ISSN: 2538-2152; ECOPERSIA 2024;12(2):121-134.

Tarbiat Modares University

Investigating the Relationship between Meteorological and Agricultural Droughts in Northwest Iran

ARTICLEINFO

Article Type
Original Research

Authors
Setareh Bagheri, *Ph.D.*[1]
Pouyan Dehghan Rahimabadi, *Ph.D.*[2]
Hassan Khosravi, *Ph.D.*[3]
Hossein Azarnivand, *Ph.D.*[4*]

How to cite this article
Bagheri S., Dehghan Rahimabadi P., Khosravi H., Azarnivand H. Investigating the Relationship between Meteorological and Agricultural Droughts in Northwest Iran. ECOPERSIA 2024;12(2): 121-134.

DOI:
10.22034/ECOPERSIA.12.2.3

[1] Ph.D. in Range Management, Department of Arid and Mountainous Regions Reclamation, University of Tehran, Iran
[2] Ph.D. in Combat to Desertification, Department of Arid and Mountainous Regions Reclamation, University of Tehran, Iran
[3] Associate professor, Department of Arid and Mountainous Regions Reclamation, University of Tehran, Iran
[4] Professor, Department of Arid and Mountainous Regions Reclamation, University of Tehran, Iran

*** Correspondence**
Address: Professor, Department of Arid and Mountainous Regions Reclamation, University of Tehran, Iran
Email: hazar@ut.ac.ir
Telel: +982632227765
Fax Number: +982632222045

Article History
Received: December 16, 2023
Accepted: April 22, 2024
Published: May 20, 2024

ABSTRACT

Aims: This study aims to assess the variations in drought trends using indices in Northwest Iran, as vegetative cover plays a vital role in environmental stability.
Materials & Methods: To achieve this goal, the study includes three stages: determining the Standardized Precipitation Evapotranspiration Index (SPEI) using monthly temperature and precipitation data from meteorological stations, calculating the Vegetation Health Index (VHI) based on derived datasets from MODIS satellite images for the period 2001-2021, and examining the correlation between indices to determine the duration of vegetation cover response to water scarcity and identify trends at 3, 6, 9, and 12-month time scales.
Findings: Based on the results of the Mann-Kendall test, the stable (48.56%) and increasing (50.43%) trends cover most of the studied areas, and a smaller area had a decreasing trend (1.01%). Additionally, positive correlations between VHI and SPEI were observed across all time scales. The SPEI-3 months showed the highest Pearson correlation (R^2= 0.83) with VHI values for the growing season, indicating that water accumulation in the past three months significantly impacted vegetation cover.
Conclusion: This study emphasizes the necessity of monitoring and managing drought, focusing on vegetation cover status in the Northwest of Iran, especially in East Azerbaijan Provinces. It also introduces drought indices as a crucial component of the drought monitoring system.

Keywords: Trend Analysis, Drought Index, Time Scale, Northwest of Iran.

CITATION LINKS

[1] Zhang Z., Chang J., Xu C., ... [2] Ahmadi S., Azarnivand H., ... [3] Li H., Xie M., Wang H., Li S., Xu M. Spatial heterogeneity ... [4] Dehghan P., Azarnivand H., Khosravi H., Zehtabian G., Mogha[5] Xu M., Kang S., Chen X., ... [6] Huho J.M., Kosonei R.C. Understanding extreme climatic even... [7] Hossain M.L., Li J. ... [8] Wu D., Zhao X., Liang S., Zhou T., Huang K., Tang B., Zhao [9] McKee T. B., Doesken N. J., Kleist J. The relationship of d... [10] Vicente-Serrano S.M., Beguería S., López-Moreno J. I. A mul... [11] Kogan, F.N. Remote sensing of weather impacts on vegetation... [12] Sheffield J., Wood E.F., Pan M., Beck H., Coccia G., Serrat... [13] Holben B. N., Tucker C.J., Fan C.J. Spectral assessment of ... [14] Heydari Alamdarloo E., ... [15] Safari Shad M., Ildoromi A. ... [16] Bagheri S., Tamartash R., Jafari M., Tatian M.R., Malekian ... [17] Dehghan Rahimabadi P., Azarnivand H. Assessment of the effe... [18] Potop V., Boroneanţ C., Možný M., Štěpánek P., Skalák P. Ob... [19] Tirivarombo S., Osupile D., Eliasson P. Drought monitoring ... [20] Bazrafshan O., Mahmoudzadeh F., ... [21] Hosseini Pazhouh N., Ahmadaali K., ... [22] Wang F., Lai H., Men R., Sun K., Li Y., Feng K., Tian Q., G... [23] Prasad A. K., Chai L., Singh R. P., Kafatos M. Crop yield e... [24] Kogan F., Salazar L., Roytman L. ... [25] Hanafi A. Study of climatic characteristics of the northwes... [26] Razmi R., Sotoudeh F., Salahi B. Spatio-temporal analysis a... [27] Mishra A. K., Singh V.P. Drought modeling-a review. J. Hydr... [28] Mohammed S., Alsafadi K., Enaruvbe G. O., Bashir B., Elbelt... [29] Shamshirband S., Hashemi S., ... [30] Bhuiyan C., Singh R.P., Kogan... [31] Choi M., Jacobs J.M., ... [32] Vicente-Serrano S. M., Gouveia C., Camarero J. J., Begueria... [33] Xiujia C., Guanghua Y., Jian G., Ningning M., Zihao W. Appl... [34] Ma J., Zhang C., Li S., Yang C., Chen C., Yun W. Changes in... [35] Fathi-Taperasht A., ... [36] Mann H.B. Nonparametric ... [37] Sen P. K. Estimates of the regression coefficient based on ... [38] Feizi V., Mollashahi M., Farajzadeh M., Azizi G. Spatial an... [39] Pogačar T., Žnidaršič Z., ... [40] He C., Zhang Q., Li Y., Li X., Shi P. Zoning grassland prot... [41] Xiao X., Zhang Q., Braswell B., Urbanski S., Boles S., Wofs... [42] Penereiro J.C., Badinger A., Maccheri N.A., Meschiatti M.C.... [43] de Oliveira R.G., Júnior... [44] Karimi Z., Talebi. A. An Integration of Remote Sensing and ... [45] Mohammadzadeh A., Mahdavi... [46] Mirgol B., Nazari M., Eteghadipour M. Modelling climate cha... [47] Zhang R., Shangguan W., Liu J., Dong W., Wu D. Assessing me... [48] Dehghani Sargazi H., ... [49] Manafi Mollayousefi M., ... [50] Sholihah R.I., Trisasongko B.H., Shiddiq D., La Ode S.I., K... [51] Raja A., Gopikrishnan T. Drought analysis using the standar... [52] Musei S.K., ... [53] Piao S.L., Mohammat A., Fang J., ... [54] Zhang X., Goldberg M., Tarpley ... [55] Seddon A.W., Macias-Fauria M., Long P.R., Benz D., Willis K... [56] Chen T., De Jeu R., Liu Y.Y., Van der Werf G.R., Dolman A.J... [57] Guo L., Zuo L., Gao J., Jiang Y., Zhang Y., Ma S., Zou Y., ...

