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Space-Time Variability of Drought in Tay Nguyen Provinces, Vietnam Using Satellite-Based Vegetation Time Series from 2000 to 2023

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ABSTRACT

Droughts are among the most costly hazards in Tay Nguyen (known as Vietnamese Central Highlands), causing significant threats to agriculture and vegetation ecosystems. This study investigated the spatial and temporal dynamics of vegetation-based drought in the Tay Nguyen Provinces of Dak Lak and Dak Nong, using a long-term series of Moderate Resolution Imaging Spectro-radiometer (MODIS) Vegetation Condition Index (VCI) from 2000 to 2023. The results exhibited a high positive correlation (R=0.73) between VCI and soil moisture-based drought index in drought-detected areas. Monthly analysis revealed severe drought events during the dry months, notably in 2005, 2010, 2013, 2016, and 2019. In contrast, wetter conditions were primarily observed during 2017-2018 and 2022-2023. Despite temporal variability of drought, larger trends of decreasing and increasing vegetation-based drought were detected during the dry season. These trends remained a relatively stable during the rainy season. Among vegetation types, shrubland exhibited the lowest VCI trends. This research offers valuable insights for stakeholders and policymakers to develop targeted strategies for sustainable land management and regional drought resilience.

1. INTRODUCTION

Drought, a recurring and inherent climatic phenomenon, exerts profound and far-reaching impacts on the environment and the economy (Gampe et al., 2021; Ha et al., 2022). It is a widespread occurrence, affecting nearly all climate zones and ecosystems across the globe. Traditionally, drought monitoring relied on station-based climate indices, and the Standardized Precipitation Index (SPI) was probably the most used drought index over the past decades (Mishra and Singh, 2010; Vicente-Serrano et al., 2010). However, in-situ climate observations are challenging to collect over large areas, especially in remote areas. Historical climate data records are often incomplete and fragmented, complicating long-term drought trend analysis and the derivation of spatial and temporal drought characteristics (AghaKouchak et al., 2015). Also, developing countries with limited resources often face challenges in establishing and maintaining a comprehensive network of weather and soil monitoring stations (Vu et al., 2018).

Recent advances in remote sensing enable near-real-time, consistent, and frequent drought observations over large areas (Le et al., 2020a). Also, open-source data policies in recent years have unlocked the archive of long-term remote sensing time series. Consequently, several satellite-derived vegetation-based drought indices have been developed for deriving vegetation-based drought information. Among the different vegetation-based drought indices, the Normalized Difference Vegetation Index (NDVI) was the most widely used index for detecting vegetation health and drought-related details (Kogan, 1990). However, this indicator has been criticized due to its susceptibilities to soil background reflectance and atmospheric interferences (Ha et al., 2023; Kogan,

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1990). The Vegetation Condition Index (VCI) has emerged as a compelling alternative, demonstrating superior effectiveness in tracking drought-related conditions associated with vegetation (Le et al., 2021). Several recent studies have employed the VCI for monitoring and characterizing drought patterns across scales and climate zones (Marumbwa et al., 2020; Shahfahad et al., 2022; Wei et al., 2021; Zou et al., 2020).

In the Tay Nguyen Provinces, known as the Central Highlands in English, the agricultural sector plays a significant role in the local and national economy. Coffee crops in this region, such as Dak Lak and Dak Nong Provinces, account for nearly 90% of Vietnamese coffee production (Maskell et al., 2021). However, this region is drought-prone and frequently suffers from intense drought conditions. Ha et al. (2023) have reported multiple drought events (e.g., drought events in 2004-2005, 2015-2016, and 2019-2020) across Mainland Southeast Asia, including Vietnam. Also, Tran et al. (2023) reported a high risk of drought in some provinces of the Central Highlands, such as Dak Lak. Statistically, the 2015-2016 drought event damaged nearly 11 thousand hectares of cropland, including seasonal and industrial crops in the Central Highlands (Byrareddy et al., 2021; Le et al., 2021). Alarming projections indicate that drought hazards in this region are poised to intensify and occur more frequently in the coming decades (Nguyen-Ngoc-Bich et al., 2021). Consequently, there could be a threat of disruptions to crop production, posing a substantial risk to food security in the region.

In this study, our primary objectives are to monitor and assess the spatiotemporal variability of vegetation-based drought conditions using long time-series MODIS-based VCI observations in large-area industrial croplands and forest ecosystems of the two Vietnamese Central Highlands provinces. Firstly, we cross-verified the quality and reliability of time-series vegetation-based drought products. Subsequently, we assessed the spatial and temporal patterns of vegetation-induced drought conditions using monthly MODIS-based VCI time series during the dry and rainy seasons from 2000 to 2023. Lastly, a detailed analysis of spatiotemporal trends of vegetation-induced drought was explored in consideration of various land cover types over the study period. The findings of this study could provide valuable information for local agricultural and natural ecosystem management in mitigating vegetation-related drought impacts and developing drought adaptation plans in the face of the ongoing climate crisis.

2. METHODOLOGY

2.1 Study area

The study area spans the two provinces of Dak Lak and Dak Nong, located in the Central Highlands of Vietnam (Figure 1). Plateau landscapes and various elevations mainly characterize this area. Climate conditions are primarily controlled by tropical characteristics with annual temperature and precipitation ~22ºC and ~1,800 mm, respectively. There are two main climate seasons in the Central Highlands, Vietnam (Vu-Thanh et al., 2014): dry (November-April) and rainy (May-October) seasons. This area often lacks precipitation during the dry season, resulting in water and vegetation stress. By contrast, heavy rainfall during the rainy season impacts topsoil, such as soil erosion.

In the Central Highlands, basalt soils are predominantly distributed, accounting for nearly 60% of Vietnamese basalt soil. Due to its unique climate, soil, and elevation characteristics, Dak Lak and Dak Nong are considered the provinces of industrial crops (e.g., coffee and pepper) and had diverse vegetation types. Here, we classified the area into four main land cover types from Copernicus's land cover service product (Buchhorn et al., 2020): cropland, forests, shrubland, and others (e.g., built-up, water bodies, and bare land). Croplands account for 40% of the area and is primarily distributed in Dak Lak province, whereas forests ranked second with nearly 45% and mainly distributed in Dak Nong Province.

