Impacts of Climate Change and Socioeconomic Development on Electric Load in California*

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Abstract. In order to develop policies to mitigate the impact of climate change on energy consumption, it is imperative to understand and quantify the impact of climate change and socioeconomic development on residential electric load. This paper develops a feed-forward neural network to model the complex relationship among socioeconomic factors, weather, distributed renewable generation, and electric load at the census block group level. The influence of different explanatory variables on electric load is quantified through the layer-wise relevance propagation method. A case study with 4,000 census block groups in southern California is conducted. The results show that temperature, housing units, and solar PV systems have the highest influence on net electric load. The scenario analysis reveals that net electric load of disadvantaged communities are much more sensitive to rising temperature than the non-disadvantaged ones. Hence, they are much more vulnerable to climate change.

Keywords: Climate change · Disadvantaged community · Electric load · Layer-wise relevance propagation · Socioeconomic factors.

1 Introduction

One of the most compelling evidences for global climate change is the rapid rise in global temperature. Around the world, people are already experiencing the effects of climate change. For example, the rise in temperature will lead to increased cooling need and electricity consumption from air conditioning systems. It is also expected that the disadvantaged communities will be disproportionately affected by climate change. In this paper, the impacts of climate change and socioeconomic development on residential net electric load in southern California will be explored. In particular, we intend to answer questions such as whether electricity affordability will get worse for disadvantaged communities due to climate change and how income growth affects electricity consumption for disadvantaged and non-disadvantaged communities. In addition, we are interested in modeling the relationships among socioeconomic factors, meteorological variables, renewable energy interconnection, and electric load.

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Understanding and quantifying the impacts of climate change and socioeconomic development on residential electric load for both disadvantaged and non-disadvantaged communities is critical to policy makers. For example in California, the funds received from the cap-and-trade program can be used for projects that further reduce emissions of greenhouse gas as well as mitigate the impact of climate change on poor communities. Without a clear understanding of how the electricity consumption and affordability of various communities are impacted by the climate change, it will be difficult to determine how much investment should be made for disadvantaged and non-disadvantaged communities.

Previous studies have shown that weather conditions significantly affect residential electric load in China [16], the United States [2], and Europe [4]. The relationship between socioeconomic factors and residential electric load has also been studied extensively in the past decades. For instance, [11] shows there is an almost linear relation between the electricity consumption and the household income based on the analysis of 1110 households in Greece. Based on the analysis of 5980 sample households, [18] discovers that families with higher educational attainment tend to consume more electricity in China. [7] finds that occupants' age is significantly correlated with electricity consumption. In particular, it shows that households with individuals over 55 or between 19 and 35 years old tend to use less electricity in the United States. A comprehensive review of impacts of socioeconomic factors on residential electricity consumption can be found in [6]. However, little work has been done to compare the impacts of climate change and socioeconomic development on electricity consumption of communities with different backgrounds. In addition, there has been no rigorous analysis to quantify the influence proportion of various input factors on residential electric load. Lastly, most of the previous works focus on studying sample data of individual households instead of electricity consumption at the community level such as census block groups (CBGs).

This work fills the knowledge gap by developing a feed-forward neural network (FNN) to capture the relationship among weather, socioeconomic variables, and net electric loads at the CBG level. The layer-wise relevance propagation (LRP) method is used to quantify the impacts of input factors on residential electric load. Finally, a comprehensive case study is conducted in southern California to analyze the impacts of climate change and socioeconomic development on electric loads of both poor and affluent communities.

The rest of this paper is organized as follows. Section 2 presents the overall framework of the data-driven approach to explore the relationships among climate change, socioeconomic factors, and electric load. Section 3 introduces the technical methods. Section 4 presents the case study with 4,000 CBGs in southern California. The conclusions are given in Section 5.

2 Problem Description

In order to quantify the impacts of climate change and socioeconomic development on net electric load, we need to first establish a model to estimate average electric loads of local communities based on census, weather, and distributed renewable generation data. These three sources of data are crucial to estimating residential electric load due to the following reasons. First, socioeconomic and dwelling information have been shown to be highly correlated with the residential electricity consumption [10]. Second, the operation schedule and electric load from residential heating, ventilation, and air conditioning (HVAC) systems are highly dependent on weather related variables such as temperature. According to residential energy consumption surveys, space cooling alone accounts for 15% of the total electricity consumed by American homes, which ranks first among all the end-uses. Third, residential smart meters typically measure the net electric load [17], i.e., the electric load minus distributed renewable generation in the behind the meter systems. With increasing penetration of residential solar photovoltaic (PV) systems [15], the net electric loads become highly dependent on the amount of distributed renewable generations.

