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Publication Date
2021

DOI
10.2139/ssrn.3767157

Peer reviewed

DOI: 10.2139/ssrn.3767157

Building Technologies & Urban Systems Division
Energy Technologies Area
Lawrence Berkeley National Laboratory

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Energy Technologies Area
January 2021

http://dx.doi.org/10.2139/ssrn.3767157

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Building Technologies of the United States Department of Energy, under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

U.S. building energy efficiency and flexibility as an electric grid resource

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Summary

Buildings consume 75% of U.S. electricity; therefore, improving the efficiency and flexibility of building operations could increase the reliability and resilience of the rapidly-changing electricity system. We estimate the technical potential near- and long-term impacts of best available building efficiency and flexibility measures on annual electricity use and hourly demand across the contiguous U.S. Co-deployment of building efficiency and flexibility avoids up to 742 TWh of annual electricity use and 181 GW of daily net peak load in 2030, rising to 800 TWh and 208 GW by 2050; at least 59 GW and 69 GW of the peak reductions are dispatchable. Implementing efficiency measures alongside flexibility measures reduces the potential for off-peak load increases, underscoring limitations on load shifting in efficient buildings. Overall, however, we find a substantial building-grid resource that could reduce future fossil-fired generation needs while also reducing dependence on energy storage with increasing variable renewable energy penetration.

Introduction

The U.S. electricity system is undergoing rapid transformation. Electricity generation from renewable sources surpassed coal-fired generation for the first time in the U.S. in April 2019 [1]. From 2010–2019, the cost of utility-scale solar photovoltaics (PV) declined 82%, and the costs for onshore and offshore wind declined 39% and 29%, respectively [2]. These continued decreases make solar and wind cost-competitive with conventional sources of electricity generation, even without including subsidies [3]. Accordingly, the U.S. Energy Information Administration (EIA) projects renewables will account for the largest share of electricity generation in the U.S. by 2050 [4], while other studies project this will happen as soon as 2035 [5, 6].

At high levels of renewable electricity penetration, the variability of renewable generation presents numerous technical and economic challenges to reliable operation of the electric system [7, 8]. Grid flexibility is an essential component of reducing the costs and ensuring the reliability of power systems in these contexts [9–15]. There exists a range of supply- and demand-side measures that can provide flexibility, such as construction of new flexible generation capacity, investment in expanded grid infrastructure, various forms of energy storage, greater conventional plant dispatch flexibility, traditional demand-side management, and more sophisticated electricity demand management that reduces or shifts the timing of electric load. Of these measures, improved electricity demand management has several distinct advantages, including lower capital and investment costs as well as reduced technical and environmental risks [16–20]. Indeed, demand management technologies can be beneficially deployed alongside energy storage to meet grid flexibility needs in a high renewable electricity future [15] while also deferring investments in new electricity generation, transmission and distribution capacity [21]. The U.S. Federal Energy Regulatory Commission (FERC) Order 2222, which enables participation of aggregated distributed energy resources (DERs) in wholesale electricity markets, portends an important role for demand management technologies in future electricity systems [22].

Residential and commercial buildings account for 75% of U.S. electricity consumption [4] and are therefore a primary demand management resource for the electric grid. Building technologies such as highly-efficient heating and cooling equipment, advanced windows, solid-state lighting, and variable speed motors offer substantial efficiency gains, while connected appliances and smart controls enable buildings to actively manage electric loads to provide flexibility services to the grid while still meeting occupant comfort and productivity requirements [23]. Previous studies of the U.S. building-grid resource at the national scale suggest that such building technologies can reduce more than 200 GW of summer peak load by 2030 [11, 24–27]; regional studies lend further support to these findings [28–36].

While the importance of the U.S. buildings sector as a grid resource is well-established, the magnitude and breadth of this resource remain elusive due to key study limitations, including: narrow focus on maximum peak demand reductions from specific technology measures and deployment scenarios; reliance on data sets that are out of date, limited in their geographic and temporal resolution, or that do not include long-range projections; lack of results disaggregation to particular building types or electric end uses; and simplistic or missing consideration for the joint impacts of energy efficiency and flexibility technologies when deployed together (for example, total peak reductions from the adoption of more efficient HVAC and more flexible HVAC is not necessarily equal to the sum of these measures' individual peak reductions). Furthermore, existing studies do not adopt a common and reproducible analytical framework for assessing the potential grid resource from buildings, which would enable more holistic and comparable analyses of the grid impacts from emerging building technologies and operational approaches.

In this paper we conduct a comprehensive analysis of the near- and long-term technical potential bulk power grid resource offered by best available U.S. building efficiency and flexibility measures. We pair bottom-up modeling of measures' building-level impacts with regional representations of the building stock and its projected electricity use to estimate the impacts of multiple building efficiency and flexibility scenarios on regional system loads across the contiguous U.S. in 2030 and 2050. Results are communicated at both the national and regional scales and are disaggregated by building type and end use, facilitating a quantitative understanding of the role that buildings as a whole and specific building technologies or operational approaches can play in the future evolution of the U.S. electricity system.

Building efficiency and flexibility scenarios and grid metrics

Table 1 provides an overview of key analysis assumptions. We estimate the technical potential impacts of three building measure sets—energy efficiency only (EE), demand flexibility only (DF), and packaged efficiency and flexibility (EE+DF)—on annual U.S. residential and commercial building electricity use and seasonal peak and off-peak demand. Measure impacts in 2030 and 2050 are assessed within each of the 22 2019 U.S. Energy Information Administration (EIA) Electricity Market Module (EMM) regions, with certain outputs aggregated into the 10 2019 U.S Environmental Protection Agency (EPA) AVERT regions for simplicity of presentation (Figure 1). Throughout, we use hourly regional system loads *less wind and solar generation* to define *net* peak and off-peak demand periods, i.e., we consider variable renewable power resources to operate more like negative loads than generation in our analysis. Renewable electricity penetration levels vary on a regional basis, but average to 30% nationally. Additionally, we focus on *average daily non-coincident* peak and off-peak hour impacts across the summer (Jun–Sep), winter (Dec–Mar) and intermediate (all other months) seasons. Additional detail on measure assumptions, analysis approach, and assessment metrics is available in the Experimental Procedures and Supplemental Information sections.

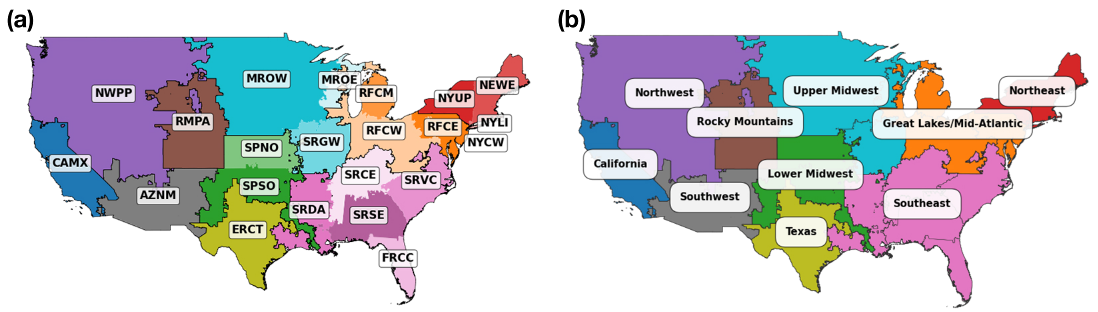

Figure 1: Regional boundaries used to generate and aggregate results. Scout measure impacts are assessed within each of the 22 2019 U.S. EIA EMM regions shown in (a). Outputs can be aggregated into the 10 2019 U.S. EPA AVERT regions shown in (b).

Results

Baseline building electricity by end use and region

First, we analyze the distribution of baseline annual electricity use and net peak demand in U.S. buildings across end uses and regions. Figure 2 presents the annual electricity use and average daily summer and winter net peak demand from U.S. buildings in 2030; 2050 results are shown in Supplemental Figure S1. In 2030, buildings are responsible for 2870 TWh of annual electricity use (71% of the contiguous U.S. annual total [37]) and 485 GW and 431 GW of summer and winter net peak demand, respectively. By 2050, these totals grow to 3249 TWh, 562 GW, and 478 GW, respectively. Residential buildings account for the largest share across each of these metrics, and differences between residential and commercial buildings are greater in the case of peak demand, where residential buildings contribute 1.4–1.5 times more peak summer and 1.7 times more peak winter demand than commercial buildings do.

Table 1: Overview of primary analysis components, assumptions, and data sources.

Analysis Component	**Summary**	**Assumptions and Data Sources**
Energy use sector	U.S. residential and commercial buildings	Consistent with sector definitions in the U.S. EIA Annual Energy Outlook (AEO) [4].
Assessment metrics	Annual electricity use Average net non-coincident peak demand Average net non-coincident off-peak demand	Daily peak and off-peak periods are defined by season (summer, winter, intermediate) and region based on total system load net renewable electricity generation (see SI section 2.1); net system load profiles reflect 2050 renewable penetration in 2019 AEO Reference Case [37]; averages are taken across all net peak and off-peak hours in a given season.
Baseline building demand scenario	2019 EIA AEO Reference Case	Projections between 2015–2050 from [37].
Alternative building demand scenarios	Best energy efficiency only (EE) Best demand flexibility only (DF) Best efficiency and flexibility (EE+DF)	Best available efficiency levels generally correspond to those in the Scout Core Measures data set [38]; best available flexibility levels maximize intended reductions or increases in hourly electricity demand without compromising minimum building service levels (see Table 2 and SI section 4 for detailed measure definitions and assumptions).
Technology stock dynamics	100% annual stock turnover (technical potential diffusion); static snapshots in 2030/2050	Consistent with Technical Potential Scenario assumptions in Scout [39, 40].
Geographic boundary and resolution	Contiguous U.S. 22 2019 EIA EMM regions 10 2019 EPA AVERT regions	Analysis is conducted at the geographic resolution of the 2019 EIA EMM regions; certain results are aggregated and presented using the 2019 EPA AVERT regions for simplicity (see Figure 1).
Time horizon and resolution	2020–2050 model time horizon Hourly temporal resolution	Time horizon is a subset of that used in the 2019 EIA AEO [37]; annual electricity projections are translated to an hourly basis using representative residential and commercial end use load shapes simulated in EnergyPlus (see SI section 2.2).

Figures 2 and S1 show that thermal end uses—in particular, cooling—are key drivers of 2030 and 2050 annual electricity use in both residential and commercial buildings. Other end uses that make large contributions across the metrics shown include water heating, refrigeration, and home electronics in residential buildings and office electronics, refrigeration, and ventilation in commercial buildings. Notably, a sizeable portion of both residential and commercial loads fall into the "unclassified" or "non-building" categories, which include end uses that are not captured by EIA surveys [41] and commercial loads such as water distribution pumps, street lighting, and telecommunication; such categories are not readily addressed by building efficiency or flexibility measures and thus limit the potential magnitude of the building-grid resource.

Geographically, U.S. building electricity use and peak demand are strongly concentrated in the Great Lakes/Mid-Atlantic and Southeast AVERT regions. These regions aggregate multiple EMM regions with high population density, building square footage, and annual electricity use (see Supplemental Figure S7) [41–43]; in the Southeast, annual electricity use and peak demand are further driven by significant cooling needs and a large installed based of electric heating [41, 43, 44]. While baseline electricity use and demand tend to be highest in the Southeast, a notable exception is summer peak demand for commercial buildings, which is concentrated most strongly in the Great Lakes/Mid-Atlantic region. Summer peak periods in this region tend to fall into the afternoon hours (see Experimental Procedures and Supplemental Information section 2.1), which are more coincident with peaks in commercial building energy use profiles; by comparison, summer peak periods in the Southeast tend to occur later in the day, when commercial building loads are decreasing. Regional baseline electricity attributions in Figure 2 and S1 are therefore reflective of the size of the region's building stock, energy intensity of required building services, and the seasonal net system peak periods assumed.

National grid resource from building efficiency and flexibility

Next, we analyze how adoption of energy efficiency, demand flexibility, or both measure types affects annual electricity use and net peak demand in U.S. buildings at the national scale. Figure 3 presents the potential impacts of building efficiency and flexibility on annual U.S. electricity use and average daily summer and winter net peak and off-peak demand in 2030; 2050 results are shown in Supplemental Figure S2. Annual and net peak period reductions are highest in the scenario that deploys building efficiency and flexibility measures together (EE+DF), which avoids 742 TWh of annual electricity use and 181 and 119 GW of summer and winter net peak demand in 2030, respectively. By 2050, these reductions grow to 800 TWh annual and 208 and 121 GW summer and winter net peak, respectively. The annual reductions are 32% and 30% of total projected U.S. fossil-fired generation in 2030 and 2050, respectively, while the summer peak reductions in these years are 26% and 22% of total projected fossil-fired capacity and 122% and 50% of new capacity additions after 2020 [4]; this suggests that aggressive deployment of building efficiency and flexibility would substantially offset future needs for fossil-fired base and peak load generation. Moreover, at least 59 GW of summer peak reductions in the EE+DF scenario are attributed to dispatchable flexibility measures, growing to 69 GW by 2050; the dispatchable portion of the EE+DF reductions is calculated by subtracting efficiency–only scenario (EE) results from efficiency and flexibility scenario (EE+DF) results. In the flexibility–only scenario (DF), the dispatchable resource reaches 96 GW in 2030 and 112 GW by 2050. By comparison, the EIA projects diurnal battery storage to grow to up to 98 GW by 2050 [4]; thus, the dispatchable resource we estimate from building flexibility in 2050 is 70%–114% of EIA's most optimistic storage capacity projections for that year

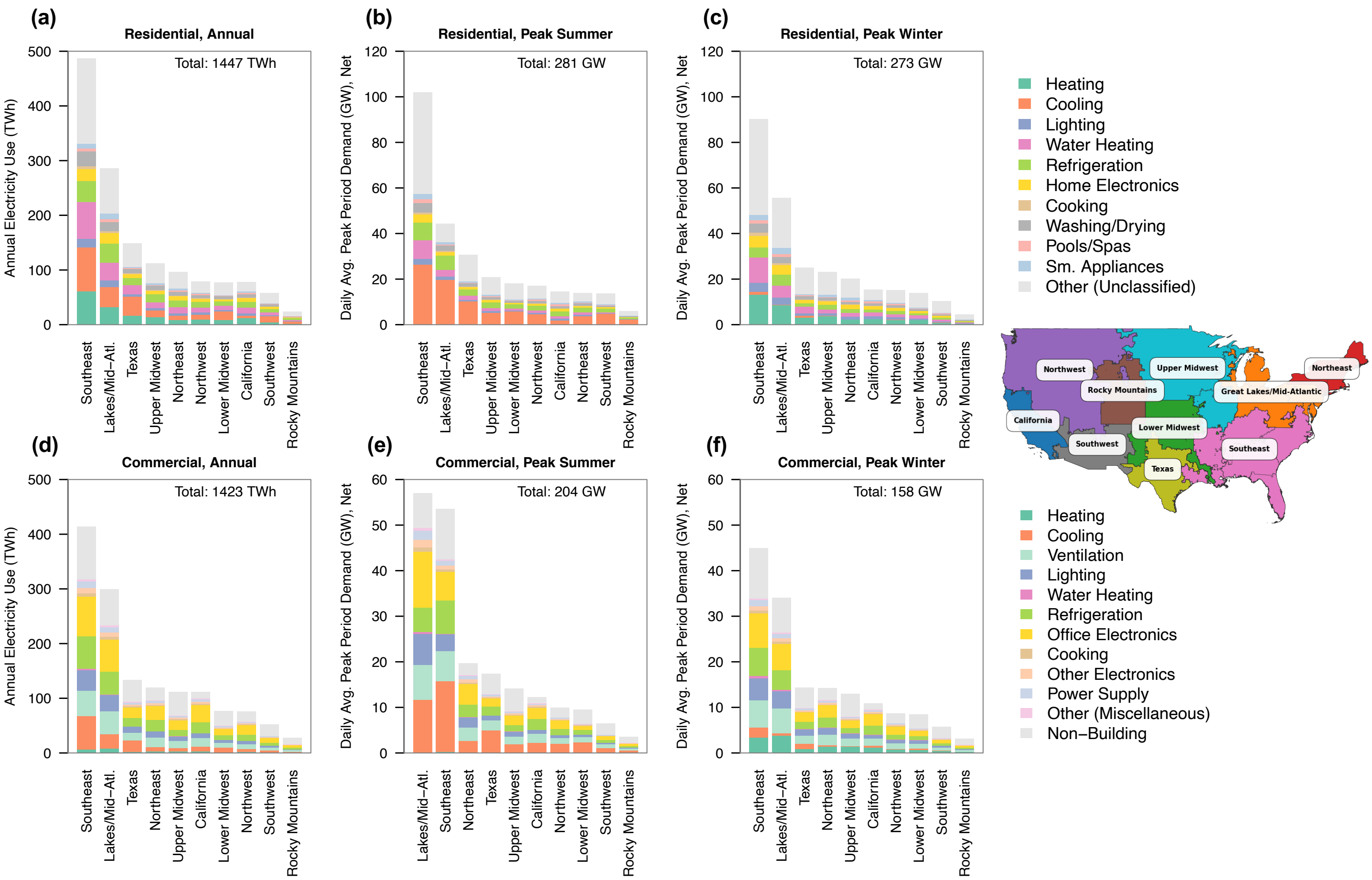

Figure 2: Baseline annual electricity use and net peak demand from U.S. buildings in 2030. Baseline residential (a-c) and commercial (d-f) annual electricity use and peak summer and winter demand are broken out by end use and the 10 2019 EPA AVERT regions (map at right), which are aggregations of the 22 2019 EIA EMM regions (see Figure 1). Baseline projections are consistent with the 2019 EIA AEO Reference Case. Seasonal peak periods are identified in each region based on total hourly system loads less variable renewable energy supply; regional peak impacts are averaged across all weekday peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). Across regions in 2030, U.S. buildings are projected to contribute 2870 TWh to annual electricity use and 485 GW and 431 GW to daily net peak demand in summer and winter, respectively; baseline electricity use is most concentrated in the Southeast and Great Lakes/Mid-Atlantic regions.

and constitutes a significant alternative to energy storage deployment.

Across measure scenarios and projection years, residential buildings drive both annual and peak reductions, primarily through measures that affect cooling, heating, and water heating. In commercial buildings, measures that affect office electronics show consistently high relative impacts across metrics—particularly annual and winter peak reductions—while cooling measures dominate reductions in summer peak demand. The relative attribution of annual and peak reductions to specific end uses and building types mirrors the baseline distributions in Figures 2 and S1, which are therefore key to understanding the prominence of particular efficiency and flexibility measure impacts.

Increases in building demand during off-peak hours, those hours with the lowest net system loads, are muted in Figures 3 and S2, reaching totals of up to just 13 GW in 2030 and 14 GW in 2050 in the DF scenario. The vast majority of the increases (up to 13 GW) comes from residential measures that shift water heating demand into the off-peak hours; ice storage measures for cooling in large commercial buildings contribute the second highest increase (up to 2 GW in summer). This finding highlights the challenges of marrying realistic building-level operational adjustments with regional system net load balancing needs. To maximize effectiveness, for example, precooling measures reduce set point temperatures in the hours preceding the peak hour window; however, the net utility load is only low for these hours in regions with high mid-day solar generation (see Supplemental Information Figure S8). Potential load increases from precooling would be more beneficial in a high-solar penetration case where regions' low net system loads occur during mid-day hours (see the sensitivity analysis in Supplemental Information section 2.1.1). Thermal storage measures such as grid-responsive water heating and ice storage offer more potential for demand increases during off-peak periods, but concentrate these increases in just a few hours, far fewer than the total number of low net demand hours characteristic of many regional systems. Adding to these inherent limitations of the flexibility measures, the introduction of efficiency measures (EE+DF) counters additional off-peak demand by reducing the available load for flexibility measures to shift, thus *reducing* off-peak hour demand by up to 79 GW in 2030 and 88 GW in 2050.

Spatio-temporal distribution of the building-grid resource

Third, we attribute the impacts of building efficiency and flexibility to specific U.S. grid regions and sub-annual time periods. Figure 4 shows regional annual electricity use and average daily summer and winter net peak demand reduction potentials for the the EE+DF scenario in 2030; 2050 results are shown in Supplemental Figure S3. Regional variation in annual electricity and peak demand reductions is mostly consistent with the baseline variations across regions in Figures 2 and S1, again demonstrating the importance of baseline system characteristics in determining the technical potential impacts of our measure sets. In absolute terms, potential reductions are concentrated in the Southeast and the Great Lakes/Mid-Atlantic AVERT regions, following the concentration of baseline electricity in these regions. In relative terms, percentage reductions in Texas and the Southeast tend to be among the highest—particularly in residential buildings—due to the stronger influence of reductions in cooling, heating, and water heating electricity use in these regions. Relative summer peak reductions are also notably high from residential buildings in the Great Lakes/Mid-Atlantic region, where temporal coincidence between afternoon system peaks and the residential cooling peak results in large cooling electricity reductions relative to the total addressable summer peak load.

