Agricultural Water Management 320 (2025) 109832

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Optimizing regional irrigation management in arid saline areas using a process-based hydro-salt-crop model and fallow strategy

Qihua Yu [a,b,c], Shaozhong Kang [a,b,*], Hui Wu [a,b,d], Jian Song [e], Hui Wang [c], David Parsons [f]

[a] State Key Laboratory of Efficient Utilization of Agricultural Water Resources, Beijing 100083, China
[b] National Field Scientific Observation and Research Station on Efficient Water Use of Oasis Agriculture, Wuwei 733009, China
[c] College of Water Resources & Civil Engineering, Hunan Agricultural University, Changsha 410128, China
[d] Research Center of Fluid Machinery Engineering and Technology, Jiangsu University, Zhenjiang 212013, China
[e] Department of Civil and Environmental Engineering, The University of Tennessee, Knoxville, TN 37996, USA
[f] Department of Crop Production Ecology, Swedish University of Agricultural Sciences, Umeå 90183, Sweden

ARTICLE INFO

Handling Editor: Dr R Thompson

Keywords:
Multi-source water allocation
Distributed crop model
Salt stress
Spatial heterogeneity
Marginal land utilization

ABSTRACT

Agriculture in arid regions faces water scarcity and spatially heterogeneous soil salinization, compelling consideration of brackish groundwater irrigation and strategic fallowing under conditions of extreme water scarcity. A key challenge for agricultural managers is optimizing limited surface and groundwater allocation in complex, heterogeneous saline environments with varying water availability. This study introduces a gridded regional irrigation water optimization model under total irrigation water control, integrating salt effects, fallow strategy and multi-source water management. The model: (1) incorporates salt impacts on crop growth, saline groundwater use, and spatial salt heterogeneity; (2) generates surface/saline groundwater allocation and marginal land use guidance; (3) balances water scarcity and salinization trade-offs. An empirical study was conducted using cotton field data in the First Division of the Tarim Irrigation District in Xinjiang, China. The results suggest that the optimized water allocation scheme could increase cotton lint yield in the Tarim Irrigation District by up to 9959 tons (+3.3 %) compared to traditional uniform allocation. Soil salt content dominated allocation decisions. When surface water availability is limited, water distribution should prioritize high-yield fields (non-severe salinization), and supplemental brackish groundwater irrigation can mitigate yield losses. Rational fallowing can enhance total yield in the irrigation district while reducing input costs, with severely saline areas being prime candidates for fallowing policies. This research provides a scientific basis for optimizing water-salt management in cotton production, groundwater extraction, and irrigation water allocation in saline arid regions, while future work could integrate ion-specific chemistry and its crop response functions for wider applications.

1. Introduction

Water-saving agriculture is a central focus of global agricultural development, particularly in arid and semi-arid regions where water scarcity poses a critical threat to the sustainable development of irrigated areas. Projected global temperature increases and decreasing soil moisture levels may lead to more frequent agricultural droughts (Grillakis, 2019), further challenging agricultural practices in these arid regions. Alongside the constraints of limited water resources, soil salinity is a pressing concern in arid and semi-arid zones (Abuelgasim and Ammad, 2019). The total area of salt affected lands is around 1 billion hectares, with a clear increasing trend (Ivushkin et al., 2019). Among them, about 20 % of irrigated land worldwide is salt-affected (estimated at 45 million ha) (FAO, 2025). Notably, over two-thirds of salinized soils are located in arid and semi-arid regions (FAO, 2021). The coexistence of water scarcity and soil salinization in these regions creates compounded challenges for agricultural development (Mosaffa and Sepaskhah, 2019).

Salt movement is closely linked to water, and salt management is generally achieved indirectly through water management. Therefore, a primary challenge for agricultural managers in arid saline areas is the effective management of water resources under the complex and

* Corresponding author.
E-mail address: kangsz@cau.edu.cn (S. Kang).

https://doi.org/10.1016/j.agwat.2025.109832
Received 26 June 2025; Received in revised form 15 September 2025; Accepted 17 September 2025
Available online 24 September 2025

heterogeneous underlying conditions. To address this, a common approach involves optimizing the allocation of available water resources based on crop response to salt stress, thereby maximizing the role of water in supporting food production. Optimization models for irrigation water resources serve as effective tools to tackle this issue. The spatial optimization goal for agricultural water resources in irrigation districts is to allocate water in a way that maximizes overall regional benefits. Decision variables typically include crop irrigation schedules and spatial planting structures (Randall et al., 2024). Optimization generally aims to maximize yield or profit, often by addressing crop water demand and sensitivity to water deficits across growth stages. The relationship between crop yield and water use is often represented by a staged crop-water production function (Li et al., 2019; Mahmoudzadeh Varzi et al., 2019), which optimizes both irrigation timing and quantity. However, in arid saline regions, additional considerations of salinity impacts are necessary to further refine irrigation water optimization models.

Specifically, it is essential to account for crop responses to salt stress and incorporate the spatial heterogeneity of soil salinity in two-dimensional space (Valenzuela et al., 2022), enabling a more comprehensive evaluation of salinity's role in irrigation water resource management. Salt stress is a major factor limiting crop growth and development. When soil salt concentration reaches a threshold, it reduces soil water potential, subsequently affecting water absorption, crop growth, and yield (Oster et al., 2012). Therefore, salt stress is crucial in allocating irrigation water (Li et al., 2020; Minhas et al., 2020), and researchers are increasingly incorporating its effects into optimization models. For instance, Cao et al. (2023) optimized irrigation water allocation in the Hetao Irrigation District by applying a water-salt production function and analyzed the impacts of reduced water supply, minimized winter irrigation, and water-saving practices under various scenarios. Zhang et al. (2023) optimized irrigation water allocation by accounting for spatial variations in soil salinity and other soil characteristics, achieving effective regional salt accumulation control. Similarly, Zhang et al. (2021) incorporated a water-salt production function across different growth stages to improve allocation decisions. However, most studies rely on empirical crop salinity functions, which are limited in performance and may not fully meet the demands of precision agriculture. With advances in computing technology, integrating simulation models (such as crop growth models and machine learning algorithms) with optimization models is becoming increasingly influential in agricultural production and irrigation decision-making (Shen et al., 2021; Wu et al., 2022). Distributed hydro-salt-crop models are particularly valuable, as they can capture the spatial heterogeneity of salinity and quantify the impacts of salt stress on crops more mechanistically (Yu et al., 2021). Combining distributed hydro-salt-crop models with optimization models, therefore, enables more precise irrigation water allocation in arid irrigation areas under the combined influences of salt stress and spatial heterogeneity.

To address the conflict between limited freshwater resources and soil salinization, irrigation water sources can be expanded through "diversification and conservation" strategies. Unconventional water resources can be incorporated into water allocation models, and, in cases of water scarcity, selective fallowing of certain cultivated lands can help mitigate resource shortages. In arid regions with limited surface freshwater, groundwater serves as a crucial component of agricultural irrigation. Previous studies have developed joint allocation models for surface and groundwater resources to address water supply-demand imbalances (Ahmad and Zhang, 2022; Li et al., 2023b; Mattiuzi et al., 2019). However, excessive groundwater extraction and irrigation return flows have contributed to groundwater salinization and aggravated soil salinity issues. Despite these challenges, saline groundwater is increasingly regarded as a valuable resource for addressing freshwater shortages, particularly in irrigating salt-tolerant and moderately salt-tolerant crops (Chen et al., 2018; Feng et al., 2017). Incorporating saline groundwater with surface freshwater allocation is therefore a pathway for optimizing agricultural water management.

Fallowing of low-yield or marginal land is a widely used practice worldwide that can also support soil health through natural regeneration (Żarczyński et al., 2023). In regions with extensive saline soils, certain severely affected areas experience yield reductions of up to 65–75 % (Khojiyev et al., 2020) and are often considered unsuitable for cultivation. Such marginal lands may benefit from fallowing or soil improvement before being returned to production. Studies report that fallowing can alleviate issues such as soil compaction and desertification while enhancing biodiversity, ultimately improving land productivity (Li et al., 2021; Zhang et al., 2022). Furthermore, Huang et al. (2021) emphasize that establishing designated salt discharge areas is critical for controlling salinity in arable soils and ensuring sustainable use. Severely saline areas could serve as regional salt discharge outlets (Hou et al., 2023). However, few studies currently incorporate fallowing options when optimizing irrigation water allocation. Integrating a fallowing option for marginal land in modeling efforts could provide a more comprehensive approach to managing saline lands in irrigation regions.

Overall, significant tension exists between agricultural production demands and the challenges of water and salt management in arid saline districts. Given scarce freshwater resources and extensive soil salinization, rational allocation and adjustment of agricultural irrigation water are essential to achieve both high crop yields and efficient water use. Thus, under the context of broad salt-affect area, the objective of this study is to optimize the allocation of agricultural surface freshwater and brackish groundwater resources by incorporating factors such as marginal land utilization, salt effects, and spatial heterogeneity of the subsurface. This study builds upon prior research that developed a distributed hydro-salt-crop model, validated regional soil water-salt dynamics and crop growth under arid saline conditions, and established distributed irrigation water salinity thresholds (Yu et al., 2024). Three distinct irrigation water optimization models are developed with irrigation water as a fixed constraint: (1) no fallowing + irrigation with surface freshwater only, (2) fallowing permitted + irrigation with surface freshwater only, and (3) fallowing permitted + joint use of surface freshwater and saline groundwater resources. These models allow for the study of optimal irrigation water allocation strategies that account for spatial heterogeneity under varying surface water availability conditions. The hypothesis of this paper is that optimization models could improve the yield and water productivity over the study area. The findings of this research will provide a scientific basis for efficient surface and groundwater resource utilization and land management practices in arid saline irrigation districts.

2. Materials and methods

2.1. Study area

This study focuses on the Tarim Irrigation District of the First Division of the Xinjiang Production and Construction Corps in Xinjiang, China. The Tarim Irrigation District is situated in the upper reaches of the Tarim River, the largest inland river in China (Fig. 1), with geographical coordinates of 81°30′-82°00′ E , 40°23′-40°65′ N. The study area spans roughly 150 km from east to west and 40 km from north to south. The terrain is generally flat, sloping from northwest to southeast, with an elevation range of 987–1047 m and a ground slope between 1/500 and 1/4000. The study area has abundant solar and thermal resources, receiving an average annual solar radiation of 6000 MJ m^{-2} and sunshine hours of 2948 h, which is conducive to the production of crops such as cotton.

