DRAFT

Determinants of uncertainty in population exposure to climate-related extremes

Bryan Jones and Brian C. O'Neill

Introduction

Climate change risks are a function of both the nature of physical hazards related to climate and the vulnerability of society and ecosystems to those hazards (IPCC 2012, ch 2). Research has tended to focus on characterizing potential changes in the frequency and magnitude of physical hazards, including heat waves, floods, droughts, intense precipitation, and tropical cyclones. Possible changes in future vulnerability have received less attention, but recognition of the importance of this dimension is growing, as evidenced by the treatment of risk and vulnerability in the IPCC Special Report on Extremes (IPCC 2012), the forthcoming Working Group II report of the IPCC Fifth Assessment Report, and the new set of socio-economic scenarios in production for use in climate change research, which explicitly recognizes the role of vulnerability in determining climate change risk (van Vuuren et al., submitted). Vulnerability itself can be viewed as a function of the exposure and sensitivity of society to hazards as well as its capacity to adapt (IPCC 2012, ch 2). All three of these aspects of vulnerability will change over time, leading to substantial uncertainty in future climate risk. A key research task is to understand how large this uncertainty might be, and what its main determinants are, in order to better inform priorities for research and risk management strategies.

In this work we focus on the exposure component of vulnerability. The degree of exposure of the population to a given climate outcome is subject to several sources of uncertainty, including those that determine the nature and spatial pattern of climate change as well as those that determine the spatial distribution of the population. Determinants of climate outcomes include the scenario of future radiative forcing, uncertainty in global climate projections based on that scenario (typically produced by global General Circulation Models (GCMs) or Earth System Models (ESMs), and uncertainty in regional climate outcomes (typically produced by Regional Climate Models (RCMs) or statistical downscaling of global model outcomes). Determinants of population distribution include the aggregate population growth and urbanization scenario as well as the type of spatial development pattern, which might lead to more or less concentrated distributions or to regional redistribution of populations.

In this study we assess the relative contributions to uncertainty in population exposure to extreme heat in the United States. We employ alternative climate change scenarios, general circulation models, regional climate models, aggregate population scenarios, and population distribution models. Spatial information and spatially explicit data are an increasingly important component of modeling in the IAM/IAV and global change communities. Global-scale narratives such as the SRES scenarios were developed, in part, to provide structure for the spatial analysis of the drivers and impacts of global climate change, and to facilitate the assessment of alternative spatial development trajectories.

We anticipate that results will be useful to understanding possible spatial patterns of risk. Over the past five to ten years demographers, geographers, and climate scientists have taken a more active interest in examining the population structure in areas deemed vulnerable to climate-related hazards (e.g., Balk et al. 2009; McGranahan et al. 2007). To this point, however, there has been relatively little in the way of scenario-based assessment of spatially explicit risks due to climate 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.

Data and Methods

In this project we will examine exposure to extreme heat, which for purposes of this work we define as a daily high temperature above 35° C. Climate output for this work comes from the North American Regional Climate Change Assessment Program (NARCCAP), an international program 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. NARCCAP modelers run a set of RCMs driven by a set of atmosphere-ocean general circulation models (AOGCMs) over an area covering the continental United States and most of Canada at 1/2° resolution (Mearns et al. 2009). We include eleven RCM-GCM combinations in this work (See Appendix A for a complete list). All models are forced with the SRES A2 scenario (Nakicenvoic et al. 2000). Additionally, to correct for bias in the base-year climate data we employ a quantile mapping technique (McGinnis 2014). From each climate scenario we extract a gridded distribution of the projected annual number of days above 35° C for the continental United States. For purposes of negating any bias resulting from single year variability in climate models the base-year in this work will correspond to the average (climate metrics and population) over the 30-year period 1970-2000 (as such, we refer to 1985 as the base-year). Similarly, projections will correspond to the 30-year period 2040-2070 (which we refer to as 2055).

We employ one primary spatial population scenario, the NCAR A2 scenario, to match the A2 forcing scenario in the climate data. Using the gravity-based NCAR spatial downscaling model we have produced several A2 variants (Jones and O'Neill 2013). For this work we have selected our "most-likely" A2 variant that assumes a sprawling, somewhat deconcentrated pattern of development which was simulated by calibrating the model to historic data from the South census region from 1950-2000, which experience pronounced sprawl during that period. To assess the contribution of population to exposure we consider several alternative forms of this scenario in which we hold the spatial distribution of the base-year population constant at different spatial scales (i.e., national, census division), and a single scenario in which we assume no population change at all (to assess the impact of climate alone). Population data are aggregated from 1/8° to the 1/2° common grid used in climate projections.

To compare outcomes we calculate exposure to temperatures in excess of 35° C in person days, which is simply the population within a grid cell multiplied by the annual number of days the temperature in that grid cell is projected to exceed 35° C. We consider both the spatial distribution of person days, and aggregate values across census divisions and the entire US in our analysis. We begin by calculating exposure from each of the eleven climate models in the ensemble and then assess the variability in exposure resulting from alternative climate output. We then calculate an ensemble mean and assess geographic patterns in the variance of climate outcomes and exposure across models. Finally, we attempt to quantify the sources of uncertainty in exposure by systematically varying single components of the exposure equation (e.g., holding population constant and allowing climate to vary, etc).

