International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 661

A FRAMEWORK FOR ESTIMATING THE IMPACTS OF LAND USE CHANGE ON URBAN ENERGY SELF-SUFFICIENCY

Ranjitha Shivaram[1], Rishee K. Jain[1*]

1 Urban Informatics Lab, Stanford University, 473 Via Ortega, Room 269B, Stanford, CA 94305, United States
*Corresponding author. Tel.: 1-650-721-8559; Fax: 1-650-723-4806; E-mail: rishee.jain@stanford.edu

ABSTRACT

Energy production and consumption in cities are both inextricably linked to urban form that in itself is driven by land use planning. Yet, little is known as to how changes in land use can impact energy self-sufficiency in cities, whereby in-boundary energy production is able to satisfy in-boundary consumption needs. In this paper, we develop a workflow to model how urban energy self-sufficiency changes under various scenarios of land use change. We then apply this method to an empirical dataset for Palo Alto, a mid-size city in California, USA. Results indicate that as urban density is increased through land use change, urban energy self-sufficiency decreases, prompting the need for the joint consideration of energy efficiency and other measures with land use planning. In addition to demonstrating the importance of land use as an underexplored lever for urban energy use, our results have practical implications for the deployment of distributed energy resources (DERs) in cities, particularly solar energy.

Keywords: urban energy, land use, distributed energy resources, spatial bootstrapping, data analytics

1. INTRODUCTION

Cities house a majority of the world's population and account for more than 75% of global energy use and 80% of greenhouse gas emissions, making the sustainable delivery of urban energy critical to climate change mitigation. On the supply side, energy production in cities through distributed energy resources (DER) such as solar energy systems are gaining prominence and can offer significant environmental, economic and resiliency benefits since they leverage already developed land resources [1,2]. Both energy consumption and production in cities can depend significantly on the physical structure and form of cities, which is in turn influenced by local developmental controls implemented through land use planning. For instance, previous work has hinted at how compact urban form is more energy efficient from both the building and transportation energy use perspectives but can be detrimental to the deployment of solar energy [3]. As the world urbanizes, urban planners will need to more intentionally consider the tradeoffs between energy supply and demand as they relate to land use. This paper aims to develop a workflow to model how urban energy self-sufficiency changes under various scenarios of land use change. We also apply the workflow to a mid-size city in the United States to empirically evaluate the relationship between land use change and urban energy self-sufficiency.

2. LITERATURE REVIEW

2.1 Land use and urban energy consumption

On the energy demand side, early seminal research in the 1980s introduced the idea that urban density affects energy demand in buildings and transportation [4]. More recent work has shown that urban building energy consumption can be significantly influenced not just by building characteristics [5], but also various features of urban form [6] such as the street layout [7], inter-building effects [8,9], vegetation [10], microclimatic factors [11,12], and proximity between various urban systems [13]. Despite the fact that land use planning often dictates urban form - the physical shape, layout and density of cities - through zoning codes [14], there is still significant debate on whether and how changing land use patterns can influence urban building energy consumption [15].

2.2 Land use and urban energy production

On the energy supply side, prior work offers limited insights on how land use patters can impact urban energy production, such as through solar energy systems. The bidirectional interactions of land use and energy production and the need for planners to proactively consider how land use decisions can affect the deployment of energy production technologies has only recently been recognized as these technologies become more economically feasible [16]. Researchers have begun to explore connections between urban morphology and solar form [17], the effect of urban density on energy consumption and solar gains [18], and trade-offs between solar energy potential and vehicle energy consumption [3].

2.3 Land use and urban energy self-sufficiency

While it is widely accepted in planning practice that more compact cities characterized by mixed and denser land uses offer advantages in vibrancy and economic development [19], there is limited empirical analysis of how land use impacts energy self-sufficiency in cities, whereby in-boundary energy production is able to satisfy in-boundary consumption needs. For instance, while compact cities might consume lesser energy on average than sprawling cities, they might not be able to deploy as much solar power due to space and shading constraints. Further, past research has relied on simulation of building and urban energy use through existing software like *EnergyPlus* [20]. More recently, the availability of urban energy consumption and production data that is more granular both spatially and temporally has made it possible to analyze such dynamics empirically and extend simulation-based studies in the literature.

