URBAN GREEN SPACE IDENTIFICATION BY FUSING SATELLITE IMAGES FROM GF-2 AND SENTINEL-2

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ABSTRACT:

This paper combines class hierarchy construction and feature-preferred random forest classification method, and the classification results are the best. In the urban center area with complex features, this method can be used to extract small and complex features more accurately, and for urban green spaces, small auxiliary green spaces between houses can be accurately extracted. This method first constructs a class hierarchy of four sizes, and then extracts different features from simple to complex, from large to small, and classifies them by membership function for the direct selection feature rules of easily extracted features. For the subdivision of green space and the classification of features in central complex areas, feature optimization is carried out, and the optimal feature combination is selected and then extreme random tree (ERT) classification is performed. The classification accuracy is the best 89.5%, and the classification results are analyzed correctly, which correctly distinguishes the smaller land categories in the central area, reduces the misclassification of grassland and agricultural land, and the classification results are optimal.

1. INTRODUCTION

As a complex with a high concentration of resources, environment, population and socio-economy, green space has gradually become the core of building an ecological security system in urban areas. Broadly speaking, urban green space should include all artificial, semi-natural and natural vegetation, water bodies and wetlands within and around cities (Fu et al.,2020) It plays a key role in absorbing carbon dioxide, purifying pollution, regulating temperature and climate, humidifying air, preventing wind and dust. Urban green space plays an irreplaceable role in maintaining the balance, stability and coordination of urban ecology, and the traditional method of relying solely on high-resolution images for feature classification has many homogeneous and isotropic phenomena, and there are some difficulties in feature extraction. Therefore, it is necessary to introduce multispectral image data for image fusion(Fu et al.,2020).

In terms of green space extraction, object-oriented classification methods are more widely used. Feng Tiantian et al. used GoogleEarth 2m resolution remote sensing images and object-oriented remote sensing image classification method to extract urban green space, and concluded through dynamic analysis that the green space area of Weidu(Feng et al.,2023) District has continued to expand in recent years, and it is mainly concentrated in the eastern region. Xu Jing et al. used three automatic information extraction methods, namely supervised classification, normalized vegetation index (NDVI) classification and rule-based object-oriented classification, and compared and analyzed the obtained classification results with the accuracy evaluation, and the results showed that the accuracy of the rule-based object-oriented classification method was significantly higher than that of the other two methods (Xu Jing et al.,2021).

Based on this, this paper takes Guangzhou City, Guangdong Province as the research area, uses the object-oriented classification multi-scale segmentation method to construct a multi-scale and multi-feature classification rule model, extracts the green space in the research area, and analyzes the dynamic changes of green space.

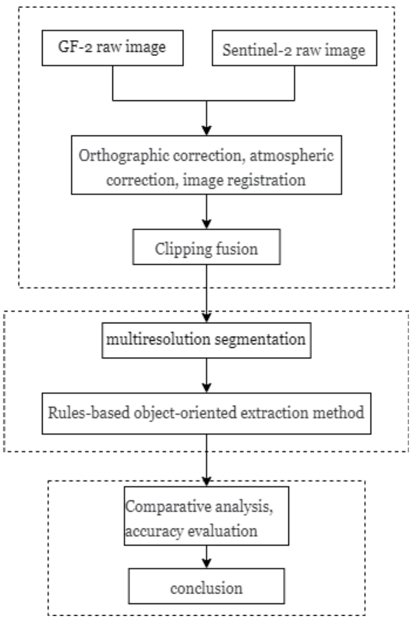

Figure 1. Technical route

2. DATA SOURCE AND PREPROCESSING

2.1 Introduction to data sources

GF-2 satellite is the first civil optical remote sensing satellite independently developed by China with a spatial resolution better than 1 meter, equipped with two high-resolution 1-meter panchromatic and 4-meter multispectral cameras.

The Sentinel-2 satellite carries a Multispectral Imager (MSI) at an altitude of 786 km, covering 13 spectral bands and a width of up to 290 km.

2.2 Data preprocessing

In this paper, Guangzhou urban area is used as the research area, and the main data include Gaofen No. 2 panchromatic and multispectral images in 2019, Sentinel-2 multispectral data, SRTM DEM data and basic geographic information data. The processing process of data mainly includes orthorectification, atmospheric correction, and radiation calibration.

