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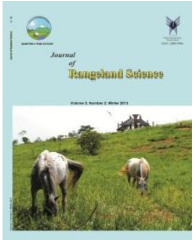

Full Length Article:

Study on the Trend of Range Cover Changes Using Fuzzy ARTMAP Method and GIS

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Abstract. The major aim of processing satellite images is to prepare topical and effective maps. The selection of appropriate classification methods plays an important role. Among various methods existing for image classification, artificial neural network method is of high accuracy. In present study, TM images of 1987, and ETM^+ images of 2000 and 2006 were analyzed using artificial fuzzy ARTMAP neural network within Mehrgan region, Kermanshah province, Iran, with an area of 5957 ha changes in range cover state in this basin during 3 periods of time from 1987 to 2000 and 2000 to 2006 were examined. In this study, initially, Land sat data for intended years were corrected geometrically and radiometric ally. Next, different land use classes were defined and training samples obtained via field visits. The obtained results show that, over time period of 1987-2000, the extent of low-density rangeland and farmland in study region had been increased by 89.09 and 321.08 ha, respectively, while good rangeland and fair rangeland faced a declining trend of 358.29 ha and 48.89 ha. Also, during time period of 2000-2006, the extent of poor rangeland and farmland within study region has increased by 64.98 and 727.12 ha, respectively, while good rangeland and fair rangeland faced a declining trend of 144.01 ha and 648.1 ha. Accuracy of vegetation maps resulting from satellite data classification using algorithm of artificial fuzzy ARTMAP neural network was 90.97% and 94% for TM (1987) images and ETM^+ (2000,2006) respectively which indicates high accuracy of ARTMAP algorithms for classifying satellite. Therefore, this study proves high efficiency and potential of artificial fuzzy ARTMAP neural network for classification of remote sensing images.

Key words: Fuzzy ARTMAP, GIS, Landsat, Cover change, Change detection, Mehrgan, Kermanshah

1. Introduction

Under hard conditions due to the lack of access to some mountainous and desert areas, having access to information on ranges at vast levels is a good justification for using remote sensing technique capable of producing information necessary to assess vegetation and to take an appropriate management practice in all regions. Given that Iran enjoys mostly arid and semi-arid climatic conditions and that 54% of its land is covered by ranges (Mesdaghi, 1995), to apply satellite data to the field of studying vegetation requires development of models specific to this type of climate. the capacity of Geographic Information System (GIS) for integrating data layers resulting from field operations, and/or from remote sensing is higher than that of traditional methods, and it is obvious that its results are more expressive and accurate (Farzaneh, 1992). In addition having updated information about land cover, and having knowledge of its changes during one period of time is also important to planners and managers (Tachizuka *et al.*, 2002). Methods of revealing changes are divided into 2 categories: the first one includes those methods providing no information about the nature of changes, finally, resulting in a binary image, and only distinguishing changes from non-changes, not dealing with changes nature. Image subtraction is among these methods. The second one includes those methods showing nature of changes in addition to their magnitude, of which method of post-classification comparison is the most common (Jensen, 1996). Major aim of processing satellite images is to prepare topical and effective maps for which selection of proper classification methods plays an important role. In order to develop advanced methods and techniques of classification, researchers have made broad and extensive efforts to improve classification accuracy, among them artificial neural network can be mentioned (Arekhi & Nyazi, 2011). Among different methods of classifying images, classification by artificial neural network has a high degree of accuracy. This method is considered as invaluable tool for classifying applications because it has made no presupposition on data distribution. For this reason, development of classification models with neural networks has attracted researchers' attention in recent years (Irmak *et al.*, 2006; Subramaniana *et al.*, 1997). There are different types of methods of artificial neural network for classifying land use and cover, of which fuzzy method is a new one that used to do classification (Wijaya, 2005; Gahegan *et al.*, 1999). Fuzzy set theory is a hypothesis for taking action under uncertain conditions. This theory is capable of listing many inaccurate and vague concepts, variables, and systems of providing grounds for expression, conclusion, control, and decision-making under uncertain conditions (Wang, 1990).

Many studies and efforts have been done in the field of classifying multispectral images in order to map vegetation and land use. Using LISS-III sensor of satellite IRS-IC, Sugumaran (2001) compared methods of neural net classification and maximum likelihood for classifying forest land. Results showed that artificial neural net method out per-formed slightly better in separating water and hand-planted forest, but made no significant difference in the classification of natural homogenous forests (Sugumaran, 2001). Del Frate *et al.* (2005) used method of artificial neural network to classify urban areas, and reveal their changes. Jianjun *et al.* (2005) employed post-dissemination algorithm and neural net method to classify cover and use of Zyian city. They introduced 6 spectral bands of TM/ETM images to neural network as inputs and classified the region into 6 types of land cover and land use. Tapiador and Casanova (2003) prepared land use map of Segovia, Spain. In their research, they had used cartographic vector information, Landsat TM and IRS-ID satellite, and images along with a set of aerial photographs. All information was entered into Geographic Information System (GIS). Data Fusion method was used to improve image resolution power and neural net method was used to perform classification appropriately. (Tapiador and Casanove, 2003). In order to classify land cover and use in Terminus region located in southeastern Mexico, Mas (2003) used multilayer perceptron (MLP) network of post-dissemination algorithm. Spectral bands 2, 3, 4, 5, and 7 of Landsat ETM$^+$ sensor were set as inputs of neural net and 6 categories of land cover were prepared as outputs. Classification accuracy was reported at 82%. Amiri *et al.* (2007) used 3 fuzzy neural network, and minimum distance methods to classify satellite Quick Bird image into 3 classes of vegetation, urban area, and water. They concluded that compare to 2 other methods, neural net classification was of higher accuracy for study region. Hosseini *et al.* (2003) also used methods of artificial neural network and maximum likelihood to classify IRS-ID images for a region in north of Iran. Pal and Mather, (2003) found out that neural net method was more accurate than maximum similarity method so that 78.5% and 86.19% were obtained for accuracy of maximum likelihood and artificial neural net methods, respectively. The aim of this research is to examine the trend of range cover changes and the effectiveness of artificial fuzzy ARTMAP neural net method in order for land use maps to be prepared by using remote sensing technique and Landsat satellite images.

