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Citation for the original published paper (version of record):

Yang, G., Chen, D., Xiao, J. et al (2026). Changes, attributions and uncertainties of global ecosystem resilience. Fundamental Research, In Press. <http://dx.doi.org/10.1016/j.fmre.2026.05.014>

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Contents lists available at ScienceDirect

Fundamental Research

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Article

Changes, attributions and uncertainties of global ecosystem resilience

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ARTICLE INFO

Article history:

Received 11 September 2025

Received in revised form 11 May 2026

Accepted 20 May 2026

Available online xxx

Keywords:

Ecosystem resilience

Uncertainty

Critical slowing down

Flickering

Climate change

ABSTRACT

Ecosystem resilience is a key indicator of proximity to tipping points in terrestrial ecosystems, with declining resilience generally reflecting a heightened risk of abrupt transitions between ecosystem states. However, quantitative assessments of resilience change remain highly uncertain, owing to the inherently multidimensional nature of ecosystem resilience, as well as inconsistencies among assessment methodologies and ecosystem state variables used to infer resilience change. By synthesizing core ecosystem resilience concepts and evaluating multiple indicators and satellite-based vegetation state variables within established theoretical frameworks, we reveal substantial inconsistencies in inferred resilience trends: 59.6% and 42.8% of pixels show disagreement under the frameworks of critical slowing down and flickering, respectively, and 69.3% of show inconsistent trends across four satellite-based vegetation state variables (EVI, CSIF, LAI and kNDVI). Integrating dynamic global vegetation model simulations with observations further identifies climate change as the dominant driver of global ecosystem resilience changes, with temperature playing a key role. Together, these findings indicate that under ongoing global warming, neglecting conceptual differences in resilience and inconsistencies in representing critical transitions can lead to systematic misinterpretation of ecosystem stability and tipping-point risks, underscoring the urgent need for ecosystem-specific resilience assessment.

1. Introduction

Ecosystem resilience broadly refers to the capacity of an ecosystem to absorb disturbances while maintaining its fundamental functions, structure, and key characteristics [1,2]. Terrestrial ecosystems are highly sensitive to climate change and increasingly intensified human disturbances [3]. When the magnitude or persistence of these drivers exceeds the tolerance thresholds, defined by biotic and abiotic feedbacks that sustain stability, ecosystems may lose balance and undergo abrupt state shifts [4,5]. Assessing the risk of such transitions, and thereby safeguarding vegetation functioning and ecosystem services, fundamentally depends on understanding ecosystem resilience [6,7]. However, the inherent complexity of ecosystems, together with the combined effects of natural and anthropogenic disturbances [8], has led to divergent conceptualizations and interpretations of resilience across studies [9,10]. Therefore,

clarifying ecosystem resilience concepts and conducting robust global assessments are essential for accurately characterizing ecosystem responses, identifying potential tipping-point risks, and informing sustainable ecosystem management.

Current quantitative assessments of changes in ecosystem resilience primarily rely on a range of resilience metrics developed under different theoretical frameworks, together with the corresponding selection of vegetation state variables. Theory and empirical evidence suggest that as ecosystem resilience declines and approaches critical transition thresholds, early warning signals, such as critical slowing down (CSD) and flickering (FLI), may emerge [11,12]. Indicators derived from these phenomena and signals have been widely employed to detect weakening of system resilience and increasing collapse risk [13–15]. Vegetation state variables, which capture key aspects of ecosystem structure and function, form the basis of resilience indicator construction and are central

Peer review under the responsibility of Editorial Board of Fundamental Research.

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to diagnosing ecological processes and system change [7,16]. However, variations in resilience metrics and state variables selection across studies have introduced substantial uncertainties in the spatial patterns, consistency, and comparability of resilience assessments [17,18]. To date, these discrepancies have not been systematically quantified or evaluated at the global scale.

The dynamics of ecosystem resilience are governed by the integrated effects of multiple driving factors [19,20]. Studies focusing on climate change have shown that the global decline in ecosystem resilience is primarily associated with increased temperature variability, rising mean temperatures, and greater precipitation variability [21,22]. Changes in atmospheric CO₂ concentration influence ecosystem resilience through both fertilization and radiative effects. While the CO₂ fertilization effect may partially alleviate the detrimental impacts of climate change by enhancing vegetation productivity, the radiative forcing associated with elevated CO₂ levels can intensify the occurrence of severe droughts, thereby accelerating the decline of ecosystem resilience [23,24]. Land use change is also emerging as a critical factor influencing ecosystem resilience, particularly at regional scales. In the Amazon rainforest, the recovery capacity of ecosystems has markedly declined in areas near human activities, with anthropogenic disturbances further accelerating the degradation of ecosystem resilience [25]. Although previous studies have explored the specific impacts of various external drivers on changes in ecosystem resilience, there is still a lack of clear understanding of which factors dominate ecosystem resilience dynamics and their spatial distribution patterns at the global scale.

In this study, we first systematically review major ecosystem resilience concepts relevant to global environmental change research, with particular emphasis on clarifying differences in definitions, theoretical linkages, and research priorities across perspectives. Building on this foundation, we focus on ecological resilience associated with critical ecosystem transitions and, using two representative theoretical frameworks, systematically evaluate uncertainties in resilience changes inferred from different indicators and vegetation state variables. By integrating dynamic global vegetation models with observational data, we further quantify the relative roles of climate change, land-use change, and atmospheric CO₂ concentration changes in driving ecosystem resilience changes. Finally, we discuss the key sources of uncertainty in ecosystem resilience assessments and outline directions for improving the quantification of ecosystem resilience.

2. Materials and methods

2.1. Data

We characterized global vegetation dynamics using four remotely sensed vegetation indices: Leaf Area Index (LAI), kernel Normalized Difference Vegetation Index (kNDVI), Enhanced Vegetation Index (EVI), and Solar-Induced Chlorophyll Fluorescence (SIF). LAI, a fundamental indicator of ecosystem structure, was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI product for the period 2003–2020 [26]. As a complementary proxy for ecosystem productivity, we employed kNDVI, which is defined as:

$$kNDVI = \tan h(NDVI^2) \quad (1)$$

and has been shown to effectively reduce saturation effects and enhance robustness to noise while maintaining strong correlations with primary productivity. The NDVI data used to construct the kNDVI dataset were derived from the MOD13Q1 product at a spatial resolution of 250 m EVI, which is widely used to characterize vegetation greenness and monitor vegetation dynamics, was also obtained from the MOD13Q1 dataset [27]. Solar-induced chlorophyll fluorescence (SIF), a mechanistically based indicator of photosynthetic activity, was acquired at an original spatial resolution of 0.05° and a temporal resolution of 4 days [28], and

was temporally aggregated to monthly means to ensure consistency with the other datasets used in this analysis. All datasets were resampled to a uniform spatial resolution of 0.1° using bilinear interpolation, and the analysis period for all datasets was consistently set to 2003–2020.

We also used leaf area index (LAI) simulated by the TRENDYv10 model intercomparison project and the Global Carbon Budget 2021 [29], including outputs from CLM5.0, ISBA-CTRIP, LPJ-GUESS, LPX-Bern, OCN, ORCHIDEEv3, SDGVM, VISIT, YIBs, to identify the controlling factors of the global resilience changes (Tables S1 and S2). All models were run under four scenarios (Table S3). These four scenario simulations enable us to quantify the impacts of the CO₂ effect, climate change, and land cover change, respectively.

