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Classification and Extraction of Rural Green Coverage Based on Object-based High-resolution Remote Sensing Images

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Keywords: High resolution remote sensing image; Multi scale segmentation; Object oriented method; Classification of rural green coverag

Abstract: Rural green space is the foundation of rural environment. In order to solve the practical problems of rural green space, this paper starts from the perspective of rural space, and studies the systematic and normative extraction method of rural green space in Jiangning District of Nanjing city. It provides a scientific basis for the development of rural green space in China. Based on the object-oriented threshold classification method, this paper divides the rural green space into cultivated land, grassland, forest land, residential green space and road green space, and other features into water, road and urban and rural land, and analyzes the land coverage. The main research contents and conclusions are as follows: (1) The multi-scale segmentation parameters are determined. The influence of spectral factor, shape and compactness factor, segmentation scale and band weight on the experimental results is analyzed. After many experiments, the optimal segmentation scale parameters are determined as follows: water layer band weight 1:1:1:1:4, shape factor 0.1, compactness factor 0.5 and segmentation scale 60; The band weight of vegetation layer is 1:1:1:1:4, shape factor is 0.1, compactness factor is 0.5 and segmentation scale is 40; The band weight of urban and rural strata is 1:1:1:1:1, shape factor is 0.3, compactness factor is 0.5 and segmentation scale is 20. (2) The feature space rule sets of different land cover types are established. According to the spectral, geometric, texture and exponential characteristics of different land cover types, combined with sample analysis, the rule sets of extracting water body are determined as NDWI≥0.139, mean_ nir≤249; The rule set of green space and blue roof building is NDVI≥0.14; The rule set of blue roof building is NDSI≤- 0.19, mean_ Blue≥416; The rule set of road extraction is length ≥ 60, GLCM_ STdD≥44.5, BBI(374，453);The rule sets of grassland and cultivated land extraction were NDVI≤0.45, GLCM_ STdD≤36.1; The rule set of extracting cultivated land is rectangular fit≥0.74, NDVI≥0.16; The rule set of extracting road green space and residential green space is rel. Area of ≤20. (3) Object oriented threshold separation results and analysis. The results show that the overall accuracy of the method is 90.4%, and the kappa coefficient is 0.815. The total area of green space in the study area, including woodland, grassland, cultivated land, road green space and residential green space, is 1117413 m2, accounting for 87.7% of the total area. The area of other land types is 321148 m2, accounting for 12.3% of the total area. The rural greening rate in the study area is as high as 87.7%.

1. Introduction

1.1 Research Background and Significance

With China's rapid urbanization in China, village construction is an important guarantee for harmonious development. The coverage rate of rural greening directly reflects the rural environment, and understanding rural green space is the basis for solving the imbalance between rural planning and the current situation. The traditional artificial method has high intensity, long time-consuming, low efficiency and slow information feedback, so it is impossible to extract the coverage of rural green space in a large area. Therefore, it is of great significance to give full play to the technical advantages of remote sensing means and comprehensively extract the land coverage of rural green space for the renovation and management of rural green space.

In recent years, with the rapid development of remote sensing technology, high-resolution remote sensing images benefit from its unique detection ability of a variety of ground features, such as clear images, vivid, texture, rich geometric shapes, etc., providing new ideas and effective data guarantee for land supervision and other fields.

With the continuous improvement of the resolution of remote sensing images, the information contained by a single image element is reduced. The traditional classification method based on the image element only uses spectral features, which cannot be fully applied for the classification and extraction of high-resolution remote sensing images. The smallest unit processed by the object-oriented method is the image object containing rich spectrum, shape, texture and other features, and uses the information extraction process closer to the human thinking mode to effectively improve the classification accuracy and efficiency.

Rural green cover is the rural revitalization of the strategic planning of a new index concept, it is mainly rural existing urban and rural land, for the boundary of the village interior and peripheral within a certain range of various types of green greening (including woodland, grassland and cultivated land, etc.) of vertical projection area and on both sides of the road green land and residents green space. Since the end of 2017, the government has paid more and more attention to rural development, and the greening coverage of rural areas and their surrounding areas has been changed frequently. From the perspective of rural land use and prevention of various disasters, how to effectively and real-time extract the rural greening coverage is an urgent problem to be solved.

In this paper, we select the villages in the south of Jiangning District of Nanjing city, as the research area, using IKONOS image as the data source, Cognition software as the experimental platform, and the object-oriented threshold classification method were used to extract the coverage of rural green space in the research area. Further exploring the methods and ways of rural green space system planning has far-reaching significance for improving the construction of rural green space system.

1.2 Research status at home and abroad

1.2.1 Application and theoretical research of object-oriented classification technology

Object-oriented classification technology uses the texture and geometric characteristics of images to enhance the classification effect of images, and improves the problems of poor classification effect and low accuracy caused by insufficient spectral information of images. Baatz[1]In 1990, the object-oriented classification idea was first proposed, and the results show that this classification method is better than that based on spectral information features. Kong class[2]Object-oriented image analysis method and multi-scale segmentation algorithm are used to establish a classification extraction model and realize the classification of urban land use in high-resolution images. Frohn class[3]Classification of land cover using the area growth segmentation algorithm and the object-oriented fuzzy classification membership function. A large number of domestic scholars have also done a lot of research on the object-oriented classification methods. Hu Wenliang et al. [4] An improved object-oriented optimal segmentation scale calculation model with good reliability is proposed. The classification results with high accuracy and reliability are obtained for the information of buildings and woodlands[5-6].

Above previous studies shows that the object-oriented classification is the predecessors in the remote sensing image classification technology, further research, the emergence of the object-based classification method can well avoid the traditional classification technology for texture and geometric characteristics of the waste of information, at the same time greatly improve the image classification accuracy, especially in land use and vegetation classification reflects the obvious superiority.

1.2.2 Research on the optimal segmentation scale

In the object-oriented methods, the images are usually divided into several objects to realize the classification. The segmentation method will directly affect the accuracy of the information extraction and classification later[7]. The commonly used segmentation algorithm for object-oriented image analysis is a multi-scale segmentation algorithm, which relies on the trial and error method to set the segmentation scale parameters. It is heavy and subjective, so it is difficult to select the optimal segmentation scale[8]. Huang Huiping[9]The maximum area method is used to determine the optimal segmentation scale for multiscale segmentation, which is poorly effective in information extraction of woodland. Ren Chong et al[10]The difference algorithm is proposed and applied to the change monitoring, achieving good results in the experiments and improving the accuracy of the change monitoring. Kim class[11]We show that the optimal scale of forest areas can be predicted using local variance and spatial autocorrelation. Many scholars have tried to use mathematical methods, such as proposing mean variance method, variation function map, objective function method, calculating Moran's index and internal segment variance, local variance method and principal component change method for the segmentation scale, to obtain the optimal segmentation scale quantitatively, and try to test and evaluate the segmentation parameters[12-17].

Previous authors have been exploring the optimal segmentation scale algorithm in the object-oriented method to reduce the impact of different image segmentation methods and different segmentation scales on the classification accuracy, but there is still a lack of a unified standard, which needs to be further improved.

