Avoided population exposure to extreme heat under two scenarios of global carbon neutrality by 2050 and 2060

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Abstract
To mitigate global warming and the resulting climate risk, many countries have accelerated the optimization of industrial structures and mixture of energy type in an attempt to achieve carbon neutrality by the second half of the 21st century. Here, we present the first assessment of the quantitative benefits of population exposure to extreme heat (defined by the heat index) during 2040–2049 under two scenarios of global carbon neutrality by 2060 and 2050, i.e. moderate green (MODGREEN) and strong green (STRGREEN) recovery scenarios, relative to the baseline scenario of Shared Socioeconomic Pathway (SSP) 2–4.5. Global mean extreme heat days increase by 12.1 d yr⁻¹ (108%) during 2040–2049 under the SSP2-4.5 scenario relative to the historical period (1995–2014). The aggravating extreme heat events could be mitigated by as much as 12% and 18% during 2040–2049 under the MODGREEN and STRGREEN scenarios, respectively. Following the changes in extreme heat days, global population exposure to extreme heat is mitigated by 27.3 billion person-days (7%) in the MODGREEN scenario and 39.9 billion person-days (11%) in the STRGREEN scenario during 2040–2049 relative to the SSP2-4.5 scenario. Such benefits from these low-carbon policies are larger in regional hotspots, including India and Northern Africa, which have experienced high population growth and have extremely limited medical infrastructure. Moreover, an early carbon neutrality (2050 vs 2060) could avoid 12.6 billion person-days exposure to extreme heat during 2040–2049. Our results provide an important scientific support for governments to drive early policymaking for climate change mitigation.

1. Introduction
Exposure to extreme heat induces cardiovascular and respiratory diseases, posing a serious threat to the human body, especially for adults older than 65 years and young children (Astrom et al. 2015, Gasparrini et al. 2015, Wang et al. 2021, Zhao et al. 2021). Estimates from the Global Burden of Disease Study showed that approximately 350,000 premature deaths in 2019 were caused by extreme heat events (IHME 2020). Excess mortalities have been observed from well-known single extreme heat events, including the 2003 Europe heatwave (~45,000 deaths) (Bono et al. 2004), 2010 Russian heatwave (~54,000 deaths) (Barriopedro et al. 2011), and 2015 South Asia heatwave (>2500 deaths) (Pattanaik et al. 2017).

Observations have shown that the frequency, intensity, and duration of extreme heat events have increased significantly around the world over the past decades (Perkins-Kirkpatrick and Lewis 2020,
Ma and Yuan 2021, Markonis et al 2021, Mukherjee and Mishra 2021). Numerous studies have attributed the increased extreme heat events to anthropogenic global warming caused by cumulative of anthropogenic greenhouse gas (GHG) emissions (Stott et al 2004, Otto et al 2012, Perkins et al 2014, King et al 2016, Wang et al 2021).

Accordingly, many studies have assessed future extreme heat and associated population exposure on local, regional or global scales (Wang et al 2017, Dosio et al 2018, Lin et al 2018, Mishra et al 2020, Zhu et al 2021). Based on projections of Coupled Model Intercomparison Project Phase 5 (CMIP5), Liu et al (2017) estimated that global population exposure to extreme heat increases by nearly ten times under Representative Concentration Pathway (RCP) 4.5 and nearly 30 times under RCP8.5 by 2100. In the United States, population exposure to extreme heat is projected to increase by 4–20 times by the late 21st century (Jones et al 2015, Dahl et al 2019). In Southeast Asia, population exposure to extreme heat is likely to increase by nearly two times from global warming levels of 2.0 °C–3.0 °C (Sun et al 2022). These studies have similarly revealed the increasing risks of population exposure to extreme heat in a warming world.

