SimBuild
2024

Eleventh National Conference of IBPSA-USA
Denver, Colorado
May 21 – 23, 2024

Equitable Energy Metrics for Integration into Building Performance Standard Tracking Platforms

Nicholas Long[1,2], Katherine Fleming[1], Isabel Langlois-Romero[1],
Gregor Henze[1,2], Sydney Applegate[3]
[1]National Renewable Energy Laboratory, Golden, CO, USA
[2]University of Colorado, Boulder, CO, USA
[3] Oak Ridge Institute for Science and Education, TN, USA

Abstract

Building Performance Standards (BPS) are being adopted globally and in the United States of America, where 14 different states and jurisdictions have a policy in place, and many others are under development (Department of Energy (DOE) 2023). Accurate and equitable data sources are essential to make informed decisions about focusing investment on upgrading buildings to meet jurisdictional goals. Multiple new tools have been developed related to Energy Equity and Environmental Justice (EEEJ). The resulting datasets need to be integrated into large building portfolios for quick access and better scalability. Integrating EEEJ data in a user-friendly format can help decision makers more quickly assess impacts and analyze the multitude of potentially significant metrics for which there is not yet consensus.

Many BPS ordinances in the US and Canada rely primarily on ENERGY STAR® Portfolio Manager® (ESPM) to capture building characteristics and energy and water consumption data. These datasets can then be imported into city-specific building tracking tools like the Standard Energy Efficiency Data Platform (SEED). Crucially, BPS decision makers require an efficient means of identifying buildings in priority communities to allocate resources and funding effectively. This process must integrate seamlessly with existing jurisdictional toolsets for optimal utility. This paper will demonstrate, for the case of Washington DC's (the District) data, a workflow that provides actionable data for building upgrade investment prioritization in disadvantaged communities.

Introduction

Building Performance Standards (BPS) are used worldwide as a policy mechanism to promote emissions and energy reductions in existing buildings. In the United States, BPSs originate at the federal, state, and local levels and vary by jurisdiction in terms of the metric for compliance and the building types included. Jurisdictions can adopt mandatory or voluntary policies and must decide whether to include commercial, multifamily, or single-family buildings in their ordinances. For example, in England, Wales, and Boulder, CO, the focus is on large residential buildings, while in New York City, France, and the State of Colorado, the focus—at least initially—is on medium and large commercial buildings. These policies often begin by selecting a baseline year for buildings to refer to when setting their annual (or cycle-specific) reduction targets. In some cases, targets become more stringent over time, and jurisdictions often start with one specific building type and gradually introduce other building types or lower the floor area thresholds as regulations evolve (Nadel and Hinge 2023).

As BPS programs continue to be adopted, there is a need for robust datasets in adjacent fields to make more informed decisions. This includes integrating data from active research areas such as Energy Equity and Environmental Justice (EEEJ). Various methodologies and impact indicators are being developed by groups such as the US Department of Energy (DOE), the US White House Council on Environmental Quality (CEQ), and the Environmental Protection Agency (Department of Energy (DOE) 2023b). The White House CEQ's Justice 40 (Justice40) initiative provides a framework for federal agencies to work with state and local communities to ensure that 40% of federal investments are directed to disadvantaged communities (Young, Mallory, and McCarthy 2021). Currently, Justice40 does not directly address how state and local BPS programs should meet the requirement. Although jurisdictions are not required to use the Justice40 goals or metrics, leveraging the existing EEEJ research and disadvantaged community (DAC) status may reduce internal administrative and financial burdens in federal funding applications to support a jurisdiction's local policy initiatives. The Climate and Economic Justice Screening Tool (CEJST) leverages the Justice40 definition of a disadvantaged community (e.g., low income, high unemployment, linguistic isolation, etc.), which is a community that can benefit from new and existing federal investments in these categories.

During the policymaking process, jurisdictions must decide which buildings to include in a BPS. Jurisdictions worldwide have different mixes of industrial, commercial, and multifamily building types in their ordinances. A jurisdiction may choose to include certain building types if it can conduct impact studies, but not all jurisdictions have this capacity. In this study, a building type of interest is multifamily properties, which often have unique barriers to compliance, such as a lack of upfront capital, time, or technical capacity (Nedwick et al. 2020). The District has become a blueprint for implementing equitable BPS policies in the multifamily affordable housing sector in the United States. The District's commitment to equity in this sector depends not only on local energy and emissions reduction goals but also on a commitment to meaningful outcomes such as lower energy bills and improved environmental quality in disadvantaged communities. For an equitable BPS, it is essential to consider multifamily buildings, as improving them can have a direct impact on families that have previously been ignored. Reducing energy bills and improving indoor environmental quality, for example, can provide tangible solutions to historic inequities in the built environment. This study focuses on multifamily housing to show what free tools and workflows jurisdictions can use to address perceived barriers to BPS compliance in multifamily buildings, which often have a significant burden to meeting investment targets but have the potential to improve the quality of life for families dramatically.

Linking BPS-built environment data and EEEJ data is necessary to provide the BPS program administrator with more actionable information when tracking their building portfolio over multiple years. The process of tracking 100's to 1,000's of buildings over a 5- or 6-year BPS program is challenging, and many smaller jurisdictions leverage spreadsheet programs, but custom solutions have been developed for more complex portfolios. This paper discusses how the Standard Energy Efficiency Data Platform (SEED) and SEED-based applications have been extended to not only track BPS programs but also integrate and optimize investments based on EEEJ data. A new API-based tool called the Building Efficiency Targeting Tool for Energy Retrofits (BETTER) (Szum et al. 2018; LBNL 2023; Li et al. 2019) was used to calculate potential energy savings and investments providing a modern and user-friendly approach to Johnson Control's LEAN model (Donnelly, Kummer, and Drees 2013) and ASHRAE's Inverse Model Toolkit (Kelly Kissock et al. 2003).

Background

Benchmarking and Building Performance Standards have been a worthwhile incentive for jurisdictions and building owners to track energy, water, and emissions by building. In the US, commercial and residential buildings account for 40% of energy consumption, 35% of emissions are caused by buildings, and 70% of electricity alone is attributed to buildings (US Energy Information Administration 2021a; 2021b). The need to achieve climate goals is critical for many jurisdictions; benchmarking and BPS programs enable jurisdictions to track and assess progress toward their goals. However, tracking buildings is challenging because the data are confusing. For example, there may be more than one building address in a building, or the data reported by the owner may be incorrect. One of the mechanisms to improve data quality is for jurisdictions to provide public access to non-proprietary information. In general, access to building data has increased significantly over the past decade, and many jurisdictions are making public data available for evaluation.

