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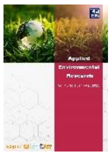

Research Article

Investigating Spatial and Temporal Changes in Vegetation via Remote Sensing Indicators and Revealing Their Trends in The Central Desert of Iran

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Abstract

Vegetation changes can significantly affect the conditions and productivity of ecosystems. Consequently, studying vegetation dynamics across various temporal and spatial scales has emerged as a critical environmental concern. The aim of this study was to investigate changes in vegetation cover via vegetation indices, including the normalized difference vegetation index (NDVI), ratio vegetation index (RVI), soil adjusted vegetation index (SAVI), and difference vegetation index (DVI), derived from multitemporal Landsat 5, 7, and 8 satellite images processed via the Google Earth Engine. The study area is located in the Damghan arid and desert watershed, which represents the central desert of Iran. Furthermore, the Mann–Kendall test was employed to investigate vegetation trends from 1995–2020. The temporal analysis of the vegetation indices via the Mann–Kendall test revealed de-creasing trends in the NDVI, SAVI, RVI, and DVI values, with slopes of -0.0014, -0.0013, -0.02, and -0.002, respectively. The vegetation changes assessed via the SAVI demonstrated the greatest consistency with the on-ground conditions, with a coefficient of determination of 0.81. In terms of this index, vegetation cover decreased in 33.21% of the watershed area, remained unchanged in 50.58%, and increased in 16.21% of the watershed area. The reduction in vegetation cover in one-third of the Damghan watershed underscores the need to incorporate these changes into environmental planning, land management, and sustainable development strategies for the region.

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Introduction

Over the past 500 years, the land surface has undergone extensive changes due to human. These activities include deforestation, the development of city areas, the destruction of pastures, and climatic factors such as decreases in rainfall, climate changes, and floods [1]. These changes affect the conditions and functioning of the ecosystem; therefore, the detection and monitoring of such changes at different temporal and spatial scales has become an important environmental issue [2–4]. Moreover, lands with vegetation are of special importance because of the influence of other land types on their degradation process and their adverse consequences for human and animal life [5–8].

Today, there are many methods for monitoring environmental changes, especially vegetation. However, in the last two decades, the use of remote sensing (RS) and satellite images, especially in large areas, has gained prominence because of its advantages, such as long-term monitoring capability, broad spatial coverage, repeatability, and cost effectiveness [9–13]. In a previous study, Munkhnasan et al. [14] used normalized difference vegetation index (NDVI) -3rd generation data from AVHRR satellite images to analyze the relationship between the freshness of plants and the trend of climate

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change. These authors reported that in the last three decades, the greatest trend of decreasing vegetation greenery, up to approximately 12% in some regions, has occurred in the midlatitude areas of the Northern Hemisphere, South America, Africa, Saudi Arabia, and South and Northeast Asia, where human activities have increased.

Furthermore, Landsat satellite images from 1972–2024 provide the longest historical archive of remote sensing images. These data are available with relatively good spatial resolution.

