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Article

Spatiotemporal Assessment of Drought Dynamics and Periodicity in Southern Districts of West Bengal, India

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ABSTRACT

Drought is a recurring issue in the southern districts of West Bengal, impacting agriculture, water resources, and livelihoods. Climate variability exacerbates these challenges, necessitating a comprehensive assessment of drought severity and trends over time. The main aim of this study is to assess the spatiotemporal dynamics of drought from 2003 to 2021 by evaluating drought severity, analyzing trends in drought severity categories, and identifying periodic cycles that influence drought conditions. Advanced drought indices such as the Standardized Precipitation-Evapotranspiration Index (SPEI), Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI) were employed. The study utilized remote sensing data and innovative trend analysis (ITA) to assess the severity, trends, and periodicity of drought. Wavelet power spectrum (WPS) analysis was also applied to examine drought periodicity across multiple time scales. Quantitative results show that severe and extreme drought conditions have significantly intensified over the past two decades. Extreme drought affected up to 7,258 km² in 2009, while severe drought reached a peak of 12,217 km² in 2021. Moderate drought remained the most prevalent category, affecting over 17,146 km² in 2009. Areas classified under no drought conditions steadily declined, from 16,327 km² in 2017 to 10,581 km² in 2021. ITA results indicate an increasing trend in extreme and severe drought areas, with more regions transitioning from mild to severe categories. Periodicity analysis revealed significant multi-year cycles (8-16 years) for extreme and severe droughts, aligning with known climate anomalies. These findings emphasize the escalating severity and frequency of drought in the region, underscoring the urgent need for adaptive management strategies, continuous monitoring, and timely interventions to sustain agricultural productivity and ecosystem health amidst intensifying climate change impacts.

1. Introduction

Drought is one of the most devastating natural disasters, characterized by prolonged periods of insufficient precipitation, leading to severe water shortages, agricultural failures, and ecosystem degradation (Zeng et al., 2022; Makula et al., 2024). The impacts of drought are multifaceted, affecting not only the natural environment but also the socioeconomic fabric of affected regions (Kulkarni et al., 2024). Droughts is classified into four types based on their defining characteristics and impacts. Meteorological drought refers to an extended period of below-average precipitation, often serving as the precursor to other types of droughts (Wang et al., 2014). Agricultural drought occurs when soil moisture levels become insufficient to sustain healthy crop production, adversely affecting agricultural output (Dalezios et al., 2014). Hydrological drought is characterized by significant reductions in surface and subsurface water resources, including rivers, reservoirs, and groundwater (Van Loon, 2015). Lastly, socioeconomic drought arises when water scarcity leads to profound social and economic repercussions, such as diminished livelihoods and increased conflicts over water resources (Mehran et al., 2015).

The causes of drought are complex and often interrelated, involving natural climate variability, anthropogenic climate change, and land use changes that affect the hydrological cycle (Cook et al., 2018; Trenberth et al., 2014). Previous studies show that the frequency, duration, and intensity of droughts are increasing due to global warming, exacerbating the risks to food security, water resources, and human health (Awange et al., 2007; Ebi and Bowen, 2016; Salvador et al., 2020). The rising danger of droughts is particularly concerning in the context of climate change, where altered precipitation patterns, higher temperatures, and increased evapotranspiration rates are expected to intensify drought conditions in many parts of the world (Cook et al., 2018; Xu et al., 2019).

The accurate assessment and monitoring of drought impacts require the integration of multiple indices that reflect different aspects of drought stress on ecosystems. The standardized precipitation evapotranspiration index (SPEI), temperature condition index (TCI), and vegetation condition index (VCI) are essential tools in this regard, as they provide a comprehensive understanding of drought effects by capturing the interplay between precipitation, temperature, and vegetation health (Han and Singh, 2023; Yin and Zhang, 2023). SPEI, a widely used index, combines precipitation and potential evapotranspiration data to quantify drought severity over time, utilizing the water balance approach, which is essential for understanding the hydrological impacts of drought, particularly in regions with already stressed water resources (Tan et al., 2023). Similarly, the TCI provides insights into the thermal stress experienced by vegetation, which can exacerbate drought conditions by increasing water demand and reducing plant productivity (Jalayer et al., 2023). The VCI, on the other hand, is a direct measure of vegetation health, reflecting the cumulative impact of both water and temperature stress on plant vitality (Dutta et al., 2015). The integration of these indices into a composite Vegetation Health Index (VHI) allows for a more nuanced assessment of drought impacts, offering a valuable tool for policymakers and resource managers in making informed decisions to mitigate the adverse effects of drought (Javed et al., 2021). This methodological approach is particularly important in the context of climate change, where traditional drought monitoring methods may no longer be sufficient to capture the complexity and severity of drought events. By utilizing advanced satellite-based indices, this study contributes to a more accurate and timely assessment of drought conditions, which is crucial for developing effective mitigation strategies and enhancing the resilience of vulnerable regions to future droughts.

Given the growing threat of droughts, there is an urgent need for effective mitigation strategies to reduce their adverse effects. These strategies include improving water management practices, enhancing drought forecasting and monitoring systems, and implementing adaptive agricultural practices such as Climate-Smart Agriculture (CSA) (Lipper et al., 2014). The development of indices such as the SPEI, TCI, and VCI plays a crucial role in monitoring and assessing drought impacts on vegetation and water resources, thereby aiding in the formulation of timely and effective responses to mitigate the adverse effects of droughts.

2. Materials and methods

The study uses Earth Observation (EO) data from multiple satellite platforms to compute and analyse the VHI, which integrates three key indices: the SPEI, TCI, and VCI. These indices collectively assess vegetation stress caused by climatic extremes, focusing on a temporal range from 2003 to 2021.

2.1 Study area

The districts situated south of the Ganges—Bankura, Paschim Bardhaman, Purba Bardhaman, Birbhum, Purulia, Murshidabad, Nadia, West Midnapore, Jhargram, East Midnapore, Hooghly, Howrah, Kolkata, North 24 Parganas, and South 24 Parganas—encompass a diverse range of geographical areas. These include the Rarh region, the elevated Western plateau and highlands, the coastal plains, the Sundarbans, and the Ganges Delta. Kolkata, serving as the state capital, forms its own distinct district. The eastern districts of the study area have a tropical maritime climate with high humidity and significant monsoon rainfall from June to September. This area features the famous and ecologically crucial Sundarbans mangrove forests, playing undeniable role in biodiversity and coastal protection. In contrast, the western districts, including Barddhaman, Bankura, and Purulia, are on the Chota Nagpur Plateau's fringes, exhibiting varied topography and a subtropical climate with distinct dry and wet seasons. Summers here are extremely hot and dry, often exceeding 40°C, and the monsoons bring moderate to heavy rainfall.

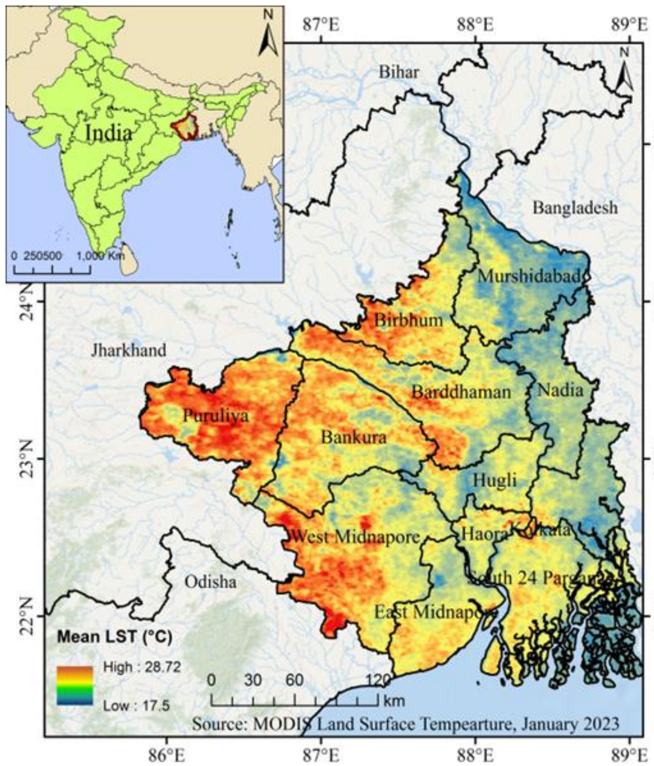

Figure 1 Location of the study area

The southern districts of West Bengal have seen significant urbanization and LULC changes in recent decades. Kolkata and nearby areas have experienced rapid urban growth, driven by industrialization and rural-to-urban migration, leading to wetland and forest encroachment and decreased green cover. South 24 Parganas, in particular, has undergone substantial land reclamation for residential and commercial purposes. Meanwhile, western districts like Barddhaman, though less urbanized, have faced deforestation and land degradation due to agricultural expansion and mining.

