Postprint: Extraction of Vegetation and Land Cover Types in Arid Regions Based on GEE Multi-Source Remote Sensing Data

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Abstract

The Nuomuhong region is a significant goji berry cultivation base in Qinghai Province, where accurate and rapid extraction of major vegetation types is crucial for sustainable development of the cultivation industry. However, as an arid region, Nuomuhong exhibits characteristics of sparse vegetation cover and pronounced soil background interference, which renders the use of limited remote sensing sources or partial features insufficient for vegetation extraction in arid areas. Therefore, integrating multiple remote sensing data sources, excavating significant features for vegetation classification, and experimenting with various classification optimization methods hold great significance for enhancing the accuracy and reliability of vegetation classification in arid regions. This study, based on the Google Earth Engine (GEE) platform, utilizes Sentinel-1 Synthetic Aperture Radar (SAR) data and Sentinel-2 optical data to investigate the importance of red-edge spectral, texture, and radar features for vegetation type extraction in arid regions, verifies the feasibility of employing the Gini Index (Gini) to identify optimal feature combinations, and applies a Support Vector Machine algorithm to extract land cover types in the Nuomuhong area of Qinghai in 2021, with subsequent optimization of the classification results. The research demonstrates that: (1) Sentinel-2 red-edge indices, texture information, and Sentinel-1 radar bands are conducive to vegetation information extraction, achieving an overall classification accuracy and Kappa coefficient of 95.51% and 0.9406, respectively; (2) Based on feature importance derived from the Gini index, classification features were reduced from 29 to 17, revealing that the importance for classification decreases sequentially for radar polarization features, spectral features, and texture features; (3) The adoption of a Simple Non-Iterative Clustering algorithm combined with a neighborhood filtering voting decision fusion method not only attained optimal overall accuracy and Kappa coefficient of 96.06% and 0.9479, but also exhibited effective suppression of isolated point noise. This study leverages the GEE remote sensing cloud

platform, multi-source remote sensing data, and machine learning algorithms to accurately, rapidly, and efficiently extract land cover information across large-scale arid regions, demonstrating substantial application potential.

Full Text

Preamble

Vegetation Feature Type Extraction in Arid Regions Based on GEE Multi-Source Remote Sensing Data

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Abstract: The Nuomuhong region is an important wolfberry cultivation base in Qinghai Province, where accurate and rapid extraction of primary vegetation types is critical for sustainable agricultural development. However, the arid nature of this region, characterized by sparse vegetation cover and significant soil background effects, means that using limited remote sensing sources or partial features cannot meet the requirements for vegetation extraction. Therefore, integrating multiple remote sensing data sources, mining significant vegetation classification features, and experimenting with different classification optimization methods are essential for improving classification accuracy and reliability in arid regions. Based on the Google Earth Engine (GEE) platform, this study utilized Sentinel-1 Synthetic Aperture Radar (SAR) data and Sentinel-2 optical data to explore the importance of red-edge spectral, texture, and radar features for vegetation type extraction in arid regions. The feasibility of using the Gini index to identify optimal feature combinations was verified, and the classification results were optimized using decision fusion methods combined with a Support Vector Machine algorithm. The results demonstrate that: (1) Sentinel-2 red-edge indices, texture information, and Sentinel-1 radar bands are beneficial for vegetation information extraction, achieving an overall classification accuracy of 95.51% and a Kappa coefficient of 0.9406. (2) Using Gini index-derived feature importance, the classification features were reduced from 29 to 17, with radar polarization features, spectral features, and texture features showing decreasing importance. (3) The simple non-iterative clustering algorithm and neighborhood filtering voting decision fusion method not only achieved optimal overall accuracy and Kappa coefficient but also effectively suppressed isolated noise. This study demonstrates that using the GEE remote sensing cloud platform, multi-source remote sensing data, and machine learning algorithms can accurately, rapidly, and efficiently extract large-scale geospatial information in arid

regions, showing significant application potential.

