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RESEARCH ARTICLE

Increasing Extreme Negative Vegetation Responses to Drought-Related Compound Events

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ABSTRACT

Vegetation growth is increasingly threatened by both extreme climate events and anthropogenic disturbances. Although considerable attention has been given to detecting large-scale vegetation anomalies, comprehensive analyses of the spatiotemporal dynamics of negative extreme anomalies in vegetation growth (NEGs) and their underlying drivers remain limited. Here, we treat NEGs as event-scale vegetation declines from onset to termination, enabling coherent tracking of vegetation decline events and their associated drivers. Applied to global leaf area index (LAI) data from 2001 to 2024, we find increasing tendencies in both NEG frequency ($0.07\% \text{ year}^{-1}$, $p = 0.13$) and affected area ($394,471 \text{ km}^2 \text{ year}^{-1}$, $p = 0.04$), reaching 39% of the global land surface by 2024. Interannual variations in NEG frequency and affected area show positive associations with annual mean CO_2 anomalies, which may suggest a potential influence on the stability of the terrestrial carbon sink. Coincidence analysis further indicates that drought-related events dominate globally: single-driver drought events, together with drought-related compound events involving temperature extremes and wildfires, account for 58.5%–59.8% of all NEGs. By the end of the 21st century, up to 50.8% of the global land surface is projected to experience NEGs annually under the high-emission scenario, approximately 1.6 times the simulated historical level. These findings highlight the urgent need for climate mitigation to reduce the intensification of compound climate extremes and underscore the importance of understanding how these events may destabilize ecosystems and amplify climate feedbacks in a warming world.

1 | Introduction

Vegetation plays a critical role in regulating Earth's climate system, supporting biodiversity, and sustaining ecosystem services (Linscheid et al. 2020; Piao et al. 2020). However, vegetation growth is increasingly threatened by climate extremes such as droughts (Chen et al. 2025), heatwaves (Dong et al. 2022), as well as by disturbances including wildfires (Xu et al. 2024) and

human activities like land-use change (Wang and Ma 2024). These extreme events cause abrupt and severe reductions in vegetation productivity, manifesting as negative extreme anomalies in vegetation growth (NEGs). NEGs are defined as the full cycle from the occurrence of a negative anomaly to its partial recovery from extreme conditions, with far-reaching consequences for ecological stability (Wernberg et al. 2016; Yang, Chen, et al. 2026) and carbon cycling (Piao et al. 2019). Understanding

the relationship between environmental extremes, including both climate-related and human-induced disturbances, and NEG is crucial for enhancing ecosystem resilience (Stuart-Haëntjens et al. 2018) and informing sustainable land management strategies under climate change (Anderegg et al. 2020; Reichstein et al. 2013).

Numerous studies have investigated the occurrence of NEG and their associations with climatic extremes (Bai et al. 2025; Legesse et al. 2025; Zscheischler et al. 2014; Zscheischler and Seneviratne 2017). These studies generally follow two main research starting points. One starts from climatic extremes (e.g., droughts or heatwaves) and examines subsequent vegetation responses and ecosystem carbon fluxes, following a cause-to-response perspective (Chen et al. 2025; Zhang, Zhang, et al. 2024). The other starts from observed vegetation anomalies and subsequently investigates their underlying environmental drivers, such as anomalies in temperature, precipitation, and radiation, following a response-to-cause perspective (Du et al. 2022; Yang et al. 2023). While both perspectives have contributed to advancing our understanding of NEG and their drivers, most existing studies focus on static or aggregated metrics and therefore fail to resolve the event-level temporal dynamics of NEG, such as their development, duration, and recovery under changing climate conditions. Moreover, attribution efforts often neglect non-climatic factors such as land-cover change, which can substantially modulate vegetation responses (Wang and Ma 2024). Therefore, to better understand the processes underlying large-scale vegetation anomalies, it is necessary to develop an integrated framework that incorporates both climatic and anthropogenic influences. Under future climate change scenarios, extreme weather events such as droughts, heatwaves, and their compound occurrences are projected to become more frequent, intense, and prolonged (Marchin et al. 2022; Tripathy et al. 2023). These intensifying climatic stressors are expected to exert increasing pressure on terrestrial ecosystems, potentially leading to more widespread and severe disruptions in vegetation growth (Gao et al. 2024; Yang, Guo, et al. 2026). Despite growing awareness of historical NEG, limited attention has been given to their possible evolution under future climate conditions. Understanding these dynamics is crucial for mitigating future climate change impacts and for improving our understanding of climate–vegetation feedbacks.

To address gaps in existing research and enhance our understanding of vegetation responses to intensifying climate change, we investigate the frequency, drivers, and future trajectories of NEG. Building on established three-dimensional connectivity-based frameworks, we develop an event-based approach that tracks the spatiotemporal evolution of vegetation anomalies throughout their full life cycle, and integrates a coincidence analysis to systematically link these events with concurrent climatic drivers and non-climatic influences such as land-use change. Using this improved approach, we first identified global NEG from 2001 to 2024 based on vegetation indices from the Moderate Resolution Imaging Spectroradiometer (MODIS), characterizing their frequency, spatial distribution, and temporal evolution. We subsequently attributed these events to their dominant climatic and anthropogenic drivers by linking vegetation anomalies with concurrent climate extremes and disturbances, including fire and land-use changes. Finally, we

assessed projected changes in the frequency and spatial patterns of NEG under future climate. Through this integrated study, we aim to answer the following key scientific questions: (1) Where and when have NEG occurred globally over the past two decades? (2) To what extent are these events driven by climatic and anthropogenic factors? (3) How are NEG projected to evolve in terms of frequency and spatial distribution under future climate scenarios?

2 | Materials and Methods

2.1 | Satellite-Based Vegetation Data

We used the MODIS leaf area index (LAI) product to characterize NEG from January 2001 to December 2024, and the MODIS normalized difference vegetation index (NDVI) product for validation. The MOD15A2H.061 dataset provides 8-day composite LAI at 500 m resolution (Yan et al. 2016), while the MOD13Q1.061 dataset offers 16-day composite NDVI at 250 m resolution (Didan et al. 2015). LAI quantifies canopy structure by representing the total one-sided leaf area per unit ground area, whereas NDVI reflects vegetation greenness and photosynthetic activity. Both LAI and NDVI are widely used and extensively validated indicators of canopy structure and vegetation greenness, jointly providing robust information for capturing large-scale vegetation dynamics (Xue and Su 2017). Prior to analysis, quality control procedures were applied using the corresponding MODIS quality assurance (QA) flags to exclude low-quality retrievals affected by cloud contamination or retrieval uncertainty. Monthly time series were then generated by aggregating LAI using the maximum value within each month to better capture peak canopy conditions, while NDVI was aggregated as the monthly mean of all valid 16-day observations. Both datasets were aggregated to a $0.5^\circ \times 0.5^\circ$ spatial resolution using area-weighted averaging to match the resolution of the climate datasets used in this study. Grid cells with a multi-year average NDVI below 0.1 were excluded from the analysis to avoid non-vegetated or sparsely vegetated areas, such as deserts and urban surfaces.

2.2 | Climate and Disturbance-Related Data

To investigate the drivers of vegetation anomalies, we used several climate- and disturbance-related variables, including temperature, precipitation, vapor pressure deficit (VPD), soil moisture, burned area, and land use data. Monthly temperature and precipitation were obtained from the Climatic Research Unit (CRU) TS v4.09 dataset at 0.5° spatial resolution (Harris et al. 2020). VPD was calculated using CRU monthly averages of daily maximum and minimum temperature, together with vapor pressure, following Tetens' formulation (Allen et al. 1998).

