Research Article
doi: 10.1590/01047760202430013269
vol(30), 2024

CERNE

Spatiotemporal dynamic of oak forest greenness in response to climate change derived drought

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FOREST ECOLOGY

ABSTRACT

Background: Climate change, which has mainly manifested in Iran in the form of intensifying periods of drought, can have profound effects on the valuable forest ecosystems of Zagros in the west of Iran. In this study, the drought trend in the period from 2000 to 2020 was investigated on the spatio-temporal dynamics of greenness of Zagros oak forests in Kohgiluyeh and Boyer Ahmad province in the west of Iran. SPI, PDSI, NDVI and EVI with modeling their relationship based on GWR was used. Also, based on two climate change scenarios RCP2.6 and RCP8.5, the simulation of drought conditions and changes in forest greenness until 2050 were studied.

Results: The results showed that the peak greenness of the oak forests has a significant sensitivity to changes in rainfall and drought at the end of the cold period of the year and in the spring season. The negative phases of the drought have been completely consistent with the periods of greenness loss. Also, both the greenness and the area of the oak forests have decreased. The EVI index showed the highest sensitivity to the PDSI, and the developed model based on these two indices had a spatial explanation coefficient between 40 and 70%.

Conclusion: The implementation of the developed model under two scenarios showed that the forest greenness will face a decrease of about 25% in the RCP8.5 scenario and about 15% in the RCP2.6 scenario until 2050. The relationship between drought and forest decline was proven in this study.

Keywords: Forest decline; EVI; NDVI; PDSI; Zagros.

HIGHLIGHTS

The greenness of the oak forests is sensitive to rainfall and drought at the end of the cold period of the year and in the spring season.
The greenness and the area of oak forests has been reduced.
EVI has shown the highest sensitivity to drought.
The greenness of oak forests will decrease in both climate scenario until 2050.

DAGHESTANI, M.; MOTLAGH, M. G.; HALIMI, M. Spatiotemporal dynamic of oak forest greenness in response to climate change derived drought. 2024, CERNE, v.30, e-103269, doi: 10.1590/01047760202430013269.

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Received: May 24/2023 Accepted: October 29/2023

Open Access
CERNE
ISSN 0104-7760
UNIVERSIDADE FEDERAL DE LAVRAS

INTRODUCTION

The forests of Zagros, as the largest vegetation area of Iran, with an area of about 5 million ha, constitute 40% of the total forests of Iran (Ghanbari Motlagh et al., 2020). This vegetation region is classified as semi-arid forests (Yaghmaei et al., 2022; Zand et al., 2022; Azizi et al., 2015). About 70% of Zagros Forest species are Quercus sp.(Imanyfar et al., 2019; Shiranvand and Hosseini, 2020b). As the second natural forest ecosystem in Iran, these forests play a very valuable role in providing water resources, preventing soil erosion, protecting plant and animal biodiversity, adjusting climate, economic, and social balance in Iran (Hosseni et al., 2017; Alirezaii et al., 2019). However, unfortunately they are facing many environmental problems. One of the issues that is known as the most important environmental threat of Zagros forests is the increasing drying of oak trees (Attarod et al., 2017; Zand et al., 2022; Ghanbari Motlagh et al., 2020). One of the most important early symptoms of the oak decline crisis is the occurrence of dryness in the tree crown; which may cause the complete drying of the tree and its death (Touhami et al., 2020; Ghanbari Motlagh et al., 2023).

In the forests of Zagros, although there are many factors involved in this situation and they should be identified through detailed studies, one of the main factors can be considered successive droughts, which reduce the greenness, health, and function of the forest canopy. Various studies have shown that drought, as one of the climatological hazards, has had significant effects on the vegetation of Zagros oak forests in western Iran and the crown decline of its forests (Imanyfar et al., 2019; Attarod et al., 2017; Shiravand and Hosseini, 2020; Alirezaii et al., 2019).

Drought is a continuous and unnatural lack of moisture in a certain period of time, which is usually one year (Filizzola et al., 2022; Allen et al., 2010; Morid et al., 2006). Drought causes a reduction in soil moisture through a decrease in rainfall. With the gradual reduction of available soil moisture, water loss occurs in plant tissues and organs, and its primary result appears as wilting and decrement in greenness appears in the crown of the tree. Finally, it leads to the gradual weakening and decline of trees (Anderegg et al., 2015; Zhou et al., 2018; Kloos et al., 2021; Gulácsi and Kovács, 2018; Prăvălie et al., 2022; Shiravand and Hosseini, 2020). Drought indirectly causes a sharp increase in the death of trees through the creation of fine dust, the occurrence of new pests and diseases, and the destruction of biological diversity in the soil. In addition, drought is one of the natural disasters that can affect the density and area of vegetation in any region, especially dry regions (Allen et al., 2010; Zhou et al., 2018; Enríquez-de-Salamanca 2022; Khosravi et al. 2016; Prăvălie et al., 2022).

The effects of drought on the vegetation appear gradually. Therefore, if the extent of changes in vegetation cover is monitored on satellite images, it is possible to identify the destructive characteristics of drought on time by examining the changes with the gradual reduction of the greenness of the vegetation cover (Anderegg et al., 2015; Filizzola et al., 2022; Guo et al., 2018; Zhang et al., 2017; Marqués et al., 2022). Also, considering drought management, information should be obtained from the time period before the occurrence of drought, when it occurs and after it. Thus, revealing the spatiotemporal dynamics of forest greenness in response to drought is very important (Zhao et al., 2022; Rahimzadeh Bajgiran et al., 2008; Alirezaii et al., 2019). One of the important and basic steps in the studies of drought and wetness in each region is to determine the indicators that can be used to evaluate the severity and continuity of drought and wet years. Most of these indices are based on meteorological criteria and examine variables such as soil moisture, temperature, and especially precipitation (Kloos et al., 2021; Morid et al., 2006; Tan et al., 2015). Among the most effective and widely used indices are the Palmer Drought Severity Index (PDSI) (Palmer, 1965) and the Standard Precipitation Index (SPI) (McKee at al., 1993), Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) (Filizzola et al., 2022; Rahimzadeh Bajgiran et al., 2008; Prăvălie et al., 2022).

The relationship between the death as well as decline of trees in the forests of the world and climate changes related to drought and heat stress has been shown in several studies using climate and satellite indicators (Allen et al., 2010; Anderegg et al., 2015; Filizzola et al., 2022; Enríquez-de-Salamanca 2022; Marqués et al., 2022; Scharnweber et al. 2011; Klos et al., 2009; Moore et al., 2016; Senf et al., 2022; Zhang et al., 2017; Prăvălie et al., 2022; Samanta et al., 2010; Saleska et al., 2007; Ji and Peters, 2003; Gu et al., 2007; Tan et al., 2015; Zhou et al., 2018). Therefore, it is necessary to test the compatibility of the hypothesis of the relationship between climate changes plus droughts and the extent along with spatiotemporal dynamics of canopy decline and greenness reduction of Zagros forests.

This study was carried out in a part of the Zagros oak forests in the west of Iran, in the province of Kohgiloyeh and BoyerAhmad. The objectives of this study are: - Spatiotemporal monitoring of drought trends and greenness indices of forests in the period 2000-2020 using satellite greenness indices (NDVI/MODIS and EVI) and drought indices (SPI and PDSI); -Examining the relationship between greenness and drought indices through the development of the GWR model and determining the appropriate index; -Simulation of future drought conditions in the region based on two climate change scenarios RCP2.6 and RCP8.5; - Prediction of changes in forest cover and greenness until 2050 based on this simulation.

MATERIAL AND METHODS

Study area

The study area of this research is Kohgiloyeh and Boyerahmad province in western Iran. Morphologically, this province is a part of the Zagros mountain range, and therefore the forests of this province are also part of the Zagros oak forests. Due to the variety of altitude from less than 150 meters to more than 4200 meters, rainfall and suitable temperature, this province has a variety of climate and vegetation. About 8740 km^2 of Zagros forests in Iran are located in this province and in the oak vegetation zone of Zagros, it is the fourth province in terms of forest area. Iranian oak (*Quercus brantii*) is the dominant species in the forests of the province. Most of the oak habitats of the province are in the northern part with a northwest-southeast trend. (Kohgiluyeh and Boyerahmad Province Land use planning, 2015) (Figure 1).

