Final Report
DOE Grant: Demographic Tools for Climate Change and Environmental Assessments

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This report summarizes work over the course of a three-year project (2012-2015, with one year no-cost extension to 2016). The full proposal detailed six tasks:

Task 1: Population projection model
Task 2: Household model
Task 3: Spatial population model
Task 4: Integrated model development
Task 5: Population projections for Shared Socio-economic Pathways (SSPs)
Task 6: Population exposure to climate extremes

We report on all six tasks, provide details on papers that have appeared or been submitted as a result of this project, and list selected key presentations that have been made within the university community and at professional meetings. The team on this proposal includes PI Brian O'Neill as well as scientists Leiwen Jiang (Task 1, 2, 4 and 5) and Bryan Jones (Tasks 3, 4, 5 and 6), and graduate research assistants Galen Maclaurin (Task 3), Raphael Nawrotzki (Task 1), and Hamid Zoraghein (Tasks 2, and 4).

Task 1: Population projection model

The goal of this task is to develop a global model for projecting population by age, sex, and urban/rural status in 31 world regions. This task has been completed, resulting in two publications on a required data product, with a first publication of the model (and code) currently in preparation (Jiang and Nawrotzki, in prep.). The model is novel relative to most existing projection models in that it explicitly distinguishes urban and rural populations and includes their separate age structures. Combining urban/rural residence and age structure can be important for both energy and land use projections as well as for vulnerability to climate impacts.

To achieve these goals, key data were obtained on population, fertility, mortality, and migration necessary for producing the global population projection model. An important and novel component of the data was the construction of estimated international migration flows between our model regions, published in Nawrotzki and Jiang (2014, 2015). This work involved compiling the age and sex profiles of the number of migrants living in each region and using these data to estimate the age and sex profiles of migration flows between regions. These data were incorporated into the projection model, which allowed us to correctly account for variations in age and gender characteristics of migrants across different regions of the world. These variations can have significant effects on the population composition and growth rates in the main sending and receiving regions.

The model itself was coded in the R language, a freely available programming language in wide use in the research community, in order to facilitate use of the model by other research groups. The structure of the model improves on most existing population projection models not only by treating urban and rural populations separately, but also in two additional, significant ways: we have incorporated changes in the age and gender profile of both fertility and mortality as levels of these variables change over time. This is an important feature often left out of standard population models. Data indicate that as total fertility rates (TFRs) fall, the average age of childbearing first falls and then increases as TFR falls below about 2.0. We have included this dynamic by employing the Brass Relational Gompertz Model and the Zeng et al (2000) extension of the Brass Model, combined with data from the Human Fertility Database, to model the relationship between changes in TFR and changes in the median age and interquartile range of childbearing. Similarly, data also indicate that as life expectancies increase, the age profile of mortality changes as well. We employed the Brass Relation Model, combined with data from the Human Mortality Database and UN Population Division, to model the relationship between changes in life expectancy and changes in age specific mortality rates. These new model features significantly improve the projection of not only total population size, but more importantly the age composition of the population.

The projection model was used to produce projections consistent with the population assumptions in the Shared Socioeconomic Pathways (SSPs; Jiang and Nawrotzki, in preparation). It can be run in two ways regarding urbanization assumptions. Either rural-urban migration rates can be supplied as assumptions and urbanization outcomes calculated, or the projected national percent urban can be supplied as a desired outcome and the model will solve for the required migration rates to produce such an outcome. The latter approach was taken in order to reproduce the SSP scenarios for population and national percent urban, for 31 regions. This projection adds a new dimension to the existing SSP information: the distribution of age- and gender-specific population by rural/urban residence. Figure 1 illustrates this result, showing the urban and rural fractions of the population above age 65. Validation analysis against UN Population Prospects revisions and IIASA population projections indicates that the model performs well. Results show that there are striking differences in many regions between age structures of urban and rural population. For example, in the South Africa (ZAF) and Rest of Southern Africa (RSF) regions, around 70% or more of the rural population is above age 65 by the end of the century in SSP1, while the figure is about 45% in urban areas.

