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Evaluating Land Use Change Detection Methods in Damavand City Using Remote Sensing

Fatah Hassan Family[a], Zahra Azizi[b*]

[a]Master of Science in Remote Sensing and GIS, Faculty of Natural Resource and Environment, Science and Research Branch, Islamic Azad University, Tehran, Iran

[b]Assistant Professor, Department of Remote Sensing and GIS, Faculty of Natural Resource and Environment, Science and Research Branch, Islamic Azad University, Tehran, Iran

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Abstract

Land-use change has significant impacts on environmental and natural resources, including water quality, air and terrestrial resources, ecosystem processes and functions, and climate systems. Therefore, accurate and timely detection of land-use changes is crucial for understanding the interactions between humans and natural phenomena and managing natural resources effectively. This study aimed to monitor land-use changes in Damavand city using remote sensing techniques. Two Landsat 5 and 8 satellite images from 1996 and 2018 were used after applying radiometric and atmospheric corrections. Four methods, including band differentiation, band ratio, principal component analysis, and post-classification image detection were employed to detect land-use changes. The results showed that man-made areas increased by 7288 hectares due to construction activities in agricultural fields, leading to a reduction of 4047 hectares of agricultural lands. Additionally, 10324 hectares of rich rangeland cover were transformed into poor pastures. The principal component analysis method using band 3 and the band difference method using band 5 effectively detected the changes in the region; however, the band ratio method did not perform well. The findings of this study can help policymakers make informed decisions about land use planning in Damavand city.

***Keywords**:* Damavand, Land Use Change Detection, Landsat, Band Ratio Method

1. Introduction

Land-use is a crucial activity that drives socio-economic growth and development by consuming natural resources, while simultaneously altering the environment's structures and processes (Helming, Pérez-Soba, and Tabbush, 2008). Land use change has a significant impact on natural resources,

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[*] Corresponding author Tel: +98-2144861709.
Email address: zazizi@srbiau.ac.ir.

environmental characteristics, and climatic ecosystem processes (Sundarakumar et al., 2012). Therefore, accurate and timely identification of changes is essential to better understand the relationships and interactions between humans and the natural environment. This understanding leads to better management and utilization of natural resources (Lu et al., 2004). Time series data can be used to observe and distinguish differences in terrestrial features and patterns (Lu et al., 2004; Singh, 1989). Remote sensing involves using two or more satellite images of a geographical area to identify and analyze changes in the area over time periods (Tian, Wan, and Yue, 2007). Remote sensing and GIS are considered superior techniques for studying changes in land use, which have had a significant impact on land management and urban planning (Safari and Azizi, 2021). As land use change usually occurs on a large scale, remote sensing technology is an important tool for studying and monitoring its changes (Arkhi, 2015).

Land use change detection using remote sensing data has been widely studied in the field of remote sensing and GIS. Various methods have been proposed to detect land use change, but no single method can be considered the best in all situations. Among these methods, post-classification comparison of classified images at different times has been recognized as the most accurate technique for detecting changes (El-Kawy et al., 2011). However, there is still a need for further comparison and analysis of these methods. In this study, we compare the effectiveness of band algebra, principal component analysis, classification, and fuzzy methods in detecting changes in Damavand city using Landsat satellite images. Land use change can occur due to various factors such as short-term events like snow or floods, urban development, or conversion of agricultural land into residential and industrial uses (Farsi and Yousefi, 2013). These changes are influenced by different factors such as population growth, economic development, climate change, cultural practices, and political decisions (Cropper and Griffiths, 1994). Population growth is one of the major drivers of land use change (Angelsen and Kaimowitz, 1999; Geist and Lambin, 2004), especially during migration or population displacement (Lambin et al., 2001). This study aims to contribute to the understanding of land use change detection techniques by comparing different methods in a specific area. By identifying areas where land use has changed over time using multidimensional datasets from Landsat satellite images and analyzing the factors that influence these changes in Damavand city, we hope to provide insights into effective strategies for managing land use change.

As the global population and economic pressures continue to rise, the demand for goods and services increases, leading to excessive land use (Millennium Ecosystem Assessment, 2005; Geist et al., 2006). Climate conditions also play a significant role in land use change (Lambin et al., 2001). Additionally, policies such as self-sufficiency in strategic products and food, decentralization, lack of investment in monitoring and protection of natural resources, nationalization, and privatization can all contribute to changes in land use (Xu et al., 1999; Becker, 1999; Agrawal and Yadama, 1997; Watts, 1989, 1994 and 1996). To accurately detect changes in land use using satellite imagery, it is crucial to fully understand the nature, scale, time and place of the studied phenomenon (Jensen, 1996; Mokhtari et al., 2017). Factors such as spatial resolution, radiometric and temporal satellite imagery, weather conditions, environmental considerations, time period, growth cycle and plant phenology must be taken into account when selecting suitable satellite images for analysis. Numerous studies have been conducted on detecting changes in land use both within Iran and globally. For example, research such as monitoring the trend of urban land use change using remote sensing technique (Case study: Kermanshah) (Heidari and Havasi Abdalani, 2016), detecting land use change using remote sensing methods and GIS (Case study: Ghaemshahr city (Sabzqabai et al., 2016), detection of land use changes and vegetation in Yasuj city using distance measurement (Omidvar et al., 2017), detection of land use changes and factors affecting it using artificial neural network (Case study: Talesh city), detection of land use change / land cover by object-oriented processing of satellite images (Case study: Tabriz city) (Sharifi et al., 2013), detection of land use change using remote sensing data (Case study: Bojnourd city) (Atyabi and Organi, 2018).

2. Material and Method

2.1. Study Area

Damavand city, located in the Tehran province of Iran, is a mountainous region with an average altitude of about 2000 meters above sea level. The city covers an area of 190522 hectares and is surrounded by the cities of Firoozkooh, Amol, Varamin, Garmsar and Tehran. The lands of the city are topographically limited between mountainous and high altitudes above 3000 meters above sea level and 2000 meters above sea level, and hilly and semi-high and southern areas that reach 1500 meters above sea level. Of the total area, 83% is national resources, 16% is agricultural land, and about 1% is urban (Figure 1).

