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Impact of Energy-Efficiency Retrofits on Office Building Energy Use, Emissions, and Peak Demand under Future Climate Scenarios in U.S. Climate Zones

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ABSTRACT

Evaluating energy efficiency measures (EEMs) under future climate conditions is critical for climate resilient design of buildings. However, the impact of EEMs on existing buildings under projected weather conditions has been insufficiently explored. This study evaluates the energy use, peak demands, and associated emissions of a prototypical medium office buildings with typical constructions properties from 1980 to 2004 across 16 U.S. climate zones, considering different EEMs under historical (TMY3) and future climate scenarios (SSP2-4.5 and SSP5-8.5 for 2050 and 2080) to provide both location specific and broader insights. The different cases include models with envelope upgrades (wall, roof, floor, and window U-values, and solar heat gain coefficient [SHGC]), cooling coefficient of performance (COP), lighting power density (LPD), energy recovery ventilation (ERV), and combined retrofit measures, where upgrades followed ASHRAE 189.1-2020 recommendations. Results showed that the energy use and emissions under projected weather conditions increased in very hot regions and decreased in very cold regions, particularly under SSP5-8.5, reducing the gap between these extreme conditions. LPD, cooling COP, and window upgrades showed highest energy savings. LPD yielded the largest savings among individual measures, except in very cold and subarctic zones, where window retrofits outperformed. Results revealed increased stress on electric grids in regions with significant cooling loads where energy use outpaces energy savings under future scenarios. Additionally, the analysis showed that clean energy production in extreme cooling- or heating-dominated regions require attention, as the high electricity-related emissions in these regions coincide with high energy loads, amplifying the associated environmental impacts.

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1. Introduction

Increased atmospheric greenhouse gas (GHG) concentrations have resulted in changes in climatic conditions. As reported by the Intergovernmental Panel on Climate Change (IPCC), one of the consequent changes is a 1.09 °C raised global surface temperatures in 2011-2020 compared to 1850–1900 [1]. Human activities have caused increased atmospheric GHG concentrations, resulting in a total human-caused share of approximately 1.07°C surface temperatures increase since the pre-industrial era [1]. These environmental changes along with the stresses on energy sectors highlight the crucial need to take actions toward reducing global energy use and the associated GHG emissions.

Buildings account for a significant portion of the energy-related CO_2 emissions. Therefore, they play an important role in achieving the environmental goals. In the U.S., commercial and residential buildings account for 34% of energy consumption [2]. Commercial buildings alone, with 15.69 quads energy consumption, share about 18% of the total building energy use in the U.S. [2]. Consequently, the building sector in general, and the commercial buildings in particular, have significant potential to reduce climate impacts through substantial reductions of energy use and the associated GHG emissions [3].

Commercial buildings in the U.S., with a median age of 36 years in 2018, is fairly old [4]. In fact, only about 12% of commercial buildings, comprising 14% of commercial floor space, have been built since 2003 [4]. Although the majority of existing commercial buildings are expected to remain in service for many decades, the building stock generally shows poor thermal performance and outdated systems that results in significantly increased energy consumption, which underscores the need for comprehensive retrofit strategies to improve energy efficiency and reduce operational emissions [5]. Additionally, the advantages of energy retrofits in buildings can go beyond reducing operating costs and have shown potential to enhance occupancy rates and increase rental revenue, hence increasing net operating income [6] as well as the social impacts and tenants' considerations [7].

Previous studies have examined the impact of building energy efficiency measures (EEMs) at various scales and in different locations. Zhai *et al*. [8] proposed a pilot-to-portfolio deep retrofit approach for commercial buildings that enables aggressive, cost-effective energy reductions. The analyses presented in the Advanced Energy Retrofit Guide for Office Building [9] showed a 33% to 43% reduction in site energy consumption in different locations in the U.S. for the standard recommended retrofit package and Existing Building Commissioning (EBCx), with 13% to 18% savings beyond only EBCx. In these standard recommended measures, high energy savings potential, cost-effectiveness, and relatively simple implementation were prioritized. In this study, more comprehensive deep retrofit scenarios yielded 45% to 53% reductions, with 23% to 30% savings beyond only EBCx in different U.S. locations. In another study, Wang *et al*. [10] reported an improvement of over 70% in their analysis of the impact of envelope and heating, ventilation, and air conditioning (HVAC) improvements in Tianjin. Results showed overall energy performance Ye *et al*. [11] perfomed EEMs sensitivity analysis for a prototype medium office across 15 U.S. climate zones. Results showed that windows, efficient lighting, and office equipment demonstrated high impact in different locations, while the impact of envelope insulation and HVAC upgrades showed more sensitivity to climate zones. Results of a study by Zhang *et al*. [12] also showed greater effectiveness of passive retrofit measures in colder climate zones. Another study showed improvements in the performance of a traditional boiler-based configuration compared with combining a cogeneration unit with a heat pump, with a payback period of about 15 years [13]. Furthermore, improved environmental performance and reduced emergy consumption was reported by coordinated building envelope and HVAC optimization [14].

Literature also includes studies that focus on emissions reductions due to building energy retrofits. A 72% to 78% emissions cut in the U.S. by 2050, close to the 80% target at mid-century, was estimated through efficiency, electrification, and renewables [15]. Several other studies have also focused on the impact of retrofits on CO_2 emissions, ranging from the analysis of specific measures such as shading [16], to studies focusing on multiple upgrades at different scales, such as the studies on optimal, cost-effective EEMs for residential buildings in Spain [17], deep retrofits [18], and building stock at the district level in the Swiss [19].

Other studies have analyzed the impact of climate change on building energy performance. Guan [20] studied the implications of global warming on office buildings in four areas in Australia. It was found that the increase in total building energy use for the sample Australian office building range from 0.4% to 15.1% depending on the future climate scenarios and the location considered. The study also showed a significant risk of overheating if the annual average outdoor temperature increases by more than 2 °C. Reducing internal load density was found to be an effective measure to eliminate or reduce the potential overheating problem. Another study analyzed the performance of a prototypical large office in three U.S. cities, Boston, Miami and San Francisco, across three future time windows, 2030, 2060, and 2090. Results showed an increase in annual primary energy consumption by 2090 under all projected climate conditions. While the specifics of the results varied across locations and projections, the increase was shown to be mainly driven by higher cooling energy loads with the most significant increase in the climate of San Francisco [21].

Another study that focused on residential and office building energy use in four representative U.S. cities in 2040–2069 projections showed a −1.64% to 14.07% change in annual energy use for residential building and a −3.27% to −0.12% change in annual energy consumption for office building under the A2 scenario [22]. In this study, the climate change was shown to reduce the difference in the energy consumption for residential buildings located in cold and hot climate regions in the U.S. Additionally, the peak electricity demand was shown to increase during cooling seasons. Also, Wang and Chen [23] analyzed two types of residential buildings and seven types of commercial buildings in 15 cities under future weather projections, which showed that by the 2080s, source energy use is projected to rise in climate zones 1–4 but decline in zones 6–7. Li *et al*. [24] also conclude that climate change affects building energy use differently across climate zones, reducing heating loads in cold regions and substantially increasing cooling loads in warmer regions.

Lou *et al*. [25] used hourly electricity emission factors and a constant emission factor for natural gas to analyze the effect of eight EEMs on emission reductions of U.S. medium office buildings across five locations. The findings showed that CO_2 emission reductions resulting from the same measure can differ across climates. Additionally, analysis of the measures based on their energy-efficiency impact versus their emission-reduction impact can result in different rankings. This variation was mainly due to differences in energy sources in different locations, as well as the different effects of measures on electricity and natural gas consumption.

In another study, projections over the next 100 years showed that electricity demand for cooling could rise by 25% and 50% in certain areas of California under the worst-case carbon emission and the most likely scenarios, respectively, with cooling-sensitive building types most affected [26]. However, only a modest increase in total building energy use was shown. A different study used climate projections for the 2056–2075 period to analyze the impacts of climate change on energy demand and comfort levels of office buildings in extremely cold, cold-humid, and cool-humid Canadian climate zones [27]. Results showed that extending temperature setpoints lowers annual energy use by 0.9% to 9.9% across the three analyzed cities, with the exact range varying for each city, and also increases the share of zones with predicted mean vote (PMV) values outside the ±0.5 comfort range. Also, simulation results of a retrofit case study of a 1970s office building in Ottawa showed that wall and roof insulation improvements, boiler upgrades, and enhanced airtightness can reduce energy use by over 52% and CO_2 emissions by about 82 tons/year [28].

