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Extraction of Vacant Lands for Baghdad City Using Two Classification Methods of Very High Resolution Satellite Images

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Abstract
The use of remote sensing technologies was gained more attention due to an increasing need to collect data for the environmental changes. Satellite image classification is a relatively recent type of remote sensing uses satellite imagery to indicate many key environment characteristics. This study aims at classifying and extracting vacant lands from high resolution satellite images of Baghdad city by supervised Classification tool in ENVI 5.3 program. The classification accuracy was 15%, which can be regarded as fairly acceptable given the difficulty of differentiating vacant land surfaces from other surfaces such as roof tops of buildings.

Keywords: Vacant lands, Classification, Satellite images, Remote sensing, supervised Classification.

استخلاص الاراضي الشاغرة لمدينة بغداد باستخدام طريقتي تصنيف لصور الفضائية عالية الدقة

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الخلاصة
اكتسبت تقنيات التحسس النائي اهتماما واسعا نظرا لتزايد الحاجة لجمع البيانات حول التغيرات البيئية. آن تصنيف صور الاقمار الصناعية هو نوع حديث نسبيا من التحسس النائي والذي يستخدم فيه تصوير الاقمار الصناعية لفهم العديد من الخصائص البيئية. تهدف هذه الدراسة إلى تصنيف واستخلاص الاراضي الشاغرة في مدينة بغداد، وذلك من خلال صور الاقمار الصناعية عالية الوضوح باستخدام اداة تصنيف الموجه في برنامج الاستشعار عن بعد ENVI 5.3. بلغت دقة تصنيف واستخلاص الأراضي الشاغرة 15 % وتعتبر هذه النسبة مرضية، حيث تبين أنه من الصعب الوصول إلى درجة عالية من الصحة في تصنيف واستخلاص الأراضي الشاغرة وذلك لتشابه الخصائص الانعكاسية بين الأراضي الشاغرة والظواهر الجغرافية الأخرى كأسطح المباني والشوارع التي أدت إلى خفض صحة التصنيف نسبيا..

1. Introduction

Remote sensing is the science of collecting information from the Earth's surface without really being in touch with it [1]. This is done by sensing and recording emitted or reflected energy and analyzing, processing and implementing that information. In much of remote sensing, the process includes an interaction between the targets of interest and incident radiation. This is illustrated by the use of imaging systems where the supporting seven elements are included. Note, however, that remote sensing also includes the sensing of the emitted energy and the use of non-imaging sensors [2]. Image

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classification is mainly divided into two categories, supervised image classification and unsupervised image classification. In supervised image classification, training stage is required, which means first we need to select some pixels from each class called training pixels [3]. The Minimum-Distance method is one of a supervised classification method that determines a mean vector for each prototype class and first analyses the training data, represented by the class center coordinates in feature space. The Minimum distance method then select the Euclidean distance from each unclassified pixel to the mean vector for each prototype class and indicate that pixel to the closest class [4]. Maximum likelihood method is a statistical supervised approach for recognizing the patterns. It allocates pixels to appropriate classes based on probability values of the pixels. Maximum likelihood is an efficient method to classify pixels of the satellite image. But it is time consuming and insufficient ground truth data produces poor results [5]. Park et al. [6] proposed an automated building detection algorithm using a line-rolling algorithm. It assumes that the rooftops of the buildings are rectangular and can extract building boundaries from one or two detected lines. L. Bruzzone and L. Carlin [7] proposed the system for the classification of VHR images. The proposed system is made up of two main blocks: 1) a feature-extraction block that aims at adaptively model the spatial context of each pixel according to a hierarchical multilevel segmentation of the scene and 2) a classification block based on SVM. Experimental results obtained on VHR images confirm the effectiveness of the proposed system and Camps-Valls et al. [8] proposed high-resolution remote sensing image target extraction method based on support vector machine.

These were proposed supervised method (minimum distance) and Maximum Likelihood Classifier using ENVI 5.3 program.

