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Change Detection in Urban Area Using Landsat Data; Gaziantep Case Study in Turkey

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ABSTRACT

Arid and semi-arid regions have different spectral characteristics relative to other temperate part of the world. Therefore, indices have been developed in order to eliminate spectral mixing between built-up and bare land classes in land use/land cover classification of these regions. In this study, various indices have been compared in order to increase the accuracy of change detection in a semi-arid region of Turkey. The aim of this study is to determine the variation of built-up/bare land boundaries using urban indices in Gaziantep city located at the Southeastern part of Turkey. For this purpose, Landsat 5 TM and Landsat 8 OLI images of two different dates (1985 and 2018) were used. The normalized difference built-up index (NDBI), Enhanced built-up and bareness index (EBBI), together with spectral bands were compared and evaluated using binary change detection method. Based on the performance evaluation, 2 σ (81.37%) and 1 σ (80%) thresholds were found appropriate for blue band and NDBI images.

Keywords: Change detection, NDBI, EBBI, Image differencing, Gaziantep

INTRODUCTION

Interacting with the natural and physical environment, cities have entered into process of rapid change due to changing needs of people and strong technological interventions. As a result of urbanization, destruction of natural and cultural environments has been inevitable. Irregular urbanization, unbalanced density distributions, lack of infrastructure, air pollution, noise, lack of green space affected human health negatively. The lands unconsciously opened to settlements consume natural resources and disrupt the ecological balance, by endangering the life of all living things [1].Therefore, the determination of change is important when making appropriate and sustainable planning decisions. In recent years, change analysis methods have been grouped in 7 categories including; (1) algebra, (2) transformation, (3) classification, (4) advanced models, (5) geographic information systems approach, (6) visual analysis, (7) other approaches [2].

The pre-classification change detection methods reduce the confusion due to classification errors which was the case for the post-classification change methods. Thus, this approach enables faster and more accurate results [3].Although there are many change detection methods within the literature however, there is no unique appropriate method. Image algebra techniques are the most widely used methods as a pre-classification. These methods provide changing binary change/no-change information using image differencing and rationing, bi-temporal linear data transformation such as principal component analysis (PCA) [4].and correspondence analysis (CA) [5].image regression [6].; [7] and spectral mixing analysis [2].Pre-classification change detection approaches, do not involve comparison of whole classified images. Instead, they have given information about the change in the spectral differences of two different time sets [8].; [9].Image differencing and rationing methods have been demonstrated in many studies that more potential than others [2, 10, 11].

The aim of this study was to determine the variation of built-up/bare land boundaries using urban indices in the case of Gaziantep city using Landsat data.

MATERIAL

Study area

Gaziantep, which is one of Turkey's most important cities with its historical, industrial, trade and touristic potential, is located in the Southeastern Anatolia Region of Turkey. The study was conducted in Şehitkâmil and Şahinbey districts and its surroundings, which constitute the main urban fabric (Figure 1). Altitudes change between 744 and 1204 meters. Elevation has gradually increased from city center to the north. Soil of Gaziantep is covered 14% with forests. These forests are dominated by oak and pine species. All the oak forests are defective so they are under protection [12]., [13].The city has a semi-arid climate, a rainy and relatively mild winter, dry and warm summer. The average annual temperature is 14.9 ° C and the average annual rainfall is 552.4 mm [14].

