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# **Assessing spatial variations of vegetative drought in Khorasan-e-Razavi province, northeast of Iran**

## **Ali Bagherzadeha,\*, Reza Mahjoubin<sup>b</sup> , Ehsan Afshar<sup>c</sup> , Ali Bakhshi<sup>d</sup>**

*<sup>a</sup>Associate Professor, Department of Agriculture, Mashhad Branch, Islamic Azad University, P.O. Box: 91735-413, Mashhad, Iran*

*<sup>b</sup>M.Sc, Department of Agriculture, Mashhad Branch, Islamic Azad University, P.O. Box: 91735-413, Mashhad, Iran*

*<sup>c</sup>Ph.D, Department of Agriculture, Mashhad Branch, Islamic Azad University, P.O. Box: 91735-413, Mashhad, Iran*

*<sup>d</sup>Assistant Professor, Department of Agriculture, Mashhad Branch, Islamic Azad University, P.O. Box: 91735-413, Mashhad, Iran*

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#### A B S T R A C T

**Background and objective**: Information concerning the spatial and temporal characteristics of vegetative drought is essential for decision-making in environmental and agricultural practices. The present study is a comprehensive Spatio-temporal analysis of vegetative drought over thirty years of observations. **Materials and Methods**: The data obtained from NOAA/AVHRR (National Oceanic and Atmospheric Administration/ Advanced Very High-Resolution Radiometer) to reveal the vegetative drought patterns across Khorasan-e-Razavi province, northeast of Iran from 1990 to 2019. Three satellite-based drought indices including the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation health index (VHI) as well as NDVI were used to characterize the dynamics of drought severity conditions and their fluctuations in the study area.

**Results and conclusion**: It was found a strong correlation between land surface temperature (LST), and TCI with VHI which indicates a definite influence of thermal stress on vegetation health in the study area. The analysis of Pearson (R), and the correlation between vegetative drought indices over the 1990–2019 period in Khorasan-e-Razavi province revealed no significant differences among drought indices except P-values. Analyzing long-term drought indices in the study area showed high thermal stress, very poor vegetation condition, and mainly weak VHI in most years of the study. The results of this study show the potential for incorporating satellite-based drought indicators into agricultural decision support systems (e.g. agricultural drought early warning systems, crop yield forecasting models, or water resource management tools) complementing meteorological drought indices derived from precipitation grids.

<sup>\*</sup> *Corresponding author.* Tel.: 0098-9155182701.

E-mail address: abagherzadeh@mshdiau.ac.ir , ORCID: 0000-0002-5499-0092

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# **1. Introduction**

A drought is a natural event that has a great impact on socio-economic, agriculture, and the environment. The conceptual definition of drought differs among regions of various climates (Dracup et al., 1980). These extreme events threaten global food security and local markets for agricultural products. (Lesk et al., 2016; Hadebe et al., 2017). Arid and semi-arid regions are more susceptible to drought as they are more sensitive to rainfall shortages and temperature extremes (Bhuiyan, 2008).

Generally, drought derives from water infrequency because of insufficient precipitation, consequences in full-size deficiency of soil moisture and reduction of crop yield, excessive evapotranspiration, and over-exploitation of water sources or any aggregate of those parameters. There are different types of droughts, like meteorological, hydrological, agricultural, and socioeconomic droughts with different indices which have been developed to characterize them (Zargar et al., 2011; Mishra & Singh, 2010). Rainfall and temperature may be crucial reasons for drought initiation, development, and persistence, specifically for vegetative drought (Bhuiyan & Kogan, 2010). Monitoring and analysis of drought are done through various indicators and indices. These indicators and indices enable the characterization of drought by providing information about the severity, location, duration, and timing of drought to determine, classify, and monitor drought conditions. Drought can be effectively monitored over large areas using remote sensing technology. Satellite remote sensing data provide a synoptic image of the Earth's surface and can therefore be used to spatially estimate the occurrence of droughts (Dehestani Ardakani, 2021; Ghane Ezabadi et al., 2021; Zarei et al., 2021; Gu et al., 2007). Several remotely sensed drought indices have been developed and applied, including duration, intensity, severity, and spatial extent (Mishra et al., 2015).

