 doi:10.20944/preprints202207.0257.v1

Article

A remotely sensed study of the impact of meteorological parameters on vegetation for the eastern basins of Afghanistan

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Abstract: The vulnerability of vegetation in the Middle East to meteorological conditions and climate change, especially those leading to drought, is high. Despite the importance of the Amu Darya and Kabul River Basins (ADB and KRB) as a region in which more than 15 million people live, and its vulnerability to global warming, only several studies addressed the issue of the linkage of meteorological parameters on vegetation for the eastern basins of Afghanistan. In this study, data from the Moderate Resolution Imaging Spectroradiometer (MODIS), Global Precipitation Measurement Mission (GPM), and Land Data Assimilation System (GLDAS) to examine the impact of meteorological parameters on vegetation for the eastern basins of Afghanistan for the period from 2000 to 2021. The study utilized several indices, such as Precipitation Condition Index (PCI), Temperature Condition Index (TCI), Soil Moisture Condition Index (SMCI), and Microwave Integrated Drought Index (MIDI). The relationships between meteorological quantities, drought conditions, and vegetation variations were examined by analyzing the anomalies and using regression methods. The results showed that the years 2000, 2001, and 2008 had the lowest vegetation coverage (VC) (56, 56, and 55% of the study area, respectively). On the other hand, the years 2010, 2013, 2016, and 2020 had the highest VC (71, 71, 72, and 72% of the study area, respectively). The trend of the VC for the eastern basins of Afghanistan for the period from 2000 to 2021 was upward. High correlations between VC and soil moisture ($R = 0.70$, $p = 0.0004$), and precipitation ($R = 0.5$, $p = 0.008$) were found, whereas no significant correlation was found between VC and drought index MIDI. It was revealed that soil moisture, precipitation, land surface temperature, and area under meteorological drought conditions explained 45% of annual VC variability.

Keywords: remote sensing, vegetation coverage, drought, meteorological conditions, Afghanistan.

1. Introduction

Abnormal climatic conditions related to climate change have been associated with the effects of human activities over the past few decades. They lead to numerous environmental and ecological problems, such as air pollution, biodiversity loss, soil erosion, and vegetation degradation [1,2]. Therefore, the knowledge of how climate change affects different ecosystems has an important role in the protection and management of vegetation cover [3]

Vegetation occupies almost half of the planet and plays an important role in providing food, fiber, and fuel, supporting animal biodiversity, maintaining climate quality, and supporting ecological processes that preserve ecosystems and landscapes [4]. Vegetation is one of the important components of the terrestrial ecosystem, which plays an effective role in preventing desertification and also plays a key role in providing various ecosystem services to adapt and mitigate climate change [5,6]. Additionally, every change in vegetation affects the climate of the region, especially temperature and air quality, through its influence on net radiation, energy partitioning, conversion of precipitation to runoff, soil moisture, evaporation, and transpiration [7]. Since global climate change has become a major topic of discussion today, the relationship between vegetation and meteorological factors is of great importance in ecological studies [8].

Remote sensing can continuously and systematically deliver information on the water cycle and vegetation variations and therefore, remote sensing drought indicators can be used for spatial and temporal drought monitoring [9]. Remote sensing is of particular importance in applications requiring actual and constantly updated information. Due to various spectral ranges and data availability, the use of remote sensing data is one of the best ways to prepare vegetation maps [10].

The NDVI index has become one of the most popular and commonly used indicators to monitor vegetation due to its universality and simple mathematical formula [11-14]. According to Huang et al. [14], the number of articles using the NDVI index to monitor changes in vegetation increased from 795 in 1990, through 3361 in 2000, to 12,618 in 2010 [15]. The NDVI index is widely used in studies related to vegetation classification, and soil erosion risk assessment, because soil erosion decreases with increasing vegetation cover [16]. By correlating NDVI data with the meteorological parameters using the long-term time series for the specific study area it can be checked how climate change affects the growth of vegetation [17]. Also, such studies can be performed to check whether persistent drought conditions occur in a given area and how they affect vegetation.

The period of instability from dry weather conditions, which leads to water scarcity, is simply known as drought [18,19]. Drought is a very complex and not well-understood phenomenon. It causes social and environmental problems, and it leads to immeasurable economic losses [20]. Drought is a serious natural hazard, especially in regions with arid and semi-arid climates [18]. Compared to other natural phenomena, drought affects wider areas over a longer period, thus causing much more damage than other natural disasters such as floods and earthquakes [21]. The study of climate change and the identification of years of drought are valuable for the management of water resources and vegetation, especially in areas with dry spell occurrence [22].

Afghanistan is a mountainous country with spatially and temporally varying ecological conditions. Mountainous areas are prone to the effects of climate change, which intensifies the pressure on natural and human systems [23]. Climate changes have caused short-term and long-term droughts that have severely affected Afghanistan's economy. According to the International Disaster Management Agency (IDD), droughts accounted for only 5 percent of natural disasters but affected about 30 percent of the population [24]. There are two main types of drought in Afghanistan: meteorological drought (usually accompanied by a lack of rainfall) and hydrological drought (usually associated with a lack of surface and groundwater flow, potentially originating in the wider river basin region) [25]. These issues may also be combined with land and crop management practices, leading to agricultural drought. Currently, Afghanistan is facing significant drought issues that have a direct impact on the livelihoods and the economy of the country [25,26].

The vegetation in Afghanistan has been severely affected by human activities, climate change, and drought, which resulted in the naturally occurring vegetation preserved intact only in a few high mountain areas and abnormally dry deserts [27]. Such a situation additionally contributes to Afghanistan's vulnerability to the effects of climate change [28]. In Afghanistan, the combined effects of climate change and four decades of civil war have destroyed vegetation and infrastructure, leading to the underdevelopment of the country. The high dependence of the majority of the country's people on small and large-

 doi:10.20944/preprints202207.0257.v1

scale agriculture means that due to the country's dry climate and the low adaptation capacity of farmers climate change creates major problems to deal with [29]. The arid and semi-arid climate of the eastern basins of Afghanistan implies that this area can be strongly affected by short and long-term fluctuations of meteorological parameters, which as a result will endanger human living conditions [30]. In Afghanistan, where a large part of the population is engaged in the agriculture sector, assessing the impacts of climate change and drought on vegetation is crucial for the implementation of sustainable agricultural practices. This is especially important for different crops that are grown annually and seasonally, for example, wheat produced in the north, northeast, and eastern regions of the country [31].

In Afghanistan, due to security problems and the lack of stations monitoring weather, not many studies have been performed on the correlation between meteorological parameters and vegetation, and only a few research were done using remote sensing data [22,27,30,32]. Therefore, the investigation of the impact of weather and climate change on vegetation for proper management and ensuring the stability of vegetation, being of particular importance for the eastern basins of Afghanistan, is still required and expected.

