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A comparative study of multiband mamdani fuzzy classification methods for west of Iraq satellite image

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ABSTRACT

In our paper, performance of four fuzzy membership function generation methods was studied. These methods were studied in the context of implementing Mamdani fuzzy classification on a set of satellite images for western Iraqi territory. The first method generate triangulate membership functions using mean, minimum (min) and maximum (max) of histogram attribute values (AV), while peak and standard deviation (STD) of these AV were used in the second. On the other hand, in the third and fourth methods, Gaussian membership functions are generated using same mentioned values in the first and second method respectively. The goal was to generate a Mamdani type fuzzy inference system the membership function (MF) of each fuzzy set and implementing the AV of western Iraqi territory training data sets. A pixel-by-pixel comparison of each method with traditional maximum likelihood method (ML) was made on data sets comprising six bands of satellite imagery of the western Iraqi region taken by the Landsat-5 satellite. Simulation results of these performance comparisons singled out that the method using Gaussian MFs together with peak and STD of the AV as the best achiever with a similarity of 83.16 percent for band (3) of the studied area.

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1. INTRODUCTION

Recently special attention has been given to image classification techniques within the remote-sensing community [1]. Classification algorithms are not of value unless they are accurate enough for the application being tackled, a matter which has impelled concerned researchers to develop more classification schemes of ever-increasing accuracy [2]. A variety of factors will contribute to the transformation of remotely sensed images into thematic maps remaining a critical issue [3]. Prominent among these factors are the complexity of the landscape being mapped, the particular selection of the remotely sensed data being processed and the suitability of the particular image processing and classification algorithms for an immediate purpose [5], [6].

A comprehensive and up-to-date review of image classification algorithms is still lacking as of the writing of this paper, despite the fact that this important subject is covered in numerous research papers [1], research monographs [4], and text books [7]. Because of the rapid development of new and improved image classification techniques each year, such a review is a pressing need for better service for both the research community and practitioners with no direct research interests [8], [9]. Facilitating the choice of what classification algorithm is best to use for a particular study would be an immediate benefit that could be reaped from such a comprehensive state-of-the-art review [10].

Image classification is an image processing operation essential to extracting patterns from remotely sensed data. Classification algorithms are either crisp or fuzzy [11]. In a crisp classification, crisp set theory is presumed and each image pixel is classified into a single well-defined subset of the universal set or a class, for adherence to the subject terminology. In some applications of image-classification, particularly in processing lower resolution images, the problem of mixed pixel values is solved by implementing a fuzzy classifier that assigns multiple class memberships to a single pixel.

Supervised and unsupervised classification schemes are in use. The principal use share goes to the supervised schemes. These schemes follow, in general, a three-stage pattern, starting with the training stage, then the allocation, and followed by the testing stage. Testing is a crucial step in both fuzzy and crisp classification schemes, the importance of which stems from the need to achieve a reasonable measure of confidence and attach that measure to the particular use and classifier before getting to deploy the classifier to end users. There exist in the literature many methods for the assessment of the performance of crisp classifiers [12]–[14]. In the present work, we study four of the direct rule generation methods' performance with no appeal to any tuning procedures that are known to be time-greedy. The triangular membership function (MF) is generated in the first and second approaches by using mean, minimum, and maximum value of the histogram attribute values (AV) in the first method and the peak and standard deviation of these AVs in the second. In the third and fourth approaches, on the other hand, Gaussian MF is generated using the mean and standard deviation (STD) of the histogram of the AV.

The above described approaches were implemented with a Mamdani type inference system in which a single fuzzy if-then rule is generated for each single class by specifying the MF of each previous fuzzy set implementing the information about AV gleaned out of training patterns. This approach then produces the same number of rules as the class numbers. It is generally acknowledged that a fuzzy-rule based system is superior to other methods in terms of memory usage and inference speed. Furthermore, the end user can examine each if-then rule separately [10]–[16].

The proposed work focuses on solving the problem of satellite images classification by Mamdani type fuzzy inference system via different MF generation system. This system is required to check the effected parameters in performance evaluation and reducing time to get the required results. In our paper, the proposed algorithm is going to be supported by results.

