Theor Appl Climatol (2018) 134:1005–1014
https://doi.org/10.1007/s00704-017-2315-2

ORIGINAL PAPER

# Predictive value of Keetch-Byram Drought Index for cereal yields in a semi-arid environment

Nasrin Salehnia[1] · Hossein Zare[1] · Sohrab Kolsoumi[1] · Mohammad Bannayan[1]

Received: 24 June 2016 / Accepted: 30 October 2017 / Published online: 19 November 2017
© Springer-Verlag GmbH Austria, part of Springer Nature 2017

**Abstract** Meteorological drought indices associated with soil moisture status have potential for varying applications including predictive power for crop yields estimation. The Keetch-Byram Drought Index (KBDI) was initially developed to estimate forest flammability, based on quantification of the moisture deficiency in upper soil layer as a function of daily precipitation and maximum air temperature. In this study, we characterized the utility of KBDI to accurately trace and monitor vegetation change and crop yield fluctuation in a semi-arid environment. It is tried to find any temporal association for both the 16-day MODIS-derived NDVI and KBDI from 2002 to 2012 and the correlation between KBDI and wheat and barley yield from 1984 to 2010. Correlation between KBDI and NDVI showed a general seasonal pattern with strongest correlation in mid-growing season, but this varied across study locations. Warmer locations with very sparse vegetation showed weaker association between KBDI and NDVI. Although a robust correlation between KBDI and winter cereal crop yield was not achieved based on winter (wet and cold season) data, spring cereal crop yield was correlated with KBDI.

## 1 Introduction

Arid and semi-arid regions of the world, which comprise approximately 40% of terrestrial earth, are mostly located in developing countries (Bannayan et al. 2010). It is predicted that semi-arid Mediterranean regions will face severe water deficit due to environmental instability during the twenty-first century (Houghton et al. 2001; Beranová and Kyselý 2015). The agricultural sector is especially vulnerable to climate variability in arid lands (Farhangfar et al. 2015). Because of its dependence on precipitation and soil moisture reserves in areas with limited irrigation infrastructure, agriculture is often impacted early by the onset of drought (Narasimhan and Srinivasan 2005; Katiraie-Boroujerdy et al. 2016).

The country of Iran with area of 1,648,000 km$^2$ covers both arid and semiarid regions with annual precipitation of about 250 mm. The coefficient of variation of annual rainfall in Iran is as high as 70%, presenting challenges to the agricultural sector and consumers. Under such conditions, crop production varies widely and drought has severe impacts (Bannayan and Sanjani 2011; Nazemosadat 2000). The 1998–2000 drought resulted in death of 800,000 livestock and $3.5 billion in total loss (Nazemosadat 2000). Most precipitation in Iran occurs in winter–early spring, but the major parts of growing period of winter cereals occur in spring and early summer. Due to the water shortage in this area, irrigated crops are also somewhat dependent on precipitation. In fact, cultivated crops are grown under supplementary irrigation. Therefore, most crops experience progressively water deficits during the growing season and disproportionately impacting the reproductive phase of crop development (Bannayan et al. 2011). Early spring precipitation determines soil moisture capacity to support crops in later stages, so any study on drought indices which focus on soil moisture may enhance our understanding of drought effects and possibly better drought management.

After precipitation, temperature (specifically maximum air temperature) during anthesis and grain-filling period (Zodaks code 60–87) is the next most important determinant of yield. Using a terrestrial biosphere simulation model, Ciais et al. (2005) estimated that primary production in Europe will be reduced by 30% as a result of precipitation deficit and summer extreme hot wave. Similar results have been reported by other

✉ Hossein Zare
h_zare@stu.um.ac.ir; hossein.zr84@gmail.com

1 Faculty of Agriculture, Ferdowsi University of Mashhad, P.O. Box 91775-1163, Mashhad, Iran

studies (Klink et al. 2014; Peltonen-Sainio et al. 2011; Trnka et al. 2004). So, a drought index which considers precipitation and maximum air temperature during the growing season seems an appropriate tool to predict yields.

The Keetch-Byram drought index (KBDI) was developed to estimate flammability in forest and wild land areas of the USA (Keetch and Byram 1968). Because it uses daily precipitation and daily maximum temperature, KBDI has the potential to describe cumulative moisture deficiency in upper soil layers (Keetch and Byram 1968). KBDI has primarily been used for planning fire management operations (Dolling et al. 2005), and it is still considered a robust indicator of wildfire probability (Arpaci et al. 2013). Other studies have applied KBDI for agricultural drought approximation (Brolley et al. 2007; Liu et al. 2010; Petros et al. 2011; Garcia-Prats et al. 2015; Taufik et al. 2015). Dimitrakopoulos and Bemmerzouk (2003) and Xanthopoulos et al. (2006) applied linear regression equations between plant water potential and KBDI, and concluded that KBDI is not only an index representing cumulative soil moisture deficiency, but also can reflect plant water deficit. Since KBDI includes maximum air temperature and precipitation changes, it follows growing season patterns in KBDI should have explanatory power over crop yield variations.

Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974) is a remotely sensed vegetation index calculated based on visible (red) and near-infrared (NIR) radiation. Due to their internal mesophyll structure, healthy green leaves strongly reflects NIR radiation, and leaf chlorophyll absorbs a large proportion of the red radiation (Gausman 1974; Sellers et al. 1992; Tucker 1979; Tucker and Sellers 1986), so NDVI indicates how much photosynthetically active radiation is absorbed by vegetation. NDVI has been widely used to assess vegetation condition (e.g., Brown et al. 2008; Chen et al. 2011; Hu et al. 2011; Wang et al. 2003) and for drought spatial monitoring (Kogan 1990, 1995; Zhang et al. 2013). Precipitation and temperature both directly impact soil water balance, which in turn influences plant growth and associated NDVI changes. Quiring and Ganesh (2010) indicated that prolonged moisture stress indices, including PDSI (Palmer Drought Severity Index), 6-month SPI, and 9-month SPI (Standardized Precipitation Index) are correlated with relative NDVI change. However, a time lag between NDVI and rainfall deficit has been observed. Zhang et al. (2013) found a 16–24-day time lag of farmland NDVI sensitivity to precipitation. Darmawan et al. (2014) examined the relationships between precipitation, KBDI and Enhanced Vegetation Index (EVI). They showed precipitation fell from January to May and from October to December and conversely KBDI increased from June and peaked in September. This seasonal analysis also showed precipitation and KBDI affected EVI, with EVI peaking before KBDI.

The purpose of the present paper is to consider the feasibility of using KBDI to trace crop yield in a semi-arid Mediterranean climate. We developed a user friendly tool for calculating KBDI, relating KBDI output to climate characteristics, and to investigate performance of KBDI in predicting crop yield and NDVI. Finally, we tested the application at six different locations to verify the universality of the predictive power of KBDI on final yield of wheat and barley.

