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US building energy efficiency and flexibility as an electric grid resource

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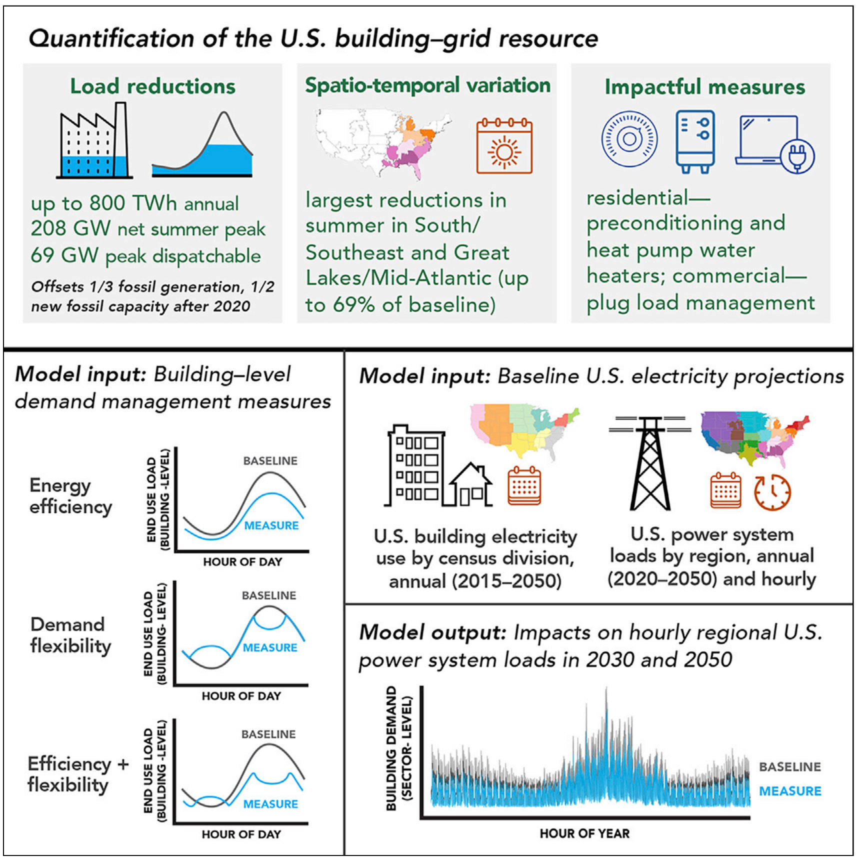

Buildings consume 75% of US electricity and could be a primary demand-side management resource for the rapidly changing electric grid. We assess the technical potential grid resource from best-available building efficiency and flexibility measures in 2030 and 2050 and find that such measures could avoid up to nearly one-third of annual fossil-fired generation and one-half of fossil-fired capacity additions after 2020. Our results quantify the role that building technologies can play in the future of the US electricity system.

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Highlights

The technical potential US building-grid resource is quantified for 2030 and 2050

Co-deployment of building efficiency and flexibility yields the largest load impacts

Up to 800 TWh generation and 208 GW daily net peak demand could be avoided

Preconditioning and plug load management are among the most impactful measures

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US building energy efficiency and flexibility as an electric grid resource

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SUMMARY

Buildings use 75% of US electricity; therefore, improving the efficiency and flexibility of building operations could provide significant value to the rapidly changing electricity system. Here, 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 United States. 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.

Context & scale

The US electricity system is undergoing a rapid transformation, with renewable generation sources projected to account for the majority of annual electricity generation as soon as 2035. While policymakers have focused on power sector decarbonization as a critical component of net zero greenhouse gas emissions pathways, emerging evidence underscores the role of demand-side technologies in facilitating a decarbonized energy system. Using a reproducible modeling framework, we quantify the grid resource from building efficiency and flexibility at the national scale, demonstrate how this resource varies across grid regions and hours of the day, and identify specific building technologies that drive grid-scale impacts. The capabilities and results that we report can improve the representation of demand-management strategies in policy development and grid planning that seeks to reduce future US fossil-fired generation needs and enable increased variable renewable-energy supply.

INTRODUCTION

The US electricity system is undergoing a rapid transformation. Non-hydro renewable energy deployment reached a record 80% of new US electric-generating capacity in 2020 and has accounted for 60% of total capacity additions in the last decade.[1] Recent projections estimate that these sources will account for the largest share of electricity generation as early as 2035.[2,3] Researchers and policymakers have focused on power-sector decarbonization as a critical component of net zero greenhouse gas emissions pathways; however, an emerging body of evidence suggests that parallel demand-side solutions are also important for achieving ambitious climate change mitigation targets.[4–6] Creutzig et al.[4] advocate for research that improves the understanding of demand-side solutions in climate change mitigation research, quantifies the impact potentials for specific demand-side technologies, and assesses interactions between demand-side solutions and the energy supply system.

Energy efficiency is a key type of demand-side solution that has been included in past decarbonization studies and featured in recent research efforts, such as that of Wilson et al.[7] A large body of research supports the notion that energy efficiency is one of the fastest and most broadly beneficial options for mitigating climate change.[8] More recently, energy flexibility,[9] which the International Energy Agency (IEA) defines as "the ability [for a building] to manage its demand and generation according to local climate conditions, user needs, and grid requirements,"[10] has emerged as a complementary demand-side solution that can reduce the costs and ensure the reliability of power systems with high levels of renewable energy penetration. Existing literature identifies and assesses the technologies and market mechanisms that can provide enhanced system flexibility,[11,12] estimates the value of flexibility to the grid,[13,14] and characterizes technology pathways that support high penetrations of renewable electricity generation,[15,16] among other topics. As the US continues to rapidly transform its electricity supply, assessing the potential for energy efficiency and flexibility measures to support this transition is a pressing research objective.

Improved demand management through energy efficiency and flexibility offers several benefits to the electric grid, including: reduced power generation capacity, operation, and maintenance costs[17–19]; provision of ancillary services and standing reserves for system balancing and reliability with lower costs and emissions[17,20,21]; and avoided capital costs for transmission and distribution equipment upgrades and voltage control.[17,22] Demand management technologies can be deployed alongside energy storage to meet grid flexibility needs in a highly renewable electricity future.[16] The recent US Federal Energy Regulatory Commission (FERC) Order 2222 enables aggregators of energy efficiency and demand response to participate in wholesale electricity markets alongside traditional generation resources, acknowledging the important role of demand management technologies in future electricity systems.[23]

In the United States, the buildings sector accounts for 75% of electricity use[24] and is therefore a primary demand management resource for the electric grid. Building technologies, such as highly efficient heating and cooling equipment, highly insulating 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.[25] Previous studies of the US building-grid resource at the national scale suggest that such building technologies can reduce at least 150–200 GW of summer peak load by 2030. For example, a landmark FERC assessment found that 2019 peak load in the US could be reduced by 150 GW using demand response (DR) measures,[26] and a comprehensive bottom-up analysis from the Electric Power Research Institute (EPRI) estimated a technical potential summer peak reduction of 304 GW from energy efficiency and 175 GW from DR by 2030.[27] A more recent Brattle study estimates nearly 200 GW of cost-effective load flexibility potential by 2030,[28] while another recent national study finds up to 40 GW of flexible reduction potential from commercial building HVAC loads alone.[29] Regional studies lend further support to these findings, and we use results from these studies to benchmark our own findings in the discussion section of this paper. Outside the US context, several international studies qualitatively describe demand management opportunities[30–33] or quantitatively demonstrate a large grid resource from building efficiency and flexibility portfolios,[34–36] though the differences between US and international electricity systems and buildings sectors preclude a direct comparison of results.

The existing US literature establishes that buildings can play an important role in power-sector decarbonization and in limiting future growth in electricity demand. To the authors' knowledge, however, no existing study quantifies the magnitude of the US building-grid resource at the national scale while also communicating its regional and temporal variability and identifying the specific building end uses and technologies that drive grid-scale impacts. Building technologies are highly heterogeneous, and few existing studies attempt to aggregate load impacts across

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multiple technology types to enable benchmarking against single-technology alternatives such as traditional power generation plants or battery storage. Moreover, studies that do aggregate across technologies tend to focus on maximum peak load impacts,[26–28] despite the need to account for the growing influence of variable renewable generation on daily system needs, and these studies rarely consider interactions between efficiency and flexibility measures when both are included (for example, total peak reduction from the adoption of more efficient and more flexible HVAC is not necessarily equal to the sum of these measures' individual peak reductions). Other key limitations of existing literature include the reliance on data sets that are outdated and/or spatiotemporally constrained, as well as the absence of a common and reproducible framework that can be updated to reflect continued changes in the energy sector.

In this paper, we conduct a comprehensive analysis of the near- and long-term technical potential bulk power grid resource offered by best-available US building efficiency and flexibility measures. Using multiple openly available modeling frameworks, we pair bottom-up simulations 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 hourly regional system loads across the contiguous United States 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 US electricity system.

Building efficiency and flexibility scenarios and grid metrics

Table 1 provides an overview of the main components of the analysis framework, supporting data sources, and key implications of the analysis design. 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 US residential and commercial building electricity use and hourly electricity demand. We model the measures that make up these measure sets using EnergyPlus; building energy modeling enables an investigation of measure impacts across the full US building stock, which is not possible with currently available metered building electricity use data. Measure impacts in 2030 and 2050 are assessed within each of the 22 2019 US Energy Information Administration (EIA) Electricity Market Module (EMM) regions, with certain outputs aggregated into the 10 2019 US Environmental Protection Agency (EPA) AVoided Emissions and geneRation Tool (AVERT) regions for simplicity of presentation (Figure 1). We design measures and assess their impacts using a framework that seeks to approximate typical daily power system conditions and operation based on economic dispatch.[37] Specifically, we use the *net* load shape for each region—the total hourly load less hourly variable renewable electricity generation—as a proxy for marginal electricity costs, and we configure flexibility measures to reduce demand during high net load and high marginal cost hours and shift loads into low net load and low marginal cost hours where possible. This framing better reflects the influence of low marginal cost variable renewable generation on grid scheduling objectives and the associated value of grid services. Renewable electricity penetration levels vary on a regional basis, but average to 29% nationally. We focus on *average daily non-coincident* net peak and off-peak hour impacts across the summer (June–September), winter (December–March), and intermediate (all other months) seasons. Non-coincident net peak is defined as the sum of individual maximum net demands across regions regardless of the times at which they occur.[38] Additional

Table 1. Overview of primary analysis components, sources, and high-level implications of the modeling framework and approach

Component		Source or definition	Description	Implications
Inputs	baseline building energy use (demand) scenario	2019 EIA AEO[39]	annual building energy use projected 2015–2050 based on business-as-usual (BAU) assumptions about technology advancement and adoption	building load electrification beyond BAU could influence load shapes and total annual electricity use; high electrification implications are explored in section S1.3
	baseline electricity generation (supply) scenario	2019 EIA AEO[39]	net load defined by hourly system loads less wind and solar generation at 29% penetration of total annual generation	use of net load reflects the influence of low marginal cost renewable generation on grid scheduling objectives and the associated value of grid services; sensitivity to higher renewable penetrations is explored in section S2.1.1
	baseline end-use load shapes	EnergyPlus models	representative end-use load shapes from EnergyPlus are used to translate baseline electricity use to an hourly basis (see section S2.2)	modeled end-use loads might not fully reflect the diversity of usage patterns, which could result in both under- and overestimation of potential from efficiency and flexibility measures, depending on the building type
	alternative building demand scenarios—	best energy efficiency only (EE)	best available efficiency levels correspond to those defined by EIA or market surveys where EIA data are not available	electricity use reductions from best available technologies relative to the baseline might be reduced in 2050 as the baseline improves and further efficiency gains become elusive
		best demand flexibility only (DF)	best available flexibility levels maximize intended reductions or increases in hourly electricity demand without compromising minimum building service levels	flexible end-use operation designed to shift load away from highest net system load hours and into the lowest net system load hours, which will reduce peak and avoid renewable energy curtailments, but might not yield the highest possible electricity market value or value to an individual utility
		best energy efficiency and demand flexibility (EE+DF)	combines EE scenario end-use efficiencies with DF scenario flexibility specifications	–
Model characteristics	energy demand segments	US residential and commercial buildings	three residential and eleven commercial building types, with building-level hourly load shapes represented by sampled residential housing units and five commercial prototype EnergyPlus models	EnergyPlus building types represent the majority of US buildings but do not capture all possible variations in stock characteristics and resulting end-use load shapes
	technology stock dynamics	technical potential technology diffusion	technical potential technology adoption equates to 100% annual stock turnover, which ensures complete adoption of measures in the building demand scenarios considered	from adoption alone, results represent an upper bound of energy savings and load shed and shift
	geographic extent and resolution	contiguous US, 22 2019 EIA EMM regions or 10 2019 EPA AVERT regions	EMM regions approximate independent system operator and North American Electric Reliability Corporation (NERC) assessment region boundaries; EPA AVERT regions are used for results aggregation for simplicity (see Figure 1)	focus is on regional and national-level impacts; building-, campus-, or feeder-level focus might yield different results
	temporal extent and resolution	2015–2050, hourly	–	–
	weather data	14 TMY3 locations	a representative location is selected for each ASHRAE 90.1–2016 climate zone in the study's geographic boundary	excludes extreme events and does not capture future weather changes due to climate-change effects
Outputs	assessment metrics—	annual electricity use	–	–
		average net non-coincident 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 section S2.1); averages are taken across all net peak and off-peak hours in a given season–	results are expected to vary under scenarios that include higher penetrations of renewable energy, especially results related to the benefits of demand flexibility measures–
		average net non-coincident off-peak demand		

Note: An extended discussion of the methodology can be found in the experimental procedures and supplemental experimental procedures sections.

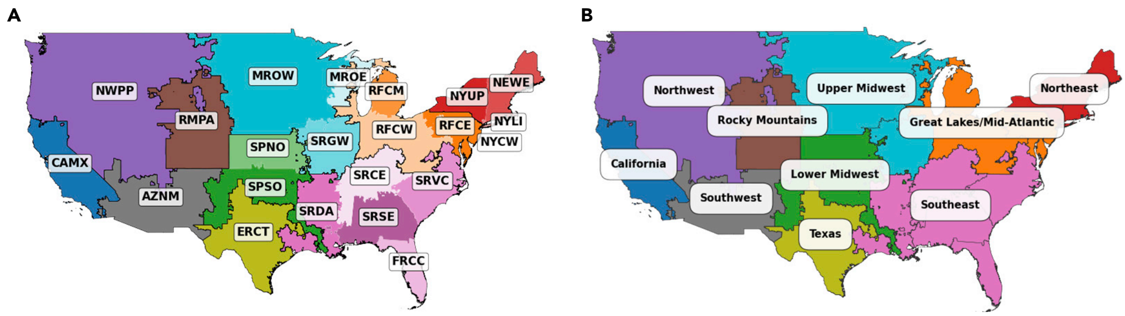

Figure 1. Regional boundaries used to generate and aggregate results
(A) Scout measure impacts are assessed within each of the 22 2019 US EIA EMM regions.
(B) Outputs can be aggregated into the 10 2019 US EPA AVERT regions.

detail on measure assumptions, analysis approach, and assessment metrics is available in the experimental procedures and supplemental experimental procedures sections.

RESULTS

Baseline annual US building electricity use and net peak demand is most strongly attributed to residential space conditioning in the Southeast and Great Lakes/Mid-Atlantic regions

First, we analyze the distribution of baseline annual electricity use and net peak demand in US buildings across end uses and regions. Figure 2 presents the annual electricity use and average daily summer and winter net peak demand from US buildings in 2030; 2050 results are shown in Figure S2. In 2030, buildings are responsible for 2,870 TWh of annual electricity use (71% of the contiguous US annual total[39]) and 485 GW and 421 GW of summer and winter net peak demand, respectively. By 2050, these totals grow to 3,249 TWh, 562 GW, and 469 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.

Figures 2 and S2 show that space conditioning end uses—in particular, residential heating and cooling and commercial cooling—are key drivers of 2030 and 2050 annual electricity use and net peak demand. 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 sizable 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[40] 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, US 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 Figure S1).[40–42] In the Southeast, annual electricity use and peak demand are further driven by significant cooling needs and a large installed base of electric heating.[40,42,43] While baseline electricity use and peak demand tend to be highest in the Southeast, a notable exception is

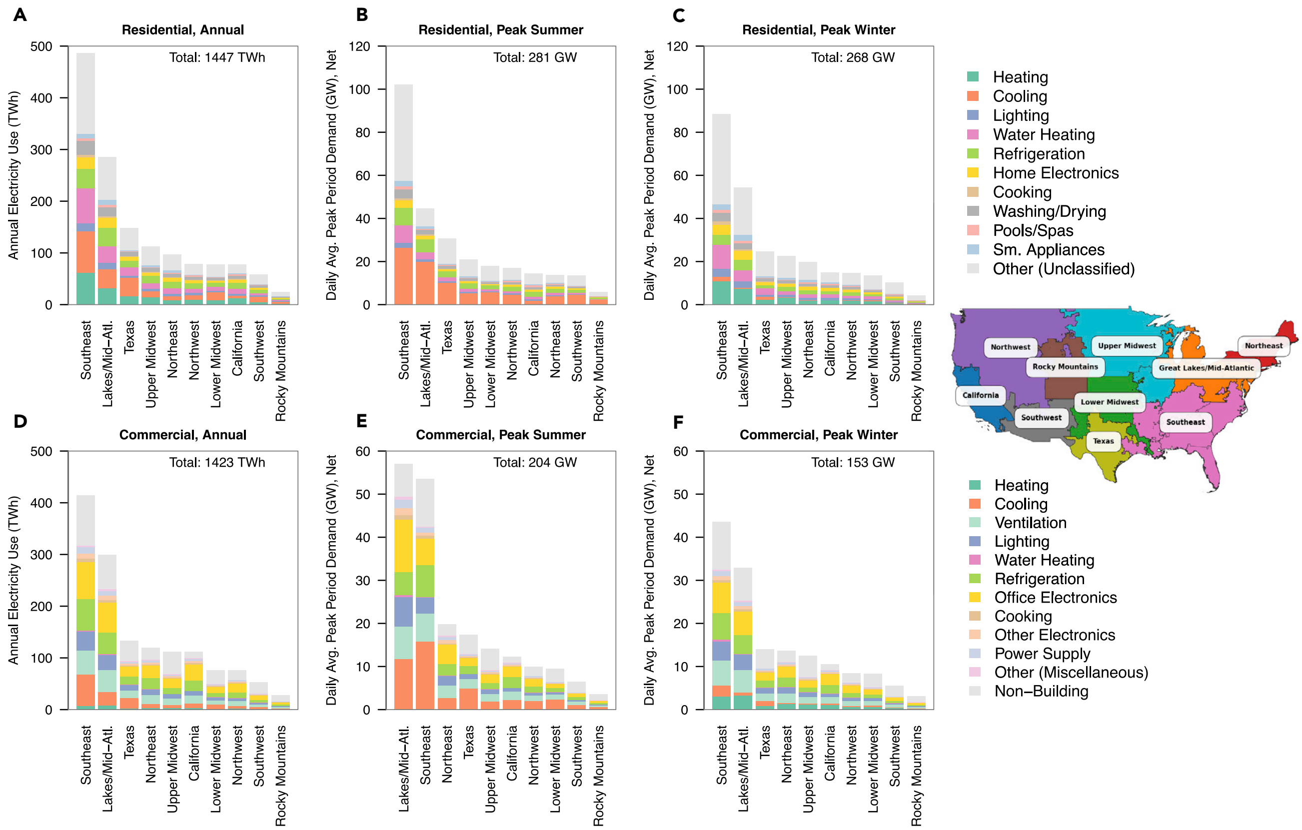

Figure 2. Baseline annual electricity use and net peak demand from US buildings in 2030

(A–F) 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 (June–September for summer and December–March for winter). Across regions in 2030, US buildings are projected to contribute 2,870 TWh to annual electricity use and 485 GW and 421 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.

