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ΣΕΙΡΑ ΕΡΕΥΝΗΤΙΚΩΝ ΕΡΓΑΣΙΩΝ

QUALITATIVE AND SPATIAL COMPARATIVE STUDY OF SATELLITE IMAGES CLASSIFIED BY SUPERVISED AND FUZZY LOGIC BASED CLASSIFICATION ALGORITHMS: A case study in Kilkis perfecture, Central Macedonia, Greece

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QUALITATIVE AND SPATIAL COMPARATATIVE STUDY OF SATELLITE IMAGES CLASSIFIED BY SUPERVISED AND FUZZY LOGIC BASED CLASSIFICATION ALGORITHMS: A case study in Kilkis prefecture, Central Macedonia, Greece

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Abstract: In a first stage a SPOT image of the survey area was classified for land use/land cover classification, using the Maximum Likelihood Algorithm (MLC). However, due to the spatial uncertainty which exist mainly between the borders of the spectral categories, as they defined by MLC, in a second stage a supervised classification based on fuzzy classifiers was applied. A sigmoid function defines the degree which every pixel belongs in each category and differentiates the results of the classification in comparison with those of the classical Boolean logic. The results of the fuzzy classification leads to the construction of another land use/land cover map. For reasons of comparison between the two methods, the results of each classified category in both methods was converted to an integer binary image. As qualitative index of agreement between the two methods, the Kappa index of agreement and for each category was used. The results are evaluated with field work.

Keywords: Satellite Image, Maximum Likelihood, Fuzzy, Classification

1. INTRODUCTION

The mixed various land cover types which are often obtained in nature led the researchers to develop other classifiers than the hard ones which are used for the last twenty years in remote sensing community. The discovery of fuzzy sets by Zadeh (1965, 1968) had the purpose to quantitatively analyze complex systems, which are characterized by imprecision and fuzziness.

Zadeh defined as fuzzy set (class) of points A from a space of points X (where the generic element is denoted by x, which means X = {x}) a class which is characterized by a membership function $f_A(x)$ and in which class every point is associated with a real number between 0 and 1 through the membership function. Thus, it can be said that any point of space X belongs, through a membership value, to class A. For the elements of X, which have absolutely no relation with class A, the value of the membership function is 0 and those which belong absolutely to class A is 1. The application of this concept in the analysis of digital satellite imageries and more specific in image classification, has been tested in various ways since then.

More specifically, if we assume the space of points X as a set of pixels of an image and class A as a land cover category, whose boundaries as well as it's pixels are mixed, then a fuzzy classification of this image will give as a result as many images as the required categories. Each image-result will characterize all the pixels of the original image from the point of the grade of membership in the specific category, which varies between 0 (for the total allien for the specific category pixels) and 1 (for the pixels that belong absolutely to the specific category).

In the category of the unsupervised classifications Bezdek et al. (1984) suggested an algorithm, with the corresponding Fortran program, for the automatization of the fuzzy cluster classification, while Key et al. (1989) applied the MLC to NOAA data with AHRR scanning radiometer for cloud classification. The same authors suggest the partition coefficient

$$F = \sum_{i=1}^{c}\sum_{k=1}^{n}(u_{ik})^2 / n$$

and entropy H

$$H = -\sum_{i=1}^{c}\sum_{k=1}^{n}(u_{ik}\log_a u_{ik}) / n \qquad 0<\alpha<\infty$$

for the validity of the results, where the fuzzy c-partition space is following Bezdek

$$M = \{U:\ u_{ik} \in [0, 1];\ \sum_{k=1}^{n} u_{ik} > 0,\ i = 1\ldots c;\ \sum_{i=1}^{c} u_{ik} = 1,\ k = 1, \ldots n\}$$

where U is a fuzzy c-partition of a sample of n observations and c clusters, and the elements of U, u_{ik} are the membership values of a particular observation x_k in the i-th fuzzy group. The length of vector x_k is p, where p is the number of spectral channels.

