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Review

A Review on the Optimization of Irrigation Schedules for Farmlands Based on a Simulation–Optimization Model

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Abstract: Agriculture is the most important sector that is consuming water resources. In the context of global water scarcity, how to use limited water resources to improve water use efficiency in agriculture or achieve maximum crop yield and fruit quality is of great significance for ensuring food and water security. Optimizing irrigation schedules is an effective measure to improve water use efficiency, where crop models also play an important role. However, there is little research summarizing the optimization of irrigation schedules based on crop models. This study provides a systematic review on how to optimize irrigation schedules based on crop models and simulation–optimization models. When optimizing irrigation schedules based on crop models, the selected models are usually mechanistic agro-hydrological models. Irrigation scenarios and optimization objectives are mainly focused on both crop and water aspects, such as maximizing crop yield, fruit quality, water productivity, and irrigation water productivity. Minimizing crop water consumption and total irrigation amounts serve as optimization objectives, and irrigation quantity, irrigation frequency, and irrigation interval serve as decision variables. In saline areas or low fertilizer utilization areas, the optimization objectives and decision variables also involve some indicators related to salt and nitrogen, such as the maximum desalination rate, minimum salt content, fertilizer utilization efficiency, nitrogen fertilizer productivity, nitrogen fertilizer utilization efficiency, nitrogen leaching rate, which serve as the optimization objectives, and the irrigation water salinity, or fertilization schedules serve as the decision variables. When optimizing irrigation schedules based on simulation–optimization models, the models have mainly been upgraded from water-production function to crop mechanism models. In addition, optimization algorithms have been upgraded from traditional optimization techniques to intelligent optimization algorithms. Decision-making techniques are used to make decisions on optimization results. In addition, the spatial scale for the optimization problem of irrigation schedules was developed from fields to regions, and the time scale was developed from the growth stage, beginning with months, and shortening to ten days, then to a day, and then to an hour. This study also provides a detailed introduction to widely used optimization algorithms, such as genetic algorithms, as well as decision techniques. At the same time, it is proposed that the future should focus on improving crop models and analyzing uncertainty in research on irrigation schedule optimization, which is of great significance for the precise regulation of irrigation schedules.

Keywords: irrigation schedule; crop model; optimization; simulation–optimization model

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1. Introduction

Water resources are a key factor in promoting sustainable socioeconomic development, as well as an important strategic resource for ensuring food security and ecological health.

Water scarcity is a global problem currently faced around the world, and agriculture is the most important sector that is consuming water resources. Agricultural water consumption accounts for 70% of the total water consumption globally, and water use efficiency is at a relatively low level [1]. The expected growth rate of the world population has led to a continuous increase in the demand for food, and the demand for agricultural irrigation water has also been increasing year by year [2]. Improving water use efficiency in agriculture is a key way to ensure both water resources and food security.

Optimizing irrigation schedules is an important measure to improve agricultural water use efficiency [3]. The crop irrigation schedule mainly includes the irrigation frequency, irrigation date, single irrigation quota, and total irrigation quota. A moderate water deficit could improve water use efficiency and fruit quality, while could not significantly decreasing crop yield [4–6]. Therefore, when water resources are insufficient and only deficit irrigation can be used, how to allocate the limited irrigation water reasonably in spaces (different regions, different crops) and time (different growth stages of crops) to achieve the highest yield or benefit, or minimize the loss of crop yield caused by this water shortage, is the core idea behind the optimization of irrigation schedules [7].

Optimization methods for irrigation schedules mainly include linear programming, nonlinear programming, and dynamic programming [8]. In addition, intelligent evolutionary algorithms such as genetic algorithms (GAs), simulated annealing (SA), and particle swarm optimization (PSO) [9,10] have also been widely applied due to the increasingly complex problems associated with the optimization and allocation of water resources. These methods simplify the evapotranspiration processes of farmlands under different irrigation schedules and their impacts on crop yield, making it difficult to objectively reflect on the yield changes under the different irrigation conditions.

The responses in crop production to irrigation schedules can be studied through a combination of field experiments and crop models. Field experiments are limited by factors such as the limited number of experimental variables and high costs, making it difficult to evaluate the crop growth and field water balance under various irrigation scenarios [11]. Crop models can overcome the influence of these limiting factors. They can serve as a tool to simulate crop growth, yield formation, and fruit quality under different field management schemes, effectively supplementing the shortcomings of field experiments in terms of manpower, time, space, economy, and resources [12].

Simulation models for crop growth can simulate the hydrological processes of farmlands and changes in crop yield under different irrigation conditions and can find the optimal solution through optimization methods [13]. The combination of both simulation models and optimization methods provides an effective way to optimize crop irrigation schedules [14,15]. The objective of this study is to (1) review how to optimize irrigation schedules based on both crop models and simulation–optimization models, (2) summarize the improvements in optimization methods for irrigation scheduling optimization, and (3) analyze the existing problems and challenges, propose future research priorities, and provide both reference and direction for further research on irrigation schedule optimization.

