

Interactive effects of severity and duration of compound dry-hot events on vegetation resistance time and recovery time in China

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ABSTRACT

Vegetation growth is increasingly affected by frequent and intense compound dry-hot events (CDHEs). However, how resistance time and recovery time of different vegetation types respond to the combined effects of multiple CDHE characteristics remain unclear. In this study, we developed a novel framework that integrates precipitation, potential evapotranspiration, soil moisture, and surface air temperature to systematically detect CDHEs, and quantified their impacts on vegetation resistance time and recovery time in China during the growing seasons from 1982 to 2022. Our results reveal that the occurrences, severity, and duration of CDHEs affecting vegetation show increasing trends in most parts of China from 1982 to 2022. Vegetation resistance shows a declining trend ($-0.27 \text{ decade}^{-1}$) while resilience exhibits an increasing trend ($0.009 \text{ decade}^{-1}$), with extreme CDHEs resulting in stronger resistance but lower resilience. The combined effects of severe severity and prolonged duration (≥ 3 months) significantly alter vegetation temporal responses: severe and long-duration CDHEs shorten forest resistance time by 2.2 months but extend recovery time by 1.3 months compared to mild and short-duration events. Vegetation resistance time and recovery time increase from arid regions (3.63 and 3.94 months) to humid areas (4.06 and 4.49 months), with grasslands showing significantly shorter response times (3.4 and 3.9 months) than forests (4.1 and 4.4 months). Additionally, precipitation emerges as the dominant driver of resistance time and recovery time. These findings underscore the need to consider interactive CDHE characteristics when evaluating vegetation vulnerability and guiding ecosystem management.

1. Introduction

Compound dry-hot events (CDHEs), characterized by the simultaneous occurrence of high temperature and drought, are climate extremes jointly driven by insufficient precipitation, rapid soil moisture depletion, and increased atmospheric evaporative demand caused by extreme heat (Perkins-Kirkpatrick and Lewis, 2020; Xu et al., 2024a; Zhou et al., 2023). Notably, such events may occur more frequently and with greater severity than non-hot droughts (i.e., precipitation-deficit droughts) (Mehran et al., 2015; Qi et al., 2022). These CDHEs have been associated with reduced photosynthesis (Arani et al., 2021; Smith et al., 2022), substantial declines in land-atmosphere carbon fluxes (Brand and Jax, 2007; Schwalm et al., 2017), and increased forest mortality (Sun et al., 2024b; Yao et al., 2022). Given that ecosystem resistance and resilience are critical for maintaining functional stability (De Keersmaecker et al., 2015; Smith and Boers, 2023), it is of great scientific significance to explore ecological response mechanisms under

CDHEs (He et al., 2022; Yao et al., 2024b; Zhang et al., 2023b).

Resistance time and recovery time of vegetation are key indicators for evaluating ecosystem responses during and after CDHEs, representing the time required to withstand disturbances and return to a pre-event state (Feng et al., 2021; Gazol et al., 2018; Whitman et al., 2019). Previous studies have mostly estimated these two temporal indicators using correlation-based methods, which are easily affected by vegetation dynamics unrelated to compound drought-heat stress and fail to capture the nonlinear and asymmetric interactions between drought and heat (Boulton et al., 2022; Forzieri et al., 2022; Tao et al., 2023). Traditional approaches relying on full time series or auto-regressive models also struggle to isolate ecosystem responses tied to the onset and end of CDHEs (Allen et al., 2019; DeSoto et al., 2020; Liu et al., 2021b). Studies show that drought impacts are especially strong during the growing seasons, the frequency, severity, and spatial extent of droughts can significantly reduce vegetation productivity (Ivits et al., 2016). However, compared to isolated droughts, CDHEs exert stronger and more

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persistent water and heat stress across the entire growing season. Analyses focusing only on short-term summer events may overlook cumulative effects and underestimate vegetation's long-term adaptive capacity (Sun et al., 2024a). These methodological limitations underscore the need for a growing-season-scale framework that explicitly links CDHE onset and cessation to vegetation temporal responses.

In addition, vegetation growth is shaped not only by CDHEs themselves but also by the multidimensional characteristics of CDHEs (Buermann et al., 2018; Zhang et al., 2025), including severity (Xue et al., 2023) and duration (Zhang et al., 2021), with their impacts varying across climatic zones and hydrothermal regimes (Hosseinzadehtalaei et al., 2024). Although more frequent droughts have been associated with significantly prolonged vegetation recovery time (Hu et al., 2021; Luo et al., 2024), severity alone does not fully capture the compound impacts of concurrent drought and heat (Jiang et al., 2025; Zhao et al., 2025a). Longer-duration events have been shown to induce xylem cavitation and hydraulic failure in trees (Wang et al., 2025a). These findings suggest that severity and duration jointly shape the impacts of CDHEs, yet current studies lack integrated assessments of how vegetation resistance time and recovery time respond to multiple characteristics of CDHEs. Such integrated assessments are particularly needed given that the relative importance of severity and duration may vary substantially across vegetation types and climatic zones.

Moreover, vegetation types differ significantly in their responses to drought and heat stress (Bai and Tang, 2024; De Keersmaecker et al., 2016; Kong et al., 2022). However, existing research has yielded contradictory and inconsistent results regarding differences in vegetation types. Some research reports suggest that grasslands recover faster than forests due to their physiological plasticity and shallow root systems that can quickly recover after rainfall (Chandregowda et al., 2023; Hoover et al., 2014), while others find that under prolonged CDHEs, grasslands experience more severe and persistent productivity losses than forests because of their limited carbon storage capacity and shallower rooting depth (Bottero et al., 2021; Xu et al., 2024c). Similarly, while forests are generally considered more resistant to short-term drought stress owing to deep root access to subsoil moisture, several studies have shown that forests exhibit disproportionately long recovery times under severe CDHEs due to cumulative carbon depletion and hydraulic damage (Kannenberget al., 2020; Müller and Bahn, 2022). Meanwhile, global and regional studies on single climate drivers have found that in the northern arid and semi-arid regions vegetation typically exhibits stronger resistance with longer recovery time, whereas in the humid regions the situations are opposite (Li et al., 2022; Yao et al., 2023). The dominant climatic factors controlling vegetation responses have been found to vary spatially depending on local environmental conditions and climate regimes (Hu et al., 2024; Yao et al., 2024a; Yao et al., 2024b). These contradictions highlight the absence of a unified, spatially comprehensive framework for systematically comparing resistance time and recovery time across vegetation types and climate zones in China, directly motivating the present study (Han et al., 2025; Xu et al., 2018; Zhang et al., 2023a). Resolving this spatial heterogeneity requires a nationally comprehensive analysis that simultaneously accounts for vegetation type, climate zone, and CDHE characteristics (Du et al., 2025; Yuan et al., 2024).

The CDHEs in China have shown significant increases in frequency, severity, and spatial extent over recent decades due to anthropogenic warming and changes in large-scale atmospheric circulation patterns (Wu et al., 2022; Yu and Zhai, 2020). Severe CDHEs have been documented across multiple regions, including the Sichuan-Chongqing Basin in 2006, Yunnan in 2010, and the middle and lower Yangtze River Basin in 2022, each causing substantial reductions in vegetation productivity and ecosystem carbon sinks (Li et al., 2020; Xu et al., 2024b; Zhang et al., 2016). Despite growing recognition of these impacts, existing studies in China have largely focused on characterizing CDHE spatio-temporal trends or quantifying their effects on gross primary

productivity and NDVI at seasonal or annual scales (Wu and Jiang, 2022; Yu and Zhai, 2020). The temporal dimensions of ecosystem responses, specifically how long vegetation can resist CDHE stress and how quickly it recovers afterward across China's diverse climatic regions and vegetation types, remain poorly understood (Du et al., 2025; Han et al., 2025). Addressing this gap is of direct practical significance for ecological risk assessment, vegetation restoration planning, and climate-adaptive ecosystem management across China (Fu et al., 2023; Yin et al., 2023).

Most existing studies have primarily focused on resistance and resilience, but resistance time and recovery time are key temporal dimensions of ecosystem responses that should not be overlooked (Li et al., 2025; Yang et al., 2023; Yao et al., 2024b). Given this context, it is necessary to systematically identify and analyze the occurrence of CDHEs during growing seasons over the past few decades and reveal how different vegetation types respond to their compound characteristics and corresponding differences. Based on previous researches, this study integrates precipitation, potential evapotranspiration, soil moisture, and surface air temperature to detect the CDHEs that affect the vegetation in growing seasons (Ali et al., 2019; Byakatonda et al., 2018) and addresses the following questions: (a) What are the characteristics of CDHEs that affect vegetation in China? (b) How do the resistance time and recovery time of vegetation vary with climate zones and vegetation types? (c) How do the different combined characteristics of CDHEs influence the vegetation resistance time and recovery time? The findings are expected to advance mechanistic understanding of vegetation responses to compound climate extremes and provide a spatially explicit scientific basis for ecological risk assessment and climate-resilient ecosystem management across China's diverse climatic regions.

2. Data and methods

2.1. Data

The data used in this study are listed as follows:

1. Near-surface (2 m) air temperature and soil moisture data at three depths (0–7 cm, 7–28 cm, and 28–100 cm) from 1982 to 2022 are derived from the monthly ERA5-land reanalysis dataset with a horizontal resolution of 0.1° (Muñoz-Sabater et al., 2021). ERA5-land provides consistent, long-term, and high-quality climate data by assimilating multiple observations, making it suitable for regional climate and hydrological studies (Li et al., 2022). The standardized precipitation evapotranspiration index (SPEI), representing drought severity and duration, is derived from the CHM drought dataset from 1982 to 2022 with the horizontal resolution of 0.1°. This dataset has demonstrated reliable performance in capturing drought events across mainland China (Zhang et al., 2025). SPEI is widely used as it integrates precipitation and potential evapotranspiration, reflecting water balance more comprehensively than precipitation alone (Ma et al., 2025).
2. The normalized difference vegetation index (NDVI), an indicator of vegetation greenness and health, is obtained from the GIMMS NDVI Version 1.2 dataset, which offers a semi-monthly (~15 days) temporal resolution and spatial resolution of 0.0833° (~10 km) from 1982 to 2022 (Zhao et al., 2022). GIMMS NDVI has been extensively validated and widely applied in global and regional long-term vegetation dynamics monitoring (Li et al., 2023).
3. The climate zone classification data for China were obtained from the National Earth Observation Data Center (Fig. 1). Climate zones were delineated based on the aridity index (AI), defined as the ratio of mean annual precipitation to mean annual potential evapotranspiration. Four climate zones were classified: arid ($AI < 0.2$), semiarid ($0.2 \leq AI < 0.5$), sub-humid ($0.5 \leq AI < 0.65$), and humid ($AI \geq 0.65$) (Tian and Tian, 2026; Zomer et al., 2022). Vegetation distribution was derived from the annual Chinese Land Cover Dataset (CLCD)

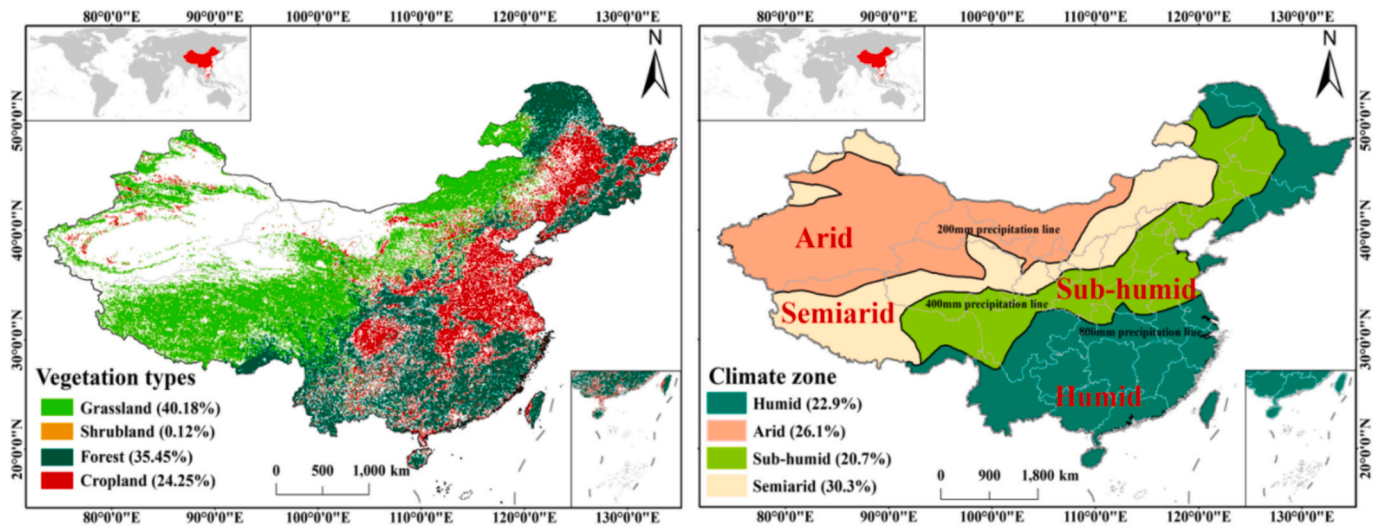


Fig. 1. Spatial distribution of major vegetation types and climatic zones in China. Vegetation types (left map) include grassland, shrubland, forest, and cropland. Climatic zones (right map) include humid, sub-humid, arid, and semi-arid regions. The numbers in parentheses indicate the percentage of the total area covered by each vegetation type (sum of all vegetation types) and each climatic zone (sum of all climate zones), respectively.

during 1985–2022 with 30 m spatial resolution (Yang and Huang, 2021). The fine spatial detail and long temporal coverage of CLCD make it particularly suitable for tracking long-term vegetation patterns and land cover changes at regional to national scales (Cai et al., 2024). In this study, vegetation was grouped into four primary classes: forest, grassland, shrubland, and cropland (Fig. 1).

