

Article

Spatiotemporal Dynamics and Evaluation of Groundwater and Salt in the Karamay Irrigation District

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Abstract

Inland depression irrigation districts in the arid regions of Xinjiang, owing to the absence of natural drainage conditions, exhibit unique groundwater-salt dynamics and face prominent risks of soil salinization, thus necessitating clarification of their water-salt transport mechanisms to ensure sustainable agricultural development. This study takes the Karamay Agricultural Comprehensive Development Zone as the research subject. The study examines the distribution characteristics of soil salinity, groundwater depth, and Total Dissolved Solids (TDS) of groundwater across diverse soil textures, elucidates the correlative relationships between groundwater dynamics and soil salinity, and forecasts the evolutionary trajectory of groundwater levels within the irrigation district. The findings reveal that groundwater depth in silty soil regions (3.24–3.11 m) substantially exceeds that in silty clay regions (2.43–2.61 m), whereas TDS of groundwater demonstrates marginally elevated concentrations in silty clay areas (19.05–16.78 g L⁻¹) compared to silty soil zones (18.18–16.29 g L⁻¹). Soil salinity exhibits pronounced surface accumulation phenomena and considerable inter-annual seasonal variations: manifesting a “spring-peak, summer-trough” pattern in 2023, which inversely transitioned to a “summer-peak, spring-trough” configuration in 2024, with salinity hotspots predominantly concentrated in silty clay distribution zones. A significant sigmoid functional relationship emerges between soil salinity and groundwater depth ($R^2 = 0.73\text{--}0.77$), establishing critical depth thresholds of 2.44 m for silty soil and 2.72 m for silty clay, beneath which the risk of secondary salinization escalates dramatically. The XGBoost model demonstrates robust predictive capability for groundwater levels ($R^2 = 0.8545$, MAE = 0.4428, RMSE = 0.5174), with feature importance analysis identifying agricultural irrigation as the predominant influencing factor. Model projections indicate that mean groundwater depths across the irrigation district will decline to 2.91 m, 2.76 m, 2.62 m, and 2.36 m over the ensuing 1, 3, 5, and 10 years, respectively. Within a decade, 73.33% of silty soil regions and 92.31% of silty clay regions will experience groundwater levels below critical thresholds, subjecting the irrigation district to severe secondary salinization threats. Consequently, comprehensive mitigation strategies encompassing precision irrigation management and enhanced drainage infrastructure are imperative.



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Keywords: salinization; groundwater; spatiotemporal distribution; TDS; machine learning

1. Introduction

Soil salinization is a major ecological challenge in arid and semi-arid regions worldwide [1]. According to the Food and Agriculture Organization of the United Nations, salinized soils now cover over 1 billion hectares globally [2], increasing by about 1 million hectares each year, with arid and semi-arid zones contributing more than 70% of newly affected areas. As a key grain and cotton production base in Northwest China, Xinjiang's oasis areas cover only 4.27% of the land but support over 95% of the regional population [3]. Severe aridity, low precipitation, and available fresh water resources make this region ecologically fragile. Inappropriate irrigation practices have further contributed to widespread soil salinization and secondary salinization, seriously threatening agricultural productivity [4,5]. Salinization disrupts soil aggregate structure, causing compaction and reduced porosity, which decrease land productivity [6]. It also impairs crop yields by inhibiting root water and nutrient uptake and disrupting plant physiological processes, potentially leading to complete crop failure [7]. In the long term, salinization accelerates land degradation and desertification, disrupts ecological balance, and undermines agricultural sustainability.

The Karamay Agricultural Comprehensive Development Zone was established in 2000 in the arid core of Xinjiang. It serves as an important agricultural base. However, it experiences serious salinization typical of irrigation districts in arid regions. Located within the enclosed Junggar Basin of northern Xinjiang, the district faces several challenges [8,9]: topographic depression (with elevations lower than surrounding terrain, preventing natural drainage and requiring artificial pumping stations for water discharge), shallow groundwater with high TDS, and ongoing imbalances in irrigation-drainage management. With elevations between 265 and 280 m, the entire area forms a depression that relies on irrigation without effective drainage. Following the district's development, improper irrigation management caused significant water seepage [10,11], raising the groundwater table—so that the mean depth decreased from 10.77 m in 1997 to 2.84 m in 2023, an increase in water table height of 7.93 m. Additionally, the Karamay Irrigation District is situated on the ancient lakebed of the Manas Lake. During the construction of the irrigation district, large-scale “soil replacement and improvement” was carried out, covering the original saline-alkali soil, but the salts were not entirely removed from the soil profile. After the establishment of the development zone, extensive irrigation management, poor drainage, and the dissolution of salts from the original soil by groundwater have collectively led to the continuous rise in highly mineralized groundwater levels. This has resulted in secondary soil salinization [12,13], seriously threatening the sustainable development of the district.

Previous studies have investigated secondary soil salinization in the Karamay Agricultural Comprehensive Development Zone [14–17]. Ren [18] used the FEFLOW model to simulate groundwater and salt dynamics in the district, showing that current water resource management practices are unsustainable. Zhao [19] investigated the influence of halophyte cultivation on salt balance in the district. Cai [20] examined seasonal variations in soil salinity under diverse land utilization patterns and their response relationships with groundwater. However, systematic investigations into how groundwater depth and TDS influence the spatiotemporal distribution of water and salt in different soil textures are lacking, limiting effective salinization management strategies.

Soil texture and groundwater level are the primary factors influencing soil salinization. Soil texture determines the capillary rise height of soil water, and water-soluble salts

dissolve in water and migrate to the surface via capillary action, consequently leading to soil salinization. The depth of the groundwater table determines whether capillary water can reach the surface, and the critical groundwater depth threshold is particularly crucial for preventing salinization and protecting groundwater resources [21]. Therefore, investigating groundwater depth under different soil textures is of great significance for revealing soil water and salt transport dynamics in irrigation districts [22]. In arid regions, however, limited monitoring well distribution and gaps in spatiotemporal data make this effort challenging. Recently, data-driven approaches utilizing machine learning and deep learning have been extensively adopted as viable alternatives [23]. When physical relationships are too complex for traditional models, machine learning and deep learning have proven effective in addressing these challenges directly. Numerous studies have demonstrated the utility of machine learning for temporal prediction of groundwater levels at fixed sampling points [24–26]. To forecast groundwater levels in both space and time, some researchers have combined machine learning-based temporal predictions with spatial interpolation methods, such as kriging [27]. However, while a wide array of machine learning algorithms were available, the XGBoost model demonstrates the most robust performance in terms of prediction accuracy, generalization ability, and computational efficiency when handling the small-to-medium-scale, structured time series data involved in this study, in comparison with other models [28]. Nevertheless, this model has not yet been widely adopted as a direct method for predicting groundwater levels in spatial domains. Therefore, whether machine learning methods can be directly applied to simulate the spatiotemporal distribution of groundwater levels remains a topic worthy of further investigation.

Therefore, this study employs the Karamay Agricultural Comprehensive Development Zone as a representative case to systematically investigate the co-evolution of groundwater and soil salinity in artificial irrigation districts within arid inland regions. It aims to develop an integrated diagnostic methodology for water-salt dynamics that combines mechanistic interpretation with predictive capability. The specific objectives are: (1) to quantify the influence of groundwater depth and TDS on soil salinity dynamics across different soil textures, elucidating the dominant controlling mechanisms and threshold responses common to various soil types; and (2) to develop a multi-scenario machine learning model for predicting groundwater depth, enabling dynamic assessment and early warning of future water-salt risks. The findings are expected to provide not only a direct scientific basis for salinization control in the study area but also a transferable theoretical framework and methodological paradigm for water-salt regulation in similar ecologically fragile irrigation districts.

2. Materials and Methods

2.1. Location of the Study Area

The study site is located within the Agricultural Comprehensive Development Zone (Karamay Irrigation District), approximately 9 km southeast of Karamay City, Xinjiang. The geographic coordinates range from 84°50′ E to 85°04′ E and 45°22′ N to 45°31′ N (Figure 1). The elevation ranges from 268 to 288 m, and the terrain is generally flat, with a gentle slope from southwest to northeast and no significant undulation. The region has a temperate continental climate, characterized by pronounced aridity, low precipitation, strong evaporation, and large diurnal temperature variations. The multi-year average evaporation is 1800 mm, precipitation is 105.3 mm, and the average temperature is 8.2 °C. Irrigation water is supplied from the surface water of the Xijiao Reservoir.