Jurisdictions that track buildings (not just tax lots) are becoming more commonplace due to new policies and public interest. In the context of BPS, buildings that do not meet the requirements may need to be retrofitted to meet compliance. The jurisdictions responsible for BPS should have access to the best data to make informed decisions, such as selecting building types, floor area thresholds, and exemption criteria. Another decision point is prioritizing investments in building retrofits for disadvantaged communities. This paper describes in more detail how the building data are tracked in SEED, how the disadvantaged communities and energy burden indicators are described, and how BETTER is used to provide upgrade recommendations.

The Standard Energy Efficiency Data Platform

SEED is an open-source, free, web-based application that is deployable on local or cloud-based resources (Taylor et al. 2012). The US Department of Energy (DOE) launched the SEED project in 2012 to reduce a jurisdiction's administrative burdens, such as costs, staff, and user time to manage benchmarking and BPS policies. Many cities have too few resources and staff. It is costly to assign new tasks to existing staff to track benchmarking and building performance standards. SEED can be hosted by the jurisdiction, or there are several SEED-based projects that cities can purchase that are less expensive than building a custom solution or using a specialized spreadsheet to track issues.

At SEED's core is a tabular view of the buildings (see Figure 1), which the jurisdiction tracks or evaluates. In SEED, data are imported from disparate data sources such as ENERGY STAR® Portfolio Manager® (ESPM), spreadsheets, or GeoJSON files. Each import requires the user to map the fields of the incoming file to the canonical fields already present in SEED. New fields are added dynamically as required. The result is a cohesive and robust list of buildings over multiple years (cycles), linked parcels, utility meter data, lists of scenarios and energy efficiency measures, and sensor data. Each data import matches records based on a set of "matching fields" and merges data together, providing a single record per building identifier. Data quality checks ensure the data are within the required bounds, and labels can be automatically applied to problematic buildings. Furthermore, SEED can directly escalate building data quality issues to Salesforce to be tracked or emailed to building owners.

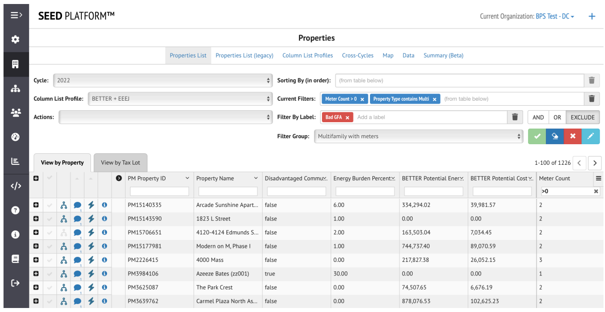

Figure 1 SEED Platform inventory page with buildings

SEED provides a user interface that allows profiles of user-displayed volumes as well as filter groups to view buildings that match specific criteria quickly. SEED has analysis pipelines to enrich data from external analyses or services (e.g., BETTER, GHG calculations, or the newly added EEEJ functionality) (Long et al. 2020).

Disadvantaged Community and Energy Burden

This work is consistent with the Justice40 Initiative, which uses the White House's definition of a disadvantaged community. The Justice40 Initiative mandates that 40% of the benefits of federal programs go to disadvantaged communities (Presidential Executive Order 14008 of January 27 2021). By using the same definition, jurisdictions using SEED can identify eligible buildings for Justice40 funding. As described in Executive Order 14008 on Tackling the Climate Crisis at Home and Abroad (Presidential Executive Order 14008 of January 27 2021), disadvantaged communities have historically been marginalized and overburdened by pollution. There has been underinvestment in housing, transportation, water and wastewater infrastructure, and healthcare. The White House has developed a Climate and Energy Justice Screening Tool (Council on Environmental Quality 2022) that defines a methodology for categorizing a community as disadvantaged using several indicators of burden as well as socioeconomic factors. The CEJST tool was developed to create a uniform definition for disadvantaged communities that can be used by all federal agencies implementing programs in support of the Justice40 Initiative (Council on Environmental Quality (CEQ) 2022).

The indicators of burden used in the CEJST tool are defined using data from public sources and are organized into eight categories: 1) climate change, 2) energy, 3) health, 4) housing, 5) legacy pollution, 6) transportation, 7) water and wastewater, and 8) workforce development. Each category is assigned to a 2010 census tract comprising one socioeconomic factor and one or more related indicators. The socioeconomic factor is the condition of being in a census tract at or above the 65th percentile for low income for most categories of burden. Low income is defined as being at or below 200% of the federal poverty level. The notable exception is the workforce development category, which has a socioeconomic factor defined as having more than 10% of people over 25 with less than a high school diploma.

The energy burden category is defined as being in a census tract that is a) either at or above the 90th percentile for energy cost or at or above the 90th percentile for PM2.5 in the air, and b) at or above the 65th percentile for low-income (Council on Environmental Quality 2022).

A community is categorized as a DAC by CEJST if one of the following conditions is true:

- The community is in a census tract that a) meets the threshold for burden in at least one of the defined categories of burden and b) meets the threshold for the associated socioeconomic indicator.
- The community is in a census tract surrounded by disadvantaged census tracts and is at or above the 50th percentile for low income.
- The community is in a census tract that is located on Federally Recognized tribal land.

Washington DC's Building Energy Performance Program: Multifamily

If successful, BPS policies can move the United States closer to meeting greenhouse gas emission reduction targets while improving the health of building occupants. However, the equitable distribution of economic, social, and environmental benefits of BPS depends mainly on the design of these policies (Nedwick et al. 2020). To design building performance standards equitably, policymakers must investigate various subgroups of their building stock, engage stakeholders, and conduct analysis to inform the policymaking process.

One critical decision for BPS policymakers to consider is whether to include multifamily buildings in their ordinance. Currently, three states and 11 cities in the US have adopted BPS policies (ASHRAE 2023). The District's Building Energy Performance Standards (BEPS) was one of the first programs to adopt an ordinance in the US and included multifamily in the policy. The District included the multifamily sector due to the localized research they conducted to understand the multifamily building stock (DOEE 2019). For example, the District worked closely with the National Housing Trust (NHT) and the Housing Association of Nonprofit Developers (HAND) to identify critical recommendations for implementing BPS in the multifamily sector (NHT and HAND 2019). This study, alongside leveraging CoStar data to help identify Naturally Occurring Affordable Housing (NOAH) in the District, suggests the significant financial capacity it takes to understand local multifamily buildings. The District's Green Bank provides access to capital and innovative financing solutions to prioritize an inclusive and affordable clean economy, and to connect the District's Green Bank with affordable housing, the Affordable Housing Retrofit Accelerator (AHRA) was created. The AHRA offers technical assistance to qualifying affordable housing buildings to meet the energy standards set in the BEPS program. Not all jurisdictions will have access to comprehensive analyses nor partnering organizations; therefore, this paper will demonstrate the free analyses leveraged through SEED as a cost-effective way for jurisdictions to prioritize equity in the multifamily building stock and estimate the cost savings potential of associated upgrades. The equity analyses integrated into SEED are designed to enable jurisdictions that lack the financial capacity to conduct high-level impact analyses to use a free workflow which prioritizes buildings by national equity standards and evaluates high-level assumptions about the cost savings from upgrades to their building stock.

