


Avoiding population exposure to heat-related extremes: demographic change vs climate change

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Abstract Heat waves are among the most dangerous climate-related hazards, and they are projected to increase in frequency and intensity over the coming century. Exposure to heat waves is a function of the spatial distribution of physical events and the corresponding population distribution, and future exposure will be impacted by changes in both distributions. Here, we project future exposure using ensembles of climate projections that account for the urban heat island effect, for two alternative emission scenarios (RCP4.5/RCP8.5) and two alternative population and urbanization (SSP3/SSP5) outcomes. We characterize exposure at the global, regional, and grid-cell level; estimate the exposure that would be avoided by mitigating future levels of climate change (to RCP4.5); and quantify the dependence of exposure on population outcomes. We find that climate change is a stronger determinant of exposure than demographic change in these scenarios, with a global reduction in exposure of over 50% under a lower emissions pathway, while a slower population growth pathway leads to roughly 30% less exposure. Exposure reduction varies at the regional level, but in almost all cases, the RCP remains more influential than the SSP. Uncertainty in outcomes is dominated by inter-annual variability in heat extremes (relative to variability across initial condition ensemble members). For some regions, this variability is large enough that a reduction in annual exposure is not guaranteed in each individual year by following the lower forcing pathway. Finally, we find that explicitly considering the urban heat island effect and separate

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urban and rural heat extremes and populations can substantially influence results, generally increasing projected exposure.

1 Introduction

Risk associated with climate change is driven both by the changing nature of physical hazards and the exposure and vulnerability of society to those hazards (IPCC 2012). Demographic change and the evolution of social, economic, and political systems will continually reshape global population characteristics, altering future exposure and vulnerability to hazards. However, climate risk research tends to focus on potential changes in the intensity, frequency, and distribution of physical hazards, often with limited attention to potential societal change. Over the course of the twenty-first century, heat extremes are projected to increase in both intensity and frequency (Collins et al. 2013; Kharin et al. 2013) as a result of climate change. While the association between climate change, heat waves, and adverse health outcomes is well established in the literature (Luber and McGeehin 2008; Li et al. 2012), the IPCC 5th Assessment Report notes that there have been few attempts to quantify potential changes in future human exposure and vulnerability to extreme heat (Smith et al. 2014). Furthermore, little is known about the relative contributions to exposure and vulnerability of changes in the physical nature of heat extremes and demographic/social change under alternative future scenarios. Exposure, defined as physically experiencing hazardous conditions, is a necessary precondition to vulnerability, typically characterized as a function of exposure and a population's sensitivity and adaptive capacity (Turner et al. 2003). A key research task is to understand the scope for future climate change risks, what its uncertainty might be, and what its main determinants are, in order to better inform priorities for research and risk management strategies (IPCC 2012). To contribute to this goal, here, we project future exposure to heat extremes at global, regional, and subnational (grid-cell) scales as a function of climate and demographic change, paying particular attention to the relative contribution of each to overall risk and uncertainty.

Heat waves are among the most dangerous climate-related hazards facing both developed and developing regions of the world. Notable events such as the 2003 European heat wave and the spring 2015 heat extremes across India led to tens of thousands of deaths. The IPCC Special Report on Extremes (IPCC 2012) suggests that it is very likely that the average annual number of warm days and nights has already increased on a global scale, a trend likely to continue for the duration of this century (Oleson et al. 2015). Heat affects humans both directly (heat exhaustion/stroke) and indirectly by exacerbating existing conditions such as those affecting the heart or lungs. While certain demographic and socio-economic indicators have been shown to impact vulnerability to heat extremes, such as age, education, and wealth (Basu and Ostro 2008; Anderson and Bell 2011), relationships across demographic and socio-economic groups in different world regions and communities are not yet well established (Smith et al. 2014). Regarding physical metrics for extreme heat, existing research includes often disparate measures, typically identifying a strong indicator of excess morbidity/mortality for a population and/or geography of interest (Barnett et al. 2010). However, over larger populations and geographic areas, no single metric exhibits significantly stronger predictive capacity, and alternative metrics are highly correlated (Barnett et al. 2010). It has also been shown that substantial variability in summertime temperature regime and/or more rapid changes in average temperatures are strongly associated with mortality (Basu 2009), suggesting that conditioning and geography are important.

Integrated models of climate and societal change are crucial to understanding the risks associated with future development trajectories (Smith et al. 2014). High-resolution projections of population change are a key, yet often overlooked component of such models. Recently, Dong et al. (2015) modeled global extreme heat risk as a function of projected hazards and vulnerability using climate projections corresponding to the Representative Concentration Pathways (RCPs; van Vuuren et al. 2014) from the HadGEM2-ES model (Jones et al. 2011) and gridded population projections¹ corresponding to the Shared Socioeconomic Pathways (SSPs, O'Neill et al. 2015) from the Inter-sectoral Model Comparison Project (Warszawski et al. 2014). Three primary future climate and socioeconomic scenarios were produced (SSP1-2.6, SSP2-6, SSP3-8.5), and at the regional level, the authors found substantial variation in projected heat waves across climate pathways, and minimal to moderate variation in vulnerability across socioeconomic pathways. Rather than directly estimating population exposure, the authors derive a risk metric and classify future populations falling within very-high, high, medium, low, and very-low risk areas.

