Use Cases and Best Practices for Map-Based Energy Data Visualization

Kiernan Salmon, UC Davis Facilities Energy & Engineering
Angela Sanguinetti, UC Davis Plug-in Hybrid & Electric Vehicle Research Center

ABSTRACT

Across a variety of energy conservation programs and tools, energy data visualizations are common components used to inform and influence behavior. Several studies have explored map-based energy data visualizations and found that they compare favorably to conventional charts and graphs, but all generated more unanswered questions about how, when, and why map-based visualizations work well. This research reviews the current state of knowledge and adds to the limited empirical work on map-based energy displays in order to articulate best practices and support broader use of maps to visualize energy data. Two online experiments were conducted with over 830 participants from Amazon Mechanical Turk to assess and compare the usability of multiple versions of map-based energy displays and bar charts. Results were consistent with past research findings that map-based energy data visualizations are more interesting and enjoyable than more basic displays (bar charts). These findings support a general use case for map-based energy displays when trying to engage a broad audience, including those unfamiliar with energy data, by telling a richer story and elevating the data to be more than a set of metrics. Results also highlight the importance of interactivity for map-based energy displays; participants who used interactive features were more accurate in interpreting energy data than those who did not. Other best practices for map-based energy data visualizations are discussed, including considerations for single-variable heat maps, proportional symbol maps, and dual-encoded proportional symbol maps.

Introduction

Energy data visualization is a common component across a variety of energy conservation programs and tools. These programs and tools target a variety of audiences, including government, building managers, the general public/energy end-users. Though diverse, applications of energy data visualizations share common goals of informing and/or influencing behavior.

Some research has also begun to articulate best practices for the design of effective energy data visualizations (Egan 1999; Sanguinetti, Dombrovski, and Sikand 2018). For example, Sanguinetti, Dombrovski, and Sikand categorized three main dimensions of eco-feedback design that have implications for behavior change: information, timing, and display. Visual style (a sub-dimension of display) influences user attitudes toward the product and perceived ease of use (Hermsen et al. 2016).

Visual styles in energy data displays can include numbers, text, charts, graphs, maps, animation, pictures, icons, and colors. When these styles are used together, it is what Tufte (2001) calls data graphics, which are used to present rich, multidimensional information. Tufte also describes the value of encoding data into a graphical visualization, "thanks to the graphic, [all that data] can be thought about in many different ways... ranging from the contemplation of general overall patterns to the detection of very fine detail." (p.16).

Spatial maps are a graphic style that may be underutilized in energy data visualizations. Murray (2017) demonstrated the increasing popularity of map-based data visualizations across a wide range of topics,[1] including the environment, social media, and transportation. With software to create interactive data visualizations and business analytics such as Tableau and Power BI, and providers of online maps and geographic information systems such as Mapbox and ESRI, map-based visualizations are becoming more accessible and easier to create. As a result, map-based data visualizations are proliferating throughout journalism and industry.

Despite the growing trend in map-based data visualizations, there seem to be relatively few examples with energy data, limited to a subset of applications. In general, spatial maps are more common in visualizations of energy-related data at larger scales, e.g., state,[2] national,[3] and international,[4] and less often in visualizations of building-level energy data.[5] Gupta, Barnfield, and Gregg (2018) explained that spatial maps for energy data are generally found in applications geared toward helping "energy-savvy stakeholders", such as authorities, retrofit providers, or utilities target areas for improvements, rather than communicating energy feedback to building occupants and communities. This may be a missed opportunity since the limited research on map-based energy data visualizations suggests that they are more engaging for lay users than more common display styles (Salmon and Sanguinetti 2016; Francisco et al. 2018) and can empower lay communities to advocate for local energy improvements (Gupta, Barnfield, and Gregg 2018; Francisco and Taylor 2019).

There is a need for analysis that integrates the knowledge and approaches of human-computer interaction and behavioral science to inform the use of map-based energy data visualizations, particularly for end-user energy feedback applications. This research reviews general best practices for map-based data visualization and adds to the limited empirical work on usability of map-based energy displays to support broader use of map-based displays across the range of energy data applications.

Literature Review

Several data visualization experts that have defined best practices for working with map-based data (Wong 2013; Yau 2013; Jones 2014; Kirk 2016). The first important point is that map-based data visualizations are appropriate when geography is important to the message portrayed in the data (Wong 2013). Geography could be important for a variety of energy data use cases, such as tracking and comparing energy usage or savings across a multiple buildings in a community, or pinpointing high-consumption appliances within a home.

