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Climate change impacts on vegetation and agricultural drought in the basin of Panjshir River in Afghanistan

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Abstract
The agricultural drought, severely affecting human life, occurs unpredictably at different times with different intensities. The conventional methods for assessing drought often relay on indices obtained using meteorological data, but due to the low spatial coverage, incompleteness and inaccuracy of these data, meteorological indices cannot be considered as a comprehensive method. Therefore, it is suggested that remote sensing constitute more versatile approach, as it allows to assess the drought using the adequate spatial and temporal coverage for the study area. In the study, performed for the Panjshir river basin in Afghanistan, the 2010-2019 period is used to evaluate vegetation rate using NDVI data from MODIS. To calculate agricultural drought indices (DSI, VCI and TCI), May and June were selected, as the peak vegetation time occurs for these months. On the base of the remote sensing indicators it was shown that during the study period the drought conditions were normal in the region, except for 2011, 2017, and 2018, which were the driest years, and for 2019, which was the wettest year. Agricultural drought indices were compared to SPI index calculated using winter and spring precipitation data recorded at the meteorological stations. It was observed that the remote sensing indices showed the highest correlation with data from Kabul meteorological station, which is located at the same altitude and climate as the dense vegetation zone. Furthermore, the comparison showed that the ground precipitation data is characterized by higher amplitudes than the remote sensing data. From the above it steams that the vegetation in the Panjshir basin is influenced by both seasonal rainfall and rivers that continuously flood the area.

Introduction

The main consequences of the climate change, which is caused by increasing greenhouse gases' concentration (especially carbon dioxide) in the atmosphere, are changes in various factors, from global temperature, solar radiation absorption, precipitation characteristics, humidity, wind speed, runoff, sea level, to water resources, energy, wildlife, ecosystems (Rousta et al. 2018a, 2013). Those changes are causing frequent floods, dust storms, hurricanes, tsunamis, glaciers melting, snowfall reduction, etc. Drought is one of the climate change consequences that, at the same time, occurs gradually and in a relatively long period affects not only agriculture and water resources, but also the social and economic sectors. This natural event occurs in almost all climatic regions, although its characteristics are completely different from one region to another (Shahabfar et al. 2012; Mashore et al. 2019). Besides, climatic phenomena such as high temperatures and low relative humidity are often accompanying drought and increasing its severity. Drought can be classified as meteorological, agricultural, hydrological, or social, depending on the environmental sectors affected (Peters 2003). Meteorological drought is due to lack of rainfall,

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agricultural drought - due to lack of soil moisture, while hydrological drought is due to declining water levels in waterways and groundwater aquifers (Tate and Gustard 2000; Rousta et al. 2020). Because rainfall is one of the most important factors that affects vegetation cover in different areas (Hadian et al. 2014; Rousta et al. 2017a,b), assessing drought occurrence and its effects on vegetation becomes a significant need. This is especially true for environmentally sensitive areas and water supply sources like the Panjshir river basin. Conventional methods for assessing and monitoring drought are often based on rainfall data recorded at meteorological stations, what makes the assessment limited to the area closest to the measurement site and in many cases – inaccurate for larger areas. As a consequence, meteorological data-based indicators cannot be treated as an adequate method to assess drought, especially for larger scales. Contrary, remote sensing techniques and remotely sensed indices can provide more accurate monitoring of drought due to their reproducibility, up-to-dateness, and a large area coverage (Rousta et al. 2020a).

One of the most effective indicators regarding vegetation is the Normalized Difference Vegetation Index (NDVI[1]), which was first introduced by Tekr in 1979 as a vegetation density health index (Jensen 1996; Rousta et al. 2018b). The NDVI index has been applied to many scientific studies worldwide (Rousta et al. 2020) assessed drought in southwest Asia (Afghanistan, Pakistan, and western India) using remote sensing data. They used MODIS[2] and AVHRR[3] imageries with optical and thermal bands. Consequently, they used NDVI and earth surface temperature to extract the distribution map of the agricultural drought indices for the period from 1982 to 2002. Jalili (2005) calculated NDVI, VCI, and SPI using AVHRR imagery and meteorological station's daily and monthly precipitation data to assess drought in Tehran province, Iran. Thereinafter, a statistical analysis on extracted indices showed an acceptable correlation between SPI and remote sensing indices. Moazen Zada et al (2012) calculated agricultural drought for Neishabour basin in Iran during 2001 to 2010 using information extracted from MODIS images and compared it to meteorological drought. The comparison showed that NDVI was correlated to six month's delayed precipitation. Besides, it was indicated by classifying VCI that SPI can't present drought comprehensively. MirMousavi and Karimi (2013) also used NDVI and SPI to monitor drought in Kurdistan province, Iran in the period from 2001 to 2009. The study concluded that a significant correlation between NDVI and SPI indices exists and a usual drought conditions were observed for 2001 and 2008. Zhang and Yamaguchi (2014) tried to evaluate drought in southeastern China during 2009 and 2010 using DSI4 agricultural drought index and MODIS imagery. In this study, the DSI has been calculated for a monthly intervals, which allowed for identification of spatial and temporal variations in drought severity. Finally, the results were compared to SPI using the Pearson correlation and the significant relationship was found. Also, by employing the regression, it was found that the DSI index showed the highest correlation with the quarterly SPI index. Kaikhesravi et al. (2016) tried to estimate the drought impacts on vegetation in Semnan province in Iran using SPI and NDVI indices. The correlation between these two indices was observed. Eshetie et al. (2016) evaluated DSI, VCI, and SPI vegetation indices and Eta5 for agricultural drought monitoring in east Amhara, Ethiopia. They found that DSI was the best out of all four indices to define agricultural drought phenomena. Roustami et al. (2017) assessed temporal and spatial variations of drought using MODIS imagery in the East Azerbaijan province of Iran. They used both remote sensing (NDVI, VCI, DSI and TCI) and meteorological (SPI) indices to evaluate drought severity. In the study a significant correlation between remote sensing and meteorological data was obtained. Khalid and Zhang (2018) used agricultural drought indices to assess the drought occurrence in Sudan in the period from 2001 to 2011, focusing on the effect of drought on the sorghum yield. They used DSI, seasonal SPI, and TRMM6 precipitation and checked the DSI correlation with the standardized variable of crop yield (St. Y) for sorghum. The study concluded that DSI can be used for agricultural drought monitoring and can be used as an alternative index to estimate crop yield over the study area. Razipoor (2019) also assessed the vegetation condition of western Herat province, Afghanistan using NDVI and VCI indicators from MODIS Aqua for the period from 2003 to 2014. Monthly VCI was used to evaluate vegetation conditions for the rainfed and irrigated lands, forests, and rangelands. Rousta et al. (2020) also tried to assess the impacts of drought on vegetation throughout Afghanistan from 2001 to 2019 using NDVI and LST products of MODIS, TRMM data, VCI, and SPI indices. The results of this study showed that these indicators can be useful for assessing and diagnosing drought in Afghanistan.