## 2 Material and method

### 2.1 The Keetch-Byram drought index (KBDI)

The KBDI, originally developed for assessment of fire risk in the southeastern forests of the USA (Keetch and Byram 1968), conceptually describes soil moisture (Dolling et al. 2005) based on daily precipitation, daily maximum temperature, and mean annual precipitation. The output value of 0 to 800 is categorized into four classes where 0 represents soil saturation and 800 indicates severe drought. More detailed explanation for the calculations of this index can be found in Keetch and Byram (1968) and Janis et al. (2002). In this study, to modify KBDI for our region (semiarid), we changed initial amount of precipitation, which is needed for KBDI to run, based on different soil types (See appendix 1).

### 2.2 Study area

Northeastern Iran is comprised of three provinces: North Khorasan, Razavi Khorasan, and South Khorasan lying between approximately 30° N and 38° N latitude and 56°E and 61°E longitude. This area covers 238,771 km$^2$ and is one of the major agricultural regions in the country. The area is categorized as generally having arid (BW) and semi-arid (BS) climates in the Koppen climate classification system. Mean annual temperature varies from 12.7 $^{\circ}C$ in Quchan to 18 $^{\circ}C$ in Sarakhs; annual precipitation varies from 137 mm in Gonabad to 308 mm in Quchan (Table 1). Temporal pattern of precipitation in Khorasan area shows that major amount of precipitation occurs in winter and spring season which states that cold months are wet months and vice versa (Eyshi Rezaei et al. 2013). In this study, six major agricultural regions with different precipitation and annual temperature characteristics were selected (Fig. 1 and Table 1). The long-term average annual changes of precipitation and temperature of the locations are presented in Fig. 2.

### 2.3 Data set

#### 2.3.1 Meteorological and crop data

The weather data of each location used in this study, daily maximum temperature (°C), and daily precipitation (mm), were obtained from Razavi Khorasan Meteorological Station for 1951–

**Table 1** Long-term (1951–2012) average annual climate variables (minimum temperature, maximum temperature, and precipitation) and geographical position of the weather station of the study location

| Location | *T*min (°C) | *T*max | Precipitation (mm) | Latitude | Longitude |
|---|---|---|---|---|---|
| Quchan | 6.1 | 19.4 | 308 | 37° 6′ 22″ N | 58° 30′ 34″ E |
| Kashmar | 12 | 23.7 | 197 | 35° 14′ 18″ N | 58° 27′ 56″ E |
| Mashhad | 7.3 | 21.2 | 251 | 36° 18′ 0″ N | 59° 36′ 0″ E |
| Neyshabur | 6.8 | 22 | 238 | 36° 12′ 48″ N | 58° 47′ 45″ E |
| Sabzevar | 10.7 | 24.3 | 186 | 36° 12′ 45″ N | 57° 40′ 55″ E |
| Torbat-e Heydarieh | 7.4 | 21.2 | 267 | 35° 16′ 26″ N | 59° 13′ 10″ E |

2012. We selected irrigated winter wheat and barley as our crops of interest because they are major crops in the local agricultural economy. Irrigated winter crops are usually planted from in late October and harvested around early July depending on the temperature. Farmers irrigate fields once in fall to emergence the seeds. During the winter and early spring, crops are irrigated only by precipitation. Crops are irrigated in mid spring based on drought condition. Generally, farmers irrigate from two times in wet and cold years to five times in dry and warm years. Historical yield data for wheat and barley of each location from 1984 to 2012 were obtained from the Khorasan Agricultural Research Station.