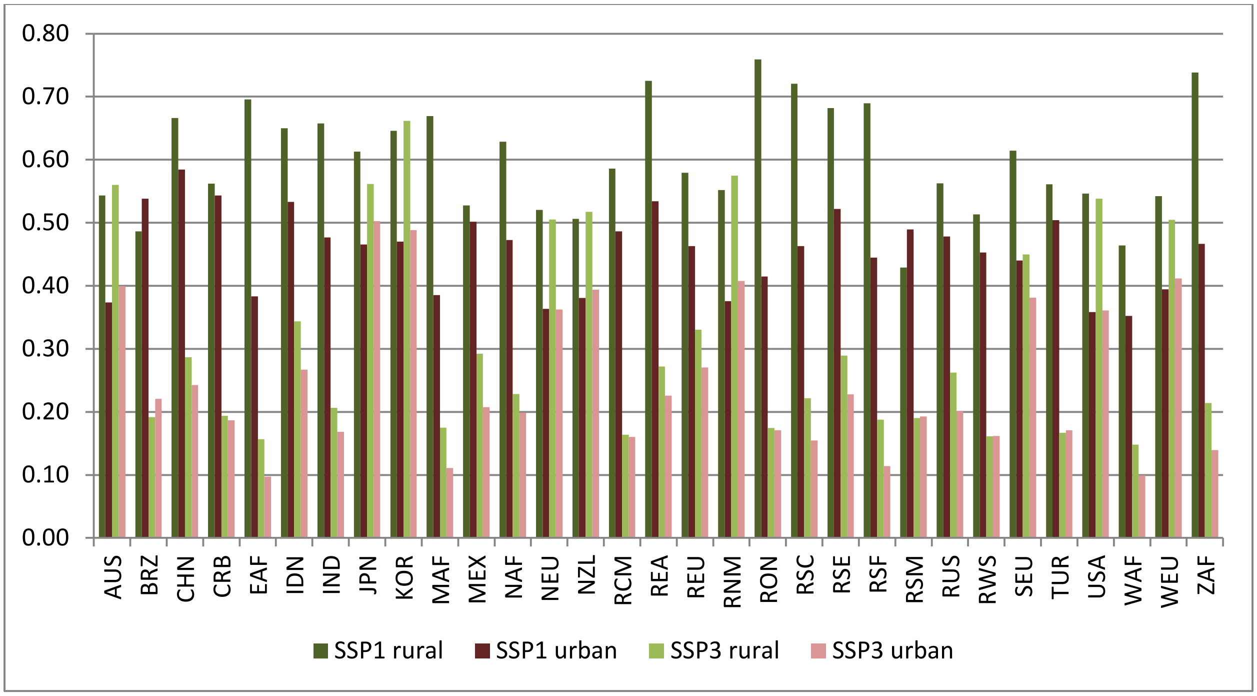

Figure 1. Projected proportion of the urban and rural populations above age 65 for 31 regions, 2100, for SSP1 and SSP3 (Jiang and Nawrotzki, in preparation).

Note: AUS - Australia, BRZ - Brazil, CHN - China, IND - India, IDN - Indonesia, JPN - Japan, KOR - Korea, MEX - Mexico, NZL - New Zealand, RUS - Russia, ZAF - South Africa, TUR - Turkey, USA - USA, EAF - Eastern Africa, MAF - Middle Africa, NAF - Northern Africa, WAF - Western Africa, CRB - Caribbean, NEU - Northern Europe, SEU - Southern Europe, WEU - Western Europe, RNM - Canada and Rest of N. America, REA – Rest of Eastern Asia, RON - R. Oceania, RSF - R. Southern Africa, RCM - R. Central America, RSE - R. South-Eastern Asia, RSC - R. South-Central Asia, RWS - R. Western Asia, REU - R. Eastern Europe, RSM - R. South America.