In this study MODIS images are used to assess the vegetation change and agricultural drought in the basin of Panjshir River in Afghanistan in the period from 2010 to 2019. Firstly, vegetation percentage

1. Normalized Difference Vegetation Index
2. Moderate Resolution Imaging Spectroradiometer
3. Advanced Very-High-Resolution Radiometer
4. Drought Severity Index
5. Evapotranspiration
6. Tropical Rainfall Measuring Mission

over the study area is evaluated for each month of the year during the covered time. As the result, May and June are deducted as the intermittent maximum vegetation time, constituting the optimal drought indicator for the year. Therefore, agricultural drought indices (DSI, VCI and TCI) and meteorological precipitation index (SPI) are calculated for May and June. Finally, the remote sensing findings are compared to meteorological data to estimate relationship between them.

Study Area

The study was conducted for the Panjshir river basin, an important agricultural area due to its proximity to Kabul city. It consists of Kabul, Parwan, Kapisa, and Panjshir provinces. Geographically, it is located between 68.1°E and 70.3°E and 34.5°N and 35.9°N. Panjshir River, a large tributary of the Kabul river, is a main catchment of this area and is connected to the Kabul River in the southern part. Climatically, the basin is a mountainous region, where the altitude varies from 1000 to 5600 meters.

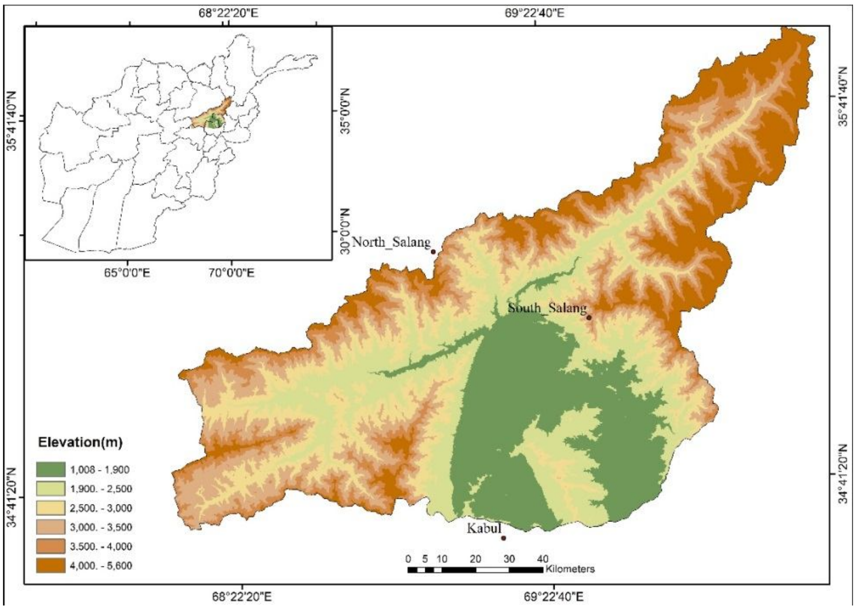

Figure 1. Map presenting the study area including an elevation profile and the location of the meteorological stations.

Materials and Methods

This study has used MODIS images to calculate agricultural drought indices. The main reasons to use MODIS is due to its temporal and spatial resolution, spectral coverage, ease of access, and no need for atmospheric correction and georeferencing of images. MODIS sensor is collecting data using 36 bands in the range of 0.4 to 14.4 micrometers and with coverage width of 2330 kilometers. The spatial resolution of these bands varies from 250 to 1000 meters. The remote sensing data used in this study are the ready-for-use products named MOD13Q1 and MOD11A1, which provide information on the time series of NDVI and LST indices. These products can be downloaded directly from the US Geological Survey website and do not require geometric, radiometric, and atmospheric corrections.

$$SPI = \frac{Pi - P}{SD} \quad (1)$$

To control the accuracy of the satellite data, the ground data of monthly precipitation recorded at three meteorological stations near the study area has been used. These data were obtained from the Afghanistan Meteorological Organization and was used to calculate the standardized precipitation index (SPI). Calculated SPI was compared to agricultural drought indices (VCI, DSI, TCI).