To slow down climate change, which is featured by the extreme heat, many countries have accelerated the optimization of industrial structures and energy mix to strive for carbon neutrality by the second half of the 21st century (Mallapaty 2020, Broadstock et al 2021). Although previous studies have examined the changes in extreme heat and associated population exposure under different climate change scenarios, there remains a gap in understanding the benefits of extreme heat exposure from the carbon-neutral policies, which is key for governments to adjust early policies.

Societal lockdowns to avoid the spread of the coronavirus disease 2019 (COVID-19) pandemic have resulted in abrupt reductions in global anthropogenic emissions (Liu et al 2020, Gettelman et al 2021), which can substantially affect global/regional climate change (Forster et al 2020, Jones et al 2021, Yang et al 2022). In order to assess the potential climate response to the COVID-19 pandemic and postpandemic recovery, a new climate model intercomparison project (CovidMIP) was proposed by the scientific community (Lamboll et al 2021). The CovidMIP includes two recovery scenarios of moderate green and strong green, which represent global carbon neutrality by 2060 and 2050, respectively (Forster et al 2020, Lamboll et al 2021). Combining 30-member ensemble simulations from the MIROC-ES2L climate model joining the CovidMIP and future population changes, this study aims to present the first assessment of the quantitative benefits of population exposure to extreme heat during 2040–2049 under two scenarios of global carbon neutrality by 2060 and 2050. Moreover, how much population exposure to extreme heat benefits from achieving global carbon neutrality 10 years earlier (2050 vs. 2060) is examined.

2. Methods

2.1. Data sources

In this study, we use large ensemble simulations from the MIROC-ES2L climate model joining the CovidMIP to quantify avoided population exposure to extreme heat by carbon-neutral policies. In CovidMIP, the baseline scenario follows SSP2.4.5 corresponding to the scenario combining SSP2-based socioeconomic and RCP4.5-based energy-emissions-land use scenarios (O’Neill et al 2016). Considering the emission changes during the COVID-19 pandemic and the possible postpandemic emission policies, three recovery scenarios from 2020 to 2050 are designed in CovidMIP: fossil-fuel recovery (FOSSIL), moderate green recovery (MODOGREEN) and strong green recovery (STRGREEN) (Forster et al 2020, Lamboll et al 2021). These recovery scenarios include the ‘two-year-blip’ period that 66% of emission reductions in the beginning of 2020 persist until the end of 2021, followed by emission recovery at the end of 2023 based on different energy supply strategies (figure S1). The FOSSIL scenario supports a strong fossil-fuel energy supply that is rebounding to 4.5% above the baseline scenario at the end of 2023. It is noted that the initial rebound has been revealed in observation (Davis et al 2022). However, the MODGREEN and STRGREEN scenarios support a low-carbon energy supply, which assumes that emissions recover slightly and never reach the baseline scenario at the end of 2023. In these two low-carbon recovery scenarios, GHG emissions will decrease by 35% and 52% by 2030 relative to the baseline scenario, which will help achieve global carbon neutrality by 2060 and 2050, respectively. Under each recovery emission scenario, MIROC-ES2L provides a 30-member ensemble of simulations from 2020 to 2049. Each simulation uses the same GHG and aerosol forcings, but starts from randomly perturbed initial conditions in the atmosphere. Such a large ensemble size allows for us to minimize climate internal variability and explore the emissions-driven changes in climate change. In this study, the ensemble mean of 30-member simulations is used to quantify avoided population exposure to extreme heat under two scenarios of global carbon neutrality by 2050 and 2060.

