

Article

Trends in Extreme Precipitation and Associated Natural Disasters in China, 1961–2021

Xinlei Han ^{1,*} , Qixiang Chen ² and Disong Fu ³¹ National Institute of Natural Hazards, Ministry of Emergency Management of China, Beijing 100085, China² State Key Laboratory of Pulsed Power Laser, College of Electronic Engineering, National University of Defense Technology, Hefei 230037, China³ Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China

* Correspondence: xinleihan@ninhm.ac.cn

Abstract: Natural disaster events caused by extreme precipitation have far-reaching and widespread impacts on society, the economy, and ecosystems. However, understanding the long-term trends of extreme precipitation indices and their spatiotemporal correlations with disaster events remains limited. This is especially true given the diverse factors influencing their relationship in China, which makes their spatial linkage highly complex. This study aims to detect recent spatial trends in extreme precipitation indices in China and link them with related natural disaster events, as well as with the spatial evolution of land use and land cover and Gross Domestic Product (GDP). Daily precipitation data from 1274 rain gauge stations spanning the period from 1961 to 2021 were used to analyze the spatial distribution characteristics of extreme precipitation index climate trends in China. The results revealed a significant increasing trend of the intensity of extreme precipitation in eastern China, but a decreasing trend of amount, frequency, and duration of extreme precipitation in southwest China, accompanied by a significant increase in consecutive dry days. Natural disaster records related to extreme precipitation trends indicated a significant increase at an annual rate of 1.3 times in the frequency of flood, storm, drought, and landslide occurrences nationwide, with substantial regional dependence in disaster types. Furthermore, the spatial evolution of land use and GDP levels showed a close association with the spatial distribution of natural disaster events induced by extreme precipitation. Although the number of deaths caused by extreme precipitation-related disasters in China is decreasing (by 51 people per year), the economic losses are increasing annually at an annual rate of USD 530,991, particularly due to floods and storms. This study holds the potential to inform decision-making processes, facilitate the implementation of mitigation and adaptation measures, and contribute to reducing the impacts of natural disasters across diverse regions worldwide.



Academic Editor: Wen Cheng Liu

Received: 28 February 2025

Revised: 25 March 2025

Accepted: 28 March 2025

Published: 4 April 2025

Citation: Han, X.; Chen, Q.; Fu, D. Trends in Extreme Precipitation and Associated Natural Disasters in China, 1961–2021. *Climate* **2025**, *13*, 74. <https://doi.org/10.3390/cli13040074>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: extreme precipitation; natural disasters; trend analysis; land cover; GDP

1. Introduction

Climate change, rapid economic development, and intensified urbanization are contributing to a rise in the frequency of extreme precipitation events. This increase in severe weather phenomena raises the likelihood of various natural disasters like floods, droughts, storms, and landslides [1–3]. Therefore, analyzing the trends of extreme precipitation events, evaluating the associated risks of natural disasters related to extreme precipitation, and identifying high-risk areas can provide a scientific basis for disaster prevention, mitigation, and risk management.

To better study the trends of extreme precipitation events and provide standardized monitoring and assessment tools, the World Meteorological Organization (WMO) and the World Climate Research Programme (WCRP) jointly established the Expert Team on Climate Change Detection and Indices (ETCCDI). This team defined 27 representative climate indices, including 11 extreme precipitation indices and 16 extreme temperature indices [4]. After 2018, the ETCCDI's activities were discontinued, and its responsibilities were transferred to the Commission for Climatology (CCI) Expert Team on Sector-Specific Climate Indices (ET-SCI) for enhancing sector-specific climate index software. These indices are widely used to analyze global and regional climate change trends, and the frequency and intensity of extreme weather and climate events [5–7].

In recent years, there has been a trend of increasing numbers, broader regional impacts, enhanced extremity, record-breaking occurrences, and sudden onset of events of extreme weather globally. The report “Human Cost of Disasters 2000–2019” published by the United Nations Office for Disaster Risk Reduction (UNDRR) highlighted a significant increase in the total number of global natural disasters during 2000–2019, particularly a remarkable growth in climate-related disasters. During 1980–1999, there were over 3600 climate-related disasters globally, increasing to over 6600 during 2000–2019. Among these, disasters related to extreme precipitation, such as floods, storms, droughts, and landslides, not only occur frequently but also often lead to substantial economic and human losses [8,9]. Therefore, studying the long-term trends of extreme precipitation and its spatiotemporal correlation with natural disasters is crucial for understanding and predicting the impacts of extreme weather and climate events.

China is a typical sensitive area to global climate change, experiencing one of the highest frequencies of drought and flood disasters worldwide [10–12]. Over the past 30 years, the annual average economic losses due to meteorological disasters have exceeded 2 trillion Chinese yuan (CNY). With the onset of global warming, most regions of China are experiencing a rising trend in temperatures, accompanied by an increasing disparity in the spatial and temporal distribution of precipitation, leading to a growing prominence of extreme precipitation and flood disasters. For example, in July 2021, Henan Province in China suffered from historically unprecedented extreme heavy precipitation, with rainfall records at the Zhengzhou station being broken, referred to as “a year’s worth of rain in a day” [13]. This extreme precipitation event triggered severe urban flooding, riverine floods, and mountain torrents, along with other associated hazards. These cascading disasters led to significant casualties and substantial property losses, classifying it as one of the most devastating natural disasters in recent history.

Over the past few decades, numerous studies have focused on extreme precipitation events in different regions of China to enhance the understanding of extreme events [14–16]. These studies utilized long time series of meteorological data to analyze the changes in frequency, intensity, and duration of extreme precipitation events over China. Most regions show an upward trend in the frequency of extreme precipitation events, as evidenced by increasing annual precipitation, daily precipitation, and total precipitation days, aligning with the global trend of climate warming. However, most precipitation indices have not demonstrated consistent or statistically significant trends across the regions [17–21]. In [22], a study was conducted using 27 extreme indices proposed by ETCCDI, analyzing the temporal changes and spatial distribution of extreme temperature and precipitation indices across China over the past sixty years (1956–2015). The findings revealed a consistent upward trend in temperature extremes across China, but variations in extreme precipitation change due to regional characteristics, climatic background, and driving factors. Additionally, the spatial trends of five precipitation indices were found to be insignificant in almost the entirety of China [23]. An analysis of four extreme precipitation indices using

a gridded dataset of ground-based observations in China spanning the years 1961–2013 was conducted in [24]. They found a discernible increase in extreme precipitation events in northwestern China and certain regions in southeastern China. Conversely, a marked decrease trend was observed across most of the southwestern region and certain areas in North China.

The increase or decrease in extreme precipitation trends is closely related to the evolution of natural disasters [25], exerting profound impacts on regional populations and economies [26]. In addition to environmental factors such as climate warming, atmospheric circulation, and topography, human activities play a crucial role in the development of natural disasters and precipitation relationships [27]. Among these, land use and land cover changes are particularly important factors influencing precipitation and natural disaster relationships. Changes in land surface cover during urbanization processes, such as increased impervious surfaces, can affect regional runoff and drainage capacity, leading to increased flood risks [28]. Therefore, intense human activities significantly impact natural disasters, particularly in regions that will become increasingly vulnerable if these factors are ignored [29–31]. Furthermore, economic capacity plays a crucial role in resilience against natural disasters [32]. Regions with stronger economies typically have more robust infrastructure, more efficient emergency response mechanisms, and ample resources to address natural disasters, thereby reducing losses and impacts more effectively. On the other hand, economically weaker regions may face greater risks and losses due to limited resources, lack of adequate preparedness, and inadequate response capabilities. Therefore, enhancing economic capacity is a key factor in strengthening resilience against natural disasters and mitigating their impacts [33].

However, previous studies have mostly relied on meteorological data from specific stations to investigate the changes in extreme precipitation in certain regions of China [17–21,34–36]. There has been limited research covering the entire country of China using the latest observational data from a high-density station network. Moreover, few studies have investigated the spatiotemporal correlation between extreme precipitation trends and related natural disasters. Understanding the relationship between extreme precipitation trends and the occurrence of natural disasters, as well as their association with human activities such as land cover changes and economic development, is particularly crucial.

To bridge this gap, our study examines the spatial trends of 10 extreme precipitation indices spanning 62 years across 1274 meteorological stations in China. These trends are linked to spatiotemporal patterns of precipitation-related natural disaster events, considering the influence of human activities such as land use changes, and economic development levels. Through detailed analysis of the correlation between precipitation trends and natural disasters in different regions of China, our work is crucial for decision-makers to assess natural disaster risks, as well as to formulate effective disaster management and mitigation measures.

2. Data and Method

2.1. Data

The precipitation data utilized in this study originate from a homogenized dataset of daily precipitation measurements spanning 1961–2021 from 2419 stations across China, provided by the National Meteorological Information Center of the China Meteorological Administration (<http://data.cma.cn> accessed on 31 December 2022). This dataset, refined from the National Basic Surface Meteorological Dataset (V3.0) released in 2012, underwent rigorous homogeneity testing and corrections to accurately reflect climate variability, considering factors like station relocation, instrument changes, and surrounding environmental alterations. For this research, a rigorous quality control process was applied, including

the exclusion of stations with more than 25% missing values, removal of erroneous precipitation records (e.g., daily precipitation values smaller than zero), standard deviation tests, and abnormal data screening. After that, 1274 stations with continuous precipitation records were selected, corresponding to the study period and ensuring reliability in assessing long-term trends of climatic extremes.

Records of natural disaster events related to precipitation are sourced from the Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters at the University of Leuven, Belgium (<https://public.emdat.be/>, accessed on 1 January 2024). EM-DAT, a widely used global disaster database, catalogs natural and technological disasters since 1900, meeting at least one of the following criteria: ≥ 10 fatalities, ≥ 100 affected people, declaration of a state of emergency, and/or a request for international assistance. It details geographical location, timeline, causality, related secondary disasters, and the human and economic impacts of each event, with economic losses monetized in U.S. dollars.

The Geographic Disaster Inventory (GDIS) dataset is a geocoded extension of selected natural disasters from the EM-DAT database. It encompasses geographic data for 39,953 locations involved in 9924 disaster events worldwide from 1960 to 2018 [37]. This dataset facilitates the integration of EM-DAT with sub-national geographic data sources for rigorous empirical analysis of disaster determinants and impacts. The GDIS developers geocoded EM-DAT records by linking location descriptions to one or more administrative subdivisions in the Global Administrative Region Database (GADM) (v.3.6; <https://gadm.org/>). GADM includes administrative subdivisions at various levels, including state and province boundaries (level 1), county and district boundaries (level 2), and smaller administrative boundaries (level 3). Each disaster record has been geocoded to administrative regions at levels 1, 2, and/or 3, depending on the location description text in EM-DAT. This study primarily utilizes level 1 data of province-level natural disaster records in China related to extreme precipitation, covering four types, floods, droughts, storms, and landslides, spanning the period from 1961 to 2021.

