Climate Hazard Assessment for Stakeholder Adaptation Planning In New York City

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Abstract

This paper describes a time-sensitive approach to climate change projections, developed as part of New York City's climate change adaptation process, that has provided decision support to stakeholders from 40 agencies, regional planning associations, and private companies. The approach optimizes production of projections given constraints faced by decision makers as they incorporate climate change into long-term planning and policy. New York City stakeholders, who are well-versed in risk management, helped pre-select the climate variables most likely to impact urban infrastructure, and requested a projection range rather than a single 'most likely' outcome. The climate projections approach is transferable to other regions and consistent with broader efforts to provide climate services, including impact, vulnerability, and adaptation information.

The approach uses 16 Global Climate Models (GCMs) and three emissions scenarios to calculate monthly change factors based on 30-year average future time slices relative to a 30-year model baseline. Projecting these model mean changes onto observed station data for New York City yields dramatic changes in the frequency of extreme events such as coastal flooding and dangerous heat events. Based on these methods, the current 1-in-10 year coastal flood is projected to occur more than once every 3 years by the end of the century, and heat events are projected to approximately triple in frequency. These frequency changes are of sufficient magnitude to merit consideration in long-term adaptation planning, even though the precise changes in extreme event frequency are highly uncertain.

1. Introduction

This paper describes a methodological approach to stakeholder-driven climate hazard assessment developed for the New York Metropolitan Region (Fig. 1). The methods were developed in support of the New York City Panel on Climate Change (NPCC; NPCC 2010). The NPCC is an advisory body to New York City's Climate Change Adaptation Task Force (CCATF), formed by Mayor Michael Bloomberg in 2008 and overseen by the Mayor's Office of Long Term Planning and Sustainability. As described in NPCC (2010), the CCATF is comprised of stakeholders from 40 city and state agencies, authorities, regional planning associations, and private companies, divided into four infrastructure workgroups (communication, energy, transportation, and water and waste), and one policy workgroup.

The CCATF effort was motivated by the fact that New York City's population and critical infrastructure are exposed to a range of climate hazards, with coastal flooding associated with storms and sea level rise the most obvious threat. Approximately 7 % (11%) of NYC area is within 1 meter (2) of sea level (Weiss et al. 2011). A recent study ranked NYC 7th globally among port cities in exposed population and 2nd globally in assets exposed to storm surge flooding and high winds (Nicholls et al. 2008). Furthermore, because NYC, like much of the U.S. (ASCE, 2009), has aging infrastructure, climate vulnerability may be enhanced. By showing leadership in the infrastructure adaptation process, the NYC effort may be able to provide lessons to other cities as they plan adaptation strategies.

Stakeholder input regarding climate information was collected in several ways. Between September of 2008 and September of 2009, each CCATF sector working group held monthly meetings in conjunction with the Mayor's Office of Long Term Planning and Sustainability. During the initial meetings, representatives from each sector identified key climate hazards; they also interacted iteratively with the scientists, seeking clarification, and requesting additional information. They commented on draft documents describing the region's climate hazards, and climate seminars were held with individual agencies as requested. The climate hazard assessment process was facilitated by prior collaborative experience between the NPCC's climate scientists and stakeholders in earlier assessments, including the Metro East Coast Study (MEC; MEC 2001), as well as work with the New York City Department of Environmental Protection (NYCDEP; NYCDEP 2008; Rosenzweig et al. 2007) and the Metropolitan Transit Authority (MTA; MTA 2007).

The climate hazard approach is tailored towards impact assessment; it takes into consideration the resource and time constraints faced by decision makers as they incorporate climate change into their long-term planning. For example, the formal write-up of the climate risk information was needed within less than 8 months of the NPCC's launch (NRC 2009); given this time frame and the broad array of stakeholders in the CCATF, a standardized set of climate variables of broad interest were emphasized, with the understanding that future studies could provide climate information tailored to more unique applications[1].

Within this framework, the NPCC worked with stakeholders to pre-select for analysis climate variables and metrics most likely to impact existing assets, planned investments, and operations (Horton and Rosenzweig 2010). For example, the number of days below freezing was identified as an important metric for many sectors, due to the impacts of freeze-thaw cycles on critical infrastructure (New York City Climate Change Adaptation Task Force, 2008-2009). Due

[1] A tailored assessment of changes in snow depth and timing of snow melt in the Catskill Mountains approximately 100 miles north of New York City (NYC DEP, 2008) would be of interest to managers of only a small but important subset of infrastructure—reservoirs and water tunnels. Such a fine-scale assessment would benefit from more complex downscaling approaches than those applied here.

to the diversity of agencies, projections were requested for multiple time periods spanning the entire 21st century.

Stakeholders also helped determine the presentation of climate hazard information. For example, because NYC stakeholders are used to making long-term decisions under uncertainty associated with projections of future revenues, expenditures, and population trends, for example, they preferred projection ranges to a single ‘most likely’ value (New York City Climate Change Adaptation Task Force, 2008-2009).

Itemized risks associated with each climate variable were ultimately mapped to specific adaptation strategies. For example, more frequent and intense coastal flooding due to higher mean sea level was linked to increased seawater flow into New York City’s gravity-fed and low-lying Wastewater Pollution Control Plants (WPCP), resulting in reduced ability to discharge treated effluent (NPCC 2010; NYCDEP 2008). NYCDEP is reducing the risk at the Far Rockaway Wastewater Treatment Plant by raising pumps and electrical equipment to 14ft above sea level based on the projections described here (NYC Office of the Mayor, 2009).

Climate hazard assessment was only one component of the NPCC’s impact and adaptation assessment. Vulnerability of infrastructure (and the populations that rely on it) to climate impacts can be driven as much by its state of repair (and how it is used) as by climate hazards (NRC, 2009). Climate adaptation strategies should be based on many non-climate related factors, such as co-benefits (e.g., some infrastructure investments that reduce climate risks will also yield more efficient and resilient infrastructure in the face of non-climate hazards; NRC 2010a) and co-costs (e.g., adapting by using more air conditioning increases greenhouse gas emissions). NPCC experts in the risk management, insurance, and legal fields provided guidance on these broader issues of vulnerability and adaptation, developing for example an eight step adaptation assessment process and templates for ranking relative risk and prioritizing adaptation strategies (NPCC, 2010). This paper focuses on the provision of stakeholder-relevant climate information in support of the broader NPCC assessment.

Section 2 describes the methodology used for the NPCC's climate hazard assessment. Section 3 compares climate model hindcasts to observational results for the New York Metropolitan Region. Hindcast results are a recurring stakeholder request, and they helped inform the global climate model (GCM)-based projection methods. Section 4 documents the regional projections, in the context of stakeholder usability. Section 5 covers conclusions and recommendations for future work.

2. Methodology

a. Observations

Observed data are from two sources. Central Park station data from the National Oceanic and Atmospheric Administration, National Climatic Data Center, United States Historical Climatology Network (NOAA NCDC USHCN) Version 1 data set (Karl et al. 1990; Easterling et al. 1999; Williams et al. 2005) formed the basis of the historical analysis and projections of temperature and precipitation. Gridded output corresponding to New York City from the National Centers for Environmental Prediction / Department of Energy (NCEP/DOE) Reanalysis 2 output (Kanamitsu et al. 2002) is also used for GCM temperature validation (section 3).

b. Climate Projections: General Approach

1) GLOBAL CLIMATE MODELS AND EMISSIONS SCENARIOS

Climate projections are based on the coupled GCMs used for the Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC; IPCC, 2007). The outputs are provided by the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (Meehl et al. 2007a). Out of 23 GCM configurations from 16 centers, the 16 GCMs that had available output for all three emissions scenarios archived by WCRP were selected (Table 1; A2, A1B, and B1; IPCC Special Report on Emissions Scenarios; SRES; Nakicenovic et al. 2000).

The 16 GCMs and three emissions scenarios combine to produce 48 output sets. The 48 members yield a model and scenario-based distribution function based on equal weighting of each GCM and emissions scenario. The model-based results should not be mistaken for a statistical probability distribution (Brekke et al. 2008) for reasons including the following: 1) no probabilities are assigned by the IPCC to the emissions scenarios[2] 2) GCMs are not completely independent; with many sharing portions of their code and a couple differing principally in resolution only, and 3) the GCMs and emissions scenarios do not sample all possible outcomes, which include the possibility of large positive ice-albedo and carbon cycle feedbacks, in addition to uncertain aerosol effects. Caveats notwithstanding, the model-based approach has the advantage (relative to projections based on single numbers) of providing stakeholders with a range of possible outcomes associated with uncertainties in future greenhouse gas concentrations (and other radiatively important agents and climate sensitivity (NRC, 2010b).

Some authors (see e.g., Smith et al. 2009; Tebaldi et al. 2005; Greene et al. 2006; Brekke

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[2] It has been argued that since high global anthropogenic CO_2 emissions growth rates (3.4 % $year^{-1}$ between 2000 and 2008; Le Quere et al. 2009) led to 2008 estimated emissions reaching the levels of the highest SRES scenario (A1FI), other SRES scenarios may be unrealistically low.

et.al. 2008; Georgi and Mearns 2002) have explored alternate approaches that weight GCMs based on criteria including hindcasts of regional climate or key physical processes. That more complex approach is eschewed here in favor of equal GCM weighting for several reasons. First, because model 'success' is often region and variable-specific, and stakeholders differ in their climate variables and geographical ranges of interest[3], production of consistent scenarios based on model weighting is a major research effort beyond the scope of New York City's initial assessment. Second, while long-term research could be geared towards developing optimized multivariate (and/or multi-region) weighting, research suggests that compensating biases tend to yield comparable model performance (Brekke et al. 2008). Third, historical accuracy may have been achieved for the 'wrong' reasons (Brekke et al. 2008) and GCM hindcasts did not share identical forcing, especially with respect to aerosols (Rind et al. 2009). Fourth, shifting climate processes with climate change may favor different models in the future. Finally, eliminating ensemble members reduces the representation of uncertainty relating to climate sensitivity.

