CLIMATE CHANGE PROJECTIONS AND INDICATORS FOR DELAWARE

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December 2013

SUMMARY

Over the coming century, global climate is expected to change in response to human emissions of carbon dioxide and other heat-trapping gases. This report documents how these global changes are expected to affect the climate of Delaware, including average annual and seasonal temperature and temperature extremes; seasonal precipitation, drought, and heavy precipitation; and indicators that combine temperature, precipitation, and/or humidity.

Future projections were developed for two very different types of scenarios, to span a range of possible changes over the coming century. The ***lower scenarios*** (corresponding to the Intergovernmental Panel on Climate Change SRES[1] B1 and RCP[2] 4.5 scenarios) represent a future in which people shift to clean energy sources in the coming decades, reducing emissions from human activities. The ***higher scenarios*** (corresponding to the SRES A1fi and RCP 8.5 scenarios) represent a future in which people continue to depend heavily on fossil fuels, and emissions of heat-trapping gases continue to grow. Scenarios are an important source of uncertainty in determining the magnitude of projected changes in average annual and seasonal temperature, and many extreme temperature and precipitation indicators, for mid-century and beyond.

Future projections are based on simulations from nine newer ***global climate models*** from phase 5 (CCSM4, CNRM-CM5, CSIRO-Mk3.6.0, MPI-ESM-LR, HadGEM2-CC, INMCM4, IPSL-CM5A-LR, MIROC5 and MRI-CGCM3) and four older global climate models from phase 3 (CCSM3, GFDL CM2.1, HadCM3 and PCM) of the Coupled Model Intercomparison Project. Differences between the models represent the limitations of scientific ability to simulate the climate system. These differences are an important source of uncertainty in determining the magnitude and sometimes even the direction of projected changes in average and seasonal precipitation, as well as the magnitude of the more extreme indicators of temperature and precipitation. Most of the projections dicussed here are based on the more recent CMIP5 simulations, unless there are important differences between what is simulated by the older CMIP3 versus the newer CMIP5 models. The full set of CMIP3 and CMIP5 projections are provided in the Excel Appendices which accompany this report.

Data from 14 long-term ***weather stations*** in the region were used in this analysis: Bear, Bridgeville, Dover, Dover AFB, Georgetown, Georgetown Sussex Airport, Greenwood, Lewes, Middletown, Milford, Newark University Farm, Selbyville, Wilmington Porter, and Wilmington New Castle County (NCC) Airport. The output from each global climate model simulation was ***statistically downscaled*** to each of the 14 weather stations using the Asynchronous Regional Regression Model.

Over the coming century, climate change is expected to affect Delaware by increasing **average** and **seasonal temperatures**.

- By near-century (2020-2039), annual average temperature increases of 1.5 to 2.5°F are projected, regardless of scenario.
- By mid-century (2040-2059), annual average temperature increases under the lower scenario range from 2.5 to 4°F and around 4.5°F for the higher scenario.

[1] Special Report on Emission Scenarios (SRES)
[2] Representative Concentration Pathways (RCP)

- By late-century (2080-2099), annual average temperature is projected to change by nearly twice as much under a higher as compared to a lower scenario: 8 to 9.5°F compared to 3.5 to 5.5°F.
- Slightly greater temperature increases are projected for spring and summer as compared to winter and fall.
- The range of spring temperature (calculated as the difference between daytime maximum and nighttime minimum temperature) is projected to increase, while the range in fall temperature is projected to decrease, due to proportionally larger increases in maximum as compared to minimum temperatures. Little change is expected in the temperature ranges for winter and summer.
- The growing season is projected to lengthen, with slightly greater changes in the date of last spring frost as compared to first fall frost.

Temperature extremes are also projected to change. The greatest changes are seen at the tails of the distribution, as represented by the number of days above a given high temperature or below a given cold temperature threshold. By mid-century, changes under the higher scenario are greater than changes under the lower scenario.

- The number of very cold days (below 20°F), which historically occur on average about 20 times per year, is projected to drop to 15 by 2020-2039, to slightly more than 10 days per year by 2040-2059, and to 10 days per year under a lower scenario and only 3 to 4 days per year under a higher scenario by 2080-2099.
- The number of very hot days (over 100°F), which historically occur less than once each year, are projected to increase to 1 to 3 days per year by 2020-2039, 1.5 to 8 days per year by 2040-2059, and by 3 and 10 days per year under the lower and 15 to 30 days per year under the higher scenario by 2080-2099.
- Heat waves are projected to become longer and more frequent, particularly under a higher as compared to lower scenario and by later compared to earlier time periods. For example, heat waves with at least 4 consecutive days warmer than the 1-in-10 historical average are expected to occur on average between 1 to 3 times per year by 2040-2059, and an average of 3 times per year under a lower and 10 times per year under a higher scenario by 2080-2099.
- Daytime summer heat index (a measure of how hot it feels, based on maximum temperature and average humidity) is projected to increase by approximately twice as much as projected changes in maximum temperature alone, due to the nonlinear relationship between heat index, temperature, and humidity.

Average precipitation is projected to increase an estimated 10 percent by late-century, consistent with projected increases in mid-latitude precipitation in general. CMIP3 and CMIP5 models do not show the same seasonality: CMIP3 shows larger overall increases in annual precipitation that are spread across winter, spring, and summer, while CMIP5 simulations show smaller annual increases that occur primarily in winter.

Rainfall extremes are also projected to increase. By late-century, nearly every model simulation shows projected increases in the frequency and amount of heavy precipitation events that is often greater under a higher as compared to a lower future scenario. This increase is consistent over a very broad range of definitions of "heavy precipitation," including accumulations ranging from 0.5 to 8 inches over anywhere from 1 day to 2 weeks.

All simulations show large increases in potential evapotranspiration and in the number of hot and dry days per year. Smaller to no significant changes are projected for relative humidity and for the number of cool and wet days per year.

There is *greatest certainty* in projected increases in annual and seasonal temperatures, high temperatures, increased evaporation, precipitation intensity, and the frequency of heavy precipitation, all of which show greater increases under the higher as compared to lower scenario and by late-century as compared to more near-term projections. There is *moderate certainty* in projected changes in cold temperatures and a slight increase in average precipitation, particularly in winter. There is *less certainty* in projected changes in precipitation in other seasons, in projected changes for moderate precipitation amounts (0.5 to 1 inch in 24 hours), and in the *magnitude* of projected changes in events that are historically rare, including extremely high temperatures (>100°F) and extremely high precipitation events.

SECTION 1

BACKGROUND

Since the Industrial Revolution, atmospheric levels of heat-trapping gases such as carbon dioxide (CO_2) and methane (CH_4) have been rising due to emissions from human activities. The main source of heat-trapping gases is the combustion of fossil fuels such as coal, oil, and natural gas (Andres et al., 1999; Stern & Kaufmann, 1998). Other activities, such as agriculture, wastewater treatment, and extraction and processing of fossil fuels also produce CO_2, CH_4, and other gases and particles that affect climate (Forster et al., 2007).

CO_2, CH_4 and other heat-trapping gases exist naturally in the atmosphere. However, artificially adding to the amounts of these gases in the atmosphere affects the energy balance of the planet. As levels increase, more of the heat given off by the earth that would otherwise escape to space is trapped within the earth's climate system. This excess heat increases the temperature, and the heat content, of the atmosphere and ocean.

Observed and Projected Future Change

In the past, climate variations were caused entirely by natural forces. These include changes in amount of energy the Earth receives from the sun, natural cycles that exchange heat between the ocean and atmosphere, or the cooling effects of dust clouds from powerful volcanic eruptions, amplified by natural feedbacks within the earth-ocean-atmosphere system. Today, however, the climate is being altered by both natural and human causes (Hegerl et al., 2007).

Over the last 150 years, the earth's long-term average near surface temperature has increased by 1.5°F (IPCC 2013). At the global scale, each decade has successively been warmer than the decade before. The heat content of the ocean has increased by more than 20 times that of the atmosphere (Trenberth et al., 2007; Abraham et al., 2013). Recent studies have concluded that human influence, specifically the increases in emissions of CO_2 and other heat-trapping gases from human activities, is responsible for most of the warming over the last 150 years, and as much as all of the warming over the last 60 years (Huber & Knutti, 2011; Foster & Rahmstorf, 2011; Gillett et al., 2012).

In the United States, average temperature has also increased by 1.5°F over the last century, with most of the increase occurring in the last 30 years (Walsh et al., 2014). Warmer temperatures are driving many changes in average climate conditions in the United States and around the world. Observed changes highlighted by Walsh et al. (2014) in the Third U.S. National Climate Assessment include:

- More frequent heavy precipitation events, particularly in the Northeast and Midwest
- Increasing risk of heat waves, floods, droughts, and wildfire risk in some regions
- Decreases in Arctic sea ice, earlier snow melt, glacier retreat, and reduced lake ice
- Stronger hurricanes, rising sea level, and warming oceans
- Poleward shifts in many animal and plant species, as well as a longer growing season

Over short timescales of years to more than a decade, natural variability has a strong effect on global and regional temperatures. Some patterns of natural variability increase the ocean's share of the heat uptake compared to the atmosphere's. This can slow the increase in, or even temporarily cool, near-surface temperature. Other patterns have the opposite effect, temporarily accelerating the long-term increase near-surface temperature. Over long-term climate timescales of 30 years or more, however, global temperature will continue to change in response to both past and future emissions of heat-trapping gases from human activities (IPCC, 2013).

Future changes depend on heat-trapping gas emissions from human activities. At the global scale, temperature increases between 2°F and 9°F are expected by end of century, accompanied in many regions of the United States by increases in extreme heat and heavy precipitation events. These future projections are consistent with observed trends (USGCRP, 2009; Walsh et al., 2014). For many impacts, higher emissions are expected to result in greater amounts of change; lower emissions, in comparatively smaller amounts of change. The 2011 U.S. National Research Council report, "Climate Stabilization Targets" (NRC, 2011) quantifies many of the impacts that would be expected to increase per degree of global warming. For example, each degree-Celsius (almost 2°F) increase in global temperature might be expected to:

- Shift the amount of precipitation that falls in many regions around the world by 5 to 10 percent
- Increase the amount of rain falling during heavy precipitation events by 3 to 10 percent
- Shift the amount of streamflow and runoff in river basins by 5 to 10 percent (with increases in the northeastern United States and decreases in the southwestern United States)

- Shrink annual average Arctic sea ice area by 15 percent (by 25 percent, for the September minimum)
- Reduce yields of common crops including wheat and maize by 5 to 15 percent worldwide
- Increase the area burned by wildfire in the western United States by 200 to 400 percent

This report and other resources are listed in the section "Further Reading".

Implications for Delaware

Future climate depends on the impact of human activities on climate, and the sensitivity of climate to those emissions. This report describes projected changes in Delaware's climate under two possible scenarios: a higher scenario in which fossil fuels continue to provide most of humankind's energy needs, and a lower scenario in which global carbon emissions peak within a few decades, then begin to decline.

Future projections are based on simulations from two groups of global climate models: the older models used in the Northeast Climate Impacts Assessment (Frumhoff et al., 2007), the Second U.S. National Climate Assessment (USGCRP, 2009), and the Intergovernmental Panel on Climate Change (IPCC) Third and Fourth Assessment Reports; and the newer set of models used in the upcoming IPCC Fifth Assessment Report and Third U.S. National Climate Assessment.

Global model projections were translated down to the local scale using a statistical downscaling model. This model relates simulated variability and changes in large-scale climate to observed conditions at 14 long-term weather stations in Delaware, then uses these relationships to estimate how global climate change might affect local conditions in the future.

Assessing the potential impacts of climate change on a given location is a challenging task. Future projections are uncertain, due to the challenges inherent to predicting human behaviour; understanding the response of the earth's climate to heat-trapping gases produced by human activities; and predicting the variability of natural cycles within the earth system that have a strong influence on local climate.

Although challenging, it is important to assess climate impacts because the information generated can be valuable to long-term planning or policies. Much of current infrastructure and other human and natural systems are predicated on the assumption of a relatively stable climate. If climate is no longer stable, these systems will have to adapt. Adaptation can be costly, but planning ahead can reduce these costs. For example, projected changes in heating or cooling degree-days can be incorporated into new building codes or energy policy. Shifts in the timing and availability of streamflow can be used to redistribute water

allocations or as incentive for conservation programs. Projected changes in growing season and pest ranges can inform crop research and agricultural practices.

The information generated by this analysis, and summarized in this report, is intended to inform such studies for the state of Delaware and relevant sectors by providing state-of-the-art climate projections that can be incorporated into future planning.

This Report

This report documents the projected impacts of climate change on a range of temperature- and precipitation-related indicators for the state of Delaware. Projected changes cover a range of future scenarios and variables, including information relevant to agriculture, ecosystems and natural resources, energy use, infrastructure and transportation, public health, and water resources.

Section 2 describes the data, scenarios, and global climate models, and explains the statistical downscaling model used to generate high-resolution projections for the individual weather stations. It also provides guidance on understanding and interpreting the range of uncertainty in future projections.

Future projections are summarized for three future time periods, relative to a historical baseline of 1981-2010: near future (2020-2039), mid-century (2040-2059) and late century (2080-2099). Section 3 discusses average annual and seasonal temperature and temperature extremes. Section 4 describes projected changes in measures of seasonal precipitation, drought, and heavy precipitation. Section 5 explores projected impacts on indicators that combine temperature, precipitation, and/or humidity. Section 6 concludes with a discussion of the implications of climate change for Delaware.

Projections shown in figures and discussed in the text are averaged across all of the latest generation of CMIP5 climate models for individual scenarios: higher (RCP 8.5) and lower (RCP 4.5). Projected changes are consistent across all 14 stations; unless otherwise indicated, plotted values correspond to the 14-station average. Projections for the older CMIP3 models and SRES higher (A1fi) and lower (B1) scenarios are provided in the Excel appendix that accompanies this report. All figures include the uncertainty that results from using multiple climate models. For CMIP3 climate models (not shown here), uncertainty was defined by the difference between the highest and lowest model projection for each scenario and time period. For CMIP5 climate models, since there are more of them, uncertainty was defined by the standard deviation of the all-model ensemble unless the distribution was significantly non-normal, or skewed, in which case the highest or lowest model projection was used to define the range instead.

SECTION 2

DATA, MODELS, AND METHODS

This section describes the specific datasets and methods used to assess projected changes in Delaware climate in response to human-induced global climate change. These datasets, models and methods include future scenarios, global climate models, long-term station records, and a statistical downscaling model. These methods represent updated versions of those used in the 2007 Northeast Climate Impact Assessment (Frumhoff et al., 2007) and the Second U.S. National Climate Assessment, "Global Climate Change Impacts in the United States" (USGCRP, 2009), and are consistent with those used in the Climate Science section of the upcoming Third U.S. National Climate Assessment (Walsh et al., 2014).

Historical and Future Climate Scenarios

This analysis uses the RCP 8.5 (higher) and 4.5 (lower) concentration pathways and SRES A1fi (higher) and B1 (lower) emission scenarios. These scenarios were chosen because they cover a broad range of plausible futures in terms of human emissions of CO_2, CH_4, and other radiatively active species and their resulting impacts on climate. Results shown in this report are based on the newer RCP scenarios only. Results from both the RCP and SRES scenarios are provided in the Excel appendix that accompanies this report.

In historical climate model simulations, climate each year is affected by external forcings or climate drivers. These external climate drivers include atmospheric levels of greenhouse gases, solar radiation, and volcanic eruptions that are consistent with observed values for each year of the simulation. The historical forcings used by the global climate model (GCM) simulations in this project are the Coupled Model Intercomparison Project's "20th Century Climate in Coupled Models" or 20C3M total forcing scenarios (Meehl et al. 2007; Taylor et al., 2012). These simulations provide the closest approximation to actual climate forcing from the beginning of the historical simulation to the year 2000 for the older CMIP3 models, and the year 2005 for the newer CMIP5 simulations. Where multiple 20C3M simulations were available, the first was used here ("run 1" for CMIP3 and "r1i1p1" for CMIP5) unless complete daily outputs were not available for that simulation, in which case the next available was used.

The historical simulation provides the starting conditions for future simulations. To ensure the accuracy of the historical total forcing scenarios, it is customary in the climate modeling community for historical simulations to end at least 5 years before present. So although most CMIP3 GCM simulations were released well after 2000, the CMIP3 historical total-

forcing scenario ends in 1999, and "future" scenarios begin in 2000. Similarly, the CMIP5 historical scenario ends in 2005, and "future" scenarios begin in 2006. In the future scenarios, most external natural climate drivers are fixed, and human emissions correspond to a range of plausible pathways rather than observed values.

Future scenarios depend on a myriad of factors, including how human societies and economies will develop over the coming decades; what technological advances are expected; which energy sources will be used in the future to generate electricity, power transportation, and serve industry; and how all these choices will affect future emissions from human activities.

To address these questions, in 2000 the IPCC developed a series of scenarios described in the *Special Report on Emissions Scenarios* (SRES; Nakićenović et al., 2000). These scenarios describe internally consistent pathways of future societal development and corresponding emissions. The carbon emissions and global temperature change that result from the SRES scenarios are shown in **Figure 1** (left).

At the higher end of the range, the SRES higher-emissions or fossil fuel-intensive scenario (A1FI or A1fi, for *fossil-intensive*) represents a world with fossil fuel-intensive economic growth and a global population that peaks mid-century and then declines. New and more efficient technologies are introduced toward the end of the century. In this scenario, atmospheric CO_2 concentrations reach 940 parts per million by 2100, more than triple preindustrial levels of 280 ppm. At the lower end, the SRES lower-emissions scenario (B1) also represents a world with high economic growth and a global population that peaks mid-century and then declines. However, this scenario includes a shift to less fossil fuel-intensive industries and the introduction of clean and more resource-efficient technologies. Emissions of greenhouse gases peak around mid-century and then decline. Atmospheric CO_2 levels reach 550 parts per million by 2100, about double pre-industrial levels. Associated temperature changes by end of century range from 4 to 9^{o}F based on the best estimate of climate sensitivity.

For this project, climate projections were based on the A1FI higher (dark red) and B1 (blue) lower scenarios. Because of the decision of IPCC Working Group 1 to focus on the A2, A1B and B1 scenarios, only four GCMs had A1FI scenarios available. For other models, daily outputs were not available for all scenarios. **Table 1**, in the next section on **Global Climate Models**, summarizes the combinations of GCM simulations and emission scenarios used in this work.

