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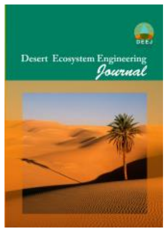

Investigating the Impact of Land-use and Climatic Factors on Land Degradation in North-East of Iran

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Abstract

Vegetation is one of the most important factors in assessing land degradation. On the other hand, remote sensing of vegetation changes can provide useful information for ecosystem management. Therefore, this study sought to investigate the trend of changes in vegetation and its correlation with land-use and climate change in northeastern Iran. To this end, the data regarding the NDVI and EVI which were extracted from the MODIS satellite and MOD13A2 product from 2000 to 2017 were used to study vegetation changes, and data obtained from the MODIS MCD12Q1 product from 2001 to 2017 were used to investigate the land-use changes. Moreover, the meteorological stations' data were examined to evaluate the trend of climate factors in the region.

The study's results showed that the trend of changes in both NDVI and EVI was significantly negative. Furthermore, the land-use analysis showed that the agricultural and rangeland area decreased and the urban and barren land area increased significantly. The temperature also increased significantly during the period while the precipitation decreased slightly. Moreover, it was found that there was a significant correlation between land-use classes, NDVI, and EVI and that the correlation between precipitation and NDVI was significant at 95% (R=0.53). on the other hand, the investigation of the relationship between climatic factors, land use, and vegetation indices based on the Pearson correlation coefficient indicated that the land-use had a higher correlation with vegetation indices compared with that of the climatic factors.

Therefore, it could be argued that degradation can be affected by human activities which in turn leads to land-use changes and the overuse of water and soil resources. The degradation can also be influenced by climate change, leading to a decrease in the available water supply to be used by natural vegetation. However, land-use and human activities were found to have more influence on NDVI, EVI, and land degradation.

Keywords: Human activities, Remote sensing, Vegetative indices, Climatic factors, Northeast of Iran.

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1. Introduction

A set of various environmental factors such as climate change and human activities such as deforestation and overgrazing leads to increased wind and soil erosion and eventually desertification (Rondeaux et al. 1996., Foggin and Smith, 1996., Batjargal, 1997). In this regard, various studies have used remote sensing to monitor land degradation worldwide (Dubovyk et al. 2017; Mariano et al. 2018; Aralova et al. 2018., Zoungrana et al. 2018., AbdelRahman et al. 2019), showing that that land degradation is a process that involves a series of synthetic factors, most of which are environmental factors such as temperature, precipitation, and human activity (Montfort, et al., 2020; Xiao and Moody, 2005; Hermans-Neumann, 2017; Fensholt et al., 2009; Herrmann et al., 2005; Xiao and Moody, 2005).

As an important component of land ecosystems, vegetation plays an important role in storing soil carbon and decreasing degradation and desertification, the destruction of which may reduce biodiversity and lead to soil and land degradation (Yengoh et al., 2015). On the other hand, vegetation changes can be related to climatic events such as drought and temperature (; Dai, 2011a, 2011b, 2013; Trenberth et al., 2014; Dai and Zhao, 2017., Manesh et al. 2019 Li et al. 2019., Li et al. 2020.,Ying et al, 2020., Peilin et al, 2020).

Many studies have so far examined vegetation degradation based on land use/land cover (LULC) changes (Binh et al. 2015; Benewinde et al., 2018; Houessou et al., 2013; Ouedraogo et al., 2010). On the other hand, several researchers have studied land degradation in terms of trends of vegetation changes (Xu et al., 2016; Kaptué et al., 2015; Harris et al., 2014; Forkel et al., 2013; Peng et al., 2012;). However, the most important climatic factors affecting natural vegetation are precipitation and temperature (Dong et al., 2019;; Peng et al., 2015; Zeng and Yang, 2009; Nezlin et al., 2005; Heydari Alamdarloo et al. 2021). To study such processes over time, spectral indices such as Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI) are commonly used as indices of vegetation health that can be estimated via remote sensing (Ardöa et al. 2018; Eckert et al. 2015).

Obtained from red and near-infrared bands, NDVI is one of the oldest and most widely used vegetation indices. Generally, the index is sensitive to vegetation changes. However, it is less susceptible to weathering and soil conditions except in cases where vegetation is sparse. For instance, Darwish and Feuer (2008) investigated the causes of rangeland destruction in Lebanon using the NDVI.. Moreover, NDVI is widely used to study vegetation changes (Brown et al., 2006., Huang and Asner, 2013., ;; Johansen et al., 2014; Gandhi et al., 2015; Vogelmann et al., 2016; Jarchow et al., 2017., Demattê et al., 2017, Krakauer et al., 2017, Richard & Poccard, 1998). In many studies, NDVI and precipitation are highly correlated with each other, while the temperature is less correlated with the NDVI (Li et al., 2004; Ji and Peters., 2004. Wang et al., 2001. Yang et al., 1998, Liu et al., 2015). On the other hand, EVI is a new useful vegetation index similar to NDVI which can be applied to quantify vegetation greenness. However, EVI is corrected for some atmospheric conditions and soil background noise, and it is more sensitive in regions with dense vegetation (Vermote et al. 2016).

Many recent studies have shown that there is a strong correlation between EVI and gross primary production (GPP) in rangelands and grasslands. GPP can also have a high correlation with climatic factors, especially temperature and precipitation, as they have a significant impact on the canopy cover (Sjöström et al., 2014; Shi et al., 2017; Ma et al., 2008). On the other hand, as temperature and precipitation are key parameters at various stages of plant phenology, photosynthesis, and transpiration, many studies have used remotely-sensed vegetation indices to investigate the relationship between vegetation and climate factors (Davenport and Nicholson, 1993.,Zeng et al., 1999; Zhang et al., 2007; Raynolds et al., 2008; Sun and Kafatos, 2007; Hawinkel et al., 2016., Wilson et al., 2019., Kalisa et al. 2019., Lamsal et al. 2019., Lawal et al. 2019., Hao et al. 2020., Zhao et al., 2020). Furthermore, considering the fact that most regions of Iran are located in an arid and semi-arid climate whose ecosystems have weakened in recent years, the land degradation trend has increased in these regions due to the impact of human activities and climate change.

Several studies have been conducted on land degradation in Iran (Kiani-Harchegani et al. 2020; Poornazari et al, 2021; Hosseini et al, 2021;; Sadeghi et al. 2019), showing an increasing land degradation trend, caused by human and natural factors. On the other hand, remote sensing techniques are considered as effective tools for assessing land degradation. However, as no study has investigated the trend of vegetation indices via statistical analysis, this study used the NDVI and EVI to study the trend of land degradation in the study area. To this end, land-use and climatic factors (temperature and precipitation) were considered as effective human and climatic factors on land degradation, respectively. Generally, the main purpose of this study was to examine the relationship between vegetation indices, land use, and climatic factors and determine the most effective factors involved in land degradation in the study area.

2. Materials and Methods

2.1. The study area

Located in northeastern Iran with an arid and semi-arid climate, the study area comprised an area of 150,000 km^2, including Khorasan Razavi and North Khorasan provinces (Fig. 1). The highest and lowest elevations were 3305 m and 231 m above the sea level in the north and the east of the study area, respectively. The northern part of the study area was mostly mountainous, including some productive plains used for agriculture with adequate precipitation and sufficient groundwater resources. However, the area of agricultural lands was negligible in the southern part of the study area due to its low rainfall, poor vegetation, and proximity to the desert.