In this paper, we focus on the exposure of future populations to heat waves. Exposure depends on future changes in the nature and spatial pattern of climate change as well as the spatial distribution of the population. We go beyond previous work by using initial conditions ensembles of climate model projections that incorporate urban heat island effects and allow us to assess uncertainty in heat wave hazards, and a new set of spatial population projections that are more realistic and provide a wider diversity of potential outcomes than a simple scaling approach. Determinants of climate outcomes include the scenario of future radiative forcing and uncertainty in global climate model projections based on that scenario (and possibly in downscaling of global model outcomes for analyses carried out at higher resolution). Determinants of future population distribution include aggregate population growth and urbanization for countries/regions as well as the type of spatial development patterns occurring within regions, which might lead to more or less concentrated distributions. This work is part of a larger project exploring the Benefits of Reduced Anthropogenic Climate changeE (BRACE; O'Neill et al. 2017), which focuses on the avoided impacts associated with alternative climate outcomes produced under RCP4.5 and RCP8.5. We compare exposure outcomes that result from the two different sets of climate projections combined with two different population projections to estimate the difference that lower levels of climate change would have on exposure. In addition to characterizing avoided impacts, our approach is unique in that we are able to assess the relative contributions of future population and climate outcomes to exposure, as well as uncertainty in exposure. Furthermore, we examine the importance of accounting for the urban heat island effect and differential urban/rural heat extremes. Related work in the BRACE project quantifies extreme heat outcomes for the USA (Oleson et al. 2015) and its implications for mortality risk (Anderson et al. 2016a; Anderson et al. 2016b).

2 Data and methods

In this study, we consider a 2×2 matrix of climate and population projections. Projections of heat extremes are from two ensemble simulations under RCP4.5 and RCP8.5. Projections of population distribution are from SSPs 3 and 5, produced with the National Center for Atmospheric Research – CUNY Institute for Demographic Research (NCAR-CIDR) spatial

¹ Produced by scaling the present-day population distribution by projected change at the national level.

population downscaling model (Jones and O'Neill 2016). From these combinations, a total of four SSP/RCP scenarios are produced. Our primary comparison in exposure outcomes is across RCPs, but we pay particular attention to how this variation depends on the choice of SSP. We also assess how exposure changes based on the choice of SSP for a given climate outcome (RCP), and whether population change or climate change is a more important determinant of the variations in outcome. Assessment of results is carried out at the global, regional, and grid-cell (1°) scale.

2.1 RCP-based extreme heat outcomes

We use the NCAR-Department of Energy (NCAR-DOE) Community Earth System Model (CESM) large ensemble (29 members) for projections of future conditions under the RCP8.5 climate scenario (Kay et al. 2014) and the medium ensemble (14 members) for projections of future conditions under the RCP4.5 climate scenario (Sanderson et al. 2015). Global projections of temperature are considered at the $\sim 1^\circ$ native CESM grid, and bias corrected before computing heat extreme metrics (Oleson et al. 2015). The CESM includes a land surface model, the Community land model (CLM) that explicitly differentiates urban from rural land cover and produces separate climate outcomes for each, thus capturing the urban heat island effect. This allows us to differentiate between urban and rural heat extremes (Oleson et al. 2015) by accounting for the general intensification of urban heat extremes relative to nearby rural areas, an effect that is lost when only grid-cell averages are considered.

The most appropriate definition of a heat wave remains an open research question. At the grid-cell level, we define a heat wave to account for two basic features of the problem: local conditioning (i.e., the range of temperatures to which local population is acclimated), and a minimum intensity, to ensure that a heat wave actually consists of dangerously warm days. We achieve this by specifying two thresholds that must be met for any two or more consecutive days: an average daily temperature (\bar{T}) that is greater than a relative threshold (\bar{T}_{rel}) specified as a percentile of the current distribution of daily mean temperature, and a maximum daily temperature (\hat{T}) that is greater than an absolute temperature threshold (T_{abs}). That is, a heat wave day must have the following:

$$\bar{T} > \bar{T}_{rel} \quad , \quad \hat{T} > T_{abs}$$

We implement this basic definition in three different ways. In all cases, we assume that the relative threshold is given by the 98th percentile of the present-day (1981–2005) distribution of daily mean temperature (\bar{T}_{98} ; see Fig. S1 in the Supplemental Materials [SM]), and that the absolute threshold is a daily maximum temperature of 35°C (T_{35}), a commonly used heat threshold (Wilder et al. 2013; Jones et al. 2015).² The first approach does not distinguish urban and rural areas, but uses grid-cell average (GCA) temperatures:

$$\bar{T}_{GCA} > \bar{T}_{98,GCA} \quad , \quad \hat{T}_{GCA} > T_{35,GCA}$$

² The most deadly extreme heat events of the past several decades have demonstrated maximum daily highs in exceedance of 40°C for several consecutive days (e.g., India 2015; France/Europe 2003; Chicago/Midwestern US 1995) while daily mean temperatures hovered between the $32\text{--}36^\circ\text{C}$ range.