Previous studies show the varying impact of EEMs with different building configurations and climate conditions. However, the literature lacks a systematic study that simultaneously analyzes the impact of EEMs on energy use, peak demand, and associated emissions of the existing building stock across different U.S. climates under the Sixth Assessment Report (AR6) common IPCC scenarios, with scaled provisions. Many previous studies primarily focus on annual energy consumption, or the analysis includes a limited number of locations, which limits broader insights and restricts comparison of EEMs in different climates. In addition, most of the previous studies rely on earlier climate projections based on Representative Concentration Pathways (RCPs) from the IPCC AR5. The use of most recent weather scenarios, however, can reveal the impact of EEMs under updated conditions. This is important given that Representative Concentration Pathways (RCPs) in the Fifth Assessment Report (AR5) are defined primarily by radiative forcing trajectories, whereas the scenarios used in AR6 are based on Shared Socioeconomic Pathways (SSPs), which explicitly couple emissions trajectories with alternative socioeconomic development pathways. Therefore, while RCPs and SSPs are closely related, they differ and the results can vary. Also, a comprehensive view can be provided by the analysis of energy use and demand.

This research investigates the effectiveness of individual EEMs on prototypical models of the existing office building stock, using updated versions of general circulation models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) [29]. The analysis evaluates EEMs aligned with high-performance building recommendations from ASHRAE Standard 189.1-2020, which enables the assessment of commonly recommended retrofit strategies under projected future climate conditions. The primary goal is to identify future potential stresses that can inform energy planning at both the building and broader scales as well as to analyze the effectiveness of EEMs in each climate zone and across climate zones in different scenarios and projections. The integrated assessment of energy use, peak demand, and associated emissions provides a comprehensive evaluation of retrofit performance, which informs both building-level decision-making in different locations and broader energy policy and planning, including strategies to reduce grid stress and emissions under future climate conditions across diverse U.S. climate zones. This section is followed by section 2, which describes the methodology used in this research. Then, section 3 provides the results and discussion, which is followed by the conclusions, provided in section 4.

2. Method

2.1. Overview of the Research Framework

In this research, the energy consumption, emissions, and electric peak demand of medium office prototype models are evaluated in 16 U.S. cities, representing different climate zones across the U.S. For each location, one baseline model, eight models including individual EEMs, and one model incorporating all measures combined are analyzed. The models were evaluated using historical weather data from the Typical Meteorological Year, version 3 (TMY3) [30], and future climate projections corresponding to SSP2-4.5 and SSP5-8.5 for the 2050, representing mid-century periods, and 2080, representing late-century periods.

2.2. Baseline Models and Locations

DOE medium office prototype models [31] were selected for this analysis. These prototypes represent a common commercial building by total square footage in the U.S. [32], and are provided for different locations in the U.S. The medium office prototype models are three-story commercial office buildings with floors measuring 49.9 m by 33.3 m, with the longer axis stretched east–west, and a 33% window-to-wall ratio (WWR) on each façade. Each floor consists of five perimeter zones and one core zone. The perimeter zones are 4.57 m deep. Each floor has a 2.74 m height plus a 1.22 m-high plenum above a false ceiling. The HVAC of the model consists of three packaged variable air volume (VAV) systems with gas-fired central heating and electric reheat, one serving each floor. A natural gas service water heater is also modeled for the whole building. Typical internal load and operational characteristics representative of conventional office use are used in the model. The main schedules used are provided in Fig. (**1**), where fraction one represents 0.054 people/m^2 for people, 16.90 W/m^2 for lighting, and 10.76 W/m^2 for equipment. In the simulations, the surrounding terrain is defined as city. In simulations, solar distribution and shading calculation method are modeled using full interior and exterior option and polygon clipping method, respectively. Conduction Transfer Function is used as the heat balance algorithm with interior and exterior surface convections were modeled using TARP and DOE-2 algorithms, respectively, and third order backward difference method for solving zone air heat balance.

Baseline models were developed using the OpenStudio Standards Library [33] within OpenStudio [34]. These models were selected to represent a common retrofit scenario for existing buildings and represent construction practices for existing buildings constructed between 1980 to 2004 in each location. EEMs are evaluated against these baselines. The medium office building energy models used in this study are based on the developed prototypes by the U.S. Department of Energy and Pacific Northwest National Laboratory, which are widely used and previously validated reference buildings developed using national datasets such as the Commercial Buildings Energy Consumption Survey and detailed assumptions. Therefore, using standardized and validated prototype models provides a reliable baseline for the energy simulation analysis.

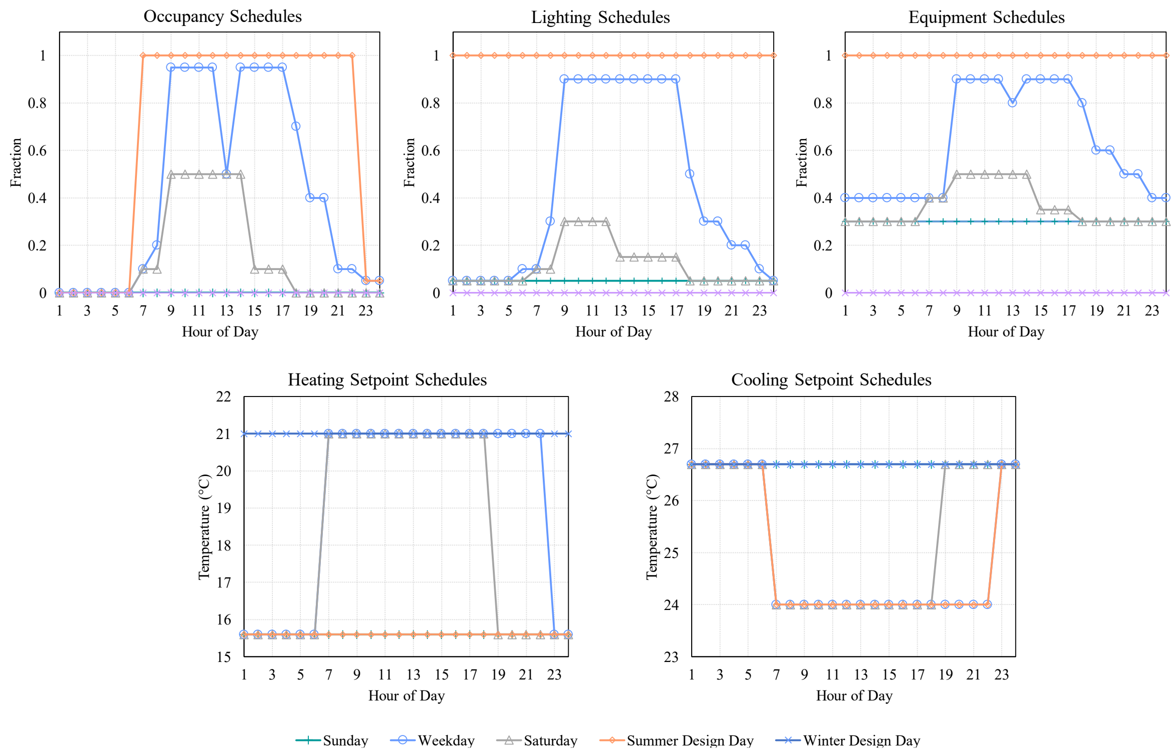

Figure 1: Medium office schedules.

2.3. EEMs Selection

EEMs were primarily defined based on the provisions provided by ASHRAE Standard 189.1-2020 [35], which represents a current existing roadmap for achieving high-performance, sustainable commercial buildings. Based on common practice and literature, several EEMs were selected, ranging from improved thermal transmittance of walls, roof, the slab-on-grade floor, and windows, solar heat gain coefficient (SHGC) of windows, to lighting power density (LPD), cooling system coefficient of performance (COP), and the use of an energy recovery ventilator (ERV) for each packaged system. Additionally, in each location, one case of deep retrofit in which all measures are applied together was included to reflect the integrated effects of the different EEMs.

The selection of EEMs in this study was based on a combination of factors, including practical relevance, potential impact, previous studies in literature, common practice, and representativeness of common EEMs for existing office buildings. Building envelope thermal performance is predominantly rated and regulated by the thermal transmittance of the components, as well as SHGC in transparent components. Consequently, given the significance of envelope parameters and to comprehensively account for building envelope parameters and allow comparisons, all these upgrades for walls, roof, floor, and windows were included in the study. For the internal heat gains, given that the number of people is governed by the square footage and equipment loads are nonregulated in common building codes, these parameters were excluded and only the LPD reduction, which is also a very common EEM in practice, was included for its immediate and measurable effect on electricity consumption. Related to HVAC systems, the most common determining factors that reflect the energy performance is the efficiency of the equipment. Consequently, improvements to cooling system COP was included to quantify the associated savings and reductions. However, given that the specific heating system used in this study has almost identical efficiency in baseline and ASHRAE Standard 189.1-2020, this parameter is excluded. Additionally, ERV, which is a very common based on the common practice, was also selected to represent feasible HVAC system enhancements that align with ASHRAE guidance. Collectively, these measures cover the primary energy-use drivers in medium office buildings. Additionally, they allow for the evaluation of both individual and integrated impacts on energy consumption, peak demand, and emissions, and the selection covers retrofit feasibility and consistency with common practice and literature, providing a robust methodological rationale for the study.

