objectives defined in this study.

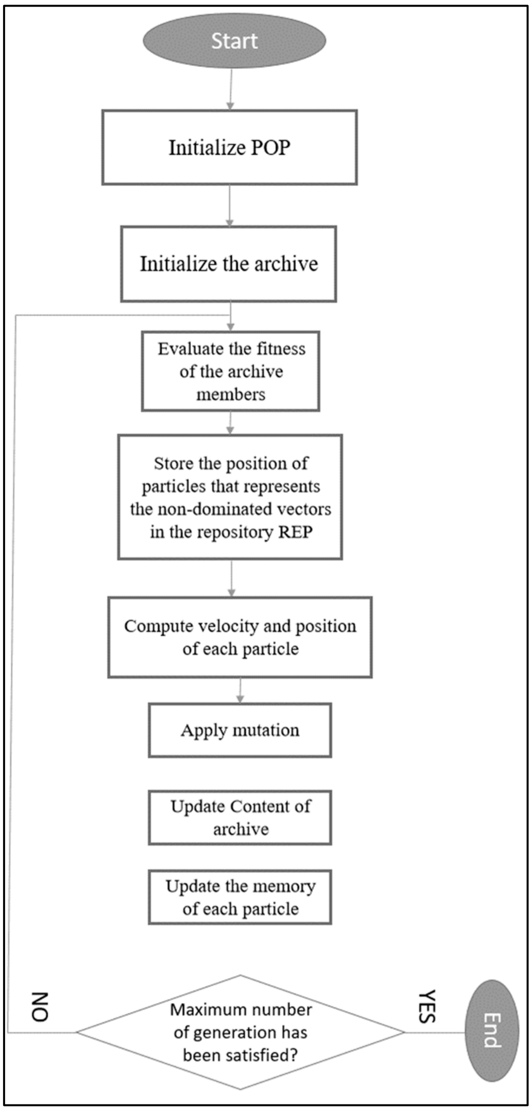

Figure 5. Multi-objective particle swarm optimization (MOPSO) flowchart [19].

It is needed to measure the performance of the optimization model. Hence, two indices were applied in this regard. The yield index was used to measure how the optimization model is able to maximize the yield of the rice, in which the ratio of the actual yield to potential yield was utilized to compute the index. Furthermore, the RSME of the optimization model was applied to measure how the optimization is able to protect the natural fish population in the water abstraction from the river, in which the difference between the fish population in the natural flow and the optimal instream flow was compared at each time step.

$$RMSE(opt) = \sqrt{\frac{\sum_{t=1}^{T}(OPI_t - NPI_t)^2}{T}} \tag{5}$$

$$yeild\ index = \frac{actual\ yeild}{Potential\ yeild} \tag{6}$$

2.5. Drought Analysis

Given the importance of optimizing drought management, we applied the simulation–optimization model under two conditions: (1) dry years and (2) normal years. To do so, it was necessary to generate the average time series of river flow for both dry and normal years. The Stream Drought Index (SDI) is a widely recognized metric for analyzing river flow in relation to drought conditions. Detailed explanations of the equations and methodology for this index can be found in the literature [12], so further discussion on its computational method is omitted here. Briefly, an SDI greater than zero indicates normal conditions, while an SDI less than zero indicates drought conditions. We analyzed the recorded river flow data for the Talar River over a 30-year period, using the average flow during drought years as the mean river flow for dry years. Similarly, the average flow from normal years was used to represent the mean river flow for normal years. It is important to note that daily time steps were used in the optimization model, meaning that the time series for river flow in both dry and normal years were generated at a daily scale.