To identify the dominant climatic drivers of ecosystem resilience change, we employed four core climate variables: temperature, precipitation, radiation, and vapor pressure deficit (VPD). The monthly temperature at 2 m above the land surface was obtained from the ERA5-Land dataset provided by the ERA5-Land reanalysis product at 0.1° spatial resolution for the 2003–2020 period (<https://cds.climate.copernicus.eu/datasets>). Air temperature was converted from Kelvin to degrees Celsius (°C) by subtracting 273.15. Monthly precipitation, vapor pressure deficit (VPD), and downward surface shortwave radiation were obtained from the TerraClimate dataset provided by the Climatology Lab [30], which is a high-resolution dataset (~4 km) widely used to analyze changes in global surface and upper-atmosphere meteorological elements. We applied the bilinear method to resample the climate data with a spatial resolution of 0.5 degrees, ensuring consistency with the model results.

2.2. Data processing and preparation

To improve robustness and cross-dataset comparability, we applied strict pixel-level quality control before calculating resilience metrics and standardized the analysis period to 2003–2020, thereby reducing biases arising from differences in temporal coverage. To reduce the influence of missing or unreliable observations, particularly in high-latitude regions where retrievals can be sparse outside the growing season, pixels with >20% missing values in the vegetation time series were excluded. Annual 500-m land-cover data (2003–2020) were then used to mask non-vegetated areas, including bare earth, snow, and anthropogenic land covers [31]. The remaining vegetated pixels were reclassified into four vegetation types: forest, savanna, shrubland, and grassland [32]. All observational data utilized for analysis were resampled to a common spatial resolution of 0.1°.

2.3. Methods

2.3.1. Resilience and trend estimation

To remove the influence of the seasonal variability, we first subtracted the monthly mean from the time series of vegetation variables (EVI, kNDVI, LAI, and CSIF). Long-term trends were removed from the deseasonalized time series using the detrend function in MATLAB [24]. The resulting residuals were then employed to calculate a suite of statistical early warning indicators, including the first-order autoregressive coefficient (AR1), variance (VAR), skewness (SK), and kurtosis (KUR) [33,34]. These indicators, along with the composite early warning indicators (CEWI), were used to quantify ecosystem resilience [35].

We applied a 5-year sliding window to quantify temporal changes in ecosystem resilience and conducted Kendall's τ to determine the direction of resilience trends for each pixel. Kendall's τ measures rank correlation, commonly used to characterize resilience dynamics [36]. Values of $\tau = 1$ and $\tau = -1$ indicate consistently increasing and decreasing trends, respectively, whereas $\tau = 0$ denotes the absence of a monotonic trend. The Pearson correlation coefficient (r) was used to assess the consistency of temporal changes in ecosystem resilience between the CSD and FLI frameworks.

2.3.2. Data Concurrence Index (DCI) and preference ratio

To quantify the consistency of ecosystem resilience changes across multiple vegetation state variables, we introduced the Data Concurrence Index (DCI) [37,38], defined as:

$$DCI = \frac{1}{ND} \sum_{i=1}^{ND} \frac{h_i ST_i}{|ST_i|} \quad (2)$$

where ND denotes the number of variables, ST_i is the trend of the i th variable, and h_i indicates whether the trend is statistically significant. The DCI integrates both the direction and significance of trends across datasets, ranging from -1 to 1 . Positive values indicate a consistent decline in ecosystem resilience, whereas negative values indicate a consistent increase. Based on the magnitude of the DCI, ecosystem resilience changes are classified into three categories: uncertainty (UNC; $-0.5 \leq DCI \leq 0.5$), likely change (LIK $\pm$; $-0.75 < DCI < -0.5$ for LIK+ and $0.5 < DCI < 0.75$ for LIK-), and certain change (CER $\pm$; $-1 \leq DCI \leq -0.75$ for CER+ and $0.75 \leq DCI \leq 1$ for CER-).

To assess the relative distribution of uncertainty (UNC) across climate zones and vegetation types, we applied a preference ratio, defined as the proportion of a given climate zone or vegetation type within the UNC category normalized by its proportion over the entire study area [39]. This metric quantifies whether uncertainty is over- or under-represented in specific regional types, with values greater than one indicating higher-than-average concentrations of uncertainty and values less than one indicating lower concentrations.

2.3.3. Drivers of resilience changes

Dynamic vegetation models (DGVMs) allow the isolation of individual drivers in scenario and factor-separation experiments, enabling quantitative assessment of the independent effects of climate change, land-use change, and atmospheric CO_2 on ecosystem resilience (Table S3). Leveraging this advantage, we analyzed LAI outputs from nine DGVMs participating in the TRENDY v10 S0–S3 scenario experiments to investigate the drivers of ecosystem resilience. The contributions of CO_2 concentration change, climate change, and land-use change to ecosystem resilience change were quantified by calculating the differences in ecosystem resilience derived from LAI across different scenarios, namely S1–S0, S2–(S1 + S0), and S3–S2. At the pixel scale, the driver associated with the largest absolute value of the resilience change difference was designated as the dominant driver. To ensure robust attribution, only grid cells where DGVM-simulated patterns were spatially consistent with observational estimates were retained for driver identification. This filtering step excluded regions where model outputs diverged substantially from observations, thereby reducing potential misattribution.

Given the limited capacity of DGVMs to distinguish the relative contributions of individual climate factors, we further incorporated observational climate data to identify the specific climate drivers in regions where DGVMs indicated climate change as the dominant driver at the regional scale. To address the strong multicollinearity among climate variables, we applied ridge regression to estimate the influence of each climate factor on ecosystem resilience changes [40,41]. Fivefold cross-validation was used to select the optimal regularization parameter, avoiding overfitting while ensuring the robustness of the regression coefficients. The climate variable with the largest absolute ridge regression coefficient was identified as the dominant climatic driver of ecosystem resilience change for each pixel.

3. Review of concepts and measurements of ecosystem resilience under global change

Terrestrial ecosystems are highly sensitive to external drivers, including press disturbances (e.g., climate warming) and pulse disturbances (e.g., extreme climatic events and natural disasters), both of which can significantly affect ecosystem resilience [42,43] (Fig. 1a). Under global environmental change, changes in ecosystem resilience can induce shifts

in ecosystem structure and function, ultimately driving transitions between ecosystem states [44] (Fig. 1a). Ecosystems differ markedly in their responses to disturbances, which directly gives rise to multiple interpretations of ecosystem resilience in both definition and measurement [45]. When disturbance intensity is low, ecosystems typically fluctuate around their current stable state and are therefore often regarded as having a single stable state (e.g., states A or B as illustrated in Fig. 1b). However, when disturbance intensity or frequency overwhelms internal stabilizing feedbacks, the system may cross a critical threshold and shift to an alternative stable state [46] (Fig. 1b). This progression from localized responses to state transitions directly underlies the divergence among resilience definitions in terms of their focal mechanisms and assessment objectives.

Within the broader framework of resilience, ecosystems can exhibit resilience in two ways: one is the time or speed required for an ecosystem to return to its original state following disturbance, and the other is the ability to withstand disturbances and avoid transitioning to a different stable state (i.e., state shift) [47,48]. Existing research distinguishes these two forms of resilience as engineering resilience and ecological resilience [49]. Ecological resilience focuses on how close an ecosystem is to a critical threshold [50,51] (Fig. 1b; i.e., tipping point), whereas engineering resilience emphasizes the ability of ecosystems to recover from disturbances [52] (Fig. 1c; i.e., Recovery). Beyond conceptual distinctions, these differences directly shape the selection of indicators, the design of methodologies, and the interpretation of results in resilience assessments.