In the present work, the performance of each used method was evaluated for the studied area of western Iraqi territory and the classification outcome was compared to the traditional maximum likelihood method. In this paper, the second section contains an elucidation of the characteristics of fuzzy systems. The third section describes in detail the studied geographical area (satellite images of the western part of Iraq). The fourth section describes the generation methods used, while the fifth section presents the summation results. The last section delineates the authors' conclusions regarding fuzzy systems' performance when applied to image classification.

2. PROPOSED FUZZY SYSTEMS

Zadeh introduced fuzzy logic and fuzzy set theory in 1965, as an extension to crisp set theory in which a non-binary MF is permissible. The intention was to formally handle uncertain and imprecise or fuzzy knowledge, so to speak, in real world applications. This mathematical theory proved, as it was intended by the founder, to be quite versatile in handling every sort of application that involves manipulating or decision-making in imprecise or noisy environments [11], [17], [18]. A fuzzy system is defined by a set of conditional linguistic statements, the validity of which is assumed based on experience and can be expressed in a variety of ways [19]:

If antecedent *Then* consequent (1)

An inference system obeying the above format with underlying fuzzy sets is called the Mamdani system. A weight is associated with each rule, which is again a real number in the interval [0, 1], [17]–[19]. The rule is applied to the number associated with the previous one. Each rule should account for evaluating antecedents, fuzzifying input, and associated fuzzy operators. It also has to involve what is known as inference, which means applying the result of this sequence of operations to the consequences. The most difficult and less-formal task is to construct a set of fuzzy rules (FR) relevant to the specific problem within the fuzzy classification system building process [17], [20]–[26]. Therefore, the essential point could be subsumed by using a rule-based system that employs fuzzy logic, referred to as a fuzzy inference system, to affect the required modeling of human reasoning for a specific application problem involving a substantial amount of data. Each such system should be comprised of main components. The first one is a fuzzifier, which transforms crisp inputs into fuzzy ones; an inference engine that carries out fuzzy reasoning on the fuzzy data to obtain a fuzzy output; the second one is a defuzzifier, which transforms the fuzzy output of the latter component into a crisp format; the third one is a knowledge base, which consists of both a set of FR, and the fourth one is a permissible set of MF known as the database [27]. The sought-for decisions are made by the inference engine utilizing members of the rule base.

2.1. Data used and study area

The Landsat group of satellites has been providing worldwide coverage for about three decades now. Landsat data has been used in a variety of applications, including land cover surveying [8]–[11] (soil, water, and vegetation) and land use (civilian and military) [5], [16], [18]. Images available through Landsat satellites are among the most commonly available data sets accessible by researchers with no more than ordinary access credentials.

Satellite images from a group of satellites are available in this work for the purpose of studying Iraq's western territory via flight path 169 and row 37, which comprise seven main classes. These include two water surfaces (shallow and deep), bare, urban, and three agricultural regions (crops, vegetation, and trees). The mentioned data set is an image represented by (512×512) pixels with a resolution of 30×30 m^2.

A description of the selected training area is given herein. Shallow water, deep water, trees, urban areas, vegetation, and crop areas dominate the cover in the chosen area. Training areas corresponding to these classes are marked in the image presented in Figure 1. In order to ascertain that the selected training areas are representative enough for the data sets, a histogram was used as shown in Figure 2.

