

Assessment of Drought in Agricultural Areas by Combining Meteorological and Remote Sensing Data

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Abstract: Droughts during the growing season are projected to increase in frequency and severity in Iran. Thus, area-wide monitoring of agricultural drought in this region is becoming more and more important. Precipitation patterns changing is caused by extreme weather events such as drought which strongly affect agricultural production. In this study, two data sources are used in drought assessment. First, by calculating the Standardized Precipitation Index (SPI) in the periods of 1, 3, 6 months, and one year in the western agricultural areas of Isfahan province in the time series from 2016 to 2019, precipitation data were used to analyze and evaluate meteorological drought's spatial and temporal dynamics. Furthermore, the average loss of rainfall was calculated using TRMM satellite monthly rainfall data and the average NDVI monthly with Landsat 8 satellite images using remote sensing data. Then, the Composite Drought Index (CDI) is produced to assess agricultural drought in the 2017-2018-2019 time series. The correlation between the CDI and SPI varies between 0.19 and 0.81 in different months in the time series. The correlation between temperature and CDI in different months varies from 0.22 to 0.75 and between evaporation and CDI from 0.25 to 0.70 in time series.

Keywords: agricultural drought; CDI; SPI; remote sensing

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1. Introduction

Drought is a complex natural phenomenon caused by the imbalance of precipitation and evaporation. This crisis often occurs with a lack of rainfall and causes a decrease in soil moisture, which also affects plant growth in the long run [1]. Therefore, drought monitoring is vital to avert and reduce disasters and losses in the agricultural economy. In general, drought is associated with climatic events. Variables such as rainfall, temperature, and river flow can provide good indicators of the occurrence or non-occurrence of drought. After that, these indicators can be converted into drought indicators that indicate the occurrence, magnitude, intensity, and duration of the drought event [2]. Drought variables can contain an input or a combination of hydrological variables [3]. For this purpose, indices that are a combination of hydrological variables lead to better results; Which variables to use depends on the situation, and the type of drought being analyzed. Also, the choice of drought index is determined based on the region of interest and data availability [4].

In recent decades, many indices such as Palmer Drought Severity Index (PDSI) [5], Standardized Precipitation Index (SPI) [6], and Standardized Precipitation Evapotranspiration Index (SPEI) [7] have been proposed and widely utilized for drought monitoring [8]. Most of the studies have emphasized that PDSI has been a good index for drought monitoring at the variate regions [9,10]. SPI index is the precipitation-determining factor

in the formation of drought but didn't consider the effects of temperature on drought, which is one of its' limitations. In the following two mentioned indicators and their challenges, SPI and PDSI were combined together which SPEI index took advantage of the multitemporal nature of SPI and sensitivity to evaporation and transpiration of PDSI. Many studies have used SPEI to analyze the spatiotemporal characteristics of drought in many regions [10,11]. In recent years, Remote sensing data with wide spatial coverage provided a good situation for extracting indicators and drought monitoring the spatial-temporal pattern of drought. An important finding from various research is that Normalized Difference Vegetation Index (NDVI) can be used for vegetation drought conditions [12,13]. In this way, according to the definition of NDVI, a number of vegetation indices such as the Vegetation Condition Index (VCI) [14,15], and Enhanced Vegetation Index (EVI) [16] were created to detect drought. However, the vegetation index is closely related to vegetation greenness and is often called the greenness index instead of the drought index [17]. Land surface temperature (LST) is sensitive to Water content and soil moisture, while land cover types can strongly influence the relationship between LST and soil moisture [18]. This means that only using LST data for drought monitoring is not applicable when the study area has different types of land cover. For example, the Crop Water Stress Index (CWSI) [19,20], was only applicable to full vegetation areas [21]. Therefore, studies have worked on the integration of NDVI and LSI and concluded that this practice can provide more complete information about drought in bare soil than complete vegetation, and scientists have created many indices by combining LST and NDVI satellite data [22].

All the mentioned cases indicate the importance of continuous monitoring in susceptible areas; Therefore, this research has focused on different goals in this field; These goals include: (a) Identifying minor spatial changes of drought using meteorological indices such as SPI and integration of indices such as NDVI and precipitation to assess agricultural drought. (b) Using parameters such as SPI, temperature data, and evaporation and transpiration obtained from synoptic stations to check the performance of the used index.

