Journal of Electrical and Electronics Engineering Research Vol. 3(8), pp. 143-150, October 2011
Available online at http://www.academicjournals.org/JEEER
ISSN – 2141 – 2367 ©2011 Academic Journals

Full Length Research Paper

Efficacious approach for satellite image classification

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Accepted 28 February, 2011

The main idea behind any image classification process is to obtain highest accuracy possible. Minimum distance and parallelepiped method yielded acceptable results for image classification but they are bounded by their inherent limitations. On the other hand, fuzzy based systems are fast and provide good accuracy. In fuzzy, accuracy depends upon the type of membership function used, and how the membership functions in the output of FIS are arranged. In this paper Mamdani fuzzy inference system is used to classify image and how the arrangements and the type of fuzzy membership functions employed in the classification, affected the results obtained, are shown.

Key words: Image classification, fuzzy logic, type of membership function, positioning of membership functions.

INTRODUCTION

Satellite image processing plays a vital role for research and developments in “remote sensing”, GIS, “agriculture monitoring”, disaster management and many other fields of study. However, processing these satellite images requires a large amount of computation time due to its complex and lengthy processing criteria. The most common barrier in an image derived from an imaging device is its imperfection. The acquired image can be inconsistent, incomplete, uncertain or a completely a-miss. All these seems to be the main barrier in real time decision making but to switch the job faster, fuzzy (Li et al., 2005; Chao and Cheng, 1998; Bezdek et al., 2005) has proved to be an efficient solution. Since, the main problem lies in providing a better and reliable technique which can provide high performance for digital image analysis (even in situations with uncertainty in Gray level, texture, contours, edges detection, relationship between two segments of an image and all other noisy input conditions), with maximum efficiency and minimum manpower utilization. Fuzzy is one such technology that can implement this with ease and in much less time by classifying the image with a procedure, which automatically categorizes all the pixels of image into land cover classes and other possible themes. The general architecture of a fuzzy logic system (FLS) which consists of four important components: fuzzifier, rules, inference engine, and defuzzifier are shown in Figure 1.

The fuzzifier transforms the crisp set values to fuzzy sets by applying fuzzification function. The rules and inference engine are the main component of fuzzy logic system which simulates the human reasoning process by making fuzzy inference on the inputs with IF THEN rules (Yiming, 1994). If we consider the satellite images, input data is not in the form of true colour image but for demonstration purpose, a three band {R (red) G (green) B (blue)} true colour image was taken (Figures 2 and 3). Each pixel has a particular colour, colour being described by the amount of red, green and blue components in it.

In this paper, the Mamdani min-operation implication method has been implemented (Jang, 1993). Defuzzifier converts the resultant fuzzy set back to a crisp value set which is the system output. Generally, rules are constructed and the output membership functions are arranged in random order without considering the effect of their position on the output, which leads to decline in accuracy of classification. However, if the arrangements

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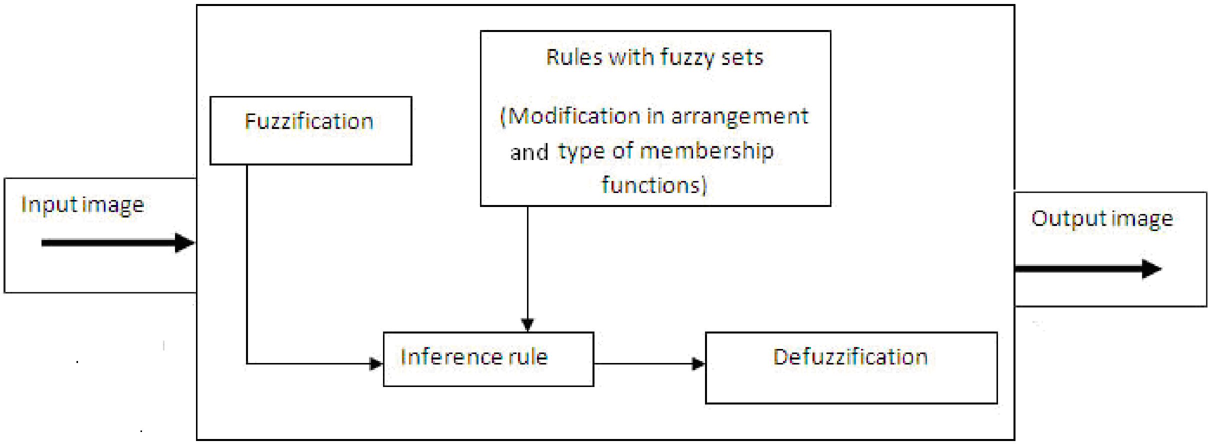

Figure 1. Architecture of fuzzy inference system.