2.2 Data Acquisition and Preprocessing

The study utilizes datasets from MODIS and CHIRPS, accessible via the Google Earth Engine (GEE) platform. The NDVI data is sourced from the MODIS MOD09GA_006 product, while land surface temperature (LST) data is retrieved from the MODIS MOD11A2 collection. Precipitation data is obtained from the CHIRPS daily dataset, and evapotranspiration data is extracted from the MODIS MOD16A2GF product. For each year within the study period, corresponding annual subsets of these datasets were filtered and clipped to the study area using a predefined geometry. The NDVI and LST data were converted to appropriate physical units, with LST transformed from Kelvin to Celsius, facilitating subsequent analysis. A consistent spatial resolution of 1000 meters was maintained across all datasets.

2.3 Methods for calculating drought indices

2.3.1 SPEI Calculation

The SPEI was computed by first deriving the water balance, defined as the difference between precipitation and potential evapotranspiration (PET). The mean and standard deviation of the water balance were calculated over the region of interest, ensuring robust statistical computation by avoiding division by zero. The SPEI was then normalized to reflect deviations from the mean water balance, following the methodology of Beguería et al. (2014) and updated approaches in climatic studies (Stagge et al., 2014; Liu et al., 2021).

2.3.2 TCI Calculation

The TCI was derived from LST data by comparing the daily LST values with the observed minimum and maximum LST values within the region. This index represents the thermal stress on vegetation, with normalization applied to maintain values within the range of 0 to 1. The TCI computation methodology adheres to the standards set by Kogan (1995), with recent enhancements incorporated as per Jiao et al. (2019) and Yin and Zhang (2023).

2.3.3 VCI Calculation

The VCI was computed by normalizing NDVI values against regional NDVI minima and maxima, reflecting the vegetation's health status relative to the best and worst conditions observed. This calculation follows the framework proposed by Kogan (1995) and recent modifications introduced by Liu et al. (2020) and Zhang et al. (2021).

2.3.4 Computation of Vegetation Health Index (VHI)

The VHI, which integrates the effects of drought (SPEI), thermal stress (TCI), and vegetation health (VCI), was computed using the weighted expression $VHI=0.5\times VCI+0.3\times TCI+0.2\times SPEI$. This weighted approach balances the impact of these indices, aligning with methodologies from recent studies focusing on agricultural and ecological resilience (Kogan, 1995). The VHI computation for each year resulted in spatial maps, which were subsequently clipped to the study area. These maps provide a temporal sequence that was used for further analysis to understand vegetation dynamics in response to climatic stressors.

2.4 Trend analysis of drought classes

An Innovative Trend Analysis (ITA) with significance calculation was conducted to evaluate long-term trends in five drought categories: Extreme Drought, Severe Drought, Moderate Drought, Mild Drought, and No Drought in South Bengal. The dataset, which spanned several decades, was analyzed by splitting each drought category's time series into two equal halves. The initial and later years constituted the first and second halves, respectively, with the means of the sorted values within each half being calculated. The trend slope (s) was determined using the formula s = 2/n × (mean of second half - mean of first half), where n represented the total number of data points in the series. To determine the significance of the identified trends, variance (var_s) and standard deviation (std_s) of the trend slope were calculated, accounting for the correlation between the two halves (Yuce et al., 2023). Confidence limits were established at a 95% confidence level using the normal distribution's critical value (z) (Tosunoglu and Kisi, 2017). A trend was classified as significantly increasing if the slope (s) exceeded the upper confidence limit, significantly decreasing if it fell below the lower limit, and non-significant if it lay between these bounds. The results were visualized through scatter plots, where each point depicted paired values from the first and second halves of the series. A 1:1 reference line was included in the plots to indicate no trend, and the respective years were annotated for clarity. This method, which integrates ITA with significance testing, was implemented in Python, utilizing the Pandas library for data handling, Matplotlib for visualization, and SciPy for statistical computations (Li et al., 2019). The results were saved as high-resolution images and exported to CSV files, facilitating further analysis and reporting. This approach has been recognized for its robustness in identifying and quantifying trends in climate-related time series data, offering valuable insights into the evolution of drought severity and frequency.

2.5 Periodicity analysis of drought classes

A continuous wavelet transform (CWT) analysis was performed on five drought categories—Extreme Drought, Severe Drought, Moderate Drought, Mild Drought, and No Drought—using the morlet wavelet ('morl') and a range of scales from 1 to 128. The CWT was applied to the time series data of each drought category, which was derived from VHI area classification data. The wavelet transform allowed for the computation of wavelet power spectra (WPS) and global wavelet spectra, providing insight into the temporal patterns and frequency components within each drought category. The wavelet power spectrum (WPS) was calculated for each drought category, revealing the distribution of power across different scales (or periods) over time. To assess the significance of the detected features, the cone of influence (COI) was calculated, which indicates the region of the wavelet spectrum where edge effects become significant, thereby helping to identify reliable regions of the WPS. The COI was determined based on the first scale of the wavelet transform, and it was ensured that the COI did not exceed the maximum scale used in the analysis. Additionally, scale-averaged time series were calculated by averaging the wavelet power over a defined scale range, specifically between 10 and 14 years. This averaging process provided a summary of the dominant periodicities within this range, yielding the variance of the wavelet power as a function of time. The results were visualized using contour plots for the WPS, global wavelet spectra plots, and time series plots of the scale-averaged variance. The entire analysis was implemented in Python, utilizing the 'pywt' library for wavelet transformations, 'numpy' for numerical computations, 'pandas' for data manipulation, and 'matplotlib' for plotting. The final outputs, including high-resolution JPEG images of the WPS and scale-averaged time series, were saved for further analysis and interpretation.

3. Results

3.1 Assessment of drought indices

The maps of the study area in Figure 2 presents the SPEI across various years from 2003 to 2021. The SPEI is a widely used drought index that integrates both precipitation and evapotranspiration to assess the moisture balance over time, providing insight into drought conditions. The maps illustrate spatial variability in SPEI values across different regions, with the colour scale indicating the degree of wetness or dryness. It is evident from the maps that significant interannual variability exists in the spatial distribution of droughts. Certain years, such as 2012 and 2016, exhibit more extensive areas of negative SPEI values, signalling severe drought conditions, whereas other years, such as 2009 and 2013, show a mix of positive and negative SPEI values, indicating varying moisture conditions across the region. This visual assessment suggests that while drought severity fluctuates over time, there are recurrent patterns of dryness in specific regions, reflecting the persistence of drought conditions. Such information is crucial for understanding the temporal and spatial dynamics of droughts, informing water resource management, agricultural planning, and climate adaptation strategies. This analysis highlights the importance of continuous monitoring and assessment of drought indices like SPEI to better predict and mitigate the impacts of droughts, which are becoming increasingly frequent and severe in the context of climate change.