To ensure consistent spatial resolution across datasets, all gridded data were resampled to 0.0833° (~ 10 km), consistent with the NDVI dataset, to enable integrated analysis.

2.2. Methods

2.2.1. Definition of compound dry-hot events

In this study, monthly standardized indices were used to detect CDHs from 1982 to 2022, including the SPEI which represents the difference between precipitation and evapotranspiration, the standardized soil moisture index (SSMI) which represents the anomalous soil moisture conditions, and the standardized temperature index (STI) which indicates the temperature anomaly conditions (Han et al., 2018; Seo and Lee, 2023). These indices capture short-term vegetation responses to the hydrothermal regime of land surface (Liao et al., 2025). The SSMI is calculated based on the soil moisture of the ERA5-Land reanalysis dataset at the top three layers of soil. Root-zone (0–100 cm) soil moisture is derived using a weighted average of the three layers: $SM_{0-7cm} \times 0.07 + SM_{7-28cm} \times 0.21 + SM_{28-100cm} \times 0.72$ (Gu et al., 2025).

Regarding the standardization of SSMI and STI, the marginal distribution of monthly accumulated soil moisture or air temperature is first fitted to obtain the cumulative probability P , which is then transformed into a standardized variable using the standard normal quantile function (Feng et al., 2021):

$$SSMI/STI = \varphi^{-1}(P) \quad (1)$$

Where $\varphi^{-1}(\bullet)$ denotes the inverse of the standard normal cumulative distribution function. This procedure ensures that both indices are dimensionless and comparable across different climatic regions and seasons.

Regarding the threshold selection, the thresholds of $SPEI \leq -0.5$, $SSMI \leq -0.5$, and $STI \geq 0.5$ were selected based on established criteria in previous studies (Cao et al., 2026; Li et al., 2026; Liao et al., 2025), corresponding to mild-to-moderate drought and above-normal

temperature anomaly conditions that are sufficient to impose measurable stress on vegetation. The combined threshold of $CDHI \leq -1.5$ directly follows from the simultaneous satisfaction of all three individual thresholds, since $CDHI = SPEI + SSMI - STI \leq (-0.5) + (-0.5) - (0.5) = -1.5$. This mathematical equivalence ensures that the CDHI threshold is not arbitrary but is directly derived from the three physically meaningful component thresholds.

Moreover, we constructed a compound dry-hot index (CDHI) to detect the simultaneous occurrence of all three indices within the same month. A compound dry-hot event (CDHE) is defined as the concurrent occurrence of $SPEI \leq -0.5$, $SSMI \leq -0.5$, and $STI \geq 0.5$ (Fig. 2a). Then $CDHI = SPEI + SSMI - STI$, so a CDHE is identified when the $CDHI \leq -1.5$, indicating that the meteorological drought, soil drought, and high temperature stress occur simultaneously (Fig. 2b).

To validate the reliability of the CDHI in detecting CDHs, two complementary approaches were employed. First, the spatial patterns of CDHI were compared against historical compound dry-hot events documented in the China Meteorological Disaster Yearbook (Hao et al., 2017; Wang et al., 2023b), including the 2006 Sichuan–Chongqing event, the 2010 Yunnan event, the 2013 Guizhou event, and the 2022 middle and lower Yangtze River basin event. Second, to assess whether the linear formulation adequately captures the non-linear synergistic interactions among drought and heat drivers, a three-dimensional Vine Copula framework was constructed to model the joint distribution of SPEI, SSMI, and STI, and its CDHE identification results were compared with those derived from the linear CDHI at four representative grid points across the study region.

The Vine Copula also known as the Pair-Copula Construction (PCC), decomposes a high-dimensional joint distribution into a cascade of bivariate conditional copulas linked through a hierarchical vine structure (Bevacqua et al., 2017). This approach offers considerable flexibility in capturing complex non-linear and asymmetric dependence structures among multiple variables (Wu and Liu, 2024). Among the two main vine structures, the C-vine (canonical vine) places a central variable at the core of each tree level, making it particularly suitable for capturing the dependencies between a dominant variable and all others. The D-vine (drawable vine) arranges variables in a chain-like sequence and is more appropriate for describing strong dependencies among ordered or adjacent variables (Sreekumar et al., 2022). In this study, the C-vine structure was adopted given the central role of STI in modulating both atmospheric water demand and soil moisture dynamics under compound dry-hot conditions. The joint probability density function of

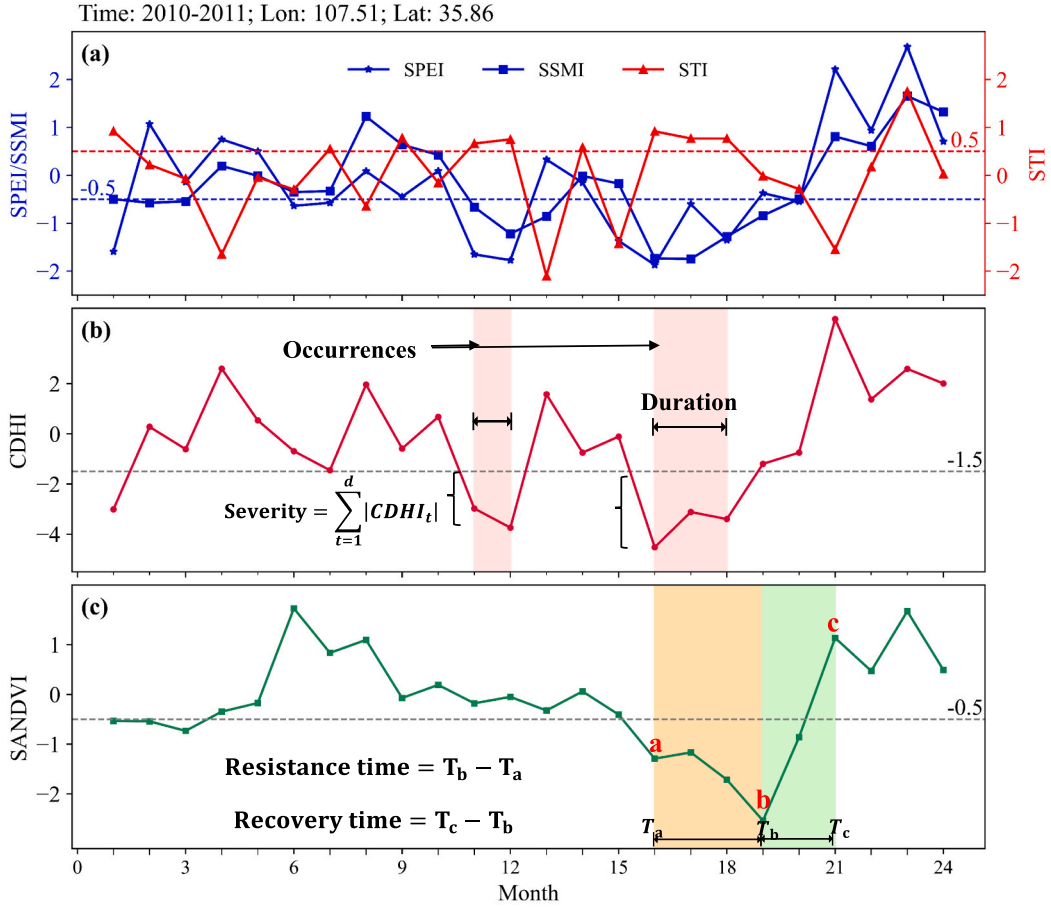


Fig. 2. Schematic illustration of the definition of CDHEs (a), their basic characteristics (b), and vegetation resistance time and recovery time during CDHEs (c). An example from a single pixel in 2010–2011 is shown. (a) shows the temporal variation of SPEI, SSMI, and STI during 2010–2011, where the blue dashed line (≤ -0.5) represents the threshold for SPEI/SSMI, and the red dashed line (≥ 0.5) represents the threshold for STI. (b) shows the CDHI time series calculated from multiple indices, where periods with $\text{CDHI} \leq -1.5$ are identified as CDHEs. Three key parameters are shown: occurrence (the number of events), duration (the length of consecutive months for a single event), and severity (the cumulative sum of the absolute CDHI values during an event). (c) shows the vegetation resistance time and recovery time during CDHEs. Resistance time is defined as the time from the onset of a CDHE (point a) to the lowest SANDVI (point b), where $\text{SANDVI} < -0.5$, calculated as $T_b - T_a$. Recovery time is defined as the time from the lowest SANDVI (point b) to the first occurrence of $\text{SANDVI} \geq -0.5$ indicating vegetation recovery (point c) and equals to $T_c - T_b$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

an n-dimensional C-vine for random variables $z = (z_1, z_2, \dots, z_n)$ is expressed as:

$$f(z_1, \dots, z_n) = \prod_{i=1}^n f_i(z_i) \cdot \prod_{j=1}^{n-1} \prod_{i=1}^{n-j} c_{j,j+i|1, \dots, j-1} (F(z_j|z_1, \dots, z_{j-1}), F(z_{j+i}|z_1, \dots, z_{j-1})) \quad (2)$$

where $f_i(z_i)$ denotes the marginal probability density function of each variable; $F(z_i)$ denotes the corresponding marginal cumulative distribution function; and $c_{j,j+i|1, \dots, j-1}$ represents the bivariate copula density linking the conditional distributions of z_j and z_{j+i} given the conditioning set $\{z_1, \dots, z_{j-1}\}$.

In this study, the C-vine was constructed for SPEI, SSMI, and STI, with STI designated as the central variable given its dominant role in modulating atmospheric evaporative demand and soil moisture dynamics under compound dry-hot conditions. A CDHE is defined as the concurrent occurrence of meteorological drought ($\text{SPEI} \leq -0.5$), soil moisture deficit ($\text{SSMI} \leq -0.5$), and heat stress ($\text{STI} \geq 0.5$). The conditional probability of soil moisture deficit given the concurrent drought and heat stress conditions is derived as:

$$P(\text{SSMI} \leq -0.5 | \text{SPEI} \leq -0.5, \text{STI} \geq 0.5) = C_{\text{SSMI}, \text{SPEI} | \text{STI}}(F(-0.5), F(-0.5) | F(0.5)) \quad (3)$$

where $F(-0.5)$ in the first argument denotes the cumulative distribution function of SSMI evaluated at the threshold -0.5 ; $F(-0.5)$ in the second argument denotes the CDF of SPEI evaluated at -0.5 ; and $F(0.5)$ denotes the CDF of STI evaluated at 0.5 . $C_{\text{SSMI}, \text{SPEI} | \text{STI}}$ represents the conditional bivariate copula density of SSMI and SPEI given STI. The three threshold conditions ($\text{SPEI} \leq -0.5$, $\text{SSMI} \leq -0.5$, $\text{STI} \geq 0.5$) correspond to the simultaneous occurrence of meteorological drought, soil moisture deficit, and above-normal temperature anomaly, respectively, consistent with the CDHE identification criteria defined in Section 2.2.1. The optimal vine structure was selected using the Akaike Information Criterion (AIC), and model parameters were estimated via Maximum Likelihood Estimation (MLE). All computations were implemented using the CDVineCopula package in R.

As shown in Fig. 2b, the characteristics of CDHEs include three facets: (1) the occurrences, which denote the total number of events within a specified period; (2) the severity, which represents the cumulative sum of absolute CDHI values during each event and was calculated as $\text{Severity} = \sum_{t=1}^d |\text{CDHI}_t|$, where d (unit: months) is the duration of a given CDHE; and (3) the duration, which refers to the number of

successive months from the beginning to the end of each event. Moreover, based on the percentile ranks of historical severity, the CDHEs are classified into mild (0-33rd percentiles), moderate (33rd-66th percentiles), and severe (66th-100th percentiles) events. In terms of the duration time, the CDHEs are categorized as short-duration (1 month), medium-duration (2 months), and long-duration (≥ 3 months) events.

2.2.2. Definition of vegetation growth

CDHEs and the corresponding negative vegetation anomalies are identified based on CDHI and vegetation data, respectively. NDVI is aggregated to the monthly scale using the maximum value composite method, with a threshold (e.g., 0.1) applied to exclude sparsely vegetated areas (Liu et al., 2016). Therefore, only regions with $NDVI \geq 0.1$ were included in the analysis. A least-squares detrending method (Deng et al., 2021) was employed to eliminate long-term trends and seasonal fluctuations from the time series of SPEI, SSMI, CDHI, and NDVI.

