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Extracting Urban Microclimates from Electricity Bills*

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Abstract

Sustainable energy policies are of growing importance in all urban centers. Climate — and climate change — will play increasingly important roles in these policies. Climate zones defined by the California Energy Commission have long been influential in energy management. For example, recently a two-zone division of Los Angeles (defined by historical temperature averages) was introduced for electricity rate restructuring. The importance of climate zones has been enormous, and climate change could make them still more important.

AI can provide improvements on the ways climate zones are derived and managed. This paper reports on analysis of aggregate household electricity consumption (EC) data from local utilities in Los Angeles, seeking possible improvements in energy management. In this analysis we noticed that EC data permits identification of interesting geographical zones — regions having EC patterns that are characteristically different from surrounding regions. We believe these zones could be useful in a variety of urban models.

Microclimates are characterized by common patterns of environmental variables, such as temperature, wind, humidity, and vegetation. Our key finding is that regions in which block groups have similar Electricity Consumption patterns over time are topographically-defined basins having common climate patterns. We call these *EC-microclimate zones*. Because they reflect local topography and climate, but are based only on EC data, they permit development of new solutions with learning methods.

Although microclimates are known to play important roles in energy management, and are important aspects of ecosystems for computational sustainability, the complexity of environmental variables makes them hard to quantify. We analyze how microclimates and household electricity consumption are linked to socioeconomic variables like income. We show how learning-based models can be useful in prediction of energy consumption. Related geostatistical methods also can be used to extend models for each microclimate zone to larger-scale models of electricity consumption.

*Data for this work was obtained from the UCLA Energy Atlas developed at CCSC (California Center for Sustainable Communities), Institute of the Environment & Sustainability, UCLA. Energy Atlas research was funded by Los Angeles County, with access to data obtained from the California Public Utilities Commission.

Introduction

Urban energy management is as a key problem facing the development of cities. In this work we describe some results of analyses on residential electricity consumption (EC), using monthly consumer data from regional energy utilities, including the Los Angeles Department of Water and Electricity (LADWP), SoCal Edison, SoCal Gas, and others. This included information on almost 17 million accounts and 500 million meter readings, altogether about 500GB of data. In this paper we describe analysis of about 5000 block group totals — a summary of EC in census-defined neighborhoods — that suggests ways to scale analysis for all of the data.

Availability of the data has now made it possible to apply learning methods in deeper analysis of patterns and processes in energy systems. This paper shows how the Los Angeles electricity consumption data clarifies the importance of climate (Erell 2008) in smart energy management. In particular, it suggests ways to identify and use microclimate zones in management of electricity consumption.

The Need for Improved Energy Management

The California Energy Commission formulates energy policies involving climate. For example, the California Energy climate zones (California Energy Commission 2013b; Pacific Energy Center 2008) impose climatic organization on electricity providers. Although these zones were chosen with energy use in mind, they will need to evolve to remain in step with the rapid growth in these areas. It is possible that a much finer zone granularity in Los Angeles could aid in characterizing and improving electricity efficiency.

These zones are important in defining rates, which are vital controls on electricity consumption. LADWP, in its rate restructuring about eight years ago (L.A. DWP 2008), defined two microclimate zones by historical temperature averages, and the western/coastal zone is generally associated with higher income. These two zones are shown in Figure 1; they have had enormous impact on energy consumption.

Faced with increasing complexity of consumer demand and energy supply options, the California Energy Commission and state-wide electricity providers evolved the California IEPR (Integrated Energy Policy Report) over the past decade (California Energy Commission 2013a; 2014; 2015b). It is 'a biennial integrated energy policy report that