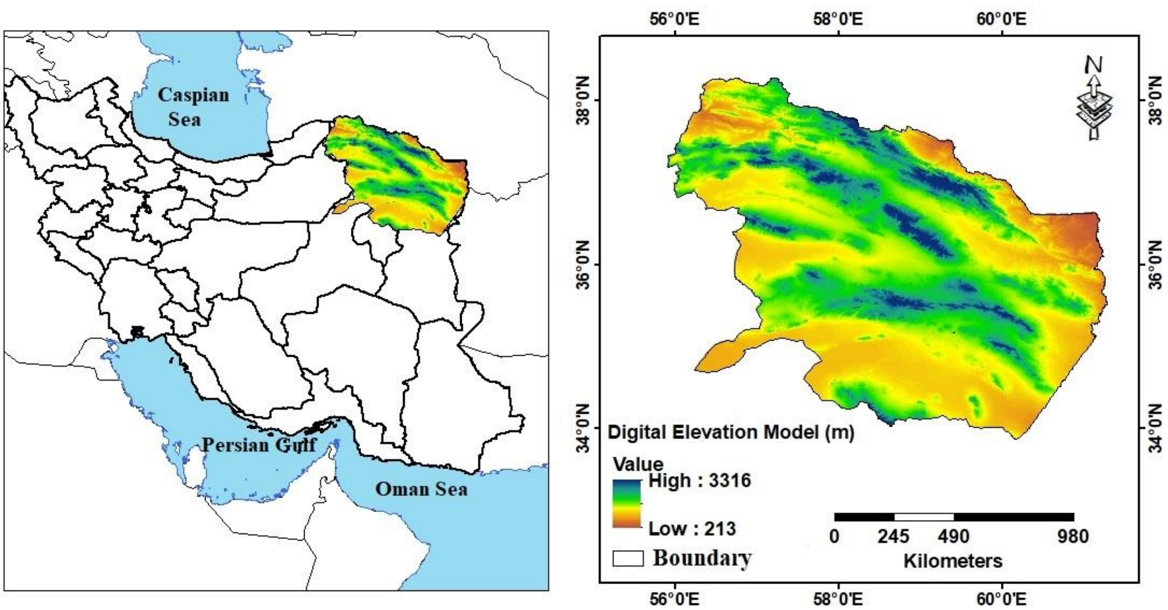

Figure (1): Location of the study area in Iran

2.2. Methodology

The process of land degradation can be

evaluated through statistical tests and remote sensing, considering the fact that remote sensing is an efficient approach for assessing land degradation, as it provides access to spatial and time-series data (Harris, 2014). Therefore, as the land degradation process is affected by both human activities (land use) and climatic factors (temperature and precipitation), this study used NDVI and EVI to examine the process. Generally, the present study was carried out in four major phases: i) Extracting vegetation indices based on MOD13A2 product and LULC (land use/land cover) based on MCD12Q1 product; ii) analyzing the trend of EVI and NDVI by Mann-Kendall test; iii) Collecting climatic factors (temperature and precipitation) and analyzing their trend via Mann-Kendall test; iv) investigating the relationship between vegetation indices, climatic factors, and land use.

Vegetative indices

Satellite data are often used for extensive study of vegetation. Moreover, to reduce the effect of undesired factors on the obtained information, vegetation is required to be differentiated from other features, which cannot be conducted via single bands (Bannari et al. 1995). As vegetation indices represent mathematical relationships of spectral bands (e.g., addition, multiplication, subtraction, and division) and show the vegetation's health and status (Byod and Danson,2005), the vegetation index (VI) is a numerical index based on concepts of biology, chemistry, and physics, which provides useful empirical information concerning the vegetation.

During the past half-century, NDVI has been widely used for vegetation mapping and monitoring and the assessment of land cover and its associated changes. On the other hand, as another index similar to NDVI which is used to quantify vegetation greenness, EVI corrects some atmospheric conditions and canopy background noise and is more sensitive in areas with dense vegetation, being extremely popular due to its ability to eliminate background and atmosphere noises. Moreover, while NDVI asymptotically saturates in high biomass regions, EVI does not do so in the same conditions. Therefore, this study used both NDVI and EVI.

Launched by NASA on the Terra satellite in 1999 and on the Aqua satellite in 2002, MODIS (Moderate Resolution Imaging Spectroradiometer) is a satellite-borne sensor that is widely used in environmental sciences. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every one or two days, acquiring data in 36 spectral bands with different spatial resolutions, including 2 bands at 250 meters, 5 bands at 500 m, and 29 bands at 1 kilometer.

MODIS is designed to measure large-scale near-surface dynamics, including cloud cover, ground irradiance, observations in the oceans, the land surface, and the lower levels of the atmosphere. Therefore, this study used Terra satellite images (MODIS sensor) to examine vegetation changes. To this end, EVI and NDVI were extracted from MODIS 16-day product (MOD13A2) with 1 km resolution and were downloaded from http://neo.sci.gsfc.nasa.gov. Then, the images (including reprojection and standardization) were preprocessed by the MCTK[1]plugin in ENVI5.1 software (Thapa et al. 2019), followed by the development of the study area's NDVI and EVI maps for the 2000-2017 period using the ENVI 5.1 software. Moreover, the average values of the indices were extracted for different years. Finally, Mann-Kendall nonparametric statistical test was performed in the Terrset software to investigate the significant trend of NDVI and EVI time series.

Preparing land-use maps

The MCD12Q1 product (with a resolution of

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500 meters) was used for preparing land-use maps.

In brief, the following steps were carried out to prepare a land-use map:

1. Reprojecting MODIS product in ENVI 5.1 using MODIS toolkit;
2. Validating land-use map based on the ground truth map using the kappa coefficient;
3. Transferring the classified images into ArcGIS 10.7 and analyzing the results;
4. investigating the trend of land-use change, estimating the area of each land-use class in ArcGIS 10.7, and analyzing their trend of changes for the 2000-2017 period in the Terrset software using the Mann-Kendall test.

Climatic factors

This study used the annual precipitation and temperature data extracted from the Mashhad meteorological station to examine the trend of climatic factors. To this end, the data were normalized using the Kolmogorov Smirnov test whose homogeneity was then investigated. Also, the Mann-Kendall test was used to study the trend of climatic factors (Table1).

Table (1). Meteorological data from the synoptic Station of Mashhad

Station	Meteorological data	Statistical period	Elevation (m)	Latitude (degree)	Longitude (degree)
Mashhad	Precipitation (mm) Temperature (°C)	1985-2017	999.2	36° 16´ N	59° 38´ E

Investigating the relationship between vegetation indices, climatic factors, and land-use

This study used the Pearson correlation coefficient to investigate the relationship between EVI, NDVI, climatic factors, and land use. Figure 2 shows the overall schematic of the research.

