Soil Salinity Prediction in the Yinchuan Plain Based on Machine Learning and Multispectral Remote Sensing (Postprint)

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Abstract

Rapid acquisition of regional soil salinization information is of great significance for salinization control and ecological environment protection. Taking the Yinchuan Plain as the study area, three soil salinity prediction models were established using salinity impact factors and salinity indices as input parameters: Support Vector Machine (SVM), BP Neural Network (BPNN), and Bayesian Neural Network (BNN). The optimal model was selected to predict soil salinization at different depths in the study area. The results showed that: (1) In the 0~20 cm soil salinity prediction model, the BNN model based on the impact factor variable group performed best, with a coefficient of determination (R^2) of 0.618 and a root mean square error (RMSE) of 2.986; in the 20~40 cm soil salinity prediction model, the BNN model based on the salinity index variable group performed best, with R^2 of 0.651 and RMSE of 1.947. Overall, the BNN model demonstrated the best predictive performance and can be used for soil salinization prediction in the study area. (2) The Yinchuan Plain is mainly characterized by non-salinized and lightly salinized soils. Severely salinized soils and saline soils in the 0~20 cm layer account for 11.59% of the total area, while those in the 20~40 cm layer account for 7.04%. The degree of soil salinization in the 20~40 cm layer is lighter than that in the 0~20 cm layer.

Full Text

Preamble

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Soil Salinity Prediction in Yinchuan Plain Based on Machine Learning and Multispectral Remote Sensing

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Abstract

Rapid acquisition of regional soil salinization information is crucial for salinization control and ecological protection. Taking Yinchuan Plain as the study area, this research established support vector machine (SVM), back propagation neural network (BPNN), and Bayesian neural network (BNN) models for soil salinity prediction using salinization influence factors and salinity indices as input parameters, respectively. The optimal model was selected to predict soil salinization at different depths in the study area. Results showed: (1) In the 0–20 cm soil layer, the BNN model based on influence factors performed best with a coefficient of determination (R^2) of 0.618 and root mean square error (RMSE) of 2.986; for the 20–40 cm layer, the BNN model based on salinity indices achieved the best performance ($R^2 = 0.651$, RMSE = 1.947). Overall, the BNN model demonstrated superior predictive capability and could be applied to soil salinization prediction in the study area. (2) Yinchuan Plain is dominated by non-salinized and slightly salinized soils, with severely salinized soils and saline crusts accounting for 11.59% of the total area at 0–20 cm depth and 7.04% at 20–40 cm depth. Soil salinization is generally lighter in the 20–40 cm layer compared to the 0–20 cm layer.

Keywords: machine learning; soil salinity prediction; Bayesian neural network; Yinchuan Plain

1. Introduction

Soil is the fundamental basis for human social production and life. Soil degradation constrains agricultural development, and monitoring soil properties plays a vital role in sustainable utilization. Soil salinization occurs across all six continents (except Antarctica, for which no survey data exist), expanding at approximately 1.5×10^{6} hm^2 annually. Salinity prediction involves constructing relational models between specific indicators and corresponding surface information, and numerous scholars have conducted relevant research on salinization forecasting.

Xu Hongtao et al. and Jiang Hong et al. constructed prediction models for different regions, demonstrating that machine learning methods achieve higher accuracy than traditional regression models. Ma Guolin et al. selected effective variables combined with XGBoost machine learning for soil salinity inversion training, significantly improving prediction performance and mapping accuracy. Yang Houxiang et al. extracted multiple salinization factors and applied a BP neural network model to monitor salinization risk in Heilongjiang Province, achieving overall accuracy above 95.49%. Liu Quanming et al. used microwave radar data for salinity inversion, finding that the BP neural network model could quickly predict soil salinity within a short timeframe. Zhang Zhitao et al. established a soil salt inversion model based on UAV multispectral remote sensing, which proved superior to multiple linear regression and geographically weighted regression models for large-area monitoring. Yang Lianbing et al. optimized input parameter subsets and hidden layer neuron numbers using genetic algorithms while refining initial weights, establishing a regional inversion model that improved homogeneity in soil salt content results.