2. Optimization of Irrigation Schedules Based on Crop Models

The optimization of irrigation schedules based on crop models can be achieved by the combination of field experiments and crop models [16]. The specific steps involved in the optimization of irrigation schedules based on crop models are as follows: firstly, based on the field experimental data, verify the applicability of the crop models in simulating the dynamics of the soil, water, heat, salt, fertilizer, crop growth, yield, fruit quality parameters, and water consumption under both different irrigation conditions and various agricultural management measures; secondly, use the validated crop models to comprehensively evaluate the effects of the various irrigation scenarios on water consumption, crop productivity and fruit quality; and finally, determine the optimal irrigation schedules under the given objectives. The specific process of irrigation schedule optimization based on crop models is shown in Figure 1. The setting of the irrigation scenarios, the setting of the optimization objectives, and the selection of the crop models will vary with the needs of the users.

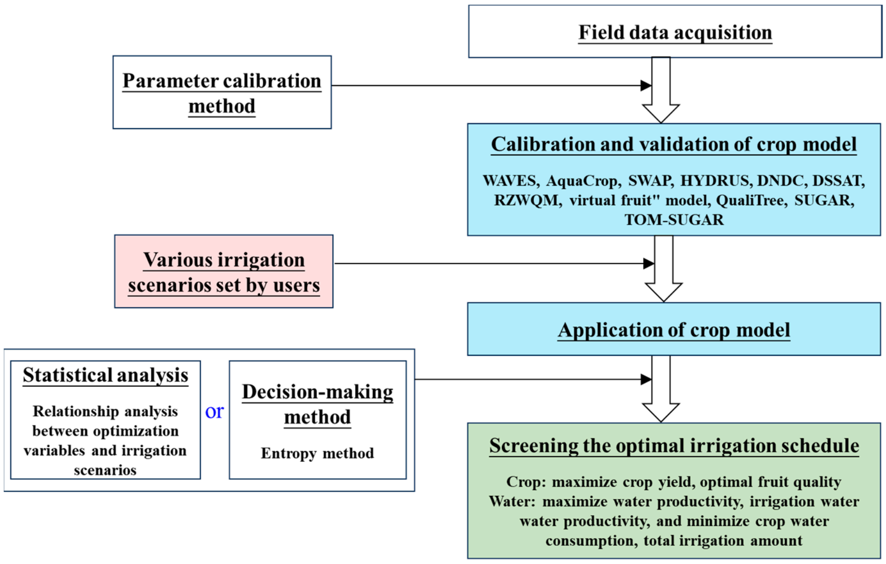

Figure 1. Flow chart of irrigation schedule optimization based on crop models.

2.1. Irrigation Scenarios

The optimization of irrigation schedules based on crop models usually involves manually inputting pre-set irrigation scenarios by users to explore the crop production situation under various irrigation scenarios. Irrigation scenarios usually reach several to tens of thousands of types, typically include an irrigation quota, irrigation frequency, and irrigation time, or a combination of two or more of these factors [17,18]. Precipitation can affect the decision-making process for irrigation schedules. Researchers make decisions on irrigation schedules for different hydrological years. The hydrological year is determined by selecting years with precipitation assurance rates of 25%, 50%, and 75% as typical representative years for wet, normal, and dry years, based on the long-term sequence data of the study area [1]. It can also be determined by the drought index with the values of >0.35, −0.35~0.35, and <−0.35 for wet, normal, and dry years [17]. Multiple upper and lower irrigation limits or combinations of the two can also be set at the different stages of crop growth, while simultaneously considering different soil textures [19,20]. In addition, the sensitivity of the crops to water at each growth stage is also determined by performing deficit irrigation at the different growth stages of the crops, while conducting sufficient irrigation at other growth stages [21]. Previous studies indicated that the seedling stage of maize was not sensitive to a water deficit, and the male ear stage, silk emergence stage, grain filling stage for maize were the most susceptible to water stress, which could affect the quality and quantity of the crop yield [22].

In areas where freshwater resources are scarce and irrigation sources rely on underground brackish or saline water, crop models were used to seek a suitable level of salinity for irrigation water, or appropriate interaction measures between both irrigation quantity and irrigation water salinity [23]. In saline areas, the appropriate range between the irrigation quotas and irrigation water salinity should be adjusted with the degree of salinization (i.e., initial soil salinity) [24,25]. In addition, leaching during the nongrowth stages of crops is considered an effective measure of salt leaching. For example, Lin et al. [26] used the SHAW model to explore a strategy of combined winter and spring irrigations for salt leaching suitable for cotton growth in Xinjiang, China. At present, in addition to water scarcity, the low efficiency of fertilization in arid regions around the world is also an important issue affecting crop production and fruit quality [27,28]. Seeking suitable water and fertilizer schedules is an important way to ensure food security. Therefore, the exploration of the optimal combination of irrigation schedules and fertilization amounts by crop models is also a hot research topic [16,29].