2. Study Area

The Baghdad city is studying the area. It is the main administrative center and the capital of Iraq. Baghdad city is the central part of Iraq where located on both sides of the Tigris River and it has geographic coordinates following: Latitude (33˚25´46˝) to (33˚24´21˝) N, Longitude (44˚15´55˝) to (44˚17´38˝) E. Baghdad is the biggest and common heavily populated city in Iraq. The Tigris River crosses through the city cutting it into two sides; Western part (Karkh) and Eastern part (Rusafa). The city is surrounded from the east by Diyala River, which meets the Tigris River southeast of Baghdad [9]. Figure-1 shows the study area.

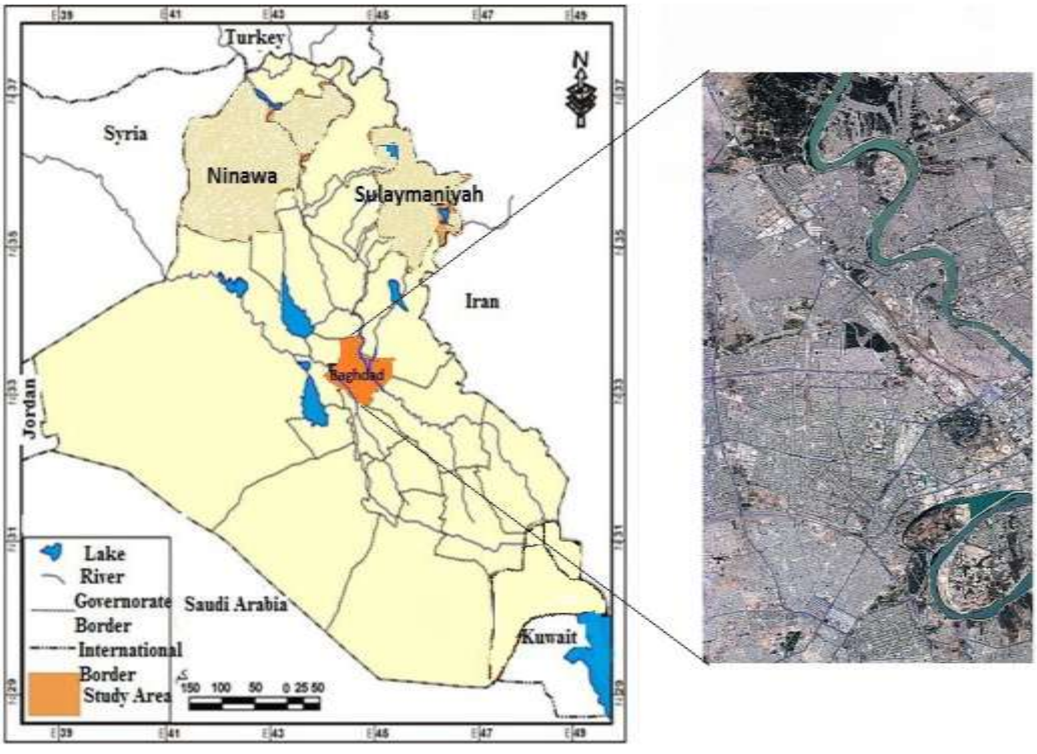

Figure -1 Area of study "Baghdad city"

3. Very High Resolution GeoEye-1 images

GeoEye-1, launched in September 2008, is the latest in a series of commercial high-resolution Earth observation satellites. In the experiment, we choose GeoEye-1 images with 1.65m high resolutions, which was achieved in 2012 and located in Baghdad, Iraq. The size is 14000 × 38000 pixels and it covers an area of about 85 square kilometers.

Very high-resolution images are ordinarily images that appear, in technological terms, “several-meter resolution", meaning that the environmental features and size of the smallest objects show clearly discerned in the several-meter image. This is the highest image property possible from non-military remote sensing satellites today. This kind of image is used in fields such as nationalist security and urban applications. The very high-resolution images give a great means for the security community to make assessments and crisis control [10].

4. Methodology

At first, we unfold the satellite image into its bands, as Figure-2 and the basic statistics for each band, as shown in Table-1.