To quantify the magnitude of vegetation anomalies, we calculated the standardized anomaly of NDVI (SANDVI) using the following equation:

$$SANDVI_{i,m,k} = \frac{NDVI_{i,m,k} - \overline{NDVI_{i,m}}}{\sigma_{i,m}} \quad (4)$$

where $SANDVI_{i,m,k}$ is the normalized NDVI anomaly at a given grid point i in the m^{th} month of a year ($m = 4, \dots, 10$, from April to October), k indicates the k^{th} year ($k = 1, \dots, 41$, from 1982 to 2022). $\overline{NDVI_{i,m}}$ is the climatic mean NDVI at the grid point i in the m^{th} month of a year, and $\sigma_{i,m}$ is the standard deviation of NDVI at the grid point i in the m^{th} month of a year.

In this study, we used a SANDVI threshold of -0.5 to identify the vegetation resistance time and recovery time (Jiang et al., 2024). In addition, only pixels that maintained the same land cover type over the past 40 years were retained to avoid the influence of land cover change (Fig. 1). Considering the vegetation dormancy period, we focused on NDVI changes during the growing seasons (April to October) (Liu et al., 2025c). Only effective CDHEs with the simultaneous occurrence of $SANDVI < -0.5$ and $CDHI \leq -1.5$ are included in subsequent analyses.

2.2.3. Impacts of CDHEs on the vegetation resistance time and recovery time

To comprehensively quantify vegetation responses to CDHEs, vegetation resistance time is defined as the interval between the onset of a CDHE and the month when vegetation experiences its maximum damage (Yu et al., 2017), as illustrated in Fig. 2c. The calculation is formulated as:

$$\text{Resistance time} = T_b - T_a \quad (5)$$

Resistance time is measured as the interval from the first appearance of $SANDVI < -0.5$ (point **a** in Fig. 2c) to the occurrence of the most severe $SANDVI$ (point **b** in Fig. 2c) after a CDHE. Specifically, the point **a** corresponds to the month T_a marking the beginning of $SANDVI < -0.5$, while point **b** corresponds to the month T_b of the lowest $SANDVI$. The resistance time is calculated as $T_b - T_a$.

Recovery time refers to the time interval from the month of vegetation maximum damage to the month when vegetation returns to its normal state (Ingrisch and Bahn, 2018), as illustrated in Fig. 2c. It is calculated as:

$$\text{Recovery time} = T_c - T_b \quad (6)$$

where T_c is the month when vegetation returns to normal defined as the first month with the $SDNDVI \geq -0.5$ after a CDHE corresponding to point **c** in Fig. 2c. Recovery time is the time interval between the T_c and T_b . Ecosystems with shorter recovery time recover more quickly, whereas those with longer recovery time exhibit lower recovery capacity and heightened vulnerability (Isbell et al., 2015; Jiang et al.,

2024).

In addition to temporal metrics, we calculated vegetation resistance capacity and resilience to better quantify ecosystem stability under CDHEs (Yao et al., 2022a). It is calculated as:

$$\text{Resistance} = \frac{T_b - T_a}{|SANDVI_b - SANDVI_a|} \quad (7)$$

$$SANDVI_a = \frac{S_{\text{onset}} + S_{\text{onset}-1}}{2} \quad (8)$$

$$\text{Resilience} = \frac{|SANDVI_c - SANDVI_b|}{T_c - T_b} \quad (9)$$

Where $SANDVI_b$ represents the negative vegetation anomaly during the month of maximum impact, while $SANDVI_a$ denotes the negative anomaly at the onset of the event. Here, we calculated the average of the negative anomaly at the event start (S_{onset}) and the previous moment ($S_{\text{onset}-1}$). $SANDVI_c$ refers to the first occurrence of the $SANDVI \geq -0.5$ after the termination of the CDHEs. The units of resistance and resilience are Months/ Δ NDVI (abbreviated as $\text{mon} \cdot \text{n}^{-1}$) and Δ NDVI/Months (abbreviated as $\text{n} \cdot \text{mon}^{-1}$), respectively (Jiang et al., 2024).

3. Results

3.1. Reliability validation of the CDHI

The spatial patterns of CDHI during four major historical CDHEs are presented in Fig. 3. During June–August 2006, pronounced negative CDHI anomalies ($CDHI \leq -1.5$) were concentrated in the Sichuan Basin and Chongqing (Fig. 3 a1–a3). Similarly, strong CDHI signals were observed in Yunnan during January–March 2010 (Fig. 3 b1–b3), in Guizhou during January–March 2013 (Fig. 3 c1–c3), and across the middle and lower Yangtze River basin during June–August 2022 (Fig. 3 d1–d3). The spatial correspondence between the CDHI-identified events and historical records confirms that the CDHI effectively captures the occurrence and spatial extent of CDHEs across diverse climatic and topographic settings in China (Chen et al., 2024; Wu et al., 2020).

At four representative grid points located in the humid subtropical climate zone, the calculated monthly time series of CDHI were further compared with the time series obtained by Copula method (Fig. 4). The region is often affected by CDHE, including Chengdu (Fig. 4a–b), Chongqing (Fig. 4c–d), Wuhan (Fig. 4e–f), and Nanjing (Fig. 4g–h). Between 1982 and 2022, the Copula based index and the calculated CDHI time evolution showed strong consistency across all four locations. In terms of the number of events, the consistency rate range between the two methods is 0.87 to 0.91, and the Kappa coefficient range is 0.68 to 0.79, indicating that the results of the two methods are basically consistent, and confirming that the calculated CDHI provides a reliable characterization of composite dry heat conditions consistent with more complex Vine Copula based methods.

3.2. Characteristics of CDHEs affecting the vegetation in China during 1982–2022

From Fig. 5a, the total occurrences of CDHEs affecting the vegetation in China during the growing seasons of 1982–2022 increase from south to north with high centers located in northern, northwestern and northeastern China. Fig. 5b demonstrates that CDHE occurrences across most China in growing seasons show positive long-term trends during 1982–2022. The histogram reveals that $\sim 70\%$ of grid points exhibit increasing trends, with statistically significant upward trends (marked by black dots) mainly located in northern Xinjiang, the Loess Plateau, and the North China Plain. Regions with increasing rates exceeding 0.2 occurrences decade $^{-1}$ account for $\sim 15\%$ of the total vegetated area. Meanwhile, the climatic mean severity of CDHEs with values ≥ 6 are primarily located in the west-central Northeast China Plain, central

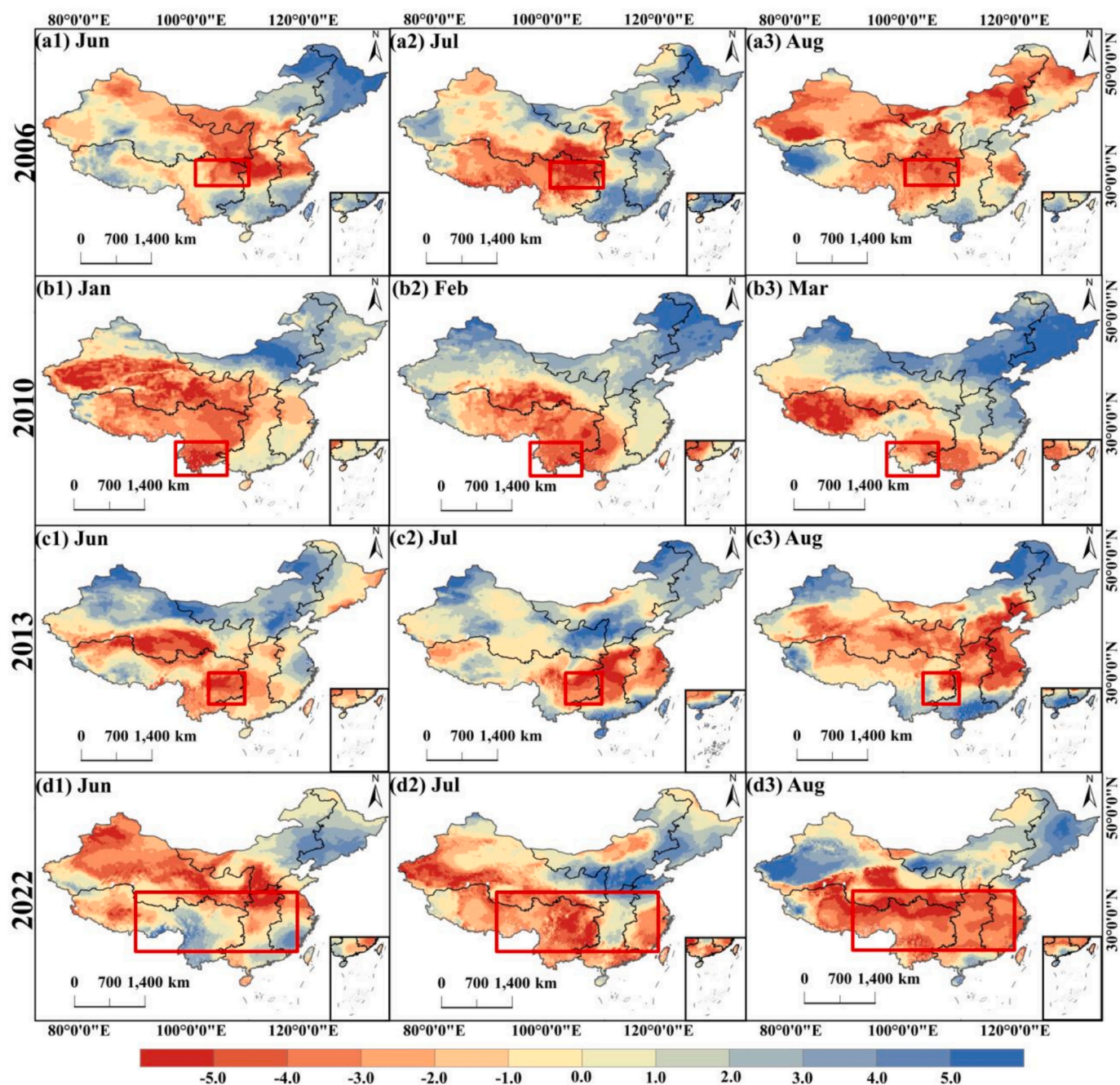


Fig. 3. Spatial patterns of the Compound Dry-Hot Index (CDHI) in typical regions of China. (a1–a3) show CDHI in Sichuan and Chongqing from June to August 2006; (b1–b3) show Yunnan from January to March 2010; (c1–c3) show Guizhou from January to March 2013; and (d1–d3) show the middle and lower reaches of the Yangtze River from June to August 2022, highlighting areas that experienced historical high-temperature and drought events.

Inner Mongolia Plateau, and northwestern parts of southeastern China (Fig. 5c). As illustrated in Fig. 5d, the severity of CDHEs in vegetated areas over most China shows increasing trends during 1982–2022. The histogram indicates that ~65% of grid points display upward trends. And the centers with significant increasing rates of severity are located in northern Xinjiang, northeastern Inner Mongolia Plateau, the Loess Plateau, and central-southern parts of Eastern China. Areas with trend values exceeding 1.0 decade^{-1} represent ~20% of the total vegetated areas. The climatic mean duration of CDHEs in China ranges from 1 to 3 months, with ~15% of vegetated regions experiencing duration exceeding 2.6 months, primarily concentrated in eastern Inner Mongolia and western Northeast China (Fig. 5e). Fig. 5f reveals that the duration of CDHEs in most China exhibits increasing trends during 1982–2022.

Histogram statistics show that ~75% of grid points demonstrate upward trends, with significant increasing trends exceeding $0.1 \text{ months decade}^{-1}$ mainly concentrated in northern Xinjiang, the Loess Plateau, northeastern Inner Mongolia Plateau, and central-southern parts of eastern China, accounting for ~30% of the total vegetated areas. Only about 20% of grid points exhibit decreasing trends.