The presented study has been conducted to monitor the fluctuations of vegetation conditions and to assess their relationship with meteorological parameters and drought conditions in the period of 2000-2021 in the eastern basins of Afghanistan. The main objectives of this study were a) to determine the trend of vegetation changes between the years (2000-2021) in the eastern basin of Afghanistan, b) to analyze the past trends in drought from the perspective of meteorology, and c) to determine the relationship between vegetation, drought and meteorological parameters for the eastern basins of Afghanistan. The results of this study can be used by governmental agencies, such as the Ministry of Agriculture, to identify dry and wet years, as well as to determine the trend of changes in meteorological parameters and vegetation for the period 2000-2021.

2. Materials and Methods

2.1. Study area

The study has been performed for the eastern basins of Afghanistan, namely the Amu Darya Basin and the Kabul Basin, with a total area of 163,840 km^2. The Amu Darya Basin, with an area of 90,692 km^2, is bordered by Tajikistan from the north, and Pakistan from the southeast. The total annual water flowing through this basin is 82 billion m^3, of which 61% comes from Tajikistan, 30% from Afghanistan, and the remaining 9% from Uzbekistan and Turkmenistan. Important Amu Darya tributaries include the Wakhan, Kokcha, Kunduz, Andarab, Khenjan, and Punjab rivers in Afghanistan. The population living in this basin was reported to be about 4.5 million people in 2015. According to the division of the Ministry of Energy and Water, it is divided into 7 sub-basins: Upper Five, Lower Five, Kokcheh, Taloqan, Upper Kunduz, Lower Kunduz, and Lower Amu [28,33].

The Kabul Basin, with an area of 72,843 km^2 is located in the eastern part of Afghanistan and is part of the Indus River Basin, which is common between Afghanistan and Pakistan. A part of this basin includes the Kabul and Kunar river basins, with an area of 53,832 km^2. Kabul Basin is the second largest basin in Afghanistan after the Amu Darya and is divided into 13 sub-basins: Upper Panjshir, Lower Panjshir, Ghorband, Central Kabul, Maidan, Logar, Laghman, Lower Kabul, Kunar, Parun, North, Khorram, and Gomel. The population living in this catchment area is estimated to be about 12.1 million in 2015 [33-35].

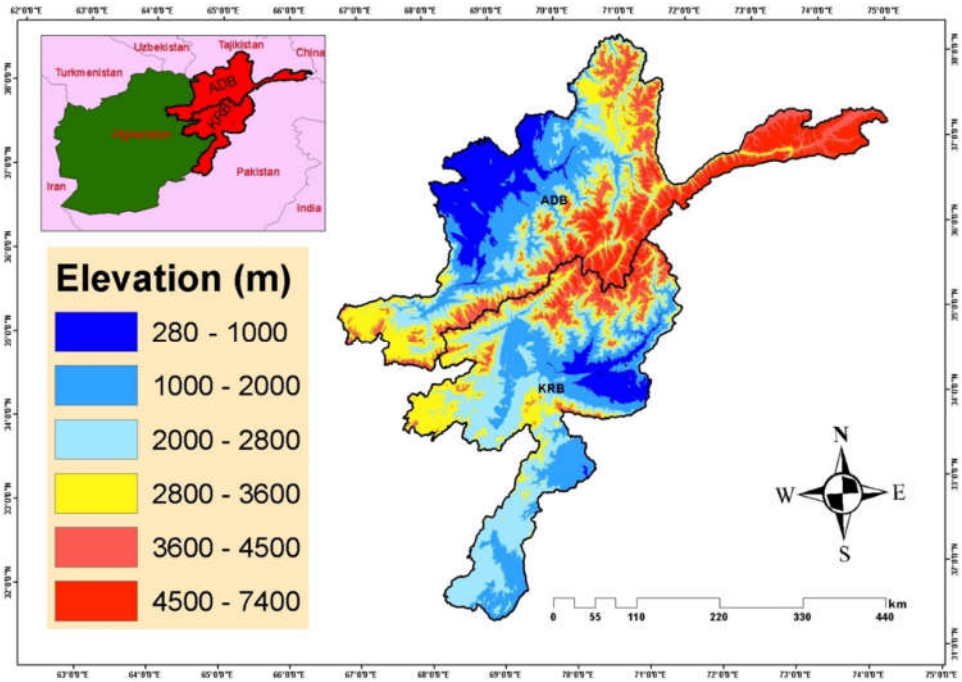

Figure 1. The elevation map presenting the study area.

2.2. Data

In the present study, the vegetation coverage variability for the eastern basins of Afghanistan was investigated for the period 2000-2021, and the impact of such factors as land surface temperature (LST), precipitation, soil moisture, and drought on vegetation coverage was assessed using regression methods. The summary of the sources of the remote sensing data used in this study is provided in Table 1, while the flowchart of data processing is presented in Figure 2. All satellite-born statistics of the surfaces belong to the bright days (hours) only.

Table 1. Remote sensing data used in this study.

No	Data	Source	Spatial resolution	Temporal resolution	File Format
1	Normalized Difference Vegetation Index (MOD13Q1)	MODIS packages in GEE	250 m	16 days	Geo tif
2	MODIS Land Surface Temperature (MOD11A2)	MODIS packages in GEE	1 km	8 days	Geo tif
3	Global Precipitation Measurement (GPM)	GPM packages in GEE	0.1° arc degree	30 minutes	Geo tif
4	Global Land Data Assimilation System (GLDAS) soil moisture (in soil layer of 0–10 cm)	GLDAS packages in GEE	1°	3 hours	NC file