The concept of ecological resilience emphasizes the existence of multiple stable states and the associated risk of critical transitions, focusing on the likelihood that a system is approaching a critical threshold and, on its capacity, to anticipate potential state shifts (Fig. 1b). Recent advances in early warning signals (EWS) have provided important theoretical and methodological tools for assessing ecological resilience [53]. Unlike engineering resilience approaches that rely on explicitly identified disturbance events, EWS do not depend on specific disturbance types; instead, they are grounded in dynamical systems theory and identify critical transitions by detecting changes in the statistical properties of ecosystem state variables as a system approaches a state shift [54,55]. Among these approaches, critical slowing down (CSD) and flickering (FLI) are widely adopted and form the core analytical framework of this study.

Critical slowing down (CSD) originates from nonlinear dynamical systems theory. As a system approaches a bifurcation or critical point, its recovery from perturbations progressively slows. This behavior is typically reflected by increases in autocorrelation and variance of key state variables and is commonly quantified using the first-order autoregressive coefficient (AR1) and variance (VAR) [56]. Owing to their relatively weak dependence on specific mechanistic assumptions and their direct applicability to observed time series, CSD-based indicators are among the most widely used and comparable early warning signals.

In some cases, critical proximity is not primarily expressed as a gradual slowing of recovery, but rather as increasingly frequent transitions between alternative stable states. To compensate for the limited sensitivity of critical slowing down (CSD) under such conditions, flickering theory (FLI) has been introduced as a complementary framework [57,58]. As systems approach critical transitions, frequent switching between stable states can alter the distributional properties of state variables, leading to systematic changes in skewness (SK) and kurtosis (KUR) [59]. These features provide information on critical proximity that is complementary to CSD. When system dynamics are dominated by such state switching, state-variable distributions deviate from single-state symmetry and exhibit enhanced asymmetry and extreme fluctuations, making FLI an effective indicator of transition risk. More broadly, both CSD and FLI can characterize critical proximity using long-term observational time series without detailed knowledge of internal system mechanisms, enabling large-scale comparisons across regions and ecosystem types.

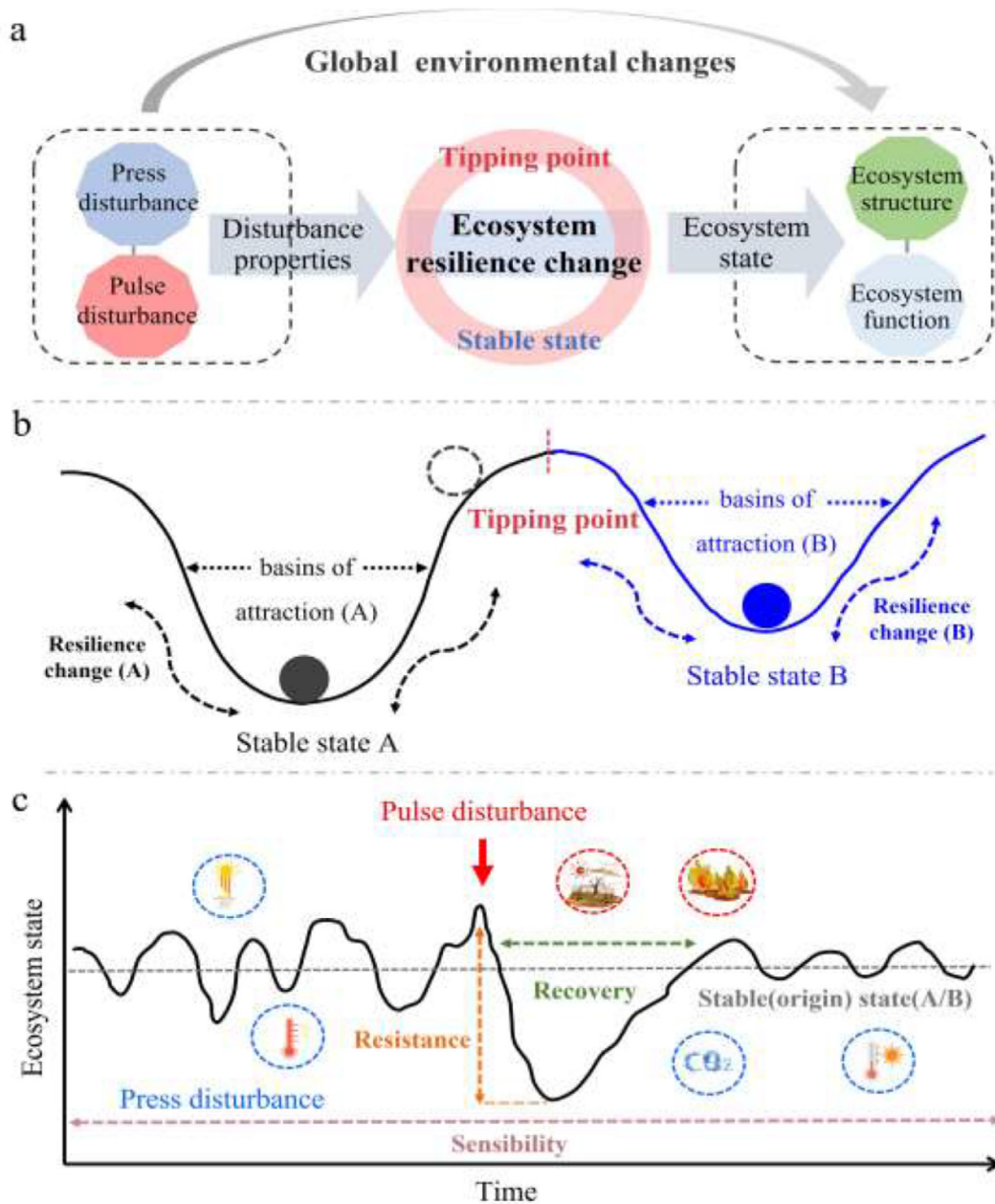


Fig. 1. Concept and key process of ecosystem resilience. (a) Schematic diagram of the drivers and impacts of ecosystem resilience changes. (b) Schematic diagram of ecological resilience. A small ball represents the stable state of each ecosystem. The arrowed vertical dashed lines represent the unique basins of attraction associated with each stable state under specific environmental conditions. A curved dotted line indicates resilience changes in different environmental conditions. A red dotted line means a tipping point. (c) Conceptual diagram of engineering resilience and related concepts. The red arrow is used to indicate a pulse disturbance.

Engineering resilience typically assumes a single attractor and focuses on the magnitude of ecosystem responses and recovery rates following (Fig. 1c). Concepts such as resistance, recovery, and sensitivity have been applied [60–62]. Resistance characterizes the ability to maintain structure and function under pulse disturbances (e.g., fires or extreme droughts), recovery describes the speed or efficiency of returning to baseline state following disturbance [63], and sensitivity reflects the magnitude of ecosystem responses to short-term climate variability or long-term pressures [64]. These indicators generally rely on identifiable disturbance events and pre-disturbance baseline states, making them suitable for event-based process analyses. However, this perspective implicitly assumes that the system remains within the same attractor and that no change in the basin of attraction has occurred. When ecosystems exhibit multiple stable states or approach critical thresholds,

engineering resilience indicators may suggest strong apparent recovery despite a substantial decline in overall system stability, thereby underestimating the risk of abrupt regime shifts.

