Analysis of early warning signal of land degradation risk based on time series of remote sensing data

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Abstract. This study explores the spatio-temporal dynamics of the Normalized Difference Vegetation Index (NDVI) to detect early signs of land degradation. Utilizing high-resolution NDVI data from the Google Earth Engine, spanning from 2004 to 2023 with a 30-meter resolution, this research analyzes monthly variations. To illustrate these dynamics, the study focuses on Sabzevar County, located in northeastern Iran, which extends over 7,217 km² and is approximately 220 kilometers distant from Mashhad. Validation of the NDVI data was performed using field observations from strategically located vegetation plots. One square meter plots were systematically established along 100-meter transects (10 transects in total), where the vegetation coverage in each plot was quantitatively assessed by experts. Comprehensive statistical analysis incorporated Kendall's tie test, alongside measurements of autocorrelation, coefficient of variation, and standard deviation, using R software to assess the trends and intensities of NDVI changes. The findings revealed a critical breakpoint in 2020, with increases in all three statistical indices—autocorrelation 0.82, coefficient of variation 0.65, and standard deviation 0.58—indicative of accelerating degradation prior to this year. Furthermore, the intensity of NDVI changes varied significantly across the study area, ranging from 0.05 in central and northern regions to 0.76 in the western parts. This research underscores the value of integrating field data with remote sensing technology to provide a robust analytical tool for early detection of land degradation. This method enables precise, timely assessment and proactive management of vulnerable ecosystems, particularly in arid regions.

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1 Introduction

Land degradation, a critical environmental issue, refers to the irreversible and adverse alterations within ecosystems, leading to a decline in their efficiency and functional capacity. This degradation primarily results from anthropogenic factors, including changes in land use, unsustainable exploitation of natural resources, and climatic alterations. The ramifications of land degradation extend beyond ecological deterioration, encompassing significant socio-economic impacts. Notably, it can diminish agricultural productivity and livestock outputs, curtail income and investments, and exacerbate humanitarian dilemmas associated with food security and nutrition. Given the profound implications of effective land management, addressing land degradation is recognized globally as a pivotal challenge that necessitates comprehensive strategies aimed at sustainable development, ecological restoration, and the judicious use of natural resources.

The advancement of remote sensing data technology and image processing tools has opened up unprecedented opportunities for monitoring and predicting land degradation [1]. Given the critical need to preserve and manage land resources effectively, the capability to identify and anticipate environmental hazards, such as land degradation, is invaluable. Accordingly, the analysis of remote sensing data and its associated time series has been acknowledged as a highly effective method for detecting and forecasting environmental risks [2]. In this context, environmental indicators derived from remote sensing data, particularly the NDVI[1], have gained prominence among researchers as potent tools for analyzing early warning signals of land degradation [3]. NDVI is a crucial remote sensing indicator that assesses changes in vegetation and ecosystems by measuring differences in light absorption across various spectral bands by plant matter [4]. Through detailed examination of NDVI temporal variations, discernible patterns can be identified that act as early warning signals of land degradation [4].

This study is dedicated to examining the spatio-temporal variations of the NDVI index as precursors to land degradation utilizing longitudinal remote sensing data. Specifically, it focuses on Sabzevar city in northeastern Iran, which has faced significant environmental challenges such as wind and water erosion, depletion of groundwater resources, and shifts in land use, indicative of an intensifying trajectory towards land degradation and desertification. This analysis aims to identify potential vulnerabilities in the degradation of natural resources, thereby enhancing the design and implementation of strategic measures for environmental protection and rehabilitation. It hypothesizes that the temporal analysis of NDVI data can effectively signal early warnings of land degradation in arid and semi-arid ecosystems in the region.

2 Study area

Sabzevar County is situated in the northeast of Iran, approximately 220 kilometers from Mashhad, encompassing an area of 7,217 km^2. Positioned at an elevation of 977.6 meters above sea level, its highest elevation reaches 2,924 meters within the Joghtai mountain range. The region experiences a mean annual rainfall of 180 mm, which escalates to 400 mm in the highland areas and diminishes to below 150 mm in the desert zones. The average annual temperature is recorded at 17.2 degrees Celsius, while the rate of evaporation varies significantly, ranging from 2,200 mm to 3,000 mm throughout the year (Figure 1).