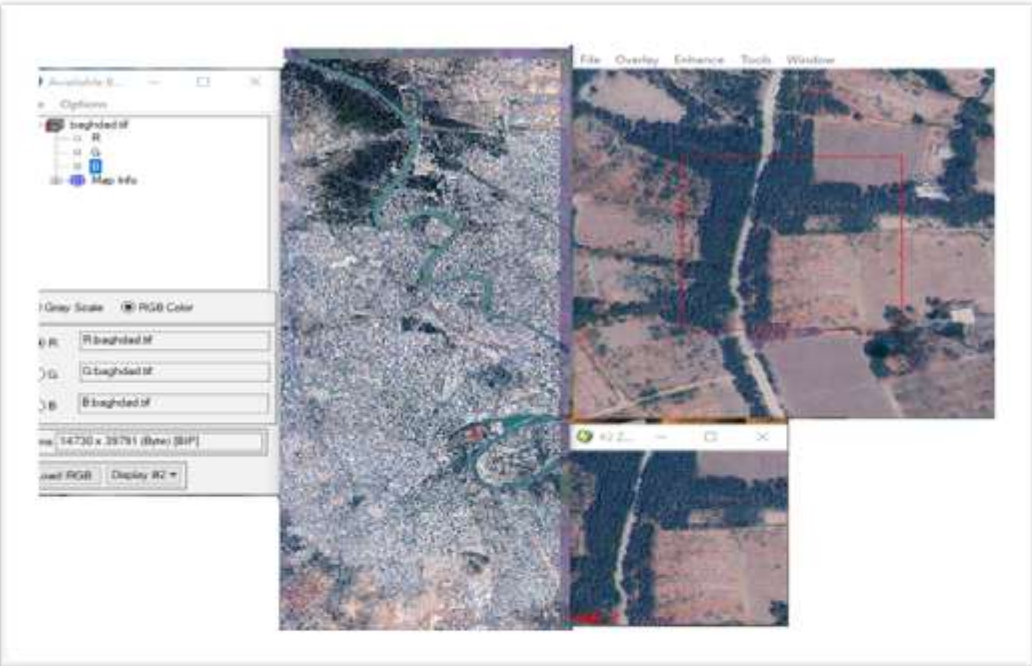

Figure 2-Represent samples of RGB bands of very high resolution images.

Table 1-The Basic statistics for each band

Basic statistics	Min	Max	Mean	Standard deviation
Band 1	0	255	123.707	57.186
Band 2	0	255	142.611	44.280
Band 3	0	255	157.742	40.804

1. Region of Interest.

The region of interest (ROI) process can be achieved by using pixel located technique. As illustrate in Figure-3. We choose the pixel index in vacant area and for more accuracy we choose multi pixels (represents classes) in multi homogenous vacant region.

