Assessment of drought conditions using HJ-1A/1B data: a case study of Potohar region, Pakistan

Adnan Aziz, Mudassar Umar, Muhammad Mansha, Mehwish Shafi Khan, Muhammad Naveed Javed, Hailiang Gao, Suhaib Bin Farhan, Imran Iqbal and Shaikh Abdullah

Pakistan Space and Upper Atmosphere Research Commission, SUPARCO Headquarters, Karachi, Pakistan; State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China

ABSTRACT
Drought is a natural disaster which causes global damages and affects people. In this work, a comparative study of different drought indices such as Normalized Difference Vegetation Index (NDVI), Deviation NDVI (DevNDVI), Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) from HJ-1A/1B multispectral data is discussed. These indices have shown potential to detect the drought severity. The objective of this study is to monitor drought in the Potohar region using HJ-1A/1B satellite data, from late November to April during 2009–2014. Additionally, results obtained from satellite data have been verified using ground-based rainfall and crop yield data. The results concluded that the Potohar region faced drought condition in 2010, which is further verified by ground data. Furthermore, NDVI and VCI in this region are found more effective than other drought indices. On the basis of validation of individual drought index with crop yield data, each index is assigned weight accordingly. Moreover, the combination of indices has the ability to detect time periods where drought is affecting the yield production. Regular monitoring and mapping of satellite-based drought indices would play an important role in predicting drought conditions.

Introduction
The periods of persistent abnormally dry weather resulting in water deficiency can trigger natural disasters such as agricultural drought, hydrological imbalance and numerous other severe environmental and ecological problems (Du et al. 2013). Effects of drought depend on the degree of water deficiency, duration, and size of affected area (Wilhite and Glantz 1985). Generally, the most prominent types of drought are meteorological, agricultural, hydrological and socio-economic drought. These types of drought are linked...
to each other; however, agriculture drought is considered as one of the most important issue in most of the countries in terms of economic, food security, and social stability (Mishra and Singh 2010; Berhan et al. 2011; Rasul et al. 2012).

Currently, various methods have been developed for agricultural drought monitoring; these methods are usually divided into in-situ, remote sensing and synergic based indices (Zargar et al. 2011). The in-situ based methods are the historic ones among the others which are based on hydro-climate variables (precipitation, temperature, relative humidity and soil water content) and able to provide quantitative and qualitative information over the area of interest (Kanellou et al. 2008; Maes and Steppe 2012). In general, these methods provide an accurate estimate of drought conditions at point locations where the input variables are acquired. However, there is an imposition of uncertainty in delineating the spatial context due to the uneven distribution of hydro-meteorological stations across the area of interest. Geographic Information System (GIS) based interpolation techniques are often used to overcome the issue but these techniques generate different outcomes despite using the same set of input variables (Li and Heap 2014).

In drought monitoring, remote sensing techniques are crucial for timely decision making because they provide rapid geospatial data and a reasonably better spatial footprint of environmental phenomena characterizing entire area compared to point locations (Park et al. 2004). Currently, remote sensing has been widely used and has delivered significant benefits in drought assessment and monitoring. Therefore, multi-source remote sensing data are helpful for drought management especially in drought monitoring (Chander et al. 2009; Patel et al. 2009; Huang et al. 2013).

Remote sensing-based drought indices have been widely used for drought monitoring and address the issue of spatial context. Generally, remote sensing based techniques for monitoring droughts are indirect as they depend on image based parameters to represent the moisture status in the soil and vegetation when the soil is obscured by vegetation cover (Nichol and Abbas 2015). The optical remote sensing data in wavelength ranges (0.4–2.5 μm) have been used as input to drought indices (Dalezios et al. 2012). In multispectral data spectral ranges: red, near infrared (NIR) and short-wave infrared (SWIR) are commonly used bands due to their response to vegetation greenness and wetness condition using vegetation indices (VIs) (Hazaymeh and Hassan 2016). VIs such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Leaf Area Index (LAI) are used to represent vegetation condition in drought indices because the state of vegetation condition normally indicates the underlying soil moisture content (MAO et al. 2012; Abbas et al. 2014). VI-based drought indices are mainly characterized into Vegetation Condition Index (VCI) (Kogan 2002), Deviation NDVI (DevNDVI) (Berhan et al. 2011), NDVI Anomaly (NDVIA) (Anyamba et al. 2001), and Standardized Vegetation Index (SVI) (Peters et al. 2002). The VCI is considered to be suitable for monitoring agro-droughts and is highly correlated with crop yield (Salazar et al. 2008).

