Deep Learning-Based Multi-Temporal Land Use Change Monitoring in Cold and Arid Regions: A Case Study of the Mosuowan Reclamation Area, Xinjiang (Postprint)

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Abstract

Conducting research on land feature extraction and land cover change monitoring in ecologically fragile cold and arid regions holds significant importance for agricultural planning, urban and rural construction, as well as ecological environment monitoring and protection. Utilizing Landsat-8 imagery from 2015-2019 for the Mosuowan Reclamation Area in Xinjiang to construct a dataset, this study compared three traditional methods: Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Random Forest (RF), along with five semantic segmentation models: DeepLabv3+ (Xception), DeepLabv3+ (MobileNet), SegNet (ResNet50), U-Net (MobileNet), and PSPNet (MobileNet). The optimal automated land feature extraction model was selected to classify four land feature types—agricultural land, construction land, water bodies, and desert—in the study area from 1998-2020, and quantitative dynamic change analysis was conducted using a land use transfer matrix and dynamic degree. The results demonstrate that the DeepLabv3+ (Xception) model can achieve more accurate and efficient land feature extraction, with Overall Accuracy (OA), Kappa coefficient, and F1 score of 96.06%, 0.96, and 0.86, respectively. The Mean Intersection over Union (MIoU) of the selected model improved by 0.03-0.39 compared to other models. Over the past 23 years, land structure transformation among desert, agricultural land, and construction land in the Mosuowan Reclamation Area has been notable, with total desert area decreasing by 15.00%, total agricultural land area increasing by 12.68%, total construction land area increasing by 2.53%, and water body area remaining relatively stable. The overall direction of land feature type transformation is conversion from desert to agricultural land and from agricultural land to construction land. This study can provide a reference for applying deep learning technology to medium-resolution remote sensing satellite imagery for dynamic monitoring of land use and change.

Full Text

Dynamic Monitoring of Land Use and Change in Cold and Arid Regions Based on Deep Learning: A Case Study of the Mosuowan Reclamation Area in Xinjiang

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Abstract

Research on ground feature extraction and land cover change monitoring in ecologically fragile cold and arid regions holds significant importance for agricultural planning, urban-rural development, and ecological environment monitoring and protection. Using Landsat-8 imagery from 2015 to 2019 for the Mosuowan reclamation area in Xinjiang, we constructed a dataset and compared three traditional methods—Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Random Forest (RF)—with five semantic segmentation models: DeepLabv3+ (Xception), DeepLabv3+ (MobileNet), SegNet (ResNet50), U-Net (MobileNet), and PSPNet (MobileNet). The DeepLabv3+ (Xception) model achieved the most accurate and efficient feature extraction, with an overall accuracy of 96.06%, Kappa coefficient of 0.96, precision of 87.69%, recall of 83.78%, F1-score of 0.86, and mean intersection over union (MIoU) of 0.77. The MIoU was 0.03–0.39 higher than other models. We then applied the optimal model to classify four typical land cover types—agricultural land, construction land, water bodies, and desert—from 1998 to 2020, and conducted quantitative dynamic change analysis using land use transfer matrices and dynamic degree metrics. Results show that from 1998 to 2020, desert area decreased by 15.00%, agricultural land increased by 12.68%, construction land increased by 2.53%, and water area remained relatively stable. The overall transformation direction was from desert to agricultural land, and from agricultural land to construction land. This study provides a reference for applying deep learning technology to medium-resolution remote sensing imagery for dynamic monitoring of land use and change.

Keywords: remote sensing image; long time-series; deep learning; DeepLabv3+; feature classification; dynamic monitoring

1 Introduction

Rapid advancements in remote sensing technology have created new opportunities for land use and cover change (LUCC) monitoring. Timely and accurate monitoring of land use changes in ecologically fragile arid regions is crucial for supporting agricultural planning, urban-rural development, and environmental management. Traditional pixel-based machine learning algorithms such as Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Random Forest (RF) rely on spectral and textural information but often suffer from "same object with different spectra,""different objects with same spectrum," and salt-and-pepper noise effects. Object-Based Image Analysis (OBIA) methods face challenges including manual parameter adjustment for segmentation and lack of contextual guidance.

