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DETERMINATION OF EFFECTIVE INDICES IN THE DROUGHT MONITORING THROUGH ANALYSIS OF SATELLITE IMAGES

SUMMARY

The aim of this research was to determine the effective drought indices such as NDVI, VCI, EVI, TVX, VTCI, VHI, TCI and NVSWI based on some criteria. The satellite-based drought indices have different data from vegetation and temperature conditions. Linear and trend analysis showed that satellite-based drought indices based on vegetation condition were not more efficient indices such as NDVI and VCI. It can be said that the indices with combination of vegetation and temperature condition have more efficiency. A good agreement was observed among drought indices and precipitation in the arid and semi-arid climatic regions. Application of NDVI, VCI and EVI was limited for real time drought monitoring. Investigation the topographic effect on drought indices indicated that VTCI and NDVI had maximum impressed from height variations. The synthesized drought indices based on effective indices led to better performance. Drought indices investigation using different criteria indicated the high performance of NVSWI, TCI, VHI and TVX. The indices have high correlation with each other. Therefore, using one of them is suitable for drought monitoring.

Keywords: Linear Analysis, Precipitation, Climatic Regions, Correlation.

INTRODUCTION

Drought is an insidious hazard of nature that has heavy damage and losses in many parts of world. The severity of drought is related to a specific climatic region and local energy and water balance status. In general, drought can be defined as a period of abnormally dry weather, which further results in vegetation cover condition changes (Shahabfar et al., 2012). Over the last three decades, the frequency and intensity of drought have increased. Drought with slow onset is different from other natural hazards, which referred to as creeping phenomenon. Unlike other natural disasters, it starts unnoticed and develops cumulatively (Shakya and Yamaguchi, 2006). Drought is a complex phenomenon that the American Meteorological Society group classifies into four categories: meteorological, agricultural, hydrological and socioeconomic drought. Meteorological drought is a precipitation deficit, agricultural drought is a total soil moisture deficit, hydrological drought is a shortage of stream flow and

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socioeconomic drought is associated with the shortage of some economic goods affected by the drought process (Du et al., 2013)

Because of drought negative impact on agricultural, ecological, environmental aspects, drought investigation and monitoring with efficient method is necessary. Classic drought monitoring approaches were based on the point- based data predominantly using meteorological observations and regional hydrologic records which include the Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI). The indices were in situ drought index, the spatial drought condition need to be estimated using spatial interpolation techniques, such as inverse distance weighted; ordinary kriging model. Their accuracy and level of spatial detail are functions of the density and the distribution of the station network. However, because of its frequency and spatial coverage, remote sensing has become the most promising tool for large-scale drought monitoring (Qin et al., 2008). Satellite based drought indices has different data requirement which are based on vegetation or temperature condition. Associated with the drought and land surface temperature (LST) increases slightly earlier than plant cover decrease. During dry conditions (there is less soil moisture availability), rising leaf temperature are good indicator of plant moisture stress and precede the onset of drought. This thermal response can occur even when plants are green, as stomata closure to minimize water loss by transpiration results in a decreased latent heat flux. At the same time, due to the requirement that the energy flux must balance, there will be an increase in the sensible heat flux, which may result in increased leaf temperatures. This increase in leaf temperature can be used for stress detection in crops. This land surface energy flux balance finally results in high land surface temperature (Wan et al., 2004). Bayarjard et al. (2006) used a vector analysis for a comprehensive study of NOAA-AVHRR derived drought indices. The groups of drought indices are based on vegetation state derived from the reflective channel surface, brightness temperature derived from the thermal channel, the combination between the reflective and thermal channel. It was found that the combination of satellite derived drought indices can identify wider drought occurred areas rather than PDSI. The relationship between the satellite-based vegetation condition index (VCI) and a number of frequently used meteorological drought indices was evaluated using data from all 254 Texas counties during 18 growing-seasons (March to August, 1982–1999). In particular, the response of the VCI was compared to that of the PDSI, Moisture Anomaly Index (Z-index), SPI, percent normal and deciles. Overall the VCI is most strongly correlated with the 6-month SPI, 9-month SPI and PDSI. It appears that the climate region is the most important determinant of the nature of the relationship between the VCI and PDSI. These results demonstrate that care must be taken when using the VCI for monitoring drought because it is not highly correlated with station-based meteorological drought indices and it is strongly influenced by spatially varying environmental factors (Quiring and Ganesh, 2010).

Rhee et al. (2010) proposed a new remote sensing-based drought index, the Scaled Drought Condition Index (SDCI) for agricultural drought monitoring in both arid and humid regions using multi-sensor data. The index combines the land surface temperature data and the Normalized Difference Vegetation Index (NDVI) data from the moderate resolution imaging spectroradiometer (MODIS) sensor and precipitation data from TRMM. SDCI performed better than existing indices such as NDVI and Vegetation Health Index (VHI) in the arid region of Arizona and New Mexico as well as in the humid region of North Carolina and South Carolina. The year-to-year changes and spatial distributions of SDCI over both arid and humid regions generally agreed to the changes documented by the United States Drought Monitor (USDM) maps (Rhee et al., 2010). Shahabfar et al. (2012) evaluated the remote sensing drought indices of MODIS such as the Perpendicular Drought Index (PDI) and Modified Perpendicular Drought Index (MPDI) against meteorological drought indices including Z-score (Z), China-Z Index (CZI) and Modified China-Z Index (MCZI) over 180 meteorological stations from February 2000 to December 2005. The results showed that there is a statistically significant correlation between the PDI and MPDI and regional surface dryness and drought conditions. Du et al. (2013) were defined the synthesized drought index (SDI) in Shandong province, China from 2010 to 2011 which was defined as a principal component of VCI, temperature condition index (TCI) and precipitation condition index (PCI). SDI integrates multi-source remote sensing data from MODIS and tropical rainfall measuring mission (TRMM) and it synthesizes precipitation deficits, soil thermal stress and vegetation growth status in drought process. Therefore, this method is favorable to monitor the comprehensive drought. Results showed that SDI is not only strongly correlated with 3-month scales standardized precipitation index (SPI3), but also strongly correlated with variation of crop yield and drought-affected crop areas (Du et al., 2013). Dutta et al. (2015) were used NOAA-AVHRR NDVI data for monitoring agricultural drought through NDVI based vegetation condition index. VCI was calculated for whole Rajasthan using the long term NDVI images which reveals the occurrence of drought related crop stress during the year 2002. The VCI values of normal (2003) and drought (2002) year were compared with meteorological based SPI, Rainfall Anomaly Index and Yield Anomaly Index; then a good agreement was found among them. The correlation coefficient between VCI and yield of major rain-fed crops ($r > 0.75$) also supports the efficiency of the remote sensing derived index for assessing agricultural drought (Dutta et al., 2015).