Task 2: Household model

The goal of this task is to improve our existing extended headship rate model by obtaining and using additional household survey data to improve our regional coverage. The original dataset included household headship rates for rural-urban areas of 30 countries, and an additional 25 countries without urban-rural distinction, derived from the IPUMS data. This task was completed and resulted in extending our coverage from 55 to 80 countries. In addition, we updated the data for 6 of the previously existing countries in our database. We purchased (or obtained for free) national household survey data from 22 countries (China, Korea, Iraq, South Africa, Tanzania, Malawi, Nigeria, Ethiopia, Ghana, Kenya, Albania, Serbia, Tajikistan, Guatemala, Panama, Papua New Guinea, Philippines, Indonesia, Vietnam, Nepal, Pakistan, and Russia), and we are in the process of acquiring a dataset from Malaysia,.

Using the obtained datasets, we derived and improved extended headship rates and applied them in the household model to project household changes in rural and urban areas of global regions for all five SSPs (see Figure 2; Jiang and Zoraghein, in preparation). As shown in the figure, there is the potential for wide variation in household living arrangements; for example, the number of elderly people living alone in urban areas (an at-risk population for climate hazards) can vary by a factor of about 3 across SSPs. -

We also studied the relationships between changes in age- and gender-specific headship rates and general demographic events (total fertility rates and life expectancy at birth). These relationships could inform future work that would improve our static headship rate model by allowing for changes in headship rates over time as fertility and life expectancy change.

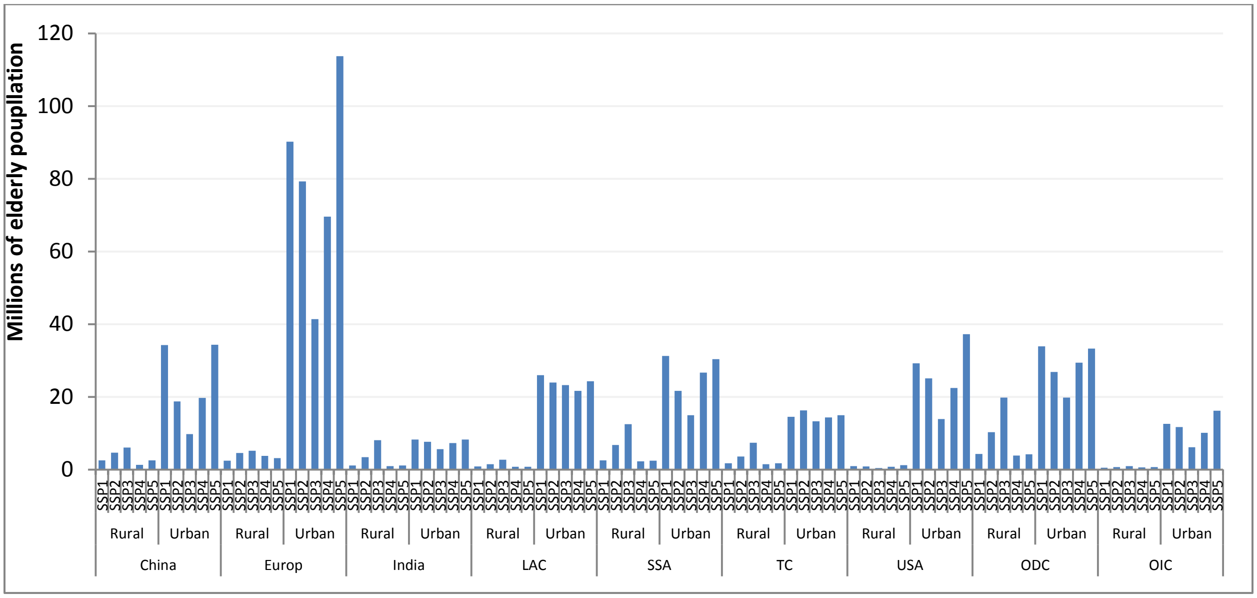

Figure 2. Projected number of elderly population (aged 60+) living alone in the rural and urban areas of global regions, in 2100, under different SSPs; from Jiang and Zoraghein, in preparation. Note: LAC-Latin America and the Caribbean, SSA-Sub Saharan Africa, TC-Transitional Economies, ODC-other developing countries, OIC-other industrialized countries

Task 3: Spatial Population Model

The primary goal of Task 3 is to extend our existing spatial population model from a single country (the US) to the world, primarily by developing new historical spatial population datasets in countries beyond the US to allow the model to be calibrated for other world regions.