3. METHODOLOGY

The proposed methodology to estimate the effect of land use change on urban energy self-sufficiency consists of three main steps (Figure 1): (1) defining scenarios of land use change (re-zoning) and compiling energy self-sufficiency metrics; (2) estimating energy self-sufficiency of rezoned units through geo-weighted bootstrapping; and (3) utilizing the outputs to inform policy on local energy efficiency and emissions targets.

3.1 Model setup

Amidst competing pressures of economic growth, real estate affordability and the need for open space, city and regional planning agencies make land use decisions

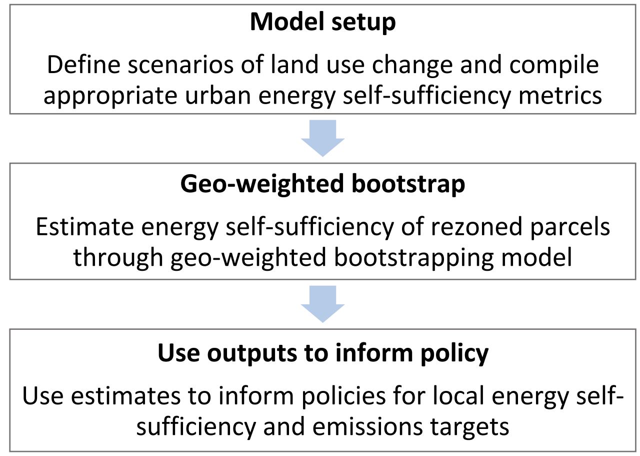

Figure 1. Proposed workflow to estimate the impacts of land use change on urban energy self-sufficiency

regularly through land use and zoning designations at the parcel level. For instance, some land parcels might be exclusively zoned to permit only single-family residential development, while others might be zoned to permit both multi-family and commercial development. In order to estimate the effect of land use change, the first step is to define land use change scenarios. Common scenarios include the "upzoning" of parcels where changes in land use enable greater development density, or changes in land use to support transit-oriented development. We thus identify the parcels that will be subject to land use change and therefore will be "rezoned".

Second, we need to define and operationalize energy self-sufficiency metrics. Energy self-sufficiency is calculated simply as the ratio of energy production to consumption within the identified system boundaries at the building, parcel, or neighborhood level.

$$Energy\ self\text{-}sufficiency = \frac{\sum Energy\ production}{\sum Energy\ consumption}$$

Buildings and transportation are the primary consumers of energy in urban areas. Therefore, energy consumption to calculate self-sufficiency can include not just building but also transportation energy use, aggregated from the per capita to the building or parcel level. While this aggregated energy use has been harder to quantify in past research, newer sources of data can be leveraged going forward. Similarly, energy production can come from a variety of distributed energy resources, including solar, natural gas micro-turbine, or any small-capacity generator or energy-storage device connected at distribution voltage levels [21]. This generalized framework for the definition of energy consumption and production allows us to take into account disruptive changes in urban energy systems such as the interactions between electric vehicles and building-integrated energy storage capacity.

3.2 *Geo-weighted bootstrap*

The next step is to develop the geo-weighted bootstrap model for the prediction of energy self-sufficiency of rezoned parcels. Conceptually, this model combines a geo-weighted regression model with bootstrap inference to account for two factors: (1) the expected similarity between the rezoned parcel and existing parcels with the same land use, and (2) the expected similarities in the effect of the surrounding urban context on the rezoned parcel and the parcels around it. For instance, when a single family residential parcel is re-zoned to a multi-family residential parcel, an accurate estimation of the expected energy use of the rezoned parcel will have to take into account the energy use of other existing multi-family residential parcels, the characteristics of the rezoned parcel, and the urban context within which the parcel is nested, including its proximity to streets, other buildings and the surrounding vegetation. This is because the energy use of a newly rezoned multi-family residential parcel in an older high-income neighborhood with significant tree cover will be different from a similarly rezoned parcel in a newer lower income neighborhood with no tree cover.