BETTER

BETTER is an open-platform web application leveraging Johnson Control's LEAN and ASHRAE's Inverse Modeling Toolkit (IMT) methodologies to generate a set of change point models (i.e., piecewise linear regression models) for each meter type in a building compared to the mean outdoor air temperature. BETTER provides a set of nominal, conservative, and aggressive targets for a particular set of locations and property types. For this analysis, multifamily buildings in the District have already been benchmarked by the BETTER team. Each change point model is compared to the benchmark value, and the savings (if any) are cataloged for the user.

BETTER also provides a range of high-level, low-to-no-cost energy conservation measures (ECMs) that a building can potentially undergo to reach the benchmarked value. These results are a powerful method to provide high-level screening results for a portfolio of buildings on which properties to prioritize. A user can quickly sort the results and prioritize buildings with the highest energy or cost savings or those with the most aggressive GHG reductions.

Methodology

The overarching goal of this analysis is to assess whether (and to what extent) the weighing of an equity metric influences the types of buildings that would be selected for "Green Bank" style investments. The result must be easily translated into action by a SEED or SEED-based user. This requires an easily understandable and defensible workflow with readily available user interfaces.

The methodology is divided into six major portions, including 1) data ingestion and preprocessing using the SEED Platform, 2) addition of EEEJ metrics to SEED, 3) running BETTER, 4) development of portfolio prioritization to select buildings, 5) comparison of buildings selected with and without EEEJ metrics, and 6) demonstration of how the prioritized metric can be used in SEED. Figure 2 shows a high-level workflow diagram of the process.

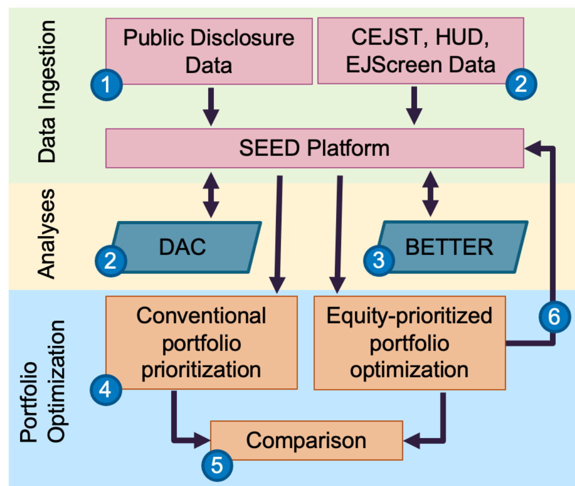

Figure 2 Workflow diagram of the methodology (the highlighted steps are described in the text)

SEED Platform Data Ingestion and Analysis

The SEED Platform was used as a data repository and connector for the buildings evaluated in this analysis. The selected dataset was from the District and included its public disclosure data (Department of Energy and Environment 2018) and data on multifamily affordable housing provided directly by the District. The District's BPS policy uses Building Energy Analysis Manager (BEAM), a SEED-based application, to manage its buildings (ClearlyEnergy 2023). BEAM directly extends SEED's code base, and extensions added to SEED end up directly in BEAM. The data import process includes the following:

1. Download public disclosure data (Department of Energy and Environment 2018).

2. Digest the CSV file into separate files that can be uploaded to SEED. This included breaking down the building properties for each year and creating JSON blocks of meter data.
3. Deploy an instance of SEED in the cloud to enable multiuser access for the analysis.
4. Use SEED's API and PySEED (Long et al. 2023) to upload, match, and merge the District's property data.
5. Run SEED's data quality checks to flag buildings with poor data, e.g., no floor area, building types, and more than zero meters.
6. Create SEED filter groups to display only multifamily buildings.
7. Add other required information, such as ASHRAE climate zone and eGrid Subregion, by uploading the file and mapping it correctly.

This SEED instance was used as the main database for the analysis. Figure 3 represents multifamily building characteristics for buildings under BPS for 2022. Most multifamily buildings are less than 250,000 square feet. There is a bimodal distribution in terms of when the buildings were built, with two major development periods between 1925 and 1975 and another in 2000 to the present. Most buildings have two meters (electricity and natural gas), but only a few have only electricity, and some have either diesel, fuel oil, or district energy. Only the buildings with electricity and natural gas were evaluated in this analysis.

EEEJ Integration

In an effort to make actionable and informed decisions, a streamlined process was used to efficiently process data related to Community Environmental Justice and Sustainability Trends (CEJST). This included extracting consensus metrics, identifying communities by priority, and visualizing impactful data.

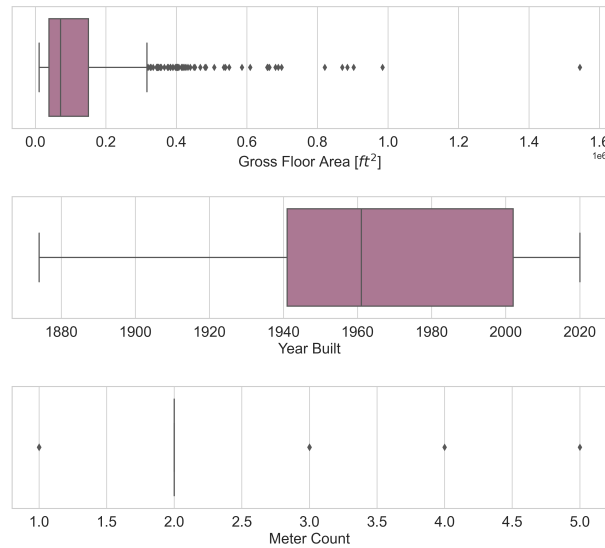

Figure 3 Multifamily Building Characteristics in the District (for buildings required under BPS ordinance)

An EEEJ analysis feature was added to the SEED Platform. This analysis can be applied to buildings to retrieve disadvantaged community classification status and other data related to EEEJ. It uses data from several different sources:

1. Disadvantaged community classification and energy burden information from the CEJST dataset (Council on Environmental Quality (CEQ) 2022).
2. US Department of Housing and Urban Development (HUD) assisted multifamily buildings and public housing developments (US Department of Housing and Urban Development (HUD) 2023a; 2023b).
3. The Environmental Protection Agency's (EPA) Environmental Justice screening and mapping tool (EJScreen) report (US Environmental Protection Agency (EPA) 2023b) includes environmental justice indices as well as demographic, environmental, and socioeconomic indicators. To learn more about the EJScreen data, visit the EPA's EJScreen website (US Environmental Protection Agency (EPA) 2023a).