Introduction

Vegetative cover is vital in soil conservation, climate regulation, hydrological processes, carbon cycles, and ecosystem stability [1]. It reflects the dynamic characteristics of terrestrial ecosystems. It is considered a sensitive indicator of ecosystems' response to climate change and human activities, fundamentally indicating the overall state of the ecological environment [2, 3, 4]. Spatial-temporal changes in vegetation cover patterns alter the regional landscape and impact ecosystem structure, leading to weaker resilience in maintaining and enhancing ecosystem sustainability [5]. Therefore, understanding the impact of water availability on vegetation cover growth in connection with climate changes is essential for predicting the dynamicity of vegetation cover against environmental changes. It also aids in developing effective policies and strategies for environmental protection and sustainability.

One of the climatic events affecting vegetation cover is vegetation drought. Recurring droughts are a primary cause of rangeland degradation and a significant factor in reducing agricultural crop yields, transforming forested lands into shrub-dominated landscapes [6]. However, since vegetation cover exhibits specific resistance to drought, the effect of drought on vegetation growth has a distinct time lag [7]. Vegetation growth affected by previous drought is called the lag time effect. For instance, a drought that occurred one month, three months, or even twelve months ago stresses vegetation growth. In other words, vegetation growth may not be primarily due to current weather conditions, but the initial climatic conditions significantly impact vegetation growth. Therefore, considering the effects of time lag is crucial when investigating the mechanisms of the interactive effects of climate and vegetation cover [8].

Several indices, such as SPI [9] and SPEI [10], have been introduced to assess drought based on meteorological station precipitation data. However, these methods are effective only for evaluating drought conditions near meteorological stations due to limited spatial coverage, low station density, and uneven distribution of stations, especially in semi-arid regions, where precipitation varies significantly over short distances [11]. In contrast, remote sensing (RS) data become the primary data source for defining drought indices due to their extensive spatial coverage and high public accessibility [12]. Drought assessment indices based on remote sensing data include VHI [13], NDVI [14], VCI, TCI [15], and EVI [16, 17].

Researchers have utilized various drought indices in their studies over the years. Potop *et al.* [18] analyzed spatial characteristics of drought and their trends at different time scales based on the SPEI index in the Czech Republic using data from 184 stations. These researchers reported a negative trend for most stations, indicating a stable or increasing trend for drought events. Tirivarombo *et al.* [19] compared SPI and SPEI in the Kafue River basin in northern Zambia. The results showed that temperature change is crucial in determining drought phenomena. Bazrafshan *et al.* [20] compared SPI, SPEI, and RDI indices in analyzing drought trends in dry and semi-dry regions of Iran for warm and dry climates, reporting an increasing trend (below -2.61) for most regions and a decreasing trend (above 2.61+) for cold and dry climates. Hosseini Pezhuh *et al.* [21] used the standardized precipitation index (SPI) and Standardized Evapotranspiration Precipitation Index (SPEI) for drought detection and evaluation in the Kesilan watershed. They reported that SPEI performed better than SPI, especially at the end of the spring and summer seasons. Wang *et al.* [22] focused on China in a study

[DOI: 10.22034/ECOPERSIA.12.2.3]

aiming to investigate spatial and temporal developments in vegetation drought. They used the Vegetation Health Index (VHI) to identify vegetation drought and the Pixel-based Trend Identification Method (PTIM) to examine its spatial and temporal evolution from 1982 to 2020. The results indicated a decreasing trend in vegetation drought during the study period, with the most prominent reduction observed in spring. Other researchers have also reported a high correlation between VHI and vegetation cover performance, especially during critical growth stages [23, 24].

Different researches show that changes in climate affect plant growth. Therefore, it is essential to understand how climate influences vegetation cover across different environmental conditions. Since the impact of climate on vegetation cover has not been investigated in the northwestern Provincess of Iran, this study specifically focuses on meteorological and agricultural droughts, aiming to comprehend the occurrence trend of drought in Northwest Iran, as these two types of droughts are more directly related to the examination of climatic factors and vegetation cover performance.

Material & Methods

Study Area

The northwest of Iran has different climate regimes and air masses, so diverse climate zones appear in its territory [25]. In this study, the Northwest of Iran encompasses the Provincess of East Azerbaijan, West Azerbaijan, Zanjan, and Kurdistan. The elevation gradually increases from east to west and decreases around Lake Urmia. The climate transitions from semi-arid to arid from north to south, and the temperature gradually rises from north to south. Due to its topographical features, location, and elevation, this region exhibits environmental, plant, and animal diversity adapted to the current climate conditions. The region's long-term fluctuation and variability in climatic factors can have significant environmental, agricultural, economic, and even human consequences [25]. The primary land covers in the study area include grasslands (56.81%), deserts (32.90%), agricultural lands (4.78%), water bodies (2.18%), and sparse shrublands (1.68%) (Figure 1).

Data collection

To calculate the SPEI, monthly temperature and precipitation data from meteorological stations in Ardabil, Khorram Dareh, Khoy, Maragheh, Sanandaj, Tabriz, Urmia, and Zanjan were utilized. These selected stations were chosen due to their common statistical period, location within the study area, or proximity to the study region. The geographical coordinates of each station are provided in Table 1. For the Vegetation Health Index (VHI), data from the MOD13Q1 sensor of the Moderate Resolution Imaging Spectroradiometer (MODIS) for 2000 to 2023 were employed.

Estimation of Drought Indices

Drought indices are essential for evaluating drought severity, modeling, and predicting drought [27]. Each of these indices is associated with one or more variables that impact environmental characteristics such as precipitation, temperature, river flow, soil moisture, and other variables [28]. Most drought indices are tailored to specific geographical areas and objectives, making their selection for achieving accurate and comprehensive analyses challenging due to the inherent complexities of the phenomenon [29]. To overcome this challenge, considering the enhanced role of temperature in drought propagation due to climate change [10], the SPEI was employed. Additionally, the Vegetation Health Index (VHI) was chosen among satellite-based indices due to its consideration of local biophysical factors (soil and slope) and climatic conditions [30, 31].

