

Increasing risk of compound heatwave-pluvial hazards in highly populated regions

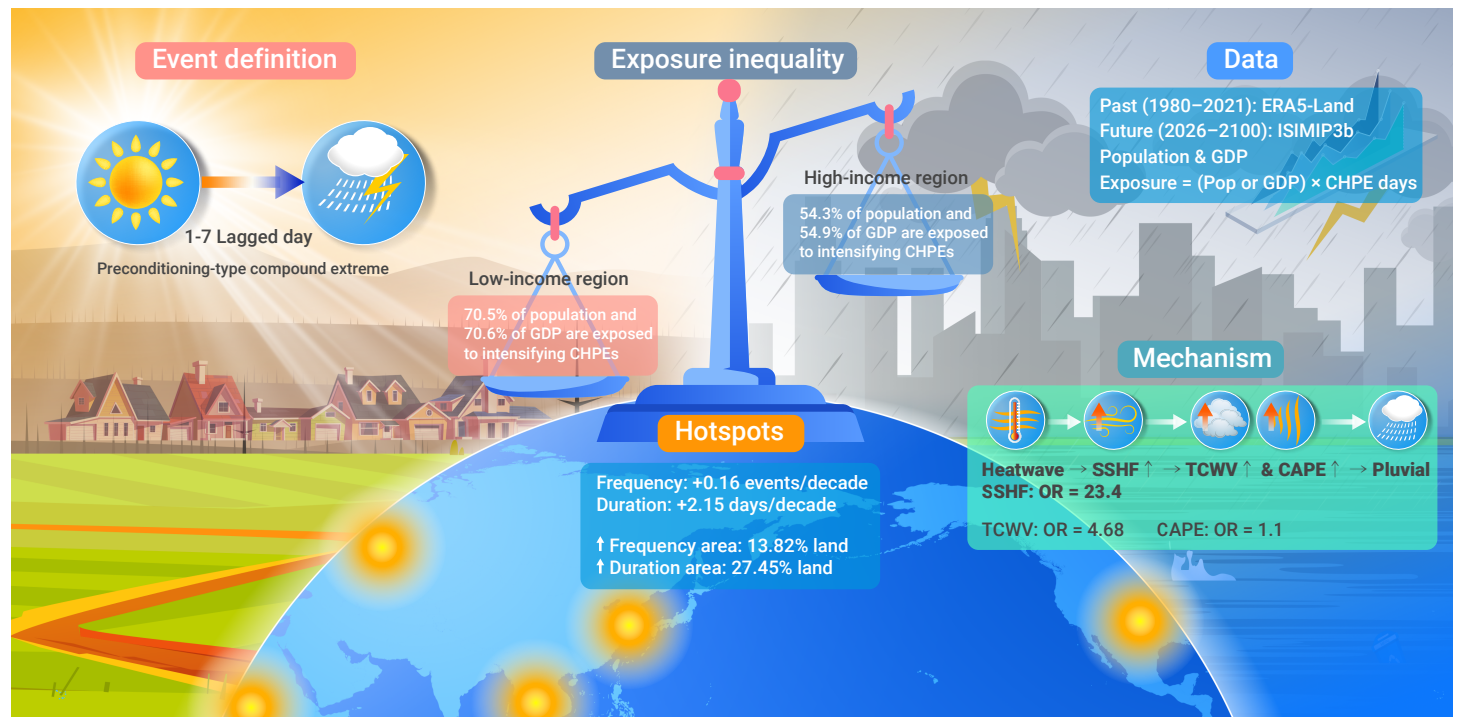
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Compound heatwave–pluvial events (CHPEs)—heatwaves followed by heavy rain within 7 days—are rising worldwide.
- 1980–2021 saw more and longer CHPEs, with hotspots in Central Europe, East Asia and North America.
- Sensible heat flux (SSHF) and total column water vapor (TCWV) promote heatwave-to-pluvial shifts.
- Under Shared Socioeconomic Pathway 5-8.5 (SSP5-8.5), exposure rises fastest in low-income countries.
- Targeted mitigation and adaptation are needed to protect dense urban hotspots and reduce climate inequality.

Increasing risk of compound heatwave-pluvial hazards in highly populated regions

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Compound heatwave-pluvial events (CHPEs) can cause severe socio-economic damage and are difficult to predict because of their complex transition processes. Moreover, their spatial patterns and impacts on socio-economic systems remain poorly understood. Using an extensive set of atmospheric reanalysis data and model simulations, we observed a significant global increase in the frequency and duration of CHPEs from 1980 to 2021, with hotspots in Central Europe, East Asia, the Tibetan Plateau, Southern Africa, the Amazon Basin, and North America. Low-income countries are projected to experience a significantly higher population (+42.2%) and GDP exposure (+46.4%) to CHPEs than high-income countries under the SSP585. These findings emphasize the ongoing disparities in exposure under future socio-economic scenarios, highlighting the urgent need to develop equitable and just mitigation and adaptation strategies, particularly in less-developed regions.

INTRODUCTION

Global warming has increased the frequency and severity of compound extreme events,¹⁻⁴ negatively affecting human life and ecosystems worldwide.⁵⁻¹⁰ As one of the most severe and intensifying climatic stressors, heatwaves are abnormally high temperatures that exceed a critical threshold and persist for days to weeks.¹¹⁻¹³ Pluvial events are generally the primary drivers of flooding, and their severity and intensity have increased in recent decades.^{14,15} Unlike several widely studied compound hazards such as heatwaves and droughts,^{11,16,17} heatwaves and pluvial events are regarded as separate or independent hazards, as these opposing weather extremes rarely occur simultaneously.^{18,19} However, considering the interactions and dependencies between temperature and precipitation, a lagged relationship could exist between heatwaves and pluvial events, forming a temporally compounded event.^{7,20,21} Compared to univariate extremes, such compound hazards typically amplify damage spatially and temporally.²²⁻²⁴ Therefore, characterizing the changes in compound heatwave-pluvial events (CHPEs) and understanding their drivers are crucial for facilitating adaptation and mitigation strategies for sustainable development.

Although heatwaves and pluvial events generally occur at different times, they may be physically linked. For example, heatwaves can decrease stability in the lower atmosphere and cause convective energy to accumulate, increasing the capacity of the atmosphere to hold moisture. Under these conditions, if a weather system conducive to pluvial events moves over an area that recently experienced a heatwave, the probability of the occurrence or intensity of pluvial events may increase.^{21,25} Such temporal compound events have gradually become more common, and heatwaves may facilitate moisture conditions that feed on extreme precipitation.²² Based on observational datasets, Chen et al. found that compound flood-hot extremes,⁷ which were previously rare, gradually became increasingly prevalent after 2000 across China because of anthropogenic climate change. Zhang and Villarini found that large-magnitude floods are prone to be connected with heat stress under warming,²¹ potentially leading to increased infrastructure damage and fatalities. These studies suggest an increase in the frequency and intensity of compound hot and extreme precipitation events under

changing climates.

