Mechanistic analysis of soil salinity evolution under long-term mulched drip irrigation in a typical oasis irrigation district of Xinjiang of China

Keshun Liu[1,2,3], Wenhao Li[1,2,3*], Tingbo Lyu[1,2*], Shuanglong Gao[1,2,3], Jucheng Wu[1,2,3], Jinyin He[1,2,3], Cunhong Zhang[1,2,3]

(1. *College of Water Conservancy & Architectural Engineering, Shihezi University, Shihezi 832000, Xinjiang, China*;
2. *Key Laboratory of Modern Water-Saving Irrigation of Xinjiang Production & Construction Group, Shihezi University, Shihezi 832000, Xinjiang, China*;
3. *Key Laboratory of Northwest Oasis Water-Saving Agriculture, Ministry of Agriculture and Rural Affairs, Shihezi 832000, Xinjiang, China*)

Abstract: Soil salinization poses a significant challenge for sustainable development in oasis irrigation districts. This study focused on mulched drip-irrigated cotton fields in the downstream area of the Manas River Basin. Using machine learning and Shapley Additive Explanations (SHAP) algorithms, the long-term dynamics of soil salinity in the 0-100 cm soil profile and its key driving factors from 2013 to 2021 were analyzed. The results revealed that prolonged drip irrigation led to a notable decline in soil salinity within the 0-100 cm profile. In Field A, average salinity decreased from 5.58 g/kg to 2.39 g/kg, while in Field B, it declined from 11.39 g/kg to 3.88 g/kg. The random forest (RF) model exhibited robust predictive performance, achieving a coefficient of determination (R^2) of 0.886 on the test dataset. The importance ranking of the influencing factors was as follows: groundwater depth>irrigation amount>groundwater mineralization>annual evaporation>annual precipitation>soil bulk density. SHAP analysis further revealed that irrigation amounts below 6500 m^3/hm^2, groundwater depths exceeding 3.3 m, and groundwater mineralization levels below 8.75 g/L were associated with reduced soil salinity accumulation. The threshold ranges for mitigating salinity were identified as a groundwater depth between 3.3 and 3.5 m and an irrigation amount ranging from 6500 to 6800 m^3/hm^2. The results can be a reference for effective soil salinity control strategies in oasis irrigation systems.
Keywords: soil salinity, influencing factors, RF, SHAP algorithm, threshold ranges
DOI: 10.25165/j.ijabe.20261904.9972

Citation: Liu K S, Li W H, Lyu T B, Gao S L, Wu J C, He J Y, et al. Mechanistic analysis of soil salinity evolution under long-term mulched drip irrigation in a typical oasis irrigation district of Xinjiang of China. Int J Agric & Biol Eng, 2026; 19(4): 165–173.

1 Introduction

Xinjiang, located in northwestern China, experiences a temperate continental arid climate. Covering a vast area of approximately 1.6649×10^6 km^2, it accounts for nearly one-sixth of China's total landmass[1]. Despite its size, Xinjiang possesses only 835×10^8 m^3 of water resources, constituting just 3% of the national total[2]. In the face of this water scarcity, Xinjiang remains a critical agricultural production region, where irrigation is vital in ensuring stable grain and cotton yields[3]. Drip irrigation was introduced in 1996 and has since been widely adopted to enhance water use efficiency, significantly improving water productivity and crop output. By the end of 2021, the total area under drip irrigation in Xinjiang had reached 4.284×10^6 hm^2, accounting for 60.85% of the cultivated land and making it the largest mulched drip irrigation region in the world[4]. Using mulch combined with drip irrigation increases crop water use efficiency by maintaining localized soil moisture and reducing surface evaporation[5]. However, long-term drip irrigation may also pose adverse effects. On the one hand, limited irrigation amounts and localized wetting can restrict the vertical leaching of salts, leading to salt accumulation in the root zone and increasing the risk of secondary salinization[6]. On the other hand, practical evidence suggests that moderately increasing irrigation amount can promote downward salt leaching and alleviate soil salinity[7]. Therefore, under long-term drip irrigation conditions, the temporal dynamics of soil salinity are governed by multiple environmental factors, including groundwater depth, annual precipitation, irrigation amount, and evaporation intensity. Understanding the dominant mechanisms through which these factors drive salinity evolution is crucial for developing scientifically sound irrigation management strategies and mitigating the risks of secondary soil salinization.

As one of the main obstacles to sustainable agriculture in arid regions, soil salinization is a complex process driven by natural and anthropogenic factors[8]. Therefore, elucidating the spatiotemporal variation and driving mechanisms of soil salinity is essential for advancing ecological understanding and promoting sustainable agricultural development. In recent years, extensive research has

Received date: 2025-06-19 **Accepted date:** 2026-07-01
Biographies: Keshun Liu, MS candidate, research interest: water-saving irrigation theory and technology, Email: l15224308086@163.com; **Shuanglong Gao**, MS candidate, research interest: water-saving irrigation theory and technology, Email: 18793387542@163.com; **Jucheng Wu**, MS candidate, research interest: water-saving irrigation theory and technology, Email: wjc20242010012@163.com; **Jinyin He**, MS candidate, research interest: water-saving irrigation theory and technology, Email: hjyxx12138@163.com; **Cunhong Zhang**, MS candidate, research interest: water-saving irrigation theory and technology, Email: 15891864830@163.com.
***Corresponding author: Wenhao Li**, PhD, Associate Professor, research interest: water-saving irrigation theory and technology. College of Water Conservancy and Architectural Engineering, Shihezi University, Shihezi 832000, Xinjiang, China. Tel: +86-13899526765, Email: lwh8510012@163.com; **Tingbo Lyu**, PhD, Professor, research interest: water-saving irrigation theory and technology. College of Water Conservancy and Architectural Engineering, Shihezi University, Shihezi 832000, Xinjiang, China. Tel: +86-15981706070, Email: lvtingbo@126.com

