Spatiotemporal Kriging Assessment of Soil Salinity Spatiotemporal Patterns in the Hetao Irrigation District Postprint

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Abstract

The large spatio-temporal variability of regional soil salinity makes it difficult to accurately determine the spatio-temporal variation trends of soil salinity with irregular sampling times and inconsistent spatial locations using classical statistical and geostatistical methods. This study analyzes the spatio-temporal variation characteristics of regional soil salinity using spatio-temporal geostatistical methods, based on 4,582 soil salinity data points from 0–1.8 m soil profiles at 68 monitoring sites in the Longsheng study area of the Hetao Irrigation District in Inner Mongolia, compares the accuracy improvement of spatio-temporal Kriging over traditional spatial Kriging interpolation, and validates the capability of spatio-temporal geostatistical methods to predict regional salinity spatio-temporal dynamics under a 50% reduction in monitoring points. The results indicate that: (1) The spatial variation coefficient of soil salinity in the study area ranges from 0.43–1.14, indicating moderate to strong variation; the 0–0.6 m root zone accumulates salts during the growing season and leaches salts during the non-growing season, while the 0.6–1.8 m soil profile leaches salts during the growing season and accumulates salts during the non-growing season, demonstrating a clear seasonal pattern of soil salinity in croplands. (2) The sum-metric model effectively fits the spatio-temporal empirical semivariance of salinity, with the Root Mean Square Error (RMSE) between predicted and observed soil salinity values for each layer being less than 0.21 dS · m-1, which is 0.02–0.09 dS · m-1 lower than that of traditional spatial Kriging. (3) The soil salinization distribution determined using this method under a 50% reduction in monitoring points shows high consistency with the results obtained from all sampling points; the Mean Relative Error (MRE) of soil salinity area between 0–0.6 m and 0.6–1.2 m layers is -13.20% and -8.35%, respectively, the RMSE is 466.67 hm2 and 494.43 hm2, and the coefficient of determination (R2) is 0.79 and 0.72. Spatio-temporal Kriging simultaneously utilizes more information

from both the temporal and spatial dimensions of soil salinity, enabling accurate estimation of soil salinity spatio-temporal dynamics from sparse monitoring point datasets, which can greatly improve the efficiency of monitoring regional soil salinity spatio-temporal patterns.

Full Text

Spatio-temporal Kriging for Evaluating Soil Salinity Patterns in the Hetao Irrigation District

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Abstract

Regional soil salinity exhibits high spatio-temporal variability, and classical statistical and geostatistical methods cannot accurately determine spatio-temporal trends of soil salinity when sampling times are irregular and spatial positions are inconsistent. Based on 4,582 soil salinity data points from 0–1.8 m soil profiles collected at 68 monitoring locations in the Longsheng study area of the Hetao Irrigation District in Inner Mongolia, this study analyzed regional soil salinity spatio-temporal variation characteristics using spatio-temporal geostatistical methods, compared the accuracy improvement of spatio-temporal Kriging over traditional spatial Kriging interpolation, and verified the capability of spatio-temporal geostatistical methods to predict regional salinity dynamics with reduced monitoring points. The results showed that: (1) The spatial variation coefficient of soil salinity in the study area ranged from 0.43 to 1.14, indicating medium to strong variability. The root zone (0–0.6 m) accumulated salt during the growing season and desalted during the non-growing season, while the soil profile below 0.6 m showed the opposite pattern. Farmland soil salinity exhibited obvious seasonal patterns. (2) The sum-metric model effectively fitted the spatio-temporal empirical semivariogram of salinity. The root mean square error (RMSE) between predicted and observed soil salinity values across all layers was less than $0.21\ \mathrm{dS \cdot m^{-1}}$, which was $0.02–0.09\ \mathrm{dS \cdot m^{-1}}$ lower than that of traditional spatial Kriging. The coefficient of determination (R^2) ranged from 0.50 to 0.66, indicating high consistency between predicted and observed values. (3) Using this method with reduced monitoring points, the mean relative error between areas of different soil salinity levels for the 0–0.6 m and 0.6–1.2 m layers was -13.20% and -8.35%, respectively, with RMSE values of $466.67\ \mathrm{hm^2}$ and $494.43\ \mathrm{hm^2}$, and R^2 values of 0.79 and 0.72. Spatio-temporal

Kriging simultaneously utilizes more information from both the temporal and spatial dimensions of soil salinity, enabling precise estimation of spatio-temporal dynamics from sparse monitoring datasets and greatly improving the efficiency of regional soil salinity spatio-temporal pattern monitoring.