1.2.3 Research on the technology and methods of green coverage rate investigation

The green coverage rate can reflect the ecological environment protection situation of a region. Zuo Du Mei et al[18]With the help of Gaofen satellite images, the green space coverage rate of Nanjing was detected and calculated, making the urban green space coverage rate data more accurate and credible under the condition of auxiliary inspection. Wang Xiaoan et al[19-21]Compared with the map spot data in the previous period, the green area and green coverage rate of Lishui city were obtained and analyzed by the ALOS image and high-resolution aerial film. Fan Yisheng et al[22]On the basis of the national geographic census, the domestic remote sensing satellite image information is processed by the remote sensing image processing tools, and the urban greening coverage and landscape layout are extracted and analyzed.

It can be seen that the current studies on the technology and methods of green coverage rate survey are focused on urban built-up areas, while there are few studies on the scope and technical methods of green coverage rate survey in rural villages. For example, Liang Wenhai et al[23]Taking Shanbei Township, Qintang District, Guigang City as an example, the investigation accuracy of village greening survey with high spatial resolution remote sensing image data and object-oriented segmentation and classification method can meet the production demand of the forestry department for rapid and accurate investigation of village greening conditions. This paper takes the research area mountain village as an example, to the village existing building objects as the boundary of Cun Tun inside and peripheral 100 m for the survey scope, using high score satellite image, through the object-oriented segmentation and classification method, efficiently and quickly extract the greening within the scope of green information, and calculate the green area and the total area, as a rural village green coverage, in order to provide theoretical support for rural construction, and enrich the research of existing methods of investigation.

1.3 Research content and technical route

1.3.1 Study Contents

Based on the object-oriented threshold classification method, this paper extracts the spectral, geometric and texture features of the object coverage of high-resolution remote sensing images. The research contents of this paper are described as follows:

(1) Study on the multiscale segmentation method. In this paper, we study the four-parameter -band weight, shape factor, compact degree factor, and segmentation scale that affect the multiscale segmentation. Combining the characteristics of various features and prior knowledge, and analyzing the effect of each parameter on the effect of segmentation through a large number of experiments, the best combination of segmentation parameters of various features is finally determined. On this basis, the hierarchy structure is established to achieve the best segmentation effect.

(2) Establishment of the feature space rule sets of various ground objects. According to the spectral, geometric and texture features of different objects, this paper expounds the commonly used feature index in ground object classification, combined with experiments and prior knowledge, to explore the optimal extraction of remote sensing index rule set of various objects.

(3) Object-oriented threshold classification to extract rural greening coverage. On the basis of in-depth exploration of the spectral, geometric and texture features of the features, this paper divides the main features in the study area into four categories: water body, road, urban and rural land and green space, among which the green space is subdivided into: road green space, residential green space, cultivated land, forest land and grassland. The corresponding rule set is established according to the different object objects, and the information extraction of the main features is realized through the object-oriented threshold classification method, and the results are evaluated with accuracy.

1.3.2 Technical route

The technical route of this paper is shown in Figure Figure 1.

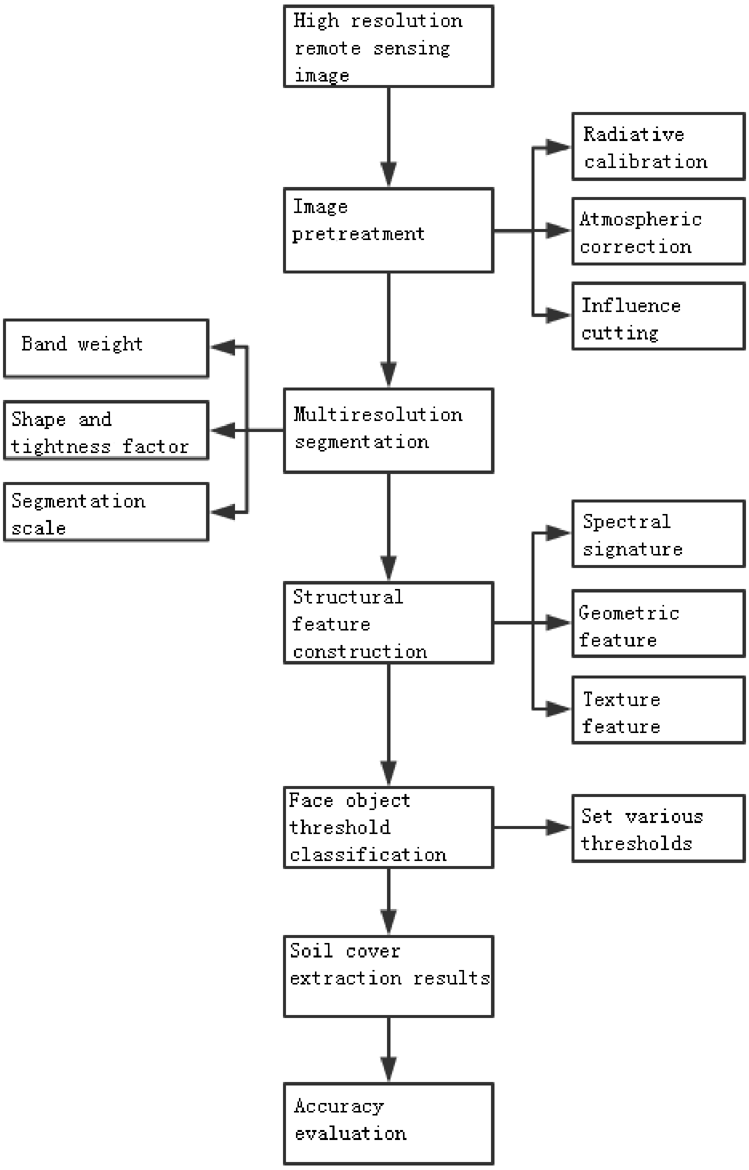


Figure 1 Technical route

2. Principle of object-oriented classification method

Multi-scale segmentation is the first step to extract object information by object-oriented method. The quality of the segmentation results greatly affects the accuracy of the final land classification extraction, so the optimal choice of various parameters during segmentation is particularly important. Firstly, the best segmentation scale of various features is determined, and then the feature space of various features is selected and constructed. According to the rule set of the corresponding feature space, all kinds of land cover information is extracted by the object-oriented threshold classification method, and finally the accuracy of the results is evaluated.

2.1 Multi-scale segmentation method and determination

2.1.1 Multi-scale segmentation method

Multi-scale segmentation, quadric tree segmentation and checkerboard segmentation are relatively common segmentation methods, and the most effective multi-scale segmentation is selected. Multiscale segmentation has minimal regional heterogeneity in the image object layer formed by image element sets with similar characteristics under scale constraints. Heterogeneity factor is composed of shape heterogeneity factor and spectral heterogeneity factor, and shape heterogeneity is divided into smoothness factor and compactness factor. In the segmentation process, if the spectral difference of the ground object is only taken into account, the roads and buildings with spatial feature information will lose more information, resulting in the destruction of the ground object boundary. Therefore, the spectral heterogeneity and image heterogeneity can achieve better segmentation effect. The concept is as follows:

(1) Spectral heterogeneity:

$$h_{color} = \sum_{c} \omega_c \cdot \sigma_c \tag{1}$$

ω_c Where, represents the weight of the layer, c represents the number of bands, and represents the variance. σ_c

n_{01} σ_c^{01} n_{02} σ_c^{02} Let,,, represent the area and variance of two adjacent regions respectively. The weight of the combined band to be included in the segmentation is, the combined area is, and the variance of the region is then: ω_c n_{mer} σ_c^{mer}

$$h_{color} = \sum_{c} \omega_c \cdot (n_{mer} \cdot \sigma_c^{mer} \cdot (n_{01} \cdot \sigma_c^{01} + n_{02} \cdot \sigma_c^{02})) \tag{2}$$

