Integration of remotely sensed spatial and spectral information for change detection using FAHP

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Abstract: Land use change mapping is one of the basic requirements for effective monitoring and management of the environment. Although several change detection approaches have been proposed and used, past experience has shown that each method may have its own advantages. Selecting the best approach is an important challenge. The integration of spectral/spatial criteria seems to lead to better results. In this study, for change detection analysis, we have used the Landsat Thematic Mapper (TM®) imagery of Zanjan city, acquired in 1985 and 2010. To map the changes, the spectral/spatial criteria were integrated with different weights by using the Fuzzy Analytical Hierarchy Process (FAHP). Results indicate that the FAHP methods generally resulted in a higher accuracy than spectral and spatial criteria. The proposed semivariogram features have a better, early and automatic change detection performance. When using spatial information, both the omission and commission errors decreased significantly. In addition, the uncertainty derived from choosing only one separate method decreases when using the FAHP method. This method will likely be widely used for the change detection of two images that have, on the one hand, the same spectral characteristics and, on the other, different texture characteristics.

Keywords: Changes detection, FAHP, spectral/spatial information

Değişim tespiti için FAHP kullanılarak uzaktan algılanan konumsal ve spektral bilginin entegrasyonu

Özet: Arazi kullanım değişim haritalaması, çevrenin etkin izlenmesi ve yönetiminde temel gereksinimlerden biridir. Çeşitli değişim tespit yaklaşımları önerilip kullanılmasına ragmen, eski deneyimler her bir metodun kendine ait bir avantajı olduğunu gösteriyor. En iyi yaklaşımı seçmek önemli ve zorlu bir iştir. Spektral/konumsal kriterlerin entegrasyonu iyi sonuçlar vermektedir. Bu çalışmada, değişim tespiti analizi için, Zanjan şehrinin 1985 ve 2010 yıllarında alınan Landsat Thematic Mapper (TM®) tasviri kullanılmıştır. Değişimleri haritalamak için, spektral/konumsal kriterler Fuzzy Analytical Hierarchy Process (FAHP) kullanılarak farklı ağırlıklarla entegre edilmiştir. Sonuçlar, FAHP metodlarının genellikle spektral/konumsal kriterlere göre daha yüksek doğrulukla sonuçlandığını göstermiştir. Önerilen semivariogram özellikleri daha iyi, erken ve otomatik değişim tespiti performansına sahiptir. Konumsal bilgi kullanılırken hem eksiklik hem de komisyon hataları önemli ölçüde azalmıştır. Ayrıca tek bir ayrı metodun seçilmesinden kaynaklanan belirsizlik FAHP metodu kulanıldığında azalmaktadır. Bu metodun, bir yandan aynı konumsal karakteristiklerine ve diğer yandan farklı doku karakteristiklerine sahip olan iki tasvirin de değişim tespiti için yaygın biçimde kullanılması muhtemel görünmektedir.

Anahtar kelimeler: Değişim tespiti, FAHP , spectral / konumsal bilgi

1. INTRODUCTION

Satellite remote sensing provides both a high probability and cost-effective source of information for land cover mapping and quantifying environmental changes. Land use cover change detection is one of the basic

requirements for effective planning and management of environmental resources. The aim of change detection is to find areas that have been exposed to significant changes in land cover during the time periods in consideration (Helmy and El-Taweel 2010) . Land cover change may be caused by either a metamorphosis in the surface components of the vegetation cover (Milne 1988) or spectral/spatial movement of the plants during the time period specified (Lund 1983).The rate of change may be slow or rapid. Some changes in the state of the land are caused by human activities (e.g.,deforestation for urban expansion and agricultural uses), whereas others are caused by natural processes, such as floods and epidemiologic diseases (Coppin et al., 2004). Depending on the types of changes and the study objectives, different methods have been used for change detection by remotely sensed data. These methods may be classified into the three main categories (Coppin et al., 2004; Dewan and Yamaguchi 2009; Singh 1989), including the following:i-classification-based comparisons (e.g.,post classification comparisons) (Yuan et al., 2005) and a direct two-date classification (Carreiras et al., 2006));ii-)spectral change analysis (e.g.,band algebra methods (Townshend and Justice 1995), regression analysis [RA] (Fraser et al., 2005), principal component analysis [PCA] (Hartter et al., 2008), and change-vector analysis [CVA]) (He et al., 2011), and iii-) object based methods (Desclee et al., 2006).

The choice of a change detection algorithm normally has significant effects on the results (Dobson and Bright 1992). Many studies have compared different change detection methods, and their advantages and disadvantages. As an example, Macleod and Gongalton (1998) compared image differencing, PCA, and post classification comparison methods.Their results indicated that the post classification comparison showed less accuracy than the two others. An important disadvantage of the post classification comparison is that its results are prone to classification errors. For deforestation mensuration, Singh (1986) concluded that image differencing is much more effective than the principle component analysis.Yuan and Elvidge (1998) evaluated 75 change detection methods by using statistical and visual methods. Initial results showed that image differencing produces far more accuracy than other tested methods. For urban expansion mapping, Li and Yen (1998) observed that the PCA method shows better accuracy than the post classification comparison.

Spectral-based change detection methods often perform well when a situation satisfies the assumption that change on earth causes considerable variations in image pixel values. These spectral variations mostly reflect environmental changes rather than differences produced by the atmosphere or other system anomalies and variations (Singh 1989). However, previous works have shown that in many cases, spectral information is not sufficient for change detection (Van Oort, 2007).

Texture information indicates the spatial relationship, distribution, and variation of neighborhood pixels. Texture is also an important factor that can compensate for deficiencies in spectral information in satellite imagery analysis (Carleer and Wolff 2006). For example, Gong et al (1992) demonstrated that spatial information is useful for the removal of spectral confusion between land cover classes. Jensen and Toll (1982) found that combination of spectral–textural image differencing can provide better change detection results using the Landsat Multi-Spectral Scanner data. In addition, each change detection approach may have its own advantages and neither of the existing methods may be preferable to others in all situations (Conchedda et al.,, 2008; Dewan and Yamaguchi 2009). Accordingly, the integration of various spatial and spectral characteristics results in useful information about different features, leading to better results.