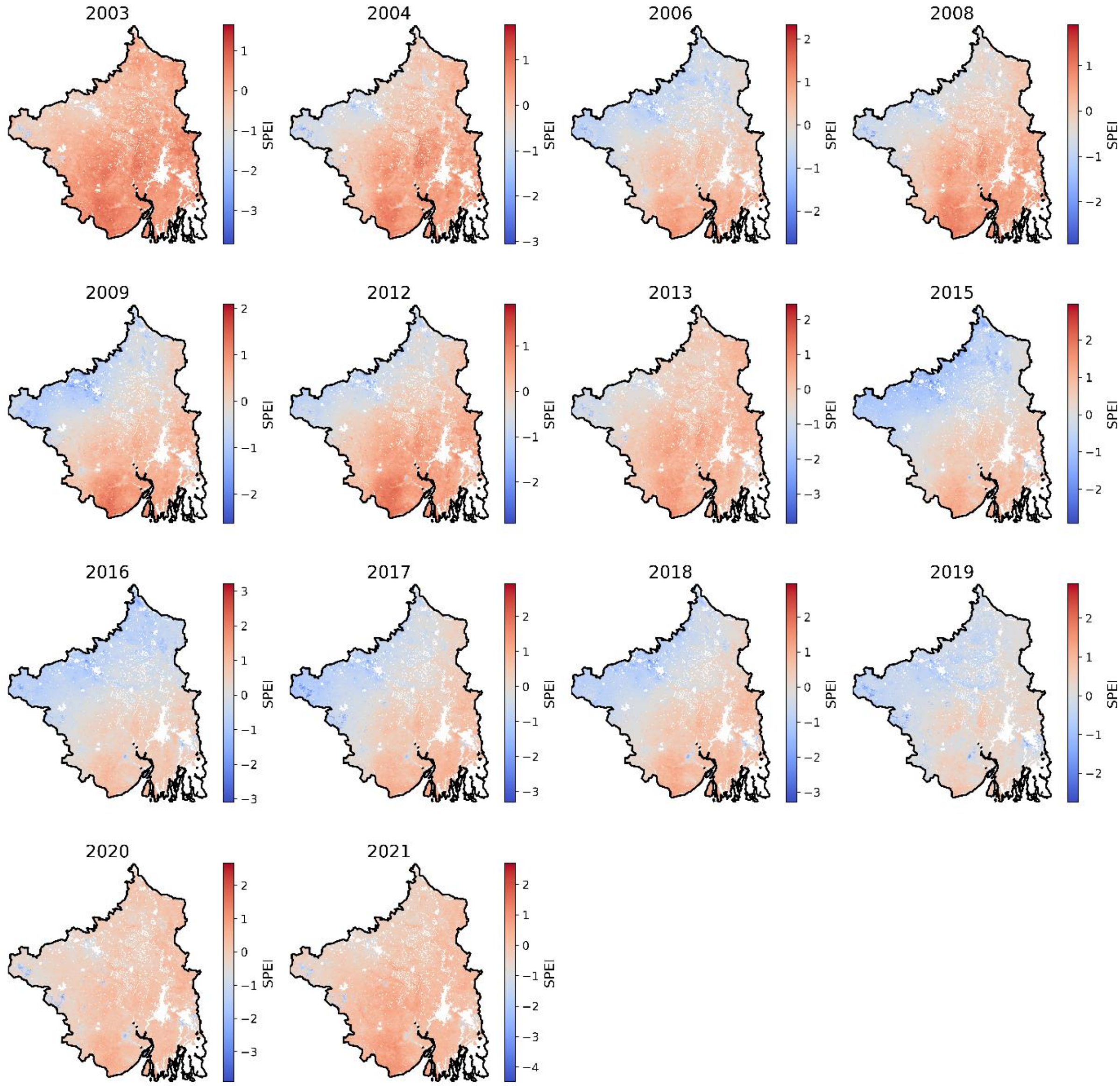

Figure 2 Spatial Distribution of the Standardized Precipitation-Evapotranspiration Index (SPEI) for Selected Years (2003-2021)

The series of maps of southern districts of West Bengal in Figure 3 represents the TCI values for various years from 2003 to 2021. The TCI is an essential drought index that quantifies the intensity of drought by evaluating temperature conditions in relation to vegetation stress. It provides a comprehensive assessment of drought severity by integrating the impact of temperature anomalies on vegetation health. The analysis reveals significant interannual variability in TCI, with years such as 2003, 2009, and 2012 showing extensive regions with low TCI values, reflecting periods of pronounced vegetation stress likely due to elevated temperatures. Conversely, years like 2016 and 2017 demonstrate a mixed distribution of TCI, suggesting a more varied impact of temperature on vegetation stress across the region. This spatial and temporal variability in TCI highlights the influence of temperature on drought conditions, with certain years exhibiting widespread stress likely exacerbated by climate anomalies. The consistent observation of low TCI values in specific areas over time suggests persistent vulnerability to temperature-induced stress, which is critical for understanding the impacts of climate variability on regional agriculture and ecosystems. These findings underscore the importance of continuous monitoring and analysis of TCI as part of an integrated approach to drought management, providing vital information for developing adaptive strategies in response to changing climatic conditions.

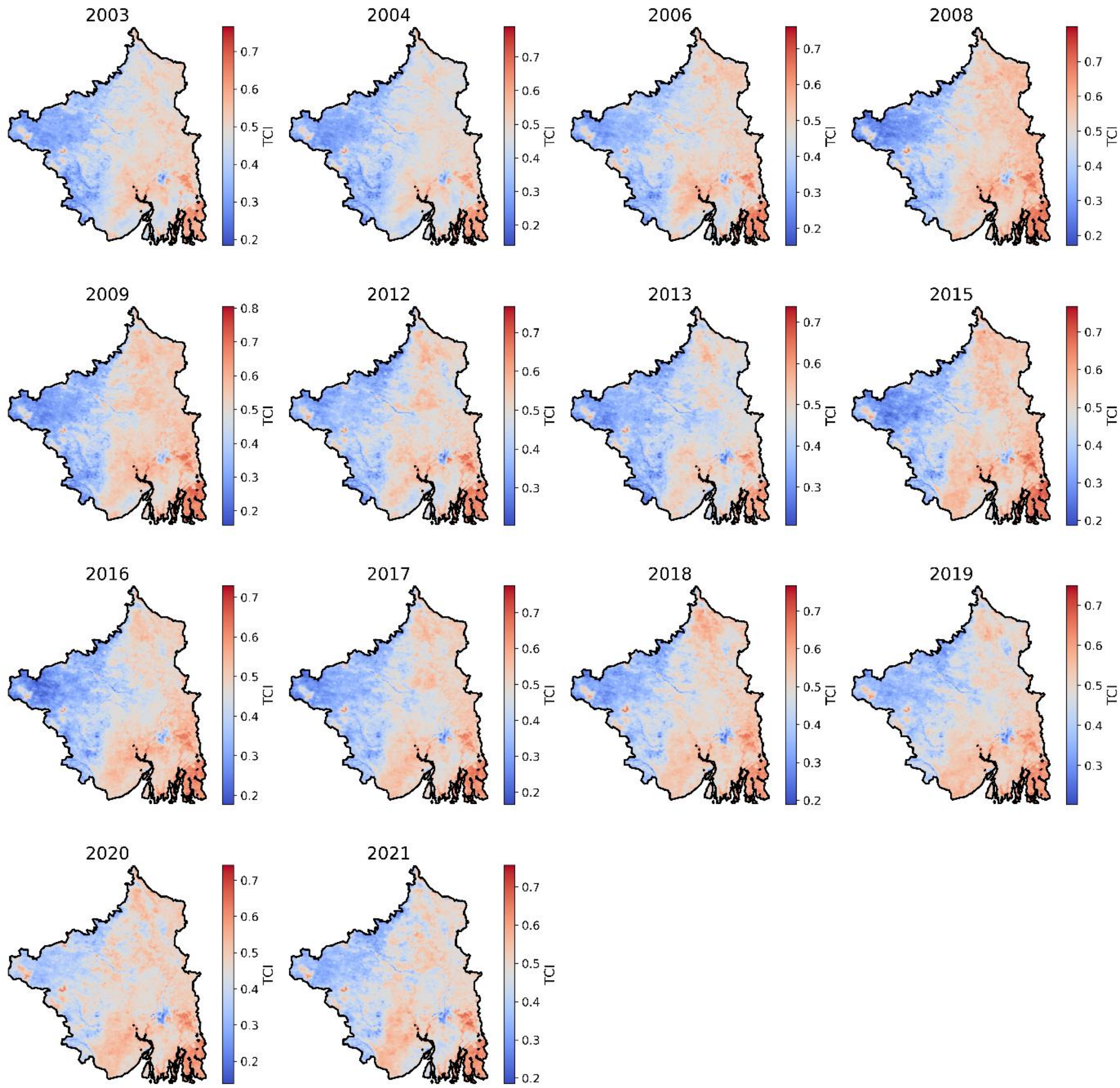

Figure 3 Spatial Distribution of the temperature condition Index (TCI) for Selected Years (2003-2021)

The maps of southern West Bengal presented in Figure 4 illustrates VCI for the years 2003 through 2021. The VCI is a critical drought assessment tool that measures the health of vegetation relative to the maximum and minimum NDVI values observed over time. It provides an accurate indication of vegetation stress and drought impact. The maps reveal that over the examined years, large portions of the region consistently exhibit high VCI values, particularly in the western and central areas, denoted by the red colour. This suggests that, despite fluctuations in climatic conditions, these areas have maintained relatively healthy vegetation, possibly due to favorable environmental factors or effective agricultural practices. However, certain years, such as 2012 and 2015, display patches of lower VCI values, particularly in the southeastern parts of the region, indicating periods where vegetation experienced stress, likely due to drought or other adverse conditions. These findings demonstrate the spatial variability of vegetation health over time and highlight the regions that are more resilient to drought versus those that are more vulnerable. The temporal consistency of VCI in certain areas points to the presence of underlying factors that sustain vegetation health, whereas the variability in other areas suggests a need for targeted interventions to mitigate the effects of drought. The VCI analysis is crucial for understanding the impact of climatic variations on vegetation, enabling more informed decisions in drought management and agricultural planning. Continuous monitoring of VCI can help identify early signs of drought, allowing for timely responses to protect vulnerable ecosystems and sustain agricultural productivity in the face of climate change.