Multiple linear regression (MLR) is the most widely used approach to model the relationship between electric load and socioeconomic factors [6]. Although MLR models often have lower load prediction accuracy than the neural network models, they are still adopted because it is very easy to interpret the MLR coefficients and results. However, as the number of explanatory variables increases, the relationship between the input variables and the output becomes highly nonlinear. Hence, it will be very difficult to develop a MLR model to capture such complex relationships. Furthermore, a few methods such as gradient-based visualization [13] and layer-wise relevance propagation [3] have been developed to provide better interpretation to the neural network models. Therefore, a FNN model is adopted in this work to model the complex relationship among weather, census variables, and electric load data collected from millions of residential customers in southern California.

3 Technical Method

In this section, a FNN is adopted to model the relationship between input data and output data. The structure and training methods of FNN are introduced in subsection 3.1. Subsection 3.2 describes the LRP method [3], which measures the relative importance of the input features.

3.1 Feed-forward Neural Network

A FNN consists of three components: input layer, hidden layers, and output layer. Each layer consists of a number of neurons. In a fully connected network, each neuron in one layer is connected to every single neuron in the previous layer by synapses. The relationship between two adjacent layers is modeled by

$$\boldsymbol{x}^{k+1} = f(W^{k \to k+1}\boldsymbol{x}^k + \boldsymbol{b}^{k+1}) \tag{1}$$

where $\boldsymbol{x}^k$ and $\boldsymbol{x}^{k+1}$ denote the outputs of kth layer and $(k+1)$th layer. $W^{k \to k+1}$ represents the weight matrix between kth layer and $(k+1)$th layer. $\boldsymbol{b}^{k+1}$ is the bias vector of $(k+1)$th layer. $f(\cdot)$ is the activation function.

The dimension of input layer is determined by the number of input features. The model output is the average electric load of a geographic region, thereby the output layer's dimension is 1 . Typically, activation functions used for the hidden layers include sigmoid function, hyerbolic tangent function (tanh), and rectified linear units (ReLU). However, the saturation problem of the sigmoid and tanh functions could lead to unreliable training outcomes in certain cases. Hence, in this work, we adopt ReLU as the activation function of hidden layers. Since we are solving a regression problem, the activation function of the output layer is the identity function.

Network Training: The goal of neural network training is to minimize an error function which is typically chosen as the negative logarithm of the likelihood function. If the output variable subjects to Gaussian distribution with an input variable dependent mean, then the error function is equivalent to the sum-of-squares error function. The gradient descent method is often used to train the network parameters. In this study, we adopt a gradient descent based algorithm called Adam [8]. There are two main advantages of Adam. First, it can automatically adapt the learning rate as the training proceeds. Secondly, it is robust to the variation of hyperparameters. The early stopping procedure will be applied as regularization to avoid over-fitting the neural network.

3.2 Layer-wise Relevance Propagation

The basic idea of LRP is to decompose the output value into a set of scores measuring input features' contributions to the output [3]. Let $g(\cdot)$ be a trained FNN and $\boldsymbol{x}$ be the input features. Our goal is to split $g(\boldsymbol{x})$ into separate relevance scores of the input features.

Within the context of LRP, all neurons in each layer of FNN are assigned with relevance scores. The basic rule is that summation of relevance scores of neurons in each layer is the same, thereby the output value can be propagated back to the input layer. In other words, the following equation has to be satisfied.

$$\sum_{p=1}^{L_1} R_p^1 = \sum_{n=1}^{L_2} R_n^2 = \cdots \sum_{i=1}^{L_k} R_i^k = \cdots = g(\boldsymbol{x}) \tag{2}$$

where R_i^k is the relevance score of ith neuron in kth layer. L_k is the number of neurons in kth layer. Let $R_{i \leftarrow j}^{k \leftarrow k+1}$ be the relevance score passed from jth neuron in $(k+1)$th layer to ith neuron in kth layer. Then, a sufficient but not necessary condition for Eq. (2) to be satisfied is

$$R_i^k = \sum_j R_{i \leftarrow j}^{k \leftarrow k+1} \tag{3}$$

$$\sum_i R_{i \leftarrow j}^{k \leftarrow k+1} = R_j^{k+1} \tag{4}$$

Eq. (3) and (4) describe two principles of relevance propagation. First, the relevance score of an arbitrary neuron (except those in output layer) is equal to the sum of relevance scores it received from neurons in the latter layer. Second, the relevance score of an arbitrary neuron (except those in input layer) is equal to the sum of relevance scores of neurons it passed to in the previous layer.

