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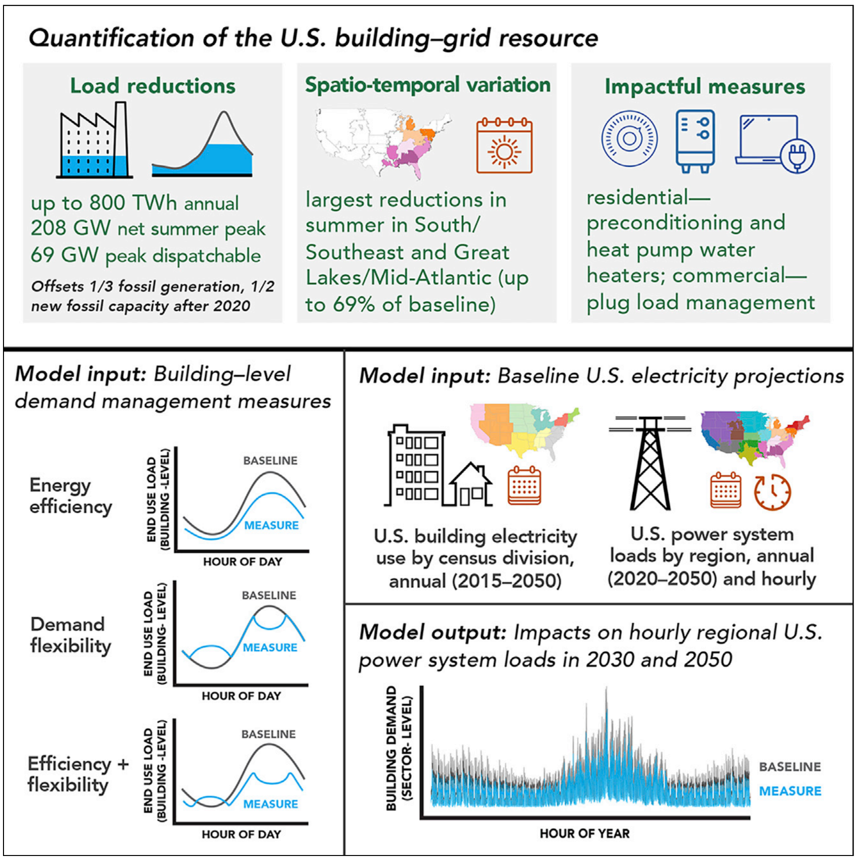
US building energy efficiency and flexibility as an electric grid resource



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

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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.

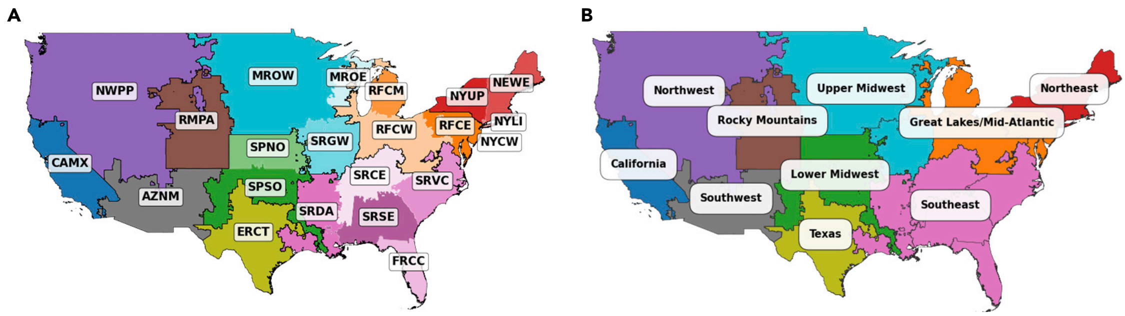

Figure 1. Regional boundaries used to generate and aggregate results
(A) Scout measure impacts are assessed within each of the 22 2019 US EIA EMM regions.
(B) Outputs can be aggregated into the 10 2019 US EPA AVERT regions.

