

Assessment of drought variability in South Punjab using MODIS data: a spatio-temporal analysis

Junaid Waseem, Muhammad Miandad

Department of Geography, University of Gujrat, Punjab, Pakistan

Corresponding Author email: 25011708-004@uog.edu.pk; muhammad.miandad@uog.edu.pk

Received: 28 June 2026 / Accepted: 24 July 2026

Abstract. South Punjab experiences recurrent pre-monsoon droughts that place severe stress on its environment and pose a serious challenge to crop production. This study examines the spatial and temporal variability of drought across South Punjab from 2000 to 2025, characterizing the region's pre-monsoon drought dynamics using six MODIS-derived indicators: land surface temperature (LST), the Temperature Condition Index (TCI), the Vegetation Condition Index (VCI), the Vegetation Health Index (VHI), the Normalized Difference Vegetation Index (NDVI), and the Normalized Difference Water Index (NDWI). Image processing was performed on the Google Earth Engine platform, and the resulting time series were analyzed using box plots, standard deviations, and Mann-Kendall trend tests. The results reveal pronounced intra-regional heterogeneity, with frequent outliers across districts. Mean VHI was lowest in 2005, recovered through 2010-2015, declined again in 2020, and reached its highest value in 2025, while LST was lowest and vegetation health greatest in 2025. NDWI nonetheless indicated severe surface-moisture deficits in both 2020 and 2025, exposing a disconnect between vegetation greenness and underlying water availability that points to the region's growing reliance on artificial irrigation to sustain pre-monsoon cropping amid escalating hydrological deficits. These findings suggest that, even as remote sensing and GIS provide an increasingly capable toolkit for drought monitoring, intensifying anthropogenic pressures mean that agro-meteorological crises in South Punjab are becoming socio-natural rather than purely geophysical hazards.

Keywords: MODIS-based indicators, drought severity, hydrological deficits, temperature, vegetation health.

1. Introduction

Drought is a prevalent global climatic hazard, which has been accelerated due to anthropogenic global warming (Ault, 2020; Pendergrass et al., 2020). This hazard devastates semi-arid regions reliant on seasonal moisture and water distribution systems (Ali et al., 2020; Goheer et al., 2023). Uneven distribution of water can intensify the effects of drought. Vulnerability varies, as high temperatures impact landless sharecroppers worse than landowners. South Punjab has hot, dry summers and limited pre-monsoon rainfall, relying heavily on canal irrigation (Shah et al.,

2024). As one of Pakistan's major agricultural regions, fluctuations in water content, vegetation health, and thermal stress during the pre-monsoon period can severely influence crop development, yield stability, and water-resource planning (Black et al., 2024; Ijaz et al., 2023). Therefore, a thorough drought analysis is critical for assessing environmental stress and enhancing agricultural resilience across this area (Akram et al., 2024). Remote sensing assessments use limited meteorological networks, which fail to capture fine-scale spatial variations across Pakistan (Bao et al., 2024; Rahman & Shang, 2023). Moderate Resolution Imaging Spectroradiometer (MODIS) derived drought indices, which are central to modern global terrestrial monitoring (Javadian et al., 2020), such as the Vegetation Condition Index (VCI), and Temperature Condition Index (TCI), among others, have found prominent applications for monitoring agricultural and hydrological droughts at broad spatial coverage and high temporal frequency over long periods (Khan et al., 2020; Shahzaman et al., 2021; R. Ullah et al., 2023). These properties make MODIS indices well suited for the local-scale spatial variations that sparse ground networks cannot capture. The increasing co-occurrence of these multivariate anomalies, specifically simultaneous heatwaves and soil moisture deficits, is now recognized as a primary global climate risk (Raymond et al., 2020; Ridder et al., 2020). The combination of vegetation, water content, and thermal data from MODIS datasets could also lead to a better-characterized compound drought situation (Rafiq et al., 2023). For instance, NDVI measures vegetation health, NDWI measures water content, and LST captures thermal stress (Arshad et al., 2023; Arshad et al., 2022). Thus, combined thermal and vegetation indices such as TCI, VHI, and VCI could diagnose vegetation stress more easily than individual indices (Ashraf & Ullah, 2022; Waseem et al., 2022). These parameters are widely used to indicate moisture anomalies, vegetation decline, and heat stress across large areas (Tabassum et al., 2023). Remote sensing provides a reliable, high-resolution monitoring system for Pakistan's drought-prone agricultural areas (Moazzam et al., 2022; Ullah et al., 2021). This aligns with recent global assessments emphasizing that atmospheric and soil water constraints fundamentally govern ecosystem production and vegetation stress (Jiao et al., 2021; Liu et al., 2020). Remotely sensed data can be used to assess thermal anomalies and vegetation stress (Abro et al., 2025). Numerous studies exist to analyze drought across Pakistan, but only a few are specifically designed to assess drought across northern Punjab, Sindh, or Baluchistan (Ahmed et al., 2023; Safdar, 2024; I. Ullah et al., 2023), and most

importantly, there seems a gap over assessment of multi-index drought over South Punjab in terms of a fixed seasonal window and a large temporal scale analysis (Ejaz et al., 2023). However, many studies analyze only precipitation-based indicators of drought or a few vegetation indices, so that the compound stress of different parameters was not addressed. Here, an analysis of pre-monsoon May, a crucial month before the onset of the summer monsoon, was selected to assess crop stress conditions (Saha et al., 2021). With extreme climatic events becoming increasingly frequent over South Asia, assessing such a crucial period can lead to developing spatiotemporal drought modeling for better prediction, to protect from wide-ranging variability in agricultural yields (Arshad et al., 2025; Shah et al., 2025), particularly since Punjab province is highly susceptible to yield variation. To fill the research gap, the current study aims to carry out a spatio-temporal analysis of drought over South Punjab, utilizing MODIS-based indicators for May over 25 years to show the extent of the drought conditions through a collection of different statistical parameters instead of just a set of spatial anomaly maps. To move beyond a physical focus on monitoring toward a socio-spatial framework, this project employs a framework of vulnerability. We move beyond a hazard-centered explanation to explore drought's intersection with the deprived landscapes of the Southern Punjab agricultural belt. This could ultimately contribute to making informed agricultural management practices and irrigation scheduling for this region.

Modern remote sensing-based drought studies face challenges in processing huge geo-informational databases, often overcome using cloud platforms such as Google Earth Engine (GEE) (Waleed & Sajjad, 2023). Thus, recent drought research is relatively more dedicated to developing automated methods to compute long-term MODIS drought indices and to apply it on regional level, overcoming large localized data storage and processing requirements, thanks to GEE (Bhowmik & Bhatt, 2024; Le et al., 2024). As such, the calculation of fine-resolution vegetation and thermal anomalies allows rapid and automated analysis for identifying diverse agrarian droughts.

Previous studies have demonstrated the use of vegetation-, thermal-, and moisture-based MODIS indices to characterize agricultural drought in Punjab (Rahman et al., 2025) applied VCI, TCI, and VHI computed from twenty years (2001–2020) of MODIS NDVI and LST data to map rabi- and kharif-season drought across Punjab, linking the indices to standardized yield-residual series for wheat,

gram, sugarcane, and rice. They found VHI to be the strongest predictor of rabi crop losses and VCI the strongest predictor of kharif losses. However, they did not isolate the pre-monsoon window specific to South Punjab, and omitted NDWI as a direct measure of canopy and surface moisture. This study provides a more precise understanding of compound drought risk during the critical pre-monsoon period and advances the multi-index literature by integrating direct moisture indicators with vulnerability assessment.

2. Study Area

The southern part of Pakistan's Punjab Province (Fig. 1) represents South Punjab, a region affected by climate change. The region features hot summers and limited pre-monsoon rainfall, relying heavily on canal irrigation and seasonal rain-fed agriculture, an important factor in the area's political ecology. The eleven districts officially considered part of South Punjab are Bahawalpur, Bahawalnagar, Rahim Yar Khan, Layyah, Dera Ghazi Khan, Muzaffargarh, Rajanpur, Lodhran, Multan, Khanewal, and Vehari (Bureau of Statistics, 2024). The landscape transitions from irrigated plains to semi-arid zones shaped by evapotranspiration, heat, and moisture scarcity. This makes South Punjab highly vulnerable to pre-monsoon vegetation stress, heat accumulation, and seasonal drought. Analyzing May drought indicators is crucial because crops like wheat and cotton respond sensitively to early summer thermal and hydrological conditions.

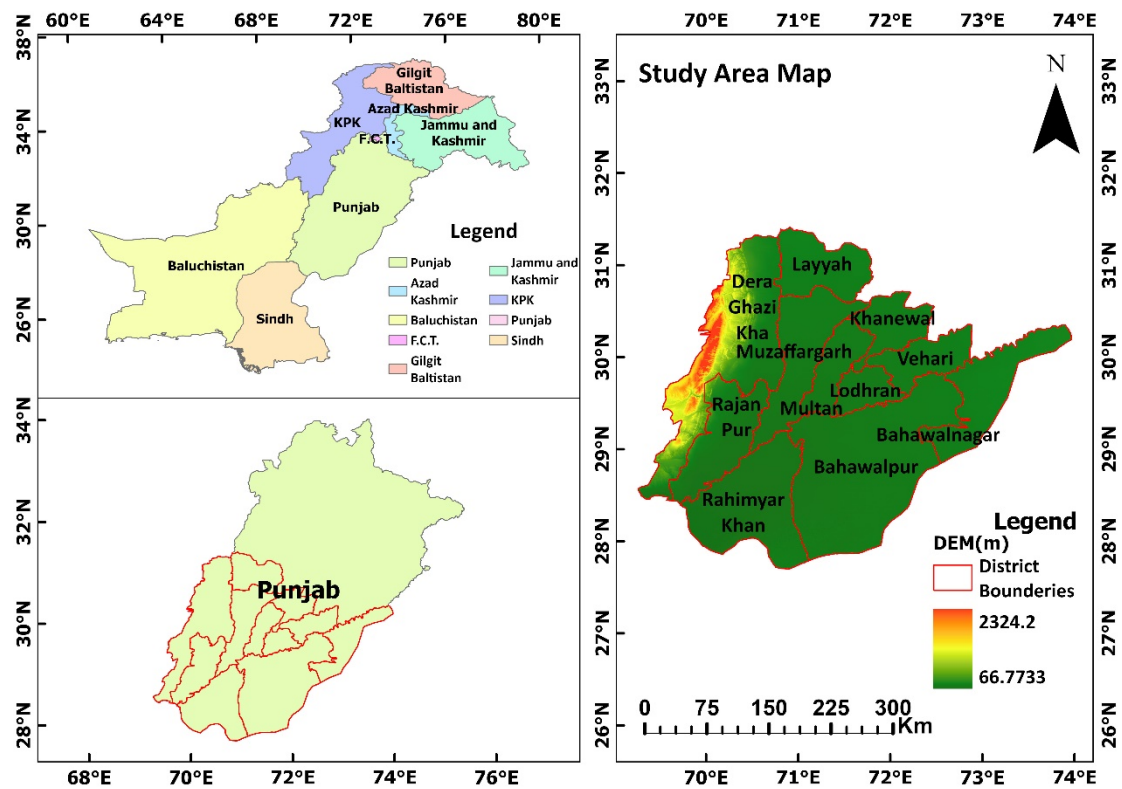


Figure 1. The study area highlights the eleven districts of South Punjab, Pakistan

3. Methodology

3.1. Data Sources and Datasets

All remote sensing data used in the study were acquired from Google Earth Engine (GEE), using long-term MODIS (Moderate Resolution Imaging Spectroradiometer) products for the period 2000-2025, which were, quality-wise, pre-processed. The indicators represent thermal stress, vegetation condition or health, water content, and integrated drought stress formulations. The required monthly composites for May were selected for all available years from 2000 to 2025.