Database of vegetation greenness indices

In this research, the EVI and NDVI indices obtained from the time series data (2000-2020) of the MOD13A3 product of the MODIS sensor were used to determine the greenness of the forest cover. (https://modis.gsfc.nasa.gov). (This index is calculated based on the relationship in Table 1). The values of this index are between -1 and +1 and tend to be 1 for dense vegetation (Allen et al., 2002; Gu et al., 2007). Another remote sensing index that is more efficient than NDVI in forest environments is the EVI (which the formula of this index is presented in Table 1)(Filizzola et al., 2022; Zhou et al., 2018; Huete et al., 2002; Abdi et al., 2018). This index is between -1 and +1. In fact, EVI is a modified NDVI in which the adjustment factor of forest cover (L) and two coefficients C_1 and C_2 are considered (Huete et al., 2002).

Determining the experimental threshold of forest cover

To determine the threshold of forest cover based on the two mentioned greenness indices, a targeted sampling of 20 points of oak forests with high health canopy in the province was used. The location of these sampling sites was recorded using a GPS device in the WGS1984 coordinate system. All samples were selected from healthy oaks that did not show signs of decline such as yellowing of leaves and brown gum discharge. By comparing the location of these field samples with that of the same points on the images, the threshold value of the indices was considered as the threshold of the presence of green and health oak forests. These experimental samplings were carried out monthly in 20 sites of the province from April to November 2021, where the values of EVI and NDVI indices were changed for these 20 locations from the MODIS product (Alirezaei et al., 2019). The results of the investigation in this study revealed that the month of June coincided with the peak greening period of the oak tree in the province. The average greenness of this month in these sites was obtained based on EVI and NDVI indices (Alirezaei et al., 2019). Next, the spatial map of the distribution of the monthly greenness indices of the oak forests of the province was created based on the threshold values obtained in June (greenness peak) for the study period in the ArcGIS environment, where its minimum, maximum, and average values were obtained during the study period.

Drought information database

Drought indices used in this study have been Palmer Drought Severity Index (PDSI) and Standard Precipitation Index (SPI). The two mentioned indices are known as the most important and common indices for drought detection and monitoring. These indices are based on rainfall data. The monthly rainfall data of 10 synoptic stations of Kohgiluyeh and Boyerahmad province for the statistical period of 2000 to 2020 were extracted from Iran's

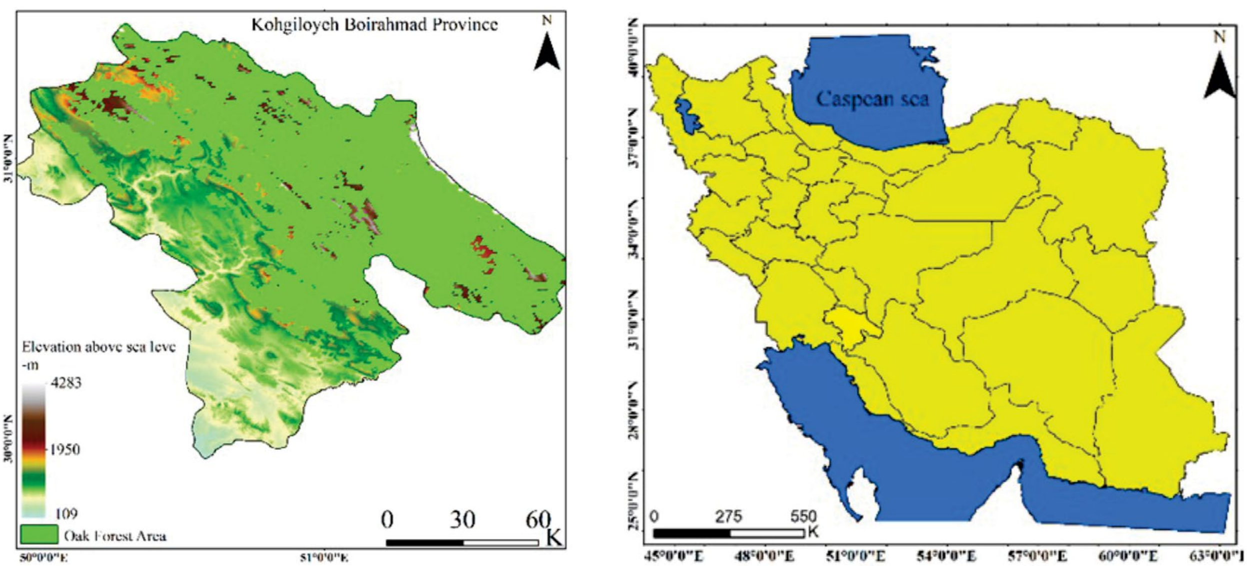

Figure 1: Location of the Study area (Kohgiloyeh and Boyerahmad Province of IRAN).

meteorological website. (www.irimo.ir). Next, the kriging interpolation method was used in the GIS environment to generate the precipitation layer (Abdi et al., 2018; Azizi et al., 2015; Zand et al., 2022). The SPI is the most widely used index for drought monitoring, which is based only on the annual or monthly rainfall recorded at the meteorological station (McKee et al., 1993). (In this method, the values of SPI are extracted using the relationship in Table 1), with different severity of drought and wet years classified according to Table 1. In this method, the drought period starts when the SPI values are continuously negative and reaches a value of -1 or less, and ends when the SPI values become positive (Table 1) (Abdi et al., 2018; Zhang et al., 2017; Khosravi et al., 2017).

Table 1: Classification of drought severity based on SPI index.

Index Value	Class
More than 2	Extremely wet
1.5 to 1.99	Very wet
1 to 1.49	Moderate wet
-0.99 to 0.99	Near normal
-1 to -1.49	Moderate dry
-1.49 to -1.99	Severely dry
-2 and less	Extremely dry

Another index is PDSI, which was presented by Palmer in the early 1960s as a standard method for quantifying drought. Palmer formulated a simple water balance model using variables of precipitation, temperature, and available soil moisture (Klos et al., 2009). To calculate it, the parameters related to soil moisture should be estimated, including the evapotranspiration index, moisture loss, moisture supply, and runoff under both actual and potential conditions.

Based on Palmer's definition, dry and wet periods are classified by this index in the Table 2 (Palmer, 1965).

Table 2: Drought severity classification based on Palmer index.

Index Value	Class	Code
less -4	Most severe drought	D_4
-4 to -3	Severe drought	D_3
-3 to -	Moderate drought	D_2
-2 to -1	Mild drought	D_1
-1 to +1	Near Normal	N
+1 to +2	Mild wet	W_1
+2 to +3	Moderate wet	W_2
+3 to +4	Severe wet	W_3
More than +4	Most severe wet	W_4

Detecting the dynamics of forest greenness in response to droughts

In order to determine the logical relationship between the variables of drought indices and greenness indices of the forest zone, Pearson Correlation Coefficient analysis was used at the probability level of 0.95 (P-Value = 0.05). (Tong et al., 2017; Ji and Peters, 2003). EVI-Jun and NDVI-Jun indices were considered as independent variables (x) while SPI, PDSI, and precipitation as dependent variables (y) in the study period. This correlation model not only shows the sensitivity and monthly changes of forest greenness to variations in precipitation and drought, but also specifies the key months that affect greenness (Table 3) (Ji and Peters, 2003). Next, the scatter plot of this relationship was prepared in the EXCEL software.

To calculate the SPI index, the monthly rainfall or total rainfall in any desired time period (3 months, 6 months, etc.) can be fit using an appropriate distribution such as gamma distribution or Pearson type three (Edwards and McKee, 1997). In this study, the SPI was used in the time scale of 3 months (Khosravi et al., 2017; Morid et al., 2006). For this purpose, after ensuring the homogeneity of the rainfall data of the stations, the time series of the 3-month data and the fitting of the data were done. The results obtained from the appropriate fit of the gamma distribution were compared to other methods (Morid et al., 2006). g(x) is the probability density function of the gamma distribution The relevant relationships are presented in Table 3.

