Connecticut Physical Climate Science Assessment Report (PCSAR)

Observed trends and projections of temperature and precipitation

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The Connecticut Institute for Resilience and Climate Adaptation (CIRCA) is a partnership between the University of Connecticut and the State of Connecticut Department of Energy and Environmental Protection. CIRCA's mission is to increase the resilience and sustainability of vulnerable communities along Connecticut's coast and inland waterways to the growing impacts of climate change on the natural, built, and human environment.

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CIRCA

Connecticut Institute for Resilience and Climate Adaptation

I. About this report: Purpose, Funders, Authors, Reviewers

The purpose of this report is to provide an assessment of the state of the science regarding observed recent changes and projections for temperature and precipitation (i.e., physical climate) for Connecticut. The Connecticut Institute for Resilience and Climate Adaptation (CIRCA) at UConn with funding from the Department of Energy and Environmental Protection (DEEP) commissioned this report to foster dialogue about the changing climate between experts in physical climate and state/municipal/community groups involved in planning and adaptation to those changes in Connecticut. Although temperature and precipitation are the primary foci of this assessment, the author team is more broadly comprised of experts in climate science, climate modeling, land-atmosphere and hydrologic processes, social studies of science, and water management. All are members of the UConn Atmospheric Sciences Group – a collective of faculty across the university working on climate related research and education.

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II. Acronyms, Data, and Indices referred to in this report.

Acronym	Definition
CIRCA	Connecticut Institute for Resilience and Climate Adaptation
CH_4	Methane
CMIP	Coupled Model Intercomparison Program (e.g., CMIP5, Taylor et al., 2012)
CO_2	Carbon dioxide
DEEP	Connecticut Department of Energy and Environmental Protection
DJF	December—January—February
ETCCDI	Expert team on climate change detection and indices
GCMs	Global climate models
GEV	Generalized extreme value
GHCN	Global Historical Climatology Network (Menne et al., 2012)
H_2Ov	Water vapor
IR	Infrared radiation
JJA	June—July—August
Livneh	Meteorological data, gridded (~6km resolution, Livneh et al., 2015)
LOCA	Localized constructed analogs (Pierce et al., 2014, 2015)
MACA	Multivariate adaptive constructed analogs (Abatzoglou and Brown, 2012)
MAM	March—April—May
METDATA	Meteorological data, gridded (~4km resolution, Abatzoglou, 2011)
NCDC	National Climatic Data Center climate divisional data (Karl and Koss, 1984)
O_3	Ozone
RCMs	Regional climate models
RCPs	Representative Concentration Pathways (e.g., RCP8.5, Van Vuuren et al., 2010)
SON	September—October—November
WCRP	World Climate Research Program

Index	Index name	Definitions	Units
Temperature Indices (daily maximum and minimum)			
TXX	Warmest day	Annual maximum value of daily maximum temp	ºF

TNN	Coldest night	Annual minimum value of daily minimum temp	ºF
Daytime Heat Indices			
SU	Summer days	Annual count when TX (daily maximum) >25ºC (77ºF)	Days
WSDI	Warm Spells	Annual count of warm spell days, where a warm spell is 6 or more consecutive days with TX>90th percentile	Days
Nightime Heat Indices			
TR	Tropical nights	Annual count when TN (daily minimum) >20ºC (68ºF)	Days
GSL	Growing season length	Annual count between first span of at least 6 days with TG>5ºC (41ºF) and first span after July 1 of 6 days with TG<5ºC	Days
Daytime Cold Indices			
ID	Ice days	Annual count when TX (daily maximum) <0ºC (32ºF)	Days
CSDI	Cold spells	Annual count of cold spell days, where a cold spell is 6 or more consecutive days with TN<10th percentile	Days
Nightime Cold Indices			
FD	Frost days	Annual count when TN (daily minimum) <0ºC (32ºF)	Days
DTR	Daily range of temperature	Annual mean difference between TX and TN	ºF

Index	**Index name**	**Definitions**	**Units**
Drought Risk			
CDD	Dry Days	Maximum number of consecutive dry days for JJA	Days
SII	Simple Intensity	Simple intensity index (average precipitation per wet day)	Inches/ Day
aPE	Annual P-PET	Precipitation minus potential evapotranspiration, annual	Inches
sPE	Summer P-PET	Precipitation minus potential evapotranspiration, JJA	Inches
N_wet	Wet Days	Annual count of wet days, Prec > 0.04 inches	Days
Flood Risk			
N_1inch	Rain Days	Annual count when daily Prec >1 inch	Days
N99	Heavy Rain Days	Annual count of days with precipitation > 99th percentile	Days
F99	Heavy Rain Fraction	Fraction of annual precipitation accounted for by N99	%
R1d	Max 1day Rain	Maximum daily precipitation	Inches
R5d	Max 5day Rain	Maximum consecutive 5-day precipitation	Inches

Return Periods			
X_10 X_20 X_50 X_100	Any index	Present climate extreme value of index with return period of 10, 20, 50, and 100 years respectively defined for various precipitation indicators X such as R1d, R5d, and low tail of aPE (annual P-PET) and sPE (summer P-PET)	See index units above
T_X_10 T_X_20 T_X_50 T_X_100	Any index	Future return period of the X_10, X_20, X_50, X_100 for precipitation index X including R1d, R5d, aPE, and sPE	years

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Key Findings

All projections analyzed for this assessment employ the high CO_2 emissions scenario (RCP8.5). There is high confidence in projected changes through mid-century. Actual temperature and precipitation changes, particularly after mid-century, will depend on mitigation actions taken in Connecticut and globally. Updates to this assessment should be performed every five years as new observations and scientific findings become available. Key findings from this assessment:

- Observed changes in temperature
    - Since 1895, increases are seen in annual (0.3°F/decade) and seasonal average temperatures, with the greatest increase experienced in winter (December—February, 0.4°F/decade).
- Projected changes in temperature for the high CO_2 (RCP8.5) scenario
    - Large increases are projected for annual changes in temperature (+5 to +8°F annual mean, mid- and late-century, respectively) and in seasonal average temperatures for all regions in the state, with the greatest increase experienced in summer (June—August, +6°F) by mid-century and fall (September—November, +10 °F) by late-century.
- Observed changes in annual temperature extremes since 1980
    - Effects of warming are seen in all temperature indices.
    - The temperature of both warmest (TXX) and coldest (TNN) days of the year has increased.
    - Increases are seen in the number of summer days (SU: Tmax > 77°F), tropical nights (TR: Tmin > 68°F), and growing season length (GSL).
    - Decreases are observed in the number of frost days (FD: Tmin < 32°F).
    - Other notable changes that do not meet the threshold for significance include:
        - Increases are being seen in the number of warm spell days (WSDI).
        - Decreases are being observed in the number of ice days (ID), cold spell days (CSDI), and diurnal temperature range (DTR).
- Projected changes in annual temperature extremes for the high CO_2 (RCP8.5) scenario
    - All temperature indices examined show large changes in response to continued, accelerating warming.
    - Tropical nights (TR: Tmin > 68°F) quadruple from 10days (present) to more than 40days at mid-century and nearly 70days in late century.
    - Warm spell days (WSDI) occur ~4/year (present), and increase to 48/year by mid-century and more than 100/year by late century.
    - Frost days (FD: Tmin < 32 °F) decrease from 124 days (present) by 39 days at mid-century and by 64 days in late century.

- Observed changes in precipitation
    - Annual precipitation over most of the state has increased, with the largest increase experienced in summer (since 1950) or fall (since 1895) and a slight decrease during winter.
- Projected changes in precipitation for the high CO_2 (RCP8.5) scenario
    - Annual precipitation across the state is projected to increase (8.5% and 9.5%, by mid- and late-century respectively), with the greatest increase projected for winter (13.4% & 16.3% respectively) and spring (10% and 16.5% respectively) and inconclusive changes in the other two seasons.
- Observed changes in precipitation extremes since 1980
    - Rainfall intensity (simple intensity index, SII) has increased and the number of wet days (N_wet) has decreased.
    - Other notable changes that do not meet the threshold for statistical significance include:
        - Potential water availability as represented by the difference between precipitation and potential evapotranspiration (aPE) has increased, reflecting slightly reduced drought risk in the recent record.
        - Increases are seen in the number of days with more than 1 inch of precipitation (N_1inch), number of heavy precipitation days (N99, with precipitation exceeding the 99th percentile), fraction of annual precipitation accounted for by heavy precipitation (F99), and daily maximum precipitation (R1d), all indicating increasing flood risk.
- Projected changes in precipitation extremes for the high CO_2 (RCP8.5) scenario
    - Potential water availability as represented by the difference between precipitation and potential evapotranspiration (aPE) is projected to decrease (by 22%, late-century), reflecting significant increase of drought risk, with greater decreases projected for summer.
    - Several extreme precipitation indices are projected to increase, including the number of days with more than 1 inch of precipitation (N_1inch), number of heavy precipitation days (N99), fraction of total precipitation accounted for by heavy precipitation (F99), and the maximum 1-day and 5-day precipitation (R1d, R5d), all indicating a substantial increase of flood risk by mid-century.
    - The frequency of previously rare extreme events, including extremely low annual and summer water availability (aPE, sPE) and extremely high 1-day and 5-day precipitation (R1d, R5d), is projected to increase by a factor of 2-4 (mid-century).

1. Introduction

1.1 Overview

Climate is changing in Connecticut. The warmest 10 years on record in Connecticut have occurred since 1990, with half of these since 2010, underscoring a statewide warming of 2.2°F since 1895. With increasing temperatures comes more humidity, which leads to more precipitation and more intense precipitation events. Superstorm Sandy, Hurricane Irene and several recent Nor'easters have resulted in unprecedented coastal damage and inland flooding. The changes we are seeing in Connecticut are part of the global trend. Globally Earth's surface temperatures have warmed by 1.8°F since 1901 and humidity has increased by 3.5% since the 1970s (Wuebbles, et al, 2017). Scientific evidence is clear that these climatic trends are expected to continue (IPCC, 2013; Wuebbles, et al, 2017; also Sections 3 and 4) through the mid-21st century, and the extent of changes thereafter depend on human decisions being made now.

The State of Connecticut has initiated research and planning for the types of actions that will be required throughout the state to adapt to a changing climate. This is in addition to the efforts already in progress to reduce the causes of warming. Planning for adaptation, however, requires localized information about expected changes in climate. Until recently the spatial scale of climate projections did not allow for detailed regional analysis. For this reason, climate assessments have been performed on global and national scales, with limited regional information.

Assessments are processes for bringing together and integrating scientific knowledge to provide relevant information to decision makers (NAS 2007). The IPCC Fifth Assessment Report (IPCC, 2013) and U.S. National Climate Assessments (USGCRP, 2014; Wuebbles et al., 2017) synthesized thousands of studies on the physical climate and its impacts on sectors such as water, energy, transportation, health, and agriculture, along with numerous potential mitigation and adaptation response strategies. These assessments also utilized a variety of monitoring, modeling, and forecasting methods to develop a range of plausible climate scenarios that provide the basis for projecting future climate change.

From past assessments and research, we know that global climate trends are likely to be accompanied by a marked increase in the frequency of many types of extreme weather events. Around the world, heat waves warmer than the warmest currently on record are expected to occur in half of summers within the next 10-20 years (Camargo and Seth, 2016; Mueller et al., 2016). In the U.S. Northeast, warm, wet weather extremes are expected to increase significantly by midcentury, with particularly heavy increases in winter precipitation in northern, coastal, and mountainous areas (Thibeault and Seth, 2014; Thibeault and Seth, 2015). Even if the baseline goals of the United Nations 2015 Paris Agreement to keep the global temperature rise below 2 deg Celsius (3.6 deg F) are met, extreme events will be more than twice as likely as under a scenario of ambitious emissions reductions, with the largest relative increases in rarer, more severe weather events (Kharin et al. 2018).

While national and international climate assessments generate cutting edge consensus-based scientific summaries for decision makers, this information often falls short of being usable for decision-making especially at local levels. Problems with usability arise primarily because of mismatches between the resolution of climate model output and the spatiotemporal scale of local decisions (Cohen 1996; Galford et al., 2016) as well as failures to produce locally actionable information (Galford et al., 2016; Kirchhoff et al. 2013; NAS 2016).

State-level climate assessments aim to align the scale of information and practitioner engagement to support local decision-making (e.g., assessments for the U.S. states of Colorado (Lukas et al. 2014), Vermont (Galford et al. 2014), and Massachusetts (EEA and Adaptation Advisory Committee 2011)). For example, statistical downscaling of global-scale climate projections are now available and can be used to more effectively represent localized scenarios of future climate (Ahmed et al. 2013; Smid and Costa 2017). Similarly, capturing regional land and ocean effects helps to capture the variation in both past and projected sea-level rise. Capturing changes in local climate and sea-level rise helps local decision makers to adapt to changing conditions and enable coastal communities to more effectively implement site-specific coastal adaptation infrastructure and planning (O'Donnell, 2017; NOAA, 2017). State-level climate assessments also help to build understanding and create opportunities for discourse about climate changes and their impacts among local stakeholders through engagement processes (Hegger et al. 2012).

Connecticut stands to benefit from state-level focus on actionable climate science. Recently, the Connecticut Institute for Resilience and Climate Adaptation (CIRCA), a multi-disciplinary center at the University of Connecticut comprising experts in the natural and social sciences, engineering, economics, business, political science, finance, and law, has made significant strides toward promoting climate research and building adaptive capacity in vulnerable communities. In partnership with the Connecticut Department of Energy and Environmental Protection (DEEP), CIRCA aims to combine research and community engagement to improve resilience and sustainability of the natural and built environment throughout Connecticut. While previous state-sponsored initiatives have focused on preparedness for climate impacts in Connecticut (Gornitz et al., 2004; CT DEEP, 2010; CT DEEP 2011), they have highlighted a need for a comprehensive state-wide scientific assessment of temperature and precipitation trends and projections. To meet the climate adaptation challenges of the coming decades, CIRCA and DEEP have issued a call for improved information on past and future temperature, precipitation, and extremes at the state level. This report answers that call.

1.2 Scope of this Assessment

This assessment describes the current state of knowledge of the physical science underpinning observed and projected climate trends and extremes in Connecticut. In addition to reviewing past changes in temperature and precipitation from station measurements and gridded meteorological datasets, *this assessment will present future scenarios based on new high-resolution downscaled projections from a suite of global climate models produced for this report*. While our geographical focus is on Connecticut, findings will be placed within the broader context of regional climate change throughout New England and the US Northeast. Analysis of sea-level rise projections for the state has been conducted prior to this report (O'Donnell, 2018). Given the focus on the physical science, a detailed analysis of climate impacts and responses, including social, economic and political dimensions of climate change such as vulnerability, resilience, and adaptation strategies, is beyond the scope of this assessment.

We present an expert assessment of recent-observed changes in and projections of temperature and precipitation for Connecticut. The intention is to initiate dialogue between experts in physical climate and practitioners involved in planning and adaptation. This assessment supports ongoing and future sector-level planning and adaptation decision-making efforts by state and local governments, commercial enterprises, and NGOs in Connecticut. The structure of the report is as follows: Section 2 provides essential knowledge of climate, weather, scenarios, model projections, uncertainties, and the data analyzed in this report. Section 3 presents a review of the literature and new analyses of observed and projected temperature changes. Section 4 follows a similar structure for precipitation changes and includes a review of mid-latitude and tropical storms affecting the state. The assessment concludes with a discussion of the critical research gaps and needs for a useable and continued assessment (Section 5).

2. Climate Model Projections

2.1 Understanding Climate Scenarios

To project future climate, we must make assumptions about changes in the major drivers of climate, the most important of which are greenhouse gases (among which CO_2 has the longest lifetime in the atmosphere). We know that temperature increases will depend on the amount of CO_2 that accumulates in the atmosphere, but we do not know how much will accumulate, because future concentrations of CO_2 will depend on our collective global decisions regarding the continued use of fossil fuels. Indeed, human choice is the largest uncertainty in projections of climate at the end of the 21st century. To address this uncertainty, a suite of scenarios has been developed to establish a plausible range of possible climate futures (Van Vuuren et al., 2011). These Representative Concentration Pathways (RCPs) are assumptions about the evolution of atmospheric CO_2 and other greenhouse gases and their effect on earth's energy balance (its "radiative forcing" of climate). Radiative forcing is the imbalance between incoming and outgoing energy due to increases in greenhouse gases and other drivers of climate change. It is measured in Watts per square meter. An imbalance of just a few W/m^2 acting over a long enough time can warm the Earth by several degrees Celsius (see Fig. SB2.1). The RCPs describe four possible climate futures, all of which are considered possible depending on rates of greenhouse gases emissions in the years to come. Each RCP (RCP2.6, RCP4.5, RCP6, and RCP8.5) is named for resulting radiative forcing value in the year 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2, respectively). These scenarios provide critical driving inputs for climate model projections of the 21st century.

The scientific history (experimental, theoretical and numerical) exploring the role of CO_2 in Earth's climate spans more than 160 years. Our best current tools for projecting future climate are 3-dimensional numerical climate models based on physical laws that govern energy and motion in the atmosphere, oceans, sea ice, land and vegetation. Climate models have been in development by more than 30 scientific groups around the world. Coordinated experiments under the World Climate Research Program (WCRP) Coupled Model Intercomparison Project (CMIP) are performed wherein each model is driven with agreed upon inputs, including the RCPs. The latest available model experiments are from the CMIP5 database (Taylor et al., 2012). CMIP6 is underway as of the writing of this report (Eyring, 2018).

RCP8.5 is a high concentration pathway and it is noted that atmospheric GHG concentrations in recent years have closely tracked RCP8.5 (Sanford et al., 2014) which has been used to drive the CMIP5 RCP8.5 future climate projections. Aggressive actions taken globally to meet the 2015 Paris Agreement objectives would require a low concentration pathway similar to RCP2.6. Because adequate global commitments are not yet in place, we focus on the high radiative forcing (RCP8.5) pathway for future projections.

It is important to understand the uncertainties inherent in climate model projections (Hawkins and Sutton, 2009). The largest uncertainty in projecting global average temperature after mid-21st century is the so-called *scenario uncertainty*, that results from how much CO_2 is accumulated in the atmosphere (the RCPs). Other sources of uncertainty can be more important in the near-term projections. Some uncertainty results from the models themselves, because the numerical representation of physical processes is not exact. This *model uncertainty* will always exist to some extent. There is also uncertainty internal to the climate system because the atmosphere, oceans, ice and land all vary on differing time scales and interact in ways that create variations from year-to-year and decade-to-decade without any external forcing. An example of this *internal variability* in the climate system is El Niño, a coupled ocean-atmosphere oscillation across the tropical Pacific Ocean that can cause worldwide drought, flooding and temperature extremes. In the near term (the next ~10-20 years) internal variability, or variations in climate that result from dynamics within the complex

Sidebox 2.1: Why are temperatures increasing?

Earth's average temperature is set by a balance between sunlight, net inflow of energy, in the form of visible radiation, and heat loss to space or outflow of energy, in the form of infrared (IR) radiation. This is referred to as Earth's radiation (or energy) balance. Any driver that influences the radiation balance will compose a "radiative forcing". For the Earth as a whole, when incoming sunlight and outgoing heat loss are equal, the global average temperature does not change. The past 10,000 years provide an example of relative stability in climate. Changes in Earth's average temperature [Level, Fig. SB2.1] occur when incoming sunlight [Inflow, Fig.SB2.1] and outgoing heat [Outflow, Fig. SB2.1] are not in balance. When there is more incoming sunlight than outgoing heat loss, earth's temperature [Level] increases. When there is more heat loss to space, Earth's temperature decreases. This means there are two primary "drivers" that can change Earth's average temperature: incoming sunlight and heat loss to space. Changes in sunlight result from earth's orbital variations on timescales of 10,000 to 100,000 years, while changes in heat loss result from the amount of greenhouse gases (carbon dioxide (CO_2), methane (CH_4), and others) [Clog, Fig. SB2.1] in the atmosphere, which absorb and direct heat downward to the surface thereby reducing the heat loss to space. Over millions of years, Earth's past temperature changes have resulted from both of these drivers. At present the known changes in sunlight are small, and human use of fossil fuels (coal, oil, gas) are adding CO_2 and CH_4 to the atmosphere at a rate unprecedented in the geologic record [increasing the Clog]. There is very high confidence (more than 95% probability) that observed temperature increases are due to the imbalance of earth's energy budget resulting from human emissions of greenhouse gases (CO_2, CH_4). Note that temperature [Level] will continue to increase until the outgoing heat loss to space [Outflow] increases enough to once again equal the incoming sunlight [Inflow].

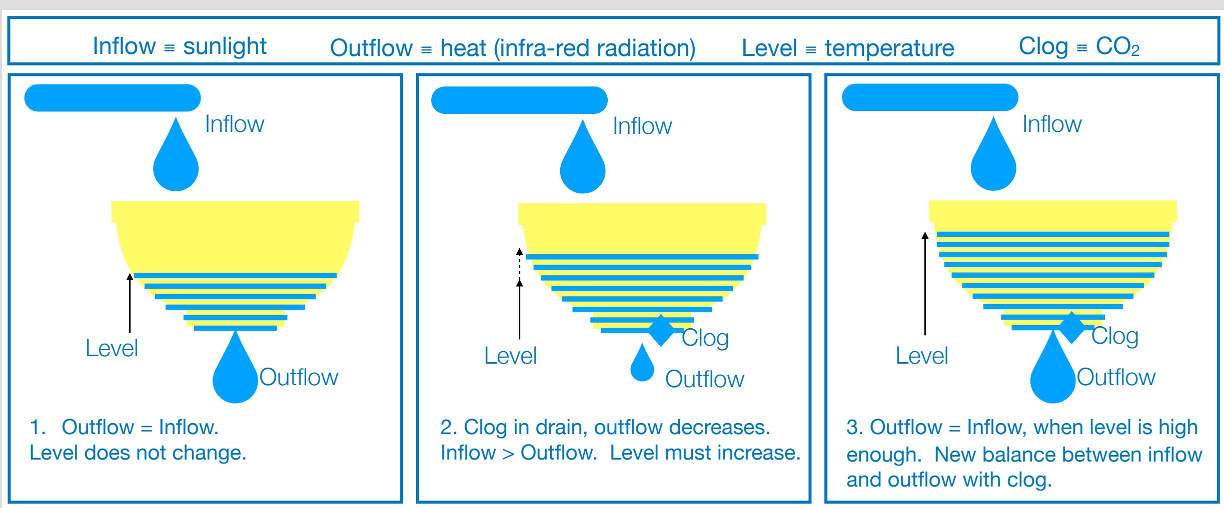

Figure SB2.1. *Earth's energy balance determines its global average temperature and can be described by a sink analogy.*

climate system, remains an important source of uncertainty. At regional and local spatial scales these variations can continue to be important even after mid-century.

2.2 Localizing Climate Projections

Climate projections are typically conducted using global climate models (GCMs) having spatial resolutions of 1-3 degrees of latitude and longitude (~100-300 km). However, development of local and state-level adaptation strategies requires climate projections at a much finer spatial scale, often at several kilometers resolution. To bridge this scale gap, climate downscaling can be used to translate the large spatial scales of the GCMs to smaller scales relevant to local decision making.

The dynamical downscaling method makes use of regional climate models (RCMs), which essentially function as a "mini-GCM" over a limited area. The boundaries of the specified region are “driven” by data from GCMs or observations. However, dynamical downscaling is still prohibitively costly, does not provide sufficiently high resolution, and may introduce additional errors (e.g., Mearns et al., 2012; Ahmed et al., 2013). For example, the North American Regional Climate Change Assessment Program (Means et al., 2019) produced dynamic downscaling of future climate projections using several RCMs but at a 50-km resolution, which is still too coarse for local and state assessment.

An alternative method is statistical downscaling, which due to its computational efficiency is frequently used to downscale a large number of GCMs and even RCMs (e.g., Ahmed et al., 2013). Many statistical downscaling approaches have been proposed (e.g., Gutmann et al., 2014; Abatzoglou and Brown, 2012; Pierce et al., 2014), and most are based on the assumption that the statistical relationships between large-scale atmosphere and local-scale observational data established for the present-day climate still hold in future climate. Two of these approaches have been applied to develop multi-model climate projection databases for the entire United States at a spatial resolution of several kilometers, including the Multivariate

Sidebox 2.2: Uncertainty in Projections of Future Climate

Uncertainties in future climate projections stem from three primary sources: natural climatic variability (internal variability), imperfect knowledge of the climate system (model uncertainty), and the unclear trajectory of future greenhouse gas emissions (scenario uncertainty). Scientists analyze simulations of earth’s climate from an array of climate models in order to understand the range of possible climate futures and their attendant uncertainties. While it is impossible to formulate universal criteria for selecting a single “best” climate model, it is common scientific practice to select a subset of models that simulate well the observed global climate and the relevant climate processes for a particular area. In this report, we discuss results from eight high-performing models that accurately reproduce historical climate trends and patterns in Connecticut, while also ensuring diversity in model response to greenhouse gas forcing. The new results presented here focus where models exhibit a high degree of agreement regarding the sign of the change, signaling areas where climate projections are likely to be robust and reliable. Such areas of model agreement change are plotted with color (non-white) on maps in this report (see, for example, Fig. 3.2 on page 17). We highlight regions where projected changes are significant – in other words, where such a change could have happened by chance less than 10% of the time. The hatching patterns indicate regions that do not show a significant change.