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

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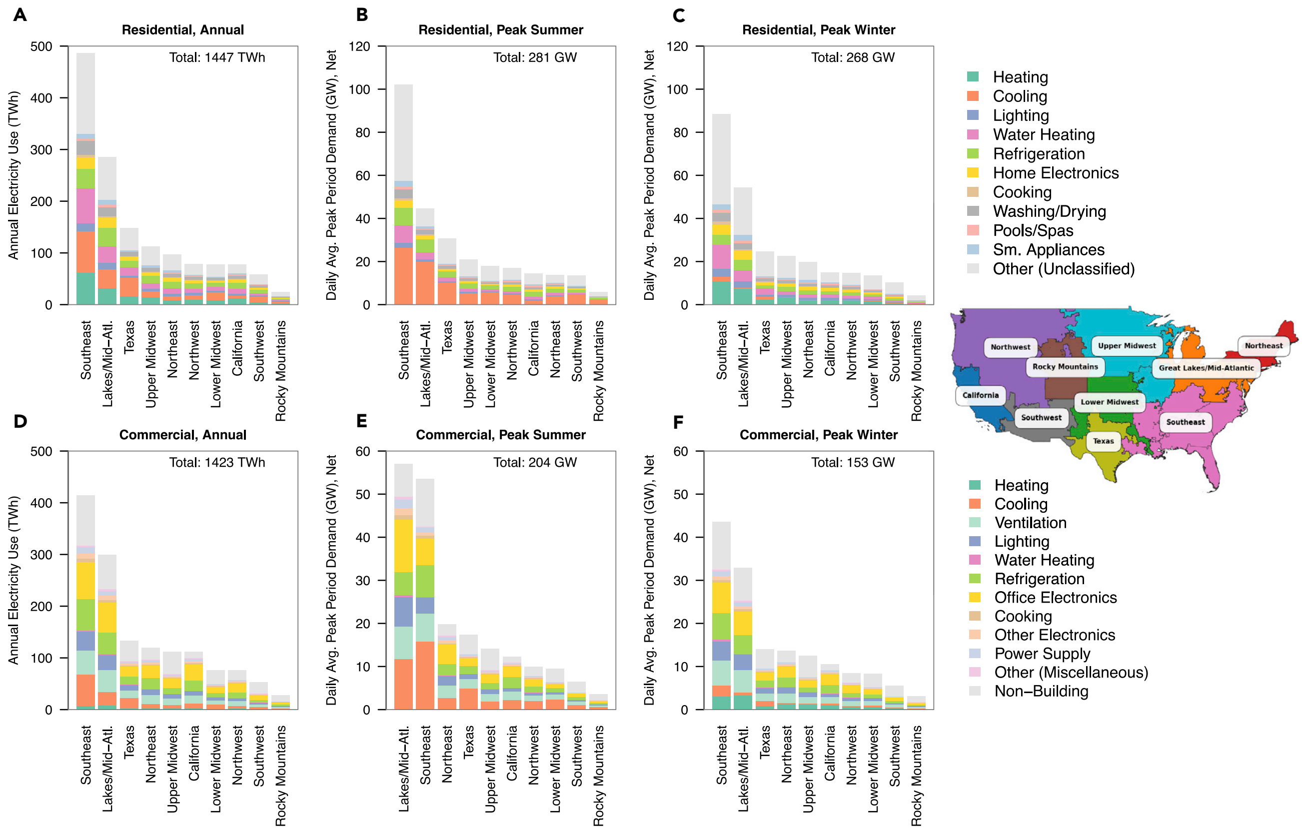

Figure 2. Baseline annual electricity use and net peak demand from US buildings in 2030

