Applicability of MODIS and Landsat Spatiotemporal Fusion Imagery in Soil Salinization Monitoring: A Case Study of the Weigan River-Kuche River Delta Oasis (Postprint)

Authors: Zhao Qiaozhen

Date: 2022-08-08T00:00:00+00:00

Abstract

Remote sensing monitoring of soil salinization relies on high spatiotemporal resolution imagery; however, due to limitations in budget, satellite revisit cycles, and weather conditions, such imagery is difficult to obtain, which restricts the application of acquiring corresponding period remote sensing images based on sampling times for soil salinization monitoring and inversion. To address this issue, we propose fusing MODIS and Landsat imagery to generate high spatiotemporal resolution images for extracting soil salinization information, thereby providing a data reference for soil salinization monitoring research using spatiotemporal imagery. Taking the Weigan River-Kuche River Oasis as the study area, the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM) and the Flexible Spatiotemporal Data Fusion (FSDAF) model were employed to perform spatiotemporal fusion of MODIS and Landsat imagery. Based on the fused image data, a Random Forest (RF) prediction model for soil electrical conductivity (EC) was constructed, and the applicability of spatiotemporal fused imagery in remote sensing monitoring of soil salinization was comparatively analyzed. The results demonstrate that the coefficient of determination (R^2) for consistency between the characteristic band reflectance of ESTARFM fused imagery and the corresponding band reflectance of Landsat validation imagery is R^2(Red)=0.8066 and R^2(SWIR2)=0.8444; for FSDAF fused imagery, the corresponding R^2 values are R^2(Red)=0.6999 and R^2(SWIR2)=0.7493. The EC prediction model constructed based on ESTARFM fused imagery achieved the highest accuracy with R^2=0.9268, the model based on FSDAF fused imagery showed good accuracy with R^2=0.8987, and the model based on validation imagery achieved R^2=0.9103. The fusion accuracy of the ESTARFM model is superior to that of the FSDAF model, and the EC prediction model constructed based on fused imagery demonstrates satisfactory performance.

ChinaRxiv 中X

Full Text

Exploring the Application of MODIS and Landsat Spatiotemporal Fusion Images in Soil Salinization Monitoring: A Case Study of the Ugan River-Kuqa River Delta Oasis

ZHAO Qiaozhen[1,2], DING Jianli[1,2,3], HAN Lijing[1,2], JIN Xiaoye[1,2], HAO Jianping[4]

[1]Key Laboratory of Smart City and Environmental Modeling of Autonomous Region Universities, School of Geography and Remote Sensing Sciences, Xinjiang University, Urumqi 830046, Xinjiang, China
[2]Key Laboratory of Oasis Ecology, Ministry of Education, Xinjiang University, Urumqi 830046, Xinjiang, China
[3]Central Asia Geographic Information Technology Development and Application Engineering Technology Innovation Center, Ministry of Natural Resources, Urumqi 830046, Xinjiang, China
[4]Ugan River Basin Management Office, Aksu Prefecture, Xinjiang, Aksu 842000, Xinjiang, China

Abstract: Remote sensing monitoring of soil salinization relies on high spatiotemporal resolution imagery, yet such data are difficult to obtain due to budget constraints, satellite revisit cycles, and weather conditions. This limitation restricts the acquisition of temporally matched remote sensing images for soil salinization monitoring and inversion based on sampling times. To address this challenge, we propose generating high spatiotemporal resolution images through fusion of MODIS and Landsat imagery to extract soil salinization information, providing a data reference for soil salinization monitoring using spatiotemporal fusion images. Taking the Ugan River-Kuqa River Delta Oasis as the study area, we employed the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM) and Flexible Spatiotemporal Data Fusion (FSDAF) to perform spatiotemporal fusion of MODIS and Landsat images. Based on the fused imagery, we constructed a Random Forest (RF) prediction model for soil electrical conductivity (EC) and comparatively analyzed the applicability of spatiotemporal fusion images for remote sensing monitoring of soil salinization. The results demonstrate that the characteristic band reflectance of the fused images shows strong agreement with the corresponding bands of the verification images, with consistency determination coefficients R^2 reaching 0.8444 for ESTARFM and 0.7493 for FSDAF. The EC prediction model built using ESTARFM fusion images achieved the highest accuracy (R^2 = 0.9268), followed by the model based on FSDAF fusion images (R^2 = 0.8987). This indicates that spatiotemporal fusion technology exhibits excellent application value and development potential in remote sensing monitoring of soil salinization in arid regions.