Keywords: soil salinity; spatio-temporal Kriging; Hetao Irrigation District; spatio-temporal pattern; sum-metric model

Introduction

The Hetao Irrigation District in Inner Mongolia is China's largest single-control gravity irrigation system, with saline-alkali land accounting for 57% of all irrigated farmland. Soil salinization represents a major challenge for agricultural development in this region. Accurate assessment and prediction of soil salinity spatio-temporal distribution is essential for achieving precision management and regulation of farmland salinity to improve agricultural productivity. However, soil and groundwater conditions are complex in the Hetao Irrigation District, and intense human activities create strong spatio-temporal variability in soil salinity, making spatio-temporal dynamic prediction extremely difficult.

Researchers have long used classical statistics and geostatistics to study soil salinity variation, achieving some results. In the Hetao Irrigation District, Xu Ying used conditional simulation theory to reproduce seasonal freeze-thaw water and salt fluctuations in the Shahao experimental area based on spatio-temporal variability of vertical soil water and salt in the unsaturated zone. Chen Yaxin et al. studied robust statistical methods for approximating spatial variograms of water and salt. Liu Quanming integrated indicator Kriging with neural network technology for evaluating soil water and salt spatial variability. Shi Haibin et al. used geostatistical methods to compare spatio-temporal variation of soil salinity in salinized irrigation districts before and after water-saving renovation. Wang Ruiping et al. used classical and geostatistical methods to study spring soil salinization spatial distribution characteristics in the Wulate sub-irrigation area of Hetao Irrigation District.

Soil salinity is a property with spatio-temporal dynamic attributes, yet current assessments mostly consider only spatial relationships. Temporal trends are generally analyzed by comparing statistical characteristics of soil salinity across multiple periods, which is not suitable for datasets with irregular sampling times and inconsistent spatial positions within sampling periods, especially sparse datasets in both time and space. Spatio-temporal Kriging represents an extension of geostatistics to spatio-temporal geostatistics, where the variance is a function of both time and space, providing more information for parameter estimation and prediction. Many studies have confirmed that spatio-temporal Kriging outperforms spatial Kriging. To date, spatio-temporal Kriging has been successfully applied in environmental science, meteorology, and soil science.

In terms of spatio-temporal Kriging for soil salinity dynamics, Douaik et al. studied Hungarian soil salinity spatio-temporal variation, while Gasch et al. used the sum-metric model to establish a dynamic model for 0–0.4 m soil layers in a 25 hm^2 field near Pullman, Washington, USA. These three studies were conducted at the field scale. At the regional scale, salinity variability increases, and the application effectiveness of spatio-temporal Kriging methods for regional soil salinity spatio-temporal modeling and prediction requires further investigation.

This study takes the Longsheng study area in the Hetao Irrigation District of Inner Mongolia as a typical research area. Based on 4,582 soil salinity data points from 0–1.8 m soil profiles collected at 68 monitoring locations over two years, we used spatio-temporal geostatistical methods to analyze regional soil salinity spatio-temporal variation characteristics, compared the accuracy improvement of spatio-temporal Kriging over traditional spatial Kriging interpolation, and verified the capability of spatio-temporal geostatistical methods to obtain regional salinity dynamics with significantly reduced monitoring points. The research results provide theoretical and scientific basis for spatio-temporal dynamic modeling and prediction of soil salinization.

1. Materials and Methods

1.1 Study Area Description The Hetao Irrigation District is located deep inland and belongs to a mid-temperate arid and semi-arid continental climate, with cold winters and little snow, and hot, dry summers. The Longsheng study area, the main monitoring zone for this research, is located in the Yongji irrigation sub-district of the Hetao Irrigation District in Inner Mongolia. It is bounded by the Yongji Main Canal to the west, Yonggang Branch Ditch to the north, Dongji Branch Canal to the east, and Yonggang Branch Ditch to the south. The area measures approximately 15.5 km from southwest to northeast and 8.0 km from northwest to southeast, with a total land area of 8,219.75 hm^2.

The Longsheng study area experiences soil freezing beginning in mid-November each year, with thawing occurring in early March of the following year. At the nearby Linhe meteorological station, the average annual rainfall is 148.8 mm, with annual rainfall of 100.5 mm in 2017 and 176.2 mm in 2018. Rainfall during the growing season was 53.1 mm in 2017 and 156.6 mm in 2018.