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 Figure S11), 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 Figures 2 and S2 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.

Best-available US building efficiency and flexibility can avoid up to 800 TWh of annual electricity use and 208 GW daily of net summer peak demand; at least one-third of peak reductions are dispatchable

Next, we analyze how technical potential adoption of EE and DF measures and measure sets affects annual electricity use and net peak demand in US buildings at the national scale. Figure 3 presents the potential impacts of building efficiency and flexibility on annual US electricity use and average daily summer and winter net-peak and off-peak demand in 2030; 2050 results are shown in Figure S3. 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 GW and

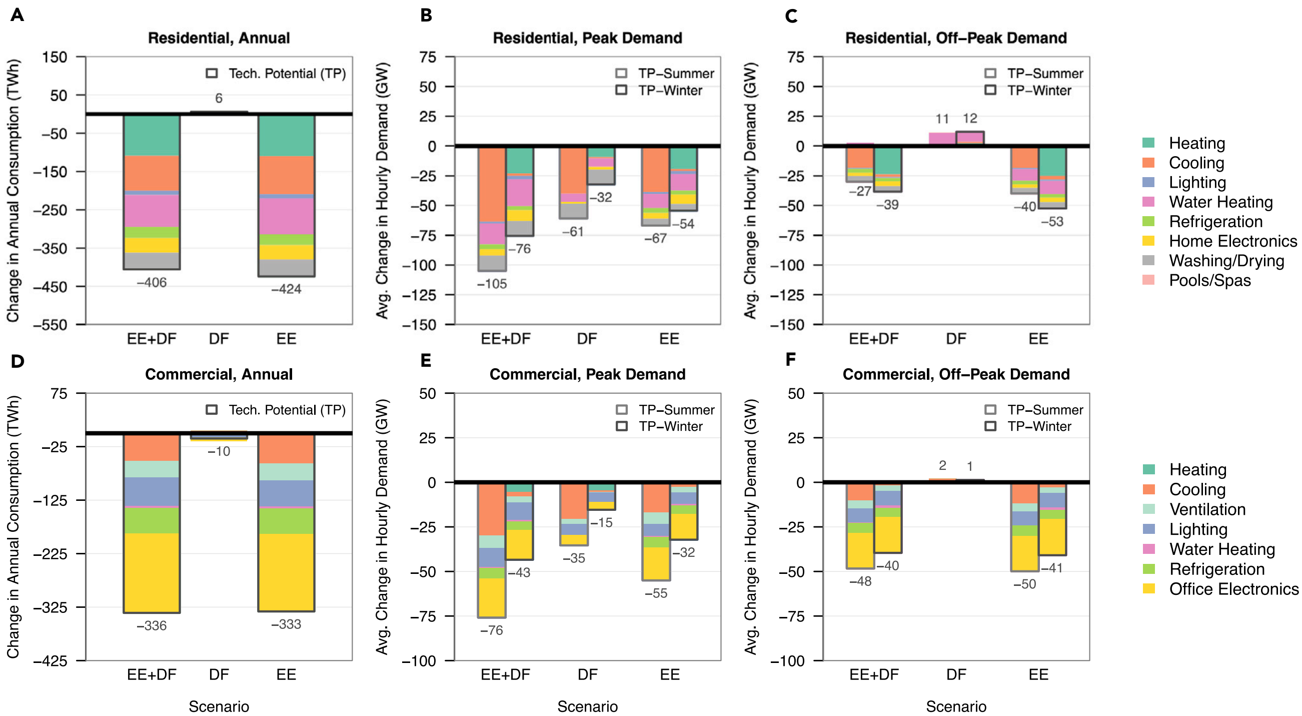

Figure 3. National impacts of best available building efficiency and flexibility measure sets on US annual electricity use and net peak and off-peak demand in 2030

(A–F) 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 (June–September for summer and December–March for winter). In 2030, when deployed together, US 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.

119 GW of summer and winter net peak demand in 2030, respectively. By 2050, these reductions grow to 800 TWh annual and 208 GW and 121 GW summer and winter net peak, respectively. The annual reductions are 32% and 30% of total projected US 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[24]; 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[24]; 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 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 S2, 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 S3, 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) come 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 setpoint temperatures in the hours preceding the peak hour window; however, the net utility load is low only for these hours in regions with high midday solar generation (Figure S11). Potential load increases from precooling would be more beneficial in a high solar penetration case where regions' low net system loads occur during midday hours (see the sensitivity analysis in experimental procedures). 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 regions' 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.

Relative load reductions from efficiency and flexibility are largest in residential buildings located in the South/Southeast and Great Lakes/Mid-Atlantic regions in the summer season, though impacts vary widely across geography and time

Third, we attribute the impacts of building efficiency and flexibility to specific US 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 EE+DF scenario in 2030; 2050 results are shown in Figure S4. Regional variation in annual electricity and peak demand reductions is mostly consistent with the baseline variations across regions in Figures 2 and S2, 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, consistent with the concentration of baseline electricity use 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 in these regions. Relative summer peak reductions are also notably high for 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 S4 tend to be higher and more variable between regions in residential buildings than in commercial buildings. While

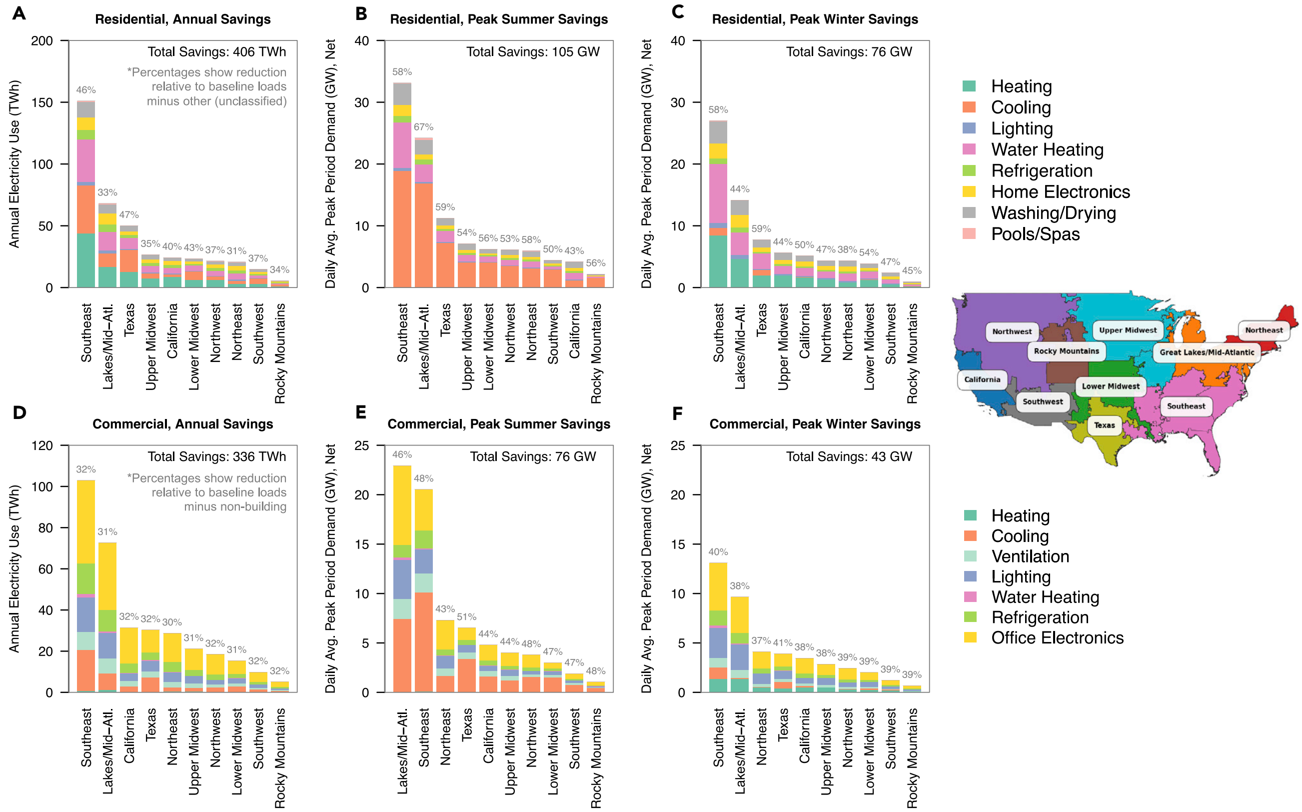

Figure 4. Regional impacts of best available US building efficiency and flexibility measures together on annual electricity use and net peak demand in 2030

(A–F) 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 (June–September for summer, December–March 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.

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 peak hours, 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 with 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 Figure S5. In both 2030 and 2050, changes in hourly demand across regions and seasons are most pronounced in

Figure 5. Average change in sector-level hourly electricity demand from building efficiency and flexibility measure sets for five US grid regions in 2030

(A and B) 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 [June–September], winter [December–March]), 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 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.

residential buildings, particularly for measure sets that include efficiency (EE, EE+DF). In these cases, residential 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 sizable in RFCW, one of the Great Lakes regions, which has an afternoon system peak in summer that coincides 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; larger midday reductions from EE in regions

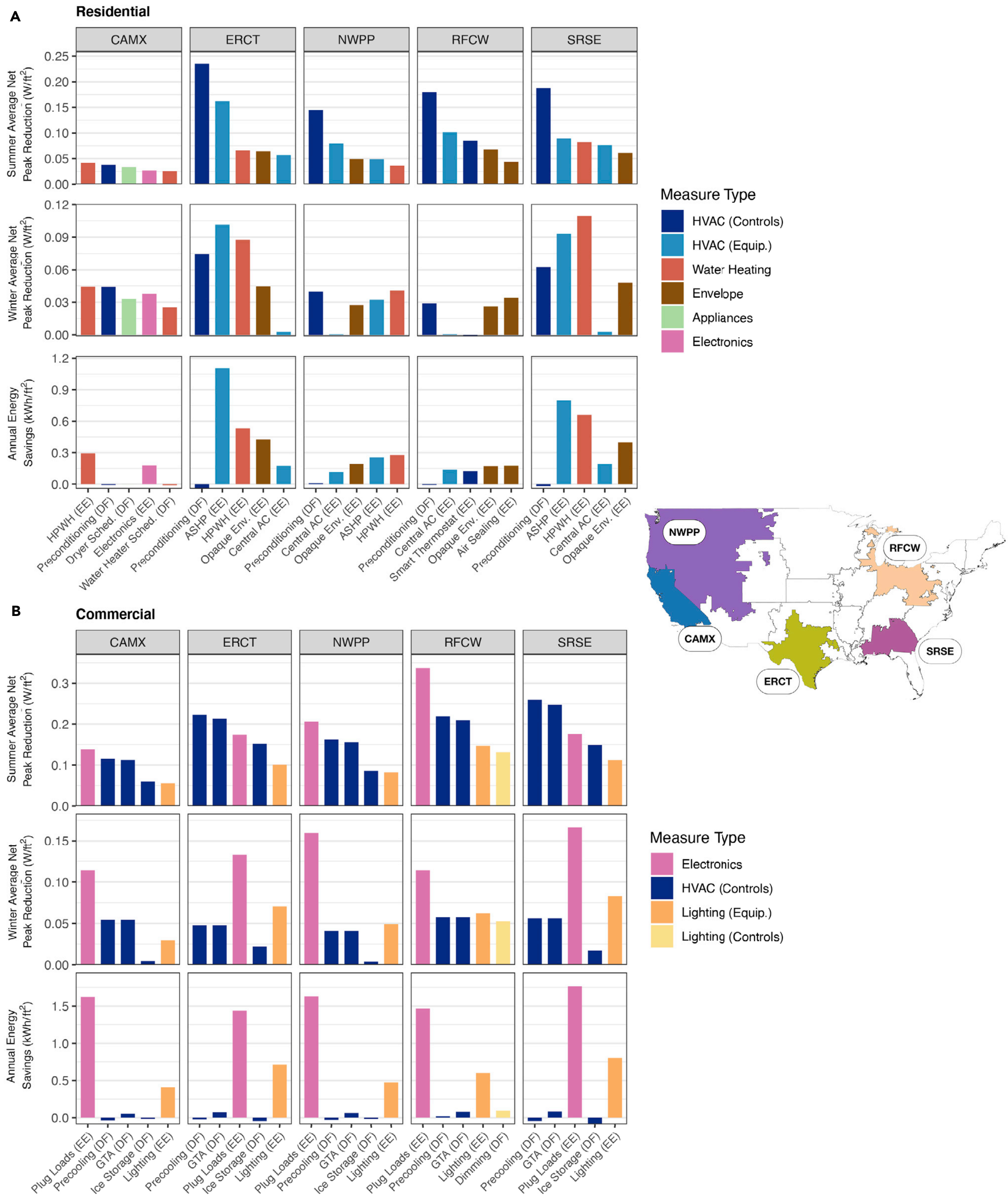

Figure 6. Individual efficiency and flexibility measures with the largest summer net peak demand intensity reductions for five US grid regions in 2030

(A and B) 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

Figure 6. *Continued*

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 (June–September for summer and December–March for winter). Individual measures on the x axes are grouped into general measure types shown in the plot legends. Preconditioning and HVAC equipment measures yield the largest summer peak reductions in residential buildings while precooling and plug-load efficiency measures yield the largest summer peak reductions in commercial buildings. Commercial plug-load efficiency also yields strong reductions across the winter peak and annual metrics.

with high solar penetration (e.g., CAMX) highlight the potential for efficiency deployment to counter load-building objectives during hours of low net system demand. 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.

Residential preconditioning as well as heat pump water heaters and commercial plug load management are among the individual measures with the largest impacts on electricity demand

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 Figure S6. 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 less-efficient 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 in major population centers, and the summer peak occurring late in the day places it past the time when cooling demand is highest, thus reducing the potential for peak reduction from 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 regions. Savings from this measure are particularly pronounced in the Great Lakes (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 California (CAMX) 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 the estimated technical potential annual electricity reductions from efficiency and flexibility in 2030 and 2050 as early retirements of remaining coal generation, and assumes nondispatchable 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.[24,44,45] These estimates do not include additional benefits to the grid such as avoided transmission and distribution infrastructure, reduced greenhouse gas emissions, and reduced air pollution.[46,47]

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, as other recent studies have demonstrated,[51] though this may not be the case for individual efficiency and flexibility packages that comprise the measure sets.[52] 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.[53] Accordingly, emerging loads such as electric vehicle charging[54] 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 US Eastern Interconnection estimates 97 GW peak demand reductions from efficiency and flexibility measures by 2030 (versus 137 GW in corresponding regions in our study); however, this study is an estimate of achievable potential, not technical potential.[55] Another study of DR potential in California finds that peak reductions in the state could reach 6–8 GW by 2025 (versus 9 GW by 2030 in our results); however, this estimate includes the industrial sector and focuses on "cost-competitive" DR.[56] In the Southeast region, Nadel[57] estimates up to 40 GW of summer and winter peak-demand reductions from incremental efficiency improvements and DR in 2030 (versus 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 flexibility measures. The Northwest Power and Conservation Council's (NPCC) Seventh Power Plan[58] finds up to 9.9 GW summer and 13.2 GW winter peak reduction potential from efficiency and flexibility in 2035 (versus 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, whereas our analysis averages net peak-hour impacts across all days in a season to estimate potential.

Our estimates of the grid resource from building efficiency and flexibility would increase with more aggressive electrification of end-use loads, which recent studies suggest is necessary to achieve net-zero emissions from buildings by midcentury.[59,60] For example, under an illustrative case in which all fossil-fired heating, water heating, and cooking is switched to electric equipment at a baseline efficiency level by 2050 (see experimental procedures), we find that annual electricity use increases by 1,081 TWh (33%), while daily net peak loads increase by 231 GW (49%) and 64 GW (11%) in the winter and summer, respectively (Figure S7). These results imply a new daily winter net peak of 700 GW that is 1.12 times larger than that of the summer months in 2050. The majority of electrified load additions are attributed to the heating end use, which, when considered independently, raises the daily net peak load in the winter by 161 GW (1.12 times summer peak) and could raise it by as much as 353 GW (1.46 times summer peak) if low-temperature degradation in heat pump performance is so significant as to require full electric resistance at peak heating demand (see discussion in experimental procedures and Figure S9). Co-deployment of best available heating and water heating efficiency and flexibility measures avoids 337 TWh (31%), 101 GW (44%), and 29 GW (45%) of the added annual, winter peak, and summer peak loads, respectively (Figure S8), effectively lowering the new winter-summer peak ratio to 1. Further study of the degree to which electrification affects the building-grid resource is warranted, however, as there is little to benchmark these estimates against. For instance, one recent study finds a somewhat larger winter-summer peak ratio of 1.6 from full heating electrification given the same regional aggregation (Table S4 in that study),[61] but the ratio is computed based on historical building heating and cooling needs (rather than projected needs in 2050), reflects total buildings peak (rather than daily net system peak), and includes detailed accounting for heating performance degradation at low temperatures, all of which affords greater peak influence from electrifying fossil-fired heating than in our modeling approach.

Finally, our results reflect a technical potential assessment of the building-grid resource. The economic potential—accounting for electricity system benefits and costs of the EE and DF measures—would likely fall short of the technical potential[62] because not all of the measures are necessarily cost effective from the utility perspective. Introducing realistic building and technology stock turnover and market penetration dynamics would also reduce our impact estimates—possibly up to two-thirds in the near-term (see experimental procedures). 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 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, follow-on analyses are needed to identify the most promising pathways and policy mechanisms for realizing this resource in the coming years.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources should be directed to the lead contact, Jared Langevin (jared.langevin@lbl.gov)

Materials availability
No materials were used in this study.

Data and code availability
The code used to generate the paper's results, results data, and supporting data sets are available at https://doi.org/10.5281/zenodo.4737655.

Model overview

Estimates of building efficiency and flexibility potential were generated using a hybrid building stock energy modeling approach that incorporates both top-down and bottom-up elements.[63] Development of potential estimates follows four steps: (1) definition of building efficiency and flexibility measures sets, (2) determination of regional power system needs, (3) development of hourly end-use load profiles at the building-level for representative locations and 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. The following subsections outline key information for reproducing our methods; further details about certain methodological elements are found in the supplemental experimental procedures section.

