

## Global socioeconomic exposure of heat extremes under climate change

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2 **Global socioeconomic exposure of heat extremes** 

3

### under climate change

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#### 20 Abstract

Growing evidence indicates that the risk of heat extremes will increase as climate 21 change progresses and create a significant threat to public health and the economy. 22 Socioeconomic exposure is the key component for assessing the risk of such events. To 23 quantify socioeconomic exposure to heat extremes for 2016–2035 and 2046–2065, we 24 use the projections of five global climate models forced by using three representative 25 concentration pathways (RCPs) and projections of population and gross domestic 26 product (GDP), and we take into account the geographic change in the distribution in 27 shared socioeconomic pathways (SSPs). The exposure of the global population for 28 29 2046–2065 is the greatest under the RCP8.5-SSP3 scenario, up to  $1037(\pm 164) \times 10^9$ person-days, and the global GDP exposure for 2046-2065 is greatest under the RCP2.6-30 SSP1 scenario, up to  $18(\pm 2) \times 10^{15}$  dollar-days. Asia has the highest exposure among 31 all continents for both population and GDP, accounting for over half of the global 32 exposure. Africa has the largest increase in exposure, with the annual population and 33 GDP exposures increasing by over 9- and 29-fold, respectively, compared with the base 34 period (1986–2005). The effect of climate makes the dominant contribution (47%–53%) 35 globally for the change in population exposure. Changes in the geographic distribution 36 of GDP cause nearly 50% of the total change in GDP exposure for 2016-2035. 37 Mitigating emissions of greenhouse gases, either at the level of the RCP2.6 scenario or 38 at a more ambitious target, is essential for reducing socioeconomic exposure to heat 39

40 extremes. In addition, designing and implementing effective measures of adaptation are

41 urgently needed in Asia and Africa to aid socioeconomic systems suffering from heat

42 extremes due to climate change.

Keywords socioeconomic exposure; heat extremes; climate change; population
 exposure; gross domestic product (GDP) exposure

#### 45 **1 Introduction**

Climatic extremes cause extensive economic damage each year, and the risks are 46 47 expected to increase with continued socioeconomic development and climate change. Risk is usually represented as the probability of occurrence of hazardous events or 48 trends multiplied by the impact if these events or trends occur. Risk is due to the 49 interaction of hazard, exposure, and vulnerability. Exposure usually refers to the people, 50 livelihoods, resources, infrastructure, and economic, social, or cultural assets in places 51 and settings that could be adversely affected (IPCC, 2014). The prediction of changes 52 in exposure to future climatic extremes could, therefore, contribute to the need to 53 54 consider effective countermeasures to reduce vulnerability and risk. Global socioeconomic exposure (i.e., exposure of the population and gross domestic product, 55 GDP) under climate change has received less attention (Burke et al., 2015; Carleton 56 and Hsiang, 2016), despite recent progress in assessing the hazards of climatic extremes 57 (Hirabayashi et al., 2013; Cook et al., 2014; King et al., 2017; Huang et al., 2017; Nath 58 et al., 2017). Such estimates are urgently needed to clarify future spatiotemporal 59 60 variation and changes in global socioeconomic exposure and thereby avoid adverse effects on public health and the economy. The importance of assessing exposure is 61 gradually being recognized, as indicated by the published reports of the 62 Intergovernmental Panel on Climate Change (Field et al., 2012; IPCC, 2013), the 63 proposal of a new set of shared socioeconomic pathways (SSPs, O'Neill et al., 2014), 64 and some recent studies of the risk of climate change that considers the effects of 65 socioeconomic factors (Ceola et al., 2015; Mora et al., 2017; Zhang et al., 2018). The 66 integration of climate change with the social economy to estimate future risk, the 67 assessment of the relative importance of different factors, and the quantification of 68 uncertainty would provide a basis for adapting to extreme climate change and reducing 69 the risk of heat extremes. 70

71 Because of climate change, the frequency and intensity of climatic extremes, such as heat extremes, have increased in recent decades and are likely to continue to increase 72 in the coming decades (IPCC, 2013). Heat extremes have been responsible for 73 74 significant public health threats and economic losses over the last 100 years. Data for historical 75 damage from the International Disaster Database (https://www.emdat.be/emdat\_db/) indicate that heat extremes affected  $1.03 \times 10^8$ 76 people, which includes the deaths of 183495 people, and caused worldwide economic 77 losses of  $6.33 \times 10^{10}$  USD from 1936 to 2019. Serious heat extremes have also occurred 78 more frequently in recent decades, such as those in Europe in 2003, 2018 and 2019 79 (Robine et al., 2008), Australia in 2008 (Vaneckova et al., 2008), Russia in 2010 80

(Trenberth and Fasullo, 2012), and China in 2013 (Sun et al., 2014). Socioeconomic
exposure and disaster risks will be magnified in a warmer future (Jones, and O'Neill,
2016; Smirnov et al., 2016), when the more frequent and intense heat extremes of this
century (Fischer and Knutti 2015; Kharin et al., 2013) combine with a greater
population and the accumulation of wealth.