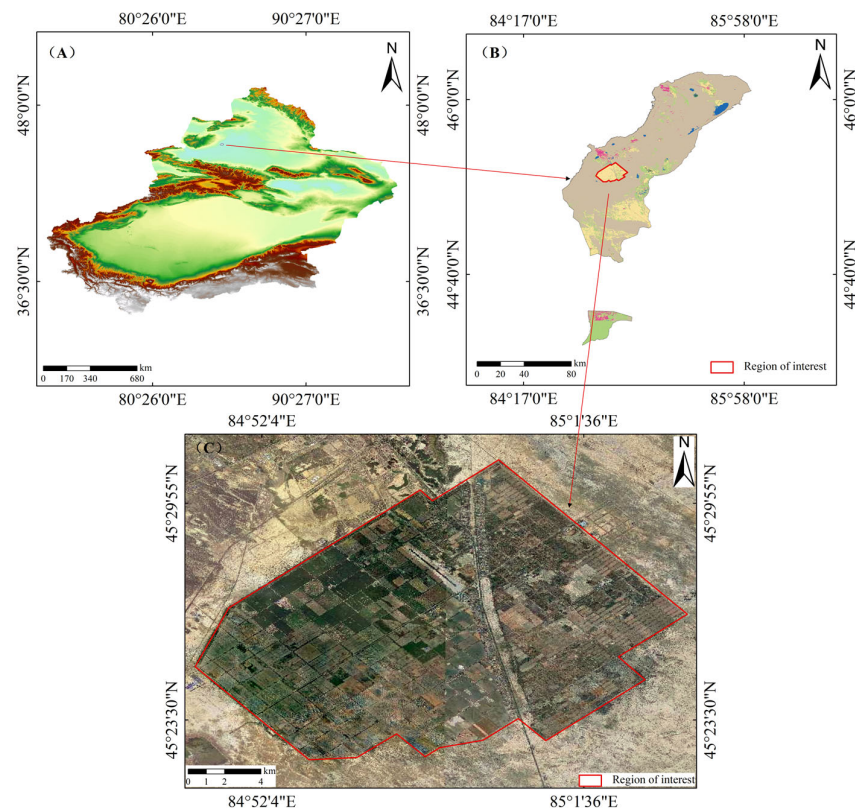


Figure 1. Geographical location of the Karamay Irrigation District. (A) Altitude distribution of the study area. (B) Distribution of regional land use types. (C) Study area map of Karamay irrigation area.

2.2. Data and Methods

2.2.1. Soil and Groundwater Sample Collection

Soil Sampling and Preparation: A systematic soil sampling program was implemented across the irrigation district using a GPS to establish a regular $2\text{ km} \times 2\text{ km}$ grid. This grid established 51 fixed sampling points. Soil samples were collected during April, July, and October in both 2023 and 2024 (Figure 2). During each campaign, a soil auger was used to collect samples at six depth intervals (vadose zone): 0–20, 20–40, 40–60, 60–80, 80–100, and 100–120 cm. For each sampling event, new boreholes were drilled adjacent to previous holes to preserve the integrity of each site. In total, six sampling campaigns yielded 1836 soil samples. Each soil sample was immediately placed in a pre-labeled, self-sealing bag, the air was removed, and the bag was hermetically sealed for storage and transport.

Groundwater Depth Monitoring: Groundwater levels were monitored monthly from April to October in 2023 and 2024 at 35 dedicated observation wells. All these groundwater sampling points utilize the existing, long-term operational groundwater dynamic monitoring wells in the irrigation district. Constructed synchronously with the development of the irrigation district, these monitoring wells possess excellent stability and long-term observability. A portable electric water level meter with an accuracy of 1 cm (Model JSY, Beijing Heli Kechuang Technology Development Co., Ltd., Beijing, China) was employed for all depth measurements. The probe and tape were cleaned before the probe was lowered into the well. The depth from the wellhead to the water table was recorded when an audible signal indicated the probe reached the water surface. To ensure accuracy, each measurement was repeated three times, and the average value was recorded. The final groundwater depth was calculated as:

$$\text{Depth to Groundwater} = \text{Measured Depth} - \text{Height of Wellhead Above Ground Surface.}$$

Groundwater Sample Collection: Immediately following the groundwater depth measurement at each well, a submersible pump (Model 51A304, Xiaonengdou, Shangqiu, China) was used for sample collection. Each well was purged by pumping at a low flow rate (30 L min^{-1}) until key parameters, especially electrical conductivity, stabilized (defined as less than 10% variation across three consecutive measurements). Once stability was confirmed, samples were collected by inserting the pump's outlet tube to the bottom of the collection bottle and filling the bottle from the bottom up to prevent aeration. The bottle was flushed by allowing it to overflow two to three times its volume, then securely capped.

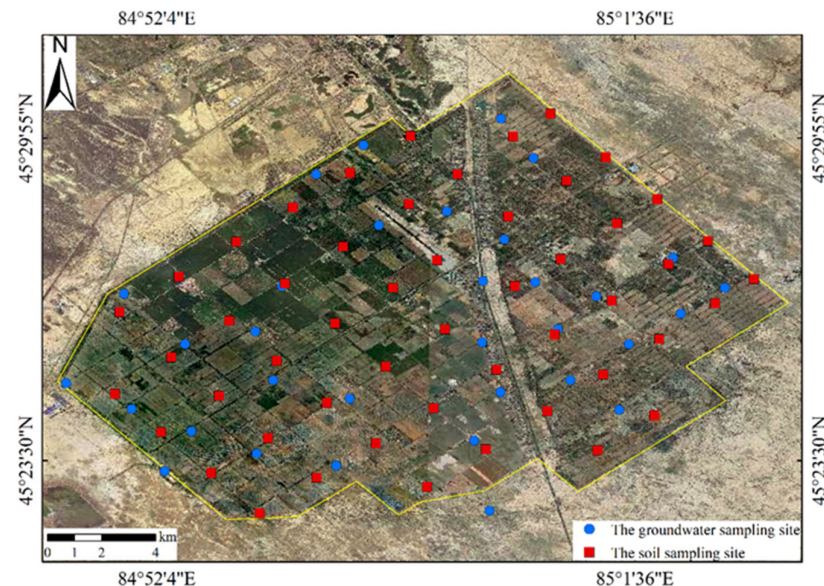


Figure 2. Distribution of soil and groundwater sampling points within the irrigation district.

2.2.2. Sample Analysis

(1) Soil salinity

The electrical conductivity (EC) of all soil samples was measured in the laboratory using a conductivity meter with an accuracy of 0.01 (DDB-350A, INESA Scientific Instrument Co., Ltd., Shanghai, China). Measurements were performed on the supernatant from 1:5 soil-to-water extracts. For samples collected in April and October 2023, both EC and total salt content were directly measured by the Xinjiang Institute of Ecology and Geography. For all other sampling periods, total salt content was estimated using a linear regression model ($R^2 = 0.973$) derived from the EC and total salt data measured in April 2023. The conversion used the following equation [29,30],

$$y = 3.4441x + 0.3985 \quad (1)$$

where y is the estimated total salt content (g kg^{-1}) and x is the measured EC (mS cm^{-1}), the numerical range of x is $0.07\text{--}7.42 \text{ mS cm}^{-1}$.

(2) Total Dissolved Solids (TDS) of groundwater

For groundwater samples collected in April 2023, both electrical conductivity (EC) and TDS were directly measured by the Xinjiang Institute of Ecology and Geography. For all other months, TDS was estimated from measured EC values using the same conductivity meter as for soil. The estimation was based on a linear regression model ($R^2 = 0.992$) established from the April 2023 data, using the following equation [29,30],

$$y = 0.6729x + 3.4307 \quad (2)$$

where y is the estimated TDS (g L^{-1}) and x is the measured EC (mS cm^{-1}), the numerical range of x is 2.41–56.7 mS cm^{-1} .

(3) Soil texture

Soil texture was determined for samples collected from 51 soil profiles within the irrigation district. In the laboratory, samples were air-dried, ground, and passed through a 2 mm sieve to remove stones and plant debris. The percentages of sand, silt, and clay were determined using the hydrometer method to classify soil texture. The procedure followed the methodology described by Chen [31].

(4) Meteorological data and reference evapotranspiration (ET_0)

Meteorological data were obtained from the China National Meteorological Information Center for the Karamay station (ID: 51243), located within the irrigation district. Reference evapotranspiration (ET_0) was calculated using the Penman-Monteith equation, as recommended by FAO [32].

(5) Irrigation schedule and water use

The gravity-fed pipeline irrigation system in the Karamay Irrigation District is equipped with water supply metering facilities on both the main and branch water conveyance pipelines. Since the system is dedicated to irrigation water delivery, pipeline irrigation water loss can be neglected. Ultimately, the average irrigation water consumption was calculated based on the monthly water supply volume and the total area of the irrigation district. The total annual agricultural irrigation volumes in 2023 and 2024 were basically the same, with the average crop irrigation quotas of 551.79 mm and 545.19 mm for the two years, respectively. A detailed breakdown of the monthly irrigation volumes is presented in Table 1.

Table 1. Average Irrigation Water Consumption for Crops in the Karamay Irrigation District.