3.2. MODIS Land Surface Temperature (LST)

LST was extracted from MODIS/061/MOD11A2. LST provides 8-day composite thermal readings representing land surface heat intensity. Temperature stress is a key driver of agricultural drought, as elevated LST increases evaporative demand and accelerates vegetation stress (Arshad et al., 2022; Shahzaman et al., 2021). LST values were extracted for each year in May and included in the statistical charts.

3.3. Normalized Difference Vegetation Index (NDVI)

NDVI was obtained from the “MODIS/061/MOD13A3” MODIS vegetation product. NDVI measures vegetation greenness, reflecting chlorophyll activity and plant vigor (Ahmed et al., 2025). It is widely used for drought monitoring due to its sensitivity to vegetation stress during water scarcity (Khan et al., 2025). NDVI time series and distributions are included in this study. While NDVI measures greenness, the Normalized Difference Water Index (NDWI) is essential for detecting the specific liquid water content in vegetation canopies, providing an early warning for moisture stress (Nasar-u-Minallah et al., 2025). By numerically merging VCI and TCI into the Vegetation Health Index (VHI), scientists can clearly determine the 'drought hotspots' that simultaneously experience moisture deficiency and severe thermal stress (Khan et al., 2025).

3.4. Normalized Difference Water Index (NDWI)

NDWI was derived from a MODIS dataset on GEE, namely MODIS/061/MOD09GA, to measure the percentage of land or vegetation and soil water content, which is particularly useful in early detection of existing hydrological stresses. Unlike NDVI, it is directly responsive to leaf water content and hence is an indicator of pre-monsoon dryness (Bao et al., 2024; Hussain et al., 2025). NDWI analysis was obtained from the MODIS surface reflectance band datasets on GEE.

3.5. Vegetation Condition Index (VCI)

The NDVI dataset was derived and used to calculate the VCI.

The VCI is defined as:

$$VCI = [(NDVI_{current} - NDVI_{min})^2 / (NDVI_{max} - NDVI_{min})] \times 100$$

This transformation standardizes NDVI within a historical range to clearly differentiate weather-driven vegetation stress from persistent ecological dissimilarities (Ashraf & Ullah, 2022). Periods with low VCI indicate high levels of vegetation stress. VCI boxplots demonstrate a high inter-annual variation, especially in the years 2005 and 2020. Further mean trend, standard deviation, and Mann-Kendall graphs were generated for time series analysis.

3.6. Temperature Condition Index (TCI)

The LST dataset, as mentioned earlier, was extracted and used to calculate the TCI.

TCI follows:

$$TCI = [(LST_{max} - LST) / (LST_{max} - LST_{min})] \times 100$$

TCI measures thermal stress, where higher temperatures imply lower TCI and greater drought-related heat stress. TCI complements VCI by providing thermal anomaly information (Ejaz et al., 2023). TCI data was analysed using a mean trend graph, boxplot/error chart, standard deviation, and Mann-Kendall.

3.7. Vegetation Health Index (VHI)

TCI and VCI, as mentioned, were calculated earlier. After that, they were used to calculate the VHI.

VHI integrates VCI and TCI:

$$VHI = 0.5(VCI) + 0.5(TCI)$$

It offers a more comprehensive drought indicator combining vegetation greenness and temperature anomalies, useful in agricultural drought assessment (Bento et al., 2020; Ellahi et al., 2023; Khan et al., 2025). The VHI data was evaluated using a mean trend graph, boxplot/error chart, standard deviation, and Mann-Kendall test.

3.8. Data Processing and Statistical Framework

MODIS indices were acquired from GEE, and high cloud percentage was filtered for NDVI, NDWI, and LST. To assess drought compared to historical conditions, VCI and TCI are calculated as a ratio of the multi-year minimum and maximum for the study time. VHI (0.5 VCI + 0.5 TCI) assesses agricultural drought by capturing the inverse relationship between vegetation greenness and surface temperature in arid regions (Ali et al., 2020), which is driven by well-documented land–atmosphere feedbacks (Ejaz et al., 2023). To analyze trends over the entire time period without bias by seasons, all parameters and minimum/maximum values are calculated using the month of May only to monitor agricultural drought in the South Punjab pre-monsoon period. All the resulting annual composite images are exported as GeoTIFFs and uploaded to the Python platform (using NumPy, Pandas, rioxarray, SciPy, and Matplotlib). Masked parameters underwent statistical analyses (means, standard deviations, box-plots) to determine seasonal trends, spatial variability, and pixel-level inter-annual variations to identify anomalies. Time series and Mann-Kendall tests evaluated long-term trends.

4. Results and Analysis

This work gives a detailed description of multidimensional drought in South Punjab (2000-2025) based on LST, NDWI, NDVI, VCI, TCI, and VHI computed from MODIS satellite data. The boxplots, mean time-series graph, standard deviation, and Mann-Kendall test with min-max normalization and fixed raster maps provide the foundation for analysis; the collective results provide integrated analysis on temperature stress, vegetation vigor, and moisture condition in the pre-monsoon month. This identifies typical years, drought years, and anomalous good years based on spatial and temporal features (Drought years 2005 and 2020, Normal years 2010 and 2015 and Good year 2025).

4.1. Vegetation Condition Index spatiotemporal and statistical analysis

In Figure 2, the VCI map clearly shows the weather related stress for the South Punjab vegetation and is separated from longer-term ecological patterns. Within these colour normalised maps, the intensity of vegetation stress is also indicated, with yellow and brown indicating extreme stress and drought, and different intensities of green illustrating more normal cropping areas. The differences in space are also shown throughout 25 years, leading to green to the north in 2025.

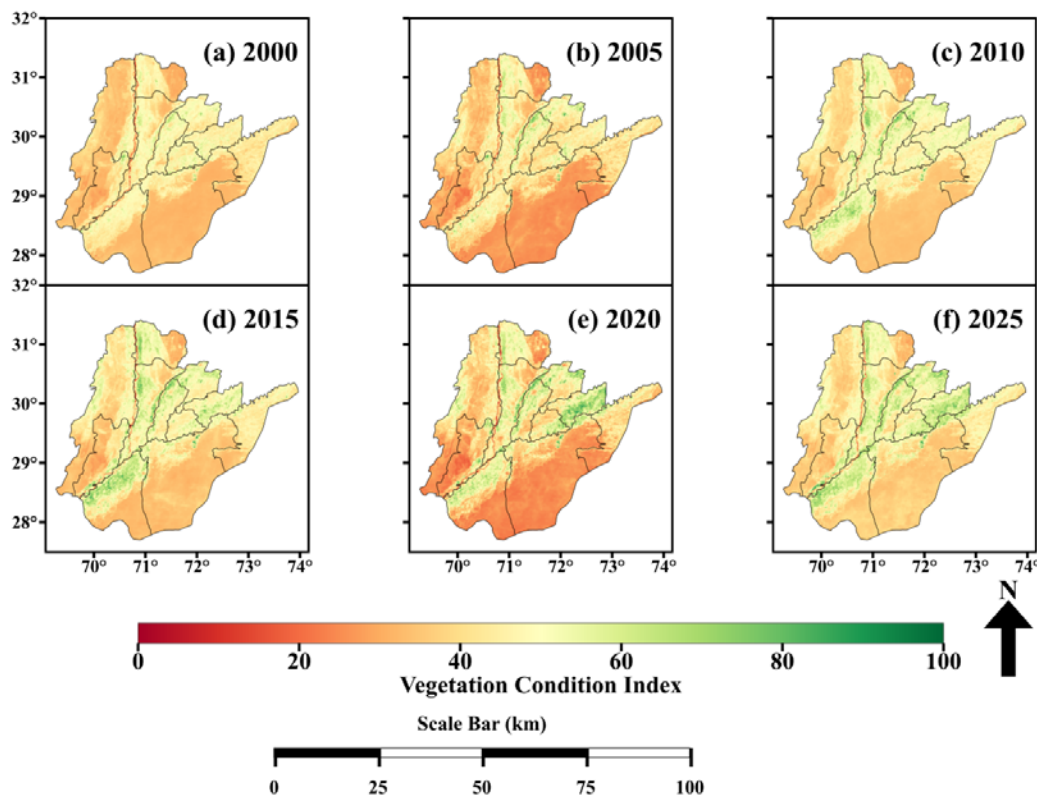


Figure 2. Vegetation Condition Index of South Punjab 2000-2025

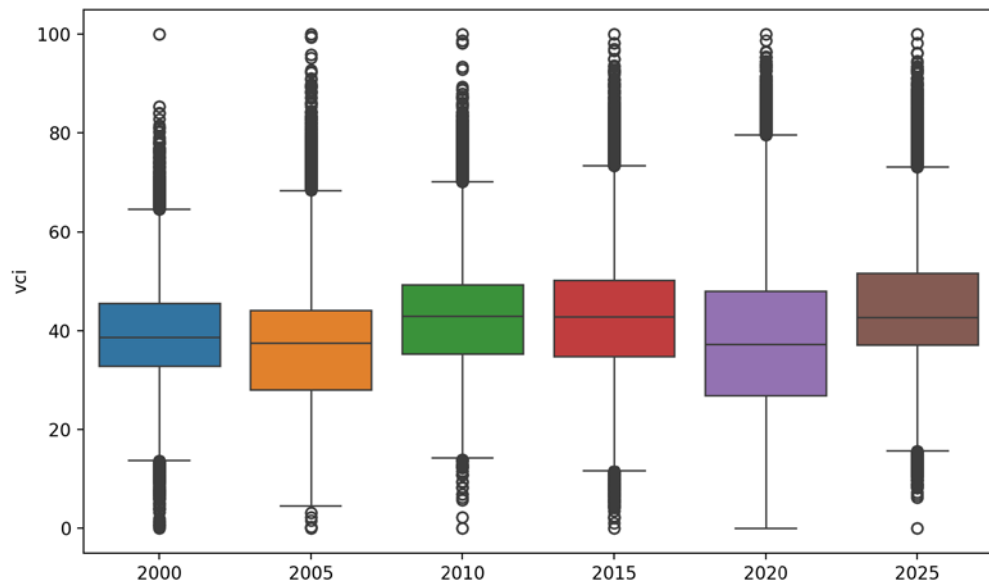


Figure 3. Box-plot showing IQR and outliers VCI of South Punjab 2000-2025

The VCI boxplot in Figure 3 illustrates vegetation greenness trends contrasted to both the past maximums and minimums. In 2000, the VCI boxplot shows a moderately high median and a tight interquartile range, indicating stable vegetation performance. However, 2005 shows a significantly low VCI median, broad IQR, and numerous low-value outliers. The 2010 and 2015 boxplots show recovery, with moderately high medians indicating wetter conditions or stable cropping. The 2020 VCI distribution broadens and falls, reflecting decreased greenness due to widespread pre-monsoon heat waves. The 2025 boxplot depicts the highest median values and stable IQR, which suggests better vegetation conditions.

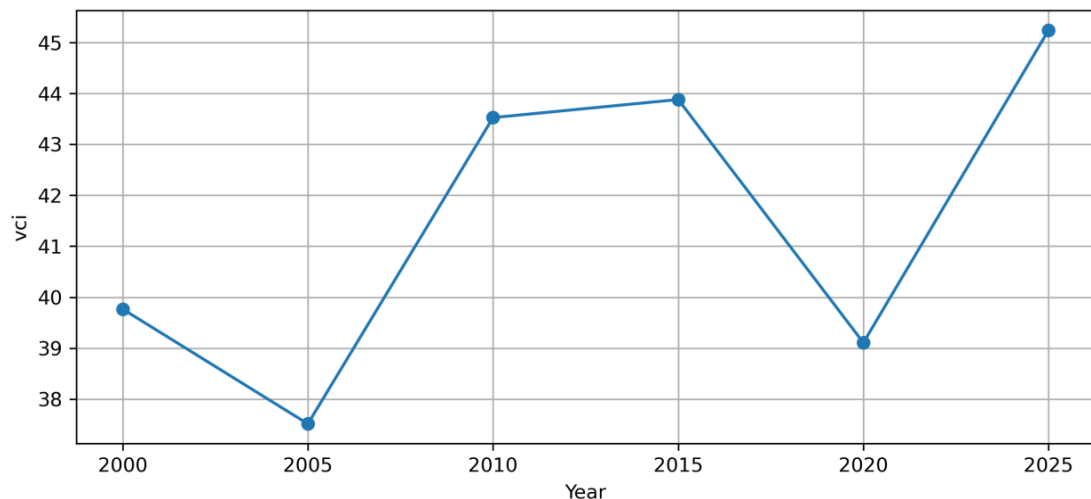


Figure 4. Mean trend of VCI of South Punjab 2000-2025

The VCI mean plot (Fig. 4) declines in 2005, recovers in 2010-2015, drops in 2020, and peaks in 2025. VCI error bars were highest in 2005 and 2020, reflecting variable drought intensity across locations; some areas were highly stressed, while irrigation likely mitigated stress in others. The VCI Mann-Kendall trend suggests no long-term worsening, but rather oscillation (Table 1).