86 In socioeconomic systems, population is most closely related to heat extremes because of its direct impact on public health (Wang et al., 2019). Various economic 87 sectors also can be seriously affected by heat extremes, such as agriculture (water 88 shortages) and industries that rely heavily on hydropower. In addition, tourism, 89 transportation, construction, and other industries are also affected by heat extremes to 90 varying degrees (IPCC, 2014). Considering the data on historical damage of heat 91 extremes (number of people affected, total damage on the economy, etc.) and the 92 93 availability of simulated socioeconomic data for the future, we selected population and economic activity, expressed as GDP, to determine the impact of heat extremes on the 94 socioeconomic system. Many studies that have quantified future socioeconomic 95 exposure have not considered changes in populations or GDP but assumed that these 96 97 variables remain constant, which is inappropriate for predicting changes in exposure 98 (Bouwer, 2013; Sun et al., 2017). Most studies have also focused on changes in exposure based on a specific pathway of emission of a greenhouse gas (GHG) or a 99 target of global mean temperature (GMT) rise such as 1.5 °C or 2.0 °C (Harrington and 100 Otto, 2018; Mishra et al., 2017). These analyses of the spatiotemporal variation in 101 exposure between scenarios and time periods are thus insufficient because the 102 population and economy (usually calculated by GDP) are both essential elements in 103 socioeconomic systems and are the factors most severely affected by climatic extremes. 104 The exposures of populations and GDP are usually predicted separately, and these two 105 elements are rarely used to assess socioeconomic exposure (Bowles et al., 2014; 106 107 Forzieri et al., 2017), although the spatial distributions of populations and economies are also consistent. Given these factors, we focus in this work on simulating the global 108 exposure to extreme heat as a function of changes in climate and population or GDP. 109 The results constitute a first step toward understanding how interactions between 110 climate change and socioeconomic systems affect exposure patterns. 111

This study systematically quantify the global spatiotemporal distribution of and 112 changes in exposure of population and GDP to heat extremes under different scenarios 113 and over different time periods. Bias-corrected projections of five global climate 114 models (GCMs, Table 1) driven by representative concentration pathways (RCPs) are 115 used to calculate the frequency of extreme heat events (see Sec. 2.1, Materials). 116 Combined with population and GDP projections in SSPs (Figs. S1 and S2), which 117 consider changes in the geographic distribution of population and GDP (see Sec. 2.1, 118 Materials), the spatiotemporal variation of global exposure to extreme heat of the 119 population and GDP is quantified in both the base period (1986-2005) and in future 120 periods (2016-2035 and 2046-2065) under various scenarios (see Sec. 2, Materials and 121 Methods). We also assess the relative importance of climatic and socioeconomic factors 122 and their uncertainties to characterize the contribution of climate change and growth in 123 population and GDP to future changes in extreme-heat exposure. The main target of 124

this study is quantifying the impact of heat extremes on socioeconomic system under climate change to characterize variation of socioeconomic exposure among scenarios and periods, distinguish high exposure regions, and identify dominant contributor for exposure change, so as to support policymakers in the development of climate change mitigation and adaptation strategies.

#### 130 2 Materials and Methods

#### 131 2.1 Materials

Daily climatic data were obtained from the Inter-Sectoral Impact Model 132 Intercomparison Project (ISI-MIP, Warszawski et al., 2014) for the Coupled Model 133 Intercomparison Project Phase 5 (CMIP5, Taylor et al., 2012) (Table 1), which contains 134 simulations from five GCMs based on RCPs. The RCP scenarios represent pathways 135 based on simulated impacts on land use, aerosol emissions, and GHGs (Vuuren et al., 136 2011). The four RCPs cover the period up to 2100 and have radiative forcings from the 137 open literature that vary from 2.6 to 8.5 W/m<sup>2</sup>. The scenarios, RCP2.6, RCP4.5, and 138 RCP8.5, which represent low, middle, and high GHG emissions, respectively, were 139 selected for analysis (Vuuren et al., 2011). RCP6.0, which is interpreted as either a 140 medium baseline or a high-mitigation case between RCP4.5 and RCP8.5, is not used. 141 The base period was 1986–2005, which is the commonly used reference period in 142 assessments of projected changes in extreme indices and climate impacts (Schleussner 143 et al., 2016). Future periods in the 2030s and 2050s were given lengths of 20 years 144 145 (2016-2035 and 2045-2065) to be consistent with the base period. The spatial resolution of the output data was offset-corrected and converted to  $0.5^{\circ} \times 0.5^{\circ}$  latitude 146 and longitude by spatial downscaling. Statistical bias-correction methods facilitate the 147 comparison between observed and simulated data during the historical reference period 148 and for a continuous transition into the future (Hempel et al., 2013). Preservation of 149 absolute changes in monthly temperature and relative changes in monthly precipitation 150 in each grid cell implies that the global warming trend and the climate sensitivities of 151 the GCMs are preserved, and the trend and the long-term mean are well represented, 152 which ensures the credibility of the simulated data (Hempel et al., 2013; Warszawski et 153 al., 2014). 154

