CURRENT AND FUTURE IMPACTS OF EXTREME EVENTS IN CALIFORNIA

A Paper From:
California Climate Change Center

Prepared By:
Michael D. Mastrandrea[1], Claudia Tebaldi[2], Carolyn P. Snyder[3], Stephen H. Schneider[1,4]

[1]Woods Institute for the Environment, Stanford University
[2]Climate Central
[3]Interdisciplinary Graduate Program in Environment and Resources, Stanford University
[4]Department of Biology, Stanford University

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Preface

The California Energy Commission's Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

The PIER Program conducts public interest research, development, and demonstration (RD&D) projects to benefit California's electricity and natural gas ratepayers. The PIER Program strives to conduct the most promising public interest energy research by partnering with RD&D entities, including individuals, businesses, utilities, and public or private research institutions.

PIER funding efforts focus on the following RD&D program areas:

- Buildings End-Use Energy Efficiency
- Energy-Related Environmental Research
- Energy Systems Integration
- Environmentally Preferred Advanced Generation
- Industrial/Agricultural/Water End-Use Energy Efficiency
- Renewable Energy Technologies
- Transportation

In 2003, the California Energy Commission's PIER Program established the **California Climate Change Center** to document climate change research relevant to the states. This center is a virtual organization with core research activities at Scripps Institution of Oceanography and the University of California, Berkeley, complemented by efforts at other research institutions. Priority research areas defined in PIER's five-year Climate Change Research Plan are: monitoring, analysis, and modeling of climate; analysis of options to reduce greenhouse gas emissions; assessment of physical impacts and of adaptation strategies; and analysis of the economic consequences of both climate change impacts and the efforts designed to reduce emissions.

The California Climate Change Center Report Series details ongoing center-sponsored research. As interim project results, the information contained in these reports may change; authors should be contacted for the most recent project results. By providing ready access to this timely research, the center seeks to inform the public and expand dissemination of climate change information, thereby leveraging collaborative efforts and increasing the benefits of this research to California's citizens, environment, and economy.

For more information on the PIER Program, please visit the Energy Commission's website www.energy.ca.gov/pier/ or contract the Energy Commission at (916) 654-5164.

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Abstract

In the next few decades, it is likely that California must face the challenge of coping with increased impacts from extreme events such as heat waves, wildfires, droughts, and floods. Such events can cause significant damages and are responsible for a large fraction of near-term climate-related impacts every year. Some extreme events have already very likely changed in frequency and intensity over the past several decades, and these changes are expected to continue with relatively small changes in average conditions. This study synthesized existing research to characterize current understanding of the direct impacts of extreme events across sectors, as well as the interactions between sectors as they are affected by extreme events. It also produced new projections of changes in the frequency and intensity of extreme events in the future across climate models, emissions scenarios, and downscaling methods for producing regional climate information, for each California county. This research evaluated historical and projected changes for a suite of temperature and precipitation-based climate indicators and conducted a return level analysis to investigate projected changes in extreme temperatures. A final analysis discusses the future likelihood of events similar in magnitude to specific historical events, such as the July 2006 heat wave.

Consistent with other projections, this study found significant increases in the frequency and magnitude of both maximum and minimum temperature extremes in many areas, with the magnitude of change dependent on the magnitude of projected emissions and overall temperature increase. For example, in many regions of California, at least a ten-fold increase in frequency is projected for extreme temperatures currently estimated to occur once every 100 years, even under a moderate emissions scenario (the Special Report on Emissions Scenarios B1 scenario). Under a higher emissions scenario (the Special Report on Emissions Scenarios A2 scenario), these temperatures are projected to occur close to annually in most regions. Also consistent with other projections, changes in precipitation extremes are more varied, and are sensitive to choice of climate model and downscaling methodology.

Lastly, a comparison of current and future expected frequencies of events comparable to recently observed extremes (the July 2006 heat wave and December 1998 freezing spell) suggest significant changes: heat waves similar in length and intensity to that experienced in 2006 will become more frequent all across the state, with some simulations suggesting that they will be an annual event by the end of this century under a higher emissions scenario. Freezing spells, on the other end, are robustly projected to become less frequent all across the state, even in locations where now they are a yearly event, becoming as rare as a one in ten-year event or less in a large fraction of California.

Keywords: Extreme events, climate change impacts, heat waves, climate model projections, return period analysis

1.0 What Are Extremes?

1.1. Motivation

Extreme weather events, such as heat waves, wildfires, droughts, and floods can cause significant damages every year and are responsible for a large fraction of climate-related impacts (Kunkel et al. 1999; Easterling et al. 2000; Meehl et al. 2000; Tebaldi et al. 2006). Meehl et al. (2007) contend that "the type, frequency and intensity of extreme events are expected to change as Earth's climate changes, and these changes could occur with relatively small mean climate changes" (p. 783). Thus, changes in extreme events are very likely to be some of the earliest impacts experienced from anthropogenic climate change. Indeed, Trenberth et al. (2007) find that some extreme events have already changed in frequency and intensity over past decades, with a confidence ranging from *likely* to *very likely.* Moreover, adaptation to extreme events can be more challenging than adaptation to gradual changes in mean climate states, and can disproportionately affect vulnerable populations that experience higher exposure (e.g., extreme heat and low-income populations without access to air conditioning or individuals living in flood-prone areas) or higher susceptibility (e.g., extreme heat and elderly individuals) to such events. Changes in climate may not only change the frequency and magnitude of individual extreme events, but may also change the likelihood of extreme climate events occurring concurrently. Vulnerability to and impacts of repeated and coincident extreme events are generally expected to be higher than similar events occurring individually (e.g., Hallegatte et al. 2007).

For these reasons, investigations of extreme events uniquely contribute to impact assessments and adaptation planning. Extreme events are also particularly of interest because they provide near-term, direct concrete experiences of potential future conditions and impacts related to climate change.

1.2. Climate Change and Extremes

How might extreme events change with changes in climate? Changes in climate extremes can be due to changes in mean climate state, changes in distribution of climate states, or a combination of both. See Figure 1 for a graphical depiction of how changes in mean and distribution affect the frequency of climate extremes. Due to the potential for changes in variance, the sensitivity of extremes to changes in mean climate may be greater than one would assume from a changed mean alone (Mearns et al. 1984; Katz and Brown 1994; Tebaldi et al. 2006). Observations confirm that changes in extremes are not always proportional to changes in the mean, such as greater changes in minimum than maximum temperatures (Trenberth et al. 2007). Thus, projections of extremes are sensitive to both changes in mean and distribution of climate variables in future climate projections. Observed changes in extremes and projected impacts from future changes in extremes are summarized in (Trenberth et al. 2007; Parry et al. 2007).

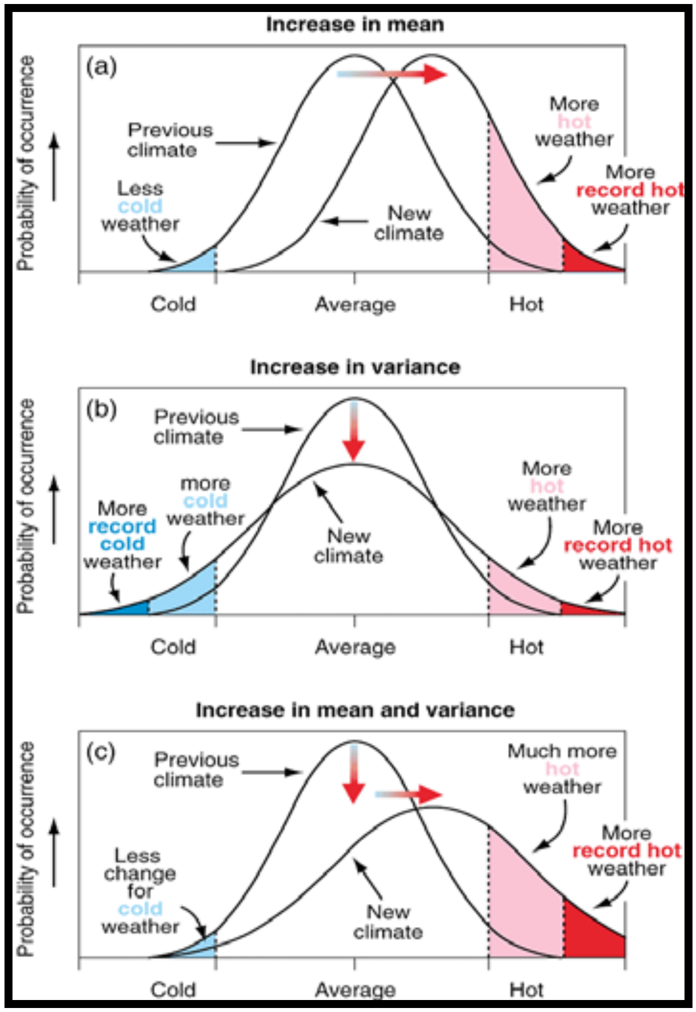


Figure 1. Schematic showing the effect on extreme temperatures.

When (a) the mean temperature increases, (b) the variance increases, and (c) when both the mean and variance increase for a normal distribution of temperature. Figure 2.32 from Folland et al. (2001)

1.3. Defining Extreme Events

The exact definition of an *extreme event* varies widely in the literature. The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) focused on six types of extreme events in discussions of observed changes in extreme events and projections of future changes: (1) daily maximum and minimum temperatures; (2) heat waves; (3) heavy precipitation events; (4) droughts; (5) intense tropical cyclone activity; and (6) incidents of extreme high sea levels (Solomon et al. 2007; Parry et al. 2007). The term also is used often to refer to floods and wildfires. The IPCC states, "Extremes refer to rare events based on a statistical model of particular weather elements, and changes in extremes may relate to changes in the mean and variance in complicated ways. Changes in extremes are assessed at a range of temporal and spatial scales" (Trenberth et al. 2007, 299). *Extreme* is generally defined as events occurring between 1% to 10% of the time at a particular location in a particular reference period (Trenberth et al. 2007).

Core to the definition of extreme events is the question: extreme with respect to what?

First, extreme events must be defined temporally. Extreme events encompass variations in physical, weather-related parameters such as temperature or precipitation over days (e.g., heat waves, heavy precipitation) or months to years (e.g., drought).

Second, extremes events must also be defined spatially. Heat waves, for example, can vary widely in their spatial extent, affecting the magnitude and nature of impacts. Spatial resolution should be chosen based on the desired output and impacts of interest. However, the resolution of the relevant observations or projections provides a fundamental constraint.

Third, the thresholds used to define what is extreme must be defined. We contend that it is important to make a distinction between extreme climate events and extreme impact events. Extreme climate events are defined purely by their statistical relationship to past climate conditions and may or may not have direct ties to impacts. Extreme impact events, in contrast, are defined directly by having nonlinear impacts on social and biological systems. For example, isolated days with temperatures above the 95th percentile for that calendar day do not necessarily cause significant impacts to natural and human systems. Some extreme impact events are sensitive to the timing of extreme climate conditions, such as temperature extremes during the flowering of rice plants reducing yield (Jagadish et al. 2007). Moreover, extreme impact events can be caused by a combination of non-extreme physical conditions, such as damage due to flooding caused by a combination of precipitation and frozen ground.

Extreme climate conditions affect components, or sectors, of biological and social systems. It is important to understand the relationships between physical conditions and particular metrics of interest in these sectors. These relationships, expressed in quantifiable terms, can be called *transfer functions.* While one can imagine a large number of sectors being affected by extreme events, we focus on those California sectors that have been identified as particularly susceptible to extreme climate events in the literature. Table 1 lists the sectors most sensitive to negative impacts from extreme climate events, and we also provide examples of metrics (quantifiable units) that can be used to measure the magnitude of extreme impact events in these sectors.

Ideally, the definition of extreme impact events and subsequent transfer functions would be arrived at by a bottom-up approach: characterize climate conditions that generate extreme impact events through an assessment involving each sector's stakeholders and analysts to identify thresholds of particular concern for on-the-ground planning. A study of such bottom-up definitions, however, does not exist, to our knowledge. We see this study as setting the stage for more formal research in this direction, building from the extensive body of literature on the impacts of climate change in California.

Table 1. California sectors most sensitive to negative impacts from extreme climate events

Sector	Sector Description	Example metrics
Air Quality	Addresses U.S. Environmental Protection Agency (EPA) criteria pollutants and other air pollution.	Concentration of ozone and particulate matter.
Agriculture	Production of crops, animal products, produce.	Farmland loss. Crop, meat, dairy, egg production and yields. Animal deaths.
Ecosystems	Natural biomes. Forests and marine/coastal ecosystems treated separately.	Loss of habitat, biodiversity, pollination services, etc.
Forestry	Includes forest, woodland, scrubland, and grassland ecosystems. Also includes lumber industry, recreation, and other human uses.	Loss of habitat and natural resources due to wildfire. Financial losses to lumber and other businesses. Loss of homes and infrastructure.
Energy	Electrical generation and transmission capacity.	Peak and baseload electrical demand. Frequency, duration, and spatial extent of blackouts and brownouts.
Marine/Coastal	Includes marine, estuary, river delta, brackish wetland, beach, and coastal bluff ecosystems. Also includes fishing and tourism, recreation, and other human uses.	Beach and coastal bluff erosion. Sewage overflow events. Damage to coastal infrastructure, interruption of coastal economic activities.
Public Health	Includes issues relating to human existence and welfare.	Incidences of death, illness, and interruption of activities due to illness or injury.
Water	Includes the quality, transportation, and management of freshwater supply. Includes flood control and sewage processing.	Flood frequency and consequent financial losses. Level of needed water conservation or rationing.

In the discussion that follows, we discuss two types of transfer functions that can be used to estimate the impacts of extreme climate events on sectors of interest. First, *inter-system transfer functions* quantify the relationship between changes in physical system conditions and resulting sectoral impacts, such as how heat wave conditions impact heat-related mortality. Multiple sectors are affected by the same climatic changes; for example, drought conditions affect water supply for urban and agricultural uses as well as for hydropower. Additionally, impacts in one sector can affect other sectors. Thus, there are also *inter-sector transfer functions* that quantify the relationship between changes in one sector and the resulting impacts on a different sector. These relationships are diagramed conceptually in Figure 2.

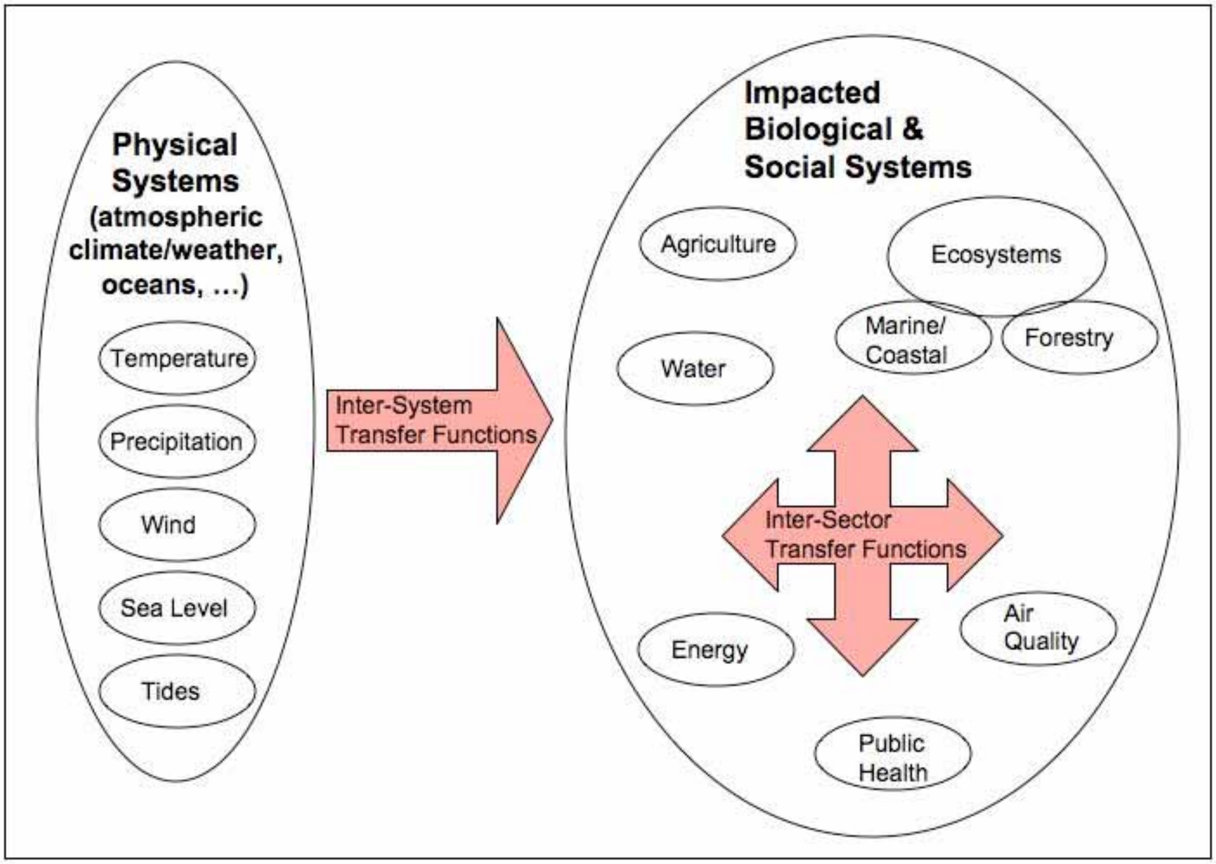


Figure 2. Interactions among physical, biological, and social systems

As used here, a transfer function does not refer only to a simple equation expressing a given impact metric as a function of one or more driving climatic variables. More broadly, a transfer function can also represent the output of models designed to calculate the impacts of changing climatic conditions on specific sectors, such as hydrologic models used to project changes in future water supply and stream flow. We document these transfer functions, where available, in Section 2. In many cases, qualitative relationships have been identified, but quantitative transfer functions have not been defined.

2.0 Current Understanding

2.1. Impacts of Extreme Events in California

This paper builds from a firm foundation of existing research on the impacts of climate change on California. In this section we summarize this work in a new synthetic framework to illustrate the potential impacts of extreme events on seven key impact sectors in California, as well as the interconnections between sectors affected by extreme events. These sectors and relationships are summarized in Figure 3. Examples of sector components affected by extreme events are displayed in each bubble. Direct influences of climate on specific sectors are represented by color-coded arrows—red for temperature, blue for precipitation, and green for “surges”—

representing other variables such as wind and storm surges. Black lines represent influences between sectors, with illustrative examples of such connections provided. We note that Figure 3 does not distinguish between influences occurring on different spatial or temporal scales, which, as discussed above, can vary widely depending on the extreme event under consideration. The figure also does not distinguish between influences that differ in strength. And finally, the interactions displayed are specific to extreme events and their impacts in California. Climate change can have many other impacts on these sectors, and there are many other interactions between sectors that do not specifically involve extreme events and their impacts. Furthermore, there are many other drivers, such as land use change, that interact with climate change and influence impacts, and we explicitly do not attempt to catalog these other drivers.

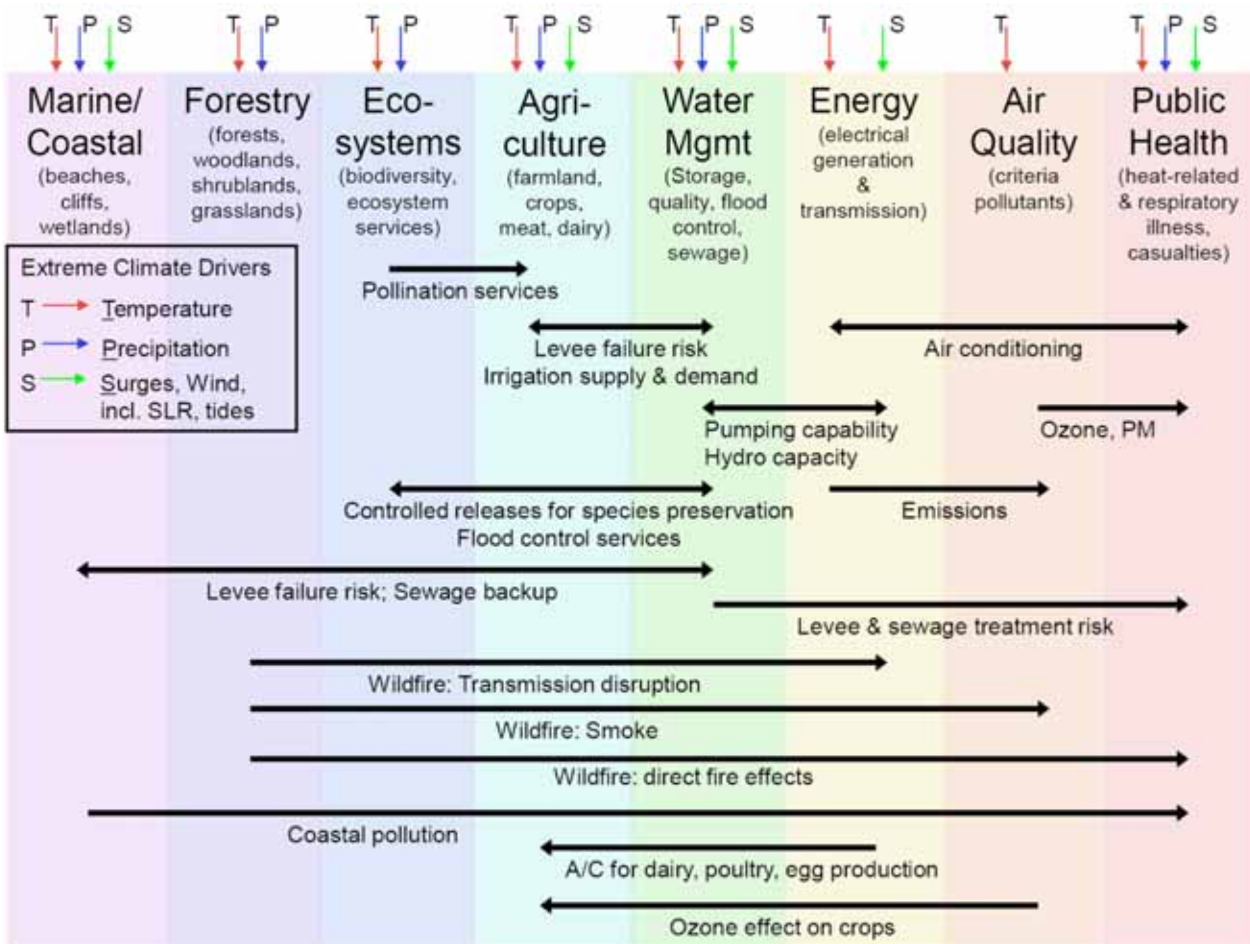


Figure 3. Extreme climate drivers and inter-sector interactions

Potential impacts of extreme events on seven key impact sectors (and components) in California and the interconnections between impact sectors. Colored arrows represent extreme climate events (see legend) directly impacting specific sectors. Black arrows between driving sectors and affected sectors represent inter-sector interactions, with illustrative examples listed below the arrow.

