WEST OF IRAQ SATELLITE IMAGE CLASSIFICATION USING FUZZY LOGIC

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Abstract

In this paper, land use/cover classification using fuzzy techniques which involves several steps, from designing the parameters of the membership functions through classification of the satellite image to the refining the final product. To decide the threshold parameters of membership functions that lead to appropriate classification of the scene, one band of landsat-5 were investigated by the features of the histogram of each area to be classified. The results of fuzzy system (Mamdani type) has been compared with the classical method (* Maximum likelihood classification *) and encourage us to use this technique for other bands with optimum rules for future works.

Keywords:- *Image classification, Fuzzy logic, West of Iraq, Histogram.*

1. INTRODUCTION

Classification is the fundamental image processing task to extract information from remote sensing data. Both crisp and soft classifications may be performed. In a crisp classification, each image pixel is assumed pure and is classified to one class. Often, particularly in coarse spatial resolution images, the pixels may be mixed containing two or more classes. Soft classifications that assign multiple class memberships to a pixel may be appropriate for images dominated by mixed pixels. Both supervised and unsupervised approaches may be adopted [1].

Knowledge of both land used and land cover is important for economy planning of a region. While the land used related to human activities residential, institutional, commercial and recreational …etc., the land cover relate to the various type of features present on the surface of the earth. For proper planning exercise information on both the above aspects should available separately. The satellite based remote sensing has been very popular and different countries have lunched their remote sensing satellite for this purpose. The collected data are processed and interpreted in different forms using digital techniques or optical techniques. Although the visual interpretation of image is being used in many applications, it does not interpret the image pixel by pixel, instead it provide aggregated information related to image features of known objects. As a consequence, the information results for land used and covered provided by human interpreter is less accurate and overlapping in many places[2].

Over the past few decades, fuzzy logic has been used in a wide range of problem domains. Although the fuzzy logic is relatively young theory, the areas of applications are very wide: process control, management and decision making, operations research, economies and, for this paper the most important, pattern recognition and classification [3]. Dealing with simple 'black' and 'white' answers is no longer satisfactory enough; a degree of membership (suggested by Prof. Zadeh in 1965) became a new way of solving the problems. A fuzzy set is a set whose elements have degrees of membership. A element of a fuzzy set can be full member (100% membership) or a partial member (between 0% and 100% membership). That is, the membership value assigned to an element is no longer restricted to just two values, but can be 0, 1 or any value in between. Mathematical function which defines the degree of an element's membership in a fuzzy set is called membership function. The natural description of problems, in linguistic terms, rather than in terms of relationships between precise numerical values is the major advantage of this theory. An idea to solve the problem of image classification in fuzzy logic manner, as well as, comparison of the results of maximum likelihood and fuzzy classification was the main motivation of this work. Behind this idea was also the question if the possible promising results can give the answer to the question of diminishing the influence of person dealing with supervised classification.

2. SATALLITE DATA USED

The Landsat series of satellites has been the most successful to date providing worldwide coverage over 27 years [4]. Landsat data have been used successfully in many applications such as land cover[4,5,6] (soil, water, vegetation) and land use (civilian, military)[4]. Landsat imagery is by far the most common source of satellite-based remote sensing data available to the civil engineer.

Landsat-5 thematic mapper (TM) launched on March 1, 1984, The TM is a remote sensor for acquisition of data in seven bands, and the wavelength range and location of the TM bands have been chosen to improve the spectral different abilities of major Earth surface features.

Table (1) lists the seven spectral bands of TM [7].

[a]Bands 6 and 7 are out of wavelength sequence because band 7 was added to the TM late in the original system design process.

Band	Wavelength (µm)	Nominal spectral location
1	0.45-0.52	Blue
2	0.52-0.60	Green
3	0.63-0.69	Red
4	0.76-0.90	Near IR
5	1.55-1.75	Mid IR
6[a]	10.4-12.5	Thermal IR
7[a]	2.08-2.35	Mid IR

3. STUDY AREA

In our work, satellite images are available in, to the area of west of Iraq (flight path 169 and row 37) comprises seven main classes. These are Water (two elements Deep and Shallow), Urban, Bare and Agricultural (three elements Tree, Crop and Vegetation) [8]. This digitally represented by (512×512) pixel (The resolution of TM is 30×30 m^2), as illustrated in figure (1).