Two additional definitions take advantage of the urban/rural climate differentiation afforded by CLM. A key question is the degree to which urban populations are adapted to urban heat island effects. We therefore consider bounding cases. In one, we calculate urban and rural relative temperature thresholds for daily mean temperature separately using urban and rural climatology. This assumes that urban and rural populations are acclimated to their respective current climates, so that current urban heat island effects pose no additional risk to urban populations:

$$\begin{aligned}\bar{T}_{\text{urb}} > \bar{T}_{98,\text{urb}}, \quad \hat{T}_{\text{urb}} > T_{35,\text{urb}} & \quad (\text{urban populations}) \\ \bar{T}_{\text{rur}} > \bar{T}_{98,\text{rur}}, \quad \hat{T}_{\text{rur}} > T_{35,\text{rur}} & \quad (\text{rural populations})\end{aligned}$$

In the other, both urban and rural relative thresholds are defined using rural climatology. This assumes that urban populations are acclimated to rural conditions, but that urban heat island effects pose an additional risk:

$$\begin{aligned}\bar{T}_{\text{urb}} > \bar{T}_{98,\text{rur}}, \quad \hat{T}_{\text{urb}} > T_{35,\text{urb}} & \quad (\text{urban populations}) \\ \bar{T}_{\text{rur}} > \bar{T}_{98,\text{rur}}, \quad \hat{T}_{\text{rur}} > T_{35,\text{rur}} & \quad (\text{rural populations})\end{aligned}$$

While there are a number of options for specifying the different parameters involved in this definition, this approach has precedent in the literature and, with the exception of the absolute threshold, it is consistent with that of other related studies in the BRACE issue (Anderson et al. 2016a; Anderson et al. 2016b; Oleson et al. 2015), all of which explicitly consider urban heat characteristics.

Urban heat projections suffer from the notable shortcoming that CLM does not explicitly model urban land change but instead holds the current distribution of urban land constant. As such, while the distribution of urban people shifts over time, the corresponding distribution of urban land, and subsequently urban heat, does not, leading to a spatial mismatch. The result is that, at any given time-step, there may be grid cells with urban population but no urban land or temperatures available from CLM, in which case it is not possible to calculate heat wave exposure when applying the separate urban/rural heat definition. The rural climatology definition is not affected. In the remainder of this paper, we consider the GCA definition, for which we have complete global coverage, as our primary result. We treat the separate urban/rural definitions as a sensitivity analysis, and to ensure consistency, we compare outcomes across definitions using only those cells that contain urban land in the CLM model. Urban/rural definitional implications are discussed in section four. From the CESM output, we calculate the gridded distribution of the annual number of heat wave days under all three definitions during current (1981–2005) and future (2061–2080) periods for each ensemble member, using the common set of 14 members for which both RCPs are available.

2.2 SSP-based spatial population projections

We use the NCAR-CIDR spatial population projections consistent with SSP3 and SSP5 (Jones and O'Neill 2016). These two pathways assume divergent global population outcomes, with SSP3 (the Regional Rivalry pathway) assuming high population growth in most regions and low urbanization, while SSP5 (the Fossil-Fueled Development pathway) assumes low population growth in most regions and high urbanization. At the regional level significant variation

in population outcomes exist within and across SSPs. At higher resolution, SSP5 presents a more sprawling pattern of development consistent with a highly energy intensive, rapid growth path, while patterns of local change are more varied under SSP3 (for additional detail see SM). The spatial population model takes national level population (KC and Lutz 2014) and urbanization (Jiang and O'Neill 2015) projections associated with the SSPs and downscales them to urban and rural population in $1/8^\circ$ grid cells using a gravity-based model with parameters estimated from historical data. Parameters are different for the two SSPs and are chosen from the calibration of regions and historical periods judged to be consistent with the nature of spatial population development described in the qualitative narrative (O'Neill et al. 2015) for each SSP. For this work, we aggregate the spatial projections to the 1° CESM grid, and population totals (urban and rural) represent the time-averaged population in each grid cell for the base and future periods.

2.3 Exposure

To calculate exposure, we overlay urban and rural spatial population projections corresponding to each period with heat wave outcomes. For each grid cell in each climate projection, we multiply the projected population by the projected annual number of heat wave days to produce a gridded distribution of the annual number of person-days of exposure to extreme heat. For each scenario, we repeat this process three times, once for each definition of heat waves (described above). As such, for each grid-cell exposure is calculated as the product of: (1) the number of GCA heat wave days and the total population, (2) the number of urban heat wave days and the urban population *plus* the number of rural heat wave days and the rural population, and (3) the average number of urban and rural heat wave days when rural climatological thresholds are applied to both and the urban and rural populations. Exposure is calculated at the grid-cell level; however, our analysis is conducted at the grid-cell, regional, and global scale. As such, we aggregate exposure in the base-period and for each SSP/RCP scenario to the global scale and 11 world regions (see Fig. S3).

3 Results

Population change and the corresponding change in heat wave frequency combine to drive exposure. The base-period population distribution (1981–2005) and projected change (2061–2080) for SSP3 and SSP5 are shown in Fig. S4. Under SSP3, global population increases to roughly 11.1 billion by 2070, while under SSP5, population peaks in 2060 before declining to just under 8.5 billion a decade later. The distribution of population change varies significantly by world region across SSPs. In general, developing nations experience very high growth under SSP3, and slower growth in SSP5. Conversely, more developed countries experience slower growth, and in many cases, population declines under the SSP3 pathway, and higher growth in the more economically optimistic SSP5 pathway. Figure S5 illustrates projected change in the average annual number of heat wave days for RCP4.5 and RCP 8.5, calculated using the GCA heat wave definition and averaged over ensemble members for 2061–2080. Many equatorial regions are projected to experience over 100 annual heat wave days by the latter part of the century, and across the majority of the mid/lower latitudes, heat wave days are projected to increase at least 3-fold to 10-fold. The geographic pattern of change is similar across pathways, but more intense under RCP8.5 (see SM for more details).

