**ORIGINAL PAPER**



# **Investigating spatiotemporal relationship between EVI of the MODIS and climate variables in northern Iran**

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### **Abstract**

Climate variability and fuctuations dramatically afect terrestrial ecosystems and their variations. Several studies have been conducted on the relationship between them in terms of use of vegetation indices. In this study, GIS-based spatiotemporal analyses were used to model the relationship between vegetation variations based on the EVI-MODIS and its response to land surface temperature (LST) and rainfall in Mazandaran province during the period of 2000–2016 in the north of Iran. The LST parameter was derived from the 17-year MODIS data, and rainfall parameter was achieved via meteorological station data in the region. Correlation and linear regression analyses at 0.95% confidence level (*P* value = 0.5) were used to study the relationship between spatiotemporal enhanced vegetation index (EVI) and two climatic parameters. The results indicated that the EVI had a rising trend over the study period. This was mostly due to the increase in paddy felds. The result also shows signifcant spatial correlation between EVI with LST values, which was direct during winter and inverse during summer. The tabulate area analysis showed that throughout the winter months, the spatial distribution of pixels matched the highest EVI values in pixels with a maximum temperature (20–27 °C), while during June to September, the maximum EVI values were related to areas where the LST was less than  $25^{\circ}$ C. Although we found no significant simultaneous relationship between EVI/MODIS and rainfall in studied area, but by 1.5–2.5 months lag time in spring season, the relation between them reaches peak.

**Keywords** EVI · LST · Rainfall · Tabulate area analysis · Mazandaran

# **Introduction**

Vegetation as a linkage between the atmosphere, soil, and water in terrestrial ecosystems plays an important role in setting the global carbon cycle, water cycle, energy exchanges, and climate stability through activities such as photosynthesis, evapotranspiration, and modifying surface albedo and roughness (Richard and Poccard [1998;](#page-10-0) Zhong et al. [2010](#page-11-0); Chuai et al. [2013](#page-9-0); Bao et al. [2014](#page-9-1); Xu et al. [2014;](#page-10-1) Luan et al.

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[2018\)](#page-10-2). Any kind of variation and fuctuation in vegetation quality and quantity, as a comprehensive index, refects the changes in its environment and its climate conditions (Ding et al. [2007;](#page-9-2) Xin et al. [2008;](#page-10-3) Guo et al. [2014b;](#page-9-3) Leilei et al. [2014](#page-10-4); He et al. [2018\)](#page-10-5).

Studies have suggested that climate has a large contribution to the distribution of vegetation types in terrestrial ecosystems, spatiotemporal variations, and their changes on a global and local scale as a dominant and controller environmental factor, especially two major parameters of temperature and rainfall (Raynolds et al. [2008;](#page-10-6) Zhong et al. [2010;](#page-11-0) Chang et al. [2014;](#page-9-4) Luan et al. [2018\)](#page-10-2). There is clear evidence regarding the strong relationship and interactions between the vegetation of ecosystems and diversity and climatic diferences, monitoring, and vegetation changes, especially determination of their spatiotemporal pattern. Indeed, its response and reaction to variability of climate parameters has become one of the most important research feld's worldwide (Richard and Poccard [1998;](#page-10-0) Kaufmann et al. [2003](#page-10-7); Xin et al. [2008](#page-10-3); Xu et al. [2014](#page-10-1)).



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Recent advances in remote sensing, especially with the abundance of information from multi-spectral and time series sensors by a wide range of satellites such as NOAA/ AVHRR, LANDSAT, and MODIS from the late 1980s (Zhong et al. [2010](#page-11-0); Chuai et al. [2013](#page-9-0); Halimi et al. [2018](#page-9-5)), have improved studies on distribution and monitoring of vegetation changes and its relationship with climatic parameters on seasonal, annual, local, regional, and global scales (Lu et al. [2015](#page-10-8); Chen et al. [2016\)](#page-9-6). Of these, the NASA MODIS sensor from the Terra and AQUA satellites have been used extensively in recent research, with 36 bands, where bands 1 and 2 have a resolution of 250 m, bands 3–7 have a resolution of 500 m, and bands of 8–36 have a resolution of 1 km (Testa et al. [2018](#page-10-9)).