Drawing on the generalized form of a geo-weighted regression (GWR) model [22],

$$\boldsymbol{y_i = \beta_{i0} + \sum_{k=0}^{p} \beta_{ik}\, x_{ik} + \varepsilon_i \qquad i \in C = \{1, 2, \dots, n\}}$$

Where $\boldsymbol{y_i}$ is the energy use of the re-zoned parcel, $\boldsymbol{C}$ is the index set of locations of $\boldsymbol{n}$ observations and $\boldsymbol{\beta_{ik}}$ is the value of the kth parameter at location $\boldsymbol{i}$. The independent variables under consideration would include building characteristics (like age, area, building like insulation etc), demographic characteristics (like income, household size etc.) and context characteristics (like tree cover, proximity to other urban systems etc).

The geo-weighted regression to predict energy use can then be fitted to repeated samples created through bootstrapping from the set of existing parcels. Bootstrap techniques [23], where the sampling distribution of a specified random variable is estimated through repeated random resampling with replacement from an existing dataset, are gradually gaining prominence in building and urban energy analysis [24]. They offer distinct advantages for smaller samples of existing energy use data and can be especially well-suited to the spatial variation in energy use based on local context [25]. In the context of urban energy use, they can be employed to draw robust estimates from existing building energy use and production information rather than using simulation or increasingly complex stand-alone models that attempt to account for a wide range of influencing factors.

3.3 *Outputs for policy*

As the world urbanizes, cities are under pressure to accommodate more people while also growing economically. Significant changes in land use policy, such as the new SB-50 bill in the California State Senate [26] or the rapid and large-scale land use changes in China for urban construction and transportation [27], are contributing to changes in urban energy systems that should be considered by planners. At the same time, cities are also developing Climate Action Plans that set targets for building and transportation energy efficiency as well as renewable energy deployment to reduce greenhouse gas emissions. Recent research in energy economics has begun to explore this phenomenon through the development of measures for the trade-offs between locational value and economies of scale for distributed energy resources [21]. Given these trends, the ability to estimate changes in urban energy patterns in conjunction with proposed land use change will be helpful to both local governments and utilities and can inform appropriate policies for local energy self-sufficiency and emissions targets.

4. CASE STUDY

4.1 *Model setup*

To demonstrate and validate the workflow described above, a simplified real-world case study is conducted for the downtown area of Palo Alto, a mid-size city in California, USA. The assessor's parcel is chosen as the unit for analysis, and this area contains 464 parcels of varying sizes and land uses, including commercial, multi-family residential and single-family residential. Two scenarios of land use change are considered (Table 1). 25% of existing single family and multi-family residential parcels are randomly selected and their land use is changed to multi-family residential and commercial respectively – these are the newly rezoned parcels whose energy self-sufficiency is to be estimated. While this is a very aggressive land use change, it is used for an accessible illustration of the workflow in our analysis. On the energy consumption side, annual energy use data is compiled for each parcel through spatial joins and normalized by lot size (area) to create parcel energy use intensity. On the energy production side, annual suitable rooftop solar area and direct current (DC) nameplate capacity (kW) at the parcel level are compiled through spatial joins and annual AC solar capacity is estimated using NREL's PVWatts tool [28,29]. Parcel solar capacity is normalized by lot area to create parcel solar intensity. We do not consider seasonal and hourly variation in energy use and solar capacity, a limitation to be addressed in future work. We discard parcels with more than 3 months of missing energy use data.

Table 1. Land use change scenarios for case study

Scenario	**% parcels rezoned**
(1) Multi-family Residential to Commercial	25%
(2) Single-family to Multi-family Residential	25%

4.2 Bootstrap

Due to data constraints, a highly simplified bootstrap is implemented in this initial study to estimate the mean and standard error of the parcel energy use intensity and parcel rooftop solar capacity for the two scenarios, resampling 10,000 times. The estimates are then rescaled by parcel area for the newly rezoned parcels to obtain parcel energy use and parcel solar capacity. While this is a streamlined version of this analysis, the ideal next steps are to create a regression model that takes a number of building, demographic and parcel characteristics identified in the literature to be important in determining energy use of buildings [30].

