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Is every kWh the same? How do energy efficiency measures stack up across regions?

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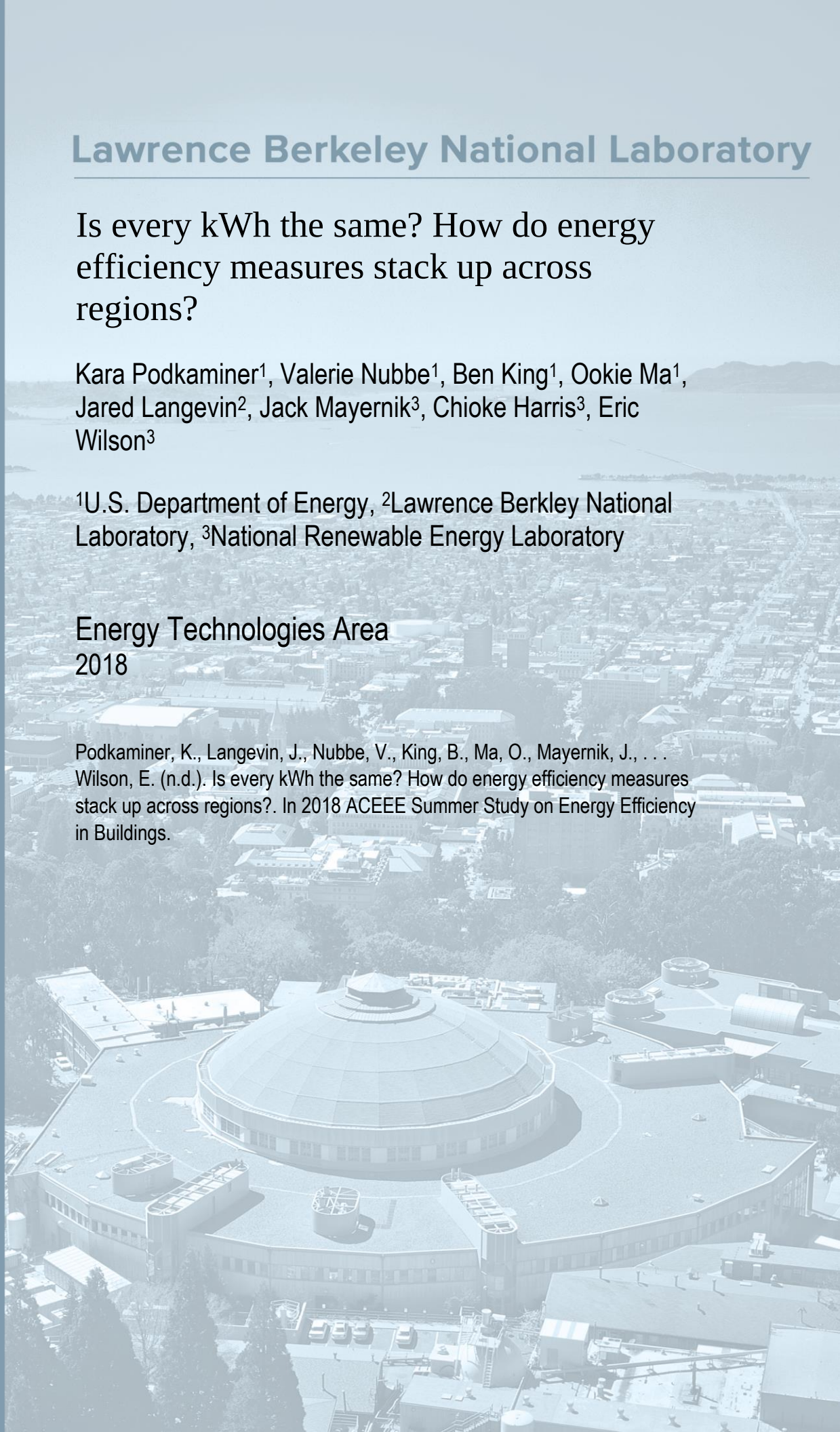

Is every kWh the same? How do energy efficiency measures stack up across regions?

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ABSTRACT

The U.S. residential building sector is responsible for thirty-eight percent of electricity use, as well as for 49%, 8%, 19% and 2% of U.S. SO_2, NO_x, CO_2 and $PM_{2.5}$ emissions, respectively. The residential building sector is also a key target of customer funded energy efficiency programs, which have typically been designed to reduce energy consumption (kWh). Today, energy efficiency is also being used to meet air emissions goals. However, not every kWh saved has the same mitigation potential. The goal of this work is to evaluate energy efficiency potential in the U.S. residential building sector and determine how energy conservation measures (ECMs) that reduce electricity consumption correlate to air emissions reductions. To assess energy efficiency potential, this analysis uses Scout, a software program developed by the U.S. Department of Energy that estimates the energy and CO_2 impact potential of various ECMs on the U.S. residential and commercial building sectors. Here, Scout is first used to assess the total long term national energy (electricity, gas, and oil), CO_2, and cost savings of deploying residential ECM portfolios. Then, electricity savings results from Scout in 2021 are used to assess the regional differences in emissions reductions with the AVoided Emissions and geneRation Tool (AVERT) model from different end uses. Better understanding the relationship between ECMs and cost-effective emission reductions will enable states, municipalities and other interested parties to meet multiple policy objectives through energy efficiency.

Introduction

The U.S. residential building sector is responsible for thirty-eight percent of electricity use and 19% of CO_2 (EIA), as well as 49%, 8% and 2% respectively of U.S. SO_2, NO_x, and $PM_{2.5}$ emission (EPAa). The residential sector is also a primary target of customer-funded energy efficiency programs. In the past, residential energy efficiency programs were established to reduce energy use and peak demand in an effort to support the reliability of the power system, mitigate environmental impacts and reduce costs. Today, such efficiency programs are also increasingly being used by states and localities as a means to achieve carbon reduction and air quality targets (ACEEE Local Government Energy Efficiency Goals; EPA, 2009). However, each MWh saved may not result in the same emissions reduction; thus, states have an incentive to prioritize energy conservation measures (ECMs) that align with emissions reductions to help achieve multiple benefits with a single intervention.

