Monitoring agricultural drought using geospatial techniques: a case study of Thal region of Punjab, Pakistan

Muhammad Amin, Mobushir Riaz Khan, Sher Shah Hassan, Aftab Ahmad Khan, Muhammad Imran, Muhammad Arif Goheer, Syeda Mahlaqa Hina and Abida Perveen

ABSTRACT

The Thal region of Punjab often experiences dry weather conditions with extreme variability in rainfall on a spatiotemporal scale during Rabi cropping season. The current study assesses the impacts of agricultural drought on wheat crops for 2000–2015. MOD13Q1 and CHIRPS data were used for identifying and assessing variation in agricultural drought patterns and severity. Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Stress Vegetation Index (STVI) and wheat crop yield anomalies were computed to characterize the gravity of drought across the Thal region. The results indicate that the wheat Rabi cropping seasons of the years 2000–2002 experienced extreme agricultural drought, with a spatial difference in severity level causing low and poor yield, while the years 2011 and 2014 were almost normal among all the years, leaving varied impacts on wheat yield. The combined agricultural risk map was generated by integrating the agricultural and meteorological droughts severity maps. The combined risk map generated using weighted overlay analysis of all the parameters indicate that the total Thal area can be classified into slight, moderate and no drought covering 28.12, 12.76, and 59.12% respectively of the total area. Hence an agricultural risk map would be extremely helpful as a tool to guide the decision-making process for monitoring drought risk on agricultural productivity.

Key words | agricultural drought, CHIRPS, GIS and RS, meteorological drought, remote sensing

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HIGHLIGHTS

- Impacts of agricultural drought on winter wheat crop at spatio-temporal level (i.e. 2001 – 2015) using MOD13Q1 and CHIRPS data.
- SPI, NDVI, VCI, STVI, and wheat crop yield anomalies have been computed.
- Risk map indicates that total Thal area can be classified into slight, moderate and no drought covering 28.12%, 12.76%, and 59.12% respectively of the total area.
- Agricultural risk map can be extremely helpful as a tool to guide the decision-making process.

INTRODUCTION

Approximately 40% of the global land surface is drylands (Reynolds *et al.* 2007). Rainfall in these areas is highly variable and very low (Lu *et al.* 2015), which results in temporal variation in the growth cycle and development of vegetation from year to year (Gibbes *et al.* 2014). Wheat is one of the major food crops and is grown under irrigated as well as rain-fed conditions from October to November and harvested in April. Agriculture is the major source of food and income for the population, especially in the wheat season when drought hits due to rainfall variation,

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the result is crucial growth of the crop yield. In this study, meteorological and agricultural drought conditions were explored. Generally, there are four types of drought: agricultural, meteorological, hydrological and socio-economic. The earlier of these are caused by rainfall deficits, streamflow, and soil moisture deficits, respectively (Chopra 2006), whereas the latter are related to the supply and demand of food, grain, water and lives in the area, which in turn causes migration, and scarcity in target societies (Wilhite & Glantz 1985). These drought conditions can affect different crop patterns.

Drought is an environmental hazard that affects crop yield badly (Du *et al.* 2013). It also affects natural and man-made features, climatic factors and basic demand for water scarcity issues in the region (Morton *et al.* 1995). The agriculture sector is most influenced by the beginning of the dry spell as it is highly dependent on the climate, atmosphere, soil moisture and so forth. Agricultural drought is decrease in the profitability of harvests because of inconsistencies in precipitation, an increase in the temperature rate and so forth, which causes a decrease in the soil moisture.

The role of remote sensing (RS) and a geographic information system (GIS) in agricultural drought identification, evaluation, and the executives has become significant nowadays as they give exceptional data in various scopes of spatial and temporal scales which are rushed and time-consuming when carried out by conventional techniques (Sruthi & Aslam 2015). Monitoring of agricultural droughts is possible through calculation of different vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI) etc. The indices are derived from RS and used for identification of vegetation health and greenness (Brown *et al.* 2008). Sruthi & Aslam (2015) demonstrated that in vegetation studies on a regional as well as a global level, NDVI may be used due to its simple calculation. To obtain better results it is always advisable to combine the NDVI along with other parameters. The NDVI and precipitation index share a solid connection where water is a noteworthy restricting variable for plant growth (Murad & Islam 2011).

The MODIS (Moderate Resolution Imaging Spectroradiometer) is broadly used for drought monitoring, snow cover, environment, and land surface analysis (Yagci *et al.* 2011). Van Loon (2015) estimated that agricultural drought is a disaster and its combination of hydrological and meteorological droughts, and when it occurs, a number of parameters are responsible such as precipitation, soil moisture, cropping pattern and crop stage. Wu *et al.* (2015) assessed the ability of MODIS imageries for monitoring agricultural drought through the investigation of time series of multiyear NDVI, NDWI, NDII, NMDI, VCI, VHI, and PDI information. Their outcomes demonstrate that the file inconsistencies were better related to the half-year Standardized Precipitation Index (SPI) than the one-month SPI and multi-month SPI, recommending these abnormalities are intelligent of agricultural drought seasonal conditions brought about by a lack of middle-scale precipitation.

Pakistan's economy is largely based on the agriculture sector and can be affected by droughts, predominantly in the rain-fed areas. Due to climate variation, the rainfall received by rain-fed areas is not sufficient for agricultural growth and thus ultimately affects the lives of the dependent people in that area. The droughts of 1998–2003 were some of the worst in the history of the country (Shaheen & Baig 2011). Drought analysis of such regions (i.e. rain-fed area) is more comprehensive because of the lack of real-time data sets. The choice of drought index is very important for effective monitoring and to draw a real picture in a region. In one of our previous studies we used NDVI, VCI and Standardized Precipitation Index (SPI12) but in this study, we used different indices and SPI6 and the results are more significant than the previous study. We also used crop mask data obtained from a Crop Reporting Service in Punjab, to analyze only droughts of wheat crop.