Therefore, drought indices can be applied effectively in the drought monitoring. On the other hand, a comprehensive study for evaluating the performance of drought indices and selection of one or some indices as the effective indices is necessary for drought monitoring. Effective indices can be modeled with some method such as artificial neural network and fuzzy regression which leads to drought forecasting. This research seeks to identify the effective drought indices based on MODIS data that can be used for meteorological drought monitoring in different climatic regions. A linear correlation analysis is applied to evaluate the performance of indices.

MATERIAL AND METHODS

Remote Sensing Drought Indices

Drought is difficult to monitor so various indices have been proposed to detect the drought intensity. This misadventure can be monitored effectively using drought indices. Compared to in situ indices, drought indices derived from remote sensing data are more suitable for spatial drought conditions monitoring (Quiring and Ganesh, 2010). The groups of drought indices are derived from the reflectance channel, the thermal channels and the combination of the reflectance and thermal channels. The indices classification is illustrated in Figure 1.

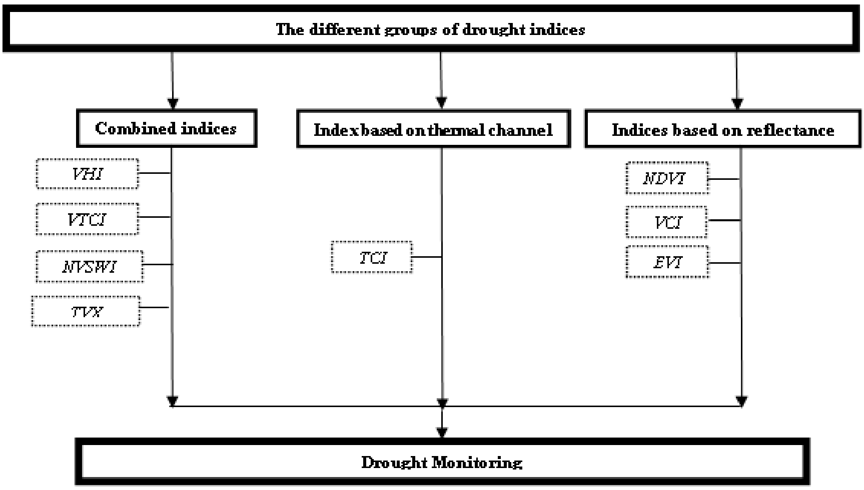


Figure 1. Drought indices classification for drought monitoring.

Each drought index has different data requirement and utilizes method to measure drought. In the following sections, drought indices are explained.

1-NDVI

NDVI has been most widely used for drought monitoring which can be derived using near-infrared and red radiation. Because when sunlight strikes a plant most of the red wavelengths in the visible portion of the spectrum are absorbed by chlorophyll in the leaves, while the cell structure of leaves reflects the majority of near-infrared radiation. Healthy plants absorb much of the red light and reflect most near-infrared radiation. In general if there is most reflected radiation in the near-infrared wavelengths than in the visible wavelengths, the vegetation is likely to be healthy (dense). If there is very little difference between the amount of reflected radiation in the visible and infrared wavelength, the vegetation is probably unhealthy (sparse) (Quiring and Ganesh, 2010). NDVI not only maps the presence of vegetation on a pixel basis, but also provides measures of the amount or condition of vegetation within a pixel. NDVI can be defined as (Tripathi et al., 2013):

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$$

Where ρ_{nir} and ρ_{red} represent pixel reflectance in the near infrared and red channel respectively. NDVI values range from -1 to +1, with values near zero indicating no green vegetation and values near +1 indicating the highest possible density of vegetation.

2-VCI

Despite the potential applications of the NDVI, numerous shortcomings have also been revealed. For heterogeneous land cover, the NDVI, which reflect vegetation greenness and vigor, are normally higher in the area with more favorable climate, soil and more productive ecosystem (forest) compared to the areas with less favorable environmental conditions (dry steppe). These differences should be taken into consideration when NDVI is used for monitoring annual weather impact on vegetation (Unganai and Kogan, 1998). Thus, Kogan (1990) proposed a vegetation condition index based on the relative NDVI change with respect to minimum historical NDVI value. This normalized index indicates percent change of the difference between the current NDVI index and historical NDVI time series minimum with respect to the NDVI dynamic range. It was defined by the following formula:

$$VCI = \frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}}$$

Where $NDVI_{max}$ and $NDVI_{min}$ are maximum and minimum NDVI respectively calculated by the corresponding pixels in same month from the entire NDVI records. VCI changes from 0 to 1, corresponding to the changes in vegetation condition from extremely unfavorable to optimal. In case of an extremely dry month, the vegetation condition is poor and the VCI is close or equal to 0 (Du et al., 2013)

3-Enhanced Vegetation Index (EVI)

A major finding on atmospheric effect minimization is the use of the difference in blue and red reflectance as an estimator of the atmosphere influence level. This concept is based on the wavelength dependency of aerosol scattering cross sections; in general the scattering cross section in the blue band is larger than that in the red band. When the aerosol concentration is higher, the difference in the two bands becomes larger. The EVI formula is written as:

$$EVI = G.\frac{\rho_{nir} - \rho_{red}}{\rho_{nir} - c_1\rho_{red} - c_2\rho_{blue} + L}$$

Where ρ_{red} , ρ_{nir}, ρ_{blue} are the reflectance of the red, near-infrared, and blue channels, respectively. C1 and C2 are coefficients and L is the canopy background brightness correction factor, and G is the Gain factor (Frag et al., 2014; Matsushita et al., 2007).