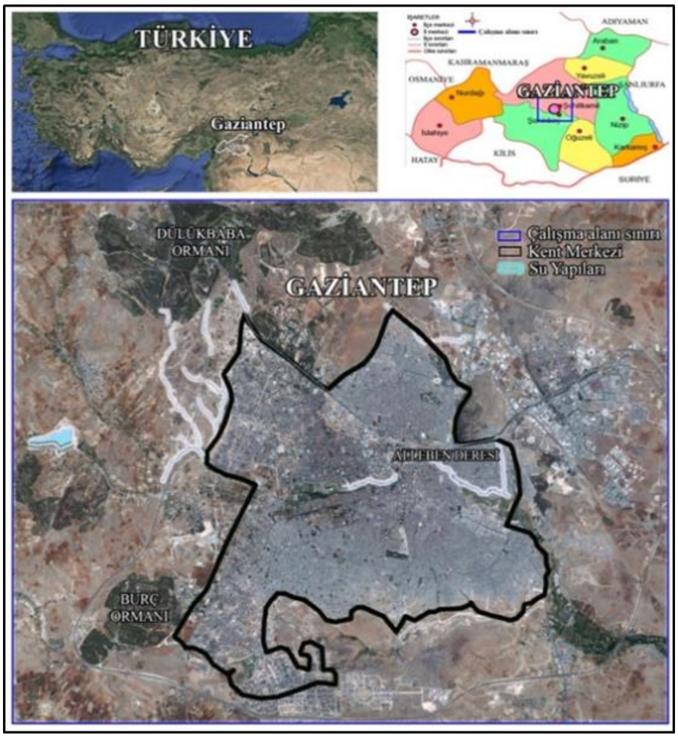

Figure 1. Geographic location of the study area

Dataset

Two Landsat TM/OLI sensor images (1984-2018) of the arid season were used [15].The data set included Landsat 5 (TM) dated 06.09.1984 and Landsat 8 (OLI) dated 20.09.2018) (Table 1 & 2). The Landsat archives provide the largest data sets and are widely used in regional inventory and change detection studies.

Table 1. Spectral band Specification of Landsat Thematic Mapper (TM)

Band	**Wavelength (micrometre)**	**Resolution (metre)**
Band 1 – Blue	0.45-0.52	30
Band 2 – Green	0.52-0.60	30
Band 3 – Red	0.63-0.69	30
Band 4 - Near Infrared (NIR)	0.76-0.90	30

Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
Band 6 – Thermal	10.40-12.50	120* (30)
Band 7 - Shortwave Infrared (SWIR) 2	2.08-2.35	30

Table 2. Landsat-8 LDCM OLI / TIRS Satellite Bands and Features

Band	Wavelength (micrometers)	Resolution (meters)
Band-1 Ultra Blue (Coastal Aerosol)	0.43-0.45	30
Band-2 Blue	0.45-0.51	30
Band-3 Green	0.53-0.59	30
Band-4 Red	0.64-0.67	30
Band-5 Near Infrared (NIR)	0.85-0.88	30
Band-6 Shortwave Infrared (SWIR-1)	1.57-1.65	30
Band-7 Shortwave Infrared(SWIR-2)	2.11-2.29	30
Band-8 Panchromatic	0.50-0.68	15
Band 9 Cirrus	1.36-1.38	30
Band-10 Thermal Infrared (TIRS-1)	10.60-11.19	100*30
Band-11 Thermal Infrared(TIRS-2)	11.50-12.51	100*30

* Thermal band is obtained with 100 meter resolution but it is re-arranged as 30 meters.

METHOD

The images were geometrically corrected and geocoded to Universal Transverse Mercator (UTM), coordinate system by using a reference image. In the next step, images were atmospherically corrected before applying image differencing.

Image differencing

Image differencing is one of the common methods used to determine changes in landscape level. However, the methods used for change/no-change areas often differ. For this reason, it is often not possible to propose a standard operating sequence and data type for the detection of changes in any landscape type. Image extraction can simply be defined as the subtraction of the corresponding pixels in the two dated images. As a result of the subtraction, 0 represents the unchanged fields, and the other values represent negative or positive change. But this does not constitute real changes. Therefore, it is necessary to determine the actual change by testing the results. Different methods have been developed and “Thresholding” is a widely used one amongst these methods [16].However, the difference image histogram has a symmetrical distribution with no specific breakpoints [16]., it is often difficult to accurately determine the threshold limit. Eastman and McKendry (1991) used the difference and the sum of the mean and standard deviation of the difference image as the determining factor of the threshold value. Simply can be defined as:
Threshold Value: Average (m) ± Standard Deviation (σ)

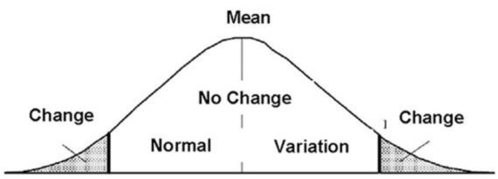

Figure 2. Thresholding method [16].