$R_{i\leftarrow j}^{k\leftarrow k+1}$ should satisfy the relevance propagation principles and also be interpretable. To achieve this, we first rewrite Eq. (1) into neuron-wise equations.

$$z_{i\to j}^{k\to k+1} = x_i^k \omega_{i,j}^{k\to k+1} \tag{5}$$

$$z_j^{k+1} = \sum_i z_{i\to j}^{k\to k+1} + b_j^{k+1} \tag{6}$$

$$x_i^{k+1} = f(z_j^{k+1}) \tag{7}$$

where x_i^k is the activated value of ith neuron in kth layer. $\omega_{i,j}^{k\to k+1}$ is the $\{i,j\}$ element of weight matrix $W^{k\to k+1}$. z_j^{k+1} is the pre-activated value of jth neuron in $(k+1)$th layer. b_j^{k+1} is the jth element of $\boldsymbol{b}^{k+1}$. Then, $R_{i\leftarrow j}^{k\leftarrow k+1}$ is defined by

$$R_{i\leftarrow j}^{k\leftarrow k+1} = \begin{cases} \dfrac{z_{i\to j}^{k\to k+1}}{z_j^{k+1}+\epsilon} \cdot R_j^{k+1}, & z_j^{k+1} \geq 0 \\ \dfrac{z_{i\to j}^{k\to k+1}}{z_j^{k+1}-\epsilon} \cdot R_j^{k+1}, & z_j^{k+1} < 0 \end{cases} \tag{8}$$

where ϵ is a small value used to avoid zero denominator. Satisfaction of relevance propagation principles is evident for this formulation. The interpretation is stated as follows. The relevance score passed between two neurons in adjacent layers is in proportional to the previous-layer neuron's contribution on latter-layer neuron's pre-activated value.

By iterating Eq. (8) and (3), we can finally transform the output value into relevance scores of input features. Note that these scores can be either positive or negative. Therefore, we introduce the influence proportion $I_d = |R_d^1| / \sum_{p=1}^{L_1} |R_p^1|$ to measure the impacts of different input features on output, where I_d is the influence proportion of dth input feature.

4 Case Study of Southern California

In this section, a case study is conducted for southern California to investigate the impacts of climate change and social economic factors on residential electric load. The residential electric load and solar PV interconnection data are provided by Southern California Edison (SCE) and aggregated at the CBG level. There are approximately 4,000 CBGs in SCE's service territory. The census and weather related data are gathered through the National Historical Geographic Information System (NHGIS) and the Weather Underground's website. The details of the data used in the case study will be discussed in Subsection 4.1. The forecasting performance of the data-driven electric load model and the importance of input features are reported in Subsection 4.2. Finally, scenario analysis is carried out in Subsection 4.3 to investigate the impacts of climate change and socioeconomic factors on electric load.

Table 1: Final input features of FNN

Data Category	Subcategory	Input Features & Ranges
Census	**Age**	*Childhood age (5 yrs old and below)* *School age (6 to 17 yrs old)* *Working age (18 to 61 yrs old)* *Retired age (62 yrs old and above)*
	Income	*Low-income (\$0-\$34,999)* *Middle-income (\$35,000-\$149,999)* *High-income (\$150,000+)*
	Education	*No college experience*, *College experience*, *Bachelor*, *Graduate*
	Employment	*Employed*, *Unemployed*, *Military service*, *Not in labor force*
	Housing units	*Number of housing units*, *Occupancy rate*
	Children	*Proportion of households with children under 18*
	Rooms	*Average number of rooms*
	Population	*Number of residents in CBG*
Weather	**Temperature**	*Average hourly temperature* *Average daily peak temperature* *Proportion of cooling degree days*
Solar PV	**Solar PV**	*Solar PV capacity*, *Solar installation rate*

4.1 Data Description

Three categories of input data are used in the case study: census data, weather data, and solar PV data. The subcategories and input features of the three data categories are discussed in detail below.

