



# OPEN Exploring vegetation health in Southern Thailand under climate stress from temperature and water impacts between 2000 and 2023

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This study provides a detailed spatiotemporal analysis of vegetation health in Southern Thailand from 2000 to 2023, focusing on the impacts of temperature and water stress on vegetation degradation. Using high-resolution Landsat-derived kernel Normalized Difference Vegetation Index (kNDVI) and Land Surface Temperature (LST), alongside precipitation (PPT), soil moisture (SM), vapor pressure deficit (VPD), and solar radiation (SR), several key indices were derived such as Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI). The study offers a robust framework to monitor vegetation health under climate stress by integrating satellite-based indices with detailed climate datasets. Our findings reveal significant temperature-induced stress during critical years like 2005 and 2016, with over 60% of the region experiencing vegetation degradation. Long-term trend analysis indicates that while 22.5% of forested areas show signs of recovery, 3.6% continue to degrade, primarily due to persistent temperature extremes and water stress. Soil moisture emerged as a critical driver during the dry season, positively influencing 11.16% of the region, while solar radiation exhibited mixed effects depending on moisture availability. These insights highlight the complex interplay of climatic drivers on vegetation dynamics, particularly in tropical ecosystems. The study underscores the need for adaptive management strategies to enhance resilience against climate extremes, providing valuable guidance for sustainable land management in Southern Thailand.

**Keywords** Vegetation health index, kNDVI, Land surface temperature, Climate stress, Drought impacts, Spatiotemporal analysis, Southern thailand, Ecosystem resilience

The increase in both frequency and intensity of climate extremes has become a critical global issue<sup>1,2</sup>, significantly impacting tropical ecosystems where vegetation is highly vulnerable to temperature changes and water stress<sup>3–6</sup>. Given these shifts, vegetation health is now seen as a critical indicator of ecosystem resilience, requiring consistent monitoring to support effective land management and conservation<sup>7–9</sup>. Southern Thailand, known for its tropical forests, mangroves, and agricultural landscapes, faces escalating impacts from rising temperatures and shifting rainfall patterns<sup>10,11</sup>. While the vulnerabilities of these ecosystems are broadly acknowledged, limited research has been conducted on the region's long-term vegetation dynamics under climate stress, highlighting a significant research gap. These climate changes pose severe risks to vegetation health, contributing to land degradation, declining productivity, and biodiversity loss<sup>12–14</sup>. Various indices, such as kNDVI, VCI, TCI, and VHI have proven effective for assessing vegetation health by capturing the complex interactions among vegetation growth, climate factors, and environmental stressors<sup>15,16</sup>. These indices provide a nuanced view

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of vegetation dynamics by accounting for biotic and abiotic stressors like drought, heat waves, and moisture availability<sup>17–19</sup>. The evaluation of vegetation health remains a core focus in ecological and environmental research, with numerous indices designed to measure vegetation vigor and stress<sup>20,21</sup>. However, while these indices are widely applied, their integration with detailed climate datasets to examine the interplay of multiple stressors across spatiotemporal scales remains underexplored in Southern Thailand's diverse ecosystems. The Normalized Difference Vegetation Index (NDVI) is the most widely utilized metric for monitoring vegetation dynamics<sup>22,23</sup>. However, recent advancements have introduced enhanced versions, such as the kNDVI, which offers improved sensitivity to vegetation changes in complex ecosystems<sup>24</sup>. The kNDVI employs kernel-based methods to overcome limitations associated with traditional NDVI, particularly in tropical regions, where dense vegetation and varied landscapes may obscure changes in vegetation health<sup>24,25</sup>. The kernel NDVI (kNDVI) was adopted because it outperforms standard NDVI in three practical ways. (i) kNDVI remains quasi-linear up to LAI  $\approx 6$ –7, whereas NDVI plateaus near LAI  $\approx 3$ –4<sup>24,25</sup>. (ii) its Gaussian kernel linearizes illumination- and sensor-induced heteroscedasticity, reducing scene-level noise by  $\approx 10$ –15% in hazy, cloud-affected imagery<sup>26</sup>. (iii) Background bias being rank based, kNDVI is far less sensitive to soil and aerosol contamination than Soil Adjusted Vegetation Index (SAVI) or Enhanced Vegetation Index (EVI), which require empirical coefficients<sup>30</sup>. Comparative evaluations at Southeast-Asian flux-tower sites show that kNDVI explains 8–11% more variance in gross primary production than NDVI or EVI<sup>31</sup>. Alongside kNDVI, indices like VCI and TCI have been designed to offer more focused assessments of specific environmental stressors<sup>27</sup>. VCI, for instance, assesses vegetation health by comparing it to historical variability, making it especially useful for identifying the effects of drought and land degradation<sup>28,29</sup>. Conversely, TCI specifically targets temperature-related stress, a growing concern in tropical areas experiencing rising temperatures and frequent extreme heat events<sup>30,31</sup>. By combining indices like TCI and VCI, the VHI provides a holistic tool for assessing biotic and abiotic stressors, making it valuable for tracking long-term vegetation trends<sup>32,33</sup>. Spatial modeling approaches, as demonstrated in recent studies on water availability and vegetation stress in India<sup>34–36</sup>, provide valuable insights for integrating climatic factors into vegetation health assessments across tropical ecosystems. In addition, optimizing land use for climate mitigation through nature-based solutions, as highlighted in Rajasthan<sup>37</sup>, reinforces the role of vegetation monitoring in guiding sustainable land-use planning. Furthermore, soil moisture anomalies have been shown to significantly impact agricultural productivity and water resource management<sup>38</sup>, underlining their critical role in understanding vegetation dynamics within moisture-sensitive regions.

### Climatic drivers of vegetation dynamics

The association between climate factors and vegetation health is well-documented, with temperature and water availability emerging as critical influences on vegetation dynamics<sup>39–42</sup>. Higher temperatures, especially during the growing season, are associated with reduced vegetation productivity and higher mortality from heat stress<sup>43–45</sup>. Like those in Southern Thailand, tropical ecosystems are particularly at risk, operating near their thermal limits<sup>46,47</sup>. Studies increasingly highlight the impact of temperature anomalies, noting that extreme heat events can significantly impair vegetation growth and lead to long-term ecosystem degradation<sup>48–52</sup>. Water availability, often estimated through precipitation (PPT) and soil moisture (SM), is critical to vegetation health. Drought conditions resulting from lower rainfall or higher evapotranspiration are linked to severe vegetation stress and land degradation in tropical regions<sup>39,53,54</sup>. VPD further complicates this relationship by intensifying water stress through increased transpiration and moisture loss during prolonged dry spells<sup>55,56</sup>. Studies show that regions with sufficient soil moisture display stronger resilience to temperature stress, highlighting the need for comprehensive assessments that integrate both temperature and moisture factors to monitor vegetation health accurately<sup>57–59</sup>.

### Vegetation dynamics in Southern Thailand

Research on vegetation dynamics in Southern Thailand has primarily focused on its biodiversity and the effects of land use changes, such as deforestation and agricultural growth<sup>60</sup>. However, the impact of long-term climate variability on vegetation health is less frequently addressed. Some studies indicate rising temperatures and shifting rainfall patterns drive vegetation degradation, especially within forests and agricultural zones<sup>61,62</sup>. Mangrove ecosystems, critical for coastal protection and biodiversity, also face threats from sea-level rise and temperature stress, posing further risks to the region's ecological stability<sup>63–67</sup>. Despite these challenges, there is limited research integrating vegetation indices that incorporate climate responsiveness, such as kNDVI, VCI, TCI, and VHI with climatic drivers to capture the interplay of stressors in these critical ecosystems.

Although numerous studies examine climate change impacts on vegetation health, a crucial gap remains in understanding the long-term spatiotemporal dynamics of vegetation health in Southern Thailand. Much research has focused on broader areas or specific vegetation types, often overlooking the distinct climatic conditions and land-use patterns unique to this tropical region. Furthermore, while traditional indices like NDVI are widely used, fewer studies have adopted advanced indices such as kNDVI alongside essential climate variables to capture the combined effects of moisture stress and energy-related variables, including temperature and solar radiation, on vegetation. Research on the resilience of different land uses, such as forests, agricultural lands, shrublands, and mangroves, to prolonged climate stress over decades is also notably limited. This study integrates widely employed indices, including kNDVI, VHI, and TCI, with detailed climate datasets in a long-term spatiotemporal framework, focusing specifically on Southern Thailand's unique tropical ecosystems. By employing a dynamic thresholding approach and analyzing ecosystem-specific responses, the study provides novel insights into the interplay of temperature and water stress on vegetation health, offering actionable recommendations for adaptive management. Given these gaps, this study hypothesizes that vegetation health in Southern Thailand exhibits distinct responses to climatic stressors, driven predominantly by temperature and water availability, with variability across land-use types and ecosystems. The objectives are: (1) Quantify

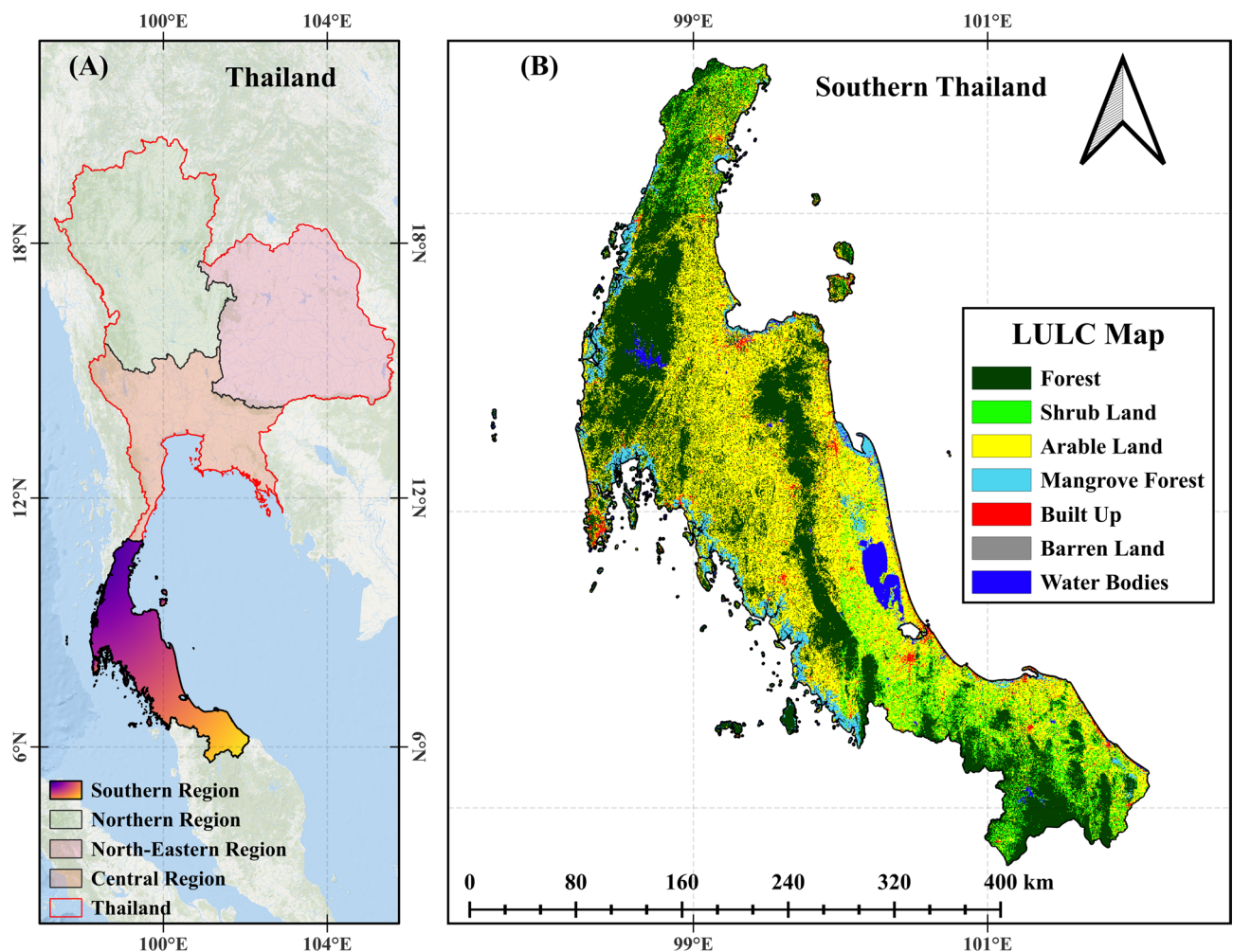
long-term vegetation stress and degradation using advanced satellite-derived indices (kNDVI, VCI, TCI, and VHI) from 2000 to 2023. (2) Analyze the contributions of key climate variables (PPT, SM, VPD, SR, and LST) to vegetation health trends across seasonal and annual timescales. (3) Identify critical years of vegetation stress and assess the severity of degradation. (4) Evaluate the resilience of different land-use types (forests, agricultural lands, shrublands, and mangroves) to climatic extremes. Ultimately, this research seeks to address the identified knowledge gaps and provide actionable insights to support adaptive land management strategies that mitigate the impacts of climate variability and enhance ecosystem resilience in tropical ecosystems.

