Postprint: Salinization Analysis of Cultivated Land in Kashgar Oasis Based on PSO-PNN Model

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Abstract

Salinization constitutes one of the primary causes of low productivity in oasis agriculture and represents a critical limiting factor for agricultural development and sustainability. To enhance the productivity of salinized cultivated land and promote sustainable development of oasis agriculture, this study focuses on the cultivated land of the Kashgar Oasis. Twenty remote sensing indices were extracted from Landsat 8 OLI imagery, cultivation years of cultivated land in the study area were calculated using land use data, and net primary productivity (NPP) data simulated by the Vegetation Photosynthesis Model (VPM) were downscaled using linear fitting. Correlation analysis between remote sensing indices and soil sampling/measurement data was conducted to obtain optimized remote sensing characteristic variables. Subsequently, a Probabilistic Neural Network (PNN) model optimized by the Particle Swarm Optimization (PSO) algorithm was employed to classify salinization degrees, obtaining the spatial distribution of salinization grades of cultivated land in the study area, which was then overlaid and analyzed with cultivation years and NPP. The results indicate that: (1) Selecting five remote sensing parameters including Enhanced Vegetation Index (EVI), Salinity Index 2 (SI2), Wetness Index (WI), MSAVI-WI-SI feature space (MWSI), and Band 6 (B6, 2.11~2.29 m) to invert salinization degree through the PSO-PNN model achieves an accuracy of approximately 80%. (2) Regions with longer cultivation years exhibit lower degrees of salinization. Newly reclaimed cultivated land is primarily distributed in the eastern part of the study area, while the western part consists mostly of old oasis agricultural zones with cultivation years exceeding 45 a. (3) Cultivated land salinization severely reduces crop productivity. Areas with higher NPP are mostly distributed in the western part of the study area, while areas with lower NPP are mostly distributed in the eastern part, which is roughly opposite to the distribution of salinization degree grades. The above research methods and results can provide references for subsequent studies on salinization inversion using remote sensing parameters and hold certain reference significance for the improvement of salinized cultivated land in arid and semi-arid regions.

Full Text

Analysis of Cultivated Land Salinization in Kashgar Oasis Based on PSO-PNN Model

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Abstract: Salinization constitutes one of the primary causes of low productivity in oasis agriculture and represents a critical limiting factor for agricultural development and sustainability. To enhance the productivity of saline cultivated land and promote sustainable oasis agriculture, this study examines the cultivated land of the Kashgar Oasis in Xinjiang, China. Using Landsat 8 OLI remote sensing imagery, we extracted 20 remote sensing indices. Land use data were employed to calculate the reclamation age of cultivated land in the study area, while the vegetation net primary productivity (NPP) data simulated by the vegetation photosynthesis model were downscaled using linear fitting. Correlation analysis between remote sensing indices and soil sampling data yielded optimized remote sensing characteristic variables. A probabilistic neural network (PNN) model optimized by particle swarm optimization (PSO) was then applied to classify the degree of salinization, producing a graded distribution of cultivated land salinization in the study area. This distribution was subsequently overlaid with reclamation age and NPP data for integrated analysis. The results demonstrate: (1) Five remote sensing parameters were selected through correlation analysis: Enhanced Vegetation Index (EVI), Salinity Index 2 (SI2), Humidity Index (WI), MSAVI-WI-SI feature space (MWSI), and Band 6 (B6, 2.11-2.29 m). The PSO-PNN model achieved approximately 85% accuracy in salinization degree inversion, confirming its effectiveness. (2) Areas with longer cultivated land reclamation histories exhibited lower salinization degrees. Newly reclaimed land is concentrated primarily in the eastern part of the study area, whereas the western region consists mainly of older oasis agricultural zones with reclamation ages exceeding 45 years. (3) Salinization significantly reduces crop productivity. High NPP areas are predominantly distributed in the west, while low NPP areas are mainly in the east, showing an inverse relationship with the spatial distribution of salinization grades. These methodological ap-

proaches and findings provide valuable references for subsequent research on salinization inversion using remote sensing parameters and offer guidance for saline cultivated land improvement in arid and semi-arid regions.