A total of 30 m (from Landsat 4) with 16-day time intervals are used in various studies, such as monitoring environmental changes, monitoring vegetation and agricultural activities, and predicting the future [15–20]. Najafi et al. [21] investigated the process of vegetation changes via Landsat satellite images in Tehran. The results of the NDVI vegetation index change trend indicated a slight increase in vegetation cover, but the Mann–Kendall test revealed that the positive trend observed in vegetation cover was not significant. Jafari et al. [22] used MODIS satellite images available from the Google Earth Engine (GEE) to calculate the normalized difference vegetation index (NDVI) and monitor vegetation from 2000–2019 in the Maharloo wetland of Iran. The Mann–Kendall test was also used to assess the trend of the vegetation changes. Liang et al. [23], in desert oases in Northwest China, which are among the most sensitive environmental locations, reported that during the past four decades, the surface area of desert areas has increased on the basis of the NDVI index; this change in vegetation cover is related to changes in weather conditions, and ecosystem management was consistent throughout the study period. Wang et al. [24] used NDVI-MODIS time series images from 2003–2013 to monitor the trends of aeolian desertification in China and reported that changes in land use and livestock pressure have led to the development of desertification and a reduction in vegetation. In recent years, advancements in remote sensing and computational tools have facilitated the analysis of vegetation dynamics across diverse ecosystems. For example, Ezaidi et al. [25] assessed and analyzed vegetation cover degradation between 1984 and 2018 in part of the Arganeraie Biosphere Reserve of Morocco. They described the ecosystem degradation scenario by using multitemporal Landsat-derived NDVI and highlighted the reasonable factors causing its degradation. Long-term and short-term NDVI changes were investigated via the image difference change detection technique and IsoData classification. Kumar et al. [26] evaluated the spatio-temporal dynamics of vegetation via the trend and rate of change in the annual median NDVI of the Eastern Indian–Himalayan region. The annual median NDVI composite of the region was prepared for each year from 1990--2019 via Landsat satellite data collection available for the entire year in GEE. The time series annual median NDVI data were analyzed for nonparametric (Mann–Kendall and Theil–Sen) trend analysis. These studies collectively highlight the growing global trend of vegetation degradation, especially in fragile arid ecosystems, and highlight the critical need for robust environmental monitoring frameworks to inform sustainable land management strategies. In arid regions, by using several vegetation indicators at the same time, owing to the special conditions of such areas, which have sparse and scattered vegetation, mainly shrubs and annuals, the condition of vegetation can be examined more precisely [27]. In this regard, Fatiha et al. [28], in a study in the Al-Ghouat region in Algeria, obtained a suitable index for the study of vegetation in arid and semiarid areas with low coverage, studied three indices, the TSAVI, SAVI, and NDVI, and reached the conclusion that the SAVI index is a suitable index for studying vegetation in semiarid and arid regions. Rokni et al. [29] introduced an index for monitoring vegetation changes. Recent findings have demonstrated that the newly proposed NDVCI outperforms traditional indices such as the NDVI and EVI in monitoring vegetation dynamics. A comprehensive review of the literature confirms that numerous studies have focused on assessing spatial and temporal vegetation changes via remote sensing techniques in conjunction with Mann–Kendall trend analysis across various regions worldwide. These studies collectively reveal that over recent decades, natural vegetation has undergone substantial transformations, particularly in developing countries, primarily due to land use changes aimed at intensifying the exploitation of natural resources [24, 30] Considering that arid and desert areas are highly vulnerable to destruction be-cause of their fragility and high sensitivity to exploitation and changes in production resources, it is very important to understand the changes in vegetation in these areas as the main indicator of land degradation. Nevertheless, studying vegetation changes via various remote sensing indicators and field studies and examining the trends of these changes in desert areas have received less attention because of the low and limited vegetation cover in these areas.

Therefore, in the present study, we investigated the vegetation cover changes and the trends of these changes over the period of 1995–2020, a timeframe selected because of the consistent availability of high-quality Landsat data, significant regional land use transformations, and relevant national development policies introduced during this period. Given the geographical location and environmental and management conditions prevailing in this region, which can be good representatives of the arid and desert regions of central Iran, the results obtained can be generalized to a large part of the arid regions of Iran and neighboring countries.

Materials and methods

1) Study area

The study area encompasses the Damghan watershed in Semnan Province, Iran, which is situated between the northern Dashte–Kavir Desert and the southern Alborz Mountain Range. Given its environmental characteristics, this region serves as an appropriate representation of the arid and desert watersheds of central Iran. It is located between latitudes 35°30′N and 36°30′N and longitudes 54°30′E and 55°45′E. The area experiences an average annual precipitation of 134 mm and an average annual temperature of 15.9°C, reflecting an arid and cold climate as classified by the Dumartin method. The watershed is divided into three subbasins: the Damghan River Basin (Damghan Rud), the West Damghan River Basin (Amirabad), and the East Damghan River Basin, covering a total area of 594,228 hectares [31] (Figure 1).