We discuss each sector and relevant interactions below. For each sector, these are summarized in text and tabular form, including quantified transfer functions where available from the literature. The first column in each of these tables contains a brief description of what can constitute an extreme impact within the sector. The next two columns describe driving forces from physical systems (e.g., climate and weather systems) and document inter-system transfer functions mapping these physical system variables to sectoral metrics that can be used to characterize extreme impact events. The final two columns list driving forces that originate in other sectors and the related inter-sector transfer functions, when available.

2.1.1. Water

The main impacts of extreme events in the water sector are on water resource management and flood control capability (Medellin-Azuara et al. 2008; Van Rheenen et al. 2004), with potential additional impacts on water transport and quality (Kiparsky et al., forthcoming). Water managers must balance between competing management demands, such as holding supply reserves, maintaining flood control capacity, and providing electricity through hydropower generation (Medellin-Azuara et al. 2008; Van Rheenen et al. 2004). Many of the relevant parameters for water resource management relate to extremes at the scale of multi-year accumulations and are sensitive to the balance between accumulation, runoff, snowpack melting, and evapotranspiration (Medellin-Azuara et al. 2008; Kiparsky et al., forthcoming). Researchers have investigated impacts on this complex system by developing detailed hydrological and engineering-economic models of California's water supply system (see Draper et al. 2004; Medellin et al. 2006; Vicuna et al. 2007). When the use of complicated water system models was not possible, researchers have focused on dry days as a proxy, recognizing that they are not the same as drought indicators (Hayhoe et al. 2004; Roos 2005; Cayan et al. 2006a; Medellin et al. 2006). Water resource management is also very sensitive to urban and agricultural water demand, which will increase during extreme heat events (Medellin-Azuara et al. 2008).

Precipitation frequency and intensity are the key parameters influencing flood control capability, but this capability is also sensitive to timing of runoff and snowpack melting (Medellin-Azuara et al. 2008). Water quality can be affected by salinity intrusions from sea level spikes, by contamination during floods, and by temperature-induced changes in water chemistry. Flood control capability and water quality can also be affected indirectly by wildfires and other damage to forests that increase runoff during heavy precipitation events and reduce filtration of water entering groundwater.

Table 2 summarizes some extreme impact events within the Water sector and notes driving conditions from climate events or from other events in other sectors, along with associated transfer functions, where known.

Table 2. Water sector extreme impact events and drivers

Extreme Events w/i Sector	Extreme Climate Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Storage below minimum standards	High temperatures may cause an exceptionally early snowmelt, causing a shift in maximum water storage to earlier in the spring. If accompanied by an exceptionally low precipitation year, the result will be dramatically lower water storage levels for use during the summer dry months.	Trends are noted in the SWE/P (snow water equivalent, normalized to precipitation) and CT (riverflow Center of Timing; i.e., date for which half of river flow occurs before and half after). Both of these measures are declining in most of California. (Barnett et al. 2008) Projections (2085 climate model, 2050 water demands & land use) with CALVIN hydrologic model: water availability and use. (Medellin et al. 2006) Projections [climate models (until 2100)], WEAP hydrologic model: inflows to, and drought frequency and persistence in, the Sacramento River Basin. (Joyce et al. 2006)	Agriculture: excessive irrigation demands may be induced by the same climate drivers that directly impact water management.	Projections [climate model (2100)], WEAP hydrologic model: agricultural demand for water in the Sacra-mento Valley. (Joyce et al. 2006)

Table 2 (cont.). Water sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Flood control capability	High temperatures may cause an exceptionally early snowmelt, causing a shift in maximum water storage to earlier in the spring. If combined with a high precipitation event, this could cause flooding if storage capacities are exceeded. High winds from severe storms can cause high waves and storm surges, creating the potential for levee failures in estuaries and river deltas, especially if occurring during a high tide period. This effect will be compounded by gradually rising sea levels. It will also be compounded if accompanied by the high temperature and high precipitation events mentioned above.	Historical tide range damping between Golden Gate and Sacramento. Historical frequency of Sacramento river and delta levee breaks. (Cayan et al. 2006b) Projection (until 2100) (climate models & historical data): increasing sea level trend, # of exceedances of 99.99 percentile sea level, and coincidence of high Sea Level Height (SLH) and low Sea Level Pressure (SLP) (as an indicator for storms), for California. (Cayan et al. 2008a)	Ecosystems: major wildfires may lead to increased run-off from high precipitation events, exacerbating the problem of flood control.	*(none identified at this time)*
Quality below minimum standards	Flooding and runoff during severe storms can lead to contamination of water supplies. High temperatures can affect water chemistry, as well as algal and microbial growth, and thus water quality.	*(none identified at this time)*	Ecosystems/ Forestry: end-user water quality could be compromised through reduced filtering of groundwater due to loss of forests through wildfire (short-term) or increased pest activity (long-term).	*(none identified at this time)*

2.1.2. Public Health

Extreme events affect public health in California primarily through heat-related morbidity and mortality and impacts on air quality (Drechsler et al. 2006). Jacobson (2008) found that additional deaths from air pollution induced by climate change were due to increased ozone levels and increases in particulate matter (PM) from enhanced stability, humidity, and biogenic particle mass. The relationships developed between heat and morbidity/mortality are location specific, and most public health studies are conducted at an individual city scale (Hayhoe et al. 2004; Ebi et al. 2006; Patz et al. 2005). Such specificity allows the construction of quantitative relationships with temperature parameters (Drechsler et al. 2006; Hayhoe et al. 2004). Heat-related morbidity/mortality can also be exacerbated by electrical outages that prevent air conditioning, and by decreased air quality during extreme heat events (Drechsler et al. 2006). Flooding and severe storms often cause direct casualties and can decrease water quality through contamination such as discharges of untreated sewage (Drechsler et al. 2006). Wildfires can cause direct casualties as well as increasing medical problems through deteriorating air quality.

Table 3 summarizes some extreme impact events within the Public Health sector and notes driving conditions from climate events or from other events in other sectors, along with associated transfer functions, where known.

Table 3. Public health sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Excessive incidence of death/ emergency room (ER) visits from health-related issues.	High temperatures can cause heat exhaustion and heatstroke, as well as increasing the probability of cardiovascular problems.	Analytic function: Based upon historical modeling and depending on particular metropolitan area, mortality is shown as linear functions of apparent temperature (AT), day position (CD), afternoon temperature (Tx), days in sequence (DIS), and/or days after May 1 (TS). (Drechsler et al. 2006; Hayhoe et al. 2004) Statistical modeling: Correlation of temperature to mortality and hospitalizations, particularly identifying affected groups. Also compares heat wave incidence rates to non-heat wave rates. (Basu and Ostro 2008)	Air Quality: Increased ozone and PM levels are associated with higher incidences of cardiovascular and respiratory ailments, including higher numbers of deaths and ER visits. Energy: Electrical blackout/brownouts from the energy sector would impact the ability to run air conditioning, especially during heat waves, when it is needed most to forestall the health issues discussed under climate drivers. Water: Failure of sewage treatment facilities because of flooding/excessive run-off may cause untreated sewage discharges into waterways used for freshwater supplies and recreation. This may lead to increase health incidences.	Analytic function: differential increases in cancer mortality/ hospital visits as a function of ozone/PM concentration, fractional increased risk per unit of concentration change, baseline health effect rate, and population exposed to ≥ min threshold. (Ostro et al. 2006)

Table 3 (cont.). Public health sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Flood casualties	Excessive stream flows can result from: (1) High temperatures creating rapid snow melt in the mountains, and (2) high precipitation levels from severe storms. High winds from severe storms can cause high waves and storm surges creating flooding and erosion in coastal areas, especially if occurring during a period of high tides. This effect will be compounded by gradually rising sea levels. In estuaries and river deltas it will also be compounded if accompanied by the high temperature and high precipitation events mentioned above.	Historical tide range damping between Golden Gate and Sacramento. (Cayan et al. 2006b) Projection (2100) (climate models & historical data): increasing sea level trend, # of exceedances of 99.99 percentile sea level, and coincidence of high SLH and low SLP (as an indicator for storms), for California. (Cayan et al. 2008a)	Water: levee failure always leads to flooding. The degree of this flooding will depend, to some extent, on the climate factors affecting this sector.	Historical frequency of Sacramento river and delta levee breaks. (Cayan et al. 2006b)

2.1.3. Air Quality

Extreme events impact air quality primarily through influences on ozone and PM levels (Cayan et al. 2006a; Drechsler et al. 2006; Medina-Roma and Schwartz 2007). Extreme heat events promote ozone formation. Jacobson (2008) found that increased water vapor and temperatures separately increase ozone, more so at locations with higher background ozone levels. Wildfires also release PM that can be broadly transported by prevailing winds. Increased energy demand also requires utilization of additional energy generation, increasing emissions of pollutants to the extent that additional energy generation involves additional fossil fuel use.

Table 4 summarizes some extreme impact events within the Air Quality sector and notes driving conditions from climate events or from events in other sectors, along with associated transfer functions, where known.

Table 4. Air Quality Sector Extreme Impact Events and Drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Excessive ozone levels	<u>High temperatures</u> enhance the formation of ozone.	Analytic function: differential increase in ozone with temperature fit to polynomial function of ozone concentration. (Jacobson 2008) Projection (2100): increasing trend in days/yr that ozone 1-hr avg. exceeds 90ppb in selected areas. (Drechsler et al. 2006)	Drivers from other sectors of marginal consequence in the context of extreme events.	*(none identified at this time)*
Excessive PM levels	<u>High temperatures</u> enhance the formation of ozone, which, in turn, increases the formation of nitrogen-based particulates.	Perturbation analysis models of historical data: expected increases in background ozone cause increased $PM_{2.5}$ in most cases.	<u>Forestry:</u> smoke from <u>wildfires</u>; <u>Energy</u>: <u>excessive emissions</u> if peak energy demands must be met with fossil fuel generation.	*(none identified at this time)*

2.1.4. Agriculture

Changes in temperature, precipitation, carbon dioxide (CO_2) concentrations, pests, and weeds all can affect agriculture (Cavagnaro et al. 2006; Baldocchi and Wong 2006; Cayan et al. 2006a). Pastures in California are potentially more sensitive to local precipitation changes because they are rain-fed, as compared to croplands that are mostly irrigated.

However, major damages to crop and livestock industries are possible with extreme events, with costs of insurance claims from specific extreme events reaching into the hundreds of millions (Lobell et al. 2009a). Specific crops are sensitive to extremes during specific stages in their development (extreme heat during fruit ripening, e.g.). Though monthly averages do not explicitly identify the impacts of extreme events, (Lobell et al. 2007a, Lobell et al. 2007b, Lobell et al. 2006) identified correlations between yields of specific crops and climate variables such as monthly averaged min/max temperature and precipitation. Schlenker et al. (2006, 2007) use a fine-scale data set to identify a highly non-linear and asymmetric relationship between temperature (in degree days) and yield in historical data for corn, soybeans, and cotton, supporting the importance of considering extreme events in addition to mean changes. Hayhoe et al. (2004) also identified specific temperature thresholds for impacts to certain industries, such as wine grapes and dairy production. Irrigated agriculture is affected by water availability during multi-year drought conditions and can be affected by short-term disruption of water supply during periods of extreme heat (discussed above), as well as increased water needs due to increased evapotranspiration (Anderson et al. 2008).

Table 5 summarizes some extreme impact events within the Agricultural sector and notes driving conditions from climate events or from events in other sectors, along with associated transfer functions, where known.

Table 5. Agriculture sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Drastic reduction in crop production	High temperatures above tolerance range of plants, low precipitation in non-irrigated areas, flooding during severe storms, all can decrease crop yield.	Historical (1993–2008) breakdown of California crop insurance and disaster payments, especially by temperature and precipitation extreme events. (Lobell et al. 2009a) Projection (2050) (climate and crop models & historical data): likelihood of impacts on the yields of California's top 20 perennial crops. (Lobell et al. 2008b) Projection (2100) (climate models & historical data): trends on winter chill duration in California's Central Valley. (Baldocchi and Wong 2008) Regression models of influence of various temperature and precipitation variables on yields for 12 major California crops. (Lobell et al. 2006)	Ecosystem: decreasing pollination services for those crops not wind-pollinated because of climate-induced changes in pollinator habitats; Water: decreased ability to supply irrigation water in either the short or long-term. Air Quality: Increased ozone concentrations can damage crop development and yields.	Projections [climate model (2100)], WEAP hydrologic model: surface and groundwater deliveries in the Sacramento Valley, with and without cropping pattern adaptation. (Joyce et al. 2006)
Drastic reduction in meat/ dairy/egg production	High temperatures increase death of farm animals or cause dramatic decrease in dairy/egg production.	Analytic function: linear decline in milk production (per degree over 32°C). (Hayhoe et al. 2004)	Energy: Outages would impact air conditioning, especially during heat waves, when it is needed to forestall the issues under climate drivers.	*(none identified at this time)*

Table 5 (cont.). Agriculture sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Flooding of farmlands	Excessive stream flows can result from: (1) High temperatures creating rapid snow melt in the mountains, and (2) high precipitation levels from severe storms. For farmland near sea level, high winds from severe storms can cause high waves and storm surges creating flooding and erosion, especially if occurring during a period of high tides. This effect will be compounded by gradually rising sea levels. It will also be compounded if accompanied by the high temperature and high precipitation events mentioned above.	Historical tide range damping between Golden Gate and Sacramento. (Cayan et al. 2006b) Projection (2100) (climate models and historical data): increasing sea level trend, # of exceedances of 99.99 percentile sea level, and coincidence of high SLH and low SLP (as an indicator for storms), for California. (Cayan et al. 2008a) Historical (1993–2008) breakdown of California crop insurance and disaster payments, especially by temperature and precipitation extreme events. (Lobell et al. 2009a)	Water: levee failure always leads to flooding. The degree of this flooding will depend, to some extent, on the climate factors affecting this sector.	Historical frequency of Sacramento river and delta levee breaks. (Cayan et al. 2006b)

2.1.5. Energy Generation and Use

Extreme events can affect energy demand (Franco and Sanstad 2008; Miller 2007), impact energy production from hydropower (Medellín-Azuara et al. 2008; Vicuña 2008) and wind, and can cause potential disruptions to the production, transmission, and fuel transport infrastructures. Potential for disruption of energy supply is particularly high during periods of extreme heat, when energy demand increases (for air conditioning, but also to meet needs such as pumping water for agricultural uses) and energy transmission infrastructure (e.g., transformers) can also be compromised (Miller et al. 2007). Reductions in water availability during periods of drought can reduce hydropower generation capacity (Medellín-Azuara et al. 2008; Vicuña 2008). Wildfires also can damage transmission infrastructure.

Table 6 summarizes some extreme impact events within the Energy sector and notes driving conditions from climate events or from events in other sectors, along with associated transfer functions, where known.

Table 6. Energy sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Planned or unplanned electrical blackouts/ brownouts	High winds associated with severe storms can blow down cables supporting high-voltage transmission capability. High temperatures can cause premature failure in transformers and other electrical distribution equipment, as well as causing electrical demand above capacity. Severe storms can create flooding and erosion, especially if occurring during high tides, and impact coastal and Delta energy infrastructure. This effect will be compounded by gradually rising sea levels.	Analytic function: linear incremental response of electrical demand/deg F (for temperatures > 82°F), with Gross Domestic Product (GDP), population held constant. Linear response to population, all else equal. (Miller et al. 2007) Analytic functions: linear formula for peak, cubic polynomial for average total, electrical daily demand based upon average maximum daily temperature. (Franco and Sanstad 2006) Projections (2100): percentage increase ranges for peak and average total electrical demand. (Franco and Sanstad 2006)	Water: a greatly reduced amount of water in the storage facilities will have a commensurate effect on the ability to support hydroelectric power generation. In addition, the water sector may have increased energy demands to transport water around the state in extreme climate situations, particularly for agricultural uses. These factors may affect the energy sector's ability to meet peak electrical demand. Ecosystem: severe wildfires may destroy high voltage transmission capabilities, which may, in turn, affect the energy sector's ability to supply electricity to some areas of the state. Public Health: increased electrical demand to run air conditioning during a major heat wave may affect the energy sector's ability to meet peak electrical demand. These inter-sector impacts can clearly combine to exacerbate the effect upon the electric generation capability of the state.	Water Trend: precipitation implies inflows which implies changes to the timing and amount of electrical energy producible from hydro. (Vicuna et al. 2006) Projections (2085 climate model and historical hydrology, 2050 & 2020 water demands and land use) with CALVIN hydrologic model: hydroelectric generation capacity. (Medellin et al. 2006) Public Health Estimate: 10% increase in peak electrical demand in 2100 from increased air conditioning demand alone.

2.1.6. Natural Ecosystems

Most research assessing the impact of climate change on natural ecosystems does not focus on extreme events. Vegetation models are used to project responses to changes in mean climate states (Lenihan et al. 2006; Hayhoe et al. 2004). An important exception is the impact of wildfires on vegetation regimes, but the ecological impact of changed wildfire regimes is not straightforward (Lenihan et al. 2006). There is also qualitative discussion of the potential interactions of invasive species, pests, and pathogens with extreme events (Cayan et al. 2006a).

Table 7 summarizes some extreme impact events within the Natural Ecosystem sector and notes driving conditions from climate events or from events in other sectors, along with associated transfer functions, where known.

Table 7. Ecosystems sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Losses of biodiver-sity, habitat, services.	High temperatures and/or changes in precipitation patterns can fall outside the tolerance range of species, particularly endemic species, leading to biodiversity loss and habitat reduction.	Mostly qualitative discussion of shifts in range, changes in morphology, behavior, reproduction, and effects at population, community, and ecosystem level. (Parmesan et al. 2000; Root et al. 2003)	Water: a lack of stored water may inhibit the ability to support controlled releases of water, which may have a direct bearing on the survival of aquatic species and the preservation of wetlands habitats. Climate changes may exacerbate this effect by lengthening the season during which such releases are necessary.	*(none identified at this time)*

2.1.7. Forestry

Wildfires are projected to increase in California with climate change (Cayan et al. 2006a). There are many models that identify a variety of environmental variables that lead to wildfires, such as annual maximum temperature, precipitation, winds, and human density. Westerling and Bryant 2006) developed a model for wildfires in California based on temperature, precipitation, and simulated hydrologic variables. Historical analysis of recent increases in wildfires in the West has identified the importance of warmer spring and summer temperatures and an earlier snowmelt (Westerling et al. 2006). The combination of high temperatures and dry conditions (e.g., low precipitation levels) generally increase wildfire risk, particularly in areas where energy rather than fuel availability is the limiting factor (Westerling and Bryant 2006).

Table 8 summarizes some extreme impact events within the Forestry sector and notes driving conditions from climate/weather or from other sectors, along with associated transfer functions, where known.

Table 8. Forestry sector extreme impact events and drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Increased likelihood of major wildfires.	High temperatures and low precipitation levels, as well as lightning during storms or in dry conditions, can lead to major wildfires, affecting biodiversity, habitats, water run-off characteristics, and human life and property.	Climate and multivariate regression modeling: Projected changes in risk of fires >200 hectares in various California regions. (Westerling and Bryant 2006) Projections (climate models 2100) with FDBMOD and CFES2 forestry models: expected number of wildfires that "escape initial attack" in several forest units in California. (Fried et al. 2008) Projections (climate models 2100) with MCI model: total annual area burned in wildfires. (Lenihan et al. 2008)	*(none identified at this time)*	*(none identified at this time)*

2.1.8. Marine/Coastal

Extremes in sea levels may occur from intense storms, heavy surf, and high tide events (Cayan et al. 2006b). Sea level extremes may exceed coastal defenses designed for historical conditions and cause coastal flooding and erosion, potentially damaging wetlands and the built environment (Cayan et al. 2006b).

Table 9 summarizes some extreme impact events within the Marine/Coastal sector and notes driving conditions from climate events or from events in other sectors, along with associated transfer functions, where known.

Table 9. Marine/Coastal Sector Extreme Impact Events and Drivers

Extreme Events w/i Sector	Climate/Weather Drivers	Inter-System Transfer Functions	Drivers from Other Sectors	Inter-Sector Transfer Functions
Erosion and flooding causing evacuation and property damage.	Excessive stream flows can result from: (1) High temperatures creating rapid snow melt in the mountains, and (2) high precipitation levels from severe storms. High winds from severe storms can cause high waves and storm surges creating flooding and erosion in coastal areas, especially if occurring during a period of high tides. This effect will be compounded by gradually rising sea levels. In estuaries and river deltas it will also be compounded if accompanied by the high temperature and high precipitation events mentioned above.	Historical tide range damping between Golden Gate and Sacramento. (Cayan et al. 2006b) Projection (2100) (climate models and historical data): increasing sea level trend, # of exceedances of 99.99 percentile sea level, and coincidence of high sea level height and low sea level pressure (as an indicator for storms), for California. (Cayan et al. 2008a)	Water: levee failure always leads to flooding. The degree of this flooding will depend, to some extent, on the climate factors affecting this sector.	Historical frequency of Sacramento river and delta levee breaks. (Cayan et al. 2006b)

2.2. Case Study of 2006 Heat Wave

During the second half of July, 2006, a severe heat wave, both in terms of magnitude and duration, affected much of California. Daily and consecutive daily maximum and minimum temperature records were broken in many locations (Gershunov and Cayan 2008; Knowlton et al. 2008). Gershunov and Cayan (2008) provide a detailed analysis of the specific characteristics and synoptic setting of the event. Because of high humidity and other synoptic characteristics, the July 2006 event was unprecedented in terms of nighttime (minimum) temperatures, simultaneously providing little relief from daytime temperatures and allowing daytime temperatures to rise from a warmer starting point.

Many impacts have been linked to this event, and it is likely that only a subset have been formally documented. At least 140 deaths from extreme heat were recorded between July 15 and August 1, 2006 (CDHS 2007). The highest mortality occurred in coastal areas where residents are generally less acclimatized to extreme heat conditions. Beyond mortality, the event also has been linked to 16,166 excess emergency room visits and 1,182 excess hospitalizations statewide for a variety of conditions, especially in the Central Coast including San Francisco (Knowlton et al. 2008). Children (ages 0–4 years) and the elderly (ages ≥ 65 years) were at greatest risk. Often, individuals from lower income brackets are also more vulnerable to extreme heat because they lack access to air conditioning.