Keywords: remote sensing (RS); geographic information system (GIS); salinization inversion; particle swarm optimization; probabilistic neural network

1. Introduction

Saline soils represent important reserve resources for cultivated land. Soil salinization and secondary salinization destroy arable land essential for human survival, posing significant threats to local economic and social development if left unchecked. Currently, soil salinization severely impacts the stability and sustainable development of agriculture in the Kashgar Oasis region. Cultivated land in the Kashgar Oasis accounts for 17.3% of Xinjiang' s total irrigated area, yet its water allocation per mu is below the regional average. Due to arid climate with scarce rainfall, enclosed topography, and inadequate water conservancy facilities, the Kashgar Oasis has developed into an agricultural region with severe salinization and extensive saline cultivated land areas. Monitoring large-scale farmland salinity information provides a scientific basis for watershed planning and rational agricultural resource allocation in the Kashgar Oasis, holding significant importance for regional ecological protection and sustainable agricultural development.

Traditional soil salinization monitoring relies primarily on indoor laboratory analysis of collected soil samples. This method is complex, time-consuming, labor-intensive, and unsuitable for large-area dynamic monitoring. In contrast, remote sensing technology has gained favor among researchers due to its simplicity and minimal constraints, with increasing applications for salinization information extraction achieving progressive advances. However, soil salinization is a dynamic, strongly nonlinear process influenced by multiple interacting factors, presenting challenges for contemporary assessment efforts. In recent years, machine learning methods have been increasingly applied to salinization research due to their autonomous learning capabilities and rapid data processing speeds, improving inversion accuracy while saving substantial human and material resources.

The probabilistic neural network (PNN) is a novel nonlinear neural network characterized by simple structure, short training time, minimal manually adjusted parameters, high classification rates, and resistance to local optima, making it frequently employed for classification problems. Particle swarm optimization (PSO) is widely applied in algorithm optimization due to its algorithmic simplicity and fast search speed. To rapidly assess the salinization status of cultivated land in the Kashgar Oasis and explore the relationships between salinization, vegetation productivity, and reclamation age, this study employs PSO-optimized PNN for salinization degree classification, aiming to provide references for local saline cultivated land management and ecosystem sustainable development.

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2. Study Area and Methods

2.1 Study Area

The Kashgar Oasis (75°24 -78°00 E, 38°25 -39°56 N) is located in the interior of the Eurasian continent in western Xinjiang, covering an area of 26.4 × 10^3 km^2, representing 4.02% of the watershed area and 4.62% of Xinjiang's oasis area. The Kashgar Oasis features a typical warm temperate continental arid climate with scarce precipitation, hot and dry summers with strong evaporation, cold winters with sufficient sunlight, and large diurnal temperature variations. Rich in light resources suitable for fruit and crop growth, the oasis possesses considerable agricultural development potential through structural adjustments. The region has a long agricultural history, with cotton, grain, and specialty fruits occupying important positions in Xinjiang' s agricultural output. Currently, 26.4 × 10^3 km^2 of land has been developed for cultivation.

2.2 Data Sources

2.2.1 Remote Sensing Imagery Data The remote sensing imagery data source used in this study was Landsat 8 OLI imagery, all downloaded from the United States Geological Survey (USGS) website (https://glovis.usgs.gov/). The acquisition time was during the 2020 growing season.

2.2.2 Cultivated Land Reclamation Age Land use data were obtained from the National Land Use Dataset established by the Chinese Academy of Sciences' Resources and Environmental Remote Sensing Survey (https://www.resdc.cn/). The reclamation age of cultivated land in the study area was derived through spatial analysis of land use data from 1975 to 2020. The specific calculation method involved overlaying the study area' s cultivated land distribution with land use maps from different years. By determining the year when cultivated land first appeared, the reclamation age was calculated as the difference between 2020 and the initial cultivation year.

2.2.3 Soil Sampling and Laboratory Analysis A total of 104 representative sampling points were selected in the Kashgar Oasis (Fig. 1), considering soil types, land reclamation age, and crop types. The sampling included 35 cotton fields, 28 wheat fields, 19 corn fields, and 22 other cultivated lands. Soil sampling was conducted in October 2020. Laboratory analysis measured total salt content, pH, and eight major ions using national standard methods.