In recent years, deep learning has demonstrated significant potential for mining massive remote sensing datasets. The development of Fully Convolutional Networks (FCN) replaced fully connected layers with convolutional layers, enabling superior feature extraction and subsequent improved semantic segmentation models. The DeepLab series has continuously evolved, with the latest DeepLabv3+ model employing an encoder-decoder architecture and Atrous Spatial Pyramid Pooling (ASPP) modules to extract multi-scale feature maps while incorporating contextual information. This approach overcomes limitations of traditional methods by restoring spatial details and enabling more complete feature representation. Scholars have successfully applied semantic segmentation networks for single or multi-feature classification tasks, achieving high localization and recognition accuracy.

However, several research gaps remain. Traditional machine learning algorithms exhibit low automation levels, requiring frequent human interaction in long time-series classification tasks, which limits both accuracy and efficiency. While some studies have applied deep learning to remote sensing change detection using dual-temporal images, research on multi-temporal land cover classification followed by change monitoring remains limited. Manual field monitoring is costly and inefficient with lagging information updates. Combining remote sensing imagery with deep learning algorithms offers a more effective and feasible approach for automated feature extraction. Cross-temporal studies spanning over 20 years are particularly scarce. Therefore, this study employs Landsat series satellite imagery from 1998 to 2020 to create a land cover classification dataset, compares three traditional methods with five semantic segmentation models, selects the optimal network for multi-temporal feature extraction, and quantitatively analyzes spatial structure changes and driving factors to provide references for natural resource monitoring and government decision-making in cold and arid regions.

2 Study Area and Data Sources

2.1 Study Area Overview

The Mosuowan reclamation area (85°52'–86°19' E, 44°23'–45°12' N) is located in the Tianshan North Slope Economic Belt of Xinjiang, along the southern margin of the Gurbantünggüt Desert and distributed along the Shimo Highway. Covering approximately 14,500 km^2, the area includes the 147th, 148th, and 149th regimental farms of the Xinjiang Production and Construction Corps, with priority development zones for chemical and new material industries. The agricultural structure is dominated by cotton cultivation, supplemented by forestry and facility agriculture. The region features a typical temperate continental arid climate with flat terrain. As an irrigated agricultural zone with abundant cultivated land resources, it represents one of Xinjiang' s primary cotton production areas with dense urban distribution and a rational industrial structure, making it a key economic development zone [Figure 1: see original paper].

2.2 Data Sources

Experimental data include Landsat series satellite imagery from 1998–2020 (Table 1) and vector land use data for the Mosuowan reclamation area. Satellite data were obtained from the Geospatial Data Cloud (https://www.gscloud.cn) and USGS (https://earthexplorer.usgs.gov). With a short revisit cycle of 16 days, Landsat data provide abundant selection options. Images from the crop growing season (May–September) were selected when vegetation spectral and textural features are easily distinguishable from other features. Images with cloud cover below 10% were chosen; one 2011 image had 6.45% cloud cover. The full image size is 1133$×$2874 pixels.

3 Methodology

3.1 Technical Workflow

The technical workflow is illustrated in Figure 2. First, Landsat series images underwent preprocessing and dataset creation. Comparative experiments between traditional methods and semantic segmentation models were conducted to select the best-performing model, ensuring reliable land classification results. Second, the optimal feature extraction model was applied to classify four typical land cover types (agricultural land, construction land, water bodies, and desert) across multiple years, validating the method' s effectiveness and applicability while generating thematic maps for visualization. Finally, land use transfer matrices and dynamic degree metrics were calculated from classification results to analyze spatial distribution characteristics and monitor changes in ground features across the cold and arid region.

3.2 Data Preprocessing and Dataset Creation

3.2.1 Data Preprocessing Preprocessing steps included radiometric calibration, atmospheric correction, study area clipping, and data format conversion. Landsat-7 ETM+ images exhibited data gaps, which were repaired using ENVI 5.5.2' s landsat_{gapfill} tool for spatial interpolation; the repaired data had minimal impact on classification accuracy. Due to hardware limitations, the full-size images were divided into smaller patches. Considering computational constraints, patch size was set to 416$×$416 pixels, yielding 1,000 image blocks after segmentation. Blank patches were filtered out, resulting in a final dataset of 630 image blocks.

