



# Spatio-temporal remote sensing evaluation of drought impact on vegetation dynamics in Balochistan, Pakistan

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## Abstract

Drought is one of the significant natural disasters that has a profound impact on human societies, particularly in arid places such as Balochistan, Pakistan. Geographic information system and remote sensing has played a major role in predicting the effect of drought events and mitigate. Therefore, the purpose of this study was firstly to evaluate the spatiotemporal patterns of drought in Balochistan, Pakistan, utilizing MODIS based satellite data and validate the PMD stations data with CHIRPS data. Secondly the objective of this research to quantify the influence of drought on vegetation anomalies and comparison between droughts patterns with vegetation response. Drought conditions in Balochistan by integrating remote sensing (RS) drought indices (RSDI).RSDI was calculated through Hargreaves method using monthly data. The following remaining indices were the main focus of the study i.e., Standardized Precipitation Evapotranspiration Index (SPEI), Vegetation Condition Index (VCI), Vegetation Health Index (VHI), Temperature Vegetation Dryness Index (TVDI), and Precipitation Condition Index (PCI). These indices offered differing perspectives, emphasizing the value of a comprehensive strategy. Approximately 60% of the area was significantly affected by drought conditions, with SPEI values for the period being less than -1.5. SPEI and TVDI performed better in identifying droughts. TVDI values ranged from 0.63 to 0.88, indicating agricultural dryness. For instance, the East experienced a severe drought between 2001 and 2022, according to SPEI. Significant drought events occurred in 2001, 2004, 2009, 2014, and 2022, allowing comparative analysis. TVDI proved more effective than VCI in predicting drought. RDI and TVDI localized drought better than PCI. SPEI, RDI, and TVDI contributed significantly to understanding drought (73.63%, 74.15%, and 72.30% respectively). Considering diverse indices is vital for long-term drought mitigation strategies. RDI, especially valuable with limited temperature data, aids in understanding drought dynamics. This analysis aids in predicting future droughts and mitigating agricultural losses in Balochistan, informing decision-making and adaptive measures.

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## 1 Introduction

Drought is a universal natural calamity that is well on its way to regaining the destructive potency that it had in the pre-agricultural era and has been a significant factor affecting many parts of the world map owing to climate change (Sheffield and Wood 2008). As a result the impact of soil is higher, the non-linearity of the correlation between NDVI and biophysical characteristics and sensitivity to the background of soil decreases. To reduce the effects of soil splendor in the otherworldly records of vegetation the change procedure is made, named as Soil adjusted vegetation index (SAVI) (Yang et al. 2012). The analysis of the climatic oscillation and water availability and concomitant vegetation response through time and space. In such areas of the country like Balochistan, which becomes susceptible to the expressions of climatic change consequences (Faisal et al. 2013). An alternative method is to identify the growth and physiological data of crops, from which variations in vegetation data may be used to estimate the severity of the drought. Vegetation index (Haroon et al. 2016). Using primary and secondary data, it reveals significant declines in agriculture and livestock health, worsening economic hardships. The findings highlight the urgent need for effective drought management and mitigation strategies, which was the effects of persistent drought on Nushki District's population Balochistan (Chand and Biradar 2017). MODIS NDVI as the second global-based vegetation index for the monitoring of the photosynthetic activity of the Earth's terrestrial vegetation over the NDVI owing to better results (Deng et al. 2018). A single indicator might not be able to sufficiently describe the beginning and severity of the drought due to its complexity (Ahmed et al. 2019). The strengths of SPEI are identifying the impacts of changes in evapotranspiration and temperature to global warming; it has high utilization rate than other indices (Ashraf et al. 2020; Blonquist et al. 2009). Out of all natural disasters, drought is distinguishable as a rather large scale disaster that influences the world and may be described as an extended period of less than nine consecutive months with significantly reduced precipitation amounts in comparison to the statistical multiple-year average resulting in visible changes in the vegetation (Amin et al. 2020) Stressing the interdependence of the environment and the incidence of variables within a specific area and time frame, the spatiotemporal analysis of drought and its effects on Balochistan, Pakistan's vegetation (Jamro et al. 2020). The determining the Spatio-temporal characteristics of drought and its effects on vegetation becomes essential. Balochistan province is an arid province lying to the southwest of Pakistan and consists of plain lands and mountains and the seasonal climate is extremely hot (Pakistan Meteorological Department 2020). Balochistan is most suitable to examine

the Spatio temporal characteristics of drought on vegetation thereby creating opportunity for similar regions across the globe to utilize. Disaster warns that droughts are socio – ecological disasters that affect ecosystems, agriculture and people by influencing the supply and accessibility of water and foods resources (Edition et al. 2020). The assessment of alterations of vegetation, moisture content in the soil, and climate conditions within large territories, thus allowing for timely and suitable decision-making in the areas that could be impacted by drought (Cahapay 2020). The water stress is analyzed using PET in relation to vegetation using data obtained from the Earth Engine database. Also included are precipitation data, calculated with the CHIRPS precipitation data from 2001 and up to 2022 (Qaisrani et al. 2021). The EVI was developed for the reasons of feedback-based approach that combined both the background and atmospheric resistance in NDVI (Hu et al. 2021). Comparative analyses of TVDI and SPEI in recent research are a strength in characterizing drought. TVDI is preferred for short-term agricultural drought identification because of its narrow time step, while SPEI is more appropriate for long-term drought analysis since it incorporates both, precipitation shortage and evapotranspiration requirements (Wang et al. 2021a, b). Droughts are difficult to monitor and forecast because of their sluggish beginning, gradual growth, and prolonged perseverance (Kloos et al. 2021). Severe weather instances have a strong, identical broad trend with the growing rate of global warming. Extreme weather and climatic conditions are also putting increasing strain on food systems (Dangulla et al. 2021). The impact of climate change on agriculture and livelihoods in Balochistan, highlighting coping strategies like crop diversification and water management. Results emphasize the need for enhanced drought resilience and climate-smart agricultural practices (Ashraf et al. 2021). By lowering the water content of plants and chlorophyll and altering the frequency and intensity of other interference factors, drought modifies the intensity of photosynthesis and has an impact on agricultural productivity (Zhou et al. 2022). The application of NDVI enables effective monitoring of vegetation dynamics and natural habitats at various levels and supports the research focused on environmental change effects on vegetation growth and the organization and components of the biotic community which the vegetation occupies (Ashraf et al. 2022a). Mean ground-based climate data of PMD are integrated at the spatial and temporal study to increase the precisely of the remote sensing observation within the context of Pakistan. Particularly, MODIS satellite data in this case, expecting to provide significant and meaningful data about the Spatiotemporal changes of drought characteristics and vegetation condition in Balochistan, Pakistan (Ullah and Akbar 2023). The aridity index (AI) and standardized potential evapotranspiration index (SPEI) are used to study drought patterns in Baluchistan province,

Pakistan. The analysis indicates major drought periods, specifically between 1998 and 2022, indicating the urgent need for effective drought management to prevent environmental and socioeconomic implications (Rafiq et al. 2023). Balochistan farmers perceive climate change and its impact on crops. A survey of 120 farmers shows decreased rainfall, higher temperatures, and frequent droughts negatively affect wheat and rice production but benefit maize in irrigated areas. The study calls for climate-resilient crops and better water management (Khan et al. 2023). The efficient framework for the management of drought in the concerned area. Research limitations provide an answer to existing gaps in the industry by presenting our work as the detailed analysis of the interactions between climatic fluctuations, water availability, and vegetation response especially within a climate change-sensitive area (Qaisrani et al. 2024).

There is still a significant gap in research on drought impact on vegetation on regional basis. In a predictable warming scenario, the prevalence of droughts may increase. Therefore an effective drought monitoring and their impact on vegetation methods is essential and can be utilized for timely policy implementation and mitigation. Based on the above mentioned background, the main purpose of this study is to investigate the spatiotemporal effects of drought on vegetation in the Balochistan province of Pakistan during the period of 2001 to 2022 using different remote sensing indices. Thus, the study aims at determining links between drought conditions and

vegetation health, studying works on vegetation stress to clarify its relation to climatic factors to develop a basis for a proper drought management and mitigation in the region. The specific objectives of this research are, firstly to evaluate the spatiotemporal patterns of drought in Balochistan, Pakistan, utilizing MODIS based satellite data and validate the PMD stations data with CHIRPS data. Secondly the objective of this research to quantify the influence of drought on vegetation anomalies and comparison between droughts patterns with vegetation response. Through these objectives, this research seeks to contribute valuable knowledge that can inform decision-making processes and support effective strategies for managing drought-related challenges in Balochistan, ultimately enhancing resilience and sustainability in the face of environmental changes. Because the arid landscape of Balochistan, Pakistan's largest province, is increasingly vulnerable to the impacts of drought, a phenomenon exacerbated by climate change and unsustainable water management practices.

## 2 Material and method

### 2.1 Study area

Balochistan, the largest province in Pakistan, sprawls over an expansive 347,000 square kilometers, encompassing more than 44% of the nation's total land area. Situated in the

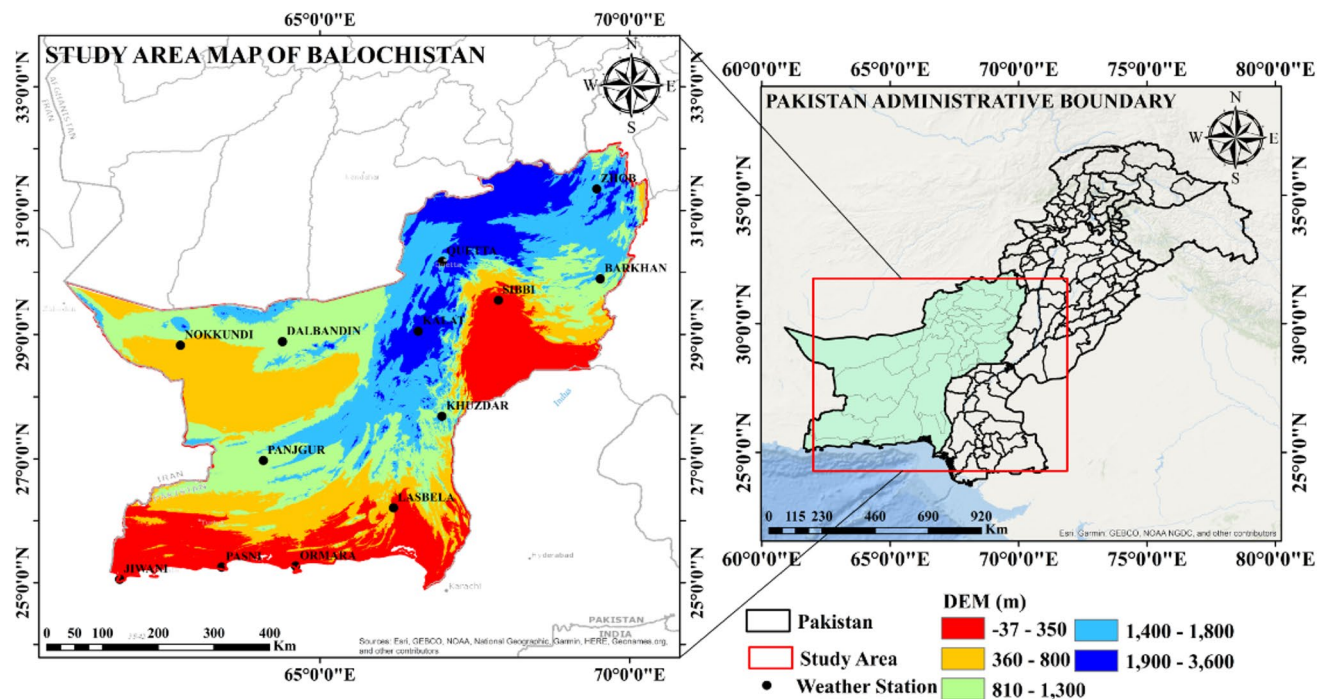


Fig. 1 Study area map

southwestern region, it shares borders with Iran and Afghanistan shown in Fig. 1. The province experiences a predominantly arid or semi-arid climate characterized by scorching summers and mild winters (Ashraf et al. 2022b). During the summer months, temperatures soar above 40°C, while winters see average temperatures around 10°C. Rainfall is scant throughout the province, averaging a mere 200 mm annually, with the majority occurring during the monsoon season. Balochistan remained severely inclined to severe spells of drought since 1998. PDMA (2013) states that after the overwhelming period of dry spell of 1998–2006, the region is still experiencing another on-going spell of drought which is influencing agriculture, livestock, and in general the socio-economic status of the area. At least twenty-three districts of Balochistan experienced mild to moderate socio-economic impacts of drought PDMA, 2012, (BUIITEMS and UNDP 2015), (Ashraf and Routray 2013). Most of the rivers of the province are termed as non-perennial rivers which are the Hingol, Dasht, Zhob, Nari and Porali and regardless of the fact that they are seasonal in nature, they provide a significant contribution to the province's water resources. The existing land cover of Balochistan also depict its unfavorable climate and its geographical features of the area. This research area holds enormous importance in respect of agriculture and ecological significance of the country. The vegetation types in this region include the thorn bush, savannah, montane, and miombo woodland that provides human livelihoods and support animal organism in the region's arid, sub arid, alpine environment. Considering the role of the region and its frequent exposure to climatic fluctuations, this study offers pertinent recommendations that can guide the policy on Balochistan's development directions.

