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Vegetation dynamics in Mainland Southeast Asia: Climate and anthropogenic influences

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ABSTRACT

Understanding vegetation dynamics and their influencing factors is essential to regional sustainable development and ecological security. However, large-scale and long-term vegetation changes and attribution pose challenges due to temporal and quality discrepancies in multi-source remote sensing data. This study developed a research framework based on multi-source data integration and conducted a case study in Mainland Southeast Asia. By integrating Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data, we generated a long-term Normalized Difference Vegetation Index (NDVI) dataset for 1982–2023. We used trend test, partial correlation analysis, and linear regression analysis to explore spatiotemporal vegetation dynamics and their links to climate and human activities. The results show: (1) the multi-year average NDVI of Mainland Southeast Asia is 0.797, with 85 % of the area exceeding 0.7, indicating robust vegetation growth across the region. The regional NDVI shows a significant increasing trend in 1982–2023, with a growth rate of 0.02 per decade. (2) The impact of rising temperatures on vegetation in Mainland Southeast Asia is mainly positive, increasing NDVI in 81 % of the area. Whereas the impact of reduced precipitation on vegetation is negligible. (3) In the quantitative attribution, temperature changes have the largest contribution to NDVI changes, contributing 70 % (0.049) to regional NDVI changes (0.056) and dominating 40 % of the area. Human activities contribute 20 % (0.014) and dominate 33 % of the area. Precipitation changes contribute 10 % (–0.007) and dominate about 5 % of the area. This study offers scientific insights and data support for understanding vegetation changes and sustainable development in Mainland Southeast Asia.

1. Introduction

The increase in carbon dioxide in the atmosphere has led to widespread and profound impacts on global ecosystems. The IPCC's Sixth Assessment Report emphasized that to meet the 1.5°C temperature target, countries need to take immediate action to achieve carbon neutrality (Livingston and Rummukainen, 2023). Vegetation, as a crucial carbon sink, plays a significant role in climate regulation, reducing atmospheric carbon concentrations, and maintaining biodiversity (Anees et al., 2024; Salim et al., 2024; Signorile et al., 2024). Therefore, it is essential to research vegetation dynamics to assess ecosystem health and provide a basis for formulating strategies to address climate change (Wang et al., 2023).

In recent years, the rapid development of remote sensing technology has provided strong support for monitoring vegetation dynamics. Remote sensing data feature extensive coverage, long time series, high resolution, and near-real-time acquisition, significantly enhancing the accuracy and reliability of vegetation dynamic analysis (Mngadi et al., 2024). Among various remote sensing indices, the Normalized Difference Vegetation Index (NDVI) has become a common indicator for assessing vegetation growth conditions due to its high correlation with Net Primary Productivity, photosynthetic efficiency, and Leaf Area Index, as well as its accessibility and wide applicability (Chouari, 2024; Hu et al., 2022; Reyes-Avila and Baxter, 2024). Vegetation dynamic monitoring based on remote sensing NDVI is a crucial area of research in climate and environmental change and provides a powerful tool for

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assessing the ecological security of global key carbon sink areas (Gandhi et al., 2015).

Existing studies consistently indicate that global vegetation indices have changed significantly due to the combined impacts of climate and human activities (Banerjee et al., 2024; Campana et al., 2024; Tuoku et al., 2024). Temperature and precipitation are regarded as key climatic factors affecting land ecosystems (Hashim et al., 2024; Yuan and Zhou, 2004). Suitable temperature and precipitation can help vegetation grow and maintain ecological balance, while extreme weather events, such as high temperature and excessive precipitation, can affect vegetation negatively. Mohammat et al. (2013) demonstrated that drought and spring cooling led to a reduction in vegetation growth in inland Asia. Zhang et al. (2016) noted that temperature and precipitation are major drivers of vegetation changes and significantly affect vegetation growth, distribution, and carbon balance functions. Furthermore, due to differences in vegetation types, terrain, and other factors across regions, the impacts of temperature and precipitation on vegetation show significant spatial heterogeneity (Pereira et al., 2024; Zahura et al., 2024). For example, Li et al. (2020) found that increased monthly temperature promotes the growth of evergreen broadleaf forests, mixed forests, and crops, while vegetation growth in tree-grasslands and typical grasslands is more significantly influenced by monthly precipitation.

Besides, human activities have significant direct or indirect impacts on the surrounding wildlife and environment (Chigbu, 2023; Ntihinyurwa et al., 2019; Pathak et al., 2021; Raycraft, 2023). For example, protecting existing vegetation and afforestation can increase vegetation coverage, while excessive cultivation and overgrazing can lead to vegetation degradation and coverage reduction. The IPCC reports have consistently highlighted that the impact of human activities on climate and environmental systems is significant and increasing (Hashim et al., 2024; Pathak et al., 2021). Geng et al. (2022) demonstrated that human activities had a significant impact on vegetation changes in China from 2000 to 2015, with different vegetation types responding differently. Zhu et al. (2016) found that land use changes contributed the most to regional greening in southeast China and the eastern United States. Lapola et al. (2023) noted that human disturbances have led to Amazon forest degradation and threatened regional ecological security, especially due to edge effects, logging, fires, and human-induced extreme drought. With the spread of environmental protection and dual carbon theories, scientific vegetation protection and restoration measures have been widely applied. This has not only improved the ecological environment and protected biodiversity but also promoted regional sustainable development. For example, Ma et al. (2023) showed that the Grain-to-Green Project has reversed the trend of decreasing vegetation area and coverage in Southwest China to an increase.

Despite existing research revealing the multifaceted impacts of climate and human activities on vegetation, most studies have been based on vegetation dynamics analysis from after 2000 due to limitations in remote sensing data sources, making it difficult to capture long-term changes and driving mechanisms comprehensively (Anees et al., 2024; Hutchinson et al., 2015). Therefore, it is necessary to extend the coverage and research period of consistent remote sensing data through multi-source data integration to explore the impacts of long-term climate change and human activities on vegetation (Alharbi, 2024). This will be significant for advancing historical vegetation dynamics research, predicting future vegetation changes, and promoting regional sustainable development.

Mainland Southeast Asia is a key region connecting the East Asian continent, the South Asian subcontinent and the Malay Archipelago, with significant geopolitical and economic importance (Wang et al., 2022b). However, existing research still lacks analysis of long-term vegetation changes in Mainland Southeast Asia (Ha et al., 2023). To address the shortcomings in long-term vegetation change research and the need for vegetation monitoring for sustainable development in Mainland Southeast Asia, this study used multi-source remote sensing data to construct a long-term, consistent NDVI dataset and conducted an in-depth investigation of vegetation dynamics in Mainland Southeast Asia. This study intends to achieve three objectives:

(1) Develop a framework for vegetation change detection and attribution analysis based on multi-source remote sensing data integration.

(2) Create an NDVI dataset covering Mainland Southeast Asia since 1982 to provide data support for long-term vegetation dynamics research in the region.

(3) Explore vegetation changes in Mainland Southeast Asia over the past 40 years and their response to climate and human activities, providing scientific insights for regional ecological protection and sustainable development.