Adaptive Constructed Analogs approach (MACA, Abatzoglou and Brown, 2012) and the Localized Constructed Analogs approach (LOCA, Pierce et al., 2014, 2015). Both MACA and LOCA are "weather analog" methods that take GCM output and find analogous weather patterns from a historical database. The two methods differ in the number of analogs used to determine the values of climate variables (especially precipitation) at each grid cell. For example, MACA averages across multiple chosen analogs, while LOCA chooses a single analog that provides the best match. Both methods apply bias corrections to the present day GCM data, but at different stages of processing.

The MACA approach (Abatzoglou and Brown, 2012) has been applied to daily output from 20 CMIP5 GCMs to develop the MACAv2-METDATA database (referred to as MACA hereafter), using gridded METDATA (Abatzoglou, 2011) as the observational reference for algorithm training and bias correction at a 1/24 degree (~4km) spatial resolution. The LOCA approach has been applied to daily output from 32 CMIP5 GCMs to develop the LOCA database (Piece et al., 2014, 2015), using the Livneh et al. (2015) gridded observational reference for algorithm training and bias correction at a 1/16 degree (~6km) spatial resolution.

2.3 Observations and Projections Used in this Report

Most recent studies of temperature and rainfall have been conducted at the regional level (i.e., Northeast U.S.). To obtain locally specific information for Connecticut, new analyses are performed based on meteorological station data for past observations, and high-resolution gridded data for past climate and future projections. Employed in this analysis are daily precipitation, and maximum and minimum temperatures. The datasets are detailed below and given in Table 2.1.

The meteorological station observations of temperature and precipitation are from the Global Historical Climatology Network (GHCN) archive (Menne et al., 2012) and the National Climatic

Table 2.1. Datasets employed in this assessment of temperature and rainfall for Connecticut.

	Data	Period	Resolution	Reference
Station Observations	GHCN	1950-2005	—	Menne et al., 2012
	NCDC Climate	1895-2015	—	Karl and Koss, 1984
Gridded Observations	METDATA	1980-2017	4km	Abatzoglou, 2011
	Livneh	1950-2013	6km	Livneh et al., 2015
Gridded Simulations and Projections	MACA	1980-2005 2006-2099	4km	Abatzoglou and Brown, 2012
	LOCA	1950-2005 2006-2099	6km	Livneh et al., 2015

Data Center (NCDC) Connecticut Climate Divisional data for statewide analysis (Karl and Koss, 1984).

Two gridded observational datasets have been examined, including METDATA (which is the training data for MACA) available for the period 1980-2017 at a 4-km resolution and the data of Livneh et al. (2015) (which is the training data for LOCA) available for the period 1950-2013 at a 6-km resolution. Because the Livneh et al. (2015) data record is longer than METDATA, in this assessment, we use the Livneh et al. (2015) data to assess the observed trends and changes of average temperature, precipitation and indicators involving temporal accumulation of precipitation. The Livneh et al. (2015) data is also used to evaluate temperature extremes. The METDATA is used to assess observed trends in precipitation extremes represented by daily statistics because of its greater fidelity to daily observation in Connecticut. The future projections for temperature, precipitation, and extremes are based on MACA data.

The greater fidelity of the METDATA can be seen in Figure A-2.1 which compares the daily precipitation from the two datasets with meteorological station data during several extreme events over southwest Connecticut. Daily precipitation in METDATA agrees remarkably well with observations from meteorological stations in Connecticut (and other states of the Northeast as well). The Livneh et al. (2015) data tends to underestimate heavy precipitation and overestimate light precipitation. However, when precipitation is aggregated over a longer time period (e.g., 5 days, monthly, annual), the difference between the two datasets becomes negligible.

2.4 Analysis Methods

Projected future changes in temperature, precipitation, and various extreme indices are assessed based on the 8-model ensemble from MACA, and our assessment focuses on both the mid-century (2040-69) and late century (2070-99) under RCP8.5 relative to the late 20th century (1970-99). Standard statistical tests are applied to determine if changes and trends are larger than would be expected from random variations alone. The MACA multi-model ensemble mean of the various extreme indices closely resemble the indices from the observational reference METDATA, as expected due to the use of bias correction in the MACA methodology. On a year-to-year basis the multi-model ensemble mean is not expected to agree with observations, since taking the multi-model ensemble mean eliminates most of the inter-annual variation associated with the model and internal variability.

To assess future changes of temperature and precipitation extremes, all indices are estimated for each of the three 30-year periods (1970-99, 2040-69, and 2070-99). For each period, most indices are defined for each of the 30 years, and their 30-year averages are used as the representative for that period. Some indices involve the estimation of recurrence interval (T) of a given event size and/or the event size (XT) corresponding to a given recurrence interval; these are defined through frequency analysis by fitting a theoretical distribution to the 30 years of data in each period for each model. Specifically, data from each of the 30 years are used to estimate the parameters of a theoretical distribution, and the derived parameters of distribution are then used to estimate the theoretical T or XT. Our frequency analysis in this report assumes normal distribution for the annual and seasonal water availability (P-PET), and assumes Generalized Extreme Value (GEV) distribution for the 1-day maximum precipitation (R1d) and 5-day maximum precipitation (R5d). The L-moments methods (Hoskins, 1990; Kharin et al., 2013) is used to estimate the GEV distribution parameters.

3. Temperature changes in Connecticut

Temperatures are changing in Connecticut, and warming is expected to accelerate for all measures of temperature and related extremes in the high CO2 (RCP8.5) scenario. In this chapter we will show that since 1895, increases are seen in annual (0.3^{o}F/decade) and seasonal average temperatures, with the greatest increase experienced in winter (December—February, 0.4^{o}F/decade). Larger increases are projected for annual changes in temperature (+5 to +8^{o}F annual mean, mid- and late-century, respectively). Projections indicate that all temperature indices examined, including nighttime heat and warm spells show large changes in response to continued, accelerating warming. Here we will first review the published literature and then present a new analysis of temperature changes for Connecticut.

3.1 Temperature in the Northeast U.S.

Expectations of temperature changes

The theoretical foundations for the "Greenhouse Theory of Climate"[1] were established in the mid-1800s as scientists investigated potential causes of the northern hemisphere glacial advance that peaked ~20,000 years ago (Fourier, 1824; Tyndall, 1861). The physical chemistry of greenhouse gases (carbon dioxide [CO_2], methane [CH_4], water vapor [H_2Ov], ozone [O_3], and others) is well understood: each of these gases interacts with earth's infra-red (IR) "heat" radiation and direct of this heat, otherwise lost to outer space, downward to warm the surface. Of the greenhouse gases, CO_2 is the most important driver of change because of its long-lifetime in the atmosphere (effectively 100s of years), in contrast to water vapor, which is more abundant but remains in the atmosphere for only weeks to months, and hence acts to amplify the changes driven by CO_2. In this way greenhouse gases are major players in earth's energy balance and, consequently, in determining our planet's average temperature, a fact that is supported by multiple lines of evidence, including theory, observations, models, and paleoclimate proxies (IPCC, 2013). The Greenhouse Theory of Climate indicates that higher concentrations of greenhouse gases result in warmer temperatures at earth's surface, while lower atmospheric concentrations cool surface temperature globally. Atmospheric CO_2 has increased from 280 parts per million (pre-industrial, 1860s value) to over 410 parts per million. Earth's surface temperature is responding to the radiative imbalance caused by the ongoing rapid increase in CO_2, and global average temperature has increased by +1.8^{o}F between 1901-2016 (Wuebbles et al., 2017).

Early calculations indicated that greenhouse warming of earth's climate would not be equally distributed; rather, polar regions would experience larger changes in temperature (because of amplifying processes related to the disappearance of ice) than those near the equator (Arrhenius, 1896). This "polar amplification", or increased warming at higher latitudes is clear in observations and climate models and has important implications for Connecticut. Another expectation from Greenhouse Theory is that changes in nighttime temperatures should be more apparent than those of daytime. During the day incoming sunlight (shortwave radiation) is dominant and can mask the smaller changes in heating (IR) due to greenhouse gases. At night IR cooling to space is dominant, and thus the effect of greenhouse gases to reduce Earth's heat loss, and redirect heat to warm the surface, leading to greater nighttime warming.

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[1] For further reading see Henson, R. (2019) *The Thinking Person's Guide to Climate Change*, AMS, pp. 576.

Review of prior research for the Northeast

Because there are no recent studies that have examined observations for the state of Connecticut, we review results from U.S. National Assessments and peer-reviewed journal articles focusing on the Northeast. The published literature indicates observed temperatures across the Northeast have increased during the 20th century. Prior analyses have also suggested continued accelerated warming through the 21st century in the case of higher greenhouse gas emissions, with the Northeast responding more rapidly than temperatures across the U.S.

Analysis of observed mean temperature changes and trends for the Northeast region, defined as the New England states, New York and the mid-Atlantic including West Virginia, indicate that annual average temperature has increased by +1.43°F, with the annual average maximum temperature increase of +1.16°F and annual average minimum temperature increase of +1.70°F (Vose et al., 2017), where computed changes are the difference between the average for a recent period (1986–2016) and the average for the first half of the last century (1901–1960). The temperature trend computed for the same region is +0.16°F/decade (over the period 1895-2011, Horton et al., 2014). Another study indicates an observed trend of +0.18°F/decade computed for a smaller Northeast region limited to New England and New York (over the period 1901-2005, Lynch et al., 2016). Seasonally the largest observed temperature trends have been seen in winter, +0.29°F/decade (Lynch et al., 2016). Variations in the magnitude of the observed trends depend on the specifications of the region and time periods analyzed.

Projections of mean temperature for the Northeast region indicate increases of +4.0-5.1°F by mid-century (2036-2065) and 5.3-9.1°F by late century (2071-2100), using 1976-2005 as the reference period and where the values represent lower and higher radiative forcing scenarios (Vose et al., 2017). For the smaller Northeast region and higher (CO_2) forcing scenario (RCP8.5) the projections of mean temperature change are +6.2°F by mid-century, and +10.1°F by late century. Consistent with observations, the largest changes are projected for winter of +11.4°F (Lynch et al., 2016). Further analysis of these climate model projections suggests that the Northeast is the fastest warming region in the contiguous U.S., projected to warm by +5.4°F when global warming reaches +3.6°F (Karmalkar and Bradley, 2017).

3.2 New Analysis of Temperature for Connecticut

Observed Annual and Seasonal Temperatures

Station observations with records beginning in 1895 have been averaged for Connecticut (Fig. 3.1), and show statistically significant trends in annual (+0.3°F/decade) and seasonal temperatures with the largest increase in winter (DJF, +0.4°F/decade). This 120 year record reveals that annual average temperature is currently near 50°F and has already increased from 47°F at the start of the 20th century. Winter temperatures averaged near 26°F at that time, well below freezing, and are now almost 30°F.

The observed trends for Connecticut are consistent with, but larger in magnitude than those computed for the Northeast. Station observations from three representative locations in CT (Storrs in northeast, Groton along south coast and Falls Village in northwest) corroborate the statewide results (Fig. A-3.1). Seasonally the observed trends have been largest in winter (DJF), consistent with earlier analysis (Lynch et al., 2016) for the Northeast.

In addition to trends in average temperature for the state, we examine maps of temperature changes (Figure 3.2). Although temperatures exhibit strong seasonality (near 30°F in winter and 70°F in summer), the spatial patterns of temperature (Fig. 3.2, left) are consistent through the year due to topography, coastline and latitude. Temperatures are relatively cooler in the northwest and northeast hills, and warmer in the Connecticut River and Hudson River valleys, with the warmest temperatures along the south coast. Thus, average temperatures are lower moving from south to north, with some added structure resulting from the topographic features in the state. The northwest hills and the northeast hills are cooler than the Connecticut River valley by several degrees.

Observed maps of temperature change (Fig. 3.2, center) shows warming through most of the state. However, for the periods analyzed (1980-2009 minus 1950-1979) significant increases (more than 1°F) have occurred only in the southern half of Connecticut. Statistical significance means that the observed trends are larger than would be expected from random temperature variations alone.

The observed time series (1950-2009) of annual and seasonal temperatures averaged for the state (Fig. 3.2, right) show the observed increase (black), with the models (red: model mean, pink shading: model range) capturing this trend reasonably well.

Projections of Annual and Seasonal Temperatures

The downscaled multi-model projections (2010-2100) indicate unabated and significant increases in annual and seasonal temperatures through the 21st century, with average winter temperatures above freezing (~35°F) by the mid-century and above 40°F by end century (Fig. 3.2f). Average summer temperatures increase to 75°F by mid-century and to near 80°F by end century. Maps depicting projected temperature change from the downscaled multi-model ensemble suggest a pattern with greater warming to the north and west (Fig. 3.3).

Table 3.1. Annual and Seasonal Mean Temperatures Projections for Connecticut. Multi-model ensemble of temperature climatology during the reference period and the changes projected in the RCP8.5 scenario for midcentury and late century, averaged over Connecticut. Units: °F. Data Source: Observed temperature (Livneh); Downscaled model projections for RCP8.5 (MACA, METDATA).

Temperature (°F)	1970-99 Reference	2040-69 Changes	2070-99 Changes
Annual Mean	50.1 ± 1.0	5.1 ± 1.3	8.3 ± 2.0
Winter (DJF)	30.2 ± 2.4	5.2 ± 1.4	8.7 ± 2.3
Spring (MAM)	47.8 ± 1.7	4.4 ± 0.9	7.1 ± 1.3
Summer (JJA)	69.9 ± 1.1	5.5 ± 1.5	8.8 ± 2.4
Fall (SON)	52.8 ± 1.4	5.2 ± 1.6	9.6 ± 2.4

Summary: Average Temperatures

Average temperatures in Connecticut have been rising since 1895 at a rate of +0.3°F/decade, with winter (DJF) temperatures increasing faster (+0.4°F/decade) than spring (MAM), summer (JJA) and fall (SON), all with observed warming rate of +0.2°F/decade (Fig. 3.1). Increasing

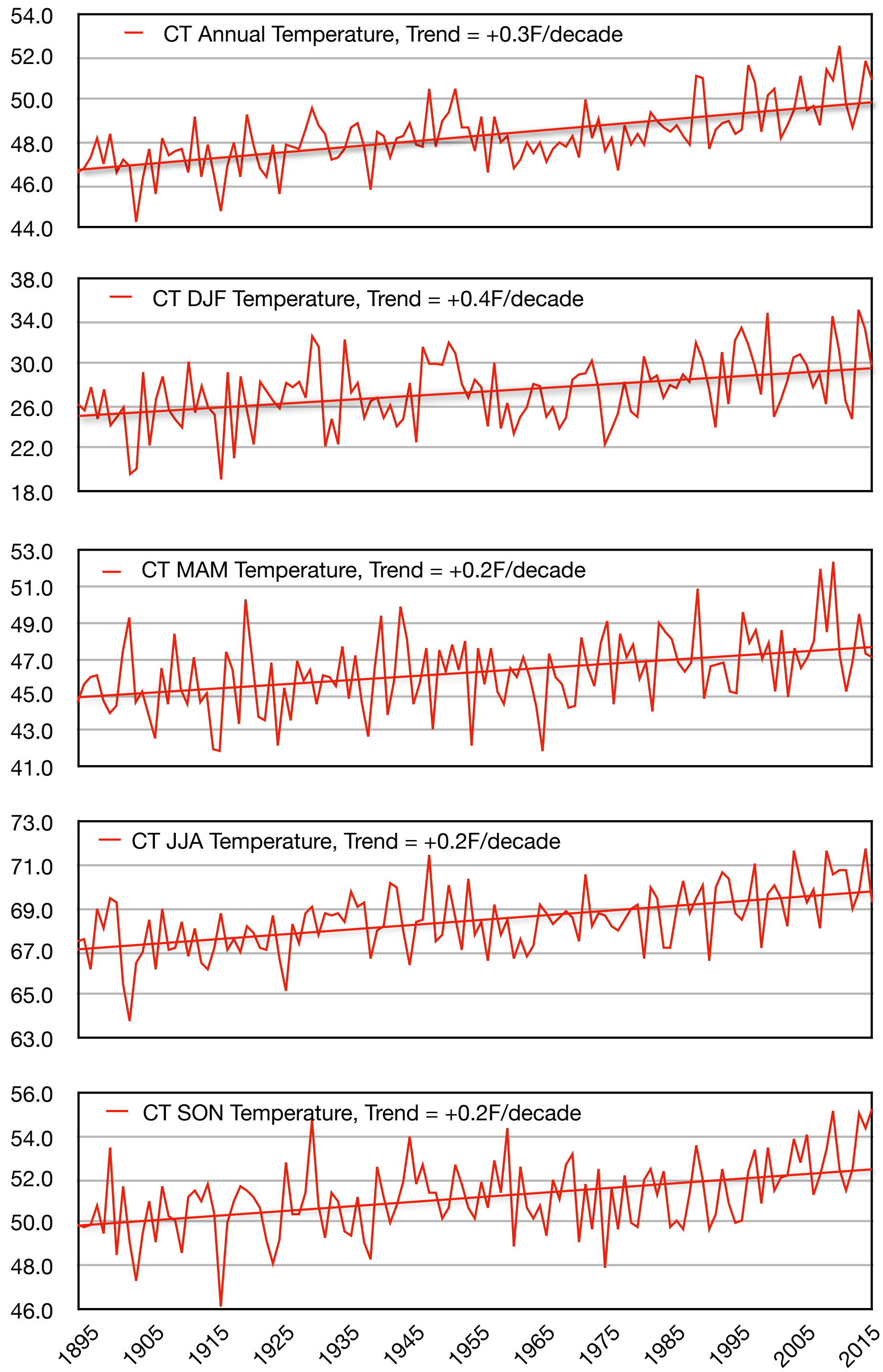

Figure 3.1. Observed Temperature Trends in Connecticut. Average annual and seasonal (December-February (DJF), March-May (MAM), June – August (JJA) and September – November (SON)) temperatures for the state of Connecticut for the period 1895 – 2015, shown with linear trend (straight line). Source: State climate division data from NOAA/NCDC.

temperature trends in annual and seasonal means can also be seen in the gridded observations analyzed here since the 1950's (Fig. 3.2, right).

Temperature projections indicate +5 to +8°F warming by mid and late century respectively. These projections are statistically significant and larger than observed changes since the 1950's (~+1°F annual mean) and also since 1895 (~+3°F). While observed temperature

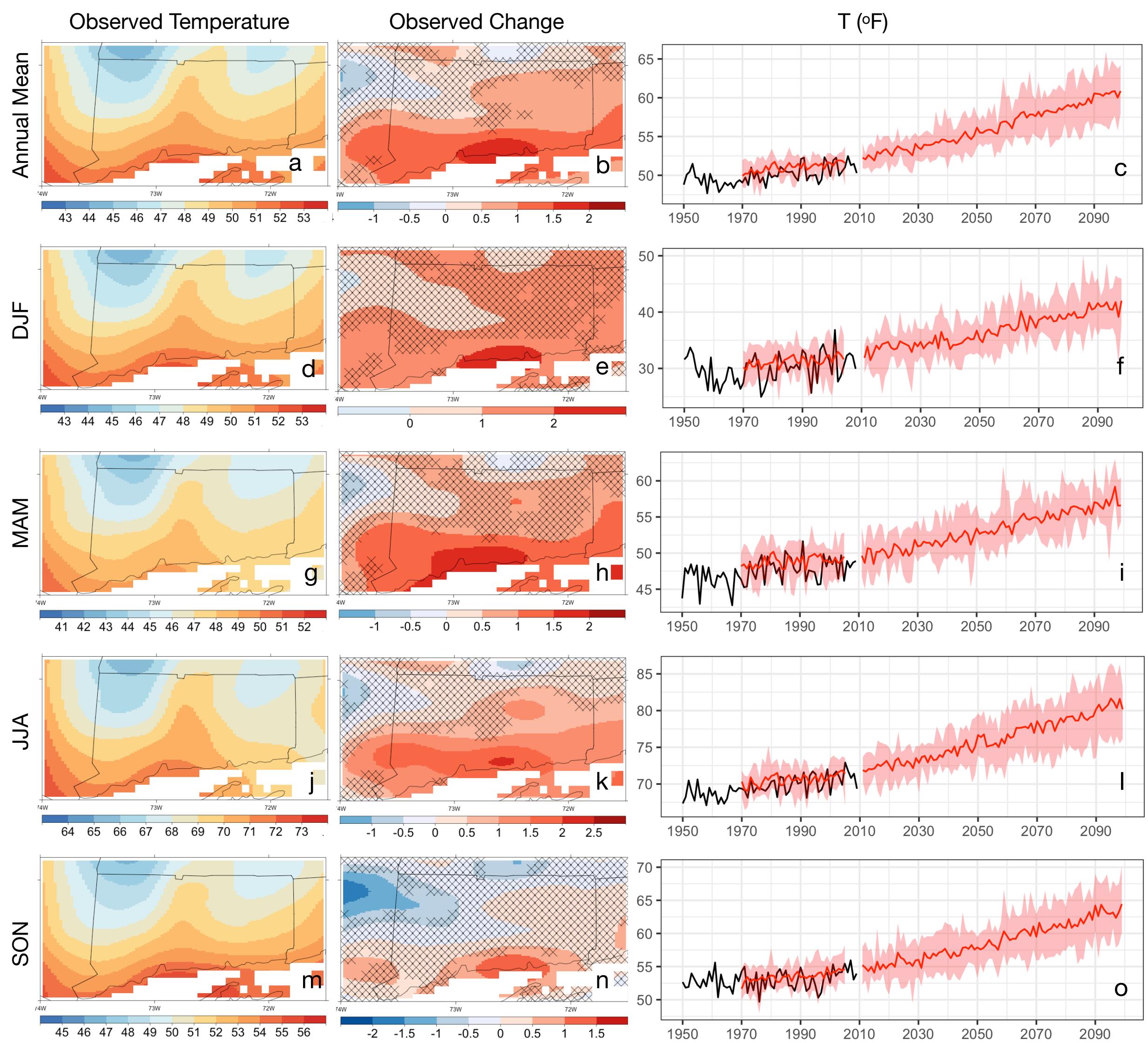

Figure 3.2. Annual and Seasonal Mean Temperature. Observed annual and seasonal mean temperatures (°F) and changes: [Left] observed annual (a) and seasonal (d,g,j,m) average temperature for the 1970-1999 reference period, [Middle] observed change in annual (b) and seasonal (e,h,k,n) average temperature (later – earlier: 1980-2009 minus 1950-1979), and [Right] observed (black) and model projected (red) time series of annual (c) and seasonal (f,i,l,o) average temperature for the state. Pink shading indicates the range (maximum and minimum) within the model projections from eight climate models for 1970-2099. Data Source: Observed temperature (Livneh); Downscaled model projections for RCP8.5 (MACA, METDATA). Black hatching indicates changes that are not significant.

increases have been largest in winter (Fig. 3.1), projections suggest that by mid-century the largest warming will be in summer (JJA, +6ºF) and by late-century the largest increase will be in fall (SON, +10 ºF) (Table 3.1). The greater summer and fall temperature increases are likely related to the surface drying that results from higher evapotranspiration rates in the absence of increases in precipitation (see Section 4).

