

Quantifying building thermal resilience under extreme heat: A change-point regression analysis of retrofit performance for urban overheating adaptation

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Abstract

Extreme heat driven by climate change increasingly challenges building energy performance and indoor thermal comfort by intensifying cooling demand. Although typical and extreme weather-year datasets are widely used to estimate future energy consumption, limited attention has been paid to how buildings physically respond to extreme heat. This study applies a three-parameter change-point regression to daily cooling energy under extreme warm-year conditions to characterize the cooling energy–temperature response through the change-point temperature (β_1), temperature sensitivity (β_2), and base load (β_3), while evaluating cooling peak demand and indoor thermal conditions. Residential and office prototypes were simulated across four Korean climate zones under SSP5-8.5 for present, mid-century, and late-century climates using Typical Downscaled Year and Extreme Warm Year weather datasets. In the extreme warm-year baseline for the Seoul medium office, β_3 increased by 112.7% and β_1 rose by 2.79 °C in the 2080s relative to the base year. Passive envelope retrofits increased β_3 by 30%, whereas active measures reduced β_2 by 25%. The combined strategy decreased β_1 by 2.3 °C and reduced β_2 and β_3 by 41% and 2.4%, respectively. Combined retrofit reduced cooling peak demand by 23%–28% for medium offices and 38%–46% for high-rise apartments. Apartments maintained near-zero SET-based heat-stress exposure, whereas medium offices showed limited or adverse warm-discomfort changes. Overall, these results suggest that operational resilience under extreme warm conditions is better assessed through complementary dimensions—cooling energy–temperature response, peak demand, and occupant thermal safety—than through aggregate energy metrics alone, while change-point parameters provide useful diagnostics for the energy-response dimension.

Keywords

change-point regression analysis
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1 Introduction

Global climate change has become a critical issue that affects various sectors, including the building environment (Liu et al. 2020). The driving force behind climate change is the increasing emissions of greenhouse gases (GHGs), which is a result of unsustainable energy consumption patterns (Cabeza et al. 2022; Huang et al. 2023). In 2019, global GHG emissions were estimated at approximately 59 GtCO₂-eq, representing increases of 12% since 2010 and 54% since 1990 (Cabeza et al. 2022). According to the Intergovernmental Panel on Climate Change (IPCC) 6th

assessment report (AR6), carbon dioxide accounts for approximately 74% of global GHG emissions, indicating that the majority is attributable to human activities (Cabeza et al. 2022).

The building sector is responsible for approximately 37% of global CO₂ emissions, including both direct and indirect emissions, which highlights its significant role in global GHG emissions (UNEP 2019; UNEP 2024). Therefore, the building sector is closely linked to climate change, and the IPCC underscores its critical role in climate-change mitigation (Cabeza et al. 2022). Figure 1 illustrates the relationship between climate change and the building sector (Vérez and

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List of symbols

D_y	L_1 distance between candidate and reference quantile function	EPW	EnergyPlus weather data file
P	30-year analysis period	EUI	energy use intensity
p	probability level for quantile comparison (0–1)	EWY	extreme warm year
$Q_{\text{ref}}(p)$	reference quantile function for month m over period P	GCM	general circulation model
$Q_y(p)$	candidate-year quantile function for month m	GHG	greenhouse gas
S_y	signed quantile deviation between reference and candidate quantile functions	GRIMs	Global/Regional integrated Model system
$T_{\text{RCM}}^p(t)$	reconstructed hourly dry-bulb temperature for period P	HadGEM3-RA	Hadley Centre Global Environmental Model version 3 regional climate model
y_{EWY}^*	selected representative year for EWY in month m	HDD	heating degree-days
y_{TDY}^*	selected representative year for TDY in month m	HVAC	heating, ventilation, and air conditioning
β_1	change-point temperature ($^{\circ}\text{C}$)	IEA EBC	International Energy Agency's Energy in Buildings and Communities Programme
β_2	slope ($\text{kWh}/(^{\circ}\text{C}\cdot\text{day})$)	IMT	Inverse Modeling Toolkit
β_3	base load (kWh/day)	IPCC	Intergovernmental Panel on Climate Change
<i>Abbreviations</i>		KMA	Korean Meteorological Administration
ACS	adaptive comfort standard	NDC	Nationally Determined Contribution
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning	PMV	predicted mean vote
CCLM	COSMO-CLM	PTAC	packaged terminal air conditioner
CDD	cooling degree-days	RCM	Regional Climate Model
COP	coefficient of performance	RCP	Representative Concentration Pathways
CVRMSE	coefficient of variation of the root mean squared error	RegCM4	Regional Climate Model system version 4
DOE	Department of Energy	SET	standard effective temperature
ECDF	empirical cumulative distribution function	SHGC	solar heat gain coefficient
		SRES	special report on emission scenario
		SSP	Shared Socioeconomic Pathways
		TDY	typical downscaled year
		TMY	typical meteorological year
		WRF	weather research & forecasting model

Cabeza 2021; Cabeza et al. 2022). It shows that building services are designed to ensure safety, comfort, and efficiency, and that the climate change driven by increased GHG and pollutant emissions significantly impacts the conditions necessary to maintain a healthy and comfortable indoor environment. For example, standards related to daylighting, ventilation, and cooling may be revised, and changes in the indoor environmental conditions are expected to significantly affect occupant-related factors such as indoor air quality and thermal comfort, which are essential for the well-being of occupants. Consequently, the demand for heating, cooling, and ventilation is likely to increase in response to these changing conditions (Cabeza et al. 2022). However, this intensified cooling operation creates a feedback loop: the increased rejection of anthropogenic heat from buildings further exacerbates the urban heat island effect, leading to severe urban overheating. Therefore, mitigating the cooling load of individual buildings is not only an energy issue but also a critical measure to reduce urban thermal stress.

In Republic of Korea (South Korea), the building sector, which is responsible for 24.7% of national GHG emissions and 47% of electricity consumption, faces significant challenges in adapting to these changes (Presidential Commission on Carbon Neutrality and Green Growth 2018). In response, the South Korean government has established the 2030 Nationally Determined Contribution (NDC) plan, which sets an ambitious goal of reducing the emissions from the building sector by 30% by 2030. This can be achieved through energy efficiency improvements, the promotion of high-efficiency equipment, and the expansion of renewable energy (Ministry of Environment 2021). While these policies emphasize decarbonization through efficiency retrofits, increasingly frequent extreme heat events also create an adaptation challenge. In particular, retrofit packages should remain effective under extreme warm conditions without compromising indoor thermal safety or exacerbating peak cooling demand, highlighting the need for evaluations that go beyond typical-year datasets and annual aggregate metrics.

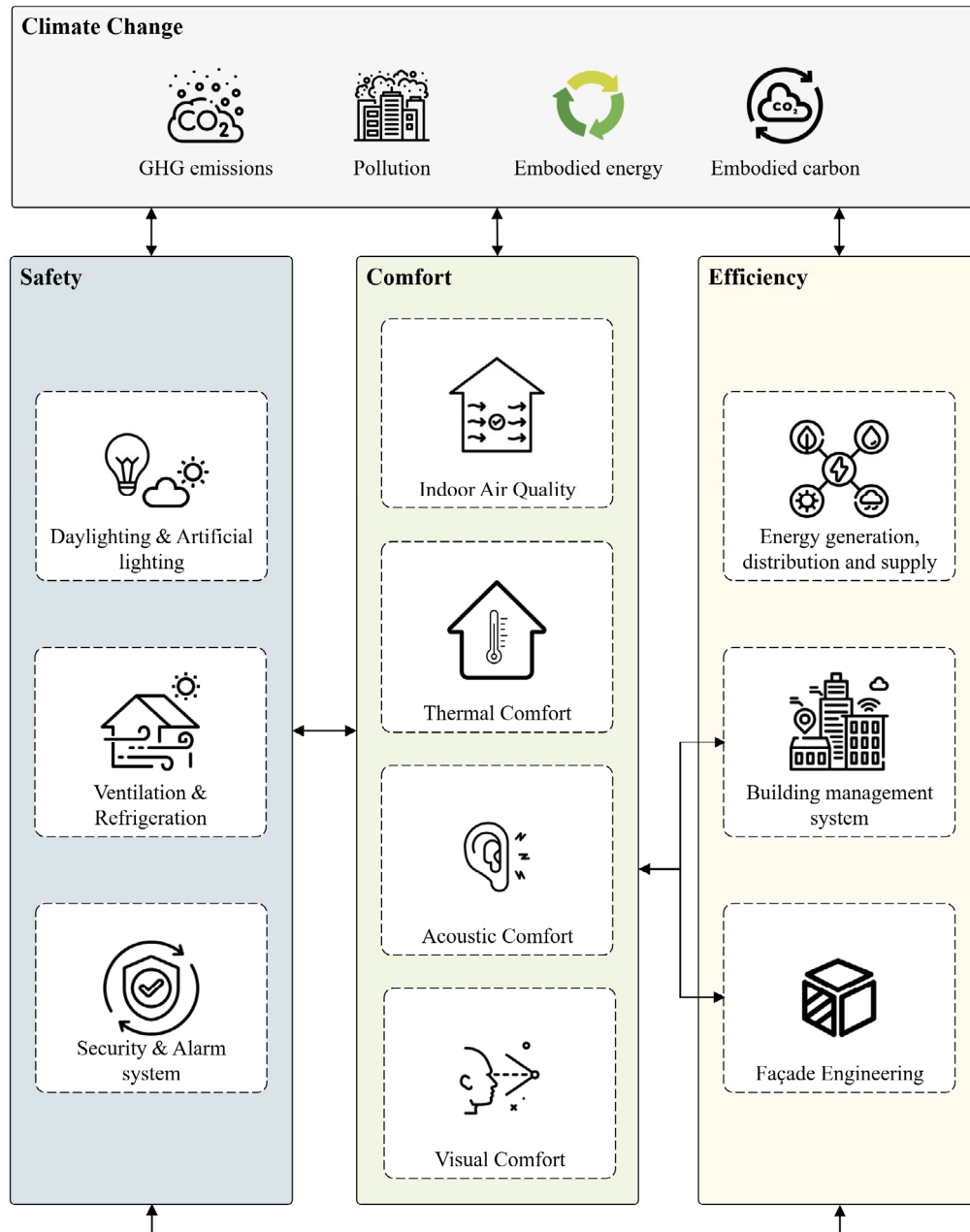


Fig. 1 Relationship between climate change and the building sector (Vérez and Cabeza 2021; Cabeza et al. 2022)