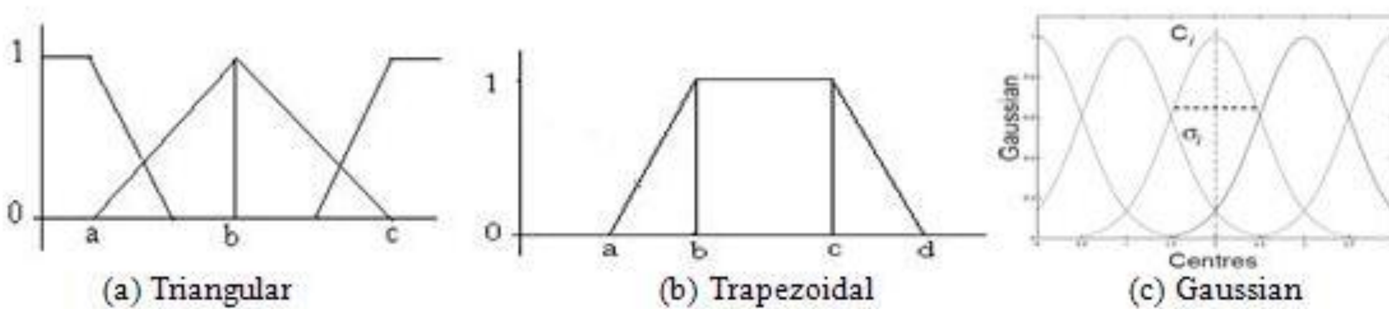

Figure 2. Membership functions.

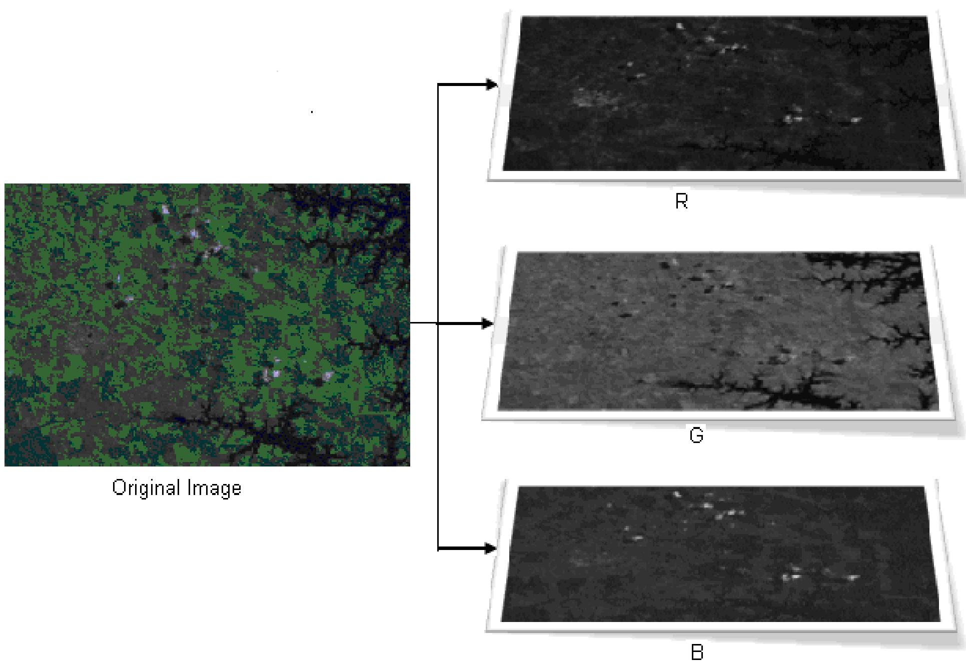

Figure 3. Image split into three bands red (R), green (G) and blue (B) bands.