2.2. Optimization Objectives

The optimization objectives are generally to maximize water productivity, irrigation water productivity, crop yield, and fruit quality, while minimizing crop water consumption and total irrigation amount [30,31]. In arid areas with water scarcity, users usually consider two or more objectives associated with both water and crop simultaneously, and there may be conflicting outcomes between multiple objectives. For example, as the irrigation amount is reduced, the soil water storage decreases, which intensifies soil water stress and leads to a reduction in crop yield. This indicates that the objective of maximizing the crop yield is contradictory to the objective of minimizing the irrigation amount [13]. Therefore, balancing two or more optimal objectives is a very difficult problem. Previous studies showed that, within a certain range of irrigation amounts, crop yields increased rapidly with the increase in irrigation amounts, and with further increases in irrigation amounts, the crop yield either increased slowly or decreased [32,33]. That is, when the irrigation amount exceeded a certain range, the crop yield was limited by other factors, such as the crop varieties or climate conditions, and the potential for a yield increase was small [34]. A moderate water deficit could significantly increase fruit quality parameters, such as soluble solids, sugar content, sugar acid ratio, carotenoids, and vitamin C [35,36]. For water productivity, it first stabilized at a certain value with an increase in irrigation amount and then decreased [24]. When determining the optimal irrigation schedules, the statistical analysis was usually conducted based on the simulation scenario results, such as establishing the correlation between the various objectives and decision variables, and then determining the optimal irrigation schedules [17,32,34]. However, there were also studies that coupled crop models with multi-objective optimization decision-making methods, such as the entropy method, to seek the optimal irrigation schedules [37]. The optimization results of the irrigation schedules might vary with the objectives set by the users. For example, Yu et al. [24] proposed that when the objective was to maximize water productivity, the recommended total irrigation amount was 275–300 mm for the arid region of Northwest China, with an annual average rainfall of 45.7 mm and a pan evaporation of 2500 mm. When the objective was to find a balance between water use and crop production, it was recommended to control the irrigation amount at around 300 mm. If the objective was to increase crop yield, further increases in the irrigation amount can be employed.

In saline areas, in addition to the objectives of both water and crop, the maximum desalination rate and the minimum salt content in the soil layer of the root zone can also be included as additional objectives [11]. The objective of soil salt content is usually achieved by adjusting the irrigation schedules during the crop growth periods or by leaching salt during the fallow periods [38]. Lin et al. [26] identified the optimal strategy of combined winter and spring irrigations for salt leaching in severely saline cotton fields in southern Xinjiang, China, with the objectives of achieving soil water, heat, and salt conditions that are suitable for the emergence of cotton seedlings, as well as the desalination rate and cotton emergence rate. Zeng et al. [39] proposed an optimal irrigation schedule for the Hetao Irrigation District in Inner Mongolia, China, with the objectives of increasing the soil moisture content and accelerating salt leaching. In areas with low fertilizer utilization efficiency, the nitrogen fertilizer productivity, nitrogen fertilizer utilization efficiency, and nitrogen leaching rate were usually included together with the water and crop production as the optimization objectives [16,40].

2.3. Crop Models

Crop models are powerful tools for evaluating the relationship between crop yield, fruit quality, and water use [41]. The crop models are usually strong mechanism models that consider the impact of natural environmental conditions on crop physiological growth, such as weather conditions, including solar radiation, air temperature, humidity, and wind speed, and soil environment conditions, including soil water, heat, and nutrients [42,43]. When optimizing irrigation schedules, crop models that can be used to reflect the relationship between crop yield and water use include the following: WAVES (WAter Vegetation Energy and Solute) [24], AquaCrop [34], SWAP (Soil–Water–Atmosphere–Plant) [23], HYDRUS [44], DNDC (Denitrification–Decomposition) [45], DSSAT (Decision Support System for Agrotechnology Transfer) [46], and RZWQM2 (Root Zone Water Quality model 2) [21]. They are often used for optimizing water and nitrogen schedules or regulating water and salt, because of their good performance as crop models for elucidating the salt and nitrogen transport processes in the soil and the crop growth processes under different agricultural management measures. The model features for some of these commonly used models are shown in Table 1 for the convenience of users who are involved in model selection. Crop models that can be used to reflect the relationship between the fruit quality and water use mainly include the "virtual fruit" [47], QualiTree [48], SUGAR [49], and TOM-SUGAR models [50]. They have been widely applied in crops such as grapes [51], blueberries [52], tomatoes [53], and pears [54] to simulate the dynamics of fruit sugar content, dynamics of water and carbon flux in plants, and vegetative growth under different water conditions [52,55].