To support such evaluations, building energy simulation is combined with three-parameter (3P) change-point regression to quantify cooling-response characteristics in terms of an operational change-point temperature, temperature sensitivity, and base load. Based on these interpretable parameters, passive, active, and combined retrofit strategies are compared and their robustness under extreme warm conditions is assessed.

2 Literature review

Previous reports on the relationship between climate change,

building energy consumption, and indoor thermal comfort across different regions are summarized in Table 1. Generally, most studies have employed climate models, such as general circulation models (GCMs) and regional climate models (RCMs), in conjunction with IPCC emission scenarios to estimate future climate conditions and to integrate downscaling techniques (that is, morphing and dynamic methods) to generate data suitable for energy simulations. The results of these simulations were used to evaluate the impact of climate change on energy consumption and to assess the effectiveness of the proposed mitigation measures. In Asia, studies have been performed in various regions,

including China, Japan, and Pakistan. Studies focusing on China (Wan et al. 2011; Wan et al. 2012; Huang and Hwang 2016; Liu et al. 2020; Chen et al. 2023; Ma et al. 2023) primarily examined the impact of climate change on building energy use across different regions and proposed various mitigation measures, demonstrating their potential to improve energy efficiency. Wan et al. (2012) examined the effects of climate change on building energy consumption and carbon emissions in fully air-conditioned office buildings across five major climate zones in China. Their findings indicated that the cooling energy demand was expected to increase in all the regions. They also highlighted that mitigation measures such as improving building envelopes, controlling internal loads, and optimizing chiller plants can enhance energy efficiency. However, their effectiveness varies by climate zone, which underscores the importance of region-specific adaptation strategies. In South Korea, the impact of climate change on building energy use has also been examined. Lim and Yun (2017) analyzed Seoul, Tokyo, and Hong Kong. They found that adaptive comfort control, nighttime ventilation, and occupancy-based lighting and equipment control effectively reduced cooling energy use, underscoring the key role of occupant behavior. Kim (2022) assessed a set of multi-use building archetypes at the 1 km × 1 km urban-block scale in Seoul under future climate conditions. The study quantified the heating-energy savings from energy-efficiency retrofit programs and emphasized the need to optimize window SHGC and improve HVAC performance. Shibuya and Croxford (2016) performed a study in Japan targeting three regions with different climates and found that the cooling loads increased significantly in all the regions except for cold cities, highlighting the importance of implementing mitigation measures. Mehmood et al. (2022) suggested that both passive and active measures should be integrated in Pakistan because of the anticipated increase in cooling demand in future climate conditions. In North America, research focused on the United States and Canada indicated that accurate predictions of building energy consumption require the consideration of social factors, such as population growth, in addition to climate change (Wang et al. 2023). The need for climate change studies to explain the performance degradation in existing buildings has also been emphasized (Baba et al. 2023). Studies in Europe (Hosseini et al. 2022; Baglivo et al. 2024) and Australia (Bamdad et al. 2021) have highlighted the need for updated design standards and energy regulations to address the increasing cooling demand.

Some studies have also investigated the impact of climate change on indoor thermal comfort in addition to building energy consumption (Huang and Hwang 2016; Liu et al. 2020; Bamdad et al. 2021; Jafarpur and Berardi 2021; Hosseini et al. 2022; Mehmood et al. 2022; Ashrafiyan 2023;

Baba et al. 2023). The indicators used to assess thermal comfort include the adaptive comfort standard (ACS) (Huang and Hwang 2016; Liu et al. 2020; Mehmood et al. 2022; Baba et al. 2023), overheating hours (Bamdad et al. 2021; Hosseini et al. 2022), and predicted mean vote (PMV) (Jafarpur and Berardi 2021; Ashrafiyan 2023). The adaptive comfort standard has primarily been applied to naturally ventilated or mixed-mode buildings without cooling systems, and often incorporates discomfort hours to determine the necessity of cooling systems under future climatic conditions. Overheating hours, which quantify the duration during which indoor temperatures exceed a predefined overheating threshold, have been used to discuss the HVAC sizing requirements in future climatic scenarios. The PMV model was used to examine the relationship between the heating and cooling energy consumption, passive mitigation measures, and indoor thermal comfort by adjusting the temperature setpoints and other control strategies. More recently, rather than relying on a single metric, studies have begun to employ multiple comfort indicators concurrently and to incorporate not only outdoor meteorological conditions but also urban microclimate effects. For example, Mu et al. (2026) generated future weather data based on CMIP6 SSP scenarios, performed EnergyPlus simulations, and evaluated climate-driven changes in thermal comfort using PMV, predicted percentage of dissatisfied (PPD), and mean radiant temperature (MRT). They further coupled CFD-derived urban wind environments with an AirflowNetwork model to quantify the influence of wind-environment changes on both energy use and thermal comfort.

Recently, alongside the use of downscaled climate data, there has been growing interest in explicitly accounting for extreme events. Li et al. (2023) proposed a new method that considers the influence of multiple meteorological variables on building energy use and employs dynamic thresholds to quantify the intensity and timing of extremes across variables. They showed that combining TMY with the proposed weather year improved simulation accuracy. Cao et al. (2025) noted that constructing a synthetic extreme year by combining extreme months from different calendar years may overestimate annual extremes, and proposed an annual-based approach that selects a single calendar year directly from long-term meteorological records. They further reported that the annual-based approach can provide more stable performance in reproducing annual extreme heating and cooling energy outcomes, underscoring the importance of clearly defining extremes and selection rules. Yu et al. (2025) developed an extreme weather year by identifying periods that represent extreme characteristics based on the monthly high-temperature distribution from long-term weather records for a subtropical high-rise office building. They applied the EWY together with future climate conditions

for the 2050s and 2080s to EnergyPlus simulations and quantified changes in cooling loads, peak cooling demand, carbon emissions, and thermal comfort (PMV). They also demonstrated that efficiency improvements, such as adopting ultra-high-efficiency chillers, can reduce annual electricity use by more than 12% under extreme heat conditions, highlighting the mitigation potential of HVAC efficiency measures under extremes. Machard et al. (2024) presented weather-file datasets for present and future building simulation that integrate complex future changes in the frequency, duration, and magnitude of extreme temperatures. Developed within IEA EBC Annex 80 (“Resilient Cooling for Buildings”), these datasets support studies on building adaptation and resilience to climate change and heatwaves.

In summary, research performed in China, Japan, and North America has highlighted the increasing demand for cooling energy owing to climate change. Studies suggest that mitigation strategies, such as enhanced building performance and optimized HVAC systems, can effectively reduce the overall energy consumption. Furthermore, studies in Europe and Australia have emphasized the need for updated building codes and energy policies to address climate-related changes in thermal comfort and energy efficiency.

Despite the extensive global research on climate-change impacts in buildings, evidence for the South Korean context remains comparatively limited, particularly in studies that evaluate both typical conditions and heat extremes in a consistent manner. In addition, many existing studies primarily report aggregate energy outcomes, such as total energy use or EUI. While informative, these aggregate metrics provide limited insight into the operational mechanisms that drive cooling-risk changes and differentiate retrofit performance under extreme heat, making it difficult to translate simulation outcomes into actionable guidance for retrofit design and climate policy.

To address these gaps, climate-induced changes in building energy demand and thermal comfort in South Korea were evaluated using simulations driven by both Typical and Extreme Warm Year (TDY/EWY) datasets. Based on the simulation results, cooling-energy behavior was interpreted using a three-parameter change-point regression that decomposes responses into the change-point temperature, temperature sensitivity, and base load, and these interpretable parameters were used to compare the robustness of passive, active, and combined retrofit strategies under future extreme warm conditions. Thermal comfort was assessed separately using simulation-based comfort indicators, enabling a complementary view of energy performance and occupant-relevant outcomes. Importantly, this approach enables a more clear explanation of why retrofit packages can exhibit different, and sometimes counterintuitive, behavior under

extreme heat beyond what aggregate energy metrics alone can reveal.

3 Methodology

This study investigated the impact of climate change on building energy performance and thermal comfort in South Korea and explored potential mitigation strategies using the four-step process described below. Figure 2 shows the research methodology used in this study.

