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Comparative Analysis of Drought Indices on Google Earth Engine

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Abstract

Drought poses significant environmental and humanitarian challenges, impacting diverse regions and ecosystems while also affecting the well-being of people. Access to precise and timely information regarding vegetation conditions is essential to mitigating its adverse effects, a goal that can be achieved through the application of remote sensing techniques. The Google Earth Engine (GEE) platform presents a robust toolkit and an extensive repository of geospatial data that can enhance efforts to monitor and address drought. In Pakistan, a nation susceptible to droughts and natural calamities, this research leverages GEE to oversee drought incidents across croplands and gauge their severity using indices such as the Vegetation Health Index (VHI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI). A time-series analysis is performed to monitor the trend of drought conditions over time. Further study of correlation is done between various kinds of drought indicators (VCI, NDVI, TCI, and VHI) and LST. The study demonstrates a substantial inverse relationship between NDVI and TVX, demonstrating that healthier vegetation corresponds with lower general environmental factors. Furthermore, VCI, TCI, and VHI show positive correlations, showing their interconnection, while TVX has a negative influence on all indices. Temporal changes showed a growing tendency in VHI and VCI, which is indicative of a future with robust vegetation in Punjab.

Keywords: Drought; Remote Sensing; Google Earth Engine; Time Series; NDVI; VHI; VCI; TVX; LST

1. Introduction:

Drought is a calamity that develops over time with cumulative consequences and is especially slow pace to manifest itself across time scales like months or weeks (Hayes, Svoboda, Wardlow, Anderson, & Kogan, 2012). Particularly, drought has affected half of the world's countries (Berner *et al.,* 2011; *Masud et al.,* 2015). Typically, vegetation indices obtained from satellite photos are used to monitor drought. With the use of current and historical knowledge, a "index" determination is a method of creating "value added" information related to drought(Azmi *et al.,* 2016; Eslamian, 2014). To assess drought and its severity, markers of drought are acquired. Instead of comparing the present with the past and detecting water shortage connected to a drought time and intensity, drought indices give more information (Yihdego *et al.,* 2019). By modelling the Land Surface Temperature (LST) using the Annual Temperature Cycle (ATC) model and the drought indicators TCI, VCI, VH, and Temperature-Vegetation Drought Index (TVDI), Zhao *et al*. (2021) managed to assess the severity of the drought. Khan & Arsalan (2014) conducted an evaluation of drought conditions, employing the Normalized Difference Vegetation Index (NDVI), and established a positive correlation between NDVI, rainfall, and soil moisture levels. In a different approach, Kogan (1995) utilized

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NDVI to create another index known as the Vegetation Condition Index (VCI). Specifically, VCI serves to identify spatial and temporal variations in vegetation status associated with stress caused by insufficient precipitation.

Additionally, Kamble *et al.* (2019); Zambrano *et al.* (2016), and Bento *et al.* (2018) conducted assessments of drought utilizing VCI and compared it with the Standardized Precipitation Index (SPI), revealing a strong correlation between VCI and SPI. To assess drought, Land Surface Temperature (LST) is employed in deriving the Temperature Condition Index (TCI), and several studies have integrated TCI with VCI for the purpose of drought monitoring.

VHI, a widely utilized drought index for applications involving drought monitoring, is created through the integration of TCI and VCI. Using VCI, TCI, and Temperature Vegetation Index (TVX), Tabassum, Arsalan, Khalid, Ahmad, and Mirza (2015)evaluated the drought state in a dry region of Pakistan. Since TVX, the LST/NDVI ratio, is obtained from both reflecting and thermal bands, it offers additional spectral information for drought monitoring (Zargar, Sadiq, Naser, & Khan, 2011) . TVX is also employed to draw moisture from the soil (Galiano, 2012). VHI was utilized by Masitoh & Rusydi (2019) and Ma'Rufah *et al.* (2017) to describe the health of the vegetation.

For processing geographical and temporal data, ArcGIS is a renowned software, and it was utilized in all of the aforementioned experiments. Following the rise of cloud computing, analyzing spatiotemporal data while downloading is simple on the GEE Platform. GEE with a remote sensing application for cloud computing is a suitable platform to identify an area with an excessive amount of data.(Mutanga & Kumar, 2019). GEE utilizes planetary-scale geospatial analysis and powerful computing power to highlight an extensive variety of challenging socioeconomic problems, including deforestation, drought, hazards, food scarcity, water supply and distribution, climate monitoring, and environmental preservation. (Gorelick *et al*., 2017). GEE can map noticeable changes, trends, and variations by jointly examining environmental conditions, agriculture, soil, water, and numerous climatic variables(Gorelick *et al*., 2017; Kumar & Mutanga, 2018). GEE was used by Wang *et al*. (2019) to observe surface water changes in lakes over an extended period of time. Through the GEE platform, Thilagaraj *et al.* (2021) created a system that efficiently tracks drought occurrences over a range of timescales utilizing remote sensing indices including LST, VCI, NDVI, TCI, and VHI. Many research investigations employed various drought indices and took into account the GEE in agricultural mapping and monitoring (Mutanga & Kumar, 2019). Drought evaluation requires long-term data that is sufficient for the scenario. The need for this information may be addressed by GEE, which offers extensive geographical data and offers worldwide coverage.