Year	January to March	April	May	June	July	August	September	October to December	Total (mm)
2023	0	23.69	55.62	102.53	156.86	134.02	79.07	0	551.79
2024	0	21.26	68.48	101.30	131.87	137.83	84.45	0	545.19

(6) Machine learning model

In arid-region irrigation districts such as the Karamay Irrigation District, characterized by intense evaporation and a lack of natural drainage, groundwater table depth is the most critical driving factor governing the migration and accumulation of salts to the topsoil layer. When the groundwater table is maintained below the critical depth, the upward accumulation of salts induced by evaporation can be effectively inhibited; even with high groundwater mineralization, severe secondary soil salinization will not be triggered. Therefore, high-precision prediction and trend simulation of groundwater tables constitute a core scientific issue for salinization control in irrigation districts. In this study, the XGBoost model was adopted for dynamic prediction of groundwater tables, primarily owing to its comprehensive advantages in processing small-to-medium sized structured time-series data. Specifically, this model not only delivers high prediction accuracy and strong generalization ability, but its built-in feature importance analysis function can also explicitly quantify the influence weights of factors such as irrigation and meteorological conditions on groundwater tables, which directly aligns with the scientific objective of identifying dominant driving factors in this study. Meanwhile, the XGBoost model’s robustness to missing values and its overfitting prevention mechanism also make it well-suited for addressing the practical characteristics of long-term monitoring data in irrigation districts.

We employed a machine learning approach to forecast groundwater levels in the irrigation district. Specifically, we selected the eXtreme Gradient Boosting (XGBoost) algorithm due to its high performance on structured data and effectiveness in time-series forecasting. The input variables included historical groundwater levels, precipitation, reference evapotranspiration (ET_0), irrigation recharge, and air temperature. When the sample size of short-sequence data is limited, the XGBoost model may suffer from inadequate training, making it difficult to accurately learn the variation patterns of groundwater levels and thus leading to decreased prediction accuracy. This is a common limitation of all machine learning algorithms. In addition, XGBoost lacks the memory capability for time-series data and fails to effectively capture the temporal trends and periodic characteristics of groundwater level changes. Its prediction accuracy is particularly poor for seasonal fluctuations and long-term variation trends. However, it exhibits high prediction accuracy for short-term interannual variations (Figure 3).

To apply XGBoost, we transformed the temporal data into a supervised learning problem by constructing features using a sliding window approach, allowing the model to capture dynamic dependencies within the time series. Specifically, for a given time series, each training instance is constructed as follows, in practical terms, this means:

$$X_t = [y_{t-L}, y_{t-L+1}, \dots, y_{t-1}] \quad (3)$$

corresponds to the target variable y_t (single-step forecasting) or y_{t+H} (multi-step forecasting, where H is the forecasting horizon).

Through this approach, the original time series is transformed into a supervised learning dataset $\{(X_t, y_t)\}$.

During model training, XGBoost incrementally builds multiple decision trees using an additive strategy, with each tree aiming to correct the residuals of the previous one. The objective function consists of a loss term and a regularization term:

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \quad (4)$$

where $\hat{y}_i$ denotes the prediction, y_i is the true value, l is a differentiable loss function (such as mean squared error), and $\Omega(f_k)$ is the regularization term used to constrain model complexity and prevent overfitting.

This study conducted its analysis based on short-term time-series monitoring data of groundwater and soil salinity in the irrigation district. Its relatively limited observation duration and temporal resolution may impose certain constraints on the robustness of some conclusions, particularly those related to long-term trend prediction. To minimize the impacts arising from such data limitations, the study adopted the following coping strategies: first, fully extract dynamic information from the time series by constructing temporal lag and rolling statistical features; second, verify the model stability using the method of repeated random splitting of training and test sets; third, explicitly define the prediction results as conditional trend early warnings under the current management scenario, rather than accurate long-term quantitative forecasts. In addition, the study did not establish separate XGBoost prediction models for different soil textures, mainly due to practical considerations regarding data sample size. Although the XGBoost model has a certain adaptability to small-to-medium-sized datasets, the length of the effective monitoring sequence in this study is relatively limited. If the dataset were further divided by soil texture (i.e., silty soil areas and silty clay areas), the sample size of each sub-dataset would decrease significantly. This would likely be insufficient to support the model in stably learning complex nonlinear temporal features, thereby compromising the accuracy and robustness of the predictions.

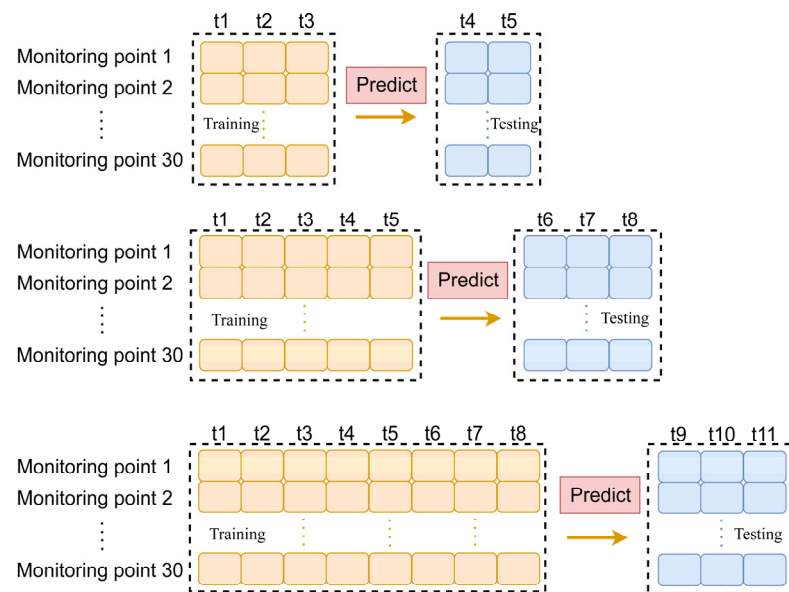


Figure 3. Machine learning modeling workflow.

We adopted the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) to evaluate the model performance. The hyperparameter settings are as follows: `n_estimators = 100`, `learning_rate = 0.05`, `max_depth = 3`, `subsample = 0.8`, `colsample_bytree = 0.8`, `reg_alpha = 0.1`, `reg_lambda = 1.0`, `random_state = 42`. The optimal hyperparameters were determined by conducting multiple training runs with different hyperparameter combinations. Using the above-mentioned evaluation metrics can avoid the one-sidedness of a single metric, thereby providing a comprehensive basis for model selection and optimization.

(7) Model performance evaluation

We assessed the predictive accuracy of the machine learning model using four standard statistical metrics: the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). A model was considered to have superior performance when R^2 was close to 1 and MAE, MSE, and RMSE were close to 0. The formulas used to calculate these metrics followed Zhang [33].

2.3. Data Processing

We processed the initial experimental data for soil and groundwater using Microsoft Excel 2020. We mapped the geographical location of the study area and generated spatial distribution maps for soil salinity, depth to groundwater, and groundwater TDS using the Kriging spatial interpolation method in ArcGIS 10.7. Graphs and figures were prepared using Origin Pro 2022. We developed and implemented the machine learning model in Python (version 3.12).

3. Results

3.1. Soil Texture Distribution in Irrigation Districts

The spatial distribution of soil texture across the study area shows substantial heterogeneity (Figure 4). Three main soil texture types were identified: silty clay loam, silt, and silty clay. Silt is the dominant texture, forming contiguous zones primarily in the central and east-central parts of the district, and is characterized by a balanced composition of sand, silt, and clay. Silty loam is distributed in fragmented patterns across the northeastern, north-central, and south-central areas, with a particle-size distribution dominated by 0.002–0.05 mm fractions, conferring good moisture retention and moderate aeration

capacity. In contrast, silty clay predominates in the western, southwestern, and localized central-western zones. It has a fine, cohesive matrix that provides high water-holding capacity but reduces both aeration and tillage suitability.

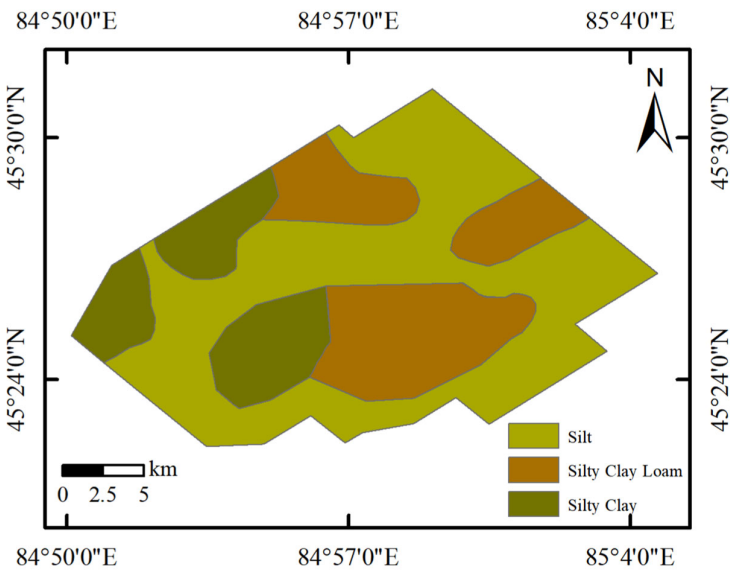


Figure 4. Soil texture distribution in the irrigation district.