- **Step 1: future climate projection and weather file synthesis**

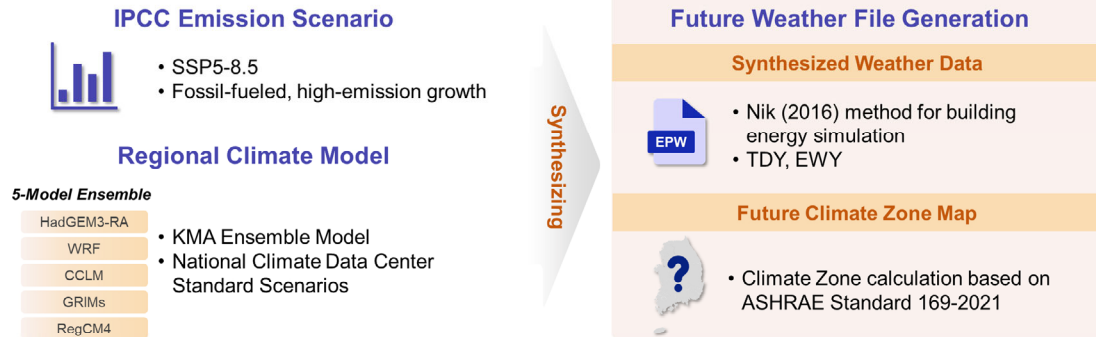
To support a consistent evaluation under both typical and extreme warm conditions, this study integrated Typical and Extreme Warm Year (i.e., TDY and EWY) datasets within a unified approach. The dual-year approach enables a consistent comparison between typical and extreme warm conditions to assess both mean performance and performance under extreme warm conditions. Future climate data for the 2050s and 2080s were derived under the IPCC SSP5-8.5 (IPCC 2023) pathway using a five-member regional climate model ensemble from the Korea Meteorological Administration (i.e., HadGEM3-RA, WRF, CCLM, GRIMs, and RegCM4). TDY and EWY datasets were synthesized using Nik’s method (Nik 2016), which selects representative and extreme months based on dry-bulb temperature quantiles. This procedure captures expected shifts in temperature extremes while maintaining statistical consistency with long-term patterns.

- **Step 2: building energy simulation**

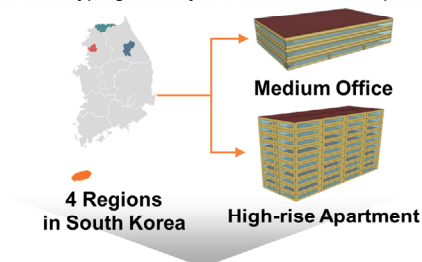
Future weather datasets were applied to OpenStudio v1.9.0 and EnergyPlus v24.2.0 to simulate building energy performance under both TDY and EWY conditions. Four representative Korean climate zones (i.e., Seoul, Jeju, Cheorwon, Daegwallyeong) were modeled using DOE reference geometries for a medium office and a high-rise apartment. Korea-based assumptions were applied to selected key inputs—envelope thermal properties (e.g., wall, roof, window U-values and window SHGC), HVAC system type, thermostat setpoints, and internal gain assumptions (people, lighting, and equipment power densities and schedules)—based on prior Korean studies (Choi 2016; Lee et al. 2021). To quantify the sensitivity of energy consumption to outdoor temperature, we adopted the ASHRAE Guideline 14 Inverse Modeling Toolkit (i.e., 3P change-point model) (Kissock et al. 2002; ASHRAE 2014). The model identifies the change-point temperature, slope, and base load, allowing a consistent comparison of temperature-load relationships across regions and future periods. These assumptions support internally consistent cross-scenario comparisons within a standardized archetype model.

Table 1 Previous studies on the impact of future climate change on building performance

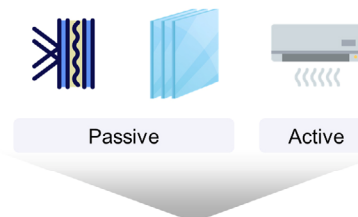
Reference	Year	Region/country	Future climate scenario	Downscaling method	Mitigation measure	Thermal comfort
Wan et al. 2011	2011	Hong Kong, China	B1, A1B	N/A	• Building envelope • Internal condition • Lighting load density • Chiller plant	N/A
Wan et al. 2012	2012	5 cities in China	B1, A1B	N/A	• Building envelope • Internal condition • Lighting load density • Chiller plant	N/A
Huang and Hwang 2016	2016	Taiwan, China	B1, A1B, A2	Morphing	• Building envelope	Adaptive thermal comfort model
Shibuya and Croxford 2016	2016	3 cities in Japan	A2	Dynamic	• Building envelope • Overhangs • Night cooling	N/A
Shen 2017	2017	USA	A2, A1F1	Morphing	N/A	N/A
Lim and Yun 2017	2017	South Korea, Japan, China	A2	Morphing	• Adaptive comfort control • Nighttime ventilation • Occupancy-based lighting & equipment system	
Liu et al. 2020	2020	Hong Kong, China	RCP2.6, RCP4.5, RCP6.0, RCP8.5	Morphing	N/A	Adaptive comfort standard
Bamdad et al. 2021	2021	2 cities in Australia	A2	Morphing	• Building envelope • Overhangs	Setpoint unmet hours
Jafarpur and Berardi 2021	2021	3 cities in Canada	RCP8.5	Morphing	• Building envelope	PMV
Hosseini et al. 2022	2022	Sweden	RCP2.6, RCP4.5, RCP8.5	Dynamic	N/A	Overheating hours
Kim 2022	2022	South Korea	RCP4.5, RCP8.5	Statistical	• Building envelope • Green roof	N/A
Mehmood et al. 2022	2022	Pakistan	A2	Morphing	• Building structure • Thermal bridges • Solar properties • Internal gains • Ventilation & filtration • Operating conditions	Adaptive thermal comfort model
Chen et al. 2023	2023	China	B1	Morphing	• Building envelope • Lighting system • HVAC system • Equipment system • PV System	N/A
Wang et al. 2023	2023	USA	RCP2.6, RCP4.5, RCP7.0, RCP8.5	Statistical	N/A	N/A
Ma et al. 2023	2023	China	RCP4.5, RCP8.5	Dynamic	• Building envelope • HVAC system	N/A
Baba et al. 2023	2023	Canada	RCP8.5	Statistical	• Night cooling • External solar shading system • Cool roof • Window & Shading • Green roof	Adaptive thermal comfort
Ashrafian 2023	2023	Türkiye	SRES A2, RCP2.6, RCP4.5, RCP8.5	Morphing	• Building envelope • PV system	PMV
Baglivo et al. 2024	2024	Italy	RCP2.6, RCP4.5, RCP8.5	N/A	• Building envelope	N/A

STEP 1: Future Climate Projection**STEP 2: Building Energy Simulation****Existing Building**

- OpenStudio Application v1.9.0
- DOE Prototype geometry & Korea-localized inputs

**STEP 3: Mitigation Measure****Retrofitted Building**

- Passive & Active measures
- Compliant with *Korean Building Energy Saving Code* (Ministry of Land and Infrastructure)

**Analysis of Building Energy Performance****Comparison of Building Energy Use**

- Cooling energy (2080s): Baseline vs. Retrofit

IMT Change Point Model

- Building energy use ↔ outdoor temperature analysis

Comparison of Building Energy Performance**Baseline vs. Retrofit**

- Analysis period: 2080s
- Metrics:
 - Annual EUI (kWh/m²·yr)
 - Peak demand (kW)

Weather Inputs

- TDY
- EWY

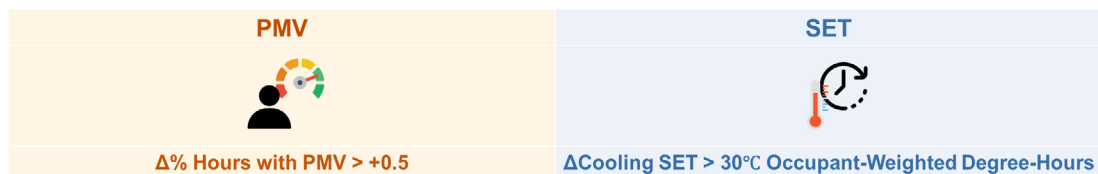
STEP 4: Indoor Thermal Comfort**Effect of Mitigation Measures on Comfort**

Fig. 2 Overall research methodology

• Step 3: applying mitigation measures

Passive and active retrofit measures were applied to evaluate adaptation potential under future climates. Passive measures enhanced the thermal insulation of building envelopes (i.e., walls, roofs, windows) according to the Korean Building Energy Code (Ministry of Land, Infrastructure and Transport 2024), while active measures improved the Coefficient of Performance (COP) of cooling systems based on ASHRAE

Standard 90.1-2022 (DOE 2023). Three retrofit cases (i.e., Passive, Active, and Combined) were tested to compare their individual and synergistic effects on energy use and peak demand. Simulation inputs followed standardized parameters to enable cross-climate comparison.

