Satellite Images Classification in Rural Areas Based on Fractal Dimension

Mohammed Sahib Mahdi
Assistant Professor
Department of Computer Science
College of Science
Alnahrain University
email: altaeimohamed@gmail.com

Aqeel Abboud Abdul Hassan
Assistant Instructor
Department of Surveying Engineering
College of Engineering
University of Baghdad
email: al_hammashi87@yahoo.com

ABSTRACT

Fractal geometry is receiving increase attention as a quantitative and qualitative model for natural phenomena description, which can establish an active classification technique when applied on satellite images. In this paper, a satellite image is used which was taken by Quick Bird that contains different visible classes. After pre-processing, this image passes through two stages: segmentation and classification. The segmentation carried out by hybrid two methods used to produce effective results; the two methods are Quadtree method that operated inside Horizontal-Vertical method. The hybrid method is segmented the image into two rectangular blocks, either horizontally or vertically depending on spectral uniformity criterion; otherwise the block is segmented by the quadtree. Then, supervised classification is carried out by means the Fractal Dimension. For each block in the image, the Fractal Dimension was determined and used to classify the target part of image. The supervised classification process delivered five deferent classes were clearly appeared in the target part of image. The supervised classification produced about 97% classification score, which ensures that the adopted fractal feature was able to recognize different classes found in the image with high accuracy level.

Key words: quadtree, box counting, fractal dimension, supervised classification.

تصنيف الصور الفضائية في المناطق الريفية بالإعتماد على البعد الكسوري

أ.م. محمد صاحب مهدي
استاذ مساعد
قسم علوم الحاسوب
كلية العلوم / جامعة النهرين

عقيل عبود عبد الحسن
مدرس مساعد
قسم هندسة المساحة
كلية الهندسة / جامعة بغداد

الخلاصة

حصلت الهندسة الكسورية على اهتمام كبير كونها توفر نموذج نوعي وكمي لوصف الظواهر الطبيعية, حيث بإمكانها إنشاء تقنية تصنيف فعالة للصور الفضائية. في هذا البحث, الصورة الفضائية المستخدمة ملتقطة بواسطة القمر الصناعي الطائر السريع حيث تحتوي على اصناف مختلفة. بعد إجراء المعالجة الأولية للصورة الفضائية, إنها تمر خلال مرحلتين: التقطيع والتصنيف. يتم تنفيذ طريقة التقطيع بإستخدام أسلوب هجين من طريقتين للحصول على نتائج جيدة. هاتان الطريقتان هما طريقة الشجرة التربيعية التي تنفذ داخل الطريقة الأفقية-الشاقولية. الطريقة الهجينة تجزأ الصورة الى مستطيلين أما أفقياً أو شاقولياً إعتماداً على معيار الأنتظامية الطيفية, أو يتم تجزأة الصورة بإستخدام طريقة الشجرة التربيعية. بعد عملية التقطيع تجري عملية التصنيف المراقب بإستخدام البعد الكسوري. حيث يتم حساب البعد الكسوري لكل جزء من الصورة ناتج من عملية التقطيع لكي يستخدم ذلك البعد الكسوري نوعية التفاصيل التي تغطيها الصورة الفضائية. عملية التصنيف أنتجت خمسة أصناف مختلفة تظهر بوضوح على الصورة المستخدمة . أثبت دقة التصنيف التي تم الحصول عليها والتي تصل الى 97% إن الصفة الكسورية المعتمدة قادرة على تمييز الأصناف المختلفة التي تظهر في الصور الفضائية وبدقة عالية.

الكلمات الرئيسية: الشجرة التربيعية, عدّ الصناديق, البعد الكسوري, التصنيف المراقب.