The application of artificial neural networks in prediction has yielded numerous achievements. Zhang Longguan et al. applied Bayesian networks to construction risk management, proving effective for predicting construction risks and development trends. Bi Chunguang et al. developed an early warning model for maize diseases using Bayesian neural networks (BNN), demonstrating high precision. BNN introduces randomness to neural network weights for regularization, equivalent to predictions from multiple networks with arbitrary weights. This approach overcomes overfitting and local minimization issues while achieving stable models and parameter distributions with limited data, offering new insights for salinity prediction.

This study takes Yinchuan Plain as the research area, constructing prediction models based on remote sensing indices and salinization influence factors combined with measured soil salinity data. The optimal model was selected to predict salinity distribution at different soil depths, providing theoretical support for soil monitoring and salinization control in Yinchuan Plain.

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2. Study Area

Yinchuan Plain (37.83°-39.38°N, 104.28°-107.65°E) is surrounded by the Tengger, Ulan Buh, and Mu Us deserts to the west, north, and east, respectively, and borders the Loess Plateau to the south. The plain belongs to a temperate arid zone with a multi-year average temperature of 5–9°C, average annual precipitation of approximately 200 mm, and an evaporation-to-precipitation ratio of about 12. Annual solar radiation ranges from 5800$\times10^{4}$ to 6100$\times10^{4}$ J·m^{-2}, with annual sunshine hours of 2500–3100 h. Yinchuan Plain consists primarily of alluvial-proluvial plains with terrain sloping from southwest to northeast. The Yellow River traverses the plain, enabling extensive irrigation development with numerous canal systems and prosperous agriculture. Major crops include rice, wheat, and corn. Irrigated warped soil and meadow soil are the main agricultural soils with high maturity. Groundwater mineralization ranges from 0.5-3 $g \cdot L^{-1}$, with shallow groundwater depth in the plain area, leading to soil salt accumulation.

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3. Data and Methods

[Figure 1: see original paper] Distribution of sampling points in Yinchuan Plain

3.1 Soil Sample Collection and Salinity Measurement

Soil samples were collected using a 5 km$×5kmgridnetwork(Fig.1).Ateachsamplingpoint,a30m×$30 m plot was established using a plum-blossom sampling method. During collection, five soil cores were taken from each plot and mixed thoroughly, with approximately 500 g retained using the quartering method. Samples from 0–20 cm and 20–40 cm depths were sealed in bags and brought back to the laboratory, with GPS coordinates and environmental information recorded. A total of 166 sampling points were obtained.

After removing impurities, soil samples were air-dried, ground, and passed through a 2 mm sieve. Extracts were prepared at a soil-to-water ratio of 1:5, with each sample prepared in triplicate and one group serving as a control. The average of the three measurements was taken as the final value. Soil salt content was determined using the electrical conductivity method:

$$S = EC \times 41.2543 \times 5 \div 2120.76$$

where S is soil salt content ($g \cdot kg^{-1}$) and EC is the measured electrical conductivity of the extract ($mS \cdot cm^{-1}$). After analysis, outlier samples were removed, yielding 152 valid samples.

3.2 Remote Sensing Image Acquisition and Processing

Landsat 8 OLI remote sensing images were obtained from the US Geological Survey (https://earthexplorer.usgs.gov/) with a spatial resolution of 30 m. Images from path/row 129/033 and 129/034 acquired on April 25, 2021, coincided with the sampling period. ENVI 5.3 software was used for atmospheric correction and preprocessing, followed by calculation and extraction of various salinity indices (Table 2).

3.3 Prediction Model Construction

3.3.1 Parameter Selection for Salinization Influence Factors Based on previous research on soil salinization formation conditions and the actual situation in Yinchuan Plain, 7 environmental variables and 3 human activity variables were selected (Table 3). Soil moisture and pH were obtained through

Kriging spatial interpolation from sampling point data and output as 30 m resolution raster data. Groundwater data were derived from literature. The digital elevation model was obtained from the Geospatial Data Cloud platform (http://www.gscloud.cn/) with 30 m resolution. Land surface temperature, enhanced vegetation index, and water body index were calculated using Landsat 8 OLI data in ENVI 5.3. Land use data were acquired from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/). Land use intensity was determined using the classification method by Zhuang Dafang, with different values assigned to unused land, grassland, forestland, cropland, residential land, and water bodies.