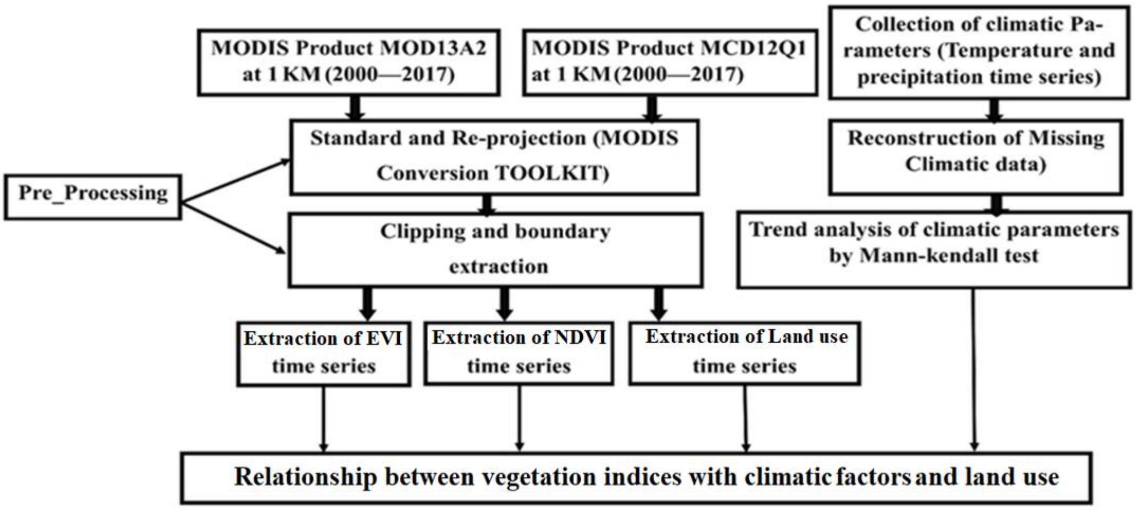
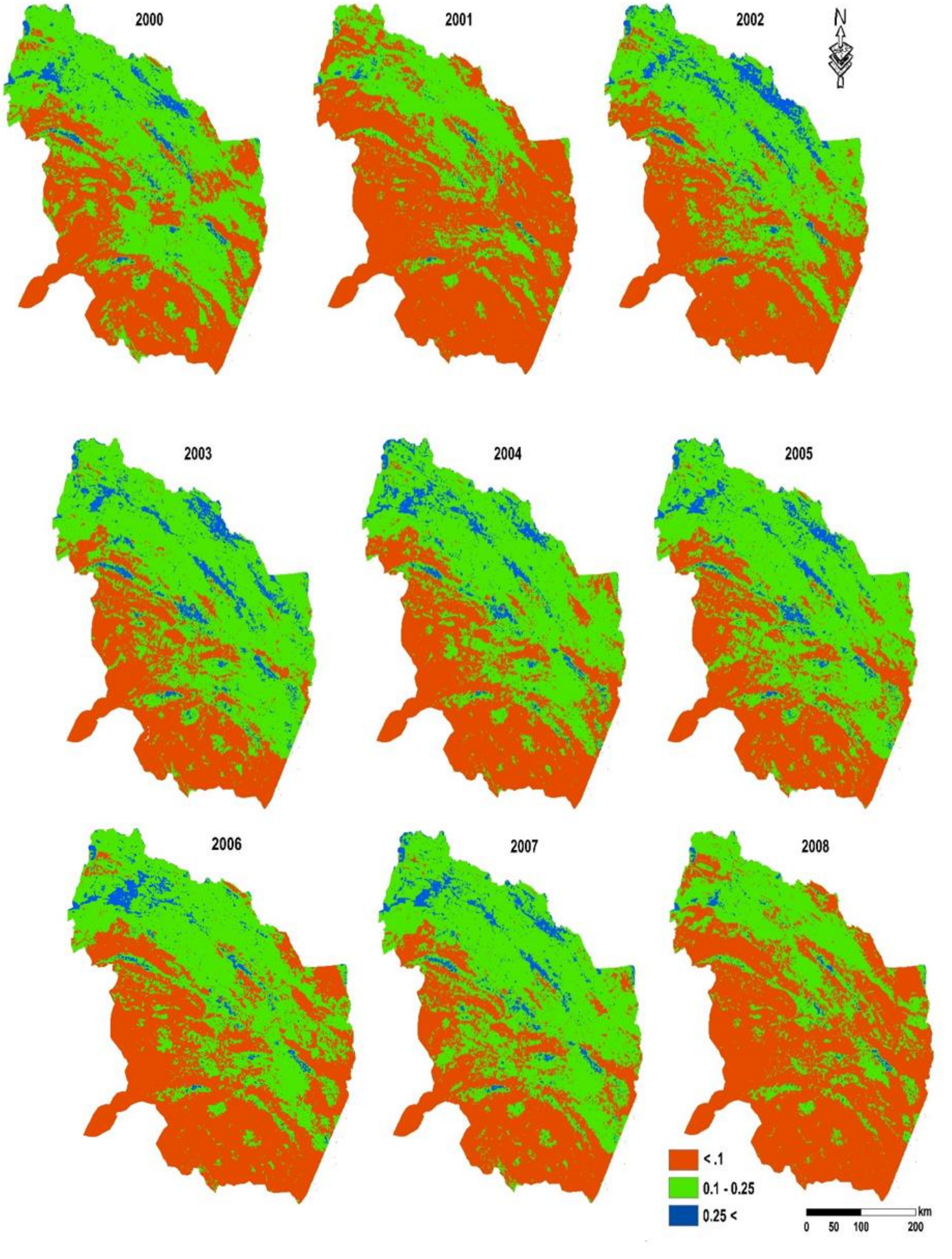


Figure (2): The overall schematic of the research

3. Results

To investigate the trend of vegetation changes in the study area, EVI maps were prepared for the month of May (when vegetation has the most density) from 2000 to 2017. According to Fig. 3, the highest and lowest EVI values were observed in the northern and southern parts of the study area, respectively, considering the fact that the northern parts are mountainous with higher precipitation and lower temperatures, providing more favorable conditions for vegetation.



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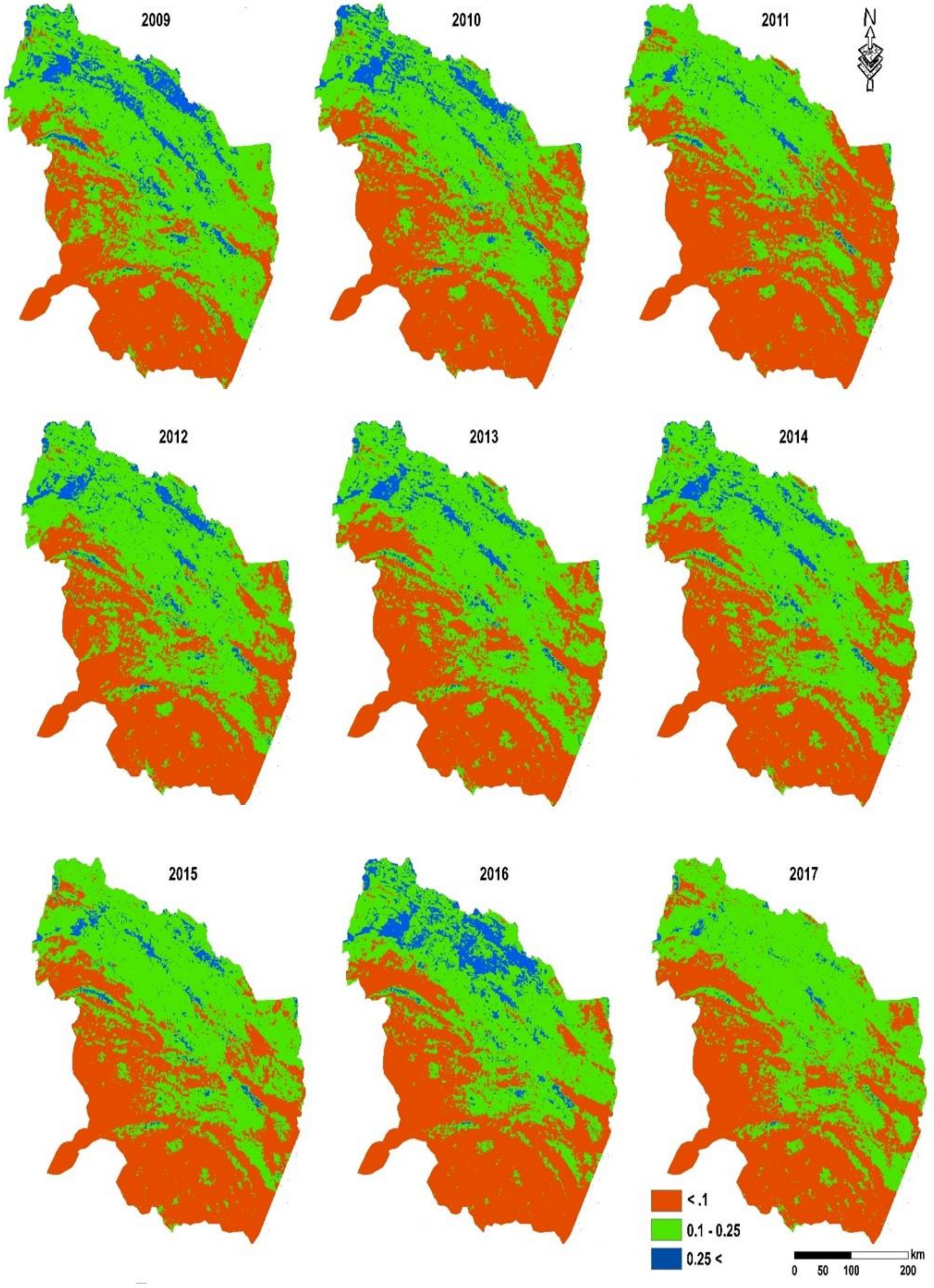