Regional reduction percentages in Figures 4 and S3 tend to be higher and more variable between

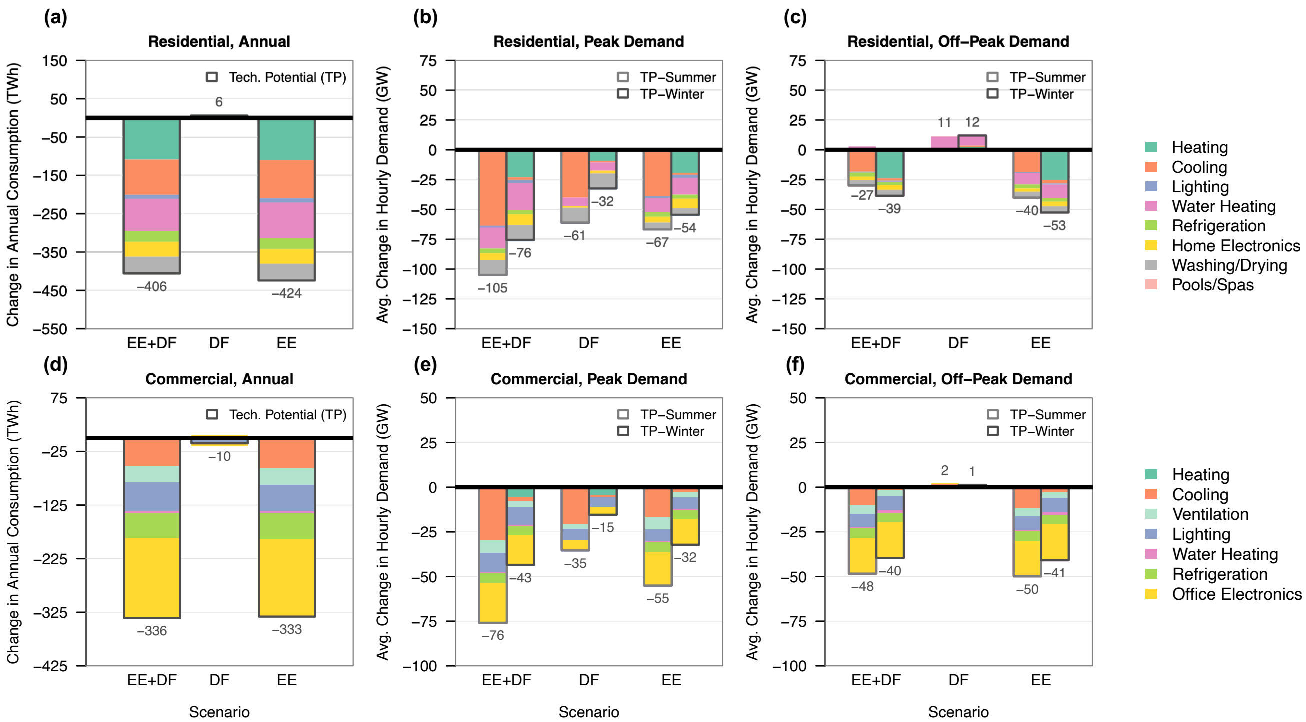

Figure 3: National impacts of best available U.S. building efficiency and flexibility measure sets on annual electricity use and net peak and off-peak demand in 2030. Technical potential efficiency and flexibility impacts on residential annual electricity use (a), peak demand (b), and off-peak demand (c) are broken out by end use and season alongside the same results for commercial buildings (d-f). Impacts are aggregated across the 22 2019 EIA EMM regions (see Figure 1), and peak impacts are non-coincident across these regions. Seasonal peak and off-peak periods are identified in each underlying region based on total hourly system loads less variable renewable energy supply; regional peak and off-peak impacts are averaged across all weekday peak and off-peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). When deployed together in 2030, U.S. building efficiency and flexibility measures (EE+DF) can avoid up to 742 TWh annual electricity use and 181 GW daily peak demand, but also decrease off-peak demand by up to 79 GW; flexibility without efficiency (DF) can add up to 13 GW to off-peak demand, with most of the increase observed in residential buildings.

regions in residential buildings than in commercial buildings. While the higher residential percentages stem from a number of factors including slower turnover in baseline equipment and building stock and higher load coincidence with system peaks, the difference in regional variability reflects the greater share of commercial reductions that are derived from non-thermal loads (e.g., lighting, refrigeration, office electronics), which are less influenced by location. Strikingly, annual and peak reductions from office electronics measures in 2030 are comparable to or greater than those of commercial cooling measures for many regions. Moreover, reductions from office electronics measures grow in magnitude by 2050, indicating the importance of future technology development to enable flexible operation of this commercial end use.

Figure 5 further demonstrates the variability of building efficiency and flexibility impacts in 2030 at a more granular level, both regionally and temporally, focusing on five EMM regions; 2050 results are shown in Supplemental Figure S4. In both 2030 and 2050, changes in hourly demand across regions and seasons are most pronounced in residential buildings, particularly for measure sets that include efficiency (EE, EE+DF). In these residential cases, demand reductions are typically largest in the morning hours in winter and the afternoon and evening hours in summer, owing to seasonal changes in baseline demand patterns. Across seasons, residential reductions are largest in ERCT (Texas), which has a larger building stock than the other regions, high cooling needs, and a large installed base of electric heating. Residential summer reductions are also sizeable in RFCW, one of the Great Lakes regions, which has an afternoon system peak in summer that coincides strongly with peaks in residential cooling demand. In commercial buildings, reductions under efficiency (EE) are smallest in the early morning, late evening, and weekend hours, when occupancy is low. Increases in commercial demand under flexibility (DF) are also more regionally consistent and temporally constrained than in residential, occurring mostly in the summer during the hours preceding the regional system peak period, when precooling occurs.

Measures with large impacts on electricity demand by region

Finally, we analyze which individual building efficiency (EE) or flexibility (DF) measures have the largest potential impacts on electricity demand in specific regions. Figure 6 identifies the five residential and commercial measures with the largest impacts on daily summer net peak demand intensity (W/ft^2) in 2030 in each of the five EMM regions from Figure 5; 2050 results are shown in Supplemental Figure S5. In both figures, the measures' net winter peak demand and annual electricity reductions are also shown to allow comparisons across metrics. In residential buildings, HVAC measures (controls and equipment) generally deliver the largest summer peak reductions across regions, led by preconditioning; preconditioning and other flexibility measures yield no change or a slight *increase* in annual energy use, however. Peak reductions from efficient air source heat pumps (ASHPs) are prominent in the South and Southeast (ERCT and SRSE), where ASHPs replace a large base of existing heat pumps and other electric heating; in the Northwest and Great Lakes (NWPP, RFCW), however, baseline heating is predominantly gas, so central air conditioners show more summer peak reduction potential. Outside of HVAC measures, heat pump water heaters (HPWH) yield high summer peak reductions across most regions and are the top measure in California (CAMX), where the marine climate leads to comparatively lower residential cooling needs, and the summer peak occurring late in the day places it past the time when cooling demand is highest, thus reducing the potential for HVAC measures.

In commercial buildings, plug load efficiency (more efficient management of loads from PCs and other office equipment) delivers the largest summer peak reduction potential in three of the five

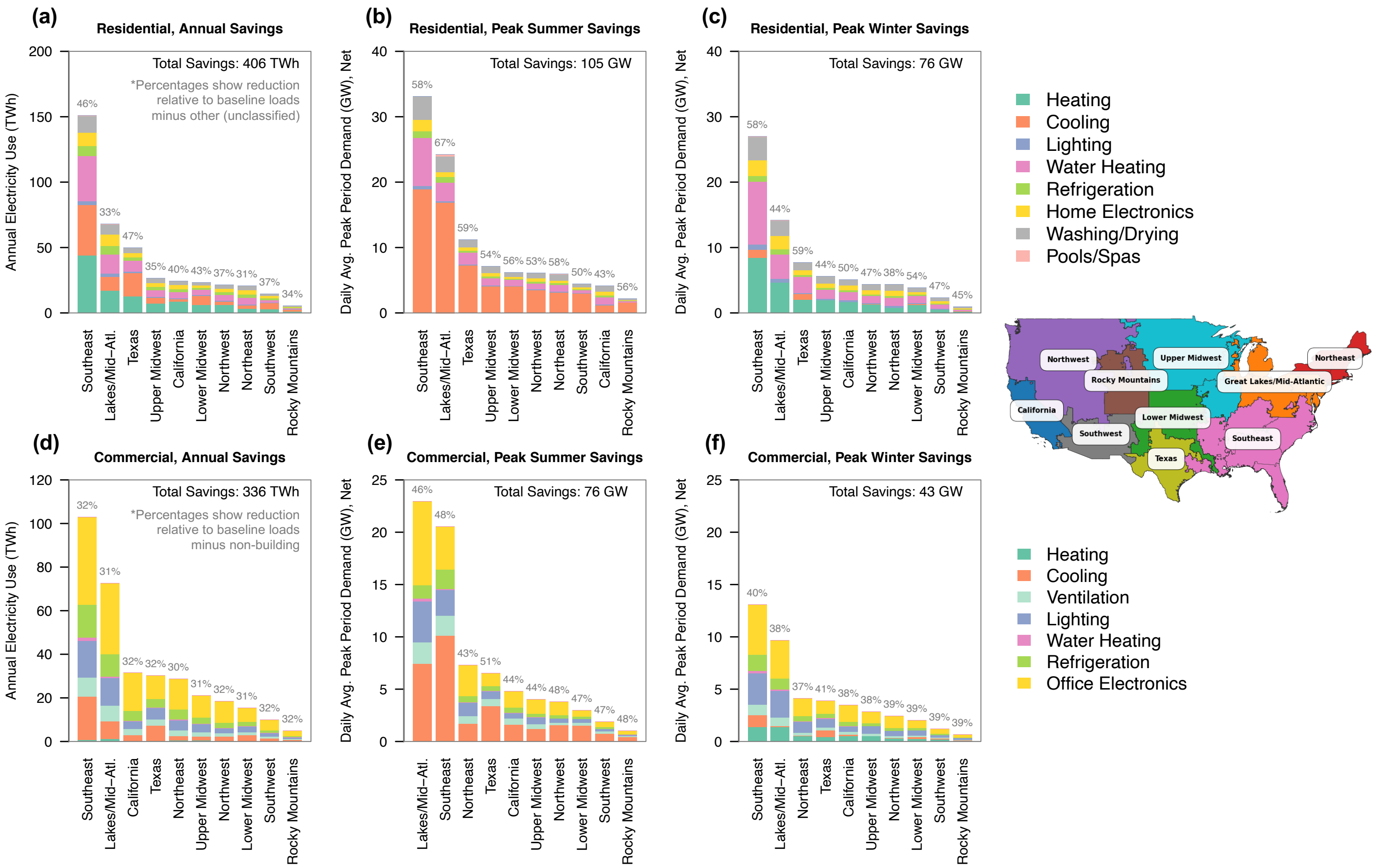

Figure 4: Regional impacts of best available U.S. building efficiency and flexibility measures together on annual electricity use and net peak demand in 2030. The technical potential of building efficiency and flexibility measures (EE+DF) on residential (a-c) and commercial (d-f) annual electricity use and peak summer and winter demand are broken out by end use and the 10 2019 EPA AVERT regions (map at right), which are aggregations of the 22 2019 EIA EMM regions (see Figure 1). Labels at the top of each bar represent the percentage of total addressable baseline electricity that is avoided by the efficiency and flexibility measure set for the given region and assessment metric; the "addressable" baseline excludes unclassified residential loads and non-building commercial loads. Seasonal peak periods are identified in each region based on total hourly system loads less variable renewable energy supply; regional peak impacts are averaged across all weekday peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). The regional concentration of savings in the Southeast and Great Lakes/Mid-Atlantic regions mirror the distribution of baseline building electricity demand in Figure 2. Reduction percentages are generally largest for the summer peak metric, when they range from 43%–67% in residential buildings and from 43%–51% in commercial buildings, and .

Figure 5: Average change in sector-level hourly electricity demand from building efficiency and flexibility measure sets for five U.S. grid regions in 2030. Technical potential demand change profiles are shown for five of the 2019 EIA EMM regions (map at right) and three measure sets (DF, EE, EE+DF) and reflect the average impacts of each measure set on hourly electricity demand across all residential (a) and commercial (b) buildings in each region for a given day type (weekday, weekend) and season (summer (Jun–Sep), winter (Dec–Mar), and intermediate (all other months)). Reductions in regional hourly demand are highest for the efficiency and flexibility measure set (EE+DF) on summer weekdays, reaching more than 12 GW and 10 GW in residential and commercial buildings in RFCW, respectively, though weekday and weekend profiles are similar for residential buildings. Increases in regional hourly demand are highest for the flexibility-only measure set (DF) on summer weekdays, reaching more than 5 GW in residential buildings in RFCW and 2 GW in commercial buildings in CAMX.

regions. Savings from this measure are particularly pronounced in RFCW, a further demonstration of the stronger coincidence between this region's afternoon system peak and commercial building load profiles. Other measures that consistently rank in the top five across regions include peak period global temperature adjustments (GTA) with and without precooling, lighting efficiency, and discharging of ice storage to meet peak cooling loads in large commercial buildings. As with residential preconditioning, commercial HVAC flexibility measures (precooling, ice storage) produce effectively no change or slight increases in annual electricity use across regions. In contrast with the residential results, however, commercial measure impacts for the CAMX region show greater parity with those of the other regions, as the larger commercial baseline load in California (see Figure 2) yields greater opportunity for peak reductions from efficiency and flexibility measures.

Discussion

Our assessment demonstrates a large potential grid resource from energy efficient and flexible building operations that could be of high value to grid operators in avoiding future fossil-fired generation investments and relieving pressure on energy storage deployments to support variable renewable energy integration. Specifically, if one values technical potential annual electricity reductions from efficiency and flexibility in 2030 and 2050 as early retirements of remaining coal generation and assumes non-dispatchable and dispatchable net peak reductions from efficiency and flexibility avoid combined cycle gas and energy storage capacity additions, respectively, the total building-grid resource is worth roughly $31 billion in 2030 and $42 billion in 2050. These estimates draw generation cost and capacity projections from the AEO 2020 "Low Oil and Gas Resource" side case [4, 45, 46] and do not include additional benefits to the grid such as avoided transmission and distribution infrastructure, reduced greenhouse gas emissions, and reduced air pollution [21, 47].

Our analysis suggests that packaging efficiency and flexibility measures yields the largest reductions in net peak electricity demand with comparable annual electricity savings to an efficiency-only case; such packages may be simpler and more cost-effective for utilities to market and can increase the value proposition of building efficiency and flexibility from a consumer perspective [48–50]. On the other hand, we find that packaging efficiency with flexibility limits the potential to shift demand into hours of low net system load, when increased electricity demand from buildings could improve the utilization of renewable energy supply. Efficiency generally reduces the load available to shift across the measure sets considered, though this may not be the case for individual efficiency and flexibility packages that comprise the measure sets [e.g., 51]. In a high renewable penetration future, load reductions from efficiency could help avoid increases in thermal generator cycling and ramping during low net system load periods, when the net load is more variable; undoubtedly, however, avoiding renewable curtailment during these periods through load shifting will also be a key challenge [52]. Accordingly, emerging non-building loads such as electric vehicle charging [53] might need to be leveraged to supplement the limited load shifting resource we estimate from buildings.

The magnitudes of our estimated demand reductions appear broadly consistent with existing studies at the regional level, though differences in approach and outputs preclude direct comparisons with previous work. For example, a study of the U.S. Eastern Interconnection estimates 97 GW peak demand reductions from efficiency and flexibility measures by 2030 (vs. 137 GW in corresponding regions in our study); however, this study is an estimate of achievable potential, not technical potential [35]. Another study of demand response (DR) potential in California finds that peak reductions in the state could reach 6–8 GW by 2025 (vs. 9 GW by 2030 in our results); however, this estimate includes the industrial sector and focuses on 'cost-competitive' DR [54]. In the Southeast

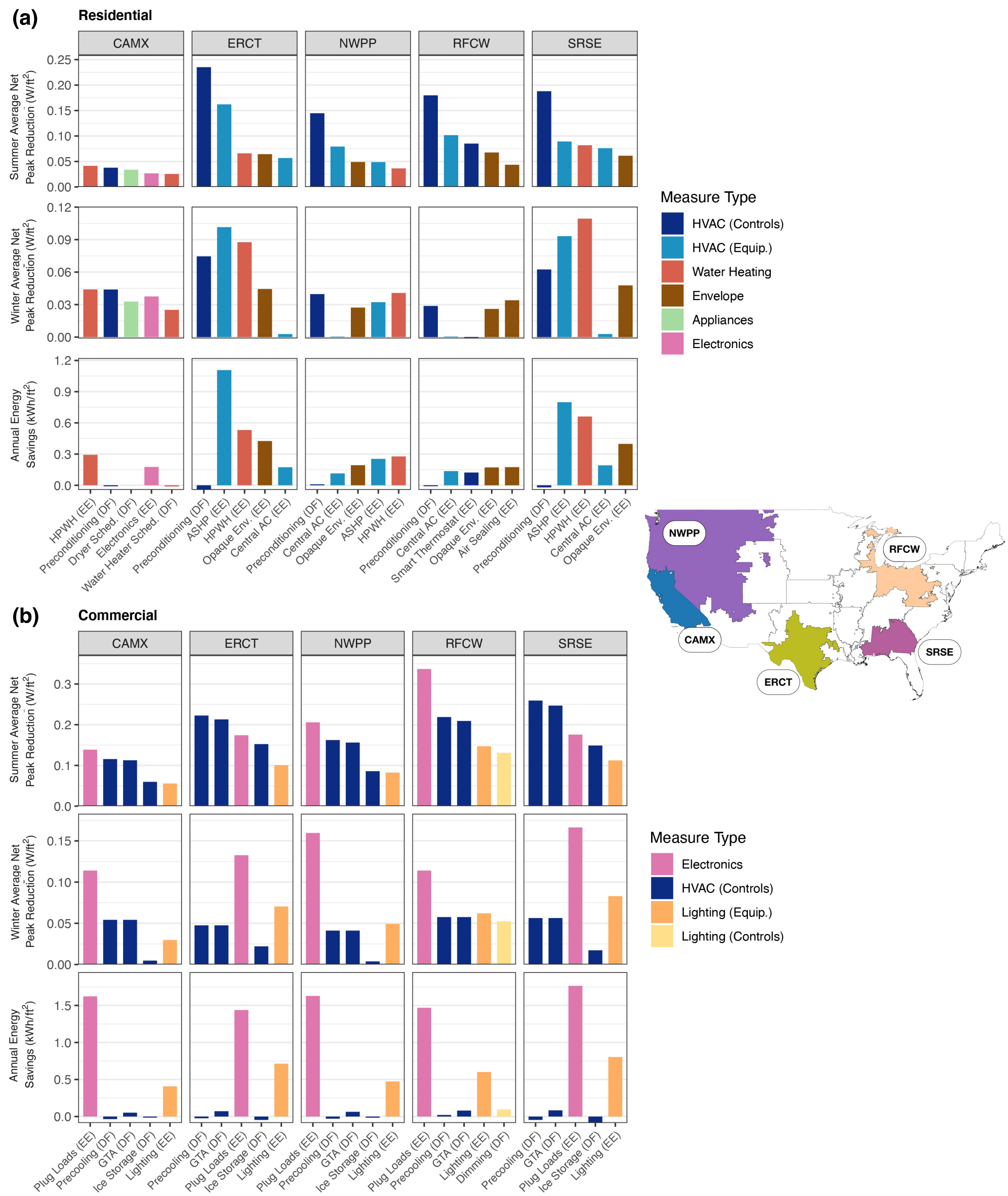

Figure 6: Individual efficiency and flexibility measures with the largest summer net peak demand intensity reductions for five U.S. grid regions in 2030. The five individual efficiency (EE) or flexibility (DF) measures with the largest technical potential reductions in residential (a) and commercial (b) summer peak demand intensity are highlighted for five of the 2019 EIA EMM regions (map at right). Measure impacts on summer peak demand (top row of each panel) are shown alongside their impacts on winter peak demand (middle row) and annual electricity use (bottom row). Seasonal peak periods are identified in each region based on total hourly system loads less variable renewable energy supply; regional peak impacts are averaged across all weekday peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). Individual measures on the x-axes are grouped into general measure types shown in the plot legends. Residential preconditioning and commercial precooling and plug load efficiency measures yield the largest summer peak reductions; plug load efficiency also yields strong reductions across the winter peak and annual metrics.

region, Nadel [34] estimates up to 40 GW of summer and winter peak demand reductions from incremental efficiency improvements and DR in 2030 (vs. 53 GW summer and 40 GW winter peak reductions in our study); again, however, this study is not a technical potential analysis and it does not consider interactions across efficiency and DR measures. The Northwest Power and Conservation Council's (NPCC) Seventh Power Plan [55] finds up to 9.9 GW summer and 13.2 GW winter peak reduction potential from efficiency and DR in 2035 (vs. 10 GW summer and 7 GW winter peak reductions in our study's Northwest region results for 2030); however, the NPCC territory excludes southern parts of our Northwest region, where cooling needs are greater. Importantly, all of these previous studies report peak reductions in terms of total system peak, where our analysis averages net peak hour impacts across all days in a season to estimate potential.

Our results reflect a technical potential assessment of the building-grid resource, and introducing realistic building and technology stock turnover and market penetration dynamics substantially reduces our impact estimates in the near-term (see Supplemental Information Figure S6 a-c). Important questions remain about which economic and policy levers would be most effective in accelerating adoption of the technology measures we consider; these might include include utility incentives, voluntary recognition programs (e.g., ENERGY STAR + Connected), codes and standards, and variable electricity tariffs, among others. Accordingly, while the current analysis establishes the potential size and distribution of the building-grid resource, future analyses are needed both to identify the most promising pathways for realizing this resource in the coming years and to guide the policy mechanisms that enable these pathways. Along these lines, future analyses should explore the sensitivity of our results to a wider range of projection scenarios, reflecting, for instance, more extreme warming trends or increased adoption of policies that accelerate renewable energy penetration or encourage electrification.

