



Assessing the spatiotemporal consistency of satellite-derived leaf area index products across the Tibetan Plateau

Yabin Ye , Zhi Huang , Zishan Wang , Hao Zheng , Linying Ma , Meirong Wang , Limin Yang , Qian Zhang, Weimin Ju , Tiexi Chen & Jun Wang

To cite this article: Yabin Ye , Zhi Huang , Zishan Wang , Hao Zheng , Linying Ma , Meirong Wang , Limin Yang , Qian Zhang, Weimin Ju , Tiexi Chen & Jun Wang (2026) Assessing the spatiotemporal consistency of satellite-derived leaf area index products across the Tibetan Plateau, International Journal of Digital Earth, 19:2, 2749203, DOI: [10.1080/17538947.2026.2749203](https://doi.org/10.1080/17538947.2026.2749203)

To link to this article: <https://doi.org/10.1080/17538947.2026.2749203>



© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



[View supplementary material](#)



Published online: 16 Oct 2026.



[Submit your article to this journal](#)



[View related articles](#)



[View Crossmark data](#)



RESEARCH ARTICLE



Assessing the spatiotemporal consistency of satellite-derived leaf area index products across the Tibetan Plateau

Yabin Ye^{a,b}, Zhi Huang^{a,b}, Zishan Wang^{a,b}, Hao Zheng^{a,b}, Linying Ma^{a,b}, Meirong Wang^{c,d}, Limin Yang^e, Qian Zhang^f , Weimin Ju^{a,b}, Tiexi Chen^{g,h} and Jun Wang^{a,b}

^aInternational Institute for Earth System Science, Nanjing University, Nanjing, Jiangsu, China; ^bJiangsu Provincial Key Laboratory for Advanced Remote Sensing and Geographic Information Technology, Key Laboratory for Land Satellite Remote Sensing Applications of Ministry of Natural Resources, School of Geography and Ocean Science, Nanjing University, Nanjing, Jiangsu, China; ^cState Key Laboratory of Climate System Prediction and Risk Management, Key Laboratory of Meteorological Disaster, Ministry of Education, Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science and Technology, Nanjing, China; ^dMèdog Field Station for Scientific Observation and Research on Atmospheric Water Cycle/Xigazê and Mèdog National Climate Observatory, Tibet Meteorological Service, Lhasa, China; ^eMeteorological Observatory of Xizang Autonomous Region, Lhasa, China; ^fCollege of Geodesy and Geomatics, Shandong University of Science and Technology, Qingdao, China; ^gState Key Laboratory of Climate System Prediction and Risk Management, School of Geographical Sciences, Nanjing University of Information Science and Technology, Nanjing, China; ^hQinghai Provincial Key Laboratory of Plateau Climate Change and Corresponding Ecological and Environmental Effects, Qinghai Institute of Technology, Xining, China

ABSTRACT

Vegetation dynamics across the Tibetan Plateau are shifting under climate change, yet our understanding remains hindered by uncertainties among satellite products. We assessed the consistency of seven Leaf Area Index (LAI) products (2001–2018) in capturing mean states and spatiotemporal trends: MODIS, GIMMS, GLOBMAP, GLASS-AVHRR, GLASS-MODIS, HIQ, and GEOV2. Results revealed high agreement on climatological means (Pearson's $r > 0.75$, $p < 0.001$), whereas agreement was much lower regarding long-term dynamics ($r < 0.6$). Only GLOBMAP, GLASS-MODIS, and GEOV2 identified significant greening (0.0059 , 0.0052 , and $0.0093 \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$, $p < 0.05$), while MODIS, GIMMS, GLASS-AVHRR and HIQ showed non-significant trends. Spatial trend heterogeneities peaked in southeastern forest-dominated regions ($< 2200 \text{ m}$), which may be related to complex canopy structures. In pixel-scale analysis, 77% of the vegetated areas lacked consistent and significant trends. Only 0.66% showed unanimous greening across all products, mainly in the northeastern Tibetan Plateau. High consistency occurred in a warm-dry core ($10\text{--}15^\circ\text{C}$, $50\text{--}150 \text{ mm}$) but weakened toward colder or wetter regimes. These patterns likely reflect sensor disparities, retrieval algorithms, and the extreme environments. These findings provide a comprehensive assessment of the consistency among multiple satellite LAI products and have important implications for monitoring vegetation responses to environmental change.

ARTICLE HISTORY

Received 26 May 2026
Accepted 11 October 2026

KEYWORDS

Tibetan Plateau; leaf area index; multi-source remote sensing products; vegetation dynamics; spatial consistency

1 Introduction

Climate change alters the vegetation state, which in turn modulates energy exchange, consequently affecting the terrestrial carbon and hydrological cycles (Cui et al. 2022). The Leaf Area Index (LAI), defined as half of the total green leaf area per unit ground area (Chen and Black 1992), is a pivotal parameter for characterizing canopy structure and simulating photosynthesis, transpiration, and land-atmosphere exchanges. Given the critical role of LAI in monitoring vegetation dynamics, a variety of long-term LAI products with high spatiotemporal resolutions have been developed since the advent of the satellite era. These products have substantially advanced our understanding of long-term vegetation dynamics and their responses to global environmental change (Li, Wang, and Chen 2024; Piao et al. 2020; Wang et al. 2025; Zhu et al. 2016), as well

CONTACT Jun Wang wangjun@nju.edu.cn International Institute for Earth System Science, Nanjing University, Nanjing, 210023, Jiangsu, China

Supplemental data for this article can be accessed online at <https://doi.org/10.1080/17538947.2026.2749203>.

© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

as their feedbacks on the climate system (e.g. changes in runoff and temperature) (Alkama et al. 2022; Bonan 2008; Chen et al. 2023).

The reliability of satellite-derived LAI products is paramount to our understanding of terrestrial biosphere dynamics, as these datasets serve as the primary ‘benchmark’ for both empirical trend analysis and numerical simulations. In land surface modeling, for instance, LAI is utilized either as a critical forcing input or as a reference to constrain autonomous simulations in Dynamic Global Vegetation Models (DGVMs). State-of-the-art LSMs (e.g. Noah-MP and DGVMs within the TRENDY project) face challenges in capturing realistic vegetation phenology and productivity (Huang et al. 2022; Seiler et al. 2022); satellite observations provide an indispensable reference for calibrating and validating model trajectories. If the underlying satellite products contain biases—stemming from sensor degradation or retrieval algorithm limitations—these biases directly compromise the estimation of gross primary productivity (GPP) and energy-water fluxes (Chen, Liu, and Liu 2025; Huang et al. 2022). Therefore, before using these products to interpret ecological shifts or drive climate models, it is imperative to rigorously evaluate their consistency and uncertainty characteristics, particularly in climatically sensitive regions.

The Tibetan Plateau serves as the ‘Asian water tower’ and is known as the Earth’s ‘Third Pole’ (Qiu 2008). Characterized by high altitude, intense radiation, and ecological fragility, it hosts extensive alpine meadows and steppes that function as a vital ecological security barrier for Asia (Sun et al. 2012). In recent decades, the Tibetan Plateau has experienced a warming rate approximately twice the global average (Piao et al. 2010; Yao 2019), accompanied by a trend towards increased humidity (Chen et al. 2013; Kuang and Jiao 2016; Yiming et al. 2026). These climatic shifts have extended the growing season and enhanced vegetation productivity, leading to an overall greening trend across much of the plateau (Huang et al. 2019; Piao et al. 2019; Zhu et al. 2016). Such shifts in vegetation exert feedbacks on climate regulation, influence land-atmosphere coupling, and impact downstream water resources (Luo, Ma, and Zhang 2025a; Shen et al. 2015; Wu et al. 2020). However, the spatial response is far from uniform; intensification of warming combined with localized precipitation deficits has led to signs of vegetation degradation in the southwestern Tibetan Plateau (Anniwaer et al. 2024; Li, Hu, and Liu 2020). Therefore, a comprehensive assessment of vegetation dynamics across the entire Tibetan Plateau is crucial for understanding the response mechanisms of alpine ecosystems.

Despite substantial research focusing on the Tibetan Plateau vegetation changes, many analyses rely on a single remote sensing product, making their conclusions highly sensitive to dataset-specific uncertainties. For instance, Wei et al. (2025) used MOD13C2 V061 to show that over one-third of the plateau lacked significant greening during 2001–2023. However, whether other datasets would yield consistent spatiotemporal patterns across the entire Tibetan Plateau remains to be examined. Variations in sensor performance, radiative calibration, inversion model design, and the handling of cloud or snow interference can lead to discrepancies among different satellite products (Fang et al. 2019; Jiang et al. 2017). These discrepancies can result in inconsistencies in trend detection and spatial stability (Luo, Ma, and Zhang 2025b; Piao et al. 2015; Zhu et al. 2016), potentially biasing LSM simulations and ecological interpretations (Liu et al. 2018). Recent sub-regional studies have begun to address these issues; for example, Luo, Ma, and Zhang (2025b) found that in the Yellow River source region, 60% of the growing season area exhibited inconsistent trend directions among three major LAI products (GIMMS LAI4g, GLASS-AVHRR, and GLOBMAP V3). Nonetheless, such comparative analyses remain localized or restricted in their spatial scope. A systematic intercomparison across the entire Tibetan Plateau—specifically addressing uncertainty characteristics and spatial consistency in long-term trend detection among diverse mainstream products—is still lacking. This gap hinders our ability to accurately evaluate and simulate vegetation dynamics and their feedbacks to the climate system on the plateau, and to scientifically formulate ecological policies.

Based on the identified research gaps, we integrate seven satellite-derived LAI products to systematically evaluate LAI dynamics over the Tibetan Plateau. The specific objectives are: (1) to objectively evaluate the consistency of vegetation changes (greening vs browning) over the Tibetan Plateau as represented by state-of-the-art satellite products over the past two decades; (2) to identify the bias and spatial uncertainty patterns among multiple data sources; and (3) to provide scientifically robust evidence for the selection of ecological monitoring datasets. Ultimately, we aim to enhance the credibility of vegetation dynamics assessments in high-altitude ecosystems and offer a reference framework for future multi-source data integration and advancements in LAI algorithms.

2 Materials and methods

2.1 Study area

The Tibetan Plateau is the highest plateau in the world, with an average elevation exceeding 4,000 meters. Its topography is characterized by significant elevation gradients, with elevations generally decreasing from west to east (Figure 1). Under the strong influence of the Asian monsoon system, the plateau exhibits a large climatic span, with pronounced spatial gradients in temperature, precipitation, and radiation. Mean annual temperatures range from -15 to 10 °C, and annual total solar radiation varies from 6,000 to 9,000 $\text{MJ m}^{-2} \text{yr}^{-1}$ (Yao et al. 2013). Precipitation exhibits marked spatial heterogeneity, decreasing from over 1,000 mm in the humid southeastern Tibetan Plateau to less than 50 mm in the arid northwestern Tibetan Plateau. This moisture gradient results in a distinct seasonal distribution, with the majority of rainfall occurring during the wet season from June to September (Kuang and Jiao 2016). Correspondingly, cloud cover is substantially higher in the southeastern Tibetan Plateau, while the northwestern Tibetan Plateau remains largely cloud-free (Wu, Gao, and Zhao 2024).

These diverse environmental conditions support highly heterogeneous vegetation types and unique ecosystems. The southern Tibetan Plateau is dominated by broadleaf forest, while coniferous forests and shrublands prevail in the eastern Tibetan Plateau. Alpine meadows are primarily distributed across the northeastern and central Tibetan Plateau, while alpine grasslands are widespread in the western Tibetan Plateau, where the landscape transitions into alpine desert landscapes in the northwestern Tibetan Plateau. These ecosystems are highly sensitive to both global climate change and anthropogenic activities, rendering the plateau one of the most ecologically fragile regions in Eurasia (Sun et al. 2012).

2.2 Multi-source satellite LAI products

In this study, seven widely used and publicly accessible Leaf Area Index products were integrated to evaluate vegetation dynamics over the Tibetan Plateau: MOD15A2H, GIMMS LAI4g, GLOBMAP LAI V3, GLASS-AVHRR, GLASS-MODIS, HIQ, and GEOV2 (Table 1). These products represent a broad spectrum of input sensors (MODIS, AVHRR, and SPOT/PROBA-V) and retrieval algorithms, ranging from physical radiative transfer models to advanced deep learning architectures (e.g. BPNN, GRNN, Bi-LSTM). This diversity facilitates both a robust cross-product intercomparison and a comprehensive assessment of product-specific uncertainties.