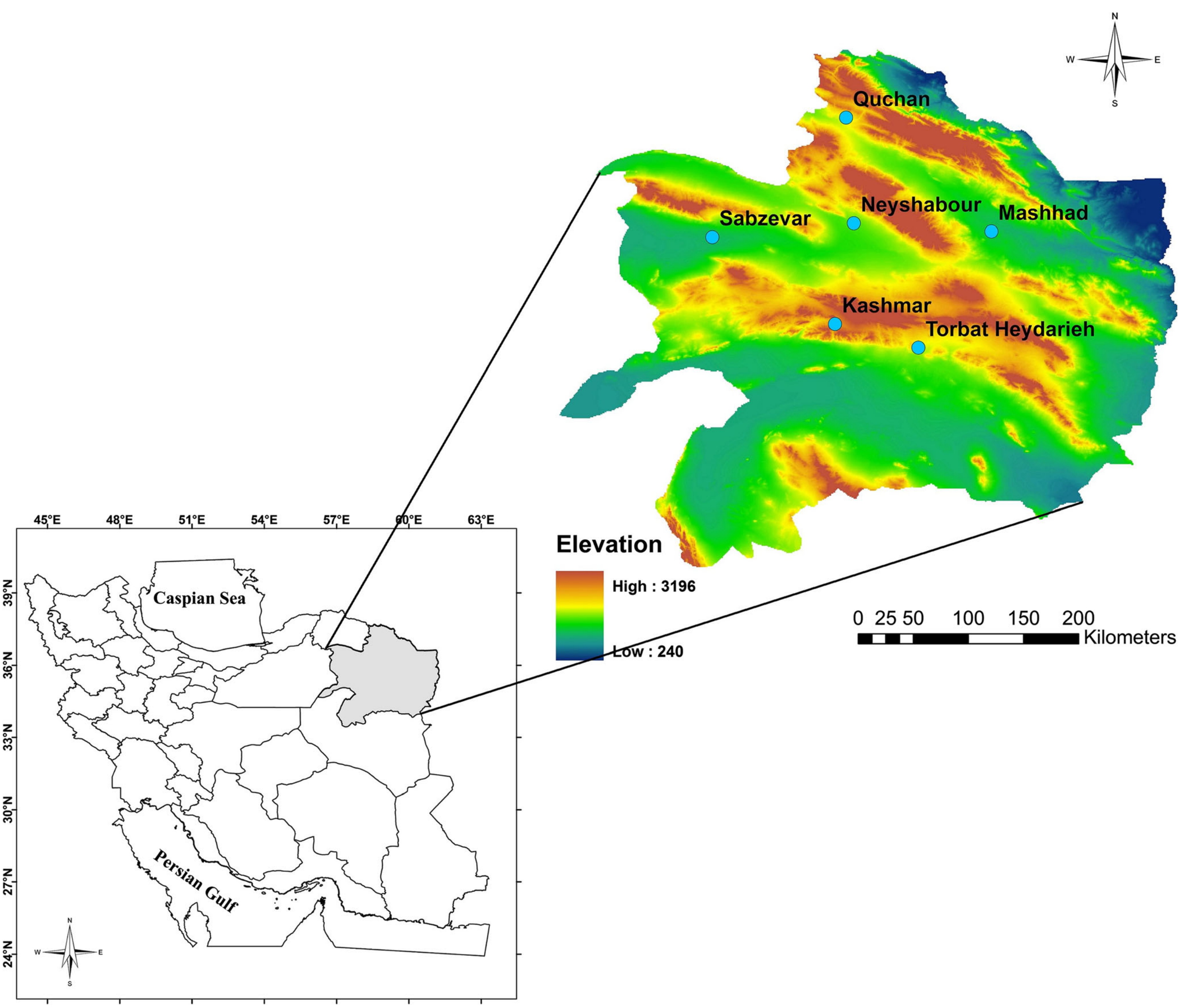


**Fig. 1** Geographical characteristics of the study area

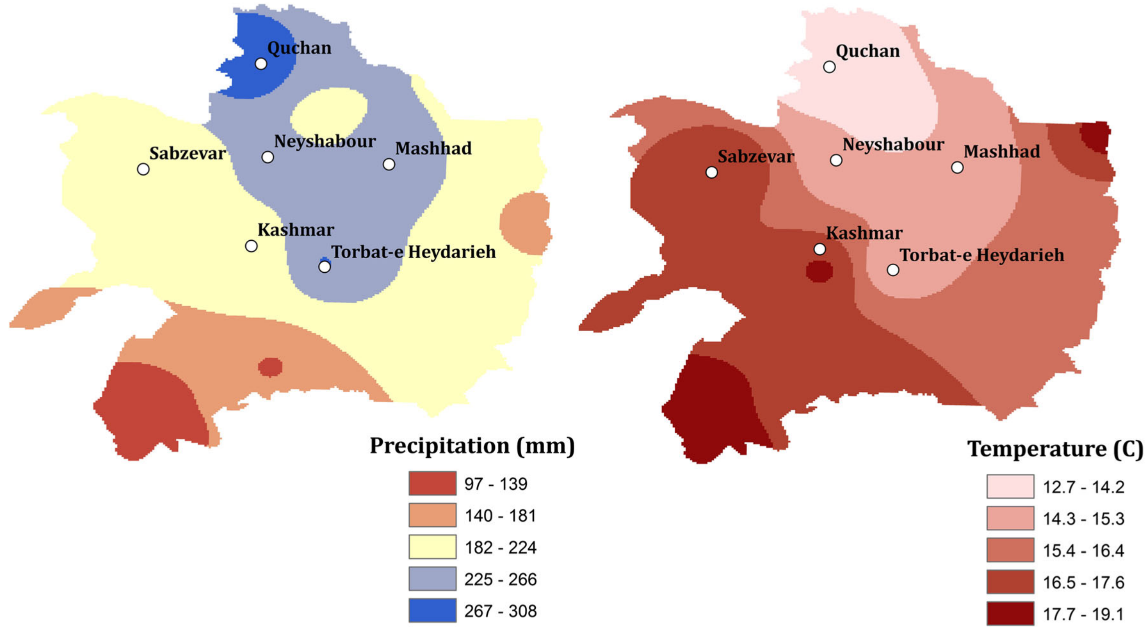


**Fig. 2** Spatial distribution of long-term average annual precipitation and temperature values in the study area

*2.3.2 NDVI*

Global MODIS (Moderate Resolution Imaging Spectroradiometer) vegetation indices are designed to provide consistent spatial and temporal comparisons of vegetation conditions. The MODIS NDVI products are computed from atmospherically corrected bi-directional surface reflectance. Vegetation index product MOD13Q1 (h22, v05) are provided every 16 days at 250-m spatial resolution as a gridded level-3 product in the Sinusoidal projection. NDVI data from 2002 to 2012 were downloaded from the U.S. Geological Survey's website (https://lpdaac.usgs.gov/). Natural vegetation of each location was masked from each tile. Pixels with NDVI < 0.1 were defined as bare soil and thus excluded from the analysis (Piao et al. 2006).

### 2.4 Correlation

To analyze performance of the drought index in this study, KBDI was defined as descriptor to show NDVI and crop yield changes. Sixteen-day average KBDI was calculated to match the 16-day NDVI product used for analysis. Average monthly KBDI values were calculated in order to examine correlations with crop yield. The statistical significance of Pearson's correlations was set for $p$ values ≤ 0.05.

## 3 Results and discussion

### 3.1 KBDI and NDVI correlation with climate variables

As expected based on its formula, KBDI increases with reductions in precipitation and increases in maximum air temperature (Table 2). Although the KBDI was originally developed for humid regions, a modified KBDI allows values to follow precipitation and maximum temperature changes of semi-arid areas as closely. As expected based on its equation, KBDI is more tightly linearly correlated to precipitation than temperature. In Quchan, which is cooler and more humid than the other areas we examined, KBDI did not show as tight a relationship to temperature and precipitation. This may be due to this region's temporal distribution of precipitation, as KBDI does not change when precipitation exceeds field capacity.

To further analyze the effect of precipitation distribution on the KBDI curve, we plotted precipitation and KBDI of Torbat-e Heydarieh over 6 years (Fig. 3). The years plotted Fig. 3 were chosen because they had similar total precipitation (325 ± 15 mm), but different patterns of temporal distribution. Most precipitation occurred from January to March in 1982; in contrast, most precipitation fell between March and May in 1992

**Table 2** Correlation between KBDI and climate variables (1990–2012) by Pearson's correlation test

| Location | KBDI vs. | |
|---|---|---|
| | *T*max | Precipitation |
| Quchan | 0.37 | −0.58** |
| Kashmar | 0.45* | −0.72** |
| Mashhad | 0.51** | −0.74** |
| Neyshabur | 0.48* | −0.61** |
| Sabzevar | 0.46* | −0.75** |
| Torbat-e Heydarieh | 0.57** | −0.73** |

