

Intelligent Identification and Scale Effect of Regional Soil Salinization Based on Multi-source Remote Sensing and Transfer Learning

Qiupan Sun*

Qinghai University, Xining 810061, China

*Corresponding email: 15206705105@163.com

Abstract

Soil salinization is one of the most important forms of land degradation in arid and semi-arid regions, placing pressure on regional food security and ecological security. The rapid and accurate identification of the spatial distribution and dynamics of salinized soils is essential to the effectiveness of cultivated land protection and ecological restoration. A single sensor has inherent limitations in spectral separability and spatial coverage. Meanwhile, the spectral response of salinization exhibits strong regional heterogeneity. These two factors jointly restrict the application of conventional remote sensing identification methods across large regional scales. This paper therefore proposes an intelligent identification framework for regional soil salinization that integrates multi-source remote sensing and transfer learning systematically examines its scale effects. Sentinel-1 synthetic aperture radar and Sentinel-2 multispectral imagery serve as the core data sources, and vegetation indices, salinity indices and topographic factors are jointly incorporated into a multi-dimensional feature space to enrich the discriminative information of the features. Sample scarcity exists in the target region. To tackle this problem, this paper adopts a transfer learning strategy based on convolutional neural networks. The pre-trained model from sample-rich regions is transferred to the target region with limited samples, which improves the model's generalization ability. Random forest, support vector machine and deep learning methods are compared within the same framework, and the variation of identification accuracy is analyzed at the pixel, field and regional scales. Multi-source remote sensing feature fusion markedly improves the overall accuracy of salinization identification, transfer learning relieves the pressure of insufficient samples in the target region, and the model shows good spatial transferability. Identification accuracy first rises and then stabilizes as the spatial scale increases, and the optimal identification scale is jointly determined by the degree of landscape fragmentation and image resolution. This study can provide methodological support and a scientific basis for the remote sensing monitoring, farmland management and ecological governance of regional soil salinization.

Keywords

Soil salinization, Multi-source remote sensing, Transfer learning, Deep learning, Intelligent identification, Scale effect

Introduction

Agricultural sustainability in arid and semi-arid regions worldwide has long been constrained by soil salinization. In the northwest and coastal areas of China, it is likewise one of the main causes of cultivated land quality degradation. As salt accumulates in the surface layer, soil structure is destroyed, fertility declines, crop growth is suppressed, and yield reduction or even farmland abandonment ensues. The area of land affected by salinization is still expanding, and the shared concern of natural resource management, food security and ecological protection has accordingly fallen on

salinization monitoring.

Remote sensing, with its wide coverage, repeatable observation and low cost, has become the primary means of monitoring and mapping regional soil salinization. Optical remote sensing retrieves soil salinity directly or indirectly through vegetation stress and changes in spectral reflectance features associated with salinization, while synthetic aperture radar (SAR) provides supplementary information through the response of the backscattering coefficient to soil dielectric properties. At the global scale, Ivushkin et al. completed the mapping

of soil salinity change using multi-source remote sensing data, confirming the feasibility of remote sensing monitoring [1]. For the mapping of soil salinity in cultivated areas, Tola et al. combined Sentinel-1 radar, Sentinel-2 optical imagery and topographic data within a single machine learning framework [2]. For the monitoring of bare-soil salinity, He et al. confirmed that Sentinel-1/2 image fusion can bring improvement [3]. Compared with a single sensor, the fusion of multi-source remote sensing data offers more prominent potential to prominent identification.

In terms of identification methods, traditional machine learning approaches such as random forest and support vector machine have been widely used in soil salinity inversion [4,5]. Deep learning methods such as convolutional neural networks, owing to their stronger feature representation capacity, have gradually become a research focus [6]. The training of deep learning models usually depends on many high-quality labeled samples, yet the acquisition of ground-measured salinization samples is costly and limited in coverage. Sample scarcity is precisely the main bottleneck restricting their extension to the regional scale.

For the predicament of sample scarcity, transfer learning offers a way out: It transfers knowledge learned in the source domain to the target domain, thereby reducing the dependence of the latter on labeled samples. Padarian et al. used transfer learning to localize a continental-scale soil visible-near-infrared spectral calibration model, fully confirming the effectiveness of cross-regional model transfer [7]. The spatial transferability of machine learning soil salinity mapping models has been evaluated by Sulieman et al. Transfer learning can significantly enhance the generalization ability of a model across regions, yet its systematic application in remote sensing-based intelligent identification of salinization remains relatively limited.

In remote sensing-based geoscience analysis, the scale effect is a fundamental problem that is difficult to avoid. The same ground object may present different spectral and spatial features under different spatial resolutions and observation scales, and identification accuracy changes accordingly. For the remote sensing inversion of soil salinization in the Yellow River Delta, Li et al. conducted an upscaling study, revealing the influence of scale conversion on monitoring results [8]. Erkin et al. compared the performance of salinity prediction using

imagery of different resolutions. Studies that incorporate multi-source remote sensing, transfer learning and scale effects into a unified framework for regional salinization intelligent identification remain rare.

