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Quantitative study of spatiotemporal changes in ecology to monitor land degradation in Alborz Province

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ABSTRACT

The expansion of human activities has caused widespread disturbances in ecosystems worldwide, necessitating the development of effective tools to monitor and quantify these changes. Remote sensing stands as a powerful tool for monitoring and quantifying ecological changes over time and space. In this study, a remote sensing-based ecological index (RSEI) was used to investigate land degradation and desertification in Alborz province during the period 2000-2020. After examining land use changes, the trend of RSEI outputs was evaluated using the Mann-Kendall test and Theil-Sen estimator. The examination of land use changes during the period 2000-2020 showed that barren lands, rangelands, shrublands and forests decreased by 2.30%, 6.25%, 1.53%, and 0.18%, respectively, while crop lands, built-up lands, and dam increased by 8.23%, 1.85%, and 0.18%, respectively. The analysis of the trend of changes in the RSEI using the Mann-Kendall test showed that the changes in 16.27% of Alborz province was decreasing, of which about 0.5% was statistically significant. This decreasing trend was also shown by the Theil-Sen estimator in 13% of this region. The results of this study using the Mann-Kendall test also showed that the RSEI values increased in 80.73% of the study area, of which about 4% increased significantly. The analysis of changes in this index using the Theil-Sen estimator showed that this index increased in 87% of this region. This study suggests that the RSEI approach performs effectively in quantifying and detecting ecological changes and, as a result, land degradation at various scales.

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1. Introduction

Land degradation has emerged as a pressing environmental concern worldwide in recent years, prompting substantial research efforts, planning initiatives, and policy debates among experts. Land degradation is defined as a temporary or permanent decrease in land productivity caused by the destruction of the physical, chemical, and biological characteristics of the land. Agricultural production, ecosystem functions, quality of life, and human livelihoods are all affected by the loss of land productivity (Badapalli *et al*., 2019; Kumar *et al*., 2020).

The reduction of productivity and ecological capacity is often caused by a lack of fundamental understanding of the nature of ecological systems and a lack of attention to people's participation and demands. Land degradation, which leads to a reduction in the productive capacity of ecosystems of different qualities, is widely regarded as one of the most pressing and significant factors in ecosystem degradation around the world (Wang *et al*., 2019). Today, the world's ecosystems are facing more problems than ever before due to human interventions and the resulting environmental changes (McDonnell and MacGregor-Fors, 2016). The increase in human activities has led to a significant increase in the destruction of natural landscapes and has caused significant disruptions to the structure of ecosystems at different scales (Williams *et al*., 2009). Ecosystem disruptions at large scales have significant impacts on the global carbon cycle (Baldocchi, 2008). As a result, this can worsen global climate change.

These ecological disruptions vary in terms of extent and duration (Levin, 1992) and therefore need to be effectively monitored and characterized. Thus, the need for appropriate models and methods to detect spatial and temporal changes in ecological status is increasingly evident.

Advancements in remote sensing have revolutionized ecosystem monitoring by providing a vast repository of land surface data, enabling the development of sophisticated methodologies for analyzing ecological conditions across various scales (Willis, 2015; Qiu *et al*., 2017). Remote sensing technology enables the assessment of ecological conditions, as it captures the Earth's surface reflectance, allowing for the identification of key components within an ecosystem, including soil, vegetation, and open water bodies (de Araujo Barbosa *et al*., 2015).

Therefore, remote sensing has been widely used in ecosystem research (Ivits *et al*., 2011; Hu and Xu, 2018). Between 1982 and 2013, a comprehensive ecological assessment project was conducted in China utilizing remote sensing data to cover the entire country (Du *et al*., 2020). Similar studies have also been reported from the United States (Willis, 2015) and other regions of the world (Caccamo *et al*., 2011; Ivits *et al*., 2011; de Araujo Barbosa *et al*., 2015).

Today, many remote sensing indices are used to quantify ecological status. Among them, the normalized difference vegetation index (NDVI) is the most widely used single index that has been utilized in a variety of ecological studies (Mishra *et al*., 2015; Dubinin *et al*., 2018). Monitoring the suitability of bird habitats in agricultural fields could be facilitated by the use of seasonal vegetation characteristics derived from SPOT NDVI data (Ivits *et al*., 2011). Another widely used vegetation index is Enhanced Vegetation Index (EVI). The use of EVI-derived ecosystem functional attributes (EFAs) as predictors for plant species distribution models were introduced by Alcaraz-Segura *et al*. (2017). The sensitivity of several spectral indices to drought in forests using Moderate Resolution Imaging Spectroradiometer (MODIS) products were evaluated by Caccamo *et al*. (2011). They found that the infrared index based on band 6 showed the highest sensitivity to drought severity. As a result, land surface temperature (LST) extracted from thermal remote sensing images has also been frequently used to study regional thermal environments. It was found to be reliable in assessing the urban heat island effect (Coutts *et al*., 2016; Huang and Cadenasso, 2016).

Relying on a single remote sensing index can paint an incomplete picture of the environment, potentially overlooking important ecological factors. Aggregated indices provide a more comprehensive and reliable assessment. Building on prior research, Tiner (2004) introduced an innovative index that merged two existing metrics: one tracking the extent of natural habitat within a watershed and another quantifying its level of disturbance. LST, NDVI, and precipitation data were used by Rhee *et al.* (2010) as the building blocks for the SDCI, a satellite-based index assigning specific weights to different drought indicators. A recent development in ecological monitoring, the RSEI (Remote Sensing-based Ecological Index), shows great potential for evaluating the comprehensive state of ecosystems by integrating data on climate and land-surface biophysics from four distinct indices (Willis, 2015; Hu and Xu, 2018; Xu *et al.*, 2018; Xu *et al.*, 2019; Zhang *et al.*, 2022).