2. Methodology

2.1. Study area

Mainland Southeast Asia is located in Southeast Asia, situated between China and the South Asian subcontinent. Its approximate latitude and longitude range are 92.0°E–109.0°E and 5.5°N–28.5°N. It includes most of the territory of five countries: Thailand, Vietnam, Myanmar, Laos, and Cambodia, covering an area of about 2.065 million square kilometers (Fig. 1). It is mainly characterized by a tropical monsoon climate, with high temperatures year-round. The rainy season lasts from June to October and is characterized by the prevailing southwest monsoon with abundant rainfall, while the dry season lasts from November to May and is characterized by the prevailing northeast monsoon with less rainfall. Its terrain generally slopes from north to south, with mountains spreading fan-shaped from north to south. The northern region is mostly plateaus, hills, and mountains, while the southern region features deltas and alluvial plains. The major mountain ranges include the Rakhine Mountains in the west, a series of ranges extending south from the Shan Plateau in the center, and the Annamite Range in the east. The major rivers include the Irrawaddy, Salween, Chao Phraya, Mekong, and Red River (Fig. 1a). The predominant land use type is forest, followed by cultivated land, shrubland, and grassland. Overall vegetation conditions are good(Fig. 1b) (Wang et al., 2022a). The population of Mainland Southeast Asia is approximately 251.4 million in 2023 and is mainly distributed in alluvial plains and coastal areas.

2.2. Methods

2.2.1. Data and preprocessing

Our foundational data includes two NDVI datasets with different periods sourced from the Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) series and the Moderate-resolution Imaging Spectroradiometer (MODIS) of the Earth Observing System (EOS) series. The time range of the AVHRR dataset is from June 24, 1981, to December 31, 2013, while the MODIS dataset has been updating from February 1, 2000, until now. This study achieved full temporal coverage of remote sensing data since 1982 by integrating these two datasets. Specific information, data downloads, and preprocessing details are as follows.

(1) The version of the AVHRR NDVI dataset is NOAA CDR AVHRR NDVI V5 provided by the National Oceanic and Atmospheric Administration (NOAA, https://www.ncei.noaa.gov). Its spatial resolution is 5 km, and its temporal resolution is 1 day. We downloaded all data from 1982 to 2013 using Google Earth Engine (GEE, https://earthengine.google.com/) and interpolated it to a spatial resolution of 1 km using the nearest neighbor method. Afterward, we used monthly averages and selected the maximum monthly value within each year to obtain the annual AVHRR NDVI data at 1 km resolution from 1982 to 2013.

(2) The version of the MODIS NDVI dataset is MOD13A3.061 provided by the United States Geological Survey (USGS, https://lpdaac.usgs.gov). It includes monthly average NDVI data from February 2000 to the present. Its spatial resolution is 1 km. We used GEE to download

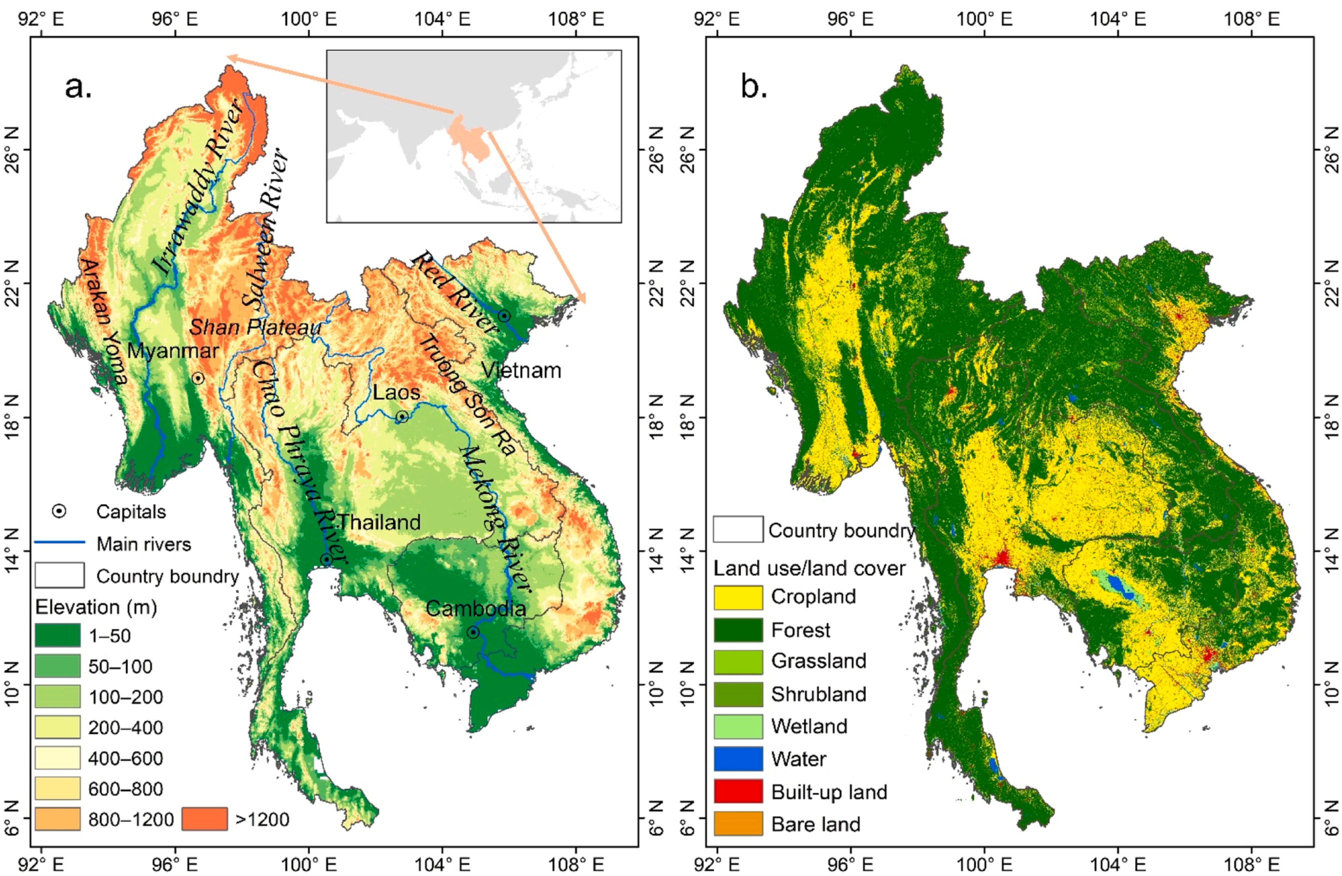

Fig. 1. Geographic information of Mainland Southeast Asia. (a) Location and topography. (b) Main types of land use/land cover.

all data from 2000 to 2023. We obtained annual MODIS NDVI data at 1 km resolution from 2000 to 2023 by synthesizing the annual maximum values.

In addition, we selected the temperature and precipitation data from the ERA5-Land reanalysis dataset to analyze vegetation change attribution. Its version is ERA5-Land Monthly Aggregated and its spatial resolution is 10 km. It includes monthly average temperature and precipitation data from February 1950 to the present provided by the European Centre for Medium-Range Weather Forecasts (ECMWF, https://www.ecmwf.int). We used GEE to download all data from 1982 to 2023 and interpolated it to a resolution of 1 km using the nearest neighbor method. We calculated the annual average for temperature data and the annual total for precipitation data based on the monthly data. Finally, we obtained annual ERA5-Land temperature and precipitation data at 1 km resolution from 1982 to 2023.

2.2.2. *Overall technical route*

The overall technical route of this study is shown in Fig. 2. First, we selected two NDVI remote sensing datasets with different periods. Next, we obtained a long-term and consistent NDVI dataset through data integration and verified the results. Based on this, we analyzed the long-term vegetation change characteristics in the region using a trend test and significance test. Afterward, we combined temperature and precipitation data to explore the relationship between multi-year temperature changes, precipitation changes, and vegetation changes using partial correlation analysis. Finally, we quantified the contributions of climatic factors and human activities to NDVI changes using linear regression and residual analysis and identified the dominant factors for NDVI changes in different regions.