However, in the category of the supervised classifications the problem of differentiating between classical and fuzzy classification should be checked in three different levels :

1. The level of the classification algorithm.
2. The level of estimations of the statistical parameters, which are used in the classification algorithm and which are estimated from the ground truth data.
3. The level of mixed pixels.

In these perspective, a number of papers have been published using fuzzy supervised classification algorithms, but all of them assumed that ground truth were absolutely pure for the estimations of the parameters that are needed for the application of the algorithm. This means that each training site contains pixels that belong to only one class (Kent J.T. and K.V. Mardia, 1988).

Concerning the classical maximum likelihood classification Richards (1986) assumed that the probability distributions for each class are of the form of multivariate normal models. The probability for a pixel x to belong to class w_i is

$$p(x/\omega_i) = (2\pi)^{-N/2}|\Sigma_i|^{-\frac{1}{2}} \exp\{-\frac{1}{2}(x-m_i)'\Sigma_i^{-1}(x-m_i)\} \qquad (1)$$

where m_i is the mean vector and Σ_i the covariance matrix of the data in class w_i.
According to the Bayesian classification rules which states that $x \in w_i$ if $p(x/w_i)p(w_i) > p(x/w_j)p(w_j)$ for all $j \neq i$, where x is the column vector of radiometric values for a pixel in the multispectral space, w_i a given spectral class and $i = 1,\ldots M$ the total number of classes.

Obviously the training data are homogenous and they are used to estimate the parameters of the maximum classifier algorithm to be used like the mean vector and the variance.

Unlike Kent and Mardia (1988), Wang (1990) introduces the concept that fuzzy parameters contribute significantly to the accuracy of MLC and supports that the membership grade for a pixel to belong in a certain class of land cover is proportional to the percentage to which the pixel contains this land cover class.
Fisher and Pathirana (1990) found that the proportion that Wang (1990) describes, fits best to well defined land cover classes in comparison with the less defined classes, and that the relationship in all cases is statistically significant.

2. THE SURVEY AREA

The survey area is located N.W of the city of Thessaloniki, Central Macedonia, Greece and it is characterized by a hilly landscape and narrow alluvial plains of Axios and Gallikos rivers (**Figure 1**). The vegetation cover consists of agricultural crops mainly winter wheat in the hilly areas, irrigated crops in the alluvial plains and patches of natural and semi-natural vegetation. The complexity of the land cover creates serious classification problems andsignificant number of unclassified and misclassified pixels.

Figure 1. Location map of the survey area.

3. METHODOLOGY

This paper, except from it's research aspect, performs a comparison between hard and soft classifiers, which are based on the double consideration of the test-sites for the creation of spectral signatures for each land cover category. The land cover categories of the survey area are six : water, natural vegetation, irrigated areas, good and poor developed wheat and urban areas.

The double consideration of the spectral signatures for every one of the six categories is based on the fact that the same test sites were used on one hand for the MLC as homogeneous for the category that each pixel represents and on the other hand for the fuzzy classification, as almost homogeneous with relatively small percentages of the other categories in each pixel. In **Figure 2** a color composite image of the survey area with the test sites on is shown.

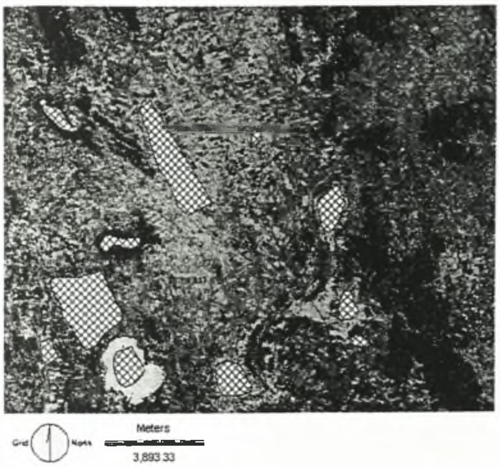


Figure 2. Composite image of the survey area with the test sites

Table 1 shows the conciseness of test sites (columns) for every one of the six land cover categories (rows). IDRISI program was used as well for the MLC as for the fuzzy supervised classification. The result of the application of MLC is shown in **Figure 3**.