## Materials and methods

### Study area

The study area covers Southern Thailand, from 97.63°E to 102.09°E longitude and 5.62°N to 11.03°N latitude. This region experiences a tropical climate with consistently high temperatures and distinct wet and dry seasons, making it particularly susceptible to extreme temperature changes and water scarcity<sup>68,69</sup>. This area's diverse ecosystems, including tropical rainforests, mangroves, and agricultural lands, exhibit varying resilience to drought and rising temperatures<sup>70</sup> (Fig. 1). These ecosystems are ecologically vital and central to the region's economy, especially in agriculture and forestry, and rely heavily on vegetation health<sup>71,72</sup>. Declined vegetation vitality due to climate stress could have significant socio-economic effects, including reduced agricultural productivity and accelerated land degradation<sup>73</sup>.

Recent trends in climate variability characterized by rising temperatures and unpredictable precipitation patterns highlight Southern Thailand's ecosystems' increasing vulnerability to persistent environmental stressors<sup>74–76</sup>. Although these ecosystems are critically important, there is a notable scarcity of long-term research specifically investigating the effects of climate variability on vegetation health. This gap makes Southern



**Fig. 1.** (A) Map of Thailand showing regional divisions with the Southern Region highlighted. (B) The Land Use/Land Cover (LULC) map of Southern Thailand displays different land cover types, including forest, shrubland, arable land, mangrove forest, built-up areas, barren land, and water bodies. The LULC map provides the spatial distribution of these categories across Southern Thailand. LULC data were obtained from the ESA WorldCover 2021 dataset (<https://esa-worldcover.org>). The map was generated using the QGIS stable version (Long Term version for Windows (3.34 L)). The software is available at <https://www.qgis.org/download/>.

Thailand an insightful case for studying the broader implications of climate change on tropical ecosystems. In such contexts, climate stress can set off a series of cascading impacts spanning ecological, economic, and social dimensions, with significant and widespread consequences.

Dataset

The dataset for this study spans 2000 to 2023 and integrates satellite-derived and climate data to evaluate vegetation health. Primary data sources include Landsat 5, 7, 8, and 9 for calculating kNDVI and LST, supplemented by environmental variables such as PPT, SM, VPD, and SR. LST values were derived on the Google Earth Engine (GEE) platform, following<sup>77</sup>’s methodology, which extracts LST from the thermal infrared bands of Landsat 5, 7, 8, and 9 (see Table 1). The GEE code repository facilitated high-resolution LST calculations, aligning them with kNDVI data for consistency<sup>78</sup>. Additionally, PPT data were sourced from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset, known for its high spatial resolution<sup>79,80</sup>. SM, VPD, and SR data were obtained from the TerraClimate database to account for moisture conditions, atmospheric demand, and energy availability for vegetation growth, respectively<sup>81,82</sup> (Table 1).

Preprocessing the datasets involved several vital steps to ensure consistency and accuracy. Landsat images were atmospherically corrected and cloud-masked using GEE functions<sup>83,84</sup>. Both kNDVI and LST were derived from the processed Landsat imagery. At the same time, the PPT, SM, VPD, and SR datasets were resampled using bilinear interpolation to match the 30-meter spatial resolution of the Landsat data. Given the challenges of obtaining clear monthly Landsat imagery in humid regions like southern Thailand, robust preprocessing steps were implemented to handle cloud cover and ensure data quality. Temporal aggregation was performed to compute annual, dry season, and wet season averages, which are the most suitable timeframes for Southern Thailand. For monthly composites, median compositing was used to reduce the influence of residual cloud contamination and ensure representative surface reflectance. Annual and seasonal composites were derived by averaging these monthly medians. In cases where more than 50% of the pixels in a month were masked due to clouds, linear interpolation was used from adjacent months to fill gaps, validated against CHIRPS precipitation anomalies to confirm that seasonal patterns were preserved ( $R^2 = 0.78, p < 0.01$ ) (Figure S5). All datasets were clipped to the study area and aligned to ensure uniform spatial and temporal scales for further analysis (Fig. 2).

Methodology  
Landsat imagery and kNDVI calculation

Landsat satellite imagery was obtained from the United States Geological Survey (USGS), providing multispectral data at a 30-meter spatial resolution. From these images, the kNDVI was calculated using the Near-Infrared (NIR) and red bands<sup>24</sup> (Eq. 1).

$$kNDVI = \frac{k(n,n) - k(n,r)}{k(n,n) + k(n,r)} \tag{1}$$

where n and r represent the reflectance of the NIR and red bands, respectively. The  $k(n,r)$  represents the kernel function (Eq. 2)

$$k(n,r) = exp\left(\frac{-(n-r)^2}{2\sigma^2}\right) \tag{2}$$

Simplifies as (Eq. 3)

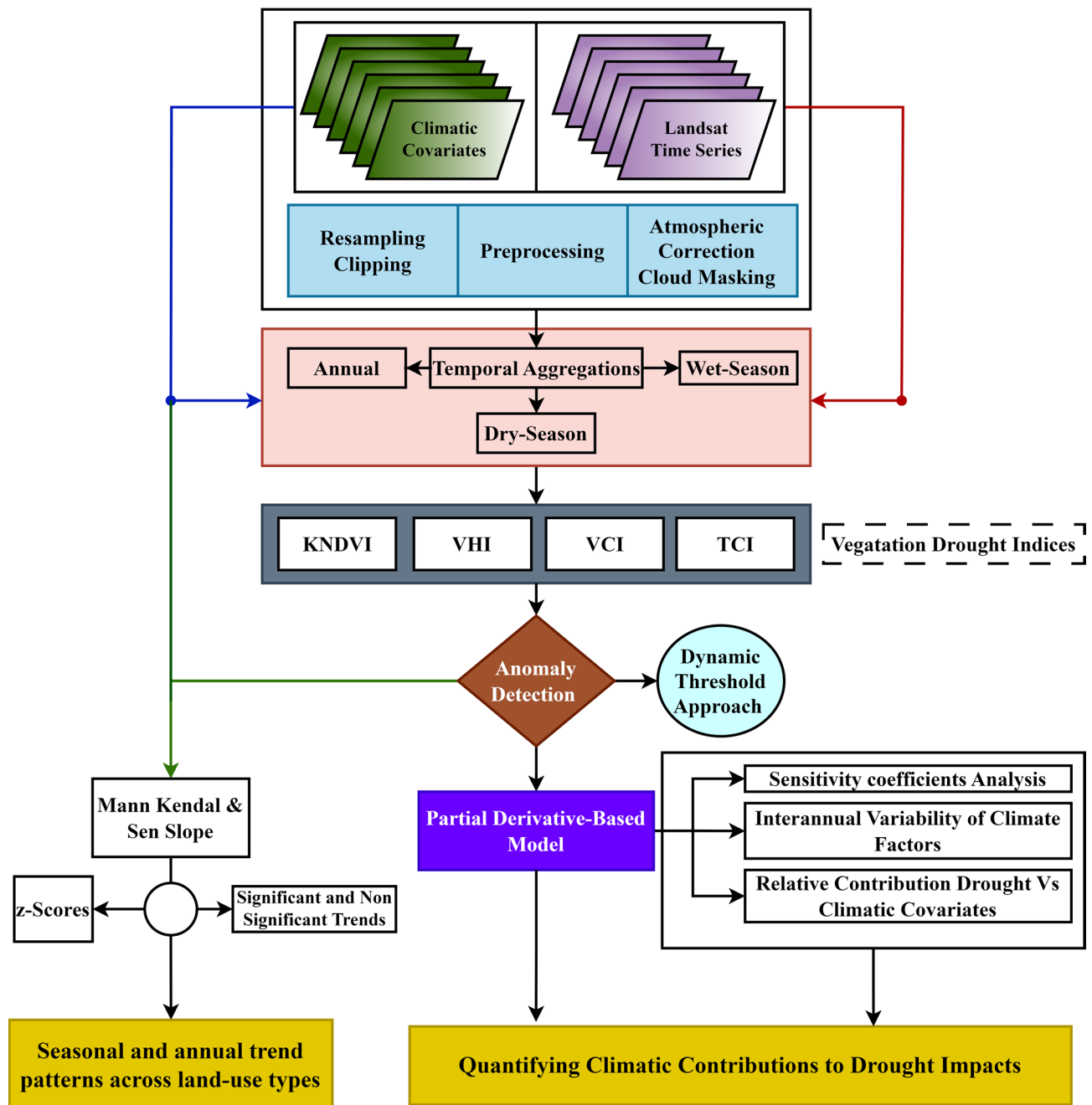
$$kNDVI_{new} = tanh\left(\frac{n-r}{2\sigma^2}\right) \tag{3}$$

Monthly kNDVI values ( $kNDVI_{new}$ ) were computed and then averaged for the growing season to represent the dominant vegetation growth for each year between 2000 and 2023. The parameter  $\sigma$  was identified pixel-wise as region-specific to ensure the accuracy of kNDVI values for the study area<sup>85,86</sup>. Dense forest areas utilized smaller  $\sigma$  values to enhance sensitivity to subtle vegetation changes, while agricultural and mixed-use areas employed larger  $\sigma$  values to account for heterogeneity. The annual and seasonal  $\sigma$  values are provided in Tables S1 and

Dataset	Variables	Spatial	Temporal	Acquisition Period <sup>†</sup>	Access URL / GEE ID
Landsat 5, 7, 8, 9	kNDVI, LST	30 m	Monthly, Annual, Dry / Wet	Jan 2001 – Dec 2023	USGS EarthExplorer <a href="https://earthexplorer.usgs.gov">https://earthexplorer.usgs.gov</a>
CHIRPS v2.1	Precipitation	0.05° (~ 5.5 km)	Monthly, Annual, Dry / Wet	Jan 2001 – Dec 2023	GEE ID: UCSB-CHG/CHIRPS/DAILY <a href="https://www.chc.ucsb.edu/data/chirps">https://www.chc.ucsb.edu/data/chirps</a>
TerraClimate	Soil moisture	1/24° (~ 4 km)	Monthly, Annual, Dry / Wet	Jan 2001 – Dec 2023	GEE ID: IDAHO_EPSCOR/TERRACLIMATE <a href="https://www.climatologylab.org">https://www.climatologylab.org</a>
	Vapour-pressure deficit	1/24°	Monthly, Annual, Dry / Wet	Jan 2001 – Dec 2023	Same as above
	Solar radiation	1/24°	Monthly, Annual, Dry / Wet	Jan 2001 – Dec 2023	Same as above

**Table 1.** Summary of datasets used in the Study. <sup>†</sup>All datasets were clipped to the study period 2001–2023 and to Landsat path/rows 129/53–130/53, 129/54, 128/55 and 127/56 that fully cover southern Thailand.





**Fig. 2.** Step-by-step process for dataset integration, analysis, and evaluation of climatic impacts on vegetation health.

S2 to enhance transparency and reproducibility<sup>87,88</sup>. The calculated kNDVI data, along with LST, were used to derive three key indices (i.e., VCI, TCI, and VHI) to assess vegetation stress and drought conditions more holistically<sup>89,90</sup>. These indices provide a robust framework for understanding the interaction between vegetation vigor, climatic factors, and temperature-induced stress, which are essential for the long-term monitoring of vegetation health.