This task was achieved through two parallel tracks (use of the model to produce new global projections, and publications based on them, is discussed in Task 5). First, we took a fast-track strategy in which we used existing global datasets that, while they cover a shorter historical period, have comprehensive global coverage that can support production of global projections relatively quickly. Second, we started a refined strategy that produced a new set of more detailed historical gridded data covering a longer time period (and more consistent over time) for a representative sample of countries across different world regions, levels of development, and socio-economic characteristics that affect patterns of spatial population change. This second set of data will eventually be used to improve projections based on the fast-track data.

Development of the fast-track data required compiling gridded population data from existing sources (Gridded Population of the World (GPW) version 3) for 1990 and 2000, classifying population as urban or rural, and ensuring consistency with aggregate county-level urbanization data from the UN. This task was achieved (see description of data in Jones & O'Neill, 2016) and included overcoming a key problem with available data: while population data for 1990 and 2000 are independent, the urban extent used in both these years is identical and based on data from 1995 (from the Global Rural Urban Mapping Project, GRUMP; CIESIN, 2005). Because our projection methodology uses urban extent data to distinguish urban and rural populations, these data produced spatial distributions of urban population that differed very little between 1990 and 2000. As a consequence, calibrating our model to observed change between 1990 and 2000 led to parameter estimates that produced very concentrated urban development as opposed to dispersion or sprawl. To address this problem, we constructed a new global set of urban extents that correspond to 1990 and 2000 by first calculating the country-specific urban population density using the urban extent data for 1995, then calculating the urban extent that would be required in 1990 and 2000 to replicate 1995 urban population density. The result is a country-specific scaling factor which we use to systematically shrink (going back to 1990) and grow (out to 2000) the GRUMP urban extents. Use of this data to produce projections is described in Task 5.

We also made substantial progress toward our refined strategy by developing improved sets of gridded population data for Brazil and India. We have now completed gridded distributions of the 1991, 2001, and 2011 Brazilian population, and the 1991 and 2001 Indian population. We also began additional refinements to our methodology to further improve estimates of urban extent (i.e., urban land cover), and work is also underway on producing historical gridded distributions for China.

The key methodological refinements to the gridding process that we made in this project include the use of additional high resolution inputs (including point-based data for smaller urban and rural settlements), an improved methodology for constructing dynamic urban extents to aid in the classification of population as urban or rural, and the development of a detailed algorithm for systematically merging census-based urban and rural population counts with spatial data to produce high resolution gridded urban and rural population counts. Figure 3 compares our new dataset for the 1991 population in the Sao Paulo-Curitiba region of Brazil to the data from the Gridded Population of the World (GPW), a widely used current data product. Note the larger number of small urban nodes and more detailed rural distribution in the NCAR data, a function of using improved spatial inputs (e.g., additional settlement points and urban extents) and aggregate urban/rural census-based population counts. These refinements are critical to producing plausible projections of changes in future urban and rural populations.

