



Investigating variations of vegetation: climatic, geological substrate, and topographic factors—a case study of Kharestan area, Fars Province, Iran

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Abstract

Kharestan basin is regarded as one of the sources of sediment production and erosion at the upstream side of the Middle East's largest embankment dam (Doroudzan Dam) whose vegetation directly affects the quality of water and soil conservation and the ecological health of the environmental. Accordingly, to investigate variations of vegetation, this study used Enhanced Thematic Mapper (ETM) long-term data for estimating Normalized Difference Vegetation Index (NDVI) with 16 days interval for the time period of 2017–2017 in Kharestan basin. Climatic factors (precipitation, temperature, evapotranspiration potential) and topography (elevation, aspect, slope, and compound topographic Index) were considered effective forces on NDVI variations. Spatial distribution of vegetation and its relationship with climatic and topographic factors in geological formations were investigated. Principal component analysis (PCA) was used to investigate collinearity, multivariate regression was used to explore the relationship between climatic factors and vegetation, and geographical weighted regression (GWR) was used to study topographic factors. The results indicated that the spatial distribution of NDVI was < 0.5 in south, north, and west, and > 0.5 (including agricultural and horticultural lands) in the center of the basin. There was a positive correlation between NDVI and precipitation; moreover, the correlations between NDVI, temperature, and evapotranspiration potential were negative. The NDVI value increased with an increase in precipitation, and decreased with the decrease of temperature to the west and north. In all formations, the highest vegetation growth was observed at the elevations from 1900 to 2900 m. The highest NDVI value was observed in Kashkan Formation at elevations of 2050 to 2100 m. The shaded aspects were more suitable for vegetation growth than the sunny aspects. In all formations, the NDVI value increased up to 15° slope, but decreased with the rise in slope (from 16° slope onwards). From among the factors mentioned, precipitation, temperature, and evapotranspiration potential had the greatest impact on NDVI. This finding is useful for biodiversity protection and constitutes a precious input to environmental and ecological research.

Keywords NDVI · Climate factors · Geological formation · Topographic factors · GWR · Remote sensing

Introduction

Vegetation plays a very significant role in controlling the content of the atmospheric CO₂, adjusting the climate, and

protecting the environment and its living species against the adverse effects of climate change. As a natural mediator among the soil, water, and the atmosphere in terrestrial ecosystems (Ma and Frank 2006a, b), vegetation also provides a

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proper ecosystem for many species including the animals, protecting them against natural threats such as landslide, rock falls, and debris flow (Ribeiro et al. 2016). Moreover, the development of cities and infrastructures, particularly in mountainous areas, relies on the protective effects of vegetation.

The important role of vegetation can be expressed in the exchange of materials and energy in the earth, which is the most sensitive part of ecosystems for climate change (Tian 2017; Shi et al. 2019). This factor could indirectly contribute to climate regulation and stabilization by affecting solar radiation, soil quality, water cycle, and carbon cycle process. It is, therefore, indirectly effective on regulating climate (Cramer et al. 2001; nemani et al. 2003; Peng et al. 2012; Zhang et al. 2016, 2019). These exchanges affect the climate at the local, regional, and global scales. Following the variation in surface features, any change in vegetation may affect climate properties. These changes together with the variations of regional climatic conditions including solar radiation, atmosphere, water, and soil energy transfer reflect the characteristics of intermittent and seasonal changes that are indicators of global climate change (Buitenwerf et al. 2015; Verbeeck and Kearsley 2016).

Land-use related vegetation variations could, in long term, affect the chemical composition of soil carbon stocks. This is the main determining factor in the vertical distribution of soil organic carbon. Although climate and soil texture are the major determinants of regional control over total carbon content, their effect on vertical distribution relies only on vegetation.

Cultivation and decomposition of plants determine the carbon input to the soil profile in a way that the presence of the plant above or under the ground, as well as shallow and deep roots, may have different effects on the relative distribution of deep soil carbon (Jobbagy and Jaconi 2000). Various vegetations could alter energy currents, carbon, and nutrients, as well as vertical and horizontal movement of water, thereby changing the land's fertility and the extent of soil's organic carbon content (Yadav 2008), in this way, the physiological diversity of plant species alters the thermal and moisture conditions of soil and determines the extent of the absorbed carbon and its transfer rate to the soil, consequently affecting the emission of the soil's CO₂ in to the atmosphere (Raich and Tufekcioglu 2000; Baldock et al. 2012; Carvalho et al. 2016).

Generally speaking, vegetation plays an important role in the spatial and temporal dynamics of the production and transport of sediment (Hilker et al. 2014). The vegetation canopy acts as a water storage system and reduces the velocity of raindrops hitting the soil, reducing the splash erosion as a result (Liu et al. 2018). Vegetation also lowers the velocity of surface water currents and increases the rate and volume of infiltration which results in the deposition of soil particles in water (Wang et al. 2010). The development of plant roots improves the physical properties of soil such as its strength,

structural stability, and aggregation which are closely related to soil erodibility (Wang et al. 2016). Therefore, due to possible changes in hydraulic parameters and runoff conditions, and the sediment yield, vegetation could significantly affect soil erosion (Zhang et al. 2017).

Topography and climate are regarded as the main factors that control the changes made in vegetation, soil, and precipitation, especially in hillsides by influencing the precipitation and the runoff (Bachmair and Weiler 2012). While temperature and precipitation are considered two main climatic factors controlling the type of vegetation and its patterning, there are three main topographic factors which influence the distribution and patterning of vegetation especially in mountainous regions, namely, the elevation, the aspect, and the slope (Huang 2002). Many studies have so far been conducted on the relationship between precipitation and the type of vegetation (Li et al. 2007; Fu et al. 2012).

The relationship between the vegetation and environmental factors such as climate, geological characteristics, and geomorphic elements especially in semi-dry regions reflects ecological and biological features (Fang and Zhang 2013). It could clearly be argued that water, soil nutrients, and surface and sub-surface erosions are influenced by geological features (Bisigato et al. 2009; Osterkamp 2008). The geological substrate (formation) adds, through affecting the soil properties and hydrological processes, to the variety and complexity of vegetation in semi-dry areas (Huang et al. 2008; Rodríguez-Moreno and Bullock 2014). However, geomorphic elements and geological substrate may affect the spatial heterogeneity of vegetation in smaller scales especially in areas with no distinct climates (Yetemen et al. 2010; Munyati et al. 2009).

Remote sensing is, as a powerful and precise tool in researching vegetation patterning, ideal for quantifying factors which are effective in spatial distribution of vegetation in large areas. It is conducted through NDVI (Coutron et al. 2014; Purkis and Klemas 2011; Yang and Chen 2010) which is derived from the reflectance of the planet in visible and near-infrared parts (De jong et al. 2011). Because of its lower sensitivity to topographic changes, NDVI is used in mountainous area (Matsushita et al. 2007).

In mountainous basins, soil and land resources have such limitations as high erodibility, high and very high sediment production, steep slopes, lots of vicissitudes, and the existence of shallow soils. Considering the fact that Kharestan mountainous area is one of the basins of the Doroudzan Dam, sedimentation is a significant factor in this basin. Located in north of Fars province, Doroudzan Dam is one of the Iranian strategic areas for agricultural production which is fraught with the problem of over-extraction of water, land degradation, and increasing desertification. On the other hand, poor vegetation and shortage of forage are some major drawbacks of the grasslands in that region. Taking the role of vegetation as one of the main elements of ecosystem and its effect on other variables of

the existing ecosystem as well as on soil and water conservation, the vegetation patterning of the study area of this research has so far been investigated only in terms of field observation, while a few studies have explored vegetation variations via remote sensing and GIS. This study, therefore, investigated vegetation variations using satellite imagery and GIS. As the study area is mountainous, the vertical distribution of its climate is clear and topography plays a major role in the climate of the region. However, the influence of long-term environmental factors on vegetation has not been studied much. Most of the studies have focused merely on the effects of climate on NDVI, trying to make a connection between climatic factors and vegetation to describe spatial features of vegetation. Although the findings of these studies are important as well, they rarely discuss the relationship between various factors and NDVI values. Moreover, many studies have paid less attention to the concurrent investigation of the effect of the variations of different factors such as slope, aspect, elevation, temperature, precipitation, land type, etc. on vegetation and how they exert such an influence. Therefore, given the limited numbers of research on the relationship between multiple factors and vegetation, this case study was carried out. In order to investigate the effect of multiple factors including slope, aspect, elevation, temperature, precipitation, and land type on NDVI variations, a model was used. In this study, all variables were concurrently taken into account and multivariate regression was used to develop the NDVI regression formula.

Given the importance of vegetation on promoting sustainable ecological and socioeconomic development, understanding and identifying vegetation variations and factors affecting them are important but challenging subjects. Considering the mountainous nature of the study area, climatic and topographic factors are expected to play a major role in the distribution and dynamics of vegetation. Therefore, Landsat data for the time period of 2017–2017 were used in the present study to investigate temporal and spatial variations of NDVI. Also, factors affecting the distribution and dynamics of vegetation were investigated in this study. The findings of this study could be useful in identifying how terrain and other regional features may influence ecosystem's response to climate change. This research could provide a scientific reference for investigating soil and water conservation, the status of ecology, forest ecosystems, wildlife sanctuaries, reconstruction and management of the environment, sustainable development, and environmental protection in southwestern Iran.