Figure (3): The changes in EVI index in the study area (2000-2017)

In Fig. 4, the significance of the trend of EVI changes from 2000 to 2017 was also examined, the results of which indicated that 68.64% of the region had a negative decreasing trend, and 0.42% of the region had a significant negative trend. Moreover, 31.36% of the region had a positive increasing trend in the EVI, and 0.15% of the area had a significant positive trend.

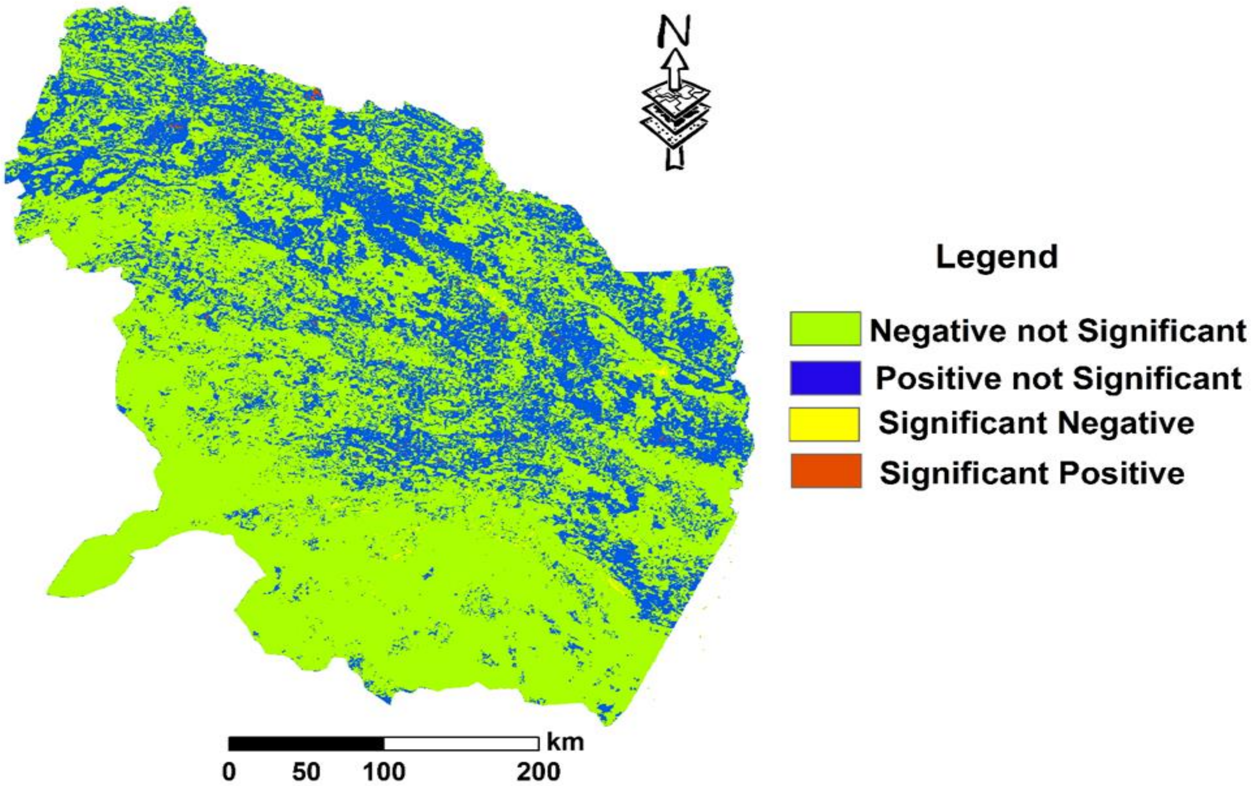
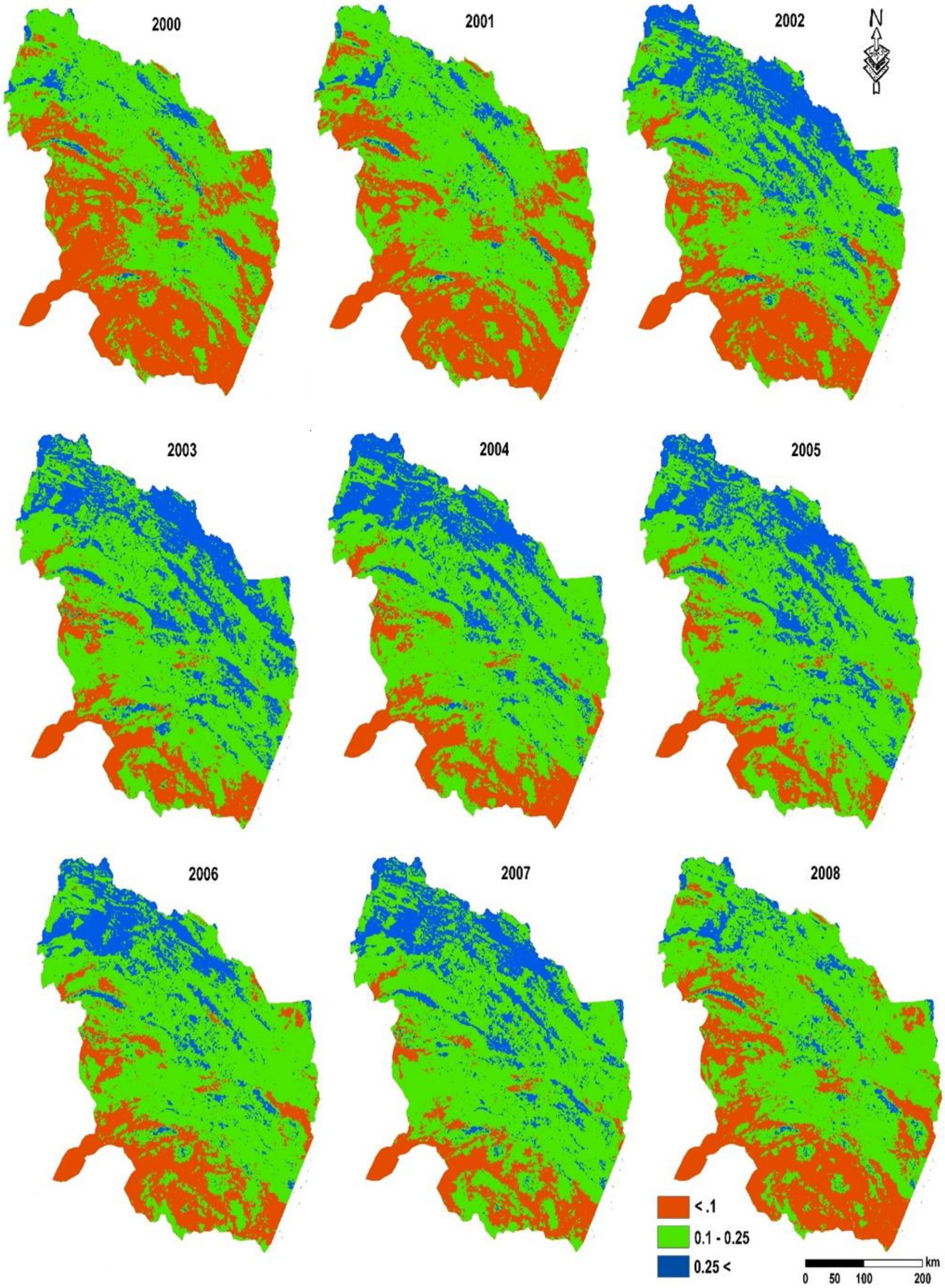