2.2 Datasets

This study utilized a set of various publicly available datasets, including time-series MODIS NDVI, Copernicus Global Land Service product, Digital elevation model (DEM), and soil moisture observations. Each dataset has different spatial resolution and coordinate systems, so we standardized them to the spatial resolution of MODIS NDVI 250 m and used a geographic coordinate system. This approach enables the power of multi-source data seamless integration for consistent, accurate, and timely drought monitoring and assessment. Although each dataset may come from different providers, these datasets are available from the Google Earth Engine (GEE) computing platform (Gorelick et al., 2017).

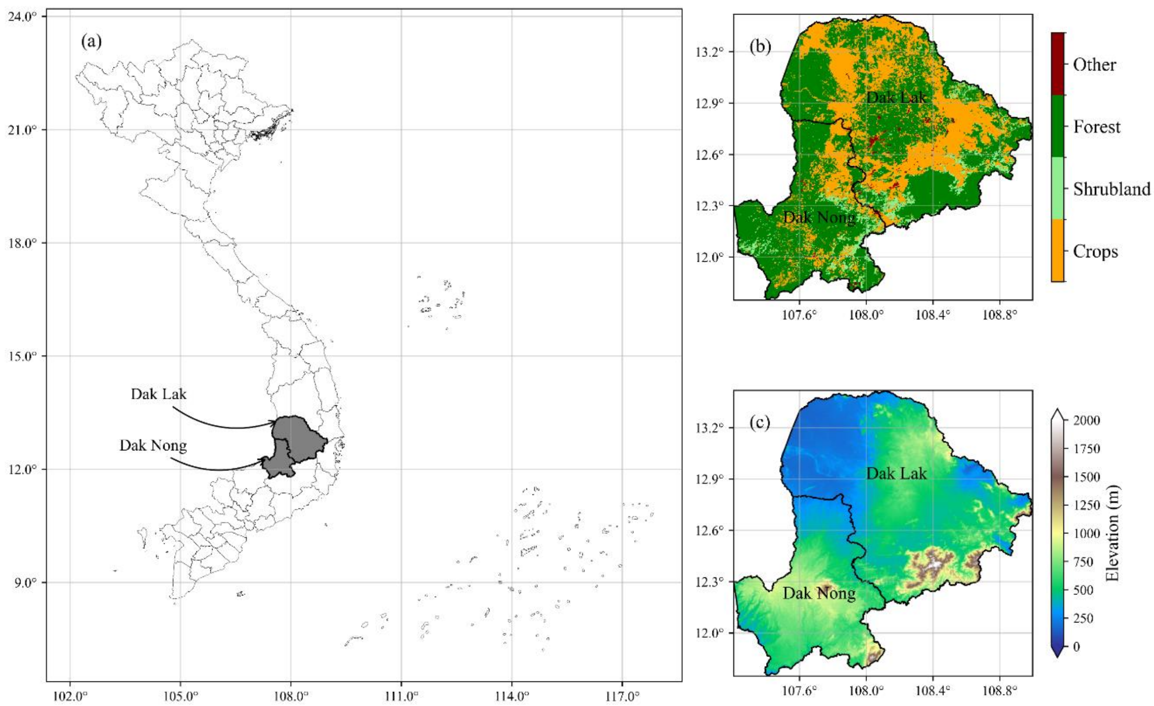

Figure 1. Map of the study area covers the two provinces of the Central Highlands Dak Lak and Dak Nong (a) and their land cover types (b) and elevation characteristics (c).

Monthly NDVI time series are aggregated from MODIS Terra (MOD13Q1 V6.1) and Aqua (MYD13Q1 V6.1) sensor collections at 250 m spatial resolution. These datasets are available through the NASA Land Processes Distributed Active Archive Center (LP DAAC) at the USGS Earth Resources Observation and Science (EROS) Center and can be accessed via the GEE catalog (https://developers.google.com/earth-engine/datasets/catalog/modis). Here, this study used both Terra and Aqua MODIS NDVI 16-day data products from 2000 to 2023 due to the challenges posed by cloud cover in tropical areas. The frequent and persistent cloud cover in these regions can significantly obstruct satellite observations (Li et al., 2018), leading to data gaps and reduced accuracy in monitoring drought dynamics. By leveraging the combined datasets from both MODIS sensors, we could mitigate the impact of cloud-related obstructions, ensuring a more comprehensive and continuous assessment of drought over the study period. Firstly, we removed cloud-related pixels from both MODIS NDVI 16-day products using its quality mask layers (DetailedQA band). Subsequently, we combined the two collections in time order and interpolated the missing observations using the linear interpolation method from the nearest temporal measurement. Next, we reconstructed the time series of MODIS NDVI observations using the Savitzky-Golay filter method with a 5-moving window and second-order polynomial (Ha et al., 2023; Savitzky and Golay, 1964). Finally, we aggregated the MODIS NDVI 16-day products into a monthly window using the median approach. A total of 287 monthly NDVI composites are used to investigate the spatiotemporal variability of vegetation-based drought conditions in the Central Highlands of Vietnam from 2000 to 2023.

The Copernicus Global Land Service provides a high-resolution, accurate, and consistent global land cover product from 2015 to 2019 at 100 m spatial resolution (Buchhorn et al., 2020) and can accessed via the GEE https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_Landcover_100m_Proba-V-C3_Global). This data product is produced from PROBA-V satellite observations using machine learning random forest algorithm with an overall accuracy of 80%, and its details can be found in a study by Buchhorn et al. (2020). This study employed the land cover product 2019, and we reclassified this data into four main land cover types, namely cropland, shrubland, forests, and others (e.g., built-up, water, and bare land). Non-vegetation types are masked from the formal analysis, and we finally resampled them to the spatial resolution of the MODIS NDVI at 250 m using the nearest neighbor method.