2. Materials and Methods

2.1. Region situation

Under-study region of Mehrgan, Ravansar, having an area of 5957 ha is situated almost in the east of Ravansar city about 3 Km apart. It is 62 Km apart from capital of the province of Kermanshah. Study region is at North latitude of 34° 45' 05"- 34° 39' 15" and East longitude of 46° 41' 07"- 46° 46' 53", which is a part of aquifer basin of Gharahsu River, of sub-basins of Gamasyab River and Karkhe Olia branch-head (Fig. 1). According to Ambrezhe method, Mehrgan region has humid cold climate. Average annual rainfall was estimated at 664.7 mm for study region, the amount of which increase as elevation increases. Maximum amount of rainfall is observed during months of January, February, and March. Most of rainfall occurs in winter and the least amount of it occurs in summer. For study region, average annual temperature is 11.5°C. Image processing and ground step's data were integrated with satellite data (Fig. 2).

Fig. 1. Location of study area

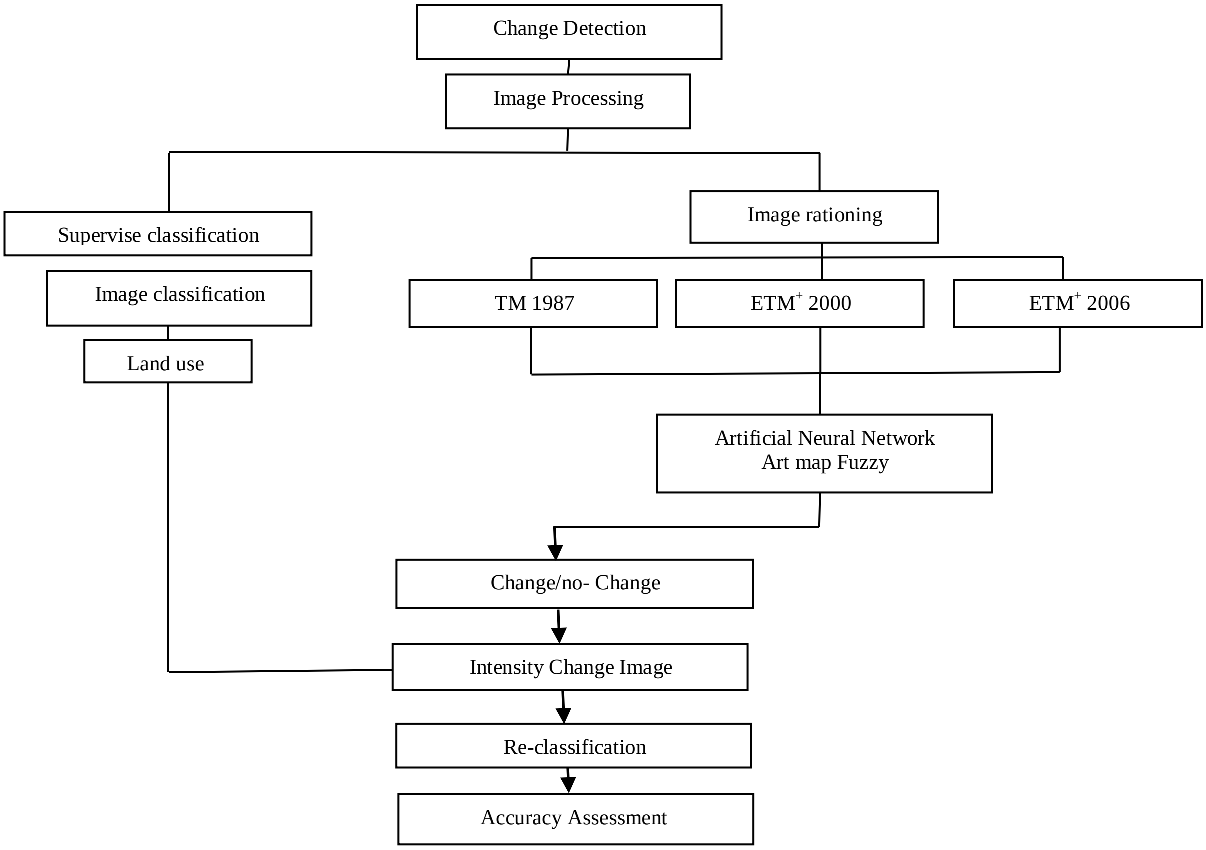

Fig. 2. Flow chart of research process

2.2. Used data

Used data in this research includes Landsat TM images dated on 09, 05, 1987; Landsat ETM$^+$ images dated on 05,06,2000 and 05,06,2006 related to the path 167 and row 36; topographic digital and paper 1:25000 maps from Cartography Organization and other digital and printed information existing for the region; IDRISI and ENVI 4.5 software of Remote Sensing; and ArcGIS10 software of Geographic Information System.

2.3. Preparing images

In order to prepare images, they were initially corrected geometrically and Radiometric. At first, geometric correction was performed by using ground control points (30 points) from topographic maps and by using global positioning system.

Resulted Errors for images 1, 2, and 3 were 0.51, 0.49, and 0.50 pixels, which are highly desirable. In the next step, images were justified and turned northward by resampling with the nearest neighborhood method. In the next step, radiometric corrections were performed on images, which is necessary for remote sensing. Elimination of climate ill effects is more felt when the aim is to compare some multi period images (Mesgari, 2002). In order to correct images Radiometric, Chavez's method including dark object subtraction (dark pixel value subtraction) was used. The values of dark pixel in images were reduced in order to have high accuracy for classification process (Chavez, 1996).