## 2.2 Data set

MODIS (Moderate Resolution Imaging Spectroradiometer) is one of the important sensors installed in NASA's Terra

and Aqua satellites delivering excellent quality worldwide data on the condition of the land surface, atmosphere, and oceans (<https://www.earthdata.nasa.gov/>). Several MODIS products are employed in drought monitoring, which include the 16-day composite NDVI at a 250m resolution. The 8-day LST at 1km resolution was collected which is very important in determining the thermal stress on vegetation since vegetation is sensitive to high temperatures. The land cover was calculated through MCD43A4 (MODIS/Terra Nadir BRDF-Adjusted Reflectance Daily L3 Global 500m SIN Grid). Precipitation satellite data was collected from the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) (<https://www.chc.ucsb.edu/data/chirps/>) for drought monitoring and assessment especially in Balochistan and CHIRPS offers precipitation data at an accuracy of 0. 05°. Also collected the monthly precipitation and potential evapotranspiration data from terra climate which is based on Penman-Montheith method (<https://www.climatologylab.org/terraclimate.html>). Ground data was also collected from Pakistan Meteorological Department (PDM) (<https://www.pmd.gov.pk/en/>).

## 2.3 Data processing

To analyze agricultural drought occurrences in Balochistan from 2001–2022 and their impacts on vegetation anomalies, MODIS data was acquired and re projected to WGS1984 coordinate system in ArcGIS 10.8 using the projection tool. ArcGIS 10.8 is a robust GIS software platform developed by Esri, offering comprehensive tools for spatial data analysis, mapping, and geospatial intelligence. Additionally, ArcGIS 10.8 supports extensive customization and automation through Python scripting with ArcPy, making it a powerful tool for a wide range of geospatial applications. All datasets were resampled to 500m resolution using bilinear interpolation to standardize analysis (Hu et al. 2021). Meteorological conditions of any area are considered as the primary

**Table 1** Datasets used in this study

| Datasets   | Year      | Spatial Resolution             | Source  |
|--|-----------|--------------------------------|---|
| MOD13Q1 (NDVI)   | 2001–2022 | 250m                           | <a href="https://www.earthdata.nasa.gov/">https://www.earthdata.nasa.gov/</a>                                   |
| MOD11A2 (LST)  | 2001–2022 | 1km                            | <a href="https://www.earthdata.nasa.gov/">https://www.earthdata.nasa.gov/</a>                                   |
| MCD43A4(Land Cover)                                    | 2001–2022 | 500m                           | <a href="https://www.earthdata.nasa.gov/">https://www.earthdata.nasa.gov/</a>                                   |
| MOD09A1(Surface Reflectance)                           | 2001–2022 | 500m                           | <a href="https://www.earthdata.nasa.gov/">https://www.earthdata.nasa.gov/</a>                                   |
| MOD16A2<br>(Evapotranspiration)                        | 2001–2022 | 250m. 500m                     | <a href="https://www.earthdata.nasa.gov/">https://www.earthdata.nasa.gov/</a>                                   |
| Precipitation and PET                                  | 2001–2022 | Monthly                        | <a href="https://www.climatologylab.org/terraclimate.html">https://www.climatologylab.org/terraclimate.html</a> |
| Precipitation, Temperature and ETo                     | 1992–2022 | Ground Data                    | <a href="https://www.pmd.gov.pk/en/">https://www.pmd.gov.pk/en/</a>   |
| CHIRPS(Climate Hazards GroupInfraRed<br>Precipitation) | 1992–2022 | 1 <sup>0</sup> ×1 <sup>0</sup> | <a href="https://www.chc.ucsb.edu/data/chirps">https://www.chc.ucsb.edu/data/chirps</a>                         |
| Boundary   | 2023      | -                              | <a href="http://surveyofpakistan.gov.pk/">http://surveyofpakistan.gov.pk/</a>                                   |



factor influencing drought. Meteorological indices provide a comprehensive trend of weather patterns and their contribution in causing drought. Therefore, using meteorological data in this study was an essential element in understanding spatiotemporal trend of drought in Balochistan. Furthermore, long-term precipitation and temperature records from ground stations across Balochistan were analyzed. The trends in these datasets were used to evaluate the impacts of meteorological drought on vegetation health and agricultural drought occurrence.

### 2.3.1 Satellite data process

MODIS based products MOD13Q1, MOD11A2, MCD43A4 and MOD09A1 were obtained from the NOAA’s Earth Observing System Data and Information System (EOSDIS) presented in Table 1. ET data (MOD16A2) was developed based on Penman–Monteith equation based on light use efficiency model to calculate PET (Liu et al. 2022). All these datasets were downloaded using MODIS library and packages in R software version R i386 4.0.3 from year 2001–2022 (<https://cran.r-project.org/bin/windows/base/>) (Baig et al. 2020). This data involves to use several indices, including NDVI, SPEI, and PCI derived using MODIS datasets to monitor the drought. Meteorological and satellite, rainfall data are collected for the study area for validation (Li et al. 2020).

### 2.3.2 Ground data process

By improving data accuracy, this study seeks to enhance climate research, disaster preparedness, and sustainable development initiatives in the region. In this research, last 30 year (1992–2022) monthly precipitation and temperature data was collected from meteorological stations (<https://www.pmd.gov.pk/en/>) of Balochistan in Table 1. The Precipitation data collected from the meteorological station is processed for the Validation of the Satellite data from the CHIRPS product for the calculation of the PCI. Annual Precipitation and Temperature variation is shown in in Table 2.

## 2.4 Methodology

The methodology of the indices which were used in the study to calculate agricultural and vegetation drought (NDVI, VCI, VHI and TVDI) and also calculated meteorological drought (SPEI, RDI, PCI and TCI). Agricultural drought is a condition where there is insufficient water in the soil to support

crops which affects agriculture. Meteorological drought can be described as a long-term occurrence of substantially reduced precipitation both for water and climate. The drought classification have four types including hydrological and socio economic drought (Zuo et al. 2019).

### 2.4.1 Validation of chirps’ precipitation with PMD data

The root mean square error (RMSE) and Pearson correlation coefficient (R) between precipitation from the ground meteorological stations (PMD) and satellite based CHIRPS data was applied to evaluate the satellite observation. RMSE approach was used to measure the spatial variability between actual values and predicted of drought and vegetation values as follow Eq. 1:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (X_i - Y_i)^2}{N}} \tag{1}$$

CHIRPS’ mean precipitation of the monsoon season from 2001 to 2022 was correlated with mean precipitation of PMD during the same time period as shown by scatter plot in Fig. 2a. There is a strong positive correlation for CHIRPS (R<sup>2</sup>=0.83). The T value returned from two tailed T Test is 0.016 which shows significant match between both variables (Srivastava et al. 2013), (Holzman et al. 2014). There is almost similar trend from 2001 to 2022 between both datasets as shown in Fig. 2b. The value of 2.88 was obtained after calculating the RMSE the model graph of RMSE in Fig. 2c proves the evaluation.

### 2.4.2 Normalized difference vegetation index (NDVI)

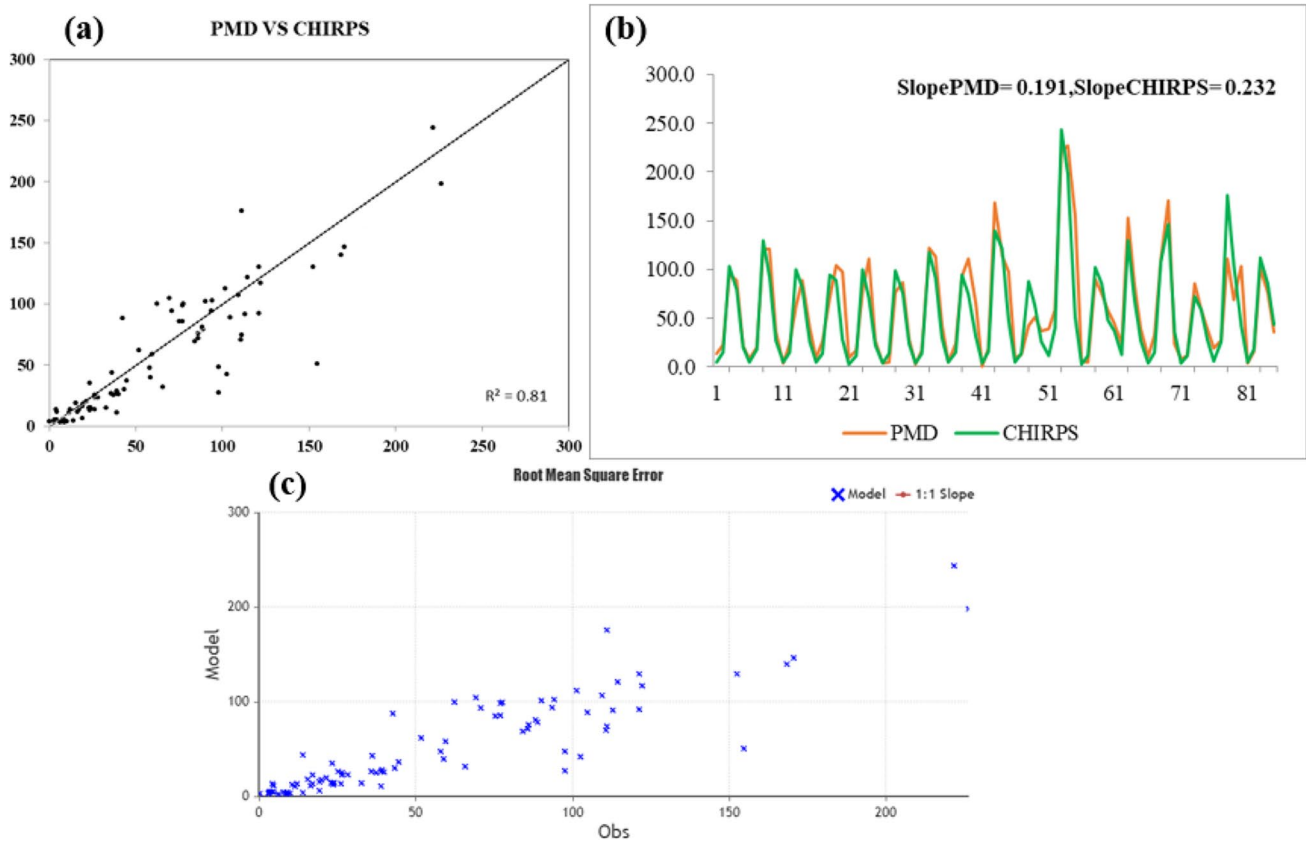
NDVI is a widely used measure to distinguish between the green leaf scattering in the near-infrared to the chlorophyll absorption (Chen et al. 2023). The value of the index ranges from -1 to 1. A common range for green vegetation is 0.2 to 0.8. The Eq. 2 shown NDVI formula.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{2}$$

Where, NIR is the reflectance in the near-infrared part of the spectrum, and Red is the reflectance in the red part of the spectrum. The purpose of NDVI was to evaluate the vegetation cover and their anomalies in region.