Since the RSEI approach facilitates the quantification, and rapid and effective detection of regional ecological changes over time and moves a step towards the possibility of transforming this technique into a relatively simple tool for detecting ecological changes at different scales, the purpose of this study is to use the RSEI model to produce time series images of the comprehensive ecological status of Alborz province to investigate land degradation in this province based on Landsat time series images in the period 2000-2020.

2. Materials and methods

2.1. Study area

The study area is Alborz Province, which has an area of 5,833 square kilometers, which accounts for 0.3% of the area of Iran. This province is located between 35°20" and 36°20" north, and from 50°10" minutes to 51°30" east. This region is affected by topographic features, and has a temperate and continental climate at low and high altitudes. Climatic data shows that higher altitudes of Alborz are affected by the northwest flow of polar air masses. Summers are dry, hot, and sunny, with intense radiation most of the time. During the dry season, water is mainly supplied by melting snow and springs. Alborz province receives 248mm of precipitation annually. Annual temperature range can be large (Pourebrahim *et al.*, 2023). This province is located between a minimum altitude of 1,081 and a maximum altitude of 4,090 meters above sea level. Figure 1 shows the geographical location of Alborz Province and its elevation map.

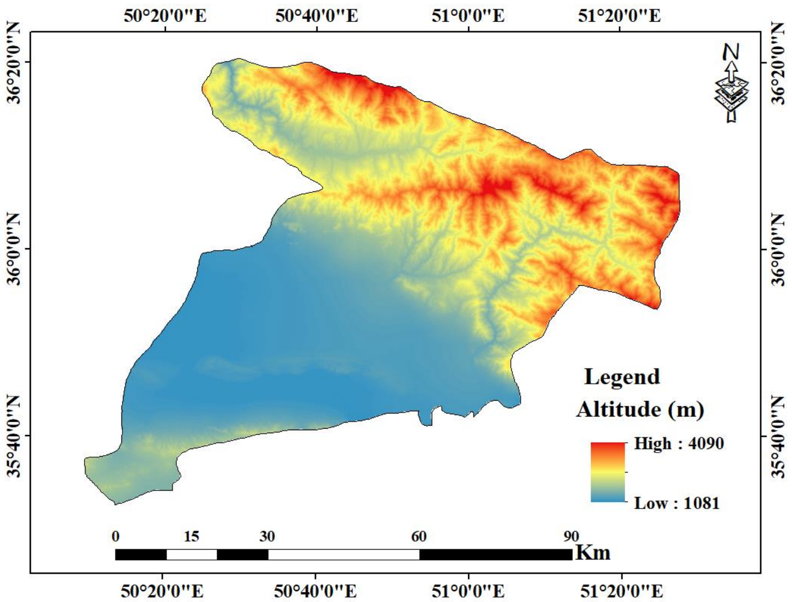

Fig. 1. Geographical location of Alborz province and its altitude changes

2.2. Data and methods

In current study, Landsat satellite images were applied to study the trend of land degradation in Alborz Province in the years 2000, 2002, 2006, 2011, 2014, 2016, 2018, and 2020. Specifically, Landsat TM images were used to create a land degradation map for the years 2000 to 2011, and Landsat OLI images were used to create the map for the years 2014 to 2020. Satellite image processing and analysis were performed using the ENVI 5.3, TerrSet, ArcGIS 10.8, and ArcGIS Pro 3.1 software packages.

2.3. LULC map

Data from the MODIS MCD12Q1 product with a resolution of 500 meters was used to study land use and land cover change from 2001 to 2020 (Eskandari Damaneh *et al*., 2019) (Figure 2).

2.4. Land degradation mapping using RSEI

The Remote Sensing-based Ecological Index (RSEI) is a novel tool for analyzing ecological changes using remote sensing data. RSEI integrates multiple index factors and has been extensively used for rapid monitoring and evaluation of the regional ecological environment (Hu *et al.*, 2018; Xu *et al.*, 2018; Xu *et al.*, 2019; Zhang *et al.*, 2022). This method is innovative in its incorporation of key ecological indices within the pressure-response (PSR) framework to construct the model, and its application of principal component analysis to combine these four indices effectively. RSEI draws upon four key indices – greenness (vegetation), moisture (soil moisture), heat (temperature), and dryness (built area) – which are commonly used to assess ecological status due to their strong correlation with ecological status (Xu *et al*., 2018; Xu *et al*., 2019). The integration of these indices shows environmental conditions more favorably than using them individually. In this study, four indices of dryness, heat, moisture, and vegetation cover were used to investigate land degradation in Alborz Province using NDBSI, LST, Wet, and NDVI, which are explained in detail below.

2.4.1. Wetness index

In the study of ecological conditions, the wetness index is a very important indicator that shows the moisture conditions of soil, water, and plants well, and is closely related to ecological changes (Zhang *et al*., 2022; Naseri and Mostafazadeh, 2023). Since its calculation is different in different Landsat sensors, how to calculate it is shown in equations (1) and (2).

$$wet(TM) = 0.0315B2 + 0.2021B3 + 03102B4 + 0.1594B5 - 0.6806B6 - 06109B7 \quad (1)$$

$$wet(OLI) = 01511B2 + 01793B3 + 0.3283B4 + 03407B5 - 0.7117B6 - 0.4559B7 \quad (2)$$

Where, Wet (TM) is the moisture component that is used with Landsat 5 and Wet (OLI) is also the moisture index that is obtained from Landsat 8. In these equations, B2, B3, B4, B5, B6, and B7 are the bands 2, 3, 4, 5, 6, and 7 of Landsat 5 and 8, respectively.