2. Materials and Methods

2.1. Study Area

The study area is located in the west of Isfahan province in Iran. It's geographical coordinates is 49° 38' 00" to 53° 12' 00" longitudes and 31° 35' 00" to 32° 58' 00" latitudes and it's area is estimated to be 41689 square meters. About 10% of the deserts in Iran are in Isfahan, and deserts make up about 33% of the area of this province. Figure 1 is the general display of the studied area.

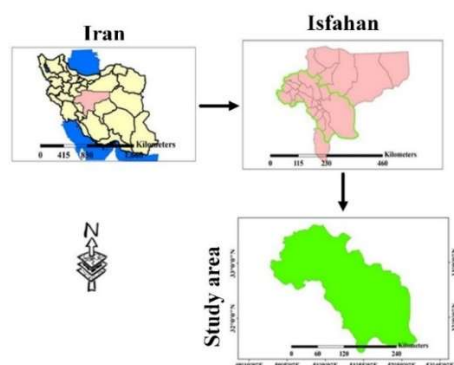


Figure 1. Location of study area.

2.2. Dataset

In this research, various remote sensing data including Landsat 8 OLI images for calculating monthly NDVI from 2016 to 2019 and TRMM monthly rainfall data were used; They were considered as input data for the combined index of agricultural drought. Also,

field data include precipitation, temperature, and evaporation data of synoptic stations located in the study area between 2016 and 2019. Synoptic station information can be seen in Table 1.

Table 1. Information of synoptic stations used in the research.

Station Name	Log	Lat	Elevation
Daran	440813	3647769	1563
Isfahan	566337	3597985	1550
Isfahan Airport	580856	3623255	1543
Golpaygan	433405	3703253	1850
Meymeh	515492	3699340	2012
Shahreza	576577	3538690	1859
Kabootar Abad	578269	3598012	1543

2.3. Proposed Method

As mentioned, we tried to use field and satellite data for providing a valid composite index for agricultural drought assessment. The flowchart of the research is shown in Figure 2.

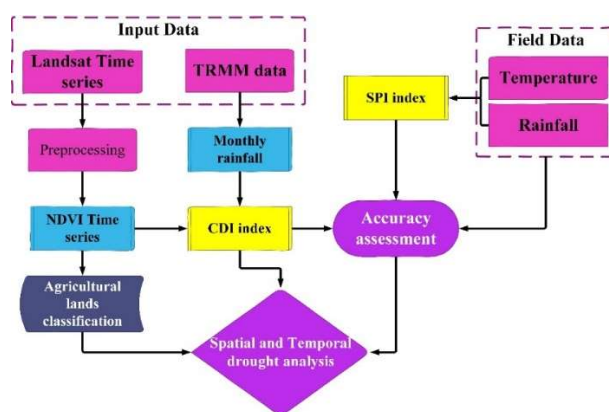


Figure 2. Proposed method flowchart.

2.3.1. Identification of agricultural areas

In this part, first, the Landsat images were preprocessed; then in order to investigate the drought in the agricultural areas, NDVI time series for one crop year were obtained from the images and classified by applying the maximum likelihood algorithm, and finally, the agricultural areas, both wet and dry, were separated. According to the prepared map in Figure 3, the most of agricultural areas are located in the northwest and center of the study area.

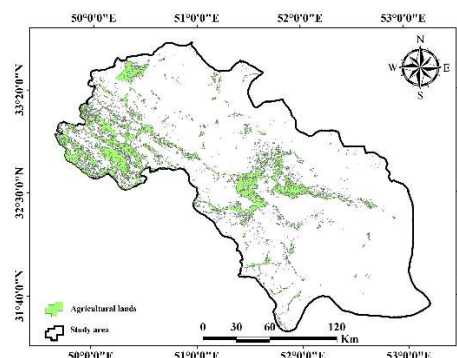


Figure 3. Agricultural lands in the study area.