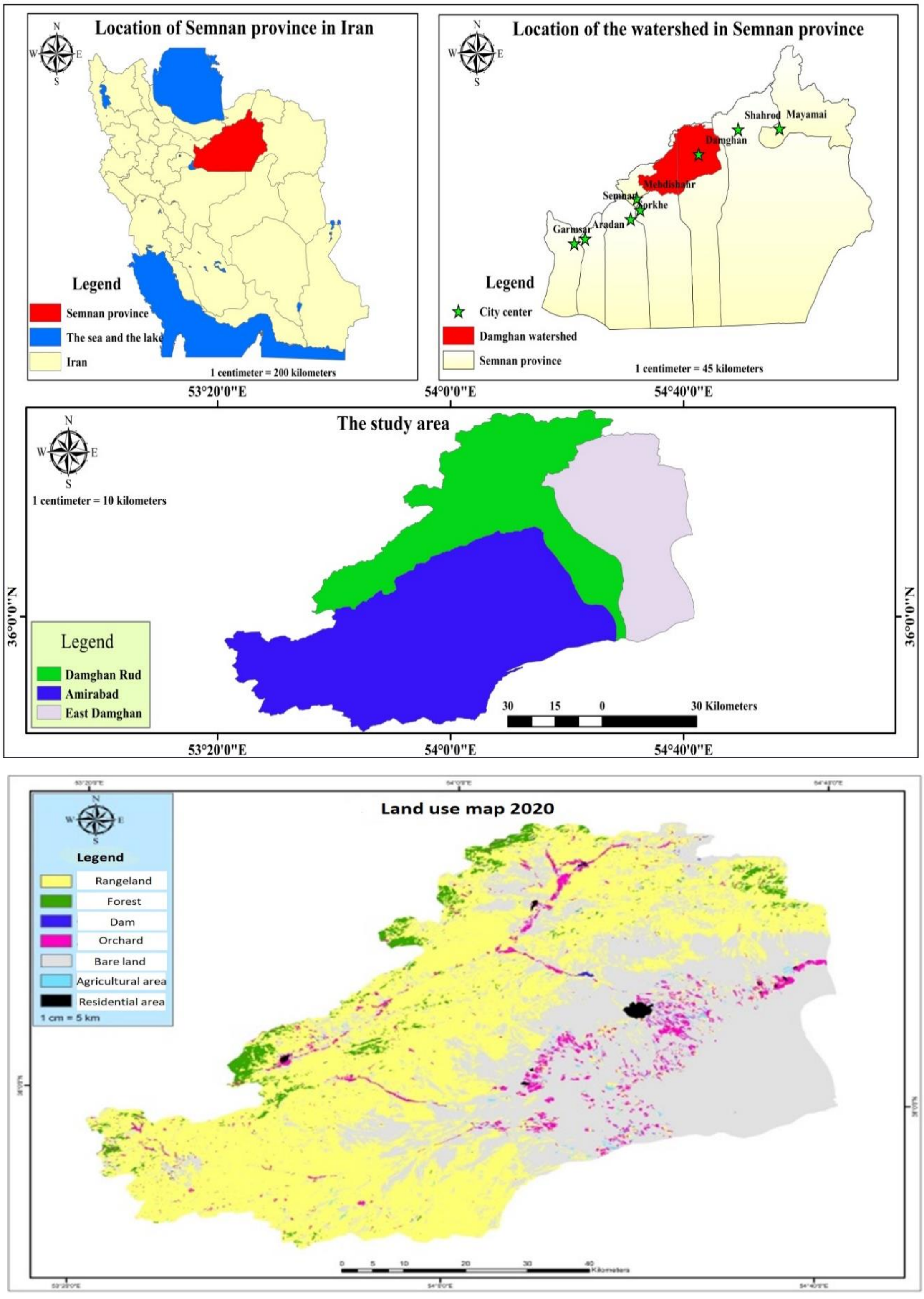

Figure 1 Geographical location of the study area and 2020 land use map [32].

2) Methodology

The primary objective of this research was to analyze vegetation changes in the Damghan Basin over the past 26 years (1995–2020) to identify the main drivers of environmental transformations. To achieve this goal, satellite imagery from Landsat 5 (1995–1999), Landsat 7 (2000–2013), and Landsat 8 (2014–2020) was processed and analyzed via the GEE (Table 1). The 2020 satellite imagery was validated via Google Earth images and regional land-use maps, which demonstrated a high level of reliability, with a kappa coefficient of 94.70% and an overall accuracy of 95.91%. [32]. All satellite images were preprocessed in GEE via built-in Landsat surface reflectance products. Cloudy pixels were masked via the QA band, and a median compositing strategy was employed to generate annual composites for the study period. This ensured consistency and minimized the influence of atmospheric and seasonal noise.