The thermal stress of the land surface has also attracted researchers, resulting in Land Surface Temperature (LST) based, Temperature Condition Index (TCI) (Jain et al. 2009) which is the combination of vegetation and temperature condition indicating the soil moisture content. TCI measurements describe the resistance of the soil and vegetation to temperature variations. It has a proportional relationship with water
content levels, therefore if water content decreases, the temperature decreases as well. Hence, the TCI is better indicator over sparse vegetation and bare lands, whereas VI-based drought estimates are good for drought indication with moderate vegetation canopy cover. Consequently, using the complementary information available from Thermal Infrared TIR and Visible Near-Infrared VNIR, thermal drought indices were developed as an integrated drought indicator.

In most of the instances, the majority of the drought studies concentrated on assessing drought using single source drought index (Quiring and Papakryiakou 2003; Tsakiris and Vangelis 2004; Cancelliere et al. 2007; Mavromatis 2007). Each index has its own data type, complexity, strengths, and weakness. Therefore, they provide different results for the same event of interest (Svoboda et al. 2002; Quiring 2009; Sun et al. 2012a). A combination of various drought indices from multiple data sources may provide a more comprehensive assessment of drought conditions than the use of a single one (Sun et al. 2012a). However, the use of synergic methods has been a challenging task due to the lack of systematic methods for combining, implementing and evaluating this phenomenon (Steinemann and Cavalcanti 2006). For example, remote sensing-based indices are unable to discriminate vegetation stress caused by sources other than drought (Sun et al. 2012b). Therefore, the combination of various indices may offer a better understanding and better monitoring of drought conditions.

Studies that investigated drought in Pakistan by using the VI\text{s} have indicated that VI\text{s} reflect the spatial distribution and development of drought and they are suitable for drought monitoring in different regions of Pakistan (Ghauri and Khan 2013; Akhtar 2014; Bilal et al. 2017). Nevertheless, most of the studies focussed either on a certain region or a specific province with low resolution satellite data. These studies aimed at the spatio-temporal variations of drought in different geographic areas. Given the vast territory, complex terrain, and diverse climate of Pakistan, the spatio-temporal features of drought in different geographic areas vary greatly. Consequently, the efficient utilization of remote sensing data for monitoring drought in different regions of Pakistan is a problem that needs to be resolved. In this study, the VI\text{s} have been used as a drought indicator to evaluate the spatio-temporal variations of drought in Potohar region of Pakistan based on analysis of drought occurrence and temporal characteristics. The study aims to investigate the pattern of drought changes in Potohar region, which can provide a baseline reference for developing and implementing drought warning and resistance measures. Therefore, keeping in view the importance of drought assessment, an effort is made to explore the potential of HJ-1A/1B satellite data for drought monitoring in the Potohar region. Additionally, results obtained from satellite data have been verified using ground-based rainfall and crop yield data.

**Study area and data sets**

**Study area**

The current study is carried out in three districts, namely: Attock, Chakwal and Rawalpindi in Pakistan (Figure 1). These three districts are known as Potohar region. This area lies in northern part of Punjab province with 72°–73° East and 33°–34° North and spans over an area \( \sim 25,000 \text{ km}^2 \) with elevation ranges from 150 to \( \sim 1100 \),
The study area lies in Potohar plateau and bounded by river Jhelum on the east and river Indus on the west. The terrain is undulating which is surrounded by Margalla Hills in the north and salt range in the south. The annual rainfall is 380–500 mm and is greatest in the north and decline to arid condition in the south. Most of the rainfall (80%) occurs in the monsoon during July to October. Agriculture in this region is mostly rainfed as there is no irrigation network except some tube wells. Therefore these districts are highly dependent on rainfall for agriculture and are called Barani areas (Rashid and Rasul 2007). The land cover of the area includes rangelands, forest, rainfed crop and natural wetlands (Figure 1). Major crops in this region comprise of Wheat, Peanuts, Barely, Jawar, Bajra and Maize (Rashid and Rasul 2007). The most grown crop is wheat and it contributes around 6% to total wheat acreage in Punjab and around 3% in term of its production. The wheat grown in the area is consumed domestically. As this is a rainfed region, drought is one of the key factors affecting the crop (wheat) yield. Therefore, prolonged absence of rainfall in the area leads to drought condition affecting the crop and food security of the population. Over the last two decades, many short term and long term drought events have been observed. A sustained drought was observed in the study area from winter 2009 to spring 2010 and is the major and frequent natural disaster in the study area.

**Data sets**

In this study HJ-1A/1B multispectral satellite data acquired from Data Sharing Services Platform (DSSP) under Asia Pacific Space Cooperation Organization (APSCO) pilot project, have been used for derivation of different VIs to delineate...
effect of drought in Potohar region. Main objective of this study is to monitor drought in Potohar region using HJ-1A/1B satellite data during late November to April from 2009 to 2014.

