Arnold Schwarzenegger
Governor

IDENTIFICATION OF EXTERNAL INFLUENCES ON TEMPERATURES IN CALIFORNIA

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Preface

The 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, managed by the California Energy Commission (Energy Commission), 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 are focused 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 Public Interest Energy Research (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.

Identification of External Influences on Temperatures in California is the final report for the Detection and Attribution of Climate Change in California project (contract 500-02-004, work authorization MR-025) conducted by the University of California, Merced. The information from this project contributes to PIER's Energy-Related Environmental Research Program.

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

This study used nine different observational datasets to estimate California-average temperature trends during the periods 1950–1999 and 1915–2000. Observed results were compared to trends from a suite of control simulations of natural internal climate variability. On the longer (86-year) timescale, increases in annual-mean surface temperature in all observational datasets are consistently distinguishable from climate noise. On the shorter (50-year) timescale, results are sensitive to the choice of observational dataset. For both timescales, the most robust results are large positive trends in mean and maximum daily temperatures in late winter/early spring, as well as increases in minimum daily temperatures from January to September. These trends are inconsistent with model-based estimates of natural internal climate variability, and thus require one or more external forcing agents to be explained. Observational datasets with adjustments for urbanization effects do not yield markedly different results from unadjusted data. These study results suggest that the warming of California's winters over the second half of the twentieth century is associated with human-induced changes in large-scale atmospheric circulation. The authors also hypothesize that the lack of a detectable increase in summertime maximum temperature arises from a cooling associated with large-scale irrigation. This cooling may have, until now, counteracted the warming induced by increasing greenhouse gases and urbanization effects.

Keywords: Climate change, climate change detection, temperature trend, California climate change, anthropogenic climate change

Executive Summary

Introduction

No matter what energy policies are adopted, climate change is likely to have significant societal impacts in California. These will likely include effects on the water supply, flood risk, levee vulnerability, air quality, agriculture, and human health. Development of adaptation measures generally takes years or longer; it is therefore important to anticipate societal impacts of climate change, so that appropriate adaptation measures can be ready when they are needed.

Confident predictions of future climate change in California, and of associated societal impacts, requires understanding of historical climate changes. This means accurate characterization of climate trends, and attribution of those trends to specific influences, either natural or anthropogenic. External factors thought to be influencing climate in California include solar variability, volcanic eruptions, several classes of aerosols, atmospheric greenhouse gases, and land-use changes (especially urbanization and irrigation). A first step in understanding historical climate trends is to determine if these trends result from one or more of the external factors just named, or are manifestations of natural internal climate variability (due for example to the El Niño or the Pacific Decadal Oscillation).

Purpose

The purpose of this project was to examine California's climate trends to better characterize their cause.

Project Objectives

The project's objectives were to:

- Characterize recent climate trends in California.
- Determine if these trends are a result of external influences.
- If so, identify what specific factor(s) (such as increasing greenhouse gases) are responsible.

Project Outcomes

This project focused on trends in near-surface temperature because this variable has been well-observed and has direct societal relevance. The research team used eight different observational datasets to estimate temperature trends during 1950–1999 and 1914–1999. These were obtained by fitting a least-squares line to time series of California-average temperatures from each dataset. In general, trends among different datasets were quite consistent. Researchers compared observed trends from these datasets to trends from a suite of control simulations of natural internal climate variability. These latter trends were obtained through the same procedure that was applied to observations: the control simulations were divided into overlapping segments of 50 and 86 years and fit a least-squares line to each segment, thus

obtaining a large sample of estimated trends due to natural internal variability. The research team then compared observed trends to the ninety-fifth percentile estimated trend from natural variability. Observed increases in annual-mean surface temperature are distinguishable from estimated climate noise in some but not all observational datasets. The most robust results are large positive trends in mean and maximum daily temperatures in late winter/early spring, as well as increases in minimum daily temperatures from January to September. These trends are inconsistent with model-based estimates of natural internal climate variability, and thus cannot be explained without invoking one or more external forcing agents.

Conclusions

This study's results suggest that the warming of California's winters over the second half of the twentieth century is associated with human-induced changes in large-scale atmospheric circulation. The authors hypothesize that the lack of a detectable increase in summertime maximum temperature arises from a cooling associated with large-scale irrigation. This cooling may have, until now, counteracted the warming induced by increasing greenhouse gases and urbanization effects.

1.0 Introduction

Human-induced climate change is a reality. Human effects on climate have been identified in many different aspects of the climate system, at global, hemispheric scales (e.g., Santer et al. 1996; Mitchell et al. 2001; Hegerl et al. 1997; Tett et al. 1999; Stott et al. 2000) and continental scales (Stott 2003; Zwiers and Zhang 2003; Karoly et al. 2003; Karoly and Braganza 2005). Attempts to detect anthropogenic effects at regional or even grid-point scales are more recent (Spagnoli et al. 2002; Santer et al. 2006; Karoly and Wu 2005. In California, there is great political and scientific interest in the question of how human-caused climate change will manifest itself. Will nighttime temperatures increase more than daytime temperatures? Will there be more warming in winter than in summer? How will precipitation and snow be affected? How uncertain are expected changes? Impacts on agriculture, water availability, human health, and other factors depend on answers to these and related questions.

Identification of "fingerprints" of anthropogenic climate change at the scale of California would enhance confidence in model projections of the regional aspects of climate change and their possible societal impacts. Part of such fingerprinting work consists in documenting the background "noise" of natural internal climate variability and determining whether or not observed trends are too rapid to be explained by this noise alone. It is impossible to determine noise characteristics from short instrumental records in which signals and noise convolved, but natural internal variability can be estimated from long climate model control simulations with no changes in external factors.

Attribution attempts to identify causal factors responsible for any detected change. Rigorous attribution of observed changes in California's climate to specific forcings would require so-called "single forcing" experiments—simulating changes in only one forcing at a time. These were not available for a broad range of climate models. Hence, the research team instead considered "20CEN" experiments[1] driven by historical changes in combined anthropogenic and natural external forcings, and then determined if these forced simulations would yield results consistent with observed changes. Consistency between the observed and 20CEN climate changes (and inconsistency between the observed changes and control run results) would imply that significant changes have been detected in California's climate, and that these changes can be attributed to external forcing(s). Inconsistencies would point toward errors in (or neglect of) important forcings and/or errors in the model response to the imposed forcings.

In small domains, detection of externally forced climate change poses special challenges. Global models are less skillful on subcontinental scales (Stott and Tett 1998), and high-resolution observational datasets are not always available. Furthermore, the noise of internal climate variability generally increases with decreasing domain size, often leading to a degradation of signal-to-noise (S/N) ratios, thus hampering identification of external factors. Finally, forcings that may be of considerable importance in understanding regional climate change (e.g., land-use change, aerosols) are often highly uncertain and spatially and temporally heterogeneous.

[1] The 20CEN runs are historical experiments for the climate of the twentieth century forced by combinations of external factors (e.g., greenhouse gases, sulfate aerosols, volcanic aerosols, solar irradiance).

