Appendix 1: Technical Support Document: Modeling Future Climate Impacts on Human Health

Contents

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Models are an important component of climate change impact projections. In general, quantitative evaluations of health impacts require projections of: 1) physical climate changes, 2) future socioeconomic characteristics, and 3) the relationships between these factors and the health outcome of interest. Uncertainties exist in each of these areas, and aligning the spatial and temporal parameters used in climate models with epidemiological data to assess health outcomes can be challenging. Despite these challenges, health impact modeling continues to improve, increasing our understanding of the quantitative impacts associated with climate change.

A1.1 Quantitative Evaluations of Health Impacts

A1.1.1 Projecting Climate Change Impacts

Since there is no universally accepted set of metrics to identify the "best" climate models, it is standard practice to use an ensemble (a collection of simulations from different models) in order to present a range of results and provide a measure of the certainty in the results. In addition, because climate model results can depend on initial conditions, even for a single model, multiple iterations can be used to similarly present a range of results and improve certainty. Climate model outputs may require intermediate calculations, such as the use of downscaling methods when higher resolutions are needed, or coupling to an atmospheric chemistry model in order to examine and incorporate changes in local air quality.

Over the past decade, climate change simulations were based primarily on emissions scenarios developed in the IPCC Special Report on Emission Scenarios (SRES) (IPCC 2000), which were used as inputs to model climate projections in the Coupled Model Intercomparison Project Phase 3 (CMIP3). However, for the IPCC's Fifth Assessment Report (IPCC 2013), modelers used the Coupled Model Intercomparison Project Phase 5 (CMIP5) model simulations, which utilize the current standard experimental protocol for studying Global Climate Models (GCMs). CMIP5 contains approximately 60 climate representations from 28 different modeling centers (Meehl et al., 2009). The spatial resolution of most models is in the range of 1° to 2° of latitude or longitude, or about 60 to 130 miles.

CMIP5 experiments are based on estimated historical radiative forcings as well as forcings from future concentration pathways for:

a) Simulations of the 20th century climate using best estimates of the temporal variations in external forcing factors (such as greenhouse gas concentrations, solar output, volcanic aerosol concentrations); and
b) Simulations of this century assuming changing greenhouse gas concentrations following various emissions scenarios.

The CMIP5 simulations use a set of scenarios called Representative Concentration Pathways (RCPs). There are four RCP scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. These scenarios are named according to the possible increase in radiative forcing (a measure of the total change in Earth's energy balance) for the year 2100 relative to pre-industrial levels, measured in Watts per square meter (W m^{-2}). For example, the RCP6.0 scenario is that in which the end-of-century radiative forcing increase is 6.0 W m^{-2} above pre-industrial levels. The range of simulated global average surface temperature changes under both the SRES and RCP scenarios is shown in Figure 1.

[Figure 1 Emissions Levels Determine Temperature Rises]

A1.1.2 Projecting Socioeconomic Development

Along with the RCP scenarios used to provide a range of possible future greenhouse gas emissions for climate models, the modeling of climate change impacts is improved by including scenarios that describe future societal characteristics. For the IPCC’s Fifth Assessment Report (IPCC 2013), impact modelers used new scenarios constructed from three building blocks:

- Representative Concentration Pathways (RCPs)
- Shared Climate Policy Assumptions (SPAs)
- Shared Socioeconomic Pathways (SSPs)

Shared Socioeconomic Pathways, or SSPs, define plausible alternative states of global human and natural societies at a macro scale, including qualitative and quantitative factors such as demographic, political, social, cultural, institutional, lifestyle, economic, and technological variables and trends. Also included are the human impacts on ecosystems and ecosystem services, such as air and water quality (Ebi 2014; O’Neill et al. 2014). Five reference SSPs are defined, and referred to as SSP1 through SSP5 (O’Neill et al. 2014); each evolves over the century, describing challenges to adaptation (efforts to adapt to climate change) and mitigation (efforts to reduce the amount of climate change) that change over time irrespective of climate change (Figure 2) (Ebi et al. 2014; O’Neill et al. 2014). The SSPs facilitate exploration of: 1) how development pathways can influence the magnitude and pattern of climate impacts; 2) the ease or difficulty of managing climate change related risks in a world on any given emission pathway; and 3) the possible consequences of different emission pathways based on a specific development pathway.