Vegetation indices were computed from satellite images within the GEE for each year from 1995–2020, ensuring that the images were captured during optimal conditions with minimal cloud cover. The calculated indices included the following:

- Normalized difference vegetation index (NDVI)

Vegetation changes and spatial–temporal fluctuations were analyzed via the monthly NDVI derived from the MODIS sensor. Typically, NDVI values below zero are indicative of wet areas or water bodies. Values between 0 and 0.3 correspond to soil and pastures, whereas values greater than 0.3 represent vegetation cover within the study area [33]. The NDVI was calculated according to Eq.1 as follows:

$$NDVI = (NIR - RED)/(NIR + RED) \qquad \text{(Eq. 1)}$$

where NIR represents the near-infrared band and RED denotes the red band.

Given the aridity of the region and the sparse vegetation, the soil's reflectance often dominates that of the vegetation. This phenomenon masks the vegetation spectral signature, thereby reducing the NDVI values [30].

- Soil adjusted vegetation index (SAVI)

This index was introduced by Huete (1984) to minimize the influence of soil reflectance on vegetation detection. It is calculated via Eq.2.

$$SAVI = [(1 + L) \times (NIR - RED)]/(NIR + RED + L) \qquad \text{(Eq. 2)}$$

In this equation, L is the soil brightness correction factor. On the basis of previous studies, the value of this factor is set at 0.5. The numerical range of the SAVI vegetation index lies between -1 and +1. Areas with dense vegetation are closer to +1, whereas regions with sparse vegetation tend toward -1 [34].

- Ratio vegetation index (RVI)

This index was first introduced by Jordan (1969). It is a band ratio-based index, with values ranging from zero to infinity. Higher values of this index are typically observed in areas with dense vegetation. This index is calculated via Eq.3.

$$RVI = NIR/IR \qquad \text{(Eq. 3)}$$

where IR represents the reflectance value of the infrared band.

- Difference vegetation index (DVI)

The vegetation difference index was presented by Everitt and Richardson (1992) and was obtained from the difference in red and infrared reflectance values [35]. This index is calculated via Eq.4.

$$DVI = NIR – RED \qquad \text{(Eq. 4)}$$

According to the reflection curves of major land cover types, the values of these indices are greater for vegetation [36].

After generating the vegetation index maps, overlapping maps for each index from 1995–2020 were used to produce vegetation change maps on the basis of these indices. This process facilitated the creation of 26-year vegetation change maps for the study area.

- Mann–Kendall test

The Mann–Kendall (MK) test is a nonparametric statistical method widely used to detect monotonic trends in time series data. In this study, it was applied to the annual vegetation indices from 1995–2020. The MK statistic (S) was calculated via Eq.5.

$$\mathbf{S} = \sum_{k=1}^{n-1}\sum_{j=k+1}^{n} \mathbf{sgn}(x_j - x_k) \qquad \text{(Eq. 5)}$$

where sgn is the sign function and x_j and x_k are data values at times j and k, respectively. The significance of the trend was evaluated via Z statistics at the 95% and 99% confidence levels. If the Z statistic is positive, the trend of the data series is considered to be upward, and if it is negative, the trend is considered to be downward [39–40].

The slope of the trend was estimated via Sen's slope estimator, and all calculations were performed via TerrSet software. Trend maps were cross-checked with field observations, high-resolution imagery and land-use change maps [32].

Table 1 Summary of Satellite Datasets

Satellite	Sensor	Time period	Spatial resolution	Temporal resolution
Landsat 5	TM	1995–1999	30 meters	16 days
Landsat 7	ETM+	2000–2013	30 meters	16 days
Landsat 8	OLI	2014–2020	30 meters	16 days

Results and discussion

An analysis of the vegetation indices from 1995–2020 and their changes over this period (Table 2) revealed that the highest values of the NDVI, SAVI, DVI, and RVI were observed in 1995. Overall, throughout the 26-year period under investigation, these indicators, and consequently the vegetation cover of the region, have shown a decline. The temporal analysis of the vegetation index changes from 1995–2020 revealed decreases in the values of the NDVI, SAVI, RVI, and DVI, with slopes of 0.0014, 0.0013, 0.02, and 0.002, respectively (Figures 2–5).