Table 1. Mean trend of VCI of South Punjab 2000-2025

<i>Year</i>	<i>Mean VCI (%)</i>	<i>Detailed Observation</i>	<i>Drought Implication</i>
2000	~39.8	Widespread yellow/orange regions indicate stress.	Existing vegetation stress.
2005	~37.6	Lowest VCI; large areas with VCI <20 in the far south.	Worst vegetation health in the time series.
2010	~43.5	Marked improvement.	Moderate vegetation health.
2015	~43.9	Slight further improvement.	Good vegetation health.
2020	~39.1	Strong decline again.	Significant vegetation stress.
2025	~45.2	Highest VCI.	Best vegetation health observed.

Trend: increasing Kendall Tau: 0.466 P-value: 0.272

4.2. Vegetation Health Index (VHI) spatiotemporal and statistical analysis

In this study, the VHI average value of the TCI and VCI images shows an integrated vegetation-health map for May in Figure 5.

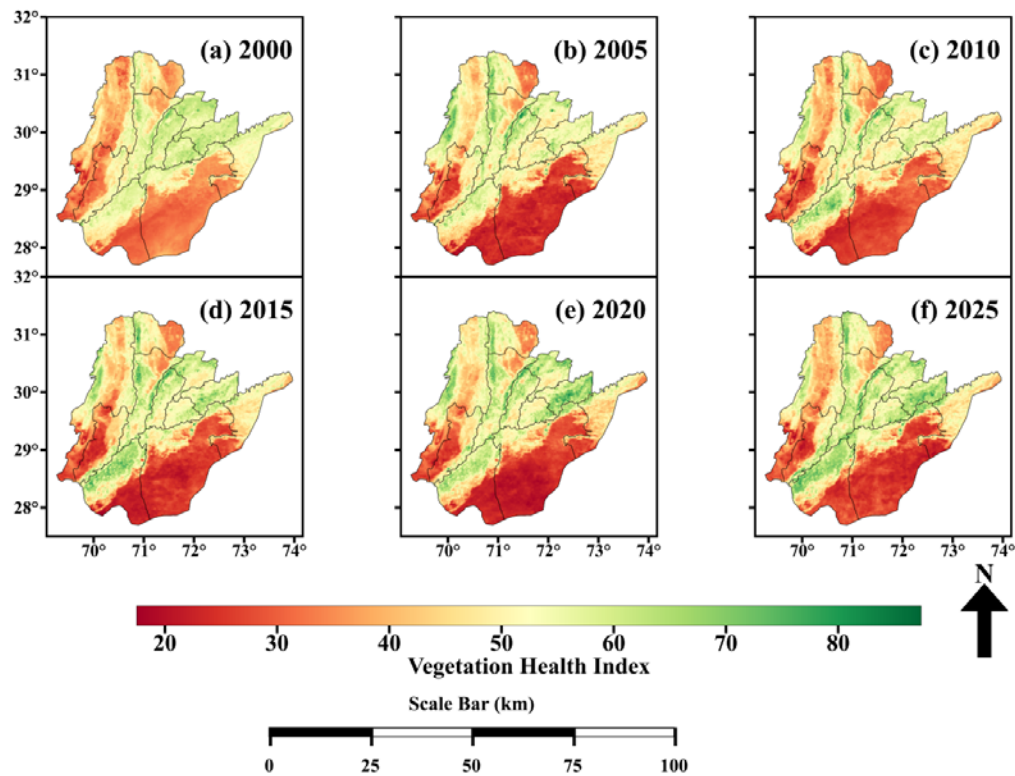


Figure 5. Vegetation Health Index of South Punjab 2000-2025

The VHI values as a whole indicate the impact of both heat and water stress simultaneously, which is characteristic of most agricultural drought scenarios that occur over the pre-monsoon period in South Punjab. These areas are highly susceptible to crop failure, requiring rapid monitoring and remediation (water rationing, emergency fodder, and livelihood relief). Medium VHI areas show resilience, likely due to irrigation or thicker soil. VHI indicates areas of combined thermal and moisture stress, requiring a rapid response to prevent crop loss. It highlights a multi-temporal assessment of drought severity across South Punjab for the period 2000–2025 based on VHI. Reduced VHI values (20–40, red, orange) indicated major crop-related drought severity and moisture stress, which were mostly in the desert areas of southern and southeast Punjab. The results also show clearly varying climatic conditions over the 25 years of the study, with the most severe drought conditions occurring in 2005 and 2020, more decline in 2010, shown as large dark red dots. Ecological conditions recovered markedly in 2015, shown in green, before drought conditions returned between 2020 and 2025.

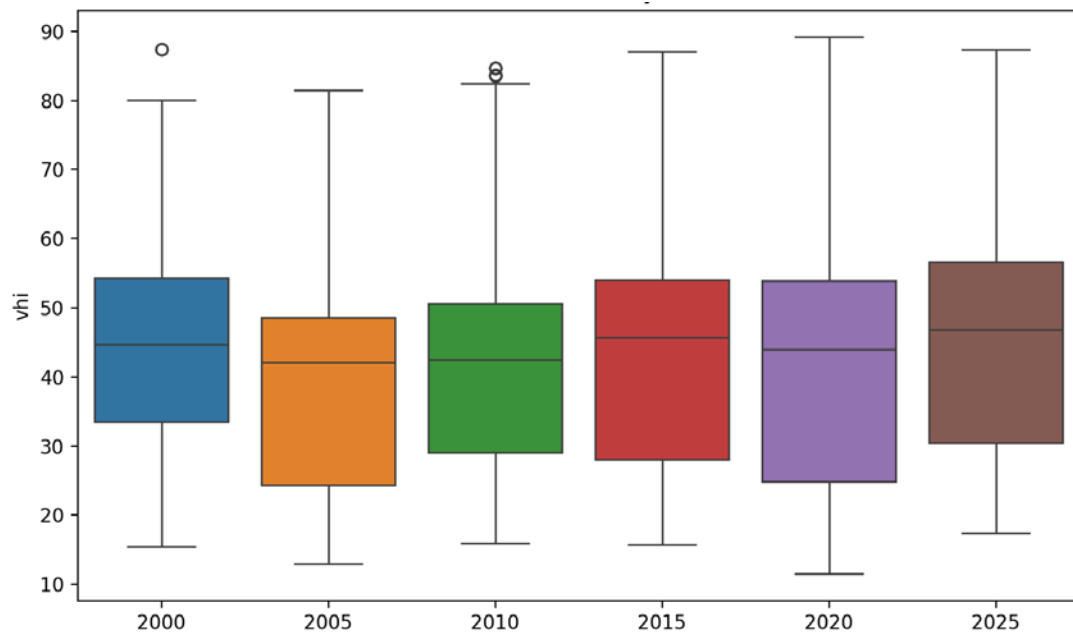


Figure 6. Box-plot of Vegetation Health Index of South Punjab 2000-2025

The VHI boxplot (Fig. 6) amplifies VCI patterns since it combines vegetation and thermal stress. The 2005 VHI boxplot shows a low median and wide range, suggesting combined stress and vegetation failure. Combining thermal and vegetation indicators provides a more effective drought measure (Ashraf & Ullah, 2022). The 2010 and 2015 boxplots show stabilization, whereas 2020 displays elevated stress.

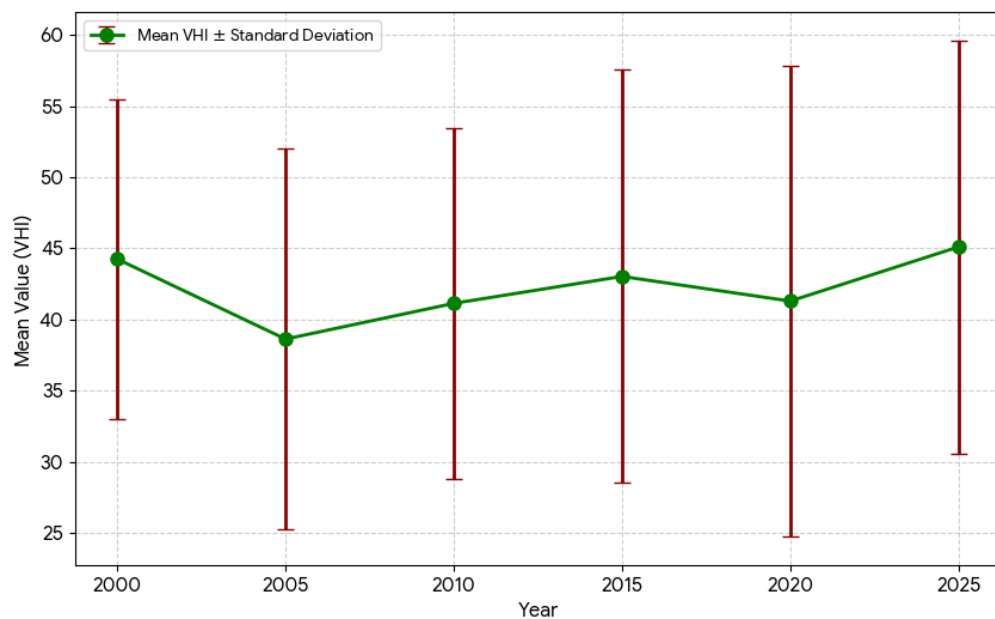


Figure 7. Mean and standard deviation trends of the Vegetation Health Index of South Punjab, 2000-2025

Table 2. Mean trend of VHI of South Punjab 2000-2025

<i>Year</i>	<i>Mean VHI (%)</i>	<i>Detailed Observation</i>	<i>Drought Implication</i>
2000	~44.2	Mostly VHI >40, some low values in the far southwest.	Low drought severity.
2005	~38.6	Lowest VHI; widespread severe drought zones.	Most severe drought
2010	~41.1	Initial recovery.	Moderate drought.
2015	~43.0	Substantial increase.	Low drought severity.
2020	~41.3	Renewed decline, with expansion of severe-drought patches.	Increased drought severity.
2025	~45.1	Highest VHI.	Lowest drought severity observed.

Trend: increasing Kendall Tau: 0.33 P-value: 0.46944

VHI integrates temperature and vegetation to measure drought intensity (<40 indicates risk). The VHI mean plot (Fig. 7) shows five phases: peaks in 2000 and 2025, troughs in 2005 and 2020, and stability in 2010-2015. During May 2005 and 2020, the VHI value fell below 40, which indicates the agricultural area suffered from drought stress. Higher standard deviation in 2005 and 2020 implies high spatial dispersion of temperature values. A comparison of the 2005 and 2025 VHI raster images highlights a significant shift in regional environmental conditions, transitioning from widespread drought to a healthy, green state. While the long-term Mann-Kendall trend is stable, seasonal data reveal cyclical vulnerability in May.

4.3. TCI spatiotemporal and statistical analysis

From the TCI map, there is a degree of thermal stress relative to the typical temperature regime; low values of TCI may indicate temperatures too hot for photosynthetic activity and vapor-transpiration, which will contribute to agricultural drought stress even if soil moisture is available.

