

# 1 Cropland and Population Exposure to Extreme Precipitation Events 2 in Central Asia Under Future Climate Change

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16 **Abstract:** Central Asia (CA) is experiencing rapid warming, leading to more Extreme  
17 precipitation events (EPEs). However, the anticipated changes in cropland and population  
18 exposure to EPEs are still unexplored. In this study, projected changes in EPEs characteristics,  
19 as well as cropland and population exposure from EPEs are quantified using global climate model  
20 simulations. Our findings reveal a significant increase in the exposure of cropland and  
21 population to extreme precipitation over time. Specifically, under the high-emission SSP5-8.5  
22 future pathway, the amount, frequency, intensity, and spatial extent of extreme precipitation in  
23 CA are projected to considerably amplify, particularly in the high mountain regions. Under the  
24 SSP5-8.5 scenario, cropland exposure in CA increases by 46.4%, with a total cropland exposure  
25 of approximately 190.7 million km<sup>2</sup> expected between 2021 and 2100. Additionally, under the  
26 SSP3-7.0 scenario, population exposure in CA increases by 92.6%, resulting in a total  
27 population exposure of about 48.1 billion person-days during the same period. The future  
28 maximum centers of exposure are concentrated over northern Kazakhstan and the tri-border  
29 region of Tajikistan, Kyrgyzstan, and Uzbekistan. Notably, the climate effect is more dominant  
30 than the other effects, whereas changes in population effect contribute to the total change in  
31 population exposure. Given the heterogeneous distribution of population and cropland in CA,  
32 it is imperative for the countries in the region to implement effective measures that harness  
33 extreme precipitation and cope with the impacts of these extreme climate events.

34 **Keywords:**

35 Extreme precipitation events; Cropland and Population Exposure; Central Asia; ISI-MIP3b

36 **Key Points:**

- 37 ● Extreme precipitation events are projected to increase substantially over the 21st century  
38 in the mountainous regions across Central Asia.
- 39 ● This study considers both population and cropland as vulnerable hazard-bearers to extreme  
40 precipitation in the exposure assessment.
- 41 ● The population exposure is greatest in the SSP3-7.0 scenario and the cropland exposure is  
42 greatest in the SSP5-8.5 scenario.

43 **Plain Language Summary:** Climate change is anticipated to intensify the risk of extreme  
44 precipitation events (EPEs). When evaluating these risks, it is crucial to consider  
45 socioeconomic factors. This study employs projections based on five Global Climate Models  
46 (GCMs) to assess the socioeconomic impacts of precipitation extremes on cropland and  
47 population under three Representative Concentration Pathways (RCPs) and Shared  
48 Socioeconomic Pathways (SSPs) across four future time periods (2021-2040, 2041-2060, 2061-  
49 2080, and 2081-2100). The findings reveal a substantial increase in the exposure of the  
50 population and cropland in CA to extreme precipitation over time. Among the scenarios  
51 examined, the SSP3-7.0 scenario exhibits the highest population exposure, while the SSP5-8.5  
52 scenario results in the highest cropland exposure in CA. It can be inferred that the climate  
53 influence is more dominant than the population and cropland, particularly for CA. Consequently,  
54 CA demands heightened attention due to the vulnerability of its population and cropland to  
55 EPEs. Moreover, CA must prioritize the implementation of effective adaptation measures due  
56 to its highly heterogeneous spatial distribution of population. Additionally, as a predominantly  
57 agricultural region with a significant reliance on water resources, the region faces exceptional  
58 challenges.

59 **1. Introduction**

60 In the context of global climate change, increasing evidence supports that climate change is  
61 responsible for triggering numerous extreme weather and climate events on a global scale  
62 (IPCC, 2021). Climate change is anticipated to accelerate the global hydrological cycle and  
63 intensify all forms of extreme weather and climate events (Ombadi et al., 2023; Zscheischler et  
64 al., 2020; Tabari et al., 2020; Zhou et al., 2023; Jong et al., 2023). EPEs are projected to become  
65 more intense, longer in duration, and more frequent (Jong et al., 2023; Huang et al., 2022;  
66 Zhang et al., 2021; Zhang et al., 2020), particularly in arid regions (Yao et al., 2021). Given the  
67 recent increase in the frequency and substantial impact of EPEs, they have garnered greater  
68 attention than ever before. To effectively prioritize research efforts and inform strategies for  
69 risk management, it is crucial to assess future risks, specifically examining the exposure of  
70 populations to specific hazards. However, it should be noted that such risks may vary by age,  
71 season, and geographical region (Samir et al., 2017).

72 EPEs led to significant consequences for substantial socioeconomic and ecological losses (Doan et  
73 al., 2022; Gao et al., 2020) also profound implications for human safety and property protection  
74 (Swain et al., 2020; Tandon et al., 2018). For instance, the extreme precipitation in China in  
75 2010 resulted in thousands of deaths and extensive property damage due to landslides and  
76 mudslides (Wang et al., 2016). Similarly, extreme precipitation in northern Pakistan in 2010  
77 claimed approximately 3,000 lives (Lau et al., 2012), while northern India experienced more  
78 than 5,000 casualties from EPEs in 2013 (Cho et al., 2016). EPEs have also been identified as  
79 a major contributor to crop yield reductions, surpassing the impacts of other extreme climate  
80 hazards (Fu et al., 2023; Hasegawa et al., 2021; Li et al., 2019; Basile et al., 2022). With further  
81 climate warming, these EPEs and associated hazards are expected to become more frequent  
82 across various regions of the world (Jiang et al., 2016; Cook et al., 2020). EPEs deserve more  
83 attention in arid and semi-arid regions. This is because arid and semi-arid regions are particularly  
84 prone to flooding, mudslides and landslides when extreme precipitation occurs (Mariotti et al., 2002;  
85 Xue et al., 2017; Xu et al., 2015; Zhang et al., 2017; Swain et al., 2015; Donat et al., 2016).  
86 Additionally, crops in arid regions are less resistant to extreme precipitation due to fragile  
87 ecosystems.

88 Central Asia (CA), a typical arid and semi-arid region, identified as a hotspot of global warming,  
89 is experiencing a temperature increase that is approximately twice as rapid as the global average  
90 (Zhang et al., 2019), and the warming trend is projected to persist throughout the 21st century  
91 (Huang et al., 2014; Guo et al., 2021). While some studies suggest a significant increase in  
92 mean precipitation and interannual variability across most of CA under future scenarios (Jiang  
93 et al., 2020; Zhao et al., 2018), the trend towards greater precipitation appears more prominent  
94 during the winter season (Yu et al., 2018). Additionally, the intensity of EPEs in CA is predicted  
95 to escalate in response to global warming (Peng et al., 2020). However, alternative models  
96 propose a potential trend towards drier summers, and projections for future drought exhibit  
97 higher uncertainty among models compared to changes in extreme precipitation (Jiang et al.,  
98 2020). The vulnerable ecosystems of CA, characterized by relatively sparse vegetation cover,  
99 are particularly susceptible to the impacts of global climate change (Hu et al., 2016; Yuan et  
100 al., 2017). CA is considered ecologically fragile, with changes in precipitation significantly  
101 influencing human production and livelihoods (Wei et al., 2023). Adverse climate events like  
102 floods have had detrimental effects on the region's delicate ecosystems, impeding  
103 socioeconomic and sustainable development (Dike et al., 2022; Scussolini et al., 2016). Given  
104 the limited resilience and adaptive capacity of the region, extreme climate change poses a  
105 significant challenge to livelihoods, exerting far-reaching impacts on various key  
106 socioeconomic sectors (Devkota et al., 2013; Liu et al., 2023). Furthermore, the economies of  
107 CA countries heavily rely on primary industries, particularly agriculture, which is highly  
108 vulnerable to changes in the local hydrological cycle (Gessner et al., 2013; Jiang et al., 2023).  
109 Modifications in precipitation patterns strongly impact the livelihoods of CA populations and  
110 the fragility of the environment. Moreover, both the population and cropland in CA are  
111 concentrated in areas prone to high flood risk, amplifying the risks associated with EPEs (Li et  
112 al., 2019). Addressing the adverse impacts of future EPEs in these vulnerable areas and  
113 quantifying the associated socioeconomic risks are imperative for policymakers and the  
114 development of climate adaptation strategies.

115 Recent studies indicate that global exposure to extreme precipitation is expected to increase in  
116 the future (Li et al., 2019; Shi et al., 2021). However, there have been relatively few long-term  
117 studies examining trends in EPEs. Furthermore, previous research on extreme precipitation in  
118 CA has primarily focused on historical and future analyses of spatial and temporal evolution,  
119 as well as attribution mechanisms (Ma et al., 2021; Zhang et al., 2021; Li et al., 2022; Jiang et  
120 al., 2021; Xu et al., 2022; Liu et al., 2022). Few studies have investigated the demographic and  
121 socioeconomic impacts of extreme precipitation in CA. As a result, there is a need to quantify  
122 future changes in extreme precipitation in the region and comprehensively assess the  
123 implications of heightened EPEs. Therefore, accurate prediction of changes in the  
124 characteristics of extreme precipitation under different future climate scenarios in CA is crucial  
125 for developing effective adaptation strategies in different regions to mitigate the risks posed by  
126 extreme precipitation.

