Cities LEAP Building Energy Data Analysis

Final Report

March 1, 2018

City of Portland
Bureau of Planning and Sustainability
1900 SW 4th Ave, Suite 7100
Portland, OR 97201

Prepared by:
Casey Stevens
Matt Tyler, P.E.
Allen Lee, Ph.D.
Jennifer Huckett, Ph.D.

The Cadmus Group LLC/ Energy Services

This page left blank.

Table of Contents

Study Background and Objectives

Background

Buildings are responsible for one-half of carbon emissions in Portland, Oregon, and improving their performance is critical to achieving the City of Portland's (the City's) climate action goals. As part of its Climate Action Plan, under its Commercial Building Energy Performance Reporting Program,[1] the City requires commercial buildings greater than 20,000 ft² to benchmark and disclose annual energy performance through ENERGY STAR® Portfolio Manager®. Portfolio Manager relies on energy billing data to assess energy usage so it provides insights into the *actual* energy performance of buildings. Building managers, tenants, energy service providers, and utility incentive administrators can make better informed decisions to reduce energy consumption and carbon emissions when they start with an awareness of energy performance.

In 2016, the U.S. Department of Energy (USDOE) awarded financial assistance to the City through its Cities Leading through Energy Analysis and Planning (Cities-LEAP) program[2] to conduct a project intended to bridge the gap between the city's commercial building energy performance reporting ordinance and commercial building permitting process. The City contracted with Cadmus to perform the Building Energy Data Analysis, one component of the project, to evaluate application of Pacific Northwest National Laboratory's (PNNL's) Building Energy Asset Score tool and rating system to commercial buildings that report to the City through its performance reporting requirement. Unlike Portfolio Manager, Asset Score provides information on *expected* energy performance of buildings based on their design and system characteristic. A Technical Advisory Committee (TAC) provided periodic reviews of the project scope and deliverables. In addition, PNNL provided technical assistance for using the Asset Score tool and interpretation of results from the tool. They also assisted with analysis of the datasets, verifying specific data points and provided guidance with filling in the missing data points.

The project manager at the City's Bureau of Planning and Sustainability (BPS) provided two datasets to Cadmus, which contained detailed information on building characteristics that were required for the Portfolio Manager and Asset Score analyses, Portfolio Manager results, Asset Score results, and permit data for 26 selected office buildings located in Portland. Appendix A: Building Data List lists the building data provided from Portfolio Manager and Asset Score. Cadmus used correlation and regression analysis to analyze the data and identify whether building operations or specific systems – mechanical, lighting, or envelope – present the best opportunities to improve energy performance.

---

[1] Portland's ordinance is at https://www.portlandoregon.gov/bps/article/510210
[2] Information on the program can be found at https://energy.gov/eere/cities-leading-through-energy-analysis-and-planning

Objectives

The primary objectives for this Cities-LEAP analysis project were to: (1) identify key building characteristics predictive of building energy performance and (2) analyze and compare measured and predicted energy performance.

Cadmus analyzed individual building characteristic data (Asset Score data) and Portfolio Manager performance data to identify the degree of correlation between building characteristics and measured building energy performance. We compared the degree of correlation between key building characteristics to measured energy performance and scores. This included characterizing building data as physical (e.g., lighting power density, window-to-wall ratio, roof type, etc.) or operational[3] [i.e., data that could be associated with the actual operation of a building such as ENERGY STAR score or energy use intensity (EUI)]. Using this distinction, we placed the 26 buildings into one of four categories based on their Asset Score and ENERGY STAR score, that allowed comparing their asset performance (Asset Score) with their operational performance (ENERGY STAR score). We then analyzed buildings in each of these four categories to identify characteristics associated with their performance.

---

[3] The original project description categorized these types of data as "operational" to contrast them with physical characteristics and we used the same nomenclature.

Data Cleaning and Validation

Cadmus received two datasets from the City and performed data cleaning and validation, collaborating with the City to verify and correct building data as needed. This section describes the datasets, data cleaning, and data validation (both activities and results).

Datasets

The project manager at the City's Bureau of Planning and Sustainability (BPS) provided two datasets containing detailed information on 26 office buildings:

- Portfolio Manager dataset including measured building energy performance and annual consumption data
- USDOE Building Energy Asset Score dataset including energy use predictions, building physical characteristics, and operational characteristics

Each dataset included numerous variables, as listed in Appendix A: Building Data List. The Portfolio Manager data includes annual energy consumption data from calendar year 2015, the first year of Portland's Energy Performance Reporting Program.

We wanted to investigate the relationships across buildings and compare findings between the Portfolio Manager and Asset Score results based on both site and source energy. Site energy is the amount of energy used on site, while source energy accounts for energy lost during generation and delivery to the site. This distinction is important when the mix of energy sources varies across buildings. The Portfolio Manager dataset included both site energy and source energy usage for each building. This allowed us to calculate the effective source-site ratios for each building.

The Asset Score PDF report includes modeled source energy use for each building, however it is cumbersome to extract for each building in the dataset. Site energy use by end use is provided through an additional report generated by the tool. We used the effective source-site ratios as calculated from the Portfolio Manager dataset, in addition to the Asset Score site energy, to estimate the Asset Score source energy for each building.[4]

The BPS project manager also coordinated with property managers to provide read-only access to their Portfolio Manager accounts. Eleven buildings agreed to provide access and Cadmus created a new Portfolio Manager account named PORTLANDLEAP. Through the PORTLANDLEAP account, we gained access to additional detailed Portfolio Manager inputs for these 11 buildings, which allowed additional analysis. Additional inputs included the number of computers, weekly operating hours, percent occupancy, and number of employees.

---

[4] This assumption introduced a small error in the source energy estimate based on the Asset Score dependent on the mix of fuel types. However, we focus most of our analyses on site energy so the error does not have a significant effect on our findings.

Data Cleaning

The BPS project manager and TAC members performed a significant amount of work to clean these datasets, verify specific data points, and fill gaps in the data. They reviewed building plans, completed measurements using Google Earth, and conducted building visits to assess data inputs. Cadmus performed some additional data cleaning simultaneously with the BPS, collaborating to review individual data points.

DOE Asset Score data issues

Inconsistencies in building floor area. Cadmus compared floor area between the DOE Asset Score dataset and the Portfolio Manager dataset by calculating differences and percent differences. We flagged 15 sites with a percent difference in floor area greater than 25% between the two datasets as a possible issue. These discrepancies were reviewed using Google Maps to update floor area in the DOE Asset Score dataset. After this review, four sites had a percent difference in floor area greater than 25% between the two datasets. The validation process for addressing the area discrepancies is further explained in the following sections.

Incorrect HVAC equipment. Two buildings were modeled with gas-fired boilers; however, they are actually electric boilers. See below for more detail in "Unavailable natural gas usage."

Portfolio Manager data issues

Alerts regarding metered data. In the Portfolio Manager dataset, four buildings reported "Possible Issue" in the "Alert - Meter has less than 12 full calendar months of data" variable. Using the PORTLANDLEAP account, we determined for all four buildings that these alerts only applied to water meters, not energy meters. These alerts were thus not applicable to this project's analysis.

Unavailable natural gas usage. In the Portfolio Manager dataset, four buildings reported that natural gas usage was unavailable. Cadmus cross-referenced the data in the Asset Score dataset with the Portfolio Manager dataset and found that two of these buildings were all-electric with no gas equipment, per the Asset Score inputs. According to the Asset Score inputs, the other two buildings were modeled with gas-fired boilers. Upon verification with the building engineers for these two sites, however, we determined they were in fact all-electric with no gas equipment. The PNNL TAC member then updated the Asset Score simulation models to include electric boilers, rather than gas boilers.

Unavailable 1-100 Score. In the Portfolio Manager dataset, one building reported "Not Available" for the score. Using the PORTLANDLEAP account, we determined that the building was not eligible for a score because more than 25 percent of the floor area was College/University, which is a non-scoreable building-use type. Cadmus omitted this building from the Portfolio Manager dataset in further analyses. Asset Scores do not have the same building-use type restrictions, thus we retained the building in the Asset Score dataset.

Table 1 provides information on the variables in the Asset Score dataset. The table indicates whether variables are calculated, inferred, user-entered, or verified onsite and how this affects the analysis.[5] When values are inferred using defaults, then the variability and accuracy are reduced.

Table 1. Asset Score Variable Descriptions

Variable	Estimated/User-Entered
Floor Area	User-entered, verified onsite or via Google Earth
Number of Floors	User-entered
Lighting Power Density	Inferred based on on-site verification of lamp types and percent area served.
Heating Efficiency Value	7 user-entered, 16 inferred based on heating type, fuel type, and year of manufacture
Cooling Efficiency Value	3 user-entered, 19 inferred based on cooling type, fuel type, and year of manufacture
Total Site System Performance Ratio	Calculated based on annual heating and cooling load divided by HVAC system energy use
Window Insulation	6 user-entered, 20 inferred/calculated based on window frame type and number of glass panes
Wall Insulation	9 user-entered, 17 inferred/calculated based on wall type and assumed insulation thickness

Data Validation

Cadmus assessed the validity of the data by comparing values in the DOE Asset Score and Portfolio Manager datasets, verifying the annual total consumption in the Portfolio Manager dataset with the detailed monthly data for 11 of the 26 buildings, and identifying any large differences between modeled and measured consumption. In some cases, we could resolve discrepancies, but in other cases we removed buildings from the analysis because we could not resolve significant discrepancies.

We compared variables reported in both the Portfolio Manager dataset and the Asset Score dataset including floor area, source Energy Use Intensity (EUI), site EUI, and year built.

- **Floor area.** Asset Score building area was based on EnergyStar Portfolio Manager data which excludes parking garages. Parking garaged are required to be analyzed separately in ESPM. However, building geometry had been entered into Asset Score tool using building plans and permit data, which includes the parking. Discrepancies arose where atriums weren't accounted for or parking garages were included in the Asset Score model. Validation process identified these issues which were resolved through on-site visits and analysis of google satellite imagery. The average percent difference in floor area between the two datasets was 14 percent and there was no consistency in which dataset reported larger or smaller values. We concluded that floor area differences less than 25 percent were acceptable.

---

[5] See Asset Score protocol for description of these approaches:
https://buildingenergyscore.energy.gov/documents/energy_asset_score_technical_protocol.pdf

- o Discrepancies: After data cleaning, four buildings reported 25 percent greater floor area between the DOE Asset Score dataset and PM dataset. One of these reported buildings included two buildings that had been built separately.
- o Resolution:
  - Cadmus removed the building that turned out to be two separate buildings from the Portfolio Manager dataset (Site ID 8829)
  - PNNL re-modeled the three other buildings with corrected building geometry using the DOE Asset Score tool and updated the corresponding data

- **Source and site EUI.** For both site and source EUI, the average percent difference between the EUI values produced by Portfolio Manager and Asset Score was 39 percent. There was no consistency in which dataset reported larger or smaller values.
  - Discrepancies: Eighteen buildings had large differences (over 25 percent) in EUI values. The differences resulted from which building-use types were modeled. Variations between ESPM and AS EUIs are expected as one dataset is based on actual building operation and one is based on standard operation assumptions, plug loads and ventilation rates. The process of weather normalization of EUI data also varies between the two tools, hence the EUIs are not directly comparable. However, in one case, this variation was revealed to be due to the presence of a data center which resulted in the building having a higher source EUI in ESPM as compared to AS.
  - Resolution: We did not make any modifications when EUIs differed between the two datasets and used the dataset-specific EUIs when performing analysis on the respective scores.

- **Year built.** There were no differences in year built. The datasets were consistent.

Cadmus identified outliers with respect to scores and EUI values using scatterplots and density plots. Of the outliers identified, each had either very large or very small scores compared to the other buildings. We determined that the extreme values were the result of building use types – several buildings included space that was either entirely or partially non-office space and should be removed from some or all of the analyses—or classification or data errors.

- We removed two buildings with significant non-office usage and another building that was an outlier in both the Portfolio Manager and Asset Score analyses:
  - **Site ID 8633:** hospice
  - **Site ID 8698:** blood donation center
  - **Site ID 8923:** an outlier for Asset Score envelope measures. The highest (worst) wall U-value is three times the next largest U-value, which appears unrealistic.

- We removed two buildings with ENERGY STAR scoring concerns from the Portfolio Manager analyses:
  - **Site ID 8929:** a data center designation for a building- that had substantial office space, resulting in an ENERGY STAR score of 100 based on data centers

- **Site ID 8642:** building-use type of college/university that resulted in un-scoreable ENERGY STAR rating

- We removed two buildings from the Asset Score analyses:

  - **Site ID 8829**: building consists of two separate buildings constructed at different time periods that could not be modeled in Asset Score

  - **Site ID 8930**: building has a configuration of heat pumps that could not be modeled in Asset Score at the time of this analysis. This building has central ground source heat pumps with reheat systems. Asset Score has the capability to model unitary ground source heat pumps and wasn't able to accurately reflect the HVAC system present in this building

Our additional data validation included the following:

- After calculating source EUI using the Asset Score data, we verified that the source-site ratios were correct by confirming that the ratio was 3.14 for the four all-electric buildings.[6]

- We compared the energy performance metrics currently in Portfolio Manager (available through the PORTLANDLEAP account) against the energy performance reported to Portland by the building owners in June 2016. Differences were less than seven percent for 10 of the 11 buildings that provided data. Any differences are because the data entered into Portfolio Manager changed between June 2016 and the date of our analysis. We concluded that the differences were negligible. We retained the totals reported to Portland in June 2016 for analysis, rather than the totals currently entered in Portfolio Manager. For site ID 8931, however, there was a 68 percent difference between the performance metrics in Portfolio Manager now versus what was reported in June 2016. Cadmus used the energy use and score from the June 2016 report for the analysis of this building because the data currently in Portfolio Manager had energy use values that seemed unreasonably low. Cadmus developed the final analysis datasets as the result of these data validation activities. Each dataset included the 21 buildings shown in Table 2 with a check mark in the corresponding column. Note that two buildings were included in the Portfolio Manager dataset, but not in the Asset Score dataset and a different two were included in the Asset Score dataset, but not in the Portfolio Manager dataset.