To enable a resilience-oriented evaluation under extreme warm conditions, operational resilience is defined as the ability of a building to maintain acceptable cooling operation

while limiting peak cooling demand and occupant heat-stress exposure under EWY conditions. Accordingly, operational resilience was assessed through complementary dimensions: cooling energy–temperature response, cooling peak demand (kW), and occupant thermal safety. In this approach, cooling peak demand was used as the demand-related indicator, and occupant-weighted SET degree-hours above 30 °C was used as the primary thermal-safety indicator, as described in Step 4. The three-parameter change-point model was used to characterize the cooling energy–temperature response through the change-point temperature, temperature sensitivity, and base load, thereby providing diagnostic support for interpreting the energy–response dimension rather than serving as a stand-alone resilience metric.

• Step 4: indoor thermal comfort analysis

Thermal comfort and heat-stress exposure were evaluated using Fanger’s predicted mean vote (PMV) and standard effective temperature (SET) indices in accordance with ASHRAE Standard 55-2023 (ASHRAE 2023). For each building type, a south-facing mid-floor zone was selected to represent typical occupied spaces. The annual percentage of occupied hours with PMV > +0.5 was used as a complementary warm-discomfort indicator, whereas occupant-weighted SET degree-hours above 30 °C were calculated as the primary heat-stress metric under extreme warm conditions. These indicators complement the demand- and energy–response analyses and support the operational resilience assessment under EWY conditions.

3.1 Future climate projection

To quantify climate change impacts on building energy performance, we estimated future climates using an emissions scenario and an ensemble of regional climate models. We adopted IPCC AR6 SSP5-8.5 to emphasize severe and uncertain warming effects on building energy demand (IPCC 2023). Following this pathway, an ensemble of five RCMs provided by the Korean Meteorological Administration (KMA) National Climate Data Center (KMA 2024) was used: HadGEM3-RA, WRF, CCLM, GRIMs, and RegCM4. The historical baseline covers 1985–2014, and future projections were analyzed for two 30-year periods, the 2050s (2041–2070) and the 2080s (2071–2100).

The RCM output was available at a daily resolution (daily $T_{\min}$ and $T_{\max}$) rather than hourly values. To obtain hourly outdoor dry-bulb temperature series for building energy simulations, hourly temperatures were reconstructed using a long-term diurnal pattern derived from KMA hourly observations for each study region.

First, the KMA hourly temperature observations were converted into continuous hourly time series, from which

daily $T_{\min}$ and $T_{\max}$ were computed for each day. Each hourly temperature within a day was then normalized to a [0, 1] scale as:

$$\text{norm}(h) = \frac{T(h) - T_{\min}}{T_{\max} - T_{\min}} \quad (1)$$

where $T(h)$ is the hourly temperature at hour h , and $T_{\min}$ and $T_{\max}$ denote the daily minimum and maximum temperatures, respectively.

The normalized values were averaged by calendar month and hour-of-day to obtain a monthly diurnal pattern $P_m(h) \in [0,1]$, where m indicates month ($m = 1, \dots, 12$) and h indicates hour-of-day ($h = 0, \dots, 23$). Using this pattern, each daily RCM record ($T_{\min}, T_{\max}$) was downscaled to hourly resolution as:

$$T_m(h) = T_{\min} + (T_{\max} - T_{\min})P_m(h) \quad (2)$$

yielding an hourly dry-bulb temperature series for subsequent representative-year selection.

From the projected climates, Nik’s distribution-based selection concept (Nik 2016) was applied to synthesize a typical downscaled year (TDY) and an extreme warm year (EWY), using outdoor dry-bulb temperature as the sole selection variable. Whereas TDY represents typical thermal conditions, EWY approximates extreme warm conditions using the same quantile-based framework, enabling a consistent comparison of building cooling responses under typical and extreme conditions. Such extreme-biased weather constructs have been reported as practical tools for resilience-oriented analyses.

For each 30-year period and each calendar month, a reference distribution was defined by pooling all hourly temperatures for that month across the period. Candidate months were evaluated by comparing their empirical quantile functions to the reference quantile function on a uniform probability grid $p \in [0,1]$. The TDY month was selected as the candidate that minimized the L_1 distance between quantile functions:

$$\text{TDY month} = \arg \min_y \sum_p |Q_y(p) - Q_{\text{ref}}(p)| \quad (3)$$

where $Q_y(p)$ is the quantile of the candidate year y at probability p , and $Q_{\text{ref}}(p)$ is the corresponding reference quantile.

The EWY month was selected using a signed criterion that favors a warmer distribution:

$$\text{EWY month} = \arg \min_y \sum_p [Q_{\text{ref}}(p) - Q_y(p)] \quad (4)$$

where more negative values indicate a warmer candidate distribution relative to the reference.

The selected 12 months were concatenated to form an 8760-hour representative year. When the number of hourly samples differed between the source month and the target month length in the representative-year calendar, linear interpolation was applied to align the hourly series.

Finally, the base EPW file was modified by replacing the dry-bulb temperature series with the synthesized TDY and EWY hourly temperatures. Relative humidity was recomputed from the original dew-point temperature and the updated dry-bulb temperature, with a saturation check applied where necessary to ensure physical consistency. All other meteorological variables were retained from the base EPW file. Accordingly, the EWY should be interpreted as a temperature-driven extreme warm scenario rather than a representation of simultaneous extremes in solar radiation, wind speed, and humidity. The complete step-by-step TDY/EWY generation procedure is summarized in Algorithm 1.

Because extreme-year constructs can vary depending

on the selection rule used to define “extreme” conditions, a robustness check was performed by generating an alternative EWY based on an XMY-inspired seasonal criterion (Crawley and Lawrie 2019; Gasparella et al. 2021), with comparative results reported in Appendix A. The appendix is available in the Electronic Supplementary Material of the online version of this paper.

In addition, South Korea’s future ASHRAE climate zones were determined using the TDY weather datasets according to ASHRAE Standard 169-2021 (ASHRAE 2020). Table 2 summarizes the classification criteria.

3.2 Building energy simulation

Building energy simulations were conducted with OpenStudio Application v1.9.0 and EnergyPlus v24.2.0. Six weather datasets were used: TDY, TDY-2050s, TDY-2080s, EWY, EWY-2050s, EWY-2080s. To assess the variations in

Algorithm 1 TDY and EWY synthesis

1	Input:
2	$T_{RCM}^P(t)$ = reconstructed hourly dry-bulb temperature for period P (Eqs. (1)–(2))
3	$P \in \{1985\text{--}2014, 2041\text{--}2070, 2071\text{--}2100\}$
4	p = uniform probability grid [0.00, 0.01, ..., 1.00]
5	
6	Start
7	for each period P do
8	for $m = 1$ to 12 do
9	$Q_{ref}(p) \leftarrow$ quantiles of all hourly $T_{RCM}^P(t)$
10	in month m pooled over the 30-year period
11	for each candidate year y in period P do
12	$Q_y(p) \leftarrow$ quantiles of hourly $T_{RCM}^P(t)$
13	in month m of year y
14	
15	$D_y = \sum_p Q_y(p) - Q_{ref}(p) $ (Eq. (3))
16	
17	$S_y = \sum_p [Q_{ref}(p) - Q_y(p)]$ (Eq. (4))
18	
19	end for
20	select $y_{TDY}^* = \operatorname{argmin}_y D_y$
21	select $y_{EWY}^* = \operatorname{argmin}_y S_y$
22	(more negative S_y indicates a warmer distribution)
23	end for
24	
25	Concatenate 12 selected months to form
26	An 8,760-hour TDY and EWY for period P
27	
28	End for
29	
30	Finish
31	

Table 2 ASHRAE climate zone definitions (ASHRAE 2010)

Zone number	Name	Thermal criteria
1	Very hot-humid (1A), dry (1B)	$5000 < \text{CDD10}$
2	Hot-humid (2A), dry (2B)	$3500 < \text{CDD10} \leq 5000$
3A and 3B	Warm-humid (3A), dry (3B)	$2500 < \text{CDD10} < 3500$
3C	Warm-Marine	$\text{CDD10} \leq 2500$ AND $\text{HDD18} \leq 2000$
4A and 4B	Mixed-humid (4A), dry (4B)	$\text{CDD10} \leq 2500$ AND $\text{HDD18} \leq 3000$
4C	Mixed-marine	$2000 < \text{HDD18} \leq 3000$
5A, 5B and 5C	Cool-humid (5A), dry (5B), marine (5C)	$3000 < \text{HDD18} \leq 4000$
6A and 6B	Cold-humid (6A), dry (6B)	$4000 < \text{HDD18} \leq 5000$
7	Very cold	$5000 < \text{HDD18} \leq 7000$
8	Subarctic	$7000 < \text{HDD18}$

energy consumption across different climatic conditions, four representative regions in South Korea were selected to examine the climate-specific changes in energy consumption: Seoul, Jeju, Cheorwon, and Daegwallyeong (Table 3). For the building energy models, the building geometries were based on the DOE reference buildings for medium office and high-rise apartment. Selected key inputs were informed by previous Korean studies, including envelope thermal properties, HVAC system type, heating and cooling thermostat setpoints, and internal gain assumptions (power densities and schedules for people, lighting, and equipment) (Choi 2016; Lee et al. 2021). Therefore, this simulation approach employs standardized DOE prototype-based archetype models to provide internally consistent cross-scenario comparisons and to facilitate mechanism-based interpretation of climate-driven impacts. Detailed information on the simulation models is presented in Table 4.