Building efficiency and flexibility measures

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/or controls (EE measure set); modifying baseline operational schedules in response to regional power system conditions (DF measure set); or by packaging these two types of changes (efficiency and flexibility (EE+DF) measure set). Detailed measure definitions are provided in section S4, and example building-level impacts from these three measure sets are shown in Figure S20.

All EE measures adhere to a "best commercially available" energy performance level. For residential buildings, best available performance is determined using the Scout Core Measures Scenario Analysis data set and the National Residential Efficiency Measures Database.[64,65] For commercial buildings, best available performance corresponds to the ASHRAE 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 section S4.2.1).

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. Across 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).

DF measures implement load shedding (for example, dimming the lights) or load shifting (for example, decreasing cooling setpoints in the hours leading up to the peak demand period to enable "coasting" with higher setpoints during the peak period, or charging thermal energy storage overnight to use to meet cooling setpoints later in the day). All flexibility measures modify baseline loads in the most aggressive manner

Table 2. Residential and commercial measure definitions.

Measure set	Name	Building type(s)	End use(s)	Description
EE	envelope insulation and air sealing	res + com	heating and cooling	current best available technology————
	HVAC equipment	res + com	heating and cooling	
	lighting	res + com	lighting	
	electronics	res + com	home and office electronics	
	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 and cooling	fixed increase or decrease of temperatures during unoccupied and nighttime hours
DF	global temperature adjustment (GTA)	commercial	HVAC	increase or decrease zone temperature setpoints during peak hours
	GTA + precooling	res + com	cooling (res + com), ventilation (com)	decrease zone setpoints in the 4 h prior to peak period, then float temperature setpoint during peak hours
	GTA + preheating	residential	heating	increase zone setpoints 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 commercial
	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	preheat 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
EE+DF	GTA + pre-cool/heat + efficient envelope & HVAC equipment; daylighting controls + dimming	commercial	HVAC and lighting	combine DF HVAC and lighting strategies with more efficient envelope and equipment, daylighting, and controls
	thermostat controls + pre-cool/heat + efficient envelope and HVAC equipment	residential	heating and cooling	combine DF heating and cooling strategies with more efficient envelope and equipment
	non-thermostat DR + EE	residential	WH, lighting, home electronics, refrigeration, 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 and 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

See supplemental experimental procedures section 4 for additional details.

possible without compromising basic building service needs, where service thresholds are determined on a load-by-load basis as described further in section S4.2.2. Specific operational schedules for the flexibility measures—the hour ranges during which load shedding and shifting is required—are determined by regional power system conditions as described in the next sub-section.

Flexibility measures address the residential and commercial electric loads that are the largest contributors to annual electricity demand and can potentially be shed or shifted in response to daily 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).

Energy efficiency and DF measures are packaged (EE+DF) to explore possible interactive effects between these measure types, for example: (1) efficiency measures reduce the available load shedding and shifting potential of flexibility measures, and (2) efficiency measures enhance the effectiveness of thermal flexibility measures—e.g., through envelope upgrades that extend the effects of precooling or discharging of thermal energy storage. In developing the measure sets, 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.

Regional power system conditions

When scaled across the building stock, each of the efficiency and flexibility measure sets considered in our analysis has a collective impact on electricity demand at the regional power system level. Accordingly, measure impacts at the building level are designed and assessed relative to typical daily power system conditions and objectives, namely: (1) reduce building electricity demand during times of high total system load with low renewable electricity supply, when marginal electricity costs are likely to be highest; and (2) shift peak electricity demand into times with lower total system load and abundant renewable electricity supply, when marginal electricity costs are likely to be lowest. These objectives are best illustrated by examining the *net* system load shape in a given region, which subtracts total hourly variable renewable electricity generation from total hourly electricity demand across the region. Measure sets that target net system peak reduction and load shifting needs yield a net system load shape that is lower and flatter than that of a baseline demand scenario. Such load shapes benefit utility operators by reducing the need for peak load capacity investments, avoiding daily curtailments of renewable electricity supply, and mitigating the need to bring generators on and offline rapidly to meet sudden changes in net demand.[66,67]

We assess our measure sets' potential to affect net system load shapes in the 22 2019 EIA EMM regions, which cover the contiguous US[68] Using regional EMM system load and generation data provided by EIA for the 2019 AEO Reference Case, which covered every five (5) projection years from 2020–2050, we first develop peak-normalized net system load profiles for each region (r), projection year (y), month (m), day type (d), and hour of the day (hd), $l^{net}_{r,y,m,d,hd}$:

$$l^{net}_{r,y,m,d,hd} = \frac{L^{net}_{r,y,m,d,hd}}{\max_{1 \le m \le 12} L^{net}_{r,y,m,d,hd}}, \qquad \text{(Equation 1)}$$

$$L^{net}_{r,y,m,d,hd} = L^{tot}_{r,y,m,d,hd} - L^{rgen}_{r,y,m,d,hd}, \quad \text{(Equation 2)}$$

where $L^{net}_{r,y,m,d,hd}$ is the net system load, $\max_{1 \le m \le 12} L^{net}_{r,y,m,d,hd}$ is the maximum value of the net system load in region r and projection year y across all months, day types (weekday, weekend, and peak day per EMM convention[39]), and hours, and the net load is derived by subtracting total renewable solar and wind generation $L^{rgen}_{r,y,m,d,hd}$ from total system load, $L^{tot}_{r,y,m,d,hd}$.

Next, we calculate the average of the normalized net system load profiles from Equation 1 across each combination of region (r), season (s), and hour of the day (hd), $\bar{l}^{net}_{r,s,hd}$:

$$\bar{l}^{net}_{r,s,hd} = \sum_{m=1}^{M_s} \sum_{d=1}^{D} \left(l^{net}_{r,y=2050,m,d,hd} \right) w_{d,m}, \quad \text{(Equation 3)}$$

where M_s is the set of months belonging to season s (summer [Jun–Sep]; winter [Dec–Mar]; intermediate [all other months]), D is the set of three EMM day types (weekday, weekend, peak day), and $w_{d,m}$ is the averaging weight for the combination of day type d and month m, defined as its proportion of the total number of days in a given season. Note that Equation 3 is based on the net system load profiles for the year 2050 only; 2050 is chosen because it is the year in which renewable penetration is at its highest saturation in the EIA data (29%); section S2.1.1 explores the implications of higher renewable penetration on our definition of system conditions and associated measure impacts, showing limited sensitivities that mostly concern the definition of low net load periods.

Finally, the average net system load profiles from Equation 3 are used to determine typical daily peak and off-peak hour ranges for each region (r) and season (s), $h^{pk}_{r,s}$ and $h^{opk}_{r,s}$:

$$h^{pk}_{r,s} = \begin{cases} \left[h^{max}_{r,s} - 3, h^{max}_{r,s} + 1\right] & \text{if } 9 \le h^{min}_{r,s} \le h^{max}_{r,s}; \\ \left[h^{max}_{r,s} - 2, h^{max}_{r,s} + 2\right] & \text{otherwise,} \end{cases} \quad \text{(Equation 4)}$$

$$h^{opk}_{r,s} = hd \in (1, 24) \left[\bar{l}^{net}_{r,s,hd} - \bar{l}^{net}_{r,s,hd=h^{min}_{r,s}} < 0.1 \right], \quad \text{(Equation 5)}$$

$$h^{max}_{r,s} = \underset{1 \le hd \le 24}{\operatorname{argmax}} \, \bar{l}^{net}_{r,s,hd} \qquad h^{min}_{r,s} = \underset{1 \le hd \le 24}{\operatorname{argmin}} \, \bar{l}^{net}_{r,s,hd} \quad \text{(Equation 6)}$$

where daily peak and off-peak hour ranges for region r and season s are based on the hours in which the average net load shape is at its maximum and minimum values $h^{max}_{r,s}$ and $h^{min}_{r,s}$, respectively. Peak periods in Equation 4 are restricted to 4 h and are weighted toward the load ramping period in regions with midday troughs in the net load shape or are centered on the maximum net load hour otherwise. Per Equation 5, off-peak periods include all hours in which the net load is within 10 percentage points of the minimum net load.

Figure 7 shows an example of the peak-normalized daily net load profiles and peak and off-peak hour ranges developed for summer and winter months in the California (CAMX) EMM region. Net regional system profiles and peak/off-peak periods 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 down-select 14 representative EMM region profiles that capture the variation in net system conditions that measure impacts are assessed against; details about the representative regions, which are subsequently denoted with the rr subscript, are available in

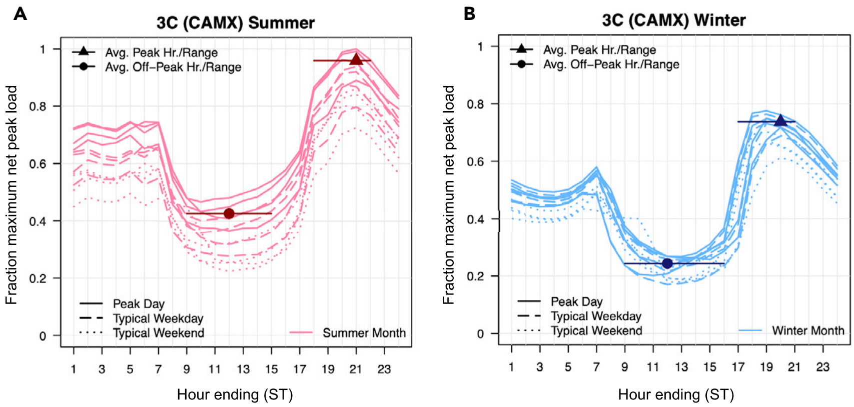

Figure 7. Peak-normalized total system loads net variable renewable energy generation for the California (CAMX) grid region

(A and B) 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 Figure S11); CAMX is used to define grid conditions in ASHRAE climate zone 3C as indicated by the plot titles. The peak load period is defined as 4 h 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 10 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 2050, which is the year with the highest projected renewable penetration in EIA EMM modeling for the 2019 Annual Energy Outlook.[69] In CAMX, the large midday 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.

Table S3; daily net load profiles are shown for all 14 representative regions in Figure S11.

End-use load profiles at the building level

Assessment of efficiency and flexibility measure impacts begins at the building level, where EnergyPlus[70] simulations of hourly building energy loads under baseline operations and with the 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[71]), 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. Hourly energy use results from EnergyPlus have been validated against empirical data for multiple buildings and thus serve as useful baselines for our analysis of measure impacts for individual buildings, though important caveats about the use of EnergyPlus are noted in the analysis limitations sub-section.[72–75]

Simulation models are developed for a representative city in each of the 14 contiguous US ASHRAE 90.1–2016 climate zones[76] and for six building types that are chosen to represent variations in typical end-use load shape patterns across the residential and commercial building stock. Single-family homes, which comprise the strong majority of residential square footage and electricity use (84% and 82% in 2020, respectively[24]), are used as the representative residential building type. Commercial building usage and load patterns are more diverse than residential and thus require a larger set of representative building types—we use medium and large offices, large hotels, standalone retail, and warehouses. Further justification for the choice of these representative commercial building types is provided in section S2.2.1.

EnergyPlus simulations of residential loads are conducted using ResStock, an analysis tool that 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).[77] 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 efficiency and flexibility measures applied. 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 EE and DF measures applied. Further details regarding the methodology behind ResStock can be found in Wilson et al.[78]

Commercial buildings loads are simulated using the commercial prototype models developed by the US Department of Energy to support assessment and compliance with local building codes.[79] The prototype models represent a cross section of common commercial building types covering 80% of new commercial construction[80]; our analysis uses the Large Office, Medium Office, Stand-alone Retail, Large Hotel, and Warehouse (non-refrigerated) prototypes, which map to the full set of prototypes as shown in Table S4 and explained further in section S2.2.1. While multiple prototype construction vintages are available, we limit our simulations to the 2004 vintage, which best balances the expected evolution in typical commercial construction characteristics across the projected time horizon (2015–2050, covered in the next subsection). EnergyPlus files for simulating the baseline case and measure sets are generated using the OpenStudio Measures capability, which automates the process of EnergyPlus model creation and modification. Baseline prototype files are generated using the existing *Create DOE Prototype Building* Measure,[81] while new Measures are developed to represent the particular sets of commercial building efficiency and flexibility measures assessed in this paper. Further details regarding the development and assumptions of the commercial prototype models can be found in Goel et al.[82] and Thornton et al.,[80] while additional details about OpenStudio Measures are available in Roth et al.[83]

Across the residential and commercial contexts examined, hourly EnergyPlus loads for each measure are translated to hourly load savings fractions for a given ASHRAE climate zone (c), representative EMM region (rr), representative EnergyPlus building type (bre), end use (u), and hour of the year (hy), $\Delta l^{meas}_{c,rr,bre,u,hy}$:

$$\Delta l^{meas}_{c,rr,bre,u,hy} = l^{meas}_{c,rr,bre,u,hy} - l^{base}_{c,rr,bre,u,hy}, \quad \text{(Equation 7)}$$

$$l^{base}_{c,rr,bre,u,hy} = \frac{L^{base}_{c,rr,bre,u,hy}}{\sum_{hy=1}^{8760} L^{base}_{c,rr,bre,u,hy}}, \quad \text{(Equation 8)}$$

$$l^{meas}_{c,rr,bre,u,hy} = \frac{L^{meas}_{c,rr,bre,u,hy}}{\sum_{hy=1}^{8760} L^{base}_{c,rr,bre,u,hy}} \quad \text{(Equation 9)}$$

where $l^{base}_{c,rr,bre,u,hy}$ and $l^{meas}_{c,rr,bre,u,hy}$ are the hourly end-use fractions of annual load under the baseline case and with measure *m* applied, and $L^{base}_{c,rr,bre,u,hy}$ and $L^{meas}_{c,rr,bre,u,hy}$ are the total (unnormalized) hourly EnergyPlus load outputs for the given combination of climate, EMM region, representative EnergyPlus building type (*bre*), and end use, under the baseline and measure case, respectively. All EnergyPlus outputs reflect a non-leap year that begins on a Sunday and are reported in local standard time.

Per Table S3, building-level measure savings profiles for each ASHRAE climate zone (*c*) may address the net system load profiles of up to two representative EMM regions (*rr*). Note, however, that regional power system conditions only influence the building-level results for energy flexibility (DF) or packaged efficiency and flexibility (EE+DF) measures, which modify baseline building loads non-uniformly across hours under the objective of shedding load during system net peak hours and shifting load to off-peak hours as described in the previous sub-section and in Table 2; by contrast, efficiency-only (EE) measures reduce loads uniformly across hours regardless of system conditions.

Building-level simulations of the measures in Table 2 account for interactive effects across certain efficiency and flexibility components in the analysis by packaging these components in the simulations—by co-simulating envelope and HVAC equipment improvements, for example. This practice ensures that aggregation of resultant measure savings shapes across a portfolio (e.g., to develop results for Figures 3, 4, 5, and S3–S5) avoids double-counting the impacts of contributing measures. We also simulate disaggregated versions of packaged measures—for example, we simulate an envelope improvement made independently of an HVAC equipment improvement, and vice versa. This parallel practice allows exploration of individual measure impacts in isolation, as in Figures 6 and S6.

End-use load profiles at the regional power system level

To scale the effects of building-level measure application to the regional power system level, we use Scout (scout.energy.gov)—an openly available modeling software originally developed to estimate the short- and long-term annual impacts of building energy efficiency on US energy use, CO_2 emissions, and operating costs. Previous Scout analyses have assessed these metrics on an annual basis for different climate zones or the US as a whole[84]; here, we adapt Scout to integrate hourly data on regional power system conditions and building-level efficiency and flexibility impacts with annual projections of building sector electricity use and demand out to 2050. Further details regarding Scout's general methodological approach can be found in the Supplemental Experimental Procedures of Langevin et al.[84]; an initial effort to translate Scout's annual data sets to a sub-annual temporal resolution, which the current work builds upon, is reported in Satre-Meloy and Langevin.[85]

First, Scout generates annual projections of building electricity use by EMM region (*r*) and AEO building type (*b*), end use (*u*), technology type (*t*), and projection year (*y*), $E^{base}_{r,b,u,t,y}$, drawing from AEO 2019 Reference Case projections of building electricity from 2015–2050 that are resolved by census division (*cd*):

$$E^{base}_{r,b,u,t,y} = \sum_{cd=1}^{CD} E^{base}_{cd,b,u,t,y} w_{cd} \qquad \text{(Equation 10)}$$

where $E_{cd,b,u,t,y}$ is the AEO 2019-projected electricity use of the given building type, end use, and technology type in census division *cd* and year *y*, and w_{cd} is an EIA

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building electricity sales-based mapping factor that determines the portion of census division cd that falls in EMM region r. Mapping factors are reported for residential and commercial buildings in Tables S5 and S6, respectively; these factors are also used to translate AEO-projected residential and commercial building square footages from a census division to EMM region resolution, for the purpose of normalizing measure load impacts by floor area as in Figures 6 and S6. Note that Scout's building types (3 residential; 11 commercial), end uses (14 residential; 10 commercial) and technology types are consistent with those used in the AEO.[39]

EMM-resolved segments of baseline building electricity use from Equation 10 are then multiplied by hourly measure load savings fractions (Equation 7) for the appropriate ASHRAE climate zone (c), representative EMM region (rr), EnergyPlus building type (bre), and end use (u), yielding hourly load savings estimates for each measure when applied to the given baseline segment, $\Delta E^{\text{meas}}_{r,b,u,t,y,hy}$:

$$\Delta E^{\text{meas}}_{r,b,u,t,y,hy} = \sum_{c=1}^{C} \sum_{be=1}^{B} E^{\text{base}}_{r,b,u,t,y} \Delta I^{\text{meas}}_{c,rr\mapsto r,bre\mapsto be,u,hy} w_c w_{be} \qquad \text{(Equation 11)}$$

where w_c and w_{bre} are mapping factors that determine the portion of ASHRAE climate zone c that falls into EMM region r and the portion of EnergyPlus building type be that comprises AEO building type b, respectively; the mappings between ASHRAE and EMM regions and between EnergyPlus and AEO building types are reported in Tables S7 and S8. For a given EMM region r, the associated representative region rr in the hourly measure load savings fraction term $\Delta I^{\text{meas}}_{c,rr\mapsto r,bre\mapsto be,u,hy}$ is selected based on the mapping between representative EMM regions and the full set of EMM regions each represents in Table S3. In the same term, the representative EnergyPlus building type bre for a given EnergyPlus building type be is selected based on the mapping between representative EnergyPlus building types and the full set of EnergyPlus building types each represents in Table S4.

