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Investigating the topographic and climatic effects on vegetation using remote sensing and GIS: a case study of Kharestan region, Fars Province, Iran

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Abstract

This study seeks to investigate the effect of topographic (slope, elevation, and aspect) and climatic (precipitation and temperature) factors on vegetation in Kharestan region using remote sensing (RS) and geographic information system (GIS) techniques. To this aim, therefore, the changes occurred in such vegetation indices as normalized difference index (NDVI), enhanced vegetation index (EVI), soil-adjusted vegetation index (SAVI), and difference vegetation index (DVI) between 2008 and 2015 were evaluated, using Landsat ETM7. The findings of the study showed that the highest density for the NDVI, EVI, SAVI, and DVI could be found at an elevation range of 2000 to 2800 and the lowest density could be found at elevations lower than 2000 and higher than 2800 m. In addition, the maximum values for the indices at elevation range of 2050 to 2250 were 0.56, 0.54, 0.4, and 0.25 respectively. Moreover, the highest values for the indices were found at such aspects as the northeast (64° and 42°) and the north (348°), while the lowest ones were observed at the eastern (74°) and southwestern (243° and 206°) aspects. As for the density of the vegetation, the maximum mean values for the indices were found to be located at slope range of 4 and 12°. These findings indicate that lower elevations, shaded sides of the domains, and gentle slope enjoy appropriate conditions for the growth of vegetation. Furthermore, there was a significant correlation between the indices, the temperature, and the precipitation ($P < 0.01$). Considering the aforementioned results, it could be argued that environmental factors such as elevation, aspect, slope, precipitation, and temperature are among the main factors, which control the vegetation in the region studied in this research.

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1 Introduction

As the significant transmitter of material and energy between the earth and the atmosphere, vegetation is regarded as the essential part of all life-related systems (Dong et al. 2018). The dependency of human beings and other living creatures on forests and plants, especially in mountainous regions, indicates the dependency on vegetation and its development from the local to the universal level (Ribeiro et al. 2016). In addition to its particular role in absorbing carbon dioxide, vegetation also protects humans and animals from natural threats such as rock falls, landslide, and debris flows (Ribeiro et al. 2016; Singh et al. 2016). Moreover, vegetation is considered one of the main pillars of arid and semi-arid ecosystems, influencing their associate variables directly.

Vegetation variations in mountainous regions are dependent on climatic factors, increasing demand from natural resources and land use alterations (Haida et al. 2016; Hedenås et al. 2016). To understand the global change of ecosystems

and their reactions to the climate, it is necessary to identify the relationship between vegetation and environment (Arneth 2015; Huete 2016; Austin 2013). Elevation, aspect, and slope are regarded as the main topographic factors in mountainous regions that indirectly affect the vegetation distribution and patterning (Huang 2002). Moreover, precipitation and temperature are climatic factors that directly contribute to the vegetation (Guo et al. 2018). Topography (elevation, slope, and aspect) and other factors of environmental processes such as regional hydrology mainly control those climate changes that are dependent on thermal and humid conditions, causing spatial differences in vegetation variations (Shao-fu et al. 2013).

Remote sensing (RS) technology and geographic information system (GIS) could be used to explore the comprehensive effects of vegetation on environmental factors and the relationship between the two, and to monitor the plant life, vegetation variations, and other relevant information (Dong et al. 2018). To monitor the terrestrial ecosystems, particularly in large areas and for long-term observations, RS provides a unique perspective (Hou et al. 2011; Fensholt et al. 2012; Wang et al. 2012). Equipped with such features as real-time, microscopic, and objective imaging, the technology is used for detecting the dynamics of vegetation in large areas (Chu et al. 2007). Developing a simple algorithm for vegetation indHoffmann et al. 2016ices could be used as an effective tool for measuring vegetative status on the ground (). Computational components of the algorithm for measuring vegetation indices include two bands concerning the characteristics of different vegetative types that are widely used for the classification of vegetation and radiometric inferencing of their structural patterns (Huete and Justice 1999).

So far, several studies have been carried out internationally on vegetation patterning and the factors affecting it. According to Jin et al. (2009), factors such as elevation, aspect, precipitation, and temperature play a determining role in vegetation distribution in mountainous regions. Dai et al. (2011) argue that in addition to natural factors such as topography and climate, human factors also contribute to vegetation distribution in northeast of China. According to Shao-fu et al. (2013), the temperature and humid-based climate changes that are controlled by the topographic factors (elevation, aspect, and slope) are the main reason for the difference in the spatial distribution of vegetation. Kayiranga et al. (2017) also explored the effect of topographic and climatic factors on vegetation distribution in Africa.

A number of studies have also been conducted in Iran on vegetation, most of which studied the topic through vegetation distribution (for example, Mokarram et al. 2016; Karkon Varnosfaderani et al. 2018; Heydari et al. 2018; Ahmadi 2010, to name a few). Mokarram and Sathyamoorthy (2015), for instance, explored the relationship between vegetation and topographic factors and found that with an increase in elevation and aspect, the vegetation indices and vegetation growth increased too. The study also found the maximum value for the vegetation indices (NDVI, EVI, and DVI) at an altitude between 1500 and 3000 with the aspect being 300° northwest. However, no significant study has so far been carried out on vegetation status via vegetation indices and its relationship with climate and topographic factors, especially in arid and semiarid areas of Fars Province (Kharestan).

Generally speaking, while other studies on the relationship between vegetation and environmental factors have focused on only one vegetation index, this study simultaneously investigated the relationship between four vegetation indices (NDVI, EVI, DVI, and SAVI) and environmental factors (climate and topographic) in a semiarid mountainous region in southwest Iran for the first time which could be regarded as one of the innovations introduced in this research. The findings of the study indicate the considerable effect of climate and topographic factors on each individual vegetation index. They could, therefore, be used to develop appropriate plans and measures for the management and use of vegetation and to predict the density of vegetation at different elevations with regard to climate conditions. Considering the fact that the region under study lacked any meteorological station and the required instruments such as rain gauge and synoptic scale measurement tools, the neighboring stations were used to investigate the temperature and annual precipitation. The required maps were then prepared using interpolation method.

This study, thus, focused on the following:

1. Analysis of the growth and spatial patterns of vegetation.
2. The response of vegetation indices such as NDVI, EVI, SAVI, and DVI to the distribution of geographical aspects (both vertical and horizontal).
3. The relationship between the dispersion of vegetation and climate factors.

2 Materials and methods

2.1 The geographical area of the study

The area that was studied in this research included the Kharestan Watershed, one of the sub-watersheds of the Doroudzan Dam, which is located in the southern plain of Zagros Mountains in Eghlid city (Fars Province). The watershed is located within the geographical area of 51° 47′ 9″ to 52° 0′ 0″ east longitude and 30° 35′ 34″ to 30° 47′ 30″ north latitude, with a total area of 12,300 ha. Its minimum and maximum altitudes are 1900, 3040, and 2337 m above the sea level respectively and its average weight is 25.67. Moreover, the average precipitation of the region is 430 mm and its average temperature is 14.2 °C. Based on the De Martonne method, the region has a semiarid climate (Shabani and Shabani 2013).

The region, with the average slope of 11.2%, is located in a mountainous region topographically. Its formations have historically been composed of Hormoz Formation, complex zones, Pabdeh-Gurpi, Kashkan, Samara, and Q4 alluvial deposits. The most important agricultural activities practiced in the region are gardening, dryland farming, and irrigation (Fig. 1). As the studies on the region's vegetation and land use showed, the study area includes grasslands with the average, weak, and very weak vegetation (Nikkami et al. 2009).