The United Nations, the World Bank, and other organizations proposed future 155 socioeconomic projections for population and GDP. Many previous studies also 156 157 combined current socioeconomic data with future climatic data for analysis, although these studies neglected to consider how changes in socioeconomic factors affect 158 exposure. We used the predictions of population and GDP from the scenarios of SSPs 159 based on the selected RCP scenarios. SSPs are reference pathways describing possible 160 alternative trends in the evolution of societies and ecosystems on a timescale of 100 161 years without climate change or implementation of climate policies (Riahi et al., 2017). 162 RCP2.6, 4.5, and 8.5 generally correspond to SSP1, 2, and 3, respectively, based on the 163 correspondence between the RCPs and SSPs provided by the IPCC (O'Neill et al., 2014, 164 Table S4). We therefore selected SSP1, 2, and 3 for this study. The RCP2.6-SSP1 165

scenario assumes low carbon emissions, sustainable development proceeding at a 166 reasonably high pace, and fewer inequalities. The RCP4.5-SSP2 scenario assumes 167 moderate carbon emissions with medium growth in population and GDP. Finally, the 168 RCP8.5-SSP3 scenario assumes high carbon emissions with a rapidly growing 169 population and a low adaptive capacity. The projections of population and GDP were 170 obtained from the National Institute for Environmental Studies, Japan (NIES), which 171 were downscaled from the International Institute for Applied Systems Analysis 172 (IIASA). The spatial resolution was also  $0.5^{\circ} \times 0.5^{\circ}$  latitude and longitude. The 173 population and GDP projections were downscaled with explicitly considered spatial 174 and socioeconomic interactions between cities, and they used auxiliary variables, 175 including road network and land cover. The downscaling results were consistent with 176 the scenario assumptions and captured the difference in urban and non-urban areas in a 177 more reasonable manner, which ensures the prediction accuracy of the SSPs (Murakami 178 and Yamagata, 2016). 179

Table 1. Description of global climate models (GCMs).		
		Atmospheric
Model	Institute	resolution
		(longitude × latitude)
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory	$2.5^{\circ} \times 2^{\circ}$
HadGEM2-ES	National Institute of Meteorological	$1.875^\circ  imes 1.25^\circ$
	Research/Korea Meteorological Administration	
IPSL-CM5A-LR	Institute Pierre-Simon Laplace	$3.75^\circ \times 1.875^\circ$
	Japan Agency for Marine-Earth Science and	
MIROC-ESM-	Technology, Atmosphere and Ocean Research	$2.8^\circ  imes 2.8^\circ$
CHEM	Institute (University of Tokyo), and National	
	Institute for Environmental Studies	
NorESM1-M	Norwegian Climate Centre	$2.5^{\circ}  imes 1.89^{\circ}$

181

180

#### 182 **2.2 Methods**

#### 183 **2.2.1 Hazards of extreme heat**

Annual days of extreme heat, which is also the frequency of extreme heat, were 184 used to quantify the hazard, which is defined as the daily maximum temperature 185 exceeding a threshold. The threshold for extreme heat was defined as the 90th percentile 186 of daily maximum temperatures for the base period (1986-2005) and was set at 25 °C 187 when the local 90th percentile was <25 °C (Garssen et al., 2005). We chose relative 188 thresholds rather than a fixed threshold to project global spatiotemporal variation and 189 190 changes in exposure because no single fixed threshold suffices for the substantial differences in climatic conditions around the world (Gasparrini et al., 2015). Relative 191 thresholds were, therefore, the simplest definitions of regionally relevant extreme heat 192 around the globe. The frequency of extreme heat was calculated as follows: 193

$$C = \sum_{i=1}^{365} (TEM_i > THR), \tag{1}$$

$$\bar{C} = \frac{\sum_{j=1}^5 C_j}{5},\tag{2}$$

where *C* is the annual number of days of extreme heat (day), *i* is the i<sup>th</sup> day of a year, *TEM* is the daily maximum temperature (°C), *THR* is the local threshold (°C),  $\overline{C}$  is the multi-model averaged value of *C* (day), and *j* is the *j*<sup>th</sup> GCM.

#### 197 **2.2.2 Exposure to extreme heat**

We measured population and GDP exposure for each grid cell as the number of 198 extreme heat days multiplied by the number of people and GDP, respectively (Jones et 199 al., 2015). Therefore, the units of population and GDP exposures are person-days and 200 201 purchasing power parity (PPP) dollar-days, respectively. To calculate exposure in the base period and in the future periods (2016–2035 and 2046–2065), we minimized 202 interannual variations by using 20-year averages of annual extreme heat days and of the 203 projections of population and GDP. The 20-year mean exposure for each projection of 204 the five climate models was calculated for the base period and for the future periods. 205 Moreover, exposure for the grid cells was also aggregated to global and continental 206 scales for further analysis. Explicitly, we have 207

$$\overline{E_P} = \frac{\sum_{m=1}^{20} C_m \times P}{20},\tag{3}$$

$$\overline{E_G} = \frac{\sum_{m=1}^{20} C_m \times G}{20},\tag{4}$$

where  $\overline{E_P}$  is the 20-year-averaged population exposure (person-day), *m* is the *m*<sup>th</sup> year of the study period, *C* is the number of annual days of extreme heat (day), *P* is the simulated population number (person),  $\overline{E_G}$  is the 20-year-averaged GDP exposure (PPP \$-day), and *G* is the GDP simulation (PPP \$).