2.3.2. Standard Precipitation Index (SPI)

The Standard Precipitation Index was developed by McKee et al. [6]. One of the main advantages of the SPI is that it only requires precipitation data as an input, which makes it ideal for areas where data collection is not as extensive. The fact that the SPI is based solely on precipitation makes its evaluation relatively easy. The standardization of this index ensures independence from geographical position as the index in question is calculated with respect to the average precipitation in the same place [23].

2.3.3. Composite Drought Index

Wisem et al. [24] created a Composite Drought Index (CDI) to evaluate multivariate droughts. The results showed that in comparison with univariate indices such as SPI, CDI provides a more comprehensive description of hidden variation in individual features of drought. In addition, it seems that the established CDI is a flexible and effective physical index that is dependent on the weather conditions of the studied region. Also, this index is a combination of precipitation, discharge, and NDVI index, the details of which are examined in [25].

2.3.4. Validation

Validation plays an important role in performance of different algorithms which confirms the accuracy of the proposed approach. After creating CDI index maps, Accuracy assessment was done by calculating the correlation between the CDI index and the SPI index and temperature and evaporation data as ground truths.

3. Implementation and results

With attention to the High importance of drought and its high impacts, this event was studied in the time series from 2016 to 2019 in the agricultural areas of west Isfahan. Moreover, in this section according to the description of section 2.3, the results from the proposed approach have been examined.

3.1. SPI index results

The index was calculated to identify the regular year between 2016 and 2019. The results show that we can consider 2016 because neither drought nor wetness has occurred. Also, for the study of drought in the years 2017 to 2019, various time periods were considered. According to the results in this part, 2017 was the driest, 2019 was the wettest, and 2018 was the most normal year.

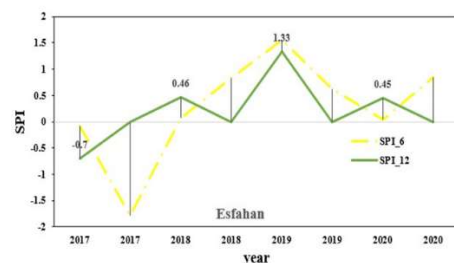


Figure 4. Six- and twelve-month SPI index of weather stations in Isfahan city.

3.2. CDI Index Results

For a more detailed investigation of the drought in the western agricultural lands, in addition to the SPI index, the CDI index was estimated, which is a combination index of the amount of vegetation and rainfall of the area. When using the CDI index, we should consider a year as a normal year and other years as current year. In this study 2017 to 2019 as the current year were considered to investigate the drought. As shown in Figure 5, in

2017 compared to 2018 and 2019, the intensity of drought is higher, especially in the north-western parts, which are agricultural lands. In 2018 and 2019, despite the occurrence of drought in the agricultural sectors, the intensity was much lower than in 2017.

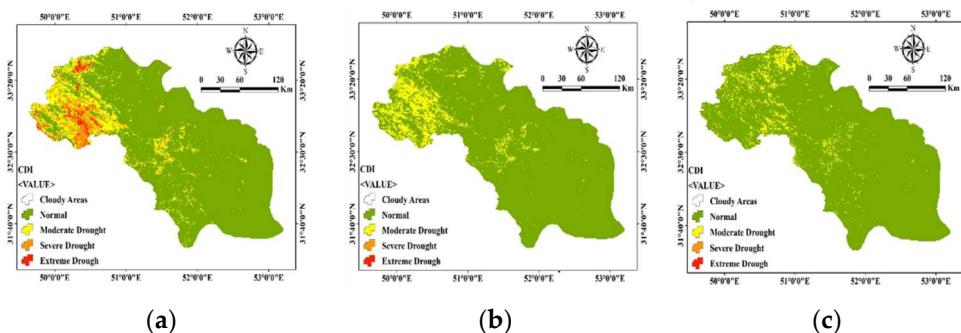


Figure 5. Annual CDI index of west Isfahan province.

3.3. Accuracy Assessment

In this section, necessary accuracy evaluations have been made to check the effectiveness of the proposed research approach.

3.3.1. Correlation between the CDI and SPI Indices

The correlation between the two indicators has been computed in various months during the years 2017 to 2019. Due to the large volume of results, the correlation table calculated only for 2017 and some of its months, which was the most important year in this research, is presented.