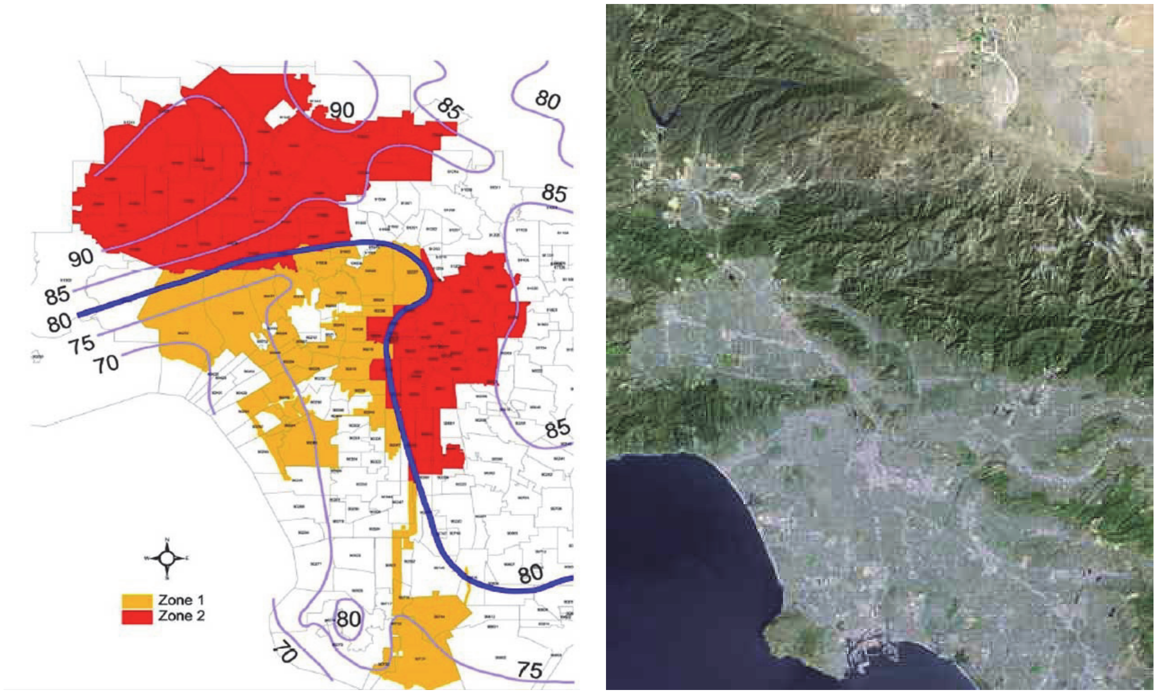


Figure 1: About eight years ago, two climate zones were proposed by LADWP for restructuring its rates, so that consumers in the warmer (and less affluent) Zone 2 paid relatively lower rates. Also, three tiers of use were identified in each zone, with consumers using more kWH paying higher rates. The satellite image shows Los Angeles topography; the microclimate of Zone 1 is considerably more pleasant than Zone 2.

assesses major energy trends and issues facing the state's electricity, natural gas, and transportation fuel sectors and provides policy recommendations to conserve resources; protect the environment; ensure reliable, secure, and diverse energy supplies; enhance the state's economy; and protect public health and safety' (California Energy Commission 2013a). In IEPR workshops (California Energy Commission 2013a; 2014; 2015b) pressing electricity issues are reviewed, with significant impact on urban policy and action plans. These workshops have recently emphasized topics including climate change, climate zones, energy demand, demand forecasting, resource adequacy, environmental impacts, environmental protection, energy saving, market transformation, and integrated energy.

Each of these topics has great importance for the changing regulatory picture of California, the possible impact of new regulations on electricity providers (L.A. DWP 2013), and the range of strategies for meeting them. Demand response, for example, and meeting urban demand with an increasing array of resources, is a key challenge now facing the local electricity industry (L.A. DWP 2013).

Better models of electricity consumption are needed. For 2015 IEPR emphasizes forecasting (California Energy Commission 2015a), as well as accurate, integrated models of urban electricity demand. Models like the ones in this paper have been proposed and evaluated (Tso and Yau 2007), including modeling of the impact of electricity pricing on use (Murdock 2013).

Smart Energy Management with Microclimates

Climate zones have well-established roles in energy policy (California Energy Commission 2013b), and Los Angeles is interesting in its diversity of microclimates. We were interested in determining how microclimates are related to Electricity Consumption (EC).