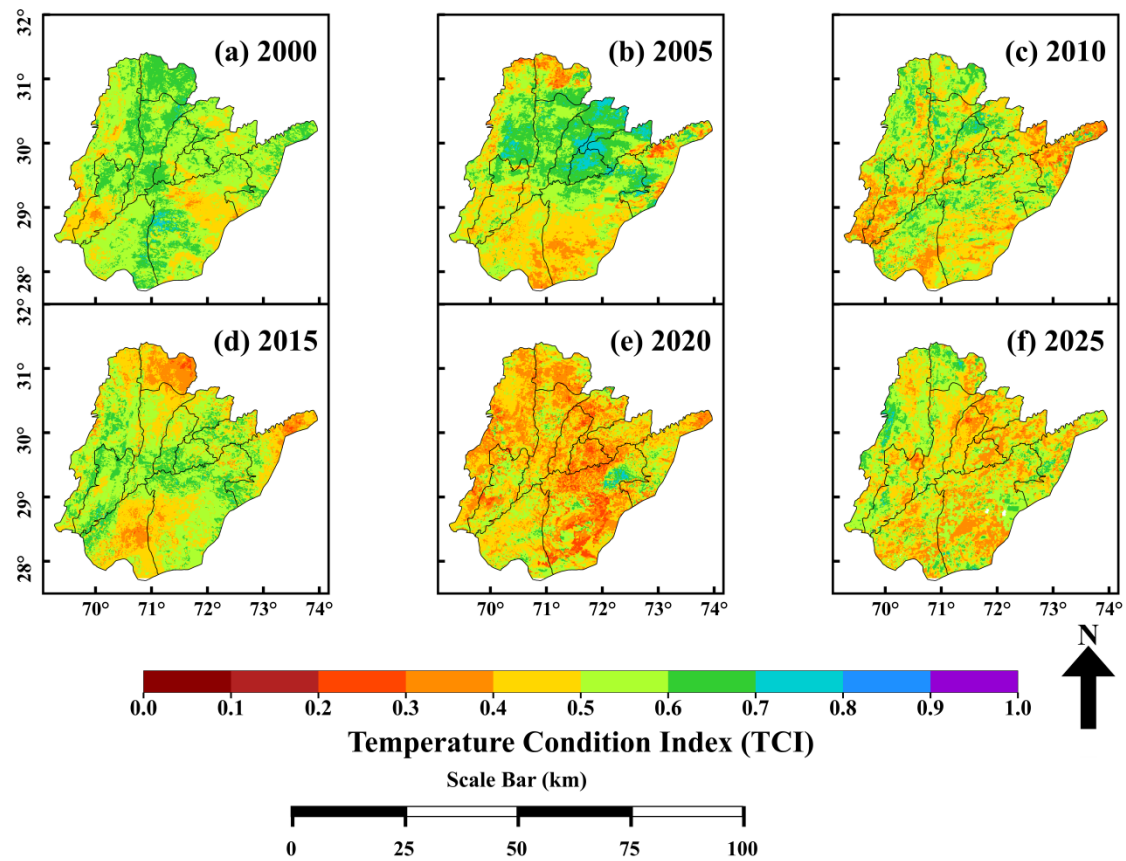


Figure 8. Temperature Condition Index of South Punjab 2000-2025

Low TCI in Figure 8 is likely related to exposed or heated bare surfaces, whereas higher TCI corresponds to cooler irrigated and riverine areas. This thermal component can be used to separate the heat component from moisture shortage with VCI and NDVI. For May across South Punjab, areas with low TCI can be encouraged for mulching, changing the planting date, and efficient irrigation.

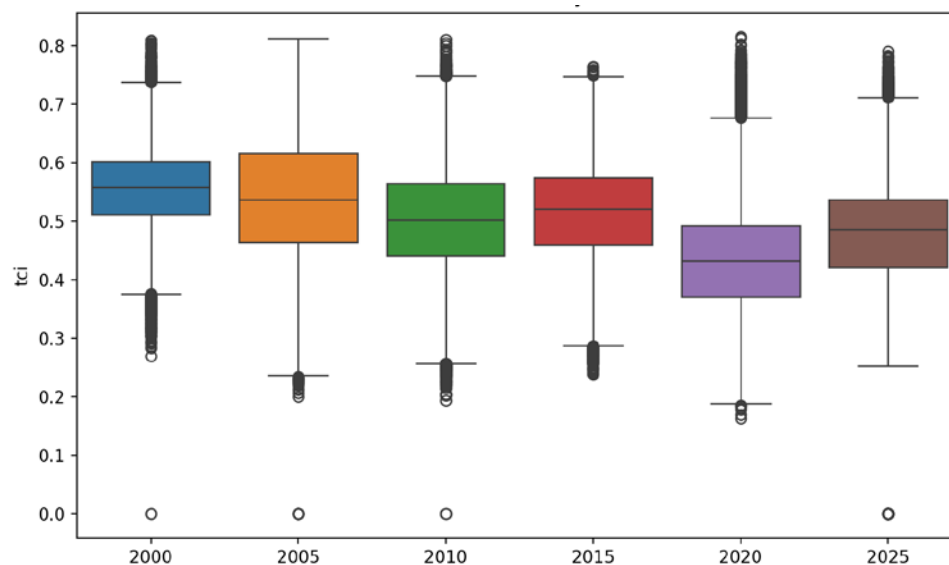


Figure 9. Box-plot of Temperature Condition Index of South Punjab 2000-2025

The TCI boxplot in Figure 9 shows that 2005 exhibits the lowest TCI (indicating the highest heat stress), consistent with elevated LST values. The widened IQR in 2005 further indicates multi-district heat anomalies. The 2010 and 2015 TCI boxplots show moderate-to-high medians, indicating favorable thermal conditions. The 2020 boxplot again declines, consistent with increased pre-monsoon heat reported across Pakistan. By 2025, TCI rebounds to a high median.

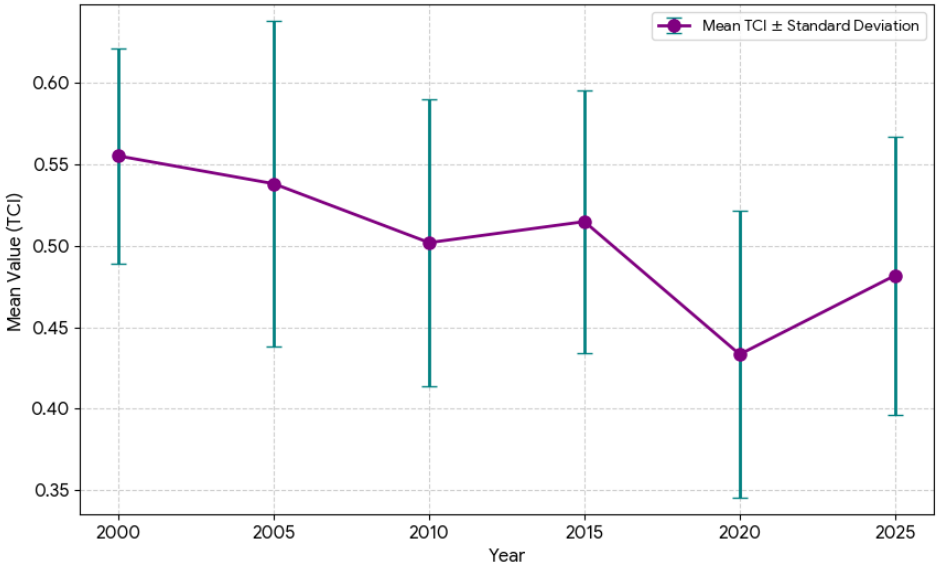


Figure 10. Mean and Standard Deviation Trends of Temperature Condition Index of South Punjab 2000-2025

The TCI mean plot (Fig. 10) exhibits oscillatory behavior similar to the VCI and VHI plots, showing an overall downward trend from roughly 0.55 in the year 2000 to 0.43 in the year 2020, with the Mann-Kendall test ($\text{Tau} = -0.733$, $p = 0.055$) approaching but not reaching conventional significance; with only six sampling years, the test has limited statistical power, and this result should be treated as suggestive rather than conclusive. This indicates that May temperatures repeatedly approached the historical maximum over this period, driving elevated thermal stress. This thermal intensity means crops face critical survival thresholds more often, worsening drought despite water availability. Table 3 summarizes the year-by-year changes. TCI standard deviation shows erratic spatial variability in thermal stress in 2005 and 2020, and the overall thermal condition, scaled to historical maxima, declined from 2000 to 2025.

Table 3. Mean trend of TCI of South Punjab 2000-2025

<i>Year</i>	<i>Mean TCI</i>	<i>Detailed Observation</i>	<i>Drought Implication</i>
2000	~0.55	Highest TCI; lowest thermal stress.	Healthy temperature conditions.
2005	~0.54	Marginal decrease.	Low thermal stress.
2010	~0.50	Pronounced decline.	Moderate thermal stress.
2015	~0.51	Moderate recovery.	Moderate thermal stress.
2020	~0.43	Lowest TCI; Highest thermal stress and drought severity.	
2025	~0.48	Recovery relative to 2020.	High thermal stress, but less severe than in 2020.

Trend: decreasing Kendall Tau: -0.733 P-value: 0.055

4.4. Land Surface Temperature (LST) spatiotemporal and statistical analysis

The May LST map in Figure 11 clearly shows heat distribution across the landscape of South Punjab. High pre-monsoon LST in May suggests elevated thermal stress and evapotranspiration demand for soils and crops.

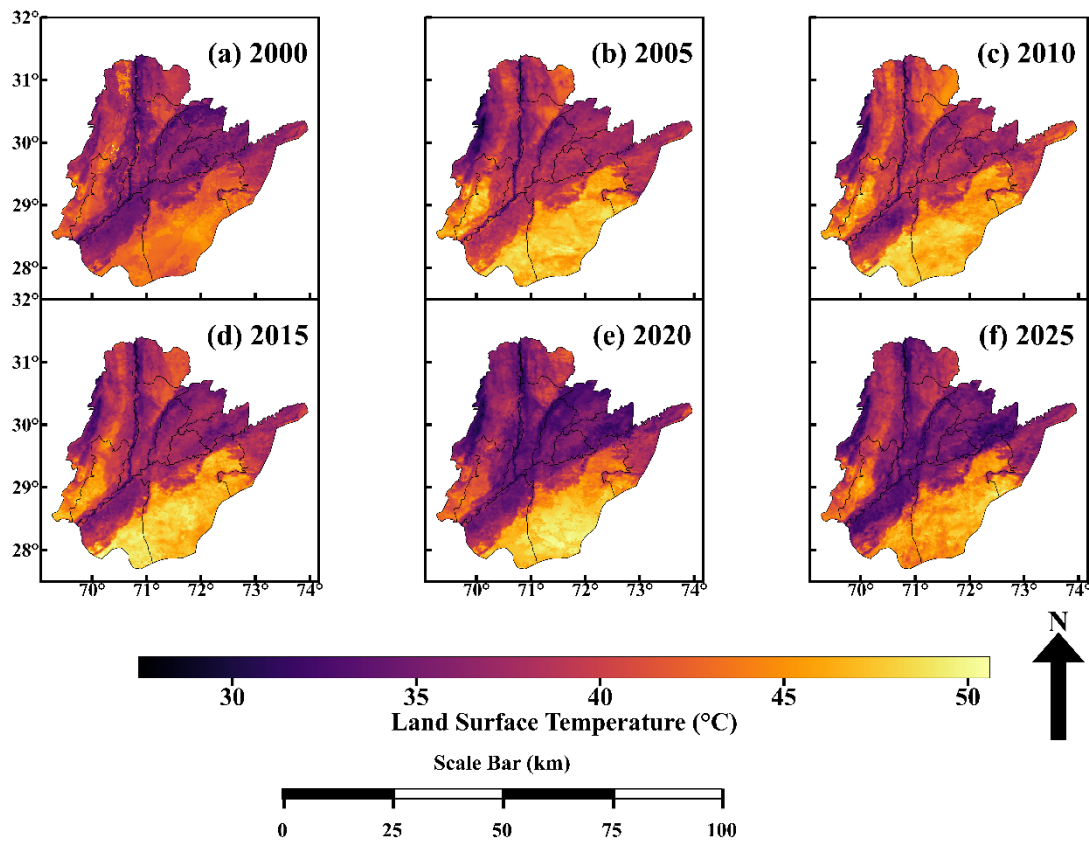


Figure 11. Land Surface Temperature (LST) of South Punjab 2000-2025

Hot LST areas are consistent with areas likely to suffer from moisture stress and faster drying rate (urban areas, bare soil, fallow land); thus, shallow-rooting crops are likely to become more prone to drought in those areas (Faheem et al., 2024). Cooler LST areas indicate water presence, which can be irrigated land, a river basin, irrigation water, or rainfall, while hotter areas represent barren land. Priorities must be set for irrigation provision and water conservation measures in hot spots, and hot LST spots serve as early warning to develop agricultural drought in relevant regions.

