

Spatiotemporal dynamics and driving factors of net primary productivity in Asian terrestrial ecosystems

Meng Li^a, Liang Liang^{a,*}, Ziru Huang^a, Huaxiang Song^b, Shuguo Wang^a, Qianjie Wang^a, Yang Sun^a

^a School of Geography, Geomatics and Planning, Jiangsu Normal University, Xuzhou 221116, China

^b School of Geography Science and Tourism, Human University of Arts and Science, Changde 415000, China

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ABSTRACT

Net Primary Productivity (NPP) serves as a critical indicator for assessing terrestrial ecosystem quality and characterizing carbon sequestration capacity. Utilizing a long-term NPP remote sensing inversion dataset, this study systematically uncovers the spatiotemporal evolution patterns of vegetation NPP in Asia through historical trend analysis, identification of mutation nodes, ecological stability assessment, multi-scale periodic feature analysis, and sustainability forecasting. The combined driving effects of topographical constraints, climate variability, and human activities are quantitatively examined using structural equation modeling (SEM), elucidating the multifactorial synergistic impact on vegetation productivity. The main findings are: (1) Temporally, Asian vegetation NPP exhibits a fluctuating upward trend with a principal cycle of approximately 20 years, marked by two distinct rise-decline transitions during the study period. (2) Spatially, a clear southeast-high/northwest-low differentiation pattern is observed, with significant NPP increases in East Asian monsoon regions and South Asian agricultural zones, contrasted by declines in tropical rainforests (notably in the Malay Archipelago) and eastern Mongolian grasslands. (3) Persistence analysis indicates that 53 % of vegetated areas exhibit random NPP variability, 4 % maintain stable conditions, and only 2 % (mainly in South and East Asian croplands) show sustained growth potential. A trend reversal from negative to positive is noted in 27 % of the regions (e.g., Malay Archipelago and eastern Mongolia), while 12 % of cropland-dominant areas may face growth stagnation or decline. (4) Driver quantification demonstrates climate factors exert the strongest explanatory power (total effect: 0.38), while topography generates complex influences through direct negative (-0.14) and indirect positive (0.04) effects. Human activities (total effect: 0.06) are primarily driven by synergistic GDP-population growth. These findings provide a scientific foundation for evaluating Asian ecosystem services and guiding regional carbon cycle management under global change scenarios.

1. Introduction

Net Primary Productivity (NPP), a core parameter quantifying photosynthetic carbon fixation capacity and energy flow in terrestrial ecosystems, is operationally defined as the difference between carbon assimilated through photosynthesis and carbon loss via autotrophic respiration (Field et al., 1998; Li et al., 2021). Recognized as a critical proxy for ecosystem productivity, NPP plays a pivotal role in global carbon equilibrium and climate regulation (Piao et al., 2005; Wang et al., 2023a). This metric serves not only as a fundamental criterion for assessing ecosystem health and sustainability but also as the cornerstone for modeling global carbon cycle dynamics and investigating climate

change feedback mechanisms (Yu, 2020). The Asian continent harbors the world's most extensive terrestrial ecosystems (accounting for 29.4 % of the global land area) and experiences the most intense human-induced pressures (supporting 59.3 % of the global population). The spatiotemporal dynamics of its NPP are therefore critical in regulating the global carbon budget. The continent's complex topographic gradients, climatic diversity, and intensive human-environment interactions collectively drive highly heterogeneous and non-linear NPP dynamics (Chen et al., 2025). Consequently, comprehensive analysis of Asian NPP's spatiotemporal dynamics and multidimensional drivers becomes critically imperative for advancing mechanistic understanding of carbon cycling processes spanning regional to global scales,

* Corresponding author at: School of Geography, Geomatics and Planning, Jiangsu Normal University, Xuzhou, China.

E-mail address: liang_rs@jsnu.edu.cn (L. Liang).

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enhancing quantitative assessments of ecosystem service functionalities, and supporting data-driven strategies for sustainable development.

To elucidate the interannual variation patterns of NPP, we calculated annual mean NPP using the dataset detailed in Section 2.2.1. Initially, the Maximum Value Composite (MVC) was applied to create monthly NPP, which effectively mitigated the influence of environmental noise like cloud cover and atmospheric disturbances. Subsequently, the annual mean NPP was obtained by averaging the monthly NPP values, and its interannual dynamic characteristics on a continental scale were analyzed.

In recent years, the integration of multi-source data with vegetation productivity estimation models has provided solutions for constructing long-term NPP datasets (Liang et al., 2015, 2023; Qiu et al., 2023). Based on this, the interannual variability and trend inflection points of NPP have been preliminarily identified through anomaly indices and Mann-Kendall mutation tests (Wang et al., 2023b). However, the multi-scale periodic oscillations of NPP remain insufficiently investigated. Notably, wavelet analysis, distinguished by its time-frequency localization capabilities, effectively captures cyclical patterns, abrupt shifts, and phase transitions in temporal sequences (Arjasakusuma et al., 2025). This study applies this technique to Asian NPP time-series analysis, specifically investigating 20–30-year scale climate oscillation response mechanisms.

Spatially, existing research predominantly focuses on static NPP distribution patterns, while the analysis of spatiotemporal co-evolutionary patterns and sustainability characteristics remains methodologically constrained. Although coefficient of variation (CV) and linear regression trend analyses partially characterize spatial heterogeneity (Liang et al., 2022; Zhou et al., 2025), they inadequately quantify long-term dependency in vegetation dynamics. The Hurst exponent, as a fundamental parameter in fractal theory, can effectively diagnose trend persistence ($H > 0.5$) or anti-persistence ($H < 0.5$) in time series through rescaled range analysis (R/S) (Emamian et al., 2021; Huang et al., 2023), which provides a suitable mathematical tool for predicting the future evolutionary path of NPP. This study proposes to establish a three-dimensional analytical framework of "fluctuation intensity–trend direction–sustainability," integrating the coefficient of variation (CV), univariate linear regression trend analysis, and the Hurst exponent. The framework aims to extract orderly spatiotemporal evolution patterns of NPP from complex vegetation dynamics in Asia, thereby providing a scientific basis for a deeper understanding of ecosystem variability across different regions of the continent.

The driving mechanisms underlying Asian terrestrial NPP dynamics remain incompletely characterized at continental scales. While existing studies have established that multifactorial drivers, including climatic parameters (temperature, precipitation) and anthropogenic disturbances (land-use changes, agricultural practices, urbanization), collectively influence NPP variations (Gu et al., 2022; Sha et al., 2022; Xue et al., 2023). Nevertheless, existing research predominantly targets localized representative areas with temporally constrained short-cycle observations, failing to deliver an integrated assessment of continent-scale long-term NPP dynamics trajectories. Furthermore, while some studies have attempted to elucidate the driving mechanisms of climate and anthropogenic factors on NPP variations, their reliance on linear statistical models limits their ability to capture nonlinear synergistic effects among drivers (e.g., interactions between topography and human activities) or identify latent mediating pathways (e.g., indirect climatic effects modulated by topography). Structural equation modeling (SEM) is a multivariate statistical technique that differs from conventional approaches such as correlation or regression analysis by simultaneously examining complex relationships among multiple dependent and independent variables, while also revealing mediation effects that are often overlooked by linear models (Li et al., 2023; Quan et al., 2023). This allows for the explicit quantification of both direct and indirect effects of climatic factors (e.g., temperature, precipitation) and human activities (e.g., population size, economic output, industrial

structure) on NPP variations. Therefore, this study analyses the driving mechanisms of NPP changes by factors such as climate and human activities through SEM models, quantifies the relative contributions of each driver, and reveals their interactions, in order to provide more comprehensive and systematic references for scientists and policy makers.

This study addresses these gaps through an integrated analytical framework: (1) Multiscale temporal variability analysis using anomaly indices and wavelet decomposition; (2) Spatiotemporal pattern identification via coefficient of variation (CV) and linear trend analysis; (3) Persistence characterization with Hurst exponent evaluation; (4) Mechanistic driver quantification through SEM implementation. The research results will provide scientific basis for adaptive management and optimisation of carbon neutral pathways in Asian ecosystems.

2. Study area and data

2.1. Study area

Asia (10°S–80°N, 25°E–170°W), the largest and most topographically complex continent on Earth, encompasses diverse geomorphological features. The region is predominantly characterized by plateaus and mountain ranges, with the Tibetan Plateau, renowned as the "Roof of the World", radiating numerous mountain chains and plains, creating a distinctive "high center with surrounding lowlands" topographic pattern. Climatically, Asia exhibits remarkable diversity, ranging from frigid to temperate and tropical zones, with particularly prominent monsoon systems (Krishnan et al., 2025) that significantly influence global hydrological cycles. The region supports diverse vegetation types, from tropical rainforests to boreal coniferous forests, forming rich ecosystems (Fig. 1). As a crucial carbon sink and heat source under the circumstances of global climate change, Asia's response and feedback mechanisms to climatic variations exert substantial influence on the global climate system. These distinctive characteristics make Asia's terrestrial ecosystems particularly valuable for scientific investigation of NPP and its driving factors, with significant practical implications.

2.2. Research data

To analyze the spatiotemporal variations of NPP and their driving mechanisms in Asian terrestrial ecosystems, multiple datasets are utilized in this study, including NPP data (5 km resolution), land cover data (30 m resolution), human activity data (statistical data), topographic data (30 m resolution), and climate data (11 km resolution). The sources and descriptions of these datasets are presented in Table 1. For the analysis of driving factors, all datasets undergo resampling to a consistent 5 km resolution, maintaining spatial uniformity and enabling comparative analysis.