Standardized Precipitation Index (SPI)

Agricultural drought can be determined by the Standardized Precipitation Index, which has been shown many times, for example by McKee et al. (1993). To calculate SPI index, the amount of precipitation for a given period (e.g. for the first 6 months of the year) is compared for each year during the study period. SPI is obtained from the equation (1):

where SPI is the standardized precipitation index, Pi is the amount of precipitation for a given period in the year i, P is the long-term average precipitation at the station and SD is the standard deviation of precipitation at the station.

Agricultural Drought indices

To monitor drought using remote sensing data or satellite imagery one needs to extract information from spectral bands to calculate long-term drought-determining indicators. In this study, NDVI and LST indices of land surface were used to calculate the Drought Severity Index (DSI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI). The values of above-mentioned indicators are obtained using the equations (2), (3) and (4):

$$DSI_i = NDVI_i - NDVI_{mean} \quad (2)$$

$$VCI_i = \frac{NDVIi - NDVImin}{NDVImax - NDVImin} \times 100 \quad (3)$$

$$TCI_i = \frac{LSTmax - LSTi}{LSTmax - LSTmin} \times 100 \quad (4)$$

where i subscript indicates the year and mean, min, and max subscripts are indicating the long-term average, minimum, and maximum value of the remote sensing indices for the study period. In Table (1) the general characteristics of the drought indicators are presented (Rousta et al. 2020b).

Table 1. General characteristics of Agricultural Drought indices

DROUGHT INDEX	USED BANDS AND INDICES	INTERVAL	NORMAL CONDITION	SEVERE DROUGHT	DENSE VEGETATION
NDVI	MODIS 1 and 2 bands	-1 to +1	Related to the area	-1	+1
DSI	NDVI and its long time mean	-1 to +1	0	-1	+1
VCI	NDVI and its long-time min and max	0 to 100%	50%	0%	100%
TCI	LST and its long-time min and max	0 to 100%	50%	0%	100%

In Table 2 the drought classification based on the values of DSI and SPI indices is shown (Johnson et al. 1993, Lashni Zand 2004)

Table 2. Drought classification according to the values of SPI and DSI indices.

Class	SPI	DSI
Extremely wet	>=2	0.71 to -.93
Very wet	1.5 to 1.99	0.49 to 0.70
Wet	1 to 1.49	0.27 to 0.48
Normal	-0.99 to 0.99	0 to 0.26
Drought	-1.49 to -1	-0.17 to -0/01
Very drought	-1.99 to -1.5	-0.38 to -0.18
Severe drought	=<-2	-0.6 to -0.39

Based on VCI characteristics, a range of values from 0 to 35% indicates different degrees of drought, a range from 35 to 50% indicates normal plant conditions and the values above 50% indicates optimal and meta-normal conditions (Kogan et al. 1995).

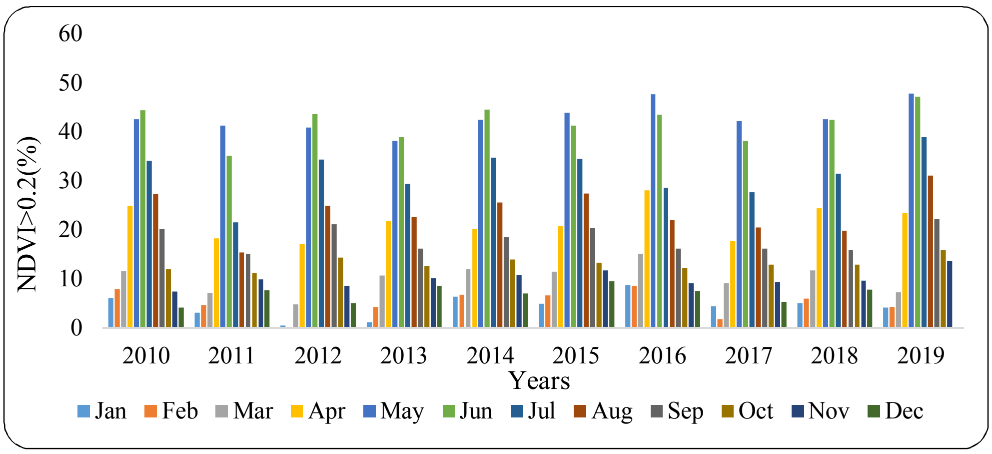

Figure 2. Changes in vegetation coverage (NDVI>0.2) for each month during the studied period.

Findings and Discussion

Figure 2 shows the temporal (monthly) fluctuations of vegetation coverage across the study area during the years 2010 to 2019, evaluated using the NDVI indicator of MOD13Q1 and Arc GIS. It can be seen that across the region of interest the densest vegetation occurs in May and June for every year. Contrary, in Dec, Jan, and Feb the minimum coverage of vegetation can be observed. Therefore, it can be assumed that changes in vegetation coverage for May and June will be representative to assess the annual variation of vegetation density. For this reason, the NDVI and LST indices of May and June were used to calculate VCI, DSI and TCI indicators used for assessing the agricultural drought.