---

[6] Source-site energy ratios are determined for grid-purchased energy by fuel type. The ratio for electric energy is 3.14, which is a national average, and is what we observed for the all-electric buildings. Based on this sample, we concluded that the source-site energy conversion calculations were implemented correctly.

Table 2. Final Analysis Datasets

Building ID	Portfolio Manager Analysis	Asset Score Analysis
8828	✔	✔
8927	✔	✔
8647	✔	✔
8724	✔	✔
8830	✔	✔
8738	✔	✔
8700	✔	✔
8692	✔	✔
8645	✔	✔
8753	✔	✔
8646	✔	✔
8928	✔	✔
8691	✔	✔
8752	✔	✔
8926	✔	✔
8924	✔	✔
8931	✔	✔
8879	✔	✔
8699	✔	✔
8930	✔	Removed
8829	✔	Removed
8642	Removed	✔
8929	Removed	✔
8923	Removed	Removed
8633	Removed	Removed
8698	Removed	Removed

Methodology

Cadmus used exploratory data analysis methods including data visualization techniques, correlation analysis, regression modeling, and summary statistics to assess relationships between ENERGY STAR scores, Asset Scores, EUIs, and variables representing building characteristics, systems, and operations.

We examined the relationship between scores and EUI values to identify which buildings have opportunities for operational improvements and system upgrades. We plotted the ENERGY STAR scores and Asset Scores and then developed a matrix with four quadrants. The score matrix quadrants are based on the Portland median ENERGY STAR score of 82. This is the median of the distribution of all Portland office buildings that reported in 2015, not just those in this analysis. Cadmus categorized each building according to its score in comparison to the median value, and thus the location in the score matrix:

- Highest performing: ENERGY STAR score > 82; Asset Score > 5

- Lowest performing: ENERGY STAR score ≤ 82; Asset Score ≤ 5

- Operational improvement opportunities: ENERGY STAR score ≤ 82; Asset Score > 5

- System upgrade opportunities: ENERGY STAR score > 82; Asset Score ≤ 5

The quadrant defined as "operational improvement opportunities" was categorized as that based on the argument that its design and systems suggested that it should perform well, but its ENERGY STAR score indicated its energy performance was below the median. The "system upgrade opportunities" quadrant was defined as such because its ENERGY STAR score indicated it was performing better than the median even though its design and systems had room for improvement. In subsequent analyses, we examined the relationships that scores and energy consumption have with building characteristics and end-uses. The results from these analyses enabled us to provide detailed recommendations for the buildings in each score matrix quadrant.

Cadmus used a variety of data visualization and quantitative analysis methods to examine the distributions of scores, source EUI, and site EUI as a function of the other variables. Our analysis methods included the following:

- <u>Summary statistics</u> providing an overview of the variables corresponding to buildings in each score matrix quadrant to allow comparing average characteristics between quadrants

- <u>Correlation analysis</u> using Pearson correlation coefficients (PCC)[7] to identify which variables are most correlated with scores and EUIs (without controlling for other variables)

---

[7]   The Pearson correlation coefficient (PCC) is a measure of the linear correlation between two variables ranging from negative one (-1) to positive one (+1). A correlation coefficient of negative one implies a perfect negative linear correlation, zero implies no correlation, and positive one implies a perfect positive linear correlation. Values anywhere in between are different degrees of strength of the relationship between the two variables.

- <u>Scatterplot matrices and boxplots</u> to examine correlations that scores and EUIs have with other variables and the variables have with each other
    - o Scatterplot matrices include plots that show the relationships that scores and EUIs have with continuous variables (e.g., lighting power density) as well as the density, which shows the distribution of each variable
    - o Boxplots show the relationships that scores and EUIs have with categorical variables (e.g., roof type)
- Regression analysis to identify which variables have significant relationships with scores and EUIs while controlling for known factors that drive energy consumption and scores (e.g., floor area). Cadmus used our expertise on Portfolio Manager regression modeling to supplement the regression analyses.

In the findings section that follows, we present the score matrix and additional analyses, providing Cadmus' conclusions and recommendations for specific buildings.
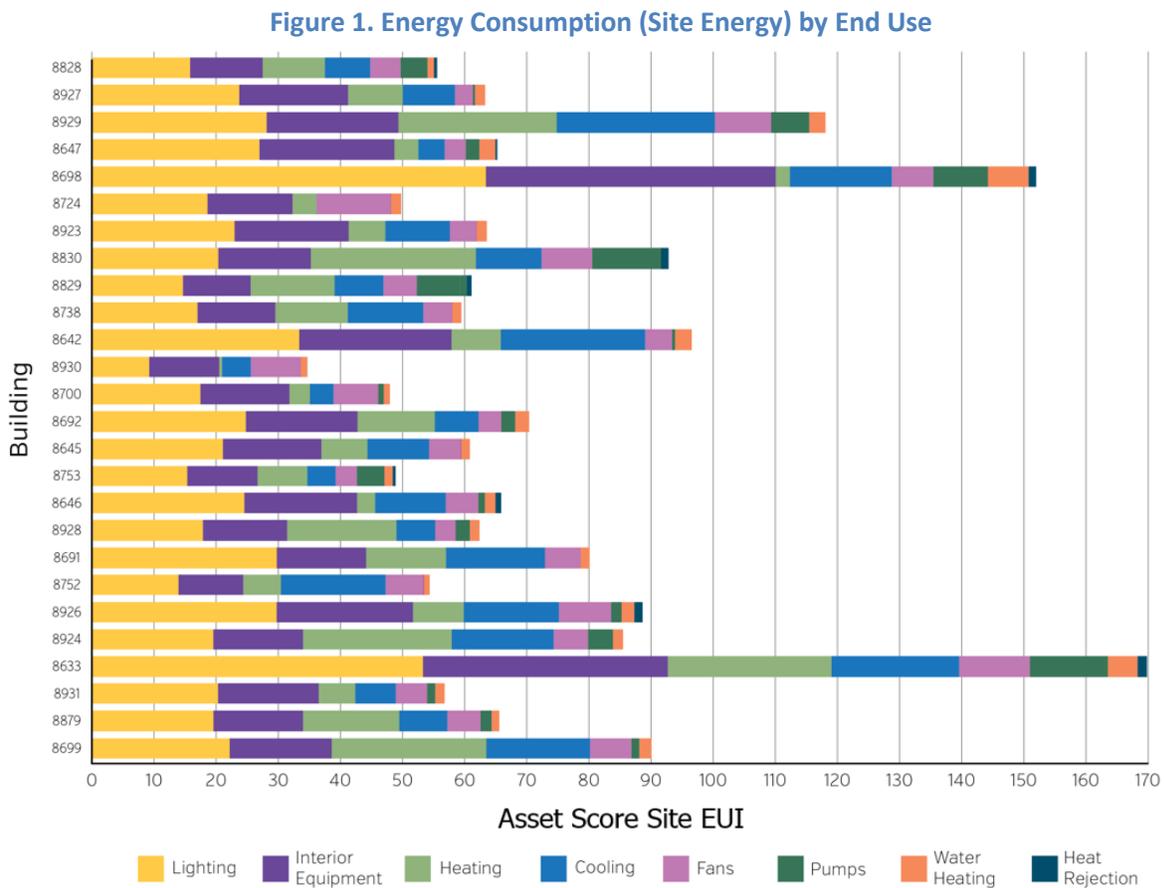
Findings

This section includes the results from the analyses described in the previous section. We plotted the ENERGY STAR score versus the Asset Score to develop a quadrant matrix. We also created a similar matrix for Asset Score site EUI versus Portfolio Manager site EUI. In addition, we identified each variable as either a building characteristic (e.g. floor area), lighting (e.g. LPD), HVAC (e.g. System Performance Ratio), or an envelope measure (e.g. insulation), then performed data visualization, summary statistics, correlation, and regression analyses within each measure-specific section.

Energy Consumption by End Use

Figure 1 illustrates the Asset Score energy consumption by end use for all 26 buildings in the sample. Lighting energy is the predominant end use in most cases, followed by interior equipment such as plug loads. Lighting energy offsets heating energy because waste heat from lighting helps meet the heating load.

Figure 1. Energy Consumption (Site Energy) by End Use

Quadrant Matrix

Cadmus populated the score matrix in Figure 2 using the Asset Scores and ENERGY STAR scores for the buildings in the sample, except for one site without an ENERGY STAR score. As described above, the

ENERGY STAR score is an indicator of operational/behavioral performance and the Asset Score is an indicator of building design/systems performance. Cadmus defines one of the four quadrants as likely providing operational/behavioral opportunities and one as likely providing system upgrade opportunities. Four of the 25 buildings are in the highest performing quadrant, nine are in the lowest performing quadrant, six are in the operational opportunities quadrant, and six are in the system upgrade opportunities quadrant. The size of each square in the plot is relative to the Portfolio Manager site EUI; the sites with larger squares have a higher EUI.

Figure 2. Score Quadrant Matrix
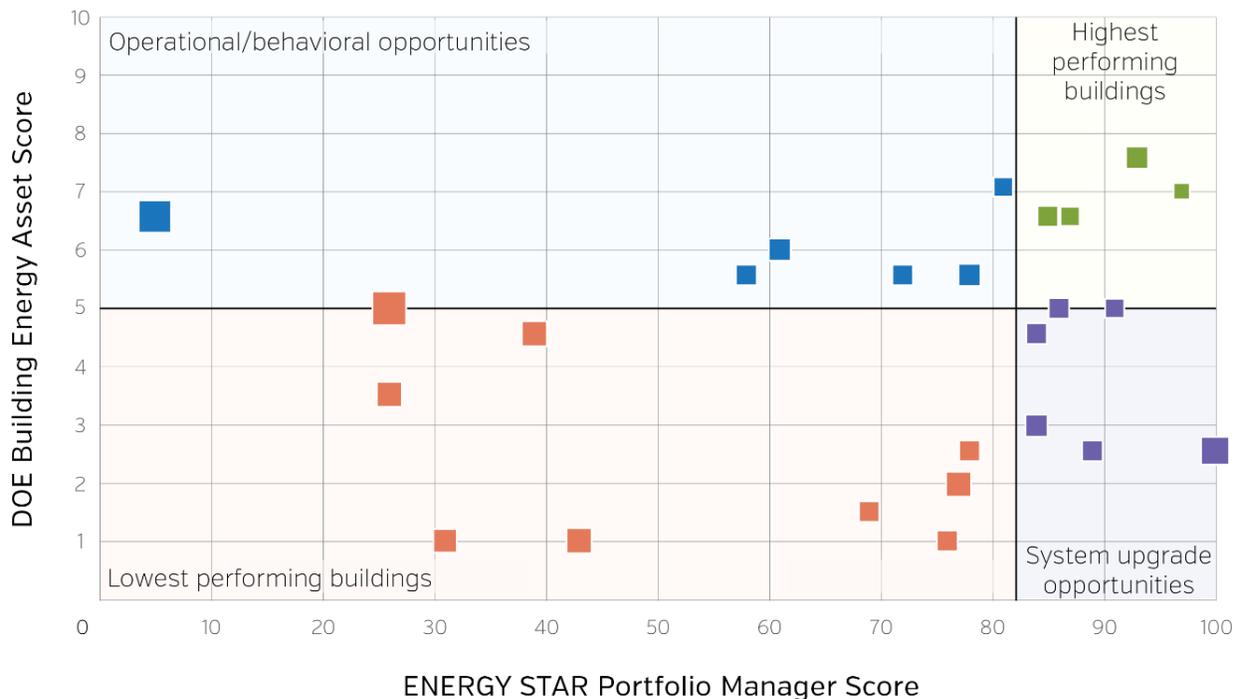
Cadmus examined the buildings that fell into each quadrant to identify the degree of correlation between various building characteristics and measured building energy performance to identify key building characteristics that impact building performance. We present our findings in Table 3 through Table 6. These are the factors with the highest correlation with energy performance. The results are specified as worst, worse, average, better, and best. The "worse" label indicates worse than average of all sites, while "better" indicates better than average of all sites. The "worst" and "best" labels indicate the worst 5% and best 5% of the values. The HVAC System Performance Ratio (SPR) is the sum of the annual heating and cooling loads divided by the HVAC system energy use. Lower values indicate more energy use to meet the load and, therefore, represent low-efficiency systems. The Wall-Window Weighted U-Factor (WWW U-Factor) is calculated as follows. The wall U-factor multiplied by the net wall area is added to the window U-factor multiplied by the total window area. This value is then divided by the sum of the net wall area and the total window area. Lower values of the WWW U-Factor indicate more window insulation and wall insulation and thus a more efficient envelope.

Table 3 indicates that the highest performing buildings had a high SPR and most had an efficient building envelope based on the WWW U-Factor. However, building ID 8927 had an inefficient envelope, with a 90% WWR and window U-factor of 0.72 Btu/ft2 f hr. Despite the inefficient envelope, a highly efficient HVAC system was able to result in relatively high performance. Table 4 shows that the lowest performing buildings usually had both low performing windows and inefficient HVAC systems. Except for building ID 8752, buildings with the lowest Asset Score tended to have the least efficient envelopes and equipment. In Table 6, most of the buildings identified in the System Upgrade Opportunities quadrant have inefficient HVAC systems and, hence, are good candidates for HVAC systems and controls retrofit.

