

Article

Rapeseed Area Extraction Based on Time-Series Dual-Polarization Radar Vegetation Indices

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Abstract: Accurate, real-time, and dynamic monitoring of crop planting distributions in hilly areas with complex terrain and frequent meteorological changes is highly important for agricultural production. Dual-polarization SAR has high application value in the fields of feature classification and crop distribution extraction because of its all-day all-weather operation, large mapping bandwidth, and easy data acquisition. To explore the feasibility and applicability of dual-polarization synthetic-aperture radar (SAR) data in crop monitoring, this study draws on two basic methods of dual-polarization decomposition (eigenvalue decomposition and three-component polarization decomposition) to construct time series of crop dual-polarization radar vegetation indices (*RVIs*), and it performs a full coverage analysis of crop distribution extraction in dryland mountainous areas of southeastern China. On the basis of the Sentinel-1 dual-polarization *RVIs*, the time-series classification and rapeseed distribution extraction impacts were compared using southern Hunan Province's principal rapeseed (*Brassica napus* L.) production area as the study area. From the comparison results, *RVI*_{3-c} performed better in terms of single-point recognition capability and area extraction accuracy than the other indices did, as verified by sampling points and samples, and the OA and F-1 score of rapeseed extraction based on *RVI*_{3-c} were 74.13% and 81.02%, respectively. Therefore, three-component polarization decomposition is more suitable than other methods for crop information extraction and remote sensing classification applications involving dual-polarized SAR data.

Keywords: polarization decomposition; radar vegetation index; crop distribution; Sentinel-1 data; rapeseed



Academic Editors: Dipankar Mandal, Lucio Mascolo and Mehdi Hosseini

Received: 11 March 2025

Revised: 11 April 2025

Accepted: 18 April 2025

Published: 21 April 2025

Citation: Zhu, Y.; Cao, H.; Wu, S.;

Guo, Y.; Song, Q. Rapeseed Area

Extraction Based on Time-Series

Dual-Polarization Radar Vegetation

Indices. *Remote Sens.* **2025**, *17*, 1479.

<https://doi.org/10.3390/rs17081479>

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1. Introduction

Monitoring the distribution of crop planting across a wide area with complete coverage is vital for directing agricultural output, ensuring food security, and protecting the health of citizens. Compared with traditional ground sampling surveys, remote sensing technology is characterized as being real-time, dynamic, and large-scale, and it is crucial in crop planting distribution monitoring. The majority of recent studies on remote sensing-based crop distribution monitoring have concentrated on optical remote sensing [1,2]. Because optical remote sensing is easily affected by meteorological conditions [3], limited optical remote sensing data can be obtained during window periods, and monitoring crops via optical data alone or partial optical data is difficult.

Synthetic-aperture radar (SAR) is very sensitive to crop structure and characteristics, and it has an all-time, all-weather observation capability that is not affected by the atmosphere, clouds, rain, etc., making it the best choice for replacing optical data for crop planting distribution monitoring [4–7]. Sentinel-1 SAR data currently represent the only free SAR data source [8]. With four different imaging modes and C-band SAR capabilities, satellites can provide all-weather and all-time SAR images for monitoring the land and ocean. The Sentinel-1 SAR system, which has a 12-day revisit period and covers the major rapeseed (*Brassica napus* L.)-producing regions in the central and lower portions of the southeastern hills of China, can supply information for the extraction of dryland crop planting distributions in the area via remote sensing [9].

Certain plant traits of crops vary over the course of their growth. In agricultural remote sensing, establishing relationships between plants in various phenological stages and particular crop planting regions via time-series remote sensing images has long been a significant research task and academic topic [10–12]. Similarity analysis, a quantitative evaluation of how closely the time series of the pixels to be categorized resemble the reference time series of the target land class via specific criteria, is necessary when classifying land cover based on the time series of remote sensing images. Euclidean distance (ED) [13,14] and dynamic time warping (DTW) [15–17] are two examples of similarity techniques. Due to things like sensor noise and pixel distortion, the value of the pixel at a specific moment in remote sensing data may be absent or aberrant. There may be significant variances when evaluating similarities between pairings of unequal-length sequences using the conventional ED [18]. The DTW algorithm, a common optimization technique built on the idea of dynamic programming, is mostly used to identify sequence pair similarities. It enables time series to be elastically transformed to identify similar forms with distinct phases [19]. Compared with other approaches for evaluating similarity, DTW can improve the matching results for similar features by mitigating the impacts of outliers, resolving the unequal-length time-series matching problem, and partially overcoming the scale displacement problem. The DTW distance can be substituted for the ED in a variety of classification methods, including neural networks, support vector machines, and nearest neighbor classifiers, to increase classification accuracy. The DTW algorithm has been used in recent years to classify remote sensing images and extract vegetation or land cover by combining it with optical remote sensing vegetation indices [20–22].

At present, research on extracting crop planting distributions on the basis of SAR data has focused mainly on rice. Research has shown that the surface scattering of water under rice is the main contributor to enhancing the accuracy of remote sensing classification, and a single SAR polarization channel (such as VH polarization) can yield good crop planting distribution extraction results [23–25]. Furthermore, the underlying surfaces of dryland crops exhibit Bragg scattering, and the microwave radiation of crops and the interaction characteristics between crops and radar microwaves are very complicated. To solve the above problems, some scholars have used the ratio of two polarizations to extract the planting distribution of rapeseed, obtaining good extraction results [26–28]. However, this simple treatment method may not be effective for hilly areas with broken plots. In fragmented hilly areas, terrain-induced variations in incidence angles and complex vegetation structures lead to more diverse microwave scattering. Simple VV and VH backscattering coefficients have difficulty accurately distinguishing crops, so other descriptors need to be considered to characterize scattering more finely [29]. Although fully polarized SAR data have compelling advantages in crop monitoring, they have limitations, such as data download speed, mapping bandwidth, energy consumption, and antenna technology, making them difficult to apply to large-scale crop monitoring [30]. Therefore, dual-polarization SAR data, represented

by Sentinel-1 data, have been widely used in large-scale crop monitoring because of the advantages of easier data acquisition, larger mapping bandwidths, and all-weather work [31]. However, the use of existing dual-polarized SAR data is often limited to the VV and VH backward scattering coefficients and their ratios, and relatively few studies have explored the polarization decomposition of dual-polarized SAR data and compared the classification effects of different polarization decomposition methods [32,33]. Currently, polarization decomposition technology and the construction of the radar vegetation index (RVI) are based mainly on fully polarized SAR data, whereas polarization decomposition methods for dual-polarized SAR data have relatively few applications, especially eigenvalue decomposition and three-component decomposition [10,34,35].

On the basis of the above discussion, to obtain full coverage extraction results for crop distribution, eigenvalue decomposition and three-component decomposition technology were applied to research dryland crop distribution extraction on the basis of dual-polarization SAR data. Taking the main rapeseed production area in southern Hunan Province as the study region, this study innovatively applied a time series of crop dual-polarization RVIs constructed on the basis of eigenvalue decomposition and three-component polarization decomposition, in combination with the DTW K-means classification algorithm, to extract rapeseed distributions in the hilly areas of southeastern China. Furthermore, the classification performance of rapeseed, based on time-series dual-polarization RVIs, was evaluated in terms of single-point recognition capability, area extraction accuracy, and the effectiveness of time-series data integration.

2. Materials and Methods

2.1. Study Region

The most crucial places for crop planting in China's southeastern hilly region are the central and lower basins of the Yangtze River. Owing to gaps in the majority of optical datasets for the central and lower sections of the Yangtze River, caused by clouds, rain, and fog, extracting crop information via remote sensing is challenging. Taking winter rapeseed as the research subject, six counties (districts) in the central and lower sections of the Yangtze River in southern Hunan Province (Hengnan, Qidong, Changning, and Leiyang in Hengyang city; Lengshuitan and Qiyang in Yongzhou city) were chosen as the research areas to compare the time-series classification effects of dryland crops on the basis of the 2 dual-polarization RVIs, RVI_{eig} and RVI_{3-c} . The entire size of the study zone is 12771 km². The *Hunan Statistical Annual 2020* (<http://tjj.hunan.gov.cn/hntj/index.html>) (accessed on 1 January 2022) states that the study region's rapeseed planting area is roughly 232,100 hectares, or 25% of southern Hunan's total rapeseed planting area. The research area is characterized by red soil and located in the subtropical monsoon climate zone. With two crops annually, single-season rice and winter rapeseed constitute the primary crop planting methods. Figure 1 and Table 1 provide a summary of the research area and the winter rapeseed growth period, respectively. From December 2020 to May 2021, a total of 13 scenes of Sentinel-1 data were obtained during the key growth period of rapeseed, which could form 8191 time-series combinations. The acquired Sentinel-1 data for all periods were preprocessed and polarization-decomposed, and the results of the preprocessing and polarization decomposition were used to construct the RVIs according to the corresponding formulae. By selecting any number of scenes from the time-series data of 13 scenes to be combined into a time series, and ensuring that at least one period of data is used, the number of combinations that can be obtained is $2^{13}-1$, which equals 8191 combinations. The entire study region includes 6 counties and spans 150 km from north to south. The study region is in southern Hunan, China, which is a hilly and mountainous area that makes it

difficult to obtain ground data. The typical test area is a small study region set up in an area of slightly flat terrain, which is relatively less difficult to sample manually than the whole study region. Additionally, if the whole study region was classified by more than 8000 time series, the number of calculations would be very large. To reduce the number of computations and quickly select the best time-series combinations on the basis of the 2 *RVIs*, the southern area of Qidong County, which covers 1024 km², was selected as a typical test area, and 13 periods of data from the full lifespan of rapeseed were selected, while time series of *RVIs* were constructed on the basis of two different polarization decompositions.