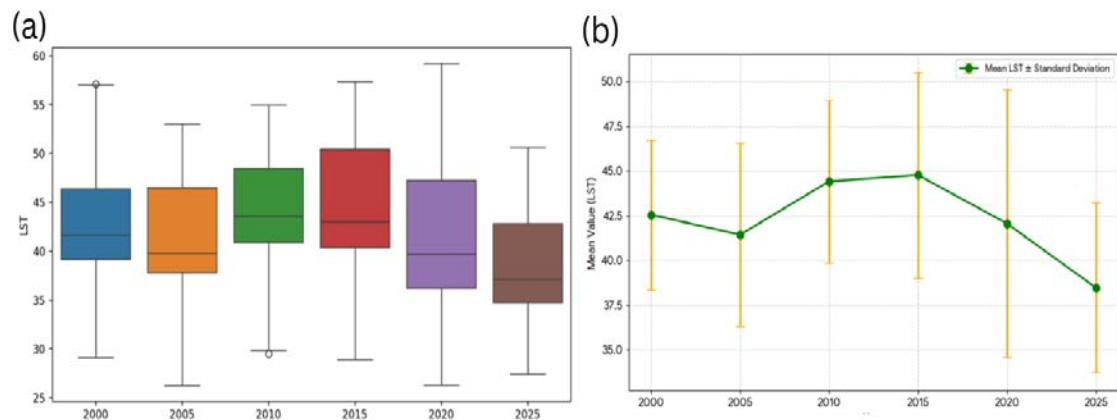


Figure 12. Land Surface Temperature (LST) year-wise Boxplot IQR (panel a) and year-wise standard deviation/mean (panel b) of South Punjab 2000-2025

The LST boxplot in Figure 12 (a) confirms that the anomalies are the highest median LST in 2005 and 2020, supporting the drought's thermal influence. IQR of the LST boxplot also shows higher variance for these years, indicating variable thermal stress across the districts. Lower median temperatures were observed in 2010 and 2015, which show favorable vegetation performance. It shows warmer gradients on the LST fixed raster image for the year of drought. Strong warm gradients for the drought year correspond with low TCI and suppressed VCI and VHI values.

Table 4. Mean trend of LST of South Punjab 2000-2025

Year	Mean LST (°C)	Detailed Observation	Drought Implication
2000	~42.5	High starting value in spatial maps indicates widespread areas exceeding 45°C in southern and western South Punjab.	Significant heat stress.
2005	~41.4	Moderate decrease from 2000.	Slightly lower heat stress.
2010	~44.4	Pronounced increase approaching the time series peak.	High heat stress; second highest in the series.
2015	~44.8	Highest LST in the entire period; extensive areas reach 45–50°C.	Peak thermal stress and severe heat-related drought.
2020	~42.1	Substantial relative to 2015.	Moderate heat stress.
2025	~38.5	Lowest LST across all years.	Lowest thermal stress recorded.

The Mann-Kendall test for LST shows a Tau: -0.2 across the entire period, although this is not statistically significant and P-value: 0.719

4.5. NDVI spatiotemporal and statistical analysis

NDVI was used for assessing vegetation health and overall vegetation cover.

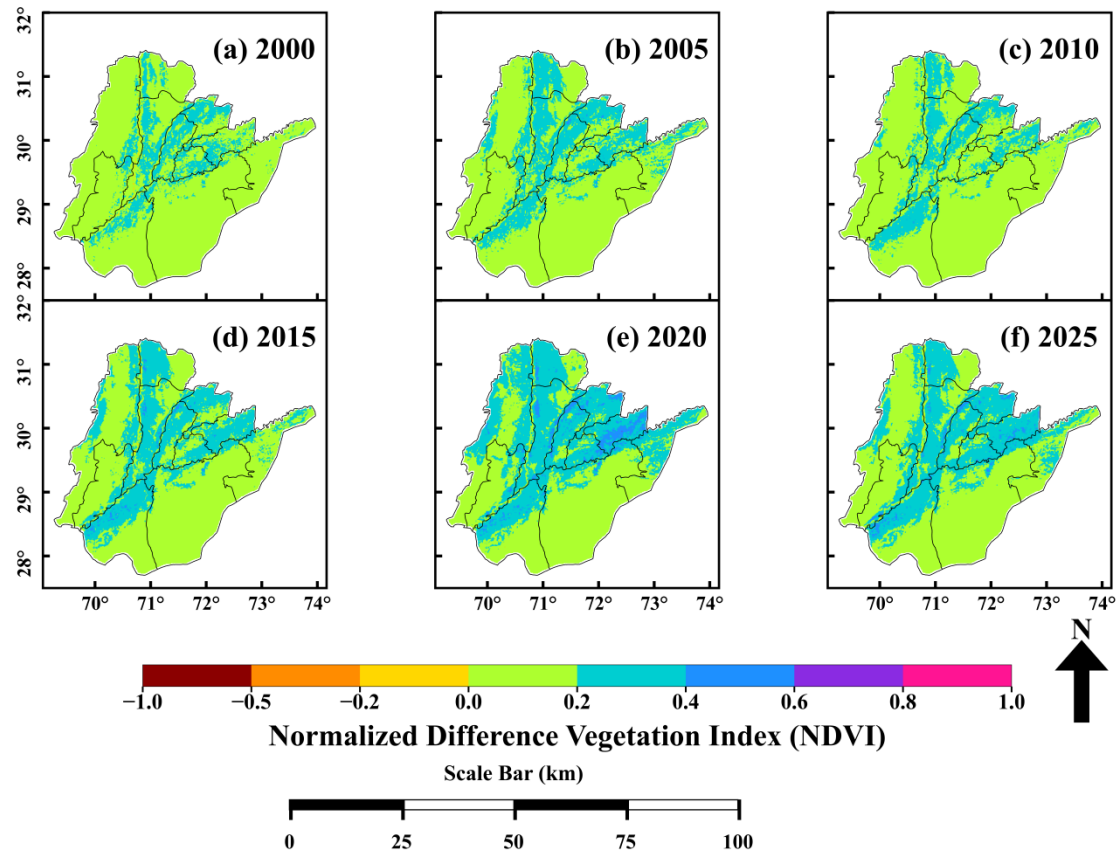


Figure 13. Normalized Difference Vegetation Index of South Punjab 2000-2025

The May NDVI map in Figure 13 shows the strength of vegetation just before the monsoon sets in. Extensive low NDVI areas may indicate early drought onset, driven by soil moisture deficits. Higher NDVI patches may represent irrigated agriculture, riparian vegetation, or surviving rabi crops. In May, as the growing season for kharif is yet to commence (mostly) and for rabi is ending, drops in NDVI from the long-term mean NDVI for May would imply threats to crop yields and the fodder supply. Targeted irrigation and monitoring are essential to mitigate seasonal drought impacts.

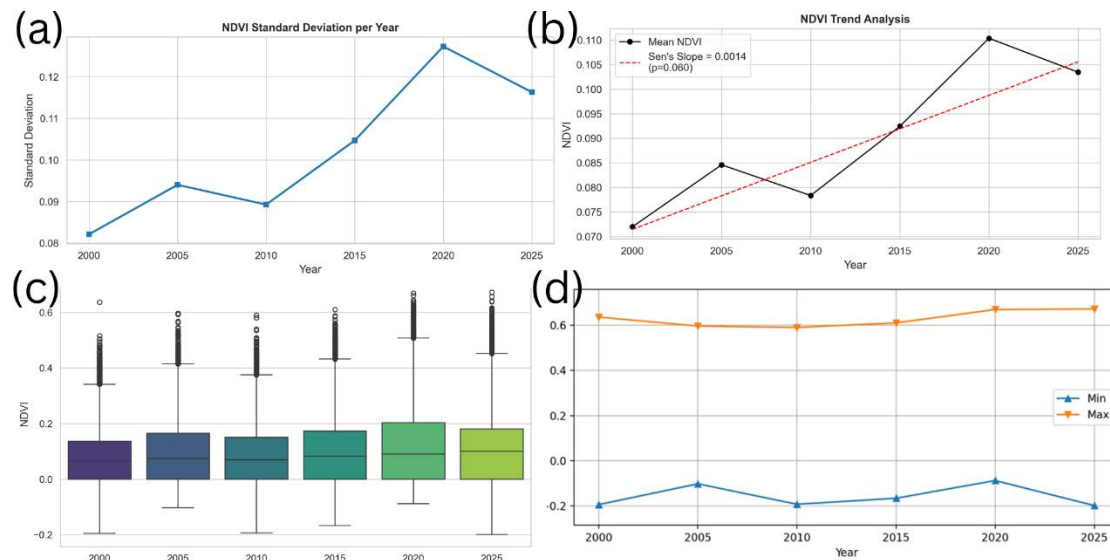


Figure 14. Normalised Difference Vegetation Index year-wise standard deviation (panel a), Mean trend (panel b), boxplot (panel c), min-max (panel d) of South Punjab 2000-2025

In order to estimate pre-monsoon vegetation stress in the drought-prone districts of South Punjab, the NDVI value for May was analyzed from the year 2000 to 2025. Given this arid pre-monsoon season, the regional mean NDVI shows a consistently low range (from 0.0720 in the year 2000 to 0.1049 in 2025). A non-parametric Mann-Kendall trend test and Sen's slope estimator were used to calculate the extent and significance of temporal changes in the vegetation condition.

Sen's slope estimator gives a value of 0.001364, while the Mann-Kendall Tau value of 0.7333 does not produce a statistically significant long-term positive trend at a 95% confidence level, as the p-value is 0.0603 ($p > 0.05$) (Fig. 14, Panel b). The region shows neither large-scale greening nor desertification. The stable NDVI MK trend reflects preserved steady-state greenness despite repeated droughts (Shah et al., 2024). Hence, robust regional stability helps South Punjab's core agricultural lands cope with cyclical, minor droughts.

However, descriptive statistics reveal internal variations despite regional stability. Over 25 years, the interquartile range of NDVI values has increased (Fig. 14, Panel a), and a change in standard deviation also corresponds to the change in mean, from 0.0821 in the year 2000 to 0.1224 in 2025 (Fig. 14, Panel c).

Increased NDVI standard deviation indicates rising spatial heterogeneity of vegetation health. The 2025 NDVI map shows spatial heterogeneity, indicating some pockets of healthy vegetation remain sustained with the canal irrigation systems or closeness to

the Indus River system, while much of the rainfed and arid lands adjacent to the Cholistan region continue to face water deficit and severe drought conditions (Fig. 14, Panel d). Thus, even as the whole region maintains its steady-state greenness at the regional level, vulnerability to drought at the micro level still varies across South Punjab. South Punjab (2000-2025). (a) Boxplots showing the distribution and increase in the range of NDVI values. (Rahman et al.) Temporal series showing regional average NDVI, superimposed by Sen's Slope line. Statistically insignificant trend $p=0.060$ ($p>0.05$) and MK Tau=0.7333 are shown. c) Standard deviation indicating increased spatial heterogeneity. (d) Spatial distribution map of NDVI for 2025, indicating regions with higher (blue) and lower (yellow-orange) vegetation health.