Single Variable Energy Maps

When a single variable (such as energy consumption) corresponding to geography is encoded in a map display, it is typically done through color-coding. For example, spatial heat maps encode a quantitative variable on a map to show how the magnitude of a variable is distributed across a space. Spatial heat maps have been used in energy conservation tools to

[1] 80 Data Visualization Examples Using Location Data and Maps: https://carto.com/blog/eighty-data-visualizations-examples-using-location-data-maps/#environmental
[2] Energy Upgrade California Example: https://www.energyupgradeca.org/californias-energy-goals/
[3] The Sierra Club Example: https://coal.sierraclub.org/coal-plant-map
[4] Department of Energy Examples: https://www.energy.gov/maps
[5] City of Bristol Example: https://opendata.bristol.gov.uk/explore/dataset/solar-potential/map

visualize temperature and comfort data (e.g., Schott et al. 2012; Pritoni et al. 2017; Gupta, Barnfield, and Gregg 2018) as well as energy data (Bonino, Corno, and De Russis 2012; Center for Sustainable Energy 2018; Francisco et al. 2018; Gupta, Barnfield, and Gregg 2018; Francisco and Taylor 2019). A green-amber-red color scheme is typically used to convey low to high energy use, respectively. Thermal imaging to identify heat losses is another example of energy-related spatial heat mapping.

Francisco et al. (2018) tested the usability of a two-dimensional (2D) and three-dimensional (3D) spatial heat map of energy usage in an apartment complex against the same data displayed in a traditional bar chart. Users reported that both the 2D and 3D map visualizations were more engaging and motivating than the bar chart. The 2D map was as easy to understand as the bar chart, but users felt the 3D map was a little distracting and not as easy to interpret.

Similarly, Salmon and Sanguinetti (2016) tested the usability of a 2D spatial heat map visualizing energy use intensity of multiple buildings on a college campus compared to a traditional bar chart in a between-subjects design with random assignment (Salmon and Sanguinetti 2016). Similar to Francisco et al. (2018), users rated the map as more interesting and enjoyable than the bar chart. Additionally, participants who viewed the map indicated it was easier to understand than the bar chart in terms of their perceived interpretation of the energy use intensity metric. However, some users interpreted the red-to-green color-coding as bad and good, respectively. Thus, the typical heat map approach may not be suitable for applications of energy data that are not intending to convey this kind of normative judgment.

Another way to display a single quantitative variable (e.g., energy consumption) on a map is through the use of proportional symbols, i.e., shapes, sized by the variable, overlaid on a map. This allows for variables to be encoded on something other than geographies (Kirk 2016), which may be useful when conveying data for discrete latitudes and longitudes dispersed across a large area (rather than all areas within the map).

Proportional symbols should be sized to correspond to the encoded variable by area (e.g., rather than width or diameter; Figure 1) because people perceive the size of shapes by their area, and not their width/diameter (Tufte 2001; Kirk 2016). It is also recommended that displays include a clear key or legend that the area of the symbols reflects the data.

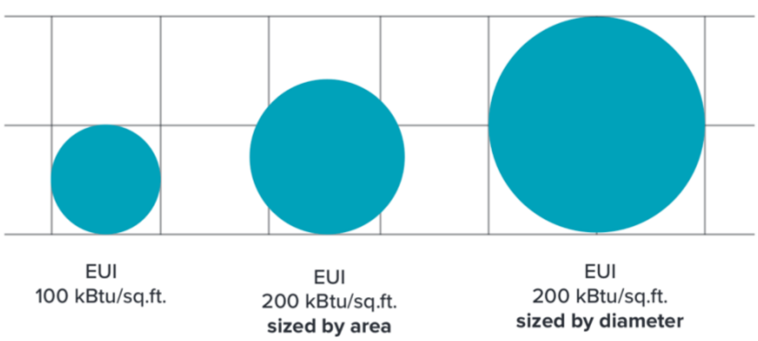

Figure 1. When sizing a proportional symbol, there is a difference between sizing by diameter and by area, and users perceive the size of symbols by their area and not their diameter or width.

Dual-Encoded Energy Maps

Maps with proportional symbols also offer the opportunity to encode a second variable for greater data richness (Wong 2013). Specifically, color-coding of proportional symbols is often used to introduce a categorical variable (Kirk 2016). Maps that have proportional symbols that are color-coded can be called dual-encoded maps.

Dual-encoded maps may be useful when energy consumption is related to a third variable (in addition to geography), such as building type. For example, the Campus Energy Education Dashboard (CEED) at University of California, Davis, aims to educate the campus community (including students and stakeholders; aged 18 and up, ranging from non-technical backgrounds to professional engineers) about energy use on campus, including factors that influence the energy use intensity of campus buildings (Salmon and Sanguinetti 2016). Building type (e.g., predominately classroom, lab, office, or community space) has a significant impact on energy use. Therefore, encoding both energy use and building type became an important goal for CEED.