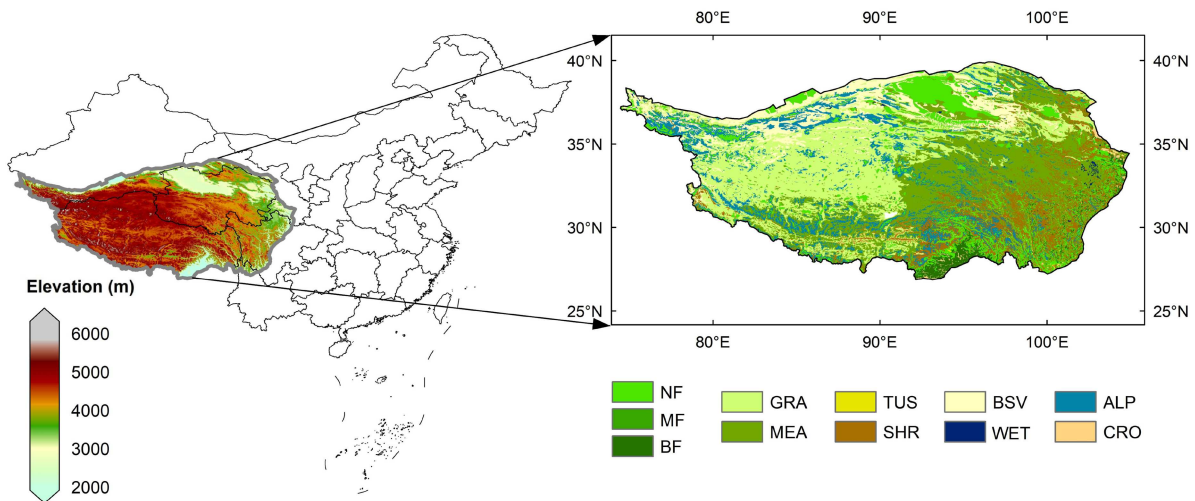


Figure 1. Spatial distribution of topography and land cover types across the Tibetan Plateau. The DEM data were sourced from SRTM V4.1, and the land cover data from the 1:1,000,000 Vegetation Atlas of China, which adopts the Chinese Vegetation Classification System. Vegetation type abbreviations: NF—needleleaf forest, MF—mixed forest, BF—broadleaf forest, GRA—grassland, MEA—meadow, TUS—tussock/tussock grassland, SHR—shrubland, BSV—barren/sparsely vegetated, WET—wetland, ALP—alpine vegetation, CRO—cropland.

Table 1. Multi-source satellite LAI product information.

LAI Product	Time Range	Temporal Resolution	Spatial Resolution	Data Source	Retrieval Algorithm	Reference
MOD15A2H	February 2000–Present	8 d	500m	MODIS reflectance	Three-dimensional radiative transfer model	Myneni, Knyazikhin, and Park (2015, 2021)
GIMMS LAI4g	1982–2020	Bi-weekly	1/12°	AVHRR, MOD15A2H, MCD15A2H	BPNN	Cao et al. (2023)
GLOBMAP LAI V3	1981–2023	8 d	0.0727273°	AVHRR, MODIS reflectance	GLOBCARBON	Liu, Liu, and Chen (2012)
GLASS-AVHRR	1981–2018	8 d	0.05°	AVHRR, MODIS reflectance	GRNN	Xiao et al. (2016)
GLASS-MODIS	2000–2025	8 d	0.05°	MODIS reflectance	Bi-LSTM	Ma and Liang (2022)
HIQ	2000–2022	8 d	5km	MOD15A2H	STICA	Yan et al. (2024)
GEOV2	1999–2020	10 d	1/112°	SPOT/VEGETATION, PROBA-V	Neural network algorithm	Verger et al. (2023)

- MOD15A2H (MODIS): This product is based on 8-day composite observations from the Terra satellite. The retrieval follows a primary algorithm utilizing a three-dimensional (3D) radiative transfer model, supplemented by a backup algorithm that establishes an empirical relationship between the Normalized Difference Vegetation Index (NDVI) and canopy LAI (Myneni, Knyazikhin, and Park 2015).
- GIMMS LAI4g (GIMMS): Derived from Advanced Very High Resolution Radiometer (AVHRR) observations and reprocessed MODIS Version 6.1 LAI (MCD15A2H and MOD15A2H), this product employs a Back-Propagation Neural Network (BPNN) for initial LAI estimation. The time series is subsequently extended to 2020 using a pixel-level Random Forest (RF) approach (Cao et al. 2023).
- GLOBMAP LAI V3 (GLOBMAP): This dataset integrates AVHRR and MODIS surface reflectance data using the GLOBCARBON LAI algorithm. For the 2001–2023 period, LAI is retrieved from MODIS 8-day surface reflectance, while the earlier 1981–2000 segment is reconstructed based on statistical relationships between AVHRR observations and MODIS-derived LAI (Liu, Liu, and Chen 2012).
- GLASS-AVHRR LAI (GLASS-AVHRR): This product utilizes a Generalized Regression Neural Network (GRNN) algorithm to extract LAI from satellite reflectance time series. It was generated from AVHRR reflectance data for the 1981–1999 period and from MODIS reflectance thereafter (Xiao et al. 2016).
- GLASS-MODIS LAI (GLASS-MODIS): As part of the GLASS V6 suite, this product applies a Bidirectional Long Short-Term Memory (Bi-LSTM) deep learning model to capture temporal features from MODIS surface reflectance (Ma and Liang 2022). While this product is available at spatial resolutions of 250 m, 500 m, 0.05°, and 0.1°, this study utilizes the 0.05° resolution version.
- HIQ LAI (HIQ): As a reprocessed version of MOD15A2H, HIQ employs the Spatiotemporal Information Composition Algorithm (STICA). It integrates raw observations, quality metrics, and spatiotemporal contextual information to mitigate noise and enhance the consistency of the MODIS LAI product (Yan et al. 2024).
- GEOV2: Developed within the Geoland2 framework, GEOV2 uses SPOT/VEGETATION and PROBA-V data as inputs for a neural network algorithm. Additionally, it fuses CYCLOPES V3.1 and MOD15A2 series data and incorporates a multi-step filtering approach to eliminate atmospheric interference and snow-related artifacts (Verger et al. 2023).

To address inconsistencies in temporal coverage and spatial resolution, all datasets were harmonized to a unified study period from 2001 to 2018. In accordance with established phenology research on the Tibetan Plateau (Shen et al. 2022), the analysis focuses on the growing season (May to October). A common mask was applied to all seven LAI products; grid cells with missing or invalid LAI retrievals in at least one product were treated as masked, and only grid cells with valid retrievals across all products were retained for subsequent analyses. We calculated the growing-season mean LAI for each product to represent the annual vegetation status. For pixel-wise intercomparison, all products were resampled to a common 0.1° grid using the nearest-neighbor method. This approach was selected to preserve the original radiometric values of the LAI retrievals and to prevent artificial spatial variability from being introduced through interpolation.

2.3 Elevation and vegetation type data

Digital elevation model (DEM) and vegetation type data for the Tibetan Plateau were obtained from the Resource and Environment Science Data Center (RESDC). The elevation data originate from the Shuttle Radar Topography Mission (SRTM) V4.1, originally acquired during the U.S. Space Shuttle Endeavour mission. To effectively characterize regional topographic variations, these data were resampled to a spatial resolution of 500 m. The vegetation distribution dataset was sourced from the '1:1,000,000 Vegetation Atlas of China', which categorizes the plateau into 11 major vegetation groups (Figure 1) and describes the spatial distribution of different ecosystems.

2.4 Statistical analysis methods

2.4.1 Trend analysis

Long-term trends in vegetation LAI were estimated using the Theil-Sen slope estimator, a non-parametric approach that is robust against outliers and missing data (Sen 1968). The trend slope is calculated as:

$$S_{LAI} = \text{median} \left(\frac{LAI_j - LAI_i}{j - i} \right), \quad \forall j > i \quad (1)$$

where S_{LAI} represents the slope of the multi-year LAI trend during the growing season; LAI_i and LAI_j denote the LAI values for years i and j , respectively. A positive S_{LAI} indicates an increasing trend, while a negative value signifies a decreasing trend.

The statistical significance of these trends was evaluated using the Mann-Kendall (MK) test (Kendall 1948). Pixels with p value less than 0.05 were identified as having experienced statistically significant changes. Significant increasing trends are defined as 'greening', and significant decreasing trends are termed 'browning' (Piao et al. 2020).

2.4.2 Correlation analysis

To assess the spatial consistency of multi-year averages and trend variations among seven LAI products, Pearson correlation coefficients were calculated for each pair of products A_i and A_j (where $i, j \in \{1, 2, \dots, 7\}$) based on the pixel values within vegetation-covered areas. The correlation coefficient is determined using the following formula (Pearson 1896):

$$r_{i,j} = \frac{\sum_{k=1}^n (X_{ik} - \bar{X}_i)(X_{jk} - \bar{X}_j)}{\sqrt{\sum_{k=1}^n (X_{ik} - \bar{X}_i)^2 \sum_{k=1}^n (X_{jk} - \bar{X}_j)^2}} \quad (2)$$

where $r_{i,j}$ represents the correlation coefficient; X_{ik} and X_{jk} denote the values of the k -th pixel for products A_i and A_j , respectively. Here, $\bar{X}_i$ and $\bar{X}_j$ are the respective mean values of all n pixels involved in the analysis. The correlation coefficient $r_{i,j}$ ranges from -1 to 1 , where values closer to 1 indicate a stronger positive correlation. Statistical significance was determined using a two-tailed t -test, with levels classified as significant ($p < 0.05$), highly significant ($p < 0.01$), or extremely significant ($p < 0.001$).

2.4.3 Vegetation trend centroid calculation

To characterize the spatial shifts and distribution of greening and browning regions, we adopted the centroid calculation method proposed by Shaw and Wheeler (1985). The coordinates of the trend centroid for increasing areas (X_G, Y_G) are expressed as:

$$X_G = \frac{\sum_{i=1}^n S_{LAI_{G,i}} \times X_{G,i}}{\sum_{i=1}^n S_{LAI_{G,i}}} \quad (3)$$

$$Y_G = \frac{\sum_{i=1}^n S_{LAI_{G,i}} \times Y_{G,i}}{\sum_{i=1}^n S_{LAI_{G,i}}} \quad (4)$$

Similarly, the centroid for decreasing areas (X_B , Y_B) is calculated as:

$$X_B = \frac{\sum_{i=1}^n S_{LAI_{B,i}} \times X_{B,i}}{\sum_{i=1}^n S_{LAI_{B,i}}} \quad (5)$$

$$Y_B = \frac{\sum_{i=1}^n S_{LAI_{B,i}} \times Y_{B,i}}{\sum_{i=1}^n S_{LAI_{B,i}}} \quad (6)$$

where $S_{LAI_{G,i}}$ and $S_{LAI_{B,i}}$ denote the trend slopes of the i -th pixel associated with the increasing or decreasing areas, while $(X_{G,i}, Y_{G,i})$ and $(X_{B,i}, Y_{B,i})$ correspond to the geographic coordinates of the respective pixels. Here, n represents the number of pixels in the respective area.

2.4.4 Consistency analysis

To evaluate the inter-product consensus regarding trend direction, we followed the methodological frameworks of Lv et al. (2023) and Luo, Ma, and Zhang (2025a). First, we identified pixels where products exhibited the same-direction trends (either increase or decrease). Based on the number of products in agreement, directional consistency was classified into four hierarchical levels: (1) Unanimous: 7 products (100% agreement), (2) High consistency: 6 products (~85% agreement), (3) Moderate consistency: 5 products (~70% agreement), and (4) Low consistency: 4 products (~55% agreement). Pixels with fewer than four products showing the same trend direction were classified as ‘Uncertain’. To further refine this, within each consistency level, we distinguished the statistically significant pixels ($p < 0.05$) to identify areas of ‘Consensus Greening’ or ‘Consensus Browning’. This hierarchical approach separates simple directional agreement from robust, statistically significant multi-product consensus.