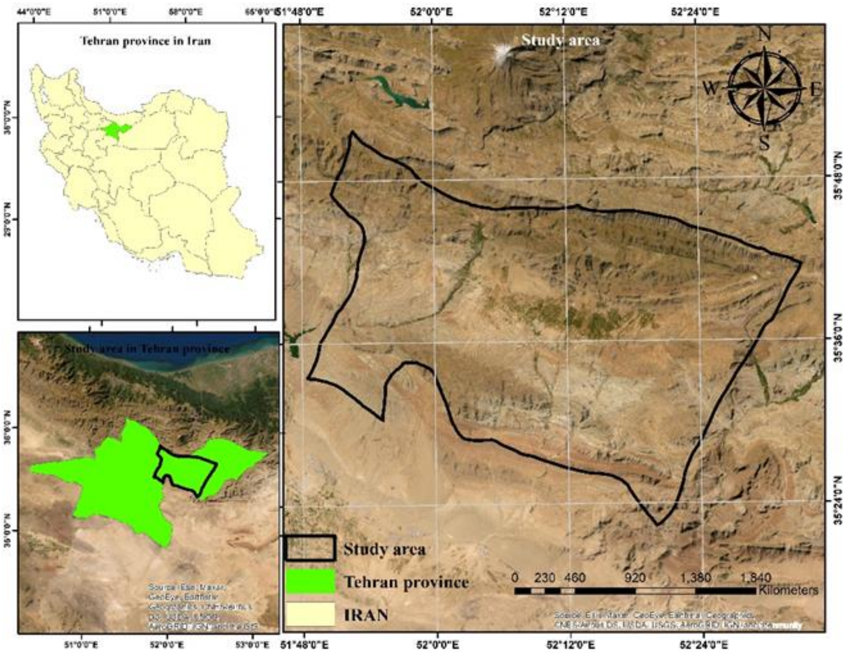


Figure 1. Location map of Damavand city in Tehran province

2.2. Methods

This study employed an applied research design with a descriptive survey method. To collect data for this study, a comprehensive literature review was conducted using various sources such as books, handbooks, dissertations and authoritative domestic and foreign articles as well as authoritative Internet sites. Landsat satellite images were used to study land use changes in Damavand city. Pre-processing was performed on these images to reduce atmospheric effects, noise and geometric corrections to ensure accurate identification of land use changes. ENVI and ArcGIS software were used for image processing. Change detection methods were implemented to identify user changes in the study area.

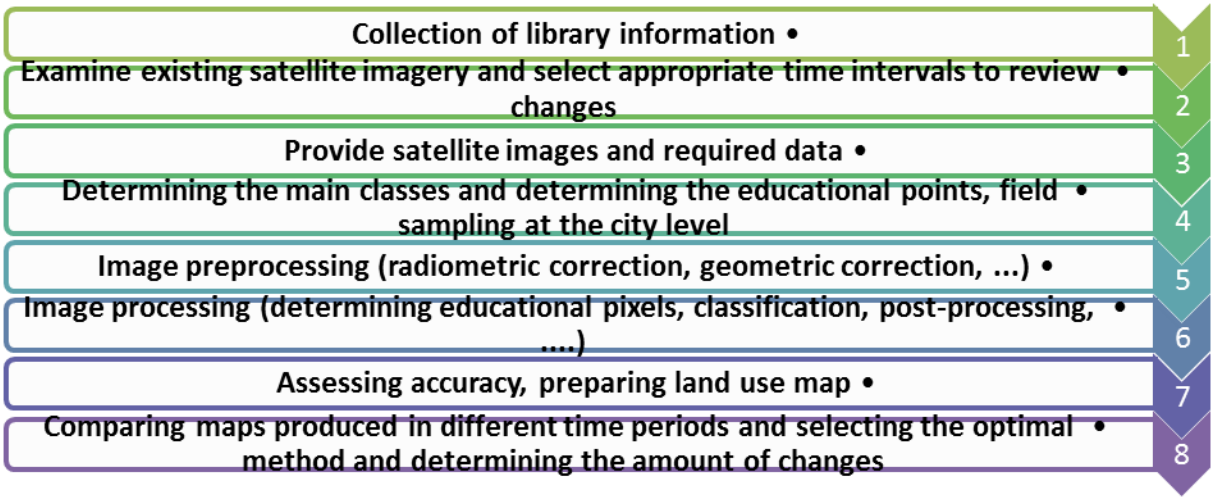


Figure 2. Stages of research

3. Data Analysis

3.1. Radiometric Correction

Radiometric correction involves adjusting the gray levels of an image to compensate for existing errors (Fatemi and Rezaei, 2012). In this study, radiometric corrections were applied by converting the DN value of the images to radiance. Additionally, Landsat 5 and 8 images were adjusted to have the same number of recording bits using relation 1 (DN is an 8-bit image band).

$$\text{change } 16-\text{bit image to } 8-\text{bit image} = \frac{DN_{8bity} * 2^{16}}{255} \quad (1)$$

3.2. Geometric Correction

Geometric correction is a two-step process involving mathematical conversion functions to calculate geographical coordinates and resampling to match a base geographic map or coordinate system (Aranov, 2012). Landsat satellite images are provided in a corrected form and do not require further geometric correction. The specifications of the corrections made on the images used in this research are presented in Table 1.

Table 1. Specifications of Points and Errors of Geometric Corrections made on images (Image File Header used).

Image specification	X-axis error in meters	Y-axis error in meters	Number of control points
Landsat 5 1996	3.85	2.3	435
Landsat 8 2018	3.4	4.29	196

3.3. Atmospheric Correction

Atmospheric correction is a crucial step in remote satellite imagery processing, aimed at eliminating atmospheric effects from satellite images and determining the true values of surface reflection. The primary objective of this correction is to restore the physical parameters of the earth's surface, including surface reflection, for accurate comparison and analysis of multi-time images. Equation 2.

$$L= (A\rho/(1-\rho_e S))+ ((B\rho_e)/(1-\rho_e S))+ L_a \qquad (2)$$

In this study, we utilized the FLAASH algorithm in ENVI software, which employs the standard equation for spectral radiation in the sensor to correct for atmospheric effects. The equation takes into account various factors such as L (spectral radius in the sensor), ρ (pixel surface reflectance), ρe (average surface reflection for the pixel and its surrounding area), S (atmospheric hemisphere albedo), and La (reflected radiation scattered from the atmosphere). Additionally, coefficients A and B are included to account for geometric and atmospheric conditions that have no relation to the surface (ENVI Wser’s Guide, 2009).