Monthly topsoil moisture (at 10 cm depth) observations were sourced from the Goddard Earth

Sciences Data and Information Services Center within the Famine Early Warning Systems Network Land Data Assimilation System (FLDAS). This dataset is produced monthly and spans from 1981 to the present at global scale, and it is commonly used to monitor agricultural drought (McNally et al., 2017). Here, soil moisture, together with soil properties (e.g., clay, sand, and organic carbon contents) was employed to derive a soil-based drought indicator from 2000 to 2023, and this index was used to cross-verify the MODIS-based drought. The soil moisture and soil properties data are in different spatial resolutions, but they are resampled to 250 m spatial resolution using the bilinear method to ensure the compatibility with the MODIS data.

The Shuttle Radar Topography Mission (SRTM) high-resolution DEM data was provided by NASA Jet Propulsion Laboratory (JPL) and downloaded from the GEE. This dataset has a spatial resolution of 30 m and covers a near-global scale. Here, we resampled the DEM into 250 m spatial resolution using the bilinear technique and converted it into a geographic coordinate system. In this study, the bilinear resampling method was chosen due to its computational efficiency and image quality. This approach produces smoother and better images than nearest-neighbor resampling, which selects the closest pixel and can result in blocky and jagged edges (Pu, 2021; Wu et al., 2022).

2.3 Vegetation-based drought index

Changes in vegetation health are reflective of altered ecosystem dynamics and can be indicative of water limitations and drought. Drought-induced shifts in vegetation cover, composition, and productivity provide more direct and early warning signs of impending water scarcity, making it a reliable and cost-effective tool for monitoring and characterizing drought. In this study, we used the Vegetation Condition Index (VCI) to monitor and assess drought dynamics in the two provinces of Central Highlands Dak Lak, and Dak Nong, from 2000 to 2023. The VCI has been developed by Kogan (1990) and is widely used for monitoring and characterizing drought conditions. The calculation of VCI relies on time series NDVI observations and is expressed in the following equation. At each pixel, monthly NDVI values are linearly scaled over the selected study period.

$$\mathrm{VCI_i} = \frac{\mathrm{NDVI_i} - \mathrm{NDVI_{min,j}}}{\mathrm{NDVI_{max,j}} - \mathrm{NDVI_{min,j}}} \times 100$$

Where; VCI_i and $NDVI_i$ are the NDVI at month i, respectively. The $NDVI_{min}$ represents minimum NDVI values at month j (j=1, 2, 3, …, 12) across the years, while $NDVI_{max}$ indicates maximum NDVI values at respective j months. The VCI values are measured in percentage and range from zero to 100, indicating extreme drought conditions (stressed vegetation) to wet conditions (healthy vegetation), respectively. Generally, the VCI values are classified into five different levels of drought severity (Kogan, 1990): extreme drought (0-10%), severe drought (10-20%), moderate drought (20-30%), mild drought (30-50%), and normal condition (≥50).

2.4 Time series trends of vegetation-based drought

In this analysis, we used non-parametric Sen's slope and Mann-Kendall (MK) methods to identify the trends of time series vegetation-based drought between 2000 and 2023. These methods are proven to be robust to non-normality and widely employed to assess the presence and significance of trends in climate and vegetation time series. Sen's slope estimator, introduced by (Sen, 1968), is a non-parametric technique that calculates the median slope of all possible pairs of data points in the time series, providing an estimate of the magnitude of the monotonic trend. This approach is particularly advantageous because it is resistant to the effects of outliers and non-normality in the data. The Mann-Kendall test is a statistical test used to determine the significance and direction of the trend (Li et al., 2021; Mann, 1945). It is a rank-based method that evaluates the correlation between time and the variable of interest, thus identifying whether a significant upward or downward trend exists in the time series.

In this study, we computed per-pixel trends within a 95% confidence interval, examining both the dry and rainy seasons. The division of the data into these two distinct seasons serves a dual purpose, including mitigating potential issues arising from seasonality and addressing concerns related to the stationarity of the vegetation time series. This way we aim to enhance the precision of our trend calculations and provide a better understanding of the temporal dynamics, shedding light on variations specific to dry and rainy periods. The trend values range from negative to positive, where negative (positive) values represent the decreasing (increasing) direction of vegetation-based drought during the study period.

2.5 Cross-validation of vegetation-based drought condition

Spatially dense in-situ data observations play a key role in assessing and validating remote sensing-based drought products. However, it is very challenging to collect time-series station-based measurements such as soil moisture in Vietnamese Central Highlands. In this study, we derived the Soil Water Deficit Index (SWDI) (Mishra et al., 2017), a soil-based drought index, from monthly time-series FLDAS soil moisture and soil properties (e.g., clay and sand contents). The SWDI values generally range from -10 to +10, where negative (positive) values indicate drought (non-drought) conditions (Fang et al., 2021; Mishra et al., 2017). Due to its sensitivity and early detection of crop water stress, the SWDI has been widely used to monitor agricultural drought and offers crucial insights into the availability of moisture for plant growth and survival (Mishra et al., 2017). Specifically, we used the SWDI to cross-check the quality of MODIS-based drought using Pearson correlation analysis. Here, we checked the agreement in the percentage of detected drought areas between the VCI and SWDI, and we subsequently calculated Pearson correlation at each pixel using time-series VCI and SWDI observations over the selected study period. The Pearson correlation coefficients range from -1 to 1, where higher negative (positive) values represent a larger negative (positive) correlation between the two drought indices.

3. RESULTS AND DISCUSSION

3.1 Cross-validation of vegetation-based drought

We assessed the spatial correlation and drought-detected areas between the two datasets using Pearson correlation analysis during the dry season. Here, we cross-verified the VCI-SWDI relationship during the dry season because of the higher frequent and severe droughts in the study region. The annual average data over the dry season was prepared, and the Pearson coefficients were computed per-pixel over the study period.

Overall, a good agreement exists between VCI-based and SWDI-based drought indices. Spatially, higher correlations were more observed along the northern area of Dak Nong Province, while lower correlations were scattered across southern Dak Nong and central Dak Lak Provinces (Figure 2(a)). Notably, nearly 91% of the study area exhibited positive correlations between VCI and SWDI indices, indicating that soil moisture is positively associated with vegetation condition (Cao et al., 2022). It is also noted that statistically non-significant correlations are found in Dak Nong and Dak Lak Provinces, accounting for 20% of the study area.