Keywords: spatiotemporal fusion; random forest; soil electrical conductivity; soil salinization

1.1 Study Area Overview

The Ugan River-Kuqa River Delta Oasis is located in the north-central Tarim Basin in southern Xinjiang, within the administrative region of Aksu Prefecture, covering Shaya County, Kuqa County, and Xinhe County. Based on field sampling areas, the study boundary was defined by geographic coordinates of 81°37 –83°59 E and 41°06 –42°40 N, with elevations ranging from 892 to 1100 m. The region experiences a typical continental warm temperate arid climate with intense evaporation and uneven precipitation distribution. The mountainous area receives an average annual precipitation of 523.76 mm, while the plain area receives only 46.5 mm, with an average annual evaporation of 1374 mm. Land use types primarily include farmland, grassland, forestland, wasteland, and saline land. The main soil types are fluvo-aquic soil and meadow soil, with additional distribution of brown calcic soil, swamp soil, and saline soil. In the lower plains, flat terrain, high groundwater levels, fine-grained subsoil with poor permeability, and strong evaporation cause salts to accumulate at the surface through capillary action, resulting in severe soil salinization. The salinized area within the irrigation district exceeds 40%, with severely salinized land comprising approximately 32.20%. The primary salt components are chlorides. Therefore, this region serves as a representative study area for improving ecological environments and agricultural development. The distribution of sampling points is shown in [Figure 1: see original paper].

1.2 Data Sources and Processing

Field Measurement Data: Field surveys were conducted on May 23–24, 2021. Soil samples were collected using the five-point method within a 30 m × 30 m plot at each sampling point. Five soil samples were taken from the 0–10 cm surface layer, mixed in situ to create representative composite samples, and georeferenced using a Strong G120 GPS. After air-drying and removing impurities, the samples were sieved through a 2 mm mesh. A 1:5 soil-water suspension was prepared by mixing 20 g of soil with 100 mL of deionized water, shaken for 30 minutes, and filtered. Soil electrical conductivity was measured using a WTW Multi 3420 Set B digital multi-parameter device equipped with a Tetra Con 925 electrode (WTW GmbH, Germany). A total of 523 valid samples were obtained after removing outliers.

Remote Sensing Imagery: Landsat and MODIS imagery were obtained from the Google Earth Engine platform. Landsat data comprised the Landsat 8 Collection 2 Tier 1 Surface Reflectance dataset, while MODIS data included the MOD09A1 (500 m surface reflectance, 8-day composite) dataset. Detailed information on the remote sensing data is provided in . All data underwent radiometric and atmospheric correction. Based on field sampling dates and cloud cover conditions, one pair of MODIS and Landsat images from May 2021 was selected for spatiotemporal fusion, with a separate Landsat image serving as verification data. All imagery included six characteristic bands: blue, green, red, near-infrared (NIR), short-wave infrared 1 (SWIR1), and short-wave infrared 2 (SWIR2). Data preprocessing, including compositing, cloud removal, and clipping, was performed on the Google Earth Engine platform. MODIS images were reprojected and resampled to 30 m resolution using ENVI 5.3 to match Landsat' s spatial resolution.

1.3.1 Spatiotemporal Fusion Models

ESTARFM Algorithm: The Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM) is an improved version of the STARFM algorithm, offering high fusion quality and broad applicability. The ESTARFM process involves: (1) identifying similar pixels based on each reference Landsat image, (2) calculating weights for similar pixels, and (3) computing predicted values at time T. The central pixel reconstruction is expressed as:

$$R(x_{i/2}, y_{j/2}, T_{pre}) = \sum_{n=1}^{N} \sum_{m=1}^{M} W_{ijm} \times R(x_i, y_j, T_n) \times T_{weight}$$

where $R(x_{i/2}, y_{j/2}, T_{pre})$ represents the fused high-resolution data at the predicted time, $R(x_i, y_j, T_n)$ denotes the high spatial resolution data from the base time phases, T_{weight} is the temporal weight, and W_{ijm} is the spatial weight. The sliding window size ω was set to 30 pixels in this experiment.