As prescribed in ASHRAE Standard 189.1-2020, the thermal transmittance of envelope components specified in ASHRAE Standard 90.1-2019 [36] were reduced by 5%, except where ASHRAE Standard 90.1-2019 does not establish a requirement. Therefore, the U-values of walls, windows, and roofs, and the F-factors of the slab-on-grade floors in ASHRAE Standard 90.1-2019 were reduced by 5%, except the F-factors of floors in climate zones 1 through 3, where ASHRAE Standard 90.1-2019 does not establish a requirement. For fenestration SHGC, this study applied a 5% SHGC reduction to all fenestrations, while ASHRAE Standard 189.1-2020 only requires a 5% reduction only for east- and west-oriented fenestrations relative to ASHRAE Standard 90.1-2019.

Regarding the LPD, the value for office buildings was directly obtained from ASHRAE Standard 189.1-2020, given that Building Area Method was used. The cooling system efficiency was defined based on the integrated coefficient of performance (ICOP) of electrically operated unitary air-conditioning systems with capacities ranging from 70 kW to 223 kW and electric resistance heating, applicable after January 1, 2023. Since the baseline boiler efficiency was already 80%, furnace efficiency was not included as a parameter in this study. ERVs were applied across all climate zones, with the sensible and latent effectiveness exceeding 60%. Table **1** provides a detailed description of the parameters used for the baseline and improved cases in each location.

2.4. Climate Data and Weather Scenarios

In this analysis, climate data used in building annual energy simulations include historical weather files and two future weather scenarios, with two projection years for each scenario, which results in five sets of simulations. TMY3 weather files, which represent long-term typical historical meteorological conditions for each location, were used as the historical weather files. Also, weather files for each scenario and projections year were generated for each location.

A selected number of IPCC SSP scenarios were used for the analysis. Working Group I of the IPCC examines the physical science basis of past, present, and future climate change. This group evaluated climate responses across five SSP scenarios covering very low to very high emissions scenarios. These scenarios range from net-zero CO_2 emissions pathways around mid-century, SSP1-1.9/2.6, to scenarios such as SSP3-7.0 and SSP5-8.5 in which emissions roughly double by mid- to late-century [1]. SSP-based scenarios are denoted as SSPx–y, where SSPx represents the underlying SSP and y shows the radiative forcing level (W/m^2) reached by 2100. Among these, SSP2-4.5 and SSP5-8.5 are widely used in climate and building energy research as representative intermediate and high-emissions futures, since SSP2 represents “middle of the road” and SSP5 represents fossil-fueled development. A review by Duan *et al*. [37] on challenges in predicting climate change impacts on thermal building performance through simulation also shows that these two scenarios appear most frequently in the previous related studies.

Examples of the studies that used SSP2-4.5 and SSP5-8.5 in building performance analyses include the study by Ran *et al*. [38], which proposed a coordinated optimization design approach for buildings and regionally integrated energy systems under TMY, SSP2-4.5, and SSP5-8.5 conditions. Another study includes Zhuo *et al*. [39] analysis where they analyzed spatial and temporal trends in photovoltaic potential under SSP2-4.5 and SSP5-8.5 in China. Other studies have also used these two scenarios to assess the contribution of green roofs to GHG mitigation through building energy savings in Shanghai [40], as well as to evaluate thermal comfort and resilience in dwellings during heat waves [41].

Two projection years, aligned with the expected service life of the baseline building stock, were selected in this study. As reported by the U.S. Department of Energy, the median lifetimes of small and large office buildings in the U.S. are 58 and 65 years, respectively, while with 33% survival these ranges extend to 82 and 92 years [42]. Another study empirically estimates the average building lifetimes [43]. The estimates were based on statistical analyses of approximately 15,000 demolished buildings across several U.S. and four European cities. Results indicated an average lifetime of 71 years for the buildings. Accordingly, the 2050 and 2080 projections were selected for this study to cover two reasonable future ranges for the 1980–2004 baseline buildings.

Future weather conditions used in this study were generated using the Future Weather Generator [44], a Java-based application developed and maintained by CURA Lab at the University of Coimbra. This tool was selected due to its use of state-of-the-art climate data, improved interpolation methods, higher spatial resolution, a larger set of morphing variables, and more comprehensive climate change timeframes and scenarios. The tool incorporates monthly climate change signals from EC-Earth3 model [45], which is developed within the Coupled Model Intercomparison Project Phase 6 (CMIP6) [29] and supported the Sixth IPCC Assessment Report published in 2022.

Table 1: Building retrofit measures used in this analysis.

Climate Zone	Location	Case	Wall U-factor W/(m²·K)	Window U-factor W/(m²·K)	Window SHGC	Roof U-factor W/(m²·K)	Floor F-factor W/(m·K)	LPD W/m²	Cooling COP	ERV Sensible ε[1]	ERV Latent ε
1A	Miami, FL	Base	2.606	6.926	0.251	0.420	1.264	16.89	2.96	–	–
		Retrofit	0.669	2.698	0.218	0.259	1.264	6.50	3.87	0.7, 0.75	0.6
2A	Tampa, FL	Base	0.852	6.926	0.251	0.375	1.264	16.89	2.96	–	–
		Retrofit	0.455	2.432	0.237	0.209	1.264	6.50	3.87	0.7, 0.75	0.6
2B	Tucson, AZ	Base	1.363	6.926	0.251	0.261	1.264	16.89	2.96	–	–
		Retrofit	0.455	2.432	0.237	0.209	1.264	6.50	3.87	0.7, 0.75	0.6
3A	Atlanta, GA	Base	0.738	4.092	0.254	0.409	1.264	16.89	2.96	–	–
		Retrofit	0.413	2.261	0.237	0.209	1.264	6.50	3.87	0.7, 0.75	0.6
3B	El Paso, TX	Base	0.909	6.926	0.251	0.273	1.264	16.89	2.96	–	–
		Retrofit	0.413	2.261	0.237	0.209	1.264	6.50	3.87	0.7, 0.75	0.6
3C	San Diego, CA	Base	0.738	4.092	0.394	0.500	1.264	16.89	2.96	–	–
		Retrofit	0.413	2.261	0.237	0.209	1.264	6.50	3.87	0.7, 0.75	0.6
4A	New York, NY	Base	0.505	3.354	0.361	0.329	1.264	16.89	2.96	–	–
		Retrofit	0.346	1.938	0.342	0.174	0.855	6.50	3.87	0.7, 0.75	0.6
4B	Albuquerque, NM	Base	0.568	1.931	0.361	0.335	1.264	16.89	2.96	–	–
		Retrofit	0.346	1.938	0.342	0.174	0.855	6.50	3.87	0.7, 0.75	0.6
4C	Seattle, WA	Base	0.522	4.092	0.394	0.363	1.264	16.89	2.96	–	–
		Retrofit	0.346	1.938	0.342	0.174	0.855	6.50	3.87	0.7, 0.75	0.6
5A	Buffalo, NY	Base	0.466	3.354	0.391	0.301	1.264	16.89	2.96	–	–
		Retrofit	0.299	1.938	0.361	0.174	0.855	6.50	3.87	0.7, 0.75	0.6
5B	Denver, CO	Base	0.466	3.354	0.391	0.290	1.264	16.89	2.96	–	–
		Retrofit	0.299	1.938	0.361	0.174	0.855	6.50	3.87	0.7, 0.75	0.6
5C	Port Angeles, WA	Base	0.466	3.354	0.391	0.290	1.264	16.89	2.96	–	–
		Retrofit	0.299	1.938	0.361	0.174	0.855	6.50	3.87	0.7, 0.75	0.6
6A	Rochester, MN	Base	0.369	2.956	0.391	0.277	1.264	16.89	2.96	–	–
		Retrofit	0.263	1.833	0.361	0.174	0.837	6.50	3.87	0.7, 0.75	0.6
6B	Great Falls, MT	Base	0.409	2.956	0.391	0.278	1.264	16.89	2.96	–	–
		Retrofit	0.263	1.833	0.361	0.174	0.837	6.50	3.87	0.7, 0.75	0.6
7	International Falls, MN	Base	0.329	2.956	0.491	0.227	1.264	16.89	2.96	–	–
		Retrofit	0.263	1.567	0.38	0.150	0.837	6.50	3.87	0.7, 0.75	0.6
8	Fairbanks, AK	Base	0.256	2.956	0.491	0.176	0.935	16.89	2.96	–	–
		Retrofit	0.201	1.406	0.38	0.150	0.712	6.50	3.87	0.7, 0.75	0.6

[1]The first value represents heating sensible effectiveness, and the second value represents cooling sensible effectiveness.

This analysis focused on SSP2-4.5 and SSP5-8.5, the two scenarios most widely used in building performance studies, although the Future Weather Generator tool can produce downscaled hourly weather files for different SSPs. These scenarios represent moderate-mitigation and high-emissions pathways, respectively. Consequently, they provide a reasonable range of future climate impacts on building energy performance. For each scenario, hourly weather files were generated for two future horizons, including 2050, representing mid-century, and 2080, representing late-century, which results in five climate cases per location: TMY3; SSP2-4.5, 2050; SSP2-4.5, 2080; SSP5-8.5, 2050; and SSP5-8.5, 2080.