According to Eastman and McKendry (1991), in a normally distributed data set, 1 σ distance from the mean is 90% of the pixel values, 2 σ deviation distances are 95%, and 3 σ distances are 99.5%. The values between the threshold values indicate no-change and the areas outside the threshold values likely represent the actual change.
In the threshold value application, "0" value was given to the fields that are assumed to represent the fields that fall between the threshold values and no change, value '1' was given to the areas that are outside the threshold values and the areas that are assumed to represent the actual changes.

Enhanced built-up and bareness index (EBBI)

The EBBI is a remote sensing index that applies wavelengths of 0.83 µm, 1.65 µm, and 11.45 µm, (NIR, SWIR, and TIR, respectively) to Landsat TM images. These wavelengths were selected based on the contrast reflection range and absorption in built-up and bare land areas [17]. EBBI was computed using Equation. 1.

Equation.1 $$EBBI = \frac{SWIR - NIR}{10\sqrt{SWIR + TIR}}$$

Normalized difference built-up index (NDBI)
Second, based on the high reflectance of built-up areas in the 1.55–1.75 µm wavelength range (TM band 5) and their low reflectance in the 0.76–0.90 µm wavelength range (TM band 4), NDBI was computed using Equation. 2 [18].

Equation.2 $$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

CONCLUSION

The aim of the study was to map the settlement and bare areas using the Enhanced Built-Up and Bareness Index (EBBI) and the Normalized Difference built-up index (NDBI). Blue and SWIR bands of Landsat 5 TM and Landsat 8 OLI Images were subtracted from each other and the most suitable threshold values were determined by calculating the mean and standard deviation values together. These values were applied as limit factors to detect the actual change. These threshold values were tested as standard deviation 3σ, 2σ, 1σ and accuracy analysis was performed in order to determine the most suitable threshold value (Figure 3a,3b,3c, Figure 4a,4b,4c).