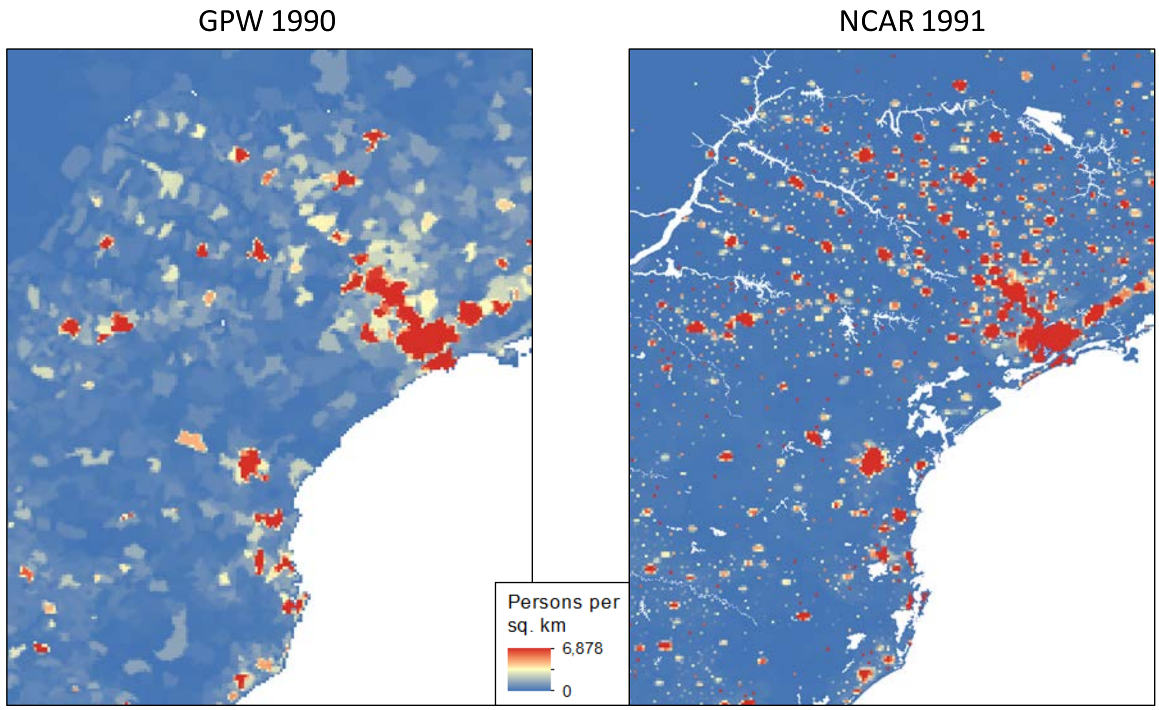

Figure 3. Gridded distribution of the population in the Sao Paulo – Curitiba region of Brazil; (a) 1990 – GPW and (b) 1991 – NCAR.

Task 4: Integrated model development

The goal of this task is to ensure that the different components of the Community Demographic Model (CDM) can function as a single integrated tool written in an open source programming language. Much of this task was completed. All components of the model have been rewritten either in the R or Python languages (Jiang et al., in preparation). The multiregional population/urbanization projection model (Task 1), our national-level urbanization model (developed outside this project), and the household projection model (Task 2) have been rewritten in R, tested, and will be posted online as part of the publicly available CDM. For the spatial downscaling model, we have chosen to convert this model, which was operating largely within a GIS framework, into Python. This choice was made because Python is more compatible with GIS systems, which are likely to be employed by many users interested in obtaining and working with our spatial projections, and also because it is more convenient for integration with an urban land cover model we are also developing (in a separate project) in Python. Python, like R, is an open source language and easily integrated with R, so we can still achieve our goals of a unified tool for making internally consistent demographic projections, and for making code publicly available in a language that is freely available to all users.

Task 5: Population projections for Shared Socio-economic Pathways (SSPs)

The goal of Task 5 is to expand on our recently completed spatial population projections for the US to produce global projections. We have completed this task by producing and publishing (Jones & O'Neill, 2016) a new set of global spatial population scenarios consistent with the national-level population and urbanization projections from the newly developed Shared Socio-economic Pathways (SSPs).

These scenarios were based on the fast-track global population data developed in Task 3. Using those data, we estimated urban and rural model parameters for representative countries for each world region, applied a geospatial mask to limit habitable land, and then used the model to produce 100-year scenarios for each SSP (Figure 4). SSP-based scenarios were differentiated from each other by choosing model parameter estimates that were representative of the spatial patterns of change implied by the qualitative narratives corresponding to each of the SSPs for each world region. That is, for regions in which a particular SSP specified sprawling development, we chose parameters estimated from countries and historical time periods in which such development took place. This allowed us the flexibility to represent different patterns of development in different scenarios but to remain grounded in historical experience.

