Abstract—Vegetation activity may be changed in response to climate variability by affecting seasonality and phenological events. Monitoring of land surface phenological changes play a key role in understanding feedback of ecosystem dynamics. This study focuses on the analysis of trends in land surface phenology derived parameters using normalized difference vegetation index time series based on Global Inventory Monitoring and Mapping Studies data in the Hyrcanian forests of Iran covering the period 1981–2012. First, we applied interpolation for data reconstruction in order to remove outliers and cloud contamination in time series. Phenological parameters were retrieved by using the midpoint approach, whereas trends were estimated using the Theil–Sen approach. Correlation coefficients were evaluated from multiple linear regression between phenological parameters against temperature and precipitation time series. Significant Mann–Kendall test analysis indicate average start of season (SOS) and end of season (EOS) increased by −0.16 and +0.14 days per year, respectively. Results of significant trend analysis showed that later EOS was associated with increasing temperature trends and we found strongest relationships between temperature and phenological parameters in the west of the Hyrcanian forests, where precipitation was abundant. Moreover, SOS correlated strongly with total precipitation and mean temperature. This study allows us to better estimate the drivers affecting the vegetation dynamics in the Hyrcanian forests of Iran.

Index Terms—End of season (EOS), land surface phenology (LSP), NDVI3g, start of season (SOS), time-series analysis, trends.

I. INTRODUCTION

WARMING of the climate system is unequivocal. The warmest 30 year period of the last 1400 years was over the period 1983–2012, as stated in the 5th assessment report by the Intergovernmental Panel on Climate Change (IPCC) [1]. Ecosystems reacted to these new conditions as recorded in recent studies by change in timing of vegetation phenology [2], [3]. Detecting and monitoring the changes in vegetation activity is considered the first primary topic in the change mechanism assessment. Forest ecosystems on a global scale have a key role in relation to climate change by absorbing atmospheric carbon dioxide and storing it in vegetation and soil.

Climate forcing is a dominant controlling factor affecting the vegetation [4]. Climate change can influence vegetation change by external disturbance, such as fire, insect attack, as well as through climate factors, such as variations in rainfall and temperature [5], [6]. Biological activity is mostly controlled by temperature in temperate zones, whereas at lower latitudes rainfall and evaporation are the main drivers [7]. Changes in these parameters may induce changes in vegetation productivity. Moreover, detecting the effects of the climate changes in vegetation growth can be used to improve our knowledge about Earth system’s feedbacks as well as ecosystem dynamics [8]. Therefore, detecting trends in vegetation provides important indicators of the nature of regional and local climate change.

Trend analysis, in general, has become increasingly popular within the last decade. Using satellite data improves our knowledge about change in vegetation and land surface phenology (LSP) [9], where vegetation phenology is defined as the periodic plant life cycle events and vital activities occurring at different times during the year [10]. Trends in vegetation phenology and climate are important since they affect carbon, water, and energy exchange between vegetation and atmosphere [6]. For instance, climate warming induced start of season (SOS) advances increase carbon uptake and reduce the amount of CO₂ in the atmosphere.

Change detection of the vegetation at the local scale is usually carried out by governmental inventories, which can be biased or unavailable. Therefore, remote sensing is a useful tool to provide independent inventories [11]. Numerous phenological observations including advanced spring and later autumn of plants using remote sensing have been documented [3], [6], [12]–[15], although these observations have shown different trends because of various data sources, variable study periods, satellite platforms, temporal and spatial resolution from national to global scales.
Different earth resources satellite data, such as advanced very high resolution radiometer (AVHRR) [4], [6], [16], moderate resolution imaging spectroradiometer [2], [17], [18], and SPOT-VEGETATION [19], have been used in the literature to detect vegetation dynamic change from local to global scale.

The normalized difference vegetation index (NDVI) [20] calculated by the nonlinear combination of red (RED) and near-infrared (NIR) spectral radiance \((\text{NIR}−\text{RED})/(\text{NIR}+\text{RED})\) has been widely used as a proxy for vegetation activity. One of the most used dataset for trend analysis is Global Inventory Monitoring and Mapping Studies (GIMMS) NDVI [21]. It is regularly published by GIMMS group from the AVHRR instrument on board the National Oceanic and Atmospheric Administration (NOAA) satellite series.