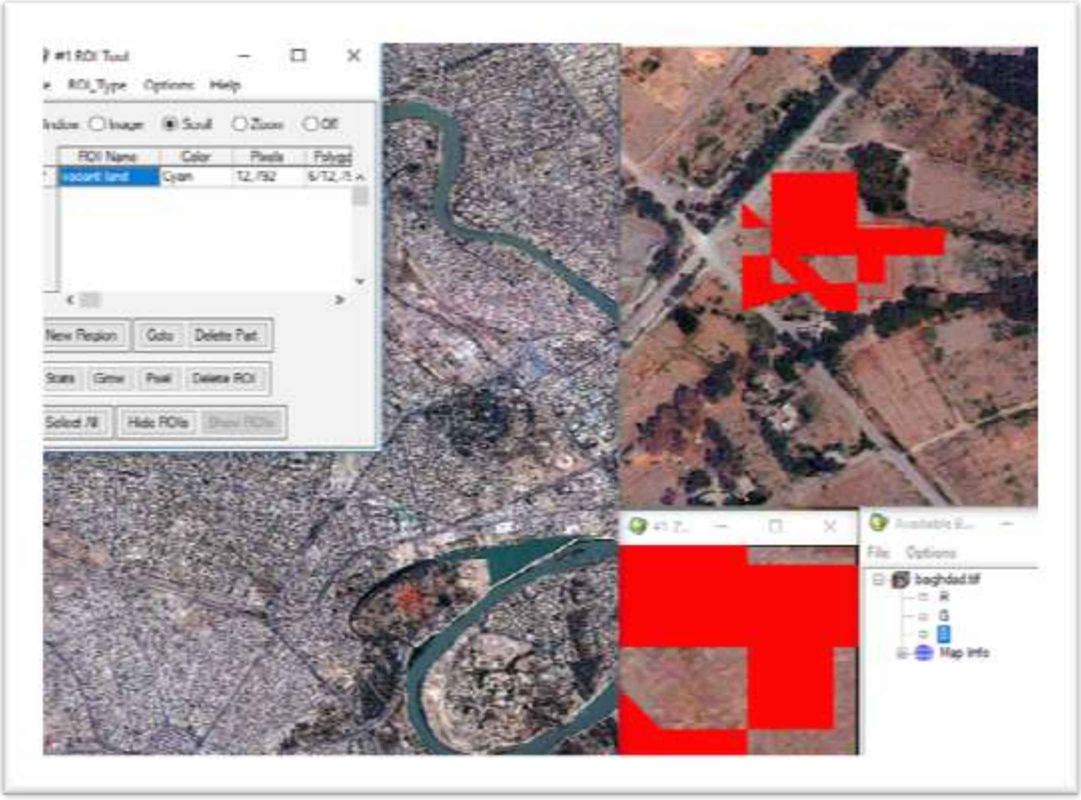

Figure 3-pixel located technique

2. Classification

Image classification is the process of subdividing any image into its constituent parts or objects. Image classification is an important part of the remote sensing, image analysis and pattern recognition. In some instances, the classification itself may be the object of the analysis. For example, classification of land use from remotely sensed data produces a map like image as the final product of the analysis. Supervised classification and unsupervised classification are the two broad types of classification processes that are used in satellite remote sensing [11] some of the supervised techniques does not use probability distribution and use some other kind of mathematical discriminate functions. Maximum Likelihood Classification, Minimum Distance Classification, Parallelepiped and Classifications come under supervised classification techniques. One of the most important methods of supervised classification is a Minimum Distance Classification [12, 13].

a. Minimum-Distance Classification

Template matching can simply be represented mathematically. Let (m1, m2, ..., mc) be templates for the c classes, and let x be the feature vector for the unknown input. Where the error in matching x versus mk is presented by|| x - mk || . Here the norm of the vector m is called || m ||. A least-error classifier measures || x - mk || for k = 1 to c and to select the class for which this error is least. Since || x - mk || is also, a minimum-distance classifier represented by the distance from x to mk. [14]. Obviously, a template matching system is a minimum-distance classifier as Figure-4 .

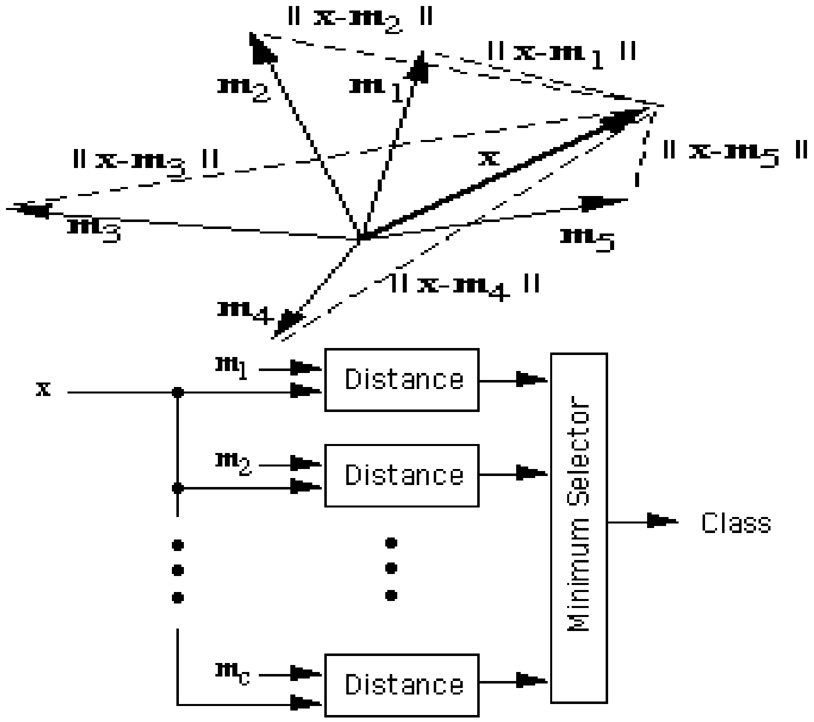

Figure 4-Scheme of the minimum distance classifier with its block diagram [14]