2.2.4 NPP Data Vegetation net primary productivity (NPP) represents the total amount of organic dry matter accumulated by vegetation per unit time and area, including branches, leaves, roots, and dead plant material. NPP can uniformly reflect ecosystem productivity at the landscape scale. This study utilized NPP data at 500 m resolution completed by the Chinese Academy of Sciences.

2.3 Methods

2.3.1 Technical Route This study employed RS/GIS technology to process growing season Landsat 8 OLI remote sensing data, extracting 7 vegetation indices, 5 salinity indices, 3 tasseled cap transformation factors, 3 underlying surface reflectance factors, and 2 band reflectance factors. NPP data were downscaled using linear fitting, and reclamation age was extracted from land use data. Correlation analysis between 20 remote sensing parameters and soil sampling data yielded optimized remote sensing characteristic variables. The PSO-optimized PNN model was then applied to classify salinization degrees, producing a distribution map of cultivated land salinization levels. Finally, overlay analysis with reclamation age and NPP data examined relationships between salinization, reclamation history, and productivity, providing references for salinization inversion research and management in arid and semi-arid regions (Fig. 2).

2.3.2 Remote Sensing Index Characteristic Variables Candidate remote sensing index characteristic variables included 7 vegetation indices, 5 salinity indices, 3 tasseled cap transformation factors, 3 underlying surface reflectance factors, and 2 band reflectance factors (Table 1).

2.3.3 Correlation Analysis To investigate correlations between remote sensing characteristic variables and measured salinity at sampling points, Pearson correlation coefficients were calculated. The Pearson correlation coefficient formula is:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where r_{xy} is the correlation coefficient between sample total salt content and remote sensing index; x_i is the total salt content of sample i ($\mathrm{g \cdot kg^{-1}}$); y_i is the remote sensing index value at sample point i; $\bar{x}$ is the mean total salt content; $\bar{y}$ is the mean remote sensing index value; and n is the sample size.

The test statistic for the correlation coefficient is:

$$T = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}$$

where T is the Pearson correlation test statistic; r is the correlation coefficient; and n is the sample size.

2.3.4 NPP Data Downscaling This study downscaled NPP data through linear fitting. The method involved: (1) traversing all pixels to identify pure pixels in the low-resolution NPP data and extracting their corresponding medium-resolution Enhanced Vegetation Index (EVI) values; (2) performing linear fitting for each land use type between NPP and EVI data using Interactive Data Language (IDL). The fitting formula was:

$$NPP_c = a \times EVI_p + b$$

where NPP_c is the low-resolution NPP value corresponding to pure pixels; EVI_p is the EVI value of pure pixels; and a, b are fitting parameters. Based on parameters a, b and high-spatial-resolution EVI from the growing season, high-spatial-resolution NPP data were generated:

$$NPP_d = a \times EVI_q + b$$

where NPP_d is the calculated high-resolution vegetation productivity data; EVI_q is the EVI obtained from band operations on growing season remote sensing imagery; and a, b are the fitting parameters.

Validation data were derived from the 2020 Xinjiang Statistical Yearbook, which contains county-level agricultural statistics with continuous records, making it feasible for NPP result verification. The verification method converted crop yields to vegetation carbon storage based on water content and harvest index values:

$$NPP = \sum_{i=1}^{N} \frac{Y_i \times (1 - MC_i) \times 0.45}{HI_i \times 0.9 \times A_i}$$

where N is the number of crop types; Y_i is the total yield of crop i (t); MC_i is the water content of harvested parts of crop i (%); HI_i is the harvest index of crop i; and A_i is the harvested area of crop i (hm^2).

Correlation tests showed significant correlation between the downscaled NPP dataset and validation data ($R^2 = 0.73$, $P < 0.001$), confirming the downscaled NPP data' s reliability for this study.

2.3.5 PNN Model Construction The probabilistic neural network (PNN) offers advantages including simple learning, fast training, good convergence, flexible network structure, excellent fault tolerance, and suitability for pattern classification problems. The network comprises four layers: input, hidden, summation, and output layers. Through Gaussian function operations, the network can approximate nonlinear outputs. The process involves: (1) substituting samples into the input layer; (2) normalizing samples to eliminate dimensional effects; (3) performing Gaussian operations in the hidden layer; (4) summing and calculating in the summation layer; and (5) outputting salinization degree classification results.