The patterns of recent change are quite different from patterns of projected changes. The observed changes reveal more warming along the south coast and in the eastern half of the

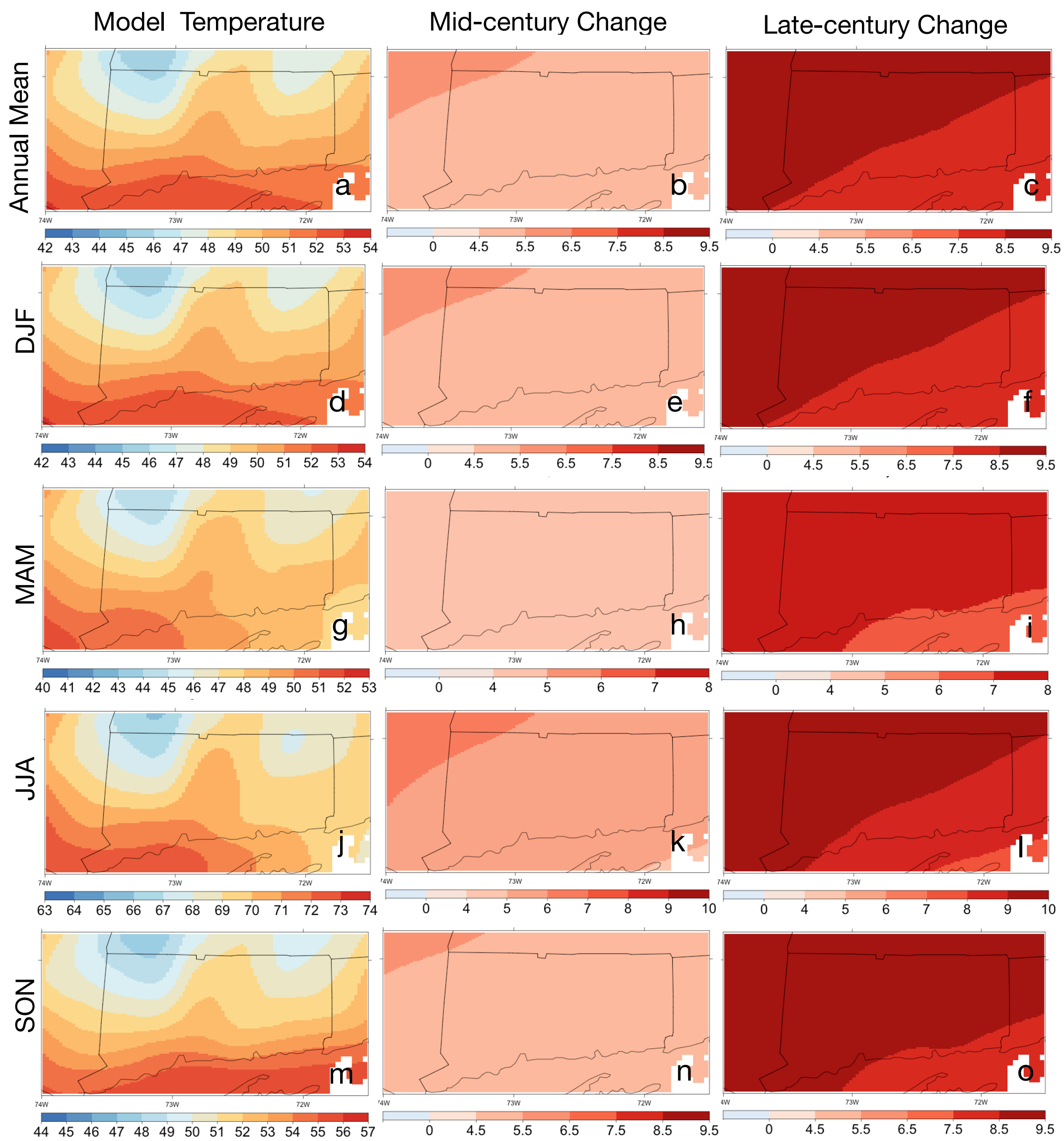

Figure 3.3. Projections of Annual and Seasonal Mean Temperature. Mulit-model mean computed from eight climate model simulations of annual and seasonal mean temperatures (ºF): [Left] Bias corrected annual (a) and seasonal (d,g,j,m) average temperature for the 1970-1999 reference period, [Middle] projected annual (b) and seasonal (e,h,k,n) changes by mid-century (2040-2069 minus 1970-1999), and [Right] projected annual (c) and seasonal (f,i,l,o) changes by late-century (2070-2099 minus 1970-1999). Data Source: Downscaled model projections for RCP8.5 (MACA, METDATA).

state (Fig. 3.2, center), while projections suggest very little spatial structure with nearly uniform warming and increase towards the north and west (Fig. 3.3, center and right). At the spatial scale for the state of Connecticut, there are many local factors that affect temperature patterns. Global climate models do not incorporate local-level details, and even the downscaling methods cannot compensate for this.

3.3 Daily Temperature Extremes in the Northeast U.S.

Review of prior research for the Northeast

As global mean temperature increases, the statistics of a distribution of daily temperatures would indicate that thresholds specifying moderate extremes (see Sidebox 3.1) would occur with greater frequency. This is the expectation in a warming climate where both the amount and rate of warming depend on greenhouse gas emissions. In addition, continents warm faster than oceans, thus daily temperature extremes on land are projected to warm faster than global annual mean temperature.

A number of indices that measure daily temperature extremes have been analyzed at the global and national scale. Globally the number of cold days and cold nights have decreased and the number of warm days and nights have increased since 1950 (Cutter et al., 2012). The frequency of heat waves has increased since the middle of the 20th century and more high temperature records have been exceeded than low temperature records. Models project substantial warming in temperature extremes by the end of the 21st century with higher CO_2 scenarios resulting in larger changes. The frequency and magnitude of warm days and nights and decreases in the cold days and nights is expected to occur through the 21st century at the global scale, and the length, frequency, and/or intensity of heat waves increase over most land areas (Cutter et al., 2012).

Studies focussed on the Northeast show a clear warming in the coldest (+2.83°F) day of the year, the warmest day of the year has cooled slightly (-.92°F) since the baseline includes the extreme heat seen in the 1930's (Vose et al., 2017). Increasing temperatures have resulted in a longer average frost free season by more than 10 days (Walsh et al., 2014, NCA). These results are consistent with two recent studies that have examined observed changes in extremes. Brown et al. (2010) analyzed temperature indices using station data from the New England states plus New York and Pennsylvania beginning in 1895. Thibeault and Seth (2014) examine temperature extreme indices for most of New England and a bit of New York since 1950. The two studies specify different regions and time periods but find consistent results. For example, both find that temperature indices based on daily minimum temperatures show substantial trends, while indices based on daily maximum temperatures show mixed changes in recent observed period.

Analysis of projected changes in temperature extremes by mid-century show warming of the coldest (+9.51°F) and warmest (+6.51°F) day of year and coldest 5-day, 1 in 10 year event (+15.93°F) and warmest 5-day, 1 in 10 year event (+12.88°F) for the Northeast (Vose et al., 2017). Changes are the difference between the average for mid-century (2036–2065) and the average for near-present (1976–2005) under RCP8.5 and derived from 32 climate models that were statistically downscaled using the Localized Constructed Analogs (LOCA) technique. These projections are consistent with recent studies focused on the Northeast, e.g., Ning et al. (2015) and Thibeault and Seth (2014).

Daily temperature indices for Connecticut

The new analysis presented in this report specifies a region relevant for planning in Connecticut. We compare the new CT results with those referenced above for the Northeast. We evaluate temperature indices suggested by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Peterson et al., 2005). Ten indices (Table 3.2), based on daily maximum or minimum temperature values, are presented in this report. Some are based on fixed thresholds that are of relevance to particular applications and are the same for all locations. Other indices are based on thresholds that vary from location to location and are typically defined as a percentile of the relevant data series. All 10 indices are computed annually using the RClimDex software developed by ETCCDI. They can be considered in five groups:

Temperature Indices examine maximum and minimum temperatures (ºF), where TXX is the warmest day of the year and TNN is the coldest night of the year.

Daytime Heat Indices count the number of days in a year that meet a threshold and include summer days (SU), and the number of days associated with warm spells (WSDI) which include extreme heat waves that pose dangerous health risks as well as periods of unusual warmth.

Nighttime Heat Indices that measure the number of days in a year that meet a threshold for warmth at night are tropical nights (TR), and the length of the growing season (GSL).

Daytime Cold Indices examine thresholds for daytime cold temperatures, including ice days (ID), and the number of days associated with cold spells (CSDI).

Nighttime Cold Indices examine nighttime cold temperatures including frost days (FD). The daily range in temperature (DTR) depends on both night time and daytime temperatures.

Table 3.2. Temperature Indices Computed for Connecticut. Definitions of 10 temperature indices presented in this study (Peterson, et al., 2005). All the indices are calculated with RClimDex on an annual basis using daily maximum temperature (TX), daily minimum temperature (TN).

Index	**Index name**	**Definitions**	**Units**
Temperature Indices (daily maximum and minimum)			
TXX	Warmest day	Annual maximum value of daily maximum temp	ºF
TNN	Coldest night	Annual minimum value of daily minimum temp	ºF
Daytime Heat Indices			
SU	Summer days	Annual count when TX (daily maximum) >25ºC (77ºF)	Days
WSDI	Warm spells	Annual count of warm spell days, where a warm spell is 6 or more consecutive days with TX>90th percentile	Days
Nightime Heat Indices			
TR	Tropical nights	Annual count when TN (daily minimum) >20ºC (68ºF)	Days

GSL	Growing season length	Annual count between first span of at least 6 days with TG>5°C (41°F) and first span after July 1 of 6 days with TG<5°C	Days
Daytime Cold Indices			
ID	Ice days	Annual count when TX (daily maximum) <0°C (32°F)	Days
CSDI	Cold spells	Annual count of cold spell days, where a cold spell is 6 or more consecutive days with TN<10th percentile	Days
Nightime Cold Indices			
FD	Frost days	Annual count when TN (daily minimum) <0°C (32°F)	Days
DTR	Daily range of temperature	Annual mean difference between TX and TN	°F

Sidebox 3.1: How do we see changes in Extremes? *Temperatures in a region tend to be characterized by a normal (bell curve) distribution, where most observations fall within a range near the mean and progressively fewer occurrences in the tails of the distribution. Thresholds for hot or cold values near the tails define extreme values. A changing climate shifts temperature distributions and can affect the mean (peak), the variance (width) and its overall shape (see Figure SB3.1). Given current societal and ecological thresholds for extreme temperatures, shifts in the distribution of temperatures can result in increased frequency of temperatures in the extreme range and possibly both tails (hot and cold) if the variance also increases. Beyond daily extremes, the accumulation of heat or cold over time and across a region, and/or the combined effects of temperature/rainfall or temperature/humidity that are not necessarily extreme independently can result in unprecedented weather and climate events. Natural variability will continue to be an important factor in shaping future extremes in addition to the effect of anthropogenic changes in climate.*

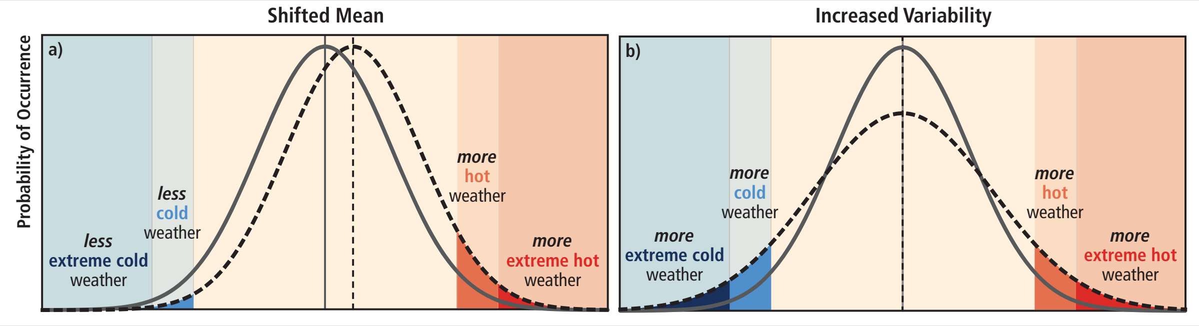

Figure SB3.1. How Extremes Are Influenced by Changes in the Distribution of Temperature. *Different changes in temperature distributions between present and future climate and their effects on extreme values of the distributions: (a) effects of a simple shift of the entire distribution toward a warmer climate; (b) effects of an increase in temperature variability with no shift in the mean. Both types of changes are expected to increase the frequency of extreme weather events. [Figure SPM.3 IPCC SREX, 2012.]*

3.4 New Analysis of Daily Temperature Extremes for Connecticut

Daily Temperature Indices

The warmest day of the year (TXX) for the recent period (Fig. 3.4a, black and Fig 3.4c), ranges from the upper 80s (ºF) to the upper 90s (ºF) across the state with the warmest temperatures in the Connecticut River valley and lower values in the western hills and along the southeast coast. Temperatures during the warmest day of the year show statistically significant increases (+2.5ºF) through the southern half of the state. The coldest night (TNN) for the recent period is colder in the western and eastern hills and less cold in the Connecticut River valley (Fig. A-3.2b,e). This coldest night index also shows warming with changes between +3-6ºF since the 1950s (Fig. A-3.2d); however these changes do not yet meet the threshold for significance.

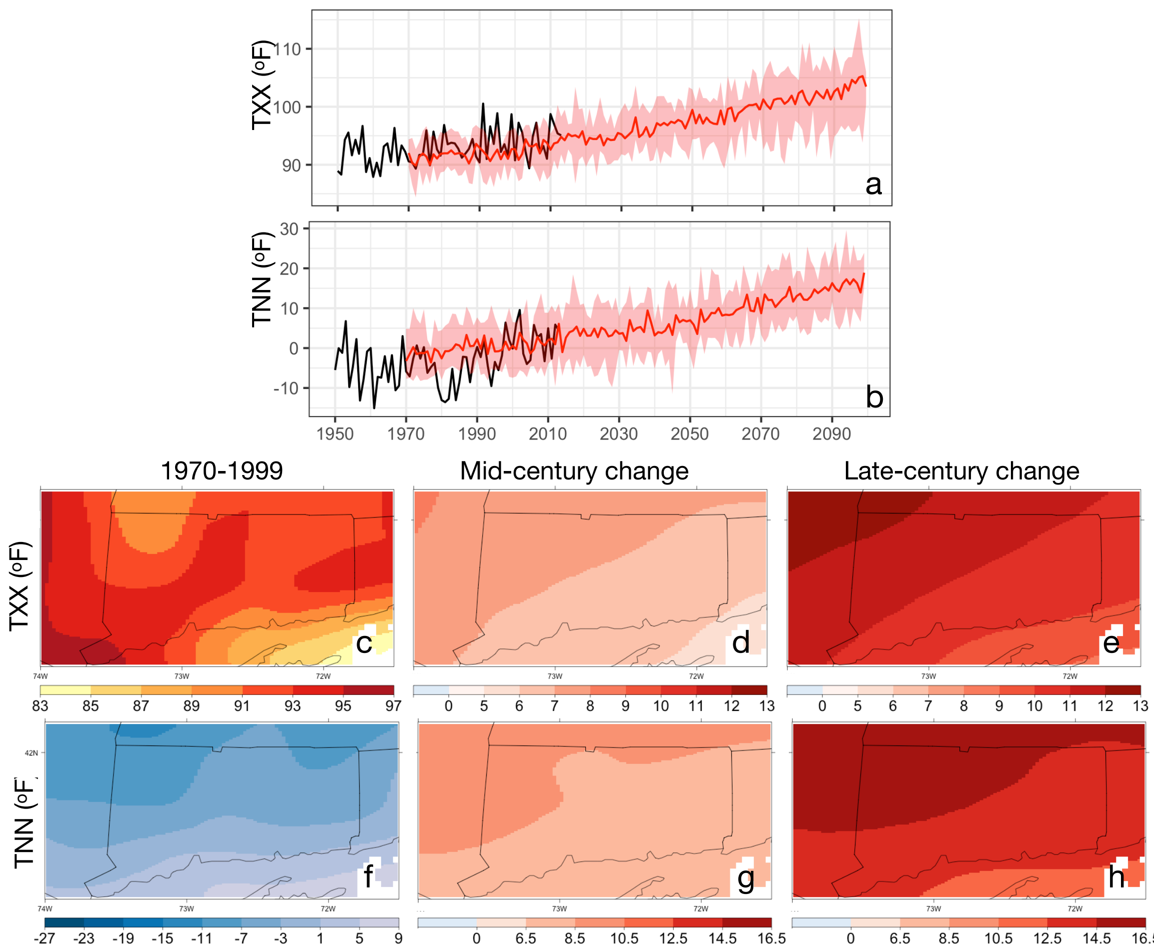

Figure 3.4. Warmest and Coldest Day of the Year. Time series of the annual warmest day (a) and coldest night (b) temperatures (ºF, TXX, TNN) with observations (black) and models (multi-model mean, red; model range pink shading). Model simulated and projected mid- and late- century changes in the warmest day (c,d,e) and coldest night (f,g,h) temperatures. Data Source: Observed temperature (Livneh); Downscaled model projections for RCP8.5 (MACA, METDATA).

The projections are consistent with the observed increases in TXX and TNN, and show significant increases that continue through the coming century, with the warmest day of the year consistently in the upper 90s (ºF) (+5-7ºF) by mid-century and well above 100ºF (+10-13ºF) by 2100 (Fig3.4d,e). The coldest night warms even more, from below 0ºF to ~ 15ºF (Fig3.4b). The projections indicate the greatest warming for both of these indices is inland (rather than along the coast) (Fig3.4g,h).

Projections of Heat Risk

Summer days (T>74ºF, SU) over recent decades average 80-100 days in the Connecticut and Hudson River valleys (compared to 50-80 days in the northwest and northeast hills (Fig. 3.5a,c). Summer days have increased in the state with statistically significant increases (5-10 days) in the southwestern region (Fig. A-3.3b,e). The observed pattern of warm spell days (WSDI) indicate that they are relatively infrequent (Fig. 3.5b,f). Since 1950 there has been a hint

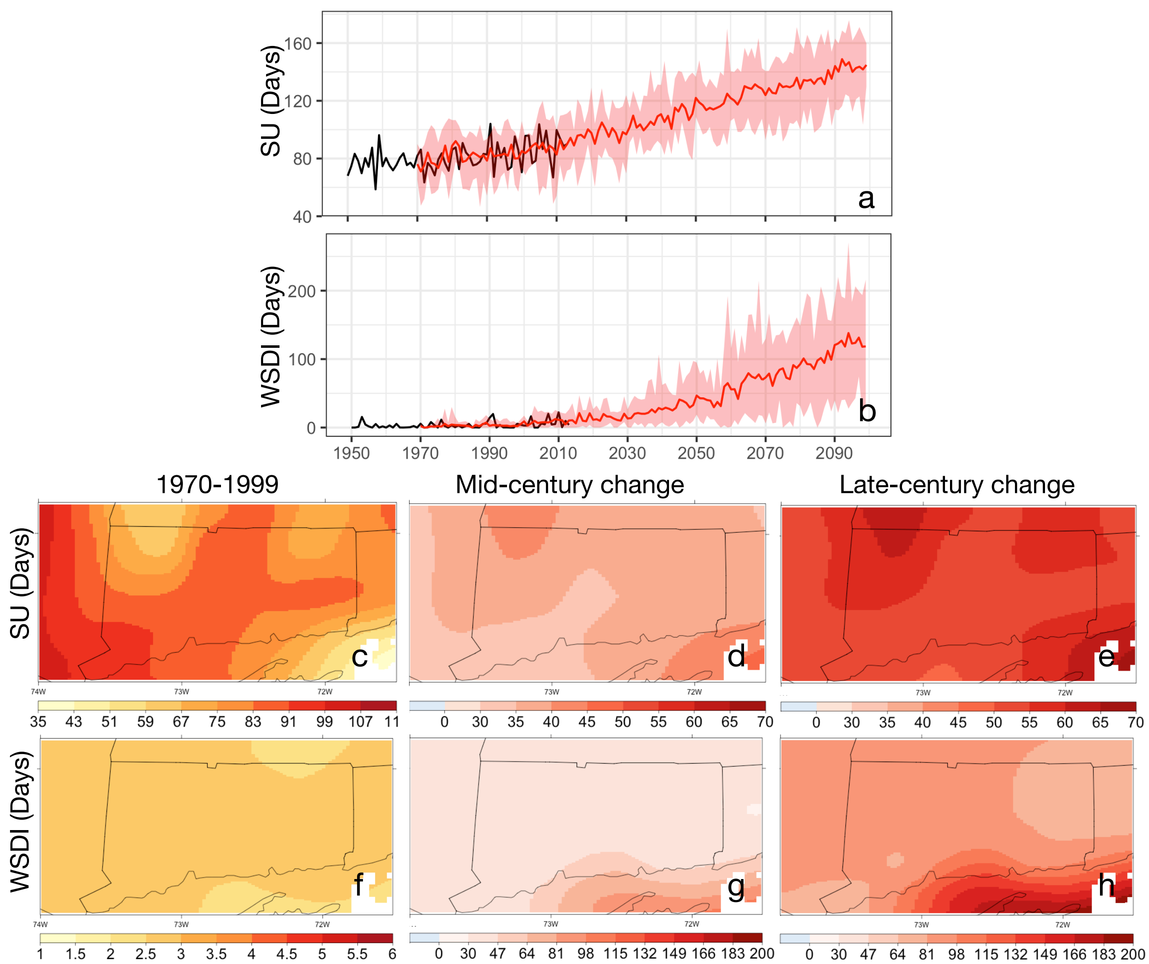

Figure 3.5. Daytime Heat: Summer Days and Warm Spells. Time series of the number of summer days (a) and warm spell days (b) (SU, WSDI) with observations (black) and models (multi-model mean, red; model range pink shading). Model simulated and projected mid- and late- century changes in summer days (c,d,e) and warm spell days (f,g,h). Data Source: Observed temperature (Livneh); Downscaled model projections for RCP8.5 (MACA, METDATA).

of increase through most of the state (Fig. A-3.3b) with no statistically significant changes between the two periods analysed.

Projected changes in these two annual indices show significant increases in the coming century (Fig. 3.5a,b). Summer days (SU) increase from a value of ~80 days (in the 1950s) to nearly 115 days in mid-century (+35 days), to more than 140 days (+60 days) in 2100. Similarly, the days associated with warm spells (WSDI) increases from less than 3 per year in the 1950s to ~50 per year by 2050 and more than 120 per year by 2100. It is notable that the increase in summer days is higher in the northwest and northeast hills (+65 days) (Fig. 3.5e).

Tropical nights (TR) in the 20th century occur on average 1-2 weeks/year in the Connecticut and Hudson River valleys (3-12 days) and less than 1 week in the northwest and northeast hills (0-6 days) (Fig. 3.6a,c). Tropical nights have increased with statistically significant increase in counts of TR (+4 to 12 days) along the southern coast (Fig. A-3.4b,e). The observed pattern of

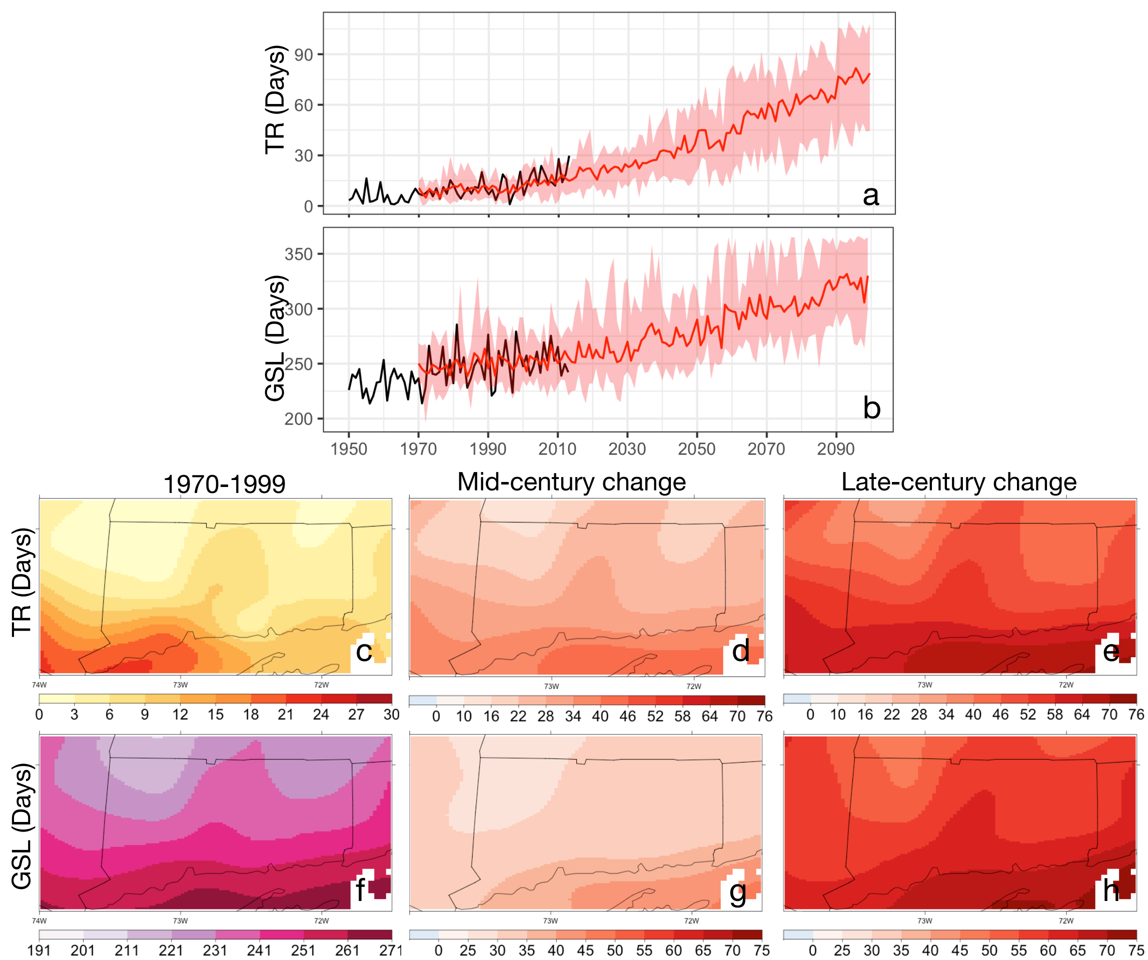

Figure 3.6. Nightime Heat: Tropical Nights and Length of Growing Season. Time series of the number of tropical nights (a) and growing season length (b) (TR, GSL) with observations (black) and models (multi-model mean, red; model range pink shading). Model simulated and projected mid- and late- century changes in tropical nights (c,d,e) and growing season length (f,g,h). Data Source: Observed temperature (Livneh); Downscaled model projections for RCP8.5 (MACA, METDATA).

the length of the growing season (GSL) indicates that it is generally longer in lower elevations and latitudes of the state (~240-260 days) and shorter in higher elevations and in the northern areas (~220 days or less) (Fig. 3.6f). Since 1950 there have been statistically significant increases (10-20 days) in the length of the growing season through most of the state except for the Litchfield hills (Fig. A-3.4d,f).