Engineering resilience characterizes local stability and recovery dynamics within an existing stable state, whereas ecological resilience captures global stability, the structure of basins of attraction, and the system's proximity to critical thresholds. Although conceptually distinct, engineering resilience and ecological resilience are closely linked in practice. Recent studies suggest that ecological resilience is a prerequisite for engineering resilience—an ecosystem can only recover to its original state if it avoids shifting to a new stable state [18]. Thus, if an ecosystem fails to recover over time, it may face an increased risk of state shift. It means the complete process illustrated in Fig. 1c takes place under both Stable state A and Stable state B corresponding to Fig. 1b. In

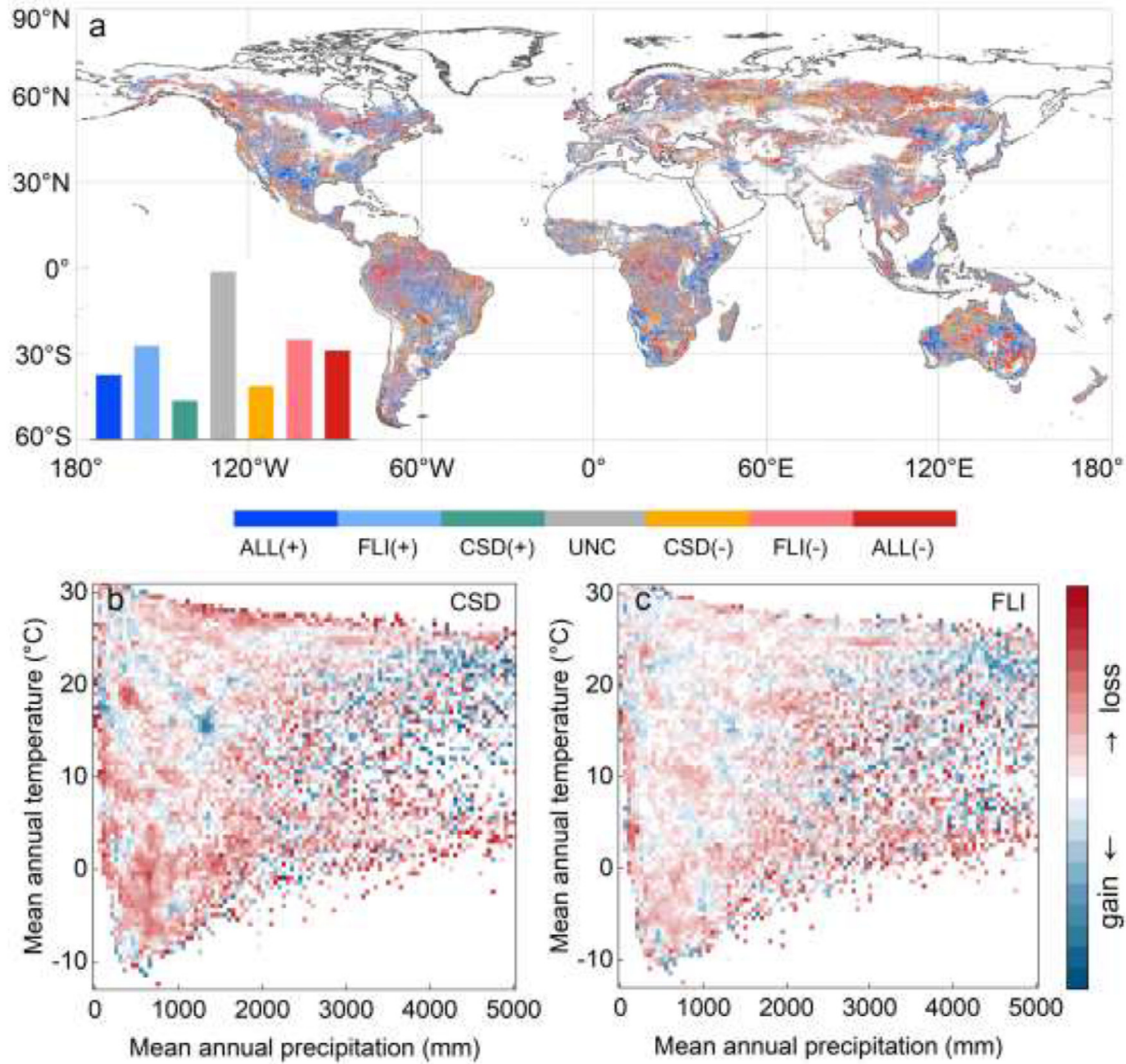


Fig. 2. Consistency of the resilience trends based on CSD and FLI. (a) Spatial distribution of the consistency of resilience trends based on CSD and FLI. CSD is defined where AR1 and VAR both show a positive or negative trend. FLI is defined where SK and KUR show a positive or negative trend. ALL donates all indicators show consistent resilience changes. UNC donates only a single indicator that exhibited a significant change under each theoretical framework. FLI donates ecosystem resilience changes detected solely through the flickering phenomenon, while CSD refers to those identified exclusively via critical slowing down dynamics. The signs (+) and (-) refer to resilience gain and loss, respectively. (b) Per-grid-cell resilience trend as a function of mean annual temperature and precipitation based on CSD, (c) as in (b), but based on FLI. The CSD is represented by the AR1 indicator, and the FLI is represented by the SK indicator.

this study, we therefore focus on ecological resilience to evaluate shifts in ecosystem critical risk under global change, and to systematically examine the consistency and uncertainty of resilience changes across multiple early warning indicators and ecosystem state variables.

4. Results

4.1. Ecosystem resilience changes under different theoretical frameworks

To ensure the comparability of results across different theoretical frameworks, we adopted the leaf area index (LAI) as a unified vegetation state variable, thereby minimizing uncertainties arising from variable selection. We first examined the overall patterns of ecosystem resilience change and associated uncertainties under the assumption that the two theoretical frameworks, critical slowing down (CSD) and flickering (FLI), operate independently (Figs. S1,S2). Under the CSD framework, resilience change was considered to be reliably identified only when the first-order autocorrelation (AR1) and variance (VAR) exhibited consistent directional trends within the same pixel. Based on this

criterion, significant resilience change was detected in approximately 40.4% of pixels (Fig. 2a, ALL and CSD), while the remaining 59.6% exhibited uncertain signals. Similarly, under the FLI framework, resilience change was deemed established when skewness (SK) and kurtosis (KUR) consistently indicated the same direction of change. Using this criterion, the FLI analysis identified clear resilience changes in 57.2% of pixels (Fig. 2a, ALL and FLI), with uncertainty persisting in the remaining 42.8%.