In a second experiment reported in Salmon and Sanguinetti (the first, described in the previous section, tested a single variable heat map), usability was compared for a dual-encoded map versus a bar chart. In the dual-encoded map, energy use intensity (EUI) was represented by proportional symbols (sized by area), and the symbols were color-coded by building type (e.g., lab, office; color-coded). The map was again rated as more enjoyable than the bar chart and perceived interpretation of the EUI metric higher. However, those who viewed the bar chart were more accurate in determining the building type with the highest energy use (95% correct) compared to those who viewed the dual-encoded map (81%). This was interpreted as similar to the finding of Francisco et al. (2018) that 3D maps were less easy to interpret than 2D maps and bar charts, indicating that more complex maps may not be competitive with more basic graphics in terms of ease of use.

Interactive features could potentially mitigate the complexity of dual-encoded energy data maps. Hegarty (2011) describes interactive features as animation (images appearing over time), filtering or adding/subtracting variables from a display, and rotating and zoom capabilities. Rheingas (2002) concluded that the ability to control or manipulate any mapped dataset increases users' confidence and accuracy in interpreting the data and enables insights they would not glean from a static visualization. Hegarty (2011) concludes that while cognitive scientists have studied data graphs and improved their design, there is still much to learn about how users understand complex displays (with interactive features) that encourage data exploration.

Energy System Maps

It is worth noting another type of map-based energy data display that could be called energy systems maps. Petersen and Frantz (2018) created the Oberlin Citywide Dashboard[6] to educate the community about resource flows, showing where water and energy are sourced and used, and where wastewater goes. These are technically data, albeit not the granular kind discussed in the prior two sections. Like CEED, the Citywide Dashboard is designed to be accessible and engaging to a broad audience, in both age and technical expertise. The Oberlin research team demonstrated that integrating their dashboard into fifth grade curriculum increased systems thinking among students (Clark et al. 2017).

[6] Oberlin Citywide Dashboard: https://environmentaldashboard.org/cwd

Present Research

Building on our previous research on CEED (Salmon and Sanguinetti 2016), we tested strategies aimed at improving interpretability as well as other aspects of usability for a dual-encoded map-based energy data visualization. Results are then integrated with insights from the literature to outline current state of knowledge for best practices for map-based energy data visualizations. We conducted two new experiments to address the following questions: (1) Does encoding building type as color-coded icons compare favorably to encoding it as color-coded proportional symbols in terms of accuracy of interpreting relationship between building type and energy use? (2) Do interactive elements in a map-based energy data visualization improve usability?

Experiment 1: Icons v. Color-Coding of Second Variable

Methodology

Given the results of our previous work, we wanted to retain the usability strengths of the map visualization, but attempt to increase interpretability of the second variable (building type). To that end, we explored the potential of a different approach to a dual-encoded map. Specifically, we tested whether the two variables, EUI and building type, would be more effectively represented as two more elements--a colored icon for building type and grey circle of varying size to represent EUI (Figure 2), compared to the single element with two attributes--a circle varying in size and color to represent EUI and building type, respectively (Figure 3). This strategy was devised by our designer and not something we found precedent for in the literature or other applications of data maps.

We also tested a hypothesis that the organization of the bar chart in our previous experiment (grouped by building type and sorted by EUI) provided additional cues for interpreting EUI. We did this by testing that same bar chart (Figure 4) against a version of the bar chart that was not organized by building type or EUI; instead, the buildings were alphabetized (Figure 5).

Figure 2. This map-based energy visualization, referred to as Icon Map, uses a colored icon to represent building type and grey circle of varying size to represent EUI.

Figure 3. This map-based energy visualization, referred to as Color Map, represents EUI with a circle varying in size and 4 different colors to represent building type.