Figure (4). Investigation of the trend of EVI changes in the study area (Significance at the level of 0.05)

The NDVI obtained from the MOD13A2 was also used to examine vegetation in the 2000-2017 period, whose results showed that the northern part of the study area possessed the highest vegetation (Figure 5). It was also found that the highest and the lowest NDVI values throughout the study period belonged to the northern and southern parts of the study area, respectively. Furthermore, the NDVI maps of the period suggested that in some years, including 2008 and 2017, the index did not follow its general trend, which can be attributed to the impact of vegetation on factors such as climatic parameters.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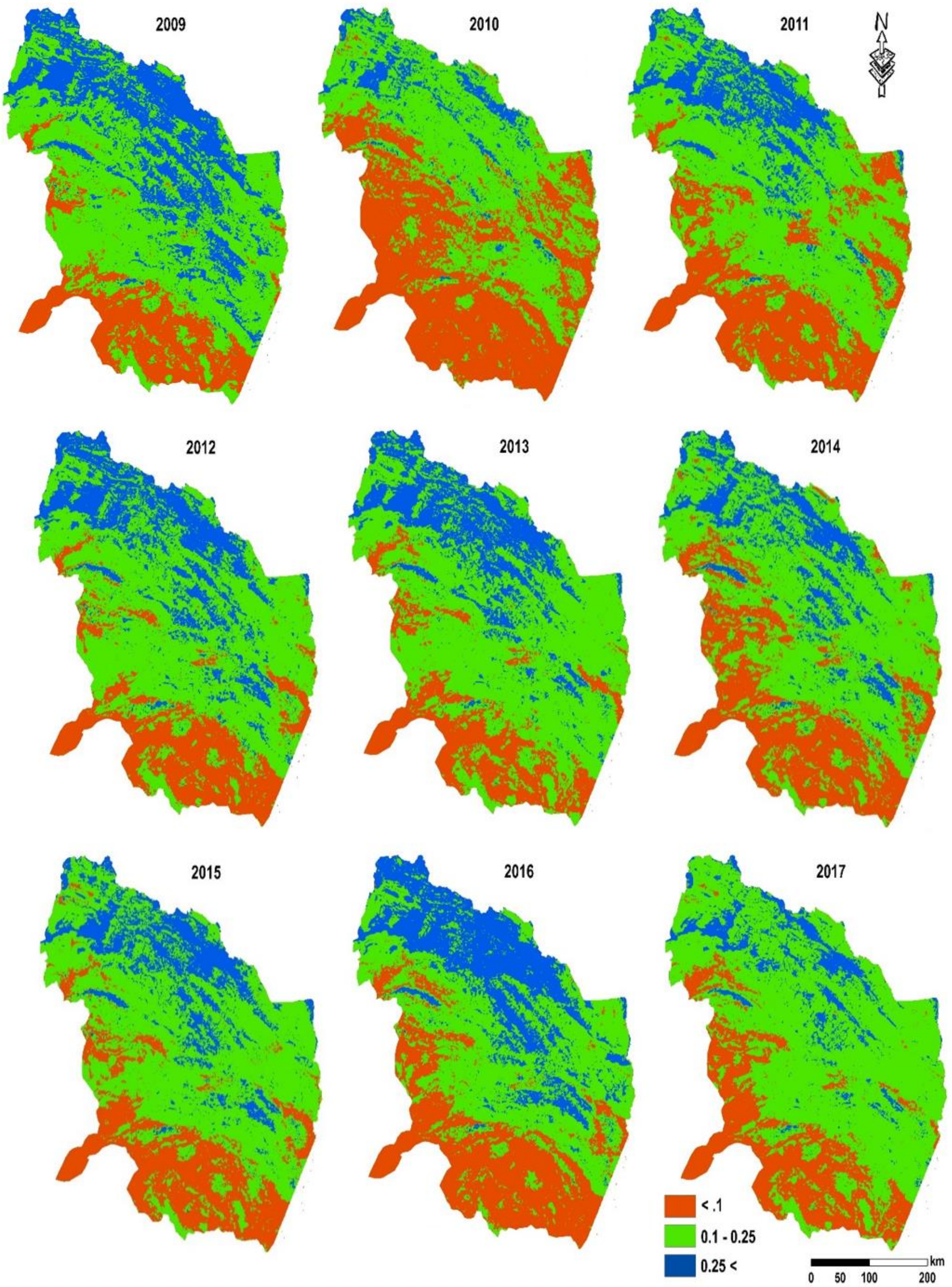


Figure (5): NDVI changes in the study area

Then, the trends of the NDVI index from 2000 to 2017 were mapped using Terrset software at the 95% confidence level (Figure 6).

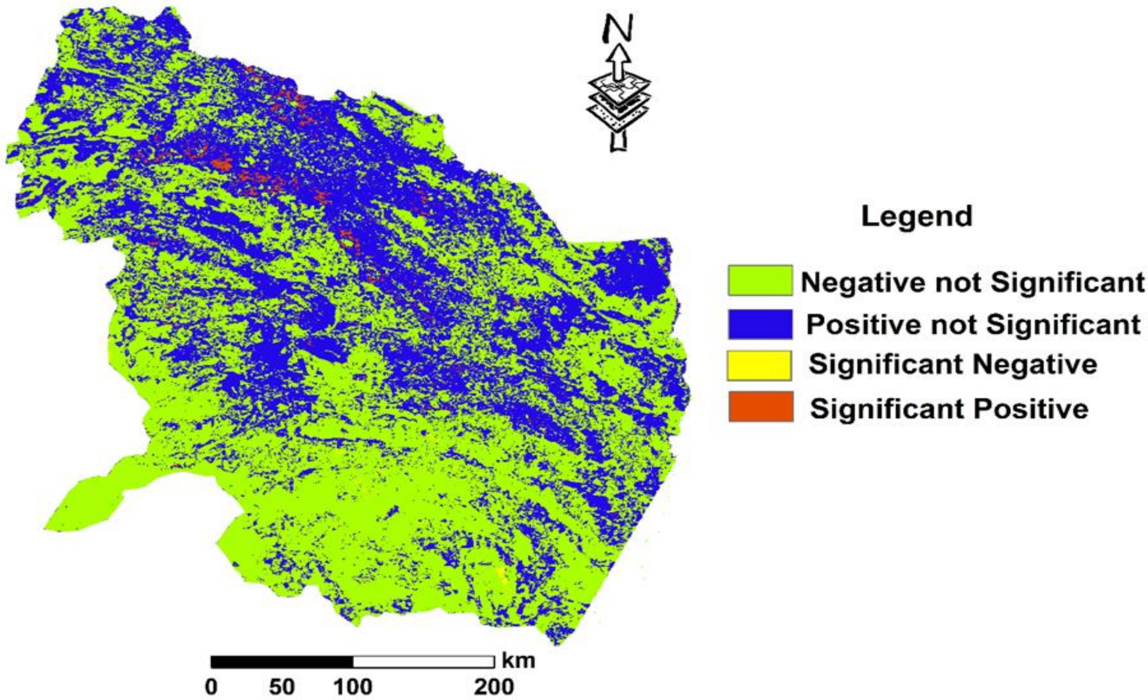


Figure (6): Investigation of the trend of changes in the NDVI index in the study area

Figure (7) shows the mean annual NDVI and EVI values from 2000 to 2017. Accordingly, the linear trend was negative in both NDVI and EVI throughout the whole period. Moreover, the trend of the two indices was mostly increasing until 2007, particularly low in 2008 and 2010, and decreasing in the rest. Also, the highest EVI value was observed in 2009. On the other hand, the highest precipitation value throughout the study period was found in 2009 (Figure 7), indicating a close relationship between vegetation and precipitation, and the strong dependence of vegetation on precipitation.