3. Research method

3.1. Trend analysis methods

In this study, the trend analysis of NPP variations across Asia is conducted using a combined approach of univariate linear regression analysis and F-significance testing. The slope of the regression equation is employed to represent the trend of vegetation NPP changes at each grid point over the study period (Liang et al., 2022). The calculation formula is presented as follows:

$$\text{Slope} = \frac{n \times \sum_{i=1}^n (i \times \text{Var}_i) - \sum_{i=1}^n i \times \sum_{i=1}^n \text{Var}_i}{n \times \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2} \quad (1)$$

In the equation, n represents the number of years in the study period, and Var_i denotes the change value for the i year. The slope of the trend line is represented by Slope, where a positive value ($\text{Slope} > 0$) indicates

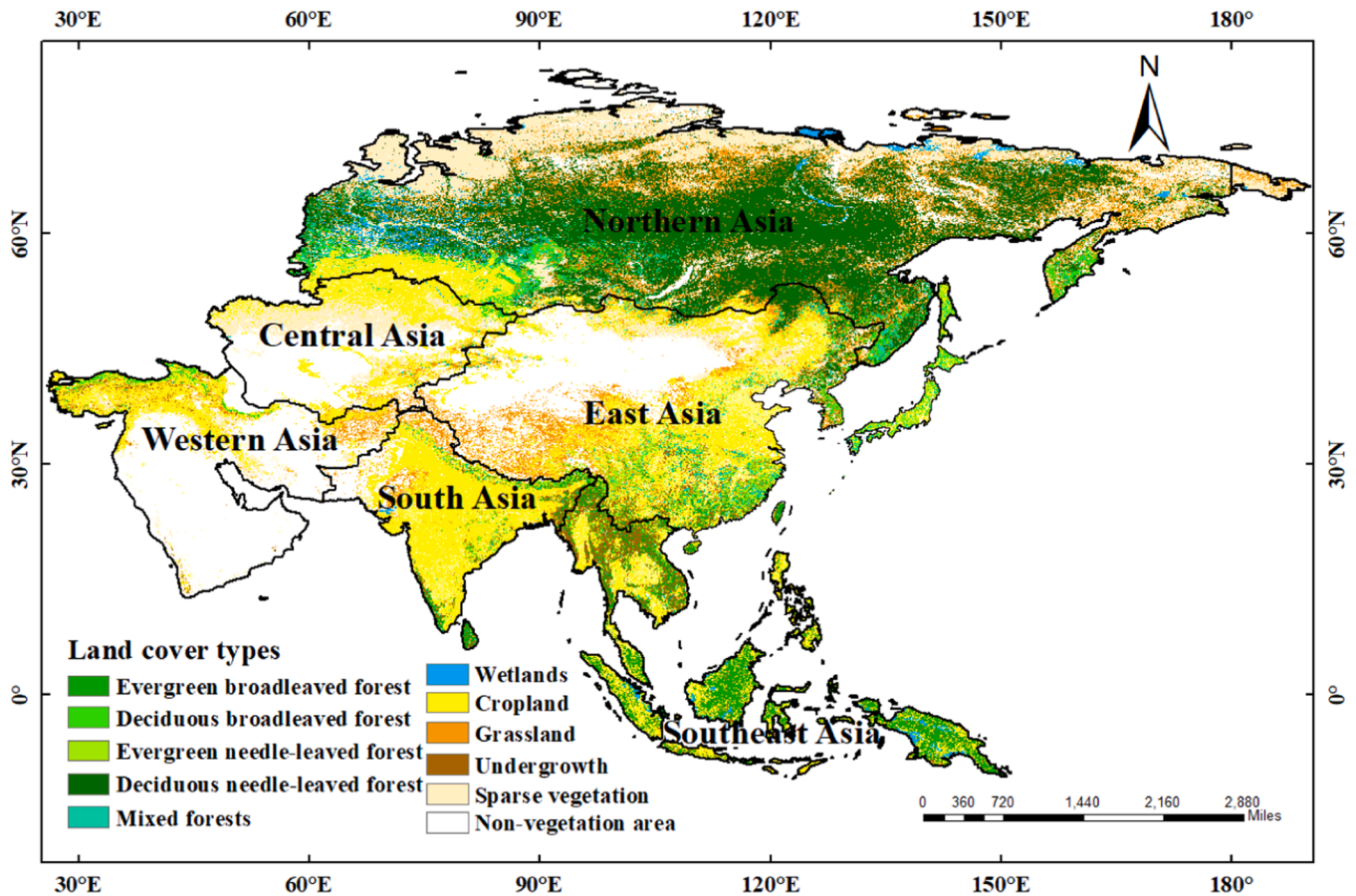


Fig. 1. Study area (with the background of remote sensing classification of vegetation types).

Table 1
Types and sources of research data.

Data type	Data name	Data source and description
Basic dataset	NPP dataset	GLASS Dataset from National Earth System Science Data Center (http://www.geodata.cn)
	Land cover data	ESA GlobCover Land Cover Data (https://www.gscloud.cn/)
Driving factor dataset	Human activity data (GDP, population, industrial structure)	World Bank Population Resources and Industrial Structure Dataset (https://data.worldbank.org)
	Topographic data (elevation, slope, aspect)	Derived from ETOPO Global Relief Model and DEM Dataset, NOAA National Centers for Environmental Information (https://www.ncei.noaa.gov/products)
	Climatic data (cumulative precipitation, mean temperature, maximum and minimum temperatures)	Climate Dataset from National Earth System Science Data Center (https://www.geodata.cn/main/)

an increasing trend in vegetation NPP over the n year study period, while a negative value ($\text{Slope} < 0$) signifies a decreasing trend.

Based on the F-significance testing critical value table, the critical values are determined as 8.531 for the 0.01 significance level and 4.494 for the 0.05 significance level. Consequently, the NPP slope values are classified into six distinct categories (Table 2).

3.2. Wavelet analysis

Wavelet analysis enables the decomposition of signals into sums of wavelet functions with different frequencies and positions, thereby

Table 2
Slope classification standard.

Slope	Level
$\text{Slope} < -8.531$	Extremely significant reduction
$-8.531 < \text{Slope} < -4.494$	Significant reduction
$-4.494 < \text{Slope} < 4.494$	No-significant change
$4.494 < \text{Slope} < 8.531$	Significant increase
$\text{Slope} > 8.531$	Extremely significant increase

revealing the time-frequency characteristics of signals. The two primary variables in wavelet transformation are scale (inversely proportional to frequency) and translation (related to time), allowing wavelet analysis to simultaneously capture signal variations in both time and frequency domains. This multi-resolution analysis facilitates the observation of periodic characteristics in signals. Among various wavelet functions, the Morlet wavelet is particularly widely applied in periodic analysis due to its excellent time-frequency localization properties. Therefore, this study employs Morlet wavelet transformation to analyze the periodic variations and temporal patterns of Asian NPP from 1981 to 2018. The continuous Morlet wavelet is defined as (Ghaderpour et al., 2023):

$$\varphi(t) = \pi^{-\frac{1}{4}} e^{-i w_0 t} e^{-\frac{t^2}{2}} \quad (2)$$

The Morlet wavelet is derived from the product of a complex sinusoid $e^{-i w_0 t}$ and a Gaussian envelope $e^{-\frac{t^2}{2}}$, where $\varphi(t)$ represents dimensionless time, w_0 denotes dimensionless frequency, and $\pi^{-\frac{1}{4}}$ serves as a normalization factor ensuring unit variance (Lara et al., 2018).

3.3. Volatility analysis

As a standardized measure of relative variability, the CV serves as an indicator of temporal stability, where higher values signify greater NPP variability and increased system instability over time, while lower values indicate relative stability (Lu et al., 2023). The CV is calculated by normalizing the standard deviation against the mean, thereby eliminating dimensional effects and enabling cross-dataset comparisons, particularly suitable for analyzing NPP across different ranges. The calculation formula is expressed as (Dong et al., 2024):

$$CV = \frac{stdev}{\overline{NPP}} \quad (3)$$

$$stdev = \sqrt{\frac{\sum_{i=1}^n (NPP_i - \overline{NPP})^2}{n - 1}} \quad (4)$$

In the equation, stdev represents the standard deviation of NPP, and $\overline{NPP}$ denotes the mean NPP over the study period.

To facilitate a more intuitive interpretation of NPP variability, the CV values are categorized into five distinct levels (Table 3) (Chen et al., 2022).

3.4. Sustainability analysis based on the Hurst index

The Hurst exponent, originating from hydrological time series analysis, quantifies long-range dependence in sequential data through Rescaled Range Analysis (R/S). This method enables robust identification of stochastic walk characteristics and persistence deviations in temporal patterns, and has become an essential tool for investigating sustainability attributes in ecological processes (Jiang et al., 2017). This study adapts the Hurst framework to assess persistence characteristics in vegetation NPP dynamics, with the core computational formula expressed as:

$$\ln\left(\frac{R}{S}\right) = H \cdot \ln(m) + C \quad (5)$$

In the equation, R denotes the subsequence extreme deviation (difference between maximum and minimum values), S represents the subsequence standard deviation, m indicates the sub-interval length, H corresponds to the Hurst exponent, and C signifies a constant.

The integrated application of the Hurst exponent with trend analysis elucidates fundamental patterns in NPP dynamics: when $H \in (0.5, 1)$, the series is persistent ($H \rightarrow 1$ persistence is enhanced) and the future trend is in the same direction as history; $H = 0.5$ is a random wandering; and $H \in (0, 0.5)$ exhibits an anti-sustainability, with the future trend inverted from history (Table 4).

3.5. Structural equation modelling

For the analysis of NPP driving factors, we employed the SEM approach. Inspired by previous research (Sha et al., 2022), the driving factors of NPP are categorized into three groups: topographic factors, climatic factors, and human activities, which are considered as unobserved variables within the SEM structure. A conceptual model is

Table 3
Different fluctuation degree of NPP defined by coefficient of variation.

