

Article

Multi-Type Change Detection and Distinction of Cultivated Land Parcels in High-Resolution Remote Sensing Images Based on Segment Anything Model

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Abstract: Change detection of cultivated land parcels is critical for achieving refined management of farmland. However, existing change detection methods based on high-resolution remote sensing imagery focus primarily on cultivation type changes, neglecting the importance of detecting parcel pattern changes. To address the issue of detecting diverse types of changes in cultivated land parcels, this study constructs an automated workflow framework for change detection, based on the unsupervised segmentation method of the SAM (Segment Anything Model). By performing spatial connection analysis on cultivated land parcel units extracted by the SAM for two phases and combining multiple features such as texture features (GLCM), multi-scale structural similarity (MS-SSIM), and normalized difference vegetation index (NDVI), precise identification of cultivation type and pattern change areas was achieved. The study results show that the proposed method achieved the highest accuracy in detecting parcel pattern changes in plain areas (precision: 78.79%, recall: 79.45%, IOU: 78.44%), confirming the effectiveness of the proposed method. This study provides an efficient and low-cost detection and distinction method for analyzing changes in cultivated land patterns and types using high-resolution remote sensing images, which can be directly applied in real-world scenarios. The method significantly enhances the automation and timeliness of parcel unit change detection, offering important applications for advancing precision agriculture and sustainable land resource management.

Keywords: cultivated land parcel pattern changes; segment anything model (SAM); spatial analysis; multi-scale structural similarity (MS-SSIM)



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1. Introduction

Change detection of cultivated land resources can comprehensively and accurately monitor the division of land parcels and changes in their functional attributes. This is of great significance for the implementation of precision agriculture management, supporting scientific decision-making by government departments, and promoting sustainable development [1]. Currently, change detection of cultivated land based on high-resolution remote sensing imagery mainly relies on manual visual interpretation, lacking efficient

methods for rapidly distinguishing changes in land parcel units. Moreover, most cultivated land change detection studies rely on annual land survey data, leading to a lack of timely and comprehensive understanding of cultivated land changes [2]. Therefore, there is an urgent need for more automated detection methods to meet the timeliness and accuracy requirements of cultivated land resource monitoring.

With the improvement of remote sensing image resolution and the richness of accessible land feature information, remote sensing technology has become the core method for detecting changes in cultivated land resources. Traditional change detection methods mainly focus on medium-resolution remote sensing images, detecting changes based on pixel features. These methods analyze the spectral differences of individual pixels or their neighborhoods, using techniques like clustering and thresholding to extract cultivated land change areas [3]. However, pixel-based methods are prone to neglecting the contextual information of land parcels, leading to detected land units lacking the semantic features of actual boundaries and being vulnerable to “salt-and-pepper” noise interference [4]. Change detection methods based on the change detection after classification strategy extract cultivated land change types by overlaying multiple land use classification results, further improving the accuracy of pixel-level change detection [5]. Previous change detection studies often overlooked the spatiotemporal relationships of geographic objects in time-series data, leading to suboptimal change detection results. Therefore, Ref. [6] proposed the spatiotemporal multi-resolution segmentation method (ST-MRS) for the first time to quantitatively measure the spatiotemporal heterogeneity, correlation, and scale characteristics of geographic objects, thus efficiently generating land cover type maps. Ref. [7] utilized Landsat time-series data and performed segmentation in both spatial and temporal dimensions to generate annual land cover types, achieving accurate identification of abandoned cultivated land. However, since the classification step requires a large number of high-quality training samples, this strategy incurs high costs in practical applications [8]. To reduce classification costs, Ref. [9] combined multi-period national land survey data with land cover data (CLCD), using patches with unchanged land use types as training samples for land use classification, successfully identifying abandoned cultivated land in key agricultural areas of the Qinghai–Tibet Plateau. Similarly, Ref. [10] integrated land cover vector data and remote sensing images, using the enhanced Simple Linear Iterative Clustering (SLIC) algorithm and clipping repair method to automatically generate training and testing datasets, achieving high-precision land cover change detection. Although the change detection after classification method can achieve high-precision change detection results, its main challenge lies in whether high-precision land use classification results can be obtained to avoid error accumulation in subsequent change detection. However, the update frequency and acquisition cost of national land survey data make it difficult to meet the practical needs of precision agricultural land management.

In recent years, deep learning-based change detection methods using high-resolution remote sensing imagery have developed rapidly, significantly improving the accuracy of cultivated land change detection [11,12]. To avoid losing contextual information between cultivated land parcels, Ref. [13] proposed a CNN-transformer network with multiscale context aggregation (MSCANet), which extracts the edges and morphological semantic attributes of cultivated land change objects from dual-temporal images. Ref. [14] introduced a Multi-task Consistency Enhancement Module (MCEM) to strengthen the learning of semantic consistency in unchanged areas between dual-temporal images, while enhancing the completeness of change features. However, dual-temporal change detection faces several challenges in practical applications, such as the need to consider the phenological diversity and image differences of different land cover types in cultivated land, the dif-

difficulty in acquiring high-resolution imagery, and the high cost of model training sample construction, which limits its transferability in cultivated land monitoring.

High-resolution remote sensing image change detection is mainly achieved by processing visual features. The visual model of the SAM [15] can segment any object in an image without annotations and supports zero-shot generalization, enabling the segmentation of unfamiliar objects and images [16]. This feature has made the SAM widely used in remote sensing change detection research [17,18]. For example, Refs. [19,20] achieved high-precision building change detection by fine-tuning the SAM visual encoder and combining it with other deep learning architectures. The powerful semantic segmentation capability of the SAM offers a new perspective for cultivated land parcel extraction and change detection. In previous studies, we have confirmed the effectiveness of the SAM in complex cultivated land parcel delineation under zero-shot and unsupervised conditions [21]. Especially in scenes with significant contrast differences [22], its segmentation results include the true boundary semantics of cultivated land. The advantage of the SAM compensates for the shortcomings of some change detection methods that rely on hard-to-obtain and outdated geographic national survey vector maps as auxiliary data, as well as the high cost of acquiring model training samples. At the same time, the SAM can fully and accurately identify land parcel units based on visual features. When the same region's land parcel unit changes between two temporal images, the land parcel units extracted by the SAM will show significant differences in both number and area. Therefore, by leveraging the zero-shot and unsupervised segmentation advantages of the SAM, it can be applied to land parcel extraction and change detection in cultivated land scenarios, meeting the timeliness and accuracy requirements for precision land management, with great potential and application prospects in the future.

Changes in cultivated land parcels are influenced by various factors, such as planting practices and land use changes, resulting in diverse types of changes, including variations in planting types, cultivation patterns, and land abandonment. Notably, changes in the spatial patterns of parcel units are often accompanied by shifts in land use types and alterations in their spatial relationships with adjacent parcels [23]. Detecting changes in cultivated land patterns at the parcel level is significant for studying the evolution of urban and agricultural landscapes and achieving refined management. For instance, Ref. [24] analyzed the spatial pattern changes of land use, revealing the social and natural landscape evolution in Monroe County, Indiana, over the past 70 years. Refs. [25,26] explored the evolution of urban spatial patterns by measuring landscape pattern indices such as the compactness of urban building parcels and their spatiotemporal relationships. In cultivated land change detection, identifying cultivated land pattern changes is as important as detecting changes in cultivated land types. However, existing change detection methods based on high-resolution remote sensing imagery mainly focus on detecting cultivated land type changes and semantic classification of crop types, neglecting the importance of pattern change detection. Currently, there is no comprehensive method for effectively classifying and distinguishing multiple types of changes in cultivated land parcels. Additionally, previous studies often use the texture features of cultivated land parcels [27] as metrics for measuring changes in parcel units. Due to the diversity of change types, relying solely on a single texture feature for cultivated land change detection in complex scenarios has significant limitations. To address this, this study employs the SAM to perform unsupervised segmentation on two-phase high-resolution time-series images under zero-shot and unsupervised conditions, generating parcel units with true boundary semantics of cultivated land without relying on existing land survey data. By analyzing the spatial relationships between cultivated land parcels in the two-phase images and measuring the texture features, structural similarity (SSIM) [28], and vegetation index

features [29] between corresponding patches, accurate detection of type and pattern change areas of cultivated land parcels in complex regions is achieved. An automated workflow framework from image segmentation to change detection has been constructed, enabling effective detection and distinction of various change types, thereby meeting the refined management needs for the classification of cultivated land parcel units and the detection of changes in their functional attributes.

2. Study Area and Data

2.1. Study Area

Meishan City in Sichuan Province is located in southwestern China, at the western edge of the Sichuan Basin, and is rich in cultivated land resources and agricultural foundations. Among its districts, Dongpo District serves as the political, economic, and cultural center of Meishan City, situated on the southwestern edge of the Chengdu Plain in the middle reaches of the Min River. The area features relatively flat terrain with moderate undulations, comprising plains, low hills, and mountainous regions, offering a unique geographic and natural resource advantage. In Dongpo District, land use is dominated by cultivated land, orchards, and construction land. Among cultivated land types, rice is predominant, accounting for approximately 86% of the total cultivated area. As a national standardized demonstration area for high-standard farmland construction, Dongpo District has been committed to farmland protection and utilization, ensuring high-quality production and efficient land-use management.