* Significant at 0.05 level, ** Significant at 0.01 level

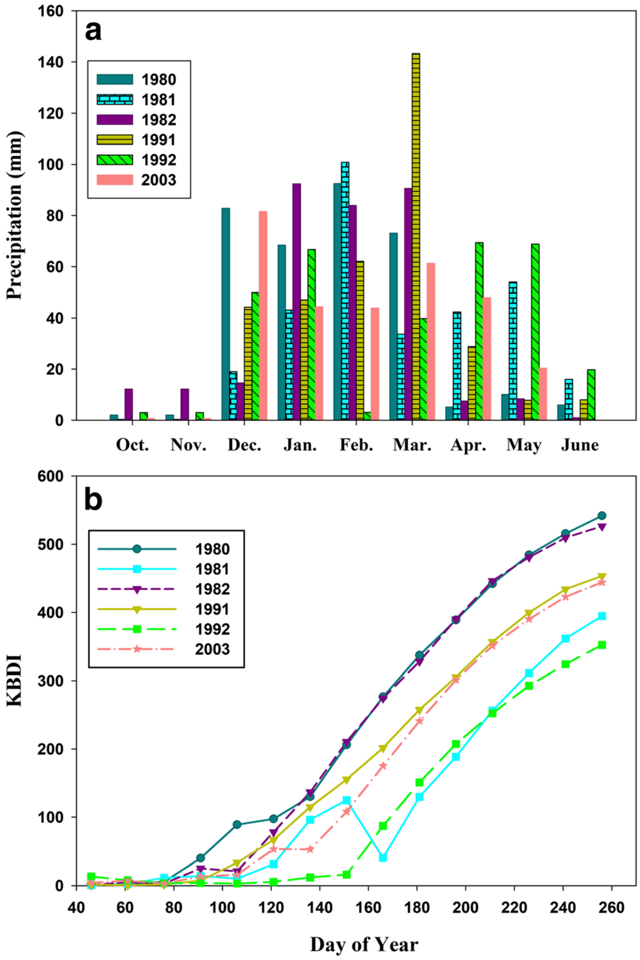


**Fig. 3** Monthly precipitation distribution of 6 years which had similar amount of precipitation (325 ± 15 mm) in Torbat-e Heydarieh (**a**) and KBDI curve for the corresponding years (**b**)

(Fig. 3a). The KBDI started increasing at the 100th day of year in 1982. By contrast, KBDI remained low until the 150th day of year in 1992 (Fig.3b). So when the same amount of precipitation is shifted from early to late spring, the KBDI remains low for a greater portion of the year.

A strong positive relationship was found between NDVI and precipitation (Table 3). Due to the dry condition, vegetation cover is completely dependent on precipitation in all areas. In spite of precipitation, temperature had a negative weak impact on NDVI in most locations. Similar with KBDI, NDVI showed that precipitation is more effective than temperature. In fact, precipitation is the determining factor for plant growth. Due to cold weather, NDVI had positive relationship with temperature in Quchan (however, it was not significant).

### 3.2 Seasonal trend of precipitation, KBDI, and NDVI

KBDI and NDVI were plotted across 2 years (2004 and 2005) as a sample (Fig. 4). Precipitation in all study locations starts

**Table 3** The relationship between NDVI and total precipitation and mean temperature (2002–2012) by Pearson's correlation test

| Location | NDVI vs. | |
|---|---|---|
| | Precipitation | Temperature |
| Quchan | 0.75* | 0.42 |
| Kashmar | 0.70* | − 0.22 |
| Mashhad | 0.91** | − 0.10 |
| Neyshabur | 0.70* | 0.27 |
| Sabzevar | 0.73* | − 0.23 |
| Torbat-e Heydarieh | 0.77* | − 0.06 |

* Significant at 0.05 level, ** Significant at 0.01 level

late fall and ends in early spring (Fig. 4). Most precipitation occurs while cool temperatures are limiting plant growth; precipitation declines as temperatures warm. Therefore, soil moisture storage capacity plays a critical role in supplying adequate water for spring crops. Normally, precipitation declines and temperatures increase during April, and KBDI gradually increases (Fig. 4). In most study locations, KBDI started to rise at about DOY 129. In Sabzevar and Kashmar, where annual precipitation is lower and temperatures are higher (Fig. 4), KBDI increases begin earlier (DOY 60–90). KBDI peaks annually (indicating the soil is the driest for the year) across the region in October. Across these two example years, KBDI in 2004 peaked at about 350 in cooler areas like Quchan, while in warmer areas like Sabzevar, KBDI peaked at 640 in 2005 (Fig. 4).

During March when soil moisture is favorable and temperatures begin to warm, NDVI increasing rapidly, peaking in late April and declining just a few days after KBDI begins its annual increase (Fig. 4). In most of the study areas, once KBDI exceeds 350, NDVI has returned to and remains at the minimum yearly baseline level. This implies that KBDI > 350, soil water content limits plant growth (agricultural drought). In both Torbat-e Heydarieh and Quchan, NDVI in 2004 peaked at higher levels than in 2005, and their maximum KBDI values were less in 2004 than 2005. So, it is expected to be a negative trend between KBDI and NDVI.

### 3.3 Temporal relationship between KBDI and NDVI

To better understand the dynamics between KBDI and NDVI, daily KBDI was converted to 16-day average daily scale, (similar to NDVI). To find out when in the growing season KBDI and NDVI are most closely inversely correlated, we analyzed their relationship between DOY 65–129 and maximum NDVI, which occurred between DOY 113 and 129 depends on the location, from 2002 to 2012 (Fig. 5). The correlation rose from non-significant on DOY 65, peaked around DOY 81, and then declined dramatically from DOY 81 to 135