From 1982 to 2022, CDHEs affecting vegetation in China exhibited a clear upward trend in occurrences, severity, and duration (Fig. 6). The annual occurrence rate of CDHEs (Fig. 6a) showed a modest yet steady increase of 0.03 times per decade, indicating that such events are becoming more common over time. In contrast, the severity of CDHEs increased significantly by 0.75 per decade, with the most severe event recorded in 2022 (Fig. 6b). Moreover, the average duration of CDHEs

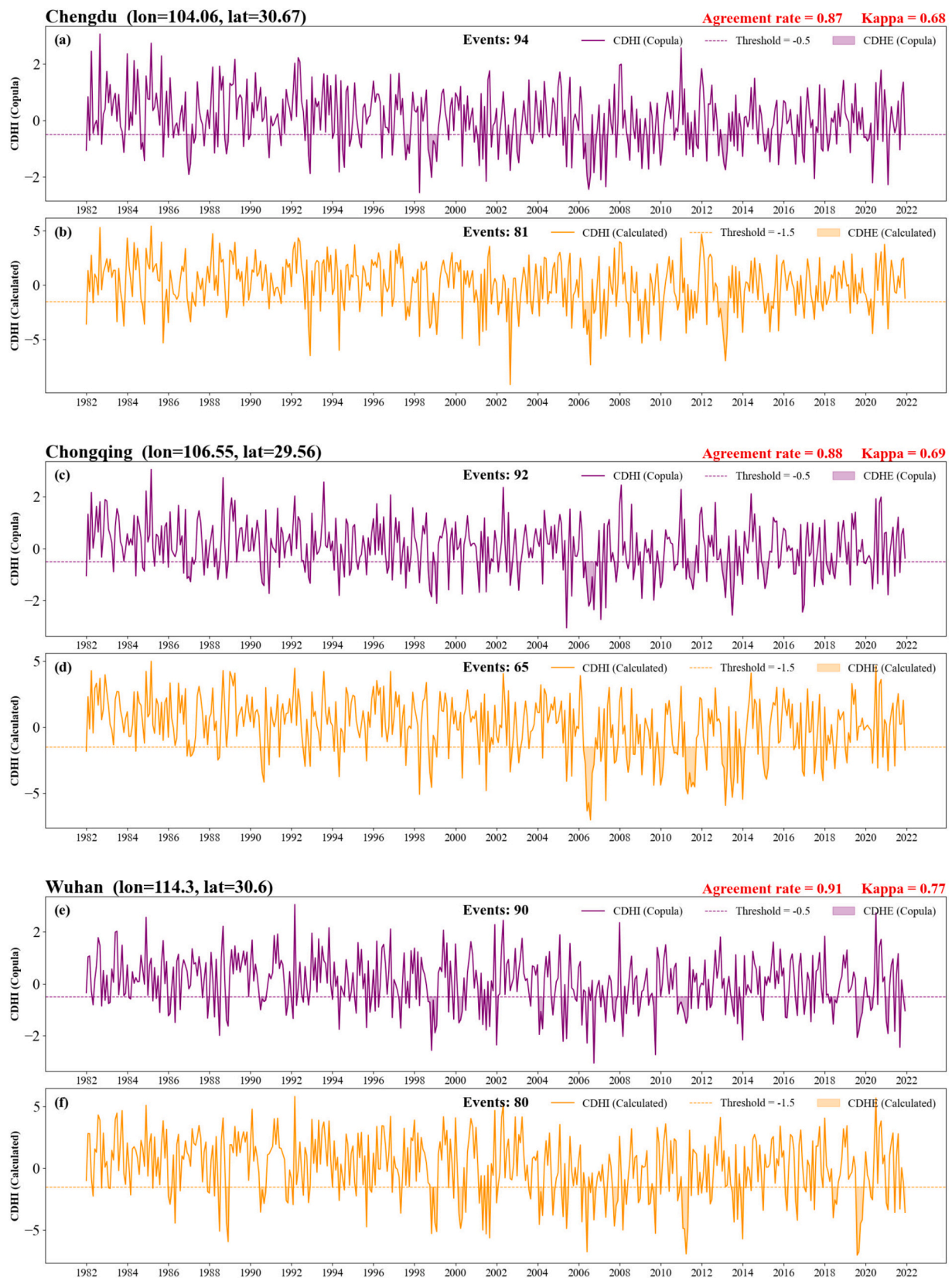


Fig. 4. Comparison of monthly time series of the Vine Copula-based index and the linearly calculated CDHI (threshold ≤ -1.5) at four representative grid points (Chengdu, Chongqing, Wuhan, and Nanjing) over the period 1982 to 2022. For each city, the upper panel (a, c, e, g) shows the Vine Copula-based CDHI with a threshold of ≤ -0.5 , and the lower panel (b, d, f, h) shows the linearly calculated CDHI with a threshold of ≤ -1.5 . Shaded areas indicate periods identified as CDHEs. Agreement rate and Kappa coefficient between the two methods are displayed in the upper right corner above each city's upper panel.

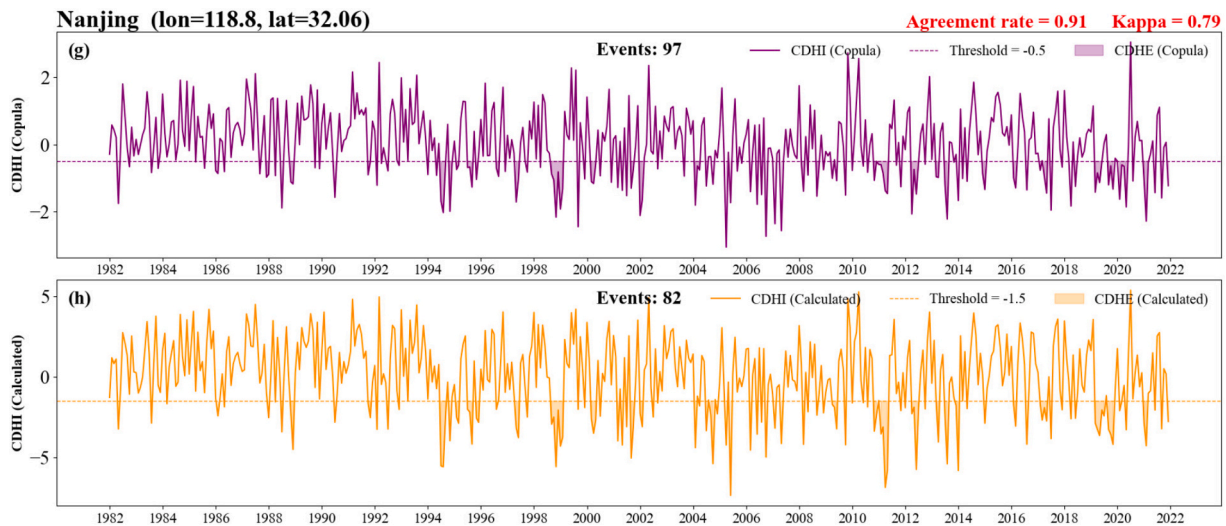


Fig. 4. (continued).

extended by 0.13 months per decade (Fig. 6c).

CDHEs exhibited pronounced seasonality, with around 40% of events occurring in April (20.1%) and May (19.9%) (Fig. 7a). Hotspots in April were found in the Qaidam Basin (5.5 times), the Loess Plateau (7.3 times), and the Yunnan-Guizhou Plateau (5.3 times), while May hotspots were mainly located in the Northeast China Plain (4.6 times). During summer (June–August), hotspots were concentrated in the Inner Mongolia Plateau (7.8 times) and the Qinghai-Tibet Plateau (3.8 times) (Fig. 7b). Overall, the long-term trends of CDHE occurrence, severity, and duration show remarkably similar spatial distributions. This indicates that the vegetation in northern Xinjiang, the Loess Plateau, northeastern Inner Mongolia Plateau, and other regions is facing increasingly severe threats from CDHEs.

3.3. The vegetation resistance time and recovery time under the CDHEs

As shown in Fig. 8a, vegetation resistance exhibits distinct spatial heterogeneity across China, with relatively high values in southeastern China (50th percentile: 34 $\text{mon}\cdot\text{n}^{-1}$) and notably lower values in the Inner Mongolia Plateau (50th percentile: 11 $\text{mon}\cdot\text{n}^{-1}$). The spatial distribution demonstrates a clear gradient pattern, with resistance values generally increasing from northwest to southeast. According to the histogram statistics, approximately 50% of the vegetated areas display resistance values between 20 and 35 $\text{mon}\cdot\text{n}^{-1}$. Fig. 8b reveals that vegetation resilience shows a contrasting spatial pattern, with high resilience areas primarily distributed in the North China Plain (80th percentile: 1.2 $\text{n}\cdot\text{mon}^{-1}$) and the Inner Mongolia Plateau (80th percentile: 1.6 $\text{n}\cdot\text{mon}^{-1}$). The spatial distribution exhibits an increasing trend from southeast to northwest, opposite to the resistance pattern. The histogram indicates that about 45% of the vegetated areas show resilience values between 0.6 and 1.0 $\text{n}\cdot\text{mon}^{-1}$, while areas with exceptionally high resilience ($>1.5 \text{ n}\cdot\text{mon}^{-1}$) represent less than 20% of the total vegetated area, mainly located in arid and semiarid regions. The climate gradient analysis (Figs. 8c–d) demonstrates that vegetation resistance gradually increases from arid to humid areas, while resilience shows an inverse relationship, decreasing along the same gradient. Regarding vegetation functional types (Figs. 8e–f), resilience values increase sequentially from forests to grasslands, while resistance follows the opposite trend.

As shown in Fig. 9a, the vegetation resistance time generally increases from north to south, with shorter resistance time (2.0–3.6 months) mostly located in the arid and semiarid regions of western and northern China, while longer resistance time (4.4–6.0 months) mainly occur in the humid southeastern coastal areas and parts of Northeast

China. According to the histogram statistics, ~40% of the vegetated areas show the resistance time between 2.8 and 3.6 months, while the areas with resistance time exceeding 5.2 months account for less than 10% of the total vegetated areas. Fig. 9b shows that the vegetation recovery time ranging from 3.0 to 18.0 months across China exhibits a similar spatial pattern to the resistance time. The centers of vegetation recovery time > 12.0 months are primarily located in the southeastern coastal regions and central-southern parts of Eastern China. The histogram indicates that about 45% of the vegetated areas shows recovery time between 6.0 and 9.0 months, while the regions with extremely long recovery time (>15.0 months) represent less than 5% of the total vegetated area, mainly concentrated in subtropical humid regions.

The comparison across climatic zones (Figs. 9c–d) demonstrates that both the resistance time and recovery time of vegetation progressively increase from arid to humid regions. In arid regions, the mean resistance time of vegetation is approximately 3.63 months with relatively low variability, while in humid regions the mean resistance time of vegetation is approximately 4.06 months with greater variability. Similarly, the recovery time of vegetation increases from 3.94 months in arid regions to 4.49 months in humid regions, suggesting that ecosystems with greater structural complexity tend to exhibit longer resistance and recovery periods following CDHE disturbances (Liu et al., 2021). Significant differences are also observed among vegetation types (Figs. 9e–f). Both the resistance time and recovery time of vegetation decrease from forests and shrublands to croplands and grasslands. Among the 4 vegetation types, the grasslands exhibit the shortest resistance time (average: 3.54 months) and recovery time (average: 3.95 months), while the forests show the longest resistance time (average: 4.18 months) and recovery time (average: 4.49 months). These findings highlight distinct adaptive strategies across vegetation types, with grasslands relying on shallow root systems and rapid regeneration to recover more effectively from CDHEs (Zhu et al., 2025).

3.4. The impact of the interaction between CDHE characteristics on vegetation

From 1982 to 2022, vegetation resistance to CDHEs in China shows a significant declining trend ($-0.2731 \text{ decade}^{-1}$), while resilience exhibits an increasing trend ($0.009 \text{ decade}^{-1}$) (Fig. 10). For extreme and long-duration (≥ 3 months) events, resistance decreases by $0.0367 \text{ decade}^{-1}$ and $0.0077 \text{ decade}^{-1}$ respectively compared to mild severity events and short-duration events (Fig. 10a–b). Resilience for mild severity and short-duration (1 month) events increases by $0.0013 \text{ decade}^{-1}$ and $0.0007 \text{ decade}^{-1}$ respectively compared to extreme severity

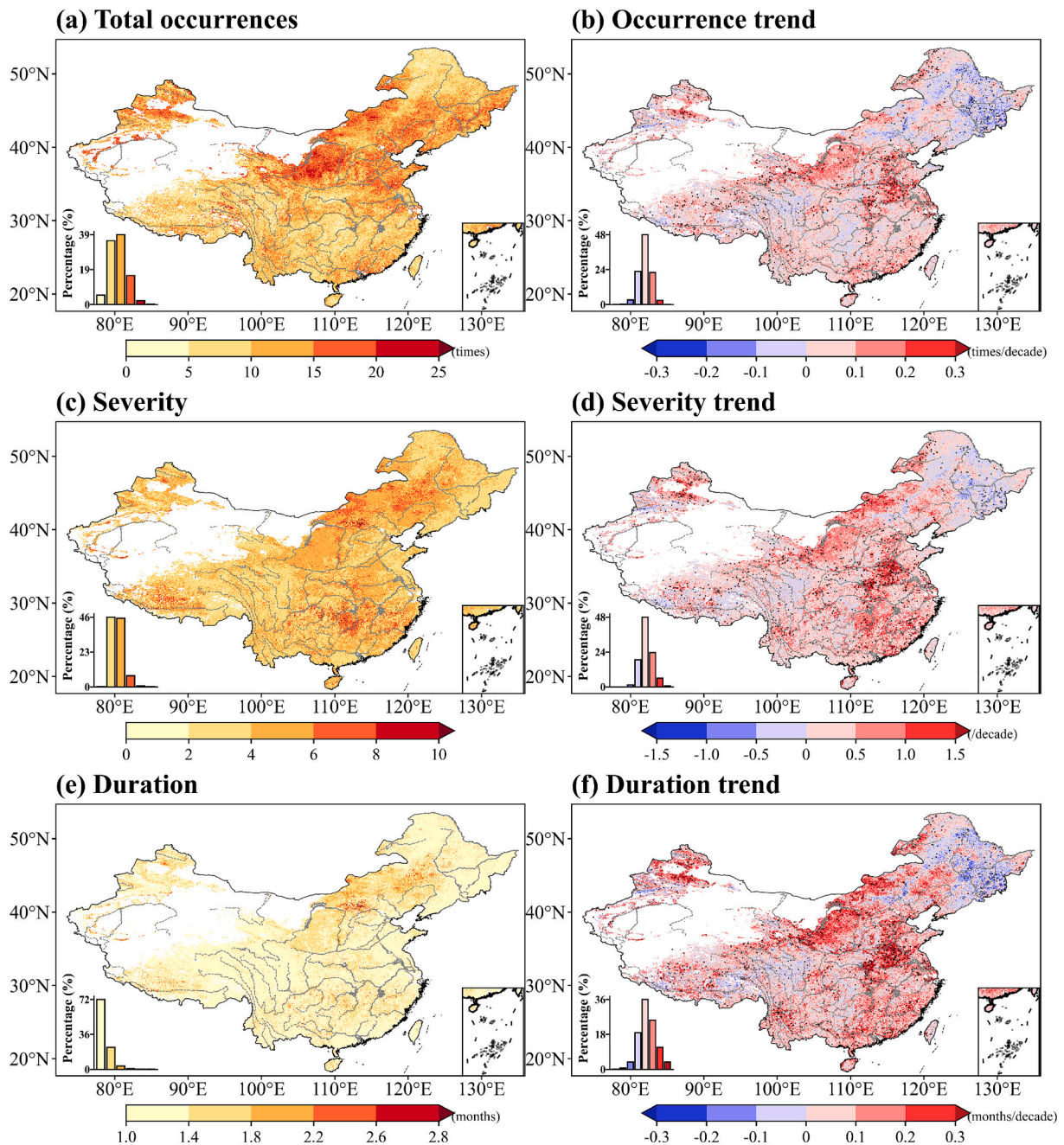


Fig. 5. Spatial patterns of CDHEs affecting vegetation in China during the growing seasons of 1982 to 2022. (a), (c), and (e) show the total occurrences of CDHEs, mean severity, and mean duration of all CDHEs during the study period, respectively. (b), (d), and (f) present the corresponding temporal trends per decade. Black dots indicate the areas with statistically significant trends at the 0.05 significance level. The inset in the lower-left corner of each panel shows the percentage of total area corresponding to each color category of the respective variable.