The objective of this work is to analyse the spatial and spectral characteristics of remotely sensed images for change detection in urban land use covers. For this purpose, a number of spectral and spatial criteria including band difference, band ratio, PCA change detection, PCA of Semivariances, total difference time lags (TDT), total ratio time lags (TRT) and slope of first minimum & maximum (SFM) have been integrated by using the fuzzy analytic hierarchy process (FAHP).

In the following sections, the materials and methods of this paper are explained, followed by the results and discussion, and a conclusion.

2. MATERIALS AND METHODS

2.1 Study Area and Satellite Data

The study area is Zanjan City, located in Zanjan Province, northwest of Iran (Figure / Şekil 1). The prolific Zanjan plain is divided into several areas according to the different rivers. An impressive climate diversity and wild habitat have caused this area to become one of the most attractive eco-tourism zones of Iran. Changes originating from both natural disaster (e.g., drought, flood, landslide, and soil/water erosion) and human activities (e.g., deforestation, urban expansion, roads, and farmland expansion) have led to a massive human migration from villages to cities. The dominant landuse cover types in the region include the built-up areas, bare lands, farmlands, and grasslands. The Landsat Thematic Mapper 5 (TM®) (Table / Tablo 1), acquired in 1985 and 2010 was used for the detection of the land use cover changes throughout 25 years, from 1985 to 2010.
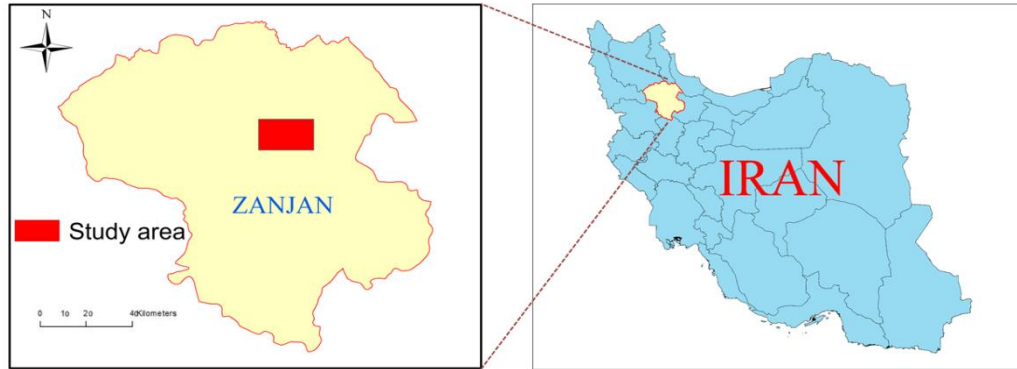

Figure 1. The study area (Zanjan city).
Şekil 1. Çalışma alanı (Zanjan şehri)

Table 1. Landsat 5 specification
Tablo 1. Landsat 5 özellikleri

Landsat 5	Wavelength (micrometers)	Resolution (meters)
Band 1	0.45-0.52	30
Band 2	0.52-0.60	30
Band 3	0.63-0.69	30
Band 4	0.76-0.90	30
Band 5	1.55-1.75	30
Band 6	10.40-12.50	120
Band 7	2.08-2.35	30

The Landsat TM® of 2010 is geo-referenced, using a 1/25000 topographic map of the area. In addition, the Landsat TM® of 1985 is co-registered for the 2010 imagery. The root mean squared error (RMSE) of less than 0.5 pixels (15 meters) has been attained. Finally, the scattergram-controlled regression (SCR) is used for radiometric normalization and reducing the influence of various factors, including the sun angle, and atmospheric and soil moisture (Elvidge et al., 1995).

2.2 Analysis Methodology

Figure / Şekil 2 depicts the methodology used in this study. This section consists of data preparation, image processing, and FAHP decision-making. After calculating the spectral and spatial criteria (using ENVI® and MATLAB®), FAHP contributes to the computation of corresponding weights of criteria. Lastly,

changed and unchanged areas are distinguished by weighted integration of criteria in a geographic information system (GIS) environment.
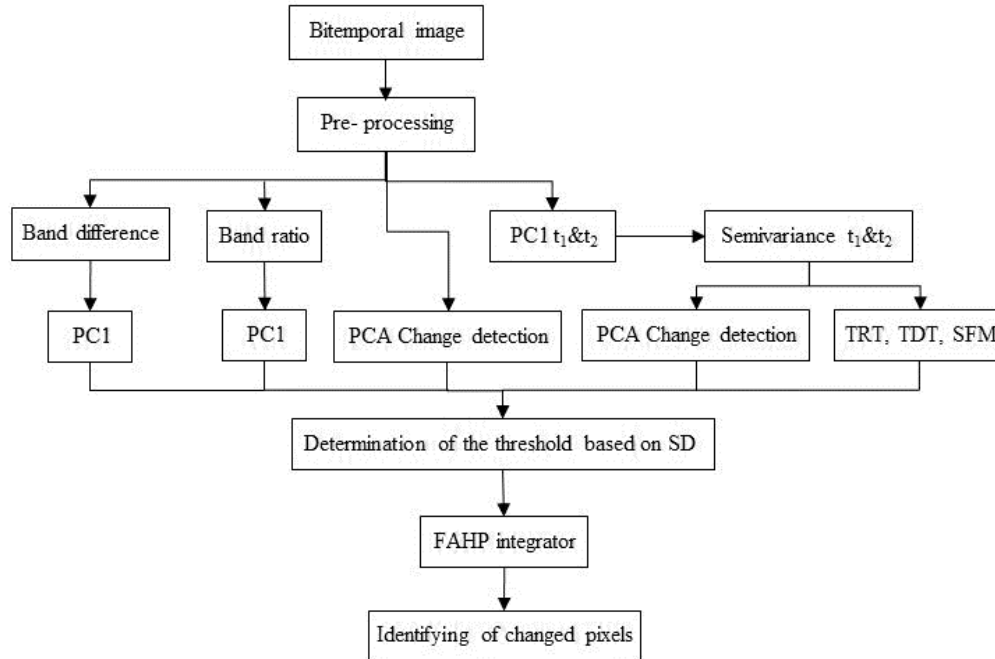