3.3.2 Data Processing To eliminate dimensional effects among different indicators, data were normalized using the formula:

$$A' = \frac{A - A_{min}}{A_{max} - A_{min}}$$

where A is the warning factor dataset, *A' _{max}* and *A' _{min}* are the maximum and minimum values of the sample data, respectively, and *A'* is the normalized value.

3.3.3 Prediction Model Construction Support Vector Machine (SVM): Based on structural risk minimization principle, SVM searches for global optimal solutions using limited samples and demonstrates good generalization for unknown points, avoiding drawbacks of small-sample learning and local extrema. This study used the radial basis function kernel, with penalty parameter (c) and kernel parameter (g) determined through sample testing.

Back Propagation Neural Network (BPNN): This model trains datasets through error backpropagation to minimize errors. With strong adaptive and self-learning capabilities, it can accurately approximate any nonlinear relationship. Using MATLAB 2020, salinity indices and influence factors served as input data, with measured salinity as output. After multiple training iterations, the number of hidden layer nodes was determined based on minimal error between predicted and actual values. The minimum error target was set at 0.001 with 1000 training iterations.

Bayesian Neural Network (BNN): BNN introduces randomness to neural network weights for regularization, equivalent to predictions from multiple networks with arbitrary weights. Unlike traditional BPNN, BNN estimates the posterior distribution probability *P(w|D)* of node weights. The prediction value y is the expectation of all possible predictions in *P(y|w, D)*. According to Bayesian theory, a Gaussian prior *P(w)* was obtained, and the posterior probability was derived using Bayes' theorem. Parameters maximizing posterior probability were selected as optimal model parameters, overcoming overfitting and local minimization.

3.3.4 Model Evaluation Metrics The coefficient of determination (R^2) and root mean square error (RMSE) were selected to quantify prediction performance. Higher R^2 and lower RMSE indicate better model fit.

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4. Results and Analysis

4.1 Soil Salinity Spatial Distribution

Using ArcGIS spatial analysis tools, the Kriging method was applied to interpolate soil salinity for 152 sampling points. Based on salinization degree classification, spatial distribution characteristics at different depths were obtained (Fig. 2). At 0–20 cm, severely salinized soils and saline crusts were mainly distributed in northern Yinchuan Plain, with lighter salinization in southern areas. Non-salinized and slightly salinized soils dominated, though severe salinization occurred in the northwest, with some areas exceeding 6 $g \cdot kg^{-1}$. Overall, salinization showed a low-south, high-north trend, with severely salinized soils and saline crusts concentrated in Shizuishan area.

4.2 Correlation Analysis and Model Comparison

4.2.1 Correlation Analysis Correlation analysis between influence factors, salinity indices, and measured soil salinity revealed strong significance for most factors except soil moisture and population density at 0–20 cm. At 20–40 cm, land use intensity, enhanced vegetation index, water body index, land surface temperature, groundwater depth, and groundwater mineralization showed extremely strong significance. For salinity indices, correlations with 0–20 cm soil salinity passed significance tests for SI1, SI2, SI3, SI5, SI6, SI7, SI8, SI9, and SI10; correlations with 20–40 cm soil salinity passed tests for SI1, SI2, SI3, SI4, SI5, SI6, SI7, SI8, and SI10. Factors and indices passing significance tests were selected as input parameters for modeling.

4.2.2 Model Construction and Comparative Analysis Models were constructed with soil salinity as the output layer and strongly correlated influence factors and salinity indices as input layers. For 0–20 cm soil, the influence factor-based BNN model achieved the best performance ($R^2 = 0.618$, RMSE = 2.986). For 20–40 cm soil, the salinity index-based BNN model performed best ($R^2 = 0.651$, RMSE = 1.947). Comparative analysis showed the BNN model consistently outperformed SVM and BPNN across variable groups, demonstrating the advantage of neural network introduction in model training.