Preliminary Results

To begin we consider a single population projection, the NCAR A2 scenario, and climate output from an eleven member ensemble. Figure 4 illustrates projected population change under the NCAR A2 scenario, in this case considering the average population by grid-cell between 1970 and 2000 (the base period) and the corresponding average population between 2040 and 2070 (the projection horizon). These averages reflect the period used in the climate models to produce eleven projections of extreme heat. The NCAR A2 scenario projects population growth throughout the major urban areas of the US as well as across most of the Southern and Western US, while population is projected to decline across rural region s of the Northeast, Upper Midwest, and Deep South.

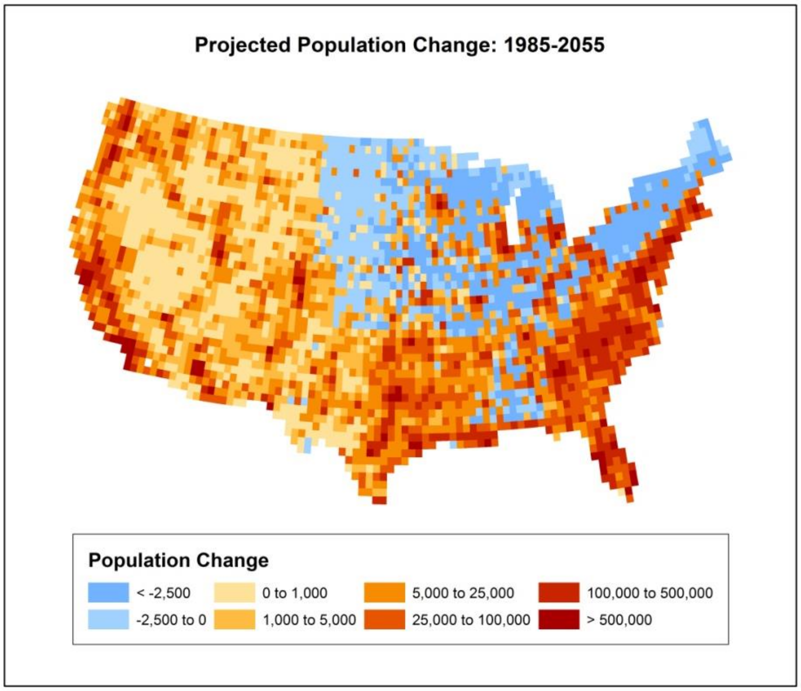

Figure 4. Projected population change, NCAR A2-Scenario 1985-2055.

For each of the eleven climate models we produced projections of annual exposure to heat above 35° C. In general the ensemble members produce fairly similar results. Aggregate exposure across the entire United States, roughly 2 billion person days annually in the base year, is projected to increase anywhere from four- to six-fold over the 50 year period (see Figure 5), with the maximum and minimum projected change in exposure varying by some 30%.