The Thal region mostly experiences droughts during Rabi season, due to changing climatic conditions, and most of the areas are badly affected because of drought, especially in the agricultural, socio-economic, physical environment, and livestock farming sectors (Sohail Gadiwala 2013; Abuzar *et al.* 2019). Amin *et al.* (2019) determined that the years 2000 and 2002 were extreme drought years while the years 2003, 2004, 2006, and 2009 were mild drought years in the drylands. In this region, the main source of livelihood depends upon agriculture. During the growing season of wheat, rainfall occurs, but most of the area remains dry which causes agricultural drought. So, we have to design beneficial policies and plans for drought mitigation in this area. This study focusses on agricultural and meteorological droughts. The main objectives of the study are: (i) to develop a drought risk map based on meteorological (SPI) and vegetation indices for selected periods (dry and wet period over the Thal region); (ii) to develop a relationship between meteorological and vegetation indices to shows the impact of meteorological variables (SPI and rainfall) on wheat crop yield in Thal region for a selected period; and (iii) to develop a combined drought risk map.

MATERIALS AND METHODS

Study area

The Thal region is located between 31°30′0″ N and 71°40′0″ E in the province of Punjab which comprises the districts Bhakkar, Jhang, Khushab, Layyah, and Muzaffargarh (Figure 1). The length and width of the area is approximately 306 and 113 km respectively. Agricultural drought is common in this semi-arid region. It resembles Cholistan deserts in southern Punjab, and the Thar desert of Sindh. Most of the area contains alluvial soil and dunes. In this region, the main source of livelihood depends on the agricultural and livestock industry. Wheat is one of the most stable crops in the area and is sown in most of the area. Wheat crop is sown during the month of September and harvested in April.

METHODOLOGY

Meteorological data acquisition and processing

Meteorological data (i.e. monthly precipitation data) was collected for the years 1981–2015. The data was downloaded from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) website. The data has a one-month temporal and 4.8 km spatial resolution. The data is freely available at www.chc.ucsb.edu/data. Six-month SPI (November–April) was calculated from the monthly precipitation data (McKee *et al.* 1993) using an SPI calculator freely available at http://drought.unl.edu/MonitoringTools/DownloadableSPIProgram.aspx. The calculator has a built-in option for one-, three-, six-, 12- and 24-month SPI calculation. The six-month SPI compares the precipitation for that period with the same six-month period over the historical

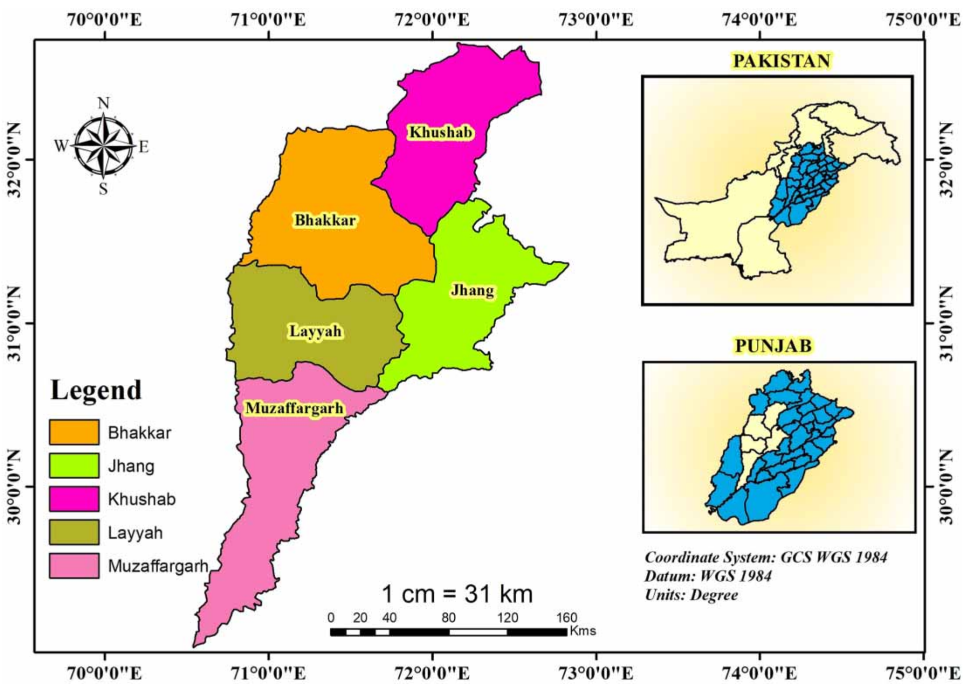

Figure 1 | Map of study area.

record. Six-month SPI is good and very effective at showing the precipitation over the specific season (World Meteorological Organization 2012). From SPI data, an SPI anomaly has been calculated using Equation (1):

$$SPI\ Anamoly = \frac{RF_i - RF_{avg}}{RF_{sd}} \tag{1}$$

where RF_i is rainfall in an individual month, RF_{avg} is the rainfall average values, RF_{sd} is rainfall standard deviation.

SPI compares precipitation with its multiyear average. It represents how many standard deviations its cumulative precipitation deficit deviates from the normalized average (Drought Watch 2010). If a value of less than zero is consistently observed and it reaches a value of -1 or less, a drought is said to have occurred (McKee *et al.* 1993). An important aspect in the development of the SPI is its ability to calculate drought levels for different time scales. McKee's index can be computed for any time period, however, typically it is applied for the three-, six-, 12-, 24-, and 48-month periods. For SPI, 30 years' of records are required but 50 years has been recommended (Guttman 1999).

Satellite data acquisition and processing

The droughts severity analysis was carried out on a temporal basis for 16 years (2000–2015) data using MODIS product MO13Q1, having spatial resolution of 250 m and temporal resolution of 16 days and were downloaded for the wheat cropping season (November–April). The data was processed in ArcMap and different vegetation indices (i.e. NDVI, VCI, and Stress Vegetation Index (STVI)) were calculated. The imageries were projected from sinusoidal projection to UTM and the appropriate scale factor was applied. From the series data set, two time periods were selected: 2001 and 2002 as drought years, and 2011 and 2014 as normal/wet years. The imageries were then processed for calculating different vegetation indices. Vegetation indices, i.e. NDVI (Li *et al.* 2004), VCI (Kogan 1990) and STVI (Viña *et al.* 2011), are calculated using Equations (2)–(4) respectively:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{2}$$

where NIR is near-infrared band, and r is Red band.

$$VCI = \frac{(NDVI_i - NDVI_{\min})}{(NDVI_{\max} - NDVI_{\min})} \tag{3}$$

where NDVI_i is the individual month, $\mathrm{NDVI}_{\max}$ is the maximum NDVI values, $\mathrm{NDVI}_{\min}$ is the minimum NDVI values.

$$STVI = MIR + \left(\frac{R}{NIR}\right) \tag{4}$$

where MIR is a mid-infrared band.

