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Long-Term Assessment of Commercial Building Energy and Carbon Reduction Potential in the Northwestern Region under Future Climate Trend

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Abstract

The future climate significantly impacts building performance and increases uncertainties in energy simulations. A rising temperature trend is expected to heighten cooling loads during summer and result in more carbon emissions. Understanding the impact of future climate on building performance is significant for policymakers to make informed decisions. Building retrofit measures can improve building energy efficiency and reduce operational carbon emissions, yet their effects under future climate conditions have not been fully investigated so far. Thus, we proposed an assessment methodology for evaluating long-term energy consumption and operational carbon reduction potential using a building stock dataset. For this study, commercial buildings in the northwestern (NW) region were utilized to assess the impacts of future climate and building retrofit. In addition, we selected Montana with a cold and dry climate as an example to analyze and discuss the carbon emission reduction potential in buildings. The main findings are: (1) Under future climate trends, changes in energy use intensity (EUI) will fluctuate due to variations in heating and cooling degree-days (HDDs and CDDs) and increasing HDDs will lead to increasing EUI. (2) After applying annual building retrofitting, the long-term EUI reduction potential of buildings in the NW region will decrease with the increasing retrofitting degree, and the short-term EUI reduction potential will be impacted by the change of heating and cooling degree days. (3) In Montana, the long-term carbon intensity reduction potential of retrofitted buildings will decrease under future climate trends with the increasing renewable energy penetration.

Introduction

The Pacific Northwest (NW) region of the United States is well-known for its rich forest resources, extensive coastline, and other diverse geographical environments. However, worsening global warming has been affecting this area for several decades. The average temperature of this region has increased by 1.3°F from 1895 to 2011 and is anticipated to continue to increase in the future (Melillo et al., 2014). The rising temperature has led to environmental deteriorations such as sea level rise (Council, 2012), a decrease in mountain snowpack area in winters (Mote, 2006), the occurrence of wildfires with unprecedented severity (Halofsky et al., 2020), etc. Moreover, the region's building energy consumption and carbon emission may be among the many aspects affected by the warmer climate. Several studies have revealed the relationship among ambient temperature, building energy consumption, and carbon emission. Santamouris et al. (2015) reviewed previous studies and summarized that for every 1°C increase in ambient temperature, the total and peak electricity demands are possible to be up to 8.5% and 4.6%, respectively. However, Zhou et al. (2013) identified due to global warming, a maximum reduction of 6% in the combined heating and cooling energy consumption in the United States by 2095, and its effect on carbon emission is negligible. Furthermore, Sun et al. (2014) discovered the effect of urban heat islands on building energy consumption through simulation studies of office buildings in representative cities in various climate zones across the United States, including three cities in the NW region (Salem OR, Boise ID, Helena MT). The result shows that the higher ambient temperature in urban areas causes higher cooling energy consumption in colder climate zones (Helena, MT) and lower total energy consumption in less cold areas (Salem, OR and Boise, ID), compared to their surrounding rural areas.

According to previous studies, it is essential to assess building performance in energy consumption and carbon emission and consider the potential influence of future weather trends. In addition, to contribute to sustainability and low-carbon development goals within the building sector, the solutions to reduce energy consumption and carbon emission are significant and should be applied to assess the building performance enhancement potential. Previous research indicates that building retrofits hold significant potential to enhance performance by reducing energy consumption and carbon emissions in specific regions (Lou et al., 2021; Sadineni et al., 2011). Therefore, a comprehensive long-term building performance assessment that accounts for changing climatic conditions is necessary. Moreover, an assessment method to evaluate the retrofit impact on large-scale buildings is required under future climate trends.