The final step in the Scout calculations determines the annual and seasonal daily average net peak and off-peak impacts of each measure in each EMM region, $\Delta E^{\text{meas}}_{r,b,u,t,y}$, $\Delta E^{\text{meas, pk}}_{r,b,u,t,y,s,dw}$, and $\Delta E^{\text{meas, opk}}_{r,b,u,t,y,s,dw}$:

$$\Delta E^{\text{meas}}_{r,b,u,t,y} = \sum_{hy=1}^{8760} \Delta E^{\text{meas}}_{r,b,u,t,y,hy} \qquad \text{(Equation 12)}$$

$$\Delta E^{\text{meas, pk}}_{r,b,u,t,y,s,dw} = \sum_{hy=1}^{8760} \begin{cases} \dfrac{\Delta E^{\text{meas}}_{r,b,u,t,y,hy}}{N^{\text{pk}}_{r,s,dw}} & \text{if } hy \in H^{\text{pk}}_{r,s,dw} \\ 0 & \text{otherwise} \end{cases} \qquad \text{(Equation 13)}$$

$$\Delta E^{\text{meas, opk}}_{r,b,u,t,y,s,dw} = \sum_{hy=1}^{8760} \begin{cases} \dfrac{\Delta E^{\text{meas}}_{r,b,u,t,y,hy}}{N^{\text{opk}}_{r,s,dw}} & \text{if } hy \in H^{\text{opk}}_{r,s,dw} \\ 0 & \text{otherwise} \end{cases} \qquad \text{(Equation 14)}$$

where $H^{\text{pk}}_{r,s,dw}$ and $H^{\text{opk}}_{r,s,dw}$ are the sets of hours that fall under the season s, day type dw (weekday, weekend), and daily peak and off-peak hour ranges for region r in season s ($h^{\text{pk}}_{r,s}$ and $h^{\text{opk}}_{r,s}$ from Equations 4 and 5, respectively), and $N^{\text{pk}}_{r,s,dw}$ and $N^{\text{opk}}_{r,s,dw}$ are the total numbers of hours in $H^{\text{pk}}_{r,s,d}$ and $H^{\text{opk}}_{r,s,d}$, respectively.

The Scout calculations yield measure impacts on stock-level electricity use (TWh) and demand (GW) that are resolved by EMM region, Scout/AEO building type, and end-use technology class; these results can be aggregated into the higher-level AVERT regions (Figure 1), residential and commercial building breakouts, and end-use-level results presented throughout.

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 EnergyPlus-simulated baseline end-use load shapes and measure impacts rather than electricity meter data or device-level measured electricity use data because these data are not available across the broad array of measure types and locations considered in this study; metered data for our measure sets is a particular challenge since we investigate the operation of technologies that are not yet widely adopted. As mentioned, previous work has validated hourly EnergyPlus simulations against empirical data[72–75]; nevertheless, we acknowledge important limitations in the methods employed with EnergyPlus in this study. In particular, we use a representative subset of building types to account for variations in baseline load profiles across the US building stock (see section S2.2); these building type models rely on either a set of operating schedules or a single schedule to represent occupancy and thermostat setpoints. To the extent that real-world operational schedules are more diverse than what is represented in our analysis, this difference might translate to greater diversity in baseline loads and, therefore, increase and/or decrease the potential load impacts of efficiency and flexibility measures. In the summer months, for example, greater diversity in residential building occupancy and thermostat setpoint schedules could lower the peak period potential from residential cooling measures by reducing the concentration of baseline cooling loads around the evening hours; conversely, increased schedule diversity for most commercial buildings could *add* cooling loads to these evening hours, thus increasing the potential for load reductions from efficiency and flexibility. While this limitation is important, the end-use load shapes used in this study constitute a significant improvement over current publicly available load shape data with national coverage,[86] which are far less granular in terms of building types and temporal resolution, and we expect to update our analysis with the outputs of ongoing work to develop calibrated end-use load profiles of the entire US building stock.[87]

Three additional limitations apply at the building scale. First, we use a single representative city in each climate zone to capture the impacts of weather on simulated measure impacts; previous research has shown that in some cases, use of multiple representative cities within each climate zone is warranted to improve the accuracy of estimated electricity use patterns.[88] 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[71] or the expectation that those warming trends will continue in the future. Our results thus exclude the option value of flexibility under more extreme weather and system loads.[89] 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 if more people work from home, or with 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, 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.[90,91] Second, the spatiotemporal granularity of our net system load shapes is limited to a subset of representative regions (Table S3) 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 spatiotemporal resolution. Finally, the scope of our analysis excludes a number of additional grid value streams for building efficiency and flexibility, including: mitigation of load ramping, which is defined by the rate of change of load with time rather than its absolute minimum and maximum; coordination of flexible loads in buildings with distributed energy resources (DERs), which might offer more potential value at specific distribution system locations and enable greater building-level resilience not reflected in our analysis; and fast response services such as load modulating for frequency regulation, which could offer additional benefits.[92]

SUPPLEMENTAL INFORMATION

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AUTHOR CONTRIBUTIONS

Conceptualization, J.L. and C.B.H.; methodology, J.L., C.B.H., A.S.-M., H.C.-P., A.S., E.P., R.A., and E.J.H.W.; investigation, J.L., C.B.H., H.C.-P., A.S., E.P., and R.A.; writing – original draft, J.L., A.S.M., A.S., and H.C.-P.; writing – review & editing, J.L., A.S.-M., C.B.H., A.J.S., and E.J.H.W.; validation, J.L., C.B.H., A.S.-M., H.C.-P., and A.S.; formal analysis, J.L., C.B.H., A.S.-M., H.C.-P., and A.S., visualization, J.L., A.S.-M., and C.B.H.; software, J.L., H.C.-P., A.S., E.P., and R.A.; resources, E.J.H.W.; data curation, J.L. and C.B.H.; supervision, J.L., C.B.H., E.J.H.W., and A.J.S.; project administration, J.L. and C.B.H.; funding acquisition, J.L. and C.B.H.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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Supplemental information

US building energy efficiency

and flexibility as an electric grid resource

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Supplemental Experimental Procedures

1 Additional results

1.1 Disaggregated baseline electricity results for Great Lakes/Mid-Atlantic and Southeast regions in 2030

Figure S1 further disaggregates the prominent 2030 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 uses more electricity annually than all other AVERT regions shown in Figure 2, aside from Texas.

1.2 National grid resource, spatio-temporal distribution, and prominent measures by region in 2050

Figures S2–S6 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, but the magnitude of results increases. These increases are driven by cooling and miscellaneous ("other") end uses in residential buildings, and by plug loads 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.

1.3 Implications of fully electrified building loads for technical potential results in 2050

Figures S7 and S8 show how much the regional baseline load and measure impact estimates of Figures S2 and S4 increase if universal building load electrification is assumed by 2050. In the baseline case (Figure S7), we assume that 100% of projected fossil-fired building heating, water heating, and cooking service demand in 2050 switches to electricity, moving to the overall baseline electric equipment efficiency levels shown for residential and commercial buildings in Tables S1 and S2, respectively; projected 2050 fossil-fired building energy use and fossil-fired and electric equipment efficiencies follow sales-weighted figures from EIA AEO 2019[1]. Baseline cooling efficiencies are assumed to remain the same as before the electrification. The incremental impacts of heating and water heating measures from this paper's integrated efficiency and flexibility measure set (EE+DF) are then calculated relative to the additional baseline electric loads (Figure S8). Importantly, the results presented in this section reflect the same net system peak assumptions used throughout the rest of the paper and detailed in Supplemental Information section 2.1, though in practice high electrification of other sectors like transportation alongside buildings could change net system load shape characteristics.

Across regions in 2050, full electrification of U.S. building loads at a baseline efficiency level adds 1,081 TWh to annual electricity use and 231 GW and 64 GW to daily net winter and summer peak demand, respectively, of which 337 TWh (31%), 101 GW (44%), and 29 GW (45%) is avoided

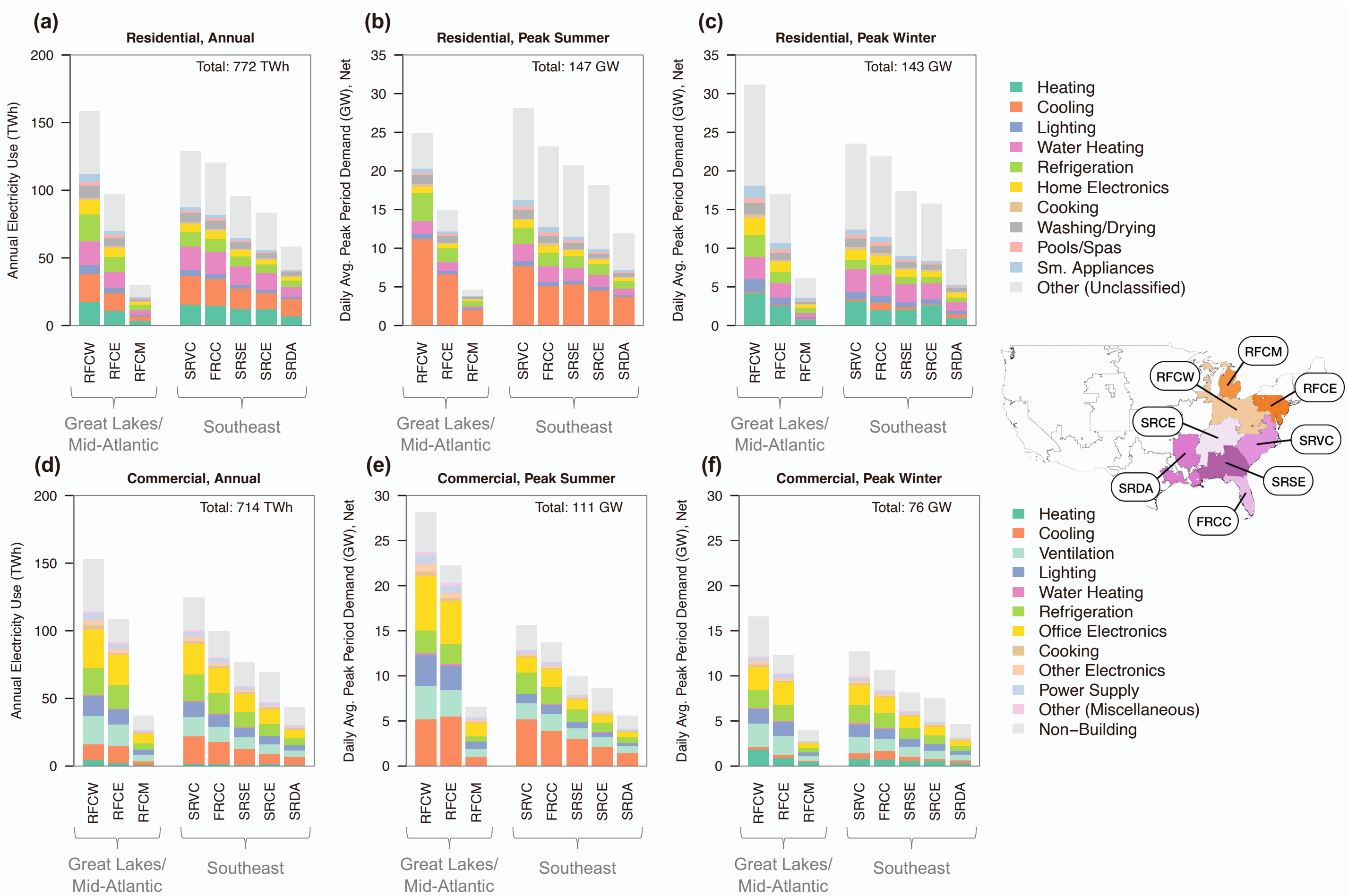

Figure S1: Attribution of 2030 baseline annual electricity use and net peak demand from buildings in the Great Lakes/Mid-Atlantic and Southeast AVERT regions to EIA EMM sub-regions. Base-case residential (a–c) and commercial (d–f) annual electricity use and peak summer and winter demand are broken out 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 and 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 uses more electricity annually than all other AVERT regions shown in Figure 2, aside from Texas.

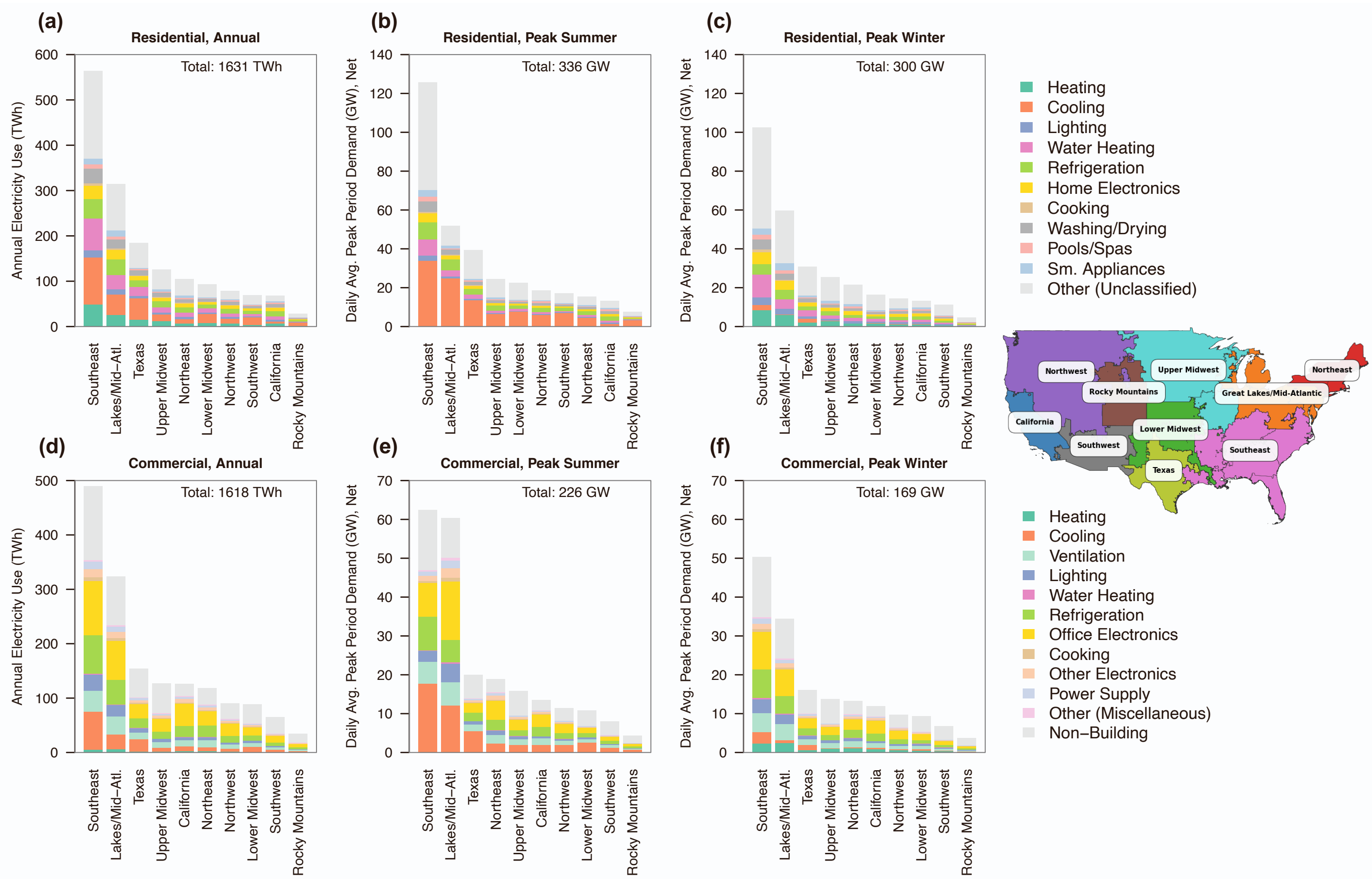

Figure S2: Baseline annual electricity use and net peak demand from U.S. buildings in 2050. Base-case residential (a–c) and commercial (d–f) annual electricity use and peak summer and winter demand are broken out by end use and the 10 2019 EPA AVERT regions (map at right), which are aggregations of the 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 and 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 3,249 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.

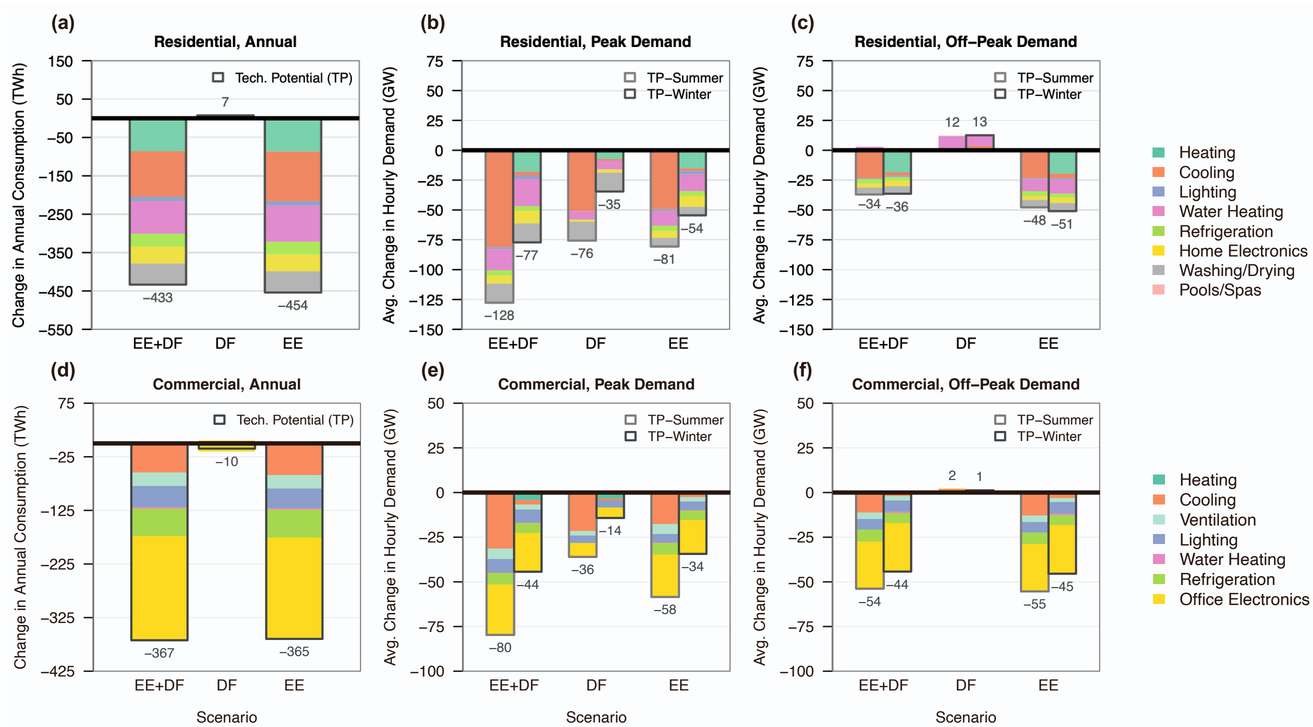

Figure S3: National impacts of best available U.S. building efficiency and flexibility measure sets on annual electricity use and net peak and off-peak demand in 2050. Technical potential efficiency and flexibility impacts on residential annual electricity use (a), peak demand (b), and off-peak demand (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 and 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.