Table 1. Comparison of model features for some commonly used models.

Model Name	Driving Factors	Modules	Crop Types	Application Aspects
AquaCrop	Soil water	Meteorological module, Crop module, Soil module (water), Management module	Maize, wheat, barley, cotton, sunflower, potato, rice and other herbaceous crops, fruit trees, vines	Biomass and yield simulation [56]; Optimization of sowing dates [57]; Optimization of irrigation measures [57]; Climate change assessment [58]
SWAP	Soil water	Meteorological module, Crop module, Soil module (water, solute, heat), Management module	Annual crops such as summer maize, winter wheat, spring barley, rice, soybean, sunflower	Yield and biomass prediction [59]; Water and salt transport [59]; Remote-sensing assimilation [60]; irrigation optimization [61]
APSIM	Soil salt	Meteorological module, Crop module, Soil module (water balance, nitrogen cycle, surface organic matter, soil phosphorus), Management module, Animal module (cattle, sheep)	Beans, maize, barley, wheat, rapeseed, cotton, rice, peanut	Biomass and yield simulation [62]; Crop management; Climate change assessment [63]; Soil water and nitrogen processes [64,65]; The interaction between genes, management, and environment [66]
DSSAT	Photosynthesis	Meteorological module, Crop module, Soil module (water, organic matter, nitrogen cycle, inorganic nitrogen, phosphorus, potassium), Soil–crop–atmosphere module, Management module	Wheat, rice, maize, legumes, perennial plants	Biomass and yield prediction [67]; Irrigation, fertilization, and pesticide management [68]; Dynamic changes of carbon and nitrogen [68]; Climate risk assessment [69]
RZWQM2	Soil water and salt	Meteorological module, Crop module, Soil water module, Soil chemical processes, Nitrogen cycling module, Carbon cycling module, Insecticide module, Cultivation module	Maize, wheat, soybean, potato, alfalfa, grass, trees	Crop productivity assessment [70]; Optimization of irrigation and fertilization [19]; Dynamic monitoring of soil water and nitrogen [71]; Chemical simulation of insecticides [72]

Before making decisions on irrigation schedules based on crop models, it is necessary to determine a set of crop and soil parameters suitable for the study area based on experimental data, that is, localizing the model parameters. The crop models mostly have the characteristics of multiple-input parameters, along with the strong spatiotemporal variability of soil and crop parameters and the significant uncertainty of model parameters. The traditional method of "trial and error" has been used to debug these model parameters [73]. This method requires the subjective debugging of the input parameters based on the researcher's own knowledge and understanding of the models. It is not only time-consuming and laborious, but also the simulation accuracy of the models is not very satisfactory [74]. On this basis, sensitivity analysis can be performed for the model parameters, and then only the parameters that have a significant impact on the model-output results need to be selected for calibration and validation, while the nonsensitive parameters in the model are briefly processed [75]. In addition, the calibration methods of the model parameters can also include a parameter calibration based on statistical theory, such as the least squares method [76] and the Markov Chain Monte Carlo (MCMC) method [77], as well as intelligent optimization algorithms such as the Genetic Algorithm (GA) [78], Simulated Annealing (SA) [9], and Particle Swarm Optimization (PSO) [10]. These methods have been widely applied in many agricultural simulation models, such as the WOFOST [79], DNDC [80], and AquaCrop models [81].

3. Optimization of Irrigation Schedules Based on Simulation–Optimization Models

The optimization of irrigation schedules based on simulation–optimization models is based on the water balance model of the farmland and the dynamic water production function model, or the crop growth model. These models can reflect the evapotranspiration process of the farmland under various irrigation schedules, and their impacts on crop yield and fruit quality. After validation of the models, they were combined with optimization techniques to obtain specific irrigation schedules.

3.1. Optimization of Irrigation Schedules Based on Water Balance–Water Production Function–Optimization Algorithm

The optimization of the irrigation schedules based on the water balance–water production function–optimization algorithm included two parts: simulation of the farmland water balance and crop yield and the optimization of irrigation schedules. The field water-balance model is a conceptual model that determines the changes in soil moisture based on the input and output of soil moisture during a certain period [1]. The calculation model of crop yield usually uses crop water-production functions, which refer to the quantitative relationship between the crop yield and water input or water consumption during crop growth and development [82]. It could reflect the ability of crops to use water to produce dry matter [82]. The specific steps of the optimization of the irrigation schedules based on water balance–water production function–optimization algorithm are as follows: at the beginning, the dynamic process of crop evapotranspiration under a certain irrigation condition was first simulated through the farmland water balance; then the relative yield was estimated using the crop water-production function and the cumulative function of water sensitivity index; and finally, optimization methods were used to determine the irrigation quota, irrigation date, and the irrigation frequency required to maximize the relative yield/benefit.