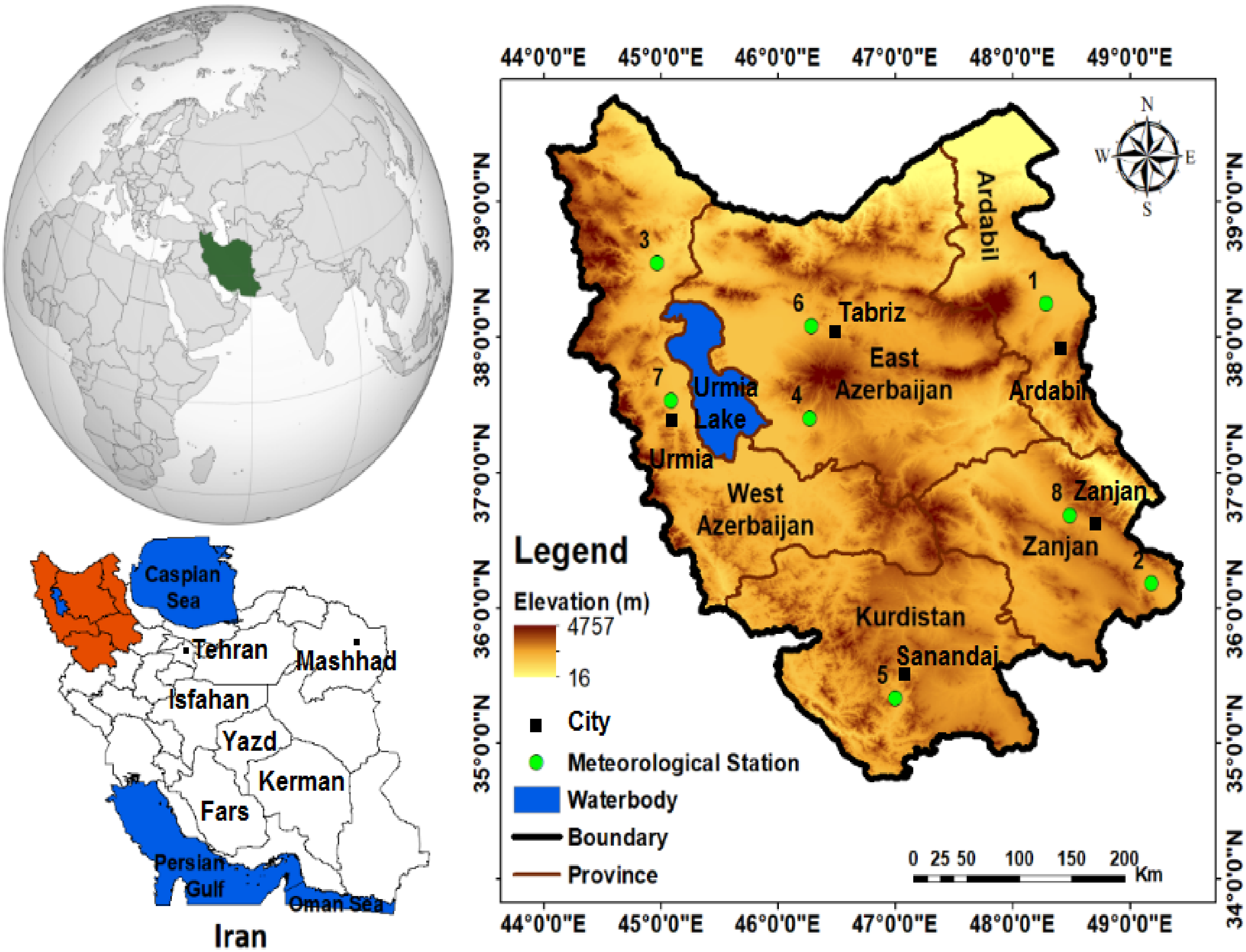

Figure 1) Geographical location of the study area in Iran.

Table 1) Meteorological station characteristics.

Row	Meteorological Station	Latitude (N)	Longitude (E)	Elevation (m)
01	Ardebil	48° 17'	35° 15'	1332
02	Khorramdareh	49° 11'	36° 11'	1575
03	Khoy	44° 58'	36° 33'	1103
04	Maragheh	46° 16'	37° 24'	1477.7
05	Sanandaj	47° 00'	35° 17'	1373.4
06	Tabriz	46° 16'	38° 05'	1361
07	Urmia	45° 05'	37° 32'	1315.9
08	Zanjan	48° 29'	36° 41'	1663

Estimation of Standardized Precipitation Evapotranspiration Index (SPEI)

The SPEI is employed to quantify the intensity and duration of drought events [32]. SPEI is based on the difference between precipitation (water supply) and potential evapotranspiration (water demand), making it applicable for assessing meteorological

[DOI: 10.22034/ECOPERSIA.12.2.3]

and hydrological droughts [10]. Drought indices based on meteorological data benefit from the advantage of long-term temporal scales [33]. SPEI is scalable for time intervals ranging from 1 to 48 months or more. SPEI-1 represents drought conditions in the current month, while SPEI-12 reflects the overall annual drought conditions. The multiscale nature of SPEI enables the identification of various types of droughts and their impacts on different systems [32].

The SPEI equation was processed for four time scales (3, 6, 9, and 12 months) using functions defined in MATLAB. MATLAB is a computational software platform that encompasses over 600 mathematical operation functions extensively utilized in climate analysis projects [34].

Estimation of vegetation health index (VHI)

VHI has been proposed to quantify vegetation drought using several years of vegetation water-deficit situations [35]. VHI is a linear combination of the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI), simultaneously reflecting vegetation cover's greenness and temperature status. The VHI was computed according to the Eqs. (1), (2), and (3) using ArcMap 10.8.2 [30].

$$\text{VHI} = 0.5 \times (\text{VCI}) + 0.5 \times (\text{TCI}) \qquad \text{Eq. (1)}$$

$$\text{VCI} = \frac{\text{EVI}_i - \text{EVI}_{\min}}{\text{EVI}_{\max} - \text{EVI}_{\min}} \times 100 \qquad \text{Eq. (2)}$$

$$\text{TCI} = \frac{\text{LST}_i - \text{LST}_{\min}}{\text{LST}_{\max} + \text{LST}_{\min}} \times 100 \qquad \text{Eq. (3)}$$

In the provided equations, EVI_i represents the EVI value of a pixel in year *i*, while EVI_{max} and EVI_{min} denote the maximum and minimum values of EVI for the same pixel from 2001 to 2019, respectively. Moreover, LST stands for Land Surface Temperature, where LST_i signifies the LST value of a pixel in the year I, and LST_{max} and LST_{min} indicate the maximum and minimum values of LST for the same pixel from 2001 to 2019, respectively.

Trend analysis

Trend determination tests are divided into two types: parametric and nonparametric. The trend test applied in this study is the nonparametric Mann-Kendall (MK) test. The Mann-Kendall test is effectively used to detect natural fluctuations or trends in the changes of a process. This rank-based test is suitable for detecting non-linear trends [36]. The advantage of the nonparametric test, such as the Mann-Kendall test, over parametric tests like the t-test is its suitability for time series that do not follow a normal distribution and for datasets with missing or deleted values [37]. The Mann-Kendall test is calculated based on the Eq. (4).

$$S = \sum_{i=2}^{n} \sum_{j=1}^{i-1} (sign(xi - xj)) \qquad \text{Eq. (4)}$$

In which xi and *xj* represent consecutive data, n denotes the length of the time series, and the sign function is computable as Eq. (5):

$$sign(xi - xj) = \begin{Bmatrix} +1 & \text{if} & (xi - xj) > 0 & \rightarrow \\ 0 & \text{if} & (xi - xj) = 0 & \\ -1 & \text{if} & (xi - xj) < 0 & \end{Bmatrix} \qquad \text{Eq. (5)}$$

The mean E(S) and variance Var(S) of the statistic *S* were calculated as Eq. (6) and Eq. (7):

$$E(S) = 0 \qquad \text{Eq. (6)}$$

$$VAR(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} tp(tp-1)(2tp+5)\right] \qquad \text{Eq. (7)}$$

Where *tp* is the number of sequences for

[DOI: 10.22034/ECOPERSIA.12.2.3]

the p^{th} value, and p is the number of values in the sequences. The second part in the above equation represents an adjustment for sensitive sequences or data. The standardized statistic *ZM* for the test is obtained from the Eq. (8):

$$Z_M = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}} & \text{if } S > 0 \quad \rightarrow \text{increasing trend} \\ 0 & \text{if } S = 0 \quad \rightarrow \text{without trent} \\ \frac{S+1}{\sqrt{VAR(S)}} & \text{if } S > 0 \quad \rightarrow \text{decreasing trend} \end{cases} \qquad \text{Eq. (8)}$$

The positive value of the *ZM* trend indicates an increasing trend, while the negative value of *ZM* indicates a decreasing trend in the time series [38]. The threshold of statistical significance at a five percent level is |*ZM*| > 1.96. The Earth Trends Modeler (ETM) in Terrset software was employed to conduct this test.