The common point of these studies is usage of a variety of vegetation indices extracted from satellites such as NDVI, EVI, SAVI and… (Bao et al. [2014;](#page-9-1) Chang et al. [2014\)](#page-9-4). Vegetation indices are an important determinant factor for the study of changes in density, canopy, growth, biomass, phenology, vegetation classifcation, etc. (Huete et al. [2002](#page-10-10); Guo et al. [2014b](#page-9-3); Chen et al. [2016](#page-9-6); Hussein et al. [2017](#page-10-11); Motlagh et al. [2018\)](#page-10-12). The NDVI is most sensitive to chlorophyll and its vegetation percentage as well as its density and dynamics (Hussein et al. [2017](#page-10-11)). On the other hand, the EVI is more sensitive and responsive to structural variables such as LAI, type, and canopy shape architecture (Huete et al. [2002;](#page-10-10) Wang et al. [2003](#page-10-13); Li et al. [2010;](#page-10-14) Zoungrana et al. [2014](#page-11-1); Phompila et al. [2015](#page-10-15); He et al. [2018](#page-10-5)) found that the average NDVI of the growing season in the large central plains of the USA was highly correlated with temperature. Ding et al. ([2007](#page-9-2)) examining the Tibetan Plateau during 17 years observed the NDVI peak during the growing season. They also found a high correlation between NDVI and rainfall in steppe and meadow in contrast to desert and forest vegetation. They study by Bao et al. ([2014](#page-9-1)) over the period 1982–2010 in the Mongolian Plateau suggested that the NDVI in the growing season had a high correlation with both temperature and rainfall variables. Guo et al. ([2014a](#page-9-7)), in their study in northern China, observed the highest NDVI values in the growing season among farmland ecosystems and stated that NDVI in the forest areas had a positive correlation with evapotranspiration and temperature, which had a negative relationship with precipitation. The study results of Leilei et al. ([2014\)](#page-10-4) on the relationship between vegetation, rainfall, and surface temperature based on the NDVI in Tibet of China showed that the correlation coeffcient between vegetation and LST in July was the lowest, while it was maximum in September between vegetation and rainfall. Zoungrana et al. [\(2014\)](#page-11-1), in the study of vegetation response to precipitation in Burkina Faso, found that both NDVI and EVI had a positive and signifcant correlation with rainfall. According to Hussein et al. ([2017\)](#page-10-11), examining the spatiotemporal relationship between EVI and vegetation cover around Erbil city, there was a signifcant relationship between climatic factors and vegetation cover. In their study in China, He et al. [\(2018\)](#page-10-5) also found that EVI had the highest correlation with rainfall, followed by relative humidity and temperature.

In this regard, Mazandaran province in northern Iran has been considered in this research owing to its temperate climate, high biodiversity, the existence of Hyrcanian forests, extensive rangelands, proximity to the Alborz Mountains, springs and rivers, high population density, as well as various land uses such as agriculture, and tourism. The aim of this study was to fnd the pattern of spatiotemporal variations of vegetation by making time series of the EVI and its response to two climatic variables, land surface temperature (LST) and rainfall, in the period 2000–2016 in Mazandaran province in northern Iran.

# **Materials and methods**

#### **Study area**

Mazandaran province is located in northern Iran, between 35°46′ to 36°58′N longitude and 50°21′ to 54°8′E latitude, covering an area of  $23,756.4 \text{ km}^2$  (Amiri-Bourkhani et al. [2017](#page-9-8)). It is surrounded from the north by the Caspian Sea and from the south by the Alborz Mountains and the Hyrcanian forests. Accordingly, a large elevation range of 100 m below the sea level to 5595 m above the sea level is observed in this province (Fig. [1](#page-1-0)). Based on the method of the De martin, the climate of the province is very humid, humid, Mediterranean, and semi-humid from the West, Center and East and in the mountains, respectively. The mean annual rainfall is 420 mm in Siah bisheh to 1380 mm in Ramsar and



<span id="page-1-0"></span>**Fig. 1** Location of Mazandaran province in Iran



Nowshahr, and its mean annual temperature ranges from 10 to 18 °C on the coast of the Caspian Sea (Emadi et al. [2016](#page-9-9)). With a fertile soil, a suitable climate and water resources, this province is an agricultural center in Iran, especially paddy felds, with a population of 3,073,943 people (Amiri-Bourkhani et al. [2017](#page-9-8)).

