Proceedings of the Pakistan Academy of Sciences: A Physical and Computational Sciences 60(4): 13-28 (2023)

ISSN (Print): 2518-4245; ISSN (Online): 2518-4253
https://doi.org/10.53560/PPASA(60-4)824

Pakistan Academy of Sciences

Research Article

Monitoring Drought Events and Vegetation Conditions in Pakistan: Implications for Drought Management and Food Security

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Abstract: Drought is an environmental and humanitarian concern, affecting various regions and landscapes with detrimental impacts on the natural environment and human lives. It is crucial to have access to accurate and timely information on vegetation conditions to mitigate its effects, which is possible through remote sensing techniques. The Google Earth Engine (GEE) platform offers powerful tools and a vast collection of geospatial data that can improve drought monitoring efforts. In Pakistan, a country prone to droughts and natural disasters, this study employs GEE to monitor drought events over croplands and determine their severity using indices such as Vegetation Health Index (VHI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI). Additionally, the study generates mean yearly and monthly VHI maps, allowing for the observation of trends in drought occurrences over time. Analysis of yearly and monthly mean VHI maps reveals that in 2001 and 2002, the Pakistan cropland experienced severe to moderate drought. From 2011 to 2021, overall drought occurrences were relatively low, and the annual VHI reflected healthy vegetation conditions. The study emphasizes the adequacy of vegetation in 2019, 2020, and 2021. Notably, agricultural areas in Punjab demonstrate sufficient soil moisture and healthy vegetation, while in Sindh, cropland is predominantly affected by severe to moderate drought, characterized by a continuous deficiency of soil moisture. Temporal variations highlight an increasing trend in VHI, indicating a promising outlook for healthy vegetation in Pakistan's cropland. This study provides valuable information for drought management, planning, water resource management, food production, and food security.

Keywords: Drought, Remote Sensing, Google Earth Engine, Normalized Difference Vegetation Index, Vegetation Health Index, Food Production and Food Security.

1. INTRODUCTION

Drought is a creeping disaster that processes with accumulative effects and is particularly a slow occurrence phenomenon according to time durations such as months or weeks [1]. Since the 1970s, a global drying trend has been observed, affecting numerous regions, particularly in high northern latitudes [2, 3]. Drought is usually monitored through the vegetation indices derived from satellite images. The "index" determination is a process of developing "value added" information connected to drought with the help of current and past knowledge [4, 5]. Indices, which are drought indicators, are obtained to measure drought and its severity. Drought indices provide more information instead of comparing current and past situations and identifying water scarcity related to a drought period and intensity [6]. Zhao *et al.* [7] assessed drought conditions by rebuilding the Land Surface Temperature (LST) using the Annual Temperature Cycle (ATC) model and drought indices (TCI, VCI, VH, and Temperature-Vegetation Drought Index (TVDI)). Khan and Arsalan [8] assessed drought conditions using Normalized Difference Vegetation Index (NDVI) and found that NDVI is positively

Received: May 2023; Accepted: December 2023
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correlated with rainfall and soil moisture. Whereas, Kogan [9] used NDVI to derive another index called VCI. Particularly, VCI identifies the spatio-temporal deviations of vegetation situations related to stress due to precipitation shortage. Zambrano *et al.* [10], Kamble *et al.* [11], and Bento *et al.* [12] assessed drought using VCI and compared it with SPI (Standardized Precipitation Index); the result showed a good correlation between VCI and SPI. LST is used to derive TCI and various studies used TCI with VCI for drought monitoring [13]. The composite of TCI and VCI gives VHI, a widely used drought index for drought monitoring applications. Tabassum *et al.* [14] assessed the drought condition in an arid region of Pakistan using VCI, TCI, and Temperature Vegetation Index (TVX). TVX, the ratio of LST and NDVI, provides more spectral information for drought monitoring because it is derived from both reflective and thermal bands [15]. TVX is also used to extract soil moisture [16]. Masitoh and Rusydi [17] and Ma'Rufah *et al.* [18] used VHI to characterize vegetation health.

ArcGIS is a famous software for handling spatial and temporal data, and all of the above studies used it [10-14]. After the popularity of cloud computing, spatiotemporal data processing with downloading is easily possible on the GEE Platform. GEE with cloud computing remote sensing application is an appropriate platform to detect a region with a large amount of data [19]. GEE performs planetary-scale geospatial analysis with the massive computational ability to identify various challenging socio-economic issues like deforestation, drought, hazards, food insecurity, water supply and distribution, climate monitoring, and conservation of the environment [20]. GEE collectively can investigate environmental conditions, agriculture, soil, water, and various climate variables and map observable changes, trends, and variations [20, 21]. Wang *et al.* [22] used GEE for monitoring the long-term surface water changes of lakes [22]. Thilagaraj *et al.* [23] developed the system through the GEE platform that effectively monitors drought events in different time durations using the remote sensing indices such as LST, VCI, NDVI, TCI, and VHI. Many research studies considered the GEE in agricultural mapped and monitor, and used different drought indices for drought conditions [19]. Drought assessment needs long-duration data with good coverage of condition. GEE can fulfill this requirement and provides global coverage with a bulk amount of geospatial data.

Food security and rural development depend on the agriculture sector's continued expansion. The agriculture sector in Pakistan contributes the most to the country's GDP about 22.7 % and it employs approximately 37.4% of the labor force [24]. In the current period of April-October 2023, it is estimated that approximately 10.52 million rural people in Pakistan, accounting for 29 percent of the analyzed 36.7 million rural population, are in IPC Phase 3 (Crisis) and IPC Phase 4 (Emergency) [25]. This population has been impacted by a number of shocks, including drought, livestock diseases, high food prices, and the COVID-19 pandemic's effects [26]. The country's arid and semi-arid regions suffer the most from the effects of drought, which include crop failure and decreased food production [27-29]. A comprehensive drought assessment for agricultural land is required to lessen these effects and increase food security.

Many studies have assessed the drought condition in Pakistan [15]. Ullah et al. [27] used in-situ observations and drought indices (SPI and SPEI) and reanalysis results to evaluate Pakistan's meteorological drought characteristics. Ali et al. [30] observed that the temporal rainfall evaluation in Pakistan indicates an average reducing trend at the country and provisional levels. The identified lowering rainfall should strengthen the probability of droughts, thereby affecting the agricultural region [30]. Ahmed et al. [29] predicted that rising temperatures caused by global warming would exacerbate the intensity and frequency of droughts in Pakistan. Jamro, et al. [28] monitored the spatio-temporal variability of drought in Pakistan and found that the droughts of 1920 and 2000, which affected all zones and persisted for over ten months in three, can be considered as among the most severe dry spells in Pakistan's history. Khan et al. [31] used machine learning for drought prediction with the help of SPEI. Pasha et al. [32] examined the reason for Sindh Drought in 2014 and concluded that it was a famine-like situation brought on by a prolonged lack of precipitation in the Thar Desert. With a large amount of geospatial data and global coverage, GEE can meet this requirement. Khan et al. [33] employed the GEE platform, incorporating diverse drought indices such as SPEI, SPI, VCI,

Table 1. List of the GEE Dataset with Product Name, Temporal Resolution, Spatial Resolution and, Time Duration

Products Name	Data Type	Spatial Resolution	Temporal Resolution	Time Duration
MOD13Q1	NDVI	250m	16-days	2001-2021
MOD11A2	LST	1km	8-days	2001-2021
GFSAD1000	Land-cover	1km		

TCI, PCI (Precipitation Condition Index), and SMCI (Soil Moisture Condition Index), to evaluate drought conditions in the non-irrigated region of Potohar plateau, Punjab, Pakistan. Notably, there is a shortage of studies utilizing GEE for drought monitoring, particularly in Pakistan's croplands. Effective drought monitoring is crucial for adequately preparing Pakistani communities to cope with the repercussions of droughts on food security. The cultivated area observation helps to monitor the crop condition, which will ultimately help in securing food security for Pakistan. By viewing this gap, this study aims to monitor vegetation conditions, particularly in the Cropland of Pakistan, with the help of drought indices like VCI, TCI, and VHI using the MODIS dataset on the GEE platform. Further, a time series analysis has been done to observe the trend of vegetation health conditions.