However, under future climate changes, current research on the long-term assessment of building performance, in terms of energy and carbon emissions with dynamically changing electricity emission factors, is not yet fully investigated. This research aims to develop an assessment methodology for evaluating long-term building performance from the year 2024 to the year 2050 under future climate trends. For this purpose, commercial buildings in the NW region were chosen as a case study to determine the effects of future climate and retrofitting. The NW region comprises four states: Washington, Idaho, Montana, and Oregon, which are characterized by three climate types: marine mix (4C), cool and dry (5B), and cold and dry (6B). From the building stock dataset, 932 commercial buildings have been identified as representative of the commercial infrastructure across the NW region. Initially, we simulated the energy consumption of all 932 commercial buildings. Subsequently, we examined the impact of retrofitting in selected years. Finally, we selected Montana with a cold and dry climate as an example to analyze and discuss the carbon emission reduction potential in buildings.

Methodology

Building Energy Model Development

A physics-based urban-scale building energy modeling tool (Lei et al., 2021) is utilized for automatic model generation, using input data from the Commercial Building Stock Assessment (CBSA) (James et al., 2020). This tool, featuring a bottom-up creation workflow, is built upon state-of-the-art building energy modeling tools and can generate large-scale building energy models based on building stock data. With the weather inputs from the EnergyPlus weather file (.epw), the commercial building's hourly energy consumption for different energy types such as electricity, and natural gas can be obtained.

Building Retrofit Strategies

Given the high level of uncertainty regarding which buildings will undergo retrofits and which retrofit measures will be implemented, a statistics-based approach can be adopted for the analysis of building stock retrofits (Filippi Oberegger et al., 2020). We operate under the assumption that the building retrofit cycle spans 10 years, meaning that once a building is retrofitted, it will not adopt another retrofit for at least the next decade. Newly constructed buildings are not included in this research due to the difficulty in predicting the number that will be built in the NW regions in the future, as well as the absence of reliable references that describe state development plans for long-term urban growth.

Energy Reduction Prediction

A building may consume different types of energy such as electricity and natural gas. Therefore, the annual energy reduction (ΔE) for a building can be obtained using the following formula:

for annual climate change

$$\Delta E_{\Delta y} = \sum_{\mathrm{h}=1}^{H} \sum_{k=1}^{K} (E_{h,k,y_1} - E_{h,k,y_2}), \qquad (1)$$

for retrofitting

$$\Delta E_{y,i} = \sum_{\mathrm{h}=1}^{H} \sum_{k=1}^{K} (E_{h,k,y,0} - E_{h,k,y,i}), \qquad (2)$$

where h represents an hour within one year, and H is the total number of hours for one year, which is 8640.The k is the energy source used in commercial buildings such as electricity, natural gas, and fuel oil, and K is the total type of energy source adopted in buildings. The y_1 means a year in the future, and y_2 represents a year next to y_1. The building retrofit measures are considered to improve building performance and reduce carbon emissions, which could be increasing the insulation of building envelopes, improving the efficiency of the HVAC system, etc. The i represents the retrofit strategies and the 0 represents the baseline model.

Carbon Emission Reduction Prediction

Before calculating the potential carbon emission reduction, we predict the hourly emission factor of different energy sources in each year with equation (1) and evaluate the retrofit impact with equation (2). Next, the energy reduction will be multiplied by the carbon emission factor to calculate the operational carbon emission. Since electricity generation dynamically uses different energy sources, the dynamic carbon emission factor is adopted and predicted with equation (3). Then, equation (8) calculates the aggregated carbon emission reduction potential.

Hourly Emission Factor of Electricity Prediction

Due to the different energy sources of electricity, the emission factor for electricity generation is dynamically changing (Gagnon et al., 2023). In the open-source tool Cambium dataset, we can acquire the state hourly carbon emission factors dataset of electricity generation for some specific years like 2035 and 2040. However, the carbon emission factors for some years are missing. Considering the seasonal pattern for energy source changing, especially renewable energy such as solar and wind, the seasonal autoregressive integrated moving average exogenous (SARIMAX) model is adopted to predict the hourly carbon emission factor for electricity generation (Li & Zhang, 2023; Singh et al., 2022). The training datasets are provided by Cambium which considers scalar increase in end-use electricity demand incorporating both the operational and structural consequences of the change (Gagnon et al., 2023).

$$(1-\phi_1 B)(1-B)Y_t = (1+\theta_1 B)\varepsilon_t, \tag{3}$$

where Y_t is the time series data of hourly carbon emission factor of electricity generation, B is backshift operator, ϕ_1 is the coefficient for the autoregressive term of lag 1, θ_1 is coefficient for the moving average term of lag 1, and ε_t is error term at time t.