(2) Shape heterogeneity:

Shape heterogeneity consists of smoothness factor and compactness factor, which is formulated as follows: h_{smooth} $h_{compact}$

$$h_{shape} = \omega_c \cdot h_{compact} + (1-\omega_c) h_{smooth} \tag{3}$$

h_{shape} ω_c h_{smooth} ω_c It represents the shape heterogeneity of the image object area; it is the weight of the tightness factor, where 01. In Equation 2.4, the compactness factor and smoothness factor are calculated using the following equation: $h_{compact}$ h_{smooth}

$$h_{smooth} = \frac{E}{L} \tag{4}$$

$$h_{compact} = \frac{E}{\sqrt{N}} \tag{5}$$

The parameters of the image area are represented by the following letters: L is the minimum value of the perimeter of the outer rectangle; E is the circumference, or the actual boundary length; and N is the pixel area or total number.

The minimum rectangle of the first two image object areas are respectively, and the actual length of the boundary is represented by. The compactness factor and smoothness factor of the merged image object area: the minimum external connection rectangle and the actual length of the boundary are, respectively. Calculate by using the following equation: L_{obj1} L_{obj2} E_{obj1} E_{obj2} $h_{compact}$ h_{smooth} L_{merg} E_{merg}

$$h_{smooth} = n_{merg}\frac{E_{merg}}{L_{merg}} - (n_{obj1}\frac{E_{obj1}}{L_{obj1}} + n_{obj2}\frac{E_{obj2}}{L_{obj2}}) \tag{6}$$

$$h_{compact} = n_{merg}\frac{E_{merg}}{\sqrt{n_{merg}}} - (n_{obj1}\frac{E_{obj1}}{\sqrt{n_{obj1}}} + n_{obj2}\frac{E_{obj2}}{n_{obj2}}) \tag{7}$$

n_{obj1} Where it represents the area before merging of image object area 1; represents the area before merging of image object area 2; and represents the area after merging of image object area. n_{obj2} n_{merg}

(3) The relationship between spectral and shape heterogeneity is as follows:

$$f = \omega \cdot h_{color} + (1-\omega)h_{shape} \tag{8}$$

h_{color} ω Where, represents the spectral heterogeneity parameter and represents the spectral heterogeneity weight, 01, Table f ω

The total heterogeneity value of the image object, representing the shape heterogeneity parameter. h_{shape}

The segmentation mode of multiscale segmentation is top-down. Any image like the first segmentation, by calculating the starting heterogeneity parameter, segmentation will form a new image, then continue to generate the next segmentation, and so on, before segmentation judgment segmentation scale square and heterogeneity parameter f size, less than f continue to segment, is greater than the f stop segmentation. According to the heterogeneity minimum criterion until the image in the image is all divided into the image object, the end of the segmentation.

2.1.2 Optimal segmentation scale

In the ideal state of the optimal segmentation scale, all kinds of ground objects obtained after the segmentation have high internal homogeneity, and there are obvious differences between the adjacent objects, which can be better distinguished.

(1) Homogeneity within the objects

The homogeneity within the object is evaluated according to the weighted spectral standard deviation of the object. The calculation formula is as follows:

$$v = \frac{\sum_{i=1}^{n} a_i \sigma_i}{\sum_{i=1}^{n} a_i} \tag{9}$$

a_i σ_i Where v represents the weighted spectral standard deviation; n represents the total number of objects obtained after image segmentation; the total number of images of the i-th segmented object, namely the area; and the spectral standard deviation of the i-th segmented object. Measure the area of objects added in homogeneity, it can effectively improve the stability of large objects. Larger v means greater within-object heterogeneity.

(2) Heterogeneity between adjacent objects

Spatial autocorrelation index refers to a good index of the spatial separation, which can well evaluate the heterogeneity between the objects. The formula is as follows:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{(\sum_{i=1}^{n}(y_i-\bar{y})^2)(\sum_{i\neq j}\sum w_{ij})} \quad (10)$$

w_{ij} w_{ij} y_i y_j $\bar{y}$ Where I is Moran's index; is the spatial neighbor of object i and object j; if object i is adjacent to object j, then =1, otherwise 0; and represents the spectral mean of object i and j respectively; is the spectral mean of the image, the lower I indicates the spatial correlation between objects, the lower the higher the heterogeneity between objects, that is, the high separation.

2.2 Object feature description

The characteristic properties of multi-scale segmented objects are important basis for information extraction and reflect the relevant information of actual objects. Through the centralized analysis of the characteristics of the image object, the features suitable for the extraction of different objects are found, and the corresponding feature space is established. Commonly used features in object-oriented land cover extraction are:

(1) Spectral characteristics. Spectral features, as the most basic features of images, still need to be used in the object-oriented method of classification. The spectral characteristics describing the image object are generally correlated with the gray value of the image. The spectral features used in the general image processing include: mean value (Mean), brightness (Brigthness), contribution rate (Ratio), etc.

(2) Geometric features. Because the actual features has certain shape and size properties, the geometric features expressed by different features are not the same in the objects formed by multiscale segmentation. Geometric features contain semantic features, the spatial toprelationship between adjacent objects. Common geometric features are: Length, Width, Length / Width, Density, Rectangular Fit, etc

(3) Texture features. Texture features describe the characteristics of an object, which are determined by the distribution between an image and adjacent images. Therefore, the object-oriented method has an advantage over image-based classification methods for reflecting texture features. The most commonly used to calculate texture features is the gray scale symbiosis matrix (GLCM), including Entropy, Standard deviation, etc.

(4) Index characteristics. The exponential features are based on the spectral features, which can better describe a certain specified attribute by linear operation. The ly used index characteristics are normalized vegetation index, brightness index, water index and soil index.

① vegetation index

The normalized vegetation index NDVI is the ratio of the difference between the NIR and the sum of the red channel. It is defined as follows:

$$\text{NDVI}=\frac{NIR-Red}{NIR+Red} \quad (11)$$

② brightness index

Brightness index BBI is mainly used to reflect the reflection intensity of various objects, showing the changes in the sum of blue and green bands. It is defined as follows:

$$\text{BBI}=\frac{Blue+Green}{2} \quad (12)$$

③ Water Body Index

Normalized differential water index NDDWI is the normalized difference between the green and near-infrared bands of remote sensing images. It is defined as follows:

$$\mathrm{NDWI} = \frac{Green-NIR}{Green+NIR} \tag{13}$$

④ soil index

Soil index NDSI is mainly used to reflect the soil content of the content, which is shown in the ratio of the difference between the red band channel and the blue band channel. It is defined as follows:

$$\mathrm{NDSI} = \frac{Red-Blue}{Red+Blue} \tag{14}$$

2.3 Object-oriented threshold classification method

Object-oriented classification method is based on rules and based on sample two kinds of classification, this paper is based on the rules of the threshold classification, namely the use of remote sensing image multiscale segmentation generated object, looking for different features between different feature elements with other elements, with certain conditions (select a suitable threshold) to the classification process. The key point of threshold classification is to find a suitable threshold value. If the image object is extracted by threshold classification according to a single rule and threshold, the accuracy of the results is low. Find the feature space of different ground object coverage types, and select the appropriate rule set for threshold classification, the effect is better than a single rule classification. For example, when extracting water body, NDWI and Mean _ NIR features are used to extract together, and NDWI 0.139 and Mean _ NIR 249 are set, and water body can be better extracted well. Finding thresholds for different features, such as spectral, texture, and geometric features, is key to threshold classification.