Figure 3 shows the spatial and temporal development of vegetation density in 2019. From this Figureure it results that the densest vegetation is developing in the flattest parts of the basin surrounding Charikar city, which is mainly agricultural. The vegetation density is gradually decreasing with the height and in mountains vegetation is limited to the valleys' floor. A highest dispersion of vegetation can be spotted for May and June.

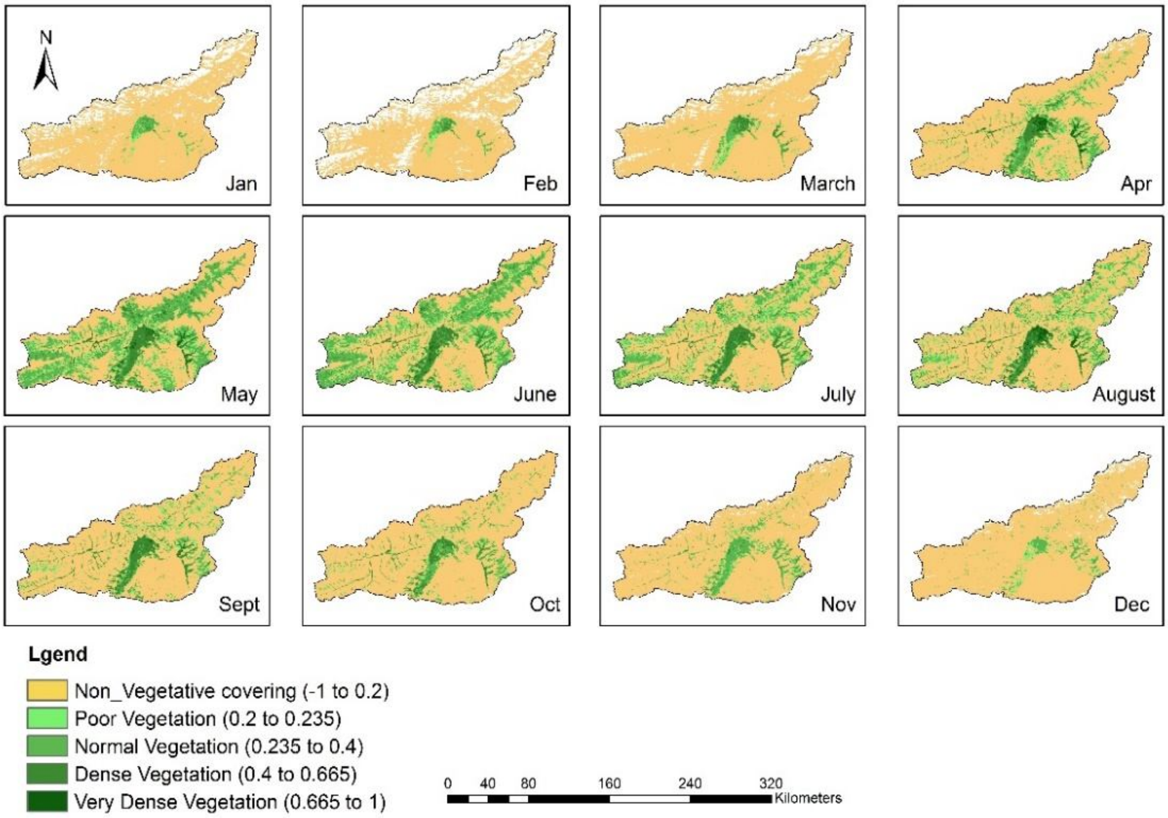

Figure 3. The spatial and temporal development of vegetation density in the Panjshir River basin in 2019

Distribution of agricultural drought indices (DSI, VCI and TCI)

Since the peak of vegetation coverage in the region of interest is seen in the remotely sensed data (NDVI) in May and June, thus DSI, VCI and TCI indicators were calculated for these months for each year of the study, from 2010 to 2019. To evaluate the accuracy of calculated indices they were compared with SPI, which was obtained from effective rainfall recorded at ground stations. On Figures 4–6 the temporal and spatial variations of DSI, VCI and TCI, respectively, are shown for each June from the period 2010 to 2019. The indices for June are given as an example due to its highest correlation with ground data used for control.

As it can be seen from Figureure 4, the DSI index has the lowest values (from -0.18 to 0) for most areas in 2011, 2017 and 2018. Despite that, these years are classified as normal. Similarly, for 2019, which is the wettest year from the study period, the most of the area has the highest values (from 0 to 0.48) and is also classified as a normal year. These variations are also presented in Figures 7 and 8, from which it results that there is a lack of severe droughts in the region of interest.