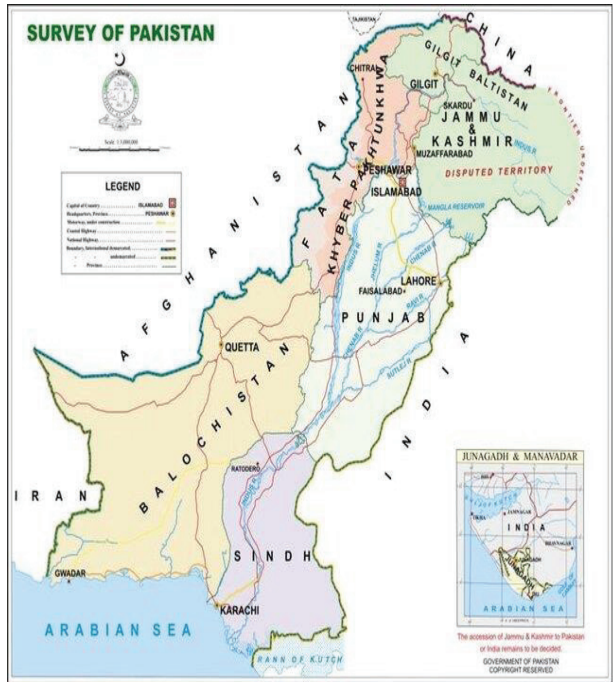

Fig. 1. Pakistan Map (Source: Survey of Pakistan (2015).

2. MATERIALS AND METHODS

2.1. Study Area

Pakistan (latitudes 30.3753°'N and longitudes 69.3451°E), located in South Asia covers an area of 881,913 km^2 (Figure 1). The country experiences four distinct seasons based on temperature because it is in the northern hemisphere; winter that is cool and dry (December to February), a hot and dry spring (March to May), a hot and humid summer (June to August), and a dry fall (Sept. to Nov.) [34]. Pakistan experiences two monsoon seasons; the Indian monsoon (July–Sep) and the western disturbance (Dec-Mar). Pakistan has a population of around 160 million people, with 32% living below the poverty line, and faces significant challenges [34]. Due to diverse topography and altitudes, the country's climate can be characterized as continental with tremendous diversity [34].

2.2. Datasets

GEE is a cloud-based computing web that provides several remotely sensed datasets and powerful geospatial processing capabilities. This paper utilized the GEE repository of freely available datasets. MODIS is an extensive program, and its datasets are extensively used for drought assessment and prediction [35]. Therefore, two MODIS products (LST, NDVI) were used in this study. The GFSAD (Global Food Security-support Analysis Data) is a High-resolution global cropland data provided by NASA, and it contributes to global food security in this era. The GFSAD1000 was used for extracting cropland of the study area. The type, spatial-temporal resolution, and time span of the data products are shown in Table 1.

2.3. Methodology

Drought assessment is crucial for four phases of hazard management (Preparedness, Response, Recovery, and Mitigation) [35]. In this regard, remotely sensed technology presents valuable geo-information as satellite images with spatiotemporal capability. It builds recurring and precise drought

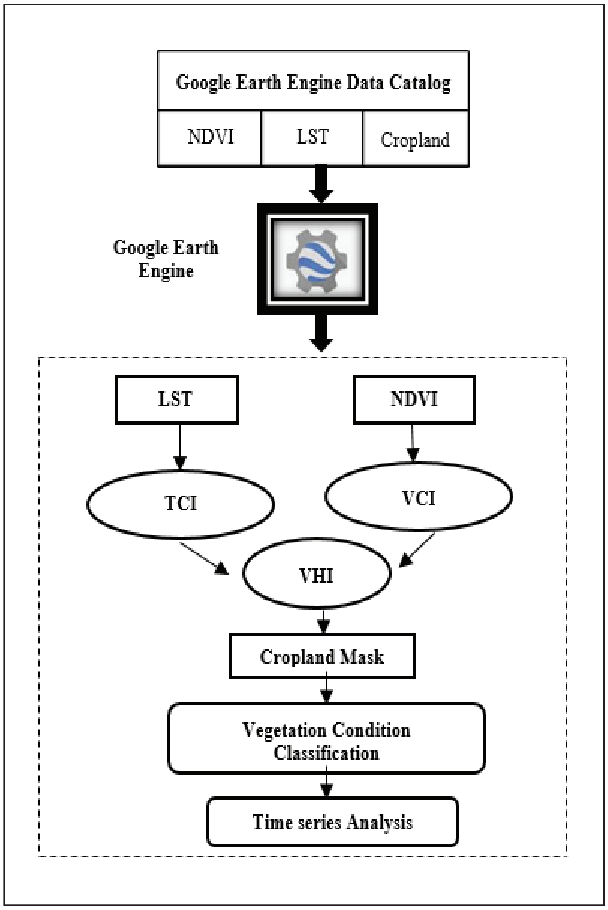

Fig. 2. Methodological Work that shows the GEE software system is utilized to determine the VCI, TCI, and VHI to observe drought conditions and Time-series Analysis.

event maps of particular regions at a specific time. The study presents spatiotemporal maps (mean monthly and yearly) for the Pakistan region spanning from 2001 to 2021, along with the yearly time series analysis and methodology depicted in Figure 1. Data for the study were collected and processed on the GEE platform. Monthly LST and NDVI from 2001 to 2021 were derived from MODIS data products. The High-Resolution Global Cropland Data (GFSAD) was utilized to apply a cropland mask to vegetated areas in Pakistan. LST and NDVI serve as inputs for calculating the indices VCI, TCI, and VHI. Applying a cropland mask provides the Vegetated areas of Pakistan. The yearly mean and monthly mean maps of VHI were produced from 2001 to 2021 to identify the drought severity, particularly in the cropland of Pakistan. Time series were also analyzed to deep monitor the trend of drought conditions over the period.

2.3.1 Satellite Based Drought Indices

The satellite-based drought indices were determined using remote sensing data products. Some of them are given below:

2.3.1.1 Normalized Difference Vegetation Index (NDVI)

NDVI is a well-known vegetation index to measure the development and the amount of vegetation and has a range from -1 to +1. For water bodies and clouds, the value of NDVI is negative; close to negative values represent the soil or build-up area, whereas equal and above 0.6 represents the healthy vegetation [36]. The near-infrared (NIR) and red bands are used to calculate NDVI. Consider that "ρ_{nir}" is the near-infrared band reflectance and "ρ_{red}" is the red band reflectance, then NDVI can be measured as shown in equation (1) [37].