2.4.2. Greenness index

Vegetation is a factor that can comprehensively reflect information on plant nutrition and growth status. Therefore, using vegetation indices derived from remote sensing data will accurately show the conditions of vegetation. One of the best and most widely used vegetation indices is the NDVI index derived from remote sensing data, which represents the quantitative status of plants. This index is calculated from the equation 3 below (Eskandari Damaneh *et al*., 2019).

$$NDVI = (NIR - R)/(NIR + R) \quad (3)$$

Where, R refers to the red band and NIR refers to the near-infrared band.

2.4.3. Heat index

The thermal index was calculated using the land surface temperature (LST) index. To calculate the land surface temperature, the emissivity contrast ε and brightness temperature Tb are calculated in the Landsat thermal infrared band. This index is shown using equations (Eskandari Damaneh *et al*., 2021) 4 to 6.

$$LST = \frac{T_b}{\left[1 + \left(\frac{\lambda T_b}{\rho}\right)\varepsilon\right]} - 273.15 \quad (4)$$

$$T_b = K_2/(\frac{K_1}{L_6} + 1) \quad (5)$$

$$L_6 = gain \times DN + bias \quad (6)$$

Where, L6 is the thermal infrared band radiance value of TM/TIRS, bias and gain are the band offset and gain values, respectively, DN is the Landsat pixel digital number value, Tb is the brightness temperature, K1 and K2 are the calibration parameters, ε is the emissivity, and λ is the wavelength of TM band 6, which is 11.5 micrometers, and wavelength of Landsat 8 band 10 is 10.9 micrometers.

2.4.4. Dryness index

Since soil drying seriously damages the ecological status of the region, this study uses the built-up area index IBI and the bare soil index SI to calculate the normalized bare soil index NDBSI, which is shown in the equations 7 to 9 below (Hu and Xu, 2018).

$$NDBSI = (SI + IBI)/2 \quad (7)$$

$$SI = [(B_5 + B_3) - (B_4 + B_1)]/[(B_5 + B_3) + (B_4 + B_1)] \quad (8)$$

$$IBI = \left\{\frac{2B_5}{B_5+B_4} - [\frac{B_4}{B_3+B_4} + \frac{B_2}{B_2+B_5}]\right\} / \left\{\frac{2B_5}{B_5+B_4} + [\frac{B_4}{B_3+B_4} + \frac{B_2}{B_2+B_5}]\right\} \quad (9)$$

Where, B1, B2, B3, B4, B5, B7 are bands 1, 2, 3, 4, 5, 7 of Landsat 5 and 8, respectively.

2.5. Development of Remote Sensing-based Ecological Index (RSEI)

After calculating the above indices, with the aim of enabling quantitative and rapid assessment of land degradation in Alborz province, the RSEI ecological model was designed. In this study, for this model, the vegetation index (NDVI), moisture (Wet), thermal index (LST), and dryness index (NBDSI) were used in an integrated and comprehensive manner to investigate ecological status and land degradation (Hu and Xu, 2018; Naseri and Mostafazadeh, 2023). Using the equation 10, the RSEI model was calculated as follows:

$$RSEI = f(Green, Wet, Dryness, Heat) \quad (10)$$

Where RSEI is the remote sensing-based ecological index, green is NDVI, wet is WET index, dryness is NDBSI and heat is LST. All the indices are explained in 2.4. and its subsections. Different classes of this index are presented in table 1. Based on this table, low values of this index indicate the maximum potential for land degradation in the study area (Hu and Xu, 2018; Xu *et al*., 2018). The higher the RSEI score, the better the ecological environment quality and the lower the possibility of land degradation.

Table1. RSEI classes

RSEI	Class
Very bad:	0–0.2
bad	0.2–0.4
Acceptable	0.4–0.6
Good	0.6–0.8
Very Good	0.8–1

2.6. Land degradation trend analysis

2.6.1. The Mann-Kendall test

The Mann-Kendall test is a non-parametric statistical method used for hydrological and meteorological data (Eskandari Damaneh *et al*., 2021). In the Mann-Kendall test, for the sequence X=(x_1, x_2,..., x_i), the Mann-Kendall test statistics (S) is calculated as follows by equations 11 to 12 below:

$$S = \sum_{i=1}^{n-1} \sum_{j=j+1}^{n} sgn(x_j - x_i) \tag{11}$$

$$sgn(x_j - x_i) = \begin{cases} 1, x_j - x_i > 0 \\ 0, x_j - x_i = 0 \\ -1, x_j - x_i < 0 \end{cases} \tag{12}$$

The trend test was conducted using the Z-statistic. The formula for Z is as shown in equations 13 and 14 below:

$$Z = \begin{cases} S/\sqrt{Var(S)}, S > 0 \\ 0, S \\ (S+1)/\sqrt{Var(S)}, S < 0 \end{cases} \tag{13}$$

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \tag{14}$$

Where n is the time interval (years). At the significance level $\alpha = 0.05$, the critical value is obtained from the following equation

$$Z_1 - \alpha / 2 = \pm 1.96$$

2.6.2. Trend analysis of Theil-Sen estimator

The Theil-Sen estimator can be used to determine the trend of long-term time series data in combination with the Mann-Kendall test (Eskandari Damaneh *et al*., 2021). This trend analysis index is calculated as follows:

$$\beta = median\frac{x_j - x_i}{j-i}, \forall_j > i \quad (15)$$

Where x_j and x_j are time series data. $\beta > 0$ means that the ecological status is showing a recovery trend, and $\beta < 0$ means that the ecological status is showing a degradation trend.

