

Supplementary Material:
**On Energy Sufficiency and the Need for New Policies to
Combat Growing Inequities in the Residential Energy Sector**

Eric Daniel Fournier ¹, Robert Cudd ¹, Felicia Federico ¹, Stephanie Pincetl ^{1,*}

¹The California Center for Sustainable Communities, Institute of the Environment and Sustainability, University of California Los Angeles, La Kretz Hall, Suite 300, 619 Charles E. Young Drive E., Los Angeles, CA 90095-1496

*spincetl@ioes.ucla.edu

Study area overview

The study area of our analysis is limited to Los Angeles County (LAC). LAC comprises a geographic area of $4,083 \text{ mi}^2$ and is home to 10.2 million people. According to the California Energy Commission LAC's total electricity consumption was 67.856 TWh and total natural gas usage was 2.9 GTherms in 2018. The contribution of the residential sector to LAC's countywide total electricity consumption during this period was 20.6 TWh , or 30%. Alternatively, the contribution of the residential sector to the LAC's countywide total natural gas usage constituted 1.1 GTherms , or 38%.

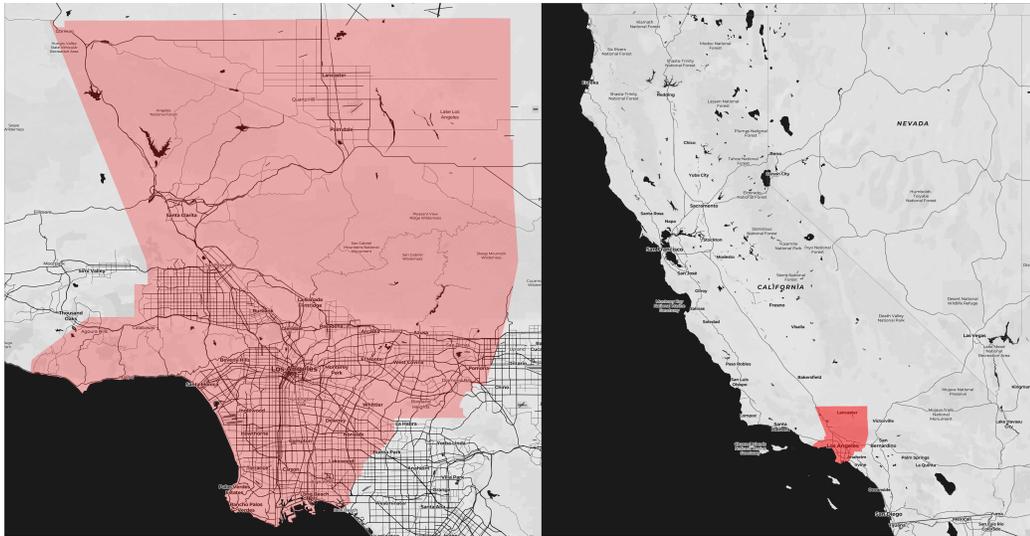


Figure 1. Maps depicting the Los Angeles County study area within the broader California context.

Zipcode level aggregation of CalEnviroScreen data

It is important to compare the attributes of the set of DAC census tracts to the set of, re-aggregated, majority-DAC zip codes to understand what, if any, inaccuracies may have been introduced into the analysis as a result of the aggregation procedure. In terms of the total number of features: 44.4% of the census tracts in the study area were designated as DACs while only 31.2% of the zipcodes were. This count discrepancy reflects the fact that census tract geographies have been explicitly designed to be population preserving while zipcodes have not. A more relevant comparison involves the total population represented between the

two. When defined at the census-tract level, DACs within LAC comprise 45.1% of the region's total population. Alternatively, when defined at the zipcode level, they represent 45.7% the total. This small difference indicates good agreement between the two.