There are many factors that affect the water-production function model, mainly including the crop types, soil types, irrigation methods, irrigation water quality, climate conditions, and field management measures [83]. The water-production function model for a specific crop in a specific region needs to be determined through years of experimentation. At present, there are two main types of mature water-production function models: additive models, including the Blank [84], Stewart [85], and Singh models [86], and multiplicative models, including the Jensen [87], Minhas [88], and Rao models [89].

During the processes of irrigation schedule optimization, the Jensen model is commonly used to reveal the relationship between crop yield and water consumption. When combining the Jensen model with the optimization methods for irrigation schedule optimization, the optimization methods initially used were 0–1 linear programming [90] and simplex search method (nonlinear programming) [91]. These optimization methods were local search methods, and if the initial value selection was unreasonable, a local optimal solution could be obtained. Usually, the decision variable is set as whether to irrigate on a certain day or the irrigation date, and the maximum relative yield is used as the optimization objective. To obtain the global optimal solution, a globally searchable genetic algorithm has been proposed to determine the optimal irrigation schedules [7]. The decision variables, constraints, and optimization objectives were diverse. Usually, irrigation date and irrigation water amount were used as decision variables, and the maximum relative crop yield and the minimum total irrigation amount throughout the entire crop growth period were used as optimization objectives, and NSGA-II (an improved Nondominated Sorting Genetic Algorithm) was used for the optimization solution [14,92–95]. To make the optimized irrigation schedules more universal, Wu et al. [96] considered the interannual variations in rainfall and established an optimization model for irrigation scheduling based on the multi-year rainfall data and proved its strong applicability.

In addition to the Jensen model, other water-production functions have also been used for optimizing irrigation schedules. Li [97] believed that the Blank and Stewart models were also suitable for evaluating the relationship between crop yield and crop water consumption for pumpkin under drip irrigation conditions with film mulching in the Hexi Oasis area of China. Even the Stewart model was more effective than the Jensen model, and the optimal irrigation strategy was proposed based on the Stewart water-production function and TOPSIS (Technique for Order Preferences by Similarity to an Ideal Solution). Li et al. [98] also determined that the Jensen and Stewart models were applicable for revealing the relationship between crop yield and water consumption in cold and arid environments. In addition, empirical crop water-production functions were also determined through experiments, such as the quadratic relationship between the crop yield and the water consumption or irrigation amount [1,99].

Considering the importance of evaluating fruit quality, a water–fruit quality model was developed to simulate the response of fruit quality parameters to water using the water-production function for reference, including additive, multiplicative, and exponential models [100,101]. The results showed that the multiplicative model was suitable for simulating the relationships between soluble solids, reducing sugars, sugar–acid ratio, fruit hardness, and water deficit for tomato fruits [100]. However, the additive model was selected for the relationships between organic acids, vitamin C color index, comprehensive quality index, and water deficit [100]. Models for the optimization of crop irrigation scheduling were also established based on the water-production function, water–fruit quality models, and NSGA-II to obtain the optimal irrigation schedules for cash crops. This can further improve water use efficiency, crop yield, and fruit quality [102].

3.2. Optimization of Irrigation Schedules Based on Crop Model-Optimization Algorithm

When optimizing irrigation schedules based on the crop model-optimization algorithm, the first step is to validate the crop model. Subsequently, the crop model is coupled with the optimization algorithm to construct an irrigation schedule optimization model. Then, the optimal solution, set based on specific objectives, is sought. Finally, decision-making methods are used to make decisions on the optimization results. The crop models are usually agro-hydrological models that can simulate crop growth and soil water, heat, nitrogen, and salt processes. They generally have complex calculation processes and high nonlinearity [81]. Their computational complexity is much higher than that of the crop water production functions, which could result in high computational costs for these optimization solutions [81]. In addition, the crop models are generally packaged software that is difficult to split and requires specific input and output file formats [13]. Traditional optimization methods of irrigation schedules are not applicable, and evolutionary algorithms, mainly genetic algorithms, are usually used for both optimization and solution.