Peak energy use in the state reached an all time high of 50,270 megawatts (MW) (Kozlowski and Edwards 2007), causing power outages for 1.5 million electrical customers, primarily due to overheating transformers (Bell and Giannini 2006). The extent to which power outages and subsequent lack of access to air conditioning contributed to heat-related mortality and morbidity is unclear. In some cases fatalities were linked to cases when individuals did not switch on working air conditioning at night (Gershunov and Cayan 2008).

The heat negatively impacted agriculture, especially the dairy and cattle industry, although yields from field crops and orchards, as well as the poultry and apiary industries, were also affected (Bell and Giannini 2006; Kawamura 2006). Estimated insured agricultural losses were $492 million (Lobell et al. 2009a). The heat stress to crops also led to increased water demand for irrigation (Kawamura 2006), although the magnitude of this effect has not been quantified.

Figure 4 summarizes these documented impacts in the context of the framework presented in Figure 3. Both direct impacts from extreme temperatures and inter-sector interactions are evident.

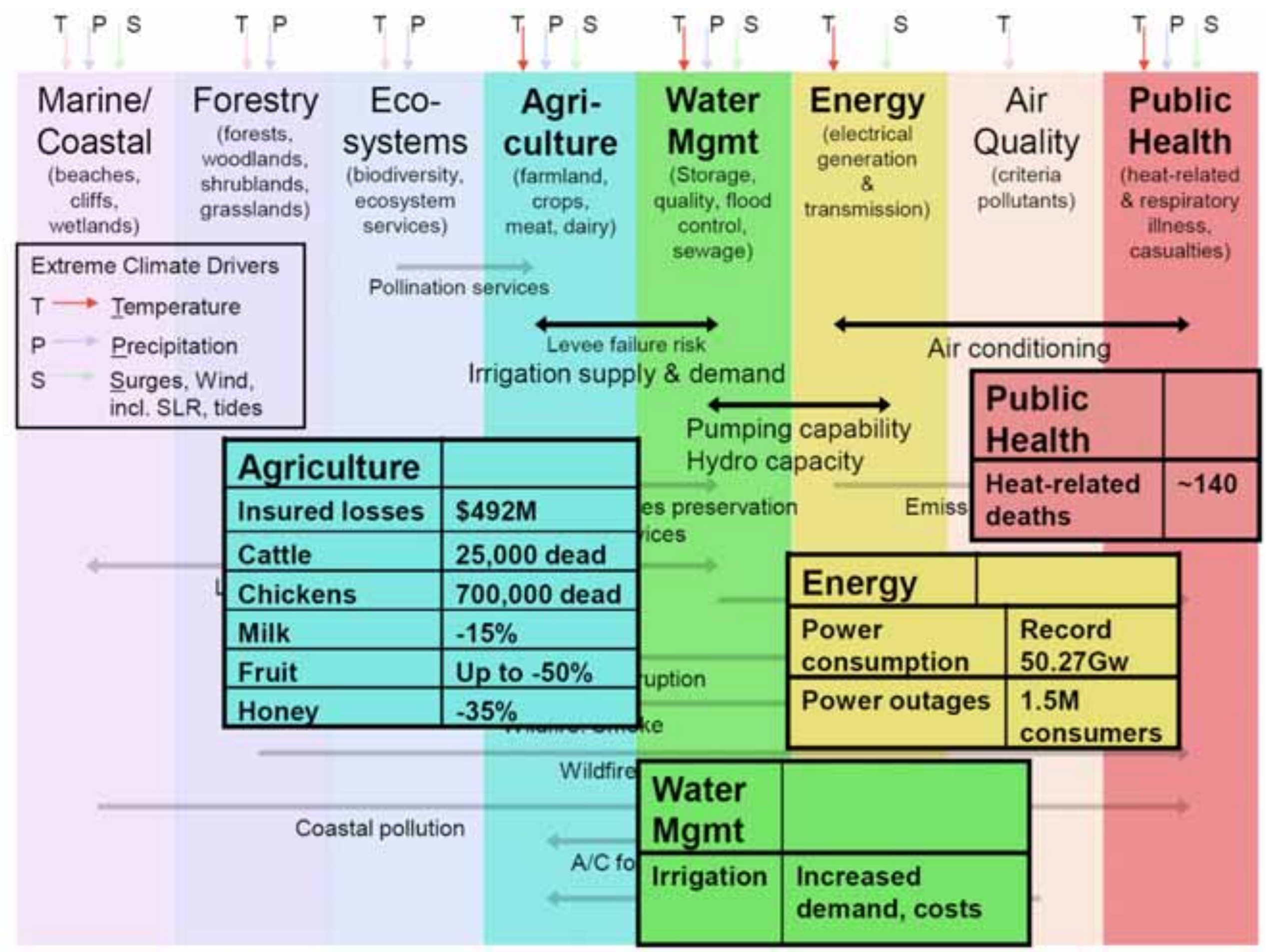


Figure 4. Extreme climate drivers and inter-sector interactions, July 2006 heat wave

3.0 Projections of Extreme Events

3.1. Overview

Given the lack of a consolidated set of bottom-up definitions of extreme impact events, we choose to take a more traditional approach for the main part of this projection study. Our goal is to provide a foundation upon which future research can build. A next step, for example, is to couple the projections presented here with research related to specific interconnections between extreme events and sectoral impacts described above, to better understand the importance of these impacts and interactions between sectors. This analysis employs downscaled climate projections from six Global Climate Models (GCMs), two emissions scenarios and two downscaling methods, produced for the 2008 Public Interest Energy Research (PIER) Scenarios Report (Cayan et al. 2008b). Previous assessments of climate change impact projections for California have used a smaller subset of climate projections and fewer categories of extreme events than are analyzed here. By using this larger suite of projections, we are able to more fully characterize the range of projected changes, addressing the issues of consistency or spread among projections.

First, we compute projections for a set of ten indicators that have been extensively studied in the recent literature (Tebaldi et al. 2006), and whose projected behavior from GCM experiments provides a ready benchmark for comparison.

Next, we rely on standard definitions of extremes dictated by Extreme Value Theory (EVT) statistics (e.g., Coles 2001), focusing on the characterization of the tail behavior of daily precipitation and maximum and minimum temperatures.

Lastly, we conduct analyses with the goal of characterizing the projected change in frequency of events similar in character to specific historical events under a changed climate.

We perform these analyses at 58 separate grid points extracted from the full set of downscaled climate projections. Each grid point is representative of a county in California (closest to the county geographical centroid), and the locations are representative of areas of importance from an economic, social, and ecological perspective (e.g., major urban areas, Central Valley, Wine Country, higher elevation regions, coastal areas).

3.2. Downscaled Climate Projections for California

Two statistical downscaling techniques have been applied to climate projections for California, the Bias Correction and Spatial Downscaling (BCSD) method (Wood et al. 2004) and the Constructed Analog downscaling (CAD) method (Hidalgo et al. 2008). These methods have produced a suite of projections for daily temperature and precipitation at a 1/8° grid scale for the entire state. Projections have been produced for simulations under a higher and lower emissions scenario, *Special Report on Emissions Scenarios* (SRES) A2 and B1, respectively (Nakicenovic et al. 2000). With BCSD, this has been done for six GCMs (NCAR PCM1, GFDL CM2.1, CNRM CM3, Max Planck Institute ECHAM5, NCAR CCSM3 and MIROC 3.2 at medium resolution), and for CAD this has been done for the first three of the same GCMs (Cayan et al. 2008b). Maurer and Hidalgo (2008) compare the ability of these methods to reproduce observed temperature and precipitation extremes. They conclude that the CAD method produces greater downscaling skill than BCSD for fall and winter low-temperature extremes and summer high-temperature extremes. For daily precipitation extremes, both methods are limited in their ability to reproduce observed wet and dry extremes. The authors note that this is a reflection of the general low skill of GCMs in reproducing daily precipitation variability.

As part of our analysis, we further compare the BCSD and CAD methods' ability to reproduce characteristics and trends in observed temperature and precipitation extremes in the context of the analyses outlined above, and we compare analyses of projections produced through both downscaling methods.

3.3. Indicators for Extreme (Impact) Events

Constructed "climatic indicators" are often developed to represent the climate conditions that can cause extreme impact events. We use a set of indicators that have become well known, at least in the climate science literature (Frich et al. 2002; Tebaldi et al. 2006). These indicators are defined as annual indices, such as the longest run of consecutive dry days in the year, or of consecutive days with maximum temperatures above a certain threshold (usually defined with respect to the climatological distribution). These indices have been designed with some practical concern in mind. For example, they are arguably mild definitions of extremes and we can expect GCM output to be appropriate for constructing them. Because they represent mild definitions, we expect the observational record to contain enough cases to allow a robust characterization of each indicator's climatological distribution and trends. They are designed in consideration of societal impacts rather than ecosystem vulnerability. Nonetheless they offer a multi-dimensional picture of changes beyond average conditions, particularly when computed from downscaled data that provides insight into potential regional changes.

In the following tables we list the climate indicators that we use to assess projected changes (Frich et al. 2002; Tebaldi et al. 2006). Admittedly, these are still far from an optimal definition of extremes in light of the needs of impact assessment studies. In fact, some criticize these indicators for their fixed thresholds, questionable impact relevance, problematic statistical properties, and biases at the boundaries of the historical period (Zhang et al. 2005; Tebaldi et al. 2006; Alexander et al. 2006). However we view these indices as a first step toward bridging the gap between an abstract definition of extremes and definitions that may be dictated by particular concerns. We hope to see such an approach complemented by future research reversing this process, i.e., defining relevant extreme-impact thresholds in consultation with stakeholders, and defining indicators that directly apply to these impacts.

Table 10. Climatic indicators of temperature extremes and associated impact events

Climatic Indicator	Impact Event
Frost Days: Number of days in a year with an absolute minimum temperature below 0ºC	Crop and plant death, Insect infestation.
Growing Season Length: Length of time between the first and last five consecutive days with mean temperature above 5ºC (41ºF).	Crop and plant growth
Warm Nights (and Warm Summer Nights): Percentage of days in the year (and in the period May through September) when the minimum temperature is above the 90th percentile of the climatological distribution for that calendar day.	Heat-related Illness
Warmest Three Nights: Warmest spell of three consecutive nights	Heat-related Illness
Heat Wave Duration: Length of the maximum period of at least five consecutive days with a maximum temperature higher by at least 5ºC (9ºF) than the climatological norm for that calendar day. Computed only over the warm season (May through September)	Heat-related Illness, Fire frequency and intensity, Electricity demand
Hot Spell Duration: Length of the maximum period of at least five consecutive days with a maximum temperature higher by at least 5ºC (9ºF) than the climatological norm for that calendar day. Computed over the entire calendar year.	Heat-related Illness, Fire frequency and intensity, Electricity demand

Table 11. Climatic indicators of precipitation extremes and associated impact events

Climatic Indicator	Impact Event
Precipitation Intensity: Annual total precipitation divided by the number of wet days.	Floods, Erosion
Consecutive Dry Days: Maximum number of consecutive dry days.	Wildfires, Water availability
10mm Days: Number of days with precipitation greater than 10 millimeters (mm).	Floods, Crop yields
Heavy Precipitation Fraction: Fraction of total precipitation from events exceeding the 95th percentile of the distribution of wet day amounts. How much of precipitation comes in heavy events?	Floods
Five-Day Precipitation: Maximum five-day precipitation total.	Floods

3.4. Indicator Results

3.4.1. Comparison to Observations

We derived time series for each of the twelve indicators described in Tables 10 and 11 for each county (each county-representative grid point, as described above), based on daily observed data and downscaled GCM simulations. We computed climatological means for both observed data and modeled datasets over the period 1950–2000. In addition, we computed trends for each of the indicators, both within the observational period (1950–2000) and over the entire length of the simulated datasets (1950–2100). We compare these results across the suite of GCMs, the two downscaling methods, and the two SRES scenarios. Note that because we compare across downscaling methods, we limit our analysis to the common subset of GCM simulations available under both methods.

Before examining future projections, it is important to investigate whether the downscaled model simulations reproduce observed characteristics of these indicators in terms of geographical distribution and magnitude. Figures 5 through 9 show maps for an illustrative set of five of these indicators: Frost Days, Heat Wave Duration, Warmest Three Nights, Consecutive Dry Days, and Precipitation Intensity.[1] In the first row of each figure, we compare climatological means computed for 1950–2000 observed, the BCSD ensemble mean, and the CAD ensemble mean (e.g., the average of the number of Frost Days for each year in the observed dataset, compared to that simulated by the BCSD and CAD ensembles). In the second row, we compare trends across the same three datasets over the same time period, with solid circles indicating statistically significant trends at the 5% level.

[1] Similar results for the rest of the indicators are available at www.stanford.edu/~mikemas/publications/ Extremes_Report_Figures_Addendum.ppt.

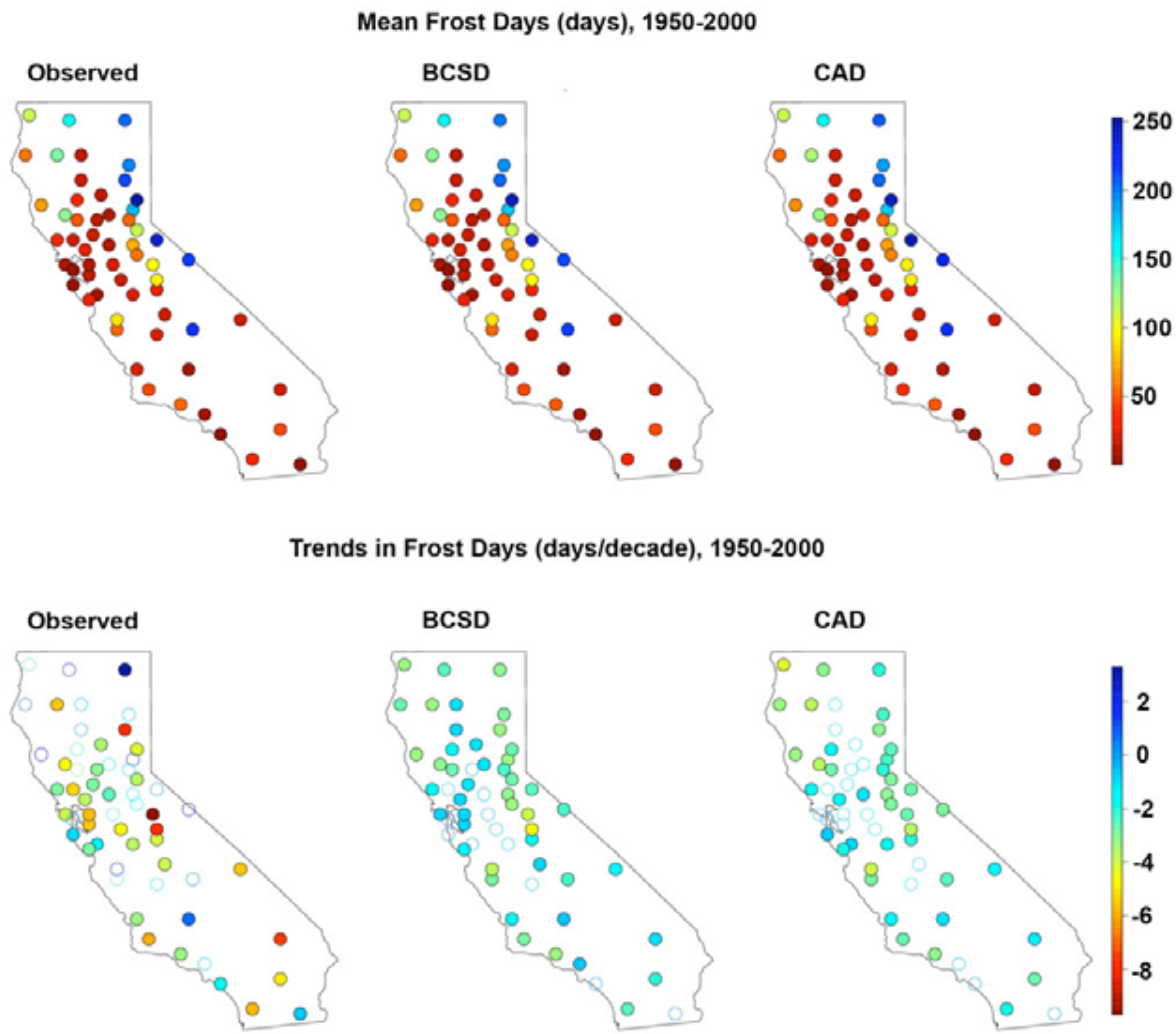


Figure 5. Climatological means and trends for frost days, 1950–1999, by county

Top row, mean values for observed (1950–1999) and downscaled GCM simulations (1950–1999) ensemble means (BCSD, center and CAD, right panels). Bottom row trend values computed from the same datasets. Filled circles indicate significant trends at the 5% level.

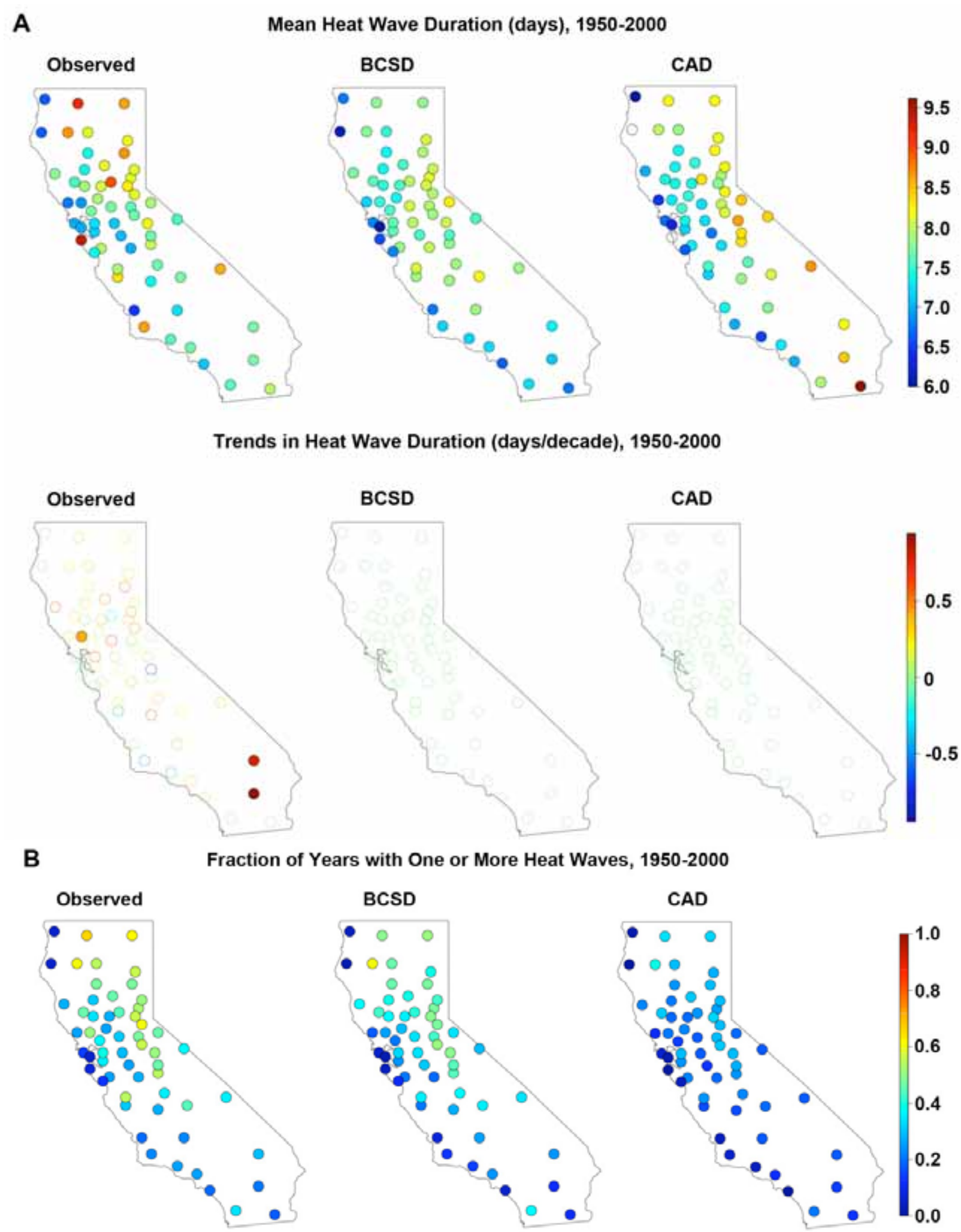


Figure 6. Climatological values and trends for heat wave duration, 1950–1999, by county

A: Like Figure 5, for Heat Wave Duration. B: Frequency of years with at least one Heat Wave.