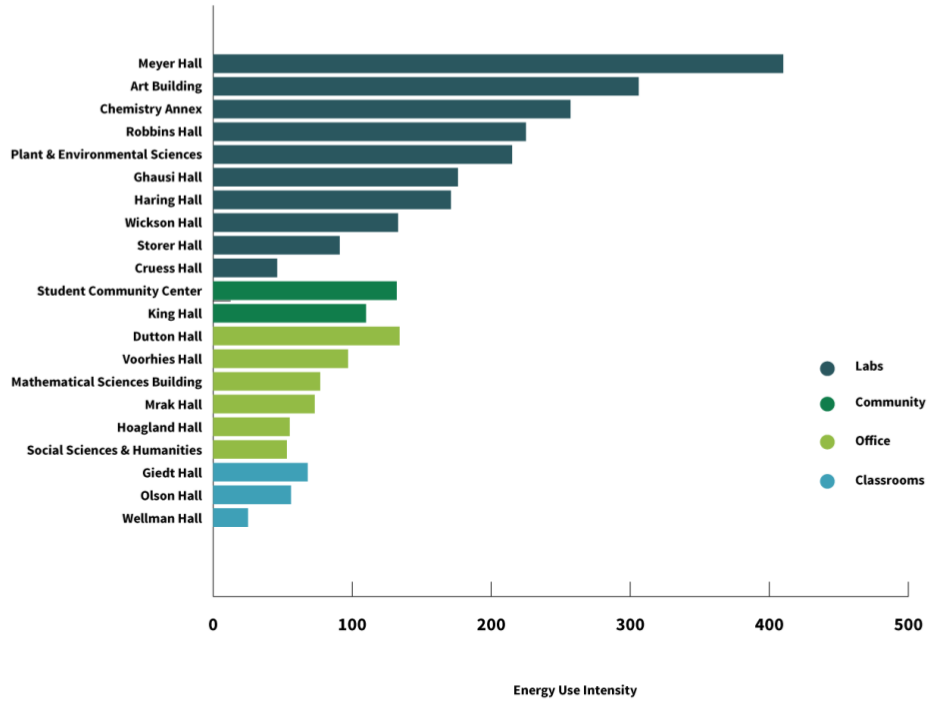

Figure 4. This energy visualization, referred to as Sorted Bar, is a bar chart representing EUI values, colored by building type, and sorted by both building type and EUI from highest to lowest.

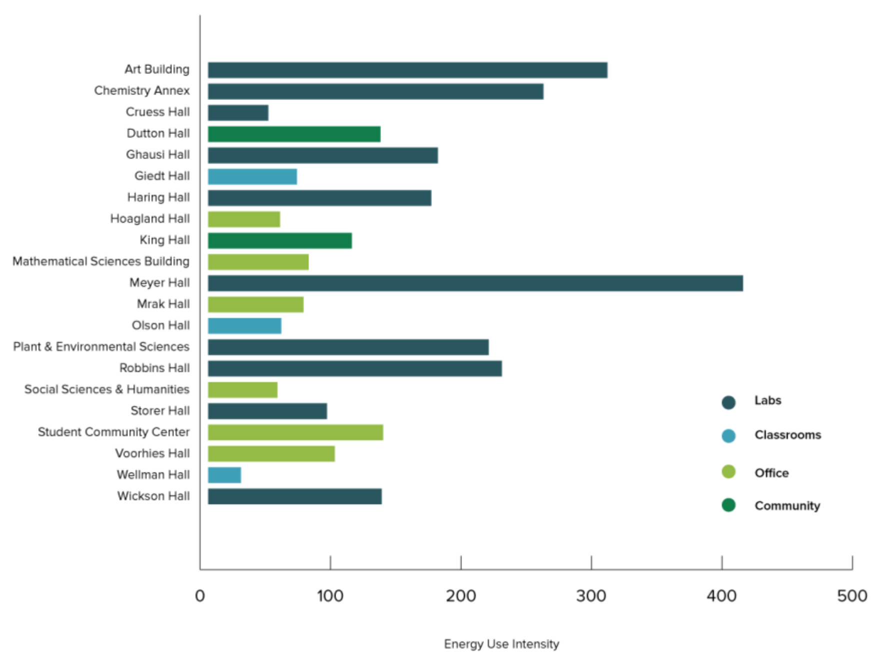

Figure 5. This energy visualization, referred to as Unsorted Bar, represents energy data with a bar chart representing building type with color, sorted alphabetically by building name.

Using Amazon Mechanical Turk, 416 participants (19 to 72 years old, *M* = 34) were randomly assigned to view one of four images: (1) bar chart organized alphabetically by building name; (2) bar chart organized by building type and EUI; (3) map with building type and EUI represented by color and size of circle; (4) map with building type represented by icon and EUI represented by size of circle. Analysis was performed on the 410 participants; 6 were removed due to not marking "Agree" to the question "I am reading the survey questions (mark "Agree")".

Participants were asked to complete our adapted version of the UPScale (Karlin 2013; Table 1) on a 5-point Likert-type response scale (Strongly agree to Strongly disagree). The responses were coded 1, 2, 3, 4, 5, reverse-scored for negative items, and summed to create subscales and a total usability score. There were also two questions included to gauge accuracy of data interpretation: "What is your opinion about the metric Energy Use Intensity (EUI)?" and "Which building type uses the most energy?