Additionally, the correlation of VHI concerning multitemporal SPEI was determined using the coefficient of determination based on Eq. (9).

$$R^2 = 1 - \frac{RSS}{TSS} \qquad \text{Eq. (9)}$$

In the given equation, R^2 stands for the coefficient of determination. *RSS* and *TSS* represent the Sum of Squares of Residuals and the Total Sum of Squares, respectively. Higher values of these parameters mean more substantial agreement between the compared data, as elucidated by Pogačar *et al.* [39].

Moreover, the slope coefficient of the VHI changes concerning multitemporal SPEI was ascertained using Eq. (10).

$$Slope = \frac{n\sum_{n}^{i=1} x_i y_i - \sum_{n}^{i=1} x_i \sum_{n}^{i=1} y_i}{n\sum_{n}^{i=1} x_i^2 - \left(\sum_{n}^{i=1} x_i\right)^2} \qquad \text{Eq. (10)}$$

In the provided equation, X_i and Y_i denote the values of the independent and dependent variables in the *i*th year, respectively. The *n* represents the years during the study period (*n=20*).

The negative slope value indicates that the dependent variable exhibits an increasing trend, while a positive slope value signifies a decreasing trend in the dependent variable.

Findings

Maximum vegetation cover

According to the map presented in Figure 2, the highest percentage of vegetation cover during the study period is observed in April, while the lowest is in June.

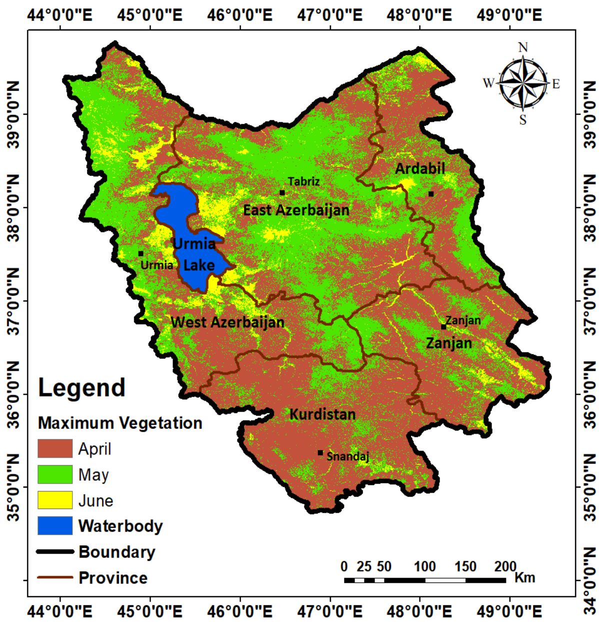

Figure 2) Map of vegetation picked in different months.

Vegetation trend

Figure 3 illustrates the trend of vegetation changes in the study areas. According to the map, yellow pixels indicate a “no-change” trend, green pixels represent an “increasing trend” (drying trend), and red pixels indicate a “decreasing trend” or relief from drought conditions. The stable (48.56%) and increasing (50.43%) trends cover most of the studied areas, while a few pixels have been allocated decreasing trend (1.01%) conditions.

[DOI: 10.22034/ECOPERSIA.12.2.3]

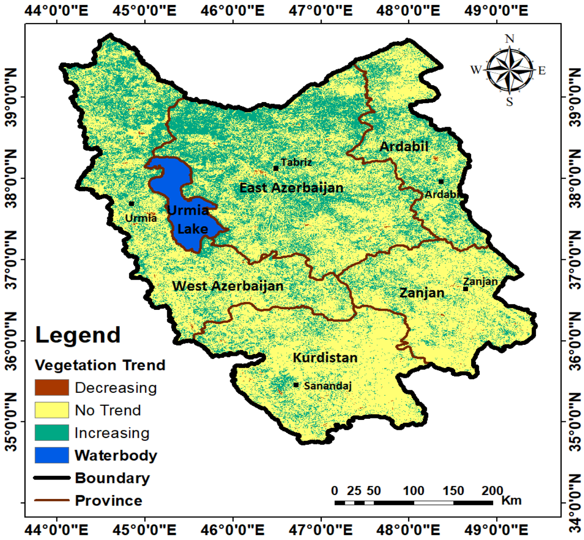

Figure 3) Map of vegetation trend over time.

The results of the Mann-Kendall test are presented in Table 2. According to the provided information, East Azerbaijan Provinces exhibits the highest increasing trend (5.68), while Kurdistan Provinces shows the lowest (4.44).

Moreover, on average, the maximum and minimum changes in the vegetation cover trend are observed in East Azerbaijan (1.79) and Kurdistan (1.02). Also, the Standard Deviation (SD) shows that the most changes occur in West Azerbaijan (1.01), while the most minor change occurs in Zanjan (0.87), which represent the heterogeneous and homogeneous changes, respectively, in these Provincess.