Table 3. Characteristics of the Highest Performing Buildings

Building ID	ENERGY STAR Score	Asset Score	Wall-Window Weighted U-Factor	LPD	HVAC System Performance Ratio
8927	85	6.5	worse	average	**best**
8724	87	6.5	better	average	better
8647	93	7.5	**best**	average	better
8930	97	7.0	**best**	average	better

Table 4. Characteristics of the Lowest Performing Buildings

Building ID	ENERGY STAR Score	Asset Score	Wall-Window Weighted U-Factor	LPD	HVAC System Performance Ratio
8699	26	3.5	better	average	**worst**
8633	26	5.0	**best**	average	worse
8691	31	1.0	worse	**worst**	worse
8926	39	4.5	**worst**	average	better
8830	43	1.0	**worst**	average	worse
8752	69	1.5	better	average	better
8829	76	1.0	worse	average	worse
8924	77	2.0	worse	average	average
8738	78	2.5	worse	average	worse

Table 5. Characteristics of the Buildings with Operational/Behavioral Opportunities

Building ID	ENERGY STAR Score	Asset Score	Wall-Window Weighted U-Factor	LPD	HVAC System Performance Ratio
8698	5	6.5	**best**	average	better
8931	58	5.5	better	**best**	better
8692	61	6.0	better	average	average
8923	72	5.5	**worst**	**best**	average
8646	78	5.5	better	average	better
8700	81	7.0	better	**best**	average

Table 6. Characteristics of the Buildings with System Upgrade Opportunities

| Building ID	ENERGY STAR Score	Asset Score	Wall-Window Weighted U-Factor	LPD	HVAC System Performance Ratio
8879	84	3.0	average	average	worse
8645	84	4.5	**best**	average	better
8928	86	5.0	worse	average	worse
8828	89	2.5	worse	average	worse
8753	91	5.0	better	average	worse
8929	100	2.5	better	better	**worst**

Additional Plots

Cadmus developed several additional plots to provide further insights into the findings. The quadrant analysis presented above identified which buildings are performing well in terms of energy consumption, but have opportunities for system efficiency upgrades. Even those buildings with relatively high Asset Scores are likely to have opportunities to improve their system or component efficiencies to reach their cost-effective optimum levels. Consequently, to explore further how well the buildings studied performed compared to their potential energy performance, we conducted additional analyses.

Figure 3 shows the actual Asset Scores compared with the difference between the potential and actual Asset Score for each building. The Asset Score tool generates the potential Asset Score based on an automated analysis of cost-effective efficiency improvements that could be implemented to provide an indication of how much more efficient a building could be through cost-effective design and system upgrades.[8]

This plot shows that the Asset Score of most buildings falls short of their potential Asset Score so there are cost-effective design and system options available to enhance the energy performance of nearly all the buildings. The highest performing buildings (green dots) appear in the lower right of this plot, as one would expect. Only one building has an actual Asset Score equivalent to its potential score so there are likely to be few cost-effective design or system improvement opportunities in this building. The worst performing buildings have the best opportunity for bigger improvement. For the buildings in this study, an Asset Score of 9.0 appears to be the practical upper limit for the potential score, which is based on the cost effectiveness of energy efficiency measures.

Figure 3. Asset Score: Actual vs. (Potential – Actual) Score

---
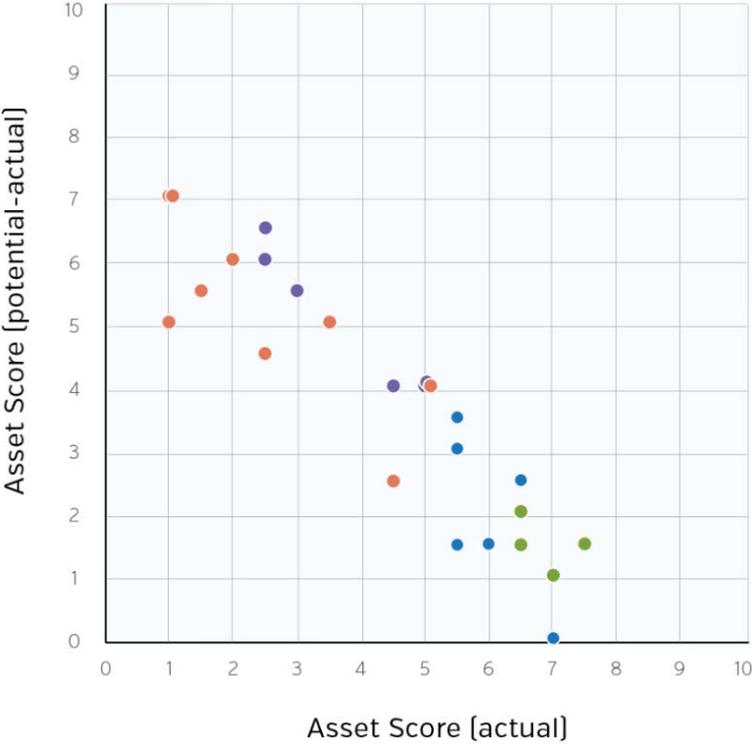
[8] A description of how the Potential Asset Score is calculated can be found in the *Program Overview and Technical Protocol* at https://buildingenergyscore.energy.gov/resources

Figure 4 shows the ENERGY STAR site EUI vs Asset Score site EUI for the buildings in this study. Buildings above the 45-degree line use more energy based on the Asset Score analysis than indicated by Portfolio Manager. This plot shows the actual energy use of most buildings is considerably higher than the modeled EUI.

The highest performing buildings (green dots) appear in the lower left of this plot, as one would expect. The lowest performing buildings (orange dots) generally have a higher ENERGY STAR site EUI than Asset Score site EUI. This indicates that Asset Score underestimates the energy consumption of these lowest performing buildings. There is a similar phenomenon with the operational/behavioral opportunities category (blue dots). Asset Score most accurately predicts the energy consumption of the buildings in the system upgrade opportunity category (purple dots).

In addition, the four buildings above the 45-degree line are not the same buildings in the upper left quadrant of the score matrix (low ENERGY STAR Score, high Asset Score; operational/behavioral opportunities). This might suggest that plotting the EUI values, as in Figure 4, is more informative than the score matrix.

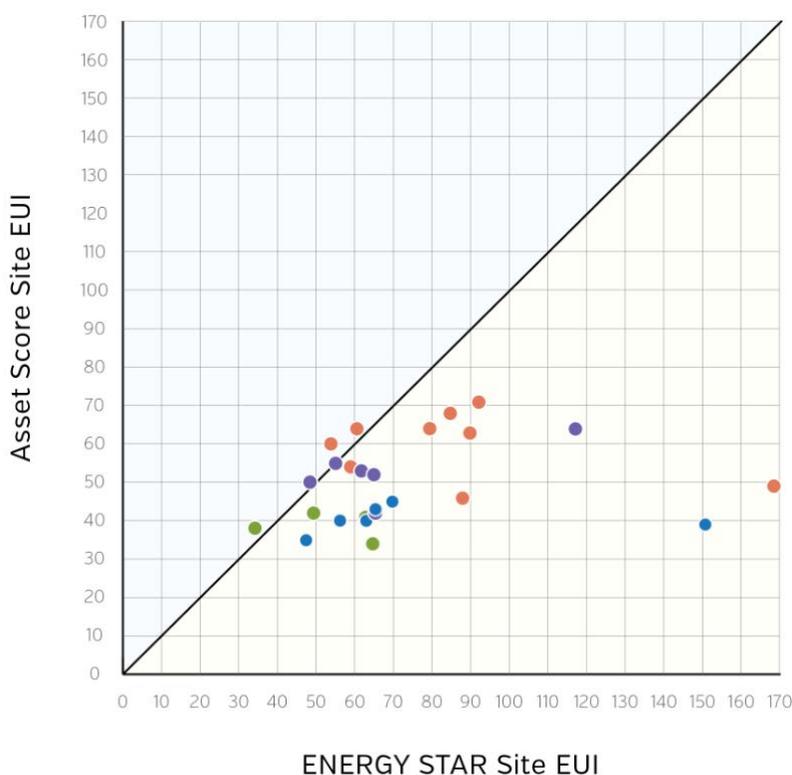**Figure 4. ENERGY STAR Site EUI vs. Asset Score Site EUI**

Figure 5 also shows the ENERGY STAR site EUI vs Asset Score site EUI for the buildings in this study, but this time in a quadrant format. The bins for the four quadrants are divided at 60.2 kBtu/sf, which is the 2015 Portland office building median ENERGY STAR site EUI. We reversed the scales in this graph to maintain the same structure shown in Figure 2 with highest performing buildings in upper right quadrant and so on, and using the same color coding used in Figure 2 with the highest performing

buildings in that figure shown in green here too. This figure suggests that the modeled energy consumption of most buildings in this study was less than the Portland median, but the actual consumption of most was higher than the Portland median. Only two of the four original highest performing homes are in the upper right quadrant in this graph; the other two are in the upper left quadrant, but just barely over the dividing line. Because the Asset Score site EUIs fell in a relatively narrow range for these buildings, there is much less dispersion vertically than indicated in Figure 2. This is likely because Asset Score is based on the source EUI, which is influenced significantly by fuel type. Figure 5 suggests there are fewer system upgrade opportunities than Figure 2 because no buildings fall into the lower right quadrant in Figure 5. Two of the lowest performing buildings in Figure 2 move to the operational/behavioral opportunities (upper left) quadrant in Figure 5 and one has the highest Energy Star site EUI. The very high Energy Star site EUI is not apparent in Figure 2 because the scores adjust for building type. Comparing the EUI values provides evidence of how an individual building is performing compared to its modeled performance and can help flag whether it is underperforming or overperforming based on its design and construction. The comparison of scores, on the other hand, provides useful information about how each building is performing compared with its peers.

Figure 5. ENERGY STAR Site EUI vs Asset Score Site EUI, Quadrant Plot
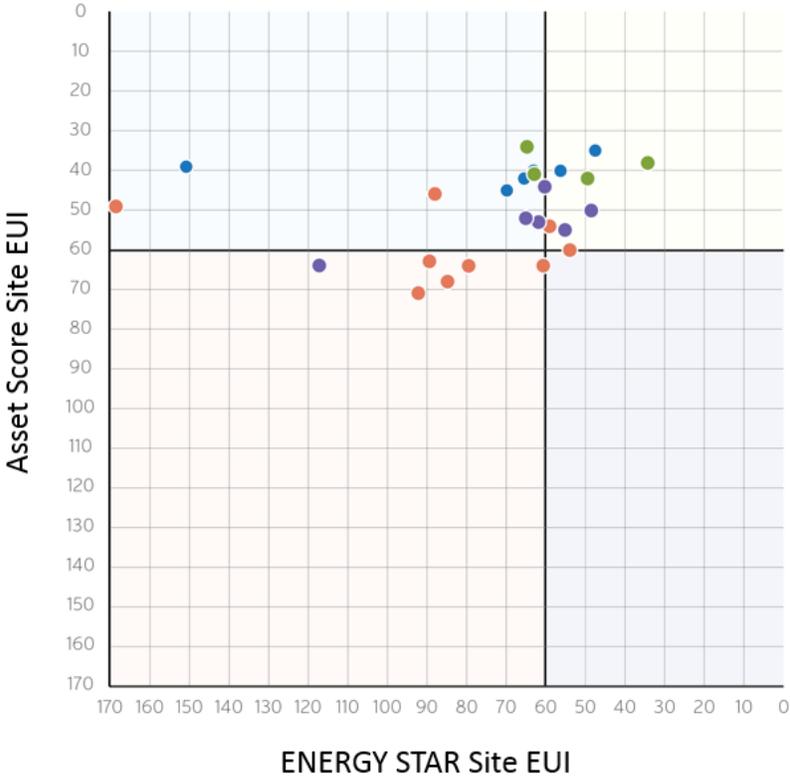
Building Characteristics

Cadmus also performed analyses to identify relationships between building characteristics and their performance. We started by examining the building characteristics and then performed analyses for three measure-specific categories: lighting, HVAC, and envelope measures. We present the findings for each category below.

The building characteristics we analyzed included some that are unlikely to change over time and unlikely to present opportunities for improved energy efficiency, e.g. floor area, number of floors, and building volume. Although these characteristics do not present efficiency opportunities, it is important to understand the relationship between them and EUI and score because they are known drivers of energy consumption. Thus, any measure-specific analyses need to account for them to provide accurate results and meaningful recommendations.[9]

We provide the summary statistics to give an overview of the similarities and differences between buildings in each quadrant of the score matrix, and then present the correlation and regression analysis results.

Summary Statistics

The building characteristics for buildings in each quadrant of the ENERGY STAR vs. Asset Score matrix are summarized in Table 7. Because the sample sizes are small for each quadrant, the average values do not provide many insights into the relationship between the characteristics and performance. The only trend suggested by the data is older buildings do not perform as well as newer ones.

---

[9] PNNL conducted similar analyses that compared EUIs reported by Asset Score and Portfolio Manager for a sample of 42 buildings. Our analysis focuses on the quadrant framework and statistical analyses, including correlations and regressions, to explore indicators of building performance that could identify opportunities for improving energy performance. We did not identify notable differences between the PNNL findings and ours. The paper is: Wang, Na, S. Goel, W. Gorissen, and A. Makhmalbaf. "Understanding Building Infrastructure and Building Operation through DOE Asset Score Model: Lessons Learned from a Pilot Project," PNNL-SA-92883, prepared for U.S. Department of Energy.

Table 7. Building Characteristics Quadrant Summaries

Operational Improvements (n = 6)	High Performing (n = 4)
Ave. year built of 1987 Ave. number of floors of 5 Ave. ES floor area of 95,034 sq.ft. Ave. AS floor area of 94,734 sq.ft.	Ave. year built of 1994 Ave. number of floors of 5 Ave. ES floor area of 87,193 sq.ft. Ave. AS floor area of 87,410 sq.ft.
Low Performing (n = 9)	System Upgrade Opportunities (n = 6)
Ave. year built of 1978 Ave. number of floors of 6 Ave. ES floor area of 112,657 sq.ft. Ave. AS floor area of 108,979 sq.ft.	Ave. year built of 1987 Ave. number of floors of 13 Ave. ES floor area of 267,898 sq.ft. Ave. AS floor area of 267,986 sq.ft.

Correlation Analysis

Cadmus plotted building characteristics with the EUI and score values from each dataset in the scatterplot matrices in Figure 6 and Figure 7. This scatterplot matrix consists of three parts. Graphs on the diagonal are univariate density plots showing the distribution of each variable. The lower half of the matrix consists of scatterplots showing the relationships between the pairs of variables, and the upper half provides pairwise correlation coefficients.