Experimental Procedures

Estimates of building efficiency and flexibility potential were generated using a hybrid building stock energy modeling approach [56] that incorporates both top-down and bottom-up elements. Development of potential estimates followed four steps: 1) definition of building efficiency and flexibility measures and scenarios, 2) determination of regional power system needs, 3) development of sub-annual end use load profiles for representative residential and commercial building types, with and without measures applied, and 4) scaling of baseline and measure end use load profiles across the building stock within each modeled region.

Measures, as listed in Table 2, modify the baseline electricity demand profile of residential and commercial buildings by improving upon the efficiency of baseline building equipment, envelope, and controls (energy efficiency (EE) measure set), modifying baseline operational schedules in response to grid needs (demand flexibility (DF) measure set), or by packaging these two types of changes (efficiency and flexibility (EE+DF) measure set). Detailed measure definitions are provided in Supplemental Information section 4, and example building-level impacts from these three measure sets are shown in Supplemental Information Figure S17.

All efficiency measures adhere to a "best commercially available" energy performance level. For residential buildings, this performance level is determined using the Scout Core Measures Scenario Analysis data set [38] and the National Residential Efficiency Measures Database [57]. For commercial buildings, best available performance is assumed to correspond to the 50% Advanced Energy Design Guides (AEDG) specifications. Where a 50% AEDG guideline is not available for a certain building type, the most applicable 30% AEDG guideline is used instead (see Supplemental

Information Section 4.2.1).

Efficiency measures cover all major end uses across the residential and commercial sectors (heating/cooling, ventilation, lighting, refrigeration, and water heating), as well as home and office electronics (TVs, personal and work computers, and related equipment)); residential efficiency measures additionally address several smaller electric appliance loads such as clothes washers, clothes dryers, dishwashers, and pool pumps. In both building types, envelope efficiency packages are assessed that implement higher performance opaque envelope components (walls, roof, floors), highly insulating windows, and air sealing; operational control measures are also represented (smart thermostats in residential, daylighting and occupancy controls in commercial).

Flexibility measures implement load shedding (for example, dimming the lights) or load shifting (for example, decreasing cooling set points in the hours leading up to the peak demand period to enable "coasting" with higher set points during the peak period, or charging thermal energy storage overnight to use to meet cooling set points later in the day). All flexibility measures modify baseline loads in the most aggressive manner possible without compromising basic building service needs, where service thresholds are determined on a load-by-load basis as described further in Supplemental Information section 4.2.2. Specific operational schedules for the flexibility measures (e.g., hour ranges during which load shedding and shifting is required) are determined by regional power system needs, as described further below.

Flexibility measures address the residential and commercial electric loads that are the largest contributors to total electric demand and can potentially be shed or shifted in response to hourly power system needs. In residential buildings, this includes heating, cooling, water heating, appliances (clothes washing, clothes drying, dishwashing, pool pumps) and electronics; in commercial buildings, this includes heating, cooling, ventilation, lighting, refrigeration, and office electronics (PCs and office equipment).

Efficiency and flexibility measures are packaged to explore possible interactive effects between these measure types, for example: 1) efficiency measures reduce the available load shedding and shifting potential of all flexibility measures, and 2) efficiency measures enhance the effectiveness of thermal flexibility measures, for example through envelope upgrades that extend the effects of precooling or discharging of thermal energy storage. In developing the measure packages, respective efficiency and flexibility measures are combined without additional modifications. For example, when precooling measures are packaged with a more efficient envelope, we do not assume any additional thermostat setback potential for the packaged version of these measures.

Table 2: Residential and commercial measure definitions. See Supplemental Information section 4 for additional details.

Measure Set	Name	Building Type	End Use(s)	Description
	Envelope insulation and air sealing	Res + Com	Heating/Cooling	
	HVAC equipment	Res + Com	Heating/Cooling	
	Lighting	Res + Com	Lighting	
EE	Electronics	Res + Com	Home/Office Electronics	Current best available technology
	Refrigeration	Res + Com	Refrigeration	
	Appliances	Residential	Washing and Drying	
	Water heater	Residential	Water Heating (WH)	
	Pool pumps	Residential	Pools and Spas	
	Thermostat controls	Residential	Heating/Cooling	Fixed increase or decrease of temperatures during unoccupied and nighttime hours
	Global temperature adjustment (GTA)	Commercial	HVAC	Increase or decrease zone temperature set points during peak hours
	GTA + precooling	Res + Com	Cooling (Res + Com), Ventilation (Com)	Decrease zone set points in the 4 hours prior to peak period, then float temperature setpoint during peak hours
	GTA + pre-heating	Residential	Heating	Increase zone set points prior to peak period then float temperature setpoint during peak hours
	GTA + precooling + thermal storage	Commercial	HVAC	Charge ice storage overnight and discharge during peak hours; limited to large commerical
DF	Continuous dimming	Commercial	Lighting	Dim lighting, and shut off lighting in unoccupied spaces during peak hours
	Low priority device switching	Commercial	Office Electronics	Switch off low-priority devices (e.g., unused PCs, office equipment) during peak hours
	Appliance demand response	Residential	Washing and Drying	Shift appliance loads before or after peak hours
	Water heating demand response	Residential	Water Heating	Pre-heat water heater setpoint during off-peak hours on the grid
	Electronics demand response	Residential	Home Electronics	Shift a fraction of plug loads to before or after peak hours
	Pool pumps demand response	Residential	Pools and Spas	Shift peak-hour pool pump loads to off-peak hours on the grid
	GTA + pre-cool/heat + efficient envelope & HVAC equip.; daylighting controls + dimming	Commercial	HVAC, Lighting	Combine DF HVAC/lighting strategies with more efficient envelope/equipment, daylighting, and controls
	Thermostat controls + pre-cool/heat + efficient envelope & HVAC equipment	Residential	Heating/Cooling	Combine DF heating/cooling strategies with more efficient envelope/equipment
EE + DF	Non-thermostat DR + EE	Residential	WH, Lighting, Home Electronics, Refrig., Washing and Drying, Pools and Spas	Shift WH and appliance loads outside of peak hours, upgrade appliances and WHs to best available efficient technology
	Device switching + efficient electronics	Commercial	Office Electronics	Combine DF electronics strategy with the most efficient PCs/office equipment
	All remaining EE ECMs	Commercial	Refrigeration, WH	Account for efficiency measures that are not a part of the packaged EE+DF measures above

When scaled across the building stock, each of the efficiency and flexibility measure sets considered in our analysis has a collective impact on total electric demand at the regional electricity system level. Accordingly, measure impacts are assessed relative to regional system needs, namely: 1) reduce electricity demand during times of high total electricity demand with low renewable electricity supply; and 2) shift peak electricity demand into times when renewable electricity supply is abundant. These needs are best assessed by examining the *net* regional system load shape in a given region, which subtracts total hourly variable renewable electricity generation across a system region from the total hourly electricity demand in that region. Measure sets that address system peak reduction and load shifting needs yield a net system load shape that is both lower and flatter than that of a baseline demand scenario. Such load shapes are desirable for utility operators because they reduce the need for peak load capacity investment, reduce curtailment of renewable electricity supply, and avoid the need to bring generators on and offline rapidly to meet sudden changes in net demand.

We assess our measure sets' potential to affect net regional system load shapes in the 22 2019 EIA EMM regions [58]. Using EMM system load and generation data from the 2019 AEO Reference Case, we first develop a normalized net system load profile for each region under relatively high renewable electricity penetration. Specifically, we use projection data from the year 2050—the last in EIA's modeling time horizon, in which renewable penetration is at its highest level of roughly 30% electricity generation—and normalize net hourly regional system loads by the maximum net peak system load (across all hours of the year). In the EIA data, hourly system load shapes and renewable generation profiles are provided for each region for three day types in each month—peak day, weekday, and weekend—yielding a total of 36 unique daily net load profiles per EMM system region. Load shedding and shifting objectives for building flexibility measures are determined by the summer (June–Sep) and winter (Dec–Mar) net system load shapes, when cooling and heating needs are at their highest, respectively.

Figure 7 shows an example of the daily net load profiles developed for summer and winter months in the California (CAMX) EMM region. On top of these profiles, we establish two periods of focus—peak and off-peak—as shown in Figure 7, with the maximum and minimum net load hours also denoted. These peak and off-peak periods are determined based on all monthly net load profiles that fall into the given season. Peak load hours are defined as the four hour range surrounding the maximum seasonal load hour; in regions with large ramps in net system load between the afternoon and evening hours (e.g., CAMX), the four hour peak range is weighted towards the ramping hours, while in all other regions the four hour peak range is symmetric around the maximum net load hour. Off-peak load hours are defined as all hours in which normalized net system load is within ten percentage points of the minimum net system load for that season.

Net regional system profiles as plotted in Figure 7 appear similar across certain subsets of the 22 EMM regions. To reduce the complexity of our measure definitions and assessment, we downselect 14 representative EMM region profiles to establish the full range of peak and low net system demand periods that measure impacts are assessed against (see Supplemental Information Section 2.1). The net system profiles for these representative utility regions and seasons are provided in Supplemental Information Figure S8. As mentioned, building efficiency and flexibility measures are assessed by their ability to reduce building demand during the net system peak period that is germane to a certain location and—in the case of flexibility measures—shift demand into the low net system load period(s) for that location.

Assessment of efficiency and flexibility measure impacts begins at the building-level, where EnergyPlus [60] simulations of hourly building energy loads under baseline operations and with the

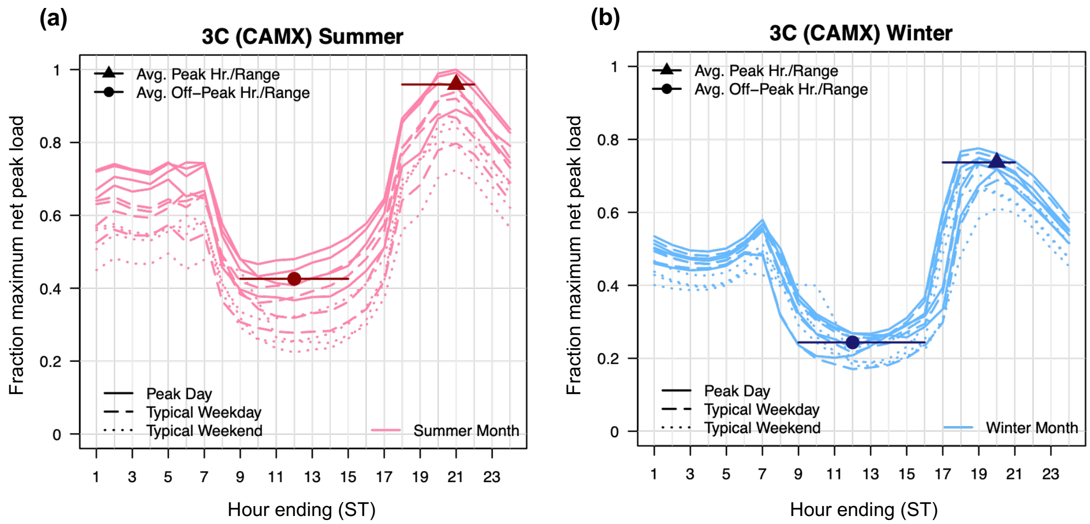

Figure 7: Peak-normalized total system loads net variable renewable energy generation for the California (CAMX) grid region. Typical daily net load shapes are shown for all months in the summer (a) and winter (b) seasons. Seasonal peak and off-peak net load periods are constructed for this and all representative utility regions in our analysis (see Supplemental Information Figure S8); CAMX is used to define grid conditions in ASHRAE climate region 3C as indicated by the plot titles. The peak load period is defined as four hours surrounding the maximum net load hour, while the off-peak window is defined as all hours in which the normalized net system load is within ten percentage points of the minimum net system load for the given season. Peak and off-peak hour ranges are represented as horizontal line segments on the plots, with maximum and minimum load hours (averaged across all load shapes for the season) marked as single points on the plots. All normalized net load profiles are based on the year with the highest projected renewable penetration in EIA EMM modeling for the 2019 Annual Energy Outlook, 2050 [59]. In CAMX, the large mid–day trough in the net load shapes reflect the high degree of solar generation projected for this region, which pushes net peak loads later into the evening hours.

measure sets applied are used to develop hourly load savings shapes for each measure in the analysis. Baseline load simulations in EnergyPlus capture the effects of changes in weather (using typical meteorological year (TMY3) data [61]), building occupancy, and equipment operation schedules in constraining the available load for efficiency and flexibility measures to affect in a particular hour of the year, building type, and location. Building simulation models are developed for a representative city [62] in each of the 14 contiguous U.S. ASHRAE 90.1-2016 climate zones, for six building types (1 residential and 5 commercial) that are chosen to represent the variations in typical end use load shape patterns across the residential and commercial building stock (see Supplemental Information Section 2.2).

For residential buildings, EnergyPlus serves as the engine for baseline and measure load simulations in the ResStock$^{\text{TM}}$ analysis tool, which allows for characterization and energy modeling of diverse single-family detached homes in the United States. ResStock generates baseline EnergyPlus building energy models through a sampling routine that assigns region-specific home characteristics and accounts for the diversity in vintage, construction properties, installed equipment, appliances, and occupant behavior within a region. Data for the baseline home properties come from numerous sources, including the 2009 Residential Energy Consumption Survey (RECS) [63]. After generating the baseline building models, ResStock leverages physics-based energy modeling in EnergyPlus and high-performance computing to simulate each baseline home, as well as homes with upgrades applied, as described in Table 2. Approximately 10,000 residential building models are generated for each representative city. By modeling many homes, we capture the diversity in the existing residential building stock, and provide a highly granular view of residential energy usage with energy efficiency and demand flexibility measures applied. ResStock outputs hourly end use load data for each home in the baseline and upgrade scenarios. For each measure, the relevant end use loads are averaged within a given representative city and written with average baseline loads from the same set of homes to a CSV file. Further details regarding the methodology behind the ResStock analysis tool can be found in [64].

Commercial baseline and measure loads are calculated using the Commercial Prototype Models that the U.S. Department of Energy publishes to support assessment and compliance with local building codes [65]. The Commercial Prototype Models are generated using the OpenStudio® Standards Measure, *Create DOE Prototype Building* [66]. Using the Measure, we generate models for five representative commercial building types (Large Hotel, Large Office Detailed, Medium Office Detailed, Retail Stand Alone, and Warehouse; see Section 2.2.1) across each representative city. With the building models in the OpenStudio® format, application of energy efficiency, demand flexibility, and packaged efficiency and flexibility Measures is highly customizable within the OpenStudio® environment [67]. Including the baseline cases, we generate a total of 1,540 scenario runs. As with the residential modeling, baseline and measure end use load profiles are written for each building type and location to a CSV file for further use in regional stock-level simulations.

To scale the effects of building-level measure application to the utility region level, we use Scout [40], an openly-available modeling software originally developed to estimate the short- and long-term annual impacts of building energy efficiency on U.S. national primary energy use, CO_2 emissions, and operating costs. Scout's general analysis approach is covered in detail elsewhere [39]; here, we focus on the methodological modifications that were required to enable assessment of the sub-annual (hourly) energy impacts of both energy efficiency and energy flexibility measures for the EMM region geographical resolution. These modifications build upon previous conceptual advances in methods for time-sensitive building efficiency and flexibility assessment [68].

First, Scout's annual projections of baseline buildings sector electricity use between 2015–2050, which reflect the outputs of EIA's 2019 AEO Reference Case [37], are translated from the Census Division breakdown that Reference Case buildings module data are provided with to the EMM region breakdown that EIA uses for its electricity system analysis. This translation uses EIA electricity sales data for the buildings sector to determine the fraction of residential and commercial building electricity sales reported for a given Census Division that falls into each of the EMM regions covered by that Census Division [59, 69]. In Scout, we apply resultant mapping fractions [70–73] directly to the raw Reference Case data by Census Division to yield alternate versions of the Scout baseline annual building end use electricity [74] and technology characteristics [75] projections that are resolved by EMM region.

Next, projections of EMM-resolved annual end use electricity are apportioned across all 8760 hours of the year using end use load shapes from the building-level baseline and measure simulations described above (see Supplemental Figure S10 for an overview of the dimensions across which these load shapes are simulated at the building level). Raw hourly end use load outputs from these building-level simulations, which are reported in units of Joules or KWh, are normalized by each building's total annual building-level electricity use, yielding the fractions of annual loads that fall into each hour of the year under either baseline operations or operations given measure application.

Multiplying these building-level baseline and measure hourly load fractions by Scout's total annual end use electricity projections at the region level yields the final attribution of the annual projections to a sub-annual, hourly basis for the baseline and measure cases. This calculation requires mapping from the ASHRAE climate zone and EnergyPlus building type breakdown of the hourly load fractions to the EMM region and AEO building type breakdown of the annual electricity use data in Scout. Here, ASHRAE climate zones are mapped to EMM regions using county-level population data collected from the U.S. Census Bureau [76]; the ResStock single family home building type is mapped 1:1 to all three AEO residential building types; and the Commercial Prototype Building types are mapped to AEO building types using EnergyPlus Reference Building literature [77] and square footage data from the EIA Commercial Building Energy Consumption Survey (CBECS) [43]. Resultant ASHRAE-EMM region and EnergyPlus-AEO building type mapping percentages are reported in Supplemental Information Section 3.

Analysis limitations

Key methodological limitations are grouped into those concerning building-level measure simulations and those concerning the representation of regional electricity system needs.

At the building scale, our analysis relies on simulated baseline end use load shapes and measure impacts rather than electricity meter data or device-level measured electricity use data, which are not available across the broad array of measure types and locations considered in this study. Insights from ongoing work to validate simulated end use load profiles with electricity meter data in both residential and commercial buildings will be incorporated into future iterations of this analysis [78]. Additionally, we use a representative subset of building types to account for variations in baseline load profiles across the building stock (see Supplemental Information section 2.2), which may miss some of the diversity in these load profiles; for commercial buildings, this issue may be further compounded by our reliance on single prototype models to represent the baseline load profiles of each commercial building type. Future work can leverage improvements to building stock modeling tools, including the expansion of commercial prototypes [79], to better assess the significance of baseline load diversity to simulated measure impacts. Along similar lines, our analysis uses a single representative city in each climate zone to capture the impacts of weather variation on simulated measure impacts; previous research has shown that in some cases, use of multiple representative cities within each climate region is warranted to improve the accuracy of estimated electricity use patterns [80]. Moreover, the TMY3 weather inputs to our building-level simulations do not encompass the most extreme variations in hourly weather patterns within a given year or represent the effects of current warming trends [61] or the expectation that those warming trends will continue in the future. Finally, our analysis holds hourly distributions of baseline end use loads and the relative load impacts of best available building efficiency and flexibility constant across the simulated time horizon (2015–2050). In practice, changes to these load distributions and relative measure impacts could be expected—for example, with new patterns of building use as more people work from home, or decreasing differences between "typical" and best available building technologies on the market over time.

At the utility scale, our use of high and low net system load periods as a proxy for grid needs has its own limitations. First, this approach does not directly address load ramping, which is best defined by the steepness of the load curve rather than its absolute minimum and maximum. Second, net load shape magnitudes alone do not fully encapsulate the many factors that can drive temporal variations in the value of efficiency and flexibility to the electric grid, including fuel supply constraints, power plant availability, and regulatory factors [81]. Third, the spatio-temporal granularity of our net system load shapes is limited to a subset of representative regions (Supplemental Table 1) and typical day types within each season, which may miss some of the variation in these net load shapes that would be captured by a higher spatio-temporal resolution. Future work can assess grid needs more directly and precisely by drawing from newly available 8760 wholesale electricity cost projections [82] across a larger number of representative regions. Future work might also expand the focus of our grid impact metrics to include changes in hourly and annual emissions alongside changes in electricity loads and costs.

Acknowledgements

This work was authored by The Regents of the University of California under Contract No. DE-AC02-05CH11231 and by the Alliance for Sustainable Energy, LLC, the manager and operator of the National Renewable Energy Laboratory for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding was provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Building Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. A portion of this research was performed using computational resources sponsored by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory. The authors gratefully acknowledge the assistance of Laura Martin and Kevin Jarzomski, U.S. Energy Information Administration (EIA), in accessing EIA NEMS Electricity Market Module (EMM) and Buildings Module data, respectively. The authors appreciate the thoughtful comments of multiple external reviewers of this work.

Declaration of Interests

The authors declare no competing interests.

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Supplemental Information

1 Additional results

Figures S1–S5 show the same information as Figures 2–6 for the year 2050 instead of 2030. Overall, the distribution of baseline electricity and measure impacts across buildings, regions, and end uses in 2050 is similar to 2030, while the magnitude of results increases. These increases are driven by cooling in residential buildings, and by office electronics and cooling end uses in commercial buildings. A notable decrease in annual residential heating reduction potential is observed, as are slight decreases in the winter peak reduction potential of residential heating and decreases in the influence across metrics of commercial lighting measures.

Figure S6 shows how the technical potential impacts of the three efficiency and flexibility measure sets for 2030 and 2050 (shown in Figures 6 and S5) are reduced when realistic baseline technology stock turnover rates and a cap on long-run technology market penetration are introduced. Stock turnover rates are consistent with the "Max adoption potential" assumptions from Scout [1], and a long-run cap of 85% market penetration is assumed to be met over a period of 20 years, consistent with previous analyses of "achievable" potential for buildings sector efficiency programs [2, 3]. The effects of introducing these adoption dynamics are most notable in the near-term: considering realistic stock turnover alone reduces technical potential impacts in 2030 by 19–21% across metrics, while adding a market penetration cap reduces 2030 impacts by 65–67% across metrics. By 2050, baseline stock turnover reaches 100% and the 85% market penetration cap is reached, thus reducing technical potential impacts by 15% across metrics.