2.4 Precision evaluation

At present, the confusion matrix (Confusion Matrix) method is commonly used. The main idea is to display the classification results and the surface truth information in the — error matrix in a confusion matrix, and accurately judge the accuracy of the classification. The error matrix is shown in Table 1

Table 1 Error matrix table

Land category	1	2	...	n	Line total
1	a_{11}	a_{12}	...	a_{1n}	Sum_{1+}
2	a_{21}	a_{22}	...	...	Sum_{2+}
...	...	...	...	...	...
n	...	...	...	a_{nn}	Sum_{n+}
List of total	Sum_{+1}	Sum_{+2}		Sum_{+n}	Sum

$a_{11}-a_{nn}$ It represents the number of images in the image, the row value represents the ground class that the user thinks the image corresponds to, and the column value represents the ground class that the classifier determines the column image corresponds to.

Overall accuracy refers to the ratio of the total number of images accurately classified to the total number of all images. The expression is as follows:

$$O = \left(\sum_{i=j}^{x} n_{ij} \right) / n \tag{15}$$

The Kappa coefficient is an indicator that can comprehensively express the accuracy of the classification results of a specific category. The expression is as follows:

$$\mathrm{K} = \frac{sum\sum_{k=1}^{n} a_{kk} - \sum_{i=1}^{n}(sum_{+i} \times sum_{i+})}{sum^2 - \sum_{i=1}^{n}(sum_{+i} \times sum_{i+})} \tag{16}$$

The value domain of the Kappa coefficient is between 0 and 1, and the evaluation criteria for the classification accuracy of the Kappa coefficient are shown in Table 2.

Table 2 Evaluation criteria for the Kappa coefficient

	evaluation criterion
Kappa=+1	The classification results are completely consistent with the reference data
Kappa=0	The classification results were presented at random intervals
Kappa≥0.75	The classification results showed high agreement with the reference data
Kappa＜0.4	The classification results showed very poor agreement with the reference data

2.5 Summary of this chapter

This chapter mainly introduces the relevant principles and methods of object-oriented classification methods. Firstly, the principle and the optimal segmentation scale are introduced. Secondly, the characteristics of the four objects: spectral features, texture features, geometric features and exponential features are described. Then, the experimental method of this paper is an object-oriented threshold classification method, and finally the method of accuracy evaluation is expounded.

3. Overview of the study area and introduction of data sources

3.1 Overview of the study area

The experimental area is located in the southern rural area of Jiangning District, Nanjing City, Jiangsu Province, with a geographical location of north latitude 31.7799245 °-31.9762681 °, and east longitude 118.5100097 °-118.8893351 °. Jiangsu province is located in the east China region of China, Nanjing city is located in the southwest of Jiangsu Province, Jiangning District is located in the south region of Nanjing city, in the north of Ma 'Anshan, and its southern section borders on Ma' Anshan. The rural landform of Jiangning area is mainly plain and low hills, which is affected by the southeast monsoon and northeast wind, and the temperature difference is large. Nanjing city is also a very important city in China, and the planning and management of rural green space in Nanjing city is particularly important.

3.2 Introduction of the data source

The data source used in this paper is IKONOS high-resolution remote sensing image data. IKONOS The satellite was successfully launched in 1999. It can collect multispectral satellite images with 1-meter resolution panchromatic and 4-meter resolution, and can integrate panchromatic and multispectral images into color images with 1-meter resolution. Detailed technical indicators are shown in Table 3.

Table 3 IKONOS Image characteristics

sensor	Spectral band	ground resolution	Band spectral range
IKONOS	Pan	1m	0.45-0.90
	blue	4m	0.45-0.53
	green	4m	0.52-0.61
	red	4m	0.64-0.72
	NIR	4m	0.77-0.88

3.3 Summary of this chapter

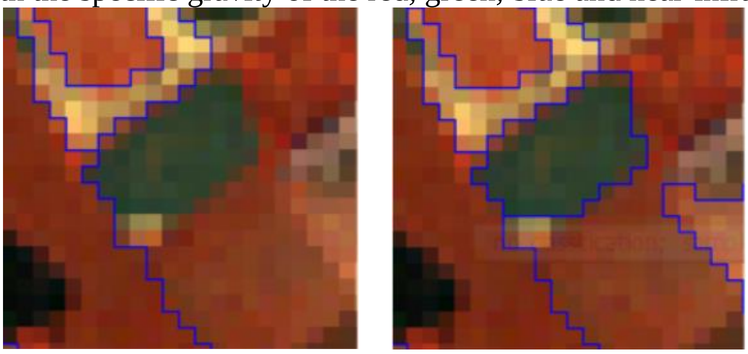
This chapter mainly introduces the general situation of the study area and the relevant information of the data sources, and introduces the preprocessing of the IKONOS remote sensing image data sources.

4. Classification and extraction of object-oriented threshold

4.1 Multi-scale segmentation

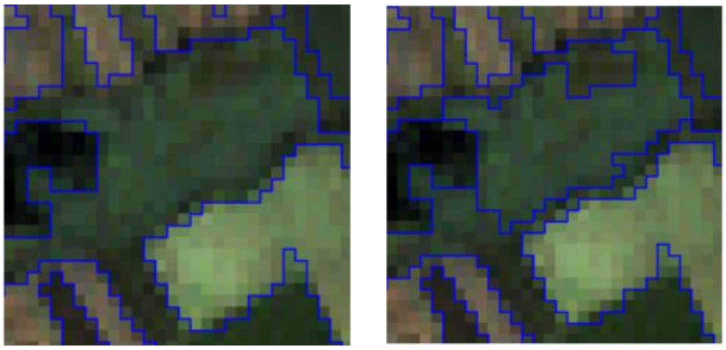
4.1.1 Band weights

The experiment using the image data for IKONOS high resolution remote sensing data, there are four multispectral band, respectively, red band, green band, blue band and near infrared band, each band has a very large spectral information, in the process of segmentation, to make full use of the spectral information is the necessary steps to achieve the best segmentation effect. According to the prior knowledge, it is found that the vegetation and water body have strong reflectivity in the infrared band. Therefore, therefore, the weight ratio of the band should be increased in the segmentation experiment. The experiment found that in the process of dividing water and vegetation, the effect of the edge of the segmentation was enhanced. The segmentation effect under different weights is shown in Figure 2 and 3, with the specific gravity of the red, green, blue and near-infrared bands.