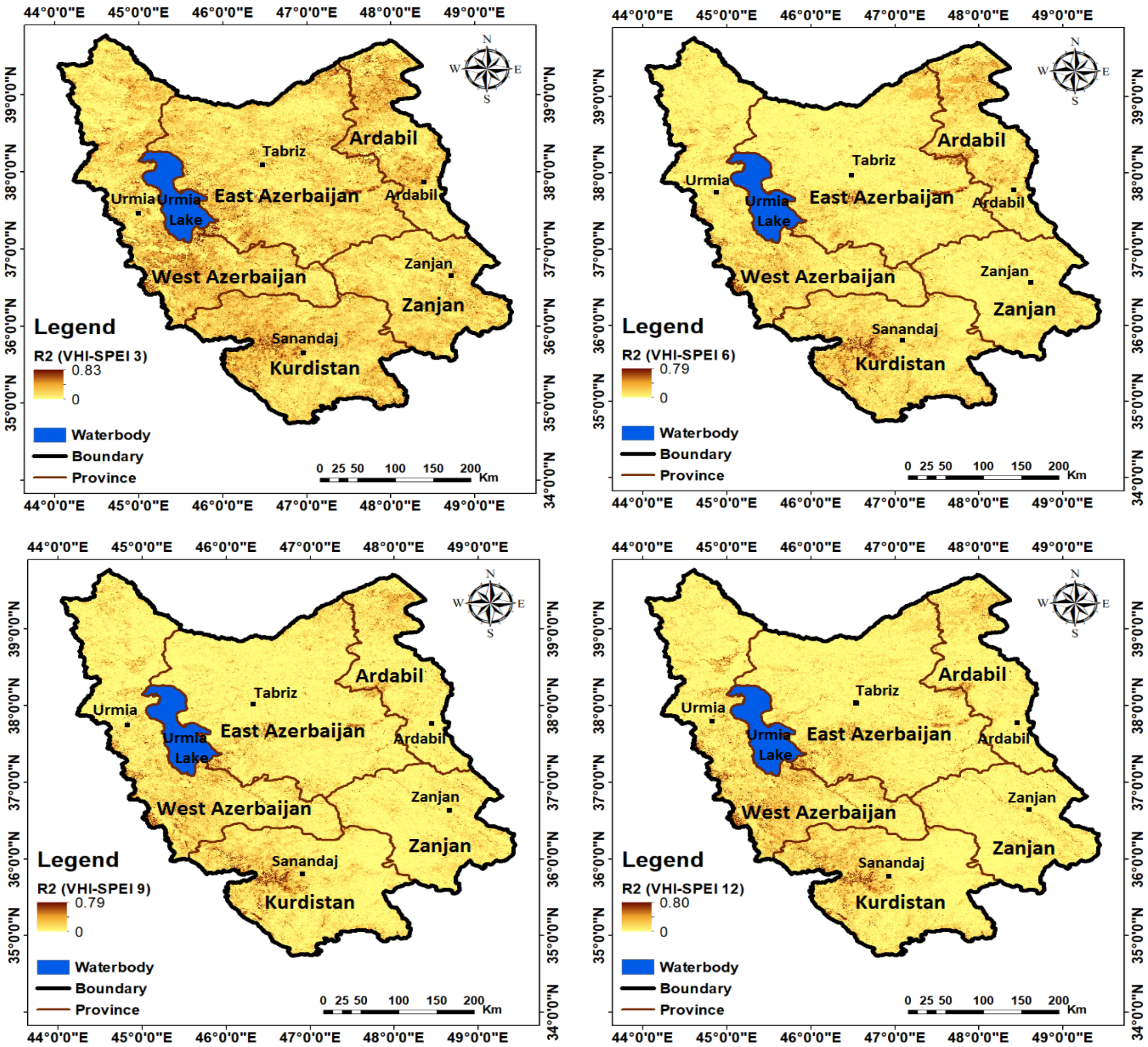

Figure 4) Maps of correlation between VHI and Multitemporal SPEI.

[DOI: 10.22034/ECOPERSIA.12.2.3]

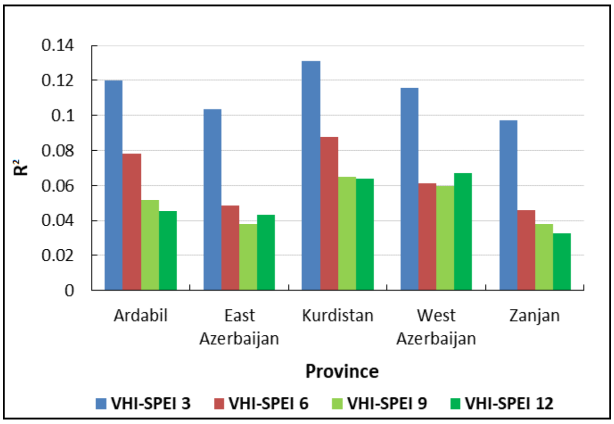

Figure 5) Correlation between VHI and multitemporal SPEI in different Provincess

Correlation between VHI and Multitemporal SPEI

The temporal response of vegetation cover to drought and the spatial distribution of correlation between VHI and multitemporal SPEI is illustrated in Figure 4. A significant positive correlation exists across the entire study area for all temporal scales. The spatial distribution of correlation coefficients gradually increases towards the southeast for all studied temporal scales. The lowest correlation values are observed in the 6- and 9-month scales. However, (SPEI-3),

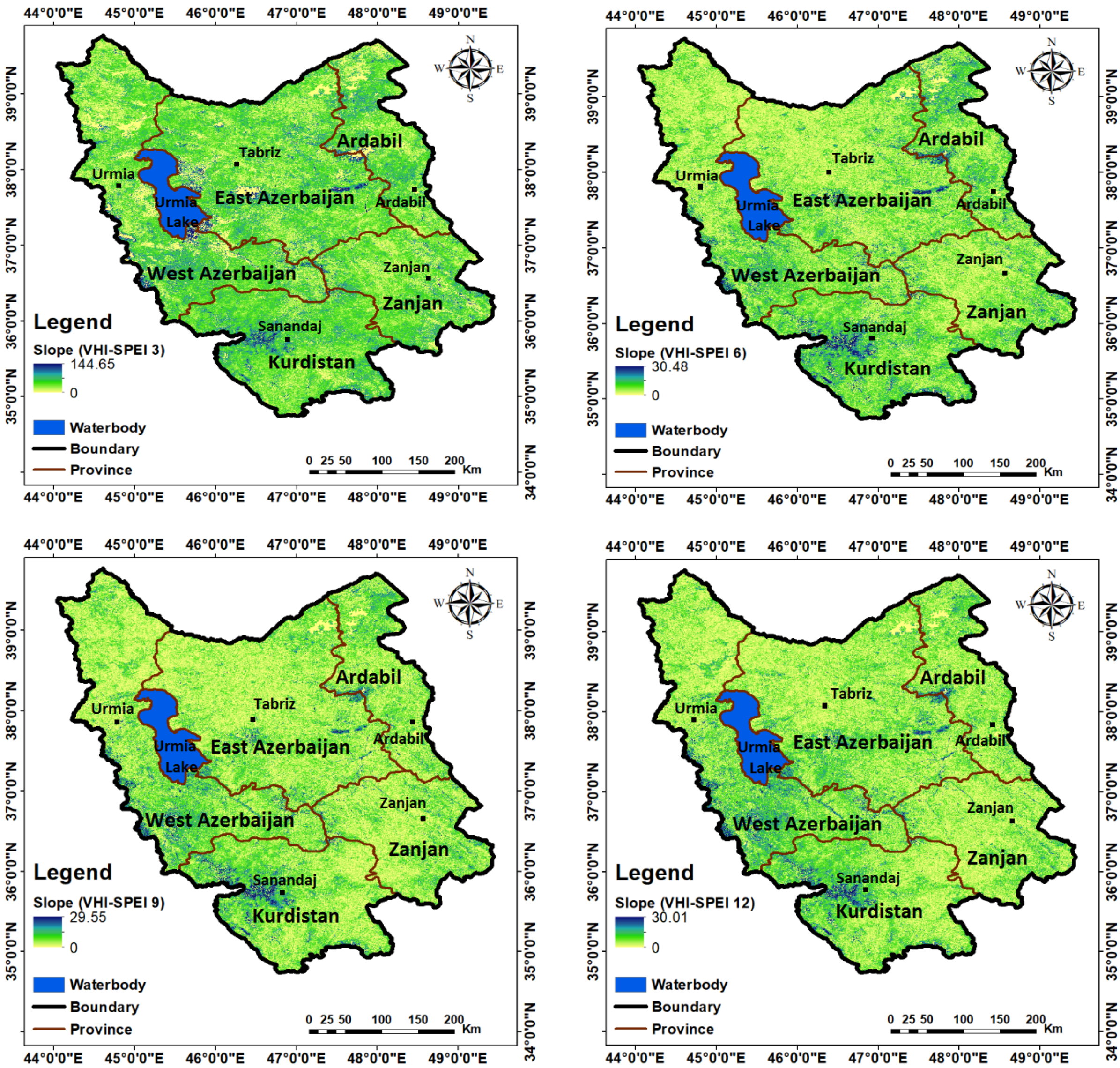

Figure 6) Maps of the absolute value of slope in the linear regression VHI and multitemporal SPEI

[DOI: 10.22034/ECOPERSIA.12.2.3]

calculated for the growing season, exhibits the highest Pearson correlation with VHI values (R^2= 0.83). In this particular scale, the northeastern and southwestern parts of the study area are identified as the most sensitive regions to drought conditions, being more prone to drier conditions (e.g., drought).
As shown in Figure 5, the correlation value decreases when the time scale increases. The highest correlation of the studied indices is observed at the 3-month scale, attributed respectively to the Provincess of Kurdistan, Ardabil, West Azerbaijan, East Azerbaijan, and Zanjan. Consequently, the 3-month scale is more suitable for determining the intensity and duration of vegetation-related drought.