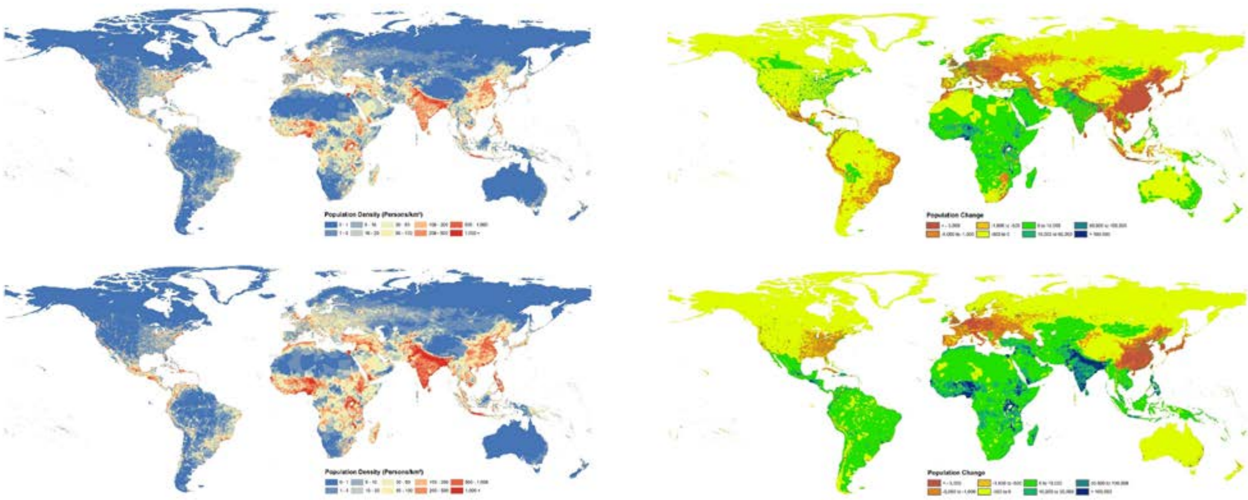

Figure 4. Global spatial population distribution for SSP1 (top) and SSP3 (bottom) from the new spatial model (Jones & O'Neill, 2016).

Task 6: Population exposure to climate extremes

The goal of this task is to apply global spatial projections/scenarios developed in Task 5 to estimate exposure to climate extremes. We achieved this task by first piloting the approach with a study we published (Jones et al., 2015) on the US, using spatial population projections for the United States (Jones and O'Neill, 2013) and projected heat waves from the North American Regional Climate Change Assessment Program (NARCCAP). Second, we have recently completed a global exposure analysis (Jones et al., in prepration) that combines our global spatial population projections with global projections of heat extremes from the CESM model.

In the US analysis, we used eleven NARCCAP climate projections, each of which was created by a unique combination of a general circulation model (GCM) and regional climate model (RCM). In this work we considered exposure to extreme heat, which we defined as a daily high temperature above 35°C. We calculate exposure to extreme heat by multiplying the projected population in each grid cell by the corresponding projected annual number of days above 35°C from the NARCCAP data. To control for inter-annual and decadal variability, we average climate (and population) outcomes over 30-year periods; to control for bias in the climate models, we bias correct all model results using a quantile mapping approach. We compare future outcomes for 2040-2070 to recent outcomes for 1970-2000.

A spatially explicit distribution of the change in exposure to extreme heat was calculated for each of the eleven GCM-RCM combinations, and from these results we calculated an ensemble mean. Figure 5 illustrates the spatial distribution of the mean change in days above 35°C, population change, and change in exposure. We find from this analysis that aggregate exposure to extreme heat increases over this period by a factor of 4 to 6. This change in exposure varies geographically, and is driven by both climate change and population change.