Finally, using the last two relationships, the standard normal distribution with zero mean and standard deviation of 1 is obtained, with the obtained results being the SPI value (Table 3) (Morid et al., 2006). The PDSI index includes 8 components, whose formulas and calculation methods are explained in Table 3 (Palmer, 1965). Palmer uses the two-layer soil model and calculates the potential evapotranspiration using the Thornthwhite method. (Thornthwaite, 1948). The values of these components are closely related to AWC. The calculation of AWC depends on the soil texture, whose values are obtained for different soils from the table provided by the American Soil Protection Organization. These values are determined according to the soil texture taken from the geological map of the Geological Organization of Iran according to the geographical coordinates of the meteorological stations. (Klos et al., 2009).

Along with the calculation of potential values (PR, PRO, PL, PET), their actual values (L, RO, R, ET) are also calculated. The rules for determining these four actual values are very complex and depend on the relationship between precipitation and potential evapotranspiration. The values of these components are calculated based on the climate of each region and with the help of α, β, γ and δ coefficients, which are called water balance coefficients. They are the average ratio of each of the actual values to the potential values. The relations are available in Table 3. Palmer drought severity index for each specific month (X_i) is obtained from the final equation of Table 3 (Alley, 1984; Palmer, 1965). The spatial distribution of greenness index (EVI-Jun/NDVI-Jun) of the oak forests is presented in Figure 2a and 2b.

Table 3: Characteristics of the indices used in the study.

References	Parameters	Formula	Index	number
McKee at al. (1993)	SPI: Drought index P_i: Average rainfall each year $\bar{P}$: Average rainfall during the study period SD: Standard deviation of precipitation in the study period g(x) probability density function of gamma distribution x is the amount of precipitation, $\Pi(\alpha)$ represents the gamma function, α is the shape parameter, β is the scale parameter. The parameter values of this formula must be greater than 0. n number of rainfall observations, $\bar{X}$: average rainfall of the desired time period Since the gamma function for 0 precipitation cannot be defined and the real precipitation data always includes a large number of observations with zero precipitation, the cumulative probability function of precipitation (H(x)) is calculated in another way. q is the probability of zero rainfall and p = 1 – q. H(x) is the cumulative probability function. In these relationships, c and d are constant values. d_1 = 3.43278 d_2 = 0.18929 d_3 = 0.003308 c_0 = 2.535537 c_1 = 0.802853 c_2 = 0.030328	$SPI = \frac{P_i - \bar{P}}{SD}$ $g(x) = \frac{1}{\beta^{\alpha}\ \Pi(\alpha)} x^{(\alpha-1)}\ e^{(-x/\beta)}$ $\alpha = \frac{1}{4A}\left(1+\sqrt{1+\frac{4A}{3}}\right)$ $\beta = \frac{\bar{x}}{4A}$ $A = \ln(\bar{x}) - \frac{\sum \ln(X)}{n}$ $g(x) = \frac{1}{\Pi(\alpha)}\int_0^x t^{\alpha-1}\ e^{-1}dt$ $H(x) = q + pg(x)$ $SPI = -\left[t - \frac{c_0 + c_1\ t + c_2\ t^2}{1 + d_1\ t + d_2\ t^2 + d_3\ t^3}\right]$ $0 < H(x) \le 0.5$ $SPI = +\left[t - \frac{c_0 + c_1\ t + c_2\ t^2}{1 + d_1\ t + d_2\ t^2 + d_3\ t^3}\right]$ $0.5 < H(x) < 1$	SPI	1
Palmer (1965) and Alley (1984)	*PET*: Potential Evapotranspiration *ET*: evapotranspiration *PR*: Moisture retention potential *R*: Moisture retention *PRO*: Runoff Potential *RO*: Runoff () *L*: moisture loss *PL*: Potential moisture loss *AWC*: Available water content *Ss*: Surface soil moisture content *Su*: Subsoil moisture content Coefficients α, β, γ and δ which are coefficients of water balance, i represents the month of the year. *P*: Actual precipitation each month $\hat{P}$: Hypothetical precipitation *D*: changes in humidity *Z*: Humidity anomaly index $\bar{D}_i$ is the absolute mean values of D for the ith month. K_i is climatic characteristics. Z_i Humidity anomaly index of each month X_i: Palmer drought severity index for each specific month	$PR = AWC - (Su + Ss)$ $PRO = AWC - PR = Su + Ss$ $PL = ((PET - Ss) \times Su\ ) / AWC + Ss$ $\alpha_i = \frac{\overline{ET}_i}{\overline{PET}_i}$ $\beta_i = \frac{\bar{R}_i}{\overline{PR}_i}$ $\gamma_i = \frac{\overline{RO}_i}{\overline{PRO}_i}$ $\delta_i = \frac{\bar{L}_i}{\overline{PL}_i}$ $D = P - \hat{P}$ $\hat{P} = \alpha_i PE + \beta_i PR + \gamma_i PRO + \delta_i PL$ $Z = D \times K_i$ $K'_i = 1.5 \times log_{10} \frac{\left[\frac{\overline{PET}_i + \bar{R}_i + \overline{RO}_i}{\bar{P}_i + \bar{L}_i} + 2.8\right]}{\bar{D}_i} + 0.5$ $K_i = \frac{17.67K'_i}{\sum_{j=1}^{12}\bar{D}_i \times K'_i}$ $X_i = 0.897\,X_{i-1} + \frac{1}{3}Z_i$	PDSI	2

Continue...

Table 3: Continuation.

References	Parameters	Formula	Index	number
Tucker et al. (1979)	P_{NIR}: Reflection in the infrared region R_{RED}: Reflection in the red region	$NDVI = \frac{P_{NIR} - R_{RED}}{P_{NIR} + R_{RED}}$	NDVI	3
Huete et al. (2002)	*EVI*: Enhanced Vegetation Index P_{NIR}: reflectance in the near infrared region P_{RED}: Reflection in the red area R_{BLUE}: reflection in the blue band $L = -1$, $C_1 = -6$ $C_2 = -7.5$ are adjustment factor or soil background, atmospheric resistance factor or atmospheric correction, respectively.	$EVI = \left[\frac{P_{NIR} - P_{RED}}{P_{NIR} + C_1 R_{RED} - C_2 R_{BLUE} + 1}\right]_{1+L}$	EVI	4
Ji and Peters (2003)	*n*: number of series observations, x_j and x_k are the data of jm and km series, respectively *r*: correlation coefficient	$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$	(Pearson Correlation Coefficient)	5
Fotheringham et al. (2002)	*y*: EVI/NDVI in location u *x*: SPI/PDSI2050 in location u. β: model spatial weighted	$y_i(u) = \beta_{0i}(u) + \beta_{1i}(u)x_{1i} + \beta_{2i}(u)x_{2i} + \ldots + \beta_{mi}(u)x_{mi} +$	GWR (Geographicaly Weigted Regression)	6

Development of GWR model in order to simulate future conditions and reveal the effect of climate change

In this research, to simulate the effect of droughts caused by climate change on the on the spatiotemporal changes in greenness of the oak forests, 2 scenarios of the release of the fifth IPCC report, namely RCP8.5 and RCP2.6 scenarios in 2050, were used. Future rainfall and temperature data were obtained from the output of HADGM2-AO atmospheric general circulation model for two scenarios in 2050 (Heydari Alamdarloo et al., 2021). Based on the calculation method of drought indices (which was explained in section 2), the final values obtained from them were entered into ArcGIS software in order to prepare Map of drought indices. In this way, the drought prediction map was made based on 2 scenarios until 2050.