The time series of nighttime annual indices show substantial and significant increases in the coming century (Fig. 3.6d,e,g,h). Tropical nights (TR) increase from less than 10 days (1950s) to nearly 45 days in mid-century (+35 days), to more than 70 days (+60 days) in 2100. Similarly, the length of the growing season (GSL) increases from ~240 days in the 1950s to ~275 days (+35 days) by 2050 and more than 300 days (+60 days) by 2100. The increase in tropical nights is lower in the northwest and northeast hills (+30-45 days) than to the south, near the coast (+ 60 to 70 days) (Fig. 3.6e).

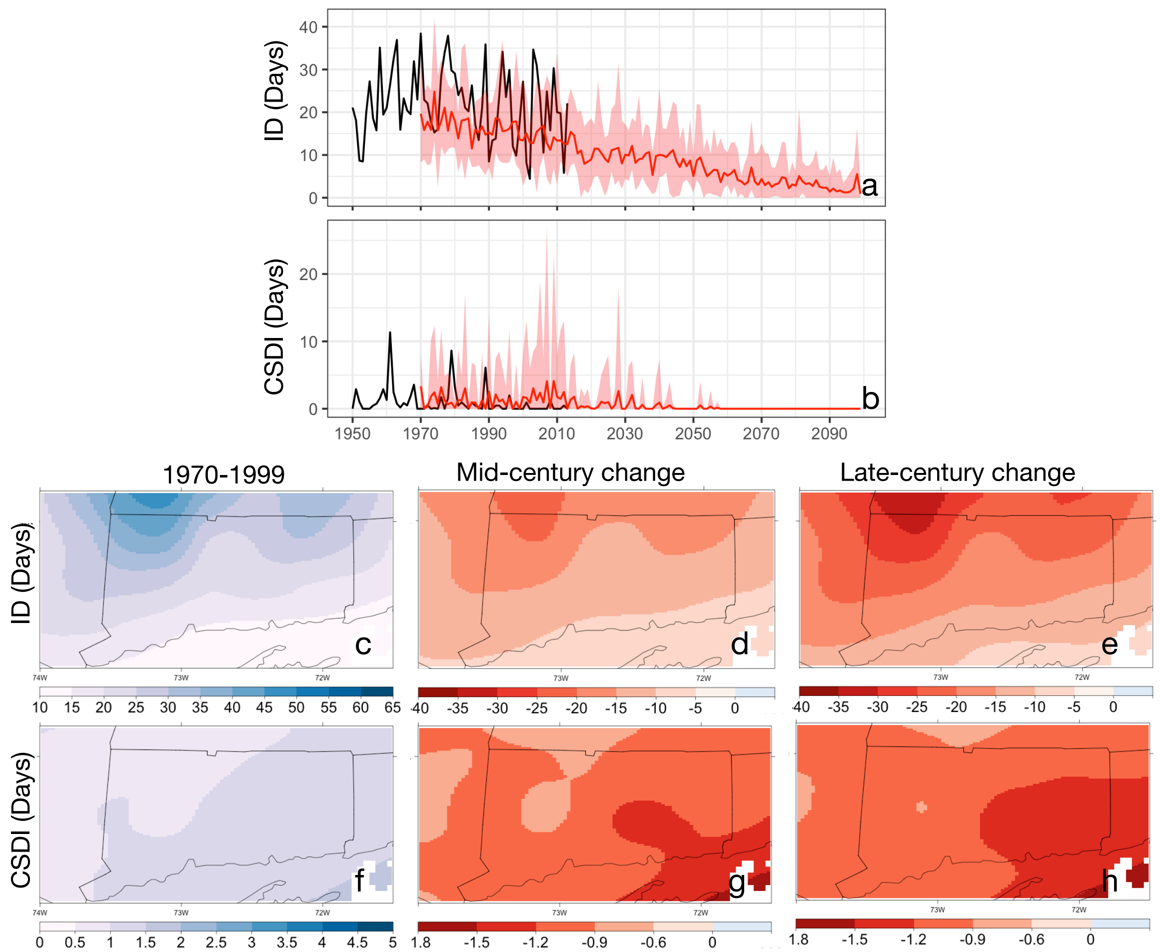

Figure 3.7. Daytime Cold: Ice Days and Cold Spells. Time series of the number of ice days (a) and cold spell days (b) (ID, CSDI) with observations (black) and models (multi-model mean, red; model range pink shading). Model simulated and projected mid- and late- century changes in ice days (c,d,e) and cold spell days (f,g,h). Data Source: Observed temperature (Livneh); Downscaled model projections for RCP8.5 (MACA, METDATA).

Projections of Cold Risk

Observed ice days (ID) show relatively fewer in the Connecticut and Hudson River valleys and along the south coast (less than 30 days) and more in the northwest and northeast hills (30 to 50 days/yr) (Fig. 3.7a,c). Changes in the number of ice days are not statistically significant although difference maps do indicate small decreases (-3 to -6 days) (Fig.A-3.5b,e). The observed pattern indicates that days associated with cold spells (CSDI) occur more often in the northern areas of the state (up to 5 per year) and are less frequent in the south central region (1 per year or fewer) (Fig. 3.7f). Since 1950 there has been a decrease, though not significant, in the number of cold spell days (Fig. A-3.5d,f).

The time series of these two indices show substantial and significant decreases in their occurrence in the coming century. The number of Ice days (ID) decrease from ~25 days (in the 1950s) to fewer than 10 days in mid-century (-15 days), and by 2100 there are ~5 or fewer ID days/yr (-20 days) (Fig. 3.7a). Similarly, the number of cold spell days (CSDI) decreases from

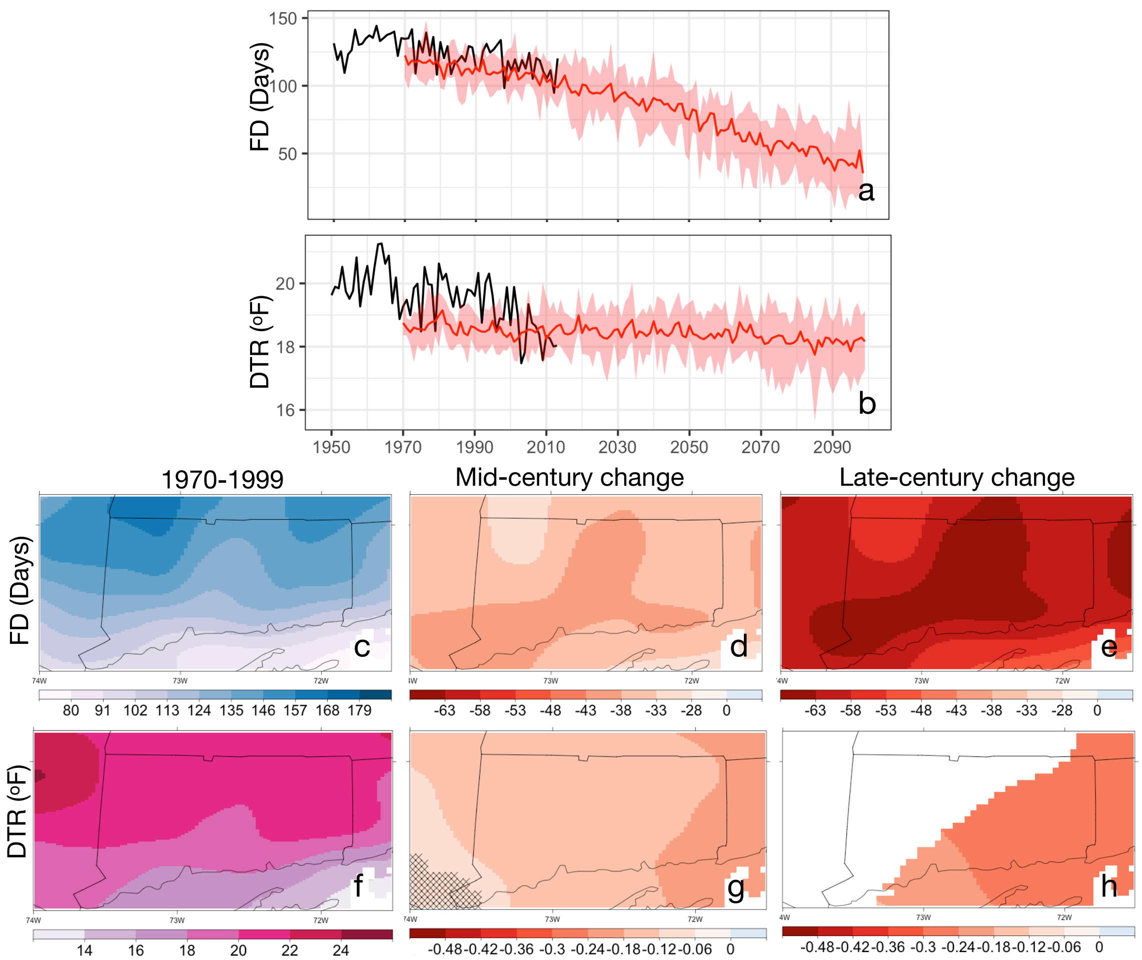

Figure 3.8. Nighttime Cold: Frost Days and Diurnal Temperature Range. Time series of the number of frost days (a) and diurnal temperature range (b) (FD, DTR) with observations (black) and models (multi-model mean, red; model range pink shading). Model simulated and projected mid- and late- century changes in frost days (c,d,e) and diurnal temperature range (f,g,h). Data Source: Observed temperature (Livneh); Downscaled model projections for RCP8.5 (MACA, METDATA).

more than ~4 per year in the 1950s to fewer than 1 per year by 2050 and zero by 2100 (Fig. 3.7b). The larger decreases in ice days in the northwest and northeast hills (-20 to -30 days/yr) is related to the fact that there are more in these regions in the present climate (Fig. 3.7d,e).

Frost days (FD) occur more often in the northwest and northeast hills of Connecticut (140-180 days) than in the lower Connecticut River valley and along the south coast (less than 125 days) (Fig. 3.8a,c). Frost days have decreased in most of the state with statically significant decrease (-13 to 26 days/yr, Fig. A-3.6b,e). The difference between daytime and nighttime temperatures (DTR) indicates that it is generally smaller in lower elevations and lower latitudes of the state (~18°F) and larger in higher elevations and in the northern areas (~24°F) (Fig. 3.8f). Since 1950 there has been a statistically significant decrease (-2°F) in DTR in the eastern half of the state (Fig. A-3.6d,f).

The time series of frost days (FD) show significant decreases in the coming century (Fig. 3.8a). Frost days decrease from 140 days (in the 1950s) to ~80 days in mid-century (-60 days), and ~50 days/yr (-90 days) in 2100. The greatest decreases in number of frost days occur in the river valley and south coast (Fig. 3.8d,e). The diurnal temperature range (DTR) shows relatively small declines by 2100 with some disagreement among the models towards the end of the century (Fig. 3.8g,h).

Table 3.3. Temperature Indices Projections for Connecticut. Multi-model ensemble of temperature extreme indices during the reference period and the projected changes for mid-century and late-century (mean ± standard deviation computed across eight models), spatially averaged over Connecticut. Units: days (unless specified otherwise).

Variables	**1970-99 Reference**	**2040-69 Changes**	**2070-99 Changes**
TXX (°*F*)	93.3 ± 2.8	6.5 ± 1.4	10.5 ± 2.9
TNN (°*F*)	-4.7 ± 4.9	7.9 ± 1.2	14.2 ± 3.0
SU *(days)*	80.6 ± 8.7	36.5 ± 9.4	54.2 ± 13.7
WSDI *(days)*	3.5 ± 4.7	44.2 ± 22.9	97.0 ± 44.3
TR *(days)*	9.6 ± 4.7	32.0 ± 10.6	57.0 ± 16.6
GSL *(days)*	246.7 ± 18.4	35.1 ± 12.5	62.3 ± 18.2
ID *(days)*	22.8 ± 8.4	-10.2 ± 1.8	-14.1 ± 2.2
CSDI *(days)*	0.9 ± 1.9	-1.0 ± 0.5	-1.1 ± 0.6
FD *(days)*	124.0 ± 10.5	-39.2 ± 10.3	-63.5 ± 13.5
DTR (°*F*)	19.6 ± 0.6	-0.2 ± 0.2	-0.4 ± 0.5

Summary: Temperature Extremes

The observed and expected changes in temperature related extreme indicies are all consistent within the context of a warming planet, with increasing mean temperatures.

In Connecticut, both the warmest day and warmest night of the year have increased in temperature since the 1950s (Fig 3.4). Daytime warm indices (summer days, and warm spells) have shown statistically significant increases (Fig 3.5) as have nighttime warm indices (tropical nights, growing season length, Fig 3.6). At the same time indices that measure cold extremes, such as ice days, cold spells, and frost days have been declining, as expected (Fig 3.7 and 3.8). The level of significance in the observed changes varies spatially and by index, with tropical nights, growing season length, summer days and frost days showing significant changes across large regions of the state.

Projections indicate significant changes across the state with continued trends that are consistent with increasing temperatures in all of the temperature extreme indices presented. Tropical nights (TR: Tmin>68^{o}F) are projected to increase from 10 days to more than 40 days at mid-century and nearly 70days in late century. Although humidity is not analyzed here, it is worth noting that tropical nights are normally associated with high humidity. Currently, ~4 days/ year are associated with warm spells (WSDI: 6 consecutive days with Tmax > 90%), meaning less than one per year on average. The projections suggest 48 days by mid-century and more than 100 by late century.

Changes accelerate through the coming century (Figs 3.7e to 3.11e) based on the higher radiative forcing scenario (RCP8.5) that assumes continued increasing emissions of CO2 (see Sidebar 2.2 on Uncertainties in Climate Projections). Reducing emissions globally would substantially mitigate changes after mid-century

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4. Precipitation Changes in Connecticut

4.1 Precipitation in the Northeast U.S.

Precipitation in Connecticut shows a clear pattern of topographic influence, ranging from less than 45 inches per year in the Connecticut River valley to over 52 inches in the elevated hill regions (Figure 4.1, 30-year average climatology, 1970-1999). The seasonality of precipitation in the state is quite weak, with similar amount of precipitation in spring, summer, and fall seasons and slightly less in winter. The year-to-year variability of precipitation in Connecticut is strong; averaged over the state, annual precipitation ranges from less than 40 inches (reaching as low as 30 inches in 1965) to over 65 inches (in 2011) (Figure 4.1). Similar to the rest of the Northeast, in the 1960s Connecticut experienced the most severe drought in recent history with record-setting low precipitation for several years in a row. Based on the 20th century climate statistics, the low precipitation of 1965 in Connecticut has a return period of approximately 125 years, and extremely low precipitation for several years in a row (as in the 1960s) is a much rarer occurrence. Moreover, due to the large magnitude of inter-annual variability, the detection time for a statistically significant change in precipitation is very long, often much longer than the available record of high-quality observational data (Ziegler et al., 2005). It is especially difficult to quantify observed precipitation trends since 1950 in Connecticut (and in the Northeast in general) due to the 1960s drought that makes the results extremely sensitive to whether the beginning of the study period is before or after the 1960s.

Literature Review of Average Precipitation

Based on data from meteorological stations (1950-2006), Hodgkins and Dudley (2011) found an increase of summer precipitation in most of New England (including four in CT), and the increase at many stations in Western New England (including two in CT) is larger than 20%.

Sidebox 4.1: Why is precipitation changing?

Increasing greenhouse gas radiative forcing and the resulting warming are expected to cause changes in precipitation characteristics, including increases in global average precipitation and precipitation intensity particularly during extreme events (Trenberth, 1999). The primary source of atmospheric water vapor is evaporation from the global oceans; continental evapotranspiration can also be important in regions where there is sufficient surface moisture. At the global scale, precipitation must balance evapotranspiration, and the energy limit on evaporation dictates an increase of approximately 2% per degree (Celsius) of warming. Precipitation intensity during extreme events is proportional to the moisture holding capacity of the atmosphere, which increases at approximately 7% per degree (Celsius) of warming according to the relationship between saturation specific humidity and temperature (known as the Clausius-Clapeyron relationship). The disparity between these two rates of increase (2% vs. 7%) suggests that while precipitation intensity increases, its frequency would decrease. Thus, dry spells between precipitating events would lengthen. Moreover, due to the increased intensity of precipitation, a higher fraction of precipitation would run off in surface flows (Parr et al., 2014) and less would be retained in the soil. These, together with the temperature-induced acceleration of evapotranspiration, are expected to increase both flooding risks and drought risks.

Most other studies have averaged station data over the Northeast, especially in the regional and national climate assessments. For example, Kunkel et al. (2013) documented a statistically significant increase in annual precipitation over the Northeast (+0.39 in/decade during 1895-2011), mostly attributed to a statistically significant increase in fall season precipitation

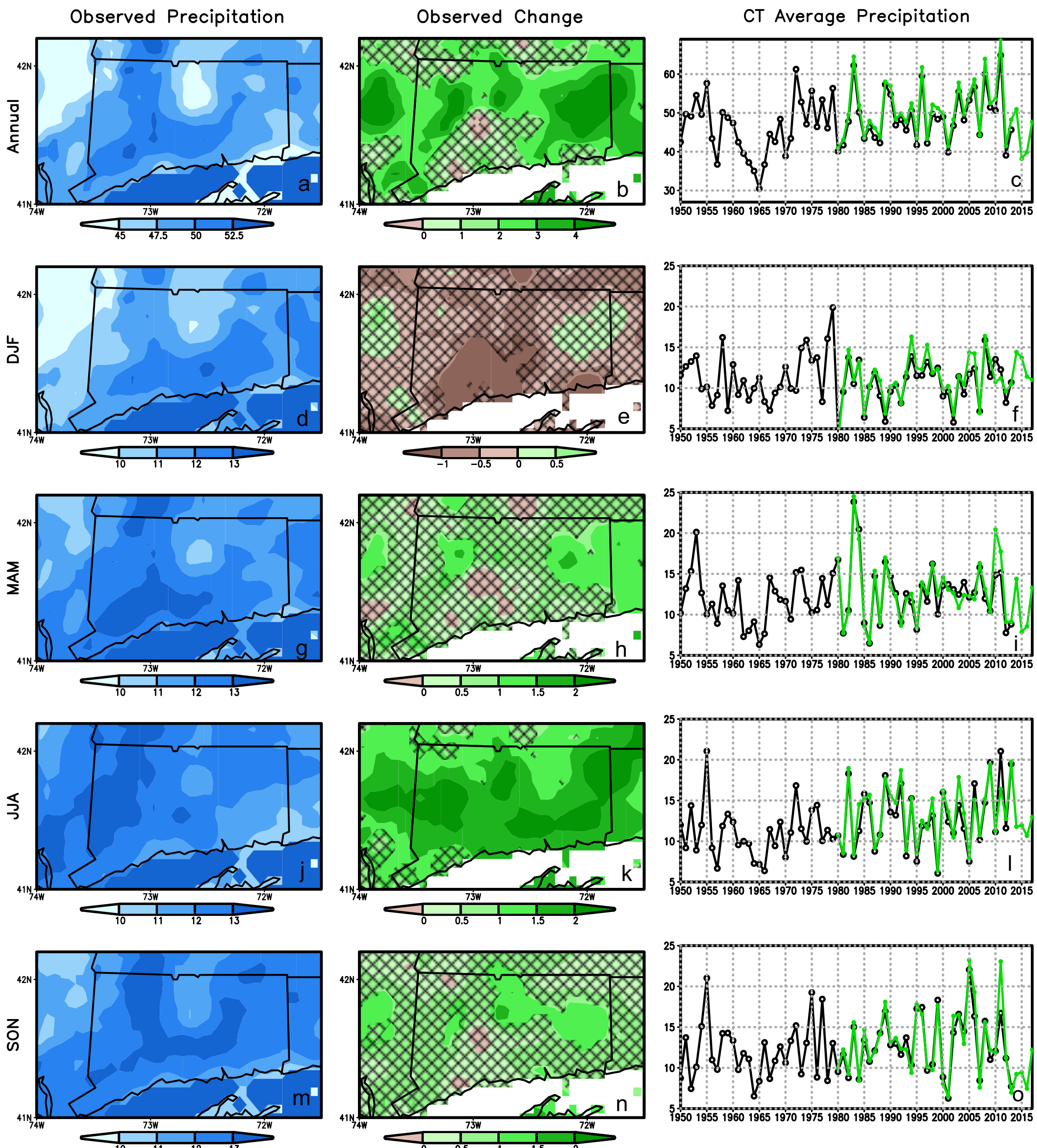

Figure 4.1 Annual and seasonal precipitation and changes, based on gridded observational data. Precipitation in the period 1970-1999 (left), change in precipitation for 1980-2009 minus 1950-1979 (middle) and time series of state averages (right). The rows present annual average (a-c), winter – DJF (d-f), spring – MAM (g-i), summer – JJA (j-l), and fall – SON (m-o). Based on the Livneh et al. data, with METDATA (green lines) for comparison. Black hatching indicates changes that are not significant.

(+0.24 in/decade). Walsh et al. (2014) found that relative to the 1901-1960 climatology, precipitation during 1991-2012 has increased by 8% in the Northeast. Easterling et al. (2017) extended the analysis to include data from more recent years, and showed that annual precipitation during 1986-2015 increased by 5-15% over most of the Northeast relative to the 1901-1960 climatology, and the largest increase was found for the fall season (+15% over most of the region). The aforementioned studies differed in the periods of analysis, and the differences among results was typically the season that contributed the most to the observed increase of annual precipitation.

Climate models project a generally wetter future for Connecticut and for the Northeast, which is consistent with theoretical expectations for increased precipitation in a warmer world. However, the projected precipitation changes for the future do not follow the seasonality of past observed changes. A regional climate model in Anderson et al. (2010) projected summer precipitation to decrease across much of the central Northeast (but increase over the southernmost and northernmost portions). Based on CMIP3 models (high CO_2 scenario), Kunkel et al. (2013) found that, relative to the last three decades of the 20th century, annual precipitation may increase by 5-6% in CT by the mid-century (2041-70), with most of the increase from winter-spring seasons and some decrease in summer. Based on output from CMIP5 models (RCP8.5), Walsh et al. (2014) and Easterling et al. (2017) found that by the end of the 21st century precipitation amount in the Northeast during winter and spring would increase significantly (by 10-30%) with a high degree of model consensus; projected changes in summer and fall seasons were either statistically not significant or inconclusive due to the lack of model consensus. Similarly, based on the CMIP5 GCMs, Lynch et al. (2016) also found a strong seasonality of precipitation changes with a peak increase in late winter–early spring (February–April). These studies consistently identified winter-spring as the seasons of strongest future increase of precipitation, while observed precipitation changes since 1950 were dominated by an increase during the fall season (see also Fig. 4.1).

4.2 New Analysis of Precipitation for Connecticut

Observations and projections of annual and seasonal precipitation

Despite differences in day-to-day variation of precipitation, the two gridded datasets (MACA and Livneh et al., see Section 2.3 for details) agree well on precipitation amount accumulated over five days or longer (Figure 4.1). We therefore use the Livneh et al. (2015) data, which offers a longer record (1950-2013), to analyze past changes of seasonal and annual precipitation in Connecticut.