Figure 2. Overview of processing approach
Şekil 2. İşlem süreci

2.3 Texture Information

Texture is the term used to characterize the tonal or grey-level variations in an image. Texture analysis has played an increasingly important role in digital image processing and interpretation. It principally provides supplementary information about image properties (Pacifici et al., 2009). Several texture extraction methods are discussed in the literature. Dekker (2003) showed the relevance of several textural parameters, including variance, a weighted-rank fill ratio, and asemivariogram that perform better than other textural features. The semivariogram is a frequently used tool in remote sensing (Curran and Atkinson 1998; Atkinson and Lewis 2000).

In this study, the proposed method is based on the extraction and analysis of the semivariogram, the TDT, the TRT and the SFM from the TM® data.

2.3.1 Semivariogram

The semivariogram is one means of quantifying the way in which a variable changes spatially (Berberoglu et al., 2007). The semivariogram shows high capabilities for effective extraction and use of the spatial properties of land use cover types. Balaguer et al (2010) used the semivariogram-based texture data for object oriented classification and concluded that the semivariogram model leads to the best classification accuracy. The semivariogram is defined as half of the expected squared difference between paired data value separated by the lag, h:

$$\gamma(\vec{h}) = \frac{1}{2N(\vec{h})} \sum_{i=1}^{N(\vec{h})} [Z(x_i) - Z(x_i + \vec{h})]^2 \qquad , \qquad (1)$$

Where Z(xi) represents the value of the variable in location xi and $\vec{h}$ is the separation between elements in a given direction.

Principal component analysis (PCA) has been applied to each of the two data sets (namely, t1 and t2) to segregate noise components, and to reduce their dimensionality. The first PC bands of t1 and t2 (namely, PC_1t_1, PC_1t_2) are used to model the semivariograms using MATLAB.

After computing the semivariogram using (1),a set of n points is available. Assuming that $\gamma_i = \gamma(h_i)$ and the value on the lags are equally spaced, the points that belong to the semivariogram can be expressed as follows:

$$\left\{ (h, \gamma_1), (2h, \gamma_2), (3h, \gamma_3), ...(nh, \gamma_n) \right\} \qquad , \qquad (2)$$

Local maximum values from the semivariogram were extracted considering linear neighborhoods of 5 positions; in an effort to reduce the detection of a false maximum due to slight local fluctuations in the semivariogram values:

$$\gamma_{max\_j} = \left\{ \gamma_i, i \in \{3,4,....n-2\} : \gamma_{i-1}\langle\gamma_i\rangle\gamma_{i+1} and \gamma_{i-2}\langle\gamma_i\rangle\gamma_{i+2} \right\} j = 1,..., M \qquad , \qquad (3)$$

Assuming that these local maximum are ordered, $h_{max\_1}\langle h_{max\_2}\langle ...h_{max\_M}$,in a similar manner, the first local minimum is defined as follows:

$$\gamma_{min\_1} = \left\{ \gamma_i, i \in \{(max\_1)+2,...,(peak\_2)-2\} : \gamma_{i-1}\rangle\gamma_i\langle\gamma_{i+1} and \gamma_{i-2}\langle\gamma_i\rangle\gamma_{i+2} \right\} , \qquad (4)$$

Where $peak\_2$ is equal to max_2 if this exists, or equal to n when there is only one local maximum. (Balaguer et al., 2010).
In this paper, a set of texture features extracted from the semivariogram is proposed and described; their usefulness for land use cover change detection is evaluated.

i)Total Difference Time lags (TDT)

This parameter works as band differencing and reveals spatial correlation changes in time intervals of t1 and t2. It provides information about earth's surface changes. If there are changes in some parts of the studied area, the images will have positive or negative values in both the histogram tails of the brightness degree of subtracted images.

$$TDT = \sum_{i=1}^{i=n} (\gamma_{it_2} - \gamma_{it_1}), \qquad (5)$$

ii)Slope of First Minimum & Maximum(SFM)

By using the SFM, we can calculate the spatial changes gradient in the first local minimum and first local maximum. Alarge gradient indicates high changes in the earth's surface and a slight gradient indicates low changes in time intervals.

$$SFM = \left(\frac{\gamma_{min\_1t_2} - \gamma_{min\_1t_1}}{\left| h_{min\_1t_2} - h_{min\_1t_1} + 1 \right|} \right) + \left(\frac{\gamma_{max\_1t_2} - \gamma_{max\_1t_1}}{\left| h_{max\_1t_2} - h_{max\_1t_1} + 1 \right|} \right) \qquad (6)$$

Where, γ_{min_1} is first local minimum and γ_{max_1} is first local maximum.

iii) Total Ratio Time lags(TRT)

A semivariance division in different temporal/spatial intervals contributes to change detection capabilities. The pixel value of the unchanged areas in a semivariance division will be close to one (Figure / Şekil 3).