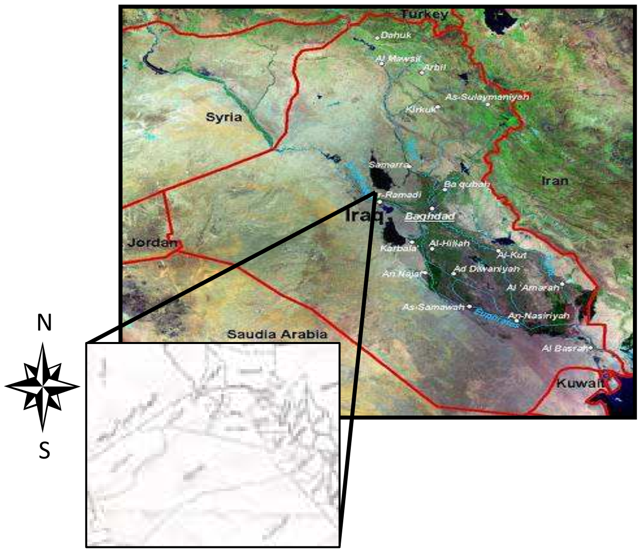


Fig. (1) Satellite image show the location of the study site.

4. DEFINITION AND VERIFICATION OF THE TRAINING AREA

As it was later used for fuzzy logic classification, the selected training area of supervised image classification will be given in brief. Selected land covers are: Shallow Water, Deep Water, tree, urban, vegeTable and crop. For these classes, training areas were pointed on the image (Figure 2.)

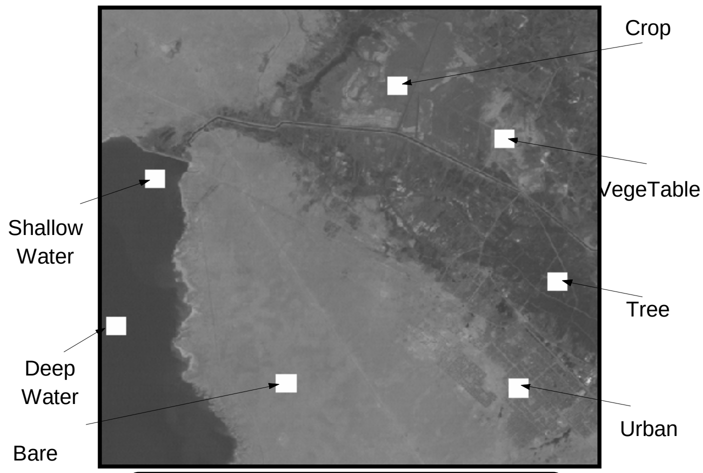


Figure 2. Training areas

In determination whether the training areas that have been selected are well represented, histogram was used: if the histogram has a single peak, then the training area is distinct and there is no confusion between it and another training area unless they have the same gray level.

A histogram with a wide distribution would indicate that there may be an ambiguity between the current and some other region. Since the *signature separability* showed that tree and vegeTable are very poorly separated (low values of *Transformed Divergence;* big overlap between the signatures of two classes). Those some uncorrected result in the classification operation will appear. The *signature statistics* gave a list of each of the classes, with the mean values and standard deviations for the class selected. These data were used later in the definition of the membership function.

5. METHODOLOGY USED

Development of Land use land cover GIS database, based on classification of remotely sensed data requires enormous efforts. The major challenge is the development of the best method that can be followed to extract and aggregate classes in a manner that can reflect the true phenomenon. This is due to the assumption that different land use or land cover classes have distinct spectral signatures. Using spectral information only, confusion between land used/land cover classes is certain [9]. This is particularly true with this study area due to surface heterogeneity. As a result, the fuzzy classification concept was attempted. The approach followed to perform membership function fuzzy classification operations is made on different object features (i.e. histogram values of the training areas) such as minimum, maximum, mean and standard deviation values. After threshold values of each class are identified, the borders of fuzzy membership functions classifying the image are specified empirically.