#### **Dataset and analysis**

#### 1. EVI-MODIS dataset

In this study, the EVI was derived from the MODIS product. The EVI is developed based on the NDVI to enhance its quality which eliminates the background efects and atmospheric noise (Li et al. [2010;](#page-10-14) Zoungrana et al. [2014](#page-11-1); Lu et al. [2015;](#page-10-8) Chen et al. [2016](#page-9-6)). The EVI is a very important quantitative index of the status of vegetation growth on the surface of the earth, whose changes can refect regional ecosystem variations (Guo et al. [2014b;](#page-9-3) He et al. [2018\)](#page-10-5). This index is estimated based on the following formula (Huete et al. [2002](#page-10-10)):

$$
EVI = G \times \frac{(NIR - RED)}{(NIR + C_1 \times RED - C_2 \times BLUE + L)}
$$
 (1)

The RED, NIR, BLUE are, respectively, refections of the red, near-infrared, and blue bands. L: canopy background adjustment or soil factor.  $C_1$  and  $C_2$  Aerosol resistance coefficients. *G*: gain factor. Adopted coefficients for making the EVI-MODIS algorithm,  $L = 1$ ,  $C_2 = 7.5$ ,  $C_1 = 6$  and  $G = 2.5$ .

In this study, in order to build the EVI time series dataset of MOD13Q1, the MODIS data were used based on the Terra satellite with a resolution of 250 m. These images are produced every 16 days during the year and are available on the site (<https://modis.gsfc.nasa.gov>). Concerning images of the study area (zones h22v05 and h22v06), time series of all months of the year from 2000 to 2016—totally 204 images were downloaded from this site. Since the products have a sinusoidal projection system and do not need a projection and only the pixel sizes in the GIS were resampled to 1 km.

#### 2. Climate dataset

The climatic data in this study included land surface temperature (LST) and rainfall. Rainfall data from 15 meteorological stations in the area were extracted from the Iranian meteorological organization [\(www.irimo.ir](http://www.irimo.ir)). Then, the Kriging interpolation method was used in GIS to generate the rainfall layer. In order to create a temperature map (LST, °C), the time series data (MOD11A2) of the MODIS with a resolution of  $1 \times 1$  km and a time resolution of 8 days were used. A total of 204 LST product during the study period.

#### 3. EVI correlation analysis and climatic variables

In this study, the Pearson correlation was used to estimate the linear correlation between two independent variables— LST and the rainfall—and dependent variable—EVI. Also, linear regression analysis was employed for simulation of the EVI trend during the study period (Bao et al. [2014](#page-9-1); Chen et al. [2016](#page-9-6); Chuai et al. [2013\)](#page-9-0). The tabulate area analysis, an analytical method for detecting the relationship between the climate information layers and the EVI in the GIS, was also utilized. In this method, the distribution of a variable such as vegetation across diferent classes was evaluated by another variable such as temperature. In order to fnd the relationship between climatic parameters and EVI, OLS linear regression analysis was used. All analyses were performed in SPSS, EXCEL, and ArcGIS 10.3 software and at confdence level of 0.05.

### **Results and discussion**

### **Spatiotemporal pattern of EVI variations in the study area**

In order to understand the interactions between changes in climate variables and ecosystems in the region, the EVI spatiotemporal pattern should be obtained. The EVI trend fuctuations were investigated based on the regression equations obtained from the average annual EVI during the study period (2016–2000). Accordingly, the variation curve and trend of average annual EVI in Mazandaran province are presented in Fig. [2](#page-3-0)a.

At first glance, the curve shows the short-term  $(2-3 \text{ years})$ periodic efects of climatic parameters on vegetation variations in the province. As can be seen, the overall trend of EVI is incremental. The long-term average of EVI during 17 years is about 0.45, with a maximum of 0.48 in 2011 and minimum of 0.42 in 2000. Figure [2b](#page-3-0), c displays the trend of EVI changes during spring and summer, respectively. The trend of the EVI changes in summer has more fuctuations.

