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Evaluating Multi-Index Remote Sensing Frameworks for Drought Monitoring in Seasonally Dry Dipterocarp Deciduous Forests: A Case Study of Yok Don National Park, Vietnam

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This study examined the effectiveness of the normalized difference vegetation index (NDVI), land surface temperature (LST), and their integrated indices in capturing dry-season drought dynamics in the dipterocarp deciduous forest ecosystems of Yok Don National Park from 2014 to 2024. Results indicate that individual remote-sensing indices captured drought processes but reflected different dimensions of drought conditions, with NDVI indicating canopy greenness and LST detecting early thermal stress. Integrated indices partially mitigated the limitations of single indicators during confirmed drought years by showing stronger correlations with reference data. The effectiveness of the integrated indices varied significantly depending on the integration framework. The spatial-normalization-based integration of NDVI and LST showed consistently strong correlations with surface evapotranspiration (ET), with correlation coefficients of approximately 0.8 across years, and was less sensitive to land-cover

heterogeneity. In contrast, the triangular NDVI–LST space integration exhibited variable relationships with ET due to its sensitivity to edge definition and phenological shifts in dipterocarp deciduous forests. Phase-dependent behavior was observed, with integrated indices maintaining more stable relationships with ET during drying periods, while NDVI showed greater sensitivity under wetter conditions. The results also indicate that VHI demonstrated a more robust and stable performance than TVDI, suggesting its suitability as a primary indicator in heterogeneous forest environments. These findings provide practical guidance for drought monitoring in heterogeneous forest landscapes by identifying adaptive integration strategies tailored to different hydroclimatic conditions.

Keywords: drought, normalized difference vegetation index, land surface temperature, vegetation health index.

Introduction

Drought is one of the most pervasive natural hazards, with profound impacts on ecosystems, agriculture, water resources, and biodiversity (AghaKouchak et al., 2021; Orimoloye et al., 2022). Remote sensing has emerged as a powerful tool in drought assessment due to its ability to provide consistent, timely, and spatially comprehensive observations of land surface conditions (AghaKouchak et al., 2015). Normalized difference vegetation index (NDVI) and land surface temperature (LST) have been widely recognized as effective for characterizing vegetation responses and thermal stress associated with drought events. Tucker et al. (1985) demonstrated the effectiveness of NDVI in detecting vegetation responses to drought across Sub-Saharan Africa, revealing strong correlations with precipitation variability. Rhee et al. (2010) further integrated NDVI anomalies with precipitation data to produce a global Drought Severity Index, enhancing the spatial characterization of drought conditions. Comparative studies, such as Vicente-Serrano et al. (2019) highlighted that while NDVI captures vegetation response to drought effectively, it often lags behind meteorological indicators, suggesting that combining NDVI with climate-based indices can improve early detection. These studies underscore the critical role of NDVI in drought monitoring, while also pointing to the benefits of integrating it with other variables to enhance accuracy and responsiveness. LST, in contrast, indicates surface energy balance and is strongly influenced by soil moisture availability and evapotranspiration rates. In 2019, Nguyen et al. (Nguyen et al., 2019) applied Landsat 8-derived LST to examine dry season thermal dynamics in Loc Ninh District, southeastern Vietnam. Mustafa et al. (2021) used Landsat thermal imagery to monitor drought from 1988 to 2020 in Freetown City, Sierra Leone, West Africa. While both indices offer

valuable insights, they reflect different dimensions of drought conditions. When combined, NDVI and LST provide complementary information, enabling a more comprehensive understanding of drought dynamics. Two widely used examples are the temperature vegetation dryness index (TVDI) and the vegetation health index (VHI). TVDI uses the relationship between NDVI and LST to assess soil moisture conditions (Ryu et al., 2021), while VHI integrates the vegetation condition index (VCI) and temperature condition index (TCI) to provide a more balanced view of vegetation and thermal stress (Zeng et al., 2023).

Remote sensing-based drought monitoring is particularly valuable in protected forest ecosystems, where continuous field-based monitoring is often limited and the early detection of vegetation stress is critical for biodiversity conservation and forest fire prevention. This is especially important in tropical deciduous dipterocarp forests, which are highly vulnerable to prolonged dry seasons because of rapid reductions in canopy moisture and increased flammability (Stibig et al., 2007; Luu et al., 2014; Kaewsong et al., 2022). Yok Don National Park, one of the largest remaining dry dipterocarp forest areas in Vietnam, provides a particularly relevant case study because it is regularly affected by seasonal drought during the dry season, while its dry dipterocarp ecosystem is widely recognized as highly fire-prone under prolonged dry conditions (Wanthongchai et al., 2011; Nguyen and Baker, 2016; Nguyen et al., 2017; Tran et al., 2021). Building on this ecological vulnerability, the evaluation of remote-sensing indicators capable of capturing drought-related stress is both scientifically meaningful and practically important for ecosystem monitoring and management. This study aims to assess the comparative effectiveness of NDVI, LST, and their integrated derivatives, namely TVDI and VHI, in capturing water stress conditions during the dry

season in Yok Don National Park. The selected indices form a physically coherent framework in which NDVI and LST reflect vegetation condition and surface thermal behavior, the two primary dimensions of drought response (Karnieli et al., 2010), while TVDI and VHI provide integrated representations of moisture status and vegetation stress based on the interaction between these variables (Kogan, 1995; Sandholt et al., 2002). As all four indices are derived from the same underlying variables, their comparative performance can be evaluated within a consistent analytical framework, thereby reducing input-related uncertainty. This enables observed differences to be attributed more directly to index formulation and provides a clearer basis for assessing the advantages of integrated indicators over individual ones.

This paper is organized into four sections. Following the Introduction, the next section describes the study area, data sources, and methods used in the analysis. Then, the results and discussion are presented, with emphasis on the performance of the selected indices in representing water stress conditions in Yok Don National Park. The final section summarizes the main findings and presents the conclusions of the study.

Study area and Materials

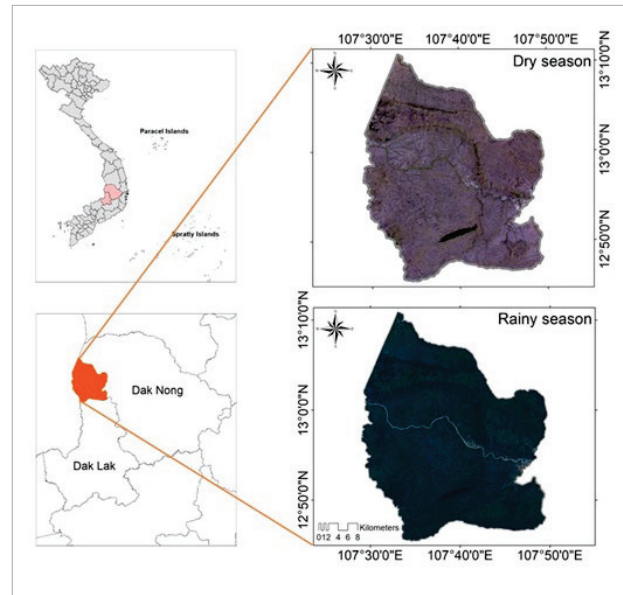
Study area

Yok Don National Park occupies a region in Vietnam's Central Highlands, bordering Cambodia (*Fig. 1*). It is one of the largest protected areas in Vietnam and plays a critical role in conserving the region's unique dry deciduous forest ecosystems. This area is highly vulnerable to seasonal droughts, which can have substantial impacts on vegetation health and biodiversity. The region experiences a typical monsoonal climate with distinct wet and dry seasons. The dry season, lasting from November to April, is marked by limited rainfall, high temperatures, and low humidity, which together create conditions conducive to drought. The wet season, from May to October, brings the majority of the annual precipitation (Nguyen et al., 2017).

