Appendix B

Temperature and Precipitation Projections

Climate Change Vulnerability Assessment

City of Cambridge, Massachusetts

November 2015

Temperature and Precipitation Projections

Climate Change Projections for the City of Cambridge

Written by ATMOS Research & Consulting; Katharine Hayhoe, Anne Stoner and Rodica Gelca

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Climate Projections for Cambridge, MA: Reconciling Disparate Sources

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Climate Change Projections for the City of Cambridge

Katharine Hayhoe, Anne Stoner, Rodica Gelca

Climate is changing: in the Northeast, across the United States, and around the world. Over the last 50 years, Massachusetts average temperatures have increased by 0.4^{o}F per decade, and winter temperatures by twice that, 0.8^{o}F per decade (NOAA, 2013). Annual average precipitation has been increasing at more than 2 inches per decade, with greatest increases in spring, summer and fall. (NOAA, 2013). Across the Northeast, the frequency of heavy precipitation, including both rain and snow events, has increased by 74% from 1958 to 2011, accompanied by an increase in the magnitude of floods (Walsh et al., 2013a). The average length of the growing season in the Northeast increased by 10 days from 1901-1960 to 1991-2011 (Walsh et al., 2013a), while extreme heat days are becoming more frequent while extreme cold days become less frequent across the entire U.S. (Walsh et al., 2013a).

In the past, climate changed as a result of natural causes, unrelated to human activity. These natural causes include increases or decreases in energy from the Sun, or natural cycles such as El Niño that operate inside the Earth's climate system, or volcanic eruptions. Today, however, if natural causes were responsible for climate change, the Earth would be cooling; instead, it is warming (for further discussion, see Commonly Asked Question H in Walsh et al., 2013b). Human activities, including burning coal, gas and oil and deforestation, are producing increasing amounts of heat-trapping gases. These gases build up in the atmosphere, trapping the Earth's heat that would otherwise escape to space and causing the planet to warm.

As the Earth's temperature increases, natural weather patterns are disrupted. The typical climate conditions used to establish building codes, design infrastructure, and manage weather risks are no longer the same as they were 50 years ago, and will be even more different 50 years from now. Model- and scenario-based projections of future climate can inform long-term planning by providing information on possible future conditions. This report summarizes projected changes in average temperature and precipitation and selected temperature and precipitation thresholds and extremes for the city of Cambridge.

Research Methods

Over the coming century, climate will continue to change as a result of human activities. How much change depends on human choices, specifically what type of energy will be used used in the future to power transportation, industry, and infrastructure around the world. Higher scenarios of carbon emissions assumed continued dependence on fossil fuels such as coal, gas, and oil as the primary energy source (Figure 1, orange and red lines). Lower scenarios envision a transition from fossil fuels to non carbon-emitting renewable energy sources (Figure 1, green lines). To quantify a range of plausible human choices, the Intergovernmental Panel on Climate Change (IPCC) has developed two families of **future scenarios**: the 2000 Special Report on Emission Scenarios (SRES; Nakicenovic et al. 2000) and the newer 2010 Representative Concentration Pathways (RCPs; Moss et al. 2010).

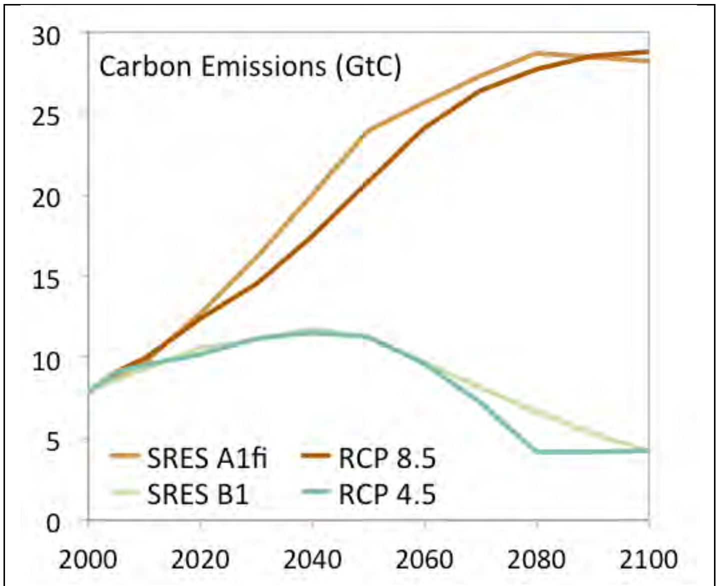

Figure 1. Future projections of climate change for Cambridge correspond to four scenarios: two higher scenarios (SRES A1fi and RCP 8.5), where human emissions of carbon dioxide and other heat-trapping gases continue to rise, and two lower scenarios (SRES B1 and RCP 4.5), where emissions peak and then begin to decline by mid-century.

Climate projections for Cambridge are based on higher and lower scenarios from both SRES and RCP: SRES A1fi and B1, and RCP 8.5 and 4.5 (Figure 1). Using the SRES scenarios ensures backwards compatibility with previous climate change impact assessments for the greater Northeast region, including the Northeast Climate Impacts Report (Frumhoff et al., 2007) and the Second U.S. National Climate Assessment (USGCRP, 2009). Using the new RCP scenarios ensures continued compatibility with new assessments such as the Third U.S. National Climate Assessment (in press).

At the higher end of the range, both the SRES and RCP higher scenarios (A1fi and 8.5) represent continued dependence on fossil fuels. In these scenarios, atmospheric carbon dioxide levels increase by more than three times compared to pre-industrial levels by 2100. At the lower end, carbon emissions in the SRES and RCP lower scenarios (B1 and 4.5) peak around mid-century and then decline.[1] Atmospheric carbon dioxide levels approximately double relative to pre-industrial levels by 2100. Global mean temperature changes resulting from higher and lower scenarios range from 4°F (under lower) to

[1] For atmospheric concentrations to decline, there would need to be a net uptake of carbon from the atmosphere. In other words, humans would have to take up more carbon than they emit. The relationship between emissions and concentrations is discussed in detail in the 2011 National Research Council report, "Climate Stabilization Targets: Emissions, Concentrations, and Impacts over Decades to Millennia" http://dels.nas.edu/Report/Climate-Stabilization-Targets-Emissions-Concentrations/12877

9°F (under higher) by 2100. This range is based on the Intergovernmental Panel on Climate Change's best estimate of climate sensitivity, that global mean temperature would increase by 3°C (5.4°F) under a doubling of atmospheric carbon dioxide relative to pre-industrial levels.

Future scenarios are used as input to **global climate models** (GCMs). GCMs are complex, three-dimensional models that are continually evolving to incorporate the latest scientific understanding of the atmosphere, oceans, and Earth's surface. Originally, "GCM" stood for General Circulation Model, since the original focus of these physics-based models was to simulate the circulation of the atmosphere and ocean. Today, however, global climate models incorporate many other facets of the Earth's climate system, including chemistry, biospheric processes, land use, etc. As output, GCMs produce geographic grid-based projections of temperature, precipitation, and other climate variables at daily and monthly scales.

Some GCMs are better than others at reproducing important large-scale features of certain regions. One example of this is sea ice in the Arctic (e.g. Wang et al., 2007). However, it is not valid to evaluate a global model on its ability to reproduce local temperature or rainfall over a given city or region. Such limitations are to be expected in any GCM, as they are primarily the result of a lack of spatial resolution rather than any inherent shortcoming in the physics of the model. In fact, previous literature has showed that it is difficult, if not impossible, to identify sub-set of "better" GCMs for the continental U.S. (e.g. Knutti, 2010; Randall et al. 2007). For this reason, no attempt was made to select a sub-set of GCMs that performed better than others over the city of Cambridge; rather, multiple GCMs with a long development history spanning the range of likely climate sensitivity were used.

Table 1. CMIP3 and CMIP5 global climate modeling groups and their models used in this analysis.

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 Météorologiques, 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 MPI-ESM-MR	4.5, 8.5 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

In this study, two sets of climate model simulations were used. The first, 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 2007 IPCC Third and Fourth Assessment Reports. Here, future projections are based on simulations from the 4 CMIP3 climate models with SRES A1fi and B1 simulations used in the 2007 Northeast Climate Impacts Assessment and the 2009 Second National Climate Assessment: CCSM3, GFDL CM2.1, HadCM3 and PCM. The second set of climate model simulations consists of models that have contributed to phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). These projections are used in the upcoming IPCC Fifth Assessment report and 2013 Third National Climate Assessment. Projections from 9 CMIP5 global climate models with daily temperature and precipitation outputs for the RCP 8.5 and 4.5 scenarios were used that are updated versions of CMIP3 models: CCSM4, CNRM-CM5, CSIRO-Mk3.6.0, MPI-ESM-LR, HadGEM2-CC, INMCM4, IPSL-CM5A-LR, MIROC5 and MRI-CGCM3. The full list of models used in this analysis is provided in Table 1.

Global climate model output is usually too coarse to be able to resolve a specific city or state. For that reason, downscaling is typically used to generate location-relevant information. Downscaling incorporates new information – which can consist of either high-resolution modeling of physical processes, or incorporation of historical observations at the location of interest – into GCM projections to produce locally-relevant projections of temperature, precipitation, and humidity at a given location. This study uses the Asynchronous Regional Regresson Model (ARRM; Stoner et al., 2012) to downscale daily maximum and minimum temperature, 24h cumulative precipitation, and daily maximum and minimum relative humidity to local weather station locations near Cambridge. ARRM is an updated version of the statistical downscaling model used in the city-level (not the gridded or state-level) projections for the 2007 Northeast Climate Impacts Assessment (Frumhoff et al., 2007) and described in Hayhoe et al. (2008; 2010). It is also the model being used to generate the high-resolution climate projections used in the 2013 U.S. National Climate Assessment.