Microclimates — also known as climatopes — can define boundaries of ecosystems. *Computational sustainability* (Gomes 2009; Ermon et al. 2011; Dietterich et al. 2012) views intelligent management of ecosystems as a central problem, and use of computational methods — machine learning models, constraint solving, optimization — as a solution. This paper focuses on microclimates, and on learning them from electricity consumption data. Other data could be incorporated, including ecosystem climate measurements.

Our key findings are as follows:

- EC data can be used to identify zones with similar EC patterns.
- these zones appear strongly related to climate, so we call them *EC-microclimate zones*.
- EC-microclimate zones are also strongly related to household income, suggesting that they could be useful in energy-related models and policy.
- more accurate models for EC can be developed by using different models for each EC-microclimate zone.

Specific findings about HEC (Household EC) patterns:

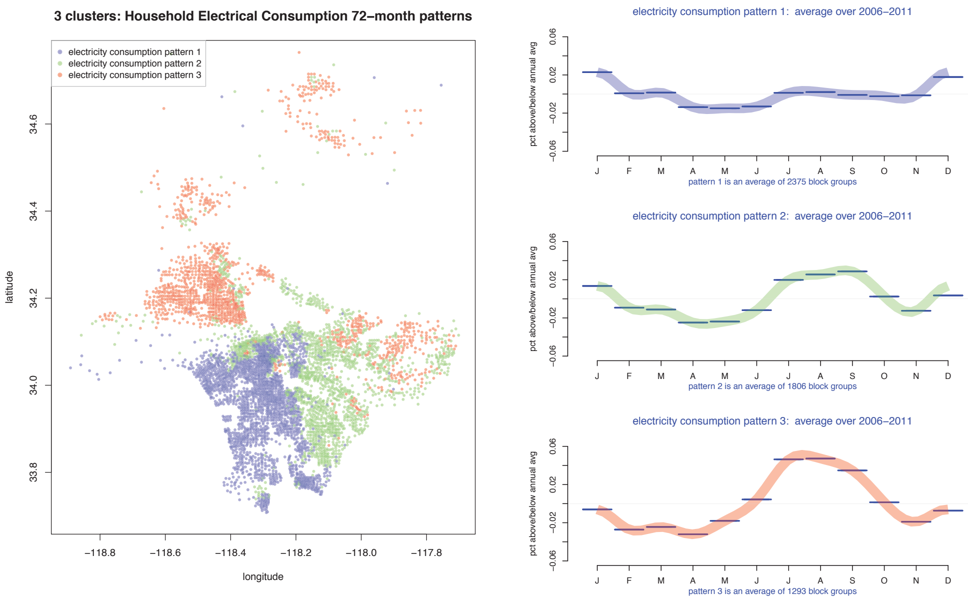


Figure 2: A map of Los Angeles, showing about 5000 individual block groups as colored dots positioned at the geographic center of the block group. The western and southern coastlines are visible as the outline of the blue region at the bottom. The three zones indicated by colors correspond to three different electricity consumption (EC) patterns. The connection between zones and topography is apparent. As they reflect climate, we refer to them as *EC-microclimate zones*. Annual household electricity consumption patterns (average 12-month cycles) are shown for each zone. In our analysis, a *pattern* is a sequence of 72 monthly $\log(\text{HEC})$ values, where *HEC = EC / households*, electricity consumption per household.

- HEC patterns are highly region-specific geographically, in ways related to topography and climate.
- HEC is influenced heavily by Household Income; for example higher Summer demand is associated with lower income, and higher Winter demand is associated with higher income. Predictive models are possible.
- in each EC-microclimate zone, $\log(\text{HEC})$ can be approximated by a GPRF (Gaussian Process Random Field).
- model accuracy can be improved by developing separate models for each EC-microclimate zone. Also Gaussian Process Regression can improve on simple regression.

Smarter Energy Management with Microclimates:

- California Energy Commission climate zones (California Energy Commission 2013b; Pacific Energy Center 2008) appear too broad for accurate electricity consumption forecasts in Los Angeles; smaller-grain geographic divisions could make a difference.
- large-scale geostatistical models of household electricity consumption, including predictive models, can be developed as a composite of models in individual EC-microclimate zones. With more data, still more accurate zones and models are possible.
- The method of using energy consumption data to learn values for difficult-to-measure variables (in this paper: ecosystem variables related to climate) might find uses in computational sustainability.