The spatial distribution of the change in exposure for each SSP/RCP scenario is illustrated in Fig. 1, averaged over all years and ensemble members for 2061–2080. Broad patterns are similar across all scenarios, with the largest increases occurring in the equatorial/mid-latitude regions corresponding to the largest increase in heat wave days and high population growth areas such as India and large portions of Sub-Saharan Africa. Exposure increases in Eastern China in all scenarios, despite widespread areas of projected population loss. As such, these changes are driven entirely by a warming climate and are mitigated by population loss, particularly outside of the major urban corridors. Across North America and Europe, increased exposure is most evident in urban areas (relative to rural), even in the higher population growth SSP5 scenarios, indicative of continued rural decline.

3.1 Regionally and globally aggregated results

The boxplots contained in Fig. 2a illustrate median global annual exposure for the base-period and each SSP/RCP scenario, as well as variability in single-year outcomes across all ensemble members. Currently, median annual exposure is roughly 15 billion person-days. Present-day inter-annual variability is limited by the heat wave definition, which by construction amounts to a maximum of roughly seven heat wave days per year in the base-period. Projected future exposure varies substantially as a function of SSP/RCP scenario. Globally, the high population growth, high greenhouse gas SSP3-8.5 scenario yields the largest increase in median exposure, reaching 535 billion person-days by the latter half of the century. In contrast, the SSP5-4.5 scenario reaches roughly 170 billion person-days of exposure over the same period, over three times less.

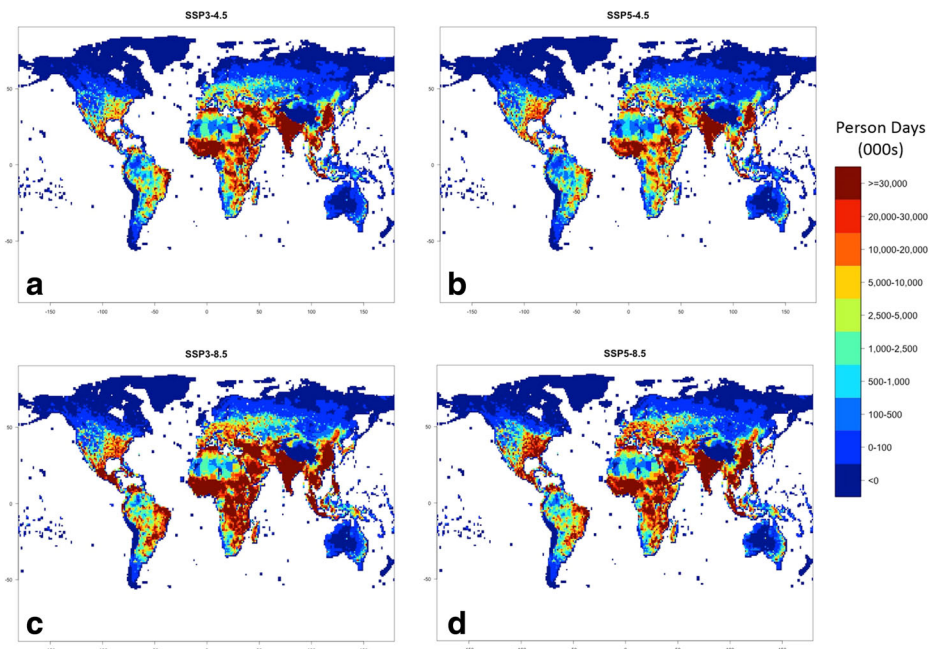


Fig. 1 Distribution of the projected change in average annual person-days of exposure (2061–2080), GCA thresholds for (a) SSP3-4.5, (b) SSP5-4.5, (c) SSP3-8.5, and (d) SSP5-8.5

