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Future population exposure to US heat extremes

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Extreme heat events are likely to become more frequent in the coming decades owing to climate change[1,2]. Exposure to extreme heat depends not only on changing climate, but also on changes in the size and spatial distribution of the human population. Here we provide a new projection of population exposure to extreme heat for the continental United States that takes into account both of these factors. Using projections from a suite of regional climate models driven by global climate models and forced with the SRES A2 scenario[3] and a spatially explicit population projection consistent with the socioeconomic assumptions of that scenario, we project changes in exposure into the latter half of the twenty-first century. We find that US population exposure to extreme heat increases four- to sixfold over observed levels in the late twentieth century, and that changes in population are as important as changes in climate in driving this outcome. Aggregate population growth, as well as redistribution of the population across larger US regions, strongly affects outcomes whereas smaller-scale spatial patterns of population change have smaller effects. The relative importance of population and climate as drivers of exposure varies across regions of the country.

Climate change risks are a function of both the nature of physical hazards related to climate and the vulnerability of society to those hazards[4]. Research has focused on characterizing potential changes in the frequency and magnitude of physical hazards, whereas possible changes in future vulnerability have received less attention. However, recognition of the importance of this dimension is growing as evidenced by the treatment of risk and vulnerability in the Intergovernmental Panel on Climate Change (IPCC) Special Report on Extremes[4], the recent Working Group II report of the IPCC Fifth Assessment Report[5], the third National Climate Assessment[6], and the new set of socioeconomic scenarios in production for use in climate change research that explicitly recognize the role of vulnerability in determining climate change risk[7]. Vulnerability itself can be viewed as a function of the exposure and sensitivity of society to hazards and its capacity to adapt[4]. These three aspects of vulnerability will change over time, potentially having a substantial influence on the magnitude of the risk from extreme events. To better prioritize research and inform risk management strategies, it is important to integrate this influence with projected change in climate to estimate future risks, evaluate the relative importance of different drivers of risk, and quantify uncertainty and its different sources in potential outcomes.

Extreme heat is responsible for more deaths in the United States than any other weather-related event[8,9], and its frequency and intensity is expected to increase over this century[10,11]. The physical effects of extreme heat on human populations are well documented[12–14], and certain demographic/socioeconomic factors heighten vulnerability to heat-related health problems[12,14]. Anticipating changes in exposure to future heat extremes is a key component of understanding future vulnerability and therefore to adequate planning and mitigation[15]. Most attempts to quantify future climate-driven changes in mortality lack consideration of explicit population scenarios[16]. In many cases constant population is assumed, which is not adequate for projecting future exposure or vulnerability[16,17] as these outcomes are heavily influenced by demographic change. In the few existing studies considering spatial population dynamics it has been found that, for example, assumptions regarding internal migration patterns are a strong driver of future exposure/vulnerability and mortality[17]. Not surprisingly, the recently completed third National Climate Assessment identifies as a key research goal 'understanding how climate uncertainties combine with socioeconomic and ecological uncertainties and improve ways to communicate the combined outcomes'[18]. Here, we focus on systematically quantifying the exposure component of vulnerability to extreme heat in the US as a function of both climate and population change. Our results represent a first step towards understanding how patterns of exposure emerge as a result of the interaction between changes in population structure and regional climate.

Here we use projections of future climate change according to the Special Report on Emissions Scenarios (SRES) A2 scenario (see Supplementary Discussion 1) based on general circulation models (GCMs) downscaled to 50-km resolution using regional climate models (RCMs) as part of the North American Regional Climate Change Assessment Program (NARCCAP). NARCCAP includes 11 GCM–RCM combinations (see Supplementary Discussion 2), allowing us to address the uncertainty in spatial climate change outcomes. We combine these with a recent spatial population projection for the US (ref. 19) consistent with the A2 scenario (see Methods).

There are many indices for measuring extreme heat, and it has been found that the best predictor of heat-related mortality for specific age groups, seasons and geographic regions can vary significantly[20]. However, averaged over larger population groups and regions, no single variable has significantly stronger predictive capabilities and alternative measures of heat extremes are highly correlated[20]. It has also been found that excess mortality related to extreme heat events can be effectively described as the independent effect of daily temperatures rather than as a function of multi-day heat waves[21]. Similarly, there are many approaches to quantifying exposure and vulnerability, and a number of studies have attempted to estimate/project changes in heat-related mortality that can be attributed to climate change at the city/regional[22] and national scales[17].