In order to analyze factors related to extreme precipitation and natural disasters, land use and land cover data for 1980 and 2020 were obtained from the China Multi-period Land Use Remote Sensing Monitoring Dataset (CNLUCC). This is a national-scale, multi-period land use/land cover thematic database for China, constructed through manual visual interpretation, with remote sensing images from the US Landsat satellite. This dataset is sourced from the Resource and Environment Science Data Center (<https://www.resdc.cn/>, accessed on 1 January 2024), with a spatial resolution of 1 km. The data are extracted based on attributes and include statistics on the areas of arable land, forest and grassland, built-up areas, water bodies, and other land types. Meanwhile, Gross Domestic Product (GDP) data expressing the level of economic development are also extracted from the data center, specifically the spatial distribution kilometer grid dataset of China's GDP. Due to the limited dataset available, spanning only six years, this study selected GDP data from the closest years to the EPI, specifically for 1995 and 2019.

2.2. Method

In this study, the analysis of extreme precipitation variability in China employs ten extreme precipitation indices recommended by ETCCDI, as detailed in Table 1. The selected 10 extreme precipitation indices can be divided into three types. The first type is extreme precipitation frequency-based indices: days of heavy precipitation (R10) and days of very heavy precipitation (R20). The second type is extreme precipitation duration-based indices: consecutive dry days (CDD) and consecutive wet days (CWD). The third type is extreme precipitation intensity-based indices: maximum 1-day precipitation (Rx1day), maximum

5-day precipitation (Rx5day), simple daily intensity index (SDII), precipitation on very wet days (R95p), precipitation on extremely wet days (R99p), and annual total wet day precipitation (PRCPTOT).

Table 1. Descriptions of extreme precipitation indices used in the study.

Indices Categories	Indices Abbreviation	Name	Definition	Units
Frequency-based indices	R10	Days of heavy precipitation	Annual total days when precipitation ≥ 10 mm	days
	R20	Days of very heavy precipitation	Annual total days when precipitation ≥ 20 mm	days
Duration-based indices	CDD	Consecutive dry days	Maximum length of consecutive dry days (daily precipitation < 1 mm)	days
	CWD	Consecutive wet days	Maximum length of consecutive wet days (daily precipitation ≥ 1 mm)	days
Intensity-based indices	Rx1day	Maximum 1-day precipitation	Annual maximum 1-day precipitation	mm
	Rx5day	Maximum 5-day precipitation	Annual maximum consecutive 5-day precipitation	mm
	SDII	Simple daily intensity index	Annual total wet-day precipitation divided by the number of wet days (daily precipitation ≥ 1 mm)	mm/day
	R95p	Precipitation in very wet days	Annual total precipitation when daily precipitation > 95 th percentile	mm
	R99p	Precipitation in extremely wet days	Annual total precipitation when daily precipitation > 99 th percentile	mm
	PRCPTOT	Annual total wet day precipitation	Annual total precipitation on wet days (daily precipitation ≥ 1 mm)	mm

Given the high density of the sites, the grid-based maps of Extreme Precipitation Indices (EPIs) in China were interpolated from 1274 sites using inverse distance weighting. This interpolation method was chosen because it produced a more reasonable range of interpolated values compared to other methods, such as Kriging, which often generated values that deviated significantly from the station data. Missing or abnormal data were interpolated using the inverse distance weighting method based on data from the 10 nearest neighboring stations, while for sparsely populated areas in the western stations, interpolation was performed using three neighboring sites. China is divided into six distinct sub-regions based on variations in temperature, water resources, soil, vegetation conditions, and geological characteristics (as shown in Figure 1) [38]. The EPIs were calculated on an annual scale, with total precipitation for the 95th and 99th percentiles determined using the 1961–1990 reference period.

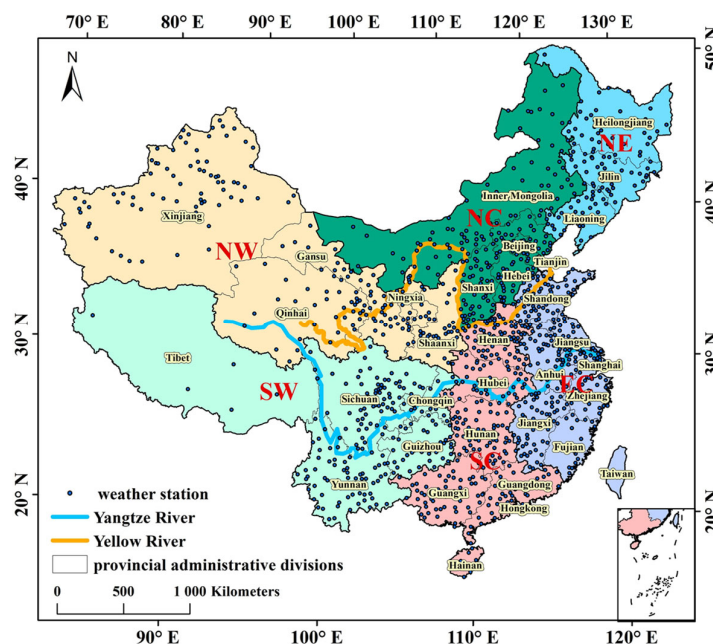


Figure 1. Geological map of the location of the 1274 national weather stations, two major rivers (the Yangtze River and the Yellow River), and the names of provincial administrative divisions (highlighted in yellow) and sub-regions in China (NE: Northeast China, NC: North China, EC: East China, SC: South China, SW: Southwest China, NW: Northwest China).

To examine the trends of EPIs, the modified Mann–Kendall test was applied to detect trends and abrupt changes in 10 EPIs across 1274 selected stations in China. As a robust, non-parametric method, it has been widely utilized in previous studies for identifying trends and abrupt changes in time series data [39]. Sen’s slope analysis was employed to assess the trend magnitude, offering a robust estimate of its strength [40].

3. EPIs Trend Analysis

Figures 2–6 present the spatial distribution of the long-term trends for 10 EPIs. In Figure 2a, the high-value areas of the annual total precipitation (PRCPTOT) increase are concentrated in the middle and lower reaches of the Yangtze River and the southeastern coastal areas, which aligns with the relevant literature [22,41]. Some regions show an increasing trend up to 6.68 mm/year. The western part of NW (Xinjiang region) and the central part exhibit an increasing trend in annual total precipitation, with these areas passing the significance test at the 0.05 level. Conversely, the eastern part of NW experiences a weak decreasing trend. The NC and SW regions show a decreasing trend in annual total precipitation, with localized reductions ranging from 6.72 to 21.06 mm/year, particularly in Yunnan and the Sichuan Basin. The northernmost part of NE, mainly the northern part of Heilongjiang, shows an increasing trend in total precipitation, with a maximum trend of 2.09 to 6.67 mm/year. Figure 2b illustrates the spatial distribution of the long-term variation trend in the mean daily precipitation intensity (SDII). Overall, changes in the SDII across China are relatively minimal, with trend magnitudes at individual stations remaining below 0.1 mm per day per year in absolute value. In SW, a decreasing trend is predominant, with some areas exhibiting a decrease of up to -0.04 mm/(day·year). Most areas in NW show an increasing trend, although the magnitude of the increase varies. The coastal areas in EC exhibit the most significant increasing trend in mean daily precipitation intensity, reaching a maximum of approximately 0.05 to 0.08 mm/(day·year). Additionally, the majority of stations in China (approximately 60%) pass the significance test at the 0.05 level.

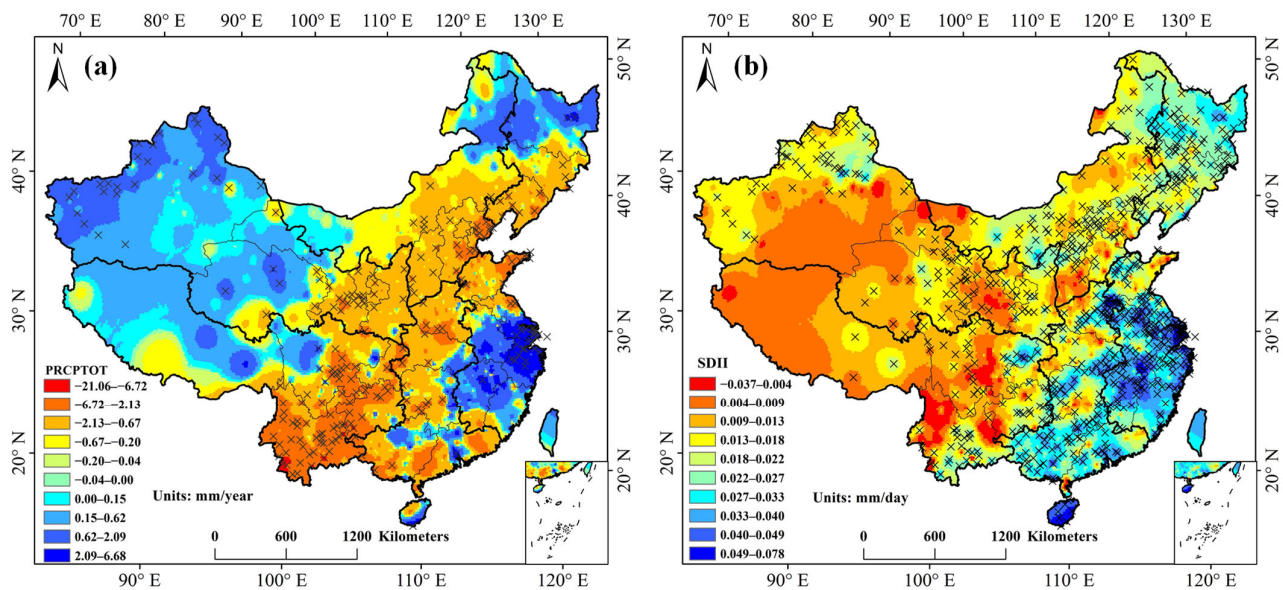


Figure 2. Spatial distribution of PRCPTOT (a) and SDII (b) annual change trends. Positive and negative trends are distinguished using different colormaps, and cross-marked points represent statistically significant trends at the 0.05 level. The darker the colormap, the stronger the trend.