Table 2) Results of the MK test.

Provinces	Min	Max	Mean	SD
Ardabil	-4.51	4.96	1.57	0.94
East Azerbaijan	-4.57	5.68	1.79	0.96
Kurdistan	-4.77	4.44	1.02	0.90
West Azerbaijan	-5.03	5.48	1.54	1.01
Zanjan	-4.57	4.64	1.14	0.87

Linear regression between VHI and multitemporal SPEI

Figure 6 illustrates the maps of the absolute value of the linear regression slope between VHI and Multitemporal SPEI. It is observed that as the time scale increases, the absolute value of the slope in the linear regression between VHI and multitemporal SPEI decreases. The highest and lowest slopes of changes are attributed to the 3-month and 9-month scales, respectively.
According to the presented data in Figure 7, the highest magnitude of slope changes is observed in the 3-month scale, respectively, belonging to the Provincess of Kurdistan, East Azerbaijan, Ardabil, West Azerbaijan, and Zanjan.

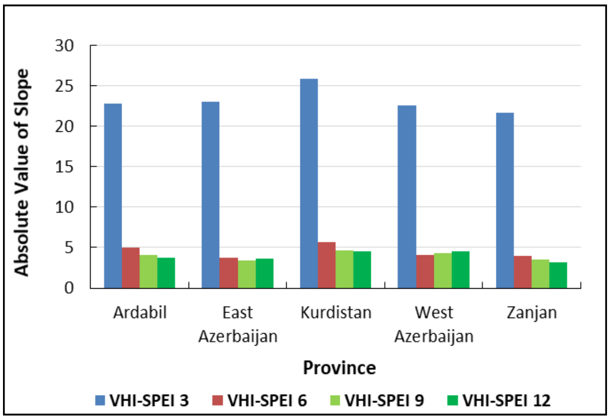

Figure 7) The absolute value of slope in the linear regression between VHI and multitemporal SPEI in different Provincess

Discussion

The highest and lowest percentages of vegetation cover were observed in East Azerbaijan and Kurdistan Provincess, respectively, during the study period. These results emphasize the importance of vegetation mapping or classification in assessing natural environments, as it provides valuable information by quantifying vegetation cover over a specific period. Such information is crucial for natural resource management and the implementation of environmental conservation and restoration programs [40,41].
Changes in drought trends, including no change, stability, and increasing trends, were evident across the study area. An increasing trend indicates a decline in vegetation cover over time, suggesting that drought is a recurring and growing phenomenon in the region. Some researchers have identified global warming [42], regional land use [43], and land cover changes [44] as potential drivers of increasing trends. Moreover, some studies have highlighted the role of global warming in assessing the sustainability of wheat and barley farming systems in the Maragheh-Bonab plain of East Azerbaijan Provinces [45]. Although it is challenging to attribute the identified trends to specific factors accurately,

[DOI: 10.22034/ECOPERSIA.12.2.3]

temperature variations have been introduced as a fundamental factor influencing climate variability in arid and semi-arid regions like Iran [46]. Previous researchers have proposed potential evapotranspiration, actual evapotranspiration, and temperature as primary factors in agricultural drought [47]. The results of this study illustrated a general increasing trend in Northwest Iran, consistent with Dehghani Sargazi *et al.* [48]. The increasing trend in East Azerbaijan Provinces, which has the largest area in the Northwest of Iran, may exacerbate the conditions of agricultural lands in this Provinces. Some research sources have indicated that 46% of agricultural lands in East Azerbaijan Provinces are located in the Lake Urmia basin, and this lake is at risk of drying up due to the expansion of agricultural activities in its watershed and the lack of natural water rights [49]. Therefore, it is essential to develop a plan to reduce the potential effects of drought on agricultural production by considering a combination of climate variables, including precipitation and temperature.

The significant positive correlation observed across the entire region for all studied time scales was confirmed. It is crucial to mention that the effectiveness of SPEI in assessing vegetation drought and, consequently, biomass production has been validated by previous studies [10]. Similarly, the effectiveness of VHI in understanding various aspects of vegetation cover [10, 24] and monitoring the onset of vegetation drought as an early warning system has also been confirmed [50], reinforcing the validity of the results in this section.

Raja and Gopikrishnan [51] compared and analyzed the performance of SPEI at time scales of 1, 3, 6, 9, and 12 months of temporal and spatial variation at 12 weather stations in Barmer arid region from 1979 to 2013. A modified MK test is used to determine the significance of drought-characteristic trends. The results showed that with the increase of the time scale, the temporal changes in SPEI became more consistent. The MK test showed that SPEI showed decreasing trends in 1and 3-month scales but increasing trends in 3, 6, and 12-month scales.

In this case, Musei *et al.* [52] used SPEI in 1, 3, 6, and 12-month time scales to evaluate the spatio-temporal changes of drought occurrence in Somalia. Temporal changes in drought showed a decreasing trend in severity and an increasing trend in drought duration with increasing time scales of SPEI. The Northeast and southwest parts of the study area were the most sensitive (vulnerable) regions to drought. Hence, these areas should be prioritized in drought planning. The 3-month time lag of vegetation response to climatic conditions was observed. One reason is the presence of annual plants and the growth form of grasses, which mainly cover the region and are dependent on short-term moisture. In other words, in the 3-month scale, the influence of climate factors on vegetation cover is more pronounced, and vegetation responds more quickly to climate in this scale. The time delay in the response of vegetation to climatic variables has been reported in various studies. For instance, a time lag of about three months was reported for the Eurasian continent [53]. In contrast, positive relationships between vegetation cover and rainfall in one month were reported in the southwestern United States [54], Australia inland [55-56], Yun–Gui Plateau, and Inner Mongolia [57].

The highest slope of changes was observed at the 3-month scale. The areas with higher slope changes are more sensitive or vulnerable to drought. Based on this, it can be inferred that SPEI-3 indicates the dominant drought pattern in the northwest part of Iran.

[DOI: 10.22034/ECOPERSIA.12.2.3]

The results of this study contribute to a better understanding of the evolution of agricultural drought in Northwest Iran in spatial and temporal dimensions during 2001- 2020. Additionally, future development plans can be directed toward supporting regions prone to agricultural drought using the obtained information.

Conclusion

This study investigated the physical characteristics of agricultural drought in the Northwest of Iran. The results of this study indicate that the time lag in vegetation response to drought is three months. The necessity of paying attention to current water resource management and adopting long-term regional policies in East Azerbaijan Provinces was highlighted due to an increasing trend in drought. Correlation results between VHI and SPEI confirmed the existence of a significant positive correlation throughout the region for all time scales, especially with 3-month time scales. These results highlighted the importance of implementing land use policies about climate change and considering the relationships between climate (processes that affect vegetation cover) and vegetation. However, considering other biophysical factors, such as soil characteristics and land characteristics, and paying attention to groundwater in the analytical framework can improve the accuracy and usefulness of the results. Also, considering that drought is the dominant phenomenon limiting vegetation growth in arid and semi-arid areas, calculating the slope of changes between indicators helps predict the occurrence of drought in the future.