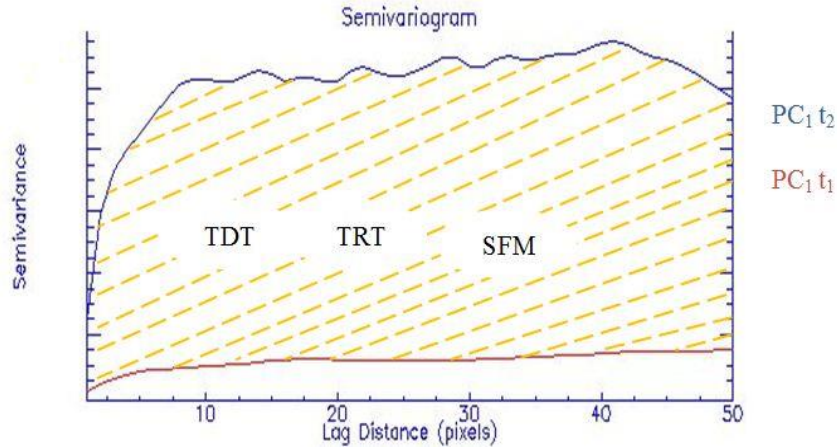$$TRT = \sum_{i=1}^{i=n} (\frac{\gamma_{it_2}}{\gamma_{it_1}}) , \qquad (7)$$

Figure 3. Graphic representation of semivariogram features.
Şekil 3. Semivariogram özellikleri grafik gösterimi

The two time semivariances (1) are stacked, and to textural change detection, the PCA change detection of the semivariance and parameters (5), (6) and, (7) are used. Accordingly, the parameters extracted from the semivariogram and raw semivariances are specified as spatial criteria for change detection.

2.4 Spectral Information

Band difference, band ratio, and the PCA procedure have each been used for spectral change detection. Each band product from the band algebra may include some of the change information. Therefore, the principal component used to produce uncorrelated output bands and to reduce the dimensionality of data sets.

Changed and unchanged areas in the spatial and spectral criteria were delineated by determining the threshold based on the standard deviation. Table / Tablo 2 indicates the criteria used in this study.

Table 2. Criterion used in this study
Tablo 2. Bu çalışmada kullanılan kriterler

Spectral criteria	Spatial criteria
Band difference (*A*)	PCA of Semivariance (*D*)
Band Ratio (*B*)	TDT (*E*)
PCA change detection (*C*)	TRT (*F*)
	SFM (*G*)

With regard to the integration of criteria, FAHP was subsequently used for the calculation of different weights.

2.5 Fuzzy Analytical Hierarchy Process

Despite its popularity, the AHP is often criticized for its inability to incorporate the inherent uncertainty and impression associated with mapping the decision makers' perceptions onto exact numbers (Deng 1999). In the FAHP method, the decision maker can choose a range of values freely, and the uncertainty can be explained through the fuzzy number (Vahidnia et al., 2009). In this method to pairwise comparison among the attributes, the fuzzy numbers, and to obtain the weights and priorities of each attributes, the geometrical mean method suggested by Buckley (1985) have been used respectively.

In order to achieve FAHP decision making, the pairwise comparison matrix was generated. When the expert judgments are expressed as triangular fuzzy numbers (Figure / Şekil 4 and 5), the triangular fuzzy comparison matrix is as follows:

$$\tilde{A} = \begin{bmatrix} (1,1,1) & (l_{12},m_{12},u_{12}) & \dots & (l_{1n},m_{1n},u_{1n}) \\ (l_{21},m_{21},u_{21}) & (1,1,1) & \dots & (l_{2n},m_{2n},u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (l_{n1},m_{n1},u_{n1}) & (l_{n2},m_{n2},u_{n2}) & \dots & (1,1,1) \end{bmatrix}, \qquad (8)$$

The priority of a) i element to j element and b) j to i element will be shown as relations (9) and (10), respectively
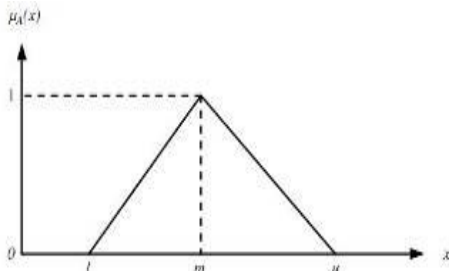

Figure 4. Triangular fuzzy number
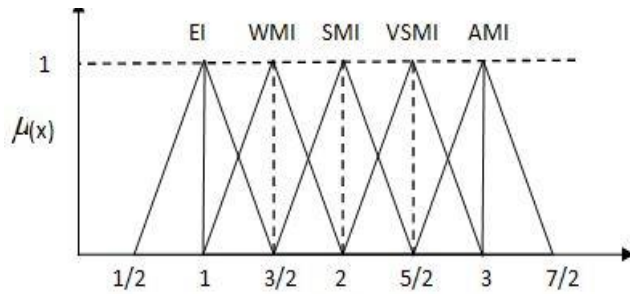Şekil 4. Üçgensel bulanık sayı

Figure 5. Triangular fuzzy numbers corresponding to linguistic variables representing levels of preference (Önüt et al., 2010).
Şekil 5. Tercih seviyelerini temsil eden dilsel değişkenlere karşılık gelen üçgensel bulanık sayılar (Önüt et al., 2010)

$$\tilde{l}_{ij} = (l_{ij},m_{ij},u_{ij}) \qquad (9)$$

$$\tilde{l}_{ji} = (\frac{1}{u_{ij}},\frac{1}{m_{ij}},\frac{1}{l_{ij}}) \qquad (10)$$

By using the geometrical mean method (11), the fuzzy weight $\tilde{w}_j$ (13) of each criterion was calculated.

$$i=1,2,\dots,n \left[l_i = [\prod_{j=1}^{n} l_{ij}]^{1/n} \right] \qquad (11)$$

$$l = \sum_{i=1}^{7} l_i \quad u = \sum_{i=1}^{7} u_i \quad m = \sum_{i=1}^{7} m_i \qquad (12)$$

$$\tilde{w}_j = (\frac{l_i}{m}, \frac{m_i}{u}, \frac{c_i}{l}) \tag{13}$$

The degree of possibilities for the fuzzy weights of the criteriain relation to each other were then calculated (14).

$$V(\tilde{M}_2 \geq \tilde{M}_1) = \sup_{y \geq x} \left[\min(\mu_{\tilde{M}_1}(x), \mu_{\tilde{M}_2}(y)) \right] \qquad , \tag{14}$$

This formula can be equivalently expressed as follows:

$$\begin{cases} (\tilde{M}_2 \geq \tilde{M}_1) = 1 & if\ m_2 \geq m_1 \\ (\tilde{M}_2 \geq \tilde{M}_1) = 0 & if\ l_1 \geq u_2 \\ (\tilde{M}_2 \geq \tilde{M}_1) = hgt(\tilde{M}_2 \cap \tilde{M}_1), & otherwise \end{cases} \tag{15}$$

Also we have the following:

$$hgt(\tilde{M}_2 - \tilde{M}_1) = \frac{l_1 - u_2}{(m_2 - u_2) + (m_1 - l_1)} = \mu_{\tilde{M}_2}(d) \tag{16}$$

In this equation, d corresponds to the highest intersection point between $\mu_{\tilde{M}_1}$ and $\mu_{\tilde{M}_2}$.