Providing the building address or latitude and longitude is a requirement for performing the analysis. Outputs include disadvantaged community classification and energy burden status that can be used to prioritize buildings for energy efficient upgrades.

The first step in conducting the analysis is to select one or more buildings from the SEED inventory page and select Run Analysis from the Actions dropdown menu. The analysis first retrieves a census tract geoid and latitude and longitude data for each building using the census geocoder service (United States Census Bureau 2023). Using the census tract information, a match is made with the CEJST and HUD datasets to retrieve the following information:

- DAC classification of the census tract
- whether the census tract is classified as low-income
- whether the census tract is energy-burdened
- the energy-burdened percentile of the census tract
- the share of neighboring disadvantaged tracts
- the number of affordable housing locations (multifamily assisted and public housing developments) in the census tract

Additionally, a link to view the EJScreen report for a 1-mile radius around the building is provided.

The retrieved information is stored in the analysis section, and the DAC classification and other fields are stored in each building record in the SEED Platform so that they can be used for filtering, labeling, and prioritization activities.

BETTER Analysis and ECM Cost Methodology

BETTER was configured with a nominal savings target to calculate nominal (median) potential energy savings and a minimum R^2 of the change points set to the software's recommended value of 0.6 to provide a reasonable number of models to be generated. The energy savings calculation is based on BETTER's benchmarked nominal change point model based on building type and climate zone. There are several evaluation factors, including the cooling parameter slope, the cooling balance setpoint, the base load reduction, the heating balance setpoint, and the heating parameter slope.

Through the LEAN project (Donnelly, Kummer, and Drees 2013), heuristics were created to provide high-level ECMs. BETTER provides a list of recommended measures for each building. The measures are high-level recommendations that can be determined by comparing two change point models (the actual building and the benchmarked building).

Kontokosta et al. and Lai, et al. (Kontokosta, Spiegel-Feld, and Papadopoulos 2020; Lai et al. 2022) evaluated over 3,600 audit reports from New York City's Local Law (LL) 84 (benchmarking) and LL87 (auditing) (City of New York 2009; 2012). Each audit was cross-referenced with permit data to determine which ECMs were implemented. Thus, the analysis determined the cost of implementation for multifamily and office buildings ECMs. The cost per ECM values were presented by building floor area with mean, median, and standard deviation. This data should be used cautiously as it only applies to offices and multifamily buildings in New York City and should be evaluated before use in other jurisdictions.

For this analysis, the mean cost was selected to represent the cost of implementing the measures recommended by BETTER. However, the measures between the LL87's data and BETTER data were not a direct mapping. In addition, the mappings were not mutually exclusive, and if a BETTER ECM is mapped to more than one LL87 ECM, then the costs incurred were assumed to have been incurred more than once. Table 1 shows the final costs of the ECMs after mapping to BETTER's recommended measure.

Table 1 Cost of ECMs based on BETTER ECM names

ECM	Mean ($\$/ft^2$)	Median ($\$/ft^2$)
Add/Fix Economizers	0.26	0.25
Add Wall/Ceiling/Roof Insulation	0.80	0.36
Decrease Heating Setpoints	0.26	0.25
Decrease Infiltration	0.80	0.36
Increase Cooling Setpoints	0.26	0.25
Increase Cooling System Efficiency	0.40	0.15
Increase Heating System Efficiency	0.39	0.10
Reduce Equipment Schedules	0.15	0.08
Reduce Lighting Load	0.05	0.03
Reduce Plug Loads	0.15	0.08
Upgrade Windows to Improve Thermal Efficiency	0.80	0.36
Upgrade Windows to Reduce Solar Heat Gain	0.80	0.36

BETTER is configured to run directly within SEED. This provides a simple interface for running multiple buildings and automatically transferring the results into SEED's column-based structure. The data are sent to BETTER using BuildingSync (Long et al. 2021) with data auto-mapped from the SEED columns for the building characteristics (property type, location, gross floor area) and the monthly meter data for each meter type (typically electricity and natural gas).

Each BETTER result was post-processed to calculate the total cost of ECM implementation (Equation 1) based on the mappings and implementation costs provided by the prior analysis of the LL87 audit results.

$$\mathrm{C_{impl}} = \mathrm{A} \sum_{k=0}^{n} C_k \qquad (1)$$

where C_{impl} is the implementation cost of all measures for the building, k is each ECM, n is the total number of ECMs, C_k is the implementation cost of the ECM per building floor area, A. The other variables of direct interest from BETTER that persisted in the SEED's building record were:

- Potential Cost Savings (USD$/year)
- Potential Energy Savings (kWh/year)
- Potential GHG Emissions Savings ($MtCO_{2e}$/year)
- BETTER Measure Recommendations

Portfolio Prioritization Methodology

The overall result of this analysis is a prioritized list of buildings that should undergo upgrades based on an investment threshold. The variables selected for prioritization must be readily available and translated into a column-based sorting system similar to Microsoft Excel's column-based sorting.

In this work, the main goal of portfolio prioritization is to maximize potential energy cost savings for the building owner. However, competing objectives lead to a multi-objective prioritization with tradeoffs that should be evaluated by the jurisdiction manager when considering the entire portfolio. The objective function variables used in this analysis include the total potential energy cost savings of the selected buildings, the total number of buildings selected for upgrade, and the percentage of buildings in a DAC census tract. In prioritizing the portfolio, the following variables were used to create the analysis parameter space.