ARRM is based on asynchronous quantile regression, a statistical technique that corrects each individual point on the distribution of daily values from historical GCM simulations to match observed values over the same time period. This correction is then applied to future projections to produce a distribution that is allowed to change over time, but more closely matches the conditions expected at the weather station on which the model is trained (Figure 2). More information on the ARRM method is provided in the peer-reviewed journal article, “An asynchronous regional regression model for statistical downscaling of daily climate variables” by Stoner et al. (2012).

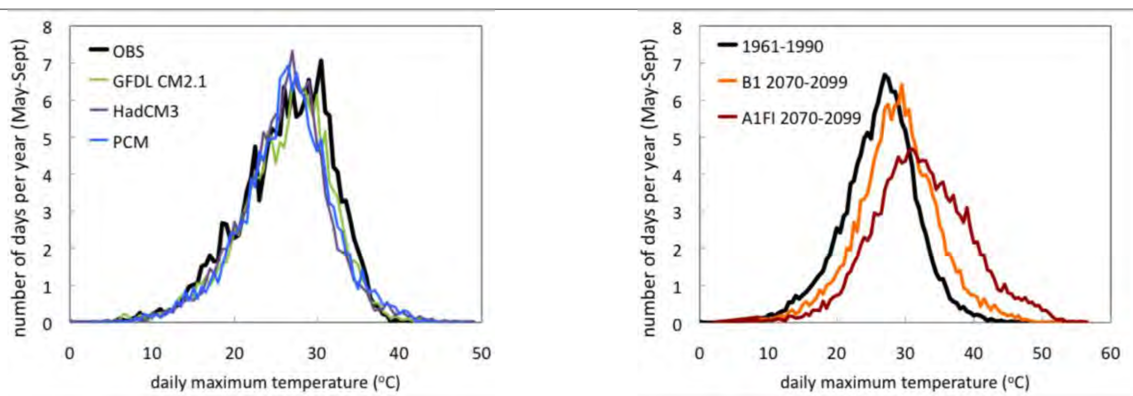

Figure 2. (a) Observed (black) and historical simulated distribution of daily maximum summer temperatures by three GCMs for a weather station in Chicago.

(b) Historical simulated (black) and future projected daily maximum summer temperature under the SRES A1FI higher (red) and B1 lower (orange) scenarios used in this analysis.

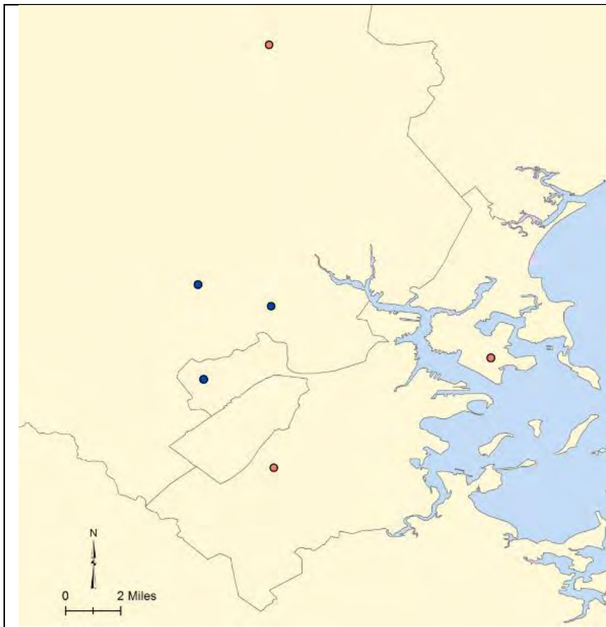

Figure 3. Long-term (red) and short-term (blue) weather stations used in this analysis.

ARRM can be trained on any observational dataset to produce future projections at the temporal and spatial scale of those observations. For this project, high-resolution projections were developed for the nearest three long-term weather stations to Cambridge: Reading, Jamaica Plain, and Boston Logan Airport. Precipitation was also interpolated from these stations to three closer short-term weather stations whose records (less than 5 years) were not long enough to train the downscaling model: Cambridge, Belmont, and Brighton (Figure 2, Table 2). Relative humidity projections were calculated for Boston Logan only, as this was the only weather station with long-term obervations available.

Table 2. Weather stations used in this analysis to generate high-resolution climate projections.

STATION NAME	ID	LOCATION	VARIABLE	LENGTH OF RECORD
CAMBRIDGE*	US1MAMD0011	42.3876 -71.1253	Pr	2010-2012
BELMONT*	US1MAMD0018	42.3988 -71.1638	Pr	2011-2012
BRIGHTON*	US1MASF0004	42.3493 -71.1607	Pr	2011-2012
READING	USC00196783	42.5242 -71.1264	Tmax, Tmin, Pr	1960-2012
JAMAICA PLAIN^	USC00193890	42.3031 -71.1239	Tmax, Tmin, Pr	1962-2012
BOSTON LOGAN INTL AP	USW00014739	42.3606 -71.0106	Tmax, Tmin, Pr, RH	1936-2012

* These locations had insufficient data available to train the statistical downscaling model. Instead, we built a quantile regression model to predict precipitation at these locations based on conditions at the three long-term stations surrounding Cambridge.

^ This station had too many missing data points in the precipitation record to produce reliable projections.

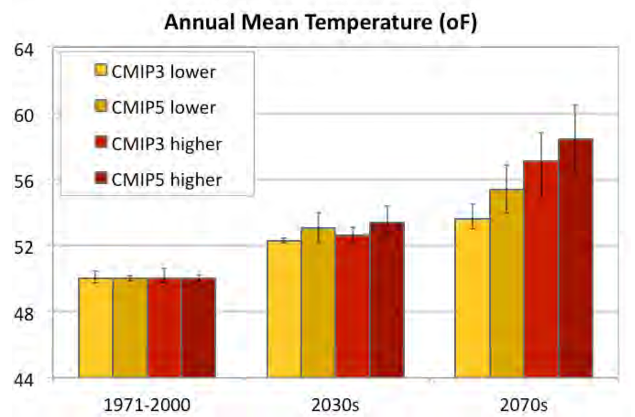

Figure 4. Historical and projected future annual mean temperature, based on the average of three long-term weather stations shown in Figure 3. Yellow bars show projected changes under lower scenarios and red bars, under higher. CMIP3 are the older generation of global climate models, and CMIP5 are the newer generation. The ranges on each bar show the projections from all the different models in each group (4 models in CMIP3 and 9 models in CMIP5).

Results

The most recent climate projections for the United States show future increases in average temperature and extreme heat, as well as decreases in the frequency of extreme cold events.

Precipitation patterns are expected to shift over broad geographical areas, with the northern latitudes generally becoming wetter and more southern latitudes drier, particularly in winter and spring (Walsh et al., 2013a).

At the scale of global climate models (accurate to broad regions, rather than individual states) these patterns are expected to persist over the Northeast: warmer average temperatures, more frequent high temperature extremes, wetter winter and spring conditions, and little change in summer and fall precipitation. Using the methods described above, this analysis transforms these qualitative projections into quantitative information tailored to the individual weather stations surrounding Cambridge. Projections are summarized for two thirty-year average periods, 2030s (2020-2049) and 2070s (2060-2089) compared to the historical period 1971-2000. This report highlights the main results from the climate analysis; bar charts for all the climate indicators calculated in this analysis are provided in accompanying Excel files.

Over the coming century, climate change is expected to increase average and seasonal temperatures in Cambridge. Average temperatures, currently around 50°F, are expected to increase by 2-3°F by the 2030s. By the 2070s, annual temperature is projected to increase by 4-5°F under lower scenarios and 7-8°F under higher (Figure 4). Similar increases are projected for dewpoint

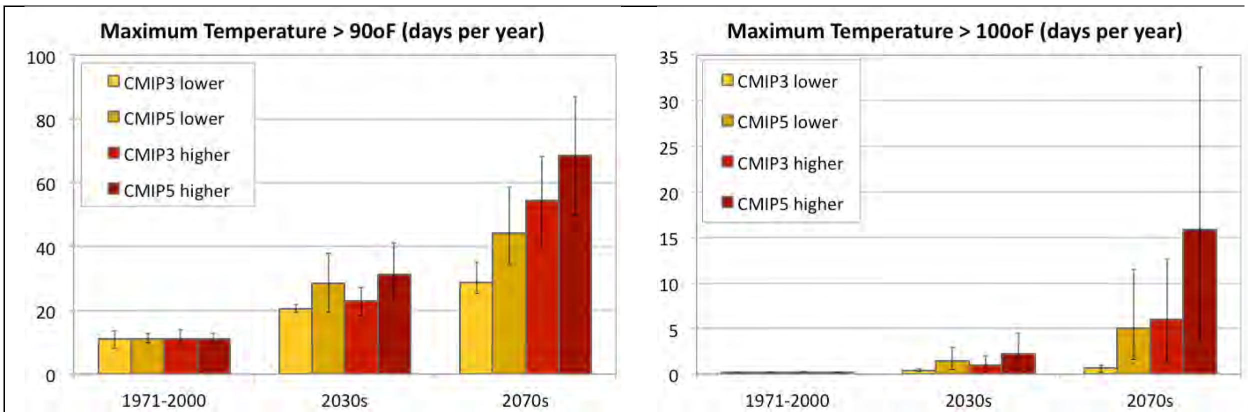

Figure 5. Historical and projected number of days per year with maximum temperature over (a) 90°F and (b) 100°F. Yellow bars show projected changes under lower scenarios and red bars, under higher. CMIP3 are the older generation of global climate models, and CMIP5 are the newer generation. The ranges on each bar show the projections from all the different models in each group (4 models in CMIP3 and 9 models in CMIP5).