focused on the evolution of soil salinity and its influencing factors. Feng et al.[9] employed structural equation modeling (SEM) to explore the synergistic effects of land use types and environmental variables on soil properties, highlighting the pivotal roles of precipitation and temperature. Tessema et al.[10] identified irrigation method, water quality, and irrigation amount as key contributors to salinization. Xie et al.[11] emphasized the role of groundwater mineralization in shaping the spatial distribution of soil salinity. Similarly, Lian et al.[12] reported that groundwater depth is the dominant determinant of soil salinity, with groundwater mineralization and surface irrigation also playing significant roles. With the advancement of remote sensing and machine learning, researchers have increasingly applied these tools to evaluate and predict soil salinity. For example, Vermeulen and Van Niekerk[13] used geomorphometric covariates combined with machine learning for salinity prediction, while Andrade Foronda and Colinet[14] applied machine learning techniques to forecast soil salinity in arid zones. Wang et al.[15] also utilized remote sensing and machine learning to assess soil salt levels. Previous studies have provided valuable insights into soil salinity dynamics and their influencing factors in arid irrigation areas. However, several limitations remain. First, most existing studies have focused on short-term observations or spatial distribution patterns, while the long-term evolution characteristics of soil salinity under continuous mulched drip irrigation are still insufficiently understood. Second, although many studies have identified potential influencing factors, the relative importance of these factors has not been systematically quantified. Third, the interaction effects among irrigation, groundwater conditions, and climatic variables on soil salinity evolution remain unclear. Finally, although machine learning models have shown strong predictive ability, their "black-box" nature often limits mechanistic interpretation and practical application[16]. Therefore, there is still a need for a long-term and interpretable analytical framework to reveal the dominant drivers and threshold effects of soil salinity evolution under mulched drip irrigation. In oasis irrigation systems, groundwater depth, irrigation amount, groundwater mineralization, evaporation, rainfall, and soil bulk density are widely considered important factors affecting soil water-salt dynamics. However, their relative contributions and threshold effects under long-term mulched drip irrigation remain unclear, especially at the profile scale. In particular, most previous studies have mainly focused on salinity regulation within the root zone, while fewer studies have examined the long-term response of the entire 0-100 cm soil profile, which is also affected by cumulative leaching, capillary rise, and groundwater fluctuations.

Therefore, this study selected two representative cotton fields under long-term mulched drip irrigation in the 121st Regiment of Paotai Town, Shihezi City, within the Manas River Basin. Based on long-term observations from 2013 to 2021, the evolution characteristics of soil salinity in the 0-100 cm soil profile and the identified major driving factors were analyzed. An RF model was established using groundwater depth, irrigation amount, groundwater mineralization, annual evaporation, annual precipitation, and soil bulk density as predictors, and the SHAP method was introduced to improve model interpretability. The specific objectives were to: 1) characterize the interannual changes in soil salinity under long-term mulched drip irrigation; 2) quantify the relative importance of major environmental and management factors; and 3) identify the threshold ranges and interaction mechanisms of key factors affecting soil salinity.

2 Materials and methods

2.1 Profile of the study area

The study was conducted from 2013 to 2021 in an oasis saline–alkali area of the Xiayedi Irrigation District, located in the lower reaches of the Manas River Basin. The experimental site was situated at the Sixth Company of the 121st Regiment, Paotai Town, Shihezi City, Xinjiang, China (84°42′-86°32′E, 44°10′-45°22′N). As depicted in Figure 1, this locale is characterized by its flat terrain, adjacency to the northern slopes of the Tianshan Mountains, and its status as a key agricultural production hub for the Xinjiang Production and Construction Corps. The area is characterized by an arid climate and scarce water resources, with an average annual precipitation of only 164.3 mm and groundwater depths typically ranging from 3 to 5 m below the surface. The soil is predominantly loamy. Meanwhile, the region receives abundant sunshine and experiences intense evaporation, with an annual average sunshine duration of 2864 h and an average annual evaporation of 2036.2 mm. The climate is characterized by extremes, with the highest temperatures reaching up to 43.1°C and the lowest plummeting to –42.3°C, indicative of a classic temperate continental climate with pronounced arid and semi-arid features[17].

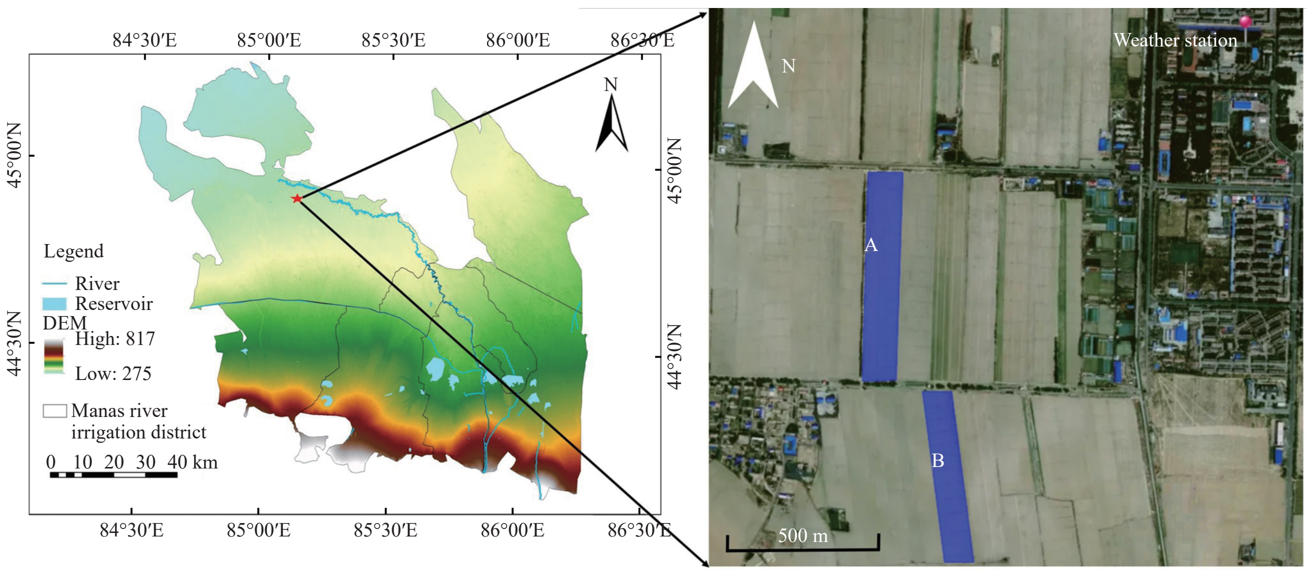


Figure 1 Overview map of the study area

2.2 Soil sampling, groundwater monitoring, and meteorological data collection

From 2013 to 2021, soil samples were collected once each year at a relatively consistent time near the end of the cotton growing season, usually in October, from two long-term fixed observation cotton fields under mulched drip irrigation in the 121st Regiment of the Xinjiang Production and Construction Corps. Field A measured 740 m×120 m, and Field B measured 610 m×102 m. This region is representative of typical mulched drip-irrigated cotton fields in Xinjiang and has strong regional representativeness and research value.

To comprehensively evaluate the salinity status of the 0-100 cm soil profile, a grid-based sampling method was adopted in each cotton field[18]. As shown in Figure 2, six fixed sampling points were arranged in a 2×3 grid pattern within each field. At each sampling point, soil samples were collected using a hand-held soil auger from five depth intervals, namely 0-20 cm, 20-40 cm, 40-60 cm, 60-80 cm, and 80-100 cm. Each depth interval was sampled in triplicate at each sampling point. From 2013 to 2021, a total of 1620 soil samples were obtained, calculated as 6 sampling points×3 replicates×5 depth intervals×2 fields×9 years.