Figure 4. Sample area for various land classes.

of membership functions in output are carefully selected, it leads to a tremendous rise in accuracy. A better arrangement will be, to put membership functions in the output, adjacent to each other if their input membership functions are close or overlapping. Which had been done and rise in accuracy with the same rules is shown in Table 4. The concept was implemented on multi spectral data lines with the spectral pattern (set of radiance measurement obtained in the various wavelength bands for each pixel) used as the numerical basis for categorization using the notion of the normalized fuzzy matrices. This can be implemented with Mamdani-type or Sugeno-type fuzzy inference techniques (Mamdani being implemented in the paper). The method has been implemented by incorporating the suggested fuzzy logic-based representations with assumptions that the fuzziness of all the optimization formulation parameters are true and only spectral and radiometric characteristic of image pixels being considered without using any geometrical and topological relation between the pixels. Finally, changes were made in the arrangement and type of membership function to analyse the variable effects of these changes on the output. The results obtained clearly demonstrate the consistency and robustness of the developed approach.

A fuzzy set is a set of ordered pairs which is given by A= ((x, μ_A(x)): x϶X), where X is a universal set and $\mu_A(x)$ is the grade of membership of the object x in A (usually $0 \le \mu_A(x) \le 1$). A membership function $\mu_A(x)$ is characterized by μ_A: X → (0, 1) where X is the universe of discourse, x is a real number describing an object or its attribute and each element of X is mapped to a value between 0 and 1. A membership functions allow us to graphically represent a fuzzy set. The various membership functions used in our classification method d can be represented as shown in Figure 4; where c_i and σ_i^2 are the centre and width of the ith fuzzy set A^i respectively.

CLASSIFICATION METHOD

The intent of the classification process was to categorize all pixels in a digital image into one of several land cover classes or themes. This categorized data can then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and indeed, the spectral pattern present within the data for each pixel was used as the numerical basis for categorization. With the help of already known (mapped) sample area the range of values for input membership functions of FIS can be determined which was used in constructing rules. After pre-processing of the image like removing noise and contouring the area under investigation, FIS (fuzzy inference system) with the names of each input variable (red (r)), green (g), and blue (b)) and those of output variable (q) was created using rules. Mamdani's fuzzy inference method is the most commonly used fuzzy methodology and it expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzification. Sugeno -type system can be used to model any inference system in which the output membership functions are either linear or constant. Here Mamdani type inference system was used. Figure 5 shows a Mamdani fuzzy inference system. It shows a simple diagram with the names of the input red (r), green (g) and blue (b). In each of the input we defined 5 membership functions (mf) because we wanted to classify the image into 5 different land classes (mf1 (water body), mf2 (clouds), mf3 (forest), mf4 (pasture), mf5 (urban)). Here we use the Gaussian/trapezoid/triangular curve for each membership function to study the effects on result. Mfl represents membership function for water body in red input variable. Again we define mf1, mf2, mf3, mf4 and mf5 in each of the other two bands for land classes. The range here lies from 0-255 for each membership function as true colour image was used. The range will vary according to image obtained from respective satellite. Based on the descriptions of the input (red, green and blue) and output variable (5 for each land class) the rules were constructed in the rule editor. Rules are defined as: IF (red is mf1) and (green is mf2) and (blue is mf3) then class (output) is mf4 (here mf1,mf2,mf3,mf4 are used asan example). The inputs were connected with AND function. By using IF-THEN rules and changing the order and type of various membership functions, we obtained different result having different accuracy.

RESULTS

The Mamdani fuzzy logic system was applied to classify the image into 5 land classes and the accuracy was determined. The type and position of output membership functions were changed to analyse changes in the result. First the input membership function of water body was

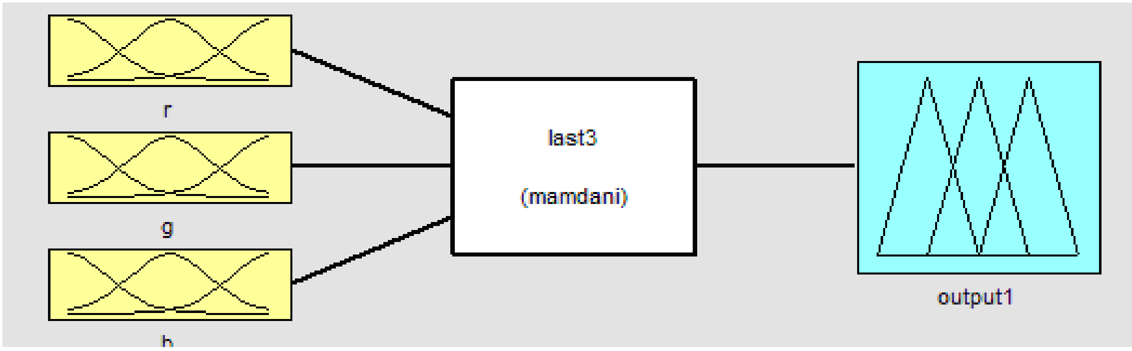

Figure 5. Mamdani FIS.

