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Variation of vegetation cover and the relationship with land surface temperature across Thailand (2007 to 2022)

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Understanding vegetation-climate interactions is essential amid escalating global climate change. This study investigates spatial-temporal and seasonal variations in Land Surface Temperature (LST) and Vegetation Index (NDVI) across six regions of Thailand (2007–2022). R esults re
LST and NDVI (*R* = 0.61 dry; 0.39 rainy; 0.72 winter). The strongest negative correlation occurred during the rainy season in 2017, highlighting complex interannual variations.
(winter-summer: 1.24, winter-rainy: -1.54, summer-rainy: -2.78, *p* < 0.001) and NDVI variations (winter-summer: 0.09, winter-rainy: 0.07, summer-rainy: -0.03, *p* < These VI as vital for understanding ecological impacts of climate change and urbanization.
associated with lower temperatures, underscoring the importance of strategies to mitigate heat and enhance climate resilience, particularly in rapidly urbanizing regions.

In recent decades, the dynamics of vegetation and its interaction with climatic variables have become increasingly important in understanding the impact of climate change on terrestrial ecosystems[1–3]. Urban expansion is recognized as a major factor influencing changes in land use and land surface temperature (LST). LST refers to the temperature experienced at the interface between the surface and the atmosphere, where long-wave radiation and turbulent heat fluxes are exchanged[4].

LST and the normalized difference vegetation index (NDVI) are the key environmental indicators used in environmental and climate change studies[5,6]which are critical indicators of environmental health and urbanization effect. Moreover, NDVI is widely used to assess plant health and biomass[7]. The relationship between LST and NDVI is characterized by a generally negative correlation, indicating that increased vegetation cover tends to lower surface temperatures. This relationship has been extensively documented across various geographical contexts, emphasizing the role of vegetation in mitigating heat, particularly in urban areas. Many studies have indicated that urbanization leads to increased LST due to the replacement of vegetation with impervious surfaces, which absorb and retain heat. The analysis of long-term vegetation index data, such as the NDVI, can give useful information about the spatiotemporal variations in vegetation cover[1]. It is particularly important for regions where vegetation growth is sensitive to changes in precipitation and groundwater availability, as in arid and semi-arid areas[8]. The paper emphasizes how NDVI serves as a major indicator in urban climate studies, revealing a consistent negative correlation with LST[9]. This correlation is significant for urban heat island (UHI) studies and can vary seasonally, as indicated by the findings. Although their study suggests that the

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relationship may be weaker in certain contexts[10]the seasonal variations in NDVI can influence the effectiveness of vegetation in moderating LST, particularly during periods of drought or excessive heat[11,12]. Moreover, the impact of land cover transitions on LST is well-documented. Many studies in China indicate that converting cropland to urban land significantly increases LST due to alterations in surface albedo and evapotranspiration processes[12,13]. However, Kaleem Mehmood's study indicates that higher LSTs are a fire risk factor because they dry out vegetation and speed up ignition, especially during the dry season in northern Thailand[14]. Moreover, environmental changes and sustainable development are associated with LST[15]. This aligns with findings that urban expansion correlates with increased LST, further exacerbating UHI effects[16]. NDVI is sensitive and allows for a comprehensive assessment of how land cover changes impact LST across different environments, from rural to urban settings. The study highlights that LST established a strong correlation[17] as 80.4% of significant correlations were negative, especially in tropical regions, according to a global analysis conducted between 2000 and 2024[18]. Studies conducted in the Masai Mara ecosystem reveal a negative correlation[19]. The use of NDVI and LST data can thus offer helpful perspectives on the ecological impacts of urbanization and climate change[20].

Urban thermal field variance index (UTFVI) is a common indicator used to assess the urban heat island effect and can be a useful tool in finding possible heat-prone areas[14,21].The significant adverse effect of UTFVI reduce urban comfort, increase mortality, and have a major impact on local wind patterns, humidity, air quality, and indirect economic losses, reduces urban comfort, and increase mortality, including more approaches to identify the hot areas in the city[22,23].

The objective of this study is to analyze the spatiotemporal and seasonal variations of land surface temperature and vegetation indices, such as NDVI, in order to use these indicators for monitoring the impacts of climate change and urbanization. This analysis focuses on their interrelationship across six regions in Thailand from 2007 to 2022. The study aims to identify patterns in NDVI and LST distribution across different seasons and years within these regions. The findings could provide helpful suggestions for developing effective urban environmental management strategies, derived from these satellite-based indicators, to mitigate the effects of increasing temperatures and facilitate adaptation to climate change in urban settings.

Material and method

Study area

Thailand, located in Southeast Asia, has a tropical climate with distinct dry wet and winter seasons. The country covers a total area of 513,120 $km^2$and ranges between latitudes 5° 37' and 20° 27' North, and longitudes 97° 22' and 105° 37' East (Fig. 1). The weather is influenced by seasonal monsoon winds. The southwest monsoon

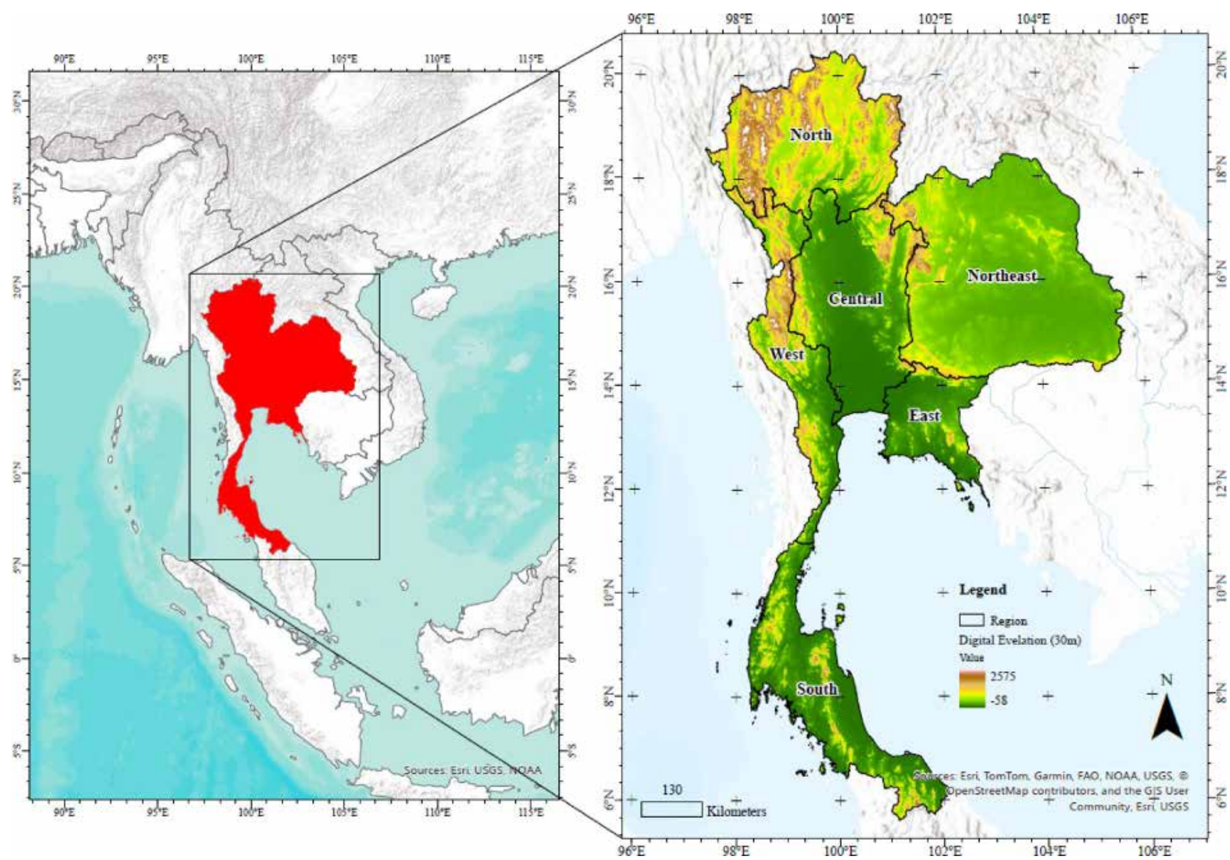

Fig. 1. Location map (left) and Digital Elevation Model (right) with the 6 regions boundaries of Thailand (right).