All soil samples were air-dried, cleared of debris, ground, and passed through a 2-mm sieve before analysis. A 1:5 soil-to-water suspension was prepared, shaken thoroughly, filtered, and measured using a DDS-11A digital conductivity meter[19]. The EC1:5 values were converted to soil salt content (g/kg) using the calibration equation established by the residue-drying method: Salinity= 0.005 59×EC1:5+1.41331.

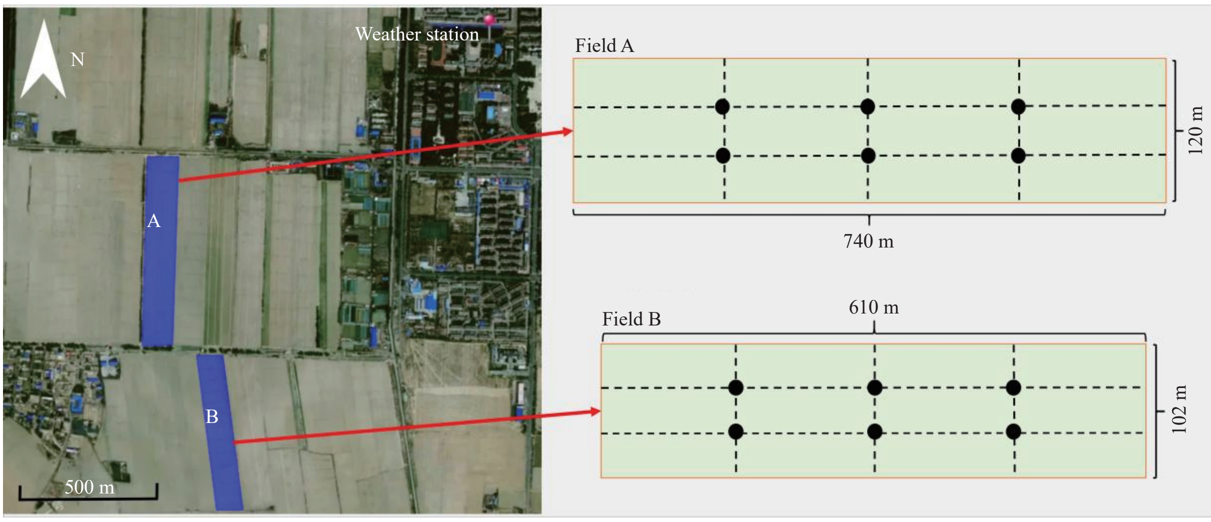


Figure 2 Spatial distribution of sampling points and field dimensions in the two experimental cotton fields

Soil bulk density was measured using the cutting ring method during each sampling event. Groundwater depth and groundwater mineralization data were obtained from long-term monitoring wells in the study area. Annual precipitation and annual evaporation data were obtained from the nearest meteorological station, which is within 2 km of the experimental fields, to assess the effects of regional climatic conditions on soil water-salt dynamics. The irrigation quota for the two experimental fields was calculated based on annual irrigation reports, using records of irrigated area and water diversion volume.

2.3 RF model and SHAP algorithm

The RF model is an ensemble prediction algorithm composed of multiple decision trees. By incorporating randomness in training samples and feature selection, this model has high computational efficiency and strong resistance to overfitting[20]. In this study, the response variable was defined as the average salinity of the 0-100 cm soil profile for each observation unit. This value was calculated from the salinity values measured separately at five soil depth intervals, namely 0-20, 20-40, 40-60, 60-80, and 80-100 cm. Because the five soil layers had the same thickness of 20 cm, the average salinity of the 0-100 cm soil profile was calculated as the arithmetic mean of the five depth-specific salinity values. This treatment was adopted because the predictor variables were mostly measured or compiled at broader temporal or field scales, and the use of profile-mean salinity helped ensure consistency between the response variable and the predictor variables. The predictor variables included groundwater depth, irrigation amount, groundwater mineralization, annual evaporation, annual precipitation, and soil bulk density.

The modeling dataset was constructed from the long-term monitoring records of the two experimental fields. Although a total of 1620 raw soil samples were collected during the nine-year monitoring period, these raw depth-layer soil samples were not directly used as independent modeling observations. For each fixed sampling point, the three replicate salinity values within the same soil layer were first averaged, and the average salinity of the 0-100 cm soil profile was then calculated from the mean salinity values of the five soil layers. Therefore, each fixed sampling point generated one 0-100 cm profile-mean salinity observation per year. Since each field contained six fixed sampling points, the two fields generated 12 profile-mean salinity observations per year. Over the nine-year monitoring period from 2013 to 2021, a total of 108 effective modeling observations were obtained, calculated as 2 fields×6 fixed sampling points×9 years. These 108 observations were then matched with the corresponding environmental and management variables for RF model construction.

Among the predictor variables, annual precipitation and annual evaporation were recorded once per year, whereas groundwater depth, groundwater mineralization, soil bulk density, and soil salinity had corresponding monitoring records at the observation-unit or annual scale. Therefore, all variables were reorganized and matched at a consistent observation-unit scale before model construction. The final dataset was randomly divided into a training set (80%) and a testing set (20%), resulting in 86 training samples and 22 testing samples[21]. The RF model was trained on the training set and evaluated on the testing set. Cross-validation was performed on the training set using the built-in modules of the PyCaret library within the Jupyter Notebook environment. Model performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE)[22], which were calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{X})^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

where, x_i represents the measured value, y_i represents the predicted value, x represents the mean value of the measured value, and n indicates the number of measured samples.

To further interpret the predictions generated by the RF model, the SHAP method was applied. SHAP is a game-theory-based additive attribution algorithm that enables the interpretation of outputs from any machine learning model[23]. Given the often opaque, "black-box" nature of machine learning models, SHAP offers a systematic approach for quantifying the impact of each feature on the model's prediction results. By calculating the Shapley value for each feature, SHAP analysis helps identify and quantify the key variables driving the spatiotemporal variation in soil salinity[24]. It also reveals the dominant environmental factors and their interaction mechanisms, thereby enhancing model interpretability and reliability. The Shapley value for a given feature is computed using the following formula:

$$\phi_j(\mathrm{val}) = \sum_{s\subseteq\{x_1,\dots,x_p\}/\{x_j\}} \frac{|s|!(p-|s|-1)!}{P!}\left(\mathrm{val}(s\cup\{x_j\}) - \mathrm{val}(s)\right) \tag{4}$$

where, $\phi_j(\mathrm{val})$ is the Shapley value of feature j, representing the contribution of this feature to the model output; s is a subset of the features used in the model; x is the input feature vector of the sample being explained; p is the total number of input features; $\frac{|s|!(p-|s|-1)!}{P!}$ is the weighting coefficient; $\mathrm{val}(s)$ refers to the model output value under the feature combinations.

Based on the Shapley values calculated for individual features using Equation (4), the prediction of the machine learning model can be decomposed into the baseline value and the sum of the contributions from all input features. Therefore, the additive explanation model of SHAP can be expressed as follows:

$$g = \phi_0 + \sum_{j=1}^{M}\phi_j \tag{5}$$

where, g is the explanatory model, M is the number of input features, ϕ_j is the Shapley value of feature j, and ϕ_0 is a constant referring to the predicted mean of all the samples.