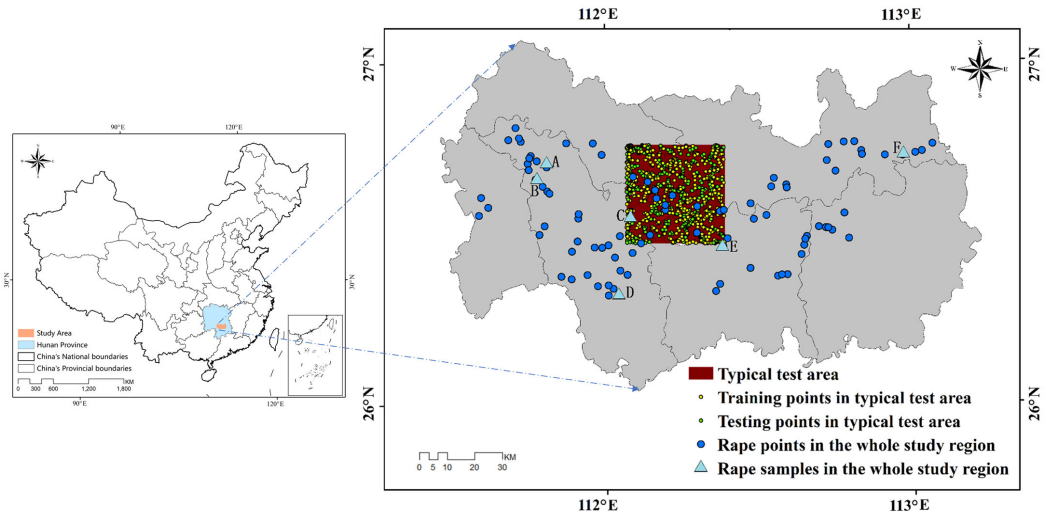


Figure 1. Study region and sample distribution. Note: In the legend, points refer to sampling points, which correspond to unique latitude and longitude coordinates, and field samples refer to plots, which are pieces of land that contain single or multiple land cover types.

Table 1. Rapeseed phenology in the study region.

Phenology	Seedling	Bolting	Flowering	Silique	Maturity
Date	Oct. to Dec.	Early Jan. to mid-Feb. of the subsequent year	Mid-Feb. to Late Mar. of the subsequent year	Late Mar. to Late Apr. of the subsequent year	Late Apr. of the subsequent year
Picture					

Winter rapeseed is harvested in mid-May of the subsequent year after it appears in October in the research area. Early January, mid-February, late March, and late April of the subsequent year mark the beginning of the winter rapeseed’s bolting, flowering, silique, and maturity periods, respectively. Table 1 displays the rapeseed growing period in the research area.

2.2. Remote Sensing Data

A time-series combination was constructed using 13 scenes of Sentinel-1 single-look complex (SLC) data, which were dual-polarized VV+VH and in interferometric wide-swath (IW) mode. The imaging dates ranged from December 2020 to May 2021, corresponding to the early bolting to maturity periods of rapeseed, as shown in Table 2. The IW mode of Sentinel-1 satellites acquires 250 km of data with a spatial resolution (single-look) of 5 m × 20 m (distance direction × azimuth direction), thus producing advantages related to the fine spatial resolution and wide coverage range. Using

SNAP 9.0 (Sentinel Application Platform) software, the downloaded Sentinel-1 data were preprocessed, including orbit correction, radiometric calibration, band debursting, multilook processing, and terrain correction. The processed experimental data had a spatial resolution of 20 m. In addition, we performed DEM masking on the Sentinel-1 data. Considering that rapeseed mainly grows at low altitudes, we removed the high-altitude areas in the study area according to the DEM to minimize the possible effects of radar shadows. After these preprocessing steps, we obtained the backscatter coefficient for the VH and VV polarization channels, and the values were expressed in decibels (dB). Sentinel-1 remote sensing data belong to the C band, and the effect of rainfall is negligible, except for heavy rainfall [36]. We chose to acquire Sentinel-1 data when there was no rain or very little rainfall, so as to ensure the accuracy of the collected SAR data. Only a tiny portion of the window period data was available in the research region, and the majority of the optical data from the rapeseed growth phase were missing. Taking Sentinel-2 data as a case in point, Table 2 presents the precipitation data for different key growth periods of rapeseed in Hengyang, where the main study area is located, along with the cloud coverage ratios of the Sentinel-2 data obtained during the corresponding periods. Moreover, the precipitation data were recorded from 08:00 on one day to 08:00 on the next day.

Table 2. List of Sentinel-1 data used.

No.	Satellite	Date	Absolute Track Number	Relative Track Number	Rapeseed Growth Stage	Precipitation 08-08 h (mm)	Cloud Coverage of Sentinel-2
1	1A	20201209	035608	11	Seedling	0.0	100.00%
2	1A	20201221	035783	11	Seedling	0.0	100.00%
3	1A	20210102	035958	11	Bolting	0.0	0.38%
4	1A	20210114	036133	11	Bolting	0.0	2.33%
5	1A	20210126	036308	11	Bolting	0.0	100.00%
6	1A	20210207	036483	11	Flowering	0.0	1.17%
7	1A	20210219	036658	11	Flowering	0.0	38.25%
8	1A	20210303	036833	11	Flowering	4.4	100.00%
9	1A	20210315	037008	11	Flowering	0.0	99.99%
10	1A	20210327	037183	11	Silique	0.0	62.65%
11	1A	20210408	037358	11	Silique	3.4	99.99%
12	1A	20210420	037533	11	Maturity	0.0	99.25%
13	1A	20210502	037708	11	Maturity	0.2	99.89%

2.3. Ground Sampling Points

The ground sampling stations were located on 3 March 2021, because rapeseed was in its flowering season at this time, and the traits of the rapeseed plants became more noticeable than those of additional land cover categories. In the typical test area, 1000 sampling points were established, of which the number of sites with rapeseed, water, bare land, woodland, and building land cover was 200. We chose the land cover types of the five locations where these 200 points were located as the typical land cover types, whereas the remaining 800 points of land cover types were more complex. In the whole research area, 6 ground samples and 94 rapeseed sampling points were established, where the sampling points refer to points with unique latitudinal and longitudinal coordinates, and the ground samples refer to plots, which represent pieces of land that contain single or multiple land cover types. The ground samples were edited, attributes were added, and then they were projection-converted and overlaid on the experimental Sentinel-1 image.

To test the integrity and extraction accuracy of rapeseed plots with 2 RVIs, a total of 6 ground samples were obtained. Ground sample mapping is the process of spatially representing the

collected ground samples on a map and analyzing their relevant attributes, but the task of ground sample mapping was arduous because of the hilly terrain and road conditions in the study region. For sample mapping, contiguous rapeseed planting fields in a typical test region and nearby counties were chosen. Among the 6 ground samples, 2 samples were in the typical test area, and they were 16.08 km (sample C) and 21.72 km (sample E) from the center of the typical test area. Among them, sample C was the smallest of the six samples, and four samples were located outside the typical test area: 36.09 km (sample D), 46.48 km (sample B), 48.48 km (sample A), and 77.31 km (sample F) from the center of the typical test area. Among them, sample B was the second smallest of the six samples. Figure 1 and Table 3 display the distribution of the ground sampling points, as well as the form and distribution of the samples within the study area. In Figure 1, the blue triangles represent the samples measured throughout the entire study region, which specifically illustrate the distribution of land cover throughout the entire plot (as shown in Table 3). The 94 dark blue circles in Figure 1 represent the measured sampling points throughout the entire study region, which include only the longitude and latitude in the plot. The green circles and yellow circles are the measured sampling points in the typical test area, half of which (green circles) were used to create a standard land cover curve, while the other half (yellow circles) were used to confirm the classification accuracy of the typical test area.

Table 3. Thumbnails of ground samples and their regional distributions.

No.	Distance from the Center of Typical Test Area (km)	Thumbnail	No.	Distance from the Center of Typical Test Area (km)	Thumbnail
Sample A	48.48		Sample B	46.48	
Sample C	16.08		Sample D	36.09	
Sample E	21.72		Sample F	77.31	

Note: In Figure 1, the 6 ground sample locations are indicated.

