Postprint: Multi-source Data-Based Precision Management Zoning of Salinized Farmland in Arid Regions

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Abstract

Precision management zoning of oasis farmland in the arid regions of southern Xinjiang based on soil salinization spatial heterogeneity is of significant importance for agricultural planting structure adjustment and refined management. This study selected typical oasis farmland in arid regions as the research object, utilizing electromagnetic induction data, terrain data, and satellite remote sensing data as data sources. Geostatistical methods were employed to analyze the spatial heterogeneity of soil salinization in the study area, while correlation analysis was used to screen vegetation indices and salinity indices for different periods. With farmland surface apparent electrical conductivity (ECh0.375) as the main variable and deep apparent electrical conductivity (ECh0.75, ECv0.75, ECv1.5), vegetation indices (RVI, GRVI, EVI), and soil salinity indices (NDSI, S5, SI-T) as auxiliary variables, an object-oriented multi-scale segmentation algorithm was adopted to partition the study area. The partitioning results were evaluated using the mean coefficient of variation (CV, Coefficient of Variation) and Moran's I within zones. The results indicated that: (1) Apparent electrical conductivity in all soil layers of the study area exhibited significant spatial heterogeneity, with extremely significant correlations between all auxiliary variables and the main variable. (2) The average coefficient of variation of each zone decreased by 60% compared to that of the entire study area, and the inter-zone heterogeneity based on multi-source data partitioning was higher than that of single-source data partitioning. (3) From the perspectives of farmland cultivation practices, segmentation effectiveness, and zoning evaluation principles, the management zoning that comprehensively utilized both surface and deep soil salinization information achieved the optimal results. This zoning outcome not only aligns with local farmland management practices but also satisfies the requirements of mechanized operations. The research findings can provide technical and methodological references for precision management zoning of oasis farmland in the arid regions of southern Xinjiang.

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Full Text

Precise Management Zoning in Arid Soil Croplands Based on Multi-Source Data

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Abstract

Precise management zoning of oasis farmland in the arid regions of Southern Xinjiang based on the spatial heterogeneity of soil salinization is crucial for optimizing agricultural planting structures and implementing fine-scale management. This study selected typical oasis farmland in an arid zone as the research area and utilized electromagnetic induction data, topographic data, and satellite remote sensing data as information sources. Geostatistical methods were employed to analyze the spatial heterogeneity of soil salinization, while correlation analysis was used to screen vegetation indices and salinity indices from different periods. The surface apparent electrical conductivity (ECh0.375) of farmland served as the primary variable, with deep-layer apparent electrical conductivity (ECh0.75, ECv0.75, ECv1.5), vegetation indices (RVI, GRVI, EVI), and soil salinity indices (NDSI, S5, SI-T) as auxiliary variables. An object-oriented multi-scale segmentation algorithm was applied to partition the study area, and the zoning results were evaluated using the mean Coefficient of Variation (CV) and Moran's I index. The results demonstrated that: (1) significant spatial heterogeneity existed in the apparent electrical conductivity across all soil layers, with all auxiliary variables showing extremely significant correlations with the primary variable; (2) the average coefficient of variation within each zone decreased by approximately 60% compared to the entire study area, and the interval heterogeneity based on multi-source data zoning was higher than that based on single-source data zoning; (3) from the perspectives of farmland cultivation practices, segmentation effectiveness, and zoning evaluation principles, the management zoning that integrated both surface and deep-layer soil salinization information achieved the best results. This zoning approach not only aligned with local farmland management practices but also satisfied mechanized operational requirements. The findings provide valuable technical and methodological references for precise management zoning of oasis farmland in the arid regions of Southern Xinjiang.