An analysis of the spatial changes in the vegetation indices NDVI, SAVI, RVI, and DVI (Supplementary materials (SM) 1–4) indicated that the lowest values of these indices were found in the north-east, northwest, and central regions of the Damghan watershed. The output maps from the Mann–Kendall test, which is based on the four indices, demonstrated that the changes in the NDVI were between a maximum of 0.80 and a minimum of -0.90. The changes in SAVI ranged from a maximum of 0.85 to a minimum of -0.91. The changes in the RAVI fluctuated between a minimum of -0.92 and a maximum of 0.67, whereas the DVI changed from a minimum of -0.82 to a maximum of 0.42 (SM 5–8).

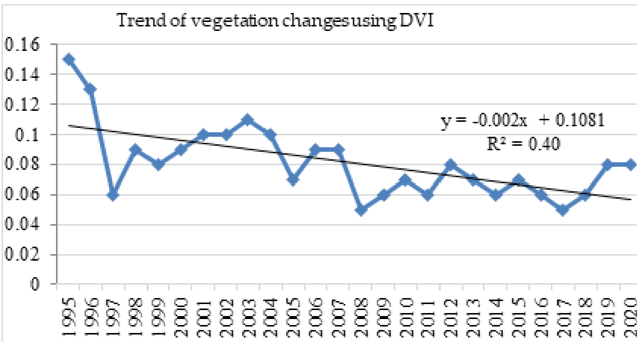

Figure 2 Temporal trend of changes in the DVI via the Mann–Kendall trend test (1995–2020).

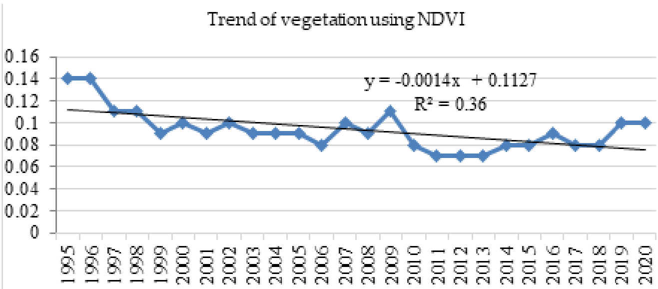

Figure 3 Temporal trend of changes in the NDVI via the Mann–Kendall test (1995–2020).

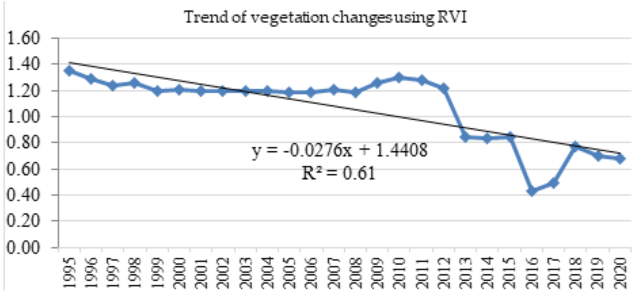

Figure 4 Temporal trend of changes in the RVI via the Mann–Kendall test (1995–2020).

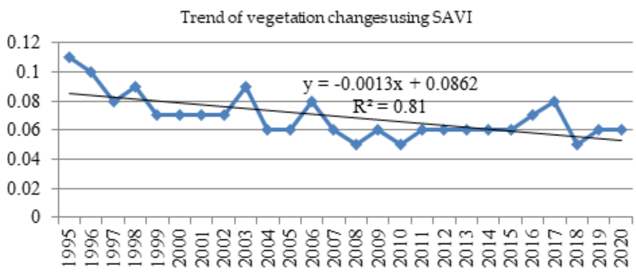

Figure 5 Temporal trend of changes in SAVI via the Mann–Kendall test (1995–2020).