AVHRR NDVI has been widely used as a common indicator for regional- and global-scale vegetation trend analysis representing changes in vegetation phenology [12]–[14], [22]–[28]. In addition, numerous international papers have focused on the relationship between variations of climatic variables, such as rainfall and air temperature, and changes in vegetation phenology [7], [29]–[31]. Park et al. [8] studied the response of vegetation green-up to local temperature in temperate forests of northern hemisphere and found that the Eurasian deciduous broadleaf forest green-up is related to increase in temperature.

The aim of this study was to analyze the vegetation seasonal dynamics in relation to climate factors in the Hycranian forests, North of Iran. Climate change can lead to a reduction of global biodiversity and the destruction of natural habitats. The Hycranian forests located in the southern coast of the Caspian Sea consist of mixed broadleaved forests. These forests have remained intact during the Tertiary Era and a number of plant archeologists consider these forests as relict and virgin ecological systems [32].

These forests are similar to the North American and East Asian forest communities that remained intact, and are nowadays seen as a Tertiary Era deciduous belt containing communities formerly associated with each other. Among these, the Hycranian region is quite intermediate through its species. The extent of the Hycranian forests changed minimally during the entire Quaternary Era. This area comprises 15% of the total Iranian forests and 1.1% of the country’s area. The Hycranian forests play a vital role in the conservation of soil and water resources [32]. It is therefore essential to monitor routinely their vegetation phenology and to understand further how these events vary over space and time. Phenometrics datasets have not yet been considered to characterize vegetation phenology dynamics in the Hycranian forests and no study, to our knowledge, has yet considered the trends in phenological parameters and climate factors (temperature and precipitation) to better interpret the observed vegetation dynamics.

II. STUDY AREA

The Hycranian forests in the north of Iran comprises a narrow strip of 1.8 million ha temperate deciduous forests located on the southern coast of the Caspian Sea, stretching within Guilan, Mazandaran, and Golestan provinces. Hycranian forests stretch out from sea level up to an altitude of 2800 m and encompass 80 different woody species (trees and shrubs) [32]. Four tree species including; Buxus hycra, Parotia persica, Populus caspica, and Gleditschia caspica are the autochthonous species to the Hycranian forests. At lower altitude, Quercus castani-folia, Carpinus betulus, and Parotia persica are the dominant trees. At middle elevation Fagus orientalis is the dominant tree, which forms the most beautiful and richest Iranian forest, and at higher elevation Quercus macranera along with Carpinus betulus are the dominant species [10]. The latitude and longitude of the Hycranian forests vary from 35° 45′ to 38° 26′ 15′′N and 38° 33′ 45′′ to 56° 11′ 15′′E, respectively (see Fig. 1). It is characterized by various ecological conditions and diverse vegetation landscape [10], [33]. In general, the Hycranian climate is warm Mediterranean in the east, and Mediterranean in the west [32]. This area is among the most unique and splendid biomes of the world as reported by UNESCO. 1.1 million ha of the Hycranian forests are currently managed based on the close to nature silviculture system over 102 watershed catchments. Total 0.34 million ha forests are protected [32] and 0.6 ha forests are disturbed [10].

III. DATA

The whole GIMMS NDVI3g dataset was used in this study (https://nex.nasa.gov/nex/projects/1349/wiki/general_data_description_and_access/). This dataset is a new generation of the GIMMS NDVI dataset, with 0.083° spatial resolution and a
temporal resolution of circa 15 days. This dataset is derived from NOAA satellite series AVHRR instrument, covering the period 1981–2012. In order to minimize the influence of atmospheric aerosols and clouds, the maximum value compositing technique has been used to create composite images. Data have also been corrected for intersensor differences and orbital drift [21], [34]. The validation of this dataset for responses of vegetation to climate variability was considered in previous research [4], [34]–[36].

In order to account for climatic controls of phenology, precipitation, and temperature, data were used for the correlation analysis. We used air temperature and precipitation data recorded by 45 and 292 weather stations, respectively, fully covering the Hycranian area and were provided by the Islamic Republic of Iran Meteorological Office and Iran Ministry of Energy. These point data were interpolated by applying a three-dimensional gradient method that considered latitude, longitude, and elevation variables. Nadi et al. [37] showed that this method outperformed other interpolation approaches, such as inverse distance weighted, kriging, and cokriging methods. Climatology dataset was created with the same resolution and geographic coordinate system as GIMMS NDVI13g dataset and used to analyze the climate influence on vegetation parameters. Forest boundaries were provided from Forests, Range and Watershed Organization of Iran and rasterized to the same spatial resolution as the GIMMS data. Since the pixel resolution is coarse and this contributes to mixed land cover within each pixel [11], and this research focused on forest areas, only pixels with more than 80% forest cover in comparison with official vector map of forest were considered in the analysis (see Fig. 1).