In recent years, Dongpo District has experienced significant non-agricultural and non-grain transformations of cultivated land, particularly the conversion of farmland into orchards. Therefore, research on detecting changes in cultivated land patterns and types in this region is of great significance. It not only provides scientific support for government decision-making but also contributes to the realization of precision agriculture. To this end, this study selects a rectangular area of approximately 142 km² in Dongpo District (103°39′~103°46′E, 30°02′~30°09′N) as the study area (Figure 1). The study area is characterized by frequent cloud cover and heavy rainfall throughout the year, which significantly affect the imaging quality of high-resolution remote sensing images, making it very challenging to select suitable high-resolution images for change detection research in this region. Additionally, the area features complex terrain, fragmented distribution of cultivated land parcels, and diverse planting types, predominantly employing a double-cultivation system within a year. These factors present substantial challenges to the proposed methods for detecting changes in cultivated land patterns and types.

2.2. Selection and Processing of High-Resolution Remote Sensing Imagery

The frequent cloud and rain in the study area severely affect image quality, posing significant challenges in selecting suitable bi-temporal high-resolution remote sensing images. Rice is the dominant cultivation type in Dongpo District. Through phenological analysis of different cultivation types in the study area and field surveys, it was determined that rice in this region is typically sown in April and harvested in September. To minimize the impact of rice phenological changes on change detection results, the images used in the experiment were acquired after rice maturation but before harvest. Therefore, this experiment utilized data from the Jilin-1 KF satellite of the Jilin-1 satellite series, which provides panchromatic images with a resolution of 0.75 m, multispectral images with a resolution of 3 m, and a swath width exceeding 136 km². After data fusion, 1 m resolution RGB remote sensing images were obtained [30]. After filtering, the acquisition dates for the bi-temporal remote sensing images were 13 August 2022, and 17 July 2023. From the overview of the study area, it can be observed that the imaging characteristics of

the corresponding regions are generally similar in both images. However, more bare land is present in the earlier image, which requires further classification in subsequent experiments. Since there are radiometric differences between the two periods, which may impact the change detection results, the 2022 image was histogram-matched to the 2023 image and underwent necessary preprocessing steps such as relative radiometric correction and orthorectification.

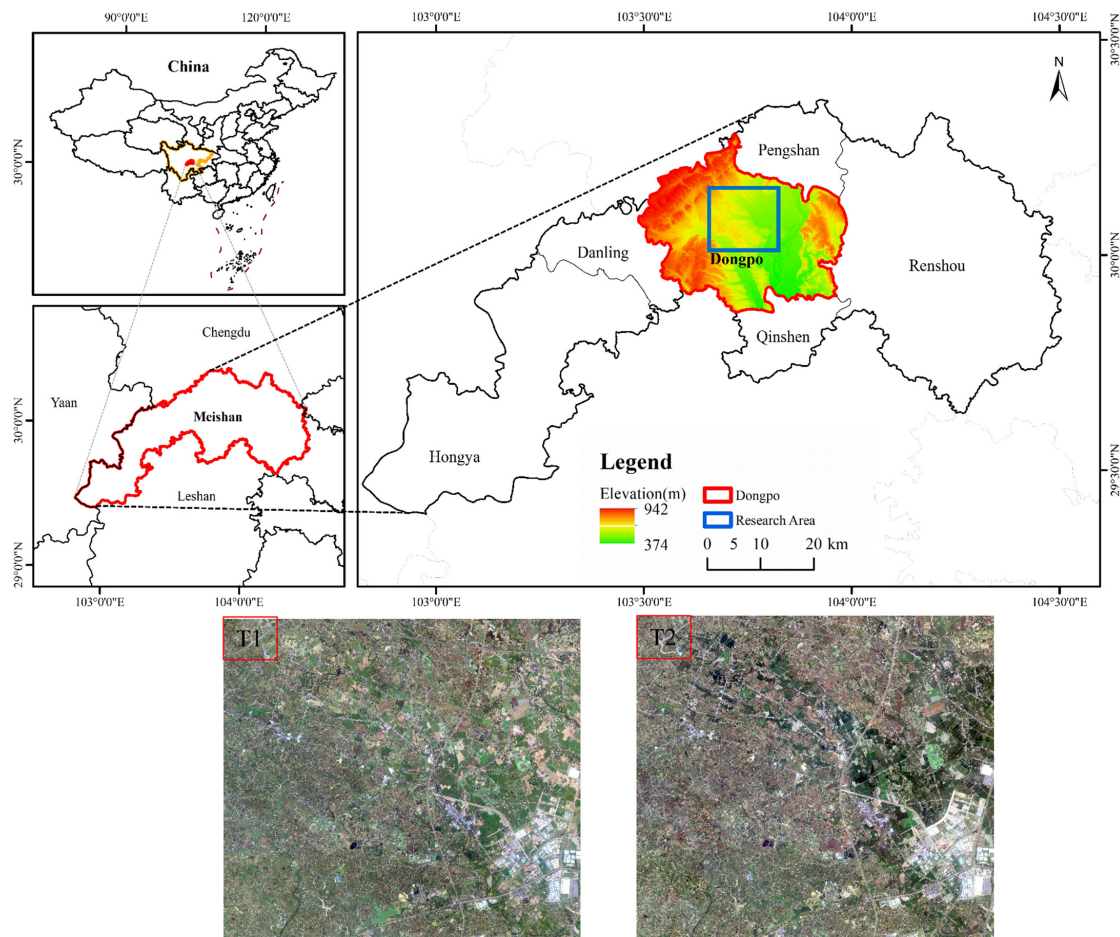


Figure 1. Overview of the study area.

2.3. NASA DEM Data

The NASA DEM [31] is a gap-free, near-global digital elevation model generated by reprocessing SRTM data with a spatial resolution of approximately 30 m (1 arcsecond). The main objective of this product is to eliminate gaps and other limitations present in the SRTM data by using datasets that were unavailable during the original processing. In this study, NASA DEM data were used to obtain elevation and slope information for the study area, which served as the basis for selecting cultivated regions with different topographic features.

3. Methods

3.1. Overall Workflow of Cultivated Land Change Detection

The diversity and fragmented distribution of cultivated land parcels make the extraction of land units and change detection challenging. In our previous research, we have demonstrated the effectiveness and transferability of the SAM for extracting complex cultivated land parcels over large areas under zero-shot and unsupervised conditions. The SAM encodes the input remote sensing imagery using a vision encoder, and the semantic

boundaries of the extracted cultivated land patches are consistent with the actual parcel boundaries, providing crucial support for accurate land parcel extraction and subsequent detection of cropping pattern and type changes. Unlike traditional change detection methods, this study uses SAM unsupervised segmentation to extract cultivated land parcels from bi-temporal imagery without relying on existing national land survey data as auxiliary information (see Section 3.2). By overlaying the vector patches from the two segmented images, analyzing the spatial relationships between patches, and integrating texture features, SSIM, and spectral features for comprehensive analysis (see Section 3.3), this approach detects cropping pattern change regions, cropping type change regions, and potential change regions (see Section 3.4). The main methodological framework of this study is shown in Figure 2.