3.4. Detection of Changes

The detection of changes using satellite imagery involves examining changes in degree of gray in images taken over time relative to a reference time. This process entails comparing different images pixel by pixel with a reference image to identify any changes. Therefore, any method that can measure two images slightly together can be used to detect changes (Jensen, 1996). The methods used in detecting changes are diverse and can vary across different fields. In this study, we employed various methods to detect changes using satellite imagery.

3.5. Extract Binary Change with Mathematical Operation

Extracting quantitative "change / non-change" binary information using two-date images is one of the most difficult methods of detecting change (Im et al., 2009, 2011; Klemas, 2011). Binary switching between two corrected images is usually done using pixel-by-pixel image algebra such as band differentiation or band ratio (Bruzzone and Prieto, 2000; Jensen and Im, 2007; Kennedy et al., 2009) or by using a combination of sets. Image data or principal component analysis (PCA) (Rokni et al., 2015.).

3.6. Bandwidth Difference

In this method, based on relation 3, the digital values of the image on the second date are reduced from the digital values of the image on the first date. This process is pixel by pixel and the result of this method is the production of an image in which positive and negative values indicate changed regions and a value of zero indicates no change between the two dates.

$$Dx = x(t1)-x(t2)+C \qquad (3)$$

In this regard, X is the value of the pixel, t1 is the first date, t2 is the second date, and C is a fixed number (Singh, 1989).

Modified and unmodified areas are detected by setting the appropriate threshold on the gray images. In an 8-bit image, the value of the pixels is between 0 and 255, and the subtraction value of the images is between -255 and +255. Finally, by selecting the appropriate threshold (which is usually chosen experimentally), the image of the final changes is obtained. One of the advantages of this method is that there is no need for atmospheric correction and it shows changes in the brightness of the pixels of the two images. One of its disadvantages is that it does not show changes from to and is very careful in determining the change threshold (Jensen, 1996).

3.7. Bond Ratio

In this method, the bands are compared with a similar spectral range. In this method, the changes are examined pixel by pixel according to Equation 4.

$$I_r(x,y) = \frac{I_1(x,y)}{I_2(x,y)} \tag{4}$$

In the above relation, I1 is the image of the first date and I2 is the image of the second date.

Crippen (1988) recommended that all data used in this method be atmospherically corrected and free of any errors in the sensor calibration problem. If the radiometric characteristics of the two bands are similar. The image range of variations in this method is between 0 and 255 for standard 8-bit data, usually using normalization operators. It is important to note that the sensor is not based solely on the spectral bands of a sensor in terms of bandwidth or difference detection. It may be extended to compare vegetation or other types of index information obtained from multiple image dates. For example, scientists often calculate NDVI on two dates and then subtract one from the other to determine change (Lunetta et al., 2006; Green, 2011; Klemas, 2011).

3.8. Principal Component Analysis (PCA)

The principal component analysis is a mathematical method that uses the statistical properties of data to convert potentially correlated datasets into unrelated datasets so that as much information as possible is preserved (Li, 2009). This uncorrelated dataset is called principal components. The number of principal components is less than or equal to the number of primary data, so this conversion can also be used to reduce the feature. PCA uses a combination of two-date image bands to detect changes by creating a multi-time dataset. This method organizes the input data based on the comparison of the amount of variance, the covariance of the correlation coefficient. The data set is rotated around a new axis to minimize the output variance between the data (Nielsen et al., 2008; Kennedy et al., 2009; Almutairi and Warner, 2010).

3.9. Detection of Post-Classification Changes

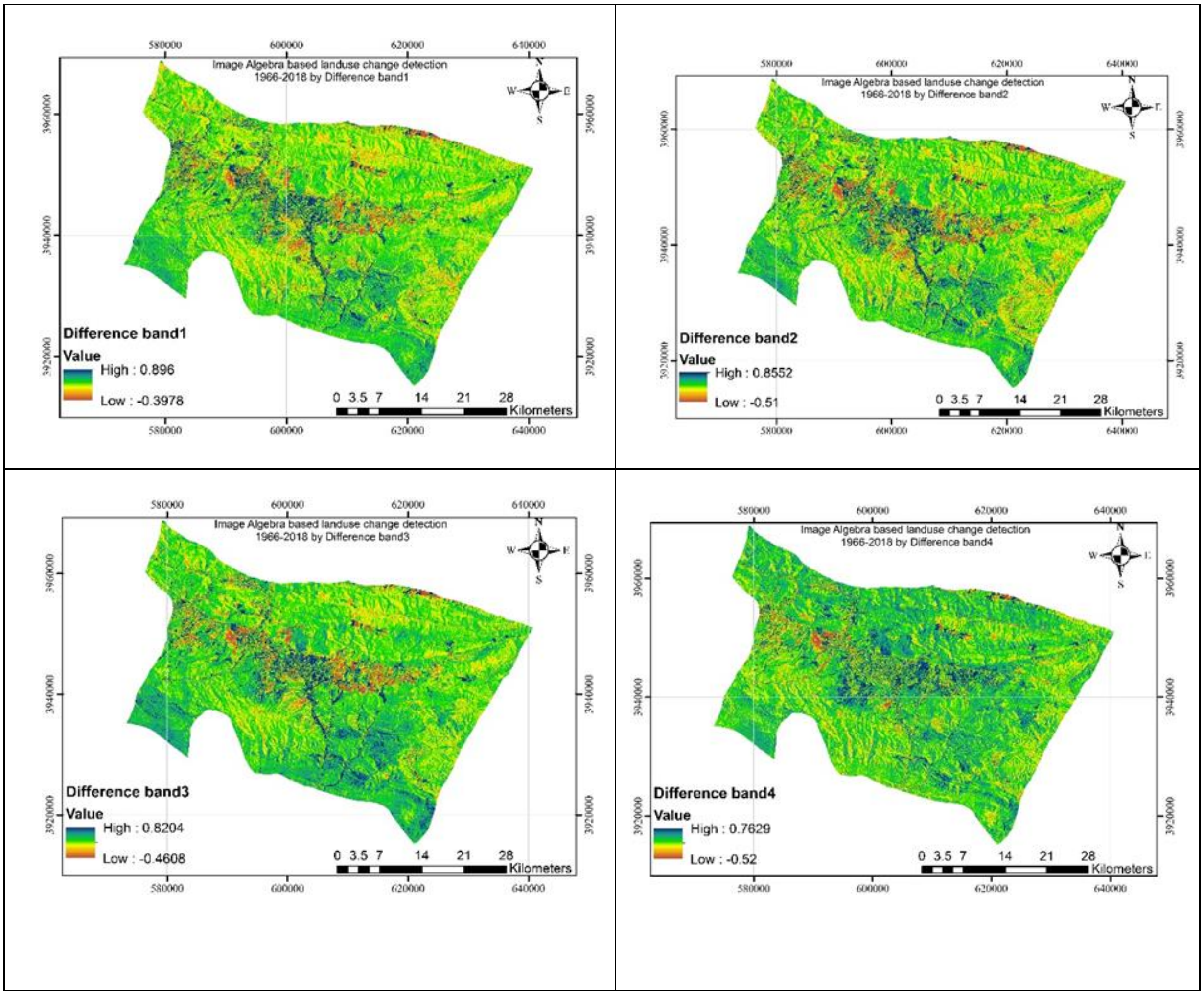
In this method, the land cover and land use of the study area in the multi-time images used are determined through classification and by comparing these classified images, information about the changes of these landscapes and land uses in the desired time period can be extracted. This method is a quantitative method that requires classified images of two dates (Jensen, 1996). In this method, two images are compared pixel by pixel (Rutchey and Velcheck, 1994). This method is commonly used and will be easy to analyze, and at higher levels it can be used to identify the product. One of the advantages of this method is that it detects changes from - to and will show the amount of change with the change location and create a single map (Arzandeh and Wang, 2003). The accuracy of this method depends on the accuracy of the classified images.