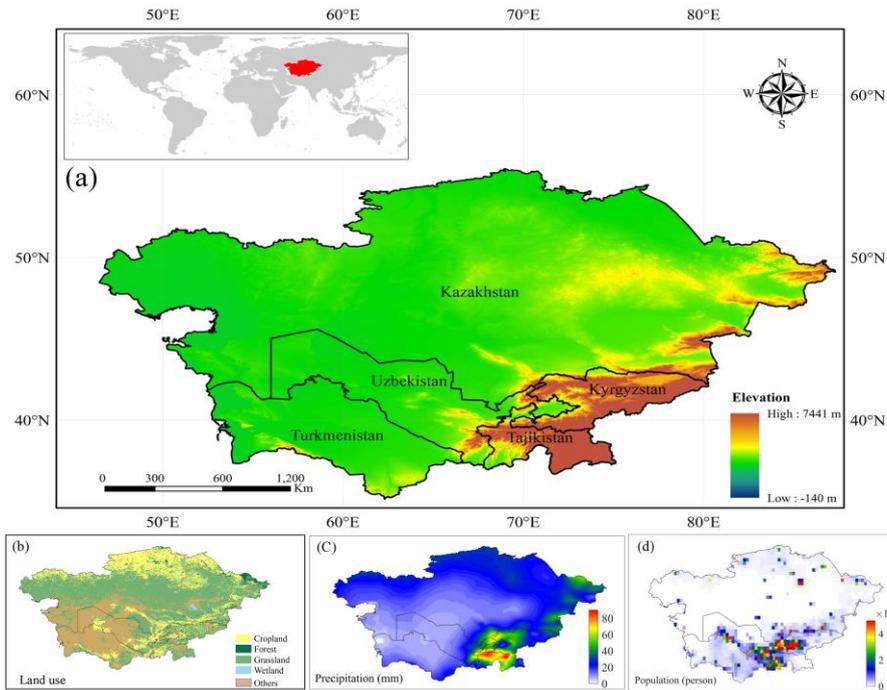
127 This study aimed to examine future changes in extreme precipitation and the resulting exposure  
128 of population and cropland in CA using multi-model projections from the ISI-MIP framework.  
129 In comparison to CMIP5 and CMIP6, the ISI-MIP framework employs a novel, more federated  
130 approach that utilizes the 1960-1999 WATCH in-analysis data to downscale and bias correct  
131 climate model outputs. Furthermore, the ISI-MIP models generally operate at finer resolutions  
132 and adhere to a standardized modeling protocol, enhancing their ability to simulate climate  
133 extremes (Gao et al., 2020; Hempel et al., 2013; Warszawski et al., 2014; Yang et al., 2020). In  
134 this research, we specifically quantify the shifts in exposure to extreme precipitation under  
135 future warming scenarios. Given Central Asia's high population density and heavy reliance on  
136 agriculture, we focus on population and cropland as primary factors influencing exposure. The  
137 findings from this investigation are crucial for understanding the region's future vulnerability  
138 and for informing effective mitigation and adaptation strategies. Importantly, this study  
139 represents an early attempt to comprehensively and quantitatively evaluate the impact of future  
140 changes in extreme precipitation on Central Asia's population and cropland.

## 141 **2. Study Area, Data and Methods**

### 142 **2.1 Study Area**

143 The CA, comprises five countries that emerged following the dissolution of the Soviet Union:  
144 Kazakhstan, Uzbekistan, Kyrgyzstan, Tajikistan, and Turkmenistan (Figure 1). Situated in the  
145 heartland of the Eurasian continent, CA exhibits a diverse topography, with elevated terrain in  
146 the east and lower elevations in the west. CA is one of the largest arid and semi-arid regions  
147 within the mid-latitudes, and its intricate topography constitutes a primary driver of  
148 precipitation variability in the area (Schiemann et al., 2008; Murnane et al., 2017). The  
149 Himalayas, the Pamir Plateau, and the Hindu Kush act as barriers, shielding the region from the  
150 influence of moist air masses originating from the Indian Ocean. Consequently, air currents  
151 from the west predominantly shape the precipitation patterns in CA, with precipitation  
152 primarily occurring on the western slopes of the mountains (Xie et al., 2021; Li et al., 2021;  
153 Zou et al., 2021). The distribution of population in the region exhibits significant heterogeneity,  
154 with a high concentration observed in the tri-border area of Uzbekistan, Tajikistan, and  
155 Kyrgyzstan. Uzbekistan stands as the most populous country in CA, boasting a population

156 density of 70 persons/km<sup>2</sup>, while Tajikistan follows closely behind with a population density  
 157 second only to Uzbekistan (61 persons/km<sup>2</sup>). Notably, Tajikistan's population density is ten  
 158 times higher than that of Kazakhstan, which holds the largest land area among the CA countries.  
 159 All five countries in CA heavily rely on agriculture, with the sector employing over 50% of the  
 160 workforce and contributing to approximately one-fifth of the total GDP. Cotton and wheat serve  
 161 as the primary crops in the region, emphasizing the paramount role of agriculture in Central  
 162 Asia's economic landscape (Hamidov et al., 2016; Sommer et al., 2013). Over the past three  
 163 decades, the region has witnessed a rapid increase in temperature, surpassing the warming rates  
 164 observed in neighboring areas and the global average (Gong et al., 2017).



165  
 166 **Figure 1.** Map of study area. (a) Location and topography in Central Asia. (b) Land use types  
 167 in Central Asia. (c) Mean monthly precipitation from 1995 to 2014. (d) Spatial distribution of  
 168 population in 2020 under SSP1-2.6 scenario simulated by the model.

169 **2.2 Dataset**

170 Gridded precipitation products are extensively utilized for the assessment of climate model data.  
 171 In this study, monthly precipitation data at a spatial resolution of 0.5° is obtained from the latest  
 172 Climate Research Unit dataset (CRU TS 4.07). This dataset is based on data collected from  
 173 over 4,000 weather stations worldwide and is widely recognized as one of the most prominent  
 174 climate datasets available. The dataset, produced by the National Centre for Atmospheric  
 175 Sciences (NCAS) in the U.K, provides monthly-scale data covering the land surface from 1901  
 176 to 2022 (Harris et al., 2020; Liu et al., 2021). The CRU dataset has been extensively employed  
 177 for various applications, including the identification of extreme precipitation, analysis of  
 178 extreme weather climates, and bias correction for General Circulation Model (GCM)  
 179 simulations (Zhang et al., 2022; Hao et al., 2018). For the purpose of this study, monthly  
 180 precipitation data from CRU was used to evaluate the data obtained from the selected GCMs  
 181 and perform necessary corrections.

182 The 5 GCMs (Table 1) including GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-  
183 ESM2-0, and UKESM1-0-LL were utilized in this study. These GCMs were provided by the  
184 Intersectoral Impact Model Intercomparison Project (ISI-MIP). These 5 models were selected  
185 based on their availability of daily data for the historical period from 1950 to 2100, covering  
186 all future scenarios and variables required for analysis. Additionally, all five models are part of  
187 both the CMIP5 and CMIP6, respectively. To ensure consistent climate change impact  
188 assessments, observational and historical model outputs were aggregated to a common baseline  
189 period of 1995-2014, as utilized in the IPCC Sixth Assessment Report (AR6). The climate  
190 scenarios employed in the ISI-MIP consist of a combination of Representative Concentration  
191 Pathways (RCP) and Shared Socioeconomic Pathways (SSP). Their detailed information is  
192 listed in Table S1 in Supporting Information S1. For this study, 3 future SSP scenarios (SSP1-  
193 2.6, SSP3-7.0, and SSP5-8.5) were selected for the periods 2021-2040, 2041-2060, 2061-2080,  
194 and 2081-2100 (Ullah et al., 2022). These scenarios provide a broad range of potential future  
195 climates, covering weak, moderate, and strong forcing. The raw outputs from the 5 GCMs  
196 mentioned above were downscaled to a horizontal resolution of  $0.5^\circ \times 0.5^\circ$  using a statistical  
197 downscaling algorithm. This process involved bias revisions based on multiple reliable  
198 observations and reanalysis data, while preserving the long-term climate trends present in the  
199 GCM raw results. The processed results have been widely applied in the study of changes in  
200 extreme climate events and their impacts, serving as inputs to various assessment models within  
201 the ISI-MIP framework. In order to reduce prediction uncertainties, the field of climate change  
202 prediction commonly employs multi-model ensemble averaging. This study also focuses on the  
203 results of multi-model ensemble averaging (MME) to assess reliability. Given the lack of high-  
204 resolution and spatial-temporal continuity in instrumental records within the study area, The  
205 CRU dataset was adopted as observational data for the study area. It is important to note that  
206 while this dataset is referred to as observational data, it is not strictly derived from instrumental  
207 observational records.

208 The Land Use Harmonization Version 2 (LUH2) dataset is employed in this study to represent  
209 historical and future land use activities worldwide from the year 850 to 2100. The dataset has  
210 been widely utilized and referenced (Chen et al., 2020; Ma et al., 2020; Hurtt et al., 2020;  
211 Eyring et al., 2016) and serves as a significant land use forcing dataset for CMIP6 (Eyring et  
212 al., 2016). LUH2 was developed based on the Global Environmental History Database (HYDE)  
213 and incorporates multiple future scenarios aligned with the SSP framework (García-Peña et al.,  
214 2021). It provides globally gridded partial land use patterns, base land use transitions, key  
215 agricultural management information, and secondary land data spanning the period from 850  
216 to 2100. The dataset has a spatial resolution of  $0.25^\circ \times 0.25^\circ$  and a temporal resolution of 1 year  
217 (García-Peña et al., 2021; Song et al., 2021). Within LUH2, land is classified into five main  
218 land use types (agricultural, rangeland, primary, secondary, and urban), each comprising twelve  
219 subtypes. For the representation of cropland, the sum of C3ann, C3per, C4ann, C4per, and  
220 C3nfx was utilized. In order to ensure consistency between datasets, the cropland data were  
221 interpolated to a resolution of  $0.5^\circ \times 0.5^\circ$  using a bilinear interpolation method, aligning it with  
222 the resolution of the climate data.

223 Future population data for the period 2020-2100 under different SSP scenarios were acquired  
224 from the NASA Socioeconomic Data and Applications Center (SEDAC) (Zhang et al., 2022).

225 It is important to note that the temporal resolution of the SEDAC population data is 10 years.  
 226 Consequently, for this study, we used the average population values in 2020, 2030, 2040, 2050,  
 227 2060, 2070, 2080, 2090, and 2100 to represent the future population from 2020 to 2100. In  
 228 order to maintain a consistent resolution between the population and climate datasets, the  
 229 population data was interpolated to a resolution of  $0.5^\circ \times 0.5^\circ$  using a bilinear interpolation  
 230 technique, ensuring alignment with the resolution of the climate data.

231 **Table 1** Details of the ISI-MIP climate models used in this study.