Materials and method

The studied area

Kharestan basin is one of the watersheds of the Doroudzan Dam in Fars Province which is located at the geographical

range of 51° and 47 °C and 9° east longitude and 30°, 47' and 30" north latitude. The area of this region is 12,300 m² in which its minimum and maximum heights and its average slope are 1900 m, 3040 m, and 11%, respectively.

Geologically, the study area consists of 6 types of formations: Hormuz salt (Hz) is located in the southwest of Iran and it is composed of inter-layers of marl, blade-like lime, and a set of marls from white to yellow. Another formation observed in the south of the study area is called Hormuz Complex (Z-C) which is composed of white, yellow, and gray marls; tuff, anhydrite, black lime; and red, gray, and green sandstones. Pabdeh-Gurpi (Pa-Gu) formations are some other formations located at the west and southeast part of the study area. The Gurpi Formation is composed of dark gray marls, shale, and some limes, and the Pabdeh Formation is composed of thin-layer clay lime with some alternating gray shales.

At the east of the study area, we found Bakhtiari Conglomerate Formation (Bk) which is composed of spherical limestone and a small amount of dark brown chert. Most of the study area is composed of Kashkan (Kn) and Asmari (As) formations. The Kashkan Formation is composed of conglomerate, sandstone, red siltstone, and marl from east to northwest, while the Asmari Formation was centrally composed of strong, hard, prominent, and massive brown lime stones. The river sediments in the study area were negligible (Fig. 1b). Figure 2a and b indicate the precipitation and temperature in the area for an 18-year period; the averages of which are 430 mm and 14.4 °C, respectively. Based on De Martonne climatic classification, the climate of the region is semi-arid.

Dataset

To explore the vegetation of the area, multi temporal images which had been taken in cloud-free conditions by Landsat 7 ETM with 163 and 39 Row/path were downloaded from <https://earthexplorer.usgs.gov> website. To precisely calculate the NDVI values, images with spatial resolution of 30 m were chosen. With regard to the time period of the study (2000–2017), 144 NDVI images were collected (with 16-day interval). As the vegetation of the study area (including indigenous and domestic ones) reveals its maximum annual vital activity from May to September, the NDVI values of those months were used for evaluation of the vegetation (Jin et al. 2009b). Digital elevation model (DEM) with the spatial resolution of 30 m was downloaded from <https://gdex.cr.usgs.gov/gdex> website.

The climate factors used in this study were the average annual precipitation, weather temperature, ground surface temperature, and potential evapotranspiration (PETR). The meteorological data for the time period of the study (2000–2017) were collected from 17 local meteorological stations on a monthly basis.

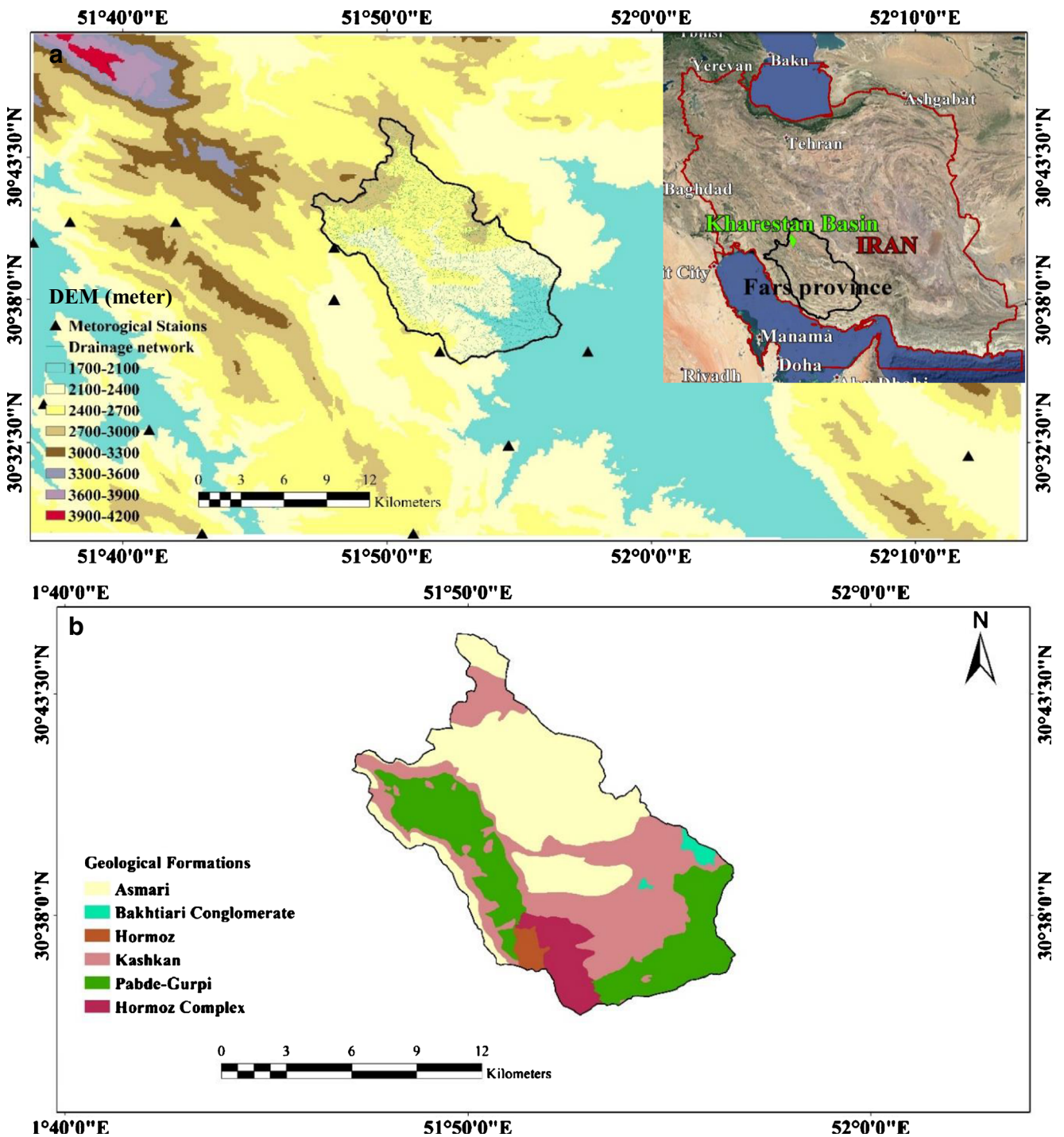


Fig. 1 Geographical Location of the study area in southwestern Iran (a) and Map of Geological formations in the studied area (b)

Methods

Image processing

Different types of initial pre-processing of the images including atmospheric and geometric corrections were performed

via ENVI software version 5.3. Vector analysis was made by Arc GIS version 10.3. Table 1 shows the classification of NDVI. Monthly NDVI was calculated through the combination of two NDVIs with a 16-day interval. The NDVI value was considered greater and lesser than 0.05 for vegetation and non-vegetation areas, respectively.

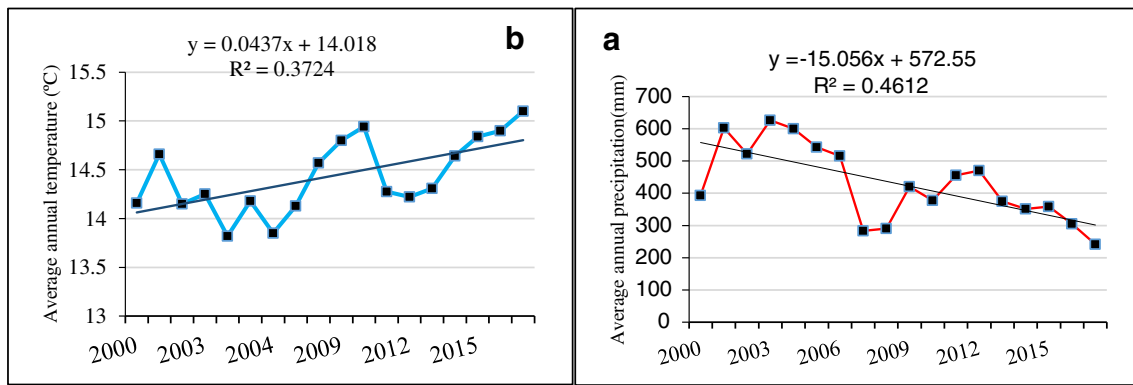


Fig. 2 Variations of precipitation (a) and temperature (b) during the last 18 years in the study area

Normalized difference vegetation index (NDVI)

NDVI index 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. According to the definition offered by Rouse et al. (1974), NDVI formula is worked out as follows:

$$NDVI = \frac{P_{nir} - P_{red}}{P_{nir} + P_{red}} \tag{1}$$

In this formula, P_{nir} stands for the reflectance of near infra-red 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 from -1 to $+1$. High values of this index indicate a high vegetation density in the area; however, clouds, snow, and water are marked with negative values (Li et al. 2009).