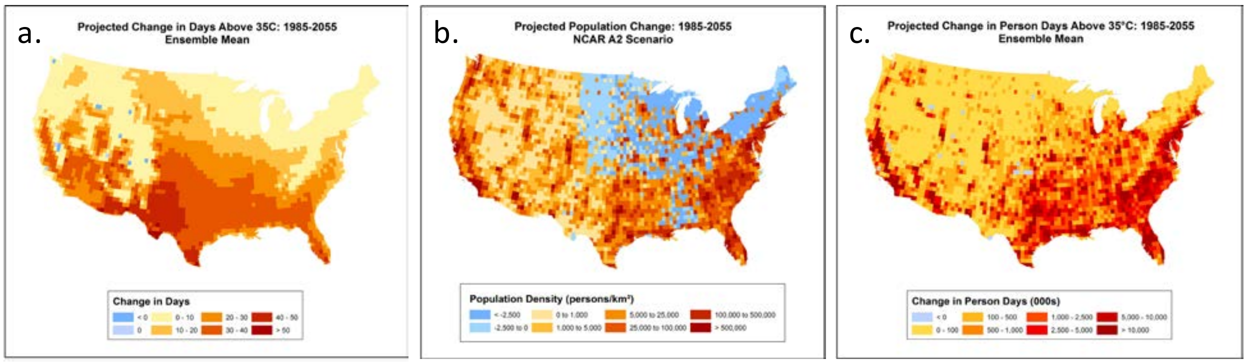

Figure 5. Projected change in (a) days above 35°C, (b) population, NCAR A2-Scenario, and (c) exposure. From Jones et al., 2015.

In the global analysis, we combined our global projections for SSPs 3 and 5 with initial condition ensembles of CESM projections of heat waves for RCPs 8.5 and 4.5. The ensemble approach to the climate modeling allowed us to account for natural variability, which could make any particular year or decade warmer or cooler than the long-term trend. Results showed that exposure to heatwaves increased substantially in both RCPs (Figure 6), and that mitigation climate change to the level in the lower forcing RCP4.5 scenario can have substantial benefits, with a global reduction in exposure of over 50% in RCP4.5 scenarios relative to RCP8.5, regardless of SSP. The population scenario also matters, with a slower population growth pathway (SSP5) leading to roughly 30% less exposure relative to SPP3 in both the RCP4.5 and RCP8.5 scenarios. At the regional level results vary in terms of relative reduction in exposure, but in almost all cases the RCP remains more influential than the SSP. We also find that uncertainty in outcomes is dominated by inter-annual variability in heat extremes (relative to variability across initial condition ensemble members) and that, 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.

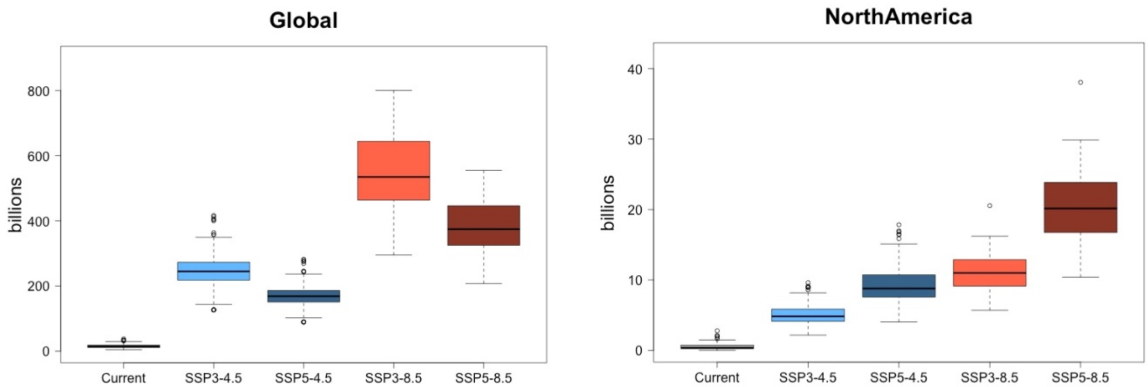

Figure 6. Population exposure to heat waves in billion person-days, for current conditions as well as for RCPs 8.5 and 4.5, assuming population follows projections in either SSP3 or SSP5. Globally aggregated results (left panel) and results aggregated for North America (right panel). From Jones et al., in preparation.

Publications

Jiang, L., Nawrotzki, R., in preparation, Urban and rural population projections for global regions consistent with Shared Socioeconomic Pathways.

Jiang, L., Zoraghein, H., in preparation, Global and regional household projections under Shared Socioeconomic Pathways.