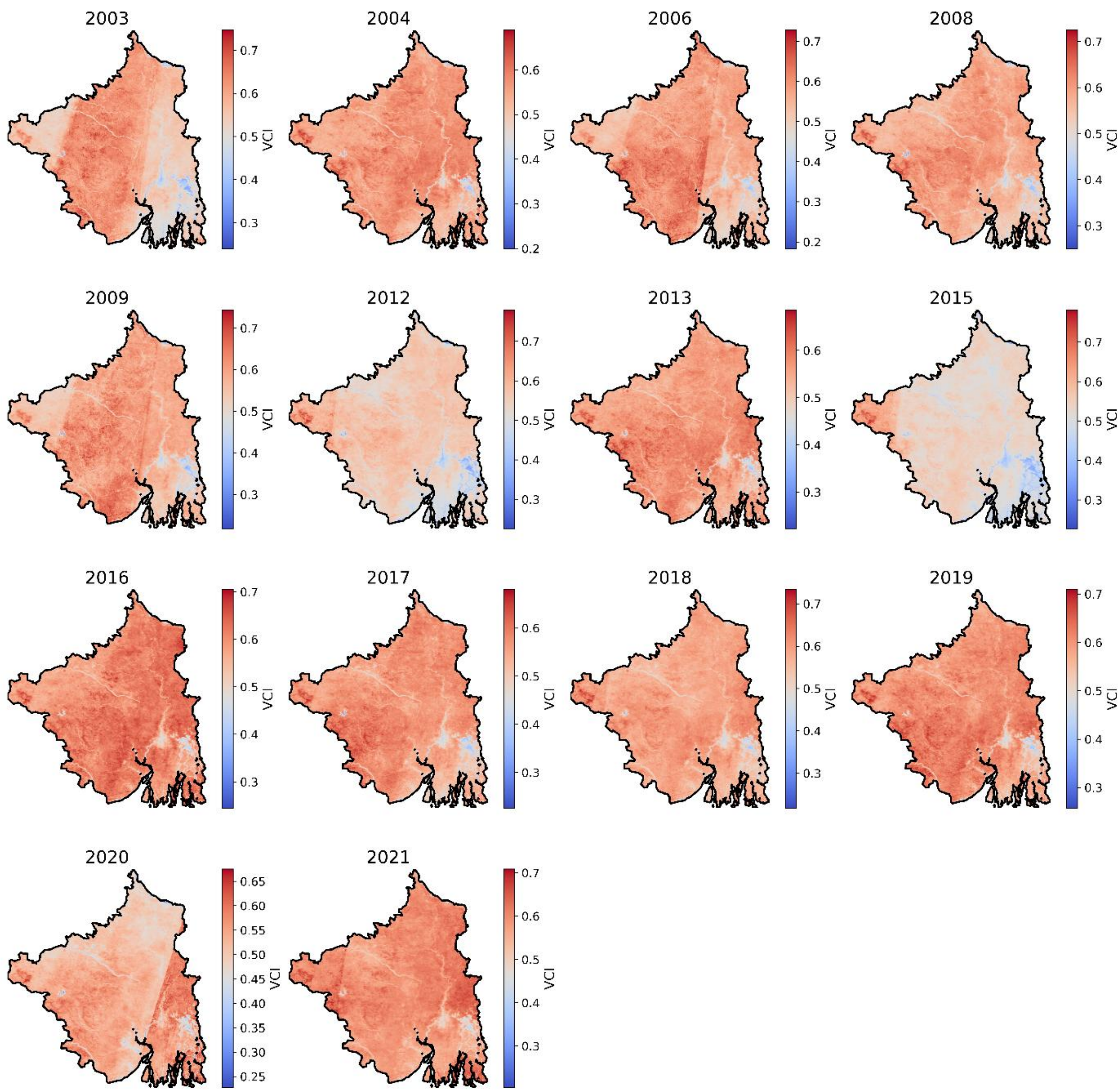

Figure 4 Spatial Distribution of the vegetation condition Index (VCI) for Selected Years (2003-2021)

The study area maps in Figure 5 display the VHI across various years from 2003 to 2021. The VHI is a composite drought index that integrates the VCI and the TCI to provide a comprehensive measure of vegetation health under the influence of both moisture and temperature stress. The analysis reveals that certain years, such as 2003, 2012, and 2019, exhibit extensive areas with lower VHI values, particularly in the eastern and southern parts of the region. These lower VHI values suggest significant stress on vegetation, likely due to unfavourable climatic conditions, such as drought or heatwaves, during these periods. Conversely, years like 2016 and 2017 show more areas with higher VHI values, indicating healthier vegetation conditions, possibly due to more favorable moisture and temperature conditions. The temporal variability observed in the VHI maps suggests that the region experiences fluctuations in vegetation health, driven by varying climatic conditions over the years. The consistent presence of low VHI values in certain areas points to regions that are more susceptible to drought and temperature stress, highlighting the need for targeted drought mitigation strategies in these vulnerable zones. This assessment of VHI underscores the importance of monitoring vegetation health as a key component of drought management. By integrating multiple indices, VHI provides a more robust understanding of the combined effects of moisture and temperature on vegetation, aiding in the development of more effective strategies for managing the impacts of climate variability on agriculture and ecosystems.

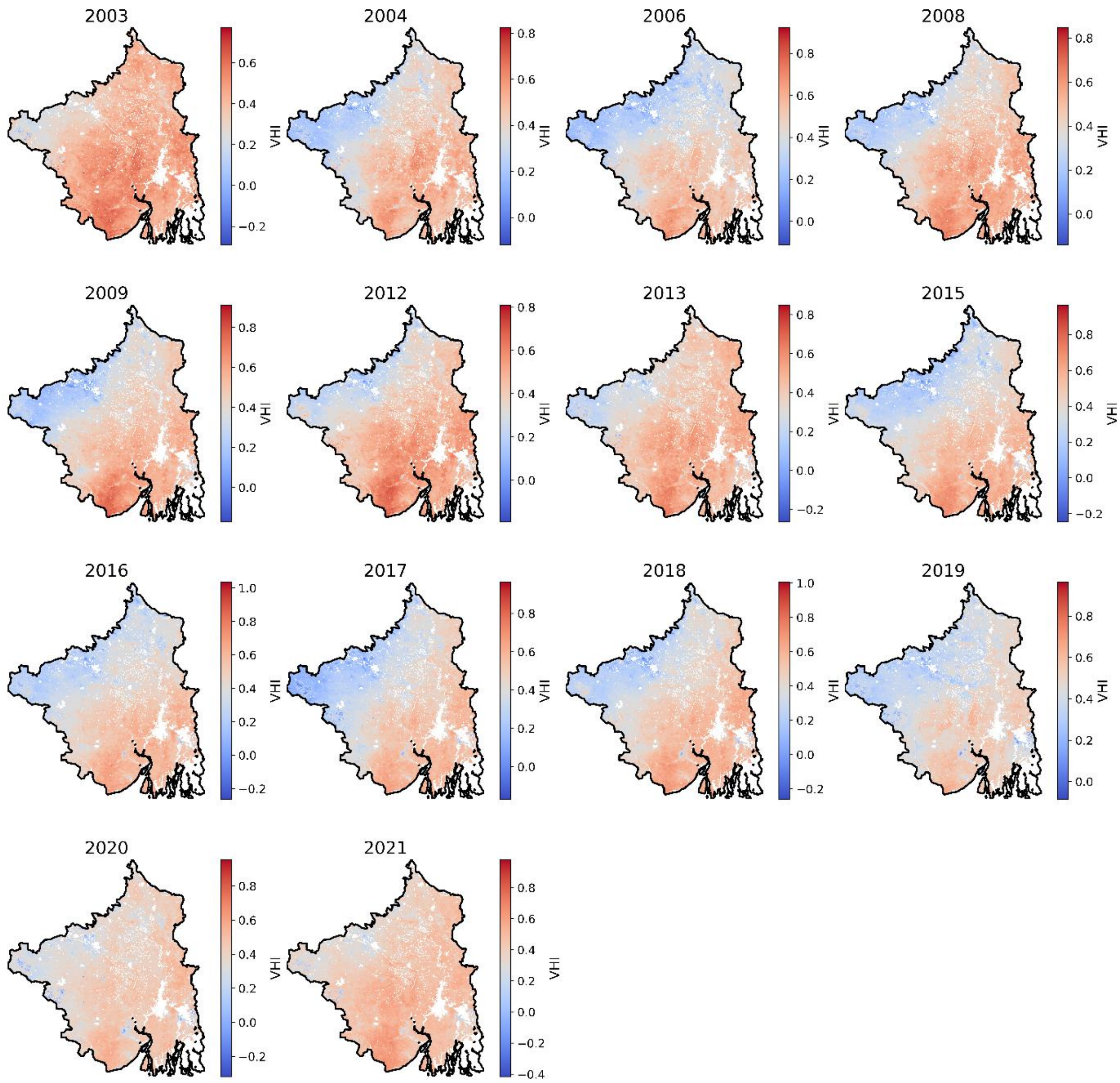

Figure 5 Spatial Distribution of the vegetation health Index (VHI) for Selected Years (2003-2021)