Census Data The U.S. Census Bureau collects and tabulates information from the decennial census, the American Community Survey, and demographic surveys at the census block level which are formed by boundaries such as streets, roads, and streams on the Census Bureau maps. The smallest geographic area for which the Census Bureau publishes sample data is CBG which is the next level above census block in the geographic hierarchy. Hence, the latest census data from 2011 to 2015 at the CBG level is used in the case study. Eight subcategories of census data are used in the study and will be discussed below.

Age: The census data record the number of residents in each of the 23 age intervals from 5 - 85 years. Four features/variables are derived from the raw age data. These features are the proportions of residents in four age groups at the CBG level: *Childhood age, School age, Working age*, and *Retired age*.

Income: The census data record the number of households in each of the 16 income groups from less than $\$10,000$ to more than $\$200,000$. Three features are derived from the raw income data. These features are the proportions of households in three income groups: *Low-*, *Middle-*, and *High-income*.

Education: The census data record the number of residents in each of the 24 levels of educational attainment ranging from no schooling completed to doctorate degree. Four features are derived from the raw education data. These features are the proportions of residents in four levels of educational attainment: *No college experience, College experience, Bachelor*, and *Graduate*.

Employment: The census data record the number of residents in four different employment statuses: *Employed, Unemployed, Military service*, and *Not in labor force*. The employment features we use in the study are the proportions of residents in each of the four employment statuses at the CBG level.

The ranges of these input features can be found in Table 1. Note that for the above mentioned four subcategories of census data, their input features sum up to 1. Therefore, one of the input features can be omitted from each of the four subcategories to avoid redundancy.

Housing units: A housing unit can be a house, an apartment, a group of rooms or any other separate living quarters. The census data record the total number of housing units and the number of occupied housing units. The housing units features we use in the study are the total number of housing units and proportion of occupied housing units at the CBG level.

Children: The census data record the number of households with at least one child under the age of 18. The proportion of these households in a CBG is used as an input feature.

Rooms: The census data record the distribution of number of rooms in the housing units of each CBG. The average number of rooms in a housing units in the CBG is calculated and used as an input feature.

Weather Data The historical hourly temperature data of cities in southern California in 2015 are collected from Weather Underground. The temperature data are then mapped to all the CBGs. Three weather related features/variables are extracted from the raw hourly temperature data. *Average hourly temperature*: The average hourly temperature of a CBG. *Average daily peak temperature*: The average daily peak temperature of a CBG. *Proportion of cooling degree days*: The proportion of cooling degree days of a CBG [1].

Electric Load and Solar PV Interconnection Data The hourly electric load data at the household level are collected by smart meters in SCE's service territory in 2015. Note that for buildings which are equipped with solar PV systems, the net electric loads are recorded by the smart meters. The electric load data are then aggregated to the CBG level. For each CBG, the average hourly electric load is calculated and used as the output data of FNN model. The census, weather, and solar PV interconnection data will be used to explain the variations of average hourly electric load at the CBG level.

The solar PV interconnection data as of the beginning of 2015 are gathered by SCE for the residential customers in its service territory. The raw solar PV interconnection data record the installation date and generation capacity of all

[1] The cooling degree days are defined as the days with average temperature (highest value plus lowest value divided by two) above 65 °F.

residential solar PV systems. The following two input features are extracted from the raw data files. *Solar PV capacity*: The sum of solar PV systems' capacities in a CBG. *Solar installation rate*: The proportion of residential customers who installed solar PV systems in a CBG.

4.2 Model Performance and Feature Importance Analysis

A FNN is trained to capture the relationships among census, temperature, solar PV systems, and electric load data. The input layer of the neural network consists of 16 input features from the census data, 3 input features from the weather data, and 2 input features from the solar PV interconnection data as shown in Table 1. The output variable is the average hourly electric load of a CBG. The FNN has two fully connected hidden layers with 200 neurons each.