Keywords: land cover; feature selection; support vector machine; classification optimization; Google Earth Engine

Introduction

Semi-arid ecosystems are crucial for regulating global carbon balance, but their dispersed land use types, fragmented landscapes, and complex surface cover structures make extraction and classification using remote sensing technology highly challenging. Traditional classification methods based on local data processing and single data sources or limited features typically result in reduced efficiency and may fail to meet the precision requirements for complex crop classification in arid regions. Previous studies have used MODIS data to extract rice paddies across South and Southeast Asia, generating specialized rice maps, while others have integrated multi-features from Landsat 8 data to identify and extract cotton from remote sensing imagery. Although these satellite series can be used for crop extraction and classification, their performance in small-area classification using single-source data has been less than ideal.

In recent years, the development of high spatiotemporal resolution satellites such as Sentinel-2 has provided excellent data support for vegetation classification. However, classification using single data sources and limited features is susceptible to external interference and often fails to amplify differences between land cover types. While some studies have used multi-temporal Sentinel-2 data for farmland land use classification, artificially selecting cloud-free images reduces temporal dimensionality and cannot fundamentally resolve issues caused by single data sources. Other research has fused two optical satellites and applied segmentation to spatial clustering for rice paddies in parts of Laos and Thailand, which can suppress "noise" from pixel-level classification to some extent. Additionally, time-series Sentinel-2 and GF-1 imagery have been used for high-precision identification and dynamic monitoring of invasive Spartina alterniflora.

Sentinel-1 is a typical SAR data source whose land cover classification is affected by certain noise but offers the advantage of being unaffected by cloud or lighting conditions. Studies have confirmed that combining Sentinel-1 polarization features with Sentinel-2 vegetation index features can improve crop classification accuracy. Similarly, other researchers have combined optical and SAR remote sensing data for vegetation classification, demonstrating that this combination can compensate for Sentinel-2' s inability to obtain effective images under cloud cover, providing more inspection details and reliable information to improve classification accuracy.

With the support of satellite image resources, various classification algorithms have been developed for mapping land cover types. In remote sensing classification, unsupervised and supervised learning are commonly used methods, with support vector machines, maximum likelihood classification, random forest, K-nearest neighbors, decision trees, and object-oriented classification widely applied to distinguish different vegetation types in remote sensing images. The support vector machine classifier has demonstrated excellent performance in previous studies, achieving high classification accuracy with Sentinel-2 imagery. Using Sentinel-2 image data and support vector machines, researchers have studied seven land cover categories using normalized difference vegetation indices, achieving good classification results. However, support vector machines perform pixel-level classification, which often produces "noise" in the results. Therefore, optimization of pixel-level classification using appropriate algorithms is necessary.

Building on previous research, this study utilized GEE platform remote sensing data sources to construct a multi-feature space including Sentinel-2 red-edge spectral features sensitive to vegetation, Sentinel-1 polarization features unaffected by clouds, and texture features representing land cover characteristics. This feature space was input into a support vector machine classifier to identify surface vegetation cover types in the Nuomuhong region of Qinghai Province. This study comprehensively analyzed feature importance and correlation, considered the impact of different feature combinations on classification results, reduced unnecessary classification features to optimize the classification feature space dataset, and employed neighborhood filtering voting decision fusion methods and simple non-iterative clustering algorithms to eliminate noise effects such as "salt-and-pepper phenomenon," thereby achieving efficient and accurate mapping of major land cover types in arid regions.