3. Results

3.1. Analysis of the trend of land use changes from 2001 to 2020

An analysis of the trend of land use changes in Alborz province between 2001 and 2020 (Figure 2) showed that this region includes seven major land use types, including barren, croplands, rangelands, shrublands, forests, built-up lands, and dam. In general, during this 20-year period, barren, rangelands, shrublands, and forests decreased by 2.30%, 6.25%, 1.53%, and 0.18%, respectively, while croplands, built-up lands, and dam increased by 8.23%, 1.85%, and 0.18%, respectively.

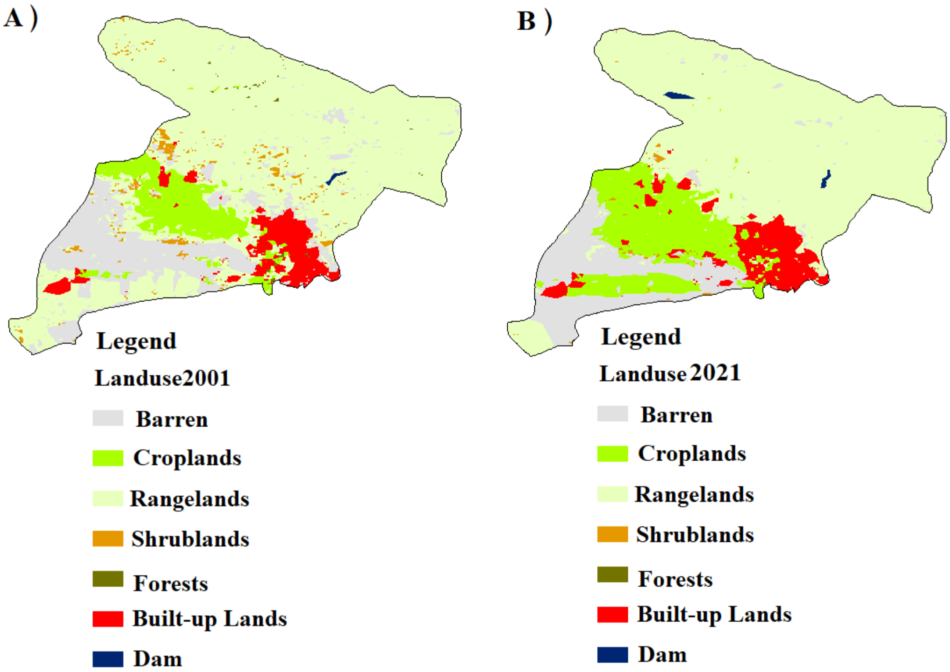

Fig. 2. Land use changes in Alborz province in the period 2001-2020

3.2. Temporal and spatial changes in Wet, NDVI, LST, NDBSI and RSEI indices

The spatial and temporal changes of the Wet, NDVI, LST, NDBSI and RSEI indices in the period 2000-2020 are shown in Figures 3a to 3e, respectively. This analysis showed that the Wet index (Figure 3-a) has a significant decreasing trend with a negative slope of 0.0038 and a coefficient of determination of 0.62 in this period. The NDVI index (Figure 3-b) has a significant increasing trend with a slope of 0.0042 and a coefficient of determination of 0.75 in this period. The LST and NDBSI (Figure 3-c and d) with positive slopes of 0.1572 and 0.0021, and coefficients of determination of 0.52 and 0.90, respectively, indicate a significant increasing trend for these two indices. The RSEI index (Figure 3-e) has a significant increasing trend with a slope of 0.005 and a coefficient of determination of 0.97.

Analysis of the spatial changes of the 20-year average of the Wet, NDVI, LST, NDBSI and RSEI indices in the period 2001-2020 (Figure 4-8) shows that the 20-year average of the Wet index (Figure 4) has a decreasing trend, with the highest values of this index scattered in the northern, western, and eastern parts, and the lowest values of this index in the southern, southwestern, and southeastern parts.