The vegetation health index (VHI) which was introduced by Kogan (1997, 2001), can be used as the most important agricultural drought index (Bhuiyan et al., 2006; Kogan et al., 2012; Quiring & Ganesh, 2010; Singh et al., 2003). Vegetation Health Index (VHI) is measured based on the vegetation condition index (VCI), and temperature condition index (TCI) with a linear combination which is more effective compared to other indices in monitoring agricultural drought (Kogan 1990, 2001; Singh et al., 2003; Bento et al., 2018). The vegetation condition index (VCI) is based on a normalized difference vegetation index and the maximum and minimum values of NDVI during the whole period of a specific time. The Normalized Difference Vegetation Index (NDVI) as a probe of vegetation health has been one of the most commonly used approaches to monitoring drought events (Ji  $\&$  Peters, 2003; Rhee et al., 2010). The VCI is usually used to estimate vegetation water stress (Bento et al., 2018), measured in percentage, and ranged from 0 to 100 (Kogan, 1995).

The VCI is used in conjunction with NDVI and TCI for assessing vegetation in drought situations. The Temperature Condition Index (TCI) based on land surface temperature (LST), has been developed by employing the thermal bands of the NOAA-AVHRR sensor to recognize the temperature-related vegetation stress (Kogan, 1995; Bento et al., 2018). Applying remote sensing data has great success in the monitoring of drought and its impact on vegetation (Kogan et al., 2005; Singh et al., 2003; Bhuiyan et al., 2006, Bhuiyan & Kogan, 2010). For instance, García-León et al., (2019) investigated the satellitebased drought indices as yield predictors of Spanish cereals. Bhuiyan et al., (2017) analyzed the impact of thermal stress on vegetation health and agricultural drought in Gujarat state, India. They showed that the combined influence of moisture and thermal stress determines the occurrence and severity of drought, which is reflected in the Vegetation Health Index (VHI). A strong correlation between airtemperature, the TCI and the VHI indicates a definite influence of thermal stress on VHI. The Khorasane-Razavi province is in a semi-arid and arid climate region in the northeast of Iran, and due to frequent droughts in recent years, it is of great interest to assess the spatial and temporal patterns of drought in this region.

The impact of drought in the study area has resulted in reducing both water availability and water quality for productive farms, grazing lands, and significant negative direct and indirect economic impacts on the agricultural sector. Drought has also contributed to insect outbreaks, increases in wildfire, and altered rates of carbon, nutrient, and water cycling all of which can impact agricultural production,

critical ecosystem functions that underpin agricultural systems, and the livelihoods and health of farming communities.

In the present study, the vegetative drought indices data derived from the Advanced Very High-Resolution Radiometer (AVHRR) sensor of NOAA satellites were used for monitoring drought occurrence in the Khorasan-e-Razavi province, northeast of Iran. The objective of this study was to analyze the long-term agricultural drought and its spatial extent using precipitation data, LST, NDVI, TCI, VCI, and NDVI in Khorasan-e-Razavi province, northeast of Iran. The study is of great importance for monitoring, understanding and managing, the occurrence of vegetative droughts through satellite observation data.

## **2. Materials and methods**

## *2.1. Study area*

 Khorasan-e-Razavi Province with a surface area of 144,802 (118,884) km2 is located in north-eastern Iran. The study area includes 39 plains located between 45°19 -61°17 east longitude and 33°52 -37°42 north latitude (Fig. 1). Iran's complex physical conditions, including topography, plant cover, and landscape, have resulted in a diverse climate (Alijani, 2008). The climatic characteristics of the plains studied in north-eastern Iran are for the most part arid and semi-arid and represent a variety of conditions, from desert to mountain. Topographical elevation ranges from 230 m a.s.l in the northeast to 305 m a.s.l in the central parts with an increasing trend from south to north of the study area. The average annual temperature varies between  $12.8^{\circ}$ C and  $17.8^{\circ}$ C with a growing trend from north to south.

The general physiographic tendency of the plains extends mainly towards the northwest-southeast. The drainage points of the plains are directed towards two large basins, including the Karakum desert to the northeast and the Kavir desert to the southwest. The higher slopes are at the north and center of the study area. The study area was covered by various geological formations and soil types with different depths and susceptibility to erosion. Agricultural practices in the study area focus on deep alluvial soils in the northern plains with dense land cover.



**Fig. 1- Geographical position of Khorasan-e-Razavi Province**

#### *2.2. Data collection*

For the analysis of vegetation health indices, remote sensing data from weekly composite validated, high spatial resolution (1 km) from VIIRS-VH of the National Oceanic and Atmospheric Administration (NOAA) in the time span of 1990-2019 were used to develop indices such as land surface temperature (LST), the normalized difference vegetation index (NDVI), vegetation condition index (VCI), thermal condition index (TCI) and vegetation health index (VHI).