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \quad (1)$$

2.3.1.2 Vegetation Condition Index (VCI)

VCI can effectively assess the drought condition by delineating the drought region for
the definite value of NDVI and VCI [38]. VCI can be computed using the following equation (2):

$$VCI = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100 \quad (2)$$

Where $NDVI_{max}$ and $NDVI_{min}$ are the maximum and minimum NDVI of each pixel determined monthly, and *i* is the current month's index.

The VCI measure in a percentage ranging from 1 to 100 and above 50% shows the normal condition of vegetation, whereas less than 50% indicates the drought condition [9]. VCI is a better identifier of vegetation response to precipitation impact because it is more sensitive to precipitation dynamics than NDVI [39]. The VCI classification is based on different drought conditions [9] and is shown in Table 2 [14].

2.3.1.3 Temperature Condition Index (TCI)

The satellite image thermal band is translated to brightness temperature (LST) and is used to

Table 2. Five *Criteria of Drought Conditions from No Drought to* **Extreme Drought** *for Different Indices (VCI, TCI, and VHI).*

Drought Condition	VCI (%)	TCI (%)	VHI (%)
Extreme Drought	1-10	1-10	1-10
Severe Drought	10-20	10-20	10-20
Moderate Drought	20-30	20-30	20-30
Mild Drought	30-40	30-40	30-40
No Drought	40>	40>	40>

develop the Temperature Condition Index (TCI). It is based on vegetative stress due to temperature and excessive wetness stress shown in equation (3) [40].

$$TCI = \frac{LST_{max} - LST_i}{LST_{max} - LST_{min}} \times 100 \quad (3)$$

Where, LST_i is the monthly brightness temperature, LST_{max} and LST_{min} represent the maximum and minimum brightness temperature over the total time duration respectively.

2.3.1.4 Vegetation Health Index (VHI)

VHI is one of the most extensively used remotely sensed drought indices [41, 42]. Many researchers used VHI in various applications like crop yield loss assessment, which is a crucial factor for food security [42]. The combination of VCI and TCI is used to assess the vegetation condition and is given in the equation (4):

$$VHI = \alpha VCI + (1 - \alpha)TCI \quad (4)$$

Where α is a weighted factor that is typically set as 0.5 [41, 42].

LST and NDVI are used to verify VHI values using correlation testing. VHI values can be classified according to their severity as shown in Table 2.

2.3.2 Time Series Analysis

2.3.2.1 Man-Kendall Test

The Man-Kendall test was used for the trend analysis of *VHI* in this research. The non-parametric Mann-Kendall test was developed by Mann [43] for trend detection, and Kendall [44] provided the test statistic distribution for testing non-linear trends and turning points [45]. Trends in hydro-meteorological time series have frequently been quantified using the Mann–Kendall statistical test [46]. The Mann–Kendall test statistic (Mann [43]; Kendall [44]) is calculated as:

$$S = \sum_{i=1}^{n-1} . \sum_{j=i+1}^{n} sgn(VHI_j - VHI_i) \quad (5)$$

A time series VHI_i which is ranked from $i = 1, 2,$ ...., n-1, and a time series VHI_j, which is ranked from $j = i + 1, 2,$ .... n, are used for the trend test. In order to compare each data point with the rest of the data points VHI_j, a reference point is used for each of them.

$$sgn\,(VHI_j - VHI_i) = \begin{cases} +1 & if\ VHI_j - VHI_i > 0 \\ 0 & if\ VHI_j - VHI_i = 0 \\ -1 & if\ VHI_j - VHI_i < 0 \end{cases} \quad (6)$$

It has been demonstrated that the statistic S has a distribution that is approximately normal with the mean when n > 8. E(S) = 0

The variance statistic is given as:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{p} t_i(t_i - 1)(2t_i + 5)}{18} \quad (7)$$

Where t_i is the number of ties up to sample *i*, and Z_S represents the test statistics.

$$Z_S = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} & if\ S < 0 \end{cases} \quad (8)$$

Here, Z_S has a normal distribution that is typical. A *Z* value that is either positive or negative indicates an upward or downward trend. A two-tailed test can also be used to test for either an upward or downward monotone trend using a significance level. The trend is deemed significant if Z_S appears greater than $Z_{\alpha/2}$ where α is the significance level.

2.3.2.2 Sen's Slope estimator Test:

The Sen's estimator predicts the magnitude of the trend. The slope *Ti* of the all data pairs is computed as:

$$Ti = \frac{VHI_j - VHI_k}{j-k} \quad (9)$$

for $i = 1,2, \ldots N$

where, VHI_j and VHI_k are the *VHI* values at time *j* and *k* $(j > k)$. The median of these N values of *Ti* is represented as Sen's estimator of slope which given as:

$$AVHI = \frac{VHI_i - VHI_{avg}}{VHI_{avg}} \quad (10)$$

Sen's estimator is calculated as $T_{N+1/2}$ if N appears odd, and it is regarded as $½(T_{N/2} + T_{(N+2)/2})$ if N appears even. The non-parametric test can then be used to determine a true slope after Q_{med} is calculated using a two-sided test with a confidence interval of 100 (1-α) %. The time series' upward or increasing trend is represented by a positive Q_{med} value, while the downward or decreasing trend is represented by a negative Q_{med} value.

2.3.2.3 Anomaly vegetation health index

Anomaly Vegetation Health Index *(*AVHI*)* is a measure of the variation in healthy vegetation compared to a long-term average. AVHI is estimated by deducting the long-term average value of VHI from the current value of VHI, and then dividing the result by the standard deviation of the long-term VHI [47, 48]. AVHI formula for estimation:

$$AVHI = \frac{VHI_i - VHI_{avg}}{VHI_{avg}} \quad (11)$$

Where, VHI_i is the vegetation health index during a particular time *i*. VHI_{avg} is the average VHI for the total time duration.

Positive values of AVHI indicate above-average vegetation health, while negative values suggest below-average vegetation health. The use of AVHI can help identify anomalies or deviations from the long-term average of vegetation health, which can be indicative of changes in vegetation conditions due to various factors such as drought, floods, or other environmental stressors. By tracking AVHI over time, it is possible to detect changes in vegetation health and monitor the impact of environmental factors on vegetation conditions the use of AVHI provides a useful tool for monitoring and assessing changes in vegetation health, which is important for various applications such as drought management, water resource planning, and food security.

3. RESULTS

This section summarizes and discusses the main findings of the work by observing the mean yearly and monthly spatial and temporal variations of VHI as well as its anomaly.

3.1 Mean Yearly and Monthly Spatial Variation of VHI

GEE platform extracted the study outcomes with the help of the two MODIS data products.

The yearly mean and monthly mean VHI maps were created from 2001 to 2021, as shown in Figure 3 and Figure 4, respectively. Two MODIS data products (LST and NDVI) help to estimate the vegetation indices TCI and VCI. The combination of TCI and VCI gives vegetation health indices, VHI, to monitor drought in cropland. The annual mean of VHI from 2001 to 2021 indicated mild to extreme drought conditions in Pakistan's vegetated areas, while the drought condition is highest in the Sindh region. In 2001 and 2002, VHI maps indicated severe drought in almost all over the study area. The vegetation conditions were healthy in 2019 and 2020.

The monthly mean maps were prepared from 2001 to 2021 and shown in Figure *5* (from January to June) and in Figure 6 (from July to December). Vegetation conditions were good in February, April, September, and October. In November, mostly cropland was affected by severe drought in the Northern parts of Pakistan. Moreover, some of the Punjab regions also showed moderate to severe drought. Most of the Sindh areas faced extreme drought conditions in July.