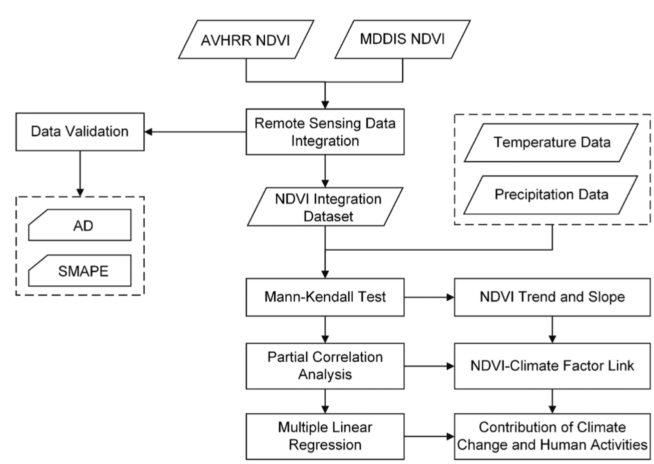

Fig. 2. The overall technical route of this study.

2.2.3. *NDVI data integration*

The AVHRR NDVI dataset and the MODIS NDVI dataset come from different remote sensing sensors and have different spatial resolutions, temporal resolutions, and time coverage. To ensure data continuity and consistency for long-term studies, we used the overlapping period (2000–2013) information to integrate data. This process includes two steps: (1) At the pixel scale, we calculated the average of the AVHRR and MODIS data for 2000–2013 and the ratio of the averages to obtain the scaling factor. (2) We used the scaling factor to integrate the AVHRR data before 2000. Through data integration, we can achieve consistent treatment of different datasets at the pixel scale to reduce systematic errors and enhance the continuity and reliability of the data in the time series. The formulas are as follows.

$$SF_{(x,y)} = \frac{\sum_{t_1} MODIS_{(x,\ y,\ t_1)}}{\sum_{t_1} AVHRR_{(x,\ y,\ t_1)}} \tag{1}$$

$$AVHRR'_{(x,\ y,\ t_2)} = SF_{(x,y)} \bullet AVHRR_{(x,y,t_2)} \tag{2}$$

Among them, $SF_{(x,y)}$ is the scaling factor for the pixel (x, y); t_1 is the year within the overlapping period of the MODIS and AVHRR data, which can be taken as 2000–2013 for this study; $AVHRR_{(x,y,\ t_1)}$ and $MODIS_{(x,y,\ t_1)}$ are the AVHRR and MODIS values for the pixel (x, y) at t_1; t_2 is the year from the AVHRR dataset, which can be taken as 1982–2013; $AVHRR_{(x,y,t_2)}$ and $AVHRR'_{(x,y,t_2)}$ are the original and integrated values of AVHRR for the pixel (x, y) at t_2.

After data integration, we used Average Deviation (AD) and Symmetric Mean Absolute Percentage Error (SMAPE) to assess the integration results and compare them with the original AVHRR data. Both AD and SMAPE are commonly used error methods. Among them, AD assesses the absolute error and SMAPE assesses the relative error between the integrated data and MODIS data. The formulas are as follows.

$$AD_{(t_1)} = \frac{1}{n} \bullet \sum_{(x,y)} AVHRR'_{(x,\ y,\ t_1)} - MODIS_{(x,\ y,\ t_1)} \tag{3}$$

$$SMAPE_{(t_1)} = \frac{1}{n} \bullet \sum_{(x,y)} \frac{2 \bullet \left| AVHRR'_{(x,\ y,\ t_1)} - MODIS_{(x,\ y,\ t_1)} \right|}{\left| AVHRR'_{(x,\ y,\ t_1)} \right| + \left| MODIS_{(x,\ y,t_1)} \right|} \tag{4}$$

Among them, n is the total number of pixels in Mainland Southeast Asia; $AD_{(t_1)}$和 and $SMAPE_{(t_1)}$ are the AD and SMAPE of the integrated data compared to MODIS data at the time t_1.

The comparison validation results of AVHRR data before and after integration with MODIS data are shown in Table 1. We observed that the AD and SMAPE of the integrated data are lower than those of the pre-integrated data across all years. Specifically, the multi-year average AD of the integrated data (–0.006) decreased by 98.5 % compared to the pre-integration value (–0.398), and the SMAPE decreased by 84.6 % from 0.683 to 0.105. These results show that data integration plays a crucial role in eliminating systematic errors and enhances the reliability and consistency of AVHRR data and MODIS data. This provides a solid foundation for subsequent research.

2.2.4. Trend test

In this study, we used the Mann-Kendall (MK) trend test method to detect trends in the annual NDVI series. The MK trend test is a non-parametric method that assesses the strength and significance of the trend by calculating the rank consistency of pairs of data in a time series.

Table 1
Validation of NDVI data integration.

Year	Before integration		After integration	
	AD	SMAPE	AD	SMAPE
2000	–0.394	0.685	–0.010	0.135
2001	–0.383	0.644	0.032	0.087
2002	–0.403	0.688	–0.009	0.108
2003	–0.373	0.630	0.041	0.102
2004	–0.394	0.682	–0.004	0.098
2005	–0.404	0.698	–0.017	0.114
2006	–0.390	0.669	0.007	0.099
2007	–0.415	0.719	–0.037	0.111
2008	–0.395	0.687	–0.015	0.109
2009	–0.409	0.703	–0.023	0.107
2010	–0.390	0.665	0.011	0.099
2011	–0.421	0.724	–0.043	0.104
2012	–0.409	0.701	–0.020	0.096
2013	–0.394	0.669	0.004	0.105
Multi-year average	–0.398	0.683	–0.006	0.105

It is an important tool for analyzing the dynamics of variables in the fields of meteorology, hydrology, and ecology. The formulas are as follows.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \tag{5}$$

$$tau = \frac{2 \bullet S}{n \bullet (n-1)} \tag{6}$$

Among them, n is the length of the time series, which is 42 in this study; S is the trend test statistic; x_i and x_j are the NDVI values for year i and year j; sgn is the sign function, when the input is greater than 0, equal to 0, and less than 0, the output values are 1, 0, and −1 respectively. *tau* is the statistic used to measure the strength of the trend in the time series. Its value range is $[-1, 1]$, where positive and negative values indicate an upward and downward trend respectively. The larger the absolute value, the stronger the trend.

After the MK test, we further tested the significance level of the trend. The formulas are as follows.

$$t = \frac{S - \mathrm{sgn}(S)}{\sqrt{Var(S)}} \tag{7}$$

$$Var(S) = \frac{n \bullet (n-1) \bullet (2n+5)}{18} \tag{8}$$

$$p = 2 \bullet (1 - \theta(|t|)) \tag{9}$$

Among them, $Var(S)$ is the expected variance of statistic S under the null hypothesis of no trend; t is the standardized statistic for trend test; θ is the cumulative distribution function of the standard normal distribution; p is the result indicator for significance test. Its value range is $[0, 1]$ and p close to 0 indicates a significant trend so that we can reject the null hypothesis (no trend).

2.2.5. Partial Correlation Analysis

This study used partial correlation analysis to research the relationship between climatic factors (temperature and precipitation) and NDVI changes. In studies involving two or more climatic factors, partial correlation analysis can effectively eliminate the interference of other factors and calculate the correlation of each factor with the dependent variable one by one. The formula is as follows.

$$R_{XY-Z} = \frac{R_{XY} - R_{XZ} \bullet R_{YZ}}{\sqrt{(1 - R_{XZ}^2) \bullet (1 - R_{YZ}^2)}} \tag{10}$$

Among them, R_{XY}, R_{XZ}, and R_{YZ} are the correlation coefficients for X with Y, X with Z, Y with Z. R_{XY-Z} is the partial correlation coefficient between X and Y without the influence of Z. A positive value indicates a positive correlation between X and Y, while a negative value indicates a negative correlation.