4-Temperature Condition Index (TCI)

Land surface temperature is a good indicator of the energy balance at the earth's surface because it is one of the key parameters in the phys
ics of land surface process on regional and global scales. The TCI was proposed to estimate the thermal impact of drought. The TCI was developed in order to approximate the thermal band contribution in assessment of vegetation condition. It was computed as:

$$TCI = \frac{LST_{\max} - LST}{LST_{\max} - LST_{\min}}$$

Where LST, LST_{max} and LST_{min} are land surface temperature, maximum and minimum LST of each pixel, respectively in same month during the study period. The values of TCI vary from 0 to 1. The low values of TCI imply serious condition of drought (Du et al., 2013).

5-Vegetation Health Index (VHI)

The synthesizing VCI and TCI together, the TCI and VCI provide a reliable additive drought detection and crop condition assessment scheme. On the base of VCI and TCI, VHI can be calculated by the following expression:

$$\mathrm{VHI} = \alpha\,\mathrm{VCI} + (1 - \alpha)\mathrm{TCI}$$

Where α and (1-α) indicate the relative contribution of VCI and TCI to the value of VHI, respectively.

In the previous studies, equal values of α are used to account for the contributions of both VCI and TCI. However, the impacts of the same temperature and the same time period of drought vary depending on how an area is vegetated. For pixels of dense vegetation coverage, drought assessment relies more on the information provided by vegetation condition and therefore the contribution of VCI in VHI increases as the vegetation coverage increases. (Feng, 2011).

6-Normalized Vegetation Supply Water Index (NVSWI)

The Vegetation Supply Water Index (VSWI) combines a vegetation index (NDVI) with the thermal image-based parameter land surface temperature and is commonly used to its simplicity and ability to represent two potential properties of vegetation stress in one index, but suffer from the mismatch in time scales, since vegetation greenness is fairly stable in the short to medium term but temperature fluctuate diurnally, and according to weather conditions as well as slope, aspect and terrain properties. The VSWI is also specific to the land cover type and measurement time of the image scene, and cannot be used as an absolute measure of drought severity. Thus, attempts to normalize the VSWI have contextualized the index within a defined period of available records.

$$VSWI = \frac{NDVI}{LST}$$

$$NVSWI = \frac{VSWI - VSWI_{min}}{VSWI_{max} - VSWI_{min}}$$

Where VSWI, $\mathrm{VSWI_{min}}$, $\mathrm{VSWI_{min}}$ are vegetation supply water index, minimum and maximum of VSWI.

NVSWI of zero indicates severest drought during the study period and NVSWI of 1 indicates wettest conditions (Nichol and Abbas, 2015).

7-Vegetation Temperature Condition Index (VTCI)

An approach developed which integrates land surface reflectance and thermal properties for drought monitoring. VTCI is defined as the ratio of land surface temperature difference among pixels with a specific NDVI in a sufficiently large study area. VTCI is defined as:

$$VTCI = \frac{LST_{NDVI.max} - LST_{NDVIi}}{LST_{NDVI.max} - LST_{NDVI.min}}$$

$$LST_{NDVI.max} = a + bNDVI_i$$

$$LST_{NDVI.min} = \acute{a} + \acute{b}NDVI_i$$

Where $\mathrm{LST_{NDVI.max}}$ and $\mathrm{LST_{NDVI.min}}$ are maximum and minimum land surface temperature of pixels which have same $\mathrm{NDVI_i}$ value in a study region, receptively and $\mathrm{LST_{NDVIi}}$ denotes LST of one pixel whose NDVI value is $\mathrm{NDVI_i}$. Coefficient a,b, $\acute{a}$ and $\acute{b}$ can be estimated from an area large enough where soil moisture at surface layer should span from wilting point to field capacity at pixel level. In general, the coefficients are estimated from the scatter plot of LST and

NDVI in the area. LST_{max} can be regarded as the warm edge where there is less soil moisture availability and plants are under dry conditions,

LST_{min} can be regarded as the cold edge where there is no water restriction for plant growth. The value of VTCI have ranges from 0 to 1; the lower the value of VTCI, the higher the occurrence of drought (Wan et al., 2004).

8-Temperature Vegetation Index (TVX)

Among indices which are used remotely sensed thermal and reflected radiation, TVX is a simple index with calculation their ratio. TVX can be defined as:

$$TVX = \frac{LST}{NDVI}$$

Where LST is land surface temperature, NDVI is normalized difference vegetation index.

TVX is graphically displayed in the LST–NDVI feature space by iso-lines of increasing slopes. TVX is negatively related to water condition. For stressed surfaces, land surface temperature increases or NDVI decreases as a result of decreased evaporation and vegetation fraction, therefore TVX dramatically increases. The major advantage of TVX is that it integrates both the reflective bands and thermal bands of remote sensing data, which offers more spectral information for drought detection. The main drawback is that there are several other factors influencing TVX values such as land cover change, sensor drift, atmospheric effect, cloud and etc. When the NDVI value is very small, the TVX value tends to infinite values. So, at places where NDVI is very small, one can use the arctangent of LST/NDVI which is expressed in degrees (Qin et al., 2008).

CASE STUDY

For evaluating the performance of drought indices, data of some metrological stations which are located in Iran were used. Figure 2 shows the location of meteorological stations.