3.2. Changes in Soil Salinity in Irrigated Areas

3.2.1. Seasonal Variations in Soil Salinity

Due to the limited sample sizes for silty clay loam and silty clay and their similar physical properties, these classes were combined and collectively referred to as silty clay in subsequent analyses. The seasonal variation in soil salinity is detailed in Table 2. During 2023–2024, both silt and silty clay exhibited differences in salinity across seasons and years. The study area was mostly characterized by non-saline and slightly saline soils. In the inter-annual comparison, in 2023, both the maximum and mean salinity values for silt and silty clay during spring and autumn were substantially higher than those recorded in 2024. However, in summer 2024, both maximum and mean salinity values exceeded those of 2023. Furthermore, the coefficients of variation for most seasons in 2024 were higher than in 2023, suggesting reduced stability of soil salinity. Within the same years and seasons, silty clay consistently showed greater salinity extremes and spatial heterogeneity compared to silt. In 2023, both textures followed the pattern “spring > autumn > summer”, with spring having the highest and summer the lowest salinity. In contrast, in 2024, the highest salinity was observed in summer, followed by autumn and spring. Summer 2024 also had the largest coefficient of variation for both textures, whereas summer 2023 was the most stable season for salinity.

Table 2. Statistical summary of soil salinity in the irrigation district.

Year	Soil Texture	Season	Maximum (g kg ^{−1})	Minimum (g kg ^{−1})	Mean (g kg ^{−1})	Standard Deviation (g kg ^{−1})	Coefficient of Variation
2023	Silt	Spring	10.33	0.91	4.32	2.77	0.64
		Summer	4.88	0.60	1.95	1.09	0.56
		Autumn	9.36	0.64	3.55	2.79	0.78
	Silty clay	Spring	14.05	1.01	3.69	3.31	0.90
		Summer	7.91	0.62	2.15	1.88	0.88
		Autumn	18.15	0.65	4.14	4.56	1.10

Table 2. Cont.

Year	Soil Texture	Season	Maximum (g kg ⁻¹)	Minimum (g kg ⁻¹)	Mean (g kg ⁻¹)	Standard Deviation (g kg ⁻¹)	Coefficient of Variation
2024	Silt	Spring	7.12	0.83	2.22	1.60	0.72
		Summer	9.34	0.65	2.47	1.96	0.79
		Autumn	6.44	0.60	2.39	1.75	0.73
	Silty clay	Spring	10.00	0.75	2.26	2.24	0.99
		Summer	22.36	0.62	3.17	4.34	1.37
		Autumn	9.59	0.51	2.49	2.22	0.89

3.2.2. Vertical Variation in Soil Salinity in Irrigated Areas

The vertical distribution of soil salinity for 2023 and 2024 is shown in Figure 5, respectively. In silty clay zones, spring 2023 showed a “decline-then-rise” trend in salinity with depth, summer had a relatively uniform and gradually decreasing profile, and autumn displayed a marked decrease in salinity with depth. In 2024, salinity across all horizons in silty clay was more uniform, with little differentiation among depths and values stabilizing around 2 g·kg⁻¹. Inter-annual comparison indicated that spring and autumn salinity concentrations in 2023 were notably higher than those in 2024, while summer salinity was similar in both years.

In silt zones, summer salinity in 2023 was much lower than spring and autumn values. All seasons presented a progressive decrease in salinity with depth, with the greatest decline in the upper 0–40 cm layer; some resurgence was observed at depths of 80–120 cm. In 2024, spring and autumn salinity levels were similar, whereas summer concentrations were significantly higher. A comparison across years revealed notable differences in summer: 2023 had higher surface salinity and lower deep-layer values, while 2024 exhibited increased deep-layer salt accumulation. For spring and autumn, surface salinity changed little between years, but deep-layer concentrations in 2024 were lower.

Overall, in both years and all soil textures, surface salt accumulation was consistently present. In 2023, spring and autumn soils had much higher salinity than in summer, whereas in 2024, except for moderately higher summer salinity in silt zones, salt concentrations for all seasonal and textural classes were largely similar.

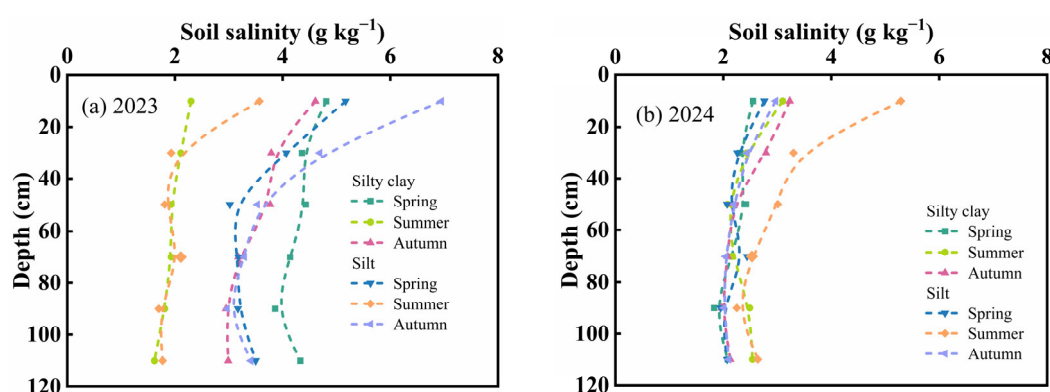


Figure 5. Vertical distribution of soil salinity in 2023 (a) and 2024 (b).

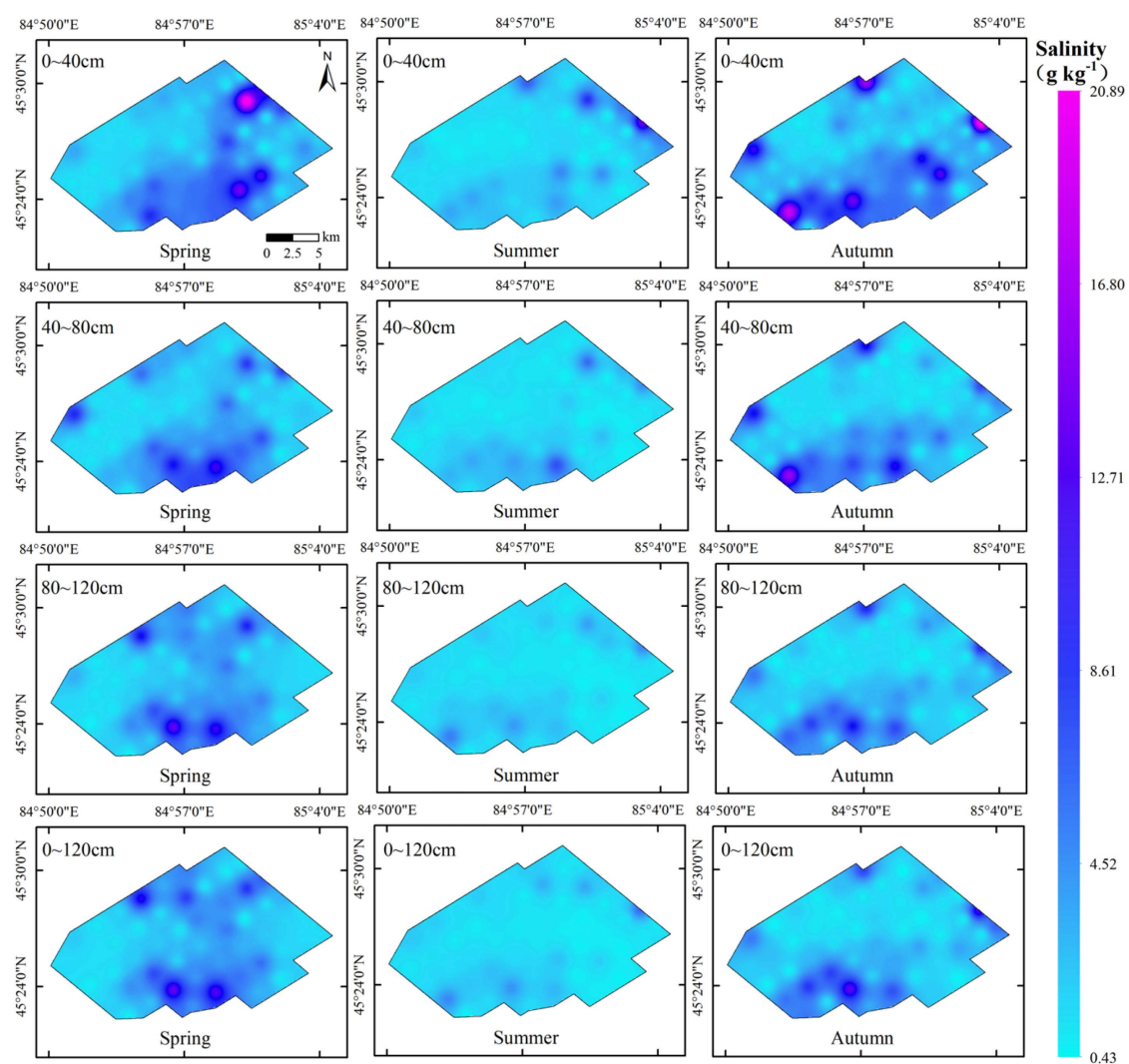
3.2.3. Spatial Distribution of Soil Salinity in Irrigation Districts

The spatial distribution of soil salinity for 2023 and 2024 is illustrated in Figures 6 and 7. In 2023, both spring and autumn showed elevated salinity throughout all soil layers, while summer exhibited a marked decline. In contrast, 2024 had relatively low salinity in spring and autumn, with a significant increase in summer. Inter-annual comparison showed that overall summer salinity in 2024 was higher than in 2023, whereas spring and autumn

values were lower. High-salinity zones were mainly located in the southern area and along the northern, eastern, and western edges.