## 212 2.2.3 Analysis of relative importance of change in exposure and cumulative 213 probability

Using techniques from a previous study (Jones et al., 2015), we evaluated the relative 214 importance of the effects of different factors by categorizing the changes in population 215 and GDP exposures in terms of the effects of climate, population, GDP, and interactions. 216 The impact of population and GDP was calculated by holding climate constant (i.e., the 217 20 year averages of annual days of extreme heat for the base period were multiplied by 218 the populations and GDPs in the RCP-SSP scenarios). Population and GDP were 219 similarly held constant when calculating the impact of climate (i.e., the population for 220 the base period was multiplied by the 20 year averages of annual days of extreme heat 221 in the RCP scenarios). The interactive effect was also calculated to determine whether 222 the areas with continued population and GDP growth experienced more heat extremes 223 under climate change. The changes in population and GDP exposure were categorized 224

as follows:

$$\Delta E_P = C_b \Delta P + P_b \Delta C + \Delta P \Delta C, \qquad (5)$$

226

$$\Delta E_G = C_b \Delta G + G_b \Delta C + \Delta G \Delta C, \tag{6}$$

where  $\Delta E_P$  is the total change in population exposure,  $\Delta E_G$  is the total change in GDP exposure,  $C_b$  is the annual days of extreme heat for the base period,  $P_b$  and  $G_b$  are the population and GDP for the base period, respectively,  $\Delta C$  is the change in annual days of extreme heat from the base period to future periods, and  $\Delta P$  and  $\Delta G$  are the changes in population and GDP, respectively, from the base period to future periods. Therefore,  $C_b\Delta P$  is the population effect,  $C_b\Delta G$  is the GDP effect,  $P_b\Delta C$  and  $G_b\Delta C$  are the climatic effects, and  $\Delta P\Delta C$  and  $\Delta G\Delta C$  are the interactive effects.

The uncertainties of changes in population and GDP exposure for future scenarios were analyzed to evaluate the possible impact of climate change and growth on population and GDP. The probability analysis of changes in population and GDP were first separately calculated in each GCM based on the cumulative distribution function (CDF). Next, the mean value and standard deviation for the five GCMs were computed. The CDE of a rendern variable *X* memoants the methodility that V < v

239 The CDF of a random variable *X* represents the probability that  $X \le x$ .

#### 240 **3 Results**

#### 241 3.1 Spatial pattern of population and GDP exposures to extreme heat

Figure 1 shows the multi-model average exposures of the population and GDP for RCP8.5-SSP3 for 2046–2065. Figure S3 shows the frequency of extreme heat, and Figs. S4 and S5 show the population and GDP exposures, respectively. Tables S1 and S2 present the statistics for population and GDP exposures globally and continentally for the RCP-SSP scenarios and the different time periods.



247 0 0.1 1 10 100 (×10<sup>6</sup> person-days) 0 1 10 1000 (×10<sup>6</sup> PPP \$-days)
248 Fig. 1: Multi-model global projections of average exposures of (a) population and (b)
249 GDP to extreme heat for the RCP8.5-SSP3 scenario for 2046–2065. PPP is purchasing
250 power parity in USD.

The spatial distribution of the frequency of heat extremes indicates latitudinal zonality in each time period and for each scenario (Fig. S3). The threshold in the base period exceeds 25 °C, except at latitudes >50° and on the Qinghai-Tibet Plateau. Heat extremes are most frequent near the equator, and their frequency gradually decreased with increasing latitude in both the base period and future periods. The frequency of extreme heat clearly increases over time. The highest frequency is 36.5 days in the base
period, whereas the frequency is projected to exceed 120 days in the RCP scenarios.
The frequency is significantly higher for 2046–2065 than 2016–2035 under each
scenario. The frequency is highest under the RCP8.5 scenario and lowest under RCP2.6,
but the difference between the scenarios is less than the difference between the time
periods.

The regions with high population and GDP exposures to extreme heat are primarily 262 concentrated in densely populated areas, such as India, China, midwestern Europe, the 263 eastern USA, and the coastal areas of South America, for both the base period and the 264 projected scenarios (Fig. 1). Exposure is also high near the equator in Africa because 265 of the frequent occurrence of extreme heat. Population exposure under the RCP 266 scenarios is highest for India and the east coast of China (> $10 \times 10^6$  person-days). GDP 267 exposure is much higher for eastern China, the Indian subcontinent, western Europe, 268 and eastern North America than other locations such as northern Asia, northern North 269 America, and Middle Oceania, with annual GDP exposure  $>100 \times 10^9$  PPP dollar-days. 270

#### 271 **3.2** Global and continental change in exposure to extreme heat

Annual exposure of the global population for the base period is  $217.80 \times 10^9$  person-272 days, which increases to  $1037.06 \times 10^9$  person-days for 2046–2065 under the RCP8.5-273 SSP3 scenario (Table S1). The increase in population exposure is largest for the 274 RCP8.5-SSP3 scenario and smallest for RCP2.6-SSP1 (Fig. 2). The increase in global 275 annual GDP exposure is largest for 2046–2065 under the RCP2.6-SSP1 scenario (Fig. 276 3), with a 10.47-fold increase in exposure relative to the base period (Table S2). In 277 contrast, the increase is smallest for 2016–2035 under RCP8.5-SSP3, with an increase 278 of only 3.71-fold relative to the base period. The reason that the highest GDP exposure 279 appears in the RCP2.6-SSP1 scenario is that SSP1 is a "sustainable" scenario that 280 assumes economic growth is shared at the global scale, so GDP increases relatively 281 more in countries that currently have less wealth. Therefore, the exposed GDP at the 282 global scale is higher in RCP2.6-SSP1, despite the hazard of extreme heat being lower 283 in RCP2.6. 284