FSDAF Algorithm: The Flexible Spatiotemporal Data Fusion (FSDAF) model combines pixel unmixing with thin-plate spline interpolation and distance weighting, enabling accurate prediction of land cover change areas. The algorithm utilizes known high- and low-resolution images at initial time t_0 and low-resolution images at prediction time t_k to generate high-resolution images at t_k. The process involves: (1) classifying the Landsat image at t_0, (2) estimating temporal changes for each class from t_0 to t_k using MODIS images, (3) computing high-resolution temporal changes at t_k, (4) predicting the high-resolution MODIS image at t_k using class-specific thin-plate spline functions, and (5) calculating residuals based on neighboring information to produce the final Landsat prediction.

1.3.2 Prediction Model Construction

Random Forest (RF) is a statistical learning theory that employs bootstrap resampling to extract multiple samples from the original dataset, constructs decision trees for each sample, and merges predictions through averaging. Different training sets increase diversity among regression models, thereby enhancing extrapolation capability. RF has demonstrated excellent performance in soil salinization prediction. This study implemented the algorithm using Python 3.7, partitioning samples into 70% training and 30% validation sets.

To evaluate model performance, we used coefficient of determination (R^2) as the primary metric, where higher R^2 values indicate greater accuracy. Feature variables contribute differently to EC prediction. Based on the imagery, we extracted six characteristic band reflectances and widely used vegetation and salinity indices. Using EC values as the target variable, we applied the XGBoost algorithm to screen for important features, selecting 6 vegetation indices and 6 salinity indices for modeling. The formulas for these indices are provided in .

3.1 Fusion Results and Accuracy Assessment

Visual interpretation was performed through false-color composite comparison. Both ESTARFM and FSDAF produced well-fused images with clear textures and accurate representation of water bodies, farmland, and roads, showing good spatial consistency with the original Landsat imagery. Detailed pixel-level comparison reveals that ESTARFM achieved higher fusion accuracy across all bands.

Quantitative accuracy assessment shows that the ESTARFM model achieved R^2 values of 0.8066 for the red band and 0.8444 for SWIR2, while FSDAF achieved 0.6999 and 0.7493, respectively . Both models performed best in the SWIR2 band and worst in the green band. Scatter plots [Figure 3: see original paper] and [Figure 4: see original paper] demonstrate strong linear relationships between fused and verification images, with ESTARFM showing superior performance. The SWIR2 band, which is sensitive to soil salinization information, exhibited R^2 values of 0.8444 for ESTARFM and 0.7493 for FSDAF, indicating robust fusion effectiveness.

3.2 Spectral Reflectance at Different EC Levels

To visualize the relationship between measured soil EC values and spectral reflectance from the spatiotemporal fusion images, spectral curves were plotted according to salinization levels [Figure 5: see original paper]. For both fusion models, soil spectral reflectance increased with EC across all bands. The ESTARFM fusion image showed the lowest reflectance for non-salinized soils (0–2 $mS \cdot cm^{-1}$) and highest reflectance for saline soils ($>16\ mS \cdot cm^{-1}$). Reflectance increased sharply from the red band, peaking in the SWIR1 band. The FSDAF fusion image exhibited similar trends, though with slightly lower overall accuracy. The consistent spectral response patterns confirm the reliability of both fusion approaches for capturing salinization characteristics.

3.3 Prediction Model Accuracy Assessment

Soil electrical conductivity effectively reflects salinization degree. Across all samples, EC ranged from 0.0476 to 108.7 $mS \cdot cm^{-1}$. After removing 6 outliers, 517 samples remained, with 362 used for training and 155 for validation. The study employed 6 characteristic bands and 12 spectral indices as input features, with 5-fold cross-validation for model verification.

Comparative analysis of prediction models [Figure 6: see original paper] reveals that the ESTARFM-based EC prediction model achieved the highest accuracy ($R^2 = 0.9268$), followed by the Landsat verification image model ($R^2 = 0.9103$) and the FSDAF-based model ($R^2 = 0.8987$). These results demonstrate that both spatiotemporal fusion models can effectively generate high-resolution imagery for soil salinization monitoring, with ESTARFM showing superior performance.

4 Discussion

Real-time fine-scale monitoring of land surface and atmospheric environments requires high spatiotemporal resolution remote sensing data. The ESTARFM model, as an improvement over STARFM, enhances prediction accuracy and applicability for heterogeneous regions. In this study, ESTARFM demonstrated higher fusion accuracy for salinization-sensitive bands and better EC fitting precision compared to FSDAF. While FSDAF integrates pixel unmixing with thin-plate spline interpolation and performs well for abrupt land cover changes such as flood monitoring, soil salinization is a gradual process where ESTARFM' s advantages are more pronounced.