2) TIMESLICES

Because current-generation GCMs used for climate change applications have freely evolving ocean and atmospheric states, they are most appropriate for detection of long-term climate and climate change signals. The 30-year timeslice applied here is a standard timescale (WMO 1989) that represents a middle ground, allowing partial cancellation of currently unpredictable interannual to interdecadal variability (maximized by including many years), while maintaining relatively monotonic anthropogenically-induced forcing trends (maximized by including few years). The '1980s' timeslice represents baseline conditions between 1970-1999;

[3] New York City's task force included corporations with national and international operations.

future timeslices for the 2020s, 2050s, and 2080s are similarly defined.

3) Climate change factors and The Delta Method

Mean temperature change projections are expressed as differences between each model's future timeslice simulation and its baseline simulation; mean precipitation is based on the ratio of a given model's future to its baseline values. This approach offsets a large source of model bias: poor GCM simulation of local baseline conditions (section 3b) arising from a range of factors including the large difference in spatial resolution between GCM gridboxes and station data.

Because monthly averages from GCMs are generally more reliable than daily output (Grotch and MacCracken 1991), monthly mean GCM changes were projected onto observed 1971-2000 daily Central Park data for the calculation of extreme events[4]. This simple and low-cost downscaling approach is known as the delta method (Gleick 1986; Arnell 1996; Wilby et al. 2004). Like more complex statistical downscaling techniques (e.g., Wigley et al. 1990), the delta method is based on stationarity (see e.g., Wilby et al. 1998 and 2002; Wood 2004), and largely excludes the possibility of large variance changes through time, although for the Northeast U.S. such changes are uncertain[5].

More complex statistical approaches, such as those that empirically link large-scale predictors from a GCM to local predictands (see e.g., Bardossy and Plate 1992) may yield more nuanced downscaled projections than the delta method. These projections are not necessarily

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[4] For coastal flooding and drought, the 20th century was used as a baseline, due to high interannual/multidecadal variability and policy-relevance of 1-in-100 year events.

[5] An exception may be short-term precipitation variance, which is expected to increase regionally with the more intense precipitation events associated with a moister atmosphere (see e.g., Emori and Brown 2005; Cubasch et al. 2001; Meehl et al. 2005)

more realistic, however. Historical relationships between large-scale predictors and more impacts-relevant local predictands may not be valid in a changing climate (Wilby et al. 2004). GCM development and evaluation has also historically been more focused on seasonal and annual climatologies than the daily and interannual distributions that drive analogue approaches. Table 2 provides a set of stakeholder questions to inform the choice of downscaling technique, a topic that is discussed further in Section 5.

4) SPATIAL EXTENT

The projections are for the land-based GCM gridbox covering New York City. As shown in Fig. 2, the 30-year averaged mean climate changes are largely invariant at sub-regional scales; the single grid box approach produces nearly identical results to more complex methods that require extraction of data from multiple gridboxes and weighted spatial interpolation. As shown in section 4e, for the metrics evaluated in this study, the GCM gridbox results also produce comparable results to finer resolution statistically and dynamically downscaled products. Since baseline climate (as opposed to projected climate change) does differ dramatically over small spatial scales (due to factors such as elevation and surface characteristics), and these fine-scale spatial variations by definition cannot be captured by course-resolution GCMs, GCM changes are trained onto observed Central Park data using the procedures described above.

5) NUMBER OF SIMULATIONS

For 13 of the 16 GCMs' Climate of the 20th Century and future A1B experiments, and 7 of the 16 B1 and A2 future experiments, multiple simulations driven by different initial conditions were available. Analysis of hindcasts (Table 3a) and projections (Table 3b) from the available NCAR CCSM coupled GCM simulations[6] revealed only minor variations in 30-year averages, suggesting that one simulation per model is sufficient. Using an ensemble for each GCM based on all the available simulations with that GCM is an alternative approach; however, the effort and data storage needs may not be justified given the similarity of the ensemble and individual simulation results shown in Table 3. Furthermore, ensemble averaging unrealistically shrinks the temporal standard deviation[7].

c. Climate Projections: Sea Level Rise

To address large uncertainties associated with future melting of ice sheets, two sea level rise projection methods were developed: these are referred to as the IPCC-based and rapid ice melt scenarios respectively.

1) IPCC AR4-BASED APPROACH

The IPCC Fourth Assessment (AR4) approach (Meehl et al. 2007b) was regionalized for New York City utilizing four factors that contribute to sea level rise: global thermal expansion, local water surface elevation, local land uplift/subsidence, and global meltwater[8]. Thermal expansion and local water surface elevation terms are derived from the GCMs (outputs courtesy of WCRP and Dr. Jonathan Gregory, personal communication). Local land subsidence is derived from Peltier (2001) and Peltier's ICE-5Gv1.2 ice model (2007) (http://www.pol.ac.uk/psmsl/peltier/index.html). The meltwater term was calculated using mass balance temperature sensitivity coefficients for the different ice masses, based on observed

[6] This GCM was selected because it provided the most 20th and 21st century simulations
[7] This is a general criticism; for the particular case when the delta method is used (as here) shrinking of the temporal standard deviation has no bearing on the results
[8] Only seven GCMs provided outputs for sea level rise projections; see Horton and Rosenzweig (2010) for additional information.

historic relationships between global mean surface air temperature, ice mass, and rates of sea level rise (Meehl et al. 2007b)[9]. Regionalization of sea level rise projections, based on the four-components described above, have been used in other studies (e.g., Mote et al. 2008).

2) Rapid ice melt scenario

Because of large uncertainties in dynamical ice sheet melting (Hansen et al. 2007; Horton et al. 2008), and recent observations that ice sheet melting has accelerated within this past decade (e.g., Chen et al. 2009), an alternative sea level rise scenario was developed. This upper bound sea level rise scenario allowing for rapid ice melt was developed based on paleo-sea level analogues, in particular the ~10,000-12,000-year period of rapid sea level rise following the end of the last ice age (Peltier and Fairbanks 2006; Fairbanks 1989). While the analogue approach has limitations (most notably, the continental ice supply is much smaller today; Rohling et al. 2008), past rapid rise is described below since it may help inform discussions of upper bounds of future sea level rise.

Average sea level rise during this more than 10,000-year period after the last ice age was 9.9 to 11.9 cm decade^{-1}, although this rise was punctuated by several shorter episodes of more rapid sea level rise. In the rapid ice-melt scenario, glaciers and ice sheets are assumed to melt at that average rate. The meltwater term is applied as a second-order polynomial, with the average present-day ice melt rate of 1.1 cm decade^{-1} for 2000-2004 used as a base. This represents the sum of observed mountain glacier (Bindoff et al. 2007) and ice sheet melt (Shepherd and Wingham 2007) during this period. The rapid ice-melt scenario replaces the IPCC meltwater term with the modified meltwater term; the other three sea level terms remain unchanged. This

[9] Corrections were not made to account for reductions in glacier area over time.

approach does not consider how rapid ice melt might indirectly influence sea level in the New York region through future second-order effects including gravitational, glacial isostatic adjustments, and rotational terms (e.g. Mitrovica et al. 2001, 2009).

d. Climate Projections: Extreme Events

Based on stakeholder feedback, quantitative and qualitative projections were made using the extreme events definitions stakeholders currently use. For example, temperature extremes were defined based on specific thresholds, such as 90ºF (~32°C), that the New York City Department of Buildings uses to define cooling requirements, whereas coastal flooding was defined by frequency of occurrence (Solecki et al. 2010).

1) QUANTITATIVE PROJECTIONS: COASTAL FLOOD EXAMPLE

The coastal flooding projections are based on changes in mean sea level, not storms. Projected changes in mean sea level (using the IPCC AR4-based approach) were superimposed onto historical data. For coastal flooding, critical thresholds for decision-making are the 1-in-10 year, and 1-in-100 year flood events (Solecki et al. 2010). The latter metric is a determinant of construction and environmental permitting, as well as flood insurance eligibility (Sussman and Major 2010).

The 1-in-10 year event was defined using historical hourly tide data from the Battery tide gauge, lower Manhattan (http://tidesandcurrents.noaa.gov; for more information, see Horton and Rosenzweig 2010). The 1-in-100 year flood was analyzed using flood return period curves based on data provided by the U.S. Army Corps of Engineers for the Metro East Coast Regional Assessment (see Gornitz 2001 for details).

Because interannual variability is particularly large for rare events such as the 1-in-10 year flood, a base period of more than the standard 30 years was used. Similarly, since each year between 1962 and 1965 was drier in Central Park than the driest year between 1971 and 2000, the entire 20th century precipitation record was used for the drought analysis. More rigorous solutions for the rarest events await better predictions of interannual to multi-decadal variability, better understanding of the relationship between variability at those timescales and extreme events (see e.g. Namias 1966; Bradbury et al., 2002) and the growing event pool of realizations with time.