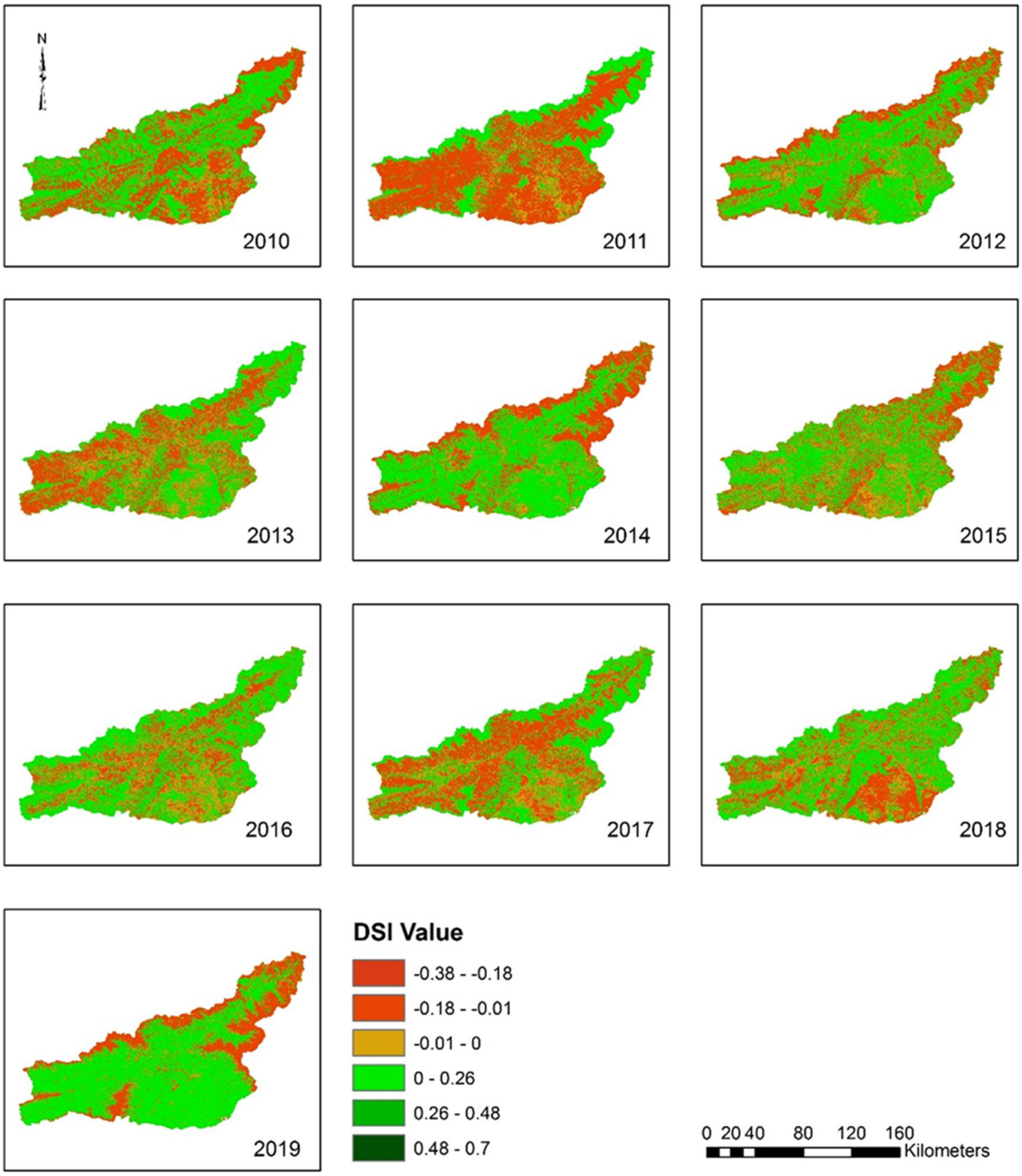

Figure 4. DSI distribution in June for the study area during the study period.

From the Figures 5 and 7 it can be seen that VCI also has lowest values in 2011, 2017 and 2018, with most of the areas occurring drought. Contrary in 2019 highest values of VCI (>50%) are recorded in most of the area, which indicated year with optimal vegetation conditions.