(mid-May to mid-October) delivers heavy rainfall from the Indian Ocean, reaching its peak in August and September, often alongside tropical cyclones. Thailand can be divided into six geographical regions: the north, northeast, central, east, west, and south regions. These six regions differ in climate, geography, and culture. The northern region is the highest in the country, with landscapes of mountains and forests cut through by river valleys. The northeastern region is a vast plateau with dry, sandy soil and less fertile land, and is primarily used for agriculture. The neutral region is a flat and fertile basin surrounding the Chao Phraya River. With conditions ideal for rice cultivation, it is the center of Thailand's agriculture. The smaller eastern region is a coastal area with fertile plains and tropical orchards, bordered by the Gulf of Thailand. The western region is mountainous and forested, featuring dense jungles and national parks, and forms a natural border with Myanmar. Lastly, the Southern region is a narrow peninsula with coastal plains, limestone hills, and numerous islands flanked by the Andaman Sea and the Gulf of Thailand.

Data sets and satellite data processing

Figure 2 illustrates the methodology utilized for this study. The datasets were collected from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument on board the Terra satellite. MOD11A1 was selected for Land Surface Temperature (LST) as it provides daily LST data at a spatial resolution of 1 km, which allows for the analysis of temporal trends over a long period while maintaining sufficient spatial detail for national-scale studies. Its high temporal frequency is particularly valuable for detecting seasonal and interannual LST variations. MOD13A3 was chosen for Normalized Difference Vegetation Index (NDVI) because it offers monthly composites that reduce noise from clouds and atmospheric conditions, making it suitable for long-term vegetation trend analysis. Although it has a coarser temporal resolution, the monthly data are more stable and reliable for examining vegetation patterns across large geographic extents[24] like Thailand. Both datasets are readily available for analysis on the Google Earth Engine platform[25]. These datasets cover the (March to May), rainy season (May to October), and winter season (November to February) in the years 2007, 2012, 2017, and 2022 at a spatial resolution of 1 km. LST images and NDVI images have been composited into a seasonal dataset for each year using pixel-averaging statistical methods. Additionally, cloud-screening processes were applied to LST and NDVI data to eliminate cloud cover from MODIS imagery. Thus, seasonal MODIS data free of cloud contamination appears suitable for detection and monitoring in this study. To ensure data quality, both the LST (MOD11A1) and NDVI (MOD13A3) datasets were subjected to the usual MODIS Quality Assessment (QA) flags. For LST, only daily observations designated as "good quality" in the QA layer were chosen, and pixels affected by cloud cover, atmospheric disturbances, or poor retrieval circumstances were removed. Similarly, for NDVI, monthly composite data that had already been adjusted to minimize cloud impacts were used. This method ensured that only accurate and high-quality data were used in the study, reducing the impact of cloud contamination and other noise in long-term spatiotemporal assessment. The MOD11A1 daily LST data, originally in Kelvin (K), were filtered for clear-sky daytime observations and subsequently converted to degrees Celsius (°C) using the standard relation LST (°C) = LST (K) – 273.15 [26]. Subsequently, these values were aggregated into seasonal periods. Similarly, the monthly MOD13A3 NDVI values were selected and composed of seasonal periods.

Data analysis

LST and NDVI values for the six regions of Thailand were processed and extracted using ArcMap (version 10.4) was used for mapping and spatial analysis. Statistical techniques were employed to analyze the spatiotemporal and seasonal variations in NDVI and LST distributions. In the analysis, descriptive statistics including mean, minimum, maximum, and standard deviation were calculated for all regions each year. Additionally, an analysis of the relationship was performed to examine seasonal variations in the relationship between NDVI and LST data using Python (version3.10) via Jupyter Notebook and Rstudio software (Version: 2025.05.0 + 496) were applied to visualization and statistical testing. In particular, the ANOVA and Pearson's correlation tests.

Thermal hot-spot detection

This research applied a hotspot analysis to differentiate regions with significant LST classify by season and focus on the areas of vigorous thermal anomalies. The Getis-Ord Gi* statistic method was used to identify spatial clustering of hot and cold spots of LST values. The Getis-Ord Gi* yields two primary statistics: the z-score, and the p-value[27]. High z-scores combined with low p-values indicate hot spots, low z-scores with low p-values indicate cool spots. Higher magnitude absolute z- scores indicate stronger clustering[28]. The method determines statistically significant thermal clusters by calculating the local aggregation of LST values in comparison to nearby features using this formula:

$$\mathrm{Gi}^{*} = \frac{\sum_{j=1}^{n} w_{i} x_{j} - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^{2} - \left(\sum_{j=1}^{n} w_{i,j}\right)^{2}\right]}{n-1}}} \tag{1}$$

where x_j is the value of attribute for feature j;
$w_{i,j}$ is the spatial weight between feature i and j;
n is the total number of features;
X and S are the mean and variance values, respectively:

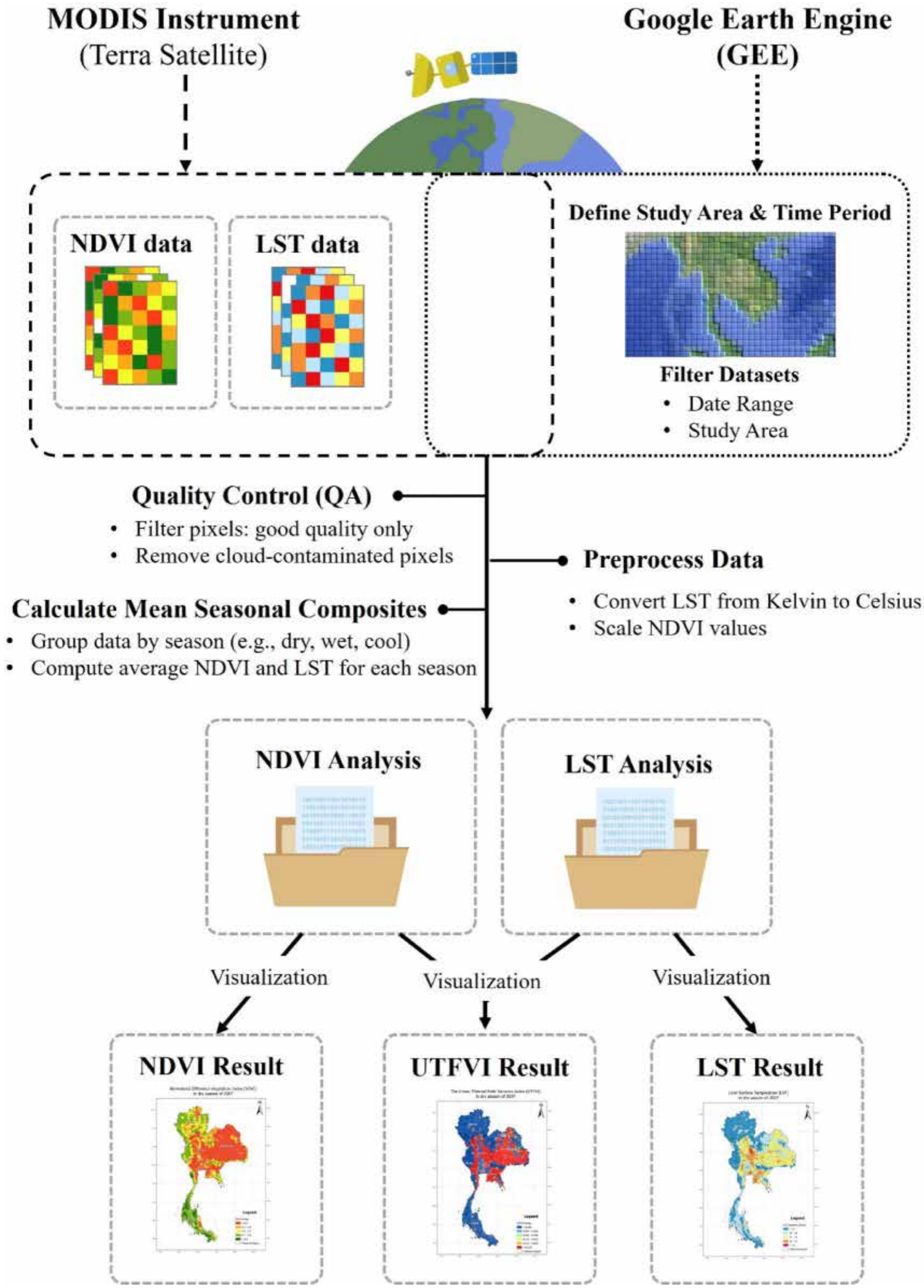

Fig. 2. Flow chart of the methodology applied.