[Figure 2. The Shared Socioeconomic Pathways]

Although the SSPs describe broad-scale global trends across multiple sectors, these trends are relevant to projections of health impacts in the United States; trends within each SSP represent different challenges for maintaining and improving the health of Americans. For example, future vulnerability to changing concentrations of air pollutants, particularly ozone, will in part depend on demographics, urbanization, and policies to control air pollutants.

SSPs are not explicitly used in the analyses highlighted in this assessment, but as they are scenarios likely to be used by the impacts modeling community over the next few years, placing the current work in context is a valuable exercise. The combination of RCP6.0 (used by most of the analyses highlighted in the Temperature-Related Death and Illness, Air Quality Impacts, Vectorborne Diseases, and Water-Related Illnesses chapters - See Section A2) and the population parameters for the SRES B2 emissions pathway (used in the Temperature-Related Death and Illness and Air Quality Impacts chapters) can be partially mapped to the SSP2 ("middle of the road", see Figure 2) storyline (van Vuuren et al., 2014). SSP2 depicts a world where global health improves, although not as quickly as in a world with fewer challenges to mitigation and adaptation (as in SSP1). Under SSP2, multiple factors contribute to some countries making slower progress in reducing health burdens, including, in some low-income countries, high burdens of climate-related diseases combined with moderate to high population growth. In the United States, challenges to public health infrastructure and health care under this scenario could include inadequate resources and international commitment for: 1) integrated monitoring and surveillance systems; 2) research on and modeling of the health risks of climate change; 3) iterative management approaches; 4) training and education of health care and public health professionals and practitioners; and 5) technology development and deployment (Ebi 2014).

A1.1.3 Projecting Health Outcomes

Public health officials often require information on health risks that are immediate (or at least within the next five years) and local. Climate models, on the other hand, are better at projecting changes on national to global scales and over timescales of decades to centuries. An example of the contrast between the spatial information most relevant to public health officials (states and counties) as compared to those used by climate models (grid cells of 1 to 2 degrees) is demonstrated in Figure 3. This figure shows two common sizes of climate model grids overlaid on a map of the northeastern United States. Currently, model projections for a single grid cell represent the simulated climate variables (for example, temperature and precipitation) averaged over that geographical area, for a given point in time under a particular emissions scenario. Models that produce output at higher resolutions (smaller grid sizes) allow for more localized projections, however, they are more computationally intensive and are not necessarily more accurate than those run at coarser resolutions (larger grid sizes).

[Figure 3. Example Spatial Resolution of Climate Models]

These climate model grids are overlaid on the outlines of counties in Figure 3. However, many public health officials and programs work at even finer spatial scales than the county level (for example, city or community). Given that the climate model outputs often cover areas larger than a county or city, public health officials are interested in downscaling climate projections to reflect county-level physical features and conditions.

In addition to higher spatial resolutions, public health officials are also generally most interested in short-term projections of future conditions (for example, one to five years). This is in part due to the fact that these officials work in resource-constrained environments where relative priorities and associated funding decisions can shift, often quickly. In addition, they provide services to populations with characteristics that are likely to change in response to changing economic conditions, immigration patterns, or impacts of extreme weather events. In this short timeframe, public health officials typically focus on information regarding the timing and magnitude of specific events or combinations of events that would stress existing programs and systems (for example, heat waves, tropical storms, wildfires, and air quality events). The one- to five-year information requirements of public health providers can contrast with the information climate modelers can develop, which project future conditions for timescales of decades to centuries and often derive impacts in 2050 or 2100. Climate models provide less guidance in terms of changes in near-term impacts because short-term variability from natural sources such as ocean circulation can obscure the long-term climate trends produced by increasing greenhouse gas concentrations. As such, climate projections over longer time periods typically serve more as a guide to emerging issues and as an input to longer-range planning.