For each location, scenario, and projection time, future weather files were generated using a morphing-based approach, in which the existing EnergyPlus Weather file (EPW) were adjusted using climate change signals derived from climate model projections. In this method, independent variables, including dry bulb temperature, dew point temperature, relative humidity, atmospheric pressure, global horizontal radiation, wind speed, total sky cover, snow depth, and liquid precipitation depth, were morphed based on three main statistical transformations of shift, stretch, and the combination of shift and stretch. The independent variables, which do not need other EPW variables to be pre-calculated to be morphed, are then calculated based on the morphed independent variables using psychrometric functions and solar model equations. These parameters include extraterrestrial horizontal and direct normal radiations, horizontal infrared radiation from the sky, direct normal and diffuse horizontal radiations, global horizontal, direct normal, diffuse horizontal, and zenith illuminances, opaque sky cover, ground temperature, and typical/extreme periods. Parameters such as wind direction, present weather observation and codes, and liquid precipitation quantity remained unchanged.

2.5. Simulations and Performance Metrics

The input data files (IDFs), generated by OpenStudio, were used with EnergyPlus v.24.2.0 [46] as the simulation engine and the corresponding weather files to perform 720 simulations, which consisted of nine cases, including the baseline, seven individual measures, and a combined measures case, across five scenarios and projection years in 16 locations. A custom Python code using Python 3.13.5 [47] was used to automate the simulation and post-process the results.

Metrics used for each case in this analysis include, total regulated site energy consumption, tons of CO_2 equivalent (tCO_2e), and peak electricity demand. For each simulation, the annual electricity use for space heating (reheat) and cooling, interior lighting, exterior lighting, fans, and pumps, as well as the annual natural gas consumption for space heating and service water heating were summed to obtain total regulated site energy consumption. To isolate the impacts attributable to envelope and systems measures, in this analysis, equipment loads were excluded.

The tCO_2e associated with the annual operational energy use were calculated using fuel-specific emission factors. State-level emission factors using eGRID2023 [48] were used to convert total annual electricity consumption to tCO_2e for each case. These factors are provided in Table **2**. For natural gas conversion, the emissions factors for GHG inventories and the 100-year global warming potential (GWP) values, accounting for CO_2, CH_4, and N_2O emissions, were used to calculate a U.S. average emission factor for converting total annual natural gas consumption to tCO_2e [49]. Total tCO_2e emissions were then calculated by summing up electricity-related emissions with natural gas consumption-related emissions for each case.

Peak electricity demand was extracted from hourly simulation outputs and includes the hourly sum of electric demand associated with heating, cooling, heat recovery, lighting, fans, and pumps. Similar to the other metrics, equipment loads were excluded to maintain consistency with the energy consumption analysis.

2.6. Measure Impact and Normalized Energy Savings

The impact of each EEM was calculated as the difference between the baseline and models with EEM for each location, climate scenario, and measure. Two normalized total energy savings percentages were computed, one using the TMY3 weather file and one using the scenario-specific weather file for each location. Equation 1 presents the calculation of the savings.

Table 2: State output emission rates [48].

Climate Zone	State (Representative City)	CO_2e Emissions Rate (lb/MWh)
1A	Florida (Miami)	789
2A	Florida (Tampa)	789
2B	Arizona (Tucson)	689
3A	Georgia (Atlanta)	717
3B	Texas (El Paso)	771
3C	California (San Diego)	395
4A	New York (New York)	467
4B	New Mexico (Albuquerque)	774
4C	Washington (Seattle)	267
5A	New York (Buffalo)	467
5B	Colorado (Denver)	1091
5C	Washington (Port Angeles)	267
6A	Minnesota (Rochester)	752
6B	Montana (Great Falls)	1064
7	Minnesota (International Falls)	752
8	Alaska (Fairbanks)	814

$$E_{savings\ m,s,l} = \frac{E_{base,l} - E_{m,s,l}}{E_{base,l}} \times 100\% \tag{1}$$

where, $E_{savings,\ m,s,l}$ is the energy savings percentage of measure *m* in location *l* for scenario and projection *s* (i.e., SSP2-4.5, 2050, SSP2-4.5, 2080, SSP5-8.5, 2050, or SSP5-8.5, 2080), $E_{base,l}$ is the energy consumption of the baseline model in location *l* simulated using the TMY3 weather file for the fixed baseline and the weather file for a given scenario and projection year for the scenario-specific varying baseline, and $E_{m,s,l}$ is the energy consumption of the measure *m* in location *l* for scenario *s*.

To assess general trends within each scenario, the average savings percentages were calculated for each location in each time frame (i.e., TMY3, 2050, 2080) and each scenario. In this step, where climate zones are divided into subtypes (i.e., moist [A], dry [B], and marine [C]) averages across climate subtypes were used to derive a single representative value for each climate zone.

2.7. Attribution of Measure Impacts

To further analyze the impact of different parameters on energy performance and peak electricity demands, a nonparametric ensemble learning method was developed. The objective was to observe the relative contribution of each of the climate conditions and the properties included in the study on the performance of the models. Gradient boosting, an ensemble machine learning technique that provides a strong predictive model by sequentially combining many weak models was used to capture nonlinear interactions between retrofit measures, climate, and time. Model inputs included climate zone, subtypes, projection years, scenarios, and retrofit measures, and the response variable was total annual energy use and peak electricity demand. Because of the similarities in tCO_2e with energy use patterns, for brevity, emissions were excluded from this part of analysis. The gradient boosting model in this study was applied to explain simulation results and not to develop a surrogate model to predict energy performance.

SHapley Additive exPlanations (SHAP), an explainable AI (XAI) method, was applied to interpret the gradient boost model and attribute energy use or peak electricity demand to specific features. SHAP uses game theory (Shapley values) to determine each feature's contribution to a model's prediction, which enables the quantification of the relative contributions of individual retrofit features. Each SHAP value corresponds to the impact of that feature on the energy use or peak electricity demand. Another important insight that can be obtained is the directionality, as SHAP reveals directional and quantitative contributions of the variables. As indicated in gradient boosting, SHAP was also used for informative, data-driven decomposition of energy use and peak electricity demand across multiple interacting factors and not for forecasting.

3. Results and Discussions

3.1. Energy Consumption, Emissions, and Peak Electricity Demand

The total site energy consumption, tCO_2e, and peak electricity demand, from the simulation results of the medium office prototype building models in 16 climate zones are shown in Fig. (**2**). The energy use of each case is represented by a stacked bar, showing the electricity and natural gas energy use, a diamond showing the peak electricity demand, and the values above each bar that shows the tCO_2e for electricity and natural gas combined.

In general, retrofit models show lower energy use compared to the baselines, with the combined measures scenario delivering the largest reductions. Peak electricity demand results do not show a specific pattern, especially when comparing historical weather data and SSP5-8.5. The most discernable trends in peak electricity demand results are the reductions due to floor, LPD, cooling COP, and ERV improvements in SSP2-4.5, 2050 and roof, floor, LPD improvements in SSP2-4.5, 2080.

Energy consumption generally increases under future climate scenarios. This trend is more significant under the more severe climate change scenario, SSP5-8.5. Retrofit measures, however, continue to provide significant savings. Yet, the magnitude and effectiveness vary by climate zone and scenario.

To better understand general trends in the simulation results, Fig. (**3**) presents box plots grouping results based on climate zones and subtypes for each scenario and projection year. Total energy consumption (top part of Fig. **3**) shows that, under the TMY3 scenario, energy use slightly decreases when moving from warmer climates toward mixed climates and increases sharply in cold and very cold locations. Both SSP2-4.5 and SSP5-8.5 scenarios show more pronounced shifts in regions with extremely hot or cold conditions in future projections, while changes in mixed climate zones remain relatively small. However, these changes differ in extremely hot and cold regions. Warmer locations experiencing significant increases in energy use and colder climates showing noticeable reductions. This is mainly driven by the higher temperatures in different regions in future projections, which amplifies the energy use in warmer climates and reduces the energy consumption in colder regions. These effects are more pronounced under the SSP5-8.5 scenario. This indicates an increased stress on electric grids in strongly cooling-dominated regions, as rising future energy consumption outweighs potential energy savings. Fig. (**4**) shows the results of the combined measures case in the 2080 projection compared with TMY3, providing a geographical illustration of this observation (climate zone number and subtype are shown in each point). In addition, systematic differences in energy use across climate subtypes are evident in all scenarios, consistent with findings reported in the literature [50, 51].

Similar to the trend of energy use, total emissions (middle plot of Fig. **3**) show higher emissions observed in extremely hot and cold areas. The high heating loads in colder climates and high cooling loads in warmer climates is primarily causing increased emissions in regions with extreme weather conditions. However, emissions in climate zones 3C, 4A, 4C, 5A, and 5C are significantly lower. This reflects the lower emissions rates shown in Table **2,** along with the comparatively lower total energy use in these areas. This finding highlights the significant attention required for clean energy production in regions with extreme cooling- or heating-dominated, as higher electricity-related emission rates amplify the environmental impacts of their elevated energy demand. Fig. (**4**) also shows this with the varying sizes as the indication of tCO_2e. Retrofit measures yield substantial emission reduction, especially in climates with extreme conditions that also have higher emission rates. The relative benefits also vary depending on state-level electricity carbon intensity and natural gas usage.