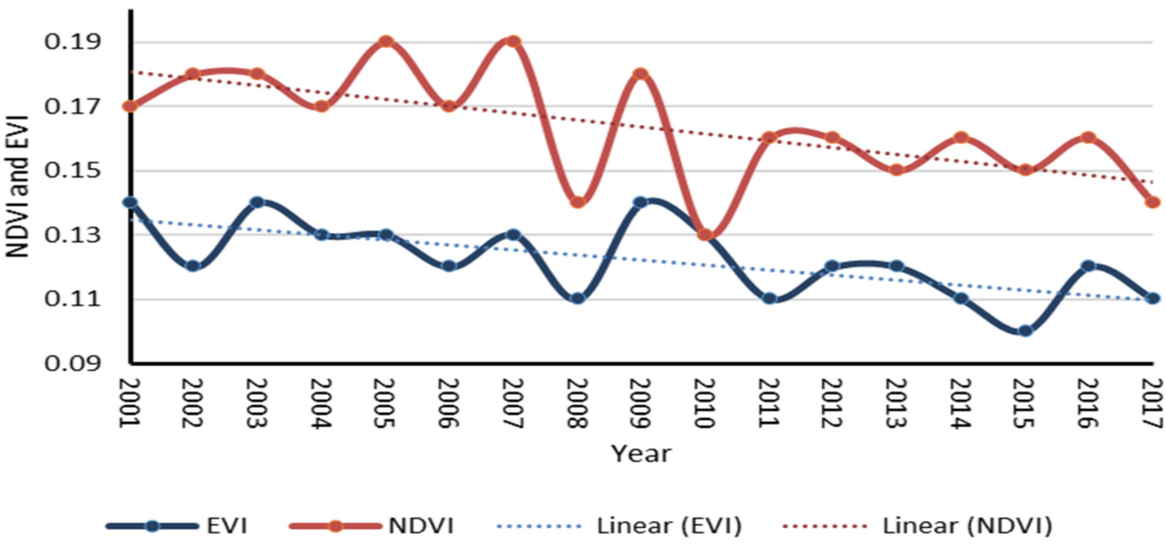


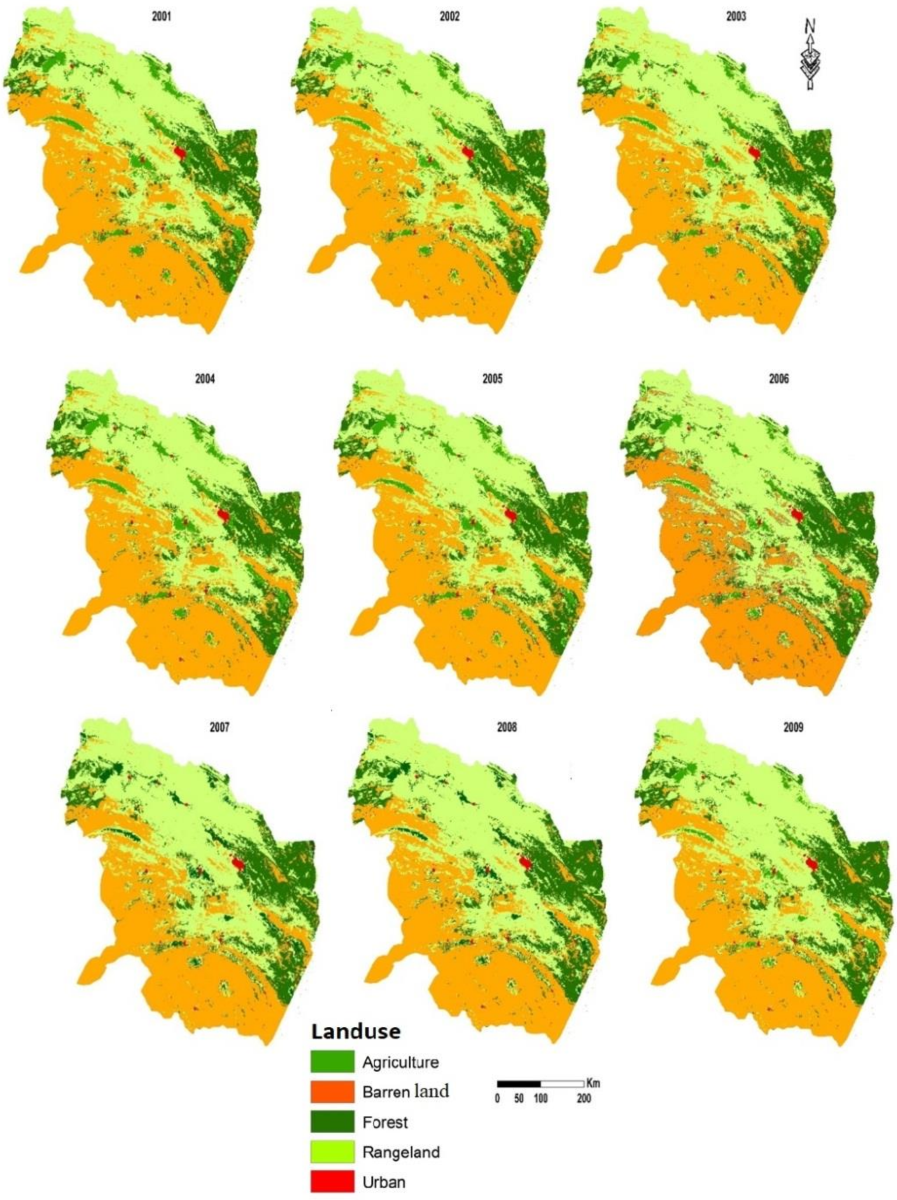
Figure (7): The trend of NDVI and EVI changes in the study area

Table (2) shows the results of the Mann-Kendall test that was used to investigate the significance of the trend in NDVI and EVI, which was decreasing and significant.

Table (2): Results of the Mann-Kendall test on NDVI and EVI (2001-2017)

Result of the test	alpha	p-value (Two-tailed)	Kendall's tau	Average value	parameter
As the obtained p-value is lower than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is positive, incremental, and significant at the 99% confidence level.	0.01	<0.0001	-0.428	0.164	NDVI
As the obtained p-value is less than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is negative, incremental, and significant at the 99% confidence level.	0.01	<0.0001	-0.420	0.12	EVI

In addition, land-use maps were prepared for the 2000-2017 period in envi5.1 software (Fig8).