The central finding is that clustering of time series of residential electricity consumption (EC) identified geographic regions having common climate patterns. These *EC-microclimate zones* were derived from EC data alone.

Household Electricity Consumption (HEC) in these zones turns out to be strongly associated with a number of variables, including income, topography, and property values. HEC patterns in each zone differ seasonally, and are influenced by economic trends over time. We argue that EC-microclimate zones have useful roles to play in sustainable energy modeling and management.

Electricity Consumption Data Analysis

We analyzed data from the UCLA Energy Atlas (Pincetl 2015) (www.energyatlas.ucla.edu) at the California Center for Sustainable Communities (CCSC), in cooperation with LADWP, containing 2006-2011 monthly electricity consumption histories for Los Angeles County. An earlier analysis of electricity consumption per capita in California (Kandel, Sheridan, and McAuliffe 2008) showed both the promise and difficulty of accurate modeling, and the importance of model choice in obtaining forecasts. To gain an understanding of electricity consumption, we analyzed data from about 5000 block groups (census-related street-level geographic regions).

In this paper, for insight into residential electricity consumption patterns, we consider aggregative results for residential block groups in Los Angeles County. Electricity consumption in a block group depends on the number

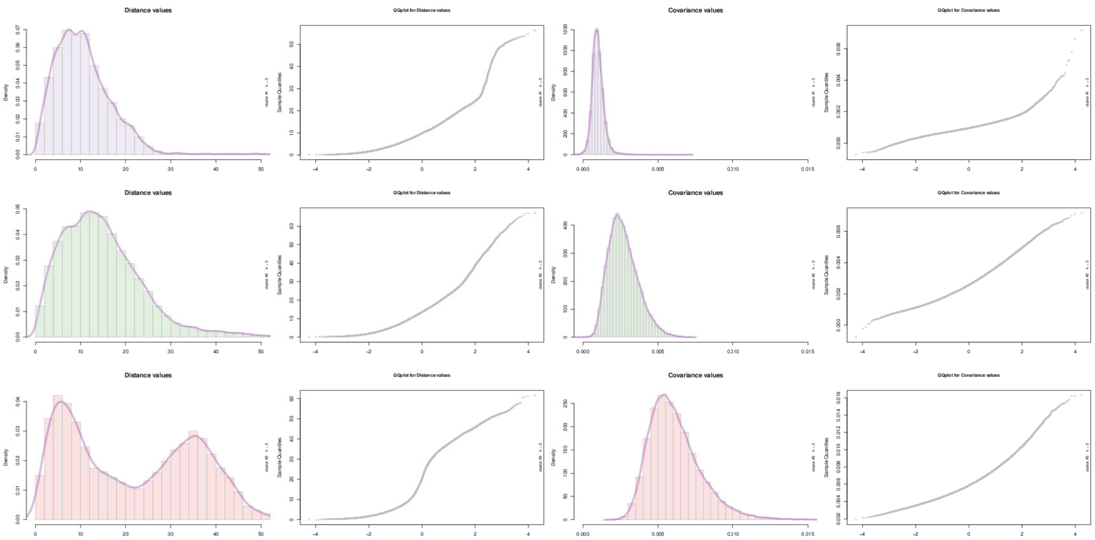


Figure 3: $\log(\text{HEC})$ can be approximated by a Gaussian Process Random Field when the data is split into the three EC-microclimate zones. The leftmost histograms show distributions of geographic distances between block groups, and the rightmost histograms show covariance (of 72-sample $\log(\text{HEC})$ sequences). The plots include QQ-plots for evaluating how close the distributions are to Gaussian; pure Gaussian distributions yields linear QQ-plots. Gaussian distributions for distance and covariance are the expected result $\log(\text{HEC})$ approximates a 2D Gaussian Process (i.e., a Gaussian Process random field). Tails of the distance distributions reflect the shape of the zones. The third zone (bottom row) shows a bi-modal distance distribution because the region has two distinct geographic parts; dividing this zone in two would eliminate the bi-modality.