**Satellite data**

HJ-1A/1B/1C corresponding to environment, disaster monitoring and forecasting small satellite constellation A/B/C including two optical satellites HJ-1A, HJ-1B and one radar satellite HJ-1C, which can carry out large-scale, all-weather and 24 h dynamic monitoring for ecological environment and disaster. These satellites are equipped with 4 remote sensors such as wide-coverage CCD scanner, infrared multispectral scanner, hyperspectral imager and synthetic aperture radar (Table 1). The primary data sets used in this study consist of HJ-1A/1B CCD and HJ1A/1B Infrared Scanner (IRS) data from 2009 to 2014. The collected data of HJ-1A/1B consist of images with least cloud cover (≤10%). APSCO DSSP provided atmospherically and geometrically corrected data.

**MODIS products**

In this study Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation ‘MODIS/Terra VIs 16-Day L3 Global 1km SIN Grid V005’ and ‘Water Vapour 1km MOD05/MYD05’ products are used for the estimation of LST. The MODIS satellite data is selected because NDVI is an essential part of algorithm in LST. The MODIS data is resampled at HJ-1A/1B level to use for estimation of LST. Furthermore, NDVI derived from HJ1A/1B could not be acquired on the similar date that of HJ-1B-IRS. Following MODIS secondary data products are used in the study:

- MODIS NDVI 16 day composites (2009–2014)
- MODIS Water vapour daily product (2009–2014)

**Precipitation data.** In order to better understand the results obtained from analysis of satellite data, rainfall data is used from 2009 to 2014 acquired from National Agriculture Information Centre (NAIC), SUPARCO, Islamabad.

**Crop yield information.** Wheat crop yield data obtained from NAIC, SUPARCO, Islamabad, is also analysed district-wise from 2009 to 2014.

The land cover map (Figure 1) of the study area is prepared from SPOT satellite data. The land cover map is produced under Food and Agriculture Organization (FAO) classification scheme. The map consists of thirteen land cover classes, viz.,

| **Table 1.** Characteristics of HJ-1A/1B satellite data. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Satellite | Instrument | Bands | Spectral range | Resolution | Swath width | Repeat cycle |
| HJ-1A | WVC | 4 | 0.43–0.90 μm | 30 m | 700 km | 4 days |
| HJ-1B | WVC | 4 | 0.43–0.90 μm | 30 m | 720 km | 4 days |
| IRMSS | 4 | 0.75–1.10 μm | 150 m | 720 km | |
| | 4 | 1.55–1.75 μm | 150 m | | |
| | 3.50–3.90 μm | 150 m | | | |
| | 10.5–12.5 μm | 300 m | | | |
Built-up, Orchards, Crop Irrigated, Crop in Flood Plain, Crop Marginal and Irrigated Saline, Crop Rainfed, Forest, Range Lands, Bare Areas, Bare Areas with Natural Vegetation, Wet Area, Natural Vegetation in Wet Areas.

Methodology

This study covers the period 2009–2014 including the notable drought of 2010. The drought observations in the current study are based on satellite derived VIs from HJ-1A/1B. Rainfall estimates are derived from ground-based data for the year 2009–2014. Different satellite-based drought indices have applied successfully for evaluating drought conditions. NDVI is the most commonly used vegetation index for assessing vegetation condition. NDVI has been developed to assess weather related impacts on vegetation (Kogan 1995b). Similarly, VCI derived from NDVI (Kogan 1995) also helps in indication of drought. On the other hand, TCI derived from LST (Kogan 1995a), suggests temperature related stress on vegetation.

The HJ-1A/1B data is used to calculate VIs and then weighted overlay analysis is performed to assess the drought prone sites in the study area. Ground based rainfall and crop yield data is also used to assess the effect and severity of drought (Figure 2).

The following remote sensing-based indices are used to analyse the impact of prevailing drought on vegetation/agriculture condition in Potohar region.

**NDVI**

NDVI is the most commonly used vegetation index for assessing vegetation condition (Chen et al. 2005). It is the ratio of highly reflective NIR and highly absorptive red wavelengths in healthy and stressed plants exhibiting decreased NIR and increased red reflectance. It is defined as:

\[
NDVI = \frac{(\rho_{\text{nir}} - \rho_{\text{red}})}{(\rho_{\text{nir}} + \rho_{\text{red}})}
\]

Where, \(\rho_{\text{nir}}\) = reflectance in NIR band \(\rho_{\text{red}}\) = reflectance in red band

NDVI values are categorized into five different (Table 2) classes based on the classification of NDVI results (Yun-Hao et al. 2003). The classification of NDVI values are performed for the indication of vegetated and non-vegetated areas and is further used to assess dry and wet areas.