The research team focused on indices of California's climate based on daily surface air temperatures: monthly mean temperature (T_{ave}), monthly mean night- and daytime temperatures (T_{min}, T_{max}) and their difference, and the diurnal temperature range (DTR). All are well observed in California, and their changes can have important societal impacts. The research team considered both seasonal and annual mean trends in these indices.

2.0 Project Methods

Observed California-mean trends in each quantity were estimated for 1950–1999 from a minimum of four and a maximum of seven gridded datasets (Table 1), as well as from stations of the U.S. Historical Climatology Network (USHCN and USHCN-U).[2]

Table 1. Observational datasets, including their spatial and temporal resolution

Acronym	Affiliation	Period*	Region	Res	Tave	Tmin	Tmax	DTR	Reference
UW1	University Washington	1949–1999	U.S.	1/8º	Y	Y	Y	Y	Maurer et al. (2002)
UW2	University Washington	1915–2003	West U.S.	1/8º	Y	Y	Y	Y	Hamlet and Lettenmaier (2005)
UDv1.02	University Delaware	1950–1999	Global	1/2º	Y	-	-	-	Willmott and Matsuura (1998)
NOAA	NOAA NCDC	1851–2000	Global	5º	Y	-	-	-	Eischeid et al. (1995)
HadCRUT2v	Hadley Center	1856–2003	Global	5º	Y	-	-	-	Jones and Moberg (2003)
CRU2.0	University East Anglia	1901–2000	Global	1/2º	Y	Y	Y	Y	Mitchell et al. (2004)
CRU2.1	University East Anglia	1901–2002	Global	1/2º	Y	Y	Y	Y	Mitchell and Jones (2005)
USHCN	Oak Ridge Nat. Lab.	variable	U.S.	N/A	Y	Y	Y	Y	Karl et al. (1990)
USHCN-U	Oak Ridge Nat. Lab.	variable	U.S.	N/A	Y	Y	Y	Y	Karl et al. (1990)

* in complete years

Use of multiple datasets enabled the research team to assess the robustness of the detection results to observational uncertainty. All datasets (except UW1) are well-suited for long-term trend analysis and include some form of adjustment for non-climatic influences (e.g., changes in instrumentation and station location). The number and coverage of California stations varies between the different observational products. Most datasets are predominantly based on adjusted HCN records. UW1 and UW2 datasets, however, have higher station coverage over California, and include both HCN and Cooperative network observations. The CRU2.0, CRU2.1, UW1, and USHCN datasets were not adjusted for urbanization effects, while the HadCRUT2v, UW2, and USHCN-U datasets attempt to account for urbanization. None of the observational datasets account for the effects of other human-induced changes in land-surface properties, such as conversion to crop-land, irrigation or other factors.

Although the datasets analyzed here rely on similar raw data and are not completely independent, the processing choices made by dataset developers can differ markedly from group to group, leading to uncertainty in the magnitude (and sometimes even the sign) of the observed trends (see Figures 1 and 2). Here, the main period of interest is 1950–1999, because it contains the most reliable historical records and is covered by all datasets. However, the research team also examined temperature changes over 1915–2000, the longest period covered by most datasets.

[2] The USHCN-U dataset accounts for urbanization, whereas the USHCN dataset does not.

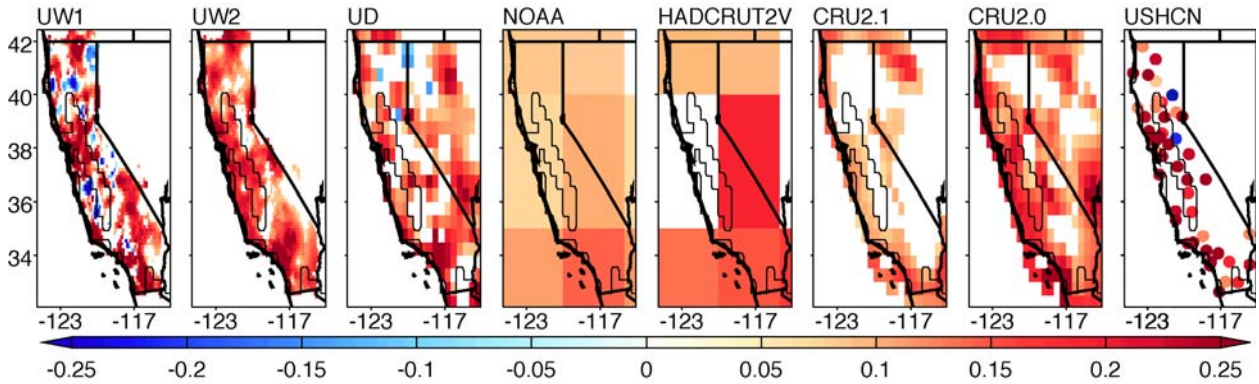

Figure 1. Spatial patterns of annual-mean temperature trends (°C/decade) in different observational datasets. At each grid-cell, trends were estimated by a least-squares linear fit to times series of temperature anomalies over 1950–1999. Trends that are not statistically different from zero at the 80% confidence level are in white. The 150 meter contour roughly delineates California's Central Valley.

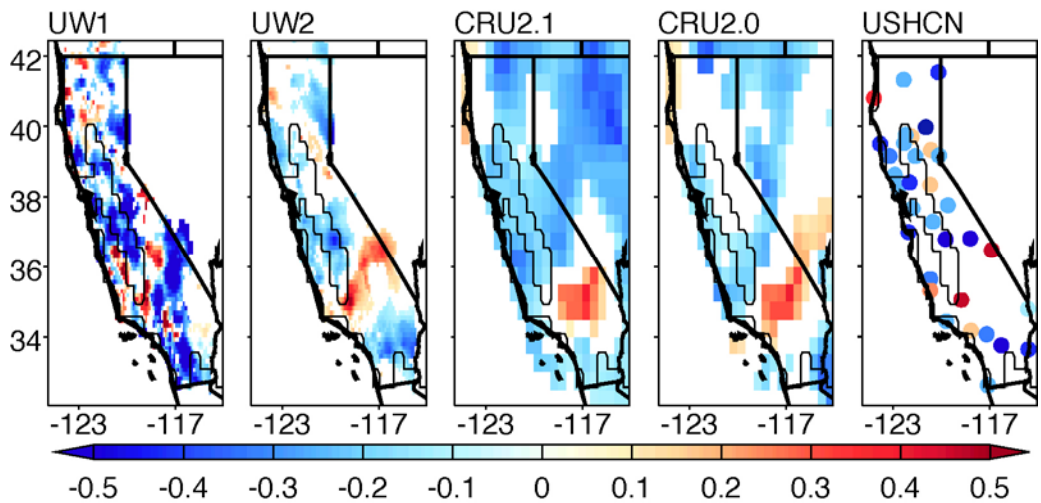

Figure 2. As for Figure 1, but for trends in diurnal temperature range

The research team investigated whether observed historical trends in California exceed climate "noise" by comparing recent observed 50-year trends in T_{ave}, T_{min}, T_{max}, and DTR to distributions of modeled linear trends from unforced control simulations (this approach has been used by Karoly et al. 2003 and Santer et al. 2006). For this purpose, the authors used 22 (for T_{ave}) or 6 (for T_{min}, T_{max}, and DTR) long control simulations. After establishing that some observed trends are inconsistent with results of unforced simulations, the research team compared the observed T_{ave} (T_{min}, T_{max}, and DTR) trends to those from 69 (15) 20CEN historical runs performed with 22 (8) different models. The 20CEN runs were forced by combinations of external factors (e.g., greenhouse gases, sulfate aerosols, volcanic aerosols, solar irradiance) that are model-dependent (Table 2). All simulations were performed in support of the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4).