Soil moisture was obtained monthly at 0.1° spatial resolution from the ERA5-Land reanalysis dataset (Hersbach et al. 2020), produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It was vertically integrated across the top three layers (0–7, 7–28, and 28–100 cm) using a depth-weighted average (Liu et al. 2020) and linearly interpolated to a $0.5^\circ \times 0.5^\circ$ grid.

Burned area was derived from the Global Fire Emissions Database (GFED) v5 (van Wees et al. 2022), which provides monthly burned area at 0.25° resolution from 2001 to 2024, based on MODIS satellite observations. These data were aggregated to 0.5° resolution using an area-weighted approach based on the actual grid-cell area, thereby preserving the total burned area within each grid cell.

Land use and land cover information was obtained from the MODIS MCD12Q1 product (Friedl et al. 2010), which provides annual global land cover classifications at a spatial resolution of 500m. We employed the International Geosphere-Biosphere Programme (IGBP) (Loveland et al. 2000) classification scheme, which categorizes 18 land cover types. The data were resampled to 0.5° resolution using a majority rule, whereby each grid cell was assigned the dominant land cover class.

To identify the dominant driving factors across different climate zones, we utilized the Köppen-Geiger climate classification (Beck et al. 2018). The global land area was divided into four major climate zones: Tropical, Arid, Temperate, and Cold regions.

In addition, as years with frequent extreme climate events are often associated with elevated annual mean atmospheric CO₂ concentrations (Piao et al. 2019), we used the annual CO₂ data from the NOAA Earth System Research Laboratory to investigate the relationship between NEG events and variations in the terrestrial carbon sink.

2.3 | Earth System Model Outputs

To investigate NEG events using LAI simulated by Dynamic Global Vegetation Models (DGVMs), we used simulations from the Trends and drivers of the regional scale terrestrial sources and sinks of carbon dioxide (TRENDY) project v10 ensemble, including eight DGVMs: CABLE-POP, IBIS, LPJ-GUESS, LPX-Bern, OCN, ORCHIDEE, SDGVM, and YIBs. We analyzed S3 monthly LAI outputs over the period 2001–2020, which were resampled to 0.5° spatial resolution for comparison with satellite-based LAI. The TRENDY models were driven by consistent climate forcing and CO₂ concentrations, allowing for assessment of each model's ability to capture interannual variability and negative vegetation anomalies, thereby facilitating comparison with observationally derived NEG events.

For future projections, we employed outputs from eight models participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring et al. 2016). We used historical simulations for 2001–2014 to establish a baseline for future vegetation anomalies and to enable comparison with existing observations, and three Shared Socioeconomic Pathways (SSPs: SSP1-2.6, SSP2-4.5, and SSP5-8.5) for the period 2015–2100 to explore potential future changes in NEG events. The selected models include ACCESS-ESM1-5, CanESM5, EC-Earth3-Veg, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, MPI-ESM1-2-LR, and MPI-ESM1-2-HR. Variables analyzed include LAI, surface air temperature, precipitation, and soil moisture. All data were interpolated to 0.5° resolution to ensure consistency with observation-based datasets.

We evaluated the performance of each TRENDY model and historical CMIP6 simulation against the observation-based LAI anomaly dataset at each grid cell using four complementary metrics: mean bias (Bias), root mean square error (RMSE), normalized standard deviation ratio, and Pearson correlation coefficient (Balhane et al. 2022). These metrics were normalized and averaged to derive a model performance score at each grid cell, which was then used to construct observation-constrained model weights. The observation-constrained weights were applied to calculate the weighted multi-model ensemble (MME) of NEG frequency and affected area for both the TRENDY and historical CMIP6 simulations. For future CMIP6 projections under SSP1-2.6, SSP2-4.5, and SSP5-8.5, the historical observation-constrained model weights were retained and applied to the corresponding model simulations to obtain the weighted MMEs.

2.4 | Identification of NEG events

We first removed the long-term trend from the LAI and NDVI time series at each grid cell using linear regression. Seasonal cycles were then removed by subtracting the climatological monthly means, and the resulting anomalies were standardized using a z-score method based on the corresponding climatological standard deviations (Du et al. 2022). The growing season was defined using a temperature threshold of 5°C and constrained precipitation conditions within the 10th–90th percentile range in arid regions (Chen et al. 2024). Within each grid cell, time steps of LAI/NDVI with z-scores below the –1.5 threshold occurring within the growing season were identified as potential negative anomalies. Applying this procedure across all grid cells produced a binary matrix distinguishing anomalous from non-anomalous states. A flood-fill algorithm based on a 6-connected neighborhood criterion was then used to group these anomalies into regions that are continuous in both space and time (i.e., three-dimensional regions) (Zscheischler et al. 2013).

Only events lasting at least two months and with a maximum affected area exceeding 10,000 km² were retained. The affected area was calculated as the projected two-dimensional spatial extent (latitude–longitude) at each individual time step to ensure that retained events exhibit a sufficiently large contiguous spatial footprint.

We also conducted sensitivity analyses for observational data by varying key parameter settings, including the definition of the growing season, z-score threshold, maximum affected area, and minimum duration.

To characterize NEG dynamics, we used four complementary metrics: occurrence, frequency, affected area, and cumulative affected area. Occurrence refers to the presence of a NEG event within a given spatial unit and time period. Frequency is defined as the proportion of growing-season time steps during which vegetation anomalies occur within a given grid cell. Affected area denotes the spatial extent (km²) of an individual NEG event at a given time step. Cumulative affected area represents the total area influenced by NEG events over a given period, calculated by summing the affected areas across all events and time steps. By comparing the cumulative affected area of different

NEGs, we identified the top ten events with the largest spatial impacts.

We quantified temporal trends in NEG frequency and affected area using linear regression. Because NEGs in a given year may be influenced by those in the preceding year, the resulting time series may exhibit first-order temporal autocorrelation, which can reduce the effective degrees of freedom and lead to underestimated uncertainty in the trend estimates. To account for this effect, we estimated the lag-1 autocorrelation of the regression residuals and used it to adjust the effective sample size and corresponding degrees of freedom. The significance of the linear trends was then recalculated using the adjusted degrees of freedom. We report both the original p -values and the AR(1)-adjusted p -values (hereafter, Adjusted p).

For the TRENDY S3 dataset, NEGs were identified individually from simulated LAI for each model using the same parameter settings and anomaly detection framework as applied to the observational datasets.

2.5 | Identification of Climate Extremes and Disturbance Events

We applied the same standardized anomaly method to temperature, precipitation, soil moisture, and VPD datasets. For all variables, positive anomalies ($z > 1.5$) and negative anomalies ($z < -1.5$) were used to define extreme wet/dry or high/low conditions depending on the physical meaning of each variable, including heatwaves and low-temperature events (temperature), precipitation surplus and deficit conditions (precipitation), soil moisture surplus and deficit conditions (soil moisture), and atmospheric dryness and wetness conditions (VPD).

Based on previous studies, we only considered fire events in which the burned area exceeded 10% of a grid cell (Liu, Peñuelas, et al. 2025). This threshold was adopted to exclude minor or fragmented disturbances and to ensure that only substantial fire events with the potential to significantly affect vegetation dynamics were included.