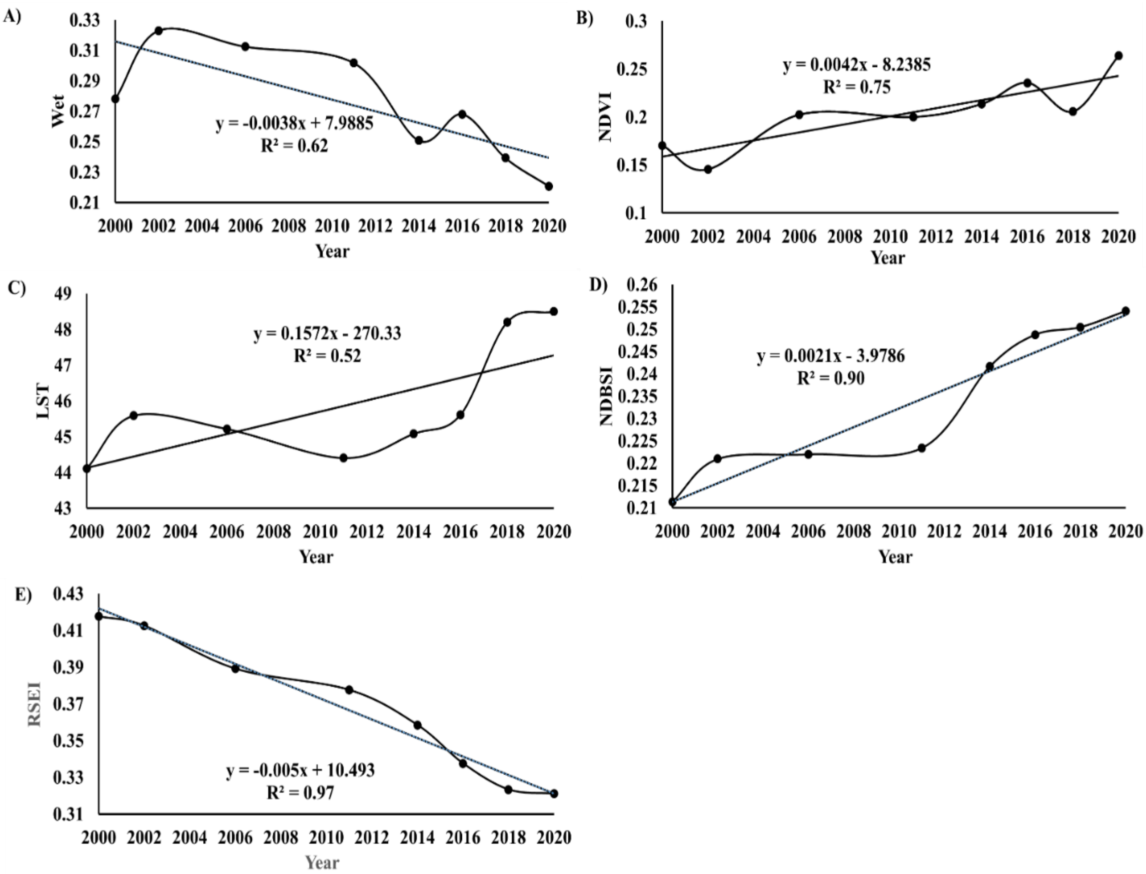

Fig. 3. Changes in NDVI, Wet, LST, NDSI, and RSEI indices for 2000-2020

This analysis for the NDVI index in Figure 5 shows that the average of this index has been increasing, with the highest values of this index in the northern, northwestern and central parts, and the lowest values of the NDVI index concentrated in the southern, western, and eastern parts. The analysis of the spatial changes of the 20-year average of the LST and NDBSI indices (Figures 6 and 7) in this period show an increasing trend, with the highest values of these indices in the southern, central, western, and eastern parts, which increase in temperature and dryness from north to south. The analysis of the RSEI model in Figure 8 shows that the lowest values of this parameter are concentrated in the southern, western, and eastern parts, and the highest values of this index are scattered in the north and central regions.

3.3. Investigating the changes in different RSEI classes in the period 2000-2020

The results of the changes in the different classes of the RSEI ecological model in the period 2000-2020 showed that the very poor and poor classes have been increasing, reaching from 62.85% in 2000 to 64% in 2020. In this period, the acceptable, good, and very good classes were 31.6%, 5%, and 0.6% respectively in 2000, reaching 30%, 5.6%, and 0.2% in 2020.