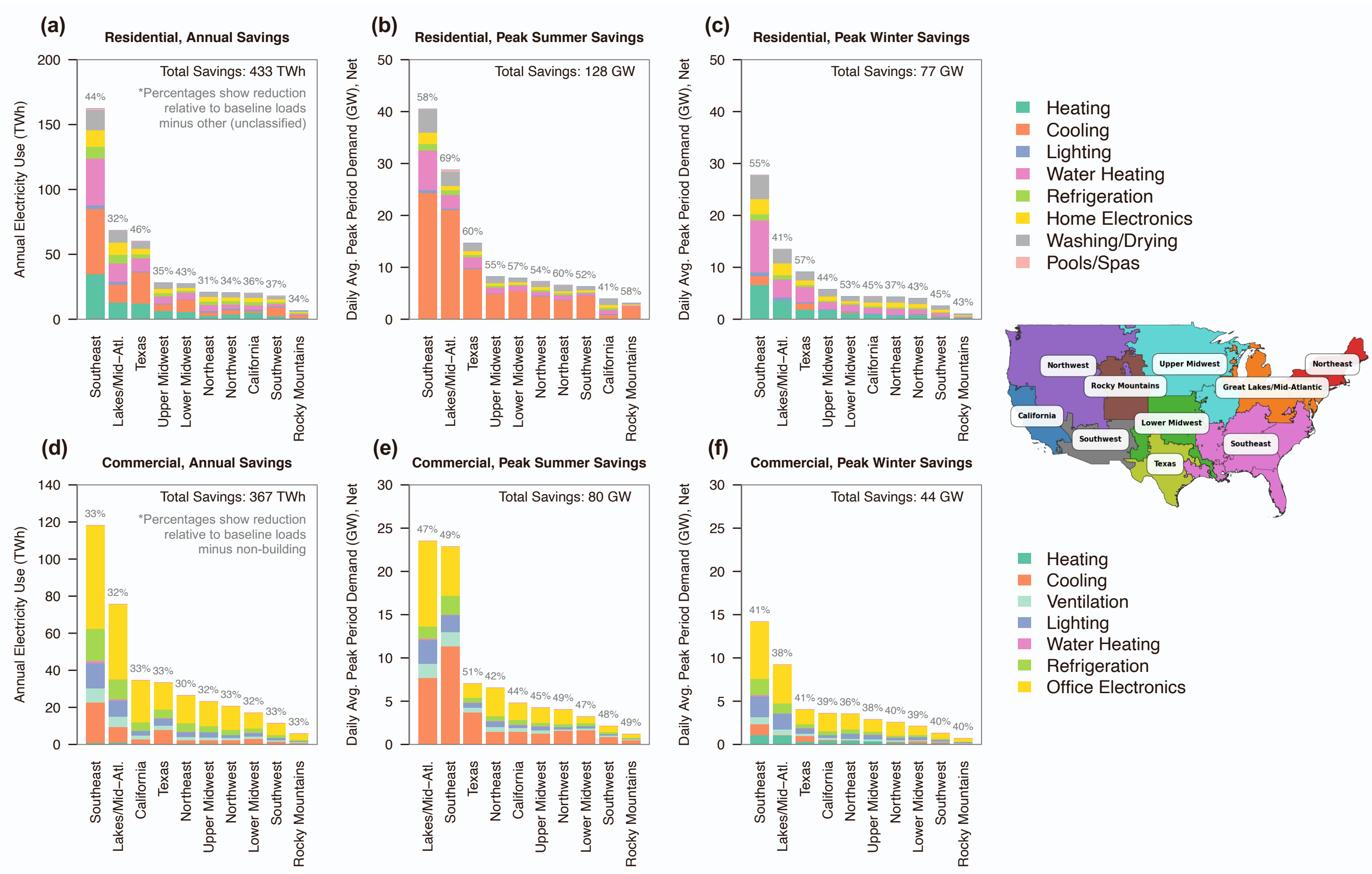

Figure S4: Regional impacts of best available U.S. building efficiency and flexibility measure sets on annual electricity use and net peak demand in 2050. Technical potential impacts of building efficiency and flexibility measures (EE+DF) on residential (a–c) and commercial (d–f) annual electricity use 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 S2. 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.

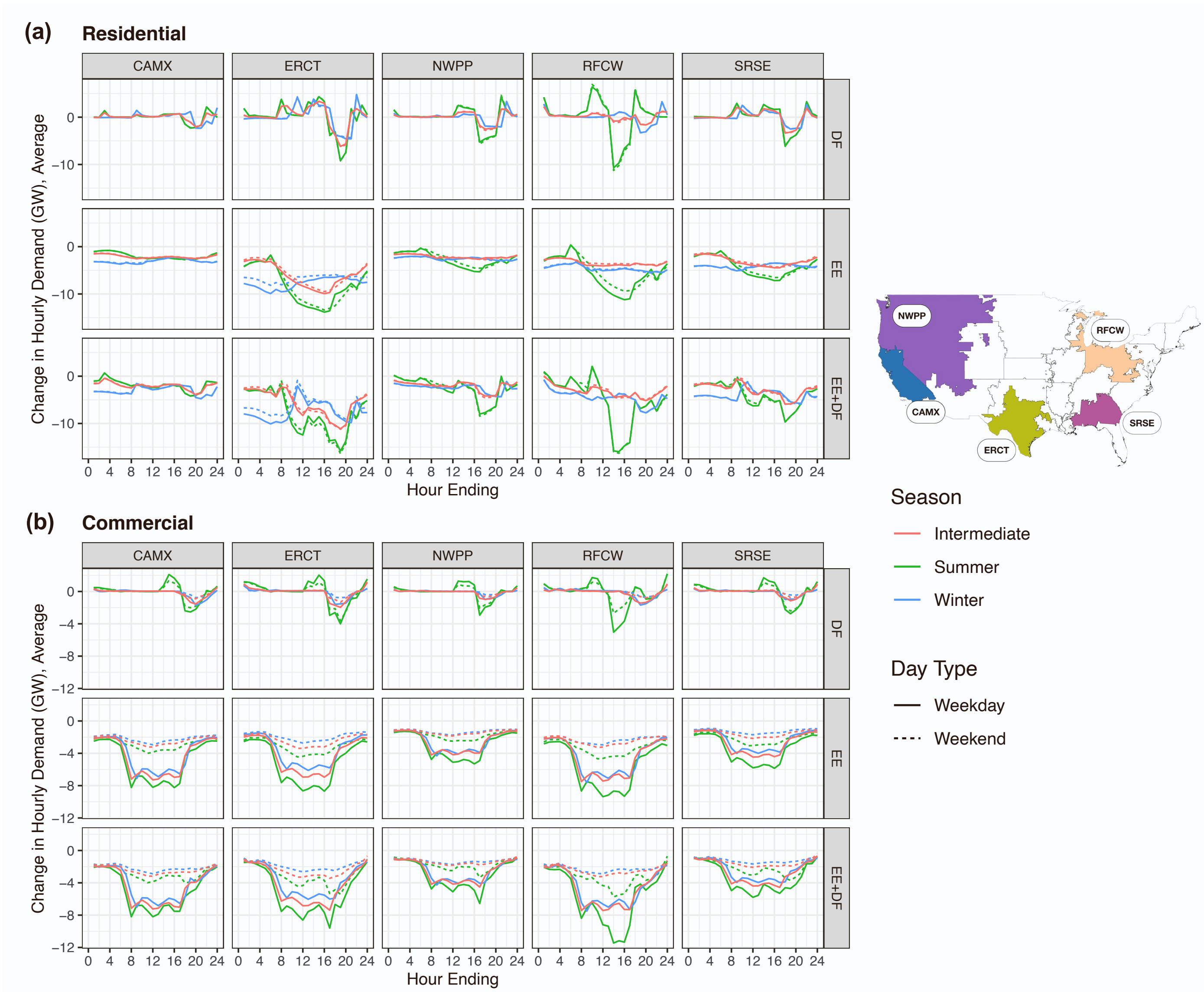

Figure S5: Typical change in sector-level electricity demand from building efficiency and flexibility measure sets for five U.S. grid regions in 2050. Technical potential demand change profiles are shown for five of the 2019 EIA EMM regions (map at right) and three measure sets (DF, EE, EE+DF) and reflect the 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.

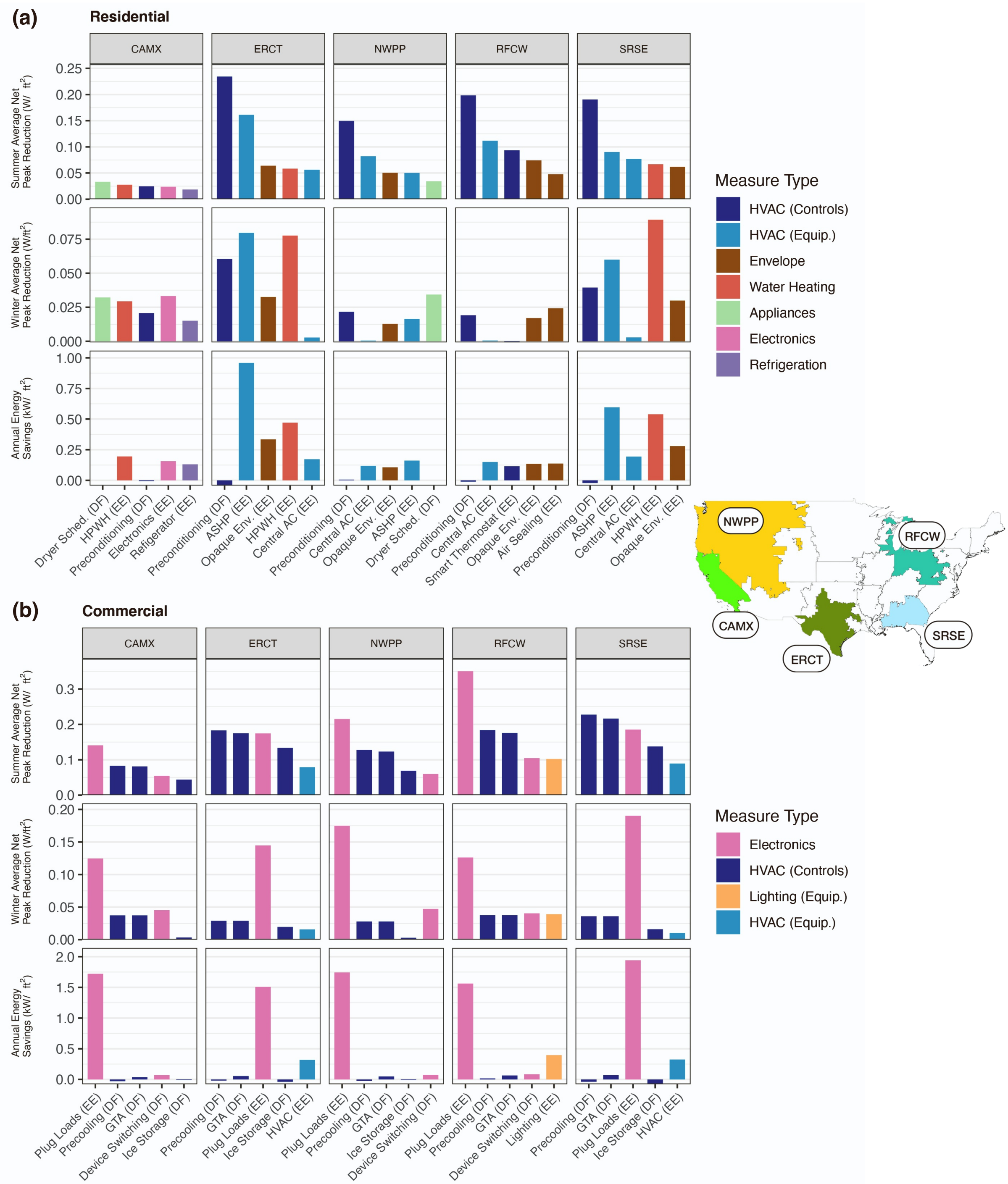

Figure S6: Individual efficiency and flexibility measures with the largest summer net peak demand intensity reductions for five U.S. grid regions in 2050. The five individual efficiency (EE) or flexibility (DF) measures with the largest technical potential reductions in residential (a) and commercial (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 and 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.

Table S1: Typical efficiency levels and portion of sales for heating and water heating equipment in 2050 residential buildings, as projected in EIA AEO 2019.[1]

End Use, Fuel Type	Equipment Type	Added Stock (# Units)	% Stock	Typical Efficiency	Efficiency Units
Heating, Fossil-Fired	Boiler (Natural Gas)	379,202	8%	0.90	*AFUE*
	Boiler (Fuel Oil)	64,354	1%	0.86	
	Furnace (Natural Gas)	4,080,097	83%	0.93	
	Furnace (Fuel Oil)	108,743	2%	0.84	
	Furnace (LPG)	221,893	4%	0.87	
	Furnace (Kerosene)	4,094	0%	0.84	
	Natural Gas Heat Pump	79,729	2%	1.30	*COP*
	Overall	***4,938,112***	–	***0.93***	***AFUE***
Heating, Electricity	Air Source Heat Pump	1,988,958	47%	2.58	*COP*
	Ground-Source Heat Pump	419,438	10%	3.70	
	Electric Resistance Furnace	1,854,557	43%	0.98	*AFUE*
	Overall	***4,262,953***	–	***1.99***	***COP***
Water Heating, Fossil-Fired	Natural Gas Storage	6,437,683	96%	0.63	*UEF*
	Fuel Oil Storage	102,817	2%	0.67	
	LPG Storage	162,172	2%	0.63	
	Overall	***6,702,672***	–	***0.63***	***UEF***
Water Heating, Electricity	Electric Storage (Resistance)	4,674,843	91%	0.93	*UEF*
	Electric Storage (Heat Pump)	464,818	9%	3.28	
	Overall	***5,139,661***	–	***1.14***	***UEF***

Table S2: Typical efficiency levels and portion of sales for heating and water heating equipment in 2050 commercial buildings, as projected in EIA AEO 2019.[1]

End Use, Fuel Type	**Equipment Type**	**Added Service Demand** (TBtu)	**% Demand**	**Typical Efficiency**	**Efficiency Units**
Heating, Fossil-Fired	Boiler (Natural Gas)	5.1	7%	0.85	%
	Boiler (Fuel Oil)	1.6	2%	0.92	
	Furnace (Natural Gas)	66.1	86%	0.81	
	Furnace (Fuel Oil)	4.2	5%	0.82	
	Natural Gas Heat Pump	0.3	0%	1.40	*COP*
	Overall	***77.3***	–	***0.82***	**%**
Heating, Electricity	Air Source Heat Pump	5.5	58%	3.40	*COP*
	Ground-Source Heat Pump	0.2	2%	3.70	
	Electric Resistance Heaters	0.7	7%	1.00	%
	Electric Boiler	3.1	33%	0.98	
	Overall	***9.5***	–	***2.45***	***COP***
Water Heating, Fossil-Fired	Natural Gas Storage	70.2	100%	0.82	%
	Fuel Oil Storage	0.3	0%	0.81	
	Overall	***70.4***	–	***0.82***	**%**
Water Heating, Electricity	Electric Storage (Resistance)	1.2	60%	0.98	%
	Electric Storage (Heat Pump)	0.5	23%	3.90	*COP*
	Solar	0.4	17%	2.70	*SEF*
	Overall	***2.0***	–	***1.95***	***COP***

by co-deployment of best available efficiency and flexibility. When combined with the results shown in Figure S2, winter peak additions for the baseline case imply a new daily net winter peak load of 700 GW, which is 12% larger than the new daily summer peak load of 626 GW. Application of the efficiency and flexibility measures reduces the new daily net winter and summer peaks to 599 and 597 GW, respectively, leaving the winter peak virtually even with the summer peak when aggregated across all regions.

The impacts of full electrification in 2050 vary widely by location. In particular, the regional hierarchy observed for the daily net winter peak metric in Figures S7 and S8 differs markedly from that observed in Figures S2 and S4. Here, regions with substantial projected heating needs met in large part by fossil fuels show the most upward movement in the hierarchy—Lakes/Mid-Atlantic, the Northeast, and California—while cooling-dominated regions that already have high electric heating and water heating penetration show the most downward movement—the Southeast and Texas.

The relative impacts of best available efficiency and flexibility on winter peak also vary widely across regions and are generally higher in regions where heating contributes less to the loads added from electrification—e.g., the Southeast and Texas. These differences are particularly pronounced in residential buildings, given the greater regional variability in the portion of electrified residential loads coming from heating in Figure S7 than for commercial buildings. In commercial buildings, heating contributes a notably larger share to winter peak savings than it does to annual savings, which are driven by water heating, demonstrating the stronger coincidence of commercial heating profiles with net system peak hours.

Finally, Figure S9 shows that estimates of added baseline load from electrification in Figure S7 are highly sensitive to assumptions about electric heating performance at low temperatures. Specifically, if one assumes that at low temperatures during winter net peak periods, baseline heat pumps operate under 100% electric resistance backup (COP=1) rather than at the rated COPs shown in Tables S1 and S2, the added load from full heating electrification increases by 192 GW, from 161 GW to 353 GW. Considered on its own, this level of heating load increase implies a new daily winter peak load of 822 GW, which is 46% larger than the original daily summer peak load of 562 GW. This result should be considered an illustrative upper bound; however, warmer climates are less likely to reach the low temperatures that would require full resistance backup heating, and newer cold climate heat pumps do not suffer as severe degradation in performance even at low ambient temperatures.[2]

1.4 Implications of realistic stock turnover and market penetration rates for technical potential results in 2030 and 2050

Figure S10 shows how the technical potential impacts of the three efficiency and flexibility measure sets for 2030 (Figure 6) and 2050 (Figure S6) 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[3], 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[4]. 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,

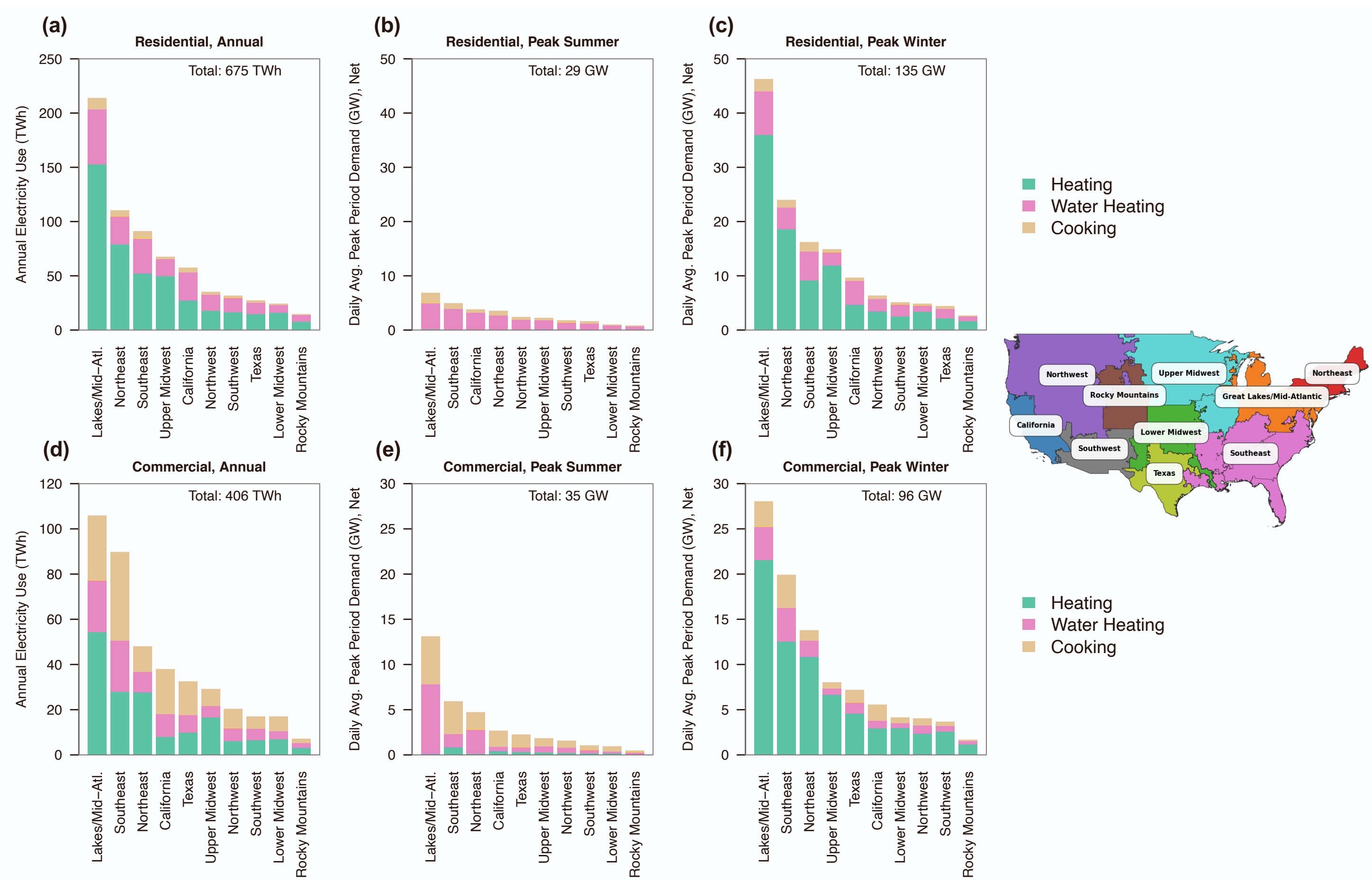

Figure S7: Additional regional baseline annual electricity use and peak demand from fully electrifying U.S. building loads in 2050. Additions to residential (a–c) and commercial (d–f) annual electricity use and net daily peak summer and winter demand from fully electrifying fossil-fired heating, water heating, and cooking end uses at a typical baseline efficiency level are broken out by end use and the 10 2019 EPA AVERT regions (map at right); the plots are otherwise interpreted in the same way as those shown in Figure S2. Across regions in 2050, full electrification of U.S. building loads at a baseline efficiency level adds 1,081 TWh to annual electricity use and 231 GW and 64 GW to daily net winter and summer peak demand, respectively.