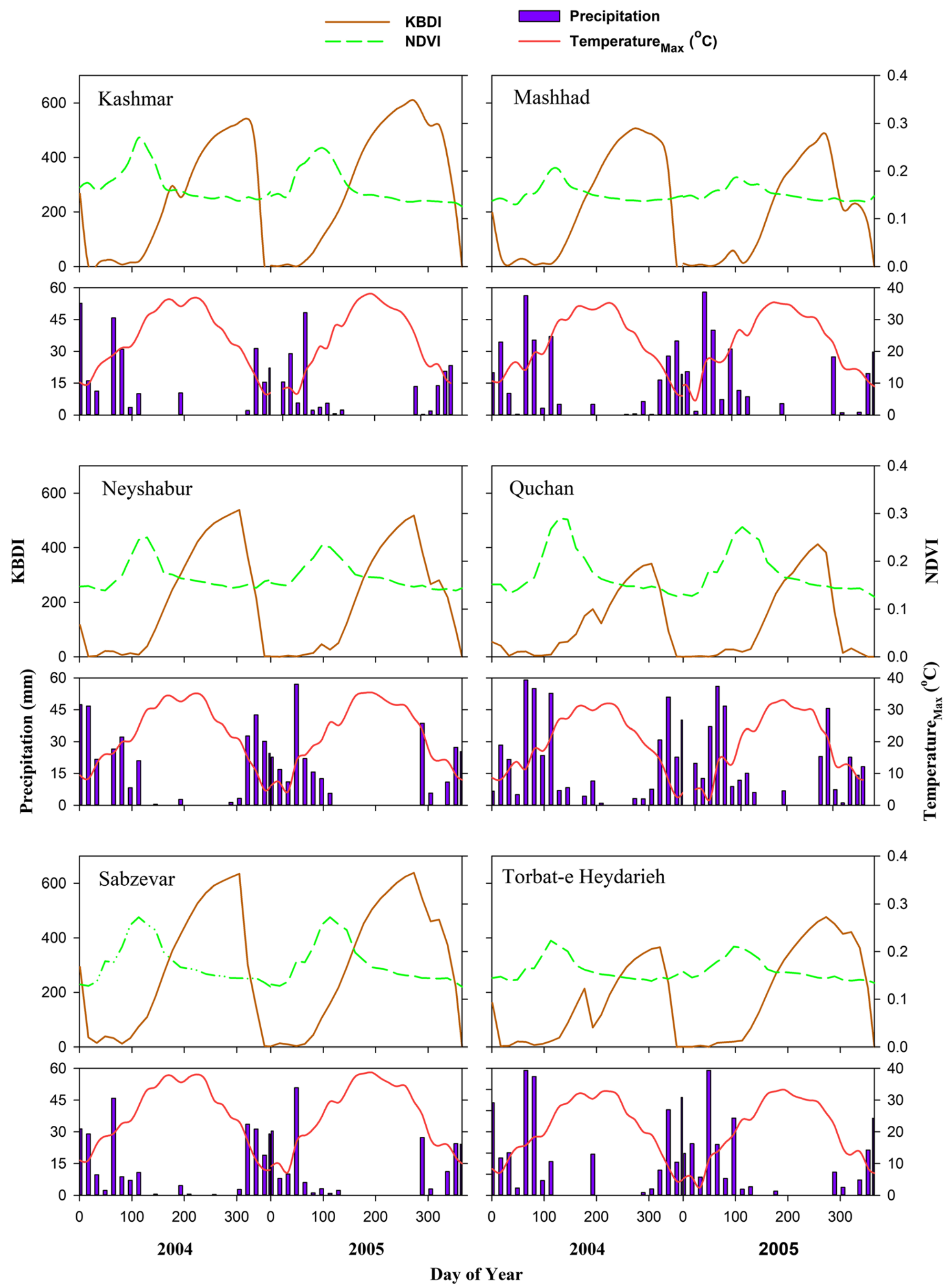


**Fig. 4** Seasonal trend of KBDI, NDVI, precipitation, and temperature from 2004 to 2005 in different locations (All KBDI, precipitation, and temperature values are aggregated to 16-day values to be matched with NDVI)

(Fig. 5). KBDI and NDVI were most tightly inversely correlated in Torbat-e Heydarieh and Neyshabur ($r^2 = 0.81^{**}$ and $0.62^{**}$, respectively) (Fig. 5) and least strongly related in the warmest and driest locations with sparser vegetation, Kashmar and Sabzevar (Table 1). In these locations, maximum NDVI was less than others. The considerable point is that a 30-day lag was found between KBDI and maximum NDVI at the highest correlation in all the locations. It should be also mentioned that it is unclear that 16 days average is the right number of days to average or should be less that, an issue which requires more research.

Xanthopoulos et al. (2006) also showed that KBDI not only characterizes cumulative moisture deficiency in deep and surface soil layers, but to some extent reflects water deficits of living plants. Their results showed a linear relation between KBDI as an independent variable and three woody plant species' water potential. Dimitrakopoulos and Bemmerzouk (2003) similarly found that tree foliage moisture content was dependent on deeper soil moisture status, while shallow-rooted herbaceous species' moisture reflects that of surface soil layers, and are consequently more sensitive to weather changes. So, KBDI is expected to closely reflect herbaceous plant moisture stress.

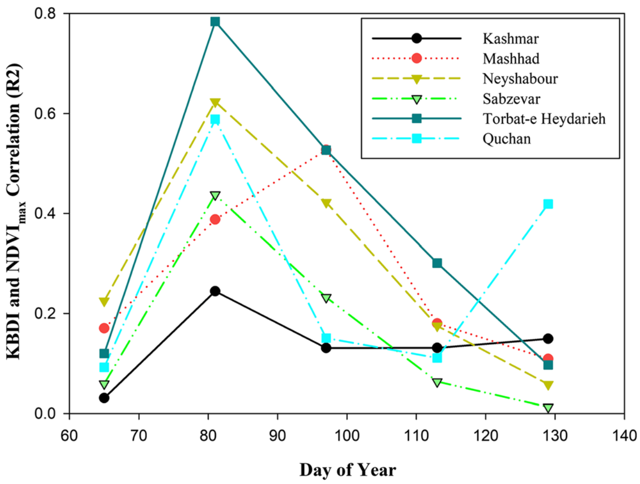


**Fig. 5** Temporal relationships ($R^2$) between KBDI and Maximum NDVI

### 3.4 Association of climate and crop yield

Temperature and precipitation during growing season are known as the most important climate variables effecting crop growth. However, the effect of these variables on crops vary among different regions. Although crop production in Iran is vulnerable due to high climate variability, the correlation between climate variables and crop yield is very complicated. No significant relationship was found between yield of wheat and barley and temperature in all locations except Mashhad (Table 4). Mean annual temperature had positive effect on crop yield in Mashhad. Bannayan et al. (2011) found that minimum temperature during late autumn and winter adversely effects wheat yield in Mashhad. Precipitation during the growing season showed stronger correlation with crop yields. In the case that total amount of precipitation (Fig. 2) is insufficient for crop (wheat and barley) water requirement, the timing of precipitation occurrence plays an important role to supply water requirement. Bannayan et al. (2011) reported that precipitation events toward the end of winter in drier areas of Khorasan are important while for less dry and cooler areas precipitation in spring and early summer are more effective.

### 3.5 Temporal relationship between KBDI and crop yield

To analyze the temporal relationships between KBDI and crop yield (Fig. 6), daily KBDI was converted to monthly average values. The correlation between monthly KBDI and crop yield (wheat and barley) showed an obvious seasonality pattern. No significant relationship was found in January and February for most locations. When temperatures warm in March, the relationship between KBDI and crop yield strengthens. In most locations, the closeness of the KBDI relationship with yield peaks in April, then decreases gradually. The maximum monthly explanatory power of KBDI over yield achieved was $r^2 = 0.42$ (April) for wheat in Neyshabur (Fig. 6). KBDI

**Table 4** The relationship between total precipitation and mean temperature and yield of wheat and barley (1990–2012) by Pearson's correlation test

| Location | Temperature vs. | | Precipitation vs. | |
|---|---|---|---|---|
| | Wheat | Barley | Wheat | Barley |
| Quchan | 0.06 | 0.14 | 0.52* | 0.54* |
| Kashmar | −0.13 | −0.00 | 0.46* | 0.21 |
| Mashhad | 0.40* | 0.57* | 0.32 | 0.05 |
| Neyshabur | 0.13 | 0.26 | 0.54* | 0.38 |
| Sabzevar | −0.14 | −0.00 | 0.45* | 0.49* |
| Torbat-e Heydarieh | 0.20 | −0.13 | 0.39 | 0.49* |

* Significant at 0.05 level, ** Significant at 0.01 level

also showed a significant relationship with yield in Kashmar, reaching 0.3 and 0.26 in April for wheat and barley, respectively. In general, April is a critical period for production of a profitable yield. Late March is when winter crops in the region (wheat and barley) pass the tillering phase and when precipitation declines. So, winter crops rely on soil water storage for the vital growth stages of flowering and grain filling. Flowering occurs from April to May, at the same time as when drought as measured by KBDI increases. The grain-filling stage for wheat is in mid-May. So, KBDI in mid-May reflects the moisture constraints on the growth of the flag leaf and provides approximately 75% of the effective leaf area that contributes to grain filling (Miller 1999). It should be noted that due to lack of measured soil moisture data, it was not possible to test the relationship between KBDI and soil moisture in our region.