- Energy Burden Percentile Weight, w_1, [0 to 1]
- Energy Cost Savings Weight, w_2, [0 to 1]
- Number of buildings selected, N, [50 to $\boldsymbol{\mathcal{N}}$]

The prioritization function was a weighting of the objective functions and was then sorted in descending order. The sorting is not needed for calculating the analysis metrics but provides the jurisdiction manager with the list of buildings in the order they would ideally provide investment. Equation 2 is the objective function used to prioritize the portfolio.

$$\begin{aligned} S_p &= sort \sum\nolimits_{n \epsilon \mathcal{N}} w_1 EB_{s,n} + w_2 C_{s,savings,n} \\ s.t.\ & w_1 + w_2 = 1, \\ & n < \boldsymbol{\mathcal{N}} \end{aligned} \quad (2)$$

where S_p is the prioritized set of buildings, $EB_{s,i}$ is the scaled energy burden percentile, and $C_{s,savings,i}$ is the scaled energy cost savings for each building, i. $\boldsymbol{\mathcal{N}}$ is the total number of buildings in the portfolio. The scaling was accomplished by dividing each instance of EB and $C_{savings}$ by EB_{max} and $C_{savings,max}$, respectively.

The parameter space was sampled 10,000 times using a Latin Hypercube Sampling (LHS) (Macdonald 2009; Helton and Davis 2003) algorithm to generate equal distributions for the entire parameter space. (With a 0.01 step in weights and including all counts of buildings, the whole mesh would be 8,240,000–this is straightforward to run; however, running with LHS provides improved interpretability of the results by not overcrowding the plots.) Each portfolio was then evaluated to identify the most important indicators. Note that each prioritized portfolio instance had a variable number of buildings selected. Key indicators included:

- Number of buildings in portfolio instance, count
- Instance of the energy burden weight, ratio
- Total portfolio energy cost saving, million USD$
- Total portfolio GHG emissions savings, mt_{CO2e}
- Total portfolio cost to implement ECMs
- Total cost of savings (which was calculated and shown in Equation 3), USD$ per kWh saved
- Percent of buildings in DAC, %
- Statistics on energy burden percentile (min, median, mean, max, standard deviation)

$$CoS = \sum\nolimits_{n \epsilon \mathcal{N}} \frac{Cost\ of\ ECM\ Implementation_n}{Potential\ Energy\ Savings_n} \quad (3)$$

where CoS is the Cost of Savings, n is the specific building for the selected subset of buildings, $\mathcal{N}$ (not bolded).

Simulation Analysis

An analysis was carried out using the District's public disclosure data. The building records were imported, cleaned, matched, and verified. The resulting dataset included 4,206 buildings for the reporting year 2022 (the most recent year for which data was reported for the District). Of the 4,206 unique buildings, only 3,199 were labeled as having a BPS target, and 1,256 were identified as multifamily. After filtering out common data issues such as missing square footage, missing location, and missing meter data, the resulting dataset contained 1,226 multifamily buildings.

Figure 4 shows the distribution of the multifamily buildings located in the District. Most buildings have a weather normalized site energy use intensity between 40 and 80 kBtu/ft^2/year. In the District, the initial BPS target for multifamily is based on the ENERGY STAR Score, which has been set at a value above 66, indicating that about two-thirds of the buildings are already compliant.

The building characteristics and meter data were translated to BuildingSync and run through BETTER to determine estimated energy and cost savings. They were then sent to an EEEJ-based tool to assess the impact of equity.

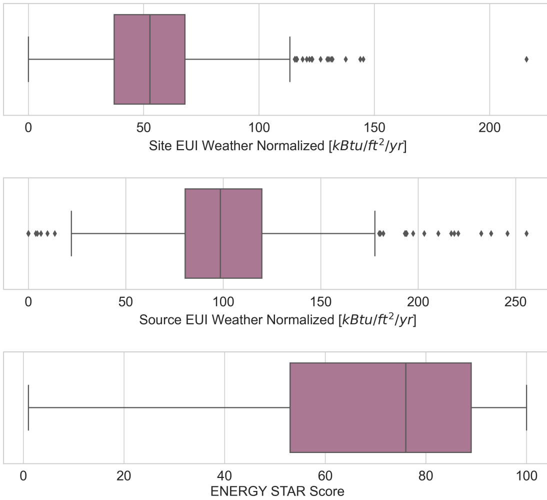

Figure 4 Site EUI, source EUI, and ENERGY STAR Scores for multifamily buildings for 2022

EEEJ Analysis

SEED was used to perform the EEEJ analysis. The public disclosure data provided by the District already contained building addresses, but more importantly, the building latitude and longitude were already populated. Each multifamily building was selected in SEED, and the EEEJ background analysis was performed. Within the EEEJ background task, each building was updated with EEEJ metrics, including energy burden percentile, DAC flag, and several others. The EEEJ analysis was completed for every building.

BETTER Analysis

Similar to the EEEJ analysis, within SEED, buildings in parcels of 100 were selected and sent through SEED's BETTER background analysis. The analysis took several hours to run for all parcels due to the computation time on the BETTER platform. The BETTER analysis was configured to use the pre-determined benchmark values for projected energy, cost, and GHG savings so that the data could be processed in batches of 100 parcels without changing the benchmark value.

Of the 1,226 cleansed multifamily buildings, 824 buildings successfully ran through BETTER. Most failed because the R^2 values for the change point models were not significant. This typically occurred when the energy data did not show a strong trend in outdoor air temperatures.

Discussion and Results

The resulting dataset included 1,256 multifamily buildings, 311 of which were identified as being located in DAC census tracts. Using the District-provided list of affordable housing and NOAH buildings, 40% of affordable housing buildings are identified by the DAC flag. In comparison, only 23% of NOAH buildings are identified by the DAC flag.

Detailed results from BETTER were downloaded for each building using PySEED. The results were post-processed using Python and showed a wide range of change point model characteristics. Figure 5 shows the 3-parameter electricity change point models. Overlayed on all change point models (in gray) are the 10th, median, mean, and 90th percentile of the change point models. A few dozen buildings fall outside the 90th percentile and a few fall below the 10th percentile. Based on the plot, the baseload parameter (the horizontal line) shows a skewness of values towards the bottom (median less than mean). The cooling change point temperature ranges from 52°F to 64°F (11°C and 18°C).