of consumers (addresses), and the ratio measures household electricity consumption. Our analysis here is based on monthly consumption and household count values in individual block groups. Logarithmically-scaled consumption is approximately normally distributed:

$$\begin{aligned}\log(\text{HEC}) &= \log(\text{Household Electricity Consumption})\\ &= \log(\text{Electricity Consumption / Households}).\end{aligned}$$

In this paper we define an *electricity consumption pattern* as a sequence of 72 monthly values (over the six years). The patterns exhibit clear annual cycles, as in Figure 2, with strong seasonal influences on consumption. The distribution of Household Electricity Consumption values appears approximately lognormal — i.e., the distribution of $\log(\text{HEC})$ is approximately normal — as shown in Figure 3.

log(HEC) as a Gaussian Process Random Field

The HEC data can be modeled as a Log-Gaussian Process over a 2D geographic space. More precisely, when $\log(\text{HEC})$ is viewed as a random variable depending on its (longitude,latitude)-coordinates, we claim it can be approximated by a Gaussian Process Random Field.

A *Gaussian Process* $\mathcal{GP}(m,k)$ is often defined as a collection of random variables, any finite number of which have joint Gaussian distributions defined the mean function m and covariance function k (Rasmussen and Williams 2006). This is interpreted as describing a distribution over *functions*, where 'a finite number of variables' corresponds to 'the function values at a finite number of input points'. Specifically, when $\mathbf{x}$, $\mathbf{x}'$ are two points of the input space (on which m and k are defined as functions), functions f are said to follow this distribution $f \sim \mathcal{GP}(m(\cdot), k(\cdot,\cdot))$ when

$$\begin{aligned}m(\mathbf{x}) &= E[\,f(\mathbf{x})\,]\\ k(\mathbf{x},\mathbf{x}') &= E[\,(f(\mathbf{x})-m(\mathbf{x}))\,(f(\mathbf{x}')-m(\mathbf{x}'))\,].\end{aligned}$$

The $\mathbf{x}$ values are from a continuous *input space*, and for each $\mathbf{x}$, the Gaussian process $f(\mathbf{x})$ is a normally distributed random variable. Given n values $(\mathbf{x}_1,\ldots,\mathbf{x}_n)$, the n random variables $(f(\mathbf{x}_1),\ldots,f(\mathbf{x}_n))$ have an n-dimensional normal distribution with mean $(m(\mathbf{x}_1),\ldots,m(\mathbf{x}_n))$ and the $n\times n$ covariance matrix K that has entries $K_{ij} = \text{cov}(f(\mathbf{x}_i),f(\mathbf{x}_j)) = k(\mathbf{x}_i,\mathbf{x}_j)$.

Generally, random processes involve index values $\mathbf{x}$ that are one-dimensional (like 'time'). However if the values $\mathbf{x}$ are d-dimensional with $d>1$, the Gaussian Process is called a *Gaussian Process Random Field*.

With our HEC data, $\mathbf{x}$ denotes a 2D (longitude, latitude)-position in degrees. If $\mathbf{x}$ and $\mathbf{x}'$ are two such positions, then the *geographical distance* $\text{dist}(\mathbf{x},\mathbf{x}')$ between them is their major-arc distance (when converted to radians), i.e., spatial distance in miles. Conceptually, ignoring curvature, $\text{dist}(\mathbf{x},\mathbf{x}') = ||\mathbf{x}-\mathbf{x}'||$.

Also, at each such 2D position $\mathbf{x}$, we have a random variable $f(\mathbf{x}) = \log(\text{HEC}(\mathbf{x}))$. For the block group located at $\mathbf{x}$, our dataset contains 72 samples of this random variable, a time series of monthly values over 2006-2011. Treating the samples as vectors, $\text{cov}(f(\mathbf{x}),f(\mathbf{x}'))$ can be estimated by covariance of the vectors.