Model name	Institution ID	Resolution	Country
GFDL-ESM4	Geophysical Fluid Dynamics Laboratory	$1^\circ \times 1.25^\circ$	USA
IPSL-CM6A-LR	Institut Pierre Simon Laplace	$1.2676^\circ \times 2.5^\circ$	France
MPI-ESM1-2-HR	Max Planck Institute for Meteorology	$1.865^\circ \times 1.875^\circ$	Germany
MRI-ESM2-0	Meteorological Research Institute	$1.124^\circ \times 1.125^\circ$	Japan
UKESM1-0-LL	National Centre for Atmospheric Science and Met Office Hadley Centre	$1.25^\circ \times 1.875^\circ$	UK

### 232 **2.3 Evaluation methods for datasets**

233 Taylor diagrams (Taylor, 2001) provide a comprehensive assessment of a model's ability to  
 234 reproduce spatial patterns of climate variables, making them a widely used method for  
 235 evaluating climate model performance and dataset suitability (Guo et al., 2021; Yue et al., 2021;  
 236 Sun et al., 2021). In this study, we compared the data from five climate models and a multi-  
 237 model ensemble mean with observed data (see Figure S1 in Supporting Information S1). The  
 238 Taylor diagrams present correlation coefficients (R), central root mean square error (RMS), and  
 239 standard deviation (SD) for each climate model, the multi-model ensemble average, and the  
 240 observations in a single plot, illustrating the level of agreement between the model datasets and  
 241 the observations. Furthermore, we assessed the model dataset's performance at a monthly scale  
 242 by calculating precipitation for each month and comparing it to the observed data (see Figure  
 243 S2 in Supporting Information S1). The closer the model data align with the observations, the  
 244 higher their accuracy. By employing the Taylor diagram method, we comprehensively  
 245 evaluated the accuracy of the CA climate model and its performance at the monthly scale. This  
 246 approach enables the selection of the most suitable dataset, serving as the best alternative to  
 247 observed data for characterizing future EPEs (see Figure S3 in Supporting Information S1).

### 248 **2.4 Definition and Characteristics of Extreme Precipitation Events**

249 The hazard metric employed in this study is the annual number of days with extreme  
 250 precipitation, which serves as an indicator of the frequency of such events. Extreme  
 251 precipitation is defined as daily rainfall exceeding a specific threshold. Previous studies  
 252 commonly utilized extreme precipitation indices with fixed absolute thresholds specific to the  
 253 study area (Raymond et al., 2020). However, the hazard associated with extreme events is  
 254 influenced by various factors such as event characteristics, geographical conditions,

255 infrastructure, and population awareness. For instance, even small amounts of precipitation in  
 256 arid and semi-arid regions can lead to floods and landslides, rendering absolute thresholds  
 257 insufficient for capturing the true hazard of extreme precipitation in these regions. Consequently,  
 258 we employed relative thresholds, specifically the 95th percentile (Thackeray et al., 2022;  
 259 Alexander et al., 2019) of wet days (precipitation > 1 mm/day) for each grid cell. Relative  
 260 thresholds consider regional differences in precipitation by accounting for regional and seasonal  
 261 factors, thereby determining location-specific thresholds based on the actual precipitation  
 262 conditions at each location. This approach is more suitable for capturing regional spatial and  
 263 temporal variability and assessing exposure changes due to the significant climatic variations  
 264 across the globe (Liu et al., 2017). In this study, we introduced four extreme precipitation  
 265 indices to characterize EPEs and analyze their variability (Chen et al., 2013; Gimeno et al.,  
 266 2022; Wang, 2005; Mondal et al., 2022):

- 267 1. Total Extreme Precipitation (TEP) is defined as the cumulative annual precipitation (in mm)  
 268 exceeding the threshold value.
- 269 2. Extreme Precipitation Event Frequency (EPEF) corresponds to the number of days (in days)  
 270 in a year associated with EPEs.
- 271 3. Extreme Precipitation Event Intensity (EPEI) is defined as the average daily precipitation (in  
 272 mm/day) per grid cell during an extreme precipitation event.
- 273 4. Extreme Precipitation Event Impact Area (EPEA) corresponds to the maximum impacted  
 274 area (in km<sup>2</sup>) by an extreme precipitation event.

## 275 **2.5 Cropland and Population exposure to Extreme Precipitation Events**

276 Population and cropland exposure in this study is quantified as the product of the number of  
 277 days with extreme precipitation, the population exposed, and the cropland area within each grid  
 278 cell (Zhang et al., 2022; Sun et al., 2023; Wang et al., 2023; Jones et al., 2015). The resulting  
 279 units are person-days of exposure and square kilometers of cropland exposed. To account for  
 280 interannual variability, exposure for future periods was determined by calculating a 20-year  
 281 average of annual extreme precipitation days and utilizing population and cropland projections.  
 282 The average annual exposure was then computed for each grid cell and aggregated to provide  
 283 an overall assessment for CA.

$$284 \quad E_{pop} = \frac{\sum_{m=1}^{20} C_m \times P}{20} \quad (1)$$

$$285 \quad E_{crop} = \frac{\sum_{m=1}^{20} C_m \times G}{20} \quad (2)$$

286 where  $E_{pop}$  and  $E_{crop}$  are indicates the 20 years mean of population exposure (person-days)  
 287 and cropland exposure (km<sup>2</sup>),  $m$  denotes the  $m$ th year of the base period,  $C$  and  $P$   
 288 represents the total number of annual EPEF and simulated population number in person, while  
 289 cropland simulation denoted by  $G$ .

## 290 2.6 Relative Changes in Exposure

291 To determine the relative contributions of climatic, population, and cropland to the total  
292 exposure. The variations in climatic, population, and cropland exposures were decomposed  
293 with respect to the climatic effect, population effect, cropland effect, and the interaction effect,  
294 respectively (Chen et al., 2020; Jones et al., 2015). Generally, the influence of population and  
295 cropland was estimated by holding climate constant while changing population. Similarly, the  
296 population and cropland were set as constant while computing the climate effect. The  
297 interaction effect was intended to describe the regions with a growing population and cropland  
298 approaches toward EPEF under changing climate. The changes in climate, population, and  
299 cropland exposure were decomposed using Equation 3 and Equation 4.

$$300 \quad \Delta E_{pop} = C_r \times \Delta P + P_r \times \Delta C + \Delta P \times \Delta C \quad (3)$$

$$301 \quad \Delta E_{crop} = C_r \times \Delta G + G_r \times \Delta C + \Delta G \times \Delta C \quad (4)$$

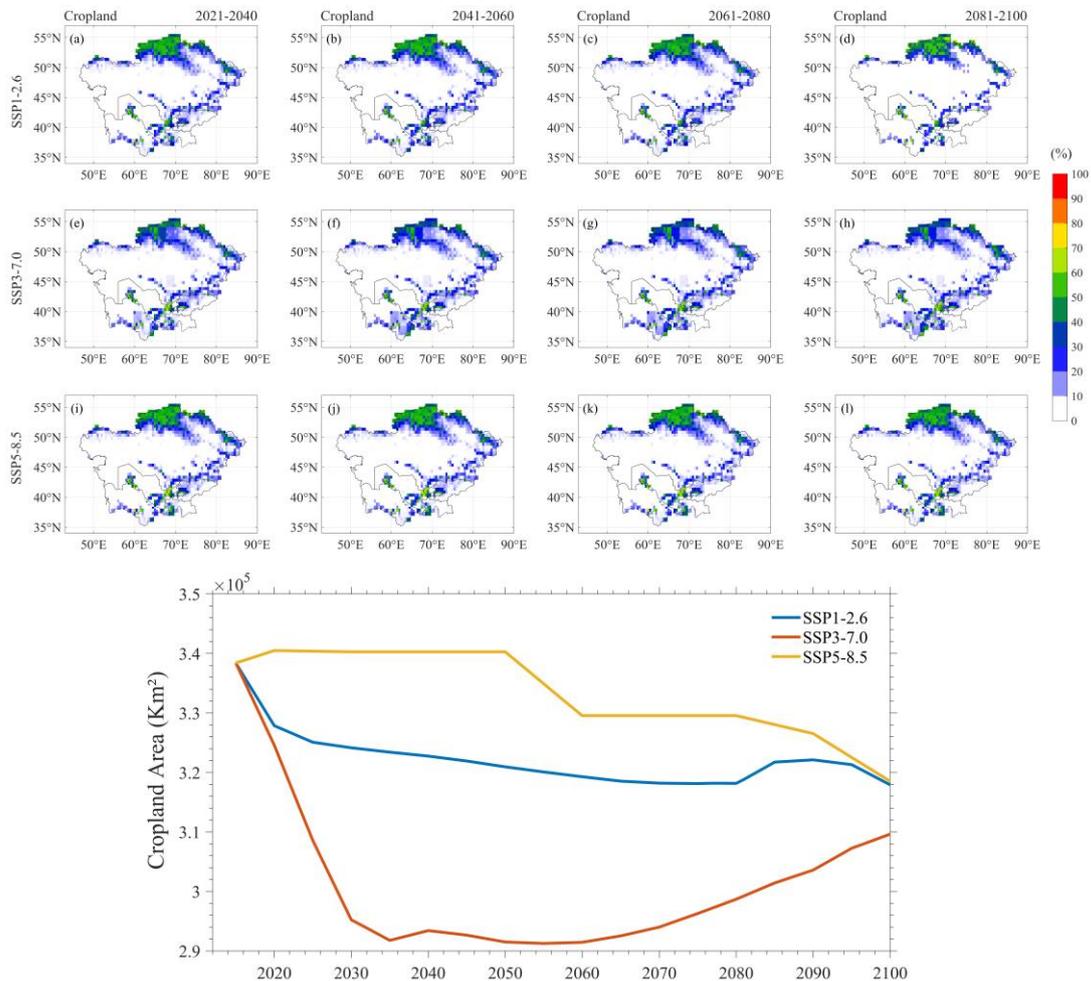
302 where  $\Delta E_{pop}$  and  $\Delta E_{crop}$  are the total changes in population and cropland exposures,  $C_r$ ,  $P_r$ ,  
303 and  $G_r$  indicates the total annual EPEF, population, and cropland for the reference period  
304 (2021-2040), respectively. Whereas  $\Delta C$ ,  $\Delta P$ , and  $\Delta G$  are the changes in annual EPEF,  
305 population, and cropland, respectively. Hence, the population effect is  $C_r \times \Delta P$ , the cropland  
306 effect is  $C_r \times \Delta G$ , the climate effects are represented by  $P_r \times \Delta C$  and  $G_r \times \Delta C$ , and the  
307 interaction effects are the  $\Delta P \times \Delta C$  and  $\Delta G \times \Delta C$ . To calculate the percentage change for each  
308 effect, we divide the above equation by the exposure in the reference period.