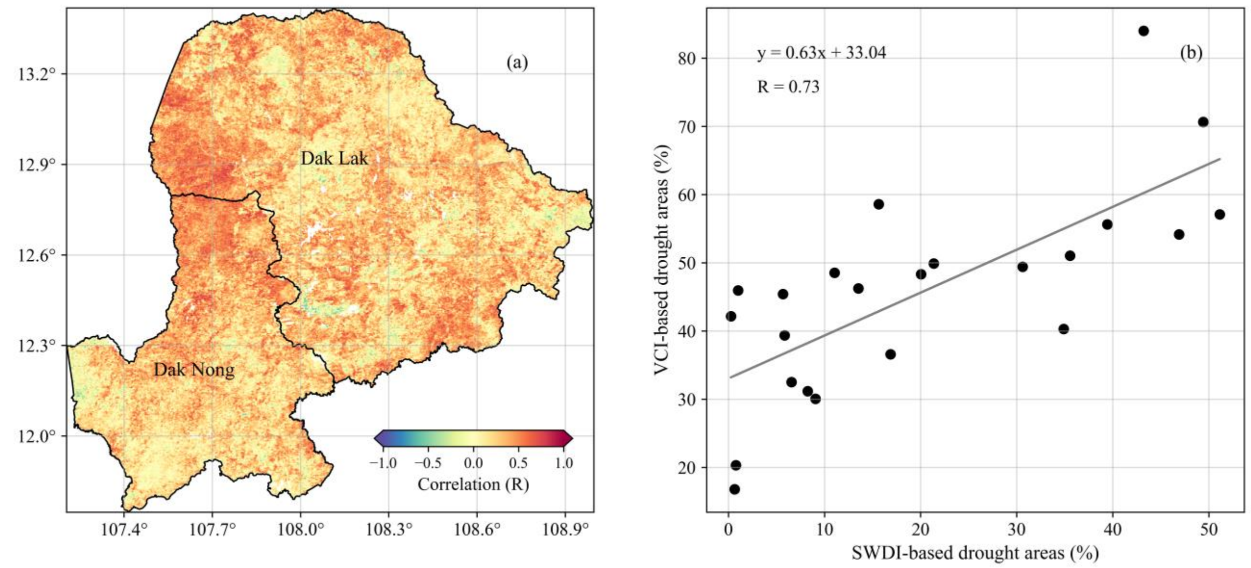

Figure 2. Spatial map and scatter plot show Pearson's correlation coefficients (a) and the agreement of drought-detected areas (b) between VCI and SWDI over the study period.

Apart from spatial assessment, Figure 2(b) displayed the agreement of drought-detected areas between VCI-based and SWDI-based drought indices. Overall, there is a high positive correlation between VCI and SWI indices in the percentage of the drought-affected areas from 2000 to 2023. The R-value is 0.73

and its relationship is linearly correlated, indicating that an increase in VCI-based drought areas is associated with an increase in SWDI-based drought areas. This agreement indicates that VCI-based drought can be effective and reliable in detecting drought-affected areas.

3.2 Spatiotemporal patterns of vegetation-based drought

3.2.1 Spatial patterns of seasonal droughts

In this section, we presented the spatiotemporal variability of vegetation-based drought (VCI) during both dry and rainy seasons from 2000 to 2023. Overall, there are significant spatial and temporal variations in VCI-based drought conditions across the study period. Notably, the dry seasons experienced higher exposure to drought vulnerability, particularly in the years 2004-2005, 2015-2016, and 2019-2020 (Figure 3). These timeframes marked critical phases of vegetation stress, possibly indicative of environmental factors such as reduced rainfall or elevated temperatures that exacerbated the impact of drought on the region's vegetation (Le et al., 2021). In addition, human activities might exaggerate the vegetation-based drought, such as agricultural shifting (Chen et al., 2023) and deforestation (Mermoz et al., 2021). Temporally, the dry season of 2005 suffered from the most severe drought (Figure 3), while the wettest conditions were observed during the periods 2017-2018 and 2022-2023. Notably, recent drought conditions were primarily found in the northern area of Dak Lak, for example, in 2019 (Figure 3).