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(Pakistan, 2022). The most recent IPC analysis of 25 districts in Balochistan, Sindh, and Khyber Pakhtunkhwa provinces in Pakistan found that approximately 4.7 million people (25 % of the population analyzed) would face severe acute food insecurity between April and June 2022(FAO, 2022). This population has been impacted by a number of shocks, including drought, livestock diseases, high food prices, and the COVID-19 pandemic's effects(FAO, 2022). The country's arid and semi-arid regions suffer the most from the effects of drought, which include crop failure and decreased food production. (Ahmed *et al.,* 2018; Jamro *et al.*, 2019; Ullah *et al*., 2021). A comprehensive drought assessment for agricultural land is required to lessen these effects and increase food security.

The drought conditions in Pakistan have been evaluated in several studies (Zargar *et al*., 2011). Pakistan's meteorological drought features were assessed by Ullah *et al*. (2021) using in-situ measurements, drought indicators (SPI and SPEI), and reanalysis findings. According to Ali *et al*. (2021) observation, Pakistan's examination of its temporal rainfall pattern shows a general tendency toward decline both nationally and temporarily. The agricultural region will be impacted by the identified decreased rainfall since droughts are more likely to occur (Ali *et al*., 2021). In Pakistan, droughts would become more severe and frequent, according to a prediction made by Ahmed *et al*. (2018) because to rising temperatures brought on by global warming. In Pakistan, Jamro *et al*. (2019) studied the spatiotemporal variability of drought and discovered the 1920 and 2000 droughts, which affected all zones and lasted more than 10 months. It can be viewed as Pakistan's most worst dry spells. Khan *et al*. (2020) utilized SPEI to predict droughts using machine learning. Pasha *et al.* (2015) investigated the cause of the 2014 Sindh Drought and determined that it was a famine-like condition caused by a prolonged lack of precipitation in the Thar Desert. Drought evaluation requires long-term, condition-specific data. Drought evaluation requires long-term, condition-specific data.

GEE can satisfy this need since it has a substantial amount of geographical data and worldwide coverage. Khan *et al.* (2020) assessed drought using the GEE platform and drought indicators (SPEI, SPI, VCI, TCI, PCI (Precipitation Condition Index), and SMCI (Soil Moisture Condition Index) in the non-irrigated

Potohar plateau area of Punjab, Pakistan. There is a scarcity of research that use GEE to monitor the drought, notably in Punjab's farmland. Drought monitoring is essential for preparing Pakistani communities for the effects of droughts on food security. The observation of cultivated areas aids in crop condition monitoring, which eventually aids in ensuring Pakistan's food security. By addressing this gap, this project intends to monitor vegetation conditions, particularly in Punjab, utilizing drought indicators such as VCI, TCI, TVX and VHI using the MODIS dataset on the GEE platform. A time series analysis was also performed to observe the trend of vegetation health conditions. Further, these indices were compared with the help of the correlation coefficient. This comparison provides a selection of the best drought indices that are more useful for drought modeling.

1.1. Objectives:

To fill the existing research gap in drought monitoring in Punjab's agricultural regions, this study aims to utilize drought indices and remote sensing techniques on the Google Earth Engine (GEE) platform. Specifically, the objectives are:

- Highlight the significance of drought monitoring in Punjab, Pakistan.
- Explore various drought indices and their application in assessing drought severity and trends.
- Address the research gap in employing GEE for drought monitoring in Punjab's farmland.
- Identify the most appropriate drought indices through correlation coefficient analysis.
- Facilitate effective drought modeling and mitigation strategies to improve food security and rural development in Punjab and similar regions.