(a)Band weights 1:1:1:1 (b) band weight 1:1:1:4

Figure 2 Weight segmentation effect of different bands in water body

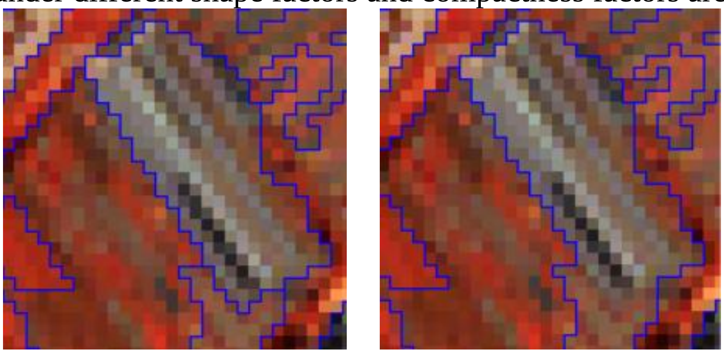


(a) Band weights 1:1:1:1　　(b) band weights 1:1:1:4

Figure 3 Weight segmentation effect of different bands of vegetation

4.1.2 Shape and tightness factor

According to the actual feature information, different feature features have different contour characteristics, and the water body, vegetation and bare soil are generally in irregular polygons, whose contour characteristics are not very obvious, while urban and rural land, cultivated land and roads have very obvious contour characteristics, generally shaped like rectangles. Therefore, in the process of multi-scale segmentation, considering the influence of shape factor and compact factor on the segmentation effect, increasing the shape factor parameters of urban and rural land and roads, has the segmentation effect of the boundary; Since the boundary shape information of green space and water is not obvious, the segmentation of the shape factor parameters has no obvious effect. The segmentation effects under different shape factors and compactness factors are shown in Figure 4.

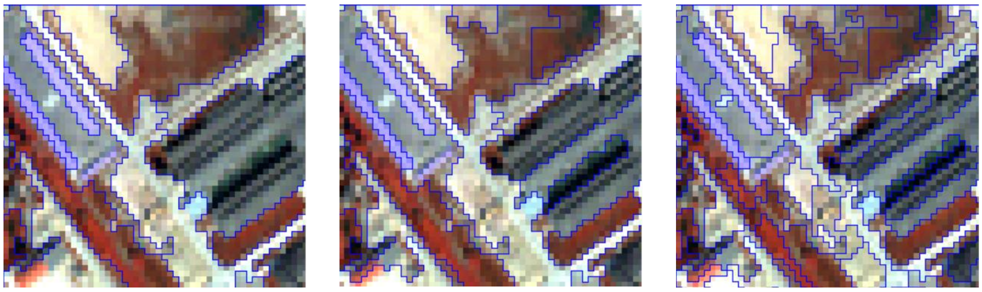


(a) Shape 0.3 compactness 0.5　(b) Shape 0.1 compactness 0.5

Figure 4 The segmentation effects of different shape factors and compact factors

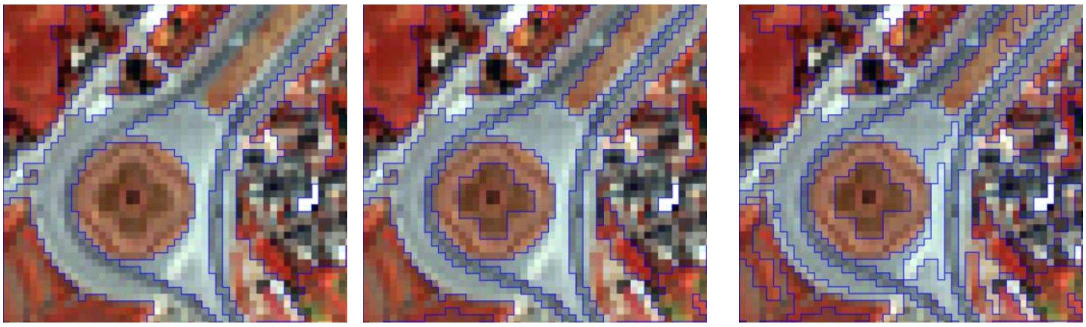
4.1.3 Division scale

The choice of segmentation scale is very important, this paper uses a hierarchical multi-scale segmentation method, using different segmentation scales for different land types, and hierarchical extraction. In order to explore the optimal segmentation scale of different land types, this paper conducts a series of segmentation experiments, starting with the segmentation scale 10, with a range of 10-100 and 10 as the step size. According to the above information, when dividing the water body and vegetation, the band weight is 1:1:1:4. When dividing the road and urban and rural land, the shape factor is set to 0.3, and the compactness factor is set to 0.5. The segmentation effect of urban and rural land, roads, green land, water body and cultivated land at different scales is shown in Figure 5-9.



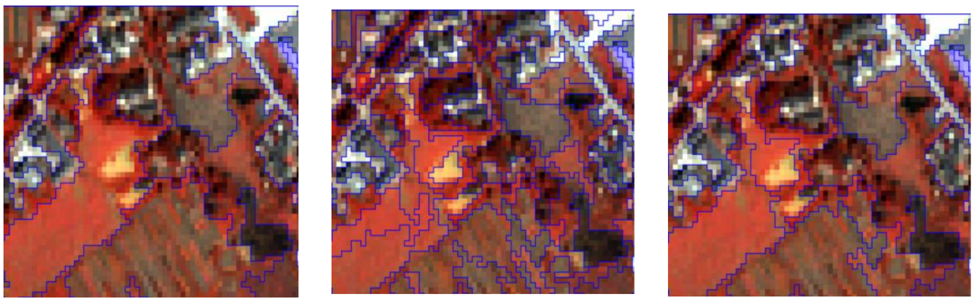
(a) Segmentation scale 60 (b) segmentation scale 40 (c) segmentation scale 20

Figure 5 Separation effect of urban and rural land at different scales



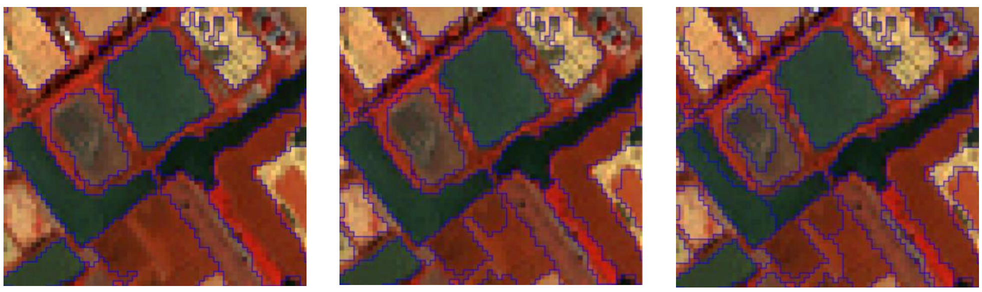
(a) Segmentation scale 60 (b) segmentation scale 40 (c) segmentation scale 20

Figure 6 The segmentation effect at different scales of the road



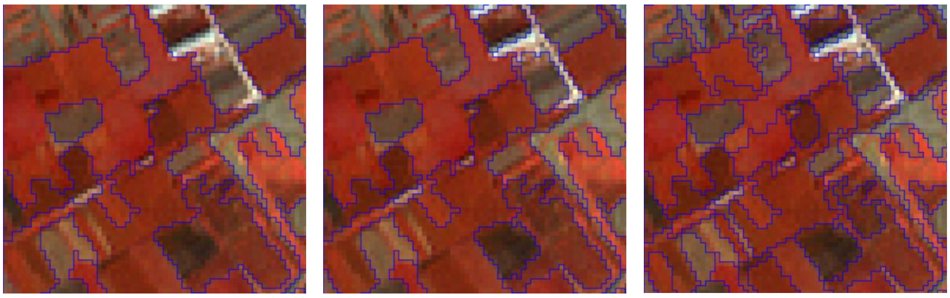
(a) Segmentation scale 60 (b) segmentation scale 40 (c) segmentation scale 20