Table 1. Input range for RGB component for various classes.

Class	Max –min value for input band red	Max -min value for input band green	Max -min value for input band blue
Sea/water	11 to 0	12 to 8	45 to 30
Cloud	190 to 140	160 to 25	245 to 205
Forest	30 to 10	75 to 50	50 to 35
Pasture	50 to 30	110 to 90	65 to 40
Urban	120 to 75	90 to 60	98 to 70

changed while keeping all the other input membership function same and the result were studied.

Total number of pixels in image 781 × 671 = 524052

Table 1 shows the loss of pixels that is misclassification when membership functions were changed. The loss (misclassification) is very high in case of trapezoidal membership function.Losses were measured taking number of pixels for waterbody in case of output for gaussmf case as the base.

From the output obtained as shown in Figure 6, it was clear that in other cases original water body pixels were wrongly classified as other land classes. Although membership functions like triangular and trapezoidal gave sharper edges but the loss of pixel that is classification error was clearly visible in case of trapezoidal and triangular membership functions. Since only input membership function for waterbody was changed, the effect on the other classes was minimal. On modifying the arrangement of membership functions and keeping the rules same, different results were obtained. In first attempt of classification, the forest and the pasture land classes, which had input membership functions having values which were very close to each other, in one or the two bands, membership function in the output for these land classes were not placed adjacent to one another.

Figure 7 shows rule editor of first case in this arrangement mf4 which represent urban land class was placed between forest (mf3) and pasture (mf5) land class which have very similar input values in one or two bands.

Figure 8 shows the output for this (first) arrangement. The misclassification in the case of urban land class was clearly visible. Many of the pixels which were pasture or forest were misclassified under urban land class.

Table 2 shows the colour taxonomy, the yellow colour was used to depict pasture similarly green for forest, blue for water body, white for clouds and red for urban.

In the second case two closely related membership functions were placed adjacent to each other and the unrelated membership function was not placed in-between them.

Figure 9 shows forest (mf3) and pasture (mf4) land class placed adjacent to each other and the urban (mf5 here) membership function, whose input range was not overlapping in any of the bands of input mf of forest and pasture, was not placed in-between them.

Figure 10 shows the result of the second arrangement. The improvement in classification was clearly visible. Original pasture and forest class pixels were not misclassified as urban. The change in arrangement did not affect the output for two other land classes- clouds and waterbody. Idea for accuracy assessment methods of classification results comes from the selecting random sample with known classes and then let methods ‘say’ what these samples are. With 100 random selected samples, Table 3 shows the comparison of two arrangements.