A1.2 Modeling Highlighted in the Assessment

The four chapters that highlight modeling studies conducted for this assessment (Temperature-Related Death and Illness, Air Quality Impacts, Vectorborne Diseases, and Water-Related Illnesses) analyzed a subset of the full CMIP5 dataset (see Table 1). The air quality analyses required the most intensive processing of the CMIP5 model output; calculating air quality changes at the appropriate geographic scale requires modelers to use a technique known as dynamical downscaling to generate climate data at the desired small-scale resolution, and then run an atmospheric chemistry model, both of which are computationally intensive processes. Thus the air quality analysis was limited to two model-scenario examples (see Table 1). By contrast, the water-related illness analyses examined results from 21 of the CMIP5 models, though only for one particular scenario.

In general, the authors of the studies highlighted in this assessment used historical data, both to calibrate their historical results and to improve geographic resolution. These downscaling approaches determine the climate signal by taking the difference between the modeled future and the modeled historical period at the grid cell resolution (often averaged over 30 years). This climate signal can then be added to observed historical data at a resolution potentially much finer than the model grid cell scale. For example, any given weather station might be, on average, cooler in the summer than the grid cell average because it is located next to a lake. By adding the modeled climate signal to the historical data from the weather station, the projected future temperatures can effectively account for microclimate effects, from lakes or other hills for example, that are smaller than the modeled grid scale. More sophisticated calibrations can also correct for model variability by using a technique known as quantile mapping (Wood et al. 2004).

The modeling studies highlighted in this assessment use different approaches. The three different historical reference periods used in this assessment (1985-2000, 1992-2007, 1976-2006) are slightly warmer than the 1971-2000 period used in NCA3, by 0.3°F to 0.8°F. In addition, different sets of models were used. A sensitivity analysis was conducted to test for potential impacts, in terms of temperature increases with respect to the NCA3 reference period of 1971--2000, of these differences in approach. As illustrated in Figure 4, a comparison of the differences between historical reference periods (in the "Reference" column) with projections for each future period indicates that the future projected warming is considerably larger than the differences between the three historical reference periods. Furthermore, Figure 4 shows that the multi-model means are similar when using 16 climate models or five climate models.

Each modeling approach requires different input from the climate models. For example, the extreme temperature analysis required only temperature data, and the waterborne disease analysis used only sea surface temperature data. However, the air quality modeling required temperature, precipitation, ventilation, and other data in order to provide boundary conditions for the dynamical downscaling approach. Besides climate data, modeling teams also used other inputs. The main sources of additional data were the Integrated Climate and Land Use Scenarios (ICLUS) model for population and the Environmental Benefits Mapping and Analysis Program (BenMAP) model for baseline mortality data, which were used for the extreme temperature and air quality modeling efforts (EPA, 2014; EPA, 2009). The waterborne disease analysis required salinity, light, and other oceanographic data not provided by the CMIP5 models.

The modeling approaches also included different geographic scales. The waterborne disease team examined individual bodies of water such as the Chesapeake Bay, Puget Sound, and Gulf of Mexico. The vectorborne disease projections of Lyme disease concentrated on the 12 U.S. states where Lyme is already prevalent. The thermal extreme mortality analysis examined 209 U.S. cities that had sufficient data for an historical epidemiology analysis. The air quality analysis was able to address the entire contiguous United States.

[Table 1. Parameters for modeling highlighted in this assessment]

A1.3 Sources of Uncertainty

The use of the term "uncertainty" in climate assessments refers to a range of possible futures. Uncertainty about the future climate arises from the complexity of the climate system and the ability of models to represent it, as well as the difficulties in predicting the decisions that society will make. There is also uncertainty about how climate change, in combination with other stressors, will affect people and natural systems (Melillo et al. 2014).

Though quantitative evaluations of climate change impacts on human health are continually improving, there is always some degree of uncertainty when using models to gain insight into future conditions. The presence of uncertainty, or the fact that there is a range in potential outcomes, does not negate the knowledge we have, nor does it mean that actions cannot be taken. Everyone makes decisions, in all aspects of their life, based on limited knowledge or certainty about the future. Decisions like where to go to college or what job to take, what neighborhood to live in or which restaurant to eat in, whom to befriend or marry, and so on are all made in light of uncertainty, which can sometimes be considerable (CCSP 2009). Recent years have seen considerable progress in the development of improved methods to describe and deal with uncertainty in modeling climate change impacts on human health.

