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Impacts of climate change on building heating and cooling energy patterns in California

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ABSTRACT

Global climate change is making California's mild Mediterranean climate significantly warmer, and a substantial impact on building energy usage is anticipated. Studies on building cooling and energy demand have been inaccurate and insufficient regarding the impacts of climate change on the peak load pattern shifts of different kinds of buildings. This study utilized archived General Circulation Model (GCM) projections and statistically downscaled these data to the site scale for use in building cooling and heating simulations. Building energy usage was projected out to the years of 2040, 2070, and 2100. This study found that under the condition that the cooling technology stays at the same level in the future, electricity use for cooling will increase by 50% over the next 100 years in certain areas of California under the IPCC (Intergovernmental Panel on Climate Change)'s worst-case carbon emission scenario, A1F1. Under the IPCC's most likely carbon emission scenario (A2), cooling electricity usage will increase by about 25%. Certain types of buildings will be more sensitive to climate change than others. The aggregated energy consumption of all buildings including both heating and cooling will only increase slightly.

1. Introduction

The energy consumption of commercial buildings accounts for about one third of California's total electricity consumption, which costs about $9 billion per year. The energy consumption associated with space cooling accounts for a significant proportion of commercial building electricity use in California, and it is increasing at a significant rate, particularly in the hotter inland areas. Space cooling plays a major role in determining the magnitude and timing of peak electrical demand.

Global climate change warming trends are shifting California's mild Mediterranean climate to a significantly warmer climate, and a particularly large impact on building cooling electricity usage is anticipated. It is important to estimate and predict the impacts of climate change on statewide building energy usage because this information may help policy-makers, utilities, and other stakeholders to respond to concerns about the impact of climate change on energy production, distribution, and consumption in the building sector.

Title 24, the existing building code in California, is based on old weather data and does not reflect future climate change. As a result, to prevent building energy consumption per unit from increasing, the building code may need to become stricter in certain climate zones. Climate change could also change the balance between cooling and heating requirements in the code. For example, because the weather is getting warmer in winter, the insulation level could be made less strict. However, because cooling energy consumption plays a more important role in overall building energy usage, the requirements for shading devices, windows, and glazing materials could be made stronger. In this paper, "cooling energy use" refers to the electricity consumption of building cooling, while "heating energy use" refers to the gas consumption of building heating.

Many other existing national codes are based on weather data generated from observations from previous years. For example, Typical Meteorological Year (TMY) data were prepared by the US from hourly data files of the Weather Services from 1954 to 1972. Typical months were identified by their closeness to long-term cumulative distribution functions. The current widely used TMY2 data are derived from the 1961–1990 National Solar Radiation Data Base (NSRDB).

Engineers use the TMY2 data not only for building code compliance calculations but also for equipment sizing and selecting an appropriate HVAC (Heating, Ventilation, and Air Conditioning) system. Some low-energy-use cooling systems, such as natural

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ventilation and radiant cooling ceilings, may not work in the future when the temperature is higher.

Because of climate change, the energy demand in various regions of California could change at different rates. In general, the demand for gas for heating could decrease, and the demand for electricity could increase. The demand for cooling energy in the coastal area of California is relatively low now because of the mild weather in the summer. However, more heat waves and overall temperature increases could increase the loads more drastically in these areas than in the inland areas, and if so, the energy distribution requirements for the grid will change. This study will help the state decide how to respond to climate change in various regions of California.

The goal of this project is to better understand and predict the changes in building energy usage due to global climate change. The primary objective of this project is to develop a detailed analysis of building space heating and cooling requirements based on climate change projections. This analysis will provide guidance for needed changes in California building codes to address global climate change impacts at the building level.

The central questions addressed in this study are the following:

- How will climate change affect building cooling and heating energy consumption?
- How will climate change affect the energy consumption of different types of buildings in the different regions of California and in the state as a whole?

In previous studies, Huang estimated that energy use for space cooling, when averaged over the four IPCC global climate change scenarios, will increase in Los Angeles by as much as 42% in residential buildings and 31% in commercial buildings [14], whereas heating will go down by 62% and 24%, respectively. For more information about these scenarios, see reference [3,19,33,44].

In addition, changes in the patterns of extreme weather events, such as the intensity, persistence, and extent of heat waves, will have a significant impact on peak cooling electricity demand. General Circulation Model (GCM) analyses of extreme heat and energy demand by Miller [27] have shown that the number of summer days in Los Angeles in the hottest 10% will increase from the present 12 days to 28–96 days toward the end of this century. This increase in extreme days was shown to correspond with energy demand peaks that may result in capacity shortages.

Studies to date on building cooling and energy demand have been based on simplified analyses using constant increases in annual average temperature or changes in cooling degree-days. These results are insufficient in detail and, hence, may be inaccurate for predicting the climate change impacts of different building energy technologies. For example, the lack of information on changes in humidity, diurnal temperature swings, and solar radiation make it impossible to assess the impact of climate change on the use of low-energy cooling systems such as natural ventilation, evaporative cooling, and nighttime cooling.

Recent improvements in global and regional climate modeling can be combined with detailed building energy simulations to study the impacts of climate change in much greater detail and with more discernment. GCM project changes in temperature, diurnal temperature range, cloud cover fraction, and relative humidity at 0.5° resolution globally for a range of IPCC emission scenarios extending out to 2100. Furthermore, Miller's climate modeling group at Lawrence Berkeley National Laboratory (LBNL) downscales GCM output both dynamically via regional climate models (RCMs) and statistically via regression techniques and canonical correlations for domains (including California) with resolution as high as 3 km. These modeling results, in conjunction with Huang's adjusted hourly weather data, provide the input needed for energy simulations of prototypical commercial and residential buildings to analyze climate change impacts.

In this study, the following research tasks were conducted to address these important issues:

- Modified hourly weather predictions were created for the 16 California climate zones under four IPCC carbon scenarios.
- Prototypical models were developed for buildings in California.
- Both residential and commercial building stocks in the state were estimated.
- Building heating and cooling energy use were simulated using the models for both residential and commercial prototypical buildings; aggregate energy usage in the future was estimated.

2. Literature review

Scott [39] observed that many studies worldwide have analyzed the climate sensitivity of energy use in residential, commercial, and industrial buildings and have used estimated relationships to explain energy consumption and to assist energy suppliers with short-term planning (Quayle and Diaz [34]; Badri [2]; Lehman [18]; Lam [16]; Yan [46]; Morris [28]; Pardo [31]; Elkhafif [10]). The number of studies in the US analyzing the effects of climate change on energy demand, however, is much more limited. In the early and mid-1990s, there was a handful of studies that attempted an "all fuels" approach and focused on whether net energy demand would go up or down in residential and commercial buildings as a result of climate change [20](Scott [38]; Rosenthal [35]; Belzer [4]), whereas some focused on other climate-sensitive uses of energy such as transportation, agricultural crop drying and irrigation pumping (Darmstadter [6]; Parker [32]; Scott [39]; Tario [40]; Nelson [41]).