To evaluate the influence of land use change, we focused on one-year changes by comparing land use maps from the year preceding each vegetation anomaly to those at the time of the event. This design targets short-term land-use disturbances that are temporally aligned with vegetation anomalies while minimizing the influence of long-term land-use transitions that evolve over multiple years and are difficult to directly attribute to individual events. The Jaccard similarity coefficient was used to quantify observed similarity in land use within the spatial extent of each anomaly (Pontius and Millones 2011). This metric is particularly suitable for categorical land-cover data, as it captures compositional changes between two time steps while being less sensitive to minor class fluctuations.

2.6 | Attribution Analysis

We performed a coincidence analysis (Yang et al. 2023) to assess whether climate extremes or disturbances co-occurred with

each identified NEG in both space and time. The correspondence between vegetation anomalies and potential drivers was established by evaluating the occurrence of climatic or disturbance anomalies at each grid cell within the full spatiotemporal extent of a given NEG event.

To determine the level of coincidence required for a variable to be considered influential on vegetation anomalies, we performed a shuffle analysis with 1000 iterations for temperature, precipitation, soil moisture, VPD, burned area, and land use. For each variable, an empirical null distribution of coincidence rates was constructed from the shuffled samples. Statistical significance was assessed against this distribution at $p < 0.10$, 0.05 , and 0.01 , and the resulting attribution fractions were compared across these thresholds to assess their sensitivity. For temperature, precipitation, soil moisture, VPD, and burned area, a variable was considered to have a significant influence if the observed coincidence rate exceeded the corresponding 90th, 95th, or 99th percentile of the shuffled distribution. For land use, since land-use change is reflected by spatial dissimilarity rather than co-occurrence, the distribution of Jaccard similarity coefficients derived from the shuffled samples was used as the null distribution. Accordingly, land-use change was identified as significant when the observed similarity fell below the corresponding 10th, 5th, and 1st percentiles, respectively, of the shuffled distribution. If multiple climatic or disturbance factors significantly coincided with a given NEG event, the event was classified as being driven by a compound event involving multiple drivers.

In addition to spatial coincidence, we further examined potential temporal lags in climatic responses. Disturbance factors such as fire and land-use change were assumed to exert relatively immediate impacts on vegetation anomalies, as they directly alter land surface conditions. In contrast, the effects of climatic factors, including temperature, precipitation, soil moisture, and VPD, may exhibit temporal lags due to vegetation physiological regulation and buffering processes (Wu et al. 2015). To account for these lagged responses, we evaluated the relationships between climatic variables and vegetation anomalies by calculating cross-correlations over lag periods ranging from 0 to 3 months.

2.7 | Future Projection

Future NEGs are defined as vegetation anomalies relative to the historical reference state. By keeping the historical baseline fixed, this definition enables persistent future vegetation declines to be evaluated relative to present-day conditions rather than being incorporated into a shifting future baseline. Although such persistent changes may partly reflect long-term vegetation adjustment or adaptation to climate change, they still represent a relative loss compared with the historical vegetation state. This approach therefore provides a consistent basis for comparing NEG frequency and spatial extent between historical and future periods.

We applied the same parameter settings and anomaly detection framework as used for the observational datasets to both historical and future LAI simulations from CMIP6 models spanning the period 2001–2100. For each model and each scenario, we calculated z -scores of monthly LAI using the mean and standard

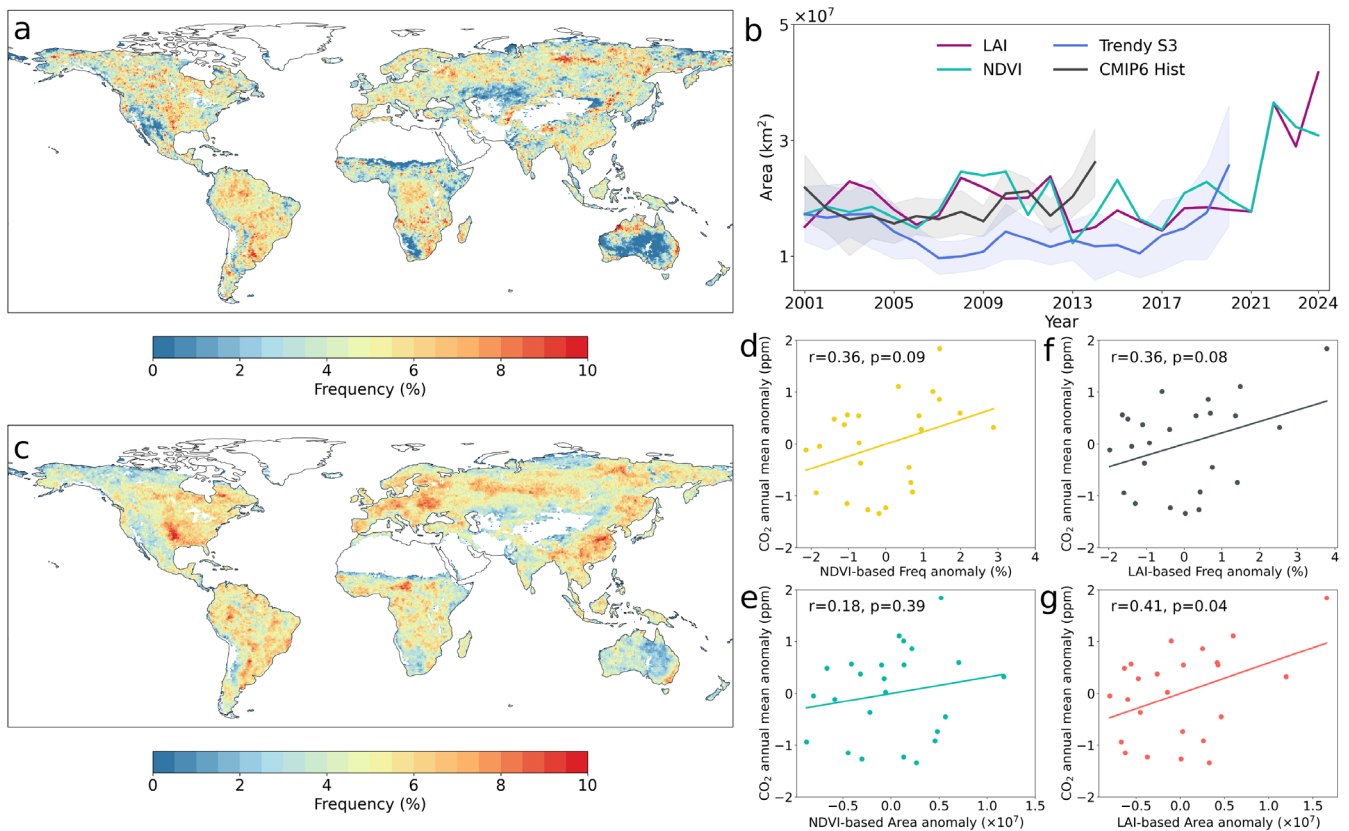


FIGURE 1 | Spatial and temporal characteristics of global negative extreme anomalies in vegetation growth (NEGs). (a) Spatial distribution of the frequency (expressed as the proportion of the growing season) of NEGs identified using LAI during 2001–2024. (b) Temporal evolution of NEG-affected area detected by LAI, NDVI, the TRENDY S3 ensemble, and CMIP6 historical scenarios. TRENDY and CMIP6 results are presented as observation-constrained, weighted multi-model means, with shaded regions indicating ± 1 standard deviation of the weighted model spread. (c) Spatial distribution of NEG frequency derived from TRENDY S3 simulations during 2001–2020, shown as an observation-constrained weighted multi-model mean. (d–g) Relationship between CO₂ annual mean anomalies and NEG frequency (d, f) and area (e, g) anomalies detected by NDVI and LAI. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

deviation from the first 30 years (2001–2030) as the baseline. We also tested additional parameter settings, including variations in the z-score threshold, event duration, and other criteria.