**Deviation NDVI**

In Deviation NDVI, the NDVI data set is used by comparing the deviation of the current satellite observation from the historical average within a certain time period, or window of interest. It is calculated as:

\[
\text{Dev NDVI} = NDVI_i - NDVI_{\text{Meani}}
\]

Where, \(NDVI_i\) = month’s NDVI \(NDVI_{\text{Meani}}\) = the monthly mean NDVI over considered time period.
Negative values of Dev NDVI indicate below normal vegetation conditions that suggest drought situation (Berhan et al. 2011).

**VCI**

During drought period, plant saves water loss by adjusting stomatal aperture. The leaf surface stomatal closure will lead to a decline in plant photosynthesis as chlorophyll content in plant decreases. In addition, LAI of the plants will be reduced in order to resist moisture stress. In order to understand weather related impacts on NDVI fluctuations, NDVI was linearly rescaled from 0 to 100 (Bhuiyan 2008). The VCI (Kogan 1994) is derived from the NDVI. It is scaling of the NDVI between its maximum and minimum value, and can be expressed as:

$$VCI = \left( \frac{NDVI - NDVI_{\text{min}}}{NDVI_{\text{max}} - NDVI_{\text{min}}} \right) \times 100$$

Table 2. Classification of NDVI.

| NDVI ranges | Drought          |
|-------------|------------------|
| <0          | Extreme dry      |
| 0–0.2       | Dry              |
| 0.2–0.4     | Moderate         |
| 0.4–0.6     | Wet              |
| ≥0.6        | Extremely wet    |

Negative values of Dev NDVI indicate below normal vegetation conditions that suggest drought situation (Berhan et al. 2011).

Figure 2. Workflow for processing and analysing data for drought monitoring.
related component of NDVI from ecological factors (Kogan 1994). The VCI not only reflects the spatial and temporal vegetation variability but also allows quantifying the impact of weather on vegetation (Kogan 1994; Unganai and Kogan 1998).

TCI

The TCI algorithm is similar to VCI, but related to the brightness temperature $T_B$ estimated from the TIR band of HJ-1B IRS. Kogan (1995a) proposed this index to remove the effects of cloud contamination in the satellite assessment of vegetation condition due to the fact that the TIR band is less sensitive to water vapor in the atmosphere compared with the visible light channels. High temperatures in the middle of the season indicate unfavourable or drought conditions while low temperature indicates mostly favourable conditions (Kogan 1995a).

TCI is defined as:

$$
TCI = \left( \frac{LST_{\text{max}} - LST}{LST_{\text{max}} - LST_{\text{min}}} \right) \times 100
$$

Where $LST_{\text{max}}$ and $LST_{\text{min}}$ are the maximum and minimum brightness temperature. TCI ranges from 0 to 100. Values between 0 and 50 show drought condition whereas 50–100 indicate healthy vegetation as shown in Table 3 (Bhuiyan 2008). Consistently low TCI values over several consecutive time intervals may point to drought presence.

HJ-1B IRS data consist of one NIR band, two SWIR bands and one TIR band. Spatial resolution of the NIR, SWIR bands is 150 m and that of the TIR band is 300 m (Directory 2000–2016). TCI is obtained by rescaling of LST as defined earlier. In estimation of LST the TIR from HJ-1B IRS is used in addition with two more parameters i.e. Land Surface Emissivity (LSE) and water vapour content. LSE and water vapour content are derived from resampled MODIS products.

LSE

LSE is an important parameter required in LST derivation. Many models have been proposed for calculation of LSE for LST derivation whereas, methods based on NDVI, first provided by Griend and Owe (1994) are common and easy to compute. These methods consider soil and vegetation to retrieve the emissivity of natural land surface. Following relationship is used for calculation of LSE from HJ-1B IRS TIR band (Zheng et al. 2013).

$$
e = 0.004*P_v + 0.986
$$

Where,

$$
P_v = \left[ \frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \right]^2
$$

MODIS NDVI product (Mod13Q1) has been used due to lack of a red band in HJ-1B IRS for estimation of NDVI.
Another essential procedure in the retrieval of LST is to obtain the atmospheric parameters including the atmospheric transmittance ($\tau$), atmospheric upward radiation ($L_\uparrow$) and atmospheric downward radiation ($L_\downarrow$). MODIS water vapour product (Mod05_L2) are acquired and processed for estimation of above atmospheric parameters (Sun et al. 2013). Finally, LST is produced to calculate the TCI. TCI values range from 0 to 100. Low TCI values i.e. close to 0 show very high temperature and indicate drought condition. TCI images are further classified into five classes: Extremely Dry, Dry, Normal, Wet and Extremely Wet, as shown in Table 3.