For the building climate sensitivity analysis of building energy consumption, we adopted the ASHRAE Guideline 14 (ASHRAE 2014) Inverse Modeling Toolkit (IMT) three-parameter (3P) change-point model (Kisssock et al. 2002) and fit it separately to heating and cooling, which are supplied by distinct energy carriers and delivery systems and thus exhibit distinct temperature response structures. The 3P model separately estimates the change-point

Table 3 Coordinates and climate zones of four locations in South Korea

City	Latitude (°N)	Longitude (°E)	Elevation (m)	Current ASHRAE climate zone
Seoul	37.53	127.02	87.1	4A (mixed-humid)
Jeju	33.50	126.53	23	3A (warm-humid)
Cheorwon	38.15	127.31	155.2	5A (cool-humid)
Daegwallyeong	37.69	128.76	774	6A (cold-humid)

temperature (β_1), the segment slope (β_2), and the base load (β_3). This structure makes explicit both the shift of seasonal boundaries (via β_1) and changes in load sensitivity across temperature ranges (via β_2). The 3P models were fitted using daily data. Outdoor dry-bulb temperature was aggregated to a daily mean, and heating and cooling energy were aggregated to daily totals. All days in each year (365 days) were retained for the fit. Leveraging this interpretability, we compared differences across future periods (TDY-2050s, TDY-2080s, EWY-2050s, EWY-2080s) and mitigation measures on a common parameter scale (β_1 , β_2 , β_3) based on the simulation outputs (Table 5). The change-point regression model relates outdoor temperature to building energy use with a small set of interpretable parameters.

3.3 Mitigation measures

In this study, three retrofit cases were considered to evaluate mitigation strategies for future climate impacts: Passive, Active, and Combined. Passive measures focused on enhancing the thermal-insulation performance of the building envelope, including exterior walls, roofs, and windows with target values taken from the Korean Building Energy Codes (Ministry of Land, Infrastructure and Transport 2024). Because Korea does not prescribe SHGC limits, we adopted SHGC requirements from ASHRAE Standard 90.1-2022 (ASHRAE 2022). Active measures improved the cooling system efficiency to align with Korea's building-sector decarbonization policy emphasizing high-efficiency equipment. The Combined case applied the Passive and Active measures simultaneously. No additional control changes were applied, and thermostat setpoints, schedules, and internal gain assumptions were unchanged across cases. The detailed retrofit input values used in the simulations are summarized in Table 6.

To evaluate the effectiveness of the proposed mitigation measures, the building energy consumption under baseline and retrofitted models was compared using the 2080s weather data. In addition to changes in energy consumption, we examined variations in the IMT 3P parameters (β_1 , β_2 , β_3) (ASHRAE 2014) to quantify how mitigation measures affect temperature sensitivity and seasonal boundaries. Model fit quality was evaluated using R^2 and CVRMSE for both TDY and EWY conditions.

3.4 Thermal comfort

To evaluate the impact of mitigation measures on indoor thermal comfort and thermal safety, Fanger's PMV and standard effective temperature (SET) were used. For both building types, a south-facing mid-floor zone was selected

Table 4 General information on the case study buildings

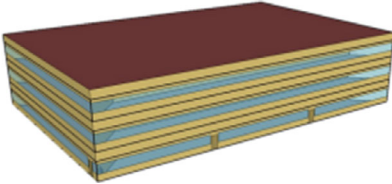
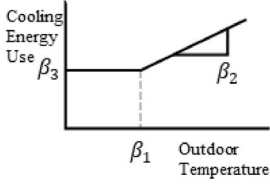
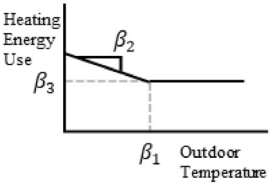
	Medium office	High-rise apartment
Building shapes		
Number of floors	3	10
Window fraction	33.0%	29.8%
HVAC system type	PTAC DX Clg HW Htg	PTAC DX Clg Gas Htg
Thermostat settings	Dual setpoint thermostat	Dual setpoint thermostat
Heating set point	21 °C occupied, 15 °C unoccupied	22 °C (constant setpoint)
Cooling set point	26 °C (constant setpoint)	25 °C (constant setpoint)
Deadband	5 °C	3 °C
Conditioned area (m ²)	4,982.18	7,059.88
Occupancy schedule	Mon–Fri (07:00–24:00) Sat (07:00–19:00) Sun (07:00–18:00)	Apartment – stay home (00:00–24:00), Apartment – working, Mon–Fri (00:00–09:00, 19:00–24:00), Sat, Sun (00:00–16:00, 17:00–24:00) Office, Mon–Fri (09:00–13:00, 14:00–15:00, 16:00–18:00)

Table 5 Inverse modeling toolkit – change-point models

	Change point model
3P cooling and heating models	$Y_c = \beta_3 + \beta_2 (X_1 - \beta_1)^+$  $Y_h = \beta_3 + \beta_1 (X_1 - \beta_1)^-$ 

as the representative analysis zone because it reflects a typical occupied perimeter space that is thermally exposed to outdoor warming. PMV was used as a complementary warm-discomfort indicator; following ASHRAE Standard 55-2023 (ASHRAE 2023), the comfort range was taken as -0.5 to $+0.5$, and changes in comfort were assessed using the annual percentage of occupied hours with $PMV > +0.5$.

As the primary heat-stress indicator in the operational resilience assessment, cooling SET occupant-weighted degree-hours above 30 °C were calculated and expressed in $\text{°C}\cdot\text{h}$. SET, as adopted in ASHRAE Standard 55 (ASHRAE 2023), integrates indoor dry-bulb temperature, relative

humidity, mean radiant temperature, air velocity, metabolic rate, and clothing level. In this study, SET was calculated using the thermal physiology model implemented in EnergyPlus, and heat-stress exposure was evaluated for the representative zone using the occupant-weighted SET degree-hour output reported by EnergyPlus. The 30 °C SET threshold was adopted as a screening threshold for elevated heat-stress exposure under extreme warm conditions, informed by the SET-based thermal survivability framework used in LEED Passive Survivability. Similar SET degree-hour metrics have been used in previous studies to evaluate thermal survivability or heat-stress exposure under extreme heat conditions (Luo et al. 2021; Sheng et al. 2023).

For both PMV and SET calculations, occupant-related inputs were specified based on assumptions adopted in previous Korean studies (Choi 2016; Lee et al. 2021) and implemented through the People object schedules in EnergyPlus. The detailed values are summarized in Table 7.

4 Results and discussion

4.1 Projected climate shifts under typical and extreme years

This section presents the estimated climate change in South Korea based on the synthesized weather data. The weather datasets indicate a consistent warming signal across South

Table 6 Overview of the retrofit input values for the Passive and Active measures by building type and climate zone. The Combined case applies both sets of measures simultaneously

		Passive						Active	
		Wall U -value ($W/(m^2 \cdot K)$)		Roof U -value ($W/(m^2 \cdot K)$)		Window U -value ($W/(m^2 \cdot K)$) (U ; SHGC)		COP (cooling)	
		Baseline	Retrofitted	Baseline	Retrofitted	Baseline	Retrofitted	Baseline	Retrofitted
Medium office	Seoul	0.363	0.240	0.182	0.150	2.045 (0.36)	1.500 (0.360)	3.0	4.0
	Jeju	0.587	0.410	0.410	0.250	2.387 (0.26)	2.200 (0.250)	3.0	4.0
	Cheorwon	0.312	0.170	0.182	0.150	2.045 (0.39)	1.300 (0.380)	3.0	4.0
	Daegwallyeong	0.278	0.170	0.182	0.150	1.931 (0.39)	1.300 (0.380)	3.0	4.0
High-rise apartment	Seoul	0.505	0.170	0.329	0.150	2.15 (0.36)	1.000 (0.360)	2.5	4.0
	Jeju	0.735	0.290	0.408	0.250	2.55 (0.26)	1.600 (0.250)	2.5	4.0
	Cheorwon	0.465	0.150	0.300	0.150	2.15 (0.39)	0.900 (0.380)	2.5	4.0
	Daegwallyeong	0.369	0.150	0.255	0.150	2.04 (0.39)	0.900 (0.380)	2.5	4.0

Note: The Combined case applied the Passive and Active measures simultaneously. No additional control changes were applied. Thermostat setpoints, schedules, internal gain assumptions, and heating system settings were unchanged across all retrofit cases.

Table 7 Overview of the comfort-model assumptions

Type	People per space floor area (people/m ²)	Metabolic rate (met)	Clothing insulation (clo)	Air velocity
Medium office	0.0538	1.15	1.0	0.1
High-rise apartment	0.0167	0.91	1.0	0.1

Korea. The TDY reproduces region-level seasonal patterns relative to TMY, with most monthly mean errors within ± 2 °C. Subsequent analyses compare future TDY and EWY for the 2050s and 2080s against TDY baseline.

As shown in Figure 3(a), monthly mean dry-bulb temperature increases by approximately +3 to +5 °C in the 2050s and from 5 to 8 °C in the 2080s. The increase is larger in summer than in winter and is more pronounced away from the coast and at higher elevations—for example, in Cheorwon and Daegwallyeong. Figure 3(b) presents the difference between EWY and TDY for each period. Winter deviations are largest across all regions, whereas the transition seasons and summer show smaller gaps. Spatially, Jeju exhibits the smallest deviations, while Cheorwon and Daegwallyeong show the largest. These patterns indicate not only mean warming but also a growing separation between typical and extreme warm conditions in winter, implying an upward shift of winter baseline during extreme warm years. Consequently, the heating season is likely to shorten and the sensitivity of heating energy use to outdoor temperature will weaken relative to typical years.