The VHI includes Temperature Condition Index (TCI) and Vegetation Condition Index (VCI). VCI uses a ratio of land surface reflectivity at visible and near-infrared wavelengths, the Normalized Difference Vegetation Index (NDVI), to assess healthy vegetation cover, while TCI uses thermal infrared emission to estimate Earth's surface temperature (LST). These VHIs, derived from NOAA's Advanced Very High-Resolution Radiometer (AVHRR) sensor data, are available on the NOAA STAR Global Vegetation Health Products website (NOAA STAR, 2016) with data dating back to the early 1980s.

Validation with ground measurements in different parts of the world has shown that these indices are successful in assessing the impact of drought (Kogan, 1997). Table 1 shows the values of the drought indices in the study area.

#### **Table 1- The annual values of precipitation, land surface temperature, NDVI, and vegetative drought indices in Khorasan-e-Razavi province over 1990-2019**



## *2.3. Vegetation drought indices*

NDVI reflects vegetation status through the ratio of responses in the near-infrared (B2) and red (B1) bands of NOAA-AVHRR. This is computed as follows:

$$
NDVI = NIR - Red / NIR + Red \tag{1}
$$

The classification of NDVI based on land cover density conditions is shown in Table 2. VCI is a proxy for moisture conditions. The VCI separates short-term variations in NDVI from long-term changes in the ecosystem (Kogan, 1990, 1995). The VCI resizes the dynamics of the vegetation between 0 and 100 to reflect the relative changes in the state of the vegetation, ranging from extremely bad to optimal (Kogan, 1995; Kogan et al., 2003). It is calculated as:

$$
VCI = (NDVI \cdot NDVI \, min / NDVI \, max \cdot NDVI \, min) \times 100 \tag{2}
$$





TCI represents the relative change in thermal state in terms of brightness temperature which is derived from the NOAA-AVHRR thermal band. Subtle shifts in vegetation health due to thermal stress are monitored by TCI data analysis (Kogan, 1995, 2001, 2002). It is expressed as:

*TCI = (LST max - LST/ LST max - LST min) × 100 (3)*

Where, LST is the seasonal average of weekly land surface temperature, LST min, and LST max are the smoothed multi-year maximum and minimum LST.

While the VCI and TCI exhibit the moisture and thermal conditions of the vegetation, the VHI illustrates the general health of the vegetation (Kogan, 2001) and is calculated as follows:

$$
VHI = \alpha \times VCI + (1 - \alpha) \times TCI \tag{4}
$$

Where  $\alpha$  is a coefficient determining the contribution of the two indices ( $\alpha$ =0.5). VHI is a representative characterizing vegetation health or a combination of estimated moisture and thermal conditions. The classifications of VCI, TCI, and VHI proposed by Kogan (2001) are demonstrated in Table 3.

Table 3- Classification of VCI, TCI and VHI drought based on (Kogan, 2001)

. VHI <b>TROL</b> 37 A T	10:	10 20	$20 -$ 30	30 40	40 60	>60
* condition	Extreme	severe	Moderate	Mild	Normal	Favorable
<b>Drought</b>		.	.			

#### *2.4. Statistical and Spatial analysis*

The values were statistically analysed by SPSS (16.0). An ordinary kriging interpolation technique with ArcGIS 10.7 was used to delineate the spatial zoning of drought indexes.

# **3. Results and Discussion**

#### *3.1. Climate and vegetation fluctuations*

Khorasan-e-Razavi province in the North-East of Iran is one of the Arid and semi-arid states, which is highly vulnerable to vegetative drought. The Precipitation values from 1990-2019 ranged from 112.40 to 304.94 with a mean value of 204.46 mm. The land surface temperature (LST) varied between 23.86 and 31.71 with an average of 28.58 °C (Fig. 2). The values of normalized difference vegetation index (NDVI) ranged from 0.057 to 0.093 with a mean value of 0.08 (Fig. 3). These low NDVI values are mainly achieved with high LST values as the vegetation is under high water stress.

