

Application of Image Texture Analysis to Improve Land Cover Classification

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Abstract: Image texture analysis has received a considerable amount of attention over the last few years as it has played an important role in the classification of the remote sensing images. This paper provides an overview of several different approaches to image texture analysis and demonstrates their use on the problem of land cover classification. We used grey level co-occurrence matrix (GLCM) method to assist the land cover classification and then compared and evaluated all of the result of classifications. In the experimentation, by comparing the classification result of contrast, energy and entropy we find out that the preferable texture features of grey level co-occurrence matrices method was contrast. In this thesis, it used the feature images helping the classification of remote sensing and obtained good result. And it also used C++ programming language to write a programme to compute the number of the feature of texture.

Key-Words: Land cover classification, Texture analysis, Grey level co-occurrence matrices method, Texture feature

1 Introduction

The study of the land cover is one of the most important factors for planning and managing activities concerning the use of land surface on this earth. Remote sensing techniques have improved mapping and interpretation of data as a means of understanding and effectively managing the present resources for sustainable development [1]. Classification of land-cover information using remotely-sensed imagery is a challenging topic due to the complexity of landscapes and the spatial and spectral resolution of the images being used. Scholars from many different nations engaged in land cover classification study had used many different data and different methods to improve the accuracy of classification, and great progress has been made. Early studies of land-cover classification used statistical methods such as the maximum likelihood classifier. Recently, however, numerous studies have applied artificial intelligence techniques for example, expert system, artificial neural networks and support vector machines – as alternatives to remotely-sensed image classification

applications[2]. Various ensemble classification methods have been proposed. These methods have been proven to improve classification accuracy considerably[3]. The use of statistical finite mixture models with groups of original pixel-scale measurements, at successive spatial scales, offers improved pixel-wise classification accuracy as compared to the commonly used technique of label aggregation [4]. The maximum likelihood (ML) procedure is, for many users, the algorithm of choice because of its ready availability and the fact that it does not require an extended training process. Artificial neural networks (ANN) are now widely used by researchers, but their operational applications are hindered by the need for the user to specify the configuration of the network architecture and to provide values for a number of parameters, both of which affect performance [7].

Surface texture is an important quality characteristic of many products. Methods include traditional statistical approaches such as gray level co-occurrence matrix (GLCM) methods, multivariate statistical approaches based on PCA

and PLS, and wavelet texture analysis [9]. It is not clear which texture measures are more accurate or informative than others, or how they might best be used in combination. This is particularly so for Mediterranean land covers where certain land cover types cover relatively small areas [10]. A very important feature for the outskirts of the city's image classification is that it contains a wide range of different types of components, and more cross-mixed. The planning of the outskirts of the city is often not thoughtful, and it is not easy to demarcate the border of the land-use types, so it is more difficult for the traditional classification of spectrum to deal with such a complex classification. The introduction of using statistical information about the texture is useful for the classification.

Several investigations indicate that the Bidirectional Reflectance Distribution Function (BRDF) contains information that can be used to complement spectral information for improved land cover classification accuracies. Prior studies on the addition of BRDF information to improve land cover classifications have been conducted primarily at local or regional scales. Thus, the potential benefits of adding BRDF information to improve global to continental scale land cover classification have not yet been explored [11]. The SSC method starts by dividing a hyper spectral image into homogeneous and heterogeneous regions based on spectral variation of pixels within a kernel. Next, the homogeneous image parts are classified using a conventional per-pixel method. The heterogeneous image sections are classified using a combination of spectral and contextual information. The method was tested and the accuracy assessed