We further combined formulas 9 and 11 to test the significance level of the correlation based on calculating the partial correlation coefficients. The formula is as follows.

$$t = \frac{R_{XY-Z} \bullet \sqrt{n-k-2}}{\sqrt{1 - R_{XY-Z}^2}} \tag{11}$$

Among them, n is the length of the time series, which is 42 in this study; k is the number of control variables, which is 1 in this study.

2.2.6. Linear regression analysis

Linear regression analysis is a commonly used method in statistics for analyzing how a dependent variable is affected by one or more independent variables. It has strong predictive and explanatory power and is widely applied in various fields such as economics, engineering, and social sciences. In the study, a multiple linear regression model was established between NDVI and temperature and precipitation to determine the regression coefficients of temperature and precipitation. So that we can calculate the contribution of temperature and precipitation changes to NDVI changes over more than 40 years. Furthermore, we quantified the impact of human activities using the residuals. The formulas are as follows.

$$Y = \sum_i a_i \bullet X_i + c \tag{12}$$

$$\Delta Y_{total} = \overline{Y}_{l5} - \overline{Y}_{f5} \tag{13}$$

$$\Delta Y_i = a_i \bullet \Delta X_i \tag{14}$$

$$\Delta Y_h = \Delta Y_{total} - \sum_i \Delta Y_i \tag{15}$$

Among them, Y is the dependent variable, which is NDVI in this study; X_i is the independent variable, where i can take values 1 and 2, with X_1 and X_2 being temperature and precipitation respectively; a_i is the regression coefficient of X_i; c is the intercept; ΔY_{total} is the change in Y over the study period, calculated as the average NDVI of the last 5 years ($\overline{Y}_{l5}$) minus the average NDVI of the first 5 years ($\overline{Y}_{f5}$). ΔX_i is the change in X_i over the study period, calculated similarly using the last 5 years (1982–1986) and the first 5 years (2019–2023). ΔY_i is the contribution of ΔX_i to the change in the dependent variable. ΔY_h is determined by regression and residual analysis to reflect the contribution of human activities.

After quantifying the impacts of temperature, precipitation, and human activities, we further calculated their contribution ratios to NDVI changes and identified the dominant factors using a threshold value of 0.5. The formula is as follows.

$$CR_j = \frac{|\Delta Y_j|}{\sum_j |\Delta Y_j|} \tag{16}$$

Among them, ΔY_j is the contribution of j-th factor. j can take values 1, 2, and 3, corresponding to temperature, precipitation, and human activities respectively; CR_j is the contribution ratio of the j-th factor.

3. Results

3.1. Vegetation Index and Changes in Mainland Southeast Asia in 1982–2023

This study generated an NDVI dataset for Mainland Southeast Asia

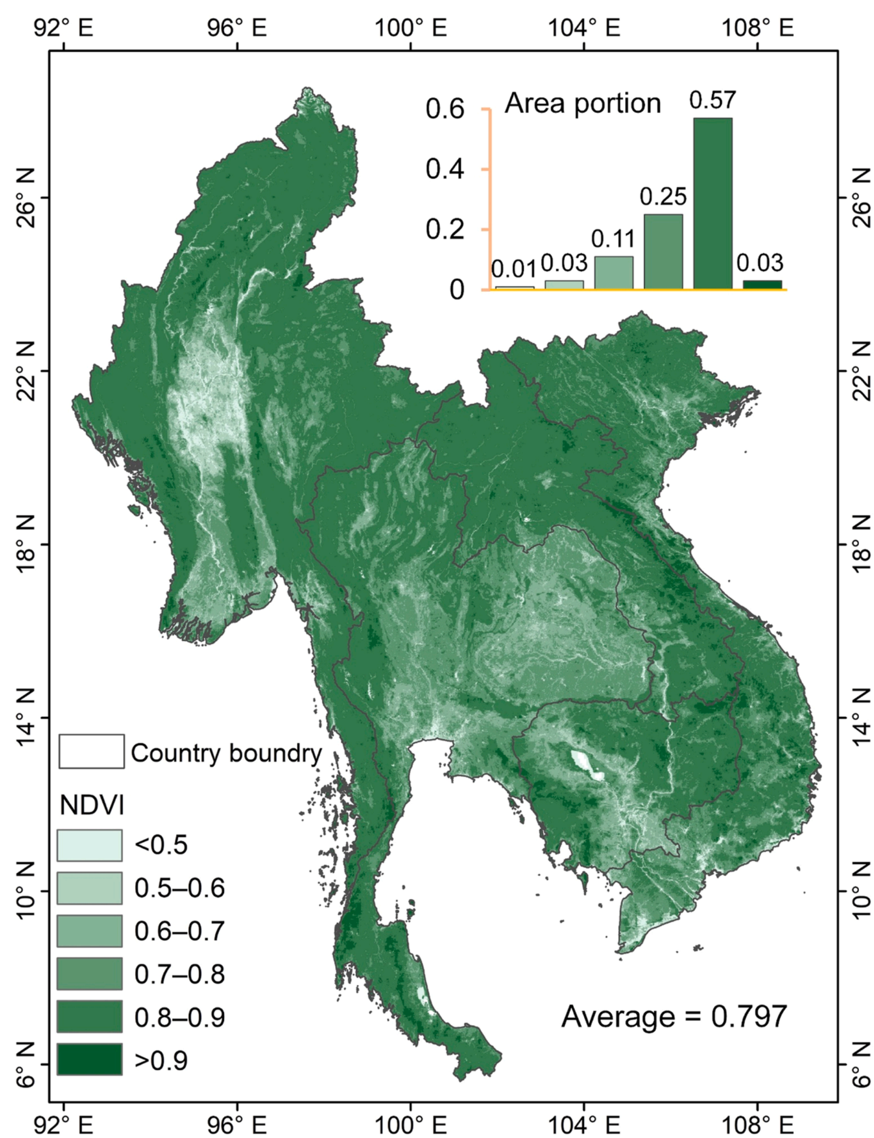

Fig. 3. Spatial distribution of multi-year average NDVI in Mainland Southeast Asia. The bar chart shows the proportion of the area in the region for each NDVI range.

from 1982 to 2023 based on remote sensing data integration and calculated the regional multi-year average NDVI. Its spatial distribution is shown in Fig. 3. Multi-year average NDVI is 0.797, with 85 % of the area exceeding 0.7, indicating robust vegetation growth across the region. Areas with average NDVI in the ranges of 0.7–0.8, 0.8–0.9, and 0.9–1.0 account for 25 %, 57 %, and 3 %, mainly distributed in higher elevation areas like mountains and plateaus. Areas with average NDVI in the ranges of 0.5–0.6 and 0.6–0.7 account for 3 % and 11 %, while areas with NDVI less than 0.5 account for only about 1 %. These results indicate that the majority of Mainland Southeast Asia has high vegetation coverage (Ha et al., 2023).

We calculated the changes in multi-year average NDVI for Mainland Southeast Asia based on 42 years long-term NDVI data by calculating the difference between the averages from 2019–2023 and 1982–1986, as shown in Fig. 4. The results indicate that NDVI increased by 78 % of the area. Among these, the proportions of areas with increases of 0–0.03, 0.03–0.06, 0.06–0.09, 0.09–0.12, and greater than 0.12 are 13 %, 18 %, 18 %, 14 %, and 15 %. NDVI decreased in 22 % of the area (Fig. 4b). Considering the overall spatial distribution and the area proportion of each value segment, the NDVI changes in Mainland Southeast Asia are mainly increasing and the average regional change is 0.054 (Fig. 4a–b).