Figure 6. ENERGY STAR Scatterplot Matrix
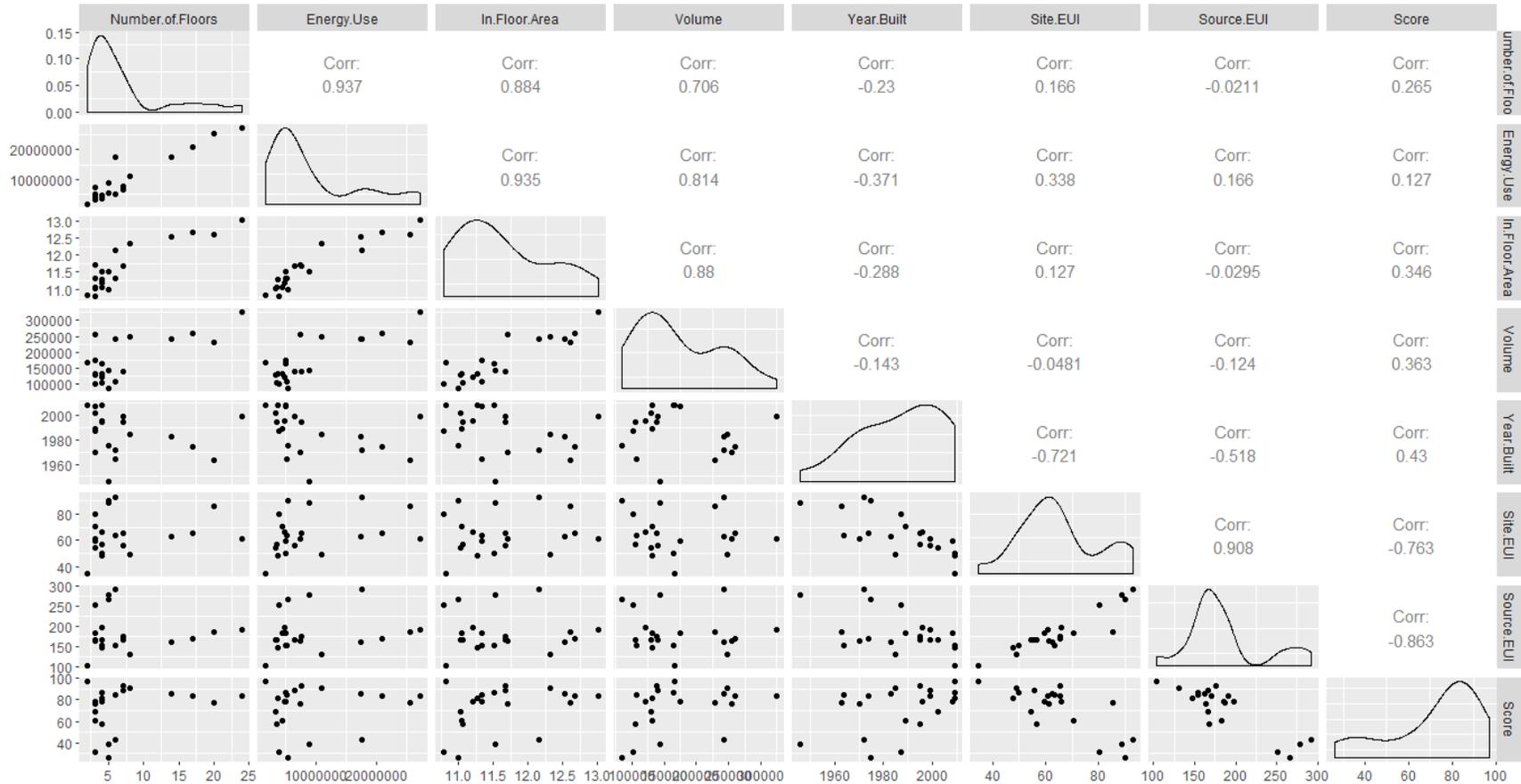
For ENERGY STAR variables of interest, we observed that year built has the strongest correlation with EUIs, where newer buildings with lower total energy use tend to have smaller EUIs. We expect a strong correlation between energy use and site EUI, but the correlation observed is only moderate, which can be explained by normalizing energy use. We observe the univariate distribution of energy use to be largely right-skewed,

whereas when energy use is normalized by floor area we observe a more symmetric and bi-modal distribution. The natural log of floor area,[10] volume, and year built have the strongest correlations with ENERGY STAR score, though each is only moderately correlated with the score; each is positively correlated with ENERGY STAR score.

For Asset Score variables of interest (see Figure 7), we observed that energy use and year built have the strongest correlations with EUIs and Asset Score. Higher energy use is moderately correlated with less efficient buildings (higher site EUIs and lower Asset Scores); newer buildings tend to be more efficient (year built is negatively correlated with site EUIs and positively correlated with higher Asset Scores).

---

[10] As described later, we transformed the floor area variable based on a visual inspection of the data.

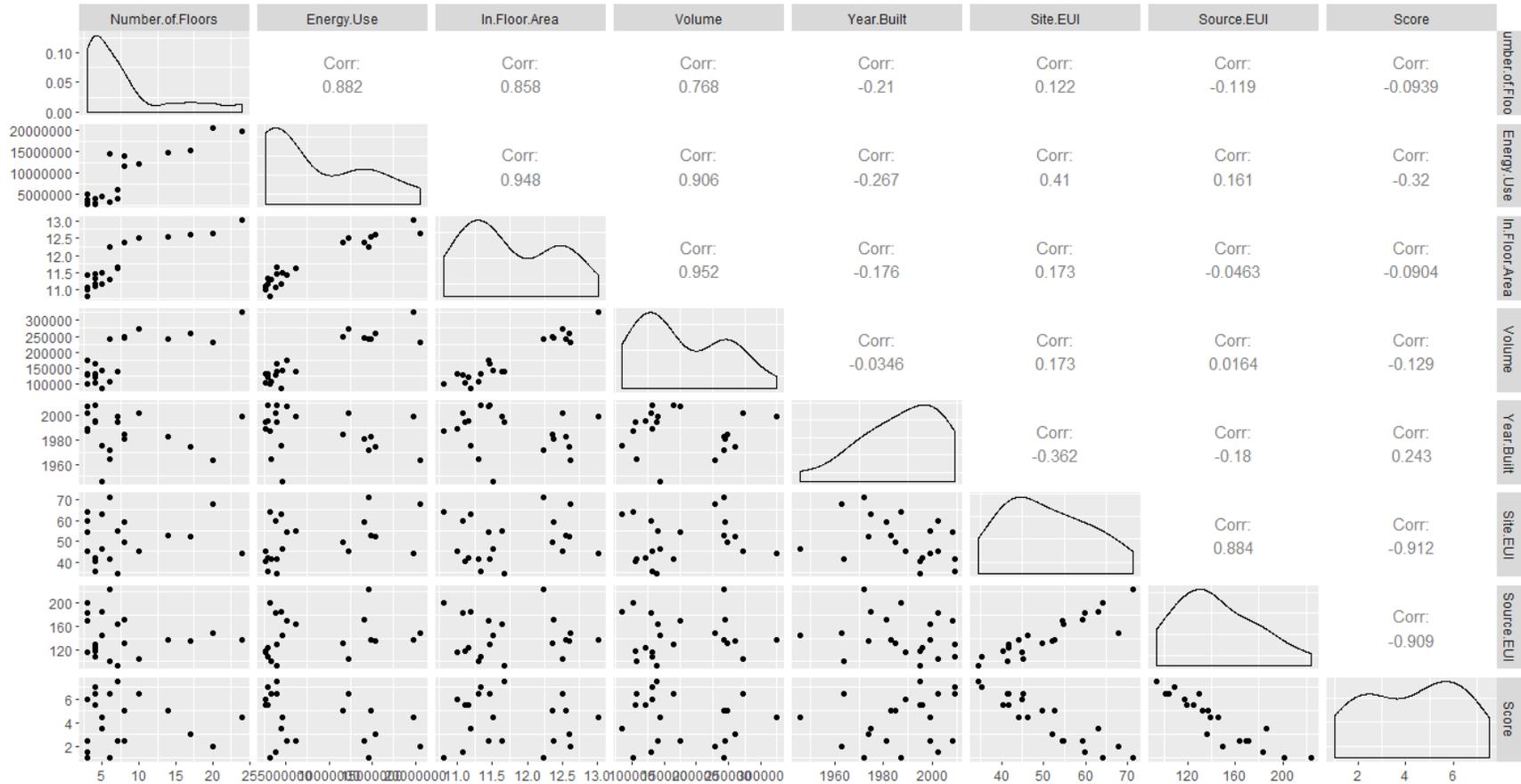**Figure 7. Asset Score Scatterplot Matrix**

Table 8 summarizes the correlations between each building characteristic, site EUI, source EUI, and score for the Portfolio Manager ENERY STAR dataset (top) and for the Asset Score dataset (bottom). The table lists the variables in order of the size of the correlation between the variable and score, starting with the largest negative correlation and increasing to the largest positive correlation.

We include details on the expected correlations between the variables and EUI and score, where a "+" indicates that we expect the correlation to be positive, a "-" indicates that we expect the correlation to be negative, and "varies" indicates that we expect the correlation to vary depending on other factors.

We also include an indicator in the table to show whether the observed correlation is in line with the expected correlation. Note that in the expected correlations, we only account for the direct effect of one variable on another and do not control for the simultaneous effects of other variables (we do account for this in the regression analysis).

Table 8. Building Characteristic Correlations

Variable	Sample Size	Site EUI	Source EUI	Score	Expected Relationship		Behaving as Expected?	
					EUI	Score	EUI	Score
Portfolio Manager Variables								
Source EUI	21	0.93	1.00	(0.86)	+	-	Yes	Yes
Total Metered Site Usage (kBtu)	21	0.34	0.17	0.13	+	-	Yes	No
Number of Floors	21	0.17	(0.02)	0.27	Varies	Varies	-	-
ln(Floor Area)	21	0.13	(0.03)	0.35	Varies	Varies	-	-
Year Built	21	(0.72)	(0.52)	0.43	-	+	Yes	Yes
Asset Score Variables								
Source EUI	21	0.88	1.00	(0.91)	+	-	Yes	Yes
Total Metered Site Usage (kBtu)	21	0.41	0.16	(0.32)	+	-	Yes	Yes
ln(Floor Area)	21	0.17	(0.05)	(0.10)	Varies	Varies	-	-
Number of Floors	21	0.12	(0.12)	(0.09)	Varies	Varies	-	-
Year Built	21	(0.36)	(0.18)	0.24	-	+	Yes	Yes

The most meaningful finding from this analysis is the relationship between year built and EUIs and scores. The Portfolio Manager results exhibit the strongest negative relationship between year built and EUIs—newer buildings tend to have smaller EUIs. The direction of the relationship is the same for Asset Score results, but the correlations are not as strong. Year built is positively correlated with both scores, though, again the relationship is weaker for Asset Score results. The Asset Score tool infers envelope thermal properties and HVAC equipment efficiency based on the year of construction of the building. The tool assumes that older buildings are more likely to have less efficient building envelope and HVAC system equipment. However, the tool also assumes HVAC system replacements based on the typical life of the equipment, unless the user specifies the year of manufacture of the equipment. This explains the weaker correlations of the Asset Score results.

In both datasets, source EUI has a strong positive correlation with site EUI; this is to be expected because site and source EUI differ only to the extent that buildings in the sample rely on a mix of fuels. Source EUI has a strong negative correlation with the scores because both scores are directly dependent on the source EUI.

We included the number of floors and the natural log of floor area to try to capture any relationship between building geometry and energy performance. However, it is not possible to predict the relationship because many building characteristics (e.g., surface area-to-volume ratio, window-to-wall ratio) besides basic geometry can affect thermal performance, and the correlation results showed no consistent, significant relationships. Nevertheless, we include the natural log of floor area in the regression analysis discussed in the next section because the values were significant predictors when included in the ENERGY STAR Portfolio Manager regression model using a more complete dataset.

In general, the observed relationships between the building characteristics, site EUI, source EUI, and scores are in line with the expectations. However, we identified one exception:

- Total metered usage (kBtu): correlation with score is slightly positive for Portfolio Manager, but we would expect it to be negative as it is with Asset Score.

The correlation analysis provided us with a summary of the relationships between building characteristics and EUI and scores. While informative as a first step, the correlation analysis does not control for the relationships that EUI and scores have with other variables. To understand that, we used regression analysis and describe the findings below.

Regression Analysis

Cadmus used linear regression of the variables listed in Table 9 on the EUI values and scores for each dataset. In the table, we identify the building characteristics that are statistically significant predictors of EUI or score (at 90 percent confidence) in the regression models with a check mark. For floor area, the data visualization revealed a non-linear relationship, and so we used a variable transformation to take the natural log of this variable, consistent with the Portfolio Manager office building regression model[11].

---

[11] ENERGY STAR Score for Offices Technical Reference: https://www.energystar.gov/buildings/tools-and-resources/energy-star-score-offices

Table 9. Building Characteristic Regression Summary

Variable	Portfolio Manager Site EUI*	ENERGY STAR Score	Asset Score Site EUI*	Asset Score
Number of Floors			✔	✔
Year Built	✔			
Total Energy Use (kBtu)	✔		✔	
Source EUI	NA	✔	NA	✔
ln(Floor Area)	✔	✔	✔	

* NA occurs because source EUI does not predict site EUI.

Based on the correlation and regression analysis results, Cadmus concluded that the following variables should be included in additional analyses of end-use specific variables to identify operations and systems improvement opportunities.

- Portfolio Manager site EUI: number of floors, year built, and total energy use (kBtu)
- ENERGY STAR score: source EUI and the natural log of floor area[12]
- Asset Score site EUI: number of floors, total energy use (kBtu), and the natural log of floor area
- Asset Score: number of floors and source EUI

When performing measure-specific analyses, we must first account for the effect of the building characteristics on scores and EUIs to accurately identify the true effects of additional predictors.

Lighting Measures

Cadmus analyzed energy performance as a function of lighting power density (LPD) after accounting for significant building characteristics based on information in the Portfolio Manager and Asset Score data.

Summary Statistics

The summary statistics in Table 10 below provide an overview of the similarities between buildings in each quadrant of the score matrix. The largest LPD is in the low performing quadrant. The LPD in the operational improvements quadrant, and its improvement over the low performing quadrant LPD, is consistent with underlying rationale for defining the quadrants.