To evaluate the model skill for heat index (HI) in the historical period (1995–2014), we obtain the hourly near-surface air temperature (T) and dew point temperature (Td) from the ERA5 reanalysis. It is noted that the near-surface relative humidity (RH) is not provided directly by the ERA5 reanalysis.
Thus, we calculate RH based on the saturation vapor pressure (es) of T and $T_d$:

$$RH = \frac{es(T_d)}{es(T)} \times 100\%.$$  \hspace{1cm} (1)

The global one-eighth degree population at 10 year intervals for 2010–2100 is obtained from socioeconomic data and applications center (Jones and O’Neill 2016). This dataset consists of the base year of 2000 and five future population scenarios corresponding to SSPs. Here, we choose the future population under the SSP2 scenario to explore the avoided global population exposure to extreme heat because SSP2 along with SSP2-4.5 are used in the CovidMIP. This scenario assumes that the population maintains the current trend. In order to maintain the consistency of spatial resolution between the population and climate model, population datasets are upscaled by the summation method to match the spatial resolution ($2.8^\circ \times 2.8^\circ$) of the climate model.

### 2.2. Daily maximum of HI

The HI is used in our study, which is distinct from most previous studies (Jones et al 2015, Ilyakaremye et al 2021, Zhang et al 2021) that typically define extreme heat using only air temperature. The HI combines near-surface air temperature ($T$) and relative humidity (RH) to describe the ‘feels-like’ temperature of the human body and is widely used for heat-related environmental health research (Anderson et al 2013, Kent et al 2014, Dahl et al 2019, Schwingshackl et al 2021, Tuholske et al 2021). The formula of HI is described in detail in the National Oceanic and Atmospheric Administration (www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml) and supporting information.

The daily maximum of HI is typically computed using hourly $T$ and RH. Given the difficulty in obtaining global hourly variables from climate models, some studies developed an approach to calculate daily maximum HI using daily maximum temperature ($T_{max}$) and minimum relative humidity (RH$_{min}$) instead of hourly $T$ and RH (Dahl et al 2019). The calculated daily maximum HI using daily $T_{max}$ and RH$_{min}$ best matched that using hourly $T$ and RH with mean square error of $<1^\circ$F for five weather stations throughout the United States (Dahl et al 2019). Here, we extend regional to global evaluation based on the ERA5 reanalysis. Similarly, the daily maximum HI calculated using daily $T_{max}$ and RH$_{min}$ is very close to those calculated using hourly $T$ and RH on a global scale (figure S2). The annual mean maximum bias is smaller than 2 $^\circ$F, and the maximum relative bias is smaller than 3%. Such high consistency consolidates our strategy in calculating the daily maximum HI using daily $T_{max}$ and RH$_{min}$.

Based on different thresholds of the daily maximum HI, people exposed to heat-humidity conditions are divided into four ranks: caution ($80^\circ$F ($27^\circ$C) $<$ HI $\leq$ $90^\circ$F ($32^\circ$C)), extreme caution ($90^\circ$F ($32^\circ$C) $<$ HI $\leq$ $105^\circ$F ($41^\circ$C)), danger ($105^\circ$F ($41^\circ$C) $<$ HI $\leq$ $130^\circ$F ($54^\circ$C)), and extreme danger (HI $>$ $130^\circ$F ($54^\circ$C)). Following the above rules, a daily maximum HI exceeding $105^\circ$F results in dangerous heat disorders. Thus, we define extreme heat with daily maximum HI exceeding $105^\circ$F in this study.

### 2.3. Population exposure

Population exposure to climate extremes is generally defined as the individuals exposed to climate extremes-prone areas. Following previous studies (Jones et al 2015, Chen and Sun 2021), we calculate the population exposure to extreme heat by multiplying the days of extreme heat by the population in each corresponding grid cell. Here, the historical population exposures are calculated based on the population from the base year of 2000, and the future population exposures under the four COVID-19 recovery emission scenarios are calculated based on the population from the corresponding scenario of SSP2. Generally, the changes in population exposures ($\Delta E$) are mainly attributed to the changes in population ($C_{HI} \times \Delta P$), climate ($P_{HI} \times \Delta C$), and population-climate interaction ($\Delta P \times \Delta C$):

$$\Delta E = C_{HI} \times \Delta P + P_{HI} \times \Delta C + \Delta P \times \Delta C$$  \hspace{1cm} (2)

where $P_{HI}$ and $C_{HI}$ represent the population and extreme heat days in the historical period (1995–2014), respectively. $\Delta P$ and $\Delta C$ represent the changes in the population and extreme heat days in the future (2040–2049) relative to the historical period.