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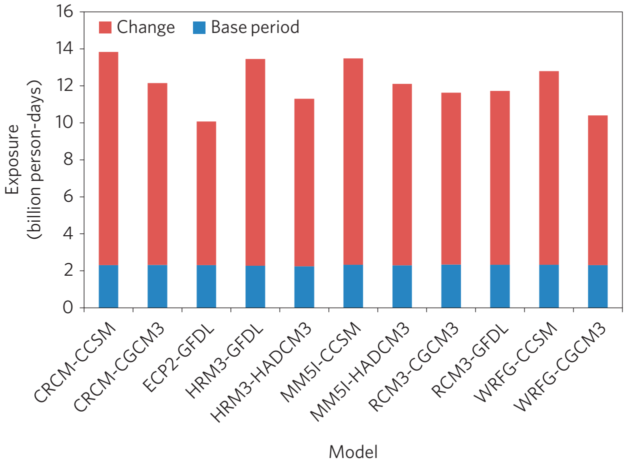

Figure 1 | Aggregate exposure for the continental US in the base period and projected change in exposure for each of the 11 climate models.

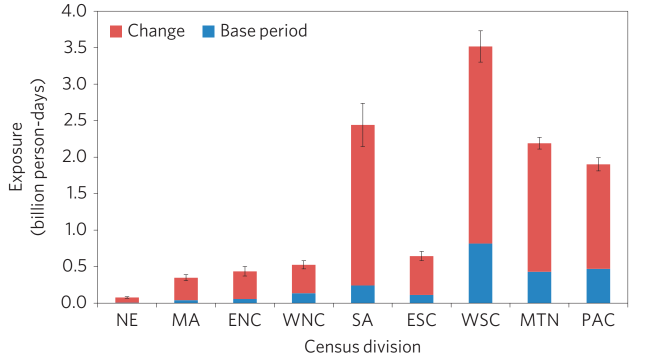

Figure 2 | Aggregate exposure in the base period and projected change in exposure (both as ensemble means) for each of the nine US census divisions. Error bars illustrate the standard deviation in projected exposure across the ensemble for each division.

As we are investigating a large geographic area and modelling effects on the total population rather than subgroups we employ a geographically uniform measure, and define a temperature extreme as a daytime maximum of 35 °C or above. Hence, our measure of exposure is the number of person-days above 35 °C (that is, the annual average number of days with a maximum temperature above 35 °C multiplied by the number of people exposed to that outcome). Although thresholds for temperature stress vary across the US, the 35 °C threshold has been used for analysis of temperature extremes even in the Southwest[23]. For each of the 11 climate projections we calculated average exposure over the period 2041–2070 and compared it with exposure over the period 1971–2000 (see Methods).

At the end of the twentieth century, aggregate annual exposure for the continental United States was, on average, 2.3 billion person-days. Under the A2 scenario, we find that exposure increases to 10–14 billion person-days by mid-century, a four- to sixfold increase over recent levels (Fig. 1). At the level of the US census division (see Supplementary Fig. 3) exposure in the base period ranges from just under 6.5 million person-days in New England, to over 815 million person-days in the West South Central Division, which includes Texas (Fig. 2). There is significant variation in projected total exposure, predictably very high levels across most of the Southern Tier and less in the Northern regions. In absolute terms the West South Central Division is projected to experience the largest increase in exposure, adding 2.7 billion person-days, and the New England Division is projected to experience the largest proportional increase relative to the base period. The South Atlantic Division, which includes Florida, also exhibits large increases in absolute and relative exposure, and the rapidly growing Mountain Division is projected to surpass the Pacific Division in total exposure.

Spatial patterns of exposure and its components also vary significantly across the country. Figure 3 presents the projected change in the spatial distribution of the population under the National Center for Atmospheric Research (NCAR) A2 scenario, the spatial pattern of change in days above 35 °C as the ensemble mean of the NARCCAP simulations, and the corresponding spatial pattern of change in person-days of exposure. The population scenario (Fig. 3a) projects growth throughout major urban areas of the US and across most of the South and West, whereas population is projected to decline across rural regions of the Northeast, Upper Midwest, and Deep South[23]. Most of the country is projected to experience an increase in extreme heat days (Fig. 3b) with more warming across the South, especially areas of West Texas and the Desert Southwest. When these two projections are combined (Fig. 3c), patterns of projected change in exposure resemble the underlying pattern of population change but with proportionally more emphasis on the cities of Southern California, Texas, and the Southeast/Lower Midwest, and less on the cooler cities of the Pacific Northwest. Areas in West Texas and the Desert Southwest, projected to experience the largest increase in days above 35 °C, exhibit a lower increase in exposure relative to neighbouring areas of Eastern Texas (Houston–Dallas–San Antonio corridor) and the Southeast (Atlanta–Charlotte–Raleigh corridor), a function of the large population and projected rapid growth in these densely populated urban areas. In contrast, areas of the upper Midwest and Northeast that exhibit population decline still see an increase in exposure, a function of the warming projected for those areas.

