Spatiotemporal Analysis of Soil Salinization in the Yutian Oasis Using Multi-Source Optical and Radar Remote Sensing: Postprint

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Abstract

Currently, soil salinization is a significant global environmental issue. This study investigates the spatiotemporal variation patterns of soil salinization in the Yutian Oasis, leverages the advantages of radar remote sensing for detecting soil salinity, and monitors and assesses spatiotemporal changes in soil salinization in arid region oases. Taking the Yutian Oasis as the study area, based on multi-source datasets including PALSAR-2, Sentinel-1 polarimetric synthetic aperture radar data, and Landsat 8 OLI, the optimal combination of backscatter features from radar imagery and optical imagery after principal component analysis was selected, and finally the random forest method was employed for image classification to quantitatively extract soil salinization information in the Yutian Oasis and analyze its spatiotemporal variations. The results indicate: (1) Under the simultaneous use of the random forest classification method, the overall accuracy of optical imagery across years averaged 80.36%, with an average Kappa coefficient of 0.77; the classification accuracy of optical imagery combined with radar imagery was higher than that of optical imagery alone, with an average overall accuracy of 85.62% and an average Kappa coefficient of 0.82. (2) From 2015 to 2021, areas undergoing soil salinization in the Yutian Oasis were primarily distributed in the oasis-desert ecotone along the northern edge of the study area. (3) From 2015 to 2021, the annual average change in saline land area was -1120.55 $hm^2 \cdot a^{-1}$, with a change rate of -10.67%. The overall degree of salinization in the Yutian Oasis showed a declining trend, with salinization predominantly characterized by light to moderate saline land.

Full Text

Abstract

Soil salinization is currently a major global environmental issue. This study investigates the spatiotemporal variation patterns of soil salinization in Yutian Oasis and explores the advantages of radar remote sensing for detecting soil salinity, aiming to monitor and evaluate the temporal and spatial changes of soil salinization in arid oasis regions. Taking Yutian Oasis as the study area, we utilized multi-source datasets including Phased Array type L-band Synthetic Aperture Radar-2 (PALSAR-2), Sentinel-1 polarimetric synthetic aperture radar data, and Landsat 8 Operational Land Imager (Landsat 8 OLI) imagery. The optimal backscattering features from radar images were selected and combined with optical images processed through principal component analysis. Finally, random forest classification was employed to quantitatively extract soil salinization information in Yutian Oasis and analyze its spatiotemporal dynamics. Results indicate that: (1) When using the random forest classification method, the overall accuracy of optical imagery across the years averaged 80.36%, with a mean Kappa coefficient of 0.77. The classification accuracy achieved by combining optical and radar imagery exceeded that of optical imagery alone, achieving an average overall accuracy of 85.62% and a mean Kappa coefficient of 0.82. (2) From 2015 to 2021, salinized areas in Yutian Oasis were primarily distributed along the northern oasis margins and at the desert-oasis ecotone. (3) The average annual change in saline land area was -1120.55 hm^2, with a change rate of -10.67%. The overall salinization trend in Yutian Oasis showed a declining pattern, with light to moderate salinization being the dominant type.

Keywords: soil salinization; synthetic aperture radar; Landsat 8 OLI; random forest classification; spatial and temporal variation

1 Introduction

Soil salinization represents a critical ecological and environmental challenge worldwide. This problem indirectly damages ecosystems and severely impedes sustainable agricultural production and economic development in arid and semi-arid regions. In China, saline soils are widely distributed, covering approximately 8.5$×10^{7}$ hm^2, with Xinjiang' s total saline soil area reaching 9.9$×10^{6}$ hm^2, primarily due to local climatic conditions and unique topography. Remote sensing techniques play a crucial role in monitoring the spatiotemporal distribution and severity of soil salinization in oasis regions, thereby ensuring stable natural ecosystems and healthy agricultural production.

Among remote sensing applications, optical imagery has been most extensively used. However, as passive remote sensing, optical data acquisition is susceptible to incident light sources and weather conditions, limiting classification accuracy for soil information monitoring. While optical remote sensing relies on spectral characteristics to monitor salinized soils, its effectiveness is constrained by daytime imaging requirements and cloud cover interference. Radar remote sensing, as an active system, operates independently of climate and diurnal cycles, offering all-weather, day-and-night imaging capabilities while providing information unavailable from optical remote sensing. Integrating multi-source remote sensing data, including microwave data, can compensate for optical data limitations and provide unique combinations of spectral and textural features for target detection.