The population exposure is highest for Asia, followed by Africa, and lowest in 285 Oceania in both the base period and the RCP scenarios. Exposure in Asia and Africa in 286 the base period is 63% and 14%, respectively (Table S1). The percentage of population 287 exposure under the three RCP scenarios decreases for Asia and increases for Africa. 288 The percentage of population exposure for 2046–2065 under the RCP8.5-SSP3 289 scenario decreases for Asia to 53% and increases for Africa to 29% of global exposure. 290 Exposure for the continental GDP in the base period ranks as follows: Asia > North 291 America > Europe > South America > Africa > Oceania (Table S2). 292

The percent of GDP exposure increases for Asia, Africa, and South America and decreases for North America, Europe, and Oceania. The increase in both continental population and GDP exposures is largest for Africa, with the annual population exposure >9.20-fold higher under the RCP8.5-SSP3 scenario for 2046–2065 than for the base period, and the change of population exposure is 1.22-fold larger over the same period and under the same scenarios for Europe than in the base period, which is the smallest change among the continents. GDP exposure increases the most in Africa,
by >29.34-fold relative to the base period under the RCP2.6-SSP1 scenario for 2046–
2065, whereas GDP exposure in North America is 3.99-fold higher for 2046–2065 than
the base period, which is the lowest among continents.

Figure 2 presents the relative changes in population exposure for the projected 303 scenarios relative to the base period. The rate of change is highest in Africa in regions 304 near the equator. Population exposure for 2016–2035 under the RCP2.6-SSP1 scenario 305 increases more than 2-fold. The increase in the coastal regions of South America is also 306 rapid, by more than 2-fold for 2046–2065 under the RCP4.5-SSP2 scenario. The rate 307 of change, however, is <50% in areas where the rate has usually been high, such as 308 China, the USA, and Western Europe. Population exposure is much higher for 2046-309 2065 than 2016–2035 under each scenario when the differences are compared between 310 different time periods, with time, the population increases gradually, and when that 311 increase is crossed with the more frequent heat extremes affected by climate change. 312 Population exposure is highest under the RC8.5-SSP3 scenario, where population 313 growth is rapid, followed by the RCP4.5-SSP2 and RCP2.6-SSP1 scenarios. 314



Fig. 2: Multi-model global projections of average relative change in population
exposure to extreme heat for the three RCP scenarios and two time periods relative to
the base period: (a) RCP2.6-SSP1, (b) RCP4.5-SSP2, (c) RCP8.5-SSP3, (1) 2016–2035,
(2) 2046–2065.

Figure 3 presents the spatial distributions of the average relative changes in GDP 320 exposure for the RCP scenarios projected by multiple models. GDP exposure for 2016-321 2035 increases most rapidly in eastern China, with a more than 9-fold increase relative 322 to the base period. GDP exposure also changes for central Africa and the South Asian 323 subcontinent, with more than 6-fold increases relative to the base period. GDP exposure 324 325 increases for 2046–2065 relative to the base period and 2016–2035. The increase in exposure is largest for Asia and is >12-fold higher than the base period in many 326 countries, such as China, India, and Mongolia. GDP exposure also changes for Africa, 327 South America, and Eastern Europe. The change in exposure is relatively small for 328 North America and Oceania, less than 6-fold relative to the base period. GDP exposure 329 is highest under the RC2.6-SSP1 scenario, where GDP growth is fastest, followed by 330 the RCP4.5-SSP2 and RCP8.5-SSP3 scenarios. 331



332 333

-1.0 0 3.0 6.0 9.0 12.0 (fold change) Fig. 3: Multi-model global projections of average relative change in GDP exposure to

extreme heat for the three RCP scenarios and two time periods relative to the base
period: (a) RCP2.6-SSP1, (b) RCP4.5-SSP2, (c) RCP8.5-SSP3, (1) 2016–2035, (2)
2046–2065.

#### 337 **3.3** Analysis of relative importance of change in exposure

To determine the relative importance of various factors, we categorize the changes in population and GDP exposures in terms of the effects of population, GDP, climate, and their interactions. Figures 4–6 show the changes in exposure and its components
for the globe and for the continents under the three RCP scenarios. The change in global
exposure of the population is primarily affected by the climate, whereas the change in
global exposure of GDP is mainly attributed to the GDP effect (Fig. 4).