Efficiency program performance has traditionally been measured primarily by electricity (MWh) saved. On a grid powered by fossil fuels, MWh savings also generally result in a reduction in criteria pollutant and greenhouse gas emissions. However, with a changing grid and

the rapid deployment of emission-free power, the historically observed correlations between MWhs saved and emissions reductions may no longer hold.

The goal of this work is to assess the national energy, CO_2, and cost impact potential of a series of residential energy conservation measures (ECMs) spanning multiple energy performance levels, and to examine the alignment of end-use electricity savings from these ECMs with regional emissions reductions. National energy CO_2, and energy cost savings are first estimated using the U.S. Department of Energy's Scout modeling program (BTO 2018); restricting the application of these ECMs to electric segments of baseline energy use, we then evaluate the regional displaced emissions over a near-term time horizon using the EPA's AVoided Emissions and geneRation Tool (AVERT) model (EPAb). Assessing the relationship between emission reductions and electricity savings across end uses can help determine which measures may have common benefits across regions and which are only beneficial for specific regions and their goals.

Methods

Estimating the national energy, CO_2, and cost impacts of building efficiency measures

The potential impacts of residential building efficiency portfolios on national energy use, air emissions, and operating costs are estimated using Scout, a software program developed by the U.S. Department of Energy's Building Technologies Office (BTO). The Scout framework allows a bottom-up exploration of the long-term impacts of one or more energy conservation measures (ECMs) on U.S. residential and commercial building energy use. Scout ECMs are characterized by their energy efficiency, installed cost, lifetime, and applicable baseline market. The energy reduction potential of an ECM m is calculated as:

$$\Delta E(y) = E_b(y) f_m(y) f_e(y) + E_b(y) \sum_{k=1}^{y-1} f_m(k) f_e(k) \qquad (1)$$

Where $\Delta E(y)$ is the total primary energy savings for the ECM in simulation year y; $E_b(y)$ is the total baseline energy use segment to which the ECM applies in year y; $f_m(y)$ is the fraction of the total baseline market that the ECM competes for and captures in year y; $f_e(y)$ is the fraction of energy use that the ECM saves at the unit level relative to a comparable baseline technology in year y; and the right hand term represents energy savings from previous years.

The magnitude of an ECM's applicable baseline building energy use segment $E_b(y)$ is generally drawn from U.S. Energy Information Administration's Annual Energy Outlook (AEO) Reference Case projection for the years 2013–2050. Baseline AEO segments are defined by climate zone, building type, building vintage, fuel type, end use, and technology type. CO_2 emissions are calculated by applying national average CO_2 emissions intensities by fuel type to the baseline energy use segments; similarly, national fuel prices are applied to the baseline energy use segments to yield baseline energy costs.[1]

In Eq. 1, the baseline market share variable $f_m(y)$ is further defined as:

$$f_m(y) = f_{co}(y) f_{cp}(y) \qquad (2)$$

[1] CO_2 intensities are derived from AEO tables A2 and A18; fuel price data are taken from table A3 (EIA 2017a).

where $f_{co}(y)$ is the fraction of the applicable baseline stock that the ECM can compete for in year y and $f_{cp}(y)$ is the fraction of the competed stock that the ECM captures in year y. $f_{co}(y)$ is calculated under two adoption scenarios: 1) a *technical potential* case where all baseline stock turns over in each year of the simulation ($f_{co}(y) = 1$), and 2) a *maximum adoption potential* case where only a portion of the baseline stock turns over in each year:

$$f_{co}(y) = \lambda_n + \lambda_{rt} + \lambda_r \qquad (3)$$

where in Eq. 3 λ_n is the rate of new stock additions (determined by new construction rates in AEO), λ_{rt} is a user-specified annual technology retrofit rate,[2] and $\lambda_r$is the rate of existing equipment end-of-life replacement.

Finally, the ECM's captured stock fraction $f_{cp}(y)$ in Eq. 2 is calculated for residential sector ECMs using the market share calculation approach used in AEO (EIA 2017b):

$$f_{cp}(y) = f_{cp,m}(y) / \sum_{k=1}^{M} f_{cp,k}(y), \quad f_{cp,m}(y) = \exp\left(\beta_i C_i + \beta_{op} C_{op}\right) \qquad (4)$$

where M is the set of competing ECMs that ECM m belongs to, C_i is the ECM's incremental installed cost over a comparable baseline technology, C_{op} is the ECM's operating cost savings over the baseline, β_i and β_{op} are regression coefficients.

Given the calculations outlined in Eqs. 1-4, energy, CO_2, and cost outputs are yielded for four scenarios: 1) technical potential *without* ECM competition, 2) technical potential *with* ECM competition, 3) maximum adoption potential *without* ECM competition, and 4) maximum adoption potential *with* ECM competition. For simplicity, results for this paper will focus on scenario 4.

Scout ECM portfolio definitions

ECMs are building technologies or operational approaches that improve the efficiency and/or operational cost of a 'business-as-usual' technology. ECMs in this analysis include lighting, appliances, water heating, HVAC, envelope/windows, and sensor and control technologies. Given the calculation approach above, the energy, CO_2, and cost impacts of three Scout ECM portfolios are explored representing a wide range of technology performance scenarios, from today's cost effective and best performing technologies to future prospective technologies that BTO is looking to develop: 1) performance standards (ENERGY STAR, IECC 2018, ASHRAE 90.1 2016), 2) best available technologies on the market, and 3) prospective technologies that exceed the efficiencies of any building technologies on the market.[3] Each ECM can be tied to published cost, performance, and lifetime data from performance standards or policy planning documents (e.g., the BTO Multi-Year Program Plan).

High Performance Standards ECMs. This portfolio consists of residential building technologies that meet the minimum performance for ENERGY STAR in 2018 (EPA 2018); for the three technologies that did not have ENERGY STAR specifications (floors, walls, and oil-fired water heaters), ASHRAE 90.1 2016 and IECC 2018 standards were used instead (ASHRAE 2016, IECC 2018). The energy efficiency data for the ENERGY STAR ECMs were obtained

[2] Set to 1% in Scout by default.