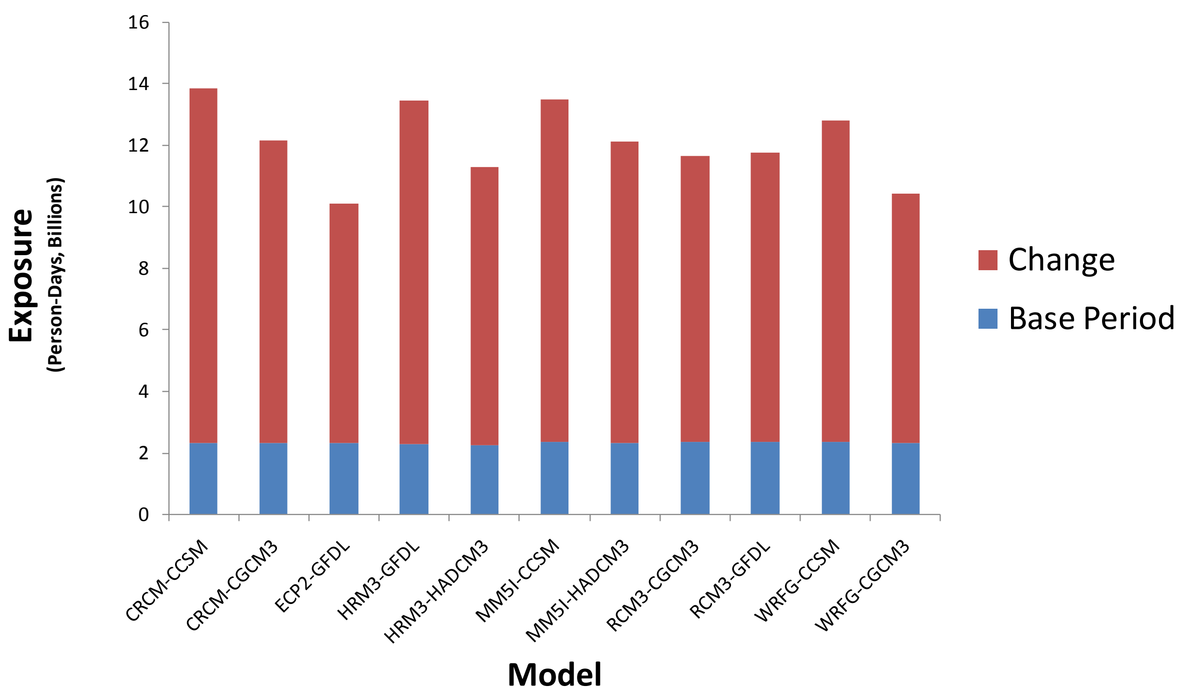

Figure 5. Aggregate exposure in the base-year and projected change in exposure for each of the eleven climate models.

From the eleven-member ensemble we calculated ensemble means for the distribution of days above 35° C and exposure in the base-year, and projected change in both metrics (Figure 6A). The vast majority of the country is projected to experience an increase in extreme heat days. The ensemble projects proportionally more warming in the Western and Southern Texas and parts of the Desert Southwest. Significant warming is also projected across the Southern Plains into the Deep South. A decrease is the number of days above 35° C is projected in only a few remote areas of the Rocky Mountains and Sierra Nevada's. Geographic patterns of projected exposure in the base-year resemble the underlying pattern of population change, however 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 (Fig 6B). Interestingly, areas in Western Texas and the Desert Southwest projected to experience the largest increase in days above 35°C exhibit a proportionally lower increase in exposure relative to neighboring areas of Eastern Texas (Houston-Dallas-San Antonio corridor) and the Southeast (Atlanta-Charlotte-Raleigh urban corridor), a function of the large population and projected rapid growth in these densely populated urban areas.

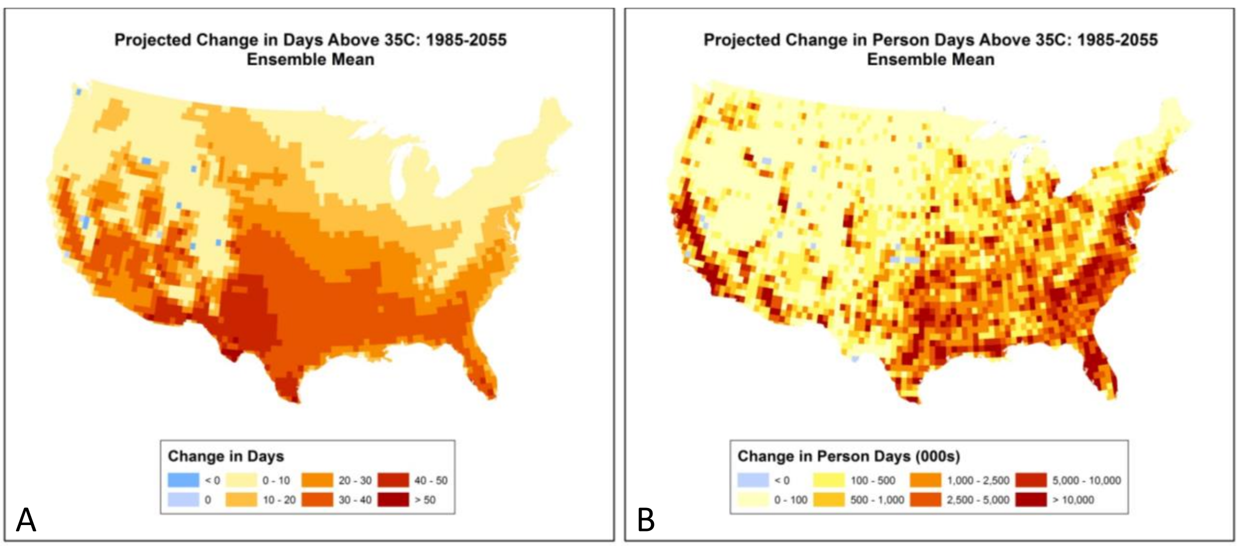

Figure 6. Projected change in days above 35°C (A) and exposure (B); mean values for the eleven member ensemble.

Between model variation in climate outcomes produces distinct geographic patterns of between model variation in projected exposure. To assess these patterns we considered the cell-specific standard deviation and coefficient of variation. The former is illustrative of geographic variation in the absolute level of variation in exposure, while the latter is representative of the degree to which exposure varies relative to the ensemble mean. Figure 7 depicts the standard deviation and coefficient of variation for both the projected change in days above 35° C and exposure side-by-side. We find that variation in the projected number of days above 35° C is largest in Central Texas, Florida, and Southern Georgia. Not surprisingly these are also areas projected to experience a large number of extreme heat days. Portions of the Central Plains, Desert Southwest (particularly Arizona), and Deep South (Louisiana) exhibit smaller standard deviations than surrounding areas despite a significant number of warm days, suggesting more agreement across models. By comparison, if we assess between model variation in days above 35° C relative to the ensemble mean (the coefficient of variation) we find the most uncertainty in the Rocky Mountains, Pacific Northwest, and Appalachian Mountains, all areas in which the projected number of extreme heat days are relatively low. Variation in the projected change in exposure is, not surprisingly, heavily influenced by projected population change, and therefore tends to be highest in urban areas. However, variation in projected exposure relative to the ensemble mean follows a pattern similar to that of projected change in extreme heat days. Uncertainty is greatest in areas of the Rocky Mountains and Pacific Northwest, as well parts of the Northern Plains.