The affected area percentages during the study period indicate 2001 as the driest year, as shown in Figure 7. Extreme drought to moderate drought occurred during the dry years (57% in 2001, 49%

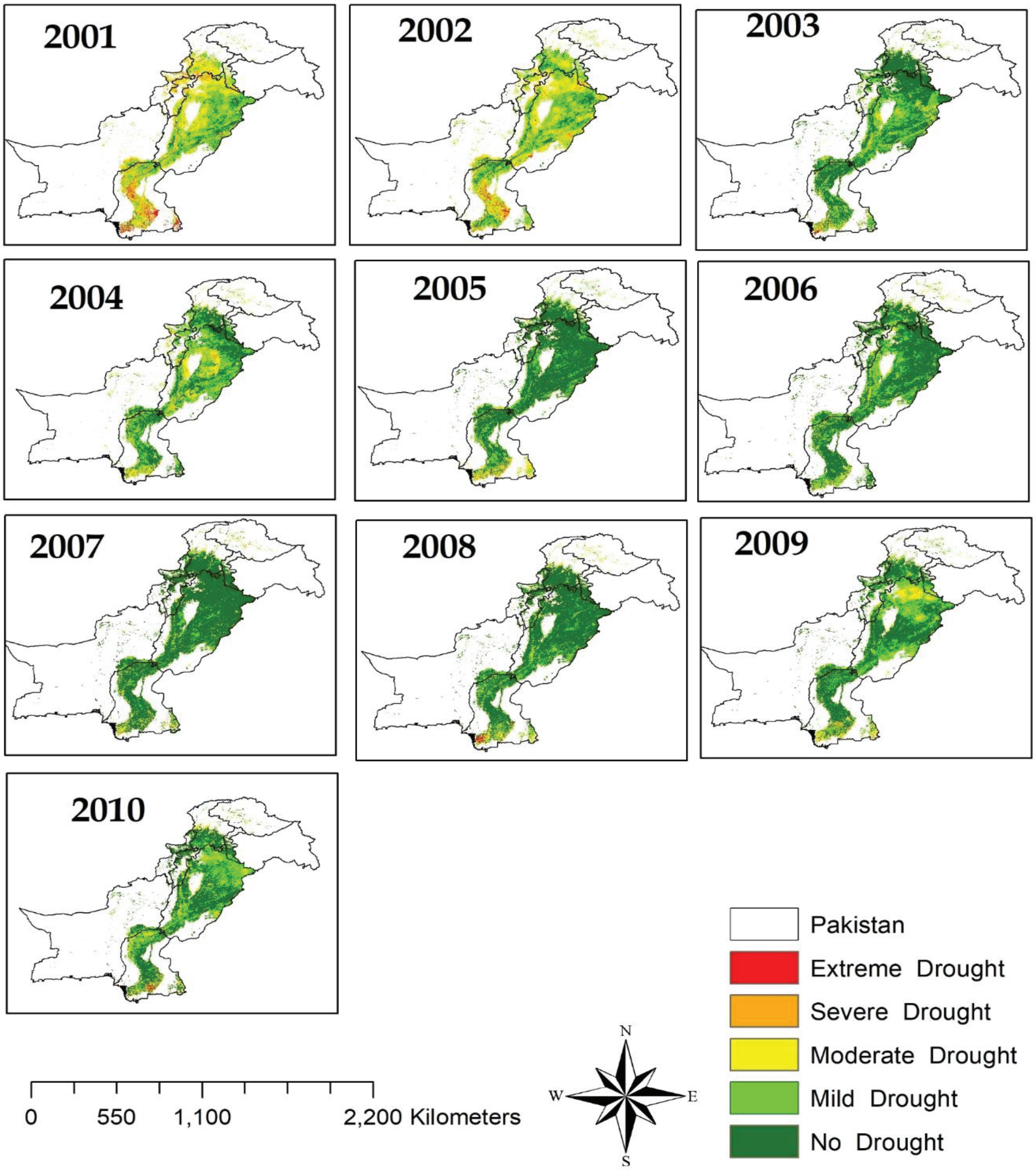

Fig. 3. Yearly mean VHI maps from 2001 to 2010 for five drought conditions: No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought.

in 2002, and 22% in 2004). In the next decade of the study period (2011 to 2021), large crop areas showed healthy vegetation with some droughts of about 5% to 12%. In contrast, during very humid years, the croplands were less affected by drought (about 6% in 2007, 5% in 2014, 2015, and 2021, and 4% in 2020). Thus, as a general feature, healthy vegetation observation from 2011 to 2021 was decreasing the drought effect in Pakistan, although only some regions have been severely affected (as shown in Figure 3 to Figure 7). The graphical representation (Figure 7) showed an annual mean value of VHI, and seasonal changes in VHI can alter these results.

3.2 Temporal Variation of VHI

The research utilized statistical techniques such as Mann-Kendall and Sen's Slope Estimator to determine the trend in VHI time series data. The