100 samples from the output of two arrangements were

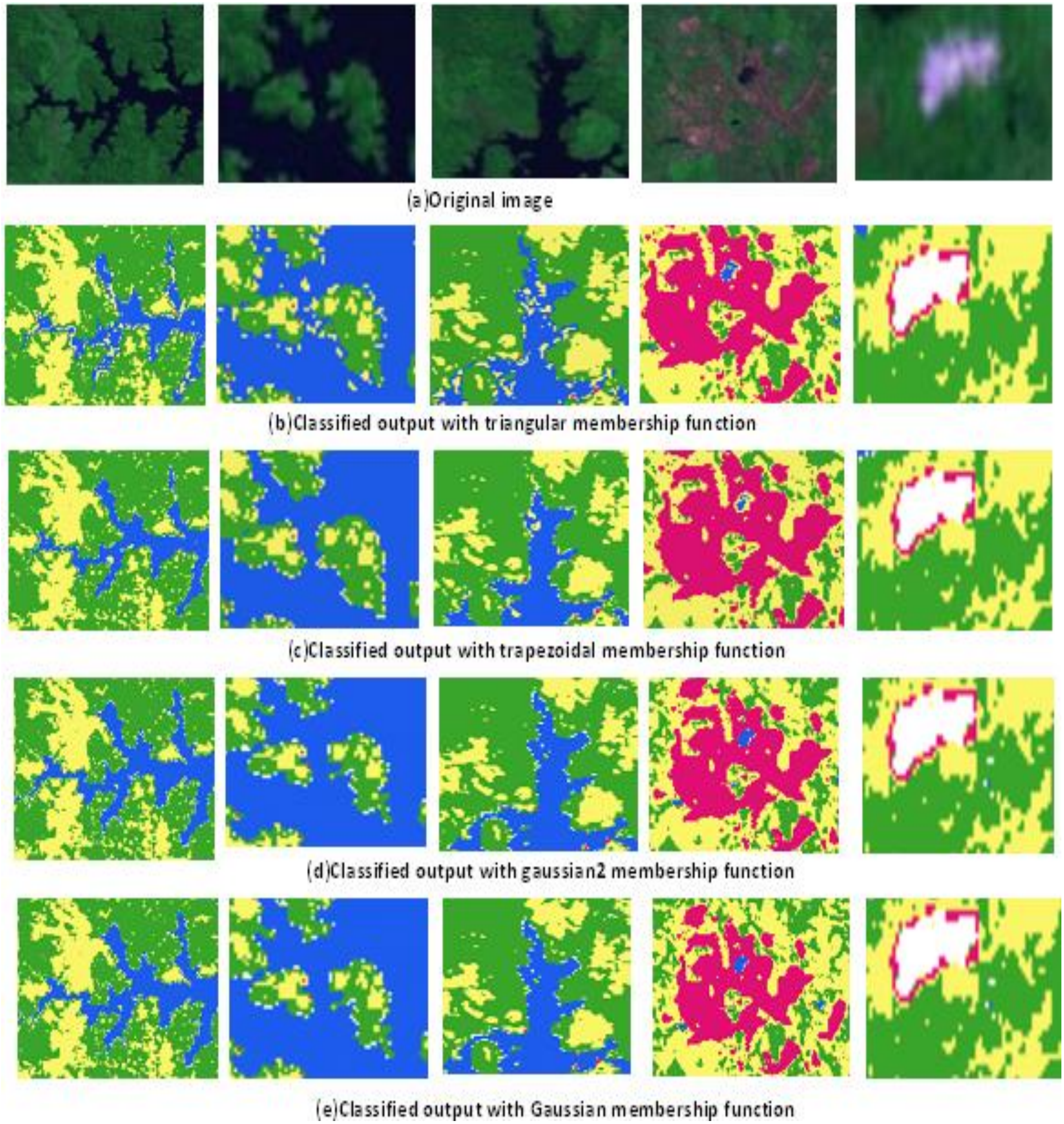

Figure 6. Classified results obtained using various membership functions.

taken and they were verified with the original image. The accuracy obtained in the first arrangement was 43% whereas the same for second arrangement was 87%.