The AquaCrop model is the most widely used model among the many models for optimizing irrigation schedules based on the crop model-optimization algorithm, due to its advantages such as its simple structure, fewer required parameters, low computational complexity, and reasonable accuracy [34]. A flow chart of an irrigation schedule optimization based on the AquaCrop optimization algorithm is shown in Figure 2. Song et al. [13] combined the AquaCrop model with the NSGA-II model using MATLAB and constructed a multi-objective simulation–optimization model for irrigation schedules based on measured data from spring wheat fields in the arid region of Northwest China. In Song et al. [13], the optimization objectives were a maximum yield and minimum irrigation amount, and the efficiency coefficient method was used to make decisions on the optimization results. A simulation–optimization model coupling AquaCrop with NSGA-III using Python was also developed and the TOPSIS method was used for decision-making based on the Pareto optimal solution, which was generated by a multi-objective optimization from Lyu et al. [103]. In the study, four objectives were considered, i.e., maximizing crop yield, minimizing irrigation amount, maximizing irrigation water productivity, and maximizing water use efficiency [103]. Then, Wang [104] further coupled the groundwater numerical model MODFLOW with the model from Lyu et al. [103] to evaluate the impact of irrigation on the groundwater level and determined the optimal irrigation schedules for the objectives of groundwater level variation and crop yield. In addition to the AquaCrop model, the DSSAT model was also combined with a genetic algorithm to determine an optimal irrigation and fertilization plan for a maize field with drip irrigation in the Tengger Desert, China, and a maize field with surface irrigation in Shandong, China [105].

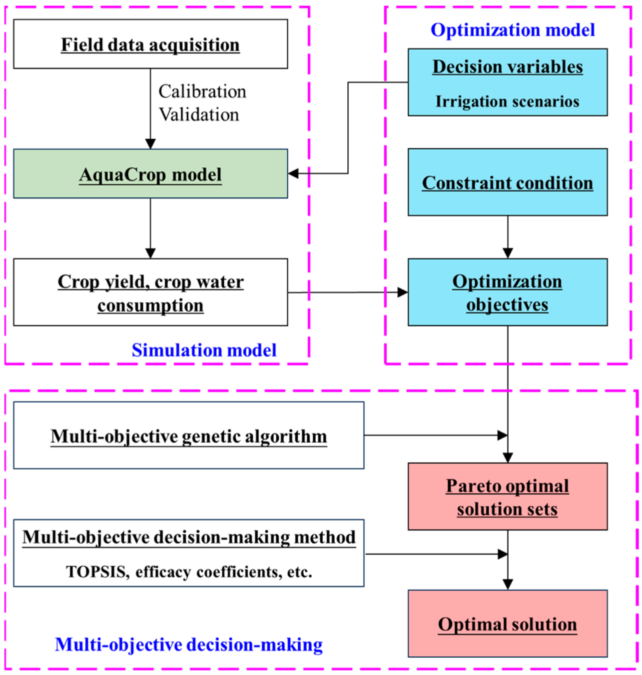

Figure 2. Flow chart of irrigation schedule optimization based on AquaCrop optimization algorithms.

Fertilizer is one of the key factors in agricultural management, in addition to the water factor, and appropriate fertilization management has a direct impact on the economic and ecological benefits associated with agriculture. When optimizing irrigation schedules based on the crop model-optimization algorithm, it is usually accompanied by either fertilization management or nitrogen loss. For example, Wu et al. [106] modified the AquaCrop model by introducing the aboveground actual nitrogen concentration, critical nitrogen concentration, and minimum nitrogen concentration to simulate the evapotranspiration of maize under nitrogen stress in Northwest China. Then, the optimal solution was determined, with the objectives of maximizing crop yield and water use efficiency, based on the NSGA-II algorithm. Decisions were made using the TOPSIS method, and the optimal irrigation and fertilization strategy was obtained. Ma et al. [107] established a simulation–optimization model for the irrigation schedules of rice based on the AquaCrop model and the NSGA-II algorithm. A stable and efficient irrigation strategy for both yield and pollution control, suitable for different hydrological years, was proposed, with the objectives of a maximum yield, minimum nitrogen and phosphorus loss, and minimum irrigation frequency.

4. Improvement of Irrigation Schedule Optimization Methods

4.1. Optimization Solution Method

As the optimization objectives of irrigation schedules shifted from a single objective to multiple objectives, and crop models shifted from a simple water-production function to agro-hydrological models, the optimization methods of irrigation schedules have also evolved from traditional linear programming, nonlinear programming, and dynamic programming to an evolutionary algorithm. A comparison of the main optimization methods for irrigation schedules is shown in Table 2. The NSGA-II algorithm is currently one of the most popular multi-objective evolutionary algorithms, which was proposed based on the NSGA (Nondominated Sorting Genetic Algorithm) [108]. The NSGA, proposed in 1994, is a genetic algorithm based on the Pareto optimal concept, which layers each individual according to their dominant and nondominant relationships [109]. Then, selection operations are performed to achieve very satisfactory results for multi-objective optimization [109]. Deb et al. [78] proposed the NSGA-II, which mainly introduces an elitist strategy on the basis of the original NSGA algorithm and uses the concept of a crowding degree to sort individuals at the same level into nondominated levels, improving the algorithm speed. The NSGA-II algorithm is mainly used to solve unconstrained multi-objective optimization problems, while most historical optimization models were multi-objective optimization models with multiple constraints [107]. Currently, the improved NSGA-II algorithm is mostly used, which introduces the Deb constraint criterion into the NSGA-II algorithm [110]. A flow chart of the improved NSGA-II approach is shown in Figure 3. Due to the poor computational performance of the NSGA-II algorithm in a high-dimensional target space, the NSGA-III algorithm, with predefined multiple reference points to maintain population diversity, has also been introduced [104].