Table 2. Characteristics of 20th century climate simulations and their associated models and included external forcings that were used to estimate natural internal climate variability. See PCMDI website (www-pcmdi.llnl.gov) for more details.

Model Designation	Resolution	Originating group(s)	R_a	R_b	Forcings	Y_1	Y_N	L	N_a	N_b
CCSM3	T85	NCAR, USA	6	2	ABCEFJK	280	509	230	19	–
GFDL-CM2.0	2.0 × 2.5°	GFDL, USA	3	–	ABCEFIJK	1	500	500	46	–
GFDL-CM2.1	2.0 × 2.5°	GFDL, USA	3	–	ABCEFIJK	1	500	500	46	–
GISS-EH	4.0 × 5.0°	GISS, USA	5	–	ABCDEFGHIJ	188	227	400	36	–
GISS-ER	4.0 × 5.0°	GISS, USA	9	–	ABCDEFGHIJ	190	240	500	46	–
MIROC3.2(medres)	T42	CCSR/NIES/FRCGC, Japan	3	3	ABCEFGHIJK	230	279	500	46	46
MIROC3.2(hires)	T106	CCSR/NIES/FRCGC, Japan	1	1	ABCEFGHIJK	1	100	100	6	6
MIUB/ECHO-G	T30	MIUB/METRI/MD	5	–	ACDJK	186	220	341	30	–
MRI-CGCM2.3.2	T42	MRI, Japan	5	–	ACJK	185	220	350	31	–
PCM	T42	NCAR, USA	4	2	ABCJK	451	107	629	58	–
UKMO-HadGEM1	1.25 ×1.87°	UKMO, UK	2	–	ABCDEFIJK	192	209	172	13	–
BCCR-BCM2.0	T63	BCCR, Norway	1	1	AC	185	209	250	21	21
CCCma-CGCM3.1(T47)	T47	CCCma, Canada	5	–	AC	185	285	100	96	–
CCCma-CGCM3.1(T63)	T63	CCCma, Canada	1	–	AC	185	219	350	31	–
CNRM-CM3	T63	CNRM, France	1	–	ABCE	193	242	500	46	–
CSIRO-Mk3.0	T63	CSIRO, Australia	3	3	AC	187	225	380	34	34
ECHAM5/MPI-OM	T63	MPI, Germany	3	–	ABCD	215	265	506	46	–
FGOALS-g1.0	T42	LASG/IAP, China	3	–	AC	185	219	350	31	–
GISS-AOM	3.0 × 4.0°	GISS, USA	2	2	ACH	185	210	251	21	21
INM-CM3.0	4.0 × 5.0°	INM, Russia	1	1	ACJ	187	220	330	29	9
IPSL-CM4	2.5 × 3.75°	IPSL, France	1	–	ACD	186	235	500	46	–
UKMO-HadCM3	2.5 × 3.75°	UKMO, UK	2	–	ABCD	185	220	342	30	–
TOTAL	–		69	15	–	–	–	–	808	137

R_a, R_b: number of 20th century climate realizations available for Tave and for Tmin, Tmax.

Forcing used in the 20th century runs (Santer et al. 2006): A: Greenhouse gases; B: Ozone; C: sulfate aerosol direct effects; D: sulfate aerosol indirect effects; E: black carbon; F: organic carbon; G: mineral dust; H: sea salt; I: land-use change; J: Solar Irradiance; K: volcanic aerosols.

Y_1, Y_N, L: model-specific choices for the starting year, the ending year, and the length (in years) of the control runs.

N_a, N_b: number of overlapping 50-year linear trends obtained from each control run for Tave and for Tmin, Tmax, and DTR (when data are supplied).

To create distributions of model-derived unforced trends, linear trends were fitted, for each control simulation, to overlapping 50- or 86-year segments (separated by 10-year intervals) of the California-average temperature time series. These multi-model distributions reflect noise uncertainties arising from differences in a wide range of model properties (e.g., physics, parameterizations, resolution), and provide the best available model estimates of natural internal variability. The significance of observed trends was assessed in two ways: (1) by comparing observed trends with the 95% confidence intervals of the unforced trend distributions, computed by assuming a Gaussian distribution of trends and multiplying the standard error of the distribution (SE) by 1.96, and (2) by determining the empirical probability that the magnitude of the unforced trends exceeds that of observed trends. The two methods give very similar results, validating the assumption of the Gaussian distribution of trends (Figure 3). While none of the control runs has a statistically significant overall temperature trend for the California domain, some integrations do show residual drift at the beginning of the run (Santer et al. 2006). Additionally, one shows a sudden jump that seems pathological. The research team opted to retain these control-run drifts, thus inflating SE and making it more difficult to reject the null hypothesis that an observed trend is due to natural internal variability.

The significance-testing procedure outlined above was applied to annual- and seasonal-mean (January–March [JFM], April–June [AMJ], July–September [JAS], and October–December [OND]) values of the four indices considered here. The research team used this somewhat unconventional seasonal definition because observed trends in December are very different from those in January (see below).

The reliability of the significance-testing results depends crucially on the fidelity with which the models used here simulate the natural internal variability of the real-world climate system. This is difficult to assess, particularly on the multi-decadal timescales of interest here, without multi-century observational records uncontaminated by human influences. However, observational data are of adequate length to make meaningful comparisons of modeled and observed temperature variability on annual and decadal timescales (e.g. Stott 2003; Braganza et al. 2004). Accurate simulation of natural variability on these shorter time scales would enhance confidence in the detection results of externally-forced multi-decadal trends.