Table 2. Correlation between CDI and SPI in 2017.

SPI Month	SPI-1	SPI-3	SPI-6	SPI-12
Feb	0.75	0.69	0.45	0.35
May	0.65	0.30	0.19	0.69
Agu	0.81	0.63	0.35	0.47
Dec	0.68	0.63	0.65	0.42

Generally, the correlation of different monthly periods was between 0.19 to 0.81 in the distinct time series.

3.3.2. Correlation between CDI index and evaporation field data

In this section, the correlation between the CDI index and of evaporation in different months of 2017 to 2019 has been estimated, and some examples were presented in Table 3. As it is understandable, the correlation between the various months is between 0.25 to 0.70. In some months, correlation has not been taken due to lack of data.

Table 3. Correlation between CDI index and evaporation.

Year Month	2017	2018	2018
Feb	0.25	-	-
Mar	0.35	0.62	0.68
Apr	0.57	0.42	0.39
Age	0.55	0.70	-
Dec	-	0.58	0.48

3.3.3. Correlation between the CDI and Temperature

The temperature is a good indicator of the energy balance on the earth's surface, which is one of the key parameters in the physics of the Earth's surface processes on a regional and global scale. Moreover it is an index that provides information about the soil moisture surface situation. In this section correlation between drought index, CDI and Temperature have been calculated. As can be seen in Table 4, these two studied data have a relatively good correlation.

Table 4. Correlation between CDI index and temperature.

Year Month	2017	2018	2018
Mar	0.52	0.65	0.45
Apr	0.48	0.42	0.39
Jun	0.40	0.56	0.45
Age	0.55	0.70	0.50
Dec	0.35	0.40	0.55

4. Conclusion

Drought is the main problem of arid and semi-arid regions, and the great variation in the time and place of drought occurrence has made it difficult and complicated to accurately diagnose its occurrence based on spatial objectives [26]. Basically, for the quantitative analysis of drought, it is necessary to have a specific index to accurately determine wet and dry periods [27]. Due to the fact that meteorological drought indicators are only valid for one place and do not have the necessary spatial resolution and are also dependent on the information of meteorological stations and these stations are often distributed far apart, the reliability of these indicators has been questioned. The characteristics of satellite data such as high spatial and temporal resolution, wide coverage of the studied areas and direct investigation of the vegetation status by means of satellite indicators have caused many studies to be done for drought modeling using this technology and the use of these indicators. to be confirmed [28]. In this study, the composite drought index (CDI) of rainfall and NDVI was investigated to evaluate the agricultural drought in the western region of Isfahan province using 4-year data (2016–2019) from remote sensing data. This index was evaluated with the help of index (SPI), temperature and evaporation during 3 years of drought. The results show the appropriate correlation between the CDI index and validation data and the efficiency of the proposed approach in drought monitoring. Researchers are trying to use a longer time series to more accurately assess the drought in this region in future studies.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Senay, G., et al., *Drought monitoring and assessment: remote sensing and modeling approaches for the famine early warning systems network*, in *Hydro-meteorological hazards, risks and disasters*. 2015, Elsevier. p. 233-262.
2. Tirivarombo, S., D. Osupile, and P. Eliasson, *Drought monitoring and analysis: standardised precipitation evapotranspiration index (SPEI) and standardised precipitation index (SPI)*. Physics and Chemistry of the Earth, Parts A/B/C, 2018. **106**: p. 1-10.
3. Hao, Z. and V.P. Singh, *Drought characterization from a multivariate perspective: A review*. Journal of Hydrology, 2015. **527**: p. 668-678.
4. Smakhtin, V.U. and E.L.F. Schipper, *Droughts: The impact of semantics and perceptions*. Water Policy, 2008. **10**(2): p. 131-143.
5. Palmer, W.C., *Keeping track of crop moisture conditions, nationwide: the new crop moisture index*. 1968.
6. McKee, T.B., N.J. Doesken, and J. Kleist. *The relationship of drought frequency and duration to time scales*. in *Proceedings of the 8th Conference on Applied Climatology*. 1993. Boston, MA, USA.
7. Vicente-Serrano, S.M., S. Beguería, and J.I. López-Moreno, *A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index*. Journal of climate, 2010. **23**(7): p. 1696-1718.
8. Shi, S., et al., *Evaluation of temperature vegetation dryness index on drought monitoring over Eurasia*. IEEE Access, 2020. **8**: p. 30050-30059.