1. INTRODUCTION

Remote sensing is the use of satellite imagery to collect a specific data from the earth about object or phenomenon without physical contact, **Asrar, 1989**. Aerial sensor technologies are used to detect and classify objects on the earth by propagated signals (i.e. electromagnetic radiation). Remotely sensed data are contributed with information from ecosystem models to offer opportunity for predicting and understanding the behavior of the earth's ecosystem reference. High spatio-temporal resolutions of sensors make the observation of precise spatial and temporal structures more accessible in dynamic scenes. Spectral and spatial dimensions combined with temporal components give a valuable information source. Such information helps to detect complex and important patterns by means applications deal with environmental monitoring and analysis of land-cover dynamics. Satellite imagery is sometimes supplemented with aerial photography for achieving an integral form about the target area. Aerial photography has higher resolution, it used for specific applications since it is more expensive than satellite imagery. Satellite imagery is sometimes contributed with vector or raster data in GIS (Geographic Information System) when the imagery needs to be spatially rectified, **Matzler, 2008**. Multi-spectral satellite imagery is an economical, precise and appropriate method of obtaining information on land use and land cover since they provide data at regular intervals and is economical when compared to the other traditional methods of ground survey and aerial photography, **Prasad, 2011**.

Many applications based on using satellite imagery in a quantitative fashion require classification of image regions into a number of relevant categories or distinguishable classes. Satellite image classification is a clustering method based on image features, the classification results are represented by visualization techniques, **Antoni and Nuno, 2005**.

Fractal geometry is the branch of mathematics which studies the properties and behavior of fractals. It describes many situations which cannot be explained easily by classical geometry. Fractal geometry provides a suitable textural image classification framework by studying the nature irregularity shapes in the image, since it allows to easily describing such fractal images. The fractal geometry can recognize small image segment that characterized by its spectral uniformity, this necessitate first to segment the image before the classification. The main characteristics of fractal images are that they are continuous but not differentiable that allows showing the fine details at any arbitrarily small scale, **Iodice, et al., 1995**.

Fractal models have been used in a variety of image processing and pattern recognition applications. Several researchers have applied fractal techniques to describe image textures and segment various types of images; Kasparis et al. in 1995 demonstrated the fractal dimension for texture segmentation. The fractal dimension was not sufficiently describing enough textural characteristics, additional features are needed. They combined the fractal dimension with a simple textural energy measure. A significant performance improvement was achieved compared to using each feature alone. The textural energy is easily computed using convolutional masks. The natural textures were segmented and classified with considering the effect of additive noise, **Kasparis, et al., 1995**, while Al-Ani in 2007 introduced a supervised classification for TM-multi-spectral satellite images. The traditional quadtree segmentation method was applied, then for each segmented block; the fractal features are computed and then used as maximum likelihood classifiers. The used fractal features are fractal dimension and lacunarity. The result showed that the fractal dimension do not have the ability to classify the image blocks whereas the lacunarity showed good classification results. It was found that the fractal geometry can assign efficient parameters for describing images, **Al-Ani, 2007**, and **Mahmood et al. in 2009** proposed a new algorithm for recognizing text object images by using fractal geometry. The fractal dimension was used to recognize text objects within images. Box-counting method was used to estimate the fractal dimension for image contents. In order to determine a threshold value for the textual objects within image, the fractal dimension was computed for a number of gray scale textual images. The fractal number of each pixel was calculated, and then the mean values of all these fractal values were computed. The threshold value was used in recognizing and retrieving the textual objects within image. The proposed algorithm has performed extremely well with recognition rates 91.5%. It is a promising technique for optical character recognition system, **Mahmood, et al., 2009**.

2. AIM OF RESEARCH

The present work aims to utilize concepts of fractal geometry to classify satellite images in rural areas. This requires analyzing remote sensing imageries to prove that the fractal models exhibit textural features of satellite images, and it offers a significant potential for improving the measurement and analysis of spatially and spectrally complex remotely sensed images.

3. AREA OF STUDY

Fig.1 shows the selected area from the overall image. This area was clipped and saved in new image file of type bitmap 24*bit/pixel*. The memory size of this file was about 12*MB* with spatial resolution of 2048×2048*pixels*. This image resolution covered a land area of about 1.25×1.25*km*, and contained a variety image features. Actually, the geographical region demonstrated in the image of training area was visited to determine the types of the landcover found in the study area. It was found that there are five distinct classes: river, bare land, vegetation and housing. The ensured training sites of were pointed on whole satellite image to be compared with the classification results. It should be mentioned that just the clipping process is done by using ArcGIS 9.3 software.