To assess potential drivers of NEGs, we focused on attributing NEGs to climatic drivers, specifically temperature, precipitation, and soil moisture. Attribution was limited to events that could be linked to anomalies in these variables, with particular attention paid to the influence of heatwaves and droughts on the frequency and intensity of vegetation anomalies in the coming decades. Land-use change and fire were not considered in this section due to the large uncertainties associated with their future projections and their complex, model-dependent representations.

3 | Results

3.1 | Spatiotemporal Patterns of NEGs

Applying the three-dimensional connectivity-based method to detrended and standardized vegetation indices, we systematically identified global NEGs and analyzed their frequency and spatial extent. Between 2001 and 2024, the spatial distribution of NEGs identified using LAI reveals several hotspot

regions, including southeastern North America, South America, Western Europe, central-southern Africa, southern China, and northeastern Australia (Figure 1a). Similar patterns were also detected using NDVI (Figure S1a), indicating consistency across vegetation indices. Over the past two decades, both the spatial extent and frequency of NEGs exhibit increasing tendencies (Figure 1b and Figure S1b). Specifically, the global area affected by NEGs detected using LAI increased at a rate of $394,471 \text{ km}^2 \text{ year}^{-1}$ ($p = 0.04$, adjusted $p = 0.11$; Figure 1b), while the global frequency showed a slight increasing trend of $0.07\% \text{ year}^{-1}$ ($p = 0.13$, adjusted $p = 0.25$; Figure S1b). Notably, NDVI-derived metrics indicate significant increases in both affected area and frequency, with trends of $421,375 \text{ km}^2 \text{ year}^{-1}$ ($p = 0.01$, adjusted $p = 0.05$; Figure 1b) and $0.09\% \text{ year}^{-1}$ ($p = 0.02$, adjusted $p = 0.05$; Figure S1b), respectively. The NDVI-based metrics were strongly correlated with their LAI-based counterparts ($r = 0.86$, $p < 0.01$), indicating broadly consistent interannual variability between the two indices.

We further examined the sensitivity of LAI-based NEG-affected area trends to key event definition parameters, including the z-score threshold, minimum duration, maximum affected area, and growing-season definition (Table S1). Across all sensitivity settings, the affected area consistently exhibited a positive trend, indicating a robust large-scale expansion of NEG-affected

regions. However, trend magnitudes were systematically influenced by event definition parameters. Stricter criteria (i.e., longer minimum durations, larger area thresholds, and more constrained growing-season definitions) generally led to weaker trend slopes, reflecting a reduction in the number of detected events under more conservative settings. In addition, the response to z -score thresholds was non-monotonic: both relaxed and stringent thresholds attenuated the detected trend, highlighting a trade-off between noise contamination under lenient definitions and information loss under overly strict ones.

The TRENDY S3 ensemble broadly captured the spatial patterns of NEG frequency observed from LAI, with 67.3% of grid cells showing positive correlations and 27.6% showing statistically significant positive correlations (Figure 1c and Figure S2b). However, the temporal variations in both NEG frequency and affected area were poorly reproduced, with no significant temporal correlations between the simulations and observations (Figure S2c,d). The CMIP6 historical simulations showed substantially weaker agreement with the observed spatial patterns, with positive correlations at only 41.1% of grid cells and statistically significant positive correlations at 6.5% of grid cells. The temporal correlation in NEG frequency was not significant, while NEG-affected area showed a negative correlation with observations (Figure S3). These results indicate that the model ensembles capture some broad spatial features of NEG variability but remain limited in reproducing its full spatial and temporal variability.

Furthermore, LAI-based NEG anomalies show a positive relationship with CO_2 anomalies, with frequency exhibiting marginal significance ($r=0.36$, $p=0.08$) and affected area showing a statistically significant correlation ($r=0.41$, $p=0.04$). Similarly, NDVI-based NEG anomalies also display a positive correlation for frequency ($r=0.36$, $p=0.09$). In contrast, the correlation with affected area is weak and not statistically significant ($r=0.18$, $p=0.39$) (Figure 1d–g). This suggests that increases in NEG frequency and extent may be associated with higher atmospheric CO_2 anomalies, indicating a potential link between vegetation anomalies and variability in the global carbon cycle. Collectively, these patterns point to an increasing exposure of global vegetation to extreme growth anomalies, implying growing ecosystem vulnerability under ongoing climatic and environmental pressures.

3.2 | Attribution of NEG to Climate and Disturbance Drivers

We applied a coincidence analysis to attribute LAI-based NEG to climatic and non-climatic drivers by systematically assessing their spatiotemporal overlap with climate extremes and disturbances, with significant driver–NEG associations identified at $p<0.05$. As shown in Figure 2a, the global distribution of dominant drivers reveals distinct regional patterns. Soil moisture deficit (SM–), representing events primarily driven by soil drought, was mainly concentrated in Australia, India, and the southeastern United States. In contrast, compound events associated with soil moisture deficit, including those coupled with low precipitation (Pre–), high VPD (VPD+), elevated temperatures (Tmp+), or fire, were predominantly clustered in northern

Africa, southern South America, and northern Australia, while compound events coupled with low temperatures mainly affected central and eastern Siberia. Fire-related NEG are mainly concentrated in Africa. In contrast, NEG associated with land-use change are more spatially scattered and do not exhibit large-scale regional clustering.

The proportion of NEG attributable to different drivers exhibits a clear latitudinal gradient (Figure 2b). Soil moisture deficit-driven events are most prevalent across all latitudes, underscoring the strong influence of SM-related drought. Fire-driven NEG show concentration within $\pm 20^\circ$, with notable peaks in the Southern Hemisphere. In contrast, drivers related to low precipitation, high temperature, soil moisture deficit, and high VPD coupling become increasingly dominant at mid- to high latitudes, particularly between 30°N and 60°N , reflecting the growing role of heat stress and atmospheric aridity in temperate and boreal ecosystems. Additionally, low temperature-driven NEG have become increasingly frequent north of 50°N . These latitudinal trends emphasize the strong coupling between regional climate zones and the dominant stressors behind large-scale vegetation anomalies.

The relative contribution of dominant drivers varies considerably across the four major climate zones defined by the Köppen–Geiger classification: Tropical, Arid, Temperate, and Cold (Figure 2c). In tropical, arid, and temperate regions, soil moisture deficit and compound drought-related conditions dominate, accounting for over half of all NEG, where drought is characterized by co-occurring low precipitation, soil moisture deficit, and high VPD, sometimes accompanied by heat extremes or fire. In cold climate zones, the influence of low temperature and SM-related drivers increases markedly.

The global land area affected by individual and compound drivers highlights the strong influence of drought-related stressors on NEG (Figure 2d). Soil moisture deficit alone accounts for 29.3%–29.6% of all NEG-affected areas (29.5%, 29.6%, and 29.3% at $p<0.01$, 0.05, and 0.10, respectively; Table S2), substantially more than any other individual driver. When including compound drought-related conditions characterized by concurrent precipitation deficit, soil moisture depletion, and high VPD, together with heat extremes or fire, the cumulative contribution reaches 58.5%–59.8% (59.2%, 58.5%, and 59.8% at $p<0.01$, 0.05, and 0.10, respectively; Table S2). This indicates that, relative to other climate and disturbance drivers, drought and drought-associated compound extremes exert the strongest influence on global NEG.