3.10. Maximum Likelihood Algorithm

In this method, the small amount of variance and correlation of the spectral values of different bands for the sample regions is calculated and the same property is used to associate an unclassified pixel to one of the groups or spectral samples. In other words, the variance matrix and the mean vector, which define the variance and the correlation of the spectral values, are used to investigate how the spectral values are distributed and the statistical probability of a pixel being related to one of the sample groups. This method is more accurate than other methods for classification. This method is based on probabilities, that is, the probability that a pixel belongs to any of the m-class sets is checked, and then the pixel is assigned to the class with the highest probability. The maximum probability classification method is still one of the most common supervised classification algorithms (Jensen and Im, 2007).

4. Results and Discussion

This study utilized two satellite images, one from Landsat 5 and the other from Landsat 8, which underwent radiometric and atmospheric corrections to ensure consistency. Four methods were employed in this research: band differentiation, band ratio, principal component analysis, and post-classification image detection. Band differentiation and band ratio methods utilized bands with similar spectral amplitudes. Since the number of bands in each satellite differed, adjustments were made to ensure comparability. Specifically, band 1 of Landsat 5 was considered equivalent to band 2 of Landsat 8, while the spectral range of each remaining band was equalized. The comparison was then made between bands n of Landsat 5 and n+1 of Landsat 8. Only spectral bands were used in this study (Figure 3).



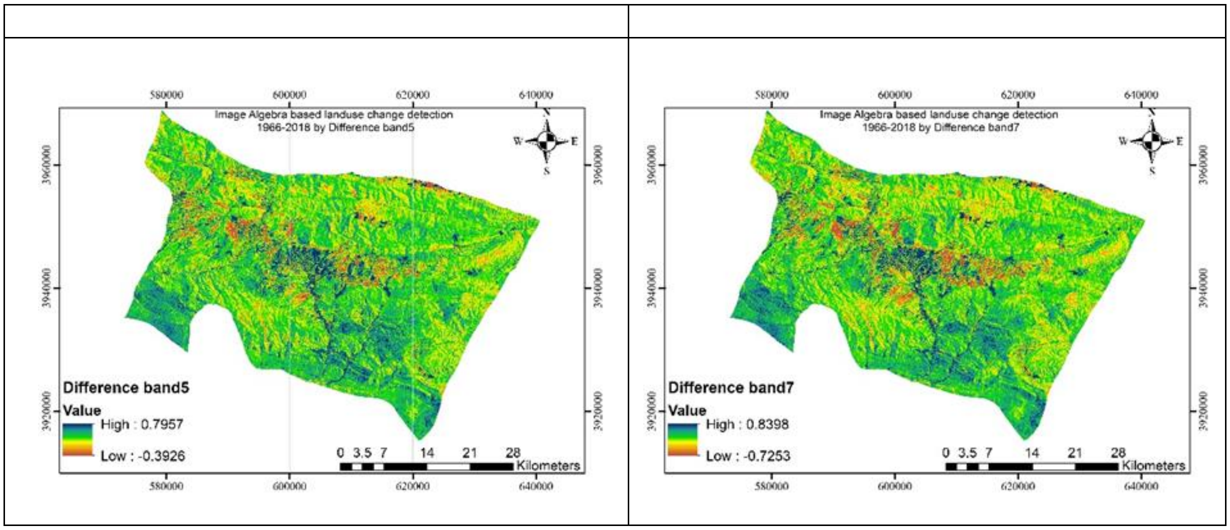
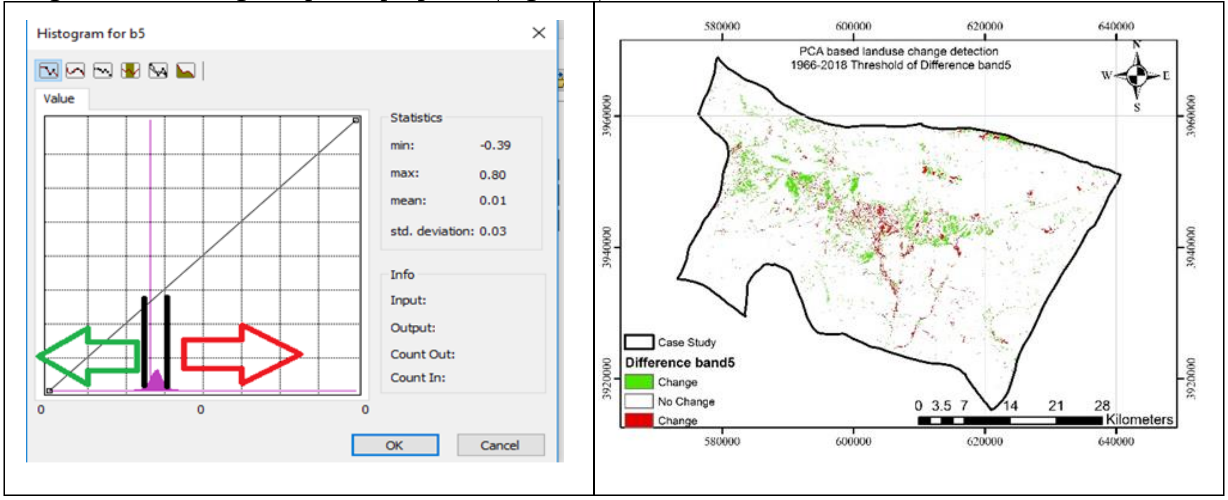