The climate in Tarim Irrigation District is also characterized by extreme aridity, with an average annual temperature of 11.3 ℃, rainfall of 46 mm, relative humidity of 48 % and pan evaporation of 2500 mm. As a result, agriculture in the area is entirely reliant on irrigation. The uncertainty of runoff in the Tarim River Basin in Xinjiang is expected to intensify under climate change, with rising temperatures potentially

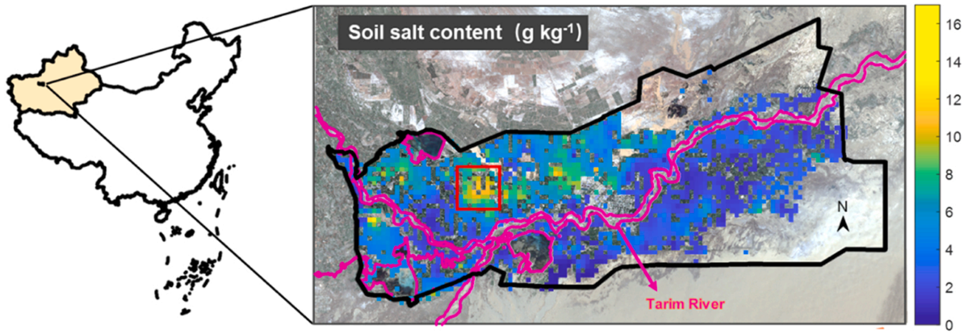

Fig. 1. Location of the study area based on a satellite image taken on June 23, 2021. The grid-scale layer is the average soil salt content in the cotton fields at a depth of 0–100 cm. The area marked by the red box in the figure is a typical area of severe salinization. The pink curve displays the water body areas of rivers and reservoirs.

weakening the role of glacial meltwater in regulating the region's water balance. Consequently, the frequency, duration, and intensity of sudden droughts in southern Xinjiang are all projected to increase (Yu et al., 2023b). Therefore, water resource management in Tarim Irrigation District must proactively develop strategies to mitigate the adverse impacts of fluctuating surface water availability on agricultural productivity and potential drought risks.

There is a marked imbalance between water supply and demand in the district, contributing to significant environmental issues, including soil salinization and secondary salinization. Groundwater depth varies from 1 to 8 m, with mineralization levels in some areas reaching up to 15 g L^{-1} (electrical conductivity (EC) of 13.88 dS m^{-1}). Soil salinity varies throughout the district, with 23.4 % of the area non-saline soil (average salt content <2 g kg^{-1}, that is electrical conductivity of the saturation paste extract $EC_e < 2$ dS m^{-1}); 37.3 % mildly saline soil (salt content of 2–4 g kg^{-1}, that is EC_e of 2–4 dS m^{-1}); 21.8 % moderately saline soil (4–6 g kg^{-1}, that is EC_e of 4–8 dS m^{-1}); and 17.5 % severely saline soil (≥6 g kg^{-1}, that is $EC_e \geq 8$ dS m^{-1}). The salinization classification refers to the (Liu et al., 2025; US Salinity Laboratory Staff, 1954; Wang et al., 1993). A typical region of severely saline soil is highlighted within the red box in Fig. 1. The saline soil in this region is mainly dominated by sulfates and chlorides and sodium adsorption ratio (SAR) is 5.33 $meq^{0.5}$ $L^{-0.5}$.

As a salt-tolerant crop, cotton is extensively cultivated in the district, occupying over 84 % of the sowing area and providing a crucial economic resource for local farmers. Tarim Irrigation District is among China's most significant regions for high-quality cotton production. Accordingly, this study centers on cotton as the primary research crop.

2.2. 2.2 Modified WAVES model and irrigation water salinity threshold

The model used in this study is WAVES (the WAter Vegetation Energy and Solute model), which was developed by CSIRO since 1993 (Zhang et al., 1996, 1999). WAVES is a process-based model at a daily time-step and strikes a good balance between complexity, usefulness and accuracy of prediction in energy, water, carbon and solute processes in a one-dimensional soil-canopy-atmosphere system. In WAVES, the infiltration of net rainfall and irrigation and soil water movement along the soil profile is simulated using a fully finite difference numerical solution of the Richards equation. Salt transport is obtained by solving convection dispersion equation assuming the solute is conservative. WAVES considers the effects of salinity on carbon assimilation by plants and water availability. In our previous study, we assessed the adaptability of WAVES in typical cotton fields within the Tarim Irrigation District and modified it to account for the effects of mulching (Yu et al., 2023a) by incorporating three functions working on potential evaporation, underlying surface albedo, and soil resistance. The modified WAVES model shown good performance with the normalized root mean square error (NRMSE) of 13 % in calibration and the NRMSE of 5 % in validation. The modification workflow is shown in Fig. 2a. Building upon this work, we developed a distributed WAVES model for the Tarim Irrigation District, integrating geographic information systems (GIS) and remote sensing to apply the model to 1700 grid units (Fig. 2b). The 1700 grid points of the cotton planting area were obtained through remote sensing inversion and ground verification(Yu et al., 2024). The model was systematically calibrated and validated using field data from saline water irrigation experiments and monitoring data from various locations within the study area in 2021 (NRMSE of 11.21 %). The distributed WAVES model integrates the processes by which groundwater depth, groundwater salinity, soil texture, soil salinity, and irrigation amount affect crop yield. Different groundwater depths can affect the availability of soil water, and results have shown that 1.5 m is the appropriate groundwater depth for relatively high cotton yields. Different levels of groundwater mineralization and soil salinity can affect the water absorption rate and carbon assimilation rate of cotton roots, while different soil textures affect soil water transport. The sandy loam soil in this study area is more suitable for cotton production. The irrigation depth affects soil moisture availability, which in turn affects root water absorption and carbon assimilation rate, ultimately affecting yield. Scenario simulations were then conducted to quantify the irrigation water salinity threshold for saline groundwater use in the district (Fig. 2c). A comprehensive criterion to determine water salinity threshold was proposed considering cotton yield (reduction ratio <10 %), water productivity (reduction ratio <10 %) and soil salt accumulation (soil salt at the end of growth stage <6 g kg^{-1}). Detailed data on surface heterogeneity and the mineralization thresholds for irrigation are provided in Yu et al. (2024). This study aims to optimize irrigation water allocation based on these findings.

2.3. Optimization model development

To maximize the spatial efficiency of agricultural irrigation water while maintaining high and stable cotton fiber yields, three spatial optimization models for irrigation water allocation were developed, each considering different scenarios and constraints.

2.3.1. Optimization Model 1: maximizing total yield under varying surface irrigation water availability

The distributed WAVES model comprehensively accounts for the impacts of groundwater depth, groundwater salinity, soil texture, soil salinity, and irrigation water volume on crop yield. By integrating the distributed WAVES model, we optimize water resource allocation within the Tarim Irrigation District with the goal of maximizing cotton yield. The total irrigation volume for each simulation unit is treated as a decision variable in this optimization framework.

Objective:

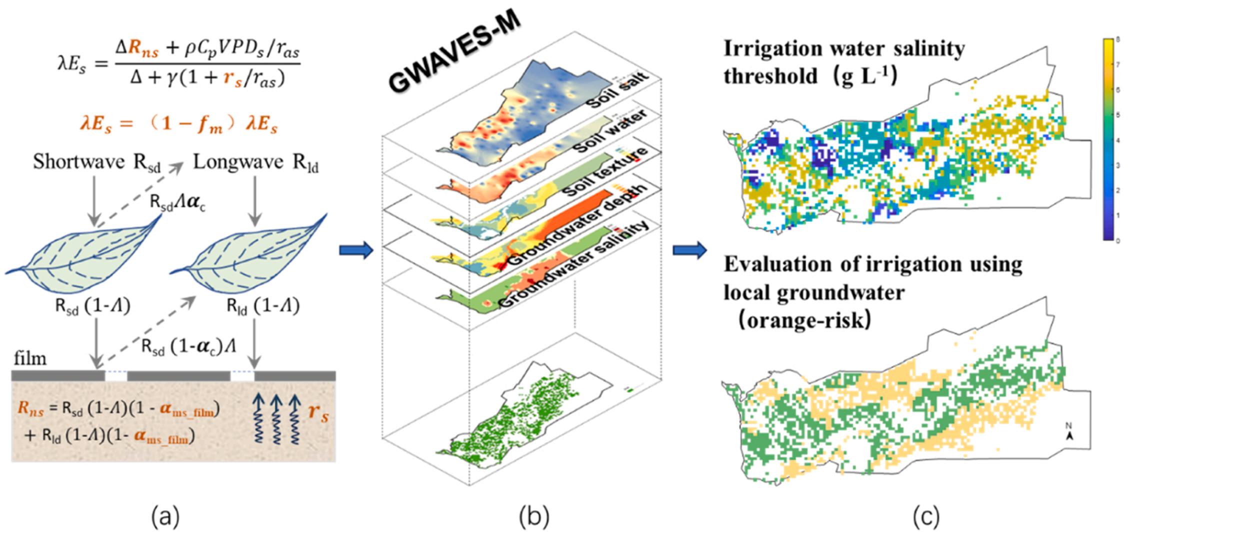

Fig. 2. (a) The modification workflow of reconstructed WAVES model considering the film mulching effect. The orange font indicates the modified part. (b) Five maps used for generating the 1700 distributed simulation units in distributed WAVES model. (c) The spatial distribution of the irrigation water salinity threshold and risk area using local groundwater for irrigation in the study area. Note: E_s is potential soil evaporation (mm), λ is the latent heat of vaporization (MJ kg^{-1}), Δ is the average gradient of the saturated vapor pressure versus temperature (kPa °C^{-1}), R_{ns} is the net radiation of the underlying surface (MJ m^{-2} day^{-1}), ρ and C_p are the density (kg m^{-3}) and the specific heat of the air at constant pressure (J kg^{-1} K^{-1}), respectively, VPD_s is the vapor pressure deficit (kPa), γ is the psychrometric constant (kPa °C^{-1}), r_{as} is aerodynamic resistance (s m^{-1}), r_s is soil surface resistance (s m^{-1}), f_m is the film cover fraction, Λ is the partial coverage of canopy, α_c is albedo of canopy, α_{ms_film} is underlying surface (soil-film system) reflectance. GWAVES-M represents GIS (geographical information system) based distributed WAVES model with mulching effect considered.