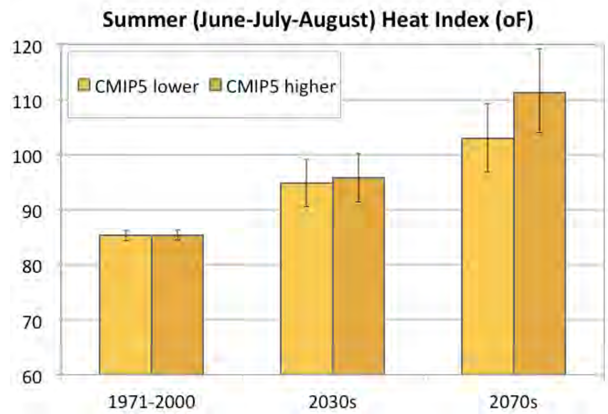

Figure 6. Historical and projected future summer heat index, based on projections for Boston Logan weather station (the nearest weather station with long-term humidity observations). Lighter gold bars show projected changes under lower scenarios and dark gold bars, under higher. Projections here are based on 8 CMIP5 models, as most CMIP3 models and one CMIP5 model did not have daily relative humidity projections available.

temperatures (see Excel files). Proportionally greater changes are also expected for summer by end of century as compared to winter (see Excel files).

Temperature extremes are also projected to change. This analysis looked at the number of days per year with maximum temperatures over 90°F and 100°F. Historically (from 1971-2000) there are an average of 11 days per year over 90°F and only one day over 100°F every seven years or so. In the future, the number of both types of days is projected to increase. Changes under higher scenarios are much greater than changes under lower scenarios. For example, the number of days over 90°F is projected to increase from the historical average of 11 days per year to between 20 to 30 days per year by the 2030s. By the 2070s, 30 to 44 days per year over 90°F are expected under lower scenarios, and 55 to 70 days per year under higher scenarios (Figure 5, left). The number of days over 100°F, which historically occur only once every seven to eight years, are projected to occur on average once per year by the 2030s. By the 2070s, there could be 1 to 5 days per year over 100°F under lower scenarios and 6 to 15 days per year under higher scenarios (Figure 5, right).

Average summer heat index offers a different way to look at the intensity of summer heat. Historically, summer temperature (night+day) averages around 70°F, while daytime summer heat index (calculated from daily maximum temperature and daily average relative humidity) hovers around 85°F. By the 2030s, summer heat index is projected to average around 95°F under both higher and lower scenarios. By the 2070s, average summer heat index is projected to exceed 100°F under lower scenarios and 110°F under higher scenarios (Figure 6).

Because extreme heat days are currently relatively rare in the historical record, the uncertainty in the exact number of days projected for the 2030s and 2070s is higher than the uncertainty in the increase in average annual or seasonal temperatures. This can be seen by comparing the vertical black bars in Figure 4 vs. Figure 5. However, it is virtually certain that the frequency of these days will increase in the future over climatological (20-30 year average) time scales. It is also very likely that these increases will be greater, on average, under higher as compared to lower scenarios by the 2070s compared to present-day.

Average precipitation is projected to increase by an average of approximately 6 to 10 inches or 15-20% by the 2070s compared to the historical period, consistent with projected increases in mid-latitude precipitation. These increases occur primarily in winter and spring, consistent with the larger pattern of the same seasons at higher latitudes becoming wetter over the coming century (Figure 7). Precipitation intensity (a measure of the average amount of precipitation falling per day, defined as total annual precipitation divided by the number of wet days per year) is also expected to increase, by around +5% by the 2030s and +15% by the 2070s (see Excel files). Historically, the direction of predicted trends is consistent with observed changes across the Northeast region. In

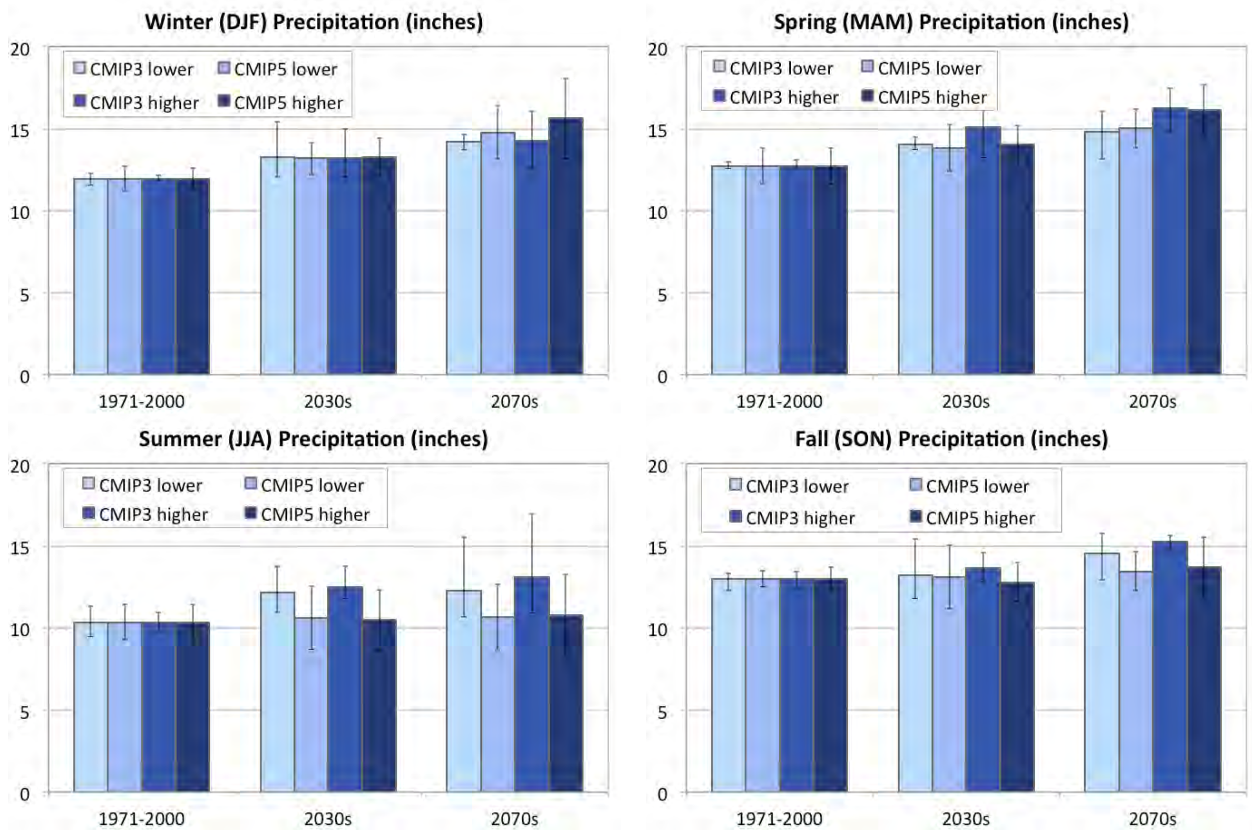

Figure 7. Historical and projected future seasonal precipitation (in inches) for the 2030s and 2070s relative to 1971-2000 for winter (Dec-Jan-Feb), spring (Mar-Apr-May), summer (June-July-Aug) and fall (Sept-Oct-Nov) for two (not three) long-term weather stations. Light blue bars show projected changes under lower scenarios and dark blue bars, under higher. CMIP3 are the older generation of global climate models, and CMIP5 are the newer generation. The uncertainty bars, as indicated by the vertical lines above and below each bar, show the range of projections from all the different models in each group (4 models in CMIP3 and 9 models in CMIP5).

the future, these trends are expected to continue, with greater changes by 2070s relative to 2030s, but little to no difference between the changes projected under higher vs. lower scenarios.

In addition to annual averages, this analysis calculated three types of indicators of extreme precipitation: (1) days with more than 2 inches of rain in 24 hours; (2) cumulative precipitation on the wettest 5 days in a row of the year; and (3) cumulative precipitation on the wettest 1, 2, 4, and 7-day periods in 2, 10, and 30 years. All metrics of extreme precipitation show increases in the future, very roughly ranging from approximately 0 to +10% by the 2030s and +10 to +30% by the 2070s (see Excel appendices for projections corresponding to each indicator). For example, the maximum 5-day precipitation amounts each year currently average around 5 inches in 5 days. By the 2030s, 5-day precipitation is projected to average between 5 and 6.5 inches; by 2070s, between 5.5 and 7 inches (Figure 8). Changes in other indicators are summarized in the Excel Appendix.

Conclusions

Climate projections for the United States show that observed temperature increases are projected to continue, as are increases in high temperature extremes. Projections for the city of Cambridge, based on three nearby long-term weather stations, show similar trends in average and extreme temperature, with higher changes projected under higher scenarios as compared to lower, and by 2070s compared to 2030s.

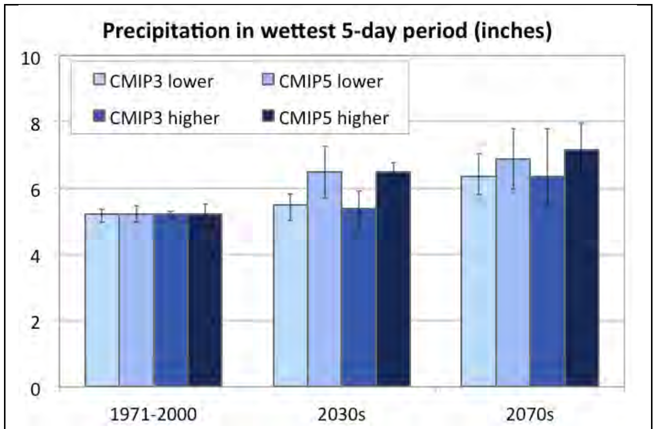

Figure 8. Historical and projected future precipitation in the wettest 5 days of the year, in inches. Light blue bars show projected changes under lower scenarios and dark blue bars, under higher. CMIP3 are the older generation of global climate models, and CMIP5 are the newer generation. The uncertainty bars, as indicated by the vertical lines above and below each bar, show the range of projections from all the different model.

In general, projected temperature changes for the city of Cambridge that are simulated using the newer generation of climate models (CMIP5) tend to be slightly higher than those simulated using the older generation of models (CMIP5). Comparing these projections with others projections generated for the state of Massachusetts will not yield the same values for several reasons. First, the projections are for a different geographic region. In particular, proximity to the ocean can mitigate projected warming compared to inland locations. As such, temperature projections for the state would be expected to be slightly higher than projections for a coastal city. Second, the projections are for weather stations as compared to a gridded set of observations. Third, the projections could have been generated using a different combination of global climate models and/or a different type of statistical downscaling model. For all of these reasons, the projections summarized in this report can be expected to be *similar* but not *identical* to other, different projections generated by other regional efforts.