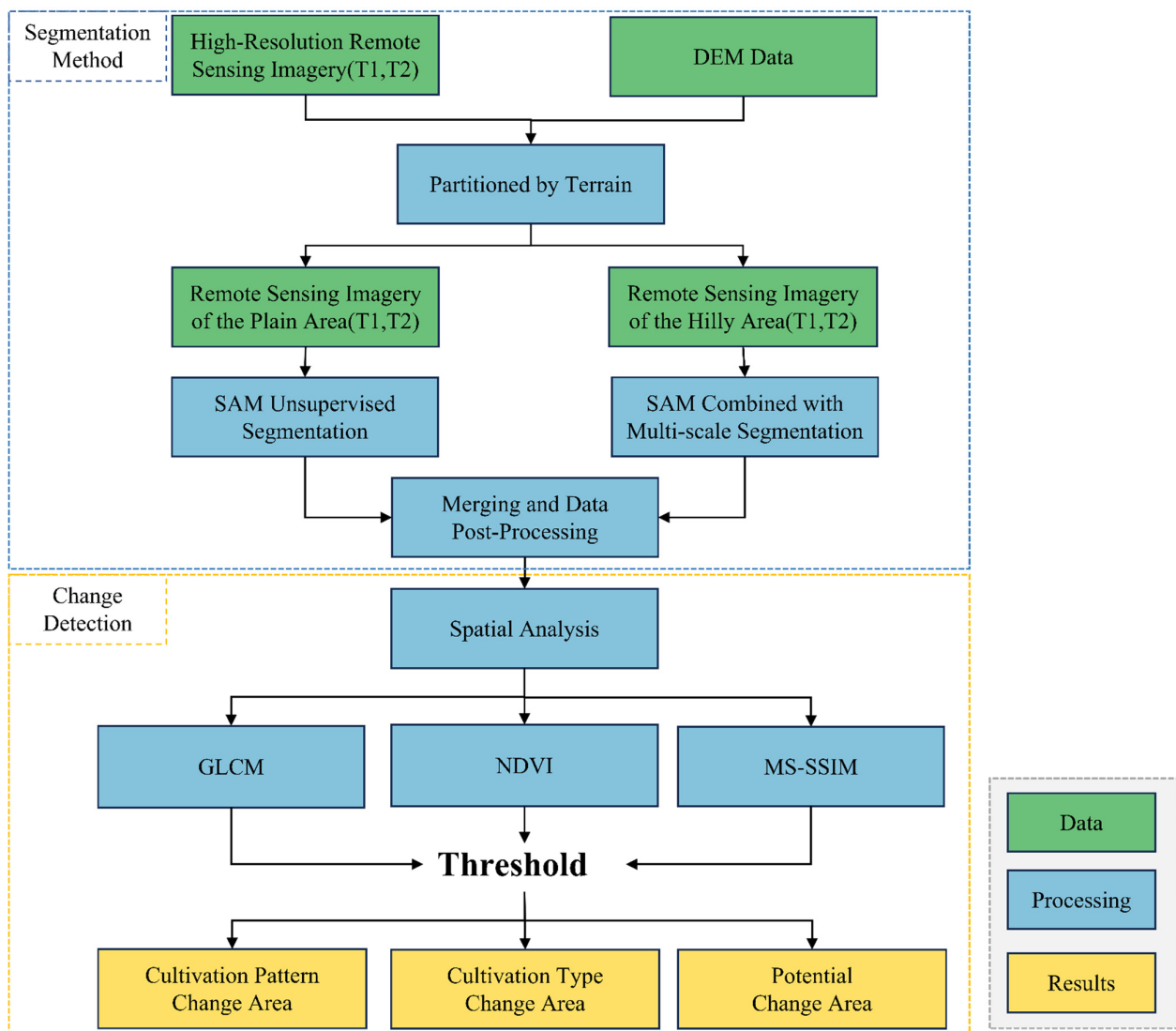


Figure 2. Workflow of the multi-type change detection and distinction method for cultivated land. The overall process is divided into two parts: cultivated land parcel extraction and multi-type change detection.

3.2. SAM Dual-Temporal Segmentation

3.2.1. Partitioned by Terrain

Complex terrain and fragmented cultivated land parcels in Dongpo District make it difficult to extract land units and perform change detection using a single segmentation method. Therefore, using NASA DEM data, the study area was divided into two parts:

plain and hilly areas, based on the median elevation and slope data of the region. Different segmentation strategies were then applied to extract the land units.

3.2.2. SAM Unsupervised Segmentation

During cultivated land parcel extraction, the SAM typically identifies cultivated land as the foreground and roads between parcels as the background, allowing effective segmentation of cultivated land parcels. However, for low-contrast and complex fragmented cultivated land parcels, the SAM may misidentify the region as the background, leading to under-segmentation. To improve the accuracy of parcel extraction using the SAM unsupervised segmentation method, this study applied percentage linear stretching and histogram equalization stretching to high-resolution remote sensing images. SAM unsupervised segmentation was then used to extract cultivated land parcels, and the intersection of segmentation results from different stretching methods was taken as the final cultivated land extraction result. For the plain area, the accuracy of cultivated land extraction using SAM unsupervised segmentation alone is close to the required level. However, for the hilly area, where cultivated land is more complex and fragmented, and boundaries are unclear, the SAM tends to misidentify such areas as background. Therefore, in the hilly area, the vector data of cultivated land extracted by the SAM will be used as constraints in eCognition Developer 9.0 (EC) for multi-scale segmentation [32], to supplement land units missed by SAM unsupervised segmentation. Multi-scale segmentation involves three parameters: compactness, shape factor, and scale. Based on previous studies, the final values for compactness and shape factor were set to 0.5 and 0.2, respectively [33,34]. The scale parameter estimation tool (ESP-2) developed by [35] was used to estimate the local variance (LV-ROC) of multi-layer images, thus determining the optimal segmentation scale.

3.2.3. Data Post-Processing

Since SAM unsupervised segmentation is category-independent, it often generates irrelevant segmentation patches (e.g., roads, forest lands) and numerous noise points. To improve the accuracy of the segmentation results, post-processing of the extracted land parcel units is required. First, the shape index of the patches is calculated [36] to exclude interference from irregular patches. Then, morphological [37] closing and opening operations are applied to fill gaps within the patches, enhance completeness, smooth the boundaries of segmented patches, and eliminate patches with an area smaller than 400 m², thereby reducing interference with subsequent spatial analysis and removing noise points. Finally, to minimize the impact of closely adjacent land parcel units on spatial analysis results, a 1 m internal buffer is created for the segmented patches. The processed land parcel units from plain and hilly areas are then merged.

3.3. Multi-Feature Distinction of Parcel Units Across Dual-Temporal Images

3.3.1. Distinguishing Morphological Changes in Parcel Units Considering Spatial Relationships

By leveraging the advantages of SAM segmentation to analyze the spatial correlation of the number and attributes of segmented patches in the same region across bi-temporal remote sensing images, it is possible to preliminarily identify areas where cropping pattern changes may have occurred in cultivated land parcels. Therefore, this study conducts multi-feature classification on the bi-temporal land units extracted by SAM unsupervised segmentation, as illustrated in Figure 3.

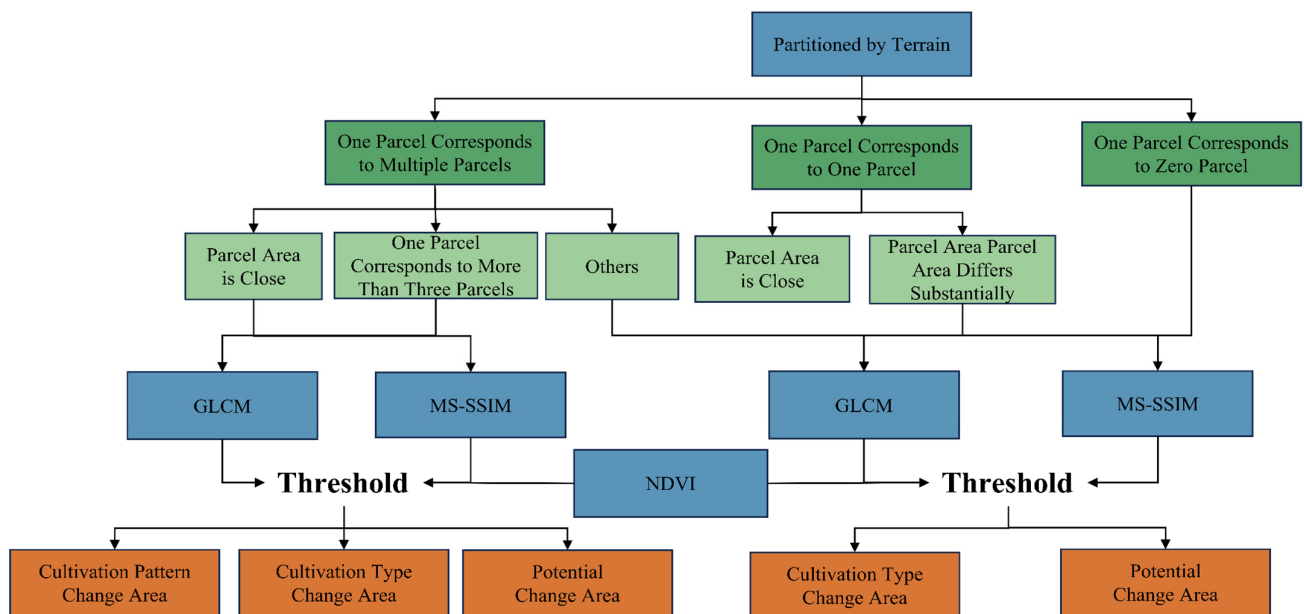


Figure 3. Workflow for multi-feature distinction of land parcels. The classification of land parcel units is based on the correspondence of patch quantities.

The SAM unsupervised segmentation method may misidentify some parcels with fuzzy boundaries or fine fragmentation as background during segmentation tasks, leading to ineffective segmentation of certain parcels. This study conducted change detection based on the parcel units derived from the two-phase SAM segmentation results. Regions identified as background in both phases were considered unchanged areas (as shown in Figure 4). Based on this foundation, spatial connectivity analysis was performed on the parcel units across the two phases.