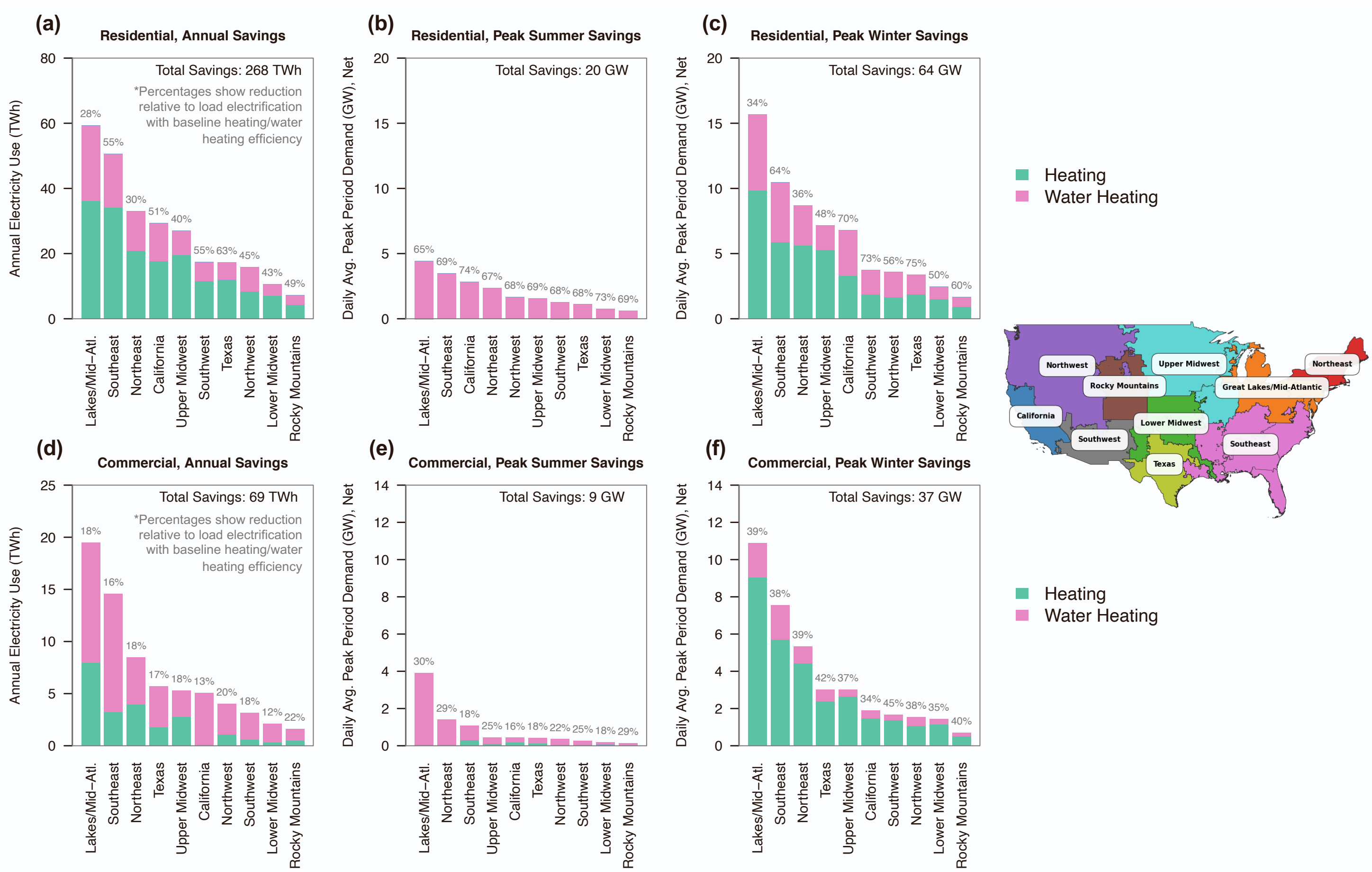

Figure S8: Avoided regional electrified load additions from best available building efficiency and flexibility in 2050. Technical potential impacts of building efficiency and flexibility measures (EE+DF) on added residential (a–c) and commercial (d–f) annual electricity use and net daily peak summer and winter demand from full electrification of fossil-fired heating, water heating, and cooking end uses at typical baseline efficiency levels (Figure S7) are broken out by end use and by the 10 2019 EPA AVERT regions (map at right); the plots are otherwise interpreted in the same way as those shown in Figure S4. Across regions in 2050, best available efficiency and flexibility avoids 337 TWh (31%) of the added annual electricity use and 101 GW (44%) and 29 GW (45%) of the added daily net winter and summer peak demand from universal building load electrification at a typical baseline efficiency level, respectively.

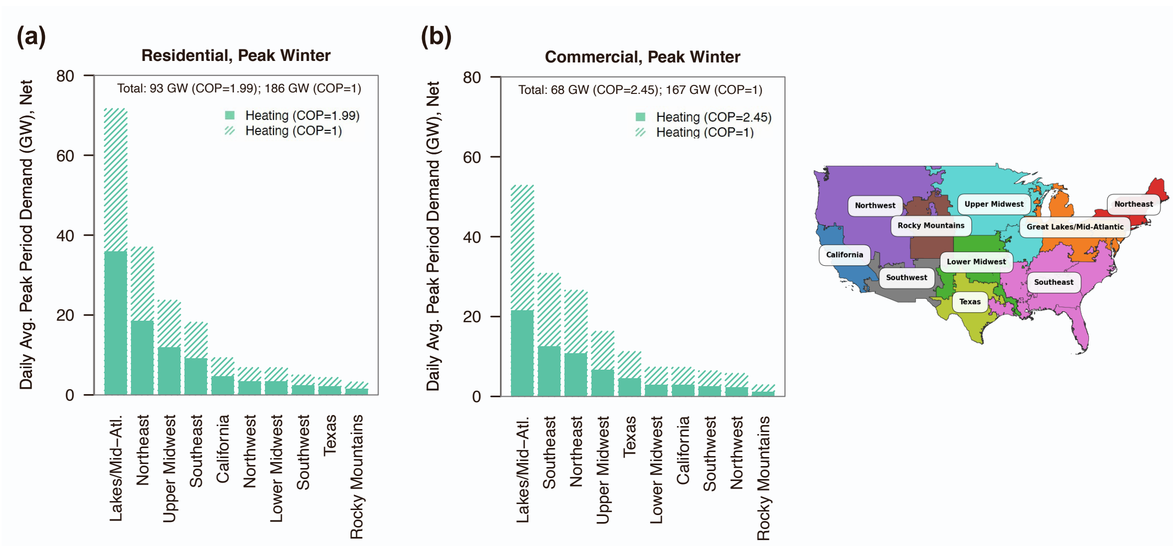

Figure S9: Sensitivity of additional regional baseline winter peak demand from fully electrifying U.S. building heating in 2050 to assumed baseline electric heating efficiency level. Additions to residential (a) and commercial (b) net daily peak winter demand from fully electrifying fossil-fired heating at both a typical baseline efficiency level (consistent with Figure S7) and decremented efficiency level consistent with 100% efficient electric resistance heating (COP=1) are broken out by the 10 2019 EPA AVERT regions (map at right). The low heating efficiency case adds 192 GW more winter peak demand than the typical heating efficiency case (353 GW vs. 161 GW, respectively). The low efficiency case assumes that heat pumps operate at full electric resistance backup during low-temperature winter peak hours, across regions. Such operation is less likely in warmer regions, and newer cold-climate heat pumps demonstrate improved performance at low temperatures; thus, estimates for this case should be considered upper bounds on the potential added winter net peak demand from heating electrification.

thus reducing technical potential impacts by 15% across metrics.

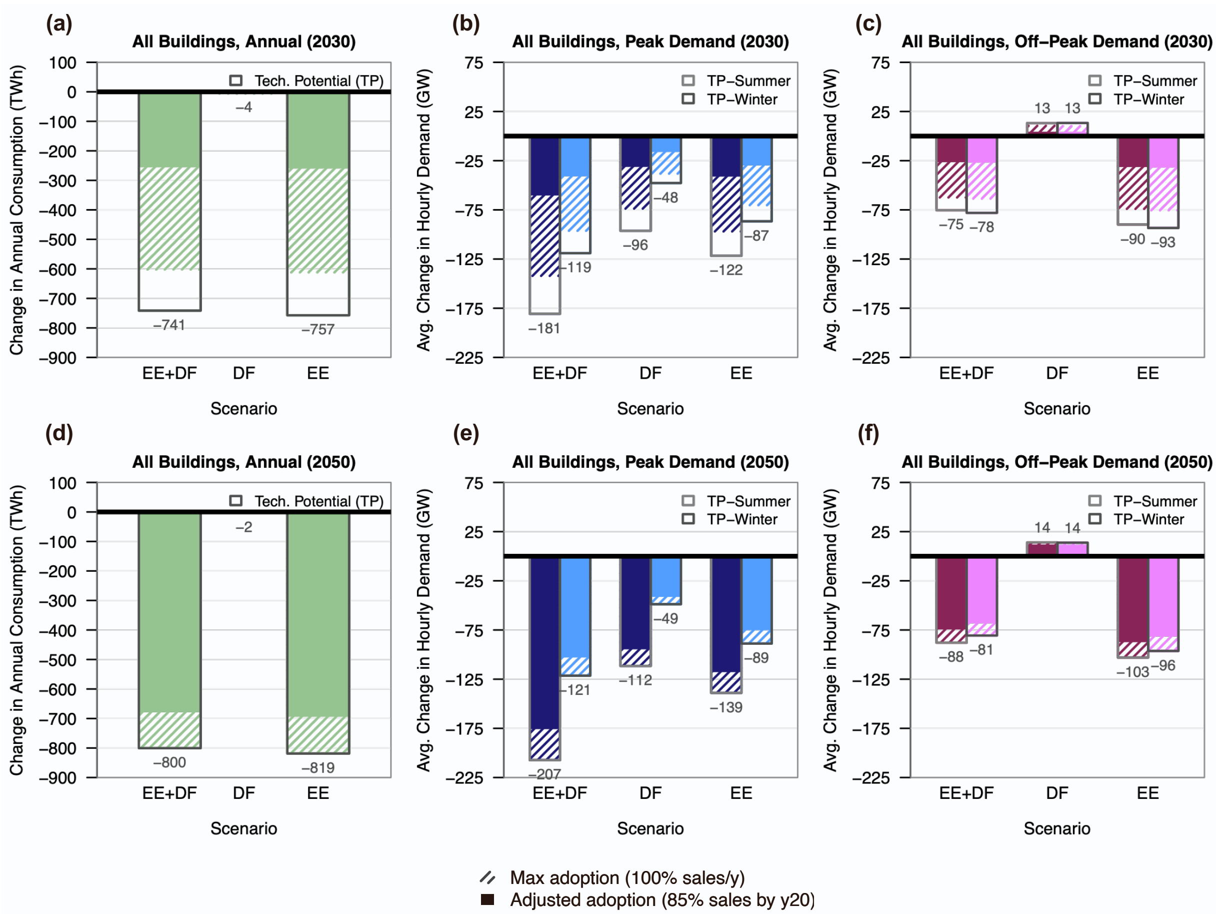

Figure S10: National impacts of best available U.S. building efficiency and flexibility measure sets on annual electricity use, peak demand, and off-peak demand in 2030 and 2050 considering baseline stock turnover and market penetration dynamics. Total technical potential building efficiency and flexibility 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 S3. 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%).

2 Representative utility system and building load shapes

2.1 Representative utility system load shapes

Table S3 shows the subset of the 22 EIA Electricity Market Module (EMM) region load shapes that are used to establish utility 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), one representative EMM region is used to establish grid-level conditions, while in larger climate zones that span several EMM regions (3–6A), 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 S11 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 renewable wind and solar energy generation, and net loads are normalized by the overall net peak hour load for the year as detailed in Experimental Procedures Equation 1. The normalized shapes in Figure S11 are based on EIA EMM projections for 2050 to best reflect utility system needs under a higher degree of renewable penetration. Net system load shapes and associated peak/off-peak periods in Figure S11 are determined by region, season, and day type (weekday, weekend).

Table S3: Summary of representative EMM utility regions, which are used to establish utility system conditions (e.g., net 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
4C	NWPP	NWPP
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

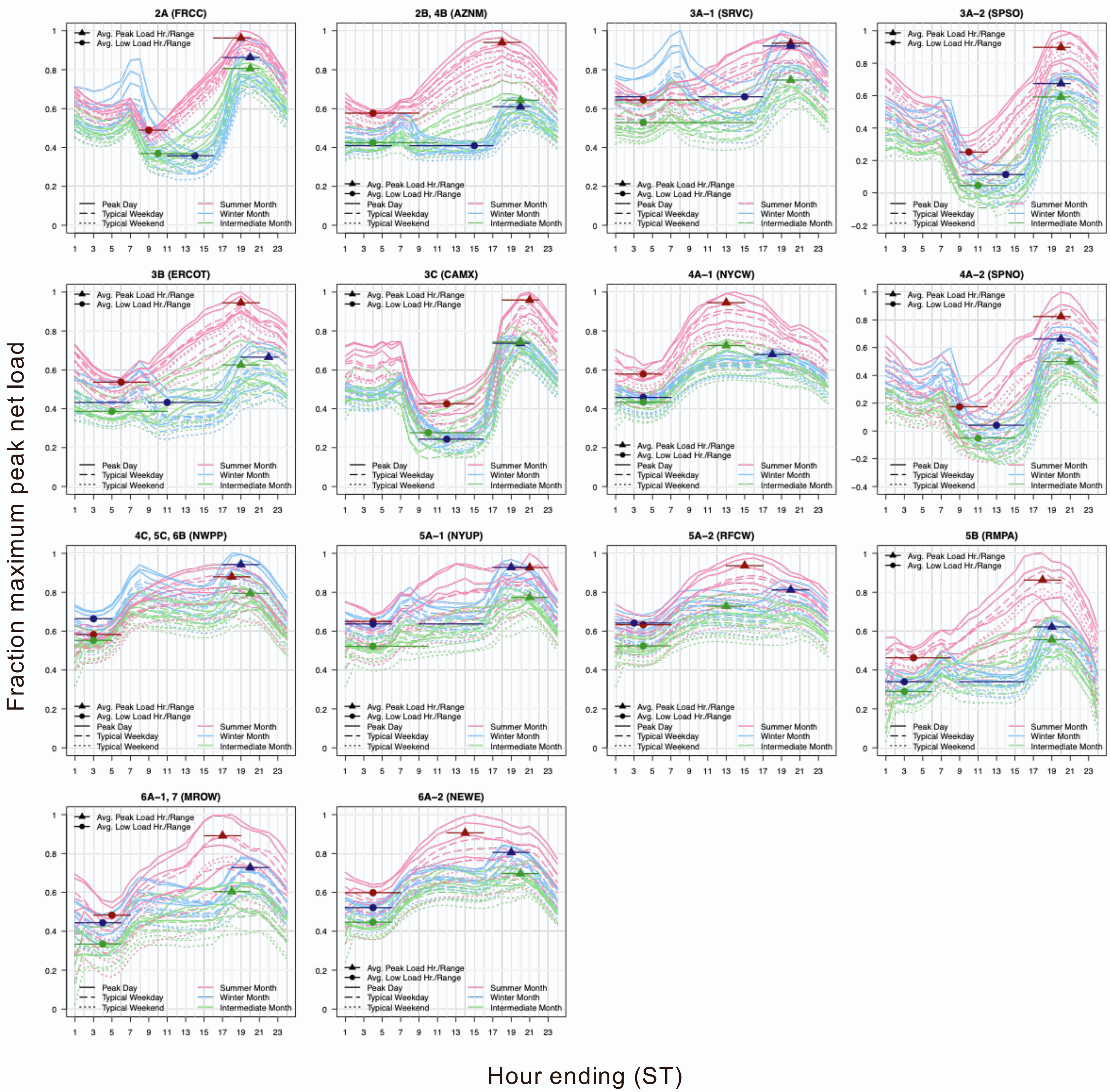

Figure S11: Peak-normalized total system loads net variable renewable energy generation for 14 representative EMM grid regions. Representative load shapes dictate peak and off-peak hours that building-level operations in a given ASHRAE climate zone are assessed against; the climate zone-to-representative-EMM region mapping is indicated by the plot titles. Each line on the plots represents the total system load shape for that region's net renewable 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 4 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 10 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 EMM modeling for the 2019 Annual Energy Outlook (AEO), 2050.[5]

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 S11). 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 4–8 PM LST peak and 10 AM–2 PM LST off-peak period assumption across regions. We focus on these two measures because (1) they are among the most impactful in the residential and commercial measure sets (see Figures 7 and S10); (2) they pertain to thermal end uses, which are most variable across different hours of the day; and (3) they 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 S11). When using the generic peak definition, we assume that each of the DF measures increases or decreases the thermostat setpoint during the peak period (4–8PM) and preheats or precools in the 4 hours preceding the peak period (12–4PM), as is assumed for the regionally adjusted peak and off-peak case.