2.4. Image classification

Satellite information classification means to separate similar spectral sets and to divide categorically those which have the same spectral behaviors. In other words, to classify pixels constituting images, to assign or introduce each of pixels to a particular class or phenomenon is called satellite information classification (Alavipanah, 2005). In satellite images classification, pixels having the same values fall in one group. Classification of satellite images is performed either in unsupervised or supervised form. In supervised classification, training samples are used to classify pixels, that is, by defining specified pixels in images for each of classes; the task of classification is carried out in the form of intended classes. In this study, the method of correlation between bands, false color composite 432 was used and created for years of 1985 and 2007 and supervised classification of artificial fuzzy ARTMAP neural network was performed. According to research aim and the types of cover existing in the region, 4 classes were identified, including dense, fair rangeland, poor rangeland and farmlands.

In order to test classification accuracy, some comparison were made with available use maps as well as field visits, that is, using other methods like field visit, reference map or ground reality were made for all parts of under-study region perfectly. It was said that typical ground reality map was prepared for about 2.78% of the region area (Table 1 and Fig. 3).

In this step, ground reality map was prepared by field survey with randomly classified sampling method. After matching produced map with ground reality one, points were determined randomly on it and all points' coordinates were exploited by GPS with field operations (Table 2). In order to examine accuracy of image classification, using test samples, it was attempted to calculate accuracy by making use of error matrix and calculation of statistical parameters such as total accuracy Kappa Coefficient, accuracy of producer and of user. Next, majority filter was exercised in order to obtain a smooth image and to delete distributed pixels on images resulting from classification. An obtained result is presented from classification (Figs. 6-8).

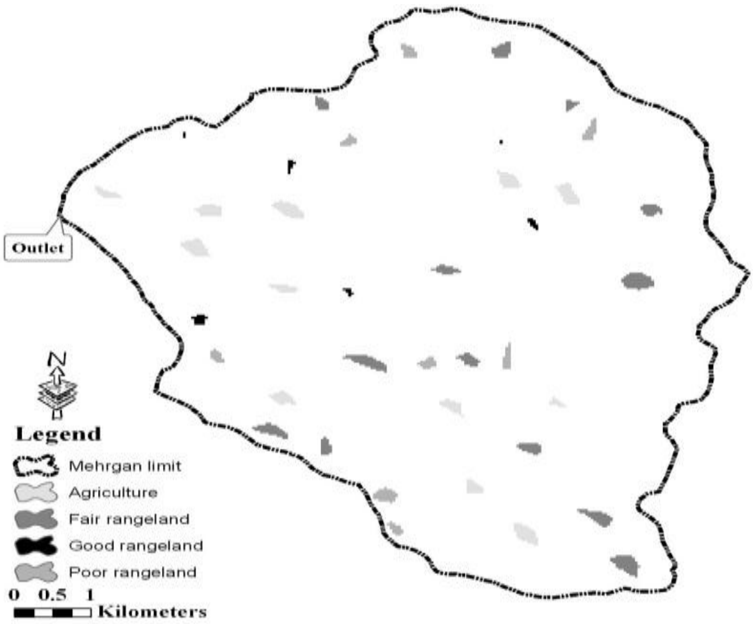

Fig. 3. Map of ground reality points

Table 1. Area of ground reality points

Land Classification	Area (ha)	Area (%)
Good rangeland	10.55	0.18
Fair rangeland	62.41	1.04
Poor rangeland	29.33	0.49
Agriculture	64.2	1.07
Total	166.49	2.78

Table 2. Characteristics of points exploited from field visits

Transects No.	X (UTM)	Y (UTM)	Land Use	Height (m)	Slop (%)	Aspect	Erosion Rates	Litter (%)	Stone and Gravel (%)	Bare Soil (%)	Vegetation (%)
15	661648	3843645	Poor rangeland	1684	10	North East	Rill	9.4	28.0	38.6	23.95
18	658530	3844763	Poor rangeland	1648	25	North East	Rill	11.5	29.3	38.0	21.20
21	656333	3843929	Poor rangeland	1446	30	North West	Surface	8.4	20.8	32.2	38.65
5	660110	3838427	Fair rangeland	1583	30	South West	Surface	6.5	22.3	26.0	45.20
7	657938	3842845	Fair rangeland	1447	5	Southwest	Rill	11.9	21.0	25.5	41.70
8	659985	3842710	Fair rangeland	1550	20	South West	Surface	2.6	26.2	31.8	39.40
9	660326	3842602	Fair rangeland	1578	20	South East	Surface	1.3	24.2	30.5	44.01
11	660910	3842503	Fair rangeland	1618	25	South West	Rill	0.0	8.5	11.0	80.50
13	660218	3844067	Fair rangeland	1576	25	North East	Surface	8.7	16.0	28.2	47.15
17	659468	3845762	Fair rangeland	1786	35	North West	Rill	9.4	21.7	32.2	36.75
24	656930	3839701	Fair rangeland	1546	15	South West	Sheet	1.8	26.0	35.0	37.24
25	658580	3840256	Fair rangeland	1497	30	North East	Surface	14.0	19.0	22.4	44.65
26	660454	3839447	Fair rangeland	1551	5	South West	Rill	12.2	16.0	28.4	43.44
27	660918	3839518	Fair rangeland	1595	20	South East	Surface	8.5	22.0	39.0	30.50
29	660117	3840139	Fair rangeland	1605	10	South East	Surface	8.7	15.9	28.8	46.61
30	650117	3840077	Fair rangeland	1537	30	North West	Rill	9.7	18.0	27.6	44.70
1	656200	3841361	Good rangeland	1429	25	South West	Surface	8.0	14.0	9.0	69.00
2	657083	3840460	Good rangeland	1474	30	North East	Surface	4.3	18.1	13.7	64.00
3	658285	3839414	Good rangeland	1510	15	South West	Rill	13.4	10.0	17.0	59.62
4	659054	3838577	Good rangeland	1583	20	West	Sheet	4.9	15.0	20.1	60.00
6	660643	3837762	Good rangeland	1647	10	South East	Rill	3.4	19.1	21.8	55.70
10	660526	3842913	Good rangeland	1562	15	South West	Surface	3.5	11.3	15.3	69.83
12	661257	3842483	Good rangeland	1685	30	South West	Rill	9.2	6.8	12.7	71.40
14	661179	3844160	Good rangeland	1664	15	North East	Surface	7.6	7.0	14.5	71.00
16	659496	3844837	Good rangeland	1627	25	North West	Surface	2.9	12.5	18.0	67.00
19	658059	3844070	Good rangeland	1515	20	North West	Surface	8.6	6.0	10.3	75.03
20	657267	3843709	Good rangeland	1451	30	East	Surface	8.7	6.4	7.0	78.00
22	656324	3841093	Good rangeland	1440	35	South West	Rill	8.6	7.0	9.8	74.65
23	656483	3840497	Good rangeland	1473	25	South West	Surface	1.3	14.1	18.2	66.40
28	660766	3840334	Good rangeland	1671	20	East	Rill	0.0	16.4	28.3	55.24