Most of the area's land use is pasture, which mainly includes shrubs and grasses. These plants include types of Astragalus, Artemisia, and Alhagi persarum. Agricultural lands in

1- Normalized Difference Vegetation Index (NDVI) the region are dedicated to the cultivation of various crops, the most important of which are wheat, barley, and saffron.

The study area is characterized by diverse climatic conditions, which significantly influence the vegetation cover and soil properties. The high variability in rainfall and evaporation rates, along with the region's topographical diversity, makes Sabzevar a representative case for studying land degradation processes. Additionally, the region faces significant environmental challenges, including wind and water erosion, depletion of groundwater resources, and land-use changes, all of which contribute to the risk of land degradation and desertification.

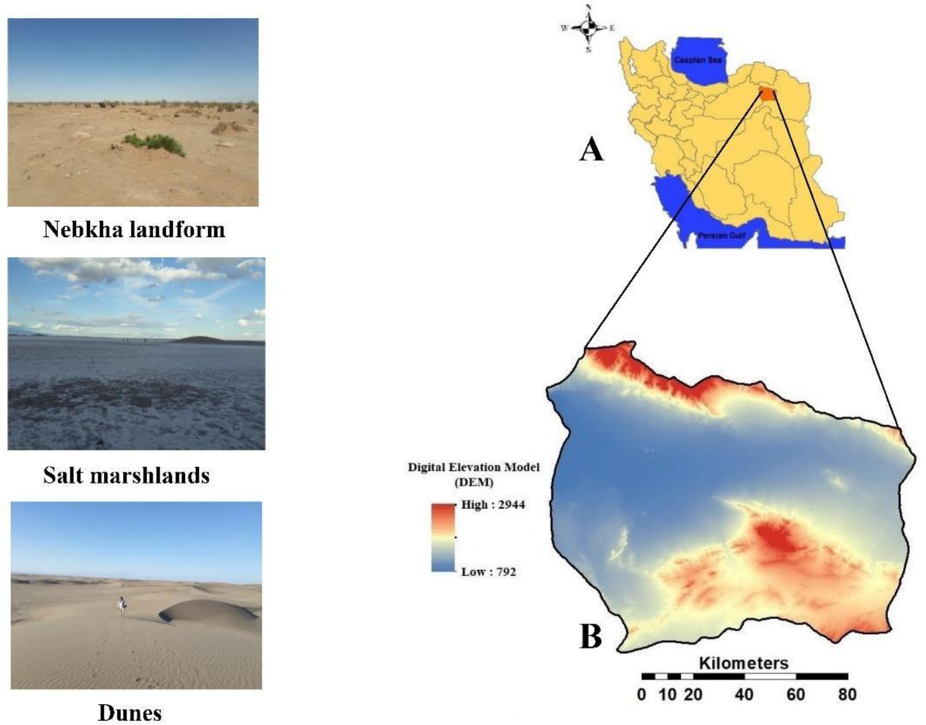


Fig. 1. The location of the studied area in the northeast of Iran. A- Map of Iran. B- Height digital model.

3 Material and methods

An early warning system is an integrated system for monitoring, collecting, analyzing and transmitting data. In order to model the risk and provide a land degradation warning system, satellite indicators can be used. In this study, the Normalized Difference Vegetation Index (NDVI) remote sensing index was employed to analyze vegetation changes. The NDVI data were sourced from the Google Earth Engine system, featuring a spatial resolution of 30 meters and a monthly temporal resolution spanning from 2004 to 2023 (Table 1). To validate the NDVI index, one square meter plots were systematically established along 100-meter transects (10 transects in total), where the vegetation coverage in each plot was quantitatively assessed by experts. In general, the use of one-square-meter plots in vegetation assessment is an effective and reliable method in ecological and botanical research due to its efficiency, ease of sampling, and standardization. All data analyses and image processing were conducted using the R statistical software and the Google Earth Engine. Key packages utilized in this research included the 'raster' package for basic raster map analysis, the 'rts' package for time series analysis [5], and the 'BFAST[1]' package for breakpoint identification [6]. This study also incorporates methodologies for detecting early and spatial warning signals of ecological thresholds [7,8].