Figure S12 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); 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 midday 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 midday 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 midday 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 spatio-temporal distribution of the building-grid resource. Even the relatively dramatic increase in summer load building potential from preconditioning and precooling DF under the midday 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 S12, 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.

2.2 Representative building load shapes

Figure S13 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 S13 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 7 and S10. Each of the five dimensions that dictates these representative load shape simulations is further described here.

- *Measure scenario.* 8 measure scenarios are considered: baseline residential and commercial cases in which no measures are implemented, as well as the three residential and three commercial measure set deployments summarized in Table 1 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 and 82% of electricity use[6], and were therefore 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

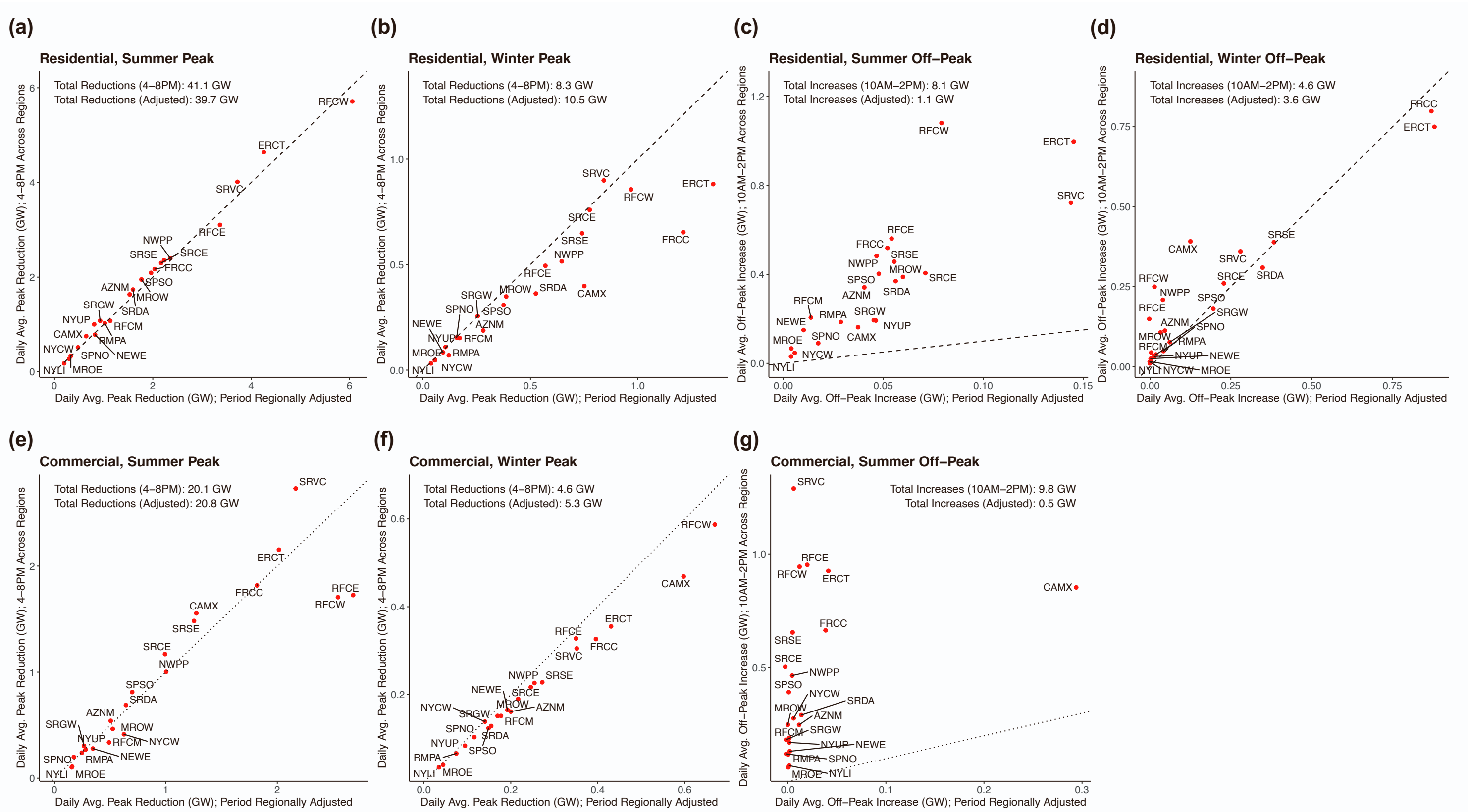

Figure S12: Residential preconditioning and commercial precooling DR impacts in 2030 under fixed vs. regionally adjusted peak and off-peak periods. Residential preconditioning DR summer and winter peak demand reductions (a–b) and off-peak demand increases (c–d) are shown alongside commercial precooling DR summer and winter peak reductions (e–f) and summer off-peak increases (g) in 2030. The DR measures shed cooling and heating demand during the 4-hour peak period and precool or preheat (residential only) in the 4 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 (x axis) that were used to generate the main results (see Supplemental Figure S11), 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 variable 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.

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. Note that clothes drying/washing, dishwashing, and pool heaters/pumps are lumped into the "Other" end use for the purposes of the figures in this paper.

- *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 loads (cooling, ventilation, and heating) are broken out by climate zone, as is further described in Section 2.2.1.

- *Electricity system.* 14 unique utility system (EIA EMM region) conditions are considered, as described in Supplemental Information section 2.1 and summarized in Table S3 and Figure S11. Figure S13 shows that certain EMM regions are used to represent the utility system conditions of multiple ASHRAE climate zones (AZNM, NWPP, and MROW).

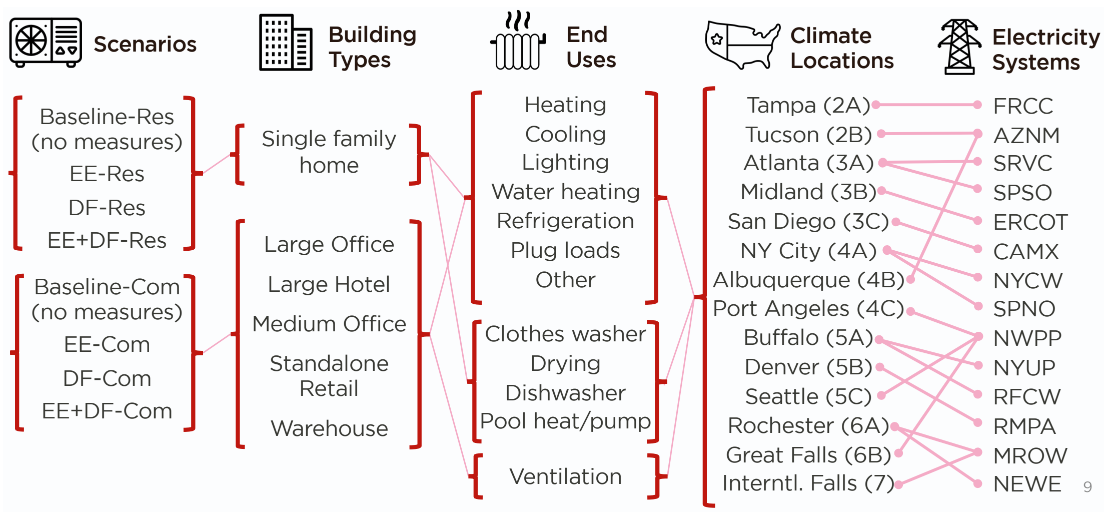

Figure S13: Simulated building end-use load shape dimensions. Variations across five analysis dimensions are captured. Measure scenarios encompass a baseline case where no measures are implemented as well as deployment of the three residential and commercial measure sets outlined in Table 1. Building 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 utility system conditions (e.g., system peak and off-peak periods) based on normalized net load shapes from up to two representative EIA 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 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 data set[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 United States. 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 S14 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 S15 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, whereas 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 S15 shows the results of a K-means cluster analysis that was conducted on the normalized cooling load shapes from Figure S15 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 S4 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 S15 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 Commercial 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 Satre-Meloy et al.[13]

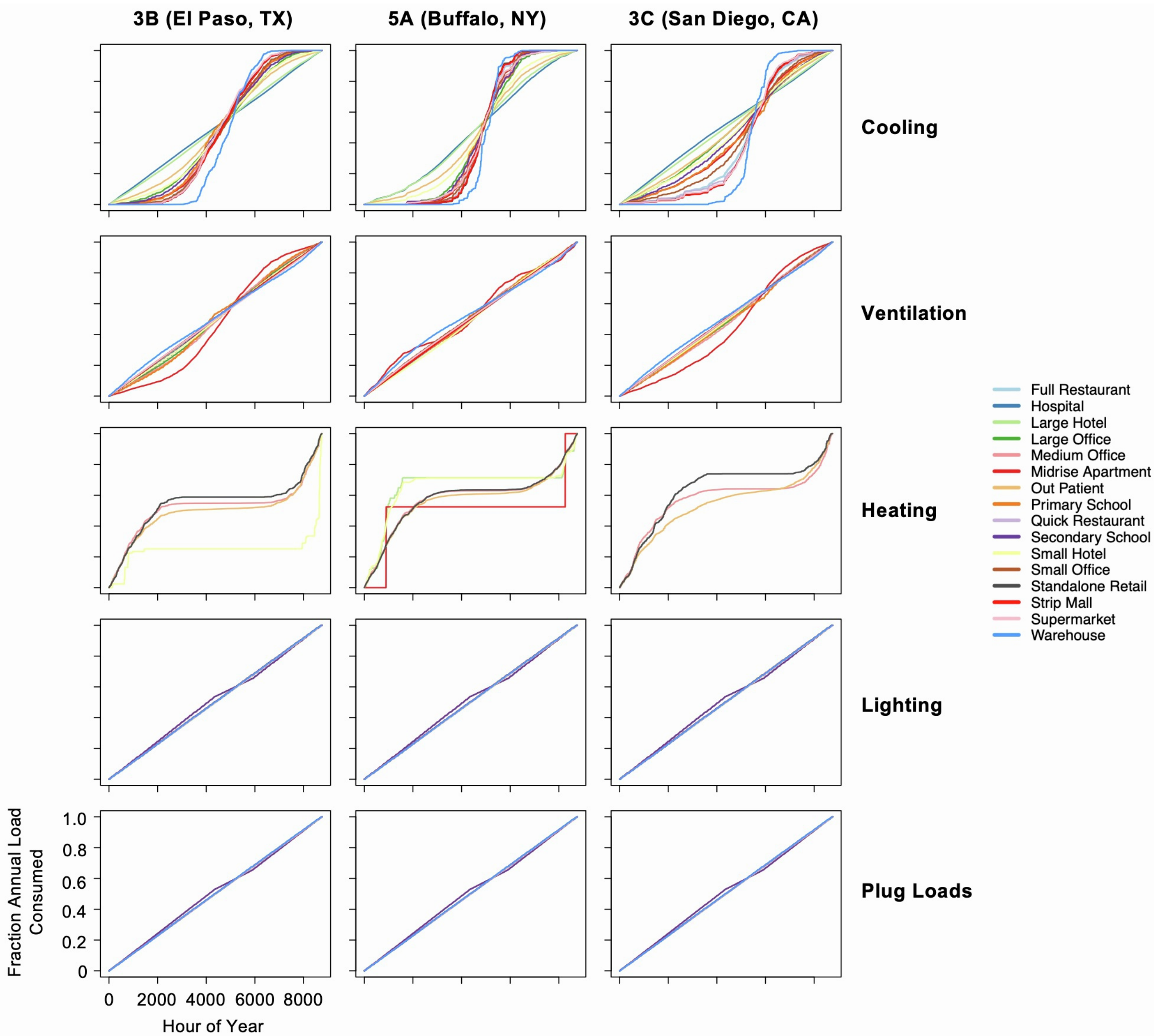

Figure S14: Cumulative hourly end-use load profiles for the DOE Commercial Reference Buildings. Each profile in the figure represents the cumulative fraction of annual load consumed (y axis) by a given hour of the year (x axis). All data for the profiles are drawn from [10]. Hourly cooling load profiles range from being highly concentrated in the summer months (e.g., hours 4,000–6,000 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.

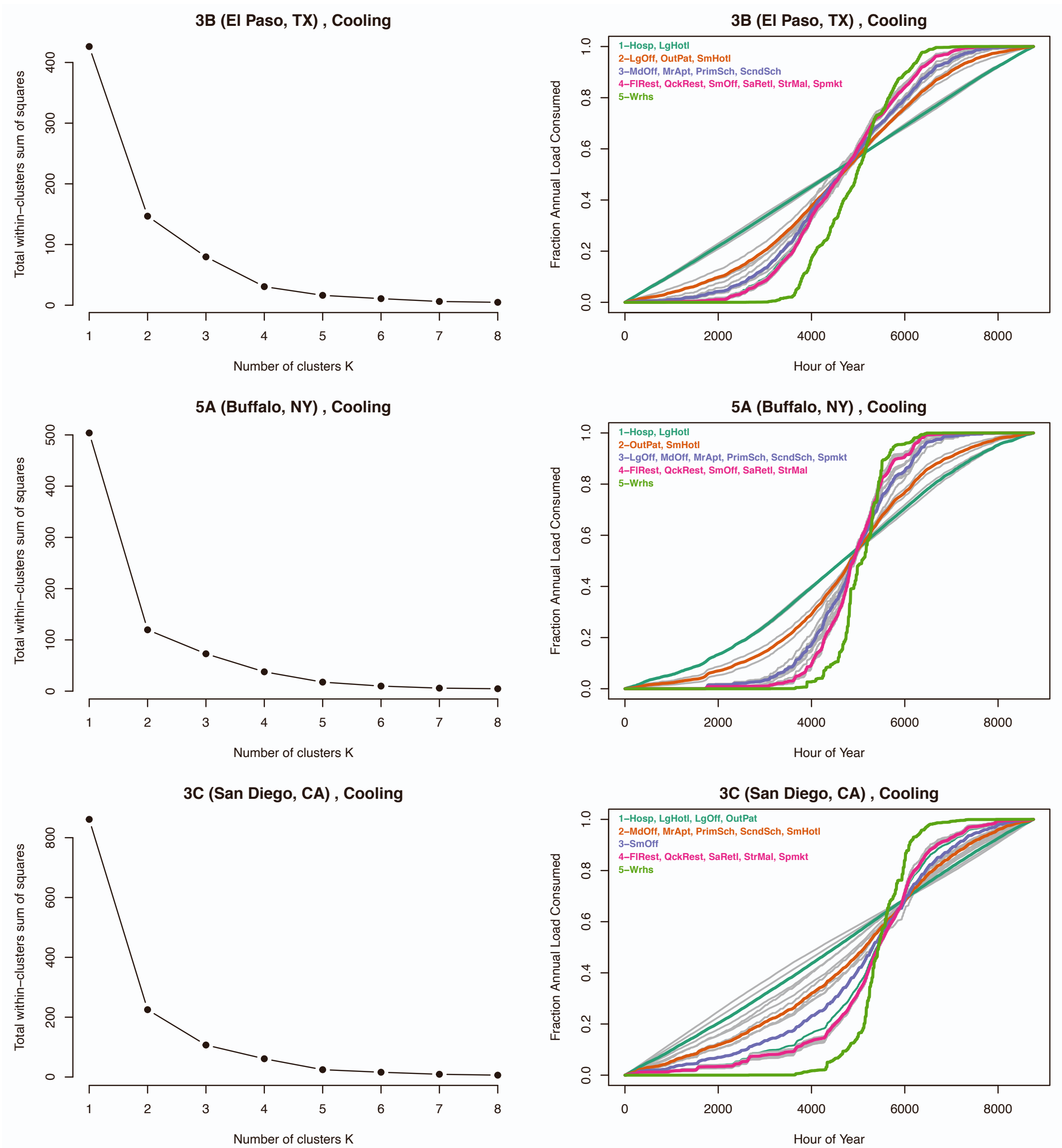

Figure S15: Results from K-Means cluster analysis on DOE Commercial Reference Building cooling end-use profiles. Elbow plots (left) show that little information is gained by organizing building types and load profiles into more than five groups; overlaying the resultant cooling profiles for the five groups on the original cooling plots from Figure S14 (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 S4: 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 Region and building type mapping factors for Scout simulations

Tables S5 and S6 report mapping percentages that are used to translate EIA Annual Energy Outlook (AEO) projections of annual building sector energy use (resolved by Census Divisions) to an EIA EMM region resolution.

Tables S7 and S8 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 EMM region and 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].

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

Table S5: Percentage of residential building electricity sales in each of the nine U.S. Census Divisions (columns) that falls in each of the 22 2019 EIA EMM regions (rows). Sales data are based on 2016 EIA surveys and are consistent with those used by EIA to map across regional definitions in the 2019 AEO; the data were obtained from EIA on request. Shown is the percentage of a given Census Division's residential electricity use that falls into a given EMM region (note that the numbers for Census Division 9 do not sum to 100 due to the exclusion of Alaska and Hawaii in the EMM regions).

		Census Division								
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
EMM Region	**1**	-	-	-	-	-	-	59	-	-
	2	-	-	-	-	32	-	-	-	-
	3	-	-	5	-	-	-	-	-	-
	4	-	-	3	52	-	-	-	-	-
	5	100	-	-	-	-	-	-	-	-
	6	-	9	-	-	-	-	-	-	-
	7	-	6	-	-	-	-	-	-	-
	8	-	23	-	-	-	-	-	-	-
	9	-	51	-	-	9	-	-	-	-
	10	-	-	17	-	-	-	-	-	-
	11	-	10	66	-	6	3	-	-	-
	12	-	-	-	-	-	7	20	-	-
	13	-	-	9	24	-	-	-	-	-
	14	-	-	-	-	17	25	-	-	-
	15	-	-	-	-	1	65	-	-	-
	16	-	-	-	-	34	-	-	-	-
	17	-	-	-	21	-	-	-	-	-
	18	-	-	-	1	-	-	20	1	-
	19	-	-	-	-	-	-	1	50	1
	20	-	-	-	-	-	-	-	-	59
	21	-	-	-	-	-	-	-	28	37
	22	-	-	-	1	-	-	-	21	-

Table S6: Percentage of commercial building electricity sales in each of the nine U.S. Census Divisions (columns) that falls in each of the 22 2019 EIA EMM regions (rows). Sales data are based on 2016 EIA surveys and are consistent with those used by EIA to map across regional definitions in the 2019 AEO; the data were obtained from EIA on request. Shown is the percentage of a given Census Division's commercial electricity use that falls into a given EMM region (note that the numbers for Census Division 9 do not sum to 100 due to the exclusion of Alaska and Hawaii in the EMM regions).