4. PROPOSED CLASSIFICATION METHOD

The concept of multi-stage query processing and features extraction has been used to model the proposed method. It is claimed that these stages can beneficially be combined and that, through the combination, a significant fast and efficient satellite image classification can be achieved. The generic structure of the proposed satellite image classification method is shown in **Fig.2**. It is shown that the proposed method is designed to be consisted of two phases: the training and recognition. The training is an offline phase, it is responsible on collecting sample image classes to be stored as comparable models in database. Whereas the recognition is an online phase, which is responsible on verifying the test image blocks in comparison with the trained models found in the database. Both phases are composed of three stages include: image preprocessing, image partitioning, and features extraction. Features extraction attempts to estimate the fractal dimension (D) and spectral power (P) for all test image blocks. Last stage is a comparison based on fractal feature between the image blocks and training classes found in the database, the result of the comparison will determine the similarity measure between the considered image blocks and then help to make the classification decision. More details about each stage are given in the following sections:

4.1. Image Preprocessing

This stage involves two stages: multiband image enhancement and conversion multiband image to grey scale image. Image enhancement is a preprocessing stage seeks to improve the visual appearance of the image under consideration that was shown in **Fig. 3**. This stage is relied on the intensity of pixels with no effect the correlation of adjacent pixels. Such enhancement leads to improve the distinguishing between image features, which can be achieved by applying the Eq. (1) on the image, **El Hassan, 2007**:

$$I_e(x,y) = round[(\frac{I_o(x,y)-l}{h-l}) \times 255] \quad (1)$$

Where, $I_e(x,y)$ represent the new enhanced image, $I_o(x,y)$ is the original image, x, and y are indices of the pixel in the image, l represent the bottom 1% of all pixel values of original image, and h represent the top 1% of all pixel values of original image. Then, the three enhanced band components (R_e, G_e, and B_e) were concatenated together to get new one enhanced image ($I(x,y)$) using Eq. (2) as shown in **Fig. 4**, **Richards and Jia, 1999**:

$$I(x,y) = 0.2989R_e(x,y) + 0.5870G_e(x,y) + 0.1140B_e(x,y) \quad (2)$$

4.2. Image Segmentation

Hybrid method was suggested to carry out segmentation process, in which the horizontal-vertical method is operated inside the quadtree method. The two methods are contributed with each other to produce high quality results. The implementation of such hybrid partitioning method requires to set some values are related the control of the partitioning process, they called control parameters. These control parameters are, **Al-Aboudy, 2002**:

a. Maximum block size.
b. Minimum block size.
c. Mean factor: represents the multiplication factor; when it is multiplied by the global mean of image it will define the value of the extended mean.
d. Inclusion factor: represents the multiple factor, when it is multiplied by the global standard deviation it will define the value of the extended standard deviation.
e. Acceptance ratio: represents the ratio of the number of pixels whose values differ from the block mean by a distance more than the expected extended standard deviation.

Fig. 5 shows the segmented image using hybrid method.

4.3. Features Extracton

The search for the fractal features in the literatures shows that there are many available fractal features can be used to describe fractal objects such as satellite images. There is an important note was noticed, which state that all the fractal features are related to fractal dimension, implies that the use of fractal dimension substitutes on using other fractal features. Therefore, it was decided to employ just the fractal dimension for satellite image classification. Fractal dimension is a fraction number restricted in between the range 2-3 for two dimensional images, which may give interfered values belonging to different classes, and leads to confuse the classification results. Such that, the researchers goes to adapt the fractal dimension to be compatible with the study case.

The next step after completing image segmentation process is the computation of fractal dimension of each block. The procedure that was used to compute the fractal dimension may be considered a novel box-counting method that was produced according to experiments to develop and eliminate the limitation of the traditional method and other methods came later.

In the present work, the novel effort is adapting the boundary conditional values of the fractal dimension estimated by the box counting method to achieve intended results. The fractal dimension computation is applied on each image block resulted from the segmentation stage.