We further assessed the overall direction of ecosystem resilience change and the associated uncertainties by integrating results from both CSD and FLI. Among pixels with clearly identified resilience trends under both theoretical frameworks, around 39.9% exhibited declining resilience (Fig. 2a, signs (-)), 32.4% showed increasing resilience (Fig. 2a, signs (+)), and 27.7% remained uncertain (Fig. 2a, UNC). Resilience decline was identified in 23.4% of pixels based on the CSD indicators (Fig. 2a, CSD(-) and ALL(-)), and in 31.1% based on FLI indicators (Fig. 2a, FLI(-) and ALL(-)). These areas are mainly located in northern and western North America, eastern and western Amazonia, central and southern Africa, central and eastern Europe, and central and southeast-

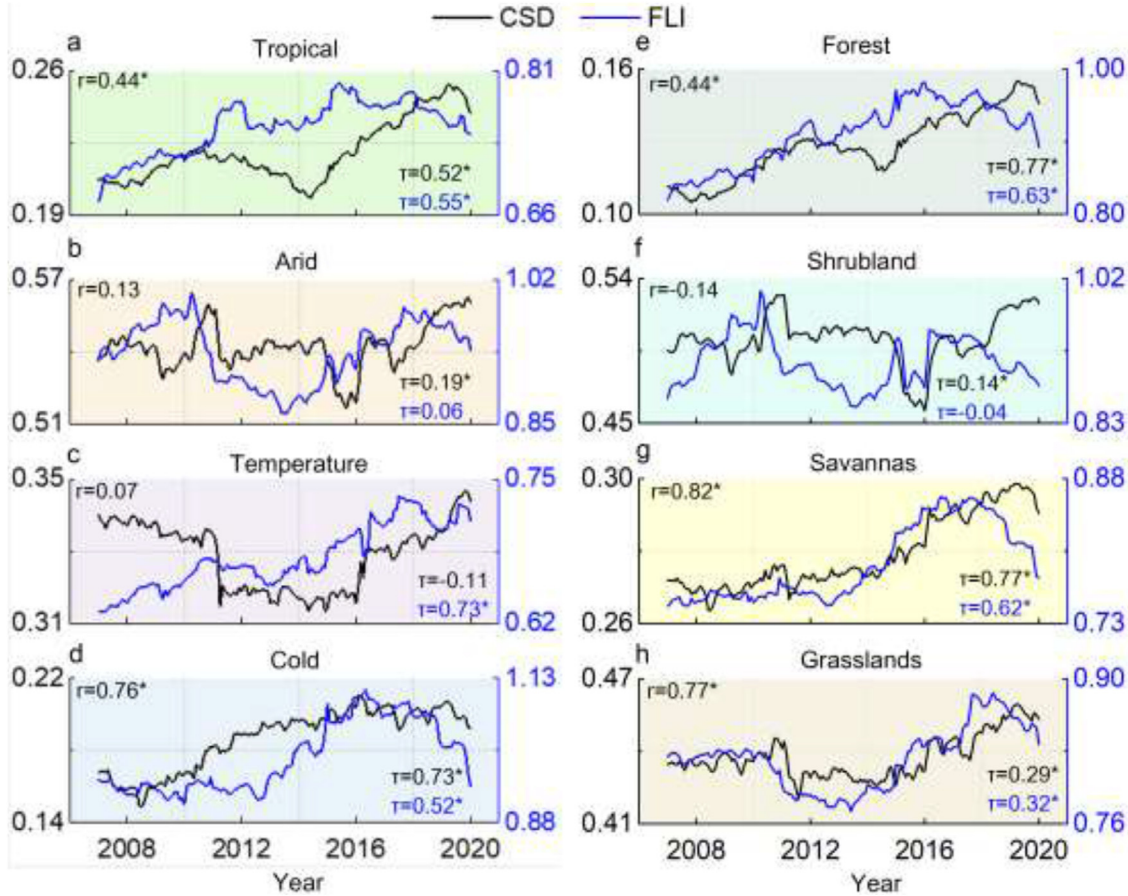


Fig. 3. Comparison of ecosystem resilience changes under two theoretical frameworks across different regions. (a–d) Temporal trends of ecosystem resilience in four climate zones. (e–h) Temporal trends of ecosystem resilience in four vegetation types. CSD is represented by the AR1 indicator, and FLI is represented by the SK indicator. “ τ ” denotes the Kendall τ of the ecosystem resilience time series, and “ r ” denotes the Pearson correlation between CSD and FLI, indicating the consistency of resilience changes under the two frameworks. “*” indicates $p < 0.05$.

ern Australia (Fig. 2a). Conversely, resilience increases were detected in 16.9% of pixels under the CSD framework (CSD(+) and ALL(+)) and in 26.1% under the FLI framework (FLI(–) and ALL(–)), respectively. Regions with increasing resilience are primarily distributed across central North America, central Amazonia, eastern Africa, Southeast Asia, and northeastern Australia (Fig. 2a). Further analysis of pixels with clearly identified resilience changes under each theoretical framework reveals that ecosystem resilience loss is more severe in areas with lower precipitation and lower temperatures (Fig. 2b,c).

In addition, focusing on pixels with clearly identified resilience changes, we systematically compared how the CSD and FLI frameworks characterize ecosystem resilience changes across different climate zones and vegetation types (Fig. 3, Methods). At the climate-zone scale, both tropical and cold regions exhibited significant declines in ecosystem resilience under CSD and FLI frameworks, as indicated by consistently positive Kendall’s τ values. In tropical regions (Fig. 3a), the Kendall’s τ for CSD and FLI are 0.52 ($p < 0.05$) and 0.55 ($p < 0.05$), respectively, while in cold regions (Fig. 3d), the corresponding values are 0.73 ($p < 0.05$) and 0.52 ($p < 0.05$). Correlation analysis further supports these findings, revealing stronger temporal consistency in resilience decline is observed in cold regions ($r = 0.76$, $p < 0.05$; Fig. 3d), followed by tropical regions ($r = 0.44$, $p < 0.05$; Fig. 3a). In contrast, resilience changes in arid (Fig. 3b) and temperate regions (Fig. 3c) exhibit substantial uncertainty, characterized in unstable trend signals, inconsistent directional assessments, and weak statistical significance across theoretical frameworks. This indicates that ecosystem responses to external disturbances in these regions are highly complex and heterogeneous, with different

resilience indicators capturing distinct aspects of ecosystem dynamics due to their differing sensitivities to underlying ecological processes.

Across vegetation types, forest (CSD: 0.77, FLI: 0.63, $p < 0.05$), savanna (CSD: 0.77, FLI: 0.62, $p < 0.05$) and grasslands (CSD: 0.29, FLI: 0.32, $p < 0.05$) all exhibited significant declines in resilience under both CSD and FLI (Fig. 3). Notably, savanna ecosystems show the strongest agreement between CSD- and FLI-based assessments, with a correlation coefficient of 0.82 ($p < 0.05$) (Fig. 3g), substantially exceeding that observed in forest ecosystems ($r = 0.48$, $p < 0.05$; Fig. 3e). Grasslands display also demonstrate high temporal consistency between the two frameworks ($r = 0.77$, $p < 0.05$; Fig. 3h). By contrast, shrubland ecosystems show a higher degree of uncertainty in resilience changes. Shrub is predominantly distributed in arid regions, and this finding is consistent with the resilience uncertainty identified at the climate zone scale in arid areas, further supporting our conclusions regarding the spatial pattern of uncertainty in ecosystem resilience changes (Fig. 3f).