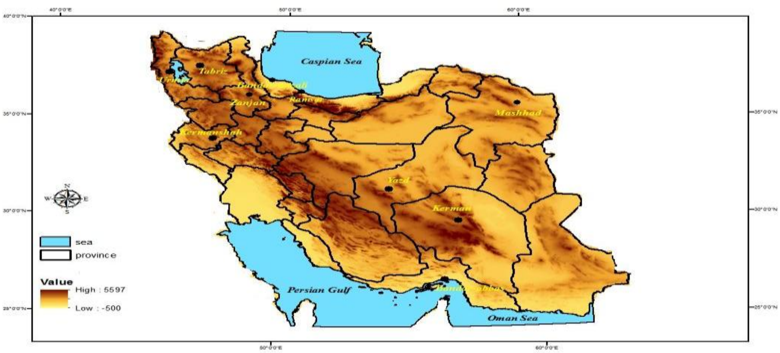


Figure 2. Spatial distribution of meteorological stations.

The stations are the different climatic regions such as arid, semi-arid and wet (based on the De Martonne classification: *Bandar- abass*, *Kerman*, *Yazd*- arid; *Bandar-anzali*, *Ramsar* –wet; *Kermanshah*, *Tabriz*, *Mashhad*, *urmia*, *Zanjan*- semi-arid).

Iran is one of the countries which suffer from severe drought. Iran's precipitation is approximately one third of global average and distribution of the monthly rainfall has been changed in recent years. The drought indices are derived from Terra MODIS data because of the sensor's moderate spectral and spatial resolution. Some process must be conducted on the images for determination the vegetation and drought indices. The nearest neighborhood method has been applied for the correction of pixels size from nadir pixels for geometric correlation (geo-referencing) using ENVI software. Growing months April, through September from 2006 to 2010 were used to assess the drought indices.

RESULTS AND DISCUSSION

In this study, some criteria have been used for determination of effective drought indices which one of them is the use of linear correlation coefficient concepts. Therefore, for meteorological drought monitoring with emphasis on precipitation, linear correlation between precipitation and drought indices for each meteorological stations were calculated which are listed in Table 1.

Table 1. Correlation coefficients among precipitation – drought indices.

Stations	NDVI	EVI	VTCI	NVSWI	VCI	TCI	VHI	TVX
Bandar -abass	0.212	-0.159	-0.025	0.326	0.213	0.26	0.348	-0.261
Bandar- anzali	-0.131	-0.45*	0.2	0.074	-0.131	0.129	-0.008	-0.082
Kermanshah	0.673*	0.66*	-0.131	0.835*	0.673*	0.848*	0.786*	-0.663*
Tabriz	-0.216	-0.39*	-0.242	0.664*	-0.216	0.763*	0.639*	-0.621*
Kerman	0.051	-0.45*	-0.206	0.619*	0.052	0.719*	0.51*	-0.59*
Mashhad	0.247	0.358	-0.151	0.691*	0.247	0.77*	0.682*	-0.72*
Urmia	-0.063	-0.163	0.285	0.87*	-0.064	0.822*	0.715*	-0.82*
Ramsar	-0.25	-0.58*	-0.135	0.23	-0.251	0.269	0.055	-0.213
Yazd	0.121	0.02	0.45*	0.6*	0.122	0.65*	0.493*	-0.57*
Zanjan	0.34	0.025	0.23	0.87*	0.344	0.849*	0.778*	-0.8*
*significantly different at the 5 % probability level.								

The maximum number of significant correlation coefficients is related to TCI, NVSWI, TVX, VHI and then EVI respectively. The number of stations with significant correlation coefficient is one in the context of NDVI, VTCI and VCI indices. It can be said that NDVI has two components: ecology and weather which can be the reason of NDVI performance with low accuracy (Rhimzadeh et al., 2008). Kogan (1990) proposed geographic filtering to eliminate that portion of NVDI spatial variability that is related to the contribution of geographic resources to the amount of vegetation. This contribution fluctuates considerably depending mainly on climate, soils, vegetation type and topography of an area. The VTCI performance can be related to the selected area because VTCI can be physically interpreted in an area large enough to provide wide ranges of NDVI and soil moisture at surface layer (Wan et al., 2004). Drought monitoring using VTCI, NDWI and NDVI indices in the Sefidroud River basin which is located in Iran, indicated that NDVI has the minimum correlation coefficient with precipitation (Parviz et al., 2011). In a study for drought monitoring in Iran using the perpendicular drought indices, VCI and EVI had poor relationship with precipitation (Shahabfar et al., 2012). Quring and Ganesh (2010) demonstrated that care must be taken when using the VCI for monitoring drought because it is not highly correlated with station-based meteorological drought indices and it is strongly influenced by spatially varying environmental factors. The VCI is suitable for monitoring agriculture drought but it has been shown to be inappropriate for monitoring meteorological drought in some regions (Quiring and Ganesh, 2010).

The maximum and minimum number of significant correlation coefficient is related to Kermanshah, Tabriz, Kerman and Ramsar, Bandar-anzali stations respectively. It is worth noting that the number of significant correlation coefficient varies among different climatic regions and increasing the number of significant correlation coefficients from wet to semi-arid and arid regions. Shahabfar et al. (2012) indicated that VCI had the highest correlation with precipitation only in some stations located in mountains and semi mountains regions. In the other case, the correlation coefficients of precipitation and drought indices were calculated basis on climatic classification and the results are shown in Table 2.

Table 2. Correlation coefficients of precipitation – drought indices based on climatic classification.

Climate	NDVI	EVI	VTCI	NVSWI	VCI	TCI	VHI	TVX
Arid	0.393*	-0.2	-0.598*	0.57*	0.421*	0.767*	0.752*	-0.723*
Semi- Arid	0.639*	0.492*	-0.17	0.939*	0.39*	0.904*	0.9*	-0.856*
Wet	-0.185	-0.537*	-0.01	0.142	-0.183	0.18	0.02	-0.146
*significantly different at the 5 % probability level.								