4.4. Training Based Classes

The stage of determining image classes is based on specifying a range of fractal dimension for each phenomenon that appearing in the used image. The field visit to the study area shows that there are five distinct classes can be found. Also, this make sure by reliance other information about covered area, such as, recently aerial images and thematic maps, reconnoitering zone or any earlier information about study area. Therefore, a specific range of fractal dimension for each class should be determined and stored in database to be used for classification of training area firstly, and then classify other adjacent areas in the same image later on. Table 1 denotes the range of fractal dimension used for each class.

4.5. Image Classification

According to the five similarity measures of each block, the block assigned to the class that gives highest similarity measure. When this procedure is applied on all the image blocks, a specific color is needed for coloring each block according to its ownership class. Also, there is a color legend should be fixed to explain the meaning of colors appear in the classification results. Then, the classification results should be compared to the actual classification information delivered from manual process based on field view in order to evaluate the classification process. After ensuring the classification results of the training area, other areas in the image can be classified with high creditability.

5. RESULTS

Throughout the classification of the training area, the fractal dimension delivers encouraging supervised classification outcomes, where each class of image has a relatively different range of fractal dimension (D_F). **Fig. 6** displays the classification result of the training area; such result should be evaluated before classifying other areas in the test image. Actually, the acceptable classification results of training area encourage completing the classification by taking other areas found in the test image. **Figs. 7** and **8** show the classification results of different selected area. It is noticeable that the classification is carried out with efficient performance, where the classification percentages reach to 97%.

6. CONCLUSIONS

Throughout the implementation of the presented work, a number of conclusions have been achieved based on the practical results. The following statements summarize the most important ones:

1. The high classification results prove that the fractal geometry exhibit the description of satellite images.
2. The normal distribution of the fractal dimension of multi conglomerates with narrow width refers to high discriminant power of fractal dimension for image classification.
3. Higher accuracy of fractal dimension estimation is achieved by allowing the height of the box at the top of each grid block to be adaptable to the maximum gray-scale of that block and the method is applicable to blocks with arbitrary sizes and shapes.

4. The uniformity of blocks' characteristics which produced by the suggested segmentation method leads to get independent range of D_F for each class. This has increased the accuracy of the classification.
5. The convergence in D_F for different phenomena and the smallness of the range of it caused to decrease the efficiency of classification.

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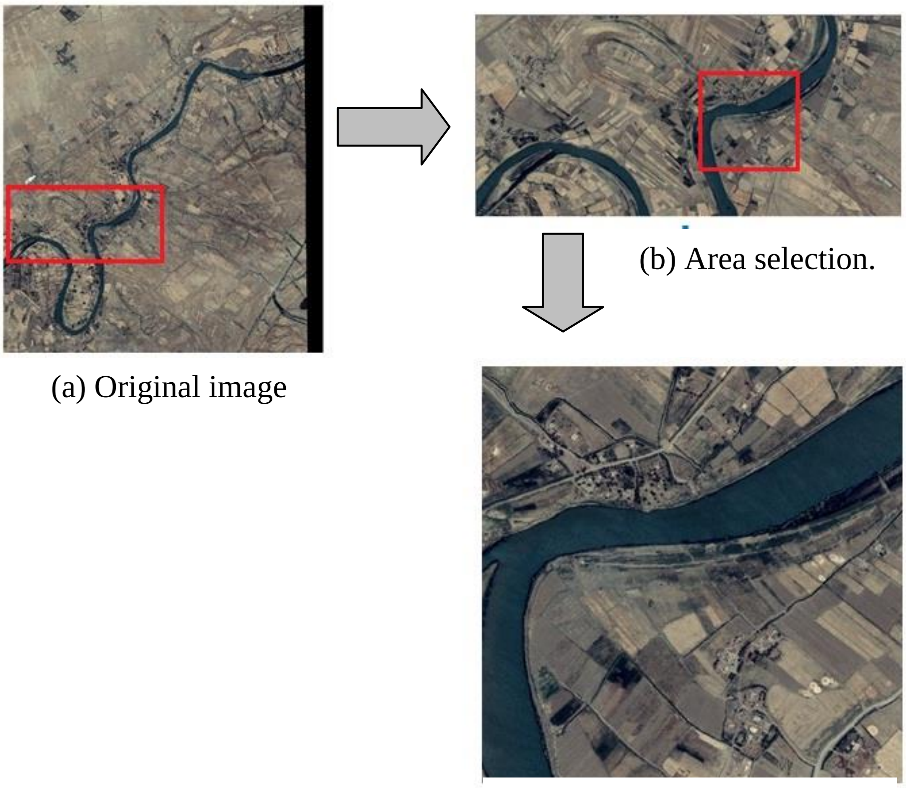
NOMENCLATURE