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{2}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} X_j^2}{n} - \left(\overline{X}\right)^2} \tag{3}$$

The Gi* statistic also gives you the probability (Gi* p-value) and standard deviation (Gi* z-score) values for each feature or area. These tell you how statistically significant each one. The higher (or lower) the z-score, the more intense is the clustering[29]. Thus, three macro groups of thermal patterns were identified:

1. (1) Cool-spot: a clustering of low LST values that is statistically significant (Gi* z-score of less than – 1.65).
2. (2) Hot-spot: a clustering of high LST values that is statistically significant (Gi* z-score exceeding 1.65).
3. (3) Neutral Areas: other areas where there is no discernible spatial relationship, (−1.65 < Gi* z-score < 1.65.)

The statistical significance of hot and cool regions is determined by the confidence level at 90%, 95%, and 99% thresholds. Regions were classified like "Cool-spot99 (cool-spot LEVEL-3)", "Cool-spot95 (cool-spot LEVEL-2)", "Cool-spot90(cool-spot LEVEL-1)", "Hot-spot90 (hot-spot LEVEL-1)", "Hot-spot95 (hot-spot LEVEL-2), "Hot-spot99 (hot-spot LEVEL-3)".

An appropriate bandwidth (meters) should be selected for Getis-Ord Gi* program processed via GIS environment to perform a reliable hot-spot analysis. For each feature/area, the output of the Gi* statistic also includes the statistical significance of the probability (Gi* p-value) and standard deviation (Gi* z-score). The strength of feature/area clustering is visualized as the Gi* z-score, while assembly patterns are statistically different from what would be expected by a random spatial process and the probability of the observed hotspot patterns being randomly distributed are represented by the Gi* p-value. Table 1 This classification offers a comprehensive view in the area of thermal dynamics. The extreme value zones (LEVEL-3) indicating the concentration of the highest or lowest LST values with a 99% confidence level were classified based on the highest standard deviation class (Gi* z-score > 2.58 or Gi* z-score < 2.58 or Gi* p-value < 0.01).

This study has applied the Urban Thermal Field Variance Index (UTFVI), based on the principle that the local LST is compared to the mean temperature of the overall study region. The employed UTFVI to measure the surface urban heat island effect[29]. In addition, the surface urban heat island effect is likely stronger in cities than in suburban and rural areas because of a greater number of impervious surfaces and a smaller amount of natural soil and vegetation. This generates significant urban thermal anomalies according to how the city is arranged. It was estimated by the following Eq. (1).

$$\mathrm{UTFVI} = \frac{\mathrm{LST} - \mathrm{LST_{mean}}}{\mathrm{LST_{mean}}} \tag{4}$$

where UTFVI = Urban Thermal Field Variance Index;

LST (°C) = Land Surface Temperature;

LST_{mean} = Average of Land Surface Temperature (°C).

The main physical motivation of UTFVI is that regions with much higher temperature than the local average represent thermal stress, which are generally caused by urban heat islands (UHI). Positive UTFVI scores indicate locations that are hotter relative to the local average, potentially indicating ecological stress zones. In contrast, negative UTFVI values identify cooler, more ecological friendly areas. The ecological assessment threshold values (Table 2) are derived from general classifications widely used in urban climatology research[17,21,30,31]. These limits are experimentally determined to represent different levels of ecological well-being and heat stress. In particular, threshold ranges were structured to separate subtle (weak), moderate (middle), strong and extreme (strongest) thermal anomalies.

Results and discussion

The annual mean changes in Land Surface Temperature (LST) across four years (2007–2020) illustrated Fig. 2, characterized by three seasons of Thailand such as dry, rainy, and winter. The study also found that the mean LST

Thermal zone categories	Confidence levels	Probability (Gi* *p*- value)	Standard deviation range (Gi* z-score)
Cool-spot99 (LEVEL-3)	99%	< 0.01	<−2.58
Cool-spot95 (LEVEL-2)	95%	< 0.05	<−1.96
Cool-spot90 (LEVEL-1)	90%	< 0.10	<−1.95
Other areas	Not significant	0	−1.65 < z-score < 1.65
Hot-spot90 (LEVEL-1)	90%	< 0.10	> 1.65
Hot-spot95 (LEVEL-2)	95%	< 0.05	> 1.96
Hot-spot99 (LEVEL-3)	99%	< 0.1	> 2.58

Table 1. Hot-spot classification by applying gi*etis-Ord gi** approach.

Threshold value	UTFVI class	Ecological evaluation index
< 0	None	Excellent
0–0.005	Weak	Good
0.005–0.010	Middle	Normal
0.010–0.015	Strong	Bad
0.015–0.020	Stronger	Worse
> 0.020	Strongest	Worst

Table 2. The threshold of ecological evaluation index and UTFVI.

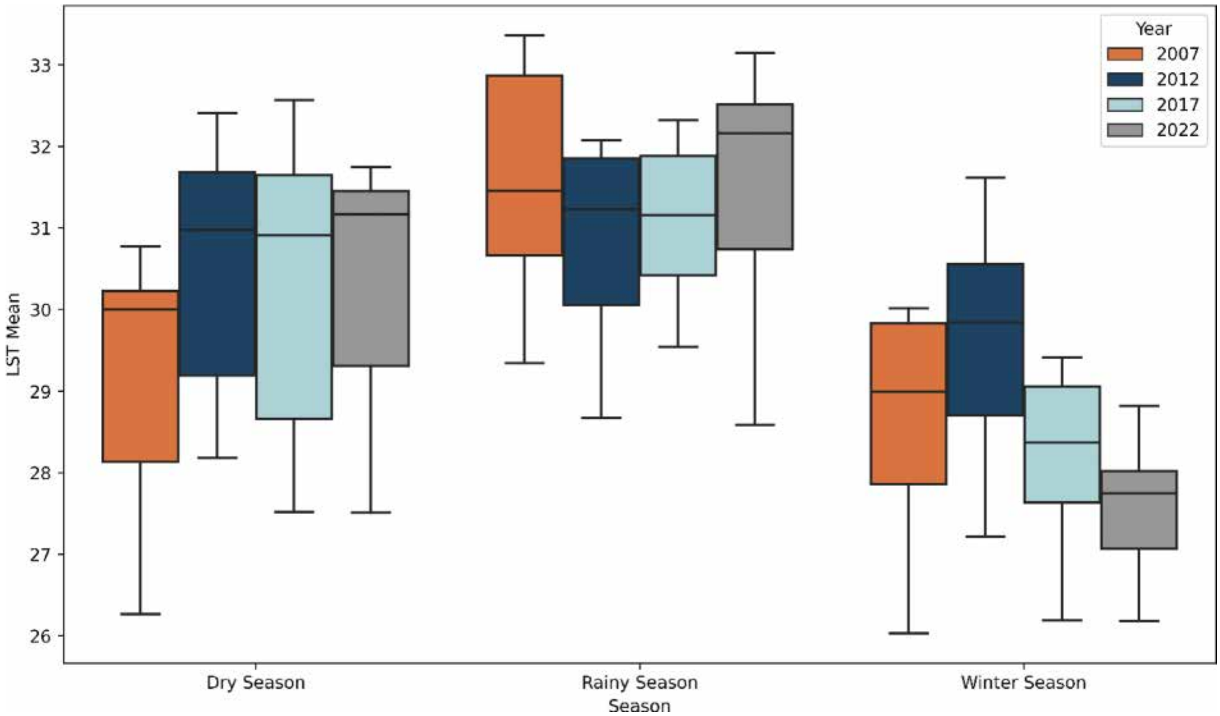

Fig. 3. Annual distribution of LST across 2007 to 2022.

increased in all six regions between 2007 and 2022 as shown in Table SS1. The distribution of LST for a specific year and season, along with the interquartile range (IQR) and median values, is clearly illustrated. The dry season exhibits a slight increase in LST over time, with relatively stable distributions. Throughout the rainy season, LST remains consistent, although 2007 shows a wider range. The winter season displays a downward trend, with the median LST consistently decreasing from 2007 and particularly in 2020. The potential seasonal and temporal variations in temperature patterns are relevant for climate studies. Figure 3 presents the annual mean Normalized Difference Vegetation Index (NDVI) across three seasons. The results show the median, quartiles, and range of NDVI values for each seasonal year. NDVI values are generally highest during the rainy season and lowest during the dry season. The interannual variability is apparent, with some years exhibiting notably higher or lower NDVI values compared to other years.