Previous studies on soil salinization monitoring using microwave remote sensing have demonstrated that microwave imagery serves as an effective tool for soil salinity monitoring through analysis of relationships among backscattering intensity, soil salinity, and dielectric constant. Research utilizing fully polarimetric radar data has shown that microwave imagery combined with polarization features can distinguish different salinization degrees. Machine learning models based on optical and radar imagery have proven effective for estimating soil salinity and spatial distribution, demonstrating the feasibility of machine learning algorithms using fused optical-radar data for salinization monitoring.

In summary, while integrated multi-source optical and radar data applications in salinization monitoring have achieved certain results, studies on spatiotemporal variation monitoring remain limited. This paper explores the use of multi-source remote sensing and field measurement data to extract effective image features for optimal feature combination, applying random forest classification to identify soil salinization distribution and analyze spatiotemporal characteristics in Yutian Oasis, thereby investigating the capability of microwave and optical data for monitoring soil salinization in arid oasis regions.

1.1 Study Area Overview

Yutian Oasis (36°30 ~37°05 N, 81°09 ~82°03 E) is located on the southern margin of the Taklamakan Desert, at the central part of the northern Kunlun Mountains foothills [Figure 36: see original paper]. It borders Minfeng County to the east, Cele County to the west, and connects with Rutog County in the Tibet Autonomous Region to the south, with an oasis area of approximately 3.95×10^{4} hm^{2}. The terrain slopes from high in the south to low in the north, with significant vertical zonation and a relative elevation difference of 4142 m, forming a "horn-shaped" topography. Seasonal rivers within the oasis originate from the Kunlun Mountains' Keriya River, which flows through Yutian Oasis and disappears into the Taklamakan Desert hinterland. The region suffers from water scarcity and a relatively closed water system. The area features a warm temperate continental arid desert climate with large diurnal temperature variations, a multi-year average temperature of 12.2°C, minimum temperature of -17.6°C, and maximum temperature of 39.4°C. Precipitation is 33.5 mm annually, with strong evaporation. Vegetation types are impoverished, biological community structure is simple, the ecosystem is fragile, and soil salinization is severe.

1.2 Data Sources

1.2.1 Remote Sensing Data Radar data were first selected from the Phased Array type L-band Synthetic Aperture Radar-2 (PALSAR-2) full-polarization data acquired by the Japan Aerospace Exploration Agency' s Advanced Land Observing Satellite-2 (ALOS-2). Additionally, dual-polarization data from the European Space Agency's Sentinel-1A satellite were selected, with imaging dates of [specific dates]. Using the ENVI 5.3 SARscape 5.2.1 module, images underwent multi-looking processing, filtering, geocoding, and radiometric calibration. To maintain consistency with Sentinel-1' s 3 m$\times$3 m resolution, the [specific] polarization mode was selected for polarization combination.

Optical remote sensing data employed Landsat 8 Operational Land Imager (OLI) data, with imaging times of [specific dates]. Detailed parameter information is shown in . Using ENVI 5.3, data preprocessing included radiometric calibration, atmospheric correction, image registration, and resampling to 30$\times$30 m resolution.

1.2.2 Field Data Based on the spatial distribution patterns of soil salinization and ecotones in Yutian Oasis, field sample collection was conducted on [specific dates], yielding 50 representative sampling points distributed as shown in [Figure 1: see original paper]. At each sampling point, 0–20 cm surface soil samples were collected, photographed, and soil type, surrounding vegetation type were recorded to establish a sampling point image library for accuracy assessment. Samples were naturally air-dried, ground, and sieved through a 1.5 mm mesh. Soil samples were mixed with distilled water at a 1:5 soil-water ratio, and electrical conductivity was measured using a conductivity meter at 25°C room temperature. Soil salt content was calculated by constructing an equation between electrical conductivity and total soluble salts.

2 Research Methods

The research workflow involved acquiring field measurement data, optical and radar multi-source data for Yutian Oasis study area. Optical and radar data were fused through feature extraction, J-M distance analysis, and random forest classification to analyze soil salinization, followed by dynamic monitoring of soil salinization changes. The specific technical route is shown in [Figure 2: see original paper].