4.2. Ecosystem resilience changes across vegetation state variables

This section examines changes in ecosystem resilience and the associated uncertainties as inferred from different vegetation state variables. To reduce the dependence of resilience assessment on indicator selection, we introduce composite early warning indicators (CEWI) to provide a unified quantification of resilience change [65,66]. CEWI was first constructed using four applied vegetation variables: LAI, EVI, kNDVI, and CSIF (Fig. S2). We then evaluated the consistency of pixel-scale resilience changes across these variables using the Data Concur-

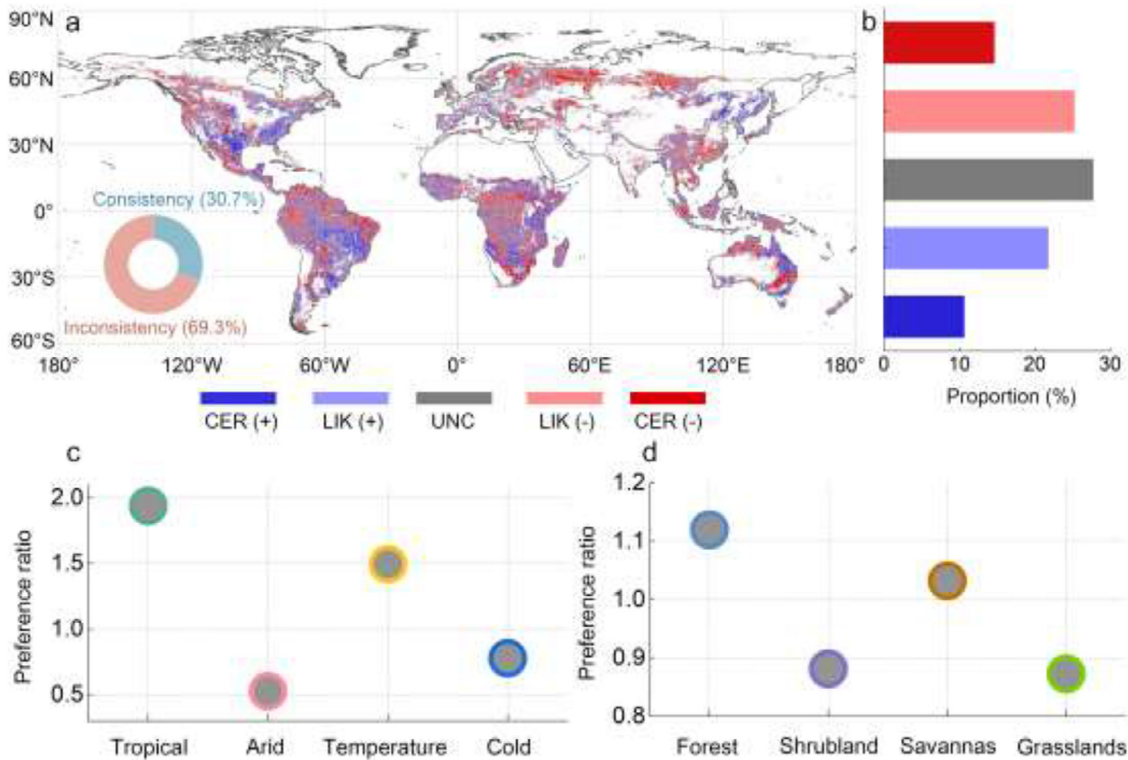


Fig. 4. Consistency of ecosystem resilience changes across vegetation variables. (a) Spatial distribution and consistency of ecosystem resilience changes based on four vegetation variables. The ring chart shows the overall consistency and inconsistency in the direction of the four state variables, indicating whether all four variables at a given pixel point toward the same direction of resilience change. (b) Spatial proportions of each consistency category corresponding to panel (a). CER (i.e., virtually certain) denotes regions with a certain gain/loss in ecosystem resilience. LIK (i.e., likely) denotes regions with a potential gain/loss in ecosystem resilience. UNC denotes areas with high uncertainty in ecosystem resilience changes. The signs (+) and (–) refer to resilience gain and loss, respectively. Pixels lacking resilience values in at least one of the studies were excluded from the comparative analysis. (c) Preference ratio in UNC regions across four climate regions. (d) Preference ratio in UNC regions across four vegetation types. Preference ratio is defined as the proportion of a given climate zone or vegetation type within the uncertainty category, divided by its proportion across the entire study area (Methods). The study area in (a) corresponds to the region covered by the CSIF dataset.

rence Index (DCI) (See methods). Overall, only approximately 30.7% of pixels exhibited consistent resilience trends across all four vegetation variables, whereas 69.3% showed substantial disagreement, highlighting considerable uncertainty in resilience assessments arising from variable selection (Fig. 4a). Based on the distribution of DCI values, global ecosystem resilience changes were further classified into five categories: certain decrease (CER–), likely decrease (LIK–), certain increase (CER+), likely increase (LIK+), and uncertain (UNC) change (See Methods). Despite the pronounced inter-variable inconsistency, the consistency analysis reveals an overall decline in global ecosystem resilience. Approximately 42.2% of pixels exhibited decreasing resilience, including 17.7% classified as CER– and 24.5% as LIK–. In contrast, 32.9% of pixels showed increasing resilience, with 12.9% and 19.9% falling into the CER+ and LIK+ categories, respectively. The remaining 24.9% of pixels were characterized by uncertain resilience changes (Fig. 4a, UNC).

To further characterize the spatial distribution of uncertainty arising from different vegetation state variables, we conducted a focused analysis of pixels classified as uncertain (UNC) using the preference ratio metric (see Methods). The preference ratio measures the relative concentration of uncertainty within a region or ecosystem type, enabling the identification of areas with disproportionately high uncertainty. Our results show that uncertainty is strongly concentrated in tropical regions, which exhibit a preference ratio of 1.9 (Fig. 4c), and in forest ecosystems, with a preference ratio of 1.1 (Fig. 4d). This indicates that these regions contribute most to the overall uncertainty in ecosystem resilience quantification and are characterized by greater variability across vege-

tation indices. In contrast, arid regions (preference ratio = 0.5; Fig. 4c) and grassland ecosystems (preference ratio = 0.9; Fig. 4d) display the lowest preference ratios, suggesting a higher level of consistency in resilience estimates derived from different vegetation indices in these areas.

4.3. Key drivers of changes in ecosystem resilience

Dynamic vegetation models offer critical support for quantifying the contribution of climate change, atmospheric CO₂ concentration, and land-use change on ecosystem resilience. Here, leaf area index (LAI) derived from model outputs was used as the ecosystem state variable, and resilience changes were evaluated separately for each indicator to account for indicator-dependent model variability. Overall, the dynamic vegetation model reproduced observed patterns of ecosystem resilience change across more than half of the study domain (Fig. S3). We limited our analysis to regions where model-simulated resilience trends were consistent with observations. The attribution results consistently indicate that climate change is the dominant driver of terrestrial ecosystem resilience change, followed by atmospheric CO₂ concentration, whereas land-use change plays a comparatively minor role (Fig. 5). For the AR1 and VAR-based indicators associated with the CSD phenomenon, climate change (including both negative and positive contributions, CLI– and CLI+) is the dominant driver of ecosystem resilience changes in 61.3% (Fig. 5a) and 63.2% (Fig. 5b) of the pixels, respectively, with predominantly negative effects. Although the SK and KUR indicators do not display clear spatial patterns, statistical analyses consistently iden-