3 Results

3.1 Spatial distribution and inter-product comparison of multi-year mean LAI

The spatial patterns of the multi-year mean growing-season LAI demonstrated a high degree of consistency across the seven products from 2001 to 2018 (Figure 2). Overall, all LAI products consistently exhibited a pronounced longitudinal and latitudinal gradient, characterized by a gradual decrease from the humid southeast to the arid northwestern Tibetan Plateau. This spatial pattern was jointly modulated by vegetation type and climate. In the southeastern Tibetan Plateau, extensive forest cover together with favorable hydrothermal conditions promoted vigorous primary productivity (Figure 1). Notably, in the southeastern Tibetan Plateau, LAI values from GLOBMAP and GLASS-AVHRR were greater than those from other datasets (Figure 2c and 2d), while in the central-eastern Tibetan Plateau, LAI values from GIMMS, GLASS-MODIS, and GEOV2 were also higher (Figure 2b, 2e, and 2g). In contrast, the spatial extent of high-value clusters in the MODIS and HIQ products was relatively restricted (Figure 2a and 2f).

On a plateau-wide scale, the growing-season average LAI ranged from 0.73 ± 0.11 to $1.06 \pm 0.09 \text{ m}^2 \text{ m}^{-2}$. Specifically, MODIS and HIQ reported the lowest average values (0.73 ± 0.11 and $0.75 \pm 0.08 \text{ m}^2 \text{ m}^{-2}$, respectively), while GIMMS and GLOBMAP yielded the highest estimates (1.00 ± 0.09 and $1.06 \pm 0.09 \text{ m}^2 \text{ m}^{-2}$, respectively). Regarding temporal stability, GLASS-AVHRR showed the highest interannual fluctuation (mean pixel-wise CV = 38.01%), followed by GEOV2 (17.69%), whereas HIQ demonstrated the most stable temporal pattern across the study period (mean pixel-wise CV = 10.82%). Furthermore, inter-product differences, indicated by the standard deviation, increased from northwest to southeast (Figure 2h). The high standard deviation regions aligned with areas of high multi-year mean LAI, predominantly in the eastern and southern Tibetan Plateau.

The pairwise correlation of multi-year mean LAI among different datasets further confirmed this spatial consistency, with correlation coefficients (r) exceeding 0.75 across all product pairs (Figure 3). This high level of agreement underscored a robust consensus in characterizing regional vegetation cover. In particular, GIMMS, HIQ, and GEOV2 consistently achieved correlations above 0.80 with other products, suggesting high stability in capturing the complex spatial heterogeneity of the Tibetan Plateau. In contrast, the correlations of MODIS with GLOBMAP, GLASS-AVHRR, and GLASS-MODIS were relatively lower, though they remained statistically significant ($r < 0.80$, $p < 0.001$).

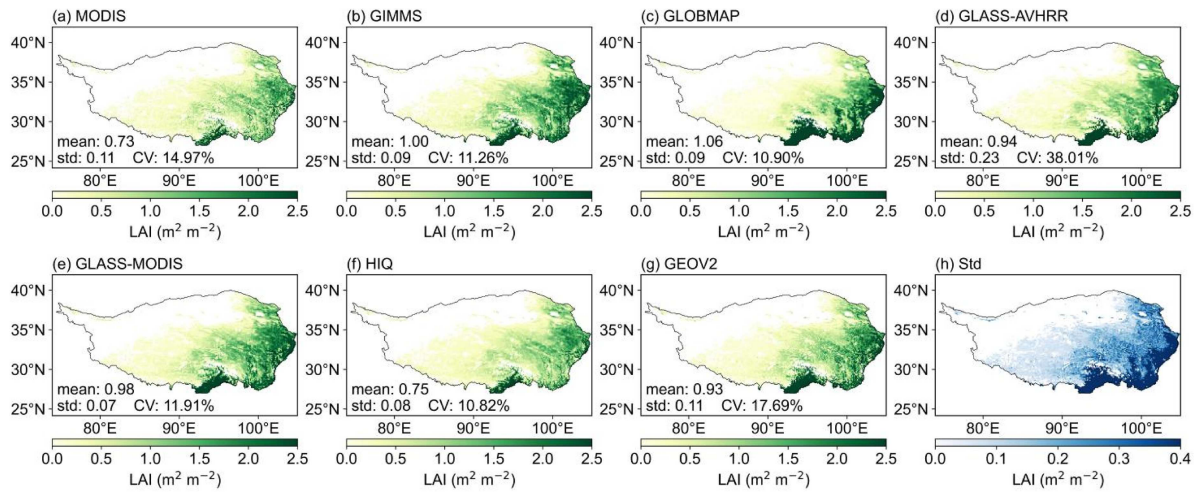


Figure 2. Spatial distribution of multi-year mean LAI. (a)–(g) Spatial pattern of the annual growing-season mean LAI across the Tibetan Plateau derived from seven different products during 2001–2018. White areas indicate masked areas. LAI and its standard deviation (std) are expressed in $\text{m}^2 \text{m}^{-2}$. The coefficient of variation ($\text{CV} = \text{std}/\text{mean}$) reflects the magnitude of LAI variability within each product. (h) Spatial distribution of the standard deviation of the annual growing-season mean LAI across seven products.

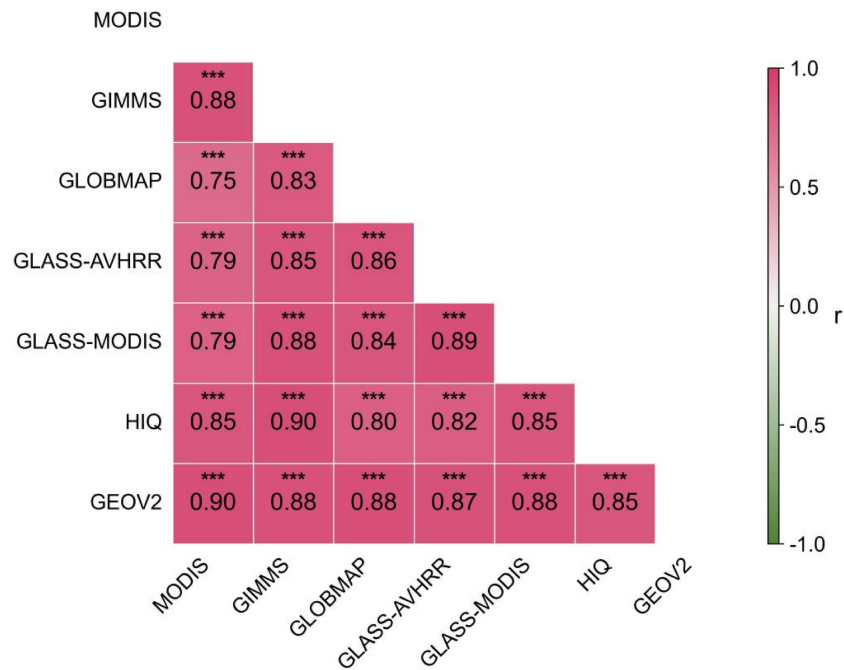


Figure 3. Pairwise pattern correlation matrix of the annual growing-season mean LAI among seven satellite products. Values represent Pearson correlation coefficients (r) calculated for each product pair. Asterisks denote the level of statistical significance: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

3.2 Spatiotemporal patterns of vegetation trends across multiple LAI products

3.2.1 Plateau-scale trends in growing-season LAI

The integrated analysis of multiple LAI products revealed substantial interannual variability between 2001 and 2018 (Figure 4). A strong coherence in interannual fluctuations was observed among MODIS, HIQ, GIMMS, and GLASS-MODIS, suggesting that these products converge in capturing the short-term response of plateau vegetation to climate anomalies. However, the long-term trends exhibited significant

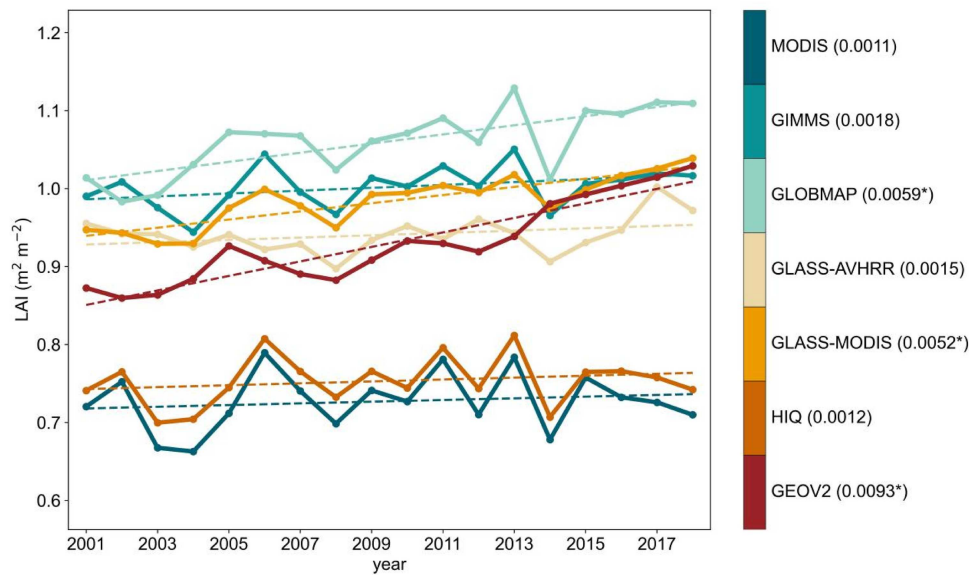


Figure 4. Long-term trends in the growing-season mean LAI over the Tibetan Plateau (2001–2018) derived from seven satellite products. Solid lines represent annual variations, and dashed lines indicate linear regression trends. Slope values (units: $\text{m}^2 \text{m}^{-2} \text{yr}^{-1}$) are provided in brackets, with asterisks denoting statistical significance (* $p < 0.05$).

inter-product divergence. Only GLOBMAP, GLASS-MODIS, and GEOV2 demonstrated statistically significant greening trends ($p < 0.05$) with rates of 0.0059, 0.0052, and 0.0093 $\text{m}^2 \text{m}^{-2} \text{yr}^{-1}$, respectively. By contrast, the remaining four products (GIMMS, GLASS-AVHRR, HIQ, and MODIS) showed no significant trends ($p > 0.05$), with slopes of 0.0018, 0.0015, 0.0012, and 0.0011 $\text{m}^2 \text{m}^{-2} \text{yr}^{-1}$, respectively. Such discrepancies underscored that different LAI retrieval algorithms and sensor characteristics lead to heterogeneous responses in vegetation dynamics on the Tibetan Plateau. These findings cautioned against drawing definitive conclusions regarding an overall greening trend based on any single product, highlighting the imperative of multi-source ensemble assessments to reduce uncertainty in regional ecological monitoring.

3.2.2 Spatial distribution and inter-product consistency

Spatially, although all LAI products captured vegetation greening in specific regions (i.e. the northeastern Tibetan Plateau), their overall patterns exhibited pronounced heterogeneities. GEOV2 displayed a widespread greening signal across most of the Tibetan Plateau, with the exception of certain areas in the central and southern Tibetan Plateau (Figure 5g). GLOBMAP and GLASS-MODIS showed extensive greening primarily in the eastern Tibetan Plateau (Figure 5c and 5e). In contrast, the remaining four products (MODIS, GLASS-AVHRR, GIMMS, and HIQ) identified only localized increasing trends concentrated in the northeastern and central Tibetan Plateau.

Regarding decreasing trends (browning), GLASS-AVHRR showed the most extensive decline among all products, particularly in the central-western and southeastern Tibetan Plateau (Figure 5d). MODIS, GIMMS, and HIQ exhibited partial decreasing trends in the central Tibetan Plateau, with a consistent browning pattern in the southern forested areas (Figure 5a, 5b, and 5f). The remaining products (GEOV2, GLOBMAP, and GLASS-MODIS) displayed only sparse and fragmented decreasing trends in the central Tibetan Plateau.