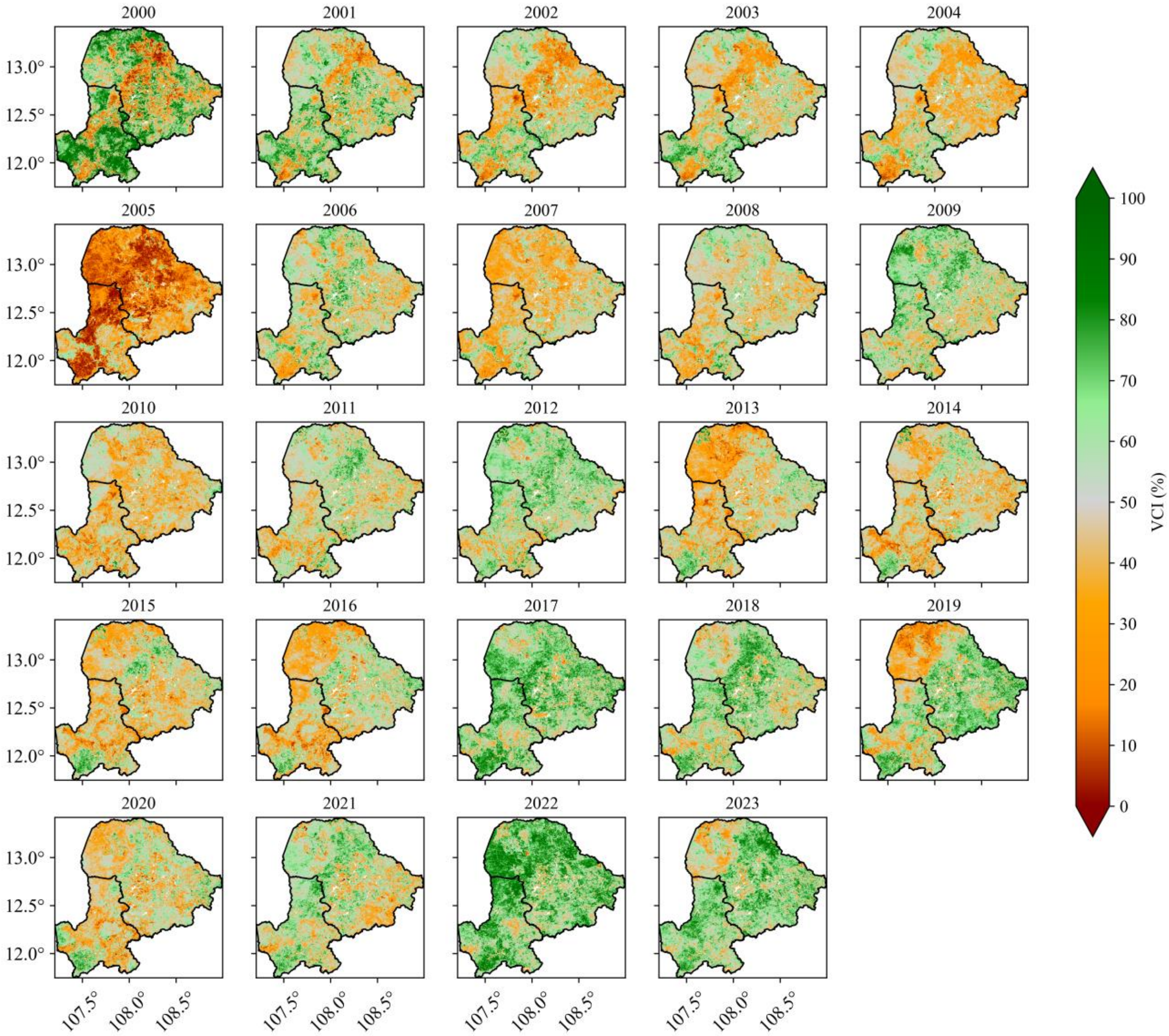

Figure 3. Annual variability of mean drought conditions during the dry seasons from 2000 to 2023. Red indicates severe drought, while green indicates wet conditions. Gray refers to normal conditions.

Likewise, the study area experienced VCI-based drought conditions during the rainy season, particularly in the early 2000s. However, the degree of drought severity was much lower compared to the dry season (Figure 4). For example, larger areas of drought were detected in Dak Lak Province from 2000 to 2005, but in recent years, the province experienced wetter conditions, especially in 2022 and 2023 (Figure 4). These findings shed light on the dynamic nature of VCI-based drought conditions, emphasizing the need for a better understanding of the interplay between climatic variables and vegetation health. The discerned patterns provide valuable insights for stakeholders and policymakers to develop targeted strategies for drought resilience and sustainable land management practices in the study area. For example, some areas in the northern Dak Lak Province and southern Dak Nong Province suffered more frequent drought, so it may require attention with respect to agriculture and vegetation ecosystems in these areas.