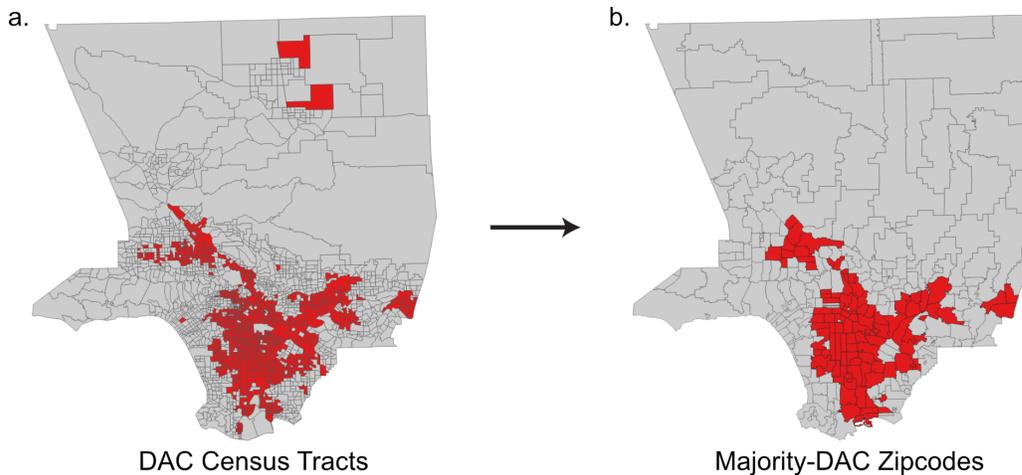


Figure 2. Maps depicting the translation of (a.) CalEnviroScreen 3.0 Disadvantaged Community (DAC) census tracts to (b.) majority Disadvantaged Community zipcodes (Majority-DAC zipcodes) within Los Angeles County.

Alternative fuel vehicle database insights

The AFVD provides some extremely important insights about the relative scale of market penetration for different categories of alternative fuel vehicle technologies. Figure 3 contains a ternary plot, with inset zoom, that depicts the fractional proportion of Conventional Fuel Vehicles (CFVs - red), Alternative Fuel Vehicles (AFVs - green), Plug-in Electric Vehicles (PEVs - blue) registered within each zipcode in Los Angeles County as of 2018. Figure 3b. shows an inset zoom on the area in which the majority of zipcodes within LAC cluster. This area comprises the 85%-100% CFV range. Zipcodes in which the levels of PEV or AFV penetration above 15% are dominated by large University, Studio, or Hotel campuses with centrally managed vehicle fleets. The categorical identity of several of these outlier zipcodes have been labeled in Figure 3a.