As climate change intensifies, the likelihood of the co-occurrence of heatwaves and extreme precipitation increases, further escalating threats to societies and ecosystems.^{19,26,27} This is supported by the dramatic increase in climate change-induced disasters such as floods and heatwaves, resulting in over two million deaths and economic losses totaling \$3.64 trillion,^{14,28,29} which significantly hinders the sustainable development of the social economy. Despite growing evidence that extreme flooding may be closely associated with extremely hot climatic conditions,²⁰ the underlying mechanisms explaining why extreme precipitation often follows heatwaves remain poorly understood. Additionally, the associated impacts of such compound hazards on socioeconomic systems require a deeper understanding to better inform adaptation measures.

To address these knowledge gaps regarding CHPEs and their socio-economic impacts, we investigated the global pattern of this type of compound event and identified major geographical CHPE hotspots using ground-based reanalysis and climate model simulations. Next, we explored the physical mechanisms driving the changes in CHPEs by examining five climate variables. Finally, we quantified the exposure of the global population and GDP to CHPEs and investigated the possible influence of CHPEs on socio-economic disparities between high- and low-income regions. Although low-income areas are highly sensitive to climate extremes, such as floods and heatwaves,^{30,31} studies quantifying the relationship between poverty and compound climate events are lacking. This highlights the need to design comprehensive and equitable strategies to address climate vulnerability in impoverished regions.

MATERIALS AND METHODS

ERA5-Land data

The ERA5-Land developed by the European Centre for Medium-Range Weather Forecasts is a reanalysis dataset that uses a state-of-the-art scheme for surface exchange over land (<https://cds.climate.copernicus.eu>).³² It provides various land variables with super-high spatial (0.1°) and temporal (hourly) resolutions from 1950 to the present. This global reanalysis dataset combines observations with model data using physical laws, and is forced by atmospheric constraints. We used the 2 m temperature (K), total precipitation (m), 2 m dew point temperature (K), and surface sensible heat flux (SSHf, J m⁻²) for 1980–2021. The 2 m and dew point temperatures were used to derive the relative and specific humidity. We also used ERA5 hourly convective available potential energy (CAPE, J kg⁻¹), total column water vapor (TCWV, kg m⁻²), and vertically integrated moisture divergence (VIMD, kg m⁻²) data to assess the physical mechanisms associated with changes in CHPEs.

Climate simulations data

We employed the climate forcing generated by Phase 3 of the Inter-Sectoral Impact Model Inter-comparison Project (ISIMIP 3b) at a 0.5° resolution.³³ The ensemble included corrected daily precipitation and temperature simulations from five CMIP6 climate models, GFDL-ESM4, IPSL-CM6ALR, MPI-ESM1-2HR, MRI-ESM2-0, and UKESM-1-0-LL, under historical (1980–2014) and future (2026–2100) scenarios. Future scenarios involve

three shared socioeconomic pathways (SSPs) under the corresponding representative concentration pathways (RCPs): sustainable (SSP1-RCP2.6), strongly fragmented (SSP3-RCP7.0), and growth-oriented (SSP5-RCP8.5) scenarios (hereafter referred to as SSP126, SSP370, and SSP585, respectively). Specifically, ISIMIP 3b used a robust method, named ISIMIP3BASD v2.5, to downscale and adjust biases in CMIP6 outputs toward the observational reference dataset, a merge of multiple sources, with version 2.0 of WFDE5 over land. This method retains the correlations between climate variables, preserves trends across quantiles, and allows for the reproduction of extreme values. The robustness of the ISIMIP dataset for assessing climate change impacts has been widely confirmed.^{34,35}

Socio-economic data

We used the global gridded 2015 population data from the Socioeconomic Data and Applications Center at Columbia University. These population data are consistent with national censuses and have been adjusted to match the 2015 Revision of the United Nations' World Population Prospects country totals, which are produced at a 30-arcsecond (~1 km at the Equator) resolution. We also used a global gridded 2015 GDP dataset at a 30-arcsecond resolution, which was produced by fully utilizing all available subnational data and the World Bank dataset.³⁶ We employed a spatially explicit global dataset produced by employing population and urbanization projection models and the Cobb–Douglas production model.³⁷ This dataset includes gridded population and GDP data under three SSPs covering 2010–2100 at a spatial resolution of 0.5°×0.5°, and has been widely used in climate change impact assessments.³⁸

Identifying CHPEs

In this study, CHPEs refer to heatwave events followed by pluvial events within 7 days. Specifically, the technique flow for identifying the CHPEs is as follows: we first extracted high-temperature events and pluvial events separately by using the locally 90th percentile thresholds of daily maximum temperature and daily precipitation during 1980–2021, respectively, according to the IPCC Extreme Climate Indices methodology.⁵ A heatwave is defined as an event in which a high temperature (i.e., > 90th percentile) occurs for at least three consecutive days. Similarly, a pluvial event is defined as an event in which precipitation exceeds the 90th percentile. If the interval between two separated heatwave events is one day, we merged these two heatwave events to one single heatwave event. Then, we labeled all heatwave and pluvial events as 1 and marked non-heatwave and non-pluvial events as 0 to create the binary time series of heatwaves and pluvial events. Finally, a CHPEs was identified when a pluvial event occurred within 7 days of a heatwave event. Figure S1 presents a detailed scheme for identifying these events.

Physical mechanism analysis

A logistic regression model can be used to assess the relationship between a binary outcome and a set of covariates, which can be interpreted using an odds ratio (OR) with a 95% confidence interval (CI). In this study, we investigate the influence of five hydroclimatic anomalies, namely CAPE, VIMC, TCWV, SSHF, and specific humidity (SH) on the CHPEs. The effect of each of the five covariates on the risk of CHPE occurrence was assessed by estimating the OR for CHPE occurrence using logistic regression.³⁹ A logistic regression was fitted using the binary sequence of heatwave events as the independent variable (X) and that of lagged events when pluvial events occurred as the dependent variable (Y), with Z as the confounding variable. The logistic regression model was defined as follows:

$$\text{Prob}(Y = 1) = \frac{e^{\beta_0 + \beta_1 \text{CAPE} + \beta_2 \text{VIMC} + \beta_3 \text{TCWV} + \beta_4 \text{SHF} + \beta_5 \text{SH}}}{1 + e^{\beta_0 + \beta_1 \text{CAPE} + \beta_2 \text{VIMC} + \beta_3 \text{TCWV} + \beta_4 \text{SHF} + \beta_5 \text{SH}}} \quad (1)$$

$e^{\beta_0 + \beta_1 \text{CAPE} + \beta_2 \text{VIMC} + \beta_3 \text{TCWV} + \beta_4 \text{SHF} + \beta_5 \text{SH}}$ represents the linear regression equation for independent variables expressed in the logit scale, rather than in the original linear format. The logit of Y is then expressed as:

$$\ln \frac{\text{Prob}(Y = 1)}{\text{Prob}(Y = 0)} = \beta_0 + \beta_1 \text{CAPE} + \beta_2 \text{VIMC} + \beta_3 \text{TCWV} + \beta_4 \text{SHF} + \beta_5 \text{SH} \quad (2)$$

Exposure to CHPEs

Socio-economic exposure to CHPEs is defined as the number of individuals

or assets exposed to CHPEs event-prone areas and is calculated by multiplying the population and GDP in each grid cell by the number of days of CHPEs for each corresponding grid cell over a specified period.⁴⁰ Here, the population or GDP exposures in the historical period were estimated based on the average population or GDP during the base years of 2010–2014 under SSP1, and the future population or GDP exposures under the four SSPs were combined with the corresponding future climate change scenarios: SSP1 with SSP1-2.6, SSP2 with SSP2-4.5, SSP3 with SSP3-7.0, and SSP5 with SSP5-8.5.