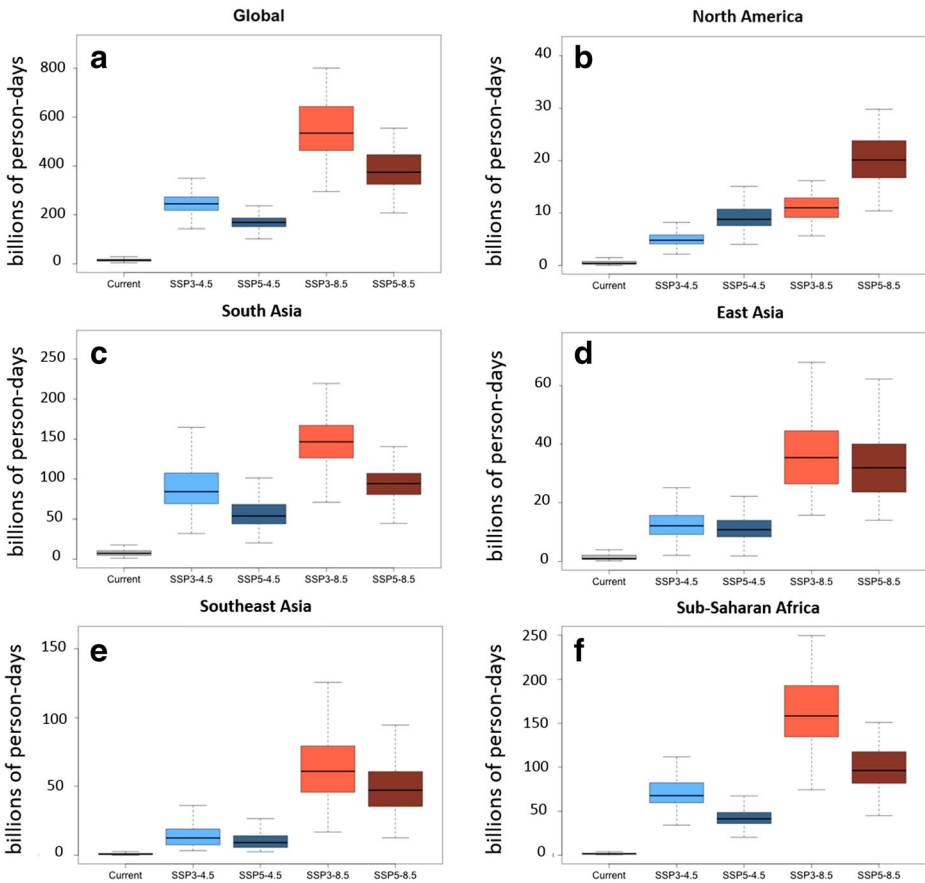


Fig. 2 Boxplots of exposure in person-days in the current period and for each SSP/RCP scenario for **a** global, **b** North America, **c** South Asia, **d** East Asia, **e** Southeast Asia, and **f** Sub-Saharan Africa. Here, as in the other boxplots in the following figures, the dots mark values outside of the 95% range covered by the boxplot whiskers

Also noteworthy, the RCP8.5 scenarios exhibit more variability in exposure outcomes. In the SSP3-8.5 scenario (Fig. 2a), the inter-quartile range of projected exposure spans some 170 billion person-days (roughly 460 to 630 billion), while the full range of outcomes ranged from 300 to 800 billion person-days. The SSP3-4.5 scenario, in contrast, has an inter-quartile range of 50 billion person-days (220 to 270 billion), and 95% of all outcomes fall between 150 and 350 billion person-days. Variability across the lower population SSP5 scenarios is less, but still larger for the SSP5-8.5 scenario relative to SSP5-4.5.

Past work (Jones et al. 2015) found that the variance surrounding the ensemble mean of extreme heat days was largest in areas projected to experience the most extreme heat days, which is to say the variance is proportional to the mean (expected behavior for a variable defined in terms of counts). In this work, we find a similar relationship (Fig. S6) where the range of heat wave day (and consequently exposure) outcomes across ensemble members and years, at the grid-cell level, increases as the projected mean number of annual heat wave days increases. Potential sources of variability include uncertainty across ensemble members and inter-annual variation in projected heat wave days. We examined the former by looking at the distribution of annual exposure averaged over the 2061–2080 period over all ensemble

members, and the latter by computing the distribution of the ensemble means of exposure over all years during that period. From Fig. S7, we find that inter-annual variability dominates, driving the vast majority of the uncertainty in exposure at the global scale for all SSP/RCP scenarios. The pattern holds regardless of extreme heat threshold. The lack of variability across ensemble members is likely due to the length of the 20-year sampling period, over which the overall mean outcomes are expected to be similar, and not strongly affected by changes in initial conditions.

Scenario-specific exposure, the relative importance of RCP/SSP choice, and inter-annual/model variability are not consistent across world regions, and in some cases, patterns deviate significantly from the global (see Figs. 2b–f). Currently, exposure is the highest in South Asia (Fig. 2c), the most populous of the world regions. South Asia also exhibits the largest net increase in exposure in the RCP4.5 scenarios, while Sub-Saharan Africa (Fig. 2f) experiences the largest increase in the RCP8.5 scenarios. Relative to base-year levels, Sub-Saharan Africa is projected to experience the largest increase in exposure in all scenarios, with Southeast Asia exhibiting a very similar relative increase (Fig. 2e) in the SSP5-8.5 scenario. All three of these regions experience substantial population growth under both SSPs (although larger in SSP3). Furthermore, in the case of Sub-Saharan Africa and Southeast Asia, population growth is concentrated in urban areas, most of which are projected to experience a significant increase in heat wave days (Fig. S4), amplifying the increase in exposure. In South Asia, both urban and rural population growth coincide with widespread growth in heat wave days across most of the Indian subcontinent, leading to a large area of very high exposure (Fig. 1). Full regional results can be found in Table S1.

3.2 Avoided impacts

At the global scale for SSP3, achieving a RCP4.5 future as opposed to RCP8.5 leads to roughly 290 billion fewer person-days of heat wave exposure (median value; Table S1). In relative terms, this equates to a 54% reduction in exposure. All world regions experience somewhat similar percentage reductions by achieving an RCP4.5 future (for SSP3), ranging from 43% in South Asia to nearly 80% in Southeast Asia. For the SSP5 pathway, the reductions in exposure associated with RCP4.5 relative to RCP8.5 are extremely similar to those of the SSP3 pathway at both the global and regional level.