		Census Division								
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
EMM Region	**1**	-	-	-	-	-	-	62	-	-
	2	-	-	-	-	29	-	-	-	-
	3	-	-	6	-	-	-	-	-	-
	4	-	-	2	53	-	-	-	-	-
	5	100	-	-	-	-	-	-	-	-
	6	-	24	-	-	-	-	-	-	-
	7	-	6	-	-	-	-	-	-	-
	8	-	18	-	-	-	-	-	-	-
	9	-	43	-	-	13	-	-	-	-
	10	-	-	20	-	-	-	-	-	-
	11	-	8	63	-	5	3	-	-	-
	12	-	-	-	-	-	9	16	-	-
	13	-	-	9	19	-	-	-	-	-
	14	-	-	-	-	16	20	-	-	-
	15	-	-	-	-	-	67	-	-	-
	16	-	-	-	-	36	-	-	-	-
	17	-	-	-	25	-	-	-	-	-
	18	-	-	-	2	-	-	21	2	-
	19	-	-	-	-	-	-	2	44	1
	20	-	-	-	-	-	-	-	-	68
	21	-	-	-	-	-	-	-	29	27
	22	-	-	-	1	-	-	-	24	-

Table S7: Mapping between ASHRAE 90.1-2016 regions (used for the building-level EnergyPlus simulations) and EIA 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 that 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 S8: Mapping between EnergyPlus building types (used for the building-level EnergyPlus simulations) and EIA 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 multifamily home	ResStock Single-Family Home	100
assembly	Hospital	100
education	Primary School Secondary School	26 74
food sales	Supermarket	100
food service	QuickServiceRestaurant FullServiceRestaurant	31 69
health care	Hospital	100
lodging	SmallHotel LargeHotel	26 74
large office	LargeOfficeDetailed MediumOfficeDetailed	90 10
small office	SmallOffice OutpatientHealthcare	12 88
mercantile/service	RetailStandalone RetailStripmall	53 47
warehouse	Warehouse	100
other	MediumOfficeDetailed	100

Lighting

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

Pool Pumps

- Pool Pumps: 0.75 hp pump (annual energy use = 1,688 kWh)
  Applied To: Homes with 1.0 hp pool pumps (annual energy use = 2,250 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[17] are further described below and shown in Figure S16.

- 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[18]
- 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[18]
- 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[18]
- 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[18]

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:

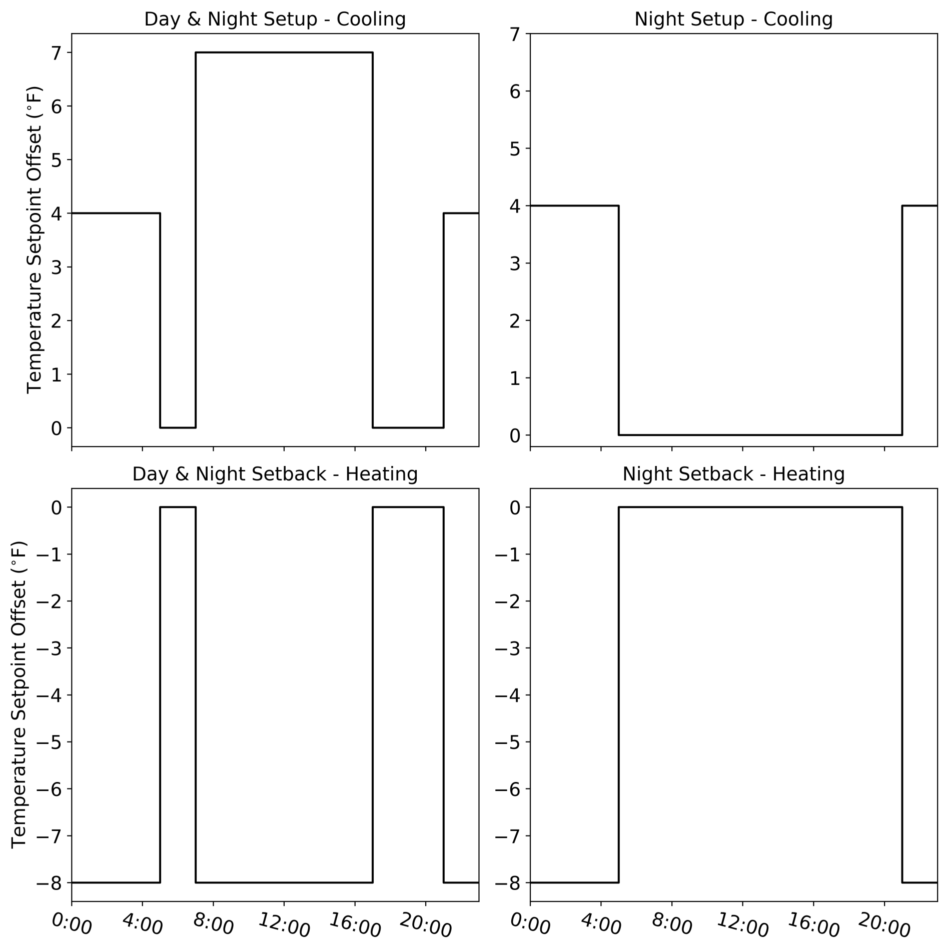

Figure S16: Example thermostat setback and setup schedules for residential cooling and heating. The "Day and Night Setback" schedules apply to homes that are unoccupied during the daytime, while the "Night Setback" schedules apply to homes occupied during the day.

- R-13 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)
- 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 preheated 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 S17. DR schedules are designed for peak and take hours and seasons specific to each EMM region. If an EMM region has two take periods, preheating begins at

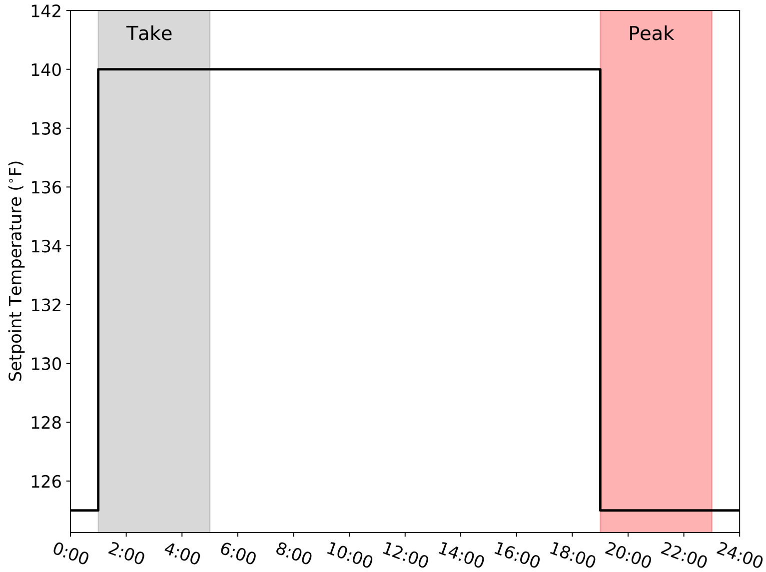

Figure S17: Example preheating schedule for residential water heating.

the start of the second take period. Schedule inputs are in the form of hourly schedules for an entire year (i.e., 8,760 schedules).
Applied To: All electric water heaters

Notes: 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 preheating 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 S18

Cooling:

- 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[18]); 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[18]); 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[18]); 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[18]); applied regardless of daytime occupancy

<u>Example Logic</u>: 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.
<u>Notes</u>: 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, preheating setpoint adjustment: 2°–3°F
- Precooling, preheating 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[19], ecobee Smart Savings Rewards (e.g., NYSEG and RG&E)[20], Broad River Electric Co-op's smart thermostat program[21], and the Arizona Public Service Cool Rewards program[22].

Appliances
Appliances considered for demand flexibility include clothes washers, clothes dryers, and dishwashers, which follow the Building America house simulation protocols for schedule generation[23]. 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

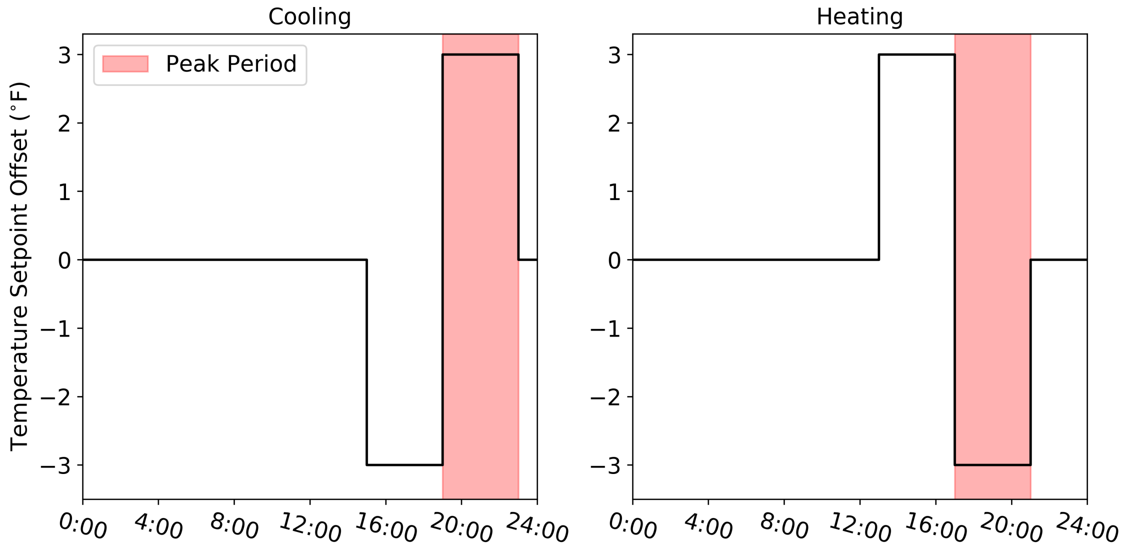

Figure S18: Example residential precooling and preheating schedules.

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[24]. 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.

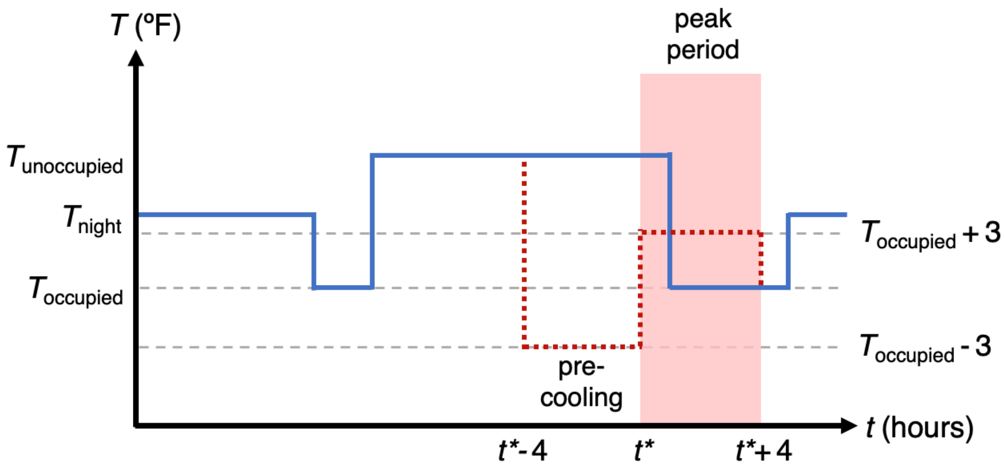

Figure S19: Example residential combined EE and DF thermostat setpoint schedule. The DF schedule (precooling) is applied when there is overlap with the EE setpoint offset schedule.

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 S19 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 S9 and fenestration for each climate zone as described in Table S14[25]. 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 S11); the Retail Stand-Alone prototype follows AEDG 50% for medium to big-box retail (see Table S10)[26], and the Large Hotel prototype follows AEDG 50% for highway lodging (see Table S12)[27].

Lighting

Lighting efficiency measures follow AEDG guidelines using the same building type mapping as presented for the envelope efficiency measure; performance specifications are indicated by lighting power density (LPD), with details given in Tables S16-S19. The lighting LPD is reduced by

Table S9: Envelope for the Advanced Case in Office Buildings (Reference: AEDG 50%, Medium Office).

Climate Zone	Roof		Above-Grade Steel-Framed Walls	
	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 S10: Envelope for the Advanced Case in Retail Building (Reference: AEDG 50% Big Box Retail).

Climate Zone	Steel-Framed Exterior Wall		Mass Exterior Wall		Roof	
	U-Factor	R-value	U-Factor	R-value	U-Factor	R-value
1	U-0.064	R-13.0 + R-7.5 c.i.	U-0.580	-	U-0.048	R-20.0 c.i.
2	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	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	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	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	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.

Table S11: Envelope for the Advanced Case in Warehouse (Reference: AEDG 30% for Small Warehouse and Self-Storage Buildings).

Climate Zone	Roof	Exterior Walls	Interior Walls
	R-value	R-value	R-value
1	R-15 c.i.	-	R-13
2	R-20 c.i.	R-5.7 c.i.	R-13
3	R-20 c.i.	R-7.6 c.i.	R-13
4	R-20 c.i.	R-9.5 c.i.	R-13
5	R-20 c.i.	R-11.4 c.i.	R-13
6	R-20 c.i.	R-13.3 c.i.	R-13
7	R-20 c.i.	R-15.2 c.i.	R-13
8	R-30 c.i.	R-15.2 c.i.	R-13

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 S16[25].

Table S12: Envelope for the Advanced Case in Large Hotel (Reference: AEDG 50%, Highway Lodging).

Climate Zone	Roof		Above-Grade Mass Walls		Floor	
	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	-
2	0.039	R-25 c.i.	0.123	R-7.6 c.i.	0.73	-
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 S13: Fenestration U-Factor and SHGC values for the Advanced Case in Large Hotel.

Climate Zone	Target		Modeled	
	U-Factor	SHGC	U-Factor	SHGC
1	0.56	0.25	0.51	0.28
2	0.45	0.25	0.44	0.24
3	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

Table S14: Fenestration U-Factor and SHGC values for the Advanced Case in Office Buildings.

Climate Zone	Target		Modeled	
	U-Factor	SHGC	U-Factor	SHGC
1	0.65	0.25	0.51	0.28
2	0.65	0.25	0.51	0.28
3	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

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 S16-S19. Note: for data center spaces in the Large Office Detailed building type, the EPD is reduced by 30%, suggested to be feasible

Table S15: Fenestration U-Factor and SHGC values for the Advanced Case in Retail Buildings.

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

by previous DOE reports[28,29]. The schedules for plug loads are consistent with the advanced case assumption in Table S16, representing plug loads controls[30].

Table S16: 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
Restroom	0.07	0.82
Stair	0	0.6
Storage	0	0.64
Vending	3.85	0.73

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[30].

Table S17: 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	-	0.52
Meeting room	0.57	1.14
Exercise room	1.53	0.78
Storage	-	0.62
Employee lounge	1.95	0.82
Restroom	0	0.74
Mechanical room	-	1.24

Table S18: 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 S19: 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	0.85
Zone 3 - bulk storage	0.6

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[31] 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[32] and summarized in the Scout baseline technology characteristics data[33] (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[34] 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[35] (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[36]. 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 setpoints. 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 to 80°F based on ASHRAE Standard 55-2017, calculated using the Berkeley Center for the Built Environment (CBE) Thermal Comfort Tool[37].
  - 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, setpoint temperature increases from 75°F to 80°F (GTA) during the peak period, and decreases from 75°F to 73°F (precooling) for the 4 hours preceding the peak period.

- Winter adjustment
  - Comfort range of 68°F to 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, setpoint temperature decreases from 70°F to 68°F (GTA) during the peak period. No preheating 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 [38] 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 [39,40]. 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 S20 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 S11, 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 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 midday to early afternoon hours for these locations.

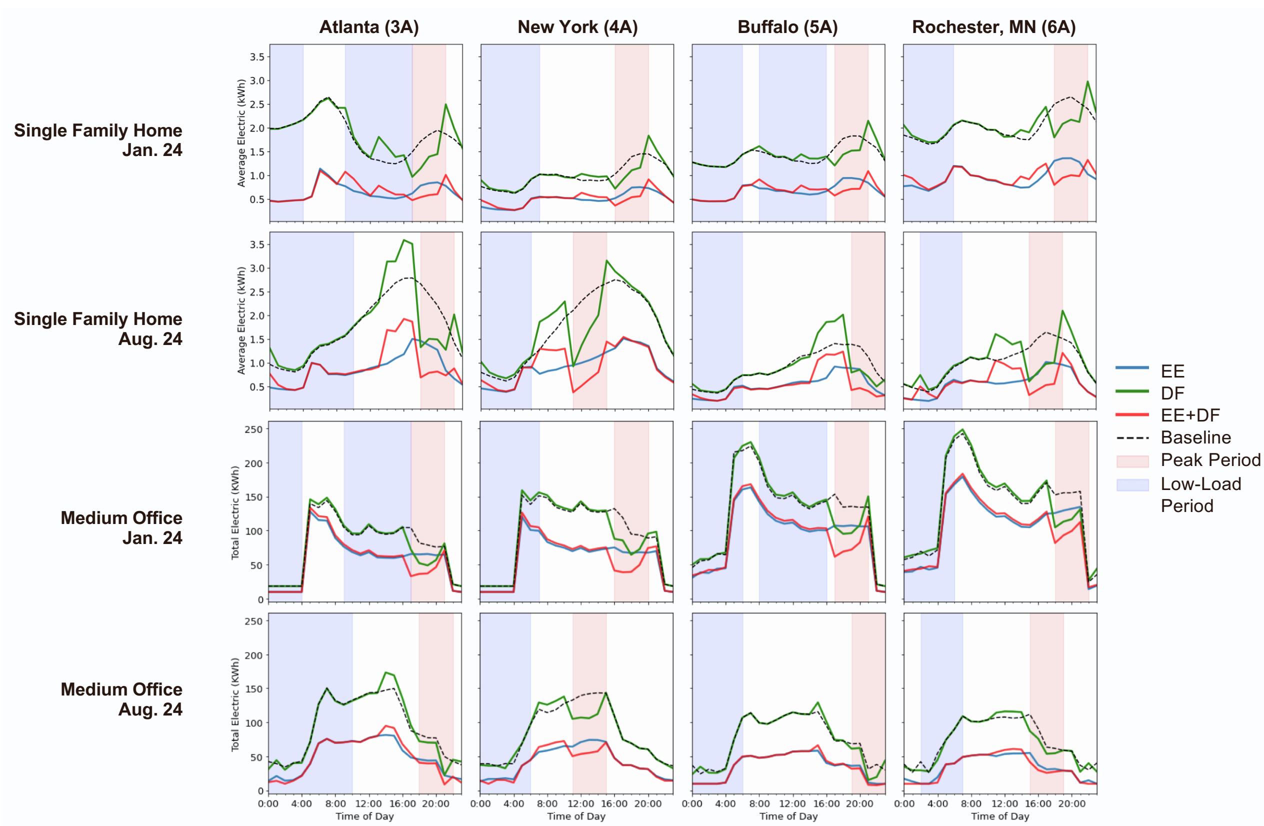

Figure S20: Building-level load profiles for a range of building types, locations, and measure sets. The profiles show strong on-peak load impacts from combined building efficiency and flexibility measures (EE+DF), as well as off-peak load increases from flexibility measures (DF) that often fail to coincide with off-peak periods for the utility system. In the warmest climate shown (Atlanta-3A), a net system peak window occurs later in the day when the baseline load shape for 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.

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