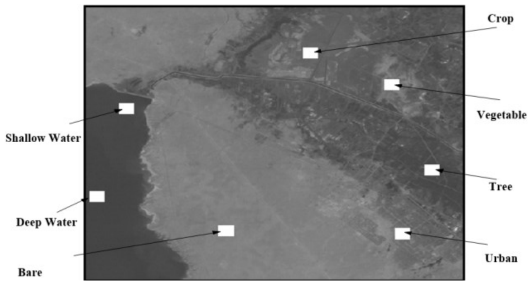

Figure 1. training area

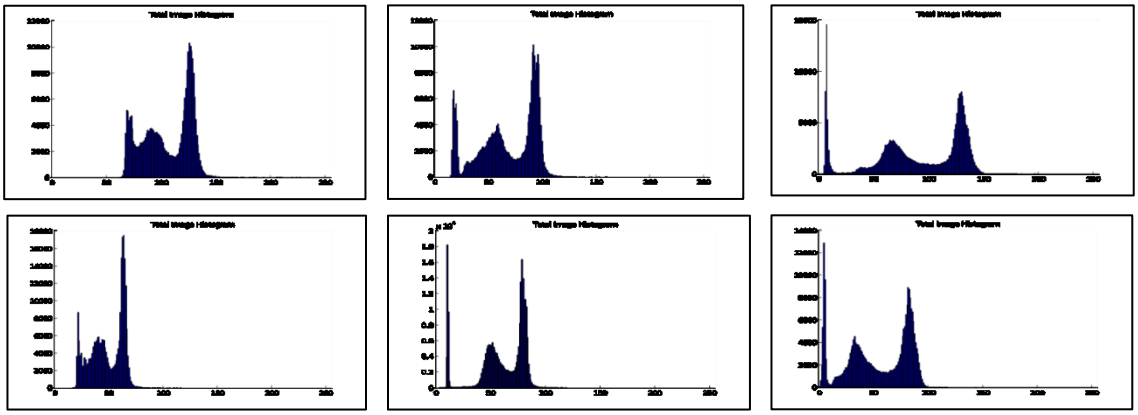

Figure 2. Histograms of the studied area

2.2. Rule generation

Mamdani-type fuzzy inference system with if-then rules made for each class, taking the training area AV into account, as is shown in Table 1. Generating the input MF is completed in accordance with the four approaches. Creation of the output MF (8 with unknown class) is done for all approaches since this is the Mamdani fuzzy inference system. Several types of Membership functions have been adapted to our work [2], [8], [21].

2.3. Membership functions

The mean, minimum, and maximum of the histogram AV are used in the 1-Triangular MF. The membership function of each antecedent fuzzy set (TMFFS) is determined using the mean, minimum, and maximum of AV (see Figure 3). Triangular MF using the peak and STD of the histogram AV In this case, TMFFS is determined by the peak and STD of the AV (see Figure 4). Gausian MF using the mean and STD of the histogram AV. The Gaussian membership function of each antecedent fuzzy set (GMFFS) is determined by the mean and STD of the AV (see Figure 5). Gaussian MF uses the peak and STD of the histogram AV. GMFFS is determined by the peak and STD of the AV (see Figure 6).

Table 1. Training area histograms attribute values of the image bands

Training area of band 1

Band-1	Min	Max	Mean	Std	Peak
Image	4	119	60	23.09	54
Deep water	9	12	11	0.58	12
Shallow water	10	13	12	0.52	13
Urban	48	82	62	6.7	60
Vegetable	47	81	66	7.11	66
Crop	47	62	53	3.28	53
Tree	37	63	52	5.08	54
Bare	74	81	78	1.05	79

Training area of band 2

Band-1	Min	Max	Mean	Std	Peak
Image	17	116	49	14.99	29
Deep water	20	24	22	0.67	23
Shallow water	24	30	27	1.03	27
Urban	43	66	52	4.52	51
Vegetable	43	66	55	4.76	56
Crop	42	51	64	1.75	47
Tree	24	48	29	2.95	29
Bare	60	66	63	1.11	64

Training area of band 3

Band-1	Min	Max	Mean	Std	Peak
Image	15	160	68	27.06	30
Deep water	15	20	17	0.88	18
Shallow water	19	23	21	0.73	22
Urban	56	96	74	8.06	70
Vegetable	59	94	78	7.53	79
Crop	54	68	61	2.38	62
Tree	25	66	31	5.44	30
Bare	87	97	92	1.70	93

Training area of band 4

Band-1	Min	Max	Mean	Std	Peak
Image	4	119	60	23.09	54
Deep water	9	12	11	0.58	12
Shallow water	10	13	12	0.52	13
Urban	48	82	62	6.70	60
Vegetable	47	81	66	7.11	66
Crop	47	62	53	3.28	53
Tree	37	63	52	5.05	54
Bare	74	81	78	1.05	79

Training area of band 5

Band-1	Min	Max	Mean	Std	Peak
Image	0	197	89	43.28	38
Deep water	5	10	7	0.82	8
Shallow water	3	10	7	0.94	8
Urban	75	130	97	12.03	91
Vegetable	72	130	103	10.8	109
Crop	63	79	70	3.04	70
Tree	31	81	41	7.73	38
Bare	120	131	126	1.87	127