4.3 Results and Discussion

Figure 2 shows the initial levels of energy self-sufficiency by parcel land use type in this mid-sized city. The dashed diagonal line represents energy self-sufficiency, where a parcel's energy use and solar capacity are equal. Parcels are energy self-sufficient above or on the diagonal, and not self-sufficient below it. We see that a lot of commercial parcels are not self-sufficient, pointing to high energy use and lower rooftop solar area and capacity. Multi-family residential and single-family residential parcels are more evenly distributed on both sides, showing potential in attaining energy self-sufficiency.

Figure 3 shows the change in energy self-sufficiency when (1) 25% of multi-family residential parcels are converted to commercial land use, and (2) 25% of single-family parcels are converted to multi-family residential land use. The dotted lines link the energy self-sufficiency values of the re-zoned parcels before and after the land use change. In both cases, energy use increases while their rooftop solar capacity decreases when land use type changes, with the change in self-sufficiency more pronounced in (1). Results indicate that, if energy self-sufficiency at the parcel level is to be maintained, then strong energy efficiency measures need to be embedded in the building codes to target reduced energy consumption. Alternatively, production capacity could be enhanced through investments in community-scale or small utility-scale solar that has greater efficiencies than rooftop solar PV. While this is a highly simplified analysis with strong assumptions, the results highlight the importance of considering land use planning in tandem with energy efficiency and decarbonization goals.

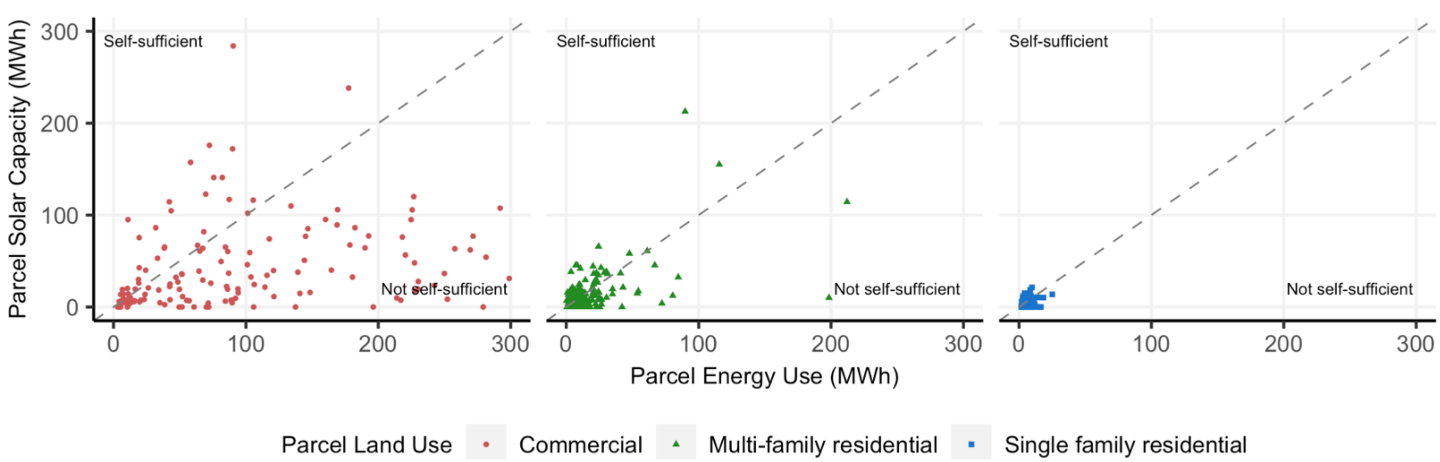

Figure 2. Energy self-sufficiency by land use type;
Note: some points are not displayed in order to scale down axes and enable better visualization.

