Climate Impact Lab

Estimating the Frequency of 90 Degree Days

While climate science has improved dramatically in recent years, predicting the severity and timing of future impacts remains a challenge – particularly at the local level.

One of the largest sources of uncertainty in projecting future changes in the climate change is socioeconomic. However, even if we knew how society's emissions rates would evolve with absolute certainty, we would still not be able to predict future warming precisely. To generate projections of temperature and precipitation underlying our effort to quantify the economic impacts of climate change, we combine projections of the probability of different levels of global average temperatures under different Representative Concentration Pathways (RCPs) from a simple climate model (SCM) with detailed projections from advanced global climate models (GCMs).

Decades of study have resulted in better measurements, instruments, data protocols, and more sophisticated models of the complex and vast climate system. Many of the key advances in climate knowledge have come from large, international, cooperative efforts by climate modeling teams. Some of the most sophisticated and high-resolution projections come from the ensemble of models in the Coupled Modeled Intercomparison Project, which has completed its fifth phase (CMIP5). This suite of GCM simulations has become the gold standard for use in global climate assessments, including by the Intergovernmental Panel on Climate Change (IPCC). These GCMs represent the statistics of weather under imposed boundary conditions, like atmospheric GHG concentrations or solar intensity, and simulate detailed earth system dynamics, typically operating at a 1-degree or 2-degree grid (70-150 miles at the mid-latitudes). They include an ever-more comprehensive set of components of the climate system: atmosphere, ocean, sea ice, land, and, in many cases, the carbon cycle.

Because of the complexity and vastness of this system and its interactions, and the limitations of computing power, certain trade-offs exist in how climate is modeled. Unlike a weather forecast model -- which has a higher spatial resolution, assimilates observed weather data, and is run for a short time period -- GCMs are not constrained to match natural variation in short-run surface observations. The coarse geographic resolution of these models also fails to capture local meteorological phenomena, such as the urban heat-island effect and small-scale land-sea interaction. Instead, GCMs are designed to represent the changing dynamics of weather systems at all points in the atmosphere and oceans. This monumental task leads to additional trade-offs that, in conjunction with the complexity of numerically solving the climate system, can result in persistent errors or "biases" in GCM representation of specific land-surface variables.

Evidence-based, data-driven inputs

Historical weather data used in today's analysis comes from gridded temperature observations from Berkeley Earth Daily Land 1-degree x 1-degree Latitude-Longitude Grid. We add finer detail to each grid cell through a process called "downscaling." We downscale the Berkeley Earth data using a historical high-resolution dataset from Princeton called the

Global Meteorological Forcing Dataset for land surface modeling, which combines historical reanalysis model output with observational products such as station and satellite data.

We also need to enhance the resolution of GCM projections. With respect to time, GCMs offer the precise measurement that we need to estimate with high frequency the local effects of climate change, described as temporal resolution. However, with respect to geography, GCM projections lack the spatial resolution to assess impacts at a local level. We need both rich spatial and temporal information to effectively study the relationship between human systems and the climate.

To produce projections, we draw on a dataset that employs a particular downscaling technique called bias-correction and spatial disaggregation (BCSD). Our raw climate projections come from NASA NEX-GDDP (project 1356) Global Daily Downscaled Climate Projections. The NASA NEX-GDDP archive includes CMIP5 projections downscaled and bias corrected to Princeton's historical high-resolution dataset using BCSD. To maintain consistency with our historical dataset, we then further correct NASA NEX-GDDP to station observations by substituting the climatological (long-run) mean 1990 – 2010 temperature from the GCMs with that of Berkeley Earth by grid cell and day-of-year. The BCSD method applied to NASA NEX-GDDP corrects biases in mean and variance in temperature and precipitation by calendar month and grid cell through "quantile mapping." It involves three steps:

1. **Identify biases in GCMs by comparing their historical simulations to the gridded observationally-derived dataset:** the probabilities of GCM temperature and precipitation in the historical simulations were compared to observed values at those probabilities from the Princeton high resolution dataset. This mapping was used to remove biases in historical and projection simulations (see Step 2).

2. **Remove biases from global climate model projections:** The NEX-GGDP team computed cumulative distributions (CDF) of observed values and historical climate model simulations over a historical time period to create a map for each grid cell and month of the year. For example, if the probability of a GCM temperature in a given month and grid cell is 0.10, its value is replaced with the observed station 0.10 temperature value for that month and grid cell. Temperature data was first detrended, due to the quasi-normal nature of the distribution of local temperatures, while precipitation was not.

3. **Downscale resulting projections to finer resolution:** the bias corrected GCM temperature was downscaled by the NEX-GDDP team to 1/4° spatial resolution by adding fine spatial detail from Princeton's GMFD.