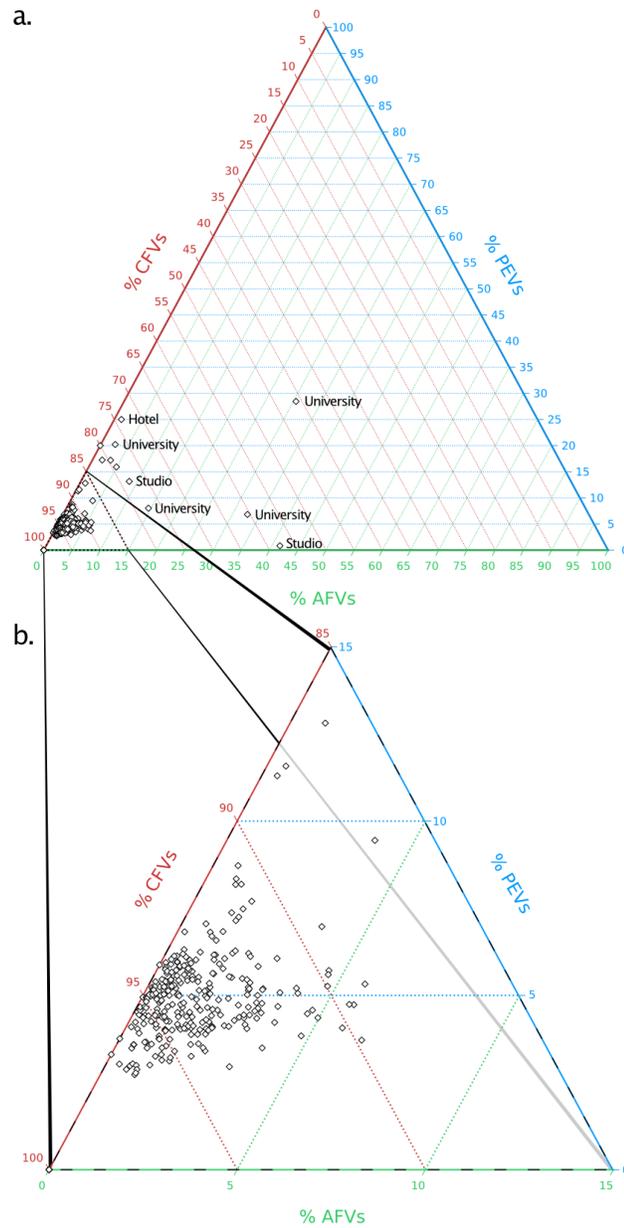


Figure 3. Ternary plot depicting (a.) the relative proportions of Conventional Fuel Vehicles (CFVs), Alternative Fuel Vehicles (AFVs), Plug-in Electric Vehicles (PEVs) registered within each zipcode in Los Angeles County through the end of 2017. (b.) Inset zoom plot.

LAC public transit options and ridership levels

Despite much publicized recent efforts both on behalf of the City of Los Angeles and the Los Angeles County Metropolitan Transit Authority (LA-Metro) to stimulate growth in public transit usage, the most recently available data indicates that ridership, particularly for buses, has declined significantly over the previous five years. It has been posited that these declines have been due to the recent introduction of popular ride-hailing services, such as Uber and Lyft. The relationship between ride-hailing service usage, public transit availability/usage, and disadvantaged community status has recently been investigated by Jin *et al* ?. Based upon their analysis of a large dataset of Uber rides within New York City they concluded that the ride-hailing service:

...competes with public transit during most hours of the day and in areas with good public transit coverage, whereas it complements public transit at midnight and in places with insufficient public transit services. The distribution of Uber services is highly unequal, and Uber's role in improving transport equity is insignificant. Correlation analysis shows that there tend to be fewer Uber pickups in low-income areas, which diverges from previous studies suggesting that Uber serves low-income areas well. In addition, a weak negative correlation is detected between the number of Uber pickups and the percentage of minorities.

Within LAC, accessibility to public transit can be quite limited within DACs due to their distance from the major rail lines connecting transit hubs within downtown population centers. The map contained within Figure 4 illustrates this phenomenon with recent data compiled by the USC Price Center for Social Innovation which estimates the percentage of individuals within each LAC zipcode who ride public transit. Overlaid on this ridership map are the locations of LA-Metro's major rail lines (black). The highest rates of public transit ridership are clustered neatly around downtown Los Angeles in the map's and the city of Long Beach in the south. These areas are directly connected by LA-Metro's rail network. As the map shows, there are numerous DACs in the eastern portion of the county which are not directly serviced by these rail lines. The long transit times associated with connecting to these lines via the local bus network majorly impacts transit ridership and is a major factor in the persistent car-dependence of the region.