### Weighted overlay

Weighted overlay analysis is performed to identify the susceptible drought prone areas with the help of VIs discussed above. Weighted overlay analysis is a technique helpful in creating integrated analyses with diverse and dissimilar inputs based on multiple criteria. This analysis is useful in visualizing combined information of different VIs at once. In this study, all the results derived from HJ-1A/1B multispectral data including: NDVI, VCI, Dev NDVI and TCI have been combined for evaluating drought prone areas from 2009 to 2014.

$$A = W_1A_1 + W_2A_2 + \ldots + W_nA_n$$  \hspace{1cm} (7)

Where,

- $A_n =$ Input raster
- $W_n =$ Criteria/weight, provided that sum of all $W_n$ is 100.

On the basis of VIs with crop yield data, each index is assigned weight accordingly. NDVI and VCI being more suitable index and validated by crop yield data, is assigned 40% and 30% weight. In case of Dev NDVI, since long term mean is not available, therefore, actual situation of drought could not be depicted by Dev NDVI. It is, therefore, assigned 20% weight. On the other hand, TCI, which is supposed to be less indicative index in drought, is assigned 10% weight. Sum of all the weights add up to 100%.

### Results and discussion

Approximately 94.38% of the area is dominated by three major land cover types which are Crop Rained (57.04%), Range lands (29.92%) and Forest & Natural Trees (7.43%) (Table 4). The elevation profile of the land cover classes (Figure 3) indicates that Crop Rainfed extends from 300 m to 900 m with a maximum cover around 600 m, whereas Range lands also range from 200 m to 1200 m with maximum cover.

| Drought          | DevNDVI (Berhan et al. 2011) | TCI and VCI (Bhuiyan 2008) |
|------------------|------------------------------|-----------------------------|
| Extreme dry      | $\leq -2.0$                  | $< 10\%$                    |
| Dry              | $\leq -1.0$                  | $< 20\%$                    |
| Normal           | $-1.0 < \& \leq -0.05$       | $< 30\%$                    |
| Wet              | $-0.05 < \& \leq 1.0$        | $< 40\%$                    |
| Extremely wet    | $> 1.0$                      | $> 40\%$                    |

### Water vapour content

Another essential procedure in the retrieval of LST is to obtain the atmospheric parameters including the atmospheric transmittance ($\tau$), atmospheric upward radiation ($L_\uparrow$) and atmospheric downward radiation ($L_\downarrow$). MODIS water vapour product (Mod05_L2) are acquired and processed for estimation of above atmospheric parameters (Sun et al. 2013).
around 600 m. However, Forest and Natural Trees occupies range from 300 m to 1200 m with major cover around 1000 m.

**NDVI**

NDVI of the study area during the analysis period derived from HJ-1A/1B CCD data, is classified into five classes (Table 2). Mean NDVI maps are prepared for the Potohar region from 2009 to 2014 for each district.

In 2010, Attock, Chakwal and Rawalpindi show 73%, 82% and 61% moderate to dry land dominancy over wet and extremely wet region respectively as compared to other years. NDVI maps are helpful in identifying the areas and time period where vegetation cover is changing with time. Comparisons of NDVI for different years suggest that the study area is more affected from dry conditions in 2010 which resulted in drought (Figure 4).

**DevNDVI**

Severity of drought is further analysed by computing difference of long term mean NDVI from monthly NDVI. DevNDVI categorized into five classes (Table 3). In 2010, Attock, Chakwal and Rawalpindi show 94%, 95.4% and 92.5% of moderate, dry and extreme dry land dominancy respectively over wet and extremely wet region as compared to other years (Figure 5). In addition to this Chakwal region shows moderately dry situation in 2012. Moderately dry conditions are also observed during 2014 in some parts of Attock and Chakwal. Moreover, in other years, situation is more or less lie in moderately dry category but severity is lesser than that in 2010 (Figure 5).
VCI characterizes moisture condition of vegetation. VCI derived from NDVI using Equation (3) is categorized into five classes (Table 3) for indicating of prevailing drought situation. Analysis of VCI for three districts (Attock, Rawalpindi and Chakwal during 2009–2014).

Figure 4. NDVI of Attock, Rawalpindi and Chakwal during 2009–2014.

Figure 5. DevNDVI of Attock, Rawalpindi and Chakwal during 2009–2014.