In 2010, the IPCC released a new set of scenarios, called *Representative Concentration Pathways* (RCPs; Moss et al., 2010). In contrast to the SRES scenarios, the RCPs are expressed in terms of CO_2 concentrations in the atmosphere, rather than direct emissions. The RCP scenarios are also named in terms of their change in radiative forcing (in watts per meter squared) by end of century: +8.5 W/m^2 and +4.5 W/m^2. RCP scenarios can be

converted "backwards," into the range of emissions consistent with a given concentration trajectory, using a carbon cycle model, so they can be directly compared with SRES emissions (**Figure 1**, center). Four RCP scenarios were developed to span a plausible range of future CO_2 concentrations, from lower to higher. At the higher end of the range, atmospheric CO_2 levels under the RCP 8.5 scenario reaches more than 900 parts per million by 2100. At the lowest, under RCP 2.6, policy actions to reduce CO_2 emissions *below zero* before the end of the century (i.e. to the point where humans are responsible for a net uptake of CO_2 from the atmosphere) keeps atmospheric CO_2 levels below 450 parts per million by 2100. Associated temperature changes by late century range from 2 to 8°F, based on the best estimate of climate sensitivity. In this analysis, climate projections were based on the RCP 8.5 higher (dark red) and 4.5 lower (blue) scenarios, because these most closely match the SRES A1fi and B1 scenarios.

As diverse as they are, neither the SRES nor the RCP scenarios cover the entire range of possible futures. Since 2000, CO_2 emissions have already been increasing at an average rate of 3 percent per year. If they continue at this rate, emissions will eventually outpace even the highest of the SRES and RCP scenarios (**Figure 1**, right; Raupach et al., 2007; Myhre et al., 2009). On the other hand, significant reductions in emissions—on the order of 80 percent by 2050, as already mandated by various organizations and regions in the United States, including the state of California—have the potential to ultimately reduce CO_2 levels below the lower B1 emission scenario (Meinhausen et al., 2006). Nonetheless, the substantial difference between the higher and lower scenarios used here provides a good illustration of the potential range of changes that could be expected, and how much these depend on future emissions and human choices.

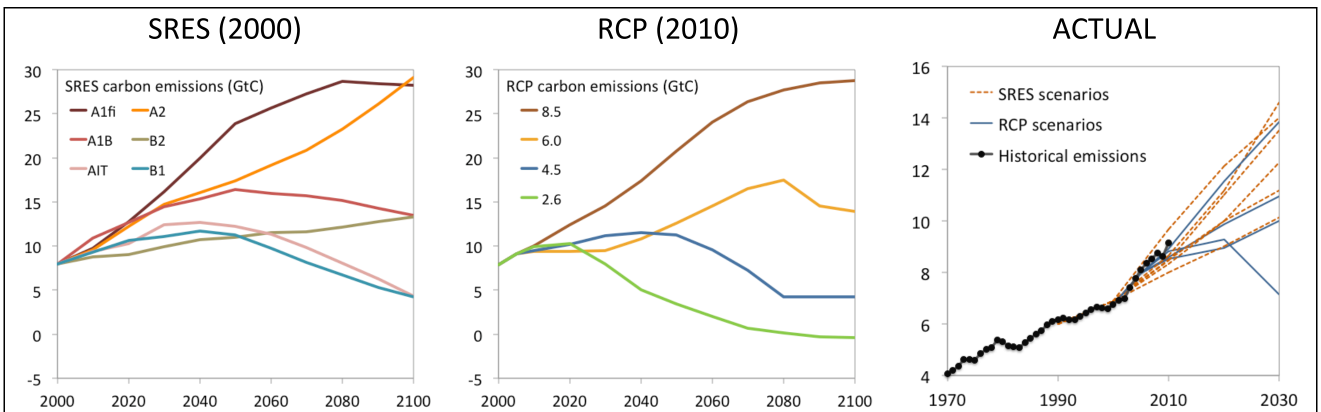


Figure 1. There are two families of future scenarios: the 2000 Special Report on Emission Scenarios (SRES) and the 2010 Representative Concentration Pathways (RCP). This figure compares the SRES (left), RCP (center), and observed historical annual carbon emissions (right) in gigatons of carbon (GtC). At the top end of the range, the SRES and RCP scenarios are very similar. At the bottom end of the range, the RCP 2.6 scenario is much lower, because it includes the option of using policies to reduce carbon emissions, while SRES scenarios do not.

Global Climate Models

This analysis uses simulations from four different CMIP3 global climate models, and nine different CMIP5 global climate models. Most of the results discussed in this report are based on CMIP5 simulations only. Projections corresponding to the full set of CMIP3 and CMIP5 models are provided in the Excel appendix that accompanies this report.

Future scenarios are used as input to GCMs, which are complex, three-dimensional coupled models that incorporate the latest scientific understanding of the atmosphere, oceans, and earth's surface. As output, GCMs produce geographic grid-based projections of temperature, precipitation, and other climate variables and daily and monthly scales. These physical models were originally known as atmosphere-ocean general circulation models (AO-GCMs). However, many of the newest generation of models are now more accurately described as global climate models (GCMs) as they incorporate additional aspects of the earth's climate system beyond atmospheric and oceanic dynamics.

Because of their complexity, GCMs are constantly being enhanced as scientific understanding of climate improves and as computational power increases. Some models are more successful than others at reproducing observed climate and trends over the past century (e.g., Randall et al., 2007). However, all future simulations agree that both global and regional temperatures will increase over the coming century in response to increasing emissions of greenhouse gases from human activities (IPCC, 2013).

Historical GCM simulations are initialized from stationary "control" simulations in the late 1800s. Over time, they are allowed to develop their own pattern of natural chaotic variability. This means that, although the climatological means of historical simulations should correspond to observations at the continental to global scale, no temporal correspondence between model simulations and observations should be expected on a day-to-day or even year-to-year basis. For example, although a strong El Niño event occurred from 1997 to 1998 in the real world, it may not occur in a model simulation in that year. Over several decades, however, the average number of simulated El Niño events should be similar to those observed. Similarly, although the central United States suffered the effects of an unusually intense heat wave during summer 1995, model simulations for 1995 might show that year as average or even cooler than average. However, a similarly intense heat wave is simulated by most models some time during the 30-year climatological period centered around 1995 (Hayhoe et al., 2010b).

This study uses two sets of global climate model simulations archived by the Program for Climate Model Intercomparison and Diagnosis (PCMDI). The first set of climate model simulations, assembled between 2005 and 2006, consists of models that contributed to phase 3 of the Coupled Model Intercomparison Project (CMIP3; Meehl et al., 2007). These are the results presented in the IPCC Third and Fourth Assessment Reports and used in the Northeast Climate Impacts Assessment (Frumhoff et al., 2007) and the Second U.S. National Climate Assessment (USGCRP, 2009).

Table 1. CMIP3 and CMIP5 global climate modeling groups and their models used in this analysis. Those marked with a (+) have only 360 days per year. All other models archived full daily time series from 1960 to 2099 (for CMIP3 simulations) and 1950 to 2100 (for CMIP5 simulations).

Origin	**CMIP3 model(s)**	**CMIP3 scenarios**	**CMIP5 model(s)**	**CMIP5 scenario(s)**
National Center for Atmospheric Research, USA	CCSM3 PCM	A1FI, B1 A1FI, B1	CCSM4	4.5, 8.5
Centre National de Recherches Meteorologiques, France			CNRM-CM5	4.5, 8.5
Commonwealth Scientific and Industrial Research Organisation, Australia			CSIRO-MK3.6.0	4.5, 8.5
Geophysical Fluid Dynamics Laboratory, USA	GFDL CM2.1	A1FI, B1	-	-
Max Planck Institute for Meteorology, Germany			MPI-ESM-LR	4.5, 8.5
UK Meteorological Office Hadley Centre	HadCM3+	A1FI, B1	HadGEM2-CC^+	4.5, 8.5
Institute for Numerical Mathematics, Russian			INMCM4	4.5, 8.5
Institut Pierre Simon Laplace, France			IPSL-CM5A-LR	4.5, 8.5
Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies, Japan			MIROC5	4.5, 8.5
Meteorological Research Institute, Japan			MRI-CGCM3	4.5, 8.5

The CMIP3 GCM simulations used in this project consist of all model outputs archived by PCMDI with daily maximum and minimum temperature and precipitation for the SRES A1fi and B1 scenarios. Additional simulations were obtained from the archives of the Geophysical Fluid Dynamics Laboratory, the National Center for Atmospheric Research, and the U.K. Meteorological Office. The list of GCMs used, their origin, the scenarios available for each, and the time periods covered by their output are given in **Table 1**.

From 2011 through the end of 2012, PCMDI began to collect and archive new CMIP5 simulations that are used in the IPCC Fifth Assessment Report (Taylor et al., 2012). The CMIP3 and CMIP5 archives are similar in that most of the same international modeling groups contributed to both. Both provide daily, monthly, and yearly output from climate model simulations driven by a wide range of future scenarios. However, the archives are also different from each other in three key ways. Over half of the CMIP5 models are new versions or updates of previous CMIP3 models, but a large number of CMIP5 models are entirely new. Some of the CMIP5 models are “Earth System Models” that include both traditional components of the CMIP3 Atmosphere-Ocean General Circulation Models as well as new components such as atmospheric chemistry or dynamic vegetation. Second, the

CMIP5 simulations use the RCP scenarios as input for future simulations, while the CMIP3 simulations use the SRES scenarios as input (**Figure 1**). Third, the CMIP5 archive contains many more output fields than the CMIP3 archive did.

Although the CMIP5 archive contains simulations from more than 40 models, a much smaller subset (only 16 individual models, from 13 modeling groups) archived daily temperature and precipitation for both the RCP 8.5 and 4.5 scenarios and even fewer of these models (9, total) represented updated versions of models already available in the CMIP3 archive. The CMIP5 GCM simulations used in this project consist of outputs from these 9 GCMs that have continuous daily maximum and minimum temperature and precipitation outputs available for historical and the RCP 8.5 and 4.5 future scenarios. No additional simulations were obtained from individual modeling group archives. The full list of CMIP5 GCMs used, their origin, the scenarios available for each, and the time periods covered by their output are given in **Table 1**.

The GCMs used in this study were chosen based on several criteria. First, only well established models were considered, those already extensively described and evaluated in the peer-reviewed scientific literature. Models must have been evaluated and shown to adequately reproduce key features of the atmosphere and ocean system. Second, the models had to include the greater part of the IPCC range of uncertainty in climate sensitivity (1.5 to 4.5^{o}C; IPCC, 2013). Climate sensitivity is defined as the temperature change resulting from a doubling of atmospheric CO_2 concentrations relative to pre-industrial times, after the atmosphere has had decades to adjust to the change. In other words, climate sensitivity determines the extent to which temperatures will rise under a given increase in atmospheric concentrations of greenhouse gases (Knutti & Hegerl, 2008). The third and last criterion is that the models chosen must have continuous daily time series of temperature and precipitation archived for the scenarios used here (SRES A1FI and B1; RCP 8.5 and 4.5). The GCMs selected for this analysis are the only models that meet these criteria.

For some regions of the world (including the Arctic, but not the continental United States) there is some evidence that models better able to reproduce regional climate features may produce different future projections (e.g. Overland et al., 2011). Such characteristics include large-scale circulation features or feedback processes that can be resolved at the scale of a global model. However, it is not valid to evaluate a global model on its ability to reproduce high-resolution local surface climate features, such as the bias in temperature over a given city or region. Such limitations are to be expected in any GCM, because they are primarily the result of a lack of spatial resolution rather than any inherent shortcoming in the physics of the model. Here, no attempt was made to select a subset of GCMs that performed better than others, because previous literature has showed that it is difficult, if not impossible, to identify such a subset for the continental United States (e.g. Knutti, 2010; Randall et al. 2007).

Statistical Downscaling Model

This analysis uses the statistical Asynchronous Regional Regression Model (ARRM) to generate high-resolution projections for individual weather stations. It was selected because it can resolve the tails of the distribution of daily temperature and precipitation to a greater extent than the more commonly used Delta and BCSD methods, but is less time-intensive and therefore able to generate more outputs as compared to a high-resolution regional climate model.

GCM simulations require months of computing time, effectively limiting the typical grid cell sizes of the models to 1 or more degrees of latitude and longitude per side. And although the models are precise to this scale, they are actually skillful, or accurate, to an even coarser scale (Grotch & MacCracken, 1991). This means that they cannot accurately capture the fine-scale changes experienced at the regional to local scale.

Dynamical and statistical downscaling represent two complementary ways to incorporate higher-resolution information into GCM simulations in order to obtain local- to regional-scale climate projections. Dynamical downscaling, often referred to as regional climate modeling, uses a limited-area, high-resolution model to simulate physical climate processes at the regional scale, with grid cells typically ranging from 10 to 50km per side. Statistical downscaling models capture historical relationships between large-scale weather features and local climate, and use these to translate future projections down to the scale of any observations—here, both individual weather stations as well as a regular grid.

Statistical models are generally flexible and less computationally demanding than regional climate models, able to use a broad range of GCM inputs to simulate future changes in temperature and precipitation for a continuous period covering more than a century. Hence, statistical downscaling models are best suited for analyses that require a range of future projections that reflect the uncertainty in future scenarios and climate sensitivity, at the scale of observations that may already be used for planning purposes. If the study is more of a sensitivity analysis, where using one or two future simulations is not a limitation, or if it requires multiple surface and upper-air climate variables as input (and has a generous budget), then regional climate modeling may be more appropriate.

In this project we used a relatively new statistical downscaling model, the Asynchronous Regional Regression Model, or ARRM (Stoner et al., 2012). ARRM uses asynchronous quantile regression, originally developed by Koenker and Bassett (1978), to estimate conditional quantiles of the response variable in econometrics. Dettinger et al. (2004) was the first to apply this statistical technique to climate projections to examine simulated hydrologic responses to climate variations and change, as well as to heat-related impacts on health (Hayhoe et al., 2004), and subsequent versions of this algorithm were used in the city-scale projections for the Northeast Climate Impacts Assessment (Frumhoff et al., 2007) and the Chicago Climate Action Plan (Hayhoe et al., 2010a).

ARRM expands on these original applications by adding (1) modifications specifically aimed at improving the ability of the model to simulate the shape of the distribution,

including the tails, (2) piecewise rather than linear regression to accurately capture the often non-linear relationship between modeled and observed quantiles, and (3) bias correction at the tails of the distribution. It is a flexible and computationally efficient statistical model that can downscale station-based or gridded daily values of any variable that can be transformed into an approximately symmetric distribution and for which a large-scale predictor exists. A quantile regression model is derived for each individual grid cell or weather station that transforms historical model simulations into a probability distribution that closely resembles historical observations (**Figure 2**, left). This model can then be used to transform future model simulations into distributions similar to those observed (**Figure 2**, right). This example illustrates how future temperatures are likely to become warmer (as the orange and red future distributions shifts towards the right-hand side of the black historical distribution), as well as how what is currently considered to be extreme heat is likely to become more frequent (as evidenced by the broading of the future distributions, meaning that there will be proportionally more days per year above historical high temperature percentiles).

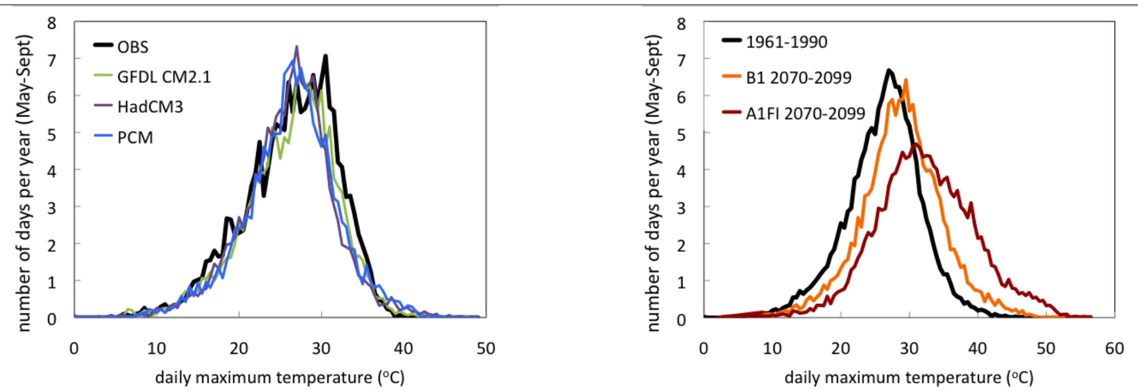


Figure 2. (a) Observed (black) and historical (blue, green, and purple) simulated distribution of daily maximum summer temperatures by three GCMs for a weather station in Chicago for evaluation period 1980-1999.

(b) Historical simulated (black) and future projected daily maximum summer temperature under the SRES A1FI higher (red) and B1 lower (orange) emission scenarios, averaged across all three GCMs.

Both statistical and dynamical downscaling models are based on a number of assumptions, some shared, some unique to each method. Two important shared assumptions are the following: first, that the inputs received from GCMs are reasonable—that is, that they adequately capture the large-scale circulation of the atmosphere and ocean at the skillful scale of the global model; and second, that the information from the GCM fully incorporates the climate change signal over that region. Statistical models are also sensitive to a crucial assumption often referred to as ***stationarity***. Stationarity assumes that the relationship between large-scale weather systems and local climate will remain constant over time. This assumption may be valid for lesser amounts of change, but could lead to biases under larger amounts of climate change (Vrac et al., 2007).

In a separate project, we are currently evaluating the stationarity of three downscaling methods, including the ARRM method used here. Preliminary analyses show that the assumption of stationarity holds true in ARRM over much of the world for both temperature and precipitation. The only situation where ARRM performance appears to be systematically non-stationary (i.e., relationships based on historical observations and simulations do not hold true in the future) is at extremely high temperatures (at and above the 99.9th quantile) along coastal areas, where we can see warm biases that increase as temperatures become more extreme. This may be due to the statistical model's inability to capture dynamical changes in the strength of the land-sea breeze as the temperature differences between land and ocean are exacerbated under climate change; the origins of this feature are currently under investigation.

This bias helps to interpret the projected changes in high temperatures generated for Delaware. Several of the station locations used in this study would be considered coastal. Estimated changes in days hotter than the 1-in-100 hottest historical day (e.g., the historical ~3 to 4 hottest days of the year) may be subject to temperature biases that increase in magnitude. For the 1-in-1000 hottest days (e.g. the hottest day in 3 years), biases may be as large as the projected changes in the temperature of those days by end of century under a higher emissions scenario.

Station Observations

This project uses long-term station data from the Global Historical Climatology Network and the National Climatic Data Center Co-op Observing Network, supplemented with additional station data provided by the Delaware State Climatologist. All station data was quality-controlled to remove possibly erroneous data points before being used to train the statistical downscaling model.