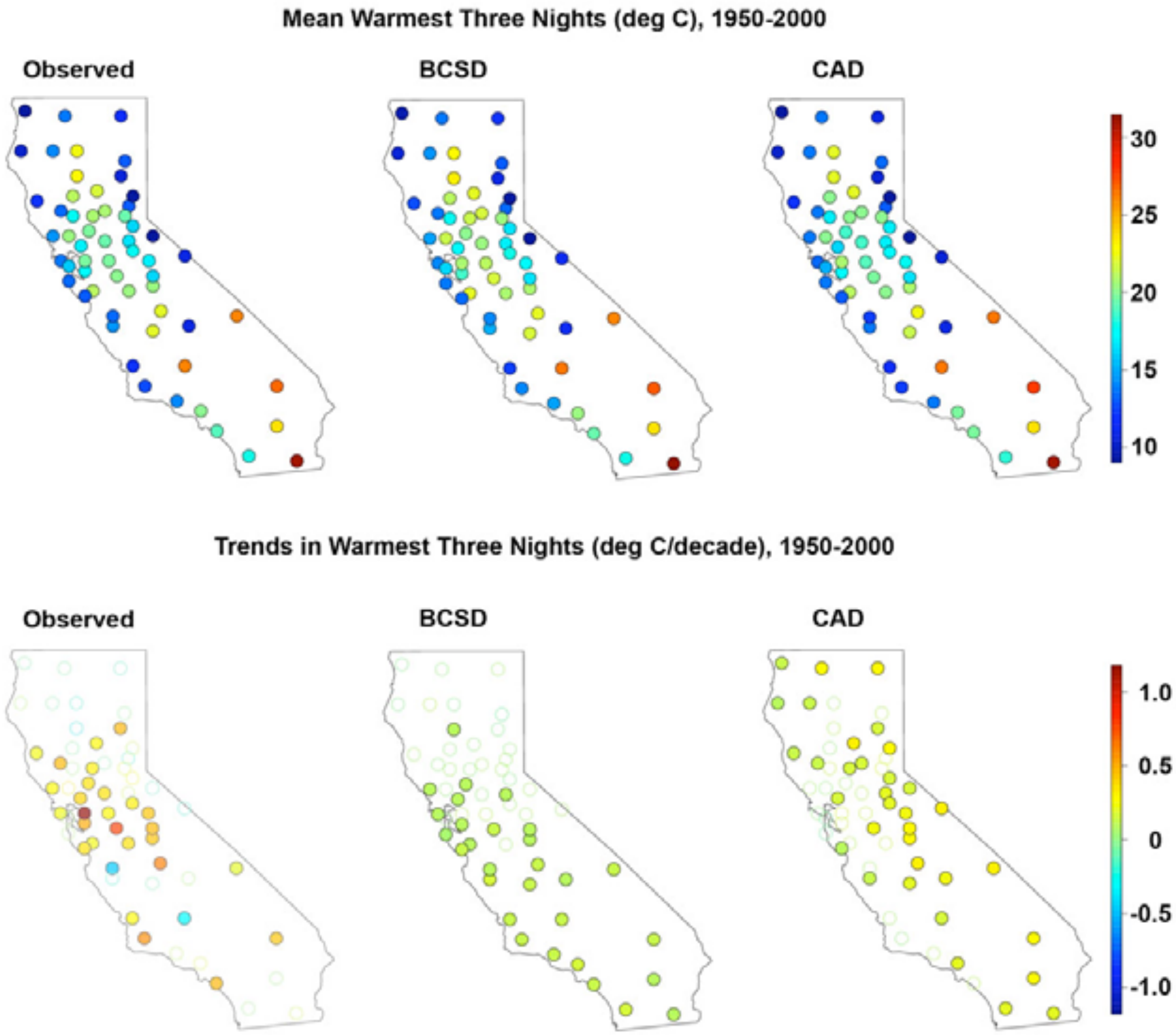


Figure 7. Climatological values and trends for warmest three nights, 1950–1999, by county

Like Figure 5, for Warmest Three Nights.

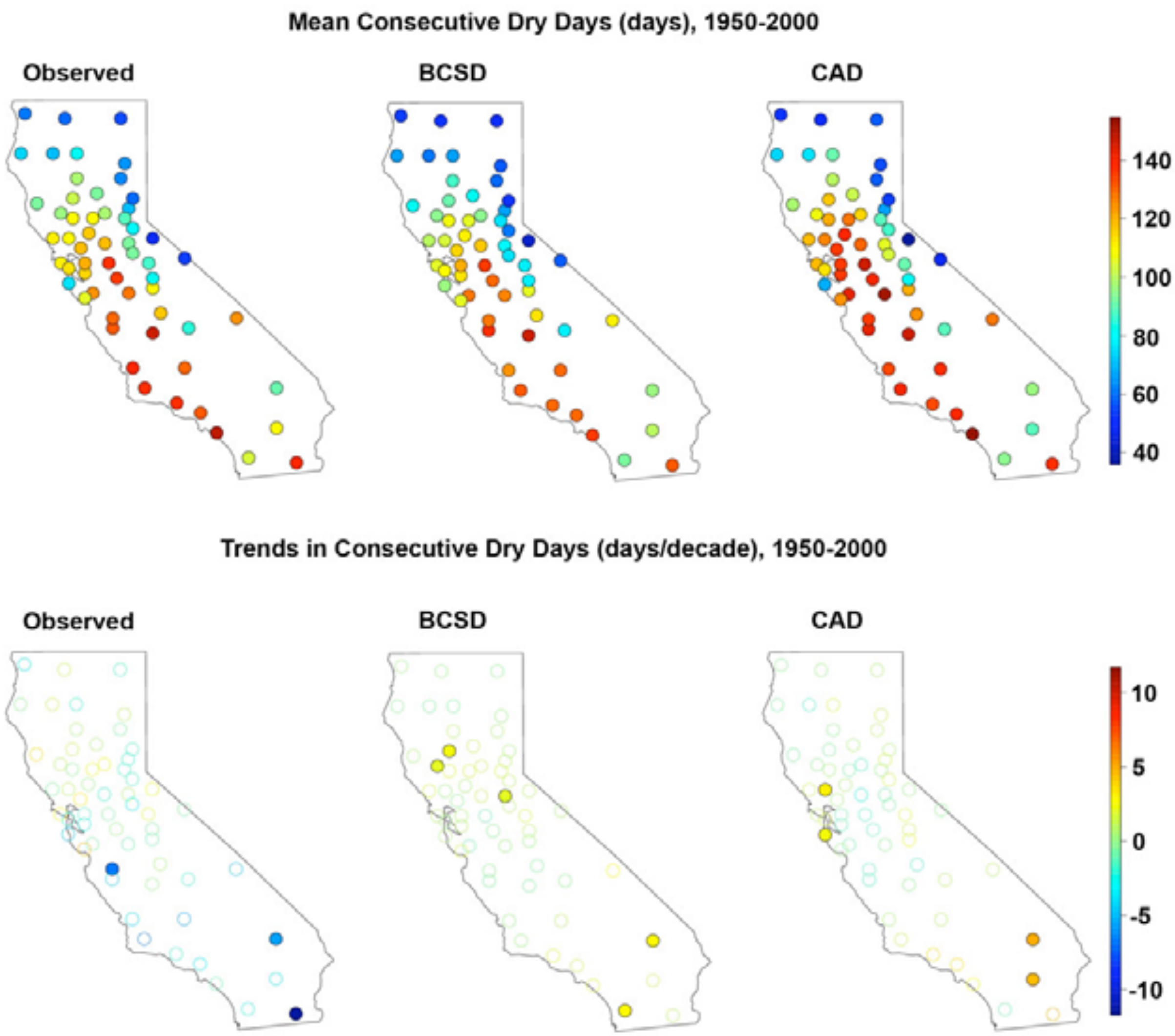


Figure 8. Climatological values and trends for consecutive dry days, 1950–1999, by county

Like Figure 5, for Consecutive Dry Days.

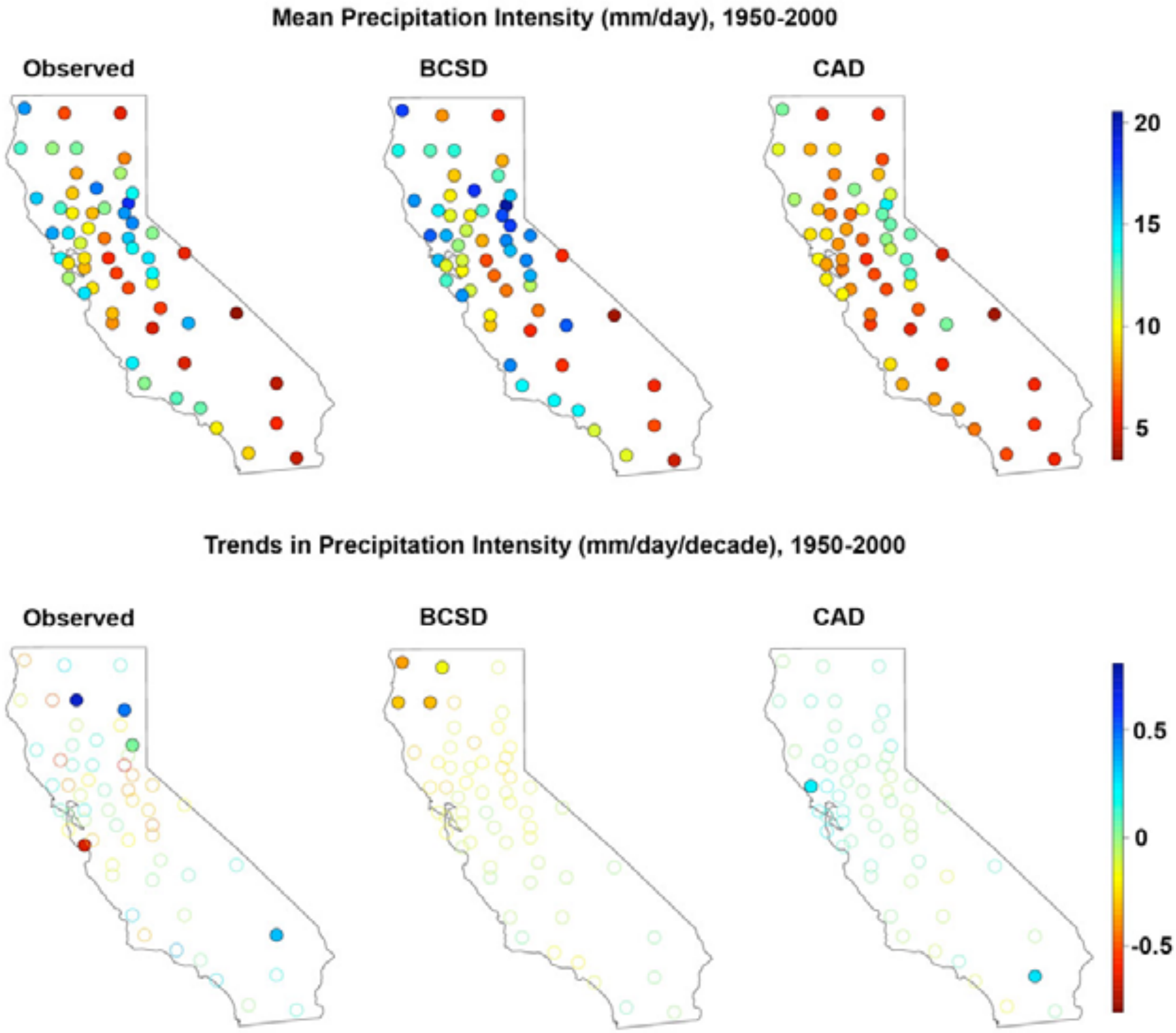


Figure 9. Climatological values and trends for precipitation intensity, 1950–1999, by county

Like Figure 5, for Precipitation Intensity.

Both downscaling approaches closely reproduce the number of Frost Days, Consecutive Dry Days, and the temperature of the Warmest Three Nights per year around the state. In general, both downscaling approaches somewhat underestimate Heat Wave Duration and the fraction of years with at least one Heat Wave, with CAD closer to observed magnitudes and BCSD closer to observed frequencies. Both generally reproduce the pattern of relative regional differences in Heat Wave Duration. CAD likewise underestimates Precipitation Intensity in some parts of the state, while BCSD slightly overestimates in limited regions, but generally reproduces the observed pattern. For the other indicators the observed climatological mean for each indicator is reproduced quite accurately, both in terms of geographical differences and actual values by the ensemble mean of the downscaled GCM simulations, with only one exception. Both methods overestimate the mean value of Heavy Precipitation Fraction (the percentage of total precipitation falling in very wet days, defined as days above the 95th percentile of the 1961–1990 climatological distribution), but they do maintain the geographically differentiated features observed.

When we consider the simulation of trends, the results are more diverse across indicators and methods. We summarize in Table 12 the agreement on the sign of the trends and their statistical significance. Here we summarize the general findings. When observed indicators show widespread significant trends, the ensemble mean of the downscaled simulations correctly estimates the direction. The downscaled simulations often, however, tend to "spread" the values and significance of the trends smoothly across space, while the observations generally show more heterogeneous spatial patterns. This is not surprising, given the statistically downscaled nature of these datasets, which may tend to conserve smooth spatial patterns from their parent coarse-grid GCM simulations. When the observed indicators do not show significant trends, the simulated values do not either. However, the underlying trends for precipitation indicators are at times in opposite directions when comparing the two downscaling methods' output. In general, BCSD displays drying tendencies across the state over the observed period while CAD suggests wetter conditions. The observed precipitation data do not help in resolving this issue, showing a mixed pattern of increasing and decreasing trends indicating large natural variability. We will discuss this issue more when considering future changes.

Some of the indicators related to temperature extremes already show within the observed period the widespread significant trends in the direction expected under a warming climate (e.g., fewer Frost Days, more Warm Nights, and warmer Warmest Three Nights). The simulation ensemble means reproduce these overall tendencies and their significance, although they generally underestimate the slope of the trends. Overall, simulations of extreme behavior related to temperature should have greater confidence due to the agreement between downscaling methods and between simulations and observations. Precipitation, as to be expected, poses a greater challenge. From the observational viewpoint, no significant trends are consistently detected in the California region. Modeled data are in agreement only on the absence of a consistent observed signal, but the underlying tendencies towards increasing or decreasing precipitation intensity are not consistent.

Table 12. Observed 1950–2000 trends in indicators of temperature and precipitation extremes and agreement with downscaled model simulations

Index	Observed	20C3M BCSD	20C3M CAD
Frost Days	Decreasing trends with scattered significant across state, and geographically heterogeneous values.	Decreasing trends, wider coverage of significant values than observed, more homogeneous values, and generally smaller in absolute value than observed	Same as BCSD
Growing Season Length	Increasing trends with scattered significant values, same patterns as Frost Days, fewer overall significant values.	Similar patterns as observed, with scattered significant values.	Same as BCSD
Hot Spells Duration	Very few and isolated significant trends, both increasing and decreasing. Likely due to chance.	More homogeneously increasing trends, but very few significant, likely random, like obs.	Same as BCSD
Heat Wave Duration	Similar to Hot Spells, with both increasing and decreasing trends, even more obviously due to chance.	Few small increasing trends, likely to be significant only by chance.	Same as BCSD
Warm (Summer) Nights	Strong pattern of increasing significant trends mainly interior and South.	Fairly uniform coverage of increasing significant trends all over the state with values lower than observed.	Same as BCSD
Warmest Three Nights	Same as Warm Nights	Increasing and significant trends, uniformly located all over the state, with smaller and more geographically homogeneous values than observed.	Same as BCSD with generally larger values of trends.
Consecutive Dry Days	Mix of non-significant increasing and decreasing trends over the state.	Same as obs.	Same as obs.
Precipitation Intensity	Mix of non-significant increasing and decreasing trends over the state.	No significant trends. Values are mostly negative.	No significant trends. Values are mostly positive.
Days w/Precip > 10mm	Generally increasing trends but very few scattered significant values. Likely randomly occurring.	No significant trends. Values are mostly negative.	No significant trends. Values are mix of positive and negative.
% Precip in Very Wet Days	Mix of non-significant increasing and decreasing trends over the state.	Same as obs.	No significant trends. Values are mostly positive
Maximum 5-day Total Precip	Mix of non-significant increasing and decreasing trends over the state.	No significant trends. Values are mostly negative.	No significant trends. Values are mostly negative.

3.4.2. *Future Projections of Indicators*

Figures 10 through 14 show future trends under the two scenarios (along the rows) and the two downscaling methods (along the columns) for the five illustrative indicators. Similar results for the rest of the indicators are available at http://www.stanford.edu/~mikemas/publications/Extremes_Report_Figures_Addendum.ppt. Indicators of temperature extremes tell a very consistent story: the trends to be expected in a warming climate are produced almost identically by the two methods' ensemble means: fewer Frost Days, longer Heat Wave Duration and more frequent Heat Waves, and warmer Warmest Three Nights. Growing Season and Hot Spell Duration also lengthen, and Warm Nights and Warm Summer Nights increase (not shown). The trends are all significant across the region, and they generally show an intensifying gradient from West to East (from the coast to the interior) with the exception of Warm Nights/Warm Summer Nights, where the gradient appears to be more North to South. There are significant differences in the magnitude of the trends when comparing SRES B1 and A2, with larger changes under the latter, as expected. These findings are in perfect agreement with a multi-GCM study of the same indices (Tebaldi et al. 2006). That study took a global and continental perspective, but the strong agreement of temperature indices allows us to find commonalities even at these very different regional scales.

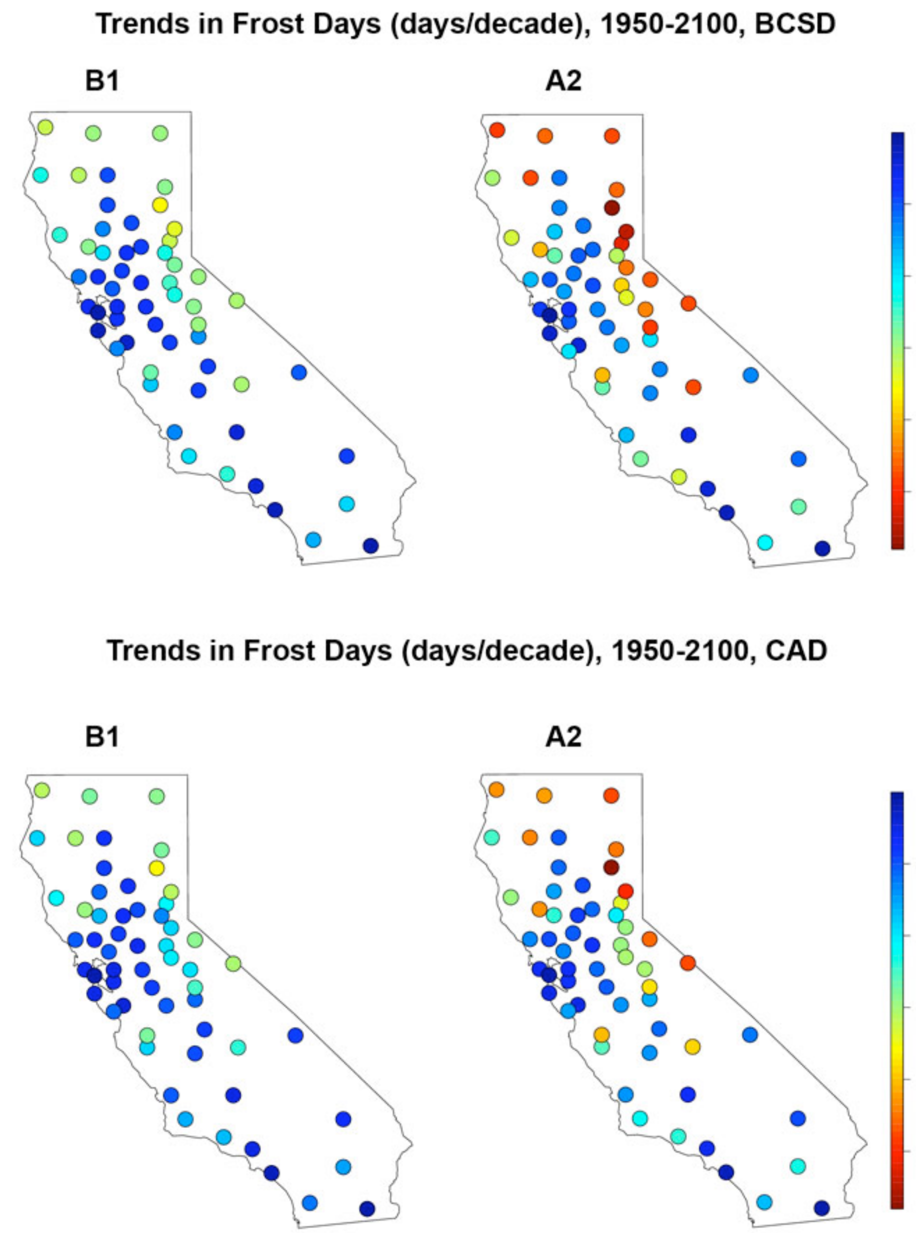
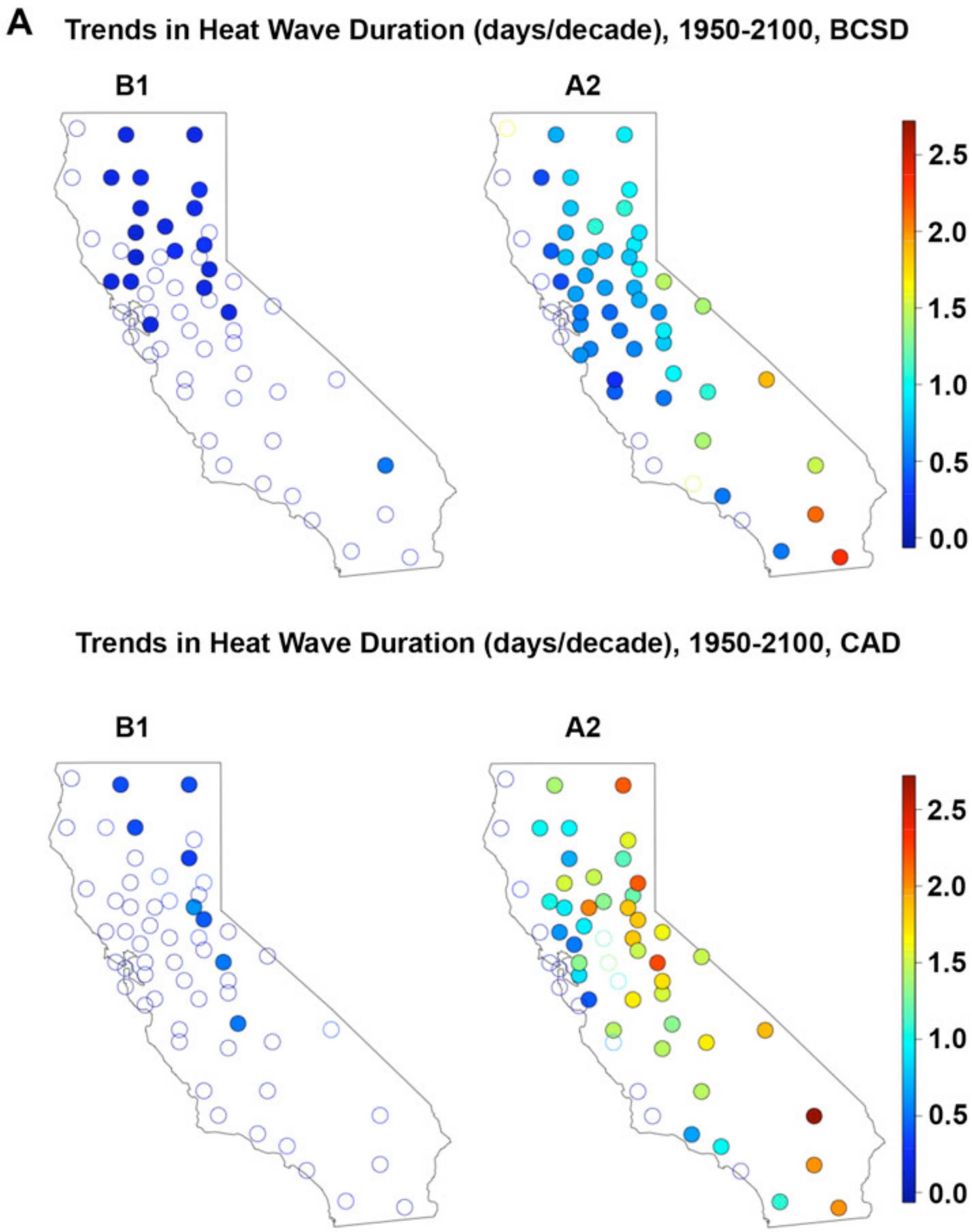


Figure 10. Trends in frost days, 1950–2100, by county

Trends under SRES B1 (left) or SRES A2 (right) computed from downscaled data from BCSD (top) or CAD (bottom). Filled circles indicate significant trends at the 5% level.