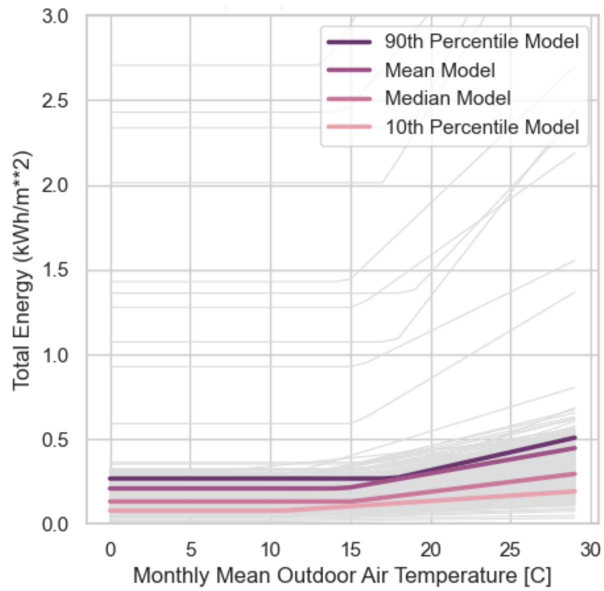

Figure 5 All 3P change point models for electricity

There were 188 buildings with a 5-parameter electricity change point model. Figure 6 shows a similar plot to Figure 5, where all change point models (gray) are plotted underneath the select metrics. As it is impossible to know the exact reason for a non-linear cold temperature dependency on electricity, it is assumed that these buildings would include electric heating or reheat. The better-performing electric heat/reheat change points are around 7°C (45°F).

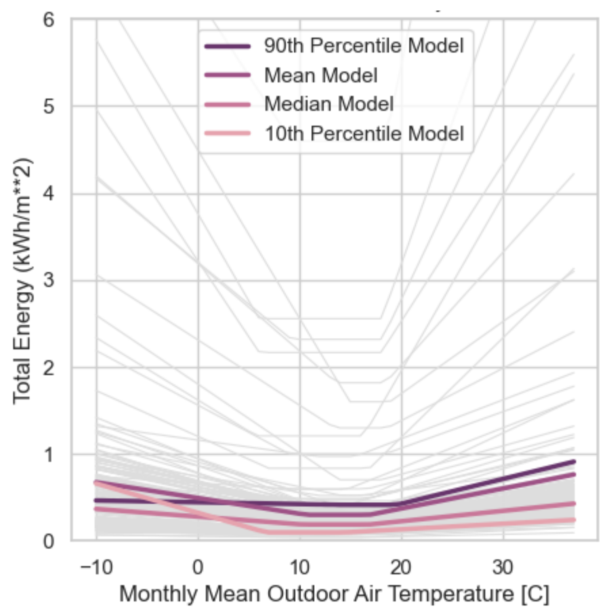

Figure 6. All 5P change point models for electricity

Portfolio Prioritization

This section describes the results of running the 10,000 portfolio prioritization models. The analysis results were exported from SEED and post-processed using Python and Jupyter Notebooks. Figure 7 shows 10,000 data points, and each data point represents a group of n buildings with total energy savings compared to the cost of implementing all ECMs for the *n* buildings. The color and size indicate the percentage of the *n* buildings in a DAC census tract.

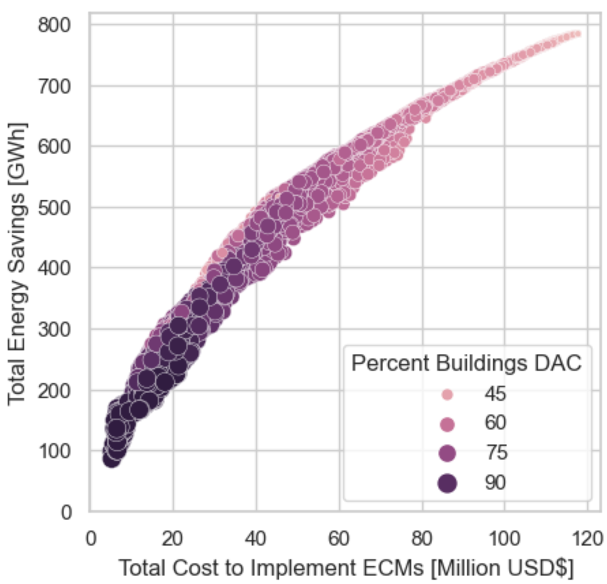

Figure 7 Portfolio prioritization total energy savings based on implementation costs

The figure shows that the return on energy savings decreases the more money is invested in ECMs. Furthermore, there is a point at which only small energy savings can be achieved by focusing on a high percentage of DAC buildings, as the number of buildings is small. At the top right are the largest energy savings and the highest investments; however, these buildings also have low percentage DAC investments. Fixing the cost of investment at a max of $30M shows that there is a slight energy savings difference between investing in a low percentage and a high percentage of DAC buildings. This result shows the potential of providing jurisdiction managers with additional data to invest in DAC census tracts.

Figure 8 shows the number of buildings, *n,* that can be improved based on the percentage of DAC buildings in *n.* The y-axis shows the cost of implementing the investment compared to the total potential energy saved (for all *n* buildings). In general, the more buildings selected, the higher the cost per kWh saved and the lower the cost per kWh saved if only a few (prioritized) buildings are affected. The figure's red and green X's are the Pareto optimal fronts. The red X's have no constraint on the number of buildings; however, the green X's have a target number of 225 to 275 buildings. Suppose there is a minimum number of buildings that a jurisdiction wants to impact. In that case, there is a Pareto optimal front showing that the more DAC buildings impacted, the lower the cost of savings (less money invested per kWh saved).

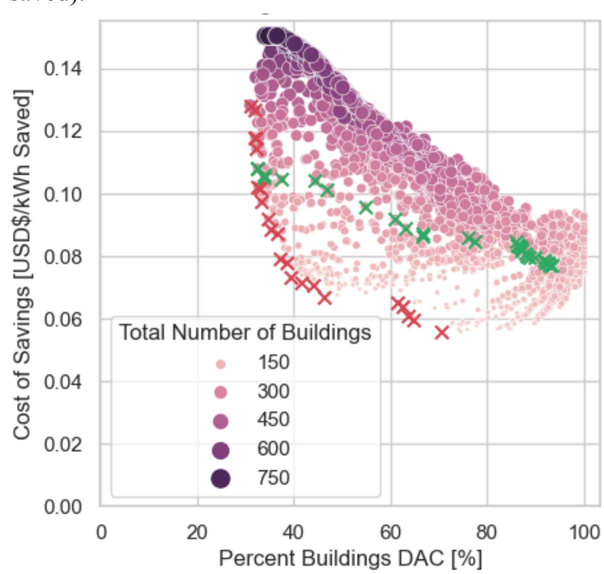

Figure 8 The result of each portfolio analysis given $30 million investment based on the cost of savings per percent DAC buildings selected in a portfolio. Red crosses indicate the Pareto front for an unconstrained number of buildings selected; green crosses are the Pareto front for 225 to 275 buildings selected.