As it can be seen in Figure(3), similar values (overlap) can be found in the used image for crop, tree and urban area classes. This is due to the similar characteristics in the spectral response (reflectance) of these classes in the wavelength range 0.5–0.59 μm.

Fortunately, they can be better separated cause of the bigger difference in other bands for future works.

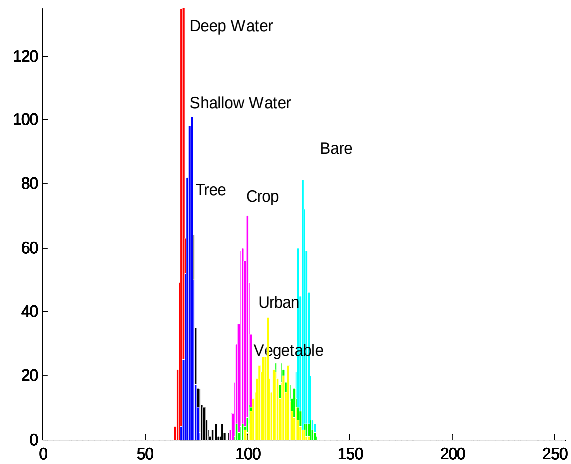


Figure 3. Classes overlapping in their Histograms

6. CLASSIFICATION PROCEDURE

Since the goal of both procedures, maximum likelihood (ML) and fuzzy logic, is to classify the image, input data must be the same. That is, one band channel is used as the starting point for the image classification based on fuzzy logic.

In this paper, Matlab's Fuzzy Logic Toolbox is used which need two parameters for the valid membership function definition: *mean* and *standard deviation* values.

The *Fuzzy Inference System* (FIS) *Editor* displays general information about a fuzzy inference system: a simple diagram with the names of the input variable (B1 channel) and those of each output variable (Shallow water, Deep water, urban area, crop, tree and vegetation).There is also a diagram with the name of the used type of inference system.

The *Membership Function Editor* is used to display and edit all membership functions associated with the input and output variables for the entire fuzzy inference system. Because of the smoothness and non-zero values, in order to define a membership function, in the process of image classification simple Triangular function is used.

Class	Min	Max	Mean	Std	Peak
Deep Water	65	73	69	1.30	137
Shallow Water	68	77	72	1.67	101
Urban	99	130	113	6.60	38
VegeTable	94	134	114	8.53	24
Crop	92	105	99	2.53	70
Tree	68	96	74	4.12	78
Bare	120	133	127	2.36	81

Table 2. Histogram Values

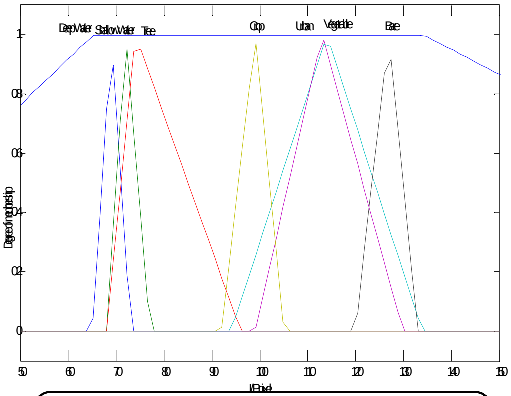


Fig.4-a Triangular Membership function for input variables with Mean, min. and max. Values