2.5. Mathematical theory of artificial neural network

Artificial neural network is, in fact, a simplified model of human brain. This network is a mathematical structure which is capable of displaying desired non-linear processes and combinations to establish relationships between inputs and outputs of any systems. This network is trained with available data during learning process and is used to make predictions in future. Neural networks consist of neural cells called neurons and connecting units called axons. In fact, neurons of artificial neural networks are a very simple form of biological neurons. Although artificial neural networks consisting of such neurons have faster speeds than biological neurons do, they possess less capability compared to them. Fig. 4 shows a simple scheme of a neural network model (Menhaj, 2000). As seen from the figure, each artificial neural network consists of 3 input, output, and latent layers (Carvajal *et al.*, 2006)

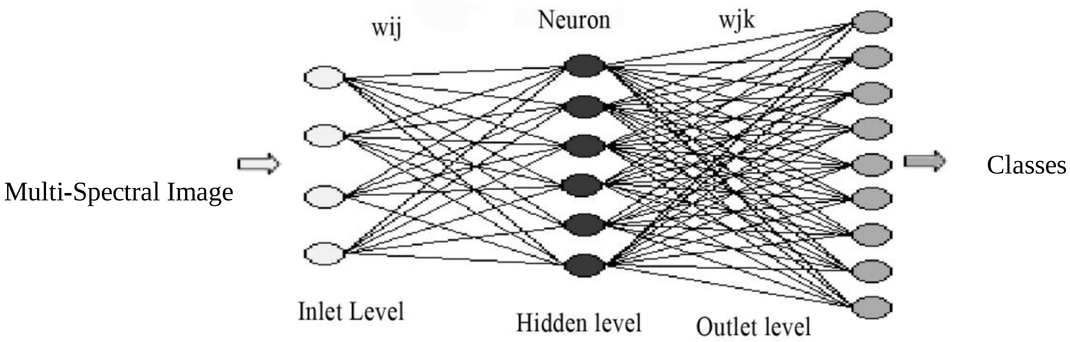

Fig. 4. A simple scheme of neural net model (Carvajal *et al.*, 2006)

On each of these layers, there are a number of neurons as processing units which relate to each other by weighed connections. Operations done within each neuron are as follows:

At first, each neuron collects all inputs arrived at the cell; next, it subtracts neuronal threshold value from that; then, it passes that over a driving or activity function; and finally, it obtains neuronal output. Errors are minimized through some processes. Driving functions are used to transfer outputs of one layer to next ones. Among driving functions, sigmoidal, linear, and threshold ones can be mentioned.

2.6. Artificial fuzzy ARTMAP neural network

Fuzzy ARTMAP is a neural network introduced by Carpenter *et al.* (1991). Artificial fuzzy ARTMAP neural network is based on adaptive resonance theory. Structure of networks based on adaptive resonance theory with supervised training which is known as ARTMAP (Carpenter *et al.*, 1991). The advantage of this method compared with traditional classification ones is that of it's fewer parameters and high speed in processing. (Fig. 5), shows the structure of ARTMAP neural network. Any ARTMAP systems is made of two modules (ART a, ART b) creating stability recognition classes in response to desired tails of input models. These two modules are linked to each other via an interface module called area graph (Fab). Binary ARTMAP employs ART 1 system as modules ART a and ART b while fuzzy ARTMAP takes advantage of fuzzy ART systems for this purpose, that is, operator Ω is replaced, for example, by fuzzy operator (Zadeh, 1965) (Fig. 3). Now, we turn to the examination of theoretical development of fuzzy.

Definition 1- activity vectors: any ART system includes 3 layers: F0, F1, and F2

Layer F0 consists of determinant nodes of current input vector. Layer F1 receives inputs from its lower (F0) and upper (F2) layers. Activity layer F0 is denoted by $I=(I_0,......,I_M)$ and normative I_i components. Activity vectors F1 and F2 are denoted by $x=(x_1,......,x_M)$ and $y=(y_1,......,y_M)$, are shown.

Definition 2- weight vector: for each node specifying some category in layer F2, weight vector $w_j=(w_{j_1},.....,w_{j_M})$ exists as a long term memory.

Definition 3- parameters: parameters of selection $(\alpha \succ 0)$, learning rate $(\beta \in [0,1])$, and supervision $(\rho \in [0,1])$ are considered in fuzzy ART network.