3.2 Assessment of drought severity analysis

The maps of in Figure 6 demonstrate the spatial distribution of drought conditions categorized by the VHI across various years from 2003 to 2021 in southern districts of West Bengal. The VHI values have been classified into distinct drought categories: No Drought, Mild Drought, Moderate Drought, Severe Drought, and Extreme Drought. The maps reveal that over the years, the region has experienced significant variability in drought severity. Several years, such as 2003, 2012, and 2016, show widespread areas categorized as experiencing severe to extreme drought conditions, particularly in the central and southern parts of the region. This indicates that these areas have been subjected to substantial environmental stress, likely affecting agricultural productivity and natural vegetation. Conversely, there are years like 2008 and 2013 where the severity of drought appears to be relatively lower, with larger portions of the region falling into the mild to moderate drought categories. Despite this, the presence of severe and extreme drought zones in these years indicates that drought conditions are a recurring challenge for the region. The spatial and temporal patterns observed suggest that drought is a persistent issue in the region, with certain areas consistently more vulnerable to severe drought conditions. This highlights the necessity for targeted drought mitigation strategies and effective water resource management practices to alleviate the impact of drought, particularly in the most affected zones. Overall, the assessment of VHI-based drought categories across the years underscores the critical need for continuous monitoring and adaptive management strategies to mitigate the adverse effects of drought, especially in light of potential climate change impacts that may exacerbate these conditions in the future.

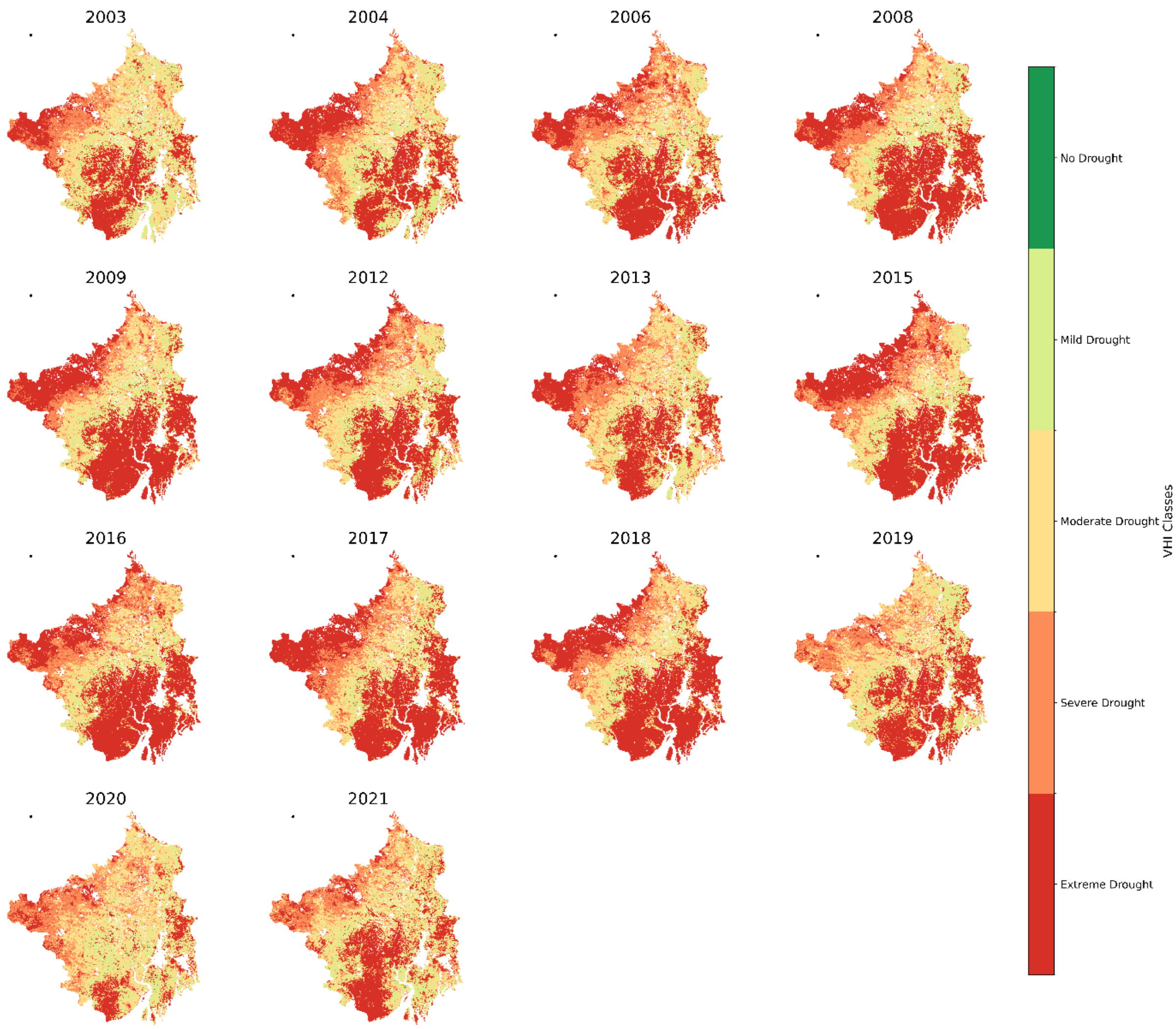

Figure 6 Drought Severity Classification Based on VHI for Selected Years (2003-2021)

Table 1 Annual Distribution of Drought-Affected Areas (km^2) Based on VHI from 2003 to 2021

Year	Area (km^2)				
	Extreme Drought	Severe Drought	Moderate Drought	Mild Drought	No Drought
2003	3904.036	7803.889	14455.9	20676.01	12750.15
2004	6327.447	8375.88	13498.71	17036.13	14351.82
2006	7200.767	11280.21	15180.76	15055.54	10874.1
2008	6112.776	8765.029	13529.14	15087.36	16097.06
2009	7258.152	9267.09	17146.25	17450.6	8470.67
2012	5866.508	10474.03	14845.05	16126.33	12280.85
2013	4448.147	8985.741	14273.99	18768.83	13116.06
2015	6560.007	10291.66	13895.52	14227.98	14617.6
2016	6170.393	11002.58	14573.69	13894.13	13951.98
2017	6582.542	9311.697	13240.82	14130.87	16326.83
2018	4182.829	9382.789	14375.28	14591.11	17060.76
2019	1879.996	11647.06	14903.83	17448.98	13712.91
2020	1105.415	10410.61	15569.68	17044.49	15462.57
2021	1589.354	12216.72	15895.87	19309.46	10581.37

The table 1 presents the area coverage (in square kilometres) for different drought severity categories, classified by the VHI, across the years 2003 to 2021. The categories include Extreme Drought, Severe Drought, Moderate Drought, Mild Drought, and No Drought. The data indicates significant variability in drought conditions over the years, with each category showing distinct fluctuations in the area affected. Extreme Drought conditions, the most severe category, have shown considerable variation, with the affected area ranging from a low of approximately 1,105 km^2 in 2020 to a high of around 7,258 km^2 in 2009. This suggests that although extreme droughts have occurred intermittently, their extent has been substantial in certain years, particularly in 2006, 2009, and 2017, indicating episodes of severe environmental stress. Severe Drought conditions have consistently affected large areas, with a peak of about 12,217 km^2 in 2021. The data reveals that certain years, such as 2019 and 2021, experienced a significant expansion in areas classified under Severe Drought, highlighting the increasing severity of drought conditions in recent years. Moderate Drought has been the most prevalent category, with areas ranging from approximately 13,241 km^2 in 2017 to over 17,146 km^2 in 2009. This category consistently covers a substantial portion of the region, indicating that moderate drought conditions are a persistent feature of the climate in this region. Mild Drought and No Drought categories exhibit an inverse relationship, where years with extensive Mild Drought conditions, such as 2003 and 2015, correspond to reduced areas classified as No Drought. For example, in 2009, a significant portion of the area (approximately 17,451 km^2) was under Mild Drought, while the area classified as No Drought shrank to around 8,471 km^2, indicating widespread drought conditions during that year. The temporal trends observed in the data suggest that the region has been increasingly affected by severe and moderate drought conditions, particularly in the last decade. The reduction in areas classified as No Drought, especially in the years following 2015, further underscores the intensification of drought conditions over time. These findings highlight the growing vulnerability of the region to drought, necessitating enhanced monitoring, effective water management practices, and the implementation of drought mitigation strategies to address the impacts of climate variability.