**Table 2** Average annual rainfall and temperature statistics data

| Climatic Variable  | Min  | Max  | Mean | Median | Variance | Std. Deviation |
|--------------------|------|------|------|--------|----------|----------------|
| Temperature (c)    | 22.3 | 28.7 | 25.5 | 25.3   | 2.21     | 1.49           |
| Precipitation (mm) | 60   | 180  | 120  | 110    | 900      | 30             |



**Fig. 2** **a** Correlation of PMD and CHIRPS; **b** slope of mean seasonal precipitation from PMD and CHIRPS where on y axis is precipitation (mm) while x axis is the number of correlated points from 2001 to 2022

### 2.5 Characteristics of D's C obtained eye chamber

The relationship between the internode coefficient of variation (CV) and the NDNN CV value indicates a growing dynamic dependence of the plant-node surface. Specifically, during the crop growth phenological phase, the NDVI internode sequence experiences a rapid increase followed by a decrease, surpassing the range of CV values for each field type (Ahmadaali et al. 2021). At this juncture, the internode object CV value is determined shown in Eq. 3.

$$\sigma = \sqrt{\frac{1}{n-1} \left[ \sum_{m=1}^n (ndvi)_m^2 - \left( \sum_{m=1}^n NDVI_m \right)^2 \right]} \tag{3}$$

$$\mu = \sum_{m=1}^n NDVI_m / n \tag{4}$$

$$CV_{ij} = \frac{\sigma_{ij}}{\mu_{ij}} \tag{5}$$

#### 2.5.1 Vegetation condition index (VCI)

VCI is valuable in understanding and managing plant health and condition, in efforts to guide mitigation strategies and inform decision-making in wetland environments, regarding restoration and management (Senhorelo et al. 2023). VCI for each pixel and time period in a year is calculated by the formula shown in Eq. 6:

$$VCI = 100 \times (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) \tag{6}$$

#### 2.5.2 Vegetation health index (VHI)

VHI is used in delineating spatiotemporal patterns for agricultural drought as it enables the identification of different categories of drought severity via a combined assessment of vegetative vigor and thermal properties. VHI combines the estimates of both moisture and thermal stress factors to provide a complete view of vegetation health and to monitor the drought conditions for the agricultural and natural resources management purposes. VHI, by combination of the VCI and the TCI, evolves as

an index capable of providing a comprehensive picture of drought conditions in Eq. 7. VHI can be calculated by the formula in Eq. 6 as explained by (Baig et al. 2021).

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI \tag{7}$$

where  $\alpha$  i.e. 0.5, determines the contribution of VCI and TCI to identify drought status. Moreover, the value of  $\alpha$  is 0.5 because it is difficult to categorize NDVI and surface temperature while measuring drought.

### 2.5.3 Temperature vegetation dryness index (TVDI)

TVDI by creating information from the visible, near-infrared, and thermal infrared spectral bands and combining vegetation indices with surface temperature. TVDI helps in evaluating vegetation moisture stress by using surface temperature and vegetation cover data, the areas that suffer from drought and thermal stress are identified. TVDI surpasses NDVI in discerning areas of dense vegetation and demonstrates enhanced resistance to thus more accurately delineating seasonal vegetation variations across regions. Several studies have developed algorithms to retrieve soil moisture using TVDI, and a composite method has been proposed to improve the calculation of TVDI through taking the time of pixel into consideration in Eq. 8 (Wang et al. 2021a, b).

$$TVDI = LST - LST_{min} / (a \times NDVI - LST_{min}) \tag{8}$$

Where:

**LST** is the land surface temperature at a given pixel, **NDVI** is the Normalized Difference Vegetation Index, **LST<sub>(min)</sub>** is the minimum land surface temperature, while **a** is constant.

### 2.5.4 PCI

CHIRPS is a dataset that provides estimates of monthly precipitation, which can be used to identify meteorological droughts. Specifically to assess and observe the alteration and sufficiency of precipitation and it aims to give information concerning irregular and diminished rainfall and its effects on vegetation and drought. The Precipitation Condition Index (PCI) is a standardized index that uses CHIRPS data and a comparable Vegetation Condition Index (VCI) algorithm to identify precipitation deficits in Eq. 9 (Mupepi and Matsa 2023).

$$PCI = \frac{(P_j - P_{min})}{(P_{max} - P_{min})} \tag{9}$$

where for all of the above equations “j” is the current time step and “min” and “max” are multiyear maximum and minimum, respectively.

### 2.5.5 TCI

Land surface temperature (LST) derived from thermal radiance bands is a good indicator of the energy balance of the Earth’s surface, because temperatures can rise quickly under water stress. TCI is usually applied to determine how the vegetation health is affected by high or low temperatures. It assists in the determination of areas that face heat stress thus facilitating management of high temperatures events on vegetation productivity and regeneration. The TCI is an initial indicator of water stress and drought. It is calculated using the following formula in Eq. 10.

$$TCI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \times 100 \tag{10}$$

### 2.5.6 SPEI

The Standardized Precipitation Evapotranspiration Index (SPEI) is a multiscalar drought index that takes into account both precipitation and potential evapotranspiration (PET) in determining drought conditions. It was developed to address the limitations of other drought indices, such as the Standardized Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI), by incorporating the effects of temperature on evapotranspiration (Ahmed et al. 2018). It is employed to identify, to evaluate and to measure the intensity and the duration of the droughts and therefore to review the climatic tendencies and water resources. The SPEI enables the measurement of both wetness (positive values) and dryness (negative values) based on the supply and demand concept of the water balance equation.. It uses the monthly or weekly difference between precipitation and PET, representing a simple climatic water balance.

$$SPEI = W - \frac{c_0 + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{11}$$

Where:

$$W = \sqrt{-2\ln(P)} \text{ for } P \leq 0.5$$

$P$  = probability of exceeding a determined D value,  
 $p = 1 - f(x)$ ;

When  $P > 0.5$ ,  $p = 1 - P$ , constants are:

|                  |                  |
|------------------|------------------|
| $c_0 = 2.515517$ | $d_1 = 1.432788$ |
| $c_1 = 0.802853$ | $d_2 = 0.189269$ |
| $c_2 = 0.010328$ | $d_3 = 0.001308$ |

### 2.5.7 Reconnaissance drought index (RDI) and potential evapotranspiration (PET) calculation

RDI is a measure of drought severity and its duration integrating hydrological and meteorological parameters i.e. precipitation, temperature, and potential evapotranspiration.. It is also applied to learn the states of increased or decreased precipitation to evaluate cases of droughts and floods, how they affect the ecosystem and agriculture. Such indices are useful for timely warning and monitoring of droughts therefore providing reliable water management and drought mitigation. RDI can be calculated by the formula in Eq. 12:

$$\alpha_k^{(i)} = \frac{\sum_{j=1}^k P_{ij}}{\sum_{j=1}^k PET_{ij}}, i = 1(1)N \text{ and } j = 1(1)k \tag{12}$$

$\alpha_k$  i.e. initial value of RDI while  $P_{ij}$  and  $PET_{ij}$  indicate precipitation along with potential evapotranspiration for  $j^{\text{th}}$  and  $i^{\text{th}}$  months,  $N$  i.e. number of years.

Potential evapotranspiration (PET) can be calculated using various methods such as the Hargreaves method, Thornthwaite method, or Penman–Monteith method. The Hargreaves method, for example, uses monthly maximum and minimum temperatures to calculate PET. The formula for calculating PET using the Hargreaves method in Eq. 13:

$$PET = 0.408 \times R \times T \times (T_{max} - T_{min}) \tag{13}$$

Where:  $R$  represents the solar radiation at the given latitude,  $T$  is the mean temperature,  $T_{max}$  and  $T_{min}$  are the maximum and minimum temperatures, and 0.408 is a constant (reciprocal of the latent heat flux of vaporization at 20 °C). Table 3 are presenting the Categories of drought indexes, according to worldwide used indices.

### 2.5.8 Linear regression analysis

Linear regression is a statistical method that is utilized to examine the association between the Drought Indices. The purpose of using linear regression in the study was to assess the relationship between drought indices and vegetation dynamics. By establishing a linear relationship, the

study aimed to quantify how variations in drought indices influence changes in vegetation health, providing insights into the impact of drought on ecological conditions. The analysis of the relationship between the drought indices is based on standard linear regression techniques (van der Wiel et al. 2023).

## 3 Results

### 3.1 NDVI time series analysis with precipitation

Figure 3 show the results the dynamics of vegetation as observed in 2001, 2002, 2004, 2009, 2014, 2018, and 2022 across Balochistan. The maps in this Fig. 4 were developed through the compilation of 22-years-worth of monthly data into two sets of images capturing intra-annual fluctuations and inter-annual trends. Due to the large number of maps, the information underlying them could only be included in a single article. These green areas were identified according to the following classification criteria:  $NDVI \geq 0.3$ , generally corresponds to vegetation;  $0 \leq NDVI < 0.3$  non-vegetated lands, and  $NDVI < 0$  aqueous zones.

Figure 4 shows the relationship and trend of NDVI and precipitation of research area. According to analysis, vegetation cover decreasing. The correlation between vegetation and precipitation in Balochistan from year 2001 to year 2022 has high fluctuation but strong relation. NDVI values which vary between 0 and 1 differed most of the time to the ranges of 0. 1 to 0. 3 in arid regions to 0. 4–0. 6 and would be higher if measured in more vegetated regions during wet periods. Average yearly rainfall ranged from less than 100mm as in the low rainfall area which include the western deserts to more than 300mm in the high rainfall area which include the northeastern highlands. The results of the analysis suggest that there is about 1 to 3 months delay in the response of vegetation to precipitation; this represents the time difference between the two in which the NDVI level reaches its maximum level two months after the occurrence of intense precipitation. Extreme droughts like in the 2001 and 2018 had the NDVI value go below 0. Average precipitation was 1

**Table 3** Classification categories of drought indexes

| Name of Class        | VCI     | VHI     | TVDI    | PCI     | TCI     | SPEI           | RDI           |
|----------------------|---------|---------|---------|---------|---------|----------------|---------------|
| Extreme drought      | 0–0.1   | 0–0.1   | -       | 0–0.1   | 0–0.1   | $\leq -2$      | $\leq -2$     |
| Severe drought       | 0.1–0.2 | 0.1–0.2 | 0.8–1   | 0.1–0.2 | 0.1–0.2 | -1.50 to -1.99 | 1.5 to -1.99  |
| Moderate drought     | 0.2–0.3 | 0.2–0.3 | 0.6–0.8 | 0.2–0.3 | 0.2–0.3 | -1.00 to -1.49 | -1 to -1.49   |
| Mild drought         | 0.3–0.4 | 0.3–0.4 | 0.4–0.6 | 0.3–0.4 | 0.3–0.4 | -0.99 to 0.99  | -0.99 to 0.99 |
| Abnormal drought     | 0.4–0.5 | 0.4–0.5 | -       | 0.4–0.5 | 0.4–0.5 | 1.00 to 1.49   | 1.0 to 1.49   |
| No drought/ Very wet | 0.5–1   | 0.5–1   | 0–0.4   | 0.5–1   | 0.5–1   | 1.50 to 1.99   | 1.5 to 1.99   |
| Extremely Wet        | -       | -       | -       | -       | -       | $\geq 2$       | $\geq 2$      |