Table 1. Conciseness of test sites (columns) for every one of the six land cover categories (rows)

A	B	C	D	E	F	G
1	0.95	0.01	0.02	0.01	0.01	0
2	0.02	0.89	0.02	0.02	0.02	0.03
3	0.05	0.02	0.85	0.04	0.04	0
4	0.01	0.02	0.04	0.9	0.03	0
5	0.01	0.02	0.01	0.03	0.9	0.03
6	0	0.1	0	0	0	0.9

where :
A : test site id
B : water
C : natural vegetation
D : irrigated areas
E : good growing wheat
F : poor growing wheat
G : urban areas

Following Wang (1990), in order to perform a fuzzy partition in a spectral space a membership function must be defined for each class. Instead of using the conventional mean m_i and the conventional covariance matrix Σ_i the fuzzy mean

$$m_c^* = \frac{\sum_{i=1}^{n} f_c(x_i)x_i}{\sum_{i=1}^{n} f_c(x_i)} \qquad (2)$$

and the fuzzy covariance matrix for the class c

$$\Sigma_c^* = \frac{\sum_{i=1}^{n} f_c(x_i)(x_i - m_c^*)(x_i - m_c^*)'}{\sum_{i=1}^{n} f_c(x_i)} \qquad (3)$$

where n is the total number of sample pixel measurement vectors.
The membership function for the cover class c is defined as follows :

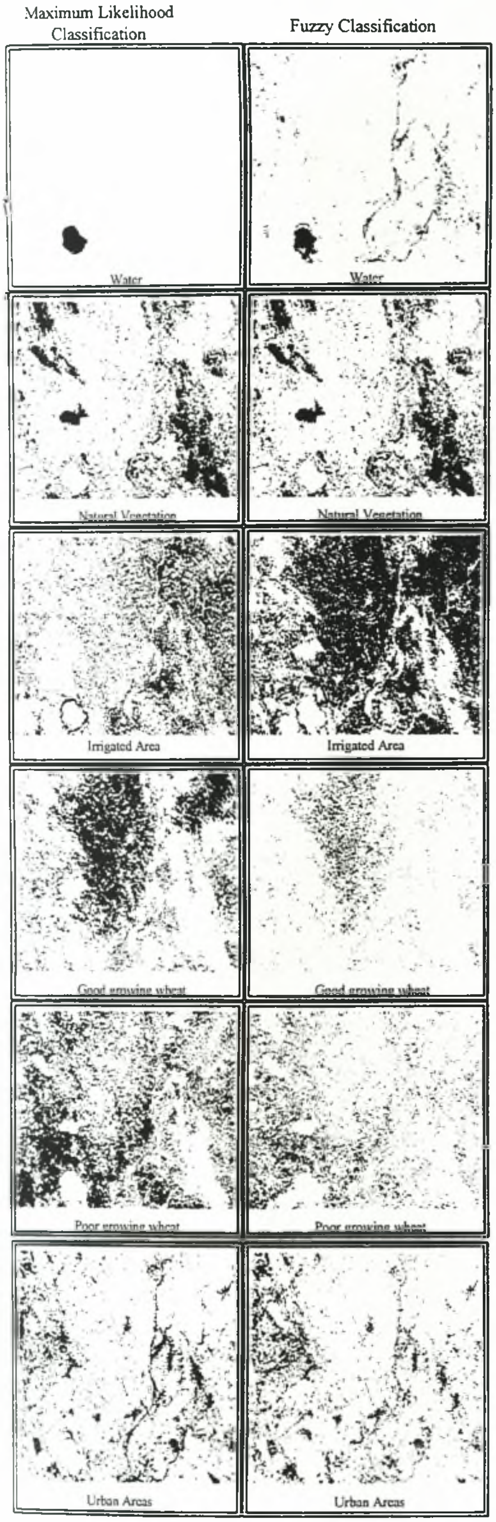
$$f_c(x) = \frac{P_c^*(x)}{\sum_{i=1}^{k} P_i^*(x)} \qquad (4)$$