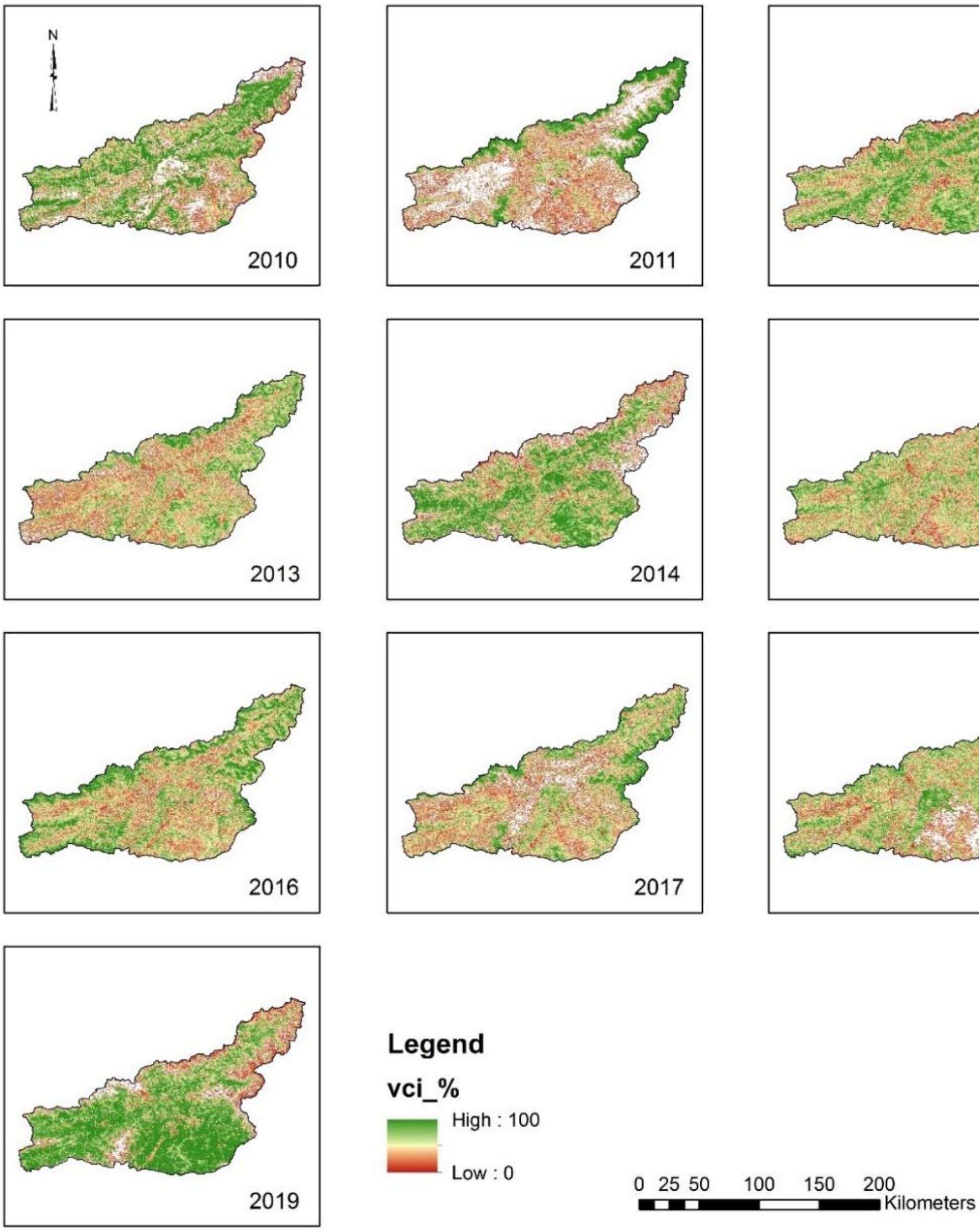

Figure 5. VCI distribution in June for the study area during the study period.

On Figures 6 and 7 it is shown that in the TCI also a lowest value can be spotted for 2011, 2012, and 2018 in most areas, whereas for 2019 high values were recorded for the studied region.