#### Climatic stress indicators of vegetation health

VCI was derived from kNDVI to monitor vegetation vigor relative to its historical range. It reflects how current vegetation conditions compare to the best and worst observed conditions over the study period<sup>91,92</sup>. By normalizing kNDVI to the historical minimum and maximum values, VCI captures the relative health of vegetation based on its growth potential under normal conditions (Eq. 4).

$$VCI = \frac{kNDVI - kNDVI_{min}}{kNDVI_{max} - kNDVI_{min}} \times 100 \quad (4)$$

where  $kNDVI_{min}$  and  $kNDVI_{max}$  represent the minimum and maximum kNDVI values observed over the study period. This index is critical for identifying periods of vegetation stress due to drought or land degradation, as it directly links current conditions to historical extremes<sup>93</sup>.

TCI reflects temperature-induced stress in vegetation and is based on LST. High temperatures can lead to moisture loss, heat stress, and reduced photosynthetic activity, which negatively impact vegetation<sup>94,95</sup>. TCI measures how far the current LST deviates from the optimal temperature range for vegetation growth<sup>96</sup> (Eq. 5).

$$TCI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \times 100 \quad (5)$$

TCI is essential for assessing the impact of extreme temperatures on vegetation, particularly in regions where heat stress is a major limiting factor for plant growth. VHI integrates both VCI and TCI to comprehensively assess vegetation health, capturing both vegetation vigor and temperature-related stress<sup>97</sup>.

VHI integrates both VCI and TCI to provide a comprehensive indicator of vegetation health, accounting for both biotic (vegetation vigor) and abiotic (temperature stress) influences<sup>97,98</sup>. (Eq. 6).

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI \quad (6)$$

Where  $\alpha$  is a weighting factor, typically set to 0.5, giving equal importance to VCI and TCI<sup>99,100</sup>. The flexible weighting allows for adjustments based on the relative importance of temperature and vegetation vigor in different regions or seasons. This adaptability is particularly useful in areas like Southern Thailand, where climatic factors and temperature stress influence vegetation during wet and dry seasons. These indices were calculated for each year from 2000 to 2023, providing a detailed, multi-dimensional assessment of vegetation health, and stress across the study period. Integrating kNDVI, LST, and climate variables allows for a more robust analysis of vegetation dynamics, helping to identify critical periods of stress and offering valuable insights into environmental management and drought mitigation.

### Anomaly calculation for vegetation health, vegetation condition, and temperature condition indices

This study assesses vegetation health from 2000 to 2023 by calculating anomalies for VHI, VCI, and TCI, which indicate deviations from long-term trends and highlight periods of vegetation stress or favorable conditions. Annual mean values for each index were calculated as the average of monthly data for each year (Eq. 7)<sup>101,102</sup>, and long-term averages were established as baselines for detecting anomalies (Eq. 8)<sup>103</sup>.

$$Mean_X^i = \frac{\sum_{m=1}^n X_m^i}{n} \quad (7)$$

$$\bar{X} = \frac{\sum_{i=1}^N X_m^i}{N} \quad (8)$$

Here,  $Mean_X^i$  represents the annual mean for index X in year i, and  $\bar{X}$  denotes the long-term mean of the index over n years. Anomalies ( $X_{anomaly}^i$ ) were expressed as the percentage deviation from the long-term mean (Eq. 9).

$$X_{anomaly}^i = \frac{Mean_X^i - \bar{X}}{\bar{X}} \times 100 \quad (9)$$

Positive anomaly values indicate better-than-average vegetation health, while negative values suggest potential stress or drought conditions<sup>98,104</sup>. A dynamic thresholding approach was applied to ensure the meaningful identification of significant anomalies.

### Dynamic threshold approach for anomaly detection in vegetation health indices

This study evaluated the annual anomalies of the VHI, VCI, and TCI from 2000 to 2023 to assess vegetation stress and drought conditions. To objectively identify significant anomalies, dynamic thresholds were established for each index based on their statistical distributions<sup>105</sup>. Specifically, a severe anomaly threshold was defined as two standard deviations below the mean ( $\mu_X - 2\sigma_X$ ), and a normal threshold as two standard deviations above the mean ( $\mu_X + 2\sigma_X$ )<sup>105,106</sup>. This approach is grounded in the empirical rule, which posits that approximately 95% of normally distributed data falls within  $\pm 2$  standard deviations from the mean, ensuring that identified anomalies are statistically significant and not due to random variability<sup>107</sup>. For each index X (VHI, VCI, TCI), the thresholds were calculated as (Eqs. 10 and 11):

$$\text{Severe Threshold} = \mu_X - 2\sigma_X \quad (10)$$

$$\text{Normal Threshold} = \mu_X + \sigma_X \quad (11)$$

where  $\mu_x$  represents the mean of the annual anomalies for index X and  $\sigma_x$  denotes the standard deviation of the yearly anomalies for index X. This method ensures that significant deviations from the norm, identified as anomalies, are statistically robust and not due to random fluctuations. Furthermore, to isolate the most critical adverse events, the 90th percentile of the severity index was employed to identify the top 10% worst years for each index. This percentile-based criterion focuses the analysis on extreme events that have the most substantial impact on vegetation health, enhancing the study's relevance for drought monitoring and environmental management. The selected thresholds are pivotal for differentiating typical variability from significant stress events in vegetation indices. By employing statistically derived thresholds, the study ensures that the identification of severe anomalies is both objective and reproducible, thereby strengthening the validity and reliability of the findings. Additionally, this study applies the dynamic thresholding approach in combination with integrated statistical and spatial analysis methods, such as the use of kNDVI and climate variables, to better capture subtle vegetation responses under complex environmental stressors. This enhanced detection of extreme stress events, tailored to the unique conditions of Southern Thailand's tropical ecosystems, provides a more detailed understanding of vegetation health dynamics compared to conventional static thresholds.

### Trend analysis

A detailed trend analysis of VHI, TCI, and VCI was conducted to assess vegetation health across distinct land use categories in Southern Thailand. This analysis involved both seasonal and annual trends, employing the Mann-Kendall test to evaluate the presence of monotonic trends and Sen's slope estimator to quantify the rate of these changes.

#### Mann-Kendall test

The Mann-Kendall test was selected due to its non-parametric nature, making it suitable for environmental time series data that often deviate from normality<sup>108,109</sup>. The test evaluates the trend by analyzing pairs of observations over time. For a time series of  $n$  observations  $x_1, x_2, \dots, x_n$ , the Mann-Kendall statistic  $S$  was computed as follows (Eq. 12):

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (12)$$

where  $\text{sgn}(x_j - x_k)$  is the sign function, defined as (Eq. 13):

$$Z = \begin{cases} \frac{s-1}{\sqrt{\text{var}(s)}} & \text{when } S > 0 \\ 0 & \text{when } S = 0 \\ \frac{s+1}{\sqrt{\text{var}(s)}} & \text{when } S < 0 \end{cases} \quad (13)$$

This test identifies whether there is a statistically significant upward or downward trend. A positive  $S$  indicates an increasing trend, while a negative  $S$  suggests a decreasing trend<sup>110</sup>. The significance level is determined using  $Z$ -statistics, enabling us to evaluate the null hypothesis of no trend.

#### Sen's slope estimator

To measure the magnitude of the trends, Sen's slope, was applied which provides a robust estimate of the rate of change<sup>111,112</sup>. This method calculates the slope ( $\beta$ ) between each pair of data points and then takes the median of these slopes as the trend magnitude. For any two points  $(i, j)$  in the time series, the slope is calculated by using Eq. 14:

$$Q_i = \frac{x_j - x_i}{j - i}, \text{ for all } 1 \leq i < j \leq n. \quad (14)$$

Here, Sen's slope offers a resilient estimate to reduce the influence of outliers and also represents the median rate of changes in VHI, TCI, and VCI anomalies.

The Mann-Kendall test and Sen's slope were applied across seasonal and annual VHI, TCI, and VCI datasets. This allowed us to observe vegetation and temperature stress patterns under varying climatic conditions. Trends in land use types, were assessed including forested regions, shrublands, agricultural land, and urban areas. The seasonal analysis captured the variability of vegetation responses during dry and wet periods, while the annual analysis offered insights into long-term trends.

### Quantitative assessment of climate factor contributions to VHI, VCI, and TCI variations

This study employs a rigorous quantitative approach to assess the relative contributions of selected climate variables LST, PPT, VPD, SM, and SR to variations in three key vegetation indices: the VHI, VCI, and TCI. The analysis utilizes a partial derivative-based model, implemented within a linear regression framework, to derive the sensitivity of each index to climate factors and the corresponding interannual variability. The results allow for the computation of the relative contributions of each factor, highlighting their influence on vegetation dynamics.

#### Modeling framework

The relationship between each vegetation index (VHI, VCI, TCI) and the climate factors was modeled using a linear regression approach. The relative contributions of each climate factor to variations in these indices were computed based on the partial derivative of each index for the respective climate variables<sup>113,114</sup> (Eq. 15). For VHI, all selected climate factors were included to capture the comprehensive influence of climate variability

on overall vegetation health. In contrast, the VCI analysis focused on PPT, VPD, SM, and SR, as these factors are more directly related to water availability and vegetation conditions. For TCI, the analysis was narrowed down to LST, VPD, and SR, as these factors are more directly related to temperature stress and its impact on vegetation<sup>115,116</sup>. This targeted approach for each index ensures the most relevant climate factors are assessed based on the specific dynamics of the studied index.

$$C_{f_i} = \beta_{f_i} \cdot \Delta_{f_i} \quad (15)$$

where  $C_{f_i}$  denotes the contribution of the  $i^{\text{th}}$  climate factor,  $\beta_{f_i}$  represents the sensitivity of VHI to the  $i^{\text{th}}$  climate factor derived from the linear regression model<sup>117</sup>. The  $\Delta_{f_i}$  signifies the temporal variation (standard deviation) of the  $i^{\text{th}}$  climate factor. The total contribution of each climate factor was calculated by combining its sensitivity with the degree of its variability over time<sup>118</sup>.

#### Sensitivity analysis

The sensitivity of each vegetation index to the selected climate factors  $\beta_{f_i}$  was also computed as the partial derivative of the index for each climate variable<sup>119,120</sup> (Eq. 16). This sensitivity reflects how responsive each index is to incremental changes in the respective climate factors. Larger absolute values of the regression coefficients indicate a stronger influence of the corresponding climate factor on vegetation dynamics, while statistical significance reflects the robustness of the estimation.

$$\beta_{f_i} = \frac{\partial \text{VHI}}{\partial f_i} \quad (16)$$

Here, the  $\beta_{f_i}$  represents the responsiveness of VHI to changes in the  $i^{\text{th}}$  climate factor. The linear regression coefficients served as sensitivity estimates, where more significant coefficients indicated a greater influence of the associated climate factor on VHI dynamics.

#### Interannual variability of climate factors

The interannual variability of each climate factor  $\Delta_{f_i}$  was quantified as the standard deviation over the study period. This measure captures temporal fluctuations in each climate factor and helps assess how much variability each factor contributes to vegetation dynamics. The variability was calculated independently for each factor.

#### Relative contribution calculation

The relative contribution of each climate factor to the variations in vegetation health indices was determined using Eq. 17<sup>121,122</sup>.

$$R_{f_i} = \frac{|C_{f_i}|}{\sum_{i=1}^n |C_{f_i}|} \times 100 \quad (17)$$

where  $R_{f_i}$  represents the relative contribution of the  $i^{\text{th}}$  climate factor to VHI variations and  $n$  denotes the number of climate factors considered. Here,  $|C_{f_i}|$  is the absolute contribution of the  $i^{\text{th}}$  climate factor, as defined earlier. This formulation ensures that the contributions are normalized, allowing for comparison across different factors, with the sum of all contributions totaling 100%. Factors with higher relative contributions exert a more substantial influence on VHI dynamics.

#### Statistical evaluation of contributions

The contributions of each climate factor were evaluated using p-values derived from the linear regression model, with factors exhibiting p-values below 0.05 deemed statistically significant. This ensured identifying the most impactful climate drivers for each vegetation index, distinguishing them from those with less significance. A classification-based method was then applied to assess various climate factors' positive and negative influences on vegetation dynamics. For VHI, all five climate factors were considered, while for VCI and TCI, the analyses were tailored to the most relevant climate factors, as previously outlined.