We also performed attribution analysis for NDVI-based NEG, and the results show regional differences compared to LAI-based NEG, with drought dominance in regions such as the Amazon and southern China (Figure S4a). However, the overall driver structure remains consistent, with soil moisture deficit accounting for 41.3%–42.7% of NEG-affected areas (41.9%, 41.3%, and 42.7% at $p<0.01$, 0.05, and 0.10, respectively; Table S3) and drought-related conditions contributing 85.6%–86.1% (86.1%, 85.6%, and 85.7% at $p<0.01$, 0.05, and 0.10, respectively; Table S3) (Figure S4b). Furthermore, over the past two decades, the expansion of NEG in spatial extent can be linked to changes in specific driving factors (Figure S5). Among

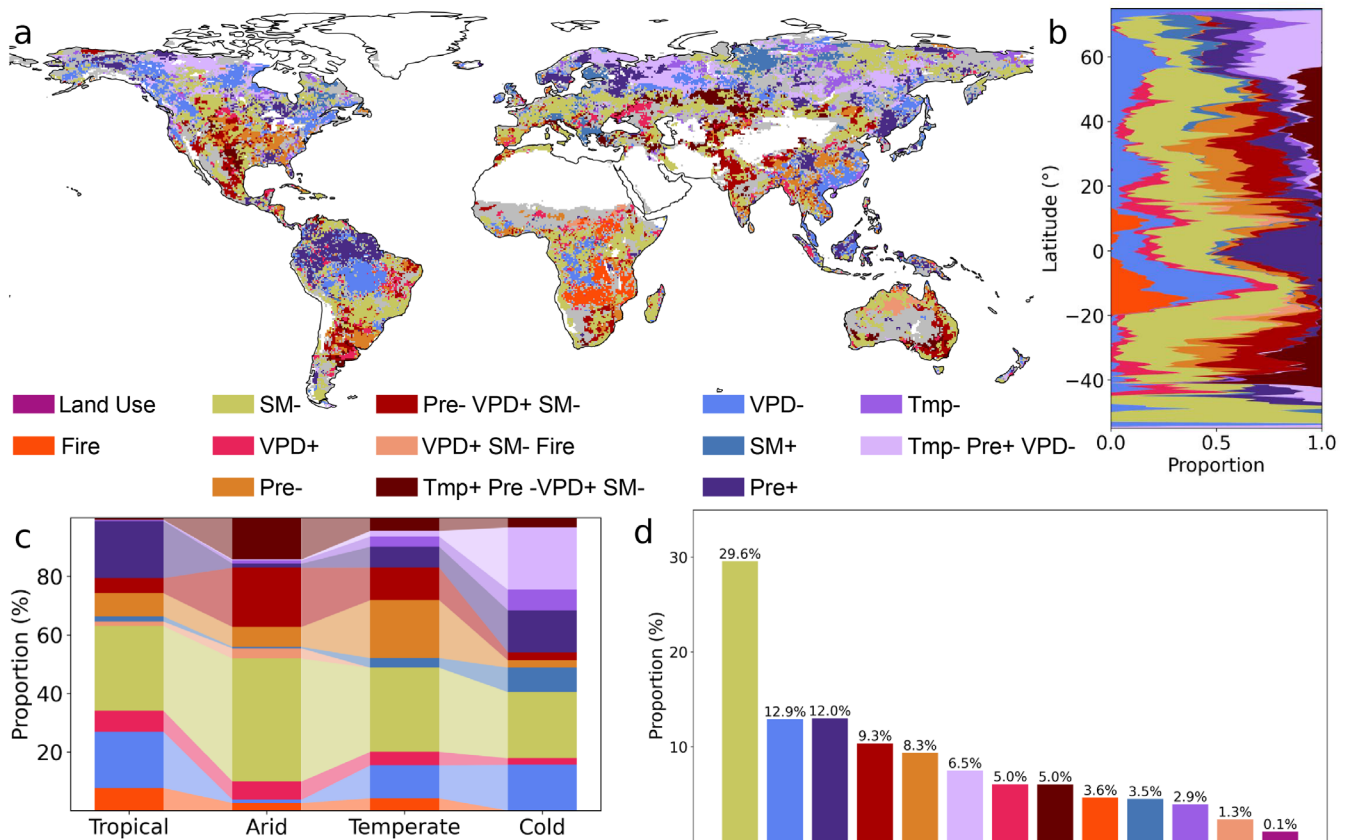


FIGURE 2 | Spatial patterns and dominant drivers of LAI-based NEGs. (a) Global map showing the spatial distribution of dominant drivers of NEGs, including land use, fire, temperature (Tmp), vapor pressure deficit (VPD), soil moisture (SM), precipitation (Pre), and their combinations. (b) Latitudinal profile of the proportion of NEGs attributed to different dominant drivers, illustrating variation across latitude bands. (c) Proportional distribution of dominant drivers across four major climate zones (Tropical, Arid, Temperate, Cold) based on the Köppen-Geiger classification, with shaded regions between the climate zones indicating changes in driver contributions. (d) Percentage of LAI-based NEG-affected area attributed to each dominant driver or driver combination. All driver attribution results shown in (a–d) are based on driver–NEG associations that passed the shuffle test at $p < 0.05$. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

these, events jointly driven by high VPD, soil moisture deficit, and fire ([VPD+] [SM–] [Fire]) show a significant increase in affected area of $26,573 \text{ km}^2 \text{ year}^{-1}$ (identified at $p < 0.05$ in the coincidence analysis; trend $p = 0.01$), suggesting a growing contribution of drought-related compound stressors to the expansion of large-scale vegetation anomalies under recent climate conditions.

3.3 | Occurrence of the Top Ten NEGs Within the Period 2001–2024

By comparing the cumulative affected areas of all identified NEGs, we selected the ten events with the largest spatial impacts. These top ten NEGs from 2001 to 2024 exhibit distinct spatial and temporal patterns, spanning multiple continents (Figure 3). Temporally, most events are concentrated in the past 10 years, suggesting a recent intensification of NEGs.

Among the top ten events, Event 1 and Event 2 both occurred during late 2019 to early 2020 and represent concurrent compound heat–drought conditions across major tropical regions. Event 1 in southeastern Amazonia was characterized by a pronounced vegetation decline associated with elevated temperature

and soil moisture deficit, contributing to widespread impacts on agriculture and hydrology (Gomes et al. 2021). These included reduced crop yields and delayed soybean sowing, as well as extremely low river levels across major South American river systems, which severely disrupted navigation, trade, and ecosystem services (Marengo et al. 2021). Similarly, Event 2 in central Africa exhibited co-occurring thermal stress and reduced moisture availability, leading to spatially extensive and sustained vegetation reductions. In contrast, Event 5 represents a prominent cold-wave episode over southern South America during 2022. This event was primarily characterized by pronounced negative temperature anomalies during the growing season. The cold-air outbreak extended across large parts of Argentina, Uruguay, southern Brazil, and adjacent regions, reflecting an extensive intrusion of polar air masses into mid- and subtropical South America.