Methodology for determining environmental factors

Climatic factors

As there is no weather station in the area studied in this research, the data collected from nearby weather stations were used to identify climatic factors. The precipitation, temperature, and potential evapotranspiration maps were extracted based on monthly data via IDW algorithm using ArcGIS

software version 10.3 (Fig. 3). The earth surface temperature was recorded through satellite images. As for the consistency with NDVI data, the climate data were also calculated annually.

PETR values were used as climate predictors. PETR is the value of PET in proportionate with annual precipitation, indicating the combined effect of temperature and precipitation (Postw et al. 1982). In most cases, PET is calculated based on meteorological data. In this study, PET was calculated according to the Thornthwaite method through the following formula:

$$PET = 16 \left(\frac{L}{12} \right) \left(\frac{N}{30} \right) \left(\frac{10T_d}{I} \right)^\alpha \tag{2}$$

Where, PET is the estimated potential evapotranspiration (mm/month), T_d is the average daily temperature (degrees Celsius; if this is negative, use 0) of the month being calculated, N is the number of days in the month being calculated, and L is the average day length (hours) of the month being calculated.

$$\alpha = (6.75 \times 10^{-7})I^3 - (7.71 \times 10^{-5})I^2 + (1.792 \times 10^{-2})I + 0.49239 \tag{3}$$

$$I = \sum_{i=1}^{12} \left(\frac{Tm_i}{5} \right)^{1.512} \tag{4}$$

Table 1 The correlation between NDVI and climatic factors (precipitation, temperature, and PETR)

		NDVI	Precipitation	Temperature	PETR
Pearson correlation	NDVI	1.000	0.585	-0.689	-0.702
	Precipitation	0.585	1.000	-0.942	-0.803
	Temperature	-0.689	-0.942	1.000	0.884
	PETR	-0.702	-0.803	0.884	1.000
Sig. (1-tailed)	NDVI	.	0.000	0.000	0.000
	Precipitation	0.000	.	0.000	0.000
	Temperature	0.000	0.000	.	0.000
	PETR	0.000	0.000	0.000	.

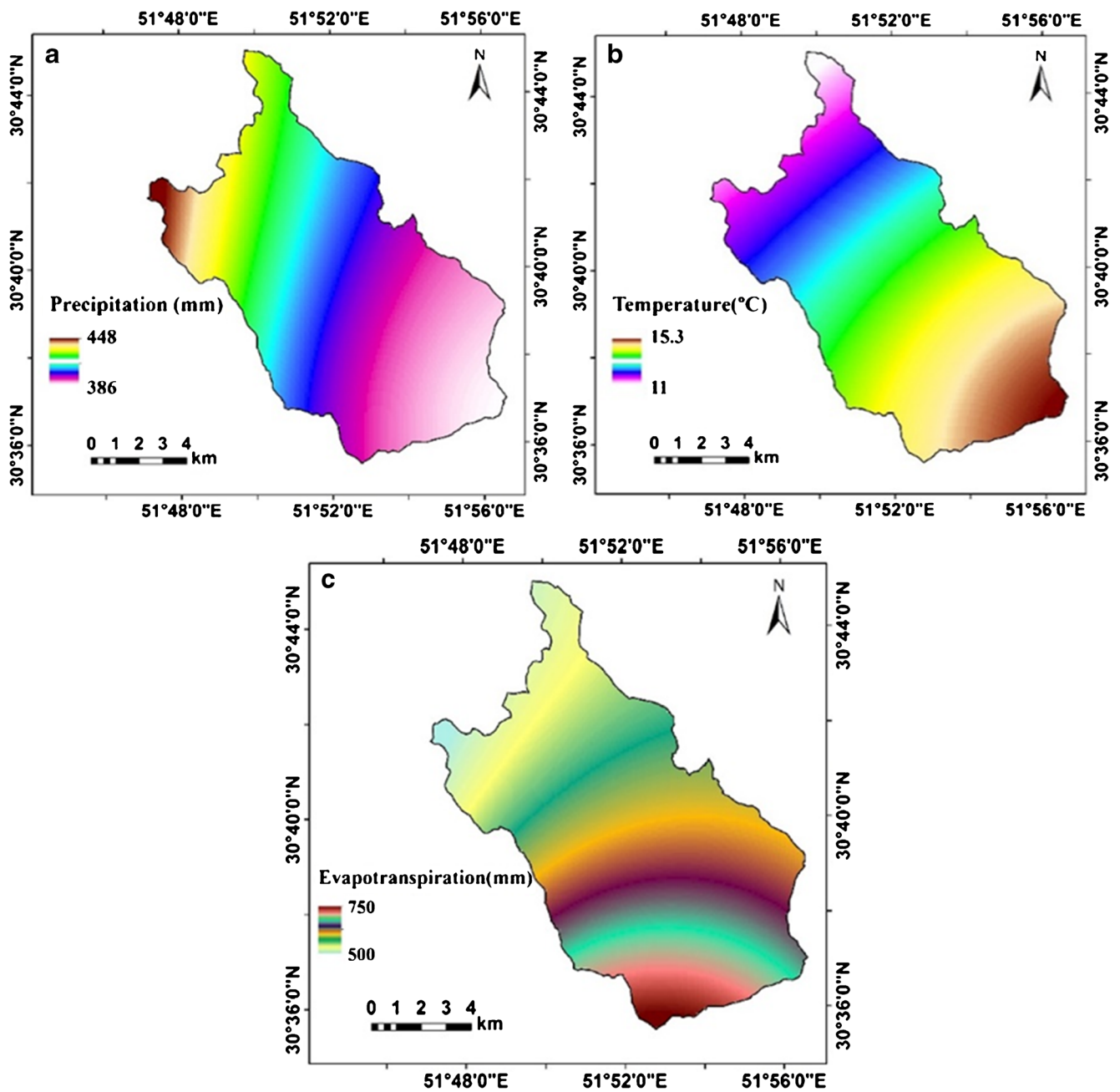


Fig. 3 Maps of precipitation (a), temperature(b), and potential evapotranspiration (c) using the IDW method

I is a heat index which depends on mean temperatures of every individual months of a year.

Topographic factors

Elevation, slope, aspect, and CTI were the main topographic factors investigated in this study. Using DEM, slope, aspect, and elevation maps were extracted from ArcGIS software. In this study, the elevation was divided into seven categories with a distance of 200 m, and the slope was divided into 5 classes, namely, < 2, 2–6, 6–15, 15–25 and > 25° According to the Four

Way method, the study area was divided into four aspects including sunny, shady, semi-sunny, and semi-shaded aspects.

CTI or soil steady state wetness index is a function for special surface and the watershed slope which is calculated according to the following equation:

$$CTI = \ln\left(\frac{As}{\tan\beta}\right) \quad (5)$$

In the above equation, As (2) is the watershed's special surface, and β is the slope gradient which was utilized to show the spatial distribution of water flow and its static state throughout the study area (Irvin et al. 1997).

Data analysis

Taking monthly climatic data into consideration, the average precipitation, temperature, and potential evapotranspiration were extracted. The correlation between NDVI and the aforementioned variables was analyzed. The maps regarding NDVI values, geology, topography, and climatic factors were transformed into the same geographical coordinate system. The 330-m Fishnet network was used to display the spatial patterns of NDVI along with climatic factors and geological map. Totally, 5400 points were collected from the network and used as sample points. The variations of NDVI under the influence of climatic and topographical factors were analyzed, using partial correlation, F, Variance Inflation Factor (VIF), GWR, and PCA tests in SPSS version 14 and Statgraphics version 17.

Principal component analysis (PCA)

Principal component analysis (PCA) is a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables. Accordingly, PCA can be used to reduce the dimension of data, thus preserving components of the data set that have the most effect on variance. The calculated model for PCA is calculated as follows:

$$Y = AX + B \tag{6}$$

In this equation, the main component is A, the $p \times p$ and E matrices are a random vector.

It should be noted that in this study, the principal component analysis (PCA) was, regarding the huge bulk of collected data, used to reduce the complexity of the analysis of the initial variables of the problem so that better interpretations could be made. In general, PCA was used here for identifying the most important factors affecting the NDVI, detecting the main source of changes made by the main and most important variables, developing the best linear composition through the main variables, and using these variables for linear regression analysis, while multiple linear regression was applied used to determine the relationship between NDVI-dependent variable and a set of climatic and topographic variables, and finally the relationship between these variables was presented as a model.