(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

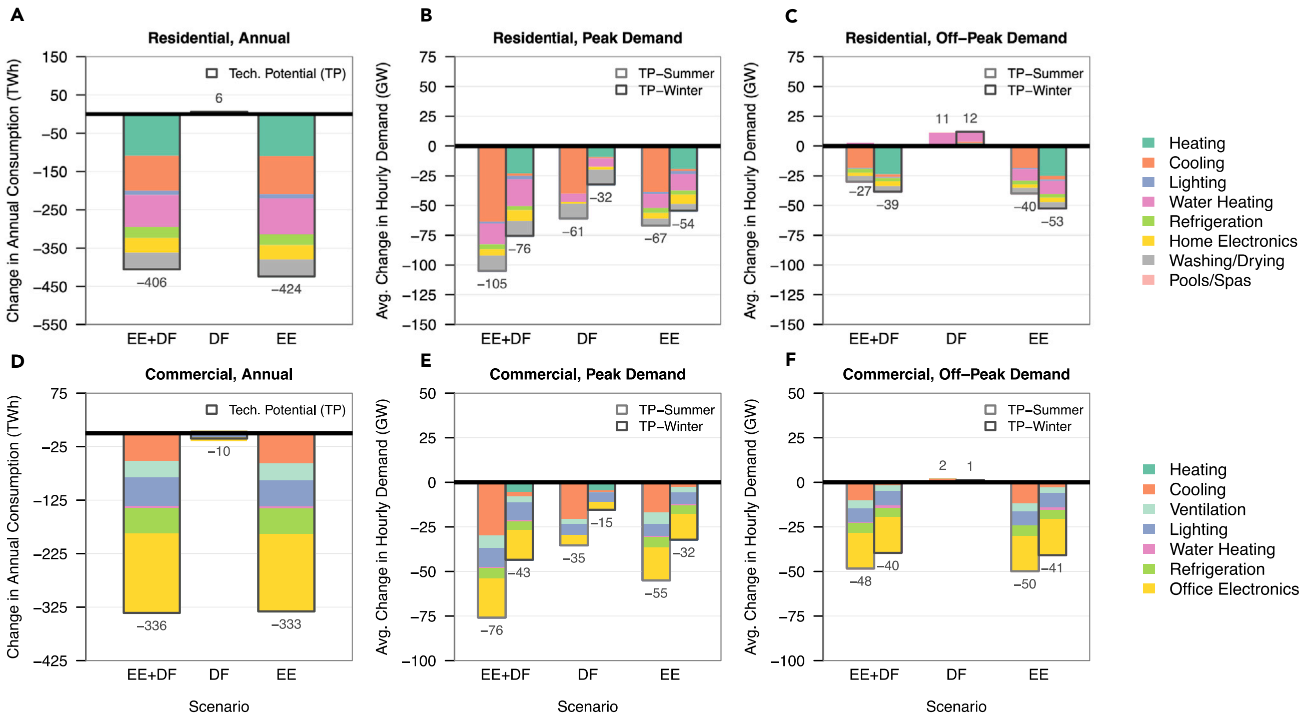

Figure 3. National impacts of best available building efficiency and flexibility measure sets on US annual electricity use and net peak and off-peak demand in 2030