and long-duration (≥ 3 months) events (Fig. 10c-d). Analysis of the periods 1982–1999 and 2000–2022 reveals that after 2000, resistance under different severity and duration events shifted from increasing to decreasing trends, while resilience transitioned from decreasing to increasing trends. Despite large-scale ecological engineering projects implemented in China since 2000, resilience changed from increasing to decreasing after 2010 ($-0.0098 \text{ decade}^{-1}$), while NDVI shows an increasing trend ($+0.005 \text{ decade}^{-1}$), indicating that vegetation greening (Fig. 11) does not necessarily enhance resilience. Box plot results (Fig. 10e-h) demonstrate that vegetation resistance is higher for extreme severity CDHEs ($+0.14$) compared to mild severity events, but lower for CDHEs with ≥ 3 months duration (-1.14) compared to one-month duration events. Resilience for CDHEs with ≥ 3 months duration is

slightly lower than for one-month duration events, while resilience for mild severity CDHEs is higher than for extreme CDHEs (50th percentile: $+0.04$). This suggests that extreme CDHEs result in stronger resistance but lower resilience, whereas long-duration CDHEs lead to both lower resistance and resilience.

As shown in Figs. 12a-b, the resistance time of different vegetation types shortens with increasing CDHE severity (from mild to severe), while the recovery time prolongs correspondingly. Compared to the mild severity of CDHEs, the severe severity of CDHEs results in the mean resistance time of grasslands and forests decreased by 0.16 months and 0.21 months but the mean recovery increased by 0.27 months and 0.33 months, respectively. As shown in Fig. 12c, the CDHEs with the duration ≥ 3 months lead to significantly shortened resistance time

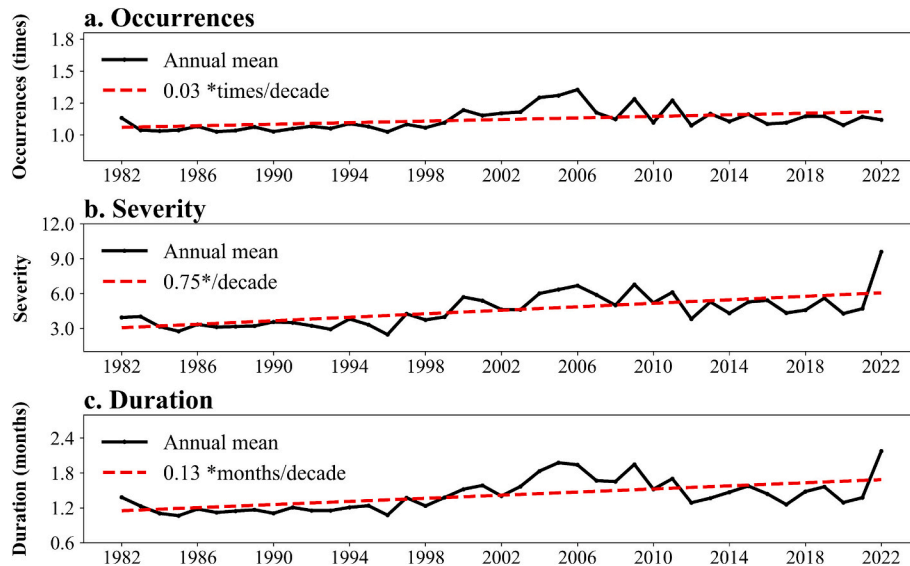


Fig. 6. Temporal changes in (a) average occurrences, (b) average severity and (c) average duration of CDHEs affecting vegetation in China from 1982 to 2022. The black solid line represents the annual average for each pixel. The red dashed line represents the linear trend calculated using the Mann-Kendall test, with the slope values of the trends marked by asterisks (*), indicating statistical significance of the trend at the 0.01 confidence level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

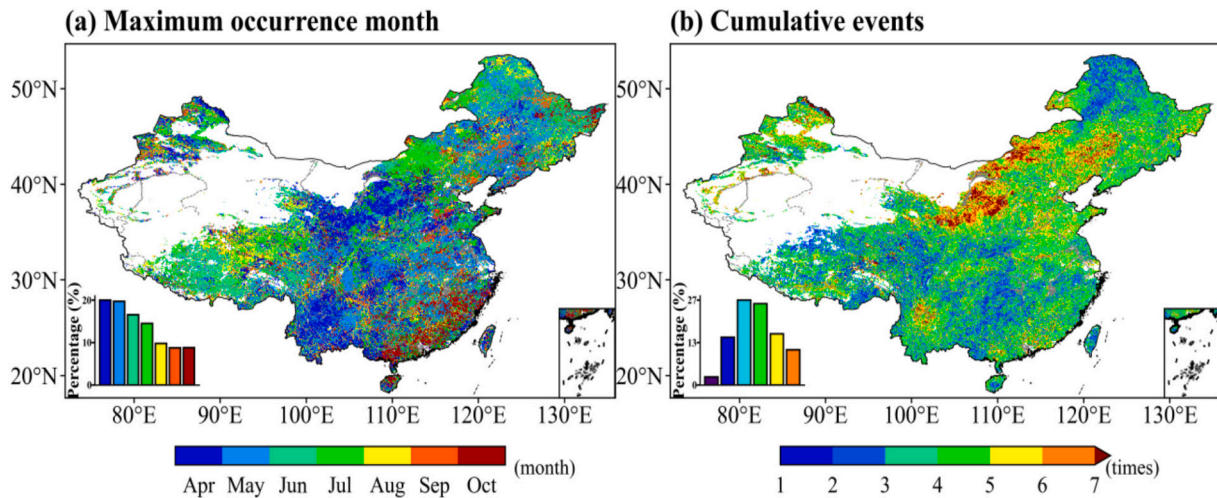


Fig. 7. Spatial distribution of the maximum occurrence months of CDHEs in vegetation in China from 1982 to 2022 (a) and the corresponding cumulative events of the months (b). (a) the color of each pixel ranges from light blue to red representing the vegetation growing season (April to October). (b) the color of each pixel represents the cumulative events for the most frequent month. The inset in the lower-left corner shows the area percentage corresponding to the color scale. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

compared to the 1-month duration events, with the grassland resistance time decreased by an average of 0.5 months. Similarly, relative to the 1-month duration events, the CDHEs with the duration ≥ 3 months lead to significantly extended recovery time, with the recovery time of forests reaching up to 5 months, which are notably longer than that of other vegetation types (Fig. 12d).

Compared to the situations under the CDHEs with mild severity and 1-month duration, under the CDHEs with severe severity and duration ≥ 3 months, the resistance (recovery) time of grassland is decreased (increased) by ~ 1.2 months (Figs. 13a-b); the croplands exhibit ~ 0.5 months shorter resistance time and ~ 1.0 months longer recovery time (Figs. 13c-d); the shrublands demonstrate reduction of ~ 1.2 months in resistance time and extension of ~ 1.2 months in recovery time (Figs. 13e-f); the forests show the strongest sensitivity, with the resistance time decreased by ~ 1.3 months and the recovery time extended by ~ 2.2 months (Figs. 13g-h). Overall, the combined effects of

CDHE severity and duration substantially intensified ecological stress. From the mild and short-duration CDHEs to the severe and prolonged CDHEs, the resistance (recovery) time of ecosystems tends to become shorter (longer).

4. Discussion

4.1. Vegetation resistance and recovery times in response to CDHE characteristics

CDHEs have emerged as key drivers of vegetation dynamics under climate change (Wang et al., 2023a). Unlike single extreme events, CDHEs impose simultaneous water and heat stress, leading to more profound ecological consequences (Diffenbaugh et al., 2015; Lu et al., 2022). In this study, CDHEs during the growing season over the past decades were systematically identified by integrating precipitation,

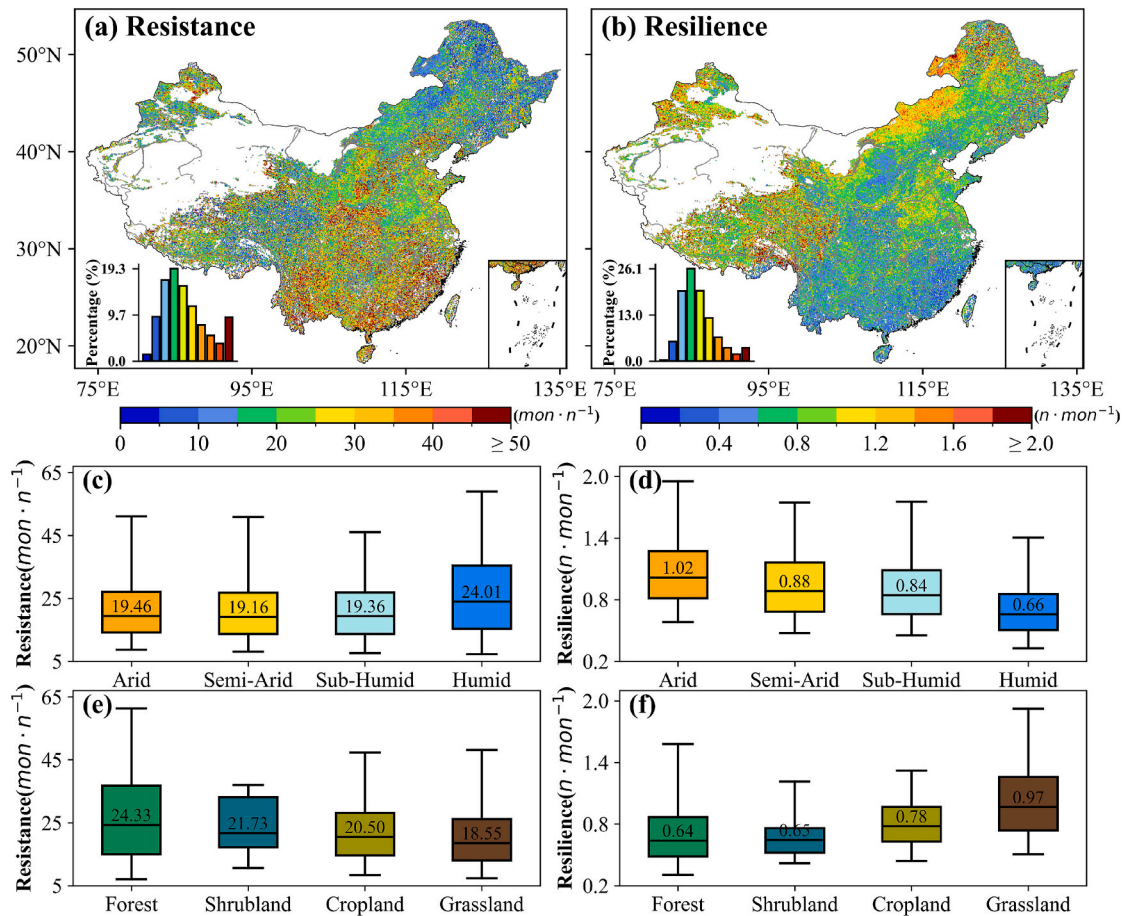


Fig. 8. Spatial patterns and classification differences of vegetation resistance and resilience across China from 1982 to 2022. (a, b) show the spatial distribution of mean vegetation resistance and resilience under the CDHEs, respectively. Insets in the lower-left corners illustrate the area proportion corresponding to each color category. (c, d) compare resistance and resilience across four climatic zones: arid, semiarid, sub-humid, and humid. (e, f) present differences among four vegetation types: forest, shrubland, cropland, and grassland. In the boxplots, boxes represent the interquartile range (25th to 75th percentile), the horizontal lines within the boxes and black numbers above indicate the median and mean, respectively, and the whiskers denote the 5th and 95th percentiles.

potential evapotranspiration, soil moisture, and surface air temperature (Feng et al., 2023; Wang et al., 2025b). This comprehensive framework goes beyond traditional drought or heatwave indices, capturing the compound characteristics and cumulative impacts of these events on ecosystems (Costa et al., 2024; Yin et al., 2023).