A
Trends in Heat Wave Duration (days/decade), 1950-2100, BCSD
B1
A2
2.5
2.0
1.5
1.0
0.5
0.0
Trends in Heat Wave Duration (days/decade), 1950-2100, CAD
B1
A2
2.5
2.0
1.5
1.0
0.5
0.0

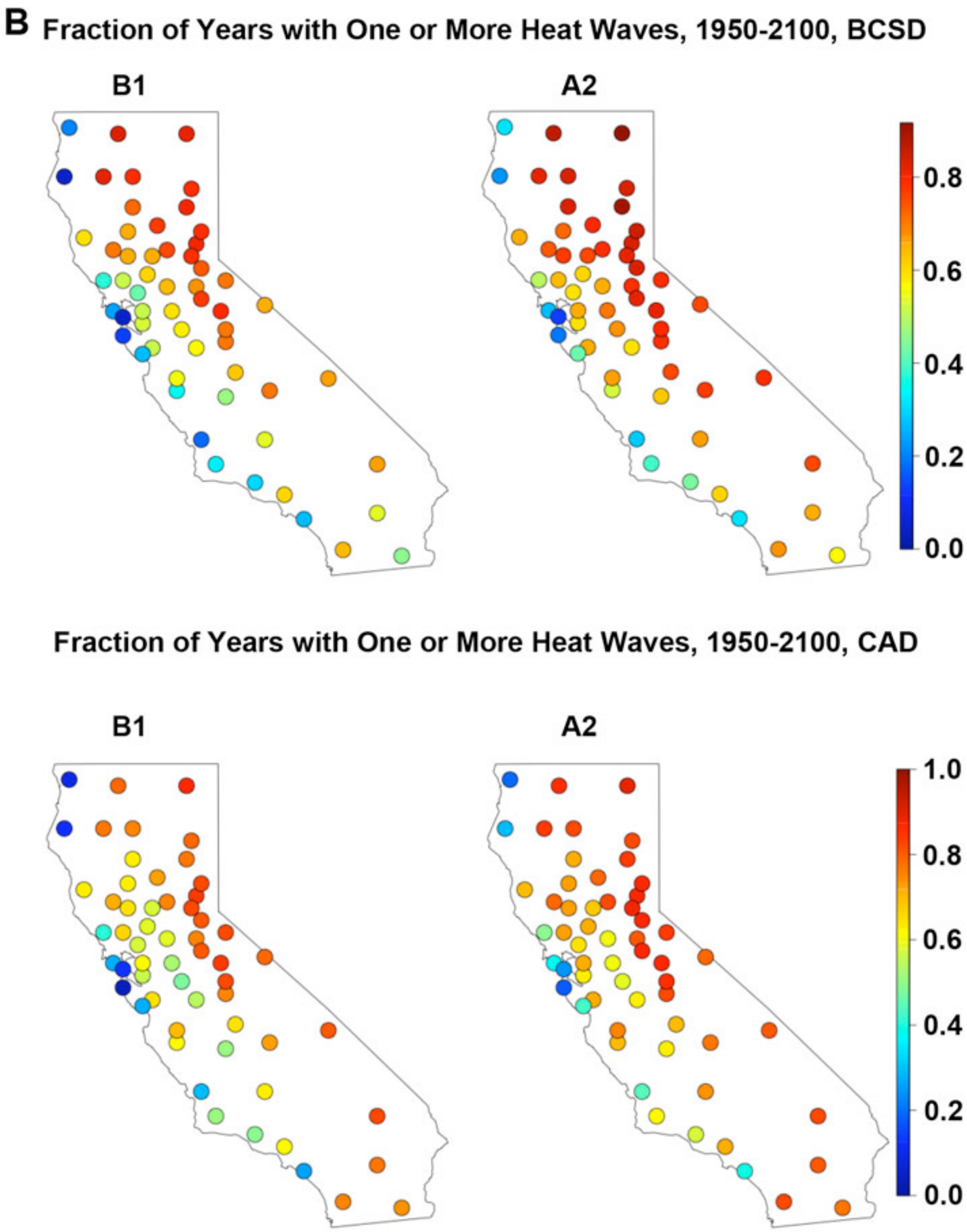


Figure 11. Trends in heat wave duration, 1950–2100, by county

A: Like Figure 10, for Heat Wave Duration. B: Frequency of years with at least one heat wave.

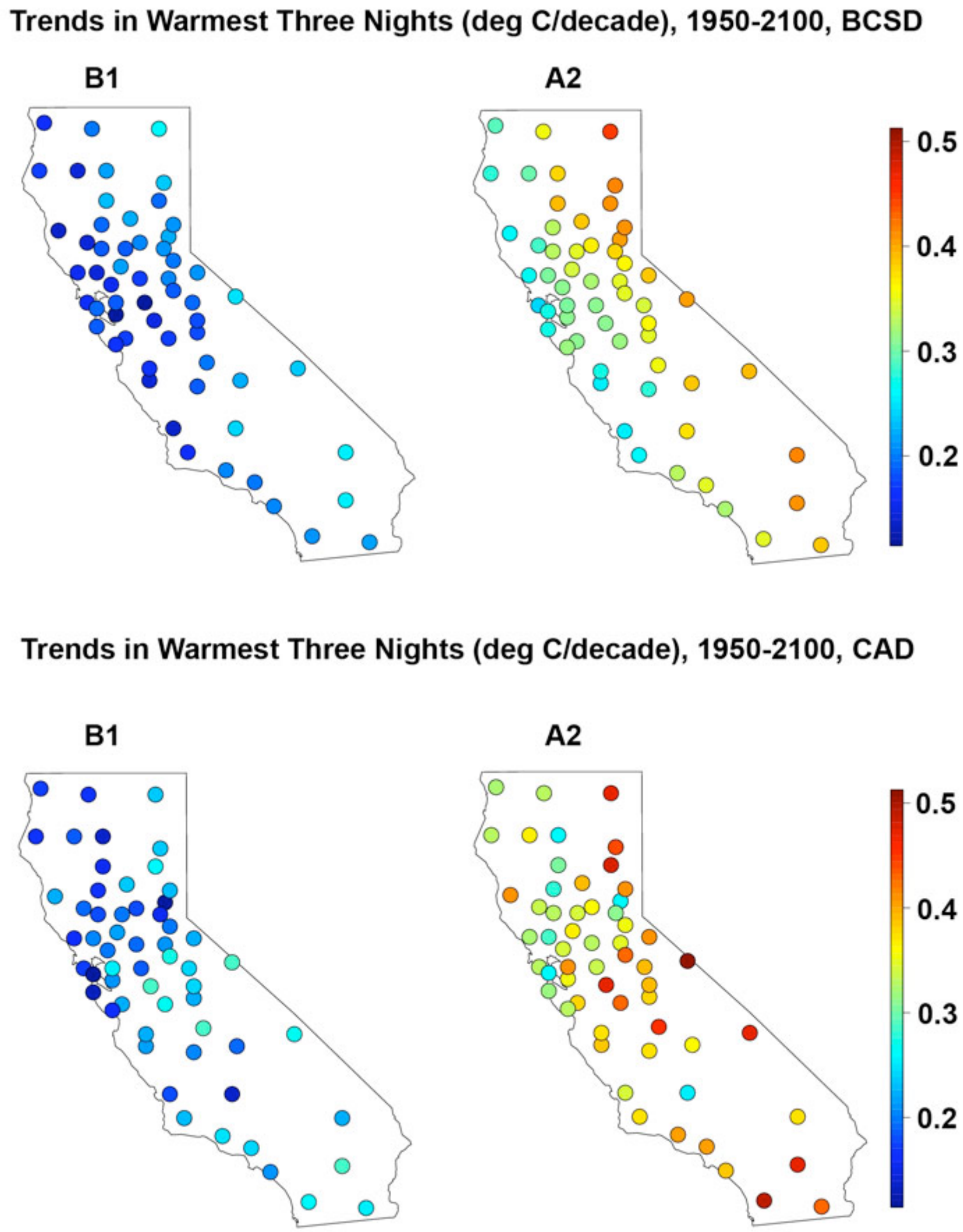


Figure 12. Trends in warmest three nights, 1950–2100, by county

Like Figure 10, for Warmest Three Nights.

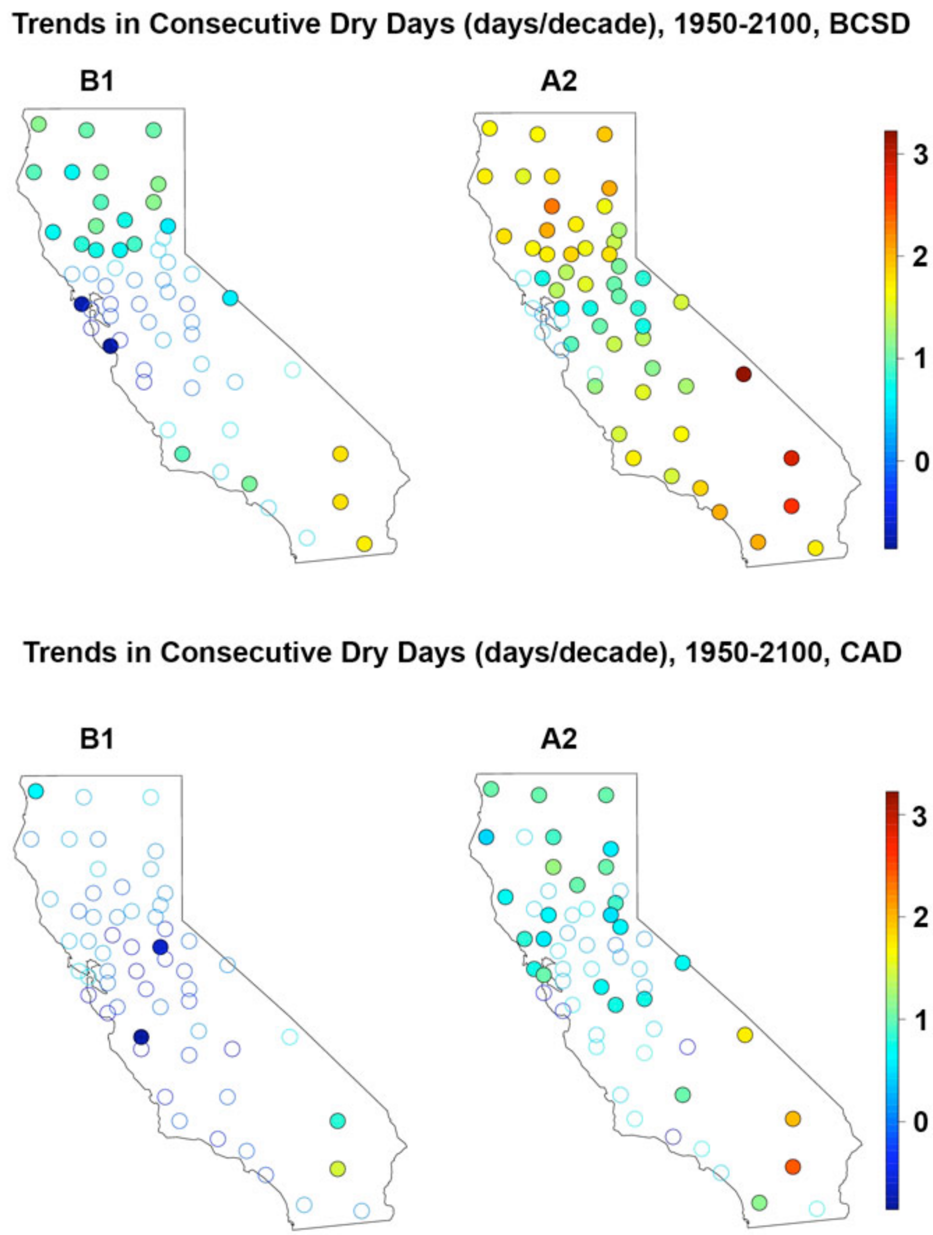


Figure 13. Trends in consecutive dry days, 1950–2100, by county

Like Figure 10, for Consecutive Dry Days.

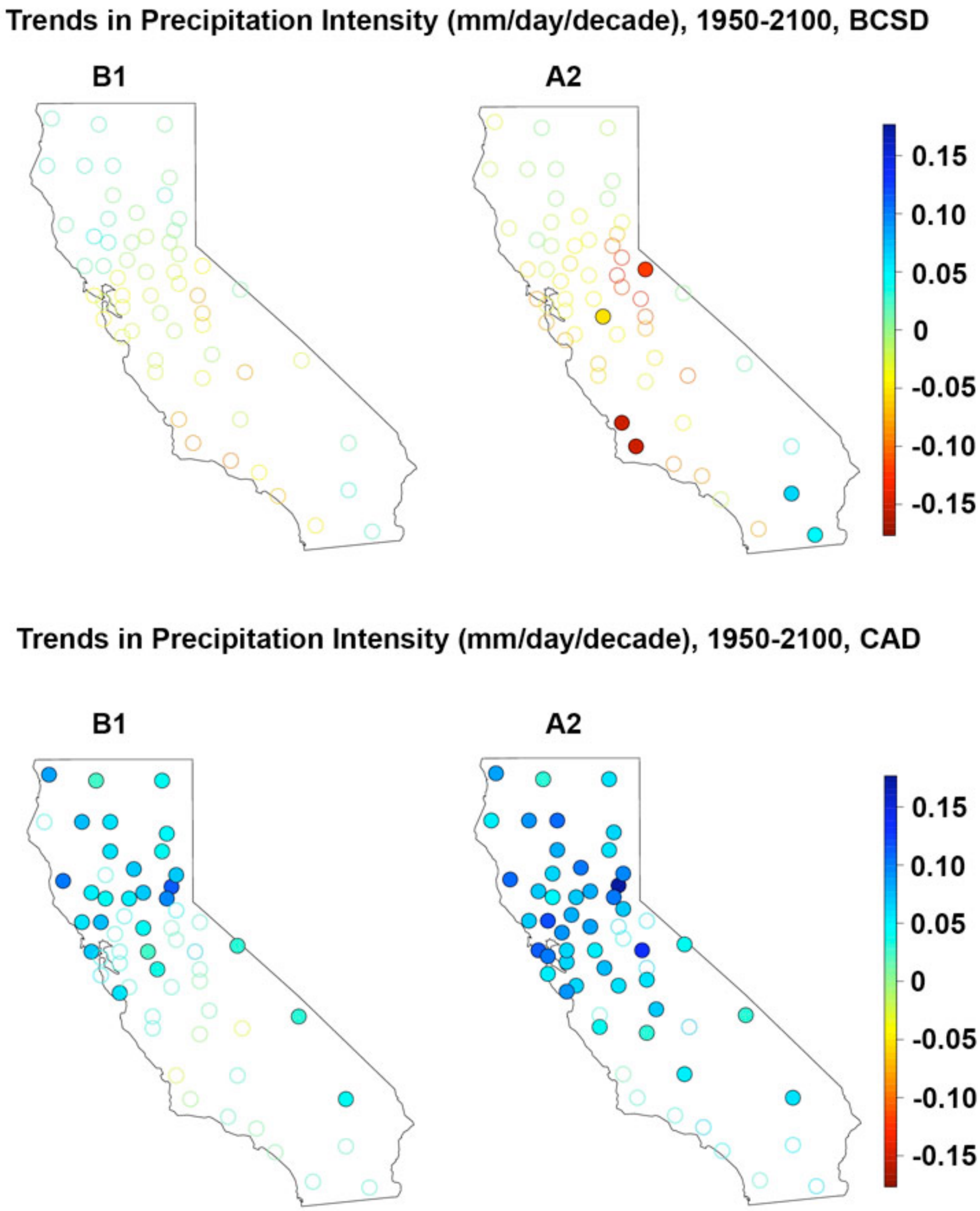


Figure 14. Trends in precipitation intensity 1950–2100, by county

Like Figure 10, for Precipitation Intensity.

The picture for precipitation extremes indicators is much less coherent. The two methods produce different projections with regard to trends and their statistical significance. Consecutive Dry Days is the only indicator that does not relate to changes in precipitation intensity. The BCSD simulations indicate significant increases in the length of dry spells, confined to the northern part of the state under B1 and more widespread under A2. CAD simulations do not attribute any significance to changes under B1, but agree with lengthening of dry spells under A2, although with less widespread significance than the other method.

The remaining four indicators look at various aspects of change in precipitation intensity. Precipitation Intensity, representing the average amount of precipitation on a wet day in a given year, is the most direct indicator. The two methods here disagree in the ensemble mean result. BCSD does not produce significant trends, and hints at diminishing intensity, while CAD shows significant increasing trends, especially in the northern half of the state. Similar behavior is shown for Heavy Precipitation Fraction. Total Five-Day Precipitation sees better agreement in the patterns across the methods, with positive but not statistically significant trends decreasing from north to south. Puzzlingly, 10 mm Days, the number of days with precipitation amounts exceeding 10 mm, shows consistently decreasing trends, relatively more so for BCSD than CAD. In general, BCSD simulations produce trends towards drier conditions and less intensifying precipitation than do CAD simulations.

We are setting the bar high in attempting to detect changes at point locations, but results at this scale are arguably more meaningful for impact analysis and local decision-making. These indicators would likely show a stronger signal if we averaged the grid point results into a regional average. Averaging of indicators' time series across a large region is expected to cancel out low frequency “wiggles” and bring out the signal that may exist at a regional level, overcoming spatial patchiness and revealing either a decreasing or increasing trend in most cases. In fact, an analysis of GCM-derived indicators (without downscaling) in the Western region of the United States (California and Nevada) for the same five precipitation indicators (not shown) showed significant increasing trends for all but 10mm Days, suggesting that the behavior is not an artifact of the downscaling process. Table 13 lists direction and significance of projected trends for each index in detail.

Finally, in Figure 15 we show plots of the actual trajectories for individual models and the ensemble mean, for the five illustrative indicators in two example counties: Shasta and Imperial. As becomes clear from these graphs, the absolute values of the trends in indicators differ across models and methods, but temperature-related indices see agreement in the direction of the trend in all cases. This is not the case for precipitation indices, where the ensemble average trend is often flat and hides contrasting tendencies in the individual members (some simulations project dryer conditions while others project wetter conditions). Such discrepancies are also often evident between the two downscaling methods. We choose projections under the A2 emissions scenario for this example, with the understanding that projections under B1 would show even larger discrepancies across models/methods for the precipitation indices.

Table 13. Direction and significance of projected trends in Indicators of temperature and precipitation extremes

Index	1950–2100 BCSD (SRES B1 and A2)	1950–2100 CAD (SRES B1 and A2)
Frost Days	Decreasing trends, All significant. A2 projections exhibit steeper trends than B1 patterns. West to east positive gradient in the values.	Same as BCSD
Growing Season Length	Similar geographical pattern as Frost Days, with all significant positive values.	Same as BCSD
Hot Spells Duration	Increasing trends, more significant under A2, west to east gradient.	Same as BCSD, with generally larger values.
Heat Wave Duration	Increasing trends, more significant under A2, west to east gradient.	Same as BCSD, with generally larger values.
Warm (Summer) Nights	Increasing significant trends all over the state.	Same as BCSD but with lower positive values
Warmest Three Nights	Increasing and significant trends, uniformly located all over the state.	Same as BCSD.
Consecutive Dry Days	Increasing trends, but becoming homogeneously significant only under A2.	Increasing trends, but only a scatter of significant values and only under A2. Values are lower than BCSD.
Precipitation Intensity	Non significant, decreasing trends.	Significant increasing trends (limited to Northern California under B1, all over under A2).
Days w/Precip. > 10 mm	Decreasing trends all over the state, significant under A2.	Decreasing trends, with scattered significance only under A2.
Percent Precip. in Very Wet Days	No significant trends for either scenarios.	Increasing and significant for the northern part of the state under B1 and more widespread under A2.
Maximum 5-day Total Precip.	No significant trends.	No significant trends.

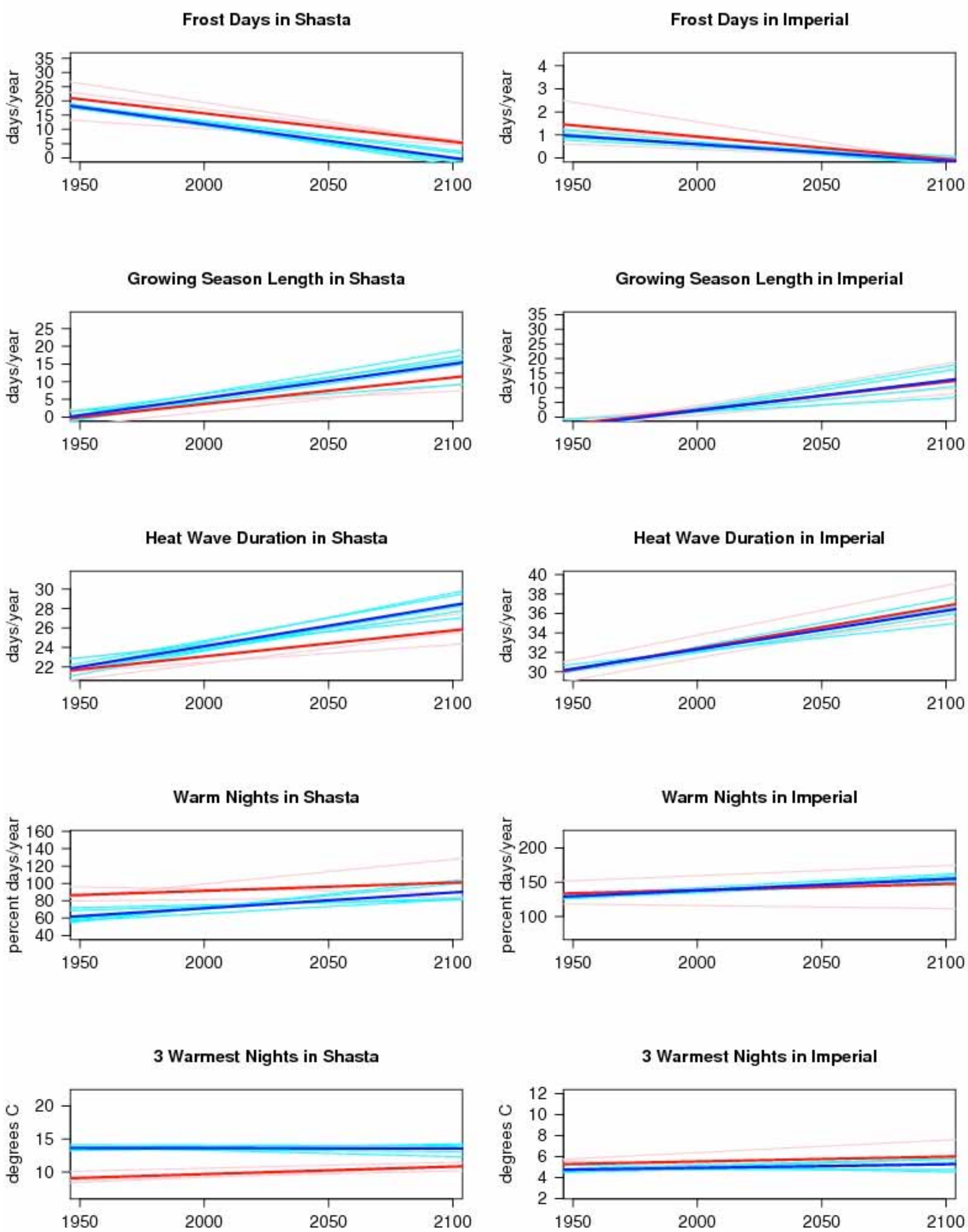


Figure 15. Range of individual model simulations for illustrative climate indicators in example counties, 1950–2100

Individual downscaled GCMs and ensemble mean trends for BCSD data (cyan and blue) and Analog data (pink and red) for five illustrative indicators, for Shasta (left column) and Imperial (right column) counties.