The exposure of the northeastern and southwestern parts of the study area to drought and the need for measures to reduce the effects of drought were also reported. Overall, the findings of this research can serve as scientific evidence for predicting future drought trends, implementing optimal management strategies, and enhancing preparedness and resilience against drought.

Ethical Permissions: The authors did not find the case.

Conflict of Interest: The author declares that there are no conflicts of interest regarding the publication of this manuscript.

Authors' Contributions: Setareh Bagheri (First author), Original researcher/ Discussion (25%); Pouyan Dehghan Rahimabadi (Second author), Methodologist/Original researcher/ Statistical analyst (25%); Hassan Khosravi (Third author), Methodologist/Original researcher/ reviewing and editing stages of the paper. (25%); Hossein Azarnivand (Fourth author) Methodologist/Original researcher/ reviewing and editing stages of the paper. (25%).

Funding/Support:
No funding was received for this work.

Reference

1. Zhang Z., Chang J., Xu C., Zhou Y., Wu Y., Chen X., Jiang S., Duan Z. The response of lake area and vegetation cover variations to climate change over the Qinghai-Tibetan Plateau during the past 30years. Sci. Total Environ. 2018; 635(1): 443-451.
2. Ahmadi S., Azarnivand H., Khosravi H., Dehghan P., Behrang Manesh M. Assessment the effect of drought and land use change on vegetation using Landsat data. Desert. 2019; 24(1): 23-31.
3. Li H., Xie M., Wang H., Li S., Xu M. Spatial heterogeneity of vegetation response to mining activities in resource regions of Northwestern China. Remote Sens. 2020; 12(19): 3247.
4. Dehghan P., Azarnivand H., Khosravi H., Zehtabian G., Moghaddamnia A. An ecological agricultural model using fuzzy AHP and PROMETHEE II approach. Desert. 2021; 26(1): 71-83.
5. Xu M., Kang S., Chen X., Wu H., Wang X., Su Z. Detection of hydrological variations and their impacts on vegetation from multiple satellite observations in the Three-River Source Region of the Tibetan Plateau. Sci. Total Environ. 2018; 639: 1220-1232.
6. Huho J.M., Kosonei R.C. Understanding extreme

[DOI: 10.22034/ECOPERSIA.12.2.3]

climatic events for economic development in Kenya. IOSR J. Environ. Sci. Toxicol. Food Technol. 2014; 8(2): 14-24.
7. Hossain M.L., Li J. NDVI-based vegetation dynamics and its resistance and resilience to different intensities of climatic events. Glob. Ecol. Conserv. 2021; 30: e01768.
8. Wu D., Zhao X., Liang S., Zhou T., Huang K., Tang B., Zhao W. Time-lag effects of global vegetation responses to climate change. Glob. Change Biol. 2015; 21(9): 3520-3531.
9. McKee T. B., Doesken N. J., Kleist J. The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology,1993;17(22)179-184.
10. Vicente-Serrano S.M., Beguería S., López-Moreno J. I. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J. Clim.2010;23(7):1696-1718.
11. Kogan, F.N. Remote sensing of weather impacts on vegetation in non-homogeneous areas. Int. J. Remote Sens. 1990; 11(8): 1405-1419.
12. Sheffield J., Wood E.F., Pan M., Beck H., Coccia G., Serrat-Capdevila A., Verbist K. Satellite remote sensing for water resources management: potential for supporting sustainable development in data-poor regions. Water Resour. Res. 2018; 54(12): 9724-9758.
13. Holben B. N., Tucker C.J., Fan C.J. Spectral assessment of soybean leaf area and lear biomass. Photogramm. Eng. Remote Sens. 1980; 46(1): 651-656.
14. Heydari Alamdarloo E., Khosravi H., Dehghan Rahimabadi P., Ghodsi M. The effect of climate fluctuations on vegetation dynamics in West and Northwest of Iran. Desert Ecosyst. Engineer. J. 2021; 3(2): 19-28.
15. Safari Shad M., Ildoromi A. Akhzari D. Drought monitoring using vegetation indices and MODIS data (case study: Isfahan Provinces, Iran). J. Rangel. Sci. 2017; 7(2): 148-159.
16. Bagheri S., Tamartash R., Jafari M., Tatian M.R., Malekian A., Peyrvand V. Studying MODIS satellite data capability to prepare vegetation canopy in Qazvin plain rangelands. J. Rangel. 2021; 15(1): 24-36.
17. Dehghan Rahimabadi P., Azarnivand H. Assessment of the effect of climate fluctuations and human activities on vegetation dynamics and its vulnerability. Theor. Appl. Climatol. 2023; 2(1): 1-16.
18. Potop V., Boroneanţ C., Možný M., Štěpánek P., Skalák P. Observed spatiotemporal characteristics of drought on various time scales over the Czech Republic. Theor. Appl. Climatol.2014;115(3-4):563-581.
19. Tirivarombo S., Osupile D., Eliasson P. Drought monitoring and analysis: standardised precipitation evapotranspiration index (SPEI) and standardised precipitation index (SPI). Phys. Chem. Earth. Parts A/B/C. 2018; 106(1): 1-10.
20. Bazrafshan O., Mahmoudzadeh F., Asgarinezhad A., Bazrafshan J. Adaptive evaluation of SPI, RDI, and SPEI indices in analyzing the trend of intensity, duration, and frequency of drought in arid and semi-arid regions of Iran. JISE. 2019; 42(3): 117-131.
21. Hosseini Pazhouh N., Ahmadaali K., Shokoohi A.R. Assessment of standardized precipitation and standardized precipitation-evapotranspiration indices for wet period detection. J. Soil Water Conserv.2019;25(6):207-221.
22. Wang F., Lai H., Men R., Sun K., Li Y., Feng K., Tian Q., Guo W., Du X., Qu Y. Spatial and temporal evolutions of terrestrial vegetation drought and the influence of atmospheric circulation factors across the Mainland China. Ecol. Indic. 2024; 158: 111455.
23. Prasad A. K., Chai L., Singh R. P., Kafatos M. Crop yield estimation model for Iowa using remote sensing and surface parameters. Int. J. Appl. Earth Obs. Geoinf. 2006; 8(1): 26-33.
24. Kogan F., Salazar L., Roytman L. Forecasting crop production using satellite-based vegetation health indices in Kansas, USA. Int. J. Rem. Sens. 2012; 33(9): 2798-2814.
25. Hanafi A. Study of climatic characteristics of the northwestern region of Iran based on multivariate statistical analysis. J. Clim. Res. 2022; 13(50): 135-150.
26. Razmi R., Sotoudeh F., Salahi B. Spatio-temporal analysis and zoning of probable occurrence of wet and dry years in North West of Iran. J. Geo. Space. 2015; 15(49): 57-74.
27. Mishra A. K., Singh V.P. Drought modeling-a review. J. Hydrol. 2011; 403(1-2): 157-175.
28. Mohammed S., Alsafadi K., Enaruvbe G. O., Bashir B., Elbeltagi A., Széles A., Alsalman A., Harsanyi E. Assessing the impacts of agricultural drought (SPI/SPEI) on maize and wheat yields across Hungary. Sci. Rep. 2022; 12(1): 8838.
29. Shamshirband S., Hashemi S., Salimi H., Samadianfard S., Asadi E., Shadkani S., Kargar K., Mosavi A., Nabipour N., Chau K.W. Predicting standardized streamflow index for hydrological drought using machine learning models. Eng. Appl. Comput. Fluid Mech. 2020;14(1):339-350.
30. Bhuiyan C., Singh R.P., Kogan F.N. Monitoring drought dynamics in the Aravalli region (India) using different indices based on ground and remote sensing data. Int. J. Appl. Earth Obs. Geoinf. 2006; 8(4): 289-302.
31. Choi M., Jacobs J.M., Anderson M.C., Bosch D.D.