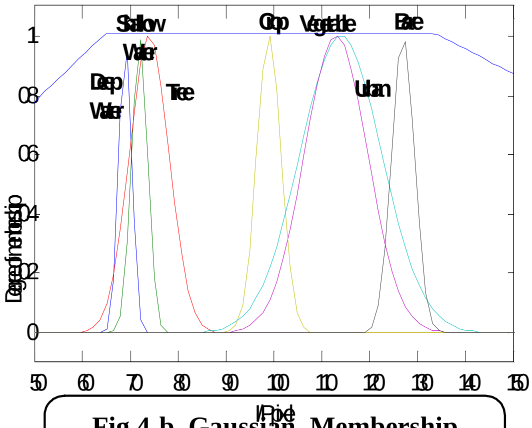
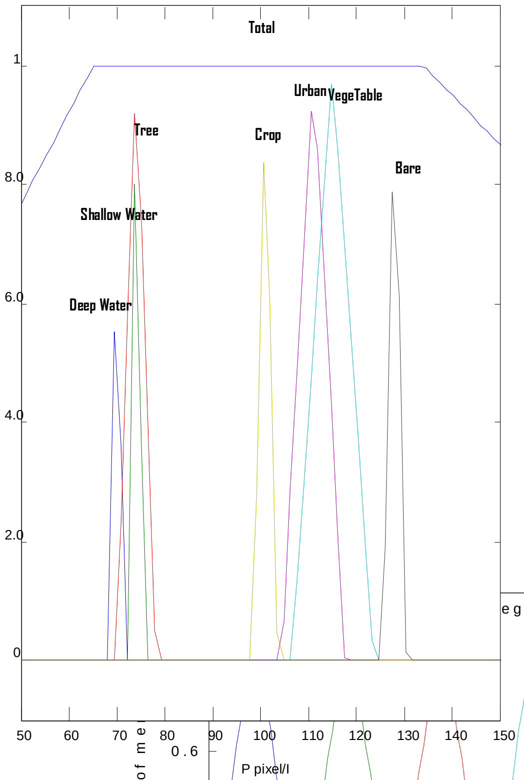


Fig.4-b Gaussian Membership function for input variables with Mean and Std values



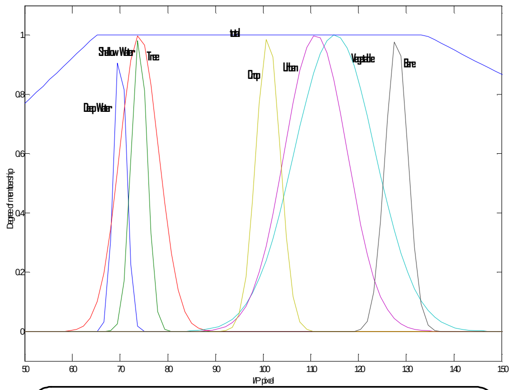


Fig.4-d Gaussian Membership function for input variables with Peak and Std values

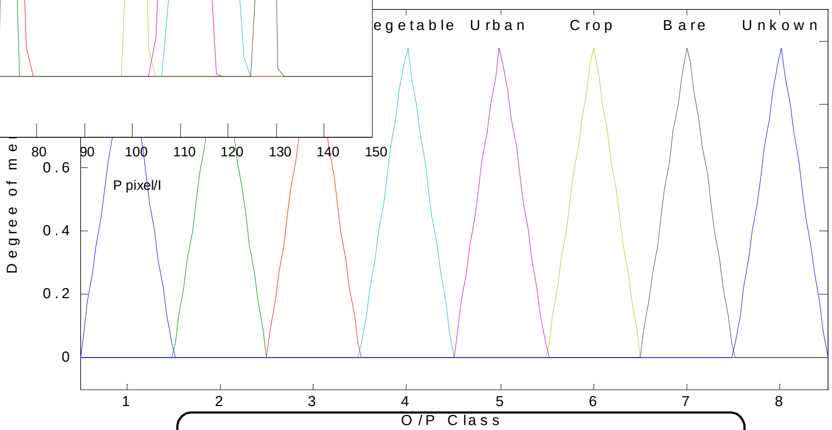


Fig.5 Membership function for output variables

Creation of the membership functions for the input variables using minimum, maximum and mean values from Table 2 for triangular function is shown in Fig.4-a , mean and standard deviation for Gaussian function is shown in Fig.4-b, peak and standard deviation for triangular function is shown in Fig.4-c and, at last, peak and standard deviation for Gaussian function is shown in Fig.4-d.

Creation of the membership functions for the output variables is done in the similar manner. For Mamdani type the triangular membership function of output variables is shown in figure(5).

Based on the descriptions of the input and output variables (Deep Water, Shallow Water, Urban, VegeTable, Crop, Tree, Bear and Unknown), the rule statements can be constructed in the *Rule Editor*.