We decompose our exposure analysis to evaluate the relative importance of population and climate drivers and their uncertainty (climate model uncertainty is discussed in more detail in Supplementary Discussion 5). We isolate the impacts of population and climate by recalculating exposure when one factor is held constant. We also calculate an interaction effect, which can be thought of as the change in exposure that results from concurrent changes in population and climate (that is, whether population is growing in areas that are experiencing more extreme heat). From Fig. 4 we find that, at the national level, the climate, population and interaction effects are of similar magnitude. Exposure in the constant population scenario (climate effect) is roughly 37% of total projected exposure, whereas exposure in the constant climate scenario (population effect) is 29%, leaving 32% due to the interaction effect. At the census division level (see Supplementary Fig. 15) there is substantial variation in the relative importance of the climate and population effects, with the population effect contributing more along the East Coast and Upper Midwest, whereas the reverse is true in the Southern Plains and Western US.

Several types of population change can influence exposure. In Fig. 4 the population effect is separated into three components: national growth, regional redistribution and local redistribution. Here 'regional redistribution' refers to the reorientation of the population across census divisions over time, which results primarily from migration. 'Local redistribution' refers to changes in spatial population distributions at the 50-km-grid-cell level within census divisions driven by, for example, suburban sprawl (at this resolution specific intra-urban patterns of change do not affect outcomes). By performing two additional calculations—holding population distribution constant over the whole domain or only within divisions (see Methods)—we can quantify the relative importance of these three components within the total population effect. We find that national population growth is responsible for just over half (57%) of the total population effect. Regional redistribution (largely towards the south and west in the A2 scenario) contributes an additional 34%. Local