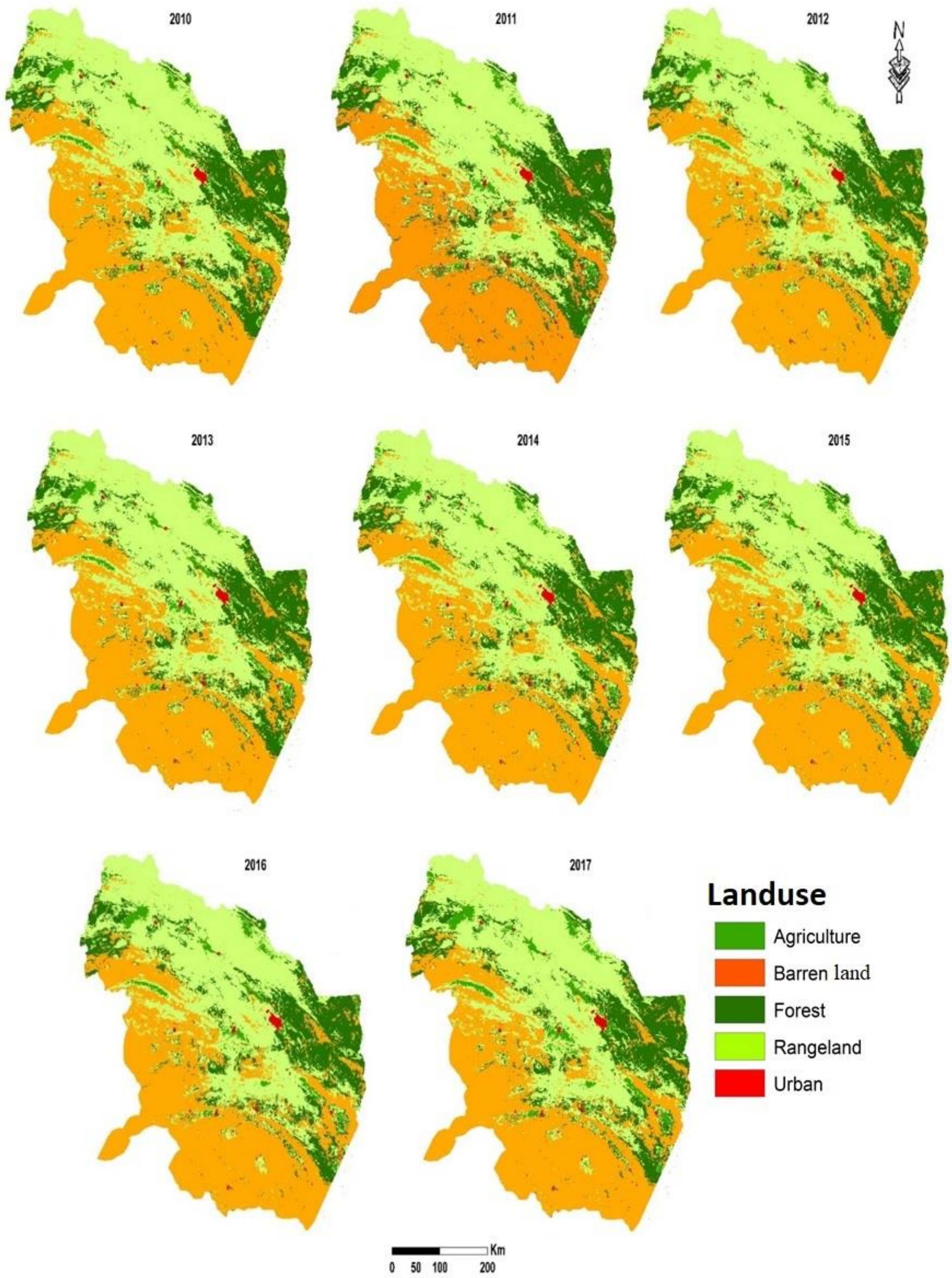


Figure (8): The trends of land-use change in the study area (2001 -2017)

Figure (9) shows the trend of each land-use change in the study area during different years. throughout the period, the area of agricultural land and rangeland decreased and that of urban land, barren land, and forest increased.

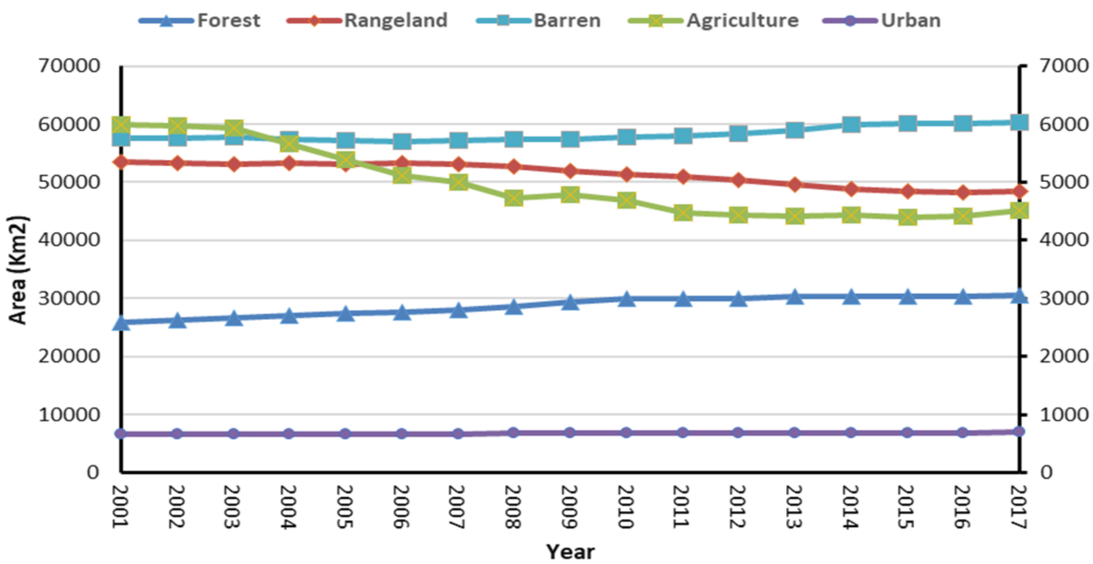


Figure (9): Investigation of the trend of land-use change throughout the study period

Table (3) shows the trend of changes in the area of each land-use class in the 2001-2017 period, according to which the trend of changes in the area of forest, urban, and barren lands is significantly positive and increasing ($p<0.01$). However, the trend of changes in the area of rangeland and agricultural land is significantly negative and decreasing ($p<0.01$).

Table (3): Results of the Mann-Kendall test for the area under each land-use category (2000-2017)

Test Result	alpha	p-value (Two-tailed)	Kendall's tau	Yearly average	parameter
As the obtained p-value is less than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is positive, incremental, and significant at the 95% confidence level.	0.05	<0.0001	0.933	28947.313	Forest
As the obtained p-value is less than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is negative, decreasing, and significant at the 95% confidence level.	0.05	<0.0001	-0.867	51269.688	Rangeland
As the obtained p-value is less than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is negative, decreasing, and significant at the 95% confidence level.	0.05	<0.0001	-0.817	4895.125	Agriculture
As the obtained p-value is less than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is positive, incremental, and significant at the 95% confidence level.	0.05	<0.0001	0.979	678.125	Urban
As the obtained p-value is less than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is positive, incremental, and significant at the 95% confidence level.	0.05	<0.0001	0.683	58243.250	Barren land

climatic parameters are one of the most important factors affecting vegetation. Therefore, the trend of changes in climate factors of precipitation and temperature in Mashhad station was studied from 2000 to 2017. Figure (10) shows the trend of precipitation and temperature changes during this period.