A comparative analysis of LST and NDVI across three seasons from 2007 to 2022, separated by regions (Fig. SS1). The LST remains relatively stable, with some variations observed between regions, particularly in the rainy and winter seasons. The seasonal LST variation in Thailand is largely a function of climatic and physical processes. In the dry season (March–May), high solar radiation, cloudless conditions, and low soil moisture lead to an increase in LST. Loss of vegetation also lowered the albedo, leading to an even more increased heat absorption. During the wet season (May–October), both cloud cover and precipitation amplify evapotranspiration, cooling the surface. November to February, winter months, were cooler due to low solar elevation angle and intrusion of cold air mass especially in the northern highlands. Such patterns are conditioned on the monsoon and filtered by land cover as well as the joint effect between climate and surface properties on LST variations. However, NDVI values establish little fluctuation over the years, remaining consistently high for most regions, stable vegetation health during this period. The highlight was seasonal and regional differences, with central regions maintaining higher LST and NDVI values throughout the years compared to other regions. Moreover, the spatial distribution of NDVI trends can be influenced by various environmental factors, including topography, climate, and human activities. Many studies have shown that NDVI trends exhibit spatial heterogeneity, particularly in the terrains complex as the Tibetan Plateau, where altitude and climate gradients significantly affect vegetation responses[32,33]. Additionally, the impact of anthropogenic factors on NDVI has been explored, indicating that human activities can alter vegetation dynamics and consequently affect the LST-NDVI relationship[33,34]. Human activities, particularly urban expansion, significantly alter LST–NDVI relationships. Landscape transformations of LST Urban LULC and LCC change play a significant role in the increasing LST; while LST and NDVI exhibit a negative relationship[35]. It is suggested that human actives, especially urban expansion, are significantly responsible for the changes in vegetation cover and productivity, thus playing an important role in shaping NDVI patterns[36]impervious landcover density grows and vegetated areas are reduced, leading to higher urban surface temperatures.

Interannual variability in NDVI across Thailand was not solely driven by seasonal climatic patterns but was also influenced by major climatic events. For instance, the pronounced NDVI decline observed in 2010 and 2015 corresponded with strong El Niño events, which are typically associated with reduced rainfall and prolonged drought conditions in Southeast Asia[37,38]. Conversely, higher NDVI values recorded in 2011 and 2017 aligned with La Niña phases[39]during which increased precipitation likely promoted vegetation growth. Additionally, extreme flood events, such as the widespread floods in late 2011, may have temporarily reduced NDVI in affected lowland areas due to waterlogging stress. These findings suggest that interannual NDVI variability reflects the complex interplay between seasonal climate patterns and large-scale climatic anomalies.

The Association between LST and NDVI across three seasons for the four years indicates a strong negative correlation present in Fig. 4. Particularly, Fig.SS2 found that correlation coefficients were 0.52 and 0.61 in dry season of western and northern regions, respectively. The central region shows a correlation coefficient of 0.39 was highest in rainy season, while the northern region exhibits the strongest negative correlation at 0.72 during the winter season. The comparison of the various studies is shown in Table 3 showed the results were according to negative relationship with LST and NDVI in all study accept the study in Europe is found positive relation. The study in Imphal city had in line with the strong negative correlations that were discovered during the winter (North: $R^2 = 0.72$; West: $R^2 = 0.46$). Weak winter correlations (Central, East, and South: $R^2 = 0.03–0.16$) are consistent with findings that vegetation-temperature coupling decreases during cool or dry seasons. The patterns of land use and seasonal changes observed in tropical climates are supported by the moderate correlations ($R^2 \approx 0.26–0.61$) found in dry is similarity with Hyderabad, India and transitional areas in all regions except the south. However, a negative LST-NDVI relation indicates locations were rising temperatures lower vegetation activity. Not all map pixels, though, show statistically significant relationships at a p-value cutoff of < 0.05[18].

A significant seasonal fluctuation of LST is confirmed for all seasons, as winter-summer was 1.24, winter-rainy was − 1.54, and summer-rainy was − 2.78 ($p < 0.001$). With Welch's 8397.1, $p < 0.001$, and Games-Howell post hoc tests revealed pairwise differences ($p < 0.001$) for all season combinations. Similarly, post hoc comparisons revealed clear variations of NDVI as 0.09 of winter-summer, 0.07 of winter-rainy, and − 0.03 of summer-rainy, and Welch's ANOVA showed highly significant differences across seasons (Welch's 3833.4, $p < 0.001$). These findings highlight how statistically significant seasonal differences in both variables provide context for the observed connections between LST and NDVI.

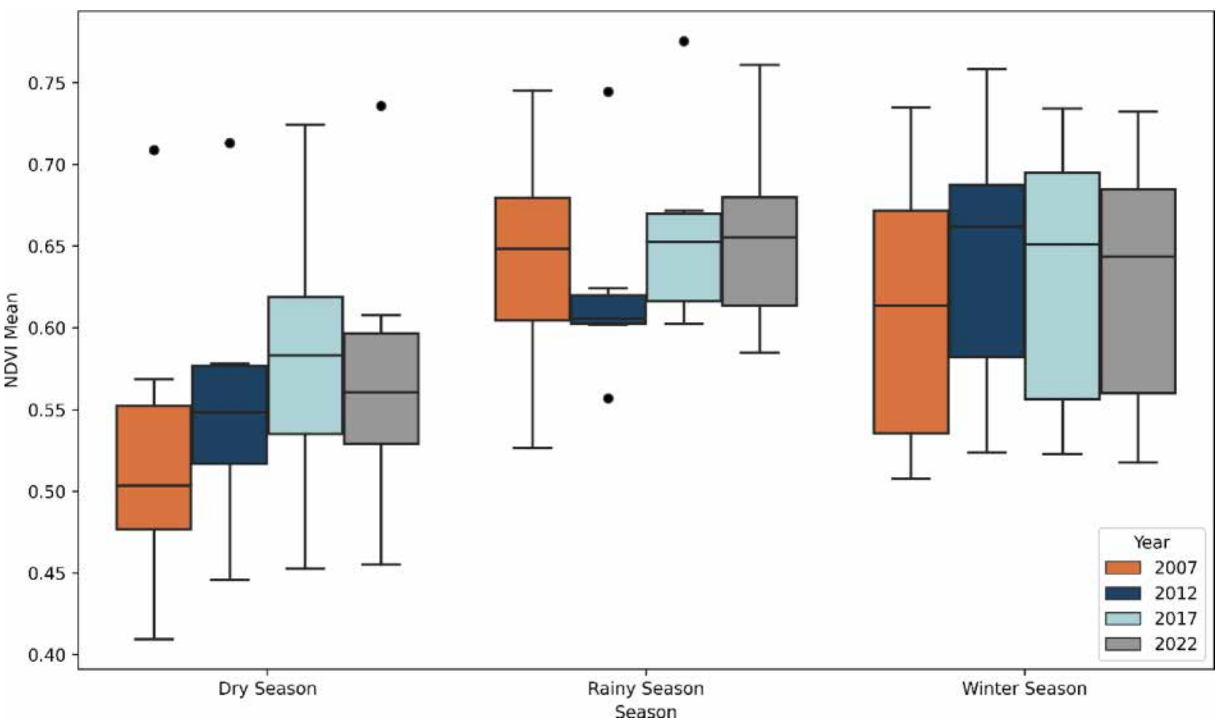

Fig. 4. Annual distribution of NDVI across 2007 to 2022.