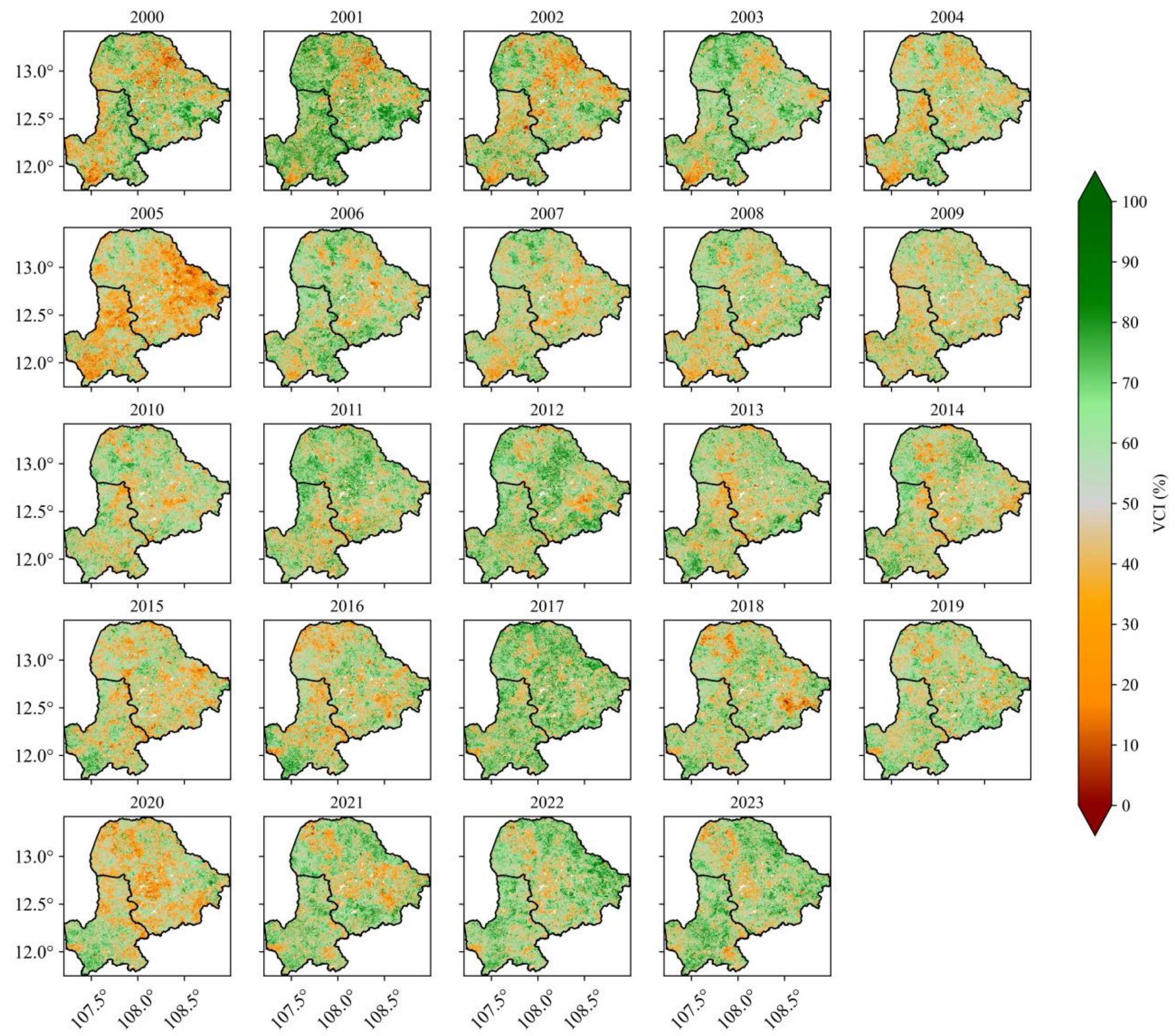

Figure 4. Annual variability of mean drought conditions during the rainy seasons from 2000 to 2023. Red indicates severe drought, while green indicates wet conditions. Gray refers to normal conditions.

3.2.2 Temporal analysis of drought

Figure 5 showed the monthly evolution of drought conditions over the two provinces of Dak Lak and Dak Nong from 2000 to 2023. It is clear that almost all drought events occurred in the region during the dry months. The lowest VCI values were observed in 2005, 2016, and 2020 (Figure 5), indicating the severe drought conditions during these periods. Also, the highest VCI values were found during the periods 2017-2018 and 2022-2023, suggesting a wetting condition during these years. The 2005 drought in the study region was the most severe, possibly due to the prolonged El Niño conditions (Phan-Van et al., 2022), which led to significantly reduced rainfall and higher-than-average temperatures, exacerbating water shortages. In addition, changes in land cover and hydrological pattern could be also responsible for variations in the vegetation-based measurements (Le et al., 2020b; Mondal et al., 2022). These observations are aligned with recent studies in Vietnam (Le et al., 2020b; Le et al., 2021; Thien et al., 2024; Tran et al., 2023) and mainland Southeast Asia (Ha et al., 2023; Li et al., 2022).

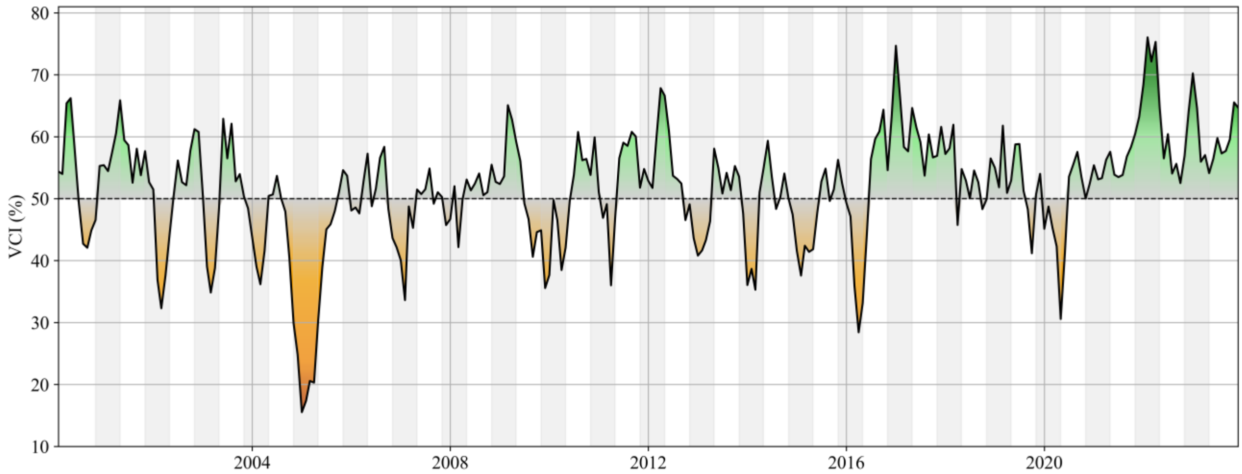

Figure 5. Temporal pattern of drought and wet conditions from 2000 to 2023. Vertical gray colors indicate the dry seasons from October to April.

Apart from the overall pattern, Figure 6 displayed the temporal pattern of the monthly VCI-based drought condition across three main land cover types from 2000 to 2023. Clearly, a similar pattern of the VCI was found in cropland, forests, and shrubland. However, forests and cropland had the lowest VCI values in 2005 (Figure 6), indicating that these types of vegetation are more sensitive to drought. Interestingly, cropland in 2010 suffered from lower VCI values than forests and shrublands. Cropland and forests had the highest VCI value in 2022, while shrublands witnessed the largest VCI value in 2000s (Figure 6). These observations might indicate that shrublands suffered from larger variations in recent years.

In recent years, however, higher VCI values were primarily observed in cropland and forests, which indicated an improvement in forest plantations or irrigated systems. In comparison, shrubland had relatively lower VCI values and had a longer duration of drought in recent years. For example, shrubland suffered from lower VCI values over nearly 12 months during the period 2020-2021. Also, the VCI values in shrubland during the last two years were lower than those of cropland and forests, suggesting not only the potential influence of drought but also the impact of human-induced activities such as land use disturbance. These patterns highlight the need for targeted conservation efforts in shrubland areas to mitigate further degradation and promote ecosystem resilience.

3.3 Time series trend of vegetation-based drought

In this study, we assessed the time-series trend of vegetation-based drought using the MK and Sen's slope tests over the two provinces of Vietnamese Central Highlands from 2000 to 2023. Overall, large areas of increasing VCI-based trends were detected in the study area over the study period (Figure 7), indicating a decline in vegetation-based drought trends. During the dry season, nearly 50% of the study area experienced significant positive VCI trends (Figure 7(a)), while the declining VCI values accounted for 20%. In comparison, the rainy season witnessed a smaller area of increasing VCI trends (~47%) from 2000 to 2023. Notably, it is estimated that the deviation of the VCI trends during the dry season was larger than that of the rainy season. For example, the estimated standard deviation of VCI trends for the dry season stood at 1.65%, in contrast to the lower figure of 1.32% observed for the rainy season. These observations suggested that the dry season witnessed more profound variations in drought than the rainy seasons and aligned with recent studies (Ha et al., 2023; Le et al., 2021; Tran et al., 2023; Vu and Ngo-Duc, 2024).