Definition 4- class selection: for each input I and each node j in layer F2, selection function T_j is defined according to Equal.1:

$$T_j=\frac{|I \Lambda w_j|}{a+|w_j|} \quad \text{(Equation 1)}$$

Where Soft operator's |0| and Λ are defined as Equals. 2 and 3:

$$|p| \equiv \sum_{i=1}^{M} |p_i| \quad \text{(Equation 2)}$$

$$(p \Lambda q)_i \equiv \min(p_i, q_i) \quad \text{(Equation 3)}$$

Selected class is specified by J, Equal. 4:

$$T_J=\max\{T_j;\ j=1....N\} \quad \text{(Equation 4)}$$

Under such conditions as $y_1=0$; j≠J and y1=1, activity vector F1 also follows Equal. 5:

$$x=\begin{cases} I & \text{If F2 is inactive} \\ I \ \Lambda\ w_j & \text{If Jth is selected from layer F2 inactive} \end{cases} \quad \text{(Equation 5)}$$

Definition 5- resonance or replacement: if the following condition holds, then resonance phenomenon takes place Equal. 6:

$$\frac{|I \Lambda w_j|}{|I|} \geq \rho \quad \text{(Equation 6)}$$

It is obvious that when above condition does not hold, non-match determinant replacement command is ordered and a new index is selected instead of J and search continues for a category meeting condition (5).

Definition 6- learning: once search process has completed, weight vector wJ is renewed on the basis of Equal. (7):

$$w_J^{(new)}=\beta(I \Lambda w_J^{(old)})+(1-\beta)_J^{(old)}$$

(Equation 7)

Inputs to ART and ART b are in the form of complementary codes of $A=(a,a^c)$ and $B=(b,b^a)$ in fuzzy ARTMAP network.

xa and ya are determinants of output vectors F_1^a and F_2^a, respectively. w_j^a Is the weight vector of j_{th} node in ARTa. A similar notation is considered for ART b. This area graph is also xab determinant of output vector Fab and w_j^{ab} is determinant of weight vector from j_{th} node of F_2^a to F^{ab}

Definition 7- area graph activity: if one of classes of ART and ART b is activated, then F^{ab} becomes active. If both ART and ART b are active, then F^{ab} will be activated in the case that ART is the very category predicted by ART b. F^{ab} output vector is determined by Equal. 8:

$$x^{ab}=\begin{cases} y^b \ \Lambda_J^{ab}; & \text{Jth of node } F_2^a \text{ is active and } F_2^b \text{ so is} \\ w_J^{ab}; & \text{Jth of node } F_2^a\ F_2^a \text{ is active but } F_2^b \text{ inactive} \\ y^b; & F_2^a \text{ Inactive and } F_2^b \text{ active} \\ 0; & F_2^a \text{ And } F_2^b \text{ are inactive} \end{cases} \quad \text{(Equation 8)}$$

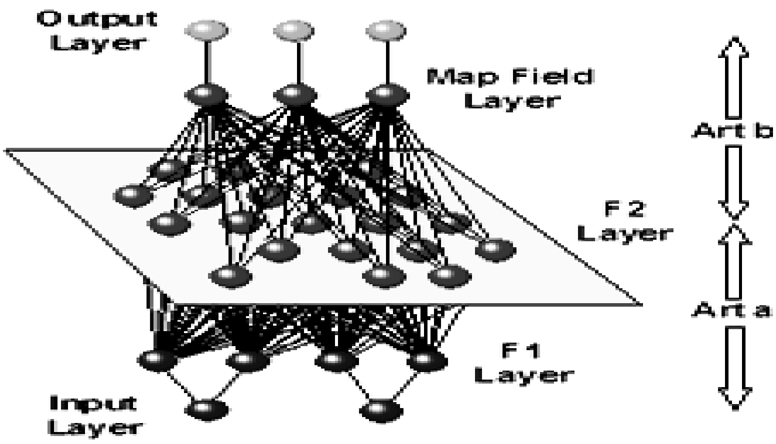

Fig. 5. Training trend in artificial fuzzy ARTMAP neural network (Ronald Eastman, 2009)

Many researchers have emphasized on the importance of selecting training data to neural networks. Quality and size of training data set has the most effect on potential for generalization of results of neural net classification and on total classification accuracy. Size of training sets must grow commensurately with an increase in the number of input nodes or spectral bands, spectral variability of target classes, and accuracy of intended classification (Omo-Irabor, 2007). Structure and architecture of the network for study region as shown in (Table 3).

Table 3. Structure and architecture of the network for study region

Rep. No.	$y_{r.}$	N= Neurons of Input Layer (F1)	N= Neurons of Classification Layer (F2)
4636	1987	12	1106
3710	2000	12	1083
4626	2006	12	1219

In addition, 5 parameters must be specified for fuzzy ARTMAP method: 1 selection parameter α (a positive small constant), 2 learning parameters β_1 and β_2 ($0 \leq \beta \leq 1$), and 2 supervision parameters $\rho 1$ and $\rho 2$ (usually set closely to 1). Initially, fuzzy ARTMAP parameters were specified, as shown in (Table 4). In order to study relationship between the classification produced and parameters of fuzzy ARTMAP. After that, each parameter was varied gradually and the levels of classification accuracy were calculated.

Table 4. The best parameter values for creating optimum network in the study region

Parameter	Value
Selection (α)	0.01
Learning ($\beta 1$)	1.00
Supervision ($\rho 1$)	0.98
Learning ($\beta 2$)	1.00
Supervision ($\rho 2$)	1.00

3. Results

In order to classify satellite TM (1987) and ETM$^+$ (2000, 2006) images, land use classes were determined under 4 groups titled good rangeland, fair rangeland, and poor rangeland as well as farm land classes, then, training samples were taken from the region by using satellite images and field visits. In the next step, land cover classes were introduced to under study area. Having specified resolution degree of classes, we attempted to perform classification by artificial fuzzy ARTMAP neural net method. In this way, land cover maps related to the years of 1987, 2000, and 2006 were obtained (Figs. 6-8). Using 1: 20000 aerial photographs by doing field operations in the next step, satellite images and random sampling from under-study region, statistical parameters of producer accuracy, user accuracy, total accuracy, and Kappa coefficient were extracted, as shown in (Table 5).