Carbon Emission Reduction Calculation

In the previous equation (2), we acquire the hourly energy reduction with building retrofit measures of different energy sources k ($\Delta E_{y,i,k}$). With equation (3), we acquire the hourly emission factor Y_t which is a time-dependent variable and dynamically changing. Then we aggregate the emission factor for each year. To make the equation more generalized, we adopt the variable $\alpha_{h,k,y}$ to represent the emission factor for each energy source k of an hour h within a year y. When the carbon emission prediction starts from a specific year s, equation (4) - (7) shows the two different kinds of adopted carbon emission factors:

for dynamical changing emission factor such as electricity generation

$$h = mod(t, 8640), \tag{4}$$

$$if \;\; y - s < \frac{t}{8640} \leq y - s + 1, \tag{5}$$

$$then \;\; Y_t = \alpha_{h,k,y}, \tag{6}$$

for constant emission factor such as natural gas, it can be simplified as

$$\alpha_{h,k,y} = \alpha_k, \tag{7}$$

Based on previous research (Lou et al., 2022; Yang et al., 2023), the carbon emission reduction due to building retrofit can be calculated by multiplying the energy reduction with the energy emission factors in corresponding time and locations. Therefore, the carbon emission reduction (ΔC) for simulation period due to retrofits for a building can be obtained using the following formula:

$$\Delta C_{y,i} = \sum_{h=1}^{H}\sum_{k=1}^{K} \alpha_{h,k,y}\Delta E_{h,k,y,i}, \tag{8}$$

where i represents the retrofit strategies, h represents an hour within one year, and H is the total number of hours for one year, which is 8640. The k is the energy source used in the commercial building such as electricity, natural gas, and fuel oil, and K is the total types of energy source adopted in buildings. The y represents each year. The α represents the emission factor of energy source, which can be dynamically changing for electricity generation (Gagnon et al., 2023) or constant depending on different types of energy source such as natural gas.

Study Design

Locations

In this study, the NW region (Washington, Oregon, Idaho, and Montana) in the United States was identified to investigate the impact of future climate trends on the buildings. According to the climate characteristics of the NW region defined by the IECC 2012 (International Code Council, 2012), the three climate zones 4C (mixed marine), 5B (cool dry), and 6B (cold dry) were identified to investigate the impact of future climate trends on the buildings, as shown in Figure 1.

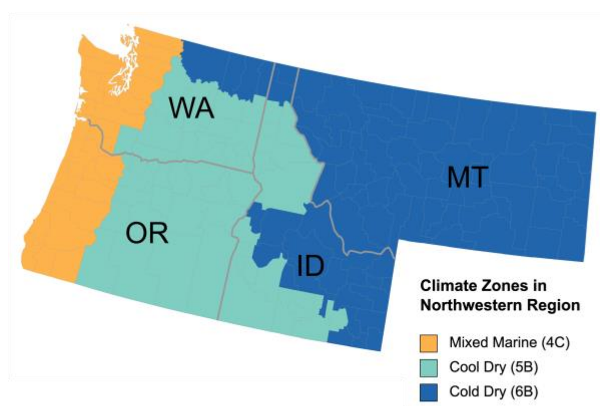

Figure 1. The northwestern regions in Unites States and corresponding climate characteristics.

Future Climate Scenarios

According to the Intergovernmental Panel on Climate Change (IPCC), four Representative Concentration

Pathways (RCPs) represent different greenhouse gas concentration trajectories used for climate modeling and research (Pachauri & Meyer, 2014). The one of popular scenarios RCP8.5 was adopted to evaluate future climate trends due to its prevalence in climate change research (Chen et al., 2017; Riahi et al., 2011; Rising & Devineni, 2020). The RCP8.5 means a radiative forcing value at 8.5 W/m^2, with assuming a continuous increase in emissions due to high fossil fuel dependency, particularly coal. This scenario models potential environmental outcomes by the end of the century.