In Fig. [3](#page-4-0), the spatial distribution of the EVI is presented in four periods (2000, 2005, 2010, and 2016). As shown in this fgure, the spatial distribution of vegetation in the region is divided into three classes of EVI values. The class with  $EVI < 0.2$ , which usually includes lands without vegetation or bare lands. The class with  $0.2 <$  EVI $< 0.4$ , including of paddy felds, can be seen around the forest areas. The forest zones  $(EVI > 0.4)$  are presented as a continuous strip from east to west.

In Table [1](#page-4-1), the area of each of the three classes presented. As can be seen, the class with  $EVI > 0.4$ , which include the forest area of the province, accounted for about 0.37% of the total area of the province  $(8865 \text{ km}^2)$  in 2000.



<span id="page-3-0"></span>**Fig. 2 a** The trend of annual EVI changes, **b** trend of annual EVI changes in the spring and **c** summer in Mazandaran province during the period 2000–2016



While in 2005 this area accounted for 0.36% of the total province. In the period of 2010 and 2016, this zone has been decreasing trend and has been 0.34 and 0.32 of the province, respectively.

As shown in Fig. [4,](#page-4-2) during the study period,  $0.2\%$  < EVI < 0.4 class, which often includes paddy fields, has a signifcant increasing trend. The increase in the area of this class due to the development of rice farms in the province.

# **Spatiotemporal correlation analysis of EVI and LST parameter in the study area**

In order to investigate the effects of climatic factors on vegetation, the relationship between these factors and the average annual EVI was investigated on a monthly scale.

Seventeen years monthly average of the EVI and LST values derived from MODIS Product is illustrated in Figs. [5](#page-5-0) and [6](#page-6-0), respectively. According to Fig. [5](#page-5-0), the maximum EVI



<span id="page-4-0"></span>



<span id="page-4-1"></span>**Table 1** The area of each EVI classes during the 4 study periods in Mazandaran province





<span id="page-4-2"></span>**Fig. 4** Trends in the area of vegetation classes in 4 study periods in Mazandaran province

values are seen in June and throughout June–September. According to Fig. [6,](#page-6-0) which represents the average monthly values of LST extracted from the MODIS, the July and January have been the hottest and coldest months in the study area, respectively.

The results of the monthly spatial correlation matrix between the two variables (EVI and LST) are presented in Table [2](#page-6-1) Based on the table, the highest spatial correlation between the two variables was observed in January, February, March, and December, respectively. In these months, the maximum EVI values were observed in areas with higher LSTs, where the relationship between the two variables was positive in the 4 months, while their spatial correlation was negative and signifcant during May to September ( $P$  value = 0.05).

Figure [7](#page-7-0)a demonstrates the standardized values (standardization according to the normal distribution) of the EVI and LST monthly association. The three correlation patterns are clearly observable in this chart.

- 1. From January to the end of May, the EVI and the LST did not seem to be associated, where the LST remained almost constant, while the EVI fell in early March and increased again.
- 2. From June to the end of August, both the EVI and the LST were steadily increasing and decreasing with a high spatial correlation where the EVI followed LST with a delay.





<span id="page-5-0"></span>**Fig. 5** Spatial distribution of the 17-year monthly average of MODIS-derived EVI for the study area. Dark green pixels represent pixels with the highest EVI value, while red pixels represent pixels with the lowest EVI

3. From September to the end of December, the EVI showed a high correlation with LST.

The results of the tabulate area analysis in Table [3](#page-7-1) as well as Figs. [5](#page-5-0) and [6](#page-6-0) show that during winter, the pixels with the maximum EVI values, mainly observed in the eastern, central and northwest of the province, spatially match the maximum LST (16–25 °C) overlap. In the spring, warm pixels  $(32-39 \degree C)$  are observed in more eastern regions with rice farms, but the pixels with the maximum EVI values overlap with pixels with LST values of about 16–27 °C. The LST spatial distribution pattern in summer is relatively similar to the LST pattern in the spring. Indeed, the highest LST values with a range of 34–42 °C are seen in the same areas. In June, an inverse spatial correlation was observed between the EVI and the LST, where the maximum EVI values conformed to the minimum LST values. Also, in July, green pixels with the highest EVI values were seen within a temperature range of 12–27 °C.