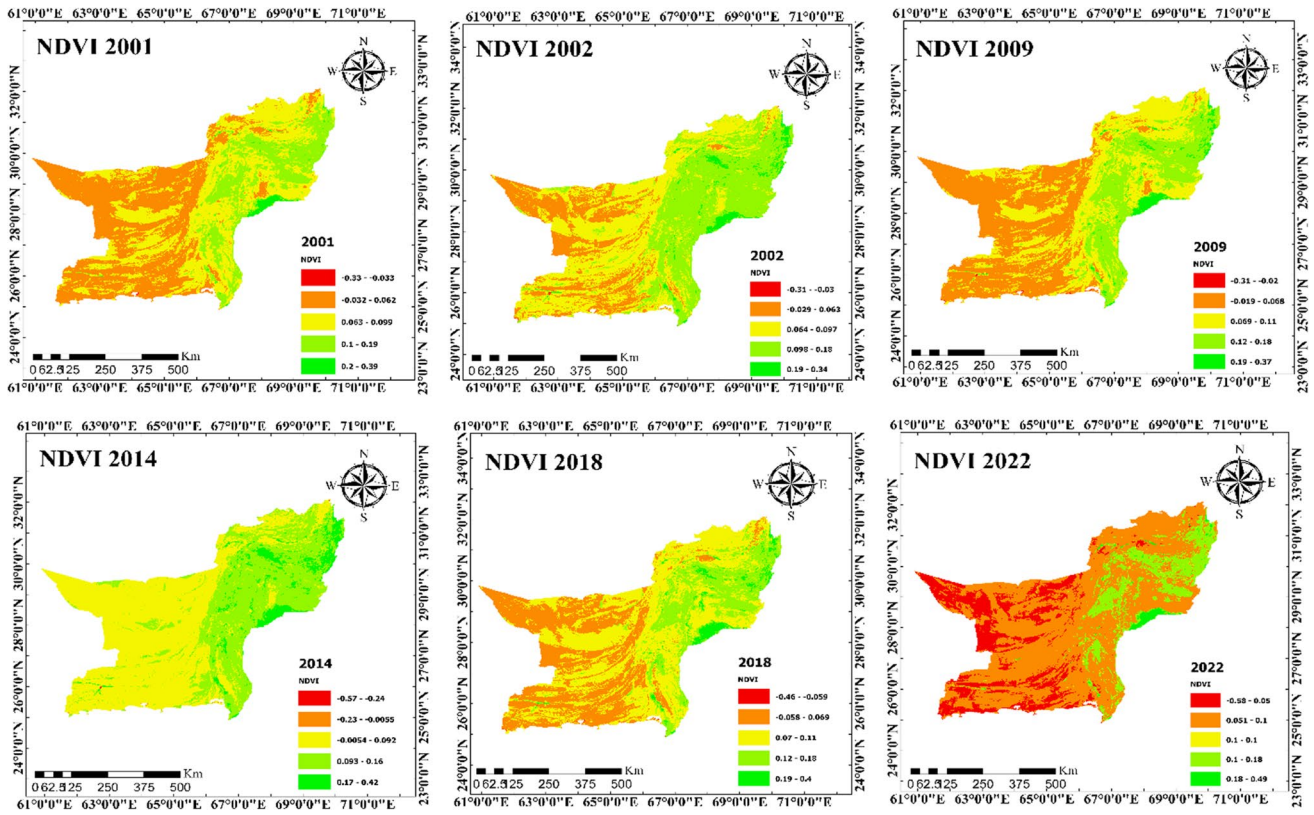
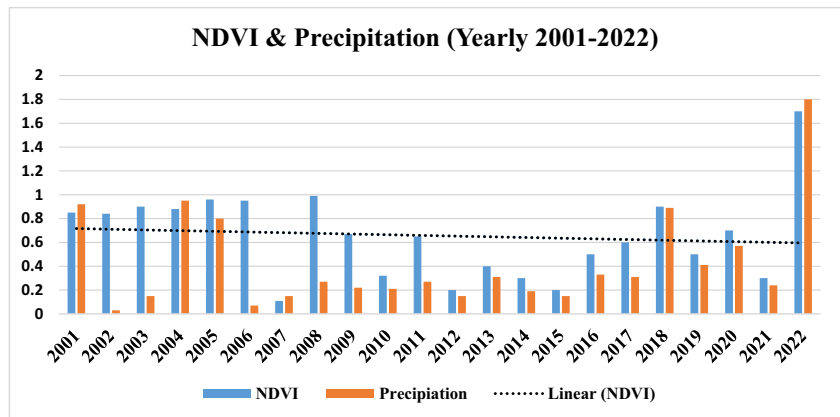


Fig. 3 NDVI time series maps

Fig. 4 NDVI and Precipitation time series analysis



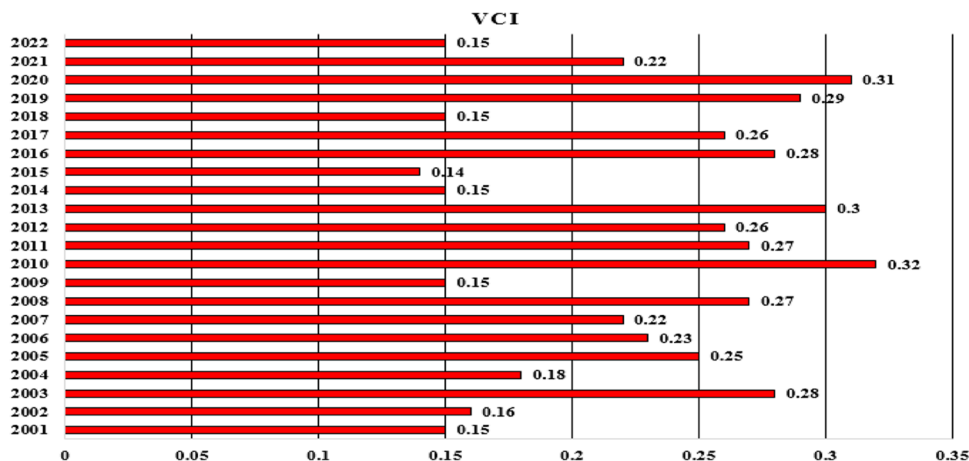
in many areas, this underscores the area’s sensitivity to water scarcity resulting from inadequate rainfall.

### 3.2 VCI derivation

The deviation of vegetation condition from normal has an indication of the intensity of impact of drought on vegetation growth. In year 2001, there were a series of drought events while in year 2022, moderate drought events appeared as shown in Fig. 5. VCI values spanning 0.15 to ~0.16 point

to severely compromised vegetation health and vigor under such an intense drought. The reduced amount of water available to vegetation during drought periods can lead to decreased photosynthetic capacity and vitality, reducing vegetation greenness. The lowest VCI value of the 2001 and 2018 drought underscores the severe level of drought stress experienced. Declining VCI values code for deteriorating ecosystem functioning, declines in agricultural productivity, and increased vulnerability to threats such as wildfires and habitat degradation.

**Fig. 5** Variation of vegetation condition index from 2001–2022



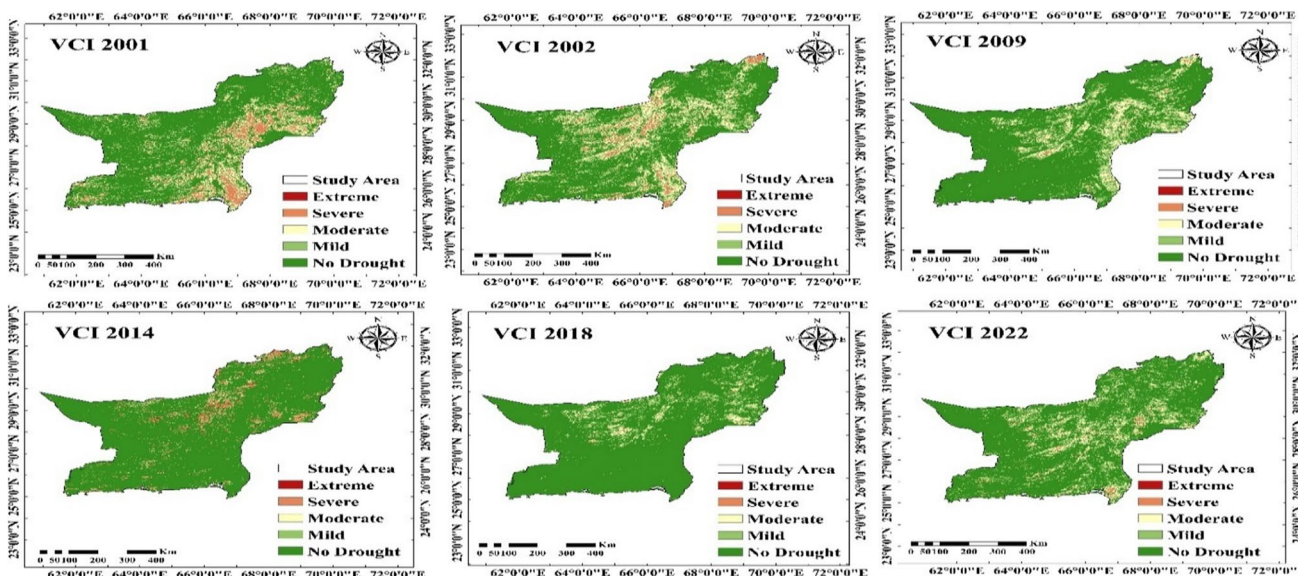
Vegetation Condition Index trends were prepared for years (2001–2022) of study area i.e. Balochistan where different trend levels of VCI were calculated showing highest growth trend in spring. The VCI increased in 64.74% pixels and increased significantly in 53.2% land of the province; the VCI decreased only in a small portion of the province of 4.4%; it decreased significantly in 2.94% areas, mainly in some pockets of the province. The VCI decreased significantly in some small patches of the three season as well. The trend was grossly different in these patches from that of the surrounding areas; this change in the VCI was due to some local effects, which had no relationship with the surroundings because of some factors specific to the Balochistan alone, like intense urbanization in place of drought. It was also a limitation of the VCI in the drought analysis; i.e., the sudden changes in the vegetation due to some artificial

changes may be taken as the drought changes by the VCI in Balochistan shown in Fig. 6.

### 3.3 VHI derivation

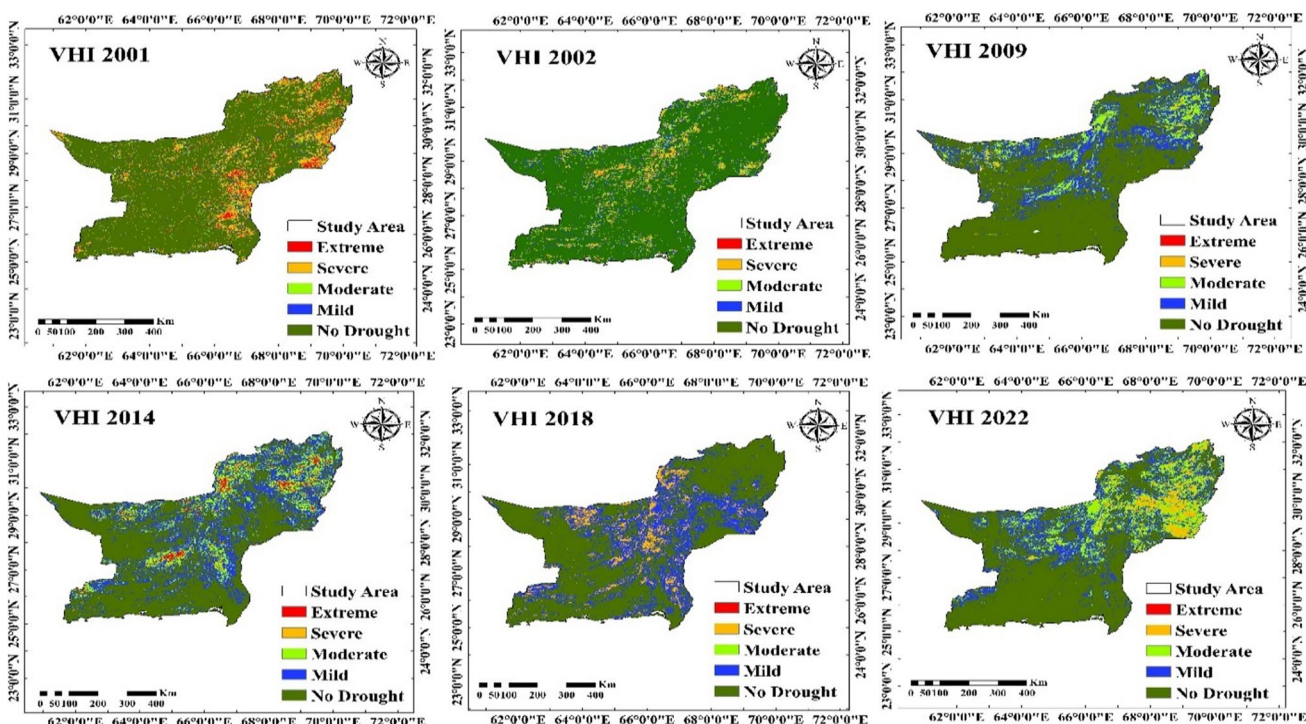
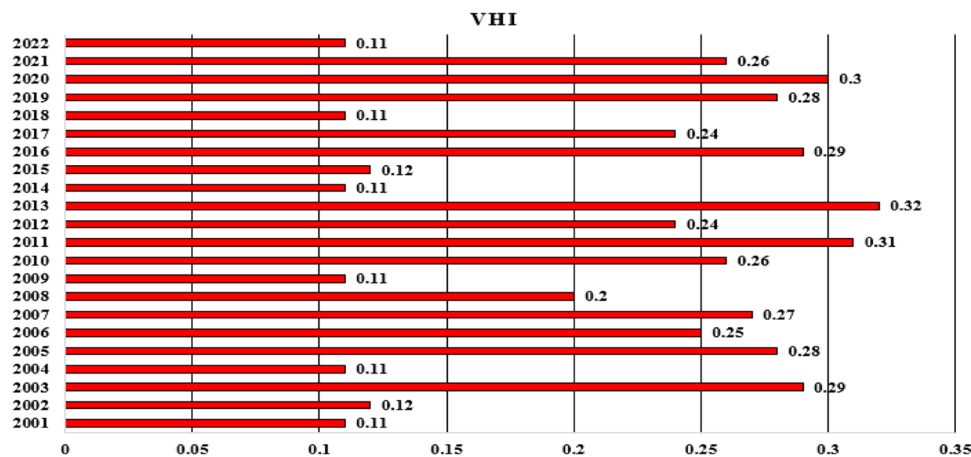
The spatiotemporal analysis presented in this study showed that most of Balochistan experienced below-average seasonal rainfall, leading directly to an agricultural drought. Figure 7 shows the agricultural drought, measured by VHI, response to the seasonal rainfall. Balochistan faced agricultural drought during the period 2001–2022. In particular, years (2001, 2002, 2009, 2014, 2018 and 2022) experienced an extreme drought period across the region with the mean VHI values attaining 0.11–0.12 respectively.