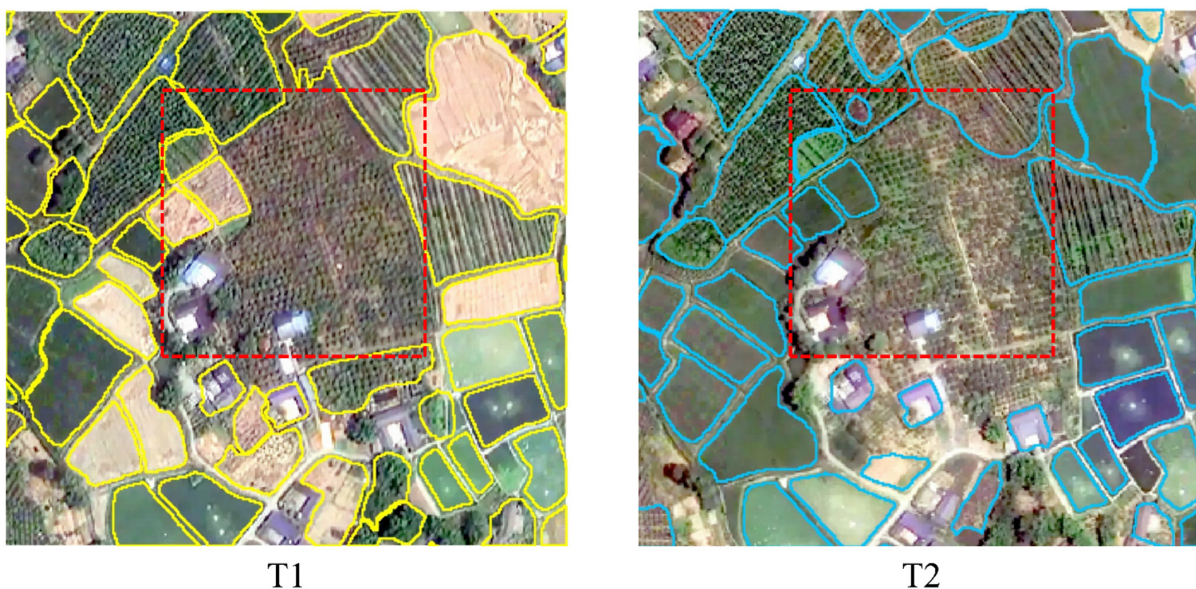


Figure 4. T1 and T2 represent the scene of two local areas of the study area for the two temporal remote sensing images and the SAM extraction results. The red dashed boxes indicate areas segmented and simultaneously identified as background by SAM, which are considered unchanged regions by default.

The primary objective of this study is to accurately detect changes in cultivated land patterns, which typically occur in areas where the segmented patches in corresponding regions

of two temporal images either merge or split. Therefore, after constructing spatial indices for the segmented vector data of the two periods, patches that undergo merging or splitting from T1 to T2 are first classified into one category, defined as one large patch corresponding to multiple smaller patches. The remaining patches can be further divided into two categories: one where a patch corresponds to exactly one patch in the other period, and another where no corresponding land parcel is extracted in the other temporal image. For the category where one patch corresponds to one patch, it can be further divided into two subcategories: those with similar areas and those with significantly different areas. Experiments indicate that when one patch corresponds to one patch with a similar area, the likelihood of change is low. Therefore, this type is regarded as an unchanged region in the subsequent processes. To further narrow down the detection range of pattern change regions and reduce computational complexity, patches that exhibit merging or splitting are further categorized into three types: (1) the area of the large patch is close to the sum of the corresponding smaller patches' areas ($0.85 \cdot A_{\text{small}} \leq A_{\text{large}} \leq 1.15 \cdot A_{\text{small}}$); (2) one large patch corresponds to more than three small patches extracted in the same area of the other temporal image; (3) the remaining patches that do not fit into the first two categories. The classification is based on the following rationale: (1) when a land parcel splits or merges between the two periods and the sum of the corresponding areas is similar, there is a high probability of pattern change; (2) if one large patch splits into multiple smaller patches and the number exceeds three (as set by this study), there is also a high likelihood of pattern change. This study assumes that cultivated land pattern changes occur only within these two types.

3.3.2. Combined Judgment of Other Features

In the Dongpo area, the most significant change in cultivated land type is the conversion of cultivated land into orchards. Since orchards and cultivated land exhibit noticeable differences in texture features in image representation, this study uses the Gray Level Co-occurrence Matrix (GLCM) to measure these texture differences. GLCM measures the contextual and structural information of land parcels by setting a moving window and performs change detection by defining a threshold [38,39]. In the experiment, four commonly used texture features—contrast, homogeneity, entropy, and Angular Second Moment (ASM)—were selected for statistical analysis. A feature difference matrix between the two temporal images was calculated and normalized. Principal Component Analysis (PCA) [40] was then applied to the feature difference matrix for dimensionality reduction, determining the number of principal components that could explain 90% of the cumulative variance, and a comprehensive change score was calculated. Based on experimental comparison, the 80th percentile of the comprehensive change score was selected as the threshold for change detection. Due to the diverse types of changes in cultivated land parcels, relying solely on a single texture feature is considerably limited. Therefore, Multi-Scale Structural Similarity (MS-SSIM) [41] was used to measure the differences in image features of corresponding regions. MS-SSIM is an index for evaluating the visual similarity between two temporal images. It comprehensively assesses the similarity of corresponding land parcels by measuring the brightness, contrast, and structural information of different bands in the images. Otsu's method (OTSU) [42] is then used to determine the change detection threshold. This study combines GLCM feature values and MS-SSIM to jointly measure the differences between corresponding patches, further distinguishing different types of changes in cultivated land.

3.3.3. Planting Period Distinction and Ambiguity Resolution

By observing the two temporal images, it was found that in some corresponding regions of land parcels, one image shows vegetation coverage while the other shows bare

land. This phenomenon could either indicate a change in cropping type or be due to temporal differences between the images, where crops in one image have been harvested. Therefore, for the change regions detected in the previous steps, the Normalized Difference Vegetation Index (NDVI) of the corresponding areas in the two temporal images was calculated. Based on the NDVI differences, land parcels that changed from crop-covered areas to bare land were identified.

3.4. Different Change Detection Types and Distinction

3.4.1. Detection of Cultivated Land Pattern Change Areas

Cultivated land pattern change refers to the change in the cultivation pattern of land parcel units in the same region at different times. During this process, the cultivation type may remain unchanged or change, which increases the difficulty of detecting cultivated land pattern change areas (as shown in Figure 5). Therefore, after performing spatial connectivity analysis of the land parcel units, GLCM features and MS-SSIM are combined for further distinction. For regions where the area of the large patch and the small patch sum is close, when the MS-SSIM is below the threshold and the comprehensive score calculated from GLCM features exceeds the set threshold, the area is considered a cultivated land pattern change area. For regions where the number of small patches corresponding to a large patch exceeds three, the classification method is as follows: exclude those unchanged regions where the GLCM texture features are below the 20th percentile and the MS-SSIM value is high; for regions where the texture features exceed the set threshold, they are considered as type change areas. The remaining patches are classified as pattern change areas. The classification basis is that the more small patches correspond to a large patch, the greater the likelihood of pattern change.

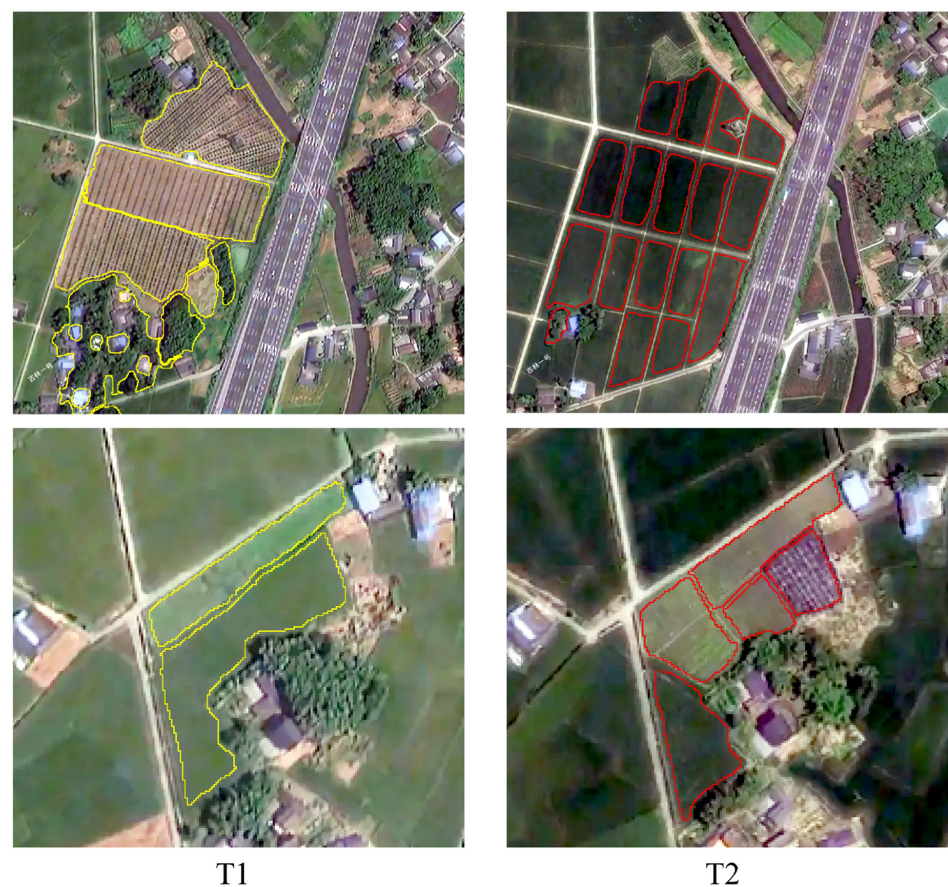


Figure 5. Shows two pairs of areas with cultivated land pattern changes. The patches in the figure are land parcel units obtained from SAM segmentation.