Among the ten most extreme NEGs identified in our analysis, nine were associated with heatwaves, low precipitation, soil moisture deficit, atmospheric aridity, or fire-related stressors. This imbalance underscores a dominant role of warming-induced stress in driving large-scale NEGs in recent decades. It also suggests that under continued global warming, the frequency and intensity of NEGs are likely to be increasingly

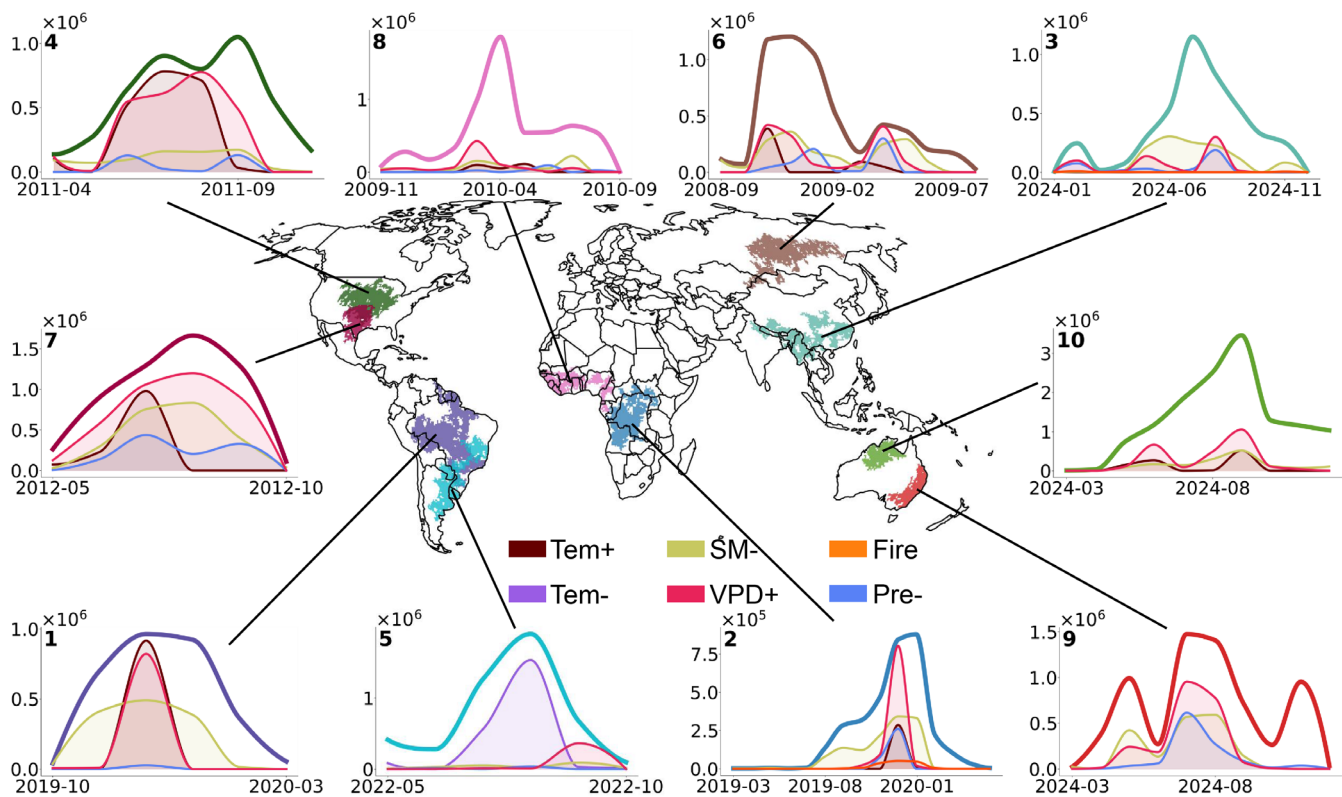


FIGURE 3 | Characteristics of the ten largest NEGs identified globally. The central map shows the geographic extent of each extreme event, color-coded to distinguish individual events. Panels 1–10 illustrate the temporal evolution of each event, including the total area (km²) affected by NEGs and the associated climatic drivers (e.g., high temperature, low soil moisture) represented by overlapping shaded regions. Climatic drivers were identified using a significance threshold of $p < 0.05$ in the coincidence analysis. Solid curves represent NEG-affected area, whereas shaded curves denote the corresponding climatic drivers. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

governed by high temperature, low precipitation, atmospheric aridity, and soil moisture deficit.

3.4 | Future Projections of Vegetation Extremes Under Climate Scenarios

Future projections based on three CMIP6 emission scenarios, including SSP1-2.6, SSP2-4.5, and SSP5-8.5, demonstrate pronounced differences in the spatial distribution of NEGs (Figure 4a–c). Under the low-emission scenario SSP1-2.6 (Figure 4a), vegetation anomalies remain relatively limited in extent, with a few localized hotspots in southern Europe, the northern Amazon Basin, parts of Southeast Asia, and southern Africa. As emissions increase, the geographic spread and intensity of NEGs expand markedly. In the intermediate emission scenario SSP2-4.5 (Figure 4b), hotspots intensify across southern Europe, northern India, eastern China, and much of Africa and Australia. Under the high-emission scenario SSP5-8.5 (Figure 4c), NEGs become widespread throughout most tropical and subtropical regions, with particularly dense clusters in southern North America, Europe, Africa, India, and southern China.

Both NEG frequency and spatial extent are projected to show increasing tendencies throughout the 21st century across all three scenarios (Figure 4d,e). Projected NEG frequency shows comparable positive trends under SSP5-8.5 (0.042% year⁻¹,

$p < 0.01$), SSP2-4.5 (0.047% year⁻¹, $p < 0.01$), and SSP1-2.6 (0.047% year⁻¹, $p < 0.01$) (Figure 4d). Projected spatial extent similarly shows positive trends, with a larger slope under SSP5-8.5 (358,643 km² year⁻¹, $p < 0.01$), followed by SSP2-4.5 (292,520 km² year⁻¹, $p < 0.01$) and SSP1-2.6 (256,676 km² year⁻¹, $p < 0.01$). Compared to the period covered by satellite observations (2001–2024), model projections suggest that, by the end of this century, NEG frequency may reach approximately 0.85, 0.97, and 1.14 times the historical levels under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, respectively (Figure 4d). Similarly, the projected affected area may reach approximately 1.05, 1.25, 1.59 times the historical extent under the same scenarios (Figure 4e). Under SSP5-8.5, the projected NEG-affected area may reach up to 50.8% of the global land area by the end of the century (Figure 4e).

We further evaluated the sensitivity of projected LAI-based NEG-affected area trends to alternative parameter settings across CMIP6 SSP scenarios (Table S4). Across all combinations, the projected trends remained positive and statistically significant ($p < 0.01$), indicating that the direction of the projected change is insensitive to the tested parameter settings. Higher-forcing scenarios generally showed larger trend slopes than lower-forcing scenarios, while stricter event-detection criteria generally resulted in smaller slopes.