In terms of vegetation cover, the park is characterized by dry deciduous dipterocarp forest, while evergreen and semi-deciduous broadleaf forests occur in smaller and more localized patches (Nguyen et al., 2014; Nguyen and Baker, 2016; Nguyen et al., 2017; Nguyen

Fig. 1. Yok Don National Park and the seasonal variation in vegetation greenness during the dry (upper right panel) and rainy seasons (lower right panel).

The right panels present vegetation greenness derived from multi-spectral Landsat 8 imagery for the two seasons in 2015.



and Huynh, 2022). A defining ecological feature of this forest type is its pronounced seasonal phenology. During the dry season, reduced rainfall, together with high temperatures and low humidity, accelerates soil moisture depletion and intensifies water stress across the ecosystem (Tran et al. 2021; Le et al., 2025). Simultaneously, substantial leaf shedding produces a more open canopy, increases solar exposure at the forest floor, and promotes the development of a dense understory of grasses, shrubs, and other light-demanding species. These hydroclimatic and structural conditions cause vegetation and surface fuels to dry progressively, thereby increasing the ecosystem's vulnerability to seasonal drought and forest fire during prolonged dry periods.

Materials

Landsat-8 operational land imager (OLI) and thermal infrared sensor (TIRS), with a 30-meter spatial resolution, were employed to derive the selected drought indices (NASA, n.d.-a). To ensure temporal consistency and comparability across years while minimizing atmospheric interference, cloud-free images were acquired from the late dry season, primarily in March, for the period 2014–2024, except for 2018 and 2023, when February images

were used due to cloud contamination in March. This period likely represents the peak drought conditions in the study area, when high background temperatures persist while precipitation remains minimal following the end of the rainy season (approximately November). As a result, vegetation stress and land surface responses to water scarcity are most pronounced, making this timing particularly suitable for drought assessment. For validation,

MODIS-based Evapotranspiration (ET) (NASA, n.d.-b) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall data (Climate Hazards Center, n.d.) were employed as independent datasets to assess the accuracy of the selected drought indicators. Details of the datasets are presented in *Table 1*. All data were accessed and processed on the Google Earth Engine (GEE) platform.

Table 1. Description of satellite observations used in this research

Sensor and platform	Band ID	Band name	Main application	Processing level and product	Spatial resolution (m)	Image acquisition date
Landsat-8 OLI, TIRS	B1	Coastal Aerosol	Atmospheric correction, coastal water analysis	Level 2, Collection 2, Tier 1	30 × 30	03 Mar 2014
	B2	Blue	Water body mapping, atmospheric scattering			06 Mar 2015
	B3	Green	Vegetation discrimination, water detection			08 Mar 2016
	B4	Red	Vegetation analysis			11 Mar 2017
	B5	Near-infrared (NIR)	Vegetation vigor, biomass estimation			10 Feb 2018
	B6	Shortwave infrared (SWIR) 1	Built-up detection, soil moisture			01 Mar 2019
	B7	Shortwave infrared (SWIR) 2	Dry soil, mineral mapping, urban features			03 Mar 2020
	B8	Panchromatic	Image sharpening		15 × 15	06 Mar 2021
	B9	Cirrus	Cloud detection		30 × 30	09 Mar 2022
	B10	Thermal infrared (TIR) 1	Land Surface Temperature (LST) retrieval		100 × 100	24 Feb 2023
	B11	Thermal infrared (TIR) 2				15 Mar 2024
MODIS (Terra/ Aqua)		MOD16A2GF–Evapotranspiration (ET) product	Monitoring surface water balance, drought assessment, vegetation water stress	Global product, 8-day composite	500 × 500	Mean values during Jan–Mar (2014–2024)
CHIRPS		Climate Hazards Group InfraRed Precipitation with Station data	Precipitation monitoring and drought assessment	v2.0/ v3, daily products	0.05°	2013–2024

Methodology

Drought indices calculation

Normalized difference vegetation index: NDVI is widely employed as an indicator of vegetation condition because it is sensitive to chlorophyll concentration and

canopy density (Tucker et al., 1985; Ji and Peters, 2003; Muraoka et al., 2013; Zou and Möttus, 2017; Vélez et al., 2023). NDVI is calculated using the standard formula (Glenn and Tabb, 2019):

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

where *NIR* and *RED* represent the red and near-infrared spectral bands.

Land surface temperature: LST is a crucial indicator of drought because it represents the surface energy balance and responds sensitively to changes in surface water availability, including soil moisture and canopy transpiration (Xiao and Weng, 2007; Cammalleri and Vogt, 2015; Nguyen et al., 2019; Mustafa et al., 2021). In this study, LST was computed strictly following the USGS Landsat Collection 2 Level-2 Surface Temperature methodology as documented in the official product guides and the Landsat 8 Data Users Handbook (USGS, 2016; 2019).

Temperature vegetation dryness index: TVDI is computed based on a triangular relationship that defines the 'dry' and 'wet' edges of the plot, which represent the limits of LST for a given NDVI value (Du et al., 2017; Ryu et al., 2021; Bian et al., 2023). The wet edge corresponds to the minimum LST values at a given NDVI, typically representing areas with healthy, well-watered vegetation, while the dry edge corresponds to the maximum LST for the same NDVI values, indicating regions affected by water stress or sparse vegetation. The positioning of each pixel within the NDVI–LST space allows for the calculation of its relative distance from the wet and dry edges, producing the TVDI value. TVDI ranges from 0 (wettest conditions) to 1 (driest conditions), offering a robust method for capturing spatial variations in soil moisture and drought stress (Przeździecki et al., 2023). TVDI is computed using the following triangular method:

$$TVDI = \frac{LST - LST_{min}}{LST_{max} - LST_{min}} \quad (2)$$

where LST_{max} and LST_{min} represent the maximum (dry) and minimum (wet) LST values for a given NDVI, respectively.

To determine the dry and wet boundaries of the NDVI–LST feature space, a scatter plot was constructed with NDVI on the x-axis and LST on the y-axis (Fig. 2). The relationship between land surface temperature and vegetation condition, represented by NDVI, was examined across different land-cover types. NDVI values were stratified into intervals of 0.02, with each interval considered representative of a specific land-surface condition. All LST observations falling within each NDVI interval were initially included. To reduce the influence of outliers, LST values were filtered using statistical constraints

under the assumption of a near-normal distribution. Specifically, only values satisfying the following conditions were retained (Tran et al., 2021; Le et al., 2025):

$$|LST_i - LST| \leq 3.5\sigma \text{ (for } n > 2000) \quad (3)$$

$$|LST_i - LST| \leq 3\sigma \text{ (for } 300 \leq n < 2000) \quad (4)$$

Samples with fewer than 300 observations were excluded to ensure statistical robustness. For each NDVI interval, the maximum (LST_{max}), minimum (LST_{min}), and mean (LST_{mean}) values were then extracted, as illustrated in Fig. 2. The and values define the dry and wet boundaries, respectively, while LST_{mean} represents average surface conditions. Linear regression was subsequently applied to these representative points to derive the dry-edge, wet-edge, and mean relationships.