Previous authors have taken different approaches to estimating the impact of climate change on energy use. Most of these researchers have used simple uniform increases in annual average temperature as the "climate" scenario, and they have not focused on transient temperature increase scenarios from General Circulation Models (GCMs) such as those analyzed by the IPCC [36]. Previous research has used building energy simulation models to analyze the impact of climate warming on the demand for energy in individual commercial buildings [39] and on energy consumption in a variety of commercial and residential buildings in a variety of locations (Loveland [20]; Rosenthal [35]). Additionally, econometrics and statistical analysis techniques have been used (most notably, the Mendelsohn papers discussed below, but also Belzer [4], Amato [1], Ruth and Amato [37], and Franco and Sanstad [12]). Another recent study "mapped" the climate changes in four IPCC scenarios on top of existing weather files for 16 US locations and then used building energy simulations of prototypical commercial and residential buildings to analyze the impacts of those climate changes on building energy use [14].

Mendelsohn performed cross-sectional analyses to determine how energy use in the residential and commercial building stock relates to climate (Morrison [29] and Mendelsohn [25]; Mendelsohn [23]), and he then used the relationships to estimate the impact of climate change in the year 2060 on all residential and commercial buildings. Mendelsohn [24] used a two-step cross-sectional model of the commercial and residential building stock, which uses US data and accounts for the probability that a building is being cooled (which increases with the amount of warming), and its overall energy consumption as a function of climate (matched on a county level to the Energy Information Administration (EIA) buildings in the Residential Energy Consumption Survey (RECS) [11] and Commercial Building Energy Consumption Survey (CBECS)

[42,43]). This was further elaborated by Mansur [21] into a complete discrete continuous choice model of energy demand in residential and commercial buildings separately. In this analysis, when natural gas is available, the marginal impact of a 1 °C increase in January temperatures in their model reduces residential electricity consumption by 3% and natural gas consumption by 2% [38]. Working with end uses rather than fuels, a 16%–60% reduction in the demand for residential space heating energy is projected by about 2080 given no change in the housing stock and winter temperature increases ranging from 2 °C to 10 °C, or roughly a 6%–8% decrease in space heating per degree Celsius increase.

Thus far, studies on building cooling and energy demand have been based on simplified analyses using constant increases in annual average temperature or changes in cooling degree-days. These results may be inaccurate and insufficiently detailed to accurately quantify the climate change impacts of different building energy technologies. Huang [14] used results from the Hadley Centre Climate Model (HadCM3). Projected changes in monthly average temperature, daily temperature range, cloud cover, and relative humidity by month for 0.5° sectors of the earth's surface under four IPCC carbon emission scenarios (A1F1, A2M, B1, and B2M) for the year 2080 were used to adjust hourly TMY2 (Typical Meteorological Year) weather files for 16 US locations. These modified weather files were then used in the DOE-2 building energy simulation program [9] to simulate the energy demand of a set of 112 prototypical single-family houses covering 8 vintages in each of the 16 locations. For the entire US residential sector, the simulations showed an increase in energy use from 0% to 7%, representing up to a 10% increase in space conditioning energy use. At the regional level, the impacts varied from a 9%–12% decrease in energy use (12%–16% decrease in space conditioning) in Boston, to as much as a 29%–58% increase in Miami, with a space conditioning increase ranging from 46% to 92%. Across the different building vintages, the impact was most adverse in newer houses (2%–11% increases of total, 2%–18% of space conditioning for 90's vintage houses) and less adverse in older houses (-1% to 6% increases of total, -1% to 10% of space-conditioning).

Archived General Circulation Model (GCM) projections were used and statistically downscaled to the site scale to use as input for building cooling and heating simulations. The GCM projections were based on the high temperature sensitivity (HadCM3) and low temperature sensitivity Parallel Climate Model (PCM) climate models for the IPCC SRES high-emission (A1F1) and low-emission (B1) scenarios. The temporal downscaling procedure was based on a series of third- to fifth-order regression equations that have parameters using the observed weather station data as predictands. Temperature and other weather variables were generated through this technique, and the resulting climatological fit closely replicates historical climatology. Sub-daily temporal resolution was generated by shifting from the historical to the projected probability distribution function (PDF) for each variable and mapping this onto the historical hourly observations to obtain an imperfect high-resolution time series for application.

The statistically downscaled temperature is an additive term, whereas precipitation is a multiplicative factor. The minimum and maximum daily temperatures and the daily cumulative precipitation provided by the GCMs were used as predictands and fitted to third- to fifth-order regressions based on the daily (and finer) temperature and precipitation observations from the nearest measurement sites. The resulting changes in temperatures and precipitation are based on the same methods used in the TAR (Third Assessment Report) and AR4 reports. Variability is not captured through statistical approaches, and consequently, the upper limits of daily maximum temperature may be underestimations.

The researchers that applied the statistical methods stress caution in the interpretation at such high temporal resolution. The methods show good agreement climatically (i.e., as 10-year mean values), but hourly results are viewed with concern. Upper limits values are smoothed out; hence, we request that a second set of calculations be performed when the dynamically downscaled full-field values are made available through the California Energy Commission Public Interest Energy Research (CEC PIER) climate projections project.

Researchers around the world did research on the impact of climate change on energy use recently. A research team from China proposed a new method to develop typical weather years for different climates and the method has applications for regular updating of weather years and climate change study [5]. The effects of climate change on the Norwegian energy system toward 2050. The impact of climate change is evaluated with an energy system model, the Market alocation model (MARKAL) Norway model, to analyze the future cost optimal energy system [8]. Hekkenberg et al. critically analyze these implicit or explicit assumptions and their possible effect on the studies' outcomes. First we analyze the interaction between the socio-economic structure and the temperature dependence pattern (TDP) of energy demand [17].

3. Methodology

3.1. Typical year weather files for future time periods

Using the procedure described in the previous section, hourly weather files were created for 63 California locations that had sufficient historical data for reliable downscaling [47]. The weather file for each location consists of hourly records of dry-bulb temperature, dew point temperature, pressure, and total horizontal solar radiation from 1995 through the year 2100, of which the data up to and including 2006 are historical, and that from 2007 are downscaled from the GCM model. The report to the California Energy Commission also lists the 73 California locations included in the new TMY3 data set based on either 24-year (taken from 1976 to 2005) or 12-year (taken from 1991 to 2005) historical data; the 10 locations included in the TMY2 data set based on 1961–1990 historical data; and the 16 California Thermal Zone (CTZ) locations based on 1941–1970 historical data. These historical "typical year" weather files are useful for determining how much climate change has already occurred in California locations and to what degree the CTZ weather files used by the Commission to analyze building energy performance may have already been outdated. Fig. 1 shows the same locations on a state map of CTZ boundaries for easier identification.

Plots of the temperature and solar radiation data for four representative locations (Oakland, Sacramento, Burbank, and San Diego) are shown in Fig. 2, with the historical data shown in red and the downscaled data in blue. It is apparent that in all four locations, the downscaled data show a gradual rise in average dry-bulb temperature over the time period to 2100, but no evident change in solar radiation.