## 309 3. Results

### 310 3.1 Future Changes in Cropland and Population

311 The spatial distribution of the projected changes in CA cropland and the temporal  
312 characteristics of cropland area changes under three future scenarios (SSP1-2.6, SSP3-7.0, and  
313 SSP5-8.5), and four defined time periods are presented in Figure 2. Examining the spatial  
314 distribution (Figure 2a-l), cropland in CA displays a high degree of consistency across all  
315 scenarios, primarily concentrated in northern Kazakhstan, southern Tajikistan, and northern  
316 Kyrgyzstan. The line graph depicts the temporal changes in cropland area, indicating a  
317 decreasing trend in recent years for both the SSP1-2.6 and SSP3-7.0 scenarios. Conversely, the  
318 SSP5-8.5 scenario demonstrates a pattern of increasing and then decreasing cropland in CA. In  
319 terms of overall change in cropland area, the largest area is projected under the SSP5-8.5  
320 scenario, followed by SSP1-2.6, with SSP3-7.0 exhibiting the smallest cultivated area.  
321 Assessing the rate of change reveals that the SSP3-7.0 scenario has the highest rate, followed  
322 by SSP1-2.6, while SSP5-8.5 exhibits the lowest rate. Between 2041-2060, noticeable changes  
323 in cropland area are observed in the border regions of northern and eastern Kazakhstan,  
324 Tajikistan, and Kyrgyzstan under the SSP1-2.6 (Figure 2b) and SSP3-7.0 scenarios (Figure 2f).  
325 In the SSP3-7.0 scenario, the most pronounced change in cultivated area within CA is evident,  
326 with a decrease from 330,000 km<sup>2</sup> in 2021-2040 (Figure 2e) to 290,000 km<sup>2</sup> in 2041-2060  
327 (Figure 2f), primarily driven by the reduction of cultivated land in northern Kazakhstan.

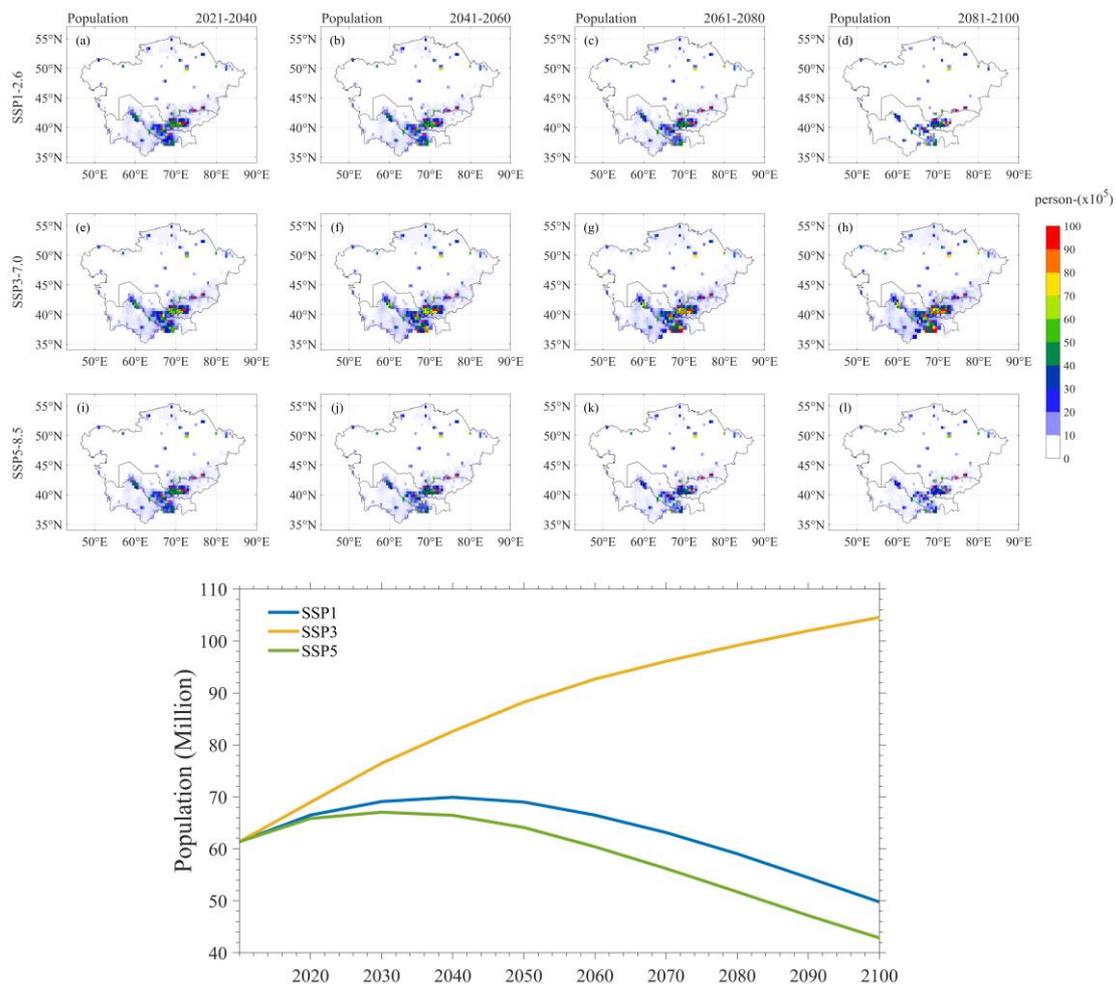
328 Subsequently, the area increases to 310,000 km<sup>2</sup> in 2081-2100 (Figure 2h). Understanding and  
 329 accounting for these divergences between projected SSPs is crucial to comprehensively  
 330 investigate the impact of future climate risks, such as EPEs, on cropland.



331  
 332 **Figure 2.** Spatial distributions of 20-year average cropland area share and projected cropland  
 333 for four defined future periods under SSP1-2.6, SSP3-7.0 and SSP5-8.5 scenarios. Line plots  
 334 depict the total cropland area of Central Asia (CA) for the period 2020-2100.

335 The spatial and temporal changes in the population of CA under future scenarios and four  
 336 selected time periods are shown in Figure 3. CA exhibits a highly heterogeneous spatial  
 337 distribution of population density, making it one of the regions with notable variation globally.  
 338 The spatial map (Figure 3a-l) reveals that the distribution of population in CA aligns closely  
 339 with the distribution of cropland across all scenarios, concentrating primarily in northern  
 340 Kazakhstan, southeastern Uzbekistan, northwestern Tajikistan, and western Kyrgyzstan. The  
 341 line graph illustrates that under the SSP3 scenario, the population is projected to consistently  
 342 increase in each future time period. In contrast, the populations under the SSP1 and SSP5  
 343 scenarios display a pattern of growth followed by a decline. These findings indicate that the  
 344 population size of CA exhibits greater variability under future scenarios. Regarding population  
 345 size, SSP3 exhibits the largest population, followed by SSP1, while SSP5 has the smallest  
 346 population. Spatially, the distribution of population in CA is highly uneven. Although  
 347 Kazakhstan boasts the largest land area, its population size falls significantly behind that of

348 Tajikistan and Uzbekistan. In fact, the population in CA is predominantly concentrated in  
 349 Tajikistan and Uzbekistan. Under the SSP1 and SSP5 scenarios, the population size peaks in  
 350 2040 at 70 and 65 million people, respectively, before gradually decreasing in subsequent years.  
 351 In the SSP3 scenario, the population of CA reaches its maximum, steadily increasing over time  
 352 to approximately 100 million people by 2100.

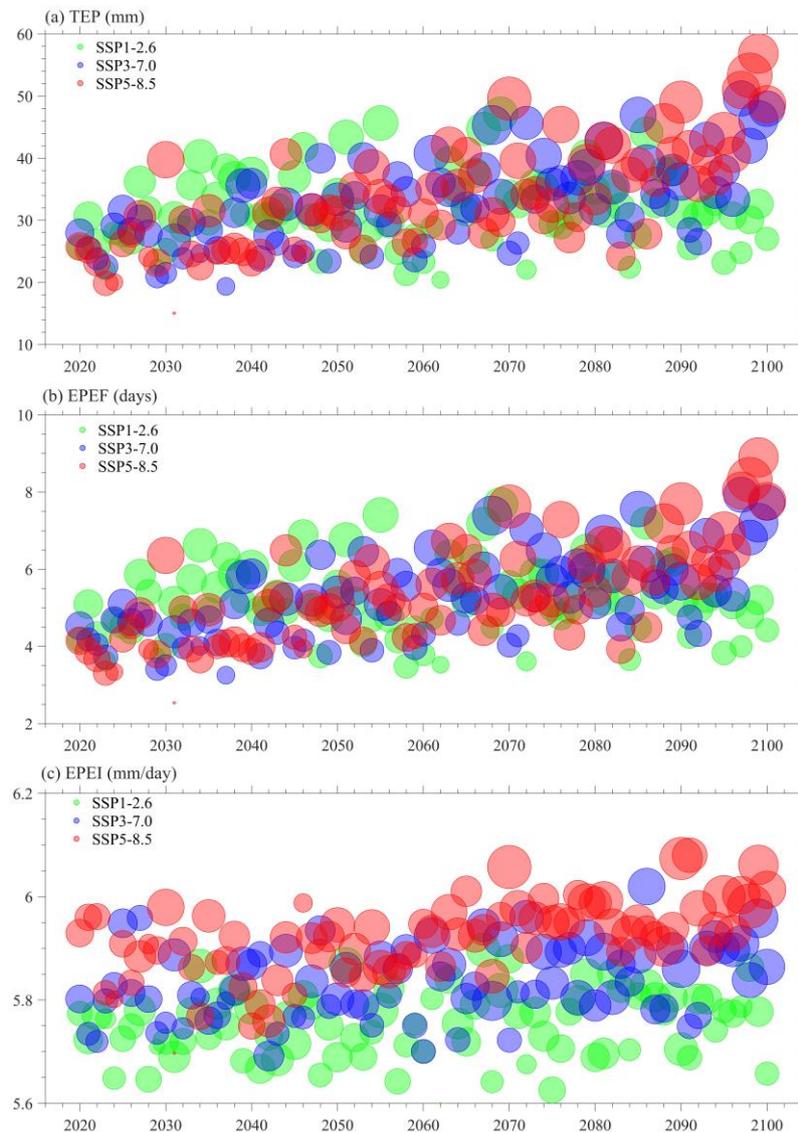


353  
 354 **Figure 3.** Spatial distributions of 20-year average number of population and projected  
 355 population for four defined future periods under SSP1-2.6, SSP3-7.0 and SSP5-8.5 scenarios.  
 356 Line plots depict the total population of Central Asia (CA) for the period 2020-2100.