The entire dataset contains 4,000 CBGs in SCE's service territory. It is divided into three datasets: training set (2,400 CBGs), validation set (600 CBGs), and testing set (1,000 CBGs). Early stopping procedure is carried out by evaluating the generalization error for the validation set. Five different sets of initial FNN weights are used as the starting points to train the FNN. The initial weights are randomly generated using "Xavier" initialization [5]. The forecasting performance of the FNN is evaluated by measuring the model's prediction error for average electric loads of CBGs on the testing dataset. The mean absolute percentage error (MAPE) and root mean square error (RMSE) of prediction are used as the evaluation metrics. The average MAPE across five fitted model is 14.88% and the average RMSE is 104.85kWh. The prediction accuracy is decent given that the geographic area of a CBG is often small.

We select the model with the lowest MAPE for the testing set as the final model. The influence proportions of all input features are calculated via the LRP algorithm discussed in Section 3. The influence proportions of input features of the same data subcategory are merged together to measure its total influence and the results are depicted in Fig. 1. As shown in the figure, temperature, housing units, and solar PV interconnection data are three most important inputs which determine the average electric load in the CBG. Together, they account for nearly 60% of the total influence. Given that HVAC systems account for around 50% of the total building energy consumption [12] and there is a significant need for space-cooling during summer in southern California, it is not surprising to see

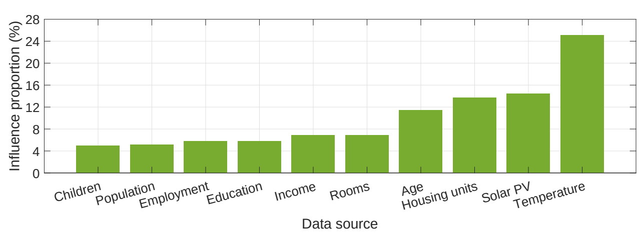


Fig. 1: The influence proportions of all data subcategories.

that temperature related variables have the highest impact on the residential electric load. Similarly, it is intuitive to see that the number of housing units is directly related to the amount of electric load in a CBG. Lastly, solar PV system can generate significant amount of electricity to offset the electric load. Hence, it is also an important factor in determining the net load.

4.3 Scenario Analysis

In this subsection, we investigate the impacts of climate change and socioeconomic development on residential electricity consumption in California. In particular, we explore if the impacts are different for affluent and disadvantaged communities using the FNN trained in Section 4.2.

Impacts of Household Income Growth on Electric Load According to the Congressional Budget Office, the U.S. gross median household income grew 46% between 1979 and 2011 after adjusting for inflation. To explore the impacts of income growth on electricity consumption, we gradually increase the average household income for each CBG by $30,000 in 30 steps from the current income level. The 4,000 CBGs in southern California are divided into two communities: disadvantaged communities (DACs) and non-disadvantaged communities (non-DACs). According to the definitions of the California Environmental Protection Agency (CalEPA) [1], DACs are communities burdened the most by environmental pollution, socioeconomic stress, and health issues. These areas typically possess concentrations of people with low income, high unemployment rate, and low education levels. As shown in Fig. 2 (a), the red regions contain the CBGs that are identified as DACs. The blue area is the SCE's service territory where electric load data are available. 1,018 out of 4,000 CBGs in SCE's service territory are DACs and the rest are non-DACs.

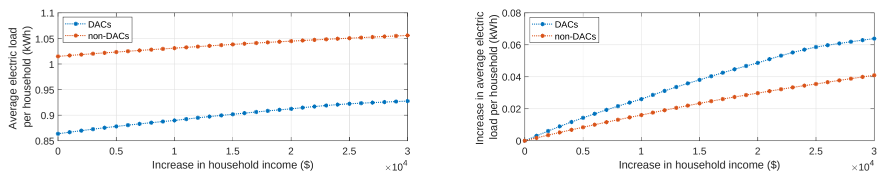
The impacts of income growth on electric load for both DACs and non-DACs are depicted in Fig. 3. As shown in the figure, the households of non-DACs on average consume more electricity than that of DACs. The electric loads of both DACs and non-DACs increase when the household income grows. The percentage change in electricity consumption for DACs is much higher than that of the non-DACs given the same amount of household income growth. This observation implies that the residents in DACs can afford to consume more electricity compared to the baseline consumption with the same income growth.

Impacts of Rising Temperature on Electric Load Due to the global warming and urban heat island effect, the average temperature is expected to rise in California. It is projected that residents of California will, on average, face a 2.4 °C temperature increase by 2060s [9]. The coastal regions will likely experience less warming thanks to the moderating effect of ocean, while the residents of the inland areas, such as the Inland Empire, are expected to suffer summers that are more than 3 °C hotter. To study the impacts of rising temperature on net electric loads in different regions, the 4,000 CBGs in southern California

(a) Disadvantaged communities.