Country income classification

Countries were categorized according to the World Bank's official income grouping. Economies are currently divided into low-, lower-middle-, upper-middle-, or high-income groups based on Gross National Income (GNI) per capita in U.S. dollars (USD). To ensure comparability, the GNI values were converted from local currencies using the World Bank Atlas method. The GNI estimates are provided by World Bank country economists. Low-, lower-middle-, upper-middle-, and high-income economies are defined as those with a GNI per capita of \$1,135 or less, between \$1,136 and \$4,465, between \$4,466 and \$13,845, and more than \$13,845, respectively, in 2022. For clarity, all the monetary values in this study are in USD.

RESULTS

Global distribution of observed CHPEs

The ERA5-Land dataset shows that the hotspots with the highest frequency and duration of CHPEs for 1980–2021 are mostly located in temperate and cold zones according to the Köppen–Geiger climate regions (Figure 1). Specifically, the high frequency of CHPEs was primarily concentrated in the mid- to high-latitude (~30–70N) regions of the Northern Hemisphere, whereas low-frequency areas were found in the low-latitude regions of Arabia and the Middle East during 1980–2021. The duration of the CHPEs showed a similar spatial distribution, with longer durations in mid- to high-latitude regions and shorter durations in low-latitude areas. The hotspots of CHPEs include Central Europe, East Asia, the Tibetan Plateau, Southern Africa, and the northern regions of North America (Figure 1A). Figure 1B indicates that regions with longer CHPEs durations are found in East Asia, the Tibetan Plateau, and higher latitudes of the Northern Hemisphere, where frequent and long-lasting CHPEs threaten human health and ecosystems.

Globally, the frequency and duration of CHPEs showed significant average increasing trends during 1980–2021, equal to +0.16 events per decade ($p < 0.001$) and +2.15 days per decade ($p < 0.001$), respectively (Figure 2). Regions with significantly increasing trends in CHPEs frequency ($p < 0.05$) accounted for 13.82% of the global land area and were mainly located in Central Europe, Mongolia, coastal East Asia, South America, Central Africa, and the central plains and eastern coast of North America. Similarly, the global trend of CHPEs duration aligned with the spatial pattern of frequency; however, the area with a significantly increasing duration trend ($p < 0.05$) was larger and represented 27.45% of the global land area, with hotspots in Central Europe, Mongolia, East Asia, South America, Central Africa, and the central plains and eastern coast of North America. These results suggest that CHPEs hotspots typically have high frequencies and long durations. A significant increase in CHPEs has been observed in certain water-limited regions such as Mongolia, which have been observed to undergo a marked warming and drying trend in recent decades.⁴¹ Warming increase column water vapor roughly at Clausius–Clapeyron rates; therefore, after heatwaves (and when lifting occurs), heavier rainfall becomes more likely. In parallel, strong land–atmosphere coupling in drylands, where dry soils suppress latent cooling and enhance sensible heating, amplifies heatwaves and preconditions a hot, deep boundary layer that can rapidly transition to a pluvial state under moisture convergence.

Mechanisms underlying CHPEs occurrence

To explore the physical processes underlying the occurrence of CHPEs, we investigated the atmospheric conditions prior to the occurrence of pluvial events (Figure 3). Overall, the SSHF plays a crucial role in the transition from heatwaves to pluvial events, exerting a strong positive effect with a global average OR of 23.4, suggesting that a one-unit increase in the SSHF might amplify the OR of CHPEs by 23.4 times. The TCWV is also an important driver