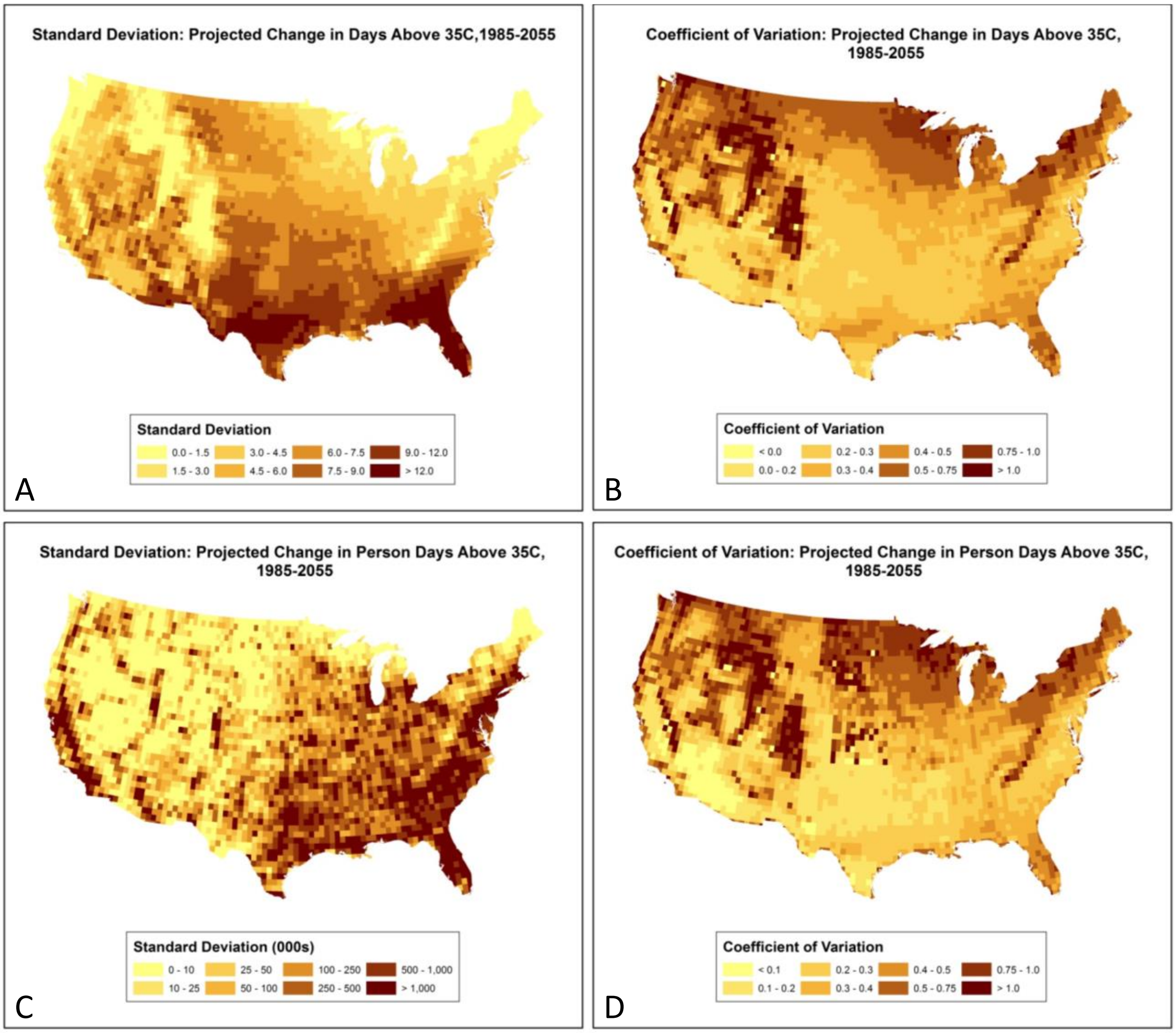

Figure 7. Standard deviation (A) and coefficient of variation (B) in projected change in days above 35°C, and standard deviation (C) and coefficient of variation (D) in exposure.

The projected change in population and exposure by US Census Division (ensemble mean) reveals significant geographic variation in the degree to which exposure rises relative to population (Figure 8). For example, the New England and Mid-Atlantic Divisions are projected to experience substantial increases in exposure despite relatively stable population. Conversely, in the western Divisions (West South Central, Mountain, Pacific), population change is more significant relative to projected change in exposure. In the former we expect that it is a changing climate driving the increase in exposure, whereas in the latter population change plays a more significant role. However, from these results we cannot comment on the degree to which climate and population change contribute to increase exposure.