Then, we used the open-source Weather Research and Forecasting (WRF) model (Skamarock et al., 2021) to generate the future climate temperature dataset under RCP8.5 scenarios as EnergyPlus weather file (.epw) for dynamic simulations under predicted climate changes. The heatmaps were applied to visualize the climate trends for climate zones 5B (Cool and Dry) and 6B (Cold and Dry) until the end of the 21st century, as shown in Figure 4, Figure 3, and Figure 4. The color intensity on these maps indicates temperature levels: darker red shades signify higher temperatures; darker blue shades signify lower temperatures and lighter shades indicate closing to zero temperature. Although the heatmap shows the dynamic fluctuation of temperature data in the 21st century, there is still a trend in temperature. In summer, the red color will become dark which means the temperature will increase, and in winter, the blue color will become light which means the temperature will also increase.

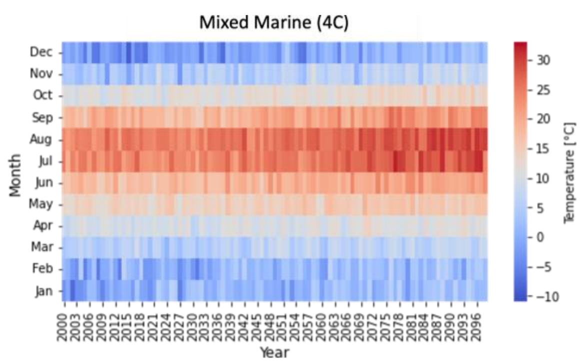

Figure 2. Future monthly temperature trends in current mixed marine climate region

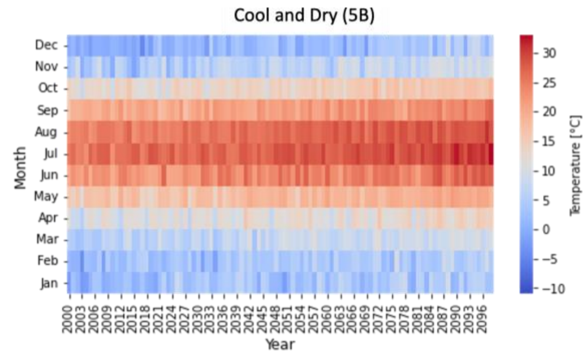

Figure 3. Future monthly temperature trends in current cool and dry climate region

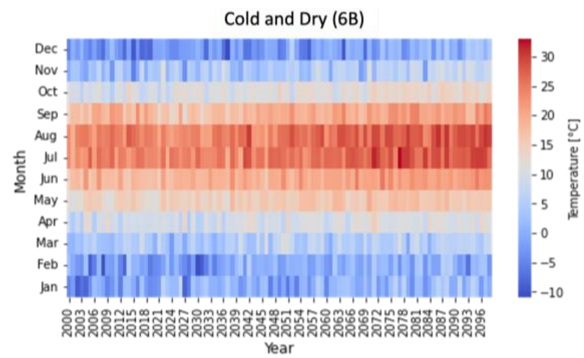

Figure 4. Future monthly temperature trends in current cold and dry climate region

Building Model Information

Baseline model

In this study, we developed 932 representative commercial building energy models based on the datasets from the Commercial Building Stock Assessment (CBSA) program. The CBSA program, as described by James et al. (2020), gathers and disseminates data on the features and energy consumption of commercial buildings in the NW region of the United States. The developed baseline model includes various types of buildings such as offices, hotels, libraries, hospitals, healthcare clinics (ranging from small clinics and doctor's offices to urgent care centers and large hospitals with elaborate emergency rooms and trauma centers), theaters, museums, religious facilities, dormitories, exercise centers, fire stations, gymnasiums, school/university, and restaurants. Since electricity and natural gas account for 94 % of the energy sources used in existing commercial buildings in the U.S., we only consider these two to predict the energy consumption of buildings (EIA, 2018). These buildings feature different HVAC types, including packaged terminal air conditioning, four-pipe fan coil systems, packaged terminal heat pumps, packaged single-zone air conditioning, packaged single-zone heat pumps, and packaged variable air volume boxes. We summarized major building configurations for building energy modeling of baseline models in Table 1.