Table 2 Trends in vegetation indicators (1995–2020)

Year	Vegetation index			
	DVI	NDVI	RVI	SAVI
1995	0.15	0.14	0.35	0.11
1996	0.13	0.14	0.29	0.1
1997	0.06	0.11	0.24	0.08
1998	0.09	0.11	0.26	0.09
1999	0.08	0.09	0.2	0.07
2000	0.09	0.1	0.21	0.07
2001	0.1	0.09	0.20	0.07
2002	0.1	0.1	0.20	0.07
2003	0.11	0.09	0.20	0.09
2004	0.1	0.09	0.20	0.06
2005	0.07	0.09	0.19	0.06
2006	0.09	0.08	0.19	0.08
2007	0.09	0.1	0.21	0.06
2008	0.05	0.09	0.19	0.05
2009	0.06	0.11	0.26	0.06
2010	0.07	0.08	0.30	0.05
2011	0.06	0.07	0.30	0.06
2012	0.08	0.07	0.22	0.06
2013	0.07	0.07	0.18	0.06
2014	0.06	0.08	0.19	0.06
2015	0.07	0.08	0.19	0.06
2016	0.06	0.09	0.20	0.07
2017	0.05	0.08	0.16	0.08
2018	0.06	0.08	0.19	0.05
2019	0.08	0.1	0.21	0.06
2020	0.08	0.1	0.28	0.06
Max	0.15	0.14	0.35	0.11
Min	0.06	0.07	0.16	0.05

Remark: Statistical trend significance was assessed over the full time series (1995–2020) via the Mann–Kendall test. The significance levels are summarized in Table 3.

The analysis of vegetation cover change trends from 1995–2020 via the Mann–Kendall test revealed the following findings:

• For the DVI, 26.34% of the area, equivalent to 156,500.3 hectares, experienced a decreasing trend, whereas 65.42% of the area, covering 4,388,767 hectares, showed no change. Additionally, 24.8% of the area, corresponding to 48,960.3 hectares, exhibited an increasing trend (Figure 6).

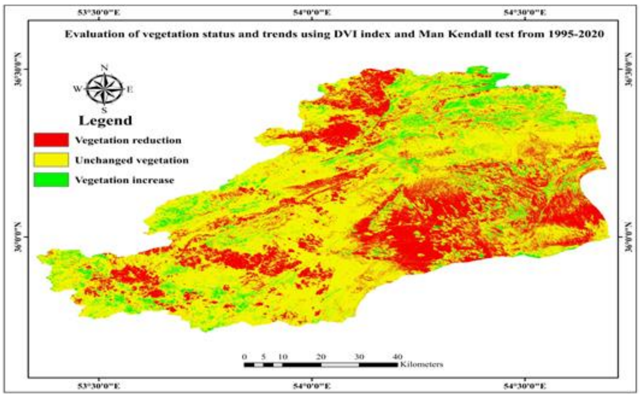

Figure 6 Analysis of vegetation status and trends via DVI and the Mann–Kendall Test (1995–2020).

• For SAVI, 33.21% of the area, or 197,329 hectares, showed a decreasing trend; 50.58% of the area, equating to 300,570.1 hectares, remained unchanged; and 16.21%, or 96,328.9 hectares, showed an increasing trend (Figure 7).

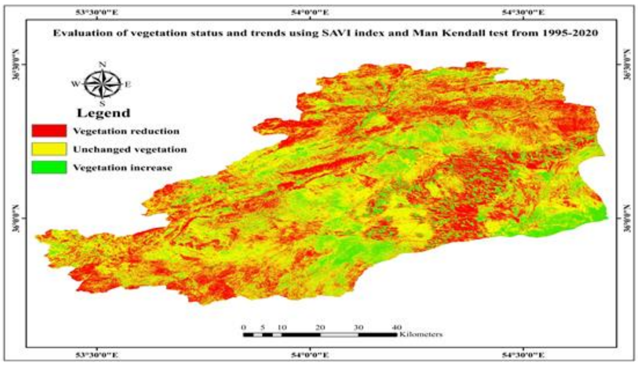

Figure 7 Analysis of vegetation status and trends via SAVI and the Mann–Kendall Test (1995–2020).

• The analysis based on the RVI indicated that 12.04% of the area, corresponding to 71,523.8 hectares, experienced a decreasing trend, 65.83% of the area (391,168.2 hectares) remained unchanged, and 22.14% (131,536 hectares) demonstrated an increasing trend (Figure 8).

• In terms of the NDVI, 66.28% of the area, or 170,308 hectares, exhibited a decreasing vegetation trend, 44.26% of the area (263,018 hectares) remained unchanged, and 27.08% (160,902 hectares) showed an increasing trend (Figure 9).