Training area of band 6

Band-1	Min	Max	Mean	Std	Peak
Image	0	144	54	28.96	16
Deep water	1	8	5	1.09	6
Shallow water	2	8	5	1.03	6
Urban	44	83	60	7.96	55
Vegetable	42	81	63	8.21	66
Crop	27	39	33	1.78	34
Tree	10	48	18	5.5	16
Bare	73	86	81	1.97	82

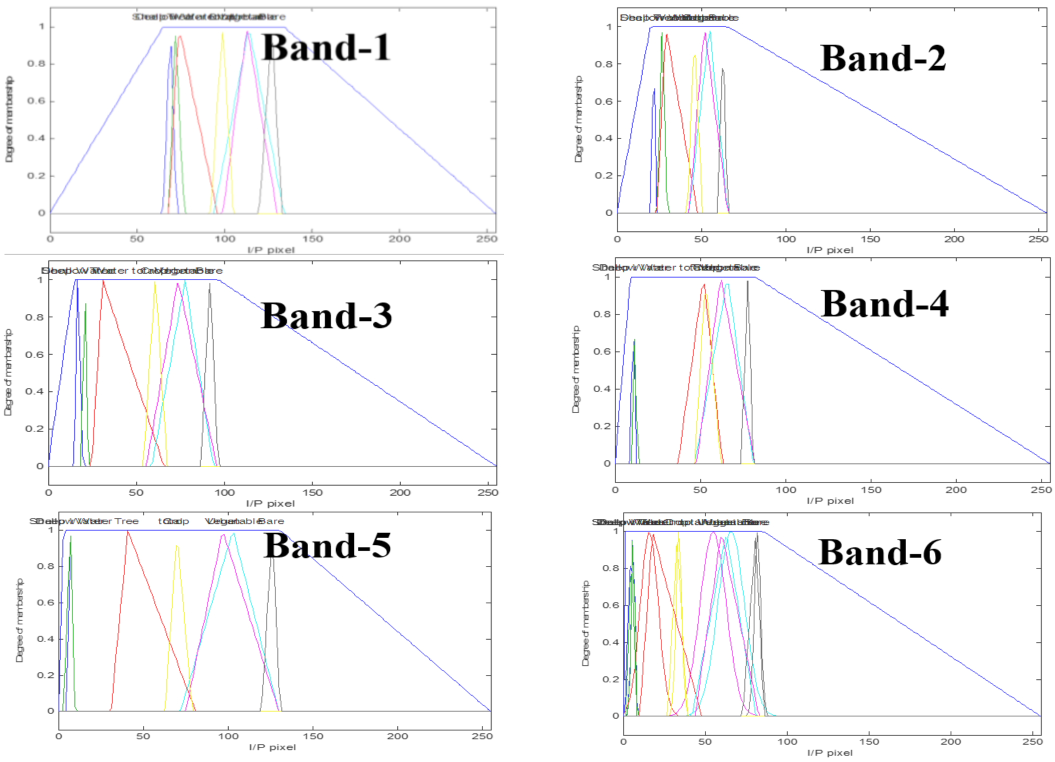

Figure 3. Triangular with mean and min & max

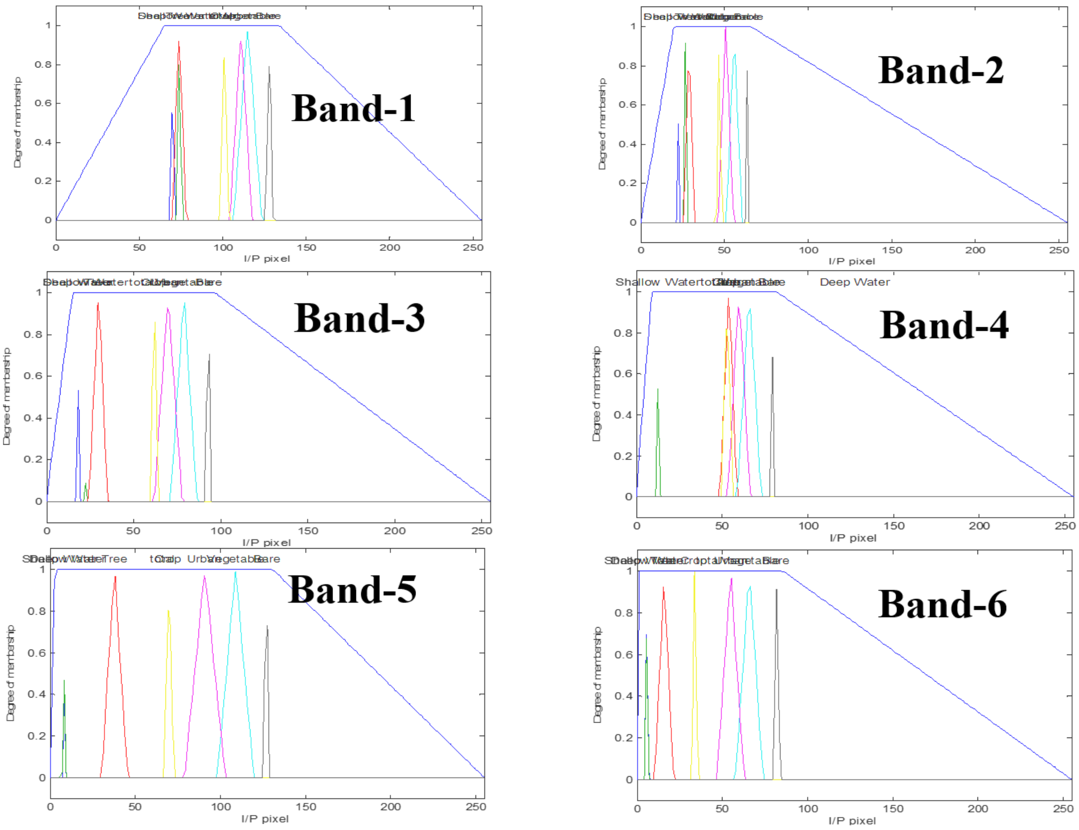

Figure 4. Triangular with peak and standard deviation

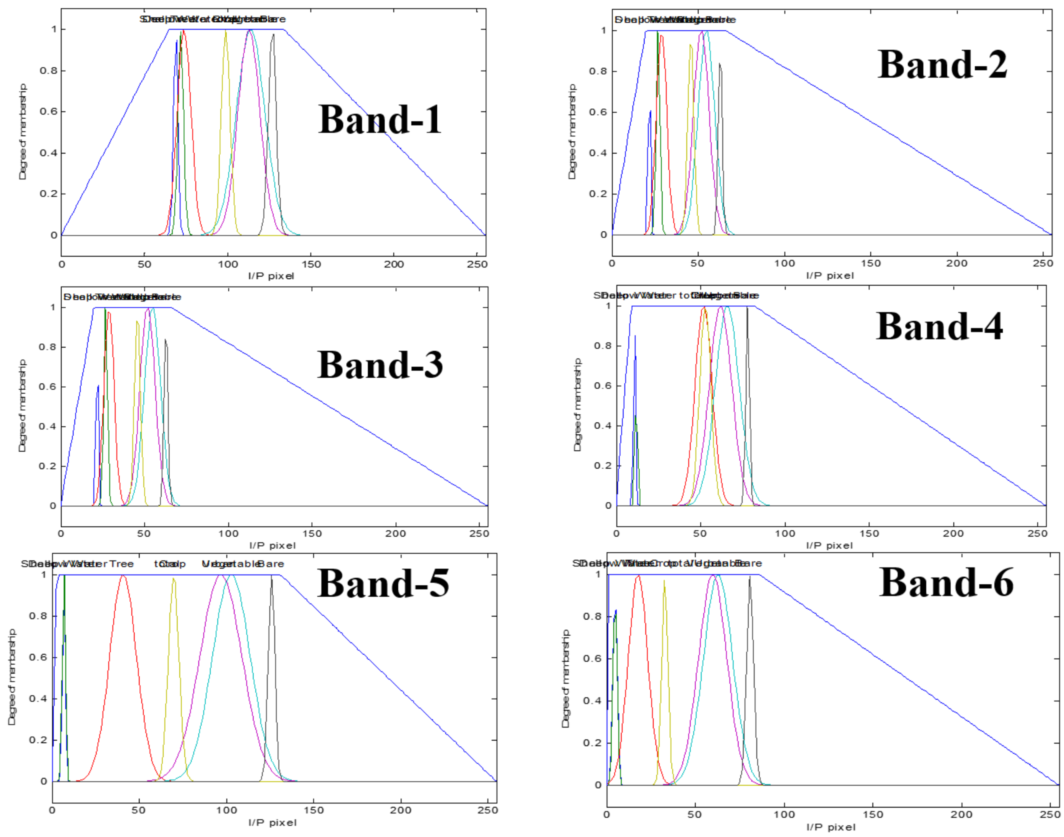

Figure 5. Gaussian with mean & standard deviation