2) Qualitative extreme event projections

The question arose of how best to meet stakeholder needs when scientific understanding, data availability, and model output are incomplete; quantitative projections are unavailable for some of the important climate hazards consistently identified by infrastructure stakeholders and/or are characterized by such large uncertainties as to render quantitative projections inadvisable. Examples in the New York City region include ice storms, snowfall, lightning, intense sub-daily precipitation events, tropical storms and nor'easters. For these events, qualitative information was provided, describing only the most likely direction of change and an associated likelihood using the IPCC WG1 likelihood categories (IPCC, 2007)[10]. Sources of uncertainty and key historical events were also described, in order to provide stakeholders with

[10] Given the large impact of these extreme events on infrastructure, stakeholders requested information about likelihood for comparative purposes (e.g. "Which is more likely to increase in frequency? Nor'easters specifically, or intense precipitation events generally?"). Assignment of likelihood to generalized categories for qualitative extremes (based on published literature and expert judgment including peer review) was possible because predictions are general (e.g., direction of change),as opposed to the quantitative model-based projections.

context and the opportunity to assess sector-wide impacts of historical extremes.

3. GCM Hindcasts and Observations

The results of the GCM hindcasts and observational analysis described in this section informed the development of the projection methods described in section two. Stakeholders commonly request hindcasts and historical analysis (see e.g. NYCDEP 2008) as they provide transparency to decision-makers who may be new to using GCM projections as a planning tool.

a. Temperature and Precipitation Trends

As shown in Table 4, both the observed and modeled 20th century warming trends at the annual and seasonal scale are generally significant at the 99 percent level. While GCM 20th century trends are generally approximately 50% smaller than the observed trends, it has been estimated that approximately 1/3 of New York City's 20th century warming trend may be due to urban heat island effects (Gaffin et al. 2008) that are external to GCMs. Over the 1970-1999 period of stronger greenhouse gas forcing, the observed annual trend was 0.21ºC decade^{-1}, and the ensemble trend was 0.18ºC decade^{-1}.

Modeled seasonal warming trends in the past three decades and both annual and seasonal precipitation trends over the entire century for New York City generally deviate strongly from observations, consistent with prior results for the Northeast (see e.g. Hayhoe et al. 2007). Observed and modeled trends in temperature and precipitation at a particular location are highly dependent on internal variability, and therefore highly sensitive to the selection of years. For example, the 1970-1999 observed Central Park annual precipitation trend of -1.77 cm decade^{-1} shifts to 0.56 cm decade^{-1} when the analysis is extended through 2007. This is especially true for the damaging extreme events[11] (Christensen et al. 2007) that are often of particular interest to infrastructure managers. In coupled GCM experiments with a freely evolving climate system, anomalies associated with climate variability generally will not coincide with observations, leading to departures between observed and modeled trends (Randall et al. 2007).

For stakeholders trained in analyzing recent local observations, it is challenging but important to emphasize that: 1) trends at continental and centennial timescales are often most appropriate for identifying the greenhouse gas signal and GCM performance, since (unpredictable) interannual to interdecadal variability is lower at those scales (Hegerl et al. 2007); and 2) during the 21st century, higher greenhouse gas concentrations and other radiatively important agents are expected to increase the role of the climate change signal, relative to climate variability.

b. Temperature and Precipitation Climatology

Comparison of station data to a GCM gridbox is hindered by the spatial scale discrepancy; New York City's low elevation, urban heat island (see e.g. Rosenzweig et al. 2006), and land sea contrasts are not captured by GCMs. As shown in Fig. 3a, the observed average annual temperature over the 1970-1999 period for New York City exceeds the GCM ensemble by 2.6ºC, and is higher than all but two of the 16 GCMs. When the GCMs are contrasted with the spatially comparable NCEP Reanalysis gridbox, the annual mean temperature bias is reduced

[11] Among 20th Century Central Park trends in observed extremes, only trends in cold extremes have been robust. For the number of days per year with minimum temperatures below freezing, both the 100-year trend of -2 days decade^{-1} and the 30-year trend of -5.2 days decade^{-1} are significant at the 99% level. GCM hindcasts of extreme events were not conducted due to the small signal to noise ratio.

to 1.1ºC. The departure of the Central Park station data from the GCM ensemble is largest in July and smallest in January, indicating that the annual temperature cycle at this location is damped in the GCMs (Fig. 3b).

While Figure 3c reveals that the GCM ensemble of average annual precipitation from 1970-1999 is 8% below observations for Central Park, the ensemble average lies well within the range of precipitation for New York City as a whole; GCM precipitation exceeds the LaGuardia Airport station by 9%. Most of the GCMs are able to capture the relatively even distribution of monthly precipitation throughout the year (Fig. 3d).

The above analysis reveals that mean climatology departures from observations over the hindcast period are large enough to necessitate bias correction such as the delta method as part of the GCM projection approach, rather than direct use of model output.

c. Temperature and Precipitation Variance

1) Interannual

Eleven (ten) of the 16 GCMs overestimate the 1970-1999 interannual standard deviation of temperature, relative to the station data (NCEP reanalysis). The similarities between GCMs, reanalysis and station data suggest that spatial-scale discontinuities may not have a large impact on interannual temperature variance. All 16 GCMs underestimate interannual precipitation variability relative to Central Park observations, and 14 of the 16 GCMs underestimate variance relative to two other stations analyzed (Port Jervis and Bridgehampton). The large difference between the GCMs and station data suggests that spatial-scale discontinuities, likely associated with features like convective rainfall that cannot be resolved by GCMs, may be partially responsible for the relatively low modeled interannual precipitation variance. Observed interannual temperature variance is greatest in winter, a pattern not captured by seven on the 16 GCMs.

2) HIGH-FREQUENCY

The daily distribution of observed Central Park temperature (Fig.4 a-c) and precipitation (Fig. 5) was compared to single gridbox output from 3 of the 16 GCMs used in the larger analysis. The three models were part of a subset with daily output stored in the WCRP / CMIP3 repository and were selected because (of the subset) they featured the highest [Max Plank Institute for Meteorology ECHAM5/MPI-OM (MPI, Jungclaus et al. 2005) and Commonwealth Scientific and Industrial Research Organisation CSIRO-MK3.0 (CSIRO, Gordon et al. 2002), both at 1.88ºlat. x 1.88ºlon.] and lowest [National Aeronautics and Space Administration (NASA) / Goddard Institute for Space Studies (GISS) GISS-ER (GISS, Schmidt et al. 2006), at 4ºlat. x 5ºlon.] resolution. Analysis was conducted on summer (June-August) daily maximum and winter (December-February) daily minimum temperature.

Summer maximum temperature distribution for the region in all three GCMs is narrower than observations, and the warm tail is more poorly simulated than the cold tail. During winter, CSIRO and MPI underestimate variance relative to the station data, while the GISS GCM has excessive variance.

Figure 5 shows the number of days with precipitation exceeding 10 mm, a level of rainfall that can trigger combined sewer overflow events at vulnerable sites in New York City (PlaNYC 2008). Relative to Central Park data, all three GCMs underestimate the frequency of daily precipitation above 50 mm--a level of precipitation that can lead to widespread flooding and drainage problems including in subways (MTA 2007).

Given that precipitation in GCMs of this class and spatial resolution is highly parameterized to the gridbox spatial scale and seasonal/decadal climate timescales, departures of the distribution from observed daily station data can be expected. The low model variance at daily timescales for temperature and precipitation, and at interannual timescales for precipitation, reinforces the need for statistical downscaling approaches such as the delta method that apply monthly mean model changes to observed high frequency data.

d. Sea-Level Rise

Sea level was also hindcast for the 20th century, based on a 1990-1999 projection relative to the 1900-1904 base period.[12] The ensemble average hindcast is a rise of 18 cm, while the observed increase at the Battery is 25 cm. The five-year average local elevation term in the models meanders through time, frequently with an amplitude of 2-3 cm, with a maximum range over the century of approximately 7 cm, suggesting decadal variability (primarily in the local elevation term) and spatial resolution may explain the discrepancy between models and observations.

4. Future Projections

a. Mean Temperature and Precipitation

[12] In this calculation, the land subsidence term was identical to that used for the 21st century projections. The same surface mass balance coefficients used by the IPCC, based on global average temperature changes over a 1961-2003 baseline were used for the 1900-1904 base period, which likely leads to a slight overestimate of the meltwater here. The effect is negligible though as the meltwater term is a minor contributor to the overall 20th century sea level rise.

1) ANNUAL

Table 5 shows the projected changes in temperature and precipitation for the 30-year periods centered around the 2020s, 2050s, and 2080s relative to the baseline period. The values shown are the central range (middle 67%) of the projected model-based changes.

Figure 6 expands upon the information presented in Table 5 in three ways. First, inclusion of observed data since 1900 provides context on how the scale of projected changes associated with forcing from greenhouse gases and other radiatively important agents compares to historical variations and trends. Secondly, tabulating high and low projections across all 48 simulations provides a broader range of possible outcomes, which some stakeholders requested (New York City Climate Change Adaptation Task Force, 2008-2009). Finally, ensemble averaging of results by emissions scenario as they evolve over time is informative to stakeholders involved in greenhouse gas mitigation (and adaptation), since it reveals the large system inertia: not until the 2030s and 2040s do the B1 scenario projections begin to diverge from A2 and A1B, but thereafter it diverges rapidly. Thus, a delay in greenhouse gas mitigation activities greatly increases the risk of severe long-term climate change consequences, despite apparent similarity in the near-term outlook.