CV	NPP volatility
$CV \leq 0.1$	Less fluctuation
$0.1 < CV \leq 0.2$	Lower fluctuation
$0.2 < CV \leq 0.3$	Moderate fluctuation
$0.3 < CV \leq 0.4$	High fluctuation
$CV > 0.4$	Very high fluctuation

Table 4

Future NPP variability characteristics categorized by trend analysis and Hurst exponent.

NPP Trend		Hurst	Persistence	Future Change Trend
Significant Decrease	Decrease	$0.5 < H < 1$	Persistent	Continual decrease
Extremely Significant Decrease		$0 < H < 0.5$	Anti-Persistent	Degradation to improvement
Extremely Significant Increase	Increase	$0.5 < H < 1$	Persistent	Continual improvement
Significant Increase		$0 < H < 0.5$	Anti-Persistent	Improvement to degradation
No-Significant Change		$0.5 < H < 1$	Persistence	No-Significant Change
		$0 < H < 0.5$	Anti-Persistent	Stochastic variability

constructed accordingly (Fig. 2). Specifically, the observed variables for topographic factors include slope, aspect, and elevation; for climatic factors, maximum temperature, minimum temperature, mean temperature, and precipitation are considered; and for human activities, GDP, population, primary industry, secondary industry, and tertiary industry are included as observed variables.

The SEM model was assessed using four standard fit indices: the Goodness of Fit Index (GFI), the Comparative Fit Index (CFI), the Incremental Fit Index (IFI), and the Root Mean Square Error of Approximation (RMSEA). When the values of the first three indices are close to 1 and the RMSEA is near 0, the model is deemed robust and effective. After confirming a satisfactory model fit, we examined the standardized path coefficients to evaluate how different driving factors influence vegetation NPP. This yield estimates of each driving factor's direct and indirect contributions, illustrating how these factors interact to jointly influence NPP across Asian ecosystems.

4. Results and analysis

4.1. Interannual variation characteristics of Asian NPP

The annual variability of NPP across the Asian continent from 1981 to 2018 exhibits a fluctuating ascending pattern (Fig. 3). The temporal variation curve of Asian NPP can be divided into three distinct phases, with 1989 and 2000 as the boundaries. During the period 1981–1989, NPP shows significant fluctuations, particularly with a notable decline from 1986 to 1989, reaching a trough in 1989. This decline is likely associated with the strong La Niña phenomenon and the global cooling event during 1988–1989. From 1989 to 2000, NPP demonstrates a steady increasing trend, peaking in 2000. After 2001, NPP remains relatively stable, with a slight decline observed in 2008, which may be attributed to widespread precipitation and temperature anomalies in Asia caused by the La Niña phenomenon during that period. The MK mutation analysis that the UB and UF curves of Asian NPP intersect within the confidence interval, identifying 1998 as the only mutation point. The UF curve exceeds the 0.05 significance level (Fig. 4), indicating a significant mutation in the NPP time series around 1998.

The Morlet wavelet analysis is applied to the time series data of Asian NPP, with the results presented in Fig. 5. During the period 1981–2018, three distinct high-value centers (1981, 2002, and 2018) and two low-value centers (1989 and 2010) are identified (Fig. 5a). Additionally, a strong oscillation cycle is observed at the 20–35 year time scale (Fig. 5b). The analysis reveals periodic fluctuations of 28 years, 16 years, and 5 years, with the 28-year cycle being the primary period, while the 16-year and 5-year cycles represent the secondary and tertiary periods, respectively (Fig. 5c). These three temporal scales collectively influence the temporal variation characteristics of Asian NPP. The wavelet

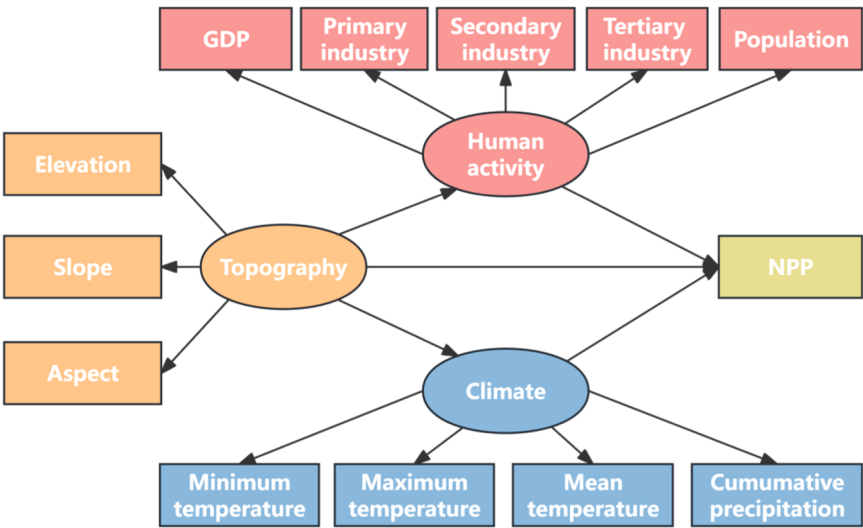


Fig. 2. Conceptual structural equation model for analyzing the driving factors of Asian NPP.

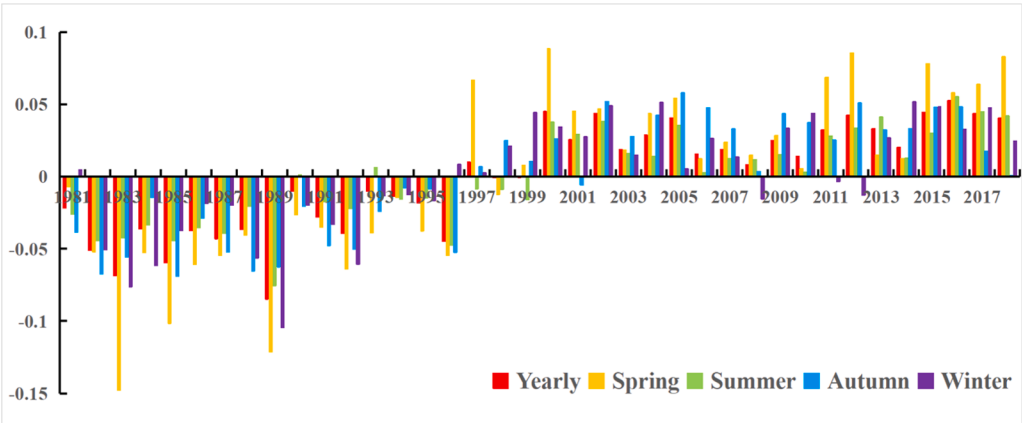


Fig. 3. Interannual and seasonal changes of NPP in Asian terrestrial ecosystems based on the anomaly index.

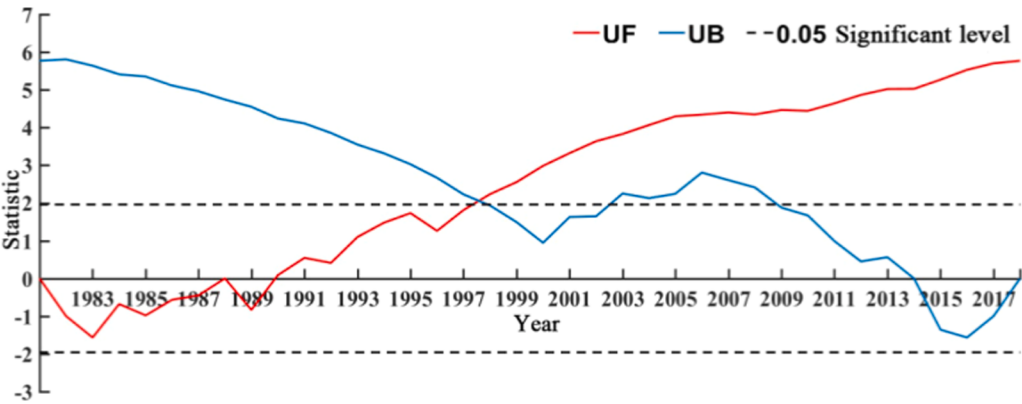


Fig. 4. MK-based analysis of NPP mutation points in Asian terrestrial ecosystems.

principal component trend under the primary 28-year cycle (Fig. 5d) demonstrates that Asian NPP exhibits an about 20-year periodic variation at this scale, undergoing two complete rise-and-fall transitions during the study period.