where $P_i^*(x)$ according to (1) becomes

$$P_i^*(x) = (2\pi)^{-N/2} |\Sigma_i^*|^{-\frac{1}{2}} \exp\{-\frac{1}{2}(x - m_i^*)'\Sigma_i^{*-1}(x - m_i^*)\} \qquad (5)$$

where N is the dimension of the pixel vectors (number of channels) and k is the number of predefined classes $1 \leq i \leq k$.

After the application of the above mentioned fuzzy classification method at the study area, six images arisen for each of the predefined land cover categories-classes. Every one of them and according to the definition of fuzzy classes by Zadeh (1965) has the dimensions of the study area and all of their pixels are characterized by a
number between 0 and 1, which represents the grade of membership of pixel in the specific class.



Water cross-tabulation of maxlike (columns) against fuzzy (rows)

	0	1	Total
0	724968	1380	726366
1	16081	6532	22613
Total	741067	7912	748979

Overall Kappa : 0.4189

Nat. vegetation cross-tabulation of maxlike (columns) against fuzzy (rows)

	0	1	Total
0	582036	16501	598537
1	48772	101670	150442
Total	630808	118171	748979

Overall Kappa : 0.7048

Irr. areas cross-tabulation of maxlike (columns) against fuzzy (rows)

	0	1	Total
0	380015	53875	433890
1	225288	89801	315089
Total	605303	143676	748979

Overall Kappa : 0.1738

Good wheat cross-tabulation of maxlike (columns) against fuzzy (rows)

	0	1	Total
0	572576	145618	718194
1	479	30306	30785
Total	573055	175924	748979

Overall Kappa : 0.2401

Poor wheat cross-tabulation of maxlike (columns) against fuzzy (rows)

	0	1	Total
0	528572	149585	678157
1	8718	62104	70822
Total	537290	211689	748979

Overall Kappa : 0.3471

Urban areas cross-tabulation of maxlike (columns) against fuzzy (rows)

	0	1	Total
0	642454	37045	679499
1	14918	54562	69480
Total	657372	91607	748979

Overall Kappa : 0.6394

Figure 3. Binary images-results of both methods and corresponding cross-tabulation.

4. RESULTS AND DISCUSSION

The adopted assumption, concerning the mixed pixels, shows that all the pixels with membership function value ≥ 0.5 in each fuzzy class belong to this class. This assumption, in comparison with the measures of information closeness, which are used by Foody (1996) or even the classical measures of attribution fuzziness proposed by Maselli (1996) as Relative Probability Entropy (RPH) leads to the realization of comparison between hard classification methods (MLC) and soft classifiers (fuzzy) using the Kapa index of agreement.

By isolating every class resulted from MLC and fuzzy classification two comparable binary images are created. The binary classification image from the fuzzy classification is resulted according to the assumption that every pixel with value ≥ 0.5 takes the value 1 and every pixel < 0.5 takes the value 0. These images spotlight the spatial distributed pixels that belong to each class and have the value 1, while every other pixel has the value 0.

Figure 3 shows two binary images for every category that resulted from the two classification methods and the corresponding one crosstabulation that indicates the common classified pixels as well as those which are appended or subtracted from every category.
Additionally, the value of the Kapa index of agreement for every land cover category is presented.

The results show that K-Index is higher in the categories that are considered as the most homogeneous. The highest coincidence of the two methods according to Table 1, shows that the percentage of existence of homogeneous per category pixels is high. According to field work, especially for the categories of water and urban, certain set of pixels are homogeneous, which means that the existence of mixed pixels is reduced.

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