Sugarcane Planting Area Classification, Extraction and Accuracy Comparison Based on Chinese High-Resolution Remote Sensing Satellite Data: A Case Study of Ningming Sugarcane Demonstration Area, Chongzuo City, Guangxi

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Abstract: Remote sensing techniques are effective in sugarcane extraction and monitoring, but most of the existing research is based on low- and medium-resolution image. Thus, the technical methodology for high-resolution image needs to be improved. Due to the good performances of deep learning algorithms in solving classification problems for the very high resolution (VHR) images, the target mask U-Net model is introduced to research VHR satellite data from China, i.e., the GaoFen-1 (GF-1), GaoFen-2 (GF-2) and ZiYuan-3 (ZY-3). First, a sugarcane area was classified and extracted in the Ningming Sugarcane Demonstration Area in Chongzuo City, Guangxi. Further, we validated and compared the extraction accuracies for different satellite data. The results showed that the extraction accuracies of the GF-1, GF-2 and ZY-3 were 79.97% (Kappa coefficient of 0.19), 94.02% (Kappa coefficient of 0.82) and 81.94% (Kappa coefficient of 0.35), respectively. The spectral and textural information of high-resolution images can effectively guarantee improvements to the accuracy of crop extraction. By comparison of data sources and traditional supervision classification methods, the GF-2 data features the best results for sugarcane extraction. The technical methods and experimental results in this paper not only confirm the feasibility of applying China’s VHR data to monitor sugarcane planting areas, but also provides reference for the relevant future studies.

Keywords: Sugarcane detection; wide-field detector; U-Net; Maximum Likelihood Classification algorithm

1. Introduction

The planting area and yield of staple crops are closely related to the stability of the international food trade and futures market, and even to the stability of developing countries. With the development of high-resolution remote sensing technology, remote sensing has gradually become an important means to investigate agricultural crop planting regions. Remote sensing image has advantages of wide-area coverage, diverse data sources, high spatial resolution and
high frequencies observation. Therefore, it can provide the timely and accurate investigations of sugarcane coverage and planting regions and is now widely used in agricultural applications. Studies on classification, area extraction as well as yield estimation of wheat, rice, maize, and soybeans, has been systematically performed[1-3]. However, more in-depth applications of remote sensing for oil and sugar crops, such as rape and sugarcane would be required [4]. It has attracted extensive attention from the international community and relevant scholars, as well as gradually becoming a new research hotspot [5].

For sugar crops, the sugarcane planting area for China is second after that for Brazil and India. China’s sucrose production ranks third in the world and its sucrose consumption ranks second in the world [6]. Huang et al. [7] noted that the main sugarcane production areas in China are located in four provinces (regions) of south China (Guangxi, Yunnan, Guangdong and Hainan). The planting area and sugar yield of sugarcane in Guangxi accounted for more than 60% of the entire country, which plays a decisive role in the balance of sugar supply and demand throughout the country. The accurate acquisition of the sugarcane planting areas is important to predict sugarcane yield, optimize the regional distribution of sugarcane and rationally plan market sales. China started late in the field of sugarcane classification and extraction, and most of the existing research is based on its spectral characteristics. For example, Ding et al. [8] used the maximum likelihood method to obtain the spatial distribution of sugarcane planting areas in Guangxi using the multi-temporal MODIS NDVI curve and the laws for the gradual decline of the sugarcane area during the production period. Ou et al. [9] used a back propagation (BP) neural network model to forecast the raw sugar cane yield in Guangxi. Ma et al. [10] used CCD data from the HJ-1A/B satellite to obtain the distribution of the sugarcane planting area in Nanning city by combining supervised classification with the multi-temporal NDVI gradual elimination method. Wang et al. [11] used HJ satellite CCD data and the spectral characteristics of sugarcane in the images at different times based on an object-oriented classification method to establish a decision tree classification rule set to extract sugarcane planting areas. Liu et al. [12] constructed a decision tree model for sugarcane extraction using multiple feature variables and high-resolution GF-1 satellite WFV remote sensing data.

Chen et al. [13] used unsupervised classification, supervised classification and NDVI elimination methods to remove other land types and extract sugarcane planting areas based on its spectral characteristics with the Landsat8 OLI (Operational Land Imager) data. Zhou et al. [14] tested the method of combining object-oriented and AdaBoost data mining algorithms to extract sugarcane planting areas. A decision tree classification method based on the broad value of the vegetation index was used. Meng et al. [15] used the methods of unsupervised classification, supervised classification and NDVI elimination to accurately extract the planting area of sugarcane. The spectral characteristics of the wide-width camera WFV data of the GF-1 were used. With the support of object-oriented technology, Zeng et al. [16] first extracted crop thematic information from high-resolution ZY-3 remote sensing images. Plot objects were integrated into the HJ-1 and GF-1 data to obtain spectral characteristics of crop growth. The crop planting information extraction model was constructed based on the laws of different crop phenological differences.