We also calculate the avoided impacts ($AI_{pop}$) of population exposure to extreme heat during 2040–2049 by carbon-neutral policies:

$$AI_{pop} = \frac{\Delta E_{pop} - \Delta E_{sup245}}{\Delta E_{sup245}} \times 100\%$$  \hspace{1cm} (3)

where $\Delta E_{sup245}$ represents the changes in population exposure to extreme heat during 2040–2049 under the SSP2-4.5 emission scenario relative to the historical period; $\Delta E_{pop}$ represents the changes in population exposure to extreme heat during 2040–2049 under the COVID-19 recovery emission scenarios, including MODGREEN and STRGREEN, relative to the historical period.

### 2.4. Bias correction method

The confidence level in projected extreme heat depends in part on the skill of climate models in reproducing the current observed extreme heat. Here, we employ the quantile delta mapping (QDM) method to correct the historical and projected HI from the MIROC-ES2L simulations relative to the observed HI calculated using the hourly ERA5 reanalysis. The QDM method is designed to use the same
empirical cumulative distribution function (CDF) for model outputs and observations and preserve the future change signal in climate projections (Cannon et al 2015). The bias-corrected results for a given climate variable \( x \) by the QDM method can be obtained as follows:

We first calculate the non-exceedence probability of \( x \):

\[
\epsilon (t) = F^{(t)}_{m,p} [x_{m,p} (t)], \quad \epsilon (t) \in \{0, 1\}
\]

(4)

where \( x_{m,p} (t) \) represents the modeled (denoted by the subscript \( m \)) value at time \( t \) in the projection period (denoted by the subscript \( p \)); \( F^{(t)}_{m,p} \) represents the time-dependent CDF of \( x_{m,p} \).

Then, the absolute changes in quantiles between the projection and calibration periods are calculated based on the inverse CDFs in the projection and calibration periods, \( F^{(t)-1}_{m,p} \) and \( F^{(t)-1}_{m,c} \):

\[
\Delta_m (t) = F^{(t)-1}_{m,p} [\epsilon (t)] - F^{(t)-1}_{m,c} [\epsilon (t)].
\]

(5)

The modeled \( \epsilon \) quantile values at time \( t \) in the projection period are corrected based on the inverse CDF estimated from observations in the calibration period, \( F^{(t)-1}_{o,c} \):

\[
\hat{x} (t) = F^{(t)-1}_{o,c} [\epsilon (t)].
\]

(6)

Finally, the bias-corrected results of \( x_{m,p} \) at time \( t \) are calculated based on adding the change signal in quantiles \( \Delta_m (t) \) to the corrected quantile value \( \hat{x} (t) \):

\[
x_{\text{corrected}, m,p} = \hat{x} (t) + \Delta_m (t).
\]

(7)

In order to evaluate the performance of the QDM method independently, we divide the 20 year observations into two periods. The period of 1995–2004 is defined as the calibration period and the period of 2005–2014 is used to evaluate the performance of the QDM method in correcting the simulated HI. The evaluation results are described in detail in section 3.1. For simulations under the SSP2-4.5, FOSSIL, MODGREEN, and STRGREEN scenarios, 20 year (1995–2014) observations are defined as the calibration period to correct the projected HI. In addition, the bias correction is applied to each model simulation separately, and the 30-members ensemble mean is used to quantify the avoided global population exposure to extreme heat by carbon-neutral policies.