Regional projections for northern mid-latitudes show increases in winter and spring precipitation, as well as increases in extreme precipitation. Again, projections for Cambridge show similar trends, with increases in annual average precipitation that are strongest in winter and spring, as well as increases in heavy precipitation and precipitation intensity. In contrast to temperature, there are few significant differences between changes projected under higher as compared to lower future scenarios. In general, however, changes projected by 2070s are usually larger than those projected by 2030s.

There is *greatest certainty* in the direction of projected increases in annual and seasonal temperatures, high temperatures, and heavy precipitation, all of which show increases consistent with observed trends. There is *moderate certainty* in the relative proportion of precipitation increases by season. Although these reflect observed trends, they are more strongly affected by regional and local climate variability.

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Climate Projections for Cambridge MA

Reconciling Disparate Sources

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October 15, 2013

Introduction

Various agencies, organizations, and municipalities in Massachusetts have recently completed or are currently conducting climate impact and vulnerability assessments. These assessments typically use climate projections to quantify future impacts, which are in turn used as input to what are often costly adaptation and mitigation strategies.

Given what's at stake, it makes sense that a practitioner or user would want to compare these projections with observations, or with other projections used in a different assessment, to see if they match up. That is certainly a fair comparison if it's apples with apples; *but not if it's apples with oranges*. The purpose of this report is to describe the different choices on future scenarios, global climate models, statistical downscaling models, and observations that may go into generating these projections, how projections can and cannot be compared across methods and observations, and how the projections developed for the 2013 Cambridge Climate Vulnerability Assessment (CCVA) compare with projections used by other organizations in the region.

High-resolution climate projections, such as those used in the 2007 Northeast Climate Impacts Assessment (NECIA) and in the Second and Third U.S. National Climate Assessments, are generally made up of four components:

1. **Future scenarios**, which are used as input to the global climate models
2. **Global climate model simulations,** which calculate future climate changes resulting from those scenarios
3. **Statistical downscaling models** that combine global model projections and high-resolution observations to create high-resolution model projections for a given location or grid
4. **Observations** (either station-based or gridded) which are used train the statistical downscaling model

When comparing one set of projections with another, the numbers will be different if any of these components are different. However, unless you know exactly which scenarios, models, observations and downscaling model were used to develop a given set of projections, it will be impossible to figure out why one set of projections differ from another, and therefore which set may be more reliable. It is essential to know which climate modeling approach and inputs were used to develop the climate projections before comparing the projections used in one assessment with any others.

Most other assessments don't have climate projections developed specifically for that project. Instead, they are obtained from a pre-existing source or already-available dataset. Reliable pre-existing sources include NECIA, or other databases such as the DOE Green Data Portal (which are used in the SimClim framework) or the USGS GeoData Portal.

Pre-existing databases are usually quite extensive, representing a significant investment of time and money. They have usually been carefully checked and validated before being released. For both of these reasons, it makes sense to use these resources, particularly for projects with a limited budget and scope. However, there are two potential risks associated with using an off-the-shelf dataset.

1. **Provenance information can be lost.** Provenance information includes original scenarios, global climate models, downscaling methods, and observations used to develop the high-resolution projections. Loss of this information complicates comparison of climate projections and impacts across assessments. Without provenance information, it is unclear whether differences between the numbers being used by one project vs. another are the result of geographic resolution (e.g. comparing projections for the entire Northeast with projections for the city of Cambridge), downscaling method (e.g. using a quantile mapping vs. a quantile regression approach), or a different combination of global climate models, scenarios and/or time frames (e.g. comparing a projection for 2020-2049 with one for 2030-2059, or projections from a mid-range scenario with a higher scenario).

2. **Inappropriate information may be used.** Climate projections may be not actually correspond to the study location, with Northeast-wide projections being used as if they were valid an individual location, for example. In addition, failure to read the small print on the downscaling method and/or the observations used to train the method might mean that a downscaling approach may be used that is inappropriate for a coastal location or for precipitation extremes. *Both of these issues appear to have occurred in projects other than the CCVA and are discussed in detail in the final Case Studies section of this report.*

The first sections of this report discuss what is a valid comparison and what is not: in terms of scenarios, global climate models, statistical downscaling methods, and observations used to generate the climate projections.

In the final Case Studies section, this report addresses three specific questions raised by the city of Cambridge regarding the correspondence between the projections our team developed specifically for the city and (a) real observations, (b) NECIA-based projections, and (c) SIMCLIM-based projections.

Reconciling Climate Projections for Cambridge

What scenarios were used?

Over the coming century, climate will continue to change as a result of human activities. How much climate will change depends on human choices, specifically what type of energy will be used in the future. Higher scenarios of carbon emissions assumed continued dependence on fossil fuels such as coal, gas, and oil as the primary energy source (Figure 1a, red line). Lower scenarios envision a transition from fossil fuels to non carbon-emitting renewable energy sources (Figure 1a, green line). After mid-century, changes in average temperature and other variables such as extreme heat days and heavy precipitation based on higher scenarios (Figure 1b, red bars) will be much larger than projections based on lower scenarios (Figure 1b, yellow bars).

In the 2007 NECIA project, future projections were based on the SRES A1fi (higher) and B1 (lower) emission scenarios. Carbon dioxide emissions (and hence the resulting climate projections) for these scenarios are nearly identical to the newer RCP 8.5 (higher) and 4.5 (lower) scenarios used in the 2013 CCVA project. Other projects, however, such as those that use SIMCLIM input, may rely on mid-range scenarios such as SRES A2 (mid-high) or A1B (mid-low). Without knowing which scenarios were used as input to the analysis, it is impossible to compare apples with apples.

Projections will be different if they were based on a different future scenario (e.g. high, medium, or low).

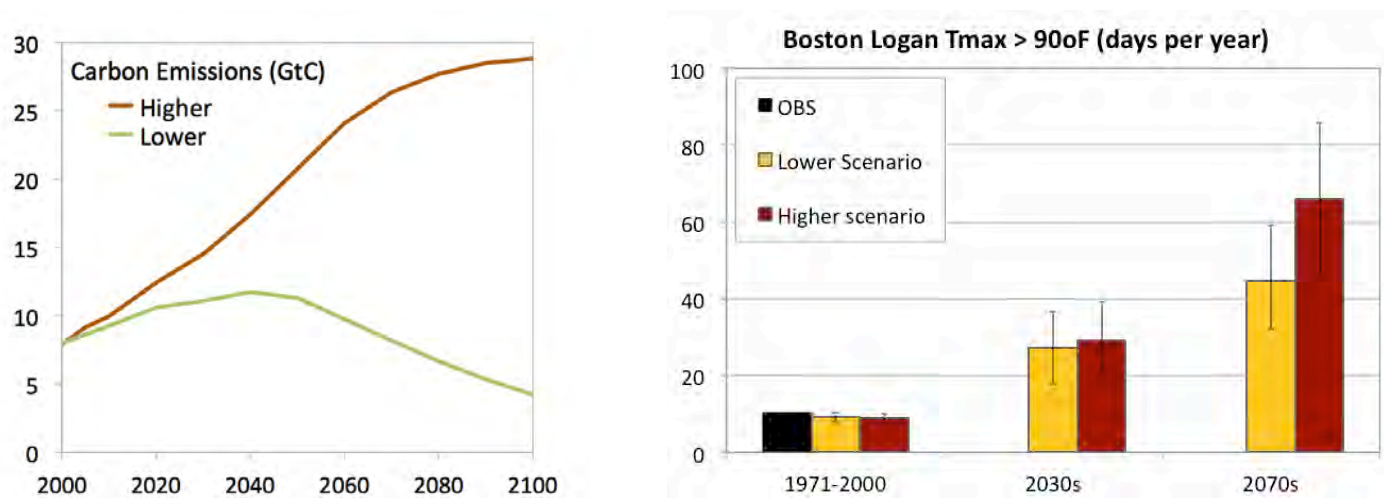


Figure 1. This figure shows how different scenarios of carbon emissions (left) will result in very different projections of changes in temperature projections (right; here, projected changes in the number of days per year with maximum temperature exceeding 90^{o}F at Boston Logan).

Which global climate models were used?

Global climate models are complex, three-dimensional models of the atmosphere, oceans, and Earth's surface. These models are all based on the fundamental physics of the Earth system. However, they can differ from one another in how they represent the various processes at work within the Earth's climate system. There is no single perfect global model. Each one has different strengths and weaknesses. For this reason, best practice is to use multiple models. Future projections can then be based on the average (as indicated by the colored bars in Figure 2) and the range of projections resulting from the multi-model ensemble (as shown by the black lines or "whiskers" on each bar in Figure 2).

For regional climate assessments, differences in how global climate models represent various physical processes might mean that one model estimates a different pattern of precipitation changes over a region as compared to another model. One model might be more sensitive than another model, producing a larger change in temperature for the same increase in carbon dioxide emissions. These differences between models mean that, although all models show future warming and most models show future increases in winter and spring precipitation over the Northeast, the exact numbers produced by different models can differ and there is no way to know for sure which model is "correct" (if any!) until the future happens.

The NECIA project used projections from 3-4 CMIP3 global climate models; the CCVA project uses projections from 9 CMIP5 global climate models. For some variables, such as the wettest day in two years, the first set of models (blue) gives nearly the same result as the second set of models (green; Figure 2, left). The black "whisker" lines all overlap; this means that there is no statistically significant difference between the projections. On the other hand, for other variables such as summer precipitation the first set of models (blue) shows increases of 1-2 inches by 2070s, while the second set of models (green) show no change at all (Figure 2, right). This is a big difference; but if you didn't know which models were used to generate the projections you were using, you wouldn't know if the differences were due to different global climate models or not.