3.3 Trend analysis of drought categories

The ITA plots displayed in Figure 7 provide a comparative assessment of drought categories in the study area—Extreme Drought (ED), Severe Drought (SD), Moderate Drought (MD), Mild Drought (mD), and No Drought (ND)—between two periods: the first half (2003-2013) and the second half (2015-2021). Each plot represents the relationship between the areas affected by each drought category in the first and second periods, with the red dashed line indicating the 1:1 line where no trend would be observed (i.e., equal areas in both periods). For Extreme Drought, the plot shows that the points lie significantly above the 1:1 line, indicating an increasing trend in the area affected by extreme drought conditions in the second half compared to the first half. This suggests a worsening of extreme drought conditions over time. The Severe Drought plot similarly displays points above the 1:1 line, though with more variability. The data suggest an overall increasing trend, with a more pronounced expansion in areas affected by severe droughts in recent years, reflecting growing severity in drought conditions. In the case of Moderate Drought, the points are close to or slightly above the 1:1 line, indicating a relatively stable trend with only a slight increase in the affected area. This suggests that while moderate drought conditions remain prevalent, they have not exhibited as significant an increase as the more severe categories. For Mild Drought, a mixed pattern is observed, with some points below the 1:1 line, indicating a reduction in the area affected by mild drought conditions in the second period. This could imply that regions previously experiencing mild drought have transitioned to more severe drought conditions. The No Drought category exhibits points below the 1:1 line, signalling a decrease in the area unaffected by drought over time. This finding is consistent with the observed trends in other drought categories, indicating an overall decline in areas experiencing no drought, further emphasizing the intensification of drought conditions in the region. Overall, the ITA plots reveal a clear trend towards increasing drought severity, with more areas experiencing extreme and severe droughts in recent years, coupled with a decrease in regions unaffected by drought. These trends underscore the need for proactive drought management and adaptation strategies to mitigate the escalating impacts of climate-induced droughts in the region.

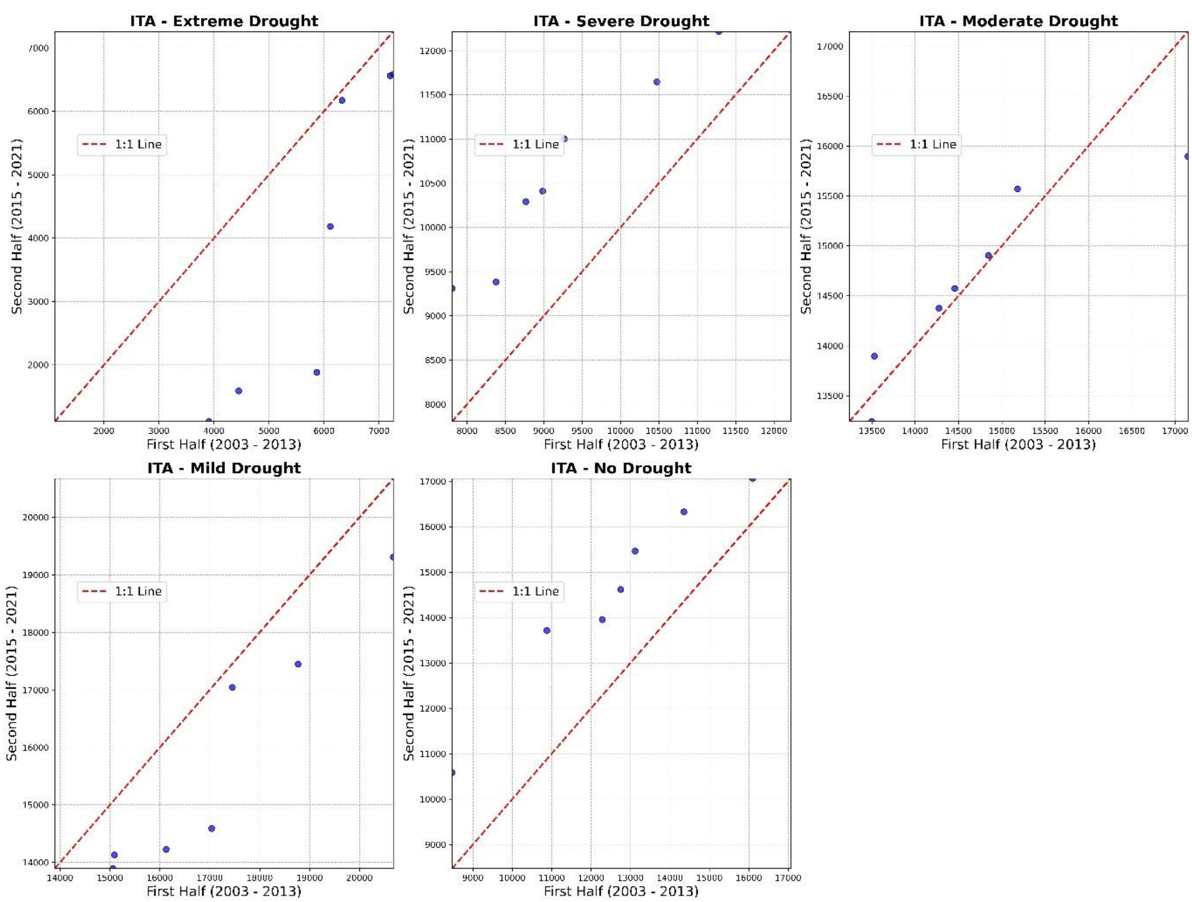

Figure 7 Innovative Trend Analysis (ITA) of Drought Severity Classes from 2003 to 2021

Table 2 Slope Estimates of Drought Severity Trends Using ITA

Classes of drought	Slope	Lower Limit	Upper Limit
ED	-266.271	-927.107	394.5643
SD	190.0251	190.0251	190.0251
MD	-9.69613	-9.69613	-9.69613
mD	-194.975	-423.745	33.79503
ND	281.0881	281.0881	281.0881

The trend analysis of drought categories, as indicated by the slope values and confidence intervals, provides insight into the direction and significance of changes in drought-affected areas over time (Table 2). The slope values represent the rate of change in the area (in square kilometres) affected by each drought category from the first half (2003-2013) to the second half (2015-2021). For Extreme Drought, the slope is negative (-266.271), suggesting a decreasing trend in the area affected by extreme drought conditions over time. However, the confidence interval, which ranges from -927.107 to 394.5643, includes zero, indicating that this trend is not statistically significant. Therefore, while a reduction in extreme drought area is observed, the trend cannot be conclusively determined as either increasing or decreasing with confidence. The Severe Drought category shows a positive slope of 190.0251, with no variability in the confidence limits, implying a consistent and statistically significant increase in the area affected by severe drought conditions. This suggests a clear and concerning trend toward more severe droughts impacting larger areas over time. Moderate Drought, with a slope of -9.69613, shows a slight decreasing trend in the area affected, but similar to extreme drought, the confidence interval does not vary, indicating a lack of statistical significance in the trend. Thus, no strong conclusions can be drawn about changes in moderate drought conditions over the observed period. The Mild Drought category also exhibits a negative slope (-194.975), indicating a reduction in the area affected by mild drought. However, the confidence interval (-423.745 to 33.79503) spans zero, suggesting that this decrease is not statistically significant, and the trend remains uncertain. For the No Drought category, a positive slope of 281.0881 is observed, with a consistent confidence interval, indicating a statistically significant increase in the area experiencing no drought conditions. This positive trend suggests that, despite the increasing severity in some drought categories, there has been an expansion in regions unaffected by drought over the analysed period.

3.4 Periodicity analysis of drought severity categories

The wavelet power spectra (WPS) and global wavelet spectra displayed in Figure 8 provide a detailed periodicity analysis of various drought categories in southern districts of West Bengal, including Extreme Drought, Severe Drought, Moderate Drought, Mild Drought, and No Drought, over the period from 2003 to 2021. The WPS plots, which illustrate the distribution of power across different periods (in years) over time, are complemented by the global spectra that summarize the overall power distribution for each drought category. The WPS for Extreme Drought shows a concentration of significant power around the 8-16 year periodicity, particularly prominent between 2006 and 2012. This suggests a long-term cyclical pattern in the occurrence of extreme drought conditions, with notable periods of high intensity during the aforementioned years. The global spectrum confirms this by showing a peak in power within the same periodicity range, indicating a dominant multi-year cycle affecting extreme drought severity. For Severe Drought, the WPS reveals a similar pattern with substantial power concentrated around the 8-16 year periodicity, particularly evident in the years leading up to 2016. This implies that severe droughts also follow a multi-year cycle, with periods of intensified drought occurring roughly every decade. The global spectrum supports this observation, highlighting a significant peak in power within this periodicity range, suggesting that severe drought conditions are influenced by recurring long-term climatic factors. The Moderate Drought category exhibits a broader distribution of power, with significant periodicity observed in both shorter (2-4 years) and longer (8-16 years) cycles. The WPS indicates that moderate drought conditions are subject to both short-term and long-term variability, with noticeable shifts in power across different periods over time. The global spectrum aligns with this, showing multiple peaks across various periodicities, reflecting the complex and variable nature of moderate drought conditions. Mild Drought is characterized by a more diffuse power distribution in the WPS, with lower overall intensity and a less distinct periodicity pattern. The global spectrum shows relatively lower power levels, suggesting that mild drought conditions are less influenced by strong cyclical patterns compared to more severe drought categories. The lack of clear peaks in the global spectrum indicates that mild droughts are more sporadic and less tied to specific periodic climatic events. The No Drought category displays significant power in shorter periodicities, particularly in the 2-4 year range, as observed in the WPS. This suggests that periods without drought conditions are more influenced by short-term climatic variability, with fluctuations occurring on a multi-year scale. The global spectrum further supports this, showing a pronounced peak in the lower periodicity range, indicating that no drought conditions are more susceptible to frequent changes, likely due to interannual climate dynamics.