Table 1. Usability scale adapted from UPscale (Karlin 2013).

Ease of use	I am able to get the information easily.
	The information is difficult to understand.
	I feel confident interpreting the information.
	A person needs to learn a lot to understand the information.
Trust	I trust the information.
	I do not have confidence in the accuracy of the information.
Interest	I find the information interesting.
Enjoyment	The information is provided in a fun manner.
Engagement	The information would be useful to the UC Davis campus community.

Results

There was no significant difference in the overall usability score across the four visualizations [$F(3,406)$, $p = .491$]: Unsorted Bar [$n = 109$, $M(SD) = 35.2$ (6.8)], Sorted Bar [$n = 104$, $M(SD) = 35.0$ (6.6)], Color Map [$n = 90$, $M(SD) = 36.2$ (6.5)], Icon Map [$n = 107$, $M(SD) = 36.0$ (7.1)]. However, looking at the specific usability sub-scales (ease of use, engagement, interest, trust and enjoyment), interest and enjoyment were rated higher for the map visualizations compared to the bar charts. Results are summarized in Table 2.

Table 2. Usability scores: mean (standard deviation)

Usability Construct	Unsorted Bar	Sorted Bar	Color Map	Icon Map	$F(3, 406)$
Ease of use	14.7 (3.5)	14.4 (3.5)	14.8 (3.5)	14.5 (3.8)	0.83
Engagement	7.3 (1.6)	7.3 (1.5)	7.4 (1.4)	7.2 (1.6)	0.41
Interest	3.4 (1.0)	3.4 (1.1)	3.7 (0.9)	3.7 (0.8)	2.76*
Enjoyment	2.8 (1.0)	2.9 (1.0)	3.5 (1.1)	3.4 (1.1)	13.26***
Trust	7.0 (1.6)	7.0 (1.4)	6.8 (1.5)	7.3 (1.5)	1.81

$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

There was no significant overall effect of visualization type on perceived accuracy in interpreting the Energy Use Intensity (EUI) metric [(X_2(3) = 5.71; p = .127]. However, when looking at pairwise comparisons (Fisher's exact tests), the Icon Map group was significantly more confident about EUI (87% reported to "get the gist of it") compared to the Sorted Bar group (75%); there were no differences involving the other groups (Color Map: 84%, Unsorted Bar: 80%). Visualization type also had a significant effect on accuracy (i.e., identifying the most energy-intensive building type) [(X_2(3) = 10.73; p = .013]. Looking at pairwise comparisons (Fisher's exact tests), participants who viewed the Unsorted Bar (95%) and the Icon Map (93%) were accurate more often than those who viewed the Color Map (82%); the Sorted Bar group was not significantly different from any other group (90% accurate).

Experiment 2: Impact of Interactivity on Usability

Methodology

To expand on our first experiment, we attempted to increase interpretability of the energy data map by adding interactive functionality. Specifically, a hover feature allows users to hover over each building to see the EUI value in kBtu/sq.ft., filter buttons that allow users to remove/add each building type from the map, and a slider filter for users to change the range of EUI values shown on the map. Using Amazon Mechanical Turk, 418 participants were randomly assigned to view one of two websites (alternate, limited versions of CEED, programmed specifically for the experiment): (1) map-based energy visualization with no interaction options; (2) map-based energy visualization with interactive options including a hover, building type buttons to add/remove building types from the map, and a filter for EUI values (Figure 6). Analysis was performed on 285 of the participants (20 to 70 years old, M = 38); 133 were removed due to not marking "Agree" to the question "I am reading the survey questions (mark "Agree")", self-reporting color-blindness, and/or irrelevant answers to the free response question to "After exploring the map, describe the main message you took away from the data display."