In silty clay zones, spring and autumn 2023 had high salinity in all layers, with some high-salinity pockets remaining in summer. In 2024, high-salinity areas in silty clay were sparse in spring and autumn, but widespread in summer. For silt zones, both years exhibited consistently low salinity in spring and autumn, with negligible accumulation in summer. Notably, summer 2024 showed greater salt accumulation in silty clay areas, with salinity showing increased sensitivity to both seasonal and textural variation. Across both years, silty clay zones consistently had higher salinity than silt zones.

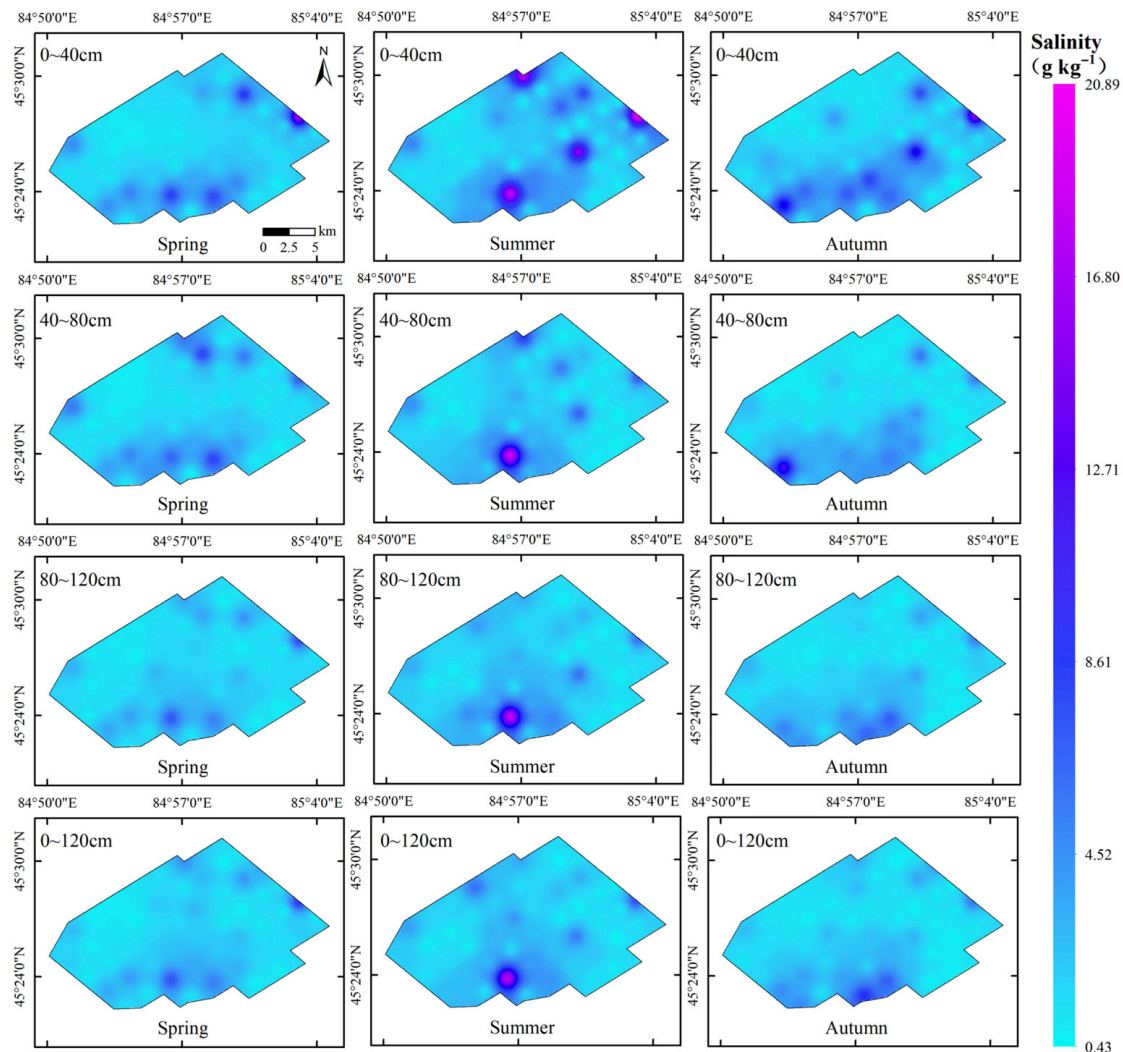
Regarding depth profiles, surface soils (0–40 cm), directly affected by evapotranspiration and irrigation, showed substantially higher salinity compared to the middle (40–80 cm) and deeper (80–120 cm) layers. The trend of salinity variation throughout the entire 0–120 cm soil profile was consistent with the patterns observed in individual stratified layers.



Note : (1)The soil salt content of 0 ~ 40, 40 ~ 80, 80 ~ 120cm is the average value of two layers of soil salt respectively.

(2)0 ~ 120cm soil salt is divided into six layers of soil salt content average.

Figure 6. Spatial distribution of soil salinity in 2023.



Note : (1)The soil salt content of 0 ~ 40, 40 ~ 80, 80 ~ 120cm is the average value of two layers of soil salt respectively.

(2)0 ~ 120cm soil salt is divided into six layers of soil salt content average.

Figure 7. Spatial distribution of soil salinity in 2024.

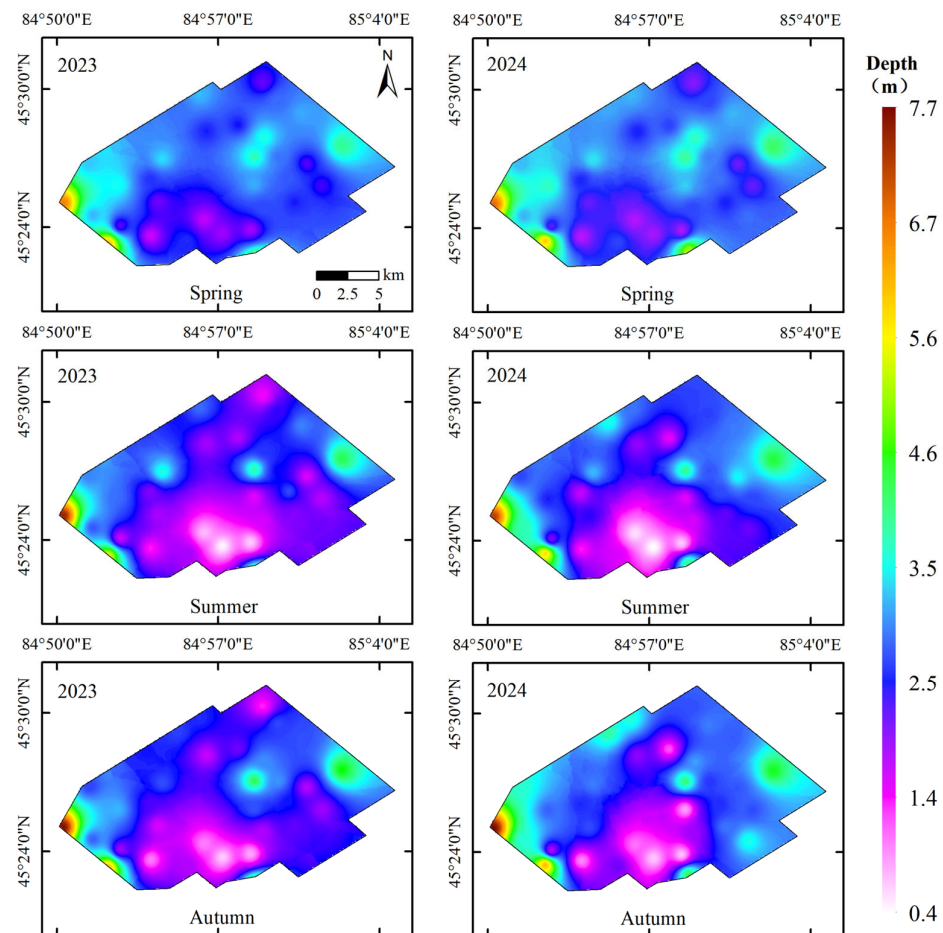
3.3. Distribution of Groundwater and TDS in Irrigation Districts

3.3.1. Spatial Distribution of Groundwater Depth

The spatial distribution of groundwater depth during spring, summer, and autumn for 2023 and 2024 is shown in Figure 8. In spring 2023, groundwater tables were deepest along the eastern and western margins (average ~4 m, maximum > 6 m) and shallowest in the southern and central areas (generally < 2 m, with some areas below 1 m). Spring was the season with the greatest overall groundwater depth. In summer, the extent of shallow groundwater expanded significantly, reflecting a regional rise in the water table. Groundwater depth increased moderately in autumn compared to summer, but remained less than in spring. Overall, groundwater depth followed the seasonal pattern: spring > autumn > summer.