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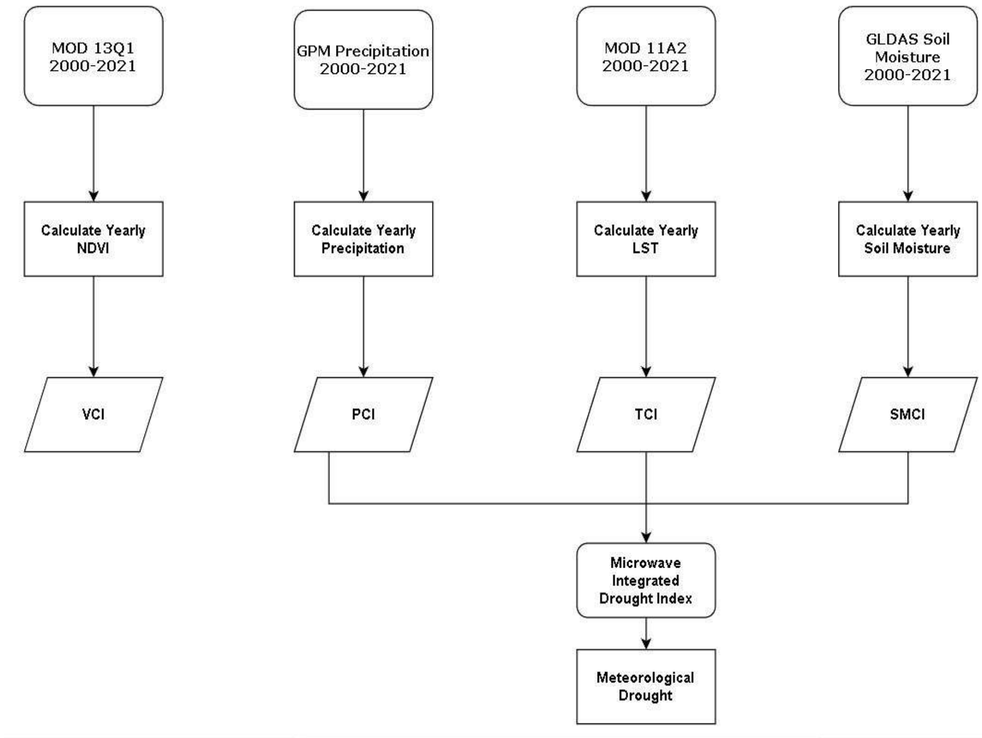

Figure 2. Flowchart of the data processing.

2.2.1. Normalized Difference Vegetation Index (NDVI) data

The Normalized Difference Vegetation Index (NDVI) is one of the most important and widely used vegetation indicators and its application in satellite assessment for global vegetation monitoring has been well proven in the two last decades [36-38]. It is commonly used as a detector of surrounding greenness areas and in epidemiological studies to investigate the health effects of green space in urban environments [39]. The NDVI is the index that is less affected by factors such as topography and brightness than other vegetation indices and it indicates the level of photosynthetic activity of the vegetation [40,41]:

$$NDVI = \frac{Rnir-Rred}{Rnir+Rred}, \quad (1)$$

where *Rred* and *Rnir* represent surface reflectance averaged over visible (RED) ($\lambda \sim 0.65$ µm) and near-infrared (NIR) ($\lambda \sim 0.85$ µm) regions of the spectrum [15,42]. The range of NDVI values is between -1 and 1, with the vegetation having NDVI between 0.2-1.0, while the values lesser than 0.2 indicate areas without vegetation cover, usually barren, or with rock, snow, water, or ice [27,43,44].

In this study, the time-series of the NDVI 16-Day L3 Global 250 m from MOD13Q1 MODIS product [45] for a period from January 2000 to December 2021 (22 years, 528 images in total) have been downloaded using the Google Earth Engine (GEE) platform. The data was converted to the spatial resolution of 1 km using the bicubic method.

To obtain the yearly values of the NDVI the data were averaged as:

$$\text{Yearly NDVI} = \frac{\sum_{i=1}^{23} \text{NDVI}_i}{23}, \quad (2)$$

where *i* is consecutively numbering the timely ordered images from a specific year. Based on the NDVI, vegetation coverage was calculated as the area with any type of vegetation by summation of the number of the pixels with NDVI > 0.2 and multiplying their number by the area of one pixel.

2.2.2. Land Surface Temperature (LST) data

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In the study, the time-series of the LSTDay-8Day-1km from MOD11A2 MODIS product with a spatial resolution of 1 km and temporal resolution of 8 days data was used. The data from 2000 to 2021 (22 years, 1056 images in total) were downloaded using the Google Earth Engine (GEE) platform and then averaged to yearly values using:

$$\text{Yearly LST}=\frac{\sum_{i=1}^{46}\text{LST}_i}{46}, \quad (3)$$

2.2.3. Precipitation data

The precipitation was derived from the Global Precipitation Measurement (GPM) product. It is an international satellite mission to provide next-generation observations of precipitation and snow worldwide every three hours [46]. The GPM data were obtained using the Google Earth Engine (GEE) platform and then averaged to yearly values.

2.2.4. Soil moisture data

The purpose of the Global Land Data Assimilation System (GLDAS) was to employ a source of data for the assessment of the environmental and food security in developing countries, such as Afghanistan, that do not have access to terrestrial data [47,48]. The overall goal of the GLDAS model was to drive multiple offline LSMs and integrate large amounts of observation-based data, to be implemented globally with high resolution. GLDAS offers a product with a spatial resolution of 0.25° and 1° and a temporal resolution of 3 hourly. The data is available from January 1948 up to the present [49]. In this study, the Global Land Data Assimilation System (GLDAS) data was used to obtain information on the soil moisture from a depth of 0-10 cm. To match the same spatial resolution as for the other data, the bicubic method has been used to re-sample the soil moisture data to a 1km grid. The GLDAS dataset was accessed using the GEE.

2.3. Methods

2.3.1. Vegetation Condition Index (VCI)

Since 2014, Kenya's National Drought Management Authority (NDMA) uses the vegetation condition index (VCI) as the basis for providing disaster contingency funds to counties in drought conditions [50]. VCI is a normalized pixel-based NDVI to separate long-term ecosystem changes from short-term climate-related NDVI fluctuations and to reflect relative changes in vegetation conditions from very poor to optimal [51,52]. VCI compares the current time vegetation with the minimum long-term NDVI and shows how close the current time step is to the long-term minimum NDVI, taking into account the difference between the maximum (indicating the best conditions of vegetative growth) and minimum values (indicating the worst conditions of vegetative growth), which reflect somehow the conditions of the local vegetation [53]. The range of VCI is between 0 and 1, with smaller VCI values indicating worse vegetation growth conditions and, at the same time, higher degrees of drought. Based on the literature regarding aridity classification standards, VCI lower than 0.5 indicates drought conditions [54, 55]. VCI is defined as:

$$\text{VCI} = \frac{\text{NDVI}_\text{i} - \text{NDVI}_\text{min}}{\text{NDVI}_\text{max} - \text{NDVI}_\text{min}} \quad (4)$$

where 'min' and 'max' are multiyear maximum and minimum, respectively, and 'i' denotes the current time step.

2.3.2. Temperature Condition Index (TCI)

The Temperature Condition Index (TCI) is one of the indicators of drought, which assumes that the occurrence of drought phenomenon reduces soil moisture and creates thermal stress on the surface of the earth, which results in the monthly LST in the year of drought greater than for the same month in normal years [52]. It is calculated as:

$$\text{TCI} = \frac{\text{LST}_\text{i} - \text{LST}_\text{min}}{\text{LST}_\text{max} - \text{LST}_\text{min}} \quad (5)$$

where 'min' and 'max' are multiyear maximum and minimum, respectively, and 'i' denotes the current time step.