Table 5. Accuracy statistics for the classification result

Class	TM-1987		ETM$^+$-2000		ETM$^+$-2006	
	Producer's Accuracy	User' Accuracy	Producer's Accuracy	User' Accuracy	Producer's Accuracy	User' Accuracy
Good rangeland	93.10	99.12	85.74	70.91	82.57	81.67
Fair rangeland	98.86	97.08	94.22	94.43	97.57	95.58
Poor rangeland	97.24	93.07	89.93	95.77	97.11	94.63
Agriculture	99.87	98.61	92.43	95.11	99.68	94.73
Overall accuracy	98.27	-	92.09	-	95.23	-
Kappa coefficient	97.55	-	90.05	-	94.77	-

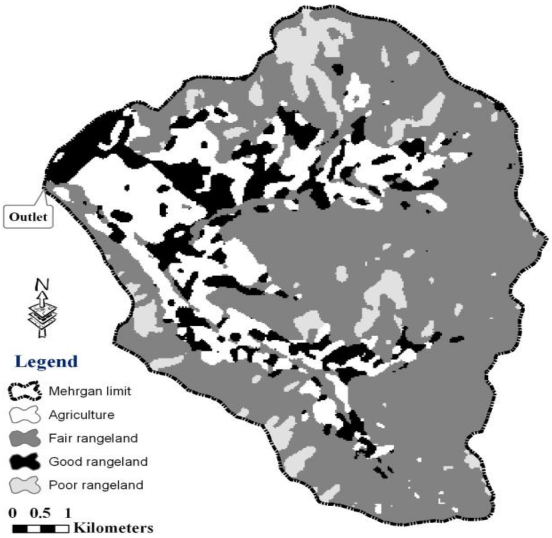

Fig. 6. Land use/cover classification map of study area, using Landsat TM 1987

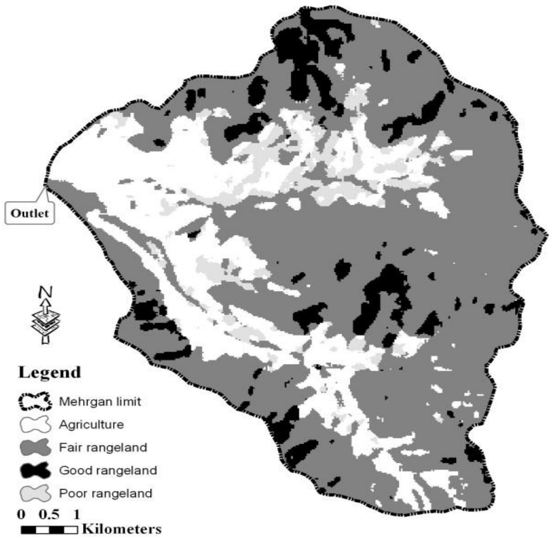

Fig. 7. Land use/cover classification map of study area, using Landsat ETM$^+$ 2000

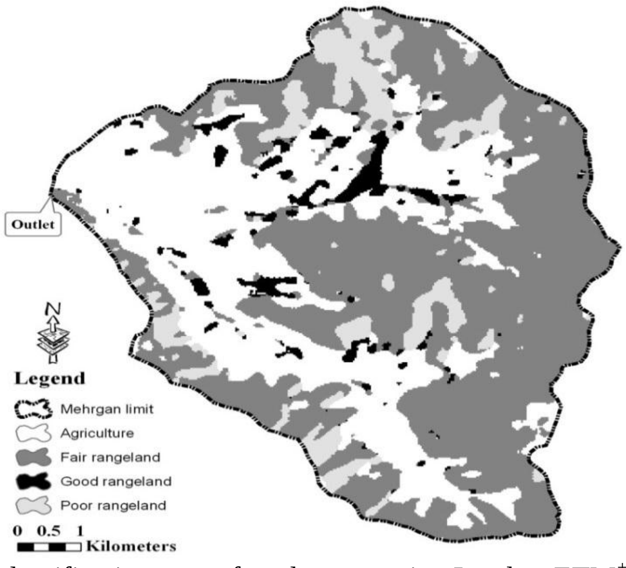

Fig. 8. Land use/cover classification map of study area, using Landsat ETM$^+$ 2006

From analysis of (Table 4), it can be concluded that, firstly, the highest degree of producer accuracy over 92% was observed with farmland cover class (for all 3 periods of time), indicating high potential of spectral resolution for this class. Secondly, based on the results, the lowest degree of producer accuracy was observed with good rangeland class. This class with producer accuracy of 82% was classified for the image of this region for year of 2006 In addition, the highest degree of user accuracy (over 94%) was observed with farmland cover class, which was classified for this region images. On the other hand, the lowest degree of user accuracy related to good rangeland class. Having used accuracy of 70.91%, this class was classified for the year of 2000, which can be due to the complexity or proximity of boundaries' resulting from high spectral similarity to other classes and pixels mixed in training and experimental samples.

3.1. Post-classification comparison

Having prepared land use/ vegetation maps for all 3 periods of time, we obtained areas of 4 land use classes. In order to make better comparison, changes occurred during 3 periods of time have been putted in (Table 6 and Fig. 9), showing that during period of 1987-2000, extent of poor rangeland and farm lands in the study region increased by 89.09 and 321.08, respectively, while good rangeland and fair rangeland faced a declining trend of 358.29 ha and 48.89 ha, respectively. In other words, it can be said that during this 13-year period of time, percentages of poor rangeland and farmland reached 8.38% and 23.53% in 2000, respectively, from 6.94% and 18.14% in 1987. On the other hand, percentages of good rangeland and fair rangeland density reached 6.33% and 61.76% in 2000, respectively, from 12.34% and 62.58%.