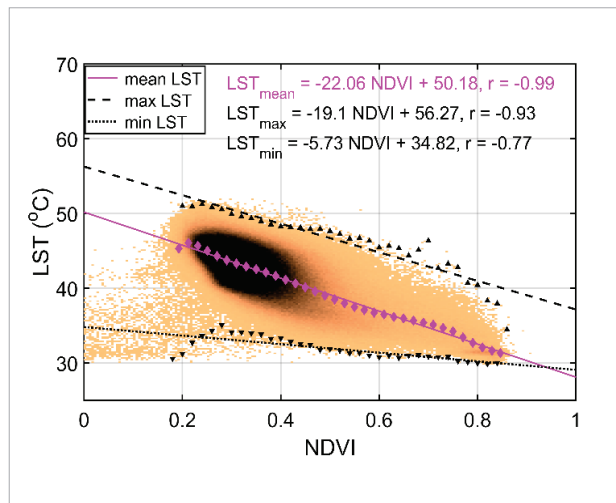
Fig. 2 presents the distribution of NDVI and LST values over the study area in 2019, with pixel density depicted by a color gradient ranging from brown to black, where darker tones indicate a higher concentration of similar NDVI–LST patterns. For each consistent NDVI value (interval of 0.02), the upper and lower black triangles represent the maximum and minimum LST values, corresponding to the dry and wet edges, respectively, while the purple triangles denote the mean LST. The upper dashed black line, middle solid purple line, and lower dotted black line indicate the linear regressions fitted to the dry edge, mean LST, and wet edge, respectively; the regression equations and correlation coefficients are shown in the upper-right corner of the figure.

Within this feature space, the upper envelope (high LST) represents dry surface conditions, while the lower envelope (low LST) reflects wet surface conditions, forming a characteristic triangular pattern. A clear negative relationship between NDVI and LST is observed, indicating that areas with denser vegetation and higher moisture availability tend to exhibit lower surface temperatures. In addition, LST shows systematic variation within each NDVI interval, with dry-condition points consistently associated with higher temperatures and wet-condition points with lower temperatures. It is emphasized that the NDVI–LST relationship used for TVDI calculation is determined separately for each year based on actual data. Therefore, the results shown in Fig. 2 represent only a typical example (2019), while the same procedure is applied independently to all years in the study period to ensure the reliability and temporal consistency of the analysis.

Vegetation health index: VHI is computed as a weighted integration of the vegetation condition index (VCI) and the temperature condition index (TCI). While VCI measures vegetation greenness anomalies by normalizing each pixel's NDVI value relative to the minimum and maximum NDVI values observed across the entire image, TCI is derived from LST anomalies and reflects thermal stress, which is often linked to limited soil moisture and reduced evapotranspiration (ET) (Kogan, 1995; Bento et al., 2018). By incorporating both vegetation vigor (via VCI) and surface temperature anomalies (via TCI), VHI provides a more balanced and comprehensive assessment of drought conditions than using

Fig. 1. Scatter plot of NDVI versus LST across Yok Don National Park in the 2019 dry season.

Pixel density is shown by the color gradient from brown to black, with darker tones indicating a higher number of pixels sharing similar NDVI–LST values. For each consistent value of NDVI (the interval of 0.02), the upper and lower black triangles represent the maximum and minimum LST values, corresponding to the dry and wet edges, respectively, while the purple triangles denote the mean LST. The upper dashed black, middle solid purple, and lower dotted black lines indicate the linear regressions fitted to the dry edge, mean LST, and wet edge, respectively; the regression equations and correlation coefficients are shown in the upper-right corner of the figure.



vegetation or thermal indices alone. It is particularly effective for detecting early signs of drought, as well as prolonged water deficits, which affect both plant health and water availability. The index is calculated as:

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI \quad (5)$$

where α is a balancing factor, normally set at 0.5, equally weighting the vegetation and temperature conditions (Kogan 1995). VCI and TCI are calculated as follows:

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (6)$$

$$TCI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \quad (7)$$

where $NDVI_{min}/NDVI_{max}$ and LST_{min}/LST_{max} denote the respective minimum and maximum NDVI and LST values in the study area at the observation time.

The resulting VHI values range from 0 to 1, where higher values (closer to 1) indicate healthy, well-watered vegetation with minimal drought stress, and lower values (closer to 0) reflect vegetation under severe water stress, reduced greenness, or exposed bare soil.

Validation

The effectiveness of the selected drought indices was evaluated by assessing their ability to capture known drought events and to align with precipitation and ET trends over the study area. Specifically, Pearson correlation coefficients were calculated to quantify the relationship between each index and ET derived from the MOD16A2 product, which serves as an independent indicator of drought severity due to its sensitivity to soil moisture and vegetation water availability. This dataset has been rigorously validated against flux tower measurements and is widely accepted as a reliable independent reference for agricultural drought assessment, given its ability to capture crop water stress and surface moisture dynamics (Running et al., 2019; Degano, et al., 2021; Ronco and Borgogno Mondino, 2025). Due to the inconsistency in spatial resolution between the ET data and the drought indices, the drought index datasets were resampled to match the resolution of the ET data prior to the evaluation, ensuring a consistent basis for comparison (Le et al., 2025). A spatial analysis was conducted to compare the indices in terms of their ability to reflect drought impacts in vegetated areas. This involved examining spatial patterns and assessing how well each index distinguished between stressed and healthy vegetation. The results provide insights into the relative strengths and limitations of each index, particularly in heterogeneous landscapes with diverse vegetation cover, such as Yok Don National Park.

In addition, satellite-derived precipitation from CHIRPS was incorporated to independently contextualize hydroclimatic phases. CHIRPS provides quasi-global rainfall fields by blending geostationary thermal infrared estimates with rain gauge observations at 0.05° spatial resolution and temporal resolutions ranging from daily to monthly. For this study, CHIRPS data were accessed and aggregated in Google Earth Engine to produce monthly and seasonal totals (millimeters) for 2014–2024. Area-masked summaries for Yok Don were used to derive annual means and mid-dry season totals, and anomaly fields were also computed relative to the study period mean to identify wetting and drying episodes. These precipitation metrics were then compared qualitatively with the spatial distributions of the indices and quantitatively with ET, allowing the convergence of evidence across rainfall forcing, vegetation response, surface thermal stress, and evapotranspiration