Keywords: soil salinization; multi-source data; apparent electrical conductivity; object-oriented segmentation; precise management zoning; arid area

1. Study Area Overview

The study area is located in the 12th Regiment of Alar City, First Division, Xinjiang Uygur Autonomous Region [Figure 1: see original paper], with geographic coordinates of 81°19$‘31“*E*, 40°29’52”$N. Situated in the northwestern Tarim Basin, on the northern edge of the Taklamakan Desert and at the southern foothills of the Tianshan Mountains, the region is characterized by four major water systems: the Yarkant River, Hotan River, Aksu River, and Tarim River. The climate features cold winters, hot summers, long sunshine hours, scarce precipitation, and strong evaporation, representing a warm temperate extreme continental arid desert climate. The multi-year average precipitation is 48.5 mm, while the average evaporation reaches 1988 mm, yielding an evaporation-precipitation ratio as high as 41. The terrain is flat with sandy loam as the dominant soil texture. Cotton is the primary crop, cultivated using under-film drip irrigation during the growing season, while flood irrigation is employed for spring and winter irrigation. The latter aims to leach salts accumulated in the surface soil during the cotton growing season down below the plow layer, thereby reducing salt stress for subsequent crops. Irrigation water is sourced primarily from the Tarim River. The study area exhibits substantial variation in soil salinization levels and a monotonous planting structure. The uniform irrigation volume applied during winter and spring irrigation often results in incomplete salt leaching in some fields, leading to salt damage, or excessive leaching in others, causing water waste. This situation underscores the urgent need for variable-rate irrigation and crop layout adjustments based on different salinization levels.

2. Materials and Methods

2.1 Data Acquisition

2.1.1 Electromagnetic Induction Data
Soil apparent electrical conductivity data were collected using an EM38-MK2 ground conductivity meter in early November after cotton harvest and before winter irrigation. During each data collection session, the instrument was set to manual measurement mode, preheated, and calibrated to zero. At each sampling point, the instrument automatically recorded geographic coordinates while simultaneously collecting data in both vertical and horizontal modes. The horizontal mode measured apparent electrical conductivity for soil depths of 0–0.375 m (ECh0.375) and 0–0.75 m (ECh0.75), while the vertical mode measured 0–0.75 m (ECv0.75) and 0–1.5 m (ECv1.5) depths. The sampling interval was less than 300 m, yielding approximately 300 sets of apparent electrical conductivity data across the study area [Figure 1: see original paper]. Descriptive statistics are presented in .

2.1.2 Remote Sensing and Terrain Data
The study utilized Landsat 8 imagery with a 30 m spatial resolution and 16-day revisit cycle, obtained from the United States Geological Survey (USGS). Images were selected for two periods: the vigorous cotton growth stage (July 17, 2020) and post-harvest pre-winter irrigation bare soil conditions (November 25, 2020). After preprocessing steps including radiometric calibration, atmo-

spheric correction, and image cropping, ENVI 5.3 software was used to calculate three vegetation indices (RVI, GRVI, EVI) and three soil salinity indices (NDSI, S5, SI-T). Terrain data were downloaded from the Geospatial Data Cloud (http://www.gscloud.cn) with 30 m spatial resolution. Using ArcGIS 10.7, depression filling, image cropping, geometric correction, and elevation data extraction were completed.

2.2 Object-Oriented Multi-Scale Segmentation

2.2.1 Segmentation Algorithm
Object-oriented multi-scale segmentation is a pairwise merging process of image objects, beginning with uniformly distributed image objects [20]. For each image object, the algorithm identifies adjacent objects that minimize heterogeneity change. At the point of minimum heterogeneity change, two objects merge into a larger object, with each object processed once per cycle until the heterogeneity of segmented objects exceeds a user-defined threshold, at which point merging stops [21]. This study attempted to partition soil salinization spatial variation based on multi-source data. In eCognition, appropriate shape factor (0.1) and compactness factor (0.5) were first determined, followed by adjusting the segmentation scale parameter to maximize heterogeneity between zones while maximizing homogeneity within zones.

2.2.2 Determining Optimal Management Zones
Since the principle of object-oriented segmentation is to maximize heterogeneity between segmented objects while maximizing homogeneity within them [22], identifying the optimal segmentation scale is essential for enhancing within-zone homogeneity and between-zone heterogeneity. Previous research indicates that the optimal segmentation scale can be determined using changes in the Average Segmentation Evaluation Index (ASEI), plotted against scale parameters. The scale parameter immediately preceding the point where ASEI begins to change significantly is considered optimal [23].