When the variables have been named and the membership functions have appropriate shapes and names, everything is ready for writing down the rules.

Rules for image classification procedure in verbose format are as follows:

IF (band is mf1) THEN (class is Deep water)

IF (band is mf2) THEN (class is shallow water)

IF (band is mf3) THEN (class is urban)

IF (band is mf4) THEN (class is vegeTable)

IF (band is mf5) THEN (class is crop)

IF (band is mf6) THEN (class is tree)

IF (band is mf7) THEN (class is bare)

IF (band is mf8) THEN (class is unknown)

At this point, the fuzzy inference system has been completely defined, in that the variables, membership functions and the rules necessary to calculate classes are in place. Classification is conducted by the Matlab's m-file.

7. RESULTS

Output images coming from maximum likelihood classification (using TNTmip2010software) shown in figure 6 and fuzzy classification (using Matlab) shown in Fig.7 and Fig.8 can be compared.

These gray scale images are produced in such way that pixels coming from the same class have the same digital numbers in both

mages: Deep Water(1), Shallow Water(2), Tree(3), VegeTable(4), Urban(5), Crop(6), Bare (7) and Unknown(8).

This is the basis for image comparison. Percentage of classified pixels in both methods is given in the Table 4. (Overall number of image pixels is 262144).

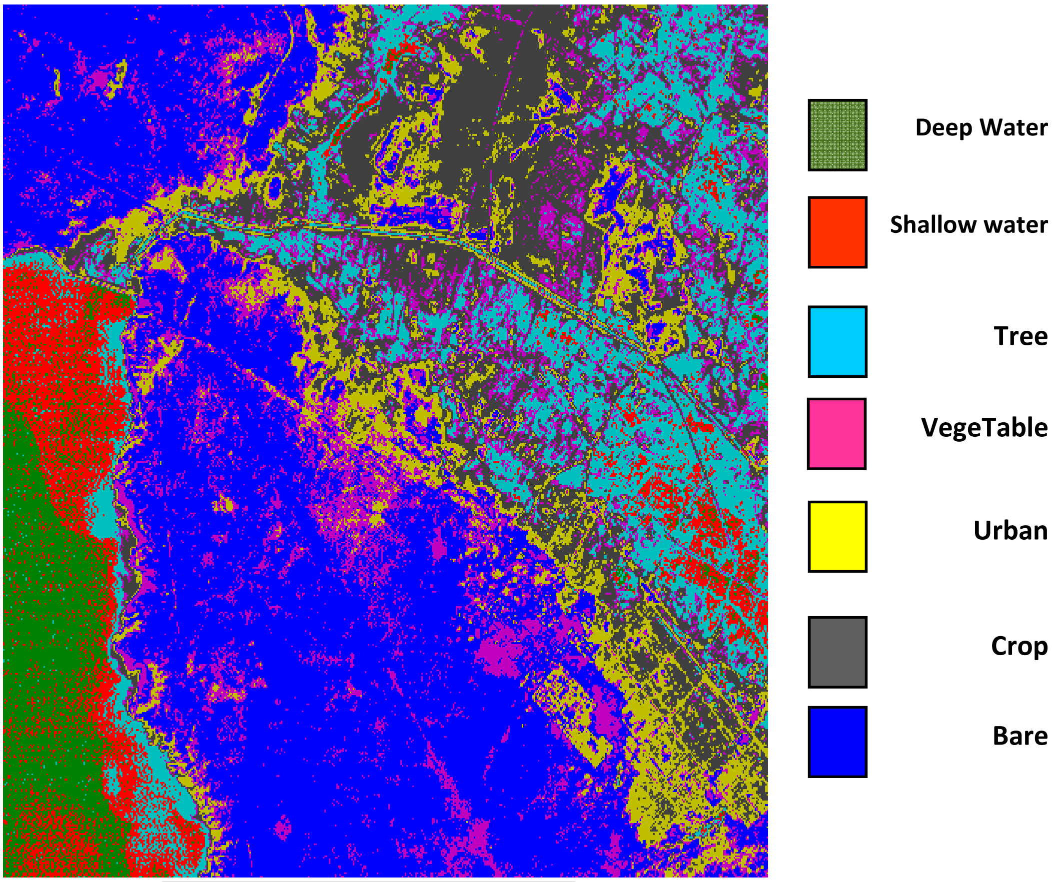


Fig 6. Classified image with

(ML Classifier)