Inter-product spatial variations in trend intensity were consistent with the spatial distribution of the multi-year mean LAI standard deviation, revealing a stronger discrepancy in the eastern and southern Tibetan Plateau (Figure 5h and Figure 2h). However, the probability density functions (PDFs) of trend intensity were unimodal across all products (Figure 5i). HIQ, GLOBMAP, and MODIS were characterized by exceptionally narrow peaks with high amplitudes; in contrast, GLASS-AVHRR and GEOV2 displayed broader and lower peaks, reflecting more dispersed distributions. Positive median trends were observed for all products, except GLASS-AVHRR, which exhibited a slight decreasing trend ($-0.0002 \text{ m}^2 \text{m}^{-2} \text{yr}^{-1}$). In

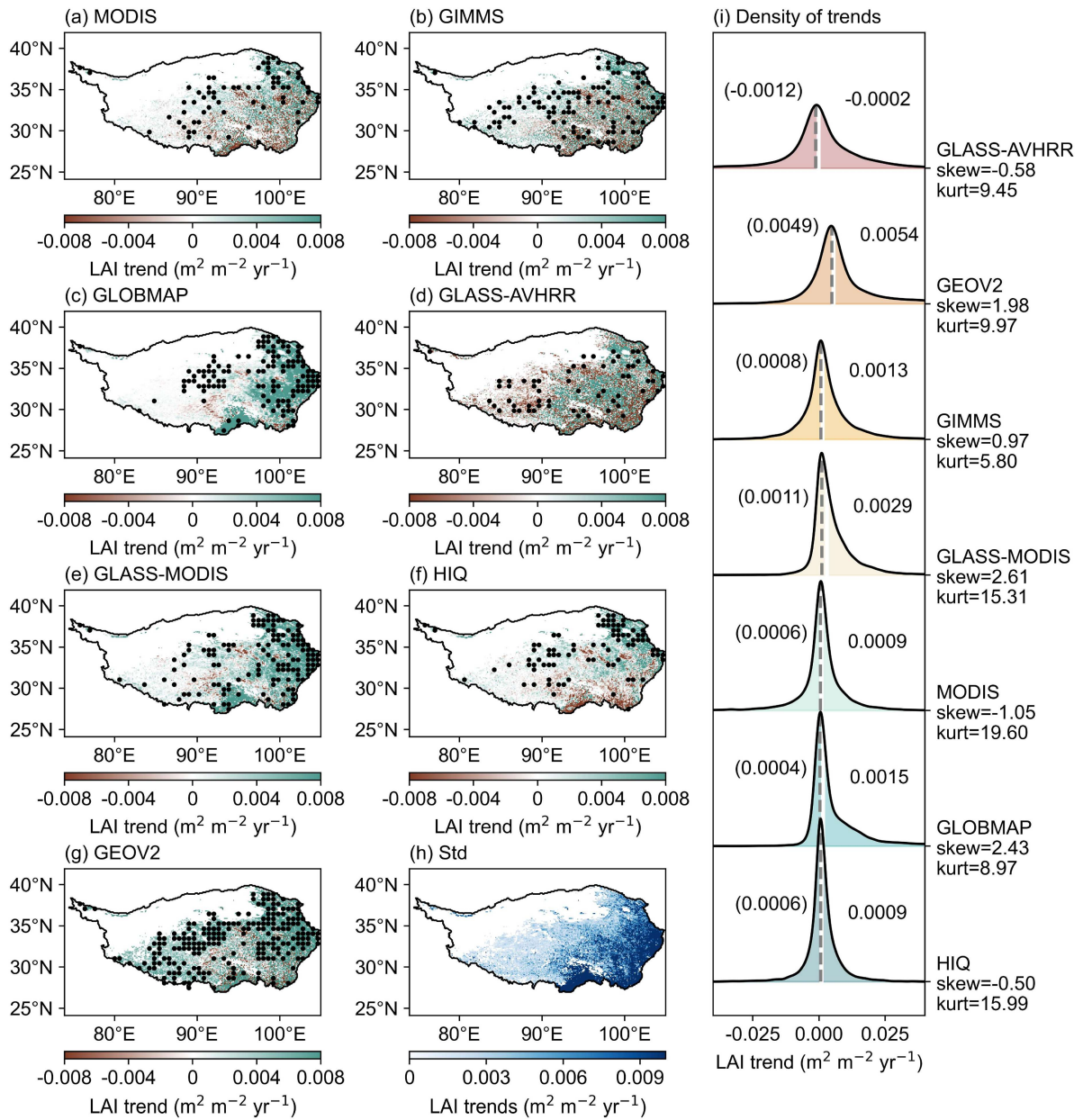


Figure 5. Spatial patterns of LAI trend. (a)–(g) Spatial patterns of growing-season LAI trends across the Tibetan Plateau derived from seven different products. White areas indicate masked areas. Black dots denote pixels exhibiting statistically significant trends ($p < 0.05$). (h) Spatial distribution of pixel-level trend standard deviation across the seven products. (i) Probability density distributions of trend intensity. Product baselines are equally spaced. For each product, the mode is indicated by a grey dashed line (with its value labelled in parentheses to the left of the curve), and the median by a solid white line (with its value labelled to the right of the curve); skewness and kurtosis values are also provided.

addition, GEOV2 demonstrated the highest median increasing trend among these products ($0.0054 \text{ m}^2 \text{m}^{-2} \text{yr}^{-1}$). Skewness analysis revealed a clear divergence in the distribution symmetry among products. MODIS, GLASS-AVHRR, and HIQ exhibited negative (left) skewness, with MODIS showing the most pronounced asymmetry (skewness = -1.05). Conversely, the remaining products displayed positive (right) skewness—most notably GLASS-MODIS (skewness = 2.43)—indicating a higher frequency of strong greening pixels. Marked contrasts were also evident in kurtosis; MODIS, HIQ, and GLASS-MODIS presented substantially elevated values (19.60 , 15.99 , and 15.31 , respectively), reflecting highly leptokurtic distributions with sharper peaks. Notably, the extreme tails of the distributions differed markedly: extreme negative values dominated the distributions in MODIS and HIQ, whereas extreme positive values were more prevalent in GLASS-MODIS.

To quantify the spatial agreement of these dynamics, we evaluated the pairwise spatial correlations of LAI trends across all products (Figure 6). The results showed that spatial correlations for trends were considerably weaker than those observed for the multi-year mean state (Figure 3), indicating that while the datasets effectively converge on the long-term climatological mean, they diverge substantially in capturing long-term vegetation dynamics. Among all pairs, only GLASS-MODIS and GLOBMAP achieved a correlation coefficient exceeding 0.5, reflecting their high spatial congruence in the eastern Tibetan Plateau (Figure 5c and 5e). Moderate agreement ($0.4 < r < 0.5$) was found between MODIS and HIQ, GEOV2 and GLOBMAP, and GEOV2 and GLASS-MODIS. Notably, GLASS-AVHRR displayed correlation coefficients below 0.1 with all the other six products, highlighting a fundamental discrepancy between this dataset and the rest of the ensemble in capturing long-term LAI trajectories.

3.2.3 Trend magnitude and spatial extent

To further characterize the divergence among the seven LAI products, we quantified the variations in trend rates and associated proportions of pixels (Figure 7 and Supplementary Figure 1). Overall, the magnitudes of increasing and decreasing trend rates were generally comparable across products; however, the spatial extents (pixel proportions) of these trends exhibited pronounced disparities. The mean increasing trend rates ranged from 0.0043 to 0.0121 $\text{m}^2 \text{m}^{-2} \text{yr}^{-1}$, while decreasing rates varied between -0.0096 and $-0.0022 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$ (Figure 7a). Notably, the proportion of pixels with increasing trends (50.92%–87.64%) significantly outweighed the proportion with decreasing trends (13.95%–53.31%) (Figure 7b). This marked asymmetry confirmed that while localized browning occurred, greening remained the predominant and more widespread trajectory across the Tibetan Plateau.

Among the products, GEOV2 recorded the highest increasing trend rate ($0.0121 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$), followed by GLASS-AVHRR ($0.0096 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$), whereas HIQ yielded the most conservative estimate ($0.0043 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$) (Figure 7a). For decreasing trends, GLASS-AVHRR exhibited the most intense browning rate ($-0.0096 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$), followed by GEOV2 ($-0.0072 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$), while GLOBMAP displayed the weakest rate ($-0.0022 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$). The range between increasing and decreasing rates was largest for GLASS-AVHRR ($0.0209 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$) and smallest for HIQ ($0.0089 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$). Analysis of statistically significant pixels further strengthened these signals, with GLASS-AVHRR reaching the highest greening and browning rates (0.0255 and $-0.0205 \text{m}^2 \text{m}^{-2} \text{yr}^{-1}$, respectively), as shown in Supplementary Figure 1.

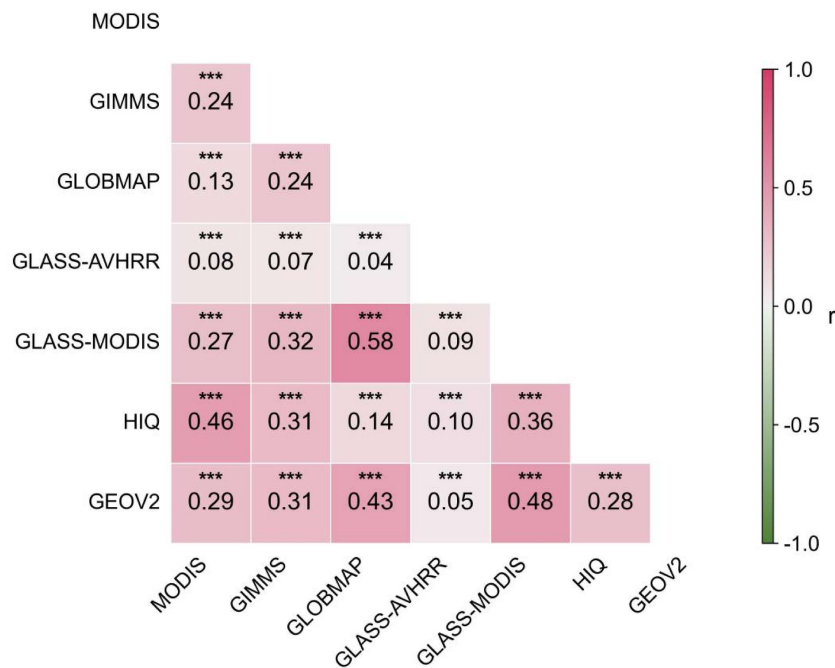


Figure 6. Pairwise spatial correlation matrix of growing-season LAI trends among the seven satellite products. Values represent the Pearson correlation coefficients (r) calculated between each pair of products based on their trend patterns. Asterisks indicate the level of statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

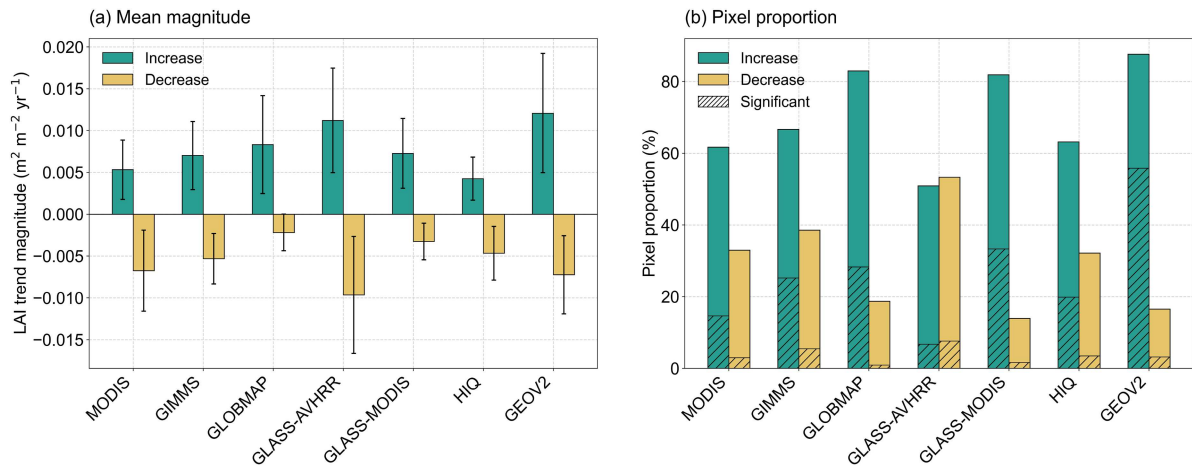


Figure 7. Statistical analysis of mean trend magnitude and proportion of pixels. (a) Inter-product comparison of the mean magnitudes of increasing and decreasing LAI trends across all valid pixels for each product. Error bars represent 0.5 times the standard deviation of the pixel-level trend values. (b) Proportions of pixels exhibiting increasing and decreasing trends across the seven satellite products, with hatched bars denoting the proportions of all valid pixels that show significant greening or browning trends.