The geological structure of the study area consists of lacustrine and fluvial alternating deposition layers. Soil texture is dominated by silty loam, silt, and sandy loam, with extremely uneven horizontal distribution and strong spatial variability. Vertically, the soil profile structure is relatively complex, with multiple layers of clay, fine sand interlayers, sandy clay, and silty clay in the 0–2.5 m soil structure.

1.2 Soil Salinity Sampling and Testing In 2017, 68 farmland soil water and salt monitoring points were uniformly arranged in the study area (Fig. 1), with each monitoring point spaced approximately 900 m apart. Observations were conducted four times at each point: May 2017 (Y1705), September 2017 (Y1709), May 2018 (Y1805), and September 2018 (Y1809). Within the 0–1.8

m depth range, soil samples were collected every 0.2 m. In spring, where the groundwater table was shallow, sampling was stopped upon reaching the water table. At each observation point, three replicates (boreholes) were collected with a soil auger, yielding a total of 4,582 valid salinity samples. Soil salinity was measured using a conductivity meter (DDSJ-308F) to test the electrical conductivity of soil extracts at a 1:5 soil-water ratio. The salinity values used in this study are expressed as electrical conductivity.

Spatio-temporal Kriging methods can be used to evaluate soil salinity spatio-temporal dynamics. Ordinary spatio-temporal Kriging typically involves three steps: (1) calculation of empirical spatio-temporal semivariograms; (2) fitting empirical semivariograms with theoretical spatio-temporal semivariogram models; and (3) spatio-temporal prediction using spatio-temporal Kriging. The accuracy of predictions is assessed using leave-one-out cross-validation. Detailed calculation methods for each step are as follows:

The spatio-temporal empirical semivariogram $\gamma(h_S, h_T)$ describes the correlation attributes of soil parameter spatio-temporal distribution:

$$\gamma(h_S, h_T) = \frac{1}{2N(h_S, h_T)} \sum_{i=1}^{N(h_S, h_T)} [Z(s_i, t_i) - Z(s_i + h_S, t_i + h_T)]^2$$

where h_S is the spatial separation distance or lag distance between two sample points; h_T is the temporal lag distance; $Z(s_i, t_i)$ is the soil salinity value at spatio-temporal location (s_i, t_i); and $N(h_S, h_T)$ is the number of observation sample pairs when the spatio-temporal separation distance is (h_S, h_T).

Spatio-temporal Kriging interpolation, similar to spatial Kriging, estimates the soil salinity value $Z(s_0, t_0)$ in a grid cell from the salinity values of n nearest sampling points:

$$Z(s_0, t_0) = \sum_{i=1}^{n} \lambda_i Z(s_i, t_i)$$

where λ_i is the weight coefficient of known observation points for the estimated point. The weight coefficients can be determined based on the requirements of unbiased estimation and variance minimization, which can be transformed into the following matrix equation:

$$\begin{bmatrix} \gamma(s_1 - s_1, t_1 - t_1) & \cdots & \gamma(s_1 - s_n, t_1 - t_n) & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \gamma(s_n - s_1, t_n - t_1) & \cdots & \gamma(s_n - s_n, t_n - t_n) & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \vdots \\ \lambda_n \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma(s_0 - s_1, t_0 - t_1) \\ \vdots \\ \gamma(s_0 - s_n, t_0 - t_n) \\ 1 \end{bmatrix}$$

where $\gamma(s_i - s_j, t_i - t_j)$ is the spatio-temporal semivariance value with spatial lag distance h_S and temporal lag distance h_T; μ is the Lagrange multiplier for minimization; and n is the number of observations in the search neighborhood.

The sum-metric model was used to fit the spatio-temporal empirical semivariogram. This model divides the spatio-temporal semivariogram $\gamma(h_S, h_T)$ into three independent components: spatial variance $\gamma_S(h_S)$, temporal variance $\gamma_T(h_T)$, and joint variance $\gamma_{ST}(h_{ST})$, with the relationship expressed as:

$$\gamma(h_S, h_T) = \gamma_S(h_S) + \gamma_T(h_T) + \gamma_{ST}(h_{ST})$$

where $\gamma_S(h_S)$ and $\gamma_T(h_T)$ are independent and typically represented by spatial theoretical semivariogram models such as spherical, Gaussian, or exponential models. In the joint variance $\gamma_{ST}(h_{ST})$, a geometric anisotropy ratio α is often introduced to calculate the spatio-temporal lag distance h_{ST}:

$$h_{ST} = \sqrt{h_S^2 + (\alpha \cdot h_T)^2}$$

All three independent variance components were fitted using spherical models. The spherical model is defined as:

$$\gamma(h_i) = \begin{cases} 0 & h_i = 0 \\ C_0 + C\left(\frac{3h_i}{2a} - \frac{h_i^3}{2a^3}\right) & 0 < h_i \le a \\ C_0 + C & h_i > a \end{cases}$$

where C_0 is the nugget effect; C is the sill; a is the range; and i represents spatial, temporal, and spatio-temporal variables. Referring to the concept of spatial correlation degree, the ratio of the sum of nugget effects to the sum of sills from each independent semivariogram component (STD) was used to evaluate spatio-temporal correlation. STD < 0.25 indicates strong spatio-temporal correlation, STD > 0.75 indicates weak correlation, and values between represent medium correlation.

Leave-one-out cross-validation was used to evaluate spatio-temporal Kriging interpolation effects. During cross-validation, the observed value at the validation point was removed from the dataset, and the remaining data were used to predict soil salinity at that spatio-temporal point. The goodness-of-fit between observed and predicted soil salinity values was then compared to assess the spatio-temporal Kriging model. Evaluation metrics included mean relative error (MRE), root mean square error (RMSE), and coefficient of determination (R^2). Specific calculation methods are detailed in reference [27].

This study used a genetic algorithm to estimate variogram parameters based on the Matlab environment, and completed plotting of experimental semivariogram scatter plots and theoretical model fitting surfaces. Spatio-temporal interpolation distribution maps were completed in ArcGIS 10.3. Classical statistical analysis of soil salinity was performed using Excel 2019.

2. Results and Analysis

2.1 Seasonal Variation Characteristics of Soil Salinity Table 1 shows that the spatial mean of soil salinity in different soil layers varied between 0.25–0.35 $dS \cdot m^{-1}$, averaging at non-salinized levels [28]. The kurtosis of soil salinity ranged from 0.71–18.52, with skewness ranging from 1.05–4.18, indicating severe right-tail distribution. Soil salinity at all layers and sampling times was non-normally distributed. The spatial variation coefficient of soil salinity ranged from 0.43–1.14, with stronger variability closer to the surface due to more intense effects of rainfall, irrigation, and evaporation at the upper boundary, causing greater salt fluctuations over time.

The spatial mean of soil salinity varied within a narrow range of 0.31–0.32 $dS \cdot m^{-1}$ across different observation periods, with variation amplitude not exceeding 0.02 $dS \cdot m^{-1}$, making the 0.4–0.6 m layer the most stable. Taking the root zone (0–0.6 m) as an example, soil salinity was 0.29 $dS \cdot m^{-1}$ at the beginning of the 2017 growing season, 0.30 $dS \cdot m^{-1}$ at the end of the 2017 growing season, 0.32 $dS \cdot m^{-1}$ at the beginning of the 2018 growing season, and 0.32 $dS \cdot m^{-1}$ at the end of the 2018 growing season. The root zone soil salinity accumulated during the growing season. Autumn irrigation and freeze-thaw action reduced root zone soil salinity by 14.7% from the beginning to the end of the growing season. This is consistent with Sun et al.'s [29] autumn irrigation salt leaching experiments in the Hetao Irrigation District, which showed that 180 mm of Yellow River water for autumn irrigation reduced soil salinity by 10.86%–26.14% before spring sowing the following year.

Soil salinity in layers below 0.6 m at the beginning of the growing season was significantly higher than at the end of the growing season. Ignoring the leaching effect of heavy rainfall in 2018 on 0–1.0 m soil salinity, the entire soil profile showed salt accumulation during the non-growing season and desalination during the growing season. The salt distribution at the end of May 2018 decreased sequentially from top to bottom, which is typical of irrigation-evaporation type soil salinity distribution.

2.2 Spatio-temporal Semivariance of Soil Salinity Using log-transformed 0–1.8 m soil salinity data, empirical spatio-temporal semivariograms were calculated (Fig. 2). All semivariograms increased with increasing temporal and spatial lag distances within the range, indicating that soil salinity similarity decreased with increasing temporal and spatial distances. The spatio-temporal semivariance values gradually reached a constant value, and the log-transformed soil salinity data were spatially uniform and temporally stable [12,14].