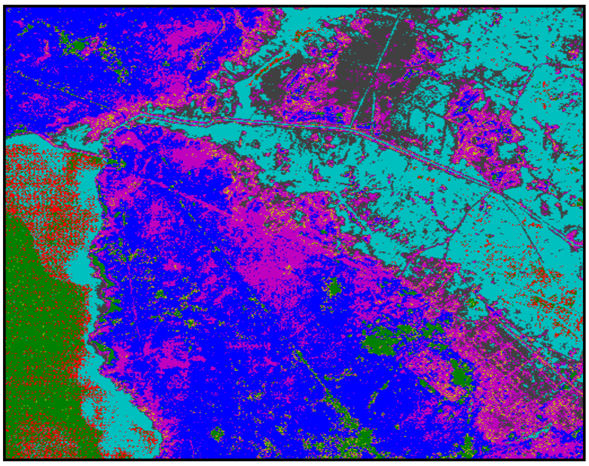


Figure 7.a Classified image

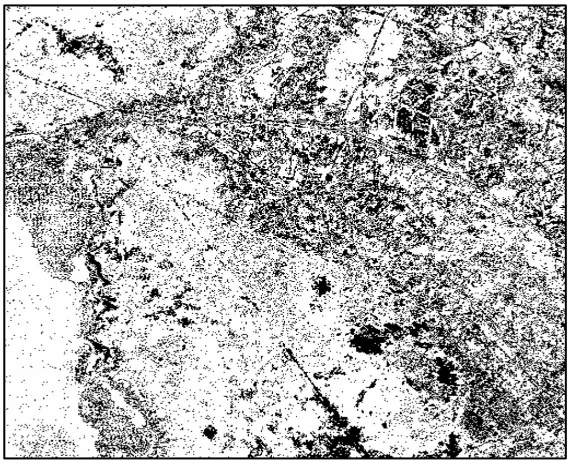


Fig.7.b Difference of ML with Classified image

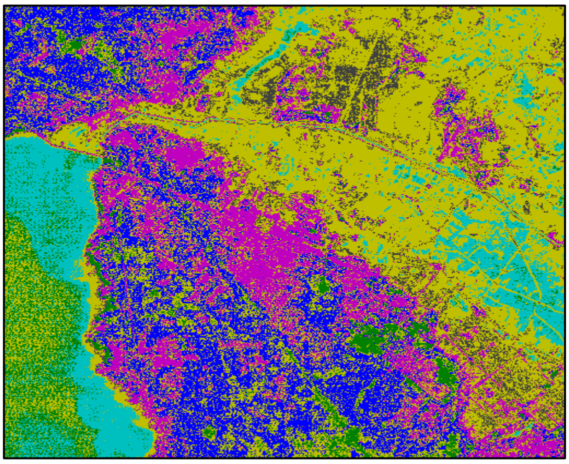


Figure 8.a Classified image

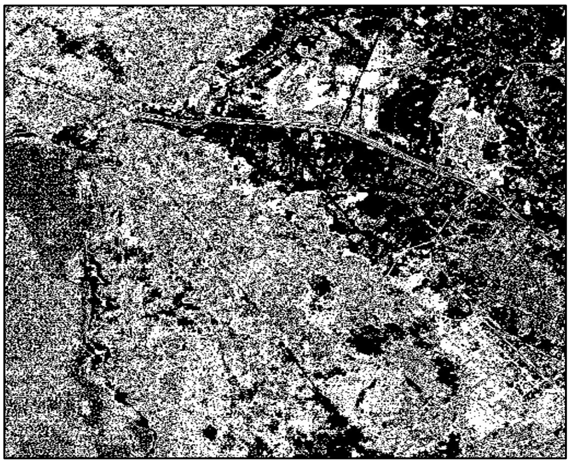


Fig 8.b Difference of ML with Classified image

	Name	Fuzzy	ML	Absolut Deference
1	Deep Water	5.9574	5.9574	0
2	Shallow Water	3.4286	6.6509	3.2223
3	Tree	23.3974	11.9579	11.4395
4	VegeTable	20.5708	15.2283	5.3425