Finally, Figure S7 further disaggregates the prominent baseline annual electricity use and peak demand results in Figure 2 for the Great Lakes/Mid-Atlantic and Southeast EPA AVERT regions by Electricity Market Module (EMM) sub-region. These AVERT regions combine multiple EMM regions with high electricity use, topped by the RFCW sub-region in the Great Lakes/Mid-Atlantic and SRVC sub-region in the Southeast, each of which consumes more annual electricity than all other AVERT regions shown in Figure 2 aside from Texas.

2 Representative regional system and building load shapes

2.1 Representative regional system load shapes

Table S1 shows the subset of the 22 EIA EMM regions that are used to establish representative regional system conditions (peak, off-peak hours) for the building-level simulations in each of the 14 contiguous ASHRAE 90.1-2016 climate zones. For smaller ASHRAE climate zones that do not span many EMM regions (2A, 2-6B, 2-6C, 7), system load data from one representative EMM region are used to establish grid-level conditions, while in larger climate zones that span several EMM regions (3-6A), system data from two representative EMM regions are used to establish these conditions. In all, normalized net system load shapes from 14 unique representative EMM regions are generated as in Figure S8 and used to determine regional peak- and off-peak periods for the analysis. Here, "net" refers to the total hourly load on a system minus variable solar and wind energy generation, and net loads are normalized by the overall net peak hour load for the year. The normalized shapes in Figure S8 are based on EIA EMM projections for the year 2050 to best reflect regional system needs under the highest projected penetration of variable renewables in EIA's 2019 Annual Energy Outlook Reference Case data, or roughly 30% of total electricity generation [4]. Net system load

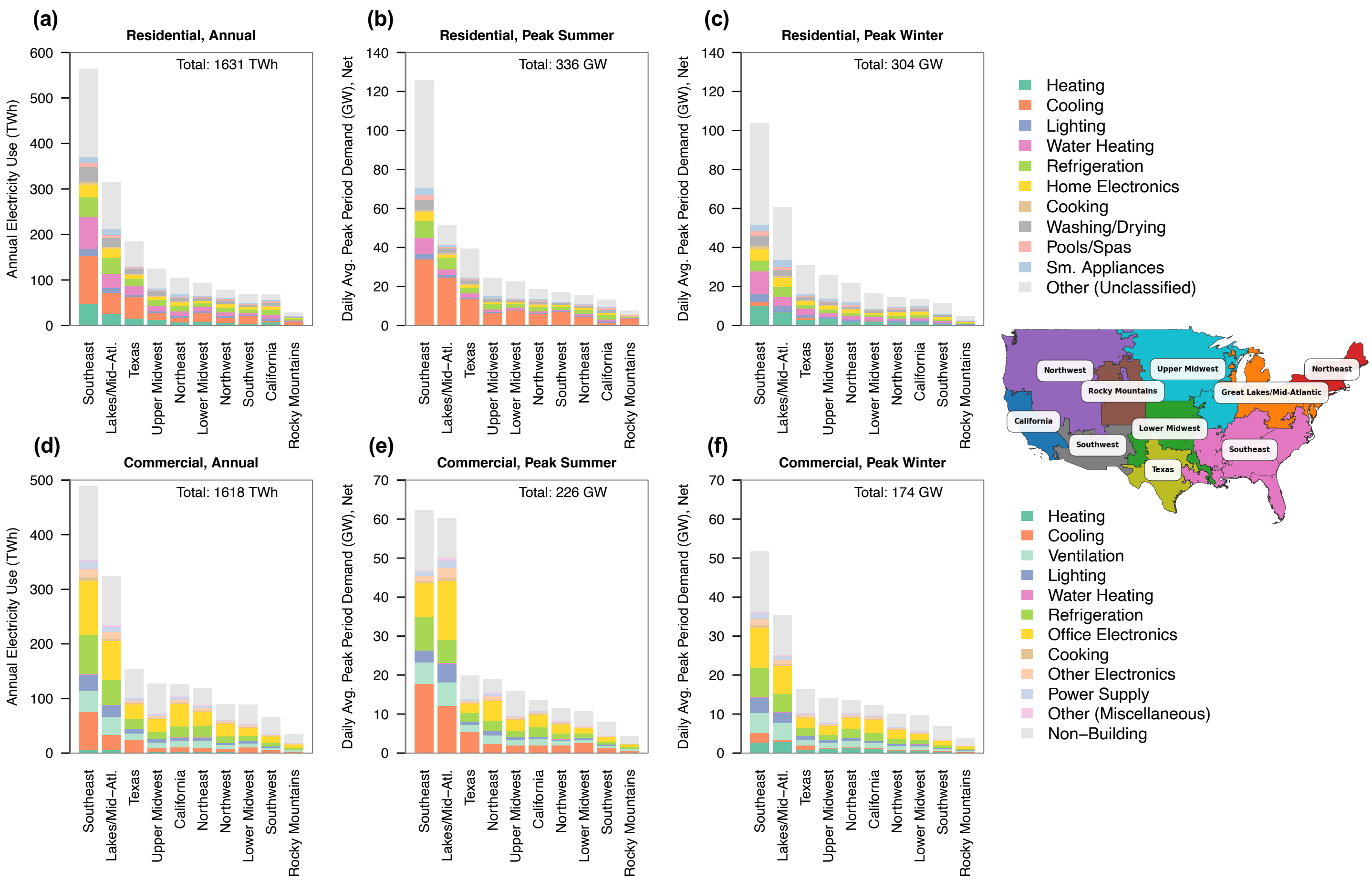

Figure S1: Baseline annual electricity use and net peak demand from U.S. buildings in 2050. Base-case residential (a-c) and commercial (d-f) annual electricity use and peak summer and winter demand are broken out by end use and the 10 2019 EPA AVERT regions (map at right), which are aggregations of the 22 2019 EIA EMM regions (see Figure 1). Base-case projections are consistent with the 2019 EIA Annual Energy Outlook Reference Case. Seasonal peak periods are identified in each region based on total hourly system loads net variable renewable energy supply; regional peak impacts are averaged across all weekday peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). Across regions in 2050, U.S. buildings are projected to contribute 3249 TWh to annual electricity use and 562 GW and 478 GW to daily net peak demand in summer and winter, respectively; as in 2030, base-case annual electricity use and demand is most strongly concentrated in the Southeast and Great Lakes/Mid-Atlantic regions.

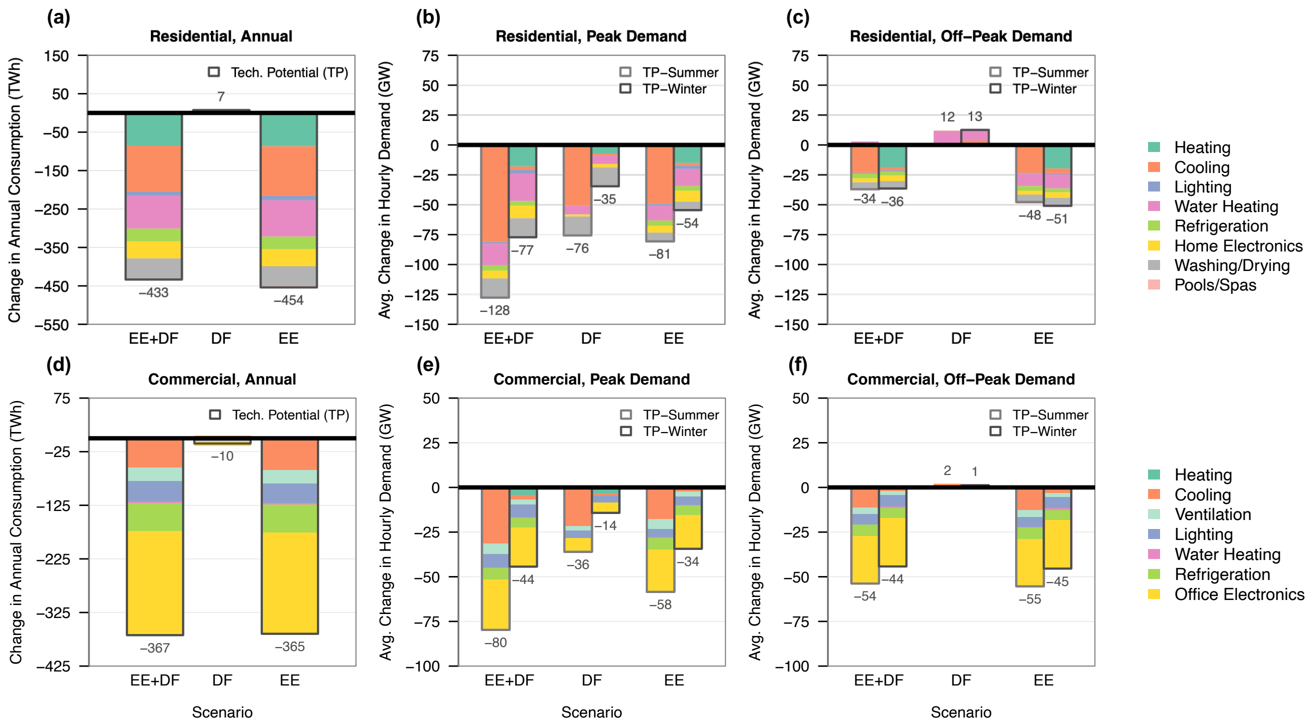

Figure S2: National impacts of best available U.S. building efficiency and flexibility measure sets on annual electricity use and net peak and off-peak demand in 2050. Technical potential efficiency and flexibility impacts on residential annual electricity use (a), peak demand (b), and off-peak demand (c) are broken out by end use and season alongside the same results for commercial buildings (d-f). Impacts are aggregated across the 22 2019 EIA EMM regions (see Figure 1), and peak impacts are non-coincident across these regions. Seasonal peak and off-peak periods are identified in each underlying region based on total hourly system loads net variable renewable energy supply; regional peak and off-peak impacts are averaged across all weekday peak and off-peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). When deployed together in 2050, U.S. building efficiency and flexibility measures (EE+DF) can avoid up to 800 TWh annual electricity use and 208 GW daily peak demand, but also decrease off-peak demand by up to 88 GW; flexibility without efficiency (DF) can add up to 14 GW to off-peak demand, with most of the increase observed in residential buildings.

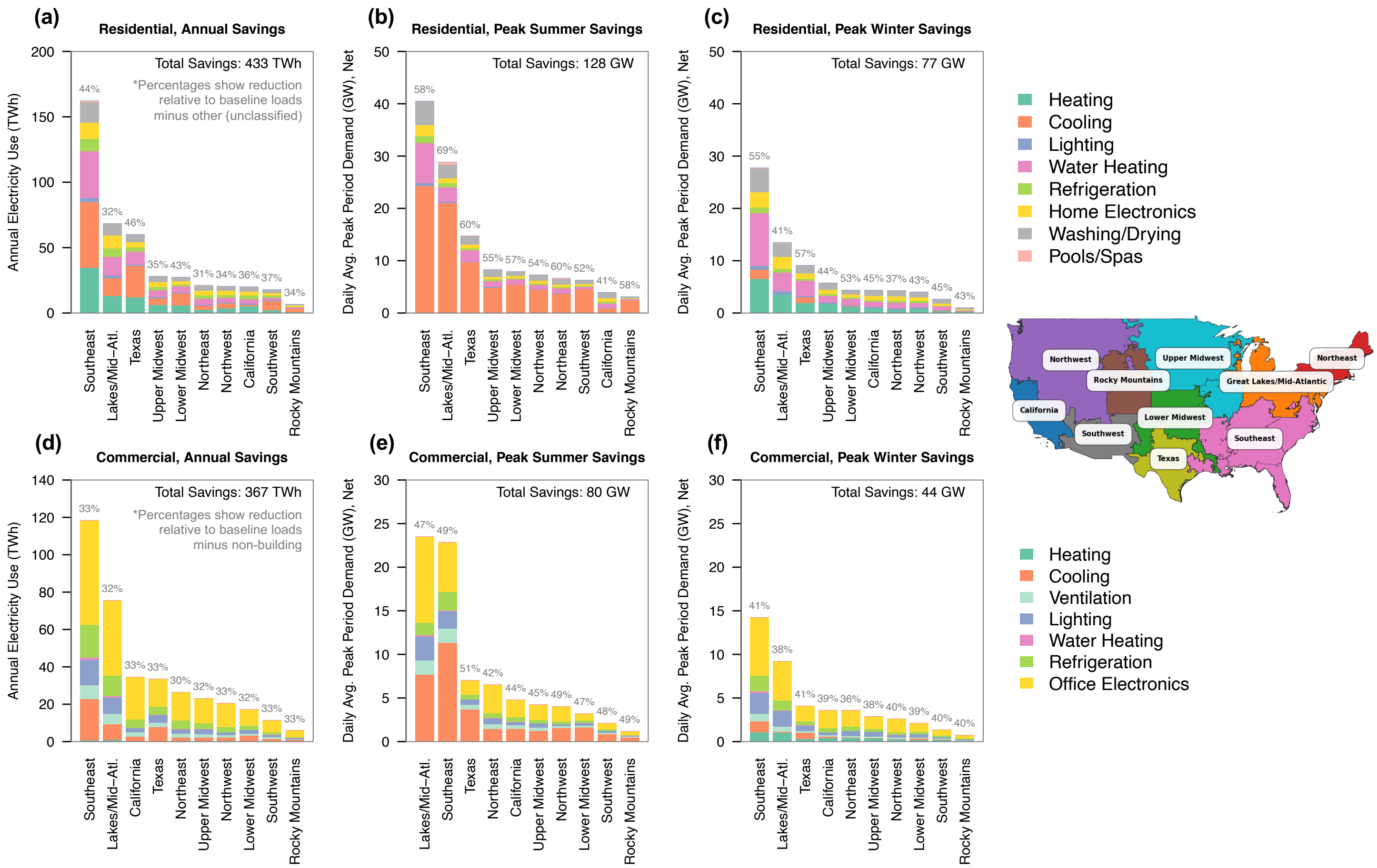

Figure S3: Regional impacts of best available U.S. building efficiency and flexibility measure sets on annual electricity use and net peak demand in 2050.. Technical potential impacts of building efficiency and flexibility measures (EE+DF) on residential (a-c) and commercial (d-f) annual electricity use and peak summer and winter demand are broken out by end use and the 10 2019 EPA AVERT regions (map at right), which are aggregations of the 22 2019 EIA EMM regions (see Figure 1). Labels at the top of each bar represent the percentage of total addressable base-case electricity that is avoided by the efficiency and flexibility measure set for the given region and assessment metric. Seasonal peak periods are identified in each region based on total hourly system loads net variable renewable energy supply; regional peak impacts are averaged across all weekday peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). Regional concentration of savings in the Southeast and Great Lakes/Mid-Atlantic regions mirror the distribution of base-case building electricity in Figure S1. Reduction percentages range from 31–69% in residential buildings and from 30–51% in commercial buildings, and are generally largest for the summer peak metric.

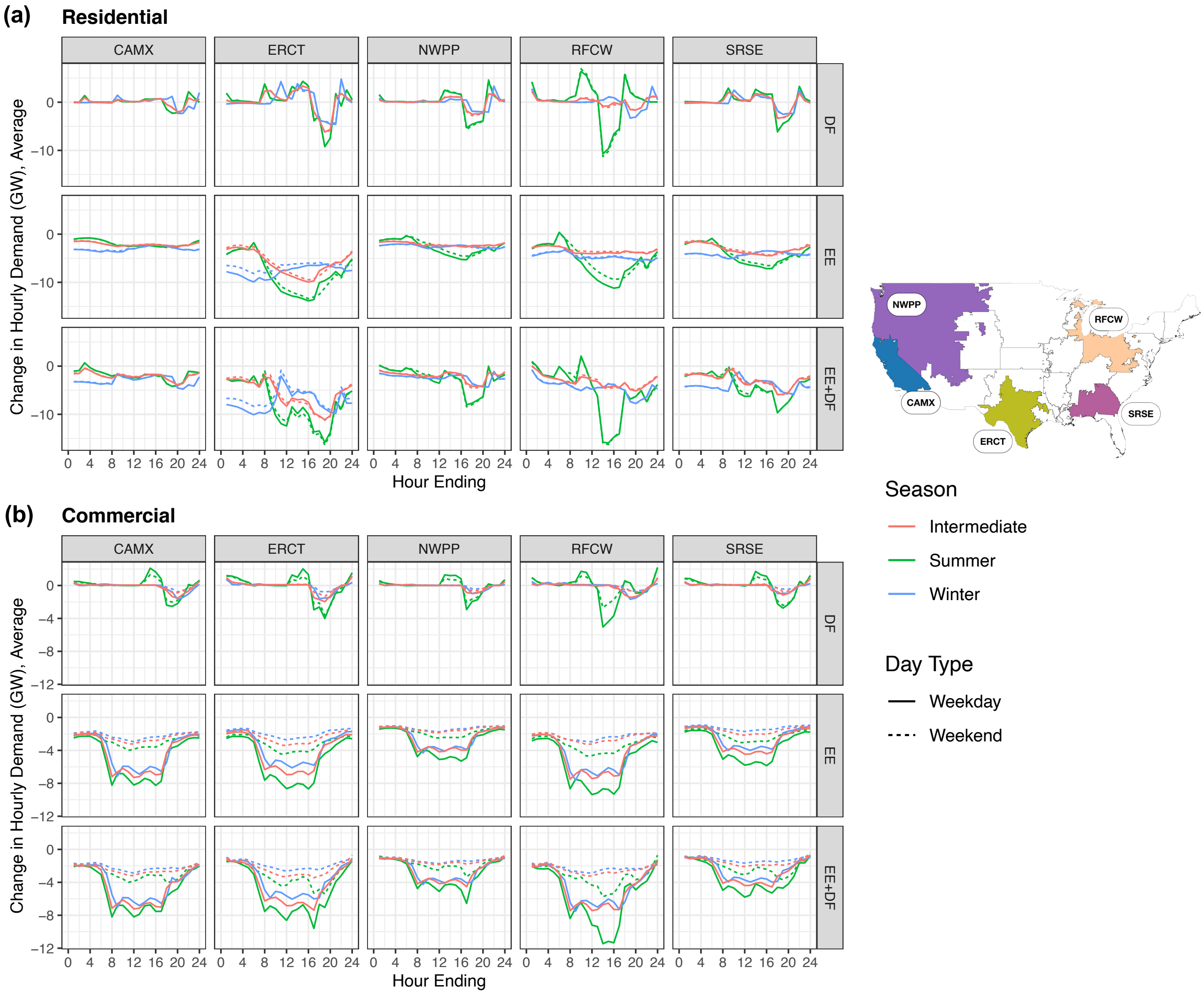

Figure S4: Typical change in sector–level electricity demand from building efficiency and flexibility measure sets for 5 U.S. grid regions in 2050. Technical potential demand change profiles are shown for 5 of the 2019 EIA EMM regions (map at right) and three measure sets (DF, EE, EE+DF) and reflect the impacts of each measure set on typical daily electricity demand across all residential (a) and commercial (b) buildings in each region. Profiles are broken out further by day type (weekday, weekend) and season (summer (Jun-Sep), winter (Dec-Mar), and intermediate (all other months)). Reductions in regional hourly demand are highest for the efficiency and flexibility measure set (EE+DF) on summer weekdays, reaching more than 15 GW and 11 GW in RFCW residential and commercial buildings, respectively, though weekday and weekend profiles are similar for residential buildings. Increases in regional hourly demand are highest for the flexibility–only measure set (DF) on summer weekdays, reaching more than 5 GW in RFCW residential buildings and 2 GW in CAMX commercial buildings.