Figure 7 Segmentation effect at different scales of green space



(a) Segmentation scale 60 (b) segmentation scale 40 (c) segmentation scale 20

Figure 8 Separation effect of water body at different scales



(a) Segmentation scale 60 (b) segmentation scale 40 (c) segmentation scale 20

Figure 9 Partitioning effect at different scales of cultivated land

The experiment shows that when the segmentation scale is 60, the outline of water edge is clear, while the boundary contour of other land types is not obvious, and there is more or less segmentation phenomenon. When the segmentation scale is 40, the segmentation scale of cultivated land, grassland, forest land, residents is best, the urban and rural land area is intact, and the edge information of urban and rural land is relatively complete, while other features have signs of excessive segmentation, and the same site is divided into multiple objects, resulting in the fragmentation of features. Therefore, this paper establishes the hierarchical structure of this paper with three segmentation scales (60, 40, 20). The hierarchical structure is shown in Table Table 4.

Table 4 Table of the article's hierarchy

administrative levels	Land category	Optimal segmentation scale	form factor	Factor of compactness
1	Water layer	60	0.1	0.5
2	Green formation	40	0.1	0.5
3	Urban and rural strata	20	0.3	0.5

4.2 Feature space

Image objects contain a variety of feature information, such as spectrum, texture and space, and they can classify different feature information with obvious differences in different feature types. Two selected spectral features, 1 texture features, 3 spatial features and 4 index features, and a total of 10 features are used to construct the feature space. As shown in Table 5.

Table 5 Feature space

Feature category	Feature name
spectral signature	Mean_Blue, Mean_NIR
Spatial features	Length, Rectangular Fit, R el.area of
textural features	GLCM STdD(all dir.)
Index characteristics	NDVI, BBI, NDSI, NDWI

According to different land cover types, appropriate features are selected after a lot of experiments to establish their corresponding feature space and establish the corresponding rule set.

4.3 Object-oriented threshold classification experiment

4.3.1 Construction of the hierarchical model for multiscale segmentation

Segmentation scale is the previous work that affects classification. Under the principle of heterogeneity principle, the segmentation will be divided into polygon objects of different sizes, which is the minimum basic unit of ground extraction. The quality of the segmentation result directly affects the quality of the object, and further determines the accuracy and applicability of the segmentation. According to the results of the best segmentation scale of different land types, the land types are divided into water area, green space (woodland, grassland, cultivated land, green land, road and residential green space), road and urban and rural land (including blue roof buildings), and establish the hierarchical model structure of this paper. The hierarchical structure model is shown in Figure 10.

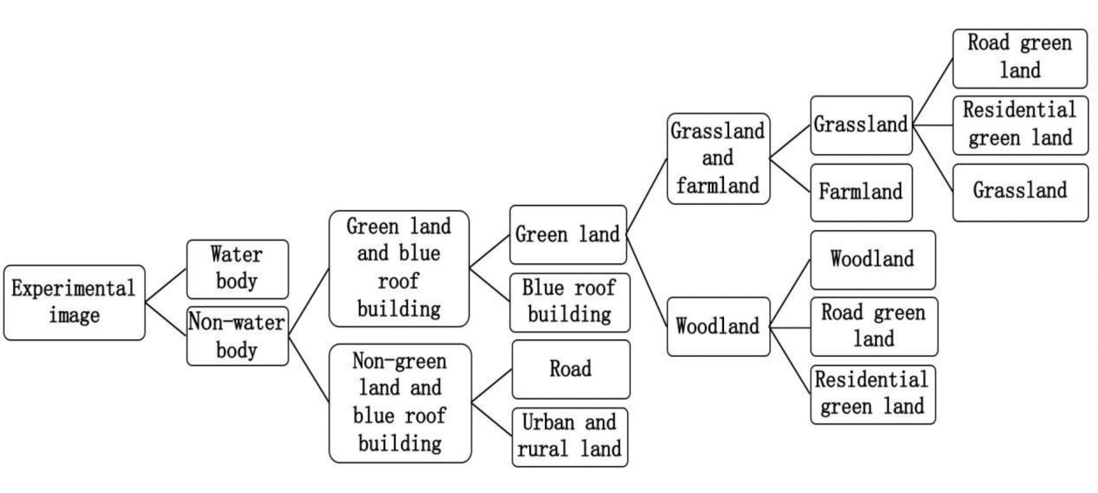


Figure 10 The hierarchical structure model of this paper

4.3.2 Object-oriented main object information extraction

According to the main site types in the test area, Level1, Level2, Level3, Level1 is divided according to the maximum scale, mainly extracting the water area, and the information of the water area is extracted according to the combination of characteristics. Level2 On the basis of the Level1, inherited the characteristics of the waters for the second division, join the green space, blue roof building rules of function, extract the green space and blue roof building information, has taken out the waters do not need to participate in the subsequent classification, and then the green strata subdivision, divided into grass cultivated land and forest land, forest land subdivided into forest land, road green space, grassland and cultivated land for grassland and cultivated land, grassland subdivided into road green space, residents green space and grassland. Level3 On the basis of L evel2, it first inherits the attribute information of non-vegetation and blue-top buildings, and then divides it for the third time. First, the roads with obvious feature information are extracted, and the remaining land types are classified as urban and rural land. Since the remote sensing image time of this experiment is in April, there is no bare land in the research area. In this paper, the land cover extraction of 8 land types in 3 levels was finally completed according to 3 segmentation scales.

(1) Water body feature extraction. After experimental summary, the optimal segmentation scale parameter combination of water body is: segmentation scale 60, shape factor 0.1, compactness factor 0.5, and band weight 1:1:1:4. The reflection characteristics of the water body in different bands, the

mean value of the near-infrared band, and the normalized water body difference index NDWI were used to extract the water body. After many trials, when the normalized water index NDWI 0.139.

(2) Extraction of vegetation and blue-top building features. Through experiments, the optimal segmentation scale parameters of vegetation and blue-top buildings are: segmentation scale 40, shape factor 0.1, compactness factor 0.5, and band weight 1:1:1:4. It is found that when the vegetation information is extracted by using the normalized vegetation index NDVI 0.14, some blue ceiling buildings will be extracted. Therefore, in the subsequent classification process, the blue tripod buildings should be removed from the green space for separate extraction.

(3) Extraction of blue-top building features. The study found that the soil index NDSI and the blue band mean Middle _ Blue are used to effectively distinguish between blue-top buildings and vegetation. After many experiments, when NDSI-0.19, Middle _ Blue 416.

(4) Road feature extraction. Through experiments, the optimal segmentation scale parameters of vegetation and blue-top buildings are: segmentation scale 20, shape factor 0.3, compactness factor 0.5, and band weight 1:1:1:1. In the process of road extraction, due to the geometric characteristics of road objects, it is found that the road information can be effectively extracted when length 60 Pxl, GLCM _ STdD 44.5, BBI (374,453).

(5) Information extraction of grassland and cultivated land. Because grassland and cultivated land have slightly lower NDVI index compared to forest land, the texture characteristics are not very obvious. After study, it was found that WP and GLCM _ STdD 36.1 separated when NDVI 0.45.