[3] Download the ECM JSONs: https://www.dropbox.com/s/r4ivp0mhykkgjf7/ecms_full_ACEEE_run.zip?dl=0. Note that fuel switching is generally assumed for all heat pump ECMs in the 'Prospective' portfolio.

from the latest version of the ENERGY STAR Program Requirements Product Specification for each technology. For the IECC ECMs, Chapter 4- Residential Energy Efficiency of the 2018 International Energy Conservation Code was used to obtain energy efficiency data. All data on the installed costs and lifetimes of the technologies were found in the 2016 version of the U.S. Energy Information Agency's Updated Buildings Sector Appliance and Equipment Costs and Efficiencies (EIA 2016). Data were taken from the corresponding table for each technology from the 2013 'ENERGY STAR' column; the median lifetime and installed cost were taken from the reported ranges.

Best Available Technology ECMs. This portfolio consists of residential building technologies that represent the most efficient technologies that will be market available in 2020. Data for energy efficiency, installed cost, and lifetime were drawn from the 2016 version of the U.S. Energy Information Agency's Updated Buildings Sector Appliance and Equipment Costs and Efficiencies (EIA 2016). Data were taken from the corresponding table for each technology from the 2020 'High' column; the median lifetime and installed cost were taken from the reported ranges. For each lighting ECM, the energy efficiency data were taken from the highest ENERGY STAR fluorescent and LED light bulb available on the market according to the ENERGY STAR Certified Light Bulbs site (EPA 2018); cost and lifetime data were found from online retailers.

Prospective Technology ECMs. This portfolio consists of residential building technologies that represent target efficiency and cost levels for technologies in 2020-2030 developed by BTO. These technologies exceed the efficiency levels of the most efficient technologies available in the market. Most efficiency and cost levels for each technology were taken from Emerging Technology's sub-program goals in BTO's Multi-Year Program Plan (BTO 2016).[4] Additionally, new cost and efficiency targets developed for the Sensors and Controls sub-program were included (the reader is referred to the posted ECM definitions for details). Lifetime data for non-controls ECMs were drawn from the 2016 version of the U.S. Energy Information Agency's Updated Buildings Sector Appliance and Equipment Costs and Efficiencies, using the 2020 'High' column in the technology tables.[5]

All ECMs. In this portfolio, all ECMs included in the three portfolios above compete for market share based on installed cost and operating cost savings (see Eq. 4). Additionally, an 'electric-only' version of this scenario was developed for subsequent use in an AVERT analysis (next section). Here, only electric ECMs are included and their application is restricted to electric segments of baseline energy use (e.g., no fuel switching is assumed). Such a portfolio allows a more focused exploration of the power sector's potential for energy and emission reductions as a result of building efficiency improvements.

Estimating regional emissions reductions potential

While Scout calculates national level avoided air emissions, it does not capture all of the criteria air pollutants and does not provide regional data for avoided emissions; moreover, Scout's air emission estimates are based on average emissions intensities. In order to calculate

[4] Specifically, the data were adapted from the tables found in sections 2.1, 2.2, and 2.3.

[5] The controls technologies are assumed to be limited by the typical lifetime of supporting sensing equipment, which is assumed to be 10 years.

regional emissions reductions using marginal emissions estimates, 2021 electricity savings identified in Scout were run in AVERT. The reduction in generation is used to calculate avoided emissions in AVERT which is based on a statistical analysis of historical generation, heat input and emissions data. AVERT calculates avoided emissions associated with reduced generation but does not asses at the impact of those changes on atmospheric concentrations or the interaction among pollutants, which requires additional air quality modeling. Potential changes to the grid, such as new transmission resources, generator retirement, emissions controls or others, make it difficult to estimate the dynamics of generator dispatch on the grid. Thus without scenario data to determine a future grid and generator dispatch order EPA recommends that AVERT not be used to assess scenarios further than five years from the base case using the default inputs (EPA 2017). Since the current version of AVERT uses 2016 generation data, savings data for this regional emissions analysis uses the 2021 results from Scout. Additional limitations and caveats to the AVERT model can be found in the User Manual (EPA 2017).

In order to convert between Scout and AVERT, the 2021 annual climate zone level savings from the electric-only version of the All ECM scenario in Scout were mapped to the AVERT grid regions shown in Figure 1. Each county within an AIA climate zones (derived from Baechler et al. 2015), was prescribed a portion of the zone level savings based on the county's fraction of 2015 residential electricity use within the climate zone. These savings were then re-aggregated into AVERT regions to determine MWh savings for each measure and portfolio.

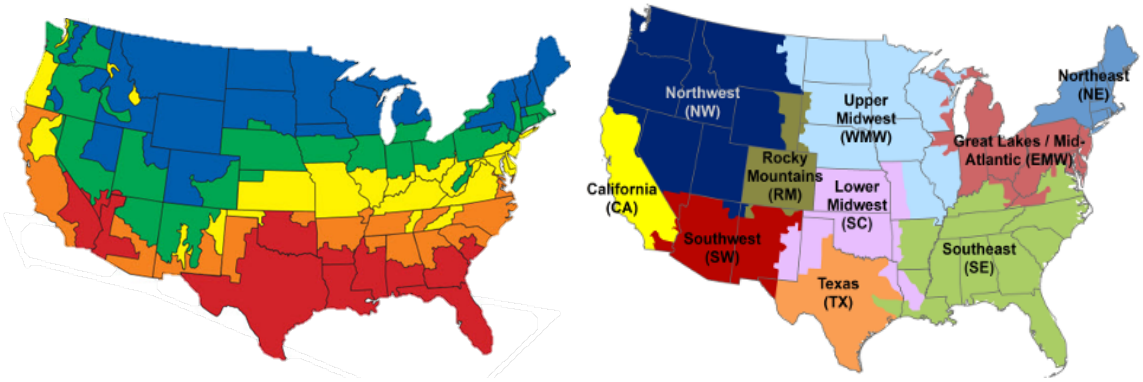

Figure 1: Maps of the Scout climate zones (left) and AVERT grid regions (right) used in this analysis.