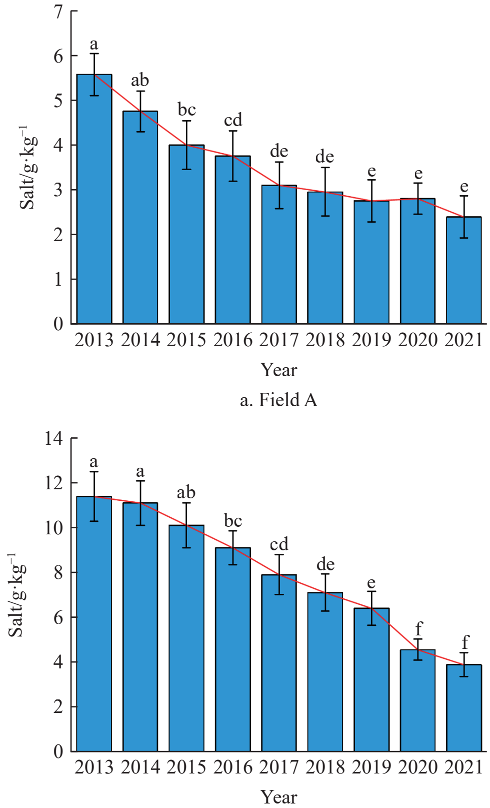
2.4 Data processing

In this study, Microsoft Excel 2021 was used for data organization and preliminary processing. Descriptive statistical analysis and multicollinearity diagnostics were performed using SPSS 26.0 (IBM Corp., Armonk, NY, USA). ArcGIS 10.8 (ESRI, Redlands, CA, USA) conducted trend analysis, spatial information extraction, and figure editing. Origin 2021 (OriginLab Corp., Northampton, MA, USA) was employed for data visualization and plotting. All model construction, training, and SHAP interpretation were implemented in Jupyter Notebook using the PyCaret library within the Anaconda development environment.

3 Results and analysis

3.1 Dynamic changes in soil salinity

From 2013 to 2021, the average salinity of the 0-100 cm soil profile showed a decreasing trend in both experimental fields (Figure 3). In Field A, the average salinity decreased from 5.58 g/kg in 2013 to 2.39 g/kg in 2021. Similarly, in Field B, the average salinity decreased from 11.39 g/kg to 3.88 g/kg over the same period. The initial salinity in Field B was approximately 2.04 times that in Field A, indicating a higher initial level of salt accumulation in Field B.



a. Field A

b. Field B

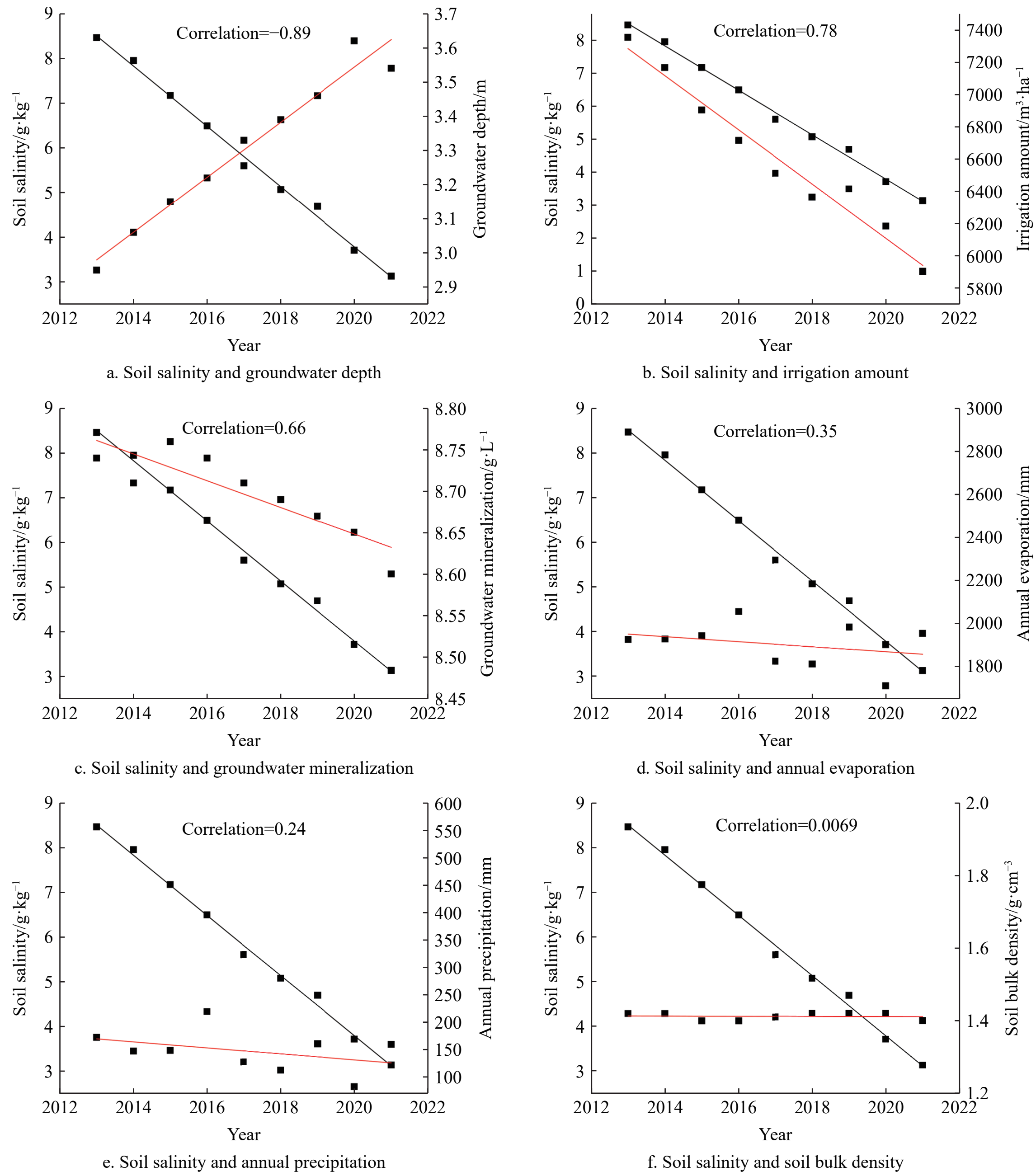
Figure 3 Interannual variation in average soil salinity of the 0-100 cm soil profile in experimental fields A and B from 2013 to 2021

From 2013 to 2018, soil salinity in Field A decreased continuously, with the largest reduction occurring between 2013 and 2014, when salinity declined from 5.58 g/kg to 4.75 g/kg, representing a decrease of approximately 15%. From 2018 to 2021, soil salinity in Field A tended to stabilize, fluctuating between 2.39 and 2.88 g/kg. Overall, Field A showed a total salinity reduction of approximately 57%. In contrast, Field B showed only a slight decrease in soil salinity from 2013 to 2014, with a reduction of approximately 2%. However, after 2014, the rate of decline accelerated, and soil salinity eventually decreased to 3.88 g/kg in 2021, with a total reduction of approximately 66%.