---

[12] Source EUI is used as a predictor in the regression models for ENERGY STAR Score and Asset Score. We know that scores are calculated based on source EUI; therefore, we cannot accurately and precisely identify significant relationship between scores and other predictors without first accounting for the effect of EUI on scores.

Table 10. Lighting Measure Quadrant Summaries

Operational Improvements (n = 6)	High Performing (n = 4)
Ave. lighting power density of 1.26 W/sf 33% of buildings have 66.6% T8, 33.3% CFL	Ave. lighting power density of 1.47 W/sf 100% of buildings have 66.6% T8, 33.3% CFL
Low Performing (n = 9)	**System Upgrade Opportunities (n = 6)**
Ave. lighting power density of 1.63 W/sf 67% of buildings have 66.6% T8, 33.3% CFL	Ave. lighting power density of 1.49 W/sf 83% of buildings have 66.6% T8, 33.3% CFL

Correlation Analysis

We plotted LPD with the EUI and score values from each dataset in the scatter plot matrix; please see Figure 8 and Figure 9. Both figures show that most values of LPD cluster around 1.5 W/sf. The values that are larger and smaller suggest visually the expected positive correlation with EUI and negative correlation with ENERGY STAR score and Asset Score.

Figure 8. ENERGY STAR Lighting Scatterplot Matrix
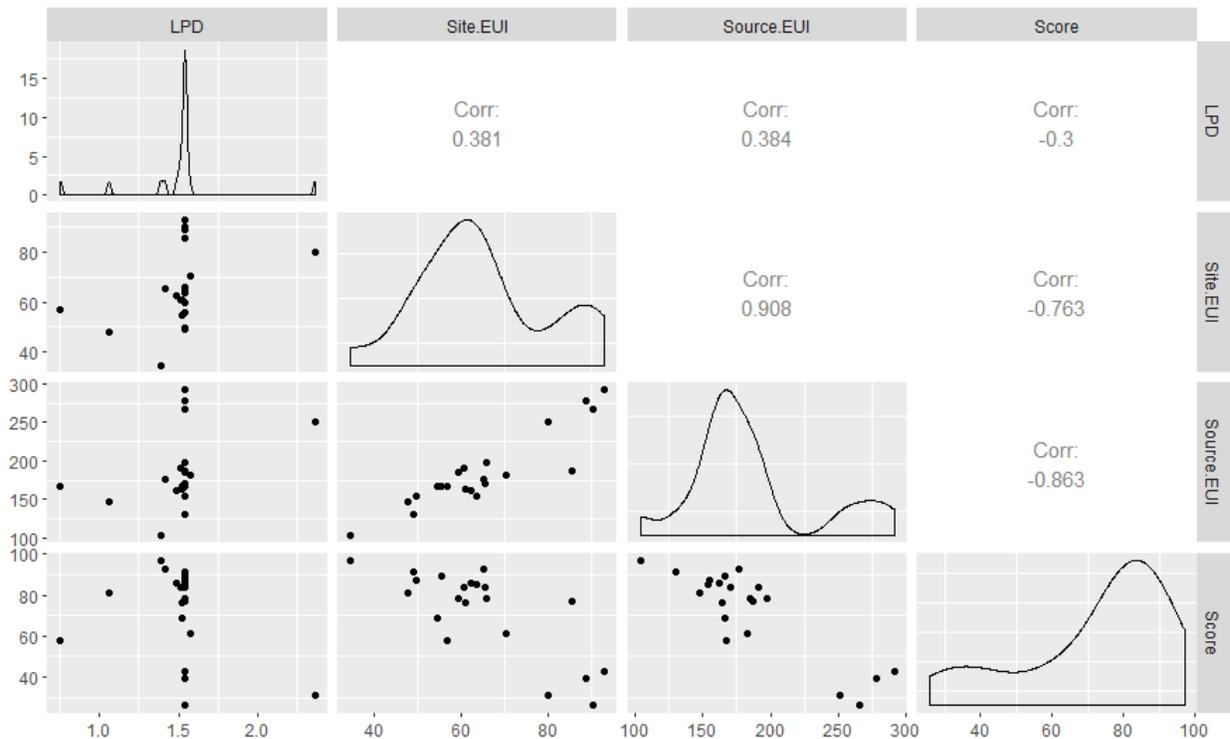
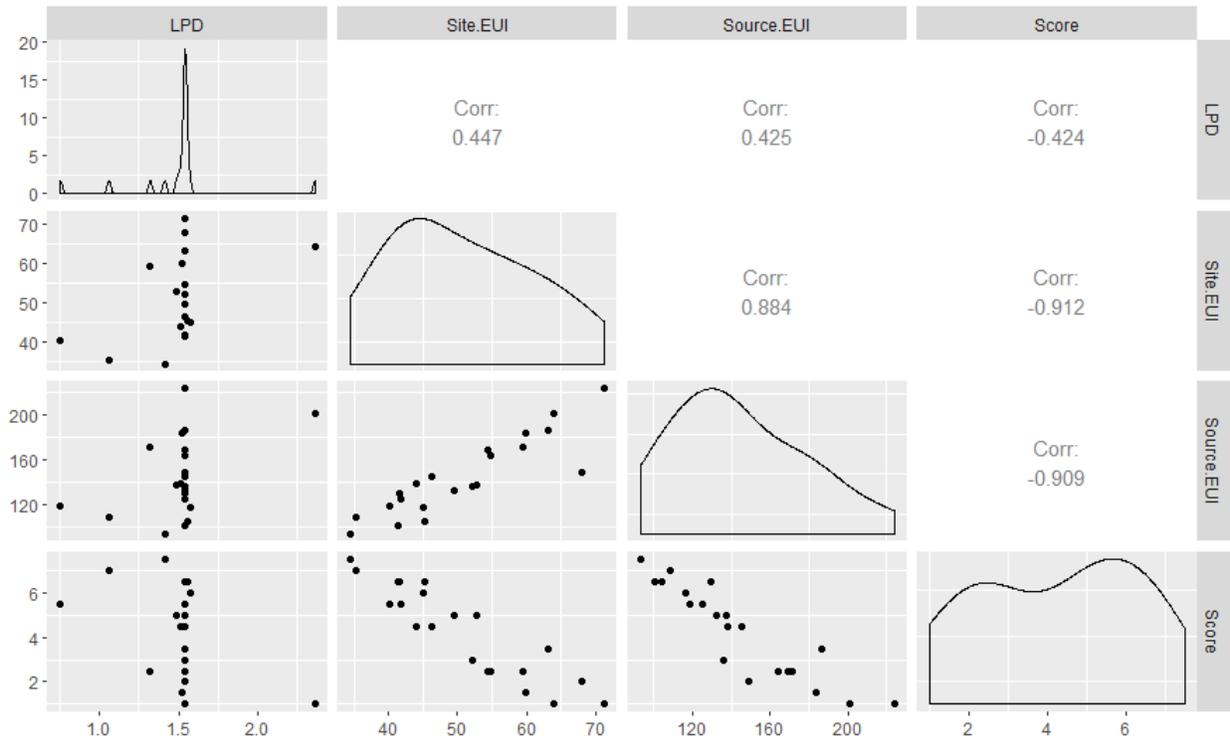## Figure 9. Asset Score Lighting Scatterplot Matrix

Table 11 summarizes the correlations between LPD and site EUI, source EUI, and scores in both datasets. The signs are as expected and the correlations are stronger for the Asset Score results, probably because they are based on modeling results and unaffected by the variations in operations and behavior that affect the Portfolio Manager results.

Table 11. Lighting Correlation Results

Variable	Sample Size	Site EUI	Source EUI	Score[3]	Expected Relationship		Behaving as expected	
					EUI	Score	EUI	Score
Portfolio Manager Variables								
Lighting power density	21	0.23	0.26	(0.26)	+	-	Yes	Yes
Asset Score Variables								
Lighting power density	21	0.45	0.42	(0.42)	+	-	Yes	Yes

We observed that LPD has the expected positive correlation with site and source EUI and a negative correlation with score in both datasets. As LPD increases, site and source EUI increase and score decreases. Due to the observed correlations, in addition to the high percentage of total energy use due to lighting (33 percent on average), we used regression analysis to quantify the effects of LPD on score and EUI. We present the results below, along with recommendations on how decreasing LPD could affect EUI and scores for the buildings in the sample.

Regression Analysis

Table 12 presents the regression results where we identified LPD as a significant predictor (90 percent confidence level) in models of site EUI for both data sets, after accounting for building characteristics. Models for source EUI resulted in the same base regression models. We identify the building characteristics and measures that are statistically significant predictors of EUI or the score at 90 percent confidence in the regression models with a check mark.

Table 12. Lighting Regression Summary

Variable	Portfolio Manager Site EUI**	ENERGY STAR Score	Asset Score Site EUI**	Asset Score
Number of Floors			✔	✔
Year Built	✔			
Total Energy Use (kBtu)	✔		✔	
Source EUI	NA	✔	NA	✔
ln(Floor Area)	✔	✔	✔	
Lighting power density	✔		✔	

* NA occurs we do not use source EUI to predict site EUI in regression analysis.

Lighting power density was correlated with EUI and a significant predictor of EUI in the regression analysis. Because score is a function of EUI, Cadmus conducted a sensitivity analysis to illustrate the potential effect that decreasing LPD could have on scores. Due to the relationship that source EUI has with score and LPD, we determined that a change in LPD would practically impact the score. We used the following steps in the sensitivity analysis to predict potential changes in the Asset Scores[13] due to a 20 percent decrease in LPD for sites in the System Upgrade Opportunities quadrant of the score matrix.

1. Predict new source EUI values by plugging the following values into the regression model:
    a. Use actual values for the number of floors and natural log of floor area.
    b. Use the actual total energy use, but reduced 2% by a decrease in lighting energy. This corresponds to a 20% decrease in LPD.
2. Predict new scores by plugging the predicted source EUI values and decreased LPD into the score regression model.

Table 13 presents the observed Asset Score along with the predicted scores assuming a decrease of LPD by 20 percent. While the sensitivity analysis resulted in Asset Scores with accuracy to the nearest tenth, we chose to list results as a range because Asset Scores are only accurate to the nearest five-tenths. For example, the actual Asset Score for Site 8929 is 3.0, and the predicted score for Site 8929 is 3.4, however the table lists a predicted range of 3.0-3.5.

---

[13] Buildings in this quadrant had higher than median ENERGY STAR scores, but lower than average Asset Scores.

As the table indicates, the score increased with the decrease in LPD for all sites except Site 8928, where the score decreased slightly in the raw results, but not significantly when rounded to the range of possible values.

Table 13. Sensitivity Results – System Upgrade Opportunities Quadrant

Building ID	Observed Asset Score	Predicted Asset Score Range	Change in Score
8828	2.5	5.5-6.0	↑
8929*	3.0	3.0-3.5	↑
8879	3.0	5.5-6.0	↑
8645	5.0	5.5-6.0	↑
8928	5.0	4.5-5.0	—
8753	5.0	5.0-5.5	↑

* The building identified was not used to fit the regression models on which this sensitivity analysis is based, but was still included in the sensitivity analysis to predict potential score with a decrease in LPD. This results in a less confident prediction for this building.

We performed a similar analysis for buildings in the Low Performing quadrant of the score matrix (with ENERGY STAR scores below the Portland median and Asset Scores below average) to predict potential changes in scores due to decreasing LPD in these buildings. We list the observed scores and ranges of predicted scores in Table 14, assuming a decrease in LPD of 20 percent. In most buildings, we observe significant increases in both Asset Score and ENERGY STAR score, resulting from a decrease in LPD.

Table 14. Lighting Sensitivity Results – Low Performing Quadrant

Building ID	Observed Asset Score	Predicted Asset Score Range	Change in Score	Observed ENERGY STAR Score	Predicted ENERGY STAR Score Range[14]	Change in Score
8691	1.5	2.0-2.5	↑	31	50-55	↑
8830	1.0	1.5-2.0	↑	43	40-45	—
8699	3.5	4.5-5.0	↑	26	55-60	↑
8926	4.5	6.0-6.5	↑	39	55-60	↑
8829*	1.0	3.5-4.0	↑	76	85-90	↑
8752	1.5	4.0-4.5	↑	69	70-75	↑
8924	2.5	2.5-3.0	↑	77	65-70	—
8738	3.0	5.0-5.5	↑	78	75-80	↑
8633*	5.0	4.5-5.0	—	26	25-30	↑

* The buildings identified were not used to fit the regression models on which this sensitivity analysis is based, but were still included in the sensitivity analysis to predict their potential score with a decrease in LPD. This results in less confident predictions for these buildings.

Findings

Based on the results of the regression analysis and sensitivity results, we expect a decrease in LPD of 20 percent to increase Asset Scores by an average of 1.5 points and ENERGY STAR scores by an average of 15 points.

On a building-by-building level, the changes in scores would mean that the building would be re-categorized in the score matrix. In particular, Table 15 identifies buildings that would move from the System Upgrade Opportunity quadrant to the High Performing quadrant and from the Low Performing quadrant to either the Operational Improvements Opportunity quadrant or the System Upgrade Opportunity quadrant. We note that a 20 percent reduction in the average LPD of buildings in the System Upgrade Opportunities quadrant would decrease their average LPD to 1.19 W/sf, which would be less than the average LPD in the High Performing quadrant. For site 8829, the current Asset Score is only 1.0 and, even though the hypothetical LPD decrease would produce a large predicted increase in the Asset Score and ENERGY STAR score, the predicted Asset Score is not large enough to move the building into either the Operational/Behavioral Opportunities or High Performing quadrants.

---

[14] Ranges were used for ENERGY STAR predictions due to uncertainty in the predictions, as well as providing comparable results with Asset Score predictions.