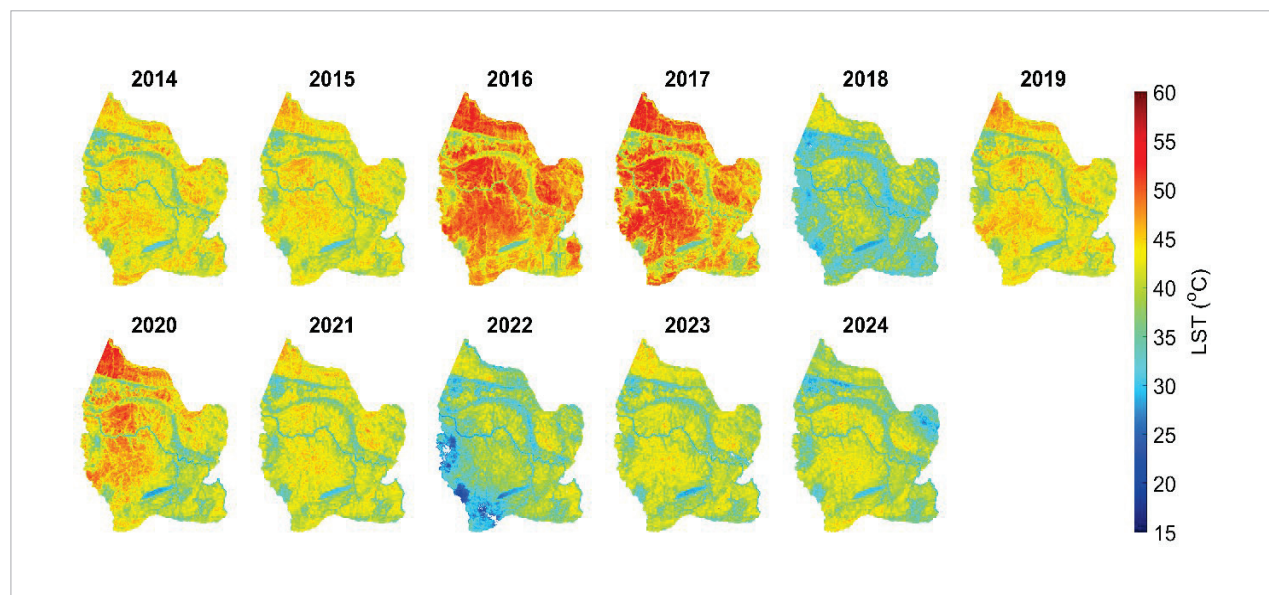
Results and Discussion

Spatial distribution of NDVI, LST and there's integrations

The spatial distributions of LST, NDVI, TVDI, and VHI for Yok Don during the dry seasons of 2014–2024 are shown in Fig. 3, Fig. 4, Fig. 5, and Fig. 6, respectively.

In Fig. 3, the highest LST values are observed in 2016–2017, when widespread yellow–red tones indicate elevated surface temperatures, whereas cooler backgrounds characterize 2018–2019 and especially 2021–2022. Conditions in 2023–2024 return to moderate levels, with localized cool patches. Cooler areas consistently follow the Srepok River and nearby water bodies, reflecting riparian cooling, while repeated hot spots occur in higher, more open or deciduous areas, especially in the north–central region and the warmer northwest corner in 2020. The interannual amplitude is greatest in 2016–2017 and 2022; however, the spatial pattern of warm and cool zones remains relatively stable, suggesting that land cover exerts primary control, while climate primarily modulates intensity. The markedly cooler thermal background in 2022 is associated with persistent La Niña conditions, which exerted a cooling effect and were linked to wetter conditions (WMO, 2022). The low-temperature zone in the central-western part of the study area corresponds to dense vegetation cover, consistent with the high NDVI values shown in Fig. 4, whereas the other two low-temperature patches in the western–southwestern and southwestern sectors are influenced by cloud shadow. Ecologically, higher LST is consistent with leaf-off dipterocarp stands or bare soils with reduced ET cooling, whereas lower LST corresponds to evergreen/riparian vegetation and surface water.

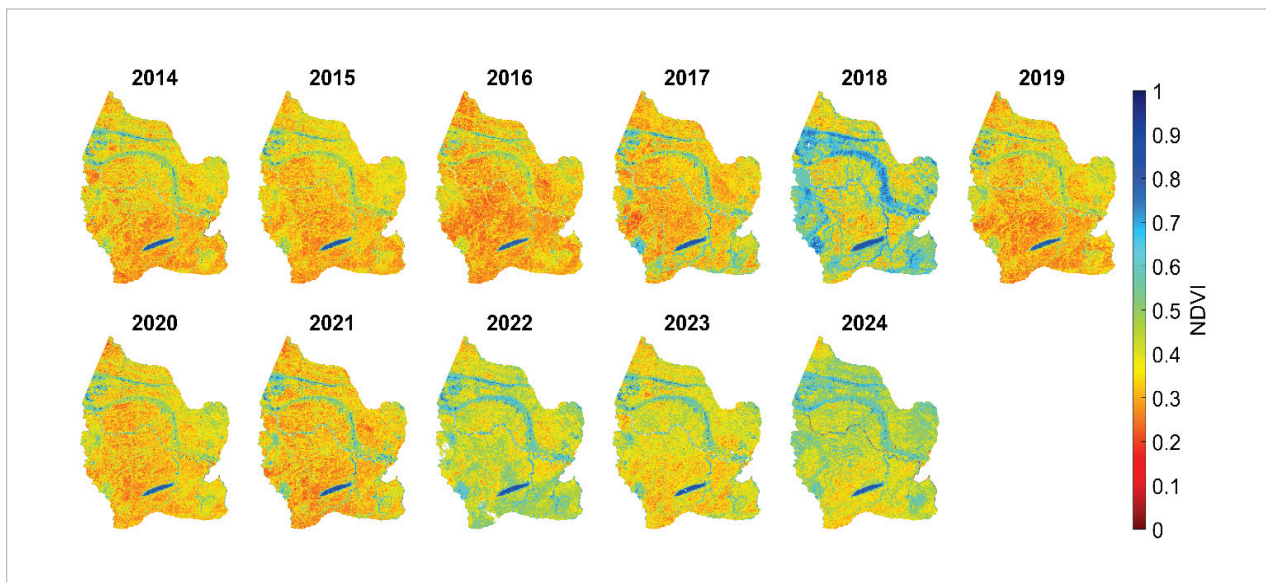
Fig. 3. The spatial distribution of LST across Yok Don National Park – the mid-dry season from 2014 to 2024



NDVI values (Fig. 4) reveal persistently low-to-moderate greenness across upland deciduous areas (from 0.2 to 0.4), while the highest values are concentrated along the Srepok River and major water bodies where riparian/evergreen cover is maintained. Lower NDVI values were observed in 2014–2017, consistent with widespread leaf-off and moisture limitation. Then, a partial recovery emerges in 2018, primarily along riverine belts. The most extensive rebound occurs in 2022, when broad swaths shift to the 0.4–0.6 range with enlarged

high-NDVI patches, followed by more moderate conditions in 2024, during which riparian vigor persists but upland greenness contracts relative to 2022. The geographic distribution of high versus low NDVI remains largely stationary, indicating strong land-cover control, whereas interannual amplitude appears driven by hydroclimatic forcing. Ecologically, low NDVI is associated with leaf-off dipterocarp stands and exposed soils, whereas elevated NDVI characterizes evergreen/riparian zones with sustained moisture and canopy density.