By adjusting the segmentation scale parameter in the multi-scale segmentation algorithm, the study area was divided into m zones. The standard deviation of each zone and the mean absolute difference between each zone and its neighbors were calculated. Homogeneity within zones was represented by standard deviation (δ), while heterogeneity between zones was represented by mean absolute difference (C_L). The Segmentation Evaluation Index (SEI) and ASEI were constructed as follows:

$$SEI = \frac{1}{m}\sum_{i=1}^{m}\frac{C_{Li}}{\delta_i}$$

$$ASEI = \sum_{i=1}^{m}\frac{A_i}{A} \times SEI_i$$

where: n represents the number of pixels in a zone; C_{Li} is the attribute value of the i-th pixel; C_L is the mean attribute value of the zone; δ is the standard deviation; L is the zone perimeter; N is the number of adjacent zones; L_i is the length of the common boundary with the i-th adjacent zone; C_{Lp} is the mean attribute value of the p-th adjacent zone; C_L represents the mean absolute difference between the zone and its neighbors; SEI is the segmentation evaluation index; A is the total study area; A_i is the area of the i-th zone; m is the number of zones; SEI_i is the SEI of the i-th zone; and ASEI is the average segmentation evaluation index. A smaller C_V indicates lower within-zone variation, representing greater homogeneity.

2.3 Evaluation Methods

2.3.1 Within-Zone Homogeneity
Based on the standard deviation and mean of pixel attribute values within each zone, the coefficient of variation for each zone was calculated. Considering differences in zone areas, appropriate weights were assigned to compute the weighted mean of within-zone coefficients of variation (C_V) as a measure of homogeneity:

$$C_V = \sum_{i=1}^{m} \frac{a_i}{A} \times C_{Vi}$$

where C_{Vi} is the coefficient of variation for the i-th zone and a_i is the area of the i-th zone.

2.3.2 Between-Zone Heterogeneity
Global Moran's I index was used to assess spatial autocorrelation and determine between-zone heterogeneity:

$$I = \frac{m}{S_0} \times \frac{\sum_{i=1}^{m} \sum_{j=1}^{m} W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{m} (y_i - \bar{y})^2}$$

where m is the number of zones; y_i is the mean attribute value of zone i; $\bar{y}$ is the mean attribute value of the entire study area; W_{ij} is the spatial weight between i and j (W_{ij} = 1 if adjacent, otherwise 0); and S_0 is the sum of all spatial weights. Moran's I indicates the degree of spatial correlation, with values approaching 0 indicating lower correlation (higher heterogeneity) between zones, which represents better zoning results.

3. Results and Analysis

3.1 Spatial Heterogeneity of Soil Salinization

To justify management zoning based on soil salinization, spatial heterogeneity of apparent electrical conductivity must be demonstrated. Geostatistical semi-variogram analysis was employed, requiring normally distributed data to avoid proportionality effects. The original data showed skewed distribution but approximated normality after square root transformation. Variogram models were optimized using software, with parameters shown in .

All soil layers exhibited exponential models as the optimal variogram, with determination coefficients >0.95 and residuals <0.05, indicating good representation of soil salinization spatial patterns. Nugget values (3.05–4.52) reflected spatial heterogeneity caused by random factors, while sill values (6.27–10.79) represented maximum spatial heterogeneity from both random and structural factors. The nugget-to-sill ratio (~0.5) indicated that both random and structural factors influenced spatial heterogeneity. The range of spatial autocorrelation (1383–2579 m) exceeded the sampling interval (<300 m), confirming that the sampling design could accurately reveal soil salinization spatial heterogeneity and support management zoning.

3.2 Correlation Between Apparent Electrical Conductivity and Spectral Indices

Correlation analysis between surface apparent electrical conductivity (ECh0.375) and terrain data, as well as spectral indices derived from multi-temporal remote sensing images, was conducted. Among six vegetation indices during the cotton growth period, only three showed extremely significant correlations with soil apparent electrical conductivity ($p < 0.01$). Analysis of six soil salinity indices from post-harvest bare soil imagery revealed that five indices were significantly correlated, with three showing extremely significant positive correlations .

All vegetation indices except NIR/R showed negative correlations with apparent electrical conductivity, while soil salinity indices showed positive correlations, consistent with previous research [14]. Terrain data (DEM) showed no significant correlation with apparent electrical conductivity, primarily due to the flat terrain weakening topographic control and human management activities altering original salt distribution patterns. Based on correlation analysis, three vegetation indices (RVI, GRVI, EVI) and three soil salinity indices (NDSI, S5, SI-T) with correlation coefficients $r \geq 0.10$ were selected as auxiliary variables for precise management zoning.