Conclusion

The positioning of membership functions have a close

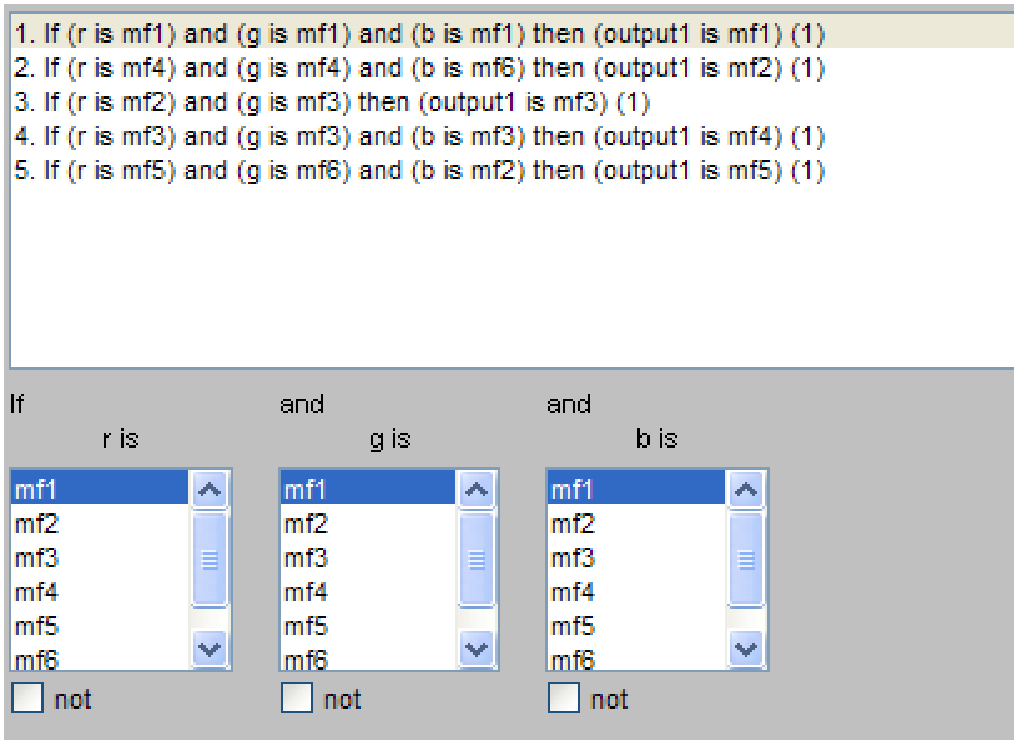

Figure 7. Urban mf placed in between forest (rules).

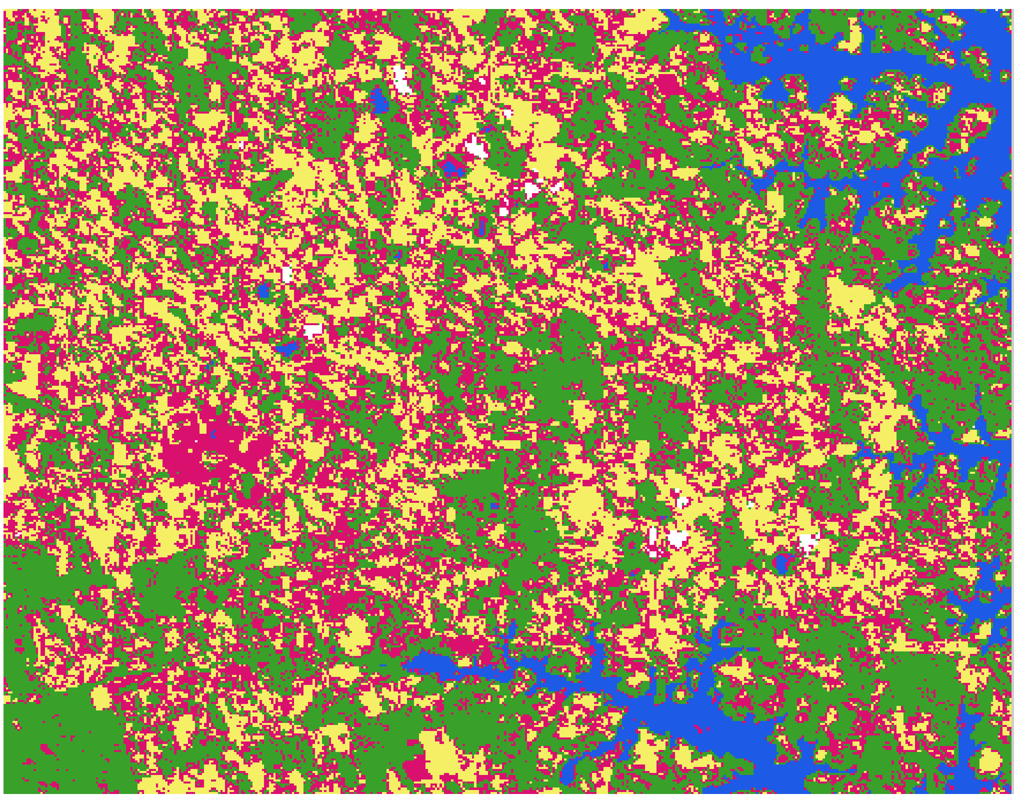

Figure 8. Output of 1st arrangement.

Table 2. Results of classification with different membership functions.