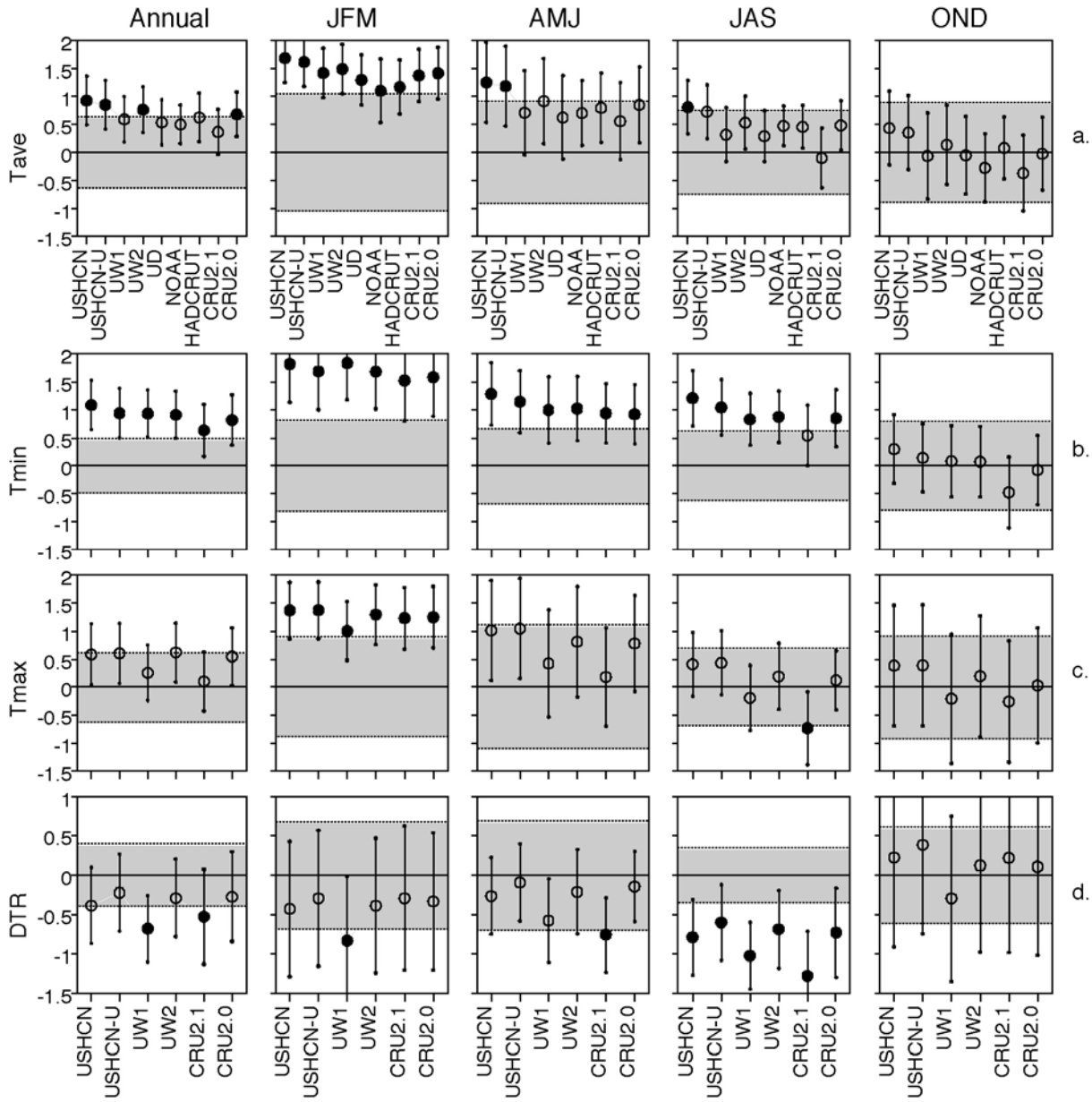

Figure 3. Observed temperature trends over 1950–1999 (solid dots) and model-derived estimates of the 95% confidence interval natural internal variability. Climate noise estimates are based on multi-model unforced 50-year trend distributions (see main text). The horizontal dotted lines represent the 95% confidence intervals of the trend distributions and were computed as 1.96 × s_E, the standard error of the sampling distribution of unforced trends. Results are for (a) daily-mean temperature; (b) daily minimum temperature; (c) daily maximum temperature; and (d) diurnal temperature range. Vertical bars represent the standard error for the trend accounting for the temporal autocorrelation of the regression residuals (Santer et al. 1999) × 1.641 to assess the statistical significance of the trends (one-tailed t-test). Circles are closed when the empirical probability for the magnitude of the unforced trends to exceed that of observed trends is less than 5%. Data from different USHCN stations are equally weighted.