1.1 Study Area Overview

The study area is located in Nuomuhong Township, Dulan County, Haixi Mongolian and Tibetan Autonomous Prefecture, Qinghai Province, situated on the southeastern margin of the Qaidam Basin, bordering Xiangride Town to the east and Golmud City to the west [Figure 1: see original paper]. The region has a plateau arid continental climate with an average elevation of 2775 m, mean annual temperature of 4.3°C, annual precipitation of 37.9–180.5 mm, and evaporation of 1358–1765 mm. The study area belongs to the southern Qaidam Basin oasis agricultural zone, characterized by abundant light resources and high potential for light-temperature production, which is favorable for crop growth. The southern part is a human settlement area where the main vegetation types include wolfberry plantations and shelterbelts. The northern vegetation consists primarily of Haloxylon ammodendron forests and herbaceous plants, while other land cover types include bare land and buildings. Based on the distribution of land cover types in the study area, they were subdivided into vegetation and non-vegetation categories. Vegetation includes natural vegetation (Haloxylon ammodendron, grassland, and shelterbelts) and artificial vegetation (primarily wolfberry plantations). Non-vegetation types include buildings and bare land. Sample data were selected based on field survey data combined with Google imagery to ensure reliability and accuracy. The final sample selection included

30 wolfberry plantation sample areas, 30 building sample areas, 30 Haloxylon ammodendron forest sample areas, 30 grassland sample areas, and 30 shelterbelt sample areas, with stratified random sampling used to divide the samples into training and validation sets at a 7:3 ratio. Field photographs of the main vegetation types in the study area are shown in [Figure 2: see original paper].

1.2 Data Sources and Processing

In this study, Sentinel-2 multispectral data and Sentinel-1 satellite data were accessed and processed online through the Google Earth Engine platform, supplemented by field survey data [Figure 3: see original paper]. Sentinel-2 optical data includes 13 spectral bands and 6 spectral vegetation indices (Table 1). Preprocessing steps included geometric correction, radiometric calibration, atmospheric correction, and cloud removal using the "QA60" band. To ensure data reliability and reduce noise effects, thermal noise removal, radiometric calibration, and terrain correction were applied to Sentinel-1 data. Considering the vegetation development stage in the study area and to improve classification accuracy, cloud-free Sentinel-2 image datasets from 2021 were selected for cloud masking and median compositing to generate high-quality cloud-free images. Although Sentinel-1 imagery is unaffected by weather conditions, it is significantly influenced by observation angle, with pixels farther from the imaging center exhibiting stronger noise. Therefore, the preprocessed data were processed pixel-by-pixel to calculate median values within the temporal range, reducing noise effects. Sentinel-1 is an active microwave remote sensing satellite capable of all-weather, day-and-night observation with single-polarization, dual-polarization, and other polarization modes. This study utilized VV/VH dual-polarization data for polarization radar feature calculation and applied median compositing on the temporal scale.

1.3 Research Methods

This study achieved extraction of vegetation types in arid regions based on the GEE remote sensing cloud platform. The main research content and technical flow are shown below [Figure 3: see original paper].

1.3.1 Feature Space Construction Based on preprocessed Sentinel-2 optical imagery, extracted spectral features included 10 spectral bands and 6 spectral vegetation indices (Table 1). However, optical imagery suffers from "same object with different spectra, different objects with same spectrum" phenomena, where relying solely on optical features can lead to misclassification of some land cover types. Since texture information reflects spatial variations in images and can represent land cover characteristics such as size, shape, density, and regularity, incorporating texture information can improve misclassification to some extent. According to existing research, the Sentinel-2 B8A band was selected to generate grayscale images through weighted linear combination (Equation 1), and Gray-Level Co-occurrence Matrix (GLCM) was used to calculate 7 common statistical measures: Angular Second Moment, Contrast, Correlation, Entropy, Variance, Inverse Difference Moment, and Sum Average.

Gray = 0.3 × NIR + 0.59 × RED + 0.11 × GREEN

where NIR represents near-infrared band reflectance, RED represents red band reflectance, and GREEN represents green band reflectance.