Overall, both cotton fields in the downstream irrigation area of the Manas River Basin exhibited clear soil desalinization trends under long-term mulched drip irrigation, although the magnitude and rate of salinity reduction differed between the two fields. These differences suggest that soil salinity evolution may be jointly affected by initial salinity conditions, irrigation management, groundwater characteristics, and climatic factors.

3.2 Variation of influencing factors and correlation with soil salinity

Figure 4 illustrates the temporal variation in soil salinity and its correlations with several environmental and management factors, including groundwater depth, groundwater mineralization, annual precipitation, annual evaporation, soil bulk density, and irrigation amount. During the monitoring period, soil salinity showed an overall decreasing trend. Meanwhile, irrigation amount and groundwater mineralization also decreased gradually. Annual evaporation declined slightly with limited fluctuation, whereas annual precipitation showed slight interannual variability without a clear overall trend. The relatively regular decline in annual irrigation amount was mainly associated with the gradual optimization of irrigation scheduling and the implementation of water-saving management practices in the study area during the monitoring period.



a. Soil salinity and groundwater depth

b. Soil salinity and irrigation amount

c. Soil salinity and groundwater mineralization

d. Soil salinity and annual evaporation

e. Soil salinity and annual precipitation

f. Soil salinity and soil bulk density

Figure 4 Changes and correlation of salinity and influencing factor

According to Pearson correlation analysis, an absolute correlation coefficient greater than 0.8 is considered a strong correlation, 0.5-0.8 a moderate correlation, 0.3-0.5 a weak correlation, and values below 0.3 a very weak correlation. The results showed a strong negative correlation between groundwater depth and soil salinity (r=−0.89). Irrigation amount and groundwater mineralization showed moderate positive correlations with soil salinity, with correlation coefficients of 0.78 and 0.66, respectively. Annual evaporation was weakly positively correlated with soil salinity (r=0.35). In contrast, annual precipitation and soil bulk density showed very weak correlations with soil salinity, with correlation coefficients below 0.3.

Based on the absolute values of the correlation coefficients, the influencing factors were ranked as follows: groundwater depth>irrigation amount>groundwater mineralization>annual evaporation>annual precipitation>soil bulk density. Although annual precipitation and soil bulk density showed weak linear correlations with soil salinity, they were still included in the modeling process. This is because RF and SHAP methods can evaluate the overall contribution of each variable to model prediction and help identify potential nonlinear effects and interactions that may not be fully captured by simple Pearson correlation analysis.

3.3 Model construction and performance

To assess potential multicollinearity among the selected influencing factors and reduce bias in the interpretation of variable importance, variance inflation factor (VIF) analysis was conducted using SPSS 26.0 (Table 1). A VIF value greater than 10 is generally considered to indicate severe multicollinearity[25]. In this study, the VIF values of all selected predictor variables were below 10, indicating that severe multicollinearity was not detected among the variables.

Table 1 Variance inflation factor analysis of influencing factors

Influencing factors	VIF
Groundwater depth	3.47
Groundwater mineralization	2.21
Annual precipitation	6.86
Annual evaporation	6.47
Irrigation amount	1.32
Soil bulk density	3.12

The performance of the RF model in predicting soil salinity based on the selected influencing factors is presented in Table 2 and Figure 5. The model showed high predictive accuracy, with coefficients of determination (R^2) of 0.987 for the training set and 0.886 for the testing set. The corresponding MAE and RMSE values were 0.30 and 0.39 for the training set, and 0.35 and 0.44 for the testing set, respectively. These results indicate that the RF model effectively captured the predictive relationships between soil salinity and the selected environmental and management variables.

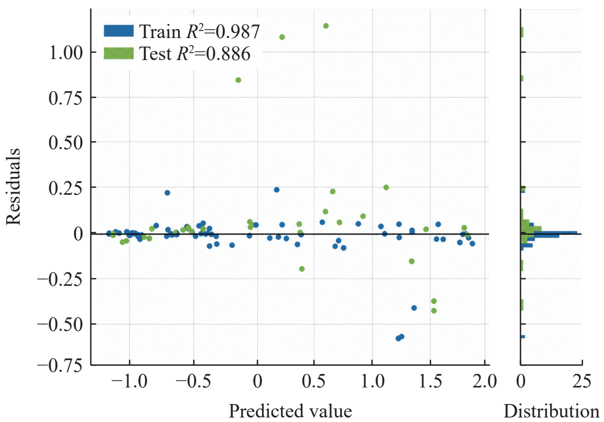


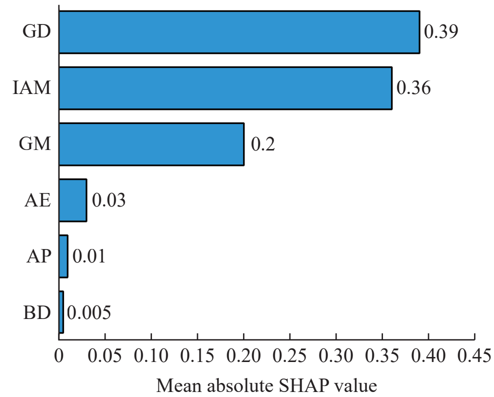
Figure 5 Performance of the RF model for soil salinity prediction

Table 2 Performance of the RF model for soil salinity prediction

Indicators	Category	Sample size	R^2	MAE	RMSE
Salinity	Train	86	0.987	0.30	0.39
	Test	22	0.886	0.35	0.44

3.4 Analysis of factors influencing soil salinity

The SHAP-based interpretation of the RF model is illustrated in Figure 6. As shown, groundwater depth, irrigation amount, and groundwater mineralization were identified as the primary contributors to soil salinity, with SHAP values of 0.39, 0.36, and 0.20, respectively. In contrast, the SHAP values for annual evaporation, annual precipitation, and soil bulk density were relatively low, at 0.03, 0.01, and 0.005, respectively. The ranking and magnitude of SHAP values indicate that groundwater depth, irrigation amount, and mineralization substantially impact soil salinity more than the other factors. Therefore, these variables were identified as the dominant predictors of soil salinity variation in the random forest model.



Note: Abbreviations: GD, groundwater depth; GM, groundwater mineralization; AP, annual precipitation; AE, annual evaporation; IAM, irrigation amount; BD, soil bulk density. The same as the figures below.