Statistical data

Statistical data related to crop mask and crop yield data of wheat crop for the years 2000–2015 were obtained from the Crop Reporting Service, Punjab. Crop mask data was used to extract wheat crop area and yield data was used to calculate yield anomaly and to check the effect of drought on yield. Yield anomaly was calculated using Equation (5):

$$Yield\ Anomaly = \frac{(Y_i - Y_t)}{Y_t} \tag{5}$$

where Y_i is the yield in a particular year and Y_t is the yield trend in 20 years. Yield trend data were obtained from the Bureau of Agricultural Statistics, Pakistan.

Analysis of agricultural drought using various drought indices (anomaly)

NDVI, VCI and STVI indices were used to check the spatio-temporal variation and severity of seasonal agricultural drought. Equations (6)–(8) were used to analyze drought severity. These indices were classified into different drought severity classes (shown in Table 1):

$$NDVI\ Anomaly = \frac{(NDVI_i - NDVI_{avg})}{NDVI_{sd}} * 100 \tag{6}$$

$$VCI\ Anomaly = \frac{(VCI_i - VCI_{avg})}{VCI_{sd}} \tag{7}$$

$$STVI\ Anomaly = \frac{(STVI_i - STVI_{avg})}{STVI_{sd}} \tag{8}$$

Table 1 | Drought severity classification (Nazareth 2014)

Drought index	No drought	Slight drought	Moderate drought	Severe drought	Very severe drought
SPI	Above 0	0 to –0.99	–1 to –1.49	–1.50 to –1.99	Below –2.0
NDVI anomaly	Above 0	0 to –10	–10 to –25	–25 to –50	Below –50
VCI anomaly	Above 0	0 to –10	–10 to –25	–25 to –50	Below –50
STVI anomaly	Above 0	0 to –10	–10 to –25	–25 to –50	Below –50

where $i =$ particular value, avg $=$ average value, sd $=$ standard deviation.

Table 2 | Numerical weights and ranked value assigned to the subclasses of drought vulnerability

S. no.	Parameter	Classes	Reclassified ranked value	Weighted value (%)
1	SPI	Very severely dry	10	40
		Severely dry	8	
		Moderately dry	6	
		Wet	4	
		Extremely wet	2	
2	STVI	Very severe	10	25
		Severe	8	
		Moderate	6	
		Slight	4	
		No	2	
3	VCI	Very severe	10	20
		Severe	8	
		Moderate	6	
		Slight	4	
		No	2	
4	NDVI	Very severe	10	15
		Severe	8	
		Moderate	6	
		Slight	4	
		No	2	

Combined agriculture drought map

The combined agriculture drought map was produced from the combination of each of the derived indices map and yield map. Yield maps were generated using Inverse Distance Weighting (IDW) interpolation in the ArcMap environment (Nazareth 2014). The maps were produced as a result of Equations (6)–(8) and were reclassified and combined in ArcMap using Weighted Overlay Analysis to obtain the final risk map. Weights were assigned to each parameter based on their importance and from a comprehensive literature review, as shown in Table 2. While assigning the weights, the influence of each thematic layer and its features on the potentiality of drought conditions were considered. The aggregate score from a linear combination factor model was computed and then each parameter was reclassified into five drought classes, i.e. no, slight, moderate, severe and very severe droughts. All the parameters for both time periods, i.e. drought and normal years, were then combined for the generation of a combined final drought risk map. The final risk map was then reclassified into three different classes to show the overall image of droughts of the study area. The detailed methodology is shown in Figure 2.

RESULTS AND DISCUSSIONS

Standardized precipitation index (SPI)

Six-month SPI (Shaheen & Baig 2011; Adnan *et al.* 2018) was calculated from CHIRPS precipitation data (Quesada-Montano *et al.* 2019) for the wheat cropping season (November–April) and for the time period of 38 years (1981–2018). The analysis of SPI (Figure 3) revealed that drought occurrence and severity was different in different areas for the wheat crop season. The drought span of 2000–2002 was found to be very severe based on SPI values for the concerned period. The rainfall anomaly, i.e. SPI, shows the change in seasonal precipitation. The negative anomalies indicate that rainfall was less than the average rainfall for the study area. On the basis of SPI, during 2000–2002 the northern part of Khushab district faced very severe drought, while Bhakkar, Layyah and the southern part of Khushab faced severe drought. Similarly, the eastern part of Bhakkar, Layyah and the northern part of Jhang and Muzaffargarh faced moderate drought. Jhang and Muzaffargarh faced a