(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

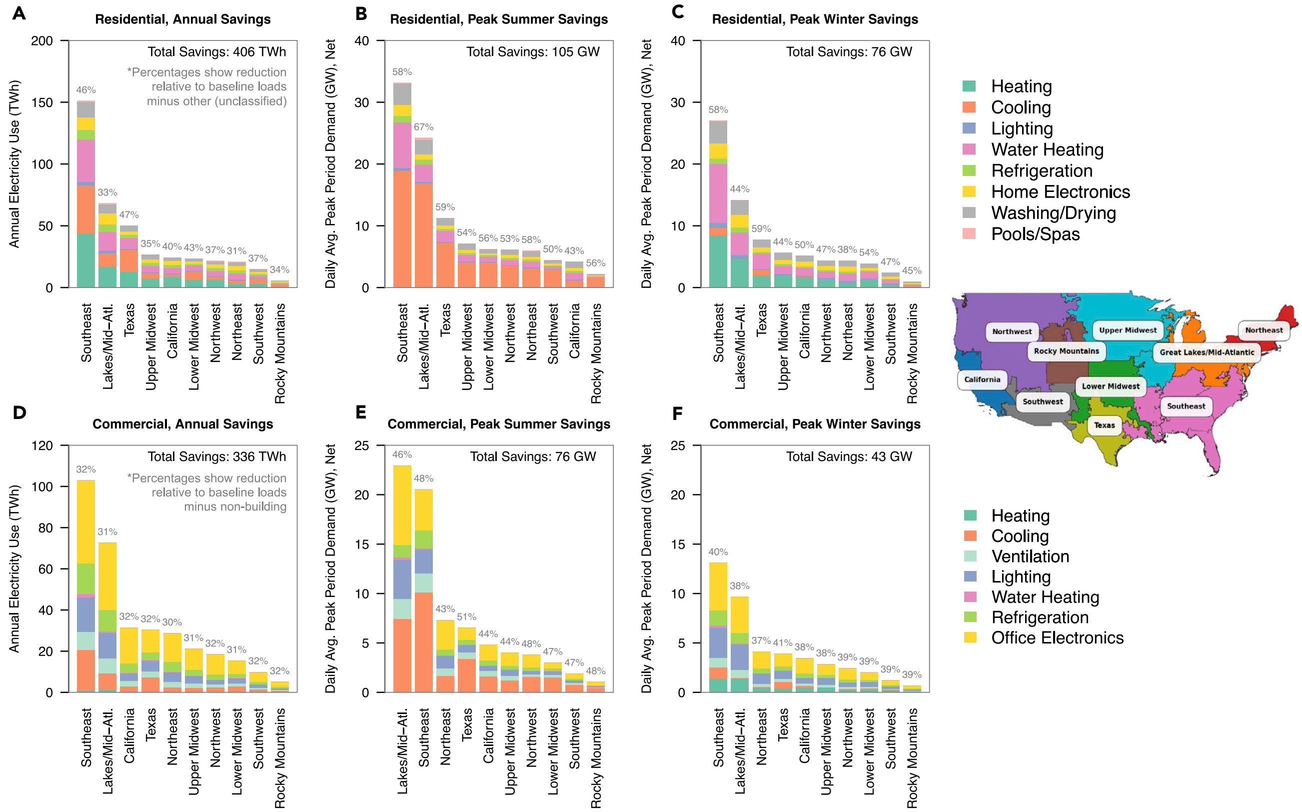

Figure 4. Regional impacts of best available US building efficiency and flexibility measures together on annual electricity use and net peak demand in 2030