2.2 Dataset

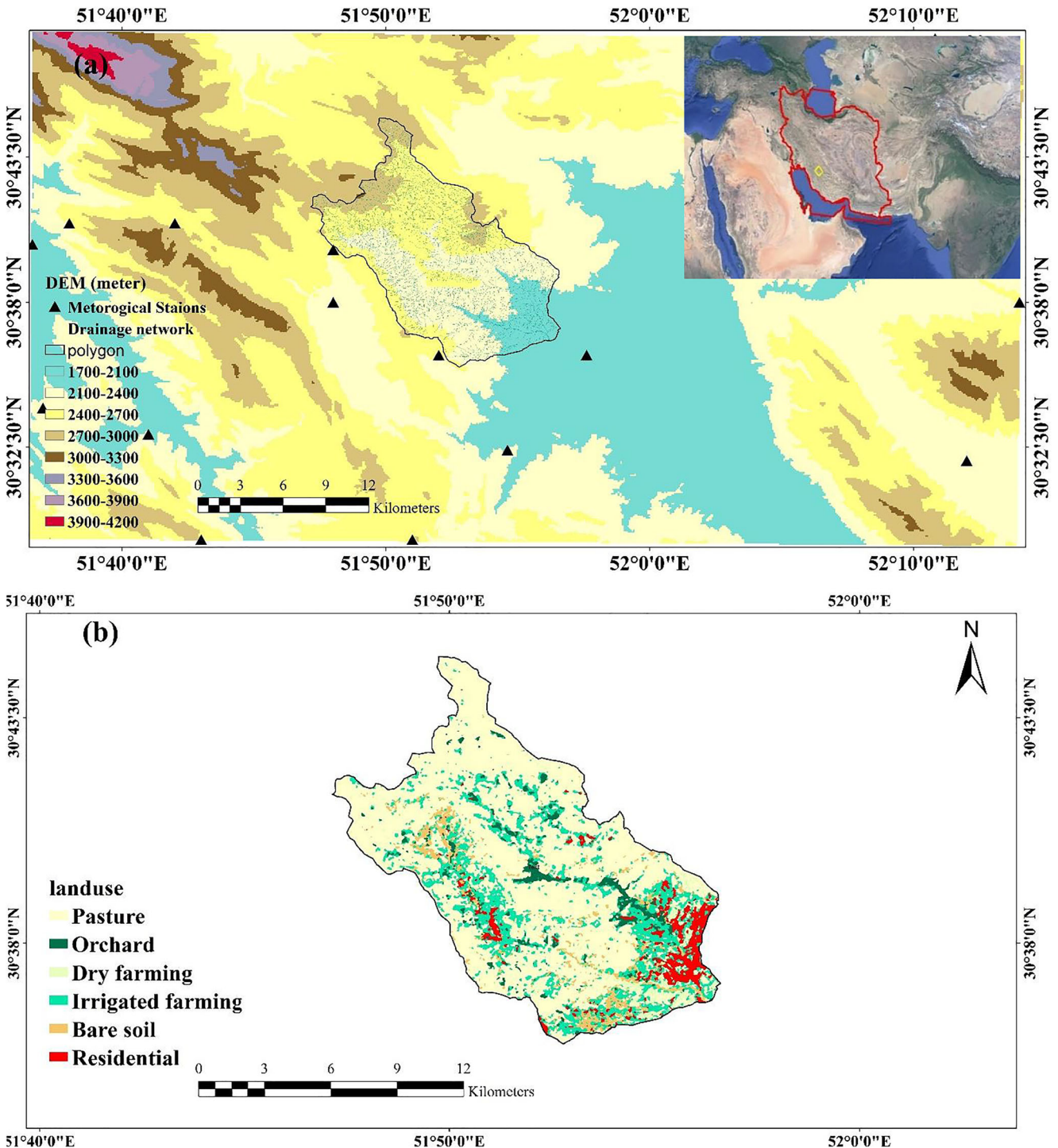Different indices of vegetation and the factors affecting it mainly explore the spatiotemporal changes of vegetation

Fig. 1 a Study area in southwestern Iran. Black lines boundary field. Black triangular meteorological stations. Drainage network blue lines. **b** Land use map of the studied area

Table 1 Environment factors and the vegetation index which were evaluated in this study

Vegetation indices (VIs)	Climate factor	Topographic factor
Normalized difference vegetation index (NDVI)	Precipitation	Elevation (m)
Enhanced vegetation index (EVI)	Temperature	Aspect (°)
Soil-adjusted vegetation index (SAVI)		Slope (%)
Difference vegetation index (DVI)		

growth. In this study, the dynamics of vegetation was investigated based on the relationship between NDVI, topographic, and climate factors, using images of Landsat ETM7 (Table 1).

The multiple temporal images used in the study were taken from https://earthexplorer.usgs.gov in cloud-free conditions, with the Row/Path being 163 and 39. The images were then undergone geometric and atmospheric correction, and initial preprocessing in ENVI software version 5.3. Moreover, to measure the NDVI values, space images with the spatial differentiation of 30 m were used during May, June, July, August, and September. In total, in an 8-year period (2008–2015), 64 NDVI images (with 15-day intervals) were taken in the months mentioned. The climate data for the period (2008–2015) were collected on a monthly basis from 17 meteorological stations of the Iranian meteorological organization. The average precipitation and the average annual temperature rates were calculated according to the monthly data. Then, using the interpolation algorithm (IDW) in ArcGIS 10.2 software, their relevant maps were extracted. In order to achieve consistency with the NDVI data, precipitation and temperature data of the same period (2008–2015) were also taken into account. Using DEM which was downloaded from https://gdex.cr.usgs.gov/gdex, elevation, aspect, and slope values were calculated.

2.3 Data processing

2.3.1 Data pre-processing

A gap-filling tool (Landsat Gap Fill for SLC-OFF Images) was used to fill the image gaps. All images related to the period under study (2008-2-15), which had been taken from the Landsat ETM7 satellite, were processed in ENVI version 5.3 and then classified via ArcGIS software version 10.2. To improve the quality of the images in the ENVI software, radiometric calibration (to remove the errors caused by the sensor itself or satellite), dark atmospheric correction (to remove the effect of particles, water vapor, etc.), and geometric correction were applied to all of them.

Inverse distance weighting (IDW) The IDW model was used for interpolating effective data for the climate parameters. IDW interpolation explicitly works on the assumption that things that are close to one another are more similar to each other than those that are farther apart. To predict a value for any unmeasured location, IDW uses the measured values surrounding the prediction location. It assumes that the value of

an attribute z at any non-sampled point is a distance-weighted average of sampled points lying within a defined neighborhood around the point. Essentially, it is a weighted moving average (Burrough et al. 1998):

$$\widehat{z}(x_0) = \frac{\sum_{i=1}^{n} z(x_i)d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}} \tag{1}$$

In the above formula, x_0 stands for the estimation point and x_i represents the data points within a chosen neighborhood. The weights (r) are related to distance by d_{ij}.

2.3.2 Data analysis

All the analyses and calculations mentioned were carried out by ArcGIS software. At first, the NDVI, EVI, SAVI, and DVI values were calculated monthly, and then, the mean of the annual NDVI was calculated based on the mean of monthly NDVI. Using the same process, the other three indices of the vegetation were calculated based on the monthly registered data of the annual values. As for the meteorological data used in the study, the average annual precipitation was calculated for each year based on the monthly precipitation recorded. Through the same procedure, the mean of the annual temperature was calculated for the time period studied (2008–2015). The elevation values were calculated directly from the digital elevation model (DEM), and the values for slope and aspect were obtained using spatial analyst tool in ArcGIS software.

Vegetation indices Normalized difference vegetation index (NDVI)

NDVI is regarded as one of the most important indices used in vegetation. It could be used as a basic index to determine other vegetation parameters. Based on the definition of Rous et al. (1974), NDVI formula is worked out as follows:

$$NDVI = \frac{P_{nir} - P_{red}}{P_{nir} + P_{red}} \tag{2}$$

In this formula, P_{nir} stands for the reflectance of near-infrared band (0.7–1.3 μm) and P_{red} stands for the reflectance of red band (0.6–0.7 μm). The index values vary between -1 and $+1$. High values of this index indicate a high vegetation

density in the area while clouds, snow, and water are marked with negative values (3).

Enhanced vegetation index (EVI)

EVI is an optimized vegetation index that mitigates the unwanted effects of factors such as soil background that reduce the chance of obtaining reliable information from satellite imagery and prevent the detection of less than 30% vegetation density in arid and semiarid regions where the soil type and sparse vegetation are combined. The value range of this index varies between -1 and $+1$, reducing the effects of the atmosphere and the diffusion of aerosol (Li et al. 2009). The EVI is calculated according to the following formula:

$$EVI = G \times \frac{P_{nir} - P_{red}}{P_{nir} + (C_1 \times P_{red} + C_2 \times P_{blue}) + L} \quad (3)$$

In this equation, P_{blue} stands for the reflection of the blue band (0.4–0.5 μm) which is recorded by the sensor, L stands for the soil adjustment factor, and C_1 and C_2 stand for the coefficients of the correction of the fine parcels' dispersion in the red band via the blue group. Generally, $G = 2.5$, $C_1 = 6$, $C_2 = 7.5$, and $L = 1$ (Huete et al. 1997). The index values vary from -1 to $+1$.

Soil-adjusted vegetation index (SAVI)

The sparse vegetation in arid and semiarid regions makes the vegetation reflectance overshadowed by the effects of the soil reflectance. SAVI is the modified form of NDVI, reducing the effects of soil background and soil moisture on the NDVI. The SAVI is calculated according to the following formula (Huete 1988):

$$SAVI = \frac{P_{nir} - P_{red}(1 + L)}{P_{nir} + P_{red} + L} \quad (4)$$

In the above formula, L stands for the modifying factor of the soil effect whose value varies between 0 for regions with dense vegetation and 1 for those with sparse vegetation. The index is 0.5 for medium coverage vegetation. The index values vary from -1 to $+1$.

Difference vegetation index (DVI)

DVI enjoys a simple computational algorithm, calculated according to the following equation (Tucker 1979):

$$DVI = P_{nir} - P_{red} \quad (5)$$

This index which is calculated by the distraction of the reflectance of the infrared band from the red band is sensitive to the soil background, and its value is positive for vegetation,

negative for water, and close to 0 for soil and rock. The index values vary from -1 to $+1$.