2. Materials and Methods:

2.1. Study Area:

Punjab, Pakistan is located in Asia's southernmost region. It is located between latitudes 27.42° and 34.02° N and longitudes 69.81° and 75.23° E. Punjab is the second-largest province, covering 205,344 square kilometers and varying in altitude from 300 to 2000 meters. The middle region of Punjab is at a level of about 600 m, while in the north, near Murree hill station, height reaches 2291 m (7516 ft.) amidst lush and deep woods. Punjab's agricultural land is presently around 12.51 million hectares, with a total area of existing farmland of 2.06 million hectares(Mallik *et al.*, 2021). Presently, Punjab has an estimated population of approximately 100.6 million, with a population density of 460 individuals per square kilometer. The population is growing at a rate of approximately 2.05%, and urban areas account for roughly 32% of the province's population(Qadir *et al.*, 2008). Punjab stretches considerably from east to west, resulting in diverse climatic conditions depending on the elevation. Upper Punjab experiences higher precipitation levels, upper central Punjab is semi-arid, and southern Punjab is arid (Fig 1). The population of Punjab (Pakistan) was estimated to be 110 million as of the 2017 census (Pakistan Bureau of Statistics ("Pakistan Bureau of Statistics," 2017). Although the greatest summer temperature can reach 50 °C and the lowest winter temperature can reach 10 °C, the average yearly temperature is about 10 °C below zero. With significant seasonal and diurnal variations in rainfall and temperature, the climate varies from arid to semi-arid. Punjab is residence to over 50% of Pakistan's population and produces 60% of the nation's agricultural production (Amjad *et al.*, 2019). The monsoon season is defined as July through September. The average annual rainfall in sub-mountain locations is 89 centimeters, compared to only 43 centimeters in the plains. Canals and irrigated water are used for agricultural production instead because the following months only receive roughly 50 mm of rainfall each month.

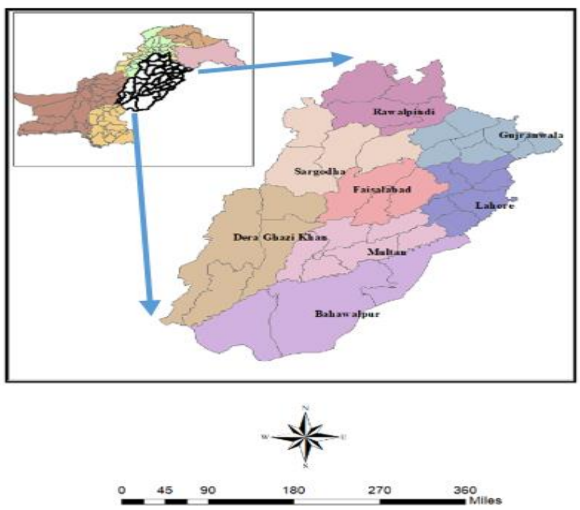

Figure 1: Study Area "Punjab"

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 (Aksoy *et al*., 2019). Therefore, two MODIS products (LST, NDVI) were used in this study. The type, spatial-temporal resolution, and time span of the data products are shown in Table-1.

2.3. Methodology:

Drought evaluation is essential for each of the four phases of hazard management (preparation, response, recovery, and mitigation)(Aksoy *et al*., 2019). In this context, remotely sensed technology provides crucial geo-information in the form of spatiotemporal satellite images. It generates repeated and extensive drought event maps of particular regions at certain times. The study provides the spatiotemporal maps for the area of Punjab, Pakistan from 2003 to 2022 and time series analysis and methodology work shown in Fig. 2. The GEE Platform was used to gather and process data for the study. The indices VCI, TCI, and VHI were driven by the MODIS data products LST and NDVI. The VHI is calculated using a combination of VCI and TCI. From 2003 to 2022, VHI yearly mean maps were created to detect the severity of drought, notably in Punjab's agricultural land. Time series was analyzed as well to track the trend of drought conditions all over time. Further correlation analysis has been done between the different types of drought indices and LST.

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	2003-2022
MOD11A2	LST	1km	8-days	2003-2022

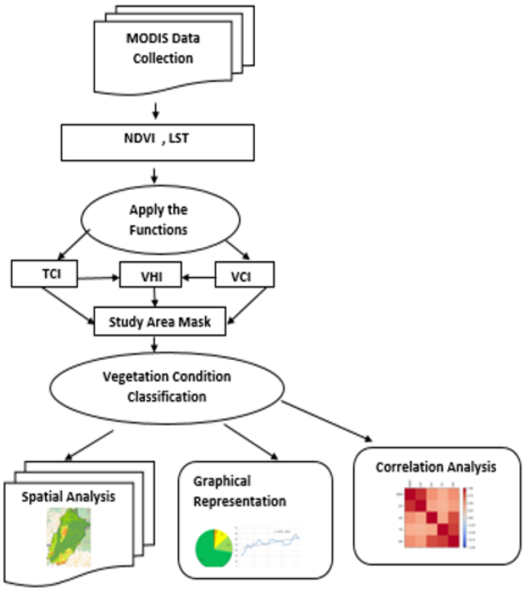

Figure 2: Methodological Work that shows the GEE software system is utilized to determine the VCI, TCI, and VHI to observe drought conditions, Correlation and Time-series Analysis.