A1.3.1 Uncertainty in Projecting Climate Change

Two of the key uncertainties in projecting future global temperatures are: 1) uncertainty about future concentrations of greenhouse gases; and 2) uncertainty about how much warming will occur for a given increase in greenhouse gas concentrations. Future concentrations depend on both future emissions and how long these emissions remain in the atmosphere (which can vary depending on how natural systems process those emissions). Because of uncertainty in future greenhouse gas concentrations, climate modelers analyze multiple future scenarios in order to determine the range of varying impacts of lower emissions compared to higher emissions. In terms of how much warming will occur for a given increase in greenhouse gas concentrations, the most recent assessment by the Intergovernmental Panel on Climate Change (IPCC) found the most likely response of the climate system to a doubling of carbon dioxide (CO_2) concentrations lies between a 1.5°C and 4.5°C (2.7°F to 8.1°F) increase in global average temperature (IPCC, 2013) (see Figure 1).

Climate scientists have greater confidence in predicting the average temperature of the whole planet than what the temperature will be in any given region or locale. Global average temperatures may not, however, be particularly informative for determining health impacts at a local scale. An increase in global temperatures will, at local scales, result in different warming rates in different locations, different seasonal warming rates, different warming rates during the day compared to the night, and different changes in day-to-day or year-to-year variability. Despite these possible differences, it is highly likely that warming will occur almost everywhere (Walsh et al. 2014). In addition to temperature, changes in precipitation, humidity, and weather systems are all important drivers of local impacts, however, future changes in these variables are less certain than changes in temperature.

A1.3.2 Uncertainty in Public Health Surveillance and Monitoring

The first step in understanding future health impacts is to understand current health impacts. Obtaining this understanding is complicated by the fact that in the United States, there is no single source for health data and surveillance often involves acquiring, analyzing, and interpreting data from several sources across various systems. This is further complicated by a number of additional limitations, including the fact that data are often incomplete, may not include a representative sample of all members of society, and rely on self-reporting of disease status. Estimates of disease patterns or trends may also vary across geographic locations. Understanding the surveillance and monitoring limitations regarding population health data and spatial variability can enable more accurate estimations of the confidence in the links between health impacts and climate drivers, and this can be used to estimate uncertainty in future projections of health impacts.

Having complete socioeconomic, geographic, demographic (race, age, gender), and health data at an individual level would improve our understanding of connections between these attributes and deaths and illnesses. However, such complete data are not available for both practical and confidentiality reasons. Mandatory reporting, disease records, and administrative sources, including data from medical records or vital records, can be used to estimate incidences of given health impacts and these counts can be divided by population estimates to produce health impact rates. Uncertainty in the data can differ depending on the type of population health estimate and the existing surveillance data source used (such as using registries versus surveys).

In addition to uncertainty regarding the quality of data, confidence in the estimation of health impact rates depends on the volume of useable data. In general, the larger the data set (larger populations or longer time periods), and the more common the health condition, the more confidence there is in estimated rates, and changes in those rates, across time periods, demographic groups, or other attributes.

A1.3.3 Uncertainty in Estimating Exposure-Response Relationships

Exposure response relationships describe the change in the health effect caused by different levels of exposure over time. Often the relationship linking the exposure with the health outcome is expressed as an exposure-response function (see Chapter 1: Introduction, section 1.4). In general, this involves describing the statistical relationship between an exposure of interest, such as ground-level ozone concentrations, with a metric describing the health outcome, such as daily counts of asthma attacks.

In recent decades, great strides have been made in developing these exposure-response functions for a wide range of climate-sensitive environmental health outcomes. In recent years, we have gained a better understanding of the relationships between daily maximum temperatures, daily average concentrations of ozone and fine particulate matter, and a range of illnesses and premature death (see Ch. 2: Temperature-Related Death and Illness and Ch. 3: Air-Quality Impacts). These functions are often used in modeling efforts to project the health impacts of climate change. However, it is important to carefully consider uncertainty when developing and using exposure-response functions, as the environmental processes affecting human health are complex.

One major challenge in characterizing the relationship between exposure and health impacts is determining when a relationship is correlative, as opposed to causative. For example, statistical analyses would adjust for other factors that could be influencing health outcomes, such as age, race, year, day of the week, insurance status, and the concentrations of other air pollutants. By holding these other factors constant, researchers can get a better idea if changes in ozone concentrations are an important cause of health impacts. As evidence mounts, as is the case for associations between ozone concentration and adverse health impacts (Bell et al. 2004, Jerrett et al. 2009, Ji et al. 2011, Fann et al. 2012, Vinikoor-Imler et al. 2014), the hypothesis of a causal relationship is strengthened, and observed exposure-response associations can be used with greater confidence.