Table 1. Building information of baseline model

Major Building Configurations	Unit	Inputs
Building Type	-	Offices, Hotels, Hospitals, Restaurants, Healthcare clinics, Religious facilities, School/University, etc.
Construction year	-	[1853, 2018]
Wall material	-	Wood framed, Metal building, Steel framed, Mass
Conditioned area	m^2	[0, 102164]
Heating setpoint	°C	[7, 27]
Cooling setpoint	°C	[16, 29]
HVAC system	-	Packaged terminal air conditioning, Four-pipe fan coil systems, Packaged terminal heat pumps, Packaged single-zone air conditioning, Packaged single-zone heat pumps, Packaged variable air volume boxes, etc.
People density	People/1000m^2	[0, 160]
Lighting power density	W/m^2	[0,429.26]
Plug load density	W/m^2	[0.14, 424.31]

Source: CBSA program (James et al., 2020)

Building Retrofit Measures

In this study, we adopted an annual retrofit rate of 5%, with each building eligible for retrofitting once every ten years. After a building has been retrofitted, it will not be retrofitted within the subsequent decade. After a decade, the building will be back in the pool as one of the potential candidates for retrofitting. A uniform distribution has been used to select the standard measures. The summary of building retrofit measures and the annual retrofit range or value is presented in Table 2.

Table 2. Building retrofit measures

Measure	Units	Annual Retrofitting Value
Setpoint adjustment	Heating °C Cooling °C	[-3, 0] [0, 3]
Add wall insulation	U factor W/(m^2·K))	-0.05
Add roof insulation	U factor W/(m^2·K)	-0.05
Replace window	U factor W/(m^2·K) SHGC	-0.05 -0.05
Replace energy efficient electrical equipment	Heating Cooling	[0, 2.13] [0, 0.66]
Improve service water heater efficiency	Heater thermal efficiency	0.05
Replace energy efficient lighting equipment	Lighting power density W/m^2	-0.05
Replace energy efficient equipment	Plug load density W/m^2	-0.05
Add overhangs	-	(Yes, No)
Add occupancy control for the HVAC system	-	(Yes, No)
Add occupancy control for lighting devices	-	(Yes, No)

Result and Discussion

Energy Use Intensity

Based on the proposed method, we calculate the long-term EUI for the NW region in the United States. Then, we investigate the impact of future climate and building retrofitting on the change of EUI from 2024 to 2050. The results and analysis are included in the following subsections.

Impact of Future Climate

Based on future climate predictions, the annual EUI change can be calculated for a baseline from the year 2024 to the year 2050, as shown in Figure 5. The positive value of change of EUI means the EUI will increase, and the negative value of change of EUI means the EUI will decrease. Among the three climate zones, the change of EUI varied year by year, and the fluctuation of climate zone 6B with colder climate characteristics is greater than climate zones 4C and 5B.