Furthermore, the cumulative event statistics reveal a contrast among the projected scenarios: while SSP5-8.5 exhibits a slightly

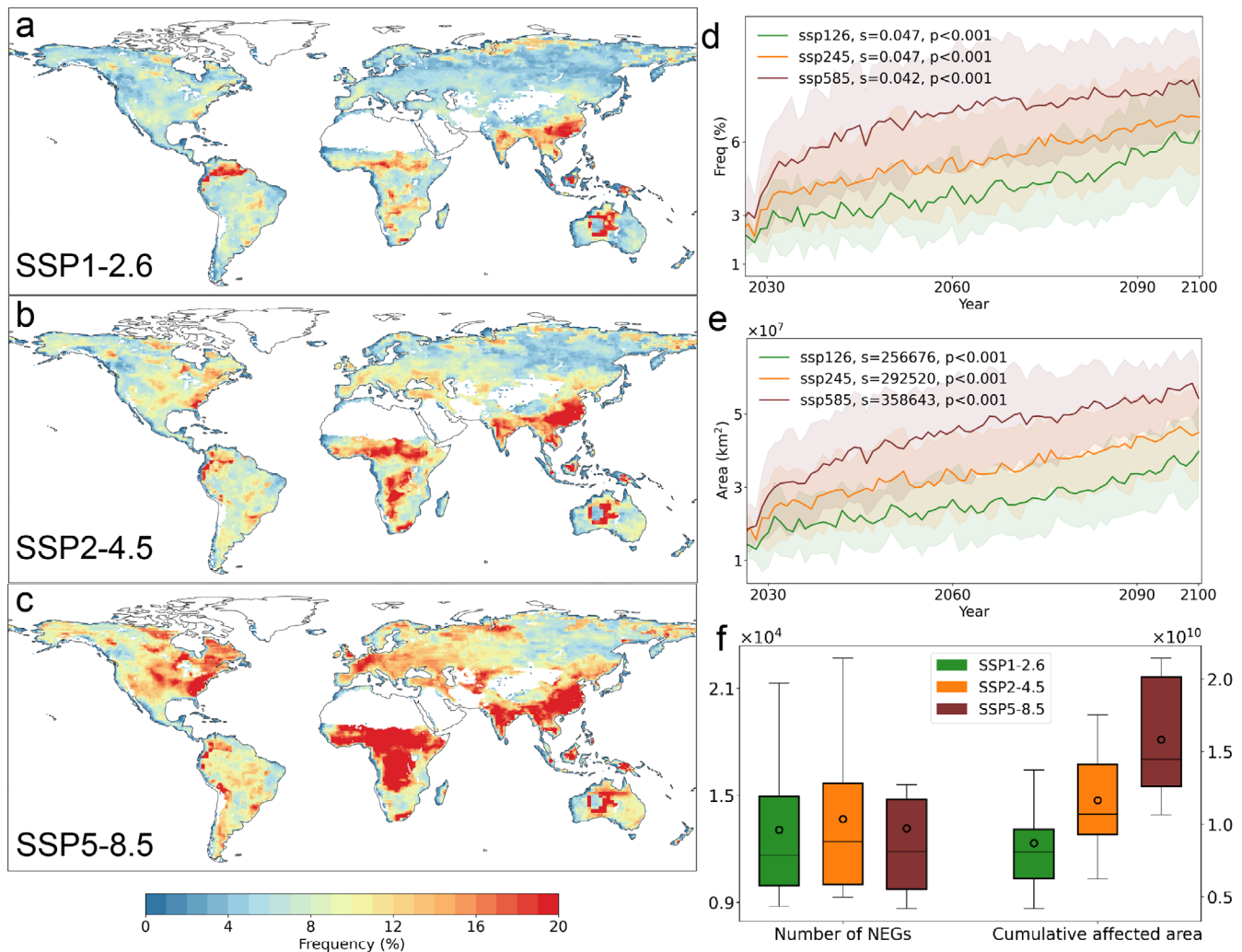


FIGURE 4 | Future Projections of NEG frequency under CMIP6 Climate Scenarios. (a–c) Spatial distribution of projected NEG frequency during 2030–2100 under three CMIP6 emission scenarios: SSP1-2.6 (a), SSP2-4.5 (b), and SSP5-8.5 (c). Values represent observation-constrained weighted multi-model means across CMIP6 models. Panels d and e depict temporal trends in the total frequency (d) and spatial extent (e) of NEG from 2030 to 2100 for each SSP scenario. Results are presented as multi-model means weighted using observation-constrained model weights, with shaded areas representing ± 1 weighted standard deviation across models. Linear regression lines are fitted with corresponding slopes and p -values indicating statistically significant increasing trends. (f) Total number of NEG and their cumulative affected area for each scenario. Boxplots represent the distribution across models, with the horizontal line indicating the median, the top and bottom of the box representing the 75th and 25th percentiles, and the whiskers showing the full range of the data. Circle markers denote the multi-model mean. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

lower number of NEG than SSP2-4.5, it is characterized by a substantially larger cumulative affected area (Figure 4f). This indicates that in high-emission scenarios, NEG tend to be fewer in number but larger in spatial scale. In SSP5-8.5, extreme NEG are projected to exhibit multimodal patterns in their affected areas, with some years showing relatively smaller impacted regions while the overall events persist continuously. Such a shift in event characteristics, from numerous smaller-scale anomalies to fewer, more spatially extensive events, may indicate an increasing ecological risk under high-emission scenarios.

By attributing future NEG to precipitation, soil moisture, and temperature, we found that the projected affected areas (Figure S6) associated with drought and heat–drought compound events show increasing trends across all scenarios. These projections suggest a potential increase in the occurrence and

spatial extent of NEG associated with drought and compound heat–drought stress in the future, without accounting for land-use change and fire.

4 | Discussion and Conclusion

In this study, we provide a global assessment of negative extreme anomalies in vegetation growth (NEG) and their spatio-temporal dynamics over the past two decades. Using established three-dimensional connectivity approaches, we characterize NEG by integrating multi-source observations and model simulations and further examine their dominant drivers and future changes through coincidence attribution and CMIP6 projections. Results indicate that both the frequency and spatial extent of NEG show increasing trends over the study period,

suggesting a potential increase in the exposure of terrestrial ecosystems to large-scale NEG events under ongoing climate variability and extremes. Consistent with this interpretation, periods characterized by more coherent and persistent NEG events tend to coincide with higher atmospheric CO₂ concentrations, suggesting a potential linkage between widespread vegetation stress and reduced terrestrial carbon uptake under climate extremes (Virkkala et al. 2025).

Our results demonstrate that drought-related stressors dominate the occurrence of NEG events globally. Nearly 58.5%–59.8% of all NEG events are associated with drought-related conditions, including single-driver drought events driven by soil moisture deficit, high vapor pressure deficit, or low precipitation, as well as drought-related compound events involving concurrent temperature extremes and wildfires. Importantly, the severity of NEG events scales with the extent to which drought is compounded by additional stressors: among the ten largest global NEG events, nearly all occurred under conditions of drought combined with heat extremes and, in some cases, wildfires. This pattern indicates that drought acts as a central constraint on vegetation growth, while co-occurring stressors primarily serve to amplify drought impacts through nonlinear interactions that exceed the additive effects of individual drivers (Gu et al. 2025; Zhang, Zhang, et al. 2024). Together, these processes increase the likelihood that drought manifests as compound stress in already vulnerable ecosystems (Chandanpurkar et al. 2025; Yuan et al. 2025).

CMIP6 projections suggest that the magnitude of NEG frequency and affected area is generally higher under stronger radiative forcing scenarios. However, the long-term trends in NEG frequency remain broadly similar across the three scenarios, indicating that stronger forcing is associated with a higher magnitude of NEG occurrence but not with a correspondingly steeper increase in frequency. Furthermore, while the projected number of NEG events under SSP5-8.5 is only marginally lower than under SSP2-4.5, the affected land area is substantially larger. This difference suggests a potential shift in future NEG characteristics toward fewer but larger and more spatially connected vegetation anomaly events (Gao et al. 2024). Such changes in the spatial characteristics of NEG events may have implications for ecosystem processes (Armstrong McKay et al. 2022). The spatial overlap between projected future hotspots and present-day climate-vulnerable regions suggests that existing ecological stresses may persist or intensify in some regions (Zscheischler et al. 2018). At the same time, the emergence of new high-risk zones in currently stable regions, such as central Africa, indicates that climate-driven vegetation instability may expand beyond historically vulnerable biomes, potentially increasing ecosystem vulnerability in these regions (Liu et al. 2023).