VCI

VCI characterizes moisture condition of vegetation. VCI derived from NDVI using Equation (3) is categorized into five classes (Table 3) for indicating of prevailing drought situation. Analysis of VCI for three districts (Attock, Rawalpindi and
Chakwal) reveals that Chakwal and Rawalpindi are severely affected with dry condition in 2010 (Figure 6). 2010 dry land dominancy (90%) clearly shows the drought condition in Chakwal and Rawalpindi as compared to other years. Similar dry conditions are also observed for Attock and Chakwal during 2014 (Figure 6). It is observed that VCI exhibits clear dry and wet condition in the study area as compared to other indices. Moreover, VCI clearly distinguish between the dry and extremely wet conditions in the study area for 2009-2014 (Figure 6).

**TCI**

Temperature is another reason of dryness besides less rain which ultimately leads to less vegetation. Re-scaled LST values i.e. TCI, provide drought conditions from worst to normal as: extreme dry, dry, normal, wet and extremely wet, as shown in Table 3. HJ-1B IRS data for 2009 and 2013 is not available for the analysis. TCI values show dry and extremely dry condition in most of the area during 2010 to 2012 and 2014. However, the result of TCI indicates above normal weather condition thus affecting the moisture state in the study area (Figure 7).

The analysis of VIs shows the vegetation condition during the crop cycle (i.e. November–April) and reveals the dry and wet conditions in the study area. The growing cycle of crop starts from November and reaches maturity stage in February and March. The temporal span of 2010 drought also indicates the driest time during drought spell of 2010. The analysis of NDVI, DevNDVI and VCI indicates approximately 80–90% of the area under dry conditions. It is observed that the NDVI shows clear dry to extremely dry condition during the drought spell as compared to other VIs. NDVI also exhibits the clear differentiation between dry and extremely wet conditions in the study area during 2009-2014. Furthermore, during the analysis NDVI is found more accurate in discriminating dry and wet condition during the study period.
Analysis of rainfall data

The rainfall data is analysed to support the result of VIs. It is evident from the ground rainfall data that three districts receive less amount of rainfall during 2009–2014 (Figure 8). The absence of rainfall resulted in short term and long term drought spell which is evident from VIs analysis. It is evident that there is less rainfall in 2010 as compared to other years (Figure 8). The absence of rainfall also affected the crop yield which also indicates the drought spell in the study area.

Analysis of crop statistics

Wheat crop production in the study area from 2009 to 2014 show less production in 2010 (Figure 9). It is evident from the wheat crop production during 2009–2014 that drought spell (2010) affected the crop production as compared to other normal years.
supporting the VIs result in the study area. It is observed from the analysis of VIs, rainfall and wheat crop production that 2010 and 2014 were affected from dry conditions and a drought spell prevailed in the region. Hence a weighted overlay analysis is carried out to indicate the drought prone zone.

Analysis of weighted overly clearly depicts that 2010 is more susceptible to dryness and drought spell of 2010 confirms the dryness in 90% of the study area (Figure 10). Overall analysis shows that most part of the study area experienced dryness during 2010 as compared to the other years. Moreover, weighted overlay helped in delineating the spatial extent of susceptible dryness area. Weighted overlay analysis depicts that lower part of Attock, Chakwal and Rawalpindi are more susceptible to short

![Figure 9. Wheat crop production (000 tons) in the study area for 2009–2014.](chart)

![Figure 10. Drought prone zones on the basis of weighted overlay analysis.](map)
term and long term drought. The low wheat production in 2010 support the result acquired through weighted overlay analysis.

It is observed during the analysis of VIs, rainfall and wheat crop production that drought situation prevailed during 2010 bringing a short drought spell. The 2010 drought spell affected the 90% of the study area including the Crop Rainfed (58%) and Range Lands (30%). Furthermore, it is also observed that VIs can effectively help in identification of dry and wet area affected by short or long term drought spell.

Conclusions
In this study, the application of remote sensing-based VIs for assessing drought condition as opposed to classical drought indices along with rainfall is assessed. The results demonstrated that the VIs can be effectively exploited as indicators of spatio-temporal characteristics of dryness and wetness conditions. The effect of drought on the vegetation in the study area was assessed using remote sensing approach in terms of severity of drought spell. It was found that between the three dominate land cover classes, forest was the least affected class during the drought spell as compared to Crop Rainfed and Range lands classes.

The comprehensive results suggested that central part of Potohar region remained moderately dry from 2010 to 2014 except in 2011. Moreover, the southern part of the region faced drought conditions throughout the study period except in 2012, while southeastern and northern parts of the region showed extremely wet conditions except in 2010. Whereas, the year 2010 is considered as a severe drought year in most parts of the region due to moderate and extremely dry conditions. Analysed rainfall data also showed least or no rainfall for most of the region in 2009 and 2010. Crop yield data verified the results of satellite-based drought indices for the study area.