Fig. 4. The spatial distribution of NDVI across Yok Don National Park – the mid-dry season from 2014 to 2024



The TVDI series (Fig. 5) reveals persistently high surface-moisture deficit across interior upland deciduous zones, whereas low TVDI is maintained along the Srepok River and major water bodies. Elevated TVDI dominates 2014–2017, consistent with high LST and low NDVI, implying strong drought stress. Conditions ease in 2018, especially along riparian corridors, although upland dryness persists. The most pronounced relief occurs in 2022, when extensive blue-green patches indicate the lowest TVDI of the decade; values rebound to near average in 2023, and dry conditions intensify again in 2024 over the central uplands while locally moist zones remain in the southeastern lowlands. The spatial pattern remains largely stationary, suggesting primary control by land cover and proximity to water, with interannual hydroclimatic variability modulating the magnitude. Ecologically, high TVDI

aligns with leaf-off dipterocarp stands or bare soils, whereas low TVDI coincides with evergreen/riparian areas and higher soil moisture.

VHI (Fig. 6) reveals a clear decadal swing in vegetation condition. Broad areas of low VHI dominate 2014–2017 across upland deciduous tracts, indicating widespread drought stress, with a pronounced peak in early 2016. Conditions improve in 2018, as high VHI expands along riparian belts and lowlands and penetrates into the interior, consistent with a moister background. A slight drought event may have occurred in 2019, after which greenness recovery is evident in 2022 with extensive high-VHI patches. This is followed by near-average conditions in 2023 and a mixed pattern in 2024, wherein riparian zones remain relatively healthy while upland sectors revert to moderate VHI.

VHI exhibits broad concordance with the other indicators: low VHI coincides with high LST, low NDVI, and high TVDI during 2015–2016 and 2019–2020, whereas the widespread high VHI in 2018 and 2022 aligns with cooler LST, greener NDVI, and low TVDI. Minor discrepancies arise where phenological leaf-off suppresses NDVI while temperatures remain moderate, dampening VHI through its thermal component;

where localized cooling near water reduces LST and TVDI but modest canopy vigor limits VHI increases; and where weighting or saturation in the VHI formulation attenuates extremes relative to TVDI. Overall, VHI functions as a conservative, integrated descriptor that captures the prevailing signal while smoothing anomalies driven solely by thermal or greenness variations.

Fig. 5. *The spatial distribution of TVDI across Yok Don National Park – the mid-dry season from 2014 to 2024*

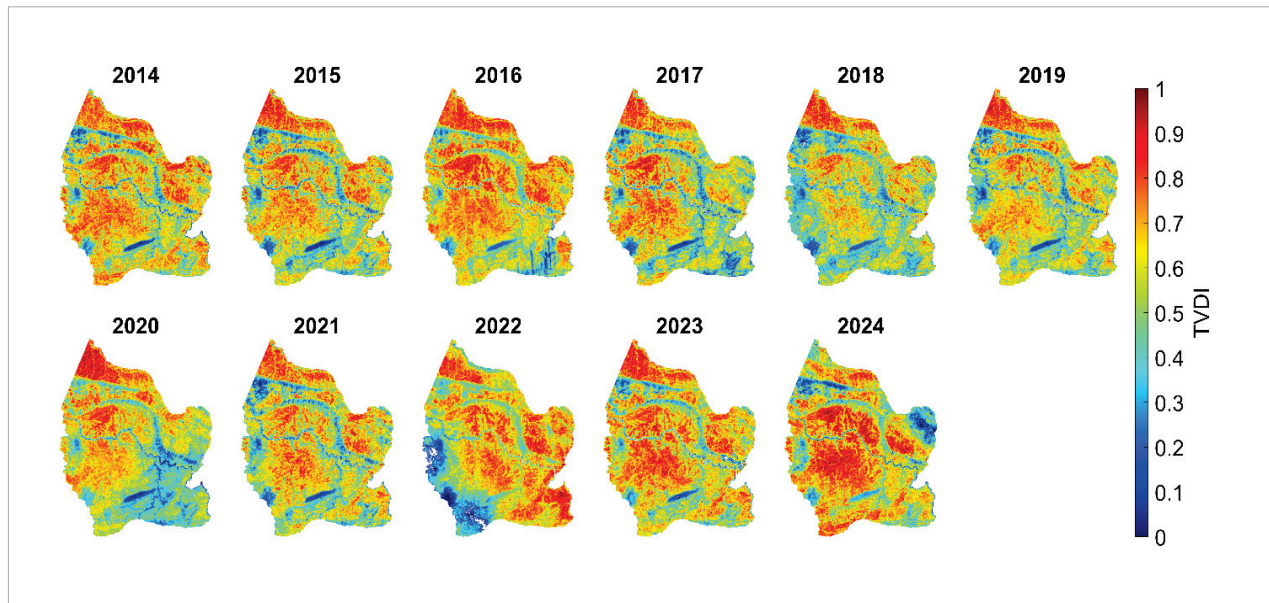
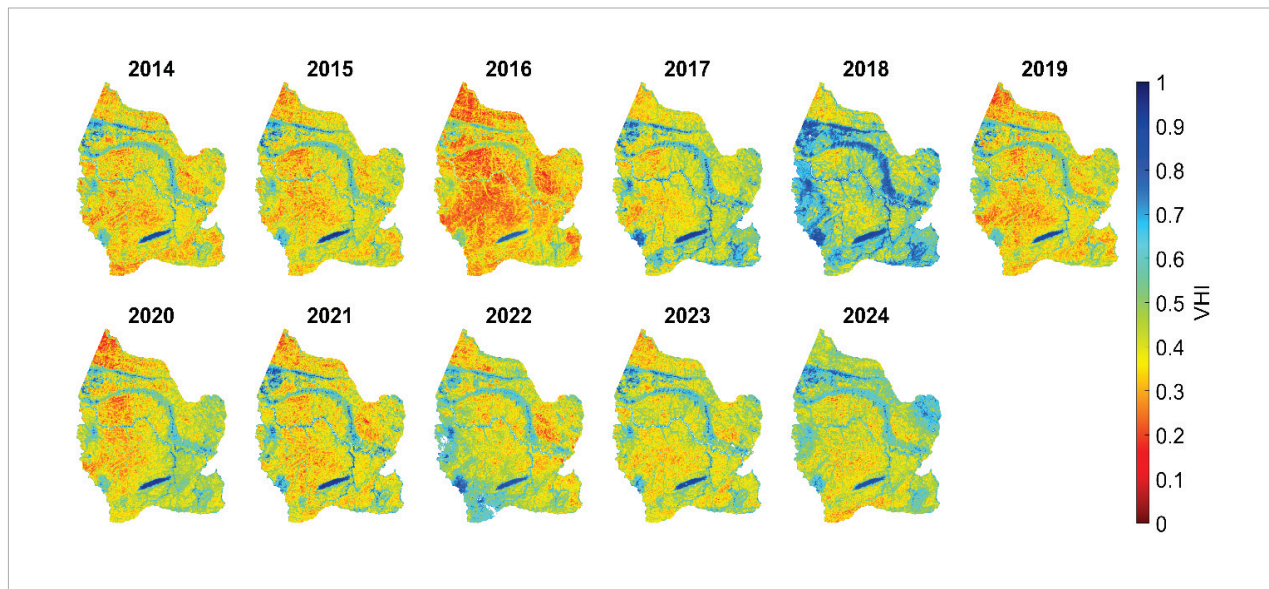


Fig. 6. *The spatial distribution of VHI across Yok Don National Park the mid- the dry season from 2014 to 2024*



Effectiveness of indicators in drought assessment

The effectiveness of the selected indices for drought assessment was verified against the MOD16A2 ET product during the dry seasons of 2014–2024 over Yok Don National Park (Fig. 7). The ET exhibits a stable spatial structure, with the highest values along the Srepok River and major water bodies and lowest values over interior upland deciduous areas. Interannually,

dry-season ET tracks hydroclimatic variability, being depressed in 2015–2016 and 2019–2020, markedly elevated in 2017 and especially 2022, with a partial rebound in 2021 and moderate levels in 2023–2024. Pearson correlation coefficients, computed from all available pixels and applied consistently across years to ensure spatial comparability and minimize sampling bias, are reported in Table 2.