2.3.3. Precipitation Condition Index (PCI)

Precipitation Condition Index (PCI) was used to evaluate the variation of precipitation and drought conditions from GPM DATA [56,57]. It is defined as:

$$\mathrm{PCI} = \frac{\mathrm{P_i} - \mathrm{P_{min}}}{\mathrm{P_{max}} - \mathrm{P_{min}}} \tag{6}$$

where 'min' and 'max' are multiyear maximum and minimum, respectively, and 'i' denotes the current time step.

2.3.4. Soil Moisture Condition Index (SMCI)

Soil moisture data (GLDAS) was used to drive the soil moisture condition index (SMCI) as:

$$\mathrm{SMCI} = \frac{\mathrm{SM_i} - \mathrm{SM_{min}}}{\mathrm{SM_{max}} - \mathrm{SM_{min}}} \tag{7}$$

where 'min' and 'max' are multiyear maximum and minimum, respectively, and 'i' denotes the current time step.

2.3.5. Microwave Integrated Drought Index (MIDI)

Microwave Integrated Drought Index (MIDI) integrates the PCI, TCI, and SMCI indices with flexible weights α, β, and γ:

$$MIDI = \alpha PCI + \beta \mathrm{SMCI} + \gamma \mathrm{TCI} \tag{8}$$

where $\alpha+\beta+\gamma=1$. In this study, based on the literature recommendations, in which the best correlation with the short-term SPI was obtained [58,59], weights $\alpha=0.5$, $\beta=0.3$, and $\gamma=0.2$ were used. The range of MIDI values is between 0 and 1, where the value between 0 to 0.1 indicates extreme drought conditions, the value in the range from 0.11 to 0.2 indicates severe drought conditions, from 0.21 to 0.3 - moderate drought conditions, from 0.31 to 0.4 - low drought conditions and from 0.41 to 1.0 indicates that area under consideration is not experiencing drought.

2.3.6. Z-score calculation

Z-score, also known as the standardized anomaly, informs how large the deviations of the quantity under consideration are. The Z-score is calculated using the formula [60]:

$$\mathrm{Zij} = \frac{\mathrm{Xij} - \mathrm{U}}{\sigma \mathrm{ij}}, \tag{9}$$

where i represents the assessed period and j stands for the time scale, Xij is an analyzed parameter in a given year, U represents the mean value for the analyzed statistical period, whereas σij indicates the standard deviation. Positive values of the standardized anomaly indicate that the values under consideration are larger than the mean, the negative values of the standardized anomaly indicate that the values are smaller than the mean, and the values >|2| indicate that the result is abnormal [61].

3. Results

3.1. Analysis of VC variations

Figure 3 shows the average intra-year vegetation coverage of the eastern basins in Afghanistan throughout the study period. The VC had a slightly decreasing trend from the first of January (~12% of study area covered in vegetation, 19,662 km^2) until the 2 February (~11% of study area covered in vegetation, 18,063 km^2). From 2 February to 25 March vegetation coverage increased from ~2% to 46% of the study area (75,635 km^2). Then, from 25 March, it decreased from 46% to 13% of the study area on 19 December (about 20679 km^2). The vegetation cover increase was very high from 25 March to 26 June, same as the

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decrease from 26 June to 17 November, whereas between 17 November and 19 December, it was relatively slow. From the above results, we can conclude that the peak of VC in the eastern basins of Afghanistan is observed in May and June.

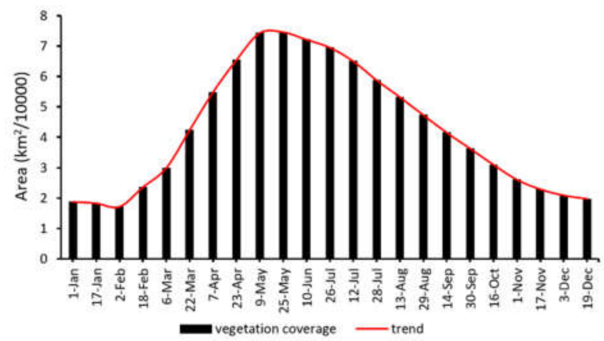

Figure 3. The average intra-year vegetation coverage of the eastern basins in Afghanistan during 2000-2021.

Figure 4 presents the relationship between annual vegetation coverage and the annual mean of the area affected by drought conditions for the eastern basins of Afghanistan during the studied period (2000-2021). The annual mean of the area affected by drought conditions was calculated using the percentage range value of the VCI index. If the value was between 0 and 50% it indicated that the area (pixel) under consideration had bad vegetation growth conditions and was affected by drought conditions (DAV), whereas values from 50.1 to 100% indicated good vegetation growth conditions, and that the area was not affected by drought conditions (NDAV). It is worth mentioning here that DAV can take larger values than VC because for the calculation of the area the values of NDVI < 0.2 (barren land, rocks, buildup areas) are also taken into account. The maximum VC was observed for 2005, 2010, 2013, 2016 and 2020 (70%, 71%, 71%, 72% and 72 % of the study area, with 113,894, 116,570, 116,718, 117,821 and 118,389 km^2, respectively), while for 2000, 2001, and 2008 the minimum VC was recorded (56, 56, and 55% of the study area, with 91,747, 91,847, and 90,576 km^2, respectively). The maximum DAV was observed in 2000 and 2001 (87 and 89% of the study area, 142,638 and 146,195 km^2, respectively), whereas the minimum DAV was recorded in 2010, 2012, and 2020 (81, 82, and 82% of the study area, with 133,221, 134,110, and 134016 km^2, respectively). The relationship between VC and DAV assessed with the use of the linear regression model was significant at the 95% confidence level (R=0.78, p-value<0.05).

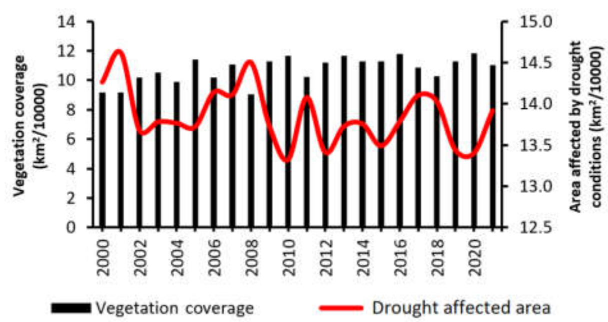

Figure 4. The average annual vegetation coverage (black bars) and average annual area affected by drought conditions (red line) of the eastern basins in Afghanistan during 2000-2021.