IV. METHODS

A. Time-Series Reconstructions

In order to remove remaining gaps caused by atmospheric and cloud contamination in the time series, the iterative interpolation for data reconstruction (IDR) method was applied pixel by pixel to GIMMS NDVI13g data. Several techniques have been developed to reconstruct NDVI time series. This method, however, has the advantage of providing the highest fidelity to original data while retaining the values of pixels without contamination during the iterative reconstruction [38].

The IDR method implements a pixel by pixel linear fit from the two closest temporal neighbors of the selected value. This alternative value is then compared with the original value, and the higher of these two values is replaced in the original time series. This procedure is iterated until the difference between interpolated and original values is below a given threshold of 0.02 NDVI units, corresponding to the accuracy of the NDVI estimation [38], [39].

B. Extraction of Phenology and Climate Parameters

LSP change is usually studied through temporal monitoring of NDVI as a proxy of the phenological state of land cover. Therefore, annual values of phenology parameters were retrieved for each pixel of the study area using the midpoint technique. White et al. [40] showed that this technique is more consistent with the ground measured phenology than other methods. This method consists of the identification of phenological dates (SOS, EOS) based on midpoint in the annual range of NDVI values. In summary, this technique first searches for minimum and maximum values for each pixel and individual year and determines the threshold value, and then retrieves SOS and EOS dates. In this method, starting or ending points of a season correspond to the date for which 50% of the annual amplitude is reached through an increase or decrease in NDVI values [13]. Climate parameters influence vegetation phenology and NDVI time series react to the climate. In order to extract climate parameters, all of these analyses were performed for temperature and precipitation. Six phenology and eight climate parameters were thus extracted (see Table I).

C. Phenological Trend Analysis

Trends for annual phenological parameters time series were retrieved by the Theil–Sen estimator [41] for each pixel over the Hycranian forests. Theil–Sen median slope is a robust nonparametric operator for trend analysis that is resistant to the effects of outliers, and calculates the median slope between every pairwise combination over time [25].

The slope of \( N \) pairs of data \( Q_i \) is first computed as

\[
Q_i = \frac{x_j - x_k}{j - k} \quad \text{for } i = 1, \ldots, N
\]

where \( x_j \) and \( x_k \) are NDVI values at times \( j \) and \( k \) (\( j > k \)), respectively, \( N = n \times (n - 1)/2 \) and \( n \) is the total number of observations.

The median of these \( N \) values of \( Q_i \) is the slope of Sen’s estimator. If \( N \) is odd, then Sen’s estimator is computed as

\[
Q_{med} = Q_{\lfloor (N+1)/2 \rfloor}.
\]

If \( N \) is even, then Sen’s estimator is computed as

\[
Q_{med} = 0.5 \left( Q_{\lfloor N/2 \rfloor} + Q_{\lceil (N+2)/2 \rceil} \right).
\]

Positive slope shows increasing trend, whereas negative slope indicates negative trend [42].
The significance of trends in GIMMS dataset was examined by the nonparametric Mann–Kendall significance test [43], [44], which has also a low sensitivity to outliers. For a time series \( X = \{x_1, x_2, \ldots, x_n\} \), the Mann–Kendall test statistic is calculated as:

\[
S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i)
\]

where \( n \) is the number of data points, \( x_i \) and \( x_j \) are the data values in time series \( i \) and \( j \) (\( j > i \)), respectively, and \( \text{sgn}(x_j - x_i) \) is the sign function as follows:

\[
\text{sgn}(x_j - x_i) = \begin{cases} 
+1 & \text{if } (x_j - x_i) > 0 \\
0 & \text{if } (x_j - x_i) = 0 \\
-1 & \text{if } (x_j - x_i) < 0.
\end{cases}
\]

The variance is computed by [43]

\[
\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i (t_i - 1)(2t_i + 5)}{18}
\]

where \( n \) is the number of data points, \( m \) is the number of tied groups and it denotes the number of ties of extent \( i \). A tied group is a set of sample data with the same value. In cases where the sample size is more than 10, the test statistic \( Z_n \) is computed as

\[
Z_n = \begin{cases} 
\frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\
0 & \text{if } S = 0 \\
\frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0.
\end{cases}
\]