Table 2. Main methods for solving simulation–optimization models for irrigation schedules.

Optimization Method	Classification	Features
Traditional mathematical programming	Linear programming [90], nonlinear programming [91], and dynamic programming [111]	Simple calculation but has limitations when dealing with complex problems
Artificial intelligence search	Genetic algorithms [112], simulated annealing [113], particle swarm optimization [114], free search algorithm [115], and neural network [116]	Fast computing speed, strong stability, adaptability, and robustness

The optimization method, such as the NSGA-II, cannot provide the optimal solution to the optimization problem and can only provide several sets of Pareto solutions with good results (i.e., several irrigation schedules) [1]. Therefore, decision-making methods are necessary to further determine the optimal irrigation schedules. The decision-making methods used for optimizing irrigation schedules mainly include the analytic hierarchy process (AHP), entropy weight (EW), principal component analysis (PCA), grey relational analysis (GRA), and the technique for order preference by similarity to an ideal solution (TOPSIS) [117]. The AHP, EW, and PCA belong to a single evaluation method [117], which only evaluates a single indicator, such as evaluating the influencing factors in irrigation water efficiency or irrigation water productivity [118,119]. These methods usually cannot determine the optimal treatment and have certain limitations [120]. To address these limitations, comprehensive evaluation methods such as the GRA and TOPSIS were proposed, which greatly improved the robustness and universality of the results [121]. The TOPSIS method ranks each candidate solution by calculating the distance between the evaluation object (a solution), the ideal solution (the best value in the scheme), and the negative ideal solution (the worst value in the scheme), so as to determine the solution that is closer to the ideal solution and farther away from the negative ideal solution [122]. In the TOPSIS method, the weights of several objectives are determined, where the larger the fluctuation of the objectives, the smaller the entropy weight, and therefore the greater the weight of the objectives [122]. These comprehensive evaluation models were used for quantifying the fruit–quality index [121], developing optimal irrigation and fertilization strategies [123], as well as balancing yield, fruit quality, crop water productivity, and environmental benefits [124].

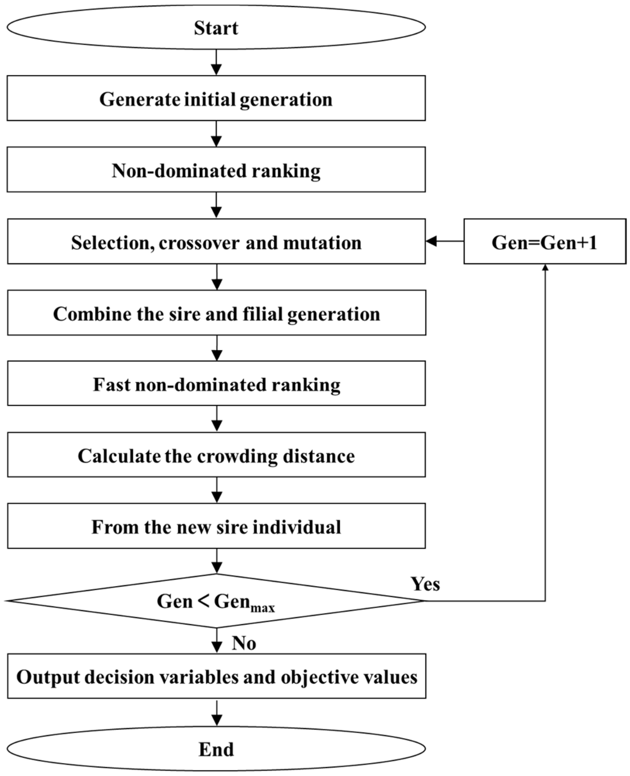

Figure 3. Flow chart of improved NSGA-II (Elitist Non-dominated Sorting Genetic Algorithm).

4.2. Spatiotemporal Scale of Irrigation Schedule Optimization

The optimization problem of irrigation schedules based on crop models initially focused on a field scale, while in recent years, it has been developed to solve irrigation water allocation problems on a regional scale. For example, Li et al. [1,125] considered the distribution of soil types and irrigation areas in their study area and solved the optimal irrigation plan for the typical irrigation areas in the middle reaches of the Heihe River in the arid region of Northwest China under the current situation and in typical climate years. Wang et al. [126] considered the spatial heterogeneity of the soil types, crop types, and weather types in the Yingke irrigation area in the middle reaches of the Heihe River and proposed an irrigation plan based on the maximum field water-use efficiency or the net economic benefits of using an irrigation schedule optimization model.