Each factor was classified as contributing either positively or negatively to vegetation health, and these classifications were summed to determine the overall impact in each region. Regions where all factors contributed positively or negatively were classified as having predominantly positive or negative impacts, respectively<sup>123</sup>. To further refine the analysis, the dominant climate factor representing the most substantial positive or negative influence was mapped for each area, providing a comprehensive spatial assessment of the factors driving vegetation health. The analysis then identified the dominant climate factor in regions experiencing both positive and negative impacts, facilitating mapping the most influential drivers. The spatial extent of these effects was measured, offering a clearer picture of the relative influence of each factor across the study area. By integrating a partial derivative-based analysis with this classification approach, the study thoroughly evaluates the effects of climate factors on vegetation health at both annual and seasonal scales. This dual approach enhances the understanding of short- and long-term climate impacts on vegetation dynamics, providing critical insights for developing effective climate adaptation strategies.

## Results

### Vegetation stress and drought severity

The vegetation health indices (VHIs) from 2000 to 2023 highlight critical years of vegetation stress in Southern Thailand. A dynamic threshold approach was employed to identify severe anomalies, which allowed for the



objective differentiation of significant stress events from normal fluctuations. In 2005, all three indices indicated considerable stress, with 21.52% of the area classified as severely stressed by VHI and 60.36% experiencing severe temperature anomalies, according to TCI. This combined impact of vegetation health deterioration and temperature stress made 2005 particularly challenging for vegetation health. In 2016, stress persisted, with 17.03% of the area under severe conditions, according to VHI, and 65.31% experiencing severe temperature stress, as indicated by TCI (Fig. 3). In Fig. 3, the Less Severe category represents areas where vegetation health indices deviate moderately from the long-term mean falling between one and two standard deviations below the average. These regions indicate mild to moderate stress, distinct from the most critical zones classified as Severe.

VCI values across all analyzed years, including 2005 and 2022, showed less variability, with 3.18% of the area classified as severely stressed, indicating relatively stable vegetation conditions and fewer extreme drought impacts than VHI and TCI. Comparative analysis across the indices suggests that temperature anomalies had the most significant impact on vegetation stress, as evidenced by the higher proportion of severe areas in TCI compared to VHI and VCI, and the years 2005 and 2016 emerged as the most critical, with substantial areas affected by severe anomalies. While VHI provided a balanced assessment of overall vegetation health, TCI captured more acute stress driven by temperature variability, emphasizing the importance of considering multiple indices for a comprehensive understanding of drought impacts. These findings underscore the need for targeted mitigation strategies addressing temperature-induced stress to enhance vegetation resilience in Southern Thailand.

### Trend analysis

#### *Vegetation anomalies and land use dynamics: seasonal and annual VHI trends*

The analysis of VHI anomalies across Southern Thailand's land use classes reveals complex seasonal and annual vegetation patterns. In forested areas, 55.4% show insignificant decreasing trends on a yearly basis, suggesting short-term variability rather than a consistent decline. However, 22.5% of forests demonstrate significant increases, indicating regions of recovery, while 3.6% experience marked decreases. During the dry season, 53% of forests experience minor decreases, reflecting vulnerability under limited water conditions, while 30.2% exhibit significant improvements. The wet season presents a more refined perspective, with 25.8% of forests showing significant recovery due to ample water availability, while 55.9% exhibit slight declines.

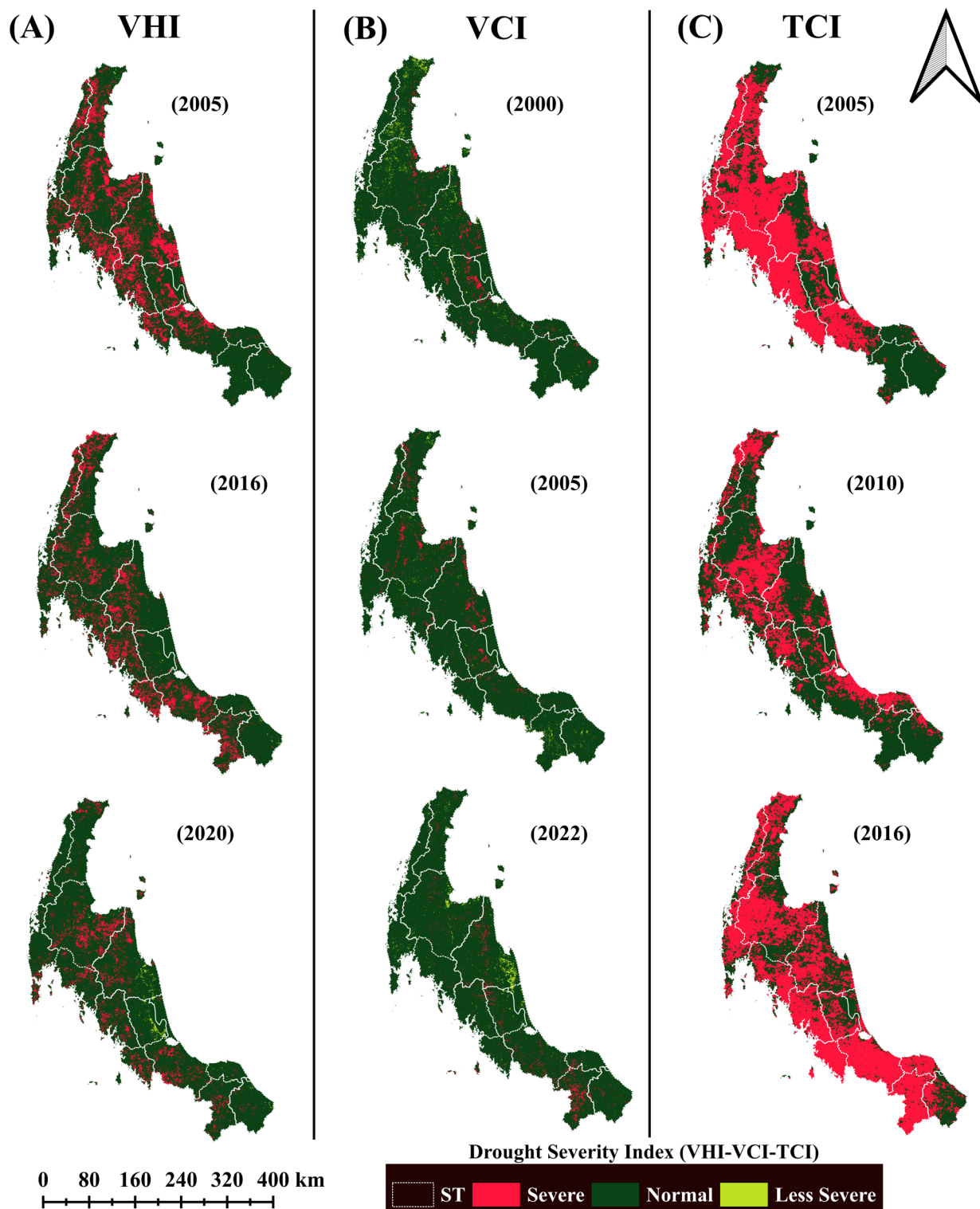
The analysis of VHI anomalies across Southern Thailand's land use classes reveals complex seasonal and annual vegetation patterns. In forested areas, 55.4% show insignificant decreasing trends on a yearly basis, suggesting short-term variability rather than a consistent decline. However, 22.5% of forests demonstrate significant increases, indicating regions of recovery, while 3.6% experience marked decreases, likely due to deforestation or water stress. During the dry season, 53% of forests experience minor decreases, reflecting vulnerability under limited water conditions, while 30.2% exhibit significant improvements, potentially due to adaptive ecological processes. These improvements suggest that some forested areas may be recovering naturally, emphasizing the importance of maintaining these regions for long-term resilience. Notably, 4.4% of these areas face significant declines, likely driven by persistent drought stress or other environmental pressures (Fig. 4).

The wet season presents a more refined perspective, with 25.8% of forests showing significant recovery due to ample water availability, while 55.9% exhibit slight declines, possibly indicating stabilization rather than full recovery. Yet, 3.4% of forest areas continue to degrade, suggesting unresolved stressors potentially related to soil quality or human activities. A similar trend is observed in shrublands. This persistent degradation highlights the need for targeted reforestation and soil management strategies to address long-term ecological challenges. During the dry season, 47.9% show insignificant declines, reflecting overall vulnerability, though significant changes are minimal. In the wet season, 42.5% of shrublands also exhibit insignificant decreases, highlighting that even favorable water conditions may not lead to full recovery.

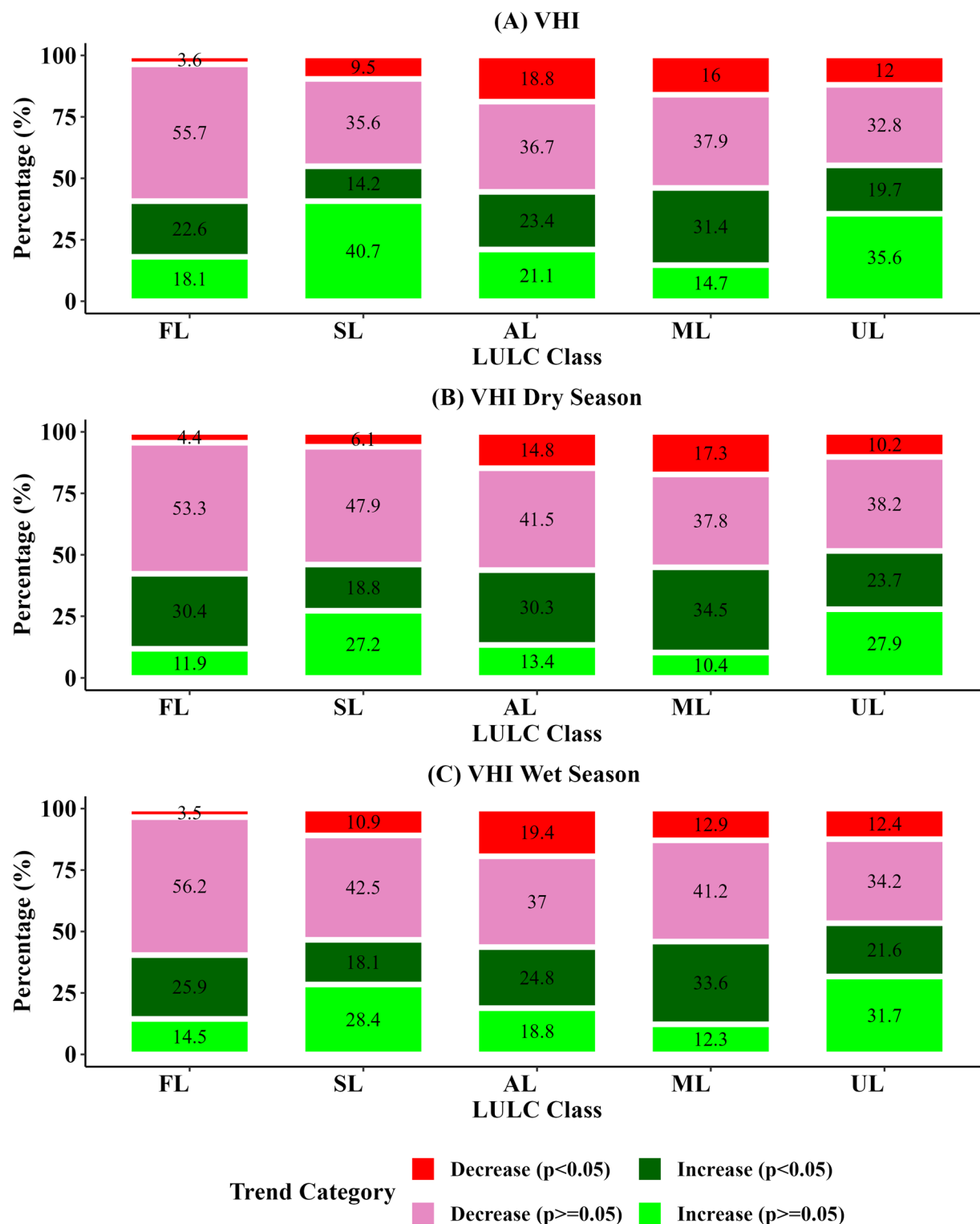
Arable land, being more sensitive to water availability, presents a mixed response. Dry season data suggest some resilience, likely aided by irrigation practices, while wet season improvements hint at a more robust recovery driven by sufficient rainfall. These contrasting responses across different land use types emphasize the significant impact of seasonal dynamics on vegetation health. While forests and arable lands show signs of resilience and potential recovery, the shrubland remains particularly vulnerable, indicating the need for focused management strategies. These findings underscore the importance of targeted interventions to mitigate environmental stressors and promote long-term sustainability across various ecosystems. Targeted water management and sustainable agricultural practices can mitigate stress in arable lands and shrublands, ensuring long-term vegetation health.