Positive values of \( Z_n \) indicate increasing trends, whereas negative \( Z_n \) values show decreasing trends. The trend significance is assessed by comparing \( Z_n \) and the reference value at the pre-specified level of statistical significance. Significant trend exists when \( |Z_n| > Z_{1-\alpha/2} \), \( Z_{1-\alpha/2} \) is obtained from the standard normal distribution table. In this study, we chose a significance level \( \alpha = 0.1 \), which corresponds to \( Z_{1-0.1/2} \) values of 1.645 [45].

In order to compare the influence of climate parameters with different magnitudes, the first processing step is the normalization over parameters (temperature, precipitation, and phenological parameters) by calculating their standardized anomalies according to [7]

\[
z = \frac{x_t - \bar{x}}{S}
\]

where \( z \) is the resulting normalized value of parameters, \( x_t \) is the original value, \( \bar{x} \) is the mean value, and \( S \) is the standard deviation. This normalization was applied to all parameters (temperature, precipitation, and phenological parameters).

To further explore the climatic factors driving phenological changes, correlations between phenological parameter anomalies (SOS, EOS, NDVI\(_{\text{max}}\), NDVI\(_{\text{min}}\)), and climate variables anomalies (temperature, precipitation) were quantified using an ordinary least-squares regression. The regression equation was estimated as follows:

\[
\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 \text{Time} + \varepsilon
\]

where \( \gamma \) is the standardized anomaly of interannual variation of phenological parameters, \( X_1 \) and \( X_2 \) are the standardized anomaly interannual variations of precipitation and temperature, respectively, and \( \varepsilon \) is the stochastic error term. In order to remove stochastic trend component (nonstationary) of time series, time was used as a deterministic variable in the model.

V. RESULTS

A. Trend Results

Phenological parameters have been retrieved using the midpoint method for 1981–2012. The average of SOS derived from GIMMS NDVI3g time series ranged from day 77 to 158 with a mean of day 103, whereas average of EOS ranged from day 256 to 318 with a mean of day 299 in the Hyrcanian forests. SOS and EOS derived from GIMMS NDVI3g time series increased by −0.16 and +0.41 days per year, respectively.

Observations of the trends in phenological parameters from NDVI over the period 1981–2012 data using the Theil–Sen method show that most regions of the study area present an advance (negative value) in SOS and delay (positive value) in EOS, resulting in an overall lengthening of the growing season period.

Fig. 2 represents the statistically significant trends at 90% confidence level obtained for the six phenological parameters over the Hyrcanian forests. We observed that in a small number of pixels, significant earlier SOS occurred, whereas significant latter EOS appeared in most areas and a strong delay in EOS is observed for low altitudes. Moreover, increasing significant trends in NDVI\(_{\text{max}}\) was found at high altitude over the Hyrcanian forests, whereas for NDVI\(_{\text{min}}\) aggregation of increasing trends was mainly located in the central and eastern study area. Earlier NDVI\(_{\text{max}}\) was recorded in a few pixels in Guilan and Mazandaran provinces. No trend was found in Golestan for these parameters, whereas the dates of minimum NDVI value showed negative trends for four pixels in Guilan province.

Fig. 3(a), (c), (e), and (g) shows significant trends in precipitation. Prec\(_{\text{total}}\) trends ranged between −17.84 mm per year in the west and +12.22 mm per year in the east. One can observe that the areas with highest negative trends in Prec\(_{\text{total}}\) were located in the west of the Hyrcanian forests, Guilan province, and the highest positive trends were found in the far east of this region. Trends in Prec\(_{\text{max}}\) closely followed this pattern. This forested area had no significant positive trend in Prec\(_{\text{min}}\) whereas a few pixels in the centre of Guilan province showed high negative trends. Results showed up to 0.21 day per year delay in Prec\(_{\text{max}}\) in central Hyrcanian forests.