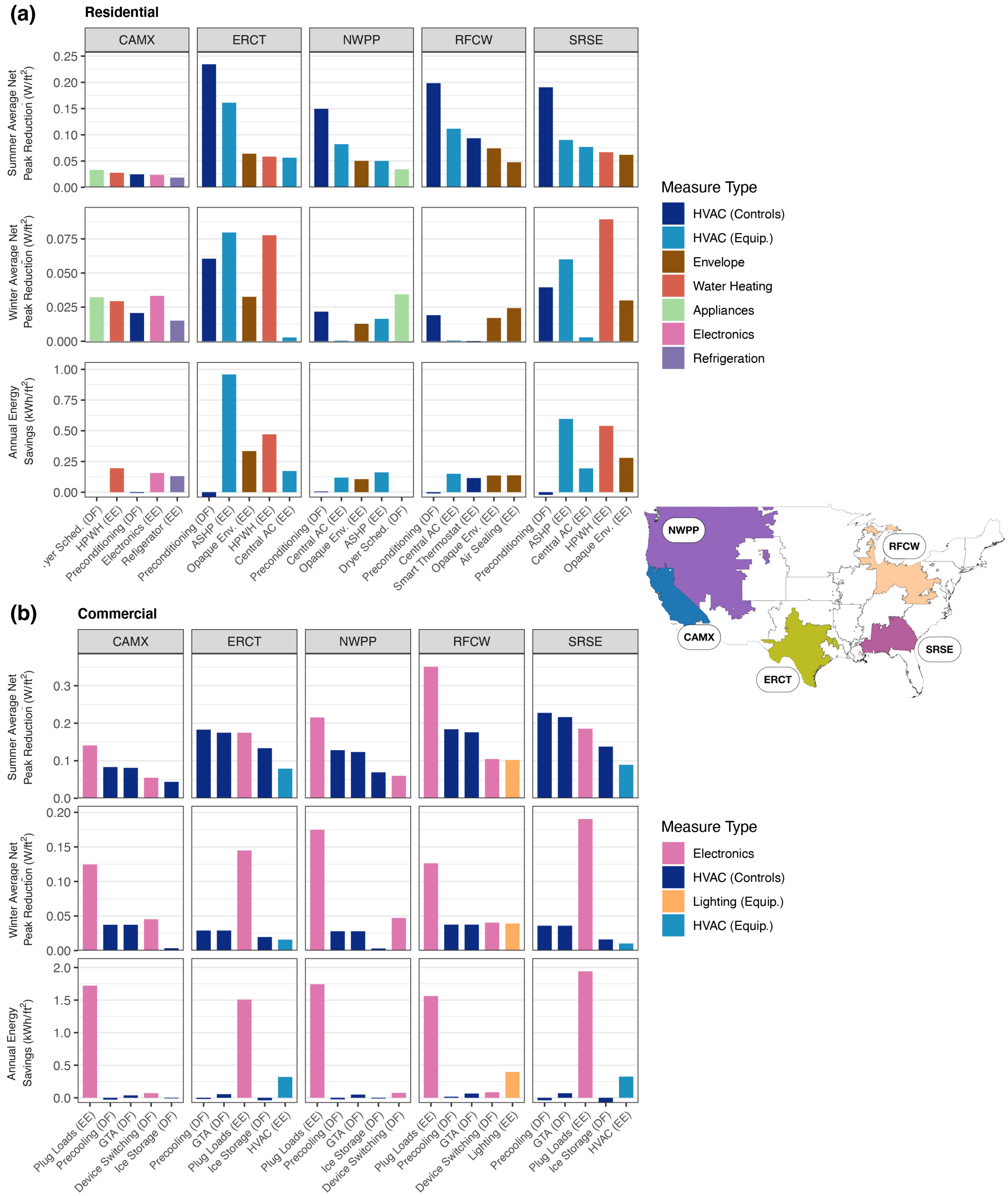

Figure S5: Individual efficiency and flexibility measures with the largest summer net peak demand intensity reductions for five U.S. grid regions in 2050. The five individual efficiency (EE) or flexibility (DF) measures with the largest technical potential reductions in residential (a) and commercial (b) summer peak demand intensity are highlighted for five of the 2019 EIA EMM regions (map at right). Measure impacts on summer peak demand (top row of each panel) are shown alongside their impacts on winter peak demand (middle row) and annual electricity use (bottom row). Seasonal peak periods are identified in each region based on total hourly system loads net variable renewable energy supply; regional peak impacts are averaged across all weekday peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). Individual measures on the x axes are grouped into general measure types shown in the plot legends. Residential preconditioning and commercial precooling and plug load efficiency measures yield the largest summer peak reductions; plug load efficiency also yields strong reductions across the winter peak and annual metrics.

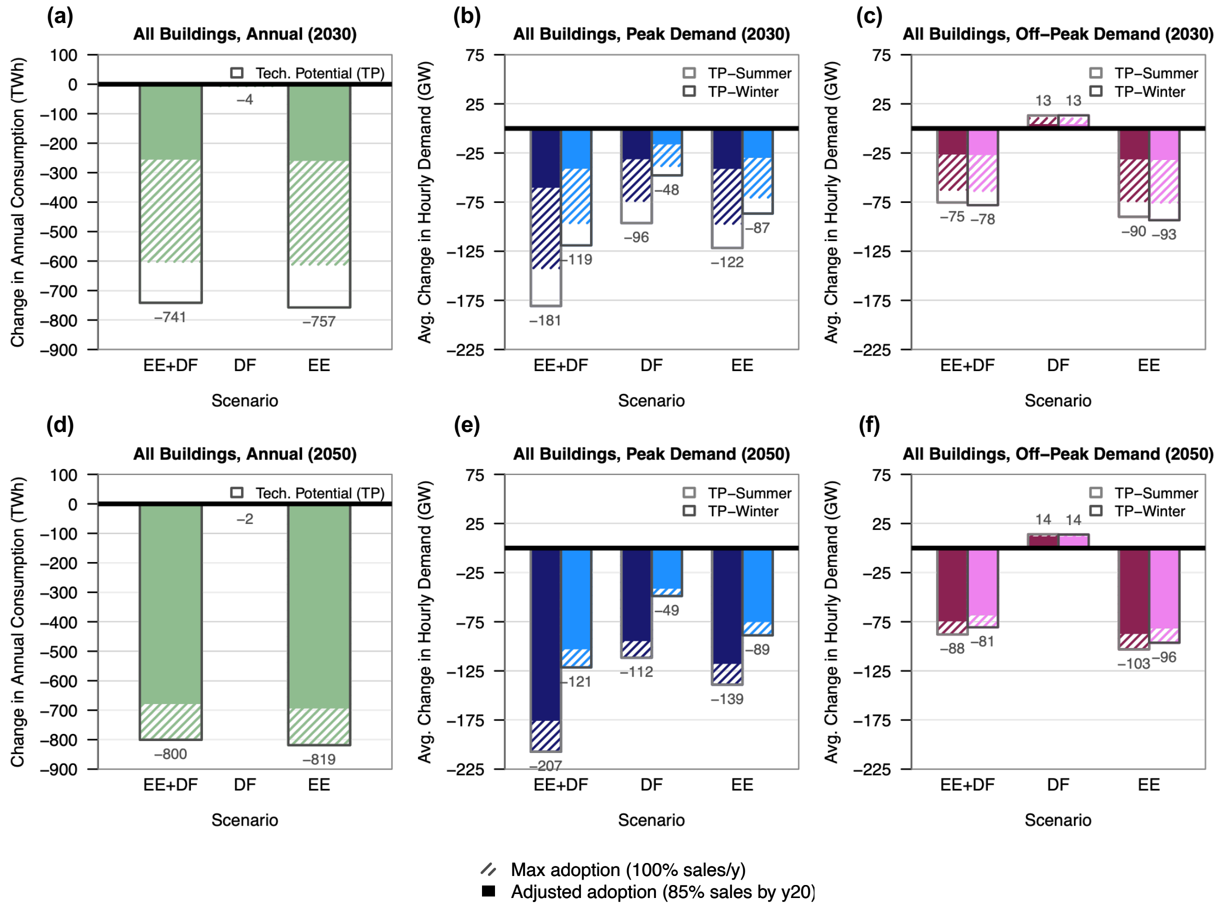

Figure S6: National impacts of best available U.S. building efficiency and flexibility measure sets on annual electricity use and net peak and off-peak demand in 2030 and 2050 considering baseline stock turnover and market penetration dynamics. Total technical potential building efficiency and flexibility impacts (shown as gray outlines) are re-estimated for 2030 (a-c) and 2050 (d-f) given additional consideration for realistic baseline stock turnover and sales penetration. Two alternate adoption cases are explored: the first assumes realistic, measure-specific rates of turnover in the comparable baseline technology stock with 100% sales penetration ("Max adoption (100% sales/y)"); while the second combines realistic stock turnover with annual sales penetration of 85% over 20 years ("Adjusted adoption (85% sales by y20)"). All measures enter the market in 2021. Interpretation of the peak and off-peak metrics is the same as in Figures 3 and S2. In 2030, adding realistic stock turnover decreases annual and peak electricity reductions from co-deployment of efficiency and flexibility by 19–21%, while adding both stock turnover and reduced sales penetration decreases these reductions by 65–67%. By 2050, only the 85% sales penetration cap affects the technical potential reductions (reducing them by 15%).

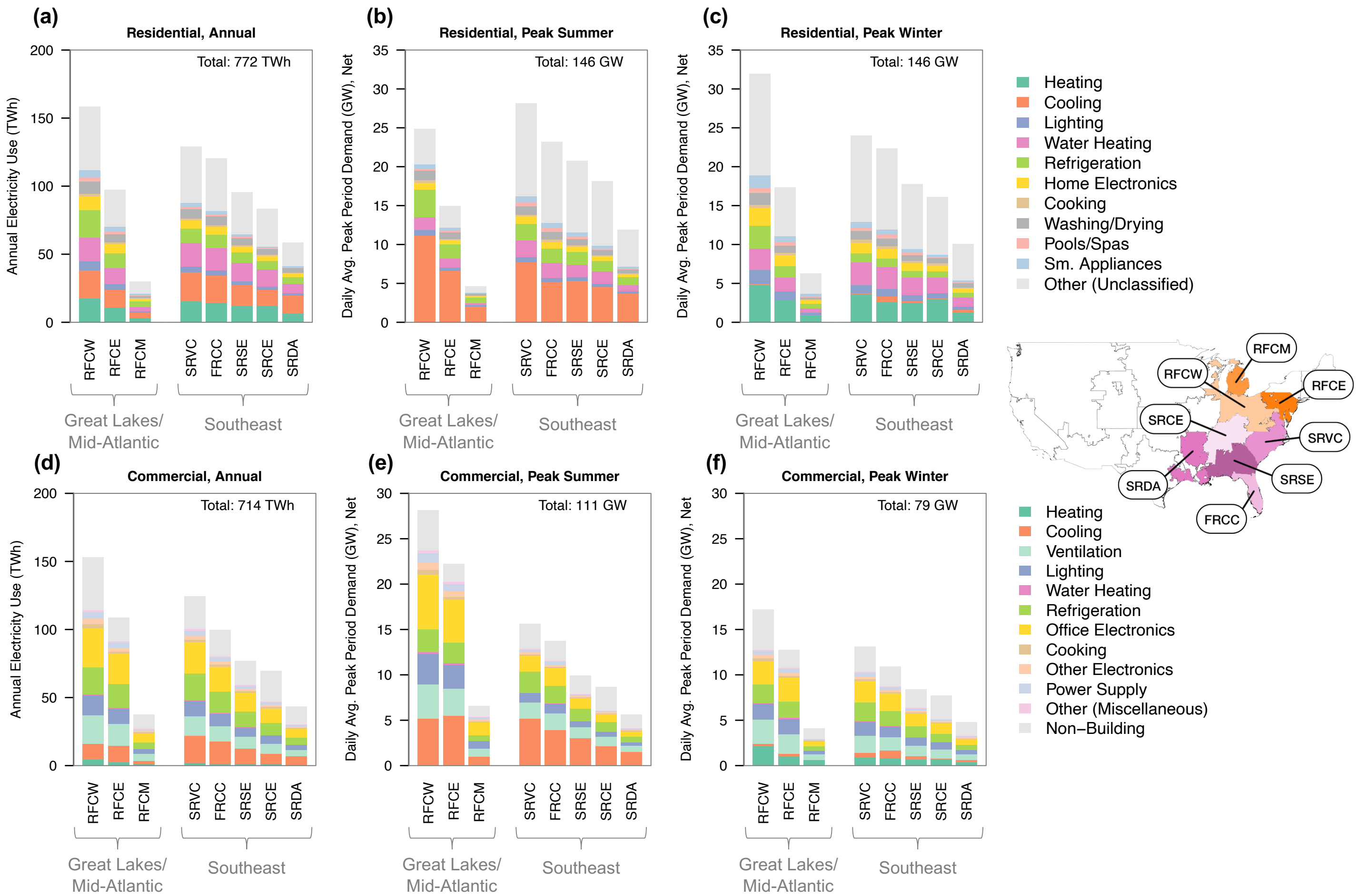

Figure S7: Attribution of 2030 baseline annual electricity use and net peak demand from buildings in the Great Lakes/Mid-Atlantic and Southeast AVERT regions to EIA EMM sub-regions. Base-case residential (a-c) and commercial (d-f) annual electricity use and peak summer and winter demand are broken out by end use and the 2019 EIA EMM sub-regions (map at right) that aggregate into the Great Lakes/Mid-Atlantic and Southeast AVERT regions (see Figure 1). Base-case projections are consistent with the 2019 EIA Annual Energy Outlook Reference Case. Seasonal peak periods are identified in each region based on total hourly system loads net variable renewable energy supply; regional peak impacts are averaged across all weekday peak hours in the season (Jun–Sep for summer, Dec–Mar for winter). Both the Great Lakes/Mid-Atlantic and Southeast regions combine multiple EMM regions with high electricity use, topped by RFCW in the Great Lakes/Mid-Atlantic and SRVC in the Southeast, each of which consumes more annual electricity than all other AVERT regions shown in Figure 2 aside from Texas.

shapes and associated peak/off-peak periods in Figure S8 are determined by EMM region, season (summer, winter, intermediate), and day type (weekday, weekend).

Table S1: Summary of representative EMM utility regions that are used to establish regional system conditions (e.g., peak, off-peak hours) for the building-level simulations conducted in each of the ASHRAE 90.1-2016 climate zones, as well as the full set of EMM regions that each represents.

ASHRAE 90.1-2016 Region	Representative EMM Region	Represented EMM Regions
2A	FRCC	FRCC, ERCT, SRDA, SRSE, SPSO
2B	AZNM	AZNM, ERCT
3A-1	SRVC	SRVC, ERCT, SRDA
3A-2	SPSO	SPSO, SRSE, SRCE, SPNO
3B	ERCT	ERCT, SPSO, AZNM, CAMX, NWPP
3C	CAMX	CAMX
4A-1	NYCW	NYCW, NYLI, RFCE, RFCW
4A-2	SPNO	SPNO, SPSO, SRDA, SRGW, SRSE, SRCE, SRVC
4B	AZNM	AZNM, SPSO, CAMX, RMPA
5A-1	NYUP	NYUP, MROW, SRGW, SRCE, SRVC, SPNO
5A-2	RFCW	RFCW, MROE, NEWE, NYCW, RFCE, RFCM, RMPA
5B	RMPA	RMPA, NWPP, AZNM
5C	NWPP	NWPP
6A-1	MROW	MROW, NYUP, RMPA
6A-2	NEWE	NEWE, MROE, RFCE, RFCM, RFCW
6B	NWPP	NWPP, RMPA
7	MROW	MROW, MROE, RMPA

2.1.1 Sensitivity analysis of peak and off-peak impacts by region

Estimates of daily net peak and off-peak period impacts from the measure sets examined in this paper may be influenced by the particular regional peak and off-peak period definitions chosen for the analysis (Figure S8). To further explore this sensitivity, we assess how the regional peak- and off-peak demand impacts from the residential preconditioning and commercial precooling DF measures change under a generic 4–8PM Local Standard Time (LST) peak and 10AM–2PM LST off-peak period assumption across regions. We focus on these two measures because they are among the most impactful in the residential and commercial measure sets (see Figures 7 and S6); pertain to thermal end uses, which are most variable across different hours of the day; and cover both on-peak demand decreases from thermostat setbacks and off-peak demand increases from preheating or precooling. The generic peak and off-peak periods reflect a net system load shape that would result from a high degree of solar electricity penetration across regions (CAMX is the closest proxy in the net load shapes of Figure S8). When using the generic peak definition, we assume that each of the DF measures increase or decrease the thermostat set point during the peak period (4–8PM) and preheat or precool in the 4 hours preceding the peak period (12–4PM), as is assumed for the regionally-adjusted peak and off-peak case.

Figure S9 compares EMM region-resolved measure impacts in 2030 under regionally adjusted peak and off-peak periods (x axis) to the same under generic peak and off-peak periods (y axis);

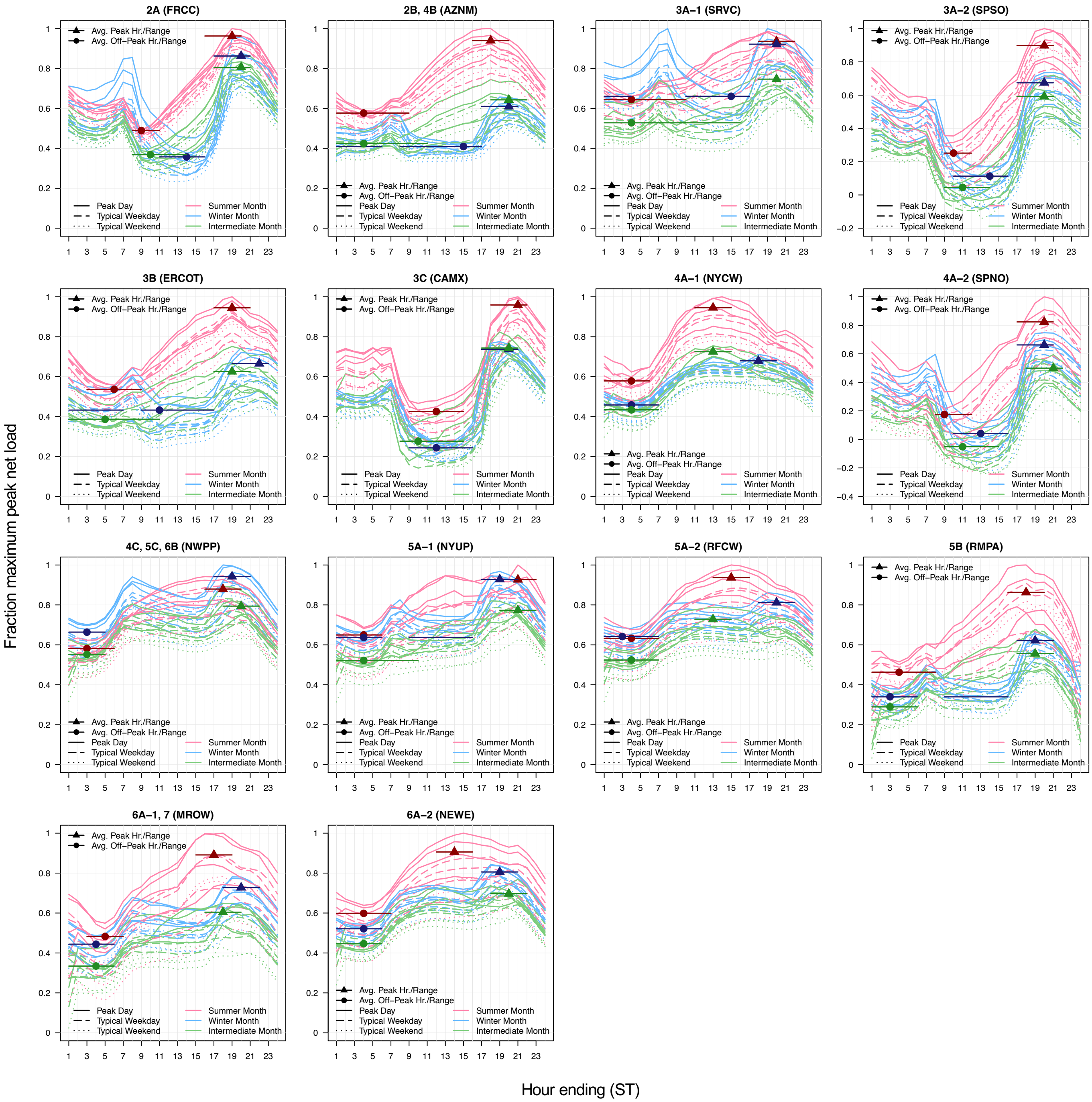

Figure S8: Peak-normalized total system loads net variable renewable energy generation for 14 representative EMM grid regions. Representative load shapes dictate peak and off-peak hours that building-level operations in a given ASHRAE climate zone are assessed against; the climate zone-to-representative EMM region mapping is indicated by the plot titles. Each line on the plots represents the total system load shape for that region net solar and wind energy supply for a given month of the year and day type (weekday/weekend), normalized by maximum peak net load across all months/day types. Maximum and minimum net load hours (averaged across months/day types) are indicated by triangle and circle points on the plots, respectively, while peak and off-peak hour ranges around these points are indicated by horizontal lines. The peak period is defined as the four hours surrounding the maximum net load hour, while the off-peak period is defined as all hours in which the normalized net system load is within ten percentage points of the minimum net system load for the given season. All normalized net load profiles are based on the year with the highest projected renewable penetration in EIA Electricity Market Module (EMM) modeling for the 2019 Annual Energy Outlook (AEO), 2050 [5].

a perfect match would fall on the 1:1 line shown on each plot, which would indicate the results do not vary for that region given varying peak/off-peak period definitions. Across regions and building types, the change to generic peak and off-peak periods has the most notable affect on potential demand increases from DF—particularly in the summer, when use of the generic approach adds 7 GW and 9.3 GW to these increases for residential preconditioning and commercial precooling, respectively. This result reflects the tendency for summer off-peak periods to occur overnight under the regionally-adjusted approach, which misses the effects of pre-peak cooling in the afternoon. On the residential side, the change to the generic approach also has notable effects on winter off-peak demand increases in some regions—in particular, the Great Lakes RFCW, RFCE, and RFCM regions, which again have overnight low net load periods under the regionally-adjusted approach that do not capture preheating effects. Aggregated across regions, however, the effects of using generic winter off-peak periods on residential preheating are relatively small—adding only 1 GW in potential—as many regions' winter off-peak periods already occurred around mid–day under the regionally-adjusted approach.

In comparison to using regionally-adjusted peak and off-peak period definitions, using generic definitions has relatively minimal effects on peak reductions from the DF measures overall, adding 6 GW and 1 GW to summer and winter peak reductions from residential preconditioning across regions and shaving 0.7 GW off both the summer and winter peak reductions from commercial precooling across regions. Examining the results by region, most regions show similar peak impacts between the regionally-adjusted and generic approach to defining the peak period. Notable exceptions on the residential side include Texas (ERCT) and Florida (FRCC), where the generic peak setting is less coincident with later evening peaks in the residential heating load shape—thus removing 0.6 GW from the peak reduction potential of the residential preconditioning measure in these regions. On the commercial side, notable discrepancies occur for the Great Lakes RFCW and RFCE regions in the summer, which have an afternoon summer system peak period that is moved out of coincidence with the mid-day peak in commercial building loads under the generic setting—thus decreasing the peak reduction potential of the commercial precooling measure by 0.8 GW and 1 GW, respectively.