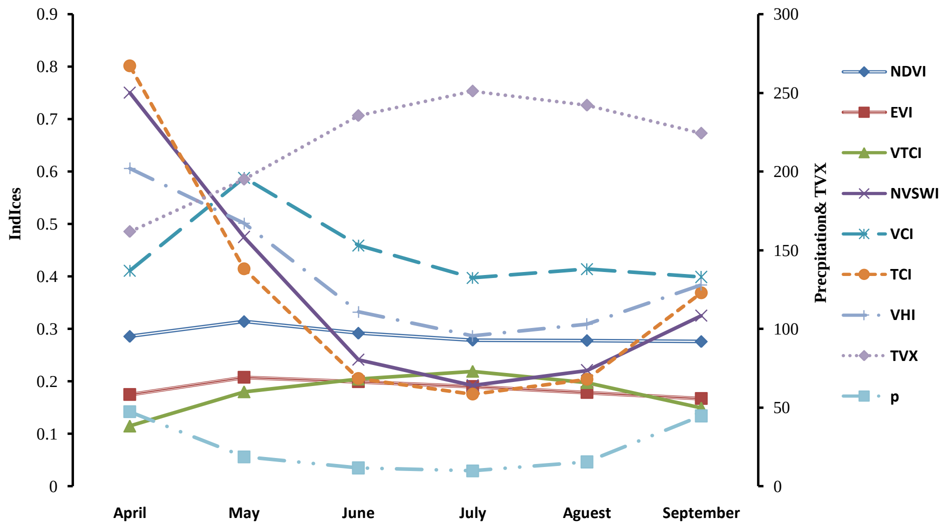
The maximum and minimum number of significant correlation coefficients is related to arid, semi-arid and wet regions, respectively (Table 2). Among drought indices, EVI only has significant correlation coefficient in wet region with no significant correlation coefficient in arid region. Shahabfar et al. (2012) indicated that EVI showed poor relationship with precipitation data, as a vegetation index rather than a drought index. In the different climatic regions, the VTCI have the minimum number of significant correlations. The results of correlation analysis based on climate and time aspect are listed in Table 3.

Table 3. Correlation coefficient based on climate and time aspect.

NDVI	April	May	June	July	August	September
Arid	0.52	-0.7	0.92*	-0.2	-0.317	
Semiarid	0.96*	0.76	0.05	0.64	0.315	-0.33
Wet	-0.8	0.26	-0.43	0.81	-0.72	0.2
VTCI	April	May	June	July	August	September
Arid	-0.241	-0.317	0.287	0.379	-0.383	
Semiarid	0.033	0.047	0.128	-0.361	-0.036	0.14
Wet	-0.074	-0.214	-0.352	-0.293	-0.162	-0.524
NVSWI	April	May	June	July	August	September
Arid	0.58	-0.57	0.914*	-0.12	-0.008	
Semiarid	0.98*	0.94*	0.47	0.73	0.26	0.65
Wet	0.77	0.569	0.73	0.62	-0.004	0.26
VCI	April	May	June	July	August	September
Arid	0.45	-0.71	0.96*	0.33	-0.28	
Semiarid	0.84	0.76	0.028	0.69	0.211	-0.4
Wet	-0.77	0.58	-0.44	0.79	-0.72	0.18
EVI	April	May	June	July	August	September
Arid	-0.143	-0.71	0.178	-0.56	-0.063	
Semiarid	0.94*	0.63	0.083	0.53	0.27	-0.33
Wet	0.89*	-0.31	-0.59	0.64	0.03	-0.26
VHI	April	May	June	July	August	September
Arid	0.54	-0.56	0.97*	-0.23	0.026	
Semiarid	0.98*	0.91*	0.55	0.72	0.24	0.5
Wet	0.24	0.73	0.32	0.7	-0.31	-0.046
TVX	April	May	June	July	August	September
Arid	-0.56	0.56	-0.86	0.099	0.103	
Semi- arid	-0.98*	-0.83	-0.29	-0.44	-0.4	-0.29
Wet	-0.84	-0.51	-0.63	-0.59	0.095	0.277
TCI	April	May	June	July	August	September
Arid	0.29	0.79	0.44	0.54	0.917*	
Semiarid	0.906*	0.82	0.96*	0.51	0.068	0.96*
Wet	0.78	0.37	0.84	0.17	0.42	-0.44
*significantly different at the 5 % probability level.						

The maximum number of significant correlation coefficients in all climatic regions is related to TCI and then VHI and NVSWI. VTCI has not significant correlation coefficients in any climatic regions and months (Table 3). In wet regions, significant correlation coefficients of EVI are in April and maximum precipitation is in September. Maximum number of significant correlation coefficients of arid and semi-arid regions is related to June and April.

Also, maximum precipitation in arid and semi-arid climate is in April. Therefore, the similarity between the month with maximum number of significant correlation and the month with maximum precipitation is high in semi-arid climatic region. The maximum and minimum values of coefficient are in April and August, respectively. Therefore, it can be said that the correlation coefficient values are increased from dry to wet seasons Investigation the equation of indices indicated the direct relationship among precipitation and drought indices except in TVX index which increasing of indices implies the precipitation increasing. Therefore, the monthly variation of all drought indices and precipitation are illustrated in Figure 3a.



Maximum values of precipitation and VHI, NVSWI and minimum value of TVX happened in April (Figure 3a). It can be said that NVSWI, TCI, VHI, TVX has temporal coordination with precipitation. Better performance of VCI rather than NDVI is evident from the Figure 3a.

The reason of VCI performance can be related to the effect of index normalization. Drought indices with direct relationship are decreased from April to July and after that month, indices increases with precipitation increasing according to Figure 3b. The trend of drought indices with direct relationship indicated the decreasing of indices values from April to July and then with precipitation increasing from August, the indices values are increased