The sum-metric model was used to fit the empirical spatio-temporal semivariograms, and cross-validation was repeated for all spatio-temporal locations. The selected spatio-temporal semivariogram models and parameters are shown in Table 2. It is usually difficult to distinguish the nugget effects of spatial, temporal, and joint components [21]. The parameters C_0 in the table represent the sum of partial nugget effects. The sum-metric model reasonably characterized the spatio-temporal structure of soil salinity and achieved accurate prediction results.

The spatio-temporal correlation degree (STD) for the 0.4–0.6 m layer was 0.06–0.18, indicating strong spatio-temporal correlation. STD values for other layers ranged from 0.0371–0.0618, indicating medium correlation. The spatial structure of soil salinity is influenced by natural conditions and human activities. Taking the 0.4–0.6 m layer as an example, the ranges for the four sampling times differed significantly: Y1705 was 6,180 m, Y1709 was 1,680 m, Y1805 was 1,801 m, and Y1809 was 1,610 m. If sampling occurred only at Y1809, one might incorrectly conclude that the range of soil salinity was about 1,600 m, far exceeding the actual range. This would lead to serious bias in understanding regional soil salinity spatial structure characteristics. Therefore, multiple monitoring periods are needed for comprehensive analysis to determine regional soil salinity spatial structure characteristics. Spatio-temporal Kriging can simultaneously utilize salinity information from different monitoring times, providing a powerful tool to solve this problem.

2.3 Cross-validation and Prediction of Soil Salinity Spatio-temporal Distribution The spatio-temporal Kriging cross-validation results for soil salinity are shown in Fig. 3. The RMSE between predicted and observed soil salinity values for each layer was less than 0.21 $dS \cdot m^{-1}$. The RMSE for the 0–0.2 m layer was 0.15 $dS \cdot m^{-1}$, and for other layers it was 0.21 $dS \cdot m^{-1}$. The coefficient of determination (R^2) between predicted and observed soil salinity values ranged from 0.50–0.66. These results are far better than the soil salinity spatio-temporal Kriging cross-validation results reported by Gasch et al. [22] (R^2 of 0.12) and are basically comparable to the validation results reported by Douaik et al. [21] (R^2 of 0.60).

As shown in Fig. 3, except for a few cases where soil salinity values were large but predictions were underestimated, most predicted soil salinity values matched well with measured data, indicating that the sum-metric model can reasonably characterize soil salinity spatio-temporal structure and achieve accurate prediction results.

In addition, the spatial semivariogram models for each period calculated using traditional spatial Kriging are detailed in reference [30]. Fig. 4 compares the cross-validation results of traditional spatial Kriging and spatio-temporal Kriging for soil salinity across different periods and soil layers. The RMSE of spatio-temporal Kriging was 0.02–0.09 $dS \cdot m^{-1}$ smaller than that of traditional spatial Kriging, significantly improving soil salinity prediction accuracy.

Based on semivariogram analysis, spatio-temporal Kriging interpolation was used to evaluate the spatial distribution of soil salinity in different layers at various sampling times. Soil salinity spatial distribution showed temporal stability, with basically consistent spatial distribution patterns across different times [31]. As shown in Fig. 5, the spatial distribution of soil salinity in different layers within 0–1.8 m depth in May 2018 (Y1805) demonstrates similar distribution patterns among different layers at the same time. Soil salinity high and low value locations were relatively consistent across layers, particularly for adjacent layers where salt patch positions were more uniform, with only differences in patch size and scope. This indicates that vertical soil salinity distribution is relatively continuous, with closely related salinity content across layers.

The 0–0.6 m root zone soil salinity showed high and low values interspersed in a mosaic pattern. The 0.6–1.8 m soil layers showed banded distribution along the northeast-southwest direction in the central and northern parts of the study area, with low-to-high salinity distribution patterns from west to east. Overall, soil salinity content was high in the eastern and northeastern parts of the study area, and low in the northwestern and southern parts.

2.4 Capability of Spatio-temporal Geostatistics to Obtain Sparse Monitoring Point Salinity Dynamics Among the 68 monitoring points, 32 long-term monitoring points were determined based on an improved temporal stability method for validating the capability of spatio-temporal geostatistical methods to obtain regional salinity dynamics with reduced monitoring points. The specific determination method is detailed in reference [24].

The spatio-temporal semivariogram models and parameters for the 0–0.6 m and 0.6–1.2 m layers are shown in Table 2. Leave-one-out cross-validation results are presented in Table 3. The RMSE of spatio-temporal Kriging was smaller than that of traditional spatial Kriging, with observed values of 0.02–0.09 $dS \cdot m^{-1}$. The R^2 values were 0.79 and 0.72 for the 0–0.6 m and 0.6–1.2 m layers, respectively, significantly improving soil salinity prediction accuracy.