3. Results and Discussion

First, it is necessary to present the outputs of the developed ecological models, which were integrated into the structure of the optimization model. Figure 6 illustrates the training and testing process of the dissolved oxygen model, which serves as an example of the results. Additionally, Table 2 displays the NSE and RMSE values for the water quality models. According to the literature, an NSE value greater than or equal to 0.5 indicates that the model's performance is acceptable. We adopted this criterion to assess the models, meaning that the predictive capabilities of the water quality models are deemed acceptable based on Table 2. It is important to note that the maximum value of the NSE is 1, indicating a perfect match between the model and the observations. Furthermore, the RMSE values for the models demonstrate their ability to simulate water quality parameters with low error, supporting their use in the simulation–optimization model. In the next step, the robustness of the ecological model to evaluate the potential fish population is assessed. Figure 7 shows the multivariate linear model used to estimate the potential fish population, along with the corresponding NSE and RMSE values. These indices confirm the model's acceptable capability to predict the potential fish population, comparable to the performance of the water quality models in the case study.

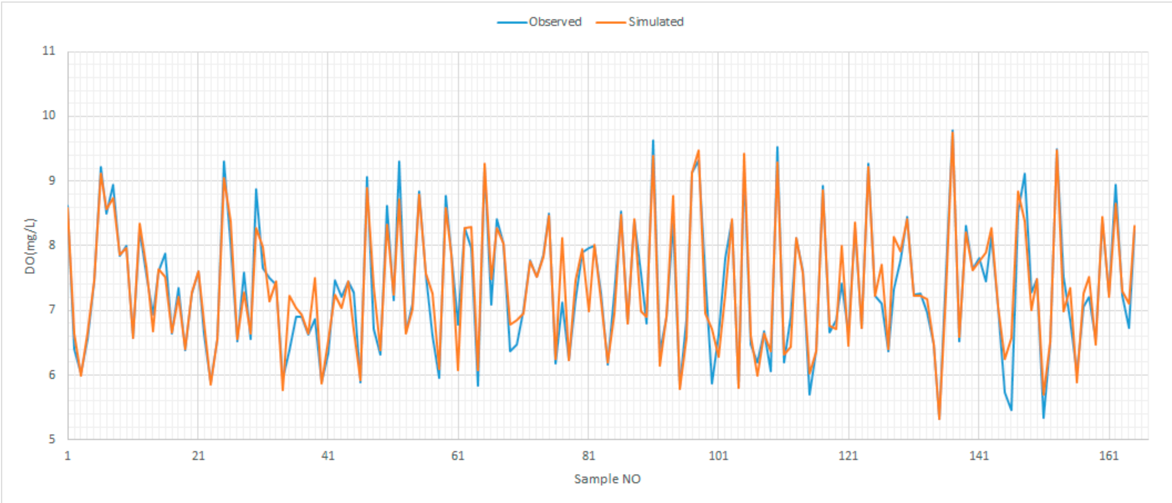

Figure 6. Training and testing process of DO model.

Table 2. Measurement indices of water quality models.

Model	NSE	RMSE
EC	0.61	51
DO	0.9	0.31
NH4	0.72	0.02
PO4	0.55	0.61
NO3	0.68	1.8
Turbidity	0.88	3.7
Total hardness	0.51	18.3
pH	0.6	0.28