# **Spatiotemporal correlation analysis of EVI and rainfall in the study area**

The overall spatial correlation between rainfall and EVI in the area has been insignificant. Figure  $8$  demonstrates a monthly average of 17 years rainfall in Mazandaran province. The distribution of rainfall from the east to the west decreased, and the maximum rainfall occurred in fall, which was minimum in summer (August). According to this figure, the maximum rainfall  $(>60 \text{ mm/month})$  in the north and northwest (the Caspian Sea) occurred in fall. In winter, the maximum rainfall  $(>50 \text{ mm/month})$  was seen in the same areas. On the other hand, in the warm season, rainfall was signifcantly reduced to 15 mm per month.

Table [2](#page-6-1) outlines the spatial correlation of rainfall distribution and EVI. In the spring, the maximum rainfall occurred in regions with higher temperatures.

Figure [7](#page-7-0)b illustrates the seasonal trend of standardized EVI values and rainfall, which generally shows no correlation between the two variables. Specifcally, the





<span id="page-6-0"></span>**Fig. 6** 17-year monthly average of MODIS Land Surface Temperature (LST, °C) for the study area. Dark red pixels represent pixels with the highest LST value, while dark blue pixels represent pixels with the lowest LST

<span id="page-6-1"></span>**Table 2** Spatial correlation (*R*) between 17-year monthly average LST and EVI, and spatial correlation of EVI and rainfall in study area at 0.95 confidence level ( $P$  value=0.05)

Spatial correlation average LST and EVI			Spatial correlation of EVI and rainfall	
EVI	R	Sig	R	Sig
Jan	0.83	0.008	$-0.02$	0.85
Feb	0.81	0.008	$-0.17$	0.22
Mar	0.72	0.01	$-0.29$	0.041
Apr	0.31	0.072	$-0.27$	0.045
May	$-0.14$	0.025	$-0.12$	0.27
Jun	$-0.58$	0.02	$-0.01$	0.87
July	$-0.59$	0.02	0.005	0.95
Aught	$-0.46$	0.03	$-0.05$	0.85
Sep	$-0.29$	0.09	0.017	0.95
Oct	0.10	0.39	0.02	0.85
Nov	0.65	0.02	$-0.02$	0.85
Dec	0.76	0.01	$-0.02$	0.85

relationship between these two variables has generally been insignifcant and negative. However, in Fig. [7b](#page-7-0),

- 1. A delay of 1.5–2.5 months from May to July is observed in the correlation of rainfall with the EVI in spring.
- 2. During the fall and winter, there is a spatial correlation between EVI and rainfall.

Scatterplots between EVI and LST as well as between EVI and rainfall are demonstrated in Fig. [9](#page-9-10)a, b, respectively. The scatterplot, based on the OLS linear regression model, predicts EVI based on rainfall and LST. In Fig. [9](#page-9-10)a, there is a linear spatial relationship between LST-MODIS and EVI-MODIS in both summer and winter. Specifcally, this relationship has been negative during the warm season and positive in the cold season.

The relationship between rainfall and EVI in scatterplot of Fig. [9](#page-9-10)b indicates that there is no signifcant spatial relationship between rainfall and EVI in either the warm season or the cold season. The spatial relationship between rainfall and EVI in the warm season is generally negative. In the cold season, the maximum rainfall values have occurred at high altitudes, matching the cold pixels, and because of the low LST range, the EVI values have been minimized.





<span id="page-7-0"></span>**Fig. 7 a** Spatiotemporal association of 17-year monthly average of the seasonal trend of EVI and LST, **b** 17-year monthly average of EVI and rainfall (vertical axis has been standardized)

<span id="page-7-1"></span>**Table 3** Tabulate area analysis between MODIS EVI and LST

Period of year	LST range of the period $(^{\circ}C)$	The ranges of LST that EVI spatially matches with it $(^{\circ}C)$	Description
December-March (cold season)	$-19$ to 27	16 to 25	Maximum of EVI matches (spatially matches) with maximum of LST
April, May, October–November (moderate season)	$-15$ to 37	12.1 to $25$	Maximum of EVI matches with Moderate of LST
June–September (warm season)	4.6 to 41.6	12 to 27	Maximum of EVI matches with LST 12-27