Figure 6 SHAP importance ranking of influencing factors for soil salinity prediction

The SHAP summary plot is shown in Figure 7. Among the factors influencing soil salinity, samples with greater groundwater depths generally exhibited negative SHAP values, indicating that a deeper groundwater table was associated with reduced soil salinity in the mulched drip-irrigated cotton fields of the studied oasis irrigation area. In contrast, higher values of irrigation amount, groundwater mineralization, and annual evaporation were associated with positive SHAP contributions to soil salinity, suggesting that elevated levels of these factors tend to intensify salinity accumulation in the soil.

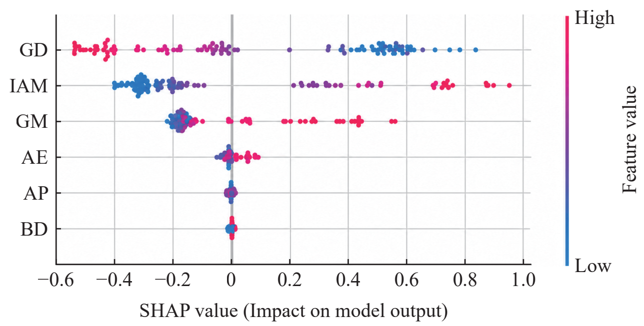
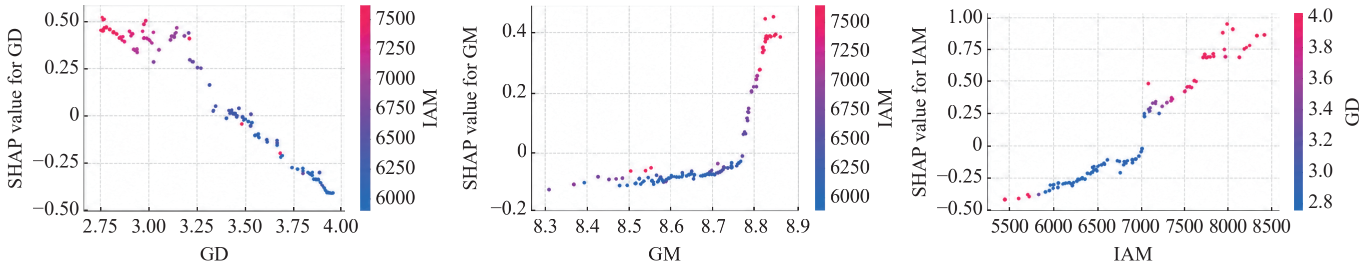


Figure 7 SHAP summary plot of influencing factors for soil salinity prediction based on the RF model

SHAP dependence plots were used to analyze the response trends and threshold effects of key influencing factors, as shown in Figure 8. In Figure 8a, the SHAP values of groundwater depth showed a general decreasing trend as groundwater depth increased, indicating that deeper groundwater had a stronger negative contribution to predicted soil salinity. This suggests that increasing groundwater depth was associated with reduced salt accumulation. The threshold range for groundwater depth was identified as approximately 3.3-3.5 m. When groundwater depth was less than 3.3 m, SHAP values were generally positive, particularly under higher irrigation amounts, suggesting a greater tendency for salt accumulation. In contrast, when groundwater depth exceeded 3.5 m, SHAP values became more negative, especially under lower irrigation amounts, indicating an enhanced salinity-suppression effect. As shown in Figure 8b, the influence of groundwater mineralization on soil salinity followed an overall upward nonlinear trend. The threshold was approximately 8.75 g/L. When groundwater mineralization was below this threshold, SHAP values were generally negative or close to zero, indicating a weak or salinity-reducing contribution to predicted soil salinity. In contrast, when groundwater mineralization exceeded 8.75 g/L, SHAP values became positive, particularly under higher irrigation amounts, suggesting that high groundwater mineralization combined with greater irrigation input may increase the risk of salt accumulation in the soil profile. As shown in Figure 8c, the effect of irrigation amount on soil salinity exhibited a nonlinear increasing trend, with a threshold transition range of approximately 6500-6800 m³/hm². Irrigation amounts below 6500 m³/hm² generally showed negative SHAP values, indicating that they may influence the reduction in soil salinity. However, when irrigation amount exceeded 6800 m³/hm², SHAP values became positive, and shallower groundwater depths further amplified this salinity-accumulating effect.



a. Groundwater depth and irrigation amount b. Groundwater mineralization and irrigation amount c. Irrigation amount and groundwater depth

Figure 8 SHAP dependence plots of key influencing factors affecting soil salinity prediction

4 Discussion

4.1 Characteristics of soil salinity evolution in typical cotton fields

The evolution of soil salinity is a highly complex process influenced by multiple interacting factors. Soil salinization varies across regions due to differences in natural geographic conditions, hydrogeological settings, and anthropogenic activities. As a representative inland arid region, Xinjiang exhibits a salinization process that differs from both inland humid and coastal areas. According to Li et al.[26], intense evaporation, limited precipitation, and frequent wind events in this region are the key climatic drivers promoting upward migration and surface accumulation of salts. This unique climate combination leads to rapid soil water evaporation and continuous salt concentration near the surface, resulting in widespread saline-alkali soils. The Manas River Irrigation District, one of the earliest areas in Xinjiang to adopt mulched drip irrigation as a water-saving technology, provides a representative case for understanding soil salinity dynamics under long-term drip irrigation. Long-term monitoring revealed a three-stage salinity change pattern: a rapid decline in the early years, a slower decline in the intermediate phase, and stabilization in later years (Figure 3). This trend is consistent with the findings of Zong et al.[27], who reported that the salinity evolution under mulched drip irrigation typically includes a rapid desalinization phase during years 1–4, a stabilized desalinization phase during years 5–11, and a salinity stabilization phase after 12 years. The sustained decline in soil salinity observed in this study area can be attributed to the combined effects of several factors, including the gradual reduction of irrigation amount, increasing groundwater depth, decreasing annual evaporation, and declining groundwater mineralization. Specifically, as groundwater is the primary source of irrigation in this region, reductions in both irrigation amount and groundwater mineralization limited salt accumulation in the soil. Moreover, continuous leaching during drip irrigation facilitated salt ions' downward movement. Increasing groundwater depth also lengthened the upward migration pathway of dissolved ions[28], further contributing to salt leaching and a decrease in salinity within the 0-100 cm soil profile. Additionally, the decline in evaporation played a favorable role in salinity reduction by weakening the upward transport of salts from deeper layers[29]. Although precipitation is generally considered an important factor influencing soil salinity, its impact in this study area was minimal due to the inherently low and relatively stable annual precipitation (Figure 4), and thus can be considered negligible in this context.

This study focused on the long-term evolution of profile-mean soil salinity within the 0-100 cm soil profile. The 0-100 cm profile can comprehensively reflect the combined effects of long-term drip irrigation, cumulative leaching, groundwater fluctuation, and salt redistribution within the soil profile on soil salinity evolution[30]. Therefore, the 0-100 cm profile-mean salinity is suitable for evaluating long-term profile-scale salinity evolution in typical mulched drip-irrigated cotton fields. More detailed seasonal and layer-specific monitoring is still needed in future studies to further clarify the vertical redistribution of soil water and salts under long-term drip irrigation.