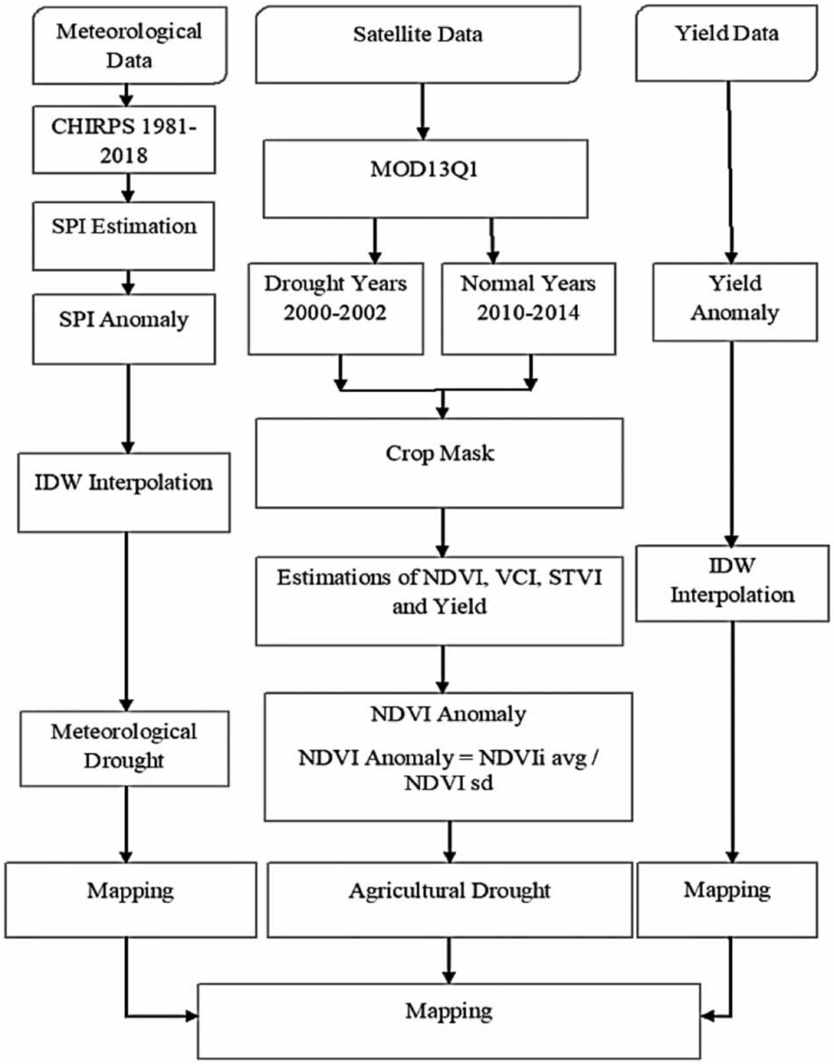

Figure 2 | Methodology flow chart.

slight drought. From 2010 to 2014 only Khushab district faced slight drought; similarly, in Bhakkar, Layyah, Jhang, and Muzaffargarh, there was no drought.

ANALYSIS OF AGRICULTURAL DROUGHT USING DIFFERENT VEGETATION INDICES

Normalized difference vegetation index (NDVI)

The Normalized Difference Vegetation Index is a simple graphical indicator that can be used for drought assessment because it is a simple calculation and easy to understand. It is used to monitor the health of vegetation. It is calculated using Equation (2). NDVI was derived from MODIS imageries for four different years for checking vegetation health and distribution. From the NDVI values, the NDVI anomaly was also calculated, which is a good indicator for drought assessment (Das *et al.* 2013). The NDVI value ranges between –1 and 1. It has been observed from the results that during the crop season of 2000–2001, the minimum NDVI value was –0.15 while the maximum NDVI value was observed to be 0.67 during 2013–2014. The results show that 2000–2002 were drought years and 2010–2014 were normal years on the basis of NDVI (Figure 4). The yearly images show that there was slight to severe drought

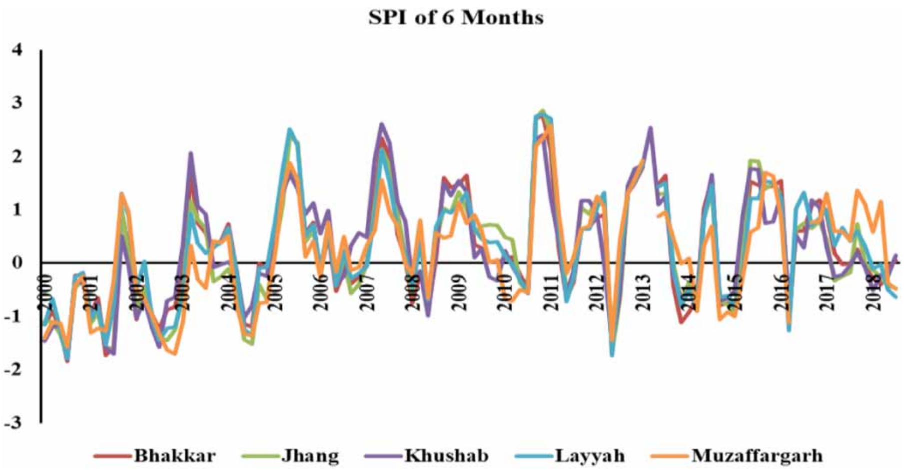

Figure 3 | Six-month SPI of the study area (Thal Region).

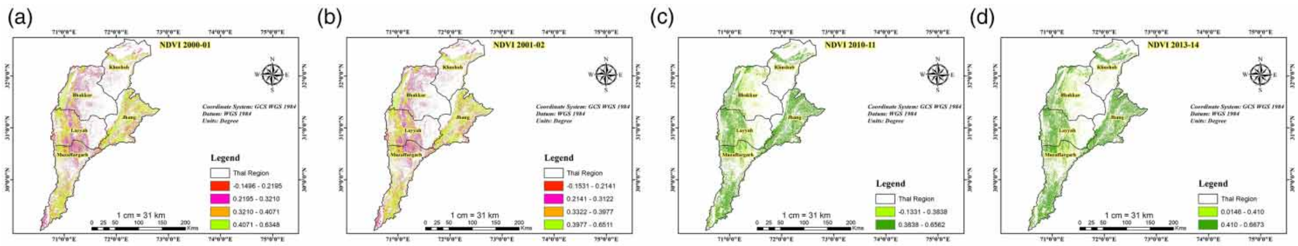

Figure 4 | Spatial pattern of NDVI for drought year: (a) 2000–2001; (b) 2001–2002; and, normal year: (c) 2010–2011; (d) 2013–2014.

during 2000–2002 and slight to no drought in normal years, i.e. 2011 and 2014. The figure shows that during 2000–2002, much of the areas of Bhakkar, Layyah and Khushab were under severe drought.

Vegetation condition index (VCI)

VCI is also an important parameter for agricultural droughts monitoring. VCI is calculated on the basis of NDVI. It compares the current NDVI values and observed previous year values. It was developed by taking the range of NDVI values between the study years and calculated using Equation (3). The results of VCI are shown in Figure 5. The minimum and maximum values are –0.27 and 0.6 and were observed during 2001–2002 and 2013–2014 respectively. The results show that most of the area of Khushab, Layyah, and Bhakar was under severe to moderate drought while most of the area of Jhang and Muzaffargarh faced mild droughts during 2001–2002, while in 2011 and 2014 some parts of the Khushab district faced slight droughts.

Stress vegetation index (STVI)

The Stress Vegetation Index represents stress in crops during cropping season and was calculated using Equation (4). The seasonal maps of STVI for the selected period are shown in Figure 6. The value of STVI varies between $+1$ and -1. The results show that STVI follows the same trend as NDVI and VCI except for Jhang, where there was a mild drought in small areas even during non-drought periods. The highest value of STVI, i.e. 0.38, was observed during 2000–2001, while the lowest value, i.e. 0.05, was observed during 2013–2014.