2.4. Methodology

In this study, eigenvalue decomposition and three-component polarization decomposition technology were used for reference, and dual-polarization RVIs were constructed for dual-polarization radar data. The spatial distribution of rapeseed planting was then retrieved from the Sentinel-1 SAR data via two RVIs, in conjunction with the DTW K-means classifier. Finally, a comparison of the effects of dual-polarization RVIs on rapeseed time-series extraction was conducted from the perspectives of single-point recognition capability, area extraction accuracy, and time-series data combination. Figure 2 displays the technical flowchart, and the particular steps were as follows:

(1) Polarization decomposition:

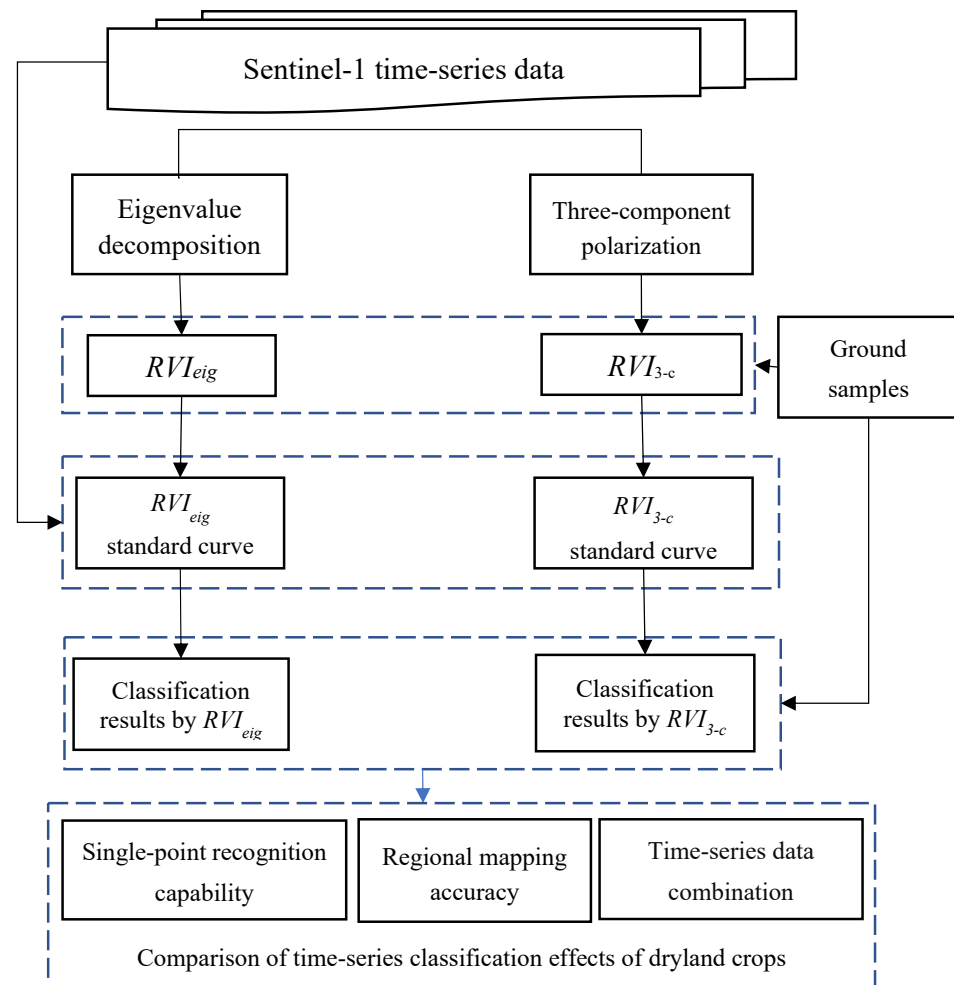


Figure 2. Overall research framework. Note: The equations for RVI_{eig} and RVI_{3-c} are described in detail in Sections 2.4.1 and 2.4.2.

Dual-polarization 2×2 covariance matrices were obtained by preprocessing the temporal dataset for this investigation. First, the Sentinel-1 data were imported into SNAP, and operations—including orbit correction, band debursting, track calibration and updating of state variables, and image calibration—were performed. The multilook covariance matrix (C2 matrix) or coherence matrix (T2 matrix) was produced by co-registering all of these calibrated images from various dates, with subpixel accuracy, via a digital elevation model (DEM) and orbit data in the SNAP “Sentinel-1 Back Geocoding” operator. The covariance matrix entries for every date were then used to produce the RVIs. Then, using range Doppler terrain correction, the images were geocoded to UTM projected coordinate systems [37,38]. The eigenvalue decomposition and three-component polarization decomposition were

processed on a Sentinel-1 C2 or T2 matrix, and the polarization decomposition components were obtained to calculate the corresponding *RVIs*.

(2) Calculating the standard curves of the *RVIs*:

The standard time-series curves of the *RVIs* of common land cover types in the research region were computed using data that fell within the confidence range of 90%, in conjunction with ground samples. First, according to Equation (3) in Section 2.4.1 and Equation (7) in Section 2.4.2, the corresponding *RVI* time-series images were calculated from the 13-scene preprocessed Sentinel-1 images, the ground samples in the study area were matched to the calculated *RVI* time-series images according to latitude and longitude, and the land cover types (rapeseed, bare land, woodland, water, and building) and the *RVIs* of each land cover type sample point in each period were calculated. The standard time-series curves of the *RVIs* for each type of land cover were then constructed, and the *RVI* data within the confidence range of 90% were used to guarantee the model's dependability.

(3) Time-series classification and class merging:

To avoid the dependence of machine learning or deep learning algorithms on training datasets, their sensitivity to hyperparameters, and their lack of mechanistic interpretability in classification, a universal and stable classification method, DTW and K-means clustering, was chosen as the classifier, and complex deep learning was not chosen. The idea behind DTW is to explain the temporal correlation between the input and reference sequences via a time-warping function that meets specific requirements. When the two sequences match, the warping function that corresponds to the least cumulative distance is then solved. Compared with other approaches for evaluating similarity, DTW can improve the matching results for similar features by mitigating the impacts of outliers, solving the matching issue with unequal-length time series, and partially overcoming the scale displacement problem. When the DTW algorithm is applied at the pixel level, it traverses the time-series curves of each pixel for classification and compares them one by one with the standard time-series curves when a large amount of data make up the time series. This leads to high computational complexity and numerous invalid calculations. The most popular dynamic iterative unsupervised classification technique for classifying remote sensing images is K-means. The K-means algorithm has fast computation speed and good clustering performance. The spatiotemporal data for land cover extraction and remote sensing classification are accounted for by substituting DTW for the Euclidean distance in the K-means method. This method lessens the effort required to explore and compare the time-series curves of every pixel that needs to be classified, in addition to overcoming the inaccuracy caused by the image outlier at a single point in time.

DTW distance was utilized to assess how similar the curves of the pixels and *RVIs* were. The following formula was used to calculate the DTW distance, which is the smallest sum of the curved path's distance elements in the construction matrix of two time series:

$$D = \min \sum_{i=1}^k d(x_i) \quad (1)$$

where x_i is the coordinate of the i -th point on a certain path in the construction matrix of the two-time sequence, $d(x_i)$ is the distance component corresponding to the coordinate x_i , and $k \in [\max(p, q), m + n - 2]$ represents the total number of elements on the path.

Iterative K-means clustering was used to create K clusters and matching clustering centers in order to classify the land cover based on the computed DTW distance, the provided K value, and a random starting center. Lastly, to extract the findings for the distribution of rapeseed planting in the area, categories with comparable or the same land cover were combined.

2.4.1. Eigenvalue Decomposition and RVI Calculation

The principle of dual-polarization eigenvalue decomposition is similar to that of full polarization. Eigenvalue decomposition of the dual-SAR coherence matrix is performed to obtain eigenvalues that distinguish different scattering mechanisms [39].

The coherence matrix T of Sentinel-1 data can be decomposed into [34]

$$T_2 = \sum_{i=1}^2 \lambda_i u_i u_i^H \quad (2)$$

where $u_i = e^{j\phi_i} [\cos\alpha_i \quad \sin\alpha_i \cos\beta_i e^{j\delta_i}]^T$, $i = 1, 2$ is the unit eigenvector of T_2 , α_i represents the target scattering mechanism, β_i is the target azimuth angle, and ϕ_i and δ_i are the target phase angles; λ_i is the eigenvalue of $\langle T \rangle$, which satisfies $\lambda_1 \geq \lambda_2$.

$$RVI_{eig} = \frac{2\lambda_2}{\lambda_1 + \lambda_2} \quad (3)$$

The value range of RVI_{eig} is [0,1]. For an affirmatory objective, $\lambda_1 = 1$, $\lambda_2 = 0$, and $RVI_{eig} = 0$; for a completely random objective, $\lambda_1 \approx \lambda_2 \approx 1$, and $RVI_{eig} = 1$. When the scattering proportion is close to 1, the scattered echo is completely depolarized, and the electromagnetic vector is distributed in a random direction. In the vegetation area, the electromagnetic wave enters the vegetation canopy, the components of the volume scattering are significantly greater than those of the surface and dihedral scattering, and the eigenvalues λ_1 and λ_2 tend to be the same.

2.4.2. Three-Component Decomposition and RVI Calculation

Three-component decomposition, which is based on an assumed physical scattering model, decomposes the scattering of features into three typical scattering mechanisms—surface scattering, dihedral scattering, and volume scattering—to separate the contributions of different scattering mechanisms. The depolarized and fully polarized components can be separated from the polarized waves:

$$g = \begin{bmatrix} (1-m)g_0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} mg_0 \\ g_1 \\ g_2 \\ g_3 \end{bmatrix} \quad (4)$$

where $\{g_0, g_1, g_2, g_3\}$ are Stokes vectors, and m is the degree of polarization.

Volume scattering is described as multiple scattering caused by a layer of randomly oriented particles, and the volume, surface, and dihedral scattering models are shown in Equation (5) [40].

$$\begin{aligned} J_v &= f_v \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \\ J_s &= f_s \begin{bmatrix} |\beta|^2 & -j\beta^* \\ j\beta & 1 \end{bmatrix} \\ J_d &= f_d \begin{bmatrix} |\alpha|^2 & -j\alpha^* \\ j\alpha & 1 \end{bmatrix} \end{aligned} \quad (5)$$

where f_v is the complex coefficient of the volume scattering mechanism, $f_s = \frac{|S_{VV}|^2}{2} e^{j\varphi_s}$, $f_d = \frac{|R_{gV}R_{tV}|^2}{2} e^{j\varphi_d}$; $\beta = \frac{|S_{HH}|}{|S_{VV}|} e^{-j\varphi_{sVH}}$, $\alpha = \frac{R_{gH}R_{tH}}{R_{gV}R_{tV}} e^{-j\varphi_{dVH}}$, R_{gV} , R_{tV} , R_{gH} , and R_{tH} are the Fresnel coefficients; the subscripts g and t represent the ground surface and crop plants, respectively; V and H represent the vertical and horizontal polarizations, respectively; φ_d is

the phase of the dihedral scattering; and φ_s is the phase of the surface scattering, where both φ_{VH}^s and φ_{VH}^d represent the phase difference between the H and V polarization channels.