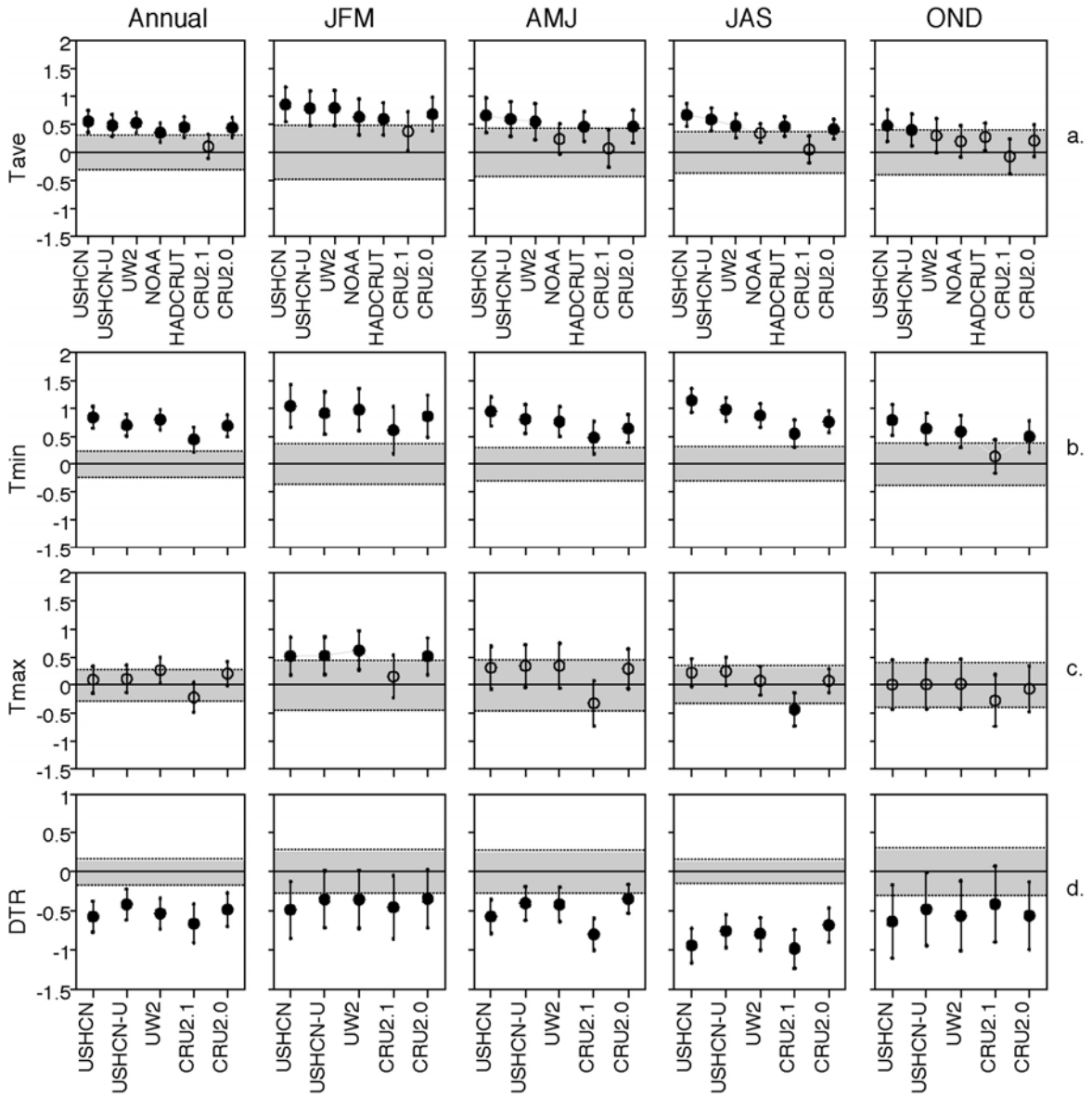

Figure 4. Same as Figure 3, but observed trends are computed over the period 1915–2000, and the range of natural internal variability is based on multi-model unforced 86-year trend distributions.

The research team compared the observed interannual and decadal variability of each temperature index with corresponding values from the 20CEN realizations. The (varying) length of the observational record dictated the period used for calculating model and observed temporal standard deviations. All standard deviations were computed after first removing the overall linear trend from the area-average data, which constitutes a zero-order estimate of the influence of external forcing. The interannual variability is simply the standard deviation of the residuals. The decadal standard deviation is computed after low-pass filtering the regression residuals with a Lynch and Huang (1992) digital filter with half-power at a period of 119 months (Santer et al. 2006). The results of this variability comparison are discussed in Section 4.

3.0 Project Results

All gridded observational datasets show a consistent pattern of increasing annual-mean temperatures and decreasing annual-mean DTR over the period 1950–1999. Over most California, these observed trends are different from zero with a high degree of statistical significance (Figures 1 and 2). Similar results are found for the USHCN station data. Such consistency across multiple datasets increases confidence in the reality of these annual-mean T_{ave} and DTR changes. Annual-mean T_{ave} increased by 0.36°C to 0.92°C over 1950–1999, depending on the observational dataset considered. Using the distribution of the unforced trends, four of the nine observed trends (for USHCN, USHCN-U, UW2, and CRU2.0) are significantly different from the model-derived internal climate variability at the 5% confidence level or better (Figure 3). T_{ave} changes are largest in wintertime and exceed model-derived noise estimates in all nine observational datasets. This strongly suggests that external forcing(s) are required to explain the observed JFM trends in T_{ave}. Two datasets (USHCN and UW2) have significant T_{ave} trends in spring. No observational dataset yields significant T_{ave} trends in summer or fall.

This analysis of daily-mean temperatures masks interesting information in the diurnal cycle of temperature change. Substantial nighttime warming occurs in every month except in December (not shown), and trends in T_{min} are inconsistent with internally generated climate noise in every season except OND (Figure 3b). In contrast, monthly trends in observed daily maximum temperatures exceed estimated internal variability only in late winter/early spring (Figure 3c), with largest warming of T_{max} in January and March (1.5°C over 50 years), reduced warming in February (0.5°C over 50 years), and cooling in December. Observed trends in DTR exceed the estimated noise during summer only (Figure 3d), reflecting the much greater increase in minimum temperature than in maximum temperature in those months. Although the amplitude of nighttime warming is smaller in USHCN-U than in the USHCN dataset, the detection results are not sensitive to the inclusion of adjustments for urbanization effects (compare USHCN versus USHCN-U, CRU2.0, and CRU2.1 versus HadCRUT2v, and UW1 versus UW2).

Californian temperature changes over 1915–2000 are even more difficult to explain by internal climate noise alone (Figure 4). In all but one dataset, the estimated increase in annual-mean T_{ave} is significant at the 5% level. Positive detection is not limited to the winter season, but extends to the spring and summer seasons for most observational datasets. Similarly, trends in T_{min} and DTR are inconsistent with internally generated climate noise during all seasons. Again, those results are not sensitive to the inclusion or exclusion of urbanization adjustments. Enhanced detectability at longer timescales is an expected characteristic of a slowly evolving greenhouse-gas signal, as is evident in Santer et al. (1996, 2006). The research team considered next whether observed changes in California temperature indices are consistent with results from 20CEN simulations with combined anthropogenic and natural forcings (Table 2). In general, the models failed to reproduce the observed seasonality of changes in T_{ave}, T_{min}, T_{max}, and DTR (Figure 5,

lower panels). While most simulations capture the observed JAS trends in T_{ave}, T_{min}, and T_{max} (but not DTR), they tend to underestimate the observed JFM trends in T_{ave}, T_{min}, and T_{max}.

Such deficiencies in the simulation of regional trends are not surprising, and have a number of possible explanations. First, many of the 20CEN runs examined here do not incorporate changes in spatially and temporally heterogeneous forcings like land use, carbonaceous aerosols, indirect aerosol effects, and others (Santer et al. 2006). These forcings have probably contributed significantly to regional-scale climate change. Second, even models that include some representation of heterogeneous and highly uncertain forcings may lack the spatial resolution to reliably represent the climate response to the imposed forcings: the entire state of California is represented by a minimum of five and maximum of 35 grid-boxes in the AR4 models analyzed here. Third, comparison of multiple 20CEN realizations performed with the same model reveal that individual realizations can have very different 50-year trends. Reliable estimation of the true response to the imposed forcing changes may require larger ensemble sizes than were available in the IPCC AR4 database (Table 2). Finally, the model-versus-observed differences may reflect real model errors, both at large scales and at regional scales.

Karoly et al. (2003) performed a detection analysis similar to that performed for this study, focusing on land surface temperature changes over North America (between 30N° to 65°N). They found that the increase in annual-mean surface air temperature from 1950 to 1999 and from 1900 to 1999 (in HadCRUT2v) could not be explained by natural internal variability. This study's results for Californian temperature changes over the last 50 and 86 years are broadly consistent with Karoly et al.'s findings. However, while Karoly et al. reported an observed DTR decrease that was indistinguishable from control-run noise, over 1950-1999, distinctly different from unforced variability over the period 1900-1999, this study's researchers obtained significant annual-mean DTR decreases at both timescales in most observational datasets.

The conclusion of this study's researchers that external factors are perturbing the climate in California depends on the reliability of the model-based noise estimates. As discussed above, it is not possible to evaluate the model noise simulations on the multi-decadal timescales that are most relevant to the detection issues addressed here. However, observational data are of adequate length to test model simulations of interannual and decadal-timescale noise; nonetheless, confidence in the trend significance results presented here would be diminished if the models systematically underestimated noise on these shorter timescales. There is no evidence that this is the case (Figure 5, top panels). For T_{ave}, while Stott and Tett (1998) found that an earlier version of the Hadley Centre models used here (HADCM2) generally underestimated climate variability at spatial scales below 2000 kilometers, none of the AR4 models have interannual variability below the lower end of the range of observational estimates—and only two models (GISS-ER and MRI-CGCM2.3.2) systematically underestimate the decadal variability (i.e., each 20CEN realization lies below the observational range).