	Name	Fuzzy	ML	Absolut Deference
1	Deep Water	3.8834	5.9574	2.074
2	Shallow Water	0	6.6509	6.6509
3	Tree	10.4630	11.9579	1.4949
4	VegeTable	14.1670	15.2283	1.0613

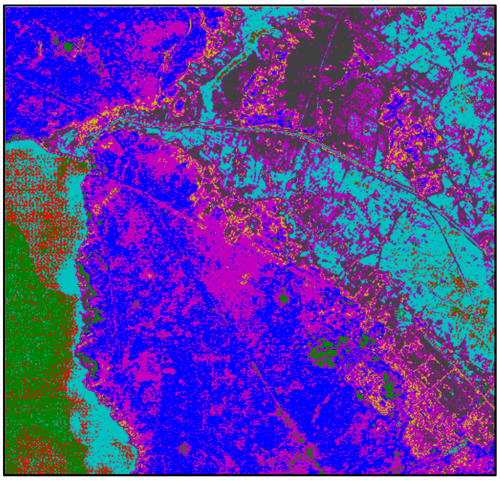


Figure 9.a Classified image
(Gaussian with mean and std values)

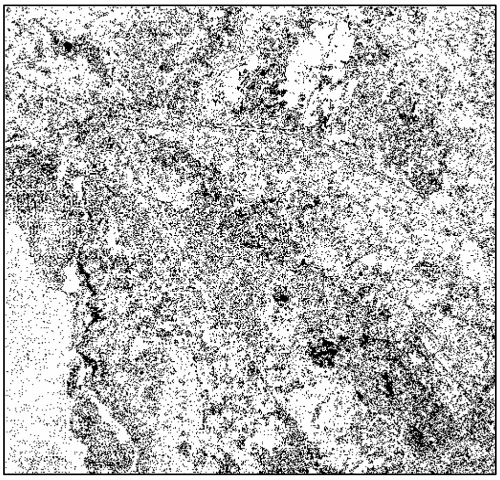


Fig. 9.b Difference of ML with Classified image
Similarity = 73.3967%

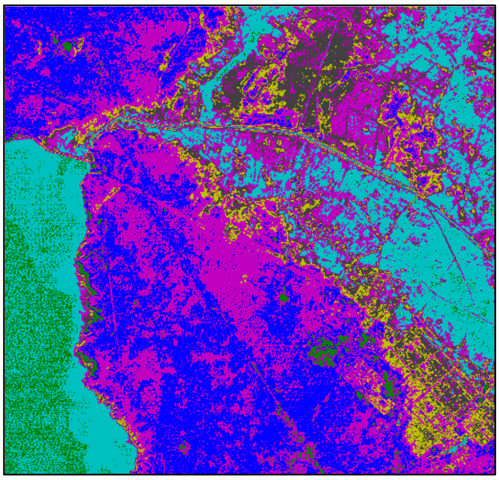


Figure 10.a Classified image
(Gaussian with Peak and Std Values)

Fig. 10.b Difference of ML with Classified image
Similarity = 66.0923%

	Name	Fuzzy	ML	Absolut Deference
1	Deep Water	5.7446	5.9574	0.2128
2	Shallow Water	3.4286	6.6509	3.2223
3	Tree	16.6660	11.9579	4.7081
4	VegeTable	33.6208	15.2283	18.3925
5	Urban	3.0678	10.5350	7.4672
6	Crop	12.3558	16.0618	3.706
7	Bare	24.0017	33.6086	9.6069
8	Unknown	1.1147	0	1.1147
	Total Absolut Difference =			48.4305