Stokes vectors are used to represent the three scattering components, and the target echo can be decomposed into

$$S = 2f_v \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \left(f_s \begin{bmatrix} |\beta|^2 + 1 \\ |\beta|^2 - 1 \\ 2(\beta) \\ -2\Re(\beta) \end{bmatrix} + f_d \begin{bmatrix} |\alpha|^2 + 1 \\ |\alpha|^2 - 1 \\ 2(\alpha) \\ -2\Re(\alpha) \end{bmatrix} \right) \quad (6)$$

A comparison of Equations (4) and (6) reveals that, while surface scattering and dihedral scattering are described as deterministic scattering processes with high polarization degrees that can roughly correspond to the fully polarized component of the wave, volume scattering is described as a completely random scattering process with a zero degree of polarization. As a result, the powers of the echo-depolarized component and the volume-scattered component are roughly similar.

$RV_{I_{3-c}}$ is calculated as shown in Equation (7):

$$RV_{I_{3-c}} = \frac{P_v}{P_d + P_v + P_s} \quad (7)$$

where $P_s = f_s(1 + |\beta|^2)$, $P_d = f_d(1 + |\alpha|^2)$, and $P_v = (1 - m)g_o$.

The value range of $RV_{I_{3-c}}$ is [0,1]. Affected by the stems and leaves of the crop canopy, electromagnetic waves scatter multiple times between the leaves after they are incident on the canopy layer. In crop areas, radar microwave scattering mainly results in volume scattering, and the surface scattering and secondary scattering components are small. Water mainly shows surface scattering, and buildings mainly show dihedral angle scattering, in the SAR images. Therefore, the $RV_{I_{3-c}}$ value of vegetation is large because of the large proportion of volume scattering to total scattering.

2.4.3. Comparative Indicators of the Extraction Effect

In the single-point recognition capability section, only the temporal separability of land cover types was considered, meaning that the spatial relationships between them were not considered. Furthermore, the area extraction accuracy section compares the accuracy of land cover extraction by considering the temporal and spatial separability of land cover.

(1) Single-point recognition capability:

The time-series curve should be able to describe the characteristics of the target crop and have a certain feature distinguishability to distinguish the target crop from the background objects. The smaller the feature difference among the same type of land cover, the greater the feature difference between different types of land cover, and the better the classification effect of remote sensing images. Additionally, crops have regular and distinct plant traits that vary during their growth. The more obvious the corresponding time-series curve characteristics are, the more conducive they are to extracting the crop planting distribution. Other land cover types in the crop planting region, such as buildings and water, do not change much over time, and the more stable the corresponding time-series curve is, the better the extraction effect of the crop planting distribution. In this study, single-point recognition capability was evaluated by the DTW distance matrix and the variation coefficient.

To evaluate the recognition capability of time-series curves of sampling points without being affected by the spatial relationship, a distance matrix was constructed to evaluate the single-point recognition capability, whose number of rows and columns was equal to the

number of land cover categories. If there are C types of land cover in the study region, then the representation of the distance matrix is

$$D_{c \times c} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1c} \\ d_{21} & d_{22} & \cdots & d_{2c} \\ \vdots & \vdots & \cdots & \vdots \\ d_{c1} & d_{c2} & \cdots & d_{cc} \end{bmatrix} \quad (8)$$

where d_{ij} is the element of matrix $D_{c \times c}$. When $i = j$, d_{ij} is the maximum DTW distance of all of the sampling points of a certain land cover category. The smaller d_{ij} is, the smaller the internal variability of the land cover, which is more conducive to image classification and land cover recognition. When $i \neq j$, d_{ij} is the minimum DTW distance between the i -th and j -th land cover types; the larger d_{ij} is, the larger the difference between different land cover types, and the more conducive it is to image classification and land cover recognition.

In addition, the variation coefficient was used to evaluate the degree of component variation in the polarization decomposition. The variation coefficient calculation formula is as follows [41]:

$$C_v = \frac{\delta}{\mu} \quad (9)$$

where δ is the variance of the polarization decomposition component, and μ is the mean value of the polarization decomposition component.

(2) Mapping accuracy:

On the basis of the standard curve of the RVI in the typical test area, the overall accuracy and F-1 coefficient were used as evaluation indices to assess the rapeseed mapping accuracy across the entire study region and the typical experimental area. The mapping accuracy of rapeseed throughout the entire study region can also partially reflect the regional scalability of the RVI .

The following formula was used to calculate the overall accuracy:

$$A = \frac{n_0}{n} \times 100\% \quad (10)$$

where A represents the overall accuracy, n_0 represents the overall amount of successfully extracted rapeseed sampling points, and n represents the entire amount of sampling points.

The F-1 score formula is as follows [42]:

$$F_1 = 2 \frac{P \cdot R}{P + R} \quad (11)$$

where $P = \frac{T_p}{(T_p + F_p)}$ represents the precision and $R = \frac{T_p}{(T_p + F_n)}$ represents the recall. The cases marked T_p , F_p , and F_n are true positives, false positives, and false negatives, respectively.

(3) Time-series data combination:

The time-series data combinations were composed of multiple time data, and the impact of each time dataset on the classification accuracy was also different. When time-series data are utilized for classification, the less the classification accuracy is impacted by fluctuations in single time-series data, the more stable the time-series data combination is. The stable combination features indicate that the feature can provide reliable information for classification, which, in turn, improves the reliability and accuracy of classification. The random forest (RF) technique was used in this work to quantify the impact of time data on classification accuracy [43]. In random forest

models, the Gini coefficient is a crucial metric that compares the relative relevance of variables by calculating the effect of each variable on the heterogeneity of observations at each node of the classification tree. A variable is more significant if its mean decline in the Gini index value is greater. Therefore, the influence of time data on classification accuracy is expressed by the mean decrease in the Gini coefficient. If the time-series data combination has a more stable mean decrease in the Gini index over time, it is less affected by time changes and has stronger classification robustness. The specific calculation process is as follows:

Assuming that there are K categories in the dataset, the Gini coefficient of node m is as follows [44]:

$$GI_m = 1 - \sum_{k=1}^K p_{mk}^2 \quad (12)$$

where K represents the number of categories and p_{mk}^2 represents the percentage of category K in node m .

Then, the importance of feature x_i in the i -th tree is

$$VIM_{ij} = \sum_{m \in M_i} N_m * GI_m - N_l * GI_l - N_r * GI_r \quad (13)$$

where M_i is the node set of features x_i as the splitting feature in the i -th tree, and N_m , N_l , and N_r represent the number of samples of node m and its left and right child nodes, respectively. The global importance of feature x_j is the average weighted impurity of feature x_j across all trees in the RF:

$$VIM_j = \frac{1}{N} \sum_{i=1}^N VIM_{ij} \quad (14)$$

The value range of the Gini coefficient is $[0,1]$. The smaller the Gini coefficient, the smaller the influence of time data on the classification accuracy. As per the international division standard, a distribution is considered to be an absolute average if its Gini coefficient value is less than 0.2, a relative average if it falls between $[0.2,0.3]$, a reasonable distribution if it falls between $[0.3,0.4]$, and a large gap if it exceeds 0.5 [45].

3. Results

3.1. Single-Point Recognition Capability

The C2 matrix or T2 matrix was produced by preprocessing the Sentinel-1 data from December 2020 to May 2021. Eigenvalue decomposition and three-component polarization decomposition were then performed on the Sentinel-1 matrix, and the polarization decomposition components were obtained to calculate the corresponding RVIs. The volume scattering components of rapeseed rose as the number of flowers and plant volume increased throughout the flowering period; thus, the flowering period was a characteristic period of rapeseed microwave remote sensing. Taking data from the rapeseed flowering stage (15 March 2021) as an example, the components of the two polarization decompositions are shown in Figure 3, and Table 4 displays the variation coefficients of the polarization decomposition component.