### Spatiotemporal dynamics of VCI anomalies across LULC

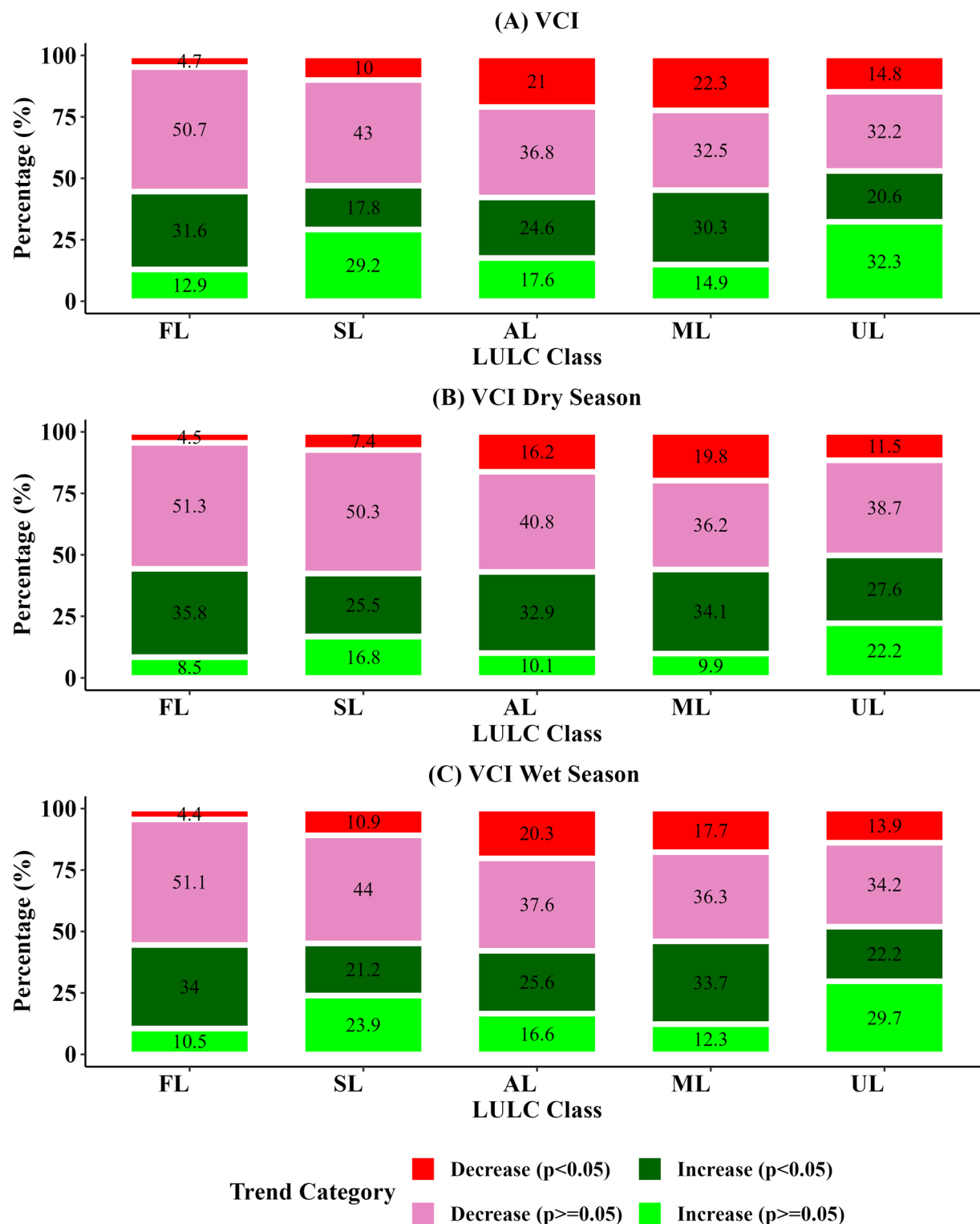
The spatiotemporal analysis of VCI anomalies in Forest Land (FL) shows that 31.6% of the area shows notable increasing trends in vegetation health, likely to indicate successful reforestation efforts or favorable climatic conditions. However, 4.7% of the forested regions exhibit significant declines, raising concerns about ongoing deforestation or the impacts of prolonged drought, particularly during dry periods. Seasonal analysis indicates that 35.7% of forested areas show VCI improvements during the dry season, which may reflect enhanced water management strategies. In contrast, 4.4% show declines, potentially signaling stress caused by insufficient water availability. In the wet season, 33.9% of forests exhibit VCI increases, benefiting from ample rainfall, while another 4.4% face declines, suggesting persistent environmental challenges that remain even during more favorable periods (Fig. 5). Resilience is evident in mangrove forests (MF), especially during the wet season, where 33.9% of areas show VCI improvements, likely benefiting from favorable water conditions. In contrast, 4.4% of mangrove regions experience declines, which may be attributed to environmental challenges like coastal erosion or human activities impacting these sensitive ecosystems. During the dry season, significant VCI increases across 35.7% of arable land are likely the result of enhanced irrigation systems or the use of drought-tolerant crops (Fig. 6E).



**Fig. 3.** Drought severity in Southern Thailand (2000–2023) based on VHI, VCI, and TCI indices. Critical years of vegetation stress include 2005 and 2016, with VHI and TCI indicating extensive, severe stress areas, mainly driven by temperature anomalies captured by TCI. The analysis underscores the impact of temperature-induced stress on vegetation health in the region. The map was generated using the QGIS stable version (Long Term version for Windows (3.34 L)). The software is available at <https://www.qgis.org/download/>.



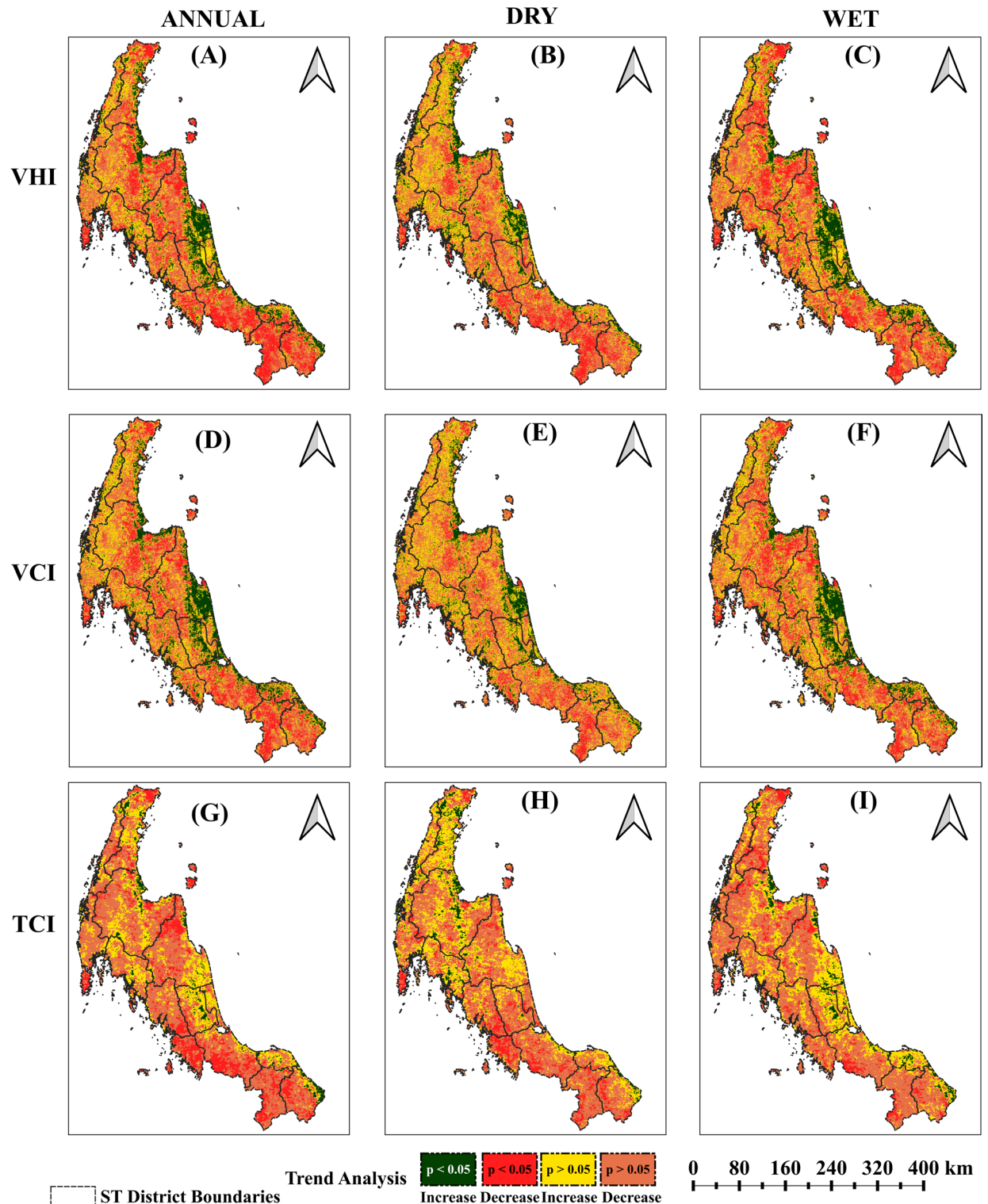
**Fig. 4.** Seasonal and annual VHI trends across LULC classes in Southern Thailand, showing the distribution of vegetation health trends. (A) Annual VHI, (B) Dry season VHI, and (C) Wet season VHI reveal varying responses to environmental conditions. Forest and arable lands display resilience with notable increases in VHI, while shrublands show persistent vulnerability. This indicates that shrublands are inherently less resilient to environmental stress, requiring interventions to enhance their adaptive capacity.



**Fig. 5.** Seasonal and annual VCI trends across LULC classes in Southern Thailand. (A) Annual VCI, (B) Dry season VCI, and (C) Wet season VCI display varying responses among LULC classes. Forest and upland areas exhibit resilience with significant increases, while arable and shrubland areas show more mixed trends, with some regions experiencing substantial declines.

However, many agricultural areas face insignificant decreases during the wet season, revealing vulnerabilities in productivity caused by fluctuating water availability. This variability underscores the need for sustainable agricultural practices, such as improving drainage infrastructure and optimizing irrigation strategies, to mitigate the risks to food security. (Fig. 6 ABCDFGHI).





**Fig. 6.** Spatial distribution of annual, dry, and wet season trends in VHI (ABC), VCI (DEF), and TCI (GHI) across Southern Thailand. The maps display areas of significant increase and decrease in each index, highlighting the seasonal variability in vegetation health and stress. Green areas indicate substantial increases, while red areas show significant reductions, with darker shades representing higher confidence ( $p < 0.05$ ). The map was generated using the QGIS stable version (Long Term version for Windows (3.34 L)). The software is available at <https://www.qgis.org/download/>.

Minimal significant trends appear in shrubland (SL), with much of the area showing insignificant decreases in seasonal and annual analyses. This indicates that shrublands may be less affected by seasonal variations, likely due to their adaptive nature and low vegetation density. However, localized factors such as land management practices or grazing could explain the few areas showing notable trends. As anticipated, urban land (UL) exhibits mostly insignificant VCI trends, reflecting the limited vegetation typical of urban landscapes. The few significant changes observed are likely tied to shifts in urban green spaces or the impact of infrastructure development on vegetation. This analysis underscores the importance of seasonal and environmental conditions in influencing vegetation dynamics across LULC categories. Forest lands exhibit signs of recovery but also contain areas requiring attention due to decreasing trends. Mangrove forests demonstrate resilience but still face localized stressors. Agricultural areas show adaptive capacity in the dry season but remain vulnerable during wetter periods. Shrubs appear less responsive to seasonal changes, and the urban regions exhibit relative stability, with occasional vegetation changes tied to urban development<sup>124,125</sup>. These findings emphasize the need for land-use-specific interventions, such as reforestation, agricultural water management, and urban green planning, to enhance vegetation health and resilience across ecosystems.