3.2. Hourly weather predictions

Future weather data were generated for three carbon emission scenarios using the IPCC SRES scenarios [30], namely A1F1, A2, and B1. These scenarios are described in the IPCC's Third Assessment Report (TAR) and Fourth Assessment Report (AR4). A1F1 is the worst carbon scenario, and it is characterized by rapid economic growth and an emphasis on fossil fuels. The A2 family of scenarios is characterized by slower and more fragmented technological changes and improvements in per capita income. B1 is the best

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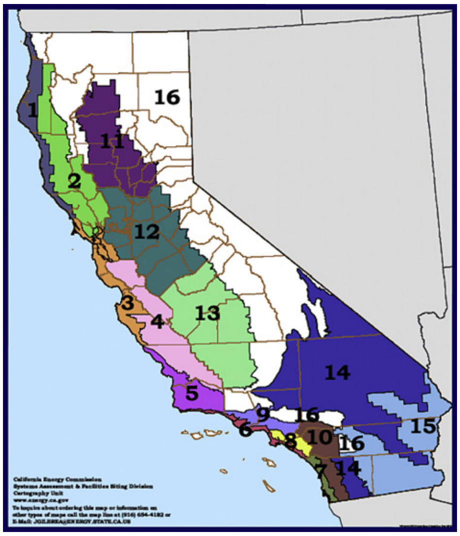

Fig. 1. California weather stations.

carbon scenario. It relies on reductions in material intensity and the introduction of clean and resource efficient technologies.

Developing statistically downscaled input requires the availability of observations of state variables for a time period sufficiently long that model calibration and verification can be performed for separate time periods that capture the variability of today's climate. Potential obstacles include ensuring that there are adequate data and the assumption that the projected climate is stationary. California has sufficient data available and does not pose a problem. The stationarity of the climate cannot be determined in advance. Testing to evaluate dynamic climate regimes was performed through an ongoing California Energy Commission (the Energy Commission)-supported project, the Regional Climate Model Intercomparison and Baseline Evaluation (REBI), wherein statistically and dynamically downscaled climate projections were tested [26].

Miller [26,27] has produced climate analyses for the Energy Commission as a contribution to the California Climate Assessment. Miller has simulated downscaled climate fields both through statistical and dynamic procedures using state-of-the-art techniques. This work is representative of the current knowledge base. Site scale models downscaled at hourly intervals provide an extension of current techniques. The statistical downscaling technique applied in this study is based on statistical approaches developed by Wilby and Dettinger [7] and a projected variance transform based on mapping distribution functions developed by Miller and his group. The variance transform is simply an added temperature or multiplied precipitation ratio based on the statistical downscaling that reflects the climate change sensitivity of each variable for each location.

The statistical downscaling approach is based on the application of third- to fifth-order linear equations with coefficients trained using historical observations. The predictors are the set of single-point observed temperature and precipitation observations for each location, and the predictands are the resulting temperature and precipitation outcomes with high temporal resolution. The observations only covered 8–15 years, resulting in minimally trained regression models. We fitted the 3rd- to 5th-order coefficients using odd years and verified them using even years as shown in the following equation.

$$\text{Predictor} = \text{A} \times \text{predictand} + \text{B} \times \text{predictand}^2 + \text{C} \times \text{predictand}^3$$

Statistical downscaling through regression is a common approach that has been well documented in the literature (Wigley et al. 1990; Wilby et al. 1998; Huth 1999; Wilby et al. 2002; Wilby and Dawson 2004). Statistical downscaling procedures have the advantage of being computationally efficient, but as they rely on historical relationships between large-scale climate fields and local variables, partial stationarity (non-changing conditions with regard to the extreme end-members of the historical period) over time must be assumed.

Grid-cell values of each predictor and for the reference period were rescaled by simple monthly regressions. This ensured that the overall probability distributions of the simulated daily values closely approximated the observed probability distributions at selected long-term weather stations located in urban centers. Observed daily maximum and minimum temperatures, cumulative precipitation, and humidity for each of the weather stations were used to develop a set of third-order regression equations to transform the large-scale temperature values from the GCM simulations into local-scale daily maximum temperatures while preserving the distribution of the observed mean and variance. The resulting model was then verified using observations from

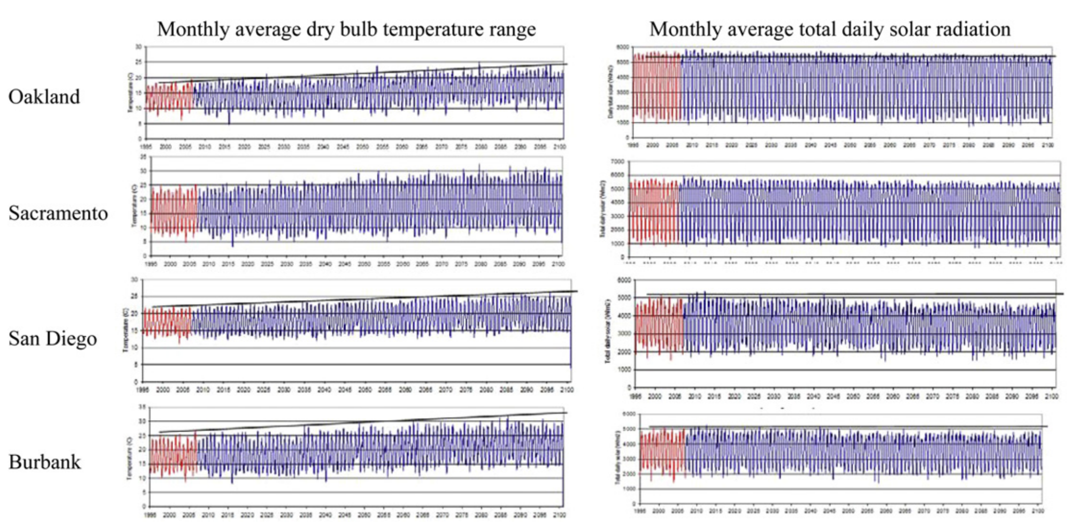

Fig. 2. Temperature and solar radiation data for four representative locations.

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a separate time period. The downscaled time-series results in a near-exact fit to observations. The ability of this method to successfully reproduce observed daily distributions is illustrated in Fig. 3, which provides a comparison between the observed and the statistically downscaled annual distributions of maximum daily temperature for Sacramento and Los Angeles. Although the modeled distributions tend to be somewhat smoother than the observations, in general the Geophysical Fluid Dynamics Laboratory (GFDL) and PCM-based simulations capture a distribution very similar to what was observed, whereas the HadCM3-based simulations tend to show a slightly broader distribution.

The same regression relations were then applied to future simulations such that the rescaled values share the weather statistics observed at the five stations. At the daily scale addressed by this method, the need to extrapolate beyond the range of the historically observed parts of the probability distributions was rare even in the future simulations (typically $<1\%$ of the future days, implying that stationarity is valid for this type of analysis) because climate change involves more frequent warm days more than it involves warmer-than-ever-observed days [7].

Future projections were then averaged for three time periods (2005–2034, 2035–2064 and 2070–2099) to produce near-term, mid-term, and long-term climatological projections of daily maximum, average, and minimum temperatures for California on which to base estimates of future shifts in the timing and magnitude of electricity demand.

Because of the stochastic variations in weather from year to year, building energy simulations have generally been done using "typical year" weather data that reflect average weather characteristics over a selected period of record. Recent data sets developed by the National Renewable Energy Laboratory (NREL) include 239 TMY2 weather files developed from historical weather data from 1961 through 1990 [22] and 1020 TMY3 weather files developed using either 24 years taken from the 1976–2005 historical data for 226 locations or 12 years taken from the 1991–2005 data for the remaining 800 or so locations [45].