AVERT allows the user to describe how the MWh savings are distributed over the 8760 hours of the year. Ideally, observed hourly *savings shapes* for each ECM portfolio in each AVERT region would be available for use in the tool. However, such data is very limited and is expensive to collect and was not available for this analysis. In lieu of hourly savings shapes, end-use load shapes can be used, meaning that energy savings are assumed to be distributed based on the hourly consumption of the end use that the ECM addresses. For end uses such as lighting, that assumption is reasonable. For others, such as cooling or water heating, savings may not mimic the underlying end use and thus this assumption can be inaccurate. Availability of end-use load shape data is also very limited. Mims, Eckman, and Goldman (2017) provide a detailed review of existing and planned end-use and savings shape data collection efforts.

Despite these limitations and because observed hourly savings or end-use load shape data are not available for the entire U.S., we used NREL's ResStock tool to generate modeled

estimates of end-use load shapes for single-family detached housing in each AVERT region, using 2012 weather, which was the year most readily available (Wilson et al. 2017). ResStock uses physics-based subhourly simulations of hundreds of thousands of representative homes, statistically sampled from a relational database of housing stock characteristics, to achieve a high-level of granularity and accuracy in modeling energy efficiency potential across diverse housing stocks. ResStock can also generate hourly savings shapes for various ECMs, but end-use load shapes were used at this stage of the analysis.

The ResStock end-use load curves for 350,000 households were aggregated up to average end-use load shapes for each AVERT region. The 2021 annual savings for each end use (cooling, heating, lighting, water heating, refrigeration, washer/dryer, peak reduction) at the AVERT region were then distributed in proportion to the respective 8760 load shape. For example, if a given hour represents 1% of the yearly electricity use for lighting, it was given 1% of the annual savings for lighting. Load shapes were available by end use for cooling, heating, lighting, and water heating derived from ResStock and weighted by the number of households in each county. The refrigeration and washing/drying savings identified in Scout do not have corresponding 8760 load shapes available from ResStock. Because no specific load shape was available for these measures, the load shape for interior equipment load shape from ResStock was used to allocate the savings for these end uses.

In addition to the Scout-derived end-use electricity savings described above, an additional scenario was constructed in AVERT to represent a peak reduction ECM. AVERT has a built-in function that lets the user specify the percentage of "top hours" in terms of fossil generation and the percent reduction, which was used to construct this representative scenario. The top hours represent the hours throughout the year that have the highest fossil generation. To model a peak reduction ECM and to be able to compare it to another end use, the annual electricity savings identified for cooling were distributed to 10% of the top hours. At each of these identified hours, the percent reduction in generation was calculated for each region to make the electricity savings match the input regional cooling savings. Across regions this percent reduction ranged from 1.31% to 4.96%. This scenario is identified as 'Peak Reduction' in the analysis. To illustrate these differences, Figure 2 shows the savings over the course of the year for cooling and peak in the Northwest region, both representing 722 GWh of savings.

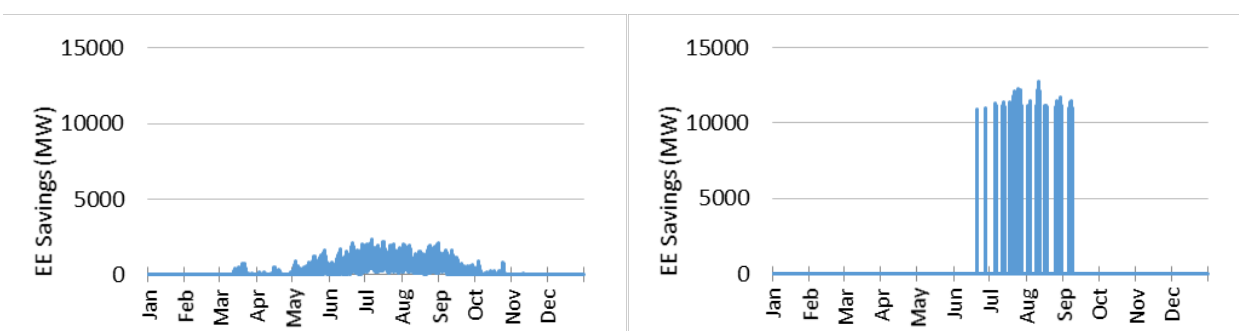

Figure 2. Representative load curve savings for cooling (left) and peak reduction (right) for the Great Lakes/Mid Atlantic region.

The resulting hourly reductions in electricity demand were input into AVERT, which determines avoided emissions based on the dynamics of electricity dispatch using historical

regional data.[6]

Results

National energy use, CO_2, and cost reductions of ECM portfolios

Figure 3 compares the national primary energy, CO_2 emissions, and energy cost savings potential of the three ECM portfolios separately, and when all ECMs are simulated together. All results are shown for the maximum adoption potential in Scout, meaning that realistic stock turnover dynamics are considered and ECMs may take several years to fully penetrate their baseline markets. Accordingly, total energy savings, avoided CO_2 emissions, and energy cost reductions generally increase over time in Figure 3. In 2020, reductions are highest in the 'All' ECMs scenario (1.32 quads, 72 Mt CO_2, and $16 billion); by 2050, reductions are highest in the 'Prospective' ECM scenario (5.91 quads, 270 Mt, and $93 billion).