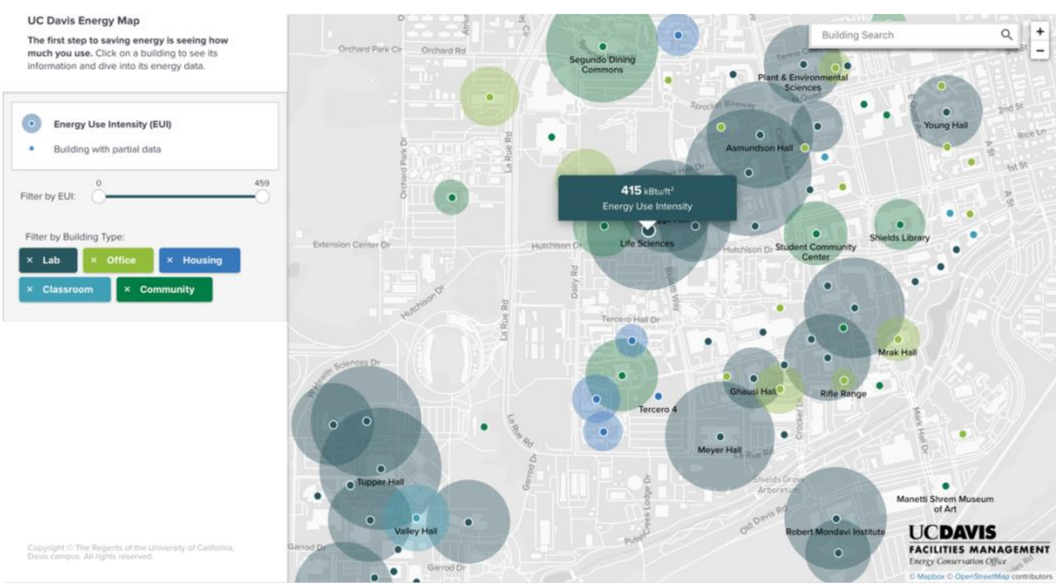

Figure 6. The map-based energy visualization with interactive features: hovers, and filters for building type and Energy Use Intensity (EUI).

We included the same adapted version of the UPScale (Karlin 2013) and data interpretation questions as Experiment 1, as well as two additional questions: "There were circles overlaid on the map, a larger circle indicates: (options: The building consumes less/around the same amount/more energy compared to other buildings)"; and "After exploring the map, describe the main message you took away from the data display" (open-ended). We also asked about use of each interactive feature: "What was your experience with the feature allowing you to select which building types are displayed?": (options: noticed it and used it, noticed it but did not use it, didn't notice and didn't use, didn't notice at first but went back and used after seeing this question).

Results

There was no significant difference between the No Interactivity and Interactivity group in terms of overall usability (Table 3) or any subscale. Honing in on the effects of *using* the interactive features, we tested for a difference in usability between those who used each interactive feature before answering the usability questions compared to those who did not (even if they saw the version in which it was available or went back and used the feature after seeing the question about it). Those who used the EUI slider filter feature rated overall usability higher on average than those who did not (Table 3). There was no difference in overall usability between groups based on use of the hover feature or button filter feature. Looking at the usability subscales, the higher rating among those who used the slider filter feature is attributed to ease of use [$t(283) = -2.21$, $p = .028$; No Slider Use: $n = 206$, $M(SD) = 2.8\ (3.2)$, Slider Use: $n = 79$, $M(SD) = 3.7\ (2.6)$] and enjoyment [$t(283) = -1.71$, $p = .054$; No Slider Use: $n = 206$, $M(SD) = 3.5\ (1.0)$, Slider Use: $n = 79$, $M(SD) = 3.7\ (0.7)$].

Table 3. Usability scores for the EUI Slider: mean (standard deviation)

Usability Construct	Overall Usability	*t*(283)
No Interactivity (n=131)	38.3 (6.3)	0.27
Interactivity (n=154)	38.1 (5.9)	
No Slider Use (n=206)	37.8 (6.4)	-1.81
Slider Use (n=79)	39.2 (5.1)	
No Hover Use (n=172)	37.9 (6.1)	-0.83
Hover Use (n=113)	38.5 (6.0)	
No Button Use (n=172	38.2 (6.3)	0.19
Button Use (n=113)	38.1 (5.7)	

*p < .05, **p < .01, *** p < .001

The Interactivity group was marginally more accurate in interpreting the meaning of the circle size representing building EUI (93.5% were correct) compared to the No Interactivity group (87.0%); $X_2 = 3.47$, $p = .063$. When comparing those who used any or all of the interactive features to those who did not (No Interactivity group plus eight people in the Interactivity group who did not use the features), the difference increases slightly (to 93.8% v. 87.1%); $X_2 = 3.47$, $p = .051$. There was no significant difference between the Interactivity and No Interactivity groups in terms of perceived ability to interpret the EUI metric; Linear-by-Linear Association = 0.06, $p = .815$.