Location	Correlation (LST-NDVI)	Reference
Thailand	• Moderate to strong negative correlation in dry and winter season were 0.46–0.72 in North and West of Thailand	**This study**
Pakistan	• Negative correlation between LST and elevation (−0.51)	[45]
India	• Strong negative on plants (−0.74 to −0.49), moderate negative on barren/urban (−0.42 to −0.21), insignificant on water (0.27 to 0.05)	[46]
India	• Strongest negative in monsoon (−0.59 to −0.27), weakest in winter (−0.35 to −0.05), moderate negative pre-monsoon (−0.43 to −0.16), weak negative post-monsoon (−0.28 to −0.13)	[47]
India	• Strongest negative in post-monsoon (−0.63), weakest in winter (−0.17), strong negative on vegetation (−0.51), moderate positive on water (0.45)	[48]
Brazil	• Strong negative correlation	[18]
Western Ethiopia	• NDVI was substantially negative relationship with LST (0.99)	[26]
Netherlands	• Strong negative relationship (0.83) between mean LST and positive NDVI values.	[49]

Table 3. Summary of correlation coefficients between LST and NDVI from different studies across various regions.

Year	Region	Excellent [%]	Good [%]	Normal [%]	Bad [%]	Worse [%]	Worst [%]	NA [%]
2007	Central	38.67	2.59	2.40	2.05	2.44	51.84	0.00
	East	44.58	2.38	1.75	2.24	2.24	46.68	0.14
	North	79.66	1.49	0.93	1.05	1.29	15.58	0.00
	Northeast	30.02	3.35	3.21	3.68	3.61	56.13	0.00
	South	89.01	1.69	1.20	0.65	1.11	6.16	0.18
	West	40.18	2.76	2.84	3.51	2.92	47.79	0.00
2012	Central	46.62	2.89	2.49	2.61	2.24	40.61	2.54
	East	58.35	2.87	2.66	2.73	2.80	30.54	0.07
	North	84.10	1.09	1.01	0.85	0.85	8.80	3.31
	Northeast	26.92	1.95	2.20	2.68	2.74	61.68	1.84
	South	87.47	1.45	1.17	1.26	0.98	7.48	0.18
	West	40.10	3.59	2.92	3.26	3.59	45.95	0.58
2017	Central	39.91	2.70	2.56	2.85	2.57	46.87	2.54
	East	54.93	2.31	2.38	2.80	2.24	34.87	0.49
	North	79.66	1.21	1.49	1.09	0.77	15.29	0.48
	Northeast	27.62	2.15	1.98	2.66	2.71	59.76	3.11
	South	89.41	1.35	1.63	1.39	1.17	4.86	0.18
	West	44.03	3.17	3.09	2.92	4.18	42.11	0.50
2022	Central	32.20	3.43	4.09	3.50	3.53	53.08	0.17
	East	42.28	2.73	3.49	2.87	3.14	45.49	0.00
	North	80.31	1.53	1.25	1.45	1.69	13.76	0.00
	Northeast	34.50	3.54	3.45	4.33	4.19	49.95	0.05
	South	90.18	1.51	1.11	1.26	1.05	4.71	0.18
	West	37.34	1.84	2.26	2.76	2.92	52.88	0.00

Table 3. The percentage of UTFVI values categorized into six ecological evaluations.

The seasonal fluctuation of LST-NDVI correlation over time, for the rainy season shows a fluctuation with a peak in 2012 (Fig.SS3), followed by a decline, and while the winter season demonstrates relatively stable but moderate negative correlations. These findings suggest that LST and NDVI are inversely related, with varying intensities across seasons and years, reflecting the complex interaction between climate and vegetation dynamics. It is essential to highlight the importance of differentiating between LST and near-surface air temperatures, noting that urbanization can decouple these temperatures significantly, sometimes by as much as 20 °K[40]. Similarly, there was a strong negative relationship ($R^2 = 0.83$) between mean LST and NDVI was reported in the Netherlands, reinforcing the idea that vegetation effectively reduces surface temperatures[41]. In this study, although no formal sensitivity analysis was conducted, we qualitatively examined the spatial correspondence between UTFVI classes, NDVI values, and land surface temperature (LST) distributions across various regions and seasons. The consistency observed between high UTFVI values, low NDVI zones, and areas of intensive urbanization or land degradation supports the general applicability of these thresholds in the Thai context. Several previous studies have demonstrated a strong relationship between the Urban Thermal Field Variance Index (UTFVI), Land Surface Temperature (LST), and the Normalized Difference Vegetation Index (NDVI), supporting the validity of using UTFVI to assess ecological thermal stress, particularly in urban environments.

UTFVI typically shows a strong positive correlation with LST and a negative correlation with NDVI, reflecting the influence of land cover and vegetation density on local thermal conditions. A study in Gazipur, Bangladesh found a perfect positive correlation between UTFVI and LST, while NDVI showed a negative relationship with LST[42]. Similarly, in Addis Ababa, Ethiopia, NDVI was found to be strongly and negatively correlated with LST ($R^2 = 0.98$), indicating the cooling effect of vegetation in urban areas[43]. In another case in China reported that UTFVI had a significant positive correlation with urban areas and NDBI, and a negative correlation with NDVI, reinforcing its applicability in urban thermal assessment[44]. These findings support the robustness of UTFVI classification thresholds when used in conjunction with NDVI and LST, even in diverse climatic contexts. Therefore, while thresholds should be interpreted with caution in tropical climates like Thailand, previous research provides a strong basis for their continued use in evaluating urban ecological conditions. Nevertheless, to enhance the precision of ecological stress assessments, future studies should consider conducting localized sensitivity analyses or calibrating UTFVI thresholds specifically for tropical environments. This would help refine interpretations of thermal stress across diverse land use types, particularly in regions where natural climate variability, such as seasonal monsoon cycles, may significantly affect surface temperature dynamics.

The LST-NDVI relationship may change with seasons and locations. A study carried out in Hyderabad, India reported that the negative relationship between LST and NDVI was strongest during monsoon season and weakest during winter[47]. Moreover, the strongest negative correlation was obtained in 2017 (0.82) indicating that increased vegetation cover in this season reduces surface temperatures strongly. Weaker negative correlation between the weighted NDVI in May 2012 and temperature in the rainy season (0.48) in contrast indicated less contribution of vegetation at reducing the surface temperature in this year and season. Moreover, there was no correlation between NDVI and ENSO in southern Africa. Plant growth was delimited during El Niño years. However, NDVI levels were higher during La Niña, demonstrating the varying impacts of these climate anomalies[50]. In Thailand, a major climate anomaly like the El Niño-Southern Oscillation (ENSO) had a significant impact on interannual variability in LST and NDVI in addition to seasonal climatic patterns. Significant NDVI declines and LST increases were noted in high El Niño years, particularly 2010 and 2015[51], which corresponded with widespread drought conditions recorded during these years. Image processing techniques were employed to estimate LST from the collected satellite data. The accuracy of these estimates is supported by previous research demonstrating robust correlation between satellite-derived LST and ground-based measurements from the Meteorological Department[52]. Their analysis, using correlation methods, showed a strong correlation coefficient ($R = 0.99$), indicating a high degree of consistency between satellite and observational data. The strong correlation between satellite-derived LST data and ground-based measurements validates the accuracy of MODIS satellite data for assessing surface temperature patterns. This confirms the effectiveness of remote sensing for large-scale environmental monitoring, particularly in areas lacking comprehensive ground-based data.

Figure 5 illustrates the association between LST and NDVI for six regions of Thailand during the dry, rainy, and winter seasons. The regional points appear in all panels with NDVI on the x-axis and LST (°C) on the y-axis. The negative relationships between NDVI and LST in all regions across seasons were clearly seen from the regression lines and fitted equations, which indicate that land areas with higher vegetation density tend to have lower surface temperatures. The degree of this relationship is different for each deme and from season to season. The slope of the regression line is more negative in the North (13.5–18.7), Northeast (12.8–14.6), and West regions (14.7–16.8), indicating a stronger cooling effect of vegetation. In contrast, the negative relationship in the South tends to be much weaker, implying a limited cooling effect of vegetation on surface temperature. There are also seasonal changes and the highest LST is during the wet and the lowest during the winter months. In general, the result shows a moderate effect of the vegetation in retarding LST over various climatic and geographical regions of Thailand.