3.1 Detection of breakpoints in the time series of data

In this research, the Additive Decomposition method is used to analyze the time series. This method uses the STL (Seasonal-Trend Decomposition using LOESS) algorithm, one of the most used and efficient methods in this field. Using the STL algorithm, the data were decomposed into three main components: trend, seasonal, and residual. In this research, the BFAST (Breaks for Additive Season and Trend) method was used to detect the break points in the time series. BFAST is an effective method for identifying breakpoints in trend and seasonal components of time series. BFAST algorithm with default settings was applied to detect breakpoints in the data.

The term "breakpoint" refers to the most substantial abrupt change within the NDVI index time series spanning from 2004 to 2023, serving as a potential indicator of ecological degradation. Initially, monthly NDVI maps were generated using the Google Earth Engine platform. Subsequently, the time series of this index was decomposed into its seasonal and trend components. The trend component illustrates long-term changes, while the seasonal component addresses periodic and short-term fluctuations.

To identify temporal trends in areas of degradation versus non-degradation, the BFAST method was applied at the pixel level, allowing for precise detection of changes [6]. Upon determining the breakpoint in degraded regions, the analysis was specifically narrowed to the period from 2004 until two years prior to the detected sudden change. This methodological approach aligns with protocols established in prior research [3,9].

Table 1. List of the datasets utilized in this study.

Name	Formula	Range	Product	Ground surface data	Spatial resolution and sensor	Year	Ref.
NDVI*	$\frac{NIR - RED}{NIR + RED}$	(-1,1)	Landsat (5-7-8)	Soil surface profile	30 - M	2004 - 2023	[10,11]

* In this formula, the value of NDVI for healthy vegetation will be close to 1, and for non-vegetated and water surfaces, it will be close to 0 and negative. Also, NIR: Near-Infrared Band and RED: Red Band.

3.2 Identifying early warning signals of land destruction

This study utilized the statistical indices of autocorrelation coefficient, standard deviation, and coefficient of variation to detect early warning signals through the analysis of temporal NDVI changes (Table 2). The findings indicate that as the system approaches a critical threshold, there is a significant increase in these statistical measures, suggesting critical slowing down, which serves as an early warning signal for impending transitions in the system [8]. Additionally, the Kendall rank correlation test was employed to assess the strength of changes in the NDVI autocorrelation over time. The Kendall's tau test, a non-parametric measure, spans from -1 to +1, where values approaching +1 signify strengthening trends. In terms of the land degradation process, the higher the Kendall's tau values in a pixel, the higher the degradation in that area.

1- package for Breaks for Additive Seasonal and Trend ('BFAST)

Kendall's test was applied at the pixel level across the entire study area to evaluate the strength of spatial changes in vegetation cover. This analysis allows for the identification of areas exhibiting significant changes in vegetation, which are subsequently classified as regions at risk of land degradation.

Table 2. Statistical indicators were examined in this research. A. lag-1 autocorrelation, B. Coefficient of variation, C. standard deviation.

$P_1 = \frac{E[\langle Z_t - \mu\rangle\langle Z_{t+1} - \mu\rangle]}{\sigma^2}$	$CV = \frac{\sigma}{\mu}$	$SD = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n} \langle Z_t - \mu\rangle^2}$
(A)	(B)	(C)

4 Results and discussion

To investigate the correlation between field data (vegetation plots) and the NDVI index, the statistical parameters of the Pearson correlation coefficient, the Root mean square errors (RMSE), and the detection coefficient[1] (R^2) were used. In this research, the Pearson correlation coefficient (0.85), RMSE (3.54), and the detection coefficient (R^2 = 0.64) indicate the suitability of the NDVI index to investigate the vegetation in the region. Analysis of NDVI index trends in both degraded and non-degraded areas revealed that the most pronounced breakpoint occurred in 2020 (Figure 2). Prior to this breakpoint, an increasing trend in vegetation cover was observed in areas later identified as degraded. Post-breakpoint, these same areas experienced a sharp decline in vegetation cover. Conversely, non-degraded areas demonstrated a consistent pattern of uniform changes throughout the period studied (Figure 2). Bestelmeyer et al (2013) considered it very important to investigate the trend of NDVI changes in selected pixels. Because in the degraded areas considered in a single pixel, there may be drought-resistant species in addition to vulnerable species. This causes a false negative warning in the NDVI values [12].