A broadly similar trend to total energy consumption is observed for peak electricity demand (bottom part of Fig. **3**). In general, peak electricity demand increases as we move toward colder climates. Unlike annual energy use, however, climate zone 1 does not exhibit higher peak demand, primarily due to smaller annual temperature swings that result in steadier load profiles rather than sharp spikes. Trends highlight growing challenges for grid capacity under high-warming scenarios, particularly in hotter climates.

Figure 2: Energy consumption, carbon emissions, and peak electricity demand across ASHRAE climate zones and retrofit scenarios (values above each bar chart is the tCO_2e for electricity and natural gas combined).

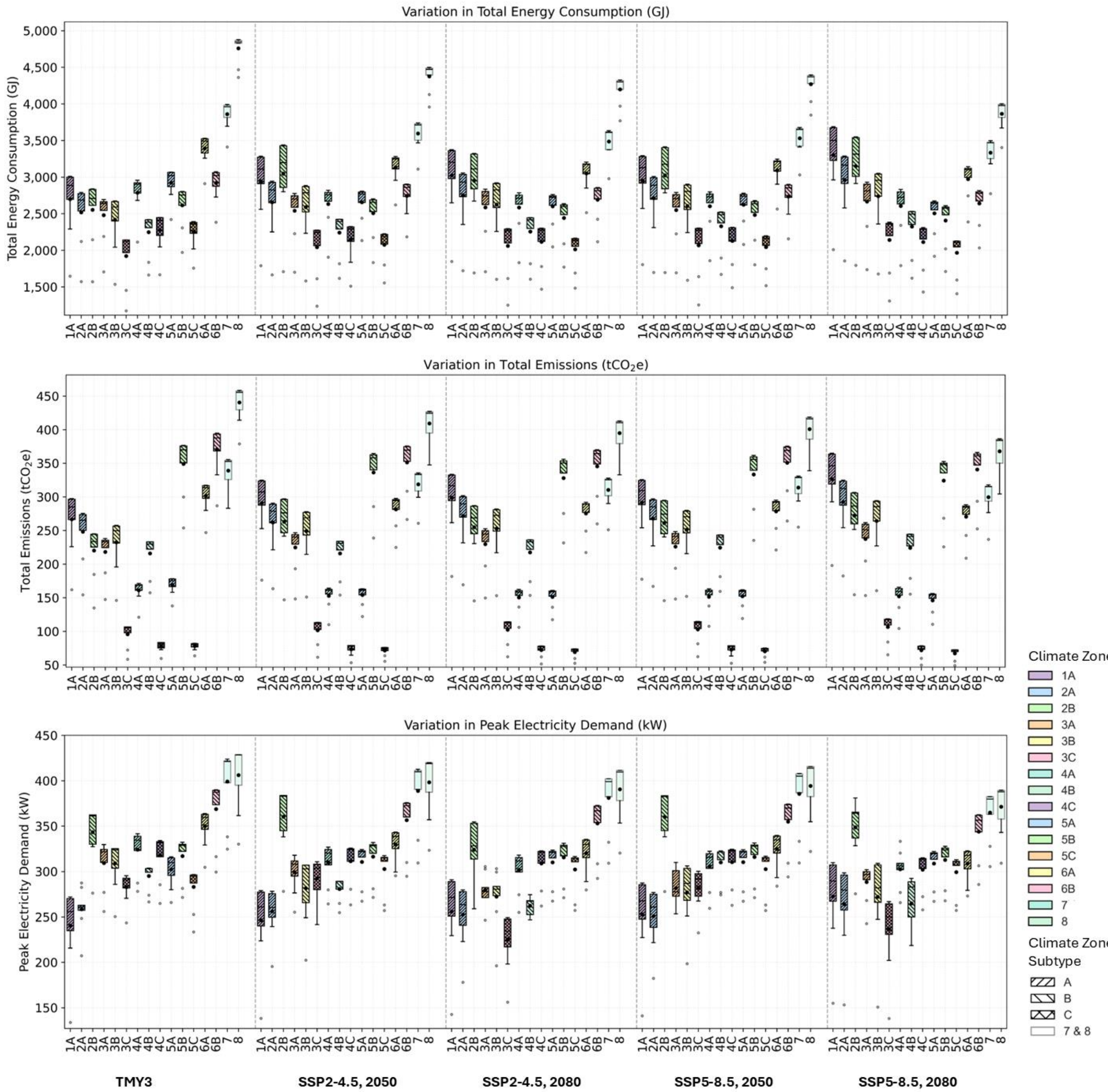

Figure 3: Variation in total energy consumption, carbon emissions, and peak electricity demand by climate zone and future scenario.

3.2. Normalized Energy Savings and Peak Electricity Demand Reductions

Fig. (**5**) illustrates the changes in normalized total energy savings (%) for different cases across different climate zones under TMY3, SSP2-4.5, and SSP5-8.5 scenarios. Results are shown for historical conditions (TMY3) and future projections for 2050 and 2080, normalized using a single TMY3 baseline (filled markers and solid lines) and scenario-specific varying baseline (hollow markers and dashed lines).

As a general trend, across nearly all climate zones and measures, energy savings show clear sensitivity to both the time horizon and emissions pathway. When compared with the fixed TMY3 baseline, energy savings generally decline from TMY3 to 2080 in climate zones 1–3 and increase in climate zones 5–8 under both SSP2-4.5 and SSP5-8.5 scenarios. This indicates that energy use grows faster than savings in hotter climates, resulting in a diminishing effect on savings. In significantly colder climates, however, the impact of growing savings is combined with the reduction in energy use, which results in increased savings percentages. Under SSP5-8.5, the decline or increase in savings is more pronounced. Amon EEMs related to opaque envelope components, window improvements outperform other opaque envelope measures across most climate zones, except in 1A and 2A.

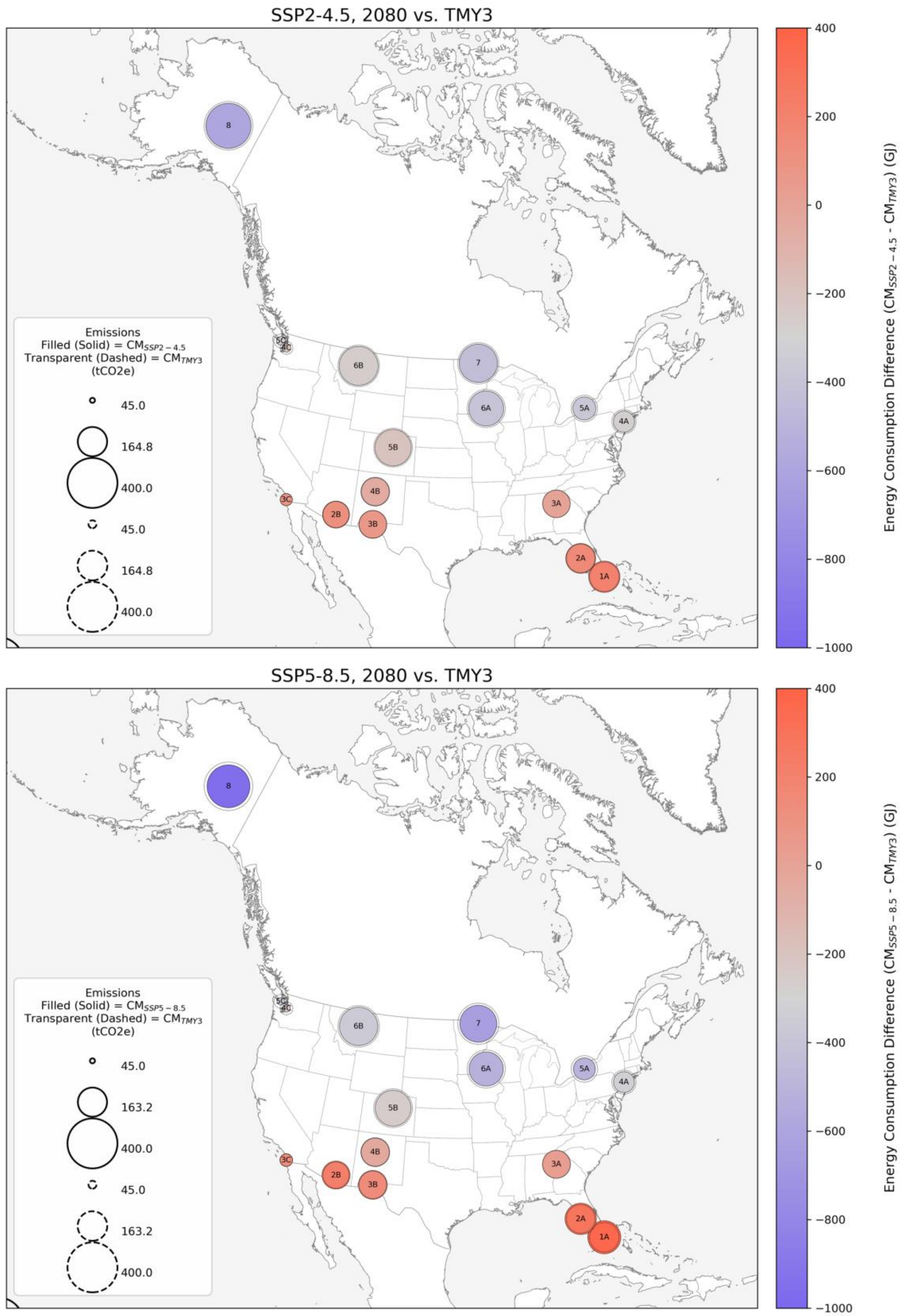

Figure 4: Projected energy consumption differences for the combined measures case in 2080 under the SSP2-4.5 (left) and SSP5-8.5 (right) scenarios. CM denotes the combined measures case.