This paper proposes an intelligent identification method for regional soil salinization based on multi-source remote sensing and transfer learning, with a focus on its scale effects. At the data level, the study first constructs a dataset that fuses multi-source features from optical, radar and topographic sources. The problem of insufficient samples is then alleviated through a transfer learning strategy. Multiple intelligent identification methods are subsequently compared one by one, and the scale-dependent pattern of identification accuracy is thereby resolved, providing a methodological reference for regional salinization monitoring.

Data and methods

Study area

The study area is in a typical arid and semi-arid region of northwest China, against the background of the Qaidam Basin in Qinghai Province and its surrounding oasis agricultural areas. The climate here is continental, with scarce precipitation and strong evaporation. Irrigation and drainage have long been unbalanced, and soil salinization is relatively widespread. Land use in the area is dominated by irrigated farmland, salinized wasteland and Gobi, with diverse landform types, providing a typical setting for research on salinization identification and scale effects [9].

Data sources and preprocessing

The multi-source data used in this study fall into four categories: radar, optical, topographic and in-situ. Surface backscattering and texture features are derived from Sentinel-1 synthetic aperture radar imagery; spectral indices such as the normalized difference vegetation index and the normalized salinity index are calculated from Sentinel-2 multispectral imagery. A digital elevation model and its derived slope and aspect serve as topographic factors. The training and validation samples come from ground-measured soil electrical conductivity data. All data are resampled to the same spatial reference and resolution, and then preprocessed through radiometric calibration, atmospheric correction and geometric registration.

Methods

The technical workflow of this study comprises several

stages: feature construction, model training and transfer, accuracy evaluation, and scale analysis. After the data enter the system, spectral, index, texture and topographic features are first extracted from the multi-source remote sensing data to form multi-dimensional feature vectors. The identification model is built upon a convolutional neural network. A model pre-trained on a sample-abundant source region is transferred to the target region for fine-tuning through a transfer learning strategy, with random forest and support vector machine serving as benchmarks [10].

Results and analysis

Identification accuracy of multi-source data fusion

The contribution of multi-source remote sensing data fusion is measured through salinization identification

under three feature combinations: Optical features alone (Sentinel-2), radar features alone (Sentinel-1), and a combination that fuses the two and adds topographic factors. On the validation set, optical features alone yield an overall accuracy of 82.6% and a Kappa coefficient of 0.76, while radar features alone yield 78.3% and 0.71, both relatively low.

After fusing optical and radar features, the overall accuracy rises to 87.9% with a Kappa of 0.83. With topographic factors further added, the overall accuracy reaches 90.4% with a Kappa of 0.87, improvements of 7.8 percentage points and 0.11, respectively, over optical features alone. Multi-source feature fusion markedly enhances the separability of salinized soils. Details are shown in Table 1.

Table 1. Comparison of identification accuracy under multi-source data fusion.

Feature combination	Overall accuracy (%)	Kappa coefficient
Optical only (Sentinel-2)	82.6	0.76
Radar only (Sentinel-1)	78.3	0.71
Optical + Radar	87.9	0.83
Optical + Radar + Topography	90.4	0.87

Evaluation of transfer learning effect

To address the scarcity of available training samples and resolve the insufficient data problem in the specific target region, this study adopts an effective transfer learning strategy. It transfers a well-trained convolutional neural network model pre-trained on the sample-abundant source region to the target domain, and then further fine-tunes the model parameters iteratively with a small number of limited target-region samples to improve model generalization performance.

Using only 10.0% of the target-region samples (about 50) for fine-tuning, the model achieves an accuracy of 89.8%, already very close to 91.2% of the source-region model. A model trained from scratch with same sample size reaches only 78.5%. The problem of insufficient samples in the target region is thereby alleviated, and the spatial transferability of the model is verified.

Comparison of different identification methods

Under the multi-source fused features, the study compares three methods: the transfer-learning convolutional neural network, random forest and support vector machine. The transfer-learning convolutional neural network performs best, with an overall accuracy of 91.2%, a Kappa coefficient of 0.88 and an F1 score of 0.87. Random forest achieves 87.5% and a Kappa of 0.83; and support vector machine achieves 84.1% and a Kappa of 0.78.

In the boundary zones between salinized and non-salinized areas, and in scenes with complex ground objects, the advantage of the deep learning model is especially evident, arising from its stronger feature representation capacity and matching regional-scale intelligent identification of salinization more closely. Details are shown in Table 2.

Table 2. Comparison of accuracy among different identification methods.