The increase in LST and the decrease in NDVI contribute to significant water stress that can trigger the onset of agricultural drought. Our results showed that the stress of vegetation was due to rising surface temperature. The vegetation condition index (VCI) varied between 25.45 and 73.90 with an average of 51.51 and the temperature condition index (TCI) ranged from 21.58 to 73.46 with a mean value of 38.83 (Fig. 4). Also, the values of vegetation health index (VHI) ranged from 31.42 to 66.37 with an average of 45.17 (Table 1). According to our findings, 1990 and 2006 had the most variations in the yearly land surface temperature. However, over the experiment period the annual precipitation experienced relatively large and unpredictable changes.

The analysis of Pearson (R), and the correlation among vegetative drought indices over the 1990– 2019 period in Khorasan-e-Razavi province revealed that except for P-values no significant differences between the drought indices were observed (Table 4). The results of our study are consistent with the findings of Gidey et al. (2018) that investigated the long-term agricultural drought on duration frequency, severity, and spatial extent on vegetation health index (VHI) in northern Ethiopia.



**Fig. 2-The fluctuations of yearly land surface temperature and precipitation over 1990-2019 in Khorasan-e-Razavi province**



**Fig. 3- The fluctuations of NDVI over 1990-2019 in Khorasan-e-Razavi province**





## *3.2. Spatio-temporal variations of vegetative drought indices*

 The fluctuations of NDVI over the 1990-2019 time period in Khorasan-e-Razavi province were exhibited in figure 3. As shown, the highest annual values of NDVI in the region were found in 1998, where 4.46% (5171.26 km2) of the area ranked bare, which was located in the west of the study area, 95.38% (110573.91 km2) classified into sparse, which located in the north, central and east parts of the province, and 0.156% (180.61 km2) assessed into moderate land cover density, which focused in the south, west and scattered parts in the east of the province. The lowest annual NDVI values were determined in 2000, were 42.55% (49332.7 km2), and 57.45% (59771.23 km2) grouped into bare, and sparse land cover density, respectively (Table 5, Fig. 4).

#### **Table 5 -The threshold values (surface area and the percent) of NDVI in Khorasan-e-Razavi province over 1990- 2019**





**Fig. 4 - The zonation of minimum and maximum values of NDVI over 1990-2019 in Khorasan-e-Razavi**

The minimum annual values of TCI, VCI, and VHI over the observation period were found in 2001, 2000, and 2001, while the maximum values were observed in 1994, 1998, and 1994, respectively. The highest and the lowest correlations between VHI and other drought indices were found with TCI (R2=0.712), and precipitation (R2=0.209), respectively. The annual fluctuations of drought indices VCI, TCI, and VHI over the 1990-2019 time period in Khorasan-e-Razavi province were demonstrated in Fig. 5.



As shown, the higher threshold values of VCI in Khorasan-e-Razavi province were observed in 1998, where 0.02% (22.86 km2) of the area was categorized into moderate, 0.46% (537.24 km2) was classified into mild, 13.26% (15369.74 km2) ranked into normal, and 86.26% (99995.93 km2) grouped into favorable drought VCI classes, which dominate throughout the study area (Table 6). The spatial distribution of normal, mild, and moderate drought VCI classes concentrated in the middle, north and northwest of the study area (Fig. 6). The lower threshold values of VCI were assessed in 2000, where

0.91% (1053.91 km2), 28.56% (33107.93 km2), 44.71% (51829.17 km2), 18.46% (21407.45 km2), 7.1% (8227.83 km2), and 0.26% (299.48 km2) classified into extreme, severe, moderate, mild, normal, and favorable drought classes, respectively (Table 6). Where the extreme class of VCI focused in the east, the severe and moderate classes were found in the east, northeast, south, and west parts of the province. The mild, normal and favorable drought VCI classes concentrated mainly in the south, west and scattered parts in the east of the study area (Fig. 7).





The higher threshold values of TCI in the study area were assessed in 1994, where 0.03% (36.58 km2) of the area was classified as mild, 8.47% (9818.99 km2) as normal, and 91.50% (106070.2 km2) ranked into favorable drought classes which dominate throughout the study area (Table 6). The classes of normal and mild were found as scattered parts mainly in the middle, west and northwest of the province (Fig. 6). The lower threshold values of TCI were found in 2001, where 1.99% (2304.43 km2), 42.80% (49620.75 km2), 40.18% (46580.18 km2), 12.52% (14510.15 km2), 2.42% (2825.67 km2), and 0.07% (84.59 km2) categorized into extreme, severe, moderate, mild, normal, and favorable drought classes, respectively (Table 6). The spatial distribution of TCI classes revealed that extreme conditions was found in scattered parts in the center and south of the province, while severe and moderate conditions were dominant classes all over the study area. The mild, normal, and favorable conditions of TCI were found mainly in the middle and western parts of the region (Fig. 7).