Temperature and rainfall are two major climatic factors afecting the growth and dynamics of vegetation (Hussein et al. [2017\)](#page-10-11). In general, the correlation between climatic factors of LST and rainfall with EVI values of vegetation showed that the vegetation of the region responded to temperature fuctuations. However, there was no signifcant correlation with rainfall. The maximum EVI values from June to September were observed at the peak of the growing season. In the cold season (December to April), the average values of the EVI pattern responded to LST and showed a strong positive spatial relationship between the two variables. Conversely, this relationship has been negative in the summer. This can be attributed to summer drought stress and high evapotranspiration in this season, with no maximum temperature pixels with maximum EVI overlap. The temporal EVI estimation results refect the growth pattern and growing season for diferent vegetation types in the region. In this regard, the beginning of the growing season in this region, which is generally April (Marvi-Mohajer [2005](#page-10-16)), has been associated with increasing seasonal temperatures, advent of spring, especially the greenness of forest trees in the region and the start of agricultural activities (paddy felds). Therefore, increasing EVI in the spring is a natural consequence of the beginning of the season of growth and warming of the region's climate. With the advance of the growing season and the accelerated vegetation activity, this trend is intensifed in the summer. According to Fig. [5,](#page-5-0) the points with the highest EVI values in these two seasons are seen in the Hyrcanian forest areas and rice farms. By the end of the growing season in December and with the fall of trees as well as the end of agricultural activity, the values of EVI are sharply reduced. In examining the efects of human activities, the results of analysis of vegetation classes in the 5-year intervals indicated that increasing the total EVI values by 0.0015 per year in the study period, despite the decreasing trend of vegetation class  $(EVI > 0.4)$ —forest zones. Because the class  $(0.2 < EU < 0.4)$ , which included paddy felds, had a signifcant increasing trend. This indicates that human activities are involved in the results.

The relationship between EVI and the rainfall has been weak. In the occurrence of rainfall in the region, there are several factors that affect the main role of Caspian Sea as the main source of humidity of rainfall systems and Alborz Mountains. In general, the study area has rainfall almost throughout the year. The results of Alijani's study [\(2013\)](#page-9-11) show that rainfall decreases with increasing of altitude. On the other hand, in areas near the sea, with the rise in temperature, evaporation and rainfall also grow.

In the present study, rainfall in the Alborz Mountains, which is the location of mountainous ecosystems in the



<span id="page-8-0"></span>**Fig. 8** 17-year average monthly rainfall (mm). Dark blue pixels represent pixels with the highest rainfall, while bright blue pixels represent pixels with the lowest rainfall

province, has been less than in the Caspian Sea. At altitudes where the vegetation is sparser, the effect of earth surface Albedo caused by snow has led to a sharp drop in the EVI. In addition, the role of other climate factors such as humidity, evapotranspiration potential, minimum temperature as well as natural hazards during research years (which have a signifcant impact on the vegetation pattern) has been ignored in this study.

### **Conclusion**

Nowadays, climate and its fuctuations are one of the most infuential factors in the temporal and spatial dynamics of vegetation. There is a large part of temperate forest (Hyrcanian forests) in northern Iran, especially Mazandaran province. In last decades, it has undergone signifcant variation due to land use changes and fuctuations in temperature and rainfall regime of the region.

This study, during a period of 17 years (2000–2016), using spatial correlation analysis, tabulate area analysis and OLS linear regression analysis, attempted to reveal the spatiotemporal relation between the EVI and the climate factors.

The results of the spatial analysis of vegetation changes indicated that during the study period, the 17-year trend of the EVI in the region was a smooth upward trend with a slope of 0.0015 per year.

The forest areas  $(EVI > 0.4)$  decreased from 2000 to 2016 (decrease of  $1198 \text{ km}^2$ ), but the results of the annual EVI trend analysis showed that EVI trend has been observed despite decrease in the forest areas in the province. This was due to the expansion of agriculture, especially rice farms  $(0.2 < EU < 0.4)$ , in the Bare land (EVI $< 0.2$ ).

The results of correlation analysis demonstrated that due to the presence of sufficient humidity and rainfall in the study area during the year, the spatial distribution of temperature is the main climate controller of EVI spatial distribution in the region.