4.2. Spatiotemporal dynamics of Asian NPP

4.2.1. Spatial distribution patterns of Asian NPP

Spatial analysis reveals that Asian NPP exhibits a general distribution pattern of higher values in the southeast and lower values in the northwest (Fig. 6). The highest NPP values are observed in Southeast Asia, a region predominantly influenced by tropical rainforest and

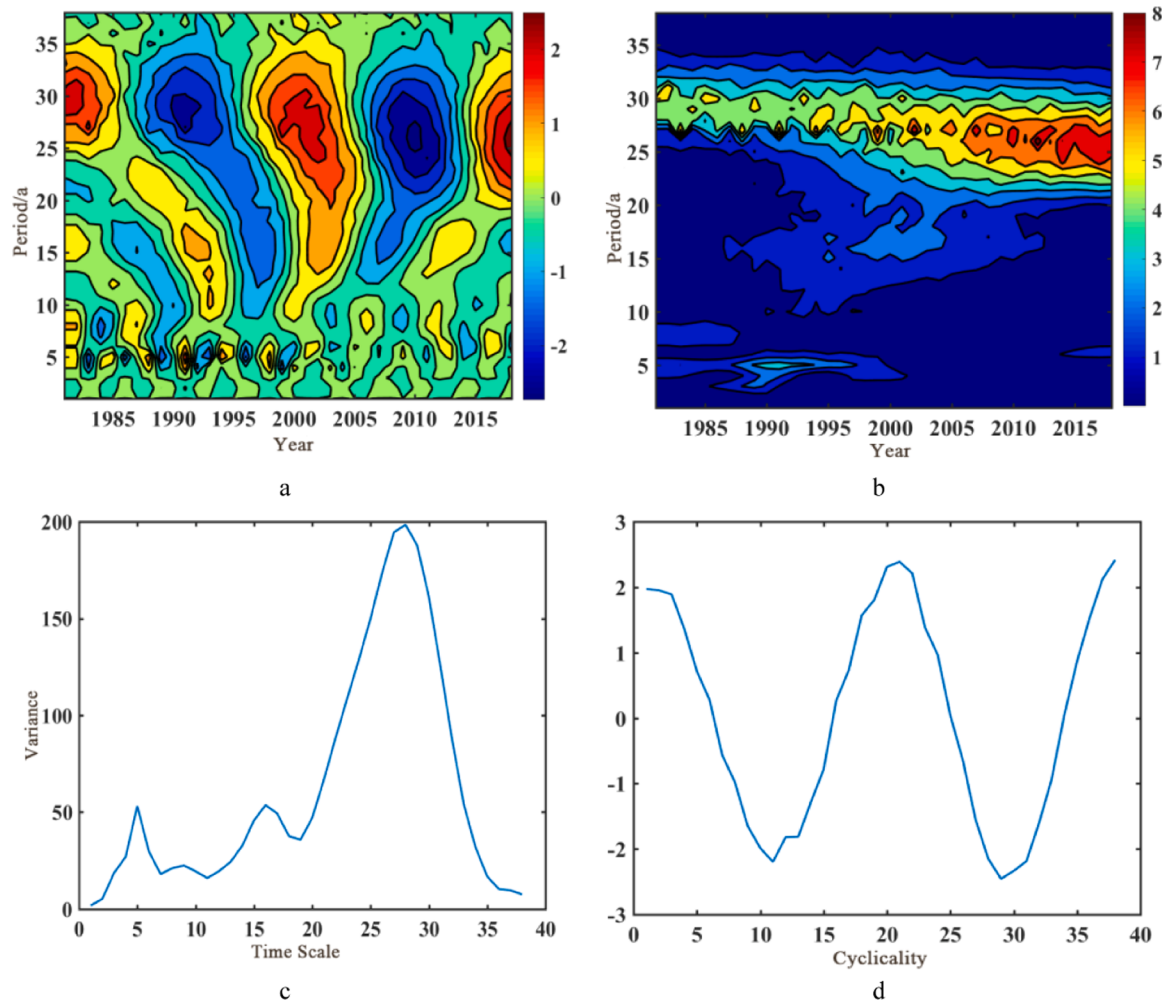


Fig. 5. Wavelet multiscale decomposition analysis of periodic NPP fluctuations in Asian terrestrial ecosystems (a. wavelet coefficient real contour graph; b. wavelet modulus square graph; c. wavelet variance graph; d. wavelet main cycle trend graph).

monsoon climates characterized by high temperatures and abundant rainfall. This region is primarily characterized by tropical rainforests and subtropical evergreen broadleaved forests, supporting lush vegetation and ranking among the most biodiverse regions globally. Relatively high NPP values are also found in southeastern East Asia and South Asia. Southeastern East Asia, governed by temperate and subtropical monsoon climates, experiences humid conditions with widespread subtropical evergreen broadleaved forests and temperate deciduous broadleaved forests. South Asia, primarily influenced by tropical monsoon climates, hosts diverse vegetation types, contributing to its elevated NPP levels. Notably, the needle-leaved forest region in central and southern North Asia also demonstrates relatively high NPP values. This area, characterized by a subarctic coniferous climate, features long, harsh winters and short, warm summers, yet maintains relatively high humidity levels, providing suitable conditions for needle-leaved forest growth. In contrast, Central Asia, Western Asia, and northwestern East Asia present a markedly different scenario. These regions are predominantly controlled by tropical and subtropical desert climates, as well as temperate continental climates, experiencing cold winters, hot summers, and scarce annual precipitation. Vegetation in these areas is primarily composed of grasslands and deserts, including the renowned Karakum Desert. Due to extremely low vegetation coverage and sparse distribution, these regions exhibit overall low NPP values.

4.2.2. Stability analysis of NPP in different areas of Asia

The CV serves as an effective quantitative indicator for characterizing the stability of NPP. In this research, the CV of Asian vegetation NPP from 1981 to 2018 is calculated and analyzed to reveal its temporal fluctuation characteristics (Fig. 7). The results indicate that 36 % of the Asian region exhibits low NPP variability. These areas primarily include subtropical evergreen broadleaved forests and tropical rainforests in Southeast Asia, temperate deciduous broadleaved forests and subtropical evergreen broadleaved forests in eastern East Asia, subarctic coniferous forests, tropical rainforests, tropical monsoon forests, and subtropical evergreen broadleaved forests in South Asia, as well as coniferous forests in central and southern North Asia. These forest ecosystems, due to their strong self-regulating capacity, demonstrate high adaptability to climate change, resulting in relatively low NPP variability. Conversely, 34 % of the Asian region shows high NPP variability, predominantly concentrated in the desert areas of Central Asia and Western Asia (including peripheral desert regions), the grassland regions of northwestern East Asia, and the tundra zones of northern North Asia. The vegetation ecosystems in these regions possess relatively weaker self-regulating capabilities, making them more susceptible to climate change and consequently exhibiting higher NPP variability.

Overall, the degree of NPP variability across Asia displays significant regional differences. These variations are closely associated with the distribution of vegetation types and their self-regulating capacities, while also reflecting the varying impacts of climate change on distinct

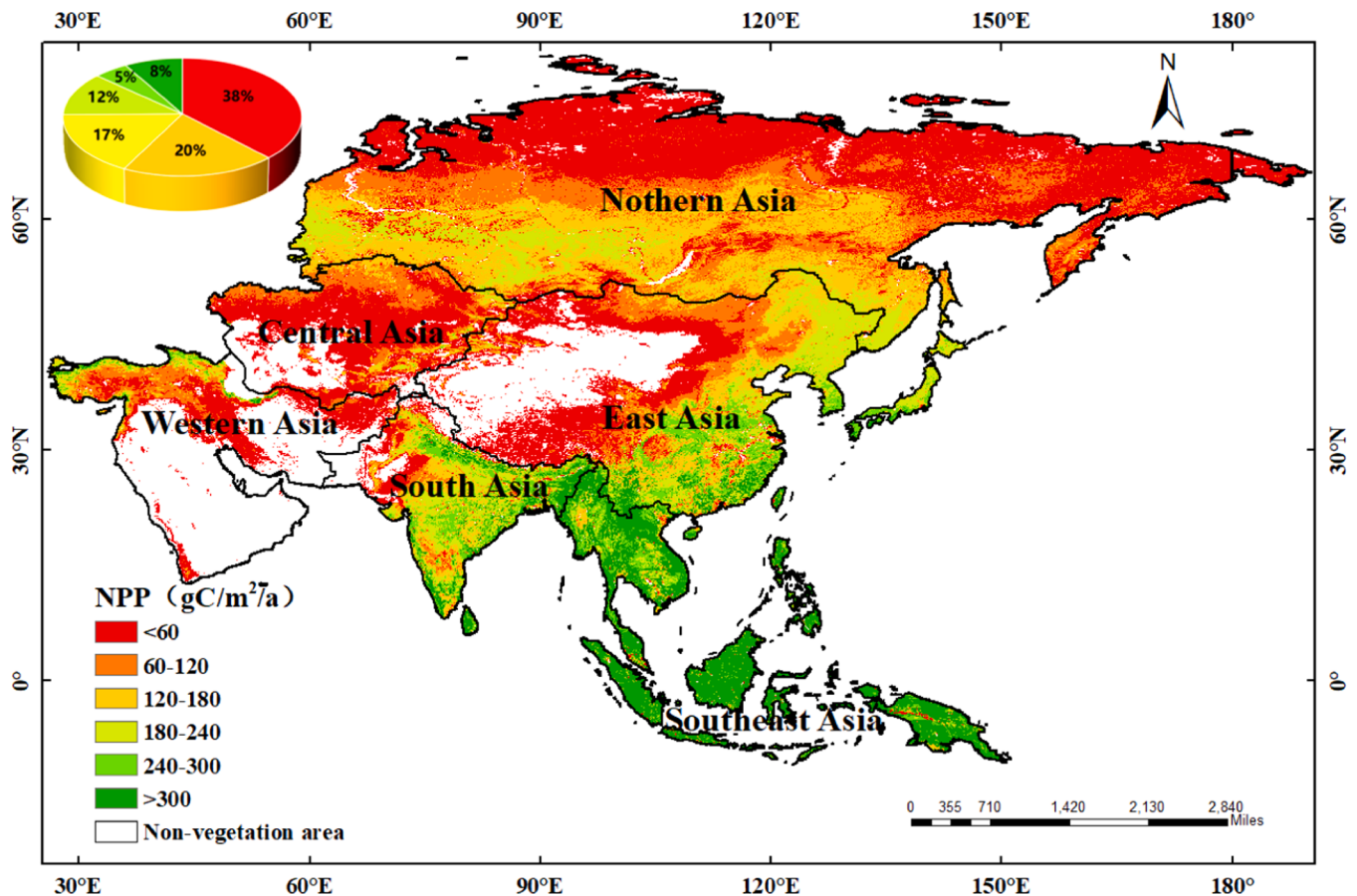


Fig. 6. Spatial distribution patterns of NPP in Asia terrestrial ecosystems from 1981 to 2018.

ecological systems.