$$obj = \max YIELD = \max \sum_{i=1}^{1700}\left(FY_i \cdot WAVES_{(i,f(i))} \cdot A \cdot 10^2\right), i = 1, 2, \cdots 1700 \quad (1)$$

$$WAVES_{(i,f(i))} = function\left(\frac{\varphi + w_{osm}(-2C_{f(i)} \cdot R \cdot T)}{\psi_{wilt}}, GW_{f(i)}, GWS_{f(i)}, texture_i, salt_{f(i)}\right), i = 1, 2, \cdots 1700 \quad (2)$$

Where, *YIELD* is the total cotton lint yield (kg) in the Tarim Irrigation District; *i* represents different simulation units, where the cotton planting area within the district was divided into 1700 homogeneous grid cells, numbered sequentially from 1 to 1700; FY_i represents the cultivation status of the *i*-th simulation unit, serving as an indicator for determining fallowing, here in model 1, all units are being cultivated without fallowing, that is, FY_i equals to 1; $f(i)$ is the decision variable, which is the total irrigation volume (mm) using surface water in the whole growing season for the *i*-th simulation unit; $WAVES_{(i,f(i))}$ is the cotton yield (kg ha^{-1}) for the *i*-th simulation unit obtained using the WAVES model under a specified irrigation volume of $f(i)$; *A* is the area (km^2) for the simulation unit, which is set to 1 km^2 in this study; $GW_{f(i)}$, $GWS_{f(i)}$, $texture_i$ and $salt_{f(i)}$ correspond to groundwater depth (m), groundwater salinity (g L^{-1}), soil texture, and soil salt content (g kg^{-1}) for the *i*-th simulation unit, respectively, and the detailed values are provided in Yu et al. (2024); φ is the water potential (m); w_{osm} is the salt sensitivity factor; ψ_{wilt} is the water potential at the wilting point (m); π is the osmotic potential (m); $C_{f(i)}$ is the solute molarity in the soil water of the *i*-th simulation unit (mol m^{-3}); R is the universal gas constant (J K^{-1} mol^{-1}); T is absolute temperature (K).

Constraints：

(1) Constraint on the total available surface irrigation water

$$\sum_{i=1}^{1700}\left(FY_i \cdot f(i) \cdot A \cdot 10^3\right) \leq W, i = 1, 2, \cdots 1700 \quad (3)$$

Where *W* represents the total available surface irrigation water (m^3). Four different surface irrigation water availability scenarios are set as follows: a future scenario with a 50 % reduction in available surface water due to climate change (W1, 340 million m^3); a future scenario with a 50 % reduction in surface water availability (W2, 510 million m^3); the current surface water availability scenario based on existing inflow conditions (W3, 680 million m^3); and a future scenario with a 25 % increase in available surface water (W4, 850 million m^3). The average irrigation volume in the Tarim Irrigation District is 200, 300, 400 and 500 mm for W1 to W4, respectively. Other symbols have the same meanings as previously defined.

(2) Constraint on surface water allocation criterion

$$f(i) \geq 150, i = 1, 2, \cdots 1700 \quad (4)$$

$$f(i) \leq 600, i = 1, 2, \cdots 1700 \quad (5)$$

The minimum irrigation volume during the growing season is set at 150 mm according to the water requirements of cotton, while the maximum irrigation depth is set at 600 mm.

2.3.2. Optimization Model 2: maximizing total yield through inclusion of fallowing as an option under varying surface irrigation water availability

The findings of Yu et al. (2024) indicate that severely saline soils significantly reduce cotton yield, resulting in low input-output efficiency. Fallowing these areas can lower input costs while sustaining overall yield. Consequently, the second optimization model allows for the fallowing of low-yield fields to optimize irrigation water allocation across the district. The optimization objective is to maximize cotton yield, with irrigation volume for each simulation unit serving as the decision variable.

Except for the value of FY_i, the objective and constraints are the same as Optimization Model 1. FY_i is defined as follow to include fallowing strategy:

$$FY_i = \begin{cases} 0, \text{noirrigationinthisunit, indicatingfallowing.} \\ 1, \text{normalirrigationinthisunit, indicatingcultivation.} \end{cases}; i = 1, 2, \cdots 1700 \quad (6)$$

$$\sum_{i=1}^{1700} FY_i \leq 1700, i = 1, 2, \cdots 1700 \quad (7)$$

2.3.3. Optimization Model 3: minimizing brackish groundwater extraction with fallowing and varying surface irrigation water availability

Optimization Model 3 considers the extraction of local brackish groundwater for irrigation to alleviate surface water shortages. The objective of this optimization model is to minimize brackish groundwater use, with irrigation volumes for each simulation unit as decision variables. The model also permits selective fallowing of low-yield fields to ensure total yield across the district while optimizing irrigation water distribution.

Objective:

$$obj = \min I_s = \min(\sum_{i=1}^{1700}(SY_i \cdot s(i) \cdot A \cdot 10^3)), i = 1, 2, \cdots 1700 \quad (8)$$

Where I_s represents the total brackish groundwater extraction (m^3); SY_i represents the irrigation water quality status of the i-th simulation unit, serving as an indicator for determining whether brackish groundwater irrigation is used; $s(i)$ is the decision variable, which is the total irrigation volume (mm) using local saline groundwater in the whole growing season for the i-th simulation unit; Other symbols are as previously defined.

Constraints：

Optimization Model 3 builds upon models 1 and 2 by incorporating additional constraints related to brackish groundwater irrigation and fiber production security.

(1) Constraint on the total available surface irrigation water

The same as Eq. (3) in Optimization Model 1, while two different surface irrigation water availability scenarios are set as follows: a future scenario with a 50 % reduction in available surface water due to climate change (340 million m^3, W1) and the other scenario with a 25 % reduction in available surface water (510 million m^3, W2).

(2) Constraint on surface water allocation criterion

The same as Eqs. (4) and (5) in Optimization Model 1.

(3) Constraint on surface water irrigation area (fallowing)

The meanings of different values of FY_i vary slightly compare to Eq. (6), as shown below. Eq. (7) is also applied here.

$$FY_i = \begin{cases} 0, \text{irrigationwithoutsurfacewaterinthisunit.} \\ 1, \text{irrigationwithsurfacewaterinthisunit.} \end{cases}, i = 1, 2, \cdots 1700 \quad (9)$$

(4) Constraint on groundwater water allocation criteria

$$s(i) \geq 150, i = 1, 2, \cdots 1700 \quad (10)$$

$$s(i) \leq 600, i = 1, 2, \cdots 1700 \quad (11)$$

The groundwater irrigation volume $s(i)$ during the growing season is set from 150 to 600 mm as the same of surface water irrigation.

(5) Constraint on groundwater water irrigation area (fallowing)

$$SY_i = \begin{cases} 0, \text{irrigationwithoutgroundwaterinthisunit.} \\ 1, \text{irrigationwithgroundwaterinthisunit.} \end{cases}, i = 1, 2, \cdots 1700 \quad (12)$$

$$\sum_{i=1}^{1700} SY_i \leq 1700, i = 1, 2, \cdots 1700 \quad (13)$$

(6) Constraint on irrigation water salinity threshold

$$SY_i = 0, i \in T \quad (14)$$

Where T represents the set of all simulation units where brackish groundwater irrigation introduces risks of yield reduction, decreased water productivity, and salt accumulation, according to the findings of Yu et al. (2024), as illustrated in Fig. 1c. Optimization Model 3 allows groundwater extraction for irrigation only in areas free of these risks.

(7) Constraint on irrigation water quality

$$FY_i + SY_i \leq 1, i = 1, 2, \cdots 1700 \quad (15)$$

Optimization Model 3 assumes that the irrigation water quality in each simulation unit can be in one of three states: brackish groundwater irrigation, surface water irrigation, or no irrigation (fallowing). When both variables of FY_i and $SY_i$are set to 0, it indicates that the i-th simulation unit is fallow.

(8) Constraint on total stable fiber production requirements

$$\sum_{i=1}^{1700}\left(FY_i \cdot WAVES_{(i,f(i))} \cdot A \cdot 10^2 + SY_i \cdot WAVES_{(i,s(i))} \cdot A \cdot 10^2\right) \geq Y_0, i = 1, 2, \cdots 1700 \quad (16)$$

$$WAVES_{(i,s(i))} = function\left(\frac{\varphi + w_{osm}(-2C_{s(i)} \cdot R \cdot T)}{\psi_{wilt}}, GW_{s(i)}, GWS_{s(i)}, texture_i, salt_{s(i)}\right), i = 1, 2, \cdots 1700 \quad (17)$$

Where, $WAVES_{(i,s(i))}$ is the cotton yield (kg ha^{-1}) for the i-th simulation unit obtained using the WAVES model under a specified groundwater irrigation volume of $s(i)$; Y_0 is the total yield target (kg ha^{-1}) for the irrigation district, three stable production targets are defined based on the cotton yield in 2021, which serves as the baseline (target output): these targets are set at 100 %, 90 %, and 80 % of the 2021 yield. The scenarios composed of different production targets and available water volume combinations are detailed in Table 2. $GW_{s(i)}$, $GWS_{s(i)}$ and $salt_{s(i)}$ correspond to groundwater depth (m), groundwater salinity (g L^{-1}) and soil salt content (g kg^{-1}) for the i-th simulation unit when irrigated with saline groundwater, respectively. Other symbols are as previously defined.

2.4. Solution of the optimization models

When solving the established optimization models with a genetic algorithm, the model's high number of decision variables (1700) significantly reduced computational efficiency. Direct interaction between the optimization model and WAVES hindered the ability to achieve a global optimal solution, making direct resolution of the model challenging. To address this, an alternative approach was developed: fitting the relationship between yield and irrigation volume for each simulation unit based on WAVES outputs, and then using this fitted relationship in place of parameters $WAVES_{(i,f(i))}$ and $WAVES_{(i,s(i))}$ for spatial water resource optimization. This approach reduces the complexity of solving large-scale nonlinear optimization problems. Upon fitting, a quadratic function effectively characterized the relationship between yield and irrigation volume. This aligns with the findings of Wang et al. (2016), who demonstrated a parabolic relationship between yield and irrigation volume, and Tong and Guo (2013), who also utilized a quadratic function to model yield relative to cotton water use in irrigation optimization. The fitting formula used in this study is as follows:

Surface freshwater irrigation:

$$WAVES_{(i,f(i))} = FY_i \cdot (a_i f(i)^2 + b_i f(i) + c_i), i = 1, 2, \cdots 1700 \quad (18)$$

Groundwater saline irrigation：

$$WAVES_{(i,s(i))} = SY_i \cdot \left(as_i \cdot s(i)^2 + bs_i \cdot s(i) + cs_i\right), i = 1, 2, \cdots 1700 \quad (19)$$

Where a_i, b_i, and c_i represent the three regression constants under surface water irrigation in the i-th simulation unit; a_i, b_i, and c_i represent three regression constants in the i-th simulation unit under underground saline irrigation.