The maximum spatial correlation between the EVI and LST was observed in the cold season, while the maximum spatial correlation between rainfall and the EVI was seen with 1.5–3.5 months lag in May–July.

The results of this investigation showed that MODIS product has a high potential for monitoring the spatiotemporal climatic parameters and vegetation, as well as revealing





<span id="page-9-10"></span>**Fig. 9 a** Scatter plot inspection of EVI versus LST, **b** Scatter plot inspection of EVI versus rainfall

the impact of climate and human factors such as land use changes in the vegetation communities of the region.

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### **Compliance with ethical standards**

**Conflict of interest** There is no confict of interest.

# **References**

- <span id="page-9-11"></span>Alijani B (2013) Weather in Iran (geography). Payame Noor University Press, Tehran, p 236 **(in Persian)**
- <span id="page-9-8"></span>Amiri-Bourkhani M, Khaledian R, Mashrafzadeh A, Shahnazari A (2017) The temporal and spatial variations in groundwater salinity in Mazandaran Plain, Iran, during a long-term period of 26 years. Geofzika 34(1):119–139
- <span id="page-9-1"></span>Bao G, Qin Z, Bao Y, Zhou Y, Li W, Sanjjav A (2014) NDVI-based long-term vegetation dynamics and its response to climatic change in the Mongolian Plateau. Remote Sens 6(9):8337–8358
- <span id="page-9-4"></span>Chang CT, Wang SF, Vadeboncoeur MA, Lin TC (2014) Relating vegetation dynamics to temperature and precipitation at monthly and

annual timescales in Taiwan using MODIS vegetation indices. Int J Remote Sens 35(2):598–620

- <span id="page-9-6"></span>Chen Z, Jiang WG, Tang ZH, Jia K (2016) Spatial–temporal pattern of vegetation index change and the relationship to land surface temperature in zoige. Int Arch Photogramm Remote Sens Spat Inf Sci 41:849–852
- <span id="page-9-0"></span>Chuai XW, Huang XJ, Wang WJ, Bao G (2013) NDVI, temperature and precipitation changes and their relationships with diferent vegetation types during 1998–2007 in Inner Mongolia, China. Int J Climatol 33(7):1696–1706
- <span id="page-9-2"></span>Ding M, Zhang Y, Liu L, Zhang W, Wang Z, Bai W (2007) The relationship between NDVI and precipitation on the Tibetan Plateau. J Geogr Sci 17(3):259–268
- <span id="page-9-9"></span>Emadi M, Shahriari AR, Sadegh-Zadeh F, Jalili Seh-Bardan B, Dindarlou A (2016) Geostatistics-based spatial distribution of soil moisture and temperature regime classes in Mazandaran province, northern Iran. Arch Agron Soil Sci 62(4):502–522
- <span id="page-9-7"></span>Guo L, Wu S, Zhao D, Yin Y, Leng G, Zhang Q (2014a) NDVI-based vegetation change in Inner Mongolia from 1982 to 2006 and its relationship to climate at the biome scale. Adv Meteorol. [https://](https://doi.org/10.1155/2014/692068) [doi.org/10.1155/2014/692068](https://doi.org/10.1155/2014/692068)
- <span id="page-9-3"></span>Guo W, Ni X, Jing D, Li S (2014b) Spatial–temporal patterns of vegetation dynamics and their relationships to climate variations in Qinghai Lake Basin using MODIS time-series data. J Geogr Sci 24(6):1009–1021
- <span id="page-9-5"></span>Halimi M, Sedighifar Z, Mohammadi C (2018) Analyzing spatiotemporal land use/cover dynamic using remote sensing imagery and GIS techniques case: Kan basin of Iran. GeoJournal 83(5):1067–1077