1.3.2 Feature Space Optimization Random Forest is an ensemble learning algorithm that integrates multiple decision trees. Its basic idea is to independently generate each decision tree by randomly selecting samples and features. Random Forest exhibits good robustness and generalization capability, effectively handles high-dimensional and large-scale datasets, and achieves high classification accuracy. When decision tree nodes split, the ideal state is that subnode samples belong to the same class, as determined by the optimal splitting feature. The Gini index measures sample set impurity—the smaller the Gini index, the lower the probability of sample misclassification. Random Forest-based feature optimization evaluates feature importance by comparing the average contribution rate of features on decision trees, typically using Gini index or out-of-bag error rate as evaluation criteria. This study used the Gini index for evaluation, using the mean of all feature contribution rates as a threshold to select features with contribution rates greater than the mean for classification.

Assuming m features X_1, X_2, ···, X , the Gini index for node m is calculated as:

GI = Σ p p ’ = 1 - Σ p ^{2}

where K represents the number of classes and p represents the proportion of class k in node m. Assuming the number of trees in the Random Forest is n, the feature importance score for feature X is calculated as:

VIM = Σ Σ M VIM = GI - GI - GI

where set M represents nodes where feature X appears in decision tree i, and GIm, GIl, and GIr represent the Gini index of the node before splitting and the two nodes after splitting, respectively.

1.3.3 Classification Result Optimization The superpixel segmentation classification result optimization method based on Simple Non-Iterative Clustering effectively improves clustering efficiency and classification results. Superpixel segmentation optimization first generates a series of clusters with identical features, then performs classification on these cluster units. This optimization approach not only significantly suppresses certain noise but also provides better smoothing effects on land use type classification boundaries. Additionally, generating clusters before classification accelerates computational processes to some extent. Image segmentation was performed based on the Simple Non-Iterative Clustering superpixel segmentation concept, with parameter settings including "image," "seeds," "compactness," "connectivity," and "neighborhoodSize." The "image" parameter refers to the image participating in segmentation. "seeds" refers to the spacing between pixel-based superpixel seed positions, i.e., segmentation size. "compactness" controls the regularity of post-segmentation clusters —higher values produce more square-like segmentation results, set to 10 in this study. "connectivity" represents pixel adjacency, selecting either 4-adjacency or 8-adjacency. "neighborhoodSize" represents the neighborhood size, generally selecting 4 or 8.

The neighborhood filtering and majority voting decision fusion method is based on the first law of geography: everything is related to everything else, but near things are more related than distant things. In remote sensing imagery, spatial connections between land covers are even tighter, so adjacent pixels have higher correlation and greater probability of belonging to the same class. Inspired by this principle, this study employed neighborhood filtering majority voting decision fusion on classification results. The main idea is to apply a majority filter to each classification result, replacing isolated pixels with surrounding values, then use maximum voting to fully reflect the advantages of each classification result.

1.3.4 Support Vector Machine Classification Model Support Vector Machine is a generalized machine learning method proposed based on statistical learning theory, widely applied in image classification. The algorithm first selects support vectors that minimize the confidence range, projects classification data into high-dimensional space, constructs the optimal hyperplane (optimal function) with maximum tolerance to training sample limitations or noise effects, and uses this optimal function to classify image data. This achieves optimal balance between learning precision and generalization ability under limited sample information conditions, giving classification objects strong generalization capability. SVM can be extended to non-linearly separable data using kernel functions that map input features to high-dimensional space. Common kernel functions include linear, polynomial, Radial Basis Function (RBF), and Sigmoid. While effective, SVM may be computationally expensive and require hyperparameter tuning such as kernel functions and regularization parameters.

1.3.5 Classification Accuracy Evaluation To validate the accuracy of land cover classification in Nuomuhong, this study used confusion matrices and sample points collected from high-resolution Google Earth imagery. Overall accuracy, Kappa coefficient, producer's accuracy, and user's accuracy were calculated to evaluate classification algorithm performance. Overall accuracy measures the proportion of correctly classified samples to total validation samples. The Kappa coefficient reflects consistency between ground truth data and predicted values, serving as an important indicator for evaluating classification accuracy. Producer' s accuracy and user' s accuracy are also crucial metrics that reflect algorithm accuracy and bias across different land cover types. User' s accuracy represents the ratio of correctly classified verification points to all points falling on that class in the classification map. Producer' s accuracy represents the probability that ground truth reference data (verification samples) of a specific class are correctly classified. Comprehensive analysis of these indicators enables thorough evaluation of classification algorithm accuracy and effectiveness.