Table 15. Lighting Sensitivity Results – Predicted Quadrant Changes

Building ID	Current Quadrant	Predicted Quadrant
8828	System Upgrade Opportunities	High Performing
8879	System Upgrade Opportunities	High Performing
8645	System Upgrade Opportunities	High Performing
8753	System Upgrade Opportunities	High Performing
8926	Lowest Performing	Operational/Behavioral Opportunities
8738	Lowest Performing	Operational/Behavioral Opportunities
8829	Lowest Performing	System Upgrade Opportunities

These results suggest that buildings with less efficient lighting systems could be good targets for efficiency improvements through lighting upgrades. Reducing the LPD through replacement of existing lighting with new, efficient LED technologies offers an obvious first step for making significant efficiency improvements. Although we did not have sufficient data to explore other options associated with lighting, even efficient lighting equipment could benefit from control upgrades or improved schedule management that would have a significant impact on EUI.

HVAC Measures

Cadmus analyzed energy performance as a function of HVAC measures after accounting for significant building characteristics based on information in the Portfolio Manager and Asset Score data. HVAC measures include inputs such as heating and cooling efficiency values and year of manufacture, and HVAC System Performance Ratios (SPR).[15] The SPR includes the energy use of all system components, including fans, pumps, heat rejection, and heat recovery equipment. It also includes the energy impact of controls such as supply air temperature reset or economizer control. Hence, it provides a complete assessment of total system performance, which is not possible through an assessment of the rated efficiency by itself. We assessed the qualitative and quantitative relationships that HVAC measures have with scores and EUIs after accounting for the effects of building characteristics.

Summary Statistics

Table 16 summarizes the HVAC measures for buildings in each quadrant of the score matrix. Similar to the PNNL paper[16] cited before, the quadrants exhibit almost no relationship to the average rated HVAC system efficiency. The SPR is the only characteristic that appear partially related to performance with the largest average value in the High Performing quadrant and the smallest in the Low Performing quadrant.

---

[15] Goel, S., V. Mendon, N. Wang, M. Rosenberg. Performance-Based Building System Evaluation for DOE Energy Asset Score.

[16] Wang, Na, S. Goel, W. Gorissen, and A. Makhmalbaf. "Understanding Building Infrastructure and Building Operation through DOE Asset Score Model: Lessons Learned from a Pilot Project," PNNL-SA-92883, prepared for U.S. Department of Energy.

Table 16. HVAC Measure Quadrant Summaries

Operational Improvements (n = 6)	High Performing (n = 4)
Ave. HVAC Year Manufactured of 2003 Ave. Heating Efficiency Value of 76% Ave. Cooling Efficiency Value of 3.00 COP Ave. Total Site System Performance Ratio of 1.12 100% of buildings have central HVAC systems	Ave. HVAC Year Manufactured of 2006 Ave. Heating Efficiency Value of 82% Ave. Cooling Efficiency Value of 3.05 COP Ave. Total Site System Performance Ratio of 1.90 50% of buildings have central HVAC systems
Low Performing (n = 9)	**System Upgrade Opportunities (n = 6)**
Ave. HVAC Year Manufactured of 2009 Ave. Heating Efficiency Value of 91% Ave. Cooling Efficiency Value of 3.74 COP Ave. Total Site System Performance Ratio of 0.83 89% of buildings have central HVAC systems	Ave. HVAC Year Manufactured of 2005 Ave. Heating Efficiency Value of 78% Ave. Cooling Efficiency Value of 3.91 COP Ave. Total Site System Performance Ratio of 0.81 60% of buildings have central HVAC systems

Correlation Analysis

Cadmus plotted the rated HVAC system efficiency with the EUI and score values from each dataset in the scatter plot matrix; please see Figure 10 and Figure 11.

The following figures show a random distribution of heating efficiency values, which could explain the small and unexpected correlations with scores and EUIs. Cooling efficiency values tend to cluster around 3.0 and HVAC year of manufacture tends to cluster around 2006 to 2008. In the Asset Score matrix, we identified a strong negative correlation between HVAC System Performance Ratio (SPR) and EUI and strong positive correlation with score, as expected, and similar, but weaker correlations, in the ENERGY STAR matrix. The observed relationship between the HVAC system performance ratio with site EUI, source EUI, and scores matches our expectations. The observed relationships between HVAC year of manufacture, heating efficiency value, and cooling efficiency value have unexpected relationships with EUIs and Scores. We expected heating and cooling efficiency values and year of manufacture to have negative correlations with EUI. The unexpected observed relationships are potentially due to the small sample size and lack of variation in the data. The PNNL Study (Wang 2013) had reached a similar conclusion where HVAC system rated efficiency was not found to have a strong correlation with Asset Score. The PNNL study drew the conclusion that the HVAC system design (including the air and water distribution systems and controls) affects the system energy use and building loads contribute to the overall building energy use. Hence, a single parameter like rated equipment efficiency is less likely to have a strong relationship with overall building performance. Using variables with stronger correlations, we conducted regression analysis to quantify the effects of HVAC measures on scores and EUIs.

Table 17 summarizes the correlations between HVAC measures and site EUI, source EUI, and scores in both datasets.

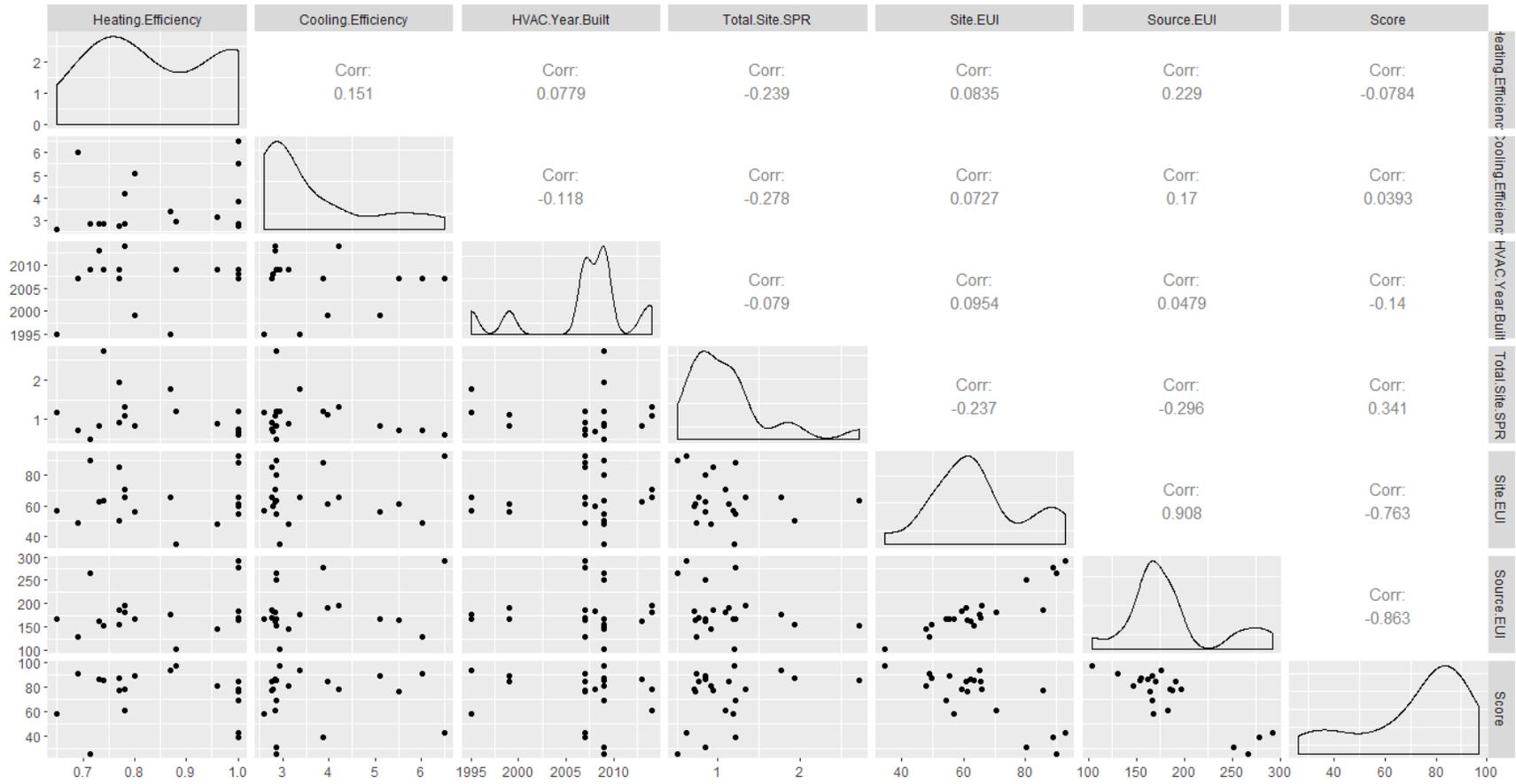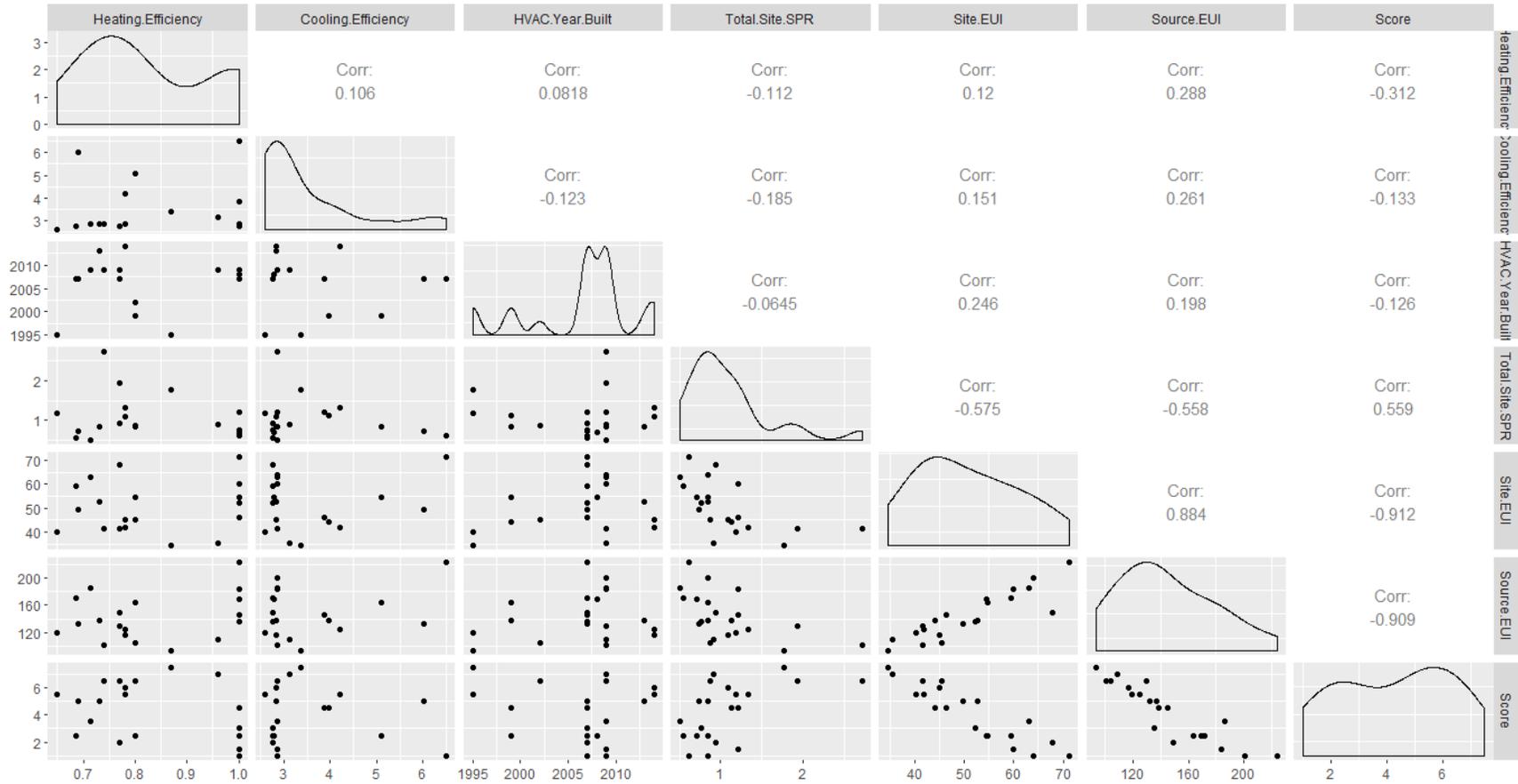**Figure 10. ENERGY STAR HVAC Scatterplot Matrix**

Figure 11. Asset Score HVAC Scatterplot Matrix

The observed relationship between the HVAC system performance ratio with site EUI, source EUI, and scores matches our expectations. The observed relationships between HVAC year of manufacture, heating efficiency value, and cooling efficiency value have unexpected relationships with EUIs and Scores. We expected heating and cooling efficiency values and year of manufacture to have negative correlations with EUI.[17] The unexpected observed relationships are likely due to the small sample size and lack of variation in the data, so Cadmus decided to remove these variables from the remaining analyses. Due to the observed correlations, we used regression analysis to quantify the effects of HVAC measures on scores and EUIs.

<div align="center">Table 17. HVAC Correlation Results</div>

Variable	Sample Size	Site EUI	Source EUI	Score[3]	Expected Relationship		Behaving as expected	
					EUI	Score	EUI	Score
Portfolio Manager Variables								
HVAC Year of Manufacture	21	0.10	0.05	-0.14	+	-	No	No
Heating Efficiency Value	19	0.08	0.23	-0.08	-	+	No	No
Cooling Efficiency Value	19	0.07	0.17	0.04	-	+	No	Yes
HVAC System Perf. Ratio	21	-0.24	-0.30	0.34	-	+	Yes	Yes
Asset Score Variables								
HVAC Year of Manufacture	21	0.29	0.24	-0.20	+	-	No	No
Heating Efficiency Value	19	0.12	0.29	-0.31	-	+	No	No
Cooling Efficiency Value	19	0.14	0.25	-0.19	-	+	No	No
HVAC System Perf. Ratio	21	-0.57	-0.56	0.54	-	+	Yes	Yes

Regression Analysis

We summarize the multiple linear regression results in Table 18, where check marks identify the building characteristics and measures that are statistically significant predictors of EUI or score at 90 percent confidence in the regression models. In the multiple linear regression model, we observe HVAC SPR as the only significant predictor in the model for ENERGY STAR score, after accounting for building characteristics. SPR is not identified as a significant predictor of EUI or Asset Score when included in the full regression model even though strong correlations were observed.