Figure 3. Detection map of changes based on band differentiation method (band 1 upper left drunk, band 2 upper right, band 3 middle left, band 4 middle right, band 5 lower left and band 7 middle right)

The results obtained through the band difference method showed that changes detected in bands 1, 2, and 4 were weak compared to those detected in bands 3, 5, and 7. The modified areas were represented by negative (green) and positive (red) values. Appropriate threshold values for the binary map were determined experimentally based on changes observed in the slope of the histogram (Figure 4). Changes in Figure 4 are indicated by two red arrows (reduced areas between two dates) and a red arrow (increased areas between two dates). The changes observed in band 5 proved to be particularly informative for detecting changes within the region.

In the bandwidth method, as with the bandwidth difference method, bands with similar spectral amplitude were assigned to each other. In this method, the values of changes will be determined by the interpreter based on the threshold. According to Figure 5 in this method, the changed areas are noticeably blue and brown. In this method, band 5 band ratio was selected as the best band to detect changes and its change map was prepared (Figure 4).


Histogram for b5

Statistics
min: -0.39
max: 0.80
mean: 0.01
std. deviation: 0.03

Info
Input:
Output:
Count Out:
Count In:

Figure 4. Using the histogram (left) to detect changes (right)

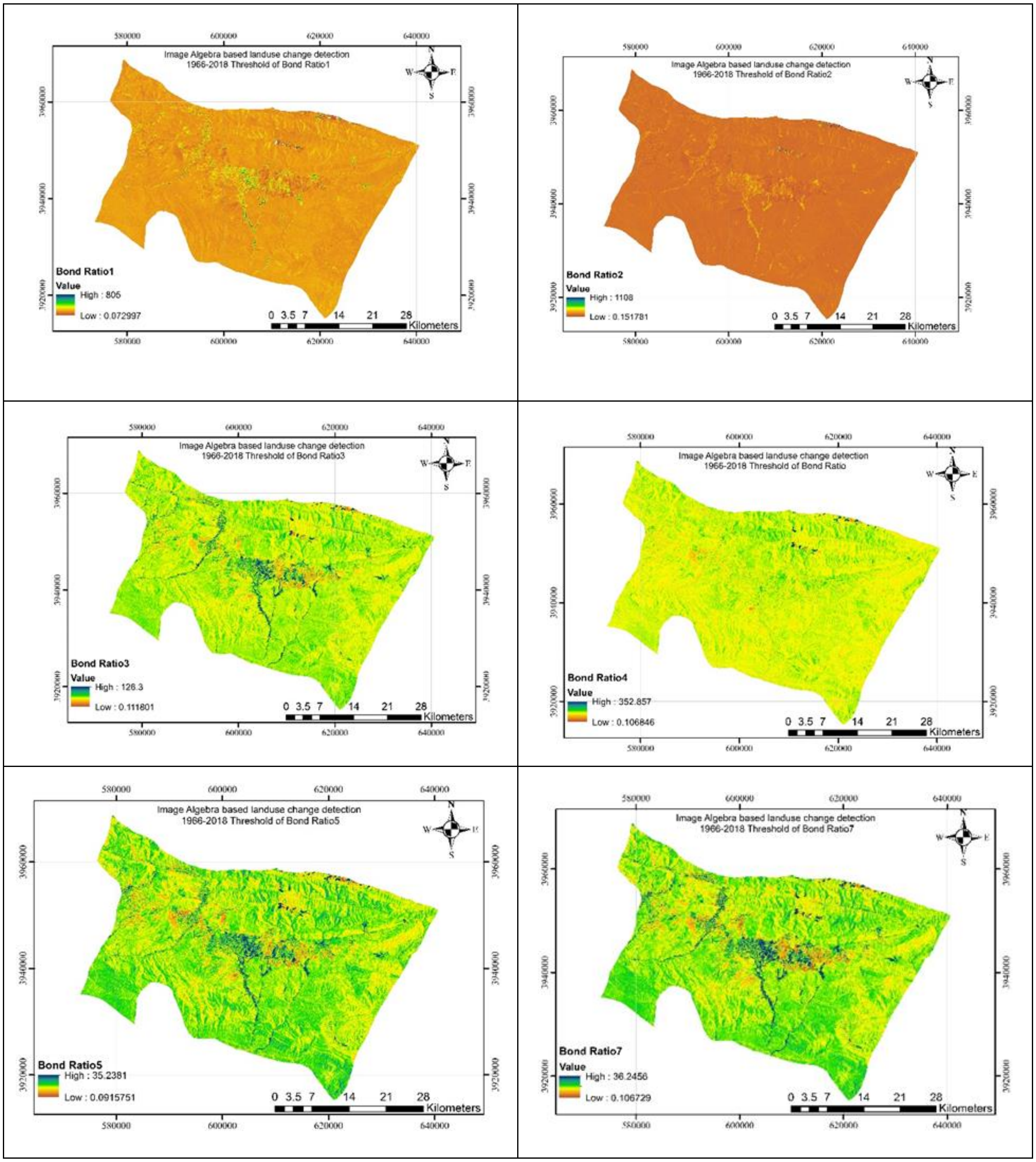


Figure 5. Detection map of changes based on the band ratio method (band 1 upper left drunk, band 2 upper right, band 3 middle left, band 4 middle left, band 5 lower left and band 7 middle right)