I_e= new enhanced image, dimensionless.
I_o= original image, dimensionless.
x , y= indices of the pixel in the image, dimensionless.

l= the bottom 1% of all pixel values of original image, dimensionless.
h= the top 1% of all pixel values of original image, dimensionless.
I= grey enhanced image, dimensionless.
R_e= red color components of enhanced image, dimensionless.
G_e= green color components of enhanced image, dimensionless.
B_e= blue color components of enhanced image, dimensionless.



(a) Original image

(b) Area selection.

(c) Training area clipping.

Figure 1. Training area selection**.**

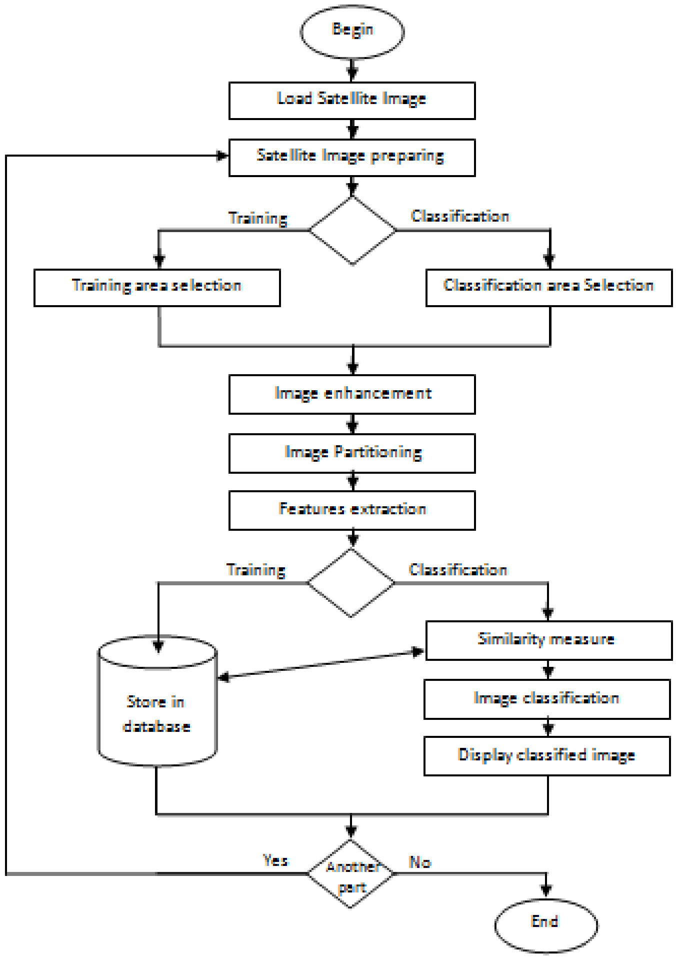


Figure 2. Block diagram of the proposed satellite image classification method.

Figure 3. Original image.

Figure 4. Grey enhanced image.