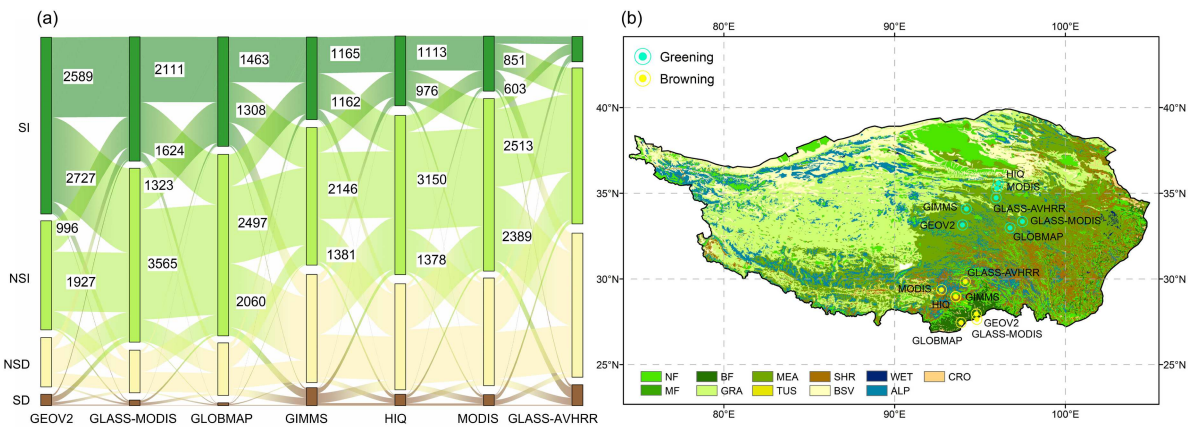


Figure 8. Inter-product transitions of trend categories and spatial shifts in trend centroids. (a) Sankey diagram illustrating the pixel-level transitions of vegetation trends across the seven LAI products. Flow widths are proportional to the number of pixels, representing category shifts at the same spatial locations between adjacent products. SI: significant increase; NSI: non-significant increase; NSD: non-significant decrease; SD: significant decrease. (b) Spatial distribution of vegetation trend centroids derived from the seven LAI products. Blue and yellow symbols denote the geographical centroids of greening and browning trends, respectively.

Regarding spatial coverage, GEOV2 not only showed the highest trend magnitude but also the largest pixel proportion of increasing trends (87.64%) (Figure 7b). In sharp contrast, GLASS-AVHRR was the only product where the proportion of decrease (53.31%) exceeded the proportion of increase (50.92%), resulting in a negative net areal difference of -2.38% . GLASS-MODIS recorded the smallest spatial footprint of decreasing trends. This inter-product disparity was most evident in the net proportion (increase minus decrease), which peaked at 71.11% for GEOV2. These patterns remained robust when restricted to statistically significant trends, with the exception of GLOBMAP, which exhibited the smallest significant browning proportion (0.92%).

3.2.4 Category flow and centroid patterns

The transfer pathways among trend categories between adjacent products revealed substantial discrepancies in LAI trends at the pixel level (Figure 8a). For each transition, pixel counts and their relative

proportions were quantified to assess inter-product stability. For significantly increasing (SI) pixels, the consistency rate (remaining in the SI category) ranged from 41.33% to 52.51% across most adjacent product pairs. While this represented the most common single outcome, it indicated that over half of the significant greening signals were inconsistent between datasets. Specifically, from GEOV2 to GLASS-MODIS, the proportion of SI pixels that downgraded to non-significant increase (47.75%) slightly exceeded that of pixels maintaining their SI status (45.33%). A more striking divergence occurred from MODIS to GLASS-AVHRR, where the SI population shrank markedly as pixels shifted into non-significant categories. For significantly decreasing (SD) pixels, inter-product consistency was the lowest, with the vast majority of SD pixels redistributing into non-significant increasing (NSI) or non-significant decreasing (NSD) categories rather than exhibiting a sustained browning signal.

To further elucidate spatial discrepancies, we examined the spatial distribution of product-specific trend centroids. While all products generally agreed that increasing centroids were situated within the central alpine meadows and decreasing centroids were concentrated in the southern forested regions, notable inter-product shifts were evident (Supplementary Figure 2). Specifically, the centroids of both increasing and decreasing trends for GEOV2, GLASS-MODIS, and GLOBMAP were shifted southward compared to the other products.

These spatial differences were markedly amplified when the analysis was restricted to pixels exhibiting statistically significant trends (Figure 8b). Regarding greening centroids, HIQ, MODIS, and GLASS-AVHRR migrated further north, in closer proximity to typical steppe areas, whereas GIMMS and GEOV2 were positioned slightly more centrally, towards higher-altitude regions. In contrast, GLASS-MODIS and GLOBMAP showed a marked eastward shift towards lower-elevation areas. For the browning centroids, this southward migration was intensified, positioning these centroids in close proximity to the low-altitude broadleaf forest zones. Furthermore, the browning centroids of HIQ and GIMMS exhibited remarkable spatial proximity, indicating a robust consistency between these two datasets in capturing the core areas of vegetation decline. This alignment further corroborated the coherent browning patterns observed in their respective spatial distributions (Figure 5b and 5f).

3.2.5 LAI trend magnitude across environmental and ecological gradients

To further investigate inter-product differences, we examined the distribution of LAI trend magnitudes across elevational and vegetation-type gradients (Figure 9). Along the elevational gradient, trend magnitudes across all products exhibited a unimodal pattern, characterized by an initial increase followed by a subsequent decline, with a distinct turning point identified at approximately 2200 m (Figure 9a). Below this threshold, MODIS showed the steepest elevational increase in trend magnitude (OLS slope = $21 \times 10^{-6} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1} \text{ m}^{-1}$), whereas GIMMS and

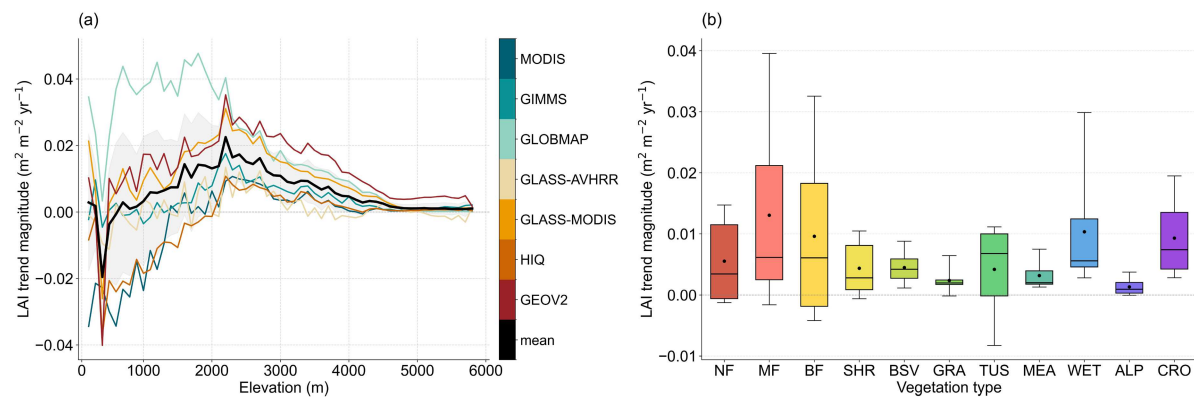


Figure 9. Variations in LAI trend magnitude across elevational and ecological gradients. (a) Elevational gradient: Colored lines represent individual LAI products, the thick black line is the multi-product ensemble mean, and the gray shading shows the inter-product uncertainty (± 1 standard deviation). (b) Vegetation types: Box plots summarize the distribution of mean trend rates ($\text{m}^2 \text{ m}^{-2} \text{ yr}^{-1}$) across products for each type. The boxes indicate the interquartile range (IQR) with the median (black line) and the mean (black circle). Whiskers extend to the minimum and maximum values within the datasets.

GLASS-AVHRR displayed the most gradual rates of increase (OLS slopes = $6.0 \times 10^{-6} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1} \text{ m}^{-1}$ each). Above 2200 m, GLOBMAP displayed the most rapid decline (OLS slope = $-9.0 \times 10^{-6} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1} \text{ m}^{-1}$), while HIQ showed the most stable trend with the slowest decrease (OLS slope = $-2.0 \times 10^{-6} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1} \text{ m}^{-1}$). A comparable pattern was observed for inter-product uncertainties, with the most pronounced discrepancies concentrated below 2200 m. Notably, in these low-elevation regions, GLOBMAP exhibited a substantially stronger greening signal than other products, whereas MODIS and HIQ were characterized by a predominance of decreasing trends.

Regarding vegetation types, the greatest inter-product discrepancies occurred in broadleaf forest (BF), followed by mixed forest (MF) and needleleaf forest (NF), with interquartile ranges (IQRs) of 0.020, 0.018, and $0.012 \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$, respectively (Figure 9b). Furthermore, the mean trend magnitudes for these categories exceeded their respective medians, indicating that a subset of products estimated notably strong greening trends for these complex canopy structures. In contrast, grassland (GRA) and alpine vegetation (ALP) showed much narrower box plots with IQRs of only 0.001 and $0.002 \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$, respectively, reflecting a high degree of inter-product convergence.

3.2.6 Spatial consensus of trend directions

To further assess the robustness of vegetation trends among the seven LAI products, we analyzed their spatial consistency (Figure 10). Overall, most products indicated coherent greening signals across the Tibetan Plateau, with the most pronounced spatial consensus identified in the northeastern and central Tibetan Plateau. Specifically, the northeastern Tibetan Plateau exhibited High consistency (85% agreement) in greening trends, while the central Tibetan Plateau was characterized by Low consistency (55% agreement) (Figure 10a).

Among the areas with increasing trends (accounting for approximately three-quarters of the vegetated plateau), the proportion of significant greening pixels that were directionally consistent reached 15.19% (Figure 10b). Within this consistently identified greening area, the highest fraction of significant pixels (6.93%) corresponded to the Low consistency level (55% agreement), followed by the Moderate (70% agreement) and High (85% agreement) consistency levels, which accounted for 4.60% and 3.00% of the significant pixels, respectively. Notably, pixels unanimously identified (100% agreement) as greening by all seven products accounted for only 0.66% of the significant pixels, highlighting substantial inter-product divergence even in greening regions.

In contrast, areas with decreasing trends were sporadically distributed across the central and southern Tibetan Plateau (Figure 10a), covering approximately 16.49% of vegetated pixels. Among these, pixels consistently identified as browning by a majority of products accounted for only 0.18%. Furthermore, no pixels were unanimously identified (100% agreement) as exhibiting a significant browning trend by all seven products (Figure 10b), underscoring the limited cross-product consistency in detecting vegetation decline. Additionally, trend directions remained inconsistent across 7.21% of the plateau's vegetated pixels.

A pronounced gradient in inter-product consistency emerged within the temperature–precipitation (T-P) space (Figure 10c). Unanimous agreement on significant greening was primarily concentrated within a warm-dry core (approximately $10\text{--}15^\circ\text{C}$ and $50\text{--}150 \text{ mm}$), around which zones of progressively lower consistency were organized. As climatic conditions shifted toward colder or wetter regimes, the cross-product consensus on greening signals weakened systematically. These results suggested that inter-product uncertainties were closely coupled with regional hydro-thermal conditions; specifically, the divergent methods used to correct environmental constraints (e.g. snow cover in cold regions or cloud contamination in wet regions) likely acted as primary drivers of the observed discrepancies.