4.2.3. Analysis of NPP change trends in different areas of Asia

The trend of NPP changes across Asia from 1981 to 2018 is calculated at the pixel scale using a combination of slope analysis and F-significance testing (Fig. 8). The analysis shows that the majority of the Asian region (59 %) shows no significant change in NPP. Regions exhibiting upward NPP trends (12 %) are primarily distributed in the southeastern region of the Asian continent (including southeastern China, the Indian Peninsula, and parts of the Indochina Peninsula) and in Turkey in Western Asia. The increase in NPP in southeastern Asia can be attributed to sufficient precipitation driven by monsoon climates under global warming, as well as improved vegetation productivity due to ecological conservation projects and advancements in agricultural management. In Turkey, the relatively abundant precipitation compared to other Western Asian countries, influenced by Mediterranean and temperate maritime climates, along with large-scale afforestation initiatives, has led to significant improvements in forest area and vegetation conditions.

Regions with significant NPP declines (29 %) include the Malay Archipelago in Southeast Asia, eastern Mongolia, northeastern Inner Mongolia in China, and the Irrawaddy River Basin in the Indochina Peninsula. The reduction in NPP in the Malay Archipelago is primarily caused by human activities such as agricultural expansion, urbanization, and logging, which have led to the destruction of primary forests. In eastern Mongolia and northeastern Inner Mongolia, despite being home to some of the world's most intact natural grasslands, vegetation cover has fluctuated and shown degradation trends during the last three decades owing to climate change (rising temperatures and reduced precipitation) and human activities such as mining and overgrazing. In the upstream section of the Irrawaddy River Basin, shifting cultivation

practices by ethnic groups in northern Kachin have expanded forest clearings, transforming dense forests into shrublands or sparse woodlands. In the midstream valley, overharvesting of valuable tree species has reduced the area of monsoon rainforests, while downstream delta regions have seen swamp forests replaced by farmland due to large-scale agricultural activities, resulting in severe vegetation degradation across the entire basin.

In summary, the trends in NPP changes across Asia exhibit significant regional heterogeneity. While NPP increases in southeastern Asia and parts of Western Asia are driven by favorable climatic conditions and ecological conservation measures, NPP declines in the Malay Archipelago, eastern Mongolia, northeastern Inner Mongolia, and the Irrawaddy River Basin are largely attributed to human activities, highlighting the urgent need for targeted ecological protection measures.

4.3. Asia NPP sustainability analysis

Hurst exponent analysis indicates that 92 % of Asia's vegetated areas exhibit $H < 0.5$ (mean = 0.4), demonstrating anti-persistent characteristics in vegetation NPP time series (Fig. 9). This suggests potential future trend reversals in vegetation NPP (e.g., a shift from previous increases to future decreases). However, integrated trend analysis reveals that over 50 % of these areas currently show no statistically significant NPP changes. This implies that despite the anti-persistence pattern, most ecosystems have not yet developed definitive upward or downward NPP trends. Persistent areas ($H > 0.5$) constitute merely 8 % of the total study area, showing a fragmented distribution pattern, mainly concentrated in the fringes of the Thar Desert in South Asia and localised areas in Kalimantan in Southeast Asia.

Integrated analysis combining trend evaluation with Hurst exponent outcomes enables projection of future vegetation NPP trajectories across

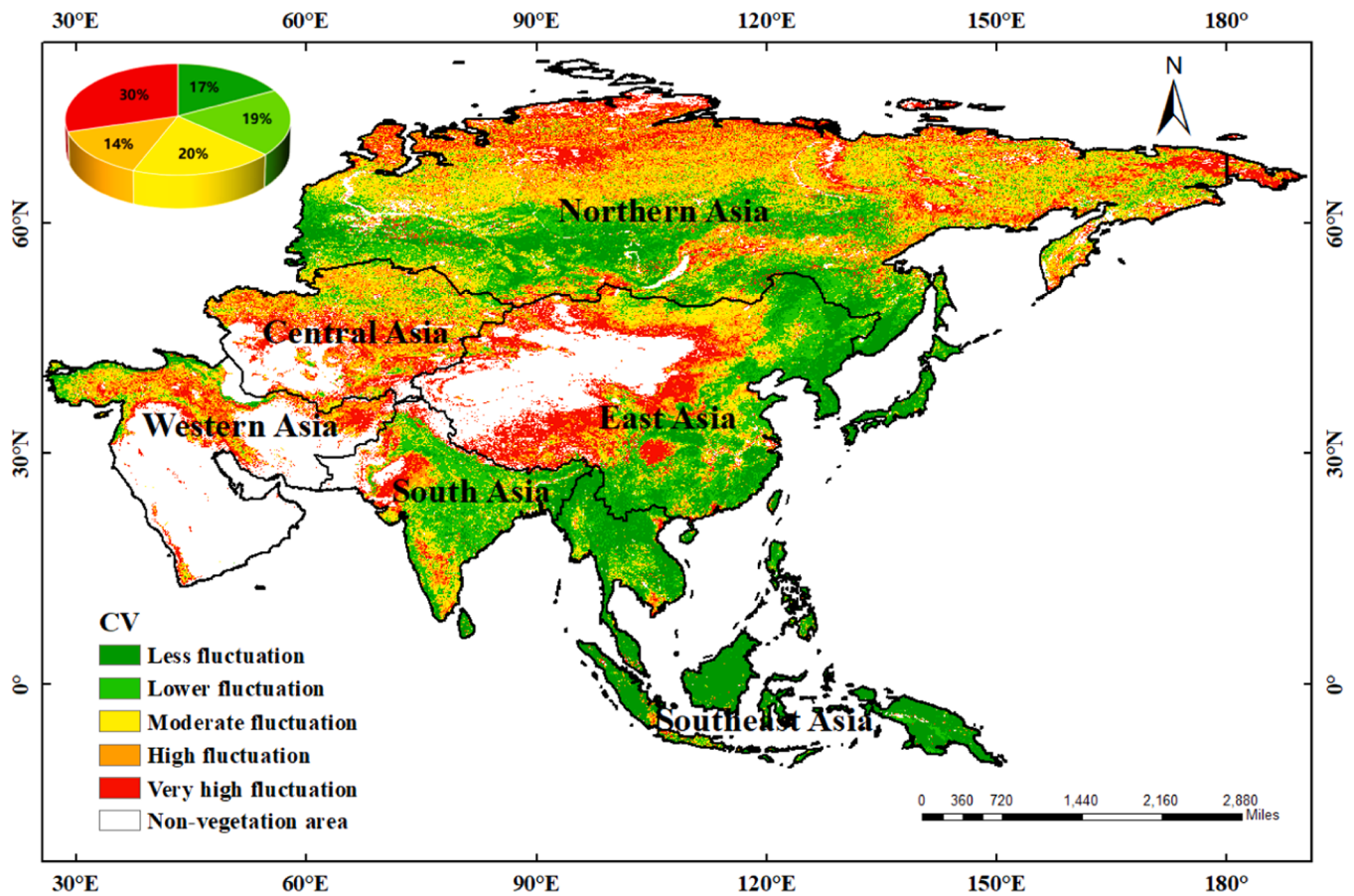


Fig. 7. Analysis results of NPP fluctuation intensity in Asian terrestrial ecosystems based on coefficient of variation.

Asia (Fig. 10). The synthesis reveals that 53 % of vegetated areas exhibit stochastic variability in NPP levels, while continual improvement persists in merely 2 % of territories—sparsely distributed across South Asian and southeastern East Asian croplands. Notably, degradation-to-improvement transitions are anticipated in 27 % of the study domain, predominantly concentrated in the Malay Archipelago, eastern Mongolia, northeastern Inner Mongolia (China), and the Irrawaddy River Basin. Approximately 12 % of the study area shows potential reversal of current growth trends, primarily concentrated in agricultural regions of South Asia and southeastern East Asia. This phenomenon may be attributed to systematic degradation (e.g., soil erosion and salinization) induced by prolonged agricultural intensification, which ultimately constrains vegetation productivity by reducing both soil fertility and water-use efficiency.

4.4. Analysis of driving mechanisms of Asian NPP

In this study, SEM is employed to evaluate the impacts of natural factors (temperature, precipitation, and topography) and human activities (population, GDP, and economic structure) on Asian NPP. The model demonstrates good fit and reliability, with GFI, CFI, and IFI values of 0.773, 0.805, and 0.806, respectively, and an RMSEA value below 0.228. As illustrated in Fig. 11, all factors except for the tertiary industry and aspect are found to significantly influence NPP, as their effects pass the significance test.

The results indicate that climate is the primary driving factor of vegetation NPP in Asian terrestrial ecosystems, with a total impact coefficient of 0.38, reaching a highly significant level. Among climatic factors, mean temperature is the dominant contributor, with an impact coefficient of 0.98, followed by minimum temperature, maximum temperature, and precipitation, with influence of 0.91, 0.83, and 0.39,

respectively. This suggests that although both temperature and precipitation are critical factors influencing vegetation growth and development, temperature exerts a stronger regulatory effect on vegetation NPP within the study area (vegetated regions of Asia).

Human activities exhibit a relatively minor direct impact on NPP, with a total impact coefficient of 0.06. GDP is identified as the primary contributor (impact coefficient of 0.98), followed by population, primary industry, and secondary industry, with influence coefficients of 0.85, 0.62, and 0.37, respectively. This indicates that economic development primarily influences NPP through GDP, while population and industrial structure also play a role in shaping NPP variations.