3.4.2. Detection of Cultivated Land Type Change Areas

The conversion of cultivated land types exhibits significant differences in the imagery. There are large texture differences between different types, and there are obvious tonal differences visually (as shown in Figure 6). The patches that correspond to multiple patches, categorized as other types, patches where one patch corresponds to one patch with a large area difference, and patches where one patch corresponds to no patch, are merged to classify cultivated land type change areas. The union of the results where the comprehensive score calculated from the GLCM feature exceeds the set threshold and the MS-SSIM value is below the threshold obtained by OTSU is classified as cultivated land type change areas.

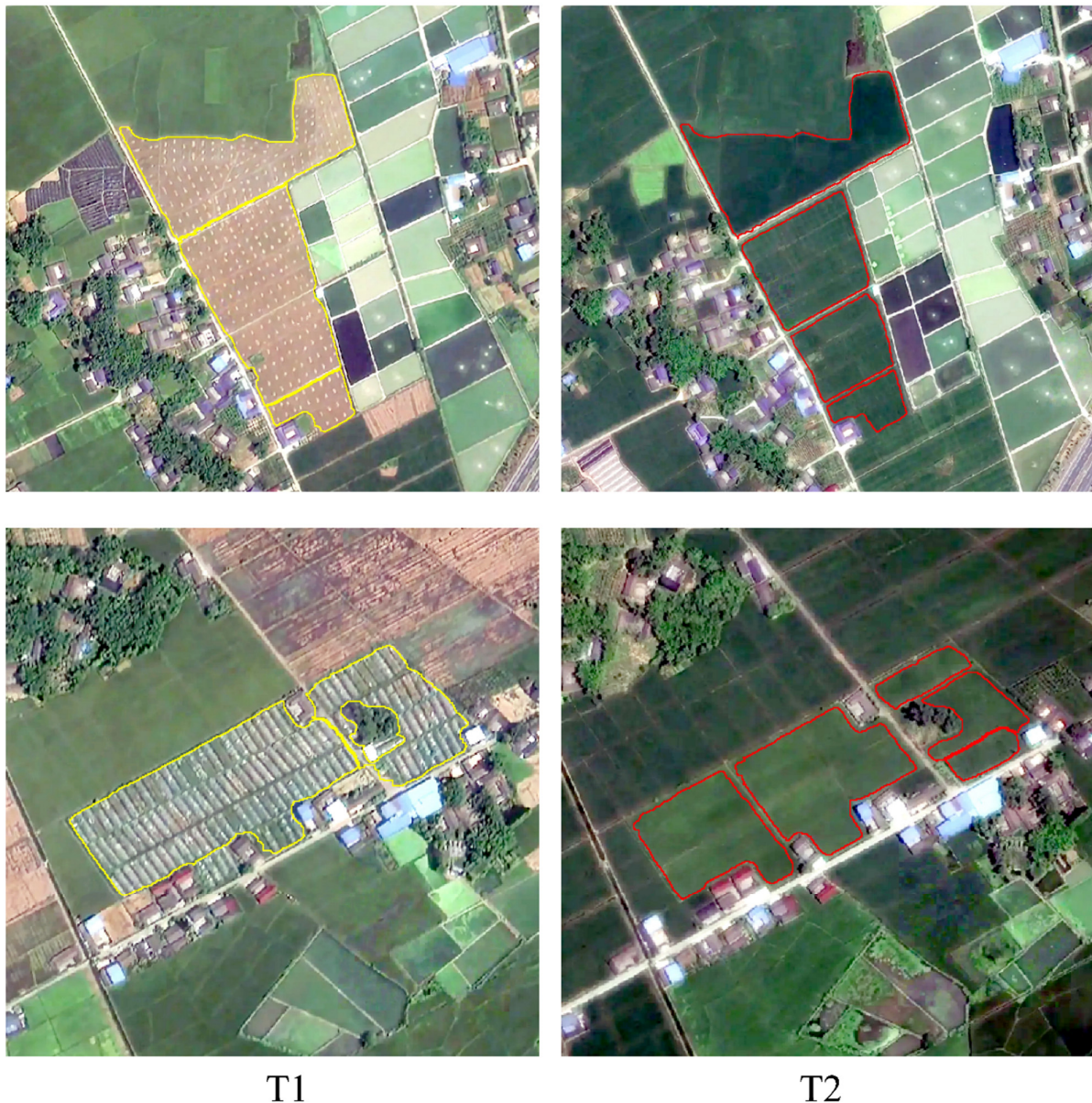


Figure 6. Shows two pairs of areas with cultivated land type changes. The patches in the figure are land parcel units obtained from SAM segmentation.

3.4.3. Detection of Potential Change Areas

The two temporal remote sensing images selected for this study were captured on 13 August 2022, and 17 July 2023. Since the earlier image was taken close to the crop harvest period, there were more bare land areas present in the image. To reduce misclassification caused by different crop growth cycles and temporal differences between the images, land

parcels identified as cropping pattern or type changes that show bare land in one image and vegetation coverage in the other were separately selected and categorized as potential change regions (as shown in Figure 7). The NDVI values of the corresponding regions in the two temporal images were calculated, and patches with NDVI values ranging from low to high were selected. By visually adjusting the threshold, parcels with significant NDVI differences were identified and categorized separately as potential change regions.

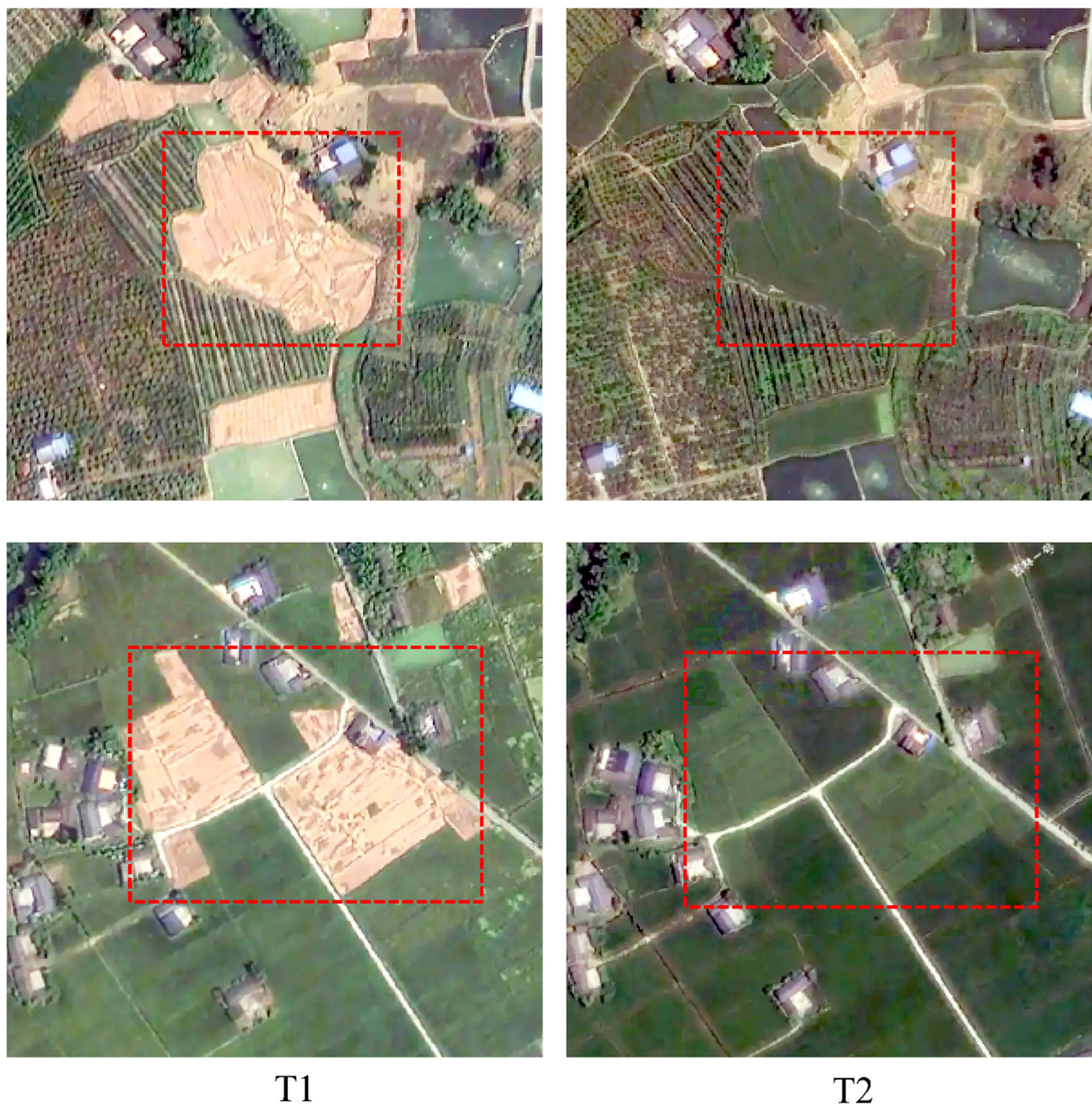


Figure 7. Shows potential change areas where bare land has transformed into vegetation (red rectangle).