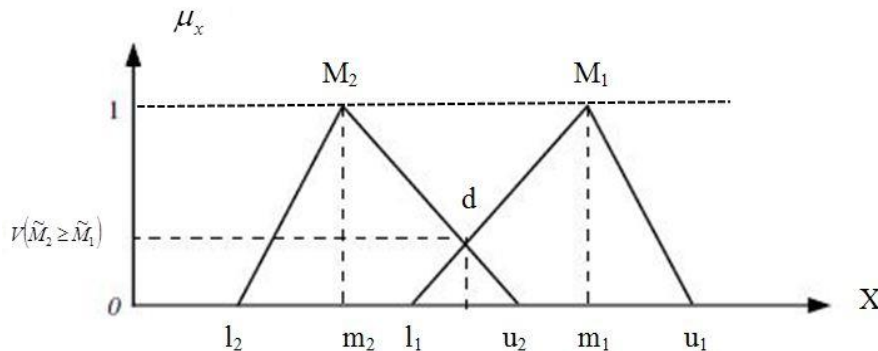Figure 6 illustrates $V(\tilde{M}_2 \geq \tilde{M}_1)$.

Figure 6. The degree of possibility
Şekil 6. Olasılık derecesi

By using the corresponding weights, the spectral and spatial criteria were integrated by the weighted overly. The changed and unchanged areas were then discriminated.

3. RESULT AND DISCUSSION

In this section, the capability of spatial and spectral information and their integration in land use change maps are investigated. Figure / Şekil 7 and 8 depict the change maps resulting from the spatial and spectral criteria. As can be seen, there are evident differences between change and unchange classes.

Consideration of the correlations between the complete set of spatial and spectral parameters (Table / Tablo 3) indicates that there is a low correlation between the spectral and spatial criteria. Each of the spatial

criteria includes useful and specific change information, which may not be detectable by the spectral criteria. Therefore, the information about the changes, provided by the spatial and spectral criteria can be complementary rather than redundant. Moreover, their integration can lead to more reliable map of the changes.
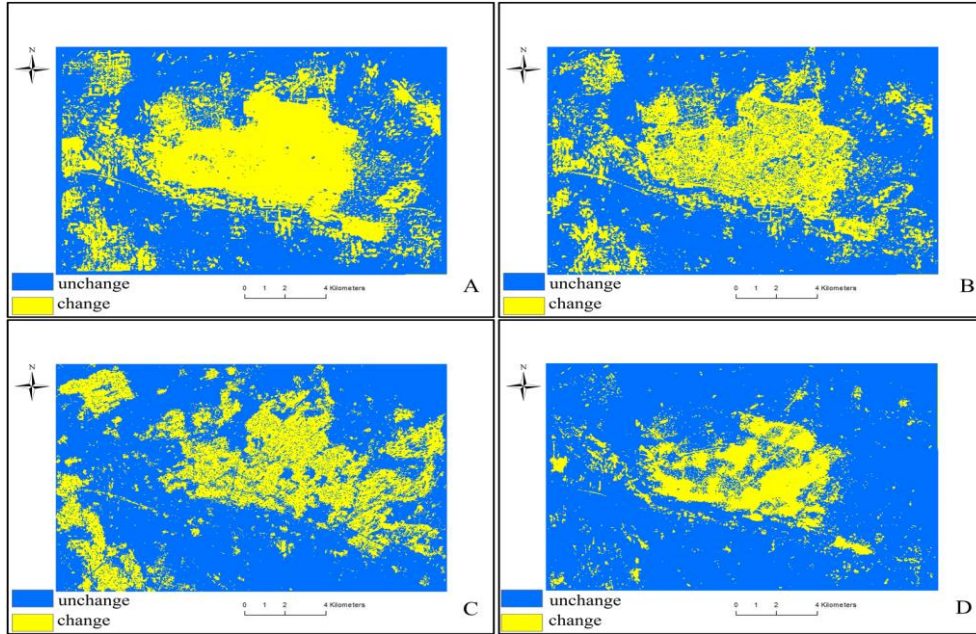

Figure 7. Change map resulting from (A) TDT, (B) SFM, (C) TRT and (D) Principal component of semivariances of t1 and t2.
Şekil 7. (A) TDT, (B) SFM, (C) TRT ve (D) t1 ve t2 yarı varyans ana bileşeninden üretilen değişim haritaları
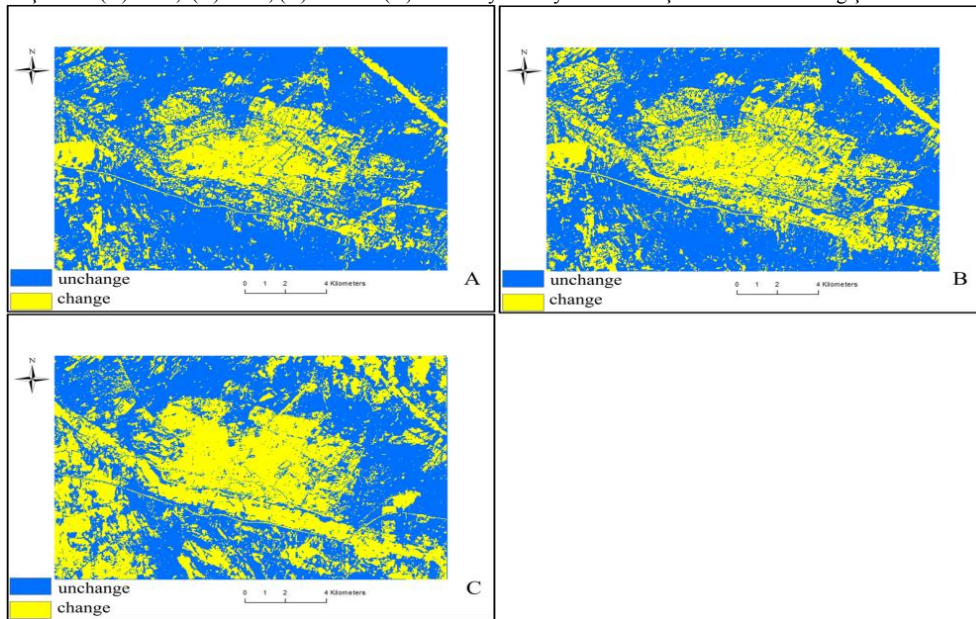