2.3.1. Satellite Based Drought Indices:

Remote sensing data products were used to calculate the satellite-based drought indicators. Some of them are as follows:

2.3.1.1. Normalized Difference Vegetation Index (NDVI):

The NDVI is a well-known vegetation indicator that ranges from -1 to +1 and is used to measure the development and the amount of vegetation. The value of NDVI is negative for water bodies and clouds; near to negative values represent soil or built-up areas, while equal to or more than 0.6 reflects healthy vegetation(Dobri, Sfîcă, Amihăesei, Apostol, & Țîmpu, 2021). The near-infrared (NIR) and red bands are utilized to determine NDVI. If " ρ_{nir} " is the near-infrared band reflectance and " ρ_{red} " is the red band reflectance, then NDVI may be calculated as given in **Error! Reference source not found.**

$$NDVI = \frac{\rho nir - \rho red}{\rho nir + \rho red}$$

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>

2.3.1.2. Vegetation Condition Index (VCI):

VCI can efficiently assess the drought condition by delineating the drought area for the definite value of NDVI and VCI.(Vaani & Porchelvan, 2018). VCI may be calculated using Equation-2:

$$VCI = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100$$

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 metric is expressed as a percentage range from 1 to 100, with greater than 50% indicating normal vegetation condition and less than 50% indicating drought condition(Kogan, 1995). Because VCI is more sensitive to precipitation dynamics than NDVI, it is a better predictor of vegetation response to precipitation influence (Kogan, 1990). The VCI categorization is based on different drought situations (Kogan, 1995) and is shown in Table 2 (Tabassum *et al*., 2015).

2.3.1.3. Temperature Condition Index (TCI):

The thermal band of a satellite image is converted to brightness temperature (LST) and used to calculate the Temperature Condition Index (TCI). It is based on the vegetative stress caused by high temperatures and excessive moisture, as illustrated in **Error! Reference source not found.** (Singh, Roy, & Kogan, 2003).

$$TCI = \frac{LST_{max} - LST_I}{LST_{max} - LST_{min}} \times 100$$

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):

One of the most frequently used remotely sensed drought indexes is VHI (Kogan, 1997, 2001). Many researchers employed VHI in a variety of applications, including crop yield loss assessment, which is critical for food security (Kogan, 2001). The combination of VCI and TCI is used to determine the condition of the vegetation and given in the Equation-4.

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

Where α is a weighted factor that is typically set as (a=0.5)(Kogan, 1997, 2001). Correlation testing is performed to validate VHI values using LST and NDVI. VHI values can be categorized according to their severity as shown in Table-2.

2.3.1.5. Temperature Vegetation Index (TVX):

TVX, or the ratio of LST to NDVI, incorporates both the reflecting and thermal bands of remotely sensed data, providing additional spectral information for drought identification(Tabassum *et al.*, 2015). Examining the local moisture level is another application for it (Tabassum *et al.*, 2015). It has the following definition (Equation-5):

$$TVX = LST/NDVI$$

2.3.2. Time Series Analysis:

2.3.2.1. Man-Kendall Test:

In this study, the trend analysis of VHI was conducted using the Man-Kendall test Mann, (1945) created the non-parametric Mann-Kendall test to identify trends, while Kendall, (1975) presented the test statistic distribution to evaluate non-linear trends and turning points (Mondal *et al*, 2012).

The Mann-Kendall statistical test has been widely used to quantify trends in hydro-meteorological time series (Da Silva *et al.*, 2015). The Mann-Kendall is computed as follows (Equation-6) (Mann, 1945; Kendall, 1975):

$$S = \sum_{i=1}^{n-1} \cdot \sum_{j=i+1}^{n} sgn\left(VHI_j - VHI_i\right)$$

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 VHI_i with the rest of the data points VHI_j, a reference point is used for each of them (Equation-7).

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

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 (Equation-8):

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

Where t_i is the number of ties up to sample i, and Z_S represents the test statistics (Equation-9).

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

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 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 $Z_{\frac{\alpha}{2}}$, 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 with Equation-10:

$$Ti = \frac{VHI_j - VHI_k}{j-k}$$

for i = 1,2, ... N

where, VHI_j ans 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:

Sen's estimator is calculated as $Q_{med} = T_{\frac{N+1}{2}}/2$ if N appears odd, and it is regarded as

$Q_{med} = \frac{1}{2}\left(T_{\frac{N}{2}} + T_{\frac{N+2}{2}}\right)$ if N appears even. The non-parametric test can then be used to determine a true slope after Qmed 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 Qi value, while the downward or decreasing trend is represented by a negative Qi value Equation-11.

$$Qi = \begin{cases} T_{\frac{N+1}{2}} & N\ is\ odd \\ \frac{1}{2}\left(T_{\frac{N}{2}} + T_{\frac{N+2}{2}}\right) & N\ is\ even \end{cases}$$

2.3.2.3. Anomaly Vegetation Health Index:

Anomaly drought Index (ADI) is a measure of the variation in healthy vegetation compared to a long-term average. ADI is estimated by deducting the long-term average value of DI from the current value of DI, and then dividing the result by the standard deviation of the long-term DI (Baniya, Tang, Xu, Haile, & Chhipi-Shrestha, 2019; Liang *et al.*, 2017). ADI formula for estimation:

$$ADI = \frac{DI_i - DI_{avg}}{DI_{avg}}$$

Where, DI_i is the drought index during a particular time *i.* DI_{avg} is the average DI for the total time duration. Positive values of ADI indicate above-average vegetation health, while negative values suggest below-average vegetation health.