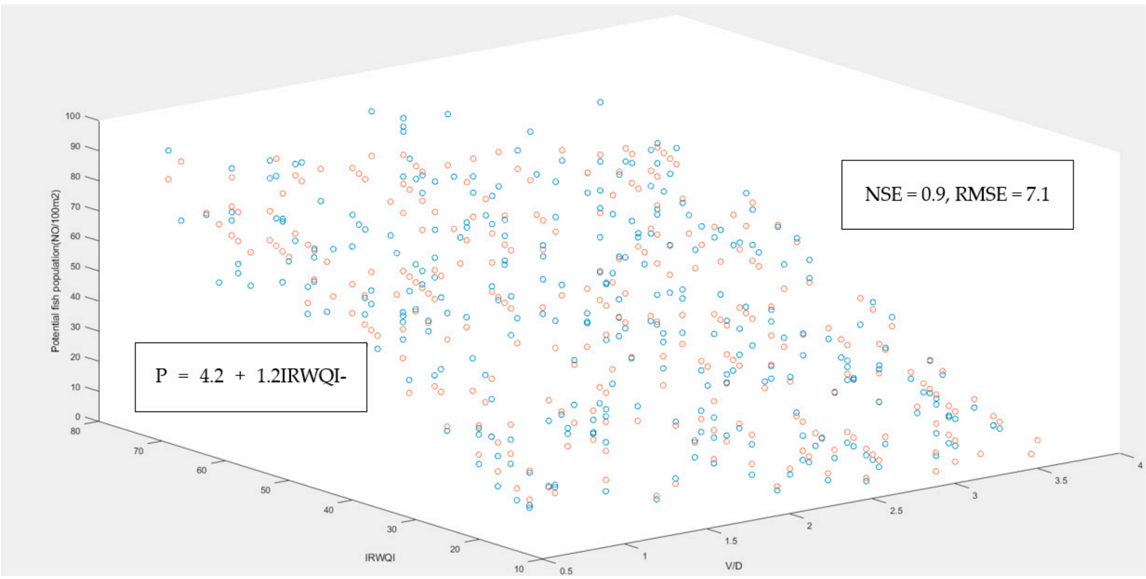

Figure 7. The multivariate linear regression model of the potential fish population (blue: observations; orange: simulations).

In the next step, the outputs of the optimization model need to be presented. The MOPSO algorithm generates non-dominated solutions based on the selected population within the algorithm. From these proposed solutions, the best one should be selected. However, selecting the best solution can be challenging, and an appropriate method is necessary to choose the most suitable option for each problem. In the developed model, the goal is to sustain rice production. In other words, the objective of the optimization model is to balance rice production and the ecological impacts of irrigation supply. Therefore, the best solution is one that minimizes the difference between production loss and ecological loss in the case study. To select the best response, we used the squared difference between the proposed values of the objectives. Figure 8 shows the Pareto front for the case study in both dry years and normal years, with the best solutions selected as [0.476, 0.477] for dry years and [0.4267, 0.4268] for normal years. In this figure, the x-axis is the normalized environmental impact, which should be minimized in the optimization process. Moreover, the y-axis is the normalized rice production, which will be maximized through the optimization model.

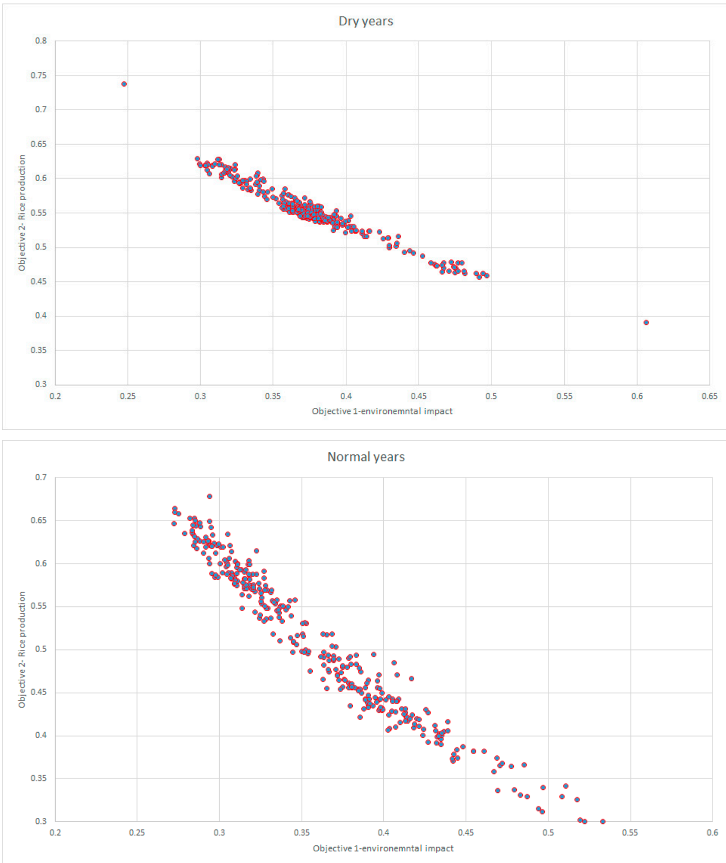

Figure 8. Pareto front according to MOPSO (Blue circles with red line are dominant solutions).