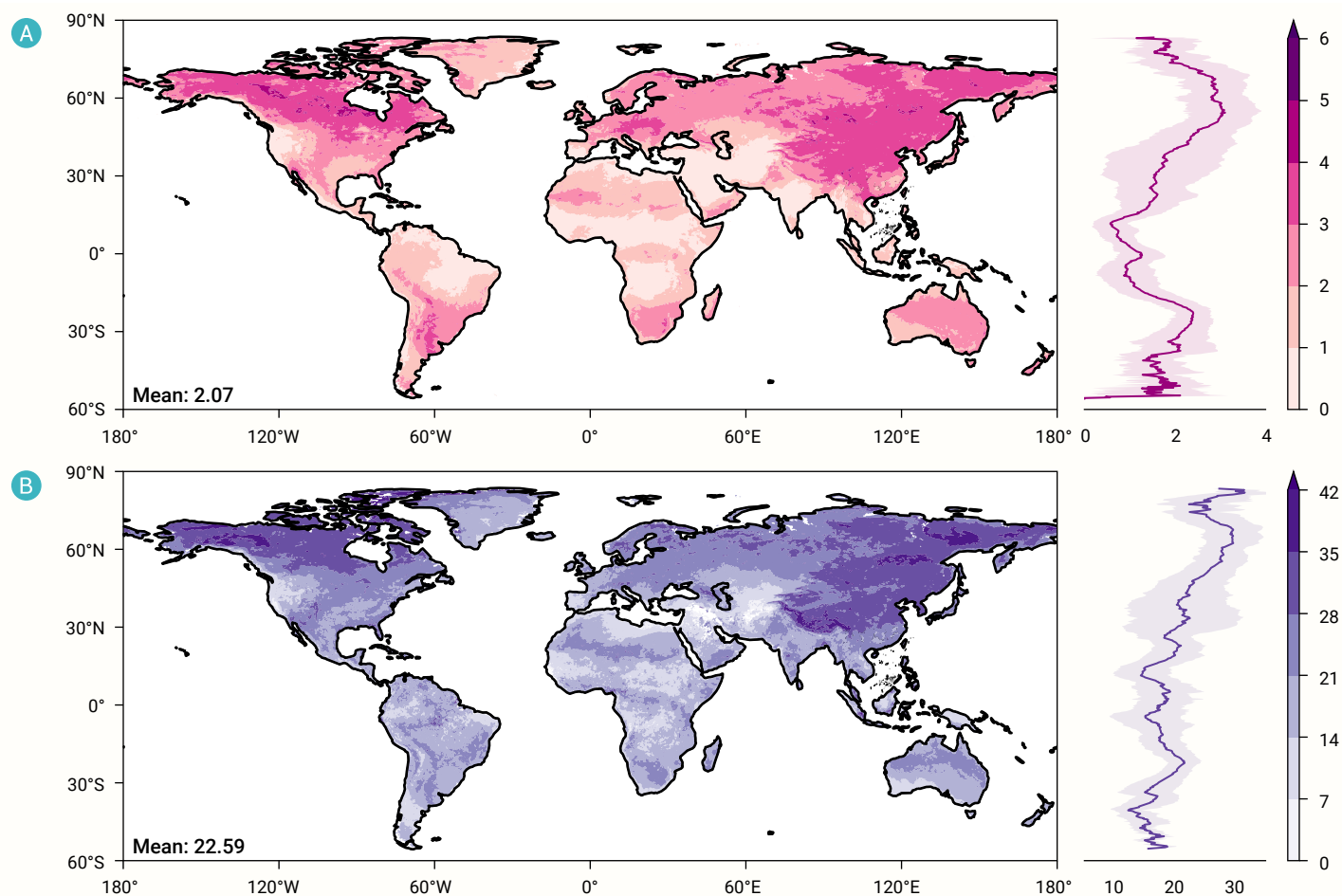


Figure 1. Spatial characteristics of compound heatwave-pluvial events (CHPEs) from 1980 to 2021 (A) Spatial distribution of the annual average CHPEs frequency during 1980–2021 (number of events per year); the right columns present the latitudinal distribution of CHPE frequency. (B) Spatial distribution of the annual average CHPE duration during 1980–2021 (days per event); the right columns present the latitudinal distribution of CHPEs duration.

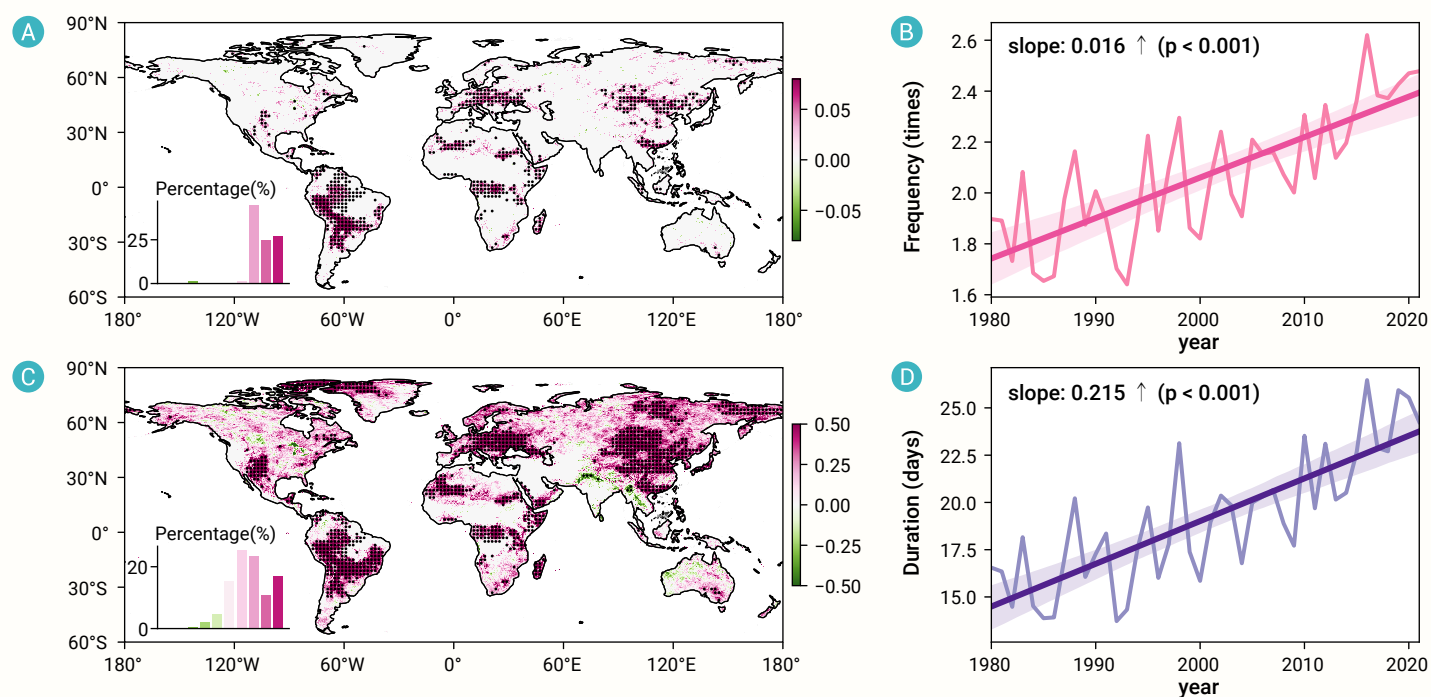


Figure 2. Trends in CHPEs frequency and duration (1980–2021) Spatial patterns of local linear trends in CHPEs frequency (A) and duration (C); stippling denotes trends significant at $p < 0.05$. Time series of global-mean CHPEs frequency (B) and duration (D) trends; shading indicates the 95% confidence intervals.