3.5. Evaluation Metrics

This study selects evaluation metrics from two aspects: the quantity of change detection and the area of detected parcels, to assess the performance of the proposed method in recognition ability and geometric accuracy. In terms of quantity, the overall recognition rate (OR) is used as a global indicator of accuracy in the entire region, defined as follows:

$$OR = \frac{N_{acc}}{N_{gt}}, \quad (1)$$

where N_{gt} represents the total number of land parcels that truly underwent changes, and N_{acc} represents the number of land parcels accurately detected in the corresponding area.

In terms of area, precision, recall, and Intersection over Union (IoU) are used to evaluate the performance of the change detection results [43]. The area of overlap between the detected land parcel units and the sample parcels is defined as true positives (TPs). The area of undetected sample parcels is considered false negatives (FNs), while the area of non-sample regions incorrectly identified as change areas is classified as false positives (FPs) (as shown in Figure 8).

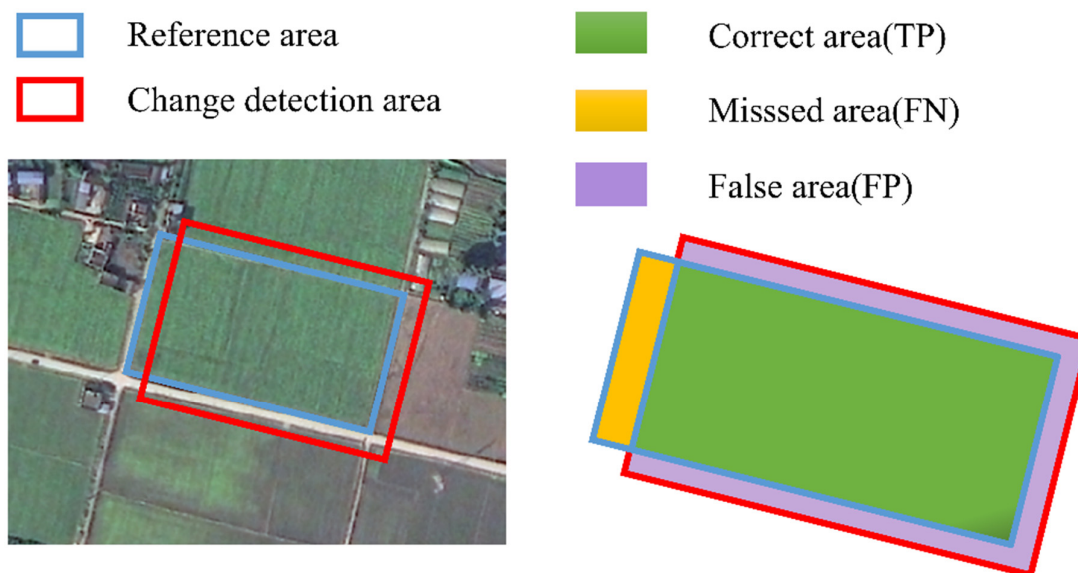


Figure 8. Diagram showing the correct, missed, and incorrect areas of detected land parcel units.

The precision, recall, and IoU for land parcel change detection are evaluated using Equations (2)–(4):

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{IoU} = \frac{TP}{TP + FP + FN} \quad (4)$$

4. Results

4.1. Land Parcel Extraction Results and Accuracy Evaluation

The local extraction results and accuracy evaluation of cultivated land parcels in this study are shown in Figure 9 and Table 1, respectively. From the spatial characteristics of the cultivated land parcels, the plain areas in the study region have larger parcel sizes, regular shapes, and are mostly concentrated in continuous patches, while the cultivated land parcels in the hilly areas are smaller, irregularly shaped, and spatially fragmented, which increases the difficulty of accurately extracting the parcels.

Without relying on existing national land survey data, this study used the SAM unsupervised segmentation method to extract land parcel units in the plain areas. The extraction results show that the average precision, recall, and IoU of the two-phase segmentation results reached 87.97%, 84.39%, and 79.43%, respectively. For the hilly areas, the SAM unsupervised segmentation method combined with multi-scale segmentation was used to extract land parcel units, improving the extraction accuracy of complex, fragmented parcels with unclear boundaries. The average precision, recall, and IoU for the land parcel

extraction in the hilly areas reached 85.54%, 82.32%, and 75.65%, respectively. The SAM unsupervised segmentation method achieved high accuracy in land parcel extraction for different terrains. Since land parcel extraction supports subsequent change detection experiments, if the land parcels in the same region during both time phases are identified as background by the SAM, they are considered unchanged areas.

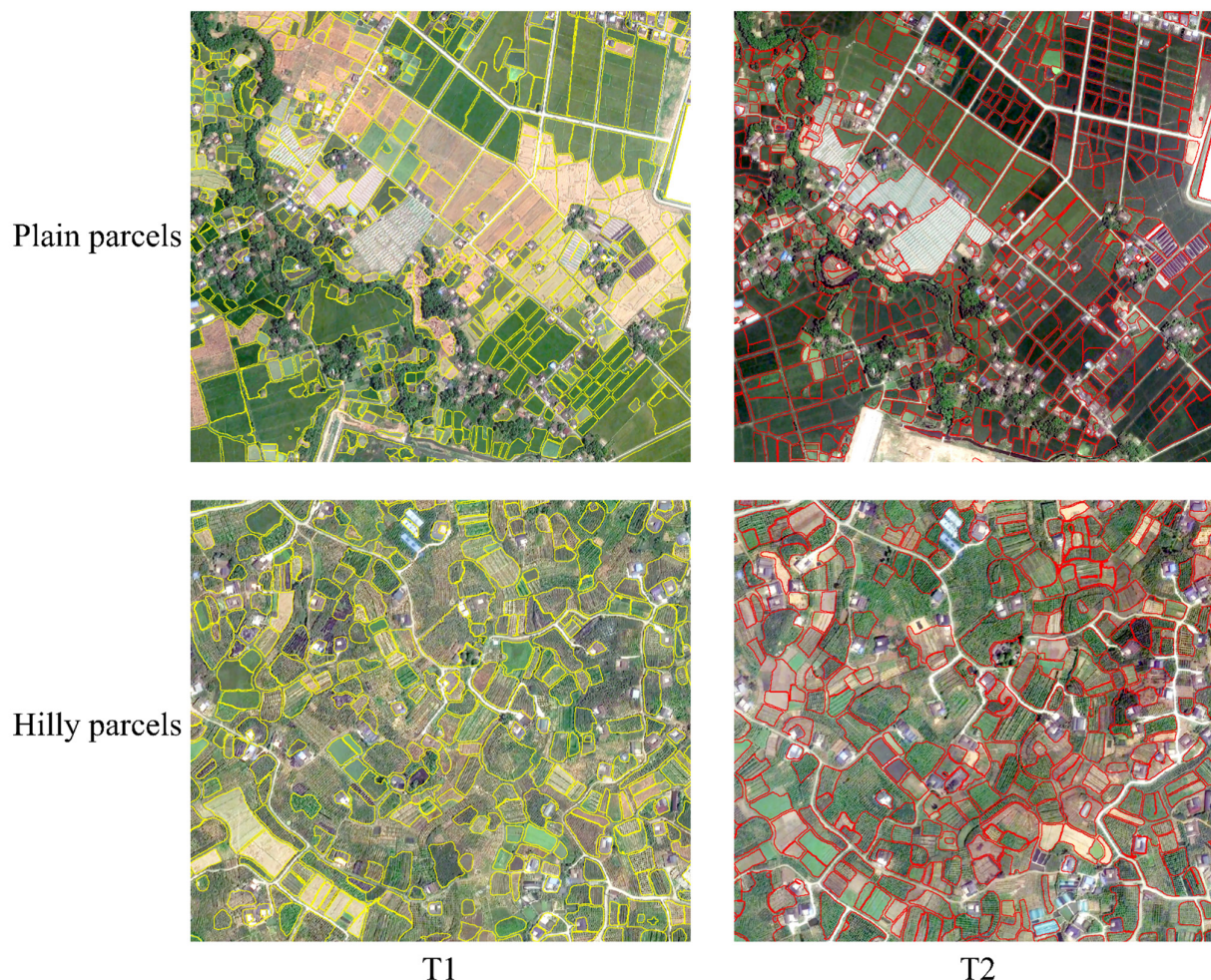


Figure 9. Local segmentation results for different terrains in the study area are shown.