**Fig. 6 -The zonation of maximum values of TCI, VCI, and VHI over 1990-2019 in Khorasan-e-Razavi**



**Fig. 7- The zonation of minimum values of TCI, VCI, and VHI over 1990-2019 in Khorasan-e-Razavi**

The higher threshold values of VHI in the region were found in 1994, where 0.08% (93.73 km2) of the area was categorized as mild, 21.49% (24909.82 km2) was classified as, and 78.43% (90922.22 km2) grouped into favorable drought classes, which dominate all over the study area (Table 7). The spatial distribution of normal and mild drought VHI classes was concentrated mainly in the middle, north and northwest of the province (Fig. 6).

The lower threshold values of VHI were observed in 2001, where 5.06% (5863.96 km2), 39.39% (45661.15 km2), 43.68% (50640.37 km2), 11.86% (13751.16 km2), and 0.01% (9.14 km2) ranked into severe, moderate, mild, normal, and favorable drought classes, respectively (Table 7). The mild drought VHI along with normal class dominates overall the study area, mainly in the middle and western parts of the province. The moderate and severe classes were focused mainly in the east, north, and scattered parts in the south of the region (Fig. 7).

The finding results of Garcia-Leon et al. (2019) revealed the potential for including satellite-based drought indices in agricultural decision support systems (e.g., agricultural drought early warning systems, crop yield forecasting models or water resource management tools) complementing meteorological drought indices derived from precipitation grids. Bhuiyan et al. (2017) found that agricultural production has a direct correspondence with the VHI, and since vegetation health is strongly influenced by the thermal state in vegetation, low vegetation productivity is directly or indirectly associated with the thermal stress developed in the vegetation.

<b>VHI</b>									
Drought class	Upper threshold (1994)		Lower threshold (2001)						
	area $(km2)$	$\frac{6}{6}$	area $(km^2)$	$\frac{0}{0}$					
Extreme	۰	٠	۰						
Severe	۰	٠	5863.96	5.06					
Moderate	۰	٠	45661.15	39.39					
Mild	93.73	0.08	50640.37	43.68					
Normal	24909.82	21.49	13751.16	11.86					
Favorable	90922.22	78.43	9.14	0.01					

**Table 7- The threshold values (surface area and the percent) of VHI in Khorasan-e-Razavi province over 1990-2019**

## *3.3. Characterization of drought-affected areas*

Regarding the fluctuations of land surface temperature, precipitation, moisture and thermal stress over the observation period the percent of drought-affected areas in Khorasan-e-Razavi province over the 1990-2019 time period was demonstrated in Table 8. In 2008 the highest percentage of the study area (15.34%) was affected by extreme drought conditions (VHI<10), while the lowest percentage of the surface area under extreme drought (0.03%) was found in 1994. Also, the highest and the lowest percentages of the study area under severe conditions of drought (10<VHI<20) were observed in 1990 and 1994 with 22.20% and 0.34%, respectively. The highest and the lowest percentages of the study area under moderate drought conditions (20<VHI<30) were exhibited in 1990 and 1994, respectively, where 25.92% and 1.87% percentage of the study area were affected by moderate drought. As well, the highest and the lowest percentages of the surface area under mild conditions of drought (30<VHI<40) were revealed in 2012 (24.77%), and 1994 (6.19%).

The highest and the lowest percentages of the study area under normal drought conditions (40<VHI<60) were demonstrated in 1999 and 1990, respectively, where 47.96% and 16.60% of the study area were affected by normal drought. In addition, the highest and the lowest percentages of the surface area under favorable conditions of drought (VHI>60) were revealed in 1994 and 1990, where

55.04% and 2.45% of the surface area were affected by favorable drought, respectively. Analysis of the vegetation health index reveals that the spread and intensity of vegetative drought appear when both moisture- and thermal stresses were high. The percentage of departure of the VHI was greater in those years when the departure of both the VCI and the TCI was high relative to their respective mean values over the observation period.