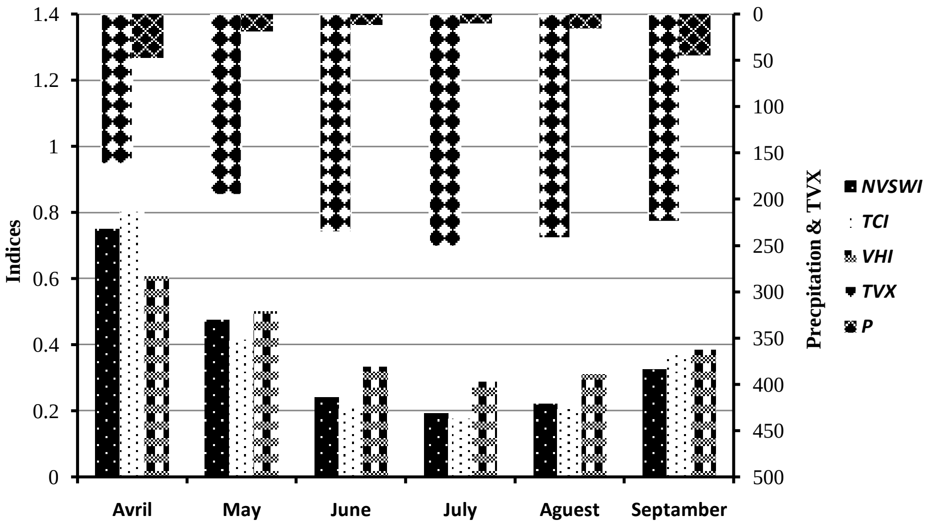


Figure 3. Monthly variation of all drought indices
and precipitation (a), some indices (b)

Maximum and minimum values of precipitation are in April and July respectively. From drought indices with direct relationship, TCI has the minimum and maximum values. In this regard, TCI has more similarity with precipitation. Therefore, it can be said that TCI has more sensitivity to precipitation. TVX with inverse relationship has maximum and minimum value in July and April which is similar with minimum and maximum value of precipitation. In this aspect, TVX and TCI can be regarded as the selected indices. The precipitation and TCI average percentage of reduction and TVX average percentage of increasing from April to July are 37.75%, 38.21%, 15.97% respectively. In addition, the precipitation and TCI average percentage of increasing and TVX average percentage of reduction from July to September are 47.47%, 121.9%, 5.46% respectively. It is evident that TCI is more similar with precipitation.

Based on the other criteria, comparison among drought indices and precipitation was conducted annually. The mean precipitation of ten meteorological stations indicated that the maximum value of precipitation is in 2007 and then in 2009 but the minimum value of precipitation is in 2008. The annual variation of drought indices is illustrated in Figure 4.

NDVI and EVI has constant annual trend and they cannot show the variation of maximum and minimum precipitation completely (Figure 4). Inverse relationship of TVX with precipitation preserves the trend of precipitation in all years.

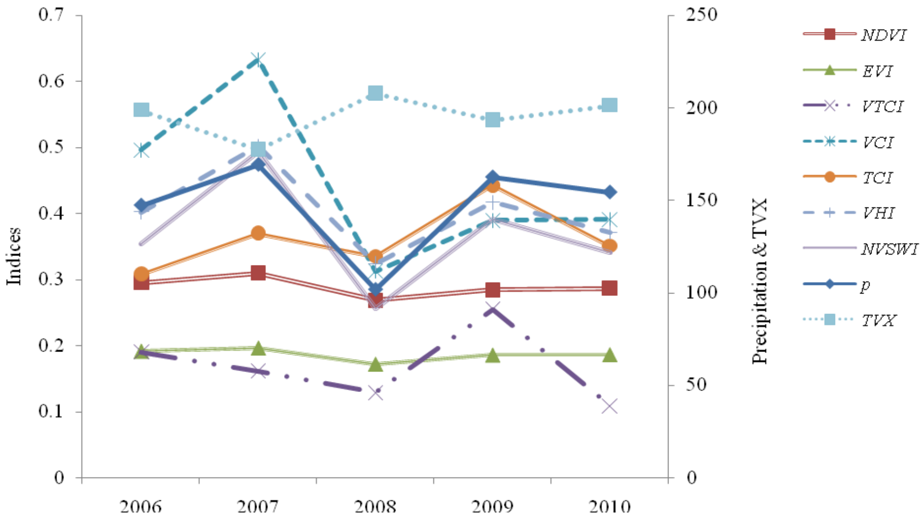


Figure 4. Annually variation of drought indices and precipitation.

VCI, VHI, NVSWI indices have similar trend with precipitation. In the other case, the slope of precipitation and drought indices time series were calculated using the trend line of time series and their results are shown in Figure 5.

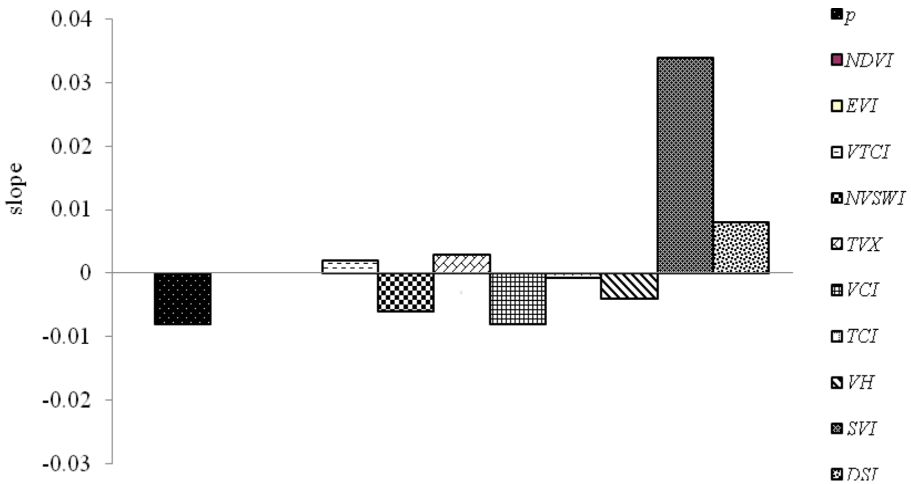


Figure 5. Slope of precipitation and drought indices.

The slope of NDVI and EVI time series is zero and they cannot be the efficient indices in explanation of precipitation variations. The sign of precipitation slope is negative which the slope of NVSWI, TCI, and VHI with negative sign and TVX with positive sign is coordinate with precipitation. The other criterion is the use of correlation coefficients which the correlation coefficients of drought indices with precipitation in all meteorological stations are listed in Table 4.