In general, we have more confidence in the projections from the CMIP5 models than the CMIP3 models for two reasons: first, in the CMIP5 average we used more models, so the average and range are based on a larger ensemble; and second, the CMIP5 models represent updated versions of older CMIP3 models. The updated versions of global climate models are usually either comparable or better than the previous versions of those same models.

Projected changes will often differ if they were generated using a different set of global climate models

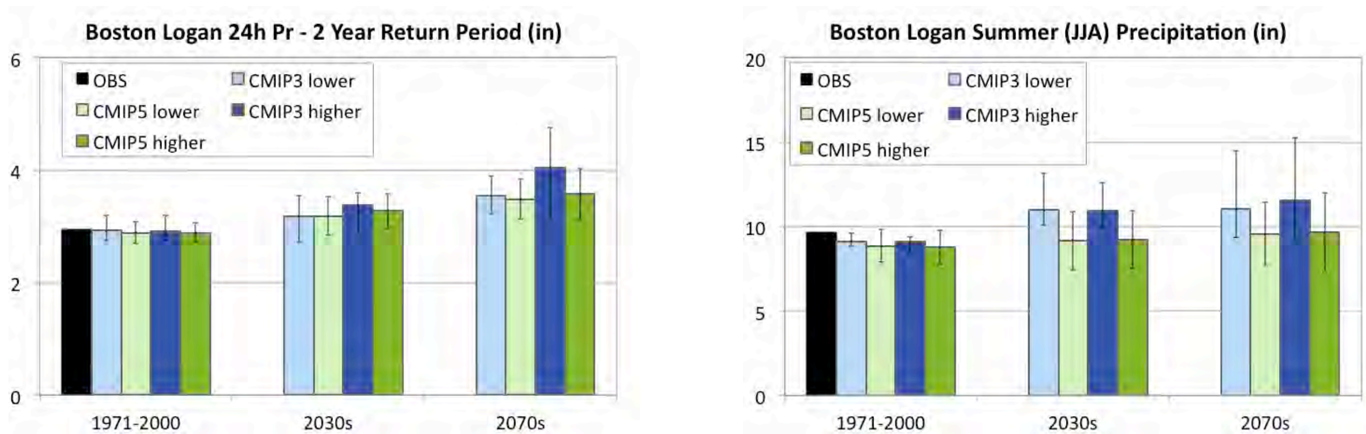


Figure 2. This figure shows how different combinations of global climate models—here, four older CMIP3 models, in green, and nine newer CMIP5 models, in blue—may give very <u>similar</u> results for some variables, such as the wettest day in two years (left), but very <u>different</u> results for other variables, such as summer precipitation (right).

Which statistical downscaling model(s) were used?

Even the highest-resolution global climate model output is too coarse to be able to resolve a specific city such as Boston or Cambridge. For that reason, statistical downscaling models are usually used to generate more location-relevant information. (In some cases, high-resolution regional climate or dynamical downscaling models are also used. However, these models still produce output for grid cells ranging from 10 to 50km in size. As discussed in the next section on station-based vs. gridded observations, for city-scale analysis. the output from these regional climate models would still need to be downscaled by a statistical model to an individual weather station, in order for projections to accurately reflected the impacts of local topography, such as the urban heat island effect or proximity to a coastline, on simulated climate.)

Statistical downscaling combines global climate model simulations with historical records of at least 20 years of daily observations (to cover a range of weather conditions) to produce locally relevant projections of temperature and precipitation. Some methods, such as ARRM, can also downscale other variables such as solar radiation or humidity. Statistical downscaling models are "trained" using these observational datasets to produce future projections. Future projections are at the same temporal and spatial scale of the observations. As discussed in the next section, these projections "look" like the observations for the historical period, but change in the future as simulated by the global climate model.

In the 2007 NECIA project, we trained the BCSD statistical downscaling model (the same one used to generate the projections available via the DOE Green Data Portal and used as input to the SimClim framework) on global climate model simulations (Figure 3, left) and a large 1/8th degree gridded dataset of daily maximum and minimum temperature and precipitation covering the entire Northeast. The resulting gridded projections were used for region- and state-wide averages (Figure 3, center). In addition, however, an early version of the ARRM statistical downscaling model was trained on individual weather stations for cities throughout the Northeast (e.g. Boston, Concord, New York). These projections were used for city-scale analysis of projected changes, focusing on extreme heat and precipitation (Figure 3, right).

For the 2013 CCVA project, the latest version of the ARRM statistical downscaling model was trained on the nearest three long-term weather stations to Cambridge: Reading, Jamaica Plain, and Boston Logan Airport. These three long-term stations were used in downscaling because the three closer stations—Belmont, Brighton, and Cambridge—had no more than 2 years of data each. However,

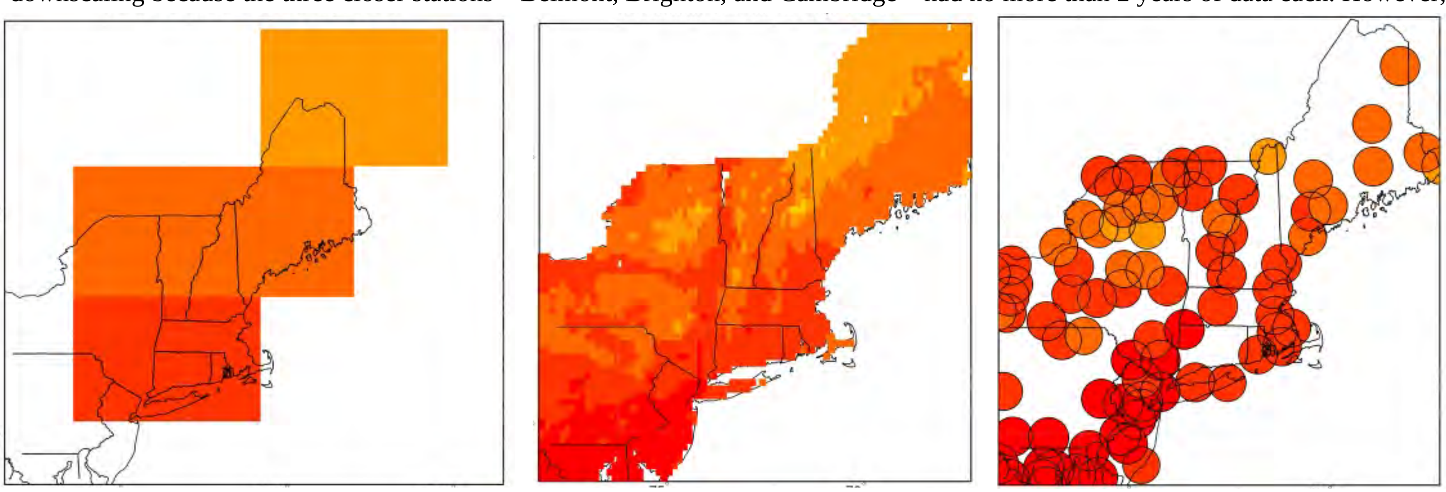


Figure 3. This figure compares the climate projections generated by a global climate model (left), statistical downscaling to gridded observations (center) and statistical downscaling to individual weather stations (right) covering the U.S. Northeast. Source: Hayhoe et al. 2008

because the long-term stations were not directly located in Cambridge, our analysis took one more step. Using the very short records, we developed a multivariate regression model (a linear model for temperature, and a quantile model for precipitation) connecting conditions at the short-term stations to what might be happening at the longer-term stations. Projections for the short-term stations, particularly for extreme values of temperature and precipitation such as the number of days per year over 100^{o}F or the wettest day in 2 or 10 years, are clearly less reliable. However, this regression approach can at least provide a general picture of Cambridge's future climate and how it might differ from conditions at the longer-term stations.

Statistically downscaled projections can differ in two key ways. First, they can differ based on the observational data used to train them. These differences are discussed in the next two sections on observational data. Second, they can differ based on the statistical downscaling model used. These differences are the focus of this section.

Each model is based on a different statistical technique. Some simple techniques are easy and simple, but may not do a good job reproducing extremes, such as high or low temperatures or heavy precipitation events. Some more complex approaches do a better job at extremes, but may be more expensive and complicated to run.

The research I am conducting with colleagues at the Geophysical Fluid Dynamics Laboratory, the leading climate modeling center in the eastern U.S., addresses exactly this issue. We compare different statistical downscaling methods to extremely high-resolution global model simulations for the end of the century under a higher scenario. Our goal is to assess the strengths and weaknesses of the different statistical methods.

Based on our initial research, we can compare three downscaling methods: first, the monthly "quantile mapping" approach that is used in the BCSD method (e.g. region-wide downscaling in NECIA, 2007; Second National Climate Assessment, 2009); second, the daily "quantile mapping" approach such as is used in the BCCA method (e.g. SimClim); and third, the daily "quantile regression" approach that is used in ARRM (e.g. city-specific downscaling in NECIA, 2007; Third National Climate Assessment, 2013; CCVA, 2013).

For average temperature, this initial comparison shows that any of these three methods is reliable (Figure 4, top row).

For extreme cold temperatures, both monthly and daily *quantile mapping*-based methods such as are used in BCSD and BCCA exhibit a large bias that makes them unreliable at higher latitudes such as the U.S. Northeast (Figure 4, middle row).

For extreme high temperatures, all methods show biases over some locations. Over the Northeast, however, the *daily quantile mapping* method as used in BCCA has by far the largest biases, ranging from 5 to 10^{o}C (9-18^{o}F) by end of century. This bias is about the same size as the projected change; hence, this statistical method is likely unreliable for projecting high temperature extremes in the Northeast (Figure 4, bottom row).

This initial research is the basis for our recommendation of the use of the quantile regression-based method ARRM (Figure 4, right column) to develop the climate projections used in the Third National Climate Assessment (2013) and the Cambridge Climate Vulnerability Assessment (2013). A publication that compares these methods for other variables, including minimum temperature, precipitation, and relative humidity, is in preparation.

Projected changes, especially temperature and precipitation extremes, will differ if they were generated using different statistical downscaling models.