During period of time of 2000-2006, extent of poor rangeland density and farm land of under-study region increased by 64.98 and 727.12 respectively, while good rangeland and fair rangeland faced a declining trend of 144.01 ha and 648.1 ha, respectively. In other words, it can be said that during this 6-year period of time, percentages of poor rangeland density and farmland reached 9.48% and 35.73% in 2006 from 8.38% and 23.53% in 2000, respectively. On the other hand, percentages of good rangeland and fair rangeland density reached 3.91% and 5.88% in 2006 from 6.33% and 61.76% in 2000, respectively.

In general, it can be said that during this 19-year period of time (1987-2006), percentages of poor rangeland density and farm land increased by 2.5% and 17.59%, respectively, while percentages of good rangeland and fair rangeland density decreased by 8.43 and 11.7, respectively. These results indicate general destruction trend in the region through replacement of good rangeland and fair rangeland density by poor rangeland density farm lands.

On the other hand, during this period of time, the amount of farm lands exhibited an exponential trend indicating population growth as well as increased human pressure within the study area.

It should be noted that fair rangeland density accounts for most part of the region use, suggest better condition of the region in the past.

Table 6. Area and percentage of change of different land use/cover classes of 1977, 2000 and 2006 classified images

Class	1987		2000		2006		1987-2000	2000-2006
	(ha)	%	(ha)	%	(ha)	%	(%)	(%)
Good rangeland	735.34	12.34	377.05	6.33	233.04	3.91	-6.01	-2.42
Fair rangeland	3728.23	62.58	3679.34	61.76	3031.24	50.88	-0.82	-10.88
Poor rangeland	413.52	6.94	499.61	8.38	564.59	9.48	+1.44	+1.1
Agriculture	1080.78	18.14	1401.86	23.53	2128.98	35.73	+5.39	+12.2
Total	5957.86	100	5957.86	100	5957.86	100	0	0

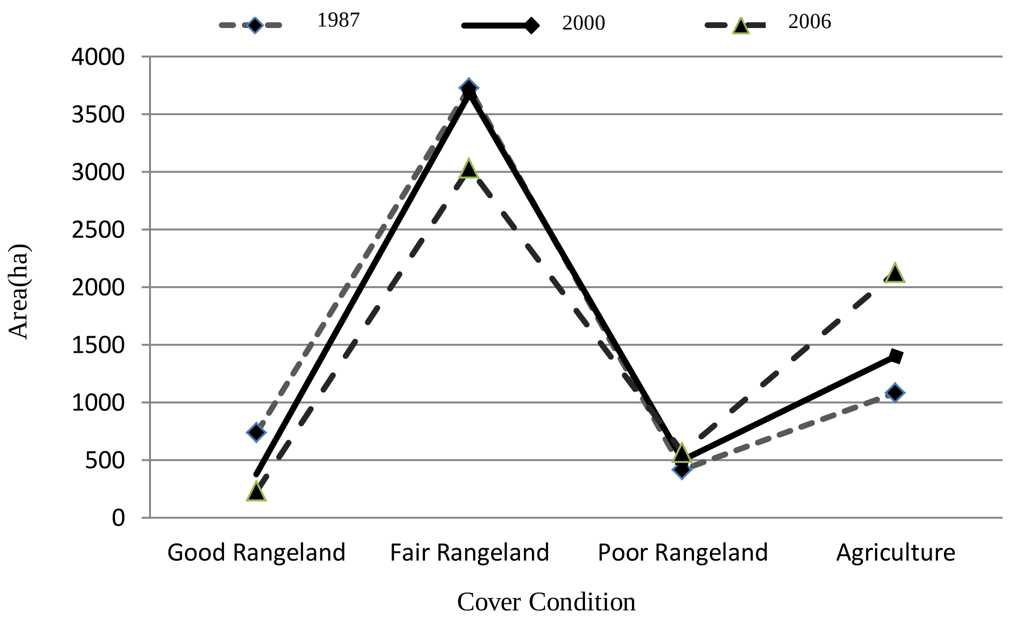

Fig. 9. Areas of land use/ cover classes of the Mehrgan region

4. Discussion and Conclusion

Geometric and atmospheric corrections of multi-time images are a prerequisite for any surveillance of change projects. Selection of proper dates for acquiring images and using an accurate method of change surveillance are major factors for performing study of change trends successfully. In this study, once geometric and radiometric corrections have been exercised, method of supervised fuzzy ARTMAP neural net classification was employed to study the change trends.

Since the changes in land use/ cover were evident in Mehrgan region, above- mentioned method was used to reveal (surveillance of) changes occurred in the region. The aim of changes surveillance was to compare the same region over time.

Many people have shown in their studies that the method of post-classification comparison is one of the accurate methods of surveillance of changes in land cover; in this field, research done by Joyce *et al.* (1980), Sunar (1996) and Mas (1999) can be mentioned.

Since the major aim of processing satellite imagery is to prepare topical and effective maps, selection of an appropriate classification algorithm plays an important role in this field. Currently, various types of classification method exist. Typical classification methods employ statistical techniques parametrically, including maximum likelihood, minimum distance, etc. Another new method used to perform classification in different areas is Fuzzy method. Fuzzy set theory which is used to resolve ambiguity in data is a new concept which displays information in such more complex situations as mixed covers or intermediate conditions better.

The aim of present study is to examine the trend of range cover changes in Mehregan region by using supervised classification method of artificial fuzzy ARTMAP neural network for 1987, 2001, and 2006. After making necessary corrections and initial imagery pre-processing, it was attempted to classify satellite images by intended method. By comparing degrees of accuracy of classifications resulting from artificial fuzzy ARTMAP neural net algorithm for the years of 1987, 2000, and 2006, it was known that 1987 Kappa Coefficient was 97.55% which was of higher accuracy of 7.5% and 2.78% than those of the years of 2000 and 2006, respectively. Also, it was observed that the maximum producer accuracy (over 99%) related to farm land class (for 1987), indicating high spectral resolution potential for that class. According to the results obtained, the lowest degree of producer accuracy was observed with good rangeland density class. Having produced accuracy of 82%, this class was classified for images of the region (for 2006).