The climate effect accounts for nearly half of the total change in population exposure 344 345 (47%–53%) in each scenario and for each period. The effect of population change for 2016–2035 is larger than the interactive effect, which reverses for 2046–2065. The GDP 346 effect is responsible for nearly 50% of the total change in GDP exposure for 2016–2035, 347 with approximately 30% and 20% attributable to the effects of climate and interactions, 348 respectively. The change in GDP exposure for 2046–2065 under the RCP4.5-SSP2 and 349 RCP8.5-SSP3 scenarios is dominated by the interactive effect, at 49% and 53%, 350 respectively, followed by the effects of GDP and climate. The increase in the influence 351 of the interactive effect highlights the importance of the interactions between GDP and 352 climate change in increasing GDP exposure under the scenarios of high GHG emissions. 353



354

Fig. 4: Categorization of projected aggregate global changes in (a) population and (b)
GDP exposure to extreme heat under the RCP2.6-SSP1, RCP4.5-SSP2, and RCP8.5SSP3 scenarios. Error bars are the standard deviations for the results of the five GCMs.
PPP is purchasing power parity in USD.

The relative importance of the factors of change in population exposure at the 359 continental level varies between regions (Fig. 5). As noted above, the percent of 360 population exposure worldwide is highest for Asia and Africa, but the dominant 361 contribution to the change differs between the two continents. The effect of climate is 362 the dominant contribution for Asia, Europe, North America, and South America for all 363 scenarios and periods. This result indicates that an increased frequency of heat extremes 364 amplifies population exposure, even in the absence of population increases on these 365 continents. In contrast, the contribution of the three factors (i.e., the effects of 366 population, climate, and the interaction) for Africa is nearly identical for 2016–2035 367 because of the strong population increase projected for this continent. The interactive 368 effect, however, becomes the primary contribution for 2046–2065, particularly under 369 the RCP8.5-SSP3 scenario, accounting for 53% of the total change, which is more than 370 the sum of the population and interactive effects. The contributions of the GDP and 371 interactive effects for Oceania are nearly the same for 2016-2035 under the three 372 scenarios. In contrast, the interactive effect makes the primary contribution to the 373 change in GDP exposure for 2046–2065 under the RCP4.5-SSP2 and RCP8.5-SSP3 374

#### 400 600 Total change (a) Africa (b) Asia Population effect 300 Climatic effect 400 nterative effect 200 200 10°) 100 Change in population exposure (person-days, 0 40 80 (c) (d) Europe North America 30 60 20 40 10 20 10 80 (f) (e) Oceania South America 60 6 40 4 20 2 2050s 2030s 2050s 2030s 2050s 2030s 2050s 2030s 2050s 2030s 2050s 2030s RCP2.6 RCP4.5 RCP8.5 RCP4.5 RCP2.6 RCP8.5 Scenarios and time periods Scenarios and time periods

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375

scenarios.

Fig. 5: Categorization of projected aggregate continental change in population exposure
to extreme heat under the RCP2.6-SSP1, RCP4.5-SSP2, and RCP8.5-SSP3 scenarios.
Error bars are the standard deviations for the results of the five GCMs: (a) Africa, (b)
Asia, (c) Europe, (d) North America, (e) Oceania, (f) South America.

Between continents, the differences in relative importance to GDP exposure to the 381 effects of GDP, climate, and interactions are clear (Fig. 6), and the contribution of GDP, 382 climatic, and interactive effects under the various scenarios and periods also varies 383 among continents. The largest contribution for Asia and North America is from GDP 384 385 for 2016–2035 under the three scenarios and for 2046–2065 under the RCP2.6-SSP1 scenario, whereas the interactive effect is the dominant contribution for 2046–2065 386 under the RCP4.5-SSP2 and RCP8.5-SSP3 scenarios. The GDP effect for Africa and 387 South America is the primary contributor for 2016–2035, whereas the interactive effect 388 is the primary contributor for 2046–2065. The difference between the interactive and 389 GDP effects also increases for the pathways involving high GHG emissions in these 390 two continents. The interactive effect for the RCP8.5-SSP3 scenario accounts for 64% 391 of the total change for Africa, exceeding the contribution of 35% for the GDP effect. 392 The interactive effect accounts for 58% of the total change for South America, whereas 393 the GDP effect accounts for only 22%. The increase in GHG emissions leading to 394 climate change and more frequent heat extremes can account for the increase in the 395 difference between the interactive and GDP effects. The interaction between climate 396 and change in GDP amplifies the exposure, but the GDP effect decreases, and the 397 interactive effect increases as GDP growth slows under the pathways with high GHG 398 emissions, which leads to the large difference between the effects under the RCP8.5-399 SSP3 scenario. The GDP effect is the primary contributor for Europe and Oceania for 400

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all periods and scenarios, except for 2046–2065 under the RCP8.5-SSP3 scenario,
which implies that GDP exposure on these two continents would increase quickly
without the impact of climate change. For almost all continents, GDP exposure is
dominated by the GDP effect under the RCP2.6-SSP1 scenario because GDP grows
fastest under this scenario.



Fig. 6: Categorization of projected aggregate continental change in GDP exposure to
extreme heat under the RCP2.6-SSP1, RCP4.5-SSP2, and RCP8.5-SSP3 scenarios.
Error bars are the standard deviations for the results of the five GCMs. PPP is
purchasing power parity in USD: (a) Africa, (b) Asia, (c) Europe, (d) North America,
(e), Oceania, (f) South America.