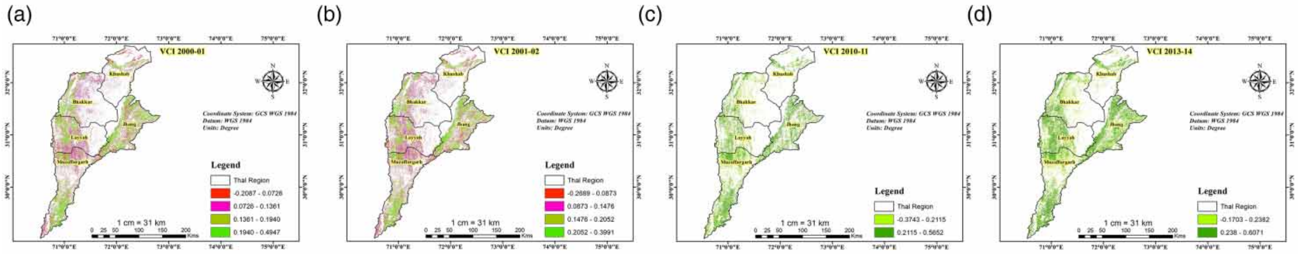

Figure 5 | Spatial pattern of VCI for drought year: (a) 2000–2001; (b) 2001–2002; and, normal year: (c) 2010–2011; (d) 2013–2014.

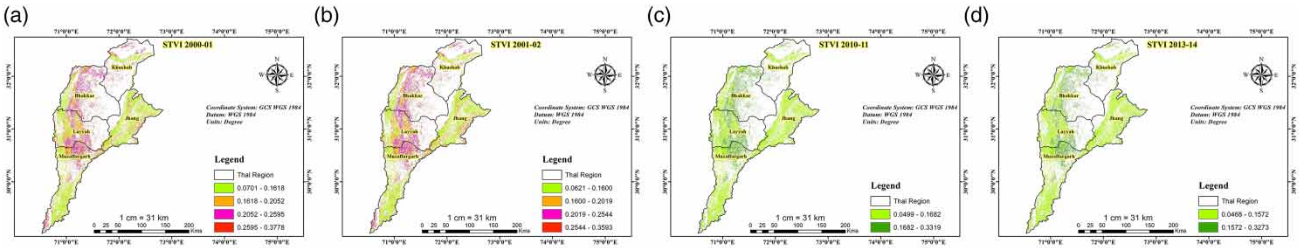

Figure 6 | Spatial pattern of STVI for drought year: (a) 2000–2001; (b) 2001–2002; and, normal year: (c) 2010–2011; (d) 2013–2014.

SPATIAL PATTERNS OF SPI, VEGETATION INDICES, AND YIELD ANOMALIES

SPI anomaly

SPI anomaly maps are shown in Figure 7. The maps show that the study area faced very severe to slight droughts during 2000–2002 while 2010–2011 and 2013–2014 are normal years. The results of the 2000–2001 drought (Figure 7(a)) show that much of the area of Khushab faced very severe droughts, i.e. about 12.87% of the total area. The major part of Bhakkar, southern part of Khushab and the northwestern part of Layyah district, covering 33.33% of the total area, were under severe drought. Of the total area covering the northern part of Muzaffargarh, Layyah, eastern area of Bhakkar, and the northern part of Jhang districts, 16.1% was under moderate drought conditions, while slight droughts were observed in Muzaffargarh, Jhang, and in the southern part of Layyah district, over 37.80% of the total area. Similarly, the spatial analysis of SPI anomaly

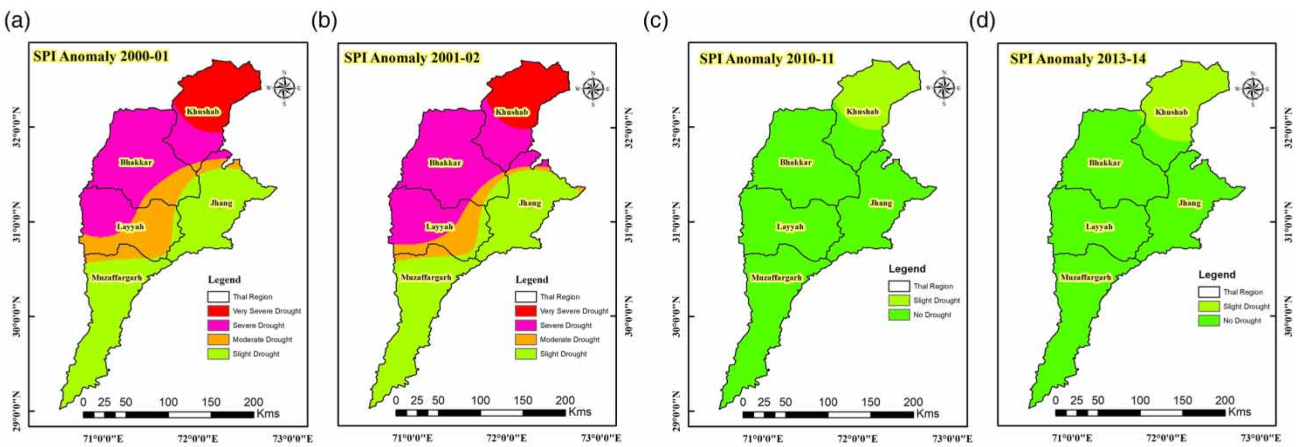

Figure 7 | Spatial pattern of SPI anomaly for drought years: (a) 2000–2001; (b) 2001–2002; and, normal years: (c) 2010–2011; (d) 2013–2014.

for the wheat season 2001–2002 (Figure 7(b)) shows that very severe drought occurred in 11.97% of the total area, whereas 40.37, 38.64 and 9.01% of the total area were under severe, moderate and slight drought, respectively. The study area is rain-fed and production mainly depends on variation and amount of rainfall. Thus, the results indicate that there was a rainfall deficit in the wheat-growing season of 2000–2001 and 2001–2002 and therefore it was the worst growing season.

The SPI anomaly for the season 2010–2011 (Figure 7(c)) shows slight to no drought. The results show that 11.80% of the total area was identified under slight drought conditions whereas 88.20% of the area was identified without drought condition for the time period concerned. Similarly, the SPI anomaly for the wheat season in 2013–2014 (Figure 7(d)) shows that the area had faced slight to no drought. The results show that most of the area of Khushab district (i.e. 13.32% of the total area) had faced slight drought, while 86.68% of the total area had no drought. Overall the results indicated that Khushab district is under drought stress based on SPI even during normal years.