While the precise numbers in Table 5 and Figure 6 should not be emphasized due to high uncertainty and the smoothing effects of ensemble averaging, the stakeholder sees that in the New York Metropolitan Region: 1) mean temperatures and sea levels are projected to increase in all simulations this century, at rates exceeding those experienced in the 20^{th} century; 2) while precipitation is projected to increase slightly in most simulations, the multi-year precipitation range experienced in the past century due to climate variability exceeds the 21^{st} century climate change signal[13]; and 3) climate projection uncertainties grow throughout the 21st century, in step with uncertainties regarding future emissions and the climate system response.

2) SEASONAL

Warming in the New York City region is of similar magnitude for all seasons in the GCMs, although seasonal projections are characterized by larger uncertainties than annual projections (Fig. 7a). Since interannual temperature variability is smallest in summer this suggests the summer warming may produce the largest departures from historical experience. Some impacts and vulnerabilities are also amplified by high temperatures. Energy demand in New York City is highly sensitive to temperature during heat waves, due especially to increased reliance on air conditioning. This increased demand can lead to elevated risk of power shortages and failures at a time when vulnerable populations are exposed to high heat stress and air pollution (Kinney et al. 2001; Kalkstein 1995; Hill and Goldberg 2001; Hogrefe et al. 2004).

GCMs tend to distribute much of the additional precipitation during the winter months (Fig. 7b), when water supply tends to be relatively high and demand relatively low (NYCDEP 2008). During September and October, a time of relatively high drought risk, total precipitation is projected to decrease slightly in many models.

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[13] The projection lines in Figure 6 depict the 'predictable' anthropogenic forcing component, while capturing some of the uncertainty associated with greenhouse gas concentrations and climate sensitivity at specific points in time. Because decadal variability is unpredictable in the Northeast, it was not included in the time-specific projection portion of the figure. It was however emphasized to stakeholders that while interannual variability appears greatly reduced in the projection portion of the figure, the observed portion (black line) reflects the type of unpredictable variations that have been experienced in the past and will likely exist on top of the mean change signal in the future.

b. Sea Level Rise

Addition of the two regional components leads to higher sea level rise projections for the region than the global average (by ~15 cm for end-of-century projections; Meehl et al. 2007b; Peltier 2001). This is due both to land subsidence and higher sea level rise along the northeast U.S. coast, the latter largely due to geostrophic constraints associated with projected weakening of the Gulf Stream (Yin et al. 2009) in many GCMs (Meehl et al. 2007b).

As shown in Table 6, the rapid ice melt scenario projections diverge from the IPCC-based approach as the century progresses. The 2100 value of up to ~2 meters associated with this scenario (not shown) is generally consistent with other recent results that roughly constrain sea level rise globally (see e.g., Pfeffer et al. 2008; Rahmstorf, 2007; Horton et al. 2008; Grinsted 2009; Rignot and Cazenave 2009) and regionally (see Yin et al. 2009; Hu et al. 2009) to between ~1m and ~2m. The consistency with other studies supports the usefulness of ~2m as a high end for a risk-averse approach to century-scale infrastructure investments including bridges and tunnels, rail lines, and water infrastructure.

At the request of agencies that manage some of these long-term investments, two presentations were given to technical staff specifically describing the rapid ice melt methodology and projections. While these and other stakeholders wanted to know the probability of the rapid ice melt scenario relative to the IPCC-based method, it was emphasized that such probability statements are not possible given current scientific understanding.

c. Extreme Events

1) STAKEHOLDER PROJECTIONS BASED ON THE DELTA METHOD

Table 7 shows projected changes in the frequency of heat waves, cold events, intense precipitation, and coastal flooding in the New York City region. The baseline average number of extreme events per year is shown, along with the central range (middle 67%) of the projections. Because the distribution of extreme events around the (shifting) mean could also change while mean temperature, precipitation, and sea level rise shift, stakeholders were strongly encouraged to focus only on the direction and relative magnitudes of the extreme event changes in Table 7.

The key finding for most stakeholders is the extent to which mean shifts alone can produce dramatic changes in the frequency of extreme events, such as heat events and coastal storm surges. Based on the central range, the number of days per year over 90 ºF is projected to increase by a factor of approximately three by the 2080s. The IPCC-based sea level rise projections alone, without any changes in the historical storm climatology and surge levels, lead to a more than threefold increase in the frequency of the baseline 1-in-10 year coastal flood event by the 2080s.

In contrast to relatively homogeneous mean climate changes, it was emphasized to stakeholders that absolute extreme event projections like days below freezing and days with more than one inch of precipitation vary dramatically throughout the metropolitan region, since they depend for example on microclimates associated with the urban heat island and proximity to the coast. Similarly, maps were generated for stakeholders to show that the surge heights for the open estuary at the Battery are higher than corresponding heights in more protected riverine settings.

It was emphasized to stakeholders that due to large interannual variability in extremes, even as the climate change signal strengthens, years with relatively few extreme heat events (relative to today's climatology) will occur. For example, Central Park's temperatures in 2004 only exceeded 90°F (~32°C) twice. The delta method suggests that not until the middle of this century would such a relatively cool summer (as 2004) feature more days above 90°F (~32°C) than are typically experienced today.

High year-to-year extreme event variability may already give some stakeholders a framework for assessing sector-specific climate change impacts; even if climate adaptation strategies for extremes are not already in place, short-term benefits may be evident to planners. For example, Central Park in 2010 experienced temperatures of higher than 90°F (~32°C), on 32 different days, which is consistent with projections for a typical year around mid-century. This suggests that some of the infrastructure impacts of extreme heat (such as voltage fluctuations along sagging power lines and increased strain on transportation materials including rails and asphalt; Horton and Rosenzweig 2010) may have been experienced in 2010 to an extent that may become typical by mid-century. However, adaptation strategies designed for an extreme year today (such as a fixed level of mandatory energy use reductions and a fixed level of reductions of train speeds) may be inadequate or unpalatable in the future due to the increase in frequency, duration and intensity of extreme heat (for example) associated with climate change (see e.g., Meehl et al. 2009; Tebaldi et al. 2006; Meehl and Tebaldi 2004).

2) GCM changes in intra-annual distributions

Since high frequency events are not well-simulated in GCMs, the results described here were not included in the New York City adaptation assessment; they are explored here as an exercise, since there is the possibility of distributional changes in the future. The daily distribution of: a) maximum temperatures[14] in summer (JJA), and b) minimum temperatures in

[14] Precipitation was excluded, based on the preliminary analysis of hindcast daily precipitation described in section 3d.

winter (DJF) are analyzed in the three GCMs described earlier (CSIRO, GISS and ECHAM5; section 3d), both for the 1980-1999 hindcast and the 2080-2099 A1B experiment.

The results indicate that GCM temperature changes in the region in some cases do reflect more than a shifting mean. The intra-annual standard deviation[15] of winter minima decreases in all three GCMs (in two cases by approximately 10 %), while summer standard deviation changes are negligible. One tail of a season's distribution can be more affected than the other; as shown in Fig. 8 for CSIRO, the winter minimum changes are more pronounced on anomalously cold days than anomalously warm days. All 3 GCMs show a larger shift in the coldest 1% of the distribution than the highest 1%. This asymmetry at the 1% tails is most pronounced in CSIRO, where the future coldest 1% event occurs 8 times more often in the baseline, while the baseline warmest 1% event occurs three times more often in the future.

d. Comparison of GCM gridbox based-projections to other downscaling methods

The GCM grid box results used for the New York assessment were compared to statistically downscaled results from Bias-Corrected and Spatially-Downscaled (BCSD) Climate Projections at 1/8 degree resolution derived from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 3 (CMIP3) multi-model dataset. The BCSD projections are available at: http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/ (Maurer, 2007). Results were also compared to simulations from four parings of GCMs and RCMs (Table 8) contributing to the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2009). Comparison of the three methods is limited to the

[15] As calculated separately for each year and then averaged across the 20 years, to minimize the role of interannual variability.

2050s timeslice under the A2 emissions scenario relative to the 1970-1999 baseline, since NARCCAP projections are not available for other emissions scenarios or time periods. The comparison focuses on projections rather than validation, since the BCSD methodology by definition includes bias correction whereby the baseline GCM outputs are adjusted to match the observed mean and variance. Preliminary analysis of NARCCAP results indicates that these simulations, like GCM projections, require bias correction.

The ensemble mean changes for the GCM gridbox, BCSD, and RCM approaches differ from each other by no more than .3ºC for temperature and 3% for precipitation. The intermodel temperature range is slightly larger for the GCM gridbox approach than BCSD, while the opposite is the case for precipitation. The four RCM simulations perhaps not surprisingly feature a smaller intermodel range than the 16 ensemble members for the GCM gridbox and BCSD approaches.

The number of days above 90 ºF was evaluated as a measure of extremes events. The delta method applied to the GCM gridbox and BCSD[16] produce virtually identical results (increases of approximately 185 and 180 percent respectively in the number of days above 90ºF). When actual daily values from RCMs are used the increase is approximately 170 percent. When the delta method from the RCMs is applied to the observations, the increase is approximately 195 percent.