Geographical weighted regression (GWR) GWR is an extension of traditional regression techniques such as OLS as it comprises of local rather than global parameter estimates (Fotheringham et al. 2002). This model runs for point observations in the form of weighted matrices. The GWR model is expressed as the following:

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k=1}^{p} \beta_k(\mu_i, v_i) x_{ik} + \varepsilon_i \quad (6)$$

In this formula, y_i, x_{ik}, and ε_i represent the dependent variable, the independent variables, and the random error term at location, respectively, i. $\beta_0(\mu_i, v_i)$ is the intercept for location, i, and $\beta_k(\mu_i, v_i)$ are the slope coefficient for x_k at location i.

Regression coefficients are obtained through the following equation:

$$\beta(\mu_i, v_i) = \left(X^T W(\mu_i, v_i) X\right)^{-1} X^T W(\mu_i, v_i) y \quad (7)$$

In this equation, $\beta(\mu_i, v_i)$ stands for the unbiased estimate of the regression coefficient β, $W(\mu_i, v_i)$ is the weighting matrix to ensure that observations near the specific point have larger weight value, and X and Y are matrices for independent and dependent variables respectively.

Weighting the kernel function could be stated using the exponential distance decay form:

$$\omega_{ij} = \exp\left(-\frac{d_{ij}^2}{b^2}\right) \quad (8)$$

In this formula, ω_{ij} represents the weight of observation j for location i, d_{ij} expresses the Euclidean distance between points I and j, and b is the kernel bandwidth. If observation j coincides with i, the weight value is 1. If the distance is greater than the kernel bandwidth, the weight will be set to 0.

The GWR output contains several parameters, among which the local R^2 coefficient is usually used to measure the model. This parameter is obtained from the following equation:

$$R^2 = 1 - \frac{SS_E}{SS_T} \quad (9)$$

$$SS_E = \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2 \quad (10)$$

$$SS_T = \left(y_i - \overline{y}_i\right)^2 \quad (11)$$

In this formula, n is the number of observations, y_i is the i's observation, $(\widehat{y}_i)$ is the estimated value of the observation i, and $\overline{y}$ is the mean of observations. In this study, GWR analysis

was performed using ArcGIS10.3 software and all maps were produced through this software.

2.3.3 Statistical analysis and relationship calculations

Statistical values used for the analysis of the changes in NDVI, EVI, SAVI, and DVI in relation to the elevation, aspect, and slope were calculated in ArcGIS software, using geographically weighted regression. For this purpose, first a 250-m network was designed for each of the parameters in GIS environment and 1900 points were extracted for it as sample points to determine the relationship between vegetation indices and topographic and climatic parameters. Effective spatial correlation between these four indices and climate factors (precipitation and temperature) was measured via GWR. Moreover, to evaluate the spatial distribution of vegetation and the relationship between its spatial patterns and climatic factors, GWR method was applied while Moran's index was used to examine the extant of dependency between the variables (Abliz et al. 2016). Then, the dependency of vegetation indices on topographic factors (elevation, aspect, and slope) and climatic factors (temperature and precipitation) were evaluated and its relevant diagrams were drawn in SigmaPlot 14 software.

3 Results

3.1 Variations of vegetation growth in the study area

The analysis of the vegetation changes from 2008 to 2015 in the study area was carried out using NDVI, EVI, SAVI, and DVI. Generally, in those watersheds that absorbed the maximum amount of the near-infrared radiation, the NDVI proved negative. Using linear regression method to analyze the changes of the indices under study, the mean values for each of the indices in the growth season were calculated through the mean of the maximum monthly value from April to October. The pixels lower than 0.05 value in the growth season were considered vegetation-free regions (Liu et al. 2015). Figure 2 a–d show the annual mean values for NDVI, EVI, SAVI, and DVI. According to this figure, maximum vegetation with NDVI and EVI > 0.5, SAVI > 0.4, and DVI > 0.2 was found in central parts of the study area that are agricultural lands. Low vegetation with values < 0.1 for four indices in the southwestern parts of the study area belonged to a residential area. The variation range mean values for NDVI, EVI, SAVI, and DVI were calculated as 0.14–0.15, 0.1–0.13, 0.1–0.12, and 0.07–0.08 respectively. The results of the study indicated that from 2008 until 2015, the average values for NDVI, EVI, SAVI, and DVI varied from 0.56 to 0.68; 0.46 to 0.69; 0.4 to 0.49; and 0.28 to 0.32 respectively. The maximum plant growth for all of the indices was found in 2012 and 2015, whereas the minimum growth rate for NDVI and EVI was

recorded in 2008, and the one for SAVI and DVI was found in 2009 (Fig. 2e–h).

3.2 Geographical distribution of vegetation

Taking topographic factors into account, the geographical distribution of vegetation was analyzed from three aspects: (1) the vertical position which indicates the spatial distribution of vegetation at all elevations (in meters above the sea level); (2) the horizontal position which indicates spatial distribution of vegetation in all aspects (in degree); and (3) the slope which is effective in vegetation variations as a natural factor. In this study, the elevation was classified into eight categories with altitudinal intervals of 200 m; the aspect was divided into 12 categories with angular intervals of 30°; and the slope was divided into 20 categories with a distance of 2°. Finally, the relationship between each vegetation index and the elevation, aspect, and slope was separately examined.

As the results of the study showed, the maximum vegetation density for the four indices (NDVI, EVI, SAVI, and DVI) was found at an altitude of 2000–2800 m while the lowest density was observed at such altitudes as less than 2000 m and more than 2800 m. Moreover, the highest values for the vegetation indices were found at an altitude of 2050 to 2250 m, while the lowest values were found to be located at such altitudes as less than 2000 and more than 3000 m. In general, the results are indicative of an increasing value in all four indices at elevations up to 2900 m. The highest mean values for NDVI, EVI, SAVI, and DVI were reported as being 0.56, 0.54, 0.4, and 0.25 respectively at the altitude of 2100 m (Fig. 3).

Moreover, the highest density of NDVI, EVI, SAVI, and DVI was found at such aspects as the north (0–22.5°), the northeast (22.5–67.5°), the east (67.5–112.5°), the southeast (112.5–157.5°), the south (157.5–202.5°), the southwest (202.5–247.5°), the west (247.5–292.5°), and the north (337.5–360°). The NDVI values (0.54, 0.56, and 0.52) were found in the northeast (42° and 64°) and in the north (348°) respectively. For EVI, the high mean values (0.5, 0.54, and 0.49) were observed in the northeastern (42° and 64°) and in the north (348°) respectively. For the SAVI, the highest mean values (0.40, 0.37, and 0.37) were observed in the northeastern (42°, 64°) and the north (348°) respectively. The highest DVI mean values (0.25, 0.24, and 0.24) were found in the northeast (42° and 64°) and the north (348°) respectively.

The lowest mean values for the NDVI (0.03, 0.04) were observed in the east (74°) and the southwest (206° and 243°) aspects respectively (Fig. 4). The lowest mean values for EVI (0.03, 0.048, and 0.042) were found in turn at the east (74°) and the southwest (206° and 243°) aspects. For SAVI, the lowest values (0.02, 0.031, and 0.036) were found at the east (74°) and the southwest (206° and 243°) aspects respectively. Moreover, the lowest mean values for DVI (0.015, 0.029, and
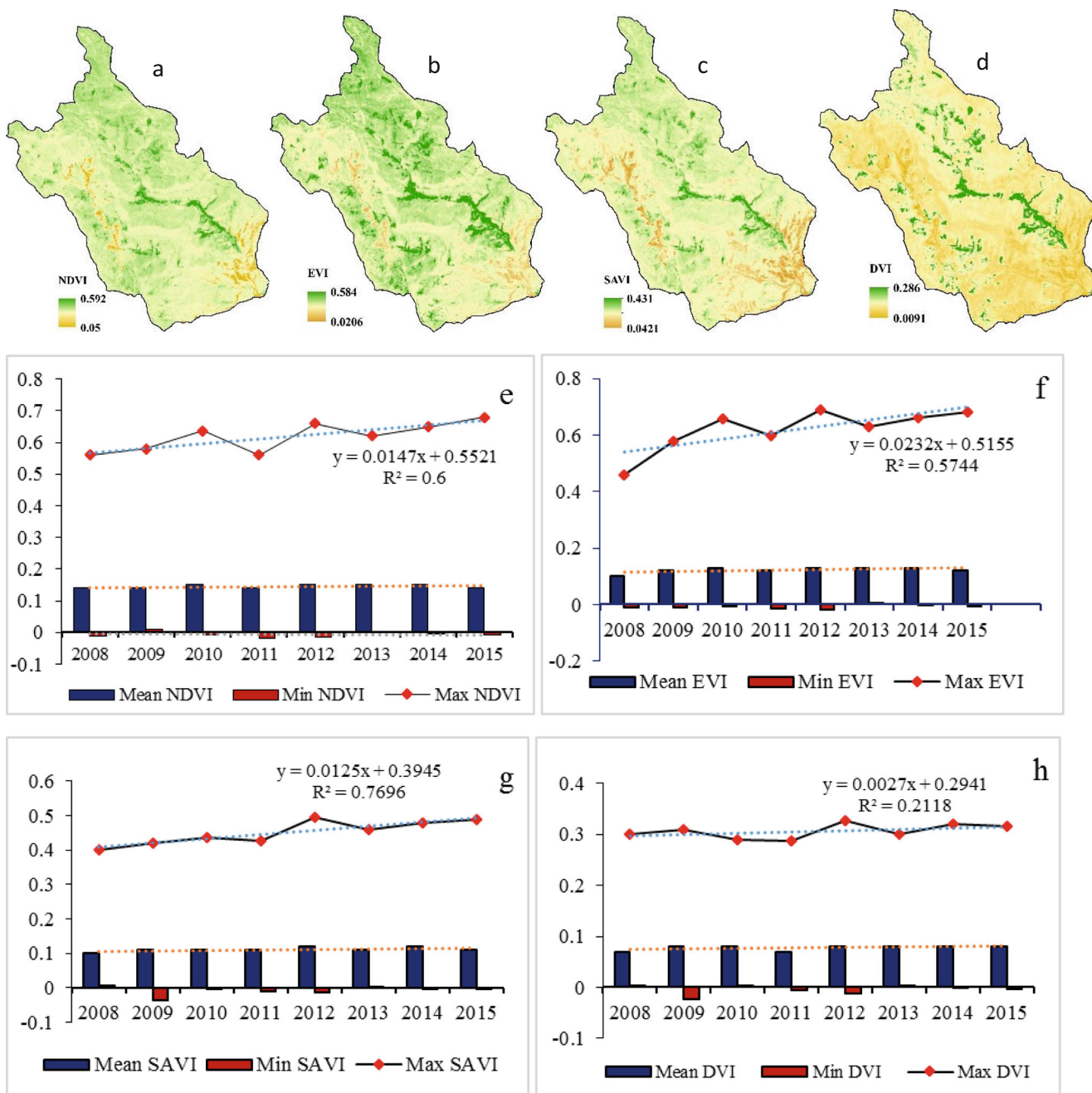
Fig. 2 The spatial distribution of NDVI (**a**), EVI (**b**), SAV I (**c**), and DVI (**d**) and temporal distribution of NDVI (**e**), EVI (**f**), SAVI (**g**), and DVI (**h**) in Kharestan from 2008 to 2015