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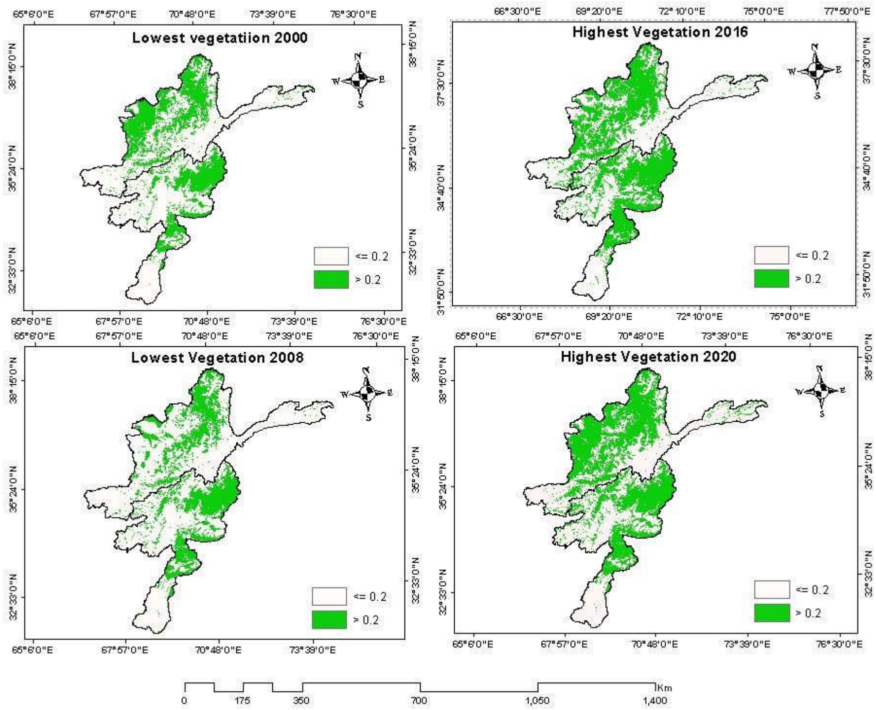

Figure 5. The maps of annual means of NDVI for the eastern basins of Afghanistan for the years with the lowest (2000 and 2008) and the highest (2016 and 2020) vegetation coverage from the studied period (2000-2021).

Figure 5 shows the maps of vegetation coverage in the eastern basins of Afghanistan Afghanistan for the years with the lowest (2000 and 2008) and the highest (2016 and 2020) vegetation coverage. Better vegetated areas were observed in the northern and northeastern areas of ADB and the eastern and southeastern areas of the KRB, whereas in the eastern, southeastern, and southwestern areas of the ADB, and the western and southwestern areas of the KRB vegetation occupied a much smaller area.

3.2. Annual variations of MIDI

In Figure 6 the maps of the spatial variations of MIDI in the eastern basins of Afghanistan are presented separately for each year from the studied period (2000-2021), whereas in Figure 7 the same information is aggregated into a column plot for better comparison of temporal changes. In 2000, which can be recognized as the year affected by extreme and severe drought to the highest degree among the years analyzed, most of the studied area (32%, 51,968 km^2) was affected by severe drought conditions. Severe drought affected most of the southwestern and western areas of the KRB, and the northwestern and western areas of the ADB in the Kunduz sub-basin, while the extreme drought conditions were affecting some parts of the KRB in the Gomal sub-basin only (~1% of the study area, 1218 km^2). For most of the central and northeastern areas of these two basins (20% of the study area, 34,121 km^2), no drought conditions were observed. In 2001, most of the southwest and west areas of KBR, and northwest of ADB were affected by moderate drought (33% of the study area, 54,596 km^2). In 2002, areas without drought, mild drought, and moderate drought almost have the same size (27, 29, and 29% of the studied area, 44,778, 48,098, and 47,449 km^2, respectively), and severe drought had affected very few areas of the southwest KRB (6% of the study area, 9829 km^2). In 2003, most of the central areas had no drought conditions (39% of the study area, 63,928 km^2), however, some areas in the southwest of KRB and the northeast of the ADB had been affected by moderate drought (26% of the study area, 42,272 km^2).

