METHODOLOGY

Climate Projections

The climate projection methodology is described in full in Rasmussen et al. (2016). The climate projections shown are based on Representative Concentration Pathway (RCP) 4.5 and 8.5 (van Vuuren et al., 2012) experiments run by global climate models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) exercise (Taylor et al., 2012). RCP 4.5 represents a moderate scenario, in which countries achieve their current pledges to the Paris Agreement and global greenhouse gas emissions peak around mid-century, while RCP 8.5 represents a scenario in which global emissions continue to climb to high levels for the rest of the century. The Climate Impact Lab used downscaled CMIP5 climate projections prepared by the US Bureau of Reclamation (Brekke et al., 2013). This dataset is bias-corrected and downscaled using the Bias-Correction Spatial Disaggregation (BCSD) method (Thrasher et al., 2012).

CMIP5 projections do not inherently constitute a probability distribution; rather, they are an ensemble of runs conducted by climate modeling teams participating on a voluntary basis and running models that roughly represent 'best-estimate' projections of climate behavior. To produce a probabilistic ensemble that captures the full range of climate responses to greenhouse gas emissions, the Climate Impact Lab used the Surrogate Model/Mixed Ensemble (SMME) method of Rasmussen et al. (2016). This method weights projections by comparing their global mean surface temperature projections to those of a probabilistic simple climate model, in this case (as in Rasmussen et al., 2016) the MAGICC6 model (Meinshausen et al., 2011). The target global mean temperature distributions for 2080-2099 used were identical to those of Rasmussen et al. (2016). As in that paper, potential temperature outcomes produced by the probabilistic simple climate model but not represented within the downscaled CMIP5 dataset were represented by simulated 'model surrogates', produced using linear pattern scaling. Pattern scaling involves computing a statistical relationship between global average temperature change and local temperature change around the globe in select global climate models, which is used to develop a distribution of high-resolution daily climate variables.

The gridded projections were aggregated to regional estimates by first transforming the daily min, average, or maximum temperature at the grid scale, then aggregating to regions using a weighted average. Annual average temperatures are weighted using the shares of each region's land area within each grid cell; estimates of days above 95°F/35°C and below 32°F/0°C are weighted using the shares of each region's population within each grid cell.

The Climate Impact Lab's future research priorities include updating this climate information to be consistent with the most recent cycle of the Coupled Model Intercomparison Project (CMIP6). As part of CMIP6, the Intergovernmental Panel on Climate Change developed a novel tool for flexible spatial and temporal analyses of much of the observed and projected climate change information underpinning its Sixth Assessment Report. Visit the Interactive Atlas and explore the latest CMIP6 climate data: https://interactive-atlas.ipcc.ch/

Damage Projections

Mortality impacts

The methodology for estimating the mortality impacts of future climate change is described in full in Carleton et al. (2022). This study uses comprehensive historical mortality records to quantify how death rates across the globe have been affected by observed weather variation. Carleton et al. (2022) compile the largest sub-national vital statistics database in the world, detailing hundreds of millions of deaths across 40 countries accounting for 38 percent of the global population. By combining these records with decades of daily and local temperature observations, the authors show that extreme cold and extreme heat have important effects on death rates, consistent with prior epidemiological and econometric evidence covering more limited regions. These relationships are then found to be strongly modified by the existing climate and income levels of the affected population. For example, higher incomes and warmer average climates correspond to lower death risks of heat. Carleton et al. (2022) use these results to develop a statistical model quantifying how observed levels of adaptation influence the sensitivity of a population to extreme temperatures.

Estimates of the mortality-temperature relationship are used to generate projections of the future impacts of climate change on mortality rates for areas across the globe, dividing the world into 24,378 distinct regions (each containing, on average, 300,000 people). Using a revealed preference technique to additionally measure the total *cost* of adaptive behaviors and technologies, these projections capture the full mortality risk of climate change, accounting for both adaptation costs and direct mortality impacts shown in the platform.

Here we present climate change's estimated impact on mortality rates based on emissions scenarios RCP 4.5 and RCP 8.5, socioeconomic scenario SSP3 (from the IIASA Shared Socioeconomic Pathways database) and using climate model-weighted means over 33 climate models and 1,000 Monte Carlo simulation runs, allowing for an assessment of the uncertainty surrounding any particular projection. These estimates therefore reflect statistical uncertainty related to the underlying economic and health data as well as climatological uncertainty.

Energy consumption impacts

The methodology for estimating the energy consumption impacts of future climate change is fully described in Rode et al. (2021). This study uses comprehensive historical energy consumption data derived from International Energy Agency data files to quantify how a population's use of electricity and other fuels (for example, natural gas, oil, and coal) energy consumption responds to climate changes. The authors utilize the World Energy Balances dataset of the International Energy Agency, which describes electricity and direct fuel consumption across residential, commercial, industrial, and agricultural end-uses in 146 countries during 1971-2010.

By combining these records with decades of detailed daily and local temperature observations, the authors discover that extreme cold and extreme heat have important effects on energy consumption. These relationships differ by energy type (electricity, other fuels) and are modified by the income levels and climate of the affected population. The study uses these results to model how income growth and adaptation affect the sensitivity of energy consumption to extreme temperatures.

The authors then use these estimates of the energy-temperature relationship to generate projections of the future impacts of climate change on electricity and direct fuel consumption for areas across the globe, dividing the world into 24,378 distinct regions. Each region contains roughly 300,000 people. The projected impacts capture the effects of adaptive behaviors that populations undertake as they become richer and exposed to warmer climates.

Here we present climate change's estimated impact on energy consumption based on emissions scenarios RCP 4.5 and RCP 8.5, socioeconomic scenario SSP3 (from the IIASA Shared Socioeconomic Pathways database) and using climate model-weighted means over 33 climate models and 1,000 Monte Carlo simulation runs, allowing for an assessment of the uncertainty surrounding any particular projection. These estimates therefore reflect statistical uncertainty related to the underlying economic and health data as well as climatological uncertainty.

Labor impacts

The methodology for estimating the labor impacts of future climate change is fully described in Rode et al. (2022). Evidence shows that workers in agriculture, construction, manufacturing, transport, and utilities (i.e., high-risk sectors) reduce their hours worked when outdoor temperatures deviate from average temperatures. This study uses individual work hours data from time-use surveys and labor force surveys for seven countries, representing nearly one-third of the global population, and daily variation in the weather to econometrically evaluate the impact of daily temperature on labor supply. The labor response is estimated to be an inverted U-shaped relationship, with lost labor occurring at extreme hot and cold temperatures for high-risk, weather-exposed sectors. The relationship is similar, though the impacts are smaller in magnitude for low-risk sectors.

The authors then use these estimates of the labor supply-temperature relationship to generate projections of the future impacts of climate change on time spent working in high-risk and low-risk sectors for areas across the globe, dividing the world into 24,378 distinct regions. Each region contains roughly 300,000 people. The projected impacts capture predicted shifts in the global workforce towards less weather-exposed industries as populations become richer and exposed to warmer climates.

Here we present climate change's estimated impact on the labor supply based on emissions scenarios RCP 4.5 and RCP 8.5, socioeconomic scenario SSP3 (from the IIASA Shared Socioeconomic Pathways database) and using climate model-weighted means over 33 climate models and 1,000 Monte Carlo simulation runs, allowing for an assessment of the uncertainty surrounding any particular projection. These estimates therefore reflect statistical uncertainty related to the underlying economic and health data as well as climatological uncertainty.

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