The above-mentioned "typical year" weather files were created by splicing together twelve calendar months from the historical period of record judged to be the most representative using different criteria and weighting. In developing the original TMY weather files, NREL established a methodology for selecting a typical month that is straightforward and flexible. In brief, the selection is made by calculating the Cumulative Distribution Function (CDF) of each climate variable (temperature, solar radiation, and wind speed) for each month of historical data and comparing these CDFs to the long-term CDF using the Finkelstein–Schafer (FS) statistic as a measure of the closeness of fit [13]. The FS statistic is the sum of the differences between the individual and long-term CDFs. The FS statistic for each variable is multiplied by its weight and then added to produce a cumulative FS. The month with the smallest cumulative FS is selected as the typical month.

There are at least three methods of creating typical year weather files for future time periods based on downscaled data, each with its advantages and disadvantages:

Treat the downscaled data the same as historical data to select typical months and build "typical year" weather files for future periods from them. The problem with this method is that the downscaled data do not contain all the climatic variables needed in a simulation weather file, such as wind speed and direction. Although these variables are available in the original GCM data, they are not regarded with much credibility or relevance. Therefore, even if such weather files based completely on computer model results could be created, there would be an open question whether differences from the historical data are due to the modeled climate change or are artifacts of the synthetic weather data.

Obtain a long-term CDF from the downscaled data but use the historical data set to select the typical months. The advantage of this method is that the future year weather file produced would still be "real" data, and thus, it avoids the questions mentioned for the previous method. The two assumptions of this method are (a) the long-term CDFs predicted up through 2100 are within the range of variability in the historical data, and (b) climate change does not affect the underlying climate patterns. The first assumption can be tested by comparing the CDFs from the downscaled data to those from the historical data, but the second assumption is impossible to test. Although this method has its appeal, it was not used in this project because it was not assured to work in all cases and because it also requires much more effort than the third method described in the following paragraph.

Compute the average changes in climatic variables (i.e., temperature, humidity, solar) in the downscaled data over time and then map those changes onto existing "typical year" weather files such as the CTZ, TMY2, and TMY3 data sets. This method shares the same assumption as the previous one that climate change would not cause large changes in the underlying climate pattern. The

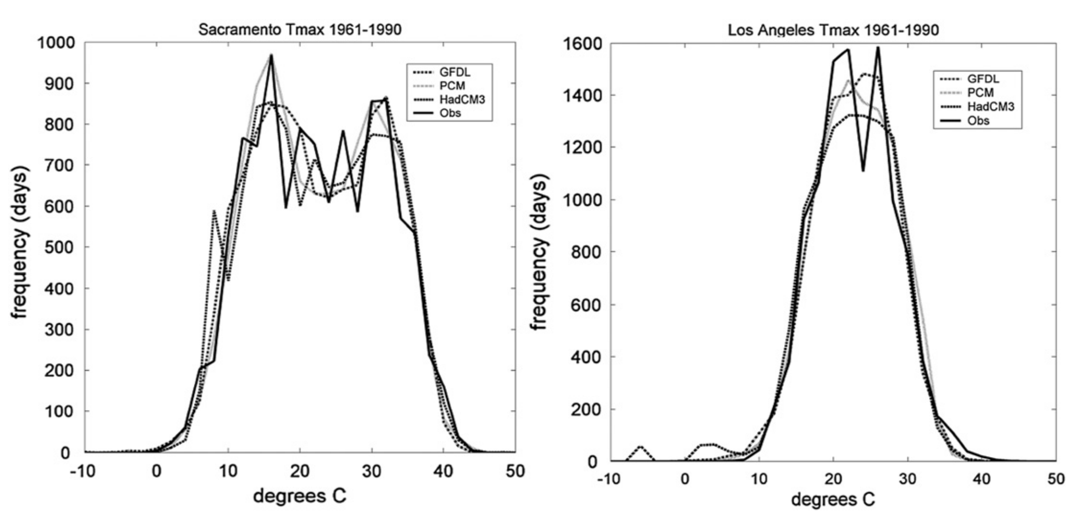

Fig. 3. Comparison of observed and statistically downscaled annual maximum-daily temperature distributions for Sacramento and Los Angeles.

advantage of this method is that it relies on the existing “typical year” weather files to establish the underlying climate patterns (such as the occurrence of heat storms, the correlations of wind and solar with other variables) and uses the downscaled data only to adjust the average monthly values for dry-bulb temperature, dew point temperature, solar radiation, pressure, and the diurnal swings of dry-bulb and dew point temperatures. In other words, this method uses the downscaled data not to represent future weather but only to represent the expected deviations in the weather from the historical record.

For both technical and practical reasons, we chose Method 3 to generate the future year “typical year” weather files. The same method was used by Huang for a previous study on the potential impact of climate change on building energy use in the US [14], and software procedures had already been developed. The downscaled data for the 63 California locations consist of large (56 MB) text files with 106 years of hourly records of dry-bulb and dew point temperature, pressure, and total solar radiation from 1995 through 2100. These were analyzed and condensed first into average daily mean and range for the dry-bulb and dew point temperatures and into average daily mean only for the total solar radiation for each month of every year. These data were then further condensed into monthly means and ranges for each decade starting with 1995, i.e., 1995–2004, 2005–2014. Because they were obtained from historical data, the means and ranges calculated for the first decade, i.e., 1994–2005, are taken as the baseline against which the means and ranges for the subsequent decades are compared. The changes in the monthly means and ranges are then “mapped” onto the TMY3 weather file for that location, resulting in a modified weather file for each decade extending to 2100.

Although the technique has been developed to produce future “typical year” weather files for any decade up through 2100, only four snapshot decades were analyzed: TP2 (2005–2014), TP4 (2035–2044), TP6 (2055–2064), and TP9 (2085–2094). Furthermore, due to the absence of building stock data for the smaller locations, computer simulations were conducted in only 16 of the 63 available locations corresponding roughly to the locations used to develop the original 16 CTZ weather files. Table 1 shows the heating and cooling degree days for downscaled locations under three climate change scenarios in four future time periods (the first 25 locations), and Fig. 4 shows the heating and cooling degree days for the 63 locations for the TMY3 base case and the four snapshot decades.

The degree-day statistics in Fig. 4 are shown with the stations grouped by color depending on their geographical location: dark blue for mountain areas, dark green for the northern coast, orange for the north Central Valley, yellow for the south Central Valley, light green for the southern coast, and red for desert areas. Fewer lines extend to the left because there were only 16 CTZ and 11 TMY2 locations compared to the 53 downscaled locations with either TMY3 or NCDC weather data.

3.3. Commercial building prototypes

Building energy usage was estimated through a bottom-up approach by simulating prototypical commercial buildings differentiated by vintage, building use, and climate. By combining these simulation results with the building stock information and the amount of building floor area represented by each prototype, a reasonable assessment of energy use characteristics of the entire building stock in California can be produced. Sixteen commercial and residential building prototypes were used – most of these prototypical building models were developed during previous LBNL research projects [15]. These building models were used as the basis for developing future prototypical building models by referring to the trends in building technologies and to the building code. The models were developed by two building simulation models, EnergyPlus and DOE-2.1E [9]. The simulation analysis was started using EnergyPlus, but then it was switched to DOE-2.1E when it became clear that using EnergyPlus would require several weeks of time for the simulations alone. Detailed descriptions of these building simulation models are also given elsewhere [47]. Table 2 is a classification of different commercial building prototypes.

4. Result

4.1. Impact on building energy intensity

In the calculation, we assumed building square footage to be constant. Therefore, the change in peak energy usage intensity is proportional to the change in the aggregated energy usage. Energy intensity is defined as total energy usage per square foot (KBtu/ft2).