3.2.2 Dataset Creation Based on Landsat spatial resolution and regional land cover distribution, and referencing the "Current Land Use Classification" standard (GB/T21010-2017), land cover types were categorized into five classes: construction land, agricultural land, water bodies, desert, and background (Table 2). Visual interpretation was performed on Google Earth imagery using the LabelMe annotation tool, with annotations converted to color-coded masks. Spectral and textural interpretation keys were established: urban built-up areas appear as compact white blocks with some red/blue spots; desert appears brown/yellow in irregular patches; agricultural land appears dark green in large continuous irregular shapes; water bodies show varying green tones in fixed continuous areas with clear boundaries.

3.2.3 Data Augmentation To address overfitting from limited samples, two-stage data augmentation was applied. The first stage, before model training, used image rotation, Gaussian noise perturbation, and small sample copying to expand the dataset to 1,224 images. The second stage, during training, employed random color jittering, scaling, and horizontal flipping in the data generator, further enhancing model robustness. The final dataset comprised 918 training images, 204 validation images, and 102 test images.

3.3 DeepLabv3+ Model Architecture

The DeepLabv3+ model (Figure 3) employs an encoder-decoder architecture [19]. The encoder uses DeepLabv3+ with serial followed by parallel atrous convolution for feature extraction. Parallel atrous convolutions with different dilation rates enable multi-scale feature resampling to encode global context features. Atrous convolution expands the receptive field without increasing parameters, balancing accuracy and computational speed. The decoder upsamples encoder output features 4× using bilinear interpolation, concatenates them with low-level features from the serial atrous convolution output to fuse high-level and low-level information, then applies another 4× bilinear upsampling to obtain final classification results.

The model combines atrous convolution with depthwise separable convolution into atrous separable convolution, applied in the ASPP module and decoder structure. This combination maintains classification accuracy while reducing computational load. The Xception backbone aims to improve performance, while MobileNet reduces parameters to increase speed but with less significant improvement in feature extraction effectiveness. Comparison shows that with the same depthwise separable convolution structure, Xception provides superior feature extraction.

3.4 Experimental Environment and Parameters

All five network models were implemented on the Keras deep learning platform with TensorFlow backend. The hardware platform included an Intel Xeon Silver 4110 CPU @ 2.10GHz and NVIDIA Quadro P4000 GPU. Key hyperparameters were set as: learning rate = 0.001, learning rate decay exponent = 0.9, epochs = 100, patience = 10 for learning rate updates, and batch size = 4.

3.5 Evaluation Metrics

Six metrics based on the confusion matrix were selected: Overall Accuracy (OA), Kappa coefficient, precision, recall, F1-score, and Mean Intersection over Union (MIoU). Kappa coefficient measures consistency between predictions and ground truth. F1-score is the harmonic mean of precision and recall. MIoU calculates the intersection-over-union for each class and averages across all classes. Formulas are as follows:

$$\text{OA} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{precision} = \frac{TP}{TP + FP}$$

$$\text{recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{MIoU} = \frac{1}{n} \sum_{i=1}^{n} \frac{TP_i}{FP_i + FN_i + TP_i}$$

$$\text{Kappa} = \frac{p_o - p_e}{1 - p_e}$$

where TP = true positive, TN = true negative, FP = false positive, FN = false negative, and p_o, p_e are observed and expected agreements.

3.6 Change Detection Methods

3.6.1 Land Use Transfer Matrix The transfer matrix reveals conversion relationships between land cover types across different periods and quantifies transition rates, representing a Markov model application in LUCC monitoring. Using classification results, the transfer matrix was computed in SILVAS software as:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

where a_{mn} represents the area (km^2) of land type m in the initial period converting to type n in the final period.

3.6.2 Dynamic Degree The single land use dynamic degree quantitatively shows the evolution process, change speed, and intensity:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%$$

where K is the annual change rate (%/year), U_a and U_b are the initial and final areas (km^2), and T is the time period (years).