The Interactivity group was also more accurate in identifying which building type uses the most energy (77% were correct in identifying Labs as the highest users) compared to the No Interactivity group (63%); $X_2 = 5.99$, $p = .014$. Comments in the free-response question revealed confusion regarding the color code for building type. Specifically, users had difficulty distinguishing the colors for Lab versus Housing buildings, some noting that the transparency of the circles made it difficult to match the circle color to the key (which used non-transparent dots). To attempt to control for this, we reran the analysis to include Housing as a correct response for the building type that uses the most energy (in addition to Lab). With this adjustment, the Interactivity group was 86.4% accurate and the No Interactivity group was 76.3% accurate; $X_2 = 4.77$, $p = .029$. Again, the difference increased when adjusting the groups to distinguish between those who used interactive features and those who did not (to 87.0% v. 76.3%); $X_2 = 5.49$, $p = .019$.

Discussion

When geography is a relevant factor, spatially framing an energy dataset can augment the message and interpretation of the data (Tufte 2001; Wong 2013; Yau 2013; Jones 2014; Kirk 2016). Map-based data visualizations can be rich, with the potential to yield an array of interpretations. They can engage energy-savvy and non-energy-savvy users alike and can be leveraged for a variety of applications, including household- and community-level tools for energy-related education and feedback.

This paper presented two new empirical studies that compared the usability of dual-encoded map-based energy displays and bar charts. Findings were consistent with prior research (Salmon and Sanguinetti 2016; Francisco et al. 2018;) that map-based energy visualizations are more interesting and enjoyable than bar charts. Findings regarding accuracy of interpretation were consistent with our past CEED research (Salmon and Sanguinetti) in that the dual-encoded map with colored circles seemed more difficult to interpret. However, data from an open-ended comment field in Experiment 2 revealed that this was likely due to the color palette and transparency of the overlaid circles used in the CEED map, rather than a general effect of the use of colored overlaid shapes. Thus, there may not be sacrifices in interpretability when using dual-encoded map-based energy data displays. Future research should confirm and continue to build best practices to enhance interpretability.

One such best practice is interactivity. Experiment 2 yielded some evidence that interactivity can improve usability, including accuracy of data interpretation, consistent with prior research from other fields (Rheingas, 2002; Fischer, 2008; Hegarty, 2011). Further research should expand on this finding to examine different interactive features and determine which perform best for different types of datasets and use cases.

This research revealed the importance of careful data vetting when using Mechanical Turk as a recruitment platform. Many participants did not provide meaningful data. The inclusion of an open-ended question in Experiment 2 proved crucial in determining the validity of data and revealing specific issues with the data display (color-coding/transparency). We recommend including at least one mandatory open-ended question and more than one “attention check” question in surveys deployed on Mechanical Turk. Using Mechanical Turk also limited the validity of our results since the sample was not drawn from the population of intended users of CEED (UC Davis campus community). However, they do represent general populations of non-energy-savvy potential consumers of energy data displays.

Best Practices for Map-Based Energy Data Visualization

General map use.

- Use spatial maps to visualize energy data when geography can give meaningful context to your dataset (e.g., when latitude and longitude contribute to the interpretation of the data, or when a map helps situate the user within a campus or city).
- Use maps when you want to tell a richer story with your data—to have it been seen as more than a set of statistics or metrics.
- Maps are appropriate when you are trying to engage any type of user, including broad audiences who are not familiar with or not particularly interested in energy data.
- Include interactive functionality to promote ease of use and enjoyment. Consider including multiple interactive features, such as hovers and different types of filters.

Single variable maps.

- Use red-green color schemes in spatial heat maps to convey normative messages about the data (e.g., poor v. good performance in occupant-facing energy feedback), but avoid them in educational applications intended to convey relationships between fixed variables and energy use. While the red-green color scheme is a good tool to indicate performance, keep in mind it might be difficult to use for people with color-blindness.
- Proportional symbol maps can be useful when you wish to convey a quantitative variable (e.g., energy use) for a small number of geographic locations that are physically separated by long distances (e.g., energy use for metropolitan cities spread out across the United States would be well suited for a proportional symbol map, compared to a heat map which would leave a lot of the country blank with no corresponding data).
- Proportional symbol maps may also be useful if the data correspond to geographies of greatly varying sizes but the sizes are not an important variable. This can prevent misinterpretation of normative data (e.g., a large red building interpreted to be performing worse than a small red building of the same shade).
- Size proportional symbols such that their area corresponds to your quantitative variable.

Dual-encoded maps.

- Dual-encoded proportional symbol maps are useful when you want to convey a categorical variable in addition to a continuous variable. Color-code the symbols according to levels of the categorical variable.
- With dual-encoded proportional symbol maps, avoid similar colors and use the same level of transparency for symbol fill and the key/legend. Again, consider implications for color-blindness and what colors will look like when they are transparent and overlapping.