4.2 Analysis of dominant mechanisms driving soil salinity variation

This study identified groundwater depth and irrigation amount as the dominant drivers of soil salinity variation in oasis irrigation zones by constructing a model linking soil salinity to its influencing factors. The threshold range for the impact of groundwater depth on soil salinity was found to be 3.3-3.5 m. When groundwater depth was deeper than 3.3 m, the combined effect of reduced evaporation and weaker capillary rise decreased the upward transport of salt ions. This allowed more salts to be retained in deeper soil layers, thus reducing salinity in the upper soil profile. In contrast, shallower groundwater (<3.3 m) enhanced capillary rise, shortened the transport path of deep salt ions, and increased surface evaporation, leading to salt accumulation in the upper layers. This finding aligns with previous research. For instance, Ming et al.[31] reported that groundwater depths of around 3.5 m, combined with mulched drip irrigation and seasonal surface irrigation, can effectively suppress salt accumulation while protecting native vegetation. Similarly, Abliz et al.[32], using the FEFLOW model and vegetation distribution patterns, found that groundwater depths below 4 m in the Keriya Oasis significantly increased soil salinity. These studies suggest that moderately deep groundwater levels are beneficial for salt control; however, it is important to note that if groundwater depth exceeds 7–8 m, it may severely hinder root water uptake and crop growth in inland arid areas[33]. Therefore, groundwater extraction strategies must be aligned with local water resource conditions to avoid exacerbating irrigation shortages or ecological degradation. This study also revealed that irrigation and groundwater mineralization jointly influence soil salinity, with threshold ranges of 6500-6800 m^3/hm^2 and 8.75 g/L, respectively. It should be noted that the annual irrigation amount reported in this study referred only to irrigation during the cotton growing season under dry sowing and wet emergence, and did not include winter irrigation. When irrigation amounts exceed 6800 m^3/hm^2 and groundwater mineralization is above 8.75 g/L, the contribution to salinity becomes strongly positive, reducing the effectiveness of leaching. This is because, under these conditions, excessive irrigation leads to downward salt migration, but the high salt content in groundwater makes it more likely that salt ions will be retained in the soil during the leaching process[34]. Conversely, when the irrigation amount is within the threshold range (6500-6800 m^3/hm^2) and groundwater mineralization is low (<8.75 g/L), a significant negative contribution to salinity is observed (Figure 8), promoting effective salt leaching. Under such conditions, the low concentration of salt ions in irrigation water reduces salt retention in the soil. Combined with an appropriate leaching volume, this synergistic effect enhances desalinization. This finding is consistent with previous studies, which indicated that once soil moisture reaches field capacity under a fixed irrigation cycle and frequency, increasing irrigation volume can promote further salt dissolution and removal from the soil profile[35]. Therefore, irrigation water quality is critical; poor-quality water can lead to salt accumulation in the root zone, especially under drip irrigation[36]. Hence, effective salinity control should account for both groundwater quality and irrigation practices. According to Wang et al.[37], factors such as irrigated area, surface water use, groundwater extraction, and evaporation are key determinants of groundwater depth in the Shihezi Irrigation District. These insights highlight the importance of integrated management strategies for regulating soil salinity in oasis agricultural systems. Although the RF model showed good predictive performance, uncertainty associated with sample size and long-term field heterogeneity should still be considered when interpreting the threshold values. In practical management, priority should be given to maintaining a suitable groundwater depth, optimizing irrigation scheduling, and controlling irrigation water salinity, rather than relying solely on increasing irrigation volume.

5 Conclusions

Using long-term field data from 2013 to 2021, this study applied an RF model integrated with SHAP to systematically investigate the temporal evolution and driving mechanisms of soil salinity within the 0-100 cm profile of mulched drip-irrigated cotton fields in an oasis irrigation district. The results revealed a consistent desalinization trend over the study period. In Field A, soil salinity stabilized within the range of 2.39-2.88 g/kg after several years of drip irrigation, while in Field B, it declined significantly from 11.39 g/kg to 3.88 g/kg. This reduction was primarily attributed to three key factors: increased groundwater depth, optimized irrigation management, and reduced groundwater mineralization. The model evaluation showed that the RF approach effectively captured the variation in soil salinity, achieving a coefficient of determination of R^2=0.886. SHAP analysis further revealed the relative importance of the influencing variables in the following order: groundwater depth>irrigation amount>groundwater mineralization>annual evaporation>annual precipitation>soil bulk density. Among these, the top three factors had higher SHAP values and exhibited clear trends and threshold effects in the feature dependence plots, identifying them as the dominant controlling variables. The study concludes that when groundwater depth is maintained between 3.3 and 3.5 m, irrigation amount is controlled within 6500-6800 m^3/hm^2, and groundwater mineralization remains below 8.75 g/L, the risk of soil salinity accumulation can be substantially reduced. These findings offer a robust scientific basis and practical insights for formulating effective water–salt regulation strategies in arid-region oasis agricultural systems.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (Grant No. 52209064), the National Key Research and Development Program of China (Grant No. 2021YFD1900802-2), Xinjiang Strategic Talent Development Program—First-Class Scientific and Technological Leading Talent Project (Grant No. XJRC-2025-BTKJ-PY-KJLJ-002), Outstanding Youth Project of the Corps (Grant No. 2025DB001), and the Major Science and Technology Project of the Xinjiang Uygur Autonomous Region (Grant No. 2023A02002-5). The data supporting the findings of this study are available from the corresponding author upon reasonable request.

[References]

[1] Feng L, Wan S M, Zhang Y L, Dong H Z. Xinjiang cotton: Achieving super-high yield through efficient utilization of light, heat, water, and fertilizer by three generations of cultivation technology systems. Field Crops Research, 2024; 312: 109401.

[2] Shen Y J, Li S, Chen Y N, Qi Y Q, Zhang S W. Estimation of regional irrigation water requirement and water supply risk in the arid region of Northwestern China 1989-2010. Agricultural Water Management, 2013; 128: 55–64.

[3] Zhou Y Q, Li F, Xin Q C, Li Y M, Lin Z D. Historical variability of cotton yield and response to climate and agronomic management in Xinjiang, China. Science of the Total Environment, 2024; 912: 169327.

[4] Geng Y H, Cao G J, Wang L C, Wang M, Huang J X. Can drip irrigation under mulch be replaced with shallow-buried drip irrigation in spring maize production systems in semiarid areas of northern China? Journal of the Science of Food and Agriculture, 2021; 101(5): 1926–1934.

[5] Zhang W Q, Dong A H, Liu F L, Niu W Q, Siddique K H M. Effect of film mulching on crop yield and water use efficiency in drip irrigation systems: A meta-analysis. Soil and Tillage Research, 2022; 221: 105392.