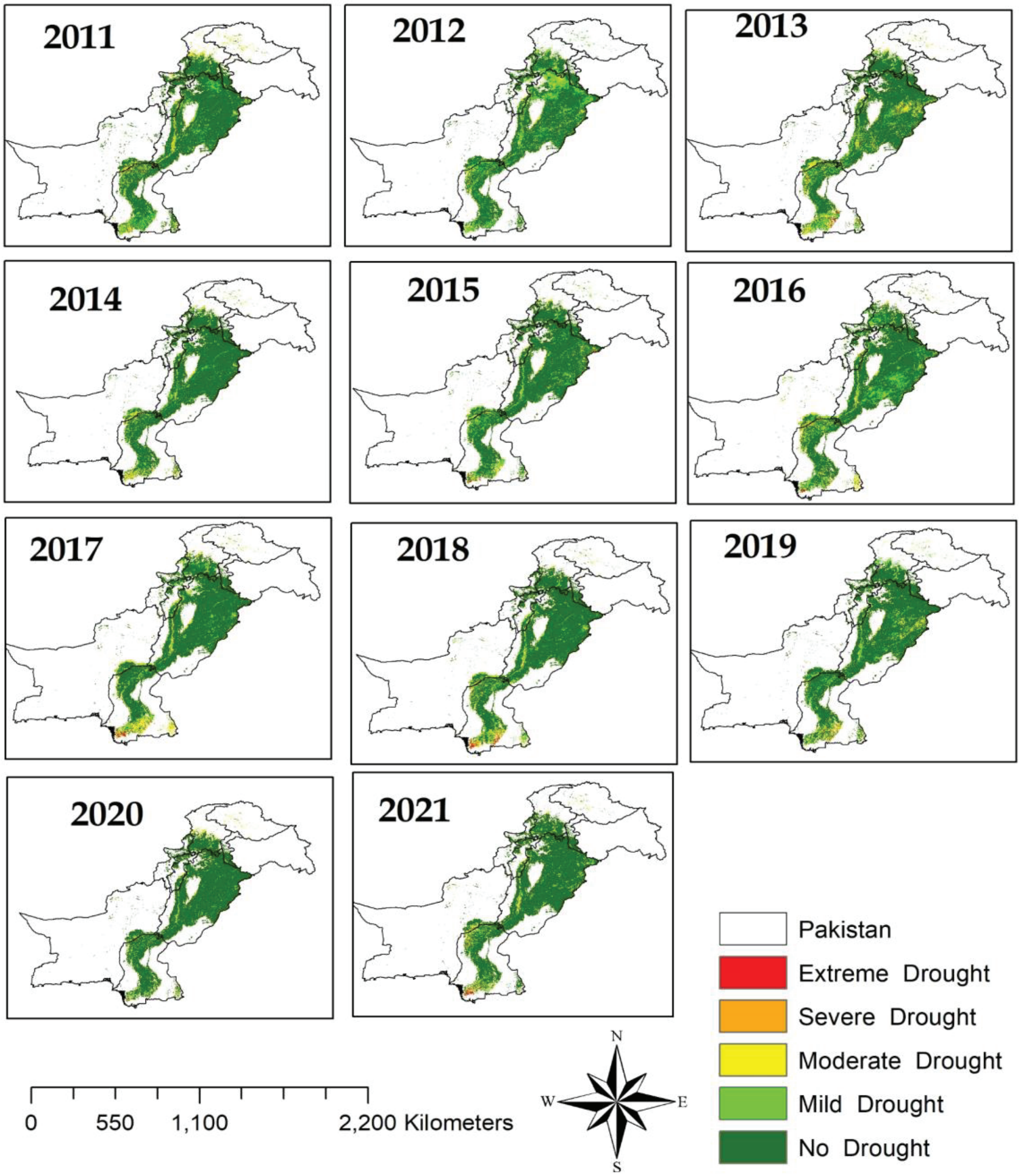

Fig. 4. Yearly mean VHI maps from 2011 to 2021 for five drought conditions: No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought

Table 3. Statistical Test Results that show Trend, Min, Max, P-value, Z value, Tau, Standard deviation, Variance, and Slope of the time series

Trend	Min	Max	Mean	P.Value	Zs	Tau	S	Var(S)	Slope
Increasing	20.53	57.98	43.1	0.006	2.74	0.4	92	1096.67	0.85

results indicated a positive trend in VHI, as shown by positive values of *Zs* (2.74) and a p-value of 0.006 (Table 3). The Sen's slope estimator was also used to calculate the annual mean trend increase in VHI, which was found to be 0.85 (Table 3), reflecting healthy vegetation. These findings were verified by the annual VHI time series data, as shown in Figure 8, and were attributed to adequate rainfall, as predicted by Ahmed, *et al.* [49].

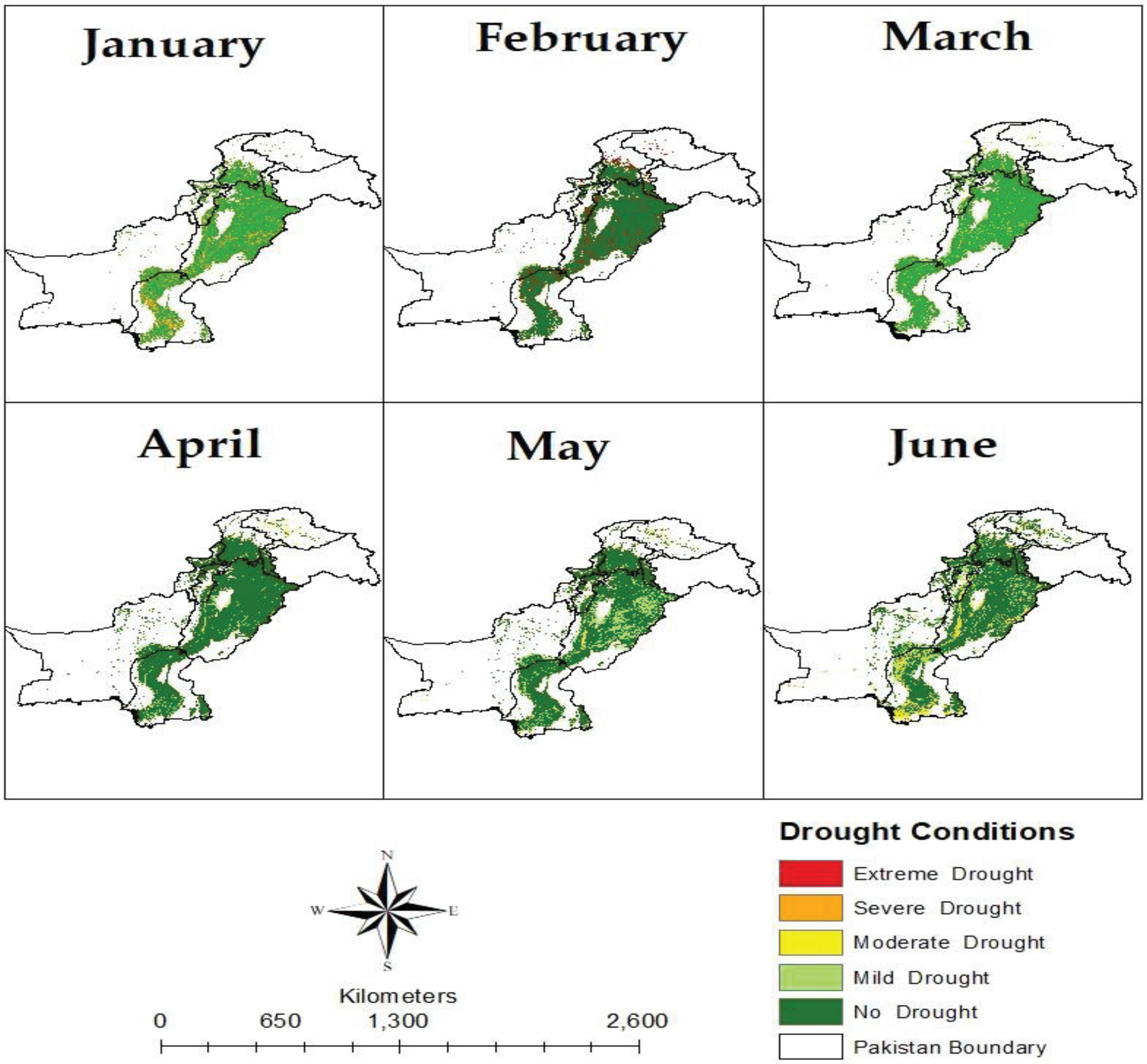

Fig. 5. Monthly mean VHI maps from January to June (2001-2021) for five drought conditions (No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought)

Overall, the use of statistical techniques employed in the present study provided important insights into the trend of vegetation health in Pakistan, highlighting the positive impact of sufficient rainfall on vegetation conditions. Figure 9 shows the VHI annual mean variations with the help of horizontal lines for three drought conditions (severe, moderate, and no drought). The threshold of severe drought indicates by the red line at 20%, moderate drought with the yellow line (20% to 30%), and healthy vegetation with the green line (above 30%). Figure 9 shows that severe drought was observed in 2001, while moderate in 2002 on the annual time scale. Moreover, crop conditions were healthy in 2007, 2011 to 2015, and 2019 to 2021.

3.3. Anomaly VHI

Anomaly Vegetation Health Index (AVHI) represents the soil moisture content efficiency and deficiency. The anomaly observations from 2001 to 2021 vary from -0.52 to 0.35, as shown in Figure 10. According to AVHI, the length of mild to extreme drought was eleven years (2001 to 2006, 2009 to 2010, and 2016 to 2018), and two years (2001 and 2002) were the driest years. Cropland Soil moisture content was satisfactory in 2007, between 2011 and 2015, and from 2019 to 2021. In the first decade (2001 to 2010), the study area faced a dry spell, whereas, in the next decade (20011 to 2121), vegetation condition was satisfied.