Table 6 Percentage of classified pixels using Gaussian with mean and Std values

	Name	Fuzzy	ML	Absolut Deference
1	Deep Water	3.8834	5.9574	2.074
2	Shallow Water	0	6.6509	6.6509
3	Tree	21.9559	11.9579	9.998
4	VegeTable	35.6354	15.2283	20.4071
5	Urban	6.1611	10.5350	4.3739
6	Crop	9.2270	16.0618	6.8348
7	Bare	22.0226	33.6086	11.586
8	Unknown	1.1147	0	1.1147
	Total Absolut Difference =			63.0394

Table 7 Percentage of classified pixels using Gaussian with Peak and Std values

Fig. **7.**a show the result of fuzzy classification using the Triangular membership function with mean, min and max values. Fig 7.b show the similarity (White point) between fuzzy logic classification and ML classification with 71.5206%. While Table.4 related to Fig.7 show the percentage pixels of each class in both fuzzy and ML and the absolute difference between them.

Fig**.** 8**.**a show the result of fuzzy classification using the Triangular membership function with peak and standard deviation values. Fig 8.b show the similarity (White point) between fuzzy logic classification and ML classification with 44.3829 %. While Table.5 related to Fig.8 show the percentage pixels of each class in both fuzzy and ML and the absolute difference between them.

Fig**.** 9**.**a show the result of fuzzy classification using the Gaussian membership function with mean and standard deviation values. Fig 9.b show the similarity (White point) between fuzzy logic classification and ML classification with 73.3967%. While Table.6 related to Fig.9 show the percentage pixels of each class in both fuzzy and ML and the absolute difference between them.

Fig**.** 10**.**a show the result of fuzzy classification using the Gaussian membership function with peak and standard deviation values. Fig 10.b show the similarity (White point) between fuzzy logic classification and ML classification with 66.0923%. While Table.7 related to Fig.10 show the percentage pixels of each class in both fuzzy and ML and the absolute difference between them.

From comparing the similarity from the previous results it can be show that membership function of type Gaussian with mean and standard deviation values which used with Mamdani type of Fuzzy Inference System is the best one for classification purpose in our study case with 73.3967% similarity. While the worst result was membership function of type Triangular with peak and standard deviation with 44.3829% similarity.

7. CONCLUSIONS AND FUTURE WORKS

In conclusion there are several points:

1. Gaussian membership function with mean and standard deviation values has best smooth and training area separability which cover the most universe of discourse yields to good results in our work.
2. Mamdani type with separable triangular output membership function with **unknown** class suiTable for classification purpose.
3. For accuracy assignment the similarity value is good indicator for result comparting ascompare with percentage absolute diference value since it related with pixels position rather then number and class type, which is an important requirement in classification task.

This paper present starting point as future works such as:

1. For image classification using fuzzy logic for other bands (band 2 through 6) and study possibility of rule optimization with membership function parameters.

Since the band histogram range in our study area have a small gap between training area gray level value which effect the fuzzy accuracy classification in one way or

2. another , that is good point to discuss in future work.
3. Another type of fuzzy inference system is Takagi-Sugeno need to be study and compare with our paper result in future.

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الخلاصة:

تم اجراء عملية تصنيف الأراضي المستخدمة والمغطاة باستخدام المنطق الضبابي والتي تحتاج إلى عدة خطوات بدا من تصميم متغيرات دوال الانتماء وصولا إلى تصنيف صورة الأقمار الصناعية للنتيجة المطلوبة. لتقرير قيم العتبة المناسبة لعملية التصنيف ، تم دراسة آحد الاطوال الموجية لصورة من القمر الصناعي لاند سات-٥ لمنطقة غرب العراق ودراسة المخطط التكراراي (Histogram) لكل منطقة من مناطق التدريب وكيفية الاستفادة من هذه المميزات لاستخدام المنطق الضبابي في عملية كتابة القواعد المناسبة لعملية التصنيف ، تم مقارنة نتائج النظام الضبابي (نوع Mamdani *) مع احدى الطرق التقليدية للتصنيف (طريقة Maximum likelihood) وكانت النتائج المستحصلة مرضية لتطبيق المنطق الضبابي على بقية الاطوال الموجية وإيجاد القواعد والاطوال الموجية الأمثل لعملية التصنيف في الأعمال المستقبلية