The relationship for SPR with the responses is obscured due to multicollinearity[18] between SPR and energy use. Since SPR is highly correlated with energy use, multiple linear regression modeling will only be able to identify statistical significance between variables with the strongest relationships. To quantify the univariate relationships for SPR with Asset Score and Asset Site EUI, we performed simple linear regression modeling with SPR as the only predictor of each response. We summarize the simple linear regression results in Table 19.

---

[17] We note that the PNNL study cited earlier showed only a moderate negative correlation between the cooling EUI and air conditioning efficiency.

[18] Multicollinearity occurs when two or more predictor variables in a multiple linear regression model are highly correlated, meaning that one can be linearly predicted from the others with a considerable degree of accuracy.

Table 18. HVAC Multiple Linear Regression Summary

Variable	Portfolio Manager Site EUI	ENERGY STAR Score	Asset Score Site EUI	Asset Score
Number of Floors			✔	✔
Year Built	✔			
Total Energy Use (kBtu)	✔		✔	
Source EUI	NA	✔	NA	✔
ln(Floor Area)	✔	✔	✔	
HVAC System Perf. Ratio		✔		

* NA occurs because source EUI does not predict site EUI.

Table 19. HVAC Simple Linear Regression Summary

Response	Predictor	Statistically Significant
Portfolio Manager Site EUI	HVAC System Perf. Ratio	
ENERGY STAR Score	HVAC System Perf. Ratio	✔
Asset Site EUI	HVAC System Perf. Ratio	✔
Asset Score	HVAC System Perf. Ratio	✔

Findings

These results provide evidence that SPR is a significant predictor of ENERGY STAR score, Asset Score, and Asset Site EUI, not accounting for other predictors. Because the SPR accounted for broader HVAC system characteristics it would be the preferred characteristic to investigate more thoroughly.

Envelope Measures

Finally, Cadmus analyzed energy performance as a function of envelope measures after accounting for significant building characteristics based on information in the Portfolio Manager and Asset Score data. Envelope measures included inputs such as wall-window weighted U-Factor (WW U-Factor),[19] window-to-wall ratio (WWR), and window-to-floor ratio (WFR). We assess the qualitative and quantitative relationships that envelope measures have with scores and EUIs after accounting for the effects of building characteristics.

Summary Statistics

Table 20 summarizes the envelope measures for buildings in each quadrant of the score matrix. The WWR values exhibited relationships mostly consistent with expectations. The average WWR for the High Performing quadrant was less than for the System Upgrade Opportunities quadrant, which was less than the value for the Low Performing quadrant. WW U-Factor exhibited the most relationships most consistent with expectations, having the smallest value in the High Performing quadrant and a value

---

[19] The WW U-Factor was calculated from the window and wall areas and the assumed U-factors for these components based on the recorded construction characteristics. The WW U-Factor captures the overall estimated thermal conductivity of the building envelope.

more than twice large in the Low Performing quadrant. The WFR did not exhibit a pattern consistent with expectations.

Table 20. Envelope Measure Quadrant Summaries*

Operational Improvements (n = 6)	High Performing (n = 4)
Ave. WWR of 0.36 Ave. WFR of 0.015 Ave. WW U-Factor of 0.45 83% had double pane windows 33% had metal with thermal break window frames	Ave. WWR of 0.41 Ave. WFR of 0.017 Ave. WW U-Factor of 0.31 100% had double pane windows 50% had metal with thermal break window frames
Low Performing (n = 9)	**System Upgrade Opportunities (n = 6)**
Ave. WWR of 0.63 Ave. WFR of 0.022 Ave. WW U-Factor of 0.66 78% had double pane windows 0% had metal with thermal break window frames	Ave. WWR of 0.59 Ave. WFR of 0.019 Ave. WW U-Factor of 0. 55 100% had double pane windows 17% had metal with thermal break window frames

***The quantitative values in the table are U-factors, which are equivalent to inverse R-values, and are expressed in units of Btu/(hr-ft·°F).

Correlation Analysis

The envelope measures with the EUI and score values from each dataset are shown in the scatter plot matrix in Figure 12 and Figure 13. Both figures show relationships as expected between all envelope measures and EUIs and scores. For example, the WWR and WFR are positively correlated with EUIs and negatively correlated with scores.

Figure 12. ENERGY STAR Envelope Scatterplot Matrix
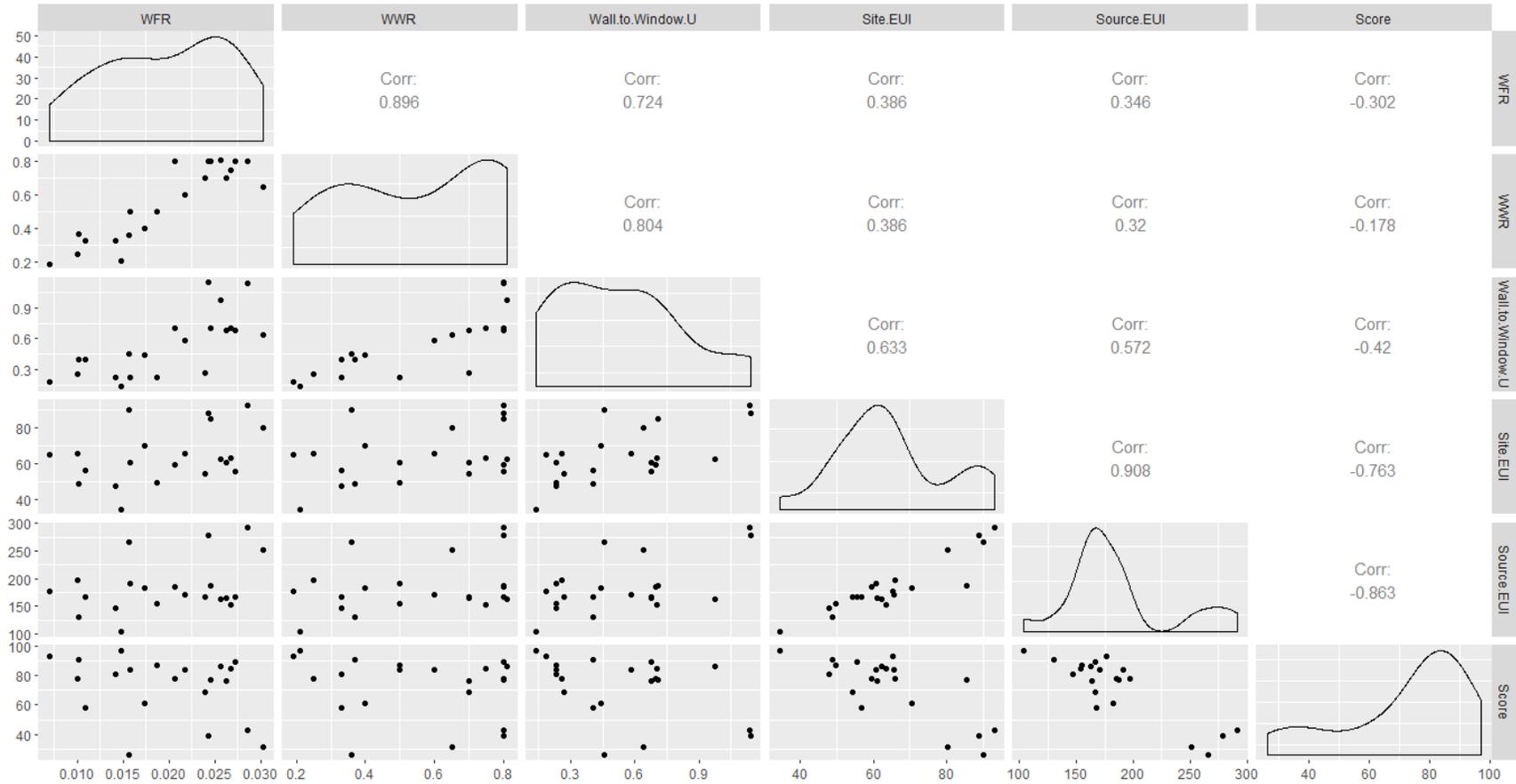
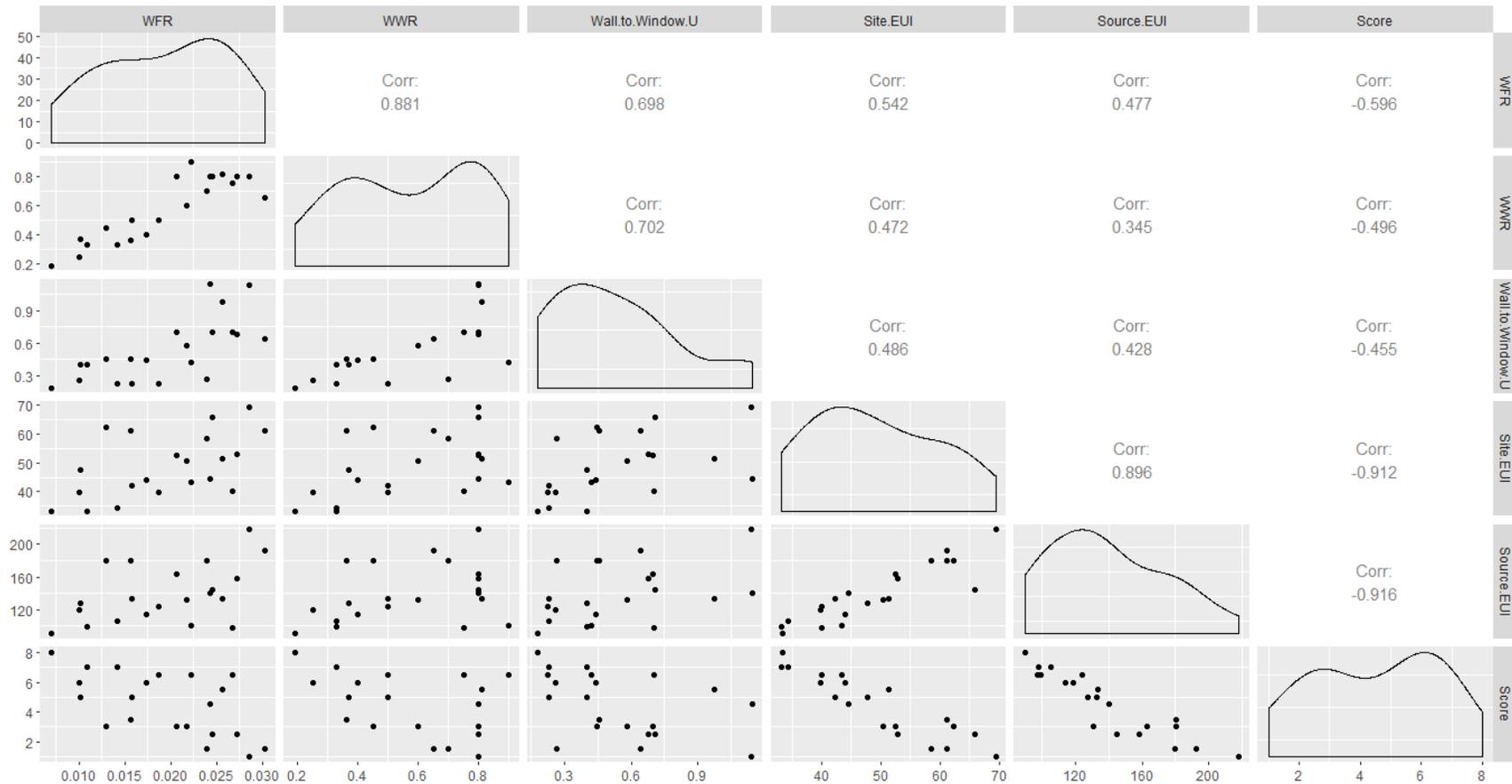**Figure 13. Asset Score Envelope Scatterplot Matrix**

Table 21 summarizes the correlations between envelope measures and site EUI, source EUI, and scores in both datasets.

Table 21. Envelope Measure Correlation Results

Variable	Sample Size	Site EUI	Source EUI	Score[3]	Expected Relationship		Behaving as expected	
					EUI	Score	EUI	Score
Portfolio Manager variables								
Window-Floor Ratio	21	0.39	0.35	-0.30	+	-	Yes	Yes
Window-Wall Ratio	21	0.39	0.32	-0.18	+	-	Yes	Yes
Wall-Window U-Factor	21	0.63	0.57	-0.42	+	-	Yes	Yes
Asset Score variables								
Window-Floor Ratio	21	0.54	0.48	-0.60	+	-	Yes	Yes
Window-Wall Ratio	21	0.47	0.35	-0.50	+	-	Yes	Yes
Wall-Window U-Factor	21	0.49	0.43	-0.45	+	-	Yes	Yes

The observed relationships between all envelope measures, site EUI, source EUI, and scores agree with our expectations. We observed a strong positive correlation between WWR and WFR. Since we observed larger differences between the quadrants for WWR, Cadmus did not include the WFR in the regression analysis.

Regression Analysis

We summarize the multiple linear regression results in Table 22, where a check mark identifies the building characteristics and measures that are statistically significant predictors of EUI or score at 90 percent confidence in the regression models. Window framing type is a significant predictor in the models for ENERGY STAR score and Asset Score site (and source) EUI, as well as WW U-factor as a significant predictor in the model for ENERGY STAR score, after accounting for building characteristics.

Due to multicollinearity[20] between the window variables, we performed simple linear regression using each window variable to predict scores and EUIs, not accounting for other variables. We summarize the simple linear regression results in Table 23.

---

[20] Multicollinearity occurs when two or more predictor variables in a multiple linear regression model are highly correlated, meaning that one can be linearly predicted from the others with a considerable degree of accuracy.