At the end of this process, we have a daily time series of high spatial resolution temperature, precipitation and other climate variables with the same mean and variance as historical observations.

We estimate the number of days over 90 degrees Fahrenheit by counting the number of days per year in which the daily maximum temperature in the datasets described above meet or exceed 90F. We first remove observations for February 29 on leap years, to ensure each year's count is of a consistent 365-day total. After calculating the days above 90F in each year, we perform a rolling 21-year average, centered on the reported year, to ensure that we are reporting true shifts in climate rather than annual weather variability. These results are then weighted and joined into a distribution using the SMME method described above, resulting in a full probability distribution of expected counts of days over 90F.

As a final step, we assess our confidence in these projections and exclude estimates in locations where the modeled projections fail to meet our standards. We estimate model projection error in the number of days over 90F, averaged over the period 1990-2010, relative to the downscaled Berkeley Earth historical temperature observations over the same period. Where the range of model projections falls more than 50% off of the historical value, we exclude these locations.

Capturing the full range of climate sensitivity

We know certain feedbacks within the climate system may amplify or diminish the effect of rising GHG concentrations. These feedbacks include increased water vapor in the atmosphere; decreased reflectivity as snow and ice coverage shrinks; changes in the rate at which land, plants, and the ocean absorb carbon dioxide; and changes in cloud characteristics. A better understanding of the role these longer-term feedbacks play will help paint a clearer picture of how future climate change will impact human systems.

The suite of GCMs is not designed to capture the full range of possible future climate responses. GCMs are rooted in climate physics, built with physical and empirically-based parameters, and benchmarked against historical climate evolution. Collectively, this ensemble of models produces a range of future climate outcomes for a given RCP emissions scenario, but in each model, the amount of warming projected in response to changes in GHG concentrations is an emergent property. In other words, it is something that is affected by many different processes and interactions and reflects each modeling team's best estimate of the dynamics of the global climate system.

Our method incorporates projections from both GCMs and SCMs. While GCMs provide the rich temporal and spatial detail necessary for our work, the CMIP5 ensemble is not designed to capture the full range of climate responses to GHG emissions. That's one reason why we could never use the set of CMIP5 outputs alone as a full representation of all possibilities of future climate change. SCMs are not sufficiently complex to represent the spatial patterns of changes in climate, but they are computationally efficient. We can run thousands of simulations and generate a probabilistic ensemble that takes into account the full range of climate sensitivity. Our final product is tied closely to observed surface temperature observations, incorporates fine grain spatial and temporal resolution, and yields full probability distributions for future climate change variables.

To convert the ensemble of climate model runs available from the CMIP5 project into a true probability distribution of weather outcomes, we construct a mixed-model ensemble with a technique called Surrogate/Model Mixed Ensemble (SMME) (Rasmussen, 2016). This means using an SCM to produce a probability distribution showing the wider range of possible temperature responses to changes in GHG concentrations, then supplementing CMIP5 projections with simulated "surrogate" GCM projections to fill in the tails.

Our SCM, in this case, is the Model for the Assessment of Greenhouse Gas Induced Climate Change (MAGICC) version 6 (see Meinshausen et al. 2011). MAGICC represents the atmosphere, ocean, and carbon cycles at a hemispherically averaged level. Specifically, we use MAGICC in probabilistic mode because we can vary the ECS as an input parameter. We constructed our distribution of input parameters from a statistical analysis, based on both historical observations and the probability distribution of ECS estimated using multiple lines of evidence in IPCC's AR5. For each RCP analyzed in our work we use 600 MAGICC model runs reflecting a range of equilibrium climate sensitivity (ECS) from 1.5 to 5.9 degrees Celsius.

To develop a distribution of high-resolution daily climate variables, we use a method called pattern scaling to produce surrogate GCMs. Pattern scaling involves computing a statistical relationship between global average temperature change and local temperature change around the globe in select GCMs. We use this relationship to produce synthetic GCM simulations by varying local temperature change based on SCM global average temperature projections that are hotter or colder than the CMIP5 outputs.

The end result of this is a mixed-model ensemble of CMIP5 models and constructed model surrogates which together exhibit the wider distribution of climate sensitivity. Each of these "models" is a realization of our high temporal and spatial resolution climate simulations. The global mean temperature pathway predicted for late century (2080-2099) in these simulations is used to define weights based on where they fall in the full SCM temperature distribution. For each socioeconomic impact that we study, we then sort and weight those simulation results based on these weights. The temperature distribution of end-of-century warming matches the SCM's modeled uncertainty in the climate's response to increased GHG concentrations.