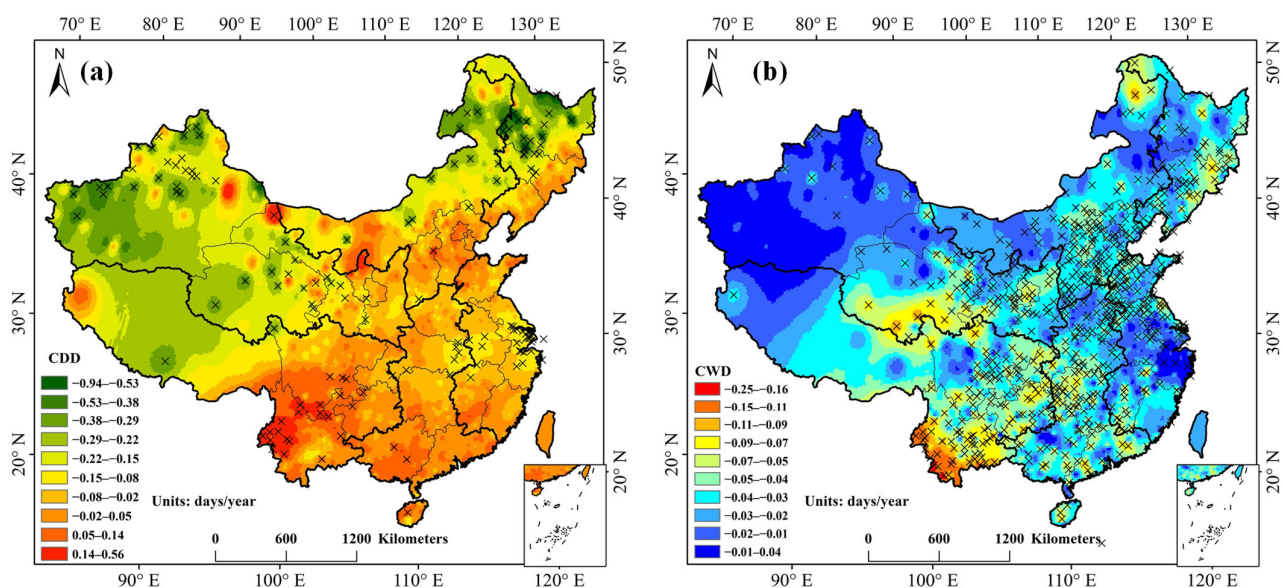


Figure 3. Spatial distribution of CDD (a) and CWD (b) annual change trends. Positive and negative trends are distinguished using different colormaps, and cross-marked points represent statistically significant trends at the 0.05 level. The darker the colormap, the stronger the trend.

Figure 3a,b depict the long-term trends in consecutive dry days (CDD) and consecutive wet days (CWD), respectively. A noteworthy finding is that the overall trend in CDD is significantly more pronounced than that in CWD. Other studies also found trends in similar but not coincident periods [1,5,22]. For CDD, the NW region primarily exhibits a decreasing trend, although there are isolated areas with an increasing trend. The northeastern and northern parts of NC demonstrate a downward trend, with the most significant decline ranging from approximately -0.52 to -0.94 . The middle and lower reaches of the Yangtze River exhibit a weak decreasing trend, while most areas in SC, SW, and NC show a gradual increase over time. Regarding consecutive wet days, the trend generally opposes that of consecutive dry days, with over two-thirds of stations nationwide exhibiting growth over time.

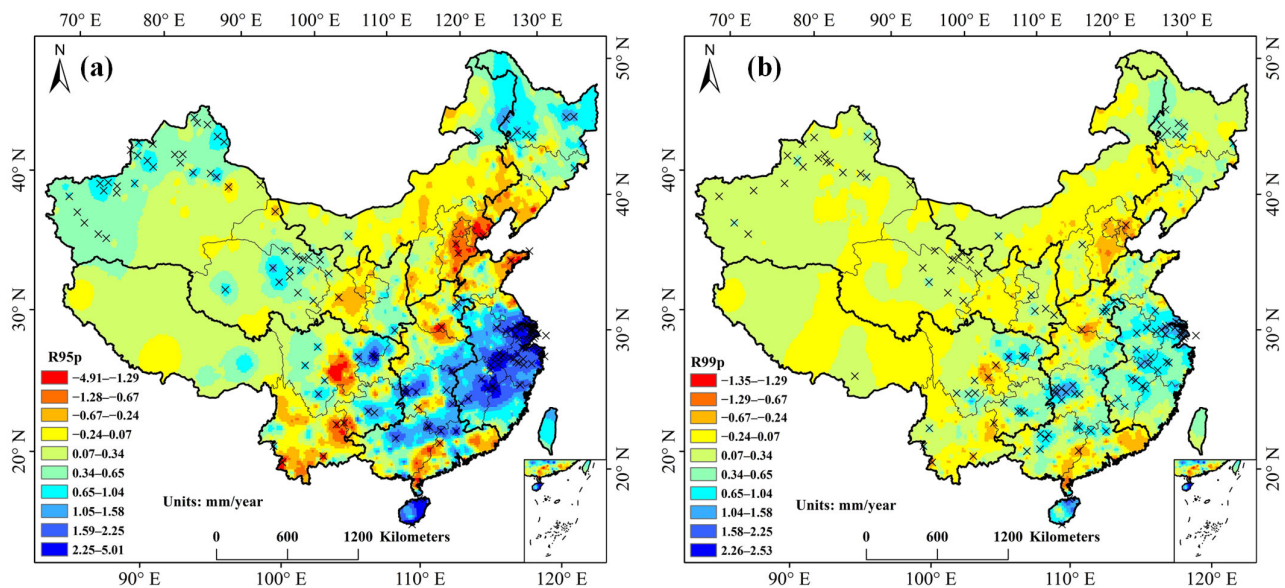


Figure 4. Spatial distribution of R95p (a) and R99p (b) annual change trends. Positive and negative trends are distinguished using different colormaps, and cross-marked points represent statistically significant trends at the 0.05 level. The darker the colormap, the stronger the trend.

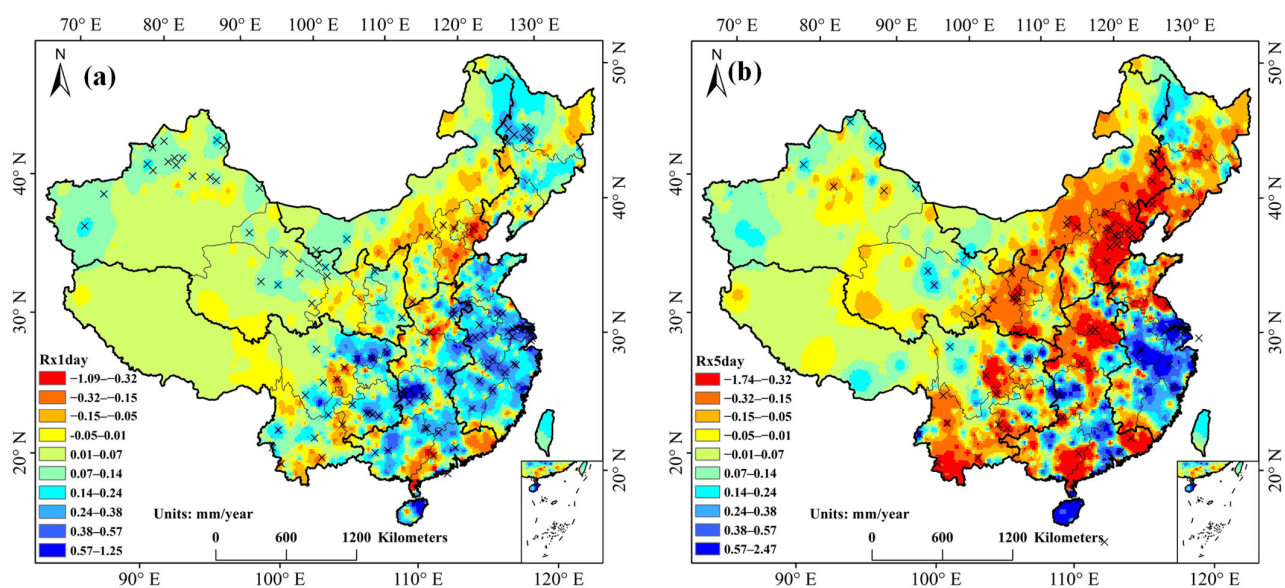


Figure 5. Spatial distribution of Rx1day (a) and Rx5day (b) annual change trends. Positive and negative trends are distinguished using different colormaps, and cross-marked points represent statistically significant trends at the 0.05 level. The darker the colormap, the stronger the trend.

According to Figure 4a, the increasing trend of R95p in the NW region ranges from 0.07 to 1.04 mm/year, especially in northern Xinjiang, where the trend can reach 0.65 to 1.04 mm/year. Similar trends are observed in the northern region of NE. The central region of NC shows a decreasing trend, with certain areas experiencing a decline of 1.29 to 4.91 mm/year. Some areas in SW exhibit lower trends, with a decrease of approximately 1.29 to 4.91 mm/year. The southeastern coastal areas and most of SC show a significant increasing trend, with an increment of above 1.58 mm/year. This is consistent with the observed fact that heavy precipitation events in NC are decreasing while those in NW are increasing. Some individual stations show an increase exceeding 5 mm/year. In Figure 4b, over half of the stations nationwide exhibit an increasing trend in extremely heavy precipitation (R99p), mostly concentrated in the range of 0.34 to 0.65 mm/year. However, a few

stations in NC still show a decreasing trend, with a decline of about 0.67 to 0.24 mm/year. The long-term trend in extremely heavy precipitation follows a spatial distribution similar to that of heavy precipitation.

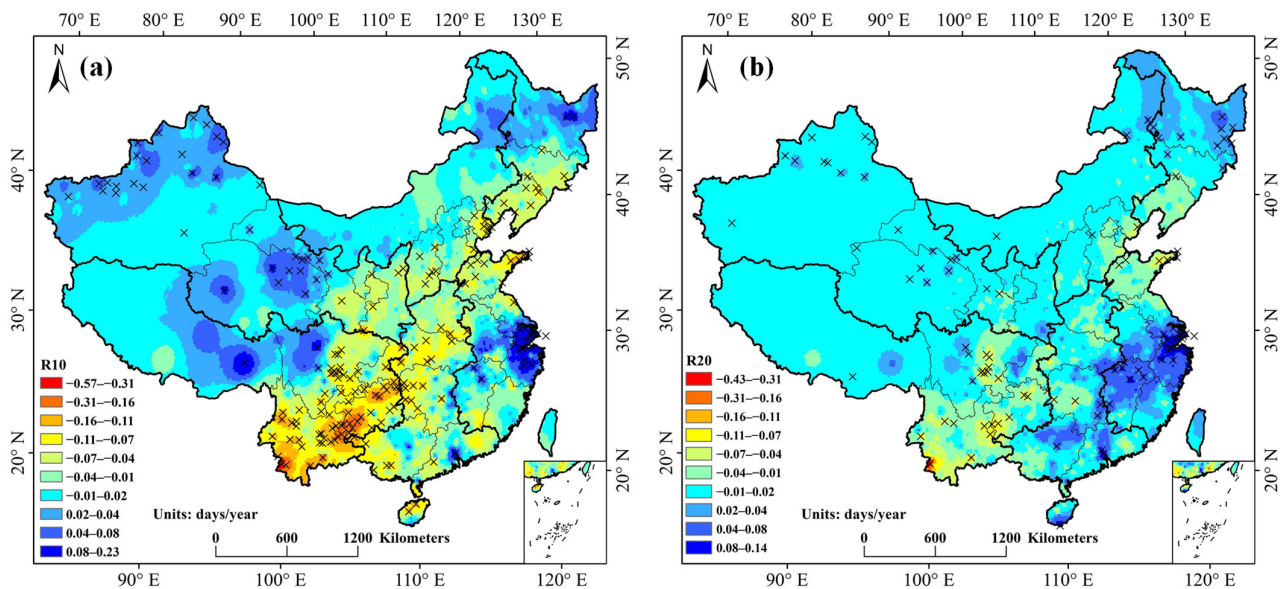


Figure 6. Spatial distribution of R10 (a) and R20 (b) annual change trends. Positive and negative trends are distinguished using different colormaps, and cross-marked points represent statistically significant trends at the 0.05 level. The darker the colormap, the stronger the trend.