The shaded plots in Figure 4.1 show the 30-year (1970-99) average of annual and seasonal precipitation, and the changes from the 1st 30 years (1950-79) to the 2nd 30 years (1980-2009) of the data record. Over most of the state, annual precipitation increased significantly, by more than 2 inches, due primarily to increases in summer precipitation. Summer precipitation increased significantly over the entire state, with the absolute change exceeding 1.5 inches over most area, a relative change of 10-20%. During 1950-2013 and averaged over the state (line plots in Figure 4.1), summer precipitation increased at a rate of 0.58 in/decade and annual precipitation at a rate of 0.98 in/decade. Spring and fall in Connecticut also experienced more precipitation but the changes were not statistically significant over most of the state. During winter, most of Connecticut experienced a decrease of precipitation, although the trend was not statistically significant. The seasonality of precipitation changes is not unique to Connecticut and is in fact similar in most of New England. These results agree well with

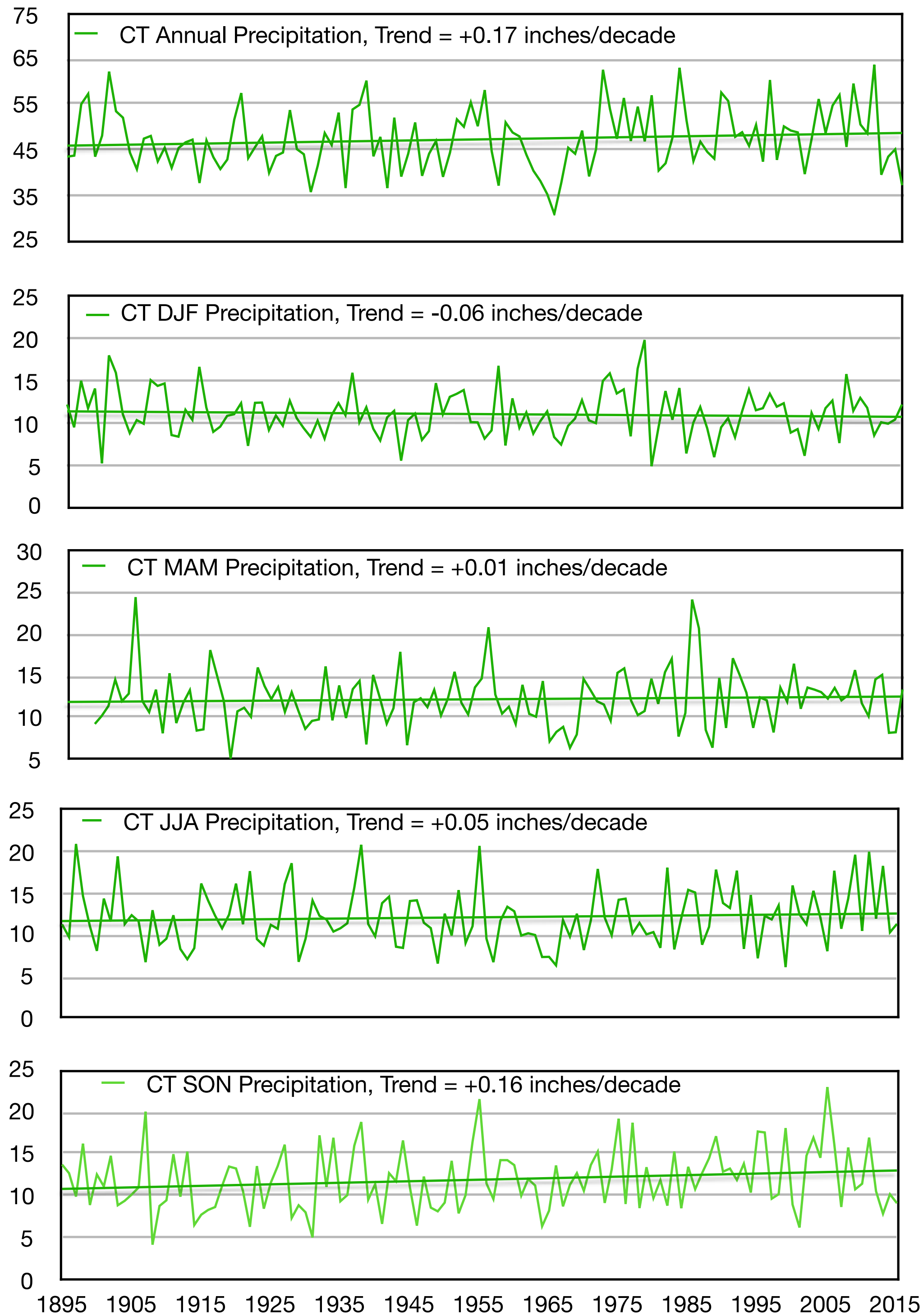

Figure 4.2 Observed annual and seasonal mean precipitation averaged for Connecticut. Linear trend computed for 1985-2017, with data from NCDC.

findings from the station-based study of Hodgkins and Dudley (2011) in identifying summer as the season of most significant changes. It is important to note that both our study and Hodgkins and Dudley (2011) use data from 1950 onward.

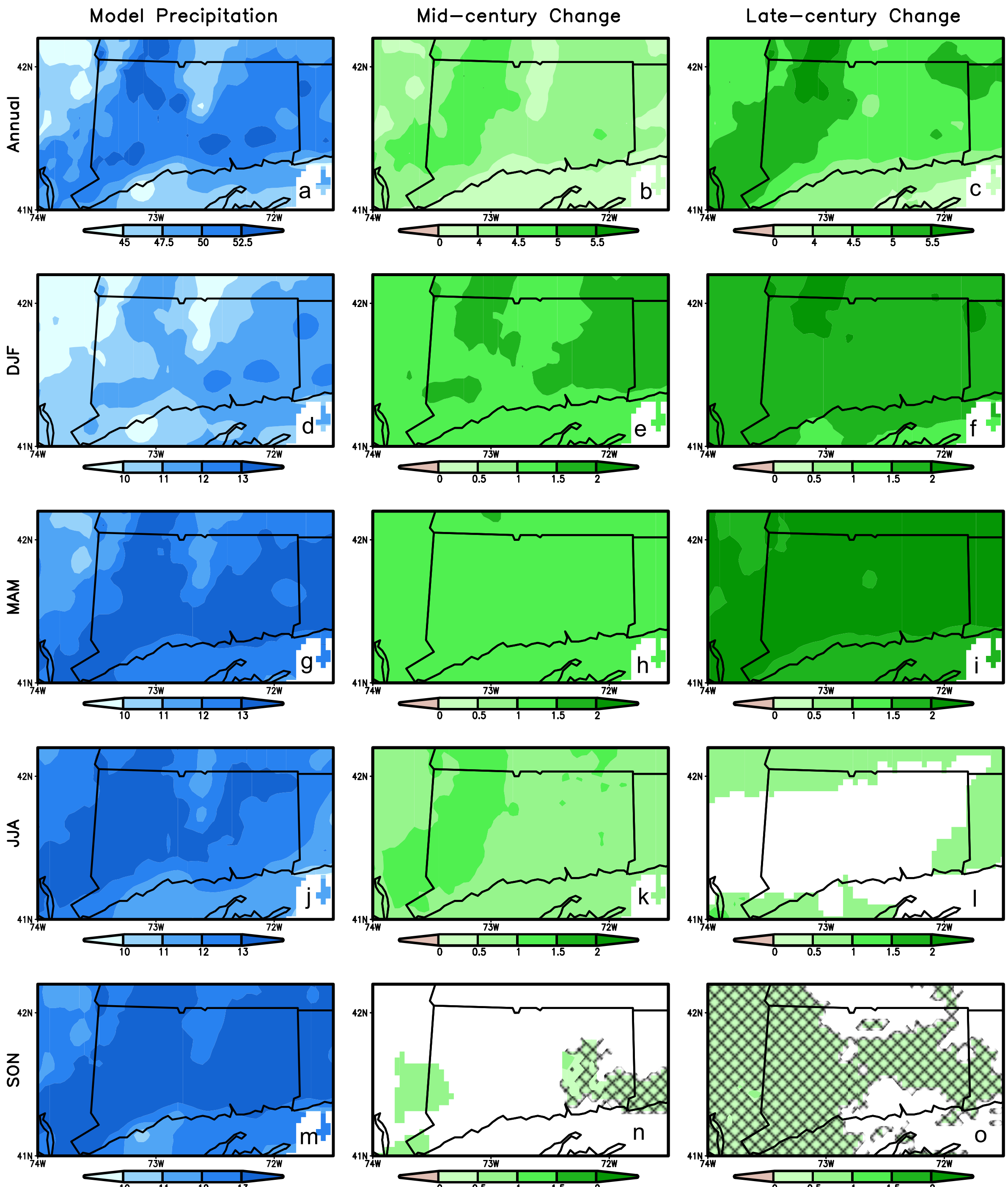

Figure 4.3 Spatial pattern of annual and seasonal precipitation. Climate model simulation for the reference period 1970-1999 (a,d,g,j,m), and projected changes in mid-century (b,e,h,k,n) and late-century (c,f,i,l,o), all in inches. Black hatching indicates changes that are not significant.

In contrast, studies based on data dated back to 1901 or earlier (especially the regional and national assessments, e.g., Easterling et al., 2017) found that the largest precipitation increases occurred in the fall season. Relative to the studies using pre-1950 data, the rate of annual and seasonal precipitation increases found in our analysis is greater due to the inclusion of the 1960s' mega drought in the early portion of our data record. As a comparison, Figure 4.2

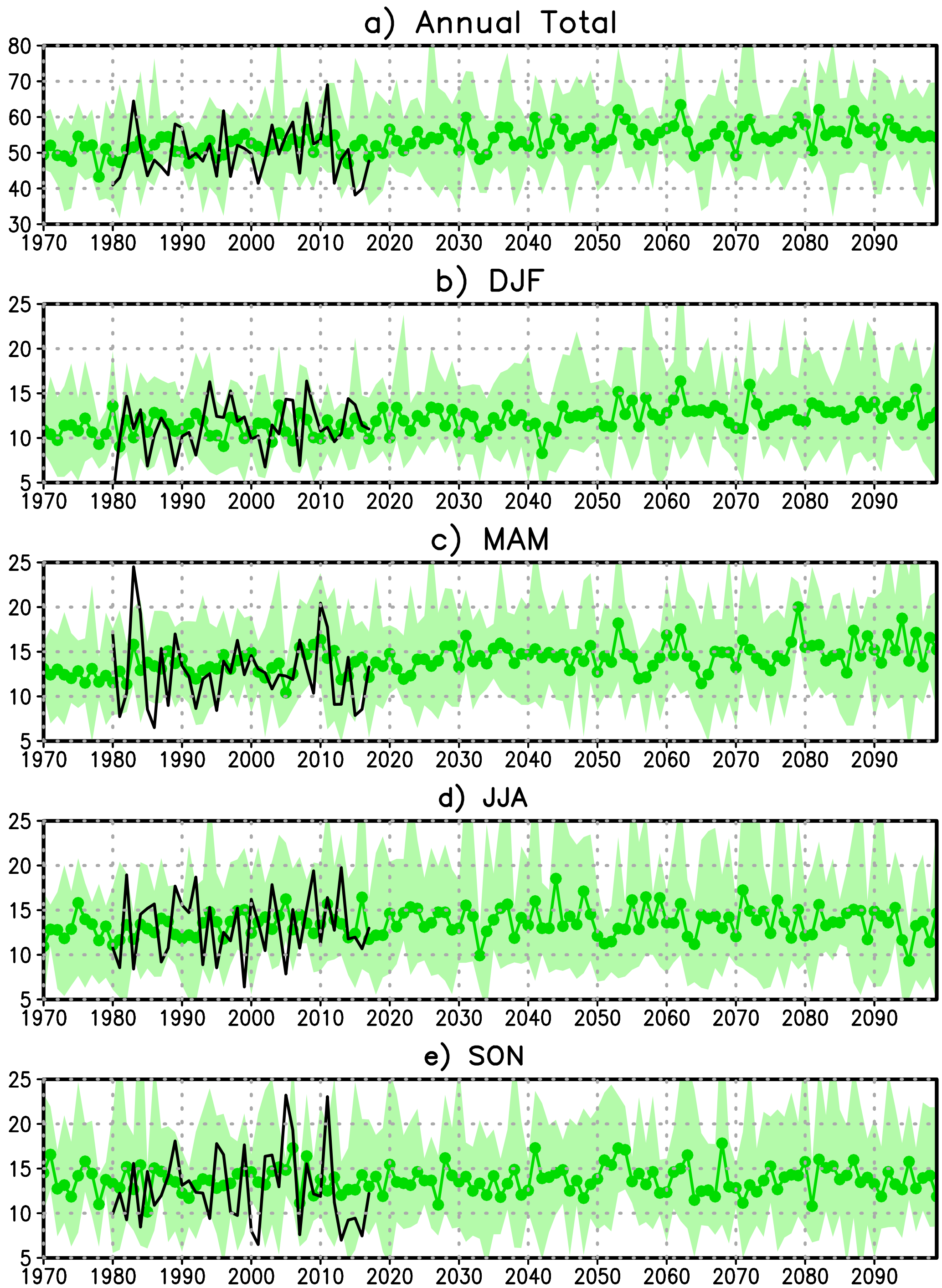

Figure 4.4 Precipitation time series. Observed (black) and climate model simulated (green) precipitation (inches).

shows the time series of precipitation averaged among multiple meteorological stations within Connecticut (NOAA NCDC climate divisional data) over the period 1895-2015, which shows an annual trend of 0.17 in/decade, and the strongest increasing trend in the fall season at 0.16 in/decade.

Based on the downscaled 4-km MACA2-METDATA, the annual and seasonal precipitation climatology derived from the 8-model ensemble mean for the period 1970-99 (left column, Figure 4.3) closely resembles observation (Figure 4.1). This is expected due to the use of bias correction in the MACA methodology. With rare exceptions, the state average of observed precipitation from the reference data is enveloped by the model spread (Figure 4.4). Note that the multi-model ensemble mean has a much smaller year-to-year variability than the observation. This is expected as the anomalies associated with the internal variability from different models compensate each other.

Table 4.1. Annual and seasonal average precipitation and projected changes for Connecticut. Multi-model ensemble of precipitation climatology during the reference period and the projected changes for midcentury and late century, averaged over Connecticut. The ensemble is presented as multi-model mean plus/minus inter-model standard deviation. Units: inches. Percentage values in parenthesis are relative changes. "*N/A*" indicates lack of model consensus regarding the direction of changes or statistically the projected changes are not significant.

Variables	1970-99 Reference	2040-69 Changes	2070-99 Changes
Annual Total	50.9±0.7	4.3±2.3 (8.5%)	4.9±3.3 (9.7%)
Winter (DJF)	11.1±0.3	1.5±1.2 (13.4%)	1.8±1.2 (16.3%)
Spring (MAM)	13.1±0.3	1.3±0.9 (10%)	2.2±0.5 (16.5%)
Summer (JJA)	13.0±0.5	1.0±0.7 (7.6%)	*N/A*
Fall (SON)	13.6±0.4	*N/A*	*N/A*

As temperature continues to warm in the future (RCP8.5), the annual total precipitation in CT is projected to increase by 4-5 inches (approximately 8.5%) by the midcentury (2040-2069) and by 4.5-5.5 inches (approximately 10%) by the late century (2070-2099) (Figure 4.3). These increases are due primarily to increases of precipitation in the winter and spring seasons in our analysis, similar to previous studies (e.g., Walsh et al., 2014; Lynch et al., 2016; Easterling et al., 2017). By midcentury averaged over the state, the increase of precipitation is projected to be approximately 1.5 inches (13.4%) for winter and 1.3 inches (10%) for spring; by the late century, these increases are 1.8 inches (16.3%) and 2.2 inches (16.5%) (Table 4.1). Across the state, all these increases (in the winter, spring, and annual precipitation) are projected with model consensus and are statistically significant. The spatial pattern of projected changes reflects an impact from topography, with stronger increases over high altitude than valleys. Projected mid-century changes during summer and fall seasons are either statistically insignificant due to the small magnitude or inconclusive due to the lack of model consensus on the direction of the change (Figure 4.4).

Summary: Average Precipitation

For the winter, spring, and annual totals, there is a clear increasing trend throughout the period of 1970-2099 not only in the multi-model ensemble mean but also in the minimum and maximum among the individual models (Figure 4.4). For the summer season, an increasing trend is evident in the early portion of the period followed by a leveling off after 2040. For the fall season, neither the ensemble mean nor the minimum and maximum among the individual models shows any clear trend. Clearly, there is a contrast in the seasonality of past observed and future projected changes of precipitation. Based on previous studies and our new analysis, strongest changes of precipitation were observed during either summer or fall in the past, and are projected to occur during winter and spring in the future. Understanding this contrast is beyond the scope of this assessment and will be the topic of follow-up research.

4.3 Daily Precipitation Extremes in the Northeast U.S.

Definition of Extreme Precipitation Indices

To quantify precipitation extremes, the World Meteorological Organisation (WMO) Commission for Climatology (CCl)/Climate Variability (CLIVAR) Working Group on Climate Change Detection proposed five extreme precipitation indicators (Frich et al., 2002): 1) the maximum number of consecutive dry days in each year (CDD), 2) the number of days with precipitation more than 10 mm (R10), 3) the simple intensity index (SII), 4) the maximum 5-d precipitation total of the year (R5d), and 5) the fraction of the annual total greater than or equal to the daily 95th percentile (R95T). Similar considerations have led to the expansion of extreme indicators such as those recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI, Zhang et al., 2011), including among others maximum 1-day precipitation and annual total precipitation due to events exceeding 99th percentile of daily precipitation. These indicators are defined for each year and have been widely used to assess GHG-induced climate changes (e.g., Ahmed et al., 2013; Thibeault and Seth, 2014), see Table 4.2. In addition to these commonly used indices, we have added the size of rare events (in the form of 1-in-N-years, with N being the "return period" or recurrence interval) as well as the future return period of the past 1-in-N-years events, as they are highly relevant indicators of climate extremes (Kharin et al., 2007; 2013) for the development of climate adaptation strategies (e.g., revising infrastructure design criteria).

Table 4.2 Precipitation indices examined for Connecticut. Indices computed to examine drought risk, flood risk, present climate return periods and future changes in return periods for Connecticut.

Index	Index name	Definitions	Units
Drought Risk			
CDD	Dry Days	Maximum number of consecutive dry days for JJA	Days
SII	Simple Intensity	Simple intensity index (average precipitation/wet day)	Inches/ Day
aPE	Annual P-PET	Precipitation minus potential evapotranspiration, annual	Inches
sPE	Summer P-PET	Precipitation minus potential evapotranspiration, JJA	Inches

N_wet	Wet Days	Annual count of wet days, Prec > .04 inches	Days
Flood Risk			
N_1inch	Rain Days	Annual count when daily Prec >1 inch	Days
N99	Heavy Rain Days	Annual count of days with precipitation > 99th percentile	Days
F99	Heavy Rain Fraction	Fraction of annual precipitation accounted for by N99	%
R1d	Max 1day Rain	Maximum daily precipitation	Inches
R5d	Max 5day Rain	Maximum consecutive 5-day precipitation	Inches
Return Periods			
X_10 X_20 X_50 X_100	Any index	Present climate extreme value of index with return period of 10, 20, 50, and 100 years respectively defined for various precipitation indicators X such as R1d, R5d, and low tail of aPE (annual P-PET) and sPE (summer P-PET)	See index units above
T_X_10 T_X_20 T_X_50 T_X_100	Any index	Future return period of the X_10, X_20, X_50, X_100 for precipitation index X including R1d, R5d, aPE, and sPE	Years

Literature Review of Precipitation Extremes

While precipitation response to greenhouse warming has been predicted by theory and numerical models decades ago (Trenberth, 1999), robust observational evidence, as expected, has only recently emerged for precipitation extremes (Fischer and Knutti, 2016). Accurate definition and assessment of extreme events requires long-term observational data. This requirement is difficult to meet for precipitation extremes because they often take place at small spatial and temporal scales, from hourly to daily over several kilometers in space, scales at which long-term observational data is scarce. For example, based on station data, Agel et al. (2015) found that most extreme precipitation in the Northeast occurs on a single day with three hours or less accounting for approximately 50% of daily accumulation. In addition to the lack of sufficiently long data record at the fine spatial and temporal resolutions, the 1960s drought makes results of any trend assessment extremely sensitive to the inclusion of that period. For these reasons it is challenging to assess trends in extreme precipitation events in Connecticut.

In the regional and national climate assessments (e.g., Easterling et al., 2014), station-level precipitation data were often gridded and then aggregated to regional level to analyze past changes. For the Northeast, both the intensity and frequency of heavy precipitation events were found to have increased, the greatest increase found in any region of the U.S. (Easterling et al., 2014). Kunkel et al. (2013) documented an increasing frequency of extreme precipitation events, but the trend is statistically not significant over the whole period of 1895-2011 and shows substantial decadal variability, with most of the increase occurring during more recent decades. For example, extreme events with a return period of 50 and 100 years based on the climate of 1950-79 occurs every 30 and 60 years, respectively, during the more recent period of 1978-2007. Thibeault and Seth (2014) assessed nine precipitation indices (for both precipitation amount and intensity) for the Northeast and found all of the wet indices experienced a statistically significant increasing trend over the period 1951-2010. In the 3rd National Climate Assessment, Walsh et al. (2014) showed a 71% increase in the amount of precipitation falling during the heaviest 1% of all daily events over the Northeast from 1958 to 2012. Extending the analysis to include more recent data in the 4th National Climate Assessment, Easterling et al. (2017) documented similar substantial increase of both extreme precipitation intensity and frequency. For intensity, the daily 20-year return level precipitation increased by 0.08-0.25 inches (depending on season) during 1948-2015, the 5-year maximum daily precipitation increased by 27% during 1901-2016, and the 99th percentile of daily precipitation increased 55% during 1958-2016. For frequency, the number of 2-day precipitation events exceeding 5-year recurrence interval increased by 74% during 1901-2016 and by 92% during 1958-2016.

Studies based on data from individual stations showed that the magnitude and significance of the increase in precipitation amount and intensity differs at state and sub-state scales (Keim and Rock 2002; Groisman et al., 2004, 2005). Griffiths and Bradley (2007) documented an increase of precipitation extremes based on station data in the Northeast during 1926-2000, but no station in CT was included. Brown et al. (2010) evaluated the past trends in precipitation indices during 1893-2005 at 40 stations in the Northeast including three in CT, and found that a very small fraction of the stations show statistically significant trend over the whole period, but most stations show a shift towards wetter and more flood-prone conditions from the first half to the second half of the time period. The consequence of these observed increases in precipitation amount as well as increased intensity and frequency of heavy precipitation events has already become detectable with widespread increases in base flow, storm flow, and flood in the Northeast and in Connecticut (Hodgkins and Dudley, 2011; Peterson et al., 2013).

The Northeast is one of the fastest warming regions in the contiguous US (Karmalkar and Bradley, 2017; Wuebbles et al, 2017). As the warming continues in the future, precipitation extremes are projected to further increase, at a rate that is the highest in the nation (Easterling et al., 2017). Results from CMIP5 RCP8.5 projections suggest significant shifts toward warmer and wetter conditions by mid-century (2041-2070), and most precipitation extreme indices are projected to be largely outside their 20th century ranges by the late century (2071-2099) (Thibeault and Seth, 2014). Based on GCM climate projections downscaled to 1/8 degree resolution, Ning et al. (2014) found an increase in both total precipitation and the frequency of extreme precipitation events in the Northeast, with greater increases in coastal areas (including CT) than inland areas.

Globally and on a relative scale, the intensity of precipitation extremes increases faster than the annual mean precipitation (Kharin et al., 2013), meaning more precipitation comes in heavier events. Specifically in the U.S. Northeast region, by the late 21st century (RCP8.5, relative to the late 20th century), the projected increase is 5-10% for annual precipitation and 10-20% for extreme events with a 20-year return period (Kharin et al., 2013). Sillmann et al. (2013b) projected a 5-15% increase for total precipitation amount and 40-70% for the amount falling during heavy precipitation events (defined as days with precipitation exceeding the 95th percentile of the present climate). In the 4th NCA, using LOCA downscaled data Easterling et al. (2017) showed that the projected relative increase of the 1-in-20-years daily extreme precipitation is 13% by mid-century and 22% by late century in the Northeast (RCP8.5).