4.6. NDWI spatiotemporal and statistical analysis

NDWI in this research has been used for assessing water content on the surface or in vegetation.

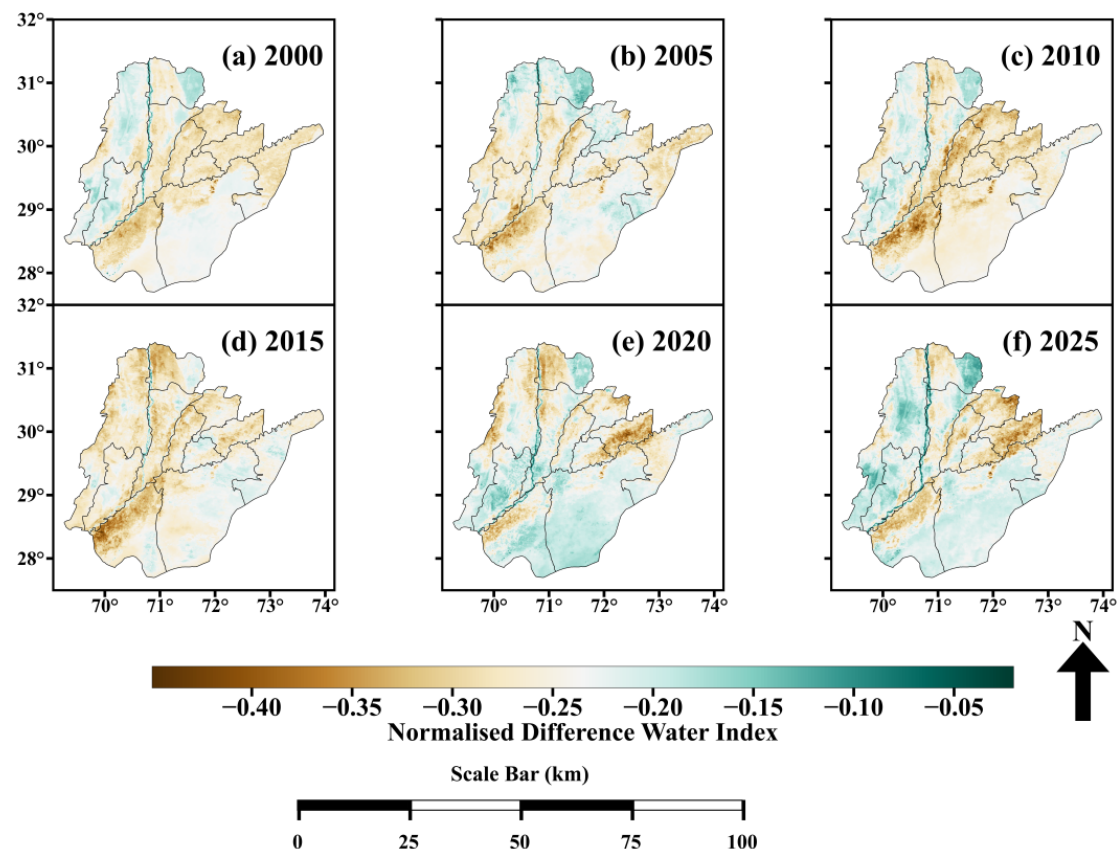


Figure 15. Normalised difference water index (NDWI) map of South Punjab 2000-2025

The NDWI map (Fig. 15) of May delineates surface water and relative water abundance/shortage. Widespread low NDWI reflects decreased surface and sub-

surface water availability. High NDWI clusters indicate local water availability from canals and reservoirs. The low NDWI in the May pre-monsoon conditions is of concern due to its impact on the availability of crop choices and an increased demand for irrigation. The intervention would be to protect important water bodies, ensuring adequate functioning of the canal system for proper distribution of water, and close observation of NDWI in combination with the rainfall forecast (P.M.D., 2025) for making crucial allocations of water and decisions on crops.

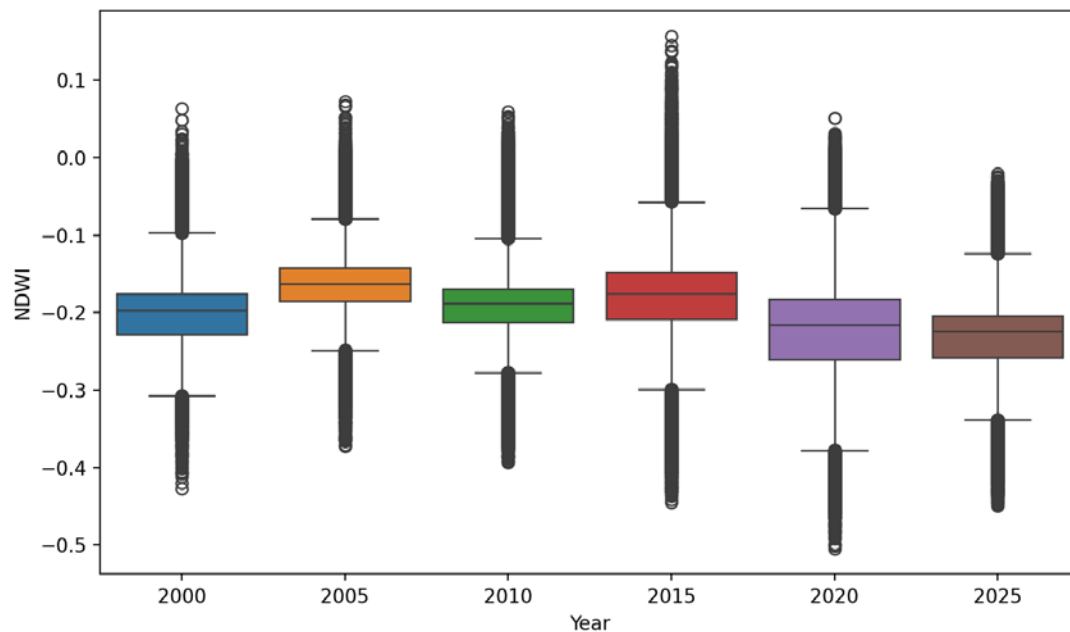


Figure 16. Normalised difference water index (NDWI) box plot for quartile ranges and error points of South Punjab 2000-2025

The NDWI boxplot (Fig. 16) shows marked downward trends in 2000, 2020, and 2025, where there are marked downward trends for the years 2000, 2020, and 2025. The median NDWI reached its minimum in 2025. This indicates a consistent decline in surface moisture. Although the years 2005 and 2015 exhibited slight recuperation with higher NDWI medians, the overall trend is downward. The extreme dryness observed in 2020 aligns with agricultural drought signals from VCI and VHI. However, the remarkably low NDWI in 2025, a year with healthy vegetation, underscores the region's reliance on irrigation to offset surface moisture deficits.

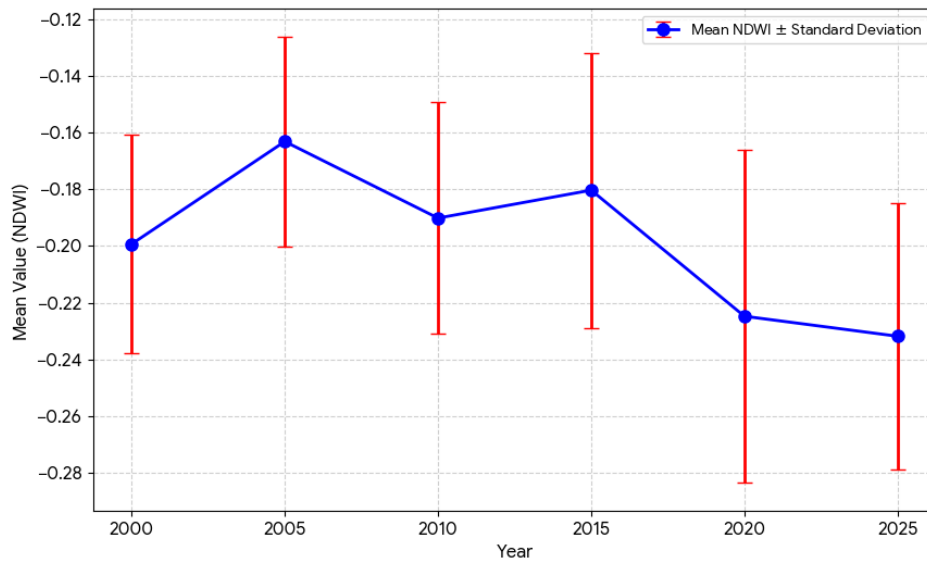


Figure 17. Normalized difference water index (NDWI) mean and standard deviation bar of South Punjab 2000-2025

NDWI in Figure 17 indicates the amount of liquid water in both vegetation and soil surfaces. While the values are always negative (-0.16 to -0.24), which is not surprising as May is in an arid region, they continuously decline from 2015 to 2025, suggesting that the water content in the canopy is declining. This is very worrisome for drought detection, implying that even if the crops are still green (reflected by NDVI), the water content in the canopy is so low that plants easily suffer wilting and yield loss; that is, the crops suffer severe physiological drought, as shown in Table 5.

Table 5. Mean trend of NDWI of South Punjab 2000-2025

<i>Year</i>	<i>Mean NDWI</i>	<i>Detailed Observation</i>	<i>Drought Implication</i>
2000	~-0.20	Large dry zones (-0.30 to -0.40) in the southwest.	High surface dryness.
2005	~-0.165	Highest NDWI (least negative).	Relatively fewer dry conditions.
2010	~-0.19	Decline from 2005.	Increased dryness.
2015	~-0.18	Small recovery.	Moderate dryness.
2020	~-0.225	Pronounced decline; with substantial expansion of the driest areas.	Very high dryness/water stress.
2025	~-0.230	Lowest NDWI in the series.	Most severe dryness.

5. Discussion

The multi-index assessment highlights severe compound drought stress in 2005 and 2020, driven by different factors. Interestingly, while absolute vegetation greenness (NDVI) was paradoxically high in 2020, extreme thermal pressure indicated by the highest values of LST and critically low TCI combined with severe soil moisture deficits (reduced NDWI), created high cumulative stress. This depressed VCI and VHI, as vegetation performed below its historical potential despite baseline greenness. Min-max normalized and fixed raster data validate this: the highest temperatures aligned with moisture-deficient regions (Miandad et al., 2025). High standard deviation indicates non-uniform drought across central and southwestern South Punjab during 2005 and 2020. This pattern is consistent with growing evidence that thermodynamic and energy-related processes increasingly govern short-term drought intensification in semi-arid and monsoon-influenced parts of Asia (Rahman et al., 2026), and it is consistent with the concept of rapid-onset or “flash” agricultural drought, in which anomalously high evaporative demand depletes soil moisture and vegetation vigor within weeks despite otherwise adequate seasonal rainfall.

Synthesizing these indices supports combining vegetative and temperature indices for accurate drought monitoring (Khan et al., 2025; Nasar-u-Minallah et al., 2025). Indices in 2010 and 2015 indicate normal to good conditions; uniquely, 2015 had the highest LST but normal TCI. Vegetation stress dominated in 2005, while thermal and water stress drove the 2020 agricultural drought. Despite the highest NDVI in 2020, depressed VCI indicates vegetation experienced acute heat shock and moisture depletion. Socially, this acute heat shock turns into a debt trap. During stressful years, Punjab's smallholders are forced to acquire high-interest informal loans from middlemen (Naurin, 2022). Anomalous years drive agrarian distress, rural-to-urban migration, and multi-generational poverty. Conversely, 2025 consistently demonstrated normal values of the indices except for dry surface water conditions (NDWI = -0.230) and low LST (38.5 °C), as summarized in Table 6, with the absolute highest VCI and VHI values (45.2 and 45.1, respectively), implying that there was substantial vegetation recovery with the lowest drought level.