We ran a simulation for each type of building using the generated hourly future weather data. The simulations were for the years 2005–14, 2035–44, 2055–64, and 2085–94.

Because the overall temperature will increase over the next 100 years, cooling energy consumption will increase and heating energy consumption will decrease. However, the increases and decreases associated with each type of building are different. For large office buildings, the shift will be less significant than for warehouses and small retail stores, which rarely need air conditioning. In general, cooling electricity usage will increase more for small buildings than for large buildings. The impact will be greater on sit-down restaurants and small retail stores than on large offices and supermarkets.

4.2. Future energy end-use

We plotted four types of energy intensity change for each type of building under different carbon scenarios. Fig. 5 shows a comparison of different types of predicted energy consumption in large office buildings and small office buildings (A2 Scenario).

The first type of energy intensity change is the change in heating energy over the next 100 years. The trend is very clear. Because of global warming, heating energy usage decreases under all carbon scenarios. For example, the heating energy consumption of a large office building will be reduced by almost 50% in all regions. In general, the percentage reduction in southern California will be more than that in northern California because buildings in southern California barely need heating now. Reductions in heating energy usage are generally larger for small buildings than for large buildings. Small buildings are more sensitive to weather changes because of their low volume to surface area ratio.

The second type of energy intensity change is the change in cooling energy over the next 100 years. Energy used for building cooling will increase significantly in all regions. For example, in southern California, under the A2 scenario, the cooling energy consumption of large office buildings will increase by 70% from their current level. This is assuming the internal load will be constant over the next 100 years. Cooling energy usage in northern California will also increase, but not as much as in southern California. Under the A2 scenario, in northern California, the cooling energy usage of large office buildings will remain nearly constant until 2044. After 2044, the cooling energy usage will start to increase significantly. It seems that until 2044, under the A2 scenario the weather in northern California will still not be hot enough to trigger a large cooling demand.

Table 1
Heating and cooling degree-days from downscaled locations under three climate change scenarios in four future time periods (the first 25 locations).

Location	CC scenario	Heating degree days 18C							Cooling degree days 18C							(Cooling degree hours)/24 26 C						
		CTZ	TM2	TM3	2005–2014	2035–2044	2055–2064	2085–2094	CTZ	TM2	TM3	2005–2014	2035–2044	2055–2064	2085–2094	CTZ	TM2	TM3	2005–2014	2035–2044	2055–2064	2085–2094
Arcata	A1FI	2700	2779	2650	2759	2577	2244	1827	0	1	1	0	1	3	10	0	0	0	0	0	0	0
(CTZ01)	A2	(2184)			2633	2792	2394	1994	(0)			0	0	1	6	(0)			0	0	0	0
	B1				2623	2426	2478	2346				1	2	1	2				0	0	0	0
Bakersfield	A1FI		1152	1111	1124	1027	858	682		1335	1295	1467	1825	2142	2586		411	405	506	704	889	1181
	A2				1102	1116	939	752				1461	1590	1738	2273				487	580	646	960
	B1				1105	1003	974	963				1442	1564	1558	1726				492	545	541	624
Bishop	A1FI			2139	2189	2009	1750	1434			806	943	1223	1504	1850			346	425	579	742	954
	A2				2159	2167	1875	1610				960	1050	1196	1595				425	498	561	791
	B1				2139	1957	1942	1906				920	1025	1041	1156				417	464	472	538
Burbank	A1FI	966	755	808	819	655	434	249	510	575	746	843	1103	1376	1793	116	166	167	217	315	400	580
/ Glendale	A2	(755)			752	825	571	313	(575)			839	868	1039	1503	(166)			198	219	277	453
(CTZ09)	B1				754	613	579	532				828	928	896	1071				206	240	225	279
Camarillo	A1FI			1055	1034	827	549	325			171	196	344	507	817			20	22	38	55	91
	A2				973	1054	744	415				213	230	309	592				21	24	34	62
	B1				991	804	801	706				212	239	229	325				26	26	27	38
China Lake	A1FI	1316		1489	1508	1371	1162	933	1694		1546	1713	2062	2395	2856	686		633	751	968	1177	1483
(CTZ14)	A2	(1655)			1474	1493	1274	1040	(1032)			1710	1830	1988	2547	(377)			734	835	908	1260
	B1				1481	1338	1318	1286				1686	1805	1807	1969				733	793	792	883
Daggett	A1FI		1013	1100	1098	978	836	647		1651	1717	1949	2374	2739	3309		605	668	820	1098	1333	1757
Barstow	A2				1093	1090	936	714				1946	2130	2283	2940				802	946	1026	1471
	B1				1061	974	923	922				1928	2054	2084	2214				811	874	892	968
El Centro	A1FI	606		476	491	437	367	225	2487		2436	2627	3018	3343	3849	1116		1046	1202	1474	1679	2082
(CTZ15)	A2	(486)			496	500	397	233	(2308)			2616	2753	2914	3530	(1010)			1168	1290	1372	1829
	B1				448	410	369	382				2594	2732	2766	2888				1174	1245	1267	1346
El Toro	A1FI	933		615	631	480	298	154	375		326	447	783	1153	1667	70		10	23	60	108	259
(CTZ08)	A2	(755)			563	635	403	204	(448)			460	478	690	1296	(83)			16	21	40	143
	B1				556	425	406	361				434	557	517	775				19	29	24	44
Fresno	A1FI	1504	1435	1274	1317	1203	1023	821	1017	1092	1238	1383	1704	2016	2422	346	380	419	515	697	888	1153
(CTZ13)	A2	(1243)			1300	1311	1097	943	(1127)			1409	1507	1677	2136	(386)			514	594	670	954
	B1				1292	1162	1138	1128				1370	1500	1500	1636				505	564	568	644
Fullerton	A1FI			736	774	590	299	89			607	712	980	1245	1740			89	120	189	251	421
	A2				676	778	447	161				720	717	900	1424				107	121	158	300
	B1				673	509	482	431				686	792	754	949				114	134	121	160
Inyokern	A1FI			1489	1508	1371	1162	933			1546	1713	2062	2395	2856			633	751	968	1177	1483
	A2				1474	1493	1274	1040				1710	1830	1988	2547				734	835	908	1260
	B1				1481	1338	1318	1286				1686	1805	1807	1969				733	793	792	883
Lancaster	A1FI			1574	1571	1418	1179	914			1165	1334	1692	2013	2468			386	489	693	888	1193
	A2				1538	1555	1322	1032				1328	1462	1610	2145				470	565	635	957
	B1				1540	1396	1372	1331				1306	1423	1419	1585				477	525	524	612
Lemoore	A1FI			1472	1424	1296	1094	870			1041	1195	1511	1792	2190			375	467	634	789	1204
	A2				1402	1413	1212	967				1187	1310	1434	1904				450	535	584	844
	B1				1396	1277	1258	1225				1168	1269	1270	1413				454	495	495	563
Lompoc	A1FI			1849	1891	1607	1084	616			5	8	22	85	240			4	4	7	15	30
	A2				1738	1953	1381	858				8	7	27	107				4	3	7	17
	B1				1743	1471	1575	1311				9	20	10	27				7	8	6	10
Long Beach	A1FI	827	744	647	666	535	344	177	392	443	458	535	752	976	1320	49	39	35	53	92	130	231
(CTZ06)	A2	(844)			603	671	446	238	(216)			533	553	692	1080	(7)			42	49	74	158
	B1				606	495	463	433				527	612	580	731				48	63	55	75
Los Angeles	A1FI		720	648	656	530	345	182		232	223	270	419	577	833		6	2	3	7	12	32
	A2				596	655	452	241				262	275	369	650				2	2	4	18
	B1				601	504	469	438				263	329	295	404				3	4	4	5