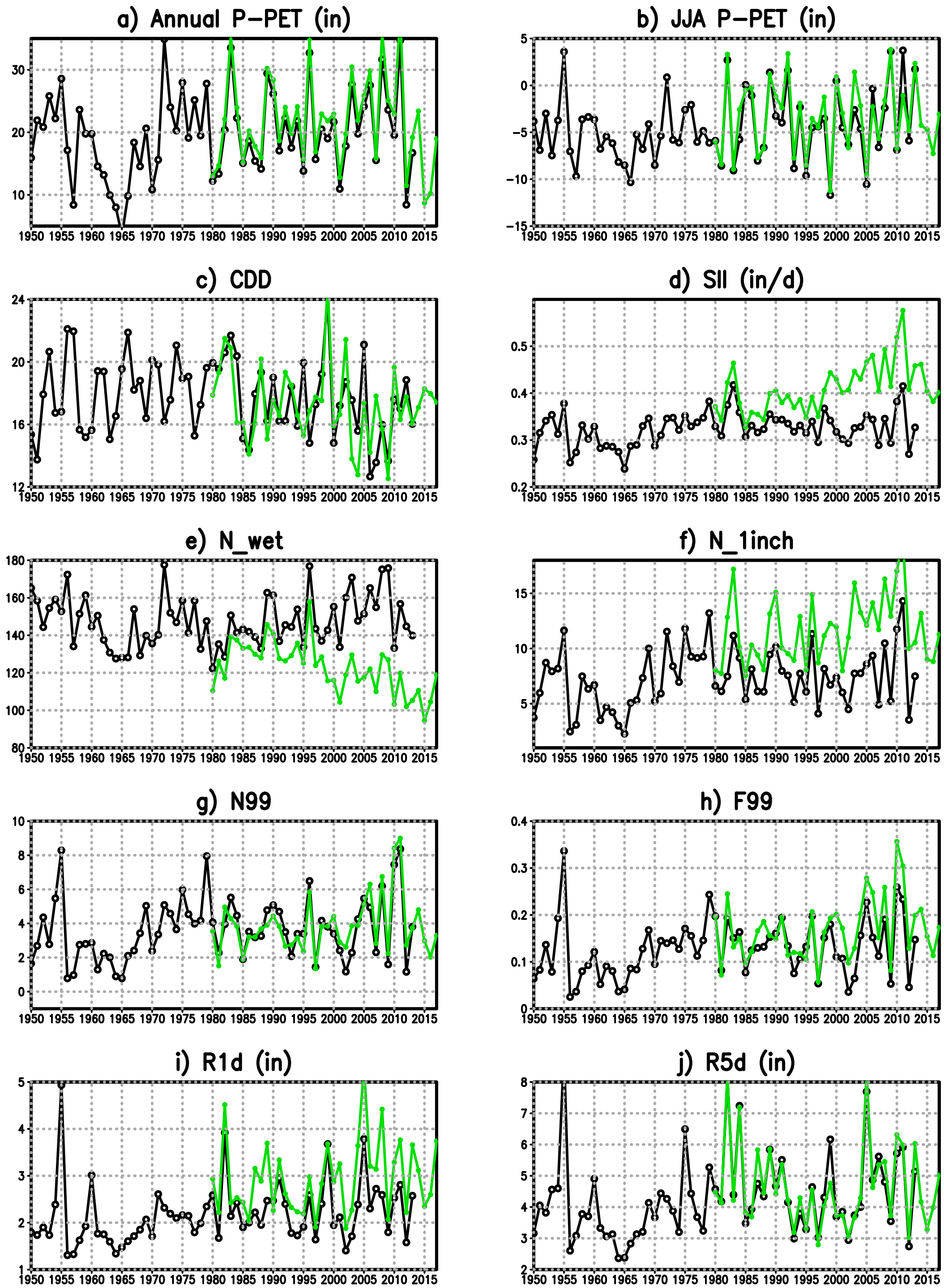

Figure 4.5 Observed precipitation indices for Connecticut. Indices based on the two gridded estimates of observations, METDATA (green) and Livneh (black).

Recent research for the Northeast suggests the frequency of extreme precipitation events is likely to increase even faster than the intensity. For example, under the SRES A2 scenario by the middle century (2041-2070), the days with precipitation exceeding 1in, 2in, 3in, and 4in would increase respectively by 21%, 41%, 56%, and 65% relative to the end of the 20th century for the Northeast, with slightly smaller increases in CT (Kunkel et al., 2013). By the late century under RCP8.5, precipitation in the wettest day of the year would increase by 20-30%, and extreme events such as daily precipitation with a return period of 20 years in the present climate would occur 3-4 times as often in the Northeast compared to the late 20th century (Walsh et al. 2014); and the 2-day 5-year extreme precipitation events would occur close to four times as often in the Northeast, the fastest increase of the nation (Janssen et al., 2014).

In summary, based on a survey of previous studies focussed on the Northeast U.S., both spatially averaged analysis and assessment of individual stations document an observed increase in precipitation and the frequency and intensity of heavy precipitation events, which substantiates the theoretical predictions for regional water cycle changes in a warming global climate. Climate model projections provide an overwhelming consensus that these increases of precipitation extreme indicators will continue as the earth further warms in the future. On the other hand, more than 75% of extreme precipitation days in the Northeast are related to extratropical storms except during September when more than 50% of extremes are related to tropical storms (Agel et al., 2015). How the tropical and extratropical storms may have changed in the past (which will be elaborated separately in Section 4.5) and how they may change in the future will help us to better understand the aforementioned changes of extreme precipitation indicators.

4.4 New Analysis of Daily Precipitation Extremes for Connecticut

Due to the fine spatial scale of precipitation extremes, averages over the Northeast examined in previous studies do not provide the spatially distributed information needed by local stakeholders. At the same time station-based assessment lacks sufficient coverage in Connecticut. Moreover, different studies tended to focus on one or two indices of precipitation extremes, which may not suit the information needs of local stakeholders. Here, we estimate the extreme indices described in Section 4.3 based on both the 4-km METDATA data and the 6-km Livneh data. In the Northeast precipitation tends to be more extreme over mountainous regions and along the coast, a spatial pattern resembling annual precipitation (see the maximum daily precipitation and the number of days with more than 1 inch of precipitation in Appendix Figure A-4.1). This general pattern holds in Connecticut but to a lesser extent. The time series of average indices computed for the state are given in Figure 4.5. Despite differences in the day-to-day variation of precipitation (as detailed in Figure A-2.1), for time indices that are cumulative over time including P – PET index and the 5-day maximum precipitation (R5d) the difference between the two datasets is negligible so we assess their trend based on the Livneh et al. data due to its longer record (1950-2013). In contrast, indices that depend on daily statistics of precipitation, differ substantially between the two datasets. Despite its shorter record (1980-2017), the METDATA is used to describe trends for these daily indices due to the better agreement with meteorological station data at the daily time scale. Extreme indices involving the definition of a return period are excluded from this analysis, as the data record (1980-2017) is too short to support the construction of two non-overlapping segments long enough to reliably define a return period of 20 years or longer.

Among the extreme indices examined, drought risks can be assessed based on the maximum consecutive dry days (CDD), the difference between precipitation and potential evapotranspiration (P – PET), and the number of wet days (N_wet) (black lines in Figure 4.5). For most years in Connecticut, CDD occurs during winter, while drought risk is of the greatest concern during summer. For this reason, here we use the summer-season CDD to examine the summer dry spells. The P – PET index reflects potential water availability, and both the annual

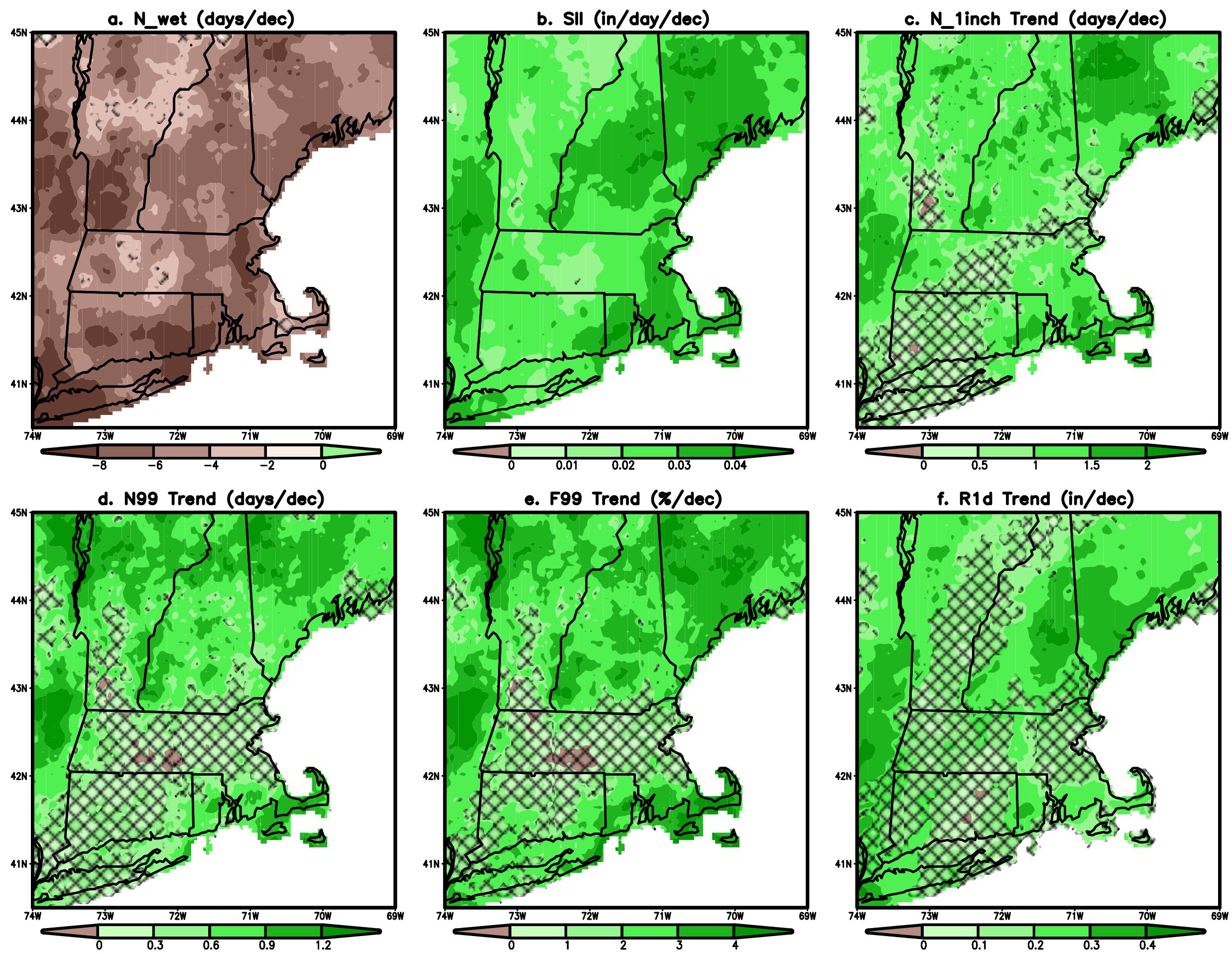

Figure 4.6 Observed 1980-2017 trends in the New England region. Precipitation indices include wet days (N_wet), simple intensity index (SII), days with more than 1 inch of precipitation (N_1inch), days with heavy precipitation (exceeding 99th percentile) (N99), fraction of annual precipitation accounted for by heavy events (F99), and maximum daily precipitation (R1d). Black hatching indicates changes that are not significant.

and summer values are relevant. Over the period 1950-2013, both the annual and summer P-PET indices showed a slight increasing trend towards greater water supply (not statistically significant), and summer CDD shows no clear trend. The number of wet days (N_wet) during the period 1980-2017 shows a statistically significant decreasing trend (-7 days/decade), which could cause drier soil conditions. Taken together however, results from multiple indices yielded no conclusive evidence for a clear change of drought risks during recent decades.

Changes in precipitation extremes that are related to flood risks are evaluated here based on SII, N_wet, N_1inch, N99, F99, R1d, and R5d during the period 1980-2017 (green lines in Figure 4.5). SII, which is the average precipitation among wet days, has increased at a statistically significant rate of +0.64 in/day/decade, which is associated with the statistically significant decrease of N_wet (-7 days/decade). Therefore, in general, precipitation frequency has decreased, but the average precipitation amount on each rainy day has increased. Moreover, despite the decrease of wet days, the number of days with very heavy precipitation has increased, and the amount of heavy precipitation has also increased. For example, the number of days with more than one inch of rain (N_1inch), days with very heavy precipitation (N99, i.e., days with precipitation exceeding the 99th percentile), and the fraction of annual precipitation accounted for by very heavy precipitation (F99) all have increased across the whole state over the period 1980-2017, although statistically these increases are not significant. On average, the annual maximum one-day precipitation (R1d) has increased slightly (and insignificantly) in most of Connecticut, which may indicate an increased risk of flash flood; the maximum 5-day precipitation (R5d), which reflects risks for major extended flood over large watersheds, has increased in west Connecticut and decreased in the east.

The general lack of statistical significance in the increase of flood-related indices in Connecticut differ from the findings of previous studies for the Northeast. For example, Thibeault and Seth (2014) found that all extreme precipitation indices for the Northeast

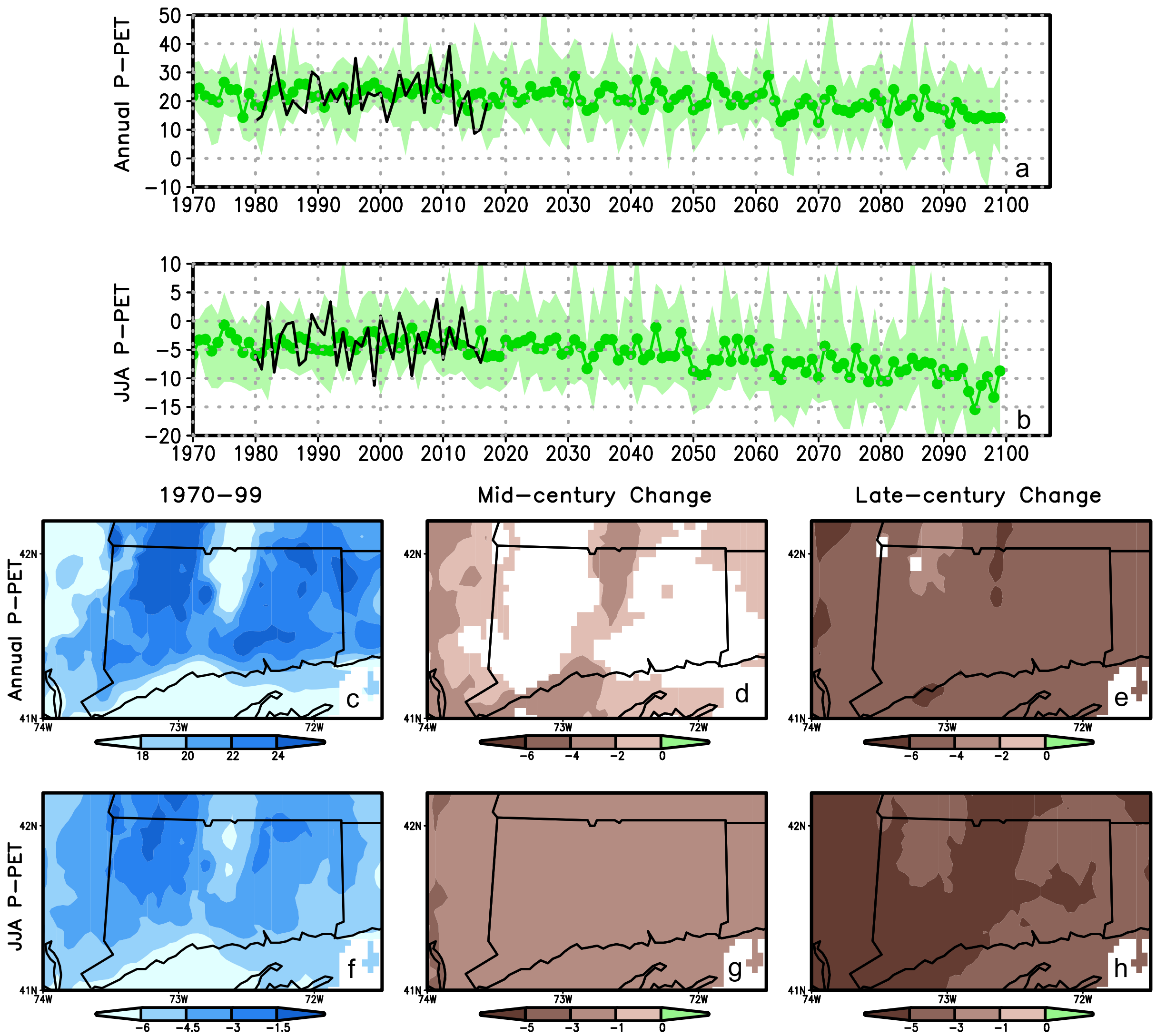

Figure 4.7 Annual P-PET (aPE) and summer P-PET (sPE). Observed (black) and projected (green) time series (a,b) for Connecticut; Model simulated spatial pattern for the reference period (c,f), projected mid-century changes (d,g) and late century changes (e,h). Brown shading reflects a decrease of potential water availability or an increase of water deficit.

experienced a statistically significant increase during 1951-2010. While the specific dataset and the analysis period play a role, the primary cause for this difference is spatial heterogeneity within the Northeast. Connecticut is an area in the Northeast where the past observed increase of precipitation extremes is weaker than most of the region and not statistically significant (Figure 4.6). With the exception of the R5d, daily precipitation extreme indices averaged over the Northeast (Appendix Figure A-4.2) show a much stronger increasing trend than for Connecticut.

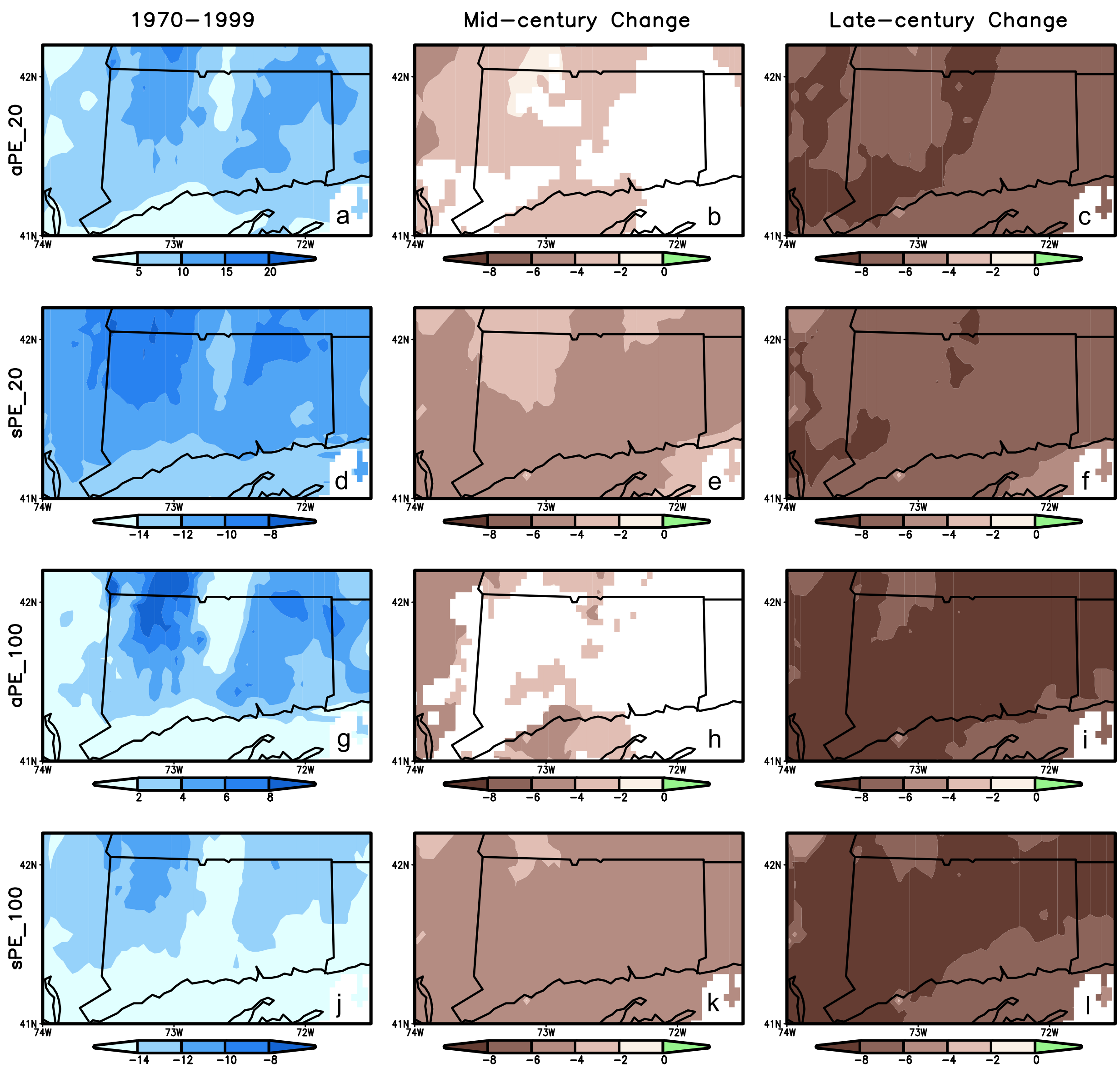

Figure 4.8 Low annual P-PET and low summer P-PET with recurrence interval of 20 years and 100 years (aPE_20, sPE_20, aPE_100, sPE_100, all in inches). Model simulated spatial patterns for the reference period (a,d,g,j), projected mid-century changes (b,e,h,k) and late century changes (c,f,i,l). Brown shading reflects a decrease of potential water availability or an increase of water deficit.

Projections of Drought Risk

Precipitation amount in Connecticut is projected to significantly increase in the future (Section 4.2), which continues the past observed trend. However, the increase of precipitation may not translate to an increase of water availability due to the increase of evapotranspiration caused by higher temperatures. Here we assess P-PET as an indicator of water availability in the future. Based on the multi-model ensemble, the annual P-PET (aPE) and summer P-PET (sPE) indices both show a slight increasing trend up to the early decades of the century (which agrees with observations in recent decades) and decrease afterwards; the decreasing trend (which indicates an increase in drought risk) is especially strong in the summer season (Figure 4.7). By the mid-century, the decrease in summer is already statistically significant across the whole state, but models disagree on the direction of the annual changes; by late century, both the projected annual and summer decreases are statistically significant and supported with model consensus (Figure 4.7). Similarly, the potential water deficit during summer droughts with recurrence interval of 10, 20, 50, and 100 years are all projected to become significantly more severe, with model consensus, for both future periods; the projected decrease of annual water availability is statistically significant by late century, but is still inconclusive in midcentury over most of the state due to the lack of model consensus (Figure 4.8).

Table 4.3 Water availability/deficit and recurrence intervals. Multi-model ensemble means for Connecticut of the annual (aPE) and summer (sPE) P-PET, including mean and threshold values for 10, 20, 50, and 100 year recurrence intervals, and their future changes. Units: inches. The percentage values in parenthesis indicate relative changes, where negative values reflect decrease of potential water availability (annual) and positive values reflect increase of water deficit (in summer); the values in bold font after the semicolon are future recurrence interval (in years) for the reference threshold values. "N/A" indicates the lack of model consensus on the direction of changes over most of the state.

Variable	1970-99 Reference	2040-69 Change	2070-99 Change
Annual			
aPE_mean	22.3±0.7	N/A	-4.9±3.3 (-22%)
aPE_10	12.2±1.4	N/A	-7±3.8 (-56%); **4**
aPE_20	9.4±1.6	N/A	-7.5±3.9 (-80%); **6**
aPE_50	6.2±1.9	N/A	-8.2±4.1 (-133%); **11**
aPE_100	4.0±2.1	N/A	-8.7±4.3 (-218%); **18**
Summer			
sPE_mean	-3.8±0.5	-2.4±1.4 (64%)	-5±3.7 (133%)
sPE_10	-9.2±1.1	-3.8±1.8 (41%); **4**	-6.8±3.3 (74%); **3**
sPE_20	-10.8±1.4	-4.2±2.0 (39%); **6**	-7.4±3.6 (68%); **3.5**
sPE_50	-12.5±1.6	-4.7±2.3 (37%); **11.5**	-7.9±4.0 (63%); **5**
sPE_100	-13.7±1.8	-5.0±2.5 (36%); **20**	-8.3±4.2 (61%); **8**

Consistent with this projected increase of drought severity is the increase of drought frequency. For example, models agree that the extreme summer drought events with a recurrence interval of 20 years in late 20th century (corresponding to an aPE value of -10.8 inches) would occur more frequently, approximately every 6 years by midcentury and every 3-4 years by late century based on multi-model ensemble mean (Figure 4.8). Averaged over Connecticut (Table 4.3), the relative increase in frequency is much faster than that in severity During winter, with model consensus P-PET is projected to significantly increase, which is similar to the projected precipitation changes as PET is negligible in cold season.