Results

The relationship between climatic factors and elevation in the study area

Figure 4a shows the relationship between precipitation and elevation. The results indicate a positive correlation between

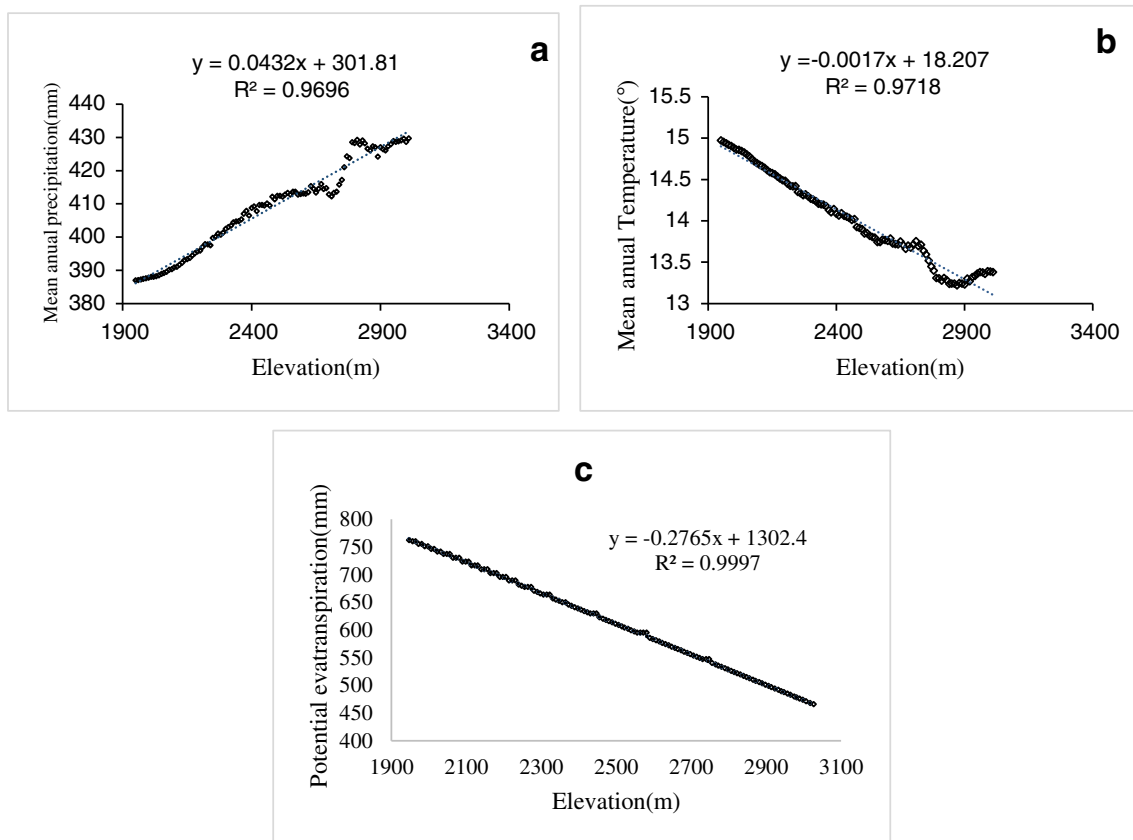


Fig. 4 The relationship between precipitation, temperature, and potential evapotranspiration with elevation

precipitation and elevation; the equation of which is as follows:

$$P = 0.0432H + 301.81 \tag{7}$$

where P is the average annual precipitation (mm), and H is elevation (m). As found in the equation, the average annual precipitation increases by 4.32 mm with the rise of every 100 m. Figure 4b shows the variations of temperature with elevation. The findings indicate that there is a negative correlation between temperature and elevation, the equation of which is as follows:

$$T = -0.0017H + 18.207 \tag{8}$$

where T is the average annual temperature ($^{\circ}\text{C}$), and H is the elevation (meter). As shown in equation No. 7, with the rise of every 100 m in elevation, the temperature decreases by 0.17°C .

Moreover, Fig. 4c shows the variations of potential evapotranspiration in proportionate with elevation. The findings of the study in this regard indicate that there is a negative correlation between potential evapotranspiration and elevation; the equation of which is as follows:

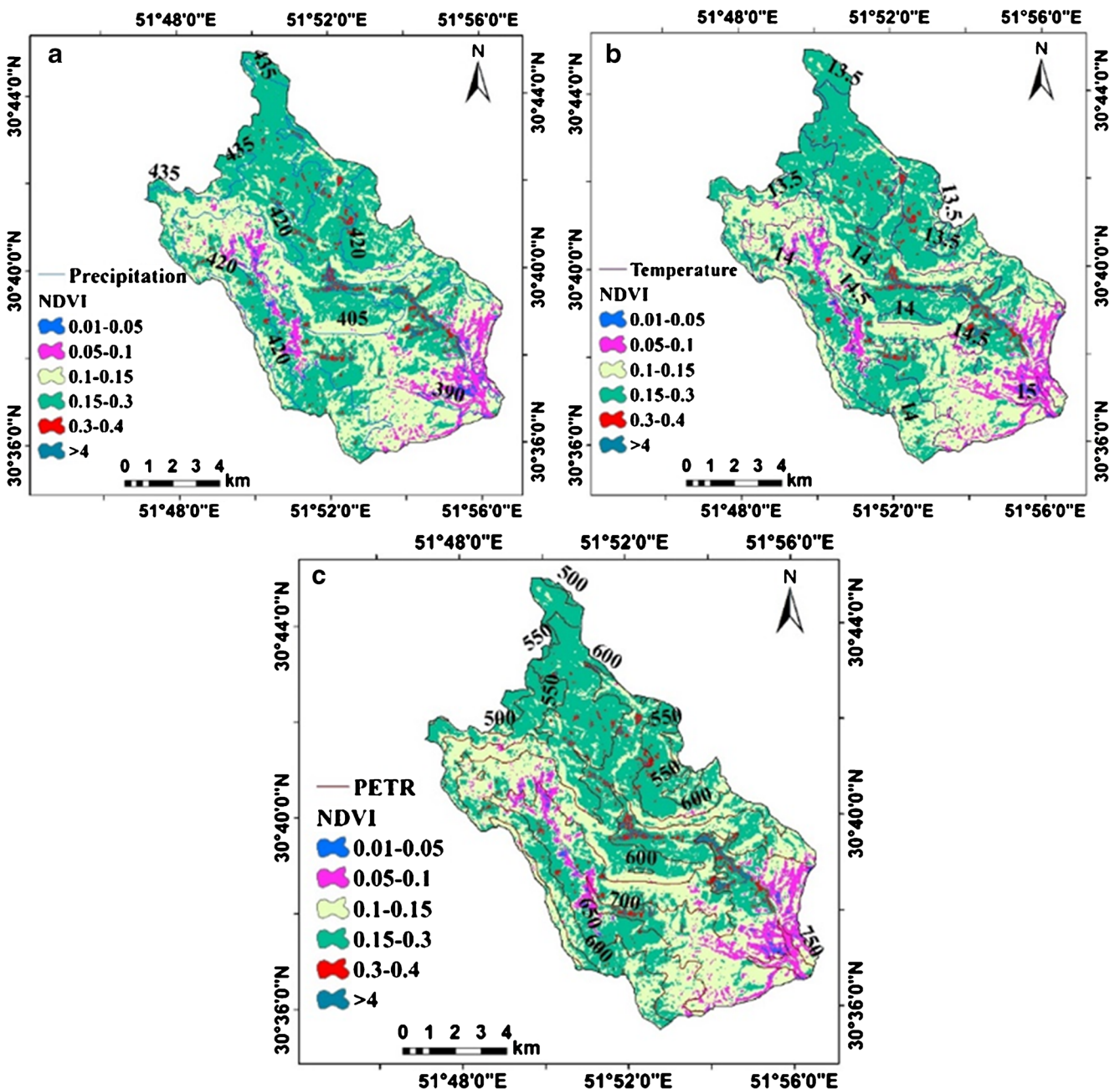
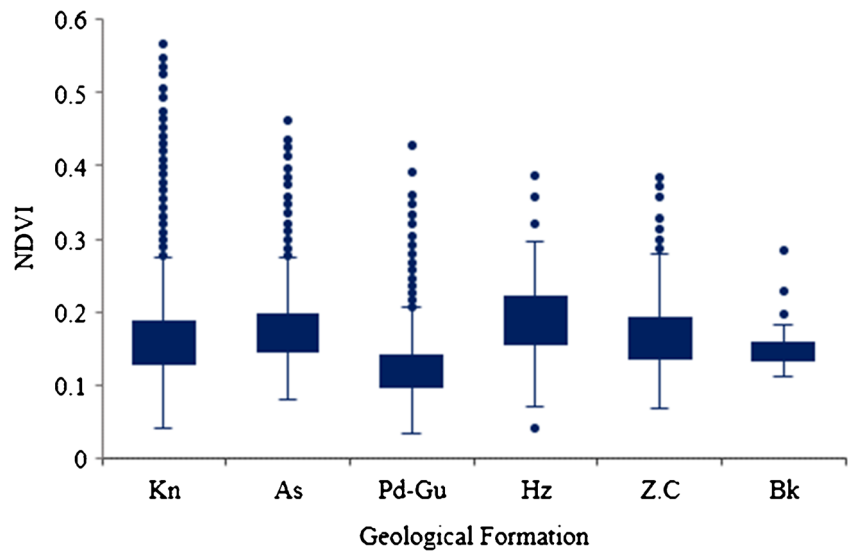


Fig. 5 NDVI and climate factors (precipitation, temperature, and potential evapotranspiration)