Jiang et al., in preparation, Integrated Community Demographic Model for climate change and environmental studies.

Jones, B. and O'Neill, B. (2013) Historically grounded spatial population projections for the continental United States. *Environmental Research Letters*, 8(4):044021.

Jones B., O'Neill B.C., McDaniel L., McGinnis S.A., Mearns L.O., Tebaldi C. (2015) Future population exposure to US heat extremes. Nature Climate Change, 5, 652-655. DOI: 10.1038/nclimate2631.

Jones, B. (2014) Assessment of a gravity-based approach to constructing future spatial population scenarios. *The Journal of Population Research*. DOI 10.1007/s12546-013-9122-0.

Jones B., O'Neill B.C. (2016) Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways. *Environmental Research Letters*. DOI: 10.1088/1748-9326/11/8/084003.

Jones, B., Tebaldi, C., O'Neill, B.C., Oleson, K., Gao, J. Avoiding population exposure to heat-related extremes: Demographic change vs climate change. In preparation for *Climatic Change*.

Nawrotzki, R., and Jiang, L. (2014) Community Demographic Model International Migration (CDM-IM) Dataset : Generating Age and Gender Profiles of International Migration Flows. *NCAR Technical Note* NCAR/TN-508+STR, 41 pp, DOI:10.5065/D6NS0RV2.

Nawrotzki R. and Jiang, L. (2015) Indirectly Estimating International Net Migration Flows by Age and Gender: The Community Demographic Model International Migration (CDM-IM) Dataset. *Historical Methods*. 48(3), 113-127.

Selected Key Presentations

Progress and outcomes from this project were presented at IAM community meetings such as the Snowmass IAM/IAV annual meeting, the Integrated Assessment Modeling Consortium annual meeting, and at the MIT and JGCRI research groups. They have also been presented at demographic disciplinary meetings such as the Population Association of America and at the United Nations.

Jiang, L., and Nawrotzki, R. International migration in NCAR Community Demographic Model (CDM). Invited talk at Joint KNOMAD-UN Population Division Seminar on the role of migration in population modeling. New York, April 29, 2014.

Jiang, L. and O'Neill, B. Global alternative long-term urbanization projections. Presented in Session 122 of Population Association of America annual meeting, April 30-May 3, 2014, Boston.

Jones, B. A Gravity Based Approach to Modeling Spatial Population Scenarios, *Center for Climate Systems Research, Columbia University/NASA GISS,* New York, NY. June 21, 2013

Jones, B. An Improved Method for Projecting Spatial Population, *Workshop on Climate Change Impacts and Integrated Assessment: Critical Issues in Climate Change,* Snowmass Village, Colorado. July 25, 2012.

Jones, B. A Potential-Based Approach to Modeling Spatial Population Scenarios, *MIT Joint Program on the Science and Policy of Global Change,* Cambridge, Massachusetts. August 10, 2012.

Jones, B. A Gravity Based Approach to Modeling Spatial Population Scenarios, *Joint Global Change Research Institute,* College Park, Maryland. January 29, 2013.

Jones, B. Historically Grounded Spatial Population Scenarios for the Continental United States, Annual Meeting of the Population Association of America, Boston, MA. May 1, 2014.

Jones, B. Determinants of Uncertainty in Population Exposure to Climate-Related Extremes, Annual Meeting of the Population Association of America, Boston, MA. May 2, 2014.

Nawrotzki, R., and Jiang, L. The indirect estimation of international migration flows by age and gender, Presented in Session P4 of Population Association of America annual meeting, April 30-May 3, 2014, Boston.

O'Neill, B.C. (26 February 2016) Demographic futures: New projections and their use in climate change research, University of Washington Center for Demography and Ecology, Seattle, WA.

O'Neill, B.C. (2 December 2015) Demographic futures: New projections and their use in climate change research, UC Berkeley Department of Demography, Berkeley, CA.

O'Neill, B.C. (28 Oct 2013) Determinants of uncertainty in population exposure to climate-related extremes. Annual Meeting of the Integrated Assessment Modeling Consortium (IAMC), Tsukuba, Japan.