[6] Guan Z L, Jia Z F, Zhao Z Q, You Q Y. Dynamics and distribution of soil salinity under long-term mulched drip irrigation in an arid area of northwestern China. Water, 2019; 11(6): 1225.

[7] Cheng M H, Wang H D, Fan J L, Wang X K, Sun X, Yang L, et al. Crop yield and water productivity under salty water irrigation: A global meta-analysis. Agricultural Water Management, 2021; 256: 107105.

[8] Tao Y L, Xie W J, Xu L, Zhang L C, Wang G M, Wang X N, et al. The characteristics of soil salinization effects on nitrogen mineralization and nitrification in upland fields. Frontiers in Environmental Science, 2024; 12: 1369554.

[9] Feng Z H, Wang L Q, Peng Q, Li J, Liang T. Effect of environmental factors on soil properties under different land use types in a typical basin of the North China Plain. Journal of Cleaner Production, 2022; 344: 131084.

[10] Tessema N, Yadeta D, Kebede A, Ayele G T. Soil and irrigation water

salinity, and its consequences for agriculture in Ethiopia: A systematic review. Agriculture-Basel, 2023; 13(1): 109.

[11] Xie W P, Yang J S, Yao R J, Wang X P. Spatial and temporal variability of soil salinity in the Yangtze River Estuary using electromagnetic induction. Remote Sensing, 2021; 13(10): 1875.

[12] Lian H D, Sun Z J, Xu C D, Gu F Y. The relationship between the distribution of water and salt elements in arid irrigation areas and soil salination evolution. Frontiers in Earth Science, 2022; 10: 852485.

[13] Vermeulen D, Van Niekerk A. Machine learning performance for predicting soil salinity using different combinations of geomorphometric covariates. Geoderma, 2017; 299: 1–12.

[14] Andrade Foronda D, Colinet G. Prediction of soil salinity/sodicity and salt-affected soil classes from soluble salt ions using machine learning algorithms. Soil Systems, 2023; 7(2): 47.

[15] Wang F, Han L L, Liu L L, Bai C J, Ao J X, Hu H J, et al. Advancements and perspective in the quantitative assessment of soil salinity utilizing remote sensing and machine learning algorithms: A review. Remote Sensing, 2024; 16(24): 4812.

[16] Sui H C, Chen D W, Yan J G, Li B, Li W, Cui B S. Soil salinity estimation over coastal wetlands based on RF algorithm and hydrological connectivity metric. Frontiers in Marine Science, 2022; 9: 895172.

[17] Li W H, Gao S L, Pei D J, Wen Y, Mu X G, Liu M J, et al. Spatio-temporal evolution and simulation of soil salinization in typical oasis water-saving irrigation area based on long series data. Agricultural Water Management, 2025; 307: 109275.

[18] Corwin D L, Lesch S M. Protocols and guidelines for field-scale measurement of soil salinity distribution with ECa-directed soil sampling. Journal of Environmental and Engineering Geophysics, 2013; 18(1): 1–25.

[19] Rhoades J D. Salinity: Electrical conductivity and total dissolved solids. Methods of soil analysis: Part 3 Chemical methods, 1996; 5: 417–435.

[20] Speiser J L, Miller M E, Tooze J, Ip E. A comparison of RF variable selection methods for classification prediction modeling. Expert Systems with Applications, 2019; 134: 93–101.

[21] Li J, Zhang T T, Shao Y, Ju Z S. Comparing machine learning algorithms for soil salinity mapping using topographic factors and Sentinel-1/2 data: A case study in the Yellow River delta of China. Remote Sensing, 2023; 15(9): 2332.

[22] Chicco D, Warrens M J, Jurman G. The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. Peerj Computer Science, 2021; 7: e623.

[23] Lundberg S M, Lee S I. A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 2017; 30: 4768–4777.

[24] Liu X, Hu Y, Li X, Du R Q, Xiang Y Z, Zhang F C. An interpretable model for salinity inversion assessment of the south bank of the Yellow River based on optuna hyperparameter optimization and XGBoost. Agronomy, 2025; 15(1): 18.

[25] Kyriazos T, Poga M. Dealing with multicollinearity in factor analysis: the problem, detections, and solutions. Open Journal of Statistics, 2023; 13(3): 404–424.

[26] Li K M, Liu H G, He X L, Li X X. Simulation of water and salt transport in soil under pipe drainage and drip irrigation conditions in Xinjiang. Water, 2019; 11(12): 2456.

[27] Zong R, Wang Z H, Li W H, Li H Q, Ayantobo O O. Effects of practicing long-term mulched drip irrigation on soil quality in Northwest China. Science of the Total Environment, 2023; 878: 163247.

[28] Wang H F, Li H C, Ren Z X. Modeling multiphase fluid flow and salt precipitation due to water vaporization in producing wells of underground gas storage. Gondwana Research, 2023; 122: 348–359.

[29] Nachshon U, Weisbrod N, Dragila M I, Grader A. Combined evaporation and salt precipitation in homogeneous and heterogeneous porous media. Water Resources Research, 2011; 47(3): W03513.

[30] Li W H, Wang Z H, Zhang J Z, Zong R. Soil salinity variations and cotton growth under long-term mulched drip irrigation in saline-alkali land of arid oasis. Irrigation Science, 2022; 40(1): 103–113.

[31] Ming G H, Tian F Q, Hu H C. Effect of water table depth on soil water and salt dynamics and soil salt accumulation characteristics under mulched drip irrigation. Transactions of the CSAE, 2018; 34(5): 90–97. (in Chinese)

[32] Abliz A, Tiyip T, Ghulam A, Halik U, Ding J-l, Sawut M, et al. Effects of shallow groundwater table and salinity on soil salt dynamics in the Keriya Oasis, Northwestern China. Environmental Earth Sciences, 2016; 75(3): 1–15.

[33] Zeng Y, Zhao C Y, Shi F Z, Schneider M, Lyu G H, Li Y. Impact of groundwater depth and soil salinity on riparian plant diversity and distribution in an arid area of China. Scientific Reports, 2020; 10(1): 7272.

[34] Xia J B, Zhang S Y, Zhao X M, Liu J H, Chen Y P. Effects of different groundwater depths on the distribution characteristics of soil-Tamarix water contents and salinity under saline mineralization conditions. Catena, 2016; 142: 166–176.

[35] Xu C D, Tian J J, Wang G X, Nie J K, Zhang H Y. Dynamic simulation of soil salt transport in arid irrigation areas under the HYDRUS-2D-based rotation irrigation mode. Water Resources Management, 2019; 33(10): 3499–3512.

[36] Mmolawa K, Or D. Root zone solute dynamics under drip irrigation: A review. Plant and Soil, 2000; 222(1-2): 163–190.

[37] Wang W Z, Tian H, Yang G, Liu B, Pan Y, Ding G L, et al. Dynamic variation of groundwater level and its influencing factors in typical oasis irrigated areas in Northwest China. Open Geosciences, 2023; 15(1): 20220493.