### Assessing temperature stress: TCI anomalies

The evaluation of TCI across Southern Thailand's land-use categories reveals varying responses to temperature stress. In forested areas, 67.8% exhibit minor, statistically insignificant decreases in TCI ( $p \geq 0.05$ ), suggesting that temperature fluctuations have a limited overall impact on vegetation in these regions (Fig. 7). However, 13.8% of forested regions show significant improvements ( $p < 0.05$ ), indicating areas where favorable temperature conditions promote healthier vegetation. Conversely, 1.6% of forested regions experience significant declines, highlighting localized vegetation loss due to temperature stress, particularly during the dry season (Fig. 61). During this period, 61.4% of forests show insignificant decreases, reflecting mild temperature stress without severe consequences. In contrast, 24.7% display significant TCI increases, implying localized climatic benefits or the presence of temperature-adaptive species. However, 3% of forested areas face significant declines, underscoring hotspots where temperature stress is a major driver of vegetation degradation. Mangrove forests show predominantly insignificant TCI decreases, suggesting that temperature fluctuations exert limited influence on overall vegetation health. Nonetheless, areas with significant increases highlight regions where favorable temperature conditions aid mangrove growth and recovery, particularly in coastal environments. Arable lands exhibit increased sensitivity to temperature stress, with insignificant TCI decreases dominating during the dry season. In the wet season, significant TCI increases reflect enhanced vegetation growth, as favorable temperature and moisture conditions boost agricultural productivity. Shrubs exhibit mixed responses, with 58.4% showing insignificant decreases in TCI during the dry season, indicating limited sensitivity to temperature fluctuations. However, small regions with significant declines point to areas adversely affected by prolonged temperature stress. Urban land, as expected, shows predominantly insignificant trends due to limited vegetation cover, with substantial trends linked to urban green spaces or temperature management strategies.

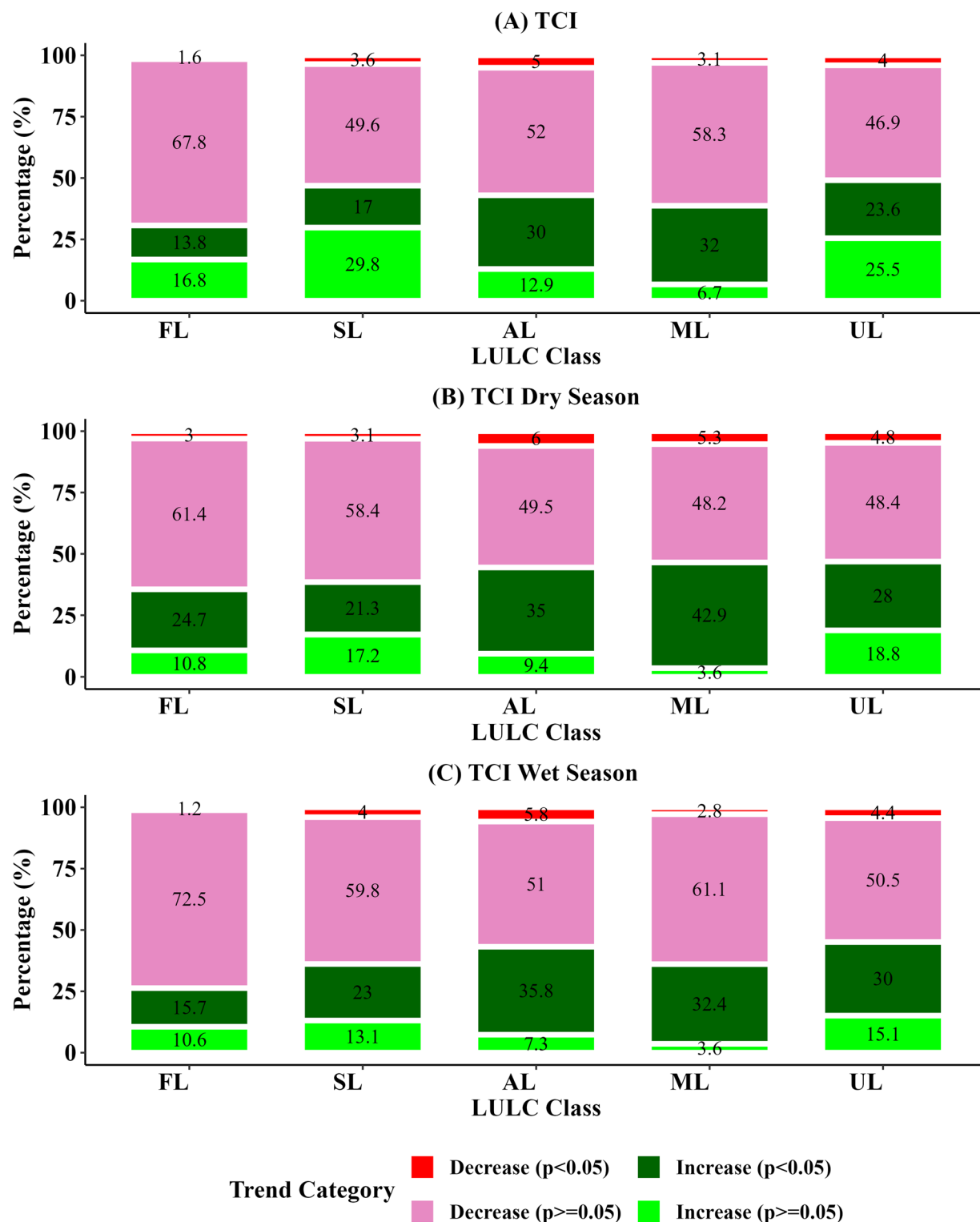
A comparative analysis of TCI's performance across these land-use types highlights its unique ability to capture temperature-related stress, particularly in regions with extreme fluctuations. For example, while traditional indices like NDVI or VHI might overlook localized stressors, TCI effectively identifies areas where temperature is a primary driver of vegetation change. This makes it especially valuable in ecosystems like arable lands and mangroves, where vegetation health is closely tied to seasonal temperature dynamics. These findings emphasize the importance of TCI in identifying temperature-induced vulnerabilities and informing adaptive management strategies to mitigate climate impacts. For forested areas, identifying hotspots with significant TCI declines underscores the need for reforestation programs with temperature-adaptive species. At the same time, the role of TCI in arable lands highlights the necessity for temperature-resilient crops and irrigation systems during dry seasons. This analysis underscores the varying degrees of temperature stress across land-use types and highlights TCI's capability to capture critical stress points. Forested areas demonstrate a mix of resilience and vulnerability, while mangroves and arable lands exhibit adaptability under favorable conditions. Shrubs show overall stability with localized stress points, and urban areas remain largely unaffected, apart from trends tied to urban greening initiatives. These insights reinforce the need for targeted strategies, such as optimizing temperature management in arable lands and strengthening mangrove conservation in coastal environments, to sustain vegetation health under rising climate pressures.

### Annual and seasonal climate contributions to vegetation health: comparative impacts on VHI, VCI, and TCI in tropical ecosystems

This study examines the impact of critical climatic factors SM, SR, VPD, PPT, and LST on vegetation health through three key indices: the VHI, VCI, and TCI. The analysis spans annual, dry, and wet seasons, allowing for the identification of seasonal variations in how these environmental variables affect vegetation. The findings below outline the contributions of each factor to the indices, followed by a seasonal comparison.

#### *Annual contributions to vegetation health*

The annual analysis highlights the significant impact of climatic variables on vegetation health, with substantial variations in their contributions across the VHI, VCI, and TCI indices. SM emerged as the dominant factor influencing VHI, with positive and negative effects. It improved vegetation health across 13.11% of the area, where optimal moisture levels supported plant growth but negatively impacted 16.41%, likely due to water stress caused by insufficient or excessive moisture. This highlights the critical role of SM in balancing water availability, as drought and waterlogging can hinder vegetation productivity. SR also played a dual role. It negatively affected 13.42% of the area by increasing evapotranspiration, leading to moisture depletion and plant stress. However, SR positively influenced regions with sufficient soil moisture, benefiting 11.93% of the area by driving



**Fig. 7.** Seasonal and annual TCI trends across LULC classes in Southern Thailand. (A) Annual TCI, (B) Dry season TCI, and (C) Wet season TCI illustrate the percentage distribution of significant and insignificant trends across different LULC types. Forest lands show high levels of stability with minor increases, while arable and upland areas display more substantial increases in TCI, particularly during the wet season, indicating temperature-driven resilience.

photosynthesis. This underscores the importance of SR in maintaining energy balance and promoting growth (Fig. 8A). PPT and LST also negatively impacted 10.81% and 10.34% of the area, respectively. These effects are likely linked to excess rainfall or heat stress. Despite this, VPD and PPT contributed more minor but significant positive effects, benefiting 9.15% and 7.32% of the area. These findings suggest that, under moderate conditions, these factors play a supportive role in maintaining healthy vegetation. As hydrological conditions significantly influence urban and vegetation health<sup>34</sup>, this study further highlights their critical role in shaping vegetation dynamics in Southern Thailand.

SR played a significant role in influencing VCI, negatively affecting 21.80% of the area. This is likely due to increased evapotranspiration, which depletes moisture, especially under high radiation, leading to water stress. In regions where moisture was not limited, however, SR positively impacted 11.39% of the area by facilitating photosynthesis (Fig. 8B). This dual role reflects SR's influence on the energy balance of vegetation. Excessive solar radiation can cause harm, while moderate levels enhance growth. SM had mixed effects as well. It negatively impacted 12.47% of the area, likely due to waterlogging, but improved vegetation health in 17.11% of the area where moisture levels were optimal. VPD and PPT followed similar patterns. VPD had a more prominent negative effect, highlighting the role of atmospheric moisture demand in vegetation stress. However, moderate VPD levels supported growth in areas under less stress, illustrating the complex relationship between atmospheric moisture and plant responses.

LST had a significant negative impact on 19.61% of the area, according to TCI, as thermal stress disrupted plant metabolism and reduced vegetation health. In contrast, moderate temperatures positively affected 11.44% of the area, allowing plants to thrive under more favorable conditions. SR significantly improved photosynthesis and benefited vegetation health across 24.53% of the area (Fig. 8C). However, excessive solar radiation negatively affected 10.58%, showing the delicate balance between helpful and harmful radiation levels. VPD also contributed positively to 23.75% of the area by promoting transpiration, a crucial process for nutrient transport in plants. Still, high VPD levels, which increase moisture demand, negatively impacted 10.10% of the area, contributing to vegetation stress, a pattern also observed with VHI and VCI. The pixel-wise climatic sensitivities ( $\beta$ ), inter-annual variability ( $\Delta$ ), absolute contributions ( $C = \beta \cdot \Delta$ ) and normalised relative contributions ( $R$ ) that underpin these percentage patterns are provided in Supplementary Figure. S4, with accompanying study-area statistics in Table S3.