NDVI anomaly

NDVI anomaly maps for the Thal region are shown in Figure 8. Based on this index, the spatial pattern of agricultural drought for drought and normal season was computed for the agricultural production area to determine the severity of agricultural drought (Figure 8(a)–8(d)). The maps show the spatial and temporal pattern of drought events and the level of drought severity ranges from very severe to no drought. The result of the wheat season for 2000–2001(Figure 8(a)) show that about 13.21% of the total area (i.e. a major portion of Khushab district) was under very severe drought conditions. Severe drought was observed in the northwestern part of the study area, covering about 35.29% of the total area. Moderate drought had been observed in the northern part of Muzaffargarh, and the eastern part of Layyah and Bhakkar districts, accounting for 14.14% of the total area, whereas the eastern and southern parts of Thal region, covering 37.36% of the total area, faced slight droughts. Figure 8(b) shows the results for the wheat season of 2001–2002. The results indicate that 15.06, 40.63, 23.33, and 20.98% of the total area faced very severe, severe, moderate and slight droughts respectively.

Based on the NDVI anomaly during the wheat season for the year 2010–2011 (Figure 8(c)), it is clearly seen that a major portion of the study area had no drought condition, while only 12.36% of the total area faced slight drought. Similarly, Figure 8(d) shows that the northern part of the Thal region had faced slight drought during the wheat season of 2013–2014, covering about 14.83% of the total area.

VCI anomaly

Like NDVI, VCI is also a good indicator of drought analysis and has developed by taking the range of NDVI values between the years of the study. VCI anomaly maps for the

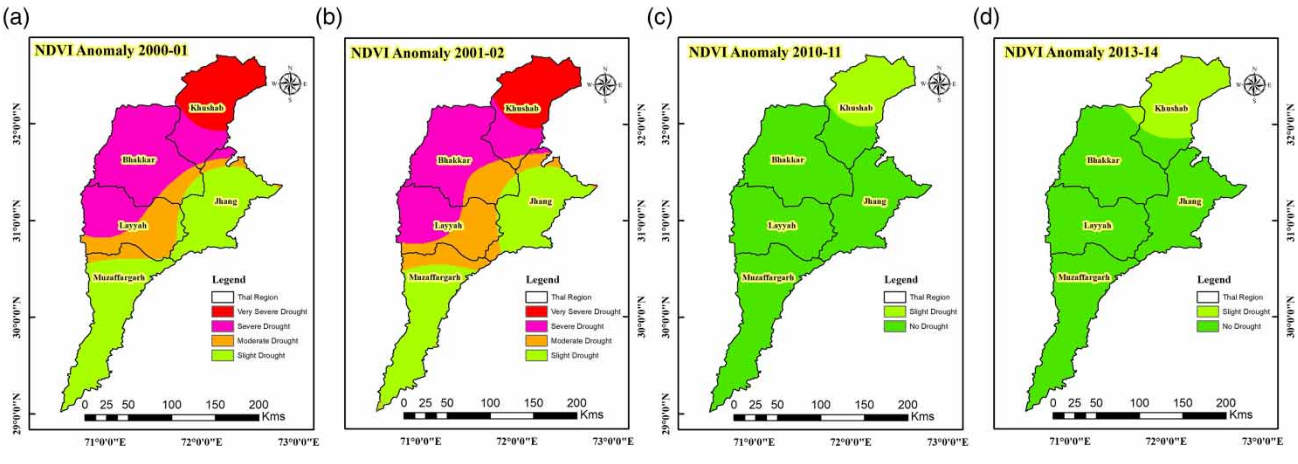

Figure 8 | Spatial pattern of NDVI anomaly for drought years: (a) 2000–2001; (b) 2001–2002; and, normal years: (c) 2010–2011; (d) 2013–2014.

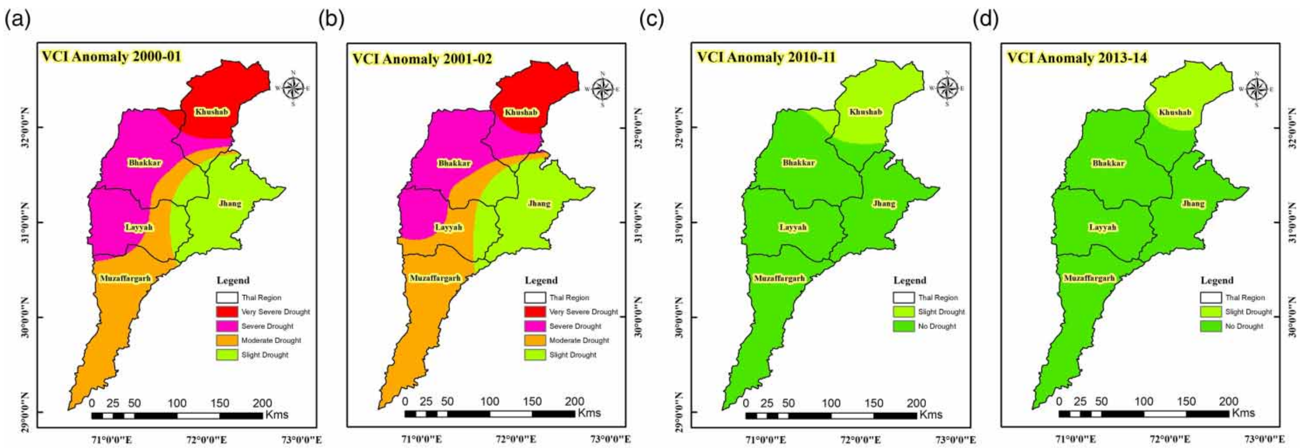

Figure 9 | Spatial pattern of VCI anomaly for drought years: (a) 2000–2001; (b) 2001–2002; and, normal years (c) 2010–2011; (d) 2013–2014.

drought years and normal years are shown in Figure 9. The results show that during the wheat season of 2000–2001 (Figure 9(a)) and 2001–2002 (Figure 9(b)), 15.74 and 13.06% of the total area, respectively, were faced with very severe drought conditions. Most of the area falls within Khushab district; 30.81, 23.43 and 30.02% of the total area were under severe, moderate and slight drought respectively during 2000–2001, whereas during 2001–2002, 28.82, 24.76, and 33.35% had faced severe, moderate and sight drought respectively. The result shows that based on VCI, 2000–2001 had a more severe drought season as compared to 2001–2002.