The specific fitting performance of the quadratic function is illustrated in Fig. S1. Due to the spatial heterogeneity of underlying surface conditions, different simulation units show variable yield responses to irrigation volumes. As the irrigation volume increases, cotton yield rises, but the rate of yield increase diminishes. The quadratic function effectively captures this trend, closely fitting the WAVES simulation results. Although some simulation units show slight deviations between the fitting curves and the simulated values, the overall correlation coefficient (R^2) exceeds 99 %, demonstrating high fitting accuracy. Spatial variability in groundwater salinity also affects yield response curves under saline irrigation across simulation units. The quadratic function accurately models the yield response curve under saline irrigation as well (Fig. S1). Fig. S2 presents a histogram of the correlation coefficient distribution for quadratic fits between cotton yield and irrigation volume across all simulation units. The accuracy of fits for surface water irrigation slightly exceeds that of saline water irrigation, with 99.5 % and 98.2 % of simulation units achieving an R^2 value above 0.95, respectively. In summary, over 98 % of simulation units show an R^2 exceeding 0.95 across both surface and saline water irrigation scenarios, indicating a high level of fitting precision.

The re-fitted relationship between cotton yield and irrigation volume includes unique fitting parameters for each simulation unit, capturing crop yield responses to varying environmental conditions across the irrigation district. The quadratic function demonstrates high fitting accuracy, requires few parameters, and facilitates coupling with the optimization model, enabling spatial allocation of irrigation water resources at a regional scale. Thus, this study employs a reanalyzed quadratic yield-irrigation model, rather than direct simulation outputs of WAVES, in combination with the optimization model to optimize irrigation water distribution. Model programming and solutions were implemented using LINGO (18.0).

3. Results

3.1. Irrigation water allocation under varying surface irrigation water availability

The spatial distribution patterns of water allocation after optimization are similar whether considering fallow or not, that is, the water allocations are similar between Optimization Model 1 (Fig. 3) and Optimization Model 2 (Fig. S3). Taking results from Optimization Model 1 as an example, when the available surface water is limited, the water allocation to severe salinization units (marked by the orange box), and simulation units near rivers and reservoirs is relatively low (Fig. 3a), approaching the lower limit of the set irrigation volume. With the increase of available surface irrigation water, the irrigation water allocated to severe salinization is the highest within the district (Fig. 3d), while there are still relatively low allocations of water to simulation units near rivers and reservoirs.

Soil salt content was the dominant factor affecting the distribution of irrigation water within the district (Figs. 4a, 4c) from analysis of Random Forest Importance Ranking. With the increase of available surface irrigation water, the distribution of irrigation water shifts in soils with different salinity levels as the available surface irrigation water increases (Fig. 5). When surface water availability is low, such as in the case of a 50 % reduction compared to the current situation (Fig. 5a-W1, Fig. 5b-W1), finite irrigation water is primarily allocated to high-yield fields (non-severe salinization), while low-yield fields (severe salinization) receive relatively less water. For example, in the region characterized by severe salinization (highlighted by the orange box in Fig. 3), the optimized irrigation volume is lower than the average irrigation volume. However, when a larger volume of surface water is available, the average irrigation volume can already meet the water demands of high-yield fields. In this case, more water is allocated to areas with higher salt content to mitigate salt stress and unlock the yield potential in those regions (Fig. 5a-W4, Fig. 5b-W4). The turning point of water allocation occurs between W2 and W3 (Fig. 5), that is, the available surface water volume between 51 and 68 billion m^3. These results demonstrate the different strategies in irrigation water distribution between high-salinity and low-salinity areas under varying water availability scenarios, reflecting an adaptation to changing water resources. Groundwater depth is the second most important factor affecting water

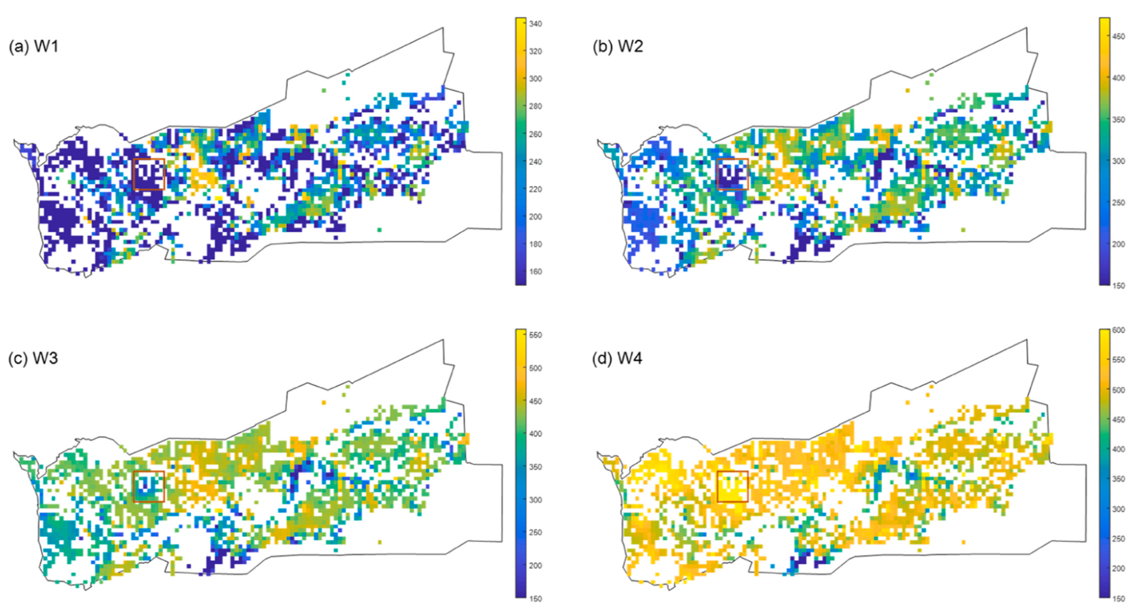

Fig. 3. The spatial irrigation water allocation solution (water depth, mm) from Optimization Model 1 under varying surface irrigation water availability from W1-W4. W1-W4 refer to the average irrigation depth within the district of 200, 300, 400 and 500 mm, respectively, which correspond to the total surface available water amounts of 340, 510, 680 and 850 billion m^3. Note: the orange box marks a typical severely saline area.

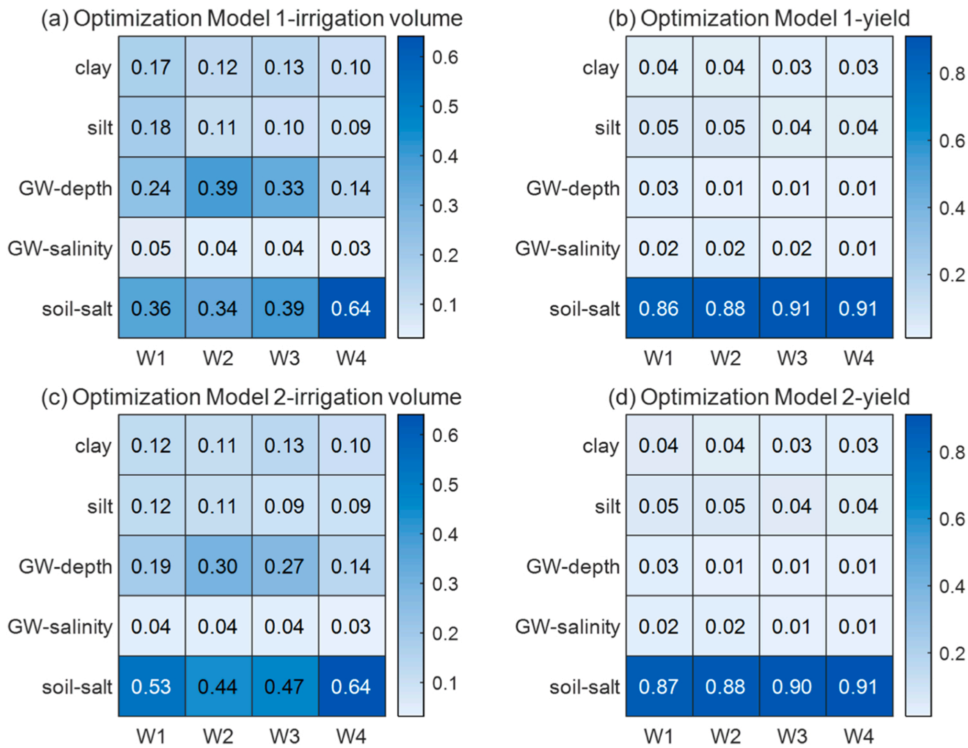

Fig. 4. The importance value of the underlying factors affecting irrigation water allocation (a, c) and regional yield (b, d) in Optimization Model 1 and 2. Note: The larger the importance value of the underlying factor, the greater the impact of its changes on water allocation. The importance value is calculated by the random forest method. W1 to W4 represent different available surface water scenarios of 340, 510, 680 and 850 billion m^3; the texts on the vertical axis represent texture-clay, texture-silt, groundwater depth, groundwater salinity and soil salt content, respectively.