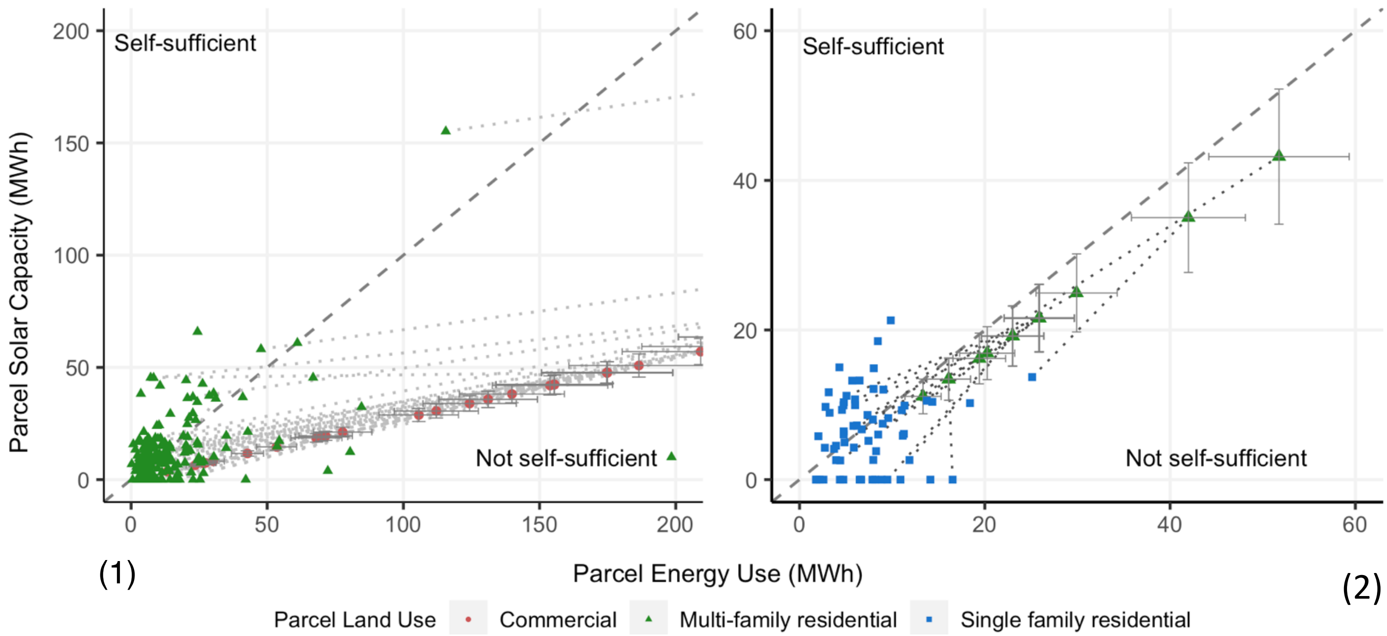

Figure 3. Bootstrapped estimates of energy self-sufficiency for parcels changed from (1) multi-family residential to commercial; (2) single family residential to multi-family residential.

Note: Dotted lines link "Before" and "After" energy self-sufficiency for the 25% of parcels whose land use is changed. Some points are not displayed in order to scale down axes and enable better visualization.

5. CONCLUSIONS AND FUTURE WORK

While the densification of urban areas, particularly through increasing the proportion of mixed and multi-family residential land uses is widely recommended as a pathway to greater urban energy efficiency, there is limited empirical evaluation of how energy self-sufficiency is impacted by municipal land use change. This paper proposes a workflow to examine and quantify this relationship through model setup, geo-weighted bootstrapping and analysis of policy implications. We apply this workflow to a case study of Palo Alto, a mid-sized city in California, USA, and find that land use impacts energy self-sufficiency in ways that are not captured by looking solely at energy consumption. Results indicate that planners will need to actively consider energy efficiency policies as well the choice of incentives for appropriate building- and transportation-integrated energy technologies in land use planning.