In summary, this sensitivity analysis suggests that even if more regions had net system load shapes with mid–day troughs and evening peaks—as might be expected under stronger penetration of solar generation than is assumed in our analysis—the effects would not be large enough to change our key conclusions regarding the size and distribution of the building–grid resource. Even the relatively dramatic increase in summer load building potential from preconditioning and precooling DF under the mid–day off–peak period—16 GW in total—would still not outweigh the off-peak load decreases from introducing building efficiency, which reach 75 GW for the EE+DF scenario in summer in Figure 3. Nevertheless, at the EMM region level, the effects of changes to the peak and off-peak period assumptions could be large enough to change the hierarchy of measure impacts in some cases—for example, in Figure S9 summer peak reductions from commercial precooling in the RFCE and RFCW (Great Lakes) regions are moved below that of the SRVC (Southeast) region given the assumption of a generic 4–8PM peak period. Accordingly, future work should carefully consider revisions to the regional net system load shapes assumed in this analysis as needed to remain current with projected electricity generation mixes in each region.

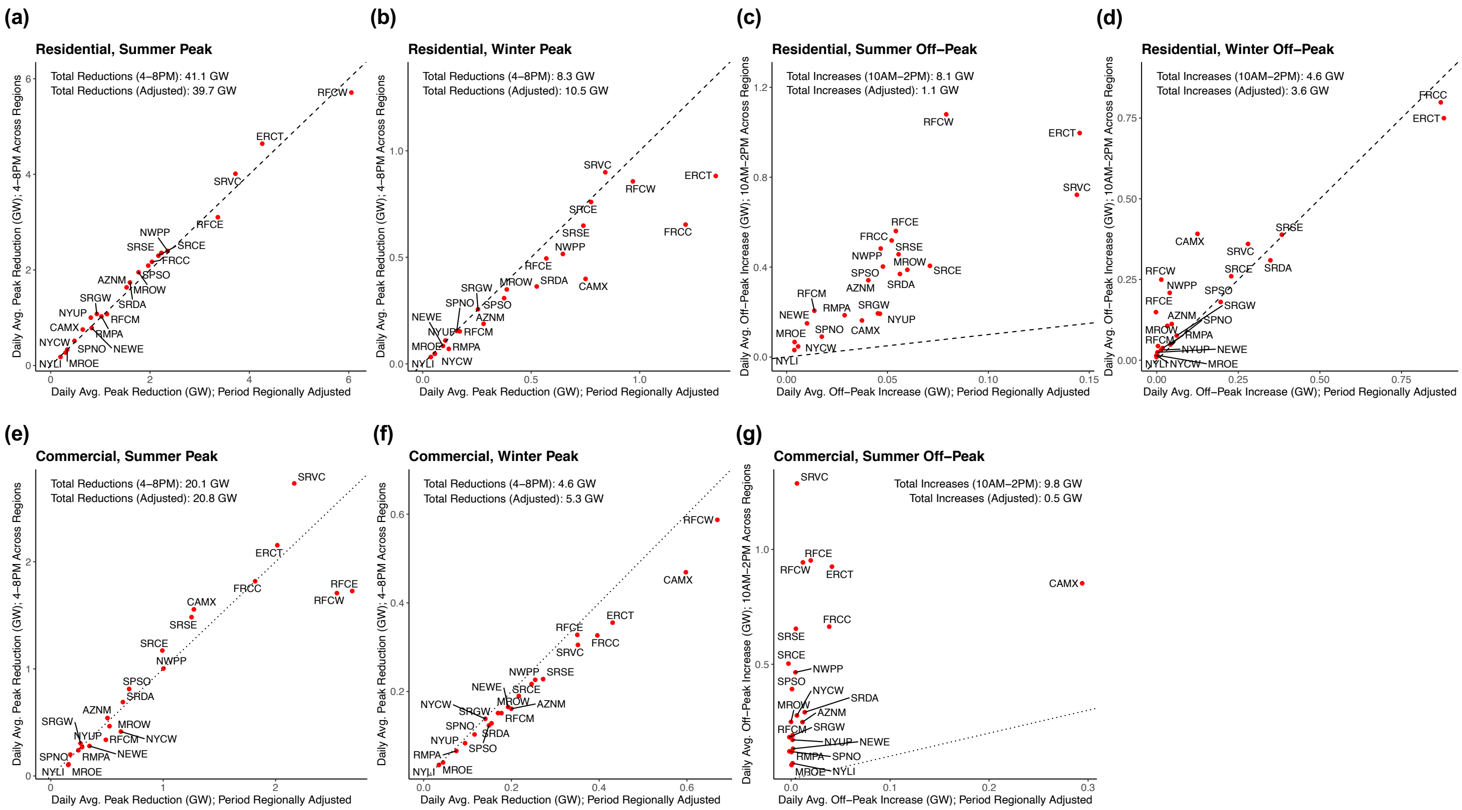

Figure S9: Residential preconditioning and commercial precooling DF impacts in 2030 under fixed vs. regionally adjusted peak and off-peak periods. Residential preconditioning DR summer and winter peak demand reductions (a-b) and off-peak demand increases (c-d) are shown alongside commercial precooling DF summer and winter peak reductions (e-f) and summer off-peak increases (g) in 2030. The DF measures shed cooling and heating demand during the four hour peak period and precool or preheat (residential only) in the four hours preceding the peak period. Each plot compares the given measure's impact on the given metric assuming either the regionally–adjusted peak and off-peak periods that were used to generate the main results (x-axis, and see Supplemental Figure S8), or generic 4-8PM peak and 10AM-2PM off-peak periods across all regions (y axis). Each plot shows a 1:1 reference line that is based on measure impacts under the regionally–adjusted periods. Estimated off-peak summer load increases from preconditioning/precooling are most sensitive to the change from regionally–adjusted to generic peak/off-peak period definitions, which adds 7 GW and 9 GW in load increase potential in residential buildings (c) and commercial building (g), respectively across regions.

2.2 Representative building load shapes

Figure S10 summarizes the five dimensions across which representative normalized building-level load shapes are developed via EnergyPlus simulations. Normalized load shapes take the cumulative hourly load consumed by each hour of the year and divide by the total load across all hours of the year; resultant hourly fractions of annual load are applied to annual energy use estimates to reapportion these estimates across all hours of the year.

The representative load shapes suggested by Figure S10 are developed as a "minimum set" that captures the variation in normalized load patterns across the residential and commercial building stock. A total of more than 11,000 load shapes were simulated for residential buildings (roughly 100 million hourly data points) and more than 8,000 load shapes were simulated for commercial buildings (roughly 70 million hourly data points) to represent the impacts of the combined EE, DF, and EE+DF measure sets. Many more simulations were run to represent the individual measure impacts shown in Figures 6 and S5. The five dimensions that dictate the representative load shape simulations are further described here.

- *Measure scenario.* 8 measure scenarios are considered: a baseline residential and commercial case in which no measures are implemented; and the three residential and three commercial measure set deployments summarized in Tables 1 and 2 and described in detail in Supplemental Information section 4.

- *Building type.* 6 building types are considered: single family homes are modeled for residential buildings, and 5 building types are modeled for commercial buildings. In 2020, single family homes represent 84% of residential square footage [6] and were thus deemed to be a suitable building type to represent the normalized load shape characteristics of the residential stock as a whole. Commercial building use types and normalized load patterns are more diverse than residential and therefore require a larger set of representative building types, as described further in Section 2.2.1.

- *End use.* 12 end uses are considered: 7 end uses (heating, cooling, lighting water heating, refrigeration, plug loads, and miscellaneous/other) are common to the residential and commercial models; 4 end uses (clothes washing, clothes drying, dishwashing, and pool heaters and pumps) are unique to the residential models; and 1 end use (ventilation) is unique to the commercial models.

- *Climate location.* The 14 contiguous U.S. ASHRAE 90.1-2016 climate zones are considered through simulations in representative cities for each climate zone [7]. Note that in commercial buildings, only thermally-related load shapes (cooling, ventilation, and heating) are distinguished by climate zone, as is further described in Section 2.2.1.

- *Electricity system.* 14 unique regional system (EIA Electricity Market Module (EMM) region) conditions are considered as described in Supplemental Information section 2.1 and summarized in Table S1 and Figure S8. Figure S10 shows that certain EMM regions are used to represent the regional system conditions of multiple ASHRAE climate zones (AZNM, NWPP, and MROW).

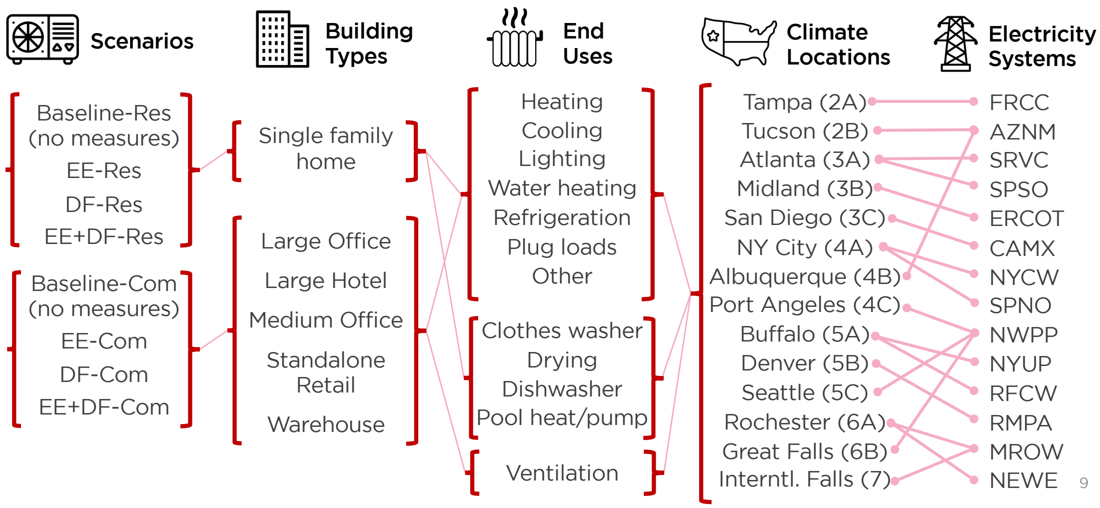

Figure S10: Simulated building end use load shape dimensions. Variations across five analysis dimensions are captured. Measure scenarios encompass a baseline case where no measures are implemented as well as deployment of the three residential and commercial measure sets outlined in Table 2. Building types encompass single family homes for residential and five commercial building types that capture variations in hourly end use profiles across the full commercial building stock (see Section 2.2.1). Major end uses (heating, cooling, lighting, water heating, refrigeration, ventilation) are covered alongside miscellaneous (‘other’) loads, plug loads, and several smaller residential end uses (e.g., clothes washing/drying, pool pumps). The 14 contiguous U.S. ASHRAE 90.1-2016 climate zones are covered by simulation in representative cities [7]; measures simulated within each of these representative cities respond to local regional system conditions (e.g., system peak and off-peak periods) based on normalized net load shapes from up to two representative EIA Electricity Market Module (EMM) regions (see Supplementation Information section 2.1)

2.2.1 Determining representative commercial building load shapes

Commercial building use types are more diverse and variable than are residential building uses, as can be seen by comparing the 16 building type categories in the EIA's Commercial Building Energy Consumption Survey [8] to the 5 categories used in the same survey for residential buildings [9]. Accordingly, a "minimum set" of representative load shapes for the commercial building stock should reflect a larger number of building types than for the residential stock, capturing the comparatively larger variation in use types across commercial buildings.

To determine this minimum set of representative commercial building types for the current analysis, we analyze a large existing dataset [10] of EnergyPlus-simulated hourly load shapes that cover the 16 DOE Commercial Reference Building Models [11] across all TMY3 weather locations [12] in the U.S. A subset of hourly load shapes for the 14 contiguous ASHRAE 90.1-2016 representative city locations [7] is selected, and the hourly load shapes are normalized such that each data point represents the fraction of annual load consumed for a given end use and Reference Building type by a given hour of the year. The normalized load shapes are then plotted across all building types, end uses, and representative cities.

Figure S11 shows the normalized load shape plots for climates 3B (El Paso, TX), 5A (Buffalo, NY), and 3C (San Diego, CA); Figure rows break out the plots by end use, and each plotted line represents the normalized load shape for a single Commercial Reference Building type. Examined qualitatively, the normalized load shapes in Figure S12 show substantial variation by building type and climate for the cooling end use, a small degree of variation for the ventilation and heating end uses, and essentially no variation for the lighting and plug loads end uses. The Figure therefore suggests that a single representative commercial building type/location combination is sufficient to represent the variation in normalized lighting and plug load shapes, while normalized heating and ventilation load shapes should at least be broken out further by climate zone, and normalized cooling shapes should be broken out by both climate zone and building type.

Figure S12 shows the results of a K-means cluster analysis that was conducted on the normalized cooling load shapes from Figure S11 to determine the minimum number of building type groupings needed to capture the variation in these cooling load shapes.[1] Elbow plots (left column in the Figure) show that across climates, little information is gained by organizing the cooling load profiles into more than 5 building type groupings. Moreover, when the cooling load profiles for the 5 groups are projected onto the original 16 cooling load shapes in each location (right column in the Figure), the grouped profiles appear to capture the full range of variation in the original profiles, and the assignment of Reference Building types to groups is relatively consistent across climates.

Table S2 reports the five building types that were ultimately chosen to represent variation in both cooling and ventilation load profiles across the full set of 16 Commercial Reference Building types. The selections (LargeHotel, LargeOfficeDetailed, MediumOfficeDetailed, RetailStandalone, and Warehouse) pull one building type from each of the five Figure S12 groups for climate 3B, the climate in the Figure with the largest cooling load. In our analysis, each of these representative building types is simulated using the Commerical Prototype Building Models [14], which are derived from the Reference Building Models.

[1] The approach to clustering building end use load profiles is based on methods devised in [13].

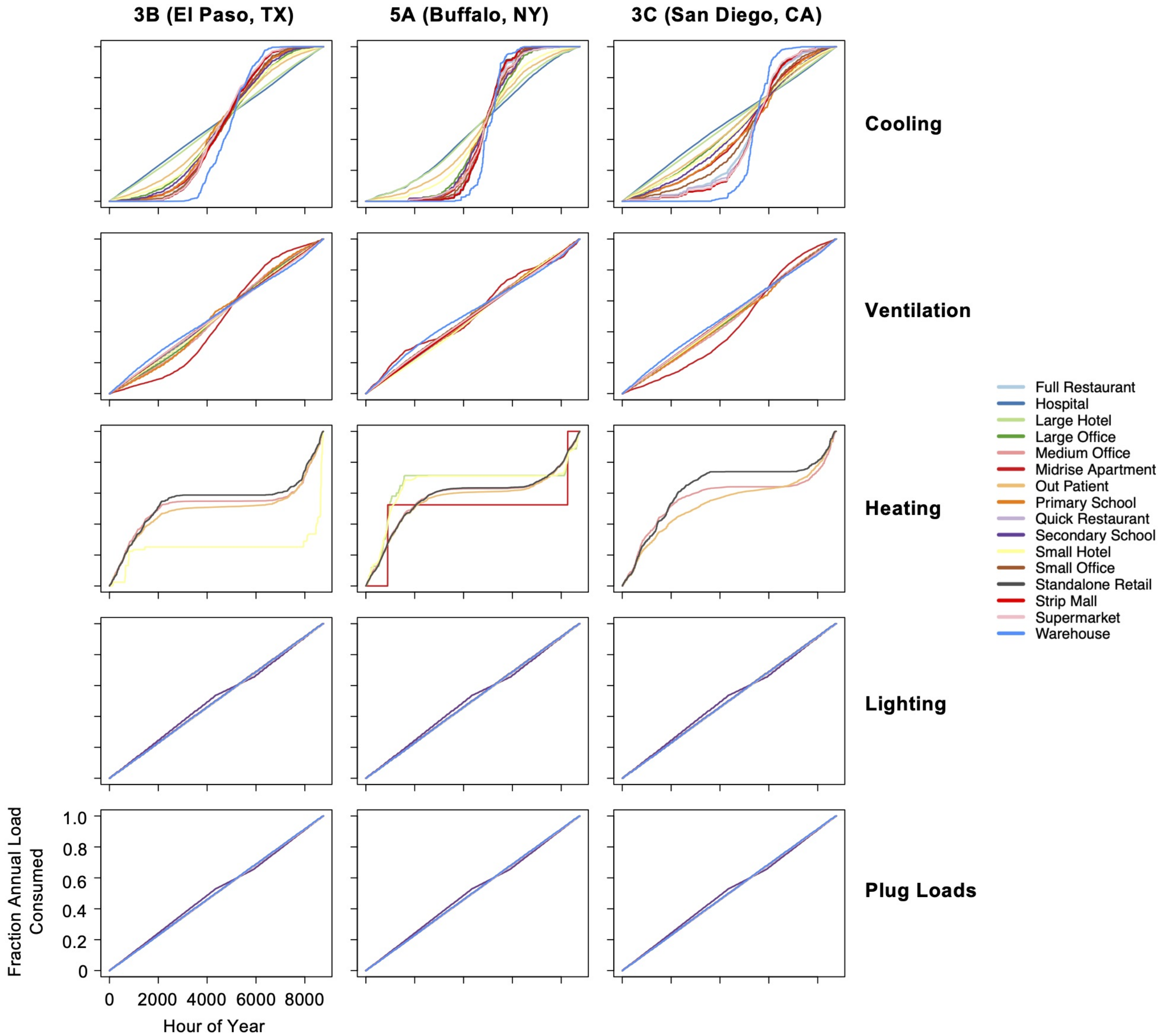

Figure S11: Cumulative hourly end use load profiles for the DOE Commercial Reference Buildings. Each profile in the figure represents the cumulative fraction of annual load consumed (y axis) by a given hour of the year (x axis). All data for the profiles are drawn from [10]. Hourly cooling load profiles range from being highly concentrated in the summer months (e.g., hours 4000-6000 for the Warehouse building type) to being more evenly spread across all hours of the year (e.g., the Hospital building type). Cooling profiles also differ by climate, with more cooling pushed earlier in the year in warm (3B-El Paso) vs. cool (5A-Buffalo) climates. Ventilation loads are spread evenly across the year with the exception of the Midrise Apartment building type, which serves a residential usage pattern. Few of the Reference Buildings have substantial electric heating loads; the profiles for those that do (Medium Office, Out Patient, Standalone Retail) appear similar across climates.

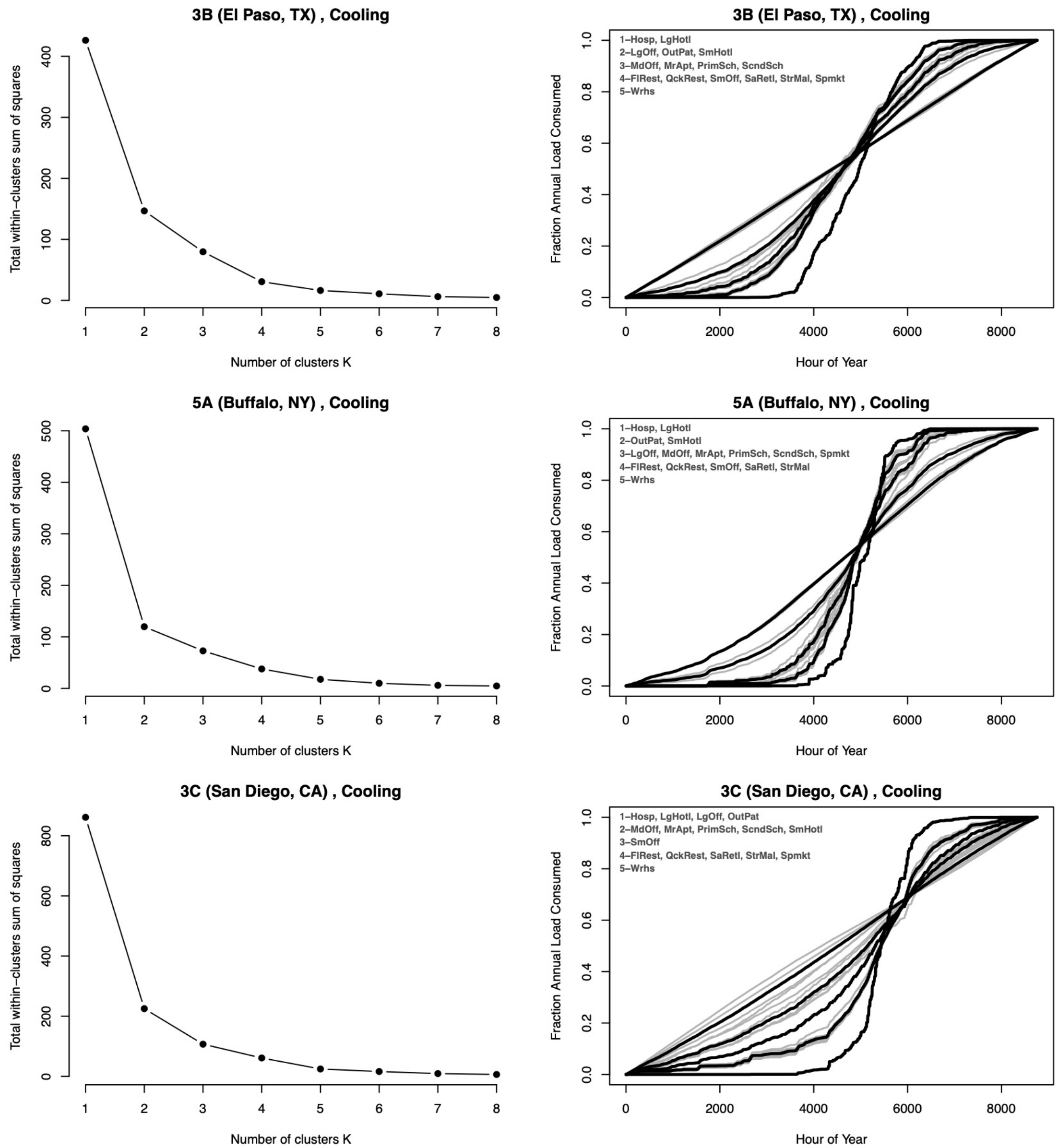

Figure S12: Results from K-Means cluster analysis on DOE Commercial Reference Building cooling end use profiles. Elbow plots (left) show that little information is gained by organizing building types and load profiles into more than 5 groups; overlaying the resultant cooling profiles for the 5 groups on the original cooling plots from Figure S11 (right) demonstrates that the group profiles capture the full range of variation in cooling load profiles across the larger set of commercial building types. Group membership (legends in the right-hand plots) is relatively stable across climates—particularly for the extreme profiles (1 and 5), which consistently include hospitals, large hotels, and warehouses.