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# 412 3.4 Analysis of cumulative probability of changes in population and GDP 413 exposures

Figure 7 shows the cumulative distribution functions for changes in population and 414 GDP exposures under the various scenarios and time periods relative to the base period. 415 The changes are smaller for 2016–2035 than 2046–2065 for both population and GDP 416 exposure, which indicates that population and GDP exposures increase rapidly over 417 time, independent of the scenario. Population and GDP exposures, however, differ 418 between the three scenarios and the two time periods. The cumulative probability of an 419 increase in population exposure is >90% for 2016–2035 and >95% for 2046–2065. The 420 change is largest under RCP8.5-SSP3, with 90% probability of a zero- to 10-fold 421 increase for both periods, followed by RCP4.5-SSP2 and RCP2.6-SSP1, with a 90% 422 probability of a zero- to 7-fold increase relative to the base period. The future increase 423 is much faster for GDP exposure than for population exposure because of the faster 424 425 growth in GDP. The change in GDP exposure for 2046–2065 under the RCP2.6-SSP1

scenario is the largest among all time periods and scenarios, with 90% probability of a 426 difference of -1- to 43-fold, with a 10% probability for an increase >43-fold relative to 427 the base period. The increase for 2046–2065 is -1- to 35-fold under RCP8.5-SSP3 and 428 -1- to 31-fold under RCP4.5-SSP2 for the same probability. The changes are much 429 smaller for 2016–2035 than for 2046–2065, with >70% probability of a zero- to 7-fold 430 increase for the three scenarios. The change for 2046-2065 is largest under RCP2.6-431 SSP1, with nearly a 15% probability of a >15-fold increase relative to the base period, 432 whereas the increases are 7- and 11-fold under the RCP4.5-SSP2 and RCP8.5-SSP3 433 scenarios, respectively, for the same probability. 434





Fig. 7: Cumulative probability of projected change in (a) population exposure and (b)
GDP exposure to extreme heat relative to the base period. Error bars are the standard
deviations for the results of the five GCMs.

#### 439 4 Discussion

#### 440 **4.1 Impact of a warmer climate on socioeconomic exposure to extreme heat**

441 Our study shows spatiotemporal variation and changes in exposure and its components at global and continental levels. The results indicate variations among the 442 continents (Figs. S4 and S5). For example, population exposure is highest in Asia (Fig. 443 S4), accounting for >50% of the global exposure, followed by Africa, North America, 444 445 Europe, South America, and Oceania. The percent of population exposure for Africa and South America is projected to increase over time and with an increase in GHG 446 emissions, whereas the percentage of population exposure for Asia, Europe, and North 447 America is projected to decrease over time. GDP exposure accounted for >50% of the 448 total exposure for Asia (Fig. S5), with likely increases under the future scenarios, 449 450 followed by North America, Europe, Africa, South America, and Oceania. The percent of exposure for developing countries, such as in Africa and South America, increases 451 for the future scenarios. In contrast, decreases would be likely for developed countries, 452 such as those in North America, Europe, and Oceania. Extreme heat under climate 453 change would thus affect Asia the most, where population and GDP exposures are 454 highest. Exposure for Africa is expected to increase rapidly in the future. Therefore, 455 more attention should be directed to Asia and Africa for deeper research on extreme 456 heat exposure and risk assessment. In addition, the design and implementation of 457 effective adaptive measures are urgently needed in regions with high socioeconomic 458

exposure, to lessen populations suffering from heat extremes and reduce the economiclosses under climate change.

We estimate future socioeconomic exposure based on SSP projections with to various 461 RCP scenarios. Because the current data are well understood and widely accepted, 462 however, some previous research is based on current spatial distributions and 463 population and GDP exposures (Hsiang et al., 2017). We also calculate exposure to 464 future extreme heat regardless of changes in population and GDP (Table S3). The 465 results indicate that socioeconomic exposure would increase significantly under climate 466 change, with distinct differences among the RCP scenarios, even if population and GDP 467 exposures are maintained at current levels. Exposure is lowest under the RCP2.6 468 scenario and highest under the RCP8.5 scenario. Population and GDP exposures are 469 1.72- and 1.67-fold higher under RCP8.5 than under RCP2.6, respectively. Both results 470 471 for the SSP projections and the current fixed values highlight the importance of reducing emissions. Overall, it is potential to mitigate the impact of climate change on 472 both extreme heat hazards and population exposures under the RCP2.6 scenario 473 compared to RCP4.5 and 8.5 scenarios. And the efficiency of reducing emissions 474 should be further quantified in future studies under RCP2.6 or other ambitious warming 475 476 target, such as 1.5°C and 2°C warming target proposed in Paris Agreement (UNFCCC, 2015), which will be helpful for making climate change mitigation strategies. 477