Confidence in this study's model-based estimates of longer-timescale climate noise is increased by the fact that most AR4 models do not underestimate decadal variability, but that does not rule out systematic errors in those estimates. For T_{min}, T_{max}, and DTR indices, fewer observational datasets and simulations are available. None of the models examined here

systematically underestimates the magnitude of decadal variability for either T_{min} or T_{max}. Interannual and decadal variability in DTR is however systematically underestimated by three models, suggesting that their covariability between T_{min} and T_{max} is too high in these models, while these indices are more decoupled in other models and in the observations.

In the following section, the research team attempted to understand the pronounced seasonality of observed temperature trends in California. Christy et al. (2006), using their own observational temperature dataset, reported rapid nighttime warming in the Central Valley over 1910 to 2003, but not in surrounding mountains. They attribute this warming to the effects of large-scale irrigation (an interpretation questioned by Bonfils et al. 2006), but do not identify the physical mechanism responsible for the change. Bereket et al. (2005) attribute nighttime warming in the Valley to increased population, urbanization, and road construction. None of these mechanisms, however, explains the pronounced seasonal variations in temperature trends.

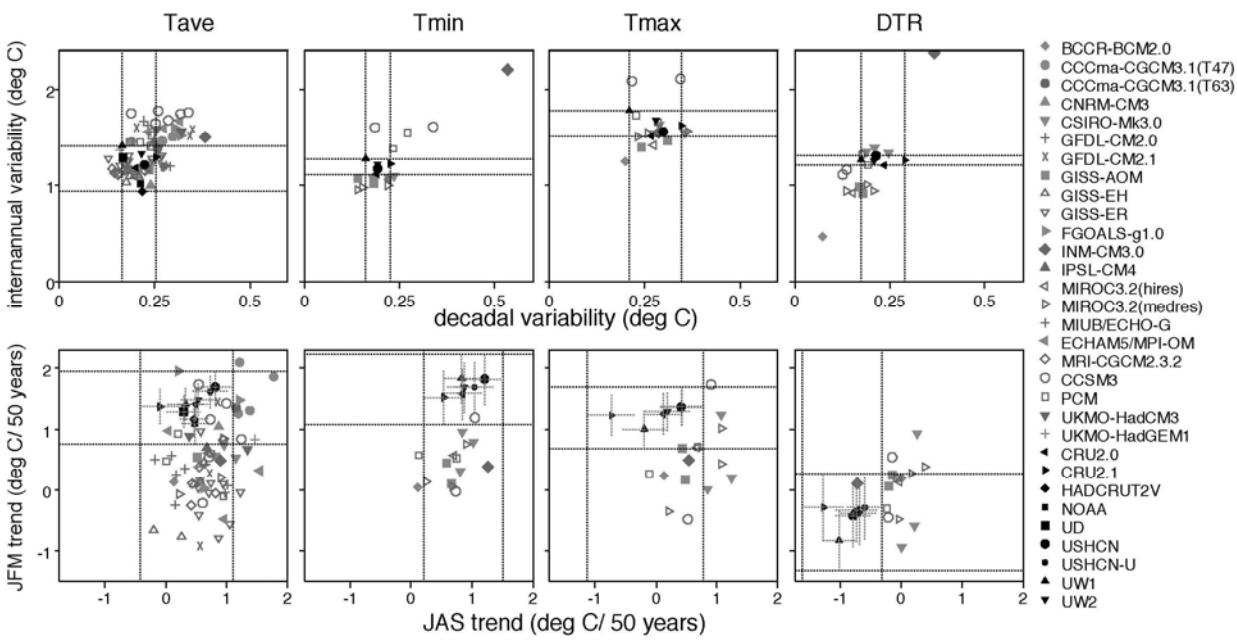

Figure 5. Comparison of statistical properties of four simulated and observed temperature indices in California. Simulations are forced 20CEN historical runs. Upper panels: standard deviations of filtered and unfiltered anomaly data for 1915–1999 (except for UW2, UW1, and UD, see text). Lower panels: 1950-1999 trends in summer (JAS) and winter (JFM). Observational datasets are in black and include a 1σ trend confidence interval adjusted for temporal autocorrelation effects. Individual realizations from 22 global climate models are in grey. Vertical and horizontal lines denote the minimum and maximum observed values, and facilitate comparison with model results.

In JFM, observed trends in T_{min}, T_{max}, and T_{ave} are unlikely to be explained by natural internal variability alone. A larger JFM warming trend is consistent with a stronger snow-albedo feedback in this season, but the spatial pattern of the observed warming does not clearly support this interpretation. A more plausible explanation is that a trend towards warmer

California winters is associated with a long-term change in large-scale atmospheric circulation over the North Pacific Ocean. This change is characterized by a southward shift of wind fields over the central North Pacific and a northward shift over the west coast of North America (Dettinger and Cayan 1994, their Figure 10d). Analysis of trends in NCEP-50 observed JAS 700 millibar (mb) height anomalies reveals that the circulation-change patterns identified by Dettinger and Cayan are very pronounced in January and March (months characterized by robust detection in trends of T_{min}, T_{max}, and T_{ave}), with a concurrent warming in coastal sea surface temperatures. This circulation change is less pronounced in February and is qualitatively different in December, consistent with observed temperature trends. The results of other studies suggest that greenhouse gas forcing is likely to be implicated in this seasonal circulation shift. First, Zwiers and Zhang (2003) found that the combined effects of greenhouse gas and sulfate aerosol forcing caused significant North American warming in wintertime only. Then, Shindell et al. (2001) linked increasing greenhouse gas concentrations with increased flow of warm air from the Pacific Ocean to western North America, consistent with Dettinger and Cayan's analysis. Finally, Gillett et al. (2005) detected an anthropogenic signal in DJF sea-level pressure trends over 1948–1998, with a coherent decrease over the North Pacific and an increase over the west coast of North America—features that coincide with those noted by Dettinger and Cayan. Gillett et al. also found that models underestimate this circulation change, which may explain why the rise in JFM T_{ave} in the AR4 simulations is weaker than in observations (Figure 5, lower panel).