3. Results

3.1. Model evaluation

The simulated frequency of extreme heat during 2005–2014 is evaluated by using ERA5 reanalysis (figure 1). The observed extreme heat shows a high frequency of 5.3 d yr\(^{-1}\) averaged in the U.S., 15.6 d yr\(^{-1}\) averaged in Eastern China, 12.4 d yr\(^{-1}\) averaged in Austria, 27.8 d yr\(^{-1}\) averaged in Northern Africa and the Amazon, respectively (figure 1(a)). Especially for Southeast Asia and India, the regional mean frequency of extreme heat exceeds 40 d yr\(^{-1}\). However, the frequency of extreme heat in Western Europe is significantly lower than that in the low latitudes. Our estimates of extreme heat days in Western Europe are generally consistent with previous global assessments, but smaller than some regional assessments (Zhao et al 2015, Li et al 2020, Carvalho et al 2021, Schwingshackl et al 2021). Such discrepancy is attributed that the application of a fixed threshold globally, which is higher than that in regional assessments in Western Europe. Compared to the observations, the original MIROC-ES2L result shows significant global biases with a spatial root mean error of 23.9 d yr\(^{-1}\) (figure 1(b)). Regionally, extreme heat frequency is overestimated in the U.S., India, Northern Africa, and Austria, but underestimated in the Amazon, Eastern China, and Southeast Asia (figure 1(d)). Using the bias-corrected HI, the biases of the simulated extreme heat frequency are greatly eliminated (figure 1(c)). The global spatial root mean error decreases from 25.2 to 4.9 d yr\(^{-1}\), and the correlation coefficient increases from 0.49 to 0.98. Regionally, the bias-corrected extreme heat frequency shows high agreement with the observations (figure 1(d)). Compared to the large bias in the original model simulation, the absolute bias is smaller than 5 d yr\(^{-1}\) in all subregions. These improvements consolidate our strategy that using the QDM bias-corrected method improves the confidence level of the model results. Thus, the results are derived from the bias-corrected HI in the following sections.

3.2. Changes in the extreme heat days

Global extreme heat days show significant changes from 1995 to 2049 (figure 2(a)). For the historical period (1995–2014), global extreme heat days increased from 9.5 d yr\(^{-1}\) in 1995 to 12.7 d yr\(^{-1}\) in 2014, with a mean value of 11.2 d yr\(^{-1}\). The projected extreme heat days continue to increase under the four COVID-19 recovery emissions scenarios but with different rates. The largest increase is projected to occur by the mid-21st century under the FOSSIL recovery scenario, followed by the SSP2-4.5 scenario, the MODGREEN recovery scenario, and the STRGREEN recovery scenario. Although global extreme heat days increase substantially, the magnitudes show significant differences on the regional scale (figures 2(b)–(e) and table S1). The largest increase of extreme heat days occurs in tropical regions including India, Southeast Asia, Amazon, and Northern Africa, reaching more than 30 d yr\(^{-1}\) during 2040–2049 under the SSP2-4.5 scenario relative to the historical period (figure 2(b)). In densely populated regions at mid latitudes, including the U.S. and Eastern China, extreme heat days increase by 5.8 and 14.1 d yr\(^{-1}\) during 2040–2049 under the SSP2-4.5
Figure 1. The observed (a) and simulated (b) annual mean extreme heat days during 2005–2014. (c) Same as (b) but calculated with the corrected heat index. (d) Comparisons of observed and simulated annual mean extreme heat days across nine subregions (marked with black boxes in (a)), including U.S. (25°N–50°N, 130°W–50°W), Amazon (AMZ, 40°S–15°N, 82°W–32°W), Western Europe (WUR, 40°N–60°N, 10°W–60°E), Northern Africa (NAF, 5°N–20°N, 20°W–60°E), Southern Africa (SAF, 35°S–0°, 0°–50°E), India (IND, 5°N–30°N, 62°E–90°E), Eastern China (ECH, 20°N–40°N, 105°E–122°E), Southeast Asia (SEA, 10°S–20°N, 90°E–150°E), and Australia (AUS, 40°S–10°S, 110°E–155°E). The black, red, and blue bars represent regional mean extreme heat days calculated from observations, simulations, and bias-corrected simulations, respectively.  

scenario relative to the historical period, respectively. In Western Europe, although the absolute increase of extreme heat days is lower than 0.5 d yr\(^{-1}\), extreme heat days increase by approximately 5-fold during 2040–2049 under the SSP2-4.5 scenario, corresponding to 0.1 d yr\(^{-1}\) in the historical period.  