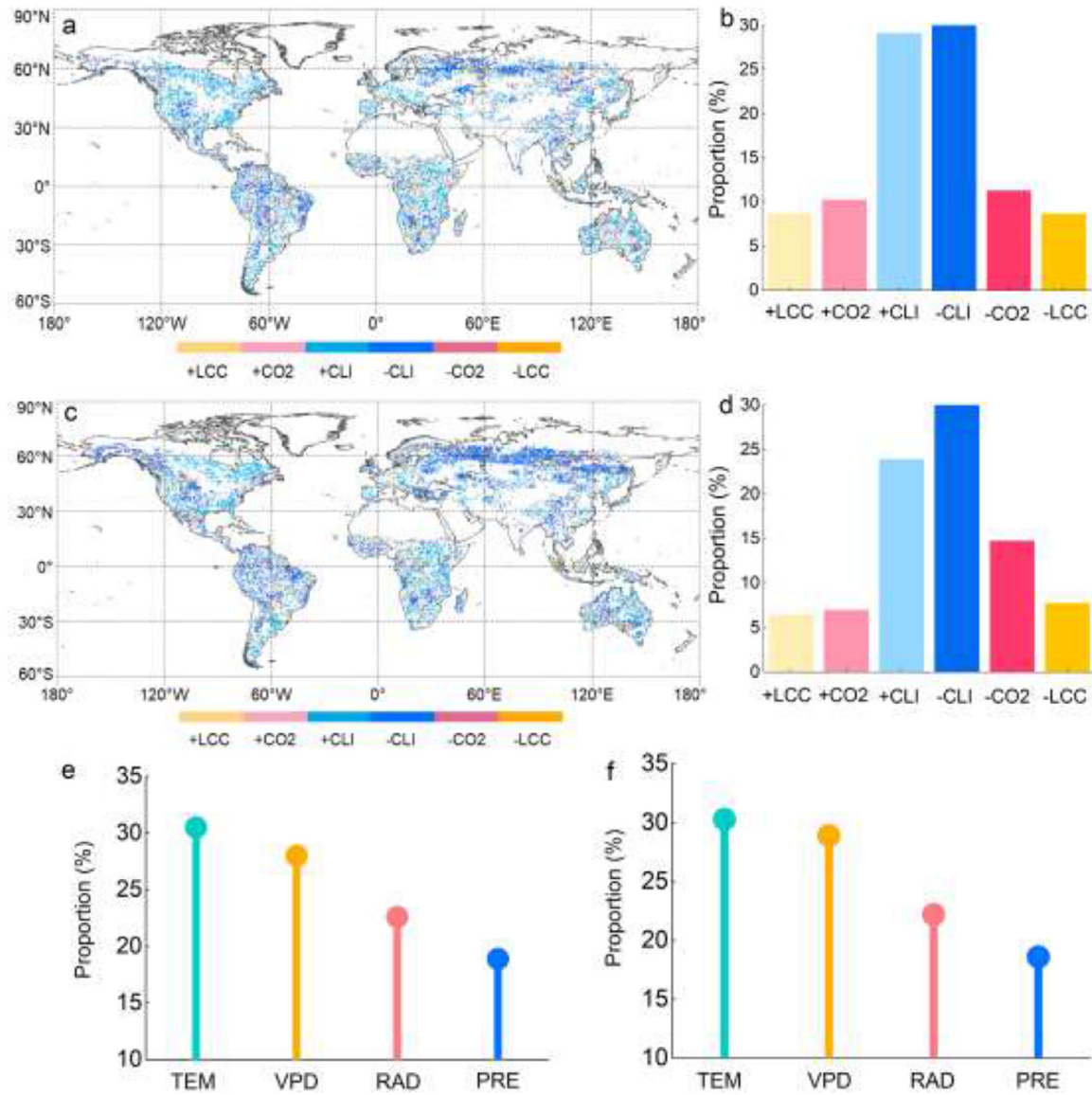


Fig. 5. Drivers of global ecosystem resilience change based on CSD. (a, c) Attribution of global ecosystem resilience trends derived from AR1 (a) and VAR (c), defined as the factor contributing most to the increase or decrease in resilience at each pixel. (b, d) Proportional distribution of dominant drivers based on AR1 (b) and VAR (d), indicating the fraction of pixels where each driver is dominant. “+” indicates a positive effect on resilience trends, and “-” indicates a negative effect. (e-f) Proportional distribution of dominant climatic drivers based on AR1 (e) and VAR (f), showing the fraction of pixels dominated by each climate variable. TEM, VPD, RAD, and PRE represent temperature, vapor pressure deficit, shortwave radiation, and precipitation, respectively.

tify climate change as the primary driver of resilience changes in 51.7% and 53.1% of pixels, respectively (Fig. S4).

After establishing that climate change is the dominant driver of ecosystem resilience changes, we further quantified the relative contributions of individual climatic factors. To this end, temperature, precipitation, radiation, and vapor pressure deficit (VPD) were selected as four core climate variables, and ridge regression was applied at the pixel scale within regions where model simulations were consistent with observational data, in order to identify the dominant climatic drivers of ecosystem resilience change (Methods). Our results indicate that temperature is the primary driver of global terrestrial ecosystem resilience change, exerting a substantially stronger influence than other climatic variables, followed by VPD (Figs. 5e,f and S4). In addition, climate change manifests not only through shifts in long-term mean states but also through changes in climatic variability. Further analyses reveal that changes in the climatic mean state exert a significantly stronger influence on ecosystem resilience than climatic variability (Figs. S5,S6), indicating that resilience responses at the global

scale are primarily driven by persistent shifts in long-term mean climate conditions.

5. Discussion and future direction

5.1. Capturing the multidimensional nature of ecosystem resilience across disturbance scenarios

We systematically reviewed the major concepts of ecosystem resilience in the current literature and found that definitions emphasizing different aspects of resilience fundamentally reflect its multidimensional nature. Further analysis indicates that quantitative assessments based on these conceptual frameworks are largely dependent on the types of disturbances experienced by ecosystems. Consequently, resilience quantified under different disturbance contexts often represents distinct ecological processes and response capacities, which, to some extent, limits the direct comparability and integrated interpretation of results across studies.

Existing resilience assessments based on resistance and recovery commonly rely on the implicit assumption that ecosystems fluctuate around a fixed reference or stable state [48,67]. However, under ongoing climate change and intensifying human influence, the use of fixed historical baselines or long-term means may obscure gradual structural and functional adjustments in ecosystems, leading to systematic misinterpretation of resilience levels. Meanwhile, climate-based sensitivity analyses provide valuable insights into ecosystem responses to long-term background changes [60,68], but these approaches typically assume linear and stationary climate–ecosystem relationships. As a result, they are better suited to persistent environmental pressures, while remaining limited in their ability to capture nonlinear responses and abrupt shifts associated with extreme or compound disturbances. In regions prone to droughts, heatwaves, or compound extremes, sensitivity metrics alone may therefore underestimate proximity to critical thresholds. We emphasize that future resilience quantification should adopt a disturbance-scenario-driven framework. This requires first identifying the dominant disturbance shaping ecosystem structure and function, and explicitly defining the disturbance context of the assessment. Reference states or stability assumptions should then be specified in a disturbance-dependent manner, rather than defaulting to historical baselines or long-term averages. Finally, cross-ecosystem comparisons should be restricted to cases with comparable disturbance contexts and reference states, while accounting for differences in ecosystem structure, function, and response characteristics, to avoid conceptual ambiguity and assessment bias.