(b) Climate zones.

Fig. 2: Disadvantaged communities and climate zones of California.



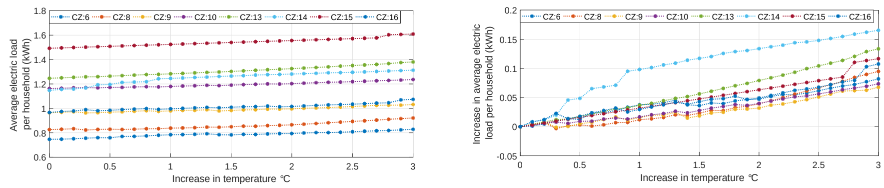
(a)

(b)

Fig. 3: Impacts of household income growth on residential electricity consumption of DACs and non-DACs.

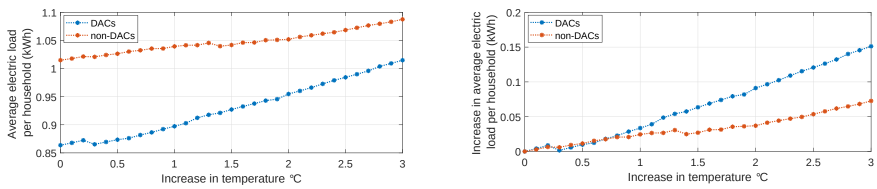
are clustered by climate zones (CZs) defined by California Energy Commission (CEC). Based on average temperatures in summer and winter, CEC partitions California's territory into 16 distinct CZs as shown in Fig. 2 (b). Each CZ has reasonably consistent weather and easily recognized boundaries. There are only 9 CZs in the study area of southern California. Hence, the 4,000 CBGs are separated into 9 clusters. CZ 5 is not included in the analysis due to its small number of CBGs. To explore the impact of rising temperature on electricity consumption, we gradually increase the average temperature by 3°C in 30 steps from the current level. The changes in forecasted CBG electric loads in different CZs with the rising temperature are shown in Fig. 4 (a) and (b). As shown in Fig. 4(a) the inland areas such as CZ 13, 14, and 15, have the highest electricity consumption per household. In addition, the electric loads in all CZs are expected to increase with rising temperature. As shown in Fig. 4(b), the increase in electricity usage for residents in inland areas are much higher than those in the coastal areas. Hence, they are more vulnerable to the climate change.

Similarly, the impacts of rising temperature on DACs and non-DACs are also evaluated separately for comparison purposes. The changes in forecasted CBG electric loads in DACs and non-DACs with rising temperature are shown in Fig. 5. As shown in Fig. 5, the electricity consumption of both DACs and non-DACs in California increase with temperature. Compared to the non-DACs, the electricity consumptions of DACs are, on average, much more sensitive to the change in temperature. There are two possible reasons why this is so. First, the insulations of buildings in DACs are typically poorer than that of non-DACs.



(a) (b)

Fig. 4: Impact of temperature increase on electric loads of different climate zones.



(a) (b)

Fig. 5: Impact of temperature increase on electric loads of DACs and non-DACs.

Second, low income communities typically have less vegetation coverage, thereby enduring a higher land surface temperature in summer [14]. The poor insulation and vegetation coverage require longer running time for air conditioning units and lead to higher electricity consumption and bills. Given that the residents of low-income communities pay a much higher percent of their income on electricity bill, and the electricity consumptions of DACs are more sensitive to rising temperature, we can conclude that DACs are much more vulnerable to climate change and rising temperatures.

5 Conclusion

This paper models the nonlinear relationships among residential electric load, socioeconomic factors, weather variables, and distributed renewable generation with a FNN. The relative importance of explanatory variables in determining the electric load is estimated by the LRP method. A case study with 4,000 CBGs in southern California is conducted. The results show that temperature, housing units, and solar PV interconnection are the most influential determinants for net electric load at the CBG level. The scenario analysis demonstrates that the electricity consumption of poor Californian communities increases much faster than that of the affluent communities when temperature rises. Given that the residents of low-income communities pay a much higher percent of their income on electricity bill, they are much more vulnerable to climate change. Therefore, it is crucial for policy makers to make targeted investments in disadvantaged communities to mitigate the adverse effects of climate change.

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