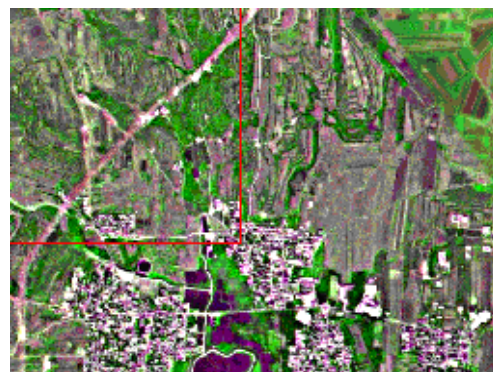
Fig.1. Location of Study Area

using airborne DAIS7915 hyper spectral images acquired over an area in southern France covered by semi-natural vegetation, agricultural fields and open mining activities. Classification accuracy is compared with results of purely spectral classifiers. Results were promising and indicate that the accuracy of the SSC classifier was higher than that of the conventional per-pixel classifiers [12]. The areas of the land consolidation projects are generally small, so the remote sensing images used in land-cover classification for the land consolidation are generally high spatial resolution images. The spectral complexity of land consolidation objects results in specific limitation using pixel-based analysis for land cover classification such as farmland, woodland, and water [13]. Most traditional classification approaches are based exclusively on the digital number of the pixel itself [14]. The system integrates processing of colour image data and information from digital spatial databases, takes into account context information, employs existing knowledge including plans of land consolidation, rules and models [15].

2 Study Area and Data

2.1 Study Area

In order to achieve the purpose of research, we chose the Beijing Fang Shan District in 2004 SPOT5 remote sensing images in this paper. There are large areas of farmland, residents and some of the water. For the purpose of calculating quickly and easily, we used a piece of the eastern part for a variety of image processing.



2.2 Data Preprocessing

2.2.1 Geometric Correction

A certain amount of radiation correction had been done before the image was supplied to use. However,

due to the high-resolution of the imaging and the satellite is relatively close to the ground, the shadow

of city building exists. So the shadow correction is very important before extracting feature information. ERDAS geometric correction module can be used to

complete this work. Correction processes are as follows:

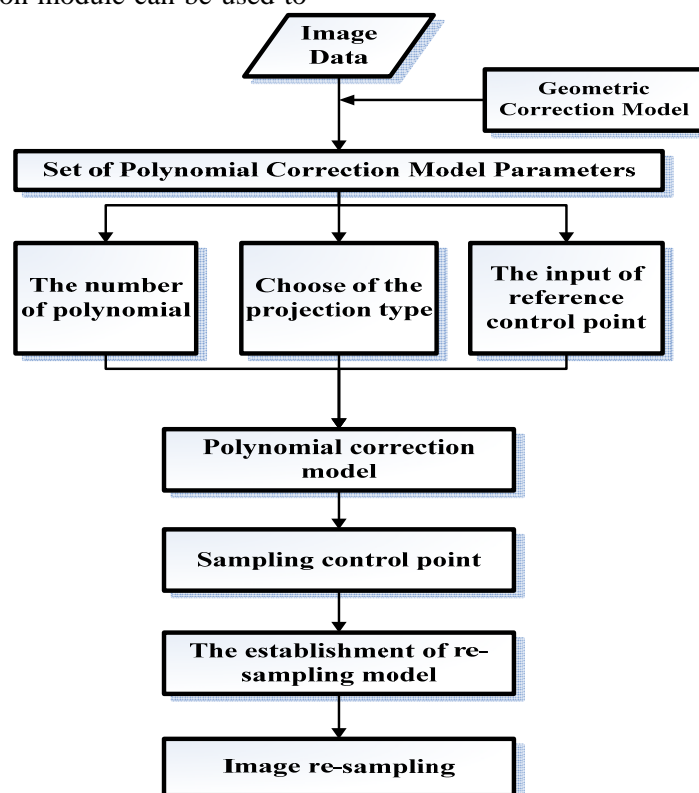


Fig.2. Geometric Correction

The correction polynomial is three times and the expressions are as follows:

$$x_0 = A + BX + CY + DX^2 + EXY + FY^2 + GX^3 + HX^2Y + IXY^2 + JY^3$$

$$y_0 = K + LX + MY + NX^2 + OXY + PY^2 + QX^3 + RX^2Y + SXY^2 + TY^3$$

According to the coordinates of control points, we can calculate the values of A, B • • • S, build a geometric correction expression and do geometric correction.

2.2.2 Radiation Correction

First of all, we do atmosphere correction by contrasting band to get each band of light scattering values through regression analysis and then the terrain correction is aimed at correction for the shadow. Shadow of the features is inevitable for the high-resolution satellite images. The large shadow from large-scale construction located in the open area has a negative impact on computer or manual interpretation, so it should be removed. But the shadow from relatively dense buildings is not obvious, it can be ignored.