Figure 3 shows histograms obtained from (distance, covariance)-pairs $(\,\text{dist}(\mathbf{x},\mathbf{x}'),\ \text{cov}(f(\mathbf{x}),f(\mathbf{x}'))\,)$ for each pair of block group positions $\mathbf{x}$ and $\mathbf{x}'$ within each of the three EC-microclimate zones, having $\log(\,\text{HEC}\,)$ vectors $f(\mathbf{x})$ and $f(\mathbf{x}')$. The distribution of these pairs approximates a 2D Gaussian; Figure 3 shows the approximately Gaussian distributions for distance and for covariance alone. Quantile-Quantile plots (QQplots) show skew of the distributions, from nonnegative distance and covariance values. Thus, $f = \log(\,\text{HEC}\,)$ approximates a Gaussian Process. Since the space of values $\mathbf{x}$ here is two-dimensional, it defines a Gaussian Process Random Field (Rasmussen and Williams 2006; Moore and Russell 2015)

It has been observed before that microclimate variables (wind speed, local temperature, wind pressure, and total solar irradiation) can be modeled as a Gaussian Process Random Field, and this has been exploited in modeling electricity consumption (Sun et al. 2014). In this paper we are doing the reverse: validating that electricity consumption can be modeled as a Gaussian Process Random Field, and then arguing that its structure reflects climate. This approach is novel, yet consistent with (Sun et al. 2014).

Seasonal Electricity Consumption Patterns and Microclimate Zones

Figure 2 shows three average electricity consumption patterns obtained by clustering. The EC patterns of each block group (a sequence of length 72 $\log(\,\text{HEC}\,)$ values, for each month over the six years 2006-2011, normalized to total to 1) were clustered into $k = 3$ clusters with the k-means algorithm. A point was then plotted at the central (latitude,longitude) location of the block group, colored according to its cluster. The map shows a connection between electricity consumption and geography, suggesting association between EC and climate.

A *microclimate* is often defined by restricted ranges or patterns of environmental variables, including temperature, wind, relative humidity, and vegetation (UK Meteorological Office 2011). Cities (such as Los Angeles and San Francisco) with diverse patterns can support distinct microclimates.

The regions defined by clusters visible in Figure 2 suggest climate zones, since their boundaries align with topographical features like hillsides, reflecting environmental characteristics that impact electricity consumption over the year. For this reason we refer to them as *EC-Microclimate Zones*.

Although they are defined only by EC patterns, these EC-microclimate zones are contiguous geographic regions linked to climate. It is well-known that microclimates affect energy use (Moonena et al. 2012), but we have not found any discussion of the reverse, i.e., that EC is sufficient to identify microclimate.

Figure 2 shows that there are interesting location effects in the Long Beach area, the coastal points in the plots that are furthest south. This also raises the question of how California Energy climate zones (California Energy Commission 2013b) relate to the microclimates defined by EC. Although the California Energy climate zones were chosen to reflect energy use, a finer zone granularity could help in improving electricity efficiency. As Figure 3 shows, different zones reflect different GPRFs, which learning can discern.

Electricity Consumption Patterns and Income

Electricity consumption is often linked to economics. For example, in (Pabla 2004, p.65) electricity consumption in the United States is linked to GNP. Furthermore it is well-known that individuals with the greatest income have the greatest consumption (Pachauri 2007), while lifeline consumers have low use (Murdock 2013).

Predictive models of consumption can be developed by including economic variables such as household income (PHI: Per Household Income). Our results above show seasonal consumption is linked to microclimate. Income distributions often resemble a mixture of lognormal distributions (Atkinson and Bourguignon 2014).

Linking Income and Electricity Consumption

Higher-income block groups are located in the western Los Angeles basin, particularly in hillside and coastal areas, while lower-income block groups are mainly in flat inland areas. The microclimates of these locations differ.

An association between microclimate and income can explain in part why higher-income consumers have different electricity consumption profiles. Figure 2 suggests that higher-income block groups have higher consumption in Winter, while lower-income block groups have higher consumption in Summer. The microclimates have different seasonal needs.