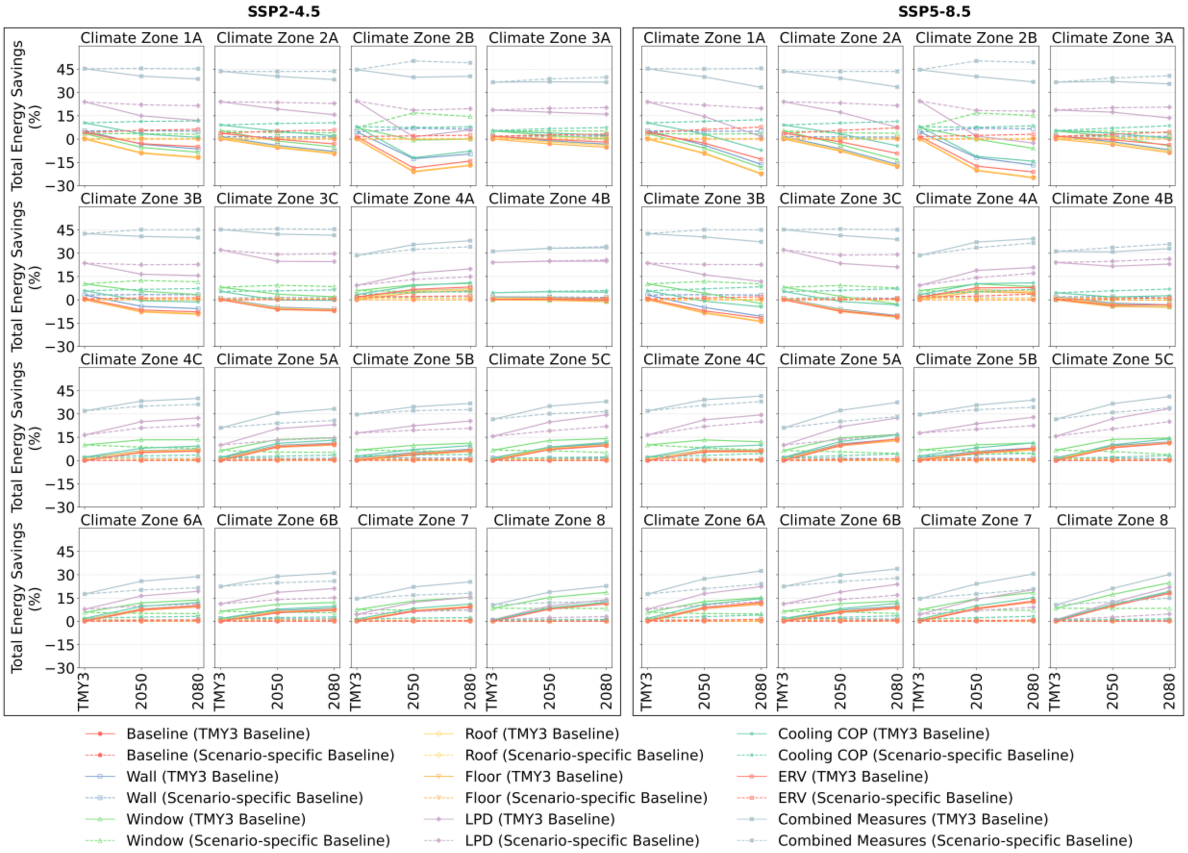

Figure 5: Normalized total energy savings (%) for different cases across different climate zones under SSP2-4.5 and SSP5-8.5 scenarios.

When using scenario-specific baselines, the differences are small, and savings percentages remain fairly constant across scenarios. The most noticeable changes are increases in savings in climate zones 4–6. While window improvements perform well across many climate zones, especially zones 3–8, their savings percentages slightly decrease in future projections in most cases in zones 4–8 under scenario-specific baselines.

Measure impacts vary based on location and scenario. In general, savings variation for selected measures shrinks moving toward colder climates, and maximum savings are reduced in colder zones. Specifically, cooling COP improvements maintain high and often increasing savings in warmer climates under scenario-specific baselines in both SSPs, with larger gains under SSP5-8.5 due to increasing cooling loads. Consistent savings can be seen from improvements on LPD across all climate zones and scenarios. The most pronounced impact of LPD reductions is seen in hotter climates. However, in very cold climates, window upgrades yield higher savings compared to LPD reductions. Percentage savings from LPD decrease slightly in hotter climates and increase in mixed, cool, and cold climates in future projections. ERV improvements demonstrate moderate savings, slightly higher than envelope measures in warmer climates, whereas window improvements outperform ERV in a number of cases in cold climates.

The combined measures scenario consistently outperforms individual measures, with savings ranging from approximately 10–45%, depending on climate zone and scenario, demonstrating strong robustness under future climate uncertainty. Combined savings show slightly less degradation than most individual measures in future projections, particularly under SSP5-8.5, in hotter climates, where individual measure savings percentages tend to decrease. This implies valuable interactions between envelope improvements and more efficient cooling systems under future conditions.

Average energy savings percentages in different climate zones and scenarios are presented in Fig. (**6**). Results for the TMY3 baseline and scenario-specific baselines are shown with solid lines and dashed lines, respectively. Two distinct patterns can be observed by comparing SSP2-4.5 and SSP5-8.5 projections for 2050 and 2080 using the TMY3 baseline versus scenario-specific baselines. The TMY3 values closely follow the scenario-specific baselines, as TMY3 effectively represents a scenario-specific case. Using a fixed TMY3 baseline, energy savings generally tend to increase with increasing climate zone number. For example, savings in climate zones 1-3 are negative because energy use in these zones grows faster than savings. Conversely, savings in colder climates are positive. The savings increase until it reaches to over 20% in climate zone 8 under SSP5-8.5. When using scenario-specific baselines, the trend reverses, where warmer climates show higher energy savings with slightly over 10% savings in climate zone 1, and the average savings steadily declines by moving toward colder climates, which eventually drops to about 3% in climate zone 8. This comparison emphasizes that the energy savings potential of retrofit measures varies across climates and highlights the need for climate-specific strategies to ensure the effective deployment of EEMs.

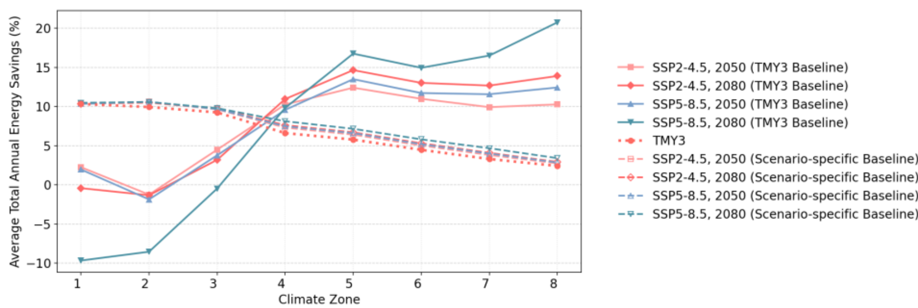

Figure 6: Average energy savings percentages across different climate zones and scenarios.