A1.4 References

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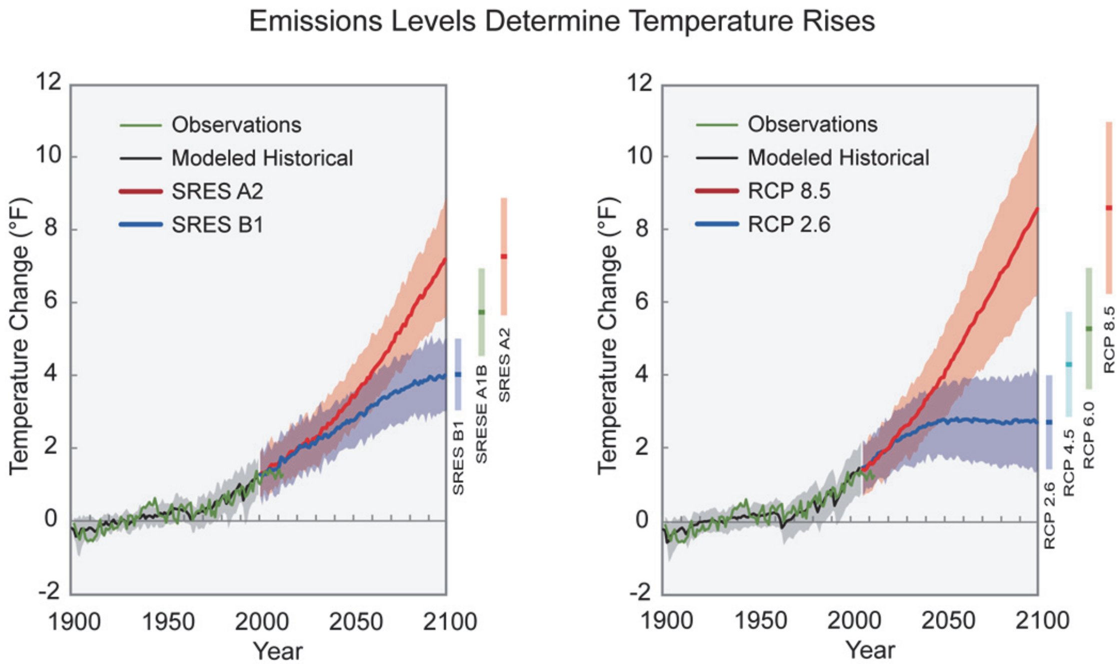
A1.5 Figures and Tables

Chapter	Modeled endpoint	Timeframe	Temporal resolution	Scenarios	Models	Bias correction and/or downscaling	Geographic Scope	Climate variables	Relevant data sources
Temperature-Related Death and Illness[1]	Mortality	2030, 2050, 2100	30 years	RCP6.0	GFDL-CM3, MIROC5	Statistical downscaling, then delta approach	209 U.S. cities	Temperature (0-5 day lags)	BenMAP baseline mortality data
Air Quality[2]	Mortality/Morbidity from changes in Ozone	2030	3 years within 11 year span	RCP6.0	GISS-E2	Dynamic downscaling	National	Temperature, precipitation, ventilation, others	ICLUS population data, BenMAP health model, SES, air condition prevalence, baseline health status data
		2030	11 year average	RCP8.5	CESM	Dynamic downscaling	National	Temperature, precipitation, ventilation, others	
	Changes in air exchange that drive indoor air quality	2040-70	30 years	SRES A2	CCSM, CGM3, GFDL, HadCM3	Dynamic downscaling	9 U.S. cities	Temperature, wind speed at 3 hour resolution	NA
Water-Related Illness[3]	Seasonality and geographic range of Vibrio bacteria	2030, 2050, 2095	10 year average of monthly data	RCP6.0	21 CMIP5 models (4 used for Alaska)	Statistical downscaling; bias correction & quantile mapping	Chesapeake bay, Alaskan Coast	SST (driven by surface air temperature)	NA
	Seasonality of Alexandrium bacteria	2030, 2050, 2095	10 year average of monthly data	RCP6.0	21 CMIP5 models	Statistical downscaling; mean and variance bias correction	Puget Sound	SST (driven by surface air temperature)	NA
	Growth rates of 3 Gambierdiscus algae species	2000-2099	Annual	RCP6.0	11 CMIP5 models	Mean and variance bias correction, then temporal disaggregation	Gulf of Mexico and Caribbean	SST	Salinity, light, and other biological and oceanographic variables
Vector-Borne Disease[4]	Lyme disease onset week	2025-2040 and 2065-2080	16 year periods	RCP2.6, RCP4.5, RCP6.0, RCP8.5	CESM1(CAM5), GFDL-CM3, GISS-E2-R, HadGEM2-ES, MIROC5	Statistical downscaling, then delta approach	12 U.S. states where Lyme is prevalent	Temp (growing degree days) precip, and saturation deficit (assume constant relative humidity)	Distance to coast in decimal degrees