Compared to the baseline scenario, there are limited changes of extreme heat days under the FOSSIL recovery scenario but a robust decrease under the two green recovery scenarios (figures 2(c)–(e)). On average, global extreme heat days are mitigated by 2.8 d yr\(^{-1}\) and 4.2 d yr\(^{-1}\) during 2040–2049 under the MODGREEN and STRGREEN recovery scenarios relative to the baseline scenario, respectively. Such benefits are more apparent in regional hotspots. For the MODGREEN recovery scenario, extreme heat days are mitigated by more than 7 d yr\(^{-1}\) in Northern Africa, Amazon, and Southeast Asia, followed by 2–4 d yr\(^{-1}\) in Eastern China, India, and Australia during 2040–2049 relative to the baseline scenario (figure 2(d)). For the STRGREEN recovery scenario, the mitigated extreme heat days are up to more than 10 d yr\(^{-1}\) in tropical regions and 3–6 d yr\(^{-1}\) in mid latitudes during 2040–2049 relative to the baseline scenario (figure 2(e)). These results indicate that mitigated extreme heat days benefit from more aggressive carbon-neutral policies. For example, when achieving global carbon neutrality 10 years earlier (2050 vs 2060), global mean extreme heat days are mitigated by 1.4 d yr\(^{-1}\) (6%) during 2040–2049.  

We also examine the changes in the intensity of extreme heat using the probability density function (PDF) during 2040–2049 under four COVID-19 recovery emission scenarios relative to the historical period (figure S3). The PDF of global extreme heat shifts toward higher values of temperature, indicating enhanced extreme heat intensity during 2040–2049 under the SSP2-4.5 scenario relative to the historical period. Compared to the baseline scenario, the intensity of global extreme heat decreases under the MODGREEN and STRGREEN scenarios. Such mitigation effects are larger in some regions, including Southeast Asia, Eastern China, Amazon, and Northern Africa.

3.3. Avoided population exposure to the extreme heat  
Prolonged extreme heat exposure can induce cardiovascular and respiratory diseases, posing a serious threat to the human body (Gasparrini et al 2015, Guo et al 2018). In 2019, more than 356 000 deaths worldwide were related to extreme heat and this number
is predicted to further increase with global warming (Ebi et al. 2021). Thus, the assessment of avoided population exposure to extreme heat driven by low-carbon policies is urgently needed for governments.

Here, we quantify the changes of population exposure to extreme heat under four recovery scenarios (figure 3 and table 1). Similar to extreme heat days, global population exposure to extreme heat increases substantially in the future under the four recovery scenarios. Relative to the historical period, the global population exposure to extreme heat increases by 228.7 billion person-days (approximately 1.5-fold) during 2040–2049 under the baseline scenario of SSP2-4.5. The regional maximums of >20 billion person-days are found in India, Eastern China, Southeast Asia, and Northern Africa, where suffer the largest increase of extreme heat days and high population growth. In Southern Africa and Western Europe, although the absolute increase is lower than 3 billion person-days, population exposure to extreme heat increases by more than 7-fold during 2040–2049 under the SSP2-4.5 scenario relative to the historical period.

However, such aggravating population exposure to extreme heat is significantly mitigated under the two green recovery scenarios. In the MODGREEN recovery scenario, global population exposure to extreme heat is mitigated by 27.3 billion person-days...
Figure 3. Changes in the population exposure to extreme heat during 2040–2049 under four recovery emission scenarios relative to the historical period. The green, yellow, and blue bars represent the changes in population exposure driven by population change, climate change, and population-climate interactions, respectively.