Fig. (**7**) shows normalized peak electricity demand reduction (%) for different cases across climate zones under SSP2-4.5 and SSP5-8.5 scenarios. Warmer climates reveal greater sensitivity to retrofit measures in terms of peak demand reductions in future projections for both SSP2-4.5 and SSP5-8.5 scenarios. Colder regions, however, show

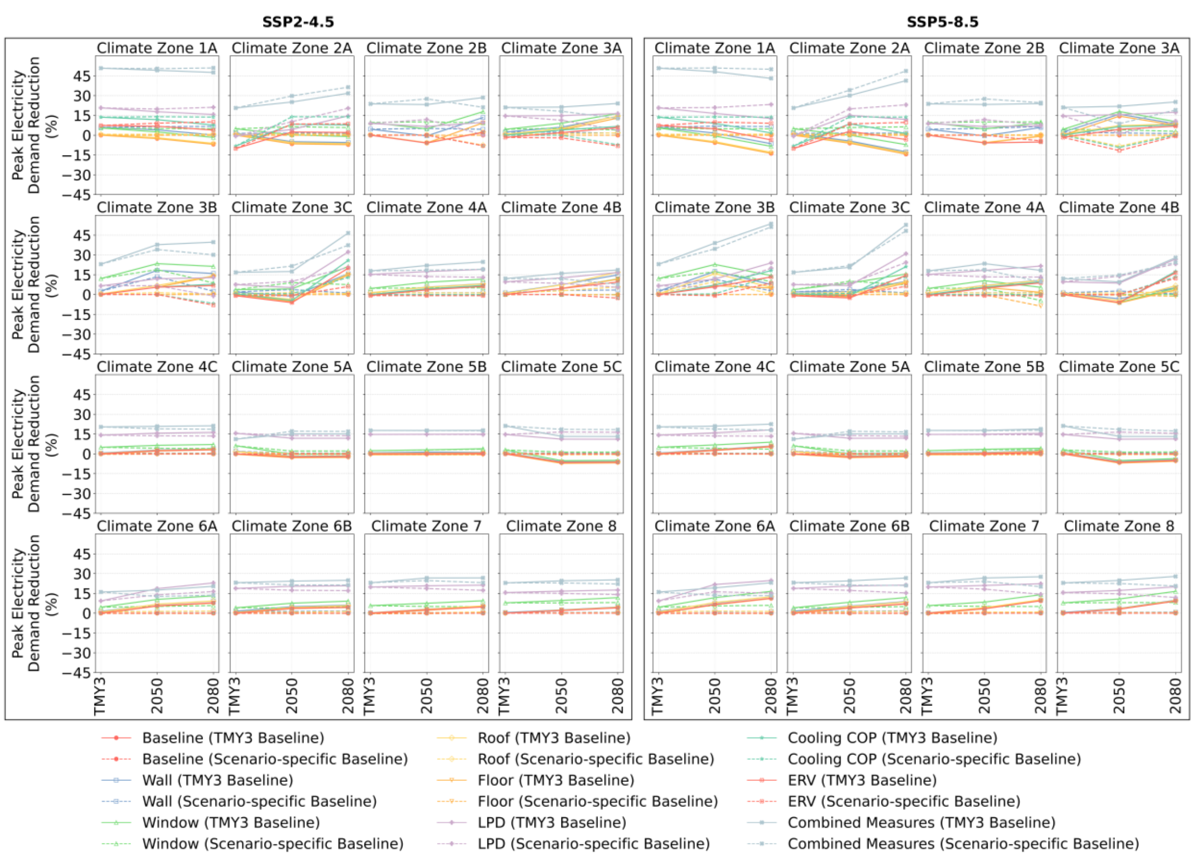

Figure 7: Normalized peak electricity demand reduction (%) for different cases across different climate zones under SSP2-4.5 and SSP5-8.5 scenarios.

a more steady response across different measures. Combined measures and LPD reductions consistently achieve the most significant demand reductions across all climates, with a few exceptions, such as in climate zones 3B and 3C where window improvements outperform LPD in some cases.

The average peak demand reduction percentages across different climate zones and scenarios based on the TMY3 baseline significantly varied with no specific pattern. The scenario-specific baseline results reveal a more consistent pattern. The average percentage reduction based on the results of scenario-specific baselines starts at 12% in climate zone 1, dropping to 4% in climate zone 4, and then slightly increasing to 5% in climate zone 5. Overall, energy-saving strategies appear to be more efficient at reducing peak electricity demand in hotter climates. This indicates that mixed and colder climate regions may need additional focus in grid resilience planning, especially considering the expected increased cooling-related electricity use.

The results also provide important implications for energy policy and retrofit prioritization across U.S. climate zones. One of the main implications of the results is that in very hot climates, where future scenarios show increasing cooling-driven energy consumption and peak electricity demand, retrofit strategies that reduce internal loads and improve cooling efficiency, such as LPD reduction and cooling COP improvement, can play an essential role in both reducing the energy consumption and reducing the stress on the grid. In addition, results show that the projected energy use under future scenarios can outpace the savings achieved by EEMs in regions with dominated cooling loads. Additionally, given that electricity-related emission factors coincide with high annual energy uses, environmental consequences are amplified in these regions. Hence, grid resiliency and environmental concerns in these areas require further attention. Therefore, prioritizing measures that target cooling loads and peak demand reduction through incentive programs and national or regional policies is essential to reduce the expected growth on the grid in these regions. On the other hand, envelope-related measures, namely window improvements, show relatively more benefits in very cold or subarctic climate conditions compared to other climates. This signifies that rather than applying uniform retrofit packages nationwide, climate-responsive retrofit strategies should be carefully tailored to align energy efficiency investments with regional climate characteristics.

3.3. Feature Contribution Analysis

Fig. (**8**) presents two types of visualizations of SHAP values to interpret feature importance in the developed machine learning model. The contribution of each feature to the model's predictions is quantified by SHAP values. The SHAP value plot (left) shows how each individual feature values impact the gradient boost model's output. The horizontal axis denotes SHAP values. Positive values result in higher prediction values and negative values indicate that the parameter has reduced the prediction values. The color gradient signifies the magnitude of the feature value. Blue indicates lower magnitudes and red higher magnitudes. As shown in Fig. (**8**) (left), features such as climate zone number reveal a broad SHAP value range, indicating it influences predictions in multiple directions. In contrast, features such as window improvement or cooling COP enhancement display more consistent directional effects, with SHAP values clearly positive or negative, which indicates a strong, predictable impact.

The bar chart of mean absolute SHAP values, shown in Fig. (**8**) (right), provides the rankings of the features based on their importance in model predictions. A stronger influence on model predictions is indicated with a higher mean SHAP values. Features like climate zone number and subtype, combined measures, and LPD show higher absolute mean SHAP values, which highlights their significance, while envelope measures (except window) show lower mean SHAP values and smaller spreads, showing lower influence.

Overall, the SHAP analysis highlights that climate severity (i.e., climate zone number and subtype) has the highest significance in gradient boost model predictions. The beeswarm plot also shows how significantly higher climate zone numbers, representing colder climates, increase SHAP values, which indicates the strong directional effects of the climate zone numbers. Among retrofit measures, combined measures and LPD showed the highest significance. Scenario variables (TMY3, SSP2-4.5, SSP5-8.5) and projection year have moderate influence, indicating that geographic climate differences overshadow temporal or scenario-based changes. Envelope and system measures (windows, roof, wall, ERV) show relatively lower effects.

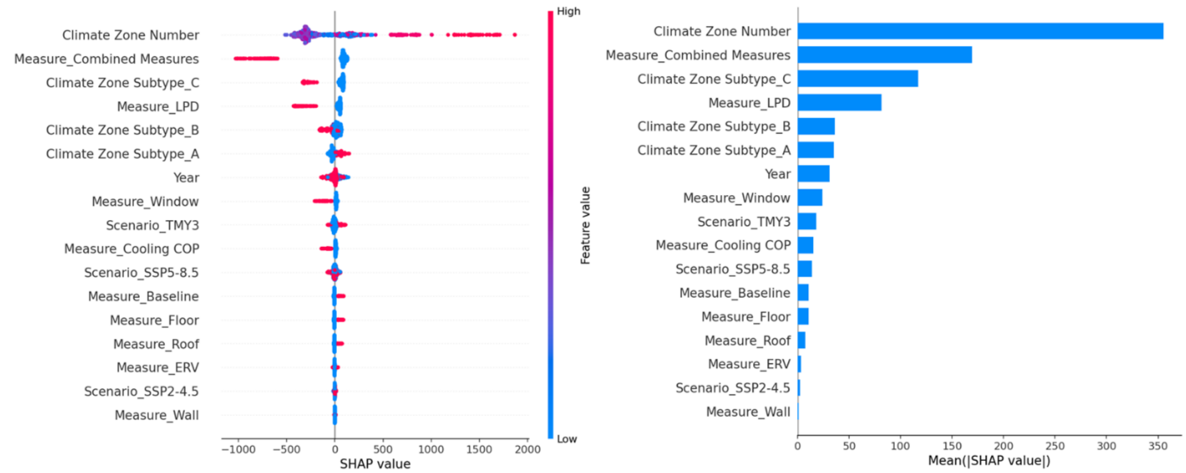

Figure 8: SHAP summary plot and feature importance for estimated energy consumption.

For peak electricity demand, shown in Fig. (**9**), the SHAP results again show that climate zone number is the dominant driver, although with a smaller overall magnitude than for energy consumption. This lower magnitude indicates a lower sensitivity of the peak electricity demand predictions by the model to climate features compared to the total energy use. Higher climate zone numbers (colder climates) generally increase peak demand predictions, mainly capturing heating-driven reheats. Similar to the results of energy use, combined retrofit measures and LPD improvements are shown to be the most influential interventions for reducing peak demand. Temporal and scenario variables play a secondary role compared to climate severity, and individual envelope measures revealed relatively lower effects.