The traditional optimization methods were based on the time scales of the growth stage, in one month or ten days, to solve the problem of water allocation between the different stages, in order to achieve the maximum yield or benefit [90,91]. In the optimization of irrigation schedules based on the water-production function, the sensitivity index of the Jensen function is reduced to a daily scale to solve for the optimal irrigation schedule on a daily scale [90,91]. At present, irrigation schedule optimization based on crop model-optimization algorithms is usually on a daily scale. However, crop models can usually simulate smaller scales (such as an hourly scale) of crop growth and soil water, heat, and nitrogen environments [4]. Optimization research on an hourly scale irrigation schedule has been attempted, such as regulating the optimal timing of the day, duration, and pressure head threshold for irrigation based on the Hydrus-1D model [127].

5. Conclusions and Future Perspectives

This study integrated previous research and summarized how to optimize irrigation schedules based on both crop models and simulation–optimization models. It elaborated on the important links involved in the optimization process from the aspects of irrigation schedule scenarios, optimization objectives, crop model selections, optimization algorithms, and decision-making techniques. It was concluded that the method of optimizing irrigation schedules based on crop models was more mechanistic in describing the physical processes of crop growth. However, this method can only answer the " what if" question and may not necessarily find the optimal solution. The method of optimizing irrigation schedules based on simulation–optimization models coupled with optimization algorithms could find the global optimal solution.

The problems and future prospects in the optimization of irrigation schedules based on simulation–optimization models are summarized in Table 3 and as follows:

Table 3. Problems and future prospects in optimization of irrigation schedules based on simulation–optimization models.

Research Objects	Problems	Future Prospects
Simulation–optimization models	(1) Only the AquaCrop model is widely used.	Other mechanism crop models should be combined with optimization algorithms.
	(2) The AquaCrop model has limitations, such as the relatively simple transport processes of soil water, salt, and nitrogen, and ignores the influence of soil heat.	
	(3) Only focusing on the one-dimensional (1D) water movement process in the soil profile.	The promotion of drip irrigation technology underneath film has demonstrated the importance of quantifying the 2D/3D water movement process.
Optimization of irrigation schedules	(1) The uncertainty of model parameters affects the accuracy of optimization results.	Based on intelligent optimization algorithms to calibrate model parameters, explore highly applicable calibration tools for intelligent optimization algorithm to improve model efficiency.
	(2) The uncertainty of the division of typical hydrological years and model upscaling simulation.	Seeking ways to reduce uncertainty in optimization.

(1) Further Development of Crop Models.

The widely used AquaCrop model is relatively simple to apply, and several new versions have been developed in recent years, using R [128], MATLAB [129], and Python [130] languages, as the transport processes of soil water, salt, and nitrogen are relatively simple and the influence of soil heat can be ignored. This model can simulate scenarios of different irrigation methods, such as surface irrigation and drip irrigation, though it is a one-dimensional model that cannot accurately describe the two-dimensional distribution of soil water, heat, salt, and nitrogen under drip irrigation conditions. The accuracy of the optimization results for irrigation schedules based on the AquaCrop model is insufficient.

Although other crop models are more comprehensive and detailed in reflecting soil water, heat, nitrogen, salt dynamics, and crop growth, they are rarely combined with optimization algorithms for irrigation schedule optimization. They can only be used to answer the "what if?" question, that is, the optimization plan for irrigation schedules is only the optimal result in the scenario given by the user and is not necessarily the global optimum.

The HYDRUS-2D/3D model is a universal 2D/3D model, but it is currently rarely combined with optimization algorithms for irrigation schedule optimization. The model also lacks a crop growth module, which limits its development.

In summary, further development of two-dimensional or three-dimensional soil water, heat, nitrogen, and salt-coupled models with crop growth, and the exploration and resolution of the problems encountered in their coupling with the optimization algorithms are necessary. This will contribute to the precise regulation of future irrigation schedules.

(2) Uncertain Analysis in Irrigation Schedule Optimization.

Agro-hydrological models can simulate the complex physical growth processes of crops, which involve many model parameters. These model parameters have uncertainty, which can affect the accuracy of the simulation results and ultimately affect the accuracy of the optimization results. Therefore, it is necessary to calibrate the model parameters based on intelligent optimization algorithms and explore intelligent optimization algorithm calibration tools with a strong applicability to improve model efficiency when conducting research on irrigation schedule optimization based on crop models.

In addition, there is uncertainty in the division of the typical hydrological year and in the simulation of model upscaling for irrigation schedule optimization, and this uncertainty can significantly affect the actual optimization effect. Therefore, how to further reduce this uncertainty in optimization is a key issue for future research.

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