Table 1. Global and regional population exposure to extreme heat (units: billion person-days) averaged in the historical period (1995–2014) and mid-21st century (2040–2049) under the four recovery emission scenarios. The percentages in the third column represent the relative changes of population exposure to extreme heat in the mid-21st century under the SSP2-4.5 scenario relative to the historical period. The percentages in the last three columns represent the relative changes of population exposure to extreme heat in the mid-21st century under FOSSIL, MODGREEN, and STRGREEN scenarios relative to the SSP2-4.5 scenario.

| Region   | Historical | SSP245 | Fossil | Modgreen | Strgreen |
|----------|------------|--------|--------|----------|----------|
| GLOBAL   | 148.0      | 376.7  | 380.3  | 349.4    | 336.8    |
| U.S.     | 1.6        | 4.9    | 5.1    | 4.4      | 4.1      |
| ECH      | 21.8       | 44.3   | 44.8   | 41.8     | 40.5     |
| SAF      | 0.3        | 2.7    | 2.8    | 2.1      | 1.9      |
| WUR      | 0.02       | 0.21   | 0.23   | 0.16     | 0.12     |
| IND      | 72.7       | 160.0  | 160.7  | 152.4    | 149.5    |
| NAF      | 10.2       | 57.8   | 59.0   | 50.9     | 47.5     |
| AUS      | 0.02       | 0.08   | 0.08   | 0.07     | 0.06     |
| AMZ      | 3.52       | 10.2   | 10.3   | 8.8      | 8.2      |
| SEA      | 16.0       | 42.2   | 42.8   | 37.7     | 35.3     |

during 2040–2049 relative to the baseline scenario. The mitigated population exposure to extreme heat varies significantly by region. The largest decreases occur in India and Northern Africa, with approximately 7 billion person-days, followed by 3–4 billion person-days in Eastern China, Southeast Asia, and Amazon. In other regions, including the U.S., Southern Africa, Western Europe, and Australia, population exposure to extreme heat is mitigated by less than 1 billion person-days during 2040–2049 under the MODGREEN recovery scenario relative to the baseline scenario, but the relative decrease can be more than 10%. More aggressive carbon-neutral policies can bring larger benefits for population exposure to extreme heat. The STRGREEN recovery scenario mitigates global population exposure to extreme heat by 39.9 billion person-days, with regional maximums of >10 billion person-days in India and Northern Africa, and 4–7 billion person-days in Eastern China and Southeast Asia during
2040–2049 relative to the baseline scenario. For relative changes, the STRGREEN recovery scenario mitigates global population exposure to extreme heat by more than 30% in Western Europe and Southern Africa, and approximately 20% in the U.S., Northern Africa, Australia, Amazon, and Southeast Asia during 2040–2049 relative to the baseline scenario. In comparison, by achieving global carbon neutrality 10 years earlier (2050 vs. 2060), global population exposure to extreme heat is mitigated by 12.6 billion person-days (3.3%) during 2040–2049.

The increased population exposure to extreme heat in the future is driven by climate change and population change. Using equation (2), we further separate the contributions from climate change and population change to increased population exposure to extreme heat under four recovery scenarios. Globally, population change and climate change make comparable contributions to changes in population exposure to extreme heat during 2040–2049 relative to the historical period. Regionally, population changes dominate the increased population exposure to extreme heat in India, where population changes account for >60% of increased population exposure during 2040–2049 under the STRGREEN scenario relative to the historical period. However, the increased population exposure to extreme heat in Eastern China, Southeast Asia, the U.S., Australia, the Amazon, and Southern Africa is dominated by climate change. Especially for Western Europe, almost all the increased population exposure to extreme heat is caused by climate change because the population achieves basically zero growth or even negative growth during 2040–2049 relative to the historical period.