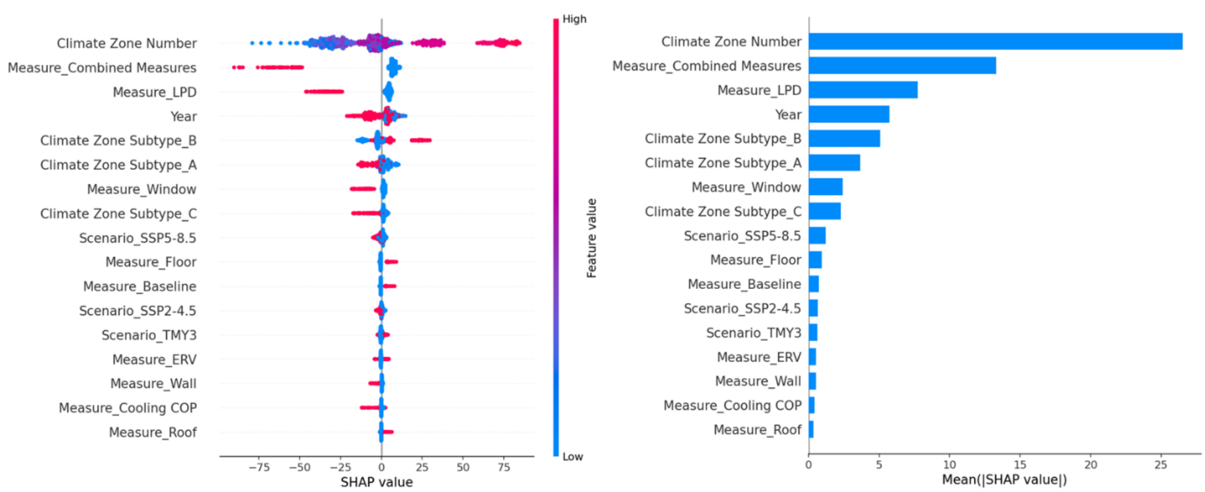

Figure 9: SHAP summary plot and feature importance for peak demand estimates.

3.4. Limitations

There are several limitations in this study that require acknowledgement. First, there are uncertainties inherently involved in Future climate projections. These uncertainties can be derived from differences among the models used for these projections, assumptions in projected scenarios, and downscaling approaches. While the models used in this study are state-of-the-art models, there exist limitations on spatial resolution, extreme event representation, and regional climate biases, given that some extreme conditions and regional conditions may occur at scales smaller than the model's grid cells. Therefore, the model utilized in this study provides one plausible representation of future climatic conditions. Consequently, while the use of a single climate model enables consistent scenario comparison, it should be noted that statistical properties of generated files may not fully capture potential future changes in climate variability. Thus, results in this study are more aimed to be interpreted as indicative and comparative trends instead of precise forecasts.

Second, building energy simulations are based on the defined assumptions in the model, such as internal heat gains and operational schedules, which can simply represent a typical building and may differ from real conditions. Additionally, there are simplifications and uncertainties in calculations in the calculations of building energy simulation engines. Therefore, while assumptions in this study follow established modeling practices, there can be differences between the results and actual building energy performance.

Finally, this study focuses on medium office buildings and certain geographic locations. Consequently, results presented in this study are specifically based on medium office buildings with the provided assumptions and may not necessarily be generalized to other building types. Additionally, while this study covers representative cities in different climate zones of the U.S., results in specific locations can vary based on the variations in locations not included.

4. Conclusion

This study evaluates the impact of EEMs on prototypical medium office models' energy performance, emissions, and peak electricity demand in different locations in the U.S. under current and future scenarios. It also addresses broader, holistic considerations across climate zones under future climate projections. Results are provided for energy use, emissions, and peak demand, normalized energy savings and peak reductions, as well as feature contributions in predictions of machine learning models, showing the significance of the parameters.

The results demonstrate that under historical TMY3 conditions, energy consumption decreases slightly from warm to mixed climates but dramatically increases in cold and very cold regions. Emissions are also higher in both hotter and colder climates due to increased cooling and heating loads, respectively, along with higher emission rates in these regions. Peak electricity demand also shows larger values in very cold and subarctic/arctic regions. Future climate scenarios (i.e., SSP2-4.5 and SSP5-8.5) demonstrate pronounced shifts at both warm and cold extremes, with comparatively smaller changes in mixed climates. These shifts are visible for energy use, emissions, and peak demands, with the strongest shifts happening under SSP5-8.5, which is primarily driven by increasing annual cooling loads in warm regions and decreasing annual heating loads in cold areas.

Across all climate zones and scenarios, combined retrofit packages is shown to be the most robust case for energy savings and peak demand reduction. After combined measures, which outperform individual measures, LPD reductions rank second in terms of energy savings across most climates. In very cold and subarctic/arctic regions, however, window upgrades slightly outperform LPD. Cooling COP improvements follow LPD in effectiveness in hotter climates. Window upgrades increasingly surpass LPD by moving from warm (excluding moist) climates toward cold climates. Generally, envelope-related parameters showed more significant results in very cold and subartcic/arctic regions. For peak demand reduction, similar to energy performance, LPD remains a dominant contributor after combined measures. However, window improvements show greater peak electricity demand reductions in a limited number of cases.

When evaluated against TMY3 baselines, energy savings decline over time in very hot, hot, and warm climates but increase in cold, very cold, and subarctic/arctic regions. This contrast becomes more pronounced under SSP5-8.5. Peak demand shows higher reductions in hotter and warmer areas. However, no specific pattern can be seen for projected years and scenarios. Scenario-specific baselines yield more consistent energy savings in future projections, with moderate drops in very hot climates and slight increases in mixed to very cold climates. Overall impacts are stronger under SSP5-8.5 than under SSP2-4.5 for both energy savings and demand reduction.

Results show more sensitivity in warmer and hotter areas to specific measures while colder climates appear less sensitive to individual interventions. Also, the trend of the performance of EEMs, in general, remain consistent in different projections and scenarios. One notable variation is observed for window improvements. Although they demonstrate strong performance across multiple climate zones, particularly zones 3 through 8, in scenario-specific baselines, their relative savings slightly decline in future projections compared to other measures in climate zones 4 through 8.

The average percentage savings of the analyzed cases with TMY3 baselines in future scenarios is lower in hotter climates, primarily due to faster growth in energy use in these regions. In contrast, due to a lower projected energy use in future scenarios in colder climates, these regions demonstrate more significant savings. However, in scenario-specific baselines, greater energy savings percentages can be seen in warmer climates compared to colder climates. These findings show that while there is an increase in the effectiveness of these interventions in warmer and hotter areas when comparing against baselines representing that period, the growth in energy use outpaces the increases in savings, which means the warmer and hotter climate zones may require further attention to tackle potential stresses.

For demand reduction under TMY3 baselines, the average percentage reduction does not show a clear pattern across climates. However, for scenario-specific baselines, demand reduction decreases from approximately 12% in very hot climates to about 4% in mixed climates, and then increases to slightly over 10% in very cold and subarctic climates.

SHAP analyses from the gradient boosting models for both energy consumption and peak electricity demand showed the dominance of climate conditions, including the climate zone number and climate subtype, in predicted values. Subtype A through C showed progressively lower loads. Combined measures, LPD upgrades, and window upgrades also showed high influence on the model predictions for both energy use and peak demands. Other envelope parameters showed relatively lower significance. Results showed that temporal effects and future scenarios are also important. However, spatial differences in climate employ a greater influence on models' predictions.

Overall, results show the significance of EEMs selection based on the regional climate characteristics. Cooling-related measures gain more significance, especially under high-emission scenarios. Improvements of envelope remain critical in colder zones. Systematic variations in climate zone subtypes signifies the need for locally calibrated retrofit guidance in different moisture regimes within each climate zone. Also, while the selected future scenarios are projected to exert additional stress on hotter and warmer regions, EEMs provide a robust pathway to mitigate these impacts. However, projected energy use under future scenarios may outpace the savings achieved by EEMs in regions with dominated cooling loads. Therefore, grid resiliency in these areas require further attention. Additionally, prioritizing clean electricity generation is critical in extreme cooling or heating demand areas as higher electricity-related emission factors coincide with high annual energy uses, amplifying the environmental consequences.

This study also has limitations. This analysis may not fully represent variability in construction practices or operational schedules, given that the prototypical building models with standardized assumptions were used. The parameters are selected based on ASHRAE 189.1-2020 while actual EEMs may go beyond these values. Also, the analysis is only performed using medium office prototype model, which does not represent all building types. Moreover, not all possible measures are evaluated. Finally, results may be influenced by the uncertainties in climate projections. Future studies can extend this study by conducting analysis on other building types and configurations, which would improve generalizability. Additionally, future studies can conduct research that integrates the analysis of EEMs with grid-scale considerations and regional utility demand response programs to reveal detailed location-specific recommendations.

Conflict of Interest

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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