Fig. 6 The relationship between NDVI and geological formations



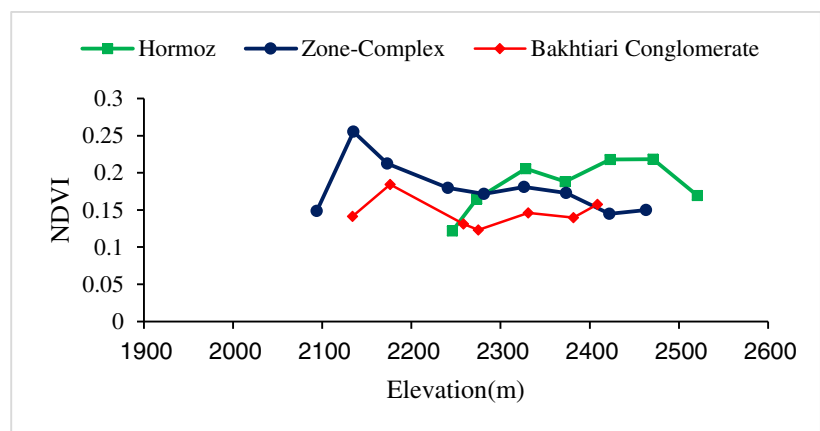
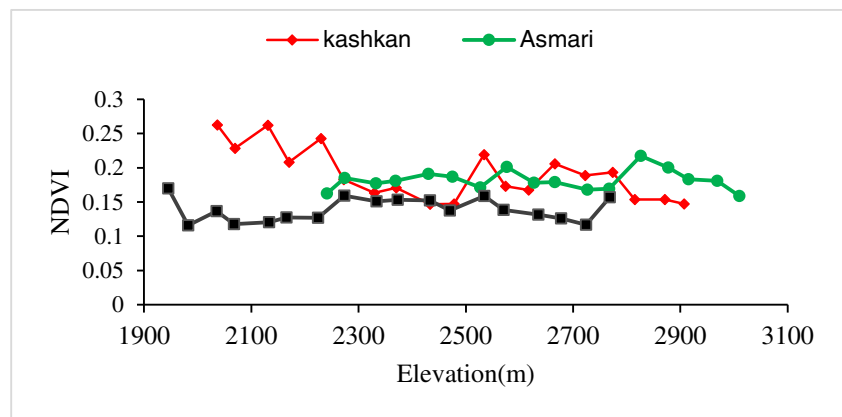
$$PETR = -0.2765H + 1302.4 \tag{9}$$

In this equation, PETR is the annual potential evapotranspiration (millimeters), and H is the elevation (meter). As shown in the equation, the potential evapotranspiration decreases by 27.65 mm with an increase in every 100 m of the elevation.

Relationship between NDVI and climatic factors

In this study, partial correlation was applied to determine the relationships between NDVI variations and precipitation, PETR, and average annual temperature; the results of which indicated that there was a positive correlation between NDVI and average precipitation, and there were negative correlations

Fig. 7 The relationship between NDVI values and elevation in each formation (a) Kn, (b) As, (c) Pd-Gu, (d) Hz, (e) z-c, and (f) Bk



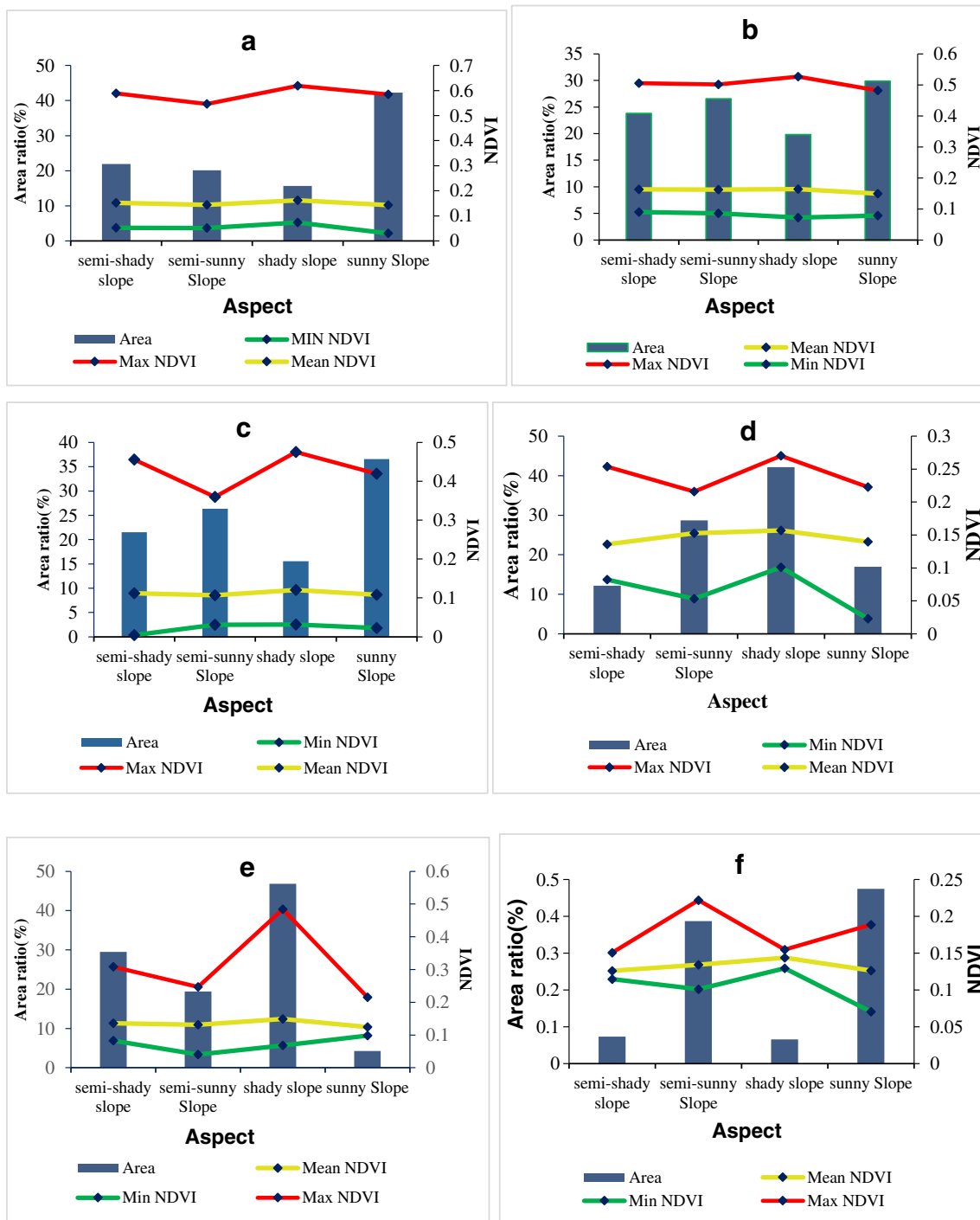


Fig. 8 The relationship between NDVI distribution and aspect in each formation: (a) Kn, (b) As, (c) Pd-Gu, (d) Hz (e) z-c, and (f) Bk

between NDVI and temperature, PETR, and the surface of the ground temperature (Table 1). The partial correlation coefficients of NDVI with precipitation, PETR, and annual average temperature were 0.585, 0.689, and 0.702, respectively ($P < 0.01$). Taking these correlations into account, $y = ax + by + \dots + c$ could elaborate on the relationship between NDVI and the three factors mentioned. The abovementioned results could be summarized as follows:

$$\begin{aligned}
 \text{NDVI} = & 0.271718 \\
 & + 0.000442337 * R - 0.0405248 * T - 0.000421022 * P
 \end{aligned}
 \tag{10}$$

In the above equation, NDVI is the average vegetation indicator, R is the annual precipitation, T is the average annual temperature, and P stands for PETR. As for the equation, F