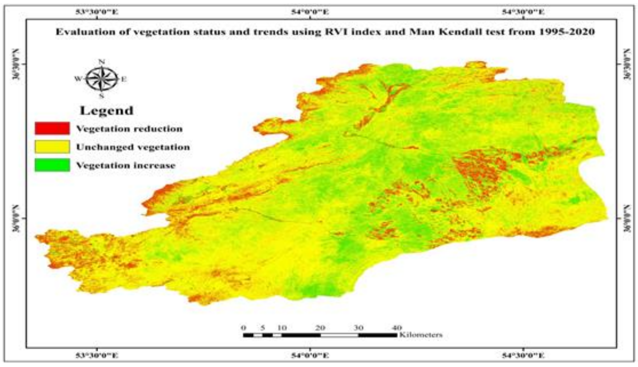

Figure 8 Analysis of vegetation status and trends via the RVI and the Mann–Kendall test (1995–2020).

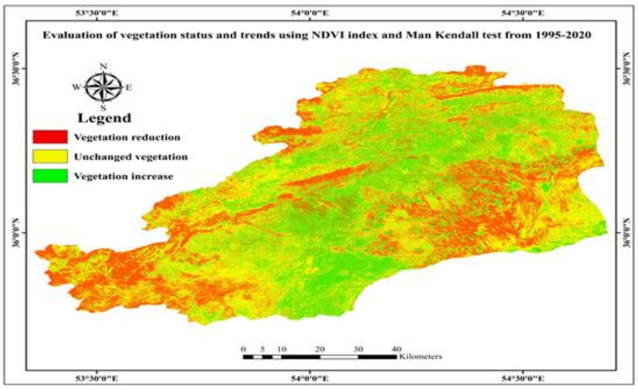

Figure 9 Analysis of the vegetation status and trends via the NDVI and the Mann–Kendall test (1995–2020).

The prepared maps were compared with field investigations conducted in 2020, Google Earth images, and maps of land use changes during this period [32]. Additionally, comparisons were made with previous studies [37–38]. These comparisons revealed the following:

• The RVI underestimated the amount of vegetation reduction in the Damghan watershed. Compared with reality, it also overestimates the amount of unchanged vegetation. Therefore, this index was not highly effective in the study area.

• The DVI significantly overestimated the amount of unchanged vegetation. However, it was effective in accurately identifying areas with reduced vegetation.

• The NDVI indicated an increase in vegetation in the region that was greater than the actual amount observed.

• Field and documentary investigations confirmed that SAVI was best suited to the vegetation conditions of the Damghan watershed.

Regression analysis via the Mann–Kendall test revealed weak correlations between vegetation status and the NDVI, RVI, and DVI. In contrast, the SAVI exhibited the highest correlation with the actual vegetation status, as indicated by its coefficient of determination (Table 3).

Vegetation indices derived from satellite imagery, particularly Landsat data, reveal vegetation changes not only in humid and semihumid regions but also in semiarid and arid areas [41–42]. Recent studies by Zhang et al. [13] and Liu et al. [6] have reinforced the importance of monitoring vegetation changes via remote sensing data, highlighting the role of satellite-derived vegetation indices in assessing land degradation and conservation progress.

According to the results, the SAVI was the most appropriate indicator of the status of and changes in vegetation in the study area. This vegetation index reduces the impact of soil brightness and color by using a soil brightness and color factor [27]. It is used for arid areas where vegetation cover is low [43]. The findings of studies by Najafi et al. [21], Vani & Mandla [44], Iman et al. [45] and Fatiha et al. [28] also support the suitability of SAVI for evaluating vegetation in arid and semiarid regions [13].

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The trend analysis of the SAVI indicated that 33.21% of the area experienced a decrease in vegetation cover. This decline could be attributed to human activities, such as overgrazing livestock, expanding roads, increasing industrial activities, increasing built-up areas, overexploitation of groundwater and inappropriate land use changes [31, 38]. Furthermore, governmental development initiatives such as rural expansion programs, groundwater extraction subsidies, and agricultural intensification policies have accelerated land use transformation in many arid regions, including the Damghan watershed. Similar findings were reported by previous studies [31–32,38–37], showing the impact of national-level development on vegetation loss. In a large area of the region, owing to unprincipled changes in land use from rangeland to agricultural land, coupled with a lack of attention to land potential, low agricultural yields have led to the abandonment of large parts of these lands [38, 46–48]. Conversely, the SAVI also revealed an increasing trend in vegetation cover over 16.21% of the Damghan watershed area. This increase was associated with the expansion of agricultural land, especially orchards and range-land seedlings. According to Bai [49–50] and Wang et al. [4], this trend may be attributed to land-use changes, such as the conversion of rangelands and forests to agricultural areas, as well as conservation and restoration efforts, including the planting of compatible species to enhance rangelands and forests, which leads to increased vegetation cover.