Conclusion

Leveraging public disclosure data, EEEJ, and BETTER allows for better decision-making that can help prioritize investments in historically disadvantaged and underinvested communities. Multiple metrics were evaluated in this analysis, including total potential energy cost savings, the number of buildings impacted, and the percentage of buildings in disadvantaged communities. Altogether, the number of dimensions is too large to make reasonable decisions; however, assuming a minimum number of buildings to invest in and a maximum investment amount, a jurisdiction can generate a DAC curve, see Figure 9. The curve shows how heavily the jurisdiction should weigh the energy burden percentile metric to achieve an impact on the number of buildings in a DAC census tract. For example, to achieve the maximum number of buildings, weighting the energy burden by one will result in ~85% of DAC buildings, but weighting by 0.45 results in slightly more DAC buildings. This curve changes depending on the available investment and is unique for each jurisdiction.

There is a clear tradeoff between all of these variables. The findings illuminate the need for streamlined, robust equity-prioritization in a jurisdiction's BPS policy for the beneficial outcomes to be distributed across a community, especially to those historically disinvested buildings and communities. Furthermore, without a clear portfolio equity prioritization, a jurisdiction cannot ensure they comply with the Justice40 Initiative and realize decarbonization in disadvantaged communities.

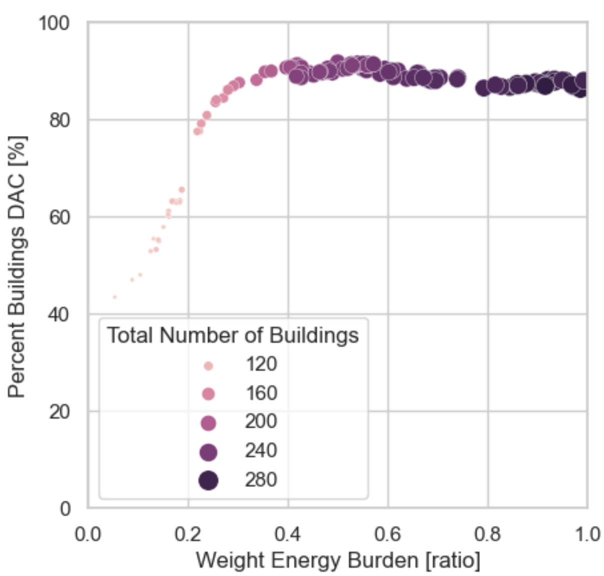

Figure 9 Weight of the energy burden percentile field and the resulting number of buildings and percent DAC buildings identified.

Table shows the results between rank sorting $30M investments in buildings based on sorting solely on potential energy cost savings versus including a weighting factor of 0.52 for the energy burden percentile. The 0.52 weighting value was chosen based on a near-optimal DAC impact based on Figure 9.

Table 2 Prioritizing DAC with $30M ECM Investment

Metric	Units	No Weight	With Weight
Number of Buildings Impacted	Count	93	241
Potential Energy Savings	GWh	388	365
Potential GHG Savings	$MtCO_{2e}$	103,200	92,200
Potential Cost Savings	Million USD$	33.0	28.4
ECM Implementation Cost	Million USD$	30.0	30.0
Percent buildings in a DAC census tract	Percent	42.0	90.5

This analysis is only the beginning of more advanced efforts that need to be conducted; however, the results show promise for better prioritization of Green Bank-style investments that cities need. Distilling the metric to a simple weighting factor can help create a transparent prioritization algorithm that can be easily integrated into existing tools jurisdictions use to manage BPS ordinances.

Figure 10 shows a map of all the prioritized buildings in SEED after applying the weighting factor of 0.52 on the energy burden percentile and 0.48 on the potential energy cost savings. The shaded areas of the plot show census tracts that are marked as disadvantaged.

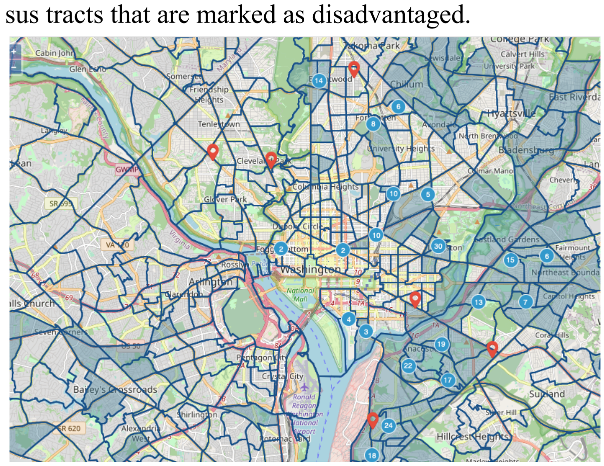

Figure 10 Looping the weighted energy burden percentile back into SEED and showing the location of the buildings.

Lastly, there is still work to be done to refine these workflows, including the following:

- Streamline the running of change point models for property types that are not already benchmarked.
- Investigate the use of other indicators, such as "share of neighboring tracts that are DAC," to identify naturally occurring affordable housing or equity-priority buildings that are not within the White House Census tracts.

Acknowledgments

The authors would like to thank the LBNL BETTER team, including Carolyn Szum, Han Li, Daniel McQuillen, and Robin Mitchell, for their technical support, as well as the extended SEED team: Alex Swindler, Alex Chapin, Hannah Eslinger, Ross Perry, and Devin Brady.

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the US Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided in part by the US Department of Energy Office of Energy Efficiency and Renewable Energy Building Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the US Government.

References

ASHRAE. 2023. Building Performance Standards: A Technical Resource Guide. www.ashrae.org/decarb.

City of New York. 2009. Local Law Number 84. https://www1.nyc.gov/site/buildings/codes/benchmarking.page.

City of New York. 2012. Local Law Number 87. https://www.nyc.gov/html/gbee/downloads/pdf/121220_audits_and_rcx_summary_forwevsitev3.pdf.

ClearlyEnergy. 2023. "Building Energy Analysis Manager (BEAM)." https://clearlyenergy.com/benchmarking?

Council on Environmental Quality. 2022. "Climate and Economic Justice Screening Tool Dataset." 2022. https://screeningtool.geoplatform.gov/en/#3/33.47/-97.5.

Council on Environmental Quality (CEQ). 2022. "Climate and Economic Justice Screening Tool: Frequently Asked Questions." 2022. https://www.whitehouse.gov/wp-content/uploads/2022/02/CEQ-CEJST-QandA.pdf.

Department of Energy (DOE). 2023. "Building Energy Codes Program - Building Performance Standards." 2023. https://www.energycodes.gov/BPS.

Department of Energy and Environment. 2018. "Building Energy Benchmarks | Open Data DC." https://opendata.dc.gov/datasets/building-energy-benchmarks.