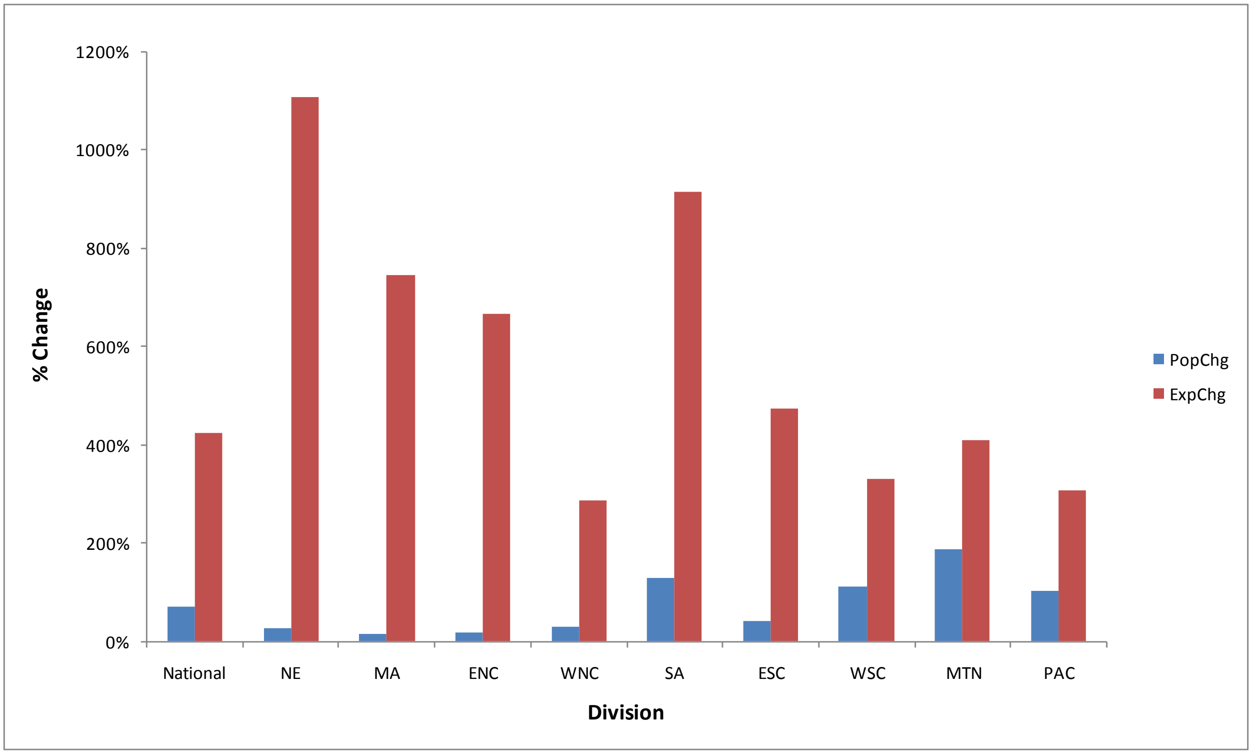

Figure 8. Projected change in population (NCAR A2 scenario) and exposure (ensemble mean) by US Census Division.

Decomposing Uncertainty

The root causes of uncertainty in exposure are of significant interest to the IAV community, and a better understanding of the drivers of exposure to extreme climate-events will inform future adaptation/mitigation action. To improve our analysis of exposure to extreme heat we attempt to decompose exposure to shed more light on the drivers of uncertainty. We begin by isolating the impacts of population and climate by recalculating exposure when one element is held constant. For example, in our constant population scenario we allow climate to vary but assume constant population over the period 1985-2055, and in the constant climate scenario we do the reverse, allow population to change but hold extreme heat days constant at their base-year levels for each of the eleven ensemble members. Finally we calculate an interaction effect, which can be thought of as the increase in exposure that results from simultaneous changes in population and climate that do not occur when one or the other is held constant.

Projected change in exposure from our constant population and constant climate scenarios are illustrated in Figure 9. In the constant population scenario change in exposure results entirely from the projected increase in days above 35°C, while in the constant climate scenario change in exposure result from population change. In the case of the former the largest increases occur in the most densely populated cities, particularly those in the South which are projected to experience the largest number of extreme heat days. Significant increases are also projected in rural regions on the South, where substantial warming drives exposure up even in areas with smaller populations. In the latter scenarios significant population growth in cities of the Southeast, Texas, California, and the Desert Southwest drive increasing exposure. Stable population coupled with a small number of extreme heat days yields a smaller projected change in the large Northeastern cities. In rural areas of the Northeast, Midwest, Great Plains, and Deep South the NCAR A2 scenario projects population loss, leading to a decrease in exposure.