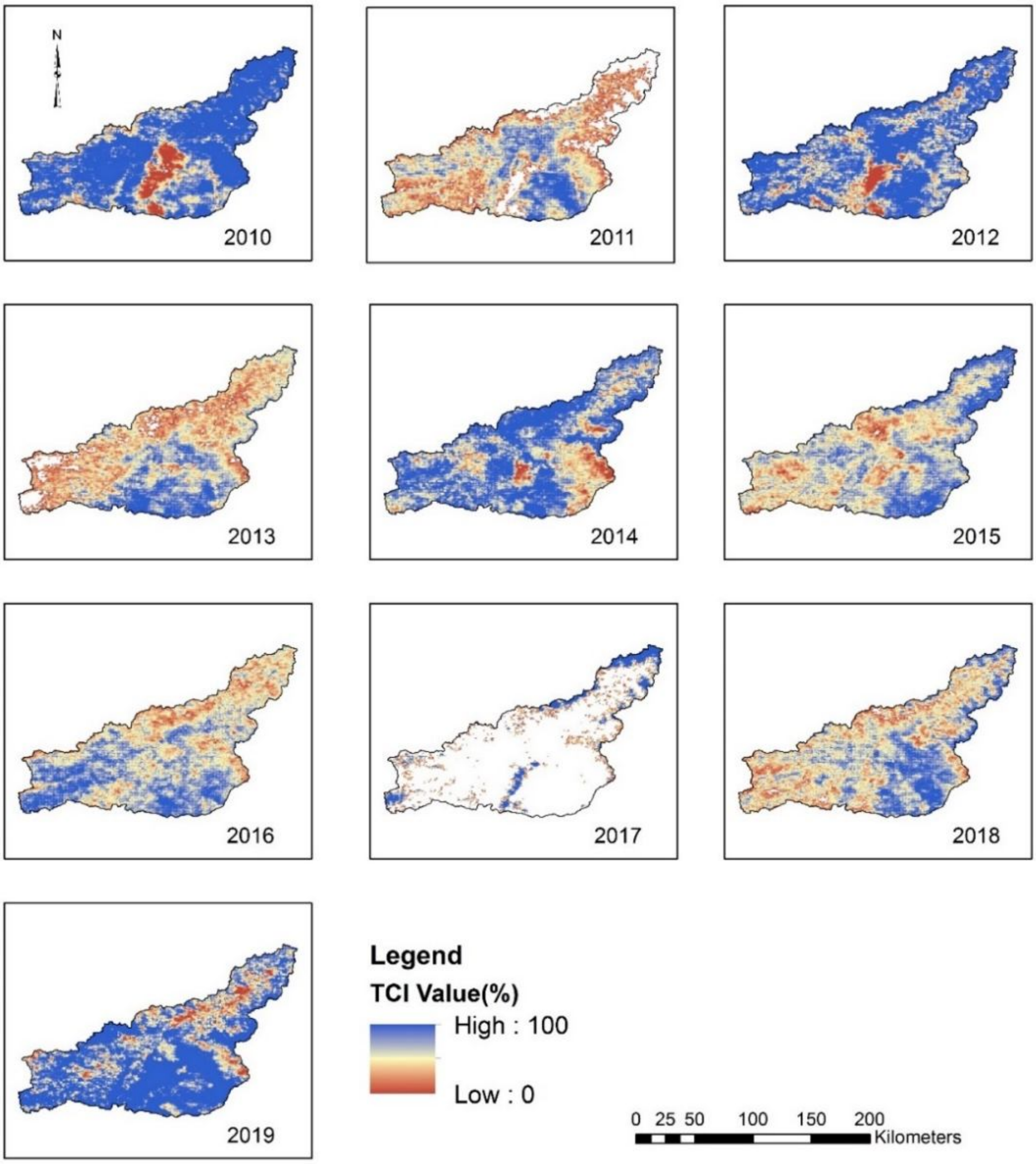

Figure 6. TCI variations in June for the study area during the study period.

On Figures 7 and 8 the temporal variations of the mean values of agricultural drought and precipitation indices (DSI, VCI, SPI, TCI) are presented for June and May, respectively. From the Figureure 7 it results that almost all indicators have shown a lowest mean value in 2011, 2017, and 2018. Observed values indicate the occurrence of drought. For 2019 the highest mean value over the assessed years is observed, with classification as: extremely wet (SPI), wet (VCI) and normal (DSI). The main reason for this classification was the heavy rainfall in the spring. Similarly, Figureure 8 shows that the lowest mean values were observed for 2017 and 2018 and the highest in 2019, although they are less correlated with each other than in June. The VCI and DSI mean values are from the range of 0.32 to 0.61 and -0.009 to 0.009, respectively, which indicates the normal conditions for vegetation and no droughts. Consequently, it can be concluded that apart from mild droughts, no severe droughts have occurred in this region. Additionally, the more pronounced changes in amplitude of the mean value of SPI than in the other indices suggest the low impact of precipitation on vegetation. Both above phenomena can be caused by Panjshir's rivers constantly flooding all agricultural lands.

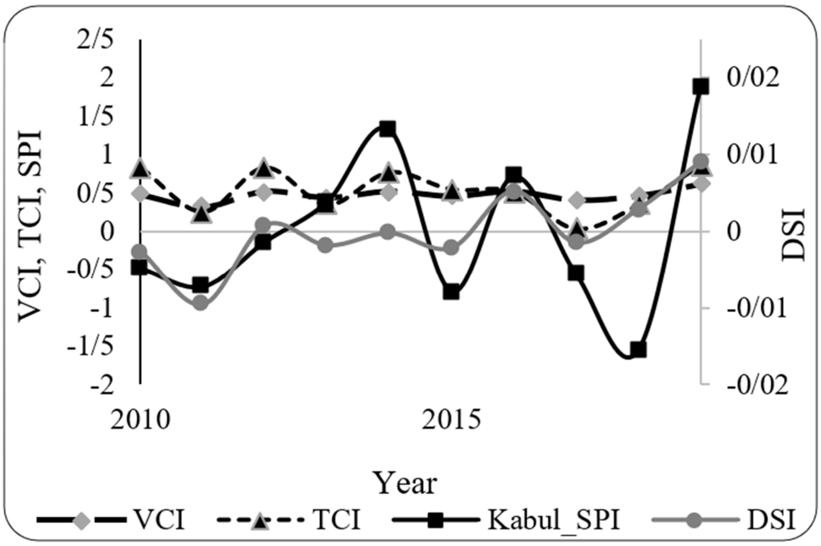

Figure 7. Temporal variations in mean values of VCI, DSI, TCI and SPI in June during the study period.

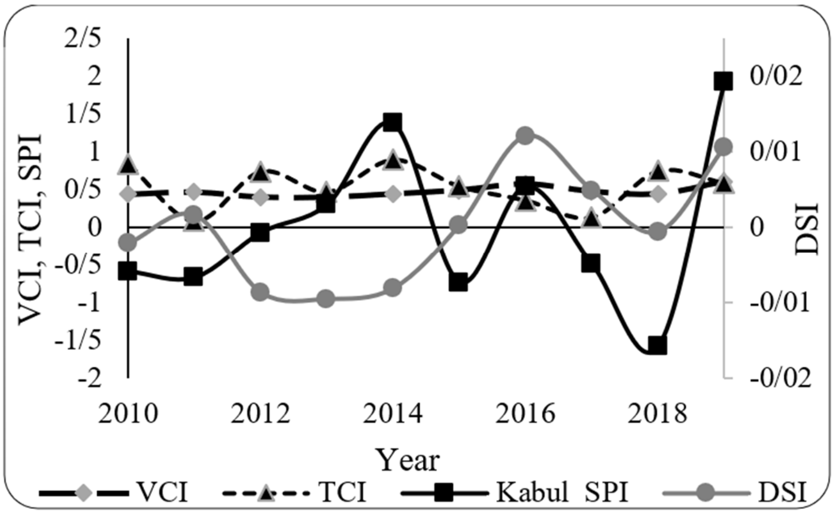

Figure 8. Temporal variations in mean values of VCI, DSI, TCI and SPI in May during the study period.