(continued on next page)

Table 1 (*continued*)

Location	CC scenario	Heating degree days 18C							Cooling degree days 18C							(Cooling degree hours)/24 26 C						
		CTZ	TM2	TM3	2005–2014	2035–2044	2055–2064	2085–2094	CTZ	TM2	TM3	2005–2014	2035–2044	2055–2064	2085–2094	CTZ	TM2	TM3	2005–2014	2035–2044	2055–2064	2085–2094
Merced	A1FI			1247	1289	1194	982	755			828	934	1166	1484	1801			293	351	467	630	794
	A2				1227	1305	1059	867				951	991	1177	1567				354	397	464	653
	B1				1228	1100	1118	1063				914	1025	1016	1157				347	389	390	455
Modesto	A1FI			1220	1269	1169	961	753			821	940	1220	1614	2030			248	303	422	608	824
	A2				1200	1280	1021	852				970	1021	1228	1727				307	353	416	639
	B1				1202	1080	1092	1042				919	1075	1042	1230				300	344	342	412
Mt. Shasta	A1FI	3032		2777	2905	2654	2326	1848	339		353	431	657	941	1181	61		132	165	265	395	518
(CTZ16)	A2	(3007)			2736	2891	2467	2113	(162)			527	534	677	1058	(68)			206	215	269	443
	B1				2763	2509	2548	2434				453	523	553	659				181	199	210	269
Needles	A1FI			540	539	476	396	257			2764	2964	3382	3778	4341			1274	1453	1783	2064	2524
	A2				554	534	428	293				2985	3156	3359	4014				1462	1609	1740	2252
	B1				492	457	420	426				2935	3087	3144	3240				1439	1532	1564	1635
Oakland	A1FI	1599		1535	1530	1317	1005	715	29		53	71	122	245	436	1		11	16	23	36	56
(CTZ03)	A2	(1437)			1457	1510	1177	854	(28)			70	74	118	283	(10)			15	16	22	38
	B1				1471	1274	1316	1178				66	85	82	112				14	17	18	21
Palm	A1FI			337	344	300	252	138			2551	2763	3222	3605	4205			1070	1242	1562	1806	2275
Springs	A2				355	357	267	144				2748	2905	3101	3856				1215	1351	1455	1984
	B1				319	278	238	254				2742	2894	2949	3079				1220	1297	1326	1421
Paso	A1FI			1537	1577	1400	1026	697			374	416	603	895	1251			212	240	324	456	614
Robles	A2				1445	1640	1198	866				439	430	625	990				242	250	328	486
	B1				1457	1250	1311	1150				445	533	478	652				253	285	266	339

The last column in the figure is total energy usage. Total energy usage is the sum of heating, cooling, domestic hot water, and fan energy consumption (which is not listed here in this paper). In general, the decrease in heating energy offsets the increase in cooling energy. However, for each region, because the changes in cooling and heating are different, the total energy consumption may either decrease or increase.

For example, under the A2 scenario, the total energy consumption of large office buildings will stay flat in northern California. However, the total energy consumption of large office buildings will increase slightly in southern California. Under the worst scenario (A1F1), total energy usage will increase slightly in northern California but drastically in southern California.

4.3. Building type variance

Although in general, cooling energy will increase and heating energy will decrease for all types of buildings, the magnitude of the changes varies among different building types. In general, small buildings are more sensitive to global warming than large buildings because the envelope heat gain (loss) of small buildings is a larger portion of their cooling (heating) load than that of large buildings.

For example, in northern California, the total energy consumption of large and medium office buildings will increase. However, the total energy usage of small office buildings in CZ16 will actually decrease. The heating consumption of small offices in this region will decrease sufficiently to offset the increase in cooling energy usage in the summer so that the total energy usage will decrease.

We observed similar results for other types of small buildings such as fast-food restaurants, primary schools, and small hotels. For small hotels, in northern California total energy usage will decrease in all 7 climate zones. For fast food restaurants, total energy usage in CZ16 will in fact decrease in the future. Total energy usage in the other 6 northern climate zones will remain flat.

4.4. Carbon emission scenarios

A1F1. In the high carbon emission scenario, cooling energy consumption increases drastically for nearly all building types. Large offices and supermarkets have the largest share of energy consumption among all types of commercial buildings. The cooling energy consumption of these two types of buildings increases by almost 50% in all major climate zones. The overall building energy usage increases slightly by about 15–30%.

B1. Under the low carbon emission scenario, cooling energy consumption does not increase as much as it does in A1F1. However, the increase is still significant. For large offices and supermarkets, overall building energy usage increases by about 15%.

A2. Scenario A2 is in between A1F1 and B1. Cooling energy consumption increases for major building types by approximately 20%. Total building energy consumption for both heating and cooling increases only slightly. However, the change is not uniform across all climate zones. For certain climate zones such as the cold zones, the increase in total energy use is higher than in the others.

4.5. Impact on aggregated building energy usage

The current building stock in California was used as a basis for the calculation [47]. Forecasting the growth of each type of building in each climate zone is difficult. The goal of this study is not to figure out the overall energy consumption changes for each