2.3.6 PSO Algorithm The smoothing parameter is critical for PNN model training, affecting classification and prediction results. This study employed particle swarm optimization (PSO) to find optimal parameters. PSO is widely used for algorithm optimization due to its simplicity and fast search speed. The optimization process is illustrated in Figure 3.

2.3.7 Error Verification Methods Cultivated land salinization estimation models typically employ cross-validation and independent dataset validation for rigorous accuracy assessment. Independent dataset validation offers a more direct method for estimating spatial uncertainty. The process uses most samples for machine learning and reserves the remainder for accuracy verification, judging estimation quality by comparing simulated and actual values. This study selected the independent dataset validation method.

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3. Results and Analysis

3.1 Remote Sensing Parameter Selection and Salinization Estimation

3.1.1 Remote Sensing Parameter Selection Correlation analysis between remote sensing indices at sampling points and total salt content (Fig. 4) was conducted to select significantly correlated and representative parameters from each category. Figure 4 shows that in the study area, indices positively correlated with total salt content include Band 6 (B6), MSAVI-WI-SI feature space (MWSI), salinity index 2 (SI2), salinity index 3 (SI3), surface albedo (Albedo), normalized difference salinity index (NDSI), and salinity index 1 (SI1). Negatively correlated indices include Fe_2O_3 mass fraction (I_{Fe}$_2$O$_3$), greenness index (GI), modified soil-adjusted vegetation index (MSAVI), humidity index (WI), enhanced vegetation index (EVI), and normalized difference vegetation index (NDVI). Non-significantly correlated indices include salinity index 4 (SI4), salinity index 5 (SI5), brightness index (BI), and yellowness index (YI).

At the $P < 0.05$ significance level, correlated indicators include WI, Albedo, and I_{Fe}$_2$O$_3$. At $P < 0.01$, correlated indicators include SI2, SI3, MWSI, and B6. At $P < 0.001$, correlated indicators include EVI, MSAVI, GI, and NDSI. Based on these results, five remote sensing parameters were selected for salinization inversion: vegetation index (EVI), salinity index (SI2), humidity index (WI), multidimensional feature space (MWSI), and band reflectance factor (B6).

3.1.2 Cultivated Land Salinization Degree Estimation For machine learning, the 104 samples were divided into training and test sets. Seventy samples were used for training, with the remaining 34 samples reserved for accuracy testing. PSO optimization parameters included: learning factor $c_1 = 1.5$, evolution iterations = 100, and population size = 20. The optimal smoothing parameter was approximately 0.5. Using this parameter in the PNN prediction model yielded a classification of cultivated land salinization degrees, with the test set achieving 85.3% classification accuracy.

The salinization distribution map (Fig. 5) shows that salinization grades increase gradually from west to east. Grades III and IV dominate, accounting for 37.58% and 35.20% of the cultivated area, respectively, followed by Grade I (14.78%) and Grade VI (11.65%). Grades II and V are least common, comprising only 0.72% and 0.07% of the area, respectively. Areas with salinization levels in Grades I–III constitute 52.43% of the total, slightly more than the 47.57% in Grades IV–VI.

At the county level, average salinization degrees from low to high are: Akto County, Shufu County, Kashgar City, Shule County, Yingjisha County, Artux City, Yuepuhu County, and Jiashi County. The proportion of cultivated land in Grades I-III decreases progressively, while Grades IV–VI increase accordingly. Jiashi County, with the largest cultivated area (2,162.34 km^2), shows concerning salinization, with 60.52% of its land in Grades IV–VI. Additionally, Artux City, Yingjisha County, and Kashgar City each have over 10% of their cultivated land in Grade VI, indicating severe salinization in eastern Artux, eastern and northern Yingjisha, and eastern Kashgar.