Membership function for waterbody	Number of pixel in classified as waterbody	% of total pixel as waterbody	Loss % as compared with gaussmf
Gaussmf	49095	9.36	-
Trapmf	35687	6.81	27.31
Gauss2mf	38098	7.27	22.39
Trimf	39827	7.60	18.87

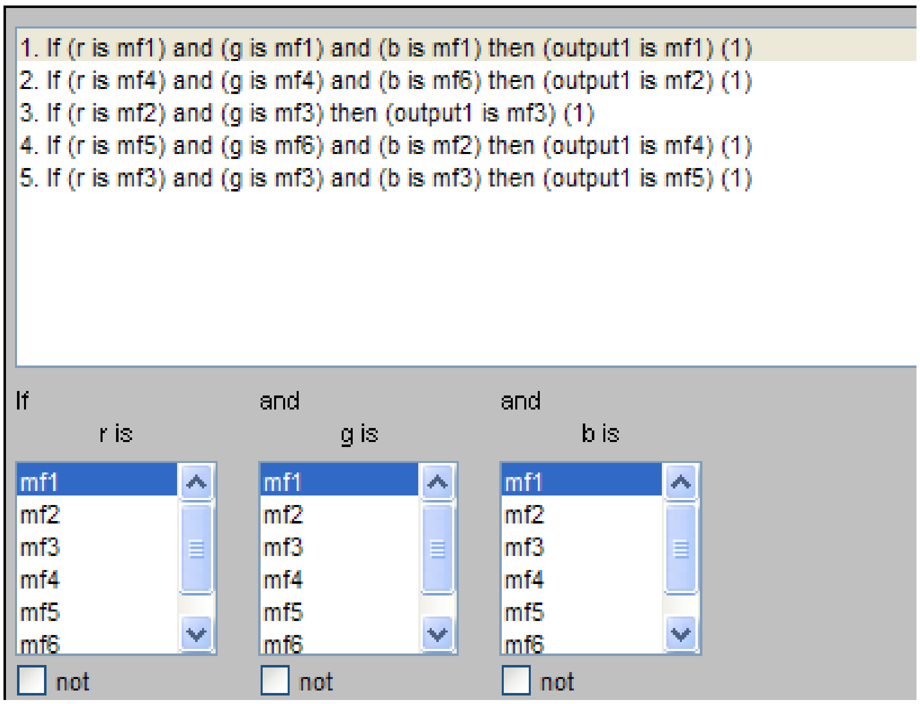

Figure 9. 2nd arrangement; urban mf placed after pasture (rules).

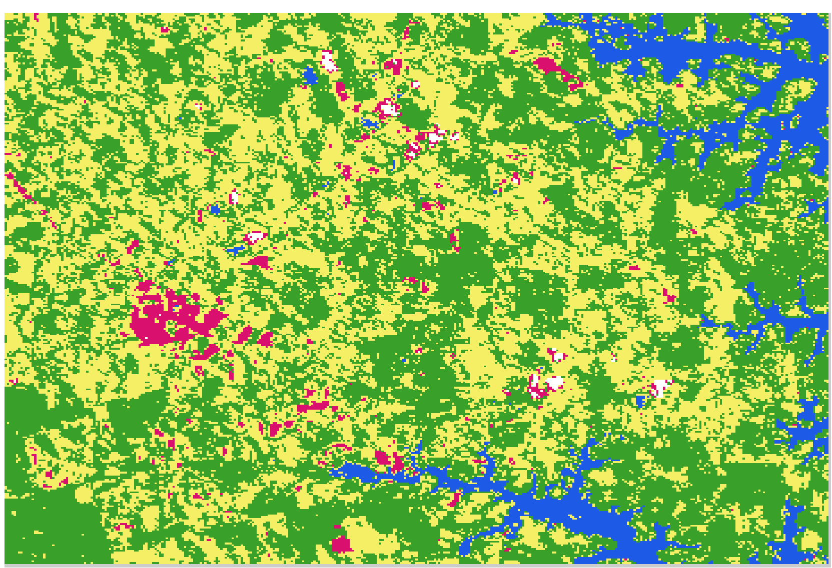

Figure 10. Classified output of second arrangement.

Table 3. Colour legend for the output image.

Yellow	Pasture
Green	Forest
Blue	Water body
White	Clouds
Red	Urban

Table 4. Comparison of arrangement of membership function.

Arrangement of membership functions	Correctly classified sample	Misclassified sample	Accuracy (%)
1st arrangement	43	57	43
2nd arrangement	87	13	87

relationship with accuracy of classification if output membership function of classes which are having input membership function overlapping or close to each other triangular lead to misclassification and loss of data of a particular class. Hence, Gaussian membership function appeared to be the best choice.

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