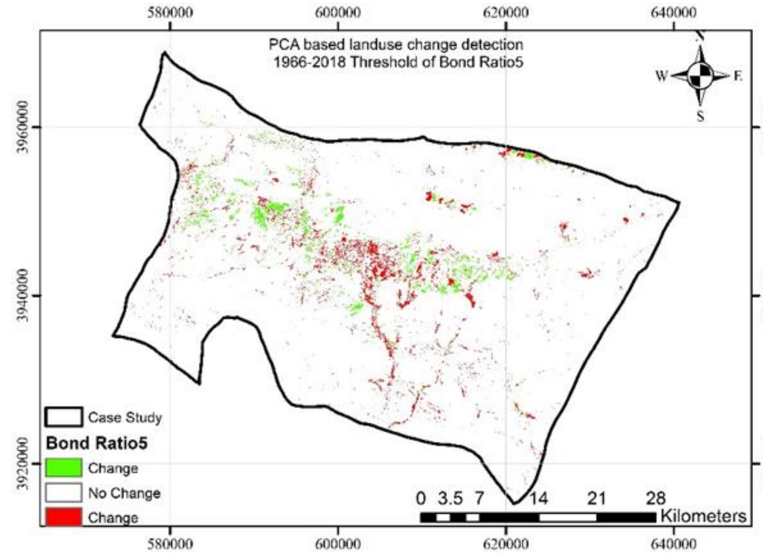
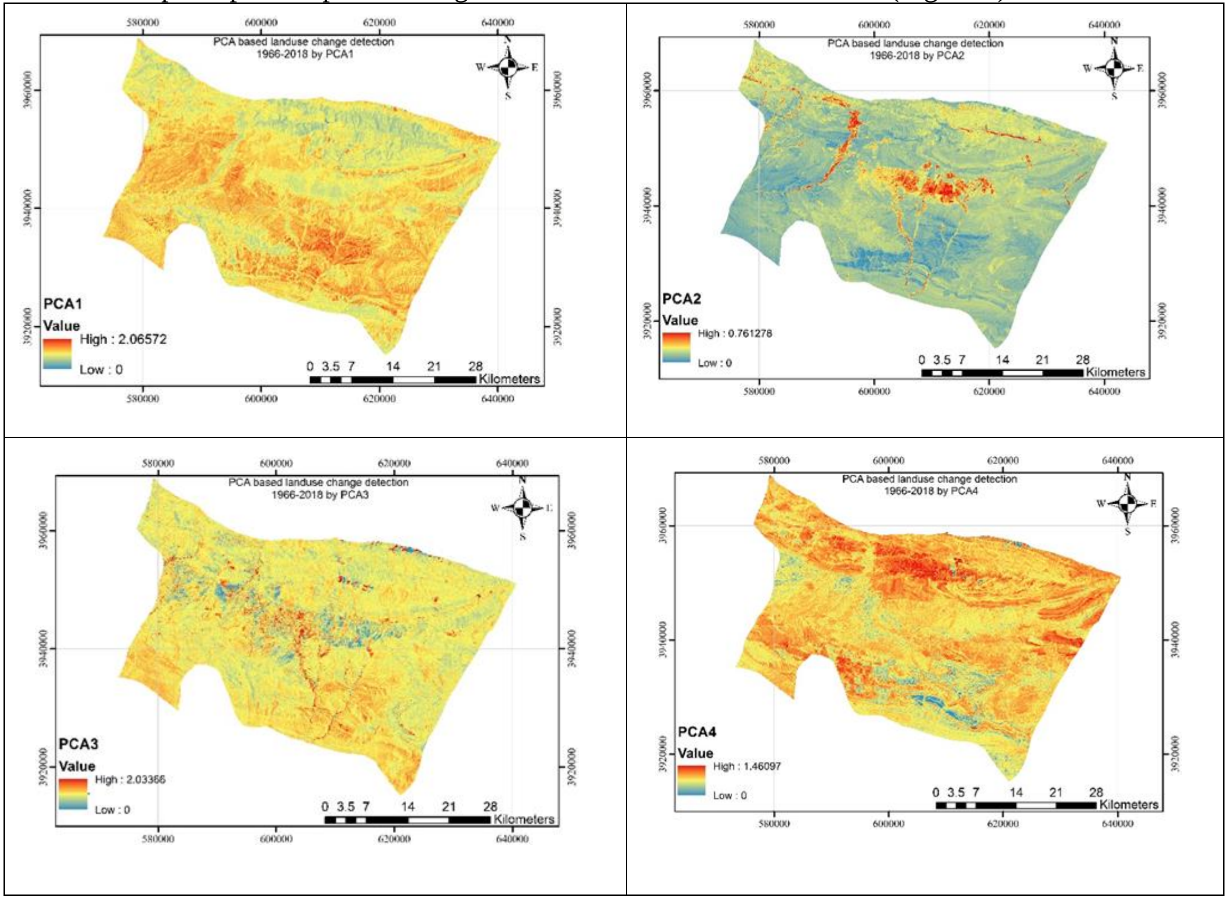


Figure 6. Determining the threshold for bandwidth changes

In the principal component analysis method, all bands of images of two combined dates were extracted. Six principal component images were extracted from this method (Figure 7).



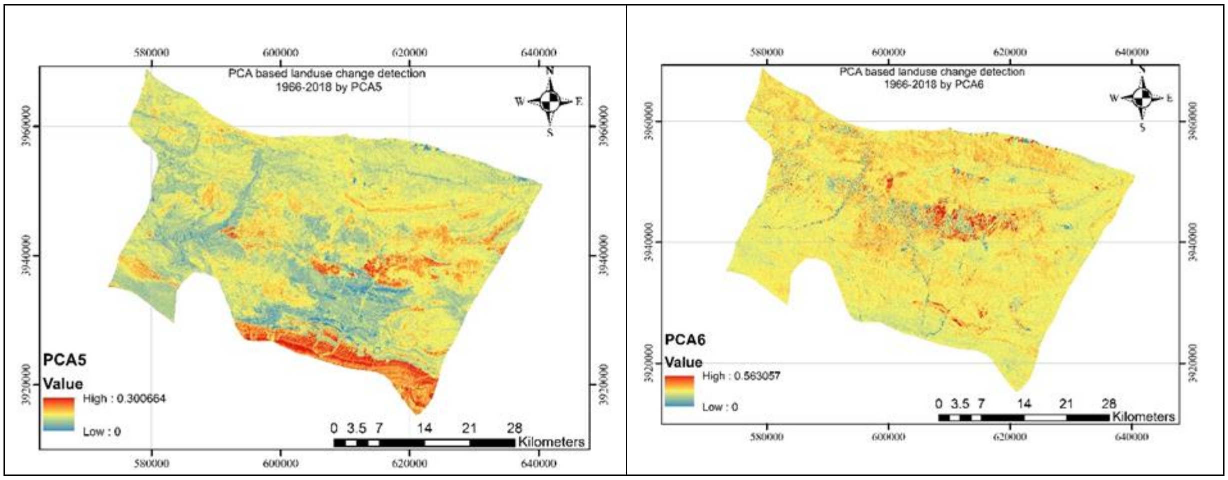


Figure 7. Change detection map based on principal component analysis method (component 1 upper left drunk, component 2 upper right, component 3 middle left, component 4 middle right, component 5 lower left and component 67 middle right)

The change detection map based on principal component analysis method consisted of six components, with component 3 being the most effective at recognizing changes. Similar to the previous methods, changed zones were located on both sides of the graph with maximum values (red) and minimum values (blue). By determining the threshold of the binary map, changes were prepared (Figure 8).