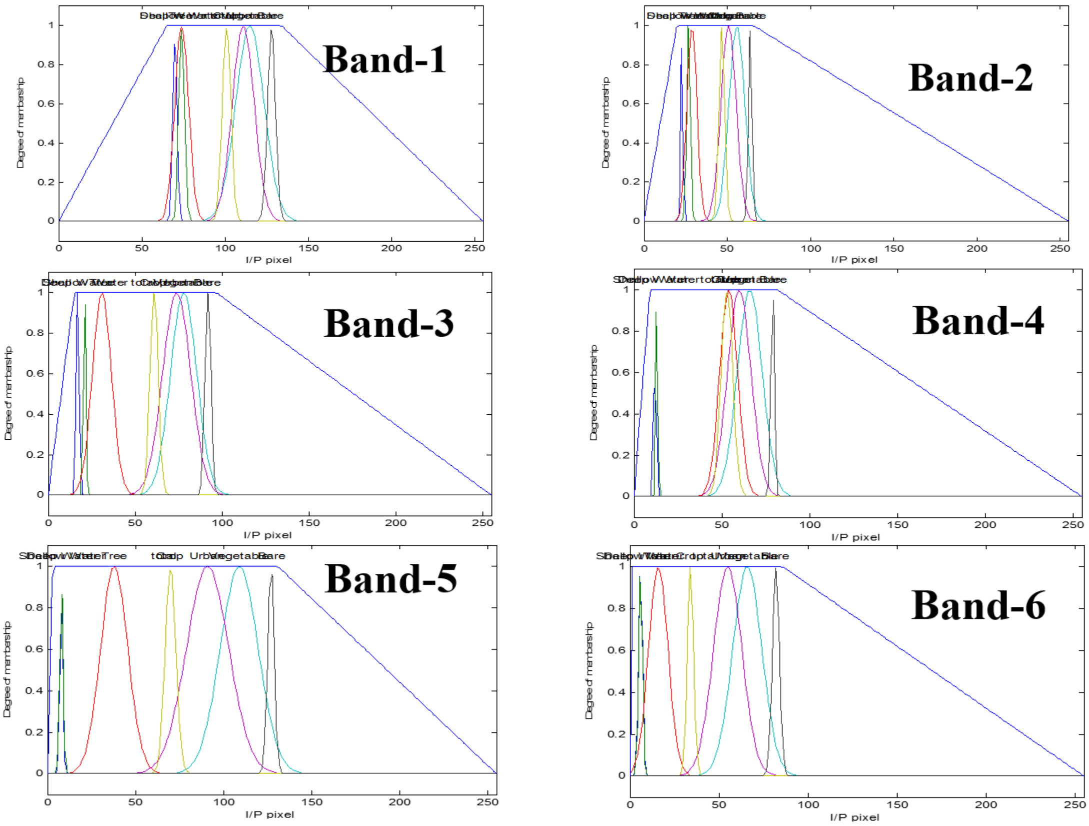

Figure 6. Gaussian with peak & standard deviation

3. RESEARCH METHOD

Image classification methods are classified into different categories; based on usage of training samples (i.e. supervised and unsupervised), based on utilization of different parameters (i.e. parametric and non-parametric classifiers), based on pixel information type (i.e. per-pixel and sub-pixel classifiers), and finally based on the output if it is specific for land cover class (i.e. hard and soft classification). In this paper, per pixel classifier (using traditional maximum liklehood method) with sub-pixel classifiers (using Mamdani-type fuzzy inference system) are compared with different MF generation methods. The spectral value for the pixel is taken as linear/non-linear with the integration of mentioned pure materials with proportional membership. There are many steps that are required to be followed in order to perform the results extraction from an image classification is given in next section indetails.