3 Method

3.1 Co-occurrence Matrix and Texture Features

3.1.1 The calculation of the co-occurrence matrix and the normalization

Co-occurrence matrix is a method which surveys image pixel and describe distribution of gray. We choose any point (x, y) in the image and another point (x + a, y + b), and we suppose the value of gray of that point is (f1, f2). If the point (x, y) can move in the whole image, there will be all different kinds of values for (f1, f2). We suppose the series value of gray as K, so the total species for the combination of f1 and f2 are K. Array the number of each (f1, f2) appearing as a matrix and then normalize the matrix. We thought table 3.2 as a digital image, and the image pixel value is sorted in the box. Table 3.3(a), 3.3(b), 3.3(c), 3.3(d) are different co-occurrence matrix corresponding to different a and b.

0	1	2	3	0	1	2
1	2	3	0	1	2	3
2	3	0	1	2	3	0
3	0	1	2	3	0	1
0	1	2	3	0	1	2
1	2	1	0	1	2	3
2	3	0	1	2	3	0

Fig.3. Image Gray Value

0	0	9	0
0	0	0	9
9	0	0	0
0	8	0	0

(a)(a=1, b=0)

0	10	0	0
0	0	11	0
0	0	0	11
10	0	0	0

(b)(a=1, b=1)

0	10	0	0
1	0	11	0
0	0	0	10
8	0	0	0

(c)(a=0, b=1)

8	0	0	0
0	9	0	0
0	0	10	0
0	0	0	9

(d)(a=-1, b=1)

Fig.4. Symmetry of the Gray Co-occurrence Matrix

Gray co-occurrence matrix normalized:

$$R = \sum_{i=0}^3 \sum_{j=0}^3 P(i, j) \quad (1)$$

$$f(x, y) = f(x, y) / R \quad (2)$$

0	0.119	0	0.119
0.119	0	0.131	0
0	0.131	0	0.131
0.119	0	0.131	0

(a)(a=1, b=0)

0	0	0.243	0
0	0	0.149	0.108
0.243	0.149	0.278	0
0	0.108	0	0

(b)(a=1, b=1)

0	0.138	0	0.1
0.138	0	0.138	0
0	0.138	0	0.125
0.1	0	0.125	0

(c)(a=0, b=1)

0.222	0	0	0
0	0.25	0	0
0	0	0.278	0
0	0	0	0.25

(d)(a=-1, b=1)

Fig.5. Gray Joint Matrix

3.1.2 Texture Features

The texture analysis is based on gray level co-occurrence matrix in this paper. Gray level co-occurrence matrix can generate some texture measures and we can use these texture measures to describe image texture. We use three of them to do research.

Table 1: Three Texture Feature

Contrast	CON	$\sum_{i=1}^n \sum_{j=1}^n P(i, j) \times (i - j)^2$
Entropy	ENT	$\sum_{i=1}^n \sum_{j=1}^n P(i, j) \times \ln P(i, j)$
Energy	ASM	$\sum_{i=1}^n \sum_{j=1}^n P(i, j)$

D.Marceau and some other researchers did some systemic research on the factors which influence the texture feature extraction based on the co-occurrence matrix based on gray-scale. The research result indicates that quantify level, the direction and distance of the pixel, mobile window size and texture feature measure are the main factors impacting the image texture analysis. D.Marceau used gray level co-occurrence matrix texture analysis to do land cover classification and chosen the third band of SPOT data linear transform. Using the average of four directions (0° , 45° , 90° , 135°) as the analyzing co-occurrence matrix and many different mobile window sizes (5×5 , 9×9 , 17×17 , 25×25 , 33×33 , 41×41 , 49×49) to analyze the image of the research area. In our research we chosen (3×3 , 5×5 , 7×7) three mobile window sizes.



Fig.6 Original image



Fig.7. 3*3 Sliding Window



Fig.8. 5*5 Sliding Window



Fig.9. 7*7 Sliding Window

It can be seen that the size of the sliding window will influence the accuracy of texture feature extraction. Analyzing window should include the adequate and necessary texture feature the choice of sub-window size is essentially to identify a suitable the scope. Therefore, the choice of sub-window texture analysis is crucial step. Different remote sensing images with different resolutions and different texture parameters, and its expression is also inconsistent.