0.021) were observed at the east (74°) and the southwestern (206° and 243°) aspects respectively.

As the findings of the study indicated, the maximum vegetation density was observed on slopes between 3 and 20° and the lowest density was observed in areas beyond the aforementioned slopes. The highest mean values for NDVI, EVI, SAVI, and DVI were found on the slope of 4–12°, and the lowest mean values were reported to be on the slopes of 0.35°, 9.8°, and 10.32° respectively (Fig. 5). In general, it was found that with the increase in slope up to the 12°, the vegetation indices increased too.

However, the vegetation index values, which were found on the slopes beyond the 12°, started to decrease proportionately.

3.3 The correlation between elevation and climatic factors (precipitation and average annual temperature) in Kharestan area

The mean value for precipitation at the elevation of 10 m was measured (Fig. 6). This figure shows the correlation between precipitation and elevation. The results indicate a positive
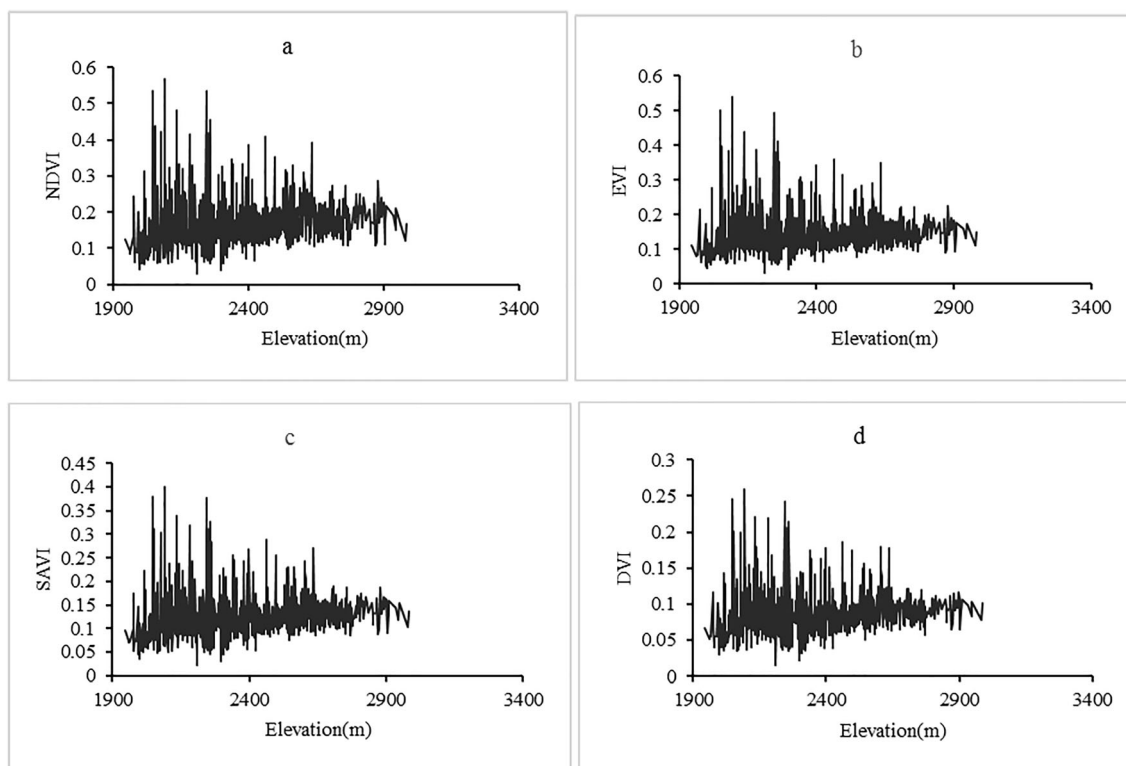
Fig. 3 Variations of NDVI (**a**), EVI (**b**), SAVI (**c**), and DVI (**d**) per elevation (vertical) in the study area in the form of scatter plot (spline connected)

correlation between precipitation and elevation, the equation of which is as follows (Eq. 12):

$$P = 0.0453H + 297.75 \qquad (12)$$

In this formula, P stands for the average annual precipitation (mm) and H stands for the elevation (meter). Moreover, the variations of the average annual temperature of the region in proportionate to the elevation are shown in Fig. 6. The temperature, which has a negative correlation with the elevation, is calculated through the following formula:

$$T = -0.0015H + 17.958 \qquad (13)$$

In this equation, T stands for the average annual temperature (°C) and H represents the average elevation (meter).

As there is no meteorological station at the altitudes, the maps that were drawn from the available stations could not be regarded as the representative of the whole elevation range of the basin. However, though in this method the obtained values were reported as less than the actual ones, they were generally indicative of a decrease in the temperature and an increase in the precipitation. It should also be noted that the region is only a small part of a large basin (the drainage basin of Doroudzan Dam) where the variations of the temperature were not much significant in proportionate to the elevation. Moreover, in some other studies that, like the current study, have been carried out in mountainous regions, the variations of the temperature have not been considerable. For instance, in a study

conducted by Gu et al. (2018) in a mountainous region measuring 74,000 m², which is larger than the region studied in this research, the annual variation range of the temperature in the growth season was 22–23 °C in an elevation range of 76 to 3200 m. In another study carried out by Guo et al. (2018) in two mountainous regions of Changbai and Appalachian, the variation ranges of the temperature in the growth season were 13.5 to 15.5 and 11.5 to 14 respectively. In fact, even though the variation of the temperature, like other similar studies, was slight in the region investigated in this research, the variations of the vegetation density at different elevations were found to be great, indicating a significant relationship between temperature and vegetation in the region.