Topographic factors influence NPP through both direct and indirect effects. The total direct impact coefficient of topography is -0.14 , with slope and elevation being the major contributors, having impact coefficients of 0.72 and 0.64, respectively, while aspect does not pass the significance test. Additionally, topography indirectly affects NPP through its influence on human activities and climate, with impact coefficients of approximately 0.40 and 0.04, respectively. Combining direct and indirect effects, the total impact coefficient of topography on NPP is approximately -0.10 . This suggests that topography has a direct negative impact on NPP, but this effect is partially offset by its indirect regulatory influence on human activities and climate.

In summary, climate exerts the strongest influence on Asian NPP variations (impact coefficient of 0.38), followed by topography (total impact coefficient of -0.10), while human activities have the least impact (total impact coefficient of 0.06). These findings demonstrate that natural factors, particularly climatic conditions, play a dominant role in regulating vegetation NPP in Asian terrestrial ecosystems, whereas the effects of topography and human activities, though relatively smaller, remain significant.

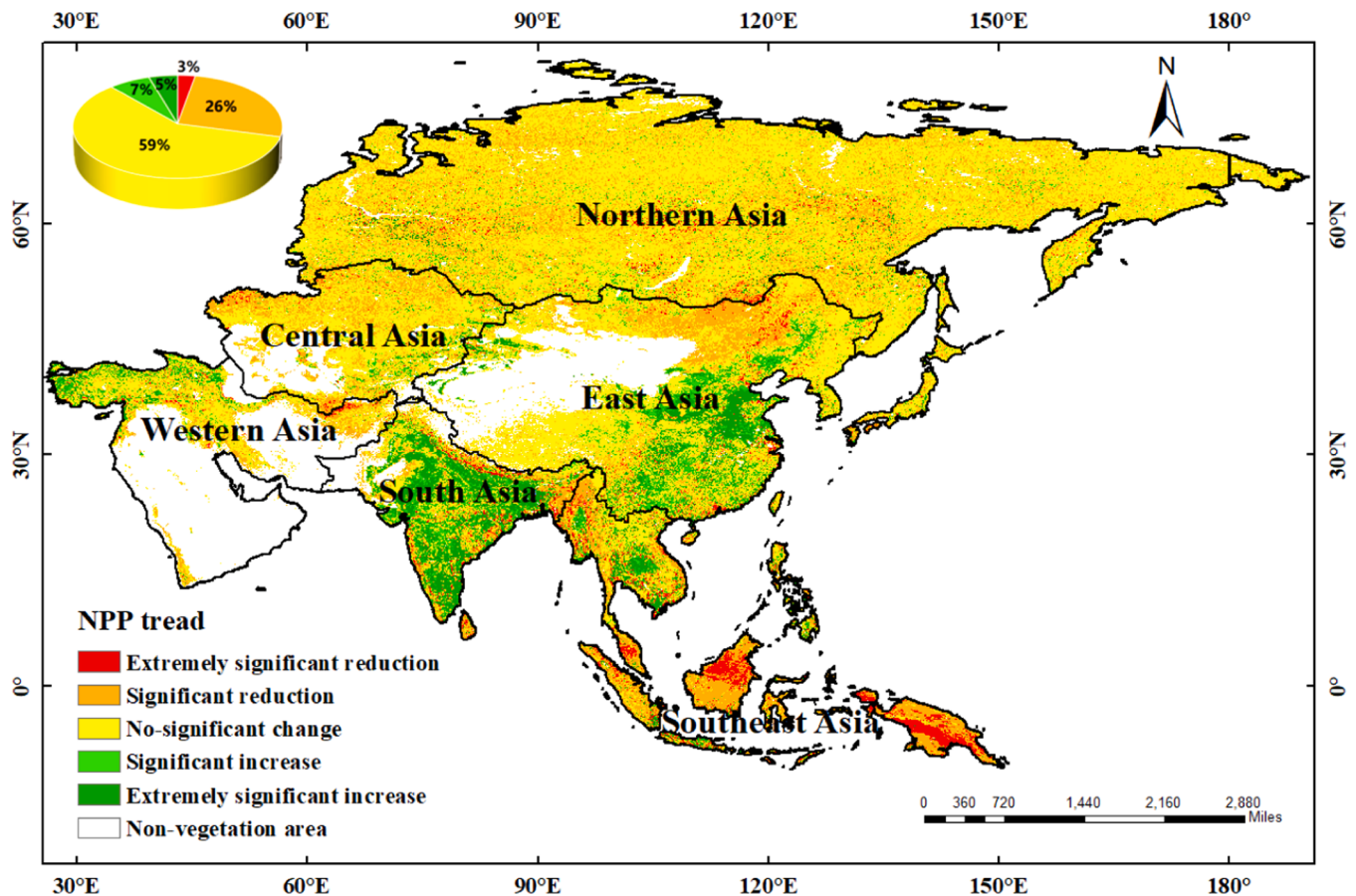


Fig. 8. Historical trends of NPP changes in Asian terrestrial ecosystems from 1981 to 2018.

5. Discussion

5.1. Characteristics of spatial and temporal changes in NPP in asia

From a temporal perspective, Asian NPP exhibits an overall fluctuating upward trend from 1981 to 2018, with a significant mutation point observed in 1998. Wavelet analysis reveals an approximately 20-year periodic variation at the 28-year time scale, during which Asian NPP undergoes two distinct rise-and-fall cycles. Notably, previous studies (Xu et al., 2017) have demonstrated that global precipitation exhibits a roughly 30-year periodic fluctuation affected by worldwide climatic patterns including the El Niño-Southern Oscillation (ENSO). In light of these findings, it is reasonable to hypothesize that the periodic variations in Asian vegetation NPP are likely a direct reflection of cyclical climatic changes, particularly in precipitation. This discovery not only enhances the understanding of the mechanisms driving NPP variations in Asian ecosystems but also provides valuable insights for predicting future trends.

Spatial analysis reveals a dominant configuration of decreased NPP in the northwestern parts and increased NPP in the southeastern regions across Asia. Specifically, Southeast Asia, southeastern East Asia, and South Asia exhibit relatively high NPP values. These regions are predominantly influenced by tropical rainforest, tropical monsoon, and temperate monsoon climates, fostering vegetation types such as tropical rainforests, subtropical evergreen broadleaved forests, and temperate deciduous broadleaved forests, as well as well-irrigated agricultural ecosystems. The dense and vigorous vegetation in these areas, coupled with relatively stable climatic conditions and abundant hydrothermal resources (Tian et al., 2025), contributes to their high NPP values and strong stability. In contrast, Central Asia, Western Asia, and northwestern East Asia generally exhibit lower NPP values. These regions are

characterized by drought-tolerant shrubs and low-growing herbaceous plants, with sparse vegetation coverage due to limited temperature and precipitation conditions, resulting in lower NPP values (Zhu et al., 2025). Similarly, the tundra zones in northern North Asia display comparably low NPP characteristics. It is noteworthy that the vegetation ecosystems in these areas are functionally simplistic and have limited adaptability to extreme climatic events (Xue et al., 2020), leading not only to low absolute NPP values but also to significant interannual fluctuations and reduced ecosystem stability.

Trend analysis reveals significant regional differences in the NPP change trends across Asia from 1981 to 2018. In southeastern East Asia and South Asia, which are influenced by tropical and temperate monsoons, abundant annual precipitation, combined with the promoting effects of global warming on vegetation growth, has led to notable increases in NPP in southeastern China and the Indian Peninsula. Particularly noteworthy is the fact that NPP in most cultivated areas within these regions has reached a highly significant level of growth. This is likely attributable to continuous improvements in agricultural management and water-fertilizer conditions, which have not only boosted crop yields but also significantly enhanced the productivity of farmland ecosystems (Wei et al., 2024). The combined effects of advanced management practices and global warming have driven NPP increases in these areas to highly significant levels. These findings further validate Zeng Ning's (Zeng et al., 2014) research on terrestrial carbon cycle patterns, indicating that Asian farmland ecosystems, particularly in China, have become important carbon sinks in recent years.

However, global warming is often accompanied by increased evapotranspiration. In regions lacking sufficient precipitation, ecosystems may become more vulnerable due to drought. In the grassland areas of eastern Mongolia and northeastern Inner Mongolia, China, vegetation productivity has declined significantly due to intensified