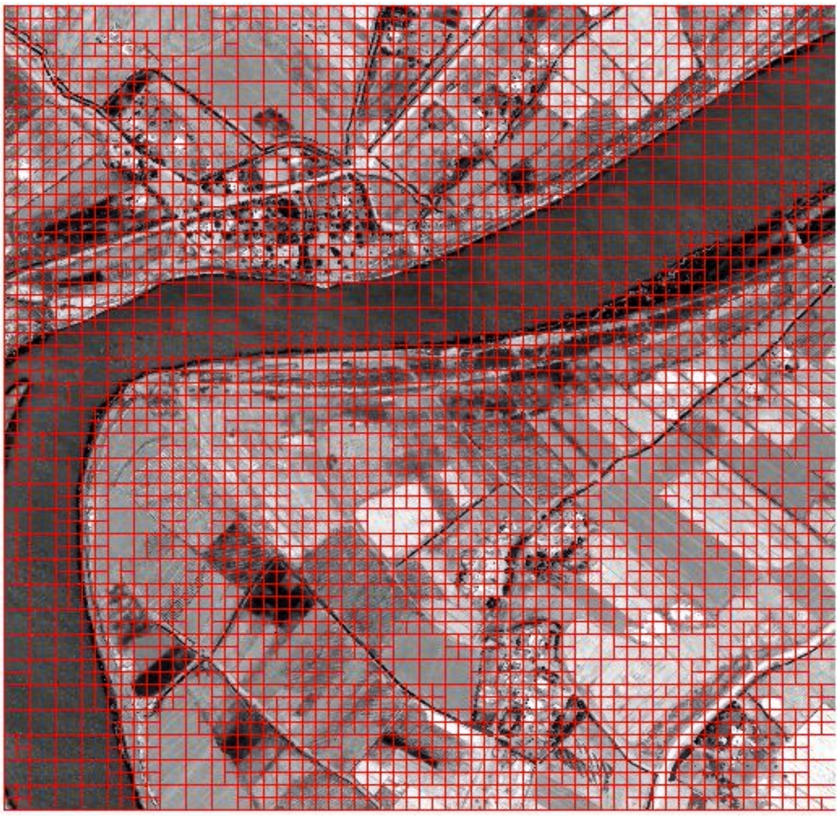


Figure 5. Partitioned image

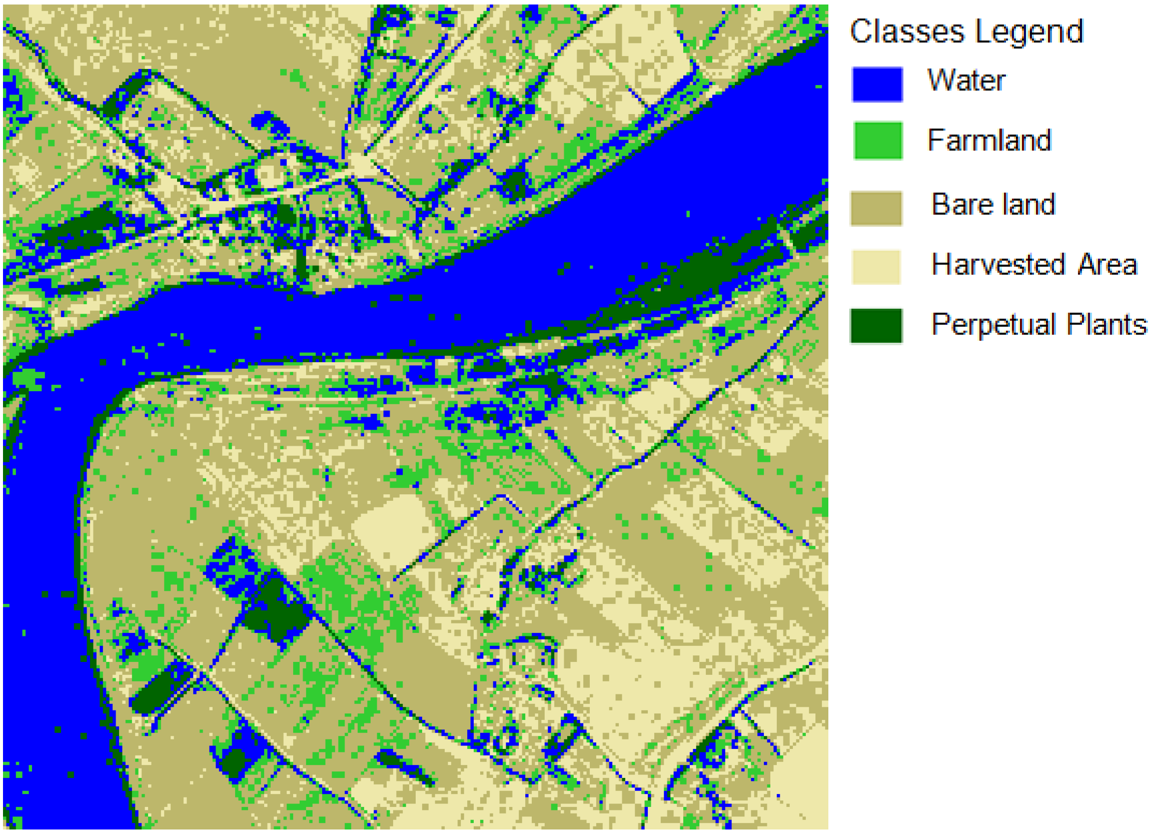


Figure 6. Classification result of the testing area.