The time of highest correlation varied across study area. In Quchan, monthly KBDI was significantly correlated with wheat and barley yield in April and June, but was poorly correlated with April yield in Torbat-e Heydarieh. Heat waves in May are the main factor limiting yield in Torbat-e Heydarieh, but are less extreme in Quchan. In Mashhad and Sabzevar, monthly KBDI did not show any significant relationship with crop yield. As is shown in Table 4, crop yield is positively correlated with temperature while no correlation was obtained with precipitation in Mashhad. Bannayan and Sanjani (2011) showed that wheat and barley yield in Mashhad and Sabzevar are significantly correlated to the minimum December and January temperatures and not determined by maximum growing season air temperature which is considered by KBDI. On the other side, improvements in management (from traditional to semi-industrial), fertilizer distribution, and new varieties have had large impacts on yield over the last 30 years. New technologies are introduced to Mashhad (the capital city) first, then to other important cities like Sabzevar; smaller cities have only limited and delayed access. Bannayan et al. (2014) simulated the effect of technology improvement of wheat in Khorasan

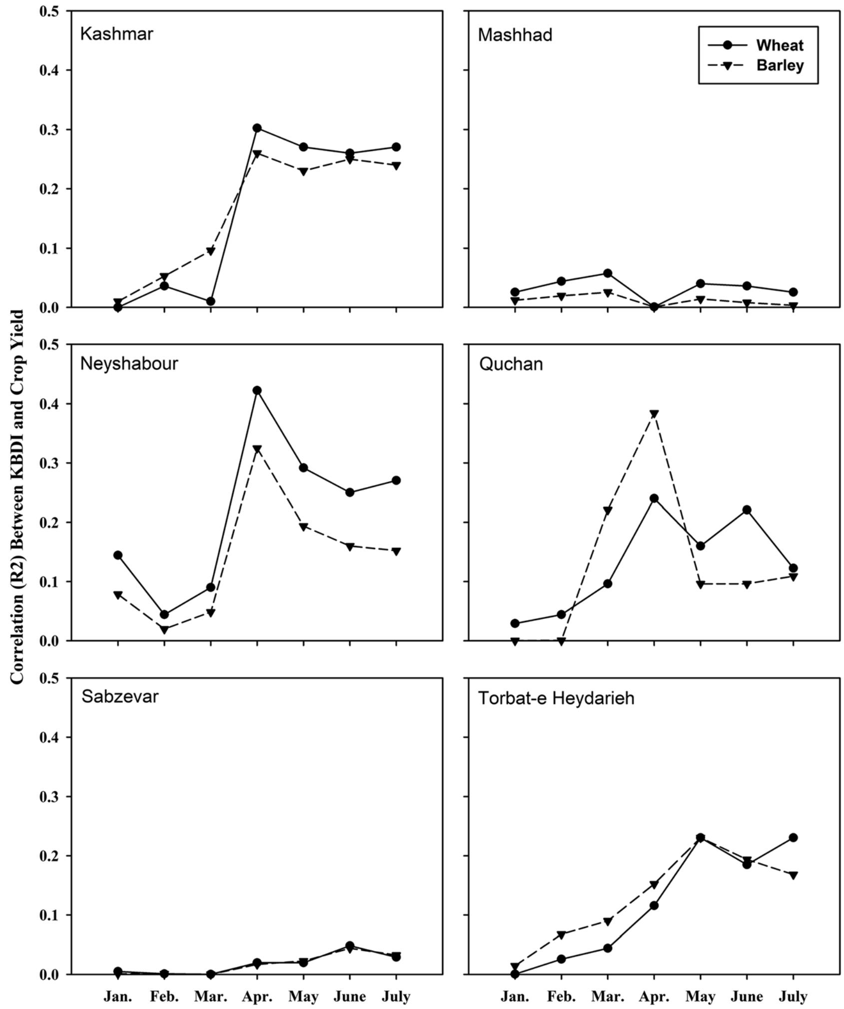


**Fig. 6** Temporal relationships ($R^2$) between KBDI wheat and barley yield

province. They showed that technology will play an important role in Mashhad (up to 75%) followed by Sabzevar, while minimum effect of technology was around 3%. In Mashhad and Sabzevar, though natural vegetation (NDVI) was correlated to KBDI (Fig. 5), wheat and barley yield was not correlated to KBDI (Fig. 6). This likely shows the importance of technological innovation on improving crop yields beyond climactic constraints.

## 4 Conclusion

We developed a user-friendly tool to calculate KBDI in order to apply it to vegetation and agricultural studies. A spatial and temporal relationship was found between KBDI and NDVI. KBDI could not capture NDVI changes in warmer locations with sparse vegetation cover. In terms of temporal relationship, the highest correlation was found between March and May (growing period) when plants rely on soil moisture status to sustain their life cycle. Since KBDI showed a good correlation with natural vegetation condition (NDVI), we expected to find a strong correlation with crop yield but it did not happen. The relation between KBDI and yield of wheat and barley was rather low compared to NDVI. The highest correlation was found in April and May in four locations. Since KBDI is a cumulative index, its status in April–May represents drought condition from the start point (winter) up to present (April–May) with the focus on present condition. However, It should be noted that crop yield in our study area is heavily impacted by degree of technological development. It seems that KBDI and indices accounting for technology improvements should be considered together to investigate yield changes. However, KBDI was not originally explicitly designed to show and monitor soil moisture, though it is related to the soil moisture status. In the future, we would like to clarify the relationship between KBDI and field soil moisture to further explore the relationship in this area.

**Acknowledgements** We would like to thank K. Grace Crummer (Institute for Sustainable Food Systems, University of Florida) for editing the manuscript to improve the language.