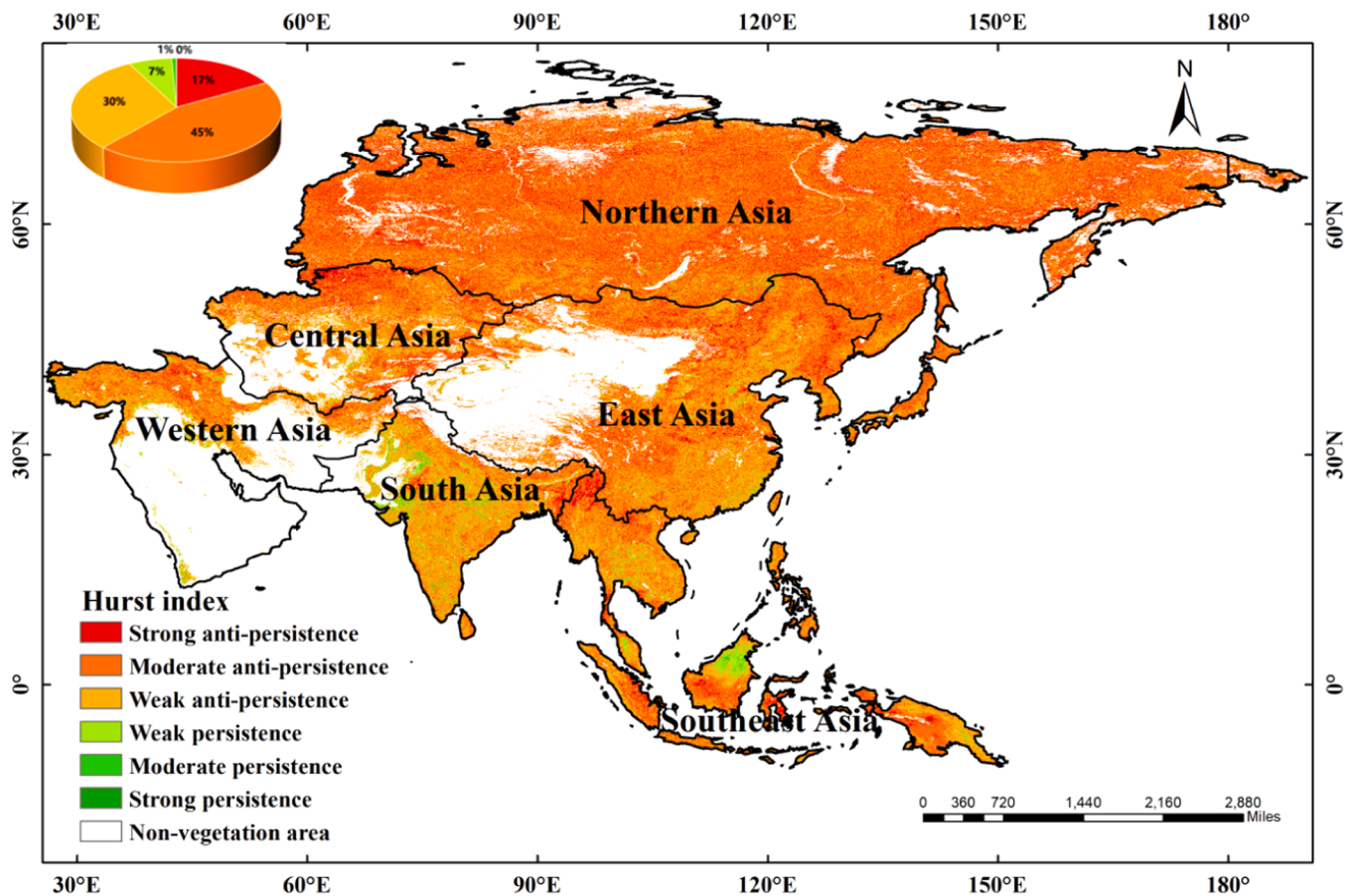


Fig. 9. Hurst exponent analysis results of NPP in Asian terrestrial ecosystems.

drought caused by global climate change, together with human activities including intensive grazing and mining practices. The most pronounced decline in NPP is observed in the Malay Archipelago of Southeast Asia. Despite abundant rainfall, further increases in global temperatures no longer promote vegetation growth in this tropical region. Since the beginning of the 21st century, large-scale deforestation has been carried out across the islands to expand palm oil plantations and timber industries (Huang et al., 2023), causing a dramatic reduction in vegetation cover and a significant drop in carbon sequestration capacity. Additionally, forest fires have become a major contributor to the reduction in vegetation cover in this region. For example, the 1983 forest fires in Kalimantan and the 1997 Indonesian forest fires destroyed thousands of hectares of tropical rainforest (Hansen et al., 2019). These frequent natural disasters have further exacerbated the declining trend in NPP in the local tropical rainforests.

5.2. NPP sustainability characteristics in asia

Spatiotemporal analysis based on the Hurst exponent reveals marked regional heterogeneity in the sustainability of Asian vegetation NPP. Contrasting persistence patterns emerge between the Thar Desert periphery in South Asia and localized sectors of Kalimantan Island in Southeast Asia, exhibiting persistent enhancement and degradation respectively. Specifically, intensive irrigation networks in the western Indus Plain sustain stable agroecosystems (Hasan and Fatima, 2025), while the eastern region demonstrates climate buffering capacity through the water-retention properties of black cotton soils (Tagore et al., 2014) combined with drought-tolerant vegetation adaptations. Conversely, extensive oil palm conversion replacing primary forests in Kalimantan (Botterill-James et al., 2024) has precipitated biodiversity loss and NPP persistence decline, given oil palm's inferior productivity

compared to native rainforests, highlighting the ecological consequences of monoculture land-use systems.

Projected trend analyses reveal that approximately half of Asia's vegetated areas, primarily distributed across northeastern East Asia and northern Asia, exhibit stochastic variability in NPP. The stochastic variability is primarily attributed to intensified interannual fluctuations in summer monsoon precipitation in northeastern East Asia, which drive frequent switches between water-surplus and drought conditions. This leads to alternating resource constraints on vegetation growth (e.g., enhanced growth during wet years followed by carbon loss during subsequent hot-dry years), thereby inhibiting long-term trend formation (Guo et al., 2022). In northern Asia, the positive effect of climate warming-induced growing season extension is offset by negative impacts from permafrost thaw, including soil water loss and land subsidence, resulting in an alternating pattern of vegetation productivity responses.

Notably, regions including the Malay Archipelago, eastern Mongolia, and the Irrawaddy River Basin may exhibit improving NPP trends. This improvement primarily stems from integrated measures such as sustainable forestry management (Liu et al., 2024b), farmland-to-forest conversion programs (Chen et al., 2023b), and rare tree species conservation policies (Kyaw et al., 2024). Through vegetation community reconstruction and ecosystem function restoration, these measures have effectively reversed previous NPP declines caused by human activities like agricultural expansion. These spatiotemporal patterns reveal the dual role of human intervention: intensive development triggers ecological degradation, while scientific governance can drive system recovery. The findings validate a regional-scale "stress-response-recovery" coupled human-environment dynamic process, providing a replicable model for ecological restoration in developing countries.

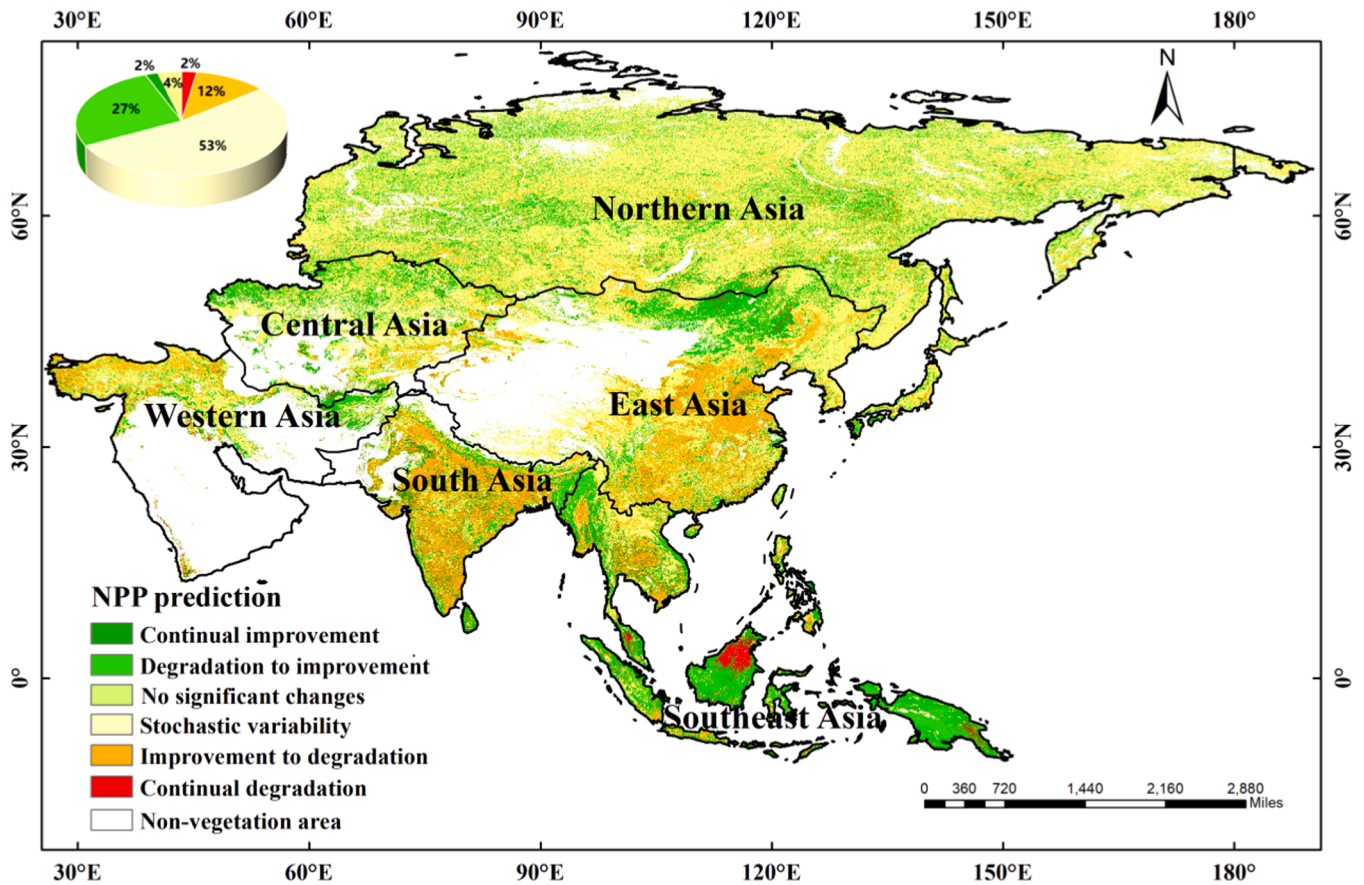


Fig. 10. Future sustainability analysis results of NPP in Asian terrestrial ecosystems.