Long-term weather station records were obtained from the Global Historical Climatology Network (GHCN)[3] and supplemented with additional records from the National Climatic Data Center cooperative observer program (NCDC-COOP)[4] and the State Climatologist for Delaware (D. Leathers, *pers. comm.*).

To train a statistical downscaling model, the observed record must be of adequate length and quality. To appropriately sample from the range of natural climate variability at most of the station locations, and to produce robust results without overfitting, each station in the analysis was required to have a minimum of 20 consecutive years of daily observations overlapping GCM outputs with less than 50 percent missing data after quality control. When these limits were applied, there were 14 usable stations available for with daily maximum and minimum temperature and precipitation available. The latitude, longitude, and station names of these weather stations are provided in **Table 2** and are plotted in **Figure 3**.

[3] GHCN data is available online at: http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/
[4] NCDC-COOP data is available online at: http://www.ncdc.noaa.gov/land-based-station-data/cooperative-observer-network-coop

Figure 3. This report generated future projections for 14 weather stations in Delaware with long-term historical records. Weather stations that did not have sufficiently long and/or complete observational records to provide an adequate sampling of observed climate variability at their locations were eliminated from this analysis.

Although GHCN station data undergo standardized quality control (Durre et al., 2008), all station data were additionally filtered using a quality control algorithm to identify and remove erroneous values previously identified in the GHCN database. The quality control process consists of two steps: first, individual quality control for each station; and second, a nearest neighbor approach to validate outliers identified relative to the climatology of each month. Individual quality control identified and replaced with "N/A" any values where:

1. Daily minimum temperature exceeded the reported maximum.
2. Values lay outside the range of recorded values for the continental United States (-50 to 70°C, 0 to 915mm in 25 hours).
3. More than five consecutive days had identical temperature or non-zero precipitation values to the first decimal place.

In the second step of the quality control process, up to 10 "nearest neighbors" for each individual weather station were queried to see if the days with anomalously high and low values were also days in which anomalous values occurred at the neighboring station, plus or minus one day on either side to account for weather systems that may be moving through the area close to midnight. The resulting files were then scanned to identify any stations with less than 3,650 real values and less than 200 values for any given month.

Uncertainty

The primary challenge in climate impact analyses is the reliability of future information. A common axiom warns that the only aspect of the future that can be predicted with any certainty is the fact that it is impossible to do so. However, in the case of climate change, we do know one thing: future climate will not be the same as it is today. That is why it is important to incorporate projected climate changes into long-term planning.

Although it is not possible to *predict* the future, it is possible to *project* it. Projections can describe what would be likely to occur under a set of consistent and clearly articulated assumptions. For climate change impacts, these assumptions should encompass a broad variety of the ways in which energy, population, development, and technology might change in the future.

Station Name	Latitude	Longitude	Beginning of Record	GHCN ID
Bear	39.5917	-75.7325	Apr 2003	USC00071200
Bridgeville	38.75	-75.6167	Jan 1893	USC00071330
Dover	39.2583	-75.5167	Jan 1893	USC00072730
Georgetown	38.6333	-75.45	Sept 1946	USC00073570
Greenwood	38.8161	-75.5761	Jan 1986	USC00073595
Lewes	38.7756	-75.1389	Feb 1945	USC00075320
Middletown	39.45	-75.6667	Sept 1952	USC00075852
Milford	38.8983	-75.425	May 1893	USC00075915
Newark University Farm	39.6694	-75.7514	Apr 1894	USC00076410
Selbyville	38.4667	-75.2167	Jan 1954	USC00078269
Wilmington Porter	39.7739	-75.5414	Jan 1932	USC00079605
Dover AFB	39.1333	-75.4667	Jul 1946	USW00013707
Georgetown Sussex Airport	38.6892	-75.3592	Feb 1945	USW00013764
Wilmington New Castle Airport	39.6728	-75.6008	Jan 1948	USW00013781

Table 2. Latitude, longitude, and identification numbers for the 14 weather stations used in this analysis.

Projections come with a range of uncertainty. This uncertainty arises primarily due to three different causes: (1) natural variability in the climate system, (2) scientific uncertainty in predicting the response of the earth's climate system to human-induced change, and (3) socioeconomic or scenario uncertainty in predicting future energy choices and hence emissions of heat-trapping gases (Hawkins & Sutton, 2009, 2011).

Future projections will always be limited by scientific understanding of the system being predicted. The earth's climate is a complex system. It is possible to simulate only those processes that have been observed and documented. Clearly, there are other feedbacks and forcing factors at work that have yet to be documented. Hence, it is a common tendency to assign most of the range in future projections to model, or scientific, uncertainty. However, there are other important sources of uncertainty that must be considered; some even outweigh model uncertainty for certain variables and timescales.

It is important to note that scenario uncertainty is very different, and entirely distinct, from scientific uncertainty in at least two important ways. First, although scientific uncertainty can be reduced through coordinated observational programs and improved physical

modeling, scenario uncertainty arises due to the fundamental inability to predict future changes in human behaviour. It can be reduced only by the passing of time, as certain choices (such as depletion of a non-renewable resource) can eliminate or render certain options less likely. Second, scientific uncertainty is often characterized by a normal distribution, where the mean value is more likely than the outliers. Scenario uncertainty, however, hinges primarily on whether or not the primary emitters of heat-trapping gases, including traditionally large emitters such as the United States as well as nations with rapidly-growing contributions such as India and China, will enact binding legislation to reduce their emissions or not. If they do enact legislation, then the lower emission scenarios become more probable. If they do not, then the higher scenarios become more probable. The longer such action is delayed, the less likely it becomes to achieve a lower, as compared to a mid-low, scenario because of the emissions that continue to accumulate in the atmosphere. Hence, scenario uncertainty cannot be considered to have a normal distribution. Rather, the consequences of a lower versus a higher emissions scenario must be considered independently, in order to isolate the role that human choices are likely to play in determining future impacts.

The importance of each of these three sources of uncertainty varies over time and space (**Figure 4**). Over relatively short time scales, natural chaotic variability is the most important source of uncertainty. By mid-century, scientific or model uncertainty is the largest contributor to the range in projected temperature and precipitation change. By the end of the century, scenario uncertainty is most important for temperature projections, while model uncertainty continues as the dominant source of uncertainty in precipitation. This is consistent with the results of the projections discussed in this report, where there is a significant difference between the changes projected under higher versus lower scenarios for temperature-based and heavy precipitation indicators, but little difference for mean precipitation-based indicators.

Natural variability, the first source of uncertainty in future projections, can be addressed by always averaging or otherwise sampling from the statistical distribution of future projections over a climatological period – typically, 20 to 30 years. In other words, the average winter temperature should be averaged over several decades, as should the coldest day of the year. No time stamp more precise than 20 to 30 years should ever be assigned to any future projection. In this report and accompanying data files, simulations are always averaged over multidecadal, climatological time periods: historical (1981-2010), near century (2020-2039), mid-century (2040-2059) and late century (2080-2099).

Model or scientific uncertainty, the second source of uncertainty in future projections, can be addressed by using multiple global climate models to simulate the response of the climate system to human-induced change (here, the nine newer CMIP5 and four older CMIP3 models). As noted above, the climate models used here cover a range of climate

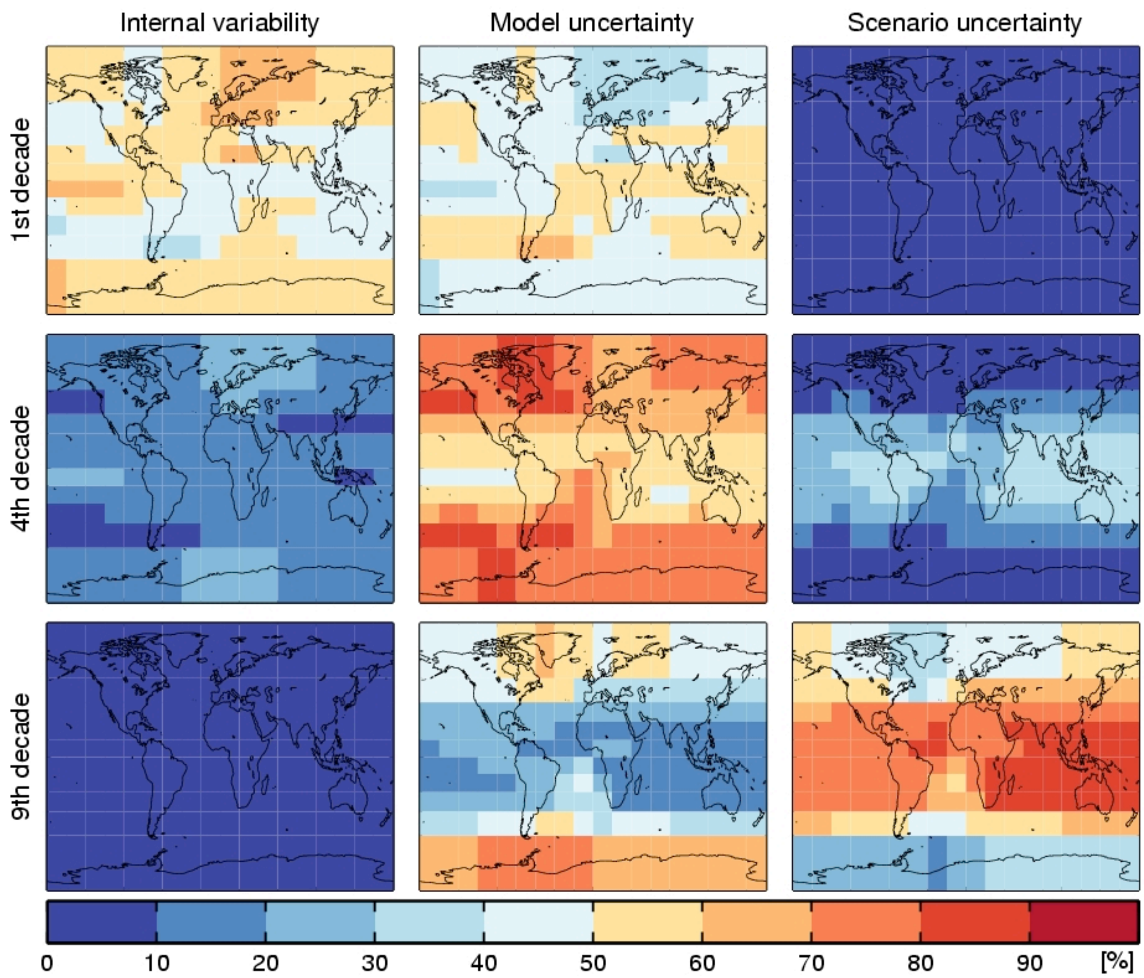


Figure 4. Percentage of uncertainty in future temperature projections one decade in the future (top row), four decades in the future (middle row) and nine decades in the future (bottom row) that can be attributed to natural variability (left column), model or scientific uncertainty (center column), and scenario uncertainty (right column). Source: Hawkins & Sutton, 2009.

sensitivity; they also cover an even wider range of precipitation projections, particularly at the local to regional scale.

As the statistician George Box famously quipped, all models are wrong, but some models are useful. Multiple studies have convincingly demonstrated that the average of an ensemble of simulations from a range of climate models (even ones of varied ability) is generally closer to reality than the simulations from one individual model—even one deemed "good" when evaluated on its performance over a given region (e.g., Weigel et al., 2010; Knutti, 2010). Only models that demonstratively fail to reproduce the basic features of large-scale climate dynamics (e.g., the jet stream or El Niño) should be eliminated from consideration. Hence, wherever possible, impacts should be summarized in terms of the values resulting from multiple climate models, while uncertainty estimates can be derived from the range or variance in model projections. This is why most plots in this report show both multimodel mean values as well as a range of uncertainty around each value.

Scenario or human uncertainty, the third and final primary source of uncertainty in future projections, can be addressed through generating climate projections for multiple futures: for example, a "higher emissions" future in which the world continues to depend on fossil fuels as the primary energy source (SRES A1FI or RCP 8.5), as compared to a "lower emissions" future focusing on sustainability and conservation (SRES B1 or RCP 4.5).

Over the next two to three decades, projections can be averaged across scenarios, because there is no significant difference between scenarios over that time frame due to the inertia of the climate system in responding to changes in heat-trapping gas levels in the atmosphere (Stott & Kettleborough, 2002). Past mid-century, however, projections should never be averaged across scenarios; rather, the difference in impacts resulting from a higher as compared to a lower scenario should always be clearly delineated. That is why, in this report, future projections are always summarized in terms of what is expected for each scenario individually.

For Delaware, by late century, scenarios are the most important source of uncertainty in average temperature, as well as an important source of uncertainty for extreme temperature and precipitation indicators. In contrast, scientific uncertainty, as represented by the various climate models, is the most important source of uncertainty in average annual and seasonal precipitation projections.

Downscaling climate projections from global models to the scale of individual weather stations introduces a fourth source of uncertainty, that of the statistical model used to relate large-scale weather patterns to local-scale varability. This uncertainty in turn can be attributed to three distinct sources: (1) the degree to which the limited set of observations used to train the statistical method fail to capture the larger range in possible weather conditions at that location; (2) the inability of the statistical model to perfectly reproduce the relationship between large-scale weather and local conditions; and (3) limitations in the ability of the global climate model to simulate regional conditions. Impacts on Delaware's climate due to global climate change will be modified by local factors, including topography (such as the proximity of the state to the ocean), small-scale feedback processes (such as changes in the type of vegetation that grows in Delaware as climate changes), and land use (including conversion of forests to suburbs, or fields to forests), all of which are difficult if not impossible to predict; hence, in this analysis, they are held fixed at current-day conditions.

SECTION 3

TEMPERATURE-RELATED INDICATORS

Observed temperatures across Delaware are increasing in all seasons, with relatively greater increases in minimum as compared to maximum temperatures. There have also been increases in the frequency of warm temperature extremes, and decreases in the frequency of cold temperature extremes. In the future, average temperature and temperature-related indicators across the state of Delaware are expected to continue to increase. This section summarizes the changes in average and extreme temperature that are projected to occur in response to global climate change.

Annual and Seasonal Temperatures

In the future, **annual average temperature** is expected to continue to increase. Over the next few decades, projected temperature changes are expected to be similar regardless of the scenario followed over that time. There is no significant difference between temperature projections from different scenarios over the short term for two reasons. First, it takes some time for the climate system to respond to differences in emissions. Second, emissions among different scenarios are not very different over the short term (see **Figure 1**). This is because of the lags in both socioeconomic and energy systems: installations of fossil fuel or renewable energy take years to design and build, and are typically used for decades. None of the scenarios considered here envision a world in which all fossil fuel use could be eliminated within a decade or two. For these two reasons, the majority of the changes that will happen over the next few decades are the result of heat-trapping gas emissions that have already built up in the atmosphere or are already entailed by our existing infrastructure.

By mid-century, temperature increases are greater under a higher scenario versus a lower, although the multi-model uncertainty range (i.e., the temperature change projected by a given model) still overlaps (**Figure 5**). By late century, the multi-model uncertainty range for a higher versus a lower scenario does not overlap: in other words, even the smallest projected change in temperature under higher scenarios is greater than the largest projected change under lower scenarios. Temperature increases are also greater for later time periods as compared to earlier ones.

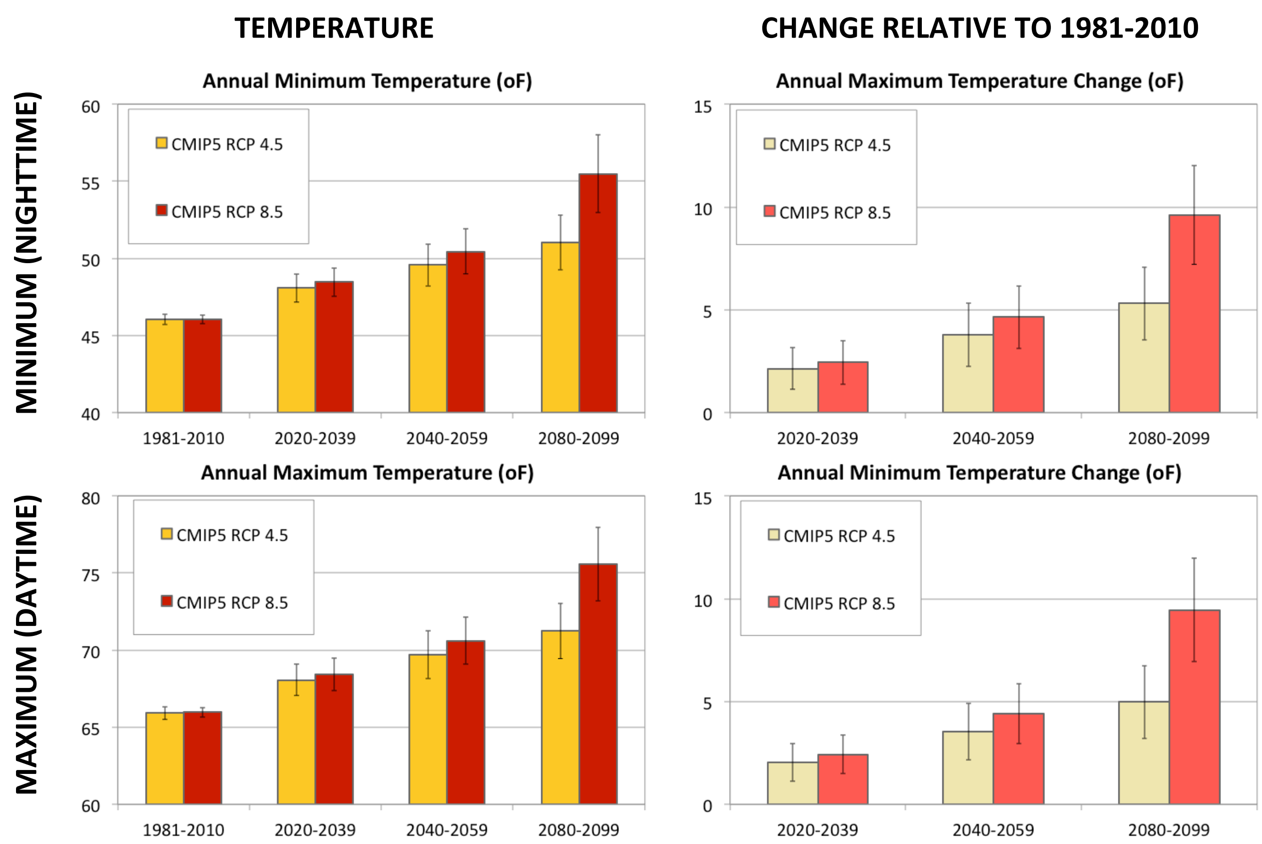


Figure 5. Projected absolute (left) and relative change in (right) **annual maximum (daytime) and minimum (nighttime) temperature** compared to 1981-2010 average values. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes under the lower scenario are shown in yellow, and projections for the higher scenario in red. The black "whiskers" indicate the uncertainty that results from using multiple climate models.