After the spatial correlation analysis determined which months the drought is the main driver of the change in the greenness of the forest area (paragraph 3), using these main drivers (drought index with a higher correlation coefficient in section 3), to developed a spatial GWR model. This model was used to simulate the forest area, under the predicted drought conditions of 2050, under the mentioned two emission scenarios. The values of forest greenness in the current period of 2000-2020 was entered as a dependent variable and the simulated values of the drought index of 2050 under two scenarios were entered into the model as an independent variable or estimator. (The general form of the developed GWR model is presented in Table 1). A map of greenness index values based on drought index in 2020, two maps of greenness index prediction values based on predicted values of drought index under two scenarios until 2050 were made in ArcGIS.

RESULTS

1) The spatio-tempotal trend of droughts and greenness in oak forests

By investigating the annual changes in the extent of greenness of the forest cover in Kohgiloyeh and Boyerahmad province during the 20-year study period, using two vegetation indices (EVI and NDVI) on a monthly basis, indicated that the highest spatial average of greenness in the forest cover of the province was in the period of 3 months, namely May, June and July, reaching its peak in June. In this month, the spatial average of greenness in the forest cover of the province reached 0.3 based on the NDVI and 0.26 based on the EVI (Figure 3). Also, the greenness index values of oak trees in the peak month of greenness, i.e. June, were on average >0.2 for EVI and >0.25 for NDVI.

The results of this periodic survey revealed that during the 20-year period, both the greenness index of the oak forests and the area of the oak forests have had a declining trend with fluctuations. In 2000, the spatial average of the greenness index based on the NDVI was equal to 0.28 and based on the EVI was equal to 0.25. The NDVI index first dropped in 2002 and after 2006 experienced a downward trend until 2016. It has shown the lowest values in 2007, 2009, and 2016 and the highest values in 2001, 2019, and 2005. After 2016, it revealed an upward trend until 2019, but at the end of the studied period, i.e. 2020, a reduction was seen again. The lowest value of EVI has been reported in 2006, 2007, 2009, and 2016 and the highest value in 2001, 2005, and 2019. This index has shown changes similar to NDVI. It had a first decline in 2002, an ascending trend until 2006 and then a descending trend until 2016 (Figure 4).

(a)

(b)

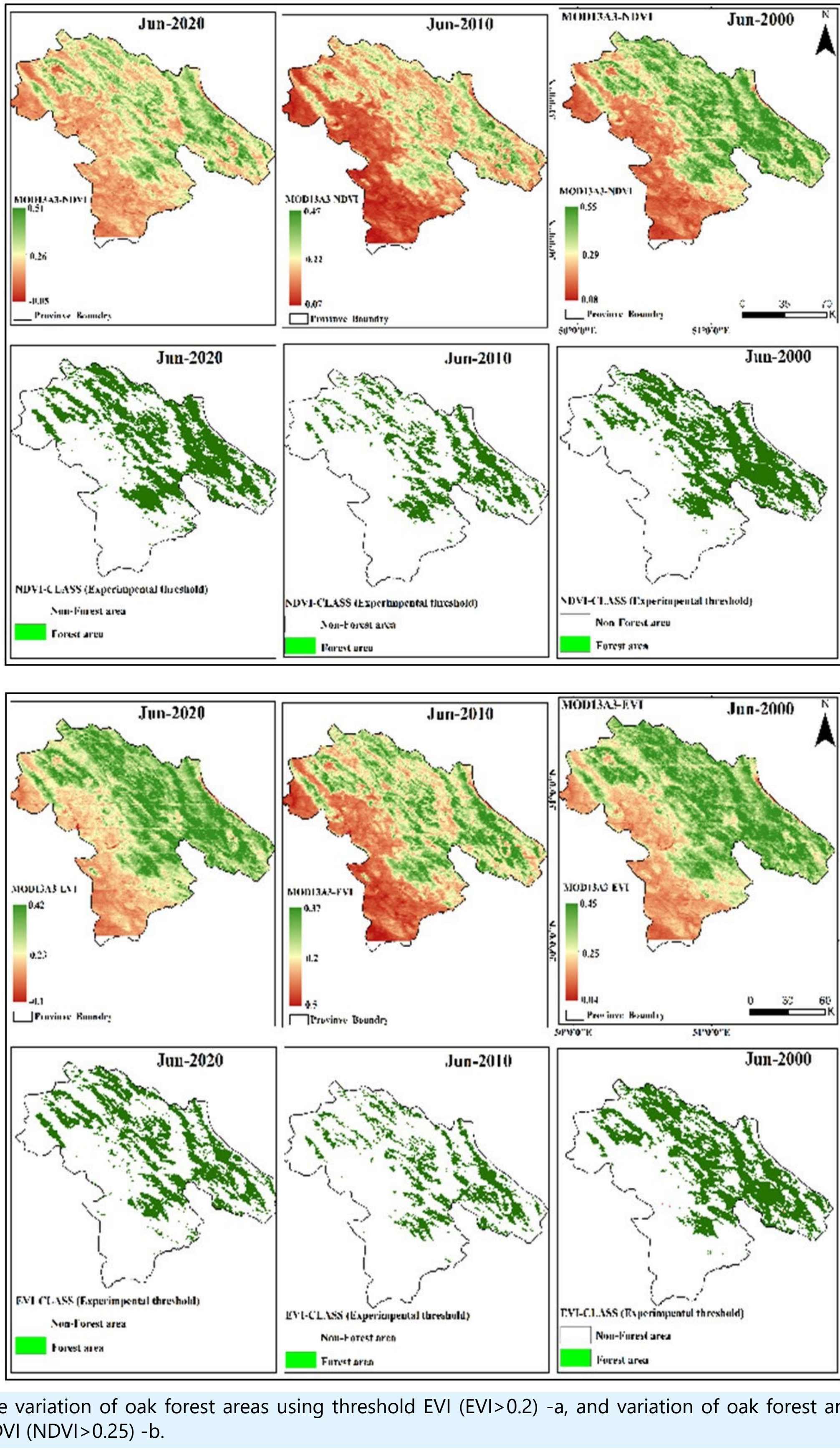

Figure 2: The variation of oak forest areas using threshold EVI (EVI>0.2) -a, and variation of oak forest areas using threshold NDVI (NDVI>0.25) -b.

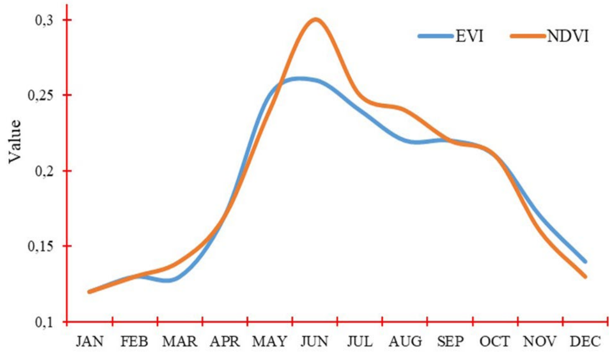

Figure 3: 20 years average of inter-annual MODIS Vegetation Indices Fluctuation.

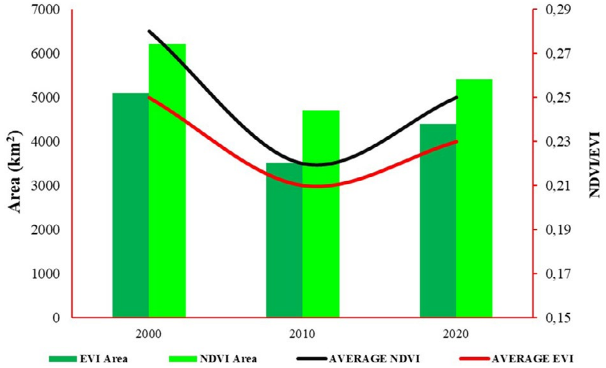

Figure 5: Variation of oak forest area using experimental threshold NDVI/EVI greenness.