4 Discussion

4.1 Inter-product consensus and discrepancies in LAI trends

We systematically evaluated the consensus in long-term vegetation trends over the Tibetan Plateau from 2001 to 2018 using seven satellite-derived LAI products. We demonstrated that, in the multi-year mean state, all LAI products exhibited highly consistent spatial patterns, which were also reported by Li, Wang, and Chen (2024). This finding indicates that the multi-product mean LAI over the plateau is robust and reliably characterizes the long-term average vegetation conditions.

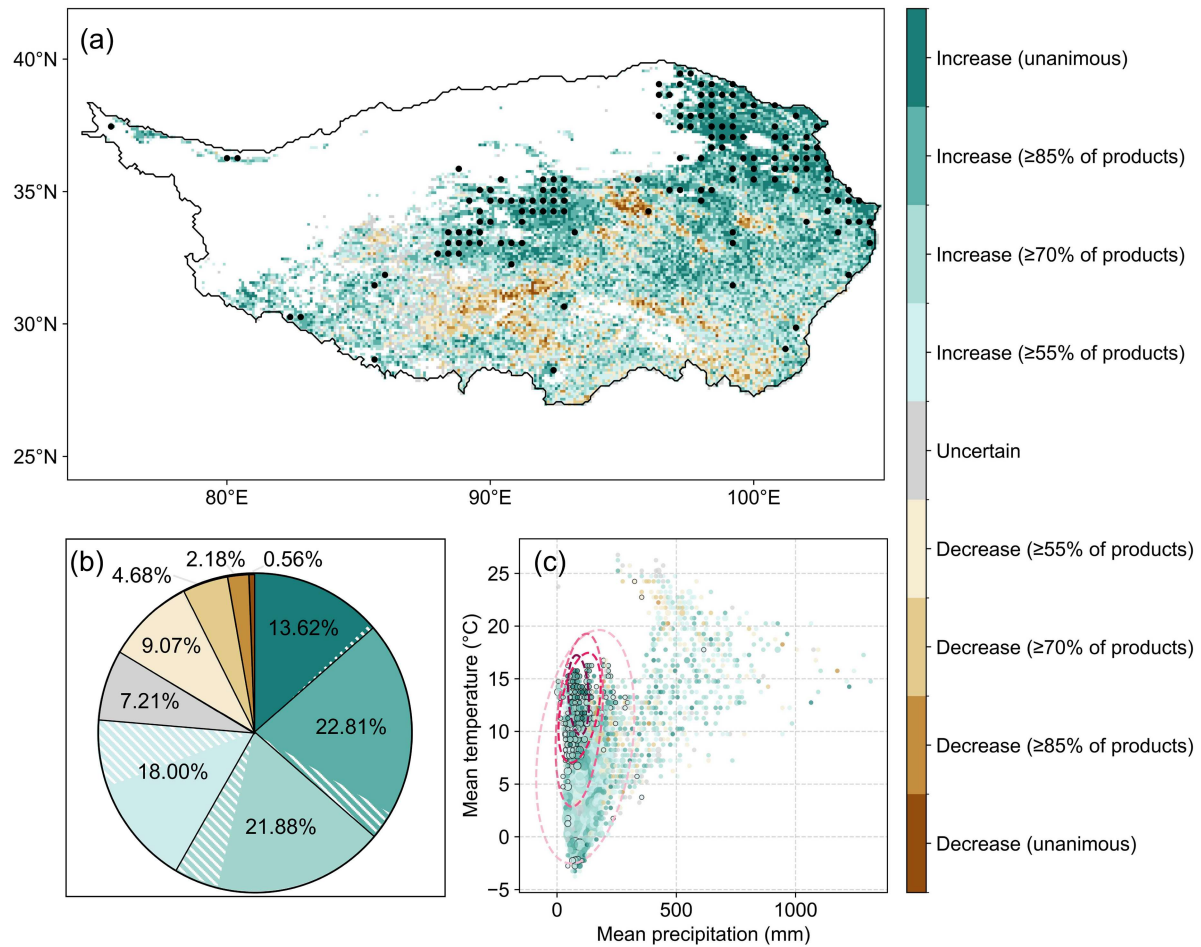


Figure 10. Spatial distribution and statistical characteristics of inter-product consistency among the seven satellite-derived LAI products. (a) Spatial patterns of consistency in LAI trends across the Tibetan Plateau, with colors indicating the proportion of products agreeing on increasing or decreasing trends. Black dots denote pixels where significant greening or browning trends are consistently identified by multiple products. (b) Pixel proportions of different inter-product agreement levels. Hatched segments in the pie charts indicate the percentage of pixels where products exhibit a synchronized direction in vegetation dynamics (greening or browning). (c) Distribution of dominant consistency levels in the temperature-precipitation (T-P) space. Each grid cell ($10 \text{ mm} \times 0.5^{\circ}\text{C}$) is represented by a point, colored by the dominant consistency level and scaled by pixel density. Cells with a significant dominant level are outlined with black borders. The red confidence ellipses delineate the climatic envelopes of varying greening consistency levels, with the innermost ellipse highlighting the region of unanimous agreement.

In contrast, substantial discrepancies emerged among products in capturing long-term changes. Our results suggest that only three products—GLOBMAP, GLASS-MODIS, and GEOV2—exhibited statistically significant greening trends (Figure 4). However, previous studies (An et al. 2024; Lv et al. 2023) identified significant increasing trends in LAI from 2000 to 2020 using MODIS alone or in combination with GLASS (V60) and GEOV2. Our findings highlight the controversy surrounding the previously reported pervasive significant long-term greening over the Tibetan Plateau. In detail, our results showed that only 15.19% of vegetated pixels were consistently identified as showing significant greening across multiple LAI products—a proportion notably smaller than those reported in studies based on individual NDVI or LAI products (Ehlers et al. 2022; Wang et al. 2022). This discrepancy suggests that, under the complex terrain and high-albedo conditions of the Tibetan Plateau, trend analyses based on a single product risk amplifying or diminishing the actual magnitude of vegetation changes. Therefore, cross-validation using multiple products is both necessary and irreplaceable for a robust understanding of vegetation dynamics in this region.

4.2 Spatial consensus and systematic biases

Furthermore, we found that most (85%) LAI products consistently identified significant greening in the northeastern Tibetan Plateau, and approximately half of the products indicated greening in the central Tibetan Plateau. This spatial pattern is consistent with previous studies using different vegetation indices. Specifically, Shen et al. (2015) compared three NDVI products (AVHRR, MODIS, SPOT-VEGETATION) and observed stable greening trends in the northeastern Tibetan Plateau. Li, Wang, and Chen (2024) and Zhang et al. (2025) further confirmed this spatial pattern of significant greening using MCD15A2H Collection 6 and MOD13Q1, reporting that significant greening areas accounting for 31% and 41.16% of the plateau, respectively—substantially higher than the 15.19% identified in this study. These differences highlight that systematic biases arising from specific indices, observational bases, retrieval algorithms, and quality control procedures can substantially influence regional trend assessments. In contrast, the multi-product consensus analysis in this study provides a more robust estimate of the extent of significant greening.

Unlike the coherent greening signals in the northeastern and central Tibetan Plateau, approximately 77% of the plateau exhibited non-significant trends, and an additional 7.21% of pixels were characterized by uncertain trend directions. Consequently, a substantial portion of the plateau lacked consensus on whether vegetation was increasing or decreasing, reflecting pervasive uncertainties in satellite observations. Taking in the southwestern Tibetan Plateau as an example, Zhong et al. (2019) reported greening trends, whereas Shen et al. (2015) and Li, Wang, and Chen (2024) suggested browning signals, and Lv et al. (2023) identified degradation in approximately 1.5% of southwestern and central-eastern pixels. Our results further indicated that pixels consistently identified as browning by the majority of products accounted for only 0.18% of the pixels, underscoring the lack of consensus on vegetation decline in this region. These findings suggest that trend assessments in such areas are highly sensitive to data source selection, highlighting these regions as priorities for future high-quality observations.

4.3 Potential causes of inconsistency

The discrepancies among satellite-derived LAI products originate from a synergy of factors, including disparities in sensor characteristics (Qiu et al. 2022), retrieval algorithm physics (Fang et al. 2012), and the extreme environmental conditions unique to the Tibetan Plateau. Among the seven LAI products, MODIS (physical LUT-based), GIMMS (trained on MODIS) (Cao et al. 2023), and HIQ (incorporating spatio-temporal post-processing) (Yan et al. 2024) yielded similar long-term trends (Figure 4). This coherence was primarily driven by their shared reliance on MODIS spectral signatures or statistical alignment with MODIS-based benchmarks. In contrast, GLOMAP (employing the GLOBCARBON semi-physical model) and GLASS-MODIS (utilizing a Bi-LSTM deep learning architecture) adopt distinct retrieval frameworks (Liu, Liu, and Chen 2012; Ma and Liang 2022), leading to the observed systematic deviations from the MODIS-centric group. Furthermore, GLASS-AVHRR inherits calibration biases inherent in cross-sensor bridging (AVHRR to MODIS) (Xiao et al. 2016). GEOV2 differs because it relies on SPOT/PROBA-V data, whose sensors have spectral and angular sensitivities fundamentally different from those of MODIS (Verger et al. 2023). These structural differences largely explain why these two products exhibited the most pronounced discrepancies in trend magnitude and direction.

Beyond algorithmic differences, the complex topography of the Tibetan Plateau, characterized by steep slopes and heterogeneous aspects, intensifies the susceptibility of satellite imagery to illumination shadowing, geometric distortions (Bian et al. 2013) and anisotropic spectral artifacts (Li et al. 2015; Li et al. 2016). In addition, the strong elevational gradients across the Tibetan Plateau pose additional challenges to retrieval consistency. Our analysis reveals that inter-product divergence in LAI trends is strongly elevation-dependent: the largest discrepancies occur below 2200 m, whereas above 4000 m, inter-product spread is minimal and all seven products show near-zero greening trends (Figure 9a). This convergence at high elevations does not imply that the products are more reliable in this region; rather, it suggests that the underlying vegetation signal itself is extremely weak. Such weak vegetation signals at high altitudes are consistent the findings of Xu et al. (2020), who reported that warming-driven greening signals are absent above approximately 4300 m based on MODIS NDVI data.

In addition to this elevational pattern, we identified a distinct climatic control on product consistency: inter-product consistency in greening trends was highest in a warm-dry core region (10–15 °C, 50–150 mm) and declined toward colder or wetter regimes (Figure 10c). This pattern suggests that in environments where cloud contamination, frequent snowfall, and high-albedo backgrounds (e.g. snow/ice and bare ground) prevail, the retrieval uncertainties are amplified by divergent strategies for snow masking, cloud-clearing, and soil-background correction (Yan et al. 2016). Consequently, achieving a standardized treatment of these environmental constraints is paramount for enhancing the robustness of vegetation dynamics monitoring across the ‘Third Pole.’

4.4 Implications for modeling and policy

Unreliable LAI estimates directly affect the accuracy of dynamic global vegetation models (Liu et al. 2018). Our finding that over 80% of the Tibetan Plateau lacks consistent and significant greening or browning signals indicates that current satellite LAI products still cannot provide sufficiently coherent information over this region. This persistent inconsistency partly explains the large simulation biases observed in LSMs when applied to high-altitude ecosystems. Conversely, the stable, consistently greening areas identified here (e.g. the northeastern and central Tibetan Plateau) can serve as essential benchmark regions for future model validation, calibration zones for LAI product fusion algorithms, and priority areas for long-term ecosystem monitoring.

Moreover, our findings carry direct policy and management implications for ecological conservation and sustainable development on the Tibetan Plateau. On the one hand, ensuring the credibility of vegetation change indicators requires a solid understanding of multi-product consistency, thereby avoiding policy misjudgments arising from the arbitrary selection of a single data source. On the other hand, the non-significant and uncertain regions identified here provide a scientific basis for strategically deploying future ground-based observation networks. These areas warrant intensified in situ measurements of LAI, vegetation structure, surface albedo, and energy balance to support the validation and refinement of satellite products (Wu et al. 2023; Xu et al. 2021). Integrating multi-source observations—such as airborne LiDAR and high-resolution UAV imagery—holds great promise for substantially reducing the uncertainties in satellite-derived LAI and further improving the precision of vegetation monitoring over the ‘Third Pole’.