4 Results

4.1 Model Performance Comparison

4.1.1 Quantitative Comparison To validate model effectiveness, we compared three traditional algorithms and five semantic segmentation models on the same test set (Table 3). Traditional machine learning methods ignore deep semantic information and rely heavily on human interaction, resulting in lower overall accuracy. Deep learning models, trained on specific datasets, enable batch processing of remote sensing images with higher automation and better extraction of high-level semantic features. DeepLabv3+ (Xception) demonstrated clear superiority with OA = 96.06%, Kappa = 0.96, precision = 87.69%, recall = 83.78%, F1-score = 0.86, and MIoU = 0.77, outperforming other models by 0.03-0.39 in MIoU. This indicates superior capability for extracting typical features from medium-resolution satellite imagery.

To verify model applicability, we tested on non-dataset images from 1998-2020. Manual visual interpretation was performed on Google Earth, and confusion matrices were calculated against model predictions (Table 5). Validation results show that test data from different years achieved accuracy close to the training data, confirming the model' s generalizability.

4.1.2 Visual Comparison of Classification Effects Figure 4 compares classification results from five models on identical dataset patches, showing original images, ground truth labels, and predictions. DeepLabv3+ (Xception) employs multi-scale feature fusion, enhancing extraction across scales and producing clear, complete boundary delineation. The model excels in three aspects: (1) more accurate extraction of small agricultural plots (patches A, D); (2) more coherent extraction of narrow, elongated construction land (patches B, C, E); and (3) finer edge details for fragmented desert areas (patches A, D, F). Compared with other models, it shows fewer misclassifications and more accurate edge extraction, faithfully reproducing the actual land cover distribution.

Other models showed deficiencies: SegNet (ResNet50) and U-Net (MobileNet) failed to maintain network coherence for small features; PSPNet (MobileNet) lacked rich spatial information decoding and exhibited salt-and-pepper noise; MobileNet-based models, while computationally efficient, sacrificed feature extraction quality.

4.2 Dynamic Change Analysis

4.2.1 Overall Temporal Changes Classification results from 23 images (excluding 2011) show that from 1998–2020, total agricultural land area increased by 12.68% (185.20 km^2), desert decreased by 15.00% (162.43 km^2), construction land increased by 2.53% (11.49 km^2), and water area fluctuated only 2.49% (4.65 km^2). These changes align with regional population growth and economic development.

4.2.2 Temporal Structure Variation Thematic maps for 1998, 2008, and 2020 visualize spatial patterns (Figure 6). Agricultural land dominates, followed by desert concentrated in central-northern areas. Water bodies are primarily distributed in the south, while construction land scatters throughout near agricultural land and water. Notable transformations include: desert reclamation to farmland ("retreating desert, advancing oasis") with agricultural land expanding from sparse to continuous patches; construction land expanding outward from 1998 centers; and water area remaining stable despite minor fluctuations.

4.2.3 Transfer Matrix and Dynamic Degree Analysis The 1998–2020 land use transfer matrix (Table 6) quantifies conversion relationships. Desert converted to agricultural land at a rate of 95.12% (1059.85 km^2), while agricultural land primarily transferred to construction land (25.58% of total transfers, 61.21 km^2) and desert (65.32%). Construction land mainly transferred to agricultural land (7.17%). Water bodies primarily transferred to desert, influenced by precipitation—shallow reservoir sections converted to desert during low-rainfall years (e.g., 2008 precipitation was 30% below average).

Dynamic degree analysis (Table 7) reveals construction land had the highest change rate at 7.17%/year, increasing 11.49 km^2. Agricultural land grew at 1.76%/year, adding 185.20 km^2. Desert decreased at -1.01%/year, losing 162.43

km^2. Water area changes were minimal. The change intensity of agricultural land was higher in 1998-2008 than 2008-2020, while construction land showed the opposite trend, reflecting national development policies: the 2000 Western Development Strategy, 2010 counterpart assistance programs, and post-2015 urbanization acceleration.

5 Conclusions

This study integrates medium-resolution satellite remote sensing with deep learning for land cover classification and quantitative change analysis using transfer matrices and dynamic degree metrics. Key conclusions are:

1) Compared with traditional machine learning, deep learning achieves higher segmentation accuracy and automation. DeepLabv3+ (Xception) performed optimally, with MIoU 0.03-0.39 higher than other models. The model' s multi-scale feature fusion advantages enable superior results for both large-scale (agricultural land, desert) and small-scale (construction land) features.