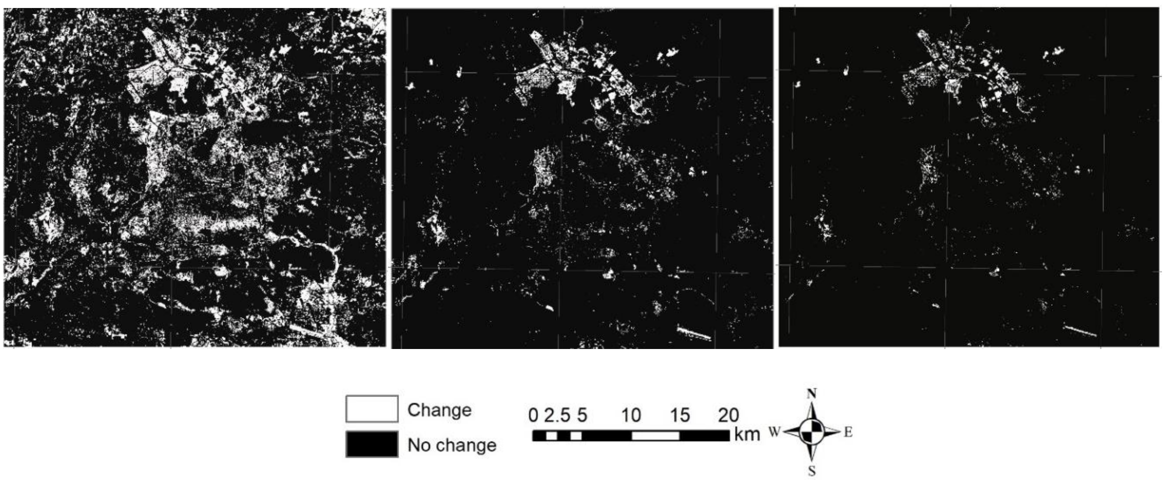

Figure3a. Blue band 1σ **Figure3b.** Blue band 2σ **Figure3c.** Blue band 3σ

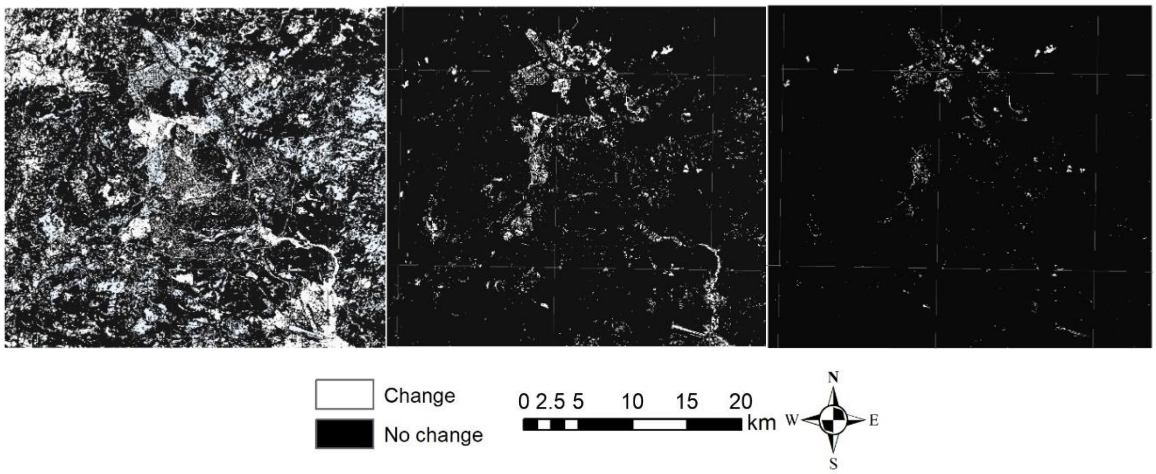

Figure4a. SWIR band 1σ **Figure4b.** SWIR band 2σ **Figure4c.** SWIR band 3σ

The difference between 1985 and 2018 was determined by applying image difference analysis. The most suitable threshold values were determined by calculating the mean and standard deviation values together (Figure 5a, 5b,5c, Figure 6a,6b,6c).