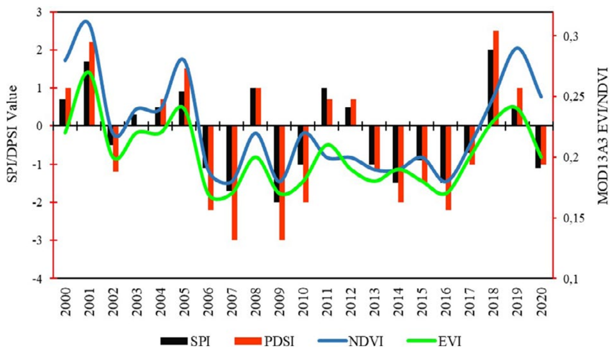

Figure 4: 20 Years trend of spatial average of NDVI/EVI-Jun and MAM-PDSI&SPI.

Analysis of the SPI index trend indicated that the most severe wet years occurred in 2018, 2001, and 2005, and severe droughts in 2009, 2007, 2006, 2016, 2014, and 2010. Two major drought periods were evident from 2006 to 2010, except for 2008 and from 2013 to 2017. Regarding the Palmer index, 2018, 2001, and 2005 have been the rainiest years, while 2009, 2007, 2006, 2002, 2010, and 2014 have been the driest years. The two periods of drought listed in the case of the SPI index have also been clearly observed in this index (Figure 4).

The results of this research showed that the area of the forest zone based on the NDVI in 2000 was equal to 6125 km^2 and based on the EVI, it was equal to 5102 km^2. However, in 2010, this area reached 4710 km^2 based on the NDVI and 3520 based on the EVI with a significant reduction of 24%. km^2 (30% reduction). In 2020, this downward trend compared to 2010 has been adjusted for both indices, but again the area of the forest zone with greenness threshold is lower than in 2000 (Figure 5). Thus, despite the annual and seasonal fluctuations in the amount of greenness and the area of the forest area of the province, in general, the amount of greenness and the area of the area with forest greenness has been decreasing over the 20-year period. This decline in greenness and area has been observed in all parts, but it is more evident in the northern and central parts.

2) Spatial correlation analysis of forest greenness in response to changes in droughts

The results of the spatial correlation analysis between the amount of greenness in June related to both forest greenness indices and the annual spatial distribution of monthly precipitation values have indicated that, the greenness of the forests, with the rainfall of a period of three months before at the beginning of the growing season, the months of March, April, and May (MAM period) have shown significant spatial correlation. Thus, the peak greenness of the forest area of the province in June has a significant sensitivity to the rainfall of the MAM period. Based on this, the precipitation of MAM period is actually the main determinant of changes in the greenness of the oak forests of the province in June. The highest correlation values were observed between EVI and monthly rainfall (This spatial correlation matrix is shown in Table 4).

Also, 20-year 4-variable trend (Figure 4) related to this section shows that the greenness of the forest is affected by the rainfall anomaly in late winter and early spring (MAM). The drought period that prevailed from 2006 to 2010, as well as the period from 2013 to 2017, has significantly reduced the greenness of oak forests. While in the periods that were relatively wet especially in 2005 and 2001, the greenness of the forest area has increased significantly. 2018 has been particularly wet, but due to the transition from a drought period, the results in the greenness of the forest area only seem to have shown themselves in 2019 (Figure 4).

In the scatterplots of Figure 6, it was observed that the greenness of the oak forests, based on two indices, showed a direct significant correlation with the two drought indices MAM-SPI and PDSI of period (average period 2000-2020). Palmer drought severity index in the MAM period has been able to explain 0.59 of the spatial changes of the NDVI index, while the EVI index in the MAM period has explained 0.74 of the spatial changes in the greenness of the forest area (Figure 6a). However the SPI index, which is based solely on precipitation anomalies, has less power than Palmer's index to explain the spatial changes in the greenness of oak forests. The R2 coefficient of this drought index is equal to 0.68 for explaining the EVI index in June and 0.5 for NDVI index (Figure 6b).

Table 4: The Spatio-temporal correlation among NDVI/EVI-JUN threshold and 20 years average monthly rainfall, SPI and PDSI (*P-value= 0.05, ** P-value= 0.01).

	Jun NDVI/ monthly rainfall Correlation(R)	Jun EVI/ monthly rainfall Correlation(R)	Jun NDVI/ monthly SPI Correlation(R)	Jun EVI/ monthly PDSI Correlation(R)	Jun NDVI/ monthly PDSI Correlation(R)	Jun EVI/ monthly SPI Correlation(R)
Jan	0.17	0.12	0.17	0.19	0.2	0.16
Feb	0.21*	0.26*	0.20	0.27*	0.23	0.21
Mar	0.41*	0.44*	0.37*	0.41*	0.36*	0.37*
Apr	0.42*	0.43*	0.35*	0.38*	0.39*	0.35*
May	0.40**	0.42*	0.35*	0.35*	0.34*	0.31*
Jun	0.17	0.12	0.17	0.20	0.19	0.11
Jul	0.012	0.15	0.00	00.00	0.0	0.0
Aug	0.01	0.07	0.01	00.00	0.0	0.0
Sep	0.00	0.05	0.04	00.00	0.09	0.0
Oct	0.00	0.09	0.12	0.09	0.18	0.11
Nov	0.052	0.11	0.12	0.08	0.08	0.05
Dec	0.095	0.14	0.15	0.17	0.11	0.15

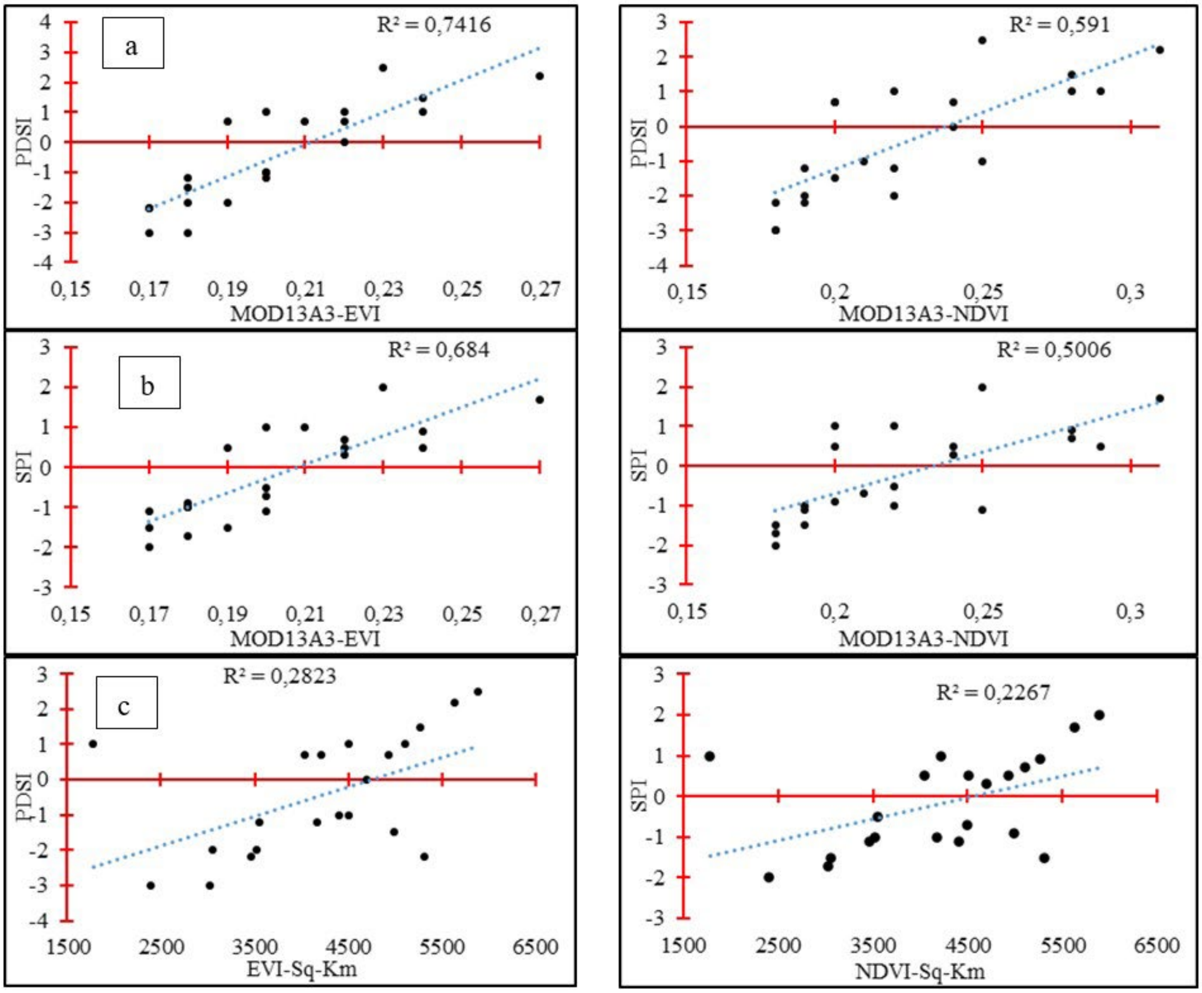

Figure 6: The temporal relationship between spatial average NDVI/EVI- Jun and MAM-PDSI & SPI.