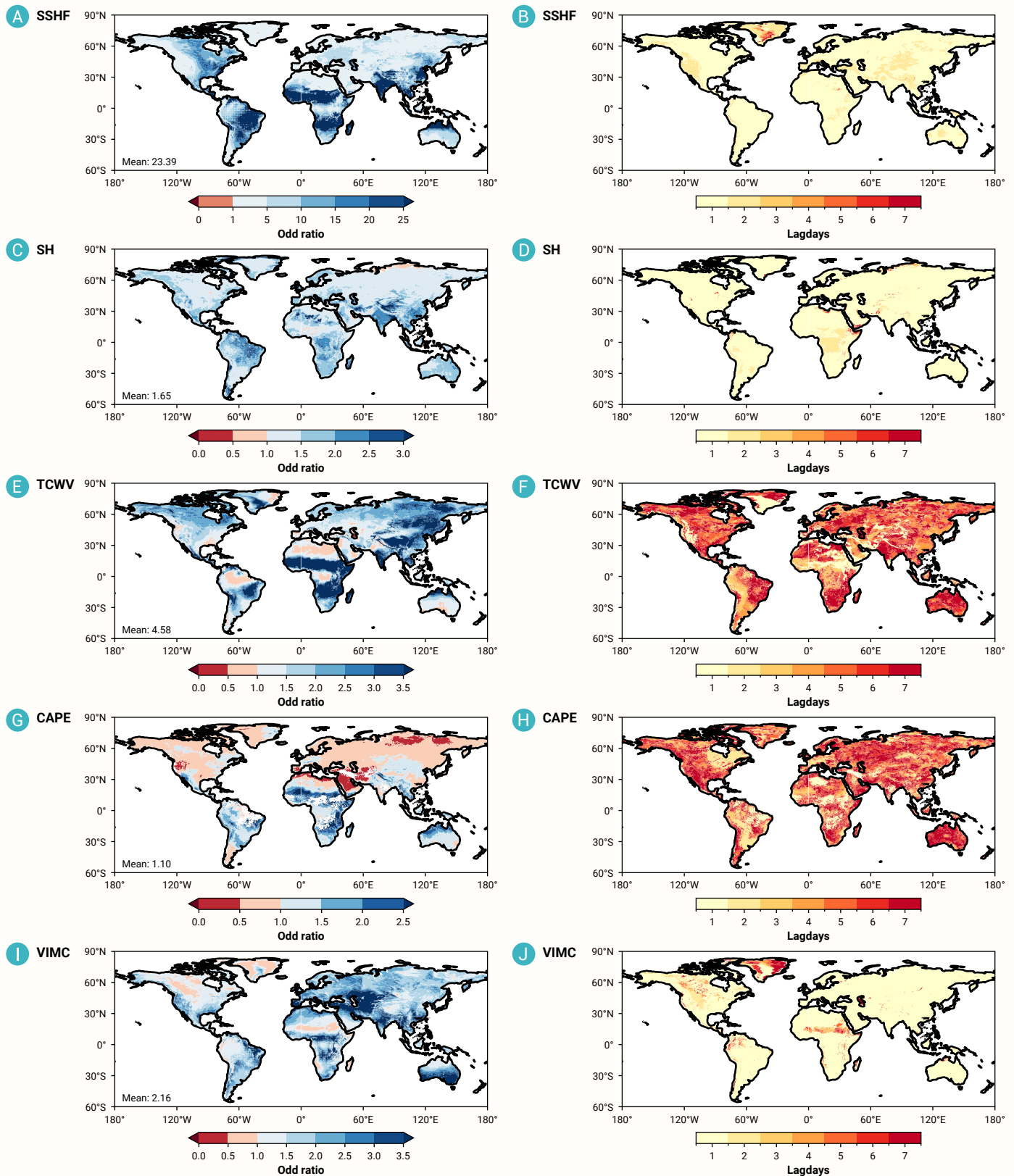


Figure 3. Influence of five hydroclimatic anomalies on the risk of occurrence of CHPs (including surface sensible heat flux [SSHf], specific humidity [SH], total column water vapor [TCWV], convective available potential energy [CAPE], and vertically integrated moisture converge [VIMC]) Left column: spatial distribution of the statistically significant ($p < 0.05$) maximum odds ratio (OR) over 1–7 lagged days; cool and warm colors represent the promoting ($OR > 1$) and inhibitory ($OR < 1$) effects of hydroclimatic anomalies on CHPs, respectively. Right column: spatial distribution of the lagged days corresponding to the maximum OR.

of CHPs, with a global average OR of 4.68. These results indicate that the atmosphere can hold more water vapor with increasing SSHf, according to the Clausius–Clapeyron equation, increasing TCWV and thus CHPs. Heat-waves, which are directly associated with the SSHf, can stimulate the

convective energy of the local atmosphere by heating air parcels, which are associated with the thermodynamic component of vertical moisture advection change. The global average OR for CAPE, which represents the convective energy factor, was 1.1, indicating a limited effect on CHPs globally.

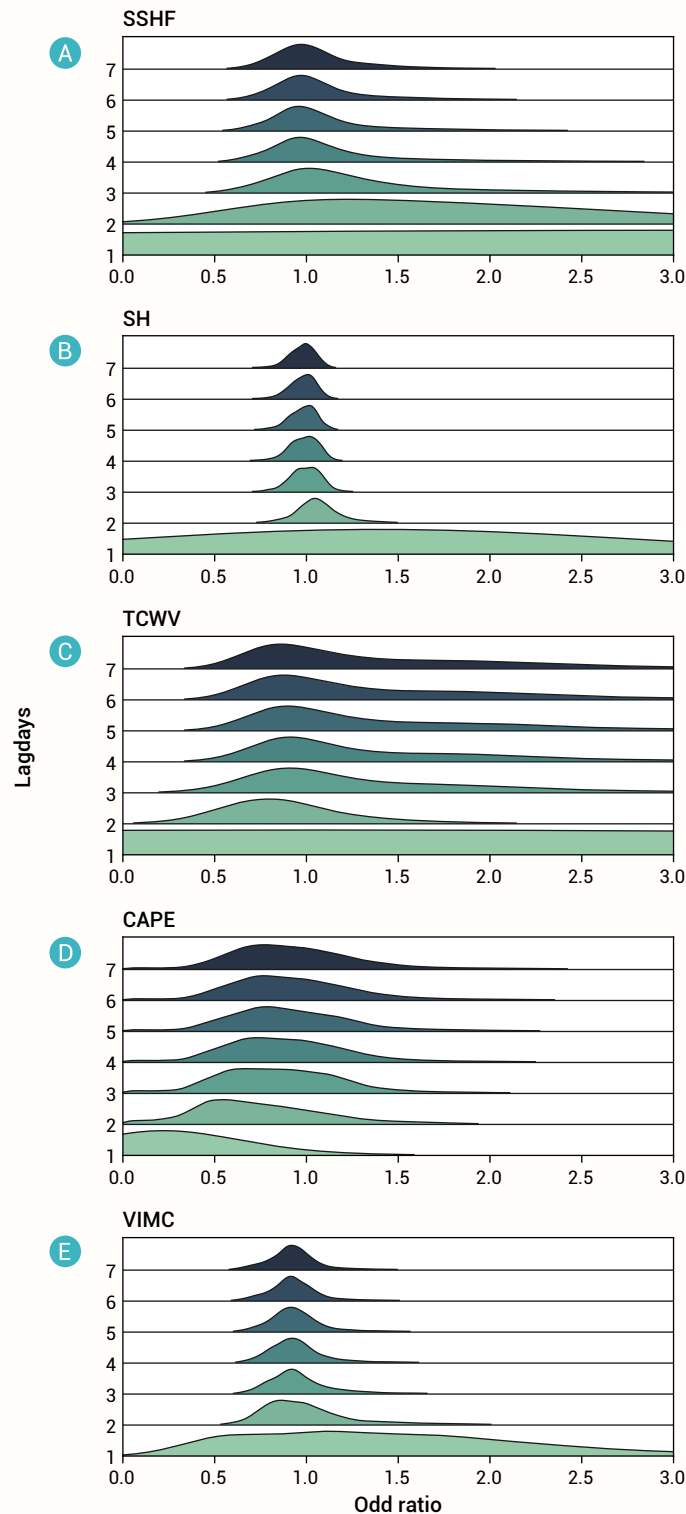


Figure 4. Distributions of odds ratios across 1–7-day lags Probability density functions of the odds ratio over 1–7 lag days, estimated using non-parametric kernel density estimation.

However, CAPE has an obvious positive effect on CHPEs in tropical regions, increasing CHPEs by enhancing atmospheric instability due to preconditioned heatwaves (Figure 3G). For the CHPEs lag days, SSHF, SH, and VIMC mainly dominated the pluvial events that lagged 1–2 days after heatwaves, whereas TCWV and CAPE influenced the CHPEs that occurred over longer intervals of 6–7 days (Figure 4). Further analysis of the changes in OR with lag time indicated that the median OR values for SSHF, SH, and VIMC shifted to the left when the lag time increased, demonstrating a notable decrease in

their influence on CHPEs as the lag time increased. Conversely, the median values for TCWV and CAPE shifted to the right as the time interval increased, indicating that their impact on CHPEs increased with increasing lag time.