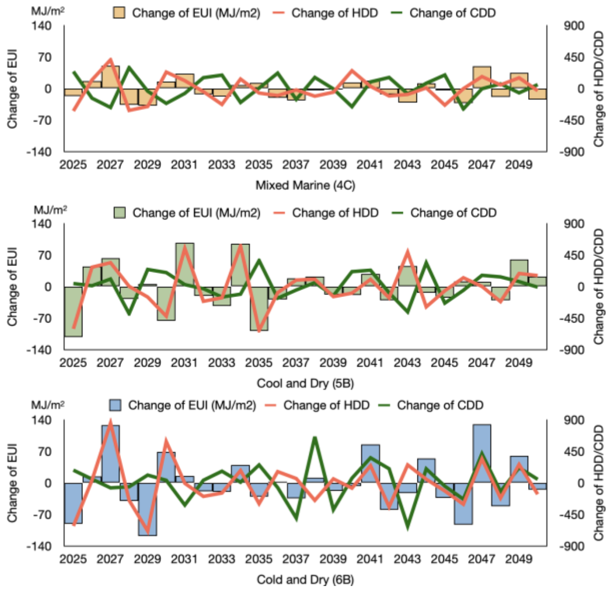

Figure 5. EUI change from 2024 to 2050 under future climate scenario

We then calculate the annual changes in HDDs and CDDs from 2024 to 2050, as shown in Figure 5. These changes affect the EUI; specifically, an increase in HDDs and a decrease in CDDs lead to an increase in EUI. This rise in EUI occurs because increasing HDDs means more heating load to maintain setpoint temperature and decreasing CDDs means less cooling load of buildings. On average, air conditioning systems for cooling have higher efficiency than heating systems. Then, the increasing heating load would be greater than the cooling load and lead to increasing overall energy consumption due to the discrepancy between heating and cooling system efficiency.

Additionally, the building with different HVAC systems will exhibit varying performance in cooling and heating due to the different HVAC efficiency. Therefore, we further investigate three buildings (health-care clinic, restaurant, school/university) from 2024 to 2050 with different heating ventilating and air conditioning (HVAC) systems: packaged terminal AC (PTAC) with natural gas heating, packaged single zone heat pump (PSZ-HP), and packaged variable air volume (VAV). As shown in Figure 6, the different HVAC systems result in varying changes in heating and cooling loads. Positive values indicate an increase in load, while negative values signify a decrease. For PTAC and packaged VAV systems, the heating load typically dominates the major change in heating/cooling load. As for the PSZ-HP system with higher cooling efficiency, it may sometimes dominate the major changes in heating/cooling with the increasing future climate trend.

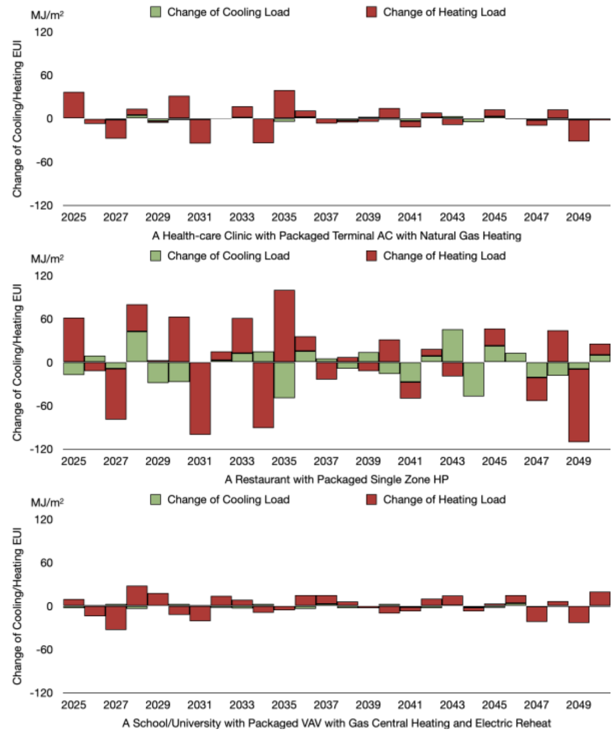

Figure 6. Change of cooling and heating load for different HVAC system

Impact of Building Retrofitting

After implementing building retrofit measures, the EUI reduction potential for buildings across three climate zones in the NW region from 2024 to 2050 was predicted, as illustrated in Figure 7. A positive value of EUI reduction potential indicates a reduction in energy consumption after implementing building retrofit measures. Under the combined influence of future climate trends and annual building retrofits, where the long-term trend of temperature is expected to increase and the number of retrofitted buildings will grow in the future, the EUI reduction potential in these three climate zones is gradually decreasing. This indicates that buildings are becoming more energy-efficient as retrofitting progresses. Moreover, in Figure 5, we present the annual changes in CDDs and HDDs. When the CDDs increase, the EUI reduction potential also increases. For example, in climate zone 4C, in the year 2036, CDDs will increase while HDDs will decrease. In this scenario, the increasing cooling load dominates the change in cooling/heating load, leading to an increase in EUI reduction potential. This suggests that the cooling efficiency in the NW region can be further improved.