The compounded anomalies in these years strongly correlate with regional meteorological conditions. A severe spring heat wave triggered the 2020 agricultural

drought. This extraordinary thermal shock caused rapid evapotranspiration, drastically reducing canopy water despite seasonal greenness. In the case of the 2005 compound anomaly, while surface moisture (NDWI) does not vary much from other years, the vegetation has failed (VCI ~37.6); this would suggest that either the failure of the vegetative cover is a consequence of entirely different thermal shocks, or specific winter crop failures and not the absence of absolute surface dryness before the monsoons.

Table 6: Comparison of all six indices of South Punjab 2000-2025

<i>Indicator</i>	<i>2005</i>	<i>2010</i>	<i>2015</i>	<i>2020</i>	<i>2025</i>
<i>LST</i>	Moderate	High	Highest	Moderate	Lowest
<i>NDVI</i>	Moderate	Low-Moderate	High	Highest	High
<i>NDWI</i>	Highest (least dry)	Moderate dryness	Moderate recovery	Very low	Lowest
<i>VCI</i>	Lowest	Moderate	High	Low	Highest
<i>TCI</i>	Low	Moderate	Moderate	Lowest	Recovery/High
<i>VHI</i>	Lowest	Moderate	High	Moderate decline	Highest

Correlation Matrix of Drought Indicators in South Punjab

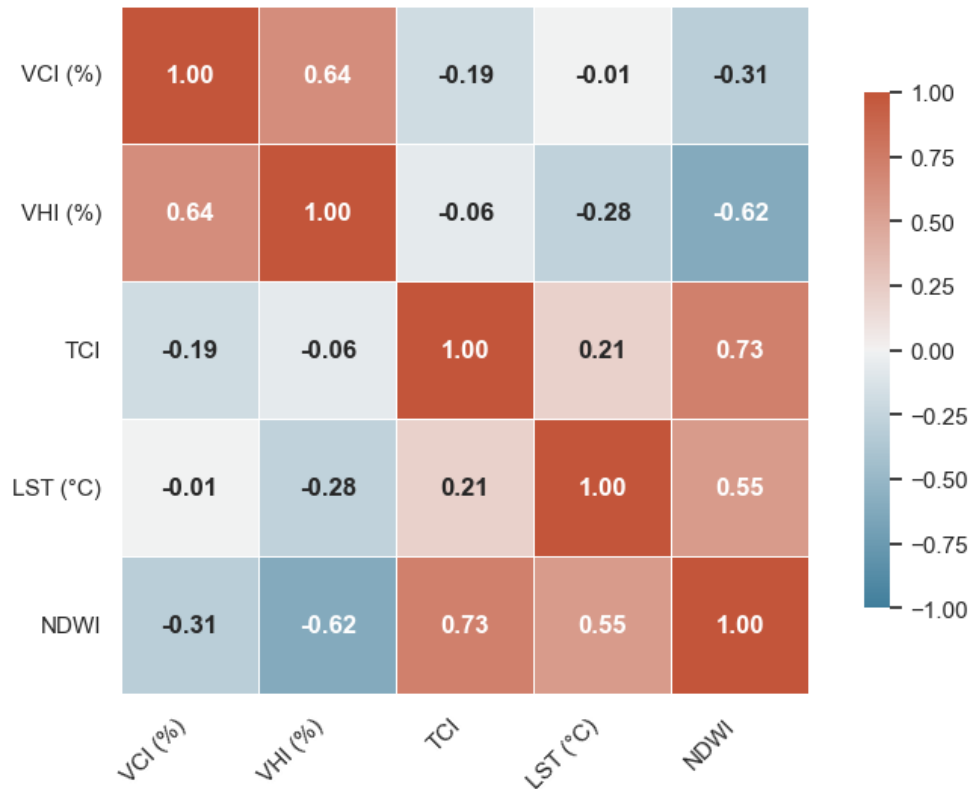


Figure 18. Correlation matrix of drought indicators in South Punjab

Figure 18 shows the correlation matrix of drought indicators in South Punjab. This correlation matrix displays the relationship between the five main remote sensing indicators of drought used to analyze pre-monsoon agricultural distress in South Punjab. Analyzing these correlations statistically validates the compound drought phenomena outlined in this study.

The Vegetation Condition Index (VCI) and Vegetation Health Index (VHI) are strongly positively correlated ($r=0.64$). As VHI is a compound index that is mathematically derived from vegetation (VCI) and thermal (TCI) parameters, it validates that the physical state of vegetation vigor is a major driving force for agriculture across South Punjab.

This indicates the strong positive correlation ($r=0.73$) between the Temperature Condition Index (TCI) and Normalized Difference Water Index (NDWI). TCI reflects the thermal stress across the land surface, and NDWI shows the relative liquid water content of the soil or vegetation. Lower temperatures support water retention, while heat waves cause rapid moisture loss. The high correlation between TCI and NDWI demonstrates that landscape 'cooling' capacity relies solely on water accessibility in

the region. This reaffirms the political ecology of the Indus Basin; people who can access canal water can avoid thermal stress, while rainfed (barani) areas suffer directly from escalating LST, exacerbating the "buffered" elite vs. the "exposed" masses dynamic.

VHI and NDWI are strongly negatively correlated ($r=-0.62$), as are VCI and NDWI ($r=-0.31$). This also confirms the crucial finding cited in the manuscript about the anomaly in 2025, where vegetation health (VHI/VCI) remained healthy, although absolute surface water content was at its lowest level of -0.230 among the five indicators. This negative correlation is clear evidence that the structural greenness in the region is maintained due to the tremendous amount of canal water irrigating it.

This indicates the negative correlation ($r=-0.28$) between the Land Surface Temperature (LST) and VHI. This negative relationship explains that when the temperature rises to more extreme levels, like the peak of 44.8°C in May 2015, evaporative demand intensifies and thermal stress starts taking over agriculture, which will directly affect vegetation vigor negatively. The identified high thermal stress in May (LST > 45°C) is fundamentally a serious issue of labor justice. The entire cotton and wheat economy of South Punjab depends on female manual laborers toiling outdoors in such a situation. The "thermal stress" measured by TCI therefore clearly signifies health risks for the most vulnerable population whose lives are linked to a terrain that is becoming uninhabitable during pre-monsoon.

This reveals the moderate positive correlation ($r=0.55$) between the Land Surface Temperature (LST) and NDWI. As negative values of NDWI for this arid region were only witnessed in May, this positive correlation indicates that it is about the variation in temperature gradients between varied land uses (e.g., irrigated fields and barren land) that will increase evaporation rates, thus reducing absolute moisture content in the crop canopy.

The correlation analysis confirms the multi-dimensional nature of the drought in South Punjab, highlighting that although canal irrigation can maintain the structural state of vegetation across the agricultural landscapes in the region, it is not sufficient to withstand extreme thermal shocks, causing a rapid decrease in surface water content, resulting in compound flash droughts. Coupling the present MODIS-based framework with such precipitation- and potential-evapotranspiration-based indices, and with attribution tools capable of ranking individual meteorological drivers, represents a natural extension of this work and would help determine whether events

such as the 2020 South Punjab drought were governed primarily by anomalous heat and evaporative demand or by an underlying precipitation shortfall compounded by high temperatures.

6. Conclusion

This study leveraged a 25-year (2000–2025) time series of MODIS-derived indicators (LST, NDVI, NDWI, VCI, TCI, and VHI) to unpack the complex, pre-monsoon drought dynamics in South Punjab. By combining remote sensing with statistical analysis, the study revealed the extent of regional vegetation stress, moisture deficits, and thermal anomalies. Boxplots and time-series highlight chronic vulnerability, with severe droughts in 2005 and 2020, and relief in 2010, 2015, and 2025. While the Mann-Kendall trend analysis suggests a weak, long-term trajectory toward stabilization, the persistent presence of wide data spreads and frequent outliers proves that regional recovery remains fragile, uneven, and highly sensitive to climate shocks. Spatially, these drought impacts are deeply unequal, with severe, enduring dryness anchored firmly across South Punjab's central and southwestern belts.

These findings show that building climate resilience requires shifting regional governance and addressing vulnerabilities in this area. Mitigating agricultural crises requires replacing old irrigation frameworks with ecologically driven water distribution. While MODIS-based indices remain invaluable for real-time early warning systems and disaster management, their true utility lies in serving as an instrument for spatial justice, guaranteeing that resources and policy priority flow directly to the marginalized communities enduring the brunt of South Punjab's changing climate.

Declarations

Conflict of interest: The authors declare that they have no conflict of interest.

References

- Abro, M. I., Elahi, E., & Korai, R. M. (2025). Attributing rainfall and drought variability across climate vulnerable area of Pakistan: Perspective from different satellite and ground-based datasets. *Theoretical and Applied Climatology*, 156(2). <https://doi.org/10.1007/s00704-024-05261-6>
- Ahmed, M., Dars, G. H., Ahmed, S., & Krakauer, N. Y. (2023). Analyzing drought trends over Sindh Province, Pakistan. *Natural Hazards*, 119(1), 643-661. <https://doi.org/10.1007/s11069-023-06082-y>
- Ahmed, N., Mahmood, S. A., Haseeb, M., Tahir, Z., & Batool, S. (2025). Enhancing food security: machine learning-based wheat yield prediction using remote sensing and climate data in Pakistan. *Theoretical and Applied Climatology*, 156. <https://doi.org/10.1007/s00704-025-05475-2>

- Akram, M., Khan, F., Ullah, H., Ali, S., & Hussain, A. (2024). Enhancing Drought Risk Assessment in the Punjab, Pakistan: A Copula-Based Modeling Approach for Future Projections. *Journal of Applied Meteorology and Climatology*, 63(10), 1207-1225. <https://doi.org/10.1175/JAMC-D-24-0041.1>
- Ali, S. M., Khalid, B., Akhter, A., Islam, A., & Adnan, S. (2020). Analyzing the occurrence of floods and droughts in connection with climate change in Punjab province, Pakistan. *Natural Hazards*, 103(2), 2533-2559. <https://doi.org/10.1007/s11069-020-04095-5>
- Arshad, A., Zubair, M., Zafar, Z., Latif, R. M. A., Zulqarnain, R. M., Abbas, Q.,...Ahmad, T. (2025). Remote sensing-based spatiotemporal assessment of agricultural drought and its impact on crop yields in Punjab, Pakistan. *Scientific Reports*, 15, 20586. <https://doi.org/10.1038/s41598-025-06095-6>
- Arshad, S., Kazmi, J., Prodhan, F. A., & Mohammed, S. (2023). Exploring dynamic response of agrometeorological droughts towards winter wheat yield loss risk using machine learning approach at a regional scale in Pakistan. *Field Crops Research*, 302, 109057. <https://doi.org/10.1016/j.fcr.2023.109057>
- Arshad, S., Kazmi, J. H., Shaikh, S., & Arshad, W. (2022). Geospatial assessment of early summer heatwaves, droughts, and their relationship with vegetation and soil moisture in the arid region of Southern Punjab, Pakistan. *Journal of Water and Climate Change*, 13(11), 4105-4129. <https://doi.org/10.2166/wcc.2022.425>
- Ashraf, M., & Ullah, K. (2022). Satellite-based impact assessment of temperature and rainfall variability on drought indices in Southern Pakistan. *International Journal of Applied Earth Observation and Geoinformation*, 108, 102726. <https://doi.org/10.1016/j.jag.2022.102726>
- Ault, T. R. (2020). On the essentials of drought in a changing climate. *Science*, 368(6488), 256-260. <https://doi.org/10.1126/science.aaz5492>
- Bao, J., Wu, Y., Huang, X., Qi, P., Yuan, Y., Li, T.,...Yang, S. (2024). Changes in Surface and Terrestrial Waters in the China–Pakistan Economic Corridor Due to Climate Change and Human Activities. *Remote Sensing*, 16(8), 1437. <https://doi.org/10.3390/rs16081437>
- Bento, V. A., Gouveia, C. M., DaCamara, C. C., & Trigo, I. F. (2020). A climatological assessment of drought impact on vegetation health index. *Agricultural and Forest Meteorology*, 290, 108002. <https://doi.org/10.1016/j.agrformet.2018.05.014>
- Bhowmik, S., & Bhatt, B. (2024). Drought Monitoring Using MODIS Derived Indices and Google Earth Engine Platform for Vadodara District, Gujarat. *Journal of the Indian Society of Remote Sensing*, 52, 941-955. <https://doi.org/10.1007/s12524-024-01922-1>
- Black, E., Maidment, R. I., Rees, E., & Nderitu, E. (2024). A new drought model for disaster risk management in the Punjab, Sindh and Baluchistan provinces of Pakistan. *Frontiers in Climate*, 6, 1332233. <https://doi.org/10.3389/fclim.2024.1332233>
- Bureau of Statistics, P. (2024). South Punjab Development Statistics 2024. Government of the Punjab, Bureau of Statistics.
- Ejaz, N., Bahrawi, J., Alghamdi, K. M., Rahman, K. U., & Shang, S. (2023). Drought monitoring using Landsat derived indices and Google Earth Engine platform: A case study from Al-Lith watershed, Kingdom of Saudi Arabia. *Remote Sensing*, 15(4), 984. <https://doi.org/10.3390/rs15040984>