The formulas for quantitative accuracy evaluation metrics are as follows:

Overall Accuracy (OA) refers to the ratio of correctly classified pixels to total pixels.

Kappa coefficient measures classification result consistency: Kappa = (OA - Expected Accuracy) / (1 - Expected Accuracy)

Producer' s Accuracy (PA) refers to the ratio of correctly classified pixels for a specific class to the total true pixels of that class.

User' s Accuracy (UA) refers to the ratio of correctly classified pixels for a specific class to all pixels classified as that class.

2 Results and Analysis

2.1 Analysis of Different Land Cover Feature Performance

Based on spectral feature analysis for each land cover type [Figure 4: see original paper], the separability of original remote sensing bands is significantly lower than calculated vegetation indices, with better performance in red-edge features. Red-edge features are closely related to vegetation biochemical information (such as leaf area index and chlorophyll content) and can better highlight inter-species vegetation differences compared to other features, facilitating identification of subtle vegetation distinctions. In original Sentinel-2 bands, wolfberry plantations and shelterbelts show significantly smaller reflectance in the B4 band compared to other land covers, making them easily distinguishable. The B11 band easily distinguishes buildings and bare land from other land covers. The B8A band effectively separates grassland from the other five land cover types.

According to different second-order statistical measures, Gray_{savg} shows the best performance, Gray_{ent} and Gray_{contrast} 次之, while Gray_{asm} shows the poorest land cover separability. Buildings exhibit significant differences from other land cover types in Gray_{var}, enabling effective building extraction. Since bare land and buildings (non-vegetation types) have lower temporal variation intensity than periodically developing vegetation, radar polarization features were calculated for grassland, shelterbelts, wolfberry plantations, and Haloxylon ammodendron forests [Figure 5: see original paper]. Multi-temporal Sentinel-1 radar data can clearly distinguish different land cover types to obtain land cover information. Different land cover types' texture features can serve as important bases for classification.

2.2 Feature Optimization Analysis

After normalizing Gini index values, the mean values of spectral, texture, and radar features were calculated to express feature importance: radar features

(0.42) > spectral features (0.35) > texture features (0.23). However, since features have certain correlations [Figure 6: see original paper], causing unnecessary data redundancy, the Gini index was used to optimize the feature space. Starting with feature importance calculations for each class using GEE platform samples, separability analysis was performed to evaluate different features' importance for major land cover type information extraction. Features were added sequentially from high to low importance while observing overall classification accuracy and Kappa coefficient changes [Figure 6: see original paper]. Initially, classification accuracy increased rapidly with more features. When the number of features was optimized to 17, the classification reached a relatively stable and high-precision state, with overall accuracy and Kappa coefficient of 95.23% and 0.9387, respectively. When features reached 21, swamp mapping accuracy peaked, after which it stabilized and began declining. Therefore, the first 17 features were used as the optimized feature space for land cover classification: Gray_{savg}, NDVIre3, Gray_{contrast}, NDVIre2, Gray_{var}, NDre1, Gray_{idm}, Gray_{ent}, Gray_{corr}, Gray_{asm}, B8A, B11, B4, B3, B5, B6, B7.