In summer, the externally forced trend toward warmer nights is captured by at least one realization of every model (except for the single realization of the BCCR-BCM2.0 model). However, most models overestimate the daytime warming (which is weak in the observations, and not separated from the noise). Consequently, significant changes in DTR are not reproduced by the models. One interpretation of this result is that the 20CEN simulations neglect an important regional forcing. An obvious candidate is irrigation, which is widely employed in California, and is generally not represented in 20CEN simulations performed with global models. Although the effect of irrigation on nighttime temperature remains uncertain, irrigation causes daytime evaporative cooling (Lobell et al. 2006; Kueppers et al. 2006). At the global scale, the much smaller annual-mean increase in T_{min} than in T_{max} (Karl et al. 1993) is not captured by global models. This may be due to either an absence of a significant cloudiness trend that is present in observations (Braganza et al. 2004) or to the lack of prognostic photosynthesis in most global models (Bonfils et al. 2004). In the Central Valley, summertime cloudiness is probably too low to be implicated in explaining differential T_{min} and T_{max} trends. Irrigation is a more credible hypothesis, and it appears consistent with the observed cooling of summer days and warming of summer nights in the Central Valley, and daytime and nighttime warming elsewhere. In summary, the JAS trends in Figure 3 can be interpreted in several ways. One explanation is that trends in T_{max} over California are due to natural climate fluctuations alone. A more plausible interpretation (in view of the large temporal changes in irrigation in the Central Valley, the likely physical impacts of these changes, and their absence in 20CEN simulations) is that irrigation-induced cooling of T_{max} has obscured a warming signal arising from the combined effects of greenhouse gases and urbanization.

4.0 Conclusions and Recommendations

This research shows that external forcing(s) are perturbing the climate of California in certain seasons. The domain size used in this study is smaller than that used in most previous regional-scale detection studies. However, by employing multiple observational and model datasets, the research team gained confidence in both the robustness of the observed signals and their detection relative to model noise estimates. This study's researchers hypothesize that the rise in late winter/early spring temperatures (T_{ave}, T_{min}, T_{max}) is associated with long-term changes in large-scale atmospheric circulations that are human-induced. It is also likely that the lack of a significant T_{max} trend in summer reflects a partial offsetting of the positive radiative effects of greenhouse gases and urbanization by the negative radiative effects of irrigation. More work is needed to solidify these findings.

One implication of these findings is that anthropogenic forcings may be more readily detectable in regional-scale ocean surface temperature changes (Santer et al. 2006) than in regional-scale land-surface temperature changes with current simulations. The latter are more strongly influenced by local factors, such as land-use (e.g., irrigation, urbanization). High-resolution, multi-decadal transient simulations of the effects of individual forcings would help to characterize the regional signatures of these forcings. Such simulations have not been performed to date, in part due to computational limitations, and in part because reliable information on the forcings themselves (e.g., detailed descriptions of historical land-use patterns) is not always available. Finally, in the case of forcings like aerosols there are still significant uncertainties in both our understanding of their climatic effects and our ability to correctly model these effects. Nevertheless, this study represents a credible first step towards the identification and physical interpretation of the effects of external forcings on California's climate.

Recommended follow-on research involves improving understanding of historical climate trends in California and their significance. Further analysis of observations is recommended, to allow observed trends to be described more confidently. Improved knowledge of past forcing trends is needed, and might be obtainable through historical research. In particular, further research might improve knowledge of historical land cover and land use practices (including irrigation and urbanization). Improved estimates of the noise of internal climate variability on 50–100 year time scales are also needed. These cannot be obtained from instrumental observations, because these records are too short and are also contaminated by effects of human activities. It might be possible to improve or at least evaluate model-derived estimates of internal climate variability by developing and applying time series of climate-sensitive geological quantities. (For example, one multicentury record of estimate flow on the Sacramento River is already available; Meko et al. 2001.)

Modeling studies are needed to characterize the climatic signatures of specific forcing agents: greenhouse gases, aerosols, urbanization, irrigation, other land-use changes, solar variability, and volcanic eruptions. This would entail performing a series of simulations in which forcing factors (e.g., greenhouse gases, aerosols) are varied one at a time, to allow the climatic effects of each to be understood in isolation. Ideally, for each forcing factor, multiple simulations would

be performed with multiple models. This would allow uncertainties in climatic effects of each forcing to be estimated. Once the climatic signatures of each forcing agent are known, they should be searched for in the recent observational record. This combination of modeling and analysis of observations would go a long way towards understanding the causes of observed climate trends in California.

4.1. Benefits to California

The understanding that recent climate changes in California result at least partly from human activities constitutes a fundamental change in thinking on the subject of climate change and its societal impacts in California. The phenomenon of human-induced climate change must now be regarded as both real and immediate; therefore, the need for assessment of potentially harmful societal impacts is immediate. This project has stimulated increased interest in characterizing and understanding recent climate trends in California. This improved understanding of historical climate trends will lead to more accurate projections of future climate change and its societal impacts.

5.0 References

Braganza, K., D. J. Karoly, and J. M. Arblaster. 2004. "Diurnal temperature range as an index of global climate change during the twentieth century." *Geophys. Res. Lett.* 31, L13217, DOI: 10.1029/2004GL019998.

Bereket, L., D. Fabris, J. E. Gonzalez, S. Chiappari, S. Zarantonello, N. L. Miller, and R. Bornstein. 2005. "Urban heat islands in California's Central Valley." *Bull. Am. Meteorol. Soc.* 86: 1542–1543.

Bonfils, C., P. B. Duffy, and D. B. Lobell. 2006. "Comment on 'Methodology and Results of Calculating Central California Surface Temperature Trends: Evidence of a Human-Induced Climate Change?'" *J. Clim.*, in press.

Bonfils, C., I. Fung, S. Doney, and J. John. 2004. "On the detection of summertime terrestrial photosynthetic variability from its atmospheric signature." *Geophys. Res. Lett.* 31, L09207, DOI: 10.1029/2004GL019453.

Christy, J. R., W. B. Norris, K. Redmond, and K. P. Gallo. 2006. "Methodology and Results of Calculating Central California Surface Temperature Trends: Evidence of a Human-Induced Climate Change?" *J. Clim.* 19: 548–563.

Dettinger, M. D., and D. R. Cayan. 1994. "Large-scale atmospheric forcing of recent trends toward early snowmelt runoff in California" *J. Clim.* 8: 606–623.

Eischeid, J. K., C. B. Baker, T. R. Karl, and H. F. Diaz. 1995. "The quality control of long-term climatological data using objective data analysis." *J. Appl. Meteor.* 34: 2787–2795.

Gillett, N. P., R. J. Allan, and T. J. Ansell. 2005. "Detection of external influence on sea level pressure with a multi-model ensemble." *Geophys. Res. Lett.* 32, L19714, DOI: 10.1029/2005GL023640.

Hamlet, A. F., and D. P. Lettenmaier. 2005. "Production of temporally consistent gridded precipitation and temperature fields for the continental U.S." *J. Hydrometeorology* 6: 330–336.

Hegerl, G. C., K. Hasselmann, U. Cubasch, J. F. B. Mitchell, E. Roeckner, R. Voss, and J. Waszkewitz. 1997. "Multi-fingerprint detection and attribution analysis of greenhouse gas, greenhouse gas-plus-aerosol and solar forced climate change." *Clim. Dyn*. 13: 613–634.

Jones, P. D., and A. Moberg. 2003. "Hemispheric and large-scale surface air temperature variations: An extensive revision and an update to 2001." *J. Clim.* 16: 206–223.