Table 1. Parameters for modeling highlighted in this assessment (see Research Highlights in Ch. 2: Temperature-Related Death and Illness; Ch. 3: Air Quality Impacts; Ch. 4: Vectorborne Disease; Ch. 5: Water-Related Illness).[1]Schwartz et al. 2014; [2]Fann et al. 2014; Ilacqua et al. 2014 (indoor air); [3]Jacobs et al. submitted (Vibrio & Alexandrium), Kibler et al. 2014; [4]Moore et al. 2014

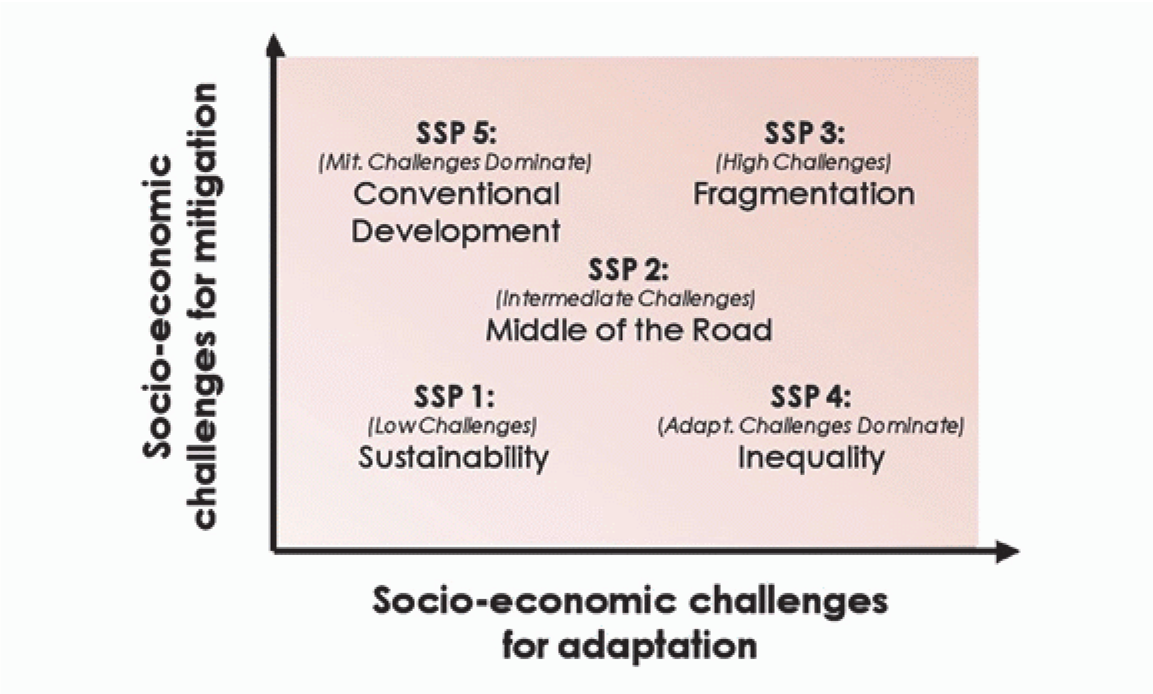
Figure 1: Emission Levels Determine Temperature Rises



Caption: Different amounts of greenhouse gases released into the atmosphere by human activities produce different projected increases in Earth's temperature. In the figure, each line represents a mean estimate of global average temperature rise for a specific emissions pathway (relative to the 1901−1960 average). Shading indicates the range (5th to 95th percentile) of results from a suite of climate models. Projections in 2099 for additional emissions pathways are indicated by the bars to the right of each panel. In all cases, temperatures are expected to rise, although the difference between lower and higher emissions pathways is substantial.