Spatio-temporal Kriging interpolation was used to evaluate the spatial distribution of soil salinity in different layers at various sampling times based on semivariogram analysis. The spatial distribution pattern of root zone soil salinity determined by the 32 long-term monitoring points was basically consistent with that determined by all sampling points. As shown in Fig. 6, the spatial distribution of root zone (0–0.6 m) and 0.6–1.2 m layer soil salinity determined by all soil salinity monitoring locations (ASML) and long-term monitoring locations (LSML) at the four sampling times were highly consistent.

The areas of different salinization levels determined by long-term monitoring points matched well with those determined by all sampling points. As shown in Fig. 7 and Table 4, the mean relative errors between areas of different soil salinity for the 0–0.6 m and 0.6–1.2 m layers were -13.20% and -8.35%, respectively. The RMSE values were 466.67 hm^2 and 494.43 hm^2, and the R^2 values were

0.79 and 0.72, indicating that the spatial distribution of soil salinity obtained by sparse monitoring points is consistent with the results from all sampling points.

Fig. 6 also shows that the spatial distribution of 0.6–1.2 m layer soil salinity determined by long-term monitoring points is highly consistent with that determined by all sampling points. The statistical results of areas with the same salinization level determined by both methods were also very close, with mean relative error of -8.35% and RMSE of 494.43 hm^2, and R^2 of 0.72. This demonstrates that using long-term soil salinity monitoring points to determine the spatial distribution of 0.6–1.2 m layer soil salinity is feasible.

A further comparison was made between the capabilities of spatio-temporal Kriging and ordinary Kriging to obtain sparse monitoring point salinity dynamics. The evaluation metrics for areas of different salinization levels determined by both methods are shown in Table 4. Spatio-temporal Kriging results were significantly better than ordinary Kriging, indicating that spatio-temporal Kriging improves the prediction accuracy of soil salinity spatio-temporal dynamics even when monitoring points are relatively sparse.

In summary, the spatial distribution of soil salinity determined by long-term monitoring points is consistent with results from all sampling points. Using spatio-temporal Kriging with only half the original monitoring points can still accurately estimate soil salinity spatio-temporal dynamics, achieving precise assessment of soil salinity spatio-temporal variation characteristics with fewer sampling data and greatly improving the efficiency of regional soil salinity monitoring.

3. Conclusions

This study used the Longsheng study area in the Hetao Irrigation District as a typical research area. Based on 4,582 soil salinity data points from 0–1.8 m soil profiles collected at 68 monitoring locations over two years, we analyzed seasonal variation characteristics of soil salinity, investigated regional soil salinity spatio-temporal variation features using spatio-temporal geostatistical methods, compared the interpolation accuracy of spatio-temporal Kriging, and further verified the capability of spatio-temporal geostatistical methods to obtain regional salinity dynamics with less than half of the original monitoring points. The main conclusions are:

1) The study area showed obvious seasonal patterns in soil salinity. The root zone (0–0.6 m) accumulated salt during the growing season and desalted during the non-growing season, while the deep soil profile (0.6–1.8 m) showed the opposite pattern.

2) The sum-metric model effectively fitted the spatio-temporal empirical semivariogram of soil salinity. The RMSE from cross-validation of spatio-temporal Kriging was less than 0.21 $dS \cdot m^{-1}$, which was 0.02–0.09 $dS \cdot m^{-1}$ lower than that of traditional spatial Kriging. By simultaneously

utilizing more information from both temporal and spatial dimensions of soil salinity, spatio-temporal Kriging significantly improved prediction accuracy compared with ordinary Kriging.

3) Soil salinity distribution patterns were similar across different layers at the same time, with adjacent layers showing consistent salt patch locations, differing only in patch size and extent.

4) The 0–0.6 m root zone soil salinity showed high and low values interspersed in a mosaic pattern. The 0.6–1.8 m soil layers showed banded distribution along the northeast-southwest direction in the central and northern parts of the study area, with low-to-high salinity distribution patterns from west to east.

5) Using sparse monitoring point data (less than half of all observation points) combined with spatio-temporal Kriging produced soil salinity spatial distributions consistent with results from all sampling points, enabling precise estimation of soil salinity spatio-temporal dynamics and greatly improving the efficiency of regional soil salinity monitoring.

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Note: Figure translations are in progress. See original paper for figures.