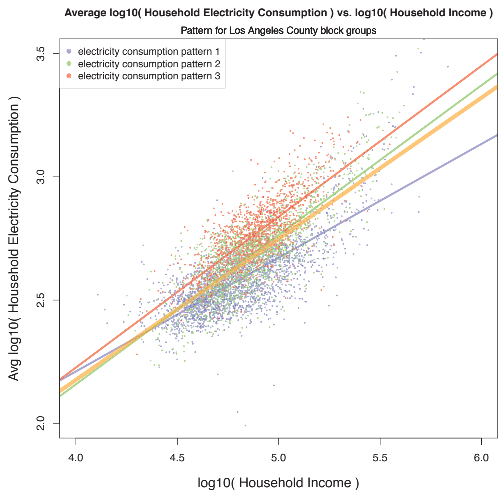
Electricity Consumption in each Microclimate Zone

In our data, division by microclimate zone (i.e., conditioning on EC-microclimate) yields more accurate models of electricity consumption. Figure 4 shows the joint distribution between $\log(\,\text{PHI}\,)$ and $\log(\,\text{HEC}\,)$. The distribution appears almost gaussian, with strong correlation. Subdividing the block groups over the three clusters gets three smaller gaussian-like distributions, with stronger correlation. Electricity consumption patterns differ visibly in each EC-microclimate zone.

It is pointed out in (Torgo and da Costa 2003) that clustered regression models are inequivalent to standard regression trees or ensemble methods, and can outperform them significantly. The 3 seasonal patterns (defined earlier in Figure 2) yield a different regression model in each of the 3 clusters. The R^2 values suggest this also, but visual confirmation is in Figure 4: the heavier line is a model for the whole dataset, and the three other lines are models for the clusters. The overall joint distribution of $\log(\,\text{HEC}\,)$ and $\log(\,\text{PHI}\,)$ appears gaussian, but divides clearly into distinct distributions by cluster.

Predicting Electricity Consumption

Gaussian Process Regression (Rasmussen and Williams 2006) is a method for learning a Gaussian Process from a given set of data points. For a function f defined by training set $(X, \mathbf{y}) = \{(\mathbf{x}_i, y_i) \mid 1 \le i \le n\}$, it derives a covariance



$\log(\mathrm{HEC}) \sim 0.57\log(\mathrm{PHI}) - 0.11$	$R^2 = 0.56$	(overall)
$\log(\mathrm{HEC}) \sim 0.46\log(\mathrm{PHI}) + 0.36$	$R^2 = 0.57$	(cluster 1)
$\log(\mathrm{HEC}) \sim 0.60\log(\mathrm{PHI}) - 0.27$	$R^2 = 0.64$	(cluster 2)
$\log(\mathrm{HEC}) \sim 0.61\log(\mathrm{PHI}) - 0.22$	$R^2 = 0.57$	(cluster 3)

Figure 4: Average Household Electricity Consumption for each of about 5000 block groups in Los Angeles County, versus Per Capita Income. This plot also shows the result of *clustered regression* – i.e., shows a regression model for each cluster; all *log*s are base 10. Three lines show linear regression models for each of the 3 zones; the wider orange line is a model for all of the data.

matrix $K = K(X, X)$ that can be used to make predictions for the function value at any new input point $\mathbf{x}_*$:

$$\overline{f}(\mathbf{x}) \;=\; \mathbf{k}(\mathbf{x}_*)^\top (K + \sigma_n^2)^{-1}\mathbf{y},$$

where $\mathbf{k}(\mathbf{x}_*) = K(X, \mathbf{x}_*)$, and $\mathrm{cov}(\mathbf{y}) = K + \sigma_n^2 I$ (i.e., σ_n^2 is the level of noise in the $\mathbf{y}$ values (Rasmussen and Williams 2006; Bishop 2006)). Figure 5 shows the result of performing Gaussian Process regression for $(\log(\mathrm{PHI}), \log(\mathrm{HEC}))$ points in each cluster (EC-microclimate zone). The regression includes ± 2-standard-error 'bands' around the mean; these bands are widest for extreme values of Household Income (PHI), high or low. EC of the wealthiest neighborhoods is most difficult to predict accurately. Earlier in this paper we discussed the emerging importance of methods for predicting Electricity Consumption, given the increasingly complex context for energy management. Kriging — basically a flexible form of interpolation in geostatistics (Chilès and Delfiner 1999) — has potential for prediction.