During this period, Balochistan experienced a severe scarcity of livestock forage, drinking water, and food as



**Fig. 6** Temporal trend of vegetation condition index from 2001–2022

**Fig. 7** Variation of Vegetation health index from 2001–2022



**Fig. 8** Temporal trend of Vegetation health index from 2001–2022

indicated by these low VHI values. In subsequent years, the VHI values showed improvement, reaching 0.32, 0.29, and 0.3. VHI values ranging from approximately 0.11 to 0.12 indicate severely stressed vegetation and decreased biomass production associated with severe drought in Fig. 8. These values reflect decreased greenness and cover associated with water stress, affecting agricultural production, ecological integrity, and biodiversity. The lowest VHI value recorded in 2001 and 2018 highlights the most severe impact of drought on vegetation health among the selected years, underscoring the need for adaptive management to mitigate the ecological and socio-economic consequences of drought-related vegetation degradation.

### 3.4 TVDI derivation

The relationship of LST-NDVI has been interpreted in terms of vegetation crops, climate, and all scales. On the other hand, LST rises fast in response to water stress, however the relationship between LST and NDVI is shown to be bounded by a cloud of dispersion space for an assumed dry area, highest values of LST are associated with the lowest values of NDVI. LST in the Balochistan area showed a significant difference ( $p \leq 0.05$ ) which indicated a trend i.e. minimum, maximum and average as 6.50, -4.06, and 1.27 °C respectively from 2001 to 2022 shown in Fig. 9.



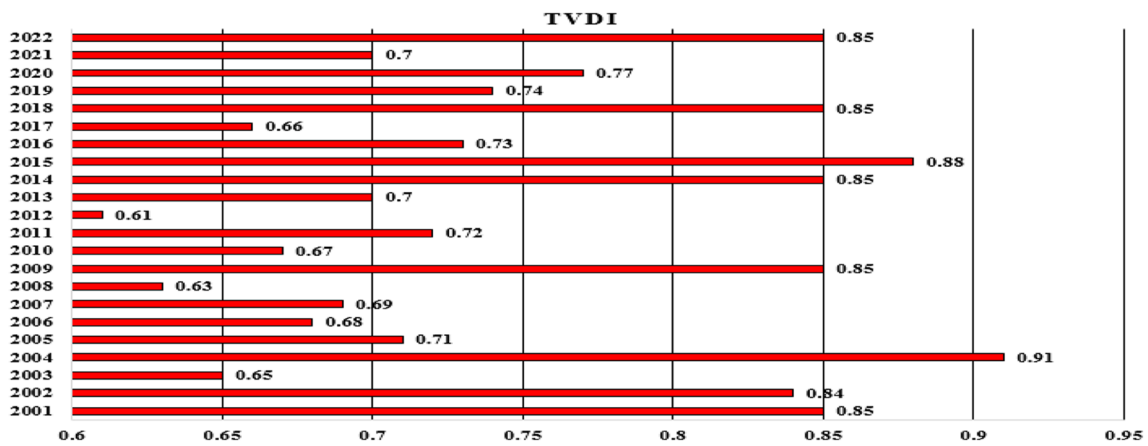


Fig. 9 Variation of Temperature vegetation dryness index from 2001–2022

It was found that land use type has much stronger effect on the LST, e.g., certain crops have mean of  $-0.4^{\circ}\text{C}$  when urban areas showed higher LST  $0.3^{\circ}\text{C}$ . However, urban areas are in limited number and less developed in Balochistan as compared to other areas in Pakistan. TVDI values ranging from approximately 0.73 to 0.85 describe severe drought conditions associated with increased vegetation temperature stress and reduced soil moisture availability. These values illustrate the combined effects of temperature and vegetation

level on the severity of drought where higher TVDI values suggest increased severity of drought. The TVDI value i.e. 0.84 recorded in 2001 indicates a severe drought event, while year 2004, TVDI value 0.91 indicate extreme drought events emphasizing the need for effective water resource management and adaptability to reduce the severity of drought impacts on both human and natural systems. As shown in Fig. 4 which indicates that all years of images in

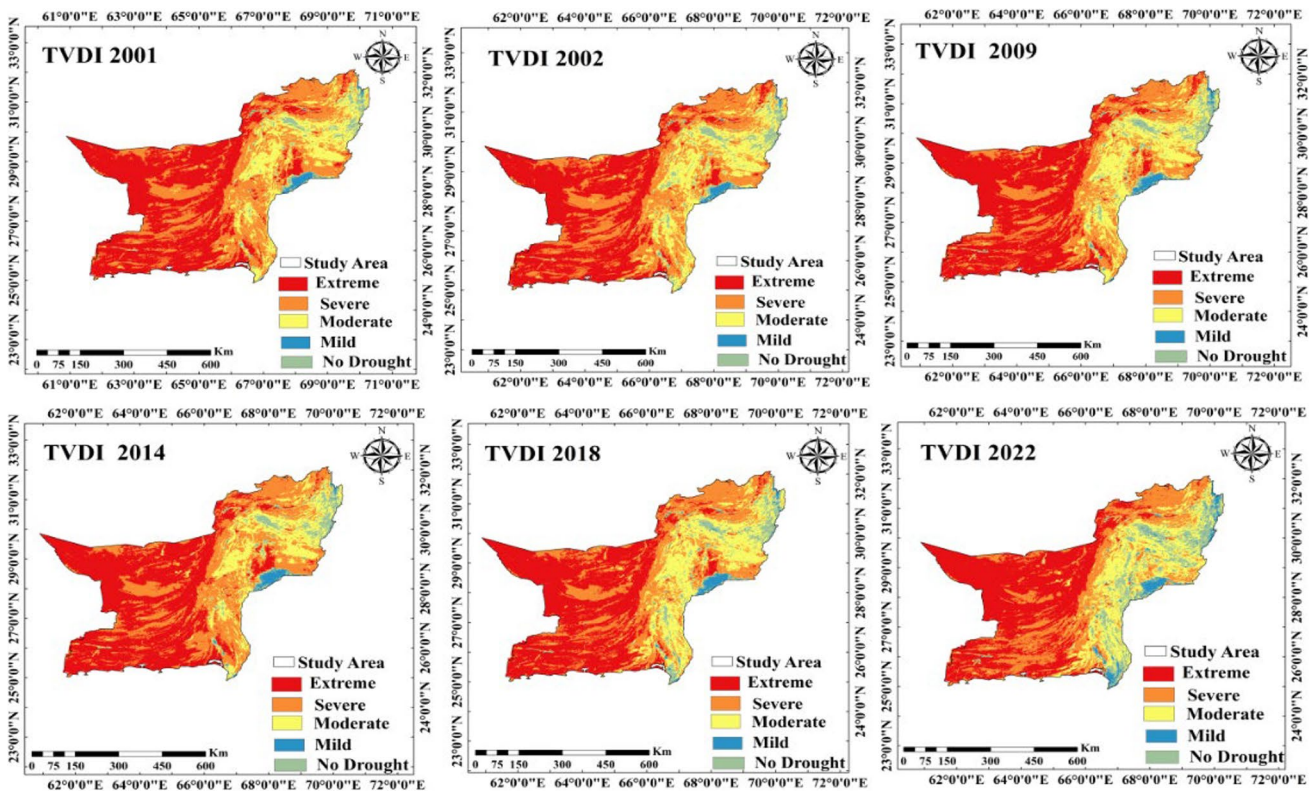


Fig. 10 Temporal trend of Temperature vegetation dryness index from 2001–2022



the Balochistan area are significantly different ( $p \leq 0.05$ ), shown in Fig. 10.

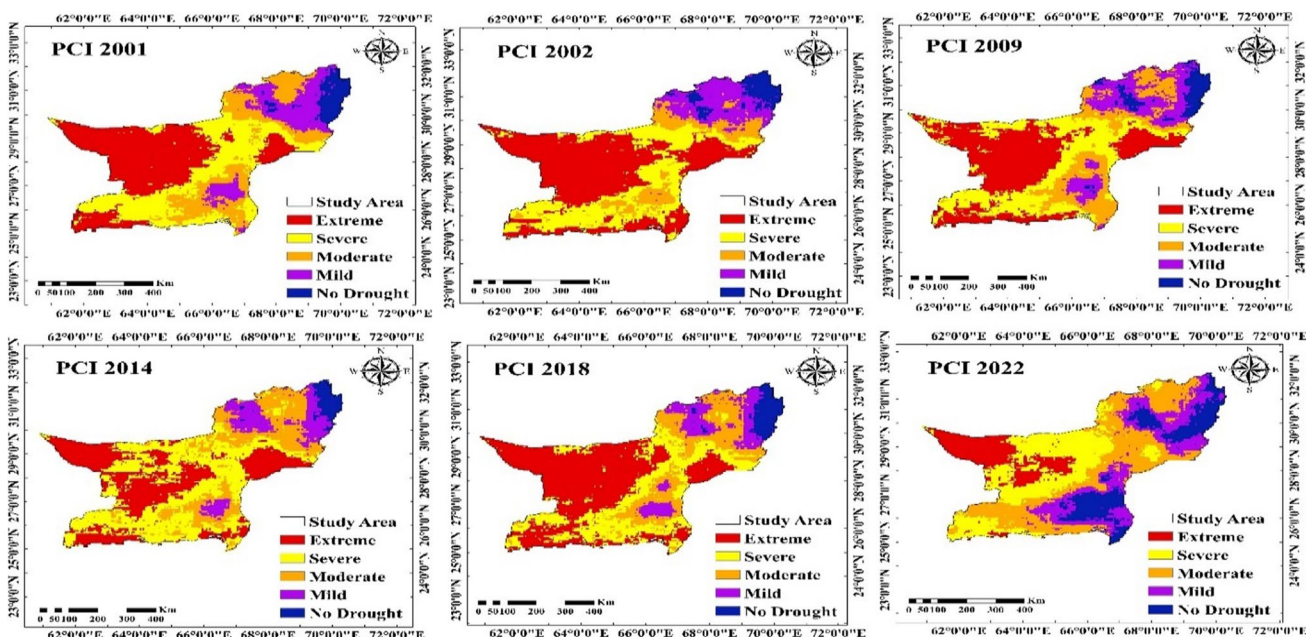
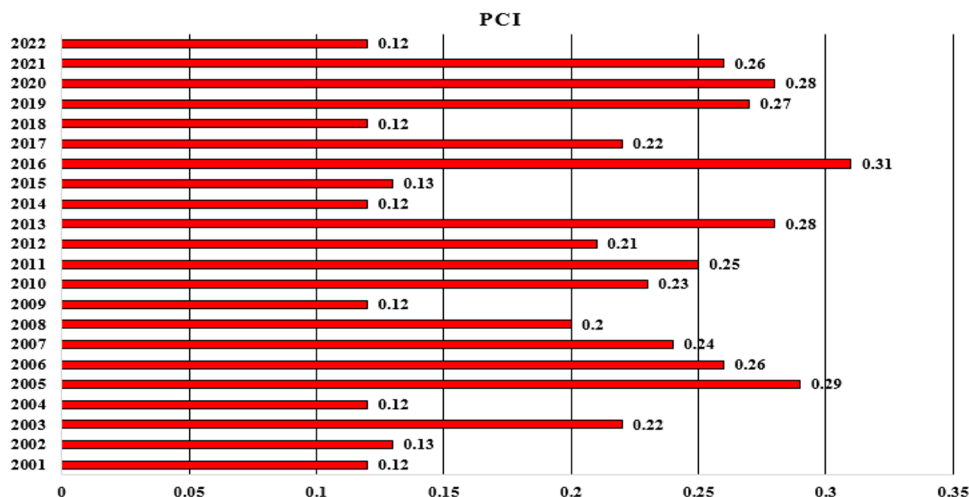
### 3.5 PCI derivation

The PCI derived from historical precipitation (2001–2022) has been explored for the study area during monsoon (Jun–Sep) season. The temporal trend of meteorological drought during monsoon season from 2001 to 2022 is shown in Fig. 11 based on the percent area affected by each drought class over the specific year. The results indicate that the area under extreme drought class has been increased more in 2022 which is 46.62% of entire area. This shows

an increasing tendency from 2001 to 2022. This increase in drought shows the probability of occurrence of low amount of seasonal precipitation. Therefore, the seasonal precipitation can be less near to this region during this period. Consequently, the temperature and evapotranspiration shall increase and this area will be more vulnerable towards drought in terms of intensity and area.