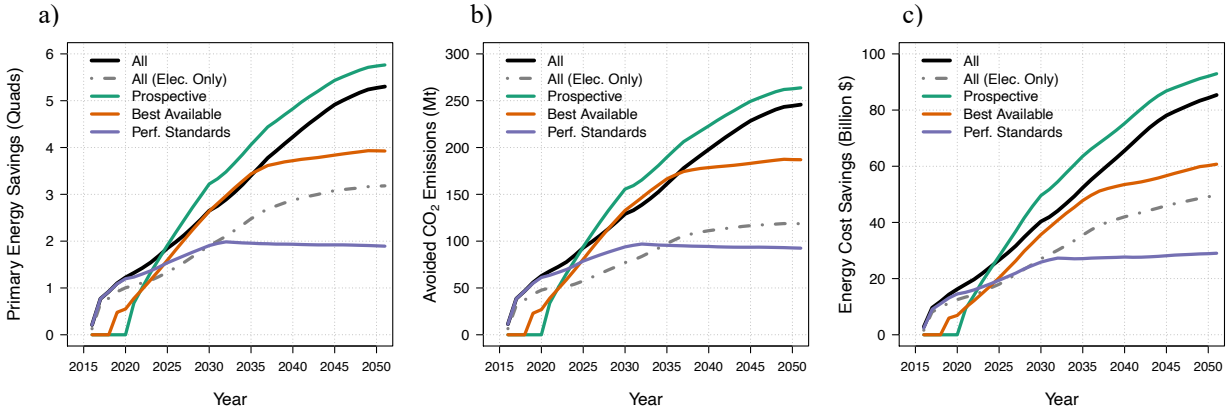

Figure 3. Total primary residential energy savings (a), avoided CO2 emissions (b), and energy cost savings potential (c) by ECM portfolio and year. Note: "electric-only" portfolio used for AVERT is shown for reference.

Figure 4 attributes the total energy savings of the 'All ECMs' scenario in Figure 3 to particular climate zones, building vintages, and end uses. Regarding climate, the most notable result is the muted reductions in climate zone 1, the coldest of the AIA climate zones. This is attributable to population, as climate zone 1 has roughly 60% the average population of the other four zones (U.S. Census Bureau 2016). Primary energy savings are also most pronounced in existing buildings, though the opportunity peaks by 2045. Finally, while lighting energy savings are most pronounced in the early years of simulation, over the long-term lighting's impact declines as the baseline lighting stock efficiency increases. By 2050, energy savings from water heating, envelope, and heating equipment ECMs are most pronounced.

[6] In addition to the annual regional displacement data presented here, AVERT also calculates the displacement data for the top ten peak days, the annual and monthly avoided emissions by county and other data.

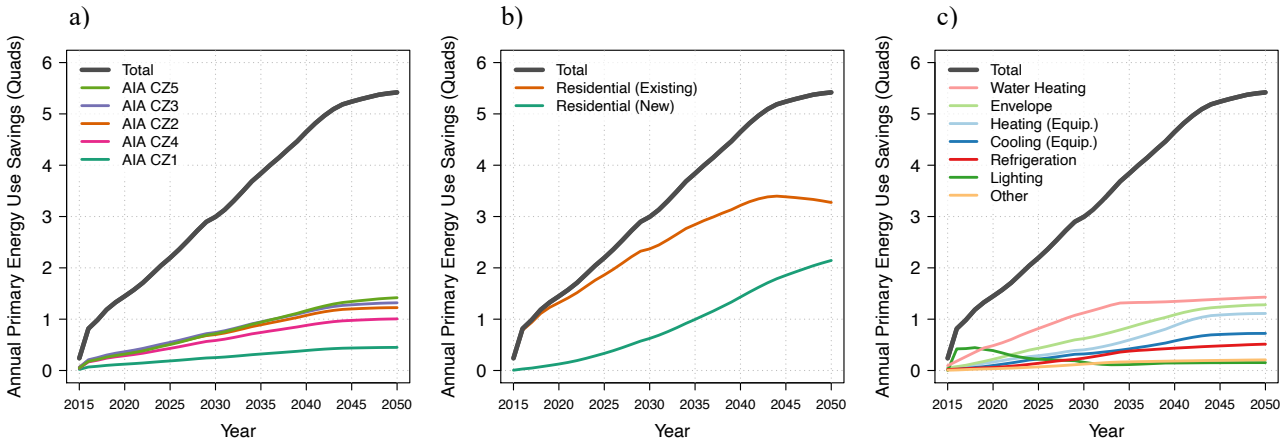

Figure 4. Breakdown of total annual savings for the 'All ECMs' portfolio by climate (a), by building class (b), and by end use (c).

Finally, Figure 5 examines the cost-effectiveness of the energy savings and avoided CO_2 emissions shown for the 'All' ECMs scenario in Figures 3 and 4, focusing on the years 2020 and 2040; Figure 5 also indicates which ECMs make the greatest contribution to the cost-effective energy and CO_2 impacts in these years. In these future years, 0.9 and 3.2 quads of primary energy savings are associated with ECMs with less than a 10-year payback; these totals represent 68% and 73% of the total energy savings for the 'All' portfolio in 2020 and 2040, respectively. Cost-effective CO_2 reductions (not shown) mirror the energy results: 43 Mt and 148 Mt CO_2 emissions are avoided cost-effectively in 2020 and 2040, representing 63% and 72% of total avoided CO_2 emissions in these years.

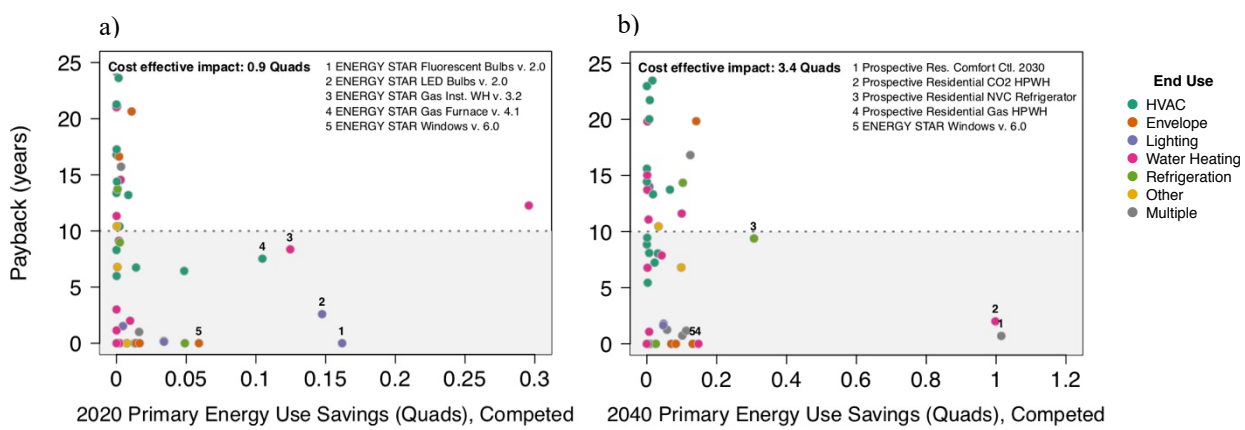

Figure 5. Cost effectiveness of primary energy savings in 2020 (a) and 2040 (b) for the 'All ECMs' portfolio, where points on the plot represent individual ECMs.