3.4 Comparison and Evaluation of Management Zones Under Different Inputs

Comparisons of optimal management zones based on different datasets revealed distinct differences due to varying auxiliary variables. From a cultivation perspective, zones based solely on ECh0.375 exhibited narrow, elongated partitions unsuitable for mechanized operations. Introducing auxiliary variables produced zones containing at least three fields, aligning with mechanized farming conditions. Segmentation scales differed between datasets, with multi-source data producing more appropriate partitions than single-source data.

Quantitative evaluation followed the principle of maximizing within-zone homogeneity and between-zone heterogeneity. Results showed within-zone coefficients of variation ranging 13.60%–18.65%, indicating weak variation and representing ~60% reduction compared to the entire study area. Moran's I values approached 0, indicating low spatial correlation and high between-zone heterogeneity. Based on cultivation practices, segmentation effectiveness, and evaluation principles, the optimal zoning integrated ECh0.375 with deep-layer apparent electrical conductivity (ECh0.75, ECv0.75, ECv1.5), producing 8 zones at a scale parameter of 90. This approach best represented both surface and deep-layer salinization patterns while meeting local management and mechanization requirements [Figure 2: see original paper], [Figure 3: see original paper], .

4. Discussion

Southern Xinjiang is a major cotton production base, but soil salinization-induced ecological degradation and declining soil fertility constrain crop productivity, making salinization zoning critically important. This study focused on the post-harvest pre-winter irrigation period when salts accumulate in the surface soil [24]. The sandy loam texture, poor water and nutrient retention, and environmental sensitivity make salinization zoning more meaningful than water or nutrient zoning in this region.

Object-oriented multi-scale segmentation is widely used for farmland management zoning, with optimal scale parameters eliminating subjective influences and enabling precise partitioning. However, optimal scale is affected by shape factor, compactness factor, image spatial resolution, and study area size. Compared with previous research [12], different image resolutions yield different optimal scales, with higher resolutions requiring smaller scales [25]. While higher resolution may produce fragmented results unsuitable for highly mechanized agriculture in Xinjiang, the 30 m resolution used here provided appropriate partitioning. The relationship between study area size and optimal scale [26] must also be considered when selecting resolution and determining optimal segmentation scale.

Multi-source data outperformed single-source data in management zoning, producing less fragmented partitions with higher between-zone heterogeneity. However, data redundancy and increased computational load remain challenges for future improvement. The optimal zoning based on ECh0.375 and deep-layer apparent electrical conductivity best met local management and mechanization needs, while ECh0.375 combined with soil salinity indices performed second best. Single-variable ECh0.375 zoning performed worst due to narrow, elongated partitions incompatible with mechanized farming.

Future research will calculate irrigation requirements for salt leaching in each zone based on salinization levels, measuring soil water content, bulk density, and field capacity to implement precise irrigation using empirical formulas [27], thereby achieving the goal of precision agriculture.

5. Conclusion

This study utilized the EM38-MK2 ground conductivity meter based on electromagnetic induction principles to obtain apparent electrical conductivity data after cotton harvest and before winter irrigation. Semivariogram analysis revealed spatial heterogeneity of soil salinization. Using 30 m resolution Landsat 8 imagery, six spectral indices were calculated. Correlation analysis with ECh0.375 identified three vegetation indices and three soil salinity indices as auxiliary variables for precise management zoning. The main conclusions are:

1) Semivariogram analysis showed nugget-to-sill ratios of ~0.5 for all soil layers, confirming spatial variation in soil salinization caused by both random and structural factors, supporting zoning based on salinization levels.
2) After correlation analysis and index screening, vegetation indices (RVI, GRVI, EVI) from July and soil salinity indices (NDSI, S5, SI-T) from November bare soil imagery showed extremely significant correlations with ECh0.375, serving as effective auxiliary variables.
3) Multi-source data management zoning based on object-oriented multi-scale segmentation effectively delineated homogeneous regions. The optimal approach integrated surface and deep-layer apparent electrical conductivity, producing eight zones that aligned with local management practices and mechanized operations while maximizing between-zone heterogeneity.

These results provide technical and methodological support for precise management zoning of oasis farmland in Southern Xinjiang's arid regions.

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