Fig. 7. Spatial distribution of cumulative ET across Yok Don National Park for the first three months of each year from 2014 to 2024, derived from MODIS products

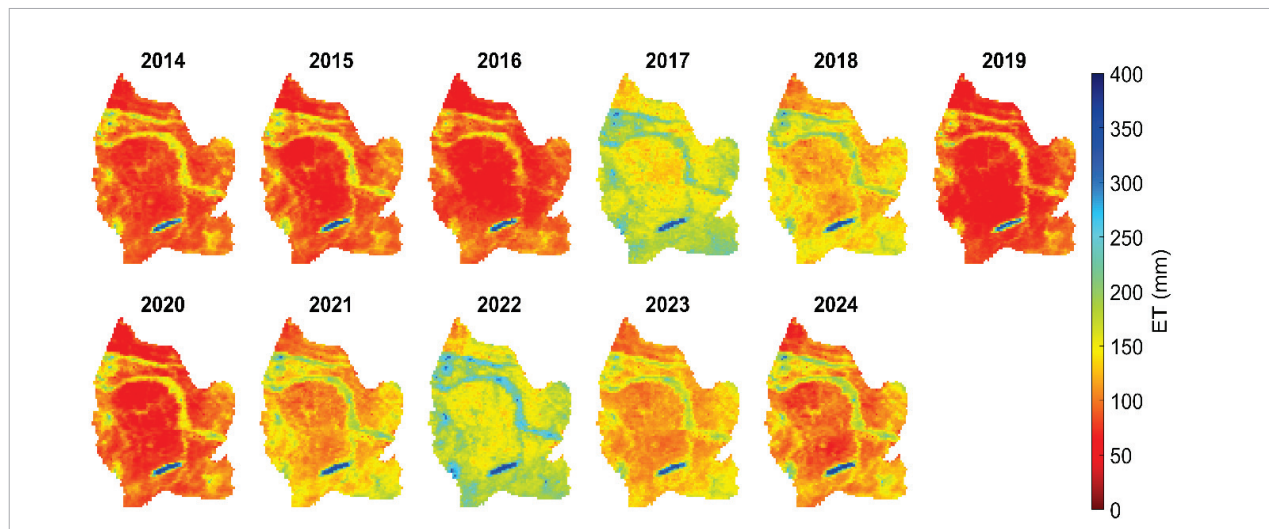


Table 2. Correlation between Drought Indices and ET over Yok Don National Park from 2014 to 2024

Years	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
LST	−0.729	−0.736	−0.696	−0.618	−0.692	−0.722	−0.671	−0.730	−0.597	−0.723	−0.656
NDVI	0.821	0.828	0.765	0.687	0.783	0.828	0.816	0.766	0.770	0.756	0.736
TVDI	−0.660	−0.652	−0.616	−0.596	−0.603	−0.635	−0.563	−0.691	−0.468	−0.675	−0.554
VHI	0.821	0.836	0.797	0.675	0.756	0.816	0.815	0.786	0.743	0.779	0.755

Performance of LST and NDVI

Table 2 shows the correlations between selected drought indicators and ET, illustrating their ability to capture drought intensity and temporal variability.

NDVI exhibited moderate to strong positive correlations with ET across all years, with correlation coefficients ranging from 0.687 to 0.828. The period of 2014–2016 coincided with severe drought conditions in the Central Highlands region (Nguyen et al., 2016; Tran et al., 2023; Nguyen et al., 2024), during which vegetation response

to water scarcity was particularly pronounced. Another notable drought period from 2019 to 2020 also showed significant correlations between NDVI and ET ($r = 0.828$ and 0.816 , respectively), with 2019 recording the highest correlation. In comparatively normal years, correlations were lowest in 2017 ($r = 0.687$), relatively high in 2018 ($r = 0.783$), and moderate in 2022–2024 ($r = 0.770$ to 0.736). The elevated NDVI–ET correlations during drought-affected periods indicate that vegetation water stress and associated declines in canopy greenness were closely aligned with reductions in ET, reflecting

physiological regulation of stomatal conductance and transpiration.

LST showed moderate-to-strong negative correlations with ET (-0.597 to -0.736), generally slightly lower in magnitude than NDVI. The most negative correlations occurred in 2014–2016 and 2019, 2021, and 2023 ($r \approx -0.70$ to -0.74), whereas weaker values appeared in 2017 and 2022 (-0.618 and -0.597). This pattern indicates a pronounced inverse relationship between surface temperature and vegetation water use under drier conditions. The results demonstrate LST's effectiveness in capturing the thermal manifestation of drought, particularly in early phases when ET declines before visible reductions in canopy greenness. Some attenuation is expected where heterogeneous land surfaces or complex topography introduce mixed thermal signals. Despite these influences, the consistently negative correlations underscore LST's value as a complement to NDVI, providing additional insight into drought-induced surface heating.