This paper represents a crucial first step in empirically quantifying the relationship between land use and energy self-sufficiency yet has several limitations. First, only a few land use change scenarios were considered, and our case study sample was limited to a mid-size city in the United States. Future work should explore more types of land use change, particularly around mixed land uses, and extend this analysis to cities with varying size, climate and demographic characteristics. A more realistic set of land use changes can simulate real-world zoning scenarios rather than simply assuming that 25% of parcels are re-zoned. Second, it is assumed that changes in land use will result in the actual "building up" of the parcel to the maximum extent possible. Previous work suggests that this might not be the case [31,32], so future work can dive deeper into appropriate scaling factors. Third, hourly and seasonal variations in energy self-sufficiency are outside the scope of this paper but are critical areas of work in the future. Finally, future iterations of this work can empirically examine the interconnections between building and transportation energy use as land use changes, which would offer a more realistic picture of urban energy use as a whole.

In conclusion, this work points to the need for a deeper understanding of land use as an underexplored pathway in urban energy efficiency and decarbonization. The proactive consideration of land use in urban energy planning will be critical to realizing decarbonization and sustainability goals of cities around the world.

ACKNOWLEDGEMENTS

The material presented in this manuscript is based in part upon work supported by a Terman Faculty Fellowship, the Emmett Interdisciplinary Program in Environment and Resources, and the U.S. National

Science Foundation (NSF) under Grant Nos. 1642315, 1461549. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of U.S. NSF. We also acknowledge the City of Palo Alto for their support and participation in this work.

REFERENCES

[1] Jain RK, Qin J, Rajagopal R. Data-driven planning of distributed energy resources amidst socio-technical complexities. Nature Energy 2017;2:17112. doi:10.1038/nenergy.2017.112.

[2] Hernandez RR, Hoffacker MK, Field CB. Efficient use of land to meet sustainable energy needs. Nature Climate Change 2015;5:353–8. doi:10.1038/nclimate2556.

[3] Ko Y, Jang K, Radke JD. Toward a solar city: Trade-offs between on-site solar energy potential and vehicle energy consumption in San Francisco, California. International Journal of Sustainable Transportation 2017;11:460–70. doi:10.1080/15568318.2016.1274807.

[4] Newman PWG, Kenworthy JR. Gasoline Consumption and Cities. Journal of the American Planning Association 1989;55:24–37. doi:10.1080/01944368908975398.

[5] Mohammadi N, Taylor JE. Urban energy flux: Spatiotemporal fluctuations of building energy consumption and human mobility-driven prediction. Applied Energy 2017;195:810–8.

[6] Ewing R, Rong F. The impact of urban form on U.S. residential energy use. Housing Policy Debate 2008;19:1–30. doi:10.1080/10511482.2008.9521624.

[7] Allegrini J, Dorer V, Carmeliet J. Influence of the urban microclimate in street canyons on the energy demand for space cooling and heating of buildings. Energy and Buildings 2012;55:823–32. doi:10.1016/j.enbuild.2012.10.013.

[8] Chen Y, Hong T, Piette MA. Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis. Applied Energy 2017;205:323–35.

[9] Pisello AL, Castaldo VL, Taylor JE, Cotana F. Expanding Inter-Building Effect modeling to examine primary energy for lighting. Energy and Buildings 2014;76:513–23. doi:10.1016/j.enbuild.2014.02.081.

[10] Perini K, Magliocco A. Effects of vegetation, urban density, building height, and atmospheric conditions on local temperatures and thermal comfort. Urban Forestry & Urban Greening 2014;13:495–506. doi:10.1016/j.ufug.2014.03.003.

[11] Bouyer J, Inard C, Musy M. Microclimatic coupling as a solution to improve building energy simulation in an urban context. Energy and Buildings 2011;43:1549–59. doi:10.1016/j.enbuild.2011.02.010.

[12] Toparlar Y, Blocken B, Maiheu B, van Heijst GJF. A review on the CFD analysis of urban microclimate. Renewable and Sustainable Energy Reviews 2017;80:1613–40. doi:10.1016/j.rser.2017.05.248.