At the regional level, the absolute reduction in heat wave exposure that results from following the lower emissions pathway is largest in Sub-Saharan Africa for both SSPs (90/54 billion fewer person-days for SSP3/SSP5, respectively). In relative terms, however, Southeast Asia stands to gain the most in a RCP4.5 future, experiencing roughly five times less exposure than in RCP8.5 regardless of SSP. The smallest reductions in exposure resulting from RCP4.5 occur in the cooler, slower-growth regions of Europe and North America, as well as Oceania. Regional variance in outcomes is similar to that at the global level, generally proportional to median exposure, and as such largest around the high-emission RCP8.5 scenarios. In many cases (e.g., South Asia), significant variation in outcomes accompanies the high population growth SSP3 scenarios as well, regardless of RCP.

We incorporate uncertainty across climate model ensemble members and annual outcomes coupled with regional variation in population across SSPs to assess the likelihood that one SSP/RCP scenario will produce more exposure than another in a given year in the period 2061–2080. To do so, we make a pairwise comparison, year-by-year within each ensemble member, and compute the fraction of those pairwise comparisons where exposure is higher for

one distribution relative to the other (e.g., the RCP8.5 distribution relative to RCP4.5, holding SSP constant). An important note here is that these likelihoods only account for the fraction of uncertainty covered by the CESM initial condition ensembles, while other sources of uncertainty (model structure and parameterization choices) are not represented.

Table S2 compares outcomes across RCPs holding SSP fixed (what is the likelihood that the SSP3-8.5 scenario will produce more exposure than the SSP3-4.5 scenario for any given year). At the global scale, RCP4.5 reduces exposure relative to RCP8.5 100% of the time regardless of SSP. This result is significant, although perhaps not unexpected given the substantial reduction in greenhouse gas concentrations in RCP4.5 relative to RCP8.5.

At the regional level, the likelihood that any SSPx-8.5 scenario will produce exposure exceeding the highest SSPx-4.5 scenario ranges from a low of 89% (Europe, SSP5) to 100%. In four regions (Latin America and Caribbean, North Africa and Middle East, Russia and Central Asia, and Southeast Asia) and in the USA when considered independently, there is 100% certainty that RCP4.5 will lead to reduced exposure regardless of the population scenario. In all other regions, likelihoods of increased exposure under RCP8.5 are over 89% for both SSPs. While unlikely, it is plausible that, for any given ensemble member and year, RCP4.5 may lead to higher exposure than RCP8.5 if, for example, inter-annual variability is such that one ensemble member projects a cooler period under RCP8.5 and a warmer period under RCP4.5. Similarly, the distribution of heat wave days relative to the underlying distribution of the population is important. If an ensemble member projects that a large portion of increased heat wave days under RCP4.5 will occur in heavily populated areas, while the corresponding distribution of heat wave days under RCP8.5 is skewed towards relatively lightly populated areas, the lower emission scenarios may yield higher levels of exposure. However, over all ensemble members and years RCP4.5 is very likely to lead to reduced exposure to heat waves globally and for all world regions.

3.3 Climate vs population effects

Here, we explore similar variation in the relative importance of climate and population by comparing the relative reductions in future exposure that occur from achieving lower levels of future climate change with those resulting from a lower global population growth pathway. Globally, the choice of RCP appears more influential than SSP in driving increased future exposure, as both RCP8.5 scenarios yield more than twice the exposure of their RCP4.5 counterparts. The reductions in exposure that result from achieving a lower growth SSP5 pathway instead of SSP3 are roughly 161 and 76 billion fewer person-days for RCP8.5 and RCP 4.5 respectively, about a 30% reduction in both cases (compared to a 54% reduction in RCP4.5 relative to RCP8.5 across both SSPs). Additionally, median projected exposure for the lower population, high-emission SSP5-8.5 scenario is larger than the higher population but lower emissions SSP3-4.5 scenario, suggesting the climate pathway is more significant (Fig. 2a).

Regionally, reduced exposure resulting from lower population growth³ ranges from roughly 10% (East Asia, both RCPs) to nearly 50% in Oceania (RCP4.5) and 45% in North America (both RCPs). Only Oceania exhibits significant variation across RCP (50% in RCP4.5, 29% in RCP8.5). By comparison, reductions associated with lower radiative forcing range from 43 to

³ In North America, Europe, and Oceania, SSP3 represents the “low population growth” scenario, in all other regions it is SSP5.

80% (see previous section). In all regions, RCP appears more influential than SSP in driving future exposure outcomes. The degree to which this is true, however, varies substantially. For example, in South Asia, the choice of SSP appears nearly as important as RCP in driving exposure outcomes. In contrast, for East Asia (Fig. 2d), projected exposure is significantly lower than in South Asia across all scenarios (a function of declining population in China/Japan and a more northerly orientation) and appears to occur almost entirely as a function of RCP.