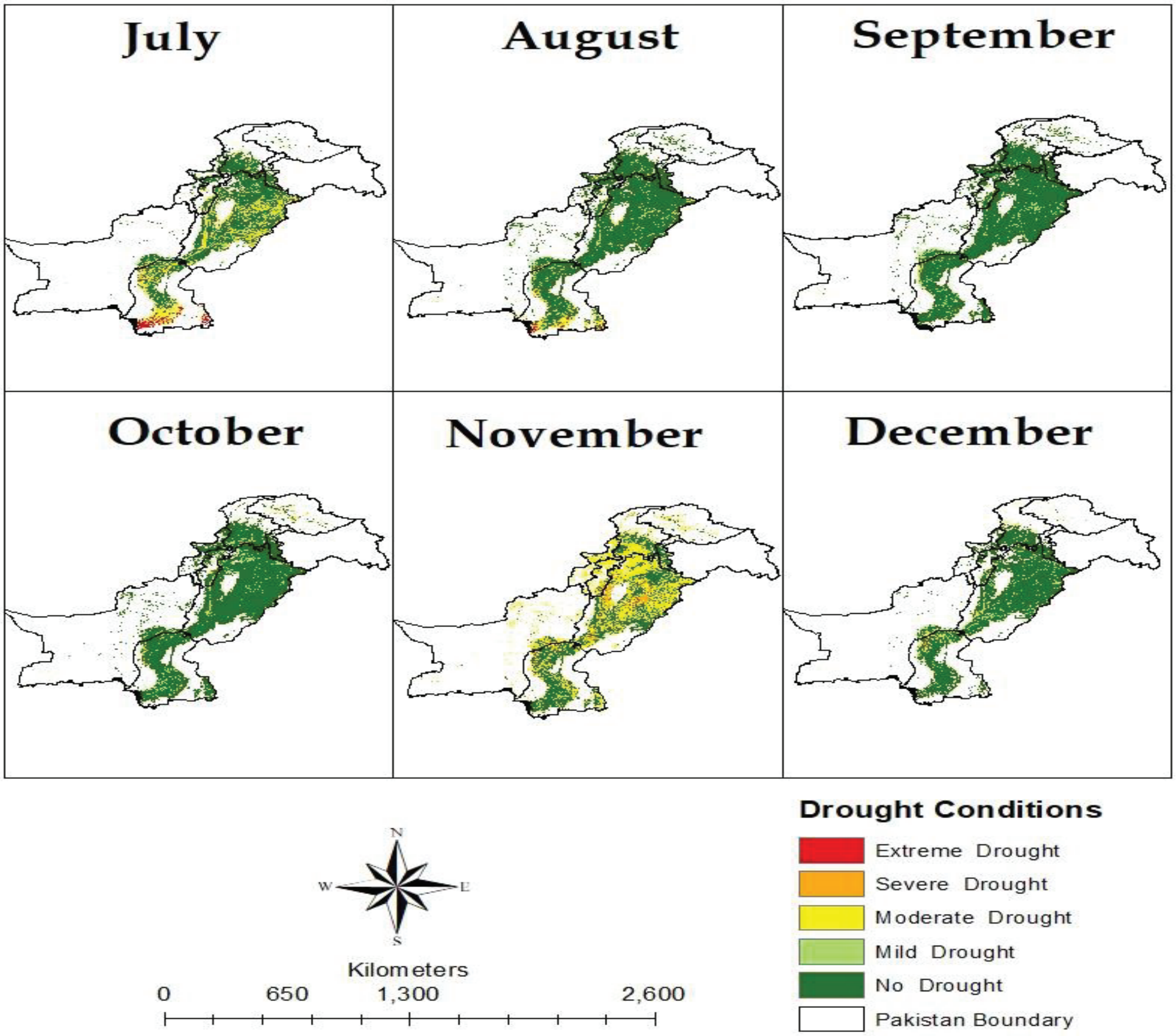

Fig. 6. Monthly mean VHI maps from July to December (2001-2021) for five drought conditions (No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought).

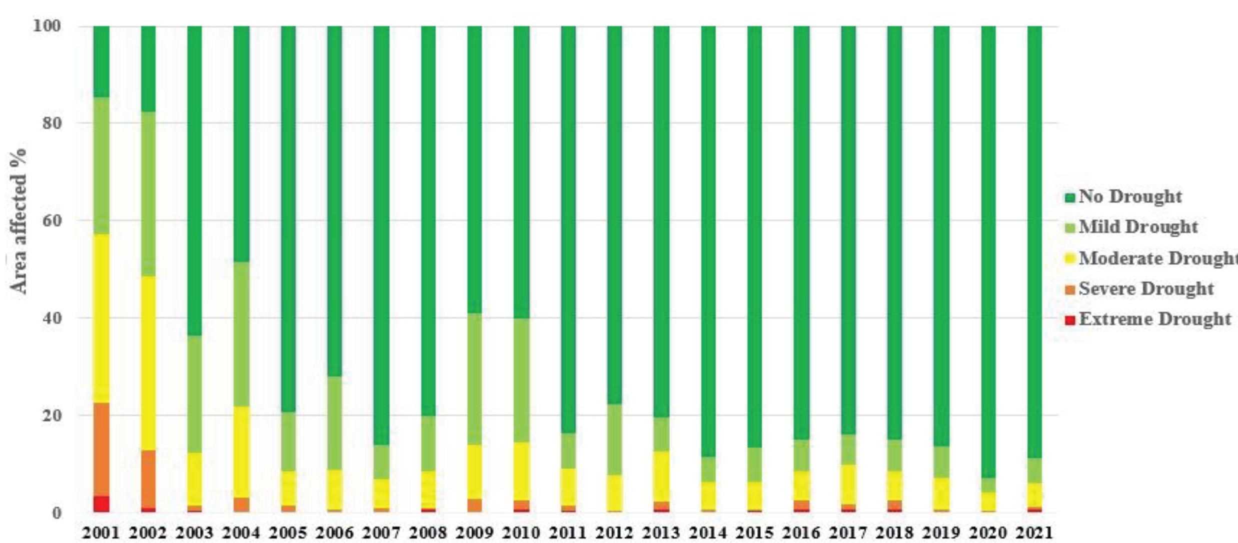

Fig. 7. The Cropland Area affected % due to drought from 2001 to 2021 for five drought conditions (No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought).