[13] Yang Z, Gupta K, Jain RK. DUE-A: Data-driven Urban Energy Analytics for understanding relationships between building energy use and urban systems, 2018: 2018.

[14] Hoch CJ, Dalton LC, So FS, editors. The Practice of Local Government Planning, 3rd Edition. 3rd edition. Washington, DC: Intl City County Management Assn; 2000.

[15] Ko Y. Urban Form and Residential Energy Use: A Review of Design Principles and Research Findings. Journal of Planning Literature 2013;28:327–51. doi:10.1177/0885412213491499.

[16] Kaza N, Curtis MP. The Land Use Energy Connection. Journal of Planning Literature 2014;29:355–69. doi:10.1177/0885412214542049.

[17] Sarralde JJ, Quinn DJ, Wiesmann D, Steemers K. Solar energy and urban morphology: Scenarios for increasing the renewable energy potential of neighbourhoods in London. Renewable Energy 2015;73:10–7. doi:10.1016/j.renene.2014.06.028.

[18] Mirkovic M, Alawadi K. The effect of urban density on energy consumption and solar gains: the study of Abu Dhabi's neighborhood. Energy Procedia 2017;143:277–82. doi:10.1016/j.egypro.2017.12.684.

[19] Hirt S. The Devil Is in the Definitions. Journal of the American Planning Association 2007;73:436–50. doi:10.1080/01944360708978524.

[20] Nutkiewicz A, Yang Z, Jain RK. Data-driven Urban Energy Simulation (DUE-S): Integrating machine learning into an urban building energy simulation workflow. Energy Procedia 2017;142:2114–9. doi:10.1016/j.egypro.2017.12.614.

[21] Burger SP, Jenkins JD, Huntington SC, Perez-Arriaga IJ. Why Distributed?: A Critical Review of the Tradeoffs Between Centralized and Decentralized Resources. IEEE Power and Energy Magazine 2019;17:16–24. doi:10.1109/MPE.2018.2885203.

[22] Fotheringham AS, Charlton ME, Brunsdon C. Geographically Weighted Regression: A Natural Evolution of the Expansion Method for Spatial Data Analysis. Environ Plan A 1998;30:1905–27. doi:10.1068/a301905.

[23] Efron B. Bootstrap Methods: Another Look at the Jackknife. Ann Statist 1979;7:1–26. doi:10.1214/aos/1176344552.

[24] Tian W, Song J, Li Z, de Wilde P. Bootstrap techniques for sensitivity analysis and model selection in building thermal performance analysis. Applied Energy 2014;135:320–8. doi:10.1016/j.apenergy.2014.08.110.

[25] García-Soidán P, Menezes R, Rubiños Ó. Bootstrap approaches for spatial data. Stoch Environ Res Risk Assess 2014;28:1207–19. doi:10.1007/s00477-013-0808-9.

[26] Bill Text - SB-50 Planning and zoning: housing development: incentives. n.d. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201920200SB50 (accessed May 14, 2019).

[27] He C, Huang Z, Wang W. Land Use Changes and Economic Growth in China. Lincoln Institute of Land Policy; 2012.

[28] City of Palo Alto Utilities. Technical Support Document for the Palo Alto Solar Technical Potential Database. Palo Alto: City of Palo Alto; 2018.

[29] NREL. PVWatts Calculator. National Renewable Energy Laboratory; n.d.

[30] Kavousian A, Rajagopal R, Fischer M. Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. Energy 2013;55:184–94. doi:10.1016/j.energy.2013.03.086.

[31] Rodríguez-Pose A, Storper M. Housing, Urban Growth and Inequalities: The Limits to Deregulation and Upzoning in Reducing Economic and Spatial Inequality. Rochester, NY: Social Science Research Network; 2019.

[32] Freemark Y. Upzoning Chicago: Impacts of a Zoning Reform on Property Values and Housing Construction. Urban Affairs Review 2019:1078087418824672. doi:10.1177/1078087418824672.