We further conducted the MK trend test on the annual NDVI series. The results show that Kendall's tau value exceeds 0.6, with a significance test p-value below 0.01, indicating a significant increasing trend in NDVI over more than 40 years in Mainland Southeast Asia (Fig. 4c). Further linear regression results show that the NDVI increased at a rate of approximately 0.02 every decade from 1982 to 2023. Notably, the NDVI from 1991 to 1996 was significantly lower than that from 1982 to 1991. This may be attributed to the climate changes caused by the violent eruption of Mount Pinatubo in Luzon, Philippines, in June 1991, which had a strong negative impact on vegetation in Mainland Southeast Asia (Santer et al., 2014). However, the vegetation index shows a significant increasing trend on the broader spatial scale of Mainland Southeast Asia and over the 40-year time scale, indicating a sustained improvement in regional vegetation.

3.2. Relationship between vegetation changes and climate factors

Next, we explored the relationship between regional vegetation changes and climate factors based on temperature and precipitation changes over the past 42 years in Mainland Southeast Asia, as shown in Fig. 5. The annual average temperature in the region shows a significant increasing trend from 1982 to 2023 (Fig. 5a), with a rate of approximately 0.15°C per decade. Conversely, the annual precipitation depth shows a significant decreasing trend (Fig. 5c), with a reduction rate of –53 mm per decade. We conducted a partial correlation analysis of NDVI with temperature and precipitation at the pixel level. Generally, the impact of rising temperatures on vegetation in Mainland Southeast Asia is mainly positive (Fig. 5b). Rising temperatures have a positive impact on NDVI across 81 % of the land, with 53 % showing significant promotion, mainly in the areas around the Irrawaddy, Mekong, and Red River. Reduced precipitation can suppress or promote vegetation in land areas of similar extent. (56 % and 44 %, Fig. 5d). Under the two impacts counterbalancing each other, the impact of precipitation on NDVI changes is not significant.

3.3. Impacts of climate changes and human activities on vegetation

Through multiple linear regression and residual analysis, we quantified the impacts of climate factors and human activities on NDVI

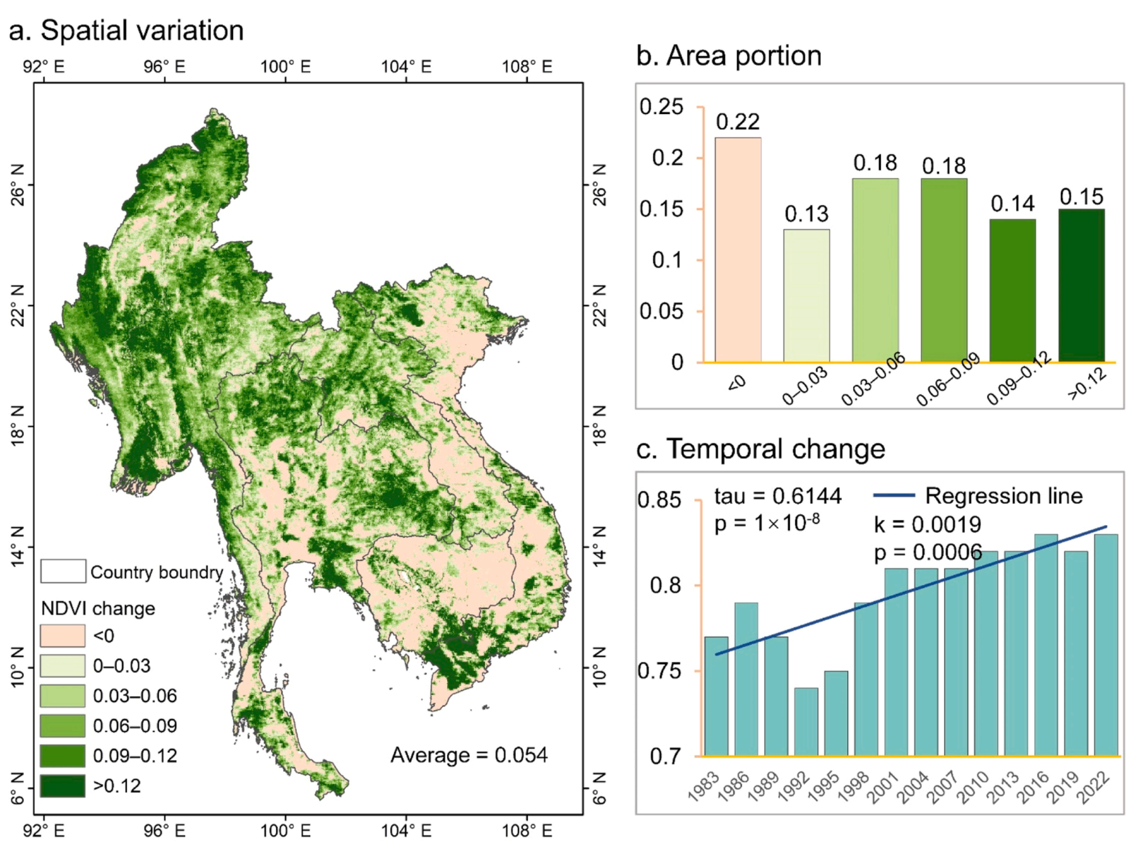

Fig. 4. Spatiotemporal variation of NDVI in Mainland Southeast Asia in 1982–2023. (a) shows the spatial distribution of NDVI changes in the region, calculated by subtracting the average value of the first 5 years (1982–1986) from the average value of the last 5 years (2019–2023). (b) shows the proportion of the area in the region for each value range. (c) displays the temporal variation, trend, and slope of the regionally averaged NDVI in the region; where the bar represents 3-year averaged values and is recorded as the middle year.