In Figure 5a, the spatial trend distribution of Rx1day is presented. NC predominantly shows a decreasing trend, with specific stations recording a decrease exceeding 1.09 mm/year. Areas of the middle and lower reaches of the Yangtze River mainly exhibit an increasing trend. In NW, an increasing trend is dominant, with an increase of approximately 0 to 0.07 mm/year. Similar trend magnitudes were previously found in some areas of China [42]. Over half of the stations nationwide show an increasing trend, mainly concentrated in the range of 0 to 0.24 mm/year.

Figure 5b illustrates the spatial trend distribution of Rx5day. It can be observed that the NW region continues to exhibit an increasing trend, with an increment ranging from 0.01 to 0.24 mm/year. In contrast, most areas in NC show a decreasing trend, with a decline of 0.16 to 0.32 mm/year. The middle and lower reaches of the Yangtze River and the southeastern coastal areas show an increasing trend, while the main trend in SC is an increase, although there are isolated areas with a decreasing trend.

Figure 6 shows the long-term spatial distribution trends of the number of days with rainfall exceeding moderate (R10) and heavy (R20) categories. Overall, the trends in these two indices are relatively subtle, exhibiting similar general patterns. The main increase is concentrated in the western and northern parts of China (including northern Heilongjiang and Inner Mongolia) and in most areas of the middle and lower reaches of the Yangtze River, corroborating with other studies [1,22]. However, the increase in the western region is smaller than that in the latter areas. Most areas in NC and SW show a decreasing trend.

Through spatial analysis of the trends in the 10 extreme precipitation indices, it is evident that the changes in extreme precipitation in China exhibit significant regional variations. The trends are not consistent nationwide, indicating clear regional patterns. The changes in extreme precipitation events in the South China, Yangtze River Basin, North China, and Northeast China regions may be influenced by the East Asian monsoon [21,43].

4. Associations of Trends to Natural Hazards

Figure 7 shows the spatial distribution of frequency of floods (a), droughts (b), storms (c), and landslides (d) during the period of 1961 to 2021 and Table 2 selects the corresponding extreme precipitation indices that have a good spatial relationship with total frequency of disasters (as shown in Figure 7) for each region. In the NE region, the increase in flood frequency is primarily due to the rising frequency of single precipitation events (R20), while the increase in drought is mainly caused by a decreasing trend in precipitation amount and intensity (PRCPTOT, R95p) in the southern part of NE. In NC, there is a lower frequency of floods and a higher frequency of droughts, which is closely related to the decrease in precipitation amount and intensity (R95p, R99p, Rx1day, Rx5day, PRCPTOT). In EC, the frequency of floods and droughts is not high, mainly related to the intensity of single precipitation events (R95p, PRCPTOT), while storms and landslides are not only related to intensity but also to precipitation frequency (R20). In SC, floods, droughts, storms, and landslides are strongly associated with precipitation intensity. As the number of consecutive dry days (CDD) increases and precipitation intensity grows, the severity of these disasters correspondingly escalates. In SW, the increase in landslides is mainly due to the decrease in precipitation frequency (R10), the prolongation of drought duration (CDD), and the weakening of precipitation amount (PRCPTOT), resulting in an increased likelihood of landslides. Flood disasters are mainly caused by the increase in intensity of single precipitation events. In NW, landslides mainly occur in the relatively drier eastern part, with increased precipitation intensity (PRCPTOT) and decreased duration (CDD) in the western part and increased duration in the eastern part.

Table 2. The extreme precipitation indices that exhibit a strong spatial correlation with disasters in each region.

	Floods	Droughts	Storms	Landslides
NE	R20	PRCPTOT, R95p		
NC	R95p, R99p, Rx1day, Rx5day, PRCPTOT	Rx1day		SDII
EC	R95p	PRCPTOT	Rx1day, R20	PRCPTOT, R95p, R20
SC	R95p, Rx1day	PRCPTOT	CDD, R20	PRCPTOT, R95p
SW	R95p, Rx1day	PRCPTOT, R10		PRCPTOT, CDD, R10
NW	PRCPTOT, CWD	PRCPTOT, CDD		PRCPTOT

Figure 8 details the temporal change in floods, droughts, storms, and landslides in the six sub-regions in China and their frequency of occurrence during the period of 1961 to 2021. It is necessary to clarify that the apparent rarity of early floods is attributable to the absence of recorded data in the EM-DAT database for China. In NE, the most significant trends are observed in the northernmost and southernmost cities. They had an increase in PRCPTOT, SDII, R95p, and Rx1day and a reduction in CDD in the north (Herbin). In the south, close to NC, they had a significant reduction in PRCPTOT, R95p, Rx5day, and R10 and an increase in CDD. Overall, it can be concluded that NE presents patterns of a wet north and dry south. These findings were validated by the occurrences of increasing floods, storms, and landslides in the extreme north. Affected by the frequent cold vortex in the northeast, the disturbance is large. Urbanization and farmland expansion in southern Northeast China have reduced vegetation cover and soil moisture retention, exacerbating drought trends, especially agricultural droughts [44,45].

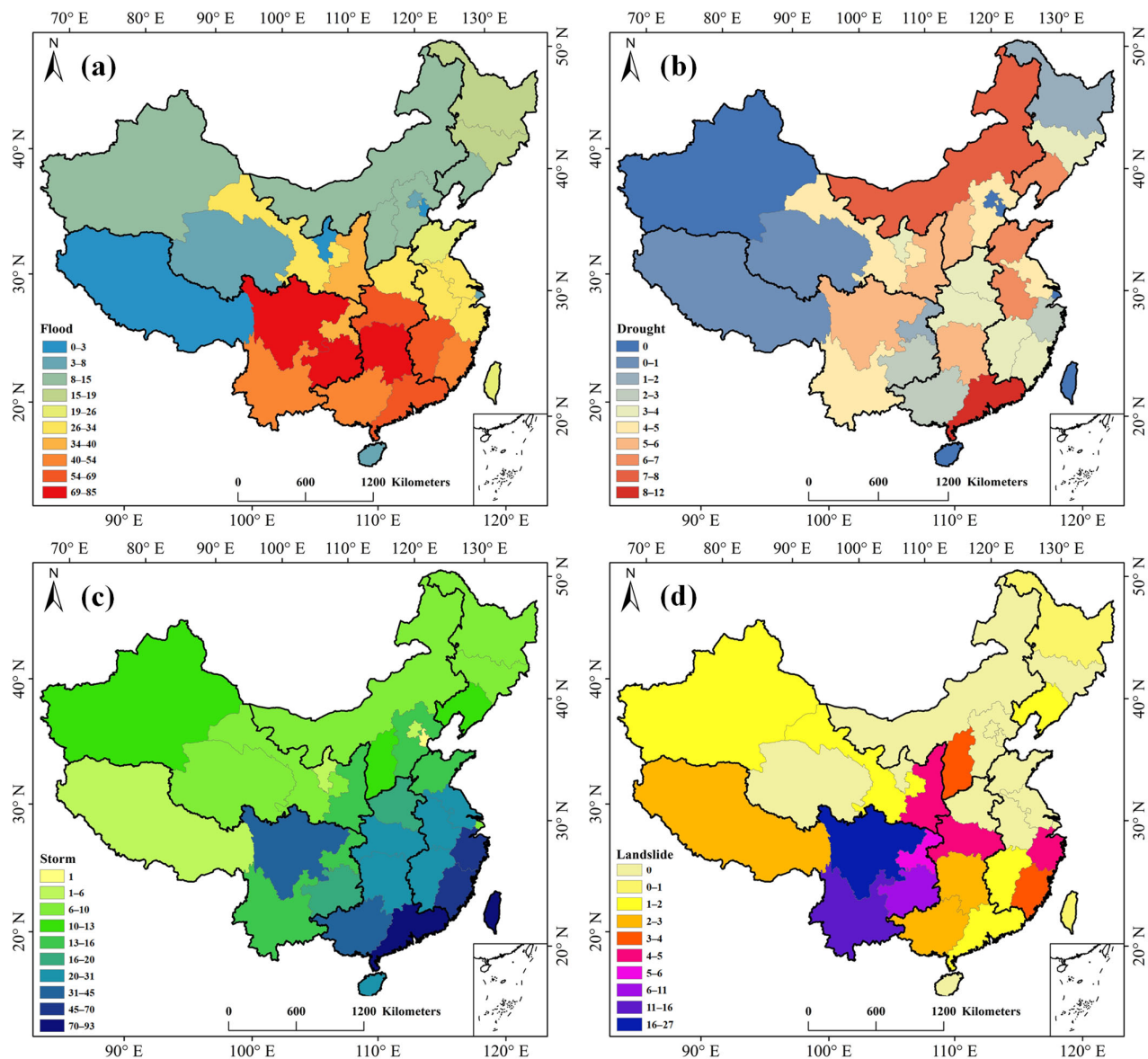


Figure 7. Spatial distribution of frequency (units: occurrences) of floods (a), droughts (b), storms (c), and landslides (d) during the period of 1961 to 2021.