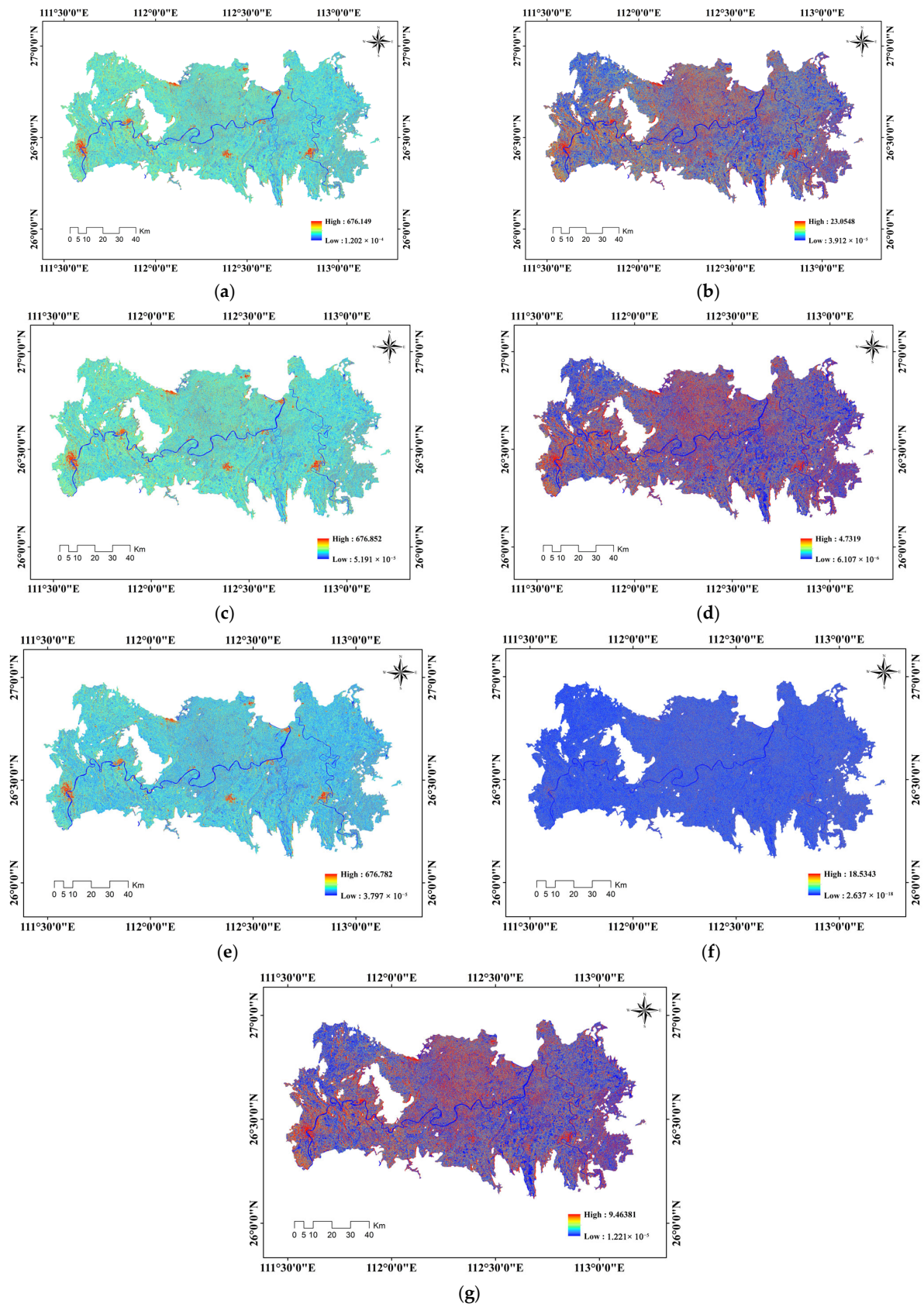


Figure 3. Dual-polarization decomposition components (taking March 15 2021 as an example): (a) VV polarization; (b) VH polarization; (c) λ_1 ; (d) λ_2 ; (e) P_s ; (f) P_d ; (g) P_v .

Table 4. Variation coefficients of the dual-polarization decomposition components.

	Whole Image	Sample A	Sample B	Sample C	Sample D	Sample E	Sample F
VV	2.38	24.32	24.85	1.15	26.75	26.16	33.79
VH	0.88	0.36	0.37	0.41	0.36	0.31	0.33
λ_1	2.36	24.55	24.59	1.16	26.73	25.53	33.59
λ_2	0.77	0.35	0.36	0.34	0.36	0.31	0.33
P_s	0.03	0.26	0.39	1.44	0.35	0.39	0.44
P_d	5.13	0.16	1.46	1.54	0.14	1.44	1.54
P_v	0.74	0.36	0.39	0.42	0.44	0.33	0.33

Figure 3 shows that the components obtained from the two polarization decomposition methods used on the Sentinel-1 dual-polarization SAR data were different from the original polarizations of the Sentinel data, especially the components obtained via three-component polarization decomposition. Additionally, among the components obtained via eigenvalue decomposition, the λ_1 component was similar to the VV polarization, and the λ_2 component was similar to the VH polarization. If the variation coefficients of rapeseed plots in the ground samples were less than those of the whole image, it was conducive to rapeseed extraction and image classification. In contrast, it would be challenging to differentiate rapeseed from other land cover types if the variation coefficients of the rapeseed plots were higher than those of the entire image. Table 4 shows that, for the VV polarization and λ_1 components, the variation coefficients of the rapeseed plots are greater than the coefficients of variation of the whole image, except for sample C. All of the variation coefficients of the P_s components of the rapeseed plots are larger than the coefficient of variation of the whole image, which is not favorable for rapeseed extraction and image classification. The variation coefficients of the rapeseed plots in the VH polarization, λ_2 , P_d , and P_v components were smaller than that of the whole image, which was conducive to rapeseed extraction and image classification. Owing to the spatial variation in VV polarization, it was difficult to extract a complete rapeseed plot directly via the ratio of VV polarization to VH polarization. λ_1 and P_s were part of the denominators of $RV I_{eig}$ and $RV I_{3-c}$, respectively, which adversely impacted the rapeseed extraction and classification accuracy.

The standard time-series curves of common RVI categories of land cover in the research area were computed using the RVI formulae. The variation in RVI standard time-series curves was analyzed, with rapeseed growth calculated on the basis of odd sampling points (500 points) in a standard test location. Prior studies have relied mostly on VV and VH polarization signals to extract the distribution of dryland crops from dual-polarization SAR data [26–28]. As a result, Figure 4 compares the time-series curves of the VV and VH polarizations, as well as the time-series curves of the two RVI s. The standard time-series curves of typical land cover types (rapeseed, buildings, bare land, water, and woodland) after normalization, along with their DTW values, are shown in Figure 4.

The standard time-series curves of the VV and VH polarizations based on odd sampling points (500 points) in a typical test area, as illustrated in Figure 4a,b, revealed that the temporal characteristics of rapeseed were not prominent, and with these two polarizations, it was challenging to distinguish between rapeseed and woodland directly. As shown in Figure 4c–e, the standard time-series curves after the polarization calculations were different from those of the original VH-to-VV polarizations. The SAR microwaves were scattered multiple times with the vegetation canopy, and the microwave signals reflected the geometric structure of the vegetation group. As a representative tall crop, the growth period of rapeseed mostly includes the seedling stage, bolting stage, flowering stage, silique stage, and maturity stage. Among them, the volume changes in rapeseed at the bolting stage and the flowering–silique stages were

the most obvious. In the later stage of rapeseed bolting, the main stem of the plant elongates and grows thicker, and the volume of the rapeseed plant increases significantly. During the flowering–silique periods of rapeseed, the volume of the rapeseed rises rapidly due to the growth of blossoms and siliques, and the above changes in rapeseed plants are reflected in the increase in volume-scattering components in the SAR images. Therefore, the bolting and flowering–silique stages are important times for distinguishing rapeseed from other land cover types in time series. In terms of the variation in the standard curve at the bolting and flowering–silique stages, the rapeseed VH/VV curve varied the least with time, followed by the $RV I_{eig}$ and $RV I_{3-c}$ curves, which varied the most with time. Compared with those of the other land cover types, the time-series curves of $RV I_{3-c}$ had more obvious differences. In particular, compared with the other time-series curves, it was possible to distinguish between rapeseed and woodland better. As shown in Figure 4, the time-series curves of buildings change over time. The scattering characteristics of buildings can be theorized to be relatively stable, but the RVI curves of buildings vary with time because of changes in the SAR observation angle, sensor noise, and calibration error, and because environmental factors such as temperature, humidity, and precipitation affect the scattering characteristics of the buildings' surfaces. With respect to the DTW distance, the rapeseed VH/VV curve resembled the other land cover categories' curves more and could be mistaken for them more readily. For this reason, we did not use VH/VV for rapeseed distribution extraction and land cover type classification in the subsequent study. Moreover, SAR data contain residual speckle noise due to interference between adjacent backscattered echoes, although they are processed via standard noise reduction techniques [46].

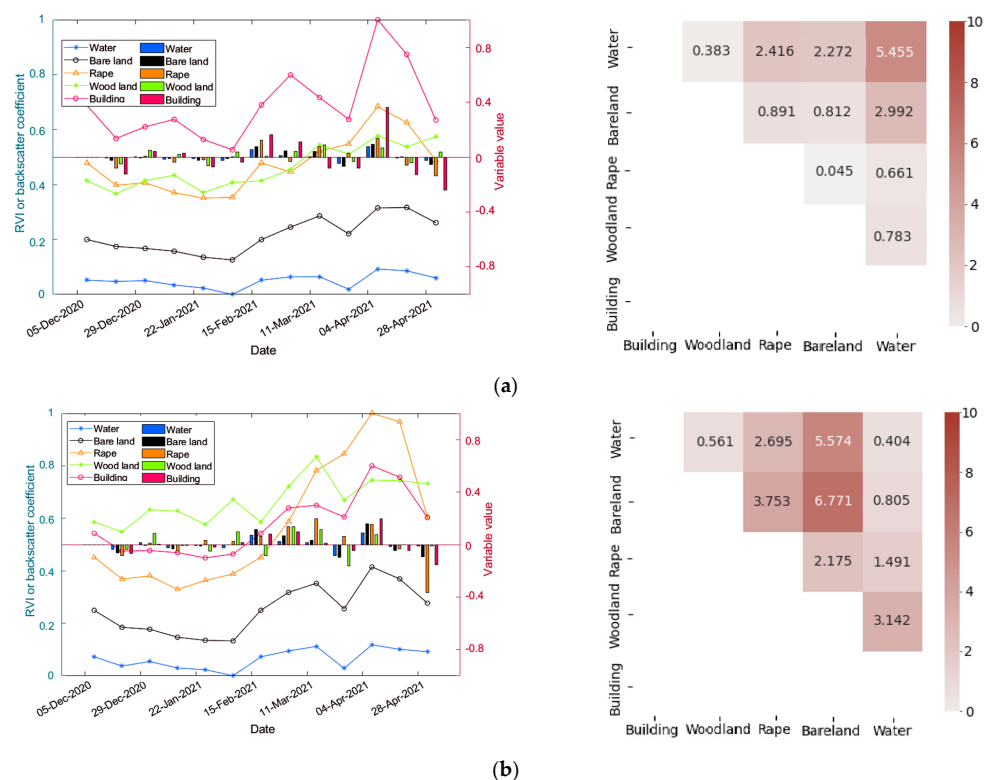


Figure 4. Cont.