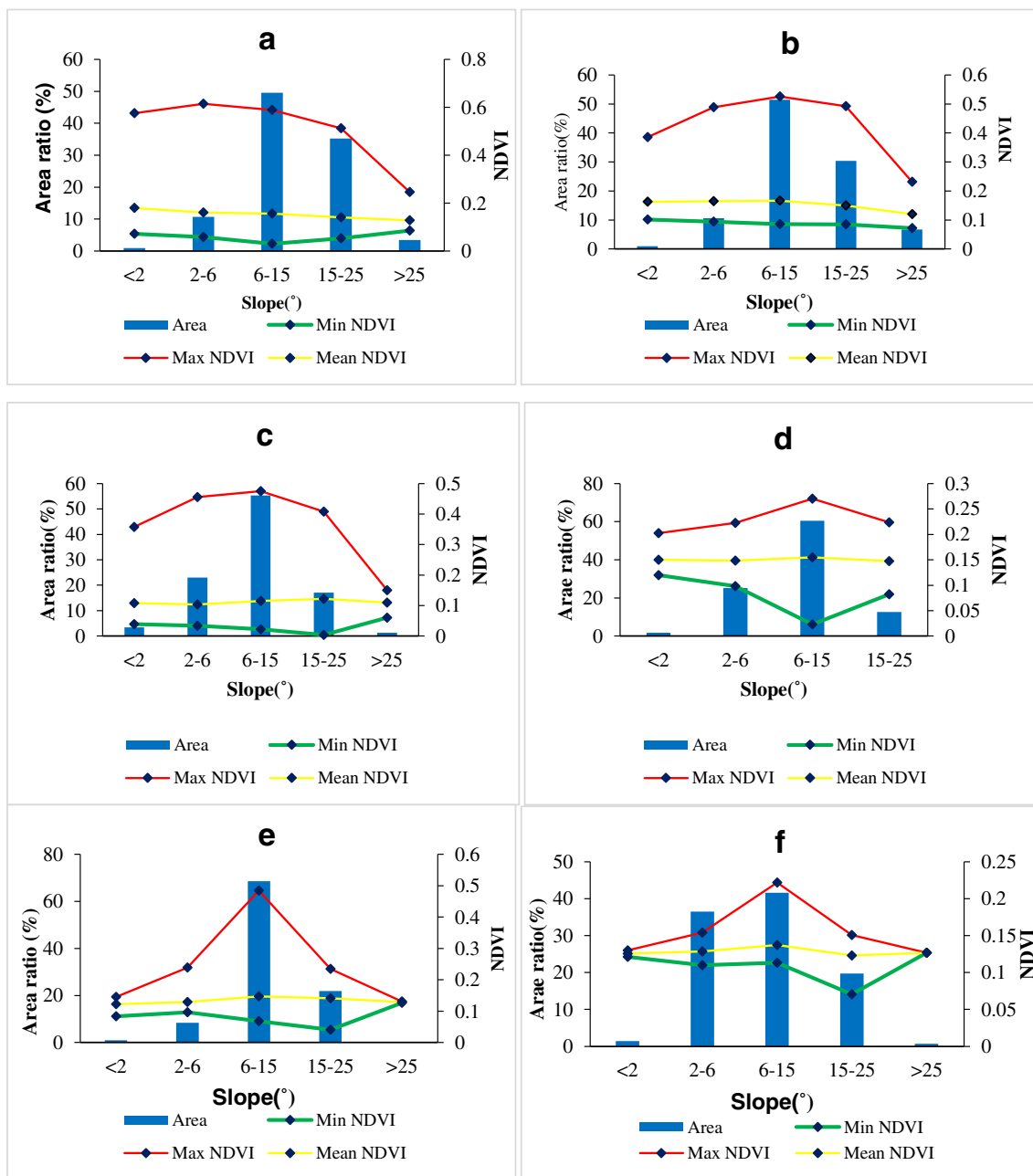
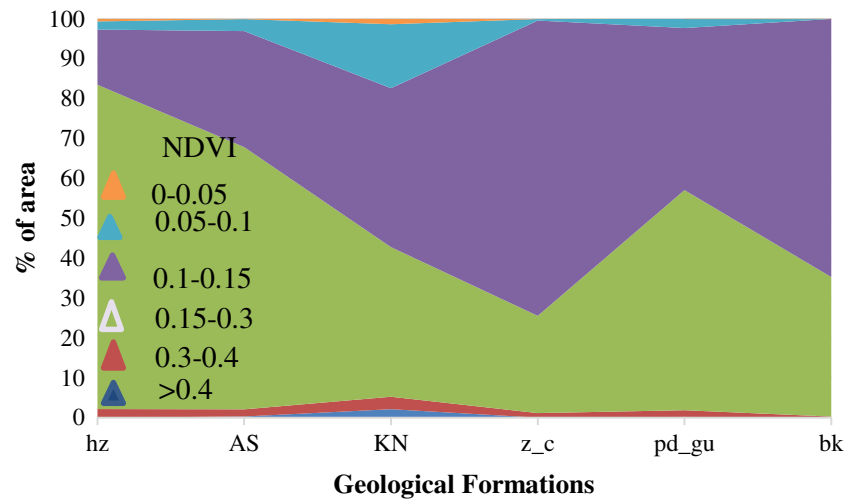


Fig. 9 The relationship between NDVI distribution and Slope in each formation (a) kn, (b) As, (c) Pd-Gu, (d) Hz, (e) z-c, and (f) Bk

test ($F = 5.99$) was reported as significant at 0.95 level ($P < 0.05$), and VIF and tolerance values were calculated as 1.31 and 0.78, respectively. It should be noted that multi-collinearity exists only when VIF is greater than 5 ($VIF > 5$) and tolerance is either less than 0.1 or much larger than 1 on average (Fang and Zhang 2013). As total collinearity contradicts the classical assumptions of the regression model, this study did not use multi-collinearity. The findings of the study indicate that NDVI has a positive correlation with precipitation and PETR, and a negative correlation with the temperature.

Figure 4a shows the relationship between NDVI and precipitation during the time period of the study (2000–2017). Greater values of NDVI ($NDVI > 0.15$) have been highlighted in green, red, and blue, with the blue color being related to the irrigated farmlands. Figure 4a, excluding the farmlands, indicates a similar trend for NDVI and precipitation, both of which getting increased from the east to the west and the north. It should be noted that 15% of the lands in the northwest of the study area has low NDVI value which is inconsistent with the precipitation. Moreover, it was found that there was an inverse relationship between NDVI (except for the

Fig. 10 Percentages of vegetation coverage in different geological formations



agricultural areas) and average annual temperature, with the NDVI getting decreased as the temperature increased (Fig. 4b). Figure 4c shows the spatial variations of NDVI in proportionate with PETR, with the NDVI value decreased as PETR increased from the south and the southeast to the west and the north (Fig. 5).

Distribution of vegetation and geological formations in the study area

Figure 6 shows the overview of NDVI for each geological formation. According to Fig. 6, the maximum and minimum densities of NDVI were reported in Kashkan and the Bakhtiari formations, respectively. Moreover, the maximum and minimum NDVI values were 0.57 and 0.03 which were observed in Kashkan and Pabdeh-Gurpi formations, respectively.

Relationship between vegetation and topographic factors in each geological formation

As indicated by the spatial vegetation of different geological formations, vegetation could be found in all geological formations located at elevation range of 1900 to 2900 m. From among the formations existed in the study area, the highest vegetation density was found in Kashkan formation and the lowest one was observed in Hormoz formation (Fig. 7). Moreover, the maximum and minimum NDVI values were found, respectively, at the elevation of 2050–2100 m in Kashkan formation and the elevation of 2200–2400 m in the Pabdeh-Gurpi formation. It should also be noted that the greatest rates of growth and distribution of vegetation were found at the initial elevations (2050–2100) of the study area which were mostly related to the farmlands.

As the overall results indicate, the northern aspects are suitable for vegetation growth. It was also found that except

for Bakhtiari conglomerate formation, shaded and semi-shaded slopes were more suitable for vegetation growth in all other six geological formations investigated in this study (Fig. 8). While the greatest NDVI value was observed in Kashkan formation and in shaded slopes, its lowest values were found in Pabdeh and Gurpi formations. It could, therefore, be concluded that the vegetation growth in each formation in Kharestan depends on the changes made in geological locations. Moreover, it could be argued that the growth of vegetation in various aspects is influenced by changes in the angle of solar radiation.

Figure 9 shows the relationship between NDVI and slope. In all six types of geological formations investigated, the highest percentage of the area covered by slope classes belonged to 6–15° slopes. In all formations, NDVI values increased up to 15° slope and decreased in slopes more than 16°. The highest and lowest NDVI values were observed, respectively, in 6–15° slopes at Kashkan formation and 15–25° slopes at Pabdeh and Gurpi formations. As the soil in areas with gentle slope absorbs more water, vegetation grows more there than in areas with precipitous slopes. Moreover, maximum NDVI values differed in the formations due to the difference in their materials and permeability. Figure 10 shows the percentage of vegetation in different geological formations according to which high NDVI values are observed in Kashkan and Asmari formations.