For mean changes and the daily extreme metric assessed here, BCSD and the four RCMs offer comparable results to the single gridbox GCM approach in the New York Metropolitan Region. Future research will assess how statistical and dynamic downscaling perform in more specialized contexts tailored to unique stakeholder needs that are beyond the scope of New York

[16] At the time of analysis, BCSD is only available at monthly resolution.

City initial assessment. For example, reservoir managers concerned with water turbidity might desire information about sequences of days with intense precipitation during particular times of year. Future research will also explore the pros and cons of projections that incorporate highly uncertain modeled changes in interannual variance through time[17].

5. Conclusions and Recommendations for Future Work

A framework for climate hazard assessment geared towards adaptation planning and decision support is described. This single GCM gridbox, delta method-based approach, designed for cities and regions smaller than typical GCM gridbox sizes that face resource and time constraints, achieves comparable results in the New York Metropolitan Region to other statistically and dynamically downscaled products. When applied to high frequency historical data, long-term mean monthly climate *changes* (which GCMs are expected to simulate more realistically for point locations than other features such as *actual* long-term mean climate or high frequency statistics) yield dramatic changes in the frequency of stakeholder-relevant climate hazards such as coastal flooding and heat events. While the precise projections should not be emphasized given the uncertainties, they are of sufficient magnitude relative to the historical hazard profile to justify development and initial prioritization of adaptation strategies. This process is now well underway in the New York Metropolitan Region.

When climate model results for the New York Metropolitan Region are used only for the calculation of monthly climate change factors based on the differences and ratios between 30-

[17] Preliminary analysis reveals that over the New York Metropolitan Region gridbox a slight majority of the GCMs show increasing interannual variance of monthly T and P, while a large majority of the BCSD and NARCCAP RCM projections do.

year future timeslices and a 30-year baseline period, three generalized findings follow. First, using multiple ensemble members from the same GCM provides little additional information, since the 30-year average intramodel ranges are smaller than the comparable inter-model range. Second, the spatial pattern of climate change factors in many regions (including New York City) is sufficiently homogeneous --- relative to the intermodel range --- to justify use of climate change factors from a single overlying GCM gridbox. Finally, for these metrics, newer statistically (BCSD) and dynamically (four NARCCAP RCMs) downscaled products provide comparable results to the GCM single gridbox output used by the NPCC.

The checklist in Table 2 provides a series of questions to help inform the selection of the most appropriate climate hazard assessment and projection methods. For example, the delta method is more justified when: 1) robust, long-term historical statistics are available, and 2) evidence of how modes of interannual and interdecadal variability and their local teleconnections will change with climate change is inconclusive. Both these criteria are met in the New York City Metropolitan Region. In contrast, more complex applications (than the delta method) of statistically and dynamically downscaled products especially may be more appropriate when spatially continuous projections are needed over larger regions with complex topography. For example, where a large mountain range is associated with a strong precipitation gradient at sub-GCM gridbox scales, percentage changes in precipitation might also be expected to be more spatially heterogeneous than in the New York Metropolitan Region.

Extreme event projections, so frequently sought by stakeholders for impact analysis, will likely improve as statistical and dynamical downscaling evolve. RCMs especially hold promise for assessing how ‘slow’ variations associated with climate change and variability will affect the future distribution of ‘fast’ extremes like subdaily rainfall events. Nevertheless, translating RCM simulations into stakeholder-relevant projections requires many of the same adjustments and caveats described here for GCMs (such as bias correction). Statistical downscaling techniques also hold promise as well for the simulation of extremes (non-stationarity not withstanding), to the extent that predictor variables are well simulated by GCMs and linkable to policy relevant local climate variables. Projections of extremes will also benefit from improved estimates of historical extremes (such as the 1-in-100 year drought and coastal flood) as long-term tree ring and sediment records (for example) are increasingly utilized.

There is also a need for improved simulation of climate variability at interannual to decadal scales, as this is the time horizon for investment decisions and infrastructure lifetime in many sectors, including telecommunications (NPCC, 2010). The limits to such predictability are beginning to be explored in Coupled Model Intercomparison Project (CMIP5) experiments initialized with observed ocean data, but this is a long-term research issue.

An absence of local climate projections need not preclude consideration of adaptation. For many locales, climate changes in other regions may rival the importance of local changes by influencing migration, trade, and ecosystem and human health, for example. Furthermore, some hazards such as drought are often regional phenomena, with multi-state policy implications (such as water-sharing agreements). Finally, since climate vulnerability depends on many non-climatic factors (such as poverty), some adaptation strategies (such as poverty-reduction measures) can be commenced in advance of climate projections.

Monitoring of climate indicators should be encouraged since it reduces uncertainties and leads to refined projections. Locally, sustained high temporal resolution observation networks can provide needed microclimatic information, including spatial and temporal variation in extreme events such as convective rainfall and storm surge propagation. At the global scale, monitoring of polar ice sheets and global sea level will improve understanding of sea level rise. Periodic assessments of evolving climate, impacts and adaptation science will support flexible/recursive adaptation strategies that minimize the impact of climate hazards while maximizing societal benefits.

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FIGURE CAPTIONS

Figure 1: Satellite map of the New York Metropolitan Region. Shown on the map are the Central Park weather station (circle) and The Battery tide gauge (triangle). Source: ESRI World Imagery.

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Figure 4: Daily distribution (number of days per year) of: a) all-year mean, b) summer (June-August) maximum, and c) winter (December-February) minimum temperature anomalies (ºC),

1980-1999 for Central Park observations (black line) and three GCMs (CSIRO, GISS, and MPI ECHAM5).

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Figure 6: Combined observed (black line) and projected: a) temperature (ºC) and b) annual precipitation (mm). Projected model changes through time are applied to the observed historical data. The three thick lines (red, green, and blue) show the ensemble average for each emissions scenario across the 16 GCMs. Shading shows the central 67 % range across the 16 GCMs and 3 emissions scenarios. The bottom and top lines, respectively, show each year's minimum and maximum projections across the suite of simulations. A ten-year filter has been applied to the observed data and model output. The dotted area between 2003 and 2015 represents the period that is not covered due to the smoothing procedure.

Figure 7: Seasonal a) temperature change (ºC) and b) precipitation change (%) projections, relative to the 1970-1999 model baseline, based on 16 GCMs and 3 emissions scenarios. The maximum and minimum are shown as black horizontal lines; the central 67% of values are boxed, and the median is the thick line inside the boxes.

Figure 8: Daily distribution (number of days per year) of winter (December-February) minimum temperature anomalies (ºC), for the New York Metropolitan Region in the CSIRO GCM. Black

line, 1980-1999 hindcast; dotted line, 2080-2099 A1B scenario.

TABLE 1. Acronym, host center, atmosphere and ocean grid box resolution, and reference for the 16 GCMs used in the analysis.

Model Acronym	Institution	Atmospheric Resolution (Lat x Lon)	Oceanic Resolution (Lat x Lon)	References
BCCR	Bjerknes Center for Climate Research, Norway	1.9 x 1.9	0.5 to 1.5 x 1.5	Furevik et al., 2003
CCSM	National Center for Atmospheric Research, USA	1.4 x 1.4	0.3 to 1.0 x 1.0	Collins et al., 2006
CGCM	Canadian Center for Climate Modeling and Analysis, Canada	2.8 x 2.8	1.9 x 1.9	Flato 2005
CNRM	National Weather Research Center, METEO-FRANCE, France	2.8 x 2.8	0.5 to 2.0 x 2.0	Terray et al., 1998
CSIRO	CSIRO Atmospheric Research, Australia	1.9 x 1.9	0.8 x 1.9	Gordon et al., 2002
ECHAM5	Max Planck Institute for Meteorology, Germany	1.9 x 1.9	1.5 x 1.5	Jungclaus et al., 2005
ECHO-G	Meteorological Institute of the University of Bonn, Germany	3.75 x 3.75	0.5 to 2.8 x 2.8	Min et al., 2005
GFDL-CM2.0	Geophysical Fluid Dynamics Laboratory, USA	2.0 x 2.5	0.3 to 1.0 x 1.0	Delworth et al., 2006
GFDL-CM2.1	Geophysical Fluid Dynamics Laboratory, USA	2.0 x 2.5	0.3 to 1.0 x 1.0	Delworth et al., 2006

GISS	NASA Goddard Institute for Space Studies	4.0 x 5.0	4.0 x 5.0	Schmidt et al., 2006
INMCM	Institute for Numerical Mathematics, Russia	4.0 x 5.0	2.0 x 2.5	Volodin and Diansky, 2004
IPSL	Pierre Simon Laplace Institute, France	2.5 x 3.75	2.0 x 2.0	Marti, 2005
MIROC	Frontier Research Center for Global Change, Japan	2.8 x 2.8	0.5 to 1.4 x 1.4	K-1 Developers, 2004
MRI	Meteorological Research Institute, Japan	2.8 x 2.8	0.5 to 2.0 x 2.5	Yuikimoto and Noda, 2003
PCM	National Center for Atmospheric Research, USA	2.8 x 2.8	0.5 to 0.7 x 1.1	Washington et al., 2000
UKMO-HadCM3	Hadley Center for Climate Prediction, Met Office, UK	2.5 x 3.75	1.25 x 1.25	Johns et al., 2006

TABLE 2. Checklist of questions to inform selection of climate hazard assessment and projection methods

Question	Possible implication for choice of method, plus NYC context
1. Are high quality historical data available for a long time period?	When little high-quality historical climate data are available, options for projections are extremely limited. Records of at least several decades are needed to sample the range of natural variability. As RCMs continue to improve, use of raw outputs from RCMs may increasingly be used in such regions, since bias correction and statistical approaches are not feasible without historical climate data. This was not an issue in data-rich NYC.
2. Are projections needed for the entire 21st century?	If yes, this may preclude RCMs due to computational expense. This was an important consideration for NYC, since some sectors such as telecommunications were focused on the 2020s timeslice, while others such as Port Authority of New York and New Jersey manage infrastructure expected to last until 2100.
3. Are multiple emissions scenarios needed, for example to emphasize how mitigation can compliment adaptation?	If yes, RCMs may not be the best approach, since computational expense generally precludes the use of more than 1-2 scenarios.