Based on other results from this research, it can be said that during a 19-year period of time (1987-2006), area percent's of poor rangeland and farm lands increased by 2.5% and 17.59%, respectively, while those of fair rangeland and good rangeland decreased by 8.43% and 11.07%, respectively. These results indicate general destruction trend in the region via replacement of fair rangeland and good rangeland by poor rangeland density and farmland. On the other hand, during this period of time, the amount of farmlands had an exponential trend, indicating population growth and increased human pressure within the study area. By integrating slope and use change maps, it was known that most changes have occurred on the slopes <20%, which is due to the suitability of such regions for farming. Since slopes >20% are less desirable for farming, less relative destruction has occurred in these regions and changes occurred are due to natural factors and regional formations. It seems that lack of accurate maps (cadaster) and of comprehensive supervision on natural areas along with socio-economic problems have made people change range lands is order to have access to more resources, changing them into other uses including irrigation/ dry farming ones depending on their needs.

Results of this research are in agreement with those obtained by some researchers within various regions. For example, Lizarazo (2006), Sugumaran (2001), and Hosseini *et al.* (2003) which estimated higher accuracy for neural net method than those for other supervised classification ones during comparing them.

By using artificial fuzzy ARTMAP neural net algorithm, degrees of accuracy of vegetation maps obtained by satellite data classification were set at 97%, 90%, and 94% for TM (1987), ETM^+ (2000), and ETM^+ (2006) images, respectively, indicating high accuracy of this algorithm in classifying satellite data which is due to non-linearity and non-parametric of artificial fuzzy ARTMAP network. In neural methods, distribution works inside training samples on the basis of data's own features and structures, and this is why neural networks are more successful in integrating data with different sources. Thus, making use of capabilities of neural networks provides possibility of increasing the number of classes and more accurately separating classes in applied projects while decreasing the rate of errors.

5. General Conclusion

In present research, maps generated by fuzzy ARTMAP neural network have some accuracy over 90% for 3 periods of time of acquiring images. So it can be said that artificial fuzzy ARTMAP neural net classification is a suitable method for preparing land use/ cover maps, having capability of classifying highly accurately. In addition, neural net methods have solved some problems with parametric methods (maximum likelihood, minimum distance, etc.) by using a non-parametric approach.

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استفاده از روش شبکه عصبی مصنوعی آرتمپ فازی جهت بررسی روند تغییرات پوشش مرتعی

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چکیده

هدف اصلی از پردازش تصاویر ماهواره‌ای، تهیه نقشه‌های موضوعی و کارآمد می‌باشد، انتخاب روش مناسب طبقه‌بندی نقش مهمی در این امر ایفاء می‌کند. در میان روش‌های مختلفی که برای طبقه‌بندی تصاویر وجود دارد طبقه‌بندی به کمک شبکه‌های عصبی مصنوعی دارای دقت بالایی می‌باشد. در این مطالعه، تصاویر سنجنده TM سال ۱۹۸۷، سنجنده ETM^+ سال‌های ۲۰۰۰ و ۲۰۰۶ با استفاده از شبکه عصبی مصنوعی آرتمپ فازی در حوزه مهرگان استان کرمانشاه با مساحت ۵۹۵۷/۸۶ هکتار آنالیز شده و تغییرات وضعیت پوشش مرتعی رخ داده در این حوزه در سه دوره زمانی، از سال ۱۹۸۷ تا ۲۰۰۰ و ۲۰۰۰ تا ۲۰۰۶ بررسی گردید. در این مطالعه، ابتدا تصحیحات هندسی و رادیومتری بر روی داده‌های ماهواره لندست سال‌های مورد نظر صورت گرفت. سپس با بازدیدهای میدانی، طبقات مختلف کاربری اراضی تعریف و نمونه‌های آموزشی انتخاب گردید. نتایج به دست آمده نشان می‌دهد طی دوره زمانی (۱۹۸۷-۲۰۰۰) وسعت اراضی مرتع کم تراکم و کشاورزی منطقه مورد مطالعه به ترتیب ۸۹/۰۹ و ۳۲۱/۰۸، افزایش‌یافته، در حالی که مرتع پرتراکم و مرتع نیمه تراکم، به ترتیب با روند کاهشی برابر با ۳۵۸/۲۹ و ۴۸/۸۹ هکتار روبرو بوده است. همچنین در طی دوره زمانی (۲۰۰۰-۲۰۰۶) وسعت اراضی مرتع کم تراکم و کشاورزی منطقه مورد مطالعه به ترتیب ۶۴/۹۸ و ۷۲۷/۱۲، افزایش یافته، در حالی که مرتع پرتراکم و مرتع نیمه تراکم، به ترتیب با روند کاهشی برابر با ۱۴۴/۰۱ و ۶۴۸/۱ هکتار روبرو بوده است. از دیگر نتایج به دست آمده این که، دقت نقشه‌های پوشش گیاهی حاصله از طبقه‌بندی داده‌های ماهواره‌ای با استفاده از الگوریتم شبکه عصبی مصنوعی آرتمپ فازی برای تصاویر TM (۱۹۸۷) و (۲۰۰۰ و ۲۰۰۶) ETM^+ به ترتیب برابر با ۹۷، ۹۰ و ۹۴ درصد بوده است که بیانگر دقت بالای این الگوریتم در طبقه‌بندی داده‌های ماهواره‌ای است. بنابراین این تحقیق کارایی و قابلیت روش شبکه عصبی مصنوعی آرتمپ فازی را در طبقه‌بندی بهتر تصاویر سنجش از دور اثبات می‌نماید.

کلمات کلیدی: آرتمپ فازی، سیستم اطاعات جغرافیایی، تغییر پوشش، تغییر کاربری، لندست، حوزه مهرگان کرمانشاه