Figure 4 presents the ECDFs of hourly outdoor air temperature in January and August, showing that the difference between TDY and EWY extends beyond a simple shift in mean temperature. For both months, across all regions and periods, the EWY ECDF is consistently located to the right of the TDY curve, indicating a systematic

rightward shift of the temperature distribution toward warmer conditions.

For January, using the historical period in Seoul as an example, the TDY-EWY gap decreases from 5.2 °C at the 50th (P50) percentile to 0.4 °C at the 95th (P95) percentile. This result suggests that wintertime EWY is characterized more by a reduction in cold-hour occurrences than by an increase in peak temperatures. In contrast, for August, the TDY-EWY gaps remain similar at both P50 and P95, indicating that summertime EWY represents more severe thermal conditions than TDY not only during typical hours but also in the extreme high-temperature range. Overall, these results support the need to account for extreme climate conditions, in addition to typical climate conditions, when estimating heating and cooling energy demands. The ECDFs and corresponding quantile values for the remaining months are reported in Appendix A.

Figure 5 illustrates projected shifts in Korea's ASHRAE climate zones. At present, most regions, including Seoul, are classified as Zone 4A; Jeju and parts of the south are 3A, and northern or high-elevation areas are in 5A and 6A. Applying ASHRAE Standard 169-2021 definitions, many regions migrate toward Zone 3 by 2100, Jeju and the southern belt move into Zone 2, and even the coldest areas approach Zone 4.

Overall, these changes point to greater cooling dominance, earlier onset and longer duration of the cooling season,

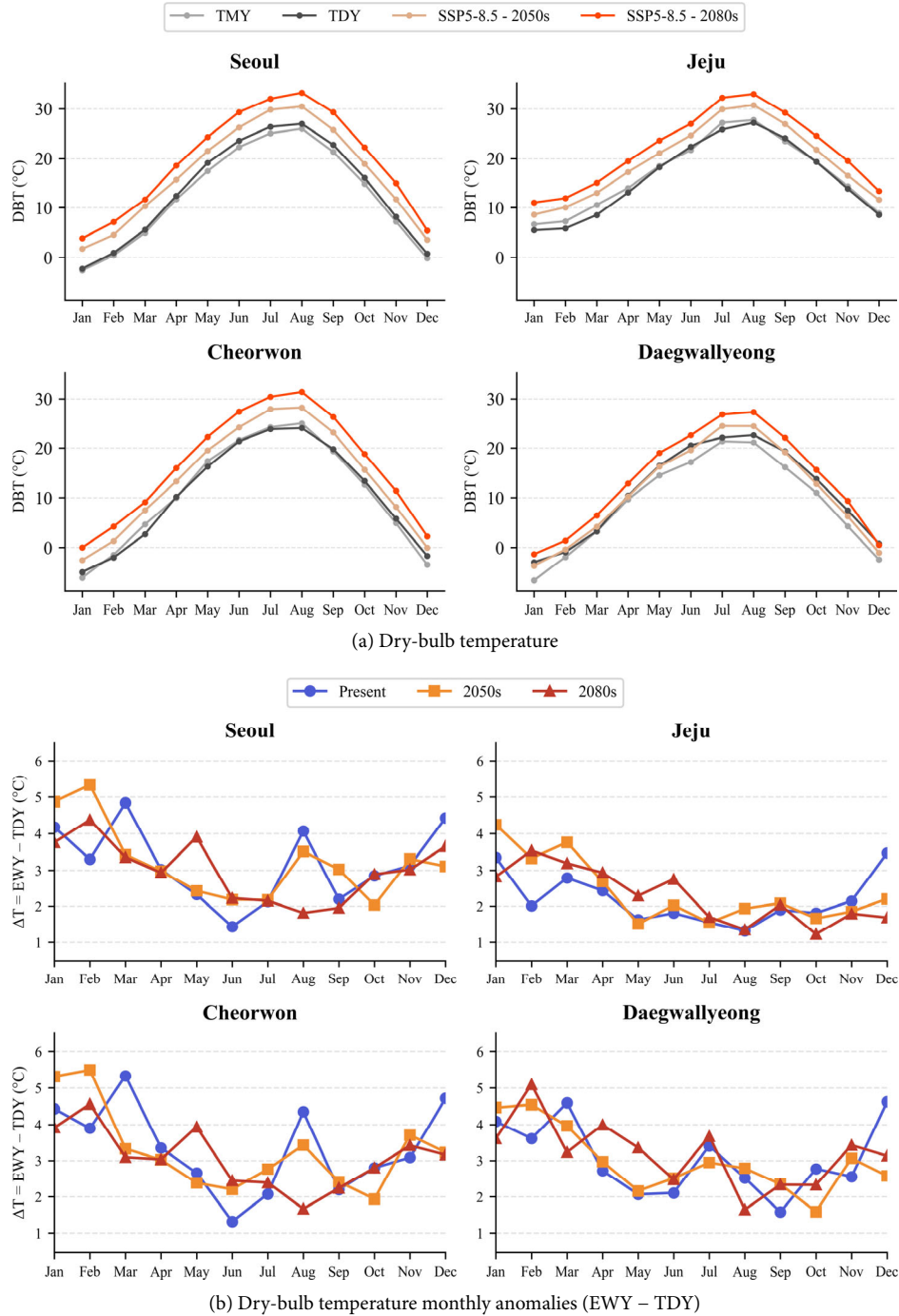


Fig. 3 Morphing results (the solid lines represent monthly average values for each city, while the shaded areas indicate the monthly maximum and minimum ranges)

and an increased need for solar-gain control and peak-load management during summer.

4.2 Building energy use under current and future climates

4.2.1 Baseline

Figures 6 and 7 show the monthly heating and cooling

energy consumption for medium office and high-rise apartments under the synthesized weather datasets.

In Figure 6, for the medium office, winter heating energy in Seoul and Jeju decreased by 94.5% and 72.3%, respectively, indicating strong sensitivity to warming. In Cheorwon and Daegwallyeong, where colder characteristics persist, annual and winter heating energy decreased by only 33% and 9%, respectively. Cooling energy increased in all cities during

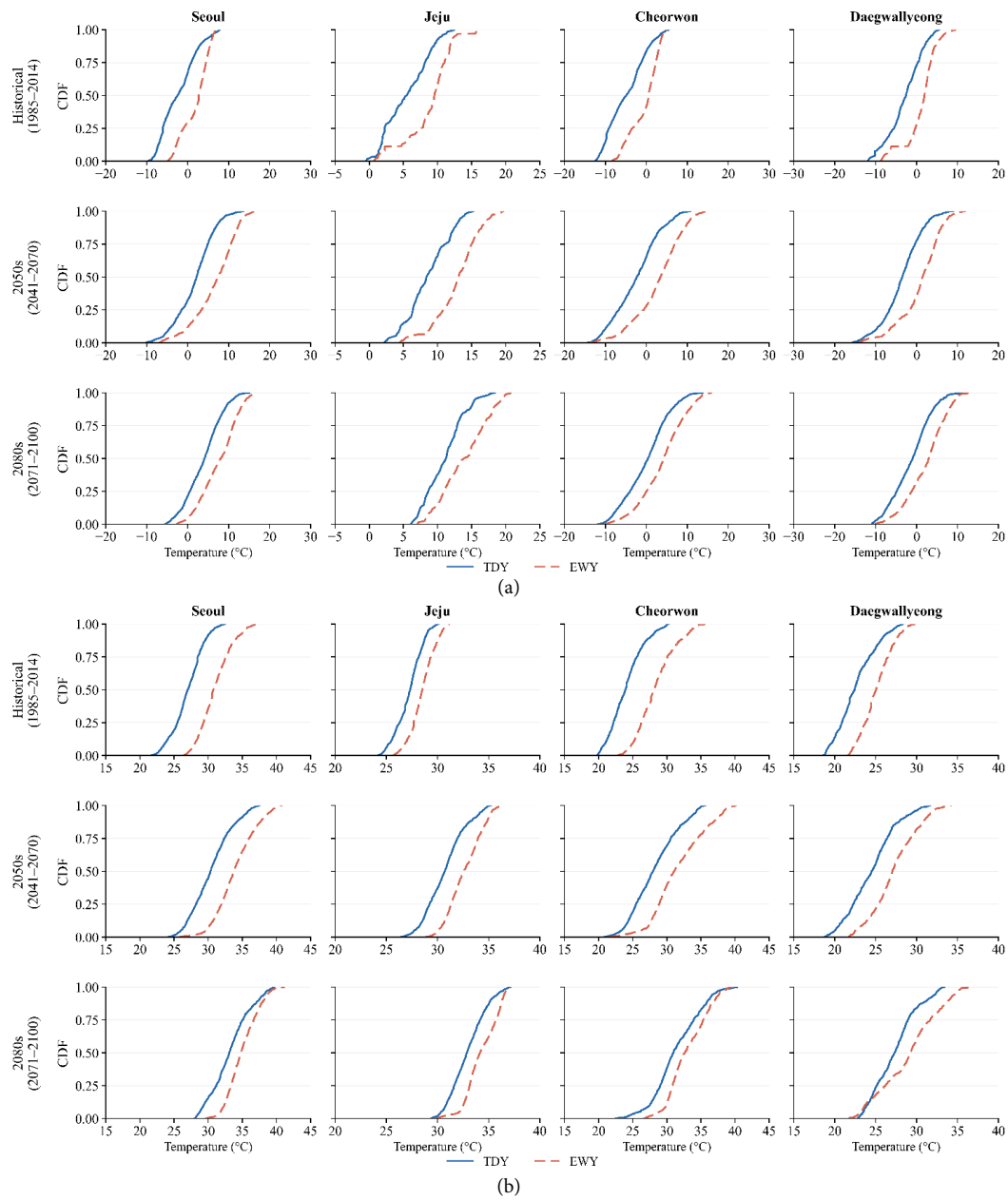


Fig. 4 ECDFs of hourly air temperature in (a) January and (b) August for Seoul, Jeju, Cheorwon, and Daegwallyeong under the Historical, 2050s, and 2080s periods based on the SSP5-8.5 scenario