	This was an important consideration in New York City, since the adaptation effort was part of a broader sustainability effort (PlaNYC) that embraced greenhouse gas mitigation.
4. Are a large group of GCMs and initializations required, in order to sample a broad range of global climate sensitivities and estimates of within-GCM variability, respectively?	If yes, RCMs may not be the best approach, since computational expense generally precludes the use of more than a few GCMs or GCM initializations per RCM. New York City stakeholders expressed interest in the full range of GCM sensitivities.
5. What climate variables are needed, and are they available at the necessary spatial and temporal resolution within public climate model archives?	In NYC, relatively few variables were needed and subdaily information was not required. Additional variable needs at subdaily resolution might argue for the use of RCM archives such as NARCCAP as they continue to be populated, instead of archives such as the first generation of BCSD (monthly temperature and precipitation only). While use of public climate model archives minimizes cost and time, even archived outputs generally require at least some bias and/or scale correction and post-processing for stakeholder applicability.

6. What level of resources are available, and in what time frame is the information needed?	Region and question specific tailored downscaling efforts, as opposed to use of archived downscaled products, may not be possible when resources and time are limited. While NYC had substantial resources available, the short time frame (~8 months) precluded developing new tailored downscaling.
7. Are projections needed for a single in-depth sectoral application and variable in one municipality, or does a large multisectoral and pan-regional group of stakeholders need a coordinated set of scenarios covering a series of standard variables?	In tailored statistical downscaling the method is optimized to the particular location and/or variable. When many variables and a larger region are included, no single optimization method will generally be best for all variables and locations, potentially leading to inconsistencies in either methods or projections across variables and locations. In NYC, the initial emphasis was on generating a common denominator of consistent scenarios based on consistent methods (the delta method) to facilitate coordination across 40 stakeholder entities.
8. Are high-frequency climate inputs that are continuous in time and	If an impacts model is to be run with climate outputs, the range of

space required, such as for input into an impacts model? (e.g., a hydrological model to assess turbidity)	climate and impact results (rather than just the 'delta' mean) will likely be of interest, which may argue for a downscaling technique that allows variance to change, such as BCSD. Statistical downscaling techniques that include weather generators (such as SDSM) may be desirable to create a long record at the needed resolution that includes a range of extreme outcomes for planning purposes. The larger the continuous geographic domain (e.g., a large watershed) the greater the need for caution regarding weather generator treatment of spatio-temporal correlation. While impacts modeling was not the initial thrust of the NYC CCATF effort, climate scenarios for impact modeling are being developed for specific sectors (e.g., NYCDEP, 2008).
9. Is the region's climate characterized by large spatial heterogeneity?	If not, applying the delta method to a single GCM gridbox may be justifiable for many applications, as it was in NYC.
10. Are modes of variability important and predictable?	If not, the use of 30-year time slices (and the delta method) that emphasize the signal of greenhouse gases and other radiatively

important agents should be emphasized, as it was in NYC.

TABLE 3. NCAR CCSM climatology of available simulations and CCSM ensemble for the gridbox covering New York City: a) 1970-1999 hindcast; b) A1B 2080s (2070 to 2099 average) relative to the same-simulation 1970 to 1999 hindcast.

a)

	1970 - 1999 Mean temperature (°C)	1970 - 1999 Mean precipitation (cm)
CCSM Run1	9.38	98.03
CCSM Run 2	9.27	91.88
CCSM Run 3	9.67	92.08
CCSM Run 5	9.42	94.87
CCSM Run 6	9.64	95.22
CCSM Run 7	9.64	91.30
CCSM Run 9	9.68	94.69
CCSM Ensemble	9.53	94.10

b)

	2080s A1B Temperature change (°C)	2080s A1B Precipitation change (%)
CCSM Run1	3.44	2.81

CCSM Run 2	3.32	10.15
CCSM Run 3	3.03	12.44
CCSM Run 5	3.24	9.75
CCSM Run 6	2.75	9.56
CCSM Run 7	2.96	12.03
CCSM Run 9	3.01	10.36
CCSM Ensemble	3.11	9.52

TABLE 4. Annual and seasonal temperature (a,b,(°C decade^{-1})) and precipitation (c,d, (cm decade^{-1})) trends, and 20th century (a,c) and 1970-1999 (b,d). Shown are observed Central Park station data, the 16 GCM ensemble, and four points on the GCM distribution (lowest, 17th percentile, 83rd percentile, and highest).

a)

20th century*	Min	16%	83%	Max	Ensemble	Observed
Annual	-0.03	0.02	0.12	0.17	0.07**	0.15**
DJF	-0.04	0.02	0.16	0.19	0.08**	0.20**
MAM	-0.05	-0.02	0.12	0.25	0.06**	0.18**
JJA	-0.02	0.03	0.11	0.15	0.07**	0.12**
SON	0.00	0.03	0.15	0.18	0.09**	0.08

b)

1970 - 1999	Min	16%	83%	Max	Ensemble	Observed
Annual	-0.11	0.10	0.28	0.39	0.18**	0.21
DJF	-0.47	-0.05	0.35	0.51	0.11	0.76
MAM	-0.36	-0.15	0.41	0.74	0.14	0.10
JJA	-0.01	0.13	0.29	0.44	0.20**	0.05
SON	-0.06	0.13	0.50	0.70	0.29**	-0.03

c)

20th century[*]	Min	16%	83%	Max	Ensemble	Observed
Annual	-1.22	-0.22	0.66	0.76	0.16	1.60
DJF	-0.23	-0.18	0.27	0.78	0.05	0.27
MAM	-0.27	-0.13	0.28	0.39	0.10	0.90
JJA	-0.69	-0.39	0.22	0.35	-0.07	-0.09
SON	-0.25	-0.08	0.32	0.46	0.10	0.61

d)

1970 - 1999	Min	16%	83%	Max	Ensemble	Observed
Annual	-3.52	0.02	2.05	5.73	0.87	-1.77
DJF	-3.21	-0.19	1.48	2.94	0.48	-0.48
MAM	-2.33	-1.37	1.05	1.98	-0.08	1.55
JJA	-2.08	-1.33	1.19	1.75	-0.03	-1.51
SON	-1.72	-0.55	1.89	2.93	0.48	-1.72

[*] Only 15 GCMs were available for the 1900-1999 hindcast.

[**] Trend is significant at the 99% level.

TABLE 5. Mean annual changes in temperature and precipitation for New York City.*

	2020s	2050s	2080s
Air temperature **	+ 0.8 to 1.7° C	+ 1.7 to 2.8° C	+ 2.2 to 4.2° C
Precipitation **	+ 0 to 5 %	+ 0 to 10 %	+ 5 to 10 %

* Based on 16 GCMs and 3 emissions scenarios.

** Shown is the central range (middle 67%) of values from model-based distributions; temperatures ranges are rounded to the nearest tenth of a degree and precipitation to the nearest 5%.

TABLE 6. Sea level rise projections for New York City[a]

	2020s	2050s	2080s
IPCC-based[b,]	+ 5 to 13 cm	+ 18 to 30 cm	+ 30 to 54 cm
Rapid ice-melt scenario[b,c]	~ 13 to 25 cm	~ 48 to 74 cm	~ 104 to 140 cm

[a] Based on 7 GCMs and 3 emissions scenarios.

[b] Shown is the central range (middle 67%) of values from model-based distributions rounded to the nearest cm.

[c] Rapid ice-melt scenario is based on recent rates of ice melt in the Greenland and West Antarctic Ice sheets and paleoclimate studies. See text for details.

TABLE 7. Extreme Events Projections.

	Extreme Event	*Baseline (1971- 2000)*	2020s	2050s	2080s
Heat & cold events [a]	# of days per year with maximum temperature exceeding:				
	90°F (~32°C)	*14*	23 to 29	29 to 45	37 to 64
	100°F (~38°C)	*0.4*[b]	0.6 to 1	1 to 4	2 to 9
	# of heat waves per year[c]	*2*	3 to 4	4 to 6	5 to 8
	Average duration (in days)	*4*	4 to 5	5	5 to 7
	# of days per year with minimum temperature at or below 32°F (0°C)	*72*	53 to 61	45 to 54	36 to 49
Coastal floods & storms[d,e]	1-in-10 yr flood to reoccur, on average	*~once every 10 yrs*	~once every 8 to 10 yrs	~once every 3 to 6 yrs	~once every 1 to 3 yrs
	Flood heights (in m) associated with 1-in-10 yr flood	*1.9*	2.0 to 2.1	2.1 to 2.2	2.3 to 2.5
	1-in-100 yr flood to reoccur, on average	*~once every 100 yrs*	~once every 65 to 80 yrs	~once every 35 to 55 yrs	~once every 15 to 35 yrs

Flood heights (in m) associated with 1-in-100 yr flood	*2.6*	2.7 to 2.7	2.8 to 2.9	2.9 to 3.2

[a] Shown is the central range (middle 67%) of values from model-based distributions based on 16 GCMs and 3 emissions scenarios.