CHPEs mechanisms also exhibited spatial heterogeneity governed by the moisture-source distance, land–sea thermal contrast, and low-level transport corridors (Figure S2). In the southern Great Plains and western-central Europe, an enhanced SSHF preconditions continental interiors with a dry–hot boundary layer and likely capping inversion. Subsequent low-level oceanic moisture transport and convergence rapidly increased the near-surface SH and TCWV, reducing inhibition and enabling CAPE, thereby facilitating the transition from the heatwave to the pluvial. In arid ocean-remote interiors, such as Mongolia, pronounced moisture import is required to elevate SH/TCWV before deep convection can occur; therefore, CAPE growth is largely moisture-controlled. An example of this occurred in Ulaanbaatar in August 2019 (Figure S3). During the heatwave phase, the SSHF was strongly positive, deepening and warming the boundary layer. This preconditioning favored low-level moisture convergence (VIMC > 0) and a steady increase in the TCWV. After the heatwave ceased, the CAPE exceeded the threshold and was released, and a pluvial had not yet formed. Although the SSHF started to decline from its peak, it remained anomalously elevated and continued to sustain moisture convergence. When the SSHF relaxed toward background levels and the TCWV reached its maximum, deep convection was initiated, pluvial ensued, and convergence subsequently weakened, marking the end of the CHPEs. This sequence indicates that energy accumulation during the heatwave preconditions the boundary layer for convection, and a persistently elevated post-heatwave SSHF can maintain moisture convergence long enough to facilitate the transition from heatwave to pluvial.

Observed socio-economic exposure to CHPEs

Figure 5 shows the spatial characteristics of the observed population and GDP exposure to CHPEs. Population and GDP exposures showed a significantly increasing trend during 1980–2021, with an increase rate of 5,000 person-days per year ($p < 0.001$) and 1.1×10^8 purchasing power parity (PPP) dollar-days per year ($p < 0.001$), respectively. The global average population exposure is 5.58×10^5 person-days, but with significant spatial heterogeneity. In tropical and subtropical regions, such as East Asia, the Indian subcontinent, Central Europe, the eastern United States, and coastal South America, population exposure is significantly higher than the global average, indicating the greater vulnerability of these regions to CHPEs (Figures 5A & C). For GDP exposure (Figures 5B & D), the global average exposure is 9.59×10^9 PPP\$-day. Spatially, wealthier regions, particularly the East Coast of North America, Western Europe, and coastal urban clusters in East Asia, show higher economic exposures, with certain regions reaching 100×10^9 PPP\$-day, indicating that regions with higher economic development and urban density are more vulnerable to GDP exposure. In addition, coastal regions near tropical cyclone paths showed significantly increased GDP exposure, reflecting the impact of natural disaster paths on the spatial distribution of economic exposure.

Future socio-economic impact of CHPEs

Based on the latest edition of the Global Subnational Atlas of Poverty and the classification of countries by income group from the World Bank to characterize global poverty, we divided the world into high-, upper-middle-, lower-middle-, and low-income countries (Figure S4). The results show that global population and GDP exposure to CHPEs will increase from 28.3% and 24.2% during the historical period to 73.5% and 73.6% by the 2060s and 2090s, respectively, and then slightly decrease to 70.5% and 70.6% by the end of the twenty-first century, respectively, for lower-income regions under SSP5-8.5. However, such a significant increase in population and GDP exposure was not observed in higher-income regions, where the exposed global fractions of the population and GDP increased from 28.3% and 24.2% to 63% and 62.3% by the 2040s and 2050s, respectively, and then decreased to 54.3% and 54.9%, respectively (Figures 6A–B).

We then quantified the GDP, population, and changes in the projected socioeconomic exposure, on a national scale (Figures 7A–B). Areas with the greatest changes in future socioeconomic exposure are located in low-income countries, such as Nigeria, Rwanda, Burundi, India, and the Philip-

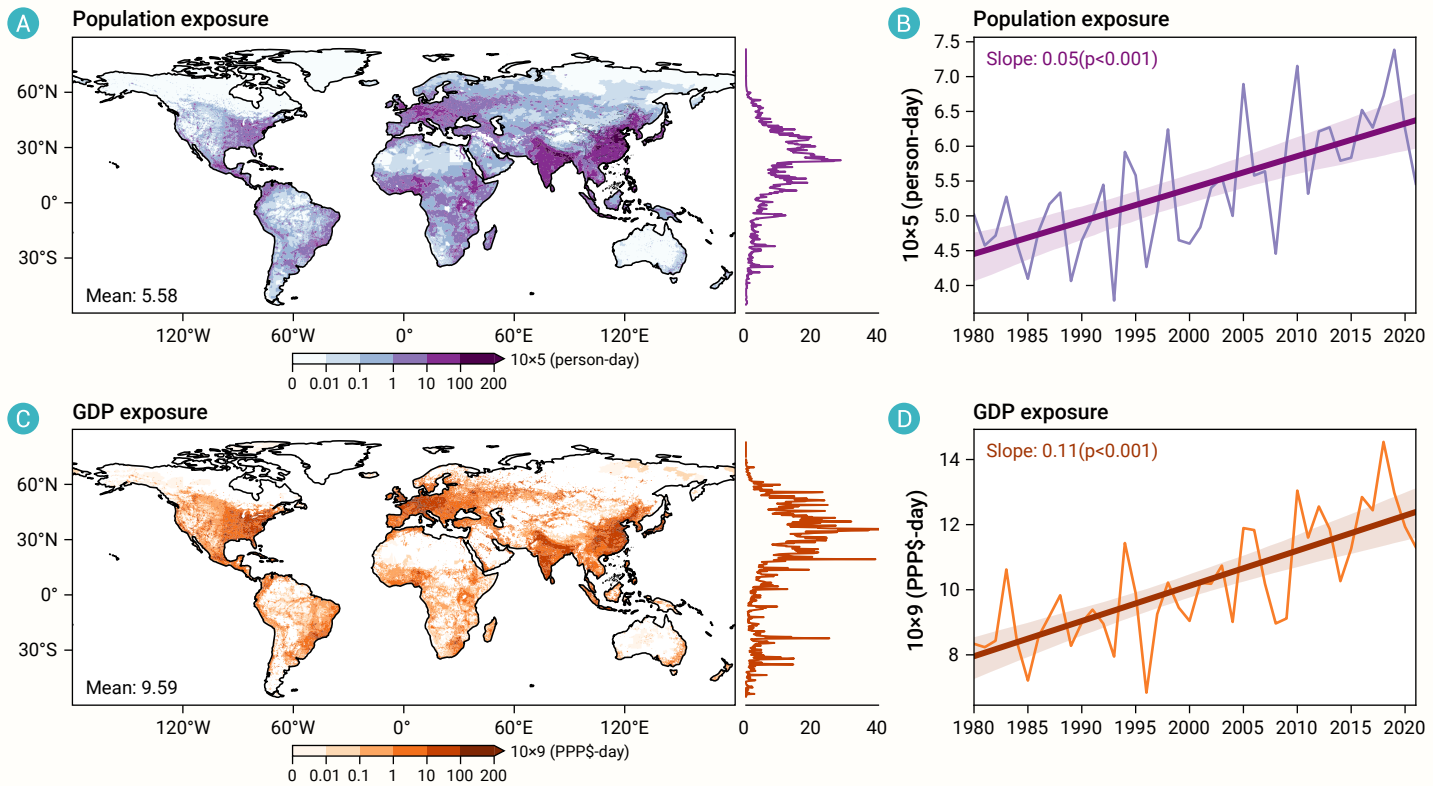


Figure 5. Spatiotemporal characteristics of population and GDP exposure to CHPEs from 1980 to 2021 The left column displays the average population (A) and GDP (C) exposure during 1980–2021, with the latitudinal distribution shown in the adjacent panels. The right column shows the global average temporal dynamics of population (B) and GDP (D) exposure. The shading area represents 95% uncertainty intervals.