It appears that the optimization model is highly reliable in balancing the objectives, as the difference between the values in both dry years and normal years is very low. Based on the proposed best solution from the optimization model, Tables 3 and 4 and Figures 9 and 10 show all the optimization results (averaged monthly) for dry years and normal years, respectively. These figures display a wide range of results, including total available river flow, instream flow (or ecological flow), and allocated water for irrigation. It seems that the optimization model increased the instream flow at many time steps to satisfy ecological requirements. However, a more thorough evaluation of the model's effectiveness in mitigating the ecological impacts of irrigation, using the linked deficit irrigation function and ecological impact model, should be carried out based on fish population loss.

Table 3. Results of optimization (average per month) in dry years.

Month	River Flow (cms)	Environmental Flow (cms)	IRWQI in Natural Flow	IRWQI in Optimal Flow	Fish Population in Natural Flow (No/100 sqm)	Fish Population in Optimal Flow (No/100 sqm)	Allocated Water for Irrigation (cms)
March	6.9	2.8	30.0	12.2	29.4	14.5	4.1
April	6.8	2.8	29.2	12.2	28.8	14.5	4.0
May	6.6	2.5	28.6	10.6	28.3	13.1	4.2
June	5.9	2.8	25.3	12.0	25.5	14.3	3.1
July	5.6	2.8	23.8	12.0	24.2	14.2	2.7
August	4.9	3.2	20.8	13.6	21.6	15.5	1.7
September	4.3	3.1	18.3	12.8	19.5	14.9	1.3
October	3.8	2.5	16.1	10.5	17.6	12.9	1.3
November	3.6	2.5	15.1	10.4	16.8	12.9	1.1
December	3.8	2.8	16.1	11.8	17.6	14.0	1.0
January	4.3	2.7	18.3	11.3	19.4	13.5	1.6
February	5.2	2.6	22.4	10.9	22.9	13.3	2.6

Table 4. Results of optimization (average per month) in normal years.

Month	River Flow (cms)	Environmental Flow (cms)	IRWQI in Natural Flow	IRWQI in Optimal Flow	Fish Population in Natural Flow (No/100 sqm)	Fish Population in Optimal Flow (No/100 sqm)	Allocated Water for Irrigation (cms)
March	9.5	4.9	40.9	21.1	38.6	22.0	4.6
April	9.4	4.2	40.5	18.1	38.2	19.4	5.2
May	9.1	5.0	39.3	21.6	37.2	22.4	4.1
June	8.2	4.3	35.3	18.6	33.8	19.8	3.9
July	7.7	4.5	33.0	19.3	31.9	20.4	3.2
August	6.8	5.1	29.1	21.7	28.6	22.4	1.7
September	6.0	3.4	25.7	14.1	25.7	16.0	2.7
October	5.3	3.7	22.6	15.7	23.0	17.3	1.6
November	5.1	3.9	21.8	16.2	22.3	17.7	1.3
December	5.1	3.5	21.5	14.7	22.1	16.4	1.6
January	5.9	3.7	25.0	15.6	25.0	17.2	2.2
February	7.0	4.9	29.8	20.9	29.1	21.7	2.1