Figure 6 displays changes in mean Normalized Difference Vegetation Index (NDVI) over time and space, as well as variations that occurred with the seasons during the research period. The spatial analysis of vegetation cover, conducted using satellite data from the MODIS sensor to examine the NDVI, revealed notable regional variations across Thailand. The results indicate that the Northeast region consistently exhibited the lowest NDVI values among the six regions studied, with values below 0.5, signifying limited vegetation cover in this area. In contrast, the southern region recorded the highest NDVI values, reflecting a more extensive vegetative cover. These findings align with the region-specific topography and land use patterns. According to land use data from the Land Development Department, the southern region contains more agricultural and forested land compared to the northeast, which explains the higher NDVI values observed. The NDVI, therefore, effectively mirrors the distribution of vegetation across these regions. Seasonal differences were examined, and in almost every region, the rainy season produced the highest NDVI readings, indicating the time of year when vegetation grows at its highest rate. It is a well-known fact in ecology and agriculture that plants grow in the rainy season, taking over woods, agricultural grounds, and even regions that were previously devoid of flora, allowing weeds to proliferate. Consequently, seasonal NDVI patterns reinforce the notion that Thailand's rainy season is the optimal time for plant growth[53] demonstrating how variations in vegetation index values are closely linked to changing seasons and land use patterns.

This seasonal variability is crucial for urban planning and management, as it highlights the need for adaptive strategies to mitigate the adverse impacts of urbanization on local climates and ecosystems[47]. Similarly, Guha[46] demonstrated that seasonal changes in LST and NDVI significantly influence ecological health, suggesting that the correlation analysis is vital for understanding land use and land cover (LULC) dynamics.

Spatial distribution and LST variation among hot-spot classes

Descriptive statistics of hotspots and their spatial representation are given in the Supplementary Material (Table SS2). There are hot spots that are nearly double the number of cool spots, and more than an area of 20% in the metropolitan has thermal anomalies. The mean LST min and LST max values of cool spots are between 20.7 °C

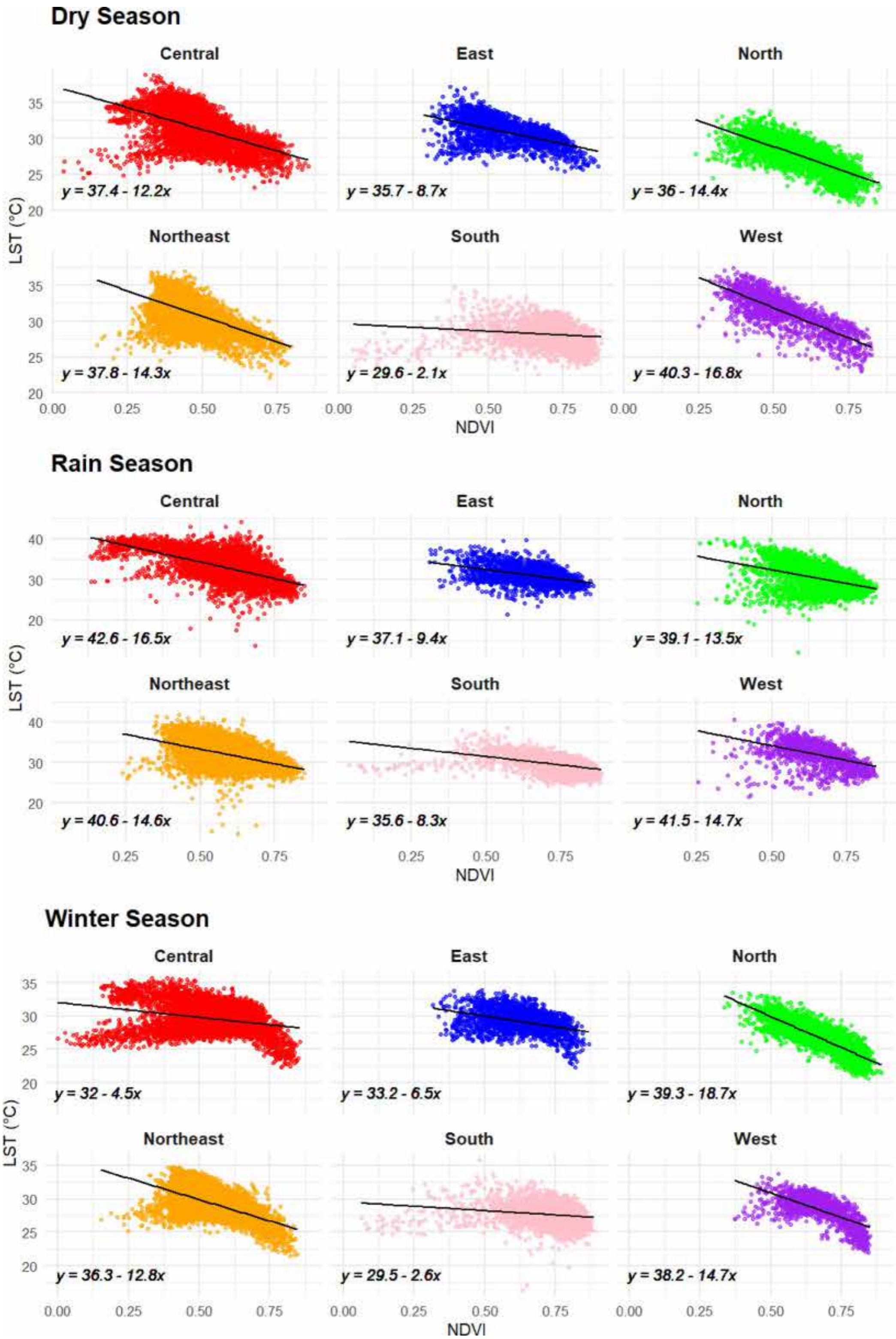

Fig. 5. The season regression equations of NDVI with LST on six regions.

and 39.0 °C in dry season, 12.0 °C and 44.3 °C in rainy season and 16.3 °C and 35.9 °C in winter season while the mean LST values for hot spots are between 20.7 °C and 39.0 °C (dry season), 12.0 °C and 44.3 °C (rainy season) and 16.3 °C and 35.9 °C (winter season). Nearly half of the communities exceeded the mean coverage threshold for cool spots in urban areas. The ratio of hot spot coverage above average as 35% of municipalities had a hot spot coverage value greater than the value for metropolitan areas. Northeast region (85 km^2) was the region with the largest surface area in cool or hot conditions and low temperatures. The other two surface areas accounted for