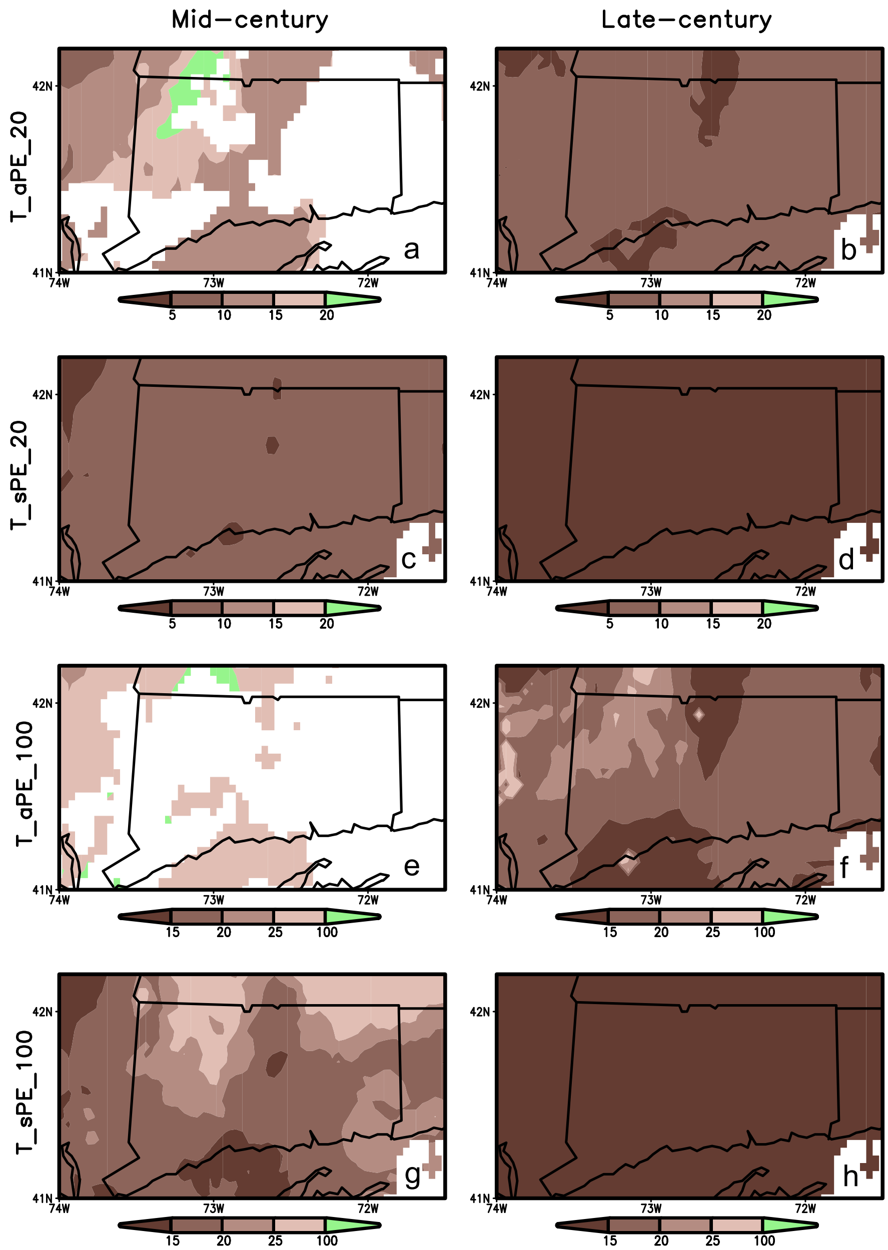

Figure 4.9 Future recurrence intervals of rare (1-in-20-years and 1-in-100-years) events for low annual P-PET and low summer P-PET (T_aPE_20, T_sPE_20, T_aPE_100, T_sPE_100, all in years). Projections for mid-century (a,c,e,g) and late century (b,d,f,h). Brown shading reflects an increase in frequency of dry year or dry summer and green reflects a decrease.

Summary: Drought Risk

The time series of summer CDD index shows no clear future trend of dry spells (Figure 4.9), which is similar to observations from the recent decades; over most of the state the models disagree on the direction of the CDD changes for both the midcentury and late century (Figure 4.10). The number of wet days, which was observed to have a statistically significant decreasing trend in the past several decades, shows no clear future trend according to the multi-model ensemble mean (Figure 4.9); in fact, even by the end of the century, models still disagree on whether the number of wet days would increase or decrease (Figure 4.10).

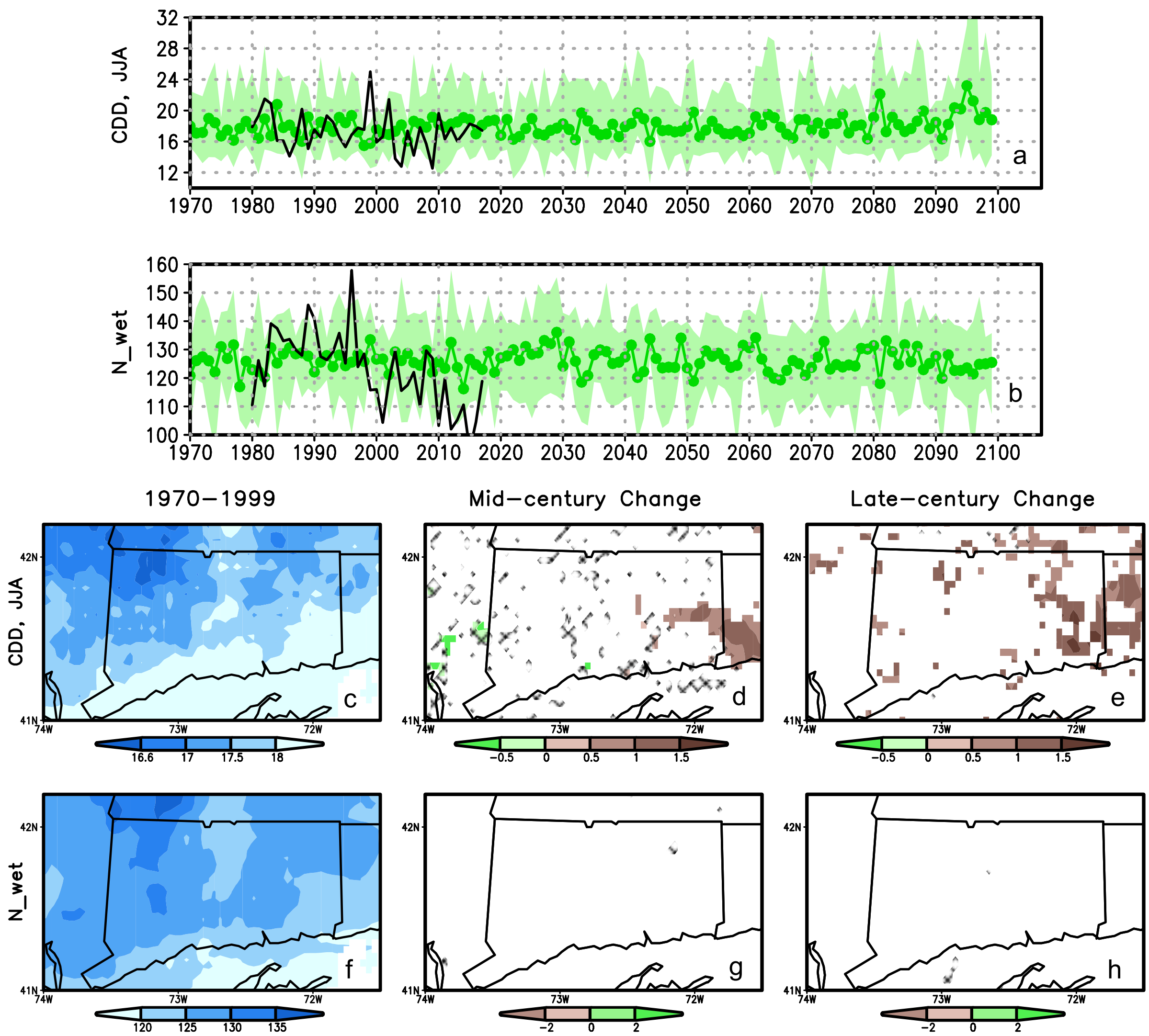

Figure 4.10 Maximum consecutive dry days during JJA (CDD) and annual total wet days (N_wet). Observed (black) and projected (green) time series (a,b) for Connecticut; Model simulated spatial patterns for the reference period (c,f), projected mid-century changes (d,g) and late century changes (e,h). Black hatching indicates changes that are not significant.

Table 4.4 Multi-model ensemble of precipitation extreme indices. Computed for the reference period and projected changes for midcentury and late century (mean ± standard deviation), spatially averaged for Connecticut. Percentage values in parenthesis are relative changes corresponding to the multi-model ensemble mean. N/A indicates the lack of model consensus on the direction of changes. Units: days (unless specified otherwise).

Variable	1970-99 Reference	2040-69 Change	2070-99 Change
CDD	17.8±0.8	N/A	N/A
N_wet	126±0.9	N/A	N/A
SII (in/day)	0.4±0.06	0.036 ± 0.02	0.04±0.03
N_1inch	11.7±0.3	1.9±1.0	2.3±1.7
N99	3.6±0.0	1.3±0.6	1.6±1.0
F99 (%)	15.4±0.5	5.6±1.8	6.0±2.9

In general, results from our analysis suggest a strong increase of drought severity and frequency in the future especially towards the later part of the century, despite the projected increase of precipitation. This projected increase of drought risks is due to the increase of potential evapotranspiration caused by the significant future warming as shown in Section 3. Results on drought conditions associated with changes in precipitation frequency (e.g., CDD and N_wet) are inconclusive and lack model consensus.

Projections of Flood Risk

All indices representing the frequency or intensity of heavy precipitation are projected to increase for both midcentury and late century (Figures 4.11, 4.12, 4.13). These increases are all statistically significant across the state and show model consensus. For indices involving accumulation throughout the year (including the simple intensity index SII, number of days with precipitation more than one inch N_1inch, number of heavy precipitation days N99, and fraction of annual precipitation accounted for by heavy precipitation F99), the mean projected increases by the late century are larger than the midcentury, indicating continuous increase over time (Figures 4.11, 4.12). Based on the multi-model ensemble mean and averaged over Connecticut, N_1inch would increase from 11.7 in the late 20th century to 13.6 and 14 days in the mid-century and late century respectively; over the same time periods, N99 would increase from a reference value of 3.6 days to 4.9 and 5.2 days for the two future period respectively, and F99 would increase from a reference of 15.4% to 21% and 21.4% for the two future periods respectively.

For the 1-day and 5-day maximum precipitation (R1d and R5d), the projected mean increases for the late century are slightly lower than the midcentury (Figure 4.13). As evident from the R1d and R5d time series, both the multi-model mean and the model spread clearly increase with time up to the midcentury, and tend to plateau or even slightly decrease afterwards. Averaged over the entire state for the midcentury and late century (Table 4-5), the projected increase mounts to 27% and 22% respectively for R1d, and 20% and 19% for R5d.

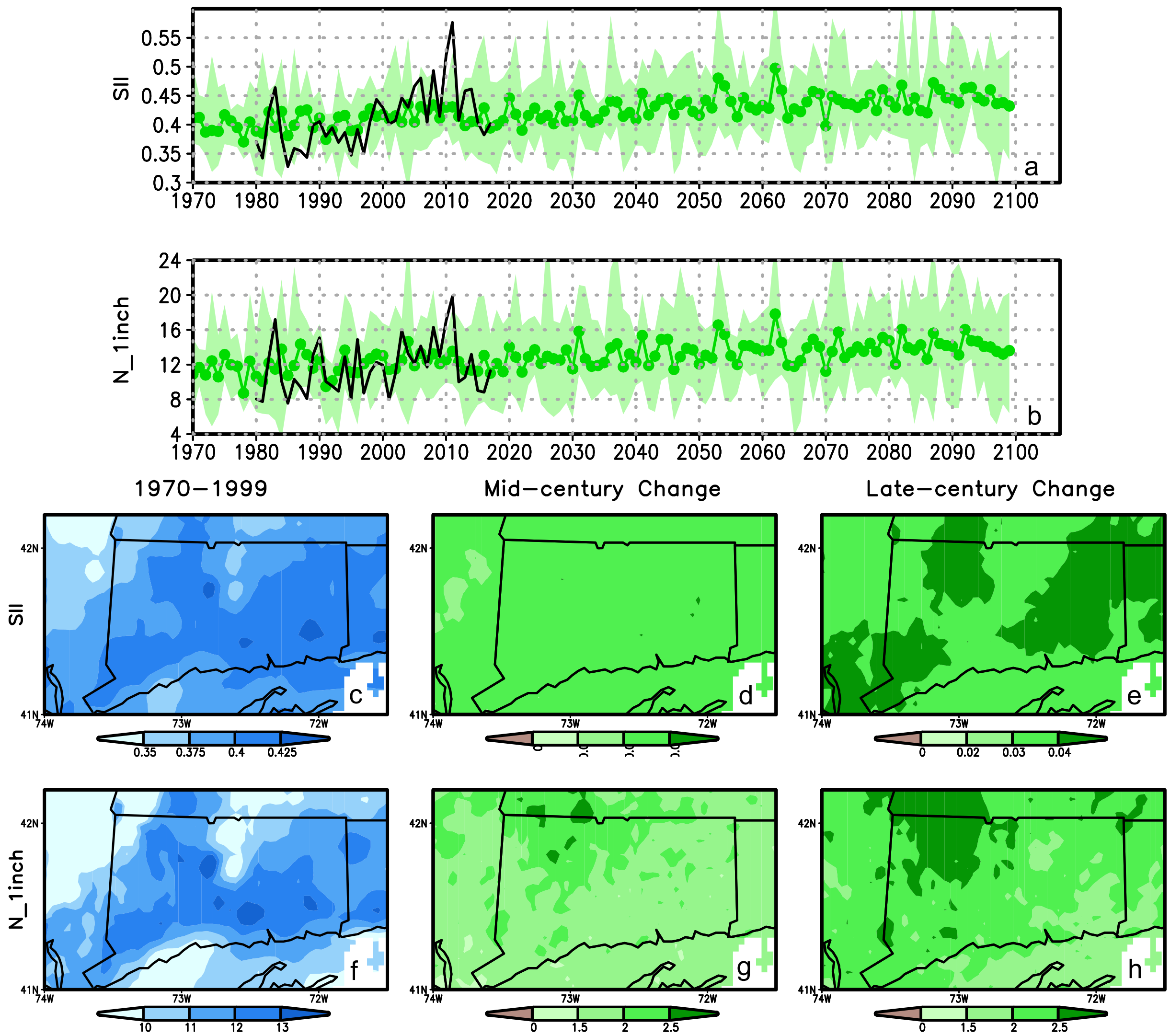

Figure 4.11 Simple intensity index (SII) and annual number of days with more than 1 inch of precipitation (N_1inch). Observed (black) and projected (green) time series (a,b) for Connecticut; Model simulated spatial pattern for the reference period (c,f), projected mid-century changes (d,g) and late century changes (e,h).

In addition to the mean changes, the severity of rare R1d and R5d events (e.g., those with recurrence interval of 10, 20, 50, 100 years) are projected to significantly increase (Figure 4.14), with faster increases for the more extreme/rare events (Table 4.5). Moreover, the contrast between midcentury and late century is stronger for more extreme events. For example, averaged over Connecticut, the R1d with a recurrence interval of 20 years is projected to increase by 59% and 36% by middle and late century, and the corresponding increases for the R1d with a recurrence interval of 100 years are 91% and 49%. Correspondingly, extreme events of a given size are projected to occur more frequently in the future (i.e., with a shorter recurrence interval), approximately 3-4 times as often during the mid-century and 2-3 times as often during the late-century (Figure 4.15).

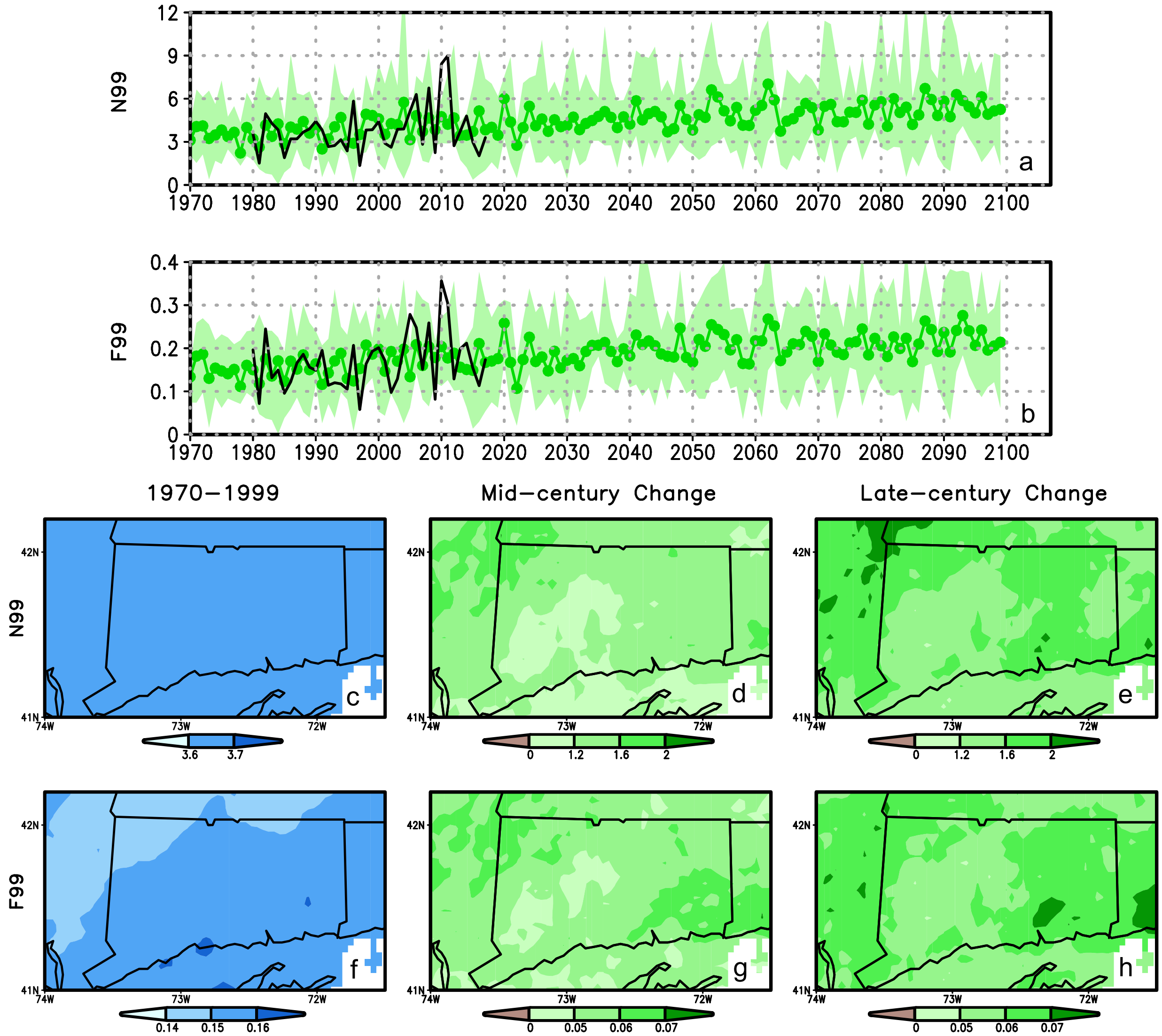

Figure 4.12 Number of days with heavy precipitation (exceeding the 99th percentile) (N99) and the fraction of annual precipitation accounted for by heavy precipitation (F99). Observed (black) and projected (green) time series (a,b) for Connecticut; Model simulated spatial patterns for the reference period (c,f), projected mid-century changes (d,g) and late century changes (e,h).

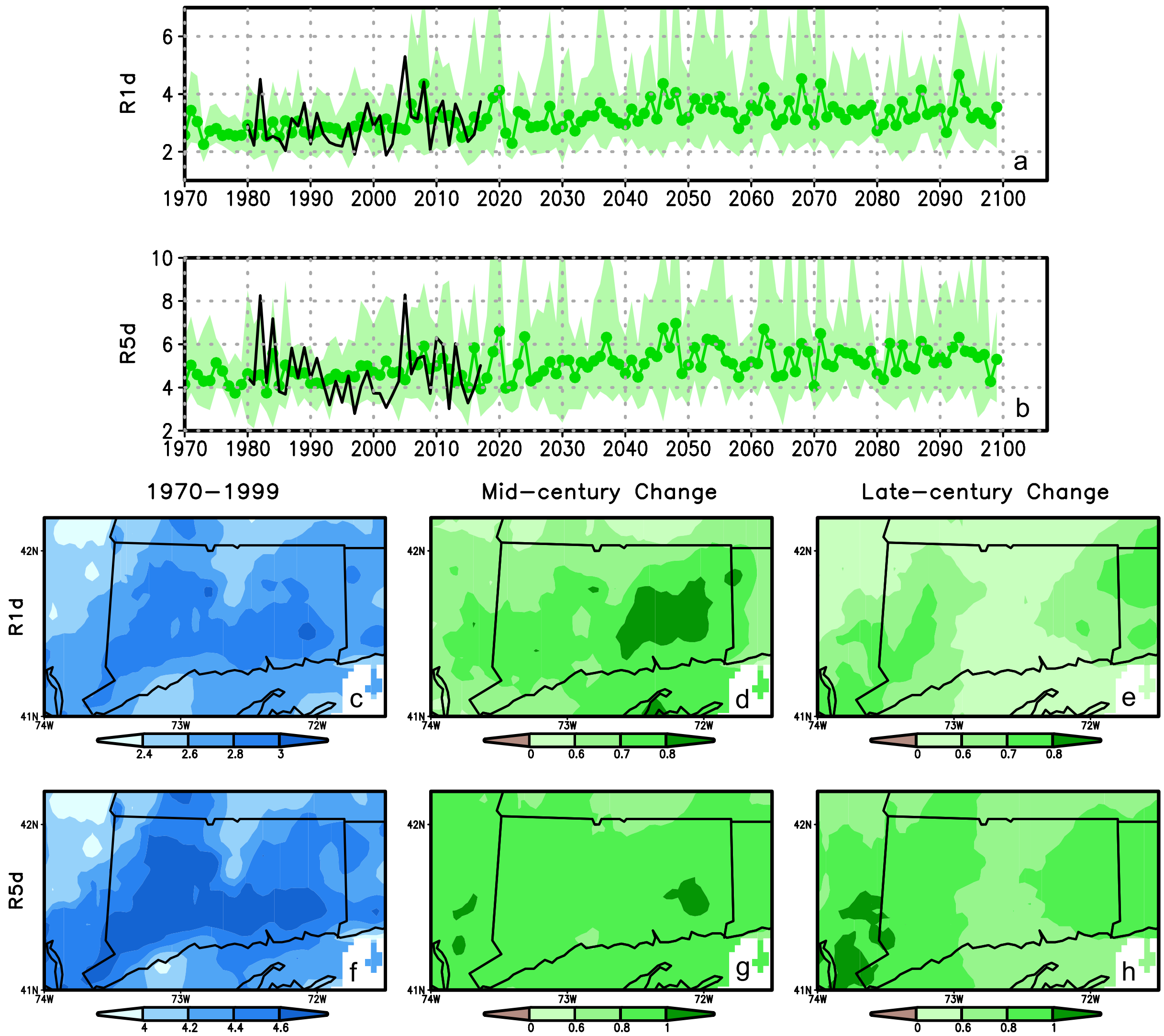

Figure 4.13 Maximum daily precipitation (R1d) and maximum 5-day precipitation (R5d). Observed (black) and projected (green) time series (a,b) for Connecticut; Model simulated spatial patterns for the reference period (c,f), projected mid-century changes (d,g) and late century changes (e,h).