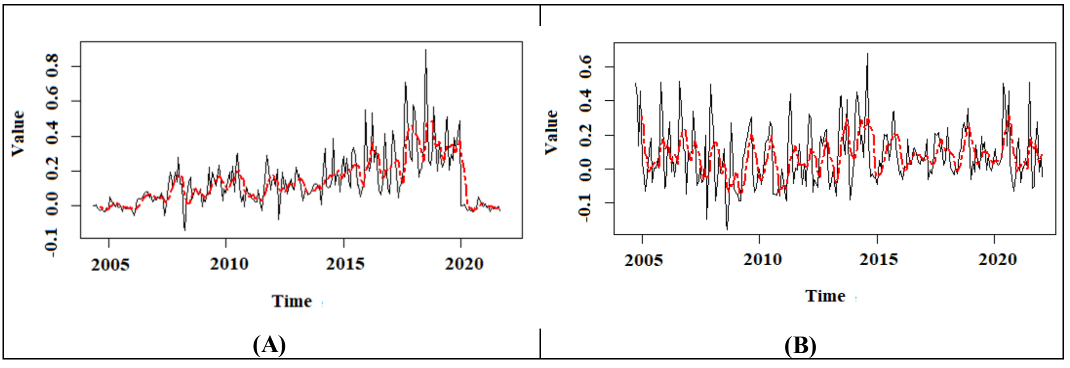
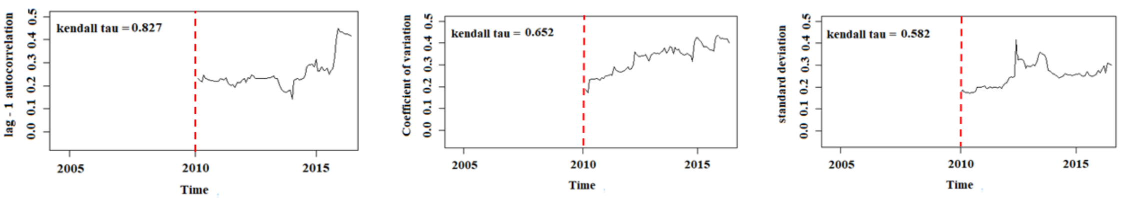


Fig. 2. Time Series Analysis of the Normalized Difference Vegetation Index (NDVI). This figure illustrates NDVI as a variable in areas affected by degradation (A) and in areas without degradation (B). Additionally, the moving average, calculated with a time step of three, is depicted with a red line to highlight trends in the data.

1- R^2 (detection coefficient) measures the degree of linear correlation between two variables. R^2 measures the ratio of changes in the dependent variable that can be attributed to the independent variable.

4.1 Time analysis of early warning signals

To determine the timing of early warning signals of land degradation, the trend of NDVI changes was analyzed at the pixel level in areas identified as degraded. In these regions, a significant increase was observed across three key statistical indices—autocorrelation coefficient, coefficient of variation, and standard deviation (Kendall tie values of 0.82, 0.65, and 0.58, respectively) (Figure 3). The trends in these indices were significant across various pixels, taking into account different combinations of rolling window sizes and filter bandwidths. To select the best moving window size and bandwidth, sensitivity analysis was used for different moving window sizes from 25% to 75% and different bandwidth sizes from 5 to 100 along the time series. (Figure 3). In this regard, Karsenberg and Birkens (2012) reached interesting results regarding the use of statistical indices in the spatial and temporal analysis of remote sensing data. They showed that the use of these indicators can be considered as early warning signals.



(A) (B) (C)

Fig. 3. Statistical Analysis of NDVI Time Series. Panels A, B, and C depict the autocorrelation coefficient, coefficient of variation, and standard deviation, respectively, of the NDVI time series for each pixel. On each graph, the y-axis represents the values of the statistical indices, while the x-axis indicates time (year) from 2004 to two years prior to the detected sudden change. The dotted red lines illustrate the rolling window sizes used in calculating each statistical index.