Overall, on the basis of the results of the vegetation indices, the major area of the Damghan watershed had poor vegetation cover, the trend of vegetation change decreased, and the area of land with low and medium vegetation also showed an increasing trend from 1995–2020. Therefore, considering the role of vegetation in environmental sustainability, necessary measures should be taken to improve the vegetation status of the study area [51]. Research by Kermani et al. [52] in the arid protected area of the Turan in central Iran revealed that the trend of vegetation changes in 30% of the area decreased between 2001 and 2015. Given that the land use in this area was rangeland, they proposed reforming rangeland management practices by reducing livestock grazing intensity to halt the decline in vegetation cover. Darvishi and Soleimani [53] also noted an increase in areas with weak or no vegetation cover over the past two decades and emphasized the need for strategies to increase vegetation cover in the semiarid area of Kermanshah Province in Iran. Zaitunah et al. [54] reported a de-crease in vegetation cover as a result of increasing built-up areas in Medan, North Sumatra, such that, in 1999, most areas were under a highly dense vegetation class, whereas in 2019, they were under a low-density vegetation class. They reported that to increase vegetated areas and maintain environmental quality, land optimization should be carried out by replanting areas with no or little vegetation cover. Guo et al. [50] reported that in arid and semiarid regions, the NDVI exhibited a decreasing trend at a global scale from 1982–2015.

Table 3 Models derived from vegetation indices (NDVI, SAVI, RVI, and DVI) via the Mann–Kendall test

Indicator	Model	Coefficient of determination	Ranking of trending accuracy
DVI	Y=-0.002X+0.1081	R^2=0.40*	3
SAVI	Y=-0.0013X+0.0862	R^2=0.81***	1
RVI	Y=-0.0276X+1.4408	R^2=0.61**	2
NDVI	Y=-0.0014X+0.1127	R^2=0.36*	4

Remark: *: significant at 90%, **: significant at 95%, ***: significant at 99%

The variable Y represents the vegetation status, and the variable X corresponds to the vegetation index

Conclusions

Remote sensing data provide a powerful tool for monitoring and analyzing vegetation changes over time, offering insights that are difficult to obtain through traditional field surveys alone. High-resolution satellite imagery and advanced remote sensing indices such as the SAVI can highlight subtle variations in vegetation cover, making them vital for comprehensive vegetation assessments and targeted management interventions. Studying vegetation trends over time—comparing past and pre-sent conditions—provides valuable insights for environmental, ecological, and urban studies. Understanding how vegetation has responded to both natural and anthropogenic influences helps identify the causes and patterns of vegetation loss and gain.

The expansion of residential and agricultural land, among other factors, has been identified as a significant driver of vegetation loss in developing regions of arid and semiarid areas. In the Damghan watershed, a comparison of available land use maps and prepared vegetation index maps from different years revealed that the conversion of rangeland to agricultural land, combined with unsustainable farming practices and overexploitation of natural resources, led to a reduction in vegetation cover.

The research findings indicated that classifying vegetation via SAVI, along with supporting data such as land use maps and Google Earth imagery, is an effective method for creating accurate vegetation cover maps. This approach is particularly suitable for arid and desert regions, where vegetation is sparse and susceptible to rapid changes. Compared with other indices such as the NDVI, the SAVI, which accounts for soil reflectance, provides a more accurate representation of vegetation in regions with low vegetation density. Additionally, the use of statistical tools such as the Mann–Kendall test to analyze trending changes in the SAVI has proven effective in assessing vegetation shifts in arid climatic conditions with low vegetation coverage. This statistical approach helps identify significant trends over time, providing a clearer picture of how vegetation is evolving and enabling better predictions for future conditions. By integrating remote sensing data with statistical analysis, decision-makers can develop targeted and informed strategies to mitigate vegetation loss, enhance land restoration projects, and promote ecological sustainability.

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