- Ellahi, A., Niaz, R., Almazah, M. M. A., Hussain, I., Al-Duais, F. S., & Al-Rezami, A. Y. (2023). A generalized framework for quantifying and monitoring the severity of meteorological drought. *International Journal of Remote Sensing*, 44(12), 3747-3770. <https://doi.org/10.1080/10106049.2023.2228261>
- Faheem, Z., Kazmi, J. H., Shaikh, S., Arshad, S., Noreena, & Mohammed, S. (2024). Random forest-based analysis of land cover/land use LCLU dynamics associated with meteorological droughts in the desert ecosystem of Pakistan. *Ecological Indicators*, 158, 111670. <https://doi.org/10.1016/j.ecolind.2024.111670>
- Goheer, M. A., Aftab, B., Farah, H., & Hassan, S. S. (2023). Spatio-temporal risk analysis of agriculture and meteorological droughts in rainfed Potohar, Pakistan, using remote sensing and geospatial techniques. *Meteorological Applications*, 30(6), 2138. <https://doi.org/10.1002/met.2138>
- Hussain, S., Qaisrani, S. A., Tariq, A., Mubeen, M., & Ullah, S. (2025). Assessing past, present, and simulated future prediction of land use land cover changes using CA-Markov chain models with Satellite data. *Results in Engineering*, 25, 105585. <https://doi.org/10.1016/j.rineng.2025.105585>
- Ijaz, M., Zafar, Q., Khan, A. A., & Hassan, S. S. (2023). Assessing drought and its impacts on wheat yield using remotely sensed observations in rainfed Potohar region of Pakistan. *Environment, Development and Sustainability*, 25(4), 3699-3721. <https://doi.org/10.1007/s10668-022-02200-1>
- Javadian, M., Behrangi, A., Smith, W. K., & Fisher, J. B. (2020). Global Trends in Evapotranspiration Dominated by Increases across Large Cropland Regions. *Remote Sensing*, 12(7), 1221. <https://doi.org/10.3390/rs12071221>
- Jiao, W., Wang, L., Smith, W. K., Chang, Q., Wang, H., & D'Odorico, P. (2021). Observed increasing water constraint on vegetation growth over the last three decades. *Nature Communications*, 12(1), 3777. <https://doi.org/10.1038/s41467-021-24016-9>
- Khan, I. A., Leghari, S. J., & Magar, K. (2025). Assessing Drought Vulnerability in Pakistan (2001-2022) Using EVI-Based Standardized Vegetation Index in Google Earth Engine. *Proceedings of the Pakistan Academy of Sciences: A. Physical and Computational Sciences*, 62(3), 193-207. [https://doi.org/10.53560/PPASA\(62-3\)843](https://doi.org/10.53560/PPASA(62-3)843)
- Khan, S., Gilani, H., Iqbal, N., & Shahid, I. (2020). Satellite-based (2000-2015) drought hazard assessment with indices mapping and monitoring of Potohar Plateau, Punjab, Pakistan. *Environmental Earth Sciences*, 79(1), 8751. <https://doi.org/10.1007/s12665-019-8751-9>
- Le, N. H., Tran, T. A., Nguyen, H. S., Le, P. C. L., Nguyen, V. A., & Nguyen, T. L. (2024). Monitoring meteorological drought in Hoa Vang district, Da Nang City, using Google Earth Engine and satellite-derived precipitation data combined with ground-based weather stations. *Journal of Water and Climate Change*, 15(3), 1142-1158. <https://doi.org/10.2166/wcc.2024.214>
- Liu, L., Gudmundsson, L., Hauser, M., Qin, D., Li, S., & Seneviratne, S. I. (2020). Soil moisture dominates dryness stress on ecosystem production globally. *Nature Communications*, 11(1), 4892. <https://doi.org/10.1038/s41467-020-18631-1>
- Miandad, M., Ansar, A., Rahman, G., Munawar, S., & Dawood, M. (2025). Spatio-temporal impact of climate variability on crop production of Potohar Region, Pakistan (1990-2017). *Ecological Questions*, 36(1), 1-25.

- Moazzam, M. F. U., Rahman, G., Munawar, S., Tariq, A., Safdar, Q., & Lee, B. G. (2022). Trends of Rainfall Variability and Drought Monitoring Using Standardized Precipitation Index in a Scarcely Gauged Basin of Northern Pakistan. *Water*, 14(7), 1132. <https://doi.org/10.3390/w14071132>
- Nasar-u-Minallah, M., Parveen, N., Shahzad, M. F., & Tabassum, R. (2025). Spatial and temporal assessment of drought dynamics in Bahawalpur (Department) using remote sensing and meteorological data. *Environmental Earth Sciences*, 84(19), 1-23. <https://doi.org/10.1007/s12665-025-12520-w>
- Naurin, A. A. (2022). The Role of Arthi in Agriculture Marketing: An Exploiter or Facilitator of Farmers? PIDE Knowledge Brief 69 (2022). <https://pide.org.pk/research/the-role-of-arthi-in-agriculture-marketing-an-exploiter-or-facilitator-of-farmers/>
- P.M.D. (2025). Pakistan Meteorological Department. Retrieved 5 October, 2025 at 9:45 from <https://www.pmd.gov.pk/en/>
- Pendergrass, A. G., Meehl, G. A., Pulwarty, R., Hobbins, M., Hoell, A., AghaKouchak, A.,...Woodhouse, C. A. (2020). Flash droughts present a new challenge for subseasonal-to-seasonal prediction. *Nature Climate Change*, 10(3), 191-199. <https://doi.org/10.1038/s41558-020-0709-0>
- Rafiq, M., Li, Y. C., Cheng, Y., Rahman, G., Zhao, Y., & Khan, H. U. (2023). Estimation of regional meteorological aridity and drought characteristics in Baluchistan province, Pakistan. *PLOS ONE*, 18(11), 0293073. <https://doi.org/10.1371/journal.pone.0293073>
- Rahman, G., Farooq, U., Kang, S., Lee, J.-H., & Kwon, H.-H. (2026). Understanding temperature-driven drought intensification in Northeast Asia through multiple drought indices. *Journal of Hydrology: Regional Studies*, 66, 103647.
- Rahman, G., Khalid, S., Arshad, S., Moazzam, M. F. U., & Kwon, H.-H. (2025). Remote sensing-based spatiotemporal assessment of agricultural drought and its impact on crop yields in Punjab, Pakistan. *Scientific Reports*, 15(1), 20586.
- Rahman, K. U., & Shang, S. (2023). Catchment-Scale Drought Propagation Assessment in the Indus Basin of Pakistan Using a Combined Approach of Principal Components and Wavelet Analyses. *Journal of Hydrometeorology*, 24(4), 625-643. <https://doi.org/10.1175/JHM-D-22-0140.1>
- Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J.,...White, K. D. (2020). Understanding and managing connected extreme events. *Nature Climate Change*, 10(7), 611-621. <https://doi.org/10.1038/s41558-020-0790-4>
- Ridder, N. N., Pitman, A. J., Westra, S., Ukkola, A., Do, H. X., Bador, M.,...Zscheischler, J. (2020). Global hotspots for the occurrence of compound events. *Nature Communications*, 11(1), 5956. <https://doi.org/10.1038/s41467-020-19639-3>
- Safdar, M. (2024). Spatiotemporal analysis of drought severity and precipitation variability in Punjab's Pothohar plateau using PDSI and SPEI. *Journal of Hydrology: Regional Studies*, 54, 101865. <https://doi.org/10.5281/zenodo.13828491>
- Saha, T. R., Shrestha, P. K., Rakovec, O., Thober, S., & Samaniego, L. (2021). A drought monitoring tool for South Asia. *Environmental Research Letters*, 16(5), 054014. <https://doi.org/10.1088/1748-9326/abf525>
- Shah, S. A. A., Wu, H., Farid, M. F., Tareen, W. U. H., & Badar, I. H. (2024). Climate Trends and Wheat Yield in Punjab, Pakistan: Assessing the Change and Impact. *Sustainability*, 16(11), 4443. <https://doi.org/10.3390/su16114443>

- Shah, W., Chen, J., & Naseer, S. (2025). Climate change and crop yields in Pakistan: A machine learning approach to understanding temperature extremes and drought effects on wheat and rice. *Theoretical and Applied Climatology*, 156. <https://doi.org/10.1007/s00704-025-05759-7>
- Shahzaman, M., Zhu, W., Bilal, M., Habtemicheal, B. A., Mustafa, F., Arshad, M.,...Iqbal, R. (2021). Remote sensing indices for spatial monitoring of agricultural drought in South Asian countries. *Remote Sensing*, 13(11). <https://doi.org/10.3390/rs13112059>
- Tabassum, R., Khan, I. A., & Arsalan, M. H. (2023). Monitoring Drought Events and Vegetation Conditions in Pakistan: Implications for Drought Management and Food Security. *Proceedings of the Pakistan Academy of Sciences: A. Physical and Computational Sciences*, 60(4).
- Ullah, I., Saleem, F., Iyakaremye, V., Yin, J., Ma, X., Syed, S.,...Omer, A. (2021). Evaluating the meteorological drought characteristics over Pakistan using in situ observations and reanalysis products. *International Journal of Climatology*, 41(9), 4437-4459. <https://doi.org/10.1002/joc.7063>
- Ullah, I., Zeng, X. M., Hina, S. S., Syed, S. S., Ma, X., Iyakaremye, V. V.,...Singh, V. P. (2023). Recent and projected changes in water scarcity and unprecedented drought events over Southern Pakistan. *Frontiers in Earth Science*, 11, 1113554. <https://doi.org/10.3389/feart.2023.1113554>
- Ullah, R., Khan, J., Ullah, I., Khan, F., & Lee, Y. (2023). Assessing Impacts of Flood and Drought over the Punjab Region of Pakistan Using Multi-Satellite Data Products. *Remote Sensing*, 15(6), 1484. <https://doi.org/10.3390/rs15061484>
- Waleed, M., & Sajjad, M. (2023). On the emergence of geospatial cloud-based platforms for disaster risk management: A global scientometric review of Google Earth engine applications. *International Journal of Disaster Risk Reduction*, 97, 104056. <https://doi.org/10.1016/j.ijdr.2023.104056>
- Waseem, M., Jaffry, A. H., Azam, M., Ahmad, I., Abbas, A., & Lee, J. E. (2022). Spatiotemporal analysis of drought and agriculture standardized residual yield series nexuses across Punjab, Pakistan. *Water*, 14(3), 496. <https://doi.org/10.3390/w14030496>