Similarly, Figure 9(c) and 9(d) show the VCI anomaly maps for a normal year (i.e. 2010–2011 and 2013–2014). The maps show that only 17.24 and 12.58% of the total area were under a slight drought during 2010–2011 and 2013–2014, respectively. The overall results conclude that Khushab district is under slight drought threat even in normal years and faces very severe droughts during drought years.

STVI anomaly

STVI represents the stress faced by the crop and is a very useful parameter for drought analysis. The results for the STVI anomaly are shown in Figure 10. The map for the drought year 2000–2001 (Figure 10(a)) shows that 17.41% of the total area covering most of the Khushab district

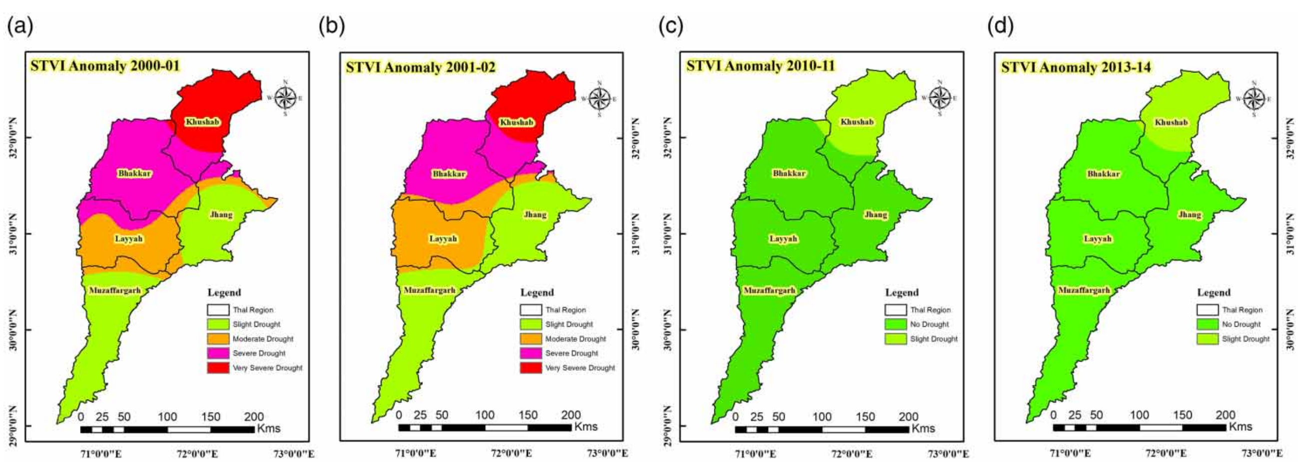

Figure 10 | Spatial pattern of STVI anomaly for drought years: (a) 2000–2001; (b) 2001–2002; and, normal years: (c) 2010–2011; (d) 2013–2014.

faced very severe droughts while 36.29, 24.01 and 22.30% of the total area faced severe, moderate and slight drought, respectively. Bhakkar, the northern part of Layyah, southern part of Khushab and northern part of Jhang were identified under severe drought conditions whereas the northern part of Layyah and Muzaffargarh and southern part of Bhakkar and Jhang were under moderate drought conditions. Most of the Jhang and Muzaffargarh districts faced slight drought. Similarly, the STVI anomaly for the drought year 2001–2002 (Figure 10(b)) shows that 12.56, 25.60, 23.70 and 38.14% of the total area were observed under very severe, severe, moderate and slight drought, respectively. Very severe drought covered most of the Khushab district, severe drought was in the Bhakkhar and lower part of the Khushab districts, moderate drought had been observed at Layyah, Bhakkar, and the northern part of Muzaffargarh, while slight drought was observed at the eastern part of Layyah, Bhakkar, Jhang, and Muzaffargarh districts.

During the wheat season of the year 2010–2011 (Figure 10(c)), it was observed that only Khushab district was marked as a slight drought area, covering 15.88% of the total area. Similarly, for the wheat season of 2013–2014 (Figure 10(d)), the results show that 14.75% of the total area were under slight drought conditions.

Yield anomaly

Agricultural drought largely affects grain yield through the reduction of various yield components of a crop. Considering the spatial pattern of yield reduction, analysis was carried out over the study area for the 2000–2015 wheat cropping season. The results show that the highest yield reduction was observed during 2000–2001, followed by 2001–2002. The results for yield anomaly are shown in Figure 11. The maps are produced using IDW techniques in the ArcMap environment. During the cropping season of 2000–2001 (Figure 11(a)), nearly the whole area was hit by very severe to slight drought. During this season most of the area of Khushab district, covering 12.23% of the total area, faced very severe drought. Severe and moderate drought was observed at Bhakkar, the southern part of Khushab and Layyah districts, covering 33.26 and 17.37% of the total area, respectively. Slight drought conditions occurred in Jhang and Muzaffargarh districts (37.13% of the total area).

Similarly, during the drought season of 2001–2002 (Figure 11(b)), yield anomaly showed very severe, severe, slight, and moderate drought conditions, and was observed over 14.49, 38.04, 37.13 and 26.41% of the total area, respectively. The yield anomaly map of the year 2010–2011 (Figure 11(c)) and 2013–2014 (Figure 11(d)) shows that Khushab district had faced a slight drought during both of the years, covering 14.6 and 18.10% of the total area, respectively.

Combined agricultural drought impacts in Thal region

The combined agriculture drought risk map (Figure 12) summarizes the drought conditions from 2000 to 2015 and was generated by integrating all drought frequency maps (i.e.