(6) Cultivated land information extraction. Because the cultivated land is generally shaped like a rectangle, the similar geometric features of the cultivated land can be fully utilized when classifying the grassland and the cultivated land. It is found that the cultivated land information can be effectively extracted when Rectangular Fit (rectangle fitting index) is 0.74 and NDVI is 0.16.

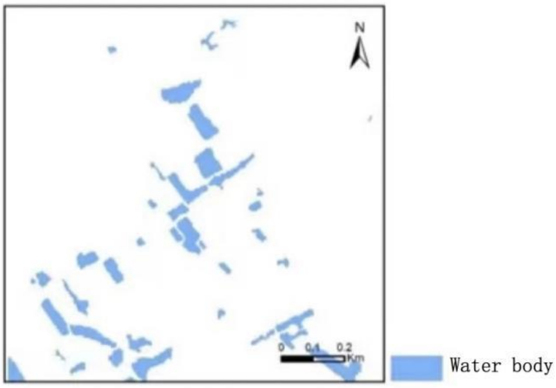
(7) Extraction of road green space and urban and rural green space. Since road and urban and rural green spaces are divided into woodland and grassland, semantic information is extracted according to the spatial expansion relationship. First, the road green space was extracted, and Rel. The woodland and grassland of area of 20 are classified as road green space; then extract the resident green space, Rel. The woodland and grassland of area of 20 are classified as residential green space.

The sets of rules are shown in Table 6.

Table 6 Rule sets of various feature space

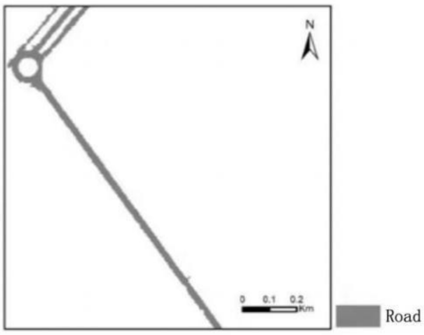
	wave	Vegetation and blue-top buildings	Blue top building	road	Meadows and arable land	plough	Roads and residential green space
NDWI	≥0.139						
NDVI		≥0.14			≤0.45	≥0.16	
NDSI			≤-0.19，				
BBI				(374，453)			
Mean_NIR	≤249						
Mean_Blue			≥416				
Length				≥60			
GLCM_STdD				≥44.5	≤36.1		
Rectangular Fit						≥0.74	
Rel.area of							≤20

According to the spatial rule set and threshold range of various features of features in Table 6, the object-oriented threshold classification experiment is conducted in this paper. The experimental results of various features in the study area are shown in Figure 11.

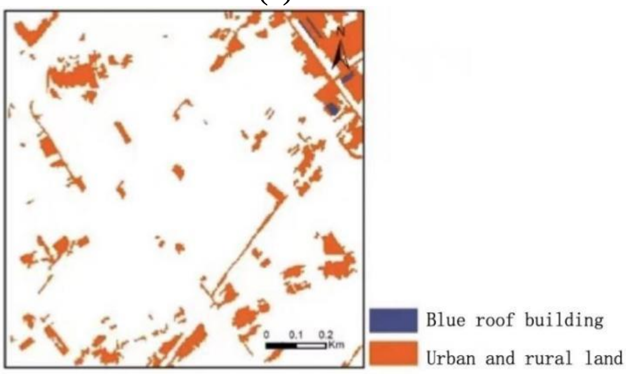


(a) water body

(b) green space



(c) road



(d) urban and rural land

Figure 11 Experimental results of various features in the study area

The blue-top buildings in the figure were classified as urban and rural land, and the experimental results were unified, and the experimental results of object-oriented threshold classification in the study area are shown in Figure 12.

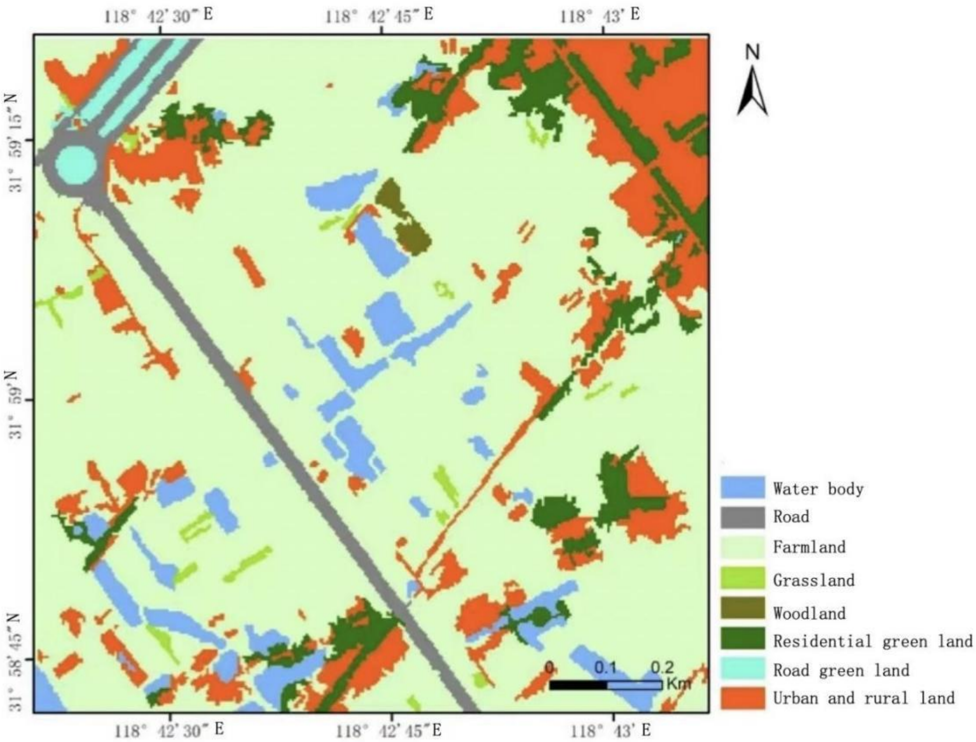


Figure 12 Experimental results of object-oriented threshold classification in the study area

4.4 Precision evaluation of classification results

According to the artificial visual interpretation results as the real land cover information standard, 500 validation points were randomly selected in the study area, and the object-oriented threshold classification results of these 500 validation points were compared with the visual interpretation results. The confusion matrix of this experiment is shown in Table 7.

Table 7 Confusion matrix for the accuracy evaluation of this experiment

	wave	road	plough	meadow	forest land	Residents green space	Road green space	Urban and rural land
wave	51	0	6	0	0	2	0	0
road	0	26	4	0	0	1	1	2
plough	10	5	645	4	1	7	3	17
meadow	0	0	0	8	0	0	0	0
forest land	0	0	0	0	3	0	0	0
Residents green space	2	1	4	0	0	53	0	3
Road green space	0	1	0	0	0	0	8	1
Urban and rural land	1	3	8	2	1	3	2	110

As it can be seen from the confusion matrix of the accuracy evaluation in this experiment, the overall accuracy of this object-oriented threshold classification experiment is 90.4%, and the Kappa coefficient is 0.815. From the information in the table, cultivated land, water body, road, grassland, forest land, residential green space, road green space and urban and rural land, all have different degrees of misclassification phenomenon. Since most of the land types in the study area of this experiment are cultivated land, there are more random points in random points; Urban and rural land and other land types also have less wrong classification phenomenon, perhaps due to the complexity of rural, urban and rural land use. In its surrounding water body, green space and other land types around, it is easy to form mixed images, thus to a certain extent it reduces the extraction accuracy; The misclassification of residential green space with cultivated land and urban and rural land, mainly because the grassland and cultivated land in the residential green space have many similar characteristic information, thus resulting in a small range of wrong classification cases. Due to the complex situation between urban and rural land and residential green space, the increase in hybrid pixels, causing a certain degree of misclassification. However, in general, the overall classification accuracy is greater than 90%, and the Kappa coefficient is also greater than 0.8, achieving relatively satisfactory classification results.