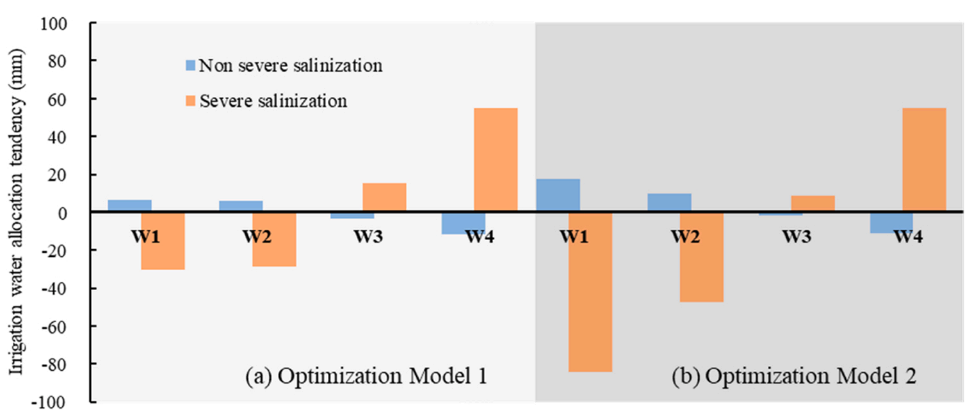

Fig. 5. Irrigation water allocation tendency in Optimization Model 1 and 2. Irrigation water allocation tendency is calculated from subtracting the average irrigation depth within the district (water depth, mm) from the allocated water quantity into each unit (water depth, mm). W1-W4 refers to average irrigation depth within the district of 200, 300, 400 and 500 mm, respectively, which correspond to the available surface water scenarios of 340, 510, 680 and 850 billion m^3. When the value in the figure is greater than 0, it indicates that more irrigation water beyond average level is allocated towards the region (severe salinization or non-severe salinization), and vice versa.

allocation (Fig. 4). The water allocation of simulation units near rivers and reservoirs is relatively low (Fig. 3), which is related to the shallow depth of groundwater. Groundwater provides more replenishment for crop growth in these regions, leading to a decrease in irrigation demand.

The distribution patterns of optimized production for model 1 (Fig. S4) and model 2 (Fig. 6) are similar. Using results from Optimization Model 2 as an example, scenarios with limited available surface water (average irrigation volume of 200 mm, Fig. 6a) lead to lower cotton yield in the north area of the Tarim River. As available surface water increases, overall yields improve across the irrigation area, though yields in high-salinity zones remain comparatively lower. Soil salinity is the main factor affecting yield distribution (Figs. 4b, 4d). Across scenarios with average irrigation volumes of 200, 300, 400, and 500 mm in Optimization Model 1, non-optimized average yields were 1780, 2199, 2503, and 2691 kg ha^{-1}, while optimized average yields increased to 1824, 2238, 2523, and 2703 kg ha^{-1} (Table 1). The optimized irrigation distribution improved cotton yields by 2.48 %, 1.77 %, 0.80 %, and 0.46 % compared to traditional uniform irrigation methods.

When fallowing is permitted as an option, the availability of irrigation water also affects the extent of fallowing. When surface water availability is low (Fig. 6a), the highest proportion of land is designated for fallowing, reaching 6.9 %, primarily concentrated in the high-salinity zones at the north area of Tarim River. As available surface water increases, the required fallow area gradually decreases and the

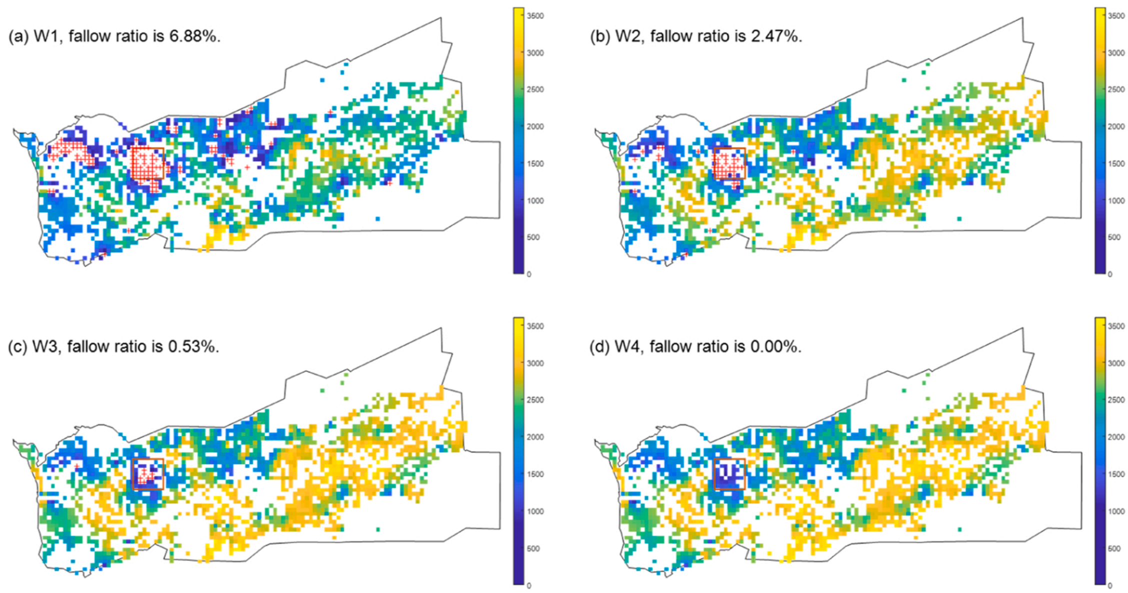

Fig. 6. The spatial cotton yield (kg ha^{-1}) solution from Optimization Model 2 considering fallowing as an option under varying surface irrigation water availability of W1-W4. W1-W4 refer to the average irrigation depth within the district of 200, 300, 400 and 500 mm, respectively, which correspond to the surface available water scenarios of 340, 510, 680 and 850 billion m^3. Note: the orange box marks a typical severely saline area; The red plus sign in the picture represents the area that should be fallow.

Table 1
Average yield comparison between Optimization Model 1 and 2. Yield increase ratio represents the value compared to the scenario using traditional uniform water distribution.

Scenarios	Average irrigation depth (mm)	200	300	400	500
Traditional uniform water distribution	Yield (kg ha^{-1})	1779.7	2199.1	2502.7	2690.6
Optimization Model 1	Yield (kg ha^{-1})	1823.8	2238.1	2522.8	2703.0
	Yield increase ratio (%)	2.48	1.77	0.80	0.46
Optimization Model 2 considering fallow	Fallow ratio (%)	6.88	2.47	0.53	0.00
	Yield (kg ha^{-1})	1838.3	2241.3	2523.3	2703.0
	Yield increase ratio (%)	3.29	1.92	0.82	0.46

areas that are fallowed all contain severely salinized soils. In scenarios with ample surface water (Fig. 6d), the optimization does not allocate any land to fallow; the additional water is allocated to high-salinity areas, which supports cotton production through promoting salt leaching. Under scenarios allowing for fallowing, as irrigation water volume increases, the optimized distribution scheme enhances cotton yield by 3.29 %, 1.92 %, 0.82 %, and 0.46 % compared to the traditional uniform water distribution approach (Table 1), translating to an increase of 9959, 7195, 3474, and 2109 tons of cotton across the irrigation district. Additionally, fallowing under limited surface water conditions contributes to further yield gains, improving yields by 0.82 %, 0.15 %, 0.01 %, and 0.00 % across respective scenarios compared to non-fallow scenarios. These findings are consistent with fallow-based water management strategies commonly employed in other agricultural systems (Ruis et al., 2023; Verburg et al., 2012). When available surface water reaches 510 million m^3, the effect of fallowing on total yield becomes minimal, though partial fallowing still reduces resource inputs, and slightly increases productivity. Figs. 6a to 6c indicate that high-salinity areas are consistently identified as prime fallow zones. This prioritization suggests that soil salinity levels in these zones exceed crop tolerance thresholds, resulting in low irrigation water use efficiency and are thus selected for fallowing. In practical applications, targeted fallowing in high-salinity areas, or deferring cultivation until after soil improvement, could support both environmental and productivity goals.

3.2. Irrigation water allocation considering saline groundwater irrigation and irrigation water salinity threshold

The minimum saline water demands calculated under various yield target scenarios differ from each other (Table 2). The results indicate that, with a limited surface water supply of 340 million m^3, using a groundwater volume of 66 million m^3 can sustain 80 % of the 2021 production levels. Increasing groundwater extraction to 192 million m^3 further narrows the production gap to 10 % below 2021 levels, while 383 million m^3 of groundwater extraction would match the 2021 production levels. These findings reveal that as target yields increase, maintaining proportional cotton yield improvements requires a higher groundwater extraction rate, subsequently reducing water productivity. To maintain 2021 production levels without yield reduction, 383 million m^3 of groundwater would need to be extracted alongside 340 million m^3 of surface water, with groundwater use exceeding surface water

Table 2
Minimum saline groundwater requirements under different scenarios and yield targets.

Scenarios	Yield targets	Groundwater needs
a. available Surface water of 340 million m^3, W1	2021 yield	383 million m^3
b. available Surface water of 340 million m^3, W1	90 % of 2021 yield	192 million m^3
c. available Surface water of 340 million m^3, W1	80 % of 2021 yield	66 million m^3
d. available Surface water of 510 million m^3, W2	2021 yield	173 million m^3
e. available Surface water of 510 million m^3, W2	90 % of 2021 yield	77 million m^3

consumption. Further, when the available surface water volume is 510 million m^3, only 7 million m^3 of groundwater extraction is necessary to limit yield loss to within 10 %. Groundwater extraction of 173 million m^3 would restore yield to 2021 levels.

The proportion of land selected for fallowing varies between 0.5 % and 4.2 % across different scenarios (Fig. 7). Consistent with the surface water irrigation patterns discussed in Section 3.1, high-salinity land is consistently selected for fallowing. In the optimization results for scenario (a) (Fig. 7a), limited surface water availability necessitates extensive groundwater extraction for irrigation, with saline water irrigation covering 42.1 % of Tarim Irrigation District (details in Fig. S5). In contrast, in scenario (e), only 1.4 % of the area requires groundwater irrigation (Fig. S5e). The total irrigation water allocation strategy (details in Fig. S6) aligns closely with the outcomes observed under the surface water-only irrigation scenario of Optimization Model 1 and 2. Specifically, when total irrigation availability is high (as in scenario (a), Table 2), the northern part of Tarim River receives a larger allocation of water resources. Conversely, when total irrigation volume is low (scenario (c), Table 2), the proportion of fallow land increases, and water allocations to high-salinity areas decrease. In terms of yield distribution (details in Fig. S7), overall production is concentrated in the southern part of Tarim River and along the Tarim River, while production is comparatively lower in the northern part of Tarim River, particularly in high-salinity zones.

4. Discussion

4.1. Optimization evaluation

The optimization results demonstrate that across various scenarios of surface water availability, the total cotton yield in the optimized irrigation district consistently exceeds that achieved under traditional fixed irrigation practices, with concurrent improvements in irrigation water productivity, regardless of fallow land considerations. Soil salt content is the dominant factor affecting water allocation. This study integrates the distributed hydro-salt-crop growth model WAVES, which comprehensively accounts for salt stress responses in cotton growth, incorporating factors such as soil background salinity, groundwater salinity, and the effects of saline irrigation, including irrigation water salinity thresholds. The WAVES model has undergone rigorous parameter calibration and validation in previous studies, accurately simulating salt stress mechanisms and processes. This enables a realistic representation of the spatial heterogeneity in salt distribution, enhancing the model's fidelity to real-world conditions.