5 Conclusions

This study conducted a systematic assessment of growing-season LAI over the Tibetan Plateau from 2001 to 2018 using seven satellite-derived LAI products. Our results demonstrate that these datasets effectively converge on the climatological mean state of vegetation ($r > 0.75$), whereas they diverge substantially in the direction of their long-term trajectories ($r < 0.6$). The robust spatial consensus on the multi-year mean LAI, characterized by a sharp southeast-to-northwest gradient, suggests that existing retrieval frameworks are relatively mature in capturing the ‘static’ background of regional vegetation cover.

However, this agreement dissolves when examining multi-decadal trends. Only GLOBMAP, GLASS-MODIS, and GEOV2 identified statistically plateau-wide greening, while the remaining products exhibited negligible or non-significant changes. These discrepancies are further amplified at the pixel level, particularly in the eastern and southern forested regions (e.g. deciduous and needleleaf forests) where inter-product standard deviations and interquartile ranges reached their peaks. In contrast, more structurally simple vegetation types such as alpine meadows and steppes showed a higher degree of inter-product convergence, highlighting by contrast the inherent challenges of LAI retrieval over complex canopy structures.

The inherent uncertainty in trend detection is further underscored by the fact that over half of the identified greening signals were inconsistent across datasets, with unanimous agreement on significant greening restricted to a mere 0.66% of the vegetated area. We found that inter-product consistency is closely coupled with regional hydrothermal conditions: high consensus was maintained within a warm-dry climatic core (10–15 °C, 50–150 mm). This agreement weakened systematically as conditions shifted toward colder or wetter regimes. The pattern implies that divergent strategies for correcting environmental

constraints—specifically snow cover in high-altitude regions and cloud contamination in humid zones—likely serve as the primary physical drivers of the observed discrepancies.

In summary, despite the reliability of multi-source LAI products in characterizing spatial patterns, their utility in monitoring long-term dynamics on the Tibetan Plateau remains limited by significant uncertainties. Our findings emphasize that a multi-product consistency analysis is an essential prerequisite for identifying robust vegetation dynamics. Such insights are paramount for refining ecosystem models and informing evidence-based ecological management in this climatically sensitive ‘Third Pole’.

Author contributions

CRedit: **Yabin Ye**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing; **Zhi Huang**: Writing – review & editing; **Zishan Wang**: Writing – review & editing; **Hao Zheng**: Writing – review & editing; **Linying Ma**: Writing – review & editing; **Meirong Wang**: Writing – review & editing; **Limin Yang**: Writing – review & editing; **Qian Zhang**: Writing – review & editing; **Weimin Ju**: Writing – review & editing; **Tiexi Chen**: Writing – review & editing; **Jun Wang**: Conceptualization, Funding acquisition, Methodology, Project administration, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research has been supported by the National Natural Science Foundation of China (Grant No. 42475129); the Innovation and Development Program of China Meteorological Administration (Grant No. CXFZ2026J035); the Youth Innovation Team of China Meteorological Administration (Grant No. CMA2024QN04); the Xizang science and technology Plan project (XZ202602YD0006).

ORCID

Qian Zhang  <http://orcid.org/0000-0002-0860-4023>

Jun Wang  <http://orcid.org/0000-0001-7359-1647>

Data availability statement

The MOD15A2H LAI product was obtained from <https://www.earthdata.nasa.gov/data/>. The GIMMS LAI4g dataset is available from <https://zenodo.org/records/8281930> (Cao et al. 2023b). The GLOBMAP LAI V3 dataset is available from <https://zenodo.org/records/12698637>. The GLASS-AVHRR LAI and GLASS-MODIS LAI products were obtained from <https://glass.hku.hk/>. The HIQ LAI dataset is available from <https://doi.org/10.5281/zenodo.8296768>. The GEOV2 LAI product was obtained from https://land.copernicus.eu/en/products/vegetation/leaf-area-index-v2-0-1km#general_info. The cropped LAI dataset for the Tibetan Plateau used in this study is available at <https://doi.org/10.5281/zenodo.20091684> (Ye et al. 2026). The data that support the findings of this research are available from the corresponding author, [J. Wang], upon reasonable request. This standardized dataset was generated by extracting and reprojecting the original global LAI products to the study region at a unified spatial resolution of 0.1° and annual timescale (growing-season mean, May–October). It serves as the fundamental input for all trend calculations and inter-product comparisons presented in this study. Elevation and vegetation type data for the Tibetan Plateau were obtained from the Resource and Environment Science Data Center (<https://www.resdc.cn/>).

References

- Alkama, R., G. Forzieri, G. Duveiller, G. Grassi, S. Liang, and A. Cescatti. 2022. “Vegetation-Based Climate Mitigation in a Warmer and Greener World.” *Nature Communications* 13 (1): 606. <https://doi.org/10.1038/s41467-022-28305-9>.
- An, R., H. Jin, H. Zhao, D. Wei, W. Zhao, and X. Wang. 2024. “Productivity Experienced a More Rapid Enhancement Trend Than Greenness Across the Tibetan Plateau.” *Science of The Total Environment* 954: 176666. <https://doi.org/10.1016/j.scitotenv.2024.176666>.
- Anniwaer, N., X. Li, K. Wang, H. Xu, and S. Hong. 2024. “Shifts in the Trends of Vegetation Greenness and Photosynthesis in Different Parts of Tibetan Plateau over the Past Two Decades.” *Agricultural and Forest Meteorology* 345: 109851. <https://doi.org/10.1016/j.agrformet.2023.109851>.

- Bian, J., A. Li, H. Jin, G. Lei, C. Huang, and M. Li. 2013. "Auto-Registration and Orthorectification Algorithm for the Time Series HJ-1A/B CCD Images." *Journal of Mountain Science* 10 (5): 754–767. <https://doi.org/10.1007/s11629-013-2545-4>.
- Bonan, G. B. 2008. "Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests." *Science* 320 (5882): 1444–1449. <https://doi.org/10.1126/science.1155121>.
- Cao, S., M. Li, Z. Zhu, Z. Wang, J. Zha, W. Zhao, Z. Duanmu, et al. 2023. "Spatiotemporally Consistent Global Dataset of the GIMMS Leaf Area Index (GIMMS LAI4g) from 1982 to 2020." *Earth System Science Data* 15 (11): 4877–4899. <https://doi.org/10.5194/essd-15-4877-2023>.
- Chen, J. M., and T. A. Black. 1992. "Defining Leaf Area Index for Non-Flat Leaves." *Plant, Cell & Environment* 15 (4): 421–429. <https://doi.org/10.1111/j.1365-3040.1992.tb00992.x>.
- Chen, R., X. Liu, and L. Liu. 2025. "Improved GPP Upscaling from Instantaneous Measurements to Daily Sums Using the Light-Use-Efficiency-Based Model." *Agricultural and Forest Meteorology* 368: 110529. <https://doi.org/10.1016/j.agrformet.2025.110529>.
- Chen, Z., W. Wang, A. Cescatti, and G. Forzieri. 2023. "Climate-Driven Vegetation Greening further Reduces Water Availability in Drylands." *Global Change Biology* 29 (6): 1628–1647. <https://doi.org/10.1111/gcb.16561>.
- Chen, H., Q. Zhu, C. Peng, N. Wu, Y. Wang, X. Fang, and Y. Gao, et al. 2013. "The Impacts of Climate Change and Human Activities on Biogeochemical Cycles on the Qinghai-Tibetan Plateau." *Global Change Biology* 19 (10): 2940–2955. <https://doi.org/10.1111/gcb.12277>.
- Cui, J., X. Lian, C. Huntingford, L. Gimeno, T. Wang, J. Ding, M. He, et al. 2022. "Global Water Availability Boosted By Vegetation-Driven Changes in Atmospheric Moisture Transport." *Nature Geoscience* 15 (12): 982–988. <https://doi.org/10.1038/s41561-022-01061-7>.
- Ehlers, T. A., D. Chen, E. Appel, T. Bolch, F. Chen, B. Diekmann, M. A. Dippold, et al. 2022. "Past, Present, and Future Geo-Biosphere Interactions on the Tibetan Plateau and Implications for Permafrost." *Earth-Science Reviews* 234: 104197. <https://doi.org/10.1016/j.earscirev.2022.104197>.
- Fang, H., S. Wei, C. Jiang, and K. Scipal. 2012. "Theoretical Uncertainty Analysis of Global MODIS, CYCLOPES, and GLOBCARBON LAI Products Using a Triple Collocation Method." *Remote Sensing of Environment* 124: 610–621. <https://doi.org/10.1016/j.rse.2012.06.013>.
- Fang, H., F. Baret, S. Plummer, and G. Schaepman-Strub. 2019. "An Overview of Global Leaf Area Index (LAI): Methods, Products, Validation, and Applications." *Reviews of Geophysics* 57 (3): 739–799. <https://doi.org/10.1029/2018rg000608>.
- Huang, A., R. Shen, C. Shi, and S. Sun. 2022. "Effects of Satellite LAI Data on Modelling Land Surface Temperature and Related Energy Budget in the Noah-MP Land Surface Model." *Journal of Hydrology* 613: 128351. <https://doi.org/10.1016/j.jhydrol.2022.128351>.
- Huang, M., S. Piao, P. Ciais, J. Penuelas, X. Wang, T. F. Keenan, S. Peng, et al. 2019. "Air Temperature Optima of Vegetation Productivity Across Global Biomes." *Nature Ecology & Evolution* 3 (5): 772–779. <https://doi.org/10.1038/s41559-019-0838-x>.
- Jiang, C., Y. Ryu, H. Fang, R. Myneni, M. Claverie, and Z. Zhu. 2017. "Inconsistencies of Interannual Variability and Trends in Long-Term Satellite Leaf Area Index Products." *Global Change Biology* 23 (10): 4133–4146. <https://doi.org/10.1111/gcb.13787>.
- Kendall, M. G. 1948. *Rank correlation methods*. Oxford: Griffin.
- Kuang, X., and J. J. Jiao. 2016. "Review on Climate Change on the Tibetan Plateau during the Last Half Century." *Journal of Geophysical Research: Atmospheres* 121 (8): 3979–4007. <https://doi.org/10.1002/2015jd024728>.
- Li, P., Z. Hu, and Y. Liu. 2020. "Shift in the Trend of Browning in Southwestern Tibetan Plateau in the Past Two Decades." *Agricultural and Forest Meteorology* 287: 107950. <https://doi.org/10.1016/j.agrformet.2020.107950>.
- Li, N., L. Wang, and D. Chen. 2024. "Vegetation Greening Amplifies Shallow Soil Temperature Warming on the Tibetan Plateau." *npj Climate and Atmospheric Science* 7 (1): 118. <https://doi.org/10.1038/s41612-024-00651-z>.
- Li, A., Q. Wang, J. Bian, and G. Lei. 2015. "An Improved Physics-Based Model for Topographic Correction of Landsat TM Images." *Remote Sensing* 7 (5): 6296–6319. <https://doi.org/10.3390/rs70506296>.
- Li, A., J. Bian, Z. Zhang, W. Zhao, and G. Yin. 2016. "Progresses, Opportunities, and Challenges of Mountain Remote Sensing Research." *Journal of Remote Sensing* 20 (5): 1199–1215. <https://doi.org/10.11834/jrs.20166227>.
- Liu, Y., R. Liu, and J. M. Chen. 2012. "Retrospective Retrieval of Long-Term Consistent Global Leaf Area Index (1981–2011) from Combined AVHRR and MODIS Data." *Journal of Geophysical Research: Biogeosciences* 117(G4): G04003. <https://doi.org/10.1029/2012jg002084>.
- Liu, Y., J. Xiao, W. Ju, G. Zhu, X. Wu, W. Fan, D. Li, and Y. Zhou. 2018. "Satellite-Derived LAI Products Exhibit Large Discrepancies and Can Lead to Substantial Uncertainty in Simulated Carbon and Water Fluxes." *Remote Sensing of Environment* 206: 174–188. <https://doi.org/10.1016/j.rse.2017.12.024>.
- Luo, Y., N. Ma, and Y. Zhang. 2025a. "Divergent Vegetation greening's Direct Impacts on Land-Atmosphere Water and Carbon Exchanges in the Northeastern Tibetan Plateau." *Global and Planetary Change* 251: 104825. <https://doi.org/10.1016/j.gloplacha.2025.104825>.
- Luo, Y., N. Ma, and Y. Zhang. 2025b. "Uncertainty in the Spatial and Temporal Patterns of Vegetation in the River Source Region of the Eastern Tibetan Plateau: Implications from Multiple LAI Products Comparisons." *Acta Ecologica Sinica* 45 (11): 5541–5556. <https://doi.org/10.20103/j.stxb.202410312658>.