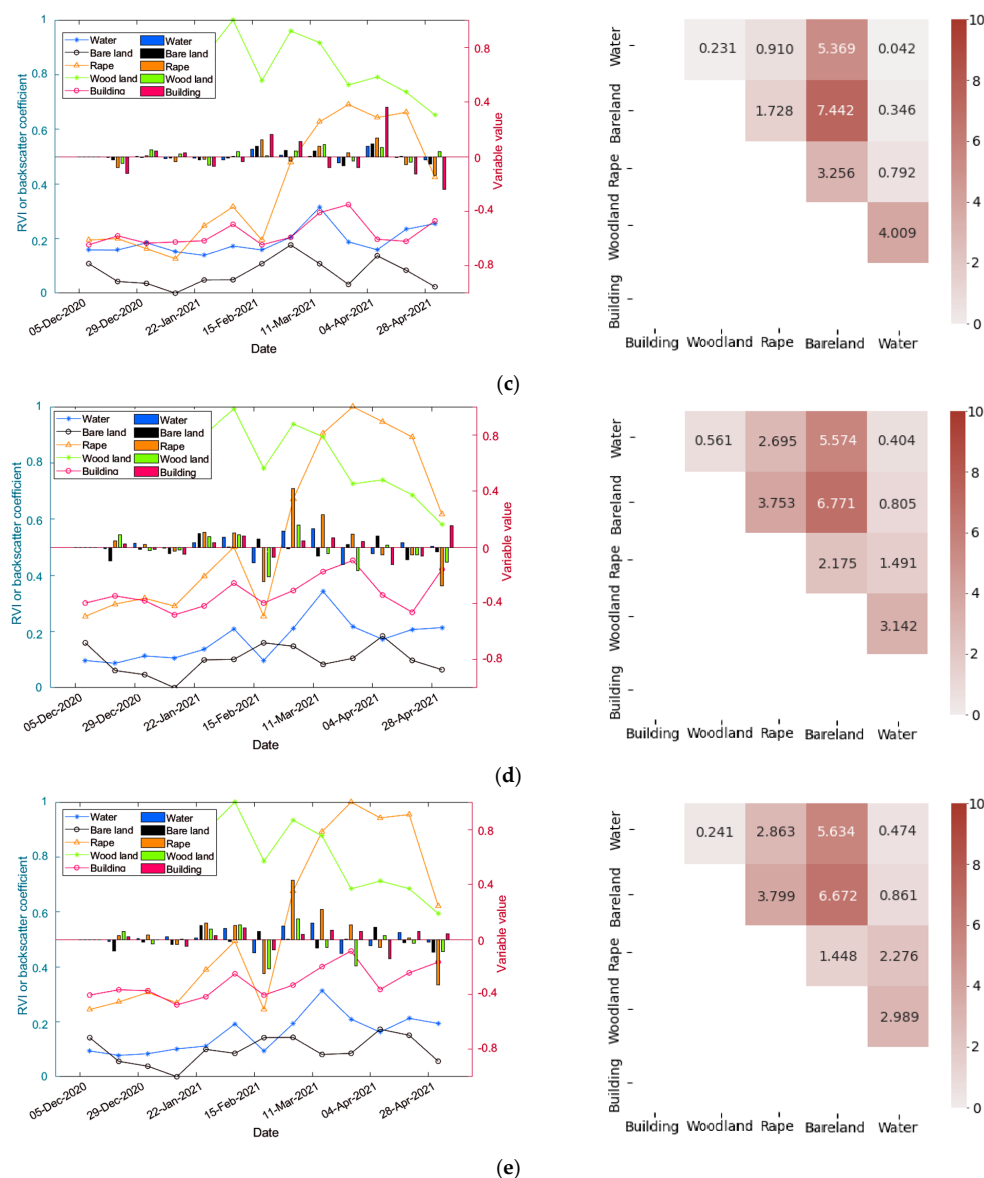


Figure 4. Average RVIs of the time-series curves of typical land cover types (after normalization) and the DTW distance matrix. In the left graphs, the main axis of the Y-axis is the RVI or backscatter coefficient value corresponding to the curve, and the secondary axis of the Y-axis is the variable value corresponding to the cylinder: (a) VV polarization; (b) VH polarization; (c) VH/VV; (d) $RVI_{I_{eig}}$; (e) $RVI_{I_{3-c}}$.

3.2. Mapping Accuracy

In this section, the regional accuracies of image classification and rapeseed extraction for two RVIs combined with time-series classification algorithms are compared. The standard time-series curves of the two RVIs were constructed from all 13 scene images and odd sampling points (500 points) in a typical test area and then combined with DTW K-means classification to extract rapeseed for the whole study area. The rapeseed mapping accuracy was evaluated throughout the whole research area and the typical experimental area, using the F-1 score and overall accuracy as evaluation indices, which were based on the standard curve of the RVI in the standard test area. The mapping accuracy of rapeseed throughout the entire study region could also partially reflect the regional scalability of the RVI. The image classification results based on the two RVIs are shown in Figure 5.

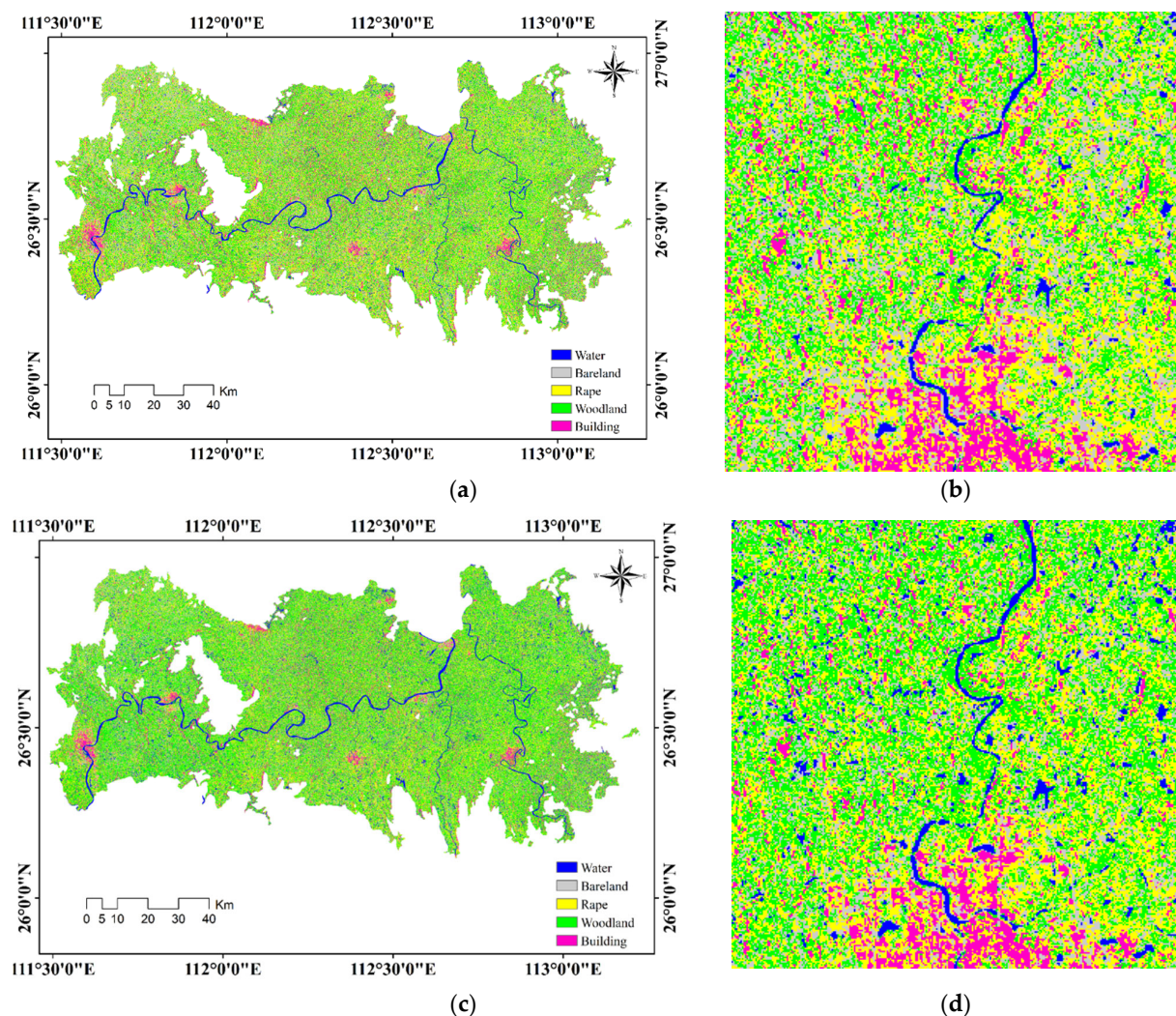


Figure 5. Results of image categorization for the entire research area: (a) RVI_{eig} ; (b) enlarged view of Figure 5a; (c) RVI_{3-c} ; (d) enlarged view of Figure 5c.