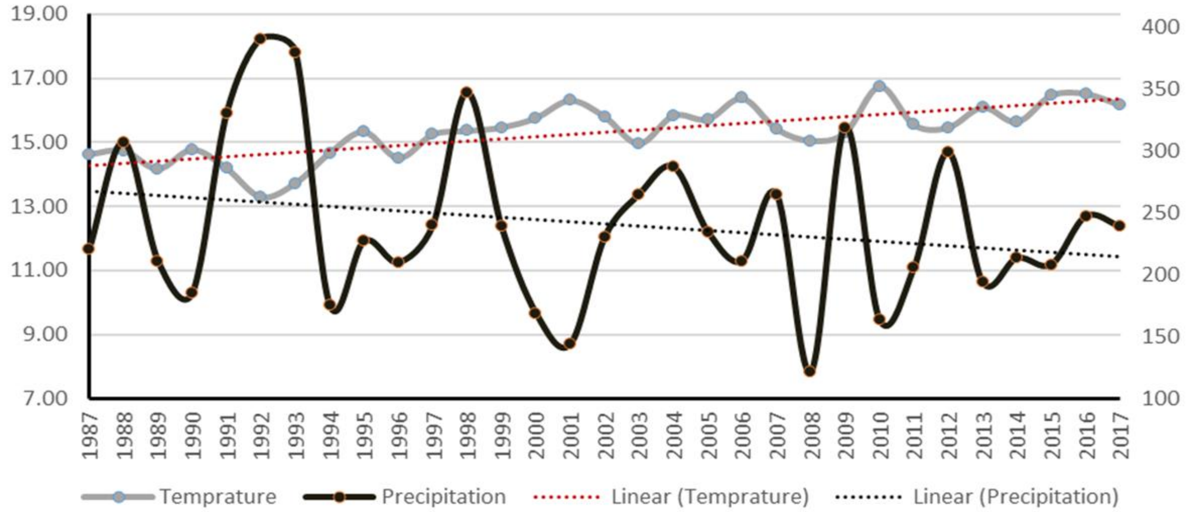


Figure (10): Variations in temperature and precipitation in the study area

Table (4) shows the results of the Mann-Kendall test on precipitation and temperature data from 2001to 2017 collected from the Mashhad synoptic station. In terms of the average temperature, given that the p-value was < 0.05, the H0 hypothesis was rejected and the H1 hypothesis was confirmed. Moreover, the trend of temperature changes was significantly positive in the study region. In terms of precipitation, as the p-value was >0.05, the trend of precipitation changes was not significant in the study region.

Table (4): Results of the Mann-Kendall test at Mashhad's Synoptic Station (2001-2017)

Test Results	alpha	p-value (Two-tailed)	Kendall's tau	Average value	parameter
As the obtained p-value is less than the significance level (0.05), the H0 hypothesis is rejected and the H1 hypothesis is confirmed. The trend is positive, incremental, and significant at the 95% confidence level.	0.05	<0.0001	0.30	15.82	Temperature average (C°)
As the obtained p-value is greater than the significance level (0.05), the H0 hypothesis is confirmed. The trend is negative, decreasing, and not significant at the 95% confidence level.	0.05	0.195	-0.07	230.68	Precipitation (mm)

In the next step, the relationship between EVI, NDVI, climatic factors, and land-use was investigated using the Pearson correlation coefficient, the results of which showed that the correlation between NDVI, EVI, and precipitation was significant at the 1% level (table5), indicating that vegetation changes depended on precipitation in the study area.

Table (5): Pearson correlation coefficient between annual values of vegetation indices, climatic parameters, and the area under each land-use category

	Forest	Rangeland	Agriculture	Urban	Barren land	EVI	NDVI	Temperature	Precipitation
Forest	1								
Rangeland	-0.88**	1							
Agriculture	-0.96**	0.79**	1						
Urban	0.75**	-0.82**	-0.66**	1					
Barren land	0.70**	-0.95**	-0.59*	0.79**	1				
EVI	0.58*	0.63**	0.63**	-0.53*	-0.60*	1			
NDVI	0.63**	0.57*	0.59*	-0.58*	-0.48*	0.59*	1		
Temperature	0.23	-0.37	-0.17	0.29	0.38	-0.18	-0.41	1	
Precipitation	0.04	-0.03	0.02	0.04	0.01	0.30	0.53*	-0.32	1

** Significant at $P < 1\%$

* Significant at $P < 5\%$

4. Discussion and Conclusion

This study uses EVI and NDVI to evaluate land degradation (da Silva, 2020; Rokni and Musa, 2019; Baeza et al. 2020). On the other hand, mathematical analysis of the data was facilitated via vegetation indices. The results suggested that the vegetation gradually changed over time due to various natural or human-induced factors that affected the ecosystem's conditions and performance. It was also found that the trends of both NDVI and EVI had similarly changed over time and that NDVI and EVI values significantly decreased in the study area from 2000 to 2017, indicating the increasing trend of land degradation in the study area, which is consistent with the results reported by Masoudi et al. (2018) in Isfahan province, Iran, who concluded that the decrease in NDVI and EVI values was a sign of land degradation. Furthermore, the findings of the studies conducted by Faramarzi et al. (2018) in western Iran and Sandra et al. (2015) in Mongolia indicated that the decrease in NDVI value led to land degradation.

Considering the fact that land degradation is affected by both human and climatic factors, this study considered land-use as an indicator of human activities, whose analysis showed that while rangelands and agricultural lands decreased significantly from 2000 to 2017, the area of forest, urban land, and the barren land significantly increased, implying human intervention in land-use change. On the other hand, the decline of rangelands could be attributed to the conversion of these lands into agricultural, urban, and barren lands, which is a form of destruction, and to water resources depletion and the decrease in water quality due to overuse of the resources.

According to the study's results, the decline of agricultural lands and rangelands decreased the NDVI and EVI values in the study area. On the other hand, the increase in forest lands could be attributed to the deforestation policies implemented by the government to prevent the spread of wind erosion and increase the green spaces. As for the influence of human factors on land degradation, it could be argued that the role of humans in the land-use change in the study area was largely due to the direct and indirect effect of government policies on land degradation. For instance, Clément et al (2008) examined the effects of government policies on land-use in northern Vietnam, concluding that to elaborate on the significance of human intervention-induced environmental changes and the role of government policies in land use, relevant macro-factors should be analyzed. The expansion of barren lands in the region could also be attributed to the abandonment of agricultural lands in the past few years due to the limited water resources and over-extraction of them in the study area.

Moreover, temperature and precipitation data were used to investigate the impact of environmental factors on land degradation. Accordingly, it was found that the temperature increased and its change trend was significant and that the precipitation decreased but its trend was not significant, leading to a decrease in the reservoirs of groundwater aquifers and the available natural water in the study area, which also confirmed the decrease in NDVI and EVI values.

While the main purpose of this study was to investigate the influence of land-use change and climate parameters on land degradation, it was difficult to separate the effects of each of them quantitatively. However, the Pearson correlation coefficient was applied to examine the relationship between land use, climatic parameters, and vegetation indices, the results of which indicated that the Pearson correlation coefficient between vegetation indices and each land-use class was significant at the 95% confidence level. In other words, the correlation between vegetation indices and land-use classes of the forest, rangeland, and agricultural lands was significantly positive, the correlation between vegetation indices and land-use classes of barren and urban lands was significantly negative, and the correlation between vegetation indices and climatic parameters was not significant.

On the other hand, while the relationship between NDVI and precipitation was significantly positiv**e** at a 95% confidence level (R=0.53), the correlation between NDVI with temperature was not significant. Generally, the study's results suggested that land-use classes had a higher correlation with vegetation indices compared to the climatic parameters. Therefore, it can be argued that land-use and human activities have more influence on vegetation indices and land degradation.

In general, land degradation in the study area can be attributed to both human and climatic factors, and unplanned land-use changes associated with climate change have resulted in reduced vegetation and consequently land degradation, which can greatly affect the security of the area in a long time. Therefore, optimal use of the study area's water and soil resources and the minimization of land-use changes are highly recommended. On the other hand, as for climate change, appropriate policies and programs must be developed to mitigate the damage to the stakeholders.

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