The spatial pattern in 2024 resembled 2023. Spring depths were slightly lower, while summer and autumn depths were somewhat higher than the previous year; however, these differences were minor. Mean groundwater depths in silt-dominated zones were 3.24 m (2023) and 3.11 m (2024), exceeding those in silty clay zones (2.43 m in 2023, 2.61 m in 2024). Silty clay regions showed the greatest fluctuations from spring to summer. This

differentiation results from the coarser texture and higher hydraulic conductivity of silt, allowing more effective infiltration and recharge.



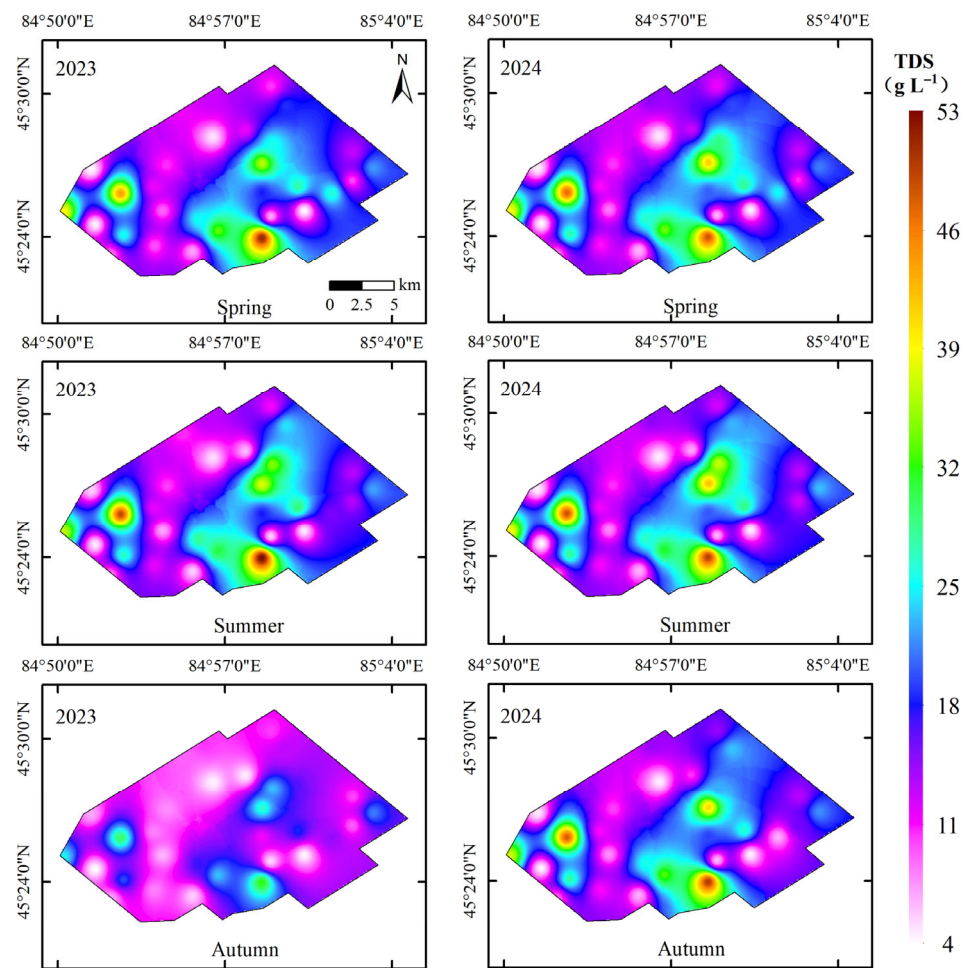
Note : The data of groundwater depth in spring, summer and autumn are April, July and autumn respectively.

Figure 8. Spatial distribution of groundwater depth in the irrigation district.

3.3.2. Spatial Distribution of Groundwater TDS

Spatial interpolation of groundwater TDS for different seasons in 2023 and 2024 is shown in Figure 9. In spring 2023, high TDS (up to 30 g L^{-1}) occurred mainly in southern, central, and western areas, while lower concentrations were observed in the east and in transition zones. In summer, high-TDS areas expanded, indicating an overall increase, while autumn saw a decline in both area and value. Patterns in 2024 were similar, though autumn 2024 demonstrated noticeably higher TDS than the previous year.

Across all seasons and both years, silty clay zones had slightly higher average TDS (19.05 g L^{-1} in 2023; 16.78 g L^{-1} in 2024) compared to silt zones (18.18 g L^{-1} in 2023; 16.29 g L^{-1} in 2024). The increased TDS in silty clay is due to its lower hydraulic conductivity, which limits percolation and enhances capillary-driven salt accumulation. An inverse relationship between groundwater depth and TDS was observed: deeper groundwater in spring corresponded to lower TDS, while shallower summer tables were associated with higher TDS. This relationship is likely a consequence of greater dissolution of surface salts into groundwater as the water table rises.



Note : The data of groundwater salinity in spring, summer and autumn are April, July and autumn respectively.

Figure 9. Spatial distribution of groundwater TDS in the irrigation district.

3.4. Groundwater Critical Depth for Different Soil Textures in Irrigation Districts

As summer and autumn are influenced by irrigation and leaching, spring (April) data from 2023 and 2024 were used for regression analyses to minimize such effects. For both silt and silty clay, soil salinity and groundwater depth exhibited strong sigmoidal relationships, with correlation coefficients of 0.77 and 0.73, respectively (Figure 10). As groundwater depth increased, soil salinity approached a baseline value. The critical groundwater depth—defined as the depth beyond which further increases result in negligible salinity reduction—was 2.44 m for silt and 2.72 m for silty clay. These differences are attributable to the distinct capillary properties and hydraulic conductivity of each soil type, with finer-textured silty clay requiring greater depth to limit surface salt accumulation.

Figure 11 shows a positive linear relationship between soil salinity and groundwater TDS, with coefficients of determination (R^2) of 0.4329 for silt and 0.5129 for silty clay, indicating that groundwater TDS explains approximately 43% and 51% of the variance in soil salinity for these textures, respectively. The correlation between soil salinity and groundwater mineralization is weak across different soil textures, which indicates that soil salinity is jointly influenced by multiple factors including groundwater table depth, irrigation regime, and evaporation intensity. In regions with intense evaporation, controlling the groundwater table is the key priority for inhibiting upward salt accumulation, and this measure exerts a significantly stronger effect than groundwater quality-related factors.

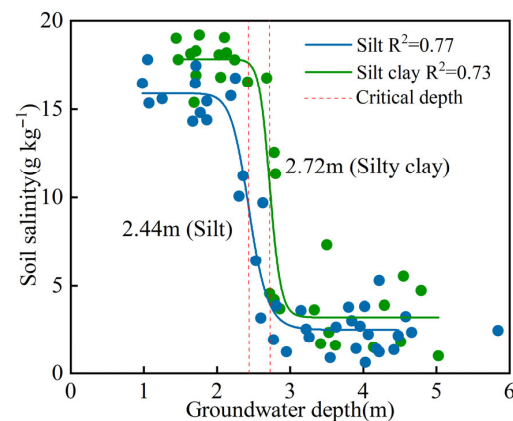


Figure 10. Relationship between groundwater depth and soil salinity in different soil textures.

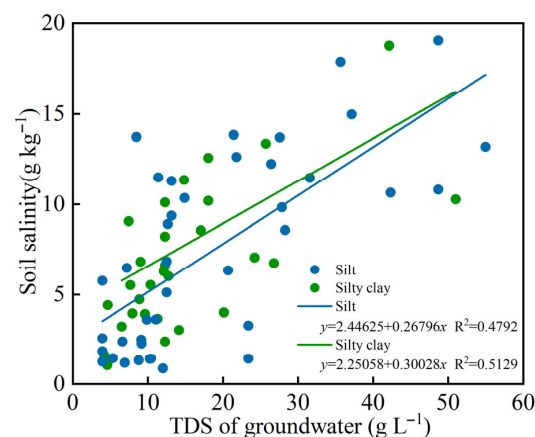


Figure 11. Relationship between groundwater TDS and soil salinity in different soil textures.