- Lv, J., W. Zhao, T. Hua, L. Zhang, and P. Pereira. 2023. "Multiple Greenness Indexes Revealed the Vegetation Greening during the Growing Season and Winter on the Tibetan Plateau Despite Regional Variations." *Remote Sensing* 15 (24): 5697. <https://doi.org/10.3390/rs15245697>.
- Ma, H., and S. Liang. 2022. "Development of the GLASS 250-m Leaf Area Index Product (Version 6) from MODIS Data Using the Bidirectional LSTM Deep Learning Model." *Remote Sensing of Environment* 273: 112985. <https://doi.org/10.1016/j.rse.2022.112985>.
- Myneni, R., Y. Knyazikhin, and T. Park. 2015. *MYD15A2H MODIS/Aqua Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V006. (dataset)*. NASA Land Processes Distributed Active Archive Center. <https://doi.org/10.5067/MODIS/MYD15A2H.006>.
- Myneni, R., Y. Knyazikhin, and T. Park. 2021. *MYD15A2H MODIS/Aqua Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V006. (Dataset)*. NASA Land Processes Distributed Active Archive Center. <https://doi.org/10.5067/MODIS/MOD15A2H.061>.
- Pearson, K. 1896. "Mathematical Contributions to the Theory of Evolution. III. Regression, Heredity, and Panmixia." *Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character* 187: 253–318. <https://doi.org/10.1098/rsta.1896.0007>.
- Piao, S., P. Ciais, Y. Huang, Z. Shen, S. Peng, J. Li, L. Zhou, et al. 2010. "The Impacts of Climate Change on Water Resources and Agriculture in China." *Nature (London)* 467 (7311): 43–51. <https://doi.org/10.1038/nature09364>.
- Piao, S., G. Yin, J. Tan, L. Cheng, M. Huang, Y. Li, R. Liu, et al. 2015. "Detection and Attribution of Vegetation Greening Trend in China over the Last 30 Years." *Global Change Biology* 21 (4): 1601–1609. <https://doi.org/10.1111/gcb.12795>.
- Piao, S., X. Zhang, T. Wang, E. Liang, S. Wang, J. Zhu, and B. Niu. 2019. "Responses and Feedback of the Tibetan Plateau's Alpine Ecosystem to Climate Change." *Chinese Science Bulletin* 64 (27): 2842–2855. <https://doi.org/10.1360/tb-2019-0074>.
- Piao, S., X. Wang, T. Park, C. Chen, X. Lian, Y. He, J. W. Bjerke, et al. 2020. "Characteristics, Drivers and Feedbacks of Global Greening." *Nature Reviews Earth & Environment* 1 (1): 14–27. <https://doi.org/10.1038/s43017-019-0001-x>.
- Qiu, J. 2008. "China: The Third Pole." *Nature (London)* 454 (7203): 393–396. <https://doi.org/10.1038/454393a>.
- Qiu, S., T. Hu, Y. Hu, Z. Ding, Y. Liu, and J. Peng. 2022. "Remote Sensing Based Global Vegetation Products: From Vegetation Spectral Index to Fusion Datasets." *Acta Geographica Sinica* 77 (5): 1102–1119. <https://doi.org/10.11821/dlxb202205005>.
- Seiler, C., J. R. Melton, V. K. Arora, S. Sitch, P. Friedlingstein, P. Anthoni, D. Goll, et al. 2022. "Are Terrestrial Biosphere Models Fit for Simulating the Global Land Carbon Sink?" *Journal of Advances in Modeling Earth Systems* 14 (5): e2021MS002946. <https://doi.org/10.1029/2021MS002946>.
- Sen, P. K. 1968. "Estimates of the Regression Coefficient Based on Kendall's Tau." *Journal of the American Statistical Association* 63 (324): 1379–1389. <https://doi.org/10.1080/01621459.1968.10480934>.
- Shaw, G. and D. Wheeler. 1985. *Statistical Techniques in Geographical Analysis*. New York: Wiley.
- Shen, M., S. Piao, S. Jeong, L. Zhou, Z. Zeng, P. Ciais, D. Chen, et al. 2015. "Evaporative Cooling over the Tibetan Plateau Induced By Vegetation Growth." *Proceedings of The National Academy of Sciences* 112 (30): 9299–9304. <https://doi.org/10.1073/pnas.1504418112>.
- Shen, M., S. Wang, N. Jiang, J. Sun, R. Cao, X. Ling, B. Fang, et al. 2022. "Plant Phenology Changes and Drivers on the Qinghai–Tibetan Plateau." *Nature Reviews Earth & Environment* 3 (10): 633–651. <https://doi.org/10.1038/s43017-022-00317-5>.
- Sun, H., D. Zheng, T. Yao, and Z. Yili. 2012. "Protection and Construction of The National Ecological Security Shelter Zone on Tibetan Plateau." *Acta Geographica Sinica* 67 (1): 3–12. <https://doi.org/10.11821/xb201201001>.
- Verger, A., J. Sánchez-Zapero, M. Weiss, A. Descals, F. Camacho, R. Lacaze, and F. Baret. 2023. "GEOV2: Improved Smoothed and Gap Filled Time Series of LAI, FAPAR and FCover 1 km Copernicus Global Land Products." *International Journal of Applied Earth Observation and Geoinformation* 123: 103479. <https://doi.org/10.1016/j.jag.2023.103479>.
- Wang, Y., W. Lv, K. Xue, S. Wang, L. Zhang, R. Hu, H. Zeng, et al. 2022. "Grassland Changes and Adaptive Management on the Qinghai–Tibetan Plateau." *Nature Reviews Earth & Environment* 3 (10): 668–683. <https://doi.org/10.1038/s43017-022-00330-8>.
- Wang, D., A. D. Ziegler, J. Holden, D. V. Spracklen, P. Ciais, L. Peng, and Z. Zeng. 2025. "Vegetation Cover Change as a Growing Driver of Global Leaf Area Index Dynamics." *Nature Communications* 16 (1): 9259. <https://doi.org/10.1038/s41467-025-64305-1>.
- Wei, S., X. Li, K. Wang, T. Wang, and S. Piao. 2025. "Two Decades of Persistent Greening in China Despite 2023 Climate Extremes." *Science China Earth Sciences* 55 (4): 1099–1108. <https://doi.org/10.1007/s11430-024-1530-7>.
- Wu, Y., J. Gao, and A. Zhao. 2024. "Cloud Properties and Dynamics over the Tibetan Plateau – a Review." *Earth-Science Reviews* 248: 104633. <https://doi.org/10.1016/j.earscirev.2023.104633>.
- Wu, S., W. Zhou, K. Yan, and X. Zhang. 2020. "Response of the Water Conservation Function to Vegetation Dynamics in the Qinghai–Tibetan Plateau Based on MODIS Products." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13: 1675–1686. <https://doi.org/10.1109/jstars.2020.2984830>.
- Wu, X., J. Wen, R. Tang, J. Wang, Q. Zeng, Z. Li, D. You, X. Lin, B. Gong, and Q. Xiao. 2023. "Quantification of the Uncertainty in Multiscale Validation of Coarse-Resolution Satellite Albedo Products: A Study Based on Airborne CASI Data." *Remote Sensing of Environment* 287: 113465. <https://doi.org/10.1016/j.rse.2023.113465>.

- Xiao, Z., S. Liang, J. Wang, Y. Xiang, X. Zhao, and J. Song. 2016. "Long-Time-Series Global Land Surface Satellite Leaf Area Index Product Derived from MODIS and AVHRR Surface Reflectance." *IEEE Transactions on Geoscience and Remote Sensing* 54 (9): 5301–5318. <https://doi.org/10.1109/tgrs.2016.2560522>.
- Xu, S., Z. Yu, D. P. Lettenmaier, T. R. McVicar, and X. Ji. 2020. "Elevation-Dependent Response of Vegetation Dynamics to Climate Change in a Cold Mountainous Region." *Environmental Research Letters* 15 (9): 094005. <https://doi.org/10.1088/1748-9326/ab9466>.
- Xu, L., N. Chen, X. Zhang, H. Moradkhani, C. Zhang, and C. Hu. 2021. "In-Situ and Triple-Collocation Based Evaluations of Eight Global Root Zone Soil Moisture Products." *Remote Sensing of Environment* 254: 112248. <https://doi.org/10.1016/j.rse.2020.112248>.
- Yan, K., T. Park, G. Yan, Z. Liu, B. Yang, C. Chen, R. R. Nemani, Y. Knyazikhin, and R. B. Myneni. 2016. "Evaluation of MODIS LAI/FPAR Product Collection 6. Part 2: Validation and Intercomparison." *Remote Sensing* 8 (6): 460. <https://doi.org/10.3390/rs8060460>.
- Yan, K., J. Wang, R. Peng, K. Yang, X. Chen, G. Yin, J. Dong, M. Weiss, J. Pu, and R. B. Myneni. 2024. "HiQ-LAI: A High-Quality Reprocessed MODIS Leaf Area Index Dataset with Better Spatiotemporal Consistency from 2000 to 2022." *Earth System Science Data* 16 (3): 1601–1622. <https://doi.org/10.5194/essd-16-1601-2024>.
- Yao, T. 2019. "Tackling on Environmental Changes in Tibetan Plateau with Focus on Water, Ecosystem and Adaptation." *Science Bulletin* 64 (7): 417. <https://doi.org/10.1016/j.scib.2019.03.033>.
- Yao, T., V. Masson-Delmotte, J. Gao, W. Yu, X. Yang, C. Risi, C. Sturm, et al. 2013. "A Review of Climatic Controls on $\delta^{18}\text{O}$ in Precipitation over the Tibetan Plateau: Observations and Simulations." *Reviews of Geophysics* 51 (4): 525–548. <https://doi.org/10.1002/rog.20023>.
- Ye, Y., Huang, Z., Wang, Z., Zheng, H., Ma, L., Wang, M., and Yang, L., et al. 2026. LAI dataset from multiple products (MOD15A2H/GIMMS LAI4g/GLOBMAP LAI V3/GLASS-AVHRR/GLASS-MODIS/HIQ/GEOV2) for the Tibetan Plateau – Data supporting 'How Consistent Are Satellite LAI Products in Characterizing Vegetation Dynamics Over the Tibetan Plateau?' (under review). (dataset). <https://doi.org/10.5281/zenodo.20091684>.
- Yiming, S., X. Shiqin, P. L. Dennis, E. B. Hylke, C. Xiaodong, Y. Zhongbo, D. Ningpeng, et al. 2026. "Intensification of Extreme Precipitation Across the Tibetan Plateau and Its Climatic Drivers over 1982–2020." *Global and Planetary Change* 256: 105182. <https://doi.org/10.1016/j.gloplacha.2025.105182>.
- Zhang, Y., Z. Yang, C. Quzong, S. Gyal, W. Mazhang, Y. Yang, G. Zhang, et al. 2025. "Spatial Variations in Carbon Dioxide Fertilization Effect on Vegetation Greening Across the Tibetan Plateau." *Global and Planetary Change* 252: 104839. <https://doi.org/10.1016/j.gloplacha.2025.104839>.
- Zhong, L., Y. Ma, Y. Xue, and S. Piao. 2019. "Climate Change Trends and Impacts on Vegetation Greening over the Tibetan Plateau." *Journal of Geophysical Research: Atmospheres* 124 (14): 7540–7552. <https://doi.org/10.1029/2019jd030481>.
- Zhu, Z., S. Piao, R. B. Myneni, M. Huang, Z. Zeng, J. G. Canadell, P. Ciais, et al. 2016. "Greening of the Earth and Its Drivers." *Nature Climate Change* 6 (8): 791–795. <https://doi.org/10.1038/nclimate3004>.