B. Phenological Trends and Their Correlations With Climate Data

Spatial distribution of the best multiple linear regression between interannual variation of phenological parameters
Fig. 2. Significant trends at 90% confidence level using the (a) Mann–Kendall trend tests in SOS date; (b) EOS date; (c) maximum value of NDVI; (d) minimum value of NDVI; (e) maximum value of NDVI date; and (f) minimum value of NDVI date. Grey pixels show insignificant trends at the 90% confidence level. Dark green and dark red pixels indicate strong negative and positive trends. All these parameters have been extracted from GIMMS3g NDVI time series using the midpoint technique.

and climate data ($\text{Temp}_{\text{mean}}$, $\text{Temp}_{\text{max}}$, $\text{Temp}_{\text{min}}$, $\text{Temp}_{\text{Tmax}}$, $\text{Temp}_{\text{Tmin}}$, and $\text{Prec}_{\text{total}}$, $\text{Prec}_{\text{max}}$, $\text{Prec}_{\text{Tmax}}$) showed no clear patterns in the Hyrcanian forests. Table II presents the percentage of pixels in the study showing significant (90%) correlation with a given set of climate parameters. There were stronger correlations between minimum value of NDVI with minimum temperature and total precipitation in most regions (34% of pixels) (see Fig. 4).

There were some contradictory correlation coefficient patterns of phenology parameters with climate data. Therefore, in order to obtain higher correlations, climate parameters were used individually in regression analysis.

Stronger correlations between EOS and $\text{Temp}_{\text{min}}$ than other temperature parameters were observed in 43% of pixels [see Fig. 5(a) and Table III]. There was a best linear regression between NDVI$_{\text{min}}$ and $\text{Temp}_{\text{min}}$ spatially in 52% of pixels (see Table III) in Guilan region, whereas, in the east of the Hyrcanian forests and at low altitudes, minimum NDVI trends were better explained by mean temperature trends [see Fig. 5(b)].

Fig. 6 indicates the pixels with positive correlations between $\text{Temp}_{\text{min}}$ and NDVI$_{\text{min}}$ spread over the study area, with negative correlations only for a few pixels. Stronger positive correlations were observed in the west of the study area.

Fig. 7 indicates pixels with best correlations with precipitation. Phenology was found to be highly affected by total precipitation in comparison with other parameters in Guilan province (see Table IV).

VI. DISCUSSION

This study retrieved LSP trends using the Theil–Sen estimator over the period 1981–2012 for the Hyrcanian forests of Iran. To assess the influence of climatological factors, we used multiple regression with phenological parameters extracted from NOAA–AVHRR time series as dependent variable and station precipitation and temperature data as independent variables.

Examining LSP in Hyrcanian forest over 1981–2012 reveals EOS trend was stronger than the SOS trend (EOS delay was 0.41 days yr$^{-1}$, compared to $-0.16$ days yr$^{-1}$ of SOS change). Based on the finding of Garrona et al. [46], [47], EOS were more widespread than SOS trends and overall growing season lengthening for 1982–2012 may increasingly be attributed to an EOS delay. This is confirmed in our regional study.

The current findings about climate trends in this study confirm increasing air temperature, as reported by IPCC [1]. This research showed a negative trend in precipitation in some parts of the west and a positive trend in the east in total precipitation for our study area, which should lead to a shorter growing season of the vegetation. It had a large effect on the minimum value of NDVI. Precipitation condition is favorable in the Hyrcanian forests of Iran and is adequate for forest growth, even in the east of this region, which has the lowest amount of precipitation. Therefore, small changes in precipitation do not influence phenological parameters and therefore should not be considered as a limiting factor. Moreover, observation of the trends in phenological parameters in some pixels showed that an
Fig. 3. Significant trends at 90% confidence level using the Mann–Kendall trend tests in (a) total precipitation, (b) average of temperature, (c) maximum precipitation, (d) maximum temperature, (e) minimum precipitation, (f) minimum temperature, (g) date of maximum precipitation, and (h) date of maximum temperature.

Table II
Percentage of pixels with best multiple linear regression of phenological parameters (EOS, Max NDVI, Min NDVI, and SOS) as the dependent variable and the corresponding statistics of precipitation and temperature as independent variables