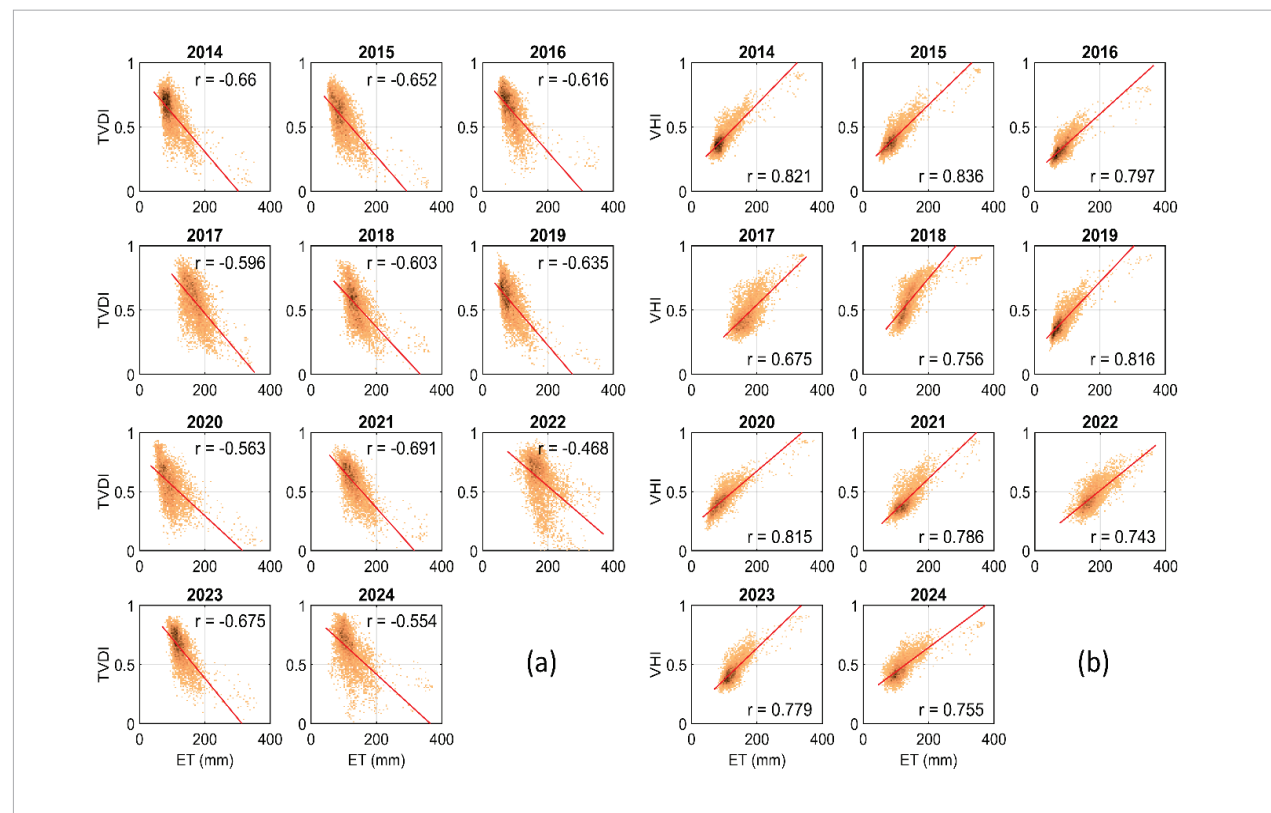
Despite these correlations, neither NDVI nor LST alone is sufficient to fully characterize the complexity of drought. However, each single indicator has important limitations. Consequently, using NDVI or LST alone cannot fully characterize drought dynamics in a heterogeneous landscape like Yok Don, even though both remain informative components of a broader assessment.

Performance of TVDI and VHI

By combining the strengths of single indicators, more reliable performance can be achieved. In this study, two established composites, VHI and TVDI, were evaluated to assess the effectiveness of combined indicators for drought monitoring. Consistent with *Table 2*, *Fig. 8* presents per-year scatterplots showing the relationships between ET and the two integrated indices for the mid-dry season across Yok Don National Park from 2014–2024.

Fig. 8. Scatter plots show the correlation between ET and TVDI (a), and VHI (b) across Yok Don National Park during the dry season (2014–2024).

Shaded dots represent data density, the red line is the linear regression, and r indicates the correlation coefficient with its value shown in each panel



A comparative reading indicates that VHI maintains strong, stable positive correlations with ET each year ($r \approx 0.675$ to 0.836), whereas TVDI shows moderate-to-strong negative correlations with greater inter-annual spread ($r \approx -0.468$ to -0.691). Although both indices draw on NDVI and LST, their performance differs because of their integration methodology and sensitivity to landscape heterogeneity. The higher stability of VHI likely reflects its normalization of temperature and greenness signals, which dampens scene-specific extremes, while TVDI's reliance on annual wet-dry edge calibration and local phenology makes it more variable across years and land-cover mosaics.

TVDI is constructed from the triangular relationship between NDVI and LST, in which scatterplots are used to delineate the “dry” and “wet” edges representing, respectively, the maximum and minimum LST for a given NDVI. Although it is theoretically grounded in surface energy-balance principles, TVDI is highly sensitive to how these edges are defined. Variations in land cover, vegetation type, and phenological stage can reshape the NDVI–LST triangular space, especially in heterogeneous landscapes. As Yok Don National Park is dominated by deciduous dipterocarp forests, this sensitivity can reduce TVDI's effectiveness. By contrast, VHI adopts a different strategy: NDVI and LST are integrated through spatial normalization rather than through predefined edges or geometric assumptions. This enables VHI to capture relative vegetation stress and thermal anomalies without presuming a fixed NDVI–LST form. Consequently, VHI is

less affected by land-cover heterogeneity and tends to be more robust in forested ecosystems with complex biophysical interactions. These differences underscore a key methodological insight: the effectiveness of integrated drought indices is largely determined by their integration frameworks. Although VHI and TVDI draw on the same inputs, their contrasting formulations yield markedly different outcomes.

To strengthen the interpretation of drought stages and year-to-year tendencies, satellite-derived precipitation from CHIRPS was incorporated as an independent driver alongside LST, NDVI, TVDI, VHI, and ET. The spatial distribution of total precipitation from the CHIRPS satellite product across Yok Don National Park from 2014 to 2024 are presented in *Fig. 9*. *Fig. 10* shows average monthly precipitation and mean annual precipitation, highlighting the strongly seasonal climate of Yok Don National Park. It is clear that the rainfall mosaics show pronounced interannual variability, with relatively low totals in 2015 and 2019, intermediate amounts in 2014, 2018, 2020, and 2024, and markedly wetter conditions in 2016–2017 and especially 2021–2023, when 2022 emerges as the wettest year. Spatially, higher rainfall repeatedly appears over the southeast lowlands and along river corridors, whereas interior uplands remain comparatively drier. These patterns are consistent with the biophysical indicators: dry years align with hotter surfaces, reduced greenness, higher TVDI, lower VHI, and depressed ET, while wet years, most notably 2022, correspond to cooler LST, greener NDVI, lower TVDI, higher VHI, and elevated ET.

Fig. 9. Spatial distribution of total precipitation from the CHIRPS satellite product across Yok Don National Park from 2013 to 2024