[b] Decimal places shown for values less than 1 (and for all flood heights)

[c] Defined as 3 or more consecutive days with maximum temperature exceeding 90°F (~32°C).

[d] Does not include the rapid ice-melt scenario.

[e] Shown is the central range (middle 67%) of values from model-based distributions based on 7 GCMs and 3 emissions scenarios.

TABLE 8. Global climate model and regional climate model pairings used from NARCCAP

Global Climate Model Driver	Regional Climate Model	Combination	RCM Reference
Geophysical Fluid Dynamics Laboratory (GFDL)	Regional Climate Model Version 3 (RCM3)	RCM3 + GFDL	Pal et al., 2007
Third Generation Coupled Climate Model (CGCM3)	Regional Climate Model Version 3 (RCM3)	RCM3 + CGCM3	Pal et al., 2007
Third Generation Coupled Climate Model (CGCM3)	Canadian Regional Climate Model (CRCM)	CRCM + CGCM3	Caya and Laprise, 1999
Hadley Centre Coupled Model, Version 3 (HadCM3)	Hadley Regional Model 3 / Providing Regional Climates for Impacts Studies (HRM3)	HRM3 + HadCM3	Jones et al., 2004

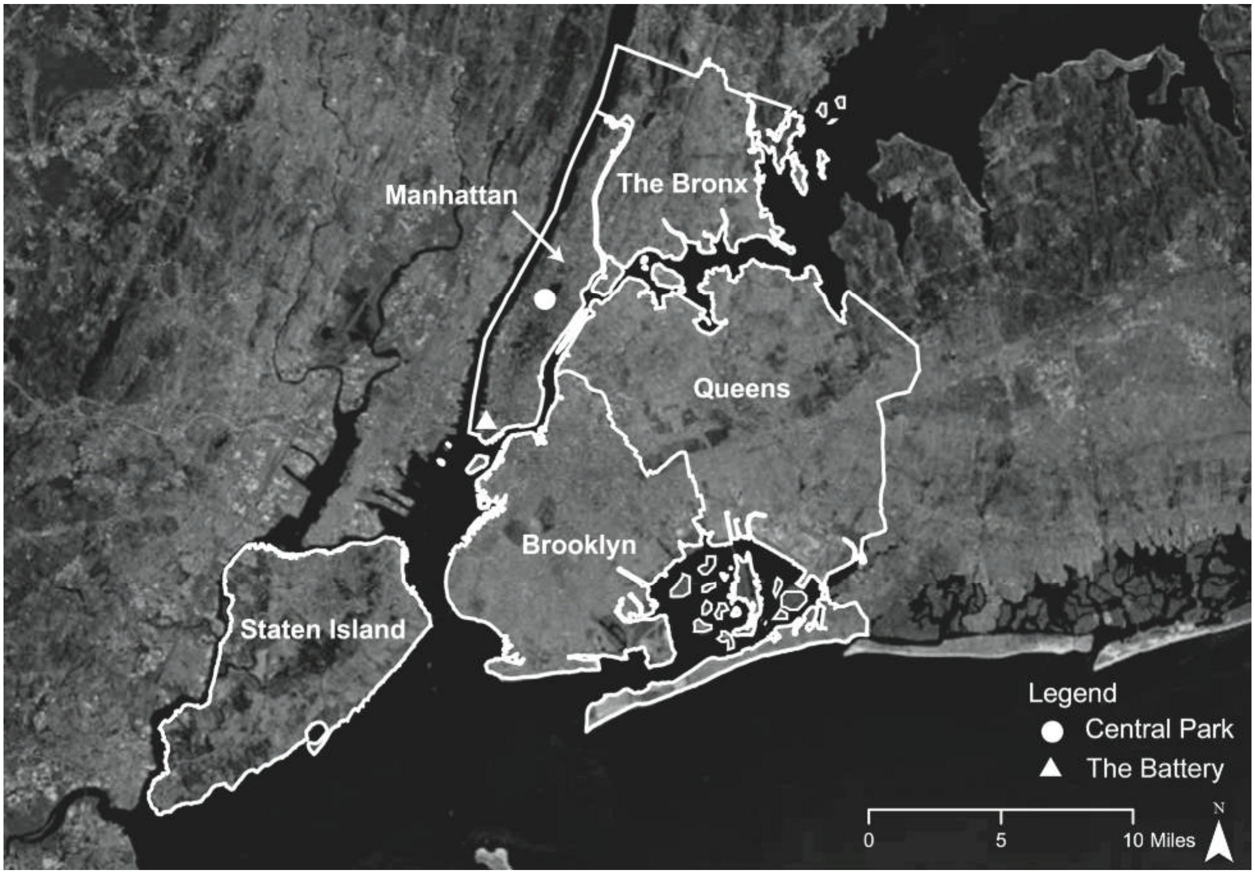

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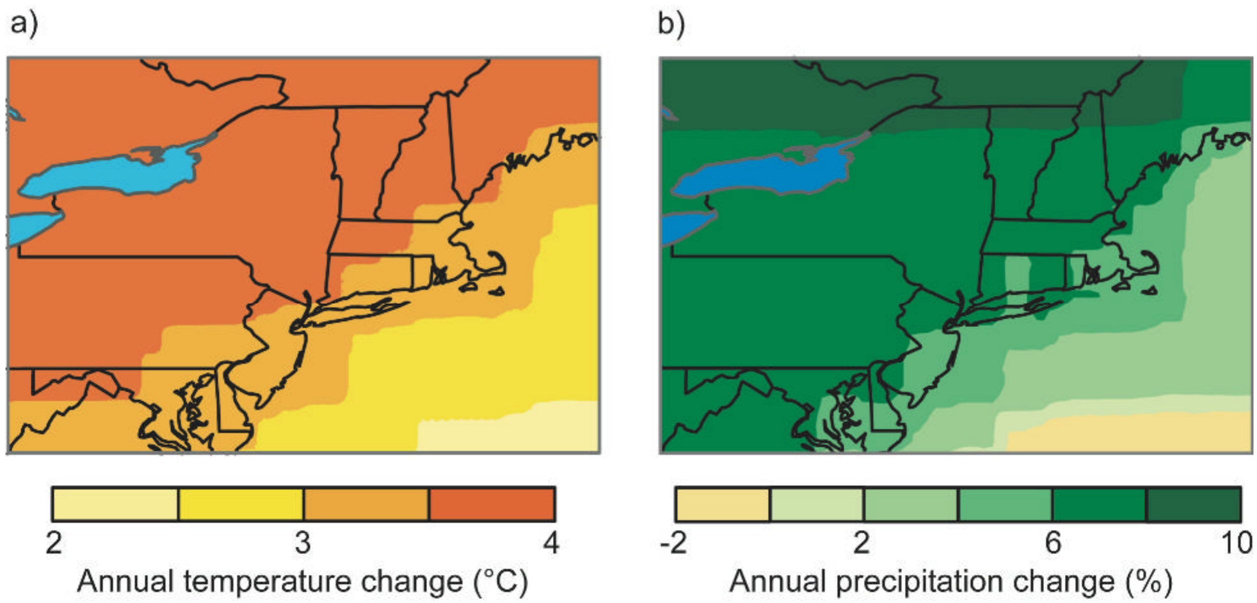
Figure 1: Locations of the Central Park weather station (circle), and The Battery tide gauge (triangle), and the 5 boroughs of New York City. Source: ESRI World Imagery.