Figure 8. Spectral changesresulting from the (A) band difference (B) band ratio and (C) PCA of the Landsat-TM® data of 1985 and 2010.

Table 3. Correlation coefficients between the spatial and spectral criteria
Tablo 3. Mekansal ve spektral kriterler arasındaki korelasyon katsayıları

Correlation	A	B	C	D	E	F	G
A	1	0.82	0.477	0.062	0.054	0.367	-0.002
B		1	0.5	0.093	0.028	0.364	-0.034
C			1	0.044	-0.076	0.270	-0.14
D				1	0.122	0.062	0.32
E					1	0.087	0.826
F						1	0.04
G							1

The ability to compute the measure on a lag-by-lag basis is an advantage of the semivariogram over other texture measures. It reveals useful information about the textural structures of land use covers; this information is very helpful in the interpretation of spatial variations.

We used the linguistic variables and their corresponding fuzzy numbers to generate a pairwise comparison matrix. The pairwise comparison matrix, the fuzzy weights $\tilde{w}_j$, and the degree of possibility for the fuzzy weights of criteria are shown in Table / Tablo 4 and 5.

Table 4. Pairwise comparison matrix and computed fuzzy weight of criterion
Tablo 4. İkili karşılaştırma matrisi ve kriterlerin hesaplanan bulanık ağırlıkları

	A	B	C	D	E	F	G	$\tilde{w}_j$	L	M	U
A	(1,1,1)	(1/2,1,3/2)	(1,3/2,2)	(3/2,2,5/2)	(1,3/2,2)	(1,3/2,2)	(1,3/2,2)	A	0.09	0.18	0.35
B	(3/2,1,2)	(1,1,1)	(1,3/2,2)	(3/2,2,5/2)	(1,3/2,2)	(1,3/2,2)	(1,3/2,2)	B	0.1	0.18	0.37
C	(1/2,2/3,1)	(1/2,2/3,1)	(1,1,1)	(1,3/2,2)	(1,3/2,2)	(1,3/2,2)	(1,3/2,2)	C	0.083	0.175	0.3
D	(2/5,1/2,2/3)	(2/5,1/2,2/3)	(1/2,2/3,1)	(1,1,1)	(1/2,2/3,1)	(1/2,2/3,1)	(1/2,2/3,1)	D	0.053	0.093	0.18
E	(1/2,2/3,1)	(1/2,2/3,1)	(1/2,2/3,1)	(1,3/2,2)	(1,1,1)	(1/2,1,3/2)	(2/3,1,2)	E	0.064	0.115	0.25
F	(1/2,3/2,1)	(1/2,3/2,1)	(1/2,2/3,1)	(1,3/2,2)	(1/2,1,3/2)	(1,1,1)	(2/3,1,2)	F	0.064	0.144	0.255
G	(1/2,2/3,1)	(1/2,2/3,1)	(1/2,2/3,1)	(1,3/2,2)	(1/2,1,3/2)	(1/2,1,3/2)	(1,1,1)	G	0.062	0.155	0.24

Table 5. Degree of possibility of fuzzy weights of criterion with respect to other criterion
Tablo 5. Diğer bir kriter ile ilgili hesaplanan bulanık ağırlıkların olasılık derecesi

V(A≥B)	1	V(B≥A)	1	V(C≥A)	0.98	V(D≥A)	0.51	V(E≥A)	0.71	V(F≥A)	0.82	V(G≥A)	0.86
V(A≥C)	1	V(B≥C)	1	V(C≥B)	0.97	V(D≥B)	0.48	V(E≥B)	0.7	V(F≥B)	0.81	V(G≥B)	0.85
V(A≥D)	1	V(B≥D)	1	V(C≥D)	1	V(D≥C)	0.54	V(E≥C)	0.74	V(F≥C)	0.85	V(G≥C)	0.89
V(A≥E)	1	V(B≥E)	1	V(C≥E)	1	V(D≥E)	0.84	V(E≥D)	1	V(F≥D)	1	V(G≥D)	1
V(A≥F)	1	V(B≥F)	1	V(C≥F)	1	V(D≥F)	0.7	V(E≥F)	0.86	V(F≥E)	1	V(G≥E)	1
V(A≥G)	1	V(B≥G)	1	V(C≥G)	1	V(D≥G)	0.65	V(E≥G)	0.82	V(F≥G)	0.95	V(G≥F)	1
Min	1	Min	1	Min	0.97	Min	0.48	Min	0.7	Min	0.81	Min	0.85