2) From 1998-2020, Mosuowan reclamation area exhibited distinct land cover changes: agricultural land increased 12.68% (185.20 km^2), desert decreased 15.00% (162.43 km^2), construction land increased 2.53% (11.49 km^2), and water area remained stable. The primary transformation was desert→agricultural land→construction land, with desert-to-farmland conversion reaching 95.12%, indicating effective desertification control. Construction land expansion accelerated after 2010, primarily around urban peripheries and industrial parks.

This research demonstrates the potential of deep learning for feature extraction and dynamic monitoring. Future work will focus on incorporating temporal resolution information into network architectures and improving algorithm efficiency while maintaining accuracy, to enable efficient and accurate monitoring of spatial resources in cold and arid regions for macro-level decision-making.

References

[1] Dong Jinwei, Wu Wenbin, Huang Jianxi, et al. State of the art and perspective of agricultural land use remote sensing information extraction[J]. Journal of Geo-information Science, 2020, 22(4): 772-783.

[2] Gaur S, Mittal A, Bandyopadhyay A, et al. Spatio-temporal analysis of land use and land cover change: A systematic model inter-comparison driven by integrated modelling techniques[J]. International Journal of Remote Sensing, 2020, 41(23): 9229-9255.

[3] Chen Jinsong, Han Yu, Chen Gong, et al. Land utilization mapping in Guangdong Province based on integration of optical and SAR remote sensing data[J]. Acta Ecologica Sinica, 2014, 34(24): 7233-7242.

[4] Li Lu, Sun Guili, Lu Haiyan, et al. Spatial-temporal variation and driving forces of ecological vulnerability in Kashi Prefecture[J]. Arid Land Geography, 2021, 44(1): 277-288.

[5] Huang B, Zhao B, Song Y M. Urban land use mapping using a deep convolutional neural network with high spatial resolution multi-spectral remote sensing imagery[J]. Remote Sensing of Environment, 2018, 214: 73-86.

[6] Song Dejuan, Zhang Chengming, Yang Xiaoxia, et al. Extracting winter wheat spatial distribution information from GF-2 image[J]. Journal of Remote Sensing, 2018, 24(5): 596-608.

[7] Noi P T, Kappas M. Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using Sentinel-2 imagery[J]. Sensors, 2018, 18(1): 7233-7242.

[8] Son S, Park S, Lee S, et al. An assessment of support vector machine for land cover classification over South Korea[J]. Earth Resources and Environmental Remote Sensing/GIS Applications X, 2019, 19(10): 2308.

[9] Zhang C, Yue P, Tapete D, et al. A multi-level context guided classification method with object-based convolutional neural network for land cover classification using very high resolution remote sensing images[J]. International Journal of Applied Earth Observation and Geoinformation, 2020, 88: 102086.

[10] Sun Kun, Lu Tieding. Research on FNEA object-oriented classification based on multi-scale partition parameters[J]. Bulletin of Surveying and Mapping, 2018(3): 43-48.

[11] Zhu X X, Devis T, Mou L C, et al. Deep learning in remote sensing: A comprehensive review and list of resources[J]. IEEE Geoscience and Remote Sensing Magazine, 2017, 5(4): 8-36.

[12] Wang Chuanjian, Zhao Qingzhan, Ma Yongjian, et al. Crop identification of drone remote sensing based on convolutional neural network[J]. Transactions of the Chinese Society for Agricultural Machinery, 2019, 50(11): 161-168.

[13] Vali Ava, Comai Sara, Matteucci Matto. Deep learning for land use and land cover classification based on hyperspectral and multi-spectral earth observation data: A review[J]. Remote Sensing, 2020, 12(15): 2495.

[14] Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2015, 39(4): 640-651.

[15] Badrinarayanan V, Kendall A, Cipolla R. SegNet: A deep convolutional encoder-decoder architecture for image segmentation[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017, 39(12): 2481-2495.

[16] Ronneberger O, Fischer P, Brox T. U-Net: Convolutional networks for biomedical image segmentation[C]//Proceedings of Medical Image Computing and Computer-Assisted Intervention. Heidelberg: Springer, 2015: 234-241.