Figure 7. Second case study.

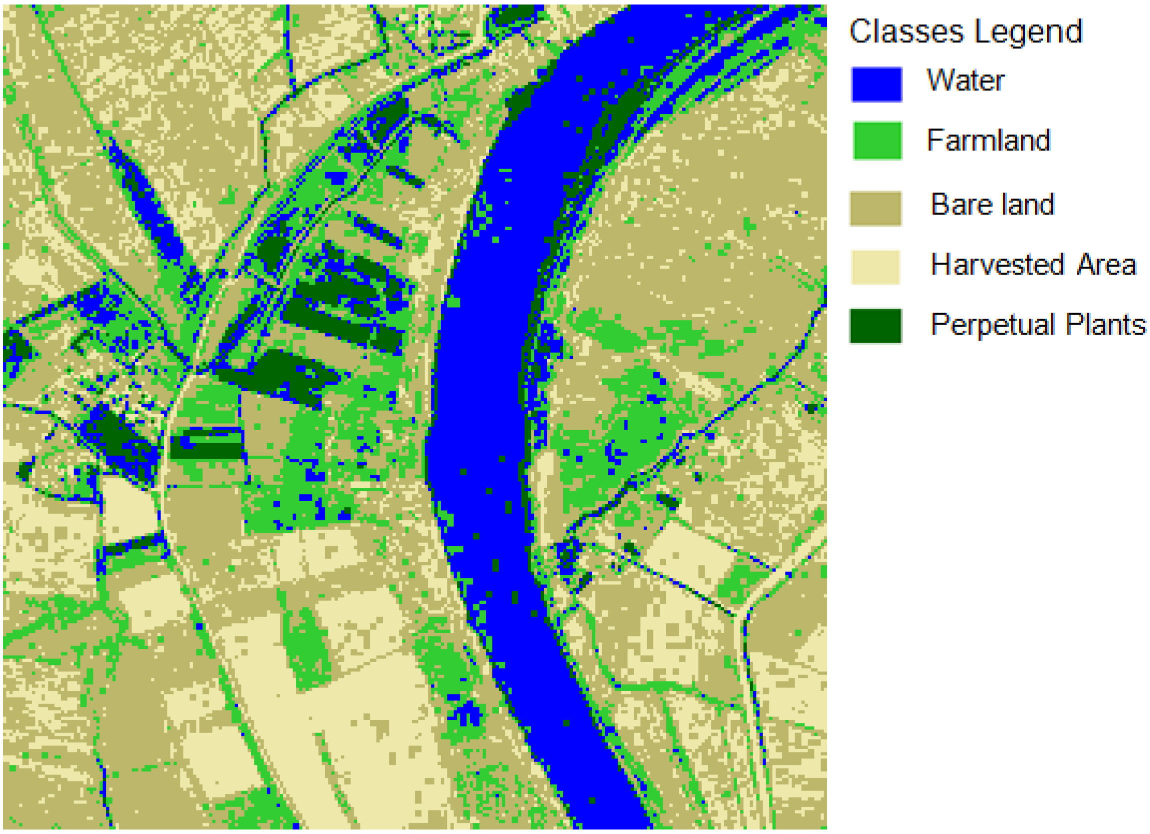


Figure 8. Classification result of second case study.

Table 1. Range of fractal dimension for each class

Class	Fractal Dimension	
	Min.	**Max.**
Perpetual plants	1.9107	2.335
Water	2.335	2.5
Farmlands	2.5	2.588
Bare lands	2.588	2.73
Harvested areas	2.73	3.13