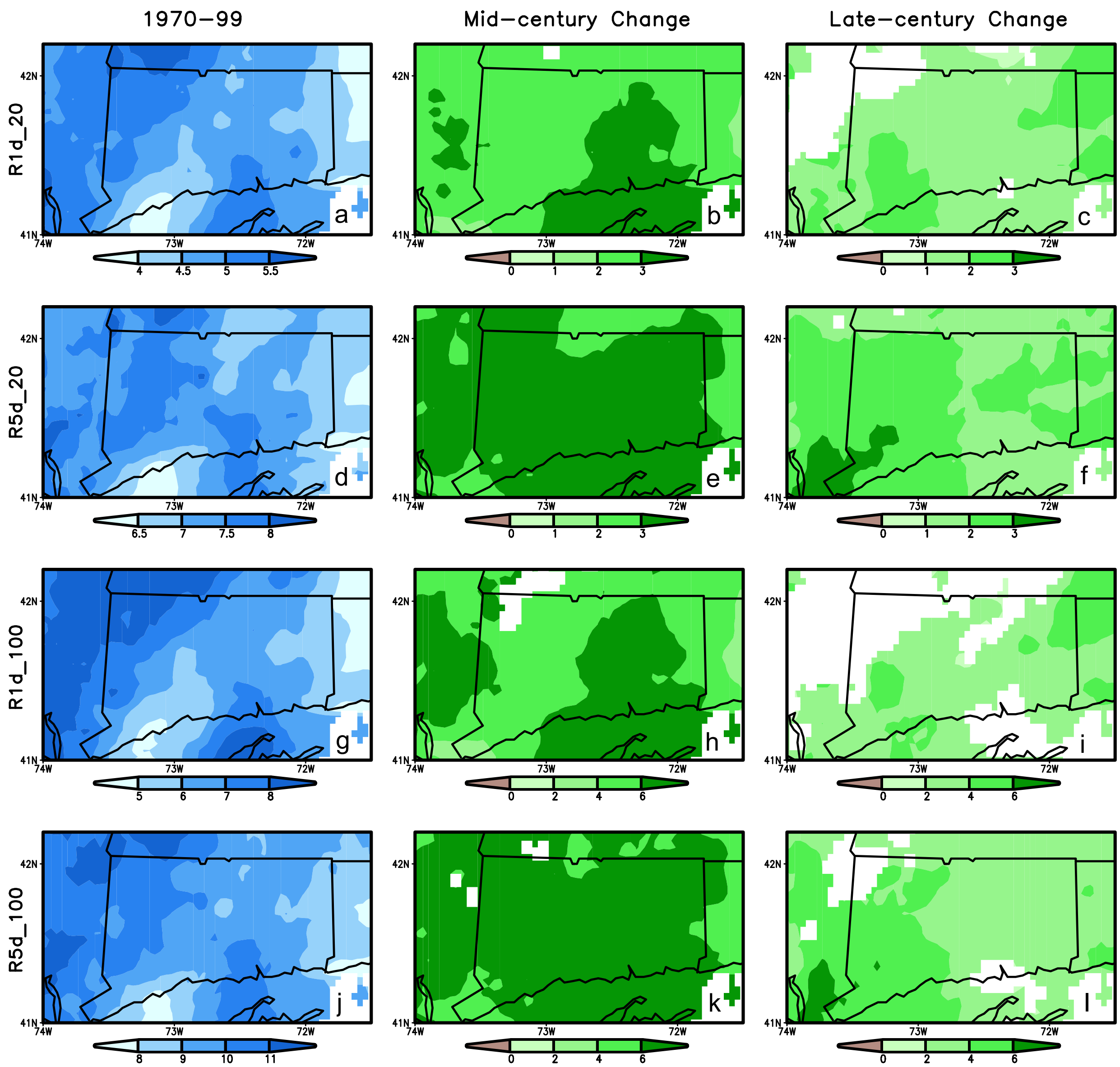

Figure 4.14 Maximum daily precipitation and maximum 5-day precipitation with a recurrence interval of 20 years and 100 years (R1d_20, R1d_100, R5d_20, R5d_100, all in inches). Spatial pattern of model simulation for the reference period (a,d,g,j), projected mid-century changes (b,e,h,k) and late century changes (c,f,i,l).

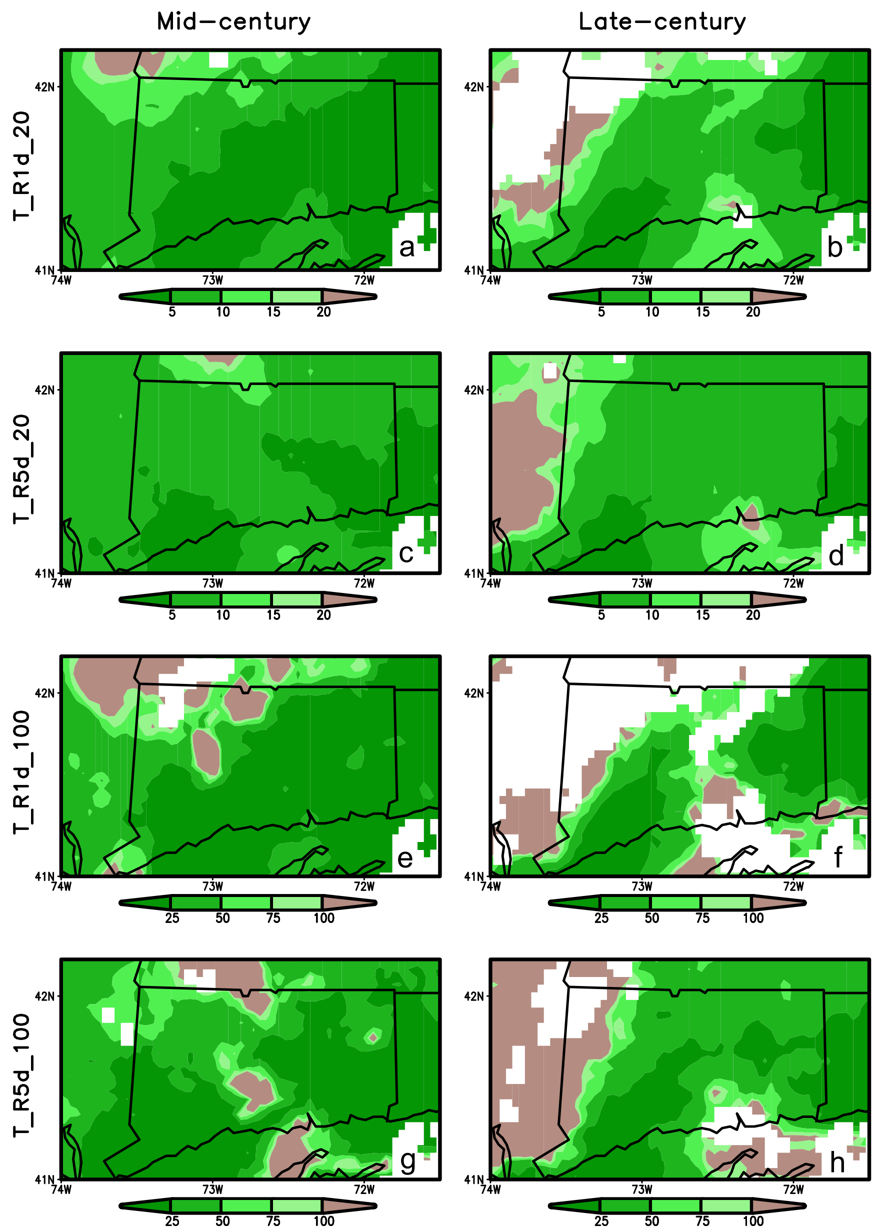

Figure 4.15 Future recurrence intervals of the past rare (1-in-20-years and 1-in-100-years) events for maximum daily and maximum 5-day precipitation (T_R1d_20, T_R5d_20, T_R1d_100, T_R5d_100, all in years). Projections for mid-century (a,c,e,g) and late century (b,d,f,h). Green shading reflects an increase in frequency and brown reflects a decrease.

Table 4.5 Multi-model ensemble of flood risk indices. State-averaged multi-model ensemble statistics of projected changes for the 1-day and 5-day maximum precipitation (R1d and R5d). These includes the mean and threshold values for different recurrence intervals (10, 20, 50, and 100 years), and their future changes. Units: inches. The percentage values in parenthesis are relative changes, and the values in bold font after the semicolon are future recurrent time (in years) for the reference threshold values. All changes are statistically significant and projected with model consensus.

Variables	1970-99 Reference	2040-69 Changes	2070-99 Changes
R1d_mean	2.8±0.1	0.7±0.2 (27%)	0.6±0.2 (22%)
R1d_10	4.1±0.2	2.0±0.8 (49%); **3**	1.3±0.8 (31%); **4**
R1d_20	4.7±0.2	2.8±1.3 (59%); **5**	1.7±1.2 (36%); **9**
R1d_50	5.7±0.3	4.3±2.4 (76%); **15**	2.4±2.2 (42%); **27**
R1d_100	6.6±0.4	5.9±3.7 (91%); **42**	3.1±3.2 (49%); **55**
R5d_mean	4.5±0.3	0.9±0.4 (20%)	0.8±0.3 (19%)
R5d_10	6.5±0.6	2.4±1.1 (38%); **3**	1.7±0.5 (27%); **4**
R5d_20	7.3±0.8	3.4±1.7 (46%); **6**	2.2±0.7 (30%); **7**
R5d_50	8.5±1.0	5.2±3.0 (53%); **15**	3.0±1.2 (43%); **26**
R5d_100	9.6±1.2	7.1±4.4 (75%); **38**	3.7±1.7 (39%); **48**

Summary: Flood Risk

In summary, results for all flood risk indices suggest a statistically significant increase of flood risks in the future, with continuous increase in the number of days with heavy precipitation and in the amount of heavy precipitation. However, the heaviest event of each year, including R1d and R5d, is found to peak in mid-century and level off or even decrease afterwards. This leveling off is not expected from our theoretical understanding. Instead, it may be a reflection of specific regional features of atmospheric circulation, multi-decadal variability of the climate, or deficiencies in statistical downscaling and bias correction, and is a topic that warrants further investigation. In addition, it should be noted that climate model resolution of extremes is challenging due to the generally coarse resolution of the GCMs and the finer spatial scale of many extreme events, and the northeast region is no exception. It is therefore desirable to revisit these projected changes based on the upcoming finer-resolution CMIP6 projections.

4.5 Storms that Affect Connecticut

Mid-Latitude Storms (Extratropical Cyclones)

Over the contiguous US, the Northeast has experienced the largest increase in total annual precipitation from 1900-2015 (Chylek et al. 2017). Historically, the majority of Northeast extreme precipitation events have been from extratropical cyclones, especially in winter and spring; nearly half of all extreme precipitation events were from extratropical cyclones occurring during winter and spring (Kunkel et al. 2012). Nonetheless, while annual regional precipitation has increased, the total number of cyclones has decreased. Over the Northern Hemisphere, the greatest decrease in strong summertime (June-August) cyclones has occurred over northeastern North America, with more than a 35% reduction since 1979 (Chang et al. 2016; Easterling et al. 2017). Over the eastern US, the number of cool season (November – March) cyclones has decreased as well, though the total precipitation on days with extratropical cyclone events has been relatively constant (Colle et al. 2013; Lombardo et al. 2015). This dichotomy can be explained by changes in the extremes. Over the last century, the number of days with extreme precipitation over the Northeast has significantly increased (Griffiths and Bradley 2007), as well as the number of extreme precipitation events from extratropical cyclones (Kunkel et al. 2012). This indicates that extratropical cyclones have been decreasing in frequency, but increasing intensity.

The global climate models struggle to represent cool season (November – March) extratropical cyclones and the associated precipitation. Considering an ensemble of 17 CMIP5 models, no individual member performed better or worse considering all performance metrics, though the models with a higher spatial grid-resolution better represented regional processes (Sheffield et al. 2013). Fine-scale models better represent cyclone structure at different stages, including cyclogenesis and deepening, cyclone track density, and the regional distribution of cyclones (Bengtsson et al. 2009; Colle et al. 2013). However, regardless of resolution, all global climate models under-predict the number of extratropical cyclones, with a large spread among the members (Colle et al. 2013).

The relationship between extratropical cyclones in global climate models and precipitation is less clear. The ability of a model to accurately represent precipitation associated with cool season extratropical cyclones is not resolution dependent (Lombardo et al. 2015). Therefore, while the dynamics of the storm may be better represented in models with smaller grid spacings, the precipitation may not. Additionally, the mean CMIP5 precipitation during the historical cool season falls within range of several sources of observation data, including the Global Precipitation Climate Project (GPCP; Adler et al. 2003), Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP; Xie and Arkin 1996, 1997), and the CPC unified daily averaged precipitation data (Higgins et al. 1996, 2000). This emphasizes the challenges in projecting changes in precipitation associated with extratropical cyclones.

In the future, changes in precipitation associated with extratropical cyclones over the region will depend on several factors, including changes in the location of the storm track, the frequency of storms, storm intensity, and precipitation (amount and rate) produced by each storm. There are consistent signals using a variety of analysis methods and techniques that provide confidence in future projections of regional precipitation, including process studies (e.g., Catto et al. 2011; Marciano et al. 2015) and ensemble analyses (e.g., Zappa et al. 2013; Colle et al. 2013; Maloney et al 2014; Lombardo et al. 2015), though there is a relatively large inter-model spread in the magnitude of these projections (Maloney et al. 2014).

The western Atlantic storm track in December-February is projected to shift northward, though the details of this shift are dependent on the analysis method. Numerical process studies in which the concentration of carbon dioxide is doubled, the upper-level jet and core of cyclone activity are displaced northeastward over the northern Atlantic Ocean (Catto et al. 2011). An ensemble of CMIP5 models indicate a northwestern shift in the extratropical cyclone storm track during the cool season (November-March), with increased activity (10-20%) over the eastern U.S. (Colle et al. 2013; Maloney et al 2014). The number of cyclones and their overall intensity is projected to decrease during the cool season over the region (Catto et al. 2011; Zappa et al. 2013; Colle et al. 2013; Maloney et al 2014; Lombardo et al. 2015), though the number of intense cyclones will increase. An ensemble CMIP5 members indicates a 10-40% increase in the number of the most intense (<980 hPa) cool season cyclones, with more rapid storm intensification along the US east coast (Colle et al. 2013). Process studies indicate that the increase in storm intensity is attributed to the increased energy associated with more water vapor within the storm (Marciano et al. 2015).

Regardless of the decrease in cool season cyclone activity, both mean and extreme precipitation is projected to increase within the western Atlantic storm track and over the eastern U.S. (Bengtsson et al 2009; Colle et al. 2013; Maloney et al. 2014; Lombardo et al. 2015). By the late-century under a high emissions scenario (RCP8.5), global climate models project a 15-25% increase in overall northeastern US cool season precipitation (Colle et al. 2013; Maloney et al. 2014; Lombardo et al. 2015), and a 20% increase in precipitation per cyclone (Lombardo et al. 2015). The number of heavy precipitation events (>25 mm/d) associated with cool season cyclones will rise 50% by the early 21st century and 4-5 times by the late 21st century, indicating a dramatic increase in the number of extreme precipitation events (Colle et al. 2013; Maloney et al. 2014). Much of this increase will occur in the form of rain, with less snow projected for future extratropical cyclones over the eastern U.S. (Marciano et al. 2015).

Atlantic Hurricanes (Tropical Cyclones)

Over the past century, there has been no significant trend in tropical cyclone (TC) activity in the North Atlantic Basin, including landfalling TCs and hurricanes (Knutson et al. 2010). Historically, TC activity was thought to have increased, with the greater frequency attributed to global warming (Mann and Emanuel 2006). More recent analysis has shown that analysis of historical TC activity is sensitive to the timeframe over which the analysis is performed, the amount of data included in the analysis, the analysis methods, and the changing observational capability over the past century. Analyzing Atlantic TC activity from 1900-2006 yields a significant positive trend, though this is highly influenced by a minimum in activity from 1910-30 (Vecchi and Knutson 2008). The trend becomes only weakly positive when the analysis includes the late 19th century as well (1878-2006). The inclusion of ship track data in the pre-satellite (1878-1965) era further alters the trend from positive to negative (Vecchi and Knutson 2011). Similar issues plague analyses of Atlantic hurricanes as well. The significant increase in activity from the late 19th century to present day becomes insignificant when the analyses begins in the mid 19th century (Knutson et al. 2010). For major hurricanes, the inclusion of an additional decade of recent data reduces the increasing trend, and causes it to become statistically insignificant (Webster et al. 2005; Klotzbach and Landsea 2015).

Additionally, the quality of historical North Atlantic TC data is questionable, especially prior to aircraft reconnaissance (1944), and deemed to be unreliable for climate-trend analyses (Landsea et al. 2006; Knutson et al. 2010). For example, studies have surmised a substantial low-bias in Atlantic TC intensity during the last half of the 19th century into the early 20th century

(Knutson et al. 2010). When these storms are adjusted to their more likely, higher intensity, the historical trend in Atlantic hurricane frequency becomes essentially flat (Knutson et al. 2010). Data associated with landfalling TCs and hurricanes are more reliable than for the Atlantic basin as a whole. Regardless, the data show no long-term increase in U.S. landfalling storms (Knutson et al. 2010). Based on more reliable satellite observations, North Atlantic TC activity has statistically significantly increased in recent decades, though it should be emphasized that these conclusions are not deduced from long-term trends (Walsh et al. 2016).

Finally, it is unknown whether these observed historical changes in North Atlantic TC activity are due to natural or anthropogenic activities (e.g., Knutson et al. 2010).For example, the number of short-duration (2 days or less) TCs was reported to increase dramatically since the late 19th century, which was attributed to the increase in Atlantic TC activity rather than global warming (Vecchi and Knutson 2008; Landsea et al. 2009), though the application of a different analysis method yielded no detectable trend (Villarini et al. 2011), emphasizing analysis issues discussed above.

In the CMIP5 models (RCP4.5 and 8.5), there is no robust signal in future tropical cyclone frequency, both globally and for the North Atlantic Basin (Camargo 2013). In part, this may be a consequence of the coarse numerical grid resolution of Global Climate Models, that is deficient at resolving tropical cyclones given the spatial and temporal scale of the phenomenon. In the historical time period, CMIP5 models underrepresent the frequency of global TCs compared to observations and inadequately represent TC tracks and development regions (Camargo 2013).

To ameliorate TC projections, a variety of analytical and numerical techniques have been employed to quantify future tropical cyclone activity, such as analyses of environmental fields associated with TC activity, statistical downscaling, dynamical downscaling, and pseudo-global warming methods. However, projections in TC frequency, intensity (central pressure, precipitation intensity), track, and duration are sensitive to the grid-resolution of the numerical model (Camargo 2013; Emanuel 2013), the numerical model used in the analyses (e.g. variations in the numerical core and physics), the representative concentration pathway, and progressions in the full ensemble (CMIP3 vs. CMIP5; Knutson et al., 2013). This makes it challenging to synthesize TC projections and obtain robust conclusions regarding future TC activity.

Generally, there is greater confidence in the projection of TC intensity and precipitation than TC frequency and storm track (Knutson et al. 2010). Both globally and over the North Atlantic, environmental trends under RCP8.5 indicate an increase in TC activity and intensity (Emanuel 2013). Conversely, dynamical downscaling suggests a statistically significant decrease in TC activity over the Atlantic Basin, with more robust trends in the CMIP3 than CMIP5 (Knutson et al. 2013). They also, however, indicate a significant increase in the most intense TCs (category 4 & 5) and an increase in TC rainfall rates. Dynamical downscaling with emphases on changes in temperature, moisture, and vertical stability (ability of the atmosphere to mix vertically) show that storms will be more intense, with deeper low pressure centers and an increase in precipitation within the storm cores (Hill and Lackmann 2011): this increase in conjunction with the projected rise in sea level could lead to an increase in storm surge (Woodruff et al. 2013). Additionally,TC activity is projected to shift poleward, though this trend is not significant in the North Atlantic basin (Kossin et al. 2016). However, these the results are sensitive to the emissions scenario (Hill and Lackmann 2011). Additionally, the atmosphere becomes more stable (less likely to mix vertically) as it warms, and this can mitigate the increase in storm intensity due to rising sea surface temperatures.

5. Research Gaps and Recommendations

In this report we have reviewed the scientific literature to highlight insights gained about recent observed trends and future projections of temperature and precipitation that are relevant for the state of Connecticut but have generally emphasized the Northeast U.S. or larger regions. We have also presented new analysis of high resolution datasets (both observations and downscaled climate model projections) with a specific geographic focus on Connecticut.

Several research gaps were identified while conducting this assessment. First, the new high-resolution gridded observations provide interesting views of spatial patterns in temperature and precipitation across the state, however, the length of the data is still insufficient to characterize long term observed trends, especially for precipitation.

Second, while the standard temperature-only extremes analyzed here show dramatic responses to future warming, a number of studies have suggested that the combined effects of changes in temperature and humidity can pose severe risks to human health. These more complex relationships will require further study and should be included in a future assessment.

Third, our analysis of precipitation extremes suggests a substantial increase in flood risk in the coming decades, beyond the changes currently seen. However, in this analysis the increase in flood risk appears to peak at mid-century and then level off particularly for the maximum daily precipitation (R1d) amount, an indicator of increased flash flood risk, and the maximum five-day precipitation (R5d) amount, an indicator of flood risk over large watersheds. These results are likely due to changing dynamics of the Atlantic high pressure system in summer (e.g., Thibeault and Seth, 2014) and will require further investigation.

Fourth, based on our analysis and previous studies, observed changes in precipitation since 1950 are significant only in summer; based on data record extending back to 1896, the largest changes are in the fall season. In contrast, for future projections, both our analysis and previous studies suggest significant increases in the winter-spring seasons with some decrease in summer and fall though these either not significant or inconclusive due to lack of model consensus. More work is needed to understand why observed precipitation changes were dominated by an increase during summer or fall season while future projections are dominated by increases in winter and spring.

Fifth, major snow storms are important precipitation mechanisms during winter and present a different challenges and risks. In this assessment, different precipitation forms were not distinguished and snow-specific risks and changes were not evaluated. This will be an important area of future research.

This assessment has focused on physical climate (temperature and precipitation) changes for the State of Connecticut. It is recognized that state assessments like this one are motivated by the need to provide information to local decision makers. For this assessment, dozens of temperature and precipitation indices were assessed; however, it is not clear how relevant these indices are for decision makers or how they will be used in decision-making. We view this assessment as the beginning of a dialog with practitioners that would benefit from a rigorous applied social science approach to explore what makes assessment information useful and what information is ultimately used in decision making. Understanding *assessment usability* is a challenge not just for this assessment but for assessments more broadly, as very little scholarly attention has been paid to understanding assessment usability at any scale (except see Galford et al. 2016, Weaver et al. 2017, and Kirchhoff et al. 2019), and especially the usability of state assessments.

In contrast to the challenges related to usability, there has been significant scholarly attention paid at the national and international assessment scale to understanding what influences perceptions of *assessment credibility* (Farrell and Jäger 2006). International and national assessments generate credibility through peer-review, through the involvement of recognized experts, and through an open, transparent process (NAS, 2007, Farrell and Jäger 2006). But questions remain whether or not approaches used at the national or international scales of assessment are necessary or sufficient for establishing credibility of state scale assessments. Moreover, we do not yet understand how assessment usability (and expectations regarding the use of climate information for local decision making) might alter the calculus for perceptions of credibility.

Recommendations for future Connecticut climate assessments include (1) the creation of an ongoing climate assessment process and ongoing process for assessing the usability of assessment information, (2) periodically assessing user climate information needs, and (3) integrating with the assessment of physical climate an analysis of potential implications of climate changes on people, businesses, and the natural environment in Connecticut and of potential adaptation actions for their effectiveness on mitigating these impacts. An ongoing assessment process is important as it would enable new insights from climate science and observed changes in the climate system to be reflected in evolving climate assessments. International and national assessment processes tend to follow this ongoing assessment model (US Global Change Research Act of 1990, IPCC) and a few states including California have initiated such a process. It is critical that ongoing assessment attends to assessing users' needs for climate information in addition to assessing the physical climate. Adopting an ongoing assessment that attends to not just the physical climate science but also to linking assessment to users' needs (i.e., social science questions) would likely result in practical benefits (an assessment that is useful for decision makers) as well as advancing our fundamental understanding of what makes assessments usable. Moreover, ongoing assessments are better able to engage with practitioners in an ongoing basis and result in mutual learning about climate science and impacts on the one hand and about user information needs on the other.

Beyond just the next Connecticut climate assessment, we also considered recommendations for future state assessments. First, while state and regional climate assessments often evaluate and select global climate models based on their ability to reliably capture the full range of uncertainty in temperature and precipitation for a given location, the same kind of rigorous evaluation is not often applied to downscaled climate data products. Instead, it is common to simply apply vetted products, such as the LOCA dataset used in the US National Climate Assessment, for local assessment needs. Results from our work suggests downscaled climate datasets should be evaluated to avoid the potential for over or underestimating extreme (very low or very high) precipitation amounts if the database does not capture the local precipitation well. For example, we found that the LOCA data tends to underestimate heavy precipitation and overestimate light precipitation, which significantly influences daily precipitation statistics, especially extremes. While this may or may not influence the relative changes projected for the future, it does influence the absolute magnitude of some quantities that are needed for infrastructure design, e.g., the magnitude of maximum daily precipitation. Out of this data quality consideration, in our assessment we adjusted how we used each dataset to take advantage of their strengths and mitigate this identified weakness.

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