4. RESULTS

In order to measure the enhancement of our proposed work. We compare it with other works in the same field. Despite the difference results produced by the classic maximum likelihood method (as implemented in the TNTmips 2010 software) were used as a basis for comparison in this work. The output of the above software was compared to the corresponding outputs given by the fuzzy classification routines in a way specifically designed to ease the comparison.

Grayscale images are created in such a way that pixels from the same band have the same digital numbers in both images: deep water is encoded as 1, shallow water as 2, urban areas as 3, vegetation as 4, crops as 5, trees as 6, and bare swaths of land as 7. Accordingly, the number of successfully classified pixels (white) and misclassified pixels (black) can be computed and the similarity percentage is computed for the covered areas as summarized in Figures 7-10. As can be seen, the performance of Gaussian MF with peak and STD on the one hand and mean and STD on the other is comparable. Our claims has been supported by the results which are reasonable in this section.

Table 2, however, illustrates that the performance of triangular MF (using peak and STD) is not good enough compared to the other approaches, since large overlaps are noticed in the training area values. This support previous. The other method, triangular MF (using the meanings of min and max), produced fairly acceptable results. Hence we indicate how the results relate to expectations and to earlier research, the approach using a Gaussian MF with peak and STD yielded the best overall outcome, scoring a classification similarity of 83.16%. From the ease of implementation point of view, rule generation using peaks and STD seems to be the best choice because it depends only on the AV of the training area.

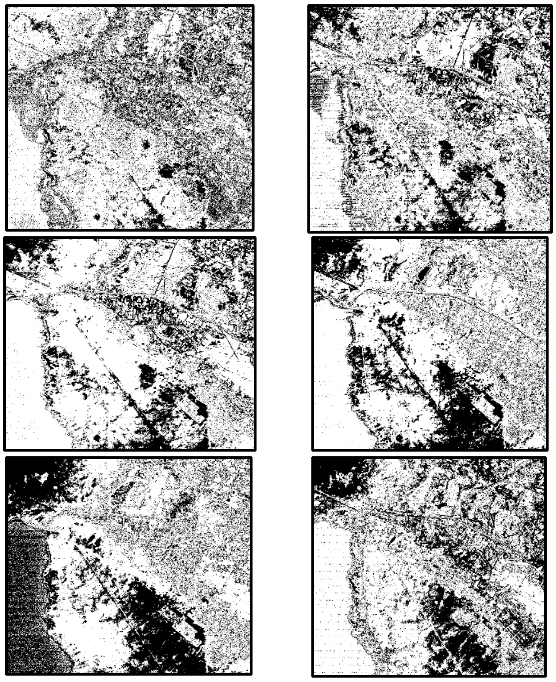

Figure 7. Mamdani classification results using triangular with mean and min and max membership function

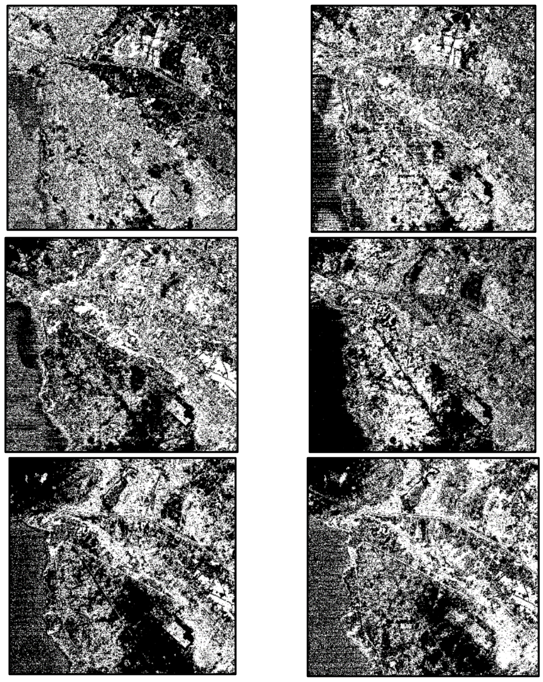

Figure 8. Mamdani classification results using triangular membership function with peak and min and max