Compared with the traditional medium and low resolution images, the high-resolution images of the same area contain more and more complex spatial information, and the problem of homogeneous or homogeneous foreign objects on the images is also more serious, so before fusion, the original multispectral band and panchromatic band images were preprocessed by geometric correction and resampling of multispectral images, among which the registration error of Sentinel-2 image was 0.203 pixels, and the registration error of high-resolution No. 2 image was 0. 242 cells, meeting the accuracy requirements of image fusion.

2.3 GS image fusion

Firstly, the region of interest is selected and cropped, and the image of the study area with high spatial resolution and multispectral spectrum is obtained. The registered image is fused. In view of the large difference in spatial resolution between GF-2 and Sentinel-2 images, this paper adopts the principle of step-by-step progression, that is, the Sentinel-2 multispectral images are first fused with GF-2 corrected multispectral images.

To ensure the complete spectral information of the fused images, the GS fusion algorithm is selected in this paper. On this basis, based on the GS algorithm, the fused image is fused with the GF-2 corrected panchromatic image. Figure 1 shows the Sentinel-2 image, and Figure 2 shows the fusion result of the GF-2 image and the Sentinel-2 image. It can be seen that the spatial resolution of the original multispectral images has been significantly improved after fusion, and the texture information of the ground objects has been significantly improved compared with the spatial details of the original multispectral images.

Figure 2. Before and after fusion chart

3. OBJECT-ORIENTED CLASSIFICATION METHOD COMBINING CLASS HIERARCHY CONSTRUCTION AND FEATURE OPTIMIZATION

As most of the existing studies have focused on suburban or mountainous land cover classification studies, little research has been done on green space extraction in urban areas. In order to maximize the high spatial resolution and multispectral characteristics of the fused images, a multi-level object-oriented classification method is selected.

It is an improved method based on fractal network evolution (FNEA) algorithm, using different segmentation scales for different features, and then object-oriented classification, in the object-oriented classification Classfier module, in the rule-based classification process, extreme random trees (ERT) can be selectedCompared with the random forest method, it can produce less variance and reduce the risk of overfitting), maximize the use of the effective features of the fusion image, and finally obtain the classification result. The main steps include: image segmentation, classification hierarchy construction, and feature rule extraction.

This paper divides the features into seven categories: construction land, traffic land, water body, forest land, grassland, agricultural land, and bare land. The classification level is divided into four levels, each level extracts different features, some easy-to-extract features such as water bodies, long roads, etc., through band feature analysis, find the extracted feature features and thresholds, convert into membership function rules for classification, vegetation and dense urban areas category subdivision is difficult to directly obtain rules, then use feature optimization after use. The following table shows the classification parameters and classification objects of each level.

hierarchy	scale	Classification object
Level 1	21	Agricultural land, bare land,buildings,grasslands, roads
Level 2	24	Grassland,woodland, agricultural land
Level 3	33	Houses mixed with bare ground, vegetation, long mixed , others
Level 4	52	Water, non-water

Note: The form factor is 0.2 and the compactness factor is 0.6

Table 1. Segmentation parameters and classification objects at various levels

This paper analyzes the image characteristics of the study area, extracts the features in four levels, and uses the classification method based on the rule mode. The rule mode is obtained by directly analyzing the object characteristics and extreme random trees, the vegetation subdivision of the L2 layer and other mixed categories of the L1 and L3 layers, using the rules optimized for the extreme random tree to classify, other categories can directly find the rules for extracting features by analyzing the features of the figures, and through experiments, find the extracted features and thresholds, compose the classification rules, and convert them into a classification rule of one by one.

According to the classification rules, the L1 layer multi-scale division is performed according to the scale from large to small, and the L2 layer construction is based on the L1 layer object and then divided, and the hierarchy is constructed in turn, so that the small-scale level objects are the sub-objects of the large-scale level, corresponding to each other, and establishing an inheritance relationship relationship. Among them, the mixed categories of LI, L2 and L3 are reclassified by calling the importance evaluation of extreme random tree (ERT) to reclassify the optimal combination of vegetation index, spectral features, shape characteristics and texture features, and evaluate the accuracy of the results based on the overall accuracy and Kappa coefficient. The following table is the characteristic information used in this article.