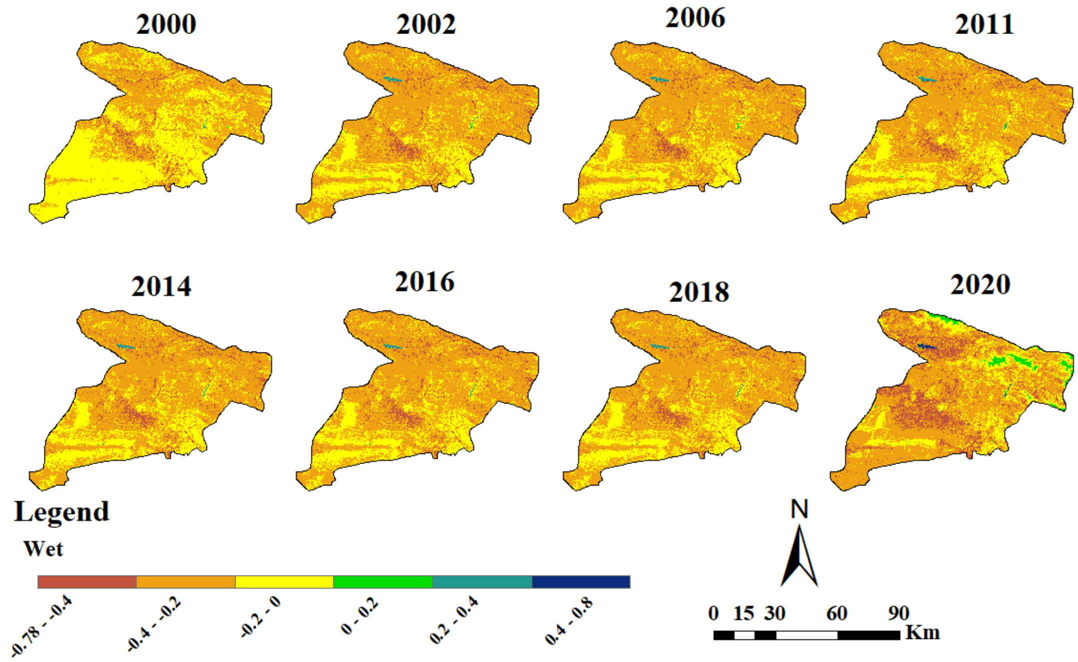

Fig. 4. Changes in the Wet index over the period 2000-2020

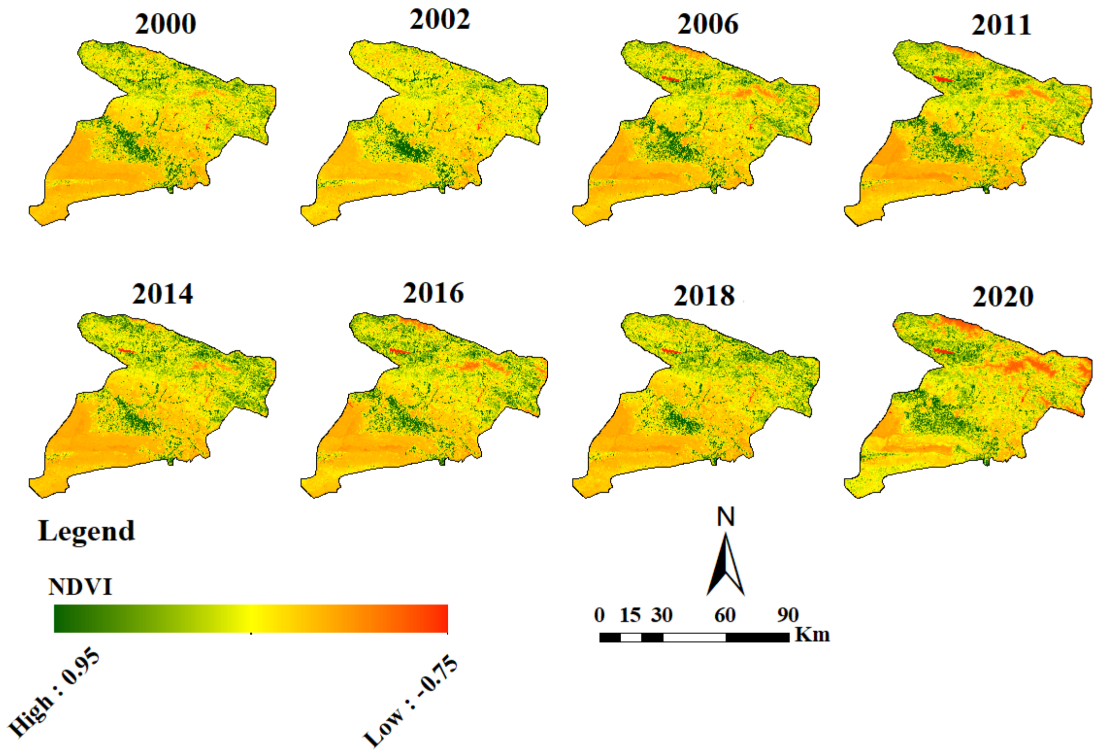

Fig. 5. Changes in the NDVI index over the period 2000-2020

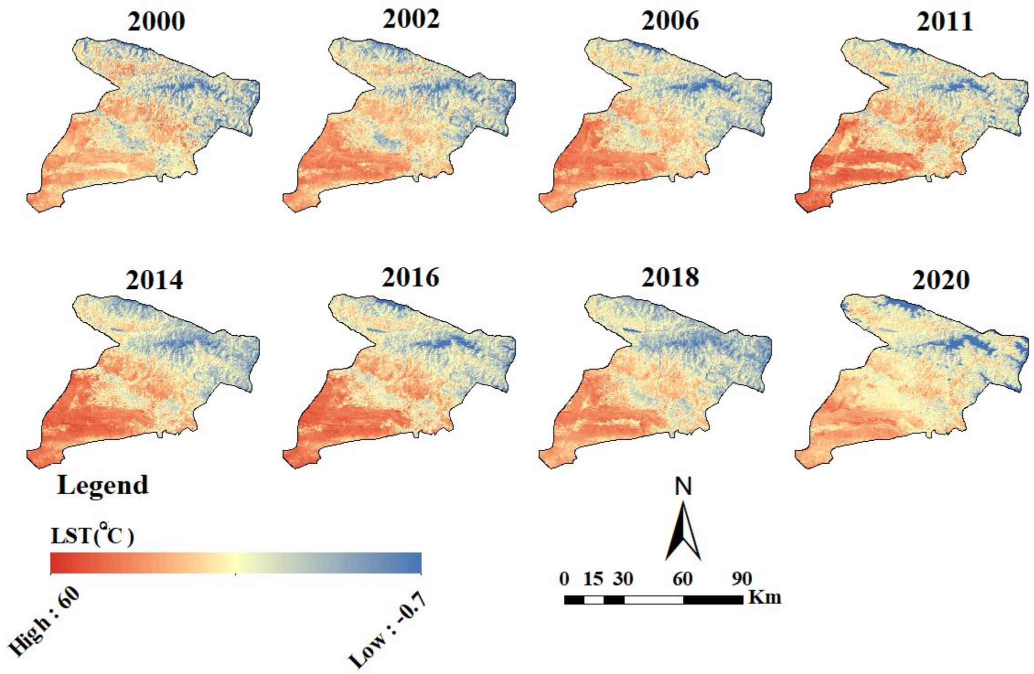

Fig. 6. Changes in the LST index over the period 2000-2020

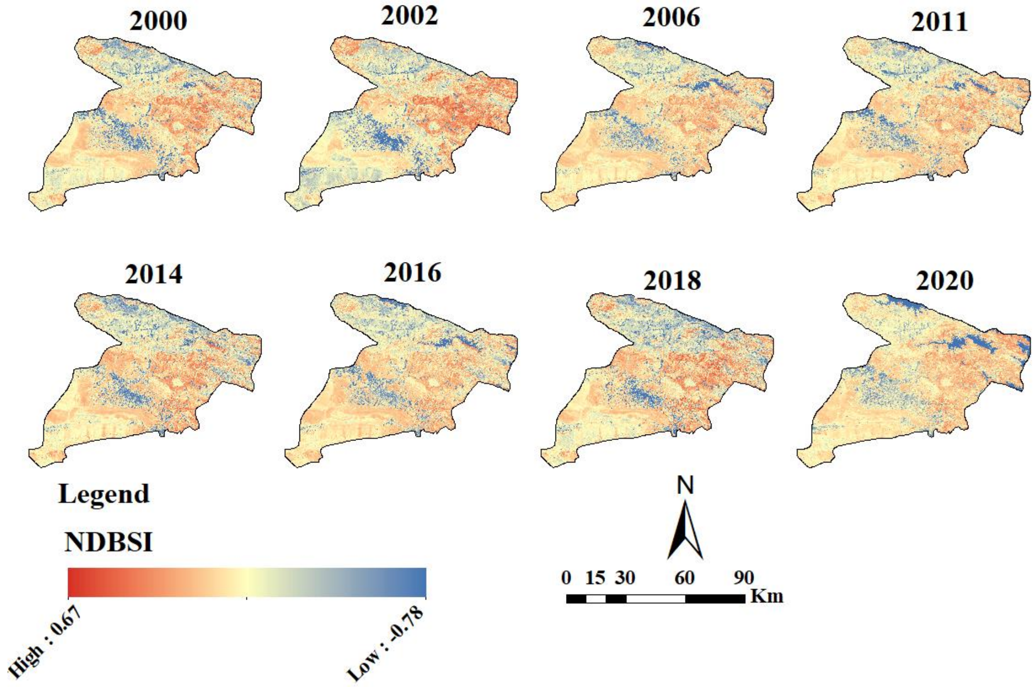

Fig. 7. Changes in the NDBI index over the period 2000-2020

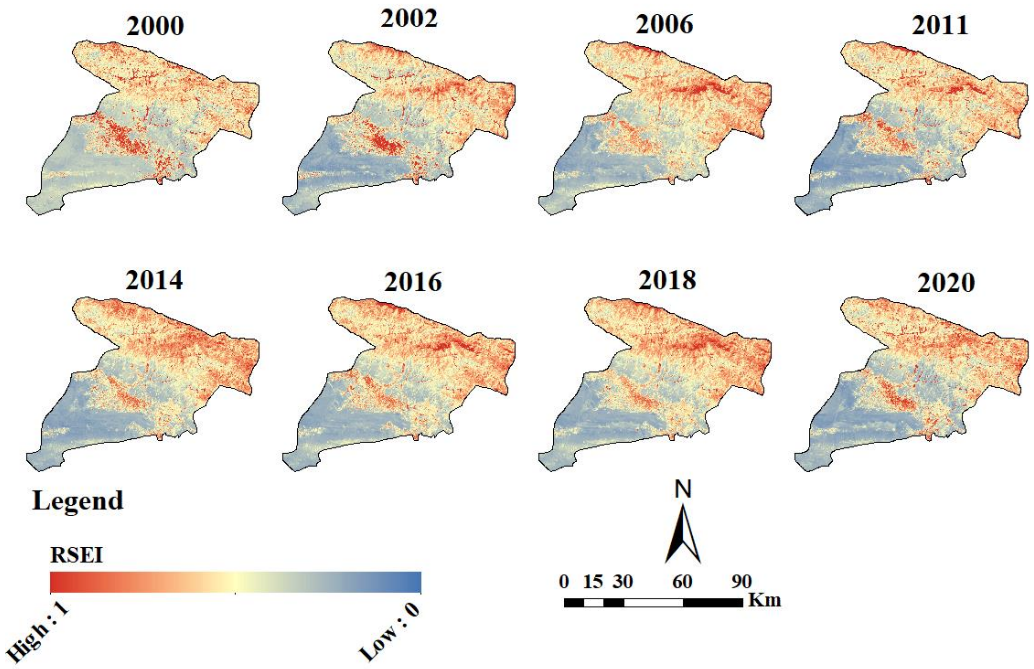

Fig. 8. Changes in the RSEI index over the period 2000-2020

3.4. Investigating the trend of changes in RSEI in the period 2000-2020

The trend of changes in the ecological index of RSEI was studied using the Mann-Kendall test and the Theil-Sen