This study shows that the combination of indices is an appropriate approach to detect time periods where drought is affecting the crop production. Hence continuous satellite-based monitoring of drought could play an important role in predicting drought conditions and permit stakeholder to prepare in advance for hazards related to drought.

Acknowledgements
This research has been conducted under APSCO DSSP projects by Earth Sciences (ES) Directorate, SUPARCO. The authors would also like to thank Muhammad Anees, Masuma Fatima and Dr. Said Rahman from SUPARCO, Dr. Sawaid Abbas from The Hong Kong Polytechnic University and Ms. Paras Siddiqui from University of Technology, Sydney, Australia for their valuable suggestions and technical support in the study.

Disclosure statement
No potential conflict of interest was reported by the authors.
References

Abbas S, Nichol JE, Qamer FM, Xu J. 2014. Characterization of drought development through remote sensing: a case study in Central Yunnan, China. Remote Sens. 6(6):4998–5018.

Akhtar IH. 2014. Identification of Drought Events from Multi years Temporal SPOT NDVI Data for Potohar region in Pakistan. Int J Remote Sens. 35(6):39–52.

Anyamba A, Tucker C, Eastman J. 2001. NDVI anomaly patterns over Africa during the 1997/98 ENSO warm event. Int J Remote Sens. 22(10):1847–1860.

Huang H, Fan Y, Yang S, Wen Q, Pan D, Fan C, He H. 2013. Application of HJ-1A/B and ZY-3 remote sensing data for drought monitoring in Hubei Province China. In: MIPPR 2013: Remote sensing image processing, geographic information systems, and other applications. International Society for Optics and Photonics.

Berhan G, Hill S, Tadesse T, Atnafu S. 2011. Using satellite images for drought monitoring: a knowledge discovery approach. J Strategic InnoV Sustain. 7(1):135.

Bhuiyan C. 2008. Desert vegetation during droughts: response and sensitivity. Int Arch Photogr Remote Sens Spatial Inf Sci. 37(B8):907–912.

Bilal M, Liaqat MU, Cheema MJM, Mahmood T, Khan Q. 2017. Spatial drought monitoring in Thar desert using satellite-based drought indices and geo-informatics techniques. Multidiscip Digital Pub Inst Proc. 2(5):179.

Cancelliere A, Di Mauro G, Bonaccorso B, Rossi G. 2007. Drought forecasting using the standardized precipitation index. Water Resour Manage. 21(5):801–819.

Chander G, Markham BL, Helder DL. 2009. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. Remote Sens Environ. 113(5):893–903.

Chen C-T, Yang C-M, Chen J-C. 2005. Satellite technology for vegetation drought monitoring in Taiwan. Crop Environ Bioinf. 2:50–60.

Dalezios N, Blanta A, Spyropoulos N. 2012. Assessment of remotely sensed drought features in vulnerable agriculture. Nat Hazards Earth Syst Sci. 12(10):3139.

Directory ep. 2000–2016. HJ-I. eo portal Directory [accessed 2016 July 21]. https://directory.eoportal.org/web/eoportal/satellite-missions/h/hj-1.

Du L, Tian Q, Yu T, Meng Q, Jancso T, Udvardy P, Huang Y. 2013. A comprehensive drought monitoring method integrating MODIS and TRMM data. Int J Appl Earth Observ Geoinf. 23(4):25–253.

Ghauri B, Khan MR. 2013. Short term drought monitoring using remote sensing technique: A case study of Potohar region, Pakistan. In: 2013 International Conference on Aerospace Science & Engineering (ICASE): IEEE.

Griend AA, Owe M. 1994. Bare soil surface resistance to evaporation by vapor diffusion under semiarid conditions. Water Resour Res. 30(2):181–188.

Hazaymeh K, Hassan QK. 2016. Remote sensing of agricultural drought monitoring: a state of art review.

Jain SK, Keshri R, Goswami A, Sarkar A, Chaudhry A. 2009. Identification of drought-vulnerable areas using NOAA AVHRR data. Int J Remote Sens. 30(10):2653–2668.

Kanellos E, Domenikiotis C, Tsirou E, Dalezios N. 2008. Satellite-based drought estimation in Thessaly. Eur Water. 23(24):111–122.

Kogan F. 1994. NOAA plays leadership role in developing satellite technology for drought watch. Earth Observ Mag. 11:1405–1409.

Kogan F. 1995a. Application of vegetation index and brightness temperature for drought detection. Adv Space Res. 15(11):91–100.
Kogan FN. 1995b. 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.