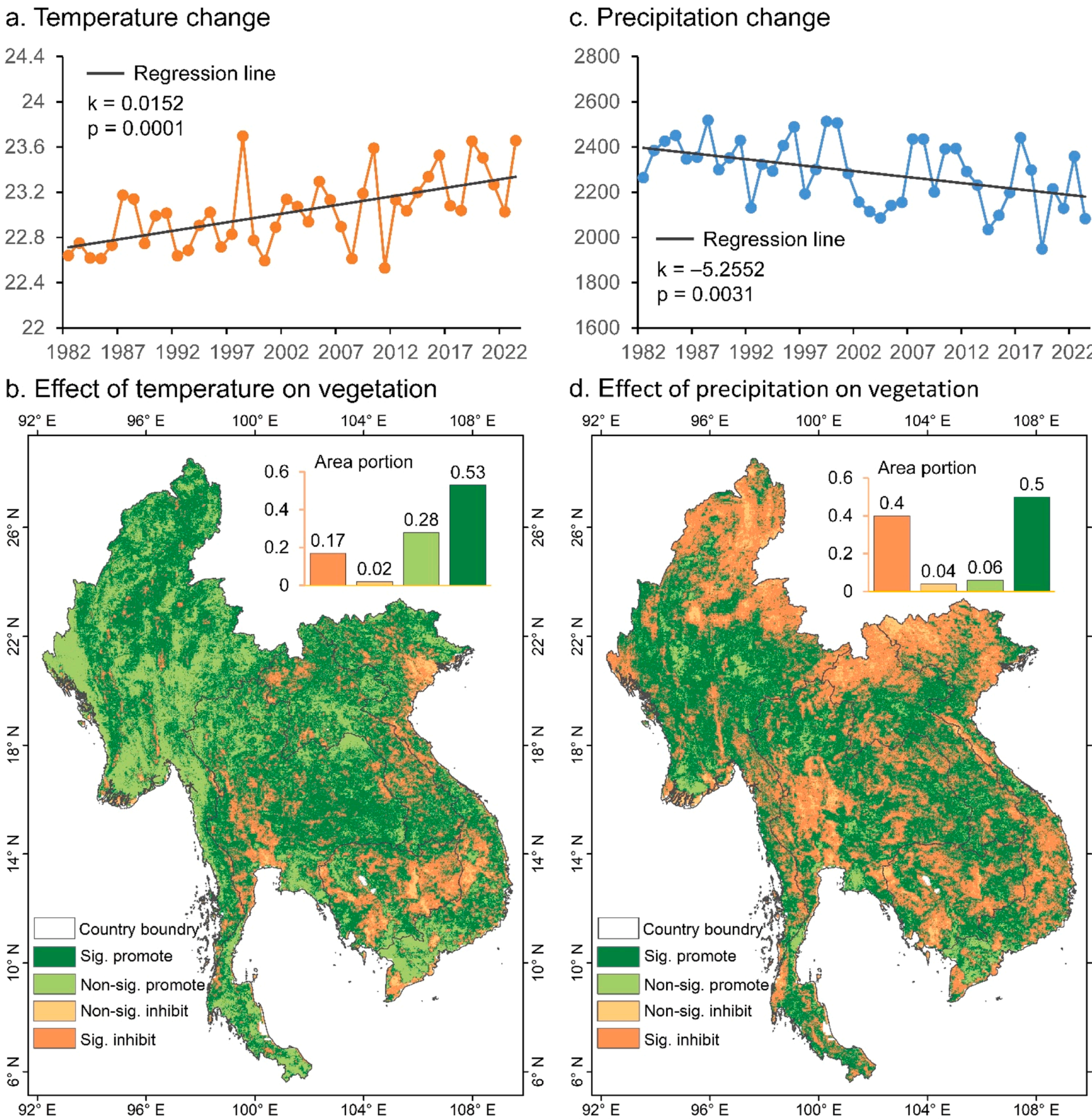

Fig. 5. Changes in temperature and precipitation in Mainland Southeast Asia in 1982–2023 and their impact on vegetation. (a) shows the temperature changes in the region, and (b) shows the spatial distribution of the temperature's impact on NDVI and the corresponding area proportion. Similarly, (c) and (d) show the results related to precipitation.

changes in Mainland Southeast Asia at the pixel level, as shown in Fig. 6. Generally, temperature changes have the largest impact on NDVI changes, contributing 0.049, which accounts for about 70 % of the regional NDVI variation. Human activities followed, contributing 0.014, approximately 20 % of the regional NDVI variation. The impact of precipitation changes is the smallest, contributing –0.007, about 10 % of the regional NDVI variation.

Specifically, temperature changes have led to an increase in NDVI for 69 % of the land, mainly distributed in the northwestern (Fig. 6a). Among them, the area with NDVI changes in the ranges of 0–0.05, 0.05–0.1, and greater than or equal to 0.1 accounts for 31 %, 20 %, and 18 %. The area where temperature changes caused a decrease in NDVI accounts for about 31 %, mainly distributed in the southeastern, especially in the middle and lower reaches of the Mekong River. Precipitation changes have resulted in an increase in NDVI for 48 % of the land, mainly distributed in the northeastern (Fig. 6b). The area where precipitation changes caused a decrease in NDVI accounts for about 52 %, mainly in the northwestern, particularly distributed in the middle reaches of the Irrawaddy River. Human activities have increased NDVI for 67 % of the land, mainly distributed in lower altitude areas (Fig. 6c). Among them, the area with NDVI changes in the ranges of 0–0.05, 0.05–0.1, and greater than or equal to 0.1 accounts for 35 %, 22 %, and 10 %, respectively. The area where human activities led to a decrease in NDVI accounts for about 33 %, mainly distributed in the upper reaches

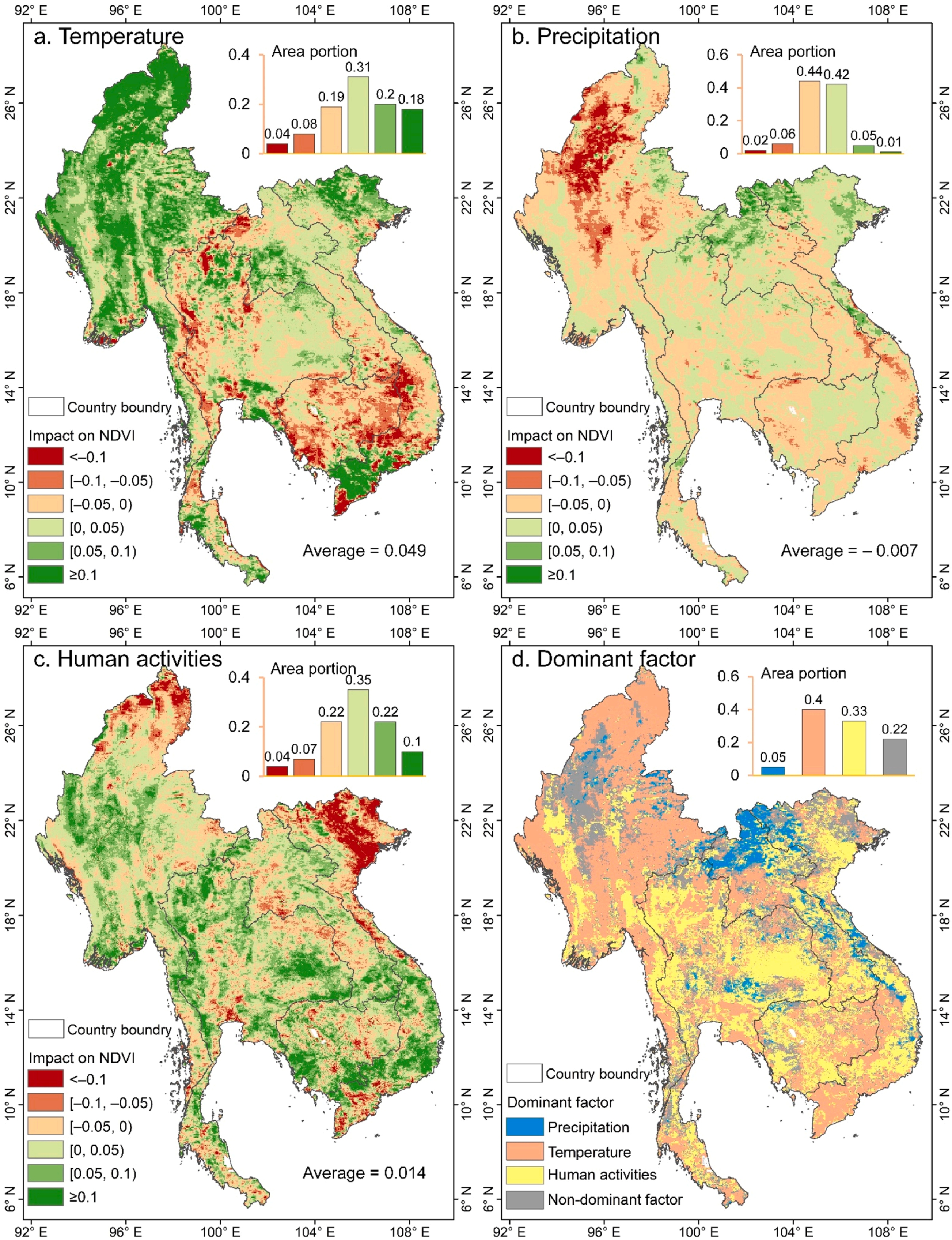

Fig. 6. The impact of temperature, precipitation, and human activities on NDVI in Mainland Southeast Asia and dominant factors. (a), (b), and (c) show the spatial distribution of the impact of temperature, precipitation, and human activities on NDVI changes, as well as the area proportion for each value range, respectively. (d) shows the spatial distribution and area proportion of the dominant factors influencing NDVI changes.

of the Irrawaddy River and the left bank of the Red River.