The gray level co-occurrence matrix texture analysis methods need to select appropriate size of the sliding window. In this paper, we choose three kinds of sliding windows: 3×3 , 5×5 and 7×7 to analyze Contrast, Entropy and Energy. Several texture images are as follows:

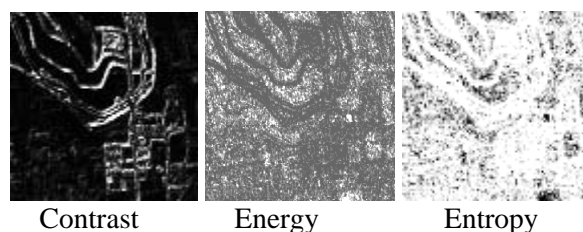


Fig.10. 3*3 Sliding Window

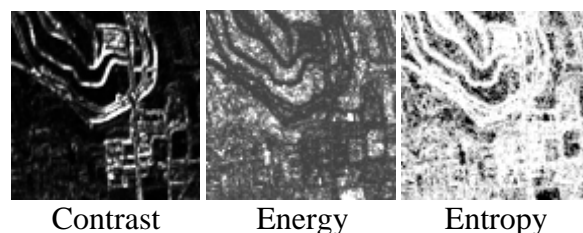


Fig.11. 5*5 Sliding Window

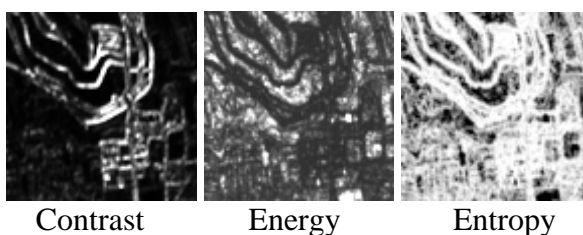


Fig.12. 7*7 Sliding Window

3.2 Selecting Samples

The choice of training samples is very important in monitoring classification of remote sensing images. Different training samples have a significant impact on the result of classification. Choosing representatives training samples is one of the key issues for the result of classification. In order to meet the requirements of the classification, four samples should be selected for each category at least. Land cover was classified as farmland, resident and

water three categories and four training samples were selected in each category.