Researchers in Brazil, Kenya and India have used low-resolution satellite image (MODIS) and medium-resolution satellite image (Landsat Thematic Mapper (TM) and Landsat Enhanced TM Plus (ETM+)) to extract sugarcane. Only a limited number of researchers have used high-resolution image (IRS-P6) to classify sugarcane. Tardin et al. [17] used the maximum likelihood method to identify coffee, citrus and sugarcane based on spectral differences in these crops. Xavier et al. [18] used multi-temporal MODIS data to extract sugarcane. Long-term images of Brazil over a wide area were obtained using the enhanced vegetation index (EVI). Gomes et al. [19] used the Spectral Angle Mapper (SAM) algorithm to classify sugarcane in Saint Boro, Brazil. Good results were achieved based on the NDVI images from the SPOT data. Vieira et al. [20] used the Landsat TM and ETM images, combined with object-oriented analysis and data mining, to map sugarcane on a large scale in Northwest Sao Paulo, Brazil. Betty et al. [21] used the NDVI to handle MODIS data from 2002 to 2010 to determine the sugarcane yield forecast in Western Kenya. Verma et al. [22] used the LISS IV 5.8 m resolution image from the
IRS-P6 satellite of India to classify sugarcane based on decision tree classification method using the ISODATA, MLC and vegetation index. Luciano et al. [23] used a random forest machine learning method and multi-temporal Landsat data from 2008 to 2016 to classify sugarcane in Sao Paulo, Brazil.

In recent years, China has launched high-resolution satellites, such as the GF-1, GF-2 and ZY-3, which have accumulated a systematic image data set. The application of the massive basic observational data to thematic information mining for the efficient extraction of scientific and reliable monitoring results is a research hotspot for Chinese researchers. In this paper, a deep learning method was introduced to classify and extract the planting conditions of some sugarcane demonstration regions in Ningming County, Chongzuo City, Guangxi. The data from these Chinese high-resolution satellites GF-1, GF-2 and ZY-3 were used. Based on this method, inductive analyses were carried out to demonstrate the feasibility of applying high-resolution satellite data from China to extract the planting areas of sugarcane and other crops. These experiments can be references for methodologies and technical approaches in relevant research.

2. Study Area and Data

2.1. Study Area

The geographic location and natural conditions of Guangxi are suitable for sugarcane production. Generally, sugarcane is sown in early March, seedlings emerge in mid-March to April, tillering is in mid-May, stem elongation is in mid-June to September, sugar accumulation is in October, technical maturity is in November and sucrose production is in mid-November to mid-March of the following year.

Guangxi has been an important sugarcane production area in China for a long time. Laibin City has a rich experience in sugarcane production and planting as it has the characteristics of a wide planting area and high annual yield. This work selected the Xingbin District (108°24′-110°28′E, 23°16′-24°29′N) of Laibin City, Guangxi Province as the study area. The study area is located in Ningming County, Chongzuo City, at the southwestern border of Guangxi, as shown in Fig. 1. There are many rocky mountains and low hills in the study area, which experiences a subtropical monsoon climate. The climate is warm, with abundant sunshine and rainfall. The geographical coordinates are 106°58′48″E~107°40′12″E, 21°35′24″N~22°22′12″N. Here, rice and other food and cash crops, such as sugarcane, bananas, fast-growing eucalyptus and vegetables, are the main products, of which sugarcane is the primary cash crop. Ningming County is an important sucrose production base in Guangxi as well as a national sucrose production base in the county. Ningming County has been listed as a key regional county in national planning to support sucrose superiority.
2.2. Data

Detailed parameters for the GF-1, GF-2 and ZY-3 satellite data are shown in Table 1.

Table 1. Main parameters for the satellite data.

| Sensor | Band         | No. of Band | Spectral range (μm) | Resolution (m) | Swath (km) |
|--------|--------------|-------------|---------------------|----------------|------------|
| GF-1   | panchromatic | -           | 0.45~0.9            | 2              | 60         |
|        | multi-spectral | 2           | 0.52~0.59           | 8/16           | 60/800     |
|        |              | 3           | 0.63~0.69           |                |            |
|        |              | 4           | 0.77~0.89           |                |            |
| GF-2   | multi-spectral | 2           | 0.52~0.59           | 3.2            | 45         |
|        |              | 3           | 0.63~0.69           |                |            |
|        |              | 4           | 0.77~0.89           |                |            |
| ZY-3   | multi-spectral | 2           | 0.52~0.59           |                | 51         |
|        |              | 3           | 0.63~0.69           |                |            |
|        |              | 4           | 0.77~0.89           |                |            |

To understand the morphological characteristics and growth distribution of sugarcane forests, as well as considering the fact that cultivated croplands have few changes in this area, the GF-2 image in 9 August 2015, the ZY-3 01 satellite image in 8 October 2014, and the GF-1 image in 1 November 2018, were selected as the sample images (Fig. 2) at the Xingbin District, Laibin City,
Guangxi Province. The GF-2 image in 11 September 2018, the ZY-3 02 image in 5 October 2018, and the GF-1 image in 3 October 2018, were used as the experimental images (Fig. 3). The sugarcane grew vigorously from July to October with clear texturing, which is conducive to sample collection and sugarcane forest extraction.

3. Material and Methods
The technical route of automatic sugarcane extraction that integrates deep learning and image processing is shown in Fig. 4, which includes three key steps: (1) data pre-processing, (2) feature extraction and (3) post-processing.
3.1. Data Pre-processing

The experimental data in this paper mainly includes the GF-1 fusion data image, the GF-2 fusion data image, and the ZY-3 fusion data image.

Before the experiment, images of the study area need to be pre-processed. ArcGIS version 10.5 was used to pre-process the data from three different sensors. Radiation calibration, atmospheric correction, and ortho-rectification were performed in turn on the panchromatic and multispectral image from each satellite. Then, these two image types were spatially registered. Finally, the multispectral and panchromatic images were fused together via pansharpen algorithm.

In August 2018, a field sampling survey was conducted in the study area, and 10,209 sample patches were selected as the training samples. Liu et al. [24] suggested that in the case of a large sample size, point validation could calculate the minimum number of random sampling points based on the following formula

$$n = \frac{u_{1-\alpha/2}^2}{\varepsilon^2} \times p \times (1-p),$$

where $n$ is the minimum number of sampling points, $p$ is percent of the correct classifications, $u_{1-\alpha/2}$ is the value from the normal distribution probability table corresponding to the confidence
level and $d$ is the allowable error range. Through the trial sample test, the confidence level is 95% when $p = 0.90$ and $\alpha$ is 0.1. Then, $u_1 - a/2 = 1.96$ as obtained from the Look-Up-Table, the error allowable range is (+5%) and at least 138 validation points are needed. As the sugarcane and non-sugarcane regions were considered in the classification, it is more convincing to add additional validation points. A total of 269 validation points was used, and the final confirmation and modification were carried out for the samples.

3.2. Feature Extraction

Ronneberger et al. [25] pointed out that the U-Net model is an improved structure of fully convolutional networks (FCN). This model follows the idea of image semantic segmentation using the FCN where feature extraction is performed using convolution and pooling layers, and image size reduction is from the deconvolution layer. The sugarcane planting area was extracted in this paper using the Targets mask U-Net model proposed by Han et al. [26]. The detailed steps are defined as in Fig. 5.

![Figure 5. Technical route of sugarcane area extraction.](image)

The validated sample vectors in the Xingbin District of Laibin City were used to generate binary raster data for the corresponding regions of the sample images from various data sources. The sample and binary raster images were then cut into 512x512 windows, which was cross-validated using 10 folds.
3.2.1. General Introduction of the Model

Two sets of convolution, activation and batch standardization layers formed the coding unit. The four coding units of the mixed maximum pooling layer were used to train the data set and extract the depth characteristics of sugarcane at different scales. Then, three upper sampling layers and decoding units were used to recover the background information. These consisted of a release layer and two convolution and activation layers. In the seven units mentioned above, the numbers of output filters for the convolution layer were 32, 64, 128, 256, 128, 64 and 32, respectively[27]. In addition, to adjust the edge and increase the training speed, jump connections were added. The final output of the decoding unit was sent through a binary sigmoid classifier to independently classify each pixel.

Fig. 6 shows the abstract diagram of the U-shaped convolutional neural network. As shown in Fig. 6, the model consists of an encoder, a decoder, and a set of cross-connections on the corresponding level between the encoder and the decoder. The basic components of the encoder are four coding unit groups. Each of them consists of two sets of convolution, activation, and batch standardization processing, notably, a high-level semantic characteristic of pooled abstract images is integrated as well; the basic components of the decoder are three decoding unit groups, each of them is consists of a random inactivation and two convolution activation processes, beyond this, an upsampling process to restore spatial information of high-level semantic features is incorporated; cross-connection enhances the flow of the shallow features information for the image, which plays a key role in the semantics edge recovery of semantic information.

![Figure 6. The architecture of target mask U-Net](image)

3.2.2. Introduction of Model Solution
A loss function was used to calculate the loss value between the real ground truth data and the prediction probability to quantify the differences between them. A smaller loss value indicates a more accurate classification.

\[
    \text{loss} = \sum y \log(y') + (1-y) \log(1-y'),
\]

(2)

where backward propagation was used to train the model through minimizing the loss function by adjusting and updating the parameters of the U-Net model. The \( y \) is the true binary value of a pixel in the mask blocks, and \( y' \) is the predicted probability of the target mask U-Net of the same pixel. The image enhancement technology was used to improve the performance of the model in generalization effect of the data. Specifically, the following steps were used for the sample image according to a certain probability:

1. Increase the radiation values of image bands from -50 to 50 with a ratio of 50% for simulating the changes in radiation values under various illumination conditions;
2. Give a weight of image bands from 0.5 to 1.5 with a ratio of 50% for simulating the situation of the image color shifting;

The batch size of the above experiment was set to 4. The parameters of the model were updated step by step using the Adam optimization algorithm[28]. The final classification model was built by iterating 99 times of the training data.

3.2.3. Image Element Extraction

After the model training, the test images were scanned through a wide-field sliding window (300x300). When the window moved, the down-sampled image was input into the trained model to obtain the coarse target score map at the pixel level. Subsequently, the prediction results were sampled to ensure that the target class score fractional map was obtained with the same size as the original image.

3.3. Post-processing

3.3.1. Binarization

Converting the continuous probability of each pixel into a binary value with a threshold is done by

\[
    y_b = \begin{cases} 
    0 & y' < \sigma \\ 
    1 & y' \geq \sigma 
    \end{cases}
\]

(3)

where \( y_b \) is binary value and \( \sigma \) is the threshold value.

3.3.2. Retention-averaging Merger

Direct merging of the feature extraction leads to a breakage of the semantic information at the image seam. Therefore, it is necessary to use the retention-averaging strategy to weaken this breakage so that the element extraction results of the entire image can be as smooth as possible.

3.3.3. Post-processing and Validation

Sugarcane is a large-area cultivated crop. In the image segmentation process, some small patches were generated and removed for field validation. To ensure the accuracy of the
evaluation, a full-scale field validation was completed in October 2018 (shown in Fig. 7). The validation indicated that rice and maize were easily confused with sugarcane (shown in Fig. 8).

Figure 7. Full-scale field validation vector map.

![Production period sugar cane](image1)
![Production period sugar cane (Different planting time)](image2)
![Corn](image3)
![Rice](image4)

Figure 8. Validation photos of sugarcane and its confused landscapes.

4. Results and Discussion

The target mask U-net model was used to analyze the sugarcane extraction from high-resolution satellite images in China. The classification maps of sugarcane in Ningming County, Chongzuo
City were obtained. The results of the sugarcane classification from various data sources were evaluated using the confusion matrix validation method. Tables 2, 3 and 4 show the results of the confusion matrix for the GF-1, GF-2 and ZY-3 images, respectively. As shown in the Table 2-4, the accuracies of the GF-1, GF-2, and ZY-3, are 79.97% (Kappa coefficient of 0.19), 94.02% (Kappa coefficient of 0.82) and 81.94% (Kappa coefficient of 0.35), respectively. Note that GF-2 gave the best performance in the sugarcane areas detection, which indicates that a higher resolution can produce better sugarcane extraction results because the color and texture are clearer.

Table 2. Accuracy evaluation for the GF-1 image

| Class (GF-1)          | Sugarcane samples | Non-sugarcane samples | Summary of samples | User’s Accuracy |
|----------------------|-------------------|-----------------------|--------------------|-----------------|
| Sugarcane samples    | 1.41 km²          | 0.68 km²              | 2.09 km²           | 67.50%          |
| Non-sugarcane samples| 7.30 km²          | 30.23 km²             | 37.53 km²          | 80.56%          |
| Summary of samples   | 8.71 km²          | 30.91 km²             | 39.62 km²          | 100.00%         |
| Producer’s accuracy  | 16.22%            | 97.80%                | 100.00%            |                 |
| Overall Accuracy     | 79.87%            | Kappa Coefficient=0.19|

Table 3. Accuracy evaluation for GF-2 image

| Class (GF-2)          | Sugarcane samples | Non-sugarcane samples | Summary of samples | User’s Accuracy |
|----------------------|-------------------|-----------------------|--------------------|-----------------|
| Sugarcane samples    | 7.35 km²          | 1.01 km²              | 8.36 km²           | 87.94%          |
| Non-sugarcane samples| 1.36 km²          | 29.90 km²             | 31.26 km²          | 95.95%          |
| Summary of samples   | 8.71 km²          | 30.91 km²             | 39.62 km²          | 100.00%         |
| Producer’s accuracy  | 84.39%            | 96.30%                | 100.00%            |                 |
| Overall Accuracy     | 94.02%            | Kappa Coefficient=0.82|

Table 4. Accuracy evaluation for ZY-3 image

| Class (ZY-3)          | Sugarcane samples | Non-sugarcane samples | Summary of samples | User’s Accuracy |
|----------------------|-------------------|-----------------------|--------------------|-----------------|
| Sugarcane samples    | 2.88 km²          | 1.33 km²              | 4.21 km²           | 68.45%          |
| Non-sugarcane samples| 5.83 km²          | 29.59 km²             | 35.41 km²          | 83.54%          |
| Summary of samples   | 8.71 km²          | 30.91 km²             | 39.62 km²          | 100%            |
| Producer’s accuracy  | 33.07%            | 95.71%                | 100%               |                 |
| Overall Accuracy     | 81.94%            | Kappa Coefficient=0.35|

As shown in Fig. 9, the spectral characteristics of GF-1 are the most obvious and have the lowest error rate when distinguishing sugarcane planting areas from farmland. However, the leakage area (blue rectangles) is also the largest among the three data sources. This is because there are some differences in the spectral characteristics due to the timing of the imaging. In addition, the fitting result of the model are not ideal. Some buildings (orange rectangles) are
miss-classified as sugarcane, which indicates that the sugarcane area fit well within the patches. These two points show that the GF-1 has some advantages in sugarcane extraction, but the model parameters need to be optimized.

![Figure 9. GF-1 extraction results map](image)

As shown in Fig. 10, GF-2 has the best sugarcane extraction result in the study area. The extracted area nearly coincides with the actual planting area, and the boundary between the large-scale sugarcane areas is clear. The texture characteristics of the sugarcane are obvious because of the high resolution of the GF-2 data. It is found that because Ningming County of Chongzuo City has a complex terrain and human activities, not all cultivated lands are sugarcane planting areas. Many sugarcane planting areas (orange rectangles) are accompanied by maize, passionfruit, weeds and other plants, and their spectral and texture characteristics are easily confused. Therefore, there are several small patches that look similar to sugarcane in the images.

![Figure 10. GF-2 extraction results map](image)
As shown in Fig. 11, the ZY-3 has good results in large area sugarcane extraction, but the results are not ideal for smaller areas. The spectral characteristics of farmland and the sugarcane planting areas are similar, and the texture features are not obvious. Therefore, it is impossible to distinguish and extract the two types of lands effectively, which leads to the highest misclassification rate for the ZY-3 image.

Figure 11. ZY-3 extraction results map (red rectangle represents correct extraction area, orange rectangle represents wrong extraction area and blue rectangle represents leakage area).

The reasons of the spatial resolution affecting the model performances were analyzed as follows: First, we notice that the training samples of the three sensors have the same image width and height, but the observations of ground area vary considerably by different spatial resolution. Comparatively, the U-shaped convolutional neural network model obtained by the solution. For the detection of the sugarcane planting area has the same space resolution, and the higher spatial resolution the image has, the smaller corresponding ground area will be. Therefore, the edges of the planting area are easily to be distinguished in GF-2, which also reveals the relatively fine graphic plaques that appear with high rate of accuracy. Secondly, the lower spatial resolution means that the spectral information of each pixel will be interfered by a variety of ground objects, the more will be loss in atmospheric transmission, and the spectrum of the original sample is more complicated. The model in the spatial resolution has better results compare with fit samples and semantic information relation. Finally, U-shaped convolutional neural networks uses the pooling treatment to reduce the spatial scale of advanced features, during learning the mathematical relationship between semantic information and images, while the upsampling process and the cross-connection cannot completely restore the edge details of the semantic information. The higher the resolution, the fewer edge details are lost, so the classification accuracy of high-resolution remote-sensing images is better than that of low-resolution.

Meanwhile, four essential factors (water, building, sugarcane and other crops) were picked respectively as the regions of interest in the experimental area, and experiments were carried out based on the extraction results of various data sources by Maximum Likelihood Classification algorithm[29]. Table 5-7 show the results of the confusion matrix for the GF-1, GF-2 and ZY-3
satellites, respectively. As shown in the Table 5-7, the accuracies of the GF-1, GF-2, and ZY-3, are 89.21% (Kappa coefficient of 0.66), 80.93% (Kappa coefficient of 0.50) and 87.11% (Kappa coefficient of 0.60). There is no significant difference in the accuracy of the images from the three data sources, among which GF-1 has the best accuracy rate, and GF-2 has the highest image misclassification rate.

Table 5. Accuracy evaluation for GF-1 image

| Class (GF-1) | Sugarcane samples | Non-sugarcane samples | Summary of samples | User’s Accuracy |
|--------------|-------------------|-----------------------|--------------------|-----------------|
| Sugarcane samples | 5.56 km² | 1.12 km² | 6.68 km² | 83.19% |
| Non-sugarcane samples | 3.15 km² | 29.79 km² | 32.94 km² | 90.44% |
| Summary of samples | 8.71 km² | 30.91 km² | 39.62 km² | 100.00% |
| Producer’s accuracy | 63.83% | 96.36% | 100.00% |
| Overall Accuracy=89.21% | Kappa Coefficient=0.66 |

Table 6. Accuracy evaluation for GF-2 image

| Class (GF-2) | Sugarcane samples | Non-sugarcane samples | Summary of samples | User’s Accuracy |
|--------------|-------------------|-----------------------|--------------------|-----------------|
| Sugarcane samples | 6.16 km² | 5.00 km² | 11.16 km² | 55.18% |
| Non-sugarcane samples | 2.55 km² | 25.91 km² | 28.46 km² | 91.04% |
| Summary of samples | 8.71 km² | 30.91 km² | 39.62 km² | 100.00% |
| Producer’s accuracy | 70.72% | 83.81% | 100.00% |
| Overall Accuracy=80.93% | Kappa Coefficient=0.50 |

Table 7. Accuracy evaluation for ZY-3 image

| Class (ZY-3) | Sugarcane samples | Non-sugarcane samples | Summary of samples | User’s Accuracy |
|--------------|-------------------|-----------------------|--------------------|-----------------|
| Sugarcane samples | 5.37 km² | 1.76 km² | 7.13 km² | 75.28% |
| Non-sugarcane samples | 3.34 km² | 29.15 km² | 32.49 km² | 89.72% |
| Summary of samples | 8.71 km² | 30.91 km² | 39.62 km² | 100.00% |
| Producer’s accuracy | 61.65% | 94.29% | 100.00% |
| Overall Accuracy=87.11% | Kappa Coefficient=0.60 |

As shown in Fig. 12-14, the extracted results are relatively complete by traditional supervision method, with relatively clear boundary. A large scale of sugarcane area can also be obtained from GF-1 and ZY-3 images effectively, but small-area other corps can’t be distinguished well. Because GF-2 image has higher spatial resolution and more Complex object feature information, the traditional method of supervised classification cannot be applied to the study of sugarcane extraction.
5. Conclusion

This work shows that the images from the GF-1, GF-2 and ZY-3 Chinese satellites can be potential data sources for crop remote sensing monitoring, recognition and extraction under
complex terrain. The spectral and texture information of high-resolution images provided by these satellites can meet the requirement of large-scale sugarcane regional information extraction with high precision and data support. By comparison of traditional supervision classification methods, and based on the algorithm of this paper, the extraction result of GF-2 has the best accuracy, which is mostly suitable for sugarcane extraction experiment.

The high spatial resolution image was effectively used for sugarcane extraction. However, there were several kinds of crops growing in the study area, and the spectral characteristics of sugarcane were susceptible to the influence of these crops. There are some shortcomings when using a single data source to extract sugarcane. The influence of other interference factors can be eliminated to the greatest extent when using multi-source or multi-temporal images. In view of the experimental results, for different scales of image data, model optimization to improve the accuracy of the planting area extraction and to reduce the false alarm rate is a direction of future research.

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