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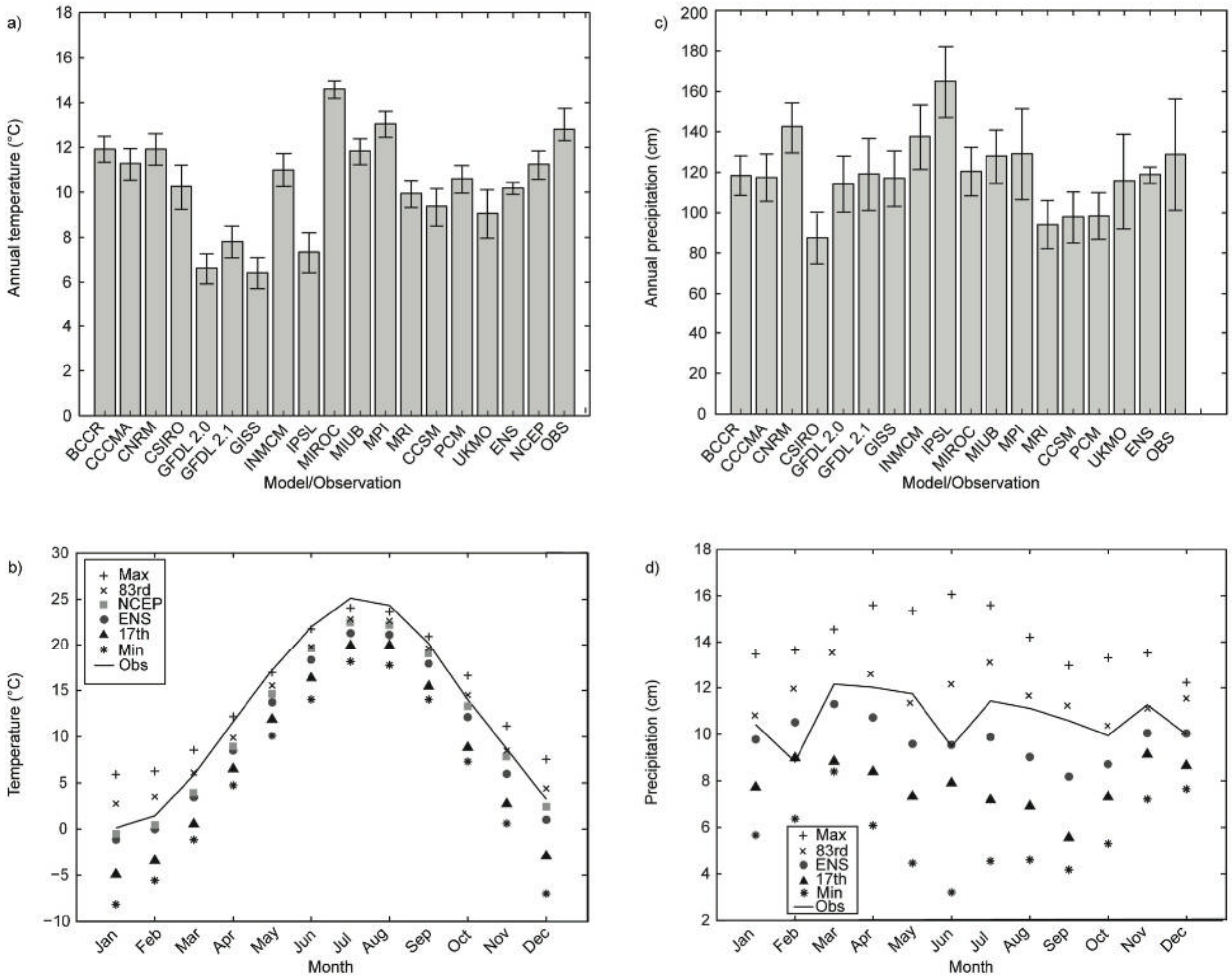

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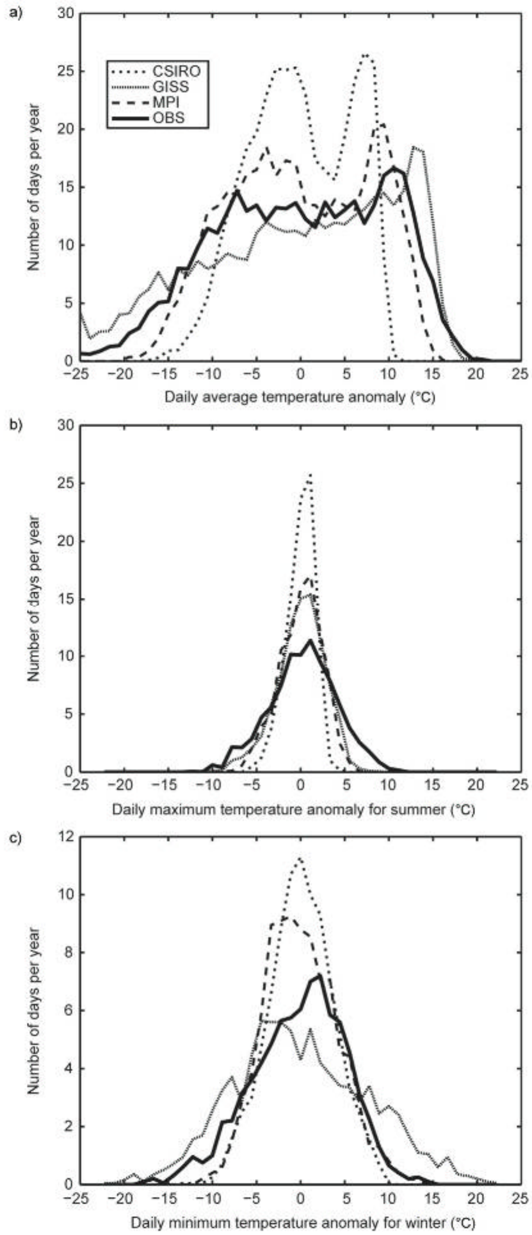

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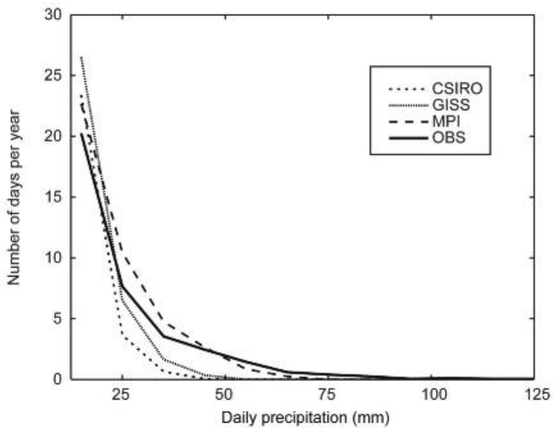

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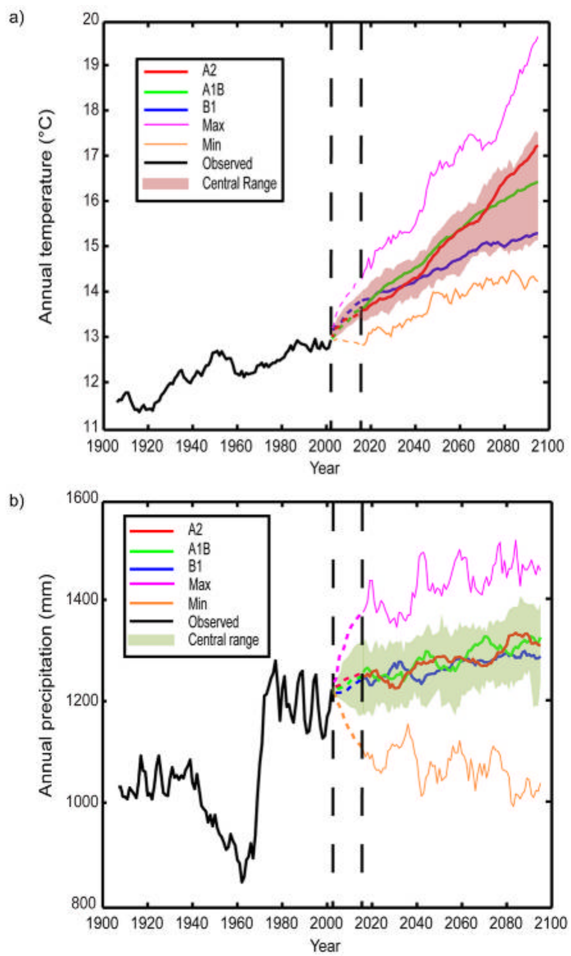

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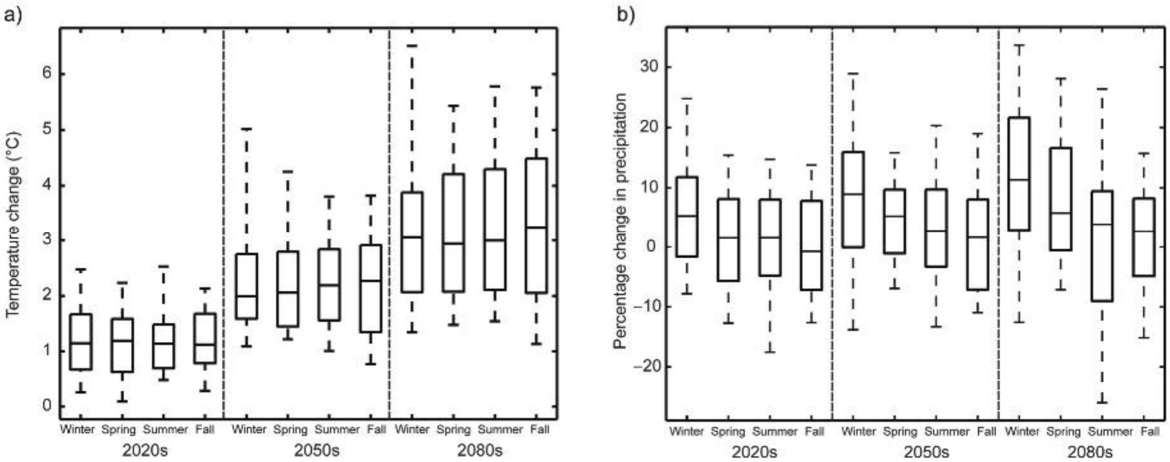

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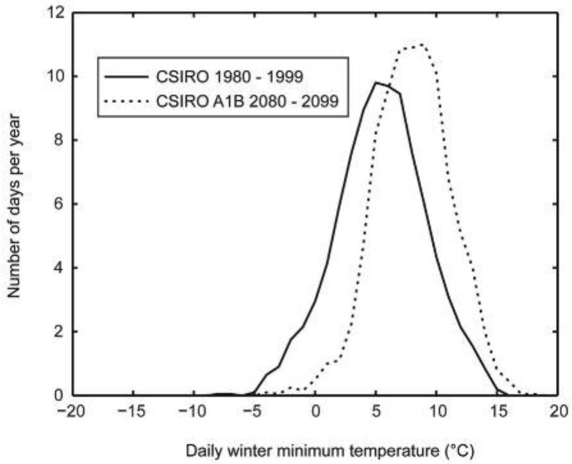

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