Simulation results further reveal that variations in underlying factors generate different water production functions (Fig. S1), leading to spatial disparities in water resource allocation that correspond with salinity distribution. These allocation patterns adjust dynamically with changes in water scarcity, demonstrating a flexible water management approach. Under conditions of severe surface freshwater scarcity, selective use of saline groundwater for supplemental irrigation effectively contributes to regional crop stability. Minhas and Qadir (2024) similarly

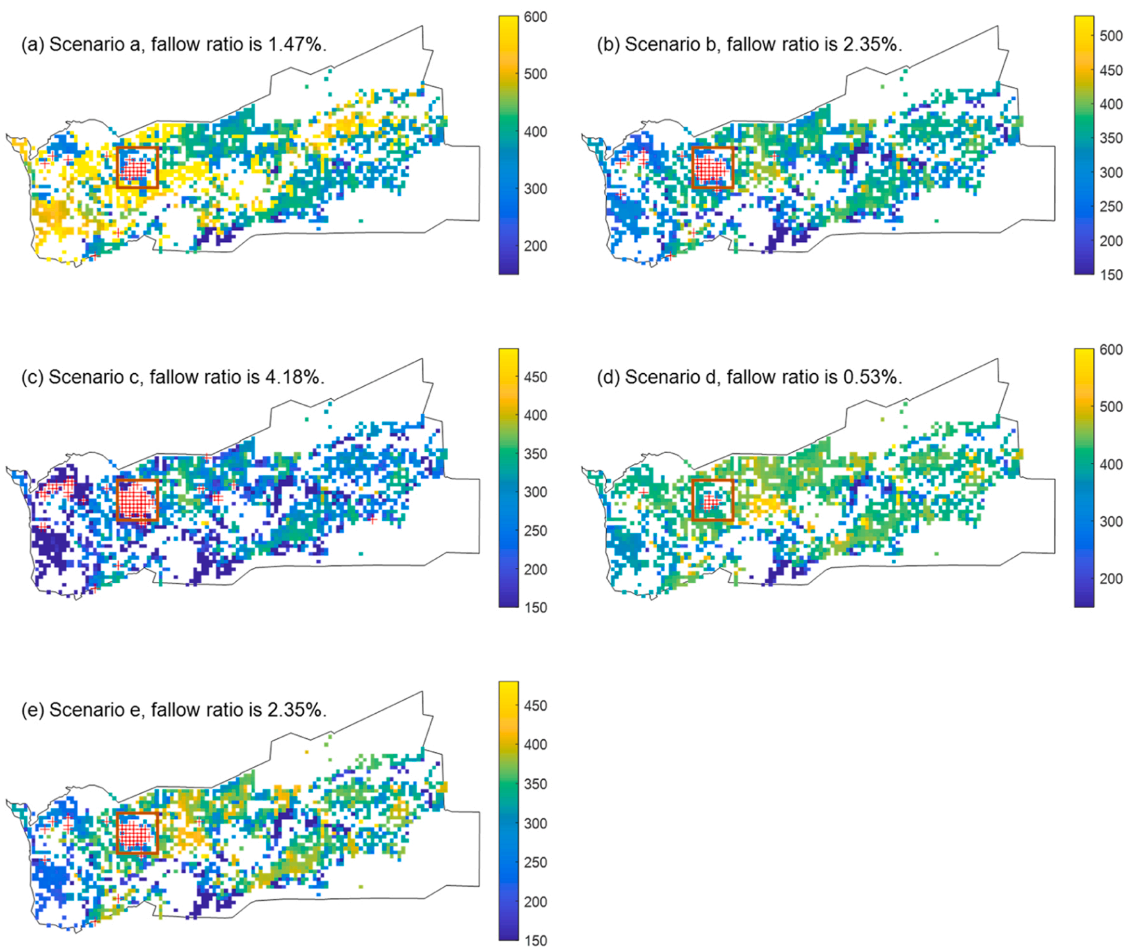

Fig. 7. The spatial irrigation water allocation (water depth, mm) solution from Optimization Model 3, using saline groundwater irrigation and considering fallowing as an option under varying surface irrigation water availability from scenarios a-e. The scenarios details are described in Table 2. Note: the orange box marks a typical severely saline area; the red plus sign in the picture represents the area that should be fallow.

highlight the role of unconventional water sources in narrowing the gap between water supply and demand, emphasizing the need for coordinated public and private investment in sustainable saline groundwater irrigation as part of future agricultural and development policies for marginal areas. Moreover, incorporating fallow land in the optimization strategy enhances yield benefits, underscoring the value of fallow land considerations in this study. In specific arid hydrological years and soil conditions, fallowing can reduce labor and input costs, aligning both with preferences of some farmers and broader irrigation district development goals. Integrating fallow practices within irrigation water optimization models proves a beneficial strategy. In summary, the water resource management model developed in this study integrated a spatially distributed hydro-salt-crop model with multi-scenario optimization (surface water, groundwater, fallowing and offers several key features: (1) Quantifying crop responses to water and salt stress, thereby increasing the precision of water allocation strategies; (2) Utilizing a distributed modeling approach that easily incorporates spatial variations in salinity, land surface characteristics, groundwater quality, and irrigation water salinity thresholds; and (3) Enabling moderate development of saline groundwater and strategic fallow scenarios, providing agricultural managers with flexible options for water resource management. This model provides a scientific basis and model framework for optimizing irrigation water allocation in arid and saline regions (for example cotton production at Uzbekistan).

4.2. Management suggestions

Soil salinity is an important factor affecting water allocation and spatial pattern of yield. When the available surface water is limited, less water should be allocated to severely saline fields. When there is an abundance of surface water, relatively more water is allocated to the severely saline fields. When the available surface water reaches 850 million m^3 within the study area, the average irrigation volume is 555 mm in high-salinity zones, while yields remain significantly below the maximum achievable yield within the district. This indicates that increasing the irrigation volume during the growing season cannot fully alleviate salt stress in these high-salinity areas. Irrigation during the growing season, particularly through subsurface drip irrigation as commonly practiced in the study area, primarily leaches salt to deeper soil layers, such as along the edge of the wetted zone. However, the leaching effect is limited; salt moves upwards to the topsoil through evaporation during non-growing periods (Wang et al., 2012). Therefore, additional engineering interventions, such as off-season salt leaching (Chen et al., 2010) and subsurface drainage systems for salt removal (Liu et al., 2021), could be useful for soil salt management. Our optimization model provides a science-based framework for dynamic water rights allocation under varying water availability. In regions with strict water rights (e.g., permits based on historical use), authorities could prioritize water allocations to low/moderate-salinity fields during droughts (maximizing yield per unit water).

Results show that when water availability is abundant, average irrigation volume is sufficient to support yield potential across the area, leaving minimal room for further yield gains through optimization. Conversely, during water-scarce years, optimizing water resource allocation largely enhances yield potential. Thus, in years with limited water supply, strategic water allocation is crucial to achieving high water-use efficiency and stable cotton production. Also, moderate underground saline water replenishment irrigation can alleviate water shortage. In the 2021 water resource management assessment for the First Division in Xinjiang, China, the groundwater extraction threshold was set at 132 million m^3; area-weighted estimates for the Tarim Irrigation District in the First Division suggest an extraction limit of 85 million m^3 for groundwater. When restricted to 85 million m^3 of groundwater extraction, cotton yield would experience a substantial decline if surface water availability is limited to 340 million m^3, with production losses exceeding 10 %. However, with 510 million m^3 of surface water, production targets can be met with yield reductions controlled to within 10 % (Table 2, scenario e). In addition, given the environmental risks associated with high levels of groundwater extraction, scenario (a) in Table 2 should be cautiously considered for practical applications. Regulators could issue conditional permits for saline groundwater use only during droughts to cap yield loss.

The optimization model developed in this study can selectively designate fields for fallowing while meeting optimization objectives, with results indicating a maximum fallow ratio of 6.9 %. When surface water availability is limited, the model favors fallowing more land to reduce labor, material, and financial input requirements, thus enhancing overall irrigation area efficiency. Similar findings by Cao et al. (2023) suggest that with greater water availability, the necessity for fallowing diminishes. In addition, fallow should prioritize high-salinity areas. For example, the area marked with an orange box in Fig. 6 could prioritize fallow in practice. This area is always chosen as fallow in optimized results and is relatively concentrated and contiguous, which makes it easier for operation of soil remediation. Soil conditions recover is mainly achieved through by reducing soil salinity (soil salt content < 6 g kg^{-1}), that is salt leaching caused by natural precipitation or artificial irrigation. When the initial salt content of the soil is 6–10 g kg^{-1}, the suitable winter irrigation leaching depth is 426–650 mm (Li et al., 2023a). Kramer and Mau (2023) also pointed out that if the soil is affected by alkalinity, saline but sodic waters require chemical amendments (e.g., gypsum) and cannot be mitigated solely by irrigation. It should be pointed out that the time required for recovery depends on the irrigation amount, initial salinity, soil characteristics (especially texture and hydraulic conductivity), climate (rainfall and distribution), and drainage conditions. In addition, moderate management of fallow land is essential for soil fertility improvement, which can be supported by cultivating salt-tolerant grasses and leguminous plants during fallow periods, aiding in land restoration (Gabriel et al., 2014; Żarczyński et al., 2023).

This model does not incorporate cultivation costs, input factors and socio-economic feasibility, which may lead to an underestimated proportion of fallow land. With a current maximum fallow rate of 6.9 %, approximately 11696 ha of land would remain fallow, affecting about 4386 workers or farmers, given the current average of 2.67 ha of arable land per worker. Not all farmers may be willing or able to implement optimized configurations. Thus, appropriate compensation and consulting services are necessary to support practice change (Wang et al., 2022). Social equity considerations should be integral to the fallow policy implementation to protect the rights and interests of affected workers or farmers. Gradual and organized subsidies or assistance with job reallocation (Cai et al., 2023) should be provided to support social stability and individual livelihoods.