Kogan F. 2002. World droughts in the new millennium from AVHRR-based vegetation health indices. Eos Trans Am Geophys Union. 83(48):557–563.

Li J, Heap AD. 2014. Spatial interpolation methods applied in the environmental sciences: a review. Enviro Modell Software. 53:173–189.

Maes W, Steppe K. 2012. Estimating evapotranspiration and drought stress with ground-based thermal remote sensing in agriculture: a review. J Exp Bot. 63(13):4671–4712.

MAO K-B, Ying M, Lang X, TANG H-J, HAN L-J. 2012. The monitoring analysis for the drought in China by using an improved MPI method. J Integr Agric. 11(6):1048–1058.

Mavromatis T. 2007. Drought index evaluation for assessing future wheat production in Greece. Int J Climatol. 27(7):911–924.

Mishra AK, Singh VP. 2010. A review of drought concepts. J Hydrol. 391(1–2):202–216.

Nichol JE, Abbas S. 2015. Integration of remote sensing datasets for local scale assessment and prediction of drought. Sci. Total Environ. 505:503–507.

Park S, Feddema JJ, Egbert SL. 2004. Impacts of hydrologic soil properties on drought detection with MODIS thermal data. Remote Sens Environ. 89(1):53–62.

Patel N, Anapashsha R, Kumar S, Saha S, Dadhwal V. 2009. Assessing potential of MODIS derived temperature/vegetation condition index (TVDI) to infer soil moisture status. Int J Remote Sens. 30(1):23–39.

Peters AJ, Walter-Shea EA, Ji L, Vina A, Hayes M, Svoboda MD. 2002. Drought monitoring with NDVI-based standardized vegetation index. Photogr Eng Remote Sens. 68(1):71–75.

Quiring SM. 2009. Monitoring drought: an evaluation of meteorological drought indices. Geogr Compass. 3(1):64–88.

Quiring SM, Papakryiakou TN. 2003. An evaluation of agricultural drought indices for the Canadian prairies. Agric Forest Meteorol. 118(1–2):49–62.

Rashid K, Rasul G. 2007. Rainfall variability and maize production over the potohar plateau of Pakistan. J Meteorol. 8:63–74.

Rasul G, Mahmood A, Sadiq A, Khan S. 2012. Vulnerability of the Indus delta to climate change in Pakistan. Pakistan J Meteorol. 8(16).

Salazar L, Kogan F, Roytman L. 2008. Using vegetation health indices and partial least squares method for estimation of corn yield. Int J Remote Sens. 29(1):175–189.

Steinemann AC, Cavalcanti LF. 2006. Developing multiple indicators and triggers for drought plans. J Water Resour Plann Manage. 132(3):164–174.

Sun L, Mitchell SW, Davidson A. 2012a. Multiple drought indices for agricultural drought risk assessment on the Canadian prairies. Int J Climatol. 32(11):1628–1639.

Sun L, Sun R, Li X, Liang S, Zhang R. 2012b. Monitoring surface soil moisture status based on remotely sensed surface temperature and vegetation index information. Agric Forest Meteorol. 166:175–187.

Sun L, Yu H, Gao T, Tian X, Li X, Sun L. 2013. Land surface temperature retrieval from HJ-1B IRS supported by MODIS. In: 2013 Second International Conference on Agro-Geoinformatics (Agro-Geoinformatics): IEEE.

Svoboda M, LeComte D, Hayes M, Heim R, Gleason K, Angel J, Rippey B, Tinker R, Palecki M, Stooksbury D. 2002. The drought monitor. Bull Am Meteorol Soc. 83(8):1181–1190.

Tsakiris G, Vangelis H. 2004. Towards a drought watch system based on spatial SPI. Water Resour Manag. 18(1):1–12.

Unganai LS, Kogan FN. 1998. Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. Remote Sens Environ. 63(3):219–232.

Wilhite DA, Glantz MH. 1985. Understanding: the drought phenomenon: the role of definitions. Water Int. 10(3):111–120.

Yun-Hao C, Xiao-Bing L, Pei-Jun S, Wen D, Xia L. 2003. Intra-annual vegetation change characteristics in the NDVI-Ts space: application to farming-pastoral zone in North China. Acta Bot Sin. 45(10).
Zargar A, Sadiq R, Naser B, Khan FI. 2011. A review of drought indices. Environ Rev. 19(NA):333–349.
Zheng S, Cao C, Wang M, Xu M, Lu S. 2013. Land surface temperature retrieval using HJ-1B/IRS data and analysis of its effect. In: 2013 IEEE International on Geoscience and Remote Sensing Symposium (IGARSS): IEEE.