Drought episodes in the MAM period, in addition to the greenness of the forest area, have also affected the forest areas with less intensity. During the period of 2000-2020, the changes in the area of forest areas have had a direct correlation with the drought index, so that years with normal rainfall are associated with the expansion of areas with peak forest greenness, while years with drought or negative rainfall anomaly have been associated with a decrease in forest area (Figure 6c).

3) Detecting the effect of climate change based on the development of GWR model

Next, the drought prediction map was simulated based on the spatial distribution of the MAM-PDSI index (2000-2020), for the period of climate change until 2050, based on the output of precipitation and humidity of the general circulation model HADCM3, the fifth IPCC climate change report, under two emission scenario RCP 8.5 and RCP2.6 (Figure 7).

The results revealed that in 2050, in the RCP2.6 scenario, the simulated MAM-PDSI index for the province is different from the current period (2000-2020) and parts of the northeast of the province will be under moderate drought. The forest area is generally affected by mild and close to normal drought. However, in the RCP8.5 scenario, in 2050, relatively larger parts in the eastern and northern parts of the oak forests are under severe drought (MAM-PDSI<-3). Moderate and mild drought, especially in the central and northern parts of the province, completely covers the forests. In general, the degree of drought in the province has increased from west to east. However, in the study period (2000-2020) there is no severe drought (Figure 7).

Regarding forest greenness (EVI-Jun) in 2050, using the simulated MAM-PDSI index of 2050, under the RCP8.5 scenario, a GWR model was developed. The coefficient of determination of this model (R^2), at the forest area of the region, varied between 0.45 and 0.75. This high explanatory coefficient indicates that the MAM-PDSI index has been able to model the greenness of oak forests (Figure 8a). The re-implementation of the GWR model based on MAM-PDSI related to the RCP2.6 scenario also led to the simulation of the EVI index of 2050. The explanation coefficient of this developed model has varied between 0.47 and 0.85 at the oak forests (Figure 8b).

The extent of simulated forest greenness (EVI-Jun) in the climate change conditions of 2050 under the RCP8.5 scenario, varied between 0.14 and 0.31 in the forests. The average spatial distribution in the oak forests was equal to 0.2, while the same index was relatively higher for the oak forests under the RCP2.6 scenario, which indicates less severe drought conditions. Also, the EVI values under this scenario in the forests of the province were between 0.15 and 0.34 with an average value of 0.22.

Reduction has been observed both in the spatial average of the EVI as well as in the minimum and maximum greenness values of the forest area of the province. While the spatial average of this index in 2050, under the RCP2.6 scenario, was 0.22; compared to the base period, it has shown a reduction of about 0.03. This decrease in the spatial average of the EVI-Jun index in the RCP8.5 scenario has been 0.06, which is almost twice as large in the RCP2.6 scenario. In the maximum greenness (Max EVI-June), the reduction rate in 2050 has been higher in both scenarios (Figure 9). At the same time, as the greenness of the forest zone of the province drops under the climate change conditions of 2050, the spatial changes of the EVI-Jun index in 2050 at the forest zone will grow compared to the base period. In the base period, the coefficient of spatial variability (CV%) of the EVI-Jun index in the forest area was equal to 8%, while in 2050, it will reach 14-16% in both scenarios. This growth in the spatial variability coefficient of the EVI-Jun index indicates the loss of the integrity of the forest cover and decline of the oak forest area of the province (Figure 10).

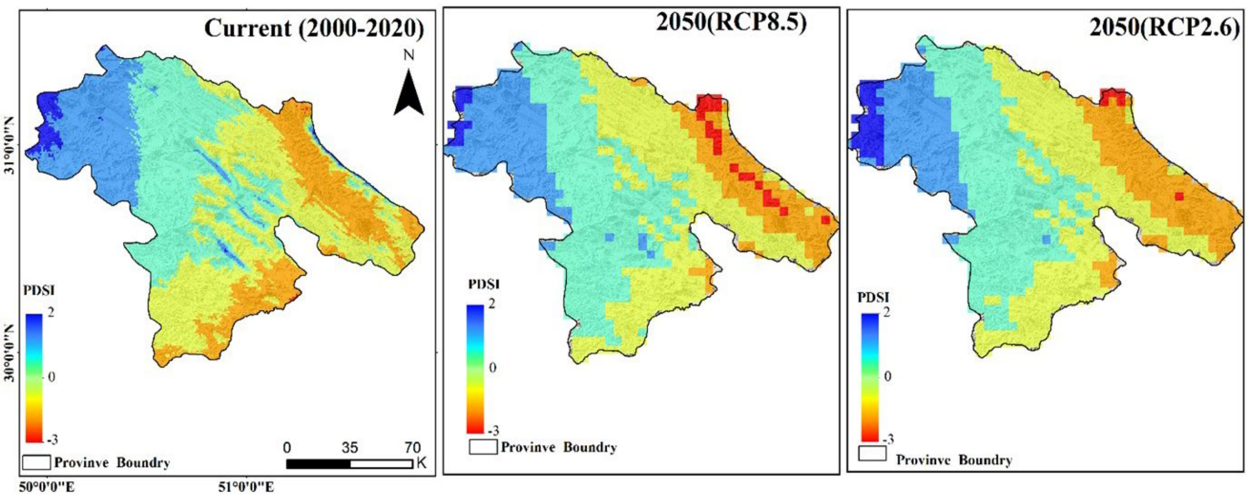

Figure 7: Spatial Distribution of MAM-PDSI in 2000-2020 period and 2050 under 2 scenarios RCP2.6 and RCP8.5.