The main disaster in NC is drought. NC showed the least amount of trends in rainfall, especially in the Beijing–Tianjin–Hebei region. In these cities, the indicator trends show a drought intensification with a reduction in PRCPTOT, R95p, and Rx5day and an increase in CDD. Also, the R10 reduces in most of the region, which indicates a reduction in mild rainfall, capable of promoting aquifer recharge, and consequently prolonging drought. This explains why the intensification of reduction trends for Rx5day is much heavier than for Rx1day. Confirming these results, NC experiences the highest frequency of droughts, making it the driest region in China from a trend perspective. The reasons include urbanization and changes in agricultural land use. With population growth, urban construction may lead to the conversion of natural land such as farmland and forestland into urban and industrial land. Urban expansion is often accompanied by intensive land use and changes in land cover types. Meanwhile, changes in agricultural practices, such as the expansion of farmland and adjustments to agricultural planting structures, may lead to changes in land cover types in agricultural areas. The drought panorama in NC has been evidenced in many studies [46–48]. The South-to-North Water Diversion Project was initiated to address the issue of uneven distribution of water resources in China, where

the southern region is relatively abundant in water resources while the northern region faces water scarcity [49]. NC has a large population and significant economic development, accompanied by high social vulnerability indices.

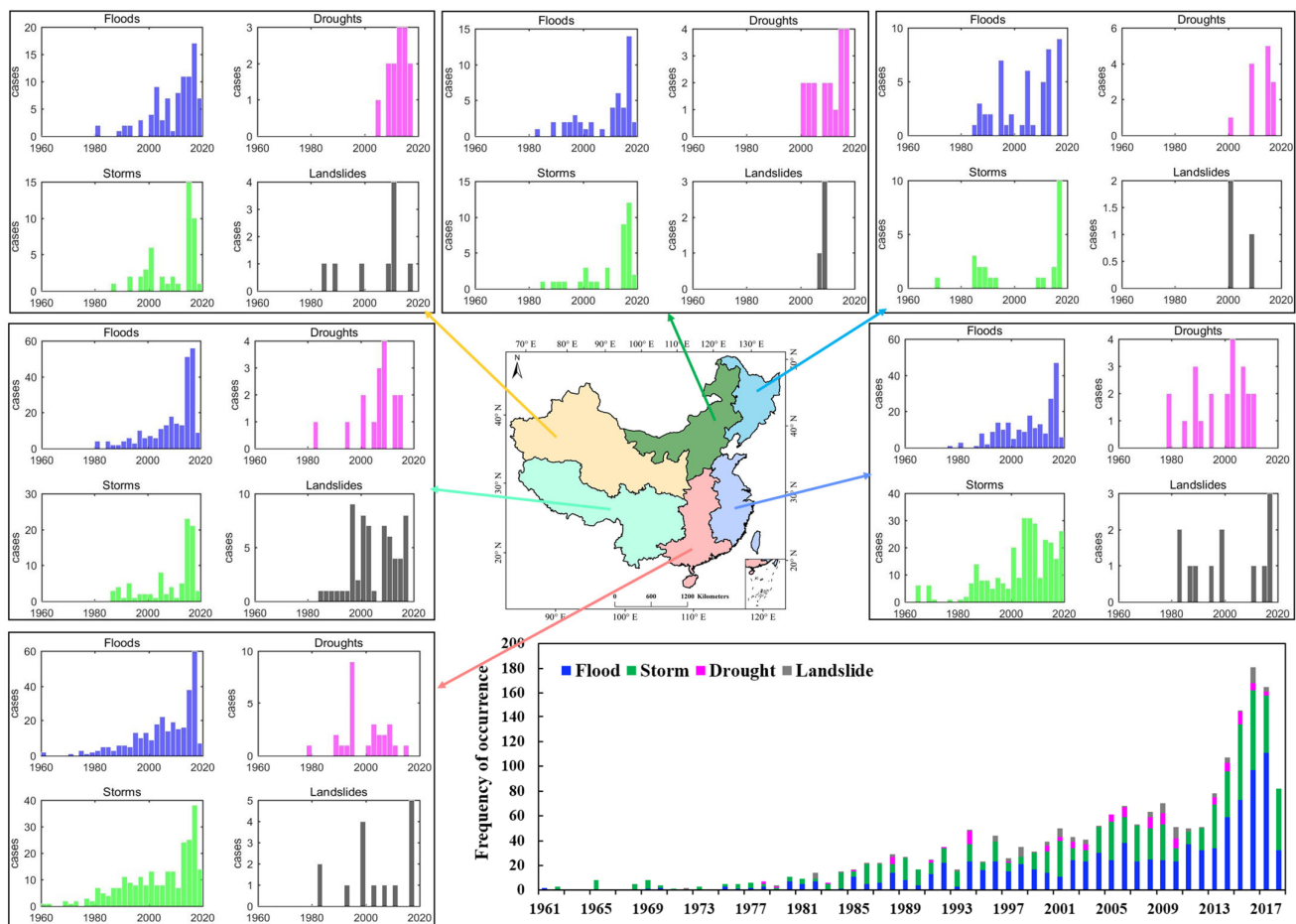


Figure 8. Temporal change in floods, droughts, storms, and landslides in the six sub-regions in China and their frequency of occurrence (units: occurrences) during the period of 1961 to 2021.

The frequency of storms and floods has increased in EC. Correspondingly, a significant upward trend in extreme precipitation associated with typhoons may help explain these variations in disasters. These trends are primarily concentrated in the Yangtze River Delta, where there has been an increase in indices such as PRECPTOT, SDII, R95p, Rx1day, Rx5day, R10, and R20, along with a decrease in CDD and CWD. In contrast, Shandong Province, which borders NC, exhibits the opposite pattern. Floods and typhoons occur most frequently and bring landslides in the southern mountainous areas, while droughts are mainly in the north region. The possible reason is the rapid development of urbanization [50]. The EC region has a developed economy and has significant effects on flood control. Although urbanization is developing rapidly, the frequency of floods in EC is not high except in 2018–2019 in the mountainous areas of Fujian, which are affected by the monsoon system.

Floods and storms are increasing significantly in SC. The extreme precipitation index has large regional differences. R95p and Rx1day increase in the central part and decrease in the north and south, which are related to the monsoon system. In addition, the severe urbanization expansion on the north and south sides, including the Pearl River Delta and Zhengzhou metropolitan areas, has led to a decrease in local-scale precipitation. Droughts and landslides are concentrated in Guangdong and Hubei provinces, respectively. The changes in disasters in other areas are not significant.

Natural disasters in NW are increasing but the frequency of occurrence is only one-third of that in EC. Indices such as PRECPTOT, SDII, R95p, and R10 are all increasing in Xinjiang, Qinghai, and the western part of Gansu. In the East and Shaanxi regions, there is a decreasing trend. Droughts mainly occurred after 2000 and landslides were mainly concentrated in mountainous areas. The impact of climate transition from warm-dry to warm-wet in the arid region of NW on the ecosystem [51] and the increased incidence of flood disasters have put forward higher requirements for water resources management.

Floods and storms in SW occurred with high frequency after 2018. The southwest region is mainly affected by terrain. PRECPTOT, CDD, and R10 have an increasing trend in high-altitude areas, while they have a significant decreasing trend in low-altitude areas of Yunnan, Sichuan, and Guizhou. Compared with other regions, the frequency of occurrence of landslides in the southwest is the highest, with the incidence rate reaching five times per year after 2000. Drought mainly occurs in Yunnan, corroborating other work [52,53]. Urbanization in the Sichuan Plain and melting snow on the Tibetan Plateau, as well as severe exposure of bare soil, have intensified the frequency of floods and landslide disaster events caused by increased extreme precipitation [54].

5. Discussion

The factors influencing the correlation between extreme precipitation and disaster events are numerous, among which land use and land cover, global warming, and GDP are significant elements. Land cover and land use changes, such as urbanization, agricultural expansion, and deforestation, significantly influence surface hydrological properties and local climate conditions, potentially affecting the frequency and intensity of extreme precipitation events. Some studies have found that urbanization contributes significantly to the impact of extreme precipitation events, e.g., approximately half of the increase in extreme precipitation risks can be attributed to rapid urbanization during the period from 1966 to 2015 [50,55]. Urbanization leads to increased impervious surfaces, resulting in higher runoff and flood risks [56]. Conversely, agricultural expansion and deforestation alter land cover, affecting evapotranspiration and local precipitation patterns, thus impacting the occurrence and severity of natural disasters related to extreme precipitation [57–59]. Analyzing the land use type changes in China from 1980 to 2020 depicted in Figure 9, the most notable observation is the significant urban expansion, especially pronounced in EC. The EC region experiences less severe natural disasters, suggesting that urban areas are more resilient to floods and storms than rural areas, largely due to their well-developed drainage infrastructure.

Daily precipitation extremes are expected to become more intense due to higher moisture levels associated with global warming, following the Clausius–Clapeyron relationship at approximately 7% per degree Celsius. However, this intensification is not uniform across all regions [60]. Global warming impacts the trend of natural disasters in China by modifying the frequency and severity of extreme weather events, including heatwaves, droughts, floods, and storms [61,62]. Warmer temperatures lead to more evaporation, contributing to drought conditions in some areas, while enhancing the capacity of the atmosphere to hold moisture, resulting in heavier rainfall and potential flooding in others [63,64]. These changing patterns underscore the need for adaptive strategies in disaster risk management and infrastructure planning in China.

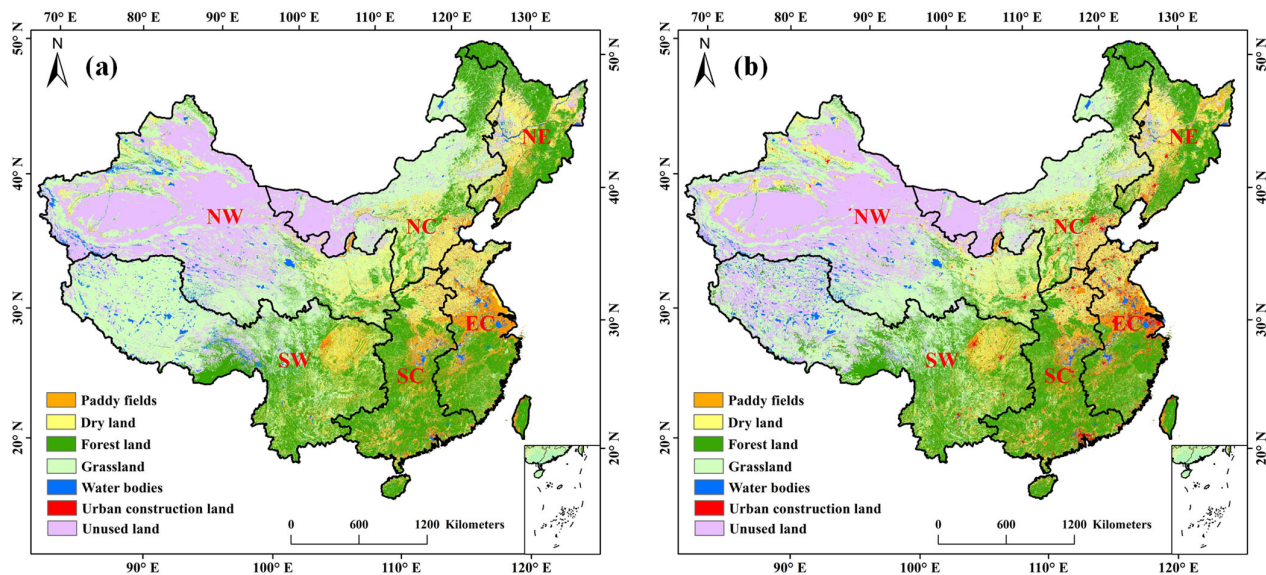


Figure 9. Land cover and land use in China for the years of 1980 (a) and 2020 (b).