Table S2: Summary of the five EnergyPlus Commercial Prototype Buildings that are used to represent variations in cooling and ventilation load patterns across the full set of commercial building types and climate locations in the building-level simulations. All other end uses are represented by the normalized load shape for MediumOfficeDetailed; for the heating end use, representative MediumOfficeDetailed load shapes are broken out by climate location, while for the remaining end uses, representative MediumOfficeDetailed load shapes are not broken out by climate location (the shapes for 2A are always used).

Representative EnergyPlus Building Type	Represented EnergyPlus Building Types
LargeHotel	LargeHotel
	Hospital
LargeOfficeDetailed	LargeOfficeDetailed
	OutpatientHealthcare
	SmallHotel
MediumOfficeDetailed	MediumOfficeDetailed
	PrimarySchool
	SecondarySchool
RetailStandalone	RetailStandalone
	RetailStripmall
	QuickServiceRestaurant
	FullServiceRestaurant
	Supermarket
	SmallOffice
Warehouse	Warehouse

3 Mapping from building-level (EnergyPlus) to stock-level (Scout) simulations

Tables S3 and S4 report mapping percentages that are used to translate building-level demand estimates in EnergyPlus (resolved by ASHRAE 90.1-2016 climate zone and EnergyPlus building type) to stock-level demand estimates in Scout (resolved by EIA EMM region and Annual Energy Outlook (AEO) building type). ASHRAE climate zones are mapped to EMM regions using county-level population data collected from the U.S. Census Bureau [15]; the ResStock single family home building type is mapped 1:1 to all three AEO residential building types; and the prototypical commercial building types are mapped to AEO building types using EnergyPlus Reference Building literature [16] and square footage data from the EIA Commercial Building Energy Consumption Survey (CBECS) [8].

Table S3: Mapping [17] between ASHRAE 90.1-2016 regions (used for the building-level EnergyPlus simulations) and EIA Electricity Market Module (EMM) regions (used for the stock-level Scout simulations). Shown is the percentage of a given EMM region's population that falls into a given ASHRAE region (note: not all rows sum to 100 due to rounding).

EMM/Scout Region	**ASHRAE 90.1-2016 Region**													
	2A	2B	3A	3B	3C	4A	4B	4C	5A	5B	5C	6A	6B	7
ERCT	60	2	34	4	-	-	-	-	-	-	-	-	-	-
FRCC	76	-	-	-	-	-	-	-	-	-	-	-	-	-
MROE	-	-	-	-	-	-	-	-	3	-	-	88	-	9
MROW	-	-	-	-	-	-	-	-	36	-	-	52	-	11
NEWE	-	-	-	-	-	-	-	-	84	-	-	16	-	-
NYCW	-	-	-	-	-	97	-	-	3	-	-	-	-	-
NYLI	-	-	-	-	-	100	-	-	-	-	-	-	-	-
NYUP	-	-	-	-	-	-	-	-	70	-	-	30	-	-
RFCE	-	-	-	-	-	62	-	-	36	-	-	1	-	-
RFCM	-	-	-	-	-	-	-	-	92	-	-	8	-	-
RFCW	-	-	-	-	-	17	-	-	75	-	-	8	-	-
SRDA	60	-	38	-	-	2	-	-	-	-	-	-	-	-
SRGW	-	-	-	-	-	71	-	-	29	-	-	-	-	-
SRSE	16	-	78	-	-	6	-	-	-	-	-	-	-	-
SRCE	-	-	21	-	-	79	-	-	1	-	-	-	-	-
SRVC	-	-	44	-	-	56	-	-	-	-	-	-	-	-
SPNO	-	-	4	-	-	90	-	-	5	-	-	-	-	-
SPSO	9	-	75	8	-	1	8	-	-	-	-	-	-	-
AZNM	-	43	-	43	-	-	8	-	-	7	-	-	-	-
CAMX	-	-	-	75	23	-	1	-	-	-	-	-	-	-
NWPP	-	-	-	1	-	-	-	50	-	35	1	-	13	-
RMPA	-	-	-	-	-	-	1	-	1	88	-	3	4	3

Table S4: Mapping [18] between EnergyPlus building types (used for the building-level EnergyPlus simulations) and EIA Annual Energy Outlook (AEO) building types (used for the stock-level Scout simulations). Shown is the percentage of a given AEO/Scout building type's square footage that is represented by a given EnergyPlus building type.

AEO/Scout Building Type	**EnergyPlus Building Type**	**Weight (%)**
single family home mobile home multi family home	ResStock Single Family Home	100
assembly	Hospital	100
education	Primary School	26
	Secondary School	74
food sales	Supermarket	100
food service	QuickServiceRestaurant	31
	FullServiceRestaurant	69
health care	Hospital	100
lodging	SmallHotel	26
	LargeHotel	74
large office	LargeOfficeDetailed	90
	MediumOfficeDetailed	10
small office	SmallOffice	12
	OutpatientHealthcare	88
mercantile/service	RetailStandalone	53
	RetailStripmall	47
warehouse	Warehouse	100
other	MediumOfficeDetailed	100

4 Measure definition details

4.1 Residential Measures

4.1.1 Residential Energy Efficiency (EE) Measures

HVAC

- Central Air Conditioning: SEER 18 Central AC
  Applied To: Homes with lower SEER AC (8, 10, 13, 14, 15) and electric baseboard or non-electric heating.
- Air Source Heat Pump: SEER 22, 10 HSPF ASHP
  Applied To: Any lower performance ASHP and all homes with electric furnaces (forced air).

Appliances

- Refrigerator/Freezers: EF 22.2 refrigerator
  Applied To: Any lower performance refrigerator
- Clothes Washer: ENERGY STAR Most Efficient (IMEF 2.92)
  Applied To: All homes with clothes washers
- Clothes Dryer: Ventless Heat Pump (CEF = 3.65)
  Applied To: All homes with electric clothes dryers
- Dishwasher: Rated 199 kWh/year
  Applied To: All homes with dishwashers

Water Heating

- Heat Pump Water Heater: 80-gal HPWH, 2.4 COP at rated conditions
  Applied To: All homes with lower performance electric water heaters

Lighting

- Interior Lights: LEDs, 112 lumens/Watt
  Applied To: All Homes

Pool Pumps

- Pool Pumps: 0.75 hp pump (annual energy use = 1688 kWh)
  Applied To: Homes with 1.0 hp pool pumps (annual energy use = 2250 kWh)

Plug Loads

- Plug Loads: Reduce plug loads usage level by half to represent high efficiency device
  Applied To: All homes

Thermostat Controls
Applied setbacks and schedules that follow the 2019 ENERGY STAR programmable thermostat guidelines [19], further described below and shown in Figure S13.

- Cooling daytime setup: Increase setpoint by 7°F, 8AM to 6PM
  Applied To: Homes with no occupants during the day on weekdays, homes without an existing cooling setup, and homes with an existing setpoint that would not be increased beyond the maximum cooling setpoint [20]
- Cooling nighttime setup: Increase setpoint by 4°F, 10PM to 6AM
  Applied To: Homes without an existing cooling setup and homes with an existing setpoint that would not be increased beyond the maximum cooling setpoint [20]
- Heating daytime setback: Decrease setpoint by 8°F, 8AM to 6PM
  Applied To: Homes with no occupants during the day on weekdays, homes without an existing heating setback, and homes with an existing setpoint that would not be decreased beyond the minimum heating setpoint [20]
- Heating nighttime setback: Decrease setpoint by 8°F, 10PM to 6AM
  Applied To: Homes without an existing heating setback and homes with an existing setpoint that would not be decreased beyond the minimum heating setpoint [20]

Envelope

- Attic Insulation: R-49 loose fill insulation
  Applied To: Homes with unfinished attics with any insulation level below R-49 (Uninsulated, R-7, R-13, R-19, R-30, R-38)
- Air Sealing: 1 ACH50 with added mechanical ventilation compliant with ASHRAE 62.2
  Applied To: All homes

Wall Insulation:

- R-13 cavity + R-20 XPS
  Applied To:wood frame exterior walls with lower existing insulation performance (Uninsulated, R-7, R-11, R-13)
- R-20 XPS
  Applied To wood frame exterior walls with existing R-19 cavity insulation; concrete masonry walls with existing furring insulation (R-7, R-11, R-15, R-19)
- R-5.5 furring insulation with R-20 XPS
  Applied To: uninsulated concrete masonry walls

Foundation Insulation:

- R-30 crawlspace ceiling
  Applied To: vented crawlspaces in AIA climate zones 1-2 with existing insulation below R-30 (uninsulated, R-13, R-19)

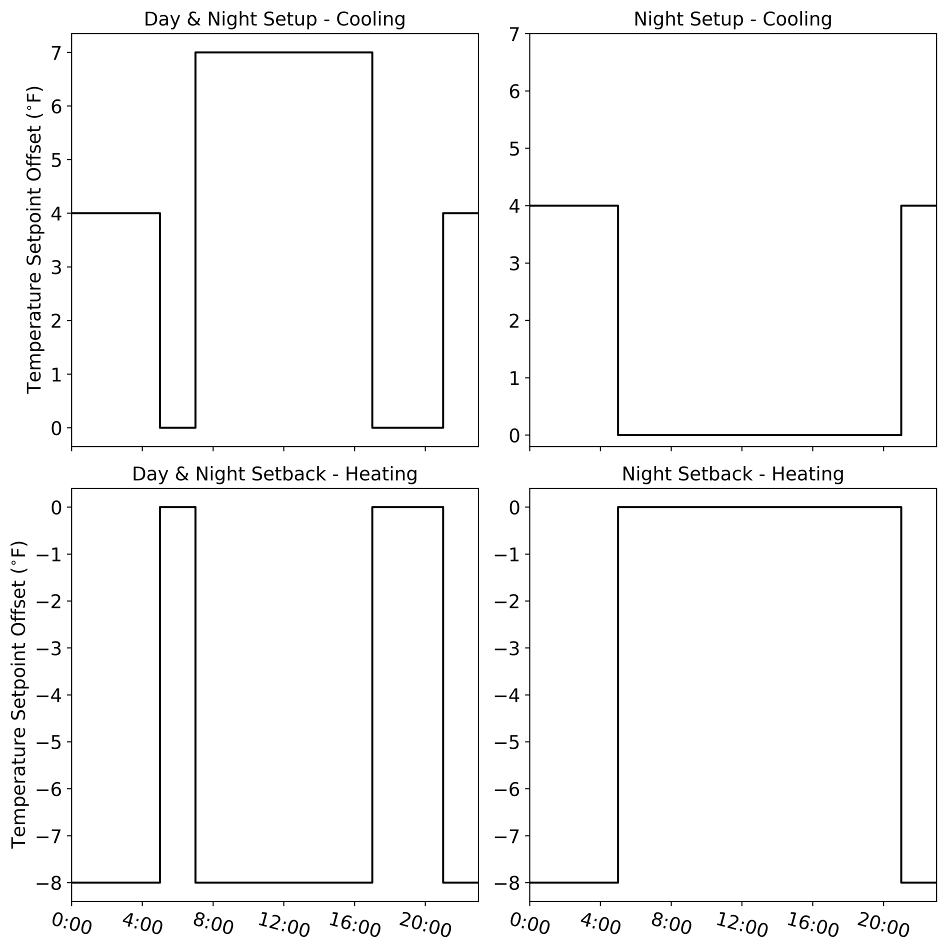

Figure S13: Example thermostat setback and setup schedules for residential cooling and heating. The "Day and Night Setback" schedules apply to homes that are unoccupied during the daytime, while the "Night Setback" schedules apply to homes occupied during the day.

- R-13 crawlspace wall
  Applied To: unvented crawlspaces in AIA climate zones 1-2 with existing insulation below R-13 (uninsulated, R-5, R-10)
- R-19 basement ceiling
  Applied To: unfinished basements in AIA climate zone 1-2 with existing insulation below R-19 (uninsulated, R-13)
- R-15 basement wall cavity
  Applied To: finished basements in AIA climate zones 1-2 with existing insulation below R-15 (uninsulated, R-5)

Windows:

- 0.17 U-factor, 0.49 SHGC
  Applied To: AIA climate zone 1
- 0.17 U-factor, 0.42 SHGC
  Applied To: AIA climate zone 2
- 0.17 U-factor, 0.27 SHGC
  Applied To: AIA climate zone 3
- 0.17 U-factor, 0.25 SHGC
  Applied To: AIA climate zones 4 and 5

4.1.2 Residential Demand Flexibility (DF) Measures

Water Heater Setpoint

- The water heater setpoint is pre-heated to 140°F at the start of the take period and maintains this setpoint up to the start of the peak period, when it is returned to the initial setpoint of 125°F, as shown in S14. DR schedules are designed for peak and take hours and seasons specific to each EMM region. If an EMM region has two take periods, pre-heating begins at the start of the second take period. Schedule inputs are in the form of hourly schedules for an entire year (i.e., 8760 schedules).
  Applied To: All electric water heaters

<u>Notes</u>: Current demand response programs with communicating water heaters (compliant with ANSI/CTA-2085) are limited to taking advantage of the deadband to time heating such that it occurs before the peak period; CTA-2085 does not support setpoint adjustments. The approach used in this measure is therefore more aggressive than what is possible today—incorporating setpoint adjustments to substantially lengthen acceptable interruption duration.

Thermostat Setpoint
Relaxed the setpoint by 3°F (increased in the cooling season, decreased in the heating season) during the peak period, preceded by a precooling or pre-heating period of 3°F (reduced in the cooling season, increased in the heating season) that starts 4 hours before the beginning of the peak period, as described below and shown in Figure S15

Cooling:

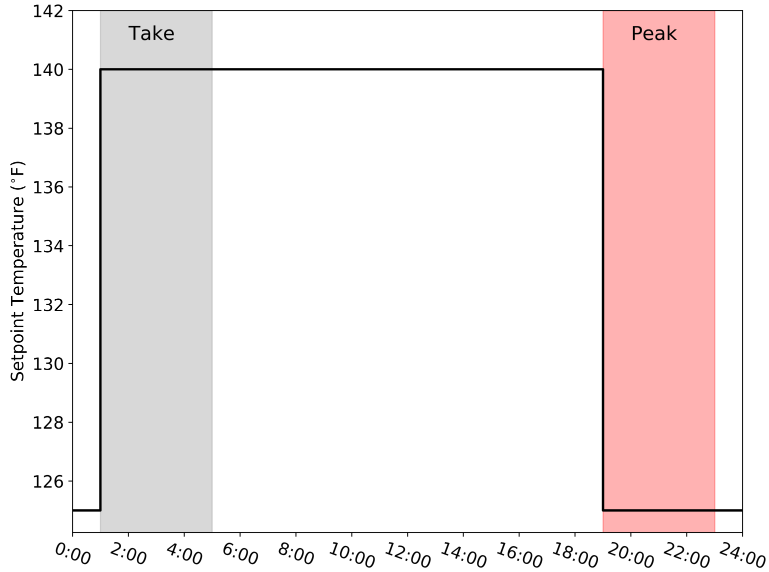

Figure S14: Example pre-heating schedule for residential water heating.

- Before peak: -3°F (relative to original setpoint), starting 4 hours before peak
  Applied To: Homes with an existing setpoint that would not be decreased beyond the minimum cooling setpoint (lowest cooling setpoint in the sampling data—RECS 2009 [20]); applied regardless of daytime occupancy

- During peak: +3°F
  Applied To: Homes with an existing setpoint that would not be increased beyond the maximum cooling setpoint (highest cooling setpoint in the sampling data—RECS 2009 [20]); applied regardless of daytime occupancy

Heating:

- Before peak: +3°F, starting 4 hours before peak
  Applied To: Homes with an existing setpoint that would not be increased beyond the maximum heating setpoint (highest heating setpoint in the sampling data——RECS 2009 [20]); applied regardless of daytime occupancy

- During peak: -3°F
  Applied To: Homes with an existing setpoint that would not be decreased beyond the minimum heating setpoint (lowest heating setpoint in the sampling data—RECS 2009 [20]); applied regardless of daytime occupancy

Example Logic: If the maximum heating setpoint is 80°F, homes with an existing setpoint of 78°F would not be subject to a preheating period increasing the setpoint to 81°F.

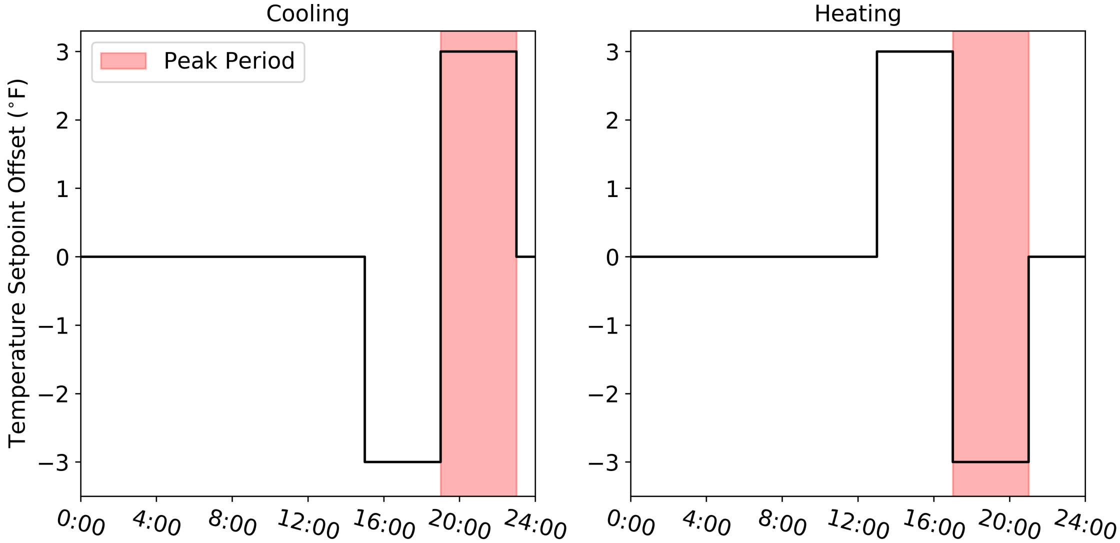

Figure S15: Example residential precooling and pre-heating schedules.

Notes: Several utilities currently operate smart thermostat demand response programs. These programs vary in their exact implementation; not all utilities document the typical timing and magnitude of setpoint adjustments, but among those that do, they typically have the following characteristics:

- Precooling, pre-heating setpoint adjustment: 2°-–3°F
- Precooling, pre-heating duration: 60—90 minutes before peak
- Peak (DR event) period setpoint adjustment: 3°–4°F
- Peak (DR event) period duration: 2—4 hours

The setpoint temperatures in this measure are thus based on these setpoint adjustments. The preconditioning duration is longer to account for the longer (4 hour) duration of the peak periods modeled; a longer preconditioning period will cool the thermal mass of the building more, which will help endure the longer peak period. We looked at (among others), Nest Rush Hour Rewards, ecobee Smart Savings Rewards (e.g., NYSEG and RG&E), Broad River Electric Co-op's smart thermostat program, and the Arizona Public Service Cool Rewards program.

Appliances

Appliances considered for demand flexibility include clothes washers, clothes dryers, and dishwashers, which follow the Building America house simulation protocols for schedule generation [21]. The schedule of the appliance is modified by shifting their operation away from the peak period. To do that, first the cluster of schedules that falls during the peak is identified. A cluster is defined as a set of run schedules that are separated by no more than 30 minutes of idle time. Once the cluster is identified, it will be attempted to be moved ahead of the peak, if possible. It might not be possible to move ahead if there is no room because there are already existing schedules or another peak period. If it is not possible to shift the cluster ahead in time from the peak, the cluster will be attempted to be shifted backward in time, provided there is room before the peak. If the cluster can neither be shifted forward or backward, the schedule is left as-is. In any of these cases, the annual energy consumption of the appliance remains unchanged, since we are only shifting the schedule.

Plug Loads

Plug loads also follow hourly varying usage level schedules like the pool pump. But instead of shifting the whole usage during the peak period, a fraction (11%) of the usage during the peak period is shifted uniformly to two hours after the peak. Another fraction (4%) of the usage during the peak is simply removed, which signifies turning off stand-by plug loads. Because 4% of the plug loads are turned off during the peak, total energy use decreases. These load shift and shed quantities are derived from the 2011 Building America Analysis Spreadsheets [22]. These spreadsheets were used to obtain 1) total plug load energy use, 2) total "shiftable" plug load energy use, 3) total standby/idle energy use (except in cases where operating power levels were lower than off/standby power plus idle power levels), and 4) the sum of the shiftable and standby energy use. The shiftable load is the difference between (1) and (2), and the sheddable load is the difference between (1) and (3). The load differences in (2) and (3) add to the load difference in (4).