The PCI values ranging from 0.11 to 0.13 throughout the specified years (2001, 2002, 2009, 2014, 2018, and 2022) indicate severe drought conditions typified by significantly below-normal precipitation. Such values are indicative of prolonged periods of critically dry conditions that can exacerbate water deficits and enhance the severity

**Fig. 11** Temporal trend of Precipitation condition index from 2001–2022



**Fig. 12** Temporal trend of Precipitation condition index from 2001–2022

of drought. The lowest PCI value observed in 2001 (0.11), underscores the most extreme drought, reflecting severely compromised water availability and correspondingly high vulnerability to drought-related impacts such as agricultural losses, water scarcity, and ecological disturbances also shown in Fig. 12.

### 3.6 TCI derivation

The LST and TCI for Balochistan were calculated and mapped for 2001–2022. Results illustrates that during 2001, the soils from southern and northwestern part exhibits higher than 30 °C, while in some areas its values were in between 25–30 °C. The river banks are predominantly covered with sand and sand showed LST higher than 35 °C. The study area during 2001 and 2009 presented LST which ranged from 25.1 to 30 °C, exception the districts in northern part where soils had higher than 30 °C. During 2013, southward areas exhibits high LST (> 30 °C), while northern districts exhibits LST in between 25.1 °C to 30 °C. During 2018, the districts in northern areas declares LST in between 20.1 to 25 °C was possibly due to wet spells. The scenario of LST is almost similar to 2005 except, in 2021 extended areas had LST more than 30 °C. Figure 13 also shows the TCI in (2001, 2002, 2009, 2014, 2018, and 2022 during the pre-monsoon period. Almost the entire region experienced extreme to moderate drought (TCI < 20–40%) during 2001, except for small area of about 6 km<sup>2</sup> in the central region, where no drought had occurred (TCI > 40%).

In 2001, the northern region displayed extreme drought (TCI < 10%); whereas, in 2009, drought events were sparse. Except for extreme to no drought events in the central and northern regions, the whole area had TCI > 40% in this year. During 2013, extreme drought (TCI < 10%) affected the southern region, with no drought (TCI > 40%) in a few

locations in the central part of the study area. In 2018, the whole region again witnessed TCI > 40%. In 2022, however, the most extreme drought events (TCI < 10%) were occurring in the northern part of the study area, with extreme to moderate drought in the central region. The TCI values ranging from 0.13 to 0.14 during the specified years are indicative of elevated temperatures. Such anomalies can exacerbate water stress and increase evaporation rates, effectively enhancing the intensity of drought conditions shown in Fig. 14. The close correspondence between TCI and PCI values highlights the synergistic relationship between temperature and precipitation in driving drought severity. Elevated TCI values reflect heightened temperature stress on vegetation and ecosystems that conspire to amplify the deleterious impacts of drought on agricultural productivity, water resources, and ecological resilience.

### 3.7 SPEI derivation

SPEI values spanning from approximately -2.20 to -0.40 throughout 2001 to 2022 reflect differing levels of drought severity. Negative SPEI values correspond to dry conditions, with more negative values representing more severe droughts shown in Fig. 15. For instance, the very lowest SPEI value occurring in 2001 (-2.20) reflects an extreme drought event which is associated with critical water shortages and escalating exposure to drought-driven impacts like agricultural losses, water restrictions, and ecosystem disruptions. Comparison with fewer negative SPEI values, such as -0.40 recorded in 2005 and 2006, indicates moderately dry conditions signaling diminished precipitation that does not rise to the severity of extreme drought events shown in Fig. 16.

Table 4 below presents various drought indices describing the environmental condition of Balochistan over the

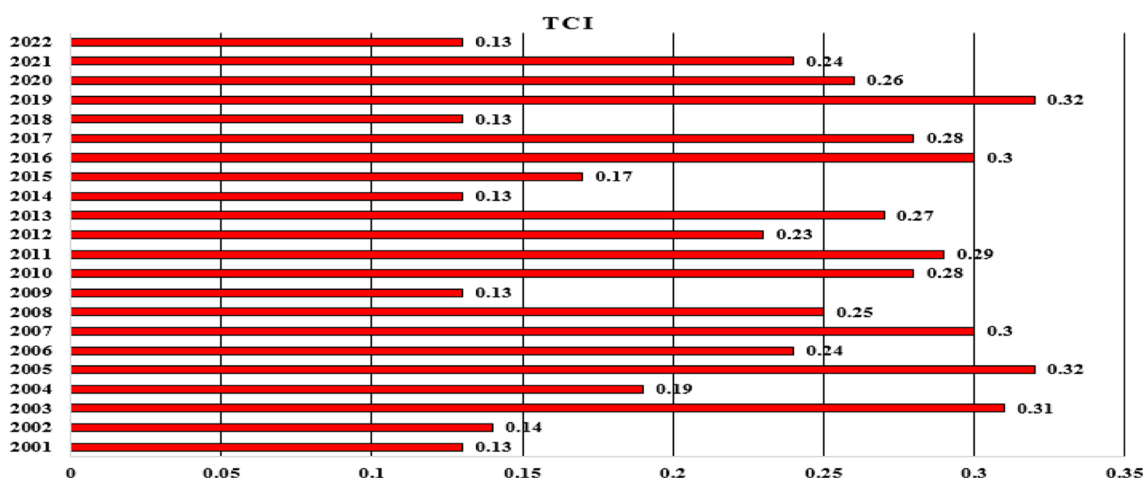


Fig. 13 Temporal trend of temperature condition index from 2001–2022

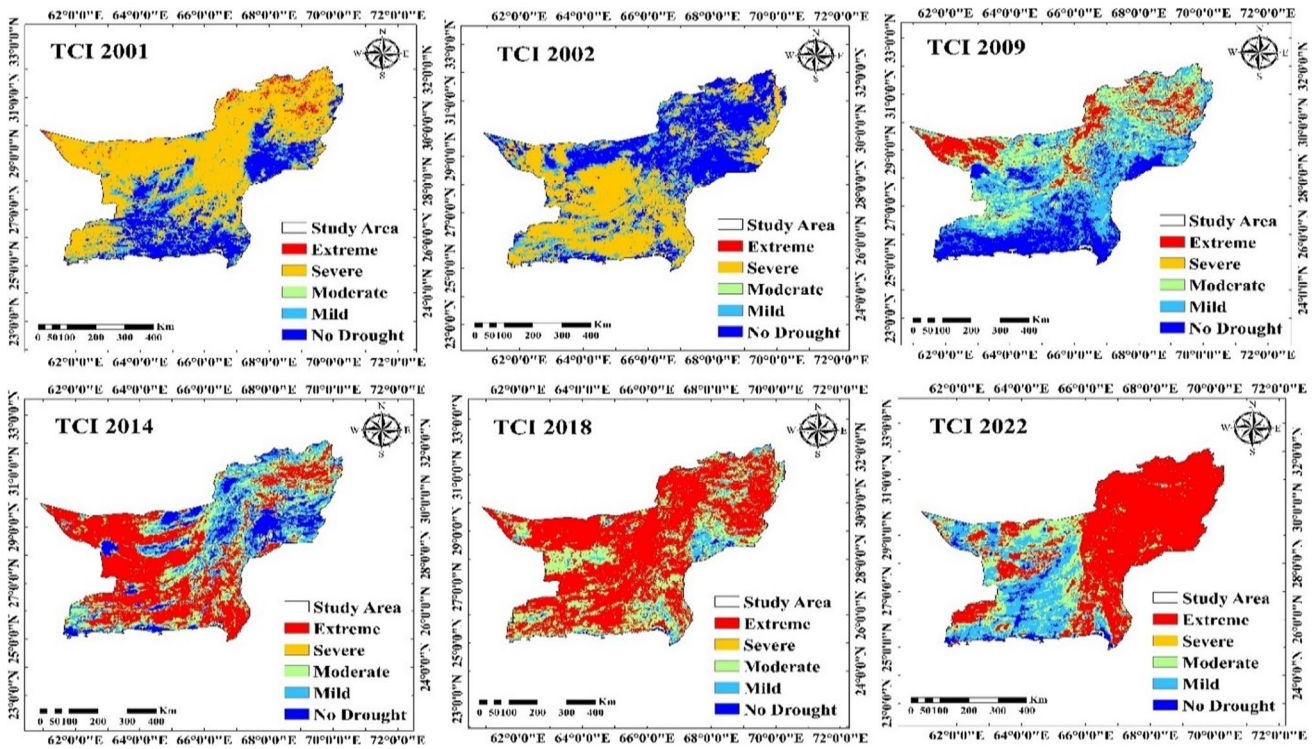


Fig. 14 Temporal trend of temperature condition index from 2001–2022

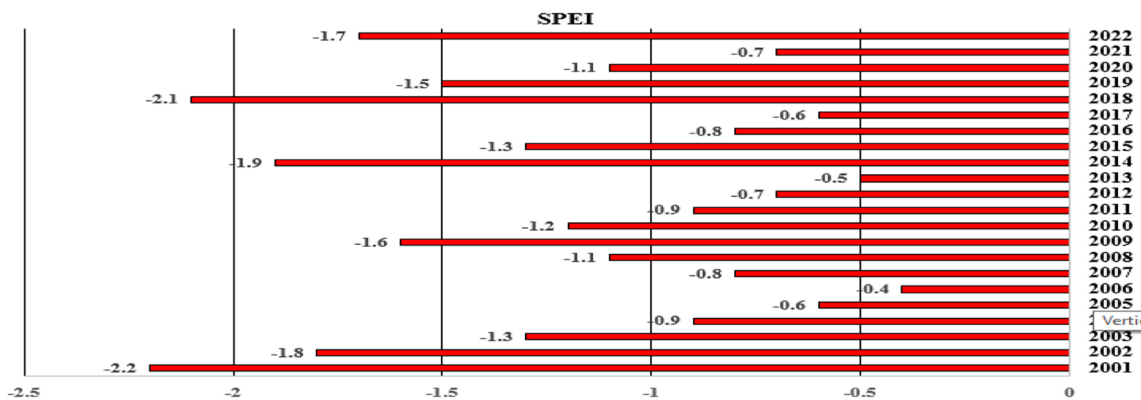


Fig. 15 Vairation of Standard Precipitation Evaporation index from 2001–2022

years. The TVDI values indicating thermal stress of vegetation depict varying conditions. Higher values of TVDI particularly in 2004 and 2018 can be related to elevated cases of thermal stress reaching as much as 0.91, evidencing intense temperature induced vegetative strain. The overall vigor of vegetation which VHI indicates fluctuates greatly. Such as 0.88 was lowest showing poor vegetation health in 2015. Also, VCI and PCI showing how much is a region relatively green and precipitation deficiency, both illustrate varying presence of climatic agents. On the other hand, TCI explains such changing thermal conditions

due to which vegetation is under. SPEI offers a numeric measure of dryness based on the number of standard deviations it falls short (or exceeds) in comparison to its historical average; negative values for this index in particular years can be associated with droughts. -1.7 shows aridity in 2022. In a nutshell, these combined indices offer an integrated perspective on climatic factors and their effects on vegetation, underlining the exposure of the region to climatic shifts.