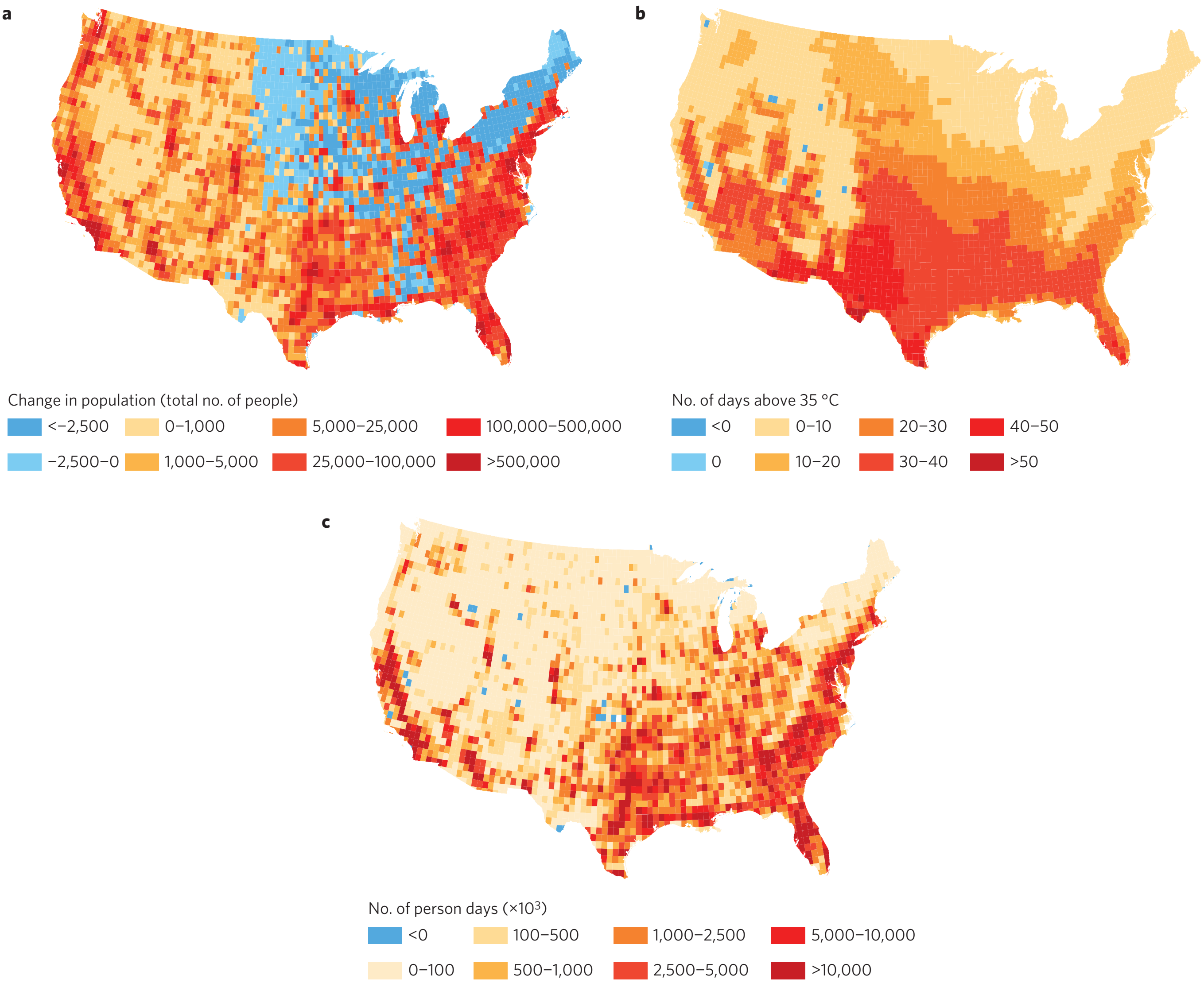

Figure 3 | Projected changes under the A2 scenario; 1971–2000 to 2041–2070. a–c, Spatial population distribution (**a**), mean annual number of days above 35 °C (**b**), and annual exposure in person-days (**c**).

redistribution is responsible for only 9% of the total population effect (see Supplementary Fig. 16 for exposure maps).

These results lead us to three key conclusions. First, there is broad agreement across climate models under the A2 population scenario that there will be a substantial increase in exposure to extreme heat in the US over the next 40–50 years. Second, both climate and population change are significant contributors to this potential increase. Third, aggregate population change and regional redistribution of the population are the largest contributors to the population effect on exposure, whereas local-scale spatial population changes contribute less. In existing analyses of future extreme heat exposure, projected changes in the size and spatial distribution of the population often take a back seat to projected changes in climate. Our results suggest that should not be the case. In the future it is important that policymakers and the research community regard population change and spatial population dynamics as a significant component of risk associated with extreme heat events.

Limitations to the study include a key caveat to the third conclusion: in our analysis we have not distinguished urban and rural temperature change, which can differ substantially owing to the urban heat island effect[24]. Using climate projections that explicitly account for the urban heat effect could well show that local urbanization patterns can substantially influence results. We have also not included demographic or socioeconomic characteristics of the population such as age, income or level of education in this analysis, which are known to impact heat-related mortality. So far there are no high-resolution long-term projections of population that include this type of information, and even at coarser resolution (that is, counties) such projections are generally shorter term and highly uncertain. Future analysis of exposure to climate extremes will benefit significantly from continued improvement in spatially explicit population projections. The existing literature suggests multiple methods for defining extreme heat; in this analysis we work with only one. It may be useful to consider alternative and/or geographically specific definitions of extreme heat, such as combinations of maximum and minimum temperature or humidex over a specific number of consecutive days, to better understand projected changes in exposure to climate extremes. Last, in this work we address uncertainty by using multiple climate models and performing sensitivity analysis, but our analysis is conditional on a single scenario (SRES A2) of national population growth and global climate forcing. A more comprehensive exploration of potential

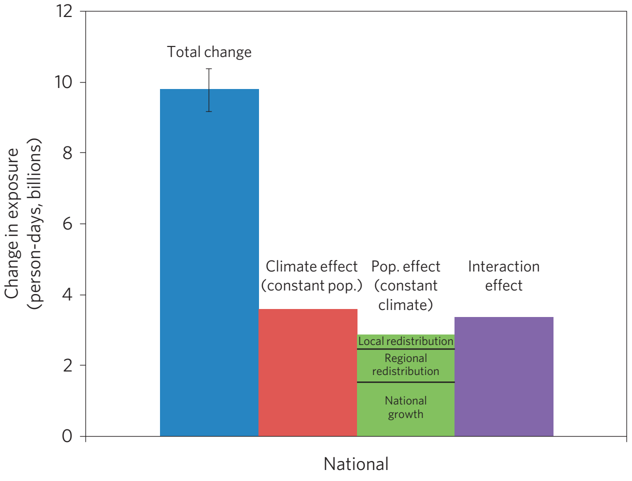

Figure 4 | Decomposition of aggregate national-level projected change in exposure (ensemble mean). Error bar represents the standard deviation in projected exposure across the ensemble.

uncertainties in outcomes would consider multiple scenarios of future socioeconomic development and emissions.