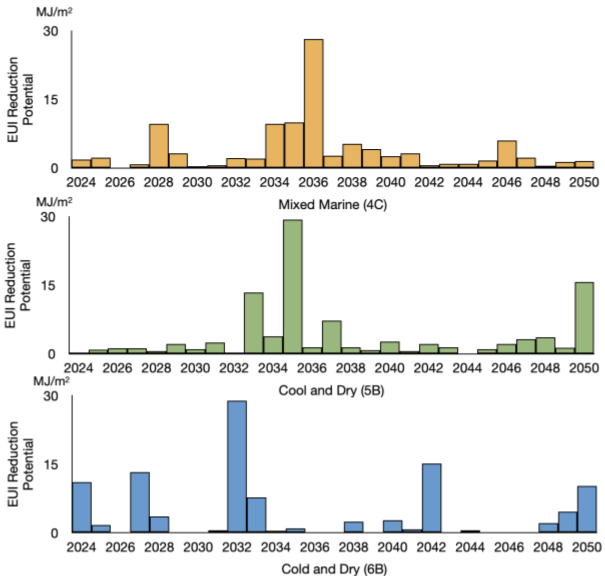

Figure 7. EUI reduction after retrofitting

Carbon Emission Reduction Potential in Cold and Dry Climate

We calculated the potential for carbon intensity reduction in Montana's cold and dry climate zones, and the carbon intensity reduction potential is depicted in Figure 8. The long-term carbon emission reduction potential is expected to decrease due to highly efficient building practices and the increasing adoption of renewable energy sources. From a long-term perspective, the carbon intensity reduction will decrease with increasing degree of building retrofitting. However, during the prediction period, the carbon intensity reduction does not always decrease and is predicted to increase in 2030 and 2041. In Cambium datasets, the long-run marginal carbon emission rate in electricity is predicted based on future renewable energy usage, and the percentage of renewable energy adoption in Montana is shown in Figure 9. The two points of increase in carbon intensity reduction correspond to two decreases in renewable energy adoption. The predicted renewable energy adoption from 2024 to 2050 in Cambium will decrease after 2030. Consequently, the use of dirty energy sources will increase to fill the energy gap, increasing carbon emissions and leading to an increase in carbon intensity reduction potential. Similarly, in the year 2040, the increasing usage of dirty energy will further enhance the carbon intensity reduction potential.

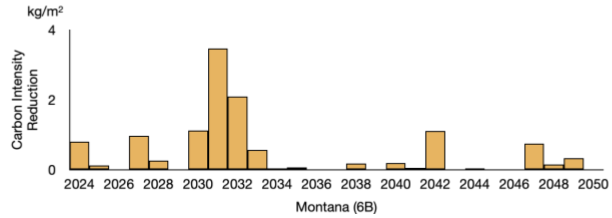

Figure 8. Carbon intensity reduction in Montana (6B)

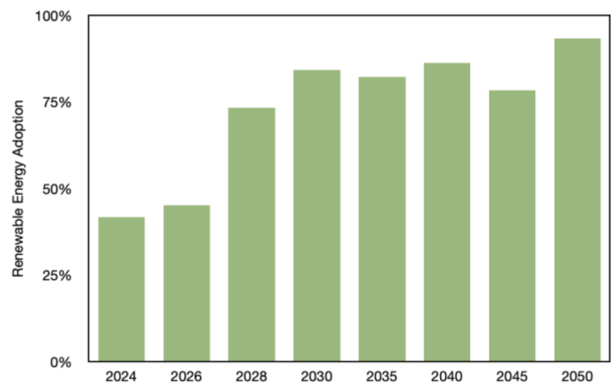

Figure 9. Renewable energy adoption in Montana (6B)