Furthermore, the long-term trends in CDHE occurrence, severity, and duration exhibit similar spatial distribution patterns (Fig. 5), indicating that vegetation in northern Xinjiang, the Loess Plateau, and northeastern Inner Mongolia is increasingly exposed to compound extreme events. Analysis of vegetation response patterns reveals distinct temporal dynamics across different CDHE characteristics (Fig. 14). Overall vegetation resistance time remains relatively stable across severity levels, ranging from 3.74 to 3.82 months, while recovery time shows slight variations from 4.32 to 4.36 months under different severity conditions (Figs. 14a, c). However, duration exerts more pronounced effects, with resistance time decreasing from 3.82 to 3.54 months as duration extends from 1 month to ≥ 3 months, while recovery time increases from 4.29 to 4.57 months correspondingly (Figs. 14b, d). Grasslands in arid regions display relatively short resistance times, suggesting that vegetation activity declines rapidly under CDHEs but moderately recovers once favorable conditions return (Figs. 9e-f). In contrast, forests exhibit longer resistance times but extended recovery periods, reflecting their structural and physiological buffering capacity as well as their higher susceptibility to legacy effects (Marchand et al., 2025; Mayne et al., 2022). Systematic detection of CDHEs at the growing-season scale thus provides a solid basis for identifying high-risk areas and assessing their

ecological impacts (Yu et al., 2024).

To assess the robustness of the detection framework, a sensitivity analysis was conducted by testing three threshold combinations: relaxed ($\text{SPEI/SSMI} \leq -0.3$, $\text{STI} \geq 0.3$, $\text{CDHI} \leq -0.9$, $\text{SANDVI} < -0.3$), original ($\text{SPEI/SSMI} \leq -0.5$, $\text{STI} \geq 0.5$, $\text{CDHI} \leq -1.5$, $\text{SANDVI} < -0.5$), and strict ($\text{SPEI/SSMI} \leq -0.8$, $\text{STI} \geq 0.8$, $\text{CDHI} \leq -2.4$, $\text{SANDVI} < -0.8$). For each scenario, the differences in resistance time and recovery time across climatic zones and vegetation types were re-examined. The results consistently reproduced the core findings across all three threshold combinations (Fig. 15), confirming the stability and generalizability of the reported patterns. Specifically, the spatial gradient of resistance time and recovery time from arid to humid regions was consistently reproduced under all threshold combinations, with humid regions consistently exhibiting longer resistance and recovery times than arid regions regardless of the threshold applied (Fig. 15a). Furthermore, the vegetation type differences were stable across all scenarios, with forests consistently showing longer resistance and recovery times than grasslands, and the rank order among vegetation types remaining unchanged under all three threshold combinations (Fig. 15b).

4.2. Complexity of vegetation responses under CDHEs

To quantify the dominant drivers of vegetation resistance time and recovery time under CDHEs, the XGBoost-SHAP method was applied (Hu et al., 2026; Yu et al., 2025). Eight predictor variables were constructed for each CDHE occurrence, including cumulative precipitation

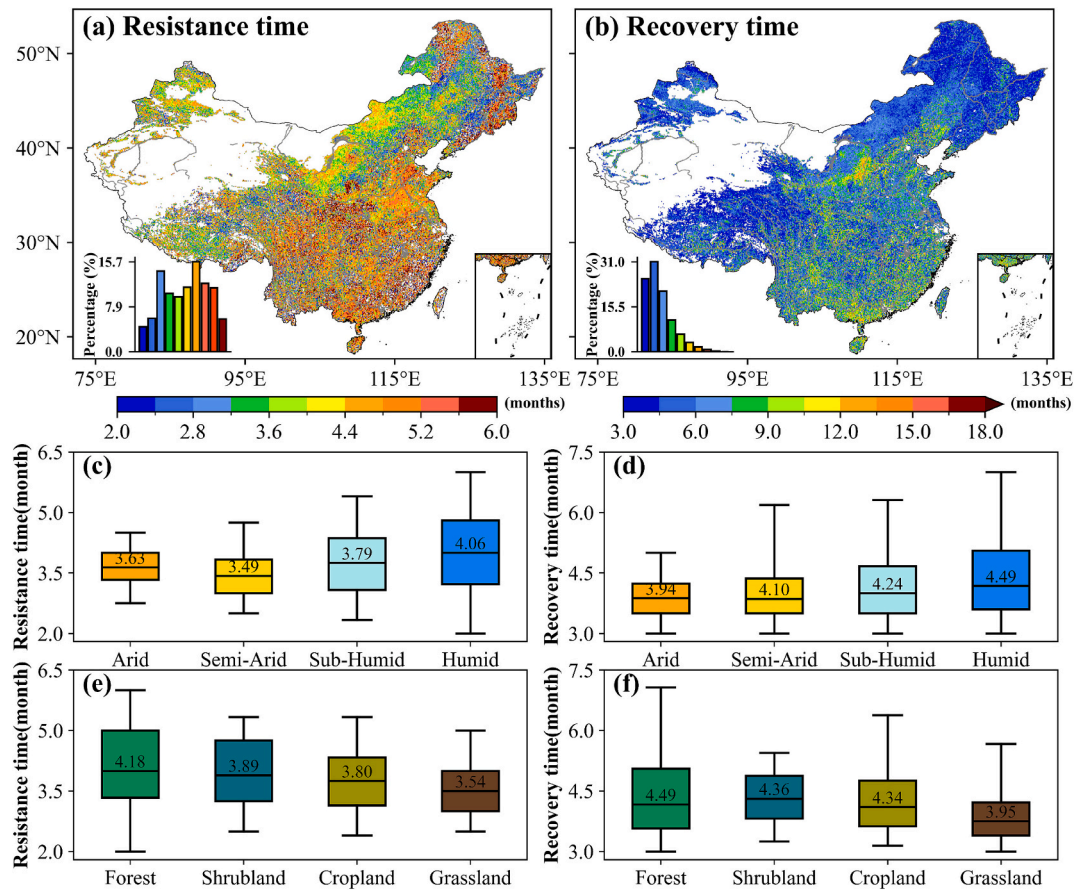


Fig. 9. Spatial patterns and classification differences of vegetation resistance time and recovery time across China from 1982 to 2022. (a, b) show the spatial distribution of mean vegetation resistance time and recovery time under the CDHes, respectively. Insets in the lower-left corners illustrate the area proportion corresponding to each color category. (c, d) compare resistance time and recovery time across four climatic zones: arid, semiarid, sub-humid, and humid. (e, f) present differences among four vegetation types: forest, shrubland, cropland, and grassland. In the boxplots, boxes represent the interquartile range (25th to 75th percentile), the horizontal lines within the boxes and black numbers above indicate the median and mean, respectively, and the whiskers denote the 5th and 95th percentiles.

(Pre), cumulative soil moisture (SM), and cumulative temperature (Tem) during the event period, together with mean annual precipitation (Mean Pre), mean annual temperature (Mean Tem), terrain elevation (DEM), population density (PD), and ecosystem service value (ESV). The XGBoost model was trained independently for resistance time and recovery time, and SHAP values were calculated to quantify the contribution of each predictor while accounting for nonlinear interactions among variables (Wu et al., 2025).

For resistance time (Fig. 16a), cumulative precipitation (Pre, mean |SHAP| = 0.420) was the most important driving factor, followed by cumulative temperature (Tem, 0.175) and cumulative soil moisture (SM, 0.138), indicating that the direct hydrothermal conditions during CDHes exert the strongest control over vegetation resistance capacity. The contributions of mean annual precipitation (Mean Pre, 0.078), mean annual temperature (Mean Tem, 0.062), DEM (0.048), population density (PD, 0.032), and ESV (0.021) decreased progressively. For recovery time (Fig. 16b), cumulative precipitation remained the dominant driver (mean |SHAP| = 0.412), followed by cumulative soil moisture (0.378). The contributions of cumulative temperature (0.095), mean annual temperature (0.082), and mean annual precipitation (0.068) were moderate, while DEM (0.051), population density (0.035), and ESV (0.024) showed the smallest effects.

The prolonged recovery times observed in forests and humid regions under severe and long-duration CDHes can be attributed to a combination of interconnected ecological and physiological mechanisms operating beyond the direct influence of precipitation (Wu et al., 2023;

Zhu et al., 2015). First, carbon reserve depletion plays a central role in delaying forest recovery (Cao et al., 2022). During prolonged CDHes (≥ 3 months), trees are compelled to draw down non-structural carbohydrate (NSC) reserves to sustain basic metabolic functions when stomatal closure and reduced photosynthetic capacity simultaneously constrain carbon assimilation (Hartmann et al., 2018; McDowell et al., 2008). Cumulative carbon starvation reduces the NSC pool available for post-disturbance tissue repair and canopy reconstruction, thereby prolonging the recovery trajectory detected through NDVI anomalies (Isbell et al., 2015; Yao et al., 2024a). This is consistent with the observed 2.2-month extension in forest recovery time under severe and prolonged CDHes (Fig. 13g-h).

Second, hydraulic damage further delays the restoration of forest productivity (Trugman et al., 2018). Severe water potential deficits can induce xylem cavitation, disrupting the continuous water column from roots to leaves (Choat et al., 2018). The restoration of hydraulic conductivity through conduit refilling or new xylem formation is both slow and energetically costly (Sperry et al., 2017; Wang et al., 2025a), explaining why forests exhibit markedly longer recovery times than grasslands, which rely on shallower root systems and can recover faster after rainfall.

Thirdly, changes in water resource allocation have brought about physiological impacts that persist until the recovery period (Sala et al., 2010; Sevanto et al., 2014). As stress intensifies, plants redirect resources from growth-supporting processes toward survival functions including osmotic adjustment and maintenance respiration (Faticchi

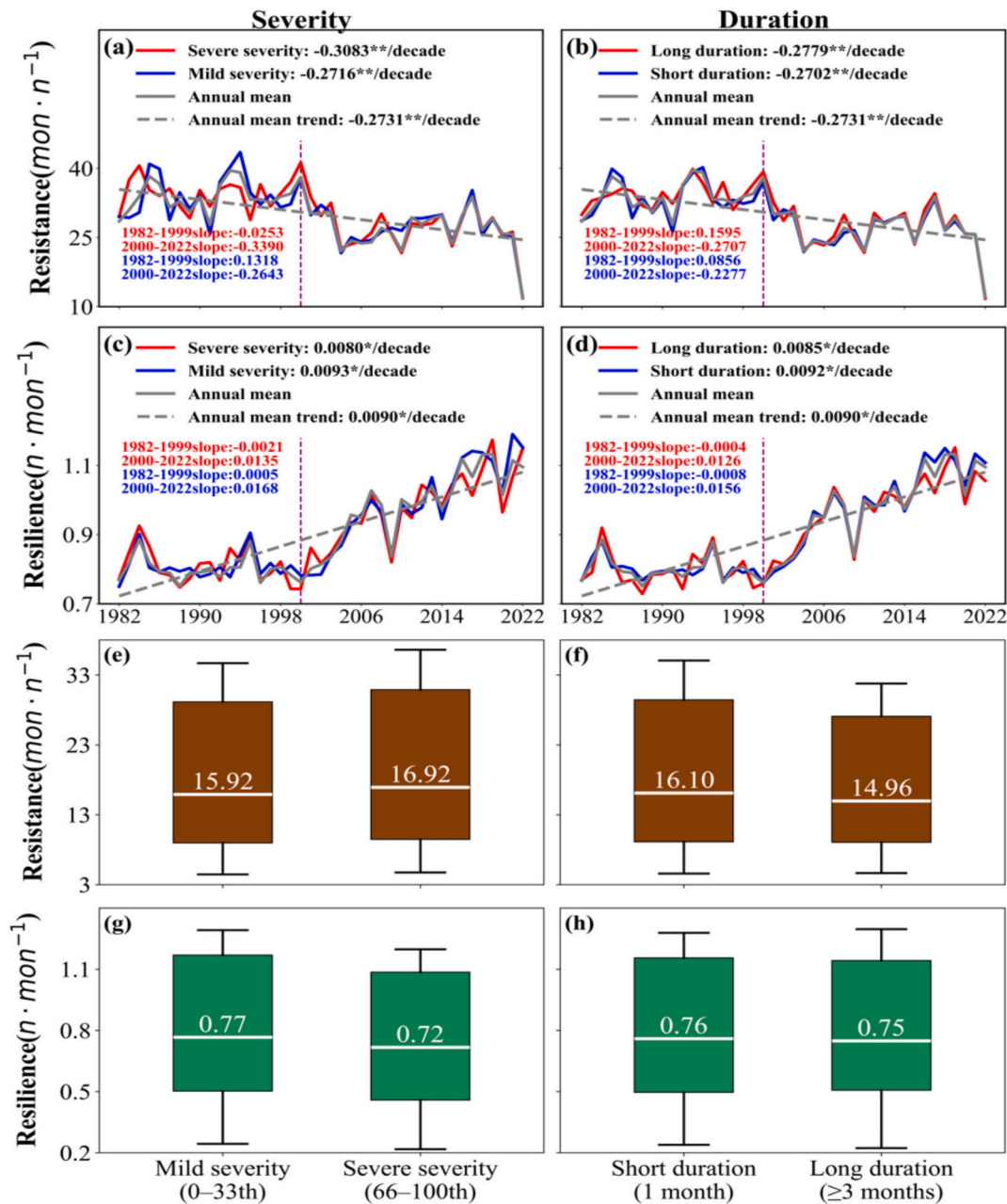


Fig. 10. Impact of CDHEs characteristics on vegetation resistance and resilience in China during 1982–2022. Events are classified by severity (mild; moderate; severe) and duration (1 month, 2 months, ≥ 3 months). Panels (a–b) and (c–d) show the resistance and resilience trends under different severity and duration events, respectively. Gray lines represent annual mean values of events for each pixel; red and blue lines indicate trends under severe and mild characteristic events. Gray dashed lines represent linear trends of annual mean values (Mann-Kendall test), with asterisks (“**”) indicating statistical significance at the 0.05 level. Vertical dashed lines represent the turning year (2000) determined by Mann-Kendall mutation test. Panels (e–f) and (g–h) show box plots of resistance and resilience under different severity and duration events, respectively. In the box plots, horizontal lines and white numbers represent median and mean values, respectively; boxes show interquartile range, and whiskers represent the 5th and 95th percentiles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

et al., 2014; Muller et al., 2011), suppressing above-ground productivity and creating a recovery lag before NDVI can return to pre-disturbance levels (Gu et al., 2024).