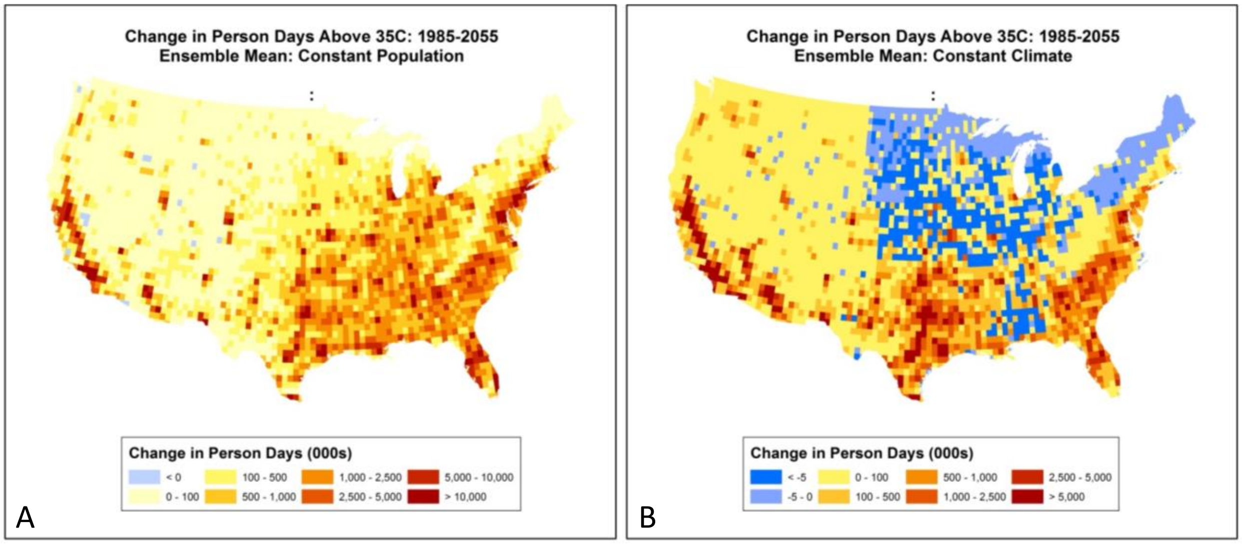

Figure 9. Projected change in exposure under the constant population (A) and constant climate (B) scenarios.

From Figure 10 we find that, at the national level, the climate, population, and interaction effects are very similar, although climate change appears to be slightly more influential than population change in driving exposure. Exposure in the constant population scenario (climate effect) is roughly 37% of total projected exposure, whereas exposure in the constant population scenario (population effect) is 29%. At the level of US Census Division (Figure 11) we find significant variation in projected total exposure, predictably very high levels in the South Atlantic and West South Central Divisions and lower levels in Northern Divisions. In the Divisions projected to experience only small population growth (e.g., New England, Mid-Atlantic) the climate effect is a far more significant drive of divisional change in exposure. In Western Divisions population change is a stronger driver of change in exposure, particularly in the Mountain Division. The degree to which climate or population drive changes in exposure varies substantially by geography, suggesting that uncertainty in exposure varies similarly.

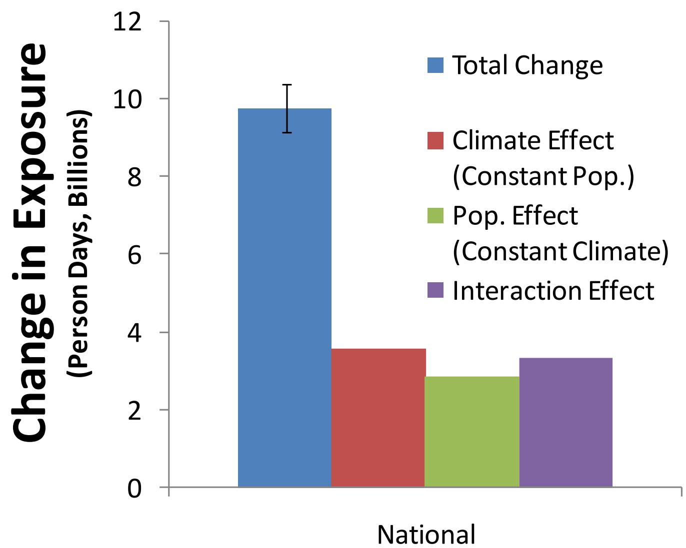

Figure 10. Decomposition of aggregate national-level projected change in exposure.