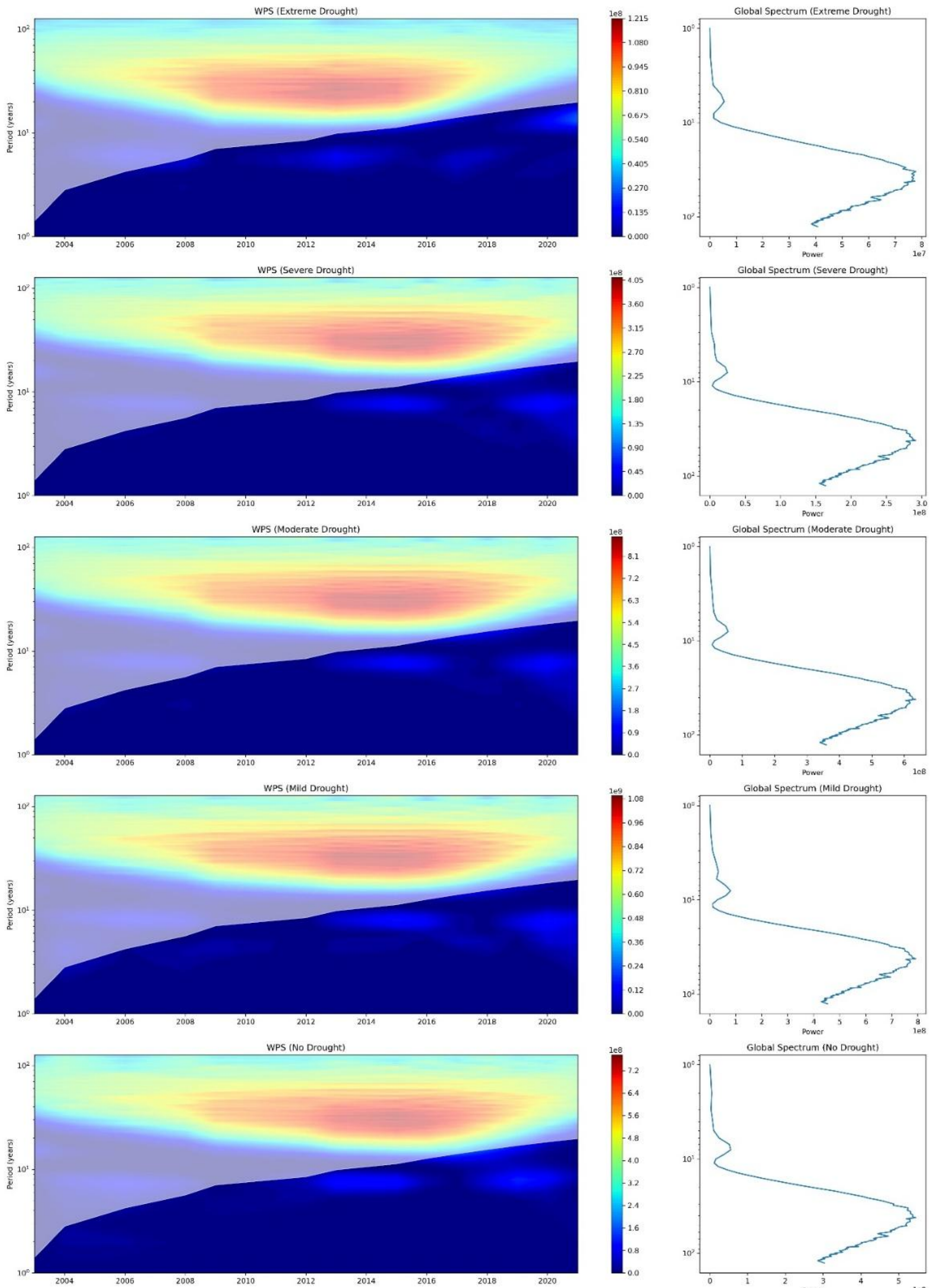

Figure 8 Wavelet Power Spectrum and Global Spectrum Analysis for Drought Severity from 2004 to 2020

Figure 9 illustrate the scale-averaged time series plots presented in the variability in the average variance of different drought categories in southern part of West Bengal—Extreme Drought, Severe Drought, Moderate Drought, Mild Drought, and No Drought—over a 10-14 year periodicity. These plots provide insight into the long-term cyclic patterns influencing each drought category from 2003 to 2021. For Extreme Drought, the plot reveals a clear peak in average variance around 2012, indicating that this period experienced the highest intensity of extreme drought conditions within the analysed time frame. Following this peak, there is a marked decline, reaching its lowest point around 2016 before showing a slight increase towards 2021. This pattern suggests a significant cyclic trend in extreme drought conditions, with periods of intensification followed by relative relief. The Severe Drought category exhibits a similar trend, with a pronounced peak around 2012 and a subsequent decline. The peak in severe drought conditions is slightly more intense compared to extreme drought, indicating that this category also follows a strong periodic cycle, with a notable drop in intensity post-2016. Moderate Drought conditions also follow a cyclic pattern, with a peak in average variance occurring slightly earlier, around 2010-2011. The decline post-2014 is less sharp compared to the severe and extreme categories, indicating a more gradual reduction in moderate drought intensity. This suggests that moderate drought conditions are influenced by a broader and more stable periodic cycle. The Mild Drought category shows a less distinct peak around 2012-2013, with fluctuations in average variance being less pronounced compared to more severe drought categories. The decrease in variance post-2015 indicates a reduction in mild drought conditions, although the overall cyclic pattern is less well-defined, suggesting more variability in the occurrence of mild droughts. For the No Drought category, the plot shows a clear inverse relationship to the severe and extreme drought categories, with a significant peak around 2013-2014 followed by a steady decline. This trend suggests that periods of no drought conditions are inversely correlated with periods of intensified drought, reflecting the natural variability in climate conditions that alternate between dry and wet phases. Overall, the scale-averaged time series analysis highlights the presence of significant periodic cycles in the occurrence of drought conditions, particularly for the more severe drought categories. The observed peaks around 2012-2014 for extreme and severe droughts align with known climatic anomalies during this period, underscoring the influence of long-term climate variability on drought intensity. These findings emphasize the importance of understanding and anticipating these cycles to enhance drought preparedness and management strategies.

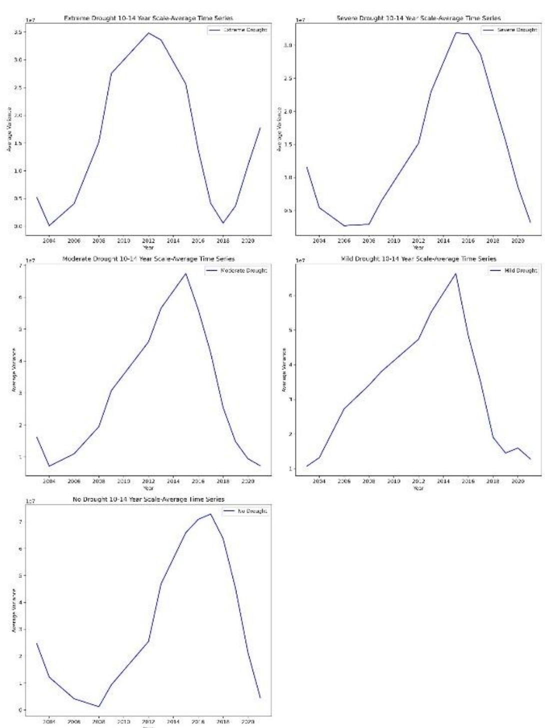

Figure 9 Scale-Averaged Time Series of Average Variance for Drought Severity Classes in Southern West Bengal (2003-2021)

4. Discussion

The results of the study provide a comprehensive assessment of drought patterns and their temporal and spatial variability across the study area from 2003 to 2021, utilizing a variety of indices, including the SPEI, TCI, VCI, and VHI. The findings indicate significant interannual variability in drought conditions, with notable years, such as 2012 and 2016, showing widespread areas of severe drought as indicated by SPEI values. Similarly, VHI-based classifications revealed that extreme and severe drought conditions were more prominent in specific years, while other years exhibited more moderate or mild drought conditions. These patterns align with global observations of increased drought frequency and intensity in many regions, driven by changes in precipitation patterns and rising temperatures (Makula et al., 2024; Tan et al., 2023). The study's focus on vegetation response through indices such as VCI and VHI is critical for understanding ecosystem health under varying drought conditions, which has been similarly documented in studies from Europe, Asia, and North America (Zeng et al., 2022; Yoon et al., 2020). The increasing severity of drought conditions, particularly the expansion of extreme and severe drought areas observed in the latter half of the study period, reflects a growing concern regarding the impacts of climate change on regional water availability and agricultural productivity. Comparable studies have shown similar trends in arid and semi-arid regions, where the frequency of extreme drought events has risen, enhancing water stress and food security challenges (Mishra, 2014; Ebi and Bown, 2016; Kogan et al., 2019). This study's findings also highlight the importance of temperature anomalies in driving vegetation stress, as evidenced by the low TCI values observed in several years. Elevated temperatures have been widely recognized as key drivers of drought-induced vegetation stress, as seen in studies from regions such as the Mediterranean and sub-Saharan Africa (Tramblay et al., 2020; Bhaga et al., 2020).