4.3 Soil Salinity Prediction in Yinchuan Plain

The trained BNN model was applied to predict soil salinity across Yinchuan Plain. Based on salinization classification, prediction maps were generated (Fig. 4). At 0–20 cm, saline crusts were mainly distributed in Dawukou District and

Pingluo County in the north, with severe and moderate salinization surrounding these areas and in eastern plains. Non-salinized and slightly salinized soils dominated southern areas. At 20-40 cm, non-salinized soils predominated, with saline crusts in western Dawukou and Pingluo, and severe salinization scattered throughout the plain.

Pixel-based calculations revealed that at 0–20 cm, non-salinized and slightly salinized soils accounted for 50.54% and 30.07% of the total area, respectively, while moderately salinized, severely salinized, and saline crusts comprised 8.07%, 12.35%, and 4.89%, respectively. At 20–40 cm, non-salinized and slightly salinized soils accounted for 33.29% and 31.86%, respectively, while moderately salinized, severely salinized, and saline crusts comprised 23.26%, 7.04%, and 2.15%, respectively. Validation against measured interpolation data showed consistency rates of 78.21% for 0–20 cm and 76.54% for 20–40 cm, indicating good agreement between predicted and measured results.

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5. Discussion

This study established soil salinity prediction models for different depths using three machine learning methods, revealing significant depth-dependent variations in model performance under identical conditions. Pearson correlation analysis identified sensitive factors including groundwater mineralization, groundwater depth, and land use intensity, consistent with findings by Yang Sicun et al. These factors can be used to explore implicit information about salinization drivers.

Correlations between soil salinity and influence factors were significantly stronger at 0–20 cm than at 20–40 cm, aligning with Liu Jilong’ s research. This may reflect that soil salinity responses to external influences vary with depth, as agricultural activities primarily affect surface soils. Salinity indices also showed depth-dependent correlation differences. As a complex system, conventional linear regression models struggle to achieve satisfactory precision, whereas machine learning effectively addresses this challenge. Many researchers have applied machine learning to salinity prediction, achieving higher accuracy than linear models.

BNN algorithms can establish stable models and parameter distributions with limited data, achieving good generalization and offering new approaches for salinity prediction. This study compared three machine learning methods, finding BNN superior to SVM and BPNN. The influence factor group performed better for 0–20 cm predictions, while the salinity index group excelled for 20–40 cm, consistent with Yang Ning et al.’ s conclusions.

The study compared multiple models under different depths and input parameters to select optimal predictions. However, environmental variations across seasons and years are substantial. During spring sampling, strong evaporation concentrated salts at the surface. As Yinchuan Plain is primarily cropland where farmers irrigate before planting to reduce salinization, future research should consider seasonal variations and multi-year data for model training and validation. Additionally, different input parameters yielded varying prediction accuracies, suggesting that combining influence factors with salinity indices could improve model performance. The applicability of these models to other regions requires further research and validation.

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6. Conclusions

Using Yinchuan Plain as the study area, this research constructed salinity prediction models with salinization influence factors and salinity indices as inputs. Model performance was compared, and the optimal model was selected for soil salinity prediction at different depths, yielding the following conclusions:

1) Among soil salinity prediction models, the BNN model achieved the best performance. Influence factors had greater impact on 0–20 cm soil salinity prediction, while salinity indices were more important for 20–40 cm predictions. Comparative analysis demonstrated that BNN outperformed other algorithms, with neural network introduction providing clear advantages.

2) According to prediction results, Yinchuan Plain is dominated by non-salinized and slightly salinized soils. Non-salinized and slightly salinized soils at 0–20 cm depth account for 50.54% and 30.07% of the total area, respectively, while severely salinized soils and saline crusts comprise 11.59%. At 20–40 cm depth, these values are 33.29% and 31.86% for non-salinized and slightly salinized soils, respectively, with severely salinized soils and saline crusts comprising 7.04%. Soil salinization is generally lighter at 20–40 cm than at 0–20 cm depth.

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