3. Results and Discussion:

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 Spatial Variation of VHI:

The two MODIS data packages were used by the GEE platform to obtain the study results. The yearly mean VHI maps were produced from 2003 to 2022, as shown in Fig. 3. Two MODIS data products (LST and NDVI) are used to estimate the vegetation indices (TCI and VCI). The combination of TCI and VCI contributes vegetation health indices, VHI, to monitor drought in cropland. The annual mean of VHI from 2003 to 2022 indicated mild to moderate drought conditions in Punjab. The overall vegetation conditions were healthy during the given time interval.

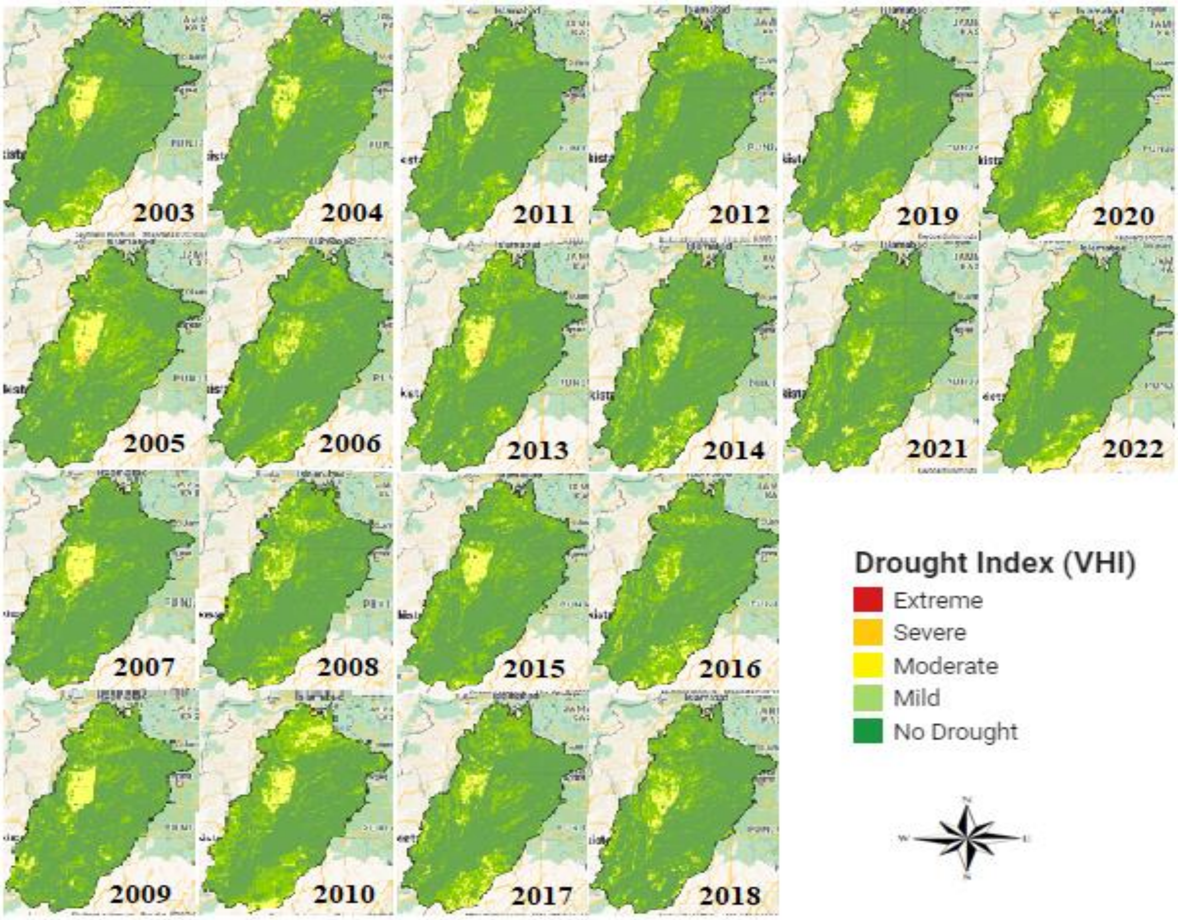

Figure 3: Yearly mean VHI maps from 2003 to 2022 for five drought conditions: No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought

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, VCI, and TCI time series data. The results shown in Table 3 indicated a positive trend in VHI and VCI as shown by positive values of Zs (3.327 and 3.01) and a p-value (0.00087 and 0.0026). No trend has been observed in TCI time series because the value of p is 0.267 which is greater than 0.05. The Sen's slope estimator was also used to calculate the annual mean trend increase, which was found to be

1.162 for VCI and 0.772 for VHI, reflecting healthy vegetation. These findings were verified by the annual time series data, as shown in , and were attributed to adequate rainfall, as predicted by Ahmed *et al.* (2019).