## Appendix 1

### Calculation of KBDI

To calculate the index, daily maximum temperature and precipitation data for a 20-year period (1990–2010) for the stations of the study area (Table 1 and Fig. 1) were collected. KBDI was then calculated as follows in C# programming language.

$$\mathrm{DF} = \frac{[800-KBDI_{t-1}][0.968\exp(0.0875T_{\max}+1.5552)-8.30]}{1+10.88\exp(-0.001736R)}\times 10^{-3} \tag{1}$$

$$\begin{gathered} KBDI_t = KBDI_{t-1} \;\; \textit{if}\; P_t = 0\,\mathrm{cm} \;\textit{and}\; TMAX_t \le 6.78^{\circ}C \\ KBDI_t = KBDI_{t-1} + \mathrm{DF}_t \;\; \textit{if}\; P_t = 0\,\mathrm{cm} \;\textit{and}\; TMAX_t > 6.78^{\circ}C \\ KBDI_t = KBDI_{t-1} + DF_t \;\; \textit{if}\; P_t > 0\,\mathrm{cm} \;\textit{and} \sum P_t \le 0.51\,\mathrm{cm} \\ KBDI_t = KBDI'_t + \mathrm{DF}_t \;\; \textit{if}\; P_t > 0\,\mathrm{cm} \;\textit{and} \sum P_t > 0.51\,\mathrm{cm} \\ KBDI'_t = KBDI_{t-1} - 39.37\sum P_t \end{gathered} \tag{2}$$

where DF is drought factor on a given day in the metric system (Janis et al. 2002), $TMAX_t$ is the daily maximum temperature ($^{\circ}C$), $R$ is the average annual rainfall in each region (cm), and $KBDI_{t-1}$ is the Keetch-Byram drought index for time $t$-1 (the day before) and $P_t$ is the daily precipitation (mm) (Janis et al. 2002). The initialization of the KBDI is crucial; it traditionally begins when a few consecutive days of rain occur and soil saturation is reached, but it should be noted that field capacity (ability to absorb water) of arable land varies according to soil and vegetation changes.

The drought increment on a given day, called the drought factor, is determined by (1) the mean annual rainfall for the study location, (2) the drought index of yesterday, and (3) the maximum temperature for today. Reduction in drought occurs only whenever the 24-h rainfall exceeds 0.20 in. (Keetch and Byram 1968). This index is a continuous reference scale to evaluate the dryness of the soil. The KBDI assumes that soil should be at field capacity through first 20 cm of soil depth. In order to increase the accuracy of the KBDI values, the application we developed allows the user to select different soil types. Soil saturation varies by geographic region but may be reached during lengthy precipitation events (Janis et al. 2002). For different soil types, the required depth of soil to hold 8 in. of moisture varies (for example, loam = 30% and clay = 25%). Though Keetch and Byram (1968) suggested that 150–200 mm of precipitation in a week is prolonged sufficient for initialization, this value does not work in semi-arid regions. In this study region, total amount of precipitation for a year is about 250 mm distributed across 6 months. Therefore, we had to modify the initialization of KBDI in our region. So, the amount of precipitation to initialize the KBDI was defined as the amount of water needed to increase soil moisture up to field capacity to a depth of 20 cm.

### Software description and use

Once downloaded, the application developed here for KBDI in installed by using InstallShield to guide the user through the install. It is free for users of all Visual Studio editions except the Express editions. Input files must follow 3-column format: Year string, maximum temperature, and precipitation values. For missing data, a zero will work, but not a missing data flag or − 9999. More details on preparation of input data files are available in the help file of the application. The application consists of a home screen with a main menu containing all the tabs related to the calculations. In the field capacity option, the user can select one of the numbers depending on soil type and moisture of the study area. The application is developed for agricultural study, particularly cereals. The depth of soil in which major part of root penetrates and absorbs water and nutrient, is assumed 20 cm. In the application (Field Capacity Option), users can select soil type, so the amount of precipitation to start KBDI will be determined. In the output file, KBDI for the selected period shows the daily format of data output. This application allows the user to save files into excel format at every stage, and can plot, graph or map all output data. The Help tab contains a video file demonstrating all analysis steps and explaining all tabs and icons for the user.

## References

Arpaci A, Eastaugh CS, Vacik H (2013) Selecting the best performing fire weather indices for Austrian ecoregions. Theor Appl Climatol 114(3-4):393–406. https://doi.org/10.1007/s00704-013-0839-7

Bannayan M, Sanjani S (2011) Weather conditions associated with irrigated crops in an arid and semiarid environment. Agric For Meteorol 151(12):1589–1598. https://doi.org/10.1016/j.agrformet.2011.06.015

Bannayan M, Sanjani S, Alizadeh A, Sadeghi Lotfabadi S, Mohamadian A (2010) Association between climate indices, aridity index, and rainfed crop yield in northeast of Iran. Field Crop Res 118:105–114. https://doi.org/10.1016/j.fcr.2010.04.011

Bannayan M, Lakzian A, Gorbanzadeh N, Roshani A (2011) Variability of growing season indices in northeast of Iran. Theor Appl Climatol 105(3-4):485–494. https://doi.org/10.1007/s00704-011-0404-1

Bannayan M, Mansoori H, Eyshi Rezaei E (2014) Estimating climate change, CO2 and technology development effects on wheat yield in northeast Iran. Int J Biometeorol 58:395. https://doi.org/10.1007/s00484-013-0635-1

Beranová R, Kyselý J (2015) Links between circulation indices and precipitation in the Mediterranean in an ensemble of regional climate models. Theor Appl Climatol 123(3-4):693–701. https://doi.org/10.1007/s00704-015-1381-6

Brolley JM, O'Brien JJ, Schoof J, Zierden D (2007) Experimental drought threat forecast for Florida. Agric For Meteorol 145(1-2):84–96. https://doi.org/10.1016/j.agrformet.2007.04.003

Brown JF, Wardlow BD, Tsegaye T, Hayes MJ, Reed BC (2008) The vegetation drought response index: a new integrated approach for monitoring drought stress in vegetation. GISci Remote Sens 45(1): 1548–1603. https://doi.org/10.2747/1548-1603.45.1.16

Chen CF, Nguyen TS, Li YC (2011) Monitoring of soil moisture variability in relation to rice cropping systems in the Vietnamese Mekong Delta using MODIS data. Appl Geogr 31(2):463–475. https://doi.org/10.1016/j.apgeog.2010.10.002

Ciais P, Reichstein M, Viovy N, Granier A, Ogee J, Allard V, Aubinet M, Buchmann N, Bernhofer C, Carrara A, Chevallier F, De Noblet N, Friend AD, Friedlingstein P, Grunwald T, Heinesch B, Keronen P, Knoh A, Krinner G, Loustau D, Manca G, Matteucci G, Miglietta F, Ourciva JM, Papale D, Pilegaard K, Rambal S, Seufert G, Soussana JF, Sanz MJ, Schulze ED, Vesala T, Valentini R (2005) Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature 437(7058):529–533. https://doi.org/10.1038/nature03972

Darmawan S, Takeuchi W, Shofiyati R, Sari D K, Wikantika K (2014) Seasonal analysis of precipitation, drought and vegetation index in Indonesian paddy field based on remote sensing data. IOP Conf Ser Environ Earth Sci 20. https://doi.org/10.1088/1755-1315/20/1/012049

Dimitrakopoulos AP, Bemmerzouk AM (2003) Predicting live herbaceous moisture content from a seasonal drought index. Int J Biometeorol 47:73–79. https://doi.org/10.1007/s00484-002-0151-1