GDP serves as a crucial indicator for socio-economic development, regional planning, and environmental and resource conservation [65,66]. The change in GDP development level affects the capacity to respond to natural disasters [67,68], with higher economic development often leading to better infrastructure, more efficient emergency response systems, and improved disaster preparedness and mitigation measures. Conversely, regions with lower GDP may have less capacity to invest in disaster risk reduction and recovery efforts, making them more vulnerable to the impacts of natural disasters. This study compared the spatial distribution of China's GDP between 1995 and 2019 as shown in Figure 10. The spatial grid dataset of China's GDP is derived from county-level data, incorporating factors such as land use, nighttime light intensity, and population density. A multi-factor weighted allocation method distributes the GDP data into 1 km resolution grid cells, revealing the detailed spatial distribution of GDP across China. The results indicate a substantial increase in GDP over 25 years, especially in the eastern coastal regions and major provincial cities, with GDP in 2019 being fourteen times that of 1995. The economic status of a society determines to a large extent its ability to handle and cope with natural disasters.

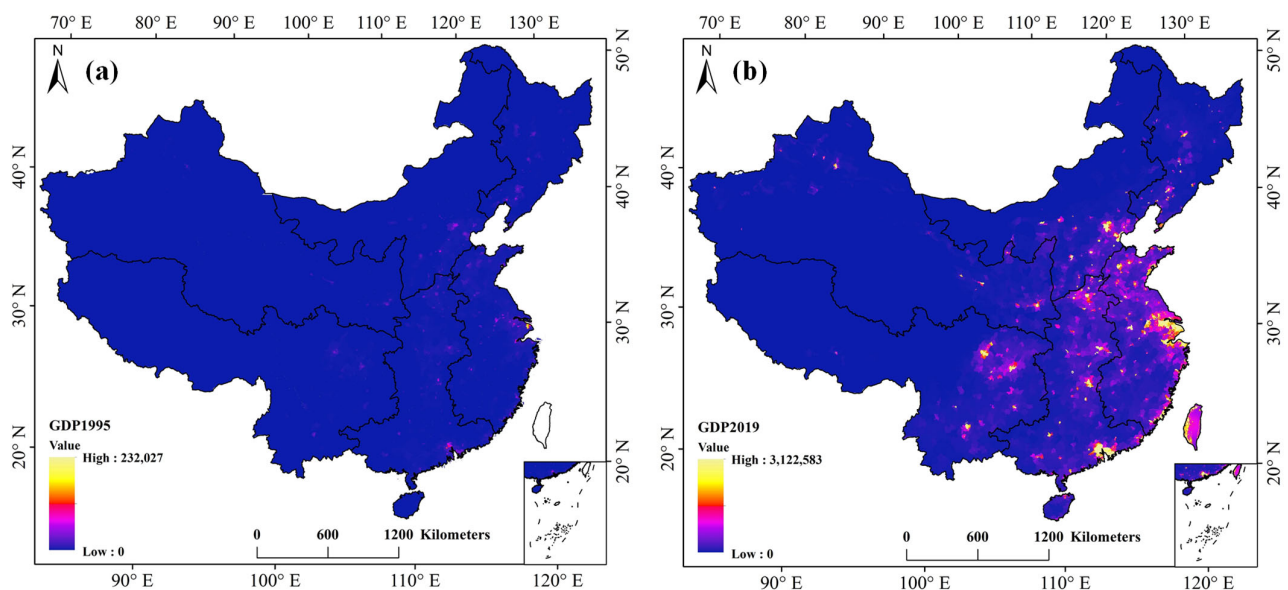


Figure 10. GDP in China for the years of 1995 (a) and 2019 (b).

The increase in extreme precipitation indices may lead to an increase in the frequency and severity of natural disasters, resulting in higher mortality rates and economic losses. At the same time, we also studied the losses caused by natural disasters related to extreme precipitation, including the total human deaths and total economic losses caused by floods, storms, droughts, and landslides in China. Figure 11 shows the time trend distribution of deaths and total economic and property losses caused by four natural disasters from 1985 to 2018. Due to incomplete data records, it is not possible to compare based on the previous partitioning. Therefore, national-level figures for disaster-related fatalities and losses are provided. Since droughts and landslides occur much less frequently, we only show the trend results for floods and storms in this figure. The red bars represent the total number of deaths in different years, and the specific values are shown on the left y-axis. The blue bar line represents the year-on-year change trend of the total economic losses caused by disasters, and the specific values are displayed on the y-axis on the right. The red and blue dashed lines represent the trend changes of the two, respectively, and the formulas on the left and right represent the magnitude and correlation degree of the linear trends of the two, respectively. The results show that the number of deaths caused by natural disasters is on a downward trend, but the economic and property losses caused by disasters are increasing year by year. In particular, the number of deaths from integrated natural disasters, floods, and storms has decreased by 51, 30, and 15 people per year, respectively, while the economic losses to property have a significantly increasing trend, with increases at an annual rate of USD 530,991, USD 302,253, and USD 203,340 for integrated natural disasters (i.e., all types of climate-related disasters), floods, and storms, respectively. This shows that although China's implementation of disaster prevention and control policies has been improving over the past 60 years and has reduced the number of disaster-related deaths, the economic losses caused by frequent disasters are still growing. There is an imperative necessity to enhance disaster prevention and management, particularly in addressing natural calamities triggered by extreme precipitation.

Due to the varying density of weather stations across different regions, particularly in northwestern China, data interpolation may introduce biases in the results. Although the modified Mann–Kendall test accounts for autocorrelation, it has limitations in capturing nonlinear changes and complex trend structures. In the results section, the spatial relationship between extreme precipitation indices and disaster occurrence frequency was interpreted visually rather than quantitatively assessed through statistical correlation analysis. This introduces a degree of subjectivity that may affect result accuracy. Additionally, when discussing the influence of human activities on natural disaster events, the analysis was limited to the potential impacts of land use changes and GDP, lacking a more comprehensive examination of other driving factors. This constraint limits a holistic understanding of the causes of extreme precipitation-related natural disasters. Future research should further refine data collection and analytical methodologies to address these limitations.

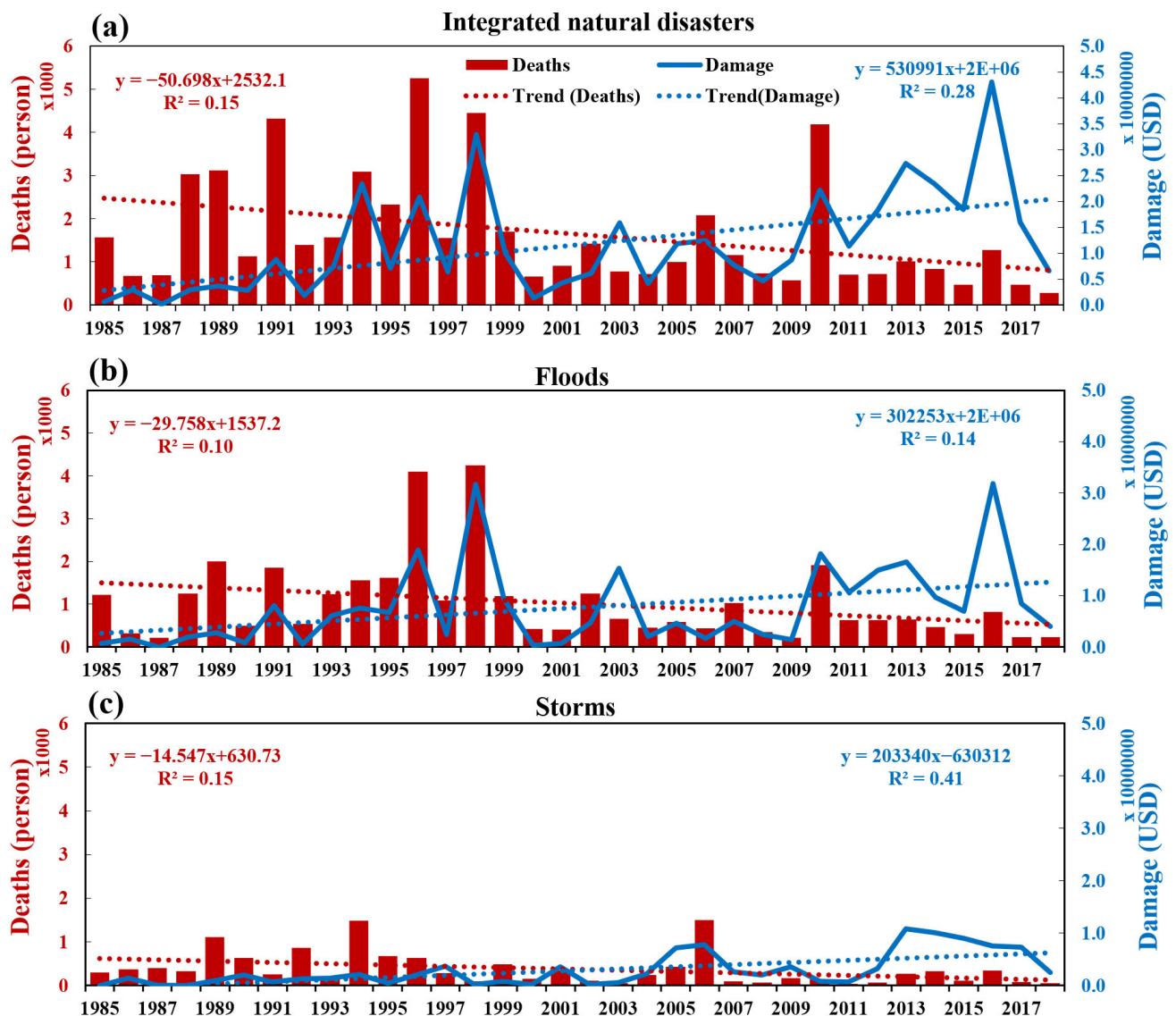


Figure 11. Life losses and economic losses caused by integrated natural disasters, floods, and storms in China during 1961–2018. (a) Integrated natural disasters, (b) floods, and (c) storms. Note: The left y-axes represent the “Deaths” index, while the right y-axes correspond to the “Damage” index. The red lines indicate the trend in deaths, and the blue lines show the trend in damage.