The affected area percentages during the study period indicate in Fig. 4. In the study period (2003 to 2022), large areas showed healthy vegetation with moderate droughts of about 5% to 10% and mild drought about 20% to 30%. Thus, as a general feature, healthy vegetation observation was decreasing the drought effect in Punjab, although only some regions of Sargodha district have been severely affected. The graphical representation of Fig. 8 showed an annual mean value of VHI, and seasonal changes in VHI can alter these results.

Overall, the study's use of statistical techniques provided important insights into the trend of vegetation health in Punjab, highlighting the positive impact of sufficient rainfall on vegetation conditions. Fig. 5 shows the VHI time series for VCI, TCI, and VHI. The figure shows that severe drought was observed in 2010, while moderate in 2006 on the annual time scale. Moreover, crop conditions were healthy during the given time period.

Table 3. Statistical Test Results that show Trend, Min, Max, P, Z, Tau, S, Variance, and Slope

Indices	Trend	Min	Max	Mean	P	Zs	Tau	S	Var(S)	Slope
VCI	Increasing	26.328	70.450	55.089	0.000875	3.327	0.501	127	1433	1.162
VHI	Increasing	35.050	69.462	52.480	0.0026	3.010	0.454	115	1433	0.772
TCI	No trend	35.174	68.120	53.793	0.267	1.109	0.169	43	1433	0.395

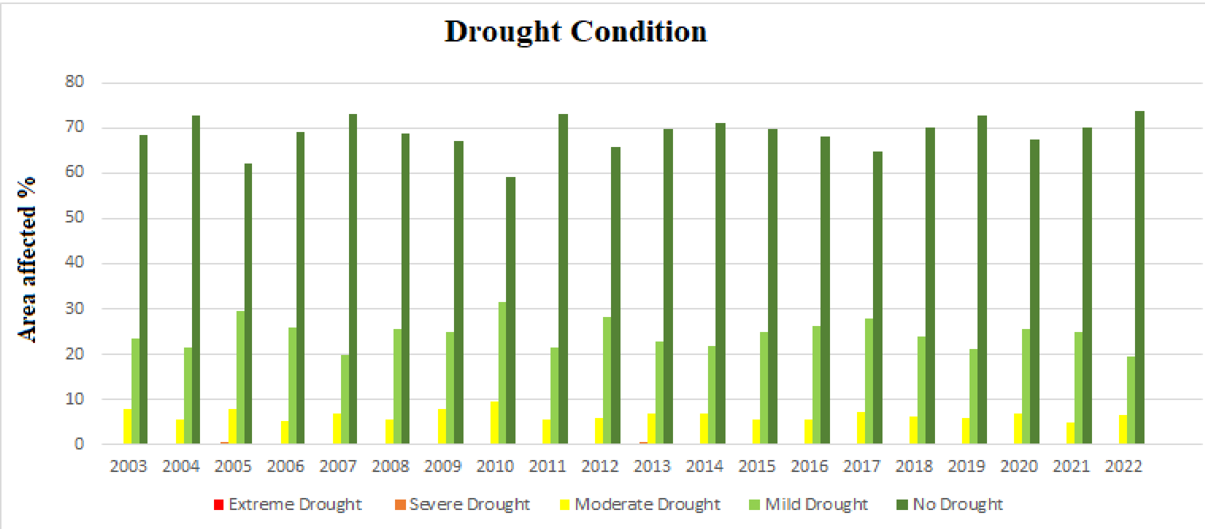

Figure 4: The Cropland Area affected % due to drought from 2003 to 2022 for five drought conditions (No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought).