The relationship among different climatic indices was revealed by the correlation matrix in Table 5, which aid in



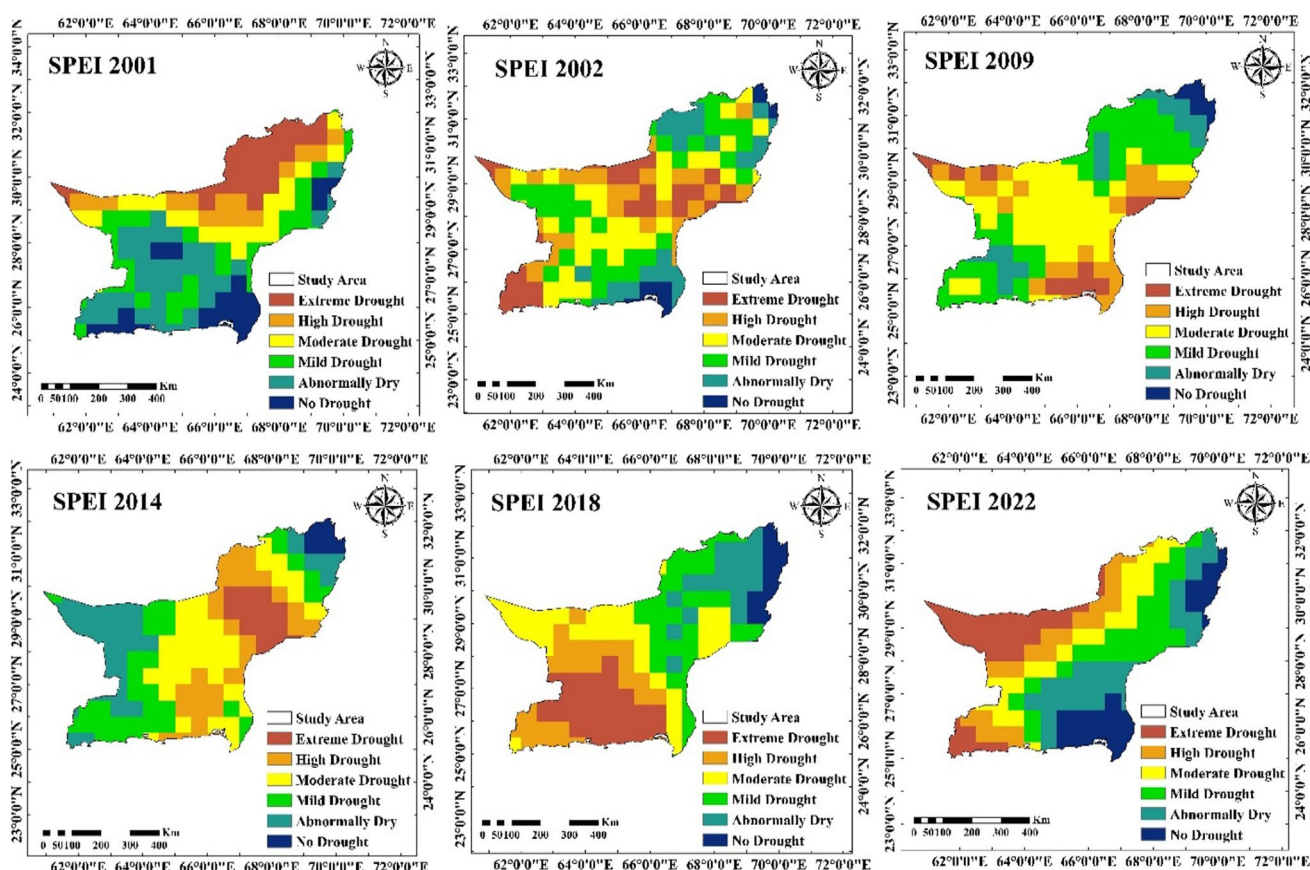


Fig. 16 Temporal trend of Standard Precipitation Evaporation index from 2001–2022

understanding the complicated dynamics which has affected the vegetation in Balochistan in past. A noticeable positive correlation i.e. 0.65729 illustrates between TVDI and VHI that suggest healthier vegetation occurred with increasing thermal stress. Also, VHI and VCI reveals an extremely strong positive correlation that is 0.990185, showing almost perfect linear relationship to specify that changes in vegetation health were in synch with variations in vegetation condition. A moderate positive correlation of 0.719361 between VCI and PCI infers that changes in vegetation condition closely follow from alternations in precipitation conditions as occurred in the historical past. Conversely, there's a strong negative correlation that is -0.97245 between PCI and TCI that shows suggested precipitation conditions improved with greater thermal stress and vice versa in the historical context. Similarly, a noticeable strong negative correlation of -0.73865 between TVDI and TCI shows a negative association among temperature-induced stress and thermal conditions in historical climatic context shown in Fig. 17.

### 3.8 Reconnaissance drought index

The Table 6 included statistics for the reconnaissance drought index (RDI) at each weather station. For each weather station, the Table 6 illustrates, the mean (RDI M), standard deviation (RDI S), and extreme (RDI E) values for RDI. The mean (RDI M) was the average severity of past rainfall deficiencies. The highest mean RDI was 6 at Station "KLT," indicating a substantial average deficiency. The standard deviation, RDI S, was the variability in past RDI values around the mean. Higher values, such as 1.87 at Station "BKN," meant greater fluctuation in past rainfall deficiencies. Extreme RDI, RDI E, was the highest (that is, most severe) observed deficiency in the historical period shown in Fig. 18. The summation of past RDI values and the standard deviation over all stations was the aggregate measure of the regional historical rainfall deficiency, and the region's variability of that historical deficiency. This detail provided coverage of the severity and consistency, and the variability of past rainfall deficiencies at various locations, allowing the comparison of regional precipitation history.



**Table 4** Results obtained post analysis of drought indices using satellite data

| Year | PCI  | SPEI | TCI  | VCI  | VHI  | TVDI | NDVI  |
|------|------|------|------|------|------|------|-------|
| 2001 | 0.12 | -2.2 | 0.13 | 0.15 | 0.11 | 0.85 | 0.085 |
| 2002 | 0.13 | -1.8 | 0.14 | 0.16 | 0.12 | 0.84 | 0.084 |
| 2003 | 0.22 | -1.3 | 0.31 | 0.28 | 0.29 | 0.65 | 0.159 |
| 2004 | 0.12 | -0.9 | 0.19 | 0.18 | 0.11 | 0.91 | 0.075 |
| 2005 | 0.29 | -0.6 | 0.32 | 0.25 | 0.28 | 0.71 | 0.100 |
| 2006 | 0.26 | -0.4 | 0.24 | 0.23 | 0.25 | 0.68 | 0.099 |
| 2007 | 0.24 | -0.8 | 0.3  | 0.22 | 0.27 | 0.69 | 0.130 |
| 2008 | 0.2  | -1.1 | 0.25 | 0.27 | 0.2  | 0.63 | 0.101 |
| 2009 | 0.12 | -1.6 | 0.13 | 0.15 | 0.11 | 0.85 | 0.191 |
| 2010 | 0.23 | -1.2 | 0.28 | 0.32 | 0.26 | 0.67 | 0.112 |
| 2011 | 0.25 | -0.9 | 0.29 | 0.27 | 0.31 | 0.72 | 0.107 |
| 2012 | 0.21 | -0.7 | 0.23 | 0.26 | 0.24 | 0.61 | 0.187 |
| 2013 | 0.28 | -0.5 | 0.27 | 0.3  | 0.32 | 0.7  | 0.105 |
| 2014 | 0.12 | -1.9 | 0.13 | 0.15 | 0.11 | 0.85 | 0.124 |
| 2015 | 0.13 | -1.3 | 0.17 | 0.14 | 0.12 | 0.88 | 0.097 |
| 2016 | 0.31 | -0.8 | 0.3  | 0.28 | 0.29 | 0.73 | 0.096 |
| 2017 | 0.22 | -0.6 | 0.28 | 0.26 | 0.24 | 0.66 | 0.076 |
| 2018 | 0.12 | -2.1 | 0.13 | 0.15 | 0.11 | 0.85 | 0.093 |
| 2019 | 0.27 | -1.5 | 0.32 | 0.29 | 0.28 | 0.74 | 0.125 |
| 2020 | 0.28 | -1.1 | 0.26 | 0.31 | 0.3  | 0.77 | 0.138 |
| 2021 | 0.26 | -0.7 | 0.24 | 0.22 | 0.26 | 0.7  | 0.106 |
| 2022 | 0.12 | -1.7 | 0.13 | 0.15 | 0.11 | 0.85 | 0.124 |

**Table 5** Correlation matrix

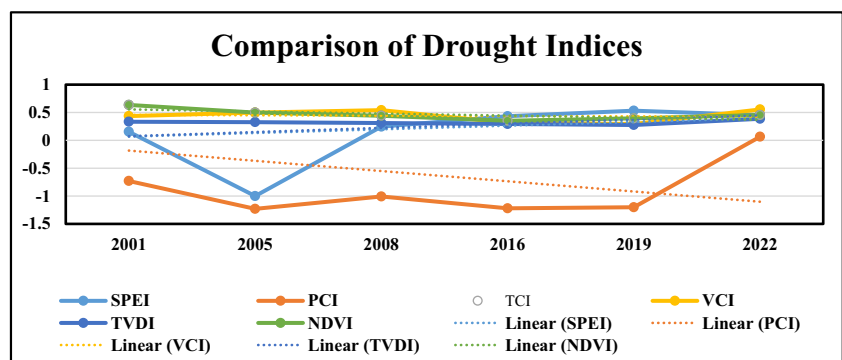
| TVDI | VHI      | VCI       | PCI      | TCI      |          |
|------|----------|-----------|----------|----------|----------|
| TVDI | 1        | 0.65729   | 0.637422 | 0.650997 | -0.73865 |
| VHI  | 0.65729  | 1         | 0.990185 | 0.768953 | -0.77315 |
| VCI  | 0.637422 | 0.990185  | 1        | 0.719361 | -0.72633 |
| PCI  | 0.650997 | 0.768953  | 0.719361 | 1        | -0.97245 |
| TCI  | -0.73865 | -0.773145 | 0.726325 | 0.972446 | 1        |

### 3.9 Relation between TVDI and drought indices

In Fig. 19, scatterplots illustrating the relationship between the Temperature Vegetation Dryness Index (TVDI) and

various other Drought Indices (VCI, VHI, TVDI, PCI, TCI, SPEI) are presented. Following the fitting of trend lines to these plots, correlation coefficient ( $r$ ) values were computed to assess the strength and direction of association between TVDI and each respective index. The obtained correlation coefficients range from 0.59 to 0.82, indicating moderate to strong positive correlations. Specifically, the correlation between TVDI and SPEI demonstrates the strongest association ( $r=0.82$ ), followed by TVDI and VHI ( $r=0.74$ ), TVDI and VCI ( $r=0.81$ ), TVDI and TCI ( $r=0.67$ ), TVDI and PCI ( $r=0.59$ ), and finally TVDI and NDVI ( $r=0.63$ ). These findings suggest that TVDI exhibits a significant relationship with each of the examined drought indices, with SPEI showing the highest

**Fig. 17** Shows the graphical comparison between SPEI, PCI, TCI, VCI, VHI, TVDI, and NDVI



**Table 6** RDI based on different drought categories as per the data collected from different weather stations in Balochistan

| Station | RDI M | RDI S | RDI E |
|---------|-------|-------|-------|
| BKN     | 3     | 1     | 2     |
| DBN     | 3     | 0     | 2     |
| JWI     | 3     | 3     | 0     |
| KLT     | 6     | 0     | 1     |
| KZD     | 6     | 0     | 1     |
| LSB     | 1     | 2     | 2     |
| NKD     | 2     | 1     | 2     |
| ORM     | 3     | 0     | 0     |
| PGR     | 0     | 2     | 2     |
| PSI     | 4     | 3     | 0     |
| QTA     | 5     | 0     | 1     |
| SIB     | 1     | 2     | 1     |
| ZHB     | 2     | 2     | 1     |
| Sum     | 39    | 16    | 15    |
| St. Dev | 1.87  | 1.165 | 0.8   |
| Mean    | 3     | 1.23  | 1.153 |

M moderate, S severe, E extreme

degree of correspondence. Such insights are instrumental for understanding the interplay between temperature, vegetation dynamics, and drought conditions, thereby aiding in effective drought monitoring and management strategies within the study area.