3.2 Relationships Between Salinization, Reclamation Age, and Vegetation Productivity

3.2.1 Salinization and Reclamation Age Table 4 reveals that nearly 4,266.72 km^2 of new cultivated land was reclaimed in the past 45 years. Among this newly reclaimed land, 27.03% falls in Grades IV–VI, while only 1.27% is in Grade I, indicating high salinization levels in new farmland. In areas with reclamation ages exceeding 100 years, 22.83% of cultivated land is in Grade I, while only 4.32% is in Grade VI, demonstrating that longer reclamation histories correlate with lower salinization degrees.

Figure 6 shows that newly reclaimed land is concentrated in the eastern study area, particularly in Jiashi County, eastern Artux, Yuepuhu County, eastern Shufu, and eastern and northern Yingjisha. Western Shufu and Akto County have less newly reclaimed land, predominantly comprising old oasis agricultural zones with reclamation ages over 100 years. Saline cultivated land with short reclamation ages is mainly located in the eastern region.

Different climates and ecological environments exist across Xinjiang. Many inherently saline lands will naturally become saline cultivated land if reclaimed without adequate salinization control. Even good-quality soils can become salinized through improper irrigation. In the study area, the primary natural factor for severe salinization in recently reclaimed land is its location in downstream river areas and oasis margins, often reclaimed from gobi (gravel desert) and other unused lands with poor conditions. Early reclamation focused on better soils in upper and middle river reaches and oasis interiors, converting grasslands and forests. Human factors include improved scientific and technological methods for salinization control over time, with agricultural practices gradually ameliorating soil conditions. Additionally, varying management levels and natural conditions create differences between eastern and western regions. The terrain slopes downward from west to east, facilitating salt transport via groundwater and surface water to the eastern plains where water flow slows and soil salts accumulate, making the eastern region more prone to salinization.

3.2.2 Impact of Salinization on Productivity Table 5 demonstrates that salinization significantly impacts crop productivity. Average NPP is 718.93 $g \cdot m^{-2}$ for Grades I-II, 674.90 $g \cdot m^{-2}$ for Grades III-IV, and 639.08 $g \cdot m^{-2}$ for Grades V–VI, showing decreasing NPP with increasing salinization. Saline soils exhibit poor drainage, suppressed enzyme activity, inhibited microbial metabolism, reduced fertility, low nutrient utilization efficiency, soil compaction, and poor aeration, all inhibiting plant growth. Field observations revealed that most cultivated land in the Kashgar Oasis uses drip irrigation, with some areas using canal or flood irrigation. Weeds are sparse in well-growing or severely salinized land. Western old agricultural areas show few salt patches with high vegetation coverage, while eastern saline land displays obvious salt patches, poor seedling emergence, and stunted growth. Many plots have been abandoned due to diverse factors, primarily including young people' s reluctance to farm, inconsistent management levels, and natural disasters such as wind-sand 侵袭. Overall, cultivated land salinization represents a natural disaster exacerbated by human activities, causing irreversible damage to land productivity.

Figure 7 shows that high NPP areas are predominantly in the west, while low NPP areas are mainly in the east, roughly inverse to the salinization distribution pattern. Low NPP areas coincide with newly reclaimed land in eastern Jiashi, Artux, Yuepuhu, Shufu, and Yingjisha, whereas high NPP areas correspond to older agricultural zones in western Shufu and Akto.

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4. Conclusions

1. This study selected five remote sensing parameters (EVI, SI2, WI, MWSI, and B6) through correlation analysis. The PSO-PNN model achieved approximately 85% accuracy in salinization degree inversion, demonstrating its effectiveness for the study area. However, the method' s generalizability to other regions requires further investigation.

2. Longer reclamation histories correlate with lower salinization degrees.

Newly reclaimed land is concentrated in the eastern study area with high salinization levels, while the western region contains older oasis agricultural zones (reclamation age >45 years) with lower salinization.

3. Salinization significantly reduces cultivated land productivity. High NPP areas are mainly in the west, while low NPP areas are in the east, showing an inverse relationship with salinization distribution. Lower salinization grades correspond to higher NPP values.

The PSO-PNN model is suitable for salinization inversion in this study area. However, data quality and image resolution affect results. Sampling point selection was limited by accessibility and preliminary assessment, and image processing introduced some uncertainties. Future research should explore different remote sensing imagery and model parameters.

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