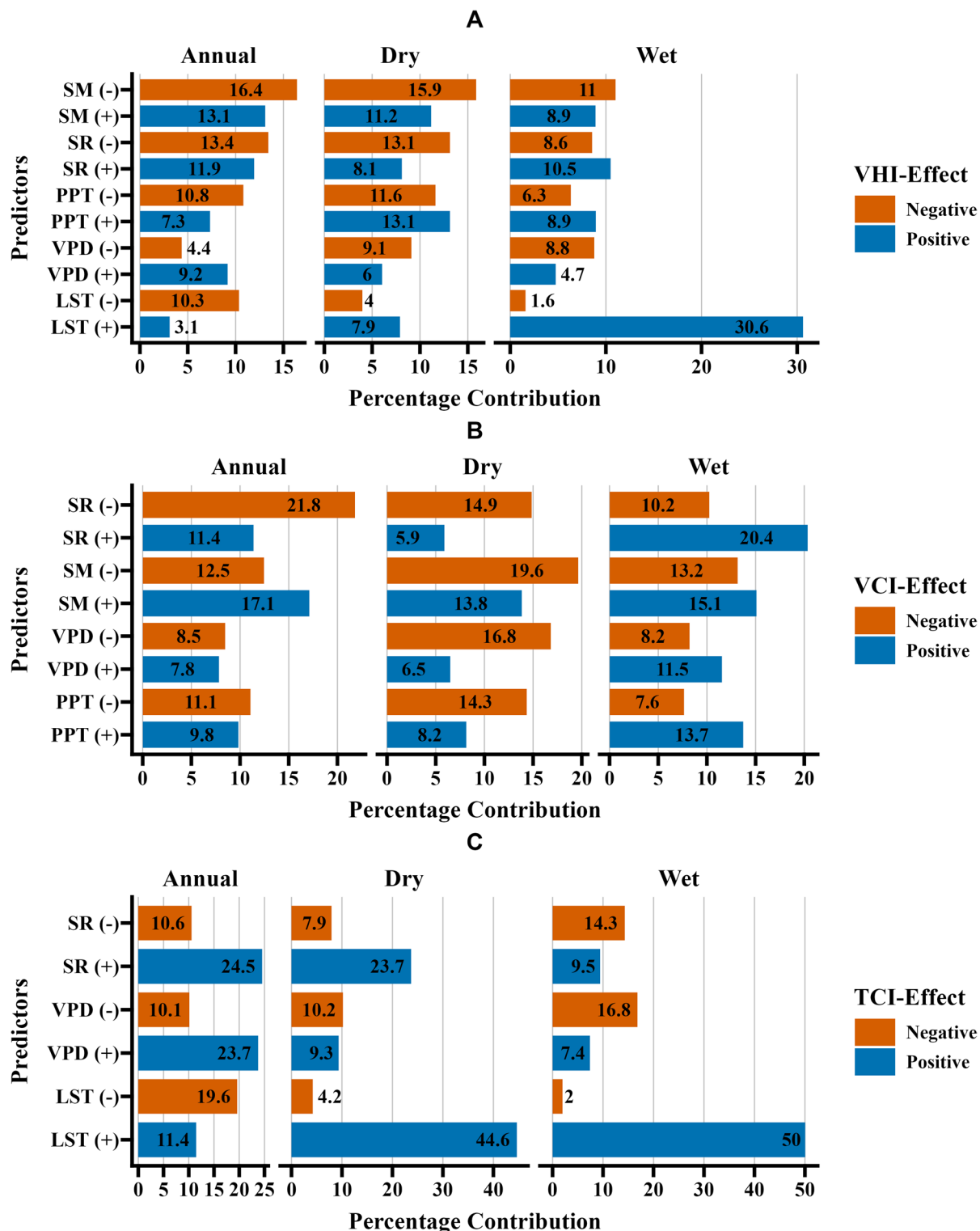
#### *Seasonal contributions to vegetation health*

In the dry season, SM remained the most significant negative contributor to vegetation health under the VHI, affecting 15.86% of the area. SR followed closely with a negative impact on 13.14% of the area. PPT and VPD also showed adverse effects, although LST had a more minor influence. Notably, PPT emerged as the most significant positive factor in this season, enhancing vegetation health in 13.13% of the area, while SM contributed positively to 11.16%. These findings underscore the importance of targeted water management practices, such as soil moisture retention and efficient irrigation systems, to mitigate stress and optimize vegetation health during the dry season. Although smaller in magnitude, SR and LST also played positive roles, indicating their relevance in supporting plant productivity under favorable conditions. During the wet season, LST showed a dramatic shift, becoming the dominant positive factor contributing to 30.61% of the area, underlining the significance of thermal dynamics during this period (Fig. 9). SR and PPT also made substantial positive contributions, while SM and VPD had more minor positive impacts. Negative influences were led by SM (11.00%) and SR (8.57%), with LST showing the least negative effect, highlighting the seasonally shifting importance of these factors.

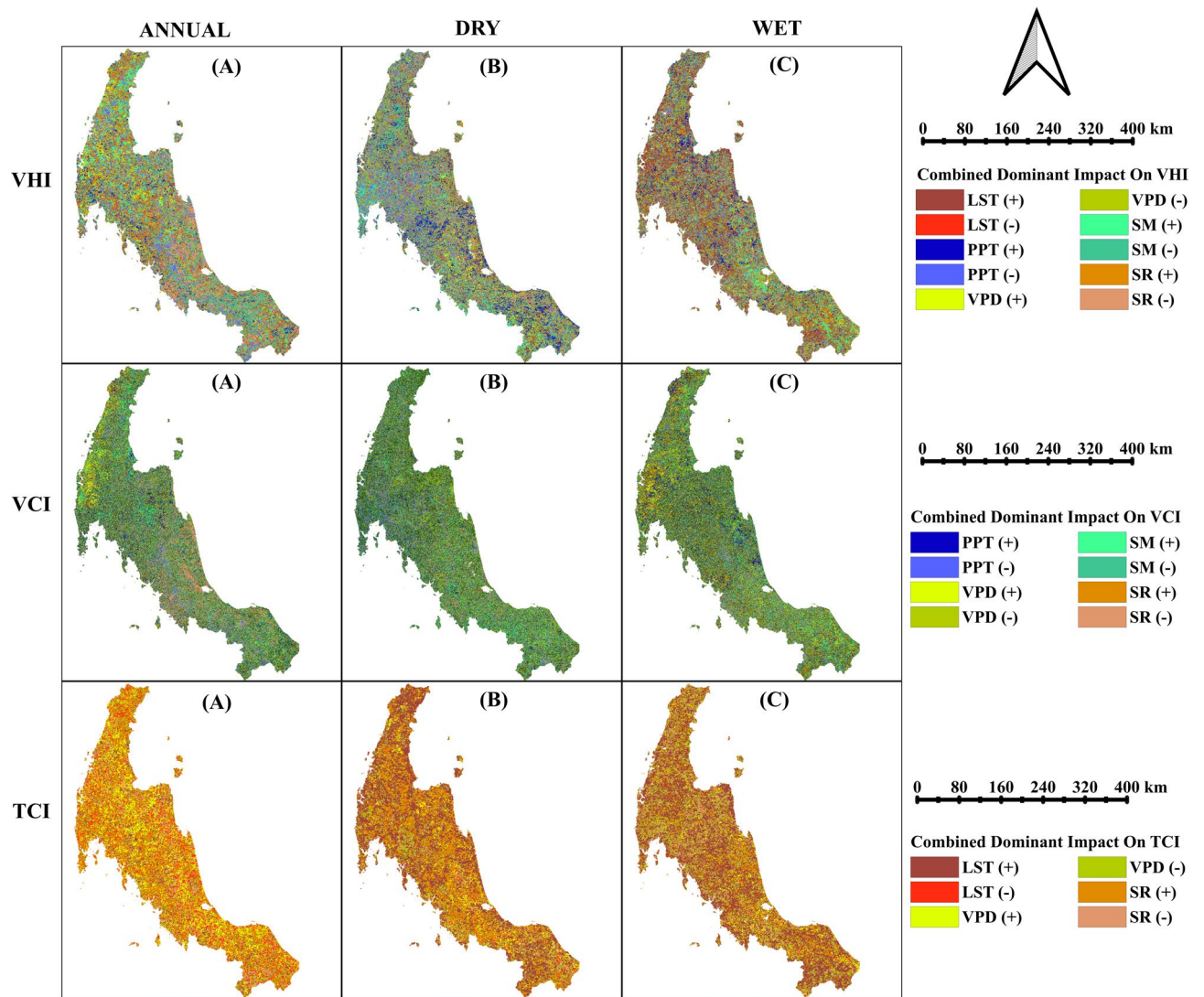
The VCI reflected similar patterns. SM and VPD had more pronounced negative impacts during the dry season, with SM affecting 19.63% of the area and elevated VPD influencing 16.81%. This underscores the vulnerability of vegetation to moisture deficits in arid conditions. SR further reduced vegetation vitality, negatively affecting 14.85% of the area, which is in line with its negative role observed in the VHI analysis. Positive contributions from SM and SR were limited, suggesting that only certain regions benefited from favorable conditions, much like the constrained positive impacts seen in the VHI. In the wet season, solar radiation positively influenced 20.36% of the area, while soil moisture supported vegetation health across 15.10% of the region, reflecting its role in VHI. The reduction in adverse effects of precipitation and the expansion of its positive influence underscores the critical role of sufficient rainfall during this period. VPD, while generally contributing to vegetation stress, played a more supportive role in the wet season, positively impacting 11.55% of the area by facilitating transpiration under more favorable moisture conditions.

The TCI highlighted the increasing importance of LST during the dry season, contributing positively to 44.63% of the area. This emphasizes the role of moderate temperatures in sustaining vegetation health when moisture is limited. The relatively minor adverse effects of LST (4.23%) indicate that while thermal stress can occur, LST remains a beneficial factor in maintaining vegetation growth in arid conditions. SR positively influenced 23.71% of the area but continued to exert adverse effects over 7.91%, demonstrating the dual impact of SR seen in both VHI and VCI. VPD's negative impact of 10.20% was more prominent, reflecting the increased atmospheric moisture demand that exacerbates water stress in vegetation during the dry season. During the wet season, LST emerged as the most critical positive factor, contributing to 50.03% of the area. This highlights the importance of favorable thermal conditions in supporting vegetation growth under well-watered conditions. However, SR's negative impact increased to 14.30%, likely due to heat stress despite moisture availability, while positive contributions were more restricted (9.45%). The negative influence of VPD also grew to 16.84%, stressing vegetation even in areas with adequate soil moisture, reflecting its role in regulating transpiration and moisture demand. This seasonal variability highlights the need for adaptive strategies that address the shifting importance of climate drivers, such as optimizing thermal conditions and balancing water availability to sustain vegetation productivity year-round.





**Fig. 8.** Percentage contribution of environmental predictors to the VHI, VCI, and TCI on an annual, dry, and wet seasonal basis in Southern Thailand. (A) VHI contributions highlight SM and SR as key influences, with positive and negative effects varying by season. (B) VCI contributions strongly influence SR and SM, particularly in the wet season. (C) TCI contributions show temperature (LST) as the dominant factor, especially in the wet season, reflecting temperature-driven vegetation stress. This analysis emphasizes the seasonal sensitivity of vegetation health to climatic variables.



**Fig. 9.** The spatial distribution of dominant climate factors impacts vegetation health Across seasons. The maps display the combined dominant impacts of Climatic predictors on vegetation health indices: VHI, VCI, and TCI for Annual (A), Dry (B), and Wet (C) seasons. The individual contributions of climatic factors SM, SR, VPD, PPT, and LST to vegetation health indices VHI, VCI, and TCI across annual, dry, and wet seasons are detailed in Supplementary Material Appendix A. Figures S1, S2, and S3 illustrate these seasonal impacts, revealing the detail and season-dependent influences of each predictor on vegetation health. The map was generated using the QGIS stable version (Long Term version for Windows (3.34 L)). The software is available at <https://www.qgis.org/download/>.

#### Synthesis and implications for vegetation management

The analysis demonstrates that SM and SR consistently emerged as the most influential variables, with their effects varying across seasons. In the wet season, LST showed solid positive contributions, underscoring its critical role in tropical vegetation dynamics during periods of high precipitation. These findings highlight the necessity for adaptive environmental management strategies that account for seasonal variability in climate drivers to enhance ecosystem resilience in tropical regions. The VCI results aligned closely with the VHI, reinforcing the importance of SR, SM, and VPD in determining vegetation health across seasons. Both indices demonstrate the dual roles of these factors: while optimal conditions promote vegetation growth, excesses or deficits can result in stress and reduced vitality. These complementary insights further underscore the need for adaptive management strategies that consider seasonal fluctuations in environmental drivers, particularly under the pressures of climate change. LST emerged as a crucial driver of vegetation health across all seasons, with its positive influence being most pronounced during the wet season. The complex, season-dependent impacts of SR and VPD suggest careful management is needed to mitigate thermal and moisture stress. The interplay between these factors, as evidenced in the VHI and VCI results, points to the importance of optimizing shading and selecting heat-tolerant species to minimize the adverse effects of climate-induced stress on vegetation.

Overall, this comprehensive analysis highlights that vital environmental factors have significant and seasonally dependent impacts on vegetation health indices (VHI, VCI, and TCI) in Southern Thailand. SM and SR were consistently identified as primary drivers across all seasons, with SM exhibiting both positive and negative effects depending on moisture availability and seasonal conditions. LST demonstrated a substantial positive influence during the wet season, affecting over 30% of the area for VHI and over 50% for TCI, supporting its role in promoting vegetation health under moist conditions. The VCI analysis further highlighted the need to manage moisture availability and mitigate excessive heat stress. SR and VPD can either exacerbate moisture stress during dry periods or support vegetation growth under optimal conditions.