[17] Zhao H, Shi J, Qi X, et al. Pyramid scene parsing network[C]//Proceedings of 2017 IEEE Conference on Computer Vision and Pattern Recognition. USA: IEEE, 2017: 6230-6239.

[18] Chen L C, Papandreou G, Kokkinos I, et al. DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2018, 40(4): 834-848.

[19] Chen L C, Papandreou G, Schroff F, et al. Rethinking atrous convolution for semantic image segmentation[J]. CoRR, 2017, abs/1706.05587.

[20] Chen L C, Zhu Y K, Papandreou G, et al. Encoder-decoder with atrous separable convolution for semantic image segmentation[C]//Proceedings of European Conference on Computer Vision. Munich: Springer, 2018: 833-851.

[21] Xu Huimin, Qi Hua, Nan Ke, et al. High resolution remote sensing image classification by combining deep learning with nDSM[J]. Bulletin of Surveying and Mapping, 2019(8): 63-67.

[22] Yang Jianyu, Zhou Zhenxu, Du Zhenrong, et al. Rural construction land extraction from high spatial resolution remote sensing image based on SegNet semantic segmentation model[J]. Transactions of the Chinese Society of Agricultural Engineering, 2019, 35(5): 259-266.

[23] Liu Wenyan, Yue Anzhi, Ji Jue, et al. Urban green space extraction from GF-2 remote sensing image based on DeepLabv3+ semantic segmentation model[J]. Remote Sensing for Land & Resources, 2020, 32(2): 124-133.

[24] Gu Lian. Detection for buildings and their changes in remote sensing images based on deep learning[D]. Hangzhou: Zhejiang Gongshang University, 2018.

[25] Venugopal N. Automatic semantic segmentation with deeplab dilated learning network for change detection in remote sensing images[J]. Neural Processing Letters, 2020, 51(3): 2355-2377.

[26] Liu R Y, Kuffer M, Persello C. The temporal dynamics of slums employing a CNN based change detection approach[J]. Remote Sensing, 2019, 11(23): 2844.

[27] Ji Shunping, Tian Siqi, Zhang Chi. Urban land cover classification and change detection using fully atrous convolutional neural network[J]. Geomatics and Information Science of Wuhan University, 2020, 45(2): 233-241.

[28] Deng Mingjiang. Development pattern of production-living-ecological spaces and construction of a smart water network system for the economic belt on the north slope of the Tianshan Mountains[J]. Arid Land Geography, 2020, 43(5): 1155-1168.

[29] Han Huiran, Yang Chengfeng, Song Jinping. The spatial-temporal characteristic of land use change in Beijing and its driving mechanism[J]. Economic Geography, 2015(5): 148-154.

[30] Ma Xinping, Han Shenshan, Wang Lei, et al. Spatial and temporal evolution of land use types in the greater Xi' an area[J]. Arid Land Geography, 2020, 43(2): 499-507.

[31] Tian Yanjun, Shi Ying, Shuai Yanmin, et al. Land cover information retrieval from temporal features based on remote sensing images[J]. Arid Land Geography, 2021, 44(2): 450-459.

[32] Bai Yanying, Gao Julin, Zhang Baolin. Extraction of crop planting structure based on time series NDVI of Landsat 8 images[J]. Arid Land Geography, 2019, 42(4): 893-901.

[33] Yan Caihong, Zhou Long, Tang Zhen, et al. Study on temperature characteristic change and daily minimum temperature forecast of dongzao in Mosuowan reclamation area[J]. Journal of Zhejiang Agricultural Sciences, 2018, 59(3): 445-448.

[34] Chen Xi, Chang Cun, Bao Anming, et al. Spatial pattern and characteristics of land cover change in Xinjiang since past 40 years of the economic reform and opening up[J]. Arid Land Geography, 2020, 43(1): 1-11.

[35] Guo Fei, Chen Wanshan, Wu Xueqin, et al. Statistical yearbook of Division 8 of the Xinjiang Production and Construction Corps: 2019[M]. Beijing: China Statistical Publishing House, 2019: 49-52.

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