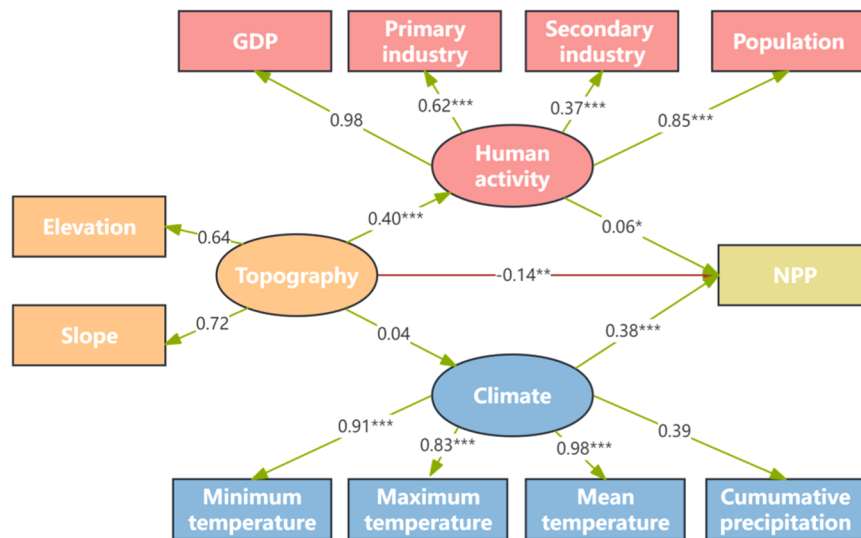


Fig. 11. SEM of the relationship between Asia NPP change and its drivers (***) Significant at the 99 % level; ** 95 %; * 90 %. The indirect effect of topography on NPP through human activities is: $0.40 \times 0.06 = 0.024$; The indirect effect of topography on NPP through climate is: $0.04 \times 0.38 = 0.0152$; The total effect of topography on NPP is: $-0.14 + 0.024 + 0.0152 = -0.1008$.

5.3. Drivers of NPP change in asia

Climate factors, such as temperature and precipitation, are generally recognized as the dominant determinants of vegetation NPP (Chen et al., 2013). The analysis based on the SEM in this study also confirms that climatic factors play a predominant role among all driving factors, with an impact coefficient of 0.38, reaching a highly significant level. Among

these factors, mean temperature exhibits the highest impact coefficient, followed by minimum temperature, maximum temperature, and precipitation.

Temperature is a critical factor controlling plant growing seasons, photosynthetic rates, and ecosystem productivity (Liu et al., 2024a). Given the significant climatic diversity across Asia, the influence of temperature on vegetation growth is particularly pronounced. In

temperate and subarctic regions, temperature often limits the growing season and growth rates of plants. Therefore, temperature variations, especially winter minimum temperatures and summer maximum temperatures, can become key limiting factors for vegetation NPP. Notably, the impact coefficient of mean temperature is the highest among all climatic factors, suggesting that vegetation productivity in Asia may be significantly affected by global warming, particularly in high-latitude and mountainous regions.

Precipitation directly affects water availability for vegetation, thereby influencing photosynthesis and plant growth, and is undoubtedly another key driver of vegetation NPP (Zhu et al., 2022). In arid and semi-arid regions such as Central Asia, Western Asia, and northwestern East Asia, scarce precipitation makes it difficult to sustain vegetation growth, resulting in vast desert and barren areas. However, this research emphasizes the effect of climatic factors on vegetation NPP and does not include these non-vegetated desert regions. In vegetated areas, the influence of temperature on NPP is greater than that of precipitation, as evidenced by the distinct latitudinal zonation observed in the distribution of Asian vegetation NPP (Fig. 6). In vegetated regions, the precipitation distribution pattern in Asia is highly complex, with monsoon climates and arid zone precipitation variations exerting different effects on NPP across vegetation types. In humid regions such as tropical rainforests and subtropical monsoon climates, precipitation is generally not a limiting condition, whereas in moisture-deficient or semi-arid areas, insufficient precipitation can significantly constrain vegetation growth and NPP generation (Fensholt et al., 2012).

Topographic elements influence vegetation NPP through both direct and indirect pathways. The direct impact coefficient of topography on vegetation NPP is -0.14 , with elevation and slope making significant contributions. Typically, high-altitude regions are characterized by scarce precipitation, lower temperatures, thin soil layers, and poor soil fertility, all of which collectively limit vegetation growth (Feng et al., 2025). Additionally, increased slope gradients exacerbate soil erosion, further reducing soil fertility and restricting vegetation growth, leading to decreased NPP (Qiu et al., 2025). Asia, the highest-elevation continent after Antarctica, has mountains, plateaus, and hills covering approximately two-thirds of its land area, with about one-third of the region exceeding 1000 m in elevation. Consequently, elevation and slope significantly negatively impact Asian NPP (Chen et al., 2023a). However, elevation and slope also generate indirect effects by influencing human activities. For instance, in low-altitude and flat areas, higher population densities and frequent human activities result in greater disturbances to vegetation NPP, whereas in high-altitude and steep-slope regions, lower population densities and reduced human activities lead to fewer disturbances (Liu et al., 2015). Thus, this study reveals that topography partially offsets its negative impact on NPP by reducing human activities. This highlights the limitations of traditional correlation analysis in comprehensively assessing the influence of topography on NPP, while the SEM model more accurately uncovers the complex relationships among factors, providing more precise evaluation results.

Human activities exhibit dual effects on vegetation NPP (Dai et al., 2023). On one hand, excessive land use, deforestation, overgrazing, and urbanization can destroy natural vegetation and reduce NPP. On the other hand, human activities such as agricultural cultivation and ecological engineering projects can also promote vegetation NPP (He et al., 2021). This study indicates that, among various factors, human activities have a relatively minor contribution to Asian vegetation NPP, with an impact coefficient of only 0.06. GDP contributes the most, followed by population, primary industry, and secondary industry, all showing positive correlations. This suggests that, although some regions in Asia (e.g., the Malay Archipelago in Southeast Asia) face destructive activities such as deforestation, overgrazing, and urbanization, human activities overall tend to have a positive impact on NPP. Countries across Asia, including China, have effectively enhanced vegetation coverage and productivity through improved agricultural management,

sustainable development policies, and ecological projects (e.g., reforestation, wetland restoration, and shelterbelt construction) (Li et al., 2025). This finding aligns with the conclusions of Section 4.3.2 regarding the trend analysis of Asian vegetation NPP, which shows a highly significant upward trend in NPP in most cultivated areas of East Asia, Southeast Asia, and South Asia. This further demonstrates that, despite the persistence of some destructive human activities in Asia, effective policy interventions and ecological restoration efforts have driven a positive trend in anthropogenic influences on NPP.

Although this study quantified the spatial differentiation mechanisms of NPP driven by the synergistic effects of multiple factors using SEM, the current model primarily elucidates driving relationships in the spatial dimension, without incorporating time series information or potential lag effects. This design choice leverages SEM's strength in testing predefined causal pathways rather than capturing temporal dependencies (Grace et al., 2016). Moreover, the study period encompasses the 28-year principal cycle of Asian NPP (Section 4.1), capturing its long-term dynamic characteristics. Nevertheless, we recognize that vegetation productivity may exhibit short-term memory effects, such as the lasting impacts of drought stress. Future research will integrate both spatial and temporal information to more comprehensively reveal the spatiotemporal regulatory mechanisms of carbon sink functions in Asian ecosystems.

6. Conclusions

Employing long-term NPP datasets, this study analyzes the spatio-temporal variations and driving mechanisms of NPP in Asian vegetation from 1981 to 2018, yielding the following key conclusions:

- (1) Throughout the research period, Asian vegetation NPP exhibits a fluctuating increasing trend, accompanied by consistent seasonal variation patterns. A mutation point is identified around 1998 in the interannual variation. Wavelet analysis reveals that Asian NPP demonstrates an approximately 20-year periodic fluctuation at a 28-year time scale, undergoing two distinct rise-and-fall transitions.
- (2) Spatial analysis indicates that Asian terrestrial ecosystems display a spatial pattern of lower NPP in the northwest and higher NPP in the southeast. High NPP values are primarily observed in Southeast Asia, southeastern East Asia, and South Asia, with these regions exhibiting strong stability. In contrast, Central Asia, Western Asia, and northwestern East Asia generally show lower NPP values with greater variability.
- (3) Trend and sustainability analyses reveal significant regional differences in NPP changes across Asia. Around 60 % of regions show no significant change, while eastern East Asia and South Asia exhibit NPP growth due to global warming, agricultural development, and ecological projects. In contrast, tropical rainforests in Southeast Asia and grasslands in eastern Mongolia experience declines due to natural disasters, deforestation, and overgrazing. Future projections suggest potential NPP declines in South Asia and southeastern East Asia's agricultural areas from long-term intensification, while regions like the Malay Archipelago, eastern Mongolia, northeastern Inner Mongolia, and the Irrawaddy River Basin may see positive shifts due to effective policies and restoration projects.
- (4) SEM identifies natural factors as the dominant drivers of Asian NPP changes, with climatic factors—particularly temperature and precipitation—being the key contributors, exhibiting an impact coefficient of 0.38. The total influence coefficient of topographic factors on NPP is determined to be -0.10 , comprising a direct effect of -0.14 and an indirect effect of 0.04 mediated through climate and human activities. This indirect effect is found to partially mitigate the negative impact of topography on NPP. Human activities have a relatively minor

influence on NPP, with contribution coefficients of 0.06, primarily driven by GDP and population density.

CRediT authorship contribution statement

Meng Li: Writing – original draft, Visualization, Software, Methodology, Data curation. **Liang Liang:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Formal analysis. **Ziru Huang:** Writing – original draft. **Huaxiang Song:** Supervision. **Shuguo Wang:** Supervision, Writing – review & editing. **Qianjie Wang:** Writing – original draft, Methodology. **Yang Sun:** Writing – original draft.

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.

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Data availability

Data will be made available on request.

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