Specifically, by 2020-2039, annual maximum (daytime) temperature is projected to increase by an average of 2 to 2.5^{o}F, and annual minimum (nighttime) temperature by an average of 1.5 to 2.5^{o}F across all scenarios. By mid-century 2040-2059, increases under the lower scenario range from 2.5 to 4^{o}F for maximum temperature and 2 to 3.5^{o}F for minimum temperature. Under the higher scenario, increases average 4.5^{o}F for both maximum and minimum temperature. By end of century 2080-2099, projected temperature changes are nearly twice as great under higher as compared to lower scenarios. Maximum temperature increases by 3.5 to 5.5^{o}F under the lower and 8 to 9.5^{o}F under the higher scenario. Minimum temperature increases by 3 to 5^{o}F under the lower and 8.5 to 9.5^{o}F under the higher scenario.

Seasonal temperatures also show increases, but at different rates than the annual average. In general, projected increases for spring and summer are greater than those projected for fall and winter (**Figure 6**). By late century, for example, average temperature is projected to increase by about 4 to 6^{o}F under a lower and 7 to 11^{o}F under a higher scenario in spring, and by 3.5 to 8^{o}F under a lower and 7 to 15^{o}F under a higher scenario in summer. Fall and winter changes are smaller: 2 to 5^{o}F under a lower and 6 to 10^{o}F under a

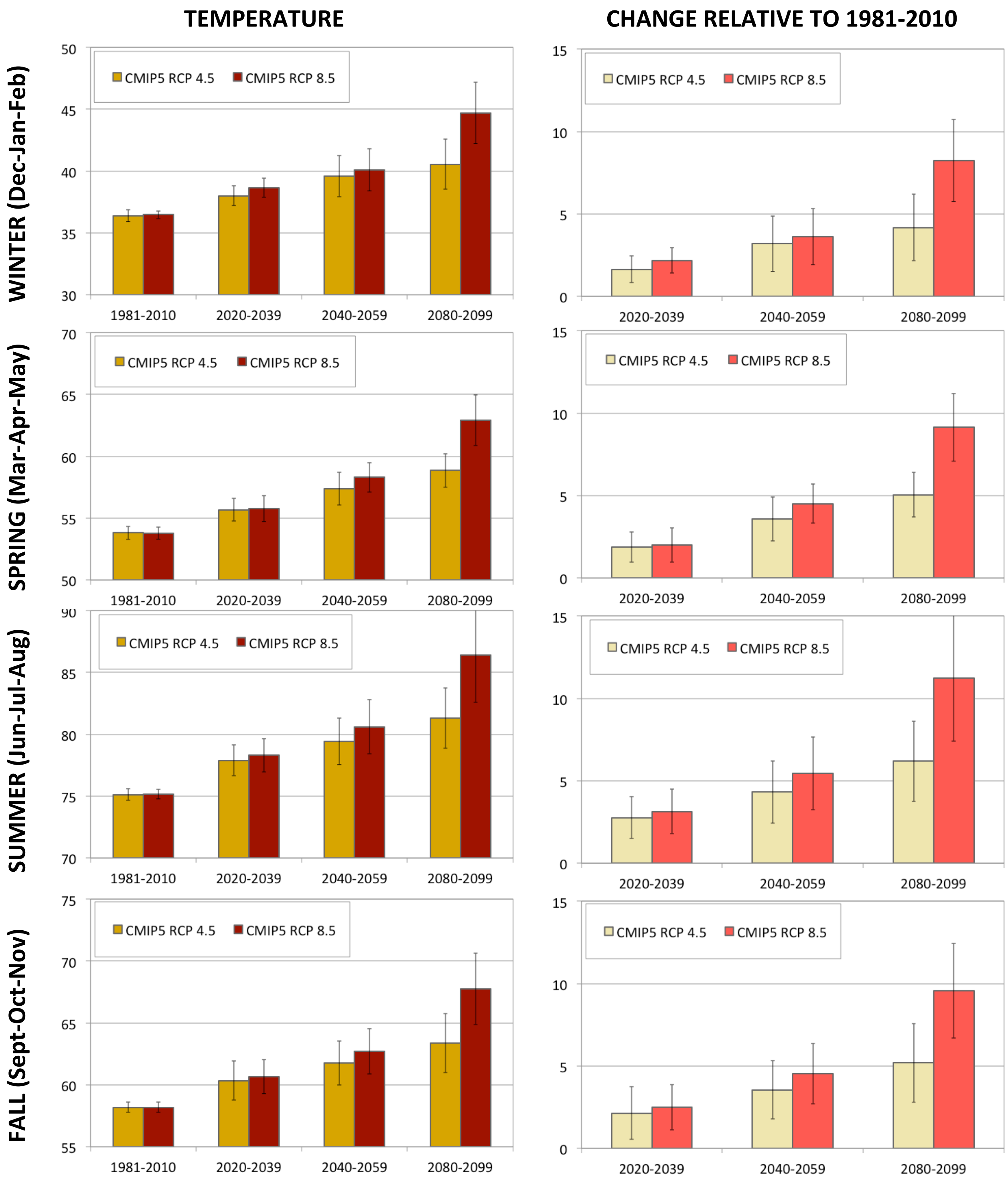


Figure 6. Projected absolute value (left) and relative change (right) in **seasonal average temperature** compared to 1981-2010 for winter (Dec-Jan-Feb), spring (Mar-Apr-May), summer (Jun-Jul-Aug) and fall (Sept-Oct-Nov). Greater changes are projected for spring and summer as compared to winter and fall. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes for the lower scenario are shown in yellow, projections for the higher scenario in red. Black "whiskers" indicate the range of uncertainty from multiple climate models.

higher scenario in fall, and 3.5 to 4°F under a lower and 6.5 to 8°F under a higher scenarios in winter.

For both seasonal and annual temperature, the increases simulated by CMIP5 models are generally higher than those simulated by CMIP3 models (not shown; plots available in Excel appendix). This difference may be due to a greater number of models in CMIP5 as compared to CMIP3, and therefore a larger sample size of projected changes. It may also reflect different processes occurring within the models, because the CMIP5 models used in this analysis represent newer and more complex versions of CMIP3 models. Comparing simulations for seasonal temperature, it appears that the SRES A1fi and RCP 8.5 scenarios (both higher) are generally close, with RCP 8.5 being slightly higher than A1fi in all seasons. In contrast, the SRES B1 and RCP 4.5 scenarios (both lower) are nearly identical in winter and spring, but extremely different in summer and fall. SRES B1 multi-model average projections and even the multi-model range is significantly smaller (by more than 3°F) than RCP 4.5 in summer and fall. This suggests that there may be different processes at work in driving summer and fall temperature change in the CMIP5 models compared to CMIP3.

Historical **temperature range** (the difference between the average maximum and minimum temperature for the season)is smallest for winter (averaging around 17°F) and largest for spring (around 21°F). **Figure 7** shows the historical and projected future range in temperature for each season. The largest and most significant change is in spring, where all models project a consistent increase in the range of temperature. Projected changes for winter and summer are inconsistent, with some models projecting an increase and others, a decrease. For fall, models project either no change or a decrease in temperature range. Projected changes in annual temperature range are negligable (not shown).

The **standard deviation of temperature** is a different type of measure; it assesses the day-to-day variability in maximum and minimum temperatures. Historically, the standard deviation of daytime maximum temperature, averaged across the 14 Delaware weather stations, is almost 18°F, while the standard deviation of nighttime temperature is slightly lower, almost 17°F. In the future, the standard deviation of temperature is projected to change slightly: for maximum temperature, an increase of around +0.5°F under lower scenarios and +1°F under higher scenarios, and for minimum temperature, an increase of around around +0.5°F under lower scenarios and +1.5°F under higher scenarios for the multi-model mean by late century (**Figure 8**). Individual models do not necessarily agree: although the mean shows an increase, some models project no change or even a slight decrease. On average, this means that future climate change may increase the range in day-to-day temperatures as compared to the historical average, but this increase is not certain.

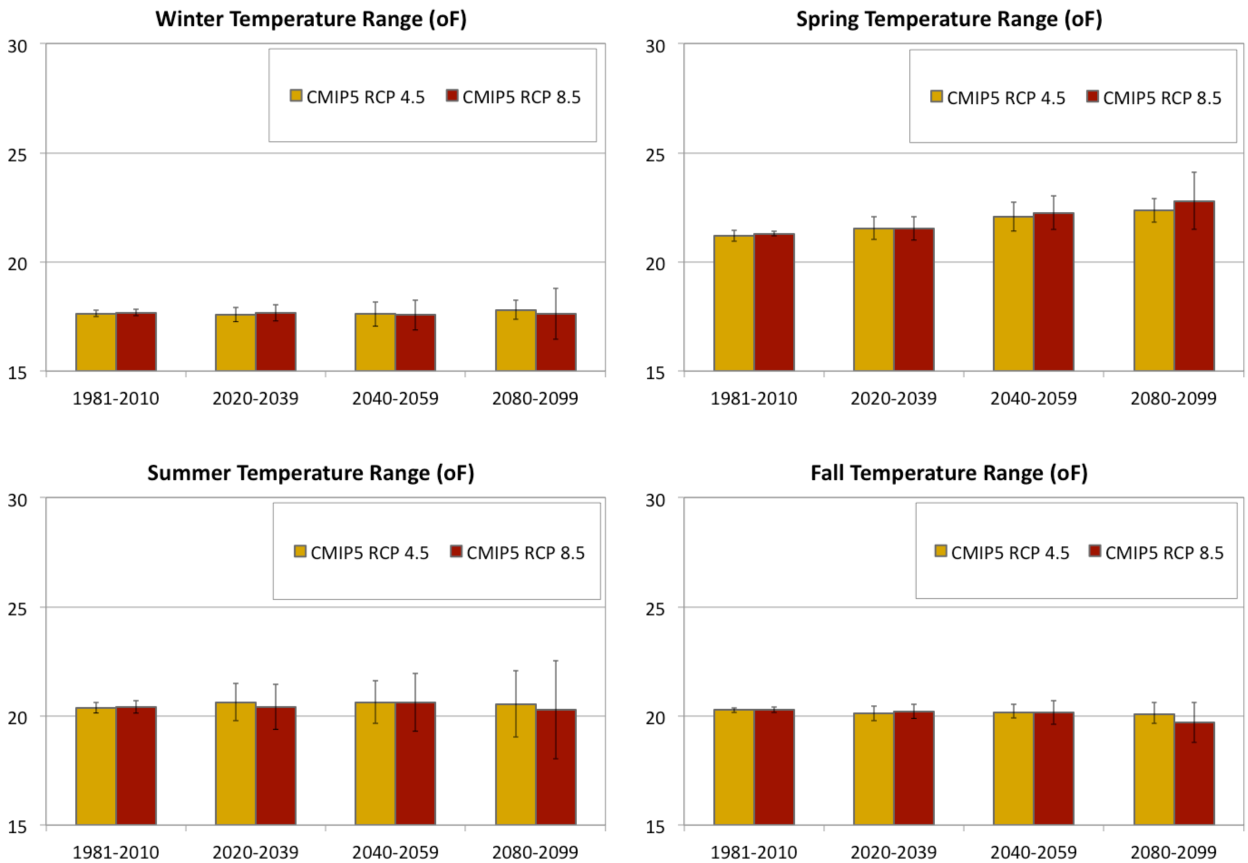


Figure 7. Historical modelled and projected future **temperature range** (maximum - minimum temperature) for winter (Dec-Jan-Feb), spring (Mar-Apr-May), summer (Jun-Jul-Aug) and fall (Sept-Oct-Nov). Increases in the range are projected in spring, and decreases in fall. No change is projected in winter and summer, nor annually. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes for lower scenarios are shown in yellow, projections for higher scenarios in red. Black "whiskers" indicate the range of uncertainty from multiple climate models.

Temperature Extremes

As average maximum and minimum temperatures increase, extreme heat is also expected to become more frequent, while extreme cold is expected to become less frequent. What is viewed as "extreme" is often location-specific: while a 90°F day may be extreme for one place, it may be normal for another. For that reason, a broad range of temperature extreme and threshold indicators were calculated in this analysis: some using fixed thresholds (e.g., days per year over 100°F or below 32°F) and others using percentiles (e.g., future days per year colder than the coldest 1 percent of days, or warmer than the warmest 5 percent of days).

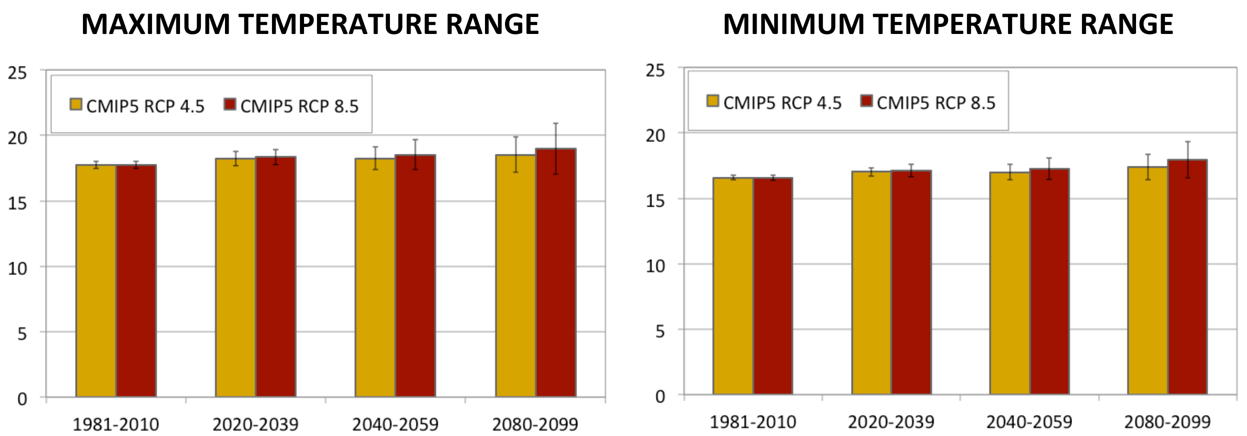


Figure 8. Historical and projected future variability in day-to-day annual maximum (daytime) and minimum (nighttime) temperature, measured as the **standard deviation** of daily values for each time period, in degrees F. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes under lower scenarios of human emissions of heat-trapping gases are shown in yellow, and projections for higher scenarios in red. The black "whiskers" indicate the uncertainty that results from using multiple climate models.

Beginning with percentiles, the temperature of the historical 1-in-100 (1 percent) and 1-in-20 (5 percent) coldest days of the year currently averages around 18 to 19°F and 27 to 28°F, respectively. As average temperatures increase, the frequency of 1-in-20 coldest days is projected to decrease from the historical average of 5 to 4 percent by 2020-2039, 3 percent by mid-century, and ultimately 2 percent by late century, with slightly greater changes by end of century under higher as compared to lower scenarios (**Figure 9**, left). Little significant change is expected in 1-in-100 coldest days: there is some indication of a small decrease in frequency, but it is not significant.

In terms of high temperatures, the temperature of the historical 1-in-20 (95 percent) and 1-in-100 (99 percent) hottest days averages around 80°F and 84 to 85°F, respectively. The frequency of the 1-in-20 hottest days, currently 5 percent, is projected to increase to 7 to 11 percent by 2020-2039, 10 to 15 percent by mid-century, and by around 15 percent under lower scenarios and more than 25 percent under higher scenarios by late century (**Figure 9**, right). The frequency of the 1-in-100 hottest day, currently 1 percent, is projected to increase proportionally more, to around 3 percent near-term, 6 percent by mid-century, and 5 to 10 percent under lower scenarios and almost 20 percent under higher scenarios by late century. In other words, the very coldest days will still occur, but very hot days will become much more frequent, particularly the 1-in-100 hottest day, which could become as much as 20 times more frequent under higher scenarios by 2080-2099. This is consistent with an increase in the standard deviation of both maximum and minimum temperature discussed previously.

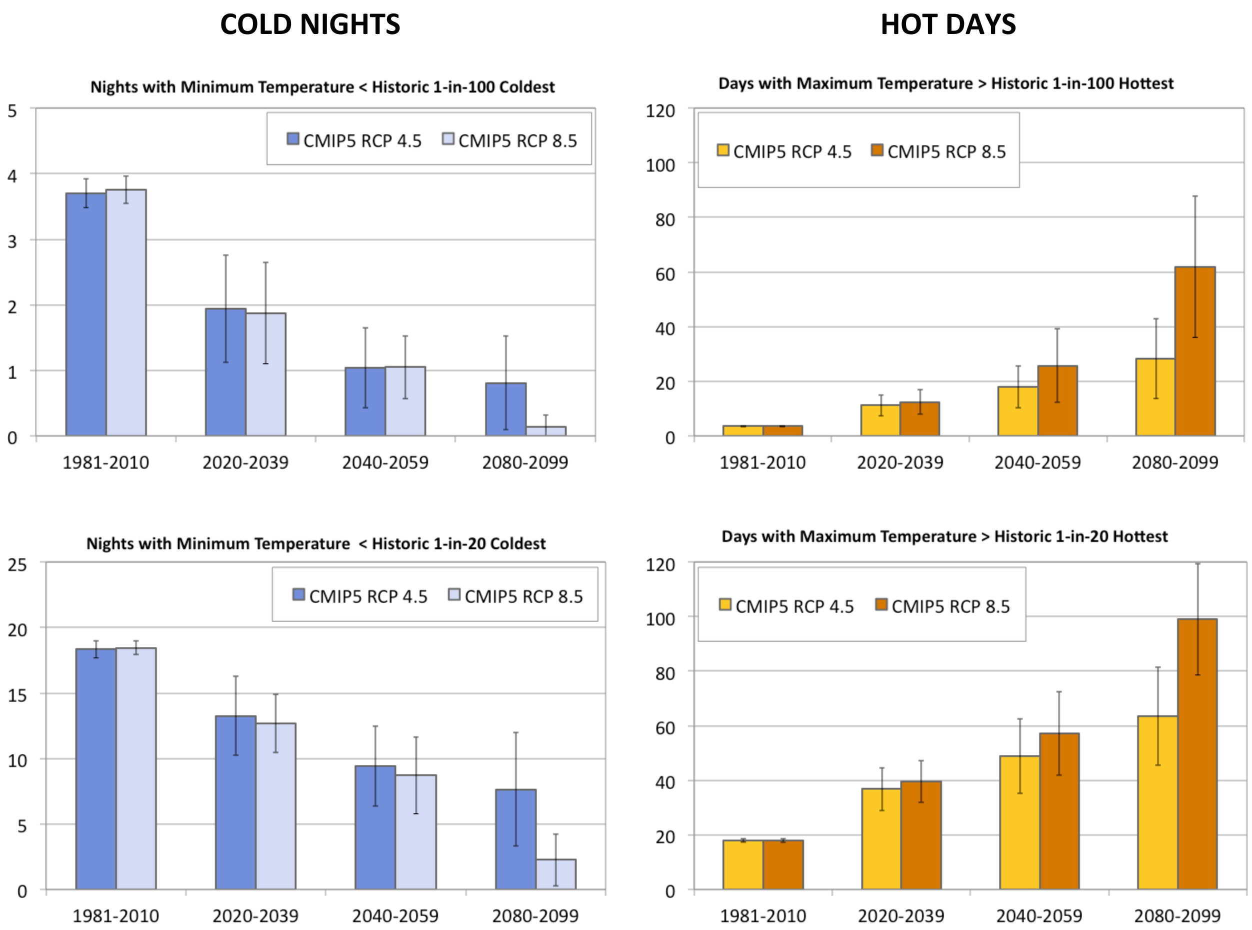


Figure 9. Projected number of **cold nights** (left) and **hot days** (right) that exceed the historical 1% (1-in-100 coldest), 5% (1-in-20 coldest), 95% (1-in-20 hottest), and 99% (1-in-100 hottest) days of the year. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes for the lower scenario are shown in dark blue and light orange, projections for the higher scenario in light blue and dark orange. Black "whiskers" indicate the range of uncertainty from multiple climate models.