To ensure that point-scale sampling represents areal salinization patterns, we designed a representative sampling scheme using MODIS data, topographic derivatives (slope and topographic wetness index), and soil texture data. Each 30 m × 30 m sampling plot was matched to corresponding remote sensing pixels after resampling, ensuring prediction accuracy. Although current spatiotemporal fusion algorithms cannot perfectly predict subtle land cover changes, continuous improvements enhance their reliability. The use of Google Earth Engine for data acquisition and preprocessing significantly improved efficiency, demonstrating the practical value of cloud platforms for soil salinization monitoring.

Future research should explore more advanced spatiotemporal fusion algorithms specifically optimized for soil salinization feature extraction. The integration of multi-source data and machine learning approaches offers substantial potential for improving monitoring precision and practical applicability in arid regions.

5 Conclusions

Both ESTARFM and FSDAF models successfully generated high spatiotemporal resolution images from MODIS and Landsat data. Visual interpretation confirmed clear spatial details and good consistency with verification imagery, indicating satisfactory fusion results. The models showed varying performance across bands, likely due to inherent algorithmic differences.

The ESTARFM-based EC prediction model achieved the highest accuracy ($R^2 = 0.9268$), while the FSDAF-based model also performed well ($R^2 = 0.8987$). Spectral curves clearly distinguished different salinization levels, with reflectance increasing with EC. This study demonstrates that spatiotemporal fusion technology holds excellent application value and development potential for soil salinization remote sensing monitoring. Comparative analysis indicates that ESTARFM fusion images are more suitable for salinity prediction than FSDAF. Further exploration of spatiotemporal fusion applications will enhance remote sensing data utilization and improve the economic efficiency and practical utility of salinization monitoring.

References:

[1] Wu Yakun, Liu Guangming, Su Litan, et al. Accurate evaluation of regional soil salinization using multi source data[J]. Spectroscopy and Spectral Analysis, 2018, 38(11): 3528-3533.

[2] Han L J, Ding J L, Zhang J Y, et al. Precipitation events determine the spatiotemporal distribution of playa surface salinity in arid regions: Evidence from satellite data fused via the enhanced spatial and temporal adaptive reflectance fusion model[J]. Catena, 2021, 206: 105546, doi: 10.1016/J.CATENA.2021.105546.

[3] Zhu X L, Chen J, Gao F, et al. An enhanced spatial and temporal adaptive reflectance fusion model for complex heterogeneous regions[J]. Remote Sensing of Environment, 2010, 114(11): 2610-2623.

[4] Huang Bo. Research progress and trend of spatial and temporal remote sensing image fusion[J]. Journal of Sichuan Normal University (Natural Science Edition), 2020, 43(4): 427-434, 424.

[5] Hilker T, Wulder M A, Coops N C, et al. A new data fusion model for high spatial and temporal resolution mapping of forest disturbance based on Landsat and MODIS[J]. Remote Sensing of Environment, 2009, 113(8): 1613-1627.

[6] Zhao Y Q, Huang B, Song H H. A robust adaptive spatial and temporal image fusion model for complex land surface changes[J]. Remote Sensing of Environment, 2018, 208: 42-62.

[7] Meng L H, Liu H J, Ustin S L, et al. Assessment of FSDAF accuracy on cotton yield estimation using different MODIS products and landsat based on the mixed degree index with different surroundings[J]. Sensors (Basel, Switzerland), 2021, 21(15): 5184, doi: 10.3390/S21155184.

[8] Ma Qianqian, Dong Bo, Xu Wangwang, et al. Evaluation of cultivated land quality and analysis of soil nutrients and salinization in arid areas: Taking Minqin Oasis as an example[J]. Arid Land Geography, 2021, 44(2): 514-524.

[9] Liu Fei, Chen Peiyuan, Yu Haichao, et al. Spatial distribution characteristics of soil water and salt under different land use types in Minqin Oasis[J]. Arid Land Geography, 2020, 43(2): 406-414.

[10] Wei Yang, Ding Jianli, Wang Fei. Optimal scale analysis of soil salinity prediction in oasis irrigated area of arid land based on Landsat OLI[J]. Scientia Agricultura Sinica, 2017, 50(15): 2969-2982.