### 357 3.2 Characteristics of extreme precipitation events under different future scenarios

358 The projected changes in the characteristics of EPEs in CA for the period 2020-2100 are  
 359 presented in Figure 4. The findings highlight that higher emission scenarios will intensify EPEs,  
 360 leading to potentially catastrophic consequences for the economy and society. The analysis  
 361 reveals varying increases in EPEs under the SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios  
 362 (Figure 4a). Overall, SSP5-8.5 exhibits the highest magnitude of extreme precipitation,  
 363 approaching a maximum value of 60 mm, followed by SSP3-7.0, with the smallest impact  
 364 observed under SSP1-2.6. Moreover, the severity of EPEs amplifies over time. Examining the  
 365 frequency characteristics of EPEs (Figure 4b), a similar pattern emerges as observed in extreme  
 366 precipitation. Under the medium and high emission scenarios (SSP3-7.0 and SSP5-8.5), EPEs  
 367 occur more frequently compared to the SSP1-2.6 scenario. Notably, the increase in event

368 frequency is more pronounced in SSP3-7.0 and SSP5-8.5, exhibiting a clear upward trend over  
 369 time. The SSP5-8.5 scenario presents an especially drastic rise in extreme precipitation  
 370 frequency (Figures 4b and 4c). Regarding the intensity of EPEs (Figure. 4c), distinct variations  
 371 are observed across different scenarios. The SSP5-8.5 scenario exhibits significantly higher  
 372 intensity compared to SSP3-7.0 and SSP1-2.6. These findings emphasize that what was once  
 373 considered rare in the past may become the norm in the future under high emission scenarios.  
 374 In summary, increasing emission scenarios will result in more frequent and prolonged EPEs in  
 375 CA in the coming decades. These findings underscore the urgent need for proactive measures  
 376 to mitigate the potential impacts of these events on the region.

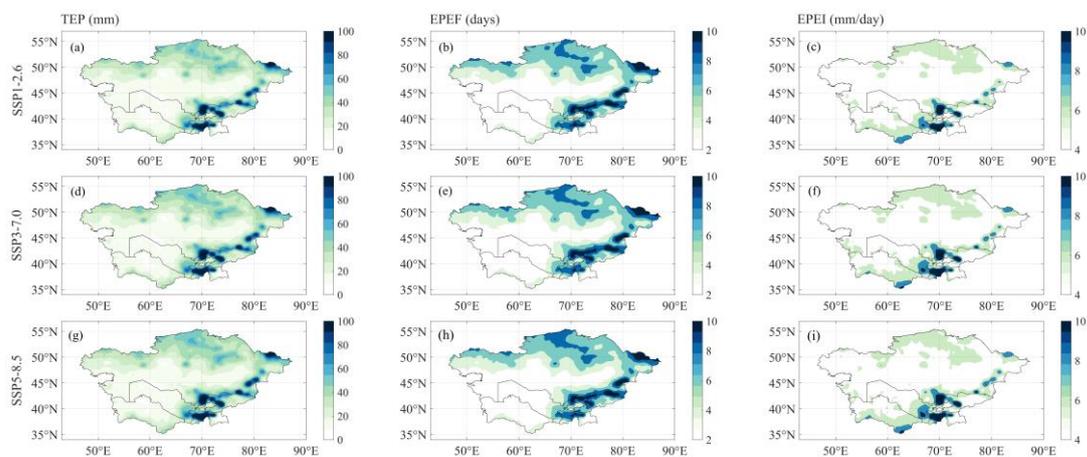


377

378 **Figure 4.** Projected temporal changes in extreme precipitation events characteristics from 2020  
 379 to 2100 under the SPP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios over Central Asia (CA). (a) TEP,  
 380 (b) EPEF, (c) EPEI. Bubble size indicates the EPEA.

381 Figure 5 presents the spatial distribution of predicted regional average changes in extreme  
 382 precipitation event characteristics (extreme precipitation amount, frequency, and intensity) for  
 383 the entire South Asia region during the period 2020-2100, under three future scenarios: SSP1-

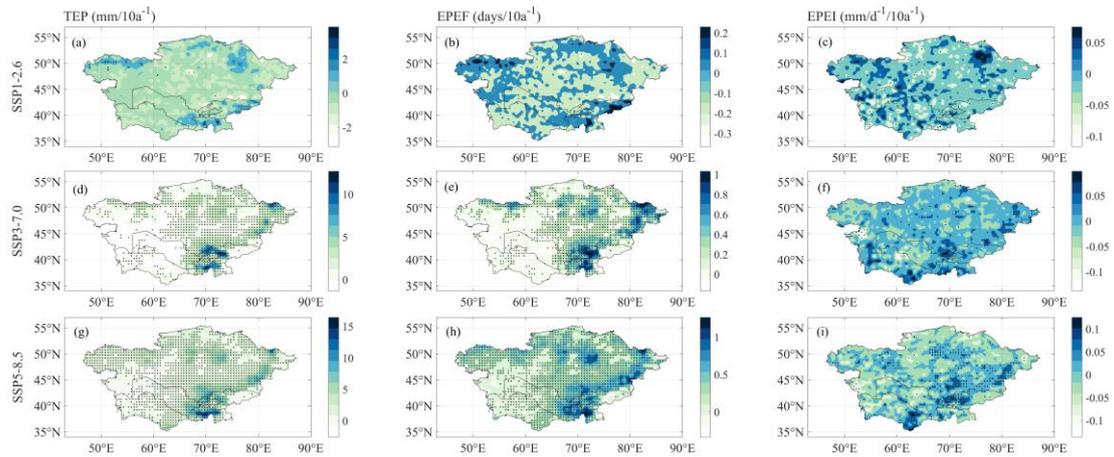
384 2.6, SSP3-7.0, and SSP5-8.5. The box plots in the Figures illustrate the variations across these  
 385 scenarios. The spatial distribution of extreme precipitation amounts (Figures 5a, 5d, and 5g),  
 386 frequencies (Figures 5b, 5e, and 5h), and intensities (Figures 5c, 5f, and 5i) exhibits a similar  
 387 pattern for all three scenarios. EPEs are widespread throughout the CA region, excluding central  
 388 Kazakhstan and northern Uzbekistan. The primary areas experiencing EPEs in CA are the  
 389 southern Tien Shan Mountains and northern Kazakhstan. Under different future climate  
 390 scenarios, the range of EPEs in CA expands, with higher values of extreme precipitation and  
 391 intensity occurring in the border regions of Tajikistan, Kyrgyzstan, and Uzbekistan.  
 392 Additionally, elevated values of extreme precipitation frequency are observed in the northern  
 393 part of Kazakhstan, alongside the southeastern region of CA. In summary, EPEs in CA  
 394 concentrate in densely populated areas and regions with significant cropland distribution. This  
 395 exacerbates the impact of extreme precipitation on both the population and cropland in CA.



396

397 **Figure 5.** Projected spatial changes in extreme precipitation events characteristics under the  
 398 SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios over Central Asia (CA). (a, d, and g) TEP, (b, e,  
 399 and h) EPEF, (c, f, and, i) EPEI.

400 Figure 6 illustrates the spatial distribution of future trends in the characteristics of EPEs in CA,  
 401 projected for the period 2020-2100, under three future scenarios: SSP1-2.6, SSP3-7.0, and  
 402 SSP5-8.5. In the SSP1-2.6 scenario (Figures. 6a-c), most of CA exhibits a drying trend, with  
 403 notable wetting areas concentrated in the northern part of CA, northern Kazakhstan, and the  
 404 southern Tien Shan Mountains. Conversely, the SSP3-7.0 scenario (Figures. 6d-f) reveals an  
 405 expansion of wetting areas across a large portion of CA, resulting in significant wetting effects.  
 406 Under the SSP5-8.5 scenario (Figure. 6g-i), extreme precipitation, as well as the frequency and  
 407 intensity of EPEs, demonstrate a substantial increase over the majority of CA, particularly in  
 408 mountainous regions. The findings indicate that the overall increase in EPEs in CA exceeds 90%  
 409 in the medium and long term under the SSP3-7.0 and SSP5-8.5 scenarios. In general, it can be  
 410 inferred that the projected future changes in extreme precipitation in CA, specifically under the  
 411 SSP5-8.5 scenario, are significant, ranging from 80% to 90%, with the highest magnitudes  
 412 observed in mountainous regions and the lowest in plains.