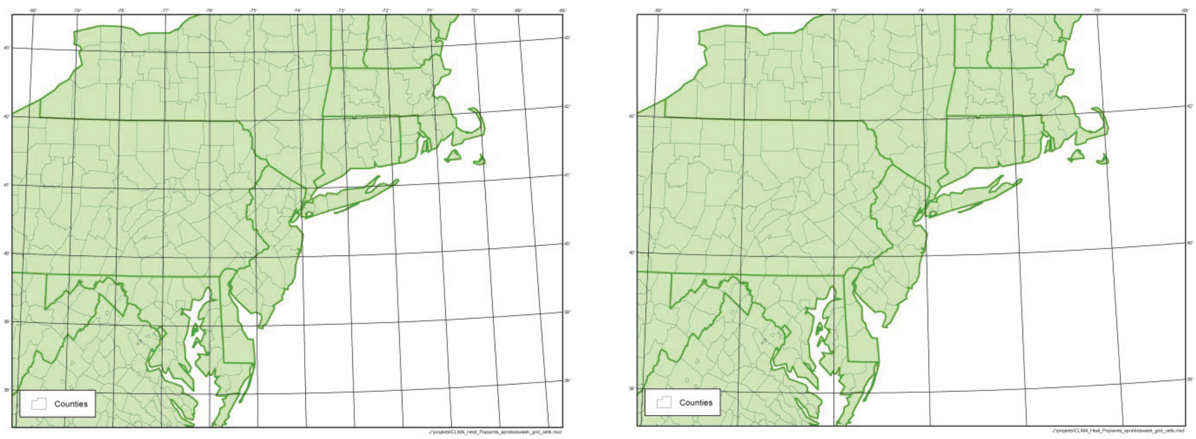
The left panel shows the two main CMIP3 scenarios (SRES) used in this assessment: A2 assumes continued increases in emissions throughout this century, and B1 assumes significant emissions reductions beginning around 2050, though not due explicitly to climate change policies. The right panel shows the newer CMIP5 scenarios using representative concentration pathways (RCPs). Some of these new simulations explicitly consider climate policies that would result in emissions reductions, which the SRES set did not. CMIP5 includes both lower and higher pathways than CMIP3. The lowest emissions pathway shown here, RCP2.6, assumes immediate and rapid reductions in emissions and would result in about 2.5°F of warming in this century. The highest pathway, RCP8.5, roughly similar to a continuation of the current path of global emissions increases, is projected to lead to more than 8°F warming by 2100, with a high-end possibility of more than 11°F. (Data from CMIP3, CMIP5, and NOAA NCDC). (Figure source: modified from Melillo et al. 2014)

Figure 2: The Shared Socio-economic Pathways (SSPs).