(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

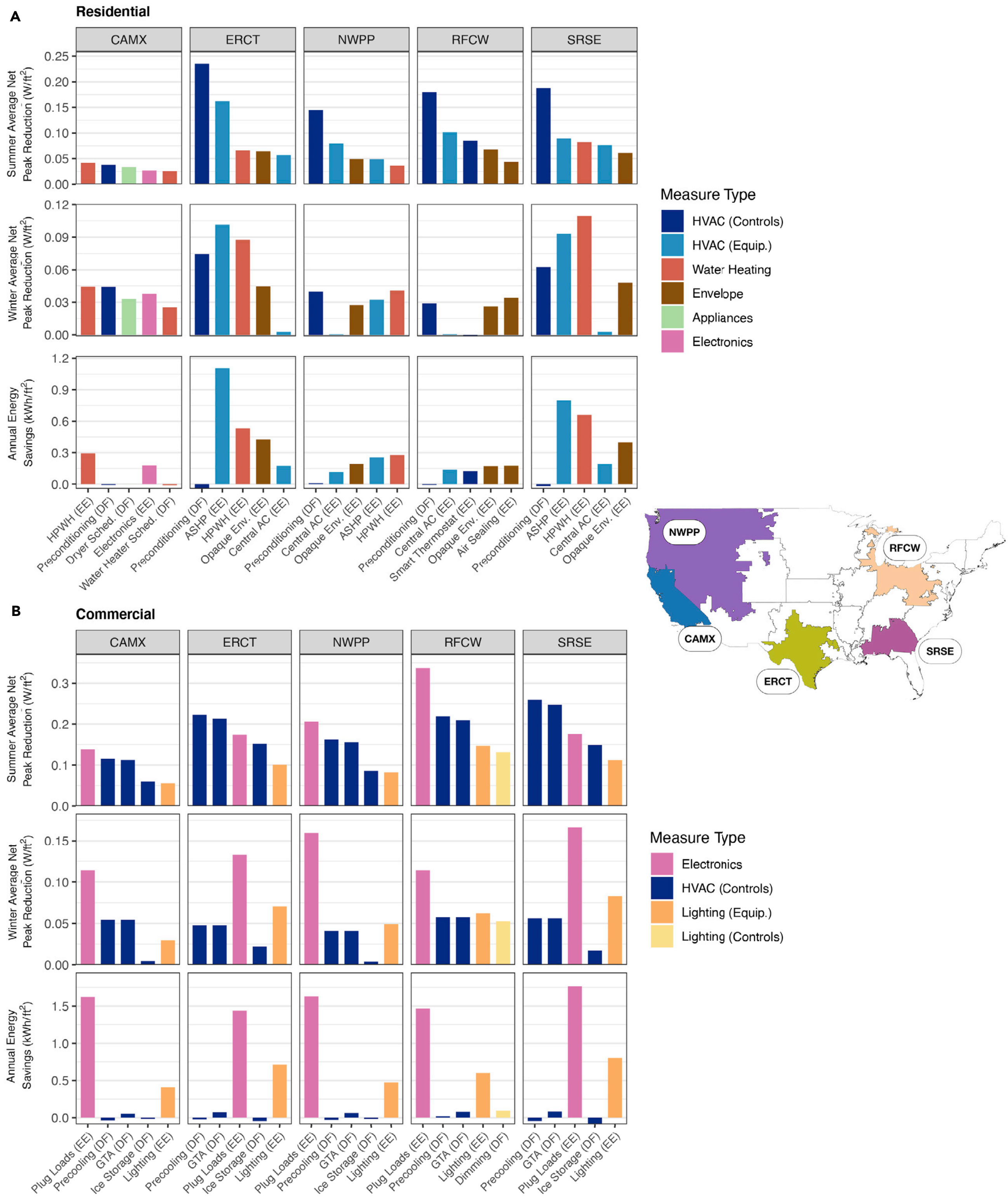

Figure 6. Individual efficiency and flexibility measures with the largest summer net peak demand intensity reductions for five US grid regions in 2030

(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), $l^{\mathrm{net}}_{r,y,m,d,hd}$:

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

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

where $L^{\text{net}}_{r,y,m,d,hd}$ is the net system load, $\max_{1 \le m \le 12} L^{\text{net}}_{r,y,m,d,hd}$ 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 $L^{\text{rgen}}_{r,y,m,d,hd}$ from total system load, $L^{\text{tot}}_{r,y,m,d,hd}$.

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), $\bar{l}^{\text{net}}_{r,s,hd}$:

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

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), $h^{\text{pk}}_{r,s}$ and $h^{\text{opk}}_{r,s}$:

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

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

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

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

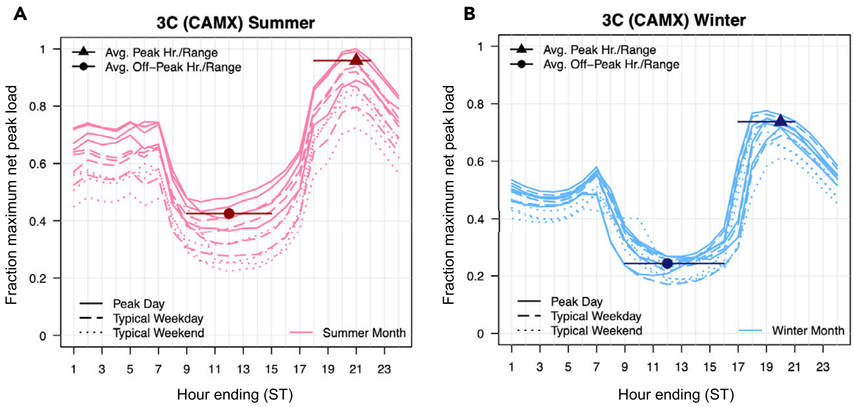

Figure 7. Peak-normalized total system loads net variable renewable energy generation for the California (CAMX) grid region

(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 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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