A triangular fuzzy number indicated the fuzzy weight of the ith criterion:

$$\tilde{w}_j = (L w_j, M w_j, U w_j) \ ,\qquad\qquad (17)$$

It should be mentioned that the acquired weights are non-fuzzy numbers. The normalized non-fuzzy weights of the criteria are shown in Table 6.
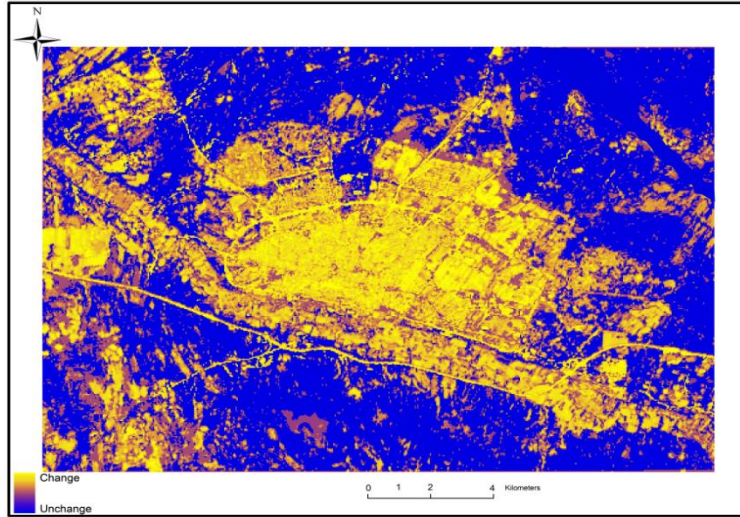
Figure 9. Change maps resulting from integration of spatial/spectral information
Şekil 9. Mekansal / spektral bilgilerin entegrasyonu sonucunda oluşan değişim haritaları

Table 6. The normalized non-fuzzy weights of criterion
Tablo 6. Kriterlerin normalize olmayan bulanık ağırlıkları

Criteria	Band difference	Band ratio	PCA Change detection	PCA of Semivariance	TDT	TRT	SFM
Weight	0.173	0.173	0.1677	0.0825	0.12	0.1395	0.1462

Figure / Şekil 9 illustrates the results of the weighted integration of spectral and spatial criteria from the FAHP method. A visual assessment of the results shows that drastic changes have occurred in areas where the spatial and spectral criteria have changed simultaneously. In addition, Figure / Şekil 9 shows, the extreme changes imposed by human activities in residential areas. Road and urban expansion have caused intense changes.

The integration of spatial and spectral information, by FAHP algorithm, can estimate both the changed areas, and the intensity of change. Thanks to integrating spatial and spectral criteria, the homogeneity and heterogeneity of a study area were provided in addition to information about changes. Therefore, it is evident that the FAHP contains far more discriminating information about change areas than any other method used in this study. There is a gradual transition between change classes, both spectrally as well as spatially, in contrast to crisp change detection methods, which reveal only changed and unchanged areas. Visual comparisons of the resulting images showed that the changes detected by the FAHP approach were more accurate than the other parameters (*A, B, C, D, E, F,* and *G*) used in this study. The visual interpretation of the change maps showed that the integration of the spatial and spectral information has resulted in the elimination of the 'salt and pepper' phenomenon, common in results of pixel-based change detection approaches. Further, a visual examination of the resulting change maps shows that linear phenomena, such as roads, are better represented when using the FAHP method. In addition, errors made by the rupture are decreased using this method. The FAHP change detection map was reclassified into two classes to be comparable with the other parameters (*A, B, C, D, E, F,* and *G*) (Figure / Şekil 10).

$$FAHP \begin{cases} DN \langle mean & unchanged \\ DN \rangle mean & change \end{cases} \qquad (18)$$
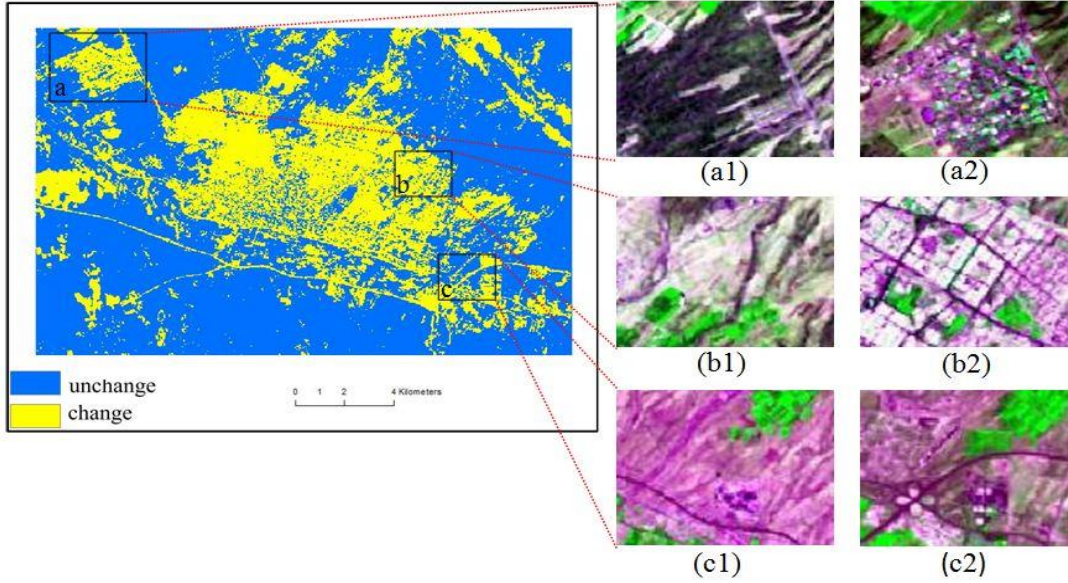
Figure 10. Change maps resulting from the FAHP method: (a) change from farmland and vegetation to built-up area, (b) urban expansion, (c) roads and farmland expansion (a1), (b1), and (c1) are subsets of the Landsat TM® image of 1985, and (a2), (b2), and (c2) are corresponding subsets in the Landsat TM® image of 2010.

Şekil 10. FAHP yöntemi ile üretilen değişim haritaları: (a) yerleşim alanı, (b) kentsel genişleme, (c) yollar ve tarım arazisi genişlemeleri (a1), (b1), ve (c1) 1985 yılı Landsat TM® alt küme görüntüsü (a2), (b2) ve (c2) 2010 yılı Landsat TM® alt küme görüntüsü

For the objective of training and testing the classifier efficiency, the reference data are collected from agricultural crops by field observations using both cadastral maps and global positioning system (GPS).