Conclusions

In this paper we have studied annual patterns of residential electricity use in Los Angeles. Specifically, we studied patterns as a sequence of 72 monthly values (over the six years 2006-2011) of household electricity consumption (HEC) in

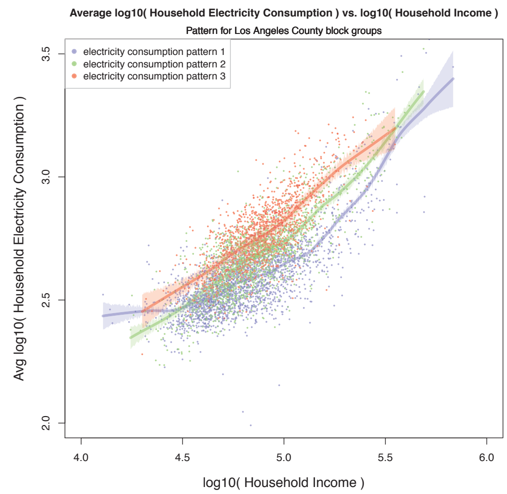


Figure 5: This plot shows the result of *clustered Gaussian Process Regression* for Average Household Electricity Consumption $(\log(\mathrm{HEC}))$ versus Household Income $(\log(\mathrm{PHI}))$ — with one model for each cluster. The three clusters are the same as in Figure 4. The shaded ± 2-standard-error bands are much wider at high or low values of PHI. Gaussian Process models fit the data more closely than linear models, and can provide more accurate prediction.

about 5000 block groups, and obtained interesting findings about the central importance of Household Income (PHI) on HEC. We found that temporal HEC patterns contain significant information about climate. Clustering normalized $\log(\mathrm{HEC})$ values yields clusters that correspond both to climate and to geographic regions. We therefore have called these regions *EC-microclimate zones*.

Why are EC-microclimate zones so clearly discernable in the EC data? Their boundaries align with topographical features like hillsides, and the $\log(\mathrm{HEC})$ random fields in each zone are different. Each approximates a Gaussian Process Random Field (GPRF) — a 2D random process in which pairs of points follow Gaussian distributions, but with covariance constrained by their geographic distance. Microclimate variables (wind speed, local temperature, wind pressure, and total solar irradiation) have been modeled as Gaussian Process Random Fields in the past (Sun et al. 2014). However, we are unaware of other work showing that $\log(\mathrm{HEC})$ approximates a GPRF.

The rest of this paper has shown how clustering can be a foundation for developing complex models. Clustered Regression is a natural extension of ordinary linear regression to cope with different zones. Clustered Gaussian Process Regression involves the same extension. Although the data can be roughly approximated by a single Gaussian distribution, dividing the data first by clustering into more homogeneous zones permits better approximations and more accurate models, as shown in Figure 4. An interesting question is how changes in the resolution of analysis — from block groups to households, and from block group EC to household electricity bills — can improve the results.

There are a number of directions for work related to computational sustainability (Gomes 2009; Ermon et al. 2011; Dietterich et al. 2012). We discussed at the start of this paper how prediction models are currently of great interest in energy management. Gaussian Process Regression models also include prediction methods that come with error bounds. Geostatistical methods like Kriging have potential for prediction of EC, as ilustrated in Figure 5. Although this direction is geostatistical (Chilès and Delfiner 1999; Moore and Russell 2015), availability of detailed EC and economic data will permit much more accurate modeling. In fact, in other work, we have shown $\log(\,\mathrm{HEC}\,)$ is highly correlated with other socioeconomic variables, such as property values and income. Very accurate zone models are possible.

Measuring variables in an ecosystem, such as those related to climate, is difficult. The idea of using other data (such as electricity bills) to infer values for difficult-to-measure variables might have broader applications in computational sustainability.

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