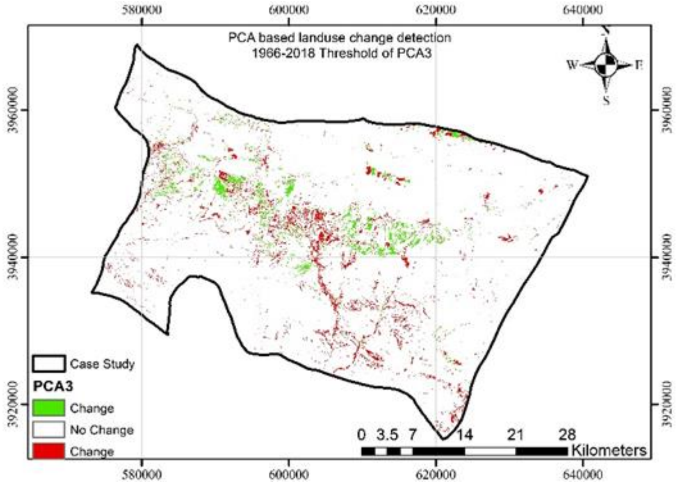


Figure 8. Binary map of changes based on principal component analysis number three

The maximum probability algorithm was used in the detection method after image classification. A two-date land use map was prepared based on visual interpretation of satellite images and knowledge of Region 6's land uses. The accuracy of user maps was evaluated using Kappa validation index, resulting in an accuracy of 0.95 for the 1986 date map and 0.83 accuracy for the 2018 date map. According to the user map, man-made areas significantly increased from 1986 to 2018 (red in Figure 9), as shown in Table 2.

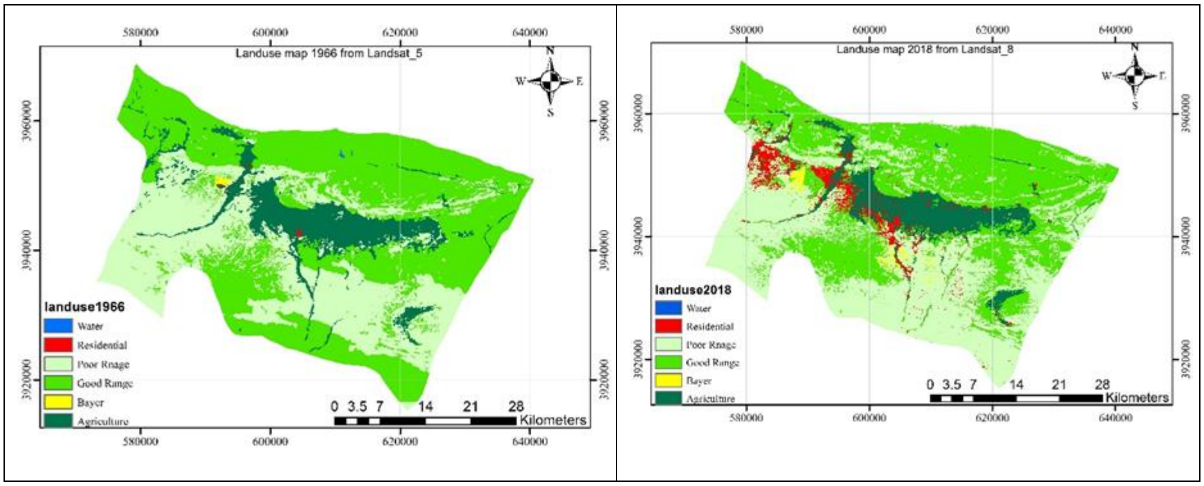


Figure 9. Land use map of 1375 (1986) (left) and land use of 1397 (2018) (right)

Table 2. Land Use Area (Hectares)

Class	Land area (hectares) in 1986	Land area (hectares) in 2018
Water	58	45
Human made	216	7504
Poor pasture	68488	78812
Rich pasture	94328	79654
Uncultivated	217	1340
Agriculture and gardening	22202	18155

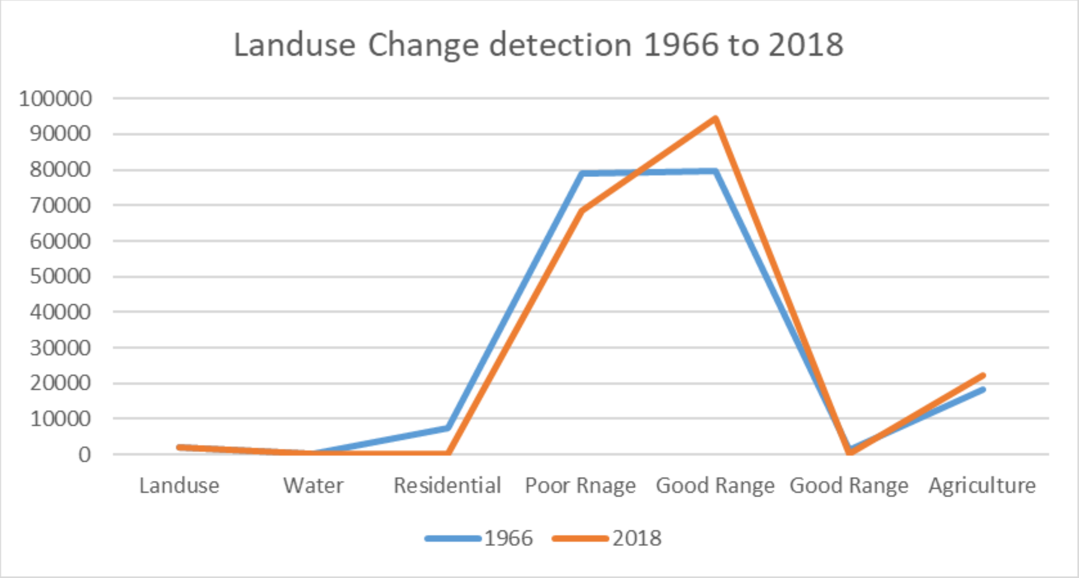


Chart 1. Land Use changes (1986 to 2018)

Based on the findings presented in Table 2 and Figure 1, there has been a decrease of 14,674 hectares in the area of rich pastures and a decrease of 4,047 hectares in agricultural fields. Conversely, there has been an increase of 10,324 hectares in poor pastures and an increase of 7,288 hectares in built-up areas. The changes from user (1986) to user (2018) are illustrated in Figure 10.