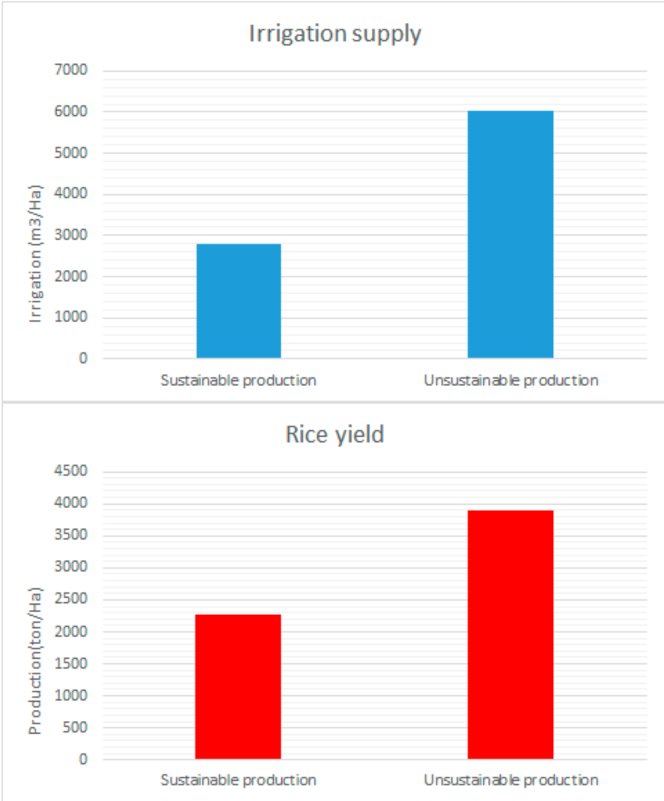

Figure 9. Water use per unit and yield of production in two statuses (dry years).

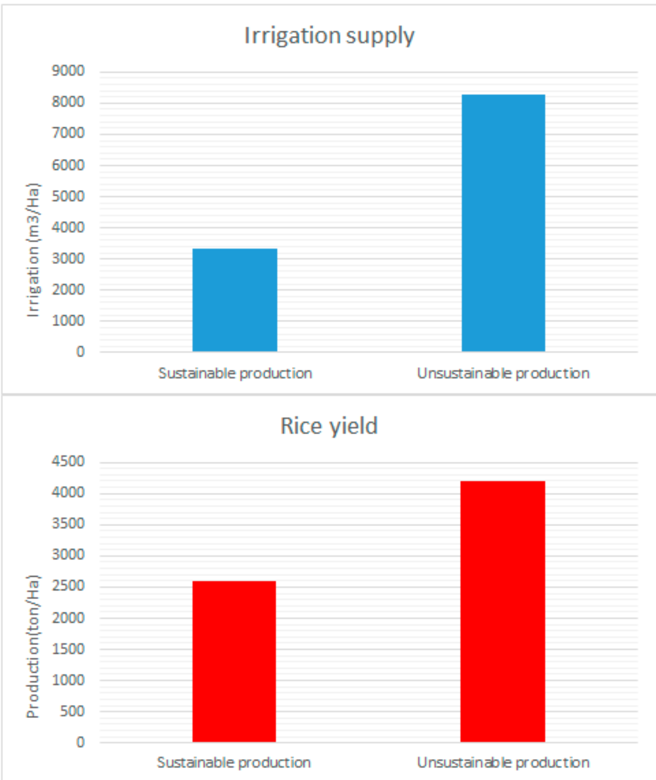

Figure 10. Water use per unit and yield of production in two statuses (normal years).

Comparing the fish population loss between dry and normal years shows that the restoration of the fish population is generally improved in normal years due to the availability of more water. However, the difference does not seem significant in many time steps.

According to Table 5, which displays the performance metrics of the optimization model, the RMSE for ecological loss is 10.8 in dry years and 13.8 in normal years. Thus, the model's performance in restoring the fish population is similar in both cases. In other words, the optimization model is capable of balancing ecological requirements and irrigation supply for sustainable rice production across different hydrological conditions. Therefore, the model is reliable for use in all hydrological conditions.

Table 5. Measurement indices of the optimization model in the case study.

	Dry Years		**Normal Years**	
	RMSE (Ecological Loss)	**Yield Index**	**RMSE (Ecological Loss)**	**Yield Index**
Sustainable production	10.83	0.53	13.87	0.62
Unsustainable production	NA	0.93	NA	1

Fluctuations in the potential fish population across different time steps may seem unusual at first glance. However, it is important to note that the optimization model attempts to balance the conflicting demands of human use and the environment. As a result, the potential fish population is reduced in some time steps to meet irrigation demands for rice fields.