Past work examining the relative importance of climate and population dynamics in driving future exposure to heat extremes in the USA (Jones et al. 2015) found a roughly similar impact at the national level with significant variation in primary drivers at the regional level. Our results, while not perfectly comparable, are somewhat similar. The lower emissions pathway leads to nearly 56% less exposure, while the lower population growth pathway leads to roughly a 45% reduction in exposure. The small variation in outcomes between studies is likely driven mainly by differences in the population and climate projections used in the work.

3.4 Importance of urban/rural distinction of heat waves

To assess the impact of introducing separate urban and rural thresholds to the heatwave definition, we consider only those grid cells that contain urban land in CLM to overcome previously noted restrictions. A total of 4436 grid cells ($\approx 20\%$ of all land cells) are included in the sample, an area comprising about 90% of the 2010 global population. At the global scale, median annual exposure in the base-period ranges from just over 13 billion person-days under the GCA definition, to roughly 29 billion person-days when applying rural thresholds to both urban and rural populations (Table S3). The separate urban/rural definition presently yields 16 billion person-days. Thus, treating urban and rural populations separately leads to an increase in estimated exposure of over 20%, while applying rural climatology to all people more than double exposure. Differences in the latter two results are indicative of the impact of expectations regarding the conditioning of rural populations. For example, assuming urban populations are conditioned to the higher temperatures associated with urban heat waves results in 45% fewer person-days of exposure than assuming both urban and rural populations are conditioned to rural climates. At the regional level, the same general patterns are evident in base-period exposure. Applying the separate urban/rural definition leads to increased exposure (over the GCA definition) in all regions, ranging from a modest 2% rise in South Asia to a 135% increase in Europe. Assuming regional urban populations are conditioned to urban climates leads to lower estimates of exposure (relative to assuming rural conditioning), ranging from 29% fewer person-days in Sub-Saharan Africa, to 69% less in North America.

At the global scale, the relative variation in projected exposure across definitions follows a similar pattern to that of the base-period (Fig. 3a). Across all scenarios, the GCA definition produces the lowest estimate of exposure while the rural climatology definition leads to the highest estimate. Applying the separate urban/rural heatwave definition leads to an increase in exposure over the GCA approach in every scenario, ranging from an increase of 7.5% in SSP3-8.5 to 19% in SSP5-4.5. The definitional change leads to larger relative increases in the RCP4.5 scenarios, while absolute increases are larger in the RCP8.5 scenarios. Relative to the rural heatwave definition, however, assuming urban populations are conditioned to urban heat regimes results in a reduction in estimated exposure of 23 and 32% on SSP3-4.5 and SSP5-4.5, and 16 and 23% on SSP3-8.5 and SSP5-8.5.

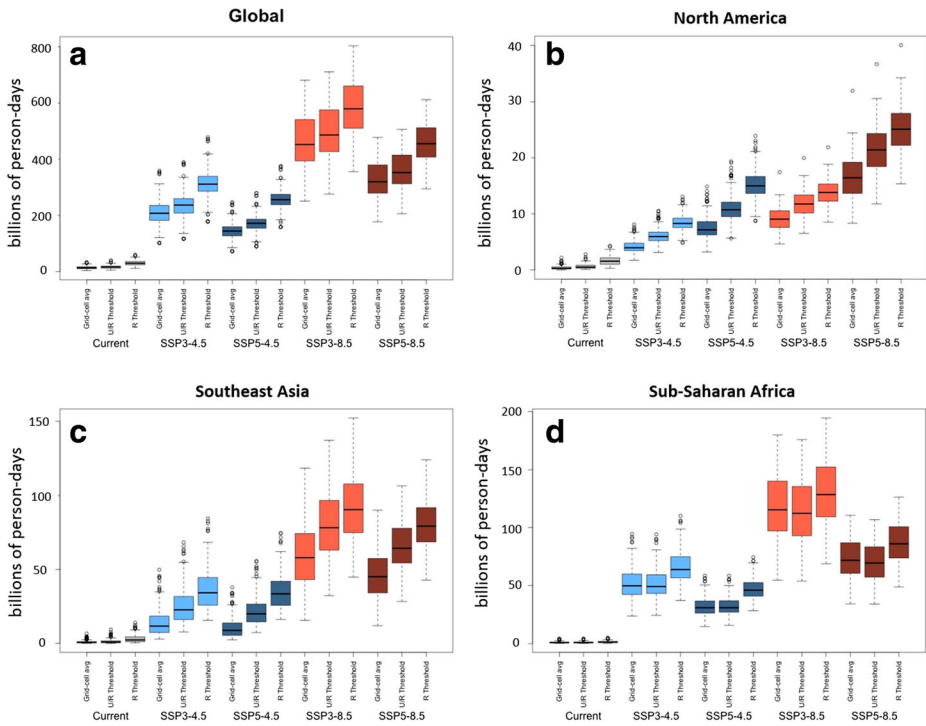


Fig. 3 Boxplots of exposure in person-days in the current period and for each SSP/RCP scenario and three heatwave definitions for **a** global, **b** North America, **c** Southeast Asia, and **d** Sub-Saharan Africa

At the regional level, patterns of exposure across the different definitions deviate somewhat from the global pattern (Table S3). For all scenarios and regions, the rural climatology definition produces the highest projections, and in most cases, the GCA definition produces the lowest. However, in some regions, such as Sub-Saharan Africa (RCP8.5) the separate urban/rural definition actually produces lower levels of projected exposure than the GCA. In other regions (North America and Southeast Asia; Fig. 3b, c), the urban/rural definition produces a large increase in exposure over the GCA definition. These regional variations are likely the result of the interaction between urbanization rates and strength of the urban heat effect. In Southeast Asia, for example, urban heat extremes are projected to increase at a much higher rate than GCA or rural extremes. In Sub-Saharan Africa, lower urbanization rates across the region lead to fewer urban people exposed to urban heat extremes, and a larger number of rural people that experience fewer extreme heat days under the rural climatology definition than under the GCA definition.