2.3 Comparison of Classification Results

2.3.1 Comparison of Three Classification Schemes [Figure 7: see original paper] shows classification results from three schemes. Overall, the spatial distribution of land covers is consistent across schemes. Scheme 1, using original bands and vegetation indices, achieved 91.42% overall accuracy and 0.8921 Kappa coefficient. While Sentinel-2 spectral information shows good effects for land cover classification in the study area, some land covers near shelterbelts appear misclassified. Scheme 2 added texture features, improving wolfberry plantation classification accuracy due to their clear and well-developed textures. Shelterbelts and Haloxylon ammodendron forests, appearing as linear or clustered forms in remote sensing imagery, also benefited from texture features. However, bare land and grassland have large spectral differences but similar textures, so adding texture features caused misclassification and reduced accuracy. Buildings were already well-distinguished by spectral features, so texture features had minimal impact. Scheme 3 incorporated multi-temporal polarization features, achieving higher classification accuracy with 95.51% overall accuracy and 0.9406 Kappa coefficient.

2.3.2 Comparison of Three Classification Optimization Results This study designed three optimization schemes to improve classification results from different perspectives: (1) neighborhood filtering voting decision fusion method; (2) simple non-iterative clustering algorithm; (3) feature space optimization. The first approach optimizes data (features) using classification feature importance evaluation metrics (Gini index) to optimize (reduce) the feature space dataset, improving classification efficiency while maintaining accuracy (overall accuracy 95.23%, Kappa coefficient 0.9387), representing an effective way to reduce data redundancy.

To reduce "salt-and-pepper phenomenon" in pixel-level classification results, two optimization schemes were proposed: neighborhood filtering voting decision fusion method and simple non-iterative clustering algorithm. Based on two high-accuracy full-feature classification results and Gini-optimized classification results, pixel cluster generation, morphological filtering, and masking were applied sequentially. Maximum voting ("same pixels take their value, different pixels select randomly") was then used to calculate optimized results. Decision-level fusion leverages different classification advantages, reduces uncertainty, achieves complementarity, and improves classification accuracy. The neighborhood filtering voting decision fusion method achieved 95.89% overall accuracy and 0.9452 Kappa coefficient.

The simple non-iterative clustering algorithm aggregates adjacent pixels into superpixels based on inter-land cover differences, then classifies these segmented objects, avoiding isolated pixels or blocks in extraction results. This algorithm works well for extracting block-shaped vegetation like wolfberry plantations and strip-shaped vegetation like shelterbelts, improving classification accuracy for shelterbelts, buildings, and bare land by approximately 2 percentage points each. The optimized feature set after Gini coefficient algorithm not only optimized the feature space but also eliminated features with minimal classification impact. Using neighborhood filtering voting decision fusion and simple non-iterative clustering algorithms comprehensively considered multiple classification results and geographic knowledge, producing clear land cover boundaries consistent with actual vegetation distribution [Figure 8: see original paper].

Overall, the three classification optimization extraction results [Figure 8: see original paper] show consistent spatial distribution with the three classification scheme results [Figure 7: see original paper]. Grassland and Haloxylon ammodendron forest are mainly distributed in the northern study area, bare land appears as two strip-shaped regions north-south of wolfberry plantations, and wolfberry plantations are concentrated in central and southern areas with shelterbelts and buildings distributed within them. The optimized classification results show more regular patches, less "salt-and-pepper phenomenon," and improved classification accuracy and effects, with final overall accuracy of 96.06% and Kappa coefficient of 0.9487.

3 Conclusions

This study, based on the GEE remote sensing computing platform, collected high spatial and temporal resolution Sentinel-2 and Sentinel-1 remote sensing data to analyze vegetation characteristics in the study area and select appropriate time-phase optical images and radar data. A feature space was constructed by extracting band features, vegetation index features, texture features, and radar features. Using a Support Vector Machine classifier, major land cover types in the study area were classified into grassland, shelterbelts, buildings, bare land, Haloxylon ammodendron forest, and wolfberry plantations. The feature space dataset and classification results were optimized to explore the feasibility of three optimization methods for improving land cover extraction effectiveness. The main conclusions are:

(1) Sentinel-2 band features, red-edge indices, texture features, and Sentinel-1 radar features are beneficial for extracting major land cover types in the study area, with classification overall accuracy of 95.51% and Kappa coefficient of 0.9406.