3.4 The analysis of the correlation between vegetation indices and climatic factors (temperature and precipitation) in Kharestan

To discover the correlation between vegetation indices (NDVI, EVI, SAVI, DVI), temperature, and precipitation, Moran's index was applied to the findings, the results of which showed 5% significance for the correlation between NDVI and precipitation (Moran's $I = 0.9$) and NDVI and temperature (Moran's $I = 0.96$) and 5% significance for the correlation between EVI and precipitation (Moran's $I = 0.95$) and EVI and temperature (Moran's $I = 0.96$). The results also showed 5% significance for the correlation between both SAVI and
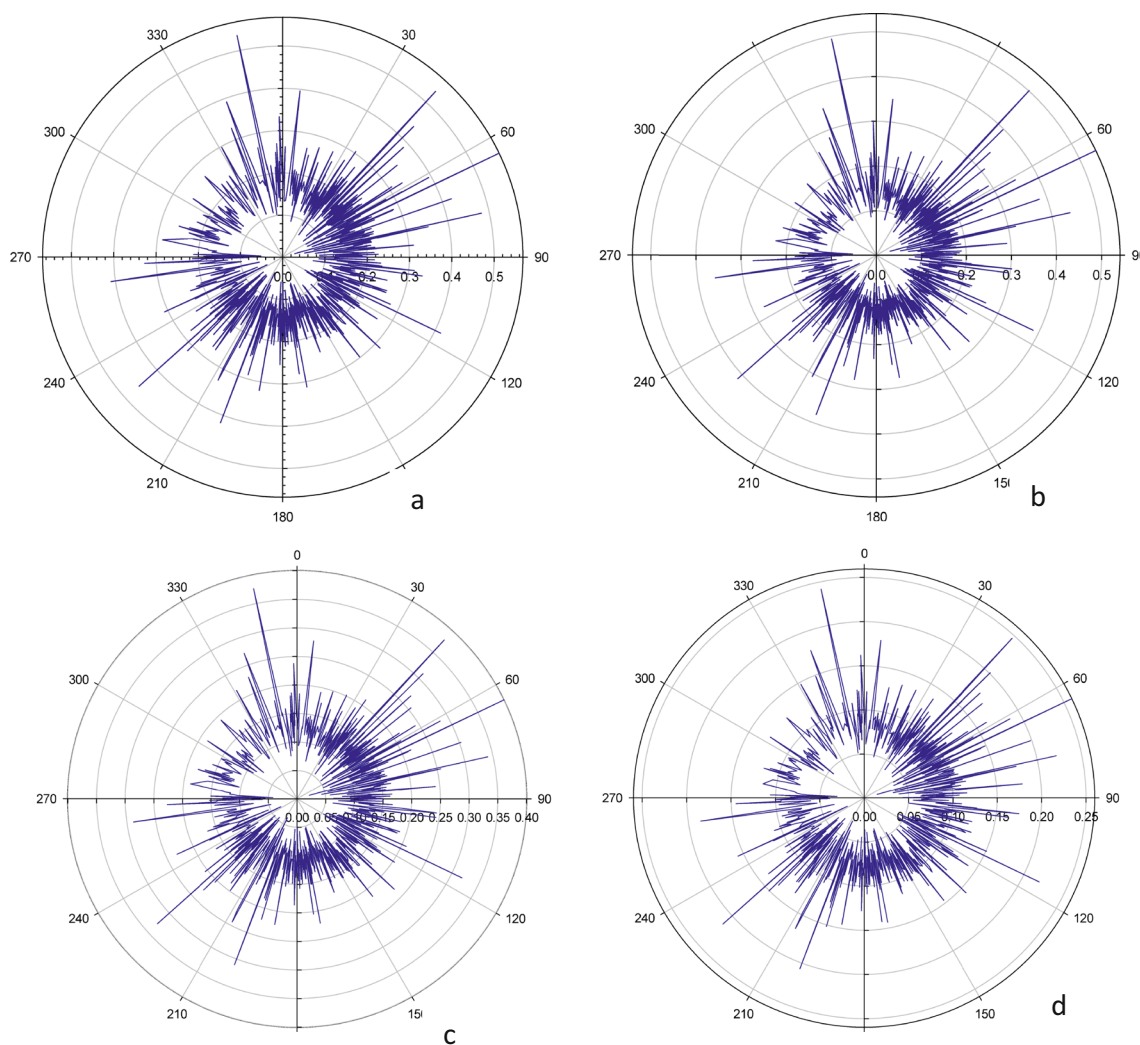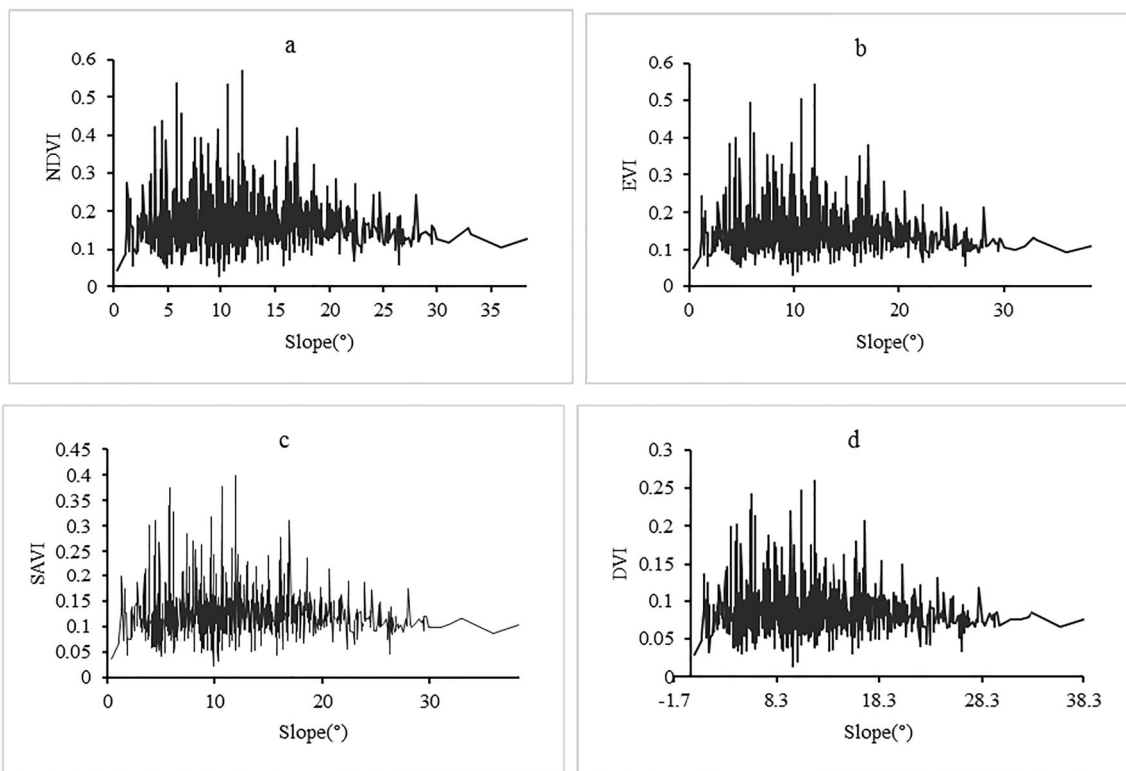
Fig. 4 Variations of vegetation indices per aspect (horizontal) in Kharestan area: NDVI (**a**), EVI (**b**), SAVI (**c**), DVI (**d**)

precipitation (Moran's $I = 0.91$) and SAVI and temperature (Moran's $I = 0.93$) and the same significance for the correlation between both DVI and precipitation (Moran's $I = 0.93$) and DVI and temperature (Moran's $I = 0.91$). Furthermore, having examined the relationship between NDVI and environmental factors through GWR model, the network cells comprising of 35,348 counts were calculated accordingly. Moreover, for the GWR model as comprising of a set of parameters (Maimaitijiang et al. 2015), a local R^2 parameter was selected for the evaluation of the performance of the model. Therefore, the regional R^2 was used for the analysis of the relationship between NDVI, EVI, SAVI, DVI, and precipitation and temperature (Figs. 7 and 8).

The results of the correlation between NDVI and precipitation indicate that the two indices are 54% correlated with each other while lacking any correlation for 46%. Moreover, their correlation quality was found to be 24.9% weak, 17.7% moderate, and 11.4% strong which is significantly high (Fig.

7a). As for the EVI, the results showed 54/77 correlation with the precipitation while lacking any correlation with the same factor for 45.23%. Furthermore, if regarded qualitatively, out of the 54.77% correlation between EVI and precipitation, 28% was weak, 18.67% was moderate, and 8% was reported as being strong (Fig. 7b). The results also indicated 54.37% correlation between SAVI and precipitation (46% lack of correlation) out of which 28.75% was weak, 18.45% was moderate, and 7.17% was strong qualitatively (Fig. 7c). Moreover, the results showed 40.85% correlation between DVI and precipitation out of which 20.24% was weak, 15.08% was moderate, and 5.52% was strong qualitatively (Fig. 7d).

In addition to what was reported above, the study also found 49.9% correlation between NDVI and temperature, out of which, qualitatively, 27.48% was weak, 14.12% was moderate, and 8.3% was strong (Fig. 7e). It was also found that there was 47.63% positive correlation between EVI and temperature (and 52.37% negative correlation between

Fig. 5 Variations of vegetation indices per slope in the form of scatter plot (spline connected) in Kharestan area: NDVI (**a**), EVI (**b**), SAVI (**c**), DVI (**d**)

the two), out of which 28.75% was weak, 12.85% was moderate, and 6.02% was strong qualitatively (Fig. 7f). Moreover, the positive correlation between SAVI and temperature was reported as being 47.3%, out of which, if looked qualitatively, 27.93% was weak, 12.7% was moderate, and 6.65% was strong which are acceptable in this case (Fig. 7g). The results also showed 42.44% positive correlation between DVI and temperature, out of which 23.61% was weak, 12.57% was moderate, and 6.36% was strong qualitatively (Fig. 7h).