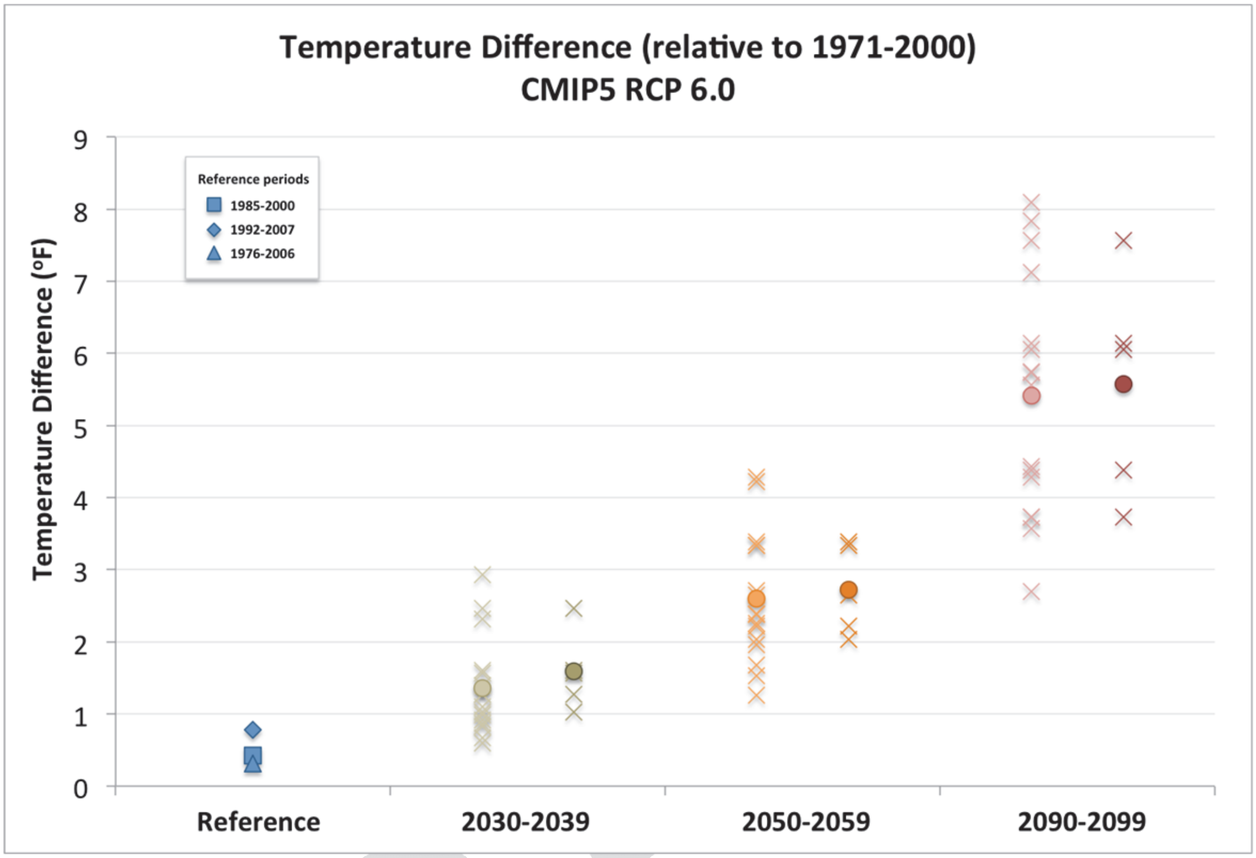
Caption: The five shared socioeconomic pathways (SSPs) are defined by the areas mapped between two axes that describe levels of socioeconomic and environmental challenges to mitigation and to adaptation. SSPs do not include climate change impacts nor do they consider any given climate policy. The two axes are gradations of challenges defined by societal or environmental factors that would make a mitigation or adaptation task easier or harder for any given emissions target or mitigation policy. Use of the term "socioeconomic" in the SSP scenario framework encompasses a wide range of aspects including demographic, political, social, cultural, institutional, life-style, economic, and technological aspects, and the conditions of ecosystems and ecosystem services, such as air and water quality (Figure source: adapted from O'Neill et al. 2014).

Figure 3. Example Spatial Resolution of Climate Models



Captions: Maps show hypothetical Global Climate Model output grids for the Northeastern United Sates at two different resolutions. Left panel shows a model output with 1° square resolution, right panel shows a lower-resolution model output, with 2° square resolution.

Figure 4: Sensitivity Analysis of Differences in Modeling Approaches



Caption: A sensitivity analysis was conducted to test for potential impacts of differences in the modeling approaches (use of different historical reference periods and use of different sets of CMIP5 models) in the research studies highlighted in this assessment (see Research Highlights in Chapters 2, 3, 4, and 5). The values in the first column are temperature changes for three different reference periods used in this assessment, relative to the 1971-2000 reference period used in NCA3. The remaining columns show future temperature changes for individual climate models for three different future periods, relative to 1971-2000. The left column at each future period shows changes for 16 climate models in CMIP5 for which the RCP6.0 scenario was available. The right column shows a subset of five models used in some of the report studies. Each "x" represents a single model. The filled-in circle is the mean temperature change for all models in the column. (Figure source: NOAA NCDC / CICS-NC)