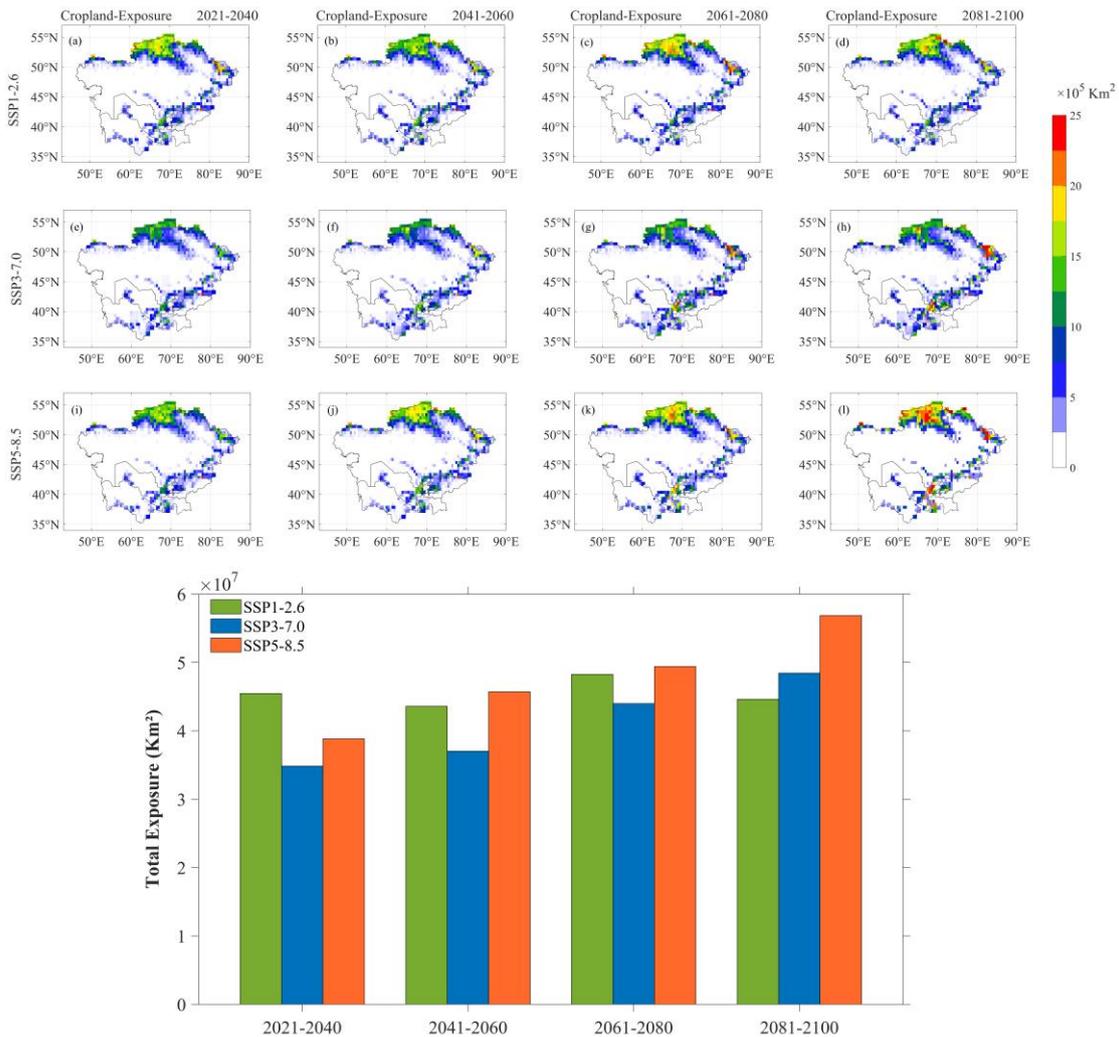
413

414 **Figure 6.** Projected spatial changes of trends in extreme precipitation events characteristics  
 415 under the SPP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios over Central Asia (CA). (a, d, and g)  
 416 TEP, (b, e, and h) EPEF, (c, f, and, i) EPEI.

### 417 3.3 Cropland and Population Exposures to Extreme Precipitation Events

418 The spatial distribution of cropland exposure to EPEs under the three SSP scenarios (SSP1-2.6,  
 419 SSP3-7.0, and SSP5-8.5) and the four defined time periods across CA are presented in Figure  
 420 7. Additionally, it illustrates the temporal variation in total cropland exposure to EPEs. In the  
 421 SSP1-2.6 scenario, regions such as northern Kazakhstan, northern Kyrgyzstan, and northern  
 422 Tajikistan exhibit faster increases in medium- and long-term cropland exposure to EPEs,  
 423 affecting an area of over 250,000 km<sup>2</sup> (Figures 7a-d). However, under the same scenario, a more  
 424 prolonged and detrimental surge in cropland exposed to extreme precipitation risk is expected  
 425 in northern and eastern Kazakhstan in the long term. Under the SSP3-7.0 scenario (Figures 7e-  
 426 h), cropland exposure increases more rapidly in the northeastern regions of Kazakhstan and the  
 427 border areas of Tajikistan and Kyrgyzstan. In the case of SSP5-8.5, higher cropland exposure  
 428 is observed during the long-term period compared to the other time periods (Figures 7i-l).  
 429 Analyzing the 2021-2040 time period, cropland exposure under the low emission scenario is  
 430 approximately 45.6 million km<sup>2</sup>, significantly higher than the 34.8 million km<sup>2</sup> and 38.8 million  
 431 km<sup>2</sup> under the medium and high emission scenarios, respectively. Total cropland exposure  
 432 increases significantly over time, with the exposure in the SSP5-8.5 scenario reaching 56.8  
 433 million km<sup>2</sup> by 2081-2100, notably higher than the exposure in the SSP3-7.0 scenario (48.4  
 434 million km<sup>2</sup>) and the SSP1-2.6 scenario (44.6 million km<sup>2</sup>). Interestingly, large-scale population  
 435 exposure is not projected in central Kazakhstan, northern Uzbekistan, northern Turkmenistan,  
 436 Tajikistan, and southeastern Kyrgyzstan. This can be attributed to the absence of future EPEs  
 437 in these regions and the fact that most of these areas are characterized by desert and alpine  
 438 mountain landscapes with limited cropland distribution. Regional sums indicate that cropland  
 439 exposure to EPEs increases by 25.7%, from 119.2 million km<sup>2</sup> in 2021-2040 to 149.8 million  
 440 km<sup>2</sup> in 2081-2100, with the highest exposure observed in the SSP5-8.5 scenario at  
 441 approximately 190.7 million km<sup>2</sup>, followed by SSP1-2.6 (182.1 million km<sup>2</sup>) and SSP3-7.0  
 442 (164.2 million km<sup>2</sup>). Regarding the time period, the highest cropland exposure to EPEs is  
 443 projected for 2081-2100. Differences in population exposure to EPEs under the same scenarios  
 444 may be attributed to variations in the frequency of such events. These findings align with the

445 spatial distribution of cropland exposed to EPEs in the selected scenarios.



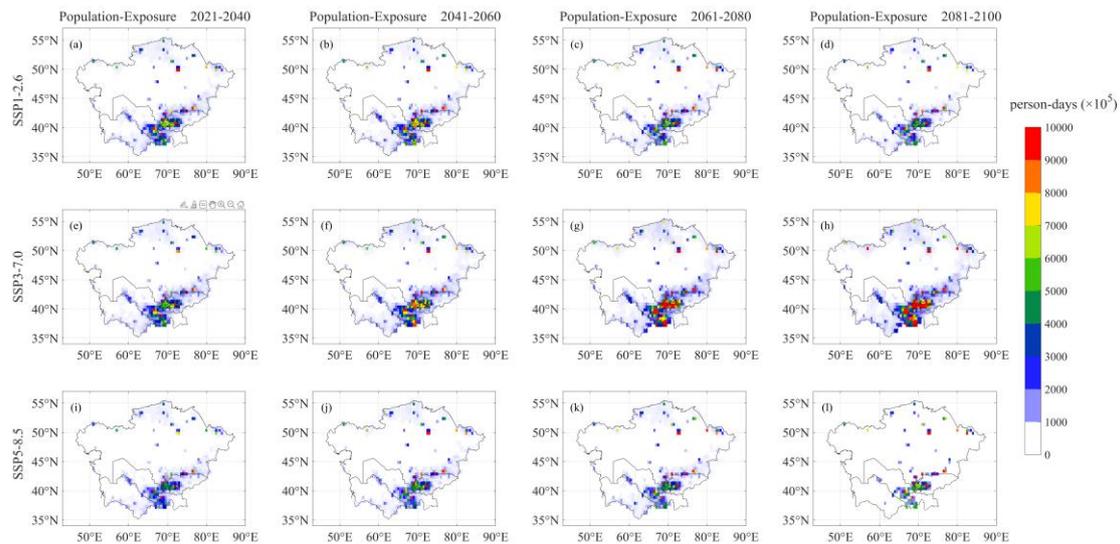
446

447 **Figure 7.** Projected changes in cropland exposure to extreme precipitation events under the  
 448 SSP1-2.6, SSP3-7.0 and SSP5-8.5 scenarios and four-time periods across Central Asia (CA).  
 449 Bar plots depict the total area affected by extreme precipitation events for four different time  
 450 periods and across CA.

451 The spatial pattern of projected changes in population exposure to EPEs in CA across four time  
 452 periods under three future scenarios are shown in Figure 8. In all three scenarios, population  
 453 exposure shows a slight increase in the short term (Figure 8a, Figure 8e, and Figure 8i).  
 454 However, over time, population exposure gradually rises under the high emission scenario. The  
 455 areas with high population exposure in CA are concentrated in northwestern Tajikistan, western  
 456 Kyrgyzstan, and southeastern Uzbekistan, with a smaller distribution in the northern part of  
 457 Kazakhstan. Bar charts represent the total population exposure in CA for all three scenarios and  
 458 four time periods. In the SSP1-2.6 scenario, population exposure exhibits a decreasing trend  
 459 over time. Under the SSP3-7.0 scenario, population exposure to EPEs exceeds 48.1 billion  
 460 person-days, with the most significant change occurring in northwestern Tajikistan, western  
 461 Kyrgyzstan, and southeastern Uzbekistan. In these regions, exposure increases by 92.6%,  
 462 resulting in a total population exposure of around 8.1 billion person-days in 2021-2040,  
 463 escalating to approximately 15.6 billion person-days in 2081-2100. Population exposure under

464 the SSP5-8.5 scenario and the SSP1-2.6 scenario is roughly comparable, with population  
465 exposure under the SSP1-2.6 scenario being higher than that under the SSP5-8.5 scenario until  
466 the 2061-2080 time period. In conclusion, the main factor contributing to the increase in  
467 population exposure to EPEs in CA is future population growth. It is noteworthy that large-  
468 scale population exposure is not observed in central Kazakhstan, northern Uzbekistan, northern  
469 Turkmenistan, Tajikistan, and southeastern Kyrgyzstan, likely due to the presence of  
470 uninhabited areas in these regions. The highly heterogeneous population distribution in CA,  
471 with population densities reaching up to 70 persons/km<sup>2</sup>, exacerbates population exposure to  
472 EPEs to some extent.