4 Discussion

Numerous studies have already been conducted on vegetation growth and distribution in mountainous and semiarid regions (like the situation of the area studied in this research) and the factors affecting them (Bing et al. 2014; Zhu et al. 2011; Mokarram and Sathyamoorthy 2015). For instance, Liu et al. (2018) and Hu et al. (2019) found in separate studies that topography (slope, direction, elevation) plays an important role in the distribution of different types of vegetation indices.

Fig. 6 The variations of annual precipitation (black diamonds) and air temperature (blue diamonds) in proportionate to the elevation between 2008 and 2015 in Kharestan area
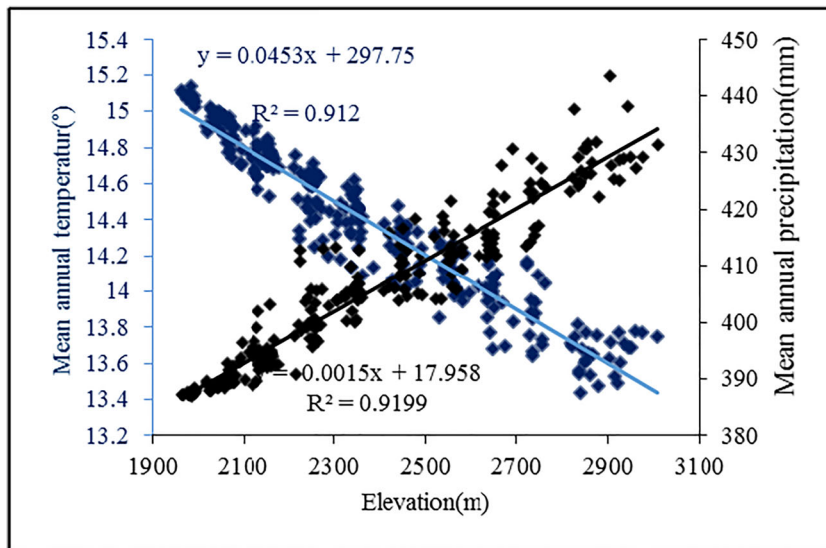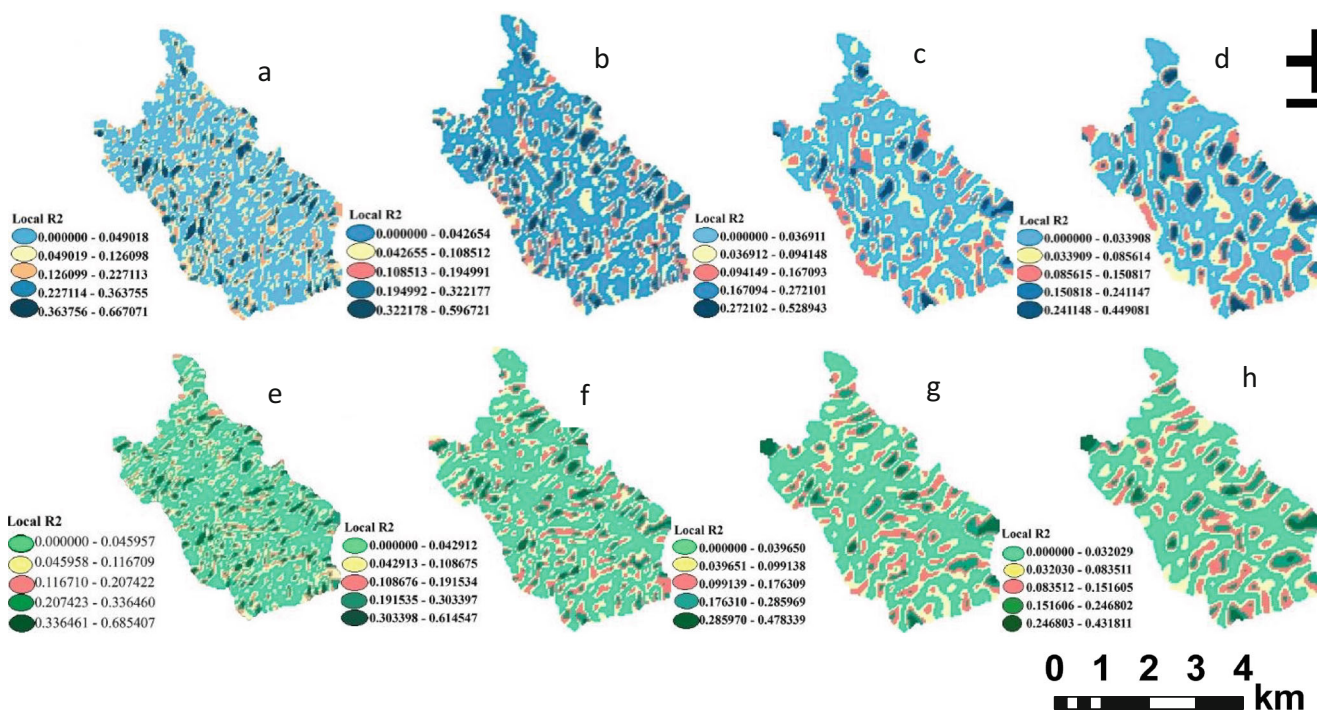
Fig. 7 The relationship between vegetation indices, precipitation, and temperature using GWR model (local R^2), results of which are as follows: **a** NDVI and precipitation, **b** EVI and precipitation, **c** SAVI and precipitation, **d** DVI and precipitation, **e** NDVI and mean annual temperature, **f** EVI and mean value for annual temperature, **g** SAVI and mean value for annual temperature, **h** DVI and mean for annual temperature

The results of their studies also indicate that the values for vegetation index differ according to the elevation, the same result, which was found in our study, too as it was found in the region studied at the elevation range of 1900 to 3100 m. Moreover, the highest mean value for NDVI, EVI, SAVI, and DVI in our study was reported as being 0.56, 0.54, 0.4, 3.65, and 0.25 respectively, observed mostly at the elevations of 2050 to 2091. As there were no significant changes in average precipitation and temperature in the region studied in this research, it could be argued that topographic factors were influential in the results obtained (as reported above).

4.1 Effect of precipitation and temperature on different vegetation indices

According to Zeng and Yang (2009), as the elevation increases, plants' growth gets dependent on the temperature conditions in such a way that any increase in the temperature may facilitate the plants growth. To verify such a claim, the relationship between vegetation and precipitation (based on NDVI, EVI, SAVI, and DVI) as obtained from the Landsat images and the average precipitation and annual temperature from 2008 to 2015 were examined, the results of which indicated a positive correlation between each of the vegetation indices, precipitation, and temperature (Fig. 7), proving that precipitation and temperature are effective in the distribution of the indices at different elevations. It was also found that the

highest values for the indices could be observed at both low elevation (2050–2250) and high elevation (2600–2700) categories. Moreover, the results indicate that precipitation increases with an increase in elevation up to 2800 m and decreases when the elevation rises beyond 2800 m. In fact, the precipitation in mountainous regions increases up to a certain elevation and reduces at elevations beyond that where the highest vegetation density could be observed (Han et al. 2017). However, at very high elevations, the temperature is regarded as the most important influential factor in vegetation dynamics (Hu et al. 2019). Furthermore, Guan et al. (2018) argue with the same regard that in mountainous regions, precipitation provides the plants with sufficient amount of water required for their growth and the temperature makes the photosynthesis increased, helping improving the plants' growth significantly.