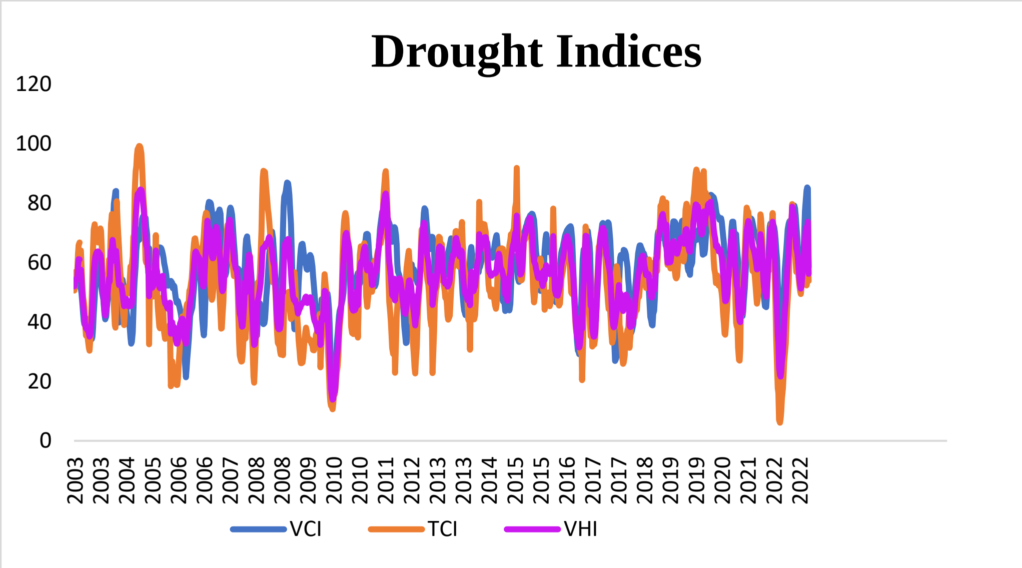

Figure*5*: VHI time series from 2003 to 2022

3.3. Drought Index Anomaly:

Drought index Anomaly represents the soil moisture content efficiency and deficiency. Fig. 6 provides a comprehensive overview of environmental and agricultural conditions from the year 2003 to 2022, with three key indices: VCI, TCI, and VHI. The VCI reflects the state of vegetation, ranging from -0.18 in 2010 to 0.28 in 2020. Meanwhile, the TCI, indicating temperature conditions, varies from -0.28 in 2009 to 0.32 in 2019. The VHI, which offers a holistic view of vegetation health, shows fluctuations from -0.346 in 2002 to 0.266 in 2019 and 2020. According to observation, the length of mild to extreme drought was five years (2003, 2006, 2009 to 2010, and 2018). Cropland Soil moisture content was satisfactory in 2007, between 2011 to 2015, and from 2019 to 2021. In the first decade (2003 to 2012), the study area faced a dry spell, whereas, in the next decade (2013 to 2122), vegetation condition was satisfied. The correlation result (Fig. 7) presents a set of correlation coefficients between several environmental and vegetation indices, including NDVI, VCI, TCI, VHI, and TVX. These coefficients indicate the strength and direction of the relationships between these indices. Notably, NDVI displays a strong negative correlation with TVX, suggesting that as NDVI values increase (indicating healthier vegetation), TVX values decrease (potentially indicating adverse conditions). It also exhibits weaker positive correlations with VCI and TCI, while its correlation with VHI is quite weak. VCI, on the other hand, shows a weak positive correlation with NDVI and a strong negative correlation with TVX, which implies that when vegetation conditions are favorable (higher VCI), TVX tends to be lower. VCI is also positively correlated with TCI and strongly correlated with VHI, indicating a close relationship between these indices. TCI demonstrates a weak positive correlation with NDVI and VCI, and a strong negative correlation with TVX. It has a strong positive correlation with VHI, suggesting that temperature conditions and vegetation health tend to align closely. VHI exhibits very weak positive correlations with both NDVI and TCI, indicating only a subtle relationship. However, it strongly correlates with VCI and TCI, reflecting that a healthy vegetation index is closely tied to favorable vegetation and temperature conditions. TVX, which represents an unspecified environmental factor, displays strong negative correlations with all the other indices, suggesting that when TVX values decrease, the health and conditions of vegetation tend to improve. In summary, Fig. 7 offers valuable insights into the interplay between these environmental and vegetation indices, helping researchers and policymakers understand how changes in one index may be associated with changes in others, ultimately aiding in environmental and agricultural decision-making. By examining the multiannual mean VHI during the analyzed period (2003–2022), about 21 % of the arable land in Punjab has suffered from moderate to extreme drought. It can be seen in Fig. 8 that about 23.3% of the arable land of the entire study area faced mild drought conditions, and 14.4% faced moderate drought. Collectively 6.8% area of the land bore severe drought.

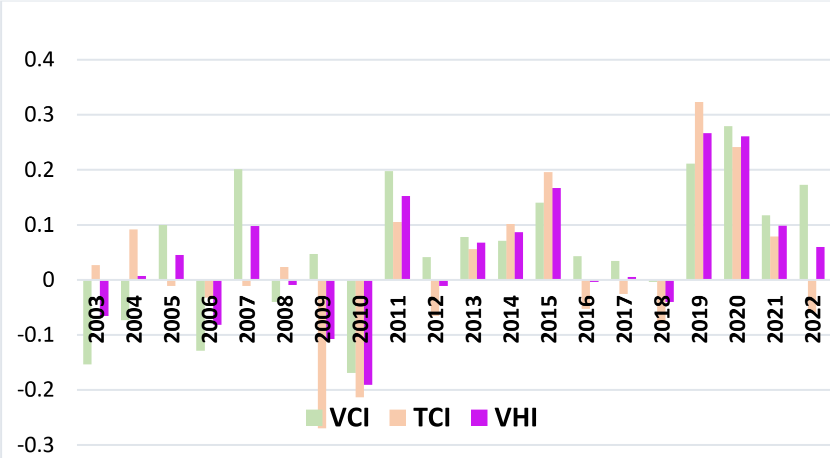

Figure 6: Anomaly Vegetation Health Index (AVHI) from 2011 to 2021.