In 2020, all cost-effective ECMs are from the ENERGY STAR portfolio, as ECMs from other portfolios are just beginning to enter the market and accrue savings. Of the ENERGY STAR ECMs, those affecting lighting and gas heating/water heating are the most cost effective, owing to their relatively low capital costs and comparatively low baseline stock performance

levels in this year.[7] By 2040, two individual ECMs make notably large contributions to the cost-effective portfolio impacts: heat pump water heaters (HPWH) and comfort-driven controls. Both of these target ECMs were developed by BTO to meet aggressive paybacks (1-3 years) with high unit-level energy performance and large applicable baseline energy use segments.[8]

Regional emissions reduction potential across all measures

To assess the regional implications of this energy efficiency potential, the 2021 nationwide savings generated through Scout for electric-only portion of the 'All' ECMs scenario were disaggregated to individual AVERT regions as described above and input into AVERT to determine the regional avoided emissions associated with these energy savings. Figure 6 shows the electricity savings potential by end use for each region that were entered into AVERT. The full set of emissions reduction rates (emissions reduction per MWh saved) calculated for each end use in each AVERT region are shown in Figures 7a-d.

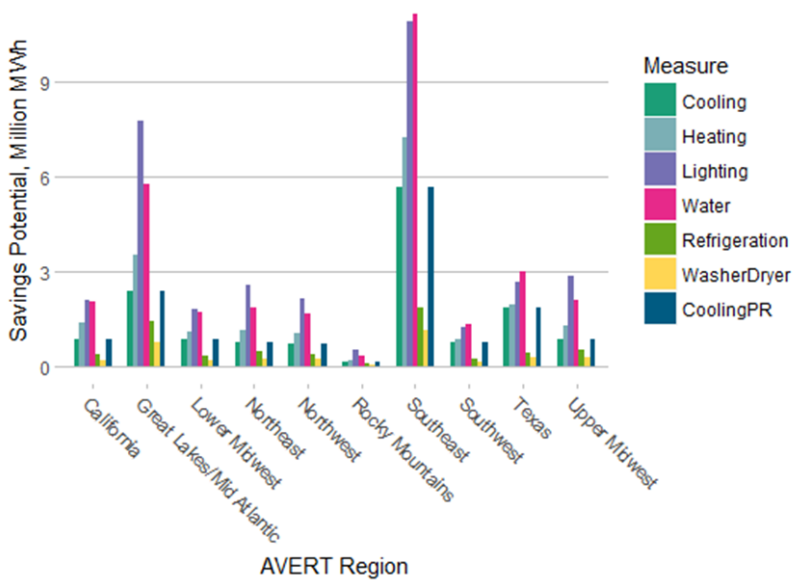

Figure 6. Total potential savings by end use for each AVERT region, as calculated based on climate zone-specific data from the ''electric-only 'All' ECMs scenario in Scout. These savings are used as the input for the regional avoided emissions analysis in AVERT.

[7] Note in Figure 5a that ENERGY STAR electric heat pump water heaters (towards the right of the plot) demonstrate large savings but do not yet meet the 10-year payback threshold in 2020.
[8] Specifically, the baseline segments are all water heating for the HPWH ECM (2.6 quads primary energy in 2040) and all heating, cooling, and lighting for the controls ECM (7.3 quads in 2040).