### 4. Discussion and limitations

Increased extreme heat exposure from climate change severely threatens severely human health worldwide. In this study, we provide the first assessment of the quantitative benefits to population exposure to extreme heat from carbon-neutral policies. Our estimates agree with those of Li et al. (2020), who showed that global extreme heat exposure would increase by approximately 2-fold by the mid-21st century. Regionally, our projected extreme heat exposure increases by approximately 2-fold in Australia, and 1.5-fold in Southeast Asia during 2040–2049 under the SSP2-4.5 scenario relative to the historical period, which is in generally consistent with previous estimates (Nishant et al. 2022, Sun et al. 2022). Compared with projections by Dahl et al. (2019), which estimated that extreme heat days increase by 2-fold in the U.S. Under RCP4.5 scenario by the mid-21st century, our study projects a lower increase of 1.2-fold over the same region. Our projection is smaller, likely because historical and future periods are defined as 1995–2014 and 2040–2049 in this study, while 1971–2000 and 2036–2065 in Dahl et al. (2019). Moreover, many previous studies showed that extreme heat exposure decreased substantially in a low relative to high emission scenario (e.g. RCP4.5 vs. RCP8.5 and 1.5 °C vs. 2.0 °C) during the coming decade (Coffel et al. 2018, King et al. 2018, Freychet et al. 2022, Ullah et al. 2022). Although there are differences in the models, extreme heat indices and emission scenarios, our results similarly highlight that climate mitigation policy is an important strategy to avoid the high risks of extreme heat exposure.

However, we also note some limitations. First, this study is based on a single climate model with 30-ensemble simulations. While such a large ensemble of simulations has the advantage of minimizing climate internal variability, we acknowledge that the extreme heat response to future emission changes is different among climate models. Future work with multiple models could address this uncertainty. Second, similar to previous global assessments (Coffel et al. 2018, Klein and Anderegg 2021, Tuholske et al. 2021), we apply a fixed threshold (HI > 105 °F) as a criterion of extreme heat on a global scale to represent dangerous heat disorders for people. Using the same threshold globally, extreme heat exposure trajectories can be estimated consistently and further compared directly on spatial scales. However, we must acknowledge that such comparison ignores regional adaption of extreme heat threshold. Generally, people at high latitudes and altitudes are more vulnerable to heat stress than those at low latitudes and altitudes (Calosi et al. 2008, Zhou et al. 2016). Therefore, it is necessary to construct a global pattern of heat threshold exceeding human biophysical tolerance based on multisource data, which will facilitate global health exposure risk assessments. Third, our study only considers population exposure and the results do not relate to mortality and economics. Indeed, the impacts of extreme heat on humans depend on both exposure and vulnerability, including population age, gender, and health conditions (Zhang et al. 2018, Folkerts et al. 2022). In the future, multisource data need to be utilized for further exploration of avoided mortality and economics by carbon-neutral policies. Finally, the population trajectory varies with emissions and climate changes. In this study, we use the same population trajectory under the baseline and three recovery emission scenarios to assess avoided population exposure to extreme heat by carbon-neutral policies. This assessment ignores the dynamic response of the population trajectory to different recovery emission scenarios. In the future, two-way coupling between the human nexus and climate change should be developed in the Earth system model to dynamically describe these complex feedback processes.

Despite these limitations, our study reveals large benefits of extreme heat exposure from carbon-neutral policies. Climate change is increasing...
the frequency and intensity of extreme heat globally, which poses a severe threat to human health. Indeed, more than 50% of the days per year will exceed human biophysical tolerance in some densely populated regions including India, Africa, and Southeast Asia, under the SSP2-4.5 scenario by the second half of the 21st century. Without government intervention, extreme heat may limit outdoor activities, leading to a sharp decline in the economy. Considering both health and economic effects, we believe that our results have important implications for ongoing policymaking on climate change mitigation.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-node.llnl.gov/search/cmip6.

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Conflict of interest

The authors declare no competing interests.

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