Spatial non-stationarity among the relationships

One simple method to identify the relationship between NDVI and the relevant factors is to use local R^2 which is derived from GWR model. The range of local R^2 varies from 0 to 1; the low values of which indicate the poor performance of the model. Figure 11 shows the GRW-drawn parameters of slope and local R^2 for NDVI and topologic variables. As reported in Table 2, there is a

Fig. 11 Spatial variation of regression outputs from the geographically weighted regression (GWR) models for the NDVI and topographical variables in the study area: (a) slope parameter for elevation; (b) local R^2 for elevation; (c) slope parameter for slope; (d) local R^2 for slope; (e) slope parameter for aspect; (f) local R^2 for aspect; (g) slope parameter for CTI; and (h) local R^2 for CTI

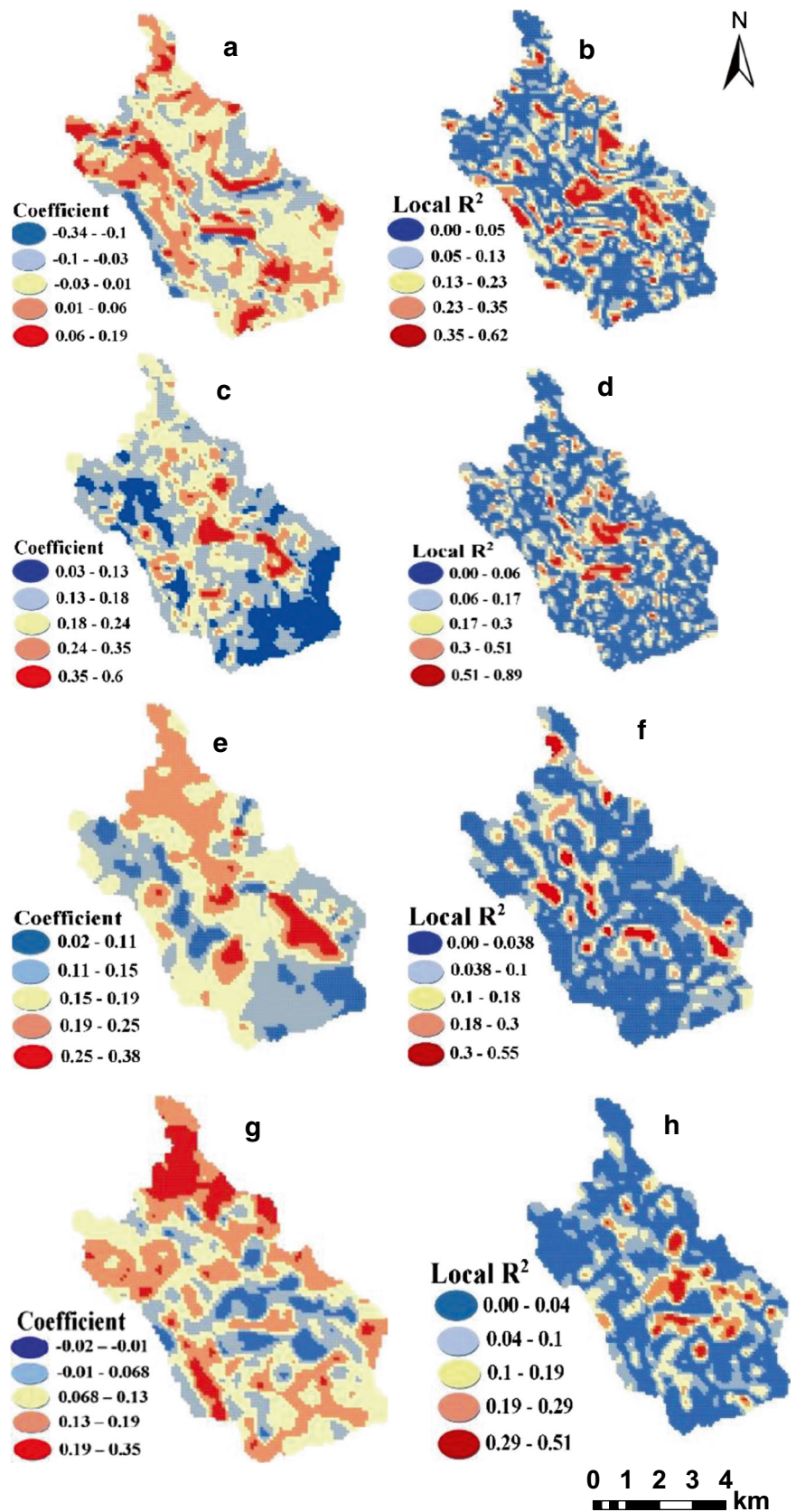


Table 2 VIF and tolerance statistics between NDVI and topographic factors using Ridge regression

Parameter	Estimate	Variance Inflation Factor	Tolerance statistic
CONSTANT	-0.14843		
Aspect	-0.0000434089	1.01201	0.988
slope	-0.000877129	1.68172	0.594
Elevation	0.00012885	1.05889	0.944
CTI	0.00140011	1.6834	0.594
MEAN		1.359	0.78

significant correlation between NDVI and elevation ($r = 0.60, P < 0.01$). However, according to Fig. 11a, there exist both positive and negative correlations between NDVI and elevation in the study area, with the negative ones observed mainly in the east and the west, and the positive ones found mostly in the center of the area. Figure 11b shows the values for Local R^2 , NDVI, and elevation, according to which there is a strong correlation between NDVI and elevation in 17.7% of the study area. Similarly, in contrast with the negative correlation between NDVI and slope ($r = -0.011, P < 0.01$), a positive correlation was found between the two in GWR model (Fig. 11c). Moreover, the strongest correlation between NDVI and slope was observed in the center of the study area. As the Local R^2 in Fig. 11d shows, there is 17.2% correlation between NDVI and slope in the study area which is very significant. Contrary to the negative correlation between NDVI and aspect ($r = -0.034, P < 0.01$), a positive correlation was observed in the southeast farmlands of the study area, using GWR model (Fig. 11e). The local R^2 between NDVI and slope in Fig. 11f indicates a strong 5.5% correlation between the two parameters. Furthermore, despite a low correlation between CTI and NDVI, both positive and negative correlations were found between the two in the study area (Fig. 11g), with the strong one found in the north and the negative one found in the center of the area. It should also be noted that most of the points with strong negative correlations usually have high local R^2 values (Fig. 11g and h).

The relationship between NDVI and soil moisture index, elevation, slope, and aspect has been illustrated in Fig. 10. Taking Fig. 10 and Table 2 into consideration, the following equation has been introduced:

$$\text{NDVI} = -0.14843 + 0.00140011 * C - 0.0000434089 * A - 0.000877129 * S + 0.00012885 * E \quad (11)$$

In this equation, NDVI is the average vegetation index, C is the soil moisture index, A is the aspect, S is the slope, and E is elevation. Furthermore, VIF tolerance statistics were reported as 1.359 and 0.78 respectively, indicating the lack of multiple collinearities between NDVI and topographic factors (Table 2).

Regression analysis of NDVI and multi-factors

To avoid instability when creating the regression equation, the impact of the factors affecting NDVI was investigated through PCA. In this study, KMO (Kaiser Meyer Olkin index) statistics were obtained as 0.75, indicating the appropriateness of the data for factor analysis. The results of Bartlett's test of sphericity also turned out to be significant, showing a positive correlation between the variables (Table 3).

$$\begin{aligned} \text{NDVI} = & -0.128\text{CTI} - 0.125\text{Precipitation} \\ & + 0.009\text{Temperature} + 0.062\text{PETR} \\ & + 0.978\text{Aspect} + 0.032\text{slope} \\ & + 0.076\text{Elevation} \end{aligned} \quad (12)$$

According to Table 4, while there are significant correlations between NDVI and elevation, PETR, temperature, and precipitation, the other three topographic factors have weak correlations with NDVI. The stepwise regression model of NDVI was calculated as follows:

$$\begin{aligned} \text{NDVI} = & 0.224047 + 0.000303135 * \text{CTI} \\ & + 0.000289835 * \text{Precipitation} - 0.034088 * \text{Temperature} \\ & - 0.0000320768 * \text{Aspect} - 0.00079407 * \text{slope} \\ & + 0.0000360153 * \text{Elevation} + 0.000335999 * \text{PETR} \end{aligned} \quad (13)$$

Fig. 12 shows the relationship between NDVI values which have been measured via image and model ($R^2 =$

Table 3 Kaiser-Meyer-Olkin (KMO) and Bartlett's test

Kaiser-Meyer-Olkin measure of sampling adequacy			0.750
Bartlett's test of sphericity	Approx. chi-square		5.366E3
	df		28
	Sig.		0.000

Table 4 Relevant statistical parameters of NDVI’s Ridge regression analysis and multi-factors (ridge coefficient = 0.1088)

Parameter	Estimate	Variance inflation factor	Tolerance statistic	Partial correlation coefficient
Constant	0.224047			
CTI	0.000303135	1.09357	0.914	0.006
Precipitation	0.000289835	1.49248	0.67	0.589
Temperature	-0.034088	1.15498	0.8658	-0.689
Aspect	-0.0000320768	0.843147	1.186	-0.046
slope	-0.00079407	1.08946	0.917	-0.011
Elevation	0.0000360153	1.56741	0.637	0.6
PETR	0.000335999	1.61682	0.618	-0.7
mean		1.26	0.83	

0.71). As the results show, more than 95% of the study area was covered with less than 30% vegetation, and the remaining 5% of the area that belonged to farmlands and agricultural areas was covered with more than 30% vegetation. Having been located at upper 2500-m elevation and thus receiving more precipitation than other regions, the north and west parts of the study area have more vegetation than the other ones. The south and the east parts of the area, which are located at lower than 2000-m elevation and have less precipitation and higher temperature in comparison with the higher aspects, are covered with less than 15% of vegetation. It should also be noted that the lowest percentage of vegetation belongs to the areas in which poor human management has destroyed vegetation.