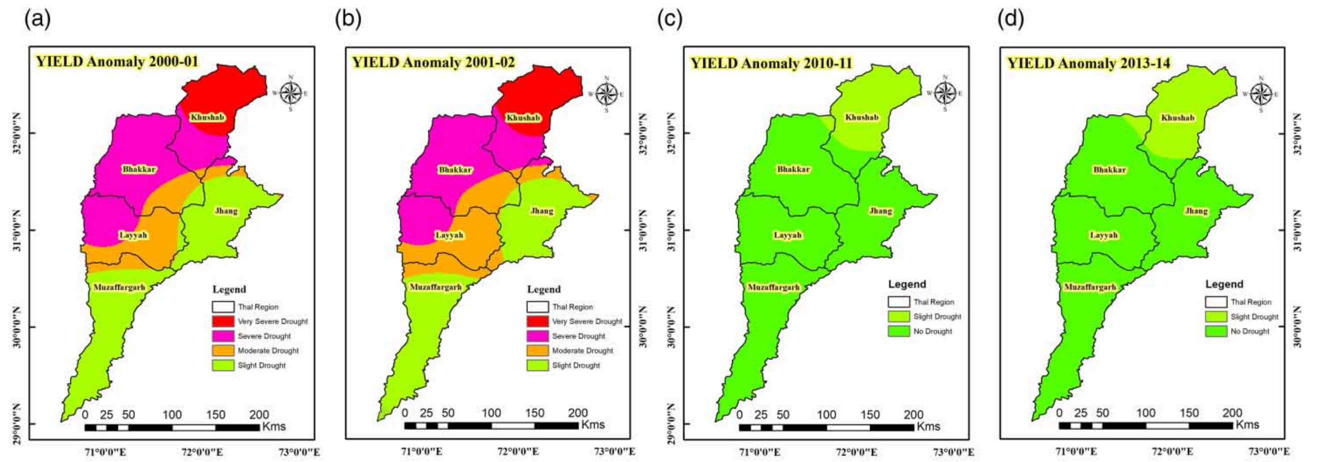

Figure 11 | Spatial pattern of yield anomaly for drought years: (a) 2000–2001; (b) 2001–2002; and, normal years: (c) 2010–2011; (d) 2013–2014.

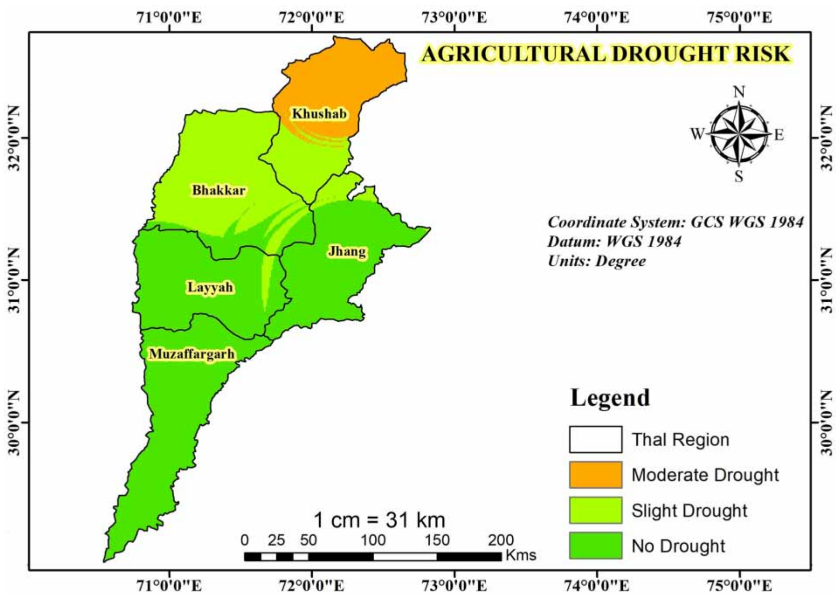

Figure 12 | Overall agricultural drought risk map.

NDVI, VCI, STVI, Yield). The map was generated using a weighted overlay analysis. The results show that Bhakkar and Khushab districts were classified into slight and moderate droughts. The combined agriculture risk map depicted in Figure 12 shows that the percentage areas affected by slight, moderate and no drought are 28.12, 12.77, and 59.12% of the total area of the Thal region, respectively. The overall results summarize that the Khushab district is facing drought conditions, followed by Bhakkar. Thus drought mitigating strategies at local and governmental levels should be designed to tackle this hazard.

CONCLUSIONS

Rainfall is one of the important climatic variables, especially in rain-fed areas, that largely determine the occurrence of droughts. In semi-arid (rain-fed) regions, rainfall is the main parameter that affects crop growth and yield. The Thal region lies in the semi-arid zone of Pakistan, where agricultural production depends mainly on rainfall. Agriculture is the most vulnerable and sensitive sector and is seriously affected by climate variability and change, usually manifested through an increase in temperature which is not suitable for germination, and rainfall variability that ultimately causes recurrent droughts. With the help of advanced techniques of remote sensing and GIS, using satellite imageries as input parameters for drought indices, spatiotemporal variation of seasonal agriculture drought patterns and sensitivity can be detected. The comparative analysis of the indices and their anomalies explain the existence of agricultural drought. In the current study, drought risk areas were delineated by the integration of satellite images, meteorological information and crop yield data.

Drought ranged from very severe to slight during 2000–2002, in different subzones of the Thal region, which affected crop yield immensely. Khushab was the most affected district in drought events while Jhang was the least affected, sustaining a marginal yield. In normal years, 2010–2011 and 2013–2014, Khushab suffered from slight drought and found a minimum decrement in its yield while Jhang, Muzaffargarh, Layyah, and Bhakkar observed no crop stress and drought conditions. The agriculture drought risk map produced by integrating all drought frequency maps derived from all drought indices indicated that out of the total area 28.12, 12.76, and 59.12% was dominated by slight, moderate and no drought, respectively. The results of the present study are being used for the development of a regional drought monitoring system. A combined drought risk map is of high importance for the policymaker to use as a predictive tool for drought risk monitoring and to reduce the impact of drought on agricultural production and productivity while identifying suitable sites for specific adaptation and mitigation.

Uncertainty and limitations

There are multiple sources of uncertainty in the process of drought analysis, including the parameter selection, ground data availability and structural uncertainties, assessment of weight overlay analysis and rank value. Hence, to improve the quality of decisions and to verify the robustness of the model, drought risk management should be based on a comprehensive assessment of the sensitivity of the analysis combined with a thorough investigation of the uncertainties involved. Another main shortcoming of this study is image resolution (250×250 m). If higher resolution imagery were used, the results obtained may be more reliable. A limited number of indices were used for analysis. If more indices, such as Desertification Vulnerability Index, Vegetation Health Index, Temperature Condition Index etc., and soil moisture data were used, then the effect from every angle can be assessed and the results will be more significant. Similarly, the data were analyzed using single satellite images (i.e. MODIS). The results could be further improved through the use of combined imagery from multiple satellites. Varying shares of water balance under different climatic conditions can be analyzed by evaporation assessment (Qasem *et al.* 2019), and accurate assessment is crucial for efficient water resource management (Ali Ghorbani *et al.* 2018) and drought analysis. Due to the unavailability of the data, we can not incorporate this parameter. If evaporation data were also included as a parameter then the analysis could be more significant.

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