Table 22. Envelope Measure Multiple Linear Regression Summary

Variable	Portfolio Manager Site EUI	ENERGY STAR Score	Asset Score Site EUI	Asset Score
Number of Floors			✔	✔
Year Built	✔			
Total Energy Use (kBtu)	✔		✔	
Source EUI	NA	✔	NA	✔
ln(Floor Area)	✔	✔	✔	
Window-Wall Ratio				
Wall-Window Weighted U-Factor		✔		
Window Glass Type				
Window Framing Type		✔	✔	

* NA occurs because source EUI does not predict site EUI.

Table 23. Envelope Measure Simple Linear Regression Summary

Response	Predictor	Statistically Significant
Portfolio Manager Site EUI	Wall-Window Weighted U-Factor	✔
	Window Framing Type	
ENERGY STAR Score	Wall-Window Weighted U-Factor	✔
	Window Framing Type	✔
Asset Site EUI	Wall-Window Weighted U-Factor	✔
	Window Framing Type	✔
Asset Score	Wall-Window Weighted U-Factor	✔
	Window Framing Type	✔

## Findings

Envelope characteristics were some of the most significant predictors of scores and EUIs with relationships consistent with expectations. Given the construction of commercial buildings, however, opportunities to upgrade envelope insulation are likely to be limited. Windows, on the other hand, can be replaced with more efficient units and the buildings in this sample had a large proportion of single-pane, and non-thermal break windows that could be replaced with more efficient systems. The simple linear regression provides evidence of significant relationships between Wall-Window Weighted U-Factor and all responses when not accounting for any other predictors. When using Window Framing Type as the only predictor for each response, we identify this as having a significant relationship with Energy Star Score, Asset Score, and Asset Site EUI.

Additional Analysis

We investigated the relationships that ENERGY STAR site EUI and score had with number of computers, weekly operating hours, percent occupancy, and number of employees from the detailed PORTLANDLEAP accounts. As expected, Figure 14 shows that increased numbers of computers, operating hours, and employees correspond to increased EUI and decreased ENERGY STAR score.[21]

Figure 14. Portfolio Manager Detailed Data Scatterplot Matrix
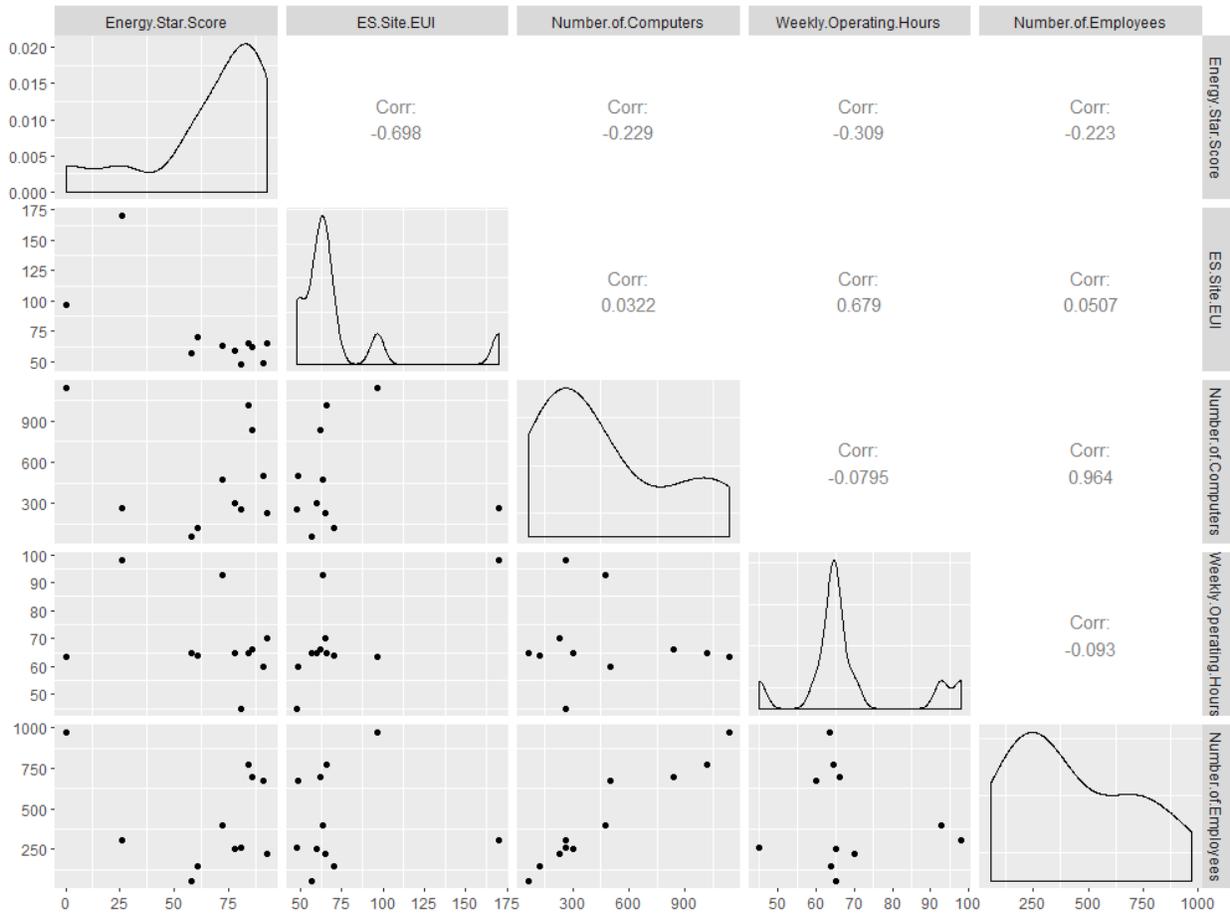
Due to the limited number of observations, we did not perform additional correlation or regression analyses using these variables.

Cadmus also investigated the relationship that LEED had with EUIs and Scores. In the sample, we observed 12 sites without any LEED certification, no sites as Certified, 1 site as Silver, 7 sites as Gold, and 1 site as Platinum. Due to the small sample sizes and the categorical nature of LEED, we are able to visualize the differences in energy use and EUI for each category, but are unable to quantify the

---

[21] It might be preferable to investigate the number of computers per square foot and number of employees per square foot. This is beyond the scope of this study, but recommended to pursue in a follow-up study.

relationship in correlation or regression analysis. Figure 15 shows how EUIs and Scores vary between the LEED levels. Due to the amount of variability in the data, we observe that the boxplots tend to overlap, and therefore we do not have strong evidence of a significant difference between LEED levels based on our data. However, we are able to visualize a decreasing trend in EUI as LEED improves, along with an increasing trend in Score as LEED improves, as one might expect.

Figure 15. Relationships between Responses and LEED Boxplot
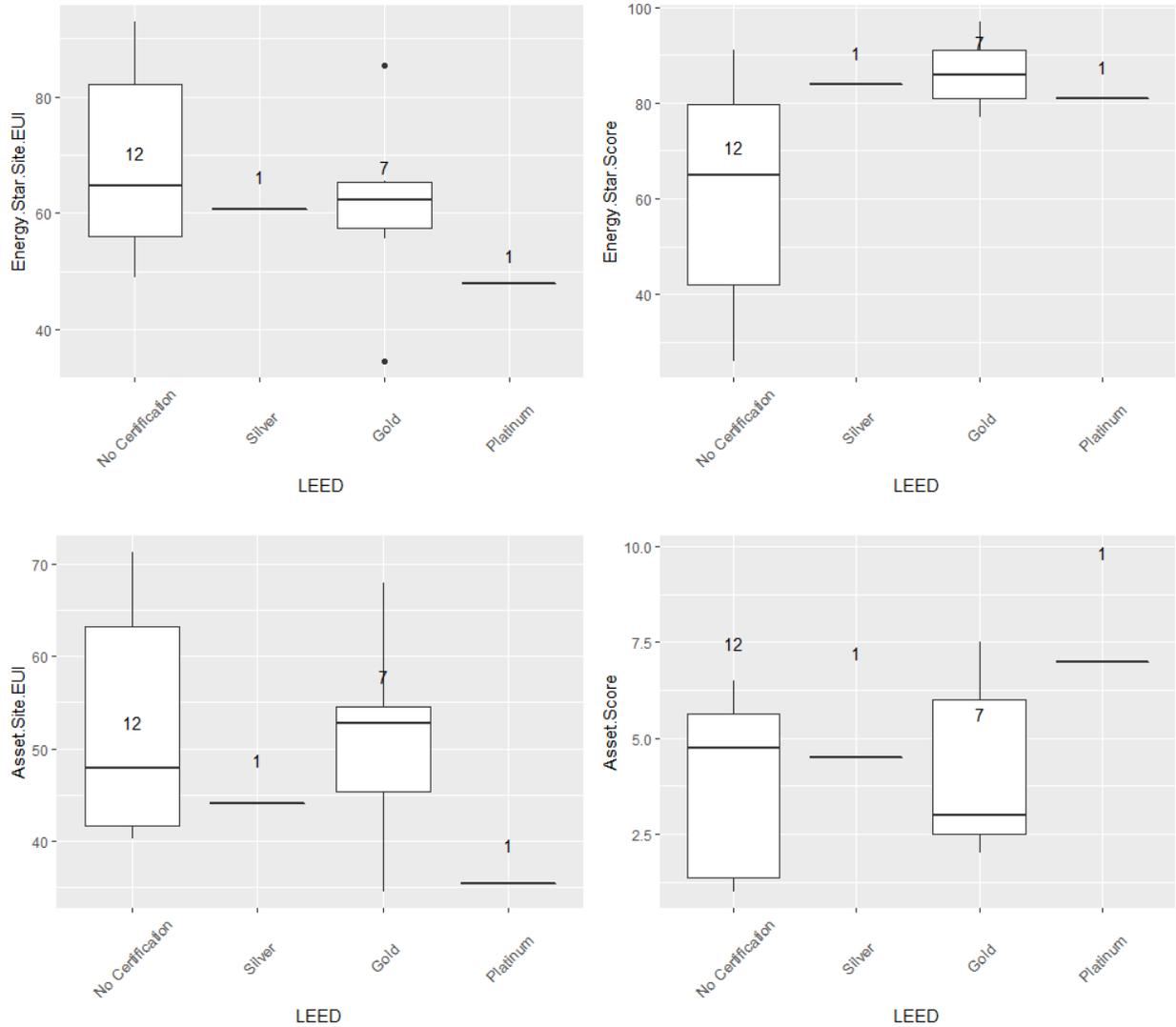
Conclusions and Recommendations

Based on the data visualization, summary statistics, and correlation and regression analysis, Cadmus concludes that any building characteristics significantly associated with EUI, ENERGY STAR score, or Asset Score should be considered in order to provide building-specific recommendations.

Cadmus provides the following end use specific recommendations:

- A decrease in lighting power density by 20% is achievable and can improve both ENERGY STAR score and Asset Score due to the significant relationships between lighting power density, EUI, and score. At a building-by-building level, the changes in scores would potentially lead to re-categorizing the building in the score matrix. Cadmus recommends using PNNL's Building Energy Asset Score tool to determine what changes in bulb type and percent area served would result in a decrease of LPD by 20% to provide this information for each building. This is beyond the scope of this study, but recommended to pursue in a follow-up study.

- Buildings in the low performing quadrant and system upgrade opportunity quadrant have room for improvement in their HVAC system performance. Improving the HVAC system performance will improve the system performance ratio and thus improve their ENERGY STAR score.

- Buildings in the low performing quadrant and system upgrade opportunity quadrant have room for improvement in their envelope performance. Replacing single-pane windows with double-pane windows with thermal breaks could potentially achieve this.

Cadmus recommends plotting EUI values (ENERGY STAR EUI vs. Asset Score EUI) in addition to scores (ENERGY STAR score vs. Asset Score) as the EUI values are more representative of actual and predicted energy use. Comparing the EUI values provides evidence of how an individual building is performing compared to its modeled performance and can help flag whether it is underperforming or overperforming relative to its performance based on modeling. The comparison of scores, however, provides useful information about how each building is performing compared with its peers.

Due to the limited number of available buildings in the sample, we did not perform additional correlation or regression analyses using some of the variables, for example number of computers, weekly operating hours, percent occupancy, and number of employees.

It might be worthwhile to investigate the number of computers per square foot and number of employees per square foot. This is beyond the scope of this study, but recommended to pursue in a follow-up study. This is because the regression equation for ENERGY STAR score for offices includes the number of computers per 1,000 sf and the natural log of the number of workers per 1,000 sf.

When performing statistical analysis, the sample size and variability of the data must be considered when determining the precision of the results. Small sample sizes decrease the power of a statistical test, making it less likely to detect a significant relationship between variables. The higher the variability

in the sample, the larger the sample size needed. Cadmus recommends pursuing a follow-up study with a sample size of 70 or more buildings to improve the accuracy and precision of the results. We recommend starting with a larger sample than needed, as the data cleaning exercises will force a number of sites to be removed from further analysis.

Appendix A: Building Data List

ENERGY STAR Portfolio Manager data

Data reported to the City for calendar year 2015:

- Building ID
- Building Type
- Secondary Use(s)
- Year Built
- ENERGY STAR score
- LEED Certification Level and Version
- Gross Floor Area (GFA)
- Green House Gas Emissions
- Electricity Use (kWh/year)
- On-Site Generation (KWh/year)
- Natural Gas Use (therms/year)
- EUI (site and source)
- Weather Normalized EUI
- National Median EUI (site and source)

Asset Score data

Physical characteristics collected from permits and plans onto Asset Score forms:

- Number of Floors
- Building Energy Asset Score
- Predicted Building EUI (site and source)
- Predicted annual natural gas use
- Predicted annual electricity use
- Building footprint dimensions
- Roof type
- Floor type
- Wall type
- Window framing type
- Window glass type (assumed based on year completed)
- Window-to-wall ratio, or number of windows and dimensions
- Lighting type, mounting type, watts per lamp, lamps per fixture, and percent area served
- HVAC system type (air handler units or zone equipment)
- Cooling system year of manufacture
- Cooling source (plus compressor type and condenser type for chillers)
- Heating source (plus heating fuel type for boilers)
- Heating system year of manufacture
- Service hot water fuel type and distribution type