## Discussion

### Climatic drivers of vegetation health in Southern Thailand

The results of this study reveal significant spatiotemporal variations in vegetation health, driven by climatic factors such as SM, SR, PPT, VPD, and LST. Vegetation in Southern Thailand shows pronounced sensitivity to seasonal and annual climate dynamics, especially under extreme temperature and moisture conditions, aligning with findings from similar tropical ecosystems.

### Impact of extreme temperature and moisture deficits on vegetation stress

Spectral monitoring has proven effective for assessing vegetation health in tropical ecosystems, particularly during seasonal extremes<sup>126</sup>. The applicability of vegetation indices to aquatic systems, such as the Dharoi Reservoir, further underscores their utility in diverse environments<sup>37</sup>. The patterns observed in Southern Thailand reflect these findings, reaffirming the capacity of indices like VHI and kNDVI to capture climate-induced vegetation stress. This stress has serious implications for agriculture, as shown in simulations from Jammu and Kashmir, where concurrent heat and drought threaten food production<sup>127</sup>. Similar risks are evident in Southern Thailand, where vegetation degradation due to temperature and moisture extremes affects food systems and livelihoods.

The VHI identified severe vegetation stress during 2005 and 2016, aligning with temperature anomalies detected by TCI. These years saw temperature-induced stress across 60.36% and 65.31% of the region, respectively, highlighting the compounding effects of heat and moisture deficits. Events like April 2016's drought, linked to ENSO and anthropogenic influences, disrupted agriculture and reduced yields<sup>128</sup>. Rising temperatures further limit evapotranspiration and intensify soil moisture deficits, suppressing productivity under prolonged heat stress<sup>129–133</sup>. These outcomes align with global trends linking heat and drought to reduced yields, reinforcing the need for climate-adaptive agriculture<sup>134,135</sup>. Forests and mangroves are especially vulnerable forests that decline rapidly under moisture deficits, while mangroves face risks from combined heat and water stress<sup>136,137</sup>. This degradation threatens biodiversity, timber production, and coastal protection. For agriculture, temperature and moisture stress reduce productivity, disrupt food supply chains, and endanger rural livelihoods<sup>138</sup>.

Southern Thailand's experience mirrors broader patterns: increasing drought and heat reduce photosynthesis and resilience, exacerbating food insecurity<sup>139</sup>. In Southern Africa, for instance, recurring ENSO-induced droughts disrupt economies and livelihoods, demanding urgent adaptation<sup>140</sup>. These challenges highlight the need for climate-smart practices like drought-tolerant crops, improved irrigation, and resilient afforestation<sup>141</sup>. High-resolution climate models also support mitigation planning under extreme events<sup>142</sup>. The interlinkage between vegetation health, ecological resilience, and human well-being necessitates proactive adaptation to protect food security and livelihoods as ecosystems approach critical thresholds.

### Drivers of vegetation degradation and resilience across land cover types

While the VCI remained relatively stable, the more significant fluctuations in TCI indicate that temperature stress, rather than water availability, is the primary driver of vegetation degradation in this region. This observation is consistent with<sup>143</sup>, who found that TCI is dominant in detecting vegetation stress, especially in dry areas. Likewise, increases in temperature caused by forest degradation and land conversion in tropical regions are known to push species closer to their thermal limits<sup>144</sup>. Temperature-driven degradation is also linked to greenhouse gas emissions from forest loss, which are often underestimated in climate models<sup>145</sup>. In subtropical wetlands, increased temperature sensitivity further intensifies vegetation stress<sup>146,147</sup>.

Trend analysis across land use categories provides insight into vegetation resilience and vulnerability. Forested areas recovered in 22.5% of the region but a decline in 3.6%, particularly during the dry season, likely due to sustained water stress or deforestation pressures. These findings mirror those from other tropical regions, where droughts have heightened forest vulnerability to fires, exacerbating degradation during dry periods<sup>148,149</sup>. These patterns suggest a variety of factors influencing forest health, including potential recovery in some areas and degradation in others. The decreases in some forested areas could be attributed to deforestation or water stress, as suggested by previous studies<sup>150</sup>. The improvements noted in some forests during the dry season could potentially be due to adaptive ecological processes<sup>151</sup>. However, the significant declines in 4.4% of areas, likely driven by persistent drought stress or other environmental pressures, highlight the need for targeted conservation efforts. The differences observed during the wet season, with 25.8% of forests showing recovery and 55.9% slight declines, indicate that while water availability is a critical factor, other issues such as soil quality or human activities might also play a role in determining vegetation health<sup>152</sup>.

This persistent degradation highlights the need for targeted reforestation and soil management strategies to address long-term ecological challenges. The spatiotemporal analysis of VCI and TCI anomalies across land cover types reveals that mangrove forests are generally resilient to seasonal fluctuations and remain vulnerable to localized stressors such as coastal erosion and human activity. This aligns with global trends of mangrove degradation, where aquaculture, urban development, and nutrient depletion have driven significant losses, as seen in Brazil and the Indian Sundarbans<sup>153–154</sup>. Global assessments show that human-driven factors accounted

for 62% of mangrove degradation between 2000 and 2016, highlighting the urgency of targeted conservation efforts<sup>155</sup>.

### Climate factors and vegetation stress dynamics

The analysis highlights the critical role of climate factors, particularly SM and SR, in shaping vegetation dynamics. SR exhibits a dual effect, promoting vegetation growth in moisture-rich areas but intensifying stress in regions with limited water availability due to increased evapotranspiration. Groundwater-rich zones are better able to sustain vegetation under high SR, while moisture-limited areas face significant stress<sup>156–158</sup>. Similarly, soil moisture plays a pivotal role, especially during the dry season, supporting vegetation in 11.16% of the study area. This underscores the importance of water retention strategies and irrigation to mitigate drought impacts, particularly as climate change exacerbates seasonal dryness. Temperature stress further compounds vegetation vulnerability. During the wet season, LST positively influenced vegetation health across 30.61% of the region, showcasing its importance in tropical ecosystems with ample precipitation<sup>159–161</sup>. However, excessive SR during the dry season negatively affected 13.14% of the area, demonstrating the need for strategies to manage SR exposure and reduce heat-induced stress. These findings underscore the sensitivity of vegetation to combined heat and moisture challenges, particularly in tropical climates where ecosystems operate near critical thresholds.

Vegetation degradation carries significant socioeconomic repercussions, particularly for forestry and agriculture. Deforestation-driven greenhouse gas emissions in forestry contribute to climate change<sup>162–163</sup> while reducing timber yields and carbon trading opportunities, undermining local and global economies<sup>164</sup>. Agricultural productivity is similarly affected, with soil erosion and irregular precipitation increasing costs and threatening food security. Rural livelihoods are disproportionately impacted by vegetation loss. Communities dependent on forest resources suffer from reduced biodiversity and ecosystem services, disrupting their income and resource stability. Vulnerable populations in developing regions are particularly at risk, making restoration an ecological imperative and a socioeconomic necessity to support human well-being and resilience. Effective restoration strategies must prioritize biodiversity recovery and ecosystem functioning. Evidence suggests that ecological restoration enhances biodiversity by 44% and ecosystem services by 25%, though full recovery often lags behind undisturbed ecosystems<sup>165</sup>. Natural regeneration (passive restoration) often surpasses active interventions in restoring biodiversity and vegetation structure. Agroforestry and sustainable land-use practices also offer dual benefits, fostering biodiversity while improving soil stability and crop yields. Restoration strategies tailored to tropical regions' unique ecological and socioeconomic conditions, such as Southern Thailand, are essential for achieving long-term impact.

Integrating monitoring frameworks into restoration efforts is critical for tracking carbon stocks and biodiversity recovery. Adaptive management approaches ensure restoration aligns with evolving ecological and socioeconomic goals, enhancing sustainability. Investments in initiatives like REDD+ exemplify the broader benefits of restoration, contributing to climate resilience, poverty alleviation, and biodiversity conservation. Moreover, restored ecosystems enhance soil properties, improving agricultural productivity and forest regeneration potential<sup>166</sup>. Restoration efforts should integrate socioeconomic considerations to maximize their benefits for ecosystems and communities. By aligning restoration with sustainable development goals, policymakers can support climate resilience, food security, and economic stability. Proactive planning that bridges ecological restoration with livelihood improvement is vital for addressing the twin challenges of climate change and land degradation.

### Strategies for Climate-Resilient vegetation management

The spatial dominance patterns of temperature, soil-moisture, precipitation, and solar-radiation stress identified in Fig. 8 provide the biophysical foundation for the management actions proposed below. These findings highlight the need for vegetation management strategies that integrate ecological and policy implications. Forested regions require targeted efforts to address deforestation, maintain biodiversity, and manage water stress. At the same time, areas with declines in VHI and TCI necessitate reforestation and sustainable land-use practices to restore ecosystems and support carbon sequestration. Arable lands and shrublands are vulnerable to wet season challenges like soil erosion and waterlogging. Adaptive water management, including drainage systems and conservation practices, is essential to safeguard crop productivity. While our study incorporated comprehensive preprocessing steps to address uncertainties in satellite-derived indices, including cloud masking using the Quality Assessment Band and multi-temporal compositing, certain limitations persist. Despite these measures, regions with frequent cloud cover may experience reduced temporal continuity. Similarly, mixed land-use areas present challenges in accurately isolating vegetation-specific responses despite our use of stratified analysis based on detailed land cover maps. Future studies should explore the integration of high-resolution satellite imagery and data fusion techniques to mitigate these limitations further and enhance the precision of vegetation monitoring in tropical ecosystems. Season-specific interventions, such as optimized irrigation, shading structures to mitigate solar radiation stress, and temperature-resilient crops, are critical for addressing the impacts of climate variability. Policy alignment with frameworks like REDD+ can leverage funding for conservation and climate adaptation. Establishing monitoring frameworks to track vegetation health and adaptive management strategies informed by climate models will ensure long-term sustainability. These actionable measures provide clear pathways for mitigating vegetation stress and enhancing ecosystem resilience in tropical regions.

### Conclusion

This study provides a comprehensive analysis of vegetation health trends across Southern Thailand from 2000 to 2023, focusing on how seasonal and annual climate factors, particularly temperature and water availability shape ecosystem resilience. Findings indicate a strong sensitivity of tropical vegetation to extreme temperatures, with notable stress recorded in 2005 and 2016. This observed sensitivity underscores the vulnerability of



these ecosystems and highlights the broader challenges tropical regions face in adapting to climate variability. Additionally, soil moisture proved crucial during the dry season, mitigating water stress in forested and agricultural areas. In contrast, high solar radiation levels increased photosynthetic activity in moisture-rich regions but heightened stress in drier areas. These findings highlight the need for integrated water resource management strategies, such as efficient irrigation systems, water retention techniques, and soil conservation practices, to combat seasonal water stress and enhance ecosystem resilience. Forested and cultivated lands demonstrated considerable resilience to seasonal stressors; however, persistent drought conditions and continued deforestation in forested areas underscore the pressing need for adaptive management strategies. Reforestation programs using temperature- and drought-adaptive species and policies that curb deforestation is critical for maintaining ecosystem stability in these areas. Although mangrove forests have shown relative resilience to short-term climate fluctuations, they are increasingly challenged by coastal erosion and human activities. Targeted conservation strategies, including mangrove restoration and coastal erosion control measures, are essential to protect these critical ecosystems. To address these challenges, a multifaceted approach is required that integrates ecosystem-specific strategies with broader adaptive management frameworks. Enhanced early warning systems for extreme weather events and policies promoting sustainable land use will strengthen climate resilience in tropical ecosystems. These findings underscore the importance of a nuanced approach to land management, one that adapts to the seasonal needs of Southern Thailand's ecosystems. Effectively addressing climate stress will require targeted actions like enhanced irrigation systems and shade structures and a broader commitment to biodiversity conservation. Transformative agricultural strategies, offer practical guidance for implementing climate-resilient land management practices, which are vital for long-term ecosystem stability and food security in tropical regions. By deepening our understanding of these intricate ecological dynamics, this study lays the groundwork for sustainable management practices that support tropical ecosystems' immediate and long-term resilience to climate change.

### Data availability

The authors confirm that the data links supporting this study's findings are within the article.

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## Declarations

### Competing interests

The authors declare no competing interests.

### Additional information

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