<table>
<thead>
<tr>
<th>Parameters Set</th>
<th>EOS</th>
<th>Max NDVI</th>
<th>Min NDVI</th>
<th>SOS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temp$<em>{max}$ and Prec$</em>{max}$</td>
<td>5</td>
<td>4.2</td>
<td>2.2</td>
<td>6.8</td>
</tr>
<tr>
<td>Temp$<em>{max}$ and Prec$</em>{total}$</td>
<td>7</td>
<td>7.5</td>
<td>1.1</td>
<td>5.2</td>
</tr>
<tr>
<td>Temp$<em>{mean}$ and Prec$</em>{max}$</td>
<td>6.3</td>
<td>10</td>
<td>1.1</td>
<td>8.1</td>
</tr>
<tr>
<td>Temp$<em>{mean}$ and Prec$</em>{total}$</td>
<td>2.9</td>
<td>5.6</td>
<td>1.8</td>
<td>7.8</td>
</tr>
<tr>
<td>Temp$<em>{min}$ and Prec$</em>{max}$</td>
<td>4</td>
<td>8.5</td>
<td>2.2</td>
<td>3.9</td>
</tr>
<tr>
<td>Temp$<em>{min}$ and Prec$</em>{total}$</td>
<td>6</td>
<td>12</td>
<td>1.1</td>
<td>5.8</td>
</tr>
<tr>
<td>Temp$<em>{mean}$ and Prec$</em>{max}$</td>
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<td>5</td>
<td>11</td>
<td>6.6</td>
</tr>
<tr>
<td>Temp$<em>{mean}$ and Prec$</em>{total}$</td>
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<td>5.3</td>
<td>10</td>
<td>3.9</td>
</tr>
<tr>
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<td>4</td>
<td>2.8</td>
<td>8</td>
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<tr>
<td>Temp$<em>{min}$ and Prec$</em>{max}$</td>
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<td>8</td>
<td>2.5</td>
<td>6.2</td>
</tr>
<tr>
<td>Temp$<em>{min}$ and Prec$</em>{total}$</td>
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<td>9.9</td>
<td>1.8</td>
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<td>5.8</td>
<td>8.5</td>
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<td>Temp$<em>{total}$ and Prec$</em>{total}$</td>
<td>9.5</td>
<td>4.5</td>
<td>34</td>
<td>5.8</td>
</tr>
</tbody>
</table>

Fig. 4. Spatial distribution of best regression between minimum value of NDVI and minimum temperature and total precipitation (green color).

Increased temperature caused an increasing trend in growing season and therefore temperature had more influence than precipitation in this area. Indeed, in our study, temperature and precipitation were considered as the main control of plant phenology, without studying the influence of other parameters, such as anthropogenic activity or deforestation, which appear as progressive changes. We found no obvious trends for many pixels, this can be due to favorable climatology conditions and/or minimal human interference in these areas. It can also be due to
the relatively short time span of the data, which leads to lower significance in trends when combined with high interannual variations. Special attention should be paid to the observed negative phenological trends, since they can lead to a reduction in vegetation and animal biodiversity, due to the capacity that some species have to adapt to the new changes in vegetation activity and climate.

Our findings illustrated strong correlations between later EOS and increasing temperatures mainly in western Hyrcanian forest, possibly related to sufficient amount of precipitation in this area. Furthermore, the Hyrcanian forests are characterized by longer growing season even over those areas where the SOS did not shift to earlier date and without precipitation trend. Moreover, EOS values were correlated positively and strongly with minimum temperature in 43% of pixels (see Table II). Later EOS trends were widely distributed over the Hyrcanian forests and significant trends in low altitude were observed in longer growing season. Increasing Temp$_{\text{min}}$ resulted in NDVI$_{\text{min}}$ increase (see Fig. 6). This means that vegetation activity increased in winter season when temperature was at its lowest during 1981–2012. The maximum value of NDVI as a proxy for greening climax in forest occurred at the same time as maximum temperature.

Some pixels of the study area experienced weak or negative correlation between NDVI$_{\text{max}}$ and maximum temperature during years. However, other climatic variables affect the variation in NDVI$_{\text{max}}$ under high temperature conditions. Other climate variables, such as precipitation, soil moisture, evapotranspiration, or photoperiod can be related to variations in vegetation productivity. In these regions (pixels with weak or negative correlation), NDVI$_{\text{max}}$ can be decelerated by increased water deficits due to higher temperatures and evapotranspiration. The water vapor deficit increases with temperature, thus maximum of NDVI value can be decreased by high temperatures in a water-limited environment. Therefore, photosynthesis can be limited by temperatures and by water deficit in the summer in high-altitude regions [48]. Furthermore, NDVI tends to asymptotically saturate at dense forest canopies or at high leaf area index (LAI) values, which might influence the correlation at the peak of NDVI.