estimator which are shown in Figure 9. Based on the results of Z Kendall in Figure 9-A, the trend of changes in 16.27% of Alborz province has been decreasing, of which about 0.5% is significant. This decreasing trend was also seen by the Theil-Sen estimator (Figure 9-B) in 13% of this region. Also, the results of this study showed that the RSEI index has been increasing in 80.73% of the region, of which about 4% has shown a significant increase. Furthermore, the Theil-Sen estimator also showed that 87% of this region has had an increasing trend (Table 2).

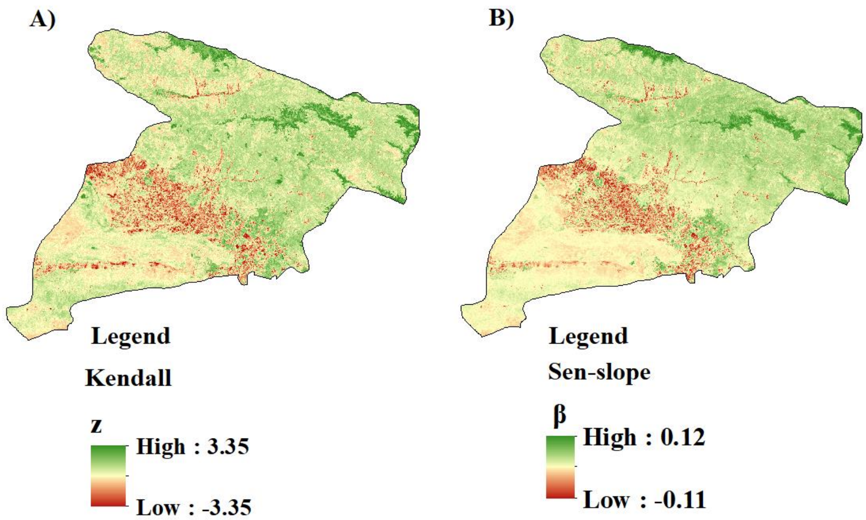

Fig. 9. Changes in RSEI index A) Kendall's Z,
B) Theil-Sen-Slope estimator over the period 2000-2020