Despite these advances, several limitations of this study point to directions for future research. First, although our event-based framework captures the full life cycle of individual NEG events, it does not explicitly account for legacy or memory effects, whereby vegetation stress in one year may alter ecosystem sensitivity, recovery capacity, and thus the likelihood and severity of NEG events in subsequent years (Liu, Zhang, et al. 2025; Zhang, Xiong, et al. 2024). Second, land-use change is only considered in a simplified, short-term manner (Figure S7). Therefore, the 0.0%–0.2% contribution likely represents only a lower bound of

the influence of land-use change on NEG events (Table S2). Its long-term effects and interactions with climate drivers are not fully captured here and may contribute more substantially to the occurrence and evolution of NEG events. Third, attribution of future NEG events was primarily constrained to temperature and water conditions, as robust projections of disturbances such as wildfire and land-use change remain highly uncertain. Given growing evidence that fire risk and other disturbances may intensify alongside warming-driven drought–heat compound extremes, incorporating more comprehensive disturbance projections will be essential for improving future risk assessments (Jones et al. 2024; Zhao et al. 2025). Finally, although land-use change was included as a disturbance factor, the framework could be further extended to represent a broader range of human influences, such as land management practices and socio-economic pressures, in order to better capture coupled human–climate–ecosystem interactions (Quilcaille et al. 2025). Taken together, our results indicate that the increasing prevalence of NEG events under compound climate extremes poses escalating risks to ecosystem stability, reinforcing the need for both effective climate mitigation and targeted adaptation strategies to limit the amplification of climate–ecosystem feedbacks in a warming world.

Author Contributions

Haoliang Zhao: writing – original draft, data curation, formal analysis, visualization, validation. **Jingfeng Xiao:** writing – review and editing. **Wei Li:** writing – review and editing. **Hans W. Chen:** writing – review and editing. **Shuiqing Yin:** writing – review and editing. **Wenping Yuan:** writing – review and editing. **Ziqian Zhong:** writing – review and editing. **Lanlan Guo:** writing – review and editing. **Yang Chu:** writing – review and editing. **Tiewei Li:** writing – review and editing. **Bin He:** conceptualization, methodology, project administration, writing – review and editing, supervision, funding acquisition.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets used in this study are publicly available from the repositories listed below. The MODIS leaf area index (LAI) data are available at: <https://doi.org/10.5067/MODIS/MOD15A2H.061>. The MODIS normalized difference vegetation index (NDVI) data are available at: <https://doi.org/10.5067/MODIS/MOD13Q1.061>. The MODIS land cover data are available at: <https://doi.org/10.5067/MODIS/MCD12Q1.061>. The ERA5–Land reanalysis product is available at: <https://doi.org/10.24381/cds.68d2bb30>. The CRU TS v4.09 gridded climate dataset is available at: https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.09. The burned area data from the Global Fire Emissions Database (GFED) are available at: <https://www.globalfiredata.org>. The Köppen–Geiger climate classification data are available at: <https://www.gloh2o.org/koppen>. The NOAA atmospheric CO₂ annual mean data are available at: <https://gml.noaa.gov/ccgg/trends/data.html>. The TRENDY project v10 ensemble

simulations are available at: <https://mdosullivan.github.io/GCB/>. The CMIP6 simulations are available through the Earth System Grid Federation at: <https://aims2.llnl.gov/search/cmip6/>. Code availability: The scripts used for the detection of negative extreme anomalies in vegetation growth (NEGs), event coincidence analysis, and the shuffle-based significance test are publicly available in a GitHub repository: <https://github.com/x1114331429/Increasing-Extreme-Negative-Vegetation-Responses-to-Drought-Related-Compound-Events>. The repository also includes documentation and examples describing the analysis workflow and implementation of the main algorithms.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure S1:** Spatiotemporal Distribution of Negative Extreme Anomalies in 27 Vegetation Growth (NEGs). (a) Global distribution of NEGs frequency during 28 2001–2024 derived from NDVI. (b) Temporal evolution of NEGs frequencies detected by LAI, NDVI, the TRENDY S3 ensemble, and CMIP6 historical scenarios. TRENDY and CMIP6 results are presented as multi-model means, with shaded regions showing ± 1 standard deviation. (c) Spatial distribution of NEGs occurrence during 2001–2014 under CMIP6 historical scenarios. **Figure S2:** Evaluation of TRENDY S3-simulated LAI-based NEGs against observations. (a) Spatial distribution of the correlation between TRENDY S3 and observed LAI NEGs, with stippling indicating statistically significant correlations ($p < 0.1$). (b) Proportion of grid cells classified by correlation type, including significant positive, non-significant positive, non-significant negative, and significant negative correlations (from left to right). (c) Scatter plot of NEG frequency between TRENDY S3 and observations, with the correlation coefficient (r) and relative bias (bias) indicated. (d) Same as (c), but for NEG-affected area. **Figure S3:** Evaluation of CMIP6 historical simulations of LAI-based NEGs against observations. (a) Spatial distribution of the correlation between CMIP6 historical simulations and observed LAI NEGs, with stippling indicating statistically significant correlations ($p < 0.1$). (b) Proportion of grid cells classified by correlation type, including significant positive, non-significant positive, non-significant negative, and significant negative correlations (from left to right). (c) Scatter plot of NEG frequency between CMIP6 historical simulations and observations, with the correlation coefficient (r) and relative bias (bias) indicated. (d) Same as (c), but for NEG-affected area. **Figure S4:** Spatial patterns and dominant drivers of NDVI-based NEGs. (a) Global map showing the spatial distribution of dominant drivers of negative extreme vegetation growth events (NEGs), including fire, temperature (T_{mp}), vapor pressure deficit

(VPD), soil moisture (SM), precipitation (Pre), and their combinations. (b) Area percentage of global land attributed to each dominant driver or driver combination. All results are based on statistically significant associations ($p < 0.05$). **Figure S5:** Area changes of vegetation negative anomalies under different driving factors. All panels show the annual affected area of LAI-based NEG_s (km²) under different driving factors identified at $p < 0.05$ in the coincidence analysis, along with the linear regression slope (S) and corresponding p -values. **Figure S6:** Changes in the affected area (km²) of NEG_s driven by drought, heat, and compound heat-drought events under different future scenarios. Drought-related events are defined as conditions with negative anomalies in precipitation and/or soil moisture. Heat-related events are defined by positive temperature anomalies, and compound heat-drought events are identified when negative precipitation and/or soil moisture anomalies co-occur with positive temperature anomalies. The green line represents the SSP1-2.6 scenario, the orange line represents SSP2-4.5, and the red line represents SSP5-8.5. Shaded areas indicate ± 1 standard deviation. **Figure S7:** Land cover transition-induced LAI anomaly at a representative grid cell. (a) Location of the anomaly point in South America. (b) Time series of LAI at the selected grid cell. The shaded red area indicates the anomaly period. The background shading represents land cover types, showing a transition from evergreen broadleaf forest to grassland, accompanied by a pronounced decline in LAI. **Table S1:** Sensitivity of LAI-based NEG-affected area trends to event definition parameters. **Table S2:** Sensitivity of LAI-based NEG attribution to different significance thresholds. **Table S3:** Sensitivity of NDVI-based NEG attribution to different significance thresholds. **Table S4:** Sensitivity of LAI-based NEG-affected area trends across CMIP6 scenarios.