Another important aspect of the results is how well the optimization model can maximize yield, which is crucial for the farmers, who are the stakeholders in the case study. We compared the yield of rice in sustainable and unsustainable production scenarios, where the latter assumes that all available water is used for irrigating the rice fields. This is not practically feasible due to the significant destructive effects on the river ecosystem. The rice yield in the unsustainable production scenario, where higher levels of irrigation are possible, is much greater than in the sustainable production scenario. It is also worth noting that fully cultivating all available farms in the case study may be an important social factor. Therefore, we considered full cultivation of agricultural lands in both models, focusing on deficit irrigation as a strategy to sustain agricultural production without altering other factors like the total cultivated area.

Generally, rice yield in normal years is higher than in dry years, which is reasonable. Interestingly, the optimization model reduced the yield in the sustainable model more than in the unsustainable production scenario, which suggests that the non-linear nature of the ecological impact function significantly influences the model's performance. Further discussion on this will be provided in the next section.

The yield index, shown in Table 5, reflects the performance of the optimization model in terms of rice production. In sustainable production, the yield indices for dry and normal years are 0.53 and 0.62, respectively. In contrast, the yield indices for unsustainable production are 0.93 and 1 in dry and normal years, respectively. Undoubtedly, reducing rice production in the sustainable scenario is necessary to protect the environment, meaning fewer resources are available for food production. In dry years, more than 45% of the yield is lost, which may not be favorable for the farmers. However, in normal years, the yield reduction is 38%, indicating that more available water improved both environmental requirements and food supply in the case study. Further details will be discussed in the next section.

An advanced simulation–optimization model was developed in the present study, and it is essential to discuss the technical and computational aspects of the model. In other words, the proposed mechanism, its advantages, and limitations should be addressed, as these could be valuable for further application of the method. First, it is necessary to explain why the deficit irrigation strategy might be a useful solution for managing the ecological impacts of irrigation supply in river basins. This strategy is already familiar to many farmers in dry regions, who use deficit irrigation during water scarcity. Therefore, the familiarity of farmers with the proposed solutions can help ensure the successful implementation of the method. In other words, we propose using deficit irrigation not only for dry years but also for all hydrological conditions to minimize the ecological impacts of irrigation supply on the river ecosystem.

One of the key advantages of the proposed method is its ability to quantify ecological impacts, which can be a significant challenge in many regions. The lack of an appropriate solution for quantifying ecological impacts in river basins can escalate conflicts between farmers and environmental advocates. Moreover, this quantitative method is integrated into the optimization model to balance the requirements for sustainable rice production. As such, this new approach could open many opportunities for managing ecological impacts in river basins or even at the farm scale. A similar optimization model, consistent with the requirements of groundwater management, could be applied to regions where groundwater resources are necessary for irrigation.

The optimization model was applied to two different hydrological conditions, including dry and normal years. Interestingly, the ecological impacts on the river ecosystem are very similar, which means the optimization model effectively integrates concerns about the impact of droughts on the river ecosystem. One of the major concerns of environmental advocates is the disregard for ecological requirements in dry years due to the social impacts of drought on farming communities. The proposed optimization model addresses this concern by balancing requirements across all hydrological conditions. Therefore, applying the proposed method, especially in dry years, is highly recommended. Environmental challenges in agriculture are expected to intensify in the future due to global warming and increasing populations, and consequently, greater demand for food. Linking food production systems with environmental impact models is vital for the sustainable development of communities. It is recommended to include population growth and climate change scenarios in future studies.

This scientific study was conducted as part of a practical project in the Talar River Basin, where the high irrigation demand for rice cultivation was a significant concern for local communities. Discussions with farmers revealed that the simulation–optimization model presented in this study is generally acceptable under normal hydrological conditions. However, its implementation during dry years poses challenges. Farmers emphasized that adopting deficit irrigation strategies should be accompanied by improvements in other key factors influencing rice production, such as nutrient management, to help maintain yield levels as much as possible.