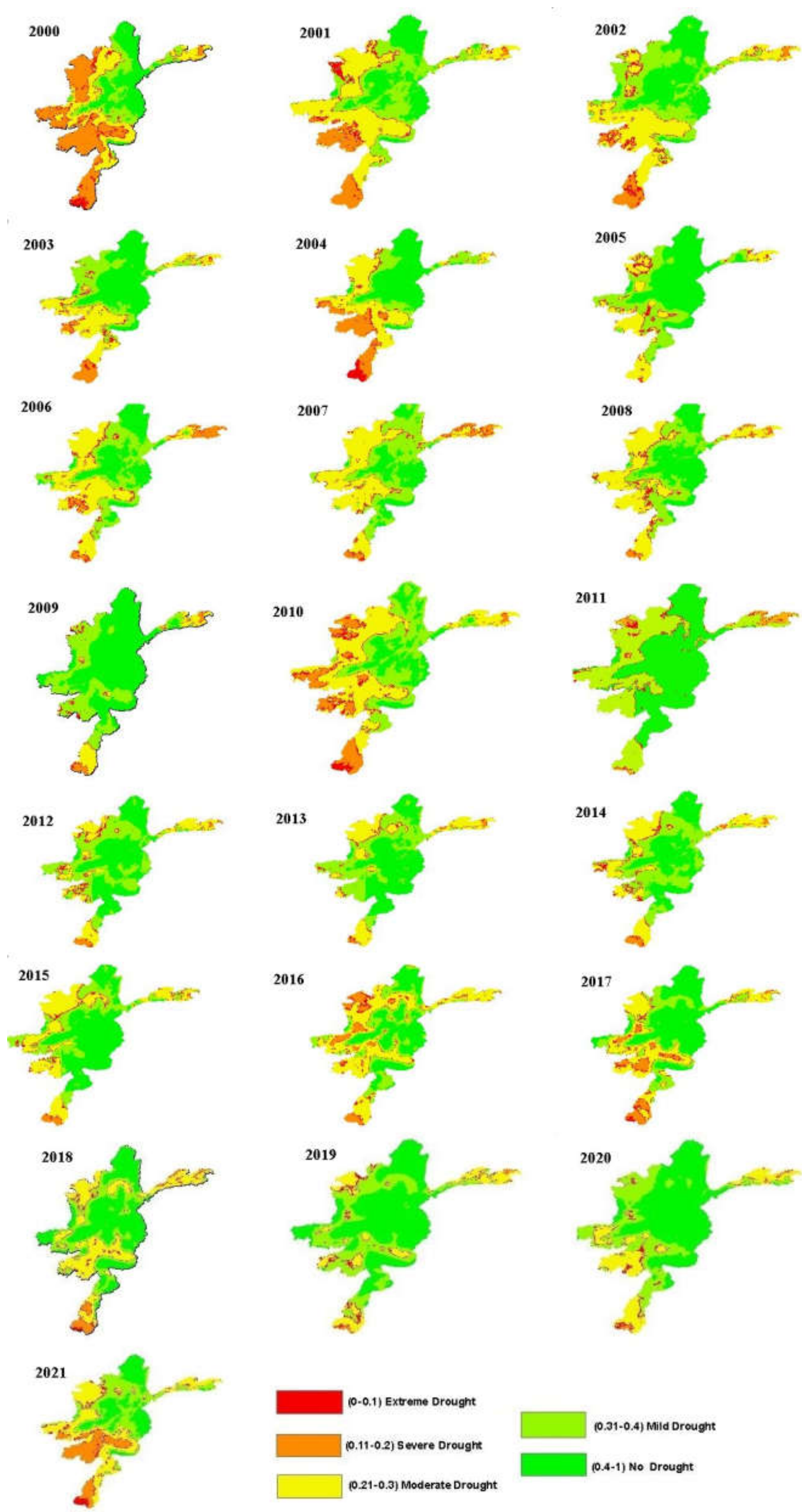

Figure 6. The maps of the spatial variations of meteorological drought expressed by the annual Microwave Integrated Drought Index in the eastern basins of Afghanistan for each year from the study period (2000-2021).

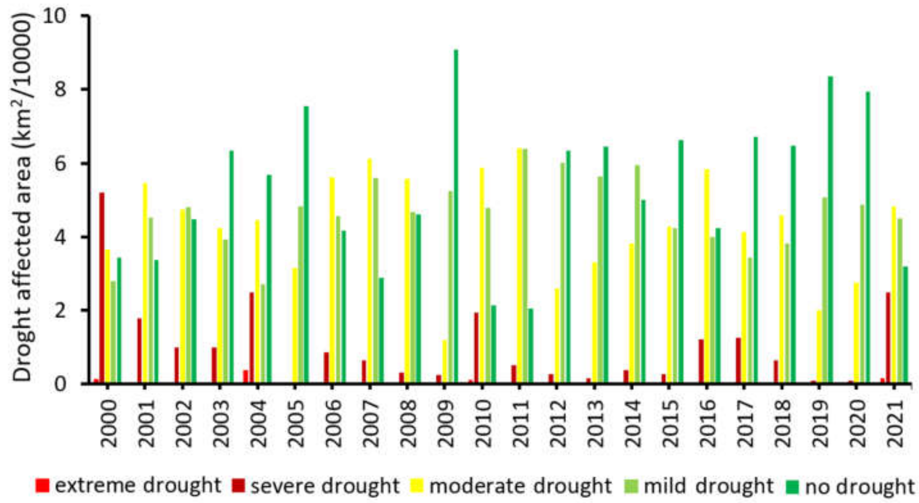

Figure 7. The temporal variations of meteorological drought expressed by the annual Microwave Integrated Drought Index in the eastern basins of Afghanistan during 2000-2021.

In 2004, most of the northern, northeastern, and central areas of the basins experienced no droughts conditions (35% of the study area, 56,889 km^2), in turn, the southwest areas of the KRB had been affected by severe drought (15% of the study area, 24,850 km^2). 2009 was one of the years least affected by the effects of extreme, severe, and moderate drought conditions from the studied period, and also had the highest area that hadn't experienced drought (55% of the study area, 90,785 km^2). Only some areas in the northeast and northwest of the ADB and the southwest of the KRB had been affected by mild, moderate, and severe drought (32, 7, and 2% of the study area, 52,499, 11,948, and 2474 km^2, respectively). In 2011, most of the central northeast, and southeast areas of the basin were under mild drought conditions (39% of the study area, 63,939 km^2), and the northwest areas of the ADB and the southwest areas of the KRB were under moderate drought (39% of the study area, 64,043 km^2). In 2016, most of the northwestern and southwestern areas of the study area and some southern areas of the ADB were affected by moderate drought (35% of the study area, 57,937 km^2), and most of the central and southwestern areas of the study area hadn't experienced drought (25% of the study area, 42,253 km^2). 2019 and 2020 were the second and the third year of the studied period with the highest area that hadn't experienced drought. In 2019, 51% of the study area (83,682 km^2) was under no drought conditions, except for some areas in the southwest of the KRB and the east of the ADB, which were affected by mild and moderate drought (12% and 40% of the study area, 20,650 and 65,654 km^2, respectively). In 2020 only some areas in the southwest of the KRB and the south of the ADB were affected by mild and moderate drought (30% and 17% of the study area, 48,654 and 27,409 km^2, respectively), while 48% of the study area (79,342 km2) was without drought conditions. From the temporal changes of meteorological drought in the eastern Basin of Afghanistan during the study period shown in Figure 7, it results that the areas affected by extreme, severe, and moderate droughts had a downward trend, whereas the trends for the areas affected by mild drought, and with no drought conditions were upwards.

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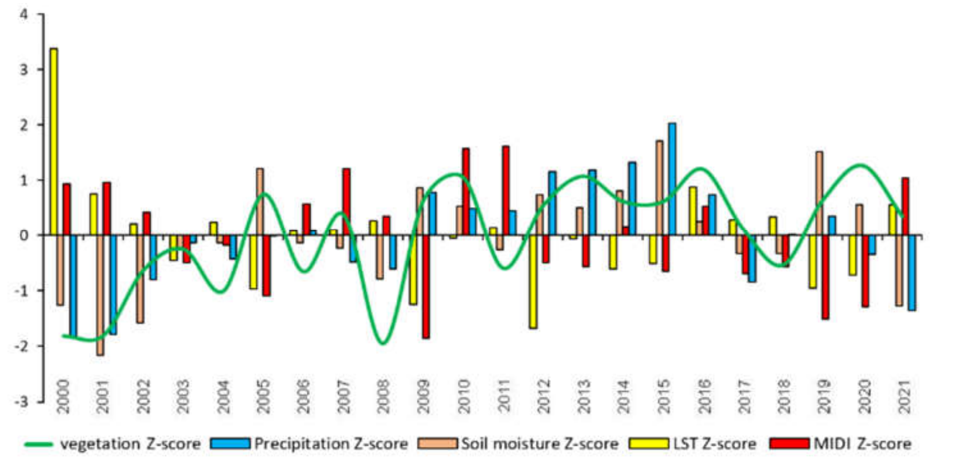

Figure 8. The annual anomalies of vegetation coverage, precipitation, soil moisture, LST, and MIDI for the eastern basins of Afghanistan during 2000-2021.