(2) Feature importance results show radar features play the most important role in land cover classification in this region, followed by spectral features (band features and vegetation indices), with texture features being relatively less important. Based on the relationship between feature importance and classification accuracy, the feature dataset was optimized, reducing features from 29 to 17.

(3) Using neighborhood filtering voting decision fusion method and simple non-iterative clustering algorithm to optimize classification results improved classification accuracy, achieving optimal overall accuracy of 96.06% and Kappa coefficient of 0.9487. These methods comprehensively leveraged advantages of multiple classification results, suppressed isolated noise and "salt-and-pepper phenomenon," and produced clear land cover boundaries consistent with actual vegetation distribution.

References

[1] Zhang P, Hu S, Li W, et al. Improving parcel level mapping of smallholder crops from vhsr imagery: An ensemble machine learn-ing-based framework[J]. Remote Sensing, 2021, 13(11): 2146.

[2] Denize J, Hubert-Moy L, Betbeder J, et al. Evaluation of using sentinel-1 and-2 time series to identify winter land use in agricultural landscapes[J]. Remote Sensing, 2018, 11(1): 37.

[3] Xiao X, Boles S, Frolking S, et al. Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images[J]. Remote Sensing of Environment, 2006, 100(1): 95-113.

[4] Wang Wenjing, Zhang Xia, Zhao Yindi, et al. Cotton extraction method of integrated multi-features based on multi-temporal Landsat 8 images[J]. Journal of Remote Sensing, 2017, 21(1): 115-124.

[5] Zhang H, Du H, Zhang C, et al. An automated early season method to map winter wheat using time series Sentinel-2 data: A case study of Shandong, China[J]. Computers and Electronics in Agriculture, 2021, 182: 105962.

[6] Wang Dejun, Jiang Qigang, Li Yuanhua, et al. Land use classification of farming areas based on time series Sentinel-2A/B data and random forest algorithm[J]. Remote Sensing for Natural Resources, 2020, 32(4): 236-243.

[7] Min Yukui, Ke Yinhai, Han Yue, et al. Dynamic Spartina alterniflora monitoring of invasive clearance via fusion of Sentinel-2 and GF-1 time series images[J]. National Remote Sensing Bulletin, 2023, 27(6): 1467-1479.

[8] Fatchurrachman, Rudiyanto, Soh N C, et al. High resolution mapping of paddy rice extent and growth stages across peninsular Malaysia using a fusion of sentinel-1 and 2 time series data in Google Earth Engine[J]. Remote Sensing, 2022, 14(8): 1875.

[9] Chakhar A, Hernández-López D, Ballesteros R, et al. Improving the accuracy of multiple algorithms for crop classification by integrating sentinel-1 observations with sentinel-2 data[J]. Remote Sensing, 2021, 13(2): 243.

[10] Ming Yiseng, Liu Qihang, Bai He, et al. Classification and change detection of vegetation in the Ruoergai Wetland using optical and SAR remote sensing data[J]. National Remote Sensing Bulletin, 2023, 27(6): 1414-1425.

[11] Zhang Li, Luo Wenting, Zhang Haohuan, et al. Classification scheme for mapping wetland herbaceous plant communities using time series Sentinel-1 and Sentinel-2 data[J]. National Remote Sensing Bulletin, 2023, 27(6): 1362-1375.

[12] Cao Wenmei, Liu Tingxi, Wang Xixi, et al. Land use and land cover classifications of Horqin Sandy Land dune-meadow areas[J]. Arid Zone Research, 2021, 38(2): 526-535.

[13] Liu Tong, Ren Hongrui. Object-oriented extraction of paddy rice planting areas using phenological features from the GEE platform[J]. Transactions of the Chinese Society of Agricultural Engineering, 2022, 38(12): 189-196.