b. Maximum Likelihood classification

It applies the probability theory to the classification task [15]. A statistical decision rule that examines the probability function of a pixel for each of classes, and assign the pixel to class with the highest probability [16]. Maximum likelihood classifier is given by equation:

$$D = \ln(a_c) - [0.5\ln(|C_{ovc}|)] - [0.5(X - M_C)^T (C_{ovc}^{-1})(X - M_C)] \quad \text{.... ....(18)}$$

Where

D = likelihood,

M_C = the mean vector of sample of class c,

C_{ovc} = the covariance matrix of the pixels in sample of *class c*,

c = a particular class,

$|C_{ovc}|$ = determinant of C_{ovc},

a_c = percent probability that any candidate pixel is a member of class c,

X = measurement vector of candidate pixel,

C_{ovc}^{-1} = inverse of C_{ovc},

Find the likelihood for all pixels for all classes. Pixel leads to the class which has the highest likelihood for this pixel, this way classification will be done.

5. Results and Discussion

As it has been mentioned above, supervised classification is the most important technique used for the extraction of quantitative information from a satellite image. Supervised classification is much more effectual in terms of accuracy in mapping considerable classes whose validity depends largely on the cognition and skills of the image specialist. The technique assumes that each spectral class in the image can be described by a probability function in multi-spectral space. In our research we choose vacant regions depend on Region of interest to see clearly the regions and to select the best region class. Our image dimension was (12000 x 17000 x 3) therefore the percentage of every class was calculated by (number of points in the class (Npts) / 12000 x 17000 x 3). Figure-5 demonstrates the result of minimum distance classification process, statistical measurements for minimum distance classification shown in Table-2. Figure-6 demonstrates the result of maximum likelihood classification process, statistical measurements for minimum distance classification shown in Table-3.from the tables under each classified image, vacant region covered 15.25 % for minimum distance classification and 15.61 % for maximum likelihood classification.