The periodicity analysis conducted through WPS in the southern districts of West Bengal further supports the cyclical nature of drought occurrences, with extreme and severe droughts showing multi-year cycles of approximately 8 to 16 years. These findings are consistent with research on drought cycles linked to large-scale climate phenomena, such as the El Niño-Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO), which have been identified as major influences on regional drought patterns (Helama et al., 2019; Knippertz et al., 2003; Hassan and Nayak, 2020). The identification of these cycles is critical for improving drought forecasting and early warning systems, which are essential for effective drought management and mitigation strategies (Hassan and Nayak, 2020).

The trend analysis of the concerned area revealed a statistically significant increase in the areas affected by severe drought conditions, with a positive slope of 190.0251 km² per year from 2015 to 2021. This is consistent with global assessments of drought trends, which have reported increases in drought severity and frequency across many parts of the world, particularly in regions with pronounced climate variability (Tramblay et al., 2020). Conversely, areas experiencing mild drought or no drought showed a declining trend, reflecting the overall intensification of drought conditions in recent years. These findings are supported by similar studies in regions such as South Asia, where drought severity has escalated due to both climatic and anthropogenic factors (Yoon et al., 2020). The spatial variability observed in the VCI and VHI maps indicates that certain regions exhibit a higher resilience to drought, likely due to favorable environmental conditions or effective water management practices. In contrast, other areas consistently experience lower vegetation health during drought periods, highlighting the need for targeted interventions in these vulnerable zones. Similar spatial patterns of drought vulnerability have been documented in studies from regions such as East Africa and the American Midwest, where vegetation health indices are used to monitor and manage drought impacts on agriculture (Yoon et al., 2020; Li et al., 2019). The persistent drought conditions in specific areas, as observed in this study, reinforce the need for localized adaptation strategies that consider both climatic and socio-economic factors (Helama et al., 2009). Thus, that the analysis of drought indices over the 2003-2021 period provides valuable insights into the evolving nature of drought conditions in the selected study area, with implications for water resource management, agricultural planning, and ecosystem conservation. The increasing frequency of severe and extreme droughts underscores the urgency of developing adaptive strategies that address both short-term variability and long-term climate change. These findings contribute to the broader understanding of drought dynamics and offer critical information for policymakers and stakeholders involved in climate adaptation efforts. The integration of drought indices such as SPEI, TCI, VCI, and VHI, as demonstrated in this study, provides a robust framework for monitoring drought impacts and guiding mitigation strategies in drought-prone regions, as seen in similar global research efforts (Bhaga et al., 2020; Mishra, 2014; Liu et al., 2020).

The study is unique in its comprehensive multi-index approach to assessing drought patterns, utilizing a combination of the SPEI, TCI, VCI, and VHI, which provides an integrated perspective on both climatic and vegetation responses to drought. This multi-faceted methodology, especially the application of WPS for periodicity analysis, is innovative as it uncovers multi-year cyclical drought trends tied to large-scale climate phenomena, a feature not commonly addressed in similar studies. Additionally, the spatial and temporal variability of drought severity in the southern districts of West Bengal, particularly the identification of regions with differing resilience and vulnerability to drought, offers new insights into regional drought dynamics. The focus on combining vegetation health with climatic indices, along with the rigorous trend analysis of drought categories, provides a unique framework for developing adaptive strategies in the context of increasing drought frequency and severity driven by climate change, thereby contributing to both the methodological advancement and content of drought studies.

The mitigation strategies proposed for addressing drought in the southern districts of West Bengal should align with global best practices while being tailored to the region's unique socio-environmental context. Short-term measures, such as improving irrigation efficiency through techniques like drip and sprinkler systems, have been shown to lead to significant water savings and increased crop yields in drought-prone regions, including Ethiopia and India (Liu et al., 2021). Implementing these techniques in West Bengal could enhance water use efficiency in agriculture, particularly in areas dependent on erratic rainfall. The adoption of drought-resistant crop varieties, as recommended for South Asia and sub-Saharan Africa, can strengthen the resilience of West Bengal's agricultural systems to climate variability (Prasad et al., 2024). Additionally, integrating weather forecasts and drought advisories into agricultural planning, as successfully implemented in Brazil and Australia, could provide farmers in the region with crucial decision-making tools to minimize the impacts of drought (Marengo et al., 2022; Haque et al., 2024). Long-term strategies, such as sustainable groundwater management, are particularly vital for West Bengal, where over-extraction poses a growing challenge. Studies from California and Spain highlight that regulated groundwater use, combined with artificial recharge, is critical for mitigating long-term drought impacts and could serve as a model for the region (Medellín-Azuara et al., 2024; Henao Casas et al., 2022). Reforestation and soil conservation practices, widely implemented in countries like China and India, are also relevant for West Bengal. Large-scale afforestation projects, coupled with soil conservation initiatives, could help restore hydrological cycles, enhance water retention, and reduce soil erosion, mitigating drought effects in the region (Li et al., 2024; Jinger et al., 2023). Nature-based solutions, such as wetland restoration and agroforestry, also offer sustainable long-term drought mitigation strategies. Reviving wetlands, as seen in Southeast Asia, can enhance water availability and biodiversity in West Bengal's drought-prone areas, while agroforestry practices, proven effective in West Africa and the Amazon Basin, could improve soil health and water retention in the region (Mishra et al., 2021; Wato and Amare, 2021; Barlow et al., 2021).

Community participation is central to the success of these strategies, particularly for rainwater harvesting and soil conservation initiatives. Evidence from Kenya and India demonstrates that locally driven projects yield more effective and sustainable outcomes (Tefera et al., 2024; Pani et al., 2021). This study emphasizes that adopting a multi-pronged approach integrating short- and long-term strategies, with a focus on nature-based solutions and community involvement, can significantly improve drought and agricultural management in West Bengal. By drawing on global experiences and tailoring solutions to local conditions, the study aims to support policymakers and stakeholders in developing robust, context-specific drought mitigation strategies that enhance agricultural resilience and ensure sustainable livelihoods in the region.

5. Conclusion

This study comprehensively assessed drought severity, trends, and periodicity across the southern districts of West Bengal from 2003 to 2021 using indices such as SPEI, TCI, VCI, and VHI. By applying ITA and WPS, we identified significant trends of increasing severe and extreme drought conditions over the study period. The analysis revealed a marked expansion in drought-affected areas, with extreme drought peaking at 7,258 km² in 2009 and severe drought covering 12,217 km² in 2021. The periodicity analysis also highlighted 8-16 year drought cycles, aligning with known climatic anomalies. This work provides critical insights into the spatial-temporal dynamics of drought, which are crucial for improving water management, agricultural planning, and climate adaptation in a region highly vulnerable to drought.

The novelty of this study lies in its multi-faceted approach, combining drought severity analysis, trend analysis, and periodicity assessment using cutting-edge techniques like ITA and WPS. This integrated methodology provides a more robust understanding of drought dynamics compared to traditional approaches, offering valuable tools for monitoring and mitigation. However, the study has limitations, including reliance on remote sensing data that may have inherent uncertainties, particularly in detecting fine-scale variations in vegetation stress and temperature anomalies. Additionally, the study focused on broad temporal cycles, which may not capture shorter-term drought fluctuations relevant for immediate agricultural decisions. Future research could address these limitations by integrating more localized datasets and real-time monitoring tools, such as ground-based sensors and high-resolution satellite imagery, to improve the accuracy and responsiveness of drought assessments. Further exploration of machine learning techniques for drought prediction could also enhance the scope of this work. In conclusion, this study underscores the urgent need for proactive drought management strategies in the context of increasing climate variability, providing a framework for more effective and sustainable drought mitigation efforts.

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