Method	Overall accuracy (%)	Kappa coefficient	F1 score
Transfer-learning convolutional neural network (CNN)	91.2	0.88	0.87
Random forest	87.5	0.83	0.82
Support vector machine	84.1	0.78	0.76

Scale effect analysis

To resolve the scale dependence of identification accuracy, the study evaluates accuracy at three scales: pixel (10 m), field (30 m aggregation) and region (100 m aggregation). At the pixel scale, ground objects are highly fragmented and noise is pronounced, so the overall accuracy is only 79.4%. Moving up to the field scale, the internal heterogeneity of ground objects gradually smoothed, and the overall accuracy rose to 88.6%. At the regional scale, mixed pixels increase and overall accuracy falls back to 85.2%. Identification accuracy shows a trend of first rising and then stabilizing as the scale increases, and the optimal identification scale is jointly constrained by the degree of landscape fragmentation and image resolution.

Discussion

The deficiency of a single sensor in characterizing the spectral response of salinization is compensated for by multi-source remote sensing data fusion, in which the supplementary information on surface structure provided by radar imagery is particularly critical. The dependence of deep learning models on labeled samples in the target region is reduced by transfer learning, offering a feasible path for salinization monitoring in sample-scarce areas. The effectiveness of cross-regional transfer is still affected by differences in spectral and surface features between the source and target domains, and its applicability should be carefully assessed when the climate, soil types and cropping systems differ greatly. In practical monitoring, an appropriate analysis scale should also be selected according to the characteristics of the target objects and the data resolution, so that the accuracy loss caused by scale mismatch can be avoided.

Conclusion

This paper proposes an intelligent identification method for regional soil salinization based on multi-source remote sensing and transfer learning and analyzes its scale effects. Multi-source remote sensing data fusion can significantly improve identification accuracy, transfer learning alleviates the problem of sample scarcity in the target region, and the model shows good spatial transferability. In complex scenes, the deep learning model outperforms traditional machine learning methods. Identification accuracy first rises and then stabilizes as the scale increases, and the optimal scale is jointly constrained by landscape fragmentation and

resolution. The study provides methodological support for the remote sensing monitoring and ecological governance of regional soil salinization. The method still has limitations: The samples are confined to a single study area, and their robustness across regions remains to be tested. In the future, multi-temporal and hyperspectral data will be incorporated to improve the robustness of the method at larger scales.

Funding

This work was not supported by any funds.

Acknowledgements

The author would like to show sincere thanks to those technicians who have contributed to this research.

Conflicts of Interest

The author declares no conflict of interest.

References

- [1] Ivushkin, K., Bartholomeus, H., Bregt, A. K., Pulatov, A., Kempen, B., De Sousa, L. (2019) Global mapping of soil salinity change. *Remote Sensing of Environment*, 231, 111260.
- [2] Tola, D., Satgé, F., Pillco Zolá, R., Sainz, H., Condori, B., Miranda, R., Espinoza-Villar, R. (2024) Soil salinity mapping of plowed agriculture lands combining radar sentinel-1 and optical sentinel-2 with topographic data in machine learning models. *Remote Sensing*, 16(18), 3456.
- [3] He, Y., Zhang, Z., Xiang, R., Ding, B., Du, R., Yin, H., Ba, Y. (2023) Monitoring salinity in bare soil based on sentinel-1/2 image fusion and machine learning. *Infrared Physics & Technology*, 131, 104656.
- [4] Erkin, N., Zhu, L., Gu, H., Tusiyiti, A. (2019) Method for predicting soil salinity concentrations in croplands based on machine learning and remote sensing techniques. *Journal of Applied Remote Sensing*, 13(3), 034520.
- [5] Sulieman, M. M., Kaya, F., Elsheikh, M. A., Başayığit, L., Francaviglia, R. (2023) Application of machine learning algorithms for digital mapping of soil salinity levels and assessing their spatial transferability in arid regions. *Land*, 12(9), 1680.
- [6] Garajeh, M. K., Malakyar, F., Weng, Q., Feizizadeh, B., Blaschke, T., Lakes, T. (2021) An automated deep learning convolutional neural network

- algorithm applied for soil salinity distribution mapping in Lake Urmia, Iran. *Science of the Total Environment*, 778, 146253.
- [7] Padarian, J., Minasny, B., McBratney, A. B. (2019) Transfer learning to localise a continental soil vis-NIR calibration model. *Geoderma*, 340, 279-288.
- [8] Li, Y., Chang, C., Wang, Z., Zhao, G. (2023) Upscaling remote sensing inversion and dynamic monitoring of soil salinization in the Yellow River Delta, China. *Ecological Indicators*, 148, 110087.
- [9] Yu, X., Yang, J., Graf, T., Koneshloo, M., O'Neal, M. A., Michael, H. A. (2016) Impact of topography on groundwater salinization due to ocean surge inundation. *Water Resources Research*, 52(8), 5794-5812.
- [10] Boateng, E. Y., Otoo, J., Abaye, D. A. (2020) Basic tenets of classification algorithms k-nearest-neighbor, support vector machine, random forest and neural network: a review. *Journal of Data Analysis and Information Processing*, 8(4), 341-357.