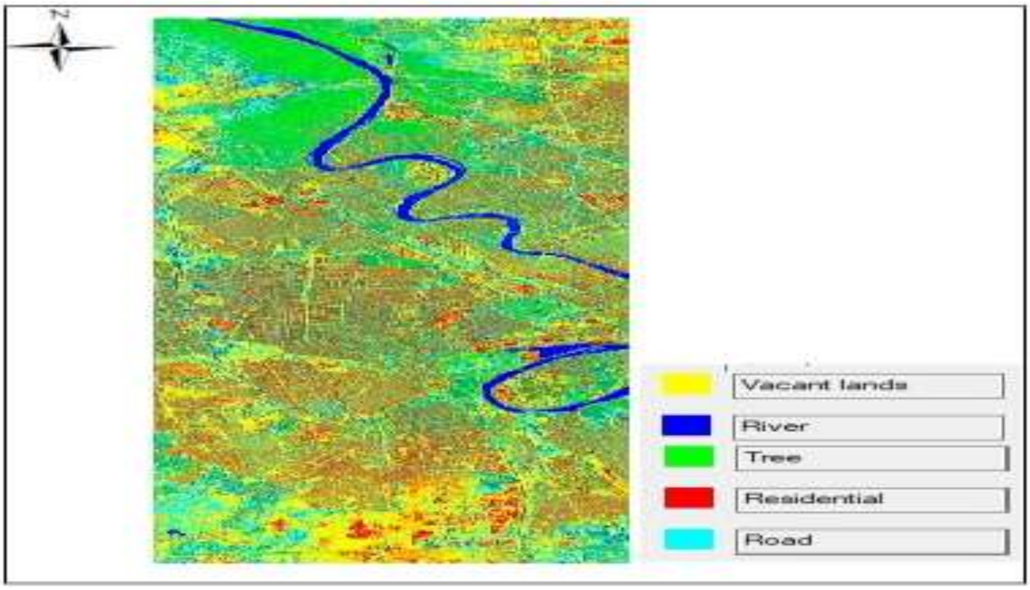

Figure 5-resulted image from minimum distance classification

Table 2-statistical measurements for minimum distance classification

Class Name	Npts	Pct
vacant land [Red]	31,833,523	15.2500%
water [Blue]	12,544,348	6.149%
road [Yellow]	25,085,376	12.748%
tree [Green]	31,072,885	15.232%
building [Cyan]	103,463,868	50.129%

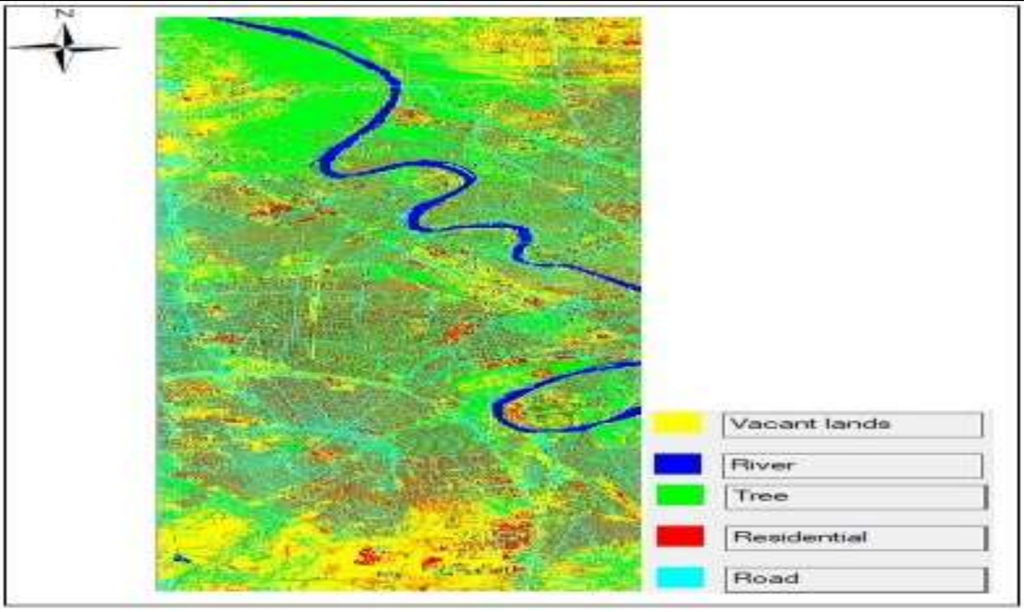

Figure 6- resulted image from maximum likelihood classificatio

Table 3- statistical measurements for maximum likelihood classification

Class Name	number of individual pixels	Percentage
vacant land [Red]	29,809,335 points	15.612%
water [Blue]	11,281,986 points	5.609%
road [Yellow]	34,174,823 points	17.164%
tree [Green]	28,177,435 points	13.812%
building [Cyan]	99,556,421 points	48.802%

6. Conclusion

The supervised classification was used for the original satellite image is done, so we get clear and separate regions (classes), Because the original satellite image has spatial resolution is 2.5 m. Therefore classified the original satellite image in supervised method in the first method (minimum distance) we get (15.25%) vacant area ratio as illustrated in figure-5 But in the second method we get (15.61%) vacant area ratio Figure-6 By comparing the two ratio we see that the first classification method is closest somewhat to the original satellite image. In addition classification gets separation regions than the original satellite image. From the statistical measurement in the (Tables-2, and 3) we see that the two supervised classification method are approximately same, this accuracy of these classifications comes from the prier-knowledge from Region of interest this process very important to choose the exact class. The second reason because we used the original satellite image which has spatial resolution is 2.5m. For more accuracy to determine the classes, we choose the region of interest over the pure and homogenous area In order to get closer to actually calculate the proportion of vacant area in the satellite image.

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