2.1 Feature Extraction and Analysis

Remote sensing imagery relies on different spectral information to distinguish land cover types, but single feature information cannot provide sufficient discrimination. Fusing different feature information addresses the one-sidedness of single features, aggregating various descriptive information to improve high-resolution image classification accuracy. First, preprocessed optical imagery underwent principal component analysis (PCA). Backscattering features were then extracted from radar imagery and combined. Pearson correlation analysis was used to calculate significance between electrical conductivity (EC) values and backscattering combination features. Based on [Figure 3: see original paper], optimal backscattering feature combinations were selected. Using PCA-processed optical imagery as the base, various classification features were overlaid and combined to establish classification feature datasets (), with the same method applied to obtain consistent classification feature datasets for different years.

2.2 J-M Distance

To quantitatively investigate separability between land cover types under different classification features, J-M distance was used to evaluate training sample separability. J-M distance values range between 0–2, with values approaching 2 indicating better separability between two types. The calculation method is as follows:

$$M = 2(1 - e^{-B})$$

where B represents the Bhattacharyya distance.

Calculation results are shown in . Under Method 3, which combines optical principal component features and Sentinel-1 image polarization combination features, the J-M distance between severe salinization and other land cover types was optimal, indicating good separability when using combined optical and radar data.

2.3 Random Forest Classification

The random forest (RF) algorithm was applied for soil salinization classification. Random forest operates as an ensemble classifier composed of numerous decision trees, offering advantages including fast training speed, strong generalization performance, and model stability. For integrated multi-source remote sensing data with multiple classification features, random forest can effectively improve classification accuracy. Xu et al. compared classification results using different features of polarimetric SAR imagery. Method 2, using only radar imagery, achieved an average overall accuracy of 67.07% after multiple classifications, which was insufficient for land cover discrimination and thus excluded. Following Xinjiang soil salinization classification standards, land cover was categorized into five types: bare land, vegetation, water body, light-moderate salinization, and severe salinization (light-moderate salinization indicates salt-tolerant vegetation coverage, while severe salinization indicates no vegetation coverage with EC > 9.5). This study used high-resolution imagery (Ovital Interactive Map) and the field image library as references for visual interpretation to select training and validation samples. The same validation samples were used for all training samples to enable scientific comparison and analysis of classification results.

3 Results and Analysis

Classification accuracy results show that Method 1 (optical imagery alone) achieved an average overall accuracy of 80.36% with a mean Kappa coefficient of 0.77. Method 3 (combined optical and radar features) achieved an average overall accuracy of 85.62% with a mean Kappa coefficient of 0.82. The feature combination classification outperformed optical remote sensing data alone. Radar imagery' s backscattering coefficient is sensitive to the dielectric constant of salinized soil, which is directly affected by soil salt content. Leveraging this characteristic, combining radar and optical imagery can compensate for radar noise interference in land cover identification, enhancing backscattering coefficient recognition of salinized areas and improving classification accuracy.

3.1 Salinization Identification Accuracy Analysis Based on Multi-source Data

Taking the 2021 classification results as an example, representative regions of Yutian Oasis were selected to compare land cover identification effects under different classification feature conditions. As shown in [Figure 4: see original paper], Region A represents the edge of Yutian Oasis' s two "horns" where desert and salinized areas intersect. This area has high soil salinity with distinct interlaced zones of light-moderate and severe salinization. Region B shows transitional distribution among bare desert, severe salinization, and light-moderate salinization gradually transitioning to water bodies.

The classification results using spectral features alone ([Figure 4a: see original paper]) show scattered misclassified vegetation points on both sides of salinized areas. Backscattering feature classification results ([Figure 4b: see original paper]) more effectively reduce scattered patch occurrence, demonstrating clear boundaries of salinization ecotones. In Region B, where land cover transitions from bare desert through severe and light-moderate salinization to water bodies, the backscattering feature imagery can capture textural information through vegetation canopies using its backscattering coefficient. Combined with optical spectral information, this enhances image separability, eliminates vegetation interference, distinguishes sparse vegetation on lightly salinized areas, and reduces its impact on land cover classification.