References

Bonino, D. F. Corno, and L. De Russis. 2012. "Home energy consumption feedback: A user survey." *Energy and Buildings* 47 (2012): 383-393.

Center for Sustainable Energy. 2018. "National Heat Map." https://www.cse.org.uk/projects/view/1183

Clark, S., Petersen, J.E.,Frantz, C.M., Roose, D., Ginn, J., Daneri, D.R. 2017. “Teaching systems thinking to 4th and 5th graders using Environmental Dashboard display technology.” *PLoS ONE* 12 (4): 1-11.

Egan, C. 1999. “Graphical Displayers and Comparative Energy Information: What Do People Understand and Prefer.” *Summer Study of the European Council for an Energy Efficient Economy.* 2: 1-13.

———, W. Kempton, A. Eide, D. Lord, and C Payne. 1996. “How Customers Interpret and Use Comparative Graphics of Their Energy Use.” *Summer Study of the American Council for an Energy Efficient Economy.* 8: 39-45.

Fischer, C. 2008. “Feedback on household electricity consumption: a tool for saving energy?” *Energy Efficiency* 1 (2008): 79-104.

Francisco, A., H. Truong, A. Khosrowpour, J. Taylor, and N. Mohammadi. 2018. “Occupant perceptions of building information model-based energy visualizations in eco-feedback systems.” *Applied Energy* 221 (2018): 220-228.

——— and J. Taylor. 2019. “Designing community-scale energy feedback.” *Energy Procedia 158* (2019): 4178-4183.

Gupta, R., L. Barnfield, and M. Gregg. 2018. “Exploring innovative community and household energy feedback approaches.” *Building Research & Information 46* (3): 284-299.

Hegarty, M. 2011. “The Cognitive Science of Visual-Spatial Displays: Implications for Design.” Topics in Cognitive Science 3 (2011): 446-474.

Hermsen, S., J. Frost, R. Jan Renes, P. Kerkhof. 2016. *Computers in Human Behavior.* 57 (2016): 61-74.

Jones, B. 2014. *Communicating Data with Tableau: Designing, Developing, and Delivering Data Visualizations.* California: O’Reilly Media.

Karlin, B., and R. Ford. 2013. “The Usability Perception Scale (UPscale): A Measure for Evaluating Feedback Displays.” *Design, User Experience, and Usability. Design Philosophy, Methods, and Tools* 8012: 312-321.

Kirk, A. 2016. *Data Visualization: A Handbook for Data Driven Design.* California: SAGE Publications Ltd.

Murray, P. 2017. *80 Data Visualization Examples Using Location Data and Maps.* June 28, 2017. carto.com/blog/eighty-data-visualizations-examples-using-location-data-maps/#environmental

Petersen, J., C. Frantz, E. Tincknell, and C. Canning. 2018. “An Animated Visual Representation of Real-Time Resources Flows Through a Community Enhances Systems Thinking.” Systems Research in Behavioral Science 35 (2018): 718-737.

Pritoni, M., K. Salmon, A. Sanguinetti, J. Morejohn, and M. Modera. 2017. "Occupant thermal feedback for improved efficiency in university buildings." Energy and Buildings 144: 241-250.

Rheingans, P. 2002. "Visualization Viewpoints: Are We There Yet? Exploring with Dynamic Visualization." IEEE Computer Graphics and Applications 22 (1): 6-10.

Salmon, K., J. Morejohn, A. Sanguinetti, and M. Pritoni. 2016. "The Iterative Design of a University Energy Dashboard." ACEEE Summer Study on Energy Efficiency in Buildings 8: 1-12. https://www.aceee.org/files/proceedings/2016/data/papers/8_466.pdf.

Sanguinetti, A., K. Dombrovski, and S. Sikand. 2018. "Information, timing, and display: A design-behavior framework for improving the effectiveness of eco-feedback." *Energy Research & Social Science* 39 (2018): 55-68.

Schott, M., N. Long, J. Scheib, K. Fleming, K. Benne, and L. Brackney. 2012. "Progress on Enabling an Interactive Conversation between Commercial Building Occupants and Their Building to Improve Comfort and Energy Efficiency." *ACEEE Summer Study on Energy Efficiency in Buildings* 7: 250-65.

Tufte, E. 2001. *The Visual Display of Quantitative Information.* Connecticut: Graphics Press.

Wong, D. 2013. *The Wall Street Journal Guide to Information Graphics: The Dos and Don'ts of Presenting Data, Facts, and Figures.* New York: W.W. Norton & Company.

Yau, N. 2013. *Data Points: Visualization that means something.* Indiana: John Wiley & Sons Inc.