473 Regional aggregations consistently demonstrate an increase in population exposure to EPEs  
474 across all scenarios, with the highest exposure observed under the SSP3-7.0 scenario at  
475 approximately 48.1 billion person-days, followed by SSP1-2.6 and SSP5-8.5. Regarding the  
476 time periods, total population exposure increases by 29.6% from 2021-2040 to 2081-2100.  
477 Population exposure to EPEs is highest in 2081-2100, followed by 2061-2080 and 2041-2060,  
478 with the lowest exposure occurring in 2021-2040. The disparities in population exposure under  
479 the same scenarios can be attributed to variations in the frequency of EPEs. These findings align  
480 with the spatial distribution of populations exposed to EPEs in the selected scenarios. In  
481 summary, population exposure to extreme precipitation is anticipated to undergo a substantial  
482 increase in response to future global warming. Even with early mitigation efforts, exposure  
483 levels are projected to rise across a significant portion of CA. This increase in exposure is  
484 largely attributable to the uneven distribution of populations in the region and poses significant  
485 threats to societies, ecosystems, and human well-being in the future. To effectively mitigate  
486 these threats, a thorough understanding of exposure changes is crucial for driving mitigation  
487 actions and addressing their underlying causes.



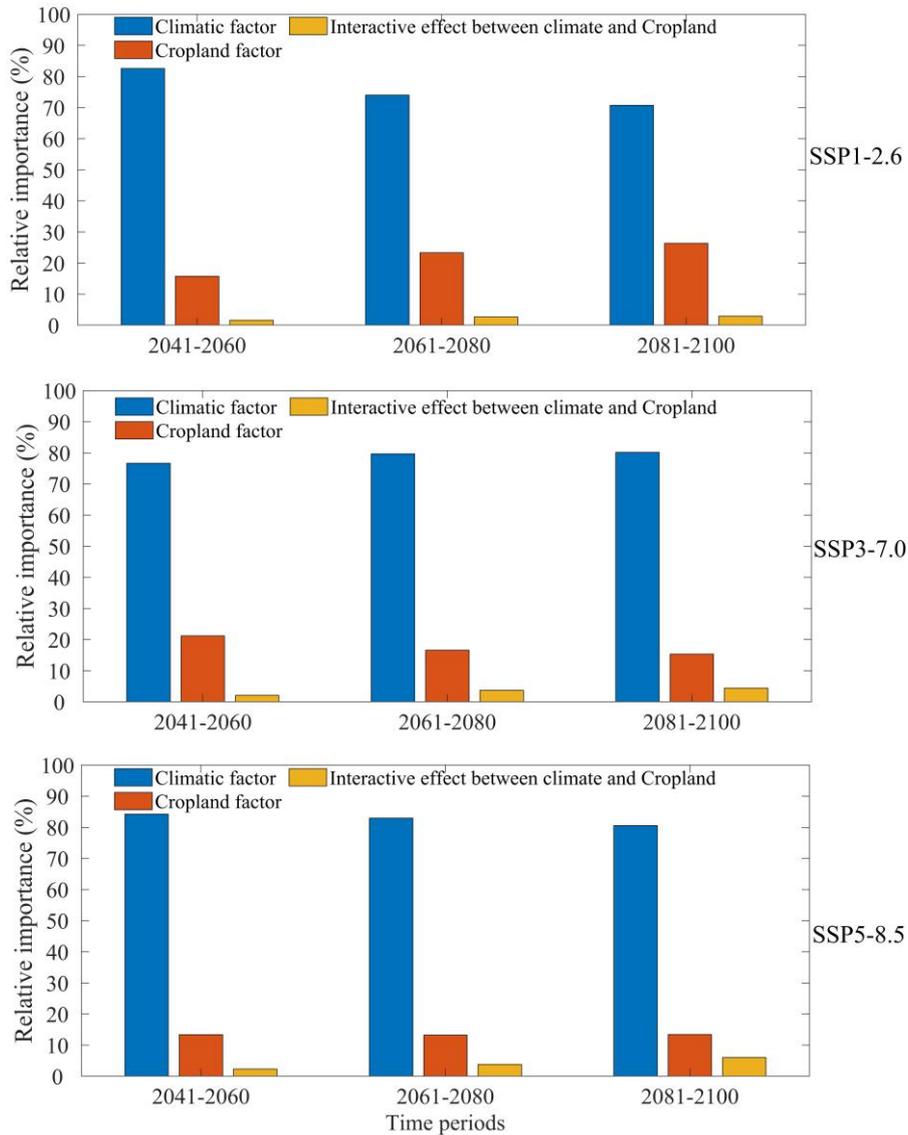
488

489 **Figure 8.** Projected changes in population exposure to extreme precipitation events under the  
 490 SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios and four-time periods across Central Asia (CA).  
 491 Bar plots represent the total number of people affected by extreme precipitation events for four  
 492 different time periods and across CA.

### 493 3.4 Exploring the Importance of Relative Changes in Exposure

494 To investigate the relative importance of different factors, we conducted a detailed analysis to  
 495 determine the contribution of population and cropland exposure to the interaction components  
 496 of CA. This analysis focused on climatic effects, population, cropland, and their interaction  
 497 effects under three emission scenarios in the mid- to late 21st century. Examining the influences  
 498 on cropland exposure (Figure 9), we observed consistent variation in the relative importance of  
 499 climate change, cropland change, and their interaction effects across scenarios. These findings  
 500 suggest that the increase in cropland exposure in CA is primarily controlled by the climate  
 501 component. Under the SSP1-2.6 scenario, the relative changes in the cropland, climate, and  
 502 interaction components of CA cropland exposure were 15.78%, 82.6%, and 1.61%, respectively.  
 503 In this scenario, negative impacts from the population and interaction components are evident,  
 504 with the increase in population exposure solely driven by the climate component. This is  
 505 primarily due to the projected shrinkage of the cultivated area by the end of the 21st century,  
 506 which, combined with the substantial impacts of climate change, counteracts the negative

507 increase. Notably, the climate component consistently outweighs the cropland component, but  
 508 the change in the cropland component and the cropland-climate interaction component is  
 509 increasing while the climate component is weakening. This is demonstrated by the fact that  
 510 relative to the base period, from 2081-2100, the cropland and climate interaction components  
 511 increase from 2.43% to 13.42%, and the cropland component increases from 15.78% to 26.35%,  
 512 whereas the climate component decreases from 82.6% to 70.73% (see Table S2 in the  
 513 Supporting Information). Interestingly, across all scenarios, the climate component tends to  
 514 decrease over time, while the population and interaction effects tend to increase. Nevertheless,  
 515 the climate effect consistently dominates in all scenarios, despite its decreasing trend.

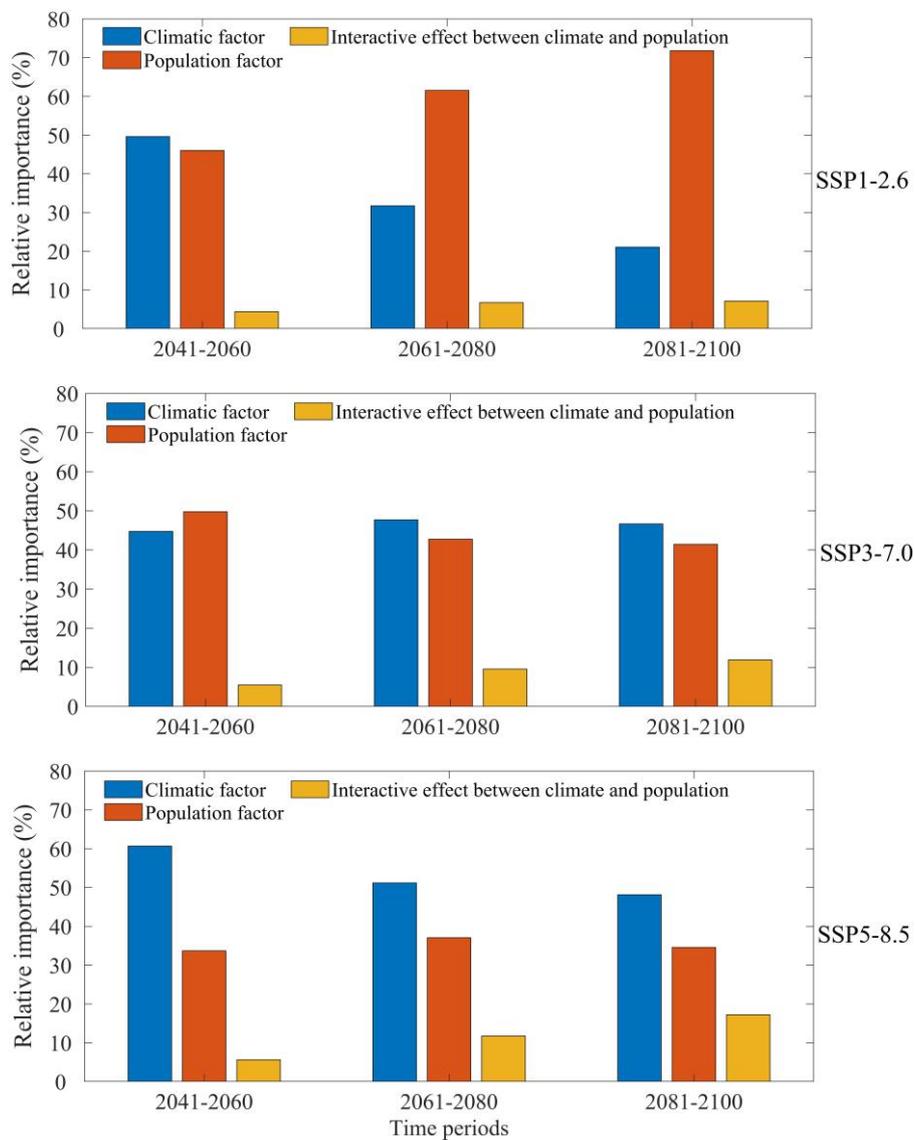


516

517 **Figure 9.** Different factors of the effects driving projected changes in cropland exposure to  
 518 EPEF over Central Asia (CA) under SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios and three-  
 519 time periods.