From the visual effect of the SAR image classification results in Figure 5, owing to the poor recognition ability of RVI_{3-c} for water and other land cover types, many pixels may be misclassified as water in the classification results based on RVI_{3-c} . In accordance with the calculation principle of RVI_{3-c} , this index is used to measure the percentage of volume scattering from a feature. Typically, the surface of a water body is dominated by specular scattering, with less volume scattering, resulting in relatively low RVI_{3-c} values. However, bare ground or agricultural land with low vegetation cover may exhibit scattering characteristics similar to those of water because of less volume scattering. In addition, when the SAR incidence angle is large, or when shallow water covers the vegetation, the water may generate random echoes similar to volume scattering, which increases the RVI_{3-c} value and the training of the water classification error, which, in turn, leads to the misclassification of different land cover categories in the image element as water.

The image classification and extraction precision of the rapeseed planting distribution based on the two RVI s were verified via the even number of sampling points (500 points) in the typical test area and 94 sampling points and six samples in the whole test area. Table 5 displays the image classification accuracy verification.

Table 5. Extraction accuracy of rapeseed planting distribution in the study region.

		Points in Typical Test Area	Points in Whole Study Region	Sample A	Sample B	Sample C	Sample D	Sample E	Sample F	Total
$RV I_{eig}$	TP	73	67	169	82	64	298	204	216	1173
	TN	362	0	4	7	3	15	0	24	415
	FP	27	27	40	72	51	97	78	215	607
	FN	38	0	2	9	2	17	0	6	74
	OA(%)	87.00	71.28	80.47	52.35	55.83	73.30	72.34	52.06	69.99
	P(%)	73.00	71.28	80.86	53.25	55.65	75.44	72.34	50.12	65.90
	R(%)	65.77	-	98.83	90.11	96.97	94.60	-	97.30	94.07
	F-1(%)	69.19	83.23	88.95	66.94	70.72	83.94	83.95	66.16	77.50
$RV I_{3-c}$	TP	73	67	180	87	66	295	204	281	1253
	TN	365	0	4	5	4	27	0	24	429
	FP	27	27	30	69	48	88	78	146	513
	FN	35	0	1	9	2	17	0	10	74
	OA(%)	87.60	71.28	85.58	54.12	58.33	75.41	72.34	66.16	74.13
	P(%)	73.00	71.28	85.71	55.77	57.89	77.02	72.34	65.81	70.95
	R(%)	67.59	-	99.45	90.63	97.06	94.55	-	96.56	94.42
	F-1(%)	70.19	83.23	92.07	69.05	72.53	84.89	83.95	78.27	81.02

Notes: True positives (TP) are samples that were correctly classified as positive, true negatives (TN) are samples that were correctly classified as negative, false positives (FP) are samples that were incorrectly classified as positive, and false negatives (FN) are samples that were incorrectly classified as negative. R is the recall, or the proportion of all actual positive samples that were accurately predicted to be in the positive category; P is the precision, or the proportion of true cases among samples expected to be in the positive group.

As shown in Table 5, the rapeseed extraction accuracy based on $RV I_{3-c}$ was greater than that based on $RV I_{eig}$. According to all of the sampling points and samples, the OA of rapeseed extraction via $RV I_{3-c}$ was 74.13%, which was higher than that via $RV I_{eig}$ (4.14%). The F-1 score of rapeseed extraction via $RV I_{3-c}$ was 81.02%, and that via $RV I_{eig}$ was 77.50%. Overall, regional rapeseed extraction based on $RV I_{3-c}$ more easily achieved higher accuracy.

3.3. Time-Series Data Combination

Multiple time data points make up the time-series data, and each time point has a distinct effect on the classification accuracy. When time-series data are used for classification, the less the classification accuracy is impacted by the fluctuation of the individual time data, the better the time series. Sentinel-1 SAR images were acquired from 13 scenes throughout the winter rapeseed growth period in the research area. According to the permutation and combination formula, $2^{13}-1$ time-series combinations could be obtained, meaning 8191 time-series combinations. The RF algorithm is used in this section to quantify the variable importance measure of a time series, which is indicated by the Gini coefficient.

The highest values of the Gini coefficients of the two $RV I$ time series were less than 0.2 on the basis of the impact of each time point on the accuracy fluctuation in Figure 6. This suggests that the two $RV I$ s are less impacted by time-series data fluctuations in remote sensing categorization. The precision of rapeseed extraction and picture classification based on the $RV I$ s was clearly affected differently by different temporal data, and the data with greater impact were mainly obtained before rapeseed flowering. The Gini coefficient of the time data for rapeseed extraction before flowering was approximately 0.1, and the Gini coefficient decreased to 0.04 after the flowering period. Before the flowering period of rapeseed, the plants were small, and the volume scattering characteristics displayed on the SAR image were not strong, making it easy to confuse them with other land cover types, so the data greatly influenced the accuracy fluctuations. Similarly, the Gini coefficient of the time-series data for image classification also decreased after the flowering period, but the decreasing trend was not obvious. The impact of different time data on $RV I$ -based image classification accuracy fluctuations was not significant. The timing of the SAR data

significantly impacted the fluctuation in the remote sensing classification accuracy based on the two RVI s, with the data that significantly impacted the classification accuracy mostly obtained in winter and spring. The data that significantly impacted the rapeseed extraction accuracy of RVI_{eig} and RVI_{3-c} were obtained from the seedling stage to the bolting stage, and from the bolting stage to the flowering stage.

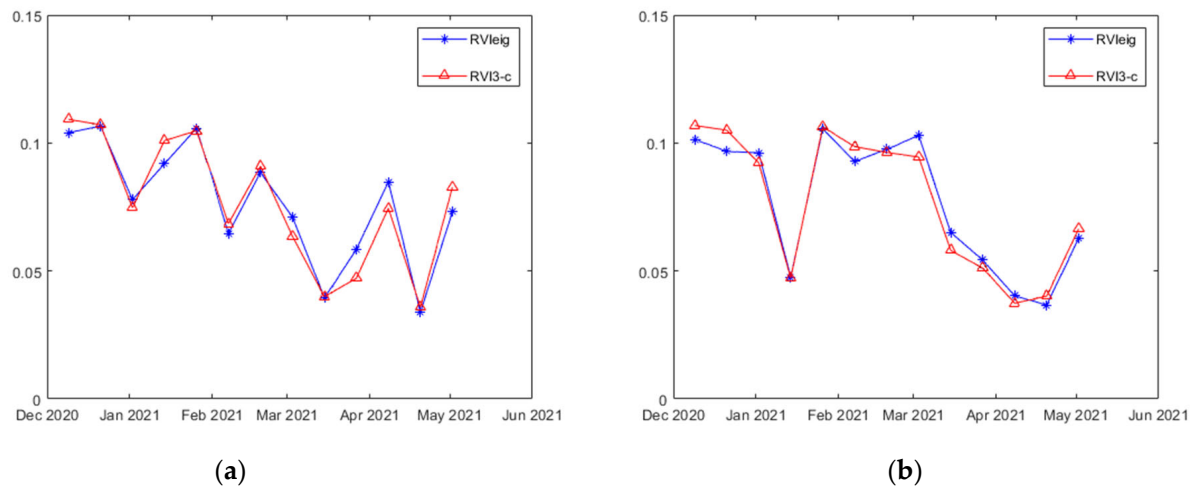


Figure 6. Gini coefficient of each time data point on the overall accuracy fluctuation: (a) image classification; (b) rapeseed extraction.

In general, the precision of rapeseed extraction and picture classification steadily rose with increasing time, especially the precision of rapeseed extraction, based on the best overall accuracy achieved by each data point participating in the classification displayed in Figure 7. The accuracy of rapeseed extraction and image classification reached 70% and 60%, respectively, at the end of the flowering period, and improved only slightly thereafter. Compared with the highest image classification accuracy available at each time for the different RVI s, the highest accuracy available at each time based on RVI_{eig} and RVI_{3-c} was relatively close.

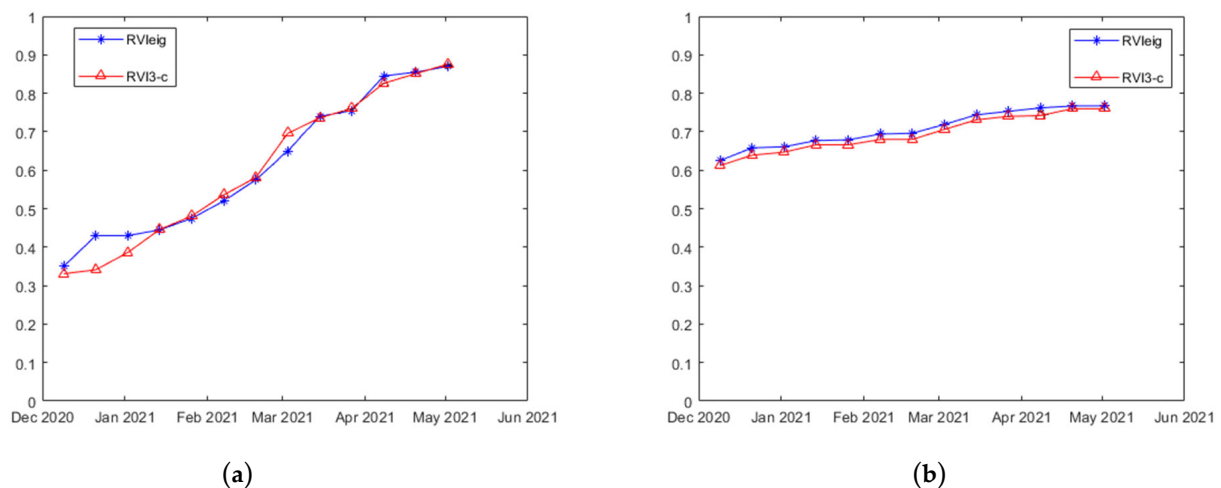


Figure 7. The highest overall accuracy obtained when each data point was included in the classification: (a) OA of rapeseed extraction; (b) OA of image classification.