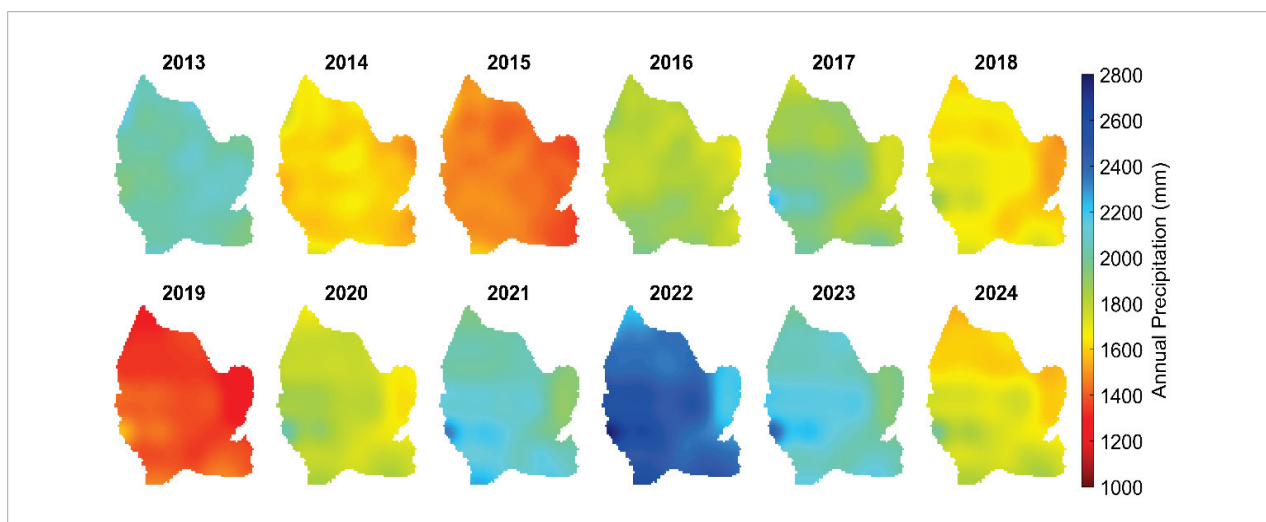


Fig. 10. Average monthly (blue bars) and annual (red diamonds) precipitation from the CHIRPS satellite product across Yok Don National Park for 2013–2024

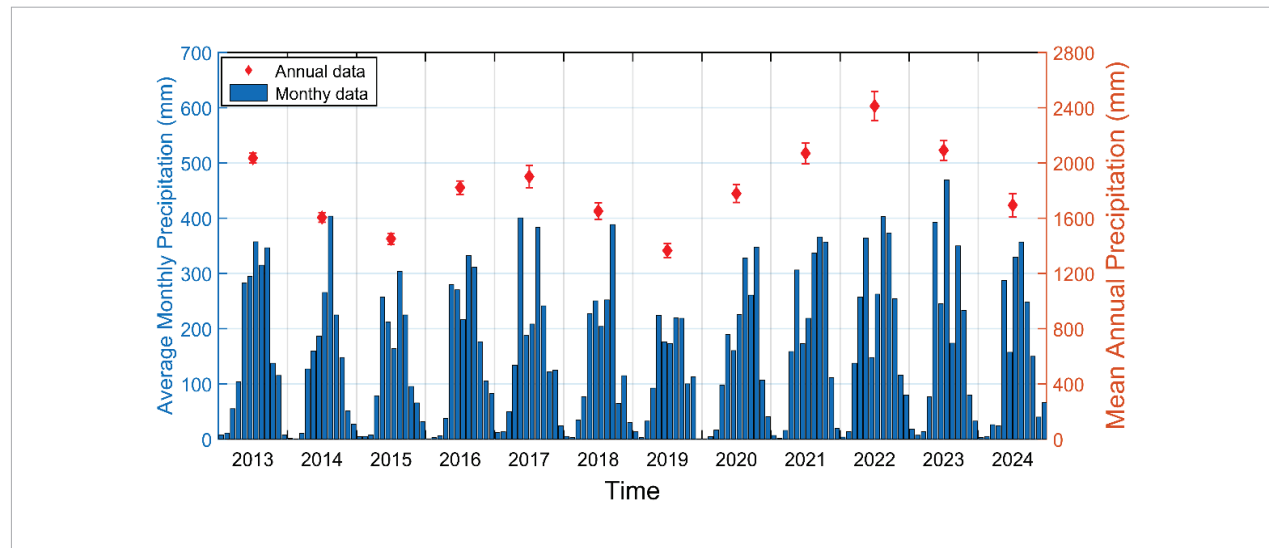
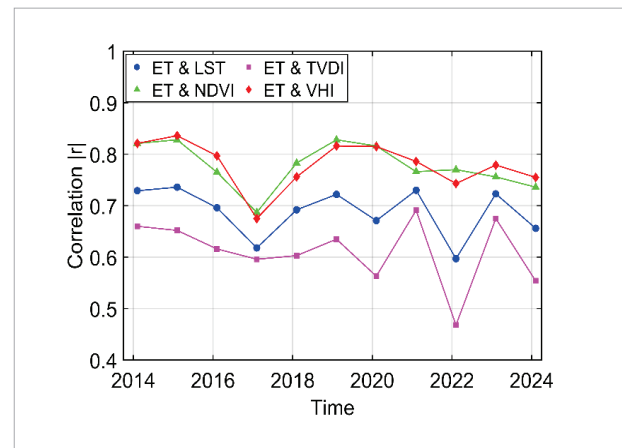


Fig. 11 summarizes how each indicator tracks drought across contrasting hydroclimatic phases. During dry-trending episodes (2013–2015, 2017–2019, and 2023–2024), as demonstrated by decreases in ET (Fig. 7) and precipitation (Fig. 10) and supported by other reports (IRI, 2024; Nguyen et al., 2024), the VHI–ET relationship is more stable than the NDVI–ET relationship, indicating that the integrated signal of canopy condition and surface thermal stress remains consistently coupled to ET as drying intensifies. During wet-trending intervals (2017–2018, 2020–2021, and especially 2022), NDVI tends to adjust more quickly, whereas VHI shows slower changes in correlation, consistent with an integrated index that moderates rapid greenness increases when moisture becomes abundant. The auxiliary curves support this interpretation: LST remains negatively correlated with ET but at a lower magnitude than VHI or NDVI, and TVDI is the weakest and most variable indicator across years. Overall, VHI serves as a more stable proxy during drying and drought conditions, while NDVI provides the clearest and faster signal during wetting phases.

Conclusions

This study evaluated the effectiveness of NDVI, LST, TVDI, and VHI for characterizing drought in the ecologically complex forests of Yok Don National Park

Fig.11. Variations in correlations between the indicators and ET over Yok Don National Park from 2014 to 2024



during the dry seasons from 2014 to 2024. NDVI and LST were both informative but captured different facets of stress. Integrated indices addressed several of these limitations, with performance depending on the integration framework. VHI, which integrates NDVI and LST through spatial normalization rather than a fixed NDVI–LST geometry, showed strong and comparatively stable positive correlations with ET across years and was relatively resilient to land-cover heterogeneity. TVDI, which relies on a triangular NDVI–LST space with predefined dry and wet edges, was negatively correlated with ET but with lower magnitude and greater

interannual variability, likely reflecting sensitivity to edge definition and phenology in mixed forest mosaics. Phase-dependent behavior was evident. During dry-trending episodes in 2015–2016, 2019–2020, and 2023–2024, the VHI–ET relationship remained more stable than the NDVI–ET relationship, indicating that an integrated signal combining canopy condition and surface thermal stress remained consistently aligned with ET as drying intensifies. Taken together, these patterns suggest a practical strategy for forests: rely on VHI during drying phases for stability, prioritize NDVI during wetting phases for sensitivity, and retain LST and TVDI as complementary layers for early warning and spatial diagnostics. These findings highlight the potential of adaptive or hybrid schemes that dynamically weight NDVI and LST according to hydroclimatic phase and land-cover class to improve accuracy and transferability across diverse landscapes. Furthermore, the results demonstrate that VHI

offers a more robust approach for drought assessment in dipterocarp forest ecosystems, outperforming TVDI despite using similar input data. This suggests that the approach can be extended and evaluated across other ecosystem types in future studies.

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