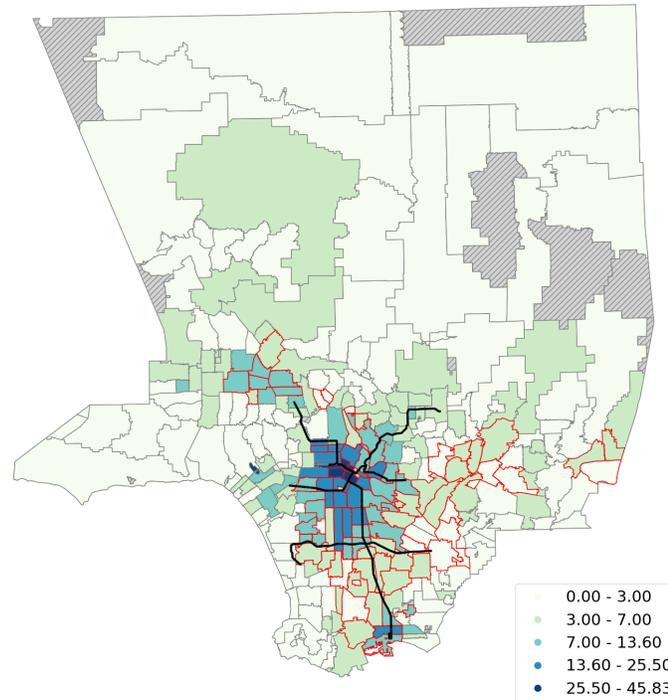


Figure 4. Map depicting the percentage of public transit riders by zipcode within Los Angeles County as of 2019. Zipcode level values have aggregated from census tract level ridership data sourced from the USC Price Center for Social Innovation’s Neighborhood Data for Social Change platform (NDSC). Rail network data (black) have been sourced from the Los Angeles Metropolitan Transit Authority (LA-Metro).

Bass diffusion model formulation

According to the Bass diffusion model the growth rate at some future point in time $f(t)$ can be expressed as a differential equation comprised of two fixed parameters (p, q) and the current level of adoption at that time $F(t)$. The terms (p, q) are commonly referred to as the coefficients of innovation and imitation. The former (p) represents the fraction of the population that is likely to adopt the product independent of existing level of adoption - i.e. "innovators." The latter (q) represents the fraction of the population that is likely to adopt the product depending upon

the current level of adoption - i.e. "imitators." The relative contribution of these two groups is illustrated graphically as in Figure 5. The Bass diffusion model has a successful track record of predicting the market adoption behavior for products in the categories under consideration here (Dong et al., 2017; Mahajan et al., 1990). Consequently, it was deemed a suitable choice for this application.

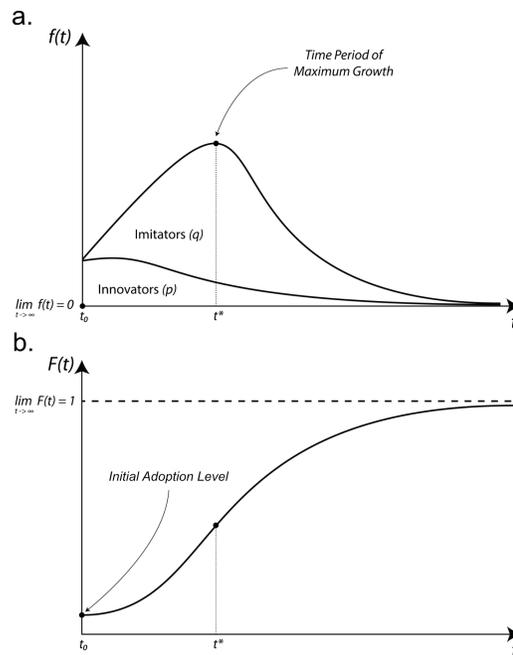


Figure 5. Conceptual illustration of the relationship between (a.) the Bass diffusion model growth rate function $f(t)$ and (b.) overall market adoption function $F(t)$.

References

- Dong C, Sigrin B, Brinkman G. 2017. Forecasting residential solar photovoltaic deployment in California. *Technological Forecasting and Social Change* **117**: 251–265. ISSN 00401625. doi:10.1016/j.techfore.2016.11.021.
- Mahajan V, Muller E, Bass FM. 1990. New Product Diffusion Models in Marketing: A Review and Directions for Research. *Journal of Marketing* **54**(January): 1–26.