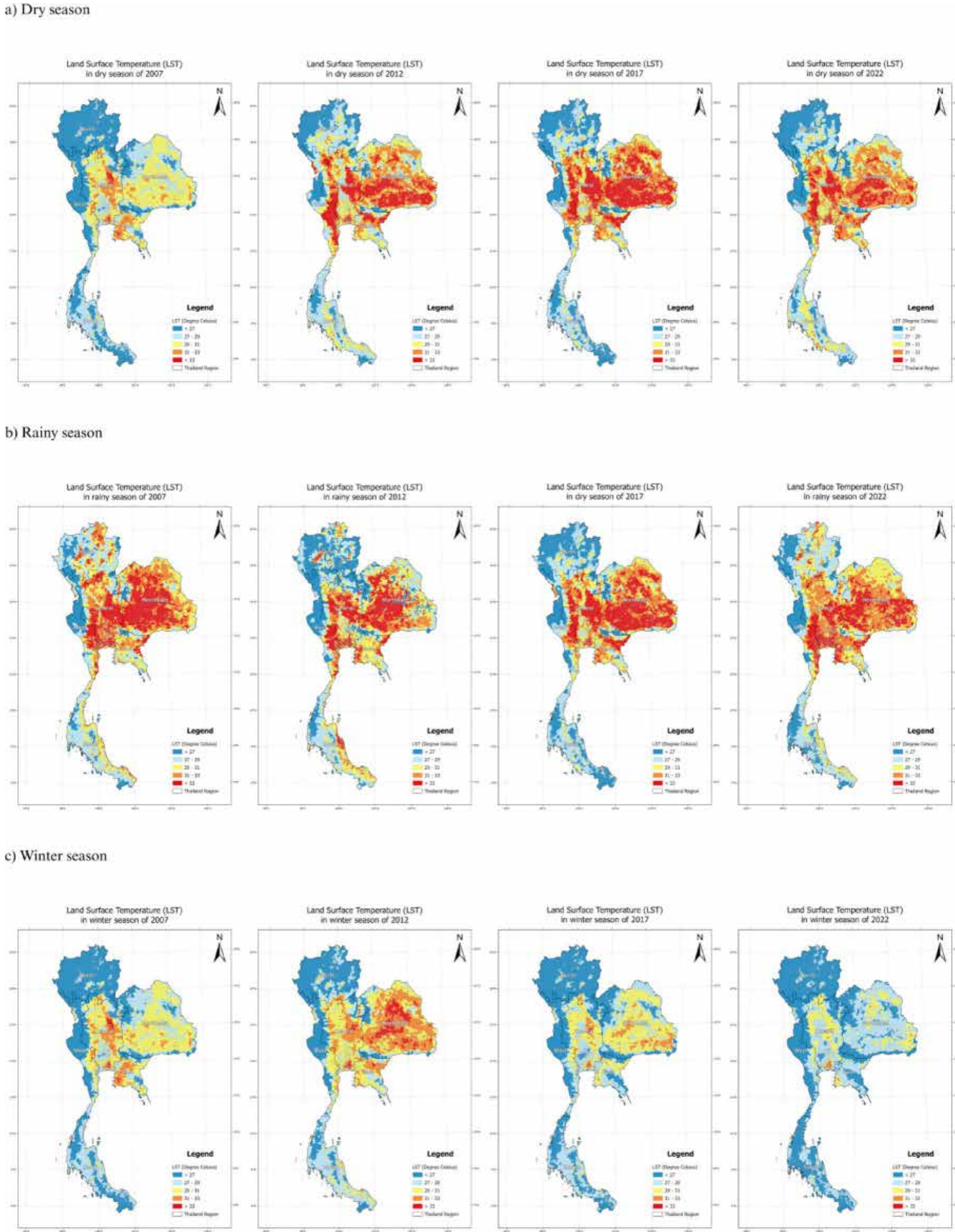

Fig. 6. Spatiotemporal and seasonal distribution of LST across four years.

only 3.7% of the total cool and hot spots area in all 3 seasons across the entire metropolitan area in this region. For the whole metropolitan area, the average increase in the LST between hot spots and cold (LEVEL-3 or 99% confidence level) was about 31.2 °C for rainy, 30.1 °C in dry season, and 28.4 °C for winter times. When we compared these two groups, the cold spot in north region showed the lowest mean LST values (about 23.8 °C), while the high spot in central region (35.0 °C) in rainy season, east region (33.5 °C) in dry season, north region (31.5 °C) in winter were recorded the highest mean LST values.

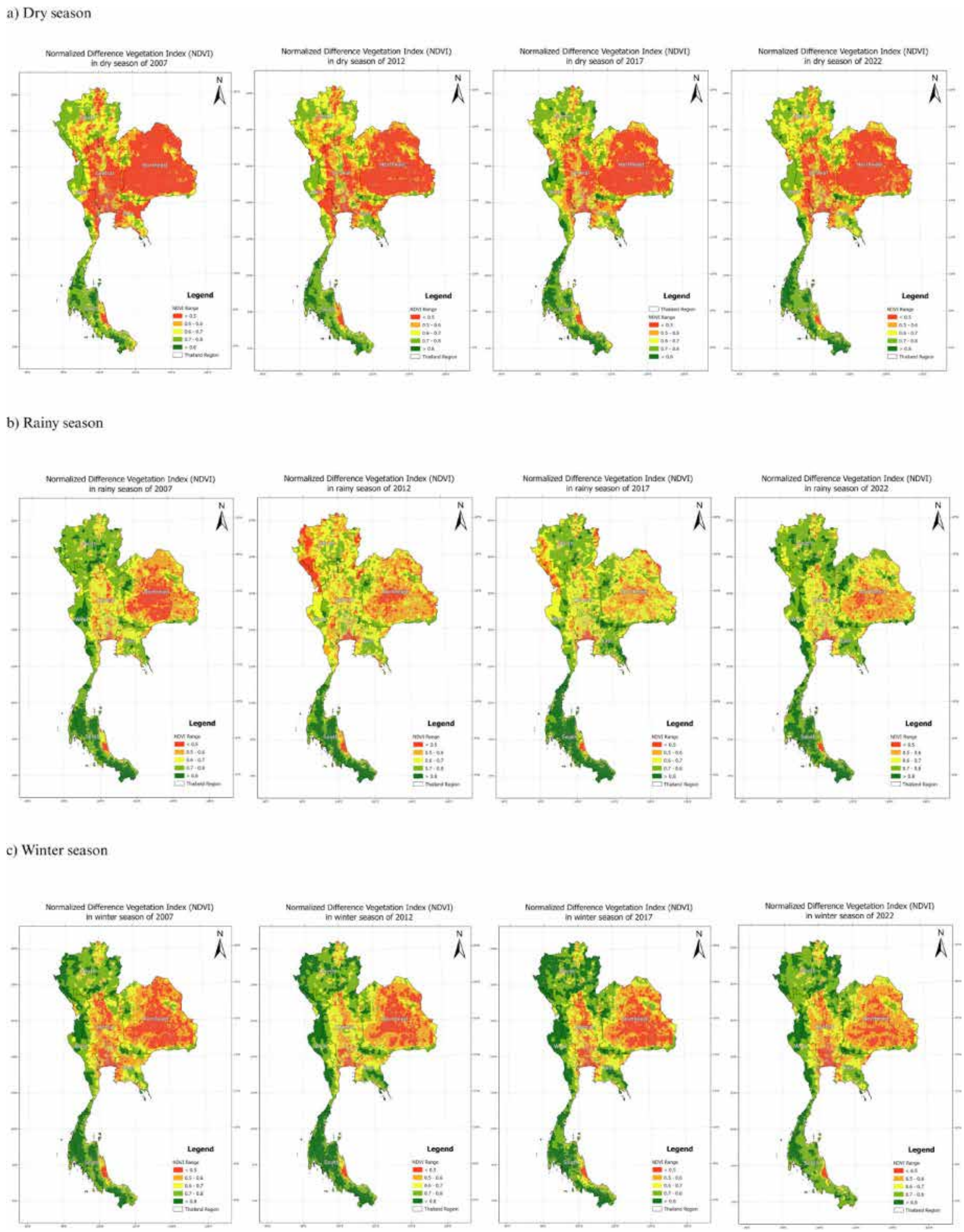

Fig. 7. Spatiotemporal and seasonal distribution of NDVI across four years.

Ecological and thermal status of Thailand

The evaluating Thailand of ecological and thermal conditions was one of the aims of the study. UTFVI values, which are categorized into six ecological evaluations as indicated in Fig. 8, were used to assess the country's thermal state. The evaluation of Thailand's ecological and thermal conditions using the Urban Thermal Field Variance Index (UTFVI) revealed clear spatial patterns related to land cover characteristics. The areas with high UTFVI values show low NDVI is similar with a study in India[31]. Areas exhibiting high UTFVI values, which correspond to lower NDVI values, indicate zones of degraded ecological quality and increased thermal stress. These findings highlight the strong influence of vegetation cover on local thermal environments. Although