Table 1. Accuracy evaluation results of land parcel segmentation for different terrains.

	Precision (%)	Recall (%)	IoU (%)
Plain parcels	87.97	84.39	79.43
Slope parcels	85.54	82.32	75.65

4.2. Analysis of Change Detection Results for Different Terrains

This study conducted spatial connectivity analysis on the two-phase cultivated land parcel units extracted by SAM unsupervised segmentation, and measured the GLCM features, MS-SSIM, and NDVI of the corresponding regions, achieving detection of cultivation pattern changes, cultivation type changes, and potential change areas. The change detection results for the land parcel units in the plain and hilly areas are shown in Figures 10 and 11, respectively, with local detection results shown in the figures.

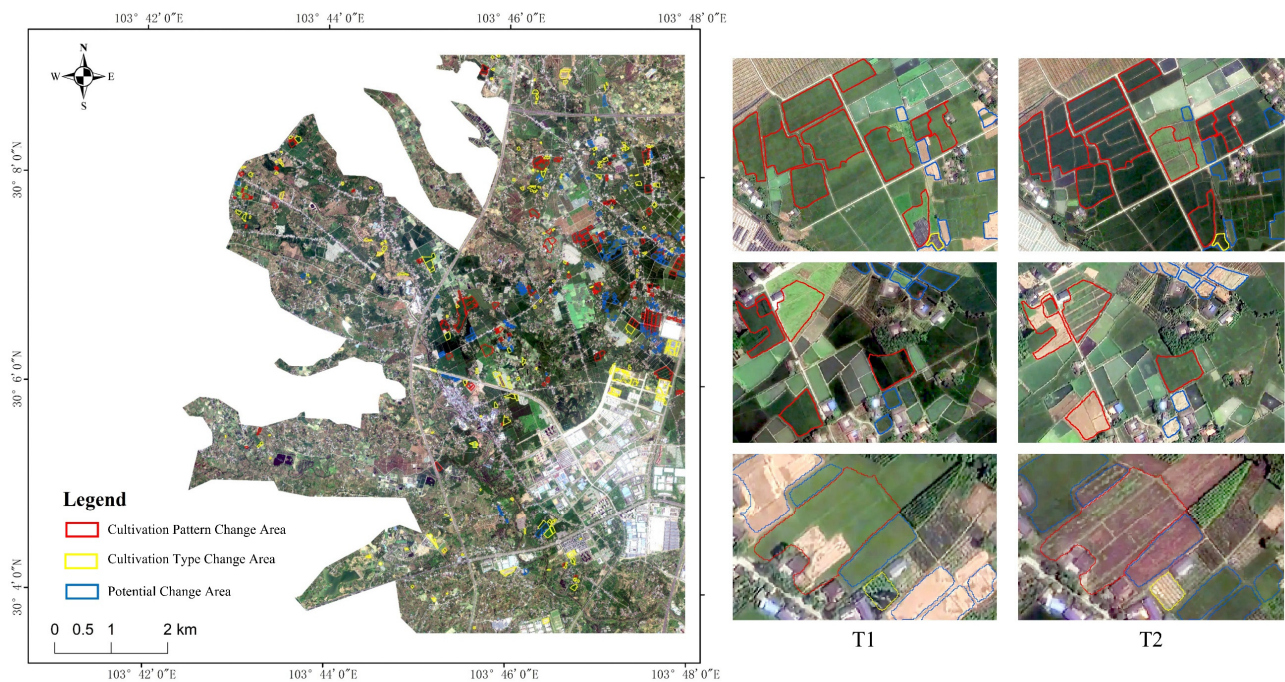


Figure 10. Detection results of different change types for land parcel units in the plain area.

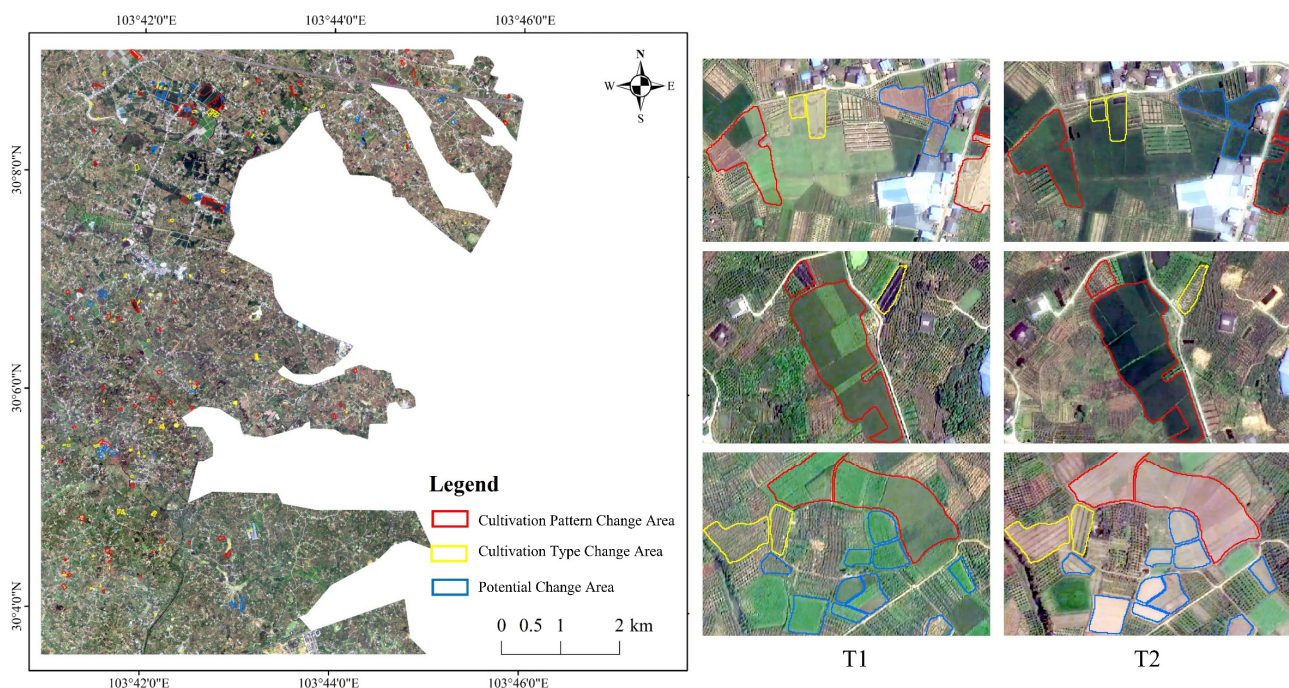


Figure 11. Detection results of different change types for land parcel units in the hilly area.

The accuracy evaluation results for different types of change detection in the plain and hilly areas are shown in Tables 2 and 3. In the plain area, the number of land parcel units with cultivation pattern changes was 126, based on expert visual interpretation and field investigation. The proposed method achieved an OR of 78.57% for cultivation pattern change detection, with precision, recall, and IoU reaching 78.79%, 79.45%, and 78.44%, respectively. In the hilly area, the OR for pattern change detection reached 64.58%, verifying the effectiveness of the proposed method for land parcel-level cultivation pattern change detection. According to the detection results in the figures and evaluation results in the tables, the proportion of potential change areas detected in both the plain and hilly areas is

relatively large, and most of these potential change areas involve the transformation of bare land into rice fields or other vegetated cultivated land. This is mainly due to the fact that the two-phase remote sensing images were captured on 13 August 2022, and 17 July 2023, respectively, with the earlier image captured close to the rice harvest season, leading to many land parcel units being identified as potential changes.

Table 2. Accuracy evaluation results of different types of change detection for land parcel units in the plain area.

Plain Parcels	N _{gt}	N _{acc}	OR (%)	Precision (%)	Recall (%)	IoU (%)
Cultivation Pattern Change Area	126	99	78.57	78.79	79.45	78.44
Cultivation Type Change Area	139	105	75.53	72.83	78.88	74.47
Potential Change Area	232	148	68.79	65.26	69.29	66.48

Table 3. Accuracy evaluation results of different types of change detection for land parcel units in the hilly area.

Plain Parcels	N _{gt}	N _{acc}	OR (%)	Precision (%)	Recall (%)	IoU (%)
Cultivation Pattern Change Area	48	31	64.58	61.10	64.75	61.12
Cultivation Type Change Area	89	62	69.66	70.98	68.17	68.15
Potential Change Area	165	93	56.36	59.55	60.07	57.32

The number of parcels that experienced changes in the plain area was higher than in the hilly area, particularly in pattern change areas and potential change areas. This indicates that in the plain region, farmland is more likely to undergo non-agricultural or non-cereal changes. Furthermore, in terms of detection accuracy in different terrains, the accuracy for various types of change detection in the plain area was higher than in the hilly area. This is mainly due to the complex and fragmented distribution of parcels in the hilly areas, with unclear boundaries, which lowered the accuracy of parcel extraction. This impacted the analysis of the correspondence in the number of parcels in the corresponding areas and the measurement of texture features and structural similarity, resulting in lower change detection accuracy in the hilly region compared to the plain area.