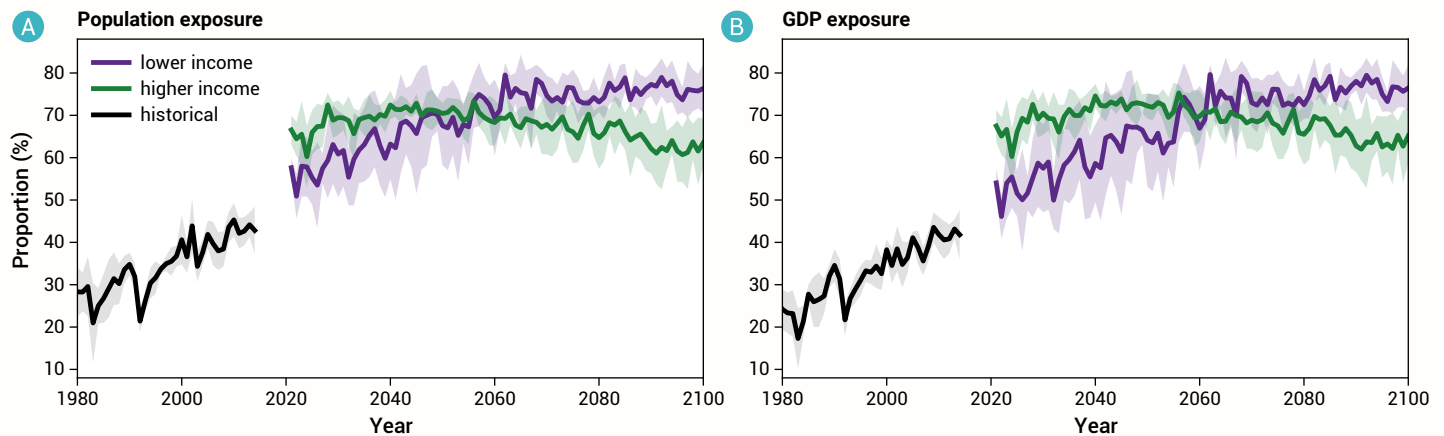


Figure 6. Temporal changes in the global average proportion for exposed population and GDP under SSP5-8.5 (A) Exposed population. (B) Exposed GDP. The black line represents the historical change, while the purple and green lines show projected changes for low- and high-income regions, respectively. Shading indicates the 95% confidence intervals.

pinus, under SSP5-8.5. Although regions with significant changes in future exposure are typically located in countries with high population densities or high GDP, the relationships between exposure, GDP, and population are not linear. The results highlight that low-income countries (represented by large circles) often face higher levels of population and GDP exposure and tend to have larger populations. Therefore, a complex interplay arises among economic status, population size, and exposure levels, where low-income regions are disproportionately impacted despite the general trend observed in high-density or high-GDP areas.

DISCUSSION

The impact of compound extreme events can result in more significant socio-economic damage than individual events.^{19,27,42} One example is Japan, in July 2018, where a short-term transition between a record-breaking heat-

wave and a devastating flood caused over 300 fatalities and substantial economic damage.⁴³ This study investigates CHPEs that have received less attention but can also have devastating socioeconomic impacts, finding that the frequency and duration of CHPEs increased significantly during 1980–2021. In the future, the frequency of CHPEs is projected to increase significantly in tropical and subtropical regions (Figures S5–S7), particularly in the Amazon Basin, Sub-Saharan Africa, Indian subcontinent, and Southeast Asia.

The intensification of CHPEs under higher emissions is expected to be driven by thermodynamic moistening, in which the TCWV increases approximately according to Clausius–Clapeyron scaling (~7% per 1°C of warming),⁴⁴ thereby enhancing the moisture availability for CHPEs. Simultaneously, land–atmosphere coupling will remain important,^{45–47} as persistent soil-moisture deficits, elevated SSHF and sustained high vapor pressure deficit

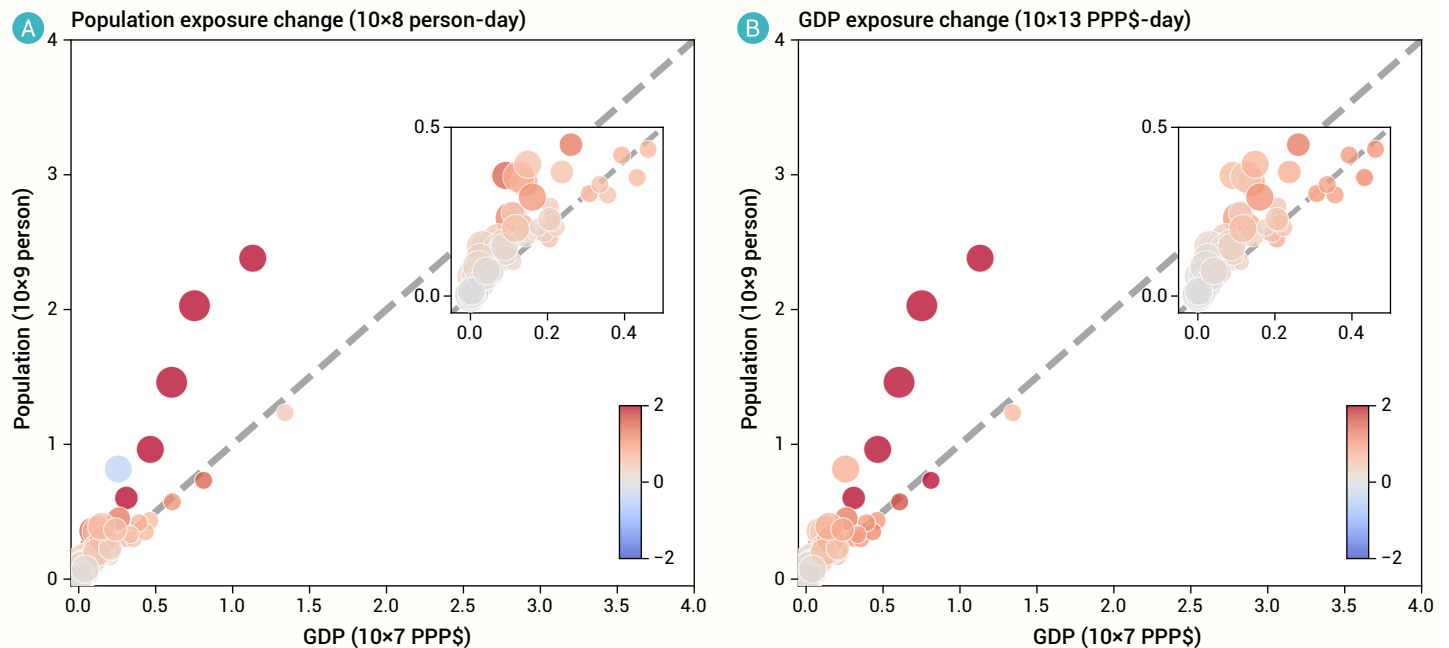


Figure 7. Changes in population (A) and GDP exposure (B) in the future (2021–2100) relative to historical (1980–2014) values are related to socio-economic factors, with statistics by country Each point on the graph represents a country or region, its color indicates the magnitude of exposure change, and its size is inversely proportional to the income level, that is, large and small points denote lower and higher incomes, respectively. We focused on the regions showing a significant increasing trend of CHPEs frequency and duration in Figure 1, resulting in 122 countries and regions.