The two cold temperature thresholds examined here are number of times per year per year when minimum (nighttime) temperature falls below 20^{o}F and below freezing, or 32^{o}F. Historically, there are typically around 20 days per year below 20^{o}F and 85 days per year below freezing (**Figure 10**). In the future the number of days below 20^{o}F is projected to drop by 5 days to an average of 15 by 2020-2039, by almost 5 more to an average of just over 10 days per year by 2040-2059, and to a minimum of 10 days per year under lower scenarios and only 3 to 4 days per year under higher scenarios by 2080-2099. In general, much larger changes in days below 20^{o}F are projected under the CMIP5 lower scenario (RCP 4.5) as compared to the CMIP3 lower scenario (B1), while projected changes under the two higher scenarios (RCP 8.5 and SRES A1fi) are similar. CMIP3 and CMIP5 projections are compared in the Excel appendix.

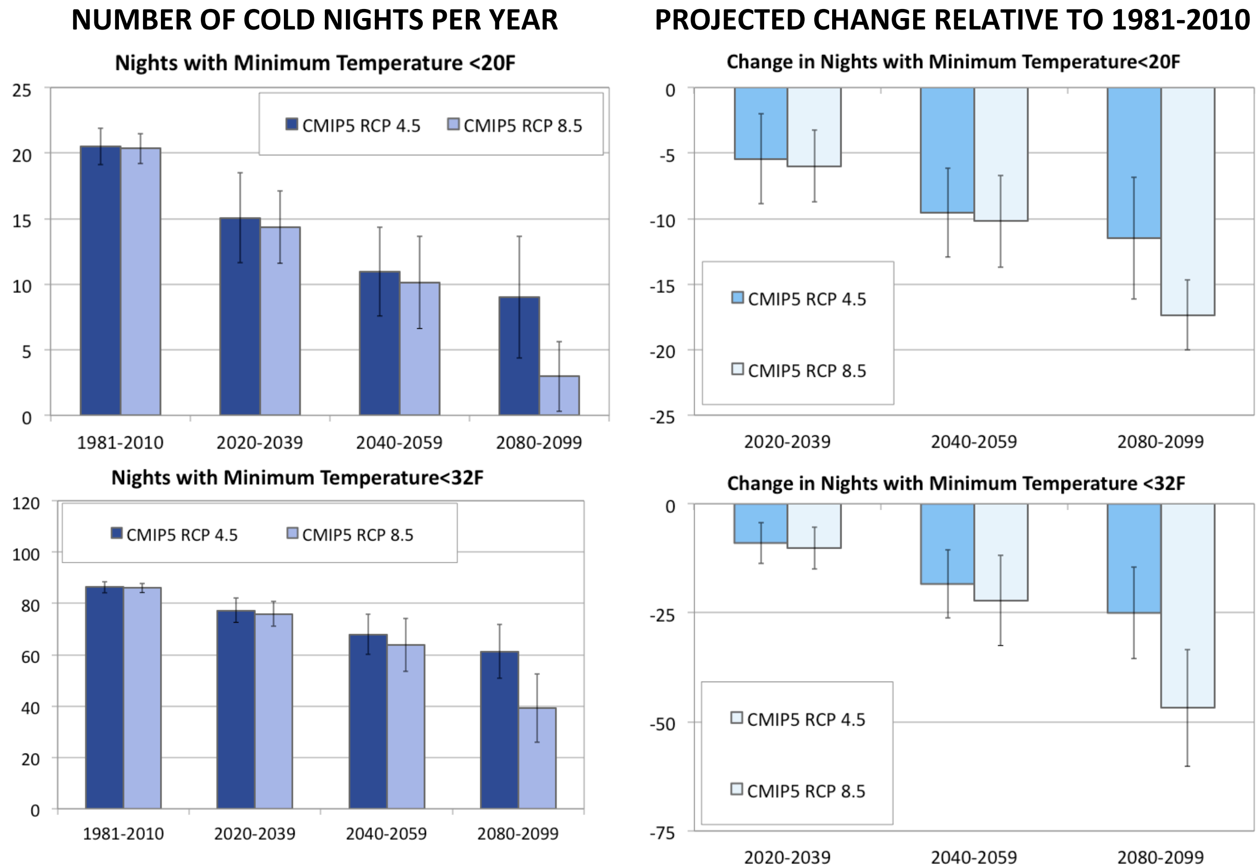


Figure 10. Historical and projected future number of **cold nights** per year (left) and projected change relative to 1981-2010 average (right) with minimum temperature below 20°F (top) and 32°F (bottom). Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes under the lower scenario are shown in dark blue, and projections for the higher scenario in light blue. Black "whiskers" indicate the uncertainty that results from using multiple climate models.

The number of times minimum temperature drops below freezing is also expected to decrease: by around 10 days by near-century, and by 20 days by mid-century (**Figure 10**). By late century there are projected to be around 60-70 nights per year below freezing under lower scenarios and 40-50 nights per year under higher scenarios. For this threshold, greater changes tend to be projected under CMIP5 scenarios as compared to CMIP3.

The first and last dates of freeze each year are closely related to the length of the growing season. Although the growing season can be defined in different ways for different crops and various regions, it is defined here simply as the "frost-free" season, counting the number of days between the last frost in spring and the first frost in fall or winter.

Across Delaware, the frost-free growing season currently averages around 210 days per year (**Figure 11**). In the future, it is projected to lengthen: by about 10 days over the near-term, around 20 days by mid-century, and from 30 days under a lower scenario up to 50

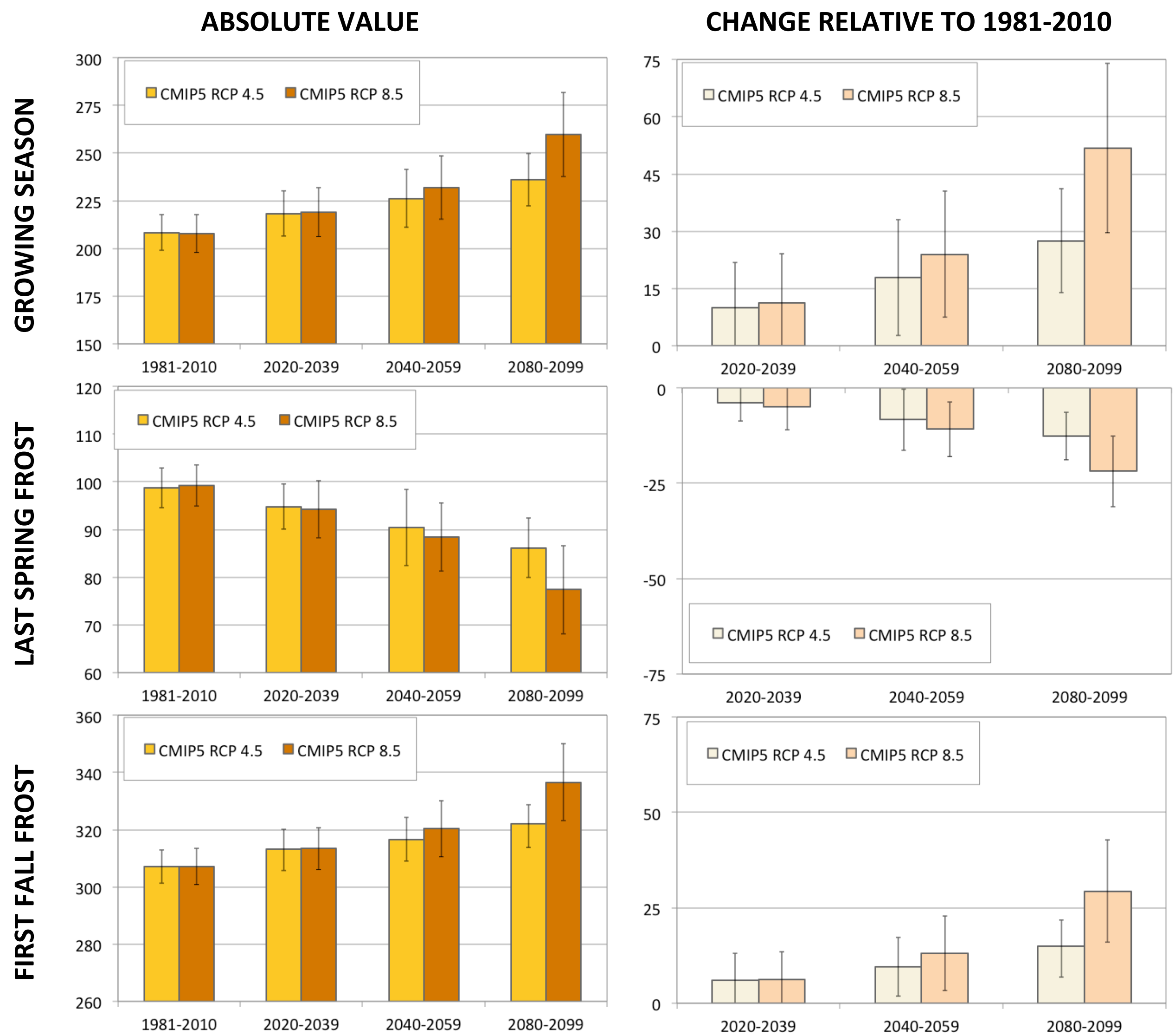


Figure 11. Projected absolute value (left) and change compared to 1981-2010 (right) in growing season (top), date of last spring frost (middle) and first fall frost (bottom) in units of days per year. Greater changes are projected for spring and summer as compared to winter and fall. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes for the lower scenario are shown in yellow, projections for the higher scenario in orange. Black "whiskers" indicate the range of uncertainty from multiple climate models.

days longer under a higher scenario for late century. Changes in the first date of fall frost are projected to be only slightly smaller than changes in the last date of spring frost, suggesting that overall the growing season is likely to lengthen into both spring and fall.

For high temperatures, the days per year above four high temperature thresholds (95, 100, 105, and 110°F) are all projected to increase, with proportionally greater increases in the absolute number of days per year, compared to historical values, for the more extreme indicators (e.g., days over 105 or 110°F) as compared to the less extreme thresholds (e.g., days over 90 or 95°F; **Figure 12**). For example, Delaware currently experiences an average of less than 5 days per year with maximum temperature exceeding 95°F. By 2020-2039,

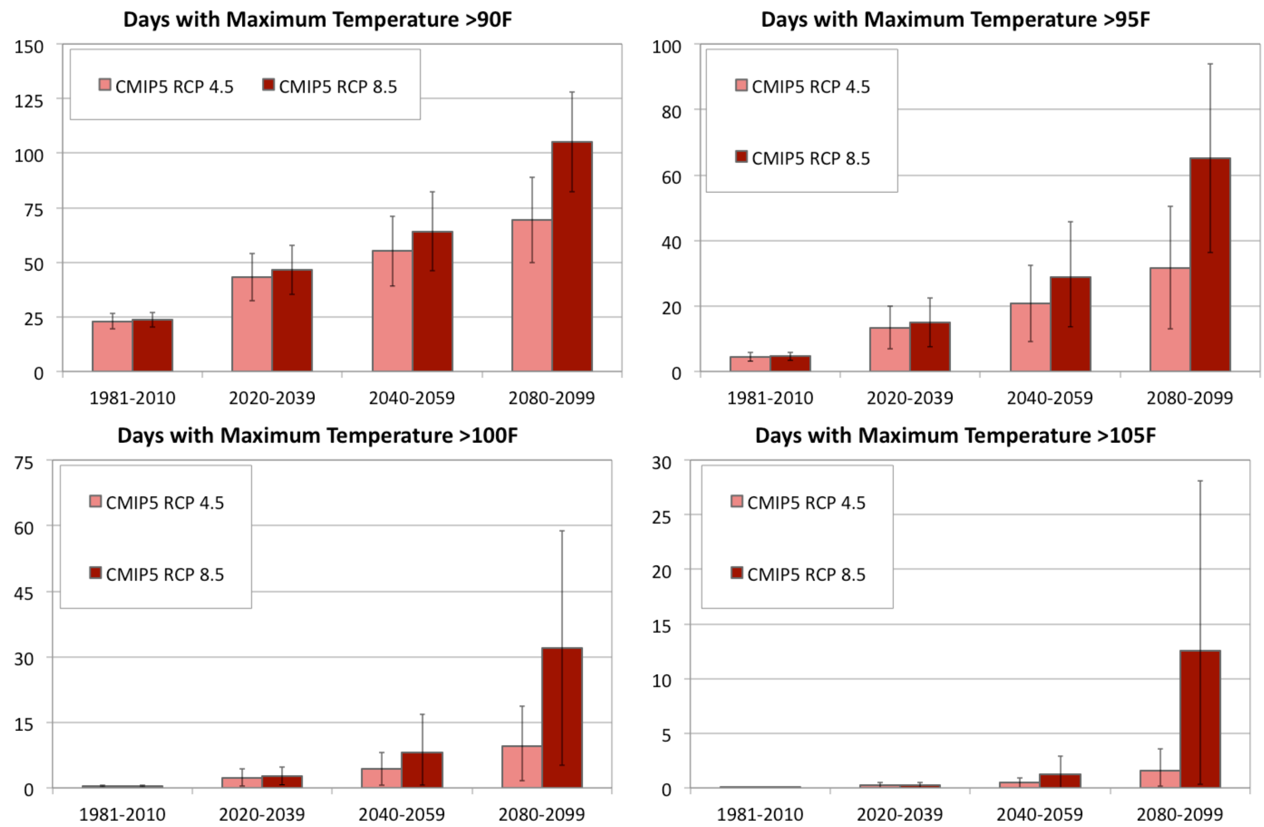
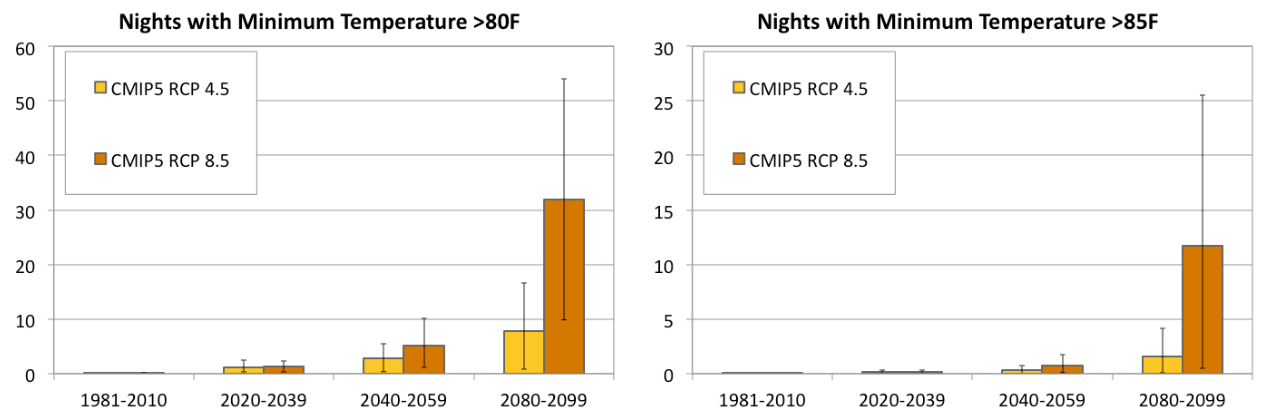


Figure 12. Historical and projected future number of **hot days** per year with maximum temperature above 95, 100, 105, and 110°F. Note different range on y-axis in each figure: from 0 to 150 days per year for 90°F to 0 to 30 days for 105°F. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes under the lower scenario are shown in light red, and projections for the higher scenario in dark red. The black "whiskers" indicate the uncertainty that results from using multiple climate models

that number is projected to increase to 10 to 15 per year. By mid-century, the range increases to 15 to 30 days per year. By late century, there could be an average of 20 to 30 days per year under lower scenarios and 50 to 65 days per year over 95°F under higher scenarios, an increase on the order of 4 to 6 times higher than historical values under lower and more than 10 times historical values under higher scenarios. In contrast, a day over 100°F occurs only once every few years in the historical record. By 2020-2039 there are projected to be between 1 and 3 such days per year, and by mid-century, between 1.5 to 8 days per year. By late century under lower scenarios there could be between 3 and 10 days per year over 100°F; under higher scenarios, between 15 and 30 days per year. For maximum temperature extremes, CMIP5 projections are generally greater than CMIP3 under both higher and lower scenarios. For minimum temperature extremes, however, both CMIP3 and CMIP5 scenarios are noticeably higher than both CMIP3 and CMIP5 lower scenarios (CMIP3 and CMIP5 projections are compared in the Excel Appendix).