3.5. Return Level Analysis

An intuitive way of characterizing extremes under current and future conditions is through the concepts of return level or return period. Such analyses are conducted by applying Extreme Value Theory (EVT) to time series of observed data or model simulations. To fit a statistical distribution to the extreme values of a climate variable, EVT uses either the maximum values over a predefined period (year, season, month) or all the values over a certain threshold (to be optimally estimated). A member of a family of parametric distributions (the Generalized Extreme Value distribution, or GEV, in the case of maximum values, or the generalized Pareto distribution in the case of excess over threshold data) is fitted to these extreme observations. Thus, the statistical characterization applies specifically to the large values of the climate variable, rather than to its entire climatological distribution (Coles 2001).

Because of the need to perform this analysis over many locations, variables, and models and for both downscaling methods, we chose to extract three-day average maxima and fit GEV distributions, rather than using threshold exceedances that would require a case-by-case choice of threshold.

After fitting a GEV distribution to a climate variable (e.g., annual highest maximum temperature at a given location as observed over the period 1950–2000), the estimated parameters of the GEV distribution determine a functional relation between values of that variable and their expected return period. Thus, for a given fit of the GEV, a value x (say 125 degrees F) of the annual maximum at a given location may be associated with a return period of y years (say 100 years), meaning that under the climate conditions represented by the record used to fit the distribution one would expect to experience that value x of annual maximum only once every y years (e.g., one would expect that the annual maximum would reach 125°F only once in a hundred years, or with probability 0.01 in any given year).

Alternatively, the concept of return level is characterized by fixing a return period, say 100 years, and determining the value of the extreme that can be expected to recur once in that period. The use of parametric statistical distributions also provides a means of characterizing confidence intervals around the estimated return values and periods and thus determining the significance of the changes projected.

Of course, any statistical analysis is conditional on the data at hand. Extreme Value Theory handles the uncertainty in the fit itself by providing confidence intervals around each individual return level curve that is fitted to a given set of records (or model data). Structural uncertainties characteristic of climate models' approximations are addressed here by fitting return level curves to an ensemble of climate models simulations, from different GCMs and two alternative downscaling methods. These models and methods span a range of structural assumptions, and thus our results should bracket a relevant set of alternative future outcomes.

By comparing return level curves derived from the observed record to those derived from model simulations of the same period, we also address the basic necessity of validating these models' ability to reproduce observed extremes behavior.

3.6. Return Level Analysis Results

In the results that follow, we focus on multiple-day extreme events (e.g., annual highest three-day average maximum/minimum temperature) to address the persistency of extreme conditions that are more likely to represent extreme impact events. Results based on daily extremes were found to be qualitatively similar (not shown).

We also focus on temperature extremes. The less coherent signal in precipitation trends found in the previous section is consistent with what was found (but not shown here) when applying EVT to daily precipitation series and comparing return levels and periods between present and future climate conditions. Consistently for two definitions of precipitation extremes (annual maximum daily amount and annual maximum three-day total amount), no significant shift in the position of the curves could be detected across methods, scenarios, and locations—supporting the idea that trends and changes in this region are confounded by either model internal variability, inter-model differences, structural defects in models, or some combination of all of these (or, of course, that no significant trend is under way).

Time series of daily minimum and maximum temperature and precipitation from downscaled model simulations were analyzed for the 58 locations representative of the 58 counties of California in two separate segments: one representative of current climate (1950–2000), and one of future conditions (2050–2100). The latter is available under two emission scenarios: SRES A2 and B1.

Observed time series at the same 58 locations are also available and can be used to assess the ability of the different models/downscaling methods to reproduce the extreme value statistics of observed climate at these locations.

By fitting GEV distributions separately to the two periods 1950–2000 and 2050–2100, we can ask several questions about the behavior of annual extremes that have an intuitive and compelling interpretation:

- How is the return period of a given extreme value expected to change, from current to future conditions?
- How does the return value change, for a given return period?
- Are there geographically differentiated trends?

3.6.1. Current Climate Simulations and Observed Records

We found good agreement between the return level curves derived from observations and the envelope spanned by the two methods' downscaled simulations. This is true for all counties and both of the climate variables that we analyzed: annual high three-day average maximum temperature and annual high three-day average minimum temperature.

Figure 16 shows results for two counties that we chose as representative of two different California climate zones (Northern vs. Southern California): Shasta and Imperial.

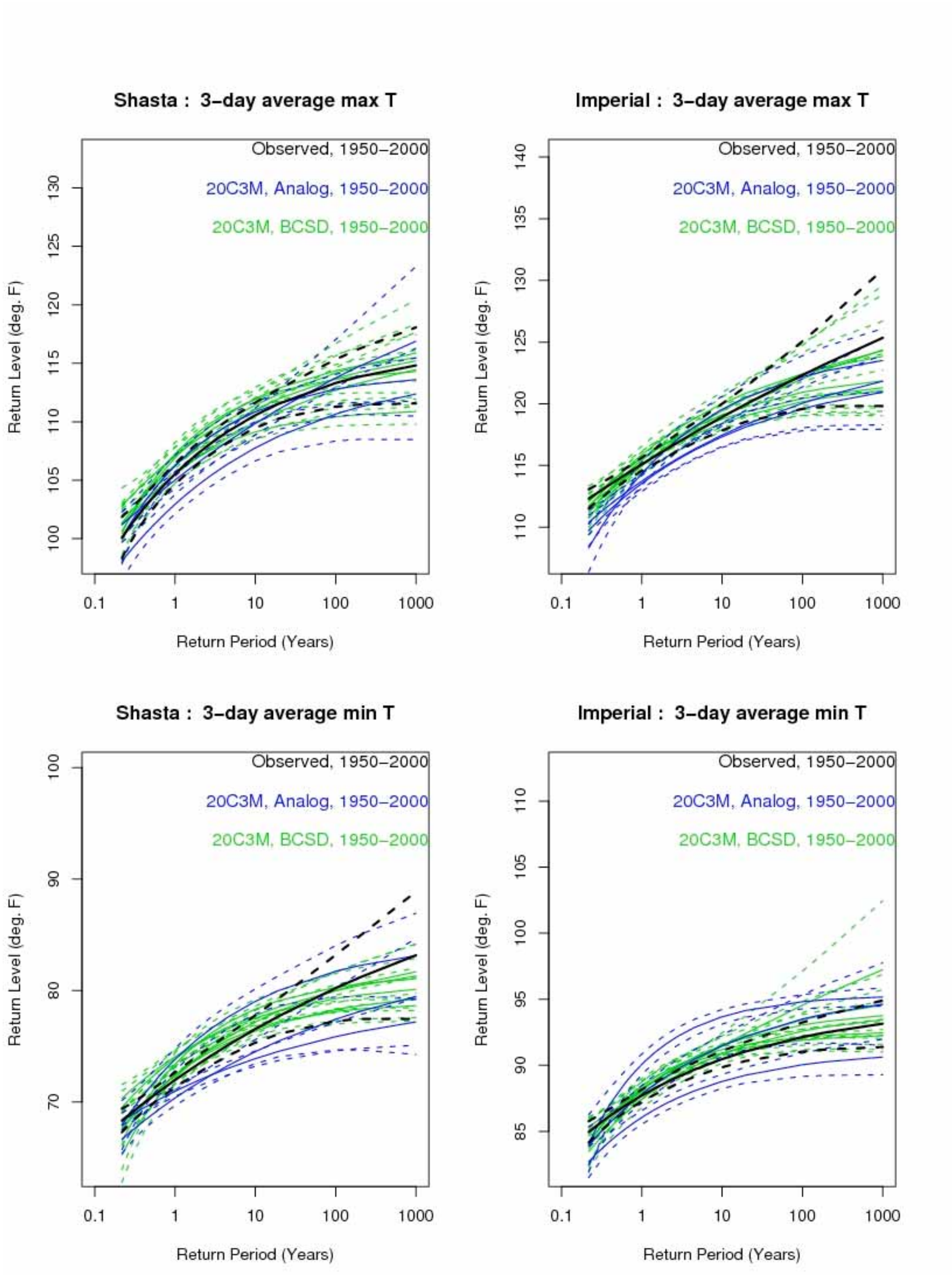


Figure 16. Return level curves for observed and model simulated three-day maximum and minimum temperature in example counties, 1950–1999

Return level curves for maximum (upper row) and minimum (lower row) three-day average temperature, estimated on the basis of annual maxima from the period 1950–1999 for Shasta (left column) and Imperial (right column) counties. Black solid line is curve estimated from observed dataset. Green lines are curves estimated using BCSD, blue lines are estimated using CAD. Dashed lines are corresponding 95% confidence intervals.

The two panels of each column figure show return level curves for one of two climate variables (maximum three-day average high temperature and maximum three-day average low temperature) in one county, based on the period 1950–2000. Blue curves are return level curves (solid) and confidence intervals (dashed) from the six GCM twentieth-century simulations using BCSD. Green curves are from the subset of three GCM twentieth-century simulations using CAD. The black lines are estimated from observations. The general message is that for all indices and counties the black solid lines are bracketed by the colored lines or very close to their envelope. As a whole, therefore, the climate simulations represent the return levels (or periods) of the observed climate for these climate variables realistically, and we are justified in taking a multi-model, multi-method approach to the projection of future changes. However, the range of uncertainty across models and methods is substantial, and therefore we focus less on specific return level or return period magnitudes. Rather, we focus on the significance of the change in these statistics, as represented by not only the changes in the ensemble mean projections under future conditions but in the envelope of uncertainty around them.

3.6.2. Future Changes in Return Period and Return Levels

We examine shifts in the curves between current and future periods, under two different emissions scenarios. At least four to five decades' worth of data are needed to fit GEV distributions, and we thus present results that lump the second half of the twenty-first century together.

First, we present an overview of projected changes in return period for each county (Figures 17 and 18), under B1 or A2 for both BCSD and CAD simulations. Colored circles represent the new return periods of temperatures that, under current climate, are expected to return only once every 100 years (smaller numbers of years associated with warmer colors). The smaller the number of years (compared to the current 100-yr period), the more frequently such temperatures will be experienced, and the larger the change toward more extreme conditions.

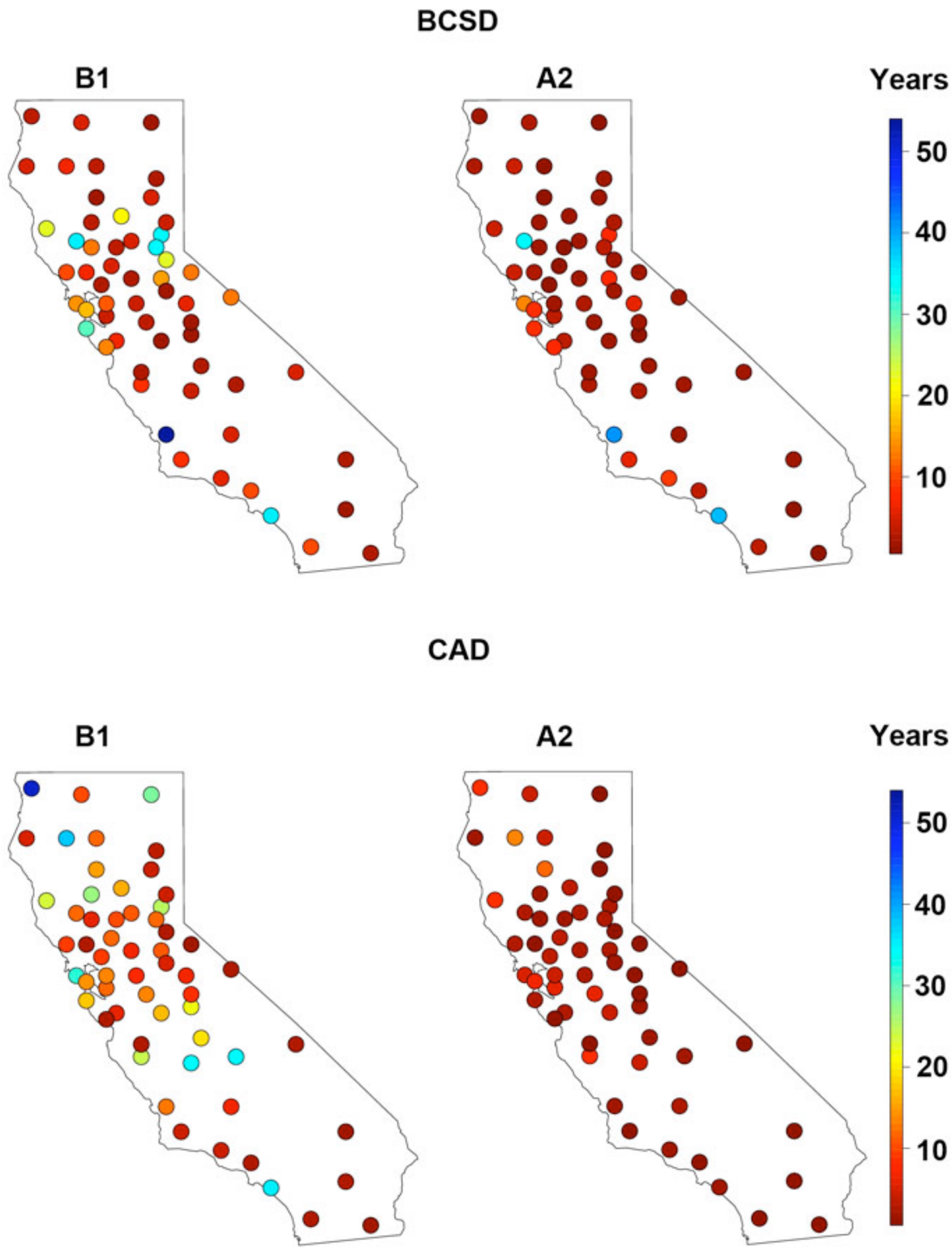


Figure 17. Projected return periods of current 100-year return levels, for maximum annual three-day mean maximum temperature, by county

Ensemble mean estimates of projected 2050–2100 return periods for current 100-year return levels, under the B1 emissions scenario (left column), and the A2 emissions scenario (right column). Panels on top row are ensemble means from BCSD downscaled GCM simulations, panels in bottom row from CAD. Values of the color scale correspond to the new return period of a current 100-year event (e.g., less than ten years for a dark red circle).

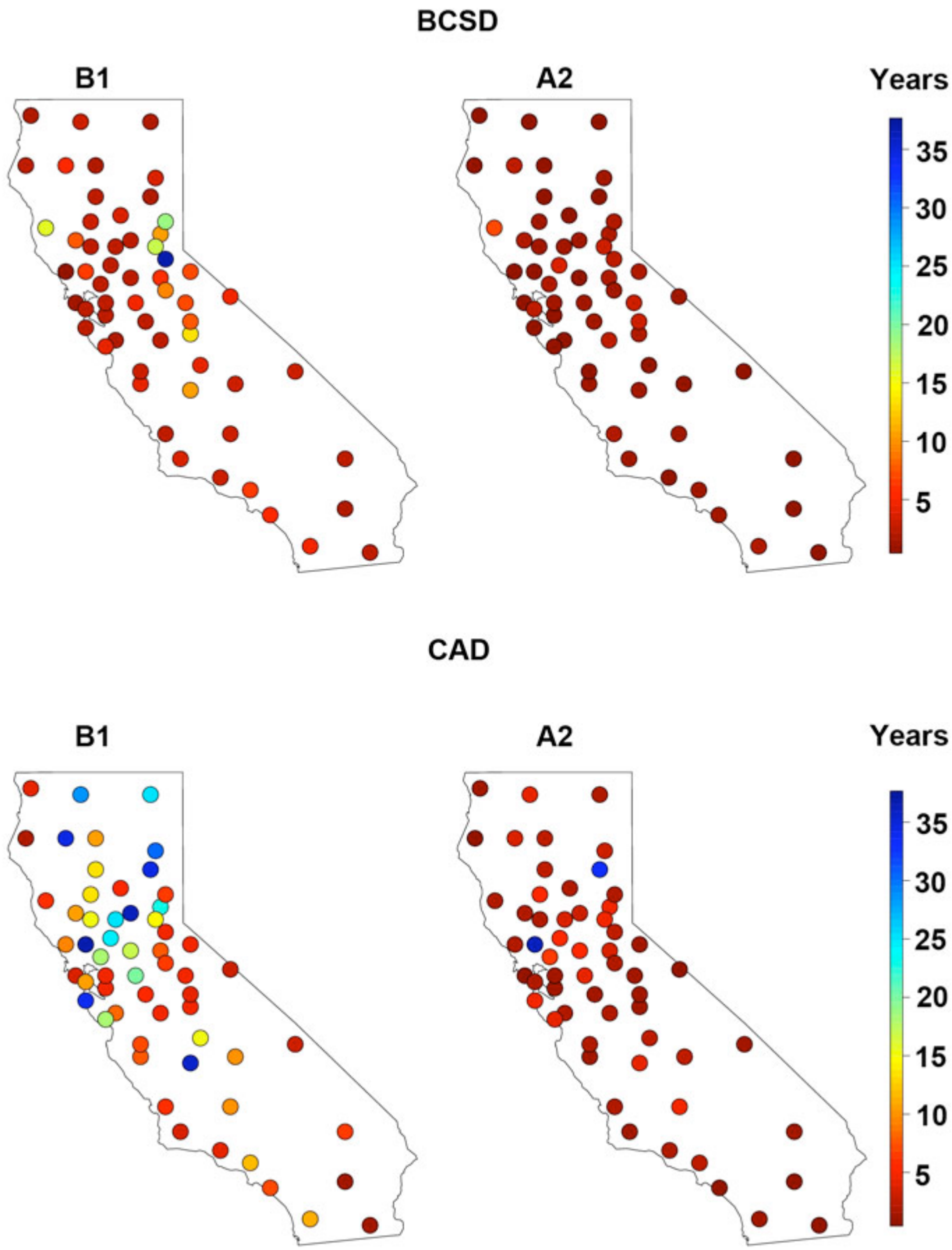


Figure 18. Projected return periods of current 100-year return levels, for maximum annual three-day mean minimum temperature, by county

Ensemble mean estimates of projected 2050–2100 return periods for current 100-year return levels, under the B1 emissions scenario (left column), and the A2 emissions scenario (right column). Panels on top row are ensemble means from BCSD downscaled GCM simulations, panels in bottom row from CAD. Values of the color scale correspond to the new return period of a current 100-year event (e.g., less than five years for a dark red circle).

There is some degree of spatial heterogeneity to the projections, mainly under SRES B1, and one can find areas where the frequency of current 100-yr extreme values "only" doubles or triples (green to blue dots). Most of the milder changes are located along the coast. However there is a large prevalence of deep red colors across the maps for both variables, indicating return periods of 10 years or less, and thus at least a ten-fold increase in the frequency of such conditions. The agreement of models (not shown here) is stronger under A2 than B1, as is the agreement between the two methods. Note that in these figures we are computing return periods only from the three GCM simulations that are common to the two downscaling methods, but including the additional 3 GCMs available for BCSD does not change the corresponding maps (i.e., the ensemble averages) appreciably.

An alternative way of characterizing the patterns of change is to ask what temperature will replace that which is associated with the current 100-year return period. Figures 19 and 20 display these results, similar maps with circles colored accordingly to temperature values (in degrees F) correspond to the 100-yr return level as it is currently estimated and as estimated under future conditions during the second half of the twenty-first century under the two scenarios. There is very good agreement between the two downscaling methods' ensemble mean projections, both in terms of values and in terms of their regionally diversified distribution. Changes are significantly stronger under the A2 scenario, with increases in the return level of double digits of degrees F across the entire region.