5.2. State variable selection and observational data challenges in ecosystem resilience assessment

From a system-level perspective of ecosystem resilience, our study demonstrates that the choice of state variables can substantially influence the inferred patterns of resilience change. Ecosystem resilience derived from a single state variable captures only one dimension of ecosystem health and thus reflects attribute-specific “local resilience”, rather than overall structural and functional stability [55]. Consequently, reliance on a single variable may overlook key processes such as structural reorganization or functional transitions, limiting a comprehensive understanding of resilience dynamics. Moreover, existing ecosystem resilience indicators are highly sensitive to data noise, posing significant challenges for reliably characterizing ecosystem resilience using observational data [69]. For instance, in high-latitude regions, short growing seasons and frequent gaps in remote sensing observations hinder the effective detection of resilience changes [70]; in tropical and forest-dominated regions, the high uncertainty of optical remote sensing indices reduces the reliability of resilience assessments [71].

To address these limitations, future research should pursue coordinated methodological and data-driven advances. Integrate multi-source remote sensing with ecosystem model simulations to address observation gaps in high-latitude regions and reduce optical remote sensing uncertainties in tropical resilience assessments. Incorporating state variables that better capture ecosystem structure and function, such as biomass and functional diversity, would improve the ecological representativeness of resilience evaluations. Priority should also be given to ecologically sensitive regions, where long-term ground observations can constrain and validate model- and remote sensing–based resilience estimates, enhancing their robustness and reliability.

5.3. Limitations and methodological challenges of early-warning signals in ecosystem resilience assessment

Ecosystem resilience assessments based on early-warning signals provide important methodological support for detecting ecosystem state transitions and the approach to critical tipping points. However, our results show that different early-warning indicators often exhibit substantial uncertainty in characterizing changes in ecosystem resilience. Most

existing early-warning approaches rely on monotonic temporal trends in key statistical properties as signals of an approaching critical transition [36]. However, such monotonic trends are highly sensitive to the choice of temporal scale [72]. In the absence of clearly constrained reference baselines, statistical trends observed at different timescales may correspond to fundamentally different ecological processes, thereby complicating a consistent ecological interpretation of resilience changes. Theoretically, early-warning signals are based on the ball-and-cup model and the multiple stable states hypothesis [73], yet under nonstationary environmental conditions, it is often unclear whether ecosystems exhibit well-defined stable states or occupy high- or low- stability regimes.

We emphasize that efforts should focus on advancing early-warning signals from simple statistical trends to state-constrained resilience diagnostics. Based on ecosystem structure and environmental context, potential stable states should be identified using empirical knowledge and ecosystem attributes to guide signal interpretation [74]. The applicability and limits of indicators should be assessed across ecosystem types and temporal scales to avoid equating statistical signals with critical transition risk. Integrating stable-state identification with time-scale differentiation can improve the reliability and ecological interpretability of state-transition detection.

5.4. Identifying the key drivers and regulatory factors of ecosystem resilience change

Our study reaffirms the central role of climate change in driving changes in ecosystem resilience and further emphasizes temperature as the dominant climatic factor shaping resilience dynamics. Previous studies consistently show that declines in ecosystem resilience are closely associated with increases in mean temperature and temperature variability [75]. On the one hand, sustained warming systematically alters plant physiological processes, thereby weakening the ecosystems’ capacity to maintain structural and functional stability [76]; on the other hand, enhanced temperature variability increases environmental instability, making ecosystems more prone to functional fluctuations and even destabilization. In addition, warming-induced droughts often act as strong pulse disturbances that directly impact ecosystems and substantially reduce their ability to withstand external perturbations [77].

Ecosystems may partially adjust to long-term warming through physiological regulation, community reorganization, or functional substitution [78,79]; however, whether these adaptive processes can effectively buffer resilience loss when warming rates exceed the system’s intrinsic regulatory capacity has yet to be systematically and quantitatively evaluated. This gap reflects the fact that existing studies have largely focused on external climatic drivers of resilience change, while comparatively underestimating the role of intrinsic ecosystem structural attributes—such as community composition, functional diversity, and structural complexity—in modulating and buffering resilience responses [80]. It is necessary to quantitatively assess the upper limits of ecosystem regulatory capacity under different warming rates and their contributions to resilience maintenance, and to explicitly incorporate ecosystem structural characteristics as key modulators within resilience assessment frameworks to clarify their buffering or amplifying effects under climatic stress. Developing an integrated framework that links climatic drivers, ecosystem structure, and multi-scale disturbance processes will further strengthen the mechanistic basis and predictive capability of ecosystem resilience assessments, thereby enhancing the identification and anticipation of ecosystem stability risks under climate change.

6. Conclusion

Under intensifying global warming and the progressive activation of multiple global tipping elements, accurately characterizing ecosystem resilience is essential for anticipating ecosystem state transitions and associated tipping risks. However, divergent conceptual interpretations of resilience, together with the use of different resilience indi-

cators and vegetation state variables, lead to substantial inconsistencies in resilience assessments, limiting the robustness of global comparisons. Our results reveal that, under the CSD and FLI frameworks, 59.6% and 42.8% of pixels, respectively, yield significantly different resilience change assessments, while approximately 69.3% of pixels exhibit inconsistent trends across four vegetation state variables.

Further analyses reveal strong ecosystem dependence in these inconsistencies: temperate regions and arid ecosystems dominated by shrublands exhibit the lowest agreement across resilience indicators, whereas tropical ecosystems dominated by forests show greater uncertainty, primarily driven by the choice of vegetation state variables. Finally, we confirm that climate change is the dominant driver of global ecosystem resilience evolution and identify temperature change as a key factor restructuring global resilience patterns. These results emphasize the need for targeted frameworks to assess ecosystem resilience under global warming by integrating resilience multidimensionality, stable state characteristics, and disturbance types, thereby minimizing systematic misinterpretation and informing management and adaptation strategies.

Data availability statement

All data used in this study are freely and publicly accessible. The EVI and NDVI were obtained from the MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V061. The LAI was obtained from the MODIS/Terra+Aqua Leaf Area Index/FPAR 4-Day L4 Global 500m SIN Grid V061. The SIF dataset is available at https://osf.io/8xqy6/?view_only=4d14a64b7be644d39564c82a371e1d20. Land cover data were obtained from the MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V061. The 2-m air temperature was obtained from the European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA5). Monthly precipitation, vapor pressure deficit (VPD), and downward surface shortwave radiation were obtained from the TerraClimate dataset provided by the Climatology Lab.

Declaration of competing interest

The authors declare that they have no conflicts of interest in this work.

CRediT authorship contribution statement

Guoyan Yang: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Deliang Chen:** Writing – review & editing, Validation, Conceptualization. **Jingfeng Xiao:** Writing – review & editing, Validation. **Yuhao Feng:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Lanlan Guo:** Writing – review & editing, Supervision, Conceptualization. **Ziqian Zhong:** Writing – review & editing, Supervision, Investigation. **Yang Chu:** Writing – review & editing, Data curation, Conceptualization. **Zhongmin Hu:** Writing – review & editing, Supervision, Investigation, Conceptualization. **Bin He:** Writing – review & editing, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization.

Acknowledgments

This work was funded by the [National Natural Science Foundation of China \(42361144877\)](#), the Carbon Neutrality and Energy System Transformation (CNEST) Program and Tsinghua University (100008001) and the Research Grants Council of the Hong Kong Special Administrative Region, China (HKU PDFS2425-7S02).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.fmre.2026.05.014](https://doi.org/10.1016/j.fmre.2026.05.014).

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