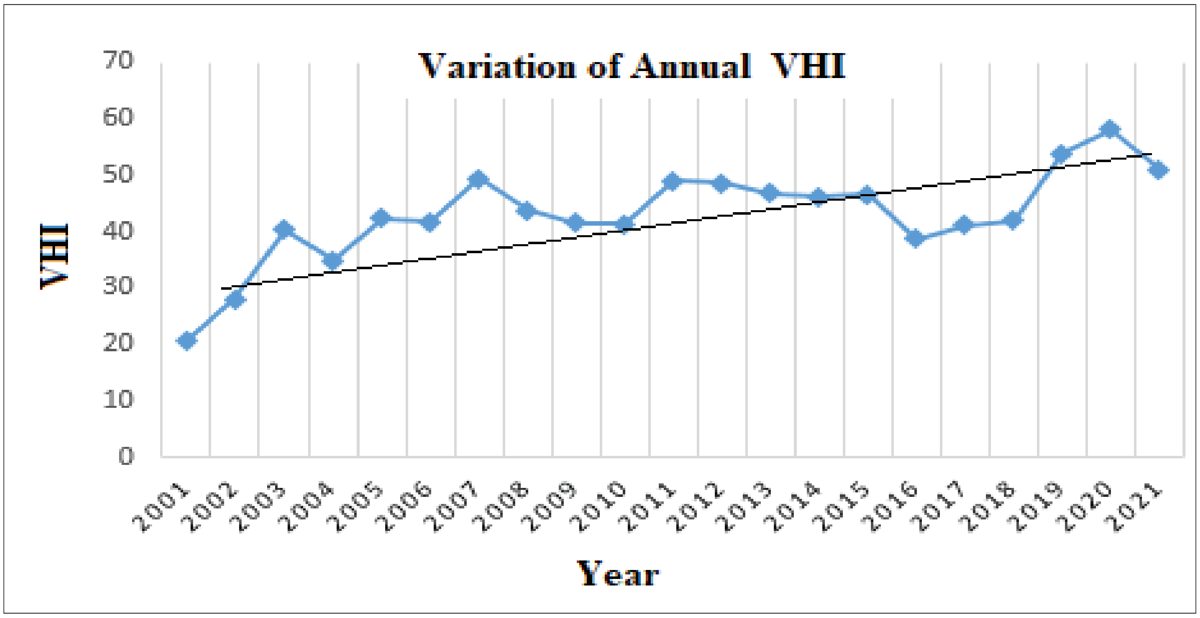

Fig. 8. Mean Annual VHI Variation from 2001 to 2021 with trend line.

By examining the multiannual mean VHI during the analyzed period (2001–2020), about 28 % of the arable land in Pakistan has suffered from mild to extreme drought. It can be seen in Figure 11 that about 14% of the arable land of the entire study area faced mild drought conditions, and 11% faced moderate drought. Collectively 3.5% area of the cropland bore extreme and severe drought.

4. DISCUSSION

The effects of climate warming, such as heat waves, droughts, and increases in salinity, pose a threat to global food security [50]. Pakistan is one of the ten worst-affected nations by climate change. Droughts, in particular, are expected to endure longer and be more severe as a result of climate change [28]. According to NDMC 's report [51], the drought conditions will undoubtedly ensnare the vulnerable regions of Pakistan if subsequent seasons fail to produce significant precipitation. Major droughts have occurred in all of Pakistan's provinces in the past [51]. The effects of drought, which include crop failure and decreased food production, are most severe in the arid and semi-arid regions of the country [27, 28]. According to the Food and Agriculture Organization of the United Nations (FAO), Pakistan is one of the countries, most likely

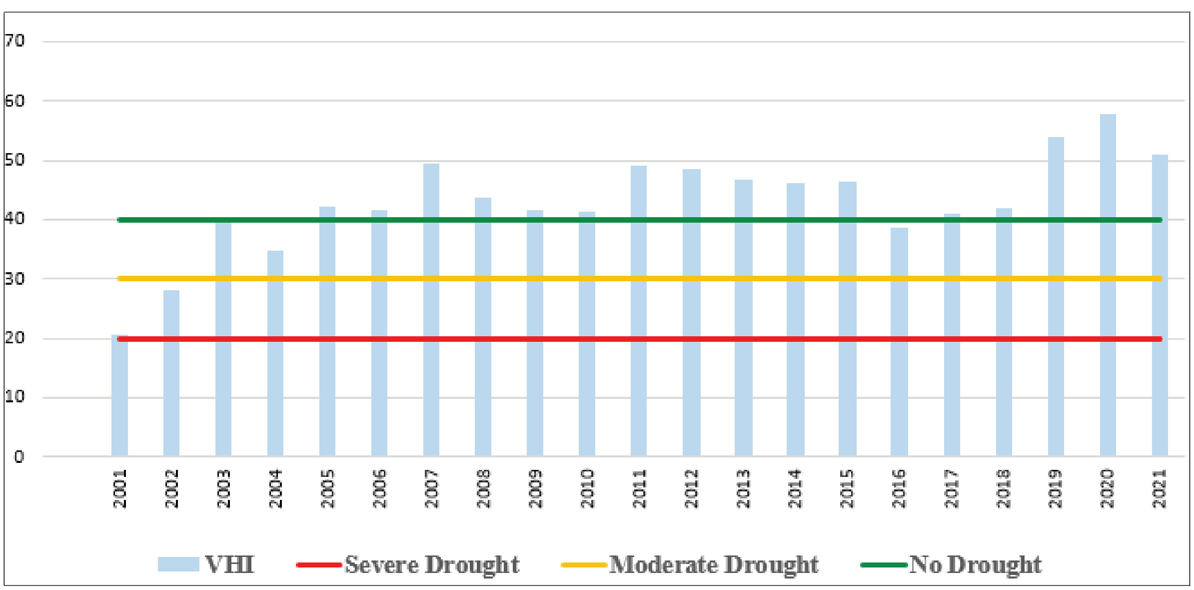

Fig. 9. Temporal variations in VHI from 2001 to 2021 for three drought conditions (No Drought, Moderate Drought, and extreme drought)

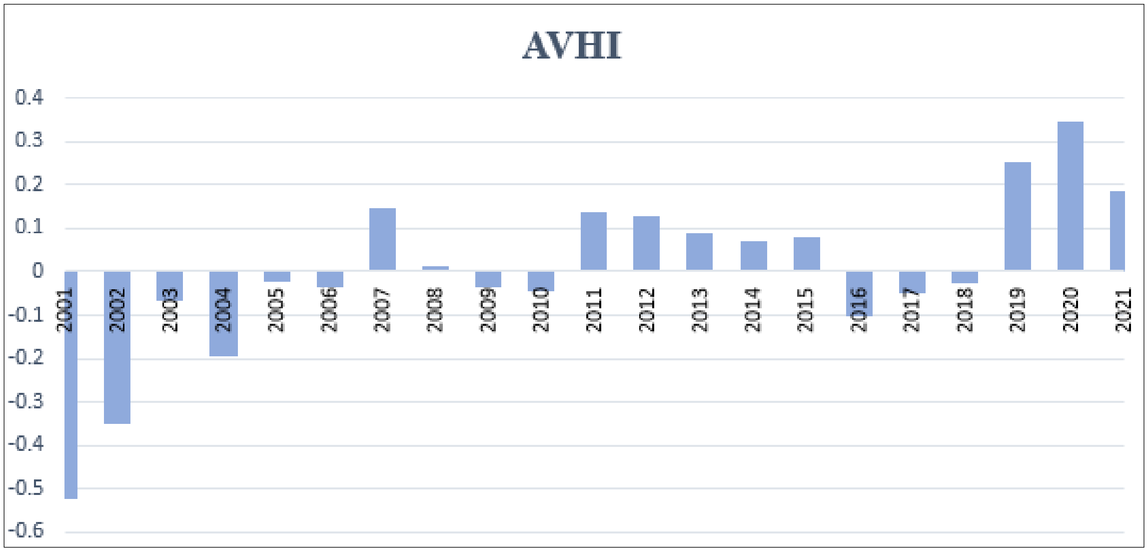

Fig. 10. Anomaly Vegetation Health Index (AVHI) from 2001 to 2021.

to experience food insecurity [52].