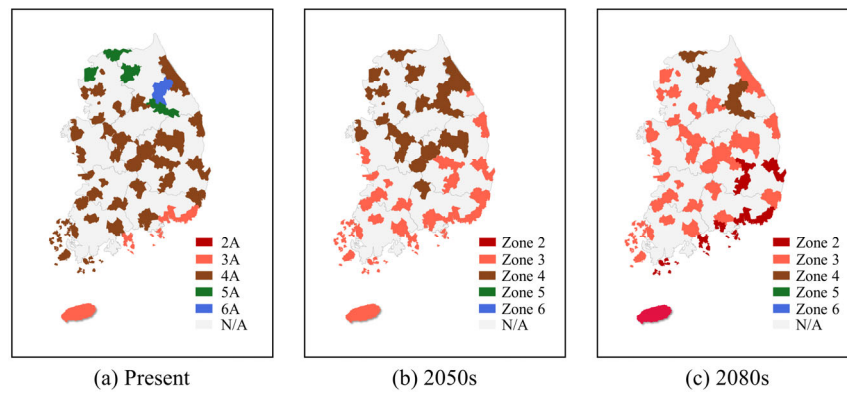


Fig. 5 Present and future climate zone map

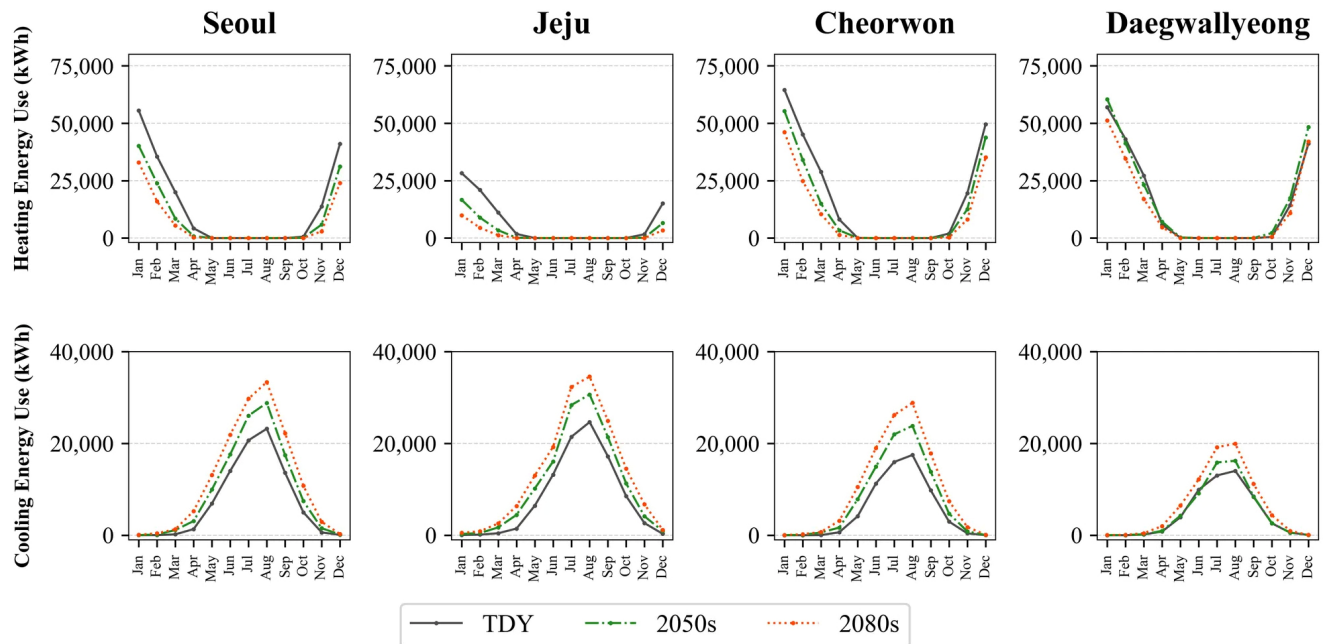


Fig. 6 Changes in the heating and cooling energy consumption of medium-office buildings in South Korea

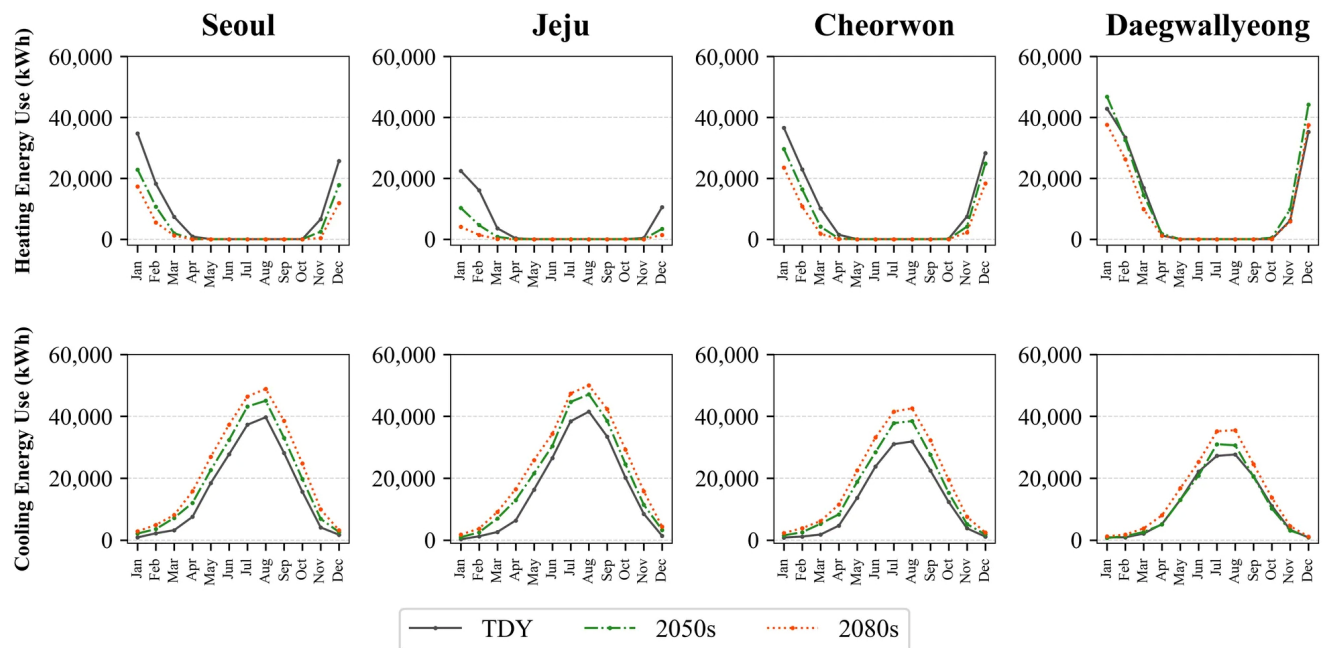


Fig. 7 Changes in the heating and cooling energy consumption of high-rise apartments in South Korea

summer, by 47% in Seoul, 45% in Jeju, 66% in Cheorwon, and 39% in Daegwallyeong.

As shown in Figure 7, high-rise apartments exhibited trends similar to those of the medium office buildings. The annual heating energy consumption decreased by 61% in Seoul, 87% in Jeju, 47% in Cheorwon, and 13% in Daegwallyeong. Cooling energy increased by 45%–50% in all regions except Daegwallyeong, where it still rose by 27%. These results suggest that regional climate exerts a stronger

influence than building type on the magnitude of heating reductions and cooling increases.

As cooling energy use increases under warmer climate conditions, humidity-related cooling energies were also examined. Specifically, annual cooling coil latent cooling energy and the latent fraction—defined as the percentage of latent cooling energy in total cooling energy—were reported for the Seoul and Jeju medium office baseline cases under both TDY and EWY weather files (Table 8).