9. Wang, Y., et al., *Annual variation in PDSI since 1897 AD in the Tengger Desert, Inner Mongolia, China, as recorded by tree-ring data*. *Journal of arid environments*, 2013. **98**: p. 20-26.
10. Yan, H., et al., *Assessing spatiotemporal variation of drought in China and its impact on agriculture during 1982–2011 by using PDSI indices and agriculture drought survey data*. *Journal of Geophysical Research: Atmospheres*, 2016. **121**(5): p. 2283-2298.
11. Li, X., J. Sha, and Z.-L. Wang, *Comparison of drought indices in the analysis of spatial and temporal changes of climatic drought events in a basin*. *Environmental Science and Pollution Research*, 2019. **26**(11): p. 10695-10707.
12. Jain, S.K., et al., *Identification of drought-vulnerable areas using NOAA AVHRR data*. *International Journal of Remote Sensing*, 2009. **30**(10): p. 2653-2668.
13. Geng, L., et al., *Validation of the MODIS NDVI products in different land-use types using in situ measurements in the Heihe River Basin*. *IEEE Geoscience and Remote Sensing Letters*, 2014. **11**(9): p. 1649-1653.
14. Kogan, F.N., *Application of vegetation index and brightness temperature for drought detection*. *Advances in space research*, 1995. **15**(11): p. 91-100.
15. Kogan, F.N., *Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data*. *Bulletin of the American Meteorological Society*, 1995. **76**(5): p. 655-668.
16. Huete, A., et al., *Overview of the radiometric and biophysical performance of the MODIS vegetation indices*. *Remote sensing of environment*, 2002. **83**(1-2): p. 195-213.
17. Jackson, T.J., et al., *Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans*. *Remote Sensing of Environment*, 2004. **92**(4): p. 475-482.
18. Son, N.T., et al., *Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data*. *International Journal of Applied Earth Observation and Geoinformation*, 2012. **18**: p. 417-427.
19. Idso, S., et al., *Normalizing the stress-degree-day parameter for environmental variability*. *Agricultural meteorology*, 1981. **24**: p. 45-55.
20. Kumar, N., et al., *Crop water stress index for scheduling irrigation of Indian mustard (Brassica juncea) based on water use efficiency considerations*. *Journal of Agronomy and Crop Science*, 2020. **206**(1): p. 148-159.
21. Hu, X., et al., *Agricultural drought monitoring using European Space Agency Sentinel 3A land surface temperature and normalized difference vegetation index imageries*. *Agricultural and Forest Meteorology*, 2019. **279**: p. 107707.
22. Carlson, T.N., E.M. Perry, and T.J. Schmugge, *Remote estimation of soil moisture availability and fractional vegetation cover for agricultural fields*. *Agricultural and Forest Meteorology*, 1990. **52**(1-2): p. 45-69.
23. Belayneh, A. and J. Adamowski, *Standard precipitation index drought forecasting using neural networks, wavelet neural networks, and support vector regression*. *Applied computational intelligence and soft computing*, 2012. **2012**.
24. Snavely, K.N., *Scene reconstruction and visualization from internet photo collections*. 2008: University of Washington.
25. Waseem, M., M. Ajmal, and T.-W. Kim, *Development of a new composite drought index for multivariate drought assessment*. *Journal of Hydrology*, 2015. **527**: p. 30-37.
26. Lin, M., C.M. Chu, and B. Tsai, *Drought risk assessment in western Inner-Mongolia*. *International Journal of Environmental Research*, 2011. **5**(1): p. 139-148.
27. da Silva, V.d.P.R., *On climate variability in Northeast of Brazil*. *Journal of Arid Environments*, 2004. **58**(4): p. 575-596.
28. Gu, Y., et al., *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*, 2007. **34**(6).