The full name of the index	symbol
Renormalized vegetation index	RDVI
Normalized vegetation index	NDVI
Green normalized difference vegetation index	GNDVI
Ratio vegetation index	RVI
Transformative vegetation index	TNDVI
Differential vegetation index	DVI
Normalized difference water body index	NDWI
Normalized red-edged index	NDRE
Enhanced vegetation index	EVI
Soil improvement and vegetation index	MSAVI

Note: NIR is the near-infrared band, R is the infrared band reflectance, G is the green band reflectance, and B is the blue band reflectance

Table 2. The formulas of index

4. GREENFIELD EXTRACTION RESULTS

The extraction results of all layers were combined into the L1 layer according to seven categories, and the classification results were derived, the accuracy of the accuracy evaluation results reached 89.1%, and the

Kappa coefficient was 0.869, and from the comparison of the classification results and details, after using hierarchical classification, the overall classification results were better, and the small attached green space between the houses could be extracted, and the greenhouse agricultural land was more accurately classified, so it had a better extraction effect on the green space and reduced the mis-division phenomenon. The optimal classification of features on the same layer is more conducive to the classification of smaller and confusing features, and the classification process is more flexible.

Type of land use	Option I		Option II	
PA/%	UA/%	PA/%	UA/%	PA/%
woodland	1	96.22	1	92.75
grassland	73.87	94.37	80.14	89.52
Agricultural land	88.72	69.25	86.27	85.74
Transportation land	85.39	82.65	94.52	85.17
Building land	97.36	89.38	94.71	94.82
body of water	85.3	1	98.21	94.52
Bare ground	90.27	94.51	93.57	93.71
Overall accuracy/%	86.33		89.5	
Kappa coefficient	0.8438		0.857	

Note: Option I(Rule-based object-oriented classification).Option II**(**Object-oriented classification method after class hierarchy construction and feature optimization.)

Table 3. Accuracy evaluation

The table shows the classification accuracy evaluation results before and after optimization, and the overall accuracy is improved by 3.17% after using class hierarchical classification. Kappa coefficient of 0.857, from the classification result map can be seen that the use of layered method of the overall extraction effect is better, especially in the extraction of detailed features is better, from the local details can be seen that the hierarchical classification scheme for the extraction results of small and rivers, the extraction results of features in dense areas are also better, and after the use of hierarchical classification, the green space between houses in the central area of the city is well extracted, and in the scheme before the optimization, some residential green spaces will be missed or misdivided into agricultural land.

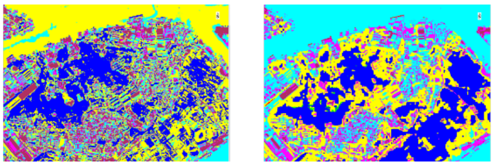

Figure 3. Preferred before-and-after comparison charts

5. CONCLUSION AND OUTLOOK

Combined with class level construction and feature optimization random forest classification method, the classification results are the best, in the urban central area with more complex features, this method can be used to extract small and complex features more accurately, and for urban green spaces, small auxiliary green spaces between houses can be accurately extracted. This method first constructs four sizes of class hierarchies, and then extracts different features from simple to complex, from large to small, and uses membership function classification for the direct selection feature rule of easily extracted features, and performs feature optimization for the subdivision of green space and feature classification in central complex areas, and then performs extreme random tree (ERT) classification. The classification accuracy is the best 89.5%, and the classification results are analyzed correctly, which correctly distinguishes the smaller land categories in the central area, reduces the misclassification of grassland and agricultural land, and the classification results are optimal.

This paper extracts urban green space, only subdivides it into grassland, forest land, agricultural land categories, does not do more detailed classification, has the limitation of data resolution, and also due to the urban green space standard classification system, can be divided into auxiliary green space, park green space, protective green space, production green space, For other green spaces, this method is to define classification based on attributes such as their location and use, so in medium-resolution images, their feature differences are small, and it is difficult to rely on computer algorithms to classify directly.

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