Grape Identification Model Based on GF-1/WFV Time Series: A Case Study of Hongsibu District, Ningxia (Postprint)

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Abstract

With Hongsibu District, Ningxia as the study area, time series spectral data for the grape growing season was constructed based on Gaofen-1 (GF-1/WFV) satellite imagery. The Jeffreys-Matusita (J-M) distance was employed to analyze the temporal curve characteristics of the Normalized Difference Vegetation Index (NDVI) for grape plots, thereby determining the optimal identification timing. A training sample set consisting of NDVI at the optimal timing, the rate of difference between adjacent timings, and curve integrals was imported into Clementine data mining software. A decision tree extraction model for grape forests was constructed using the C5.0 decision tree classification algorithm combined with the expert experience method. The results indicate that the constructed identification model can meet the requirements for grape identification, but its accuracy varies across grape plots with different coverage levels. The overall accuracy based on decision tree classification is 93.71%, with a Kappa coefficient of 0.91. Specifically, the producer' s accuracy for medium-low coverage grape forests is 90.82%, and the user' s accuracy is 88.56%; the producer' s accuracy for high coverage grape forests is 92.44%, and the user' s accuracy is 91.18%.

Full Text

GF-1/WFV Based Grape Extraction in Hongsibao, Ningxia

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Abstract: Grape is one of the most widely distributed fruit tree species, and its accurate spatial distribution is of great significance for the management and development of grape planting and wine industry. In this study, the Hongsibao area in Ningxia was taken as the study area to obtain the time series of spectrum data in grape growing season based on the Gaofen-1 satellite (GF-1/WFV). The J-M distance analysis was used to analyze the normalized difference vegetation index (NDVI) of the grape plots, and the best recognition phase was determined. The NDVI values of the best phase, adjacent to the value difference rate and curvilinear integral training samples were put into the Clementine data mining software. The extract grape model of decision tree was developed by using C5.0 decision tree classification algorithm and combining with the expert experience method. The results suggested that the established recognition model could meet the needs of grape recognition, but the accuracy was different from different grape plots due to their different coverage. The overall accuracy based on the decision tree classification was 93.71%, and the Kappa coefficient was 0.91. In which the production precision and users' precision of the grape plots with moderate or low coverage were 90.82% and 88.56%, and those with high coverage were 92.44% and 91.18%, respectively.

Keywords: grape forest; remote sensing extraction; GF-1/WFV timing data; recognition model; curve integral; decision tree; Ningxia

2 Methodology

The technical route for grape extraction based on GF-1/WFV time series data involves several key steps. First, the remote sensing images undergo radiometric calibration and atmospheric correction to ensure data quality. The NDVI time series is then calculated using ENVI 5.3 software, generating GF/WFV-NDVI products.

The J-M (Jeffreys-Matusita) distance analysis is applied to the NDVI time series data to determine the optimal temporal window for grape recognition. This statistical measure evaluates the separability between grape plots and other land cover types across different phenological phases. The analysis identifies the phase where grapes exhibit distinct spectral characteristics compared to surrounding vegetation.

For classification, the C5.0 decision tree algorithm is employed within the Clementine data mining environment. Training samples are selected based on the NDVI values from the optimal phase, along with derivative metrics including the value difference rate and curvilinear integral. The decision tree model integrates these spectral features with expert knowledge to create a robust classification framework for grape extraction.

[Figure 2: see original paper] Technology Route

2.2 NDVI Time Series Analysis

The NDVI time series is constructed from multi-temporal GF-1/WFV images acquired during the 2017 growing season (April to September). The temporal resolution of the dataset allows for capturing key phenological stages of grape development. The J-M distance calculation between grape and non-grape classes across all available phases reveals the periods of maximum separability.

[Figure 3: see original paper] Variation of Time Series of NDVI

The J-M distance analysis results indicate that the period from July to August provides the highest separability, with J-M values approaching 2.0, indicating complete separability between grape plots and other land uses. The specific band combinations showing optimal performance include 2-3-4-5-6-7-8-9-10-11 for various grape types.

Calculated Results of Jeffreys-Matusita Distance

2.3 Decision Tree Classification

Using the optimal temporal features, a C5.0 decision tree model is developed. The classification incorporates multiple variables including NDVI values from key phenological periods, texture features, and topographic factors. The model is trained with sample data representing different grape coverage levels (high, moderate, and low) to ensure robustness across varying field conditions.

The decision tree algorithm automatically selects the most discriminative features and thresholds, creating a hierarchical classification structure. Expert knowledge is integrated to refine the rules and eliminate spectrally similar confusers such as other orchard crops and mixed vegetation.

3 Results and Analysis

The classification results demonstrate high accuracy for grape extraction. The overall classification accuracy reaches 93.71% with a Kappa coefficient of 0.91, indicating strong agreement between classified results and ground truth data.

Evaluation on Classification Accuracy of the Decision Tree

The producer' s accuracy and user' s accuracy vary by coverage level: - High coverage grape plots: 92.44% and 91.18% respectively - Moderate/Low coverage grape plots: 90.82% and 88.56% respectively

The spatial distribution of classified grape plots shows good correspondence with actual vineyard locations in the Hongsibao area. The time-series approach effectively captures the unique phenological signature of grapes, particularly the distinct NDVI trajectory during the fruit development and ripening phases.

[Figure 5: see original paper] Extracted Results of Grape

4 Discussion

The integration of multi-temporal GF-1/WFV data with J-M distance analysis provides an effective method for identifying the optimal recognition period. The 16-meter spatial resolution of GF-1/WFV data proves adequate for mapping vineyard parcels in this region. The decision tree classifier, particularly the C5.0 algorithm, offers advantages in handling non-parametric data and incorporating both spectral and temporal features.

The accuracy differences among various coverage levels highlight the importance of representative training samples. Areas with sparse grape coverage exhibit lower accuracy due to mixed pixel effects and spectral confusion with background soil and vegetation. Future improvements could include incorporating higher spatial resolution data or object-based classification methods to better handle heterogeneous vineyard structures.

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