Furthermore, we compared the contribution ratios of temperature, precipitation, and human activities, and analyzed the dominant factors of NDVI changes at the pixel scale (Fig. 6d). The results indicate that temperature changes dominate NDVI changes on about 40 % of the land, mainly distributed in the northwestern, including the Rakhine Mountains, the middle and upper reaches of the Irrawaddy River, and the Shan Plateau. Next, human activities dominate NDVI changes on 33 % of the land, mainly distributed in the central and eastern parts, especially in the middle reaches of the Mekong River. Precipitation changes dominate the least area, accounting for only 5 % of the region, distributed in the northern. Additionally, in about 22 % of the area, there are two or more factors with significant contributions, but none exceeds a contribution ratio of 0.5. These lands are mainly distributed in the right bank area of the middle reaches of the Irrawaddy River.

4. Discussion

This study explored the evolution characteristics of NDVI in Mainland Southeast Asia from 1982 to 2023 and found that the region has high vegetation coverage, which is on an upward trend. The long-term average NDVI for the region reaches 0.797 %, and 85 % of the area has a multi-year average NDVI greater than 0.7. Over the spatial scale and the temporal scale of more than 40 years, the NDVI has increased at a rate of approximately 0.02 per decade and has been confirmed through a significance test. However, we also noted the spatiotemporal variability in regional vegetation changes. For example, due to the negative impacts of climate changes caused by the 1991 eruption of Mount Pinatubo in Luzon, Philippines, the average NDVI showed a significant decline from 1991 to 1996 and only recovered to previous levels after 1997. Over the 42 years, 78 % of the area in Mainland Southeast Asia experienced an increase in NDVI, while 22 % experienced a decrease. In densely populated and highly developed open middle reaches and delta areas, vegetation coverage tends to be low, but NDVI changes have shown an increasing trend, likely due to agricultural development and urban greening (Masarei et al., 2021; Shao et al., 2017). In the densely forested Annamite Range, NDVI changes have shown a decreasing trend, likely due to the combined impacts of deforestation and climate changes (Alaniz et al., 2022).

Temperature and precipitation are the most important climatic factors and affect vegetation growth by influencing processes such as energy flow, nutrient cycling, and photosynthesis (Pernicová et al., 2024; Restrepo-Coupe et al., 2024). There is a significant upward trend in long-term temperatures in Mainland Southeast Asia. Suitable warming can enhance plant respiration and photosynthetic activity, particularly in high-altitude energy-limited areas, positively impacting vegetation dynamics (Pugnaire et al., 2020). Conversely, precipitation in the region shows a significant decreasing trend. Precipitation changes have both promoted and inhibited vegetation growth in roughly equivalent areas, with these differences possibly related to elevation, geology, and vegetation types (Di Musciano et al., 2024; Hu et al., 2019; Mehmood et al., 2024). For example, reduced precipitation and increased temperatures can lead to increased evaporation and water deficit during the dry season, which is detrimental for vegetation growth. However, reduced precipitation can prevent waterlogging and flooding in the rainy season, which is beneficial for vegetation growth (Gatti et al., 2014; Shen et al., 2015).

Human activities affect vegetation dynamics significantly, besides climate changes. Urban expansion, deforestation, and timber trade are major drivers of vegetation degradation (Santos et al., 2022). Conversely, with the spread of environmental protection and ecological construction concepts, humans also play a strong role in vegetation conservation and restoration in some areas. The vegetation changes driven by human activities often exceed those affected by climatic factors in the short term and can establish a foundation for long-term vegetation dynamics, making their impacts comparable to those of climate factors in the long term (Chigbu et al., 2024; Markevych et al., 2017). In addition, the relationship between land restoration and land tenure plays a crucial role in mediating these changes. According to the UNCCD's Global Land Outlook 2, the effectiveness of land restoration efforts is closely linked to secure land tenure and governance structures, which can enhance the success of ecological restoration initiatives (Chigbu and Nweke-Eze, 2023; Rakotonarivo et al., 2023). However, the threat of land degradation, driven by poor land management and insecure land tenure, remains a major challenge in the region. The negative impact of land degradation on vegetation can be exacerbated without effective land restoration policies that integrate land tenure security (Chigbu et al., 2021, 2022).

This study used trend test, partial correlation analysis, and linear regression analysis to conduct a comprehensive study of long-term vegetation dynamics based on remote sensing data integration and the construction of an NDVI dataset in Mainland Southeast Asia, which can address the existing shortcomings in the regional studies and provide references for regional development. However, this study still has some issues. For example, the relationship between vegetation index and climatic factors is not strictly linear, and we cannot fully separate the contribution of each factor using multiple linear regression methods, which can lead to some errors. Additionally, this study did not distinguish between densely populated human activity areas and remote regions and attributed the portion of climate factors that cannot be explained directly to human activities. Although the spatial distribution pattern of areas dominated by human activities (Fig. 6c) is very similar to that of densely populated areas with human footprints (cropland and built-up land, Fig. 1b), which partially confirms the reliability of the results, we acknowledge that this attribution method may overestimate the importance of human activities' impact (Ma et al., 2023). Moreover, vegetation in different regions shows different responses to climate changes in large-scale studies, so considering more climatic factors would enhance the reliability of the results. These issues provide directions for improving the research and will be a focus of our future work.

5. Conclusion

To address the need for vegetation monitoring for sustainable development in Mainland Southeast Asia, this study used multi-source remote sensing data to construct a long-term, consistent NDVI dataset and conducted an in-depth investigation of vegetation dynamics. The key findings are as follows.

(1) The overall vegetation in Mainland Southeast Asia shows good growth, and the NDVI shows a significant increasing trend, with an average rate of approximately 0.02 per decade from 1982 to 2023.

(2) Rising temperatures have a positive impact on vegetation on 81 % of the land, while the impact of reduced precipitation on regional NDVI changes is not significant.

(3) Temperature changes contribute 70 % (0.049) to the regional NDVI variation, which is significantly greater than the impacts of human activities (20 %) and precipitation changes (10 %).

While these results provide important insights, we acknowledge some limitations. The non-linear relationship between vegetation dynamics and climatic factors, as well as the attribution of unexplained variations to human activities, may introduce uncertainties. Future research should address these limitations by incorporating additional climatic factors, distinguishing between areas with varying human activity intensities, and further refining the types and impacts of human activities. Moreover, a deeper exploration of the relationship between land restoration and land tenure could enrich our understanding of how land use policies and secure land tenure contribute to sustainable vegetation management.

Overall, this study serves as a valuable reference for future research on regional vegetation dynamics, and the generated NDVI dataset can support decision-making for land use planning and sustainable development in Mainland Southeast Asia.

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CRediT authorship contribution statement