520 Changes in population exposure to EPEs are influenced not only by variations in climatic  
 521 factors but also by alterations in population size and its spatial distribution. Figure 10 depict  
 522 the overall changes in population exposure and its contributing factors across CA for different

523 climate scenarios and three distinct time periods. The relative importance of climate change,  
 524 population change, and their interaction effects exhibits significant variation throughout CA.  
 525 Under the SSP1-2.6 scenario, changes in population exposure are primarily driven by  
 526 demographic factors. In contrast, under both the SSP3-7.0 and SSP5-8.5 scenarios, climatic  
 527 factors play a dominant role in determining population exposure. However, it is worth noting  
 528 that the decline in climatic factors is more rapid under the SSP5-8.5 scenario compared to the  
 529 SSP3-7.0 scenario. Importantly, population and climate interaction effects demonstrate a  
 530 substantial increase across all scenarios, with their significance intensifying as emissions rise.  
 531 For instance, the population and climate interaction effects experience an increase of 2.76%,  
 532 6.43%, and 11.62% for the SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios, respectively (see  
 533 Table S3 in the Supporting Information).



534

535 **Figure 10.** Different factors of the effects driving projected changes in population exposure to  
 536 EPEF over Central Asia (CA) under SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios and three-  
 537 time periods.

538 **4. Conclusions and Discussions**

539 The primary objective of this study is to examine the projected changes in EPEs in CA and their  
540 implications for population and cropland exposure. To achieve this objective, the study utilizes  
541 the state-of-the-art ISI-MIP multi-model ensemble mean, incorporating three Shared  
542 Socioeconomic Pathway (SSP) scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5) and four  
543 predetermined time periods (2021-2040, 2041-2060, 2061-2080, and 2081-2100). The analysis  
544 employs daily precipitation data from the multi-model ensemble mean to assess the future  
545 variability characteristics of EPEs in CA. Furthermore, population and cropland datasets  
546 corresponding to different SSP scenarios are utilized to investigate the changes in population  
547 and cropland exposure resulting from EPEs in the region. This study aims to achieve several  
548 key objectives. Firstly, it seeks to investigate the evolving characteristics of EPEs in CA  
549 throughout the 21st century. Secondly, it aims to assess the impacts of these events on the  
550 population and cropland in the region. Lastly, the influence of different factors (i.e., population,  
551 cropland, climate, and interaction) on EPEF and changes in socioeconomic exposure was  
552 further investigated. The study aims to provide regional evidence that can support policymakers  
553 in the development of appropriate climate change adaptation and mitigation strategies for EPEs.

554 Our study reveals three key findings. Firstly, the analysis demonstrates a broad consensus  
555 among climate models for various future scenarios, indicating a significant increase in  
556 population and cropland exposure to EPEs in CA throughout the 21st century. Contrary to the  
557 expectation of limited exposure due to scarce precipitation in the region, our findings suggest  
558 that the actual exposure is substantial. Consequently, policymakers and the research community  
559 need to acknowledge population and cropland changes as critical factors when assessing the  
560 risks associated with EPEs. Secondly, we identified that the highest exposure to extreme  
561 precipitation among the population in CA occurs under the SSP3-7.0 scenario, while the highest  
562 exposure for cropland is observed under the SSP5-8.5 scenario. Notably, both exposures exhibit  
563 a strong spatial similarity, primarily concentrating in the northern part of Kazakhstan and the  
564 southwestern part of CA. Lastly, our study highlights that EPEs in CA tend to concentrate on  
565 the windward slopes of the region's mountain ranges. These areas coincide with high population  
566 density and extensive distribution of cropland. The spatial exposure of population and cropland  
567 to extreme precipitation in CA displays a high degree of heterogeneity, warranting greater  
568 attention. Based on our findings, it is crucial to prioritize the reduction of greenhouse gas  
569 emissions to mitigate population and cropland exposure to extreme precipitation. Additionally,  
570 urgent action is required to design and implement effective adaptation measures that enhance  
571 preparedness and response to EPEs.

572 Moreover, we extensively investigate the changes in socioeconomic exposure to EPEF and their  
573 diverse effects on both local and regional scales within CA. This investigation is based on  
574 defined time periods and three distinct SSP scenarios. Overall, across all three future scenarios,  
575 the augmentation of cropland exposure in CA can be attributed to climate effects; however, it  
576 is noteworthy that the influence of climate effects is diminishing, while the impact of cropland  
577 forcing and cropland-climate interactions is increasing. As for population exposure, the  
578 predominant cause of future increases within CA is climate effects; nevertheless, the interaction  
579 between population and climate exhibits a substantial rise with escalating emissions and the

580 passage of time. Consequently, while the risk of extreme precipitation in CA is still primarily  
581 determined by future increases in precipitation, the significance of population and cropland  
582 factors should not be overlooked.

583 The future spatial and temporal patterns of EPEs in CA suggest that significant occurrences of  
584 such events are expected over most of CA under the SSP3-7.0 and SSP5-8.5 scenarios, with a  
585 notable expansion of extreme precipitation across the high mountainous regions. Recent studies  
586 on extreme climate projections in CA have been relatively scarce compared to other global  
587 regions and have primarily focused on the Paris Agreement targets (Zhang et al., 2022) and  
588 higher global warming scenarios (Zhang et al., 2020; Zhang et al., 2019). However, these  
589 studies have revealed that CA is transitioning from a warm and dry condition to a warm and  
590 relatively humid condition due to climate change and the intensification of the water cycle.  
591 Supporting these findings, our study anticipates an increase in EPEs in the high mountain  
592 regions of CA (Yao et al., 2021; Zou et al., 2021; Zhang et al., 2019; Liu et al., 2022). Despite  
593 the significance of extreme precipitation, there are few studies assessing the changes in  
594 population and cropland exposure to climate extremes in CA. Limited information is available  
595 on the spatial and temporal variability of population and cropland exposure to extreme  
596 precipitation in CA under different future scenarios and time periods. Our study aims to bridge  
597 these research gaps by quantifying the exposure of CA populations and croplands to extreme  
598 precipitation under the SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios in the 21st century. Given  
599 that CA is predominantly agricultural with high population density and a strong dependence on  
600 the spatial distribution of water resources, the risks associated with extreme precipitation to the  
601 population and cropland in the region are heightened. The results of this study will stimulate  
602 further research into the internal mechanisms governing the interactions between climate  
603 change, land cover, and social activities. Moreover, our findings provide a scientific basis for  
604 mitigating the risks associated with extreme precipitation and ensuring sustainable economic  
605 and social development.

606 Although this study estimated future population and cropland exposure to EPEs in CA, it has  
607 certain limitations that require attention in future research. One limitation is the lack of  
608 consideration for socioeconomic and demographic characteristics of the population, such as  
609 income, education level, and age, which could influence the extent of exposure to extreme  
610 precipitation in CA (Chambers, 2020; Watts et al., 2021; Park et al., 2022). We suggest that  
611 future studies estimating population exposure should incorporate a more precise classification  
612 of the age structure of the population. Currently, various studies have focused on exposure to  
613 climate extremes; however, there is no standardized definition of exposure. Some studies  
614 employ a method that multiplies the occurrence of extreme events by the population size to  
615 estimate population exposure to climate extremes (Batibeniz et al., 2020). Others define  
616 exposure as the area where extreme climate surpasses a hazard threshold during a specific time  
617 period (Zhang et al., 2018; Sun et al., 2017), while some adopt an intensity-area-duration  
618 approach to reflect changes in exposure to hazard events (Wen et al., 2019; Su et al., 2018;  
619 Wang et al., 2019). These different definitions result in variations in estimates of population  
620 exposure and the socioeconomic impacts of extreme weather events. Consequently, it is crucial  
621 to establish a scientifically grounded and uniform definition of population exposure to extreme  
622 events, considering factors such as hazard, exposure, and vulnerability, to accurately assess the

623 risk of disasters. In a warmer future, moderate increases in precipitation can have positive  
624 effects on livelihoods and economic development, leading to an anticipated rise in irrigation  
625 water demand in CA under future climate and socioeconomic scenarios (Tian et al., 2020).  
626 Therefore, future research should focus on climate sensitivity analysis for CA, aiming to  
627 quantify the net impacts of changes in water availability and use, particularly under critical  
628 levels of global warming. Such assessments are critical for effective climate change mitigation  
629 and adaptation strategies in the region.

630 More frequent and intense EPEs pose a significant threat to both the global population and the  
631 global food supply (Thomas et al., 2015). This risk is particularly pronounced in arid and semi-  
632 arid regions, where water resources play a crucial role as both a determining factor and a  
633 limiting factor for development (Gessner et al., 2013; Li et al., 2019). It is imperative to plan  
634 and implement adaptation and mitigation measures to address the adverse effects of climate  
635 extremes in CA. These measures should encompass various strategies at the individual,  
636 community, and national levels. Ensuring widespread education about extreme precipitation  
637 and its associated hazards, along with providing essential resources such as food, clothing, and  
638 medical insurance, can help mitigate the risks involved. Furthermore, the implementation of  
639 afforestation initiatives and sustainable water use policies may effectively mitigate the risks  
640 associated with extreme precipitation in the region. At the governmental level, there is a need  
641 for multilateral climate agreements and enhanced communication and cooperation among the  
642 five CA countries to collectively address the challenges posed by extreme climate hazards  
643 (Chen et al., 2021). Additionally, the increasing occurrence of extreme precipitation in arid and  
644 semi-arid zones may potentially alleviate water stress in these regions if properly harnessed. It  
645 is widely recognized that accelerated climate change can have catastrophic consequences, and  
646 exploring the utilization of extreme precipitation in arid zones from a new perspective  
647 represents an important avenue for future research.

#### 648 **Conflict of Interest**

649 The authors declare no conflicts of interest relevant to this study.

#### 650 **Data Availability Statement**

651 All data used in this study are available online. The CRU precipitation products are available  
652 from [https://crudata.uea.ac.uk/cru/data/hrg/cru\\_ts\\_4.07/cruts.2304141047.v4.07/pre/](https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.07/cruts.2304141047.v4.07/pre/). The  
653 Cropland data from 2020 to 2100 under different SSP scenarios is available from  
654 <https://luh.umd.edu/data.shtml>. The population data from 2020 to 2100 under different SSP  
655 scenarios can be obtained from the website of  
656 [https://sedac.ciesin.columbia.edu/data/set/popdynamics-1-km-downscaled-pop-base-year-  
657 projection-ssp-2000-2100-rev01](https://sedac.ciesin.columbia.edu/data/set/popdynamics-1-km-downscaled-pop-base-year-projection-ssp-2000-2100-rev01). The ISI-MIP model simulations are available from  
658 <https://data.isimip.org/10.48364/ISIMIP.842396.1>.

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