5. Discussion

5.1. Advantages of Cultivation Pattern Change Detection Based on Spatial Analysis

SAM, based on a visual encoder, can accurately and completely delineate land parcel units. When the cultivation pattern of a parcel changes, there will be significant differences in the quantity and area of the parcel units extracted by SAM during the two phases. Therefore, this study utilizes the advantage of SAM unsupervised segmentation, which extracts parcels with boundary semantic information, and combines spatial correlation analysis of the quantity and area attributes of corresponding region segments in the two-phase remote sensing images to preliminarily select potential areas with cultivation pattern changes at the parcel level. As shown in Figure 12, the preliminary distinction results of cultivation pattern changes are presented using spatial analysis. (a) and (b) show a large parcel corresponding to multiple small parcels, with the sum of the areas of the small parcels being close to the area of the large parcel; (c) and (d) show a large parcel corresponding to multiple small parcels, with the number of small parcels exceeding three. The cultivation pattern change areas shown in the figure demonstrate that analyzing the number and area relationships of the extracted land parcel units in the corresponding areas can effectively detect potential

cultivation pattern change regions. Thus, the method of detecting parcel-level cultivation pattern changes through spatial analysis of segmented patches is effective, providing a feasible technical means for detecting cultivation pattern changes in complex areas.



Figure 12. Cultivation pattern change detection results. (a,b) show a large parcel corresponding to multiple small parcels, with the sum of the areas of the small parcels being close to the area of the large parcel; (c,d) show a large parcel corresponding to multiple small parcels, with the number of small parcels exceeding three.

5.2. Effectiveness of MS-SSIM for Change Detection

SSIM measures the similarity between two images by capturing information such as brightness, color, and position [44]. Related studies [45,46] have improved SSIM and applied it to remote sensing image change detection. The improved SSIM more closely aligns with human visual perception of scene changes, confirming its effectiveness in remote sensing scene change detection. The change types of cultivated land parcels are complex and diverse. Relying solely on texture features to distinguish cultivated land pattern and type changes can lead to significant errors. Therefore, this study combines GLCM and MS-SSIM for comprehensive classification, improving the accuracy of change detection.

The results and accuracy evaluation of parcel unit type change detection under different metrics are shown in Figure 13 and Table 4. The results show that GLCM features are effective in detecting parcel units with significant texture changes, but many change areas are missed. MS-SSIM performs excellently in detecting visually distinct change areas between two time-series images. As shown in Table 4, using MS-SSIM for parcel unit change detection yields significantly higher accuracy than using only GLCM. This validates the effectiveness of MS-SSIM as a change detection metric in cultivated land change

detection. To further improve the accuracy of change detection, this study adopts a strategy of taking the union of GLCM and MS-SSIM change detection results for both cultivated land pattern and type change detection. By combining the strengths of both metrics, this method achieves more comprehensive and accurate identification of change areas.

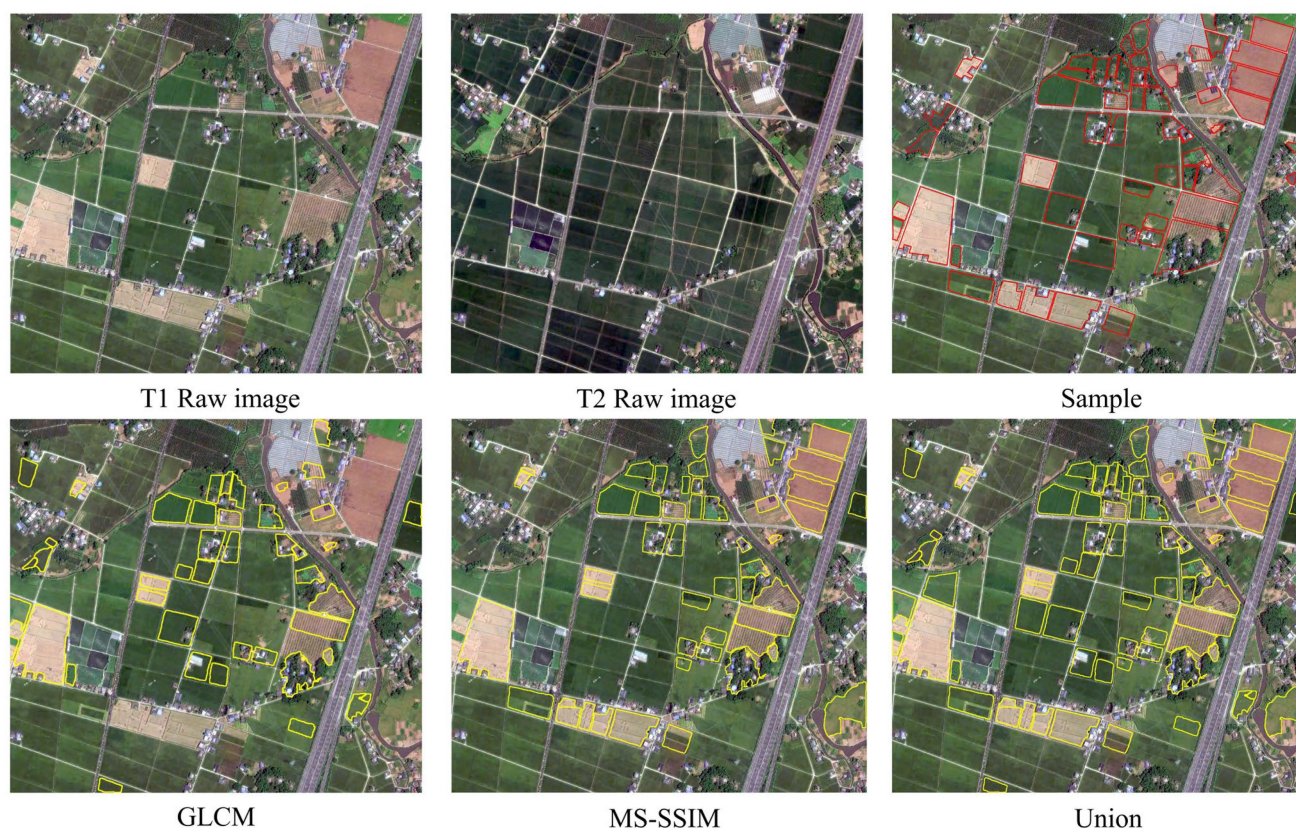


Figure 13. Evaluation results of change detection using different metrics.

Table 4. Accuracy evaluation results of change detection using different metrics.

	Precision (%)	Recall (%)	IoU (%)
GLCM	61.82	54.52	54.08
MS-SSIM	79.29	75.47	74.61
Union	84.49	81.16	79.48

5.3. Limitations and Future Work

This study uses SAM to extract cultivated land parcels, performs spatial analysis of corresponding patch areas, and employs various change detection metrics to achieve precise detection of changes in cultivation patterns and types. However, the limitations of the research method lie in its high requirements for high-resolution imagery and the difficulty of acquiring large-scale, temporally suitable dual-phase imagery in cloudy and rainy regions. Additionally, the proposed method only detects changes in cropping patterns and types, without considering vegetation type changes within the detected change regions. Furthermore, no further classification is performed for cultivated land parcels identified as potential change regions. Therefore, in future work, we will further explore methods for detecting changes in cropping patterns and types, and optimize the metrics for change detection to improve the accuracy of detecting different types of changes. Additionally, based on the current change detection method, we will integrate medium-resolution time-series imagery and utilize annual spectral characteristics of different land cover types to

classify parcels identified as potential change regions, thereby reducing misclassification caused by temporal differences in image acquisition. We aim to classify the detected change parcels, validate the change detection results obtained from bi-temporal high-resolution images, and achieve accurate remote sensing monitoring of large-scale cultivated land type and pattern changes.

6. Conclusions

For the diverse types of land changes, including land parcel-level changes in cultivation patterns and types in complex regions, this study proposes a new methodological framework. Unlike traditional methods that focus solely on cultivation type change detection, this approach emphasizes that changes in land parcel-level cultivation patterns are also an important component of land use change. For different terrain types of cultivated land, this study utilizes SAM unsupervised segmentation, which has the advantage of extracting real land parcel boundaries. Based on different segmentation strategies in the plain and hilly regions, it achieves precise extraction of land parcels from two temporal images. Spatial analysis is conducted on the land parcels extracted from both time periods, and comprehensive discrimination is performed using metrics such as GLCM, MS-SSIM, and NDVI, enabling the precise detection of changes in land parcel-level patterns and types. This study, under zero-shot and unsupervised conditions, constructs an automated detection framework for changes in cultivation patterns and types that is suitable for complex regions, effectively addressing the complexity and diversity of land resource changes. This method not only provides new detection and discrimination approaches for multiple types of changes in cultivated land parcels using high-resolution remote sensing imagery but also offers more precise monitoring tools for agricultural production and land resource management.

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Conflicts of Interest: Author Yonggang Ma was employed by the company Shaanxi Datu Information Technology Limited Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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