Our analysis indicates that increasing available irrigation water from 340 million to 680 million m^3 (equivalent to raising the average irrigation volume from 200 mm to 400 mm) could result in a yield increase from 1824 kg ha^{-1} to 2523 kg ha^{-1}, reflecting a yield growth rate of 38.3 %. Research by Kang (2022) reports that irrigation contributes approximately 36.3 % to China's grain yield increases, while findings by Wang et al. (2021) estimate that adequate irrigation contributes 34 $\pm$ 9 % and 22 $\pm$ 13 % to global wheat and corn yields, respectively. Collectively, these studies underscore the critical role of irrigation in enhancing crop yields, a role that is especially significant in the study area's extremely arid and saline conditions. Spatial optimization of irrigation can contribute to improvements in yield and water productivity. However, in scenarios of water scarcity, the potential yield increases achievable solely through irrigation optimization are limited. To ensure stable water supply under these conditions, additional measures are needed, including scientifically managed runoff and reservoir scheduling.

4.3. Uncertainty analysis

The optimization model developed in this study accounts for the heterogeneity of underlying surface conditions and incorporates moderate use of saline water resources along with fallow strategies. The model is both straightforward in form and efficient in solution, offering insights and recommendations for optimizing irrigation water allocation and enhancing water use efficiency in saline regions. However, this model focuses solely on optimizing the total irrigation volume without considering water allocation across different crop growth stages or the potential for mixed saline and freshwater irrigation during these periods. Generally, it is recommended to apply surface water irrigation during salt-sensitive growth stages of cotton, such as seedling and flowering, while utilizing saline groundwater during salt-tolerant stages. This approach could facilitate the effective use of saline water, further optimizing water resource allocation, improving yield, and enhancing water productivity. Future model developments could refine irrigation volume by targeting specific growth stages and determining optimal saline water application timings.

4.4. Limitations

In this study, WAVES model treats salinity as a bulk osmotic stressor but does not account for sodicity, specifically sodium dominance on soil exchange sites, which can lead to irreversible soil structural degradation, including reduced soil infiltration and leaching efficiency. The long-term effects of sodicity on soil involve multiple levels of physics, chemistry, and biology, which can seriously threaten soil health and agricultural sustainability, thus affect irrigation water allocation. Thus, we have to mention that current results are valid only for saline, non-sodic soils. For areas undergoing soil sodicity, it's necessary to carefully select the soil process model combined into the current framework. For example, Hydrus with the UNSATCHEM module (Šimůnek et al., 2021), HPx - Coupled Hydrus and PHREEQC model (Šimůnek et al., 2012), or SOTE (Kramer and Mau, 2020) are alternative options which could better represent ion-specific effects, including SAR dynamics, gypsum dissolution, and hydraulic conductivity decline. Besides, the current optimized model framework may fail when the crop is sensitive to certain ions. Future model iterations should integrate ion-specific chemistry and its crop response functions, to better modifier the current optimized model framework for wider applications.

5. Conclusions

To address the challenges of water scarcity and soil salinization in arid and saline regions, this study integrates the mechanism-based distributed hydro-salt-crop model WAVES under total water use constraints and constructs three irrigation water resource management optimization models. By incorporating crop responses to water and salt stress and accounting for the spatial heterogeneity of factors such as soil salinity, surface conditions, groundwater, and irrigation water salinity thresholds, this model improves the precision of irrigation water allocation. Scenarios involving saline groundwater development and fallow strategies provide more effective and feasible water management plans. The results demonstrate that optimizing irrigation resource allocation enhances both water productivity and total cotton yield in the study area. With surface water-only irrigation, optimization of water distribution increased yield by up to 3.3 %. When surface water availability is limited, optimized water allocation substantially boosts yield, underscoring the importance of rational resource allocation during drought years. The model's water distribution strategy adapts to spatial variations in soil salinity, prioritizing water for high-yield, non-severe saline fields when water is scarce. Conversely, when surface water is plentiful, the allocation can shift toward low-yield fields to fully utilize the productive potential of high-salinity areas. In the context of climate change and reduced surface water availability, limited extraction of saline groundwater can help stabilize regional production. When available surface water decreases by 25 %, drawing a modest amount of saline groundwater (7 million m^3) can maintain production losses within 10 %. Fallowing (0–6.88 %) under limited irrigation resources can increase total yield, reducing agricultural input requirements. With reduced surface water availability, larger fallow areas should be considered. Given the lower water productivity in high-salinity zones, these areas should be prioritized for fallowing until soil conditions recover (soil salt content < 6 g kg^{-1}) to support sustainable cultivation. These findings provide valuable modeling frameworks and management strategies for water resource management in other arid, saline regions, offering guidance for efficient resource allocation and sustainable agricultural productivity under water scarcity. However, current results are valid only for saline, non-sodic soils, while the optimize framework is available for future work to further consider sodicity and ion-specific chemistry.

CRediT authorship contribution statement

Jian Song: Writing – review & editing, Visualization, Methodology. **Hui Wu:** Writing – review & editing, Visualization, Software. **Shaozhong Kang:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Qihua Yu:** Writing – original draft, Visualization, Validation, Investigation, Data curation, Conceptualization. **David Parsons:** Writing – review & editing, Visualization, Supervision. **Hui Wang:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the National Key R&D Program of China (No. 2022YFD1900503).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2025.109832.

Data availability

Data will be made available on request.

References

Abuelgasim, A., Ammad, R., 2019. Mapping soil salinity in arid and semi-arid regions using landsat 8 OLI satellite data. Remote Sens. Appl. Soc. Environ. 13, 415–425. https://doi.org/10.1016/j.rsase.2018.12.010.
Ahmad, I., Zhang, F., 2022. Optimal agricultural water allocation for the sustainable development of surface and groundwater resources. Water Resour. Manag. 36, 4219–4236. https://doi.org/10.1007/s11269-022-03249-3.
Cai, S., Zhao, X., Pittelkow, C.M., Fan, M., Zhang, X., Yan, X., 2023. Optimal nitrogen rate strategy for sustainable rice production in China. Nature 615, 73–79. https://doi.org/10.1038/s41586-022-05678-x.
Cao, Z., Zhu, T., Cai, X., 2023. Hydro-agro-economic optimization for irrigated farming in an arid region: the hetao irrigation district, inner Mongolia. Agric. Water Manag. 277, 108095. https://doi.org/10.1016/j.agwat.2022.108095.
Chen, W., Hou, Z., Wu, L., Liang, Y., Wei, C., 2010. Evaluating salinity distribution in soil irrigated with saline water in arid regions of northwest China. Agric. Water Manag. 97, 2001–2008. https://doi.org/10.1016/j.agwat.2010.03.008.
Chen, W., Jin, M., Ferré, T.P.A., Liu, Y., Xian, Y., Shan, T., Ping, X., 2018. Spatial distribution of soil moisture, soil salinity, and root density beneath a cotton field under mulched drip irrigation with brackish and fresh water. Field Crops Res 215, 207–221. https://doi.org/10.1016/j.fcr.2017.10.019.
FAO, 2021. Global map of salt-affect of soils. Rome, Italy: Global Soil Partnership, FAO.
FAO, 2025. Salt-affected soils. ⟨http://www.fao.org/soils-portal/soil-management/management-of-some-problem-soils/salt-affected-soils/more-information-on-salt-affected-soils/en/⟩ (accessed 10 August 2025).
Feng, G., Zhang, Z., Wan, C., Lu, P., Bakour, A., 2017. Effects of saline water irrigation on soil salinity and yield of summer maize (*zea mays* L.) in subsurface drainage system. Agric. Water Manag. 193, 205–213. https://doi.org/10.1016/j.agwat.2017.07.026.