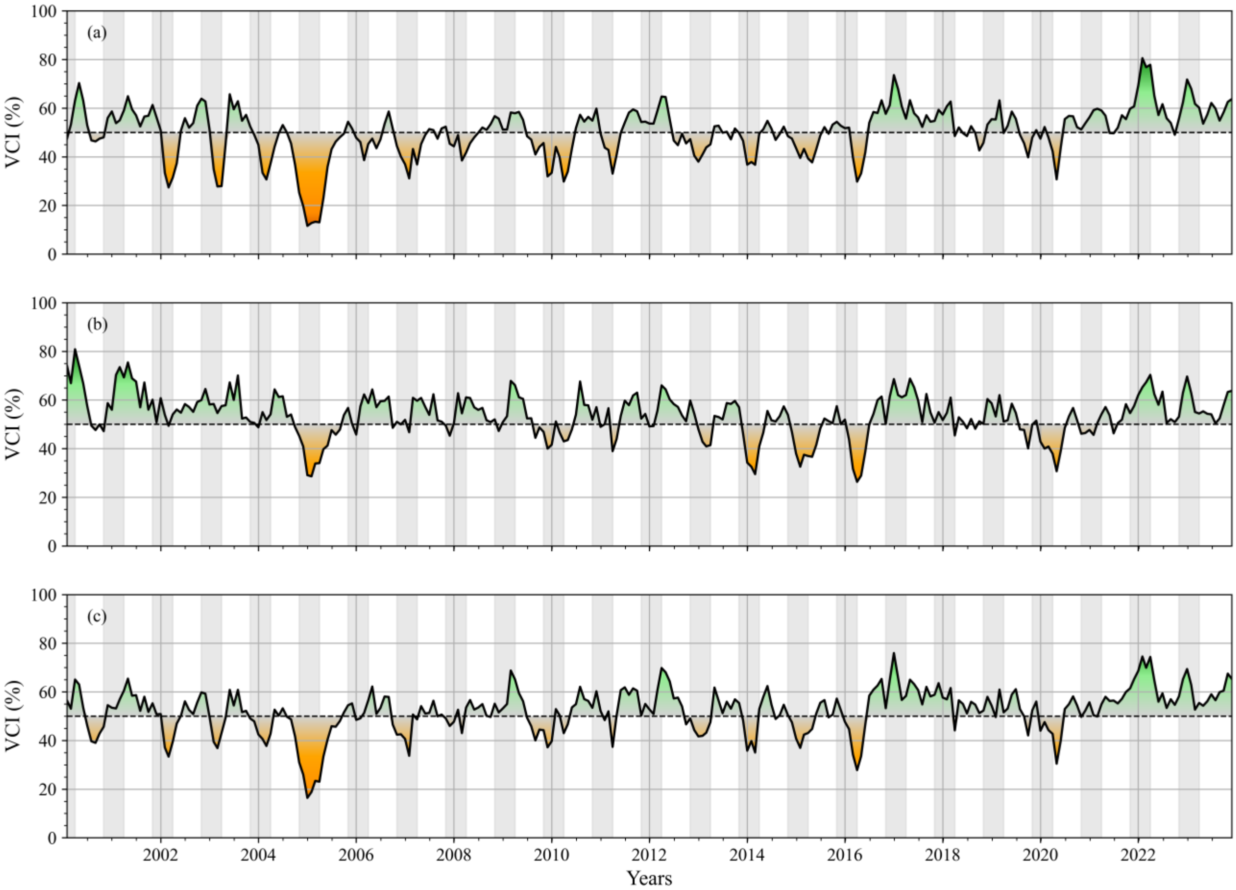

Figure 6. Monthly variability of drought conditions across land cover types (a) croplands, (b) shrubland, (c) forests across the study area. Color represents the VCI values from the lowest (red) to the highest (dark green). The gray color indicates dry season during the study period.