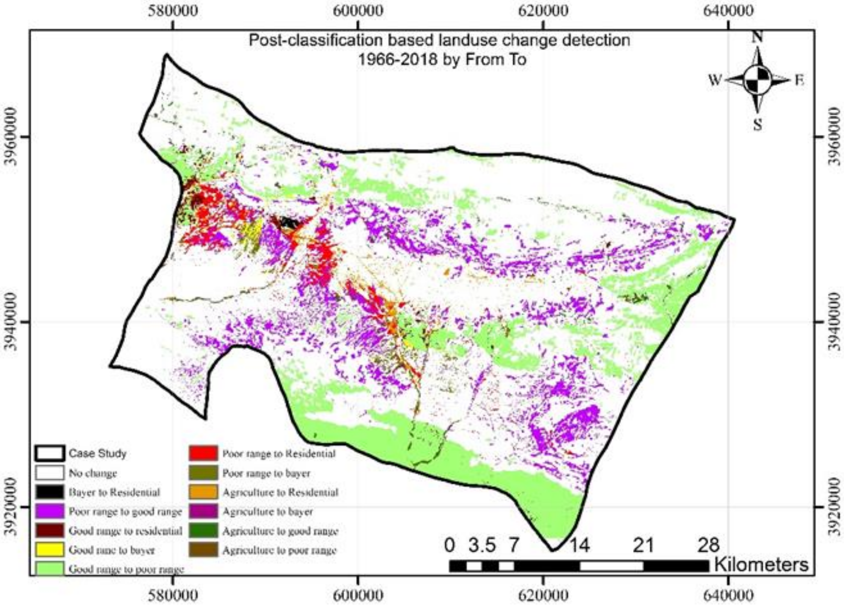


Figure 10. Map of user changes from 1986 to 2018

The table of changes for each user is given below (Table 3).

Table 3. User area changes from 1986 to 2018

Type of change	**Area (hectares)**	**Agriculture to barren land**	**48.86**	**Rich pasture to poor pasture**	**30084.66**	**Rich pasture man-made**	**1354.7**
Agriculture is man-made	2260.17	Poor pasture to barren land	928.08	Agriculture to rich pasture	1304.91	Man-made barren land	189.18
poor human made pasture	3521.34	Rich pasture to barren land	360.9	Poor pasture to rich pasture	15812.19	Agriculture to poor pasture	489.69

Urban land use planning is a crucial aspect of urban planning that involves organizing urban activities and functions based on the needs and wants of society. It aims to enhance social welfare while minimizing costs by determining land use and allocation. Given the challenges faced by modern cities and their rapid growth, this topic is particularly important and requires consideration from multiple perspectives. Optimal land use planning is essential for ensuring equitable access to resources for all city residents at minimal cost. As such, it is necessary to conduct studies that provide basic information about land characteristics and activities taking place on it. These studies can be used to analyze current land use patterns and develop maps that guide future land use decisions.

The results of this study were compared with other studies that have used similar methods for monitoring land use changes. The band 3 in the analysis of the main components and band differences were found to be effective in monitoring changes in the area with an accuracy of 93.4%. This finding is consistent with previous studies that have also found these methods to be effective in detecting changes. However, the band ratio method of last year changes did not show good accuracy, with only 73.12% accuracy. This finding is also consistent with previous studies that have found this method to be less effective in detecting changes. Principal component analysis and band difference methods were found to be effective in detecting changes, with a total change detection accuracy of 91% and change detection accuracy of 87%, respectively, in band 3. These findings are consistent with previous studies that have also found these methods to be effective in detecting changes. Overall, the results of this study suggest that the methods used for detecting land use changes are largely effective. However, there are some debatable issues such as the detection of spectral reflectance changes and determining the threshold for preparing binary maps in qualitative methods. It is important to pay attention to these issues when using satellite images to identify changes. Based on the methods used in this study, bands 3 of principal component analysis and band 5 of bandwidth difference were found to be effective in monitoring changes in the area. If land use maps are prepared with high accuracy, detection after classification can provide a clear understanding of the place and amount of changes for each land use type.

Land-use change detection is a critical aspect of natural resource management, as it helps to understand the interactions between humans and natural phenomena. This study aimed to evaluate the effectiveness of four different methods for detecting land-use changes in Damavand city using remote sensing techniques. The results showed that man-made areas increased by 7288 hectares due to construction activities in agricultural fields, leading to a reduction of 4047 hectares of agricultural lands. Additionally, 10324 hectares of rich rangeland cover were transformed into poor pastures. The findings of this study are consistent with previous research on land-use change detection using remote sensing techniques. For example, a study conducted by Wang, Li, and Wang, (2019) found that principal component analysis was an effective method for detecting land-use changes in urban areas. Similarly, another study by Zhang, Liu, and Zhang, (2018) found that post-classification image detection was an effective method for detecting land-use changes in agricultural areas. However, there are also some differences between the results of this study and previous research. For example, a study conducted by Li et al. (2020) found that the band ratio method was an effective method for detecting land-use changes in forested areas. In contrast, the results of this study showed that the band ratio method did not perform well for detecting land-use changes in Damavand city.

5. Conclusion

The findings of this study have important implications for policymakers and natural resource managers in Damavand city. The results suggest that man-made areas are increasing at the expense of agricultural lands and rangeland cover, which could have significant impacts on water quality, air and terrestrial resources, ecosystem processes and functions, and climate systems. Therefore, policymakers should consider implementing measures to protect these valuable natural resources while also promoting sustainable development in the region. In conclusion, this study provides valuable insights into the effectiveness of different methods for detecting land-use changes using remote sensing techniques in Damavand city. The results highlight the importance of accurate and timely detection of land-use changes for effective natural resource management and sustainable development.

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