#### **Table 8- The percent of drought affected areas based on VHI index in Khorasan-e-Razavi province over 1990-2019**

# **4. Conclusion**

The study is a comprehensive Spatio-temporal analysis of vegetative drought over thirty years of observations in the Khorasan-e-Razavi province in the North East of Iran. The yearly values of LSI, precipitation, NDVI, VCI, TCI, and VHI were derived through multi-channel data from the NOAA-AVHRR satellite for drought monitoring from 1990-2019 in the study area. The highest and the lowest correlations between VHI and other drought indices were found with TCI ( $R2=0.712$ ), and precipitation ( $R2=0.209$ ), respectively.

The results of our study indicated that TCI was found to be the most sensitive indicator of drought conditions, followed by LST, VCI, and NDVI. Analyzing long-term drought indices in the study area showed high thermal stress, very poor vegetation condition, and mainly weak VHI in most years of the study. The results of our study highlighted the potential of incorporating satellite-based drought indices into agricultural decision support systems, such as Agricultural drought early warning or crop yield forecast. This study may help to improve the existing agricultural drought monitoring systems carried out in Khorasan-e-Razavi province. It also supports the formulation and implementation of drought management measures in the study area.

Declarations

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**Conflict of Interest /Competing interests** (The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript)

**Availability of Data and Material** (Data are available when requested)

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**Authors Contributions** (All co-authors contributed to the manuscript)