3.5. Predicting Groundwater Depth Evolution in the Irrigation District Using Machine Learning

3.5.1. XGBoost Model Construction and Performance Evaluation

A machine learning approach was adopted to develop the groundwater depth prediction model. In the modeling process, we opted to use the dataset encompassing the entire irrigation district instead of data stratified by soil texture. This decision was made owing to the core requirements of data-driven methodologies. Specifically, the dataset covering the whole irrigation district can more comprehensively capture the complex interactions within the groundwater system, enabling the model to autonomously learn the response patterns under different variable conditions. Meanwhile, this effectively avoids the problems of insufficient sample size and overfitting caused by data subdivision, thereby significantly improving the generalization ability and robustness of the model predictions. In addition, our decision was primarily based on practical considerations regarding the data sample size. Although the XGBoost model exhibits a certain degree of adaptability to small-to-medium-sized datasets, the length of the effective monitoring sequence available in this study is relatively limited. If the dataset were further divided by soil texture (i.e., silty soil zones and silty clay zones), the sample size of each sub-dataset would decrease significantly. This would likely be insufficient to support the model in stably learning complex nonlinear temporal features, thereby compromising the accuracy and robustness of the predictions.

Input variables included monthly groundwater depth, precipitation, reference evapotranspiration (ET_0), irrigation recharge, and air temperature for 2023 and 2024, all of which were normalized using min-max scaling (Figure 12). Model hyperparameters were set as follows: 100 trees, maximum depth of 3, subsample ratio of 0.8, and L2 regularization parameter of 1. Lagged and rolling statistical features were also generated, and a rolling

window approach was applied during training, with train-test splits of 75%:25%, 50%:25%, and 25%:25%.

The XGBoost model performed well, achieving a coefficient of determination (R^2) of 0.8545, MAE of 0.4428, MSE of 0.2677, and RMSE of 0.5174, indicating strong agreement between predicted and observed values and explaining approximately 85% of the variance in groundwater depth. Feature importance analysis revealed that agricultural irrigation had the largest impact on groundwater levels, followed by ET_0 and initial groundwater level. Rainfall had relatively minor influence, likely due to the region's arid conditions. Both lagged and rolling statistical features also contributed, indicating the temporal dependence of groundwater levels. The overall performance of the model ($R^2 = 0.8545$, MAE = 0.4428 m) ranks at a high level in the field of groundwater prediction for arid-region irrigation districts, with the R^2 value falling within the upper range of that reported in comparable studies (0.7–0.9). Crucially, the mean absolute error of 0.44 m is significantly smaller than the typical fluctuation range of groundwater levels in the study area. This enables the model to clearly distinguish between the “safe” and “risky” groundwater level thresholds, satisfying the requirements for salinization early-warning. In addition, the primary driving factor identified by the model (irrigation volume) is highly consistent with the physical mechanism of groundwater recharge, which verifies the reliability of the results.

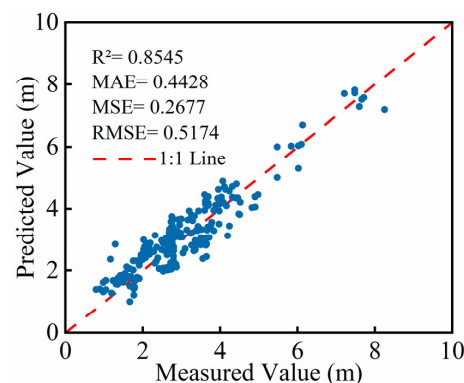


Figure 12. Comparison between simulated and observed groundwater levels.

Based on the feature weight values calculated by the model (Figure 13), agricultural irrigation has the greatest impact on groundwater levels within the irrigation area, followed by ET_0 and initial values. Rainfall exerts a relatively minor influence on groundwater levels in the irrigation area, primarily due to the region's low precipitation levels. Lag features and rolling statistical features also exert some influence, indicating that groundwater levels exhibit a certain degree of temporal self-dependency.

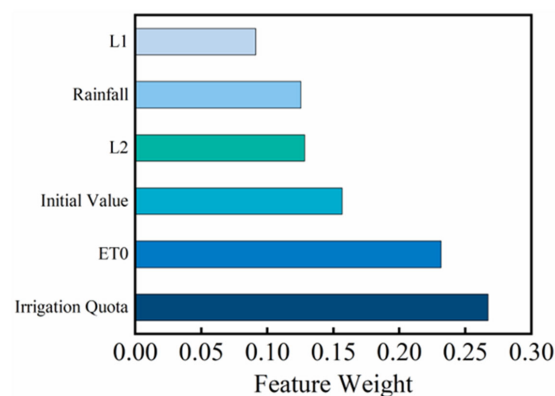


Figure 13. Weights of input variable features. Note: L1 is the lagged feature one time step behind the current time point; L2 is the lagged feature two time steps behind the current time point.

3.5.2. Future Groundwater Depth Projections in the Irrigation District

A ten-year simulation using decadal mean meteorological data and current irrigation regimes (2023–2024) projected a progressive rise in the regional water table (Figure 14). Mean groundwater depths of 2.91 m, 2.76 m, 2.62 m, and 2.36 m were forecasted for 1, 3, 5, and 10 years in the future, corresponding to water table rises of 3.68%, 8.64%, 13.38%, and 21.81% relative to 2024 baseline levels.

In silt-dominated areas, the proportion experiencing groundwater depths below the critical threshold of 2.44 m is projected to increase from 40% after one year to 73.33% after ten years. For silty clay areas, these proportions are even higher, rising from 61.54% to 92.31% over the same period. These results underline increasing risk of shallow groundwater conditions and highlight the greater vulnerability of silty clay zones, emphasizing the need for adjustments to irrigation and drainage management to reduce long-term salinization risk.

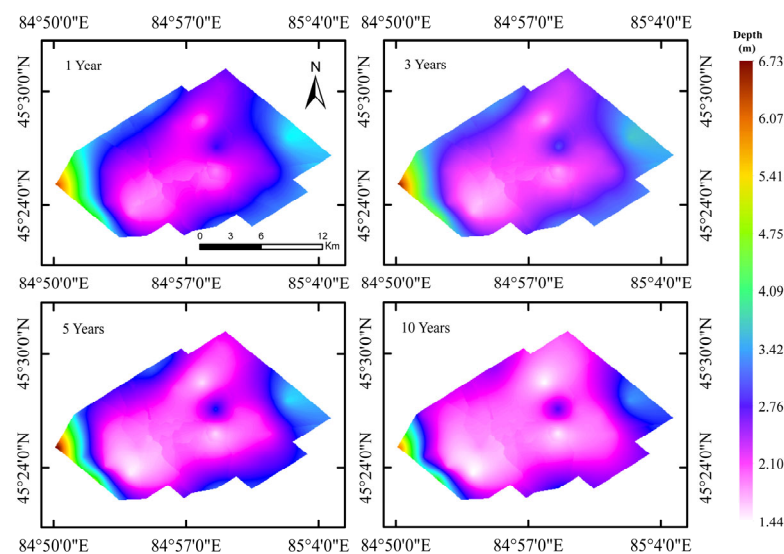


Figure 14. Predicted spatial distribution of groundwater depth over the next 10 years in the irrigation district.

4. Discussion

4.1. Mechanisms of Water-Salt Dynamics Across Different Soil Textures in the Karamay Irrigation District

Soil properties are influenced by factors such as anthropogenic activities, climate, parent material, and topography [34]. Soil salinity follows the principle that salt migrates with water movement, so any change in soil moisture transport affects salt distribution [35]. Soil texture influences infiltration and capillary rise; groundwater depth determines surface salt accumulation [36,37]; irrigation water amount and quality control salt inputs; and precipitation enables natural leaching (Figure 15).

In this study, mean groundwater depths of 2.43–2.61 m were observed in silty clay zones during 2023–2024, significantly shallower than in silt zones. Groundwater TDS was slightly higher in silty clay than in silt areas. These patterns are attributed to hydraulic differences: silty clay, with its fine particles, low porosity, and low permeability, limits infiltration, resulting in shallower groundwater depths. Strong capillary forces in silty clay also drive upward water migration and surface salt accumulation by evaporation [38]. In contrast, silt's coarser texture and higher permeability promote deeper percolation and recharge.

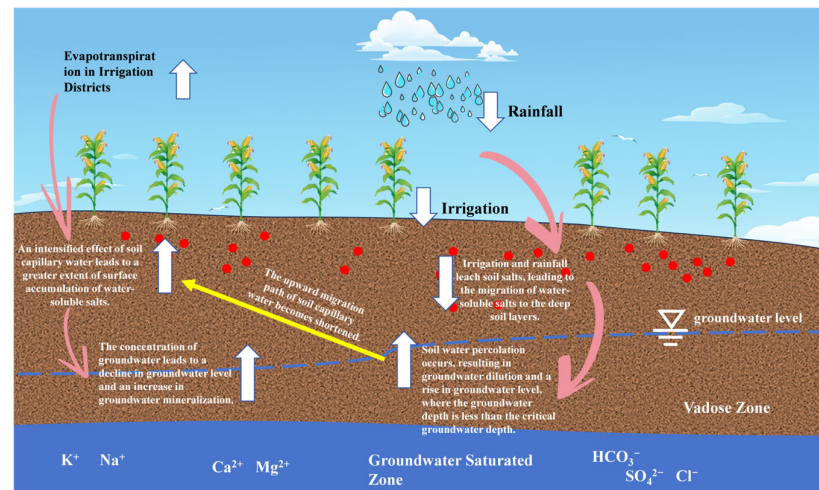


Figure 15. Mechanism of soil water-salt transport in the irrigation district.