Our initial work demonstrates how certain statistical downscaling techniques may be more (and others less) appropriate for specific geographic locations and/or temperature & precipitation extremes.

THESE PRELIMINARY RESULTS ARE UNPUBLISHED AND MAY CHANGE PRIOR TO PUBLICATION

DO NOT CITE

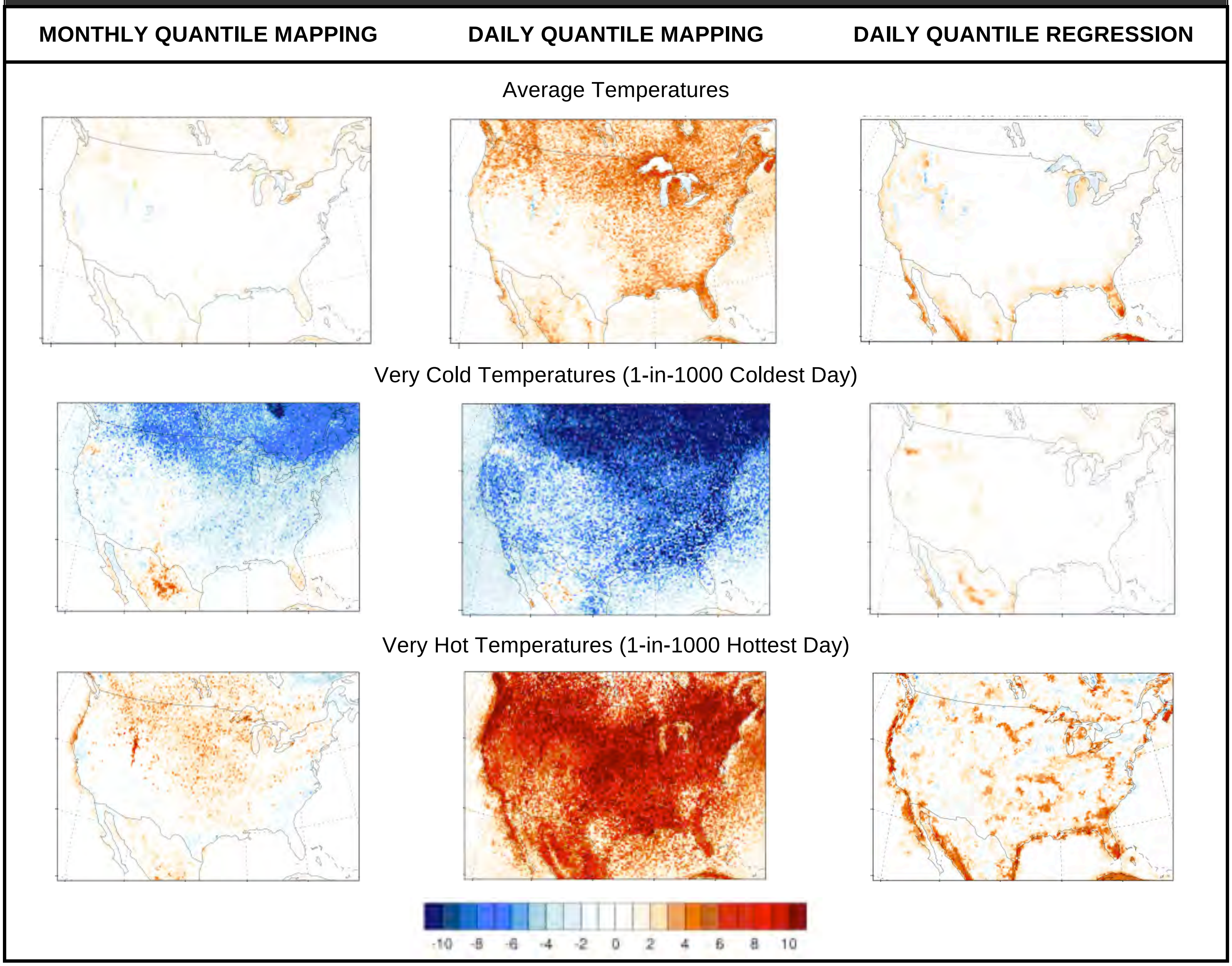


Figure 4. This figure compares the bias in maximum daily temperature projections generated by three different statistical downscaling techniques, compared to an extremely high-resolution global climate model simulations for the end of the century under a higher scenario. Different plots show the bias in extremely cold temperatures (the 1-in-1000 coldest day), average temperature (the 50th percentile), and extremely hot temperatures (the 1-in-1000 hottest day) for three methods: (left) monthly quantile mapping, as used in the BCSD method for NECIA (2007); (middle) daily quantile mapping, as used in the BCCA method for SimClim; and (right) daily quantile regression, as used by the ARRM method in CCVA (2013). Source: Hayhoe et al. 2012

Reconciling Climate Projections for Cambridge

Which observations were used: station-based or gridded?

High-resolution climate model simulations can be developed based on two very different types of observational data:

1. Weather station data, which corresponds to an individual location, and
2. Gridded data, where weather station data has been smoothed and interpolated onto a regular grid.

Climate simulations generated by a statistical downscaling model are trained to match the observations at specific weather stations, such as Boston Logan Airport, or specific grid cells, such as a 1/8th degree grid covering the Northeast.

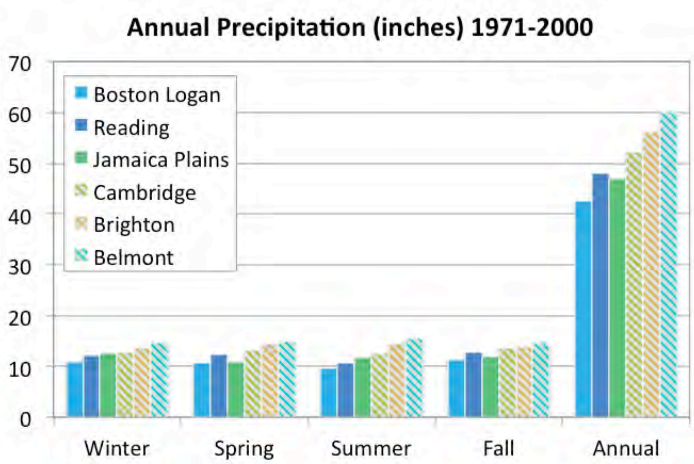
Climate projections generated for one weather station are not intended to match observations at a different station. Similarly, climate projections generated for a regular grid covering a large area or even for an individual grid cell from that grid are not intended to perfectly match observations at a weather station, even if the weather station lies in that grid cell. Climate projections are only intended to match observations for the exact observations that we used to train the statistical downscaling model.

What does this mean for station-based climate projections?

It means that you can't take temperature or precipitation projections developed for Boston Logan, for example, and compare them against historical observations from an inland location such as Reading. That is not a valid comparison. Any differences between the projections for Logan and the observations for Reading will be due to differences in the observations between those two stations, not differences between simulated vs. observed precipitation.

Because Boston is on the coast, it is located in a region with steep temperature and precipitation gradients. As illustrated by Figure 5(a), in the greater Boston area, observed average annual precipitation can differ by nearly 50% or almost 20 inches per year between one weather station vs. another. And, as shown in Figure 5(b), observed temperature also varies from one station to another. Inland locations such as Jamaica Plains or Reading have a stronger seasonal cycle, with relatively colder winters and warmer summers. More coastal locations such as Cambridge have milder winters and cooler summers, thanks to the moderating effects of the ocean on local climate. It is incorrect to compare projections corresponding to one station with observations corresponding to another.

Always compare projections for a given weather station with observations from the same weather station.



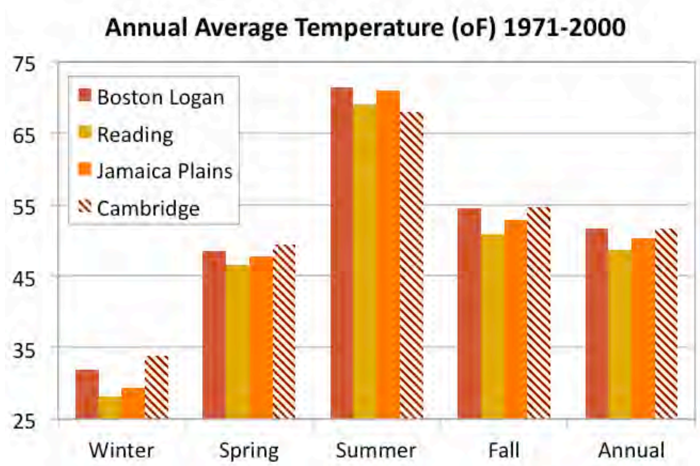


Figure 5. This figure shows observed (solid bars) and, for stations with less than 5 years of observational data, model-simulated (hatched bars) annual (a) precipitation (in inches) and (b) temperature (in degrees F) for weather stations near Boston MA averaged over the period 1971-2000. These plots illustrate how both precipitation and temperature can vary significantly from one station to the next, particularly at the seasonal scale, and hence why climate projections developed for one station should not be compared against observations from a different station.

Reconciling Climate Projections for Cambridge

What does this mean for grid-based climate projections?

First, it means that you can't take temperature or precipitation projections developed for the entire Northeast, for example, and expect them to match projections developed for an individual location such as Cambridge. That is not a valid comparison.

We already know how today, when it is snowing in New Hampshire, it can be dry in Boston. When it is raining in Boston, due to a coastal storm, for example, it might be completely dry in upper state New York. In the same way, as storm tracks and precipitation patterns shift in response to global climate, future precipitation is likely to change by a different amount over Maine, for example, as compared to Massachusetts.

Figure 6 shows the projected change in seasonal precipitation by end of century under a higher scenario across the eastern U.S.