To evaluate the performance of the FAHP change detection method in the study area, the results of all the methods are visually compared and quantitatively evaluated. The confusion matrix is used for quantitatively assessing accuracy of change detection. To this end, 2561 test samples (i.e., pixels) of changed areas and 1490 pixels of unchanged areas are collected from study area. For each method, overall accuracy, producer and user accuracies, the kappa coefficient, and errors of commission and omission are reported. The results of the accuracy assessment of different tested methods are shown in Table / Tablo 7 and Figure / Şekil 11.

Although the PCA of raw semivariance shows low accuracy, the TDT, TRT and SFM show high accuracies and promising change detection capabilities. More specifically, TDT appears to yield the most informative texture parameter. Among the spatial criteria, the PCA of raw semivariance and TDT show the highest and lowest differences between the user's and the producer's accuracies, respectively. The most balanced user's and producer's accuracies are obtained by using both the semivariogram features and the spectral information in a FAHP framework. A quantitative assessment of the results demonstrate that the spectral information present more accurate changes maps than spatial information. Accuracy assessments show that the FAHP approach increases overall accuracy by at least 8%. This improvement confirms the hypothesis that weighted integration of spatial and spectral information significantly improves change detection accuracy. Similar improvements in overall accuracy have been achieved in other studies. For example, Helmy and Taweel (2010) reported a 23% increase in accuracy for change detection when combining texture with multi-spectral bands. He et al (2011) proposed an extended CVA approach that incorporated textural change information into the traditional spectral-based CVA, increasing overall accuracy by between 4.7% and 8.0% compared to traditional spectral-based CVA.

Table 7. Accuracy of the change maps resulting from the different tested criterion
Tablo 7. Farklı test kriter kaynaklanan değişim haritalarının doğruluğu

| Criterion	Class	Prod. Acc.	User Acc.	
TDT	changed	76.24	95.6	Overall. Acc. =80.8%
	unchanged	91.69	61.99	
SFM	changed	65.82	98.14	Overall. Acc. =75%
	unchanged	97.04	54.54	
TRT	changed	59.07	94.51	Overall. Acc. =68.8%
	unchanged	91.87	48.68	
PCA of Semivariance	changed	43.44	99.48	Overall. Acc.= 60.1%
	unchanged	99.46	42.63	
Band Ratio	changed	84.5	99.58	Overall. Acc.= 88.8%
	unchanged	99.15	72.99	
Band Difference	changed	81.33	99.68	Overall. Acc.= 86.7%
	unchanged	99.38	69.23	
PCA Change detection	changed	83.22	90.59	Overall. Acc.= 82.1%
	unchanged	79.53	66.7	
FAHP Change Detection	changed	96.28	97.55	Overall. Acc.= 96.5%
	unchanged	96.95	94.06	
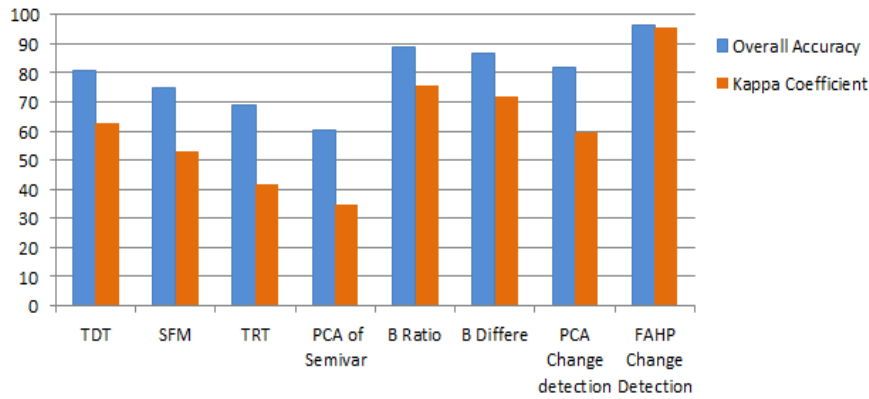
Figure 11. Overall accuracy of different change detection methods
Şekil 11. Farklı değişim saptama yöntemlerinin doğruluğu

4. CONCLUSIONS

The main purpose of this study was to integrate the capabilities of spectral and spatial information for landuse/landcover change detection. A quantitative assessment of the results, demonstrated that the integration of various spectral and spatial information due to the use of the FAHP and the semivariogram features has led to an overall accuracy of more than 96%, which is considerably higher than other spectral and spatial methods. Incorporation of the texture information, represented by the semivariogram features, leads to a considerable decrease in the omission and commission errors.

Parameters such as the TDT, SFM and TRT can have a better, more suitable performance in early and automatic change detection, and can be applied to both unclassified and classified images. In addition, the integration of the spectral and spatial measures by the FAHP method results in a reduction of the inherent uncertainties in using only one method. The FAHP approach shows great potential for land use cover

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change detection in heterogeneous areas with rich textural information. The FAHP integration approach introduces intensity change maps, which can be beneficial for mapping sensitive zones. These maps can determine which areas are vulnerable to severe water/soil erosion.

In contrast to other change detection methods, the FAHP integration of spatial and spectral information offers a wide range of decision making alternatives, which guides managers and decision makers toward extreme and risky changes. This approach has some positive results, such as decreased costs, improved time-efficiency, and higher quality change detection. Another advantage of this method is we can define a set of easily interpretable different spatial and spectral criteria with determination of intensity.

The FAHP integration of spatial and spectral information is a flexible approach which the decision maker can freely adjust for the membership degrees and weights of criteria according to the cognitive information available. The FAHP decision making method enables experts and users to efficiently select a more suitable and varied criteria for land use cover change detection. The integration of different methods of change detection can include various variables, as well as a lot of useful information, both of which are relevant to the task at hand. However, the optimal selection and integration of the spectral and textural features in the proposed FAHP change detection approach needs more consideration. This will be the subject of the next study.

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