Precipitation variations

Since there are no meteorological stations in the studied area, three stations located near the area were used. Their locations are shown in Figureure 1. Meteorological drought index (SPI) values obtained from three stations' data are given in Table 3 and 4 for June and May, respectively. The SPI values are calculated for the precipitation effectively influencing vegetation conditions, namely from first five (May) and six (June) months from the beginning of the year. The highest SPI value is observed for Kabul meteorological station in 2019, with June and May values equal to 1.86 and 1.92, respectively. These values classify 2019 as an extremely wet year. On the contrary, the minimum SPI value at Kabul station was observed in 2018, with values -1.56 and -1.58 for June and May, respectively. The 2018 can be then classified as a year with high drought. The remaining years are classified as wet, normal, and drought.

Table 3. PI values for June at three ground measuring meteorological stations for the study period.

Station/Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Kabul	-0.49	-0.73	-0.14	0.38	1.32	-0.79	0.71	-0.56	-1.56	1.86
South Salang	-1.39	-1.36	-1.13	0.59	1.43	1.32	0.67	0.41	-0.16	-0.38
North Salang	-1.84	0.65	-1.56	1.26	0.26	-0.82	0.7	0.05	0.48	0.84

Table 3, SPI values for May at three ground measuring meteorological stations for the study period.

Station/Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Kabul	-0.59	-0.67	-0.07	0.3	1.37	-0.73	0.54	-0.49	-1.58	1.92
South Salang	-1.44	-1.34	-1.11	0.56	1.47	1.31	0.58	0.46	-0.13	-0.37
North Salang	-1.89	0.68	-1.53	1.26	0.29	-0.83	0.61	0.12	0.56	0.76

Comparison of remotely sensed and ground-based indicators

The statistical comparison of SPI with agricultural drought indices shows that there is a significant relationship between remote sensing data and ground-based measurements. Therefore, the remote sensing indices allows for a comprehensive assessment of agricultural drought. On Figures 7 and 8 the temporal variations of all remotely sensed and ground-based indices were shown. From these Figureures it is obvious that correlation exists. Correlation coefficients between remote sensing indices and SPI index were calculated and are provided in Table 5 and 6 for June and May, respectively. As it can be seen in the tables, Kabul station's meteorological data is the most correlated with remotely sensed data, with all indices from remote sensing (VCI, DSI and TCI) having correlation higher than 50% with SPI in June. This is mainly because meteorological station is located at the same height and in a climate similar to this observed for a dense vegetation zone. Moreover, it's seen that SPI had higher correlation coefficient with remote sensing data in June than in May.

Table 4. Correlation coefficients between SPI and various agricultural drought indices for June.

Sation Name	R(SPI_DSI)	R(SPI_VCI)	R(SPI_TCI)
Kabul	0.54	0.687	0.523
South Salang	0.22	0.18	-0.16
North Salang	0.2	-0.07	-0.45

Table 5 Correlation coefficients between SPI and various agricultural drought indices for May.

Station Name	R(SPI_DSI)	R(SPI_VCI)	R(SPI_TCI)
Kabul	0.166	0.478	0.16
South Salang	-0.013	0.15	0.043
North Salang	0.27	0.315	-0.44

Conclusions

Climate change is affecting land temperature, energy, water levels, ecosystems, and most importantly - drought conditions. In this study the agricultural drought conditions in the Panjshir river basin during 2010 to 2019 has been assessed using NDVI and LST data from MODIS. Using the NDVI, vegetation rate was evaluated for each month of the year, and the period with peak in vegetation coverage (May and June) was selected as the reference. Based on this selection, agricultural drought indices (DSI, VCI and TCI) were calculated and discussed. From the performed analyses it can be concluded that there were no severe droughts during the study period, with the lowest mean values of the calculated indices observed in 2011, 2017, and 2018 and the highest in 2019. Furthermore, to analyze the accuracy of the results', indices calculated on the base of remote sensing methods were compared with the SPI drought index. SPI was calculated based on spring and winter rainfall data recorded at three meteorological stations in the studied region. Despite the significant correlation between DSI, VCI and TCI indices with the SPI index, fluctuations in ground measured data not seen in remote sensing indicators were observed. This indicates that the vegetation in the Panjshir basin is not only greatly affected by seasonal rains, but also by constantly waterlogged rivers of the region. Finally, as it was already shown in other scientific studies, the correlation between remote sensing and ground measured data exist, making the remote sensing data a credible method to study drought conditions. For example, in a study led by Rousta et al. (2020) for whole Afghanistan, NDVI, VCI, LST, and rainfall indices were used to investigate the impact of drought on vegetation. Rousta et al. (2020) showed that these indicators are a reliable method of drought monitoring. Likewise, in Eshetie et al (2016) study, conducted in the Amhara region of Ethiopia, NDVI, DSI, VCI, and ET (evapotranspiration) indices were used to assess the occurrence of drought. The comparison between these indices were with SPI resulted in a high and significant correlation. Rostami et al. (2017) have also confirmed the correlation between remote sensing indicators and ground-based data, which indicates the accuracy and the ability of remote sensing indicators to assess drought. Also, the findings of Rezaei Banafsheh et al. (2015) and Moazenzadeh et al. (2012) confirms the results presented in this study.

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