Dolling K, Chu P-S, Fujioka F (2005) A climatological study of the Keetch/Byram drought index and fire activity in the Hawaiian Islands. Agric For Meteorol 133(1-4):17–27. https://doi.org/10.1016/j.agrformet.2005.07.016

Eyshi Rezaei E, Mohammadian A, Koohi M, Bannayan M (2013) Comparative analysis of drought indices for drought zone scheme of northern Khorasan Province of Iran. Not Sci Biol 3(3):62–66

Farhangfar S, Bannayan M, Khazaei HM, Mousavi Baygi M (2015) Vulnerability assessment of wheat and maize production affected by drought and climate change. Int J Disaster Risk Sci 13:37–51. https://doi.org/10.1016/j.ijdrr.2015.03.006

Garcia-Prats A, Del Campo A, Fernandes TJG, Molina AJ (2015) Development of a Keetch and Byram—based drought index sensitive to forest management in Mediterranean conditions. Agric For Meteorol 205:40–50. https://doi.org/10.1016/j.agrformet.2015.02.009

Gausman HW (1974) Leaf reflectance of near-infrared. Photogramm Eng 10:183–191

Houghton J T, Ding Y, Giggs D, van Noguet M, del Linden P, Dai X, Maskell A, Johnson C A (2001) Climate change: the scientific basis. Cambridge University Press, Cambridge doi:https://doi.org/10.1002/qj.200212858119, 128, 581, 1038, 1039

Hu MQ, Mao F, Sun H, Hou YY (2011) Study of normalized difference vegetation index variation and its correlation with climate factors in the three-river-source region. Int J Appl Earth Obs 13(11):24–33. https://doi.org/10.1080/01431160210154812

Janis M, Johnson MB, Forthun G (2002) Near-real time mapping of Keetch-Byram drought index in the south-eastern United States. Int J Wildland Fire 11(4):281–289. https://doi.org/10.1071/WF02013

Katiraie-Boroujerdy P, Nasrollahi N, Hsu K, Sorooshian S (2016) Quantifying the reliability of four global datasets for drought monitoring over a semiarid region. Theor Appl Climatol 123(1-2):387–398. https://doi.org/10.1007/s00704-014-1360-3

Keetch J J, Byram O M (1968) A drought index for forest fire control. USDA For Serv Southeastern For and Range Exp Stn Res Pap SE-38

Klink K, Wiersma JJ, Crawford CJ, Stuthman DD (2014) Impacts of temperature and precipitation variability in the Northern Plains of the United States and Canada on the productivity of spring barley and oat. Int J Climatol 34(8):2805–2818. https://doi.org/10.1002/joc.3877

Kogan FN (1990) Remote sensing of weather impacts on vegetation in non-homogeneous areas. Int J Remote Sens 11(8):1405–1419. https://doi.org/10.1080/01431169008955102

Kogan FN (1995) Droughts of the late 1980s in the United States as derived from NOAA polar orbiting satellite data. Bull Am Meteorol Soc 76(5):655–668. https://doi.org/10.1175/1520-0477(1995)076<0655:DOTLIT>2.0.CO;2

Liu Y, Stanturf J, Goodrick S (2010) Wildfire potential evaluation during a drought event with a regional climate model and NDVI. Eco Inform 5(5):418–428. https://doi.org/10.1016/j.ecoinf.2010.04.001

Miller TD (1999) Growth stages of wheat: identification and understanding improve crop management. SCS-1999-16. Texas Agricultural Extension Service, the Texas A&M University System, College Station

Narasimhan B, Srinivasan R (2005) Development and evaluation of soil moisture deficit index (SMDI) and evapotranspiration deficit index (ETDI) for agricultural drought monitoring. Agric For Meteorol 133(1-4):69–88. https://doi.org/10.1016/j.agrformet.2005.07.012

Nazemosadat MJ (2000) Winter drought in Iran: association with ENSO. Drought Netw News 13:1

Peltonen-Sainio P, Jauhiainen L, Hakala K (2011) Crop responses to temperature and precipitation according to long-term multilocation trials at high-latitude conditions. J Agric Sci 148(01):49–62. https://doi.org/10.1017/S0021859610000791

Petros G, Antonis M, Marianthi T (2011) Development of an adapted empirical drought index to the Mediterranean conditions for use in forestry. Agric For Meteorol 151(2):241–250. https://doi.org/10.1016/j.agrformet.2010.10.011

Piao S, Mohammat A, Fang J, Cai Q, Feng J (2006) NDVI-based increase in growth of temperate grasslands and its responses to climate changes in China. Glob Environ Chang 16(4):340–348. https://doi.org/10.1016/j.gloenvcha.2006.02.002

Quiring SM, Ganesh S (2010) Evaluating the utility of the vegetation condition index (VCI) for monitoring meteorological drought in Texas. Agric For Meteorol 150(3):330–339. https://doi.org/10.1016/j.agrformet.2009.11.015

Rouse JW, Hass RH, Schell JA (1974) Monitoring vegetation systems in the Great Plains with ERTS. In: The third earth resources technology Satellite-1 symposium, Greenbelt, MD, 309–317

Sellers PJ, Berry J, Collatz GJ, Field CB, Hall FG (1992) Canopy reflectance, photosynthesis and transpiration. III A reanalysis using improved leaf models and a new canopy integration scheme. Remote Sens Environ 42(3):187–216. https://doi.org/10.1016/0034-4257(92)90102-P

Taufik M, Setiawan BI, Van Lanen HAJ (2015) Modification of a fire drought index for tropical wetland ecosystems by including water table depth. Agric For Meteorol 203:1–10. https://doi.org/10.1016/j.agrformet.2014.12.006

Trnka M, Dubrovsky M, Zalud Z (2004) Climate change impacts and adaptation strategies in spring barley production in the Czech Republic. Clim Chang 64(1/2):227–255. https://doi.org/10.1023/B:CLIM.0000024675.39030.96

Tucker CJ (1979) Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens Environ 8(2):127–150. https://doi.org/10.1016/0034-4257(79)90013-0

Tucker CJ, Sellers PJ (1986) Satellite remote sensing of primary production. Int J Remote Sens 7(11):1395–1416. https://doi.org/10.1080/01431168608948944

Wang J, Rich PM, Price KP (2003) Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int J Remote Sens 24(11):2345–2364. https://doi.org/10.1080/01431160210154812

Xanthopoulos G, Maheras G, Gouma V, Gouvas M (2006) Is the Keetch–Byram drought index (KBDI) directly related to plant water stress? Forest Ecol Manag 234(supplement 1):S27. https://doi.org/10.1016/j.foreco.2006.08.043

Zhang F, Zhang L, Wang X, Hung J (2013) Detecting agro-droughts in southwest of China using MODIS satellite data. J Integr Agric 12(1): 159–168. https://doi.org/10.1016/S2095-3119(13)60216-6