Table 4. Correlation coefficient of precipitation- drought indices in all stations.

NDVI	EVI	VTCI	NVSWI	TVX	VCI	TCI	VHI
0.01	-0.398*	0.16	0.66*	-0.59*	0	0.719*	0.6*
*significantly different at the 5 % probability level.							

EVI, NVSWI, TVX, TCI, VHI indices have significant correlation coefficients. Maximum values of correlation coefficients are related to TCI, NVSWI, VHI, TVH and the difference of correlation coefficient among indices is low (Table 4). Based on the other criteria for effective index determination, the trend of drought index and precipitation time series were investigated. Trend determination of time series conducted basis on Spearman and Pearson correlation test and the results of drought indices and precipitation are listed in Table 5.

Table 5. Trend analysis of precipitation and drought indices.

Correlation coefficient	Precipitation	NDVI	EVI	VTCI	NVSWI	VCI	TCI	VHI	TVX
Pearson	-0.004	-0.38*	-0.23	0.122	-0.2	-0.5*	-0.022	-0.27	0.22
Spearman	-0.049	-0.38*	-0.17	0.085	-0.2	-0.4*	*0*	-0.25	0.218
*significantly different at the 5 % probability level.									

According to Table 5, precipitation time series has not significant trend but there is significant trend in VCI and NDVI time series. It can be noted that there is not any similarity between trend of mentioned indices and precipitation. Also, the significant of Pearson coefficient among drought indices was investigated (Table 6).

The maximum number of significant correlation coefficients is related to NVSWI, VHI and TVX indices with other indices. The number of significant correlation coefficients is six which is acceptable from eight indices. EVI and VTCI indices have the minimum significant correlation coefficients. In the other case, sensitivity of drought indices to topographic effects was investigated. In this regard, meteorological stations were divided into three groups: first, second and third groups with the height average: -11.26, 1188.3, 1450.850 m, respectively.

Then the average of drought indices in each height was calculated and the results are illustrated in Figure 6.

Table 6. Correlation coefficients among drought indices.

Indices	NDVI	EVI	VTCI	NVSWI	TVX	VCI	TCI	VHI
NDVI	1	0.338*	-0.157	0.471*	-0.54*	0.93*	0.142	-0.6*
EVI		1	-0.014	0.059	-0.135	0.71*	-0.22	0.17
VTCI			1	-0.38*	0.46*	0.053	-0.42*	-0.38*
NVSWI				1	-0.97*	0.39*	0.92*	0.98*
TVX					1	-0.46*	-0.87*	-0.98*
VCI						1	0.025	0.53*
TCI							1	0.85*
VH								1
*significantly different at the 5 % probability level.								

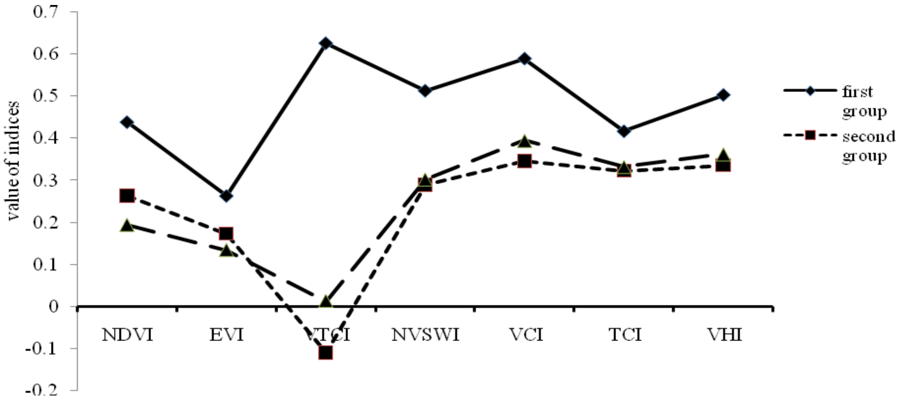


Figure 6. Average of drought indices in each height groups.

The highest variation is related to VTCI. Matsushita et al. (2007) were employed the coefficient of variation for evaluation the difference between the topographic effects on the EVI and NDVI (Figure 5). The larger coefficient of variation values was associated with a larger topographic effect and vice versa. The variation of coefficient of variation from minimum to maximum are: 1- TCI (0.14) 2- VH (0.22) 3-VCI (0.29) 4- TVX (0.31) 5- NVSWI and EVI (0.34) 6- NDVI (0.42) 7- VTCI (2.23). In this case, the maximum coefficient of variation is related to VTCI and TCI, VHI, VCI have the minimum coefficient of variation. The other criterion is the investigation of real time drought index. In this regard, the correlation coefficient of drought index with precipitation were examined in various precipitation schemes including 1-determination the correlation coefficient with precipitation with a lag time 2- determination the correlation coefficient with precipitation current month plus last two months. With one lag time, the number of significant correlation coefficients increase such as: NDVI: from one to four, VCI: from one to three, EVI: from five to six. In the second scheme the number of significant correlation coefficients increase such as:

NVDI: from one to three, VCI: from one to three, SVI: from one to two, NVSWI: from seven to eight. NDVI and then VCI indices have the maximum variations. It can be said that these indices are not only related to recent precipitation events but also related to past precipitation value and indicated that these indices cannot be used as a real time drought monitoring approach. The latest criterion is the use of the synthesized drought indices based on effective indices. The acceptable performance of TCI, NVSWI and VHI are illustrated based on some criteria in the previous sections. The average of correlation coefficient related to the synthesized index for all stations are listed in Table 7.

Table 7. Correlation coefficients of synthesized index.