[14] Awad M. Google Earth Engine (GEE) cloud computing based crop classification using radar, optical images and Support Vector Machine Algorithm (SVM)[C]//IEEE 3rd International Multidisciplinary Conference on Engineering Technology, 2021: 71-76.

[15] Virnodkar S, Pachghare V K, Patil V C, et al. Performance evaluation of RF and SVM for sugarcane classification using Sentinel-2 NDVI time series[C]//Progress in Advanced Computing and Intelligent Engineering: Proceedings of ICACIE, 2021: 163-174.

[16] Ponganan N, Horanont T, Artlert K, et al. Land Cover Classification using Google Earth Engine' s Object-oriented and Machine Learning Classifier[C]//2021 2nd International Conference on Big Data Analytics and Practices (IBDAP), IEEE, 2021: 33-37.

[17] Yao J, Wu J, Xiao C, et al. The classification method study of crops remote sensing with deep learning, machine learning, and Google Earth Engine[J]. Remote Sensing, 2022, 14(12): 2758.

[18] Liang Shunlin, Bai Rui, Sun Jiajun, Yu Zhongyi, et al. Review of China' s land surface quantitative remote sensing development in 2019[J]. Journal of Remote Sensing, 2020, 24(6): 618-671.

[19] Wang Zhenwu, Chen Xiaona, et al. Review of remote sensing image classification based on support vector machine[J]. Computer Science, 2016, 43(9): 11-17.

[20] Qiu Fengting, Guo Zhifeng, Zhang Zongke, et al. Water body area extraction from SAR image based on improved SVM classification method[J]. Journal of Geo-information Science, 2022, 24(5): 940-948.

[21] Dai Shengpei, Yi Xiaoping, Luo Hongxia, et al. Mapping land use in Hainan Island based on Google Earth Engine and Landsat time series data[J]. Chinese Journal of Tropical Crops, 2021, 42(11): 3351-3357.

[22] Pang Haiwei, Yu Dian, Ren Chengbao, et al. Remote sensing classification characteristics of typical plant communities in the semi-arid areas of eastern Ningxia[J]. Arid Zone Research, 2022, 39(6): 1930-1941.

[23] Ning Xiaogang, Chang Wentao, Wang Hao, et al. Extraction of marsh wetland in Heilongjiang Basin based on GEE and multi-source remote sensing data[J]. National Remote Sensing Bulletin, 2022, 26(2): 386-396.

[24] Yang Zehang, Wang Wen, Bao Jianxiong. Identifying crop types in early growing season in the middle reaches of Heihe River by fusing multi-source remote sensing data[J]. Journal of Geo-information Science, 2022, 24(5): 996-1008.

[25] Xiao Sentian, Ilyas Nurmemet, Nuerbiye Muhetaer, et al. Spatial and temporal analysis of soil salinity in Yutian Oasis by combined optical and radar multi-source remote sensing[J]. Arid Zone Research, 2023, 40(1): 59-68.

[26] Yao Jinxi, Wang Lang, Li Jianzhong, et al. Multi-source remote sensing and multi-feature combination ground object classification in Nuomuhong areas, Qinghai Province of China[J]. Transactions of the Chinese Society of Agricultural Engineering, 2022, 38(3): 247-256.

[27] Tassi A, Vizzari M. Object-oriented LULC classification in Google Earth Engine combining SNIC, GLCM, and machine learning algorithms[J]. Remote Sensing, 2020, 12(22): 3776.

[28] Achanta R, Susstrunk S. Superpixels and polygons using simple iterative clustering[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017: 4651-4660.

[29] Mu Xueqing, Guo Xiangyang, Ming Qingzhong, et al. Dynamic evolution characteristics and driving factors of tourism ecological security in the Yellow River Basin[J]. Acta Geographica Sinica, 2022, 77(3): 714-735.

[30] Yang Weitao, Sun Jianguo, Ma Hengli, et al. A multi-scale integrated classification method for landforms[J]. Arid Zone Research, 2022, 39(2): 638-645.

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