In interpreting these extreme heat projections, it is also important to remember that the statistical downscaling method used here has a known positive bias in extreme heat days



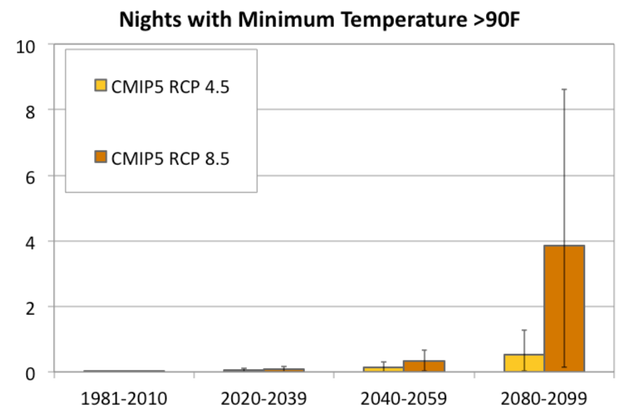


Figure 13. Historical and projected future number of **warm nights** per year with minimum temperature above 80, 85, and 90°F. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes under the lower scenario are shown in yellow, and projections for the higher scenario in orange. Black "whiskers" indicate the uncertainty that results from using multiple climate models.

for coastal areas. As a number of the weather stations used in this analysis could be considered coastal, this bias suggests that projected changes in extreme heat conditions that occur rarely in the historical record (e.g., days per year with maximum temperature over 100°F or days per year hotter than the hottest day in 1 or more years) developed using this downscaling method for the late century time frame are likely higher than the projections that would have been generated using a high-resolution dynamical climate model.

This analysis also calculated projected changes in three minimum temperature thresholds: the number of nights per year above 80, 85, and 90°F. Higher temperatures at night are often associated with health impacts, as warm nights offer no respite from high daytime temperatures. As with daytime maximum temperatures, the frequency of these nights is also projected to increase (**Figure 13**). Historically, nights over 80°F or higher are quite rare: averaged across the 14 weather stations used for this analysis, less than one per decade. In the future, an average of 3 nights per year above 80°F is projected for mid-century under a lower scenario, and 5 nights under a higher. By late century, projected changes range from 1 to 17 nights per year (with an average of 8) over 80°F in a lower scenario (and between 10 and more than 50 nights per year (with an average of 32) in a higher scenario. Projected changes in the number of nights per year above 85°F and 90°F are around one-third and one-eighth as large, respectively, as the projected changes in nights per year over 80°F by late century. The number of nights per year with minimum

temperatures below the 1st and 5th percentile of the distribution, and the number of days with maximum temperature above the 95th and 99th percentile of the distribution were also calculated as part of this analysis (not shown—see Excel Appendix).

Heat waves are another measure of extreme temperatures. Heat waves are generally defined as a period of prolonged, unusual heat. Here we use four different definitions of heat waves to examine the difference in relatively mild versus more severe events. The first definition is the number of consecutive days with maximum daytime temperature exceeding 90°F (**Figure 14**). Historically, the longest stretch of back-to-back days exceeding 90°F averages around a week. This is projected to increase to 2 weeks by the near-term period of 2020-2039, 2½ to 3 weeks by mid-century, and almost 4 weeks under a lower scenario and more than 6 weeks under a higher scenario by late century. The second and third definitions are similar: the longest stretch of days with maximum daytime temperature exceeding 95°F and 100°F. Historically, there are typically around 2 consecutive days over 95°F per year on average, but no more than one day over 100°F at a time. These numbers are also projected to increase. By end of century, the longest period of time over 95°F could average around 12 days under a lower and 25 days under a higher

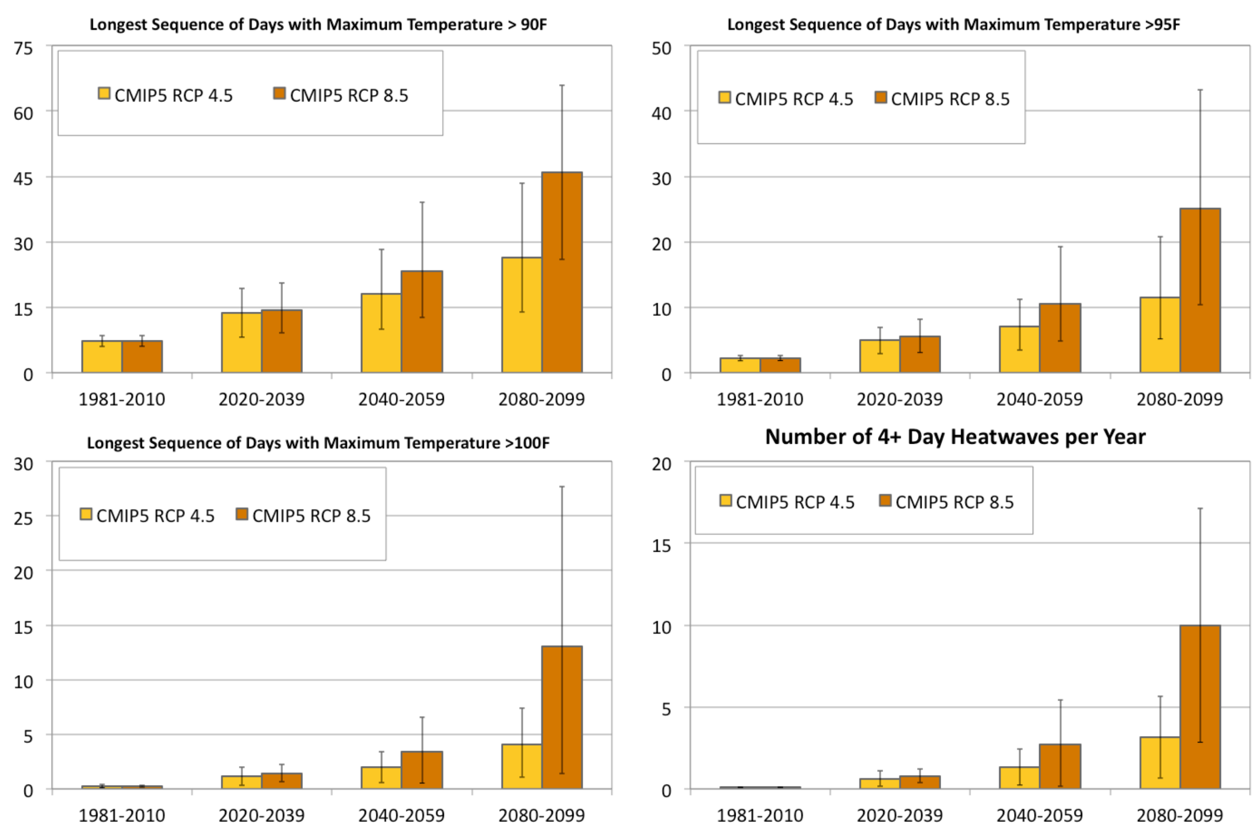


Figure 14. Historical and future longest consecutive stretches of **days with maximum daily temperature exceeding 90, 95 and 100°F,** and **average number of extreme 1-in-10 year heat waves per year**. Extreme heat waves are defined as occurring on average once per decade historically. Note different scales on y-axes of figures. Events are averaged over individual projections for 14 weather stations. Projected changes under the lower scenario are shown in yellow, while projections for the higher scenario are shown in orange. The black "whiskers" indicate the uncertainty that results from using multiple climate models.

scenario by late century. The longest period over 100°F could average around 4 days under a lower and 13 days under a higher scenario.

The definition of a very extreme heatwave based on Kunkel et al. (1999) is calculated based on the historical record of the strongest heat wave per decade. Specifically, it counts the nubmer of times where average (day plus nighttime temperature) on at least 4 consecutive days exceeds the historical 1-in-10-year event. Historically, such events are rare (**Figure 14**). Near-term, heat waves by this definition are projected to occur on average every 3 out of 5 years. By mid-century, there could be an average of one event per year under the lower scenario and two per year under higher. By late century, there are projected to be an average of 3 events per year under a lower scenario (with an uncertainty range from 1 to 5 per year) and 10 per year under a higher scenario (with an uncertainty range from 3 to 17). In other words, a heat wave that historically occurs only once per decade could be occurring between 3 to 17 times per year by late century.

Energy-Related Temperature Indicators

Cooling and heating degree-days provide a useful indicator of demand for electricity in the summer (for air conditioning) and natural gas or oil in the winter (for space heating). They are typically calculated as the cumulative number of hours per year above (for cooling) or below (for heating) a given temperature threshold, here taken to be 65°F.

As temperatures increase, cooling degree-days and hence the demand for air conditioning in the summer are projected to increase; heating degree-days and demand for space heating, to decrease (**Figure 15**). Currently, the annual average demand for cooling across Delaware is relatively small (about 1,200 degree-days per year) compared to demand for heating (about 4,500 degree-days per year). As average and seasonal temperatures warm, demand for cooling will increase while demand for heating decreases. Under a higher scenario, by late century, the demand for heating and cooling is projected to be approximately equal, around 3,000 degree-days per year for each. Under a lower scenario, demand for cooling is projected to be around two-thirds that of heating: 2,100 cooling degree-days per year as compared to around 3,500 heating degree-days per year.

This analysis makes no attempt to assess the ultimate impact on the consumer. It simply estimates projected changes in the demand for cooling: a 30 percent increase by 2020-2039, a 35 to 70 percent increase by 2040-2059, and an average increase of 50 percent under lower scenarios and 130 percent under higher scenarios by late century. Heating demand is projected to decrease: by about 10 percent near-term, nearly 20 percent by mid-century, and around 20 percent under lower scenarios and almost 40 percent under higher scenarios by late century. It is important to note that the sources of energy for heating versus cooling are generally different (electricity versus gas or oil). For that reason, increases in CDDs are not likely to be offset by decreases in HDDs but rather will have different impacts on energy supply and costs.

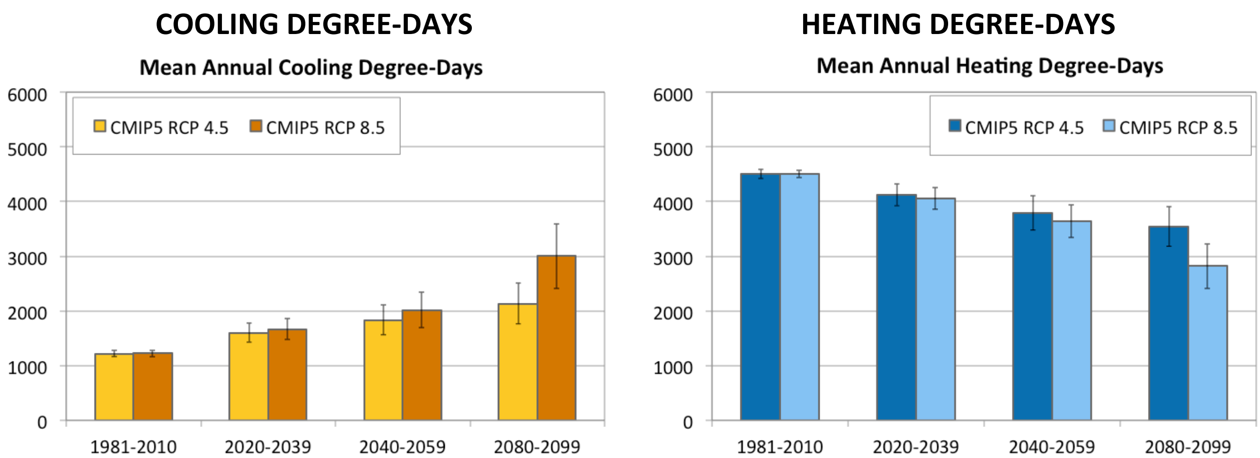


Figure 15. Historical and projected future annual cumulative **cooling** and **heating degree-days** using a temperature threshold of 65°F. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes under the lower scenario are shown in yellow for cooling degree-days (which are warm) and dark blue for heating degree-days (which are cold). Projections for the higher scenario are shown in orange for cooling degree-days and light blue for heating degree-days. The black "whiskers" indicate the uncertainty that results from using multiple climate models.

SECTION 4

PRECIPITATION-RELATED INDICATORS

Climate change is expected to alter precipitation patterns around the world. Some regions and seasons may get wetter, while others get drier. The intensity and frequency of heavy rainfalls, as well as the duration of dry periods, may be altered. Midlatitudes are generally projected to become wetter, with increases in heavy precipitation events. Across the Northeast and MidAtlantic region, heavy precipitation has already increased—by more than 70 percent over the last 60 years, in many locations (Walsh et al., 2014). This section summarizes changes in precipitation and related secondary indicators that are projected to occur across the state of Delaware in response to global climate change.

Annual and Seasonal Precipitation

Annual precipitation across Delaware averages around 45 inches per year. It is evenly distributed throughout the year, with more than 10 inches on average falling in each season. Slightly less precipitation (around 1-2 inches less) tends to fall in fall and winter as compared to spring and summer. In the future, annual average precipitation is projected to increase (**Figure 16**), consistent with a general increase in precipitation projected for mid-latitudes, including the northern half of the United States. Increases are greater and more

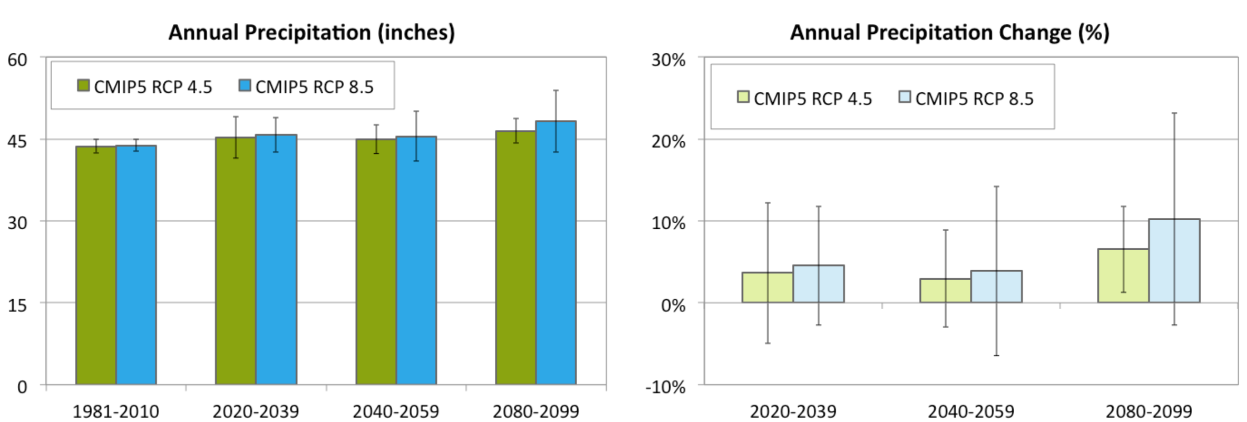


Figure 16. Historical and future simulated **annual average precipitation** (left) and change in annual average precipitation (right) as simulated under a lower (green) and higher (blue) future scenario. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. The black "whiskers" indicate the uncertainty that results from using multiple climate models.

consistent by end of century compared to earlier time periods. For both the near-term and mid-century periods, for example, the multi-model average shows an increase in precipitation under all scenarios, but some individual model simulations show decreases. By end of century, in contrast, all but one model shows an increase, as indicated by the black bars in **Figure 16**.

Seasonal changes show stronger differences between scenarios for projected precipitation increases in winter (**Figure 17**). In winter, when the largest precipitation increases are projected to occur, increases projected under a higher scenario are higher by end of century than under a lower scenario. Projected changes in spring, summer, and fall precipitation do not show significant scenario differences (or much change at all, as the ranges of uncertainty for each multi-model average all encompass both positive and negative changes, even out to the end of the century).

Even in winter, the main source of uncertainty in average and seasonal precipitation is not scenario uncertainty but rather model uncertainty. Projected increases in annual average precipitation under CMIP3 simulations tend to be higher than under CMIP5 simulations (10 to 20 percent versus 7 to 10 percent, respectively, for annual average precipitation by late century). Older CMIP3 simulations (based on four global climate models) also differ from newer CMIP5 simulations (based on nine global climate models) in seasonal projections. CMIP3 projections show increases in precipitation to be distributed evenly throughout the year (see Excel Appendix). In contrast, CMIP5 projections show precipitation increases only in winter and fall.

In addition to seasonal changes in precipitation, changes in 3-month, 6-month, and 12-month cumulative precipitation were calculated for periods beginning with each month from January to December. This information is available in the Excel Appendix that accompanies this report.

Dry and Wet Periods

As climate changes, precipitation is projected to increase, particularly in winter. However, little to no change is projected in annual dry days. This can be explained by the increase in precipitation intensity. Although there is more precipitation, the average amount of precipitation falling on wet days is also increasing: by around 2 percent over the near term, 3 to 4 percent by mid-century, and 5 percent under a lower scenario and 11 percent under a higher scenario by late century. This increase in the average amount of precipitation falling on a given wet day keeps pace with the projected increase in winter precipitation. This explains why little to no change in the number of dry days is projected (**Figure 18**).

It is important to note, however that the total number of dry days per year is another variable on which CMIP3 and CMIP5 projections for the future disagree slightly. Under CMIP3, the number of dry days *is* projected to decrease by a few days a year.