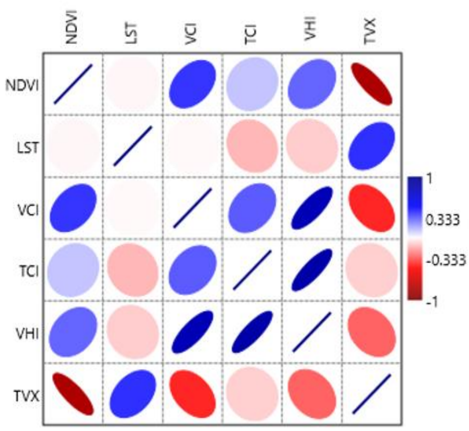

Figure 7: Correlation between the drought indices VCI, VHI, TCI, TVX, NDVI, and LST

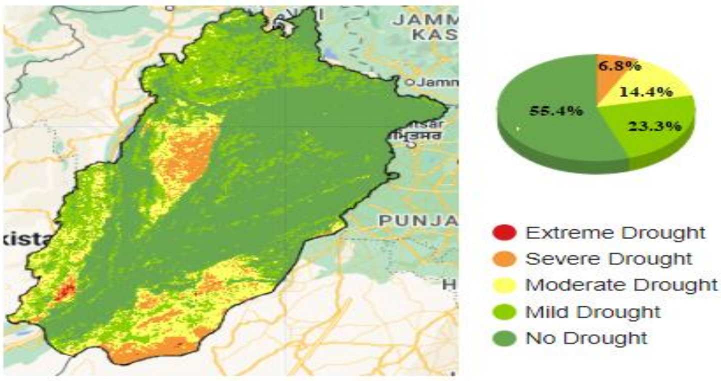

Figure 8: Overall percentage of Drought Affected Area from 2003 to 2022 for five drought conditions (No Drought, Mild drought, Moderate Drought, Severe Drought, and Extreme Drought).

4. Conclusion:

Spatiotemporal information regarding agricultural drought is essential for policymakers as well as ecological and farming uses. In Pakistan, drought is an extreme risk that may be evaluated to help choose the most effective mitigation plan. GEE is a cloud-based system that analyzes large amounts of data quickly and effectively. This work examines the spatiotemporal variance of drought-based satellite-derived VHI generated from TCI and VCI using GEE. Annual mean VHI maps showed that agriculture in the research region experienced severe to moderate drought in 2001 to 2002.

Furthermore, the AVHI data, which displayed soil moisture efficiency in the same years, confirmed this condition. The outcomes show that the vegetation was sufficient for the span of time given. Overall, all of the research results indicate sufficient soil moisture and healthy vegetation in Punjab's agricultural districts. Temporal changes showed a growing tendency in VHI and VCI, which is indicative of a future with robust vegetation in Pakistan's croplands. An annual observation reveals that the percentage of severe and moderate drought events is quite low (about 6.8% & 14.4%), whereas the number of mild drought events is 23.3% overall. The correlation graph reveals a strong inverse relationship between NDVI and TVX, indicating that healthier vegetation coincides with lower unspecified environmental factors. Additionally, VCI, TCI, and VHI exhibit positive correlations, highlighting their interconnectedness, with TVX negatively influencing all indices.

Pakistan's rural development and food security rely on the agriculture sector's continuous growth. In addition to producing 22.7 percent of the GDP, it employs around 37.4 percent of the workforce, maintains rural landscapes, and acts as an environmental buffer for ecosystems and output that is climate resilient(NDMC, 2022). Pakistan's economy depends heavily on agricultural production, which must be maintained to meet the country's expanding population's food needs.

The primary source of drought in the agricultural sector, which results in crop failure and pasture losses, is the scarcity of surface and groundwater. The government must be aware of the geographical and temporal changes in agriculture in order to create plans to lessen the effects of the drought. This research is a small approach to track the extent of the drought during the last 20 years. The findings reveal that a positive trend in the VHI time series indicates a positive indicator of improvement in the agricultural sector in recent years, as opposed to the incidence of mild to severe drought. This outcome was confirmed by the Pakistan Economic Survey report 2021–2022, which states that the agriculture sector expanded by an astounding 4.4% in 2022. This growth is made possible by improved yields, favorable government regulations, appealing output prices, insecticides, certified seeds, and credit for agriculture.

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