Table 2. Mann-Kendall Z values

RSEI trend	Area (KM^2)	Area (%)
decreasing significantly (Z <-1.96)	34.734	0.497
decreasing (0 < Z < -1.96)	816.193	15.776
increasing (0 < Z < 1.96)	4801.760	80.242
increasing significantly (1.96 < Z)	180.313	3.485
Total	5833	100

4. Discussion and conclusion

In various studies, different methods have been used to estimate land degradation as a very destructive phenomenon. Accurate and quantitative assessment of land degradation is affected by a multitude of factors; therefore, different data and information are needed for its quantitative assessment. Some of the data required for land degradation assessment include vegetation cover, soil moisture and soil dryness, thermal changes, and land use changes (Eskandari Damaneh *et al*., 2023). The use of remote sensing data with appropriate spatial and temporal resolution is an efficient and useful tool for quantitative assessment and monitoring of land degradation.

This article presents a new approach for estimating land degradation using the RSEI, which can be used directly to describe the regional ecological quality and the state of land degradation. In this ecological model for estimating land degradation, after reviewing the land use change trend of Alborz province, various indicators such as vegetation cover (NDVI), moisture (Wet), thermal index (LST), and dryness index (NBDSI) were used from Landsat 5 and 8 images for the years 2000 to 2020.

Review of the land use change trend in Alborz province showed that cropland and built-up lands have been increasing in this period, reaching 16.8% and 7.42%, respectively from 8.6% and 5.6% in 2000. The reason for this increase in agricultural land can be attributed to the conversion of natural land to agricultural land. These natural lands have a temporary potential to become agricultural lands, which causes them to lose their potential over time and become unusable for agriculture (Eskandari Damaneh *et al*., 2020).

Various studies have shown that the population has been increasing in these areas. According to the study by Pourebrahim *et al*. in 2023, the trend of population growth and urbanization in Alborz province in the period 2001 to 2023 has been increasing, which is due to the growth of urbanization, the development of industrial areas, and migration. Also, Alborz province, due to its temperate climate and rich grasslands, is one of the important agricultural and livestock farming regions in Iran. In addition, the population of the study area has been increasing caused by its proximity to the capital and the development of industries that create jobs. Therefore, this growing population needs food and housing. For this reason, land use changes resulting from the conversion of natural land to agricultural lands and residential areas have taken place.

Review of the trend of changes in the average values of Wet, NDVI, LST, NDBSI, and RSEI indices from Landsat imagery in the province in this 21-year period showed that NDVI, LST, and NDBSI indices generally had a significant increasing trend, while Wet and RSEI had a significant decreasing trend.

As the Earth becomes warmer due to global warming, the surface temperature of the earth is increasing, which leads to a decrease in moisture and an increase in dryness, as a result vegetation cover should also decrease. However, the results show that in Alborz province, vegetation cover has been increasing. This increase in vegetation cover is due to the increase in agricultural land. This increase in agricultural land will require water and changes in the use of other lands. On the other hand, with the increase in global warming and the decrease in rainfall around the country and in Alborz province, this increase in water demand has been met from other sources, especially groundwater and water entering the wetlands.

Goodarzi and Mortazavizadeh (2020) in their study of the effects of climate change on the groundwater levels of Hashtgerd in Alborz province, while confirming the increase in temperature and decrease in rainfall in the present and future, stated that with the current annual 73-centimeter drop in the Hashtgerd aquifer, this amount will be even higher in the future, which under future scenarios may experience a drop of up to 18 meters by 2040. Therefore, the status of this plain will change from critical to super critical (Safari *et al*., 2019). Safari *et al*. (2019) stated that the increase in drought and land use changes, including the increase in industrial areas in the upper reaches of the Hashtgerd plain, as well as the excessive use of groundwater for agriculture, has led to a drop in groundwater and a disruption of the water and soil balance, which in turn creates conditions for the increase in land degradation and desertification.

The analysis of the trend of changes in the RSEI using the Kendall Z showed that the trend of changes in 16.27% of Alborz province has been decreasing, of which about 0.5% is significant. This decreasing trend has also been confirmed by the Theil-Sen estimator in 13% of Alborz province. This decrease is in areas that are mostly under agricultural land and barren land, which indicates the excessive increase in agricultural land due to land use changes and the use of groundwater and water feeding the Salehiyeh wetland. This use of the water entering the Salehiyeh wetland, which is located in the west of the province, has caused the wetland to dry up and create a breeding ground for desertification and land degradation, which has annually caused dust storms and the loss of wildlife and plant species in the region and the wetland.

In general, it can be stated that using data from Landsat satellites, RSEI can be used to study and prepare land degradation maps at an appropriate scale. This map can be useful for urban planners and natural resource managers in predicting the ecological effects of their new projects. It is worth mentioning that the indicators used in this article are not specific to the study area and can also be used to estimate ecological changes and prepare land degradation maps in other regions.

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