[11] Wang Fei, Ding Jianli, Wei Yang, et al. Sensitivity analysis of soil salinity and vegetation indices to detect soil salinity variation by using Landsat series images: Applications in different oases in Xinjiang, China[J]. Acta Ecologica Sinica, 2017, 37(15): 5007-5022.

[12] Li Chao, Li Xuemei, Tian Yalin, et al. Time and space fusion model comparison of temperature vegetation drought index[J]. Remote Sensing Technology and Application, 2020, 35(4): 832-844.

[13] Chen Hongyan, Zhao Gengxing, Cheng Jingchun, et al. Remote sensing inversion of saline soil salinity based on modified vegetation index in estuary area of Yellow River[J]. Transactions of the Chinese Society of Agricultural Engineering, 2015, 31(5): 107-114.

[14] Shi Chenlie, Wang Xuhong, Zhang Meng. Analysis of the applicability of three remote sensing spatiotemporal fusion algorithms in flood monitoring[J]. Remote Sensing for Land and Resources, 2020, 32(2): 111-119.

[15] Wang Shuang, Wang Chengwu, Zhang Feiyun. Spatiotemporal variations of the summer daytime surface urban heat island of oasis city in arid area based on FSDAF model[J]. Arid Land Geography, 2021, 44(1): 118-130.

[16] He Zhenzhen, Wang Hongwei, Yang Shengtian, et al. Spatiotemporal differentiation and pattern optimization of landscape ecological security in the Ugan-Kuqa River oasis[J]. Acta Ecologica Sinica, 2019, 39(15): 5473-5482.

[17] Fan Yanguo, Zhang Weikang, Liu Jingyi. Remote sensing monitoring model of soil salinization in the Yellow River Delta Zone based on vegetation index-salt index feature space[J]. Shandong Agricultural Sciences, 2016, 48(5): 137-141.

[18] Cao Lei, Ding Jianli, Halik Umut, et al. Extraction and modeling of regional soil salinization information based on variable optimized selection and machine learning[J]. Transactions of the Chinese Society of Agricultural Engineering, 2020, 36(19): 124-131.

[19] Ma Guolin, Ding Jianli, Han Lijing, et al. Digital mapping of soil salinization in arid area wetland based on variable optimized selection and machine learning[J]. Acta Pedologica Sinica, 2016, 53(6): 1399-1409.

[20] Lobell D B, Lesch S M, Corwin D L, et al. Regional scale assessment of soil salinity in the Red River Valley using multi-year MODIS EVI and NDVI[J]. Journal of Environmental Quality, 2010, 39(1): 35-41.

[21] Zheng Yudong, Xu Yuncheng, Yan Haijun, et al. Analysis of influencing factors in wheat/maize canopy RVI and NDVI acquisition using ground based remote sensing system[J]. Spectroscopy and Spectral Analysis, 2021, 41(8): 2578-2585.

[22] Zhang Xiaochuan, Wang Jie. The analysis of eco-hydrological structure of Shengjin Lake Wetland based on spatial and temporal fusion technology of

remote sensing[J]. Remote Sensing Technology and Application, 2020, 35(5): 1109-1117.

[23] Ma Guolin. Estimation of soil salinity in Weigan-Kuqa Oasis coupling multi-source sensors and machine learning algorithms[D]. Urumqi: Xinjiang University, 2021.

[24] Kamh G M E, Ismael B, Oguchi C T. Pore size distribution and wall side orientation controlling salt susceptibility index and weathering rate of stratified pharaonic rock art[J]. Restoration of Buildings and Monuments, 2013, 19(5): 341-362.

[25] Sahana M, Rehman S, Patel P P, et al. Assessing the degree of soil salinity in the Indian Sundarban Biosphere Reserve using measured soil electrical conductivity and remote sensing data derived salinity indices[J]. Arabian Journal of Geosciences, 2020, 13(24): 1289, doi: 10.1007/S12517-020-06310-W.

[26] Nguyen K A, Liou Y A, Tran H P, et al. Soil salinity assessment by using near infrared channel and vegetation soil salinity index derived from Landsat 8 OLI data: A case study in the Tra Vinh Province, Mekong Delta, Vietnam[J]. Progress in Earth and Planetary Science, 2020, 7(1): 1-16.

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