Temperature in high altitude of the Hyrcanian forests is a limiting factor for plant growth rather than precipitation. In this study, total precipitation influenced phenological parameters of forests more than other precipitation parameters and maximum precipitation had no effect on the growth elements of forest. Fig. 7 displayed that Prec$_{\text{total}}$ has the strongest effect on phenological parameters; however, their correlation coefficient were weak. Therefore, precipitation is not a significant driver of the behavior of this forest.

On the local scale, other climatic and microclimatic variables might explain phenological changes better [7], whereas the impact of anthropogenic activities on vegetation dynamics was unknown. There are various microclimates in this region due to different slope direction, altitude, and human activities that affect the response of phenological parameters in addition to climate factors. It should be mentioned that during the Pleistocene (Ice Ages), the Hyrcanian forests were alive and glaciations had minimal impact on it, and the movement of some species to high altitude was imaginable [32].

Although many previous studies were carried out at the global or regional scales, these results cannot be easily compared with this research due to the geographical characteristics of the Hyrcanian forests, and to the spatial resolution of the dataset, leading to the relatively small number of pixels considered as forest in this study area. Similar spatial patterns of trends distribution in our study area to those observed in long-time trend analysis were
VII. CONCLUSION

In this study, we analyzed the spatial and temporal LSP trends on Hyrcanian forests and its influencing factors from 1981 to 2012 based on GIMMS NDVI3g dataset. EOS delay was 0.41 days yr\(^{-1}\), compared to -0.16 days yr\(^{-1}\) of SOS change. EOS was more widespread than SOS trends.

This study was intended to provide a preliminary overview of spatio-temporal vegetation dynamics, and to give insight into the location of change in phenological parameters across the Hyrcanian forests. Observed shifts in SOS or EOS in the Hyrcanian forests [see Fig. 2(a) and (b)] can help to identify the pixels/areas corresponding to change “hot spots,” which need greater attention to fully understand forest-based processes, such as forest successions, forest structure changes, forest management strategies, and forest disturbance. Vegetation change is influenced by natural factors, such as climate change, and human activities, like existence of livestock in the forest, deforestation, severe soil, and wind erosion. Here, we concentrated on temperature and precipitation and not considered other variables. In the present research, precipitation and temperature recorded by a few number of weather stations were interpreted, however, to fully understand the phenology and its relation to meteorological parameters, more accurate weather data should be considered.

Further study and finer resolution are needed for more accurate trend investigation and explain the reason behind the retrieved trends. This could be done by registering abrupt changes that are not correlated with climate indicators.

Several studies have highlighted limitations of NDVI3g to assess plant phenology, such as the uncertainties of coarse resolution resulting in a mixed NDVI3g signal for a heterogeneous landscape [49], not completely solved the differences between sensor characteristics of AVHRR-2 and AVHRR-3 and the more advanced sensors [34], a reasonable proportion of pixels might be flagged as missing values [50], occurrence of a well-known border effect, i.e., applying a smoother algorithm for noise removal resulted in a lower accuracy for the very last observation of the dataset, and, in general, GIMMS-derived vegetation onset is probably too early [51]. However, some studies [5], [48] have shown that the GIMMS NDVI3g dataset compares favorably to other existing datasets, and in the absence of ground phenology records over the area, there is no possibility of validating our SOS and EOS estimates.

Due to the limited vegetation area in Iran and the importance of vegetation activity, climate change might result in irreversible loss of vegetation productivity and land degradation. Therefore, several tasks regarding the assessment of vegetation activity change in Iran still need to be accomplished. The potential consequence of an earlier SOS and a later EOS is an expanded growing season. This means a longer carbon uptake period through photosynthesis, and a higher timber production. These changes may also lead to changes in species interactions, and therefore, tree community changes. Some tree species, i.e., early flowering trees, gain competitive ability compared to later-flowering trees. More forest damages may be expected because of early autumn and late spring frosts. Finally, treeline elevation may be affected, which in turn affect strongly the grazing areas of local people. The different vegetation indices (VIs) existing in the literature have different abilities to capture the phenological signals across sites and vegetation types. Therefore, we plan on using other VIs (particularly the enhanced vegetation index) in a close future. In addition to spectral indices, LAI, which is a structural attribute, should be considered as well, since LAI
is more sensitive than VIs to dense canopies. Furthermore, LAI seems to be more robust across sensors than VIs, which depend on the band properties of each sensor [52]. Therefore, similar analyses and study selections could be replicated on other biogeographic regions of Iran.

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