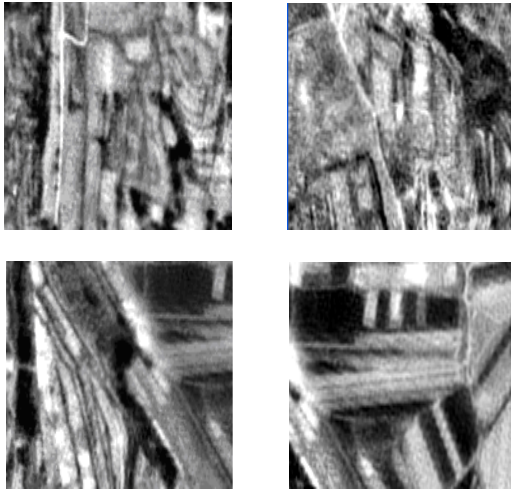


Fig.13. Farmland Samples

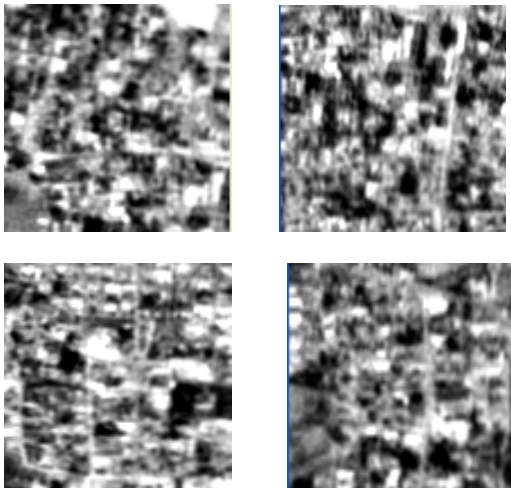


Fig.14. Resident Samples

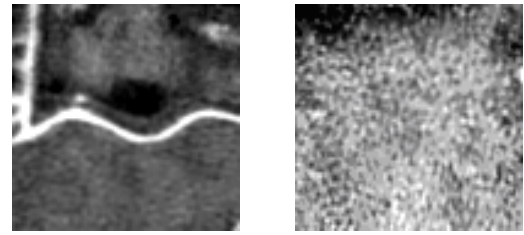
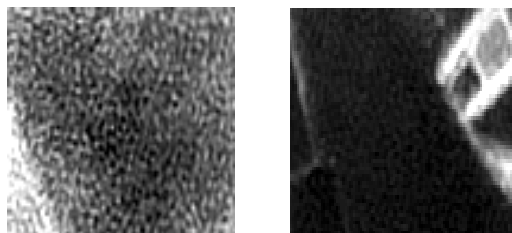


Fig.15. Water Samples

4 Results

4.1 Texture Value Calculation

There are many different texture features in one remote sensing image. In order to select good texture features, we need to compare with different texture features. In this research, we calculate the ENT, ASM and CON.

In this paper, we calculate the texture value based on 5*5 sliding window and the results are as follows:

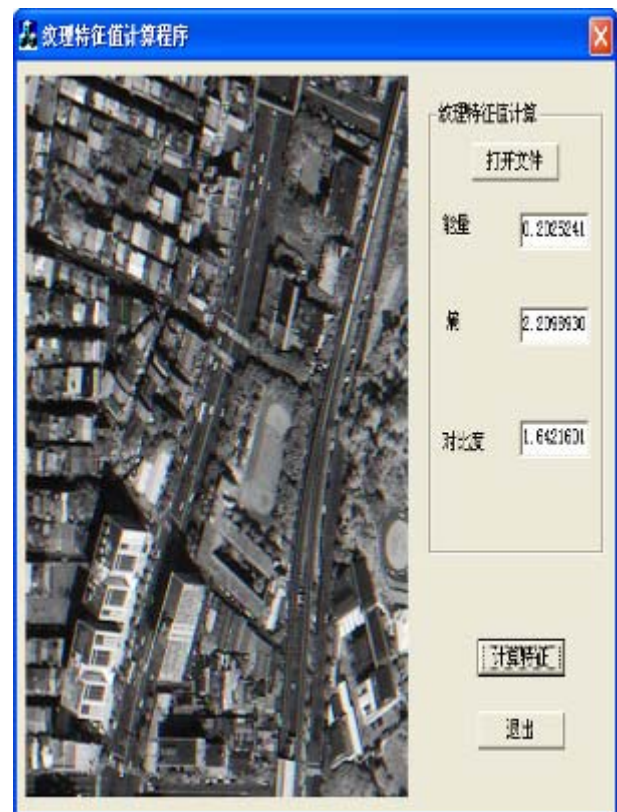


Fig.16. Calculating Programming

Table 2: Water Samples

	<i>ENT</i>	<i>ASM</i>	<i>CON</i>
Water sample1	0.965	0.111	0.123
Water sample2	0.973	0.072	0.128
Water sample3	0.966	0.095	0.136
Water sample4	0.950	0.173	0.367

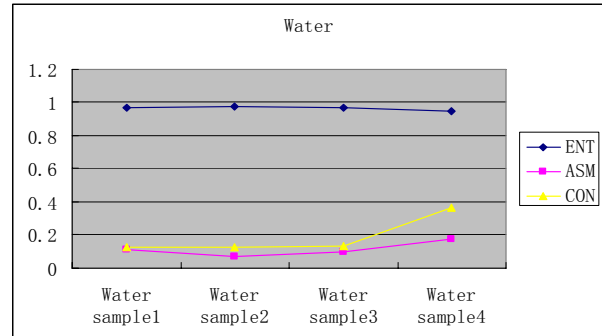


Table 3: Farmland Samples

	<i>ENT</i>	<i>ASM</i>	<i>CON</i>
Farmland sample1	0.821	0.606	1.380
Farmland sample2	0.896	0.349	0.737
Farmland sample3	0.883	0.375	0.745
Farmland sample4	0.914	0.256	0.278