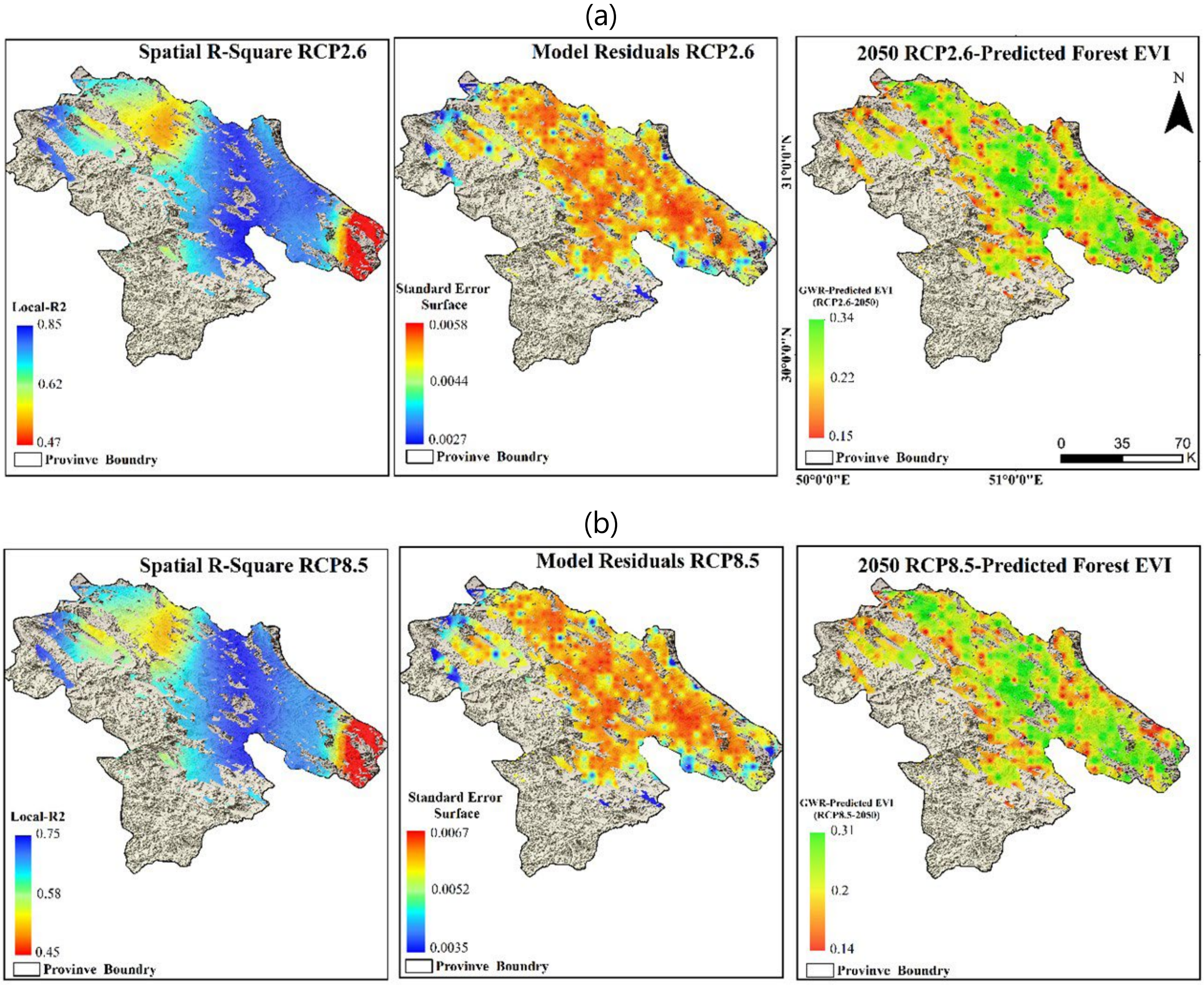

Figure 8: Developed RCP2.6 PDSI-based GWR model for predicting Oak Forest EVI- Jun 2050 -a, and Developed RCP8.5 PDSI-based GWR model for predicting Oak Forest EVI- Jun 2050 – b.

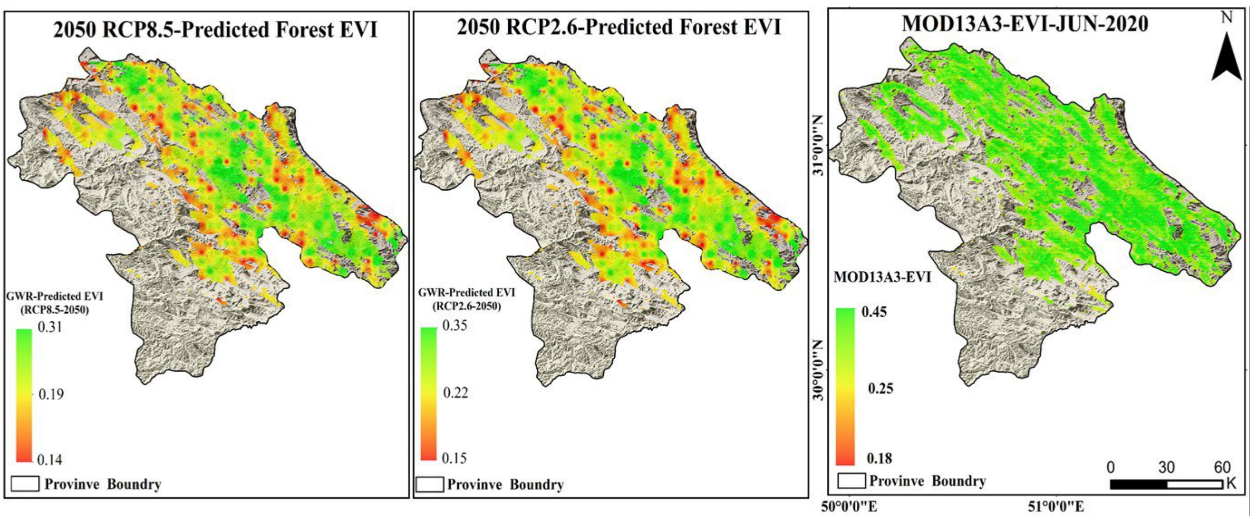

Figure 9: Developed RCP8.5 and RCP2.6 PDSI-based GWR model for predicting Oak Forest EVI-Jun 2050 under 2 scenarios.

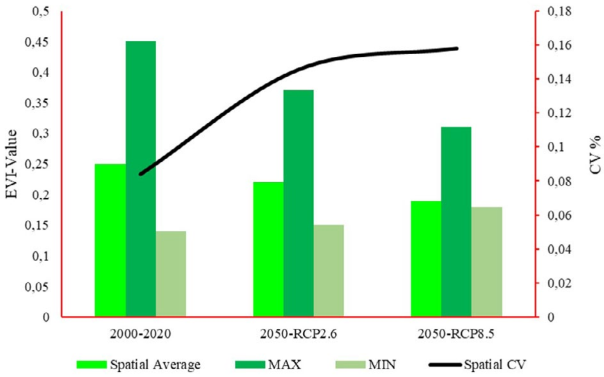

Figure 10: Spatial variation (CV%) of greenness of oak forests during the study period and 2 climate change scenarios.

DISCUSSION AND CONCLUSION

Examining changes in the extent of greenness of the forest cover in Kohgiloyeh and Boyerahmad province during the 20-year period of the study, using two vegetation indices EVI and NDVI, revealed that the highest spatial average of greenness in the forest cover occurred in the period of three months of May, June, and July. The greenness of the forest peaked. Threshold values of greenness index in the peak month of greenness, i.e. June, were >0.2 for EVI and >0.25 for NDVI. In the study of Azizi et al. (2015), on the oak forests of Ilam province in the west of Iran, the peak of greenness (NDVI/MODIS) was reported in May, and Alirezaii et al. (2019) reported EVI threshold > 0.4 as forest cover threshold in Lorestan province. The 20-year spatial distribution of two greenness indices in June showed that both the values of greenness and the area of oak forests have diminished with fluctuations (15%). This decrease in greenness values and the area of forests is more evident in all parts of the province, especially in the northern and central parts. The changes in the values of the 2 greenness indices are almost similar and the decrease of greenness in 2006 to 2017 is clearly observed. Decrease in greenness (NDVI) in the study of Azizi et al. (2015), was reported in the forests of Ilam province in the west of Iran during the period from 2000 to 2013. Investigating the time series of NDVI values of oak forests in Lorestan province in the period from 1980 to 2017 by Zand et al. (2022), showed that the first noticeable decrease in NDVI occurred in 2004 and continued with greater intensity in 2008, and the decrease was also significant in 2013-2011.

Examining the trend of drought indices has shown two distinct and major periods of drought from 2006 to 2010, except for 2008 and the period from 2013 to 2017. The negative phases of these indices, which mean drought years, are completely consistent with the periods of greenness decline, while the positive phases of these indices, which indicate wet years, are in exact accordance with periods of increased greenness. On the other hand, in wet years 2001 and 2005, the peak greenness of the oak forest area has increased significantly. In 2018, due to a long period of drought, the results have been manifested in the greenness of the forests in 2019. Changes in the area of forest areas have a direct correlation with the drought index, such that years with normal or positive rainfall are associated with the expansion of areas with peak forest greenness. While years with drought or negative rainfall anomaly, have been associated with the reduction of area in forest areas. Also, the minimum of the forest area was in 2010, which is in the middle of the drought period.