The correlation analysis indicated a significant correlation between the mean values of vegetation indices, temperature, and precipitation. The maximum precipitation (448 mm) was observed at elevation of approximately 2900 m and its minimum (386 mm) was found at elevation of about 1976 m (Fig. 8); also, the highest temperature value (15.2 °C) was found at the elevation of 1976 m and the lowest value (13.2 °C) was observed at the elevation of 2900 m (Fig. 8). Moreover, along the gradient of the elevation rise, the values for NDVI, EVI, SAVI, and DVI increased with the falling temperature and reached their pick at 2090 m.
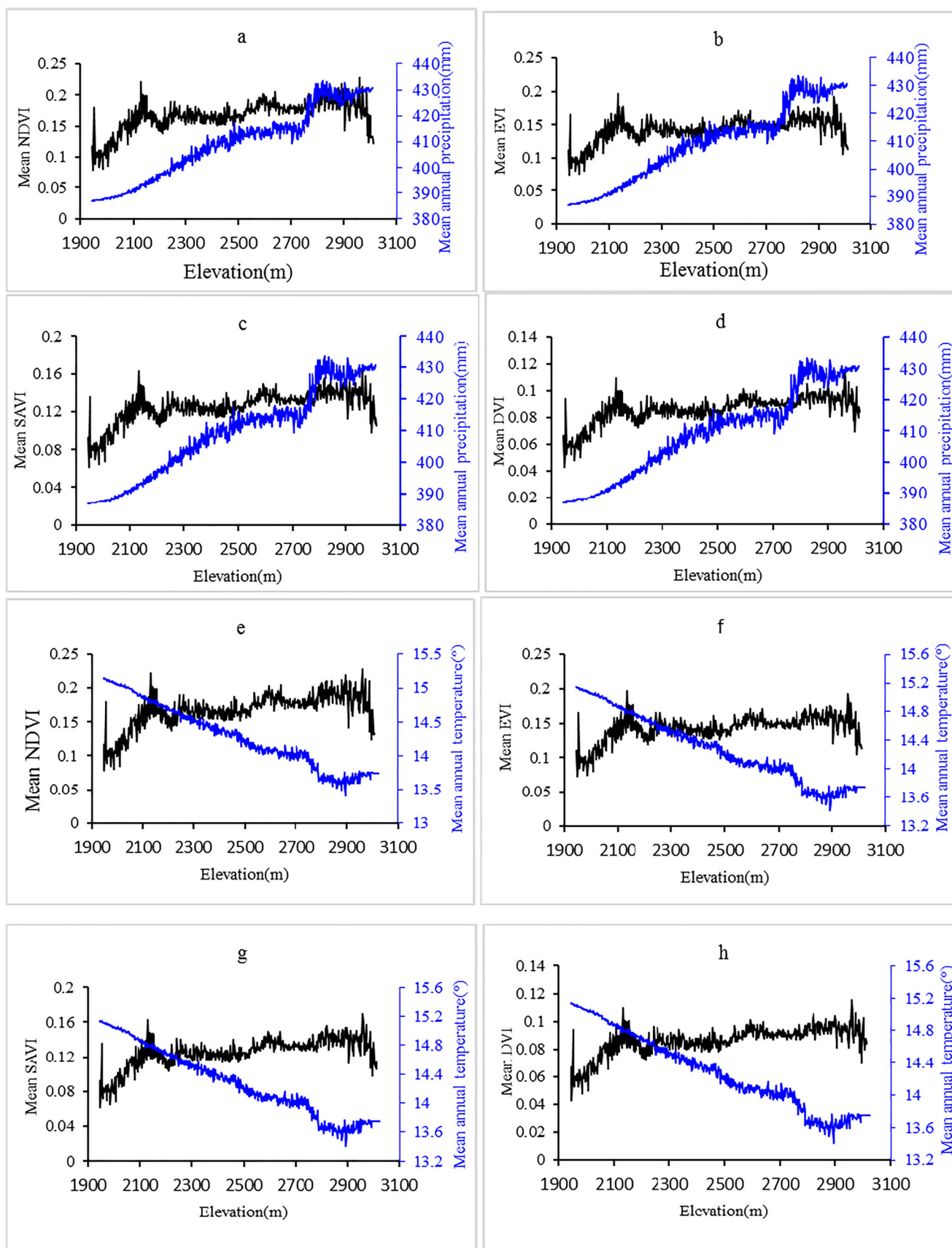
Fig. 8 Changes between vegetation index and annual precipitation per elevation: NDVI (**a**), EVI (**b**), SAVI (**c**), DVI (**d**). Changes between vegetation index and mean annual temperature per elevation: NDVI (**e**), EVI (**f**), SAVI (g), DVI (**h**)

Therefore, in mountainous regions, vegetation grows mainly at lower altitudes where the temperature conditions are more appropriate. However, at higher elevations where the temperature is usually lower and there might be some temperature limitations as the temperature is higher in sunny aspects than the shaded ones, the vegetation may develop more due to the combined effect of increasing temperature with the increasing precipitation. Furthermore, although at lower elevations the precipitation is lower than that of the higher altitudes, the vegetation will probably develop as the soil preserve the water moisture (and because of the vicinity of these areas to the surface water resources). Finally, at mid-domain elevations where the temperature could not be reduced with the rise in precipitation, any increase in temperature may lead to dryer conditions and the vegetation therefore becomes sparse. These findings are consistent with the results found by Shao-fu et al. (2013). It could, therefore, be concluded that in semiarid mountainous regions (similar to the area investigated in this study), the temperature has a negative correlation with vegetation (Muradyan et al. 2019). NDVI variations at different elevations are dependent on temperature and precipitation (Dai et al. 2011).

Moreover, aspect and slope are two other topographic factors that affect the humidity and temperature conditions of any ecosystem. In mountainous ecosystems, abiotic factors such as wind, precipitation, and solar radiation are so influenced by the aspect that the soil properties such as temperature and soil water are significantly changed under the influence of such abiotic factors (Dearborn and Danby 2017). Therefore, aspect directly affects the composition and distribution of vegetation (Kambo and Danby 2018; Orban et al. 2018) in such ecosystems.

In the region studied in this research, the highest density of the vegetation indices was found in the north, southwest, southeast, and west aspects where the highest values for NDVI, EVI, SAVI, and DVI were reported (Fig. 9). Due to the difference of sunshine time in the sunny and shaded sides of the mountains, the shaded sides experienced a lower temperature, less vaporization, and less moisture tension than those of the sunny sides. Therefore, in shaded sides, the combined effects of rising temperature and precipitation lead to the development of vegetation whereas in the sunny sides, rising temperature will lead to more vaporization, more transpiration, and more moisture tension, as a result of which plants' growth will reduce (Fig. 9). These findings, which are consistent with the ones found by Guerrero et al. (2016), Kayiranga et al. (2017), and Zhang et al. (2016), indicate that in arid and

semiarid regions, shaded slopes are more appropriate for the development of vegetation than those of the sunny slope.

Moreover, the values for the vegetation indices increase with the rise in slope up to 12° and decrease on slopes beyond 12°. The highest mean values for such vegetation indices as NDVI, EVI, SAVI, and DVI were found on slopes between 4 and 12°, which are mainly related to the agricultural and horticultural lands. As farming in precipitous slopes causes soil erosion, the farming areas were, therefore, found on slopes with less than 15° (Fig. 10). Taking these findings into consideration which are consistent with those reported by Ozturk et al. (2017), it could be argued that areas with gentler slopes are more appropriate to be used as farmlands. On the other hand, as the soil and water conditions are more suitable in gentler slopes than the steep ones, the vegetation is therefore thicker on gentle slopes (Zhang et al. 2018). Moreover, as on gentle slopes the soil could preserve more water due to the leveler surface of the ground, thus, the maximum coverage of vegetation was found in such areas (Fig. 10), while on steeper slopes, the mean values for vegetation indices were decreased due to the loss of water through the runoff.

The findings of this study, as reported above, are consistent with the results of the study carried out by Shao-Fu et al. (2013) in the Qilian Mountain. They found that at sunny side of the steep domains, the vegetation became sparse, and that the climate change depended on humidity and temperature conditions of the site which are mainly controlled by topographic factors (such as elevation, aspect, and slope), and by other factors such as local hydrology.

As the studied area is located in a mountainous region with a cold semiarid climate, both temperature and precipitation are somehow effective in the vegetation patterning of this region. Many studies which have already been conducted regarding the significant effect of climatic factors on the changes made in vegetation distribution indicate that the patterns of plants' responses to warming in arid and semiarid regions could be determined according to the water status in the area under study (Yu et al. 2003). In another study conducted by Liu et al. (2018) in the mountainous region of Hengyang, China, it was found that vegetation had a negative correlation with temperature and a positive correlation with precipitation, and that these two factors had different effects in different regions. Guo et al. (2018) also reported a negative correlation between NDVI and temperature, and a positive correlation between NDVI and precipitation in two mountainous regions of Changbai and Appalachian, and that there was a positive correlation between NDVI and temperature during the spring in both regions.