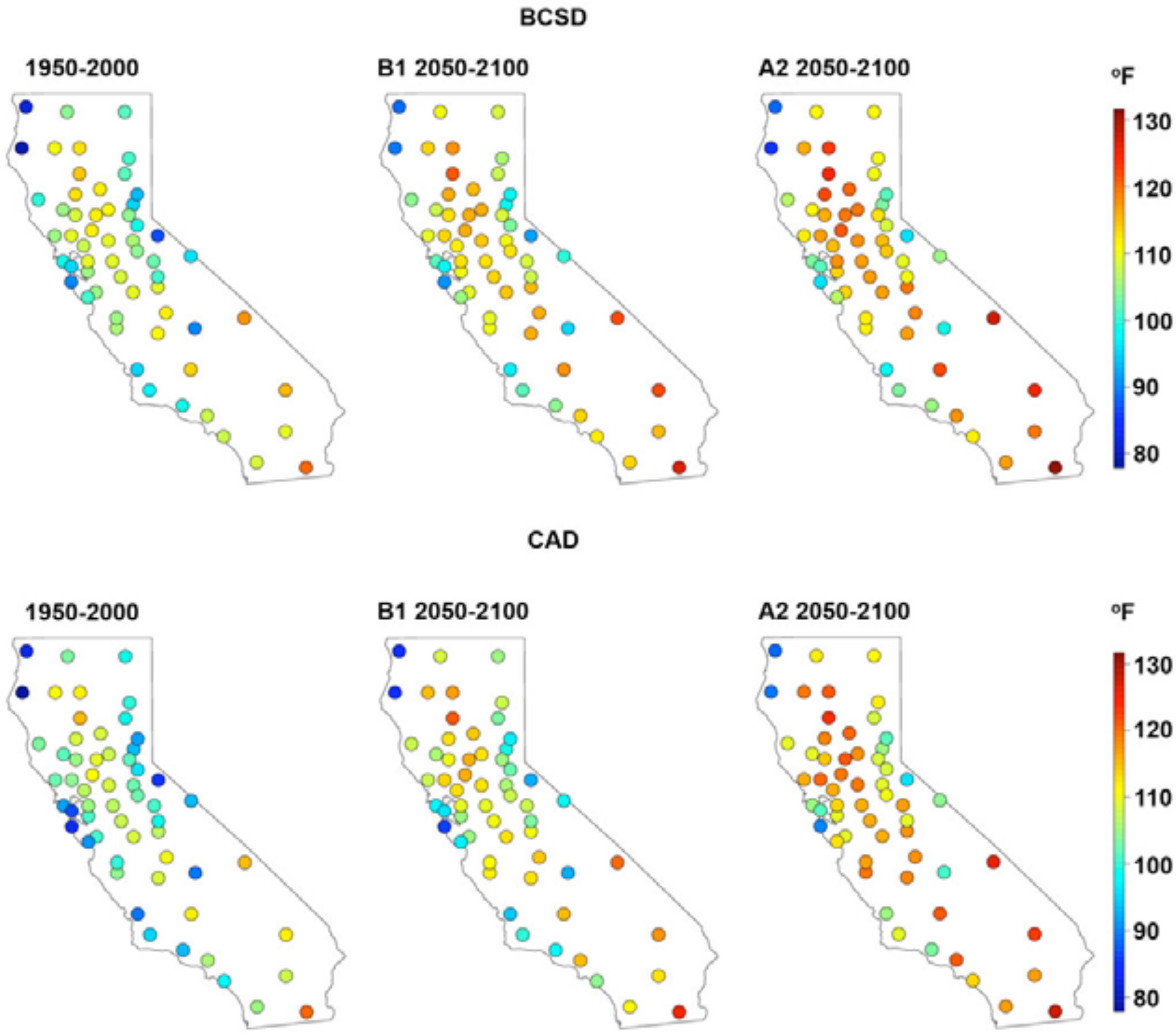


Figure 19. Simulated three-day maximum temperature 100-year return levels, 1950–1999 and 2050–2099, by county

100-year return levels of three-day annual maximum temperature (ensemble averages of three GCMs as in Figures 17 and 18), for current simulations (1950–1999; left column) and future projections (2050–2099) under SRES B1 (middle column) and A2 (right column). BCSD results along the top row, CAD results along bottom row.

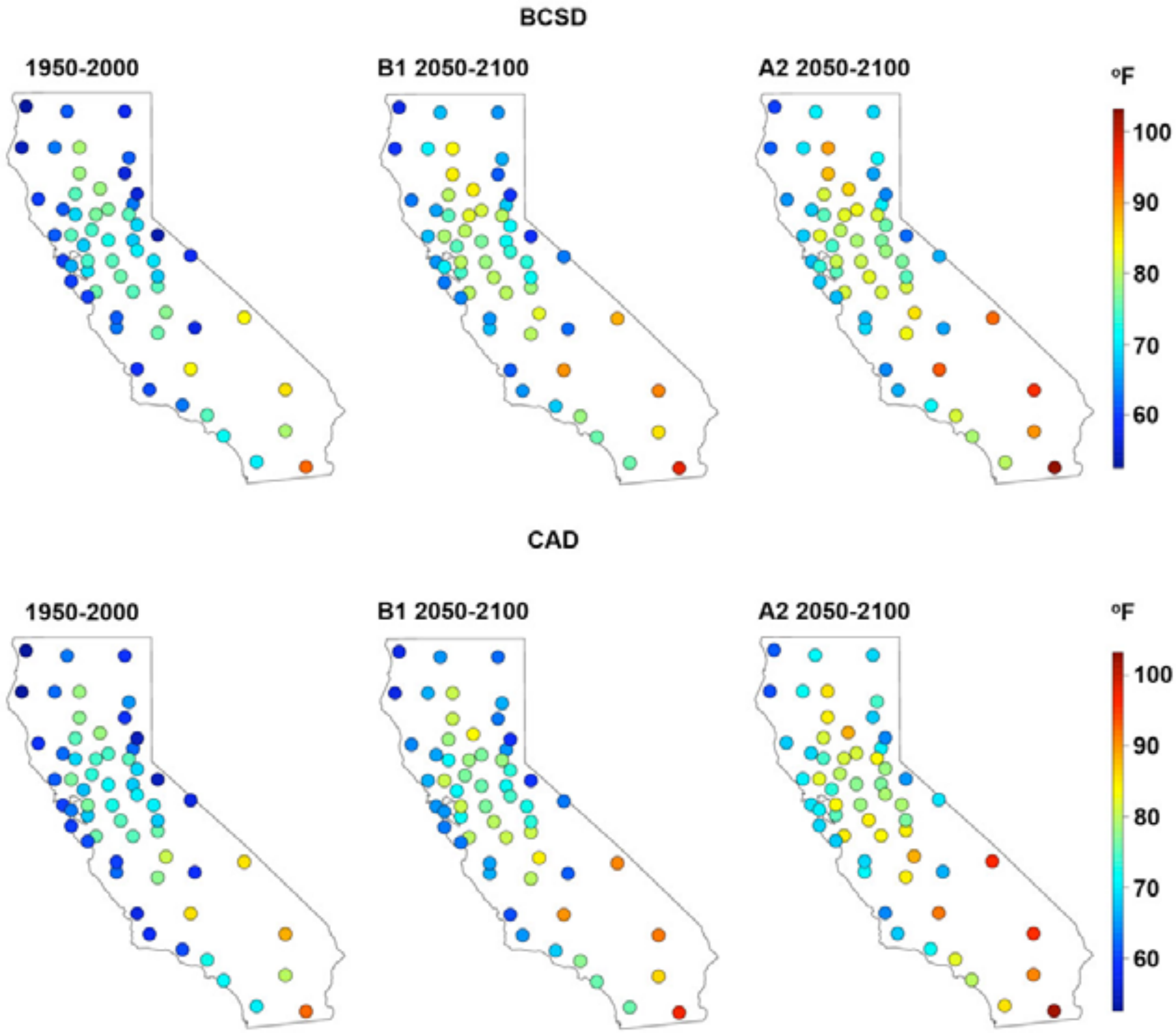


Figure 20. Simulated three-day minimum temperature 100-year return levels, 1950–1999 and 2050–2099, by county

100-year return levels of three-day annual minimum temperature (ensemble averages of three GCMs as in Figures 17 and 18), for current simulations (1950–1999; left column) and future projections (2050–2099) under SRES B1 (middle column) and A2 (right column). BCSD results along the top row, CAD results along bottom row.

To provide a measure of the inter-model spread, in Figure 21 we show sets of curves for the same two counties (one in each column) and three-day average maximum temperature as estimated on the basis of the downscaled simulations by BCSD (top panels) and CAD (bottom panels). The interpretation would be the same using return level curves derived for extremes of minimum temperatures. We call attention to two sets of comparisons.

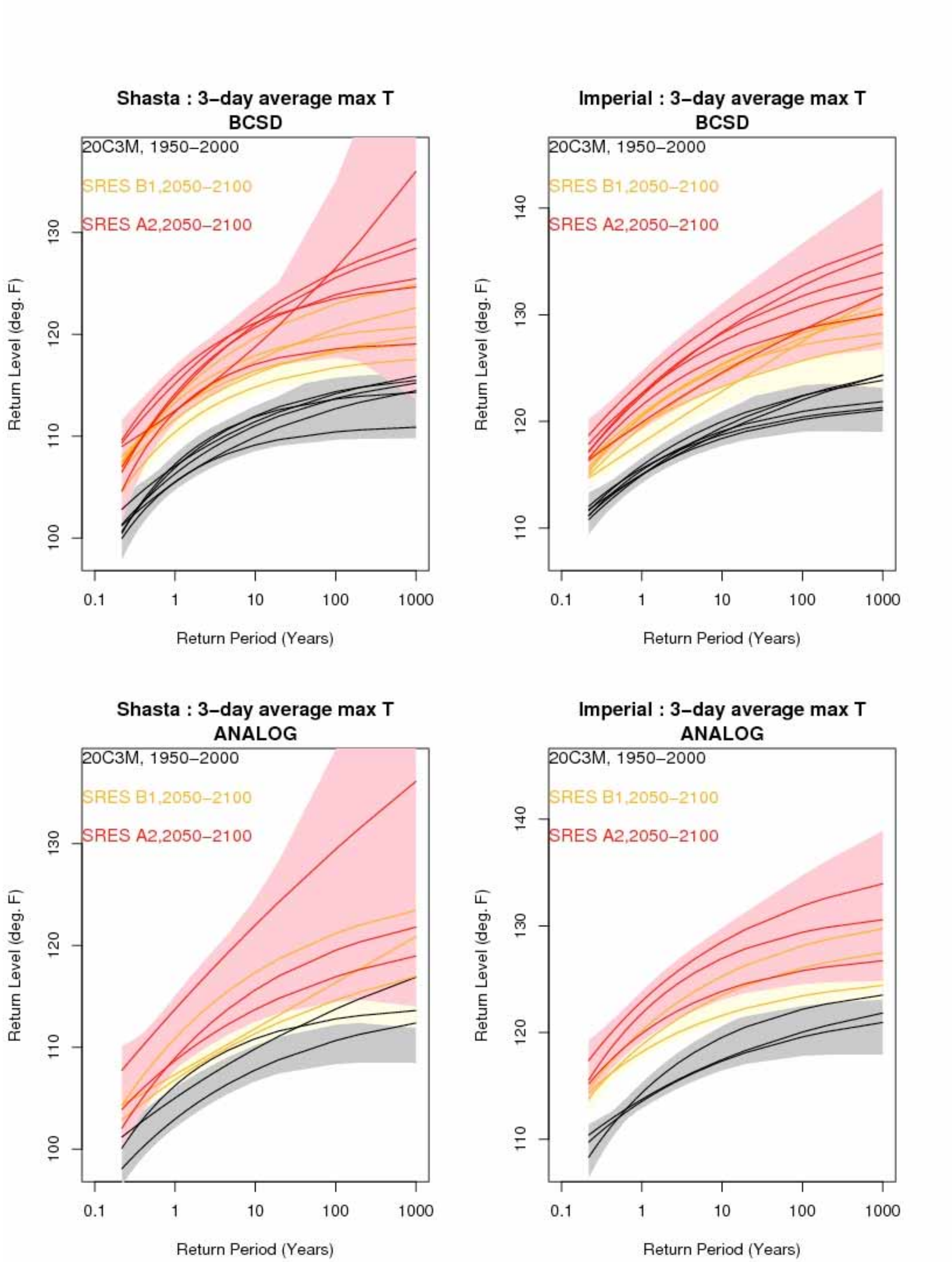


Figure 21. Individual model simulations of three-day annual maximum temperature in example counties, 1950–1999 and 2050–2099

Return level curves for annual three-day maximum temperatures for Shasta (left column) and Imperial (right column) counties. Top row projections for BCSD, bottom row projections for CAD. Each panel compares three sets of curves. Black: current climate simulations (1950-1999). Orange: B1 (2050-2099). Red: A2 (2050-2099). Shading captures the range of all 95% confidence intervals around the individual curves.

First, consider a vertical line intersecting the x-axis at 100 years. For most indices/counties the set of orange/red curves corresponding to the downscaled future simulations under respectively B1 and A2 are situated above the envelope formed by the black curves (estimated from the twentieth century segment of the simulation) indicating a significant shift of the return levels associated with the 100-yr return period. These figures display the spread of values across the methods/GCMs simulation. Again, because of this spread we do not suggest focusing on the specific magnitudes calculated, but rather on the significance of the projected shift between current and future conditions.[2] The significance of this shift is clearly demonstrated by the lack of overlap between the two sets of colored (future return levels) vs. black (current return levels) solid curves.

Second, consider a horizontal line that intersects the black curves at their 100-yr return level. The corresponding periods along the x-axis corresponding to where the line intersects the orange and red curves are the new return periods under future conditions of what is now the 100-yr return level. In this case too, the colored curves lie to the left of and do not overlap the black curves, signaling a significant shift (decrease) in the return period. Here as well the ensemble mean curve does not tell the entire story, and the ranges of new return periods can be considered substantial. There is nonetheless a clear separation between the envelope of black curves and that of the colored curves, meaning that what is now a range of extreme conditions currently associated with a given return period will recur considerably more often in the future.

3.7. Recurrence of Historical Event Magnitudes

Finally, we conduct an analysis of model projections in order to determine changes in the frequency of events similar in magnitude to specific historical extreme events. We focus on two temperature-related events: the July 2006 heat wave and the December 1998 freeze. A third event involving extreme precipitation is left out because of the failure to identify a robust signal of change in the statistics of extreme precipitation through EVT or extreme indices analysis, as mentioned in the previous sections.

The impacts of the 2006 heat wave were discussed in Section 2.2. From December 19–28, 1998, an arctic air mass moved over California, leading to a devastating freeze during which minimum temperatures fell below 0°C for more than a week, particularly in Central and Southern California. Crops, especially citrus, experienced heavy losses. Estimated agricultural losses were $682 million (Lobell et al. 2009a).

The complex make up of actual observed extreme events makes their characterization challenging. For the July 2006 heat wave, climatological thresholds corresponding to extreme quantiles of both minimum and maximum temperatures (we consider 95th and 99th quantiles) were exceeded for many days in a row. Gershunov and Cayan (2008) analyze the event in great detail, adding an in-depth characterization of the synoptic conditions leading to and maintaining the extreme event. They identify the high night temperatures (minimum daily temperatures) as the main culprit for the damaging nature of the event.

[2] Moreover, the highest temperatures produced through these statistical calculations under the A2 scenario may not be physically realistic.

Here we focus on simple definitions that represent important characteristics of these events. We focus on runs of consecutive days (six or more) where daily minimum or maximum temperatures consistently exceed the 95th quantile of the climatological distribution in that location ("hot spells"), and on runs of consecutive days (seven or more) where daily minimum temperatures fall below 0°C ("freezes"). Figures 22 and 23 display the counties within the state that met the freeze criterion and the hot spell minimum temperature criterion during these two historical events.

Figure 22. Incidence of a seven-day or longer freezing spell in winter 1998, by county

Black dots mark locations experiencing the freezing spell.

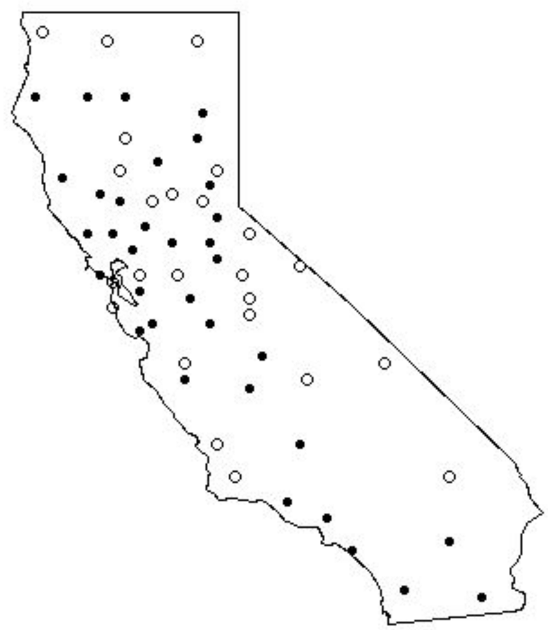


Figure 23. Incidence of a six-day or longer hot spell with minimum temperatures above the 95th percentile of their climatological distribution in July 2006, by county

Black dots mark locations experiencing the hot spell.

We use the same gridded observational dataset that allowed us to compare EVT and indicator projections to observations in the main part of this paper. The period covered by the gridded data ends at 2000, though, so we also extract National Weather Service (NWS) Cooperative Observer Program (COOP) station daily data minimum and maximum temperature data for the years 1950–2008 from the National Climatic Data Center (NCDC) website ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/all/. The stations were chosen to be closest to the locations of the grid points used to characterize model projections (downscaled) for each of the 58 California counties. We want to use time series covering the 2006 event, to make sure that our definitions for both observed events reflect actual anomalies in the observed record, which they do.

We first compute spells of freezing temperatures from observed and modeled data, the latter from the twentieth century simulations of all models available. We then compute the same statistics for the future projections available under the two scenarios, A2 and B1. The aim of the analysis is to characterize the change in the frequency of years with at least one freeze as defined above (freezing temperatures lasting seven consecutive days or longer). Figure 24 shows results of this analysis for the A2 scenario for each of the 58 counties, ordered in the figure according to increasing values of observed frequencies (black dots). The dots represent observed frequency of freezes in the period 1951–2000, and the black line indicates the range of frequencies computed from the twentieth century simulations of the six GCMs available and the two downscaling methods. The orange line extends over the range of simulated frequencies for the period 2001–2050 and the red line extends over the range simulated for the period 2051–2100.

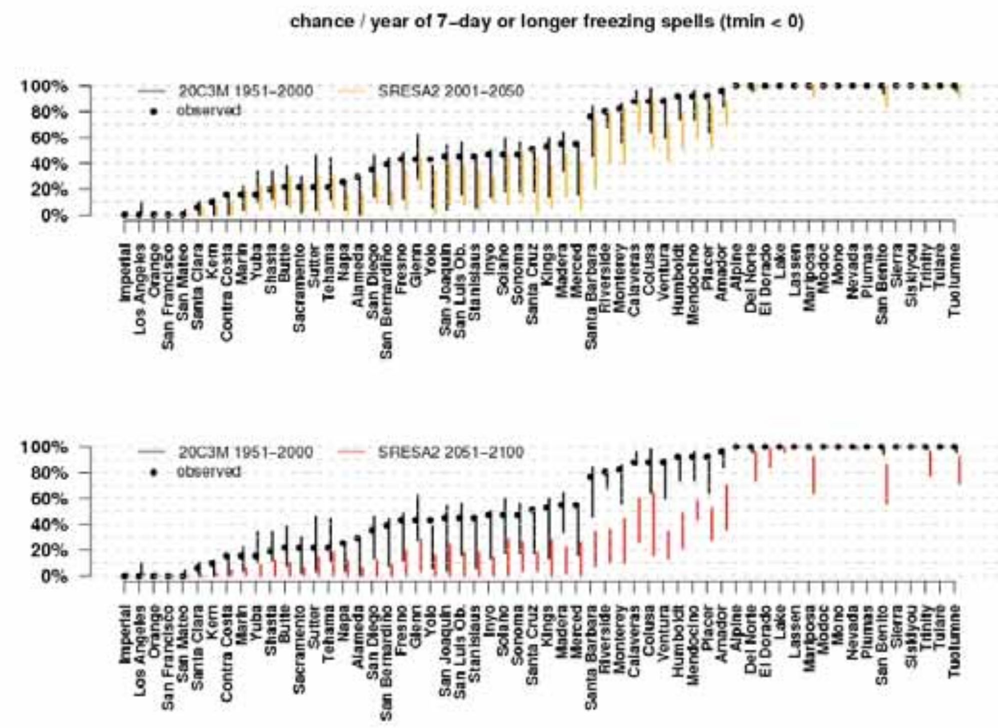


Figure 24. Frequency of observed, simulated, and projected freezing spells, by county

Chance per year of freezing spell defined as seven consecutive days or more with minimum temperatures below 0°C. Analysis for 58 locations in California representative of the 58 counties. Dots represent observed frequencies over the 50 years 1951–2000 (gridded observational dataset). Black lines indicate the range of twentieth century simulations (1951–2000) across six GCMs and two downscaling methods. Orange and red lines represent ranges of future frequencies under SRES A2 for, respectively, 2001–2050 and 2051–2100.

There is overall very good agreement between current climate simulations and observed frequencies, with the black lines bracketing the dots in almost all locations. In most cases, we also note the strong signal of decrease in frequency of freezing spells emerging by the second half of the century (when comparing each red line to its corresponding black line). For most locations the red lines do not overlap the black, indicating a significant decrease in the frequency of freezing spells. Under the A2 scenario in the second half of the twenty-first century, the lower limit of the projected frequency for many of the 58 locations indicates the possibility of these events becoming very rare, with less than one year in every ten experiencing a freeze of the same magnitude as it was experienced in 1998. Freezes are particularly damaging to the agricultural sector, and therefore we focus further on five counties in which agricultural production features prominently in the state's economy: Napa, Sonoma, Fresno, Kern, and Merced.

Table 14 highlights observed frequencies, current climate simulated ranges, and corresponding ranges for the first and second part of the twenty-first century under A2 and B1, which confirm in greater detail the general discussion above.

Table 14. Frequency of at least one freezing spell of seven consecutive days or longer for five county locations representative of important areas in the state's agricultural sector, 1950–1999 and 2050–2100

County	Observed	20th C. simulations	SRESB1 2001–2050	SRESA2 2001–2050	SRESB1 2051–2100	SRESA2 2051–2100
Napa	0.25	(0.04,0.26)	(0.02,0.10)	(0.02,0.16)	(0.00,0.08)	(0.00,0.12)
Sonoma	0.47	(0.18,0.56)	(0.10,0.32)	(0.14,0.48)	(0.04,0.38)	(0.04,0.26)
Fresno	0.44	(0.12,0.48)	(0.10,0.22)	(0.04,0.34)	(0.02,0.26)	(0.00,0.20)
Kern	0.10	(0.00,0.18)	(0.00,0.08)	(0.00,0.06)	(0.00,0.04)	(0.00,0.02)
Merced	0.55	(0.16,0.56)	(0.06,0.32)	(0.04,0.40)	(0.02,0.32)	(0.00,0.26)

We now consider hot spells as observed or simulated, whose characteristics in length and intensity lend them to a rather straightforward, if superficial, comparison to the heat wave experienced across the entire state in the second half of July 2006. We label this comparison superficial since it simply involves temperature statistics, while the full extent and gravity of heat wave impacts should involve other measures like humidity, winds, and solar radiation.