Table 8 Annual cooling coil total and latent cooling energy and latent fraction for the Seoul and Jeju baseline medium office model under TDY/EWY weather files (Base year, 2050s, 2080s)

		TDY			EWY		
		Base year	2050s	2080s	Base year	2050s	2080s
Seoul	Cooling coil total energy (Wh)	61932.58	78939.90	95313.55	75473.33	94271.64	110932.38
	Cooling coil latent energy (Wh)	17306.46	18952.27	19906.19	18920.45	19832.96	20413.43
	Latent fraction (%)	27.9	24.0	20.9	25.1	21.0	18.4
Jeju	Cooling coil total energy (Wh)	70279.10	91467.20	107987.90	81540.63	105842.24	123796.21
	Cooling coil latent energy (Wh)	22932.79	26345.86	28260.04	24989.44	27878.94	29426.18
	Latent fraction (%)	32.6	28.8	26.2	30.6	26.3	23.8

These indicators complement the temperature-based results by accounting for humidity effects. Across both regions, total and latent cooling energies increased toward future period, and EWY consistently yielded higher values than TDY for the same periods. However, the latent fraction decreases both toward future periods and from TDY to EWY in both regions, indicating that total cooling increases more rapidly than latent cooling and pointing to a larger relative contribution from sensible cooling. Notably, Jeju, a warmer climate region than Seoul, exhibits higher absolute latent fractions across all scenarios. Nevertheless, this trend is consistent across both regions, confirming that the increase in cooling demand under EWY conditions is driven primarily by sensible energy growth rather than latent energy changes, and that this conclusion is not specific to a single climate region.

Figure 8 shows changes in building energy performance under TDY and EWY conditions for the baseline model without mitigation measures. Using the medium office results for Seoul as an example, the relationship between outdoor dry-bulb temperature and daily energy use is analyzed with change-point regression to visualize climate-driven shifts in the temperature-energy relationship. Results for the high-rise apartment and for other regions are provided in Appendix B.1.

For heating, the change-point temperature shifted upward by about 2 °C by the 2080s under both TDY and EWY conditions, while the absolute slope decreased by approximately 20 under TDY and 35 under EWY. This indicates a contraction of the heating-dominant regime in future climates and a weakened sensitivity of heating energy use to a given change in outdoor temperature, as shown in Figure 8(a).

For cooling, the slope increased toward the 2080s under TDY, indicating strengthened cooling sensitivity (Figure 8(b)). Under EWY conditions in the 2080s, however, the estimated slope is lower than under TDY, while the base load increased substantially. This suggests that under extreme heat, increases in cooling demand may be explained less by temperature

sensitivity and more by an elevated base load, implying a shift in load behavior. Consequently, under extreme hot conditions, cooling demand may evolve from short-term, peak-driven responses toward a more persistent, sustained consumption pattern. The change-point temperatures, slopes, base loads, and fit statistics (R^2 and CVRMSE) for heating and cooling models are reported in Tables B.1 and B.2 of Appendix B.1 for both TDY and EWY conditions.

The results suggest that future climates may reshape both the dominant operating regimes and the base load components of heating and cooling. In the next section, we quantify the extent to which the proposed retrofit strategies mitigate these structural changes.

4.2.2 Retrofitted buildings

Figures 9 and 10 illustrate the heating and cooling EUIs and total EUI for medium office buildings and high-rise apartments under the 2080s scenarios. As specified in Table 6, three mitigation cases are evaluated against the baseline: Passive, Active, and Combined (Passive+Active).

For the medium office, total EUI is the lowest with the combined case under both TDY and EWY. Under TDY, reductions are 15.3% in Seoul, 10.2% in Jeju, 18.1% in Cheorwon, and 19.1% in Daegwallyeong. Under EWY, reductions persist but narrow to 6.4%, 10.5%, 15.4%, and 15.8%, respectively. Passive-only performs better in colder or mixed climates, whereas active-only is more advantageous in warmer locations. The TDY advantage of the combined case largely persists under EWY, although savings shrink by about 4%–10%, underscoring the growing importance of operations and peak-load management under extremes.

The cooling and heating EUIs clarify role separation. In Figure 9(b) under TDY, active lowers cooling EUI by roughly 20%–25% across all regions, whereas passive increases cooling EUI in most locations except Jeju. Under EWY, this contrast intensifies: active maintains cooling savings, but passive-only shows larger cooling penalties and, in Seoul, cooling EUI exceeds the baseline. To further examine the Passive-only cooling penalty under EWY, the

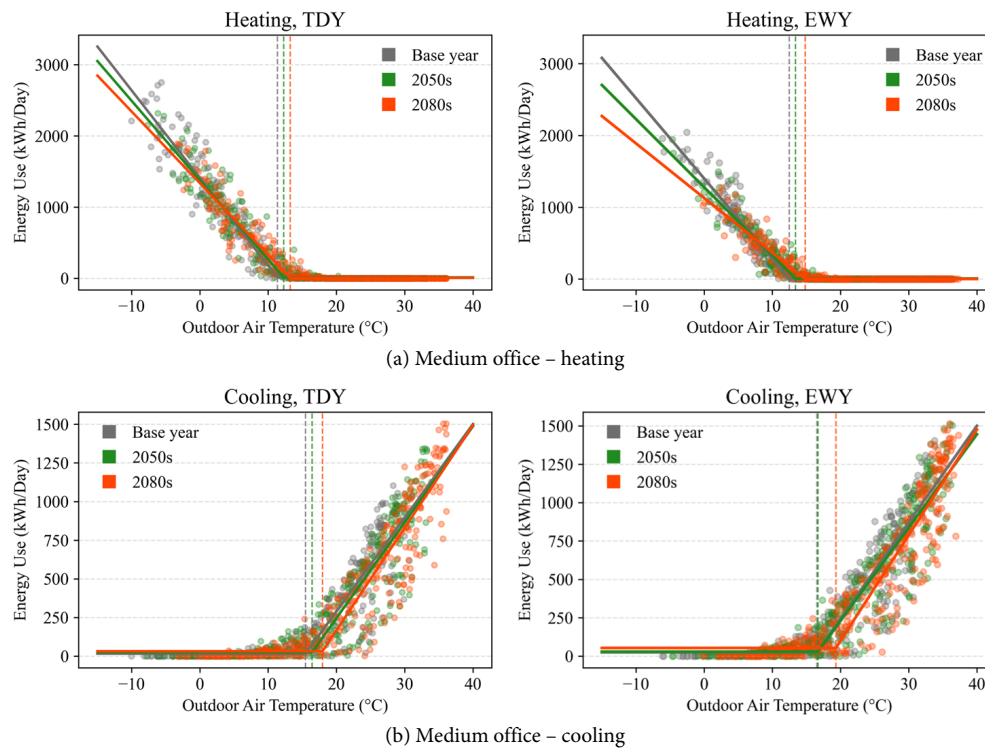


Fig. 8 Relationship between the outdoor temperature and daily energy use with 3P change-point model – medium office

3P cooling change-point results were analyzed with a focus on the base load component (β_3). Under EWY 2080s, β_3 increases from 39.88 in the Baseline to 69.16 in the Passive-only case, while the Active case remains at the Baseline level (39.88). The Combined case yields an intermediate β_3 (51.87) (Tables B.2 and B.4). Because β_3 is the constant (temperature-independent) term in the ASHRAE 3P cooling change-point model (i.e., the cooling energy baseline below the change-point temperature), the elevated β_3 under Passive-only indicates a larger non-temperature-dependent baseline cooling requirement under EWY conditions. As an additional check, the monthly cooling electricity profile shows a modest increase in annual cooling energy (+1.24%). When aggregated, the reduction from June to September totals 6772 kWh, whereas the increase across the remaining months, when cooling is typically lower, totals 8852 kWh, resulting in a net annual increase (Table B.5). At the whole-building level, the monthly results suggest that the Passive-only cooling penalty under EWY is not primarily explained by changes in internal gains or cooling setpoints. Internal gains remained nearly unchanged between the Baseline and Passive cases, and the same cooling setpoint was applied in both cases. From January to May and from October to December, window heat loss decreased substantially, while window heat gain increased, indicating reduced net outward heat transfer through windows under the Passive case. At the same time, aggregated sensible cooling energy increased from January to May and

from October to December, while decreasing from June to September (Table B.6). Taken together, these results suggest that the Passive-only EWY penalty is associated more with an increase in cooling base load (β_3), driven by higher cooling requirements during the shoulder and other lower-cooling months, than by changes in internal gains or cooling setpoints. For heating EUI, passive-only produces dominant reductions in both TDY and EWY—48%–68% under TDY and even larger under EWY—while active has little effect. Overall, active is decisive for cooling, passive is decisive for heating, and the combined case reduces both, yielding the greatest total EUI savings.

For the high-rise apartment, the combined case again delivers the lowest total EUI in each region. On average, active-only achieves 7%–11% total EUI reductions, whereas passive-only achieves 5%–7%. Under EWY, total EUI reductions are 14.5% in Seoul, 14.8% in Jeju, 13% in Cheorwon, and 11.4% in Daegwallyeong. In cooling EUI, active cuts about 38%, while passive achieves 20%–26%. For heating EUI, Passive reduces 18%–43% in Seoul, Cheorwon, and Daegwallyeong; in Jeju, baseline heating demand is very small, so absolute effects are limited. In Figure 10(b), total EUI is strongly shaped by summer cooling dominance, internal gains, solar exposure, and envelope characteristics. Detailed data for all building types and regions are provided in Table C.1 of Appendix C.1.

To provide additional insight into the cooling response under retrofit cases, Table 9 breaks down the annual cooling