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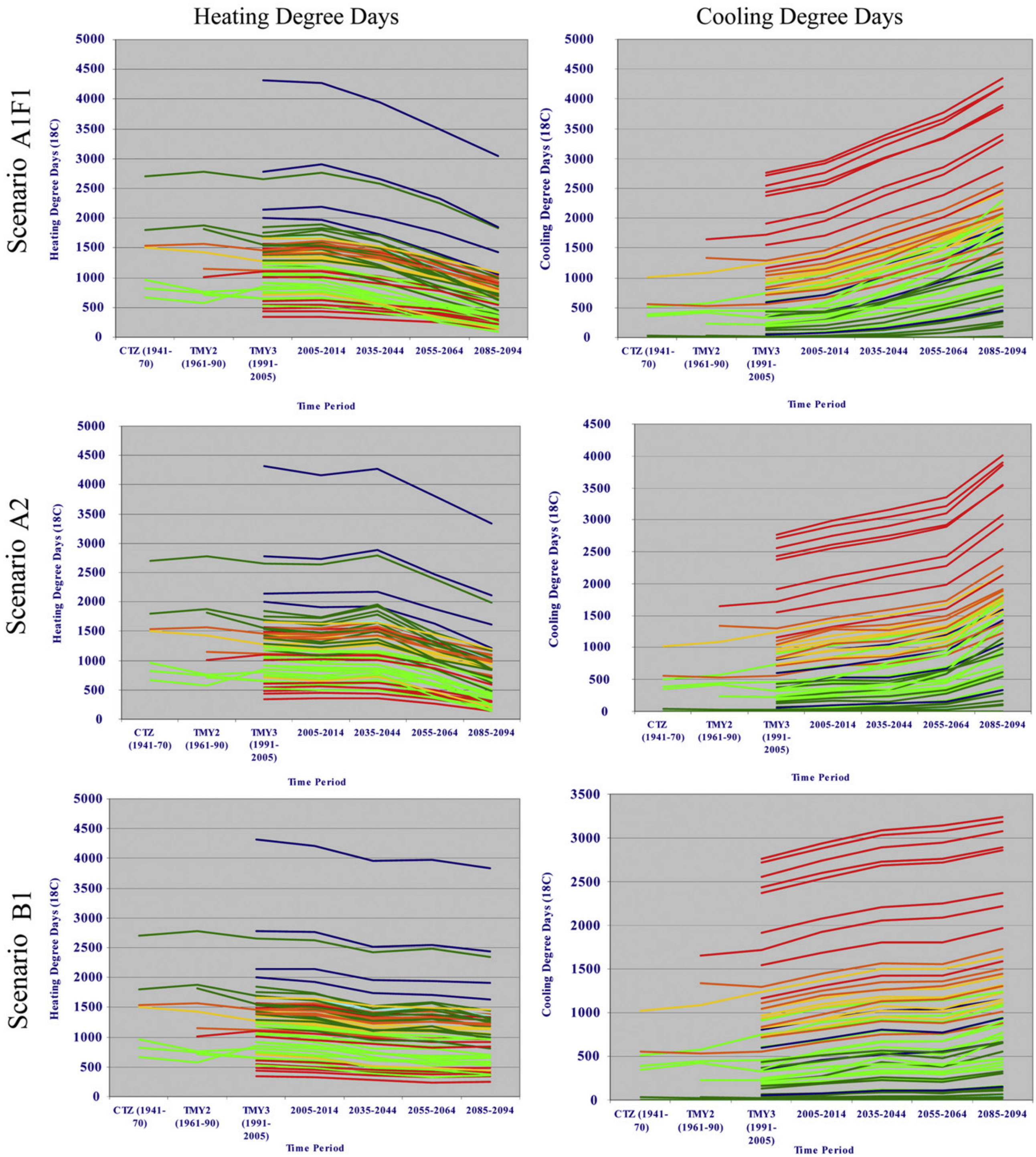

Fig. 4. Heating and cooling degree-days for 53 downscaled CTZ and 11 TM2 locations under different scenarios.

type of building but instead to determine the impact of climate change alone. Therefore, current building stock information was used as the baseline to separate out other changes such as demographic changes and new development in the Central Valley.

From the building stock data, one can determine which building type has the largest impact on total energy usage. For example, large office buildings, supermarkets, and retail stores comprise more than 60% of the total air conditioned building square footage

Table 2
Commercial building prototypes.

Hotels	Hospitals	Offices	Retail	Schools	Other
Large hotel	Hospital	Large office	Retail	Secondary school	Sit down restaurant
Small hotel	Outpatient health care	Medium office	Supermarket	Primary school	Fast-food restaurant
		Small office	Strip mall		Warehouse

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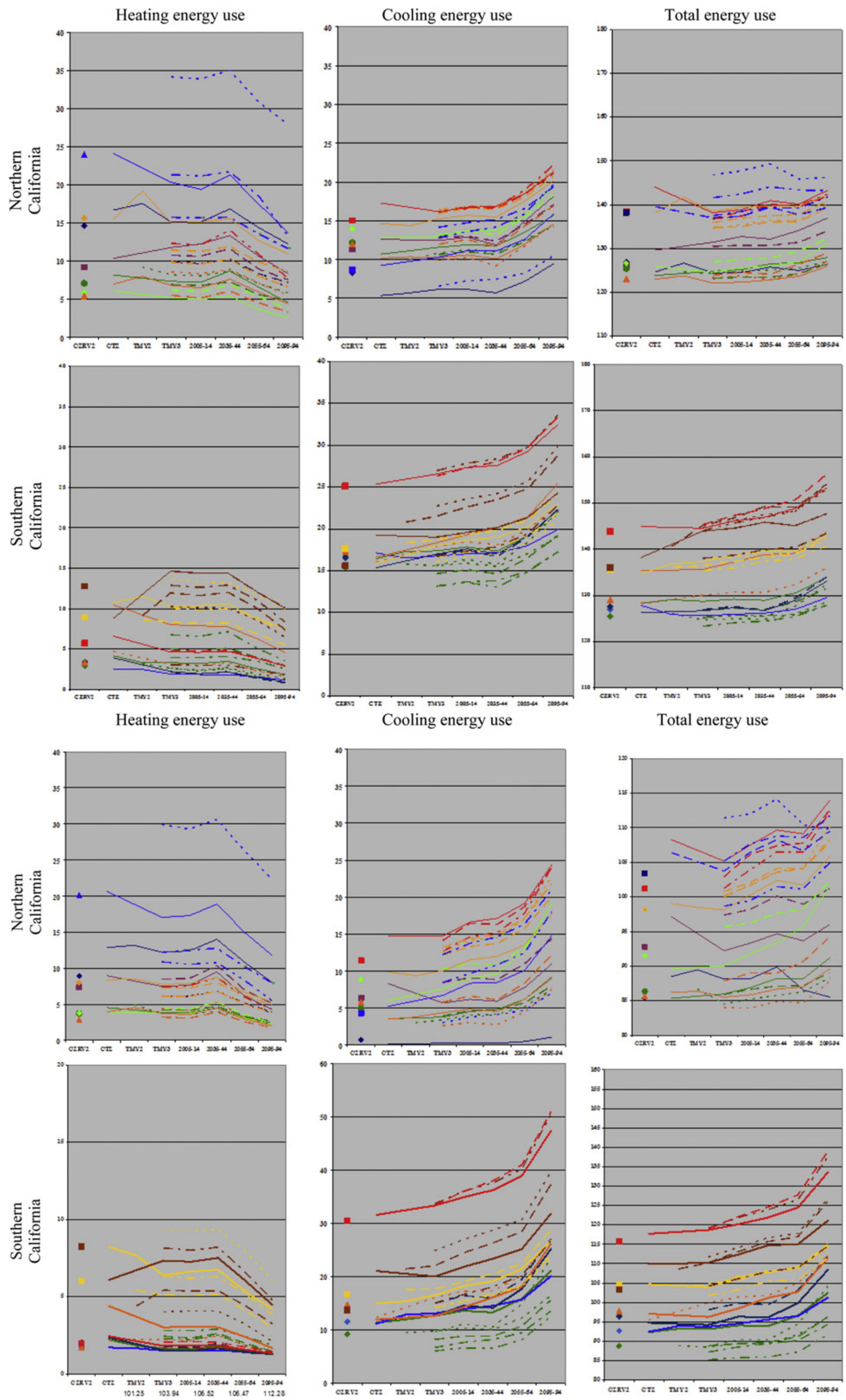

Fig. 5. Comparison of different types of predicted energy consumption in large office buildings and small office buildings (A2 scenario).

in California. The energy usage trends of these types of buildings will dominate the total aggregated building energy usage. More than 70% of these large buildings are located in climate zones 3, 6, 7, 8, and 12. The heating load of large buildings is not as sensitive to weather changes as that of small buildings. The total energy consumption will increase between 8% (zone 3) and 20% (zone 8) under the worst carbon scenario. Under the low carbon scenario, the increase in total energy consumption is between 0 (zone 3, 12) and 5% (zone 7, 8).

Table 3 shows the aggregated energy consumption changes in 2100 (A2 scenario). The total energy consumption of all buildings in the current year (2005) has not been calibrated to the actual

Table 3
Aggregated energy consumption changes in year 2100 (A2 scenarios).