DOEE. 2019. "DC's New Building Energy Performance Standards." Washington, DC: Department of Energy and Environment.

Donnelly, Melissa, Jim Kummer, and Kirk Drees. 2013. "LEAN Energy Analysis Using Regression Analysis to Assess Building Energy Performance." Washington, DC. www.InstituteBE.com.

Helton, J C, and F J Davis. 2003. "Latin Hypercube Sampling and the Propagation of Uncertainty in Analyses of Complex Systems." Reliability Engineering & System Safety 81. https://doi.org/10.1016/S0951-8320(03)00058-9.

Kelly Kissock, John, Pe S Jeff Haberl, Pe E David Claridge, and Pe Member ASHRAE Member ASHRAE Member ASHRAE. 2003. "Inverse Modeling Toolkit: Numerical Algorithms." In ASHRAE Research Project. Atlanta, GA.

Kontokosta, Constantine E., Danielle Spiegel-Feld, and Sokratis Papadopoulos. 2020. "The Impact of Mandatory Energy Audits on Building Energy Use." Nature Energy 5 (4): 309–16. https://doi.org/10.1038/s41560-020-0589-6.

Lai, Yuan, Sokratis Papadopoulos, Franz Fuerst, Gary Pivo, Jacob Sagi, and Constantine E. Kontokosta. 2022. "Building Retrofit Hurdle Rates and Risk Aversion in Energy Efficiency Investments." Applied Energy 306 (August): 1–26. https://doi.org/10.1016/j.apenergy.2021.118048.

LBNL. 2023. "Building Efficiency Targeting Tool for Energy Retrofits (BETTER)." 2023. https://better.lbl.gov/#.

Li, Han, Carolyn Szum, Sara Lisauskas, Ahmed Bekhit, Clay Nesler, and Steven C Snyder. 2019. "Targeting Building Energy Efficiency Opportunities: An Open-Source Analytical & Benchmarking Tool." ASHRAE Transactions, January 2019.

Long, Nicholas, Katherine Fleming, Christopher CaraDonna, and Cory Mosiman. 2021. "BuildingSync: A Schema for Commercial Building Energy Audit Data Exchange." Developments in the Built Environment 7 (February): 100054. https://doi.org/10.1016/j.dibe.2021.100054.

Long, Nicholas, Katherine Fleming, Alex Swindler, Fable Turas, and Paul Munday. 2023. "PySEED: SEED API Client." Golden: NREL. https://github.com/seed-platform/py-seed.

Long, Nicholas, Alex Swindler, Harry Bergmann, Ammon Reagan, Andrew Held, and Jeanine Longley. 2020. "Standardizing City Benchmarking and Reporting: Use Cases in Consolidating Building Data with SEED." In 2020 ACEEE Summer Study on Energy Efficiency in Buildings. Pacific Grove, CA. https://seed-platform.org/resources/Long-2020-Standardizing_City_Benchmarking.pdf.

Macdonald, Iain A. 2009. "Comparison of Sampling Techniques on the Performance of Monte-Carlo Based Sensitivity Analysis." In 11th Conference of International Building Performance Simulation Association, 992–99. http://www.ibpsa.org/proceedings/BS2009/BS09_0992_999.pdf.

Nadel, Steve, and Adam Hinge. 2023. "Mandatory Building Performance Standards: A Key Policy for Achieving Climate Goals." ACEEE Report, 1–102.

Nedwick, Todd, Lauren Ross, Todd Nedwick, and Lauren Ross. 2020. "Mandating Building Efficiency While Preserving Affordable Housing: Opportunities and Challenges." In 2020 ACEEE Summer Study on Energy Efficiency in Buildings, 1–17.

NHT, and HAND. 2019. "Recommendations for Implementing the District's Building Energy Performance Standard in Affordable Multifamily Housing." Washington, DC. https://assets.ctfassets.net/ntcn17ss1ow9/346y5gyApzmR3O6vrGYPeW/cf8d46f0377045a7aed9e7198980e463/BEPS_Recommendations_FINAL.pdf.

Presidential Executive Order 14008 of January 27, 2021. 2021. "Tackling the Climate Crisis at Home and Abroad." Federal Register. 2021. https://www.federalregister.gov/documents/2021/02/01/2021-02177/tackling-the-climate-crisis-at-home-and-abroad.

Szum, Carolyn, Han Li, Steven C Snyder, Ahmed Bekhit, Clay G Nesler, and Sara Lisauskas. 2018. "Building Efficiency Targeting Tool for Energy Retrofits (BETTER) Analytical Engine." https://doi.org/10.11578/DC.20190108.2.

Taylor, Cody, Paul Mathew, George Hernandez, and Andrea Mercado. 2012. "Standard Energy Efficiency Data (SEED) Platform: A Tool to Track and Transact Energy Data." In *2012 ACEEE Summer Study on Energy Efficiency in Buildings*, 289–97. Pacific Grove, CA.

US Energy Information Administration. 2021a. "Annual Energy Outlook 2021: Buildings Summary." Washington, DC. https://www.eia.gov/outlooks/aeo/pdf/06 AEO2021 Buildings.pdf.

US Energy Information Administration. 2021b. "Annual Energy Outlook 2021: Table A2 - Energy Consumption by Sector and Source." Washington, DC. https://www.eia.gov/outlooks/aeo/pdf/appa.pdf.

United States Census Bureau. 2023. "Census Bureau Geocoder." 2023. https://geocoding.geo.census.gov/geocoder/.

US Department of Housing and Urban Development (HUD). 2023a. "HUD Assisted Multifamily Properties Dataset." 2023. https://hudgis-hud.opendata.arcgis.com/datasets/HUD::multifamily-properties-assisted/about.

US Department of Housing and Urban Development (HUD). 2023b. "HUD Public Housing Developments Dataset." 2023. https://hudgis-hud.opendata.arcgis.com/datasets/public-housing-developments/explore?location=33.612068%2C-115.055412%2C4.54.

US Environmental Protection Agency (EPA). 2023a. "Environmental Justice Screening and Mapping Tool." 2023.

US Environmental Protection Agency (EPA). 2023b. "Environmental Justice Screening and Mapping Tool (EJScreen) Report API." 2023. https://ejscreen.epa.gov/mapper/ejscreenapi1.html.

Young, Shalanda, Brenda Mallory, and Gina McCarthy. 2021. "The Path to Achieving Justice40." Washington, DC. 2021. https://www.whitehouse.gov/ceq/news-updates/2021/07/20/the-path-to-achieving-justice40/.