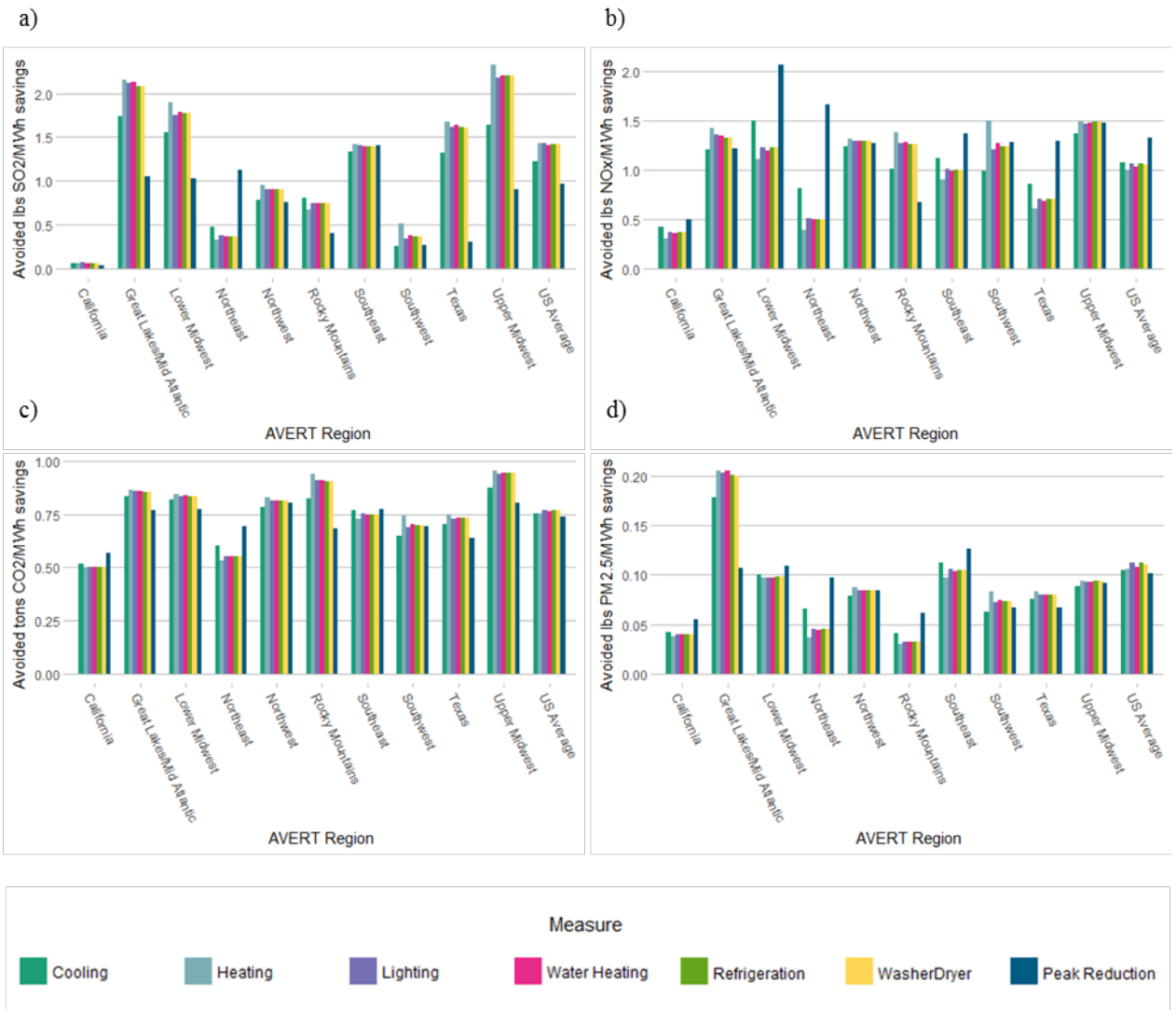

Figure 7. Emissions savings rate (emissions avoided per MWh saved) by end use for each AVERT region and the U.S. average, calculated based on total emissions reductions divided by total MWh saved for each end use as determined by AVERT for SO_2 (a), NO_x (b), CO_2 (c), and d) $PM_{2.5}$ (d).

To better illustrate the regional differences in emissions reductions, Figure 8 focuses on three regions and three end uses: cooling, lighting, and peak reduction ('Peak Reduction'). These results show that emissions reductions depend both on the grid region where energy savings occur and on the load shape for a given end use. Comparing the Cooling and the Peak Reduction cases for avoided SO_2/MWh, it is shown that the same level of savings from different end uses offer different emissions reductions in a given region. For instance, in the Great Lakes/Mid Atlantic region, cooling offers greater savings of SO_2 per MWh than the Peak Reduction savings. Cooling savings, which are distributed throughout the day, reduce load across a broader range of generators--including coal generation which is associated with SO_2 emissions (Monitoring Analytics 2017, 15). In comparison, peak reduction simulates a reduction in fossil load in the top 10% of hours, which in the Great Lakes/Mid Atlantic region is often provided by natural gas

generation, with its lower SO_2 emissions rate. The savings rate for Lighting, however, suggests greater SO_2 reductions than either Cooling or Peak Reduction, indicating higher alignment with times when coal is the marginal generator in the region. Thus if a state in the Great Lakes/Mid Atlantic region were looking to target SO_2 reductions through energy efficiency, the greatest savings from these three end uses on a per MWh basis could be achieved through lighting ECMs.