4.2 Investigating the trend of spatial changes in land degradation based on the NDVI index variations

An analysis of the spatial trends in NDVI index changes revealed that the most pronounced changes occurred in the western parts of the study region. According to Kendall's statistical test, the strength of these changes varied significantly, ranging from 0.05 in the central and northern areas to 0.76 in the western regions (Figure 4). The western regions, which have seen significant abandonment over the past two decades, are highly susceptible to wind erosion. This susceptibility is attributed to several factors: the lack of soil compaction, minimal moisture retention, and an absence of vegetation due to inadequate land management and utilization. Additionally, the formation of activated Nebkha facies in these areas signifies an increase in particle transport during wind erosion processes, further contributing to the degradation of the land. Wang et al (2019) investigated the phenomenon of Nebkha (small sand dunes covered with plants) in the semi-arid regions of northern China. Their results showed that rapid desertification has affected these regions caused by extensive exploitation of pastures. In addition, the analysis of the layering and grain size of sedges has shown that the exploitation of pastures in the semi-arid regions of North China has potential effects on land degradation at the regional level. According to the results of Wang et al (2019) the formation of dykes is a good indicator of wind erosion and land degradation in the semi-arid regions of North China.

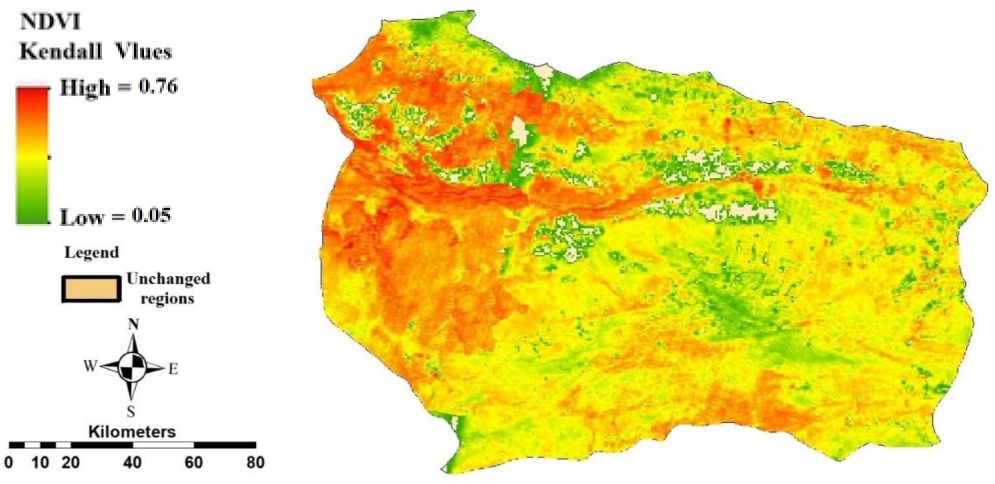


Fig. 4. Analysis of Spatial Changes in the NDVI Index Based on Kendall's Tau Values.

5 Conclusion

This research introduces a robust analytical framework that integrates field data with satellite image time series to detect early warning signals of land degradation. Through a spatio-temporal analysis of remote sensing indicators such as NDVI, this study elucidates the dynamics of vegetation cover changes associated with land degradation. The findings demonstrate that early warning signals indicative of ecosystem alterations can be effectively identified up to two years prior to a notable change. Our research showed that by using the NDVI remote sensing index, it is possible to predict vegetation changes in dry ecosystems up to two years before sudden changes. This early detection capability provides valuable insights for proactive land management and conservation efforts, enabling timely interventions to mitigate land degradation.

Among the statistical indices evaluated, the autocorrelation coefficient proved to be the most effective, exhibiting strong changes in the majority of pixels within degraded areas (Kendall 0.82). A significant increase in this index prior to 2020 in the western eroded regions provides concrete evidence of impending degradation. The analysis of large datasets can sometimes produce false alarms; hence, spatial analysis offers more granular insights into the reliability of warning signals. However, the effectiveness of these insights may be constrained by the sensitivity of the pre-processing steps. The use of Landsat satellite imagery enabled precise change detection due to its suitable spatial resolution, establishing a vital source of data for monitoring and analyzing warning signals.

Given the complex and multifaceted nature of land degradation, which impacts agriculture, environmental sustainability, and regional economies, the application of precise analytical methods is crucial. These methods enhance the ability to forecast and mitigate degradation impacts, thereby supporting the implementation of proactive management and conservation strategies. Further research and the application of such analytical methods are recommended to sustain and enhance ecosystem health, preserve water resources, and maintain biodiversity. The outcomes of the present study indicate that the use of remote sensing indicators, especially those related to the fundamental processes in an ecosystem is useful for assessing the state of the ecosystem, and these indicators can improve the ability to provide warnings before possible changes occur.

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