#### 478 **4.2 Uncertainty, limitation and further research**

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Heat extremes could be measured by using different thresholds (e.g., 90, 95, 97.5, 479 and 99th percentile of daily maximum temperatures over the base period). The spatial 480 patterns of exposure and change are generally similar, whereas the quantity of exposure 481 and the relative importance of factors differ greatly (Liu et al., 2017). Assessing 482 socioeconomic exposure under climate change has many uncertainties, except for the 483 indices that measure extreme heat. The primary sources of uncertainty include scenarios 484 of GHG emission (Maurer, 2007), GCMs (Soden et al., 2018), predictions of population 485 and GDP (Chen et al., 2018) and the calculation method of exposure (Zhang et al., 486 2018). The research of Bonan and Doney (2018) on global change in stresses on 487 terrestrial and marine ecosystems show that the uncertainty on land is mostly from 488 model uncertainty, which contributes nearly 80% of the total uncertainty in the 21st 489 century. We evaluate population and GDP exposures based on five GCM simulations 490 after downscaling and assessing the various scenarios and time periods separately. 491 Figures 4–7 show the differences between the GCMs. In addition to displaying the mean 492 value of five GCMs, the standard deviation of five GCMs is also displayed as error bars 493 in the figures. This study generates assessments by considering different sources of 494 uncertainty, so the results can be considered as reasonable with relatively high accuracy. 495 This study is also subject to some limitations. First, our study quantified 496 spatiotemporal variation of population and GDP exposures to extreme heat as an 497 important first step for estimating changes in risk, which made progress compared to 498 the previous studies ignoring the spatiotemporal variation of the socioeconomic risk 499

(Barnett et al., 2012; Gasparrini and Armstrong, 2011; Voorhees et al., 2011). However,

we do not estimate changes in vulnerability due to the lack of more advanced damage

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data due to heat extremes. In further studies, we should also concentrate on assessing 502 vulnerability when the data are available, which is also essential for assessing risk. In 503 addition, adopting measures such as the use of air conditioning and the purchase of 504 insurance should be taken into account. These factors would likely improve resilience 505 to heat extremes and thus decrease vulnerability and limit the impact of climate change. 506 507 Second, the effect of urban heat islands (UHIs) in addition to global warming is not considered explicitly in the climate change simulations in this study. UHIs are 508 confirmed to exacerbate the extent and intensity of heat extremes in urban areas and 509 increase the risk to urban residents in heat extremes (Dan and Bou-Zeid, 2013; Hajat 510 and Kosatky, 2010; Mishra et al., 2015). Recently, as the importance of urbanization in 511 climate change has come to be realized, several case studies simulating the impact of 512 urbanization on extreme temperature events been done (Chen and Frauenfeld, 2016; 513 514 Grossman-Clarke et al., 2010; Wang et al., 2012). Some research focused on intensely urbanized places such as eastern China, the eastern USA, and Western Europe, which 515 is consistent with the results of our studies on high-exposure regions. However, some 516 other regions such as western Africa and northern India are also expected to suffer high 517 exposure to heat extremes in the future. More attention should be focused on these 518 regions in future studies (see Fig. 8). However, global studies are rare because of a lack 519 of precise land-use and population data. Some other studies assess the future urban 520 climate change by using GCM (Fischer et al., 2012; Oleson, 2012). However, given the 521 coarse spatial resolution, the influence of GCM on underlying urban surfaces could not 522 be fully appreciated, so the impact of future urban development on UHIs was not 523 considered in these studies. As a result, the effect of UHIs on extreme temperature 524 events may be underestimated. Therefore, in future studies, the design and nesting of 525 urban land surface models and the estimation of UHI, especially the heat island 526 estimation during heat extremes, should be taken into account, since they are critical 527 528 for estimating exposure and risk to heat extremes in cities due to climate change.



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Fig. 8: Regions with high future exposure under climate change. E.g. Western Europe
(region 1), the eastern USA (region 2), eastern China (region 3), western Africa (region
4) and northern India (region 5), may face more risk in heat extremes coupled with the

effect of urban heat islands in intensely urbanized places.

#### 534 **5 Conclusions**

This study generated four key findings. First, the regions with the highest population 535 and GDP exposures to extreme heat are primarily concentrated in densely populated 536 areas, such as India, China, midwestern Europe, the eastern USA, and the coastal areas 537 of South America. Second, global population exposure for the years 2046-2065 is 538 highest under the RCP8.5-SSP3 scenario, with exposure increasing 3.76-fold relative 539 to the base period 1986-2005. The RCP2.6-SSP1 scenario produces the highest global 540 GDP exposure, with exposure increasing 10.47-fold for 2046–2065. Third, exposure is 541 highest for Asia for both population and GDP, which exceeds 50% of the global 542 exposure. The increase in exposure is largest for Africa, with the annual population and 543 GDP exposures 9.20- and 29.34-fold higher, respectively, than during the base period. 544 In contrast, the relative changes in population and GDP exposures are lowest for Europe 545 and North America, respectively. Fourth, the effect of climate is the dominant 546 contribution globally to change in population exposure, accounting for nearly half of 547 the total change (47%–53%). The effect of GDP is responsible for nearly 50% of the 548 total change in GDP exposure for 2016–2035, whereas the interactive effect makes the 549 primary contribution for 2046-2065 under the RCP4.5-SSP2 and RCP8.5-SSP3 550 scenarios, accounting for 49% and 53% of the total change, respectively. In conclusion, 551 mitigating emissions of greenhouse gases, either at the level of the RCP2.6 scenario or 552 at a more ambitious target of reduction, is important for reducing socioeconomic 553 554 exposure to heat extremes. In addition, designing and implementing effective measures of adaptation are urgently needed in Asia and Africa to aid socioeconomic systems 555 suffering from heat extremes due to climate change. 556

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