3.2 Spatial Dynamic Change Analysis of Soil Salinity

Classification results ([Figure 5: see original paper]) reveal that Yutian Oasis salinization primarily occurs in the northern and southwestern margins at the oasis-desert ecotone, consistent with previous research. Among salinized areas, severe salinization is mainly distributed between the two "horns" in the northern study area and in the lower reaches of the Keriya River basin, forming a transitional pattern toward the Taklamakan Desert. Light-moderate salinization distributes between vegetation and severely salinized soils in strip patterns, primarily because untreated water from drainage canals within the oasis is discharged to the margins, causing severe marginal salinization. Severe and light-moderate salinization areas are interlaced, and regions with high groundwater tables experience significant salinization accumulation due to strong surface evaporation.

Field sampling revealed that salt-tolerant vegetation such as reeds, tamarisk, and halophytic grasses can grow in light-moderate salinized soils, indirectly affecting spectral reflectance of salinized soils in optical imagery. However, backscattering features can penetrate vegetation canopies to capture underlying textural information, enhancing separability and reducing vegetation interference. For salt content information under vegetation cover, microwave scattering models are still needed to invert soil salinity. Therefore, combining passive optical and active microwave remote sensing data represents an ideal method for monitoring soil salinization. Future research should incorporate soil moisture, surface roughness, and soil dielectric constant to better explain soil salt distribution.

3.3 Temporal Series Change Analysis of Soil Salinity

To reflect temporal variation of salinized soil in Yutian Oasis from 2015 to 2021, overlay analysis was performed to obtain spatiotemporal change distribution ([Figure 6: see original paper]). The Sankey diagram intuitively visualizes structural characteristics and transfer relationships among land cover types ([Figure 7: see original paper]). Results show most areas experienced decreasing salinization, though some cultivated land around Karkax Township' s southeastern pastoral villages showed increased salinization. Within the oasis, soil salt content is relatively low under desalination measures. When irrigation and drainage are imbalanced, soluble salt ions move upward through capillary water to accumulate at the surface, forming secondary salinization. In Xiwule Township and Siyike Township northern areas where salinization increased, field investigations and [Figure 36: see original paper] reveal basin topography with relatively high groundwater levels and mineralization. The northern elevation is approximately 200 m lower than the southern area, and the arid climate intensifies evaporation, exacerbating soil salinization.

Due to PALSAR-2 image coverage limitations, the study only conducted classification based on optical imagery. Statistical results of soil salt temporal series changes show that from 2015 to 2021, Yutian Oasis saline land area changed by -6723.31 hm^2, with a change rate of -10.68%, indicating an overall decreasing salinization trend. Light-moderate salinization showed an average annual change of -1526.58 hm^2 (-22.06% rate), while severe salinization showed an average annual change of +405.47 hm^2 (+11.38% rate), indicating a slowly increasing trend. This suggests that severe salinization soil improvement is more difficult, consistent with previous predictions of different salinization degree changes in Yutian Oasis.

4 Conclusions

Taking Yutian Oasis as the study object, this research combined field measurement data with optical and radar data through feature extraction and J-M distance analysis to select optimal classification feature combinations for random forest classification. Main conclusions are:

(1) Random forest classification accuracy under different feature combinations showed optical imagery achieved average overall accuracy of 80.36% (Kappa = 0.77), while the combination of optical principal component features and radar backscattering features achieved average overall accuracy of 85.62% (Kappa = 0.82). Accuracy assessment indicates high classification precision using random forest with these features, demonstrating that adding radar imagery to optical classification represents an effective method for future salinization monitoring.

(2) Spatial dynamic change analysis of soil salinity in Yutian Oasis revealed that salinized areas from 2015 to 2021 were mainly distributed in northern oasis margins and desert-oasis ecotones. Saline land area changes showed gradually decreasing light-moderate salinization, increasing vegetation area, and fluctuating severe salinization (decreasing then increasing). Surface water body changes were not significant, though soil moisture, as the main driver of soil salt movement and change, indirectly affects local soil salt spatial patterns.

(3) Temporal change analysis of soil salinity in Yutian Oasis from 2015 to 2021 showed an overall decreasing salinization trend, with average annual saline land area change of -1120.55 hm^2 and change rate of -10.68%, indicating effective salinization control and improvement.

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