Overall, from the comparison results of the two RVI s, the time-series curves of RVI_{3-c} clearly differed from those of the different land cover types and scored high in classification assessment indices such as OA and the F-1 score. RVI_{eig} outperformed RVI_{3-c} in terms of the highest accuracy of feature classification throughout the whole growth period, but

$RV I_{3-c}$ performed better in terms of the highest accuracy of rapeseed distribution extraction during the rapeseed reproductive period.

4. Discussion

(1) Applicability of polarization decomposition for dual-polarization data:

The Sentinel-1 dual-polarization SAR data were subjected to eigenvalue decomposition and three-component polarization decomposition. Eigenvalue decomposition is based on the statistical properties of the coherence matrix, which can quantify and assess the stochastic nature of scattering but cannot distinguish between specific scattering mechanisms. Three-component decomposition is based on the assumption of the physical scattering model, which decomposes the scattered echoes from the target feature into volume scattering, surface scattering, and dihedral scattering, with a clear physical meaning, and performs well in crop distribution extraction and classification. When polarization decompositions were applied to the Sentinel-1 dual-polarization data, the scattering components obtained were different from those of the original polarizations, and the polarization components obtained by different polarization decompositions were also different. Additionally, the RVI time series that were computed via the two polarization decompositions were not identical to the original polarizations. The temporal characteristics of rapeseed, a common tall and dry land crop in the southeastern hilly region of China, were not evident in the VV and VH polarizations of the RVI time series, making it challenging to distinguish between rapeseed and woodland immediately via these two polarizations. Although the ratio of the VH and VV polarizations could partially highlight the microwave scattering changes in rapeseed plants and distinguish them from other land covers, the time-series curve of rapeseed repeatedly overlapped with those of water and bare land, which might have caused incorrect classifications of land cover. This is in line with the findings of Bhogapurapu et al. [31], who argued that there is a need to use dual-polarization descriptors characterizing different target scattering mechanisms to improve the accuracy of crop classification, rather than limiting themselves to the direct application of backscattering coefficients and their ratios from dual-polarization SAR data. In terms of the variation in the standard curve in the rapeseed bolting and flowering–silique stages, the rapeseed VH/VV curve varied the least with time, followed by the $RV I_{eig}$ and $RV I_{3-c}$ curves, which varied the most with time.

(2) Comparison of rapeseed extraction applicability based on two typical polarization decompositions:

A comparison of the results of the single-point recognition capability revealed that the waveforms of $RV I_{eig}$ and $RV I_{3-c}$ were similar, and the rapid growth characteristics of volume scattering in the flowering and silique stages of rapeseed were obvious. The $RV I_{3-c}$ time-series curve for rapeseed was more clearly distinguished from those of other land cover types than the $RV I_{eig}$ curve. The comparison results of area mapping accuracy revealed that the rapeseed extraction accuracies based on $RV I_{3-c}$ were higher in typical experimental areas or extended to the whole study region and achieved better results, as measured by the OA and F-1 score indices. $RV I_{eig}$ distinguished rapeseed from other land cover types in the time-series data, while $RV I_{3-c}$ easily misclassified rapeseed and other land cover types as water. A comparison of the time series revealed that the data that significantly impacted the rapeseed extraction accuracy of $RV I_{eig}$ and $RV I_{3-c}$ were obtained from the seedling stage to the bolting stage, and from the bolting stage to the flowering stage. $RV I_{eig}$ outperformed $RV I_{3-c}$ in terms of the highest accuracy of feature classification throughout the whole growth period, but for the rapeseed reproductive period, $RV I_{3-c}$ performed better in terms of the highest precision of rapeseed distribution. Overall, $RV I_{3-c}$ outperformed the other indices in terms of area extraction accuracy. Therefore, three-component polarization

decomposition is more suitable than other methods for crop information extraction and remote sensing classification applications involving dual-polarized SAR data.

In addition, the calculated *RVIs* based on dual-polarization decomposition were stable in the region, and the differences in crop phenology resulted in only a time-axis shift or a scale change in the *RVI* curve, without changing the curve shape of the *RVIs*. DTW was used to measure the similarity of the time series without requiring the waveforms of two time series to be identical. Therefore, although the study region spanned 150 km from east to west and there were differences in crop phenology due to meteorological factors and crop varieties, standard time-series curves were computed via ground-measured data in the standard test portion of Qidong County, and the rapeseed distributions in six neighboring counties were mapped.

(3) Limitations of this study, and future plans:

Taking the primary rapeseed production region in southern Hunan Province as the research area, combined with universal and simple classification, a comparison of the time-series classification effects of rapeseed based on the dual-polarization *RVI* was performed from the perspectives of curve distinguishability, early identification capability, and time-series data combination. Rapeseed is the most important dryland crop in southern China, and there are also typical dryland crops such as wheat and corn in northern China. Consequently, additional crop varieties and seeding techniques should be taken into account in future studies, as well as larger study areas. In terms of SAR image acquisition and preprocessing, we compared the effects of the same orbit and different orbits on Sentinel-1 data applications, and a variety of SAR image coherent noise removal methods will also be tested in the future to reduce the influence of coherent noise for SAR remote sensing in crop classification and extraction applications. In rapeseed distribution extraction and land cover type classification accuracy assessment, in the future, we will compare standard time-series curves of typical land cover types without normalization results. From the mechanism perspective, owing to the lack of some polarization information in dual-polarization data, some assumptions are set in the dual-polarization decomposition algorithm, and the SAR data are decomposed on the basis of these assumptions. The above assumption might ignore the contributions of even scattering and surface scattering to depolarization, and the overestimation of volume scattering might lead to confusion between complex urban areas and vegetation coverage areas. Follow-up research is needed to strengthen the mechanistic analysis. In the future, we will explore more algorithms applicable to the polarization decomposition of dual-polarized SAR data and decipher their principles from a mechanistic point of view for application in crop distribution extraction and classification. Moreover, in this study, crop feature extraction via dual-polarization decomposition technology for remote sensing classification was studied, and the classification algorithm was not studied or improved. In the future, with the improvement of the classification algorithm, the accuracies of SAR extraction of dryland crop planting distributions in the study region will be improved.

5. Conclusions

To obtain the full coverage of dryland crop distribution extraction in hilly areas of southeastern China and explore the feasibility of dual-polarization decomposition for monitoring crops, two kinds of dual-polarization *RVI* were constructed by using eigenvalue decomposition and three-component polarization decomposition in this study. Rapeseed from the central and lower sections of the Yangtze River in China served as the research object for both general and simple classification. The time-series classification effect of rapeseed was examined and contrasted from the perspectives of the recognition ability of single-point collected images, accuracy of regional extraction, and importance of sorting.

The results show that the two dual-polarization RVI s have different characteristics and advantages under different criteria, and that RVI_{3-c} performs better in terms of rapeseed distribution extraction and classification. From the comparison of single-point recognition ability, the waveforms of RVI_{eig} and RVI_{3-c} are similar, and the rapid growth characteristics of volume scattering at the flowering and silique stages are obvious; however, the RVI_{3-c} standard time-series curve has a more obvious differentiation than other land cover types and can recognize rapeseed more accurately. Based on the regional validation, RVI_{3-c} scored high in classification assessment indices such as OA and F-1 score, and the OA and F-1 score of rapeseed extraction based on RVI_{3-c} were 74.13% and 81.02%, respectively, indicating its effectiveness in extracting and classifying the distribution of rapeseed on a regional scale. For the time-series data combination, RVI_{eig} outperformed RVI_{3-c} in terms of the highest accuracy of feature classification throughout the whole growth period, but RVI_{3-c} performed better in terms of the highest accuracy of rapeseed distribution extraction during the rapeseed reproductive period. Combining all of the comparison results, RVI_{3-c} outperformed RVI_{eig} in terms of single-point recognition ability and area extraction accuracy. Therefore, compared with other polarization decomposition techniques, the three-component polarization decomposition technique is more suitable and practical for crop information extraction and remote sensing classification applications based on dual-polarization SAR data.

Author Contributions: Conceptualization, S.W.; methodology, Y.Z. and H.C.; validation, Y.Z. and H.C.; formal analysis, Y.Z. and Q.S.; investigation, S.W. and Y.G.; writing—original draft preparation, Y.Z.; writing—review and editing, H.C. and S.W.; visualization, Y.Z. and Q.S.; supervision, S.W.; funding acquisition, S.W. and Q.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by grants from the National Key Research and Development Program of China (2021YFD1600503), the National Natural Science Foundation of China (42271374), the Youth Innovation Program of the Chinese Academy of Agricultural Sciences (Y2023QC18), the Technology Innovation Center for Land Engineering and Human Settlements, Shaanxi Land Engineering Construction Group Co., Ltd., and Xi'an Jiaotong University (2021 WHZ0072).

Data Availability Statement: All of the data, models, and codes generated or used during this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

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