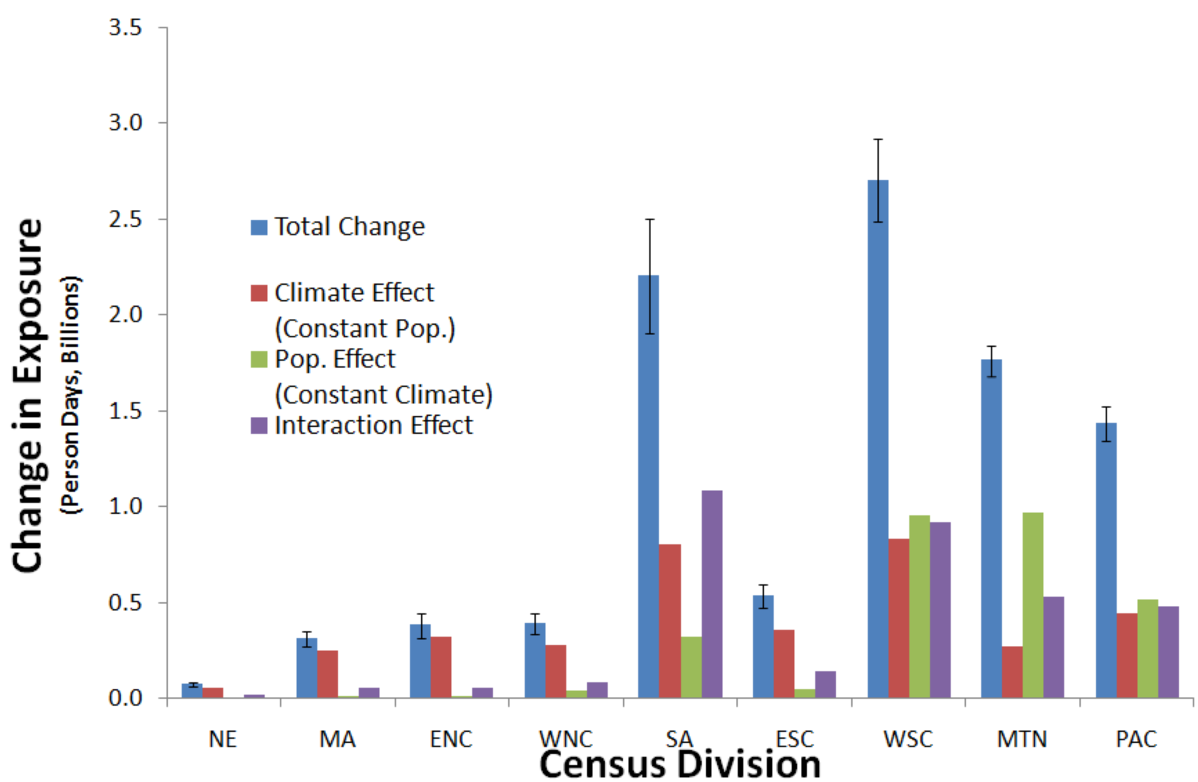

Figure 11. Decomposition of aggregate division-level change in exposure

The interaction effect is indicative of the degree to which simultaneously varying characteristics of the distribution of extreme heat days and population influence total exposure. One component of this effect is the shifting spatial distribution of the population. To isolate the importance of shifts in the spatial orientation of people over time we construct a third alternative scenario in which we allow climate to vary, but scale grid-cell population according to the national rate of change. The result is a projected distribution of exposure that includes changes in climate and aggregate population, but holds the base-year distribution of the population constant. When we compare exposure under this scenario to total projected exposure in the primary scenario (Figure 12) we find that the change in exposure is some 27% lower, indicating that projected broad-scale changes in the spatial orientation of the population (towards the South and West) is responsible for a 27% increase in exposure.

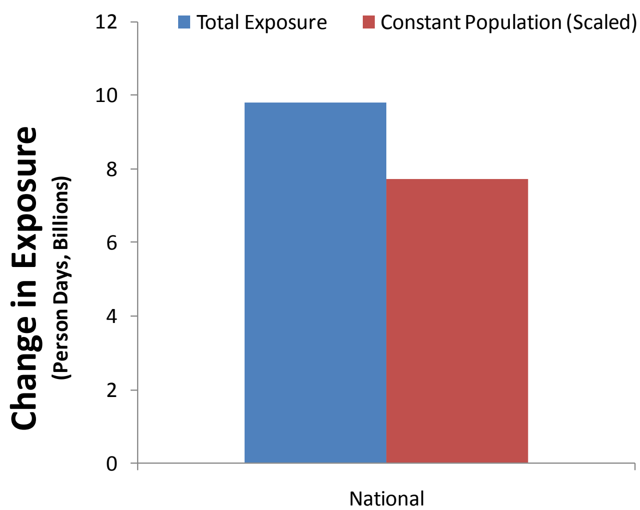

Figure 12. Projected change in exposure for (blue) NCAR A2 population scenario and ensemble mean extreme heat, and (red) scaled population scenario.

While the projected broad-scale movement of the population across census divisions (towards the divisions of the South and West) appears to have a fairly substantial impact on exposure, the projected reorientation of populations within census divisions is less significant. In a fourth scenario we allow for the broad redistribution of population between census divisions to occur as projected by the NCAR A2 scenario, but hold the spatial distribution within each division constant, again allowing climate to vary. Under this scenario aggregate national exposure is only 4% lower than in the primary scenario, and division-specific differences vary from only 0.25% in the East North Central Division to just over 12% in the Mountain Division (Figure 13). These results suggest that broad movements of the population are more significant in exposure outcomes, and thus are a greater potential source of uncertainty.