Discussion

In this study, we proposed a methodology to assess the impact of future climate trends and retrofitting on building energy and carbon reduction potential. Given the dynamical future climate trends, an assessment methodology is crucial for analyzing these trends and their impacts. We discovered a correlation between the EUI reduction potential of baseline buildings and changes in CDDs and HDDs under future climate trends. Additionally, we used three examples to demonstrate the EUI variations in different buildings with various HVAC systems. Grouping HVAC systems or building typologies could aid in further investigating the EUI performance of different building groups. This study primarily focuses on building retrofitting as a solution to enhance building performance in the face of future climate change. We proposed a retrofitting scenario by considering the uncertainties of building retrofitting with an annual retrofit rate to improve building energy efficiency. Since this study evaluates buildings from 2024 to 2050 and considers the lifespan of HVAC systems usually around 20 years, HVAC system replacement is not included in this scenario. For longer-term building evaluations, considering HVAC system replacement could make the model more realistic. Moreover, the retrofitting value of different retrofit measures can be more diversified when retrofitting different types of buildings. Further investigation is necessary to understand the correlation between future climate changes and the annual building retrofitting rate.

For building decarbonization through retrofit measures, we selected Montana, with its cold and dry climate, as an example to explore the potential for carbon intensity reduction, and the results of renewable energy adoption predictions from the Cambium dataset are used to prove the analyzed result. For other regions with different energy structures, a similar approach can be applied to assess the potential for carbon intensity reduction and to highlight spatial variability. Moreover, when evaluating the building performance under future climate trends, the increasing trend of building electrification, particularly in space and water heating, is an important factor. The high level of uncertainty in electrification adoption, along with the potential advantages of integrating electrification technologies with renewable generation and energy storage, also plays a significant role.

Conclusion

To understand the impact of future climate trends on building performance and to support the decarbonization goal of the building sector, this study proposed an assessment methodology. We evaluated long-term building performance using a building stock dataset. Commercial buildings in the NW region, encompassing four states (Washington, Idaho, Oregon, Montana) with three distinct climate features (mixed marine, cool and dry, cold and dry), were selected for investigation. Finally, we selected Montana with a cold and dry climate as an example to analyze and discuss the carbon emission reduction potential in buildings. Our findings indicate that under future climate trends, the change of EUI will fluctuate due to changes in HDDs and CDDs. When HDDs increase and CDDs decrease, the EUI will increase. Moreover, different HVAC systems will have varying performance in terms of changes in cooling and heating load, which will also impact a change in EUI. When the cooling efficiency of HVAC systems is higher, such as with heat pumps, the cooling load will gradually become dominant in the change of cooling/heating load due to future climate changes.

Under the retrofitting scenarios, our analysis indicates that the long-term EUI reduction potential will decrease with the annual building retrofit measures, and when the cooling degree day increases under future climate prediction, the EUI reduction potential will increase due to the increasing cooling load dominant to the increasing cooling/heating load. We further investigated the Montana state to predict carbon intensity reduction potential under the future climate trend. The result shows that predicted carbon intensity reduction in Montana state will be impacted by future renewable energy penetration, when renewable energy penetration increases, the carbon intensity reduction will decrease due to the less carbon emission, otherwise, when renewable energy penetration decreases, the carbon intensity reduction will increase due to more carbon emission by increasing dirty energy source.

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Nomenclature

ΔE = energy consumption reduction

ϕ = coefficient for the autoregressive term

B = backshift operator

θ = coefficient for the moving average term

ε = error term

Y = time dependent emission factor of energy generation

α = annual emission factor of energy generation

Subscripts

0 = baseline

i = building retrofitting

t = time with a unit (e.g., hour, minute)

1 = time lag

k = energy source

h = an hour within one year

y_1 = a year in future

y_2 = a year next to y_1

y = a year during the simulation period

s = a specific year which is the start year of the simulation period

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