3.3. Correlation of VC with other variables

Figure 8 shows the annual anomalies of VC, precipitation, soil moisture, LST, and MIDI for the eastern basins of Afghanistan during 2000-2021. 2000, 2001, 2016, 2017, 2018, and 2021 were the years with the highest LST (22.3, 18.6, 18.8, 18, 18, and 18.4°C on average, respectively) during the study period. In turn, 2012, 2019, and 2020 had the lowest LSTs (15.2, 16.2, 16.6°C, respectively). 2009, 2012, 2013, 2014, and 215 had the highest precipitation (525, 569, 574, 590, and 675 mm, respectively) during the study period, whereas 2000, 2001, 2017, and 2021 had the lowest precipitation (211, 217, 330 and 269 mm, respectively). For 2005, 2009, 2012, 2015, and 2019 the highest soil moisture was recorded (23, 22, 24, and 23.4 m^3m^{-3}, respectively) during the study period, and conversely, for 2001, 2002, 2008, and 2021 the lowest soil moisture was observed (17, 18, 19.4 and 18.6 m^3m^{-3}, respectively). 2000, 2001, 2004 and 2008 had the lowest vegetation coverage (91,747, 91,847, 98,750, and 90,576 km^2, respectively), while 2005, 2010, 2013, 2016 and 2020 were the greenest years with the highest vegetation coverage (113,894, 116,570, 116,718, and 118840 km^2, respectively). Meteorological drought conditions calculated with the use of MIDI indicated that in 2000, 2001, 2010, 2011, and 2021 the most area had been affected by meteorological drought (133,049, 133,554, 145,906, 146,870, and 135,398 km^2, respectively). In turn, in 2005, 2009, 2019 and 2020 the smallest area was affected by drought (91,950, 76,475, 83,511, and 87,939 km^2, respectively). In 2005, precipitation was close to the normal value (precipitation Z-score was close to 0), LST and MIDI were below normal value, but the soil moisture and vegetation cover were above the normal value. Almost the same can be observed for 2020, in which the precipitation, MIDI, and LST were below the normal value, but the soil moisture and vegetation coverage were above the normal value. It strongly suggests that soil moisture was one of the key parameters controlling the LST and had the highest impact on the variations in the vegetation coverage. The decrease in the annual mean LST for the eastern basins of Afghanistan in the studied period was -0.06°C, while an increase in the annual mean precipitation was 6.9 mm yearly. Annual mean soil moisture also had an increasing trend, whereas the area with meteorological drought had a decreasing trend during the study period.

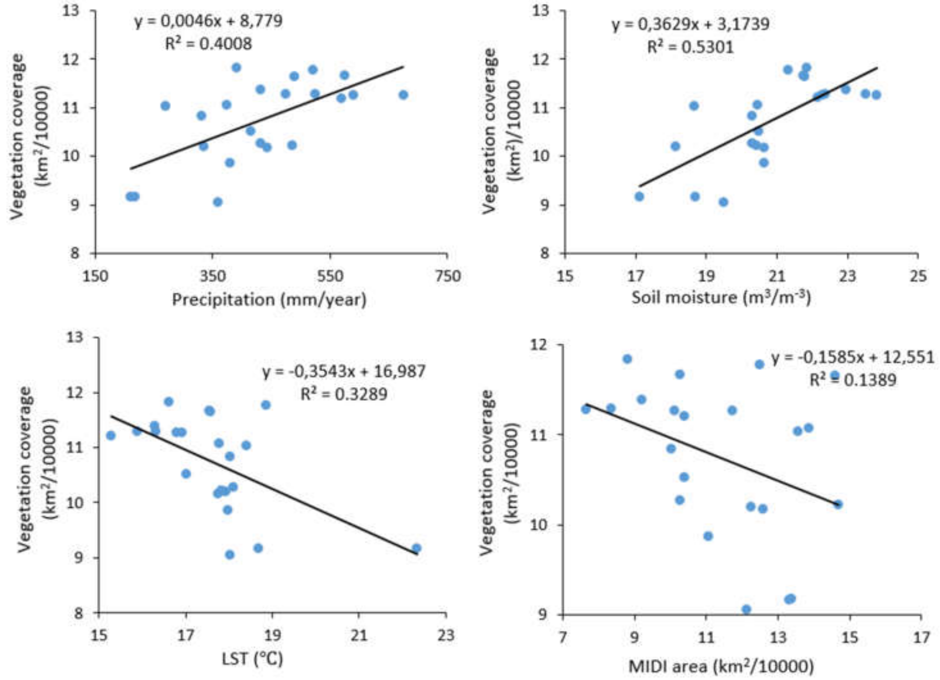

Figure 9. The scatter plots of the time series presenting the relationships between vegetation coverage and precipitation, soil moisture, LST, and MIDI for the eastern basins of Afghanistan during 2000-2021.

Figure 9 and Table 2 show the relationship between the annual mean of the vegetation cover and assessed meteorological parameters, such as precipitation, soil moisture, drought-affected area calculated on the base of MIDI (MIDI area), and LST for the studied period. A positive relationship was observed for VC and precipitation, and VC and soil moisture, whereas a negative relationship was seen for VC and LST, and VC and MIDI area. It was found that the relationships between VC and precipitation, VC and soil moisture, and VC and LST were significant (R=0.64, p=0.008; R=0.73, p=0.0004; and R=0.57, p=0.04, respectively), whereas the relationship between VC and MIDI area was not significant (R=0.36, p=0.126) at the 95% confidence level.

Table 2. The correlation (*R*) and determination (R^2) coefficients and *p*-value for relationships between annual vegetation coverage and precipitation, soil moisture, LST, and MIDI for the eastern basins of Afghanistan during 2000-2021 calculated using the linear regression method.

	R	R^2	*p*-value
Vegetation coverage – Precipitation	0.64*	0.41	0.008
Vegetation coverage – Soil moisture	0.73*	0.53	0.0004
Vegetation coverage – LST	0.57*	0.33	0.04
Vegetation coverage – MIDI area	0.36	0.13	0.126

* denotes that the correlation was significant (*p*-value = 0.05).

Table 3. The yearly multiple regression relationships between vegetation coverage, precipitation, soil moisture (SM), and LST for the eastern basins of Afghanistan during 2000-2021.

Model of vegetation coverage	R (regression coefficient)	R^2 (determination coefficient)	Multiple regression equations
yearly	0.74	0.45	$VC_{yearly} = 5.17 - 0.00029 \cdot Precipitation_{yearly} + 0.352 \cdot SM_{yearly} - 0.137 \cdot LST_{yearly} + 0.066 \cdot MIDI_{yearly}$

For the variations of VC, the multiple regression equations taking into account the relationships between VC, precipitation, soil moisture, LST, and MIDI area for the eastern basins of Afghanistan during 2000-2021 were calculated for the yearly values (Table 3). These equations allow estimating the projected value of VC. The obtained multiple regression and determination coefficients indicate that precipitation, soil moisture, and LST explained about 45% of the yearly VC variations.