<table>
<tr><td>Index</td><td>NVSWI</td><td>TCI</td><td>NVSWI</td><td>TCI</td><td>NVSWI</td><td>TCI</td><td>NVSWI</td><td>TCI</td><td>NVSWI</td><td>TCI</td><td>NVSWI</td><td>TCI</td></tr>
<tr><td>Weight</td><td>0</td><td>0</td><td>0.5</td><td>0.5</td><td>0.7</td><td>0.3</td><td>0.3</td><td>0.7</td><td>0.8</td><td>0.2</td><td>0.6</td><td>0.4</td></tr>
<tr><td>Coefficient</td><td>0.57</td><td>0.607</td><td colspan="2">0.623</td><td colspan="2">0624</td><td colspan="2">0.612</td><td colspan="2">0.628</td><td colspan="2">0.627</td></tr>
<tr><td>Index</td><td>NVSWI</td><td>VHI</td><td>NVSWI</td><td>VHI</td><td>NVSWI</td><td>VHI</td><td>NVSWI</td><td>VHI</td><td>NVSWI</td><td>VHI</td><td>NVSWI</td><td>VHI</td></tr>
<tr><td>Weight</td><td>0</td><td>0</td><td>0.5</td><td>0.5</td><td>0.6</td><td>0.4</td><td>0.4</td><td>0.6</td><td>0.3</td><td>0.7</td><td>0.2</td><td>0.8</td></tr>
<tr><td>Coefficient</td><td>0.57</td><td>0.49</td><td colspan="2">0.55</td><td colspan="2">0.54</td><td colspan="2">0.524</td><td colspan="2">0.567</td><td colspan="2">0.573</td></tr>
<tr><td>Index</td><td>VHI</td><td>NVSWI</td><td>TCI</td><td>VHI</td><td>NVSWI</td><td>TCI</td><td>VHI</td><td>NVSWI</td><td>TCI</td><td>VHI</td><td>NVSWI</td><td>TCI</td></tr>
<tr><td>Weight</td><td>0</td><td>0</td><td>0</td><td>0.2</td><td>0.6</td><td>0.2</td><td>0.25</td><td>0.5</td><td>0.25</td><td>0.5</td><td>0.25</td><td>0.25</td></tr>
<tr><td>Coefficient</td><td>0.49</td><td>0.57</td><td>0.607</td><td colspan="3">0.598</td><td colspan="3">0.601</td><td colspan="3">0.59</td></tr>
<tr><td>Index</td><td>VHI</td><td>NVSWI</td><td>TCI</td><td>VHI</td><td>NVSWI</td><td>TCI</td><td>VHI</td><td>NVSWI</td><td>TCI</td><td>VHI</td><td>NVSWI</td><td>TCI</td></tr>
<tr><td>Weight</td><td>0.25</td><td>0.25</td><td>0.5</td><td>0.2</td><td>0.2</td><td>0.6</td><td>0.15</td><td>0.15</td><td>0.7</td><td>0.05</td><td>0.05</td><td>0.9</td></tr>
<tr><td>Coefficient</td><td colspan="3">0.617</td><td colspan="3">0.619</td><td colspan="3">0.619</td><td colspan="3">0.613</td></tr>
<tr><td>Index</td><td>VHI</td><td>NVSWI</td><td>TCI</td><td>VHI</td><td>NVSWI</td><td>TCI</td></tr>
<tr><td>Weight</td><td>0.1</td><td>0.8</td><td>0.1</td><td>0.1</td><td>0.5</td><td>0.4</td></tr>
<tr><td>Coefficient</td><td colspan="3">0.589</td><td colspan="3">0.639</td></tr>
</table>

The synthesized indices were conducted using two and three indices. Using two indices, the synthesized index was based on simple weighting to each index.

The result of synthesized index using two indices indicated that the number of coefficient correlations is not changed in this case. But the average correlation coefficient comparison of different stations indicated that there is not any improvement in the synthesized of VHI and NVSWI except in the weights: 0.2-0.8 which led to 52% increasing regard to NVSWI and 14.48% increasing regard to correlation coefficient. There is the correlation coefficient improvement using NVSWI and TCI in all weights such as increasing correlation coefficient in weights 0.2-0.8 which led to 9.23% and 3.34% increasing regard to NVSWI and TCI respectively. The comparison of average correlation coefficient indicated the improvement of correlation coefficient using three indices rather than using only VHI. The maximum improvement is related to 0.1-0.5-0.4 with 23.31% increasing regard to VHI, 10.79% increasing regard to NVSWI, 5% increasing regard to TCI. NVSWI and TCI indices have the maximum improvement on correlation coefficient in the synthesized index. Du et al. (2013) proved that the synthesized index is a comprehensive drought monitoring indicator.

CONCLUSIONS

Drought is one of the natural disasters which have negative impact on several aspects. Drought can be investigated effectively using drought indices. In this regard, finding the indices which can reflect the comprehensive information of drought is necessary. Therefore, selection of one or some indices as the effective indices is important for drought monitoring. Among drought indices, TCI, NVSWI, TVX, VHI and NDVI, VTCI, SVI have maximum and minimum number of significant correlation coefficients, respectively. It can be said that, satellite based drought indices based on vegetation condition were not more efficient indices such as NDVI and VCI, whereas drought indices based on combination of vegetation condition and land surface temperature has better performance. The goal of drought investigation is regarding the precipitation variation using drought indices.

Drought indices in arid and semi-arid regions have high significant correlation coefficient rather than wet regions. Temporal coordinates between months with maximum number of significant correlation of drought indices and months with maximum precipitation is obvious in semi-arid regions. The number of significant correlation coefficient of NDVI, VCI and EVI increases with lag time. Therefore, application of indices in real time drought monitoring is limited. The investigation of topographic effect on drought indices indicated that TCI, VHI and VCI indices have minimum effect on height variations and VTCI, NDVI has maximum impact from height variations. Therefore, the effect of height must be removed from the indices. The synthesized drought indices based on effective indices led to better performance. Trend analysis of precipitation and drought indices showed any trend in precipitation time series. Drought indices must preserve the trend but NDVI and VCI has significant trend Therefore, the care must be taken for drought monitoring using the mentioned indices. Drought indices investigation using different criteria indicated the high performance of NVSWI, TCI, VHI and TVX. The indices have high correlation with each other. Therefore, using one of them is suitable AQW4 for drought monitoring. It can be said that the indices with combination of vegetation indices and land surface temperature have more efficacy

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