Zhang Yunzhi: Writing – review & editing. **Liu Zhanpeng:** Writing – original draft, Visualization, Validation, Investigation. **Cui Chenxi:** Writing – review & editing, Writing – original draft. **Hu Yunfeng:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Alaniz, A.J., et al., 2022. Multiscale spatial analysis of headwater vulnerability in South-Central Chile reveals a high threat due to deforestation and climate change. Sci. Total Environ. 849, 157930.
Alharbi, B.S., 2024. Role of remote-sensing techniques in unveiling the spatiotemporal response of vegetation to climate change in the western Makkah Province of Saudi Arabia. Environ. Chall. 15, 100926.
Anees, S.A., et al., 2024. Unveiling fractional vegetation cover dynamics: a spatiotemporal analysis using MODIS NDVI and machine learning. Environ. Sustain. Indic. 24, 100485.
Banerjee, A., et al., 2024. Evaluating the relative influence of climate and human activities on recent vegetation dynamics in West Bengal, India. Environ. Res. 250, 118450.
Campana, S., et al., 2024. The spatiotemporal stability of plant diversity is disconnected from biomass stability in response to human activities in a South American temperate grassland. Sci. Total Environ. 955, 177031.
Chigbu, U., et al., 2024. Current research and opinion on land governance for societal development in and on the global south. Land Use Policy 141, 107112.
Chigbu, U.E., et al., 2021. Fit-for-purpose land administration from theory to practice: Three demonstrative case studies of local land administration initiatives in Africa. Land 10, 476.
Chigbu, U.E., et al., 2022. Tenure-restoration nexus: a pertinent area of concern for land degradation neutrality. Curr. Opin. Environ. Sustain. 57, 101200.
Chigbu, U.E., 2023. Connecting land tenure to land restoration. Dev. Pract. 33, 762–770.
Chigbu, U.E., Nweke-Eze, C., 2023. Green hydrogen production and its land tenure consequences in Africa: an Interpretive review. Land 12, 1709.
Chouari, W., 2024. Assessment of vegetation cover changes and the contributing factors in the Al-Ahsa Oasis using Normalized Difference Vegetation Index (NDVI). Reg. Sustain. 5, 100111.
Di Musciano, M., et al., 2024. Elevational patterns of plant species richness and phylogenetic diversity in a Mediterranean island. Perspect. Plant Ecol., Evol. Syst. 65, 125815.
Gandhi, G.M., et al., 2015. NDVI: Vegetation change detection using remote sensing and GIS – A case study of Vellore district. Procedia Comput. Sci. 57, 1199–1210.
Gatti, L., et al., 2014. Drought sensitivity of Amazonian carbon balance revealed by atmospheric measurements. Nature 506, 76–80.
Geng, Q., et al., 2022. Different vegetation types' Normalized Difference Vegetation Index responses to climate change and human activities in China. Ecol. J. 42, 3557–3568.
Ha, T.V., et al., 2023. Agricultural drought conditions over mainland Southeast Asia: Spatiotemporal characteristics revealed from MODIS-based vegetation time-series. Int. J. Appl. Earth Obs. Geoinf. 121, 103378.
Hashim, B.M., et al., 2024. Statistical downscaling of future temperature and precipitation projections in Iraq under climate change scenarios. Phys. Chem. Earth 135, 103647.
Hu, Y., et al., 2019. Vegetation change and driving factors: Contribution analysis in the loess plateau of China during 2000–2015. Sustainability 11, 1320.
Hu, Y., et al., 2022. Comparative analysis and comprehensive trade-off of four spatiotemporal fusion models for NDVI generation. Remote Sens. 14, 5996.
Hutchinson, J.M.S., et al., 2015. Monitoring vegetation change and dynamics on U.S. Army training lands using satellite image time series analysis. J. Environ. Manag. 150, 355–366.
Lapola, D.M., et al., 2023. The drivers and impacts of Amazon forest degradation. Science 379, 8622.
Li, M., et al., 2020. Global vegetation change and its relationship with precipitation and temperature based on GLASS-LAI in 1982–2015. Sci. Geogr. Sin. 40, 823–832.
Livingston, J., Rummukainen, M., 2023. Making policy-relevant knowledge in the IPCC Special Report on 1.5 degrees: An analysis of reviewer comments. Environ. Sci. Policy 147, 305–314.
Ma, B., et al., 2023. Attribution of vegetation dynamics in southwest China from 1982 to 2019. Acta Geogr. Sin. 78, 714–728.
Markevych, I., et al., 2017. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. Environ. Res. 158, 301–317.
Masarei, M.I., et al., 2021. Engineering restoration for the future. Ecol. Eng. 159, 106103.
Mehmood, K., et al., 2024. Assessment of climatic influences on net primary productivity along elevation gradients in temperate ecoregions. Trees, For. People 18, 100657.
Mngadi, M., et al., 2024. A systematic review of the application of remote sensing technologies in mapping forest insect pests and diseases at a tree-level. Remote Sens. Appl.: Soc. Environ. 36, 101341.
Mohammat, A., et al., 2013. Drought and spring cooling induced recent decrease in vegetation growth in Inner Asia. Agric. For. Meteorol. 178, 21–30.
Ntihinyurwa, P., et al., 2019. The positive impacts of farm land fragmentation in Rwanda. Land Use Policy 81, 565–581.
Pathak, R., et al., 2021. Impact of human activities on forest resources and wildlife population. Comput. Ecol. Softw. 11, 83–99.
Pereira, L.F., et al., 2024. Soil and vegetation types are predisposition factors controlling greenness changes: A shift of paradigm in greening and browning modelling? Remote Sens. Appl.: Soc. Environ. 36, 101366.
Pernicová, N., et al., 2024. Impacts of elevated CO2 levels and temperature on photosynthesis and stomatal closure along an altitudinal gradient are counteracted by the rising atmospheric vapor pressure deficit. Sci. Total Environ. 921, 171173.
Pugnaire, F.I., et al., 2020. Warming enhances growth but does not affect plant interactions in an alpine cushion species. Perspect. Plant Ecol., Evol. Syst. 44, 125530.
Rakotonarivo, O.S., et al., 2023. Resolving land tenure security is essential to deliver forest restoration. Commun. Earth Environ. 4, 179.
Raycraft, J., 2023. Wildlife and human safety in the Tarangire ecosystem, Tanzania. Trees, For. People 13, 100418.
Restrepo-Coupe, N., et al., 2024. Contrasting carbon cycle responses to dry (2015 El Niño) and wet (2008 La Niña) extreme events at an Amazon tropical forest. Agric. For. Meteorol. 353, 110037.
Reyes-Avila, A.D., Baxter, R.A., 2024. Assessment of urbanization impacts in Tegucigalpa urban greenness via Normalized Difference Vegetation Index. Trees, For. People 18, 100680.
Salim, M.Z., et al., 2024. Quantitative assessment of Hurricane Ian's damage on urban vegetation dynamics utilizing Landsat 9 in Fort Myers, Florida. Phys. Chem. Earth 136, 103750.
Santer, B.D., et al., 2014. Volcanic contribution to decadal changes in tropospheric temperature. Nat. Geosci. 7, 185–189.
Santos, Y.L.F., et al., 2022. Amazon deforestation and urban expansion: simulating future growth in the Manaus Metropolitan Region, Brazil. J. Environ. Manag. 304, 114279.
Shao, L., et al., 2017. Effects of major grassland conservation programs implemented in Inner Mongolia since 2000 on vegetation restoration and natural and anthropogenic disturbances to their success. Sustainability 9, 466.
Shen, M., et al., 2015. Precipitation impacts on vegetation spring phenology on the Tibetan Plateau. Glob. Change Biol. 21, 3647–3656.
Signorile, A., et al., 2024. Riparian vegetation surveys for roughness estimation. Ecol. Eng. 209, 107414.
Tuoku, L., et al., 2024. Impacts of climate factors and human activities on NDVI change in China. Ecol. Inform. 81, 102555.
Wang, H., et al., 2022b. Consistency and accuracy of four high-resolution LULC datasets—Indochina Peninsula case study. Land 11, 758.
Wang, H., et al., 2022a. Fusion and analysis of land use/cover datasets based on Bayesian-fuzzy probability prediction: A case study of the Indochina Peninsula. Remote Sens. 14, 5786.
Wang, H., et al., 2023. Assessment of six machine learning methods for predicting Gross Primary Productivity in grassland. Remote Sens. 15, 3475.
Yuan, W., Zhou, G., 2004. Theoretical analysis and research perspectives on drought indices. Adv. Earth Sci. 19, 982.
Zahura, F.T., et al., 2024. Impact of topography and climate on post-fire vegetation recovery across different burn severity and land cover types through random forest. Ecol. Inform. 82, 102757.
Zhang, Q., et al., 2016. Vegetation change and its response to climate change in Central Asia from 1982 to 2012. Chin. J. Plant Ecol. 40, 13.
Zhu, Z., et al., 2016. Greening of the earth and its drivers. Nat. Clim. Change 6, 791–795.