After fitting the trend line between the PCI and SPEI for the years 2001–2022 the coefficient of determination ( $r^2$ ) was 0.7 for PCI, and 0.58 for the SPEI. Figure 20 shows the scatter plot of PCI and SPEI for the years 2001–2022 with the trend line.

### 4 Discussion

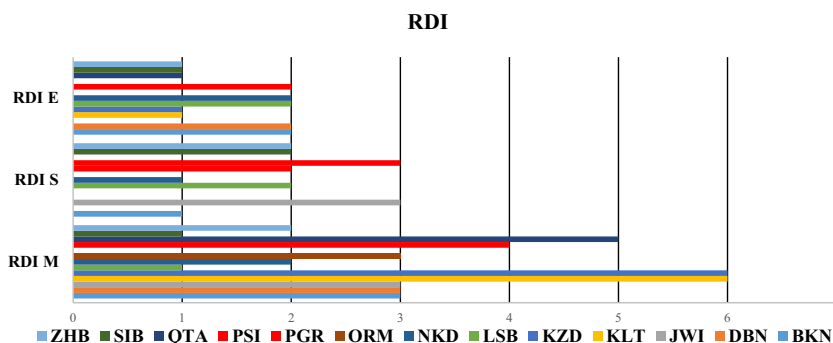
During the years i.e. 2001, 2002, 2004, 2009, 2014, 2018 and 2022, the southwestern regions of Balochistan have been found depicting the worst drought conditions. A notable decline is observed in their precipitation levels

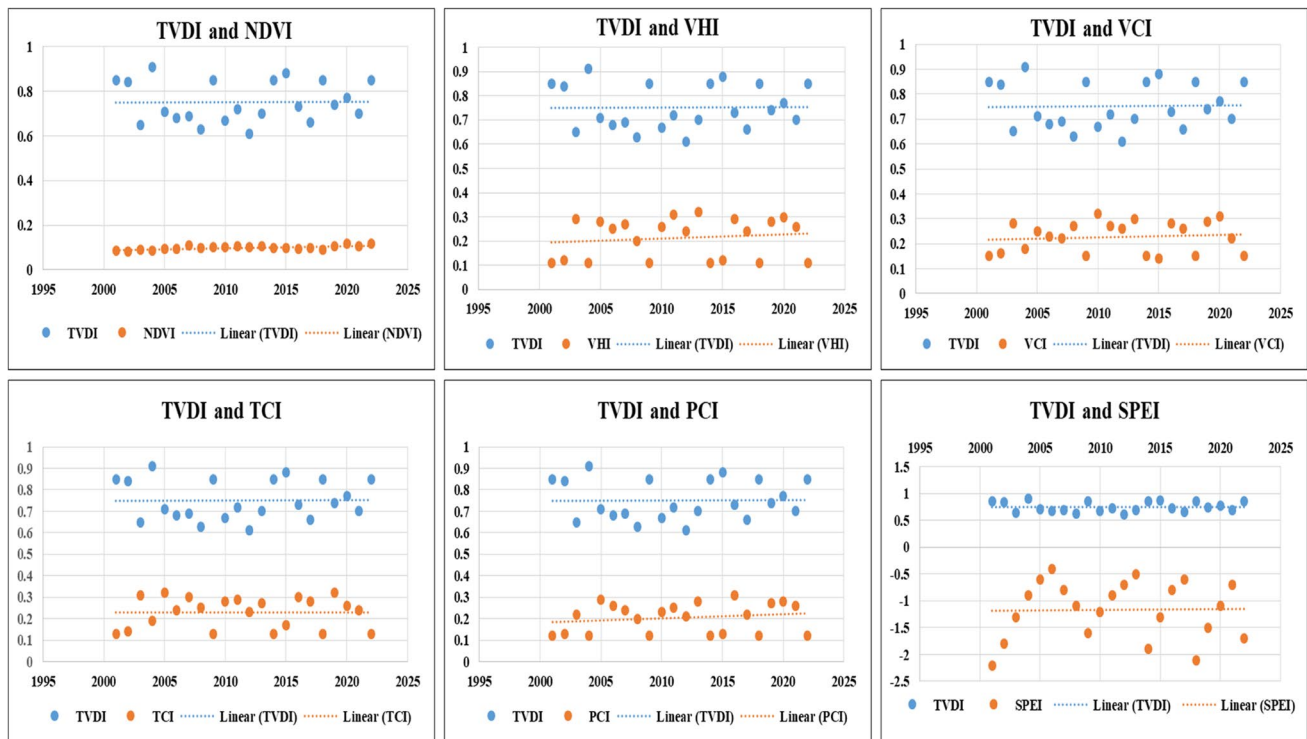
as well as in their soil moisture and vegetative cover as opposed to the rest of the areas of Balochistan. The VCI and VHI both reveal large reduction in plant density during the periods of drought and to a greater extent in arid and semi-arid areas signifying high vegetation stress. According to the results of the TVDI, vegetation is relatively more thermosensitive, which increases the effects of drought as it occurs during a dry season. SPEI emphasizes climatic water balance as being of paramount importance and through PCI it is revealed that decreased and limited rainfall contribute to increased length of dry spells. According to TCI, temperature shock and more so with generous heat stress that endures beyond vegetation’s ability to recuperate poses a profound influence to vegetation stress as well as the recuperation process. Annual trends reveal the cyclic pattern of reduction of vegetation cover in the drought years which are 2001–2002, 2009–2010, 2014, and 2018–2019 due to low VCI, VHI and SPEI values and high TVDI. These relationships between the indices reveal the high interdependencies between moisture availability, temperature stress, and vegetation health, and the importance of addressing drought comprehensively in Balochistan.

This composite methodology leverages the strengths of each index to capturing precipitation-driven drought, providing dual vegetative insights from TVDI and VCI, and depicting temperature-driven drought from TCI, thereby enhancing the accuracy of drought assessment.

The correlation matrix in Table 5 illustrates strong quantitative evidence of the relationships among various drought indices. TVDI, which represents temperature and vegetation conditions, has a statistically significant and strong positive correlation with RDI ( $r=0.72$ ), VHI ( $r=0.66$ ), and PCI ( $r=0.65$ ), showcasing a strong linear association of the higher TVDI values and higher values of VHI, and PCI. TVDI has also a moderately positive correlation with VCI ( $r=0.64$ ), which provides further support for the improved vegetation conditions. Further, there is a strong negative correlation between TVDI and TCI ( $r=-0.74$ ), indicating that as TVDI increases, reflecting drier conditions associated with drought, TCI tends to decrease, showing that the

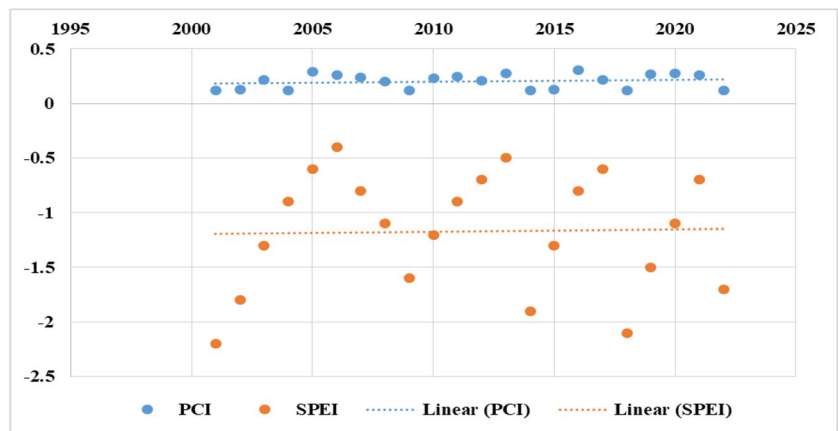
**Fig. 18** RDI for different drought categories





**Fig. 19** Scatter plot of TVDI with NDVI, VHI, VCI, TCI, PCI, and SPEI for the years 2001–2022

**Fig. 20** Scatter plot of PCI and SPEI for the years 2001–2022



temperature conditions are relatively warm during these drought events. PCI which has a strong positive correlation with TVDI ( $r=0.72$ ), is an important source of information for characterizing drought events. When compared to other studies, our findings are consistent with the global trend observed in arid and semi-arid regions, where vegetation health is highly dependent on precipitation patterns and extreme temperatures. For example, such investigations in Sahel countries of West Africa established equal patterns where both VCI and SPEI values was shown to exhibit strong negative relationship with vegetation loss. Furthermore, investigations carried out on the vegetation inputs

in the South West United States of America revealed that indices of vegetation integrated with thermal stress indicator like, TVDI, could adequately capture the influence of drought and heatwaves stresses on vegetation vitality.

Previous research had difficulty establishing joint probability distributions of drought characteristics for its computationally requirement or the difficulty in parameterizing the copula until the realization of the uniform marginal distributions for each of the drought variable and thereupon the limitation was resolved by the recent advancement of development and application of copula in the related subjects of drought. Spatiotemporal analysis of drought considering

duration, severity, area and interarrival time remains critical for immediate and long-term water management in the province. The utilization of remote sensing data represents a promising approach for tackling these issues, particularly in Balochistan, where extensive ungauged areas present significant challenge. More the development of concepts for the relations between large scale circulation and regional droughts are recommended for spatial and temporal changes as a line for further regional studies in general and for the country in particular. Potential limitations of this study include the availability and reliability of data, as certain regions in Balochistan may lack comprehensive records. Additionally, environmental factors such as soil quality and microclimatic variations were not fully accounted for, which could influence crop yields and farmers' perceptions. Future research should aim to address these gaps for a more thorough analysis. Future efforts should focus on regionalizing water demands in Balochistan, where current water needs exceed natural resources. This shift is essential to address daily, seasonal, and annual shortages effectively.

## 5 Conclusions

The comprehensive assessment of drought conditions in Balochistan was based on vegetation anomalies and relationship with precipitation. Also evaluated were the drought indices VCI, VHI, TVDI, PCI, TCI and SPEI. The temporal variability was revealed using analysis from 2001 to 2022, indicating severe drought conditions in the northern region. The VCI and VHI indices depict significant reductions in vegetation cover during the periods of drought mainly in the arid and semi-arid areas. From TVDI, vegetation's response to thermal stress was also demonstrated by worsening drought effect especially during the hottest season. SPEI emphasizes the important place of climatic water balance, and, in its turn, PCI tells that increased interannual and reduced amounts of precipitation lead to more frequently and for a longer time recurrent drought. From the TCI, it is evident that extreme temperature especially the hot temperature has deep and proportional effects on vegetation stress and recovery periods. The studies show that the future vegetation conditions are very sensitive to changes in precipitation regime, and any decrease in rainfall strongly affects the vegetation quality. Thus, there is the need for contingency management, water resource management and conservation, drought-enduring crops, and vegetation conservation in Balochistan. The complete set of systematically developed drought indices not only provide a subtler comprehension of the appendages of droughts, but also assure for an informed decision making to the end users of the indices for the effective management and mitigation strategies in the Balochistan region. Therefore, the advanced remote sensing technologies

are helpful for constant monitoring of drought for the sustainable protection of Balochistan ecological and agricultural resources. Further, the refined form of modeling should be incorporated to predict more of the future droughts based on the various climates change drafts. The study reveals that the success of combating drought in Balochistan requires an interdisciplinary approach that combines methods which include remote sensing techniques, ground observations, and policymaking that is adaptive to the region's complex climate. Regarding the limitations of the present study, it is suggested that the socio-economic characteristics associated with the drought indices should also be incorporated in the future work. Specific recommendations for local policymakers focus on developing drought-resistant crop varieties and implementing efficient water management practices. Additionally, future research should explore advanced irrigation techniques and long-term strategies to mitigate the adverse effects of drought on vegetation in Balochistan. Also, estimate how the future drought is like to be if we use advanced modeling approaches to identify environmental change risk factors, this information is useful in strategic planning for future environmental risks.

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## Declarations

**Competing interests** The authors declare no competing interests.

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