6. Conclusions

The trend analysis results of extreme precipitation indicators show that most rainfall stations in China have significant statistical trends in extreme precipitation. The most significant trends are an increasing extreme precipitation (PRCPTOT, SDII, R95p, R99p, Rx1day, and Rx5day) trend in EC, and a significantly decreasing extreme precipitation (PRCPTOT, CWD, and R10) trend in SW, with a clear increase in CDD. Additionally, the patterns of variation in these precipitation extremes exhibit significant spatial variability, with extreme precipitation events predominantly concentrated along the coastal plains, especially in the EC and SC regions. In contrast, the SW and NC regions are expected to experience decreasing moisture over time. NW and the northern parts of NE face a trend of becoming wetter.

Regarding the extreme precipitation trends associated with natural disasters, the frequency of occurrence of floods, storms, droughts, and landslides across the country presents a significant increase trend during 1961–2021, and disaster types show substantial regional dependence. In NE, the trend presents patterns of a wet north and dry south,

corroborating with the occurrences of increasing floods, storms, and landslides in the extreme north and droughts in the south with a great expansion of urbanization. In NC, the indicator trends indicate an intensification of droughts, accompanied by a decrease in PRCPTOT, R95p, and Rx5day and an increase in CDD. EC has a very significant trend of extreme precipitation. However, due to its higher urbanization and economic level and its strong ability to cope with floods and typhoon disasters, extreme precipitation disasters are not common except in mountainous areas. Floods and storms are increasing significantly in SC and droughts and landslides are mainly localized. The intensity and frequency of extreme precipitation are increasing in NW, and associated flood hazards are facing challenges. In SW, trends of decreased rainfall are observed in the Yunnan, Sichuan, and Guizhou areas, which are associated with high risks of drought and landslide hazards.

Land use and land cover changed significantly from 1980 to 2020, especially due to urban expansion in eastern China. However, cities have a higher ability to withstand disaster risks than rural areas, primarily due to their economic diversity, infrastructure, emergency response capabilities, and social organization. Furthermore, the results of GDP changes also prove that the eastern coastal regions and major provincial cities may have more capacity to invest in disaster risk reduction and recovery efforts. Thanks to China's effective disaster prevention measures, the annual number of fatalities from disasters has been decreasing. However, the escalating economic losses due to more frequent disasters underscore the continued urgency to fortify natural disaster prevention and management efforts.

Author Contributions: X.H.: Formal analysis, methodology, investigation, funding acquisition, writing—original draft. Q.C.: Resources, data curation, investigation, formal analysis. D.F.: Conceptualization, supervision, resources, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Civil Aerospace Technology Advance Research Project of China (D040306), and the APC was also funded by the Civil Aerospace Technology Advance Research Project of China.

Data Availability Statement: The precipitation data from 1274 stations across China can be found at <http://data.cma.cn>, accessed on 31 December 2022. Records of natural disaster events related to precipitation can be accessed from <https://public.emdat.be/>, accessed on 1 January 2024. The land use and land cover and GDP datasets are available at <https://www.resdc.cn/>, accessed on 1 January 2024. The life losses and economic losses dataset can be found at <https://gadm.org/data.html>.

Acknowledgments: We would like to thank the China Meteorological Administration for providing the data used in this study. The authors are grateful to the Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters at the University of Leuven, Belgium.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Wang, X.; Hou, X.; Wang, Y. Spatiotemporal variations and regional differences of extreme precipitation events in the Coastal area of China from 1961 to 2014. *Atmospheric Res.* **2017**, *197*, 94–104. [CrossRef]
2. Rodrigues, D.T.; Gonçalves, W.A.; Spyrides, M.H.C.; Andrade, L.d.M.B.; de Souza, D.O.; de Araujo, P.A.A.; da Silva, A.C.N.; e Silva, C.M.S. Probability of occurrence of extreme precipitation events and natural disasters in the city of Natal, Brazil. *Urban Clim.* **2021**, *35*, 100753. [CrossRef]
3. Wei, H.; Yu, T.; Tu, J.; Ke, F. Detection and evaluation of flood inundation using CYGNSS data during Extreme precipitation in 2022 in Guangdong province, China. *Remote Sens.* **2023**, *15*, 297. [CrossRef]
4. WMO, CCI/CLIVAR, ETCCDMI. *Report of the First CCI/CLIVAR Expert Team on Climate Change Detection, Monitoring and Indices*; WMO, CCI/CLIVAR, ETCCDMI: Norwich, UK, 2004.
5. Li, L.; Zou, Y.; Li, Y.; Lin, H.; Liu, D.L.; Wang, B.; Yao, N.; Song, S. Trends, change points and spatial variability in extreme precipitation events from 1961 to 2017 in China. *Hydrol. Res.* **2020**, *51*, 484–504. [CrossRef]

6. Ojara, M.; Yunsheng, L.; Babaousmail, H.; Wasswa, P. Trends and zonal variability of extreme precipitation events over East Africa during 1960–2017. *Nat. Hazards* **2021**, *109*, 33–61.
7. Wang, X.; Li, Y.; Yan, M.; Gong, X. Changes in temperature and precipitation extremes in the arid regions of China during 1960–2016. *Front. Ecol. Evol.* **2022**, *10*, 902813. [\[CrossRef\]](#)
8. Cui, H.; Jiang, S.; Ren, L.; Xiao, W.; Yuan, F.; Wang, M.; Wei, L. Dynamics and potential synchronization of regional precipitation concentration and drought-flood abrupt alternation under the influence of reservoir climate. *J. Hydrol. Reg. Stud.* **2022**, *42*, 101147. [\[CrossRef\]](#)
9. Fang, Y.P.; Zhu, F.B.; Qiu, X.P.; Zhao, S. Effects of natural disasters on livelihood resilience of rural residents in Sichuan. *Habitat Int.* **2018**, *76*, 19–28. [\[CrossRef\]](#)
10. Zhou, X.; Zhang, Y.; Wang, W.; Li, X.; Yang, H.; Sun, Y. Social vulnerability assessment under different extreme precipitation scenarios: A case study in Henan Province, China. *PLoS ONE* **2024**, *19*, e0299956. [\[CrossRef\]](#)
11. AghaKouchak, A.; Chiang, F.; Huning, L.S.; Love, C.A.; Mallakpour, I.; Mazdiyasni, O.; Moftakhari, H.; Papalexiou, S.M.; Ragno, E.; Sadegh, M. Climate extremes and compound hazards in a warming world. *Annu. Rev. Earth Planet. Sci.* **2020**, *48*, 519–548. [\[CrossRef\]](#)
12. Zhang, Y.; You, Q.; Ullah, S.; Chen, C.; Shen, L.; Liu, Z. Substantial increase in abrupt shifts between drought and flood events in China based on observations and model simulations. *Sci. Total Environ.* **2023**, *876*, 162822. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Wang, J.; Chen, Y.; Nie, J.; Yan, Z.; Zhai, P.; Feng, J. On the role of anthropogenic warming and wetting in the July 2021 Henan record-shattering rainfall. *Sci. Bull.* **2022**, *67*, 2055–2059. [\[CrossRef\]](#)
14. Zang, Z.; Luo, J.; Ha, Y. Interdecadal increase in summertime extreme precipitation over East China in the late 1990's. *Front. Earth Sci.* **2022**, *10*, 969853. [\[CrossRef\]](#)
15. Yao, Y.; Zhang, W.; Kirtman, B. Increasing impacts of summer extreme precipitation and heatwaves in eastern China. *Clim. Change* **2023**, *176*, 131. [\[CrossRef\]](#)
16. Wu, X.; Wang, L.; Niu, Z.; Jiang, W.; Cao, Q. More extreme precipitation over the Yangtze River Basin, China: Insights from historical and projected perspectives. *Atmospheric Res.* **2023**, *292*, 106883. [\[CrossRef\]](#)
17. Zhao, Y.; Zou, X.; Cao, L.; Xu, X. Changes in precipitation extremes over the Pearl River Basin, southern China, during 1960–2012. *Quat. Int.* **2014**, *333*, 26–39. [\[CrossRef\]](#)
18. Zhang, J.; Shen, X.; Wang, B. Changes in precipitation extremes in Southeastern Tibet, China. *Quat. Int.* **2015**, *380*, 49–59. [\[CrossRef\]](#)
19. Chen, F.; Chen, H.; Yang, Y. Annual and seasonal changes in means and extreme events of precipitation and their connection to elevation over Yunnan Province, China. *Quat. Int.* **2015**, *374*, 46–61. [\[CrossRef\]](#)
20. Sun, W.; Mu, X.; Song, X.; Wu, D.; Cheng, A.; Qiu, B. Changes in extreme temperature and precipitation events in the Loess Plateau (China) during 1960–2013 under global warming. *Atmos. Res.* **2016**, *168*, 33–48. [\[CrossRef\]](#)
21. Wang, L.; Wu, Z.; He, H.; Wang, F.; Du, H.; Zong, S. Changes in summer extreme precipitation in Northeast Asia and their relationships with the East Asian summer monsoon during 1961–2009. *Int. J. Clim.* **2017**, *37*, 25–35. [\[CrossRef\]](#)
22. Zheng, J.; Fan, J.; Zhang, F. Spatiotemporal trends of temperature and precipitation extremes across contrasting climatic zones of China during 1956–2015. *Theor. Appl. Clim.* **2019**, *138*, 1877–1897. [\[CrossRef\]](#)
23. Shi, J.; Cui, L.; Wang, J.; Du, H.; Wen, K. Changes in the temperature and precipitation extremes in China during 1961–2015. *Quat. Int.* **2019**, *527*, 64–78. [\[CrossRef\]](#)
24. Tao, Y.; Wang, W.; Song, S.; Ma, J. Spatial and Temporal Variations of Precipitation Extremes and Seasonality over China from 1961–2013. *Water* **2018**, *10*, 719. [\[CrossRef\]](#)
25. Bi, X.; Fan, Q.; He, L.; Zhang, C.; Diao, Y.; Han, Y. Analysis and evaluation of extreme precipitation trends and geological hazards risk in the lower Jinshajiang river. *Appl. Sci.* **2023**, *13*, 4021. [\[CrossRef\]](#)
26. Zhan, M.; Wu, Q.; Zhan, L.; Xin, J. Change in extreme precipitation events: Exposure and vulnerability in the Poyang Lake Basin, China. *Front. Earth Sci.* **2023**, *11*, 1125837. [\[CrossRef\]](#)
27. Gu, X.; Ye, L.; Xin, Q.; Zhang, C.; Zeng, F.; Nerantzaki, S.D.; Papalexiou, S.M. Extreme precipitation in China: A review on statistical methods and applications. *Adv. Water Resour.* **2022**, *163*, 104144. [\[CrossRef\]](#)
28. Akter, T.; Quevauviller, P.; Eisenreich, S.J.; Vaes, G. Impacts of climate and land use changes on flood risk management for the Schijn River, Belgium. *Environ. Sci. Policy* **2018**, *89*, 163–175. [\[CrossRef\]](#)
29. Alberico, I.; Iavarone, R.; Petrosino, P. A procedure for the resilience mapping in urban systems exposed to natural hazard: The Ischia Island (southern Italy) test area. *Int. J. Disaster Risk Reduct.* **2020**, *50*, 101893. [\[CrossRef\]](#)
30. He, F.; Gu, L.; Wang, T.; Zhang, Z. The synthetic geo-ecological environmental evaluation of a coastal coal-mining city using spatiotemporal big data: A case study in Longkou, China. *J. Clean. Prod.* **2017**, *142*, 854–866. [\[CrossRef\]](#)
31. AghaKouchak, A.; Huning, L.S.; Chiang, F.; Sadegh, M.; Vahedifard, F.; Mazdiyasni, O.; Moftakhari, H.; Mallakpour, I. How do natural hazards cascade to cause disasters? *Nature* **2018**, *561*, 458–460. [\[CrossRef\]](#)
32. Klomp, J.; Valckx, K. Natural disasters and economic growth: A meta-analysis. *Glob. Environ. Change* **2014**, *26*, 183–195. [\[CrossRef\]](#)