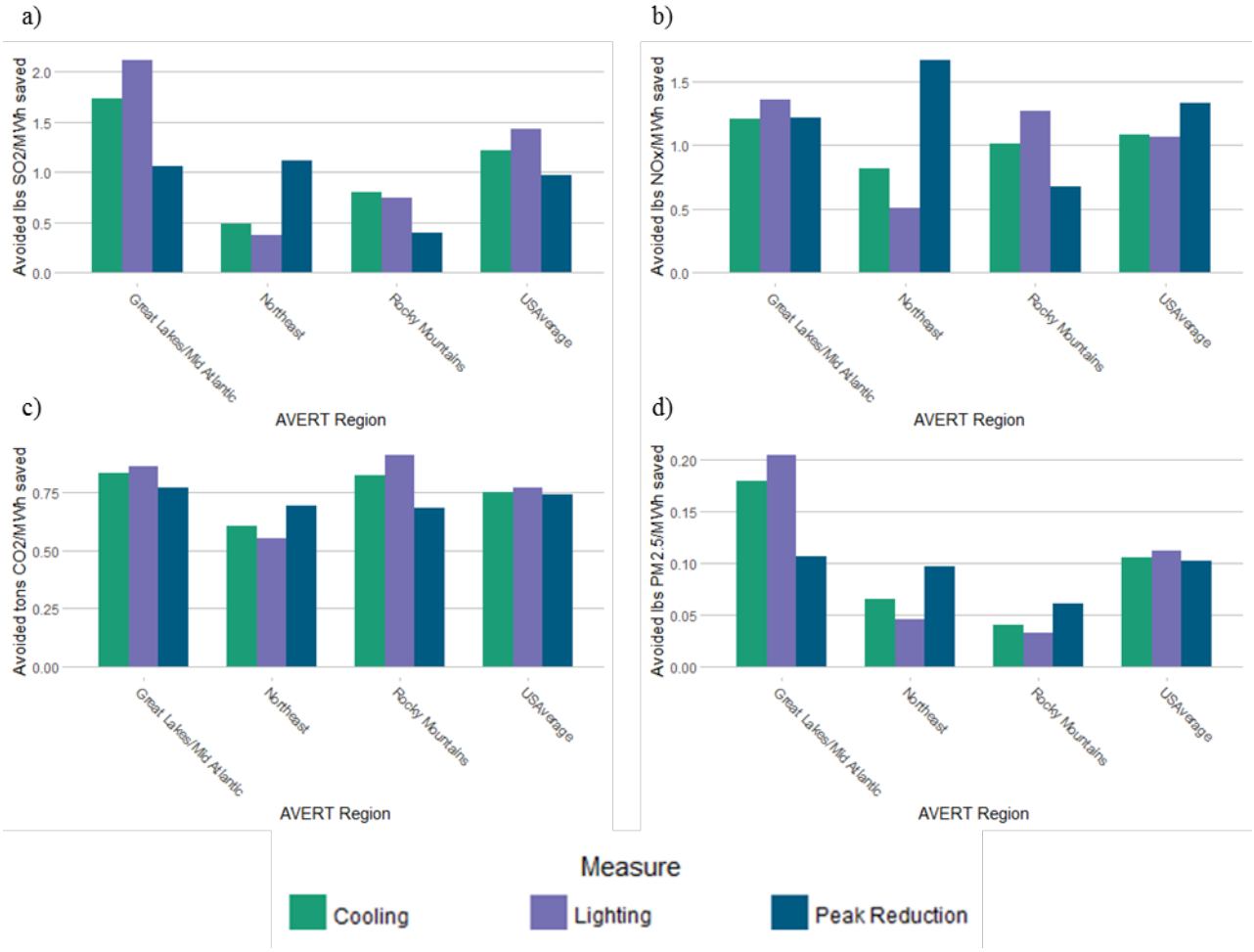

Figure 8. Emissions savings rate (emissions avoided per MWh saved by end use for Cooling, Peak Reduction and Lighting in three AVERT regions and the U.S. Average, calculated based on total emissions reductions divided by total MWh for each end use as determined by AVERT for SO_2 (a), NO_x (b), CO_2 (c), and d) $PM_{2.5}$ (d).

In the Northeast, the relative emissions rates of Cooling and Peak Reduction are reversed compared to the Great Lakes region. The lower SO_2 emissions rate for Cooling versus Peak Reduction is likely due to the use of fuel oil to meet peak demand in the Northeast (Monitoring Analytics 2017; ISO-NE 2018). In both the Northeast and the Rocky Mountains, the low SO_2 emissions rate for Cooling and Lighting relative to the national average is reflective of the lower prevalence of coal, though fuel oil, natural gas and biomass also contribute to SO_2 emissions. The results for NO_x and $PM_{2.5}$ emissions, also primarily associated with the combustion of coal, show a similar overall trend, though individual generating units and the associated emissions

controls likely drive the differences shown here. Of note is the high avoided NO_x emissions rate in the Northeast, also likely associated with fuel oil (Massetti 2017, 7).

In terms of avoided CO_2 emissions rates, there is less difference between different end uses than between regions. These differences primarily reflect the relative balance of natural gas to coal generation. The Northeast (i.e., ISO-NE and NYISO) (NREL 2018a) has very low levels of coal generation, thus resulting in lower avoided CO_2 emission rates than in regions with higher levels of coal generation. Because each end use provides roughly the same avoided CO_2 emissions, states looking to maximize carbon reductions could focus on least cost measures rather than specific avoided carbon dioxide emissions rates.

While this work does not currently assess changes on the electric grid over time, comparing the CO_2 results of the Great Lakes/Mid Atlantic, the Northeast and the Rocky Mountain gives an idea of how efficiency measures would change if renewable energy or natural gas deployment increases. A greater reliance on natural gas may lower the avoided SO_2, NO_x, CO_2, and $PM_{2.5}$ emissions rates, while a grid that sometimes relies wholly on zero-carbon energy could see more time dependent results, where only the measures that coincide with fossil generation would provide emissions savings.

Discussion

This analysis provides an initial evaluation of how energy efficiency measures and programs can be used to achieve national and regional energy and emissions goals. Identifying the measures that provide large energy savings potential and correlating those savings with emissions reductions along with costs can help states and localities pursue multiple benefits through a single program and adapt the program to meet local objectives.

Assessing the magnitude and timing of national building efficiency impacts

The three residential ECM portfolios studied at the national scale in this paper represent a range of possible building efficiency levels that can serve as benchmarks for the development of future residential building efficiency programs. In Figure 3, for example, it is shown that by 2040, introducing a prospective set of technologies that correspond with BTO's R&D portfolio more than doubles the potential national energy, CO_2, and cost reductions realized under maximum penetration of ENERGY STAR, IECC, and 90.1 ECMs.

Additionally, the consideration for stock-and-flow dynamics in the Scout modeling framework establishes the period over which continued growth in ECM portfolio impacts might be expected. Examining Figure 3 again, national energy, CO_2, and cost reductions from current ENERGY STAR technologies peak by 2030, while reductions from best available ECMs do not peak until 2050 and reductions from the prospective ECM portfolio grow through the end of the modeling time horizon. The latter result underscores the need to develop technologies with both high energy savings and rapid market penetration potential, shifting the Figure 3 savings curve for the prospective portfolio to earlier years.

Regional opportunities for emissions reductions through building efficiency

While regional differences exist, with the fuel mix of the current grid, all end uses reduce

emissions of SO_2, NOx, CO_2 and PM_2. Savings from cooling and peak reduction as modeled here resulted in larger avoided air emissions in many, but not all, regions. An individual state or region can use this analysis to focus efforts on pollutants that are larger drivers of local air quality concerns. As the grid mix changes, further evaluation of the air pollution savings from energy efficiency measures will be necessary and further model development is needed to support such analyses.

Traditionally, energy efficiency has not often been explicitly used to meet air quality targets; however, this paper shows that the regional and time sensitive emissions reductions associated with energy efficiency can be used to inform strategies for meeting both energy and air quality targets. The approach provided here is a starting point that should inform a discussion between stakeholders on the environmental benefits of different end use portfolios.

Conclusion

Using the BTO Scout and EPA AVERT tools, we evaluated the potential national energy, CO_2, and energy cost reductions from residential building efficiency measures out to 2050 and regionally assessed the avoided electricity generation emissions from those end uses in 2021. Looking ahead, the ability to assess the impacts of such measures on a future grid can inform policy makers, utility operators, and industry professionals in framing the development of new building technologies and energy efficiency programs that cost effectively reduce both energy use and air emissions at multiple scales of analysis. Updated data, including load savings shapes for each ECM and the ability to model the dispatch order of a future grid will improve the capability of these tools to assess such impacts. Partnering with utilities or evaluators who have access to additional hourly datasets and dispatch curves for future grid scenarios may also help strengthen the results and generalizability of such analysis.

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