We compute climatological distributions for each calendar day separately by pooling daily minimum or maximum temperatures from a five-day window around each date, and from the years 1961 through 1990 of the observed records and the GCM simulations. Thus, for each calendar day, the climatological quantile is computed on the basis of 150 daily values (five days from each of the 30 years). We then extract spells of consecutive days (six or more) where the 95th quantiles of these climatological distributions were exceeded. The comparison between observed and simulated current climate statistics, and between current and future climate behaviors is shown in Figure 25, for hot spells of minimum temperature, which can be interpreted as nighttime temperature. The 58 county locations are ordered by increasing upper limit of the future projected frequency of hot spells (top of the red bars). Figure 26 shows the corresponding results for hot spells of maximum temperature. Note that in-depth analyses of the 2006 event (Gershunov and Cayan 2008) and others (e.g., Karl and Knight 1997) have identified consecutive extremely warm nights as the most damaging periods during a heat wave, causing the worst risk to human and animals.

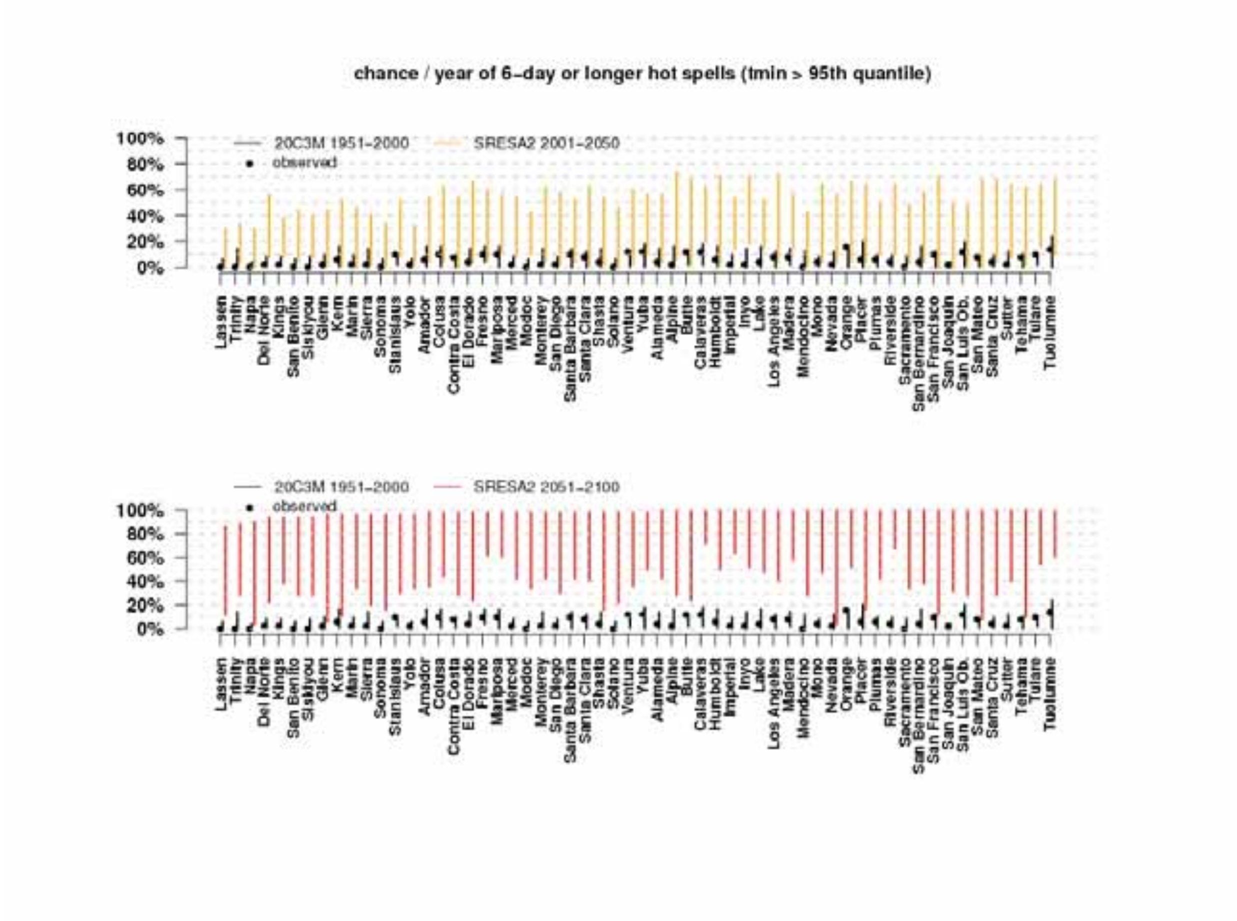


Figure 25. Frequencies of observed, simulated, and projected hot spells of minimum temperature, by county

Chance per year of hot spell of minimum temperature defined as six consecutive days or more with minimum temperatures above the 95th quantile of climatology, June through August. Analysis for 58 locations in California representative of the 58 counties. Dots represent observed frequencies over the 50 years 1951–2000 (gridded observational dataset). Black lines indicate the range of 20th century simulations (1951–2000) across six GCMs and two downscaling methods. Orange and red lines represent ranges of future frequencies under SRES A2 for, respectively, 2001–2050 and 2051–2100.

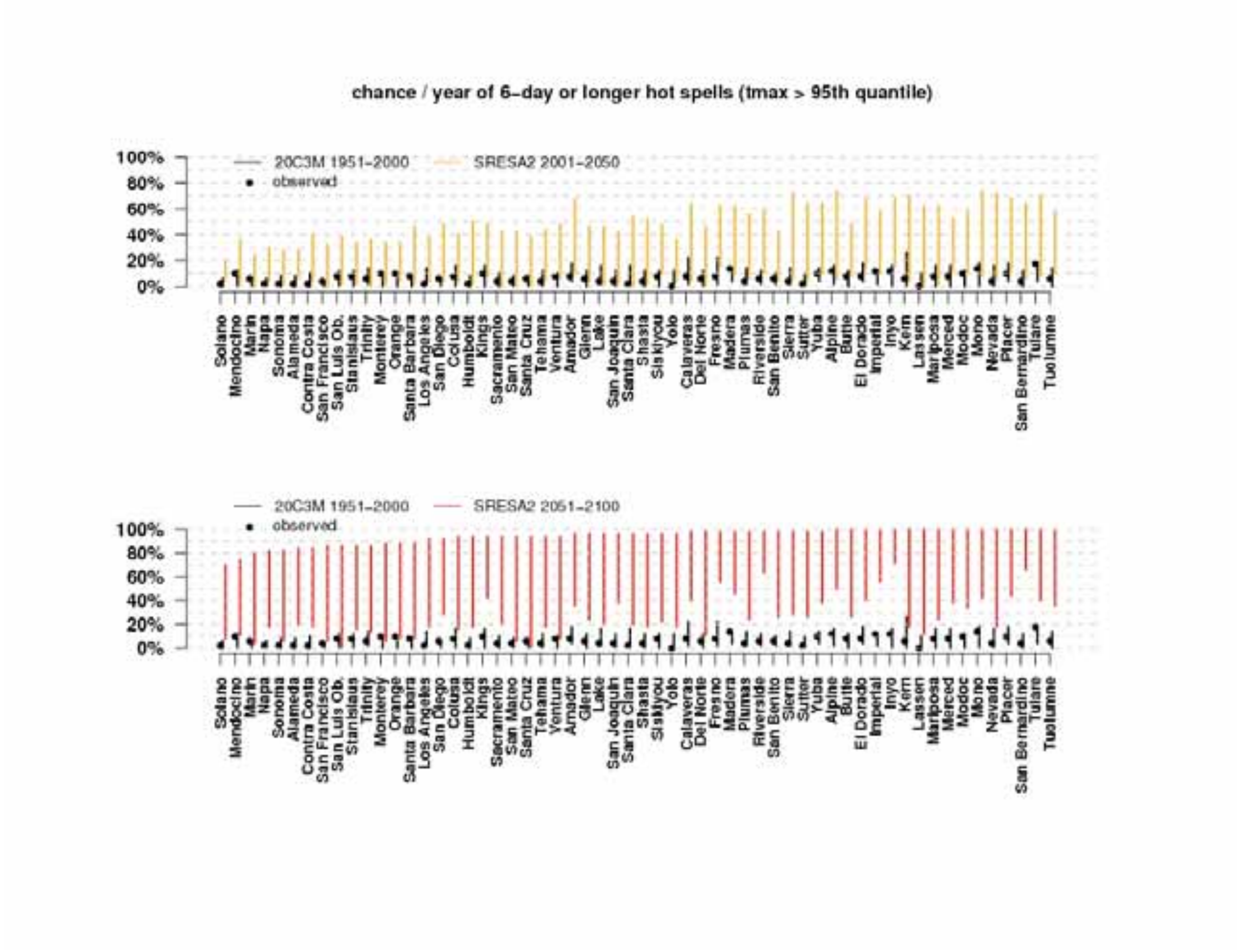


Figure 26. Frequencies of observed, simulated, and projected hot spells of maximum temperature, by county

Chance per year of hot spell of maximum temperature defined as six consecutive days or more with maximum temperatures above the 95th quantile of climatology, June through August. Analysis for 58 locations in California representative of the 58 counties. Dots represent observed frequencies over the 50 years 1951–2000 (gridded observational dataset). Black lines indicate the range of 20th century simulations (1951–2000) across six GCMs and two downscaling methods. Orange and red lines represent ranges of future frequencies under SRES A2 for, respectively, 2001–2050 and 2051–2100.

The results in these two figures are striking in the large predicted increases in the frequency of extreme hot spells starting in the first half of this century and intensifying in its second half. There is good agreement between the observed and simulated current climate statistics, for almost all counties. The range of future frequencies projected by the different GCMs downscaled by the two alternative methods is larger than the range of frequencies simulated by the twentieth century experiments, suggesting a larger uncertainty among model simulations. But in all cases, the projections cover values of 0.5 or larger, and in many counties some of the simulations project an extreme event of this kind in every year of the simulation. There is a relatively smaller increase in hot spells of maximum temperature compared to minimum temperature (very mildly so, however) and in B1 compared to A2 (not shown), but the general picture is of very significant increases in frequency across scenarios, downscaling methods, and county location.

We also compared current and future simulations of hot spells defined as runs of consecutive days with minimum (maximum) temperature exceeding the 99th percentile of climatological distribution. By definition these are events that would be observed with a frequency of less than once in a 100-yr period. The results (not shown) are very similar to what was found for the lower thresholds.

A Note on the Agreement Between Observed and Simulated Hot Spell Frequency

By defining extremely hot days as those exceeding the 95th quantile of the climatological distribution (either observed or modeled), we constrain both the observed and simulated historical frequency of such hot days to be on average no higher than 5%. By then computing spells of such hot days, however, we are not straightforwardly constraining observed and modeled hot spells to appear with similar frequency, as if we were just counting the number of exceedances of such a threshold. The good agreement of observed and modeled frequencies of at least one such hot spell is one aspect of the verification of the consistency of GCM simulations of hot temperature extremes with observed data.

A more in-depth look at the characteristics of such hot spells is given, for example, by computing their average length. Figures 27 and 28 show graphs similar to the previous ones, but the quantity along the y-axis is now length in days of hot spells, rather than their frequency over the years.

In most cases the average length of observed hot spells is within the range of hot spell duration in current climate simulations, lending further validation to the model results. These figures also indicate that the length of such hot spells is projected to increase strongly and significantly by the second half of this century.

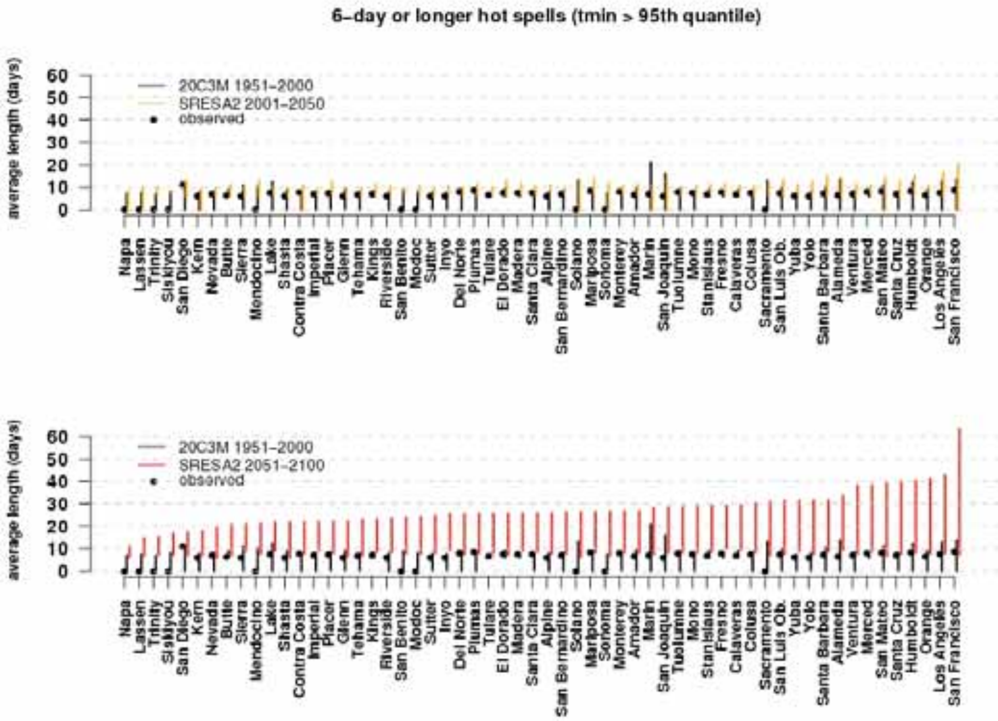


Figure 27. Average length of observed, simulated, and projected hot spells of minimum temperature, by county

Average length of hot spells of minimum temperature, as defined above. Analysis for 58 locations in California representative of the 58 counties. Black dots represent observed averages (gridded observational dataset, 1951–2000). Black lines indicate the range of 20th century simulations (1951–2000) across six GCMs and two downscaling methods. Orange and red lines represent ranges of future frequencies under SRES A2 for, respectively, 2001–2050 and 2051–2100.

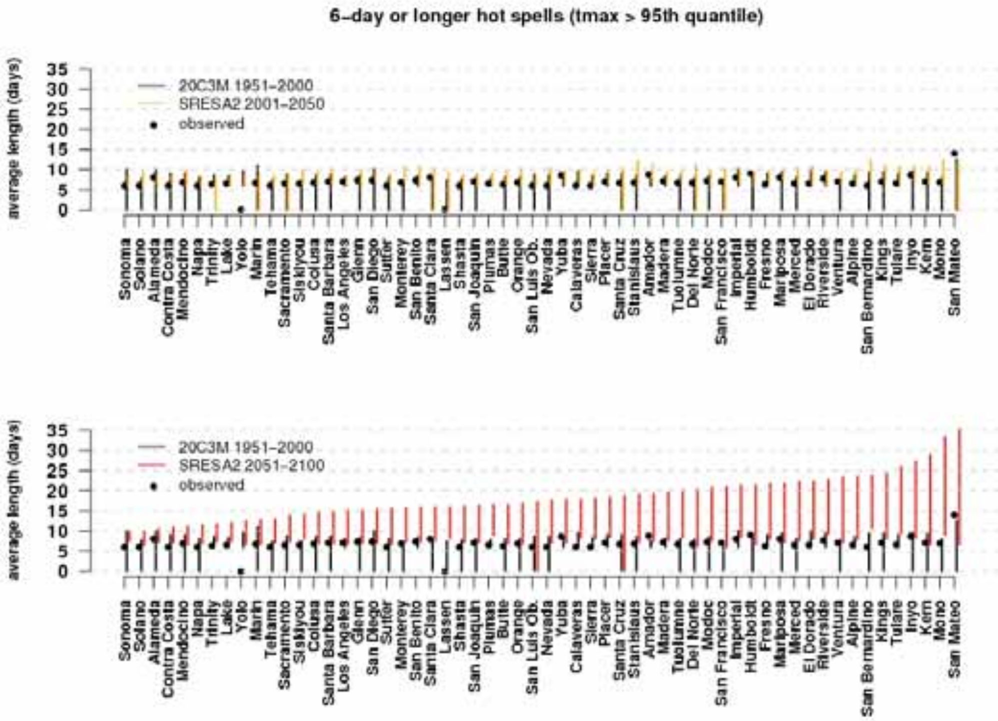


Figure 28. Average length of observed, simulated, and projected hot spells of maximum temperature, by county

Average length of hot spells of maximum temperature, as defined above. Analysis for 58 locations in California representative of the 58 counties. Black dots represent observed averages (gridded observational dataset, 1951–2000). Black lines indicate the range of 20th century simulations (1951–2000) across six GCMs and two downscaling methods. Orange and red lines represent ranges of future frequencies under SRES A2 for, respectively, 2001–2050 and 2051–2100.

4.0 Conclusions and Recommendations

This paper synthesizes existing literature on the impacts of extreme events on seven potentially vulnerable sectors in California. In presenting this information, we distinguish between two types of transfer functions that can be used to quantify such impacts. First, inter-system transfer functions quantify the relationship between extreme climate conditions and sectoral impacts. Additionally, impacts in one sector can affect other sectors. Thus, there are also inter-sector transfer functions that quantify the relationship between changes in one sector and the resulting impacts on a different sector. This exercise summarizes many qualitative and quantitative relationships drawn from the literature, and highlights areas where interactions are recognized but have not been quantitatively characterized.

In this context, we also distinguish between extreme climate events and extreme impact events. Extreme climate conditions (e.g., temperatures above a given threshold of the climatological distribution), do not necessarily induce extreme impacts. Ideally, the definition of extreme impact events and subsequent transfer functions linking them to climate conditions would be arrived at by analyzing historical events and their impacts, and by involving relevant stakeholders and analysts to better quantify the interactions we identify in section 2 and to identify thresholds of particular concern for on-the-ground planning. We see this study as setting the stage for more formal research in this direction, building from the extensive body of literature on the impacts of climate change in California.

Informed by this exercise, we also produce new projections of changes in the frequency and intensity of extreme events in the future across climate models, emissions scenarios, and downscaling methods, for each county in California. This analysis employs downscaled climate projections from six GCMs, two emissions scenarios (SRES A2 and B1), and two downscaling methods (BCSD and CAD), produced for the 2008 PIER Scenarios Report (Cayan et al. 2008b). Previous assessments of climate change impact projections for California have used a smaller subset of climate projections and fewer categories of extreme events than are analyzed here.

We evaluate historical and projected changes for a suite of temperature and precipitation-based climate indicators, and we conduct a return level analysis to investigate projected changes in extreme temperatures. Finally, we include an analysis of the future likelihood of events similar in magnitude to specific historical events, such as the July 2006 heat wave. We perform these analyses at 58 separate grid points extracted from the full set of downscaled climate projections. Each grid point is representative of a county in California, and the locations are representative of areas of importance from an economic, social, and ecological perspective (e.g., major urban areas, Central Valley, Wine Country, higher elevation regions, coastal areas).

In general, model simulations using both downscaling approaches reproduce most of the characteristics of observed patterns of extreme climate conditions in California. Some exceptions, and the range of individual model results, are outlined in Section 3. As a whole, however, we conclude that employing this multi-model, multi-method ensemble of climate simulations to project future changes in extreme events is justified.

Changes in extreme events related to high temperatures are found to be very consistent across simulations downscaled by both methods. Coherent changes over California suggest significant increases in the severity of hot spells (both in length and intensity) and decreases in frost days and—more generally—cold spells. Larger warming is projected inland compared to coastal areas. A significant difference in the magnitude of these changes in temperature extremes is found when comparing the two scenarios, A2 and B1, suggesting that mitigation would limit the severity of these changes.

For indicators and EVT analyses of precipitation, our inquiries failed to detect a significant signal of change, with inconsistent behavior when comparing simulations across different GCMs and different downscaling methods. Simulations using BCSD, for example, show a tendency toward drier conditions (longer dry spells) while simulations using CAD do not exhibit this behavior. Similarly, simulations using CAD indicate widespread significant increasing trends in precipitation intensity, which fail to be confirmed when analyzing the BCSD simulations. Parallel studies that use larger regional averages suggest a more consistent picture of a general lengthening of dry spells and increasing precipitation intensity for this region as a whole, but we cannot support the same findings at the local scale represented through our grid-point level analyses.

Lastly, a comparison of current and future expected frequencies of events comparable to recently observed extremes (heat wave of July 2006, freezing spell of December 1998) suggest significant changes: heat waves similar in length and intensity to that experienced in 2006 will become more frequent all across the state, with some simulations suggesting that they will be an annual event by the end of this century under a higher emissions scenario. Freezing spells, on the other end, are robustly projected to become less frequent all across the state, even in locations where now they are a yearly event, becoming as rare as a one in ten-year event or less in a large fraction of California.

We see this research as a first step toward informing more formal vulnerability assessment in the context of extreme events in California. Vulnerability is often considered as a function of exposure to a stress, sensitivity to that stress, and adaptive capacity to cope with that stress. The projections presented in this paper provide information regarding the exposure to extreme events in different regions of California, and the presented synthesis of impacts and interactions identified in the literature is a first step toward characterizing the sensitivity of specific sectors to extreme events. Moving forward, further refinements of information regarding exposure and sensitivity must be integrated with assessment of the adaptive capacity of specific sectors, regions, and populations, to identify specific vulnerabilities and inform strategies to reduce those vulnerabilities. Since patterns of extreme events can chance considerably even under lower emissions scenarios, vulnerability assessment in the context of extremes is particularly important for informing adaptation strategies.

5.0 References

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6.0 Glossary

AT	apparent temperature
AR4	IPCC Fourth Assessment Report
BCSD	bias correction and spatial downscaling
CAD	constructed analog downscaling
CALVIN	An economic-engineering water optimization model
CCSM3	Community Climate System Model, version 3
CD	day position
CNRM	Centre National De Recherches Météorologiques
COOP	Cooperative Observer Program (COOP)
DIS	days in sequence
ECHAM5	a general circulation model
EPA	U.S. Environmental Protection Agency
ER	emergency room
EVT	extreme value theory
GCM	global climate model
GDP	gross domestic product
GEV	generalized extreme value
GFDL	Geophysical Fluid Dynamics Laboratory
IPCC	Intergovernmental Panel on Climate Change
MCI	multiplicative competitive interaction
MW	megawatts
NCAR	National Center for Atmospheric Research
NWS	National Weather Service
PM	particulate matter
SLH	sea level height
SLP	sea level pressure
SRES	Special Report on Emission Scenarios
SWE/P	snow water equivalent / precipitation
Tx	afternoon temperature
WEAP	Water Evaluation And Planning System