In humid regions, longer recovery times are fundamentally linked to the greater structural complexity of the dominant ecosystems rather than precipitation patterns alone (Liu et al., 2025b; Oliver et al., 2015). Dense forest cover with high leaf area index (LAI), complex multilayer canopy structures, and deep root systems collectively require substantially more time and resources to restore following severe disturbance (Liu et al., 2021a; Van Ruijven and Berendse, 2010). Furthermore,

higher evapotranspiration demand in humid climates means that a larger proportion of post-disturbance precipitation is lost before reaching the root zone, delaying soil moisture replenishment and prolonging the hydraulic recovery signal captured by NDVI (Ma et al., 2025; Xu et al., 2018). This is consistent with the progressive increase in recovery time from arid (3.94 months) to humid regions (4.49 months), reflecting both climatic differences and the greater ecological complexity of humid-zone vegetation.

In the arid and semiarid regions of northwest and northern China, CDHE is mainly driven by sustained atmospheric circulation anomalies,

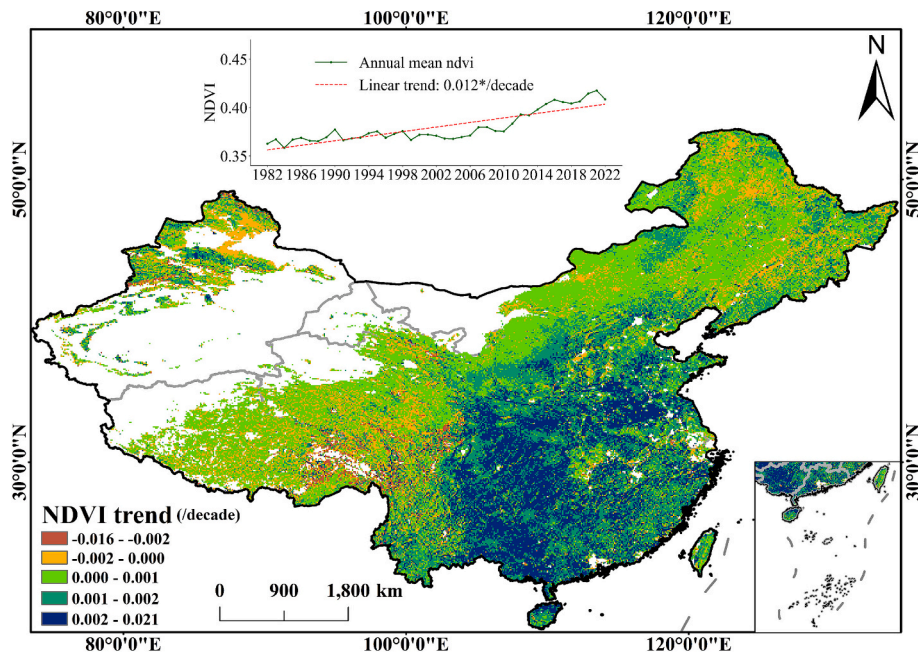


Fig. 11. Spatial distribution pattern of vegetation NDVI trends across China from 1982 to 2022. The main map illustrates the spatial distribution of NDVI change rates per decade (unit: decade⁻¹), while the inset shows the interannual variation of annual mean NDVI along with its linear trend. The red dashed line represents the linear trend estimated using the Mann-Kendall test, with the asterisk (*) indicating statistical significance at the 0.01 confidence level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

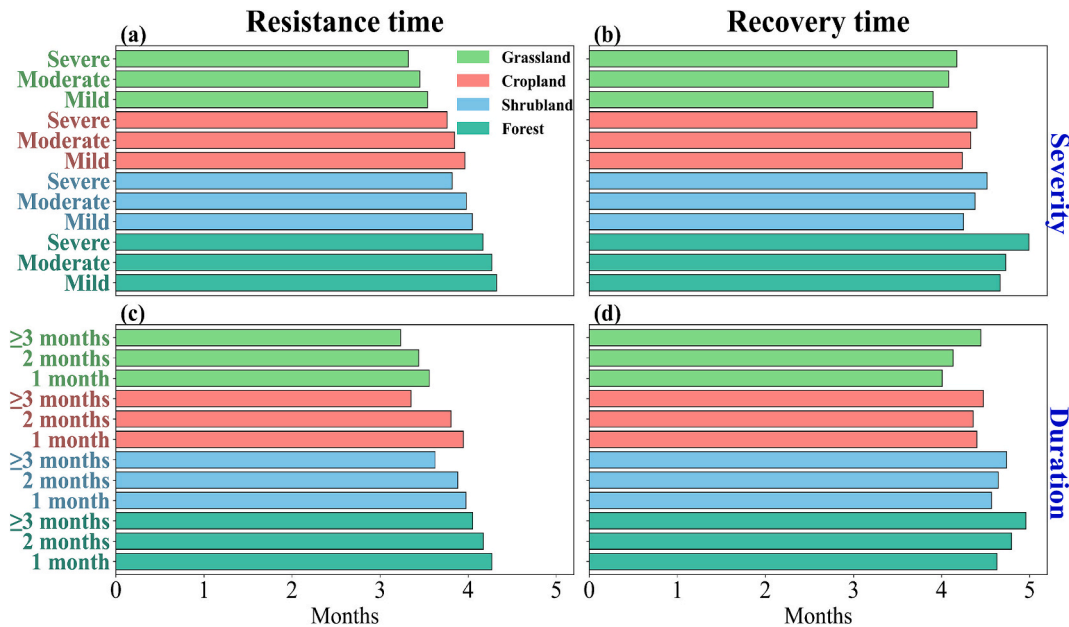


Fig. 12. Impact of CDHEs severity and duration on vegetation resistance time and recovery time across different vegetation types in China during 1982–2022. (a, c) show the mean resistance time and recovery time of each vegetation type under different severity levels (mild, moderate, and severe). (b, d) show the mean resistance time and recovery time of each vegetation type under different event durations (1 month, 2 months, and ≥ 3 months).

which simultaneously suppress precipitation and increase surface temperature, leading to rapid depletion of soil moisture and rapid but shallow responses of vegetation (Piao et al., 2010; You et al., 2015). The vegetation in these areas has evolved under long-term water limitations, forming adaptive features such as deep roots and water use efficiency (Schenk and Jackson, 2002; Zhang et al., 2022). Once water conditions improve, these features contribute to relatively rapid recovery. In contrast, CDHE in humid regions of southern and eastern China is more frequently associated with anomalous anticyclonic circulation patterns,

such as the strengthening of the Western Pacific Subtropical High, which simultaneously suppresses precipitation and traps heat near the surface, resulting in long-term and strong composite stresses (Liu et al., 2024; Yang et al., 2022). The vegetation in these areas is mainly composed of subtropical evergreen and deciduous forests, which are physiologically less adapted to sustained water and heat stress, making them more susceptible to the cumulative damage mentioned above and requiring longer periods of time to fully recover their functions (Choat et al., 2012; Deng and Chen, 2017). This is consistent with our findings of a gradual

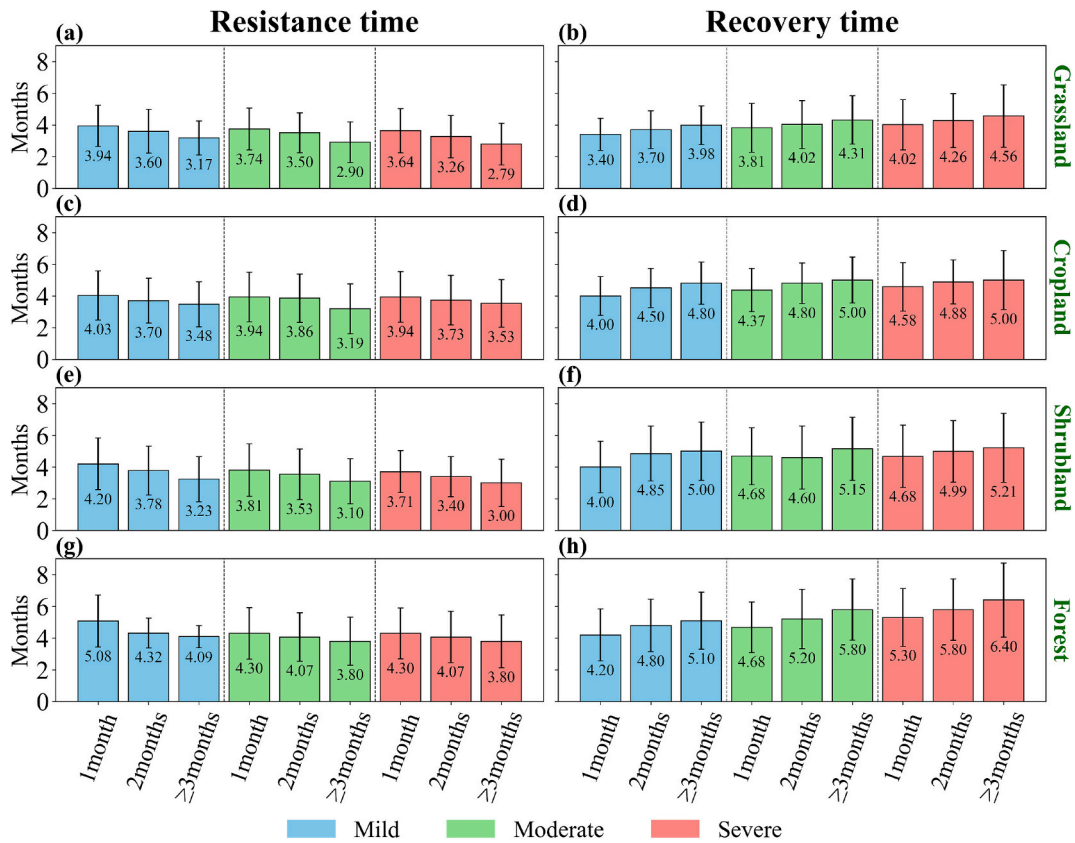


Fig. 13. Impact of different vegetation types on the mean resistance time and recovery time under various CDHE combinations in China during 1982–2022. (a, c, e, g) and (b, d, f, h) show the mean resistance time and recovery time, respectively, of each vegetation type under different combinations of CDHE characteristics (3×3 combinations of severity $\times$ duration). Error bars indicate ± 1 standard deviation across sample pixels. The numbers shown above each bar represent the mean values.

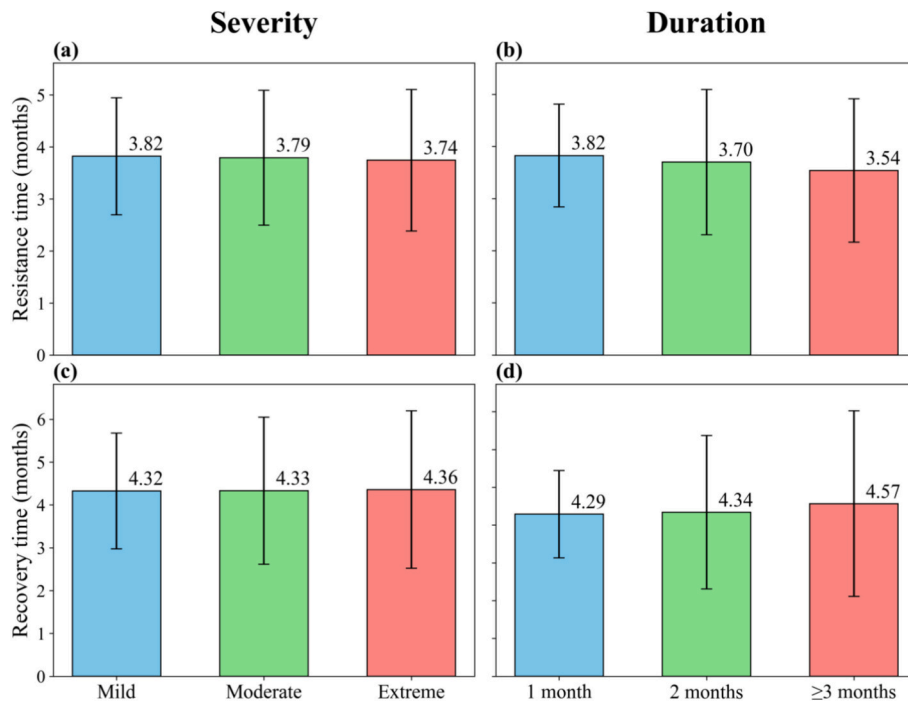


Fig. 14. Impact of CDHE characteristics on vegetation resistance time and recovery time across vegetated areas in China during 1982–2022. (a, c) show the mean resistance time and recovery time of vegetation under different severity levels (mild, moderate, and severe), while (b, d) illustrate the mean resistance time and recovery time under different duration levels (1 month, 2 months, and ≥ 3 months). Error bars indicate ± 1 standard deviation across sample pixels.