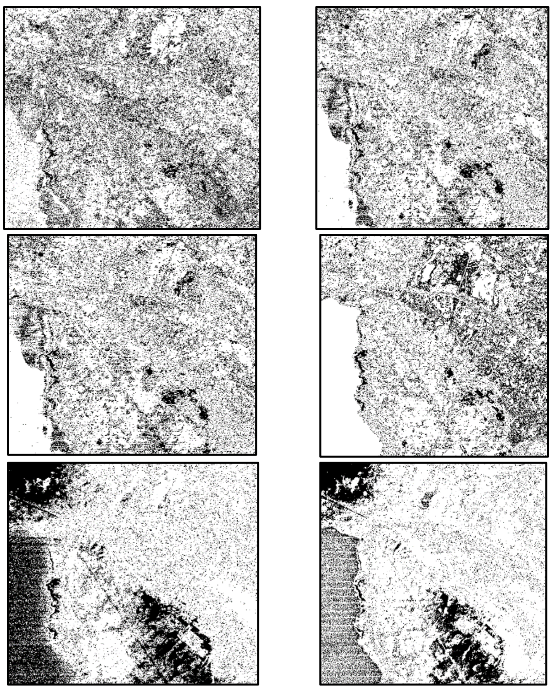

Figure 9. Mamdani classification results using Gaussian with mean and standard diviation membership function

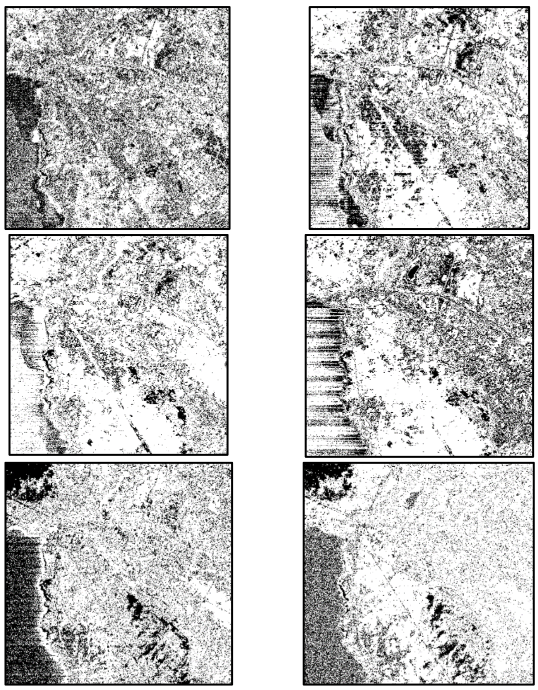

Figure 10. Mamdani classification results using Gaussian with peak and standard deviation membership function

Table 2. Mamdani best similarity with its best approach

Band no.	Max. similarity	Membership function type
1	73.3967	Gaussian (mean &std)
2	78.6018	Gaussian (mean &std)
3	83.1669	Gaussian (peak &std)
4	77.3434	Gaussian (mean &std)
5	60.8326	Triangular (mean & max. min)
6	80.9727	Gaussian (peak &std)

5. CONCLUSION AND FUTURE WORK

In the present paper, we studied the performance of fuzzy rule generation by four methods based on (if-then) rules directly from training patterns, with no appeal to time-consuming tuning routines. The triangular MF was generated in the first and the second approaches. This is done by using mean, minimum andmaximum of histogram AV by the first method and using the peak and STD of these AVs in the second approach.

In the third and the fourth approaches, the Gaussian MF was generated using the mean and STD of the histogram AV, respectively. We fine that the Mamdani approach that produces Gaussian MF using the peak and the STD of the histogram AV results in the best overall performance. The two other approaches utilizing the and STD also resulted in a good overall performance, albeit inferior to the Mamdani approach. The best results obtained in this study were those related to the band (3).

It could be concluded that a single fuzzy (if-then) rule for each class will not always suffice for undertaking any real-world pattern or image classification problem. Each of the methods discussed in this work has its drawbacks, among which fuzzy rule-based systems is characterized by their high classification ability, as shown in this paper. Optimizing feature selection and other parameters in future work is thought to improve the performance of fuzzy rule based system.

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