anomalously hot and dry boundary layers, particularly in semi-arid mid-latitudes, facilitate the transition from heatwaves to pluvial when synoptic ascent is present. This pathway is analogous to the land–atmosphere feedbacks that have been shown to amplify compound drought–heatwave events and concurrent hot–dry extremes,^{11,16,39} and suggests that transitional climate zones with strong soil–moisture–temperature coupling are sensitive to CHPEs. Dynamic adjustments in the large-scale circulation may further modulate the regional CHPEs risk. Poleward shifts in storm tracks and changes in the occurrence and persistence of atmospheric blocking can alter both residence time of heatwaves and the efficiency with which stored moist static energy is subsequently released as extreme precipitation, thereby changing the timing and intensity of heatwave–pluvial transitions.^{48–51} The future impacts of CHPEs may therefore be more prolonged and severe in Africa, the Indian subcontinent, the Middle East, the Amazon Basin, and the Gulf of Mexico. However, compared with the observation period, the frequency and duration of future CHPEs may not become prominent in East and West Asia. This could be closely related to the new pattern of “hot eastern-pluvial western” formed by the westward extension of western Pacific subtropical high and the eastward extension of the South Asian high.⁵² South Asia, Southeast Asia, and the southern part of East Asia are the wettest regions on the continent because of summer monsoon activity,⁵ where floods are also more frequent and intense. Therefore, in a warming future, the frequency and duration of CHPEs are expected to increase in regions coinciding with the major global terrestrial monsoon areas, where the concurrent occurrence of rainfall and high temperatures during the summer is influenced by warm and moist air from the oceans.^{53,54}

Our findings reveal that the hydroclimatic anomalies that trigger CHPEs vary between poor and wealthy regions. Poor regions tend to be located in the tropics and show significant increases in atmospheric instability and water vapor transport, which favor dynamically amplified CHPEs. Conversely, wealthy regions tend to be located in extratropical regions, where the dominant hydroclimatic processes (e.g., SSHF and SH) are generally weaker, suggesting that CHPEs hazards there are less dominated by strong convective amplification. Previous studies on climate inequality have primarily focused on analyzing individual extreme climate events—such as heatwaves and droughts or floods—to explore the potential unequal social and economic impacts of climate change.^{29,55} Our results complement these studies by showing that the drivers and signatures of CHPEs differ systematically between income groups. Low-income regions face dual pressures from

climate and socioeconomic inequalities.^{3,56} The vulnerability of these regions has a cascading effect on global economic and social stability. More frequent CHPEs in these areas can disrupt global supply chains and negatively affect global economic growth.^{34,57} Persistent poverty and instability may lead to large-scale migration and social conflict, further exacerbating global instability.⁵ These results suggest that CHPEs contribute to a “double burden” for many low- and middle-income countries, they are simultaneously hotspots of intensifying hazards, of rapidly increasing exposure, and of limited adaptive capacity, and disruptions there can propagate through trade, finance and migration to affect the global system.^{30,34,57}

CHPEs may also diminish ecosystem health and productivity, flipping sinks into sources and fueling positive carbon–climate feedbacks.^{42,58,59} Our results show that, in several sparsely populated mid-latitude regions where ecological vulnerability is high, the frequency and intensity of CHPEs are likely to continue to increase. In such regions, persistent heatwaves can damage plant hydraulics, reduce leaf area, depress photosynthesis and deplete soil moisture,^{8,14,60,61} while subsequent pluvial events can alter soil–moisture regimes, erosion patterns and the partitioning of evapotranspiration and runoff.^{35,60} These processes may induce large fluctuations in gross primary production and even functional degradation of ecosystems by pushing them across hydroclimatic thresholds.^{42,58,59,62} A key limitation of this study is that the impacts of CHPEs on terrestrial ecosystems were not explicitly considered. Given the nonlinear nature of ecosystem responses,^{58,62} indicators and transparent, rigorous assessment frameworks are urgently required to accurately quantify the ecological impacts of CHPEs and to link them to biogeochemical and biodiversity risk.

Our analysis is also subject to several limitations. Firstly, it has been demonstrated that the presence of uncertainties in reanalysis and climate models, particularly with regard to the representation of deep convection, land–atmosphere coupling and regional circulation patterns, has been demonstrated to affect both the magnitude and spatial pattern of CHPEs projections.^{11,45,46} The integration of CHPEs analysis within the framework of storyline and event-attribution models has the potential to facilitate the disentanglement of the roles of internal variability, circulation regimes and anthropogenic forcing.^{42,63,64} Secondly, prevailing risk metrics primarily combine hazard and exposure. However, explicit representations of vulnerability, governance capacity and adaptation measures are required in order to translate CHPEs statistics into policy-relevant risk estimates.

As anthropogenic warming is expected to intensify internal variability and

enhance moisture transport, both the frequency and severity of such events are projected to increase, particularly in densely populated low-income regions.^{1,27,44,64,65} Future research should focus on their intertwined socioeconomic and ecological impacts, including how repeated CHPEs may erode resilience, widen inequalities and induce long-term shifts in land use, livelihoods and ecosystem structure.^{34,62,63} Overall, our findings suggest an urgent need to increase societal resilience to the changing environment by devising targeted and effective adaptation strategies, particularly in lower-income regions, which pose major challenges in achieving sustainable development goals.^{13,44}

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AUTHOR CONTRIBUTIONS

Conceptualization, J.L. and X.L.; Methodology, J.L. and X.L.; Formal analysis, J.L.; Data curation, J.L.; Software, J.L. and J.S.; Visualization, J.L. and J.S.; Investigation, X.L.; Validation, D.M.; Supervision, X.L., J.Y., D.M., C.L. and A.A.; Project administration, J.L. and X.L.; Writing – original draft, J.L.; Writing – review & editing, J.L., X.L., J.Y., D.M., C.L., A.A. and J.Liu. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

ERA5 data can be downloaded from the website of ECMWF (<https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5>). ISIMIP 3b data can be obtained from <https://data.isimip.org/search/tree/ISIMIP3b%2FInputData/>. Code are available from the corresponding author upon reasonable request.

SUPPLEMENTAL INFORMATION

It can be found online at <https://doi.org/10.59717/j.xinn-geo.2026.100210>.