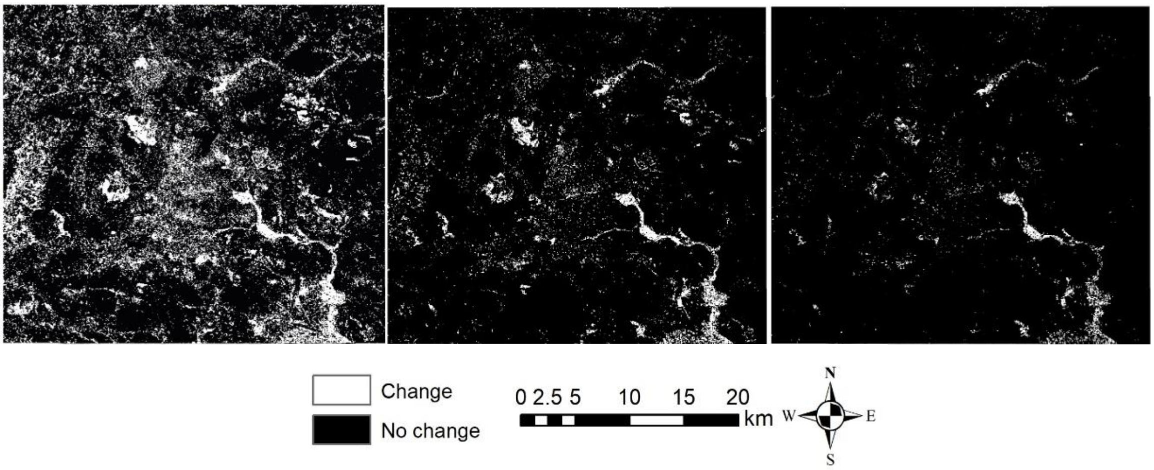

Figure5a. NDBI 1σ **Figure5b.** NDBI 2σ **Figure5c.** NDBI 3σ

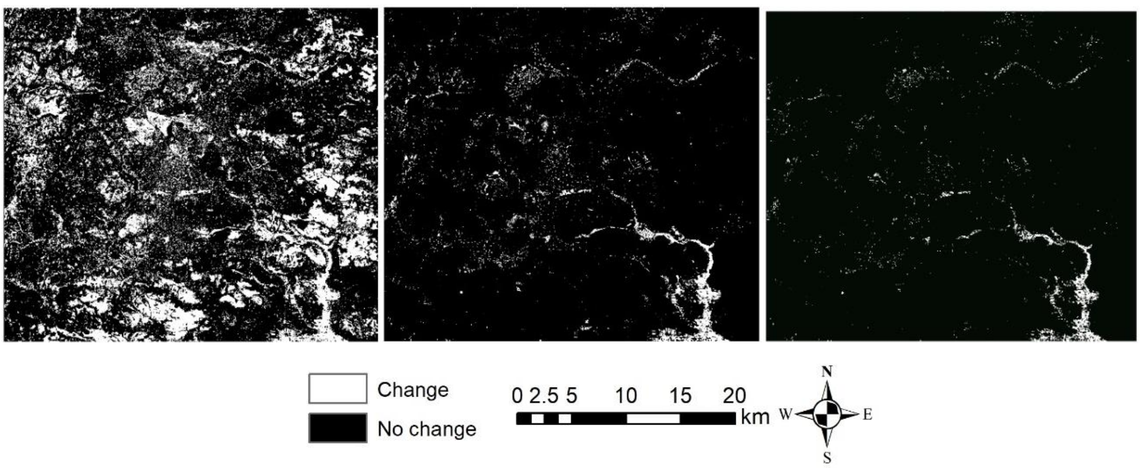

Figure4a. EBBI 1σ **Figure4b.** EBBI 2σ **Figure4c.** EBBI 3σ

Accuracy assessment

The accuracy assessment results showed that the largest accuracy for the 2σ threshold value of the blue band was overall accuracy of 81.37% (k=0.7330). The second most accurate one was the 1σ threshold value of the NDBI maps with an overall accuracy of 80.00% (k=0.8300). The results indicated that the proposed indices can be used for differentiating built up and bare land from other land use classes accurately (Table 3).

Table 3. Change detection accuracy assessment

Change of data set	Thresshold	Overall accuracy (%)	Kappa
Blue band	1σ	66.86	0,5529
	2σ	81.37	0.7330
	3σ	72.73	0.6400
SWIR band	1σ	60.00	0.5000
	2σ	76.67	0.6333
	3σ	78.33	0.7667
NDBI	1σ	80.00	0.8300
	2σ	66.67	0.6640
	3σ	66.67	0.5162
EBBI	1σ	64.00	0.5830
	2σ	76.47	0.6638
	3σ	76.00	0.6455

DISCUSSION

This study distinguished the most similar built-up and bare soil classes during land use / land cover classification. As a result, it is seen that NDBI and blue band can be included in supervised classification for high accuracy. In previous studies, blue band of Landsat images; Band 1 (0.45 - 0.52u m): was mainly used for penetration capability of water bodies together with differentiating soil and rock surfaces from vegetation and detecting cultural features [19]. In this study; it is seen that blue band can be used to detect the changes in built-up and bare soil classes with higher accuracy. Moreover this recoding simplified the interpretation of the final output (positive values indicating built-up areas), Zha, Gao, and Ni (2003) mentioned that the usage of binary images restricted any refinement of results and their approach was unable to separate urban from bare areas due to this constraint. As, it can be seen in this study, the use of NDBI with blue band have great potential to increase accuracy of change detection methods.

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