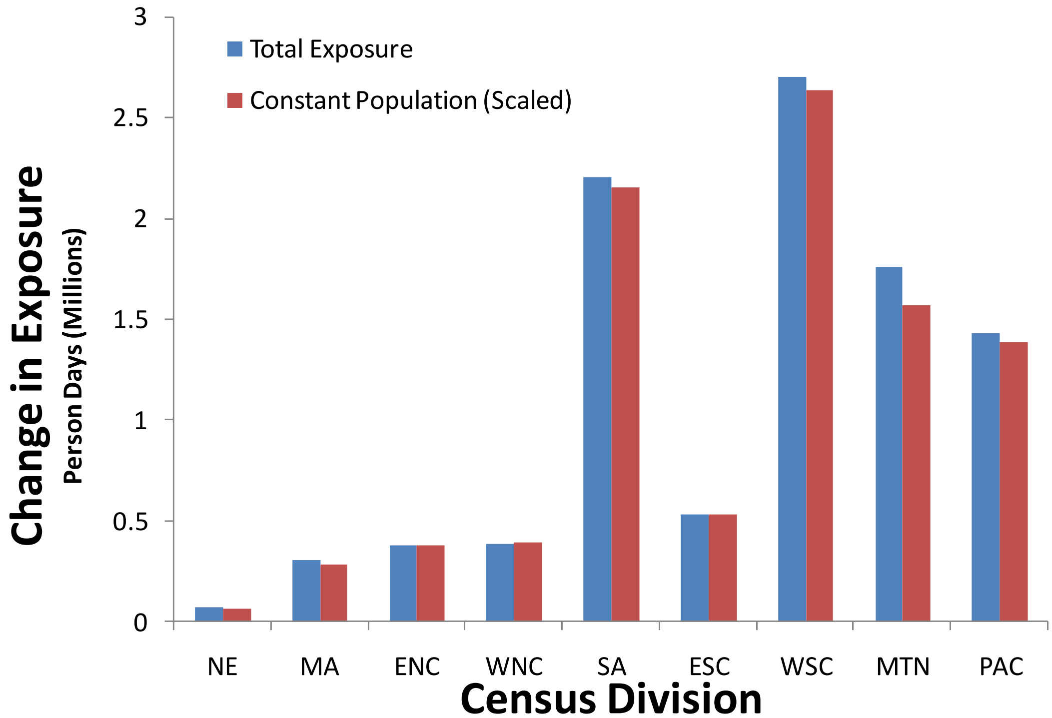

Figure 13. Projected change in exposure for (blue) NCAR A2 population scenario and ensemble mean extreme heat, and (red) scaled population scenario by census division.

Current/Future Work

Results thus far suggest that projected changes in climate and population are both important sources of uncertainty in exposure outcomes, at least for this particular extreme heat metric. There are distinct geographic patterns to the variability in climate outcomes and exposure. These patterns lead to geographic variation in the degree to which population and climate drive changes in exposure across census divisions. Broad scale population redistribution across census divisions appears more important than smaller-scale differences in population distribution such as sprawling versus more concentrated development patterns in driving exposure to extreme heat. However, a key caveat to this conclusion is that the GCM/RCM model combination that we have used does not simulate urban heat island effects, which can produce sharp differences in temperature extremes at small geographic scales. In the future we will include use of climate projections from the NCAR Community Earth System Model (CESM), which includes a representation of the urban heat island and may therefore yield significantly different conclusions. Additionally, because the NCAR population projections classify people as urban or rural, we will expand this work to consider extreme heat within the context of urban and rural populations.

In addition to considering the urban heat effect, we will enhance our investigation of uncertainty in population exposure to extreme heat by considering alternative measurements heat itself, such as wet bulb temperature and degree days. Additionally, we also intend to consider alternative climate extremes including precipitation/drought, sea-level rise, and exposure to coastal storms/flooding. The work presented thus far illustrates one methodology for assessing climate outcomes within the context of spatially explicit population projections for the purpose of informing impacts, adaptation, and vulnerability research. Additionally, this work is also a crucial step in beginning to consider how climate feedbacks may be included in future population projections.

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Appendix A: Regional Climate Models and General Circulation Models

Regional Climate Models (RCMs)		
Model	**Acronym**	**Modeling Group**
Canadian Regional Climate Model	CRCM	OURANOS / UQAM
Experimental Climate Prediatiction Center Regional Spectral Model	ECP2	UC San Diego / Scripps
Hadley Regiona Model 3	HRM3	Hadley Centre
PSU/NCAR Mesoscale Model	MM5I	Iowa State University
Regional Climate Model v3	RCM3	UC Santa Cruz
Weather Research & Forecsting Model	WRFG	Pacific Northwest National Lab
General Circulation Models (GCMs)		
Model	**Acronym**	**Sponsor**
Community Climate System Model	CCSM	National Center for Atmospheric Research
Third Generation Coupled Global Climate Model	CGCM3	Canadian Center for Climate Modeling and Analysis
Geophysical Fluid Dynamics Laboratory GCM	GFDL	National Oceanic and Atmospheric Administration
Hadley Centre Coupled Model v3	HADCM3	Hadley Centre

Source: http://www.narccap.ucar.edu/data/model-info.html