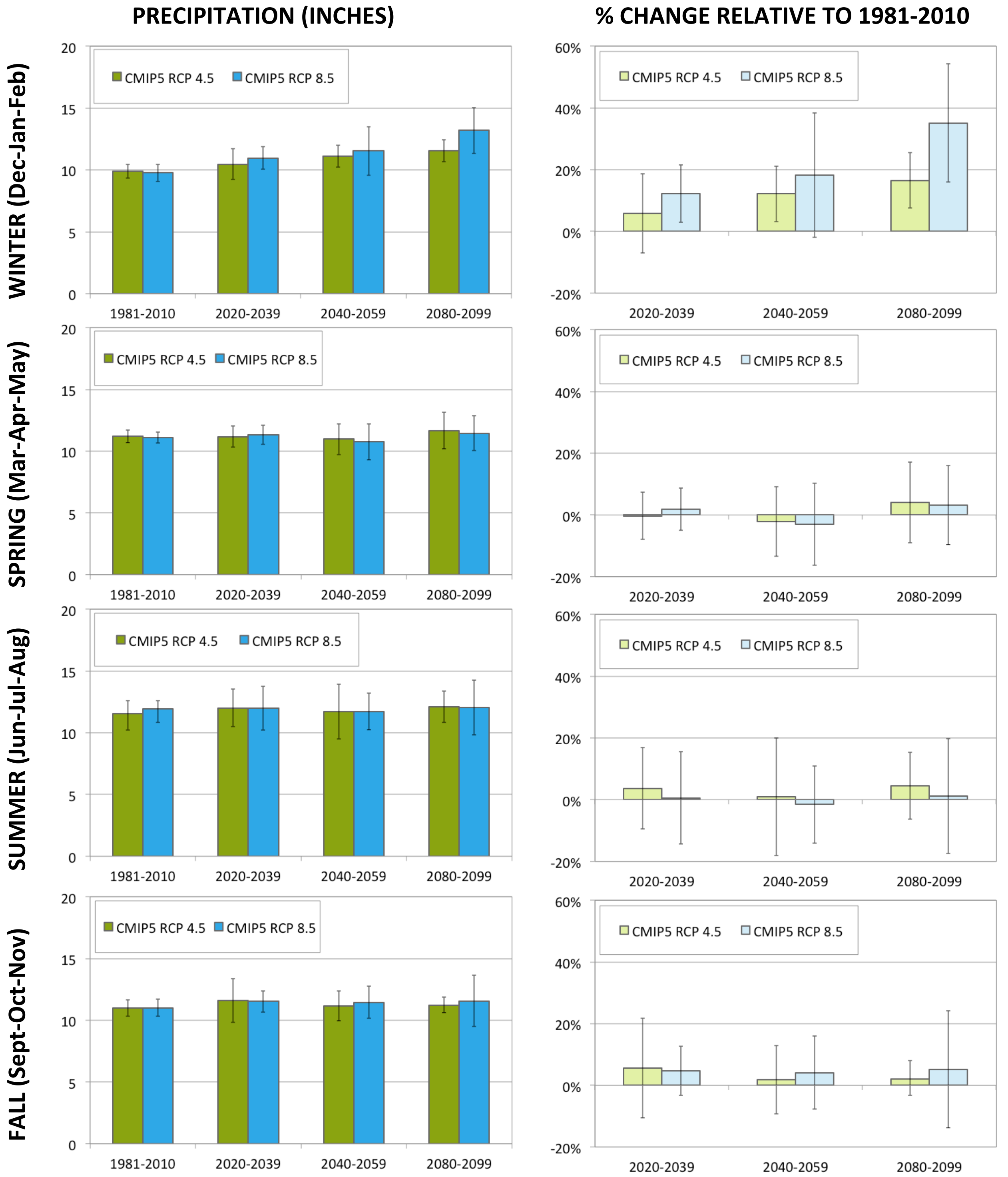
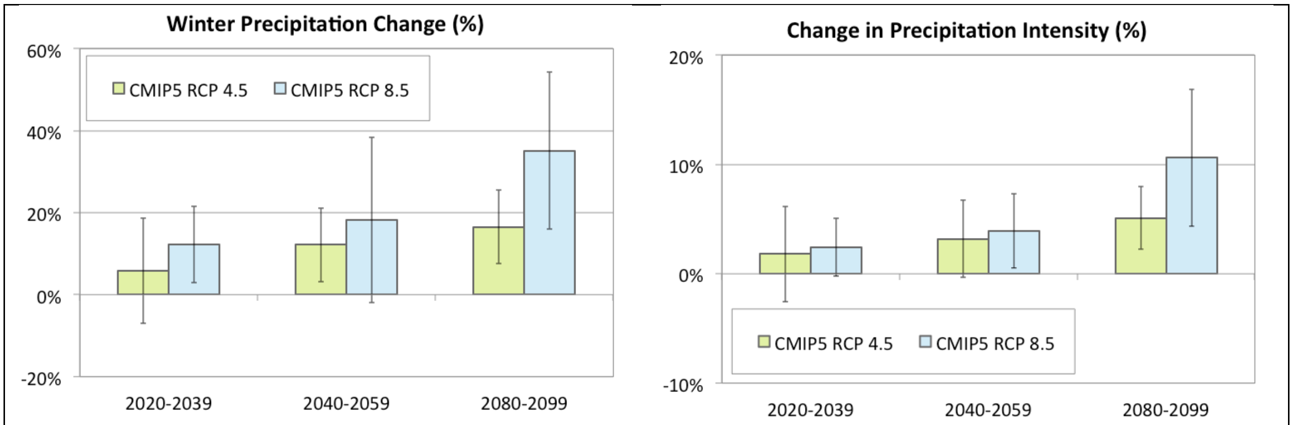


Figure 17. Historical and future cumulative **seasonal precipitation** (left) and percentage change in seasonal precipitation compared to 1981-2010 (right) for winter (Dec-Jan-Feb), spring (Mar-Apr-May), summer (Jun-Jul-Aug) and fall (Sept-Oct-Nov). Greater changes are projected for winter and fall, little change in spring and summer. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes for the lower scenario are shown in green, projections for the higher scenario in blue. Black "whiskers" indicate the range of uncertainty from multiple climate models.



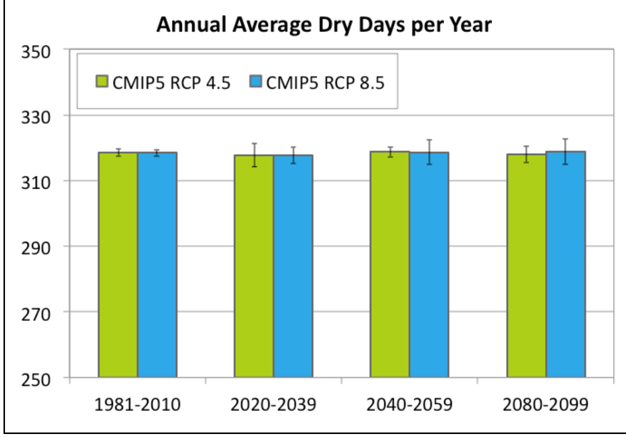


Figure 18. Historical and future percentage changes in (a) **winter precipitation** and (b) **precipitation intensity** balance out to suggest little change in (c) the overall number of **dry days** per year. Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projected changes for the lower scenario are shown in green, projections for the higher scenario in blue. Black "whiskers" indicate the range of uncertainty from multiple climate models

Under CMIP5, the number of dry days is projected to show little change. This small difference is likely the result of projected increases in annual precipitation under CMIP3 being slightly larger than projected increases under CMIP5; simply put, with that much more rain, there are a few more wet days.

The Standardized Precipitation Index (SPI) offers a different way to look at dry and wet conditions. This index is commonly used by the National Drought Mitigation Center and the National Climatic Data Center to indicate dry and wet areas within the continental United States on an ongoing basis. It is standardized, such that zero represents normal conditions for that location; negative values indicate conditions drier than average, from 0 to -7, while positive values indicate wetter conditions, from 0 to +7.

SPI projections suggest a trend towards slightly wetter conditions, with average SPI increasing by 0.1 over the course of this century, consistent with increases in average precipitation (not shown; see Excel appendix). Given an index from 0 to 7, however, this increase is very small and the uncertainty range due to multiple models encompasses zero, suggesting that some models project a slight decrease in SPI and others, an increase and overall, projected changes are not significant.

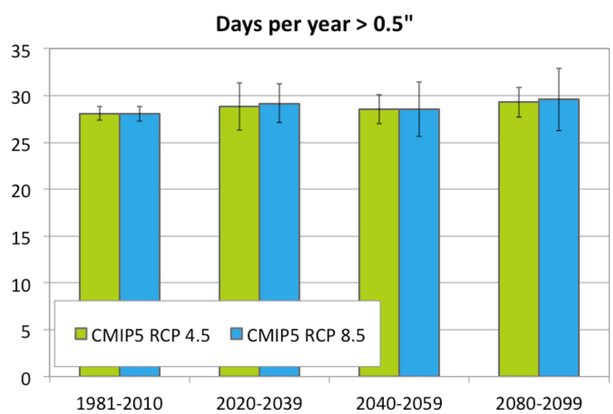
Heavy Precipitation Events

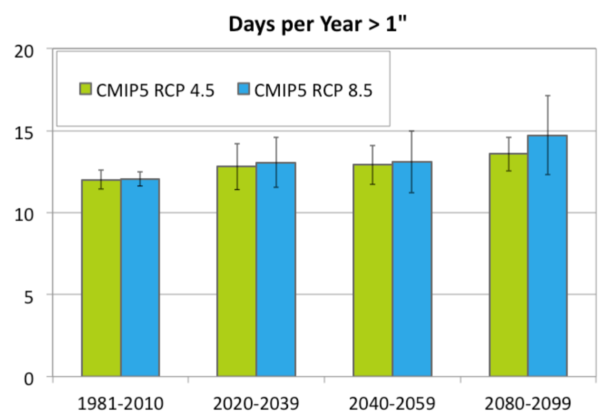
Heavy precipitation events are already increasing globally, across the United States, and across the northeast region of the United States in particular. The increased frequency of these events has been formally attributed to human-induced climate change. In many regions, the observed trend in heavy rainfall is expected to continue in the future as warming temperatures accelerate the hydrological cycle at both the local and global scale (e.g., Tebaldi et al., 2006).

National and global studies typically look at heavy precipitation over a single range; however, depending on the region, different levels of heavy snow and rain can have very different impacts. Here, a broad range of precipitation indicators were analyzed. They consist of:

- Number of days per year with more than 0.5, 1, 2, 3, 4, 5, 6, 7 and 8 inches of precipitation in 24h;
- The wettest day, 5 days, and 2 weeks in 1, 2, and 10 years; and
- Number of days per year exceeding the historical 2-, 4-, and 7-day maximum rainfall

For the state of Delaware, nearly every indicator of extreme precipitation is projected to increase in the future (**Table 3**, with highlights in **Figure 19**). This is consistent with observed trends as well as with future projected trends across the eastern United States.





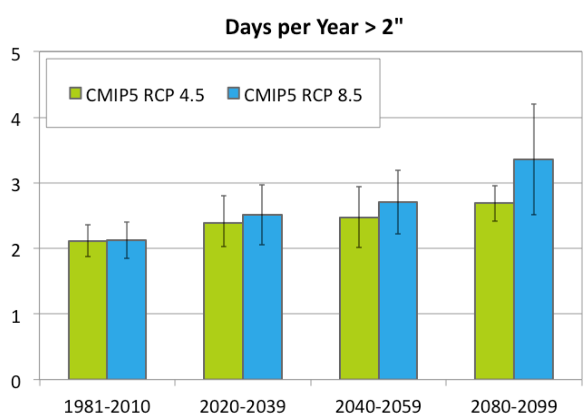


Figure 19. Projected future changes in the number of **days per year with cumulative precipitation exceeding a range of thresholds from 0.5 to 2 inches in 24 hours.** Changes are the average for the state of Delaware, based on individual projections for 14 weather stations. Projections using a lower future scenario are green; a higher scenario, blue. Black "whiskers" indicate the uncertainty that results from using multiple climate models.

For "less extreme" indicators (e.g., days per year over 0.5 or 1 inches in 24 hours), there was little difference in projected changes under a higher versus a lower scenario, although overall larger changes are projected by late century as compared to near-term. For "more extreme" indicators (e.g., days per year with 2 inches or more of precipitation in 24 hours), projected changes under a higher scenario were generally greater than projected changes under a lower scenario, although in all cases the range of uncertainty due to using multiple model projections continues to overlap, suggesting that the differences between scenarios may not be statistically significant. For "very extreme" indicators (e.g., wettest 1 or 5 days of the year or beyond), there was less of a difference between higher versus lower scenarios; projections for events that are currently extremely rare, however, are significantly less certain than projections for more frequent events. Finally, the amount of precipitation falling in the wettest 2 weeks of the year (or 2 years, or 10 years) showed little to no change over any time frame. This suggests that the largest impact of climate change will be on short-duration precipitation events which can be both convective and large-scale in nature, rather than on the frequency and duration of large weather systems that bring extended rain over multiple weeks.

In terms of thresholds, the average of precipitation records across 14 Delaware stations shows that, on average, the state currently experiences around 28 days per year with more than 0.5 inches of rain in 24 hours; 12 days with more than 1 inch; and 2 days with more than 2 inches. By late century, these numbers are projected to increase by 1 to 2 days for 0.5 inches, 2 to 3 days for 1 inch, and 0.5 to 1 days for 2 inches (**Figure 19**). Additional changes projected for other indicators are listed in Table 3.

For lower amounts of heavy precipitation (0.5 to 2 inches in 24 hours), projected changes under CMIP3 are generally greater than under CMIP5, likely because CMIP3 models project larger increases in average precipitation as compared to CMIP5. For higher levels of precipitation (3 to 8 inches), however, CMIP3 and CMIP5 projections are similar (for CMIP3 comparison with CMIP5, see Excel Appendix).

Table 3. Projected changes in indicators of extreme precipitation calculated in this analysis, including: (1) the average number of days per year where cumulative precipitation exceeds thresholds between 0.5 and 8 inches; the total amount of precipitation falling in the wettest 1, 5, and 14 consecutive days of (2) the year, (3) 2 years, and (4) 10 years; and (5) the number of times per year the historical 2-, 4- and 7-day maximum precipitation amounts are exceeded in the future.

	1981-2010	2020-2039	2040-2059		2080-2099	
			Lower	Higher	Lower	Higher
Days per year exceeding a given threshold of 24h cumulative precipitation						
0.5	28.07	28.99	28.55	28.55	29.29	29.58
1	12.04	12.94	12.92	13.10	13.57	14.71
2	2.12	2.45	2.47	2.71	2.69	3.36
3	0.67	0.75	0.80	0.85	0.86	1.17
4	0.29	0.34	0.36	0.37	0.41	0.55
5	0.14	0.17	0.18	0.19	0.23	0.29
6	0.08	0.10	0.10	0.10	0.14	0.18
7	0.04	0.06	0.07	0.07	0.09	0.13
8	0.03	0.04	0.04	0.05	0.07	0.10
In one year, wettest …						
1 day	3.28	3.46	3.53	3.64	3.77	4.25
5 days	6.40	6.60	6.69	6.84	7.09	7.41
2 weeks	14.20	14.27	14.32	14.36	14.46	14.54
In 2 years, wettest …						
1 day	4.07	4.31	4.34	4.65	4.89	5.44
5 days	7.40	7.67	7.76	8.30	8.83	8.98
2 weeks	14.41	14.47	14.62	14.74	15.20	15.07
In 10 years, wettest …						
1 day	6.24	6.67	6.70	7.13	8.09	8.58
5 days	10.74	11.10	11.37	12.72	14.28	13.29
2 weeks	15.68	15.92	16.39	17.27	18.71	17.89
Number of times historical threshold is exceeded						
2-day maximum	0.001	0.013	0.011	0.019	0.019	0.046
4-day maximum	0.000	0.005	0.005	0.013	0.008	0.024
7-day maximum	0.000	0.003	0.001	0.009	0.004	0.015

SECTION 5

HYBRID INDICATORS

Temperature and precipitation alone do not capture the full extent of relevant change in Delaware's climate. For that reason, this report also presents projected changes in humidity and in "hybrid" or multivariable indicators such as heat index (a combination of temperature and humidity that measures how hot it "feels" to the human body), potential evapotranspiration (which depends on solar radiation, humidity, temperature, winds, and other factors), and cool and wet or hot and dry days.

Relative Humidity and Dewpoint Temperature

Dew point temperature is defined as the temperature to which the air must be cooled to condense the water vapor it contains into water. **Figure 20** compares projected changes in dew point versus average air temperature by season. In general, projected changes for dew point temperature are similar to and slightly less than those projected for average temperature. This could be the result of small decreases in relative humidity projected for most seasons except spring (not shown; see Excel appendix). However, it could also be related to the fact that dew point temperature projections could be calculated only for three airport locations with long-term humidity records.

Summer Heat Index and Potential Evapotranspiration

Heat index is often used in the summer to express how hot it "feels" to the human body, based on a combination of both temperature and humidity, which affects evaporation and cooling. A related metric is potential evapotranspiration, or PET. This measures the amount of evaporation that would occur, given certain levels of temperature, wind, humidity, and solar radiation, and an unlimited water supply.

The relationships among heat index, temperature, and humidity are not linear. Despite little change to a slight decrease being projected for relative humidity in summer (**Figure 21**), projected increases in summer heat index by the end of the century are approximately double the projected changes for maximum daytime summer temperature alone. In other words, the projected increase in temperature may *feel* twice as large as it actually is, due to the interactions between humidity and temperature and their impact on the human body.

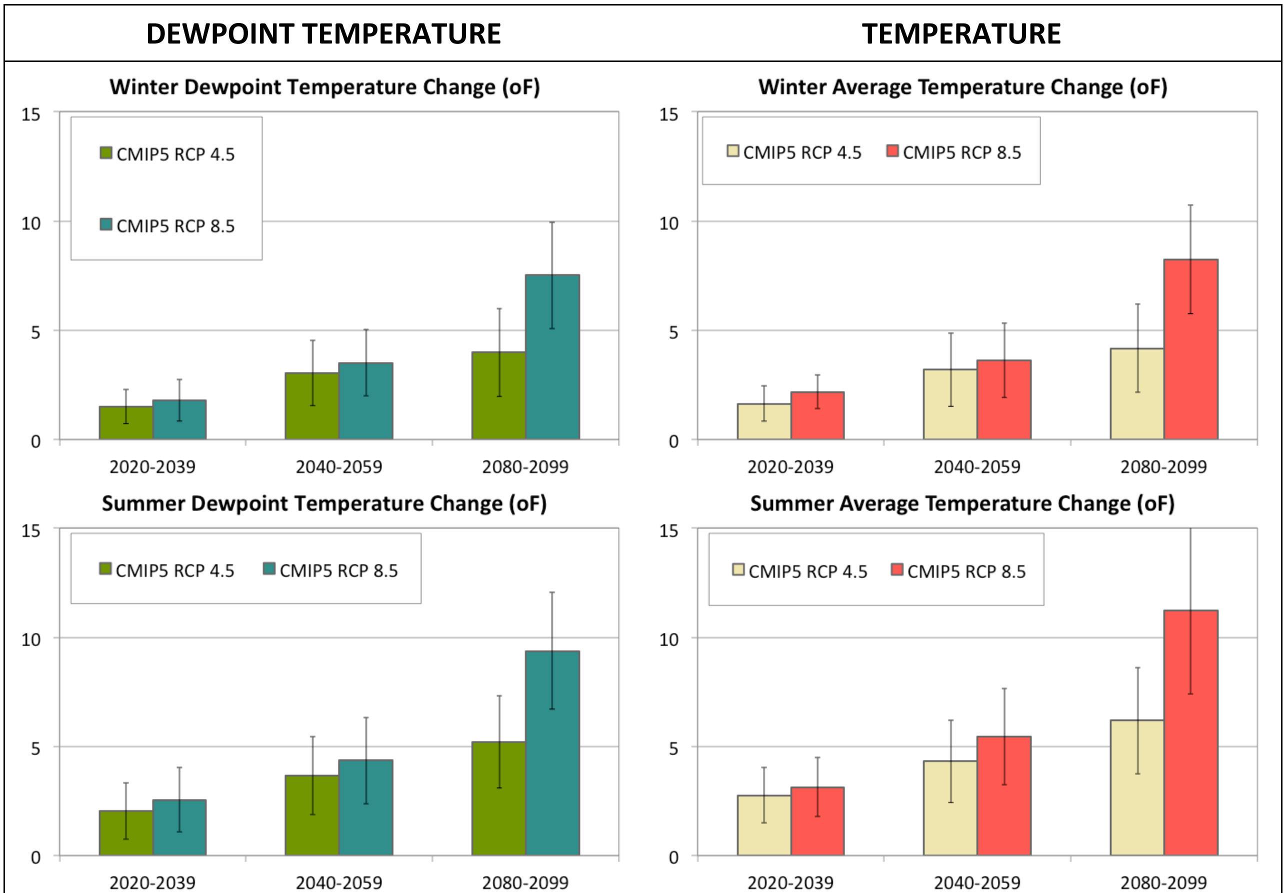
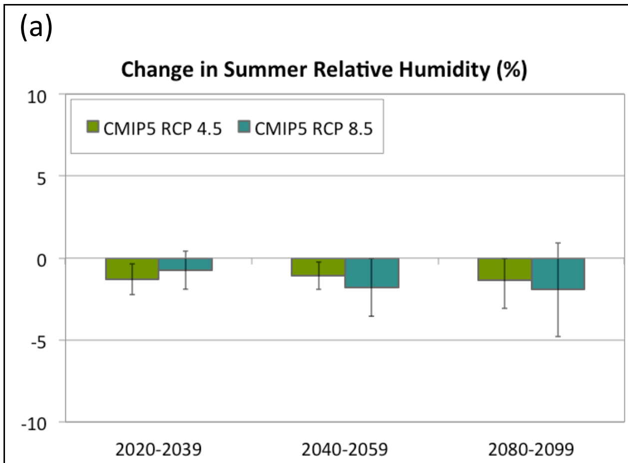
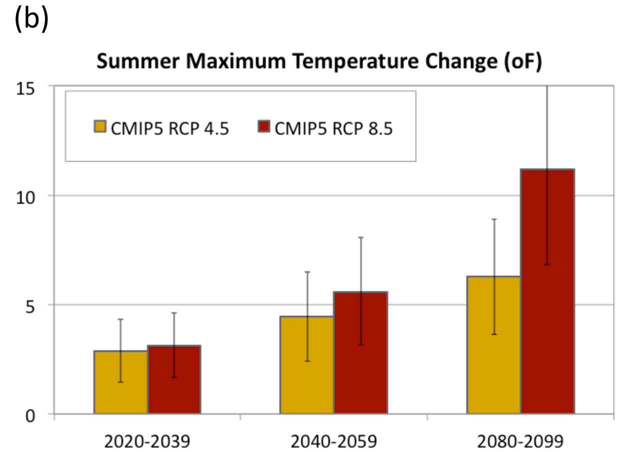