Methods

Methods and any associated references are available in the online version of the paper.

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Author contributions

B.J. produced the spatial population projections and the projections of exposure, contributed to methodological design, and wrote the paper. B.C.O'N. contributed significantly to methodological design and editing the paper. L.O.M. leads the NARCCAP team, of which L.M. and S.M. are members. All three provided climate model output, methodological guidance, and contributed to editing the paper. C.T. contributed to methodological design and editing the paper.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to B.J.

Competing financial interests

The authors declare no competing financial interests.

Methods

For the purposes of this work we define extreme heat as a daily high temperature above 35 °C. Climate output comes from the North American Regional Climate Change Assessment Program (NARCCAP), an international programme to produce high-resolution climate change simulations to facilitate the investigation of uncertainties in regional-scale projections of future climate in addition to generating climate change scenarios for use in impacts research. We used the NARCCAP simulations because it has been demonstrated that the higher-resolution regional model simulations add value over the GCMs used to drive them[25]. Moreover, it has been demonstrated that the RCMs are primarily responsible for the variability of summer temperature in the simulations (compared with the driving GCMs)[26]. NARCCAP modellers ran a set of RCMs driven by a set of atmosphere–ocean GCMs over an area covering the continental United States, northern Mexico and most of Canada at about 50-km resolution[27,28]. We include 11 RCM–GCM combinations in this work (see Supplementary Discussion 2 and Supplementary Tables 2 and 3). All models are forced with the SRES A2 scenario[3]. To correct model bias, we employ a distribution mapping technique[29] that adjusts the model output values for the current period such that they have the same statistical distribution as observational data. The same mapping is then applied to the future period of the simulation. As with most bias correction techniques, this approach assumes that bias is the same in current and future periods, and thus may not fully address biases due to interactions between variables that may be exacerbated by climate change. This factor may add uncertainty in regions where several models exhibit such biases, but otherwise, because the technique corrects the entire distribution, this bias correction performs well across all quantiles, in the extremes as well as near the mean. To apply this technique, we match the distribution of a gridded observational meteorological data set[30] for the current (1971–2000) period, and then apply a corresponding correction to the future (2041–2070) data. From each climate scenario we then extract a gridded distribution of the projected annual number of days above 35 °C for the continental United States. To minimize the effects of natural variability we use 30-year average results for both the base period (1971–2000) and the future period (2041–2070).

We employ one primary spatial population projection, the NCAR A2 scenario, to match the A2 forcing scenario driving the NARCCAP models' simulations. The projection was constructed using the gravity-based NCAR spatial downscaling model[23]. The A2 scenario projects medium/high aggregate population growth across the continental United States, increasing to just over 405 million by mid-century. The scenario assumes a sprawling, deconcentrated pattern of development that was simulated by calibrating the model to historic data from the South census region from 1950 to 2000, which experienced pronounced sprawl during that period. Population data are aggregated from a 1/8° native grid to the 1/2° common grid used in the climate projections.

Exposure to temperatures in excess of 35 °C is calculated by multiplying the population in each grid cell by the projected number of days above 35 °C for each corresponding cell during the appropriate time period. As such, exposure is expressed in person-days. A spatially explicit distribution of exposure was calculated for each of the 11 GCM–RCM combinations from which we calculated an ensemble mean (see Supplementary Figs 2–12 for GCM–RCM results). In addition to distributions, we aggregate person-days from grid cells to census divisions and the national level. To assess the drivers of exposure we conducted four additional model runs for each ensemble member. In the first, we isolate the impact of climate change on exposure by holding population constant at base-year levels but allowing climate to evolve according to the ensemble mean projection (the climate effect). In the second, we do the opposite and hold climate constant at base-year conditions but allow population to evolve (the population effect). The interaction effect, the change in exposure resulting from simultaneous change in population structure and climate, is calculated as the difference between total exposure and the combined population and climate effects. Multiple forces contribute to the population effect, including aggregate national population growth, regional population redistribution (for example, migration), and changes in local/urban spatial distribution. To further decompose the population effect we consider two additional projections. In the first, we hold climate constant and allow for population growth, but in this case holding the base-year spatial distribution of the population constant (for example, proportional scaling of the population). From this scenario we can extract the importance of aggregate population change relative to population redistribution and changes in local spatial structure. In the final projection we hold climate constant, allow population growth and migration/redistribution between census divisions, but hold the base-year spatial distribution within each census division constant. From this scenario we separate the effect of broad-scale redistributions from that of changes in local/small-scale spatial structure.

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