[DOI: 10.22034/ECOPERSIA.12.2.3]

Evaluation of drought indices via remotely sensed data with hydrological variables. J. Hydrol. 2014; 476: 265-273.
32. Vicente-Serrano S. M., Gouveia C., Camarero J. J., Begueria S., Trigo R., Lopez-Moreno J. I., Azorin-Molina C., Pasho E., Lorenzo-Lacruz J., Revuelto J., Moran-Tejeda E., Sanchez-Lorenzo A. Response of vegetation to drought time-scales across global land biomes. Biol.Sci.2013;110(1):52-57.
33. Xiujia C., Guanghua Y., Jian G., Ningning M., Zihao W. Application of WNN-PSO model in drought prediction at crop growth stages: a case study of spring maize in semi-arid regions of northern China. Comput. Electron. Agric. 2022; 199: 107155.
34. Ma J., Zhang C., Li S., Yang C., Chen C., Yun W. Changes in vegetation resistance and resilience under different drought disturbances based on NDVI and SPEI time series data in Jilin Provinces. Remote Sens. 2023; 15(13): 3280.
35. Fathi-Taperasht A., Shafizadeh-Moghadam H., Sadian A., Xu T.T., Nikoo M.R. Drought-induced vulnerability and resilience of different land use types using time series of MODIS-based indices. Int. J. Disast. Risk Reduc. 2023; 91: 103703.
36. Mann H.B. Nonparametric tests against trend. Econometrica. 1945; 13(3):245-259.
37. Sen P. K. Estimates of the regression coefficient based on Kendall's tau. J. Am. Stat. Assoc.1968;63(324):1379-1389.
38. Feizi V., Mollashahi M., Farajzadeh M., Azizi G. Spatial and temporal trend analysis of temperature and precipitation in Iran. ECOPERSIA 2014;2(4):727-742.
39. Pogačar T., Žnidaršič Z., Vlahović Ž., Črepinšek Z., Sušnik A. Grassland model-based evaluation of drought indices: a case study from the Slovenian Alpine region. Agronomy. 2022; 12 (4): 936.
40. He C., Zhang Q., Li Y., Li X., Shi P. Zoning grassland protection area using remote sensing and cellular automata modelling, a case study in Xilingol steppe grassland in Northern China. J. Arid Environ. 2005; 63(4): 814-826.
41. Xiao X., Zhang Q., Braswell B., Urbanski S., Boles S., Wofsy S., Moore III B., Ojima D. Modeling gross primary production of temperate deciduous broadleaf forest using satellite images and climate data. Remote Sens. Environ. 2004; 91(2): 256-270.
42. Penereiro J.C., Badinger A., Maccheri N.A., Meschiatti M.C. Distribuições de Tendências Sazonais de Temperatura Média e Precipitação nos Biomas Brasileiros. Rev. Bras. Meteorol.2018;33:97-113.
43. de Oliveira R.G., Júnior L.C.G.V., da Silva J.B., Espíndola D.A., Lopes R.D., Nogueira J.S., Curado L.F., Rodrigues T.R. Temporal trend changes in reference evapotranspiration contrasting different land uses in southern Amazon basin. Agric. Water Manag. 2021; 250:106815.
44. Karimi Z., Talebi. A. An Integration of Remote Sensing and the DPSIR Framework to Analyze the Land-Use Changes in the Future (Case study: Eskandari Watershed). ECOPERSIA 2023; 11(4): 319-336.
45. Mohammadzadeh A., Mahdavi Damghani A., Vafabakhsh J. Deihimfard R. Sustainability assessment of wheat and barley agro ecosystems by quantitative indices: case study for Maragheh – Bonab plain, East Azerbaijan Provinces. J. Agroecol. 2016; 6(2): 321-339.
46. Mirgol B., Nazari M., Eteghadipour M. Modelling climate change impact on irrigation water requirement and yield of winter wheat (*Triticum aestivum* L.), barley (*Hordeum vulgare* L.), and fodder maize (*Zea mays* L.) in the semi-arid Qazvin Plateau, Iran. Agriculture. 2020; 10(3): 60.
47. Zhang R., Shangguan W., Liu J., Dong W., Wu D. Assessing meteorological and agricultural drought characteristics and drought propagation in Guangdong, China. J. Hydrol. Reg. Stud. 2024; 51:101611.
48. Dehghani Sargazi H., Bazrafshan O., Zamni H. Investigation of the effect of meteorological-agricultural drought on rainfed wheat yield in Iran using SPEI. Nivar. 2021; 45 (114-115): 15-26
49. Manafi Mollayousefi M., Hayati B. Evaluating and comparing the sustainability of selected Crops production in East Azerbaijan Provinces. J. Agri. Sci. Sustain. Product. 2022;33(3):269-288.
50. Sholihah R.I., Trisasongko B.H., Shiddiq D., La Ode S.I., Kusdaryanto S., Panuju D.R. Identification of agricultural drought extent based on vegetation health indices of Landsat data: the case of Subang and Karawang, Indonesia. Procedia Environ. Sci. 2016; 33: 14-20.
51. Raja A., Gopikrishnan T. Drought analysis using the standardized precipitation evapotranspiration index (SPEI) at different time scales in an arid region. Eng. Technol. Appl. Sci. Res. 2022; 12(4): 9034-9037.
52. Musei S.K., Nyaga J.M., Dubow A.Z. SPEI-based spatial and temporal evaluation of drought in Somalia. J. Arid Environ. 2021; 184: 104296.
53. Piao S.L., Mohammat A., Fang J., Cai Q., Feng J. NDVI-based increase in growth of temperate grasslands and its responses to climate changes in China. Glob. Environ. Chang. 2006; 16(4): 340-348.
54. Zhang X., Goldberg M., Tarpley D., Friedl M.A., Morisette J., Kogan F., Yu Y. Drought-induced vegetation stress in southwestern North America. Environ. Res. Lett. 2010; 5(2): 024008.

[DOI: 10.22034/ECOPERSIA.12.2.3]

55. Seddon A.W., Macias-Fauria M., Long P.R., Benz D., Willis K.J. Sensitivity of global terrestrial ecosystems to climate variability. Nature. 2016; 531(7593): 229-232.
56. Chen T., De Jeu R., Liu Y.Y., Van der Werf G.R., Dolman A.J. Using satellite-based soil moisture to quantify the water driven variability in NDVI: A case study over mainland Australia. Remote Sens. Environ. 2014; 140: 330-338.
57. Guo L., Zuo L., Gao J., Jiang Y., Zhang Y., Ma S., Zou Y., Wu S. Revealing the fingerprint of climate change in interannual NDVI variability among biomes in Inner Mongolia, China. Remote Sens. 2020; 12(8): 1332.