33. Cavallo, E.; Galiani, S.; Noy, I.; Pantano, J. Catastrophic natural disasters and economic growth. *Rev. Econ. Stat.* **2013**, *95*, 1549–1561.
34. Guan, Y.; Zhang, X.; Zheng, F.; Wang, B. Trends and variability of daily temperature extremes during 1960–2012 in the Yangtze River Basin, China. *Glob. Planet. Change* **2015**, *124*, 79–94. [[CrossRef](#)]
35. Zhong, K.; Zheng, F.; Wu, H.; Qin, C.; Xu, X. Dynamic changes in temperature extremes and their association with atmospheric circulation patterns in the Songhua River Basin, China. *Atmos. Res.* **2017**, *190*, 77–88. [[CrossRef](#)]
36. Wang, L.; Chen, S.; Zhu, W.; Ren, H.; Zhang, L.; Zhu, L. Spatiotemporal variations of extreme precipitation and its potential driving factors in China's North-South transition zone during 1960–2017. *Atmos. Res.* **2021**, *252*, 105429. [[CrossRef](#)]
37. Rosvold, E.L.; Buhaug, H. GDIS, a global dataset of geocoded disaster locations. *Sci. Data* **2021**, *8*, 61. [[CrossRef](#)]
38. Zhou, Y.; Li, N.; Wu, W.; Wu, J. Assessment of provincial social vulnerability to natural disasters in China. *Nat. Hazards* **2014**, *71*, 2165–2186. [[CrossRef](#)]
39. de Oliveira Roza, M.P.; Cecilio, R.A.; Zanetti, S.S.; Abreu, M.C.; Lyra, G.B.; Reis, G.B. Natural disasters related to rainfall trends in Espírito Santo, southeastern Brazil. *Theor. Appl. Climatol.* **2024**, *155*, 1451–1466.
40. Onyutha, C.; Tabari, H.; Taye, M.T.; Nyandwaro, G.N.; Willems, P. Analyses of rainfall trends in the Nile River Basin. *J. Hydro-Environ. Res.* **2016**, *13*, 36–51. [[CrossRef](#)]
41. Li, X.; Zhang, K.; Gu, P.; Feng, H.; Yin, Y.; Chen, W.; Cheng, B. Changes in precipitation extremes in the Yangtze River Basin during 1960–2019 and the association with global warming, ENSO, and local effects. *Sci. Total Environ.* **2021**, *760*, 144244. [[CrossRef](#)]
42. Du, H.; Xia, J.; Yan, Y.; Lu, Y.; Li, J. Spatiotemporal Variations of Extreme Precipitation in Wuling Mountain Area (China) and Their Connection to Potential Driving Factors. *Sustainability* **2022**, *14*, 8312. [[CrossRef](#)]
43. Cui, D.; Wang, C.; Santisiriromboon, J. Characteristics of extreme precipitation over eastern Asia and its possible connections with Asian summer monsoon activity. *Int. J. Clim.* **2019**, *39*, 711–723. [[CrossRef](#)]
44. Zhang, L.; Wang, C.; Li, X.; Zhang, H.; Li, W.; Jiang, L. Impacts of agricultural expansion (1910s–2010s) on the water cycle in the songneng plain, Northeast China. *Remote Sens.* **2018**, *10*, 1108. [[CrossRef](#)]
45. Du, C.; Chen, J.; Nie, T.; Dai, C. Spatial-temporal changes in meteorological and agricultural droughts in Northeast China: Change patterns, response relationships and causes. *Nat. Hazards* **2022**, *110*, 155–173.
46. Liu, X.; Pan, Y.; Zhu, X.; Yang, T.; Bai, J.; Sun, Z. Drought evolution and its impact on the crop yield in the North China Plain. *J. Hydrol.* **2018**, *564*, 984–996. [[CrossRef](#)]
47. Wang, F.; Wang, Z.; Yang, H.; Di, D.; Zhao, Y.; Liang, Q. Utilizing GRACE-based groundwater drought index for drought characterization and teleconnection factors analysis in the North China Plain. *J. Hydrol.* **2020**, *585*, 124849. [[CrossRef](#)]
48. Chen, N.; Li, R.; Zhang, X.; Yang, C.; Wang, X.; Zeng, L.; Tang, S.; Wang, W.; Li, D.; Niyogi, D. Drought propagation in Northern China Plain: A comparative analysis of GLDAS and MERRA-2 datasets. *J. Hydrol.* **2020**, *588*, 125026. [[CrossRef](#)]
49. Zhang, C.; Duan, Q.; Yeh, P.J.-F.; Pan, Y.; Gong, H.; Moradkhani, H.; Gong, W.; Lei, X.; Liao, W.; Xu, L.; et al. Sub-regional groundwater storage recovery in North China Plain after the South-to-North water diversion project. *J. Hydrol.* **2021**, *597*, 126156. [[CrossRef](#)]
50. Lei, C.; Yu, Z.; Sun, X.; Wang, Y.; Yuan, J.; Wang, Q.; Han, L.; Xu, Y. Urbanization effects on intensifying extreme precipitation in the rapidly urbanized Tai Lake Plain in East China. *Urban Clim.* **2023**, *47*, 101399. [[CrossRef](#)]
51. Zhang, Q.; Yang, J.; Wang, W.; Ma, P.; Lu, G.; Liu, X.; Yu, H.; Fang, F. Climatic warming and humidification in the arid region of Northwest China: Multi-scale characteristics and impacts on ecological vegetation. *J. Meteorol. Res.* **2021**, *35*, 113–127. [[CrossRef](#)]
52. Li, Y.; Wang, Z.; Zhang, Y.; Li, X.; Huang, W. Drought variability at various timescales over Yunnan Province, China: 1961–2015. *Theor. Appl. Clim.* **2019**, *138*, 743–757. [[CrossRef](#)]
53. Lan, T.; Yan, X. Analysis of Drought Characteristics and Causes in Yunnan Province in the Last 60 Years (1961–2020). *J. Hydrometeorol.* **2024**, *25*, 177–190. [[CrossRef](#)]
54. Sun, Y.; Ge, Y.; Chen, X.; Zeng, L.; Liang, X. Risk assessment of debris flow along the northern line of the Sichuan-Tibet highway. *Geomatics, Nat. Hazards Risk* **2023**, *14*, 2195531. [[CrossRef](#)]
55. Li, Y.; Wang, W.; Chang, M.; Wang, X. Impacts of urbanization on extreme precipitation in the Guangdong-Hong Kong-Macau Greater Bay Area. *Urban Clim.* **2021**, *38*, 100904. [[CrossRef](#)]
56. Zhang, D. Rapid urbanization and more extreme precipitation events. *Sci. Bull.* **2020**, *65*, 516–518.
57. Leite-Filho, A.T.; Costa, M.H.; Fu, R. The southern Amazon rainy season: The role of deforestation and its interactions with large-scale mechanisms. *Int. J. Clim.* **2020**, *40*, 2328–2341. [[CrossRef](#)]
58. Leite-Filho, A.T.; Soares-Filho, B.S.; Davis, J.L.; Abrahão, G.M.; Börner, J. Deforestation reduces rainfall and agricultural revenues in the Brazilian Amazon. *Nat. Commun.* **2021**, *12*, 2591. [[CrossRef](#)]
59. Smith, C.; Baker, J.C.A.; Spracklen, D.V. Tropical deforestation causes large reductions in observed precipitation. *Nature* **2023**, *615*, 270–275. [[CrossRef](#)]
60. Martinez-Villalobos, C.; Neelin, J.D. Regionally high risk increase for precipitation extreme events under global warming. *Sci. Rep.* **2023**, *13*, 5579. [[CrossRef](#)]

61. Diffenbaugh, N.S.; Singh, D.; Mankin, J.S.; Horton, D.E.; Swain, D.L.; Touma, D.; Charland, A.; Liu, Y.; Haugen, M.; Tsiang, M.; et al. Quantifying the influence of global warming on unprecedented extreme climate events. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 4881–4886. [[CrossRef](#)]
62. Colvin, R.; Crimp, S.; Lewis, S.; Howden, M. Implications of climate change for future disasters. In *Natural Hazards and Disaster Justice: Challenges for Australia and Its Neighbours*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 25–48.
63. Dai, A. Increasing drought under global warming in observations and models. *Nat. Clim. Change* **2013**, *3*, 52–58. [[CrossRef](#)]
64. Trenberth, K.E.; Dai, A.; Van Der Schrier, G.; Jones, P.D.; Barichivich, J.; Briffa, K.R.; Sheffield, J. Global warming and changes in drought. *Nat. Clim. Change* **2014**, *4*, 17–22. [[CrossRef](#)]
65. Chiou-Wei, S.Z.; Chen, C.-F.; Zhu, Z. Economic growth and energy consumption revisited—Evidence from linear and nonlinear Granger causality. *Energy Econ.* **2008**, *30*, 3063–3076. [[CrossRef](#)]
66. World Bank. *World Development Indicators 2016*; The World Bank: Washington, DC, USA, 2016.
67. Kellenberg, D.; Mobarak, A. Does rising income increase or decrease damage risk from natural disasters? *J. Urban Econ.* **2008**, *63*, 788–802. [[CrossRef](#)]
68. Klomp, J. Economic development and natural disasters: A satellite data analysis. *Glob. Environ. Change* **2016**, *36*, 67–88. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.