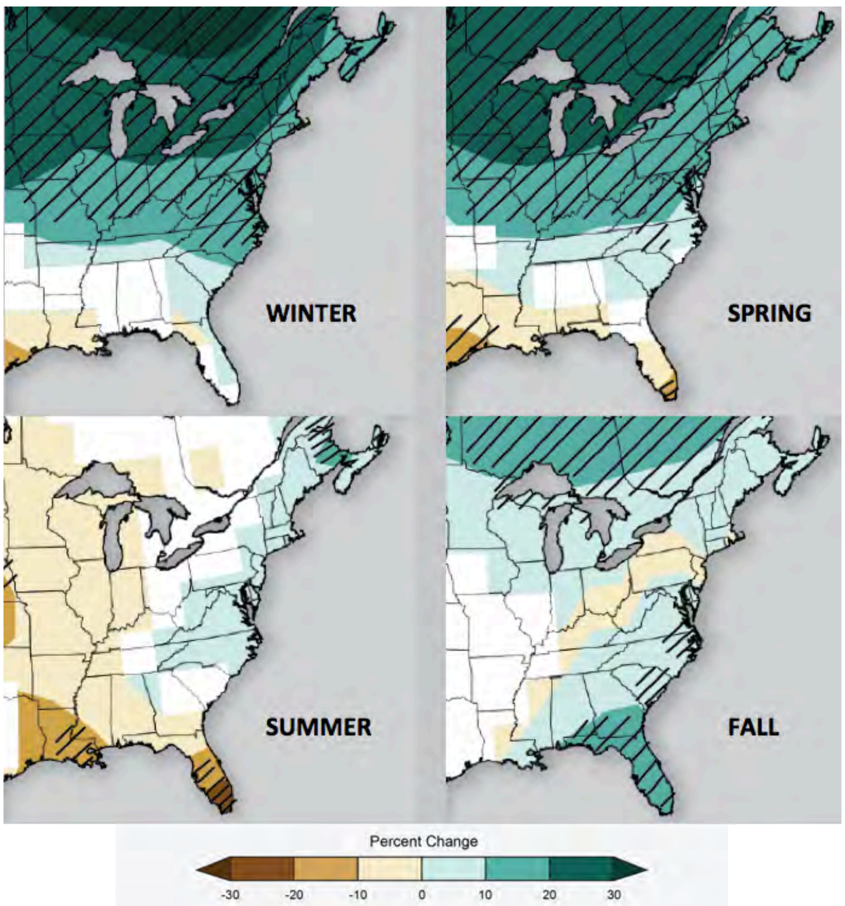


Figure 6. This figure shows the projected change in winter (Dec-Jan-Feb), spring (Mar-Apr-May), summer (Jun-Jul-Aug) and fall (Sept-Oct-Nov) precipitation by the end of the century under a higher (RCP 8.5) scenario, as simulated by a large set of the most recent CMIP5 global climate models. Precipitation changes are shown in percent relative to 1971-2000, with green colors showing areas that are projected to get wetter and brown colors showing areas projected to become drier. Images courtesy of M. Wehner as developed for the Third National Climate Assessment Chapter 2, Climate Science.

In winter and spring, there is a strong north-to-south gradient along the East Coast of the United States. More northern locations are expected to become wetter in winter and spring, while more southern locations may see little to no change. In summer, there is a coastal-to-inland gradient. Most of the mid-Atlantic and Northeast coast is projected to get a little wetter, while inland locations see no change. And in fall, most of the East Coast is expected to get wetter, except for a ribbon of projected drier conditions from Louisiana up through Pennsylvania, New York, and New Jersey and a tiny area of dry conditions over eastern Massachusetts.

So while the direction of change should be similar within a broad geographic region such as the Northeast, there is no reason to expect the exact change in precipitation or temperature projected for Maine to be identical to New Jersey, or for the whole Northeast to be identical to Massachusetts.

Projections for a larger area such as the Northeast will not match projections for a smaller area such as Massachusetts or an individual location such as Cambridge. Different local and regional climates respond differently to global change.

Reconciling Climate Projections for Cambridge

There are other more subtle issues associated with using gridded climate projections. These issues generally arise in regions where topography, and hence climate, varies over relatively small spatial scales. Such regions include mountains, and coastal areas near large lakes and oceans. They also include the greater Boston and Cambridge area. Figures 5 and 6 clearly illustrate how the coast has a noticeable effect on historical temperature and precipitation for this region.

For many datasets of gridded observations, such as the 1/8th degree VIC dataset developed by Ed Maurer and the updated 1/16th degree dataset developed by Ben Livneh, if a grid cell contains any ocean area, its value is set to N/A. That means that if a location such as Cambridge lies within a grid cell that is even partly over the ocean, the value of the entire grid cell will be set to N/A and there will not be any data available for the location you want. Instead, you'll only have access to data from a grid cell adjacent to the one you want, which might encompass the locations of Reading or Jamaica Plain, but not the locations of Cambridge nor Boston Logan because the latter are too close to the ocean.

Furthermore, a gridded dataset does not correspond to any specific weather station. It is the interpolated average of conditions over the area in the grid, informed by the nearest available weather stations. In areas where there is a sharp gradient in temperature and precipitation over a relatively short spatial scale, the grid will give you the smoothed average value, which may not actually occur anywhere in the grid.

Picture a steep mountain slope and river valley in Colorado. A single grid cell at 1/8th of a degree may contain everything from the top of the mountain to the bottom of the river valley, and half way up the other side. Temperature will be the average of that area as captured by whatever data may be available, scaled by elevation. Does the grid cell's average temperature actually occur from day to day at a specific location in the mountain or valley? It may not; the grid cell "observation" is just the average of across the entire area.

When these gridded observed datasets are used as the basis for producing high resolution climate projections with a statistical downscaling model, the output of the model looks exactly like the input observations: a regular grid, with N/A values if any part of the grid is over the ocean, and average conditions that represent the areal average over the entire grid, not what might be expected at any given point in the grid, not even the center.

Gridded datasets are ideal for use over a large area, at the scale of half a state or larger, where the user wants a continuous surface, or wants to compare what might happen over a large region. For example, the Northeast-wide and state-wide projections and maps used in the NECIA project were based on a gridded dataset (Figure 3, center). If we hadn't used gridded data, it would have been impossible to make maps. However, to look at the impacts of climate change on individual cities—Boston, New York, Concord—we did NOT use a gridded observational data set. Gridded data provides too coarse an average for a city-scale location. Even worse, for cities on the coast, such as Cambridge, Boston, or New York, the gridded data may not even have a grid cell over that location. Instead, for city-level analysis in the NECIA project we performed downscaling to individual weather stations (Figure 3, right).

Examples of high-resolution climate projections that use the Maurer et al 1/8th degree regular grid as input to their downscaling include the BCSD and BCCA approaches (available via the Green Data Oasis and as input to the SimClim visualization model), the area-wide climate projections developed for NECIA (2007), and the ARRM approach (available via the USGS GeoData Portal).

Using gridded instead of station-based projections can be problematic in areas such as mountains or coastlines where local topography and local climate conditions change rapidly from one location to another.

What was the time frame of the observations used?

Climate simulations generated by a statistical downscaling model are not only trained to match the observations at a specific location; they are also trained to match those observations over a specific time period. For NECIA, this time period was 1961-1990. For the CCVA, this period is 1960 to 2012. Climate projections are not intended to match observations for a different time period than the statistical downscaling model was trained on.

What does this mean?

It means that observed annual precipitation for Boston Logan airport for 1960-2012 should match modeled annual precipitation for Boston Logan for the same time period. However, observed annual precipitation for 1980-1989, for example, may not be a good match for modeled precipitation for the same time period. And under no circumstances should you expect modeled precipitation to capture the storm of ’02 that occurred on July 12, or the drought of ’67 that lasted from April to October - it won’t.

Why doesn’t modeled climate match observed over these shorter time scales? It’s not due to error; it’s due to the intrinsic nature of climate model simulations. Over short time frames, observations and model simulations do not match—and should not be expected to match—because climate models are physics-based, not statistics-based, models. Using nothing more than the seven primitive equations that describe the properties of energy, water, and air in the atmosphere, climate models develop their own chaotic patterns of natural variability. These patterns include both day-to-day weather and longer cycles like El Niño and the North Atlantic Oscillation. Essentially, climate models represent an “alternate Earth”, with the same emissions of heat-trapping gases from human activities and the same overall patterns of natural variability, but different day-to-day and year-to-year conditions.

Over climate time scales, typically defined as the average of 30 years or more, most natural variability averages out. Over these time scales, observations can be expected to match modeled values. Over shorter time frames, however, they cannot.

Table 1 compares observed precipitation indicators for Boston Logan airport with the same values simulated by 8 global climate models for the identical period of time used to train the statistical downscaling model, 1960-2012. This comparison shows that, while some models are slightly wetter and others, slightly drier than observed, simulated values are generally within an inch of observed values for the annual average, and a tenth of an inch for precipitation percentiles.

Always compare projections with observations over climatological time scales of 30 years or more.

USW00014739	BostonLogan			obs record 1960 to 2012						
	PRECIPITATION IN INCHES									
	OBS	ALL-MOD AVG	CCSM4	CSIRO-Mk3-6-0	CNRM-CM5	HadGEM2-CC	INMCM4	IPSL-CM5A-LR	MIROC5	MRI-CGCM3
Mean	**42.6**	**42.8**	**42.9**	**41.4**	**42.6**	**44.6**	**42.2**	**43.0**	**43.2**	**42.5**
50th Percentile (Median)	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**	**0.16**	**0.15**	**0.15**
75th Percentile	0.44	0.42	0.42	0.41	0.40	0.44	0.43	0.41	0.41	0.41
90th Percentile	0.89	0.96	0.95	0.98	0.96	0.97	0.95	0.98	0.99	0.94
95th Percentile	1.28	1.36	1.37	1.41	1.35	1.34	1.32	1.36	1.37	1.37
Highest	6.11	6.29	4.21	6.11	7.06	7.06	5.69	6.11	7.06	7.06

Table 1. This table compared observed (first column) with model-simulated (remaining columns) precipitation for Boston Logan airport station for the period 1960 to 2012, the same period used to train the statistical downscaling model used to downscale projections from each of the global models listed above. The table compares mean and median precipitation as well as the 75th, 90th, and 95th percentiles (e.g. the 1-in-4, 1-in-10 and 1-in-20 events) and the highest single-day precipitation event ever recorded in that period – in other words, the most extreme value in the record.