4. Discussion

While Afghanistan's natural ecosystems have already been destroyed during the country's many years of civil wars, unsustainable management, and over-exploitation, literature reports indicate that Afghanistan will face a wide range of new and increased climate risks. The worst adverse effects of climate change on Afghanistan are related to drought, including these leading to desertification and land degradation. Drought is estimated to be the norm by 2030, not a periodic event [62]. Currently, Afghanistan is facing significant drought issues that have a direct impact on livelihoods and the economy. The drought that occurred in 2011 has pushed millions of people into food insecurity and poverty [63]. Although few studies have determined the impact of drought events, there is still a need to assess its impact on various aspects, like vegetation coverage dynamic, especially for longer periods.

In this study, the relationship between vegetation coverage dynamic and meteorological parameters (precipitation, soil moisture, and LST) and meteorological drought conditions was assessed for the eastern basins of Afghanistan for the period 2000-2021. Despite the climate changes that are occurring in Afghanistan [27], the average annual vegetation coverage increased in the eastern basins of Afghanistan in the study period. A significant increase in VC from 2000 to 2003 was observed, after that, from 2005 to 2008, a slight decrease happened. 2008 had the minimum VC (55% of the study area), and since 2009, VC had increased (except for 2011) since 2016. Although a decreasing trend was observed from 2016 until 2018, after that, from 2018 to the end of the assessed period, there was a slight upward trend in the vegetation coverage. A strong and significant correlation between the annual mean of VC and the area affected by drought conditions expressed with the use of VCI (VCI =< 50%, R=0.78, p=0.000014) was found. Obtained results were in line with other research made for the whole Afghanistan territory [27], in which it was found that the vegetation coverage was increasing in the period 2001-2018. The authors found that the correlation between NDVI and VCI was high, whereas the correlation between NDVI and LST was low. Additionally, it was stated that in 2000 and 2008 the lowest vegetation coverage was observed, while in 2010 and 2016 the highest vegetation coverage was recorded.

In general, the area with meteorological drought conditions (MIDI =< 0.4) had a decreasing trend in the study period. The area decreased from 2000 to 2005, and then it increased from 2005 to 2007. Similarly, from 2010 to 2020 a downward trend was observed for the area with meteorological drought conditions. The areas under extreme, severe, and moderate meteorological drought were decreasing, while the area with mild drought conditions was increasing during the study period. Most areas were affected by moderate and mild droughts. These results were in line with the other research made for the Kabul river basin [64], in which it was stated that 2000 and 2004 were the years with the worst

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meteorological drought conditions from the period from 2000 to 2018 and that the trend of meteorological drought changes in KRB was downward. During the studied period most of the northwest, southwest and some eastern areas of the eastern basins in Afghanistan had been influenced by drought. The highest value of the area under meteorological drought was observed in 2000, 2001, 2007, 2010, 2011, and 2021 (81, 82, 85, 90, and 83% of the study area affected by drought, respectively).

Observed variations in annual VC were related to the changes in meteorological parameters. For example, in 2000 and 2021 annual VC was below normal value, simultaneously with annual precipitation, and soil moisture, whereas LST was above the normal value. In 2015 and 2019, annual VC was above normal value, simultaneously with annual precipitation, and soil moisture, whereas annual LST was below the normal value. Obtained results indicated that the correlation between VC and precipitation was positive and significant (R=0.64, p=0.008), and the total annual precipitation had an upward trend during the study period. The correlation between VC and soil moisture was positive and significant (R=0.73, p=0.0004), and the annual mean soil moisture had an upward trend during the study period. The correlation between VC and LST was also positive and significant (R=0.57, p=0.04), and the annual mean LST was decreasing during the study period. The correlation between VC and metrological drought was not significant (R=0.36, p=0.126) at a 95% confidence level. Obtained results are somewhat in line with the other research made for Kabul River Basin in Afghanistan [65], in which the vegetation coverage dynamics and its relation to atmospheric patterns were investigated. It was found that the vegetation dynamics in KRB was impacted by both precipitation and LST, however, the magnitude of this impact depended on the season. During the winter LST had a greater impact on VC variation than precipitation, and conversely, in summer, precipitation impacted vegetation to a higher degree than LST. In another study, the vegetation dynamics and its relationship with climatological factors for Caspian Sea watersheds in Iran was analyzed [66]. It was found that the correlations of vegetation coverage with ET and LST in winter were positive and significant (R = 0.46 and 0.55, p-value = 0.05, respectively), while the correlation with the precipitation was not significant. In the spring, the correlation between VC and precipitation was positive and significant (R = 0.55, p-value = 0.05), but the impact of LST on the vegetation coverage was negligible when the precipitation was abnormally high. In the summer, the correlation between VC and LST was negative and significant (R = –0.45, p-value = 0.05).

5. Conclusions

In the present study, the impact of meteorological parameters and meteorological drought on the vegetation coverage in the eastern basins of Afghanistan has been investigated using remote sensing data. It was found that soil moisture had a high impact on VC, and the LST impacted VC to the slightest extent from the studied meteorological parameters. The relationship between VC and the area under meteorological drought was insignificant. The correlations between VC and precipitation, soil moisture, and LST were positive and significant (R=0.64, p=0.008, R=0.73, p=0.0004, R=0.57, p=0.04, respectively). It was revealed that precipitation, soil moisture, LST, and area under meteorological drought conditions explained about 45% of the yearly VC variation in the eastern basins of Afghanistan.

The results of this research indicated that the changes in the vegetation coverage in the eastern basins of Afghanistan during 2000-2021 had an upward trend. VC increased slightly from 2000 to 2005 and decreased slightly from 2005 to 2008, with 2008 being the year with the least vegetation during the studied period. From 2008 to 2021, VC generally increased, however, a slight downward trend was observed between 2016 and 2018. Annual mean LST had a downward trend, whereas total annual precipitation had an upward trend during the study period. In most parts of Afghanistan, the vegetation depends on the winter rain, however, in the south winter rains are often irregular. Rainfall increases to the north and east resulting in better vegetation conditions in these parts. The eastern parts additionally receive some monsoon rains in summer [67]. Annual mean soil moisture had an upward trend, and the areas under extreme, severe, and moderate meteorological drought conditions were declining during the studied period. In turn, the areas with mild meteorological drought conditions had an upward trend in the study period.

Author Contributions: A.F.N. and I.R. proposed the topic. A.F.N., I.R., M.D., and H.O. commanded the data processing and analysis. A.F.N., I.R., M.D., H.O., A.S., and J.K. wrote the manuscript. J.K., A.S., P.T., and P.B. enhanced the research design, helped to analyze and interpret the results, and revised the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by Vedurfelagid, Rannis and Rannsoknastofa i vedurfraedi.

Acknowledgments: Iman Rousta is deeply grateful to his supervisor (Haraldur Olafsson, Professor of Atmospheric Sciences, Institute for Atmospheric Sciences-Weather and Climate, and Department of Physics, University of Iceland, and Icelandic Meteorological Office (IMO)), for his great support, kind guidance, and encouragement.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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