The results of the spatial correlation analysis between the extent of greenness (related to both greenness indices) and the spatial distribution of rainfall plus drought indices showed that the rainfall anomaly of the MAM period (3-month period at the beginning of the growing season, i.e. the months of March, April, and May), is actually the main determinant of green changes in oak forests. In the same period of time (late winter and early spring), drought indicators have clearly and significantly affected the greenness of the forest area. In this research, it has been seen that the decline in rainfall and drought in late winter (the beginning of the growth period) and its continuation in the spring (the decrease in precipitation during the growth period of forest) causes moisture stress and increases temperature stress, and ultimately causes a reduction in greenness. Forests of the province fall in the warm months of the year. This is because the occurrence of drought at the beginning of the growing season prevents the sprouting of plants and reduces the yield. (Attarod et al., 2015; Zhou et al., 2018; Zand et al., 2022). Vegetation usually responds more to the rainfall parameter in the early growing season; especially in arid and semi-arid climates, rainfall is very rare in summer (like as this reserch). This leads to a high dependence of summer vegetation on spring precipitation. (Rahimzadeh Bajgiran et al., 2008). This has also been seen in the study of Enríquez-de-Salamanca (2022) in Mediterranean oak forests in Spain, the study of Zhou et al. (2018) in China, and Gu et al. (2007) study in America. In the research of Zand et al. (2020), in the oak forests of Lorestan province, as with the present study, the highest correlation was found between the SPI and the greenness of the oak forests (NDVI) in the early spring. In other words, with the beginning of the forest growth period from March is reported. The maximum effect of drought on the reduction of the greenness of the oak forests of this province was at the end of the cold period of the year and in the spring season, as with the present study. In the oak forests of Ilam, the negative trend of rainfall in March is reported as one of the main factors of the reduction of greenness in the forests, on an annual scale and especially in the growing season (Azizi et al., 2015). Gu et al. (2007) reported a strong spatial correlation between NDVI and NDWI anomalies and the 2001–2006 drought conditions in the central US grasslands. The studies of Touhami et al. (2022) as well as Gentilesca et al. (2017) reported the decline of cork oak (*Quercus suber* L.) forests in the Mediterranean basin under the influence of severe drought conditions. Unlike the present study in the plains of America, the highest correlation of SPI and NDVI was observed in the middle of the growing season and lower values of correlation were observed at the beginning and end of the growing season (Ji and Peters, 2003). Samantha et al. (2010), found no relationship between drought severity and EVI values of Amazonian vegetation in the 2005 drought.

While PDSI index showed a higher explanatory coefficient with greenness indices in the MAM period, SPI index, which is solely based on precipitation anomalies, had less power than Palmer's index to explain the spatial changes of greenness of oak forests. In addition to considering rainfall anomalies, the PDSI index also captures changes in soil moisture, which can improve the efficiency of this index in explaining changes in forest greenness. Zhao et al. (2022) stated that using the PDSI as a reference, one can effectively validate the efficiency of any other drought index. Tan et al. (2015) in China report that SPEI is more suitable than SPI because it considers both rainfall and evapotranspiration data. Gulácsi and Kovács (2018) state that no single index can fully reflect the multiscale and multiple nature of drought. On the other hand, among the two greenness indices that were examined in this research, EVI had a higher sensitivity and correlation with the Palmer drought severity index (MAM-PDSI). Considering that the background effects of the canopy have been removed in this index and some atmospheric corrections have been applied to it. Therefore, for areas with forest vegetation, this index has better reflected the sensitivity of vegetation dynamics to rainfall anomalies and drought indicators.

Another point is that the R2 value of the model for the relationship between 2 greenness indices and PDSI was 0.74 - 0.68. This indicates that drought explains 0.74 to 0.68 of the changes in greenness in the forest area, and the rest is related to other parameters affecting the reduction of greenness and decline in these forests. These factors include a set of natural and human factors that can fluctuate depending on the region and habitat conditions (Attarod et al., 2017). Studies have shown that the parts of the forest that are involved with these problems are more evident in the decline of the forest and the reduction of greenness (Hosseini et al., 2017; Ghanbari Motlagh et al., 2020).

Further, the results revealed that in 2050, in both climate change scenarios, the MAM-PDSI simulated index is generally affected by different severities of drought. However, in the RCP8.5 scenario, relatively larger parts of the forest area in the north of the province will be subjected to drought. What is different is the expansion of the medium and mild drought areas in other parts of the forests. In both climate change scenarios, the amount of forest greenness and the area of oak forests in the province will diminish significantly compared to the base period. This indicates the loss of the integrity of the forest cover as well as the weakening and decline of the forests in the future. This is because the winter and spring drought shortens the length of the growing season. The reports of various studies have shown the extensive loss of forests and their growth reduction due to the increase in temperature and drought around the world (Marqués et al., 2022). In Europe, drought has been shown to be an important driver of tree mortality on a continental scale. (Senf et al., 2020). In examining the decline of oaks (*Quercus* spp.) in relation to droughts, Gentilesca et al. (2017) stated that drought is the main cause of oak decline in the Mediterranean basin and other factors such as temperature increase, pests and diseases, etc. can aggravate this decline. In the research of Scharnweber et al. (2011) in northeastern Germany, *Quercus robur* a drought-resistant species introduced, has a better position in competition with *Fagus sylvatica* under predicted climate changes. The findings of Klos et al. (2009) in America have shown that no significant change in the growth or mortality rate of oaks (*Quercus prinus* and *Quercus coccinea*) has been observed with the increase of drought intensity, which indicates the greater tolerance of oaks to drought. The results of the study of Prăvălie et al. (2022) showed that the forests of the Carpathians in Romania have been increasingly affected by climate change in recent decades. In these forests, unlike the oak forests of western Iran, climate warming may be an important driving force for more forest greening, especially in mountainous areas.

Finally, it is necessary to mention that numerous and diverse factors in the Zagros forests area are driving the decline of oak forests, which include natural and human factors. On the one hand, human activities such as agriculture in the forest, livestock grazing, and natural factors such as rainfall and temperature anomalies caused by climate change, hazards such as dust, pests and diseases, with fires are all major drivers of the process of decline of Zagros forests. In this research, only the effect of drought events was investigated while the impact of other factors was not considered.

The increase in temperature and lack of rainfall have caused the aggravation of droughts and can lead to the physiological weakening of trees. Create favorable conditions for the invasion of insects, fires and intensifying the process of reducing the health and greenness of the forest, which has been clearly observed in the oak forests of western Iran. The trend obtained in this research showed that if the current situation continues, droughts caused by climate change in 2050 can not only reduce the oak forest area, but also compromise its freshness and greenness. If the management and protection operations in the forest areas of the province improves, the damages caused by drought in the forests could be reduced. Considering that these forests will not only be affected by climate change, but also from other possible related causes such as insects and pests, fire and other human interventions. In addition, in arid and semi-arid areas such as Zagros oak forests, drought can easily lead to dust and sandstorms and soil salinity. But this research emphasizes that connecting the decline and reduction of the health and greenness of the forest with drought needs more study and it is not possible to prove the real relationship between these two phenomena with just one or two calculation indices.

However, forest management can be used as a tool to reduce the effects of drought. If the process of management and protection operations in the forest areas improves, it can be said that perhaps the damages caused by drought and climate change in the forest areas will be reduced to some extent. This operation can include various forestry operations such as conservation, pruning and thinning of extensive crowns in order to reduce competition, reforestation and management of the composition of the stands by planting and breeding species with greater adaptation to drought. Other suggested operations in order to reduce the effects of other factors affecting the decline of oaks, such as conservation these areas to prevent or limit any type of exploitation and land use changes to agricultural lands, prevent livestock grazing, control fires, and cut and cutting infected and diseased trees.

AUTHORSHIP CONTRIBUTION

Project Idea: MD, MGM, MH

Funding: MD, MGM, MH

Database: MD, MGM, MH

Processing: MD, MGM, MH

Analysis: MD, MGM, MH

Writing: MD, MGM, MH

Review: MD, MGM, MH

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