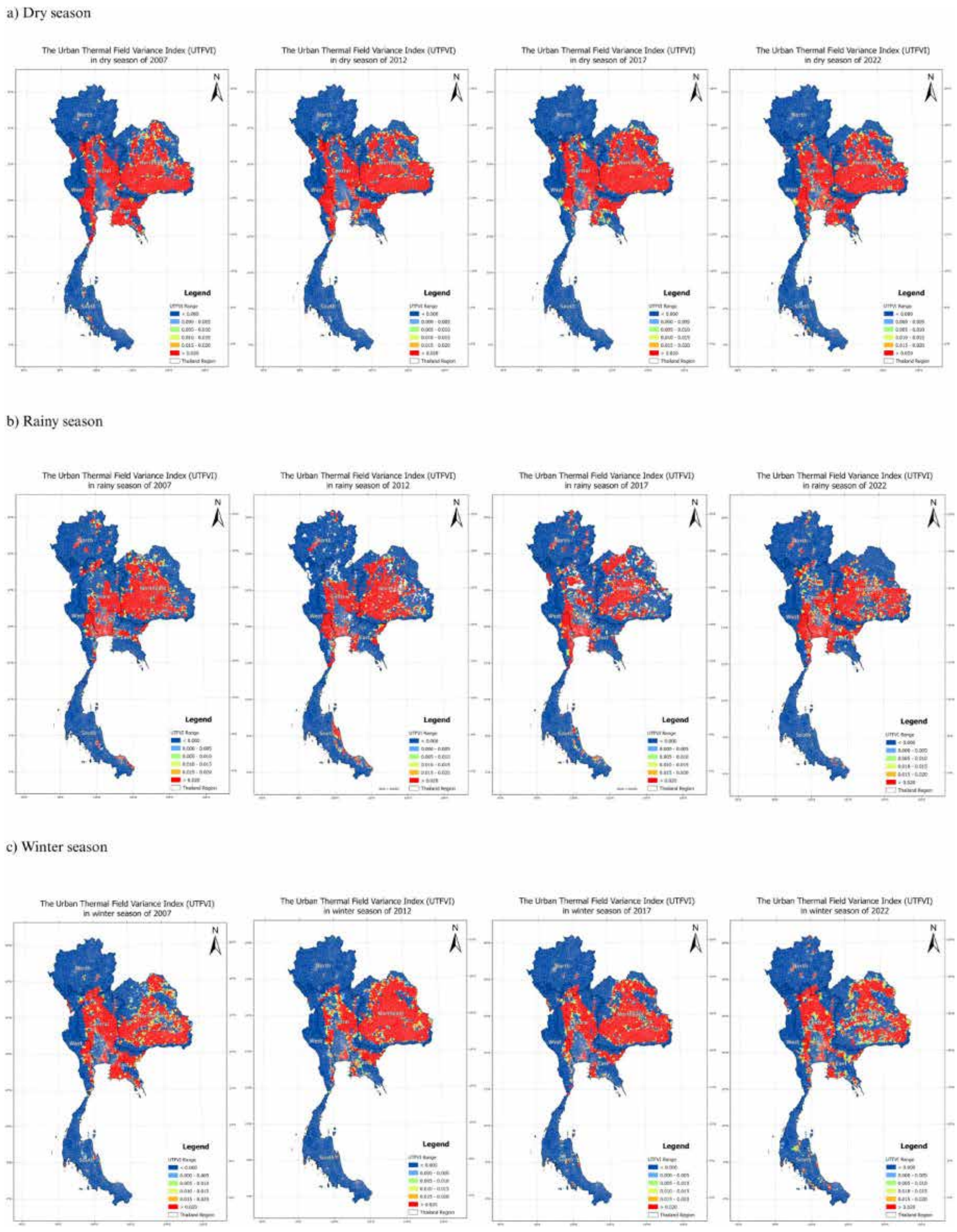

Fig. 8. Thermal status of Thailand in three seasons using UTFVI across four years.

UTFVI is a widely used indicator for assessing urban heat island (UHI) effects, its application beyond urban areas, such as in agricultural lands and forests, must be interpreted with caution. In these non-urban landscapes, high land surface temperature (LST) variability may stem from natural factors, including seasonal vegetation cycles, soil moisture fluctuations, and land management practices, rather than urbanization-driven heat emissions. Therefore, high UTFVI values in rural areas may not necessarily represent anthropogenic thermal stress. In this study, UTFVI interpretation was primarily emphasized in urban and peri-urban contexts, where urban development is the dominant driver of thermal anomalies. Future research should consider adapting or refining thermal indices to better account for natural variability across diverse land cover types, enhancing the robustness of ecological and thermal assessments at the national scale.

Table 3 shown result is according to the study in India has identified two extreme categories for ecological and thermal status "worst" (UTFVI > 0.020) and "excellent" (UTFVI < 0). These categories apply across all seasons[31]. The worst category of the ecological evaluation index was also prevalent, occurring in approximately 30–61% of the central, eastern, northeastern, and western regions. Areas with bad and worse thermal conditions (0.010 < UTFVI < 0.020) accounted for a few proportions (4%). Similarly, the percentage of areas classified as 'good' or 'normal' was around 4%. In contrast, the highest proportion of areas with excellent thermal conditions (UTFVI < 0) were most common in the southern (90%) and northern (84%) regions. Both regions constantly maintained excellent environmental quality from 2007 to 2020, with some fluctuations observed. This consistent excellence can likely be attributed to effective ecological planning and environmental management strategies.

Particularly in urban and peri-urban regions of central, eastern, and northeastern Thailand, the UTFVI results offer a dynamic insight into regional patterns of heat stress and ecological degradation. These findings highlight key recommendations for lawmakers and city planners for effective interventions and measures to mitigate[54]. To address extreme urban heat, cities most affected by heat stress should focus on developing more interventions such as green spaces, including parks, green roofs, and tree-lined streets to cool their neighborhoods[55]. Moreover, restoring degraded lands and encouraging the planting of seasonal vegetation are examples of adaptive land management techniques that can increase ecosystem services and thermal comfort. Finally, in order to facilitate proactive adaptation in the face of growing climate variability, UTFVI data ought to be incorporated into early warning systems and urban climate resilience planning[56]. These UTFVI based evaluations are an essential instrument for coordinating Thailand's urban growth with the objectives of sustainable climate adaptation.

Conclusion

In conclusion, the relationship between LST and NDVI in Thailand is influenced by various factors, including seasonal variations, spatial heterogeneity, and anthropogenic activities. Future research should continue to refine methodologies for analyzing LST-NDVI dynamics, particularly using advanced remote sensing technologies and long-term datasets to capture these complex interactions comprehensively. This study emphasizes the significant role of land cover characteristics in shaping local thermal environments, with UTFVI proving to be an effective tool for assessing urban heat island effects.

This analysis of climate change effects on LST and NDVI highlights the complex interplay between temperature, vegetation health, and climatic variables. Our research determines the importance of considering climate variability to understand its impact on vegetation, an area that has received relatively little attention to date. In revealing novel associations between LST and NDVI, this study contributed significantly to the field. The use of satellite data has proven essential in advancing our understanding of these climatological processes. While satellite data (MODIS data) provide useful long-term observations for specific regions, the 1 km detail may not be enough to see small differences in diverse urban areas. This limitation can lead to potential underestimation or overgeneralization of LST-NDVI relationships, particularly in areas where land cover types vary sharply within a single pixel. Sub-pixel heterogeneity, such as mixtures of vegetation, built-up areas, and water bodies, may influence the thermal and vegetation signals recorded. Several studies have explored the integration of higher-resolution datasets. For instance, combining Landsat 8 and Sentinel-2 imagery has been shown to enhance the spatial resolution of LST and NDVI measurements, providing more detailed insights into urban heat islands and vegetation patterns[57]. Future research could benefit from integrating these higher-resolution datasets and downscaling methods to more accurately capture localized urban thermal dynamics and vegetation cover patterns. This approach would help to further refine the understanding of LST-NDVI relationships in complex urban landscapes. Addressing the challenges of climate change impacts on vegetation requires a comprehensive approach that accounts for both environmental and anthropogenic factors. Furthermore, the accuracy of thermal assessments will be increased by creating region-specific indices that take into consideration the variety of the natural landscape. In order to reduce heat effects, improve resilience, and facilitate successful climate change adaptation, this study emphasizes the significance of sustainable urban planning solutions that take thermal stress into account and integrate green infrastructure.

Data availability

The data is available upon a reasonable request to the corresponding author.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
The Ethics Committee of Faculty of Tropical Medicine approved this study, Mahidol University TMEC 21–055 in compliance with Declaration of Helsinki, ICH guideline for Good Clinical Practice and other international Guidelines for Human Research Protection. Inform Consent is not applicable for this study due to the secondary data obtained.

Additional information
Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-025-13018-y.

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