Figure 20. Historical simulated and future projected precipitation amounts in **dew point temperature** (left) and **average temperature** (right) for winter and summer. (Spring and fall graphs provided in the Excel Appendix.) Dew point temperatures are based on projections for three airport locations only; average temperatures are based on projections for all 14 weather stations. The black "whiskers" indicate the uncertainty that results from using multiple climate models.





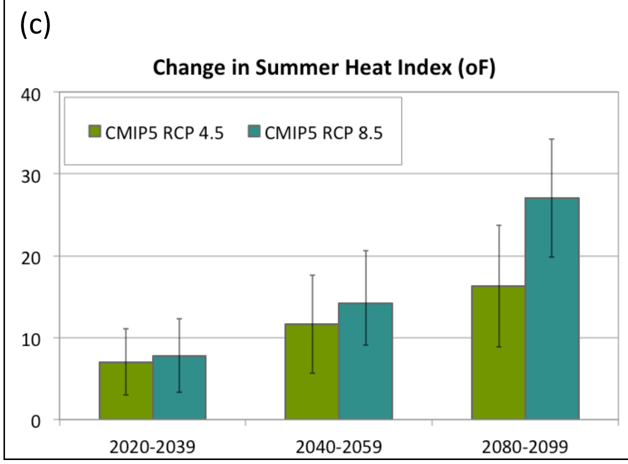


Figure 21. Historical simulated and future projected changes in summer (June, July and August) (a) **relative humidity**, (b) **maximum temperature**, and (c) **heat index**. Humidity and heat index are based on projections for three airport locations only; average temperatures are based on projections for all 14 weather stations. The black "whiskers" indicate the uncertainty that results from using multiple climate models.

Evaporation is projected to increase, primarily driven by increases in temperature. The largest increases are projected for summer, followed by spring and fall (**Figure 22**).

Hybrid Temperature and Precipitation Indicators

The final set of hybrid indicators focuses on the combination of temperature and precipitation (**Figure 22**). The number of "hot dry" days with maximum temperatures over 90°F and no measurable rain is projected to increase 50 to 100 percent over the near term. By late century there could be between twice to more than four times more hot/dry days compared to the 1981-2010 average, depending on whether human emissions follow a higher or a lower future scenario. In contrast, the number of "cool wet" days with maximum temperatures below 65°F and measurable precipitation is projected to decrease, but not by much. Slightly greater changes are projected under the higher (4 to 6 days) as compared to the lower (1 to 2 days) scenarios by late century. The amount of precipitation that falls as rain rather than snow is already quite high for Delaware, around 98 to 99 percent. In the future even more precipitation is projected to fall as rain than snow as temperatures warm; however, this is not likely to have a significant impact as it only amounts to a change of 1 to 2 percent (not shown – see Excel Appendix).

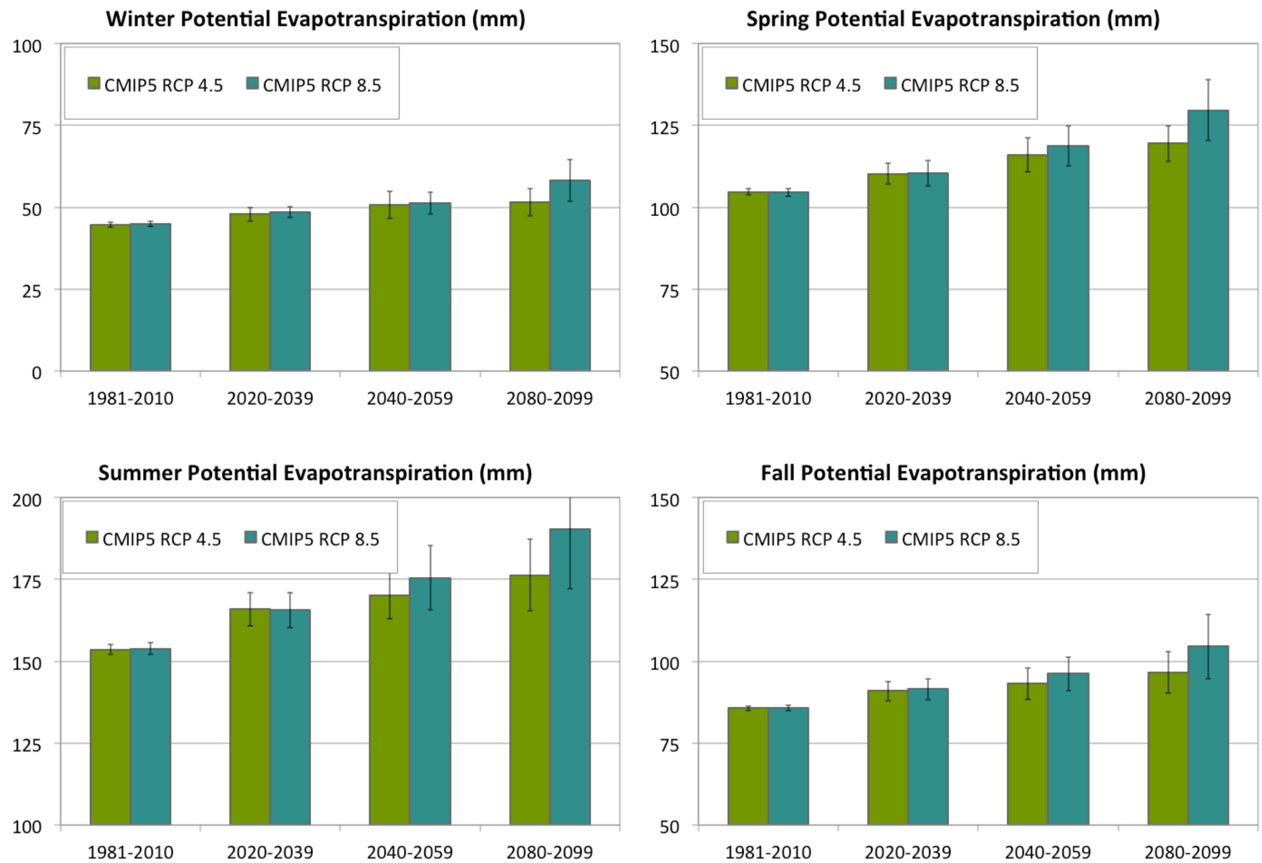


Figure 21. Historical simulated and future projected changes in **seasonal potential evapotranspiration** (PET). Although the y-axes of the plots cover a different range, the total range covered is identical (100 mm), so relative changes can be seen from one season to the next. Based on projections for three airport locations only; black "whiskers" indicate the uncertainty that results from using multiple climate models

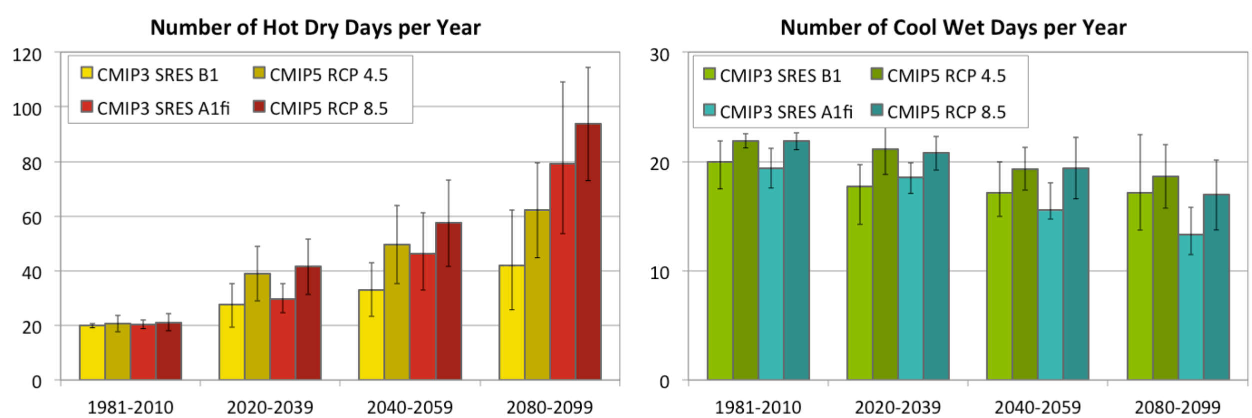


Figure 22. Historical simulated and future projected changes in the number of **hot dry days** with no precipitation (left) and **cool wet days** with precipitation (right). Based on projections for all 14 weather stations. The black "whiskers" indicate the uncertainty that results from using multiple climate models

SECTION6

CONCLUSIONS

Climate change is expected to alter average and extreme temperature and precipitation in Delaware and the surrounding region in ways that are consistent with historical trends, and consistent with future projections for the greater mid-Atlantic region. These changes have the potential to affect both human society and the natural environment in many ways.

Annual and seasonal temperatures are projected to increase, with slightly greater increases projected for summer as compared to winter. A warmer climate means that Delaware's climate will begin to feel more like that of a state further south along the Atlantic coast. Average and seasonal temperatures are also major determinants of which plant and animal species and which types of ecosystems will be native to Delaware in the future. Warmer winters can affect the growing season and phenology of plants, and agricultural crops such as fruits, that require a certain number of accumulated chilling hours in order to bloom. Seasonal temperature increases will also shift the overall demand for heating energy in the winter and cooling energy in the summer. Across the United States, buildings account for approximately 40 percent of overall energy use, and most of that energy use consists of heating or cooling the interior space. With warmer winters, less natural gas and oil will be needed to heat homes and buildings in the winter. At the same time, more electricity will be needed for air conditioning in the summer.

Extreme heat days and heat waves are projected to become more frequent. Extreme cold days are projected to become less frequent. Both high and low temperature extremes carry health risks for humans. Risks of illness and death from cold temperatures will likely decrease with a decrease in the frequency and severity of cold extremes. At the same time, the risks of illness and death from extreme high temperatures during extended heat waves will likely increase, unless these effects are mitigated by heat watch/warning systems that help people to protect themselves during these events. Cold extremes during winter can serve a useful function in keeping pests, invasive species, and disease vectors at bay; as these become less frequent, invasives and pests native to southern states could move northward into the area. Extreme heat can affect society in other ways. During heat waves, people tend to spend less time outdoors, which could affect coastal tourism.

Extreme heat can affect infrastructure, warping rail lines and even buckling pavement. Heat waves can also affect energy supply, overloading the grid with air conditioning demands and increasing the risk of brownouts and power failures.

Average precipitation is projected to increase, primarily in winter. This means that winter snowfall may not change much, since more winter precipitation means that there will still be a good chance of having precipitation on a day when it's cold enough to snow, even if cold days become less frequent. Hotter summers coupled with higher evaporation rates and no increase in rainfall imply possible reductions in water levels in rain-fed lakes and rivers, and higher demand for water in summer for irrigation and watering lawns.

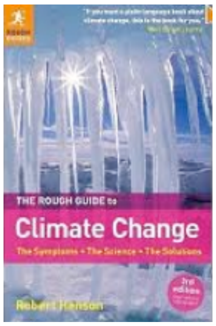
Heavy precipitation is expected to become more frequent as precipitation continues to become more intense. Increases in heavy precipitation can increase the risk of storm damages and flooding in low-lying areas. More frequent heavy precipitation events implies that current building and zoning standards, such as storm sewer capacity or flood zones, may become outdated and fail to protect people as they were designed to do based on historical standards.

A certain amount of climate change, and associated impacts, can be avoided under a lower as compared to a higher scenario. For all temperature-related indices and for many of the extreme precipitation indices, there is a significant difference between the changes expected under higher as compared to lower scenarios by late century. Most of these differences begin to emerge by mid-century. This highlights the importance of scenario, or human, uncertainty in future projections.

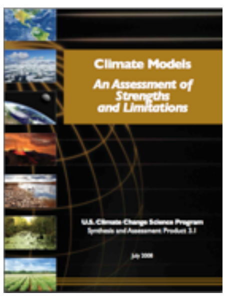
A certain amount of climate change is inevitable, even under a lower scenario. And for some impacts, the magnitude of future changes do not depend on scenarios. For average precipitation, the greatest differences are between different model simulations. This highlights the importance of scientific, or model, uncertainty in future projections.

Smart planning that accounts for future changes can help reduce the risk of negative impacts. The projections described here underline the value in preparing to adapt to the changes that cannot be avoided. Changes that likely cannot be avoided would include most changes in precipitation and, at minimum, the temperature-related changes projected to occur over the next few decades, and under the B1 or RCP 4.5 lower scenarios. However, immediate and committed action to reduce emissions may help avoid the larger temperature impacts projected under the higher A1FI or RCP 8.5 scenarios. The greater the reduction in climate forcing from human activities, the more possible it will be to successfully adapt to a changing climate.

FURTHER READING



On the science and policy of climate change:
THE ROUGH GUIDE TO CLIMATE CHANGE (3RD edition)
Henson, Robert. 2011. Rough Guides, 416 pp.
Available on Amazon or in other bookstores.



On global climate models:
CLIMATE MODELS: AN ASSESSMENT OF STRENGTHS AND LIMITATIONS
A Report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research [Bader D.C. et a.]. Department of Energy, Office of Biological and Environmental Research, Washington, D.C., USA, 124pp.
Available online at: http://www.climatescience.gov/Library/sap/sap3-1/final-report/

On climate change impacts by sector (water, agriculture, ecosystems, health, infrastructure, society) and for the Southeast and other regions of the U.S.:
GLOBAL CLIMATE CHANGE IMPACTS IN THE UNITED STATES
U.S. Global Climate Change Research Program, 2009. Cambridge University Press, 192 pp.
Available online at: http://www.globalchange.gov/usimpacts/

On synthesizing information about climate change impacts to inform decision-making and policy:
WARMING WORLD: IMPACTS BY DEGREE
National Academy of Sciences. 2011. Climate Stabilization Scenarios: Emissions, Concentrations, and Impacts over Decades to Millennia.
Available online at:
http://dels.nas.edu/resources/static-assets/materials-based-on-reports/booklets/warming_world_final.pdf

APPENDIX: CLIMATE INDICATORS FOR DELAWARE

TEMPERATURE

Annual and Seasonal Winter (DJF), Spring (MAM), Summer (JJA), and Fall (SON)

- Maximum, minimum, and average temperature
- Temperature range (average maximum minus average minimum)
- Standard deviation of maximum and minimum temperature

Extremes

- Cold nights: days per year with minimum temperature below 20°F and 32°F or below the 1st and 5th percentile of the historical distribution
- Hot days: days per year with maximum temperature above 90, 95, 100, 105, and 110°F or above the 95th and 99th percentile of the historical distribution
- Warm nights: nights per year with minimum temperature above 80, 85, and 90°F
- Number of heat wave events lasting 4 or more days (as defined by Kunkel et al. 1999)
- Longest stretch of days with maximum temperature over 90, 95, and 100°F

Other

- Date of last frost in spring and first frost in fall
- Length of frost-free growing season
- Annual cooling degree-days
- Annual heating degree-days

PRECIPITATION

Annual and Seasonal Winter (DJF), Spring (MAM), Summer (JJA), and Fall (SON)

- Annual and seasonal cumulative precipitation
- Cumulative precipitation for 3-, 6-, and 12-month running means, beginning in each month of the year

Extremes

- Precipitation intensity: annual precipitation divided by the number of wet days per year

- Heavy precipitation: days per year with cumulative precipitation exceeding 0.5, 1, 2, 3, 4, 5, 6, 7, and 8 inches in 24 hours
- Extreme events: amount of precipitation falling in the wettest 1, 5, and 14 days in 1, 2, and 10 years
- Number of future events exceeding the historical wettest 2, 4, and 7 days

Other

- Total number of dry days each year (precipitation < 0.01 inches)
- Longest dry period
- Standardized Precipitation Index (a measure of wetness and drought)

HUMIDITY and HYBRID INDICATORS

Annual and Seasonal Winter (DJF), Spring (MAM), Summer (JJA), and Fall (SON)

- Dew point temperature
- Relative humidity
- Summer heat index

Other

- Percentage of precipitation falling as rain versus snow
- Number of hot dry days per year (precipitation < 0.01” and maximum temperature > 90^{o}F)
- Number of cool wet days per year (precipitation > 0.01” and maximum temperature < 65^{o}F)

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