There was significant interannual variability in soil salinity dynamics. In 2023, both textures showed high salinity in spring, low in summer, and moderate in autumn. This pattern reversed in 2024, with lower spring and higher summer salinity. This reversal phenomenon was closely associated with the seasonal fluctuations of groundwater level. In the summer of 2023, concentrated leaching of surface soil salinity was implemented across the irrigation district, which reduced the overall soil salinity in the district. After the reduction in irrigation during autumn, the salinity rebounded to a moderate level. In contrast, frequent rainfall and intensive irrigation in the summer of 2024 led to a rapid rise in groundwater level. Driven by the combined effects of high temperature and intense evaporation, groundwater carried salts to accumulate rapidly in the surface soil. With the decrease in irrigation in autumn, groundwater depth gradually increased, and the soil salinity dropped back to a moderate level under the leaching effect of autumn irrigation. This shift coincided with seasonal groundwater table fluctuations: deeper groundwater and lower TDS in spring, but shallower depths and higher TDS in summer, reflecting a strong negative correlation. Excessive summer irrigation elevates the water table [39], and high-TDS groundwater rises via capillary action, dissolving salts that accumulate at the surface through evaporation.

Silty clay zones showed the greatest salinity variation during summer 2024, indicating highly heterogeneous and locally severe salt accumulation. Across seasons and textures, surface salt accumulation was consistently observed, with the 0–40 cm layer showing the highest concentrations and confirming that evaporation-driven upward salt migration is the dominant mechanism [40]. Spatially, high-salinity areas were found primarily in the south and at the edges of the district, in regions dominated by silty clay and shallow groundwater, reflecting a cycle of shallow water tables, high TDS, intense evaporation, and surface salt accumulation.

4.2. Accuracy and Reliability of Machine Learning-Based Groundwater Level Predictions

In the present study, an XGBoost model was employed for spatiotemporal prediction of groundwater levels in the Karamay irrigation district, with robust performance being demonstrated on the test set. This level of predictive accuracy is highly comparable and reliable relative to related domestic and international investigations [41–43]. A key advantage of machine learning methodologies lies in their capacity as data-driven techniques to circumvent the requirement for comprehensive understanding of the complex physical mechanisms governing groundwater table fluctuations [44,45], which holds sub-

stantial practical value in regions where hydrological processes are intricate and underlying mechanisms cannot be fully quantified.

Through feature importance analysis (Figure 13), the hierarchical ranking of key factors influencing groundwater levels was revealed: agricultural irrigation (highest weight) > ET_0 > antecedent groundwater depth > lagged and rolling statistical features > precipitation (minimal influence). This result aligns with the actual hydrological characteristics of the Karamay irrigation district as an arid irrigation zone characterized by minimal annual precipitation, agricultural irrigation constitutes the primary source of groundwater recharge, while intense evapotranspiration represents the dominant pathway of groundwater depletion. Previous research has demonstrated that groundwater quality exerts the most significant influence on soil salinity ion composition in both cropland and wasteland soils, followed by soil texture, suggesting that groundwater quality should be prioritized in soil amelioration initiatives within the study area [46]. Given that machine learning models require adequate data volume and temporal resolution to ensure predictive accuracy, a monthly temporal resolution spanning two years was adopted during model training to augment data availability and thereby enhance model precision. However, annual-scale projections were conducted during simulation, primarily considering that annual predictions can provide reference frameworks and empirical foundations for district-wide irrigation water allocation schemes.

Although the machine learning model employed in the current study exhibits satisfactory prediction accuracy, its black-box nature has to some extent constrained the depth of mechanistic interpretation. The integration of process-based models that are grounded in the physical mechanisms of water-salt transport in irrigation districts with data-driven machine learning models is indeed a crucial direction for enhancing the physical interpretability of models and realizing the synergy between mechanism-driven and data-driven approaches. In future studies, process-based models will be utilized to generate additional training data with physical consistency, and key physical constraints such as mass conservation and Darcy's law governing water-salt transport will be embedded into the structure or loss function of the machine learning model. This will not only improve the extrapolation reliability of the model under extreme scenarios, but also more clearly reveal the specific process pathways through which measures such as irrigation and drainage affect water-salt dynamics.

4.3. Future Groundwater Level Trends and Salinization Mitigation Strategies

Critical groundwater depth is fundamental for understanding and managing soil salinization [47,48]. Previous studies indicated that groundwater depths below 4.0 m in arid regions substantially increase salinity risks [49,50]. In this study, we determined critical depths of 2.44 m for silt and 2.72 m for silty clay in relation to salinity. Below these depths, groundwater strongly influenced surface salt accumulation via capillary rise.

Our XGBoost model predicts a continued rise in groundwater levels under current irrigation practices. After 1, 3, 5, and 10 years, projected mean groundwater depths are 2.91, 2.76, 2.62, and 2.36 m, corresponding to increases of 3.68%, 8.64%, 13.38%, and 21.81% over 2024 levels. This trend is likely to exacerbate secondary salinization. In silt zones, the proportion of area with groundwater below the critical threshold will reach 40% in one year, 60% in five years, and 73.33% in ten years. In silty clay zones, these numbers are even higher, from 61.54% in one year to 92.31% in ten years. Without adjustments in irrigation and management, the entire district faces increasing risks of widespread secondary salinization, as reported by Wang [43]. Therefore, adopting precision irrigation and enhanced drainage is essential to maintain sustainable groundwater depths and prevent salinization.

It should be noted that this study conducts a 10-year groundwater level trend prediction based on 1.4 years of observational data, and the following considerations are put forward regarding the rationality of the results. First, although the data period is relatively short, it fully covers multiple irrigation cycles and seasonal cycles, enabling the capture of the main processes and dynamic characteristics driving groundwater level changes. Second, the XGBoost model has advantages in processing limited but high-frequency time-series data, which can effectively identify nonlinear patterns and dominant factors. More importantly, this prediction is not a purely statistical extrapolation but a physically constrained conditional simulation: the input features (irrigation volume, meteorological data) and their weights of the model are highly consistent with the water balance principle; the setting of future scenarios refers to local agricultural management plans; and the prediction results reflect the groundwater level evolution trend under the continuation of the current management mode. It should be pointed out that if there are major adjustments to the irrigation regime or extreme climate events in the future, the prediction uncertainty will increase significantly, which requires dynamic correction combined with continuous monitoring.

5. Conclusions

The distribution of groundwater and soil salts exhibits significant differences between the silt and silty clay soil textures in the Karamay Irrigation District. The groundwater depth in the silt area (3.24–3.11 m) is significantly greater than that in the silty clay area (2.43–2.61 m), while the groundwater TDS in the silty clay area (19.05–16.78 g·L⁻¹) is slightly higher than that in the silt area (18.18–16.29 g·L⁻¹). The seasonal dynamics of soil salinity show interannual variations: it featured a pattern of high in spring and low in summer in 2023, which reversed to high in summer and low in spring in 2024. In terms of vertical distribution, a distinct salt surface accumulation phenomenon is observed across both soil types. High-salinity zones are concentrated in the silty clay areas in the southern and peripheral regions of the irrigation district, forming a positive feedback loop characterized by shallow groundwater depth, high TDS, and salt surface accumulation. Soil salinity shows a significant Sigmoid function relationship with groundwater depth ($R^2 = 0.73\text{--}0.77$). The determined critical groundwater depth thresholds are 2.44 m for silt and 2.72 m for silty clay; when the groundwater depth falls below these critical values, the risk of secondary salinization increases significantly. Soil salinity is more strongly influenced by groundwater depth than by groundwater TDS. Groundwater depth is negatively correlated with TDS, with greater depth and lower TDS in spring, and the opposite pattern in summer. The XGBoost model achieves satisfactory prediction accuracy ($R^2 = 0.8545$, MAE = 0.4428, RMSE = 0.5174). Feature weight analysis indicates that agricultural irrigation exerts the most dominant influence, followed by reference evapotranspiration (ET_0), initial groundwater level, and rainfall. The prediction results show that the groundwater level is projected to reach 2.91 m, 2.76 m, 2.62 m, and 2.36 m in the next 1, 3, 5, and 10 years, respectively, showing a continuous upward trend. Model evaluation suggests that after 10 years, 73.33% of the silt area and 92.31% of the silty clay area will likely have groundwater levels below the critical depth, meaning the irrigation district may face a serious threat of secondary salinization.

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