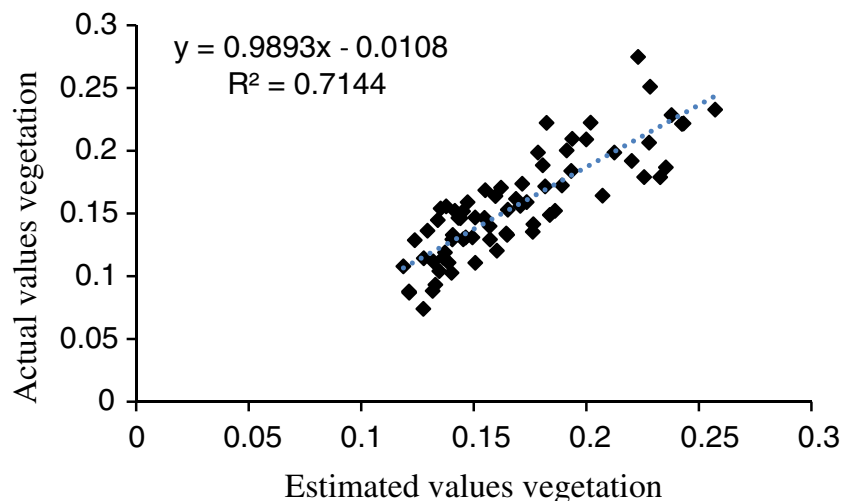
Discussion

This study investigated the effect of elevation on precipitation and proved that there was a significant correlation between elevation and relevant topographic factors. Accordingly, it could be argued that with the rise of elevation, the

precipitation increases while the temperature and PETR decrease (Zeng and Yang 2008). Furthermore, the findings of the study indicated a significant correlation between temperature variations and PETR which was consistent with what Kosa (2009) found in his study on Sri Songkhram basin in Thailand. The investigation of the effect of climate factors on NDVI proved their influence on vegetation (Kayiranga et al. 2017). The findings of also indicated that there was a positive correlation between NDVI and precipitation and a negative correlation between NDVI and temperature. As water is considered the main restrictive factor for the plant’s growth in arid and semi-arid regions, an increase in precipitation, therefore, leads to an increase in vegetation, creating a positive correlation between the two variables, while an increase in temperature leads to the decrease in vegetation, making a negative correlation between the two (Shi et al. 2019). These results are consistent with those of the Runnstorm’s study (2003) who proved that precipitation and its distribution patterns were effective on NDVI variations.

In this study, NDVI and precipitation were found to have similar trend, with their values increased from the east to the west and north; a fact that shows the positive role of

Fig. 12 Actual vegetation percentages vs. the estimated ones, using NDVI



precipitation in vegetation distribution especially in semi-arid regions. Fang and Zhang (2013), also, reported that in their study NDVI increased with the decrease of precipitation from the east and southeast to the west and northwest of the grassland of Ordos region in China. On the other hand, in our study, a reverse correlation was found between NDVI and PETR in most of the investigated areas; thus, as higher PETR means more dryness, the NDVI values (in the study area) decreased with an increase in PETR. A similar correlation between NDVI and PETR has previously been reported by Gao et al. (2012) in Qinghai-Tibet Plateau. In contrast, we observed a positive correlation between NDVI and PETR in some parts of the study area, the reason of which could be attributed to the rise of agricultural lands and cultivated gardens which significantly contribute in increasing PETR. These findings are consistent with the results found by Jin et al. (2009a, b) regarding the effect of PETR variations on the accessibility of water resources in Zangi arid region in China.

Using GWR model, this study investigated the relationship between the topographic factor and vegetation. The findings of the study indicate that there a both positive and negative correlations between NDVI and topographic factors; accordingly, it could be argued that the effect of elevation on human activities and climate may be attributed respectively to the positive and negative correlations between NDVI and elevation. The main reason for the positive and negative correlations between NDVI and elevation is the variations of temperature and precipitation in proportionate with elevation (Tang et al. 2017). Elevation as the most important topographic factor affects hydrology, temperature, light, wind, and consequently the vegetation growth (Moeslund et al. 2013). Regarding the positive correlation of elevation with precipitation and relative humidity, and the negative correlation between elevation and temperature in mountainous regions, it could be argued that NDVI values increase with the rise in elevation which is usually due to the variations of precipitation, agricultural activities, and proximity to surface water resources. However, in high altitudes where the temperature decreases with the rise in elevation, temperature is regarded as the most influential factor on vegetation dynamics (Hu et al. 2019).

As for the positive and negative correlations between vegetation and slope in our study area, it could be said that on steeper slopes, human activities (cutting and browsing damage) usually occur less, and the NDVI is, therefore, higher and this could be the reason for the positive correlation between slope and NDVI (Gao et al. 2012). On the other hand, as the soil on lower slopes has more horizons and depth, it can reserve more water while on higher slopes, much of the water gets out of the reach of the plants as it is turned into runoff; a fact that could be regarded as a reason for the negative correlation between NDVI and slope (Fu and Gong 2015; Shao-fu et al. 2013).

That the vegetation grows more in shaded aspects than in the sunny ones in the study area of this research indicates that vegetation growth depends on the variations found in geographical locations. As shaded aspects have low temperature and evaporation rates, they provide a much better ground for the distribution and growth of vegetation (Jin et al. 2009a, b; Shao-fu et al. 2013). Sunny hills receive more sunlight than the shaded ones which enhances the photosynthetic ability of the plants to grow, resulting in a positive correlation between NDVI and aspect (Zapata-Rios et al. 2015).

In ecosystems, proper location for the establishment and development of the plants' root system is a very significant factor in providing sufficient moisture for the plants throughout the dry seasons. The fissures within the rock and their permeability, or in other words, the type of formation, play an important role in the establishment of the plants that's why the plants are mostly developed on formations with accessibility to water.

Having observed the highest NDVI values in Kashkan and Asmari formations, we found in this study that the materials of a formation and their permeability are effective on NDVI (Fig. 9). As mentioned earlier, this could be attributed to the materials of a formation, as the upper parts of Kashkan formation are composed of conglomerate and siltstone-interbedded sandstone with medium permeability. Moreover, this formation has many springs that, quantitatively and qualitatively, are considered moderate/good water resources. It should be noted that in those formations that can preserve more water for the plants, vegetation grows more. Furthermore, any change in a geological formation will change the physical and chemical properties of soil, geomorphic face, and finally the vegetation (Vogiatzakis et al. 2003).

Asmari formation is composed of calcareous, massive, durable, and jagged rocks, and due to its structural features such as being equipped with plenty of fractures, faults, and joints, it could desirably influence the basin water resources both qualitatively and quantitatively and preserve a considerable amount of precipitations. The findings of this study confirm the ones found by Soleimani et al. (2008) who argued that the changes in vegetation were mainly influenced by the type of soil and geological formation. Various other studies including the Fang and Zang (2013) and Huang et al. (2008) have also reported that geological faults and the materials of the substrata play an important role in the evolution, diversity, and distribution of vegetation in semi-arid regions.

The current study also found a significant correlation between the NDVI values measured from image and the estimated values of the model ($R^2 = 0.71$). The findings of this study are comparable with some other studies carried out in the same regard. For instance, Wu et al. (2017) argued that NDVI was the most appropriate index for investigating the distribution and changes of vegetation. Moreover, in another study

conducted by Baugh and Groeneveld (2006) in Colorado (which is regarded as an arid land), USA, it was found that the accuracy of NDVI in estimating the vegetation percentage was higher than those of other similar indexes. However, land-cover indices might be used as independent factors in multiple regression equations so that NDVI could be measured more accurately through a factor analysis.

Conclusion

In this study, vegetation variations in Kharestan basin were investigated using Landsat ETM7 NDVI data for the time period of 2000–2017. Climatic and topographic factors in each geological formation were explored as the main forces affecting vegetation variations. The distribution of high values of NDVI was mainly observed in the central and low-NDVI areas located at the upstream and downstream of the basin. There was a correlation between NDVI and precipitation, temperature, and evapotranspiration. As a result, vegetation patterning was dependent on climatic factors and increased with the rise of precipitation to the west and north of the study area, whereas it showed a reverse trend with temperature, indicating the significance of topographic factors in vegetation patterning. At elevations below 3000 m of the study area, NDVI increased with the rise in elevation, with the highest vegetation growth observed at low elevations. With the rise in slope up to 15 degrees, NDVI increased too. The distribution of vegetation was more in the shaded hills than the sunny ones. Moreover, maximum NDVI was observed in Kashkan and Asmari formations which could be due to their nature and permeability. Because of the heterogeneous topography of mountainous regions, vegetation is affected by topographic factors there. It could be argued that each single parameter of height, slope, aspect, CTI, precipitation, temperature, and evapotranspiration potential alone has no significant correlation with NDVI, but if they are considered concurrently as the effective factors on NDVI, they would show a stronger relationship with it. From among the factors mentioned, precipitation, temperature, and evapotranspiration potential had the strongest correlation with NDVI. It could generally be stated that topographic (elevation, aspect, and slope), as well as geological factors (such as the type of formation, rocks fissures, and their permeability), should, in addition to climatic conditions, be taken into account in the investigation of vegetation patterning. Differences of geological formations result in differences in the population and processes of ecosystems which in turn lead to the development of different strategies for their conservation and management.

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