Moreover, Ma and Frank 2006reported that the main climatic factor affecting vegetation in the Hehe basin, especially in mountainous regions, was precipitation, and that temperature could facilitate the creation and revival of vegetation at upper areas of the shaded sides of mountains, indicating that
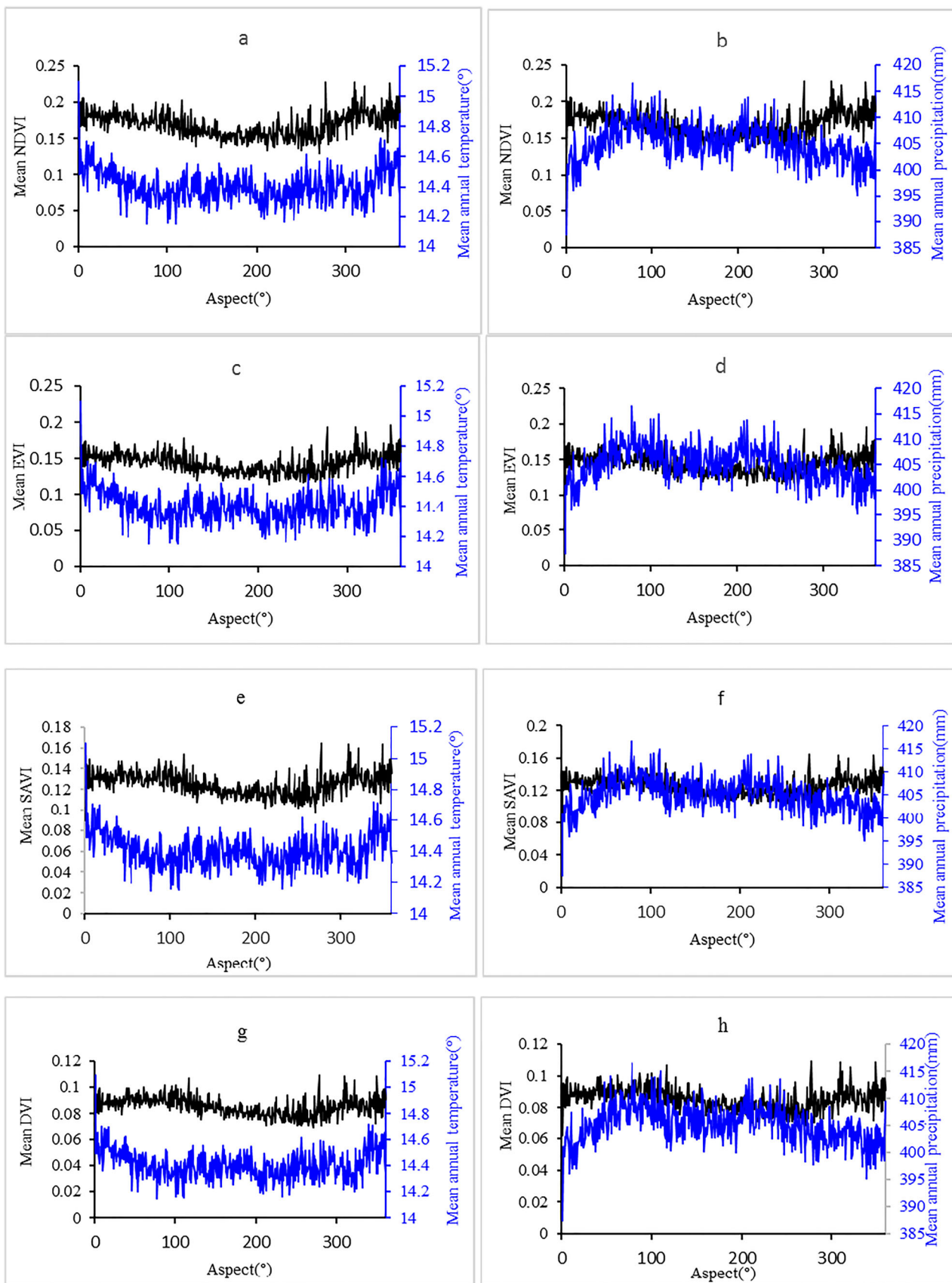
Fig. 9 Changes between vegetation index and annual mean temperature and precipitation per aspect: NDVI (**a**, **b**), EVI (**c**, **d**), SAVI (**e**, **f**), DVI (**g**, **h**)
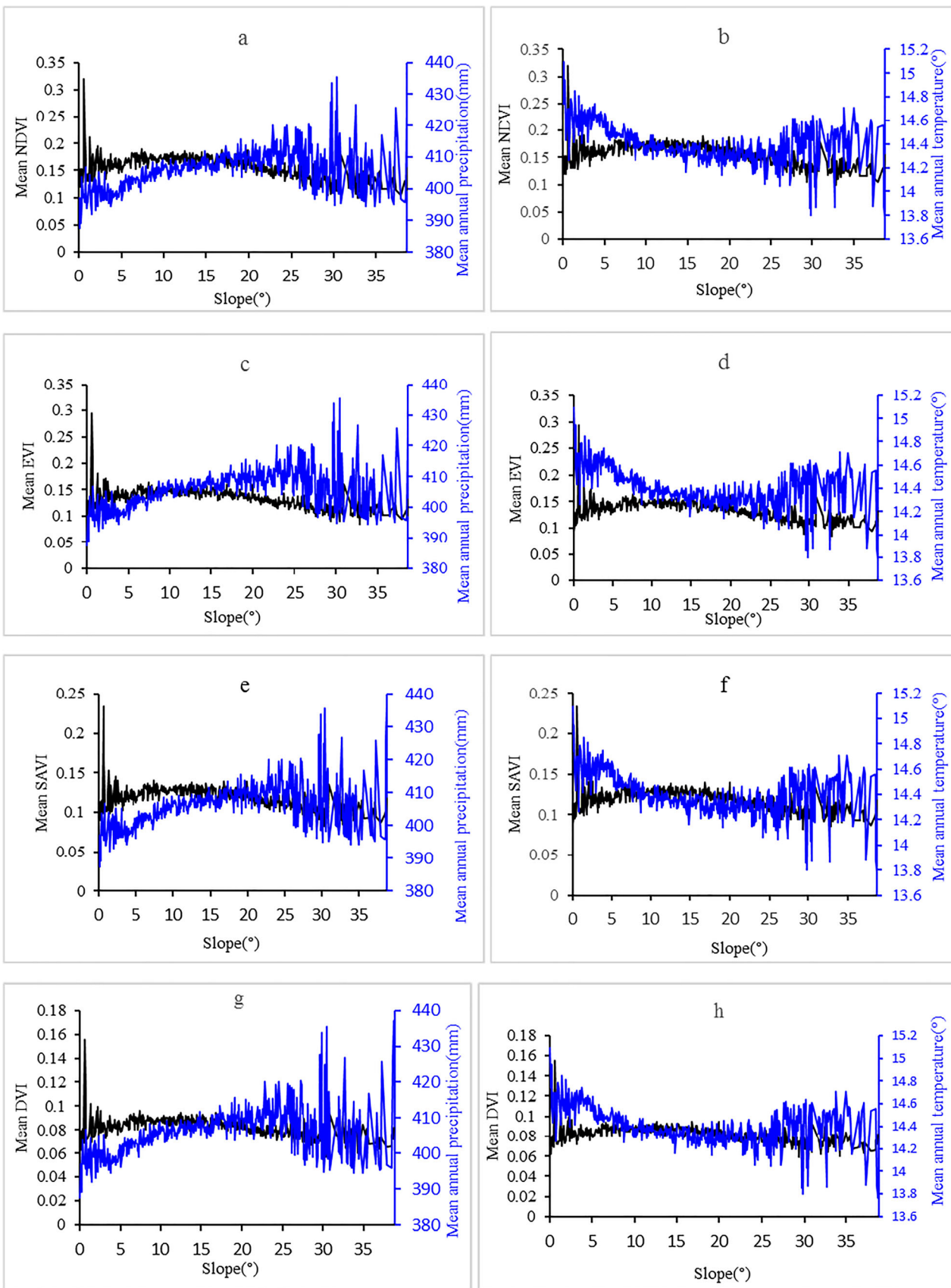
Fig. 10 Changes between vegetation index, precipitation, and annual mean temperature per slope: NDVI (**a**, **b**), EVI (**c**, **d**), SAVI (**e**, **f**), DVI (**g**, **h**)

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the temperature was also one of the important influential factors in vegetation variations in the area studied. It should also be noted that the findings of this study are consistent with the ones reported by Zang and Yang (2008), and Guo et al. (2008) who found in separate studies that there was a positive correlation between the NDVI value and precipitation, and a negative correlation between NDVI and temperature. In our study, however, we found that climatic factors had a determining effect on the vegetation distribution.

In some other studies conducted by Kayiranga et al. (2017) and Verbeken et al. (2004) in a tropical region, it was found that the changes in vegetation were mainly dependent on temperature and that precipitation was not a limiting factor. However, the studies carried out in semiarid regions are indicative of the importance of precipitation.

Considering the fact that the area studied in this research is located in a cold semiarid climate, it appears that precipitation is among the factors effective on vegetation and that at high elevations the temperature could be influential.

5 Conclusion

According to the analysis of the variations of four vegetation indices (NDVI, EVI, SAVI, and EVI) during an 8-year period, it was found that elevation, aspect, and slope together with temperature and precipitation were among the main controlling factors of the vegetation growth. The results indicated that throughout this period, the values of all four vegetation indices increased in a way that the highest value was observed in EVI (0.0024/year) and the lowest one was found in NDVI (0.0007/year). The investigation of the temporal and spatial variations showed that the highest values for each of the four indices were related to the agricultural lands and the lowest ones belonged to the residential areas. Moreover, the highest values for each of the indices were found in 2012 and 2015, and the lowest ones were observed in 2008 and 2009.

The highest vegetation growth rate was recorded at elevations between 2000 and 2800 m. The highest values of all four indices were observed at elevation range of 2050 to 2250. Furthermore, the dispersion of vegetation was observed at almost all aspects, but the highest values of all four indices were found at the north and the northeast and the lower ones at the east and southwest aspects. The values of the indices at the aforementioned aspects and on slopes between 4 and 12° were also at their maximum level. However, on slopes upper than 13°, the values of the indices decreased.

Moreover, all four indices had positive correlations with precipitation and negative correlations with temperature in the study area. As for the precipitation and temperature, it could be argued that in lower altitudes where the temperature is higher (15.2 °C), the precipitation is lower (386 mm), the slopes are gentler, and the resources of the surface waters are more accessible, the vegetation grows more. These findings which show the effect of environmental factors on distribution and vegetation patterning may contribute to the development of more researches in this regard. Therefore, considering the different response of vegetation to climatic and topographic factors, exploitation of these areas should be made in proportionate to the production capacity.

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