Karl, T. R., P. D. Jones, R. W. Knight, G. Kukla, N. Plummer, V. Razuvayev, K. P. Gallo, J. Lindesay, R. J. Charlson, and T. C. Peterson. 1993. "A new perspective on recent global warming—Asymmetric trends of daily maximum and minimum temperatures." *Bull. Amer. Meteor. Soc.* 74: 1007–1023.

Karl, T. R., C. N. Williams, Jr., and F. T. Quinlan. 1990. U.S. Historical Climatology Network (HCN) Serial Temperature and Precipitation Data. ORNL/CDIAC-30, NDP-019/R1. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tennessee.

Karoly, D. J., and K. Braganza. 2005. "A new approach to detection of anthropogenic temperature changes in the Australian region." *Meteorol. Atmos. Phys*. 89: 57–67.

Karoly D. J., and Q. Wu. 2005. "Detection of Regional Surface Temperature Trends." *J. Clim.* 18: 4337–4343.

Karoly, D. J., K. Braganza, P. A. Stott, J. M. Arblaster, G. A. Meehl, A. J. Broccoli, and K. W. Dixon. 2003. "Detection of a human influence on North American climate." *Science* 302: 1200–1203.

Kueppers, L. M., M. A. Snyder, L. C. Sloan, D. Cayan, J. Jin, H. Kanamaru, M. Kanamitsu, N. L. Miller, M. Tyree, H. Du, and B. Weare. 2006. "Multi-model comparison of the climate response to land-use change in the western United States." *Glob. Planet. Change*, submitted.

Lobell, D., G. Bala, and P. B. Duffy. 2006. "Biogeophysical impacts of cropland management on climate." *Geophys. Res. Lett*. 33: L06708 10.1029/2005GL025492.

Lynch, P., and X. -Y. Huang. 1992. "Initialization of the Hirlam model using a digital-filter." *Mon. Weath. Rev.* 120: 1019–1034.

Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier, and B. Nijssen. 2002. "A Long-Term Hydrologically-Based Data Set of Land Surface Fluxes and States for the Conterminous United States." *J. Clim.* 15: 3237–3251.

Meko, D. M., M. D. Therrell, C. H. Baisan, and M. K. Huges. 2001. "Sacramento River flow reconstructed to A.D. 869 from tree rings." *J. Amer. Water Works Assn.* 37: 1029–1034.

Mitchell, J. F. B., D. J. Karoly, G. C. Hegerl, F. W. Zwiers, M. R. Allen, and J. Marengo. 2001. "Detection of climate change and attribution of causes." *Climate Change 2001: The Scientific Basis, Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change,* J. T. Houghton et al., eds., Cambridge University Press, Cambridge, pp. 695–738.

Mitchell, T. D., T. R. Carter, P. D. Jones, M. Hulme, and M. New. 2004. "A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: The observed record (1901–2000) and 16 scenarios (2001–2100)." Tyndall Working Paper 55, Tyndall Centre, UEA, Norwich, UK. www.tyndall.ac.uk/.

Mitchell, T. D., and P. D. Jones. 2005. "An improved method of constructing a database of monthly climate observations and associated high-resolution grids." *Int. J. Climatol.* 25: 693–712.

Santer, B. D., K. E. Taylor, T. M. L. Wigley, T. C. Johns, P. D. Jones, D. J. Karoly, J. F. B. Mitchell, A. H. Oort, J. E. Penner, V. Ramaswamy, M. D. Schwarzkopf, R. J. Stouffer, and S. Tett. 1996. "A search for human influences on the thermal structure of the atmosphere." *Nature* 382: 39–46.

Santer, B. D., T. M. L. Wigley, J. S. Boyle, D. J. Gaffen, J. J. Hnilo, D. Nychka, D. E. Parker, and K. E. Taylor. 1999. "Statistical significance of trends and trend differences in layer-average atmospheric temperature time series." *J. Geophys. Res.* 105: 7337–7356.

Santer, B. D., T. M. L. Wigley, P. J. Gleckler, C. Bonfils, M. F. Wehner, K. AchutaRao, T. P. Barnett, J. S. Boyle, W. Bruggemann, M. Fiorino, N. Gillett, J. E. Hansen, P. D. Jones, S. A. Klein, G. A. Meehl, S. C. B. Raper, R. W. Reynolds, K. E. Taylor, and W. M. Washington. 2006. "Causes of ocean surface temperature changes in Atlantic and Pacific hurricane formation regions." *Proc. Nat. Acad. Sci.*, 103:13905–13910.

Shindell, D. T., G. A. Schmidt, R. L. Miller, and D. Rind. 2001. "Northern Hemisphere winter climate response to greenhouse gas, ozone, solar, and volcanic forcing." *J. Geophys. Res.* 106: 7193–7210.

Spagnoli, B., S. Planton, M. Deque, O. Mestre, and J. -M. Moisselin. 2002. "Detecting climate change at a regional scale: The case of France." *Geophys. Res. Lett.* 29, DOI: 10.1029/2001GL014619.

Stott, P. A. 2003. "Attribution of regional-scale temperature changes to anthropogenic and natural causes." *Geophys. Res. Lett.* 30, DOI: 10.1029/2003GL017324.

Stott, P. A., and S. F. B. Tett. 1998. "Scale-Dependent Detection of Climate Change." *J. Clim.* 11: 3282–3294.

Stott, P. A., S. F. B. Tett, G. S. Jones, M. R. Allen, J. F. B. Mitchell, and G. J. Jenkins. 2000. "External control of 20th century temperature by natural and anthropogenic forcings." *Science* 290: 2133–2137.

Tett, S. F. B., P. A. Stott, M. R. Allen, W. J. Ingram, and J. F. B. Mitchell. 1999. Causes of twentieth-century temperature change near the Earth's surface. *Nature* 399: 569–572.

Willmott, C.J., and K. Matsuura. 1998. "Global Air Temperature and Precipitation: Regridded Monthly and Annual Climatologies (version 2.01)." Newark, Delaware: Center for Climatic Research, Dept. of Geography, Univ. of Delaware.

Zwiers, F. W., and X. Zhang. 2003. "Towards regional climate change detection." *J. Clim.* 16: 793–797.

6.0 Glossary

AMJ	April–June
BCCR-BCM2.0	Bjerknes Centre for Climate Research Bergen Climate Model, version 2
CDIAC	Carbon Dioxide Information and Analysis Center
CIRES	Cooperative Institute for Research in Environmental Sciences
DTR	diurnal temperature range
GCPS	Global Climate Perspectives System
IPCC	Intergovernmental Panel on Climate Change
JAS	July–September
JFM	January–March
mb	millibar
NCDC	National Climatic Data Center
NCEP	National Centers for Environmental Prediction
NOAA	National Oceanic and Atmospheric Administration
OND	October–December
PCMDI	Program for Climate Model Diagnosis and Intercomparison
PIER	Public Interest Energy Research Program
SE	standard error of the distribution
S/N	signal-to-noise
UD	University of Delaware
USHCN	United States Historical Climatology Network
UW1, UW2	University of Washington temperature datasets