Another important technical aspect of the model is how the non-linear nature of ecological impacts influences the results. Historically, mitigating the environmental impacts of water abstraction on river ecosystems has been quantified by allocating environmental flow to the river, which is essentially a minimum instream flow. For instance, hydrological or desktop methods of assessing environmental flow define flow regimes without directly assessing ecological impacts on organisms. Some previous studies have demonstrated the limitations of these methods for assessing environmental flow. This study shows that not only is it unreasonable to rely on non-ecological methods such as hydrological assessments, but the ecological impacts of irrigation supply extend beyond simply assessing environmental flow. Therefore, a robust optimization framework for ecological impacts is needed. The non-linearity of the ecological impacts, demonstrated in the case study outputs, highlights the importance of utilizing advanced ecological models in future agricultural planning, especially in regions where water supply and instream flow are problematic. Hence, we recommend avoiding current environmental flow methods to mitigate ecological impacts on river ecosystems.

A fair balance between environmental requirements and agricultural needs, achieved by the proposed method, helps manage negotiations between stakeholders. However, many improvements could be made in future studies. For example, incorporating other aquatic species, such as benthos, into the model could be useful in case studies where fish populations are not a significant concern. Additionally, the model could be expanded to include other types of environmental impacts, such as drainage impacts. Integrating the water quality impact of drainage systems into the model could offer a more comprehensive solution to overcoming environmental challenges.

The computational aspects of applying the optimization system are crucial, as computational limitations can pose significant problems for the practical use of these models. Computational complexity refers to the time and memory needed to find the best solution to the optimization problem. Using advanced data-driven models increases the complexities of simulation–optimization systems. In this study, several advanced data-driven models were incorporated into the optimization model, which means high computational complexities may limit the model's applicability. It should be noted that this model should be used for numerous simulations and at various scales. Therefore, high computational complexities could reduce the model's practicality. Brainstorming ways to reduce the computational complexities of data-driven models will be important in future studies. In the case study, convergence of the optimization model for each test took more than a day, which could vary depending on the addition or removal of model inputs.

Another critical computational aspect of applying the proposed method is the optimization algorithm. Due to the complexity of the functions, using an evolutionary optimization algorithm is recommended, as used in this study. It is important to note that the problem is multi-objective, meaning the optimization model must satisfy two or more objectives simultaneously. We applied MOPSO, a well-known algorithm, which was able to find the best solution in the case study, as evidenced by the very low difference in objective function values. A significant advantage of multi-objective algorithms like MOPSO is their ability to visualize the objectives, which is very helpful for decision-making in irrigation supply management. However, multi-objective algorithms are inherently more complex than single-objective algorithms, requiring more time and memory for convergence. As discussed, this issue may be exacerbated when data-driven models are integrated into the optimization model. One potential solution could be converting the multi-objective function into a single-objective function, though this would eliminate the ability to visualize trade-offs between available solutions.

It is important to acknowledge that additional factors, such as water contamination, pest infestations, and crop diseases, can impact rice cultivation as well as river ecosystem conditions, which should be considered in future research. While the present study focuses exclusively on environmental flows and their improvement through deficit irrigation strategies, these external influences may also play a critical role in shaping agricultural outcomes and ecosystem suitability. Given the complex interplay of multiple factors affecting rice production, it is highly recommended that future studies integrate these variables as inputs into the simulation–optimization model. This enhancement would provide a more comprehensive and robust decision-making framework, ensuring greater adaptability and resilience in sustainable water management for rice farming.

4. Conclusions

This study developed a novel simulation–optimization model aimed at sustaining rice production by integrating deficit irrigation and the ecological impacts of irrigation supply on the river ecosystem. The model's multi-objective approach focused on two goals: (1) minimizing fish population loss in the river ecosystem as an environmental index, and (2) reducing the difference between potential yield and actual yield due to the use of deficit irrigation. The results from the case study demonstrate that the model effectively mitigates the ecological impacts on the river ecosystem under different hydrological conditions, including both dry and normal years. This indicates that the model successfully balances the competing objectives of ecological preservation and agricultural production. However, it is important to note that the sustainable production strategy results in a reduction in rice yield compared to using all available water for irrigation. The proposed method is particularly beneficial for minimizing ecological impacts while maximizing rice production. It is especially useful during drought conditions, which can present challenges in meeting both environmental and agricultural water needs. This approach provides a valuable tool for managing water resources in a way that supports both agriculture and environmental sustainability.

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