A2, Year 2100, Total energy consumption for 16 California climate zones (MMBtu)								
Climate zones								
	1	2	3	4	5	6	7	8
Hospital	0	559,675	2,324,360	901,642	198,543	1,414,551	382,689	2,908,929
Outpatient health care	190,783	181,937	1,201,735	1,028,461	0	2,965,205	647,674	2,137,380
Large office	218,949	2,199,321	31,112,152	8,171,651	566,808	18,931,121	19,336,246	14,721,328
Medium office	351,273	349,070	1,498,193	1,407,547	0	752,059	514,422	1,017,468
Small office	300,138	328,328	1,336,338	1,359,073	0	692,835	487,963	1,197,133
Store	40,632	1,134,605	4,248,190	1,812,191	480,964	3,212,770	2,665,720	4,713,582
Sit down restaurant	0	0	3,265,696	1,515,569	221,761	4,159,757	1,239,714	2,895,601
Super market	0	8,715,829	23,925,528	7,590,198	2,642,898	23,024,292	17,241,294	39,189,314
Strip mall	2628	55,757	157,172	34,187	8061	108,867	110,015	302,008
Small hotel	0	0	1,881,509	1,250,568	0	3,791,664	4,277,527	1,399,138
Large hotel	385,231	447,944	6,107,097	1,820,870	622,442	4,362,783	2,658,222	2,944,296
Primary school	0	3,934,933	4,498,155	4,898,516	139,505	2,798,875	3,285,755	5,546,800
Secondary school	0	1,801,687	1,521,173	715,417	0	1,635,712	1,485,231	1,894,172
Warehouse	0	2,593,511	8,828,063	4,845,720	904,024	7,484,353	3,325,760	16,425,838
Other	0	1,321,533	13,584,974	10,907,368	1,465,911	11,413,146	9,659,701	2,637,402
Climate zones								
	9	10	11	12	13	14	15	16
Hospital	1,619,077	1,192,947	71,481	2,516,188	1,032,163	57,249	181,333	988,897
Outpatient health care	3,204,894	2,201,303	501,446	1,946,272	273,400	79,180	0	1,355,111
Large office	9,763,068	5,041,510	1,822,063	21,938,249	5,160,703	1,419,293	564,823	1,101,893
Medium office	765,975	1,208,152	2,020,673	1,228,160	2,831,799	227,444	120,897	888,503
Small office	790,429	1,214,143	2,073,122	1,217,374	3,094,786	245,651	141,122	865,707
Store	2,562,334	4,128,105	1,333,179	3,365,729	11,602,527	1,134,161	35,289	152,894
Sit down restaurant	589,159	1,487,585	0	2,293,796	1,716,611	471,108	0	671,755
Super market	14,624,134	16,209,536	4,952,766	39,407,711	19,124,501	8,336,916	3,357,176	0
Strip mall	266,089	343,987	61,738	221,259	213,205	21,747	2240	3590
Small hotel	536,767	5,160,774	0	1,692,363	2,012,375	248,157	1,289,432	134,528
Large hotel	1,447,849	891,288	0	2,459,549	1,183,494	0	546,828	780,939
Primary school	5,344,325	4,469,190	2,445,850	8,166,719	2,172,340	892,206	0	1,153,897
Secondary school	2,687,882	1,889,170	534,529	2,509,160	2,798,374	338,548	719,409	0
Warehouse	8,886,817	14,107,055	1,375,018	11,449,881	2,755,606	1,046,845	1,309,787	285,169
Others	4,086,311	18,568,587	16,825,419	6,332,602	4,946,038	4,933,990	1,238,661	1,186,783
Total	**815,608,124**							

Table 4
Total building energy consumption in the year 2100 relative to 2005.

Current	A1F1	A2	B1
100	108	105	102

building consumption in California. The relative term is more important here because we want to understand the trends in energy growth [47].

In total, California building energy consumption increases about 8% under the worst carbon scenario and about 2% under the low carbon scenario if the building stock stays the same (as shown in Table 4).

5. Conclusions

In all three SRES scenarios used in this study (A1F1, A2 and B1), consistent and large increases in temperature and extreme heat drive significant impacts on temperature-sensitive sectors in California. The most severe impacts occur under the A1F1 scenario. With the rising temperature, low-energy intensity cooling systems may not work equally well in the future. For example, natural ventilation may not be as applicable to buildings in the bay area as it is now. Increased cooling demand may require buildings with traditional HVAC systems to retrofit and expand their cooling capacity. Another example is direct and indirect evaporative cooling systems in the dry inland area. Because of rising dry bulb and wet bulb temperatures, the efficiency of evaporative systems may start to decrease and the systems may no longer be economically feasible. The prediction of energy use change lies on the reliability of the temperature model prediction. Under each carbon scenarios, this study predicts the pattern change reasonably accurate, but not the exact energy consumption change.

The weather changes will not change the energy usage of different types of buildings in the same way. For example, the total energy usage of small buildings in northern California will actually decrease as the weather becomes warmer. The variance among different types of buildings needs to be considered carefully when developing future building codes. Code requirements for small buildings in northern regions should focus more on how to reduce cooling loads than heating loads. In the mean time, fresh air load is perhaps the number one contributor to the increased cooling loads in southern California for large commercial buildings. Building codes in these areas may need more rigorous requirements to address fresh air load than codes in other areas.

These findings support the conclusion that climate change will have a larger effect on areas such as the San Francisco Bay Area than inland regions where space cooling (air conditioning) dominates power usage. As such, it represents a solid starting point for assessing the detailed effects of location.

This study represents one approach to understanding how building energy consumption will change in the future. However, more fundamental issues, such as how engineering practices should be changed in response to the weather changes, have not been addressed. For example, this study shows that total energy consumption in southern California will increase by 30% over the next one hundred years under the worst scenario. To keep energy usage at the same level, engineers in the future will need to develop

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better building envelopes and HVAC systems with higher efficiency. A series of these more efficient buildings could be simulated to determine at which level the added efficiency will be enough to compensate for the energy increases from climate change.

This study generated future data files not only for 16 climate zones but also for virtually every weather station in California. The difference between these weather stations can sometimes be significant. For example, as presented in the results section above, in climate zone 16, the energy consumption of buildings at different weather stations may change differently. Future climatic data will be helpful for re-classifying the climate zones in California. Hourly data for each weather location will be useful for decision makers making long-term city plans and assessing various adaptation approaches.

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List of acronyms

AR4	IPCC's Fourth Assessment Report
CBECS	Commercial Building Energy Consumption Survey
CEUS	California Commercial End-Use Survey
CDF	Cumulative Distribution Function
CTZ	California Thermal Zone
EIA	Energy Information Administration
FS	Finkelstein-Schafer Statistic
GCM	General Circulation Model
HadCM3	Hadley Centre Climate Model
HVAC	Heating, Ventilation, and Air Conditioning
IPCC	Intergovernmental Panel on Climate Change
NSRDB	National Solar Radiation Data Base
NREL	National Renewable Energy Laboratory
PDF	Probability Distribution Function
RCMs	Regional Climate Models
RECS	Residential Energy Consumption Survey
TMY	Typical Meteorological Year
TAR	IPCC's Third Assessment Report
REBI	Regional Climate Model Intercomparison and Baseline Evaluation

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