Case Studies

Comparing CCVA Projections with Observations

For the 2013 Cambridge Climate Vulnerability Assessment (CCVA), we developed future projections for the 3 nearest long-term weather stations to Cambridge: Boston Logan, Jamaica Plains, and Reading.

Changes in temperature and precipitation and a host of secondary indicators were calculated individually for each of these stations. However, the bar charts summarizing projected changes by the 2030s and 2070s compared to the historical period initially showed the averages across these three stations. In other words, the values on the bar charts did not represent any one weather station, but rather the averages of Boston Logan, Jamaica Plains, and Reading combined.

Comparing this average to observed precipitation in Cambridge suggested that the average was too high. Examining the three weather stations, we determined that the Jamaica Plains precipitation record was too short to reliably train the statistical downscaling model and removed it from the average. However, questions remained regarding why the average did not match the record of any one station.

The problem was simple: the bar charts were showing the average over multiple stations. Moreover, these multiple stations had with very different values of annual average and total precipitation (Figure 5). Finally, nowhere in the plots nor the data files were observations compared directly to model simulations.

To address this issue, we:

1. Re-generated all daily temperature and precipitation data files so they now contain observations and model simulations side-by-side. These files are in the DropBox directory ARC_Kleinfelder/Cambridge/Data/Primary Climate Variables/Primary Indicators/

   Sample file for Boston Logan, containing observed and CMIP3 global climate model simulated precipitation in inches:

Year	Month	Day	Obs	CCSM3	GFDL_2.1	HadCM3	PCM
1960	1	1	0	0	0	0	0
1960	1	2	0	0.02	0	0.141	0
1960	1	3	0.921	0.052	1.157	0.58	0.039
1960	1	4	0	0	0.038	0	0.02
1960	1	5	0	0	0.043	0	0
1960	1	6	0	0	0	0	0
1960	1	7	0	0	0	0	0.013
1960	1	8	0	0	0	0	0
1960	1	9	0	0	0	0.05	0
1960	1	10	0.142	0	0	0.044	0
1960	1	11	0.039	0	0	0.749	0
1960	1	12	0	0	0	2.742	0.372
1960	1	13	0	0	0	0	0
1960	1	14	0	0.015	0.035	0	0

2. Calculated all secondary indicators for observations as well as for model simulations, using identical calculation methods.
3. Generated annual and 30-year average secondary indicator files for each station containing observations side-by-side with model simulated values. These files are in the DropBox directory ARC_Kleinfelder/Cambridge/Data/Secondary Climate Indicators/

Sample annual file for Boston Logan, containing observed and CMIP3-based simulations of days per year over 90°F

Year	Obs	CCSM3	GFDL_2.1	HadCM3	PCM
1960	5	8	22	6	4
1961	8	11	0	1	14
1962	3	2	3	6	8
1963	14	11	8	21	7
1964	8	7	12	2	2
1965	7	2	18	1	24
1966	9	8	19	17	3
1967	3	5	5	26	16
1968	9	8	4	8	15
1969	10	20	43	14	2
1970	8	11	15	4	1
1971	9	22	0	21	10
1972	7	10	8	6	30
1973	16	16	5	9	3

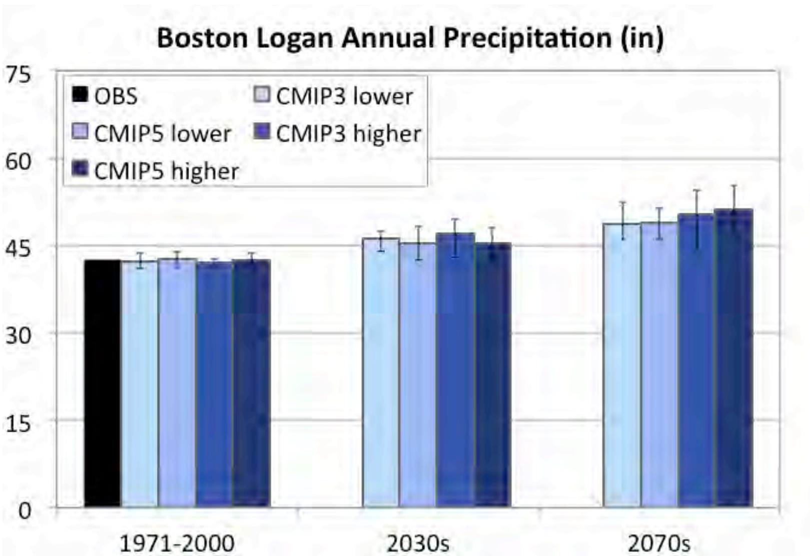
4. Created summary Excel spreadsheets comparing the mean and percentiles of historical daily temperature and precipitation for each individual weather station (observed) and climate model (simulated). Files for all weather stations and variables are in the DropBox directory ARC_Kleinfelder/Cambridge/Plots and Comparisons/ and are named "Variable.Obs.Mod.Comparison.xlsx"

Sample file for Boston Logan, comparing observed vs. CMIP3-based historical simulations of maximum temperature, including the mean, the median, the highest and lowest values in 30 years, and percentiles ranging from the 5th to the 95th.

USW00014739	BostonLogan	obs record 1960 to 2012							
	DAILY MAXIMUM TEMPERATURE IN oF								
	OBS	CCSM4	CSIRO-Mk3-6-0	CNRM-CM5	HadGEM2-CC	INMCM4	IPSL-CM5A-LR	MIROC5	MRI-CGCM3
Missing Values	76	0	0	0	295	0	0	0	0
Mean	**59.24**	**59.43**	**59.25**	**59.43**	**59.18**	**59.43**	**59.36**	**59.29**	**59.15**
Lowest	6.08	-0.78	6.69	5.95	8.19	5.144	6.08	6.458	3.866
5th Percentile	30.02	30.28	29.91	30.37	30.39	30.38	30.5	30.18	30.17
10th Percentile	35.06	35.38	34.90	34.74	34.79	35.24	35.14	34.92	34.73
25th Percentile	44.06	44.40	44.67	44.73	44.53	44.65	44.6	44.98	44.49
50th Percentile (Median)	**59**	**59.63**	**59.43**	**59.72**	**59.27**	**59.86**	**59.52**	**59.22**	**59.32**
75th Percentile	73.94	74.66	74.12	74.59	74.1	74.57	74.61	74.08	74.07
90th Percentile	84.02	83.8	83.62	83.41	83.3	83.57	83.53	83.41	83.08
95th Percentile	87.98	87.87	87.78	87.47	87.58	87.67	87.35	87.89	87.33
Highest	102.92	104.162	102.668	101.66	102.992	104.918	104	102.524	104.99
HadGEM2-CC simulations have missing values because the model only has 360 days per year. This is not an error: it is a characteristic of the model.									

5. Created individual Excel bar charts showing projected changes in secondary climate indicators for each individual station (so it is clear which projections should be compared to which station), and added historical observed values to each chart. These files are in the DropBox directory ARC_Kleinfelder/Cambridge/Plots and Comparisons/ and are named "StationName.temp.pr.indicator.bar.charts.xlsx"

   Sample plot for Boston Logan showing observed (black) and simulated (blue) annual precipitation for the historical period, and future projections for 2030s and 2070s



Comparing CCVA with NECIA Projections

In order to ensure the backwards compatibility of the 2013 Cambridge Climate Vulnerability Assessment (CCVA), we developed projections based on both the new CMIP5 global climate model simulations as well as the older CMIP3 global climate model simulations used in the Northeast Climate Impacts Assessment (NECIA). It's obvious that the older CMIP3-based NECIA projections and the newer CMIP5-based CCVA projections use different global climate models. However, shouldn't the older CMIP3-based CCVA projections match NECIA?

CMIP3-based CCVA and NECIA projections do not match *and should not be expected to match* because NECIA projections were developed for the entire Northeast region using a gridded dataset and the BCSD statistical downscaling model. CCVA projections were developed for Cambridge using individual weather stations and the ARRM downscaling method. As discussed previously, while the direction of change should be similar within a given geographic region, there is no reason to expect the exact change in precipitation or temperature at a single location to be identical to the regional average. In addition, the two approaches used different downscaling methods that will give different results for temperature and precipitation extremes (although they should give similar values for changes in average conditions).

NECIA projections developed specifically for Boston Logan weather station using an earlier version of ARRM should be very similar to the CMIP3-based CCVA projections for the same weather station. In that case, the only difference would lie in the version of the statistical downscaling model used, and the additional 6 years of observed weather data used to train the downscaling model for CCVA as compared to NECIA (the years 2007-2012 were not available when the NECIA analysis was being done).

Comparing CCVA with SimClim Output

SimClim is a visualization tool that takes high-resolution climate projections as input and interpolates them to a given region of interest. *SimClim is not a downscaling model and does not generate any climate projections*. This information comes from elsewhere and is used as input to SimClim.

Information regarding the current inputs to SimClim was not readily accessible online; hence, we contacted Peter Urich at CLIMSystems directly to inquire regarding the origins of the climate projections used in SimClim. According to Peter, the current version of SimClim uses gridded 1/8th degree BCCA downscaled projections (i.e. daily quantile mapping).

As discussed above, use of this dataset is problematic for two reasons. First, gridded projections do not resolve coastal areas. Any grid with partial ocean area is set to N/A. Although SimClim partially addresses this by interpolating to a higher-resolution grid, it does not do so by introducing any new information; the interpolation is merely statistical. Hence, it is questionable whether SimClim-based simulations actually contain any original information for a coastal location such as Cambridge.

Second, as shown in Figure 4 (center), the daily quantile mapping method is subject to relatively large biases for both extreme cold and hot temperatures (precipitation biases TBD). Based on these preliminary analyses, we would not yet recommend use of this method for future projections in this region and we expect that projected changes using the BCCA approach may be quite different than changes projected by the ARRM method (Figure 4, left), even if the same global climate models and scenarios are used.