**Code availability** (Not applicable)

#### **REFERENCES**

- Bento, V.A., Gouveia, C.M., DaCamara, C.C., & Trigo, I.F. (2018). A climatological assessment of drought impact on vegetation health index. *Agricltural and forest Meteorolgy,* 259, 286–295. https://doi.org/10.1016/j.agrformet.2018.05.014
- Bhuiyan, C., Saha, A.K., Bandyopadhyay N., & Kogan, F.N. (2017). Analyzing the impact of thermal stress on vegetation health and agricultural drought – a case study from Gujarat, India. GIScience & Remote Sensing, https://doi.org/10.1080/15481603.2017.1309737
- Bhuiyan, C. (2008). Desert vegetation during droughts: response and sensitivity. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci*, *37*, 907-912.
- Bhuiyan. C., & Kogan, F.N. (2010). "Monsoon Variation and Vegetative Drought Patterns in the Luni Basin under Rain-<br>Shadow Zone." International Journal of Remote Sensing, 31 (12): 3223–3242. Shadow Zone." *International Journal of Remote Sensing, 31 (12):* 3223–3242. https://doi.org/doi:10.1080/01431160903159332
- Bhuiyan, C., Singh, R. P., & Kogan, F. N. (2006). Monitoring drought dynamics in the Aravalli region (India) using different indices based on ground and remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *8*(4), 289-302.https://doi.org/doi:10.1016/j.jag.2006.03.002
- Darcup, J. A., Lee, K. S., & Paulson, E. G. (1980). On the definition of drought. *Water Resour Res*, *16*, 297- 302.https://doi.org/10.1029/WR016i002p00297
- Dehestani Ardakani, M. R. (2021). Dust time series analysis using long-term monthly images of MERRA2 satellites and Sentinel5 images in Google Earth Engine. *Journal of Nature and Spatial Sciences (JONASS)*, *1*(2), 16-26. <https://doi.org/10.30495/jonass.2021.1920168.1001>
- García-León, D., Contreras, S., & Hunink, J. (2019). Comparison of meteorological and satellite-based drought indices as yield predictors of Spanish cereals. Agricultural Water Management, 213: 388-396. Spanish cereals. *Agricultural* https://doi.org/10.1016/j.agwat.2018.10.030
- Ghane Ezabadi, N., Azhdar, S., & Jamali, A. A. (2021). Analysis of dust changes using satellite images in Giovanni NASA and Sentinel in Google Earth Engine in western Iran. *Journal of Nature and Spatial Sciences (JONASS)*, *1*(1), 17-26. <https://doi.org/10.30495/jonass.2021.680327>
- Gidey, E., Dikinya, O., Sebego, R., Segosebe, E., & Zenebe, A. (2018). Analysis of the long-term agricultural drought onset, cessation, duration, frequency, severity and spatial extent using Vegetation Health Index (VHI) in Raya and its environs, Northern Ethiopia. *Environmental Systems Research*, *7*(1), 1-18.https://doi.org/10.1186/s40068-018-0115-z
- Gu, Y., Brown, J. F., Verdin, J. P., & Wardlow, B. (2007). A five‐year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. *Geophysical research letters*, *34*(6). https://doi.org/doi:10.1029/2006GL029127NOAA STAR (2016). Global vegetation health products.Hadebe, S.T., Modi, A.T., & Mabhaudhi, T. (2017). Drought tolerance and water use of cereal crops: a focus on Sorghum as a food security crop in Sub-Saharan Africa *Journal of Agronomy and Crop Science*, *203*(3), 177-191 https://doi.org/10.1111/jac.12191
- Ji, L., & Peters, A.J. (2003). Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices. *Remote sensing of Environment*, *87*(1), 85-98.http://dx.doi.org/10.1016/S0034-4257(03)00174-3
- Kogan, F.N. (1990). Remote sensing of weather impacts on vegetation in non-homogeneous areas. *International Journal of remote sensing*, *11*(8), 1405-1419.https://doi.org/10.1080/01431169008955102
- Kogan, F.N. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in space research*, *15*(11), 91-100. https://doi.org/10.1016/0273-1177(95)00079-T
- Kogan, F.N. (1997). Global drought watch from space. *Bulletin of the American Meteorological Society*, *78*(4), 621- 636.://doi.org/10.1175/1520-0477(1997)078<0621:GDWFS>2.0.CO;2
- Kogan, F.N. (2001). Operational Space Technology for Global Vegetation Assessment. *Bulletin of the American meteorological society*, *82*(9), 1949-1964.http://dx.doi.org/10.1175/1520-0477(2001)082<1949:OSTFGV>2.3.CO;2
- Kogan, F.N. (2002). World Droughts in the New Millennium from AVHRR-based Vegetation Health Indices. *Eos, Transactions American Geophysical Union*, *83*(48), 557-563.https://doi.org/10.1029/2002EO000382
- Kogan, F.N., Gitelson, A., Edige, Z., Spivak, l., & Lebed, L. (2003). AVHRR-Based Spectral Vegetation Index for Quantitative Assessment of Vegetation State and Productivity. *Photogrammetric Engineering & Remote Sensing*, *69*(8), 899-906.https://doi.org/10.14358/PERS.69.8.899
- Kogan, F.N., Wei, B.G., Zhiyuan, Yang. P., & Xianfeng, J. (2005). Modeling corn production in China using AVHRR-based vegetation health indices. *International Journal of Remote Sensing*, *26*(11), 2325- 2336.https://doi.org/10.1080/01431160500034235
- Kogan, F., Salazar, L., & Roytman, L. (2012). Forecasting crop production using satellite-based vegetation health indices in Kansas, USA. *International journal of remote sensing*, *33*(9), 2798- 2814.https://doi.org/doi:10.1080/01431161.2011.621464
- Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84-87.http://dx.doi.org/10.1038/nature16467
- Mishra, A.K., & Singh, V.P. (2010). A review of drought concepts. J Hydrol, 391, 202–216. https://doi.org/10.1016/j.jhydrol.2010.07.012
- Mishra, A.K., Ines, A.V.M., Das, N.N., Khedun, C.P., Singh, V.P., Sivakumar, B., & Hansen, J.W. (2015). Anatomy of a local-scale drought: Application of assimilated remote sensing products, crop model, and statistical methods to an agricultural drought study. *Journal of Hydrology, 526,*15-29. https://doi.org/10.1016/j.jhydrol.2014.10.038
- Quiring, S. M., & Ganesh, S. (2010). Evaluating the utility of the Vegetation Condition Index (VCI) for monitoring meteorological drought in Texas. *Agricultural and Forest Meteorology*, *150*(3), 330- 339.http://dx.doi.org/10.1016/j.agrformet.2009.11.015
- Rhee, J., Im, J., & Carbone, G. J. (2010). Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. *Remote Sensing of environment*, *114*(12), 2875-2887.https://doi.org/10.1016/j.rse.2010.07.005
- Singh, R. P., Roy, S., & Kogan, F. (2003). Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. *International journal of remote sensing*, *24*(22), 4393- 4402.https://doi.org/10.1080/0143116031000084323
- STAR, N. (2018). Global vegetation health products. Center for Satellite Applications and Research, NOAA, USA.
- Zarei, M., Tazeh, M., Moosavi, V., & Kalantari, S. (2021). Evaluating the changes in Gavkhuni Wetland using MODIS satellite images in 2000-2016. *Journal of Nature and Spatial Sciences (JONASS)*, *1*(1), 27-41. <https://doi.org/10.30495/jonass.2021.1921485.1003>
- Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, *19*(NA), 333- 349.https://doi.org/10.1139/a11-013



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