Pool Pumps

The pool pump follows an hourly varying usage level schedule. The time integration of the usage during the peak period is uniformly added on top of the usage during the first take period for each EMM region. The total energy use remains unchanged.

4.1.3 Residential Combined EE and DF Measures

Thermostat Setpoint

When the thermostat DF measure is applied alongside the best thermostat (EE) measure, the setpoints based on DR operation (preconditioning setpoint, and setback/setup during the peak hours) take priority over the setbacks in the EE measure. If no DR operation applies, the setbacks/setups will match from the EE measure. Figure S16 shows an example of cooling season operation when both the EE and DF measures are applied.

4.2 Commercial measures

4.2.1 Commercial energy efficiency (EE) measures

Envelope

Envelope measures for the Medium and Large Office Detailed building prototypes follow Advanced Energy Design Guidelines (AEDG) 50% Medium Office guidelines for opaque envelope (roof, walls, and floor) with details given in Table S5 and fenestration for each climate zone as described in Table S10 [23]. Regarding envelope efficiency measures in non-office building prototypes, the Warehouse prototype follows AEDG 30% for small warehouses and self-storage (no AEDG 50% is available for this building type) (see Table S7); the Retail Stand-Alone prototype follows AEDG 50% for medium to big-box retail (see Table S6) [24], and the Large Hotel prototype follows AEDG 50% for highway lodging (see Table S8) [25].

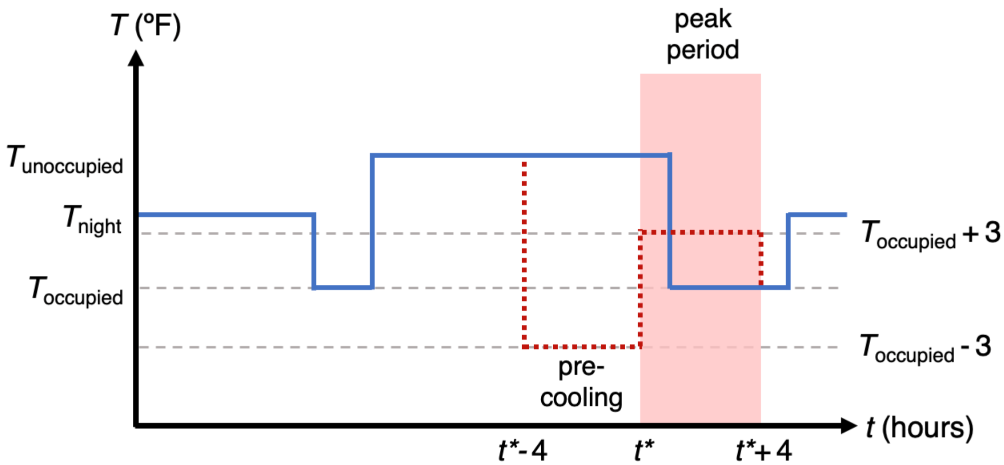

Figure S16: Example residential combined EE and DF thermostat setpoint schedule. The DF schedule (precooling) is applied when there is overlap with the EE setpoint offset schedule.

Table S5: Envelope for the Advanced Case in Office Buildings (Reference: AEDG 50%, Medium Office).

	Roof		Above-Grade Steel-Framed Walls	
Climate Zone	U-Factor	R-value	U-Factor	R-value
1	0.048	R-20 c.i.	0.064	R-13 + R-7.5 c.i.
2	0.039	R-25 c.i.	0.064	R-13 + R-7.5 c.i.
3	0.039	R-25 c.i.	0.064	R-13 + R-7.5 c.i.
4	0.039	R-25 c.i.	0.064	R-13 + R-7.5 c.i.
5	0.032	R-30 c.i.	0.042	R-13 + R-15.6 c.i.
6	0.032	R-30 c.i.	0.037	R-13 + R-18.8 c.i.
7	0.028	R-35 c.i.	0.037	R-13 + R-18.8 c.i.
8	0.028	R-35 c.i.	0.037	R-13 + R-18.8 c.i.

Table S6: Envelope for the Advanced Case in Retail Building (Reference: AEDG 50% Big Box Retail).

	Steel-Framed Exterior Wall		Mass Exterior Wall		Roof	
Climate Zone	U-Factor	R-value	U-Factor	R-value	U-Factor	R-value
1 (A)	U-0.064	R-13.0 + R-7.5 c.i.	U-0.580	NR*	U-0.048	R-20.0 c.i.
2 (A,B)	U-0.064	R-13.0 + R-7.5 c.i.	U-0.151	R-5.7 c.i.	U-0.039	R-25.0 c.i.
3 (A,B,C)	U-0.064	R-13.0 + R-7.5 c.i.	U-0.123	R-7.6 c.i.	U-0.039	R-25.0 c.i.
4 (A,B,C)	U-0.057	R-13.0 + R-10.0 c.i.	U-0.104	R-9.5 c.i.	U-0.039	R-25.0 c.i.
5 (A,B)	U-0.049	R-13.0 + R-12.5 c.i.	U-0.090	R-11.4 c.i.	U-0.032	R-30.0 c.i.
6 (A,B)	U-0.043	R-13.0 + R-15.0 c.i.	U-0.071	R-15.4 c.i.	U-0.032	R-30.0 c.i.
7	U-0.037	R-13.0 + R-18.8 c.i.	U-0.067	R-17.0 c.i.	U-0.028	R-35.0 c.i.
8	U-0.037	R-13.0 + R-18.8 c.i.	U-0.063	R-19.0 c.i.	U-0.028	R-35.0 c.i.

Lighting

Lighting efficiency measures follow AEDG guidelines using the same building type mapping as

Table S7: Envelope for the Advanced Case in Warehouse (Reference: AEDG 30% for Small Warehouse and Self-Storage Buildings).

	Roof R-value	Exterior Walls R-value	Interior Walls R-value
Zone 1 - office	R-15	NR	R-13
Zone 2 - fine storage	R-20	R-5.7 c.i.	R-13
Zone 3 - bulk storage	R-20	R-7.6 c.i.	R-13

Table S8: Envelope for the Advanced Case in Large Hotel (Reference: AEDG 50%, Highway Lodging).

	Roof		Above-Grade Mass Walls		Floor	
Climate Zone	U-Factor	R-value	U-Factor	R-value	U-Factor	R-value
1	0.039	R-25 c.i.	0.151	R-5.7 c.i.	0.73	NR
2	0.039	R-25 c.i.	0.123	R-7.6 c.i.	0.73	NR
3	0.039	R-25 c.i.	0.09	R-11.4 c.i.	0.54	R-10 for 24 in.
4	0.032	R-30 c.i.	0.08	R-13.3 c.i.	0.52	R-15 for 24 in.
5	0.032	R-30 c.i.	0.047	R-19.5 c.i.	0.51	R-20 for 24 in.
6	0.032	R-30 c.i.	0.047	R-19.5 c.i.	0.434	R-20 for 48 in.
7	0.028	R-35 c.i.	0.047	R-19.5 c.i.	0.434	R-20 for 48 in.
8	0.028	R-35 c.i.	0.047	R-19.5 c.i.	0.424	R-25 for 48 in.

Table S9: Fenestration U-Factor and SHGC values for the Advanced Case in Large Hotel.

	Target		Modeled	
Climate Zone	U-Factor	SHGC	U-Factor	HGC
1	0.56	0.25	0.51	0.28
2	0.45	0.25	0.44	0.24
3A,3B	0.41	0.25	0.4	0.24
3C	0.41	0.25	0.4	0.24
4	0.38	0.26	0.4	0.24
5	0.35	0.26	0.38	0.23
6	0.35	0.35	0.31	0.38
7	0.33	0.4	0.31	0.38
8	0.25	0.4	0.26	0.37

presented for the envelope efficiency measure; performance specifications are indicated by lighting power density (LPD), with details given in Tables S12-S15. The lighting LPD is reduced by an additional 15% from the base lighting schedule to represent occupancy controls (per AEDG modeling guidance).The daylighting controls in the perimeter zones also set at 300 lux setpoint to meet the AEDG as detailed in Table S12 [23].

Plug Loads

Plug load efficiency measures follow AEDG guidelines using the same building type mapping as presented for the envelope efficiency measure; performance specifications are indicated by equipment power density (EPD), with details given in Tables S12-S15. Note: for data center spaces in the Large Office Detailed building type, the EPD is reduced by 30%, suggested to be feasible by previous DOE reports [26, 27]. The schedules for plug loads are consistent with the advanced case assumption in

Table S10: Fenestration U-Factor and SHGC values for the Advanced Case in Office Buildings.

	Target		Modeled	
Climate Zone	U-Factor	SHGC	U-Factor	SHGC
1	0.65	0.25	0.51	0.28
2	0.65	0.25	0.51	0.28
3A,3B	0.6	0.25	0.51	0.28
3C	0.6	0.25	0.51	0.28
4	0.44	0.26	0.44	0.24
5	0.44	0.26	0.44	0.24
6	0.42	0.35	0.42	0.39
7	0.34	0.4	0.31	0.38
8	0.34	0.4	0.31	0.38

Table S11: Fenestration U-Factor and SHGC values for the Advanced Case in Retail Building.

Climate Zone	U-Factor	SHGC	VLT
1(A)	1.2	0.25	0.25
2(A,B)	0.7	0.25	0.25
3(A,B)	0.6	0.25	0.32
3(C)	0.6	0.34	0.32
4(A,B,C)	0.5	0.39	0.51
5(A,B)	0.45	0.39	0.51
6(A,B)	0.45	0.39	0.51
7	0.4	0.49	0.45
8	0.4	0.49	0.45

Table S12, representing plug loads controls [28].

Table S12: Electric Equipment Power Density and Lighting Power Density for the Advanced Case in Office Buildings (Reference: AEDG 50%, Medium Office).

Space Type	EPD (W/ft^2)	LPD (W/ft^2)
Break room	4.46	0.73
Closed Office	0.64	0.885
Conference	0.37	0.77
Corridor	0.16	0.5
IT room	1.56	0.64
Lobby	0.07	1.09
Elec./Mech. room	0.07	1.24
Open office	0.71	0.68
Print room	2.79	0.64
Rest room	0.07	0.82
Stair	0	0.6
Storage	0	0.64
Vending	3.85	0.73

Table S13: Electric Equipment Power Density and Lighting Power Density for the Advanced Case in Large Hotel (Reference: AEDG 50%, Highway Lodging).

Space Type	EPD (W/ft^2)	LPD (W/ft^2)
Guest room	0.97	0.71
Corridor	0	0.5
Lobby	1.83	0.77
Stairs	0	0.57
Office	0.71	0.85
Laundry	n/a	0.52
Meeting room	0.57	1.14
Exercise room	1.53	0.78
Storage	n/a	0.62
Employee lounge	1.95	0.82
Restroom	0	0.74
Mechanical room	n/a	1.24

Table S14: Electric Equipment Power Density and Lighting Power Density for the Advanced Case in Retail Building (Reference: AEDG 50% Big Box Retail).

Space Type	EPD (W/ft^2)	LPD (W/ft^2)
Sales floor	0.3 0.9	
Vestibule	0	0.45
Corridor	0	0.54
Restroom	0.08	0.86
Stock room	0.56	0.86
Office	0.56	0.81
Meeting room	0.56	0.81
Break room	1.95	0.45
Mechanical room	0	0.86

Table S15: Electric Equipment Power Density and Lighting Power Density for the Advanced Case in Warehouse (Reference: AEDG 30% for Small Warehouse and Self-Storage Buildings).

Space Type	LPD (W/ft^2)
Zone 1 - office	0.9
Zone 2 - fine storage	0.9
Zone 3 - bulky storage	0.6
Total	0.7

HVAC

This measure makes upgrades based on the specific HVAC components available in the buildings. When the measure is applied to the Large Office Detailed building prototype model, the measure upgrades the existing water-cooled centrifugal chiller with 5.5 COP to a chiller of the same type with 7.0 COP. The Large Hotel building type already has an efficient air-cooled chiller; this existing chiller has a 5.5 COP and there is no available reference air-cooled chiller with a higher COP within the EnergyPlus chiller library. On all other building types, e.g., Medium Office Detailed, Retail Stand-Alone, and Warehouse, the measure increases their COP of their two-speed DX Cooling Unit from 3 to 4. The burner efficiency of the heating coil in these buildings is also increased from 0.8 to 0.99. These advancements follow the AEDG for the medium office buildings on the two HVAC components [28].

Refrigeration
This measure was simulated entirely in Scout, i.e., no savings shape was calculated using EnergyPlus prototype simulations. Accordingly, measure relative reductions are consistent across all hours and total hourly reductions follow the baseline refrigeration shape (which is defined from EnergyPlus simulations). The Scout measure is published[29] and replaces all categories of commercial refrigeration technology with the best performing alternative. Best available performance levels are anchored on the year 2017 in data published by EIA [30] and summarized in the Scout baseline technology characteristics data [31] (in units of Btu out/Btu in):

- Commercial reach-in freezers: 2.4
- Commercial reach-on refrigerators: 5.4
- Commercial supermarket display cases: 3.85
- Commercial walk-in freezers: 2.7
- Commercial walk-in refrigerators:3.5

Water Heating
This measure was simulated entirely in Scout, i.e., no savings shape was calculated using EnergyPlus prototype simulations. Accordingly, measure relative reductions are consistent across all hours and total hourly reductions follow the baseline refrigeration shape (which is defined from EnergyPlus simulations). The Scout measure is published [32] and replaces all electric commercial water heating technologies with the best available heat pump water heater as an add-on to existing storage units. Best available performance level is anchored on the year 2017 in data published by EIA [33] (in units of Btu out/Btu in):

- Heat pump water heater: 3.9

4.2.2 Commercial demand flexibility (DF) measures

HVAC
There are two DR measures that adjust zone thermostat setpoints for both cooling and heating. The first is a global temperature adjustment (GTA) measure, which adjusts zone cooling temperatures upwards and zone heating temperatures downwards during the peak hours for the utility region that is associated with the representative city (see Figure 6). The second is a precooling measure that adjusts zone cooling temperatures downwards for the 4 hours preceding the peak period [34]. In simulations where we included all measures together to explore interactions, the precooling measure applies only to the Medium Office Detailed, Retail Stand-Alone, and Warehouse representative building types, while larger prototype building models (Large Office Detailed and Large Hotel) implement ice storage for active precooling (see below), which does not modify zone temperature set points. However, when running the precooling measure in isolation, we apply this measure across all of the commercial building types.

GTA and precooling zone temperature adjustments and their basis are summarized as follows.

- Summer adjustments
  - Comfort range of 73°F–80°F based on ASHRAE Standard 55-2017, calculated using the Berkeley Center for the Built Environment (CBE) Thermal Comfort Tool [35].
  - Assumptions: 50% relative humidity, 20 fpm air movement (uncontrolled by occupant), 1.1 metabolic rate (standard office work), adaptive clothing range of 0.5–0.7 (trousers with short/long-sleeve shirt).
  - Accordingly, set point temperature increases from 75°F to 80°F (GTA) during the peak period, and decreases from 75°F to 73°F (precooling) for the four hours preceding the peak period.
- Winter adjustment
  - Comfort range of 68°F–78°F based on ASHRAE Standard 55-2017, calculated using the Berkeley Center for the Built Environment (CBE) Thermal Comfort Tool.
  - Assumptions: 30% relative humidity, 20 fpm air movement (uncontrolled by occupant), 1.1 metabolic rate (standard office work), adaptive clothing range of 0.8–1.1 (trousers with long-sleeve shirt and jacket/sweater)
  - Accordingly, set point temperature decreases from 70°F to 68°F (GTA) during the peak period. No pre-heating is assumed since the risk of discomfort at 68°F is low, particularly given that the peak period begins in the evening hours, when most commercial buildings have low occupancy.

Lighting
When the lighting DR measure is applied, the lighting loads are reduced by 30% for occupied spaces and 60% for unoccupied spaces during the peak hours for the utility region that is associated with the representative city. The occupied threshold is the average of the low- and high-daylight dimming thresholds at which occupants reported noticing dimming during DR events in[36] and supported by other studies, while the unoccupied threshold is the average of the low- and high-daylight dimming thresholds that were reported as still acceptable by occupants. Acceptability is used as a criterion for unoccupied spaces for safety reasons, as these spaces may relate to occupant movement around the building (e.g., hallways, stairwells).

Plug Loads
When the plug loads DR measure is applied, the plug loads are reduced by 20% for occupied spaces and 100% for unoccupied spaces during the peak hours for the utility region that is associated with the representative city. The 20% occupied reduction threshold represents the low end of the range found by previous studies in offices, in which reductions were achieved by improved software power management, hardware control (e.g., advanced power strips), and behavioral feedback[37, 38]. It is assumed that during peak periods, plug loads can be completely turned off in spaces without regular occupancy. Data centers are excluded from the DF plug loads measure.

4.2.3 Commercial combined EE and DF measures

The commercial combined EE and DF measures package the EE and DF measure sets described above without additional modification. For example, when precooling and GTA measures are packaged with the more efficient envelope measure, we do not assume any additional thermostat setback potential. Similarly, for lighting and plug loads, no additional adjustment to the power densities are reflected in the measures when packaged.

5 Building-level impacts of measure sets

Figure S17 shows example building-level impacts of the three aggregated measure sets detailed in section 4 on baseline loads for single family homes and medium offices, across four different representative cities/ASHRAE climate zones. Peak and off-peak periods for the grid for each location, which correspond to those shown in Figure S8, are overlayed on top of the various load shapes. The figure shows varying degrees of coincidence between building-level loads and measure impacts and grid-level peak and off-peak periods, when decreases and increases in building demand have the greatest assumed value, respectively. Building-level load increases, driven in the summer by precooling measures that are constrained to the hours just preceding the peak window, appear particularly non-coincident with off-peak periods on the grid, which often do not occur during the mid-day to early afternoon hours for these locations.

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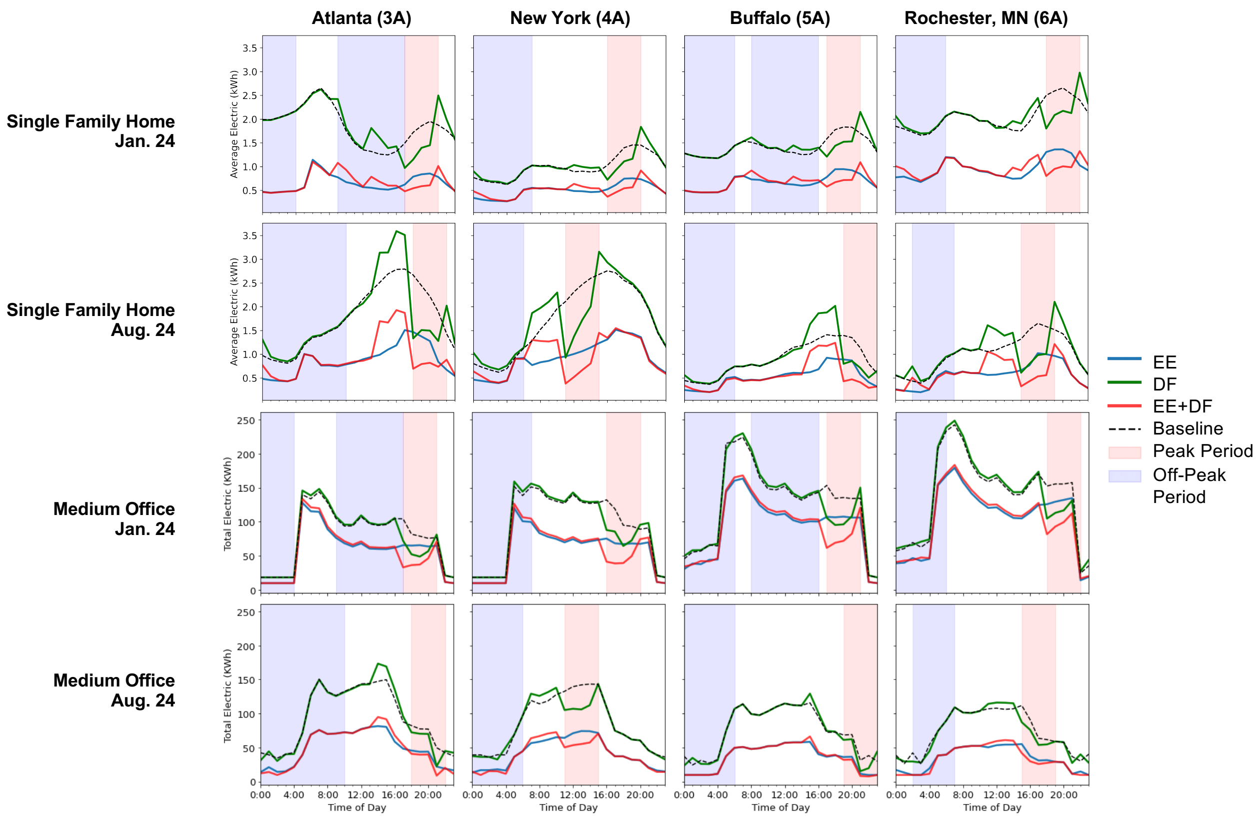

Figure S17: Building-level load profiles for a range of building types, locations, and measure sets. The profiles show strong on-peak load impacts from combined building efficiency and flexibility measures (EE+DF), as well as off-peak load increases from flexibility measures (DF) that often fail to coincide with off-peak periods for the regional system. In the warmest climate shown (Atlanta-3A), a net system peak window occurs later in the day when the baseline load shape for both residential and commercial buildings is trending downward, mitigating their reduction potential. In other cases—notably, commercial buildings in New York-4A in the summer—building- and system-level peaks are highly coincident, maximizing reduction potential. Peak and off-peak periods are consistent with those shown in Figure S8.

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