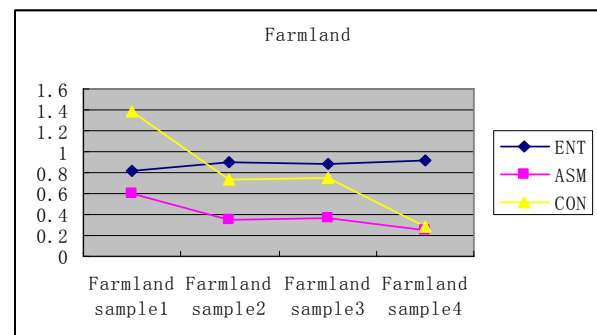
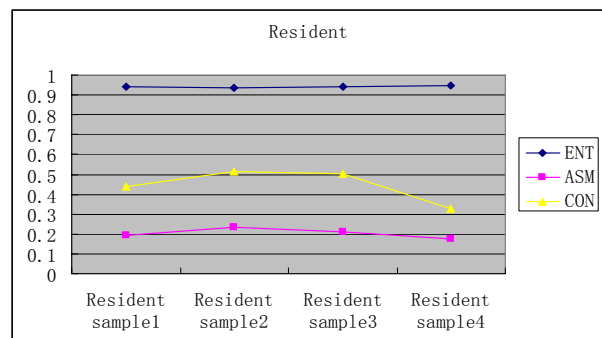


Table 4: Resident Samples

	<i>ENT</i>	<i>ASM</i>	<i>CON</i>
Resident sample1	0.944	0.194	0.438
Resident sample2	0.935	0.233	0.512
Resident sample3	0.939	0.213	0.503
Resident sample4	0.950	0.175	0.330



4.2 Classification Results

We use Maximum likelihood, contrast assistance, energy assistance and entropy assistance four methods to accomplish land cover classification. The

results of the classification are as follows. Red denotes farmland, green denotes residents and blue denotes water.