The analysis of exposure across different methods of defining urban/rural people and heat waves leads us to four conclusions. First, the urban heat island effect is substantial and has the potential to significantly impact projections of heat wave exposure. Second, assumptions regarding the conditioning of urban populations vis-à-vis urban heat effects will similarly impact projections. Third, treating urban and rural populations separately is quantitatively significant, and as such, it is important to consider, whenever possible, models that can distinguish between urban and rural areas. Finally, in light of these results, it is possible that the GCA heat wave definition under-estimates future extreme heat exposure, as this definition routinely produced lower projections of exposure in our assessment.

4 Discussion and conclusions

In this work, we explore alternative spatially explicit projections of future exposure to heat extremes at the global, regional, and subnational level. For both RCPs, we find that heat wave days are projected to increase in all areas outside of extreme northern and southern latitudes and high elevation (where temperatures are unlikely to reach the 35 °C T_{\max} requirement). Patterns of change are similar across RCP, but are exaggerated in RCP8.5, reaching an annual average of nearly 300 days in the most extreme cases. When we incorporate projected population change in SSP3 and SSP5, we find that achieving an RCP4.5 future cuts projected exposure to heat extremes by roughly half relative to RCP8.5 at the global scale, with similar results, ranging from 43 to 80%, at the regional level regardless of SSP. In contrast, a lower population pathway (SSP5) led to a reduction in exposure of roughly one-third relative to the higher growth SSP3 pathway. In the scenarios we analyzed, climate is a stronger determinant than population in driving future exposure to extreme heat; however, both are significant.

Uncertainty in exposure outcomes for all SSP/RCP scenarios was driven primarily by inter-annual variability as opposed to variability across ensemble members. In general, scenarios including RCP8.5 exhibit more variability. At the global scale, there were no single year/ensemble member permutations that led to higher aggregate exposure in an RCP4.5 future. However, at the regional level, variability was large enough to lead to the possibility that following RCP4.5 would not actually lead to a reduction in heat wave exposure in each individual year during the period 2061–2080. While that possibility is low, decadal variation in climate projections and strong spatial correlation between population density and heat wave days in RCP4.5 scenarios coupled with weak spatial correlation in RCP8.5 scenarios can lead to such outcomes.

Results for the USA are similar to those found in previous work; both climate and demographic changes are important drivers of exposure. Here, we found climate to be slightly more influential, likely a result of a larger number of heat wave days in urban areas due to the urban heat effect, and different assumptions regarding internal migration between studies which led, in this work, to larger populations in cooler areas thus reducing the perceived importance of population change. As such, it is important to be cognizant in future studies on this topic not only of the assumptions related to population outcomes, but also of the modeling mechanisms that drive them, as these will impact projected exposure outcomes.

Finally, we take advantage of CLM's separate urban and rural climate outcomes to produce three alternative heat wave thresholds for a subset of grid cells that include urban land. We find that the urban heat island effect and assumptions regarding the conditioning of urban dwellers substantially influence exposure projections. Additionally, results across alternative definitions suggest that projections of exposure produced using a GCA approach may understate future exposure. We suggest, when possible, to use models that explicitly account for urban and rural climatology in similar research. Future work would also benefit from CLM-type models that are able to explicitly project future changes in the extent of urban land.

While beyond the scope of this work, our results have several important implications that merit future consideration. We do not, for example, differentiate between heat waves that might be considered more moderate and those that meet more extreme definitions (e.g., the degree to which T_{\max} exceeds 35 °C or where T_{mean} falls relative to the 98th percentile threshold). The mortality response to more extreme heat events has been found to be significantly higher than that of more moderate events, suggesting a non-linear relationship between heat levels and deaths (Anderson et al. 2016b). Additionally, the implications of

extended periods of extreme heat relative to mortality, as well as other important socioeconomic factors such as crop yields, have been assessed in the past (IPCC 2012). In the future, it would be useful to identify regions that may be more prone to high-mortality heat waves, or where the increased number of annual heat waves may pass certain thresholds related to both the likelihood of mortality and the sustainability of certain economic activities.

The main caveat to this work is that we have carried out the analysis with initial condition ensembles from a single climate model (CESM). While this approach has the advantage of allowing for a fuller treatment of the role of natural variability, it likely underestimates the uncertainty in climate outcomes relative to a multi-model ensemble approach. Future work in a multi-model context could address this shortcoming. In addition, while we have explored future population uncertainty with two widely divergent population futures, population uncertainty at the subnational scale is likely under-represented as well. Finally, quantifying exposure is a starting point for estimating future risks, but further work is necessary on vulnerability to the impacts of extreme heat, including population age structure and income, as well as possible changes in social and institutional factors over time, which will play important roles in heat-related impacts.

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