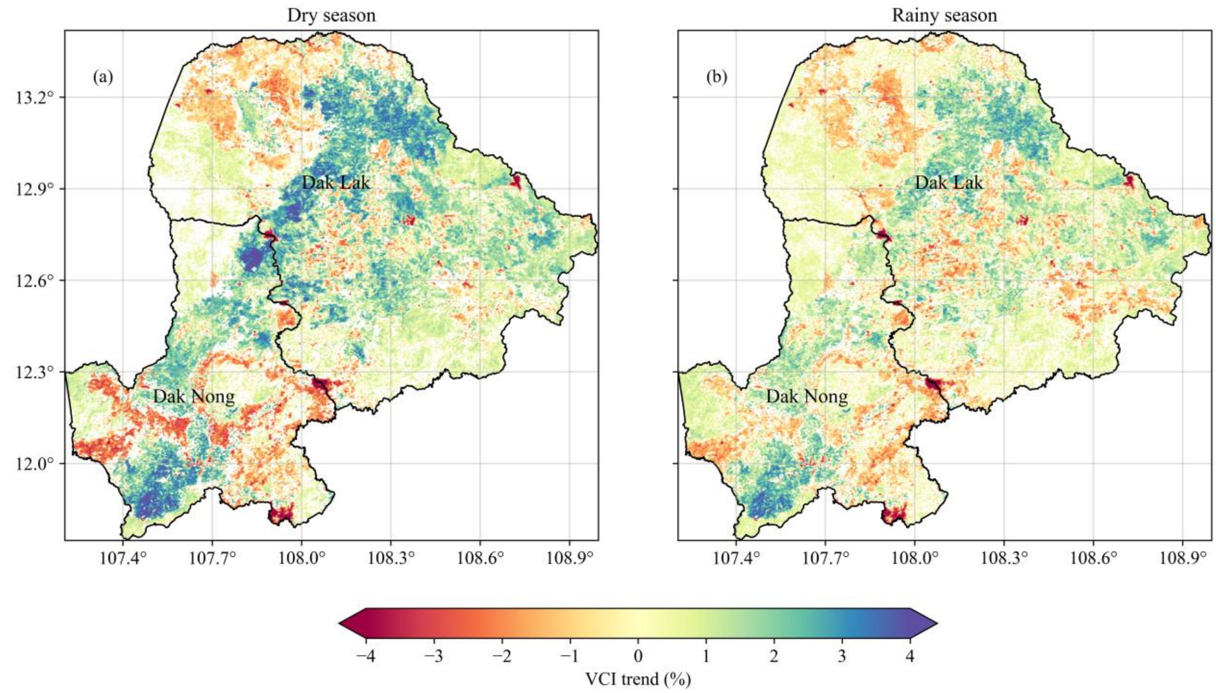

Figure 7. Spatial trends of per-pixel vegetation-based drought during the dry (a) and rainy (b) seasons from 2000 to 2023 at p-value≤0.05. Reddish color represents the declining VCI trends, while blue color indicates the increasing VCI trends.

Interestingly, significant increasing or declining VCI-based trends were primarily detected in the southern and central areas of Dak Nong and Dak Lak Provinces, respectively. For example, nearly 23% of Dak Nong Province witnessed declining VCI trends during the dry season, while Dak Lak has smaller areas of declining VCI trends (~17%) over the same period. Notably, Dak Lak Province had larger areas of increasing VCI trends compared to the rainy season, and these observations are mainly found in the forests and industrial crops. Coffee plantations are primarily detected around the central area of Dak Lak Province (Maskell et al., 2021).

The disparities observed in VCI trends between the two seasons in Dak Lak Province could be attributed to climate and human activities. For example, Dak Lak Province had large areas of industrial croplands, and farmers may store water during the dry season to cope with frequent droughts. Clearly, cropland had the highest VCI trend, an average of 1.1%, whereas the shrubland had the lowest VCI trend (-0.4%) during the dry season (Figure 8(a)). Likewise, cropland and forests experienced positive VCI trends during the rainy season. Negative shrubland VCI trends could be due to human activities such as agricultural shifting (Chen et al., 2023). Also, the rapid pace of rural urbanization across various regions has also contributed to these variable vegetation trends, reflecting the impact of expanding infrastructure and land use changes on natural ecosystems (Ha et al., 2020; Jeganathan et al., 2014).

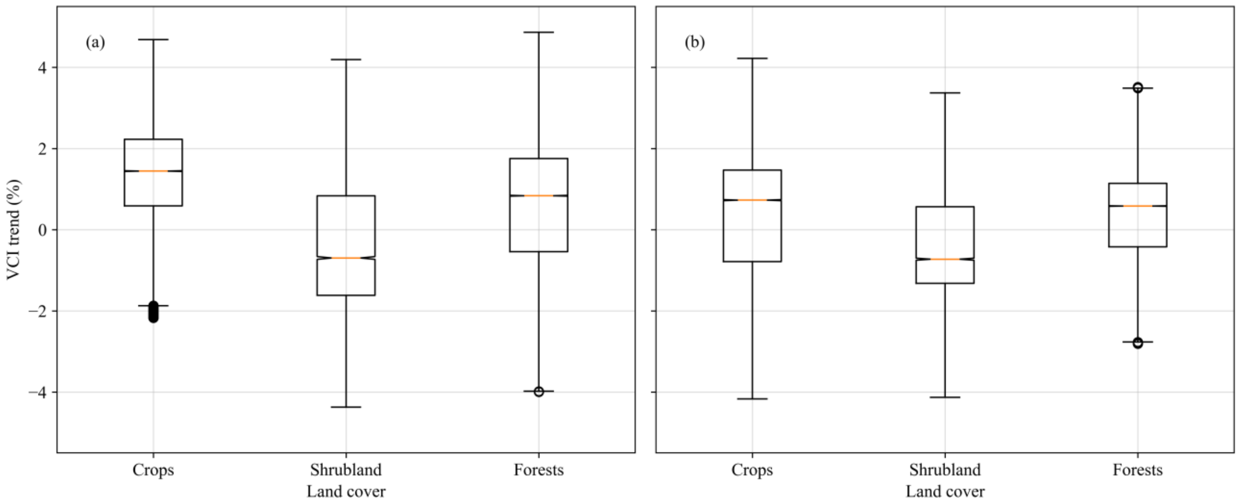

Figure 8. Trends of VCI-based conditions during the dry (a) and wet (b) seasons from 2000 to 2023 across land cover types of croplands, shrubland, forestland.

4. CONCLUSION

In this study, we employed a vegetation-based index to assess the spatiotemporal variability of drought conditions in the Vietnamese Central Highlands, Dak Lak, and Dak Nong Provinces, from 2000 to 2023. Spatial correlation analysis between the Vegetation Condition Index (VCI) and the Soil Water Deficit Index (SWDI) demonstrated a robust agreement, with nearly 91% of the study area exhibiting positive correlations. The comparison of drought-affected areas between VCI and SWDI revealed a high positive correlation (R-value=0.73), confirming the effectiveness and reliability of VCI-based drought detection.

The monthly evolution of drought conditions indicated a clear prevalence during the dry months, with severe episodes in 2005, 2010, 2013, 2015-2016, and 2019. The VCI patterns across land cover types revealed sensitivity variations, with forests and cropland being particularly vulnerable in certain years. The time-series analysis highlighted large areas of increasing VCI-based trends during both dry and rainy seasons over the study period. Nearly 50% of the study area experienced an increasing VCI trend during the dry season, whereas this figure for the rainy season was about 47%. Higher declining VCI trends were primarily detected in Dak Nong and northern Dak Lak Province.

These findings are crucial for informing stakeholders and policymakers, enabling the development of targeted strategies for drought resilience and sustainable land management practices in the region. In future studies, we would conduct a more detailed investigation into the localized impacts of extreme drought events, as well as the incorporation of additional drought indices and environmental variables. Such approaches could provide a more comprehensive understanding of drought dynamics and improve the effectiveness of adaptation and mitigation strategies in the region.

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