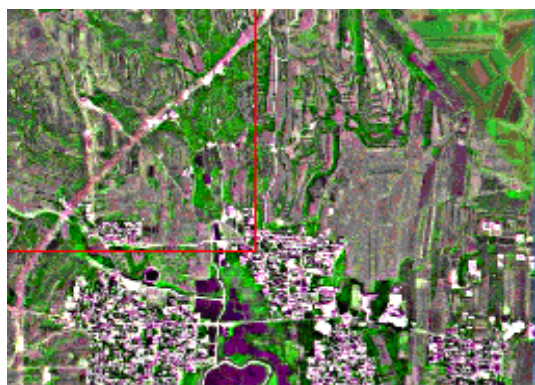


Fig.17. Original Image

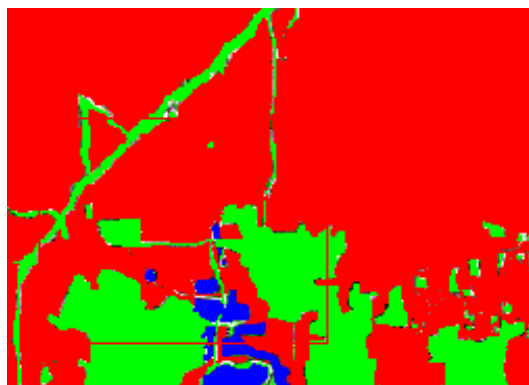


Fig.18. Visual Interpretation Classification

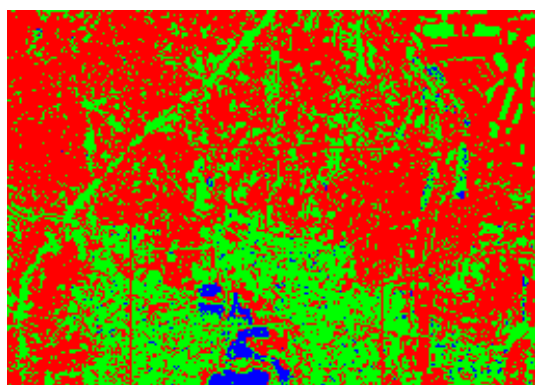


Fig.19. Maximum Likelihood Classification

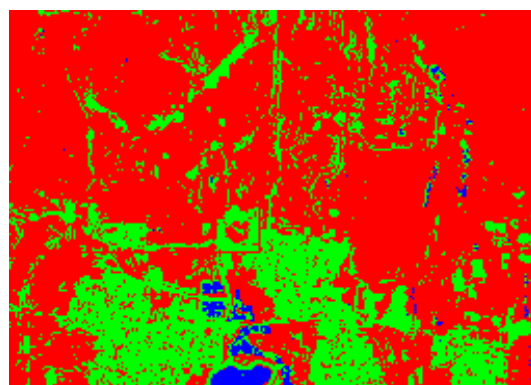


Fig.20. Contrast Assistance Classification

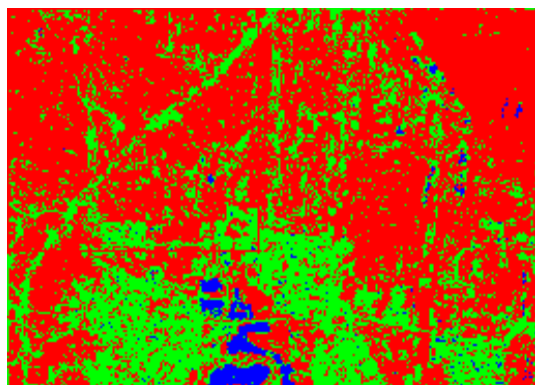


Fig.21. Energy Assistance Classification

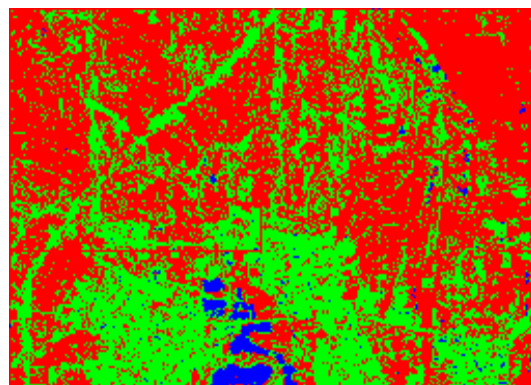


Fig.22. Energy Assistance Classification

4.3 Classification Accuracy Assessment

We can find that the using of contrast characteristics as the auxiliary image classification achieves the good results from the experimental results. But for the sake of precise description of the classification accuracy, we need to quantify the accuracy of classification. Confusion matrix is the most commonly used method for the assessment of

the remote sensing image classification. And its definition is as follows:

$$M = \begin{matrix} & \begin{matrix} m_{11} & m_{12} & \cdots & m_{1n} \end{matrix} \\ \begin{matrix} m_{21} \\ \vdots \\ m_{n1} \end{matrix} & \begin{matrix} m_{22} & m_{22} & \cdots & m_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n2} & m_{n2} & \cdots & m_{nn} \end{matrix} \end{matrix}$$

Table 5: Accuracy Assessment Result

Maximum likelihood classification	Resident	76.21	34.77	68.8110%	0.3342
	Water	59.41	63.55		
	Farmland	67.37	92.80		
Contrast assistance classification	Resident	90.97	50.53	81.4902%	0.5587
	Water	52.75	82.48		
	Farmland	80.12	97.11		
Energy assistance classification	Resident	81.33	36.97	70.5116%	0.3724
	Water	66.88	69.19		
	Farmland	68.11	94.17		
Entropy assistance classification	Resident	82.84	37.71	71.1106%	0.3837
	Water	65.84	71.50		
	Farmland	68.55	94.51		

5 Discussion and Conclusions

In terms of energy features, the difference between water and resident features is low, so it is not good for distinguishing these two land cover according to energy, but it is good farmland. In terms of Entropy features, the difference between water, resident and farmland features is low, so it is not suitable for distinguishing these three land cover. In terms of Contrast features, we can found that the difference among water, resident and farmland are significant, so it is very suitable for land cover classification.

In terms of farmland, entropy feature has a large difference from contrast feature and energy feature. Therefore, entropy feature is a very good choice for extraction farmland information. For residents, there is a significant difference among contrast, entropy and energy, so it is relatively easy to extract resident information. For water, energy feature has a large difference from contrast feature and entropy feature. Therefore, energy feature is a very good choice for extraction water information.

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