4.5 Classification results and analysis

According to the above object-oriented threshold classification results of the study area, the footprint of various land types combined with statistical knowledge is shown in Table 8.

Table 8 Floor area of various land types

Land type	Area (in unit: m^2)
wave	84704
road	49392
plough	994942
meadow	12272
forest land	4992
Residents green space	91415
Road green space	13792
Blue top building	3504
Urban and rural land 1	10915
Urban and rural land 2	172633
Sum	1438561

In the table, the blue-roofed building and the urban and rural land area are combined into a total urban and rural land area of 18,752 m^2. In the study area, the water area is 5.9%, road 3%, arable land 69.1%, grassland 0.9%, forest land 0.3%, residents 6.4%, road green land 1.0%, and urban and rural land 13%. The proportion of various land use is shown in Figure 13

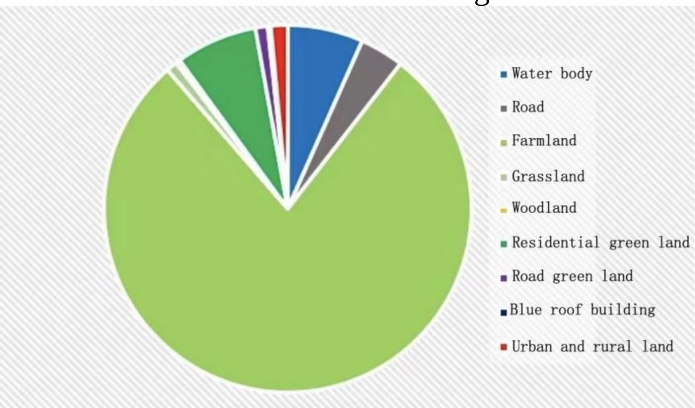


Figure 13 The portion of various land areas in the study area

According to the synthesis of chart information, the total area is 1438561m^2In the study area, the largest area, the area is 994942 m^2, Urban and rural land area is second only to arable land, with an area of 187,052 m^2, There are a small number of blue-roofed buildings, covering an area of only 3,504 m^2. The woodland and grassland also cover less area, only slightly higher than the blue-roofed building, 4992 m respectively^{2}And 12,272 m^2, Since most of the grassland and woodland in the study area are adjacent to the road or urban and rural land, they are classified as road green land and urban and rural green land by semantic information, leaving only sporadic grassland and woodland in some cultivated land, so the land area of grassland and woodland in the study area is less. The road green space covers an area of 13,792 m^2, It is mainly distributed in the green belt in the north of the road and the middle of the middle of the road, while the middle to the south have no road green space. The residential green space covers an area of 91,415 m^2, mainly distributed around the village, bordering on the village, and its divided image objects are adjacent to the urban and rural land.

In conclusion, the total green space area in the study area, including woodland, grassland, cultivated land, road green space and residential green space, was 1,117,413 m^2, The ratio of green space accounts for 87.7% of the total area, and the area of other land types is 321148 m^2, Accounting for 12.3% of the total area ratio, and the rural green rate in the study area is as high as 87.7%. It can be seen that the rural greening work in Jiangning District of Nanjing city has achieved remarkable results.

4.6 Summary of this chapter

This chapter first introduces the influence of the band weight, the shape factor, the tightness degree factor and the segmentation scale on the segmentation effect in the multiscale segmentation. Then describes the experiment of the spectral characteristics, geometry, texture and index characteristics, constructed the hierarchical structure model of the experiment, and establish different feature space rules according to different land cover types, using the object-oriented threshold classification method, extract the main ground type in the study area, and evaluate the accuracy of the experimental results. Finally, the results of the experiments in the study area were analyzed.

5. Summary and Outlook

5.1 Conclusion

In this paper, using IKONOS high-resolution remote sensing image data, we explore the object-oriented threshold classification method to extract the rural land cover types in Jiangning District, Nanjing (mainly extracting green space information), and make accuracy evaluation, and finally analyze the experimental extraction results. The following conclusions are obtained in this paper:

(1) The influence factor parameters of the multiscale segmentation are determined. According to the experiments, the influence factor parameters of multiscale segmentation of different features are determined respectively: 1:1:1:1:4, shape factor 1,0.1, compact degree factor 0.5 and segmentation scale 60; vegetation layer band weight 1:1:1:1:4, shape factor 0.1, compact degree factor 0.5 and segmentation scale 40; urban and rural stratum band weight 1:1:1:1:1, shape factor 0.3, compact degree factor 0.5 and segmentation scale 20, thus determining the classification extraction structure model of this paper.

(2) According to the spectral characteristics, texture characteristics, geometric characteristics and index characteristics of different land cover types, the feature space and corresponding rule sets of different land types in the study area are determined. The rule set for extracting the water body is NDWI 0.139 and Mean _ nir 249; The rule set for extracting green space and blue-top buildings is NDVI 0.14; The rule set for extracting the blue-top buildings is NDSI-0.19, Mean _ Blue 416; The rule set for the extracted roads is length 60, GLCM _ STdD 44.5, BBI (374, 453); The rule sets for

extracting the grassland and cultivated land are NDVI 0.45, GLCM _ STdD 36.1; The rule set for extracting the cultivated land was Rectangular Fit 0.74, NDVI≥0.16; The rule set for the extracted road and residential green spaces was taken as Rel.area of≤20.

(3) Extraction results and analysis of object-oriented threshold classification: The object-oriented threshold classification experiment uses the characteristics of the feature rule set of various features to determine the threshold range of the feature space. The overall accuracy rate and Kappa coefficient of the final extraction of the main land type information (mainly including water, road, forest land, grassland, cultivated land, cultivated land, road green land, residential green land and urban and rural land) in the study area are 90.4% and 0.815, respectively. This classification effect is very satisfactory. A relatively satisfactory classification result is obtained. The total green area of the study area is 1,117,413 m^2, including forest land, grassland, cultivated land, road green space and residential green space, of which 87.7% of the total green area and 12.3% of the other land area is 321148 m^2. The rural greening rate in the study area is as high as 87.7%.

5.2 Outlook

This paper makes relevant research on the extraction method of land cover information in the research area based on object-oriented threshold classification, and achieves relatively satisfactory classification effect and application value. However, there are still some parts that can be improved and the future development directions that can be explored:

(1) The experimental data source of this paper is only IKONOS high-resolution remote sensing image data. In future research, more data sources can be used to extract the coverage of rural green space and explore the applicability of this method.

(2) The study area of this experiment is small. In the subsequent study, the scope can be expanded to the whole rural areas of Nanjing, so as to verify the universality of this method.

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