- <span id="page-10-5"></span>He D, Yi G, Zhang T, Miao J, Li J, Bie X (2018) Temporal and spatial characteristics of EVI and its response to climatic factors in recent 16 years based on grey relational analysis in inner Mongolia Autonomous Region, China. Remote Sens 10(6):961
- <span id="page-10-10"></span>Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ 83(1–2):195–213
- <span id="page-10-11"></span>Hussein SO, Kovács F, Tobak Z (2017) Spatiotemporal assessment of vegetation indices and land cover for Erbil city and its surrounding using MODIS imageries. J Environ Geogr 10(1–2):31–39
- <span id="page-10-7"></span>Kaufmann RK, Zhou L, Myneni RB, Tucker CJ, Slayback D, Shabanov NV, Pinzon J (2003) The efect of vegetation on surface temperature: a statistical analysis of NDVI and climate data. Geophys Res Lett 30(22):4p
- <span id="page-10-4"></span>Leilei L, Jianrong F, Yang C (2014) The relationship analysis of vegetation cover, rainfall and land surface temperature based on remote sensing in Tibet, China. In: IOP conference series: earth and environmental science, vol 17, no 1. IOP Publishing, p 012034
- <span id="page-10-14"></span>Li Z, Li X, Wei D, Xu X, Wang H (2010) An assessment of correlation on MODIS-NDVI and EVI with natural vegetation coverage in Northern Hebei Province, China. Proc Environ Sci 2:964–969
- <span id="page-10-8"></span>Lu L, Kuenzer C, Wang C, Guo H, Li Q (2015) Evaluation of three MODIS-derived vegetation index time series for dryland vegetation dynamics monitoring. Remote Sens 7(6):7597–7614
- <span id="page-10-2"></span>Luan J, Liu D, Zhang L, Huang Q, Feng J, Lin M, Li G (2018) Analysis of the spatial–temporal change of the vegetation index in the upper reach of Han River Basin in 2000–2016. Proc Int Assoc Hydrol Sci 379:287–292
- <span id="page-10-16"></span>Marvi-Mohajer MR (2005) Silviculture. University of Tehran Press, Tehran, p 387
- <span id="page-10-12"></span>Motlagh MG, Kafaky SB, Mataji A, Akhavan R (2018) Estimating and mapping forest biomass using regression models and Spot-6 images (case study: Hyrcanian forests of north of Iran). Environ Monit Assess 190(6):352
- <span id="page-10-15"></span>Phompila C, Lewis M, Ostendorf B, Clarke K (2015) MODIS EVI and LST temporal response for discrimination of tropical land covers. Remote Sens 7(5):6026–6040
- <span id="page-10-6"></span>Raynolds MK, Comiso JC, Walker DA, Verbyla D (2008) Relationship between satellite-derived land surface temperatures, arctic vegetation types, and NDVI. Remote Sens Environ 112(4):1884–1894
- <span id="page-10-0"></span>Richard Y, Poccard I (1998) A statistical study of NDVI sensitivity to seasonal and interannual rainfall variations in Southern Africa. Int J Remote Sens 19(15):2907–2920
- <span id="page-10-9"></span>Testa S, Soudani K, Boschetti L, Mondino EB (2018) MODIS-derived EVI, NDVI and WDRVI time series to estimate phenological metrics in French deciduous forests. Int J Appl Earth Obs Geoinf 64:132–144
- <span id="page-10-13"></span>Wang J, Rich PM, Price KP (2003) Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int J Remote Sens 24(11):2345–2364
- <span id="page-10-3"></span>Xin Z, Xu J, Zheng W (2008) Spatiotemporal variations of vegetation cover on the Chinese Loess Plateau (1981–2006): impacts of climate changes and human activities. Sci China Ser D Earth Sci 51(1):67–78
- <span id="page-10-1"></span>Xu G, Zhang H, Chen B, Zhang H, Innes JL, Wang G, Yan J, Zheng Y, Zhu Z, Myneni RB (2014) Changes in vegetation growth dynamics and relations with climate over China's landmass from 1982 to 2011. Remote Sens 6(4):3263–3283



<span id="page-11-1"></span><span id="page-11-0"></span>Zhong L, Ma Y, Salama MS, Su Z (2010) Assessment of vegetation dynamics and their response to variations in precipitation and temperature in the Tibetan Plateau. Clim Change 103(3–4):519–535 Zoungrana BJB, Conrad C, Amekudzi LK, Thiel M, Da ED (2014) Land use/cover response to rainfall variability: a comparing analysis between NDVI and EVI in the Southwest of Burkina Faso. Climate 3(1):63–77