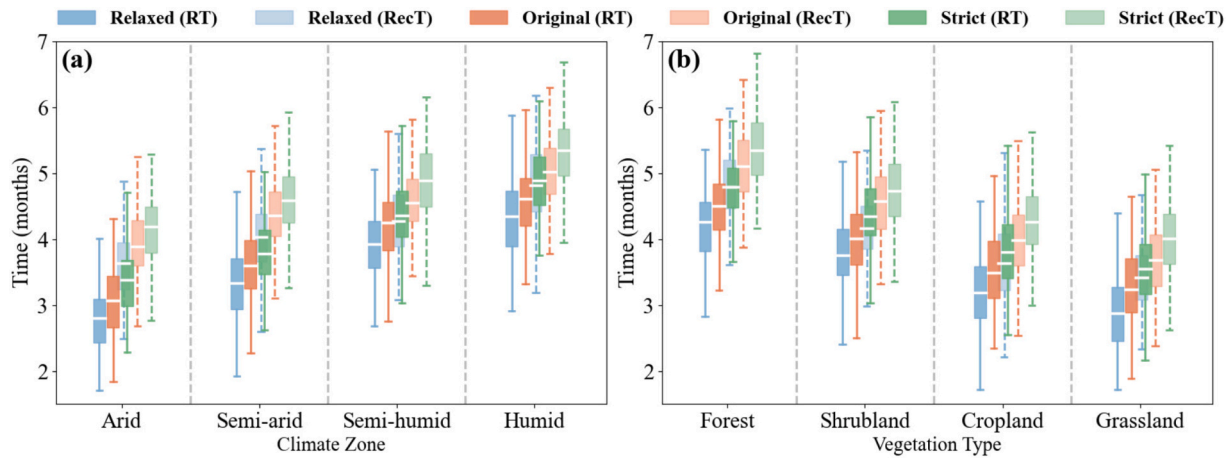


Fig. 15. Sensitivity analysis of core findings under three threshold scenarios (relaxed, original, and strict). (a) Resistance time and recovery time across climatic zones; (b) resistance time and recovery time across vegetation types. Solid-colored boxes represent resistance time (RT) and lighter-colored boxes represent recovery time (RecT) for each scenario.

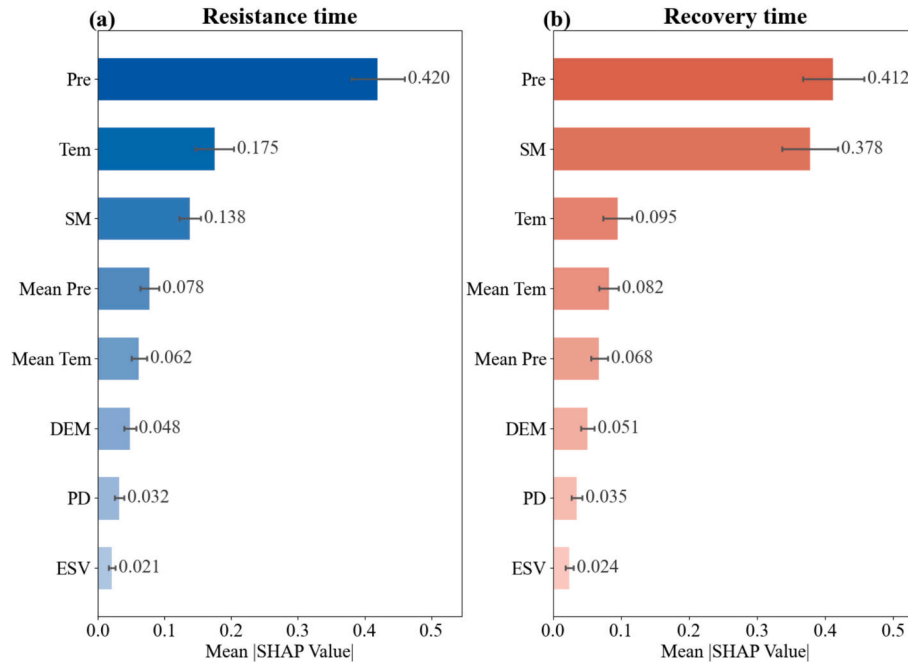


Fig. 16. Relative importance of drivers of vegetation resistance time and recovery time under CDHEs based on XGBoost-SHAP analysis. (a) Mean absolute SHAP values for resistance time; (b) mean absolute SHAP values for recovery time. Higher SHAP values indicate greater contribution to the prediction of vegetation temporal responses.

increase in recovery time from arid areas (3.94 months) to humid areas (4.49 months), reflecting the climate differences driven by CDHE and the greater ecological complexity and physiological vulnerability of vegetation in humid areas (Hartmann, 2015; Hölscher et al., 2005; Vicente-Serrano et al., 2013).

The results of this study have significant practical implications for ecosystem management and climate adaptation in China (Cao et al., 2020; Piao et al., 2020). Firstly, identifying forest and wetland ecosystems as the most vulnerable to long-term CDHEs impacts provides spatially clear guidance for prioritizing ecological monitoring and early warning systems in high-risk areas, particularly in the middle and lower reaches of the Yangtze River basin and the southeastern coastal regions (Liu et al., 2023; Xu et al., 2009; Yang et al., 2025). Secondly, quantifying how the severity and duration of CDHE jointly control resistance and recovery time provides a scientific basis for optimizing vegetation restoration strategies (Schenk, 2008; Sippel et al., 2018). This indicates

that in areas prone to severe and long-term CDHE, planting design should be beneficial for species with higher hydraulic safety margins and greater NSC storage capacity to enhance recovery after disturbance (Brodribb et al., 2020; McDowell et al., 2008; Trugman et al., 2021). Thirdly, precipitation plays a dominant role in the resistance and recovery time of most regions in China, highlighting the crucial importance of water resource management in maintaining ecosystem stability under extreme complex climate conditions, especially in semi-arid transition zones where vegetation is increasingly exposed to complex stresses (Knapp et al., 2008; Piao et al., 2019; Shao et al., 2018). Overall, these insights advance the understanding of the interaction between complex extreme climate and vegetation, and provide actionable guidance for ecological risk assessment, land use planning, and climate adaptive ecosystem restoration in different climate regions of China (Wang et al., 2025c; Weynants et al., 2024).

4.3. Uncertainties and prospects

Although this study provides a systematic analysis of vegetation resistance and recovery responses to CDHEs across China, several limitations should be considered when interpreting the findings. First, bilinear interpolation of all datasets to a uniform 0.0833° resolution may introduce minor smoothing uncertainties in topographically complex regions such as the Qinghai-Tibet Plateau and the Hengduan Mountains, where steep elevation gradients generate high spatial heterogeneity in both climate forcing and vegetation responses (He et al., 2025; Piao et al., 2010). Second, the use of monthly data limits the detection of rapid-onset CDHE dynamics, particularly flash drought-heatwave co-occurrences evolving over days to weeks, which may lead to underestimation of the frequency of short-duration events (Liu et al., 2025d; Zhou et al., 2025). Third, the linear CDHI formulation may not fully resolve fine-scale nonlinear dependencies among its component drivers, potentially causing modest underestimation of CDHE intensity in severe and prolonged cases (Liu et al., 2025a; Xuan et al., 2024; Xuan et al., 2025). Finally, the relatively long recovery times identified in humid cropland areas may be partly sustained by irrigation practices that artificially prolong NDVI-based recovery trajectories, and the trend toward longer resistance times in northern China may partly reflect legacy effects of large-scale ecological restoration programs, including the Three-North Shelter Forest Program and the Grain for Green initiative, rather than climate-driven improvements alone (Cai et al., 2022; Huang et al., 2023; Wang et al., 2025d).

Future research should prioritize elucidating the process-level mechanisms underlying ecosystem resistance and recovery under CDHEs. Integrating multi-source and multi-scale data, including remote sensing observations, eddy covariance flux measurements, tree-ring records, and long-term field ecological monitoring, would enable a more comprehensive characterization of ecosystem dynamics and water–energy–biosphere interactions (Fang et al., 2025; Xiao et al., 2025; Zheng et al., 2023). Coupled ecohydrological–meteorological–vegetation models could then reconstruct historical CDHE impacts and quantify the contributions of water availability, heat stress, biodiversity, and ecological carrying capacity to resistance and recovery times through sensitivity experiments (Jiao et al., 2017; Pappas et al., 2013). Furthermore, combining model simulations with long-term observational data would facilitate the identification of critical thresholds and tipping points that trigger ecosystem functional decline, thereby informing early warning systems and regional adaptation strategies for ecological management, vegetation restoration, and land-use planning (Hillebrand et al., 2018; Sturm et al., 2022). Finally, the adoption of high-resolution temporal data and machine learning techniques to optimize indicator thresholds would improve the ability to distinguish genuinely concurrent compound events from isolated extremes, further reducing uncertainties in CDHE monitoring and attribution studies (Raymond et al., 2020; Zeng et al., 2025; Zhao et al., 2025b).

5. Conclusion

This study systematically revealed the spatiotemporal patterns of vegetation resistance time and recovery time in response to CDHEs across China during the growing seasons of 1982 to 2022, examining their relationships with CDHE characteristics and climatic drivers. The main findings are as follows:

(1). From 1982 to 2022, the occurrence, severity, and duration of CDHEs affecting vegetation all exhibit increasing trends across most of China during the growing season. The most pronounced increases are concentrated in northern Xinjiang, the Loess Plateau, and northeastern Inner Mongolia.

(2). Temporal response patterns reveal that the vegetation resistance (recovery) time increases from 3.63 months (3.94 months) in arid regions to 4.06 months (4.49 months) in humid areas. High-value centers of prolonged recovery time (>12 months) are primarily located in

southeastern coastal regions. Resistance and resilience show contrasting spatial patterns: vegetation resistance is higher in humid southeastern China (50th percentile: 34 mon·n⁻¹) compared to arid Inner Mongolia (50th percentile: 11 mon·n⁻¹), while resilience exhibits the opposite trend, with higher values in northern arid regions (80th percentile: 1.6 n·mon⁻¹) than in humid southeastern areas.

(3). Vegetation type comparisons demonstrate that grasslands exhibit significantly shorter resistance time (3.4 months) and recovery time (3.9 months) compared to forests (4.1 months and 4.4 months, respectively), while showing higher resilience but lower resistance. This reflects grasslands' rapid response characteristics and superior regenerative abilities compared to the slower but more stable forest ecosystems.

(4). Event characteristics impacts reveal that compared to mild and duration 1 months CDHEs, severe events with duration ≥3 months shorten forest resistance time by 2.2 months and extend recovery time by 1.3 months through combined effects of severity and duration. Additionally, increased event severity reduces resistance while prolonged duration diminishes resilience, indicating that intense disturbances compromise ecosystem stability across multiple dimensions. Precipitation emerged as the dominant driver of vegetation resistance and recovery times under CDHEs.

These findings underscore the need to focus on sensitive regions in China to prevent ecological risks, including shortened resistance time, reduced resistance capacity, prolonged recovery time, diminished resilience, or even irreversible ecosystem degradation under the compounding effects of CDHEs.

CRediT authorship contribution statement

Yunfei Cai: Writing – original draft, Validation, Methodology, Conceptualization. **Anning Huang:** Writing – review & editing, Supervision. **Ying Huang:** Writing – review & editing, Supervision. **Wei Zhao:** Supervision. **Xinsheng Zhu:** Supervision.

Declaration of competing interest

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

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Data availability

We used the PKU GIMMS NDVI dataset (Version 1.2) from 1982 to 2022 (Li et al., 2023), which is available at <https://doi.org/10.5281/zenodo.8253971>. The ERA5 reanalysis data on post-processed daily statistics are obtained from ECMWF (<https://doi.org/10.24381/cds.e9c9c792>). The standardized precipitation evapotranspiration index (SPEI) data were taken from the CHM_Drought dataset (Zhang et al., 2025), which is available at https://figshare.com/articles/dataset/CHM_Drought/25,656,951/2. Land use data for China (Yang & Huang, 2021b) are retrieved from <https://doi.org/10.5281/zenodo.12779975>. The climate zone classification data for China was obtained from the National Earth Observation Data Center

from <https://noda.ac.cn/datasharing/datasetDetails/61f368c1a7e1f86b45c210db>. Digital elevation model (DEM) data, population density data, and ecosystem service value data were obtained from the Resource and Environment Science and Data Platform (<https://www.resdc.cn/>).

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