Gabriel, J.L., Vanclooster, M., Quemada, M., 2014. Integrating water, nitrogen, and salinity in sustainable irrigated systems: cover crops versus fallow. J. Irrig. Drain. Eng. 140, 1–11. https://doi.org/10.1061/(asce)ir.1943-4774.0000696.
Grillakis, M.G., 2019. Increase in severe and extreme soil moisture droughts for Europe under climate change. Sci. Total Environ. 660, 1245–1255. https://doi.org/10.1016/j.scitotenv.2019.01.001.
Hou, C., Miao, Q., Shi, H., Hu, Z., Zhao, Y., Yu, C., Yan, Y., Feng, W., 2023. Water and salinity variation along the soil profile and groundwater dynamics of a fallow cropland system in the hetao irrigation district, China. Water 15, 1–17. https://doi.org/10.3390/w15234098.
Huang, Y., Ma, Y., Zhang, S., Li, Z., Huang, Y., 2021. Optimum allocation of salt discharge areas in land consolidation for irrigation districts by SahysMod. Agric. Water Manag. 256, 107060. https://doi.org/10.1016/j.agwat.2021.107060.
Ivushkin, K., Bartholomeus, H., Bregt, A.K., Pulatov, A., Kempen, B., de Sousa, L., 2019. Global mapping of soil salinity change. Remote Sens. Environ. 231, 111260. https://doi.org/10.1016/j.rse.2019.111260.
Kang, S., 2022. Food crop production strategy based on water management and technological application (in Chinese). China Water Resour. 13, 1–5.
Khojiyev, A., Khaydarov, T., Rajabov, N., Pulatov, J., 2020. Optimal solution leaching rates with a deficit of irrigation water. IOP Conf. Ser. Mater. Sci. Eng. 883, 012091. https://doi.org/10.1088/1757-899X/883/1/012091.
Kramer, I., Mau, Y., 2020. Soil degradation risks assessed by the SOTE model for salinity and sodicity. Water Resour. Res. 56. https://doi.org/10.1029/2020wr027456.
Kramer, I., Mau, Y., 2023. Review: modeling the effects of salinity and sodicity in agricultural systems. Water Resour. Res. 59. https://doi.org/10.1029/2023wr034750.
Li, J., Fei, L., Li, S., Shi, Z., Liu, L., 2019. The influence of optimized allocation of agricultural water and soil resources on irrigation and drainage in the jingdian irrigation district, China. Irrig. Sci. 38, 37–47. https://doi.org/10.1007/s00271-019-00649-z.
Li, L., Liu, H., Gong, P., Lin, E., Bai, Z., Li, P., Wang, C., Li, J., 2023a. Multi-objective optimization of winter irrigation for cotton fields in salinized freeze-thaw areas. Eur. J. Agron. 143. https://doi.org/10.1016/j.eja.2022.126715.
Li, S., Yang, G., Wang, H., Song, X., Chang, C., Du, J., Gao, D., 2023b. A spatial-temporal optimal allocation method of irrigation water resources considering groundwater level. Agric. Water Manag. 275, 108021. https://doi.org/10.1016/j.agwat.2022.108021.
Li, G., Zhang, M., Wu, C., 2021. Short-term fallow practices drive soil bacterial community changes: a case study from China. Appl. Soil Ecol. 165, 103988. https://doi.org/10.1016/j.apsoil.2021.103988.
Li, X., Zhang, C., Huo, Z., Adeloye, A.J., 2020. A sustainable irrigation water management framework coupling water-salt processes simulation and uncertain optimization in an arid area. Agric. Water Manag. 231, 105994. https://doi.org/10.1016/j.agwat.2019.105994.
Liu, Y., Ao, C., Zeng, W., Kumar Srivastava, A., Gaiser, T., Wu, J., Huang, J., 2021. Simulating water and salt transport in subsurface pipe drainage systems with HYDRUS-2D. J. Hydrol. 592, 125823. https://doi.org/10.1016/j.jhydrol.2020.125823.
Liu, Y., Qian, Y., Zhu, Y., Xu, W., Wei, G., Huang, J., Qiao, Y., Ma, Q., 2025. Spatial estimation of large-scale soil salinity using enhanced inverse distance weighting method and identifying its driving factors. Agric. Water Manag. 317, 109645. https://doi.org/10.1016/j.agwat.2025.109645.
Mahmoudzadeh Varzi, M., Trout, T.J., DeJonge, K.C., Oad, R., 2019. Optimal water allocation under deficit irrigation in the context of Colorado water law. J. Irrig. Drain. Eng. 145, 05019003. https://doi.org/10.1061/(asce)ir.1943-4774.0001374.
Mattiuzi, C.D.P., Marques, G.F., Medellín-Azuara, J., 2019. Reassessing water allocation strategies and conjunctive use to reduce water scarcity and scarcity costs for irrigated agriculture in Southern Brazil. Water 11, 1–24. https://doi.org/10.3390/w11061140.
Minhas, P.S., Qadir, M., 2024. Promoting irrigation sustainability with saline water: the way forward. Irrigation Sustainability with Saline and Alkali Waters, first ed. Springer, Singapore.
Minhas, P.S., Ramos, T.B., Ben-Gal, A., Pereira, L.S., 2020. Coping with salinity in irrigated agriculture: crop evapotranspiration and water management issues. Agric. Water Manag. 227, 105832. https://doi.org/10.1016/j.agwat.2019.105832.
Mosaffa, H.R., Sepaskhah, A.R., 2019. Performance of irrigation regimes and water salinity on winter wheat as influenced by planting methods. Agric. Water Manag. 216, 444–456. https://doi.org/10.1016/j.agwat.2018.10.027.
Oster, J.D., Letey, J., Vaughan, P., Wu, L., Qadir, M., 2012. Comparison of transient state models that include salinity and matric stress effects on plant yield. Agric. Water Manag. 103, 167–175. https://doi.org/10.1016/j.agwat.2011.11.011.
Randall, M., Schiller, K., Lewis, A., Montgomery, J., Alam, Muhammad S., 2024. A systematic review of crop planning optimisation under climate change. Water Resour. Manag. 38, 1867–1881. https://doi.org/10.1007/s11269-024-03758-3.
Ruis, S.J., Stepanovic, S., Blanco-Canqui, H., 2023. Intensifying a crop-fallow system: impacts on soil properties, crop yields, and economics. Renew. Agric. Food Syst. 38, 1–10. https://doi.org/10.1017/s1742170523000133.
Shen, H., Jiang, K., Sun, W., Xu, Y., Ma, X., 2021. Irrigation decision method for winter wheat growth period in a supplementary irrigation area based on a support vector machine algorithm. Comput. Electron. Agric. 182, 106032. https://doi.org/10.1016/j.compag.2021.106032.
Šimůnek, J., Jacques, D., Šejna, M., Genuchten, M.Tv, 2012. The HP2 Program for HYDRUS (2D/3D), A Coupled Code for Simulating Two-Dimensional Variably-Saturated Water Flow, Head Transport, Solute Transport and Biogeochemistry in Porous Media, (HYDRUS + PHREEQC + 2D), Version 1.0, PC Progress, Prague, Czech Republic.
Šimůnek, J., Šejna, M., Genuchten, M.Tv, 2021. The UNSATCHEM Module for HYDRUS (2D/3D) Simulating Two- and Three-Dimensional Movement of and Reactions Between Major Ions in Soils, Version 2.0, PC Progress, Prague, Czech Republic.
Tong, F., Guo, P., 2013. Simulation and optimization for crop water allocation based on crop water production functions and climate factor under uncertainty. Appl. Math. Model. 37, 7708–7716. https://doi.org/10.1016/j.apm.2013.03.018.
US Salinity Laboratory Staff, 1954. Diagnosis and Improvement of Saline and Alkali Soils. UDS Handbook, 60, US Dept. of Agriculture, Washington DC.
Valenzuela, F.J., Reineke, D., Leventini, D., Chen, C.C.L., Barrett-Lennard, E.G., Colmer, T.D., Dodd, I.C., Shabala, S., Brown, P., Bazihizina, N., 2022. Plant responses to heterogeneous salinity: agronomic relevance and research priorities. Ann. Bot. 129, 499–518. https://doi.org/10.1093/aob/mcac022.
Verburg, K., Bond, W.J., Hunt, J.R., 2012. Fallow management in dryland agriculture: explaining soil water accumulation using a pulse paradigm. Field Crops Res 130, 68–79. https://doi.org/10.1016/j.fcr.2012.02.016.
Wang, R., Kang, Y., Wan, S., Hu, W., Liu, S., Jiang, S., Liu, S., 2012. Influence of different amounts of irrigation water on salt leaching and cotton growth under drip irrigation in an arid and saline area. Agric. Water Manag. 110, 109–117. https://doi.org/10.1016/j.agwat.2012.04.005.
Wang, J., Li, J., Guan, H., 2016. Modeling response of cotton yield and water productivity to irrigation amount under mulched drip irrigation in north xinjiang. Trans. ofthe CSAE 32, 62–68. https://doi.org/10.11975/j.issn.1002-6819.2016.03.010.
Wang, X., Muller, C., Elliot, J., Mueller, N.D., Ciais, P., Jagermeyr, J., Gerber, J., Dumas, P., Wang, C., Yang, H., Li, L., Deryng, D., Folberth, C., Liu, W., Makowski, D., Olin, S., Pugh, T.A.M., Reddy, A., Schmid, E., Jeong, S., Zhou, F., Piao, S., 2021. Global irrigation contribution to wheat and maize yield. Nat. Commun. 12, 1235. https://doi.org/10.1038/s41467-021-21498-5.
Wang, Z., Yin, Y., Wang, Y., Tian, X., Ying, H., Zhang, Q., Xue, Y., Oenema, O., Li, S., Zhou, F., Du, M., Ma, L., Batchelor, W.D., Zhang, F., Cui, Z., 2022. Integrating crop redistribution and improved management towards meeting China's food demand with lower environmental costs. Nat. Food 3, 1031–1039. https://doi.org/10.1038/s43016-022-00646-0.
Wang, Z., Zhu, S., Yu, R., Li, L., Shan, G., You, W., Zeng, X., Zhang, C., Zhang, L., Song, R., 1993. Saline soil in China. Science Press, Beijing.
Wu, H., Yue, Q., Guo, P., Xu, X., Huang, X., 2022. Improving the AquaCrop model to achieve direct simulation of evapotranspiration under nitrogen stress and joint simulation-optimization of irrigation and fertilizer schedules. Agric. Water Manag. 266, 107599. https://doi.org/10.1016/j.agwat.2022.107599.
Yu, Q., Kang, S., Hu, S., Zhang, L., Zhang, X., 2021. Modeling soil water-salt dynamics and crop response under severely saline condition using WAVES: searching for a target irrigation volume for saline water irrigation. Agric. Water Manag. 256, 107100. https://doi.org/10.1016/j.agwat.2021.107100.
Yu, Q., Kang, S., Zhang, L., Hu, S., Li, Y., Parsons, D., 2023a. Incorporating new functions into the WAVES model, to better simulate cotton production under film mulching and severe salinity. Agric. Water Manag. 288, 108470. https://doi.org/10.1016/j.agwat.2023.108470.
Yu, Q., Wang, F., Zou, M., Ji, S., Li, M., Kang, S., 2024. Quantifying the spatial water salinity threshold of saline water irrigation by applying distributed WAVES model. Agric. Syst. 214, 103839. https://doi.org/10.1016/j.agsy.2023.103839.
Yu, X., Zeng, X., Gui, D., Li, X., Gou, Q., Wang, D., Wu, J., 2023b. Projection of flash droughts in the headstream area of Tarim river basin under climate change through Bayesian uncertainty analysis. J. Geophys. Res. Atmospheres 128, e2022JD037634. https://doi.org/10.1029/2022jd037634.
Żarczyński, P.J., Krzebietke, S.J., Sienkiewicz, S., Wierzbowska, J., 2023. The role of fallows in sustainable development. Agriculture 13, 1–19. https://doi.org/10.3390/agriculture13122174.
Zhang, L., Dawes, W.R., Hatton, T.J., 1996. Modelling hydrologic processes using a biophysically based model-application of WAVES to FIFE and HAPEX-MOBILHY. J. Hydrol. 185, 147–169. https://doi.org/10.1016/0022-1694(95)03006-9.
Zhang, L., Dawes, W.R., Slavich, P.G., Meyer, W.S., Thorburn, P.J., Smith, D.J., Walker, G.R., 1999. Growth and ground water uptake responses of lucerne to changes in groundwater levels and salinity: lysimeter, isotope and modelling studies. Agric. Water Manag. 39, 265–282. https://doi.org/10.1016/s0378-3774(98)00082-1.
Zhang, X., Guo, P., Guo, W., Gong, J., Luo, B., 2021. Optimization towards sustainable development in shallow groundwater area and risk analysis. Agric. Water Manag. 258, 107225. https://doi.org/10.1016/j.agwat.2021.107225.
Zhang, C., Li, X., Li, G., Dai, X., Huo, Z., 2023. A simulation-based multi-objective two-level optimization decision-making approach for supporting balanced irrigation water management. Agric. Water Manag. 284, 108344. https://doi.org/10.1016/j.agwat.2023.108344.
Zhang, Y., Yuan, W., Han, L., 2022. Residue mulching alleviates coastal salt accumulation and stimulates post-fallow crop biomass under a fallow-maize (Zea mays L.) rotation system. Agriculture 12, 1–12. https://doi.org/10.3390/agriculture12040509.