For drought mitigation and food security improvement, there is a need for a comprehensive drought early warning system in the cultivated area of Pakistan. One key component of such a system is the remote sensing indices used, such as the Vegetation VHI, to assess vegetation health and vigour and monitor drought conditions [53]. VHI can be calculated using remote sensing data, such as satellite imagery or aerial photographs, to create maps of vegetation health across large areas. These maps can identify the vegetation stress regions and monitor the changes in vegetation health over time. VHI and NDVI indices are the relative values and indicate vegetation health and vigour; but cannot be directly translated into a specific amount of vegetation or chlorophyll content. Additionally, VHI can only indicate moisture stress and can be affected by other factors such as pests, disease, or human-induced changes. Therefore, considering other factors and ground measurements is essential to understand the vegetation conditions.

Remote sensing data and platforms such as GEE can play a crucial role in such a system. GEE provides access to a wealth of satellite imagery and other geospatial data to create NDVI, Standard Vegetation Index (SVI), VHI, and other indices and analyze historical data to track changes over time. However, remote sensing data is only one source of information; ground-based measurements are also necessary to complement the remote sensing data for more accurate and precise findings [54]. Because Pakistan's population is growing at almost 2% per year, there is a greater demand for food supply in the market [55]. The current food production and drought early warning system in Pakistan is not adequate for the country's huge population [51]. A system that integrates modern technology, such as machine learning and the GEE platform, is needed to secure food security in Pakistan.

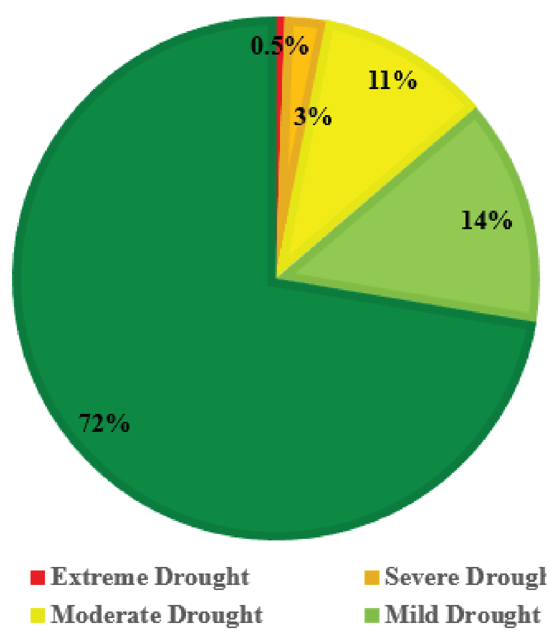

Fig. 11. Overall percentage of Drought Affected Area from 2001 to 2021 for five drought conditions (No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought).

According to the above result, VHI 's positive trend indicates the healthy vegetation condition due to the rise in rainfall. Ahmed, et al. [49] predicted that the increase in precipitation will be gradual between 2010 and 2099. By the end of this century, Pakistan's total precipitation would rise by 8 to 41% throughout the year, depending on the season. Pakistan Economic Survey Report 2021-2022 also highlighted the healthy vegetation in agricultural land. According to the report, the agriculture industry experienced remarkable growth of 4.4% in 2021 and 2022. High yields, attractive output prices, supportive government practices, and improved selection of certified seeds, pesticides, and agriculture credit are the primary drivers of this expansion [56]. The cultivated area observation facilitates crop condition monitoring, which will ultimately help Pakistan's food security. Pakistan needs to invest in building its capacity to analyse remote sensing data and integrate it with other data to develop an effective and sustainable food production and drought early warning system. In summary, remotely sensed data is beneficial for drought monitoring, food production, and food security, specifically in Pakistan's arid and semi-arid regions. This preliminary study in Pakistan's drought-prone agricultural region has laid the groundwork for the utilization of more comprehensive predictor data products (such as satellite data with reanalysis). The remotely sensed data can be a valuable tool in building a comprehensive system that can help mitigate the effects of drought and enhance food safety in the country.

5. CONCLUSIONS

Spatio-temporal information about agricultural drought is crucial for policy-makers and ecological and farming applications. Drought is an extremist risk in Pakistan, and assessing it can assist determine the best mitigation strategy. GEE is a cloud-based system that evaluates massive data sets rapidly and efficiently. In this study, GEE is used to investigate the spatio-temporal variation of drought-based satellite-derived VHI obtained from TCI and VCI. Yearly and monthly mean VHI maps indicated that in 2001 and 2002, study area cropland faced severe to moderate drought. Moreover, AVHI results verified this condition by showing soil moisture efficiency in the same years. Monthly VHI observations indicate that the most cultivated land identified severe and moderate drought in November. From 2011 to 2021, the overall drought occurrences were not so much, and annual VHI has shown healthy vegetation conditions.

The results demonstrate the adequacy of vegetation in 2019, 2020 and 2021. Overall, all observations represent that the agricultural areas of Punjab have an adequate amount of soil moisture and healthy vegetation, whereas in Sindh majority of cropland has been affected due to the severe to moderate drought with continuous deficiency of soil moisture. Temporal variations indicated the increasing trend in VHI that represents the healthy vegetation future in the cropland of Pakistan. Annual yearly observation shows that percentage of severe and moderate drought occurring is comparatively less (about 3.5%), whereas moderate drought is collectively 25%.

Pakistan's food security and rural development depend on the agriculture sector's continued expansion. It employs approximately 37.4 percent of the workforce, manages rural landscapes, and serves as an environmental shield for climate-resilient production and ecosystems while also contributing 22.7 percent to the GDP [51]. Agricultural production is a crucial contributor to the Pakistani economy, and it should be satisfied to fulfill the food demand for a growing population. The shortage of surface and groundwater is the main reason for drought in the agricultural sector and causes crop failure with pasture losses. There is a need to be aware of temporal and spatial changes in cropland so that government can develop strategies to mitigate the drought impact. This study is a small effort to observe the overall drought situation during the last two decades. The results indicate that instead of mild to extreme drought occurrence, a positive trend in VHI time series shows a good sign of improvement in the agricultural sector in recent years. Pakistan Economic Survey report 2021-22 verified this result and it says that the agriculture industry grew by a remarkable 4.4% in 2022. The increased availability of certified seeds, pesticides, agricultural credit, attractive output prices, beneficial government policies, and excellent yields contribute to this expansion.

6. ADVANTAGES AND LIMITATION OF THE STUDY

The use of Google Earth Engine (GEE) for monitoring drought events and vegetation conditions in Pakistan has several advantages. GEE provides access to a vast collection of geospatial data, which can be used to generate accurate and timely information on vegetation conditions, drought occurrence, and severity. This information is crucial for drought management, planning, water resource management, food production, and food security. The study used GEE to calculate VHI, VCI, and TCI to monitor drought events over croplands and determine their severity. The study also produced mean yearly and monthly VHI maps and observed trends in drought occurrence over time.

However, the study has some limitations. The study's preciseness depends on the quality and consistency of the data utilized in the analysis. The study also has not considered other factors such as soil moisture and rainfall, which can affect vegetation conditions and drought severity. Additionally, the study only mainly focused on croplands, and the results may not be representative of other land cover types. Therefore, further research is needed to address these limitations and provide a more comprehensive understanding of drought events and vegetation conditions in Pakistan.

7. CONFLİCT OF INTEREST

The authors declare no conflict of interest.

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