# Comparison of Extraction accuracy of Sugarcane from different resolution satellite images using Deep lab V3+ Mode

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**Abstract**

Sugarcane is an annual or perennial persistent rooted tropical and subtropical herb that grows in tropical and subtropical regions. As China's production ranks among the world's leading, sugarcane industry is an important part of agricultural economy in China. As the largest sugarcane production center in China, Guangxi is one of the most suitable areas for sugarcane cultivation in China and even in the world. Sugarcane industry, as an agricultural advantageous industry in Guangxi, not only has a significant image to the national economy of the region, but also is closely related to the issue of security of national sugar supply. Continuous cropping of sugarcane is very common in Guangxi, which is very helpful for the concentration selection of sugarcane samples. The wide application of satellite remote sensing monitoring technology has become an indispensable means of natural resources monitoring. Using optical satellite remote sensing image to identify and extract sugarcane planting areas is of great significance to quickly and conveniently grasp the information of sugarcane distribution and yield. In this paper, the precision of sugarcane extraction from GF1 and GF2 satellite images is analyzed by using deeplab V3 + model, the effect of optical remote sensing images with different resolution on sugarcane extraction accuracy was studied to provide better data support for dynamic monitoring of sugarcane planting.

## 1. Introduction

Agricultural industrialization is a new type of production and management mode and an important way to realize agricultural modernization. Sugarcane industry, as an advantageous agricultural industry in Guangxi, not only has a significant impact on the national economy of the region, but also is closely related to the security of national sugar supply(Hong-Zhao and Lin-Hua, 2018; Wei, 2014). With the development of precision agriculture in China(Song et al., 2021), fast extraction and parsing of crop information and planting area accurately monitoring has become extremely important (Gaikwad et al., 2021; Piroton et al., 2020; Giuliani et al., 2020). In this paper, Xingbin, which is a region of Laibin city in GuagnXi province is chosen as the study area. Satellite remote images are used to identify the target of sugarcane, studying different identification accuracy of continuous cane sample influenced by different resolution of satellite remote sensing images.

Satellite remote sensing technology refers to a technology that utilizes satellites to remotely detect and monitor the Earth's surface and to obtain information on the surface. By acquiring surface image data, optical satellites can carry out macroscopic and comprehensive observation and analysis of the ground. Satellite remote sensing monitoring technology has many characteristics, such as macroscopic, objectivity, periodic, convenience. Making full use of various remote sensing satellite images to obtain resources can improve work efficiency, reduce the workload of field surveys, and reduce interference from human factors. It is an essential means to improve the efficiency and quality of natural resource survey and monitoring work (Coffer et al., 2021; Ghale et al., 2019). Besides, it’s available to achieve remote sensing image data in a short time with big range, high frequency and high resolution. At present, data from optical satellites with the resolution of 2m such as ZY3, GF1, GF1-B\C\D, GF6, and the resolution of sub-meter such as GF2, GF7, BJ2, JL1, SV-1, and WV etc. are widely used.

Pan lili extracted sugarcane by unsupervised classification method based on GF2 images, with human intervention, eliminating miscalculation aims and extracting leakage targets, finally got sugarcane planting area(Pan et al, 2020). Lin Minghai used the method of supervised classification method to extract the navel orange belt, takeing the navel orange planting area in Xinfeng County, Ganzhou City as the research object, Gaofen-1 remote sensing images were selected as research data, supplemented by higher-resolution images from Google and survey data from Xinfeng County. By comparing the accuracy between the principles of supervised classification methods, a relatively reasonable and scientific supervised classification method was selected to extract the information of navel oranges. By analyzing the results of the extracted information, data support is provided for the planting development of fruit farmers. Classification accuracy are achieved by more than 95%(Li et al, 2019). Zhao Chao used World View-2 with resolution of 0.5m images and the object-oriented image analysis method, determining with CART decision tree in object-oriented rule classification, the final classification accuracy is 0.89 and the Kappa coefficient is 0.87(Zhang et al., 2015). Wang Zhen proposed a image semantic segmentation algorithm based on adaptive fusion of multi-scale features. The algorithm uses an adaptive spatial feature fusion structure to assign adaptive fusion weights to encoding features of different scales in the decoding process of Deeplab v3+, and upsamples the feature map by fusing the multi-scale features in the encoding process to achieve a more refined image semantic segmentation result(Wang et al., 2022).

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# 2. Data and Area

## 2.1 Data

Currently, there are 12 domestic public welfare land resource satellites that widely used in the monitoring of natural resources., including ZY1-02C, ZY3-01\02\03, GF1, GF1 B\C\D, GF2, GF6, ZY1-02D, GF7, which basically forms the ability of large-scale, high frequency, business acquisition of satellite images with mutual collocation of 'high, medium and low' resolution images(Chen et al., 2022). In this paper, GF1 and GF2 are used to achieve the images of a same target area.

In consideration that the best production apparent of sugarcane is during June to September, which gives better visual perform of satellite images, we choose GF2 satellite image shoot in May and GF1 satellite image achieved in June. Major parameters of GF1 and GF2 are shown in Table 1 and Table 2.

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| Parameter | GF1 | |
|---|---|---|
| Spectral band | Panchromatic image | 0.45 ~ 0.90 μm |
| | Multispectral Image | 0.45 ~ 0.52 μm |
| | | 0.52 ~ 0.59 μm |
| | | 0.63 ~ 0.69 μm |
| | | 0.77 ~ 0.89 μm |
| GSD | Panchromatic image | 2m |
| | Multispectral Image | 8 m |
| Swath width | 60 km (Combining two cameras' observation) | |
| Site re-visit period without side swing | 41 days | |

Table 1. Parameter of GF1 satellite data

| Parameter | GF2 | |
|---|---|---|
| Spectral band | Panchromatic image | 0.45 ~ 0.90 μm |
| | Multispectral Image | 0.45 ~ 0.52 μm |
| | | 0.52 ~ 0.59 μm |
| | | 0.63 ~ 0.69 μm |
| | | 0.77 ~ 0.89 μm |
| GSD | Panchromatic image | 0.8 m |
| | Multispectral Image | 3.2 m |
| Swath width | 45 km (Combining two cameras' observation) | |
| Site re-visit period without side swing | 69 days | |

Table 2. Parameter of GF2 satellite data

## 2.2 Study area

Guangxi, located in the subtropical monsoon climate zone, is in the south area of China with the geographical coordinates of 104º26'E-112 º04'E, 20 º54'N-26 º24'N. Sugarcane planting area in Guangxi can reach more than 800,000 hectares. Xingbin district, which is located in the middle of Guangxi, and the red river downstream, is the only administrative region of Laibin city. As a agricultural production area, Xingbin is one of the most important sugarcane main producing area in Guangxi and ever the whole country(Lu et al., 2021).

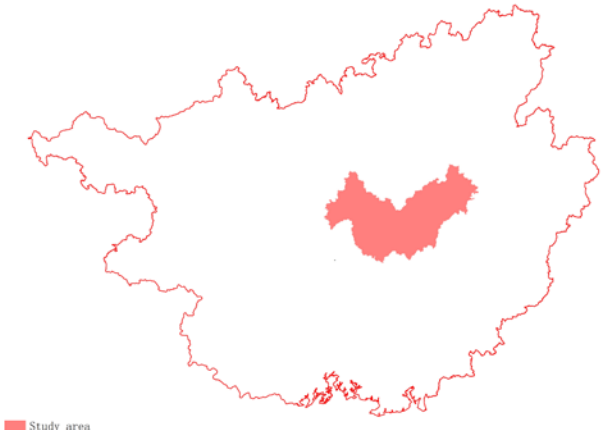


Figure 1. Location of Laibin city

Intensive farming of sugarcane in Xingbin is pretty common, which is a great help to the selection of sample concentration. Some of the sugarcane sample divisions in Laibin City are shown in Figure 2.


Figure 1. sugarcane sample divisions in Laibin City

## 3. Methods

### 3.1 Data Processing

In this paper, the correct sensor images of GF1 satellite and GF2 satellite are used. Fusing the panchromatic and multispectral sensors after radiation calibration and atmospheric correction, and then geometric registration was performed with the samples respectively. The target samples are recognized and extracted using Deeplab V3 + network modeling algorithm, and finally accuracy comparison is performed. The overall flow chart is shown in Figure 2.

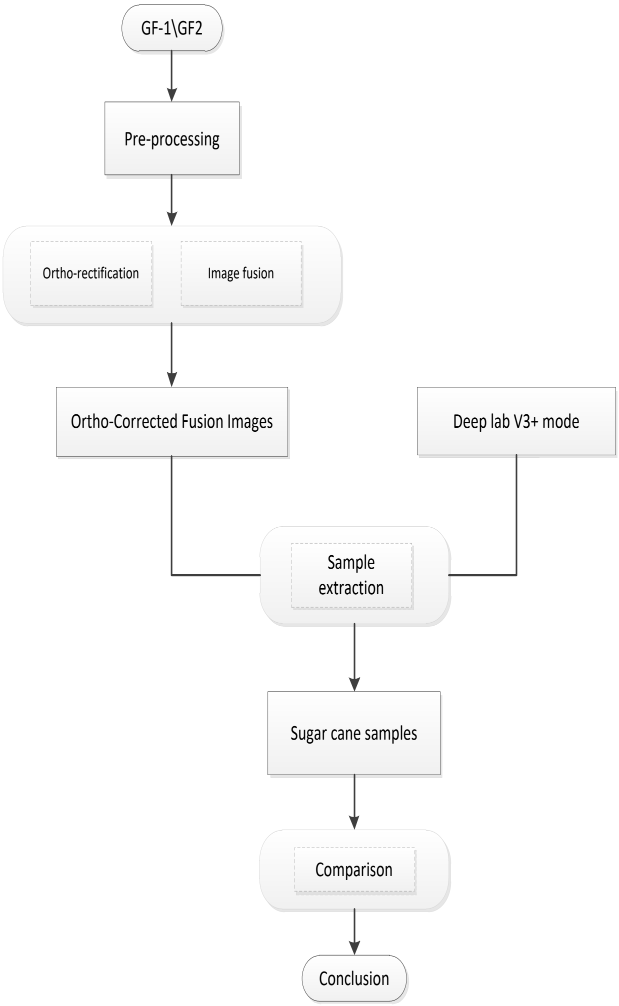


Figure 2. Flow chat for comparison of extraction accuracy

### 3.2 Deeplab V3+ Model

The convolutional neural network is a type of Feedforward Neural Networks that contains convolutional calculations and has a deep structure. It is one of the representative algorithms of deep learning. Convolutional neural networks have representation learning capabilities and can perform shift-invariant classification of input information according to its hierarchical structure, so it is also called Shift-Invariant Artificial Neural Networks(Zhang et al., 2023). It is widely applied in remote sensing science, especially satellite remote sensing, and is considered to have advantages in computational efficiency and classification accuracy in the analysis of geometric, texture and spatial distribution characteristics of remote sensing images. As shown in figure 1, the full Deeplab V3 + network is an encode-decode structure, of which the main body is the feature extraction network of DCNN with spatial convolution, and multi-scale information is introduced through the spatial pyramid module with spatial convolution. And finally, the bottom features and the upper features are further fused through the decoder module, improving the accuracy of boundary recognition for segmented objects.

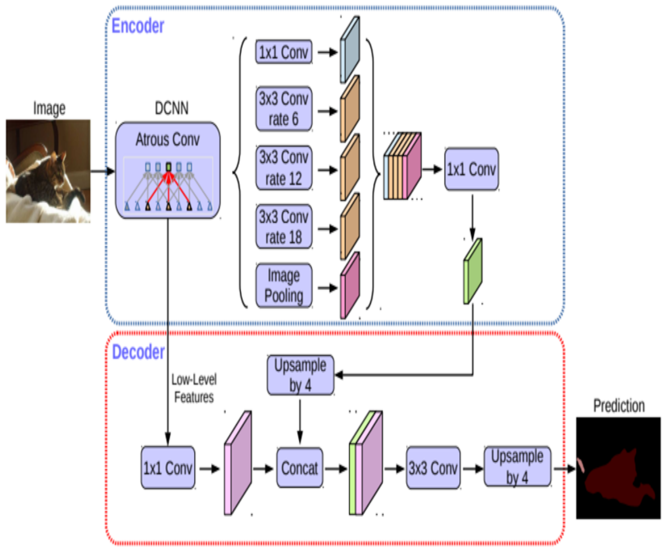


Figure 3. Encoder - Decoder network structure of Deep Lab v3 + mode

## 4. Experimental Result and Analysis

### 4.1 Comparison of different resolution images

In this research, the Deeplab v3+ model was used to compare the accuracy of sugarcane extraction from different resolution remote sensing images. As is shown in Table 2, use Pixel Accuracy(Acc)、 Mean Pixel Accuracy (Acc_class)、 Mean IOU （MIoU） and requency Weighted Intersection over Union(FWIoU)as indicators(Garcia-Garcia et al., 2018; Huiyu and Junjun, 2019; Xu et al., 2021; Liu and He, 2021).. The identification results were given in Table 3.

| Index | Calculate Formula |
|---|---|
| Pixel Accuracy | PA=∑k i=0pii/(∑ki=0 ∑kj=0 pij ) |
| Mean Pixel Accuracy | mPA=(∑ki=0 /(k+1)) pii/(∑kj=0pij) |
| MIoU | MIoU=(∑Ki=0/ (k+1))(pii/(∑k j=0pij+∑kj=0 pij- pii) |
| FWIoU | FWIoU=(1/∑ki=0 ∑kj=0 pij) ∑k i=0 ( pii∑kj=0pij/∑kj=0pij+∑kj=0 pij-pii) |

Table 3. Mainly Evaluation Index

### 4.2 Result Analysis

Semantic segmentation training experimental situation is shown in Table 4.

| **Semantic Segmentation Training Experiment Task Sheet 1** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Task** | Experiments on semantic segmentation of sugarcane fields 1 | | | | | | | |
| **Test time** | 2021.12.7-2021.12.8 | | | | | **Test mode** | Deeplab V3+ | |
| **Training data** | Sugarcane Sample Woodland Semantic Segmentation Data 10179 sheets; Scale 512*512 | | | | | | | |
| **Test records** | Train/ val | LR | Epochs | Batch size | Val_MIou | Val_Acc | Val_Acc_class | Val_fwIou |
| | 8099 : 2080 | 0.03 | 50 | 60 | 0.6113 | 0.8235 | 0.7520 | 0.7199 |

| **Semantic Segmentation Training Experiment Task Sheet 2** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Task** | Experiments on semantic segmentation of sugarcane fields 2 | | | | | | | |
| **Test time** | 2021.12.6-2021.12.7 | | | | | **Test mode** | Deeplab V3+ | |
| **Training data** | Sugarcane Sample Woodland Semantic Segmentation Data 7094 sheets; Scale 512*512 | | | | | | | |
| **Test records** | Train/ val | LR | Epochs | Batch size | Val_MIou | Val_Acc | Val_Acc_class | Val_fwIou |
| | 5600 : 1494 | 0.03 | 50 | 60 | 0.6689 | 0.8341 | 0.8254 | 0.7320 |

| **Semantic Segmentation Training Experiment Task Sheet 3** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Task** | Experiments on semantic segmentation of sugarcane fields 3 | | | | | | | |
| **Test time** | 2021.12.2-2021.12.3 | | | | | **Test mode** | Deeplab V3+ | |
| **Training data** | Sugarcane Sample Woodland Semantic Segmentation Data 9862 sheets; Scale 512*512 | | | | | | | |
| **Test records** | Train/val | LR | Epochs | Batch size | Val_MIou | Val_Acc | Val_Acc_class | Val_fwIou |
| | 7862: 2000 | 0.03 | 50 | 60 | 0.7393 | 0.8789 | 0.8608 | 0.7934 |

Table 4 Semantic Segmentation Training Experiment Task Sheet.

The pixel accuracy, mean pixel accuracy, Mean IOU, frequency Weighted Intersection over Union of the two different resolution images were given in Table 5. It can be indicated that, the MIOU of GF1 image is 61.13% and the pixel accuracy is 82.35%. The MIOU of GF2 image is 66.89% and the pixel accuracy is 83.41%. All evaluation index prove that high-resolution images are more accurate in identifying sugarcane samples.

| Data | Val_MIou | Val_Acc | Val_Acc_class | Val_fwIou |
|---|---|---|---|---|
| GF1 | 0.6113 | 0.8235 | 0.7520 | 0.7199 |
| GF2 | 0.6689 | 0.8341 | 0.8254 | 0.7320 |

Table 5. Identification accuracy evaluation

As shown in Figure 4, the blue parts of a, b and c represent the extraction results based on GF1. And the yellow parts of d, e and f show the extraction results based on GF2. The results show that GF1 segmentation is not as accurate as GF2 segmentation. Besides, the segmentation border is blurred by GF1.

(a)

(d)

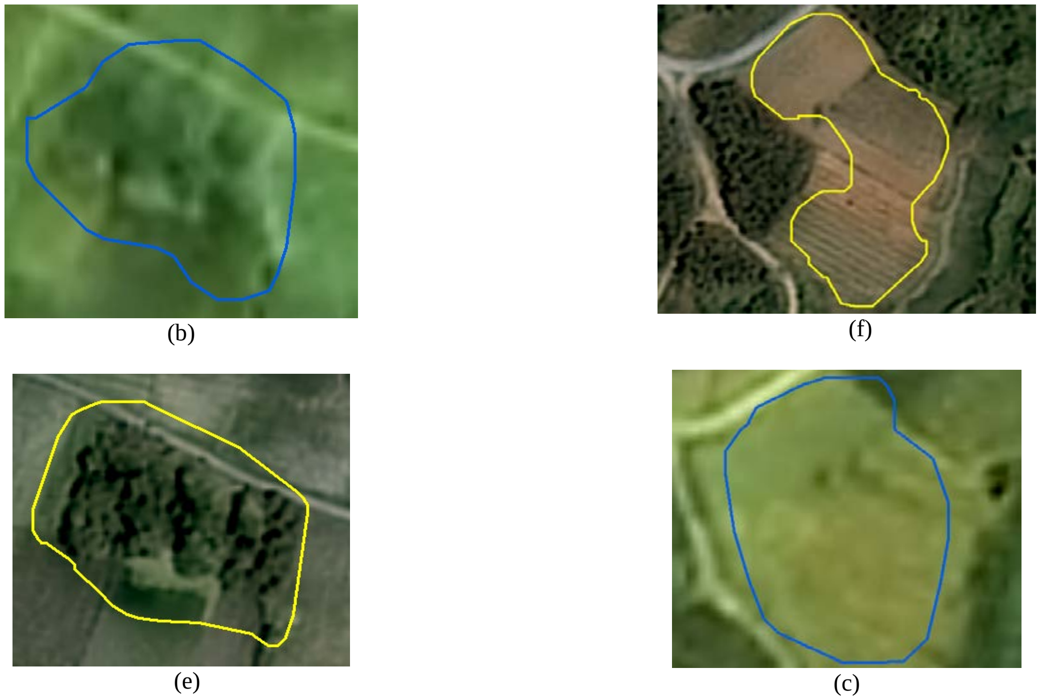


Figure 4 Extraction Results (a, b, c are segmented based on GF1. d, e, fare based on GF2).

## 5. Conclusion

Guangxi is one of the most suitable areas for sugarcane cultivation in China and even in the world, and most of the land in the region is located south of the Tropic of Cancer, in the southern subtropical monsoon climate, rich in heat and rainfall, and the growth of sugarcane is in the same season with rain and heat. Therefore, sugarcane cultivation in Guangxi has unique geographical and climatic advantages. Satellite remote sensing is the primary data source for various types of monitoring due to its large range, all-day, all-weather, and periodic characteristics, wide range of earth observation, and low cost of data acquisition and updating, and it is a necessary part of realizing efficient work by using optical satellite remote sensing data for monitoring and analysing and giving full play to the advantages of domestically produced high-resolution satellites. Image semantic segmentation based on deep learning is necessary to realize automatic extraction in monitoring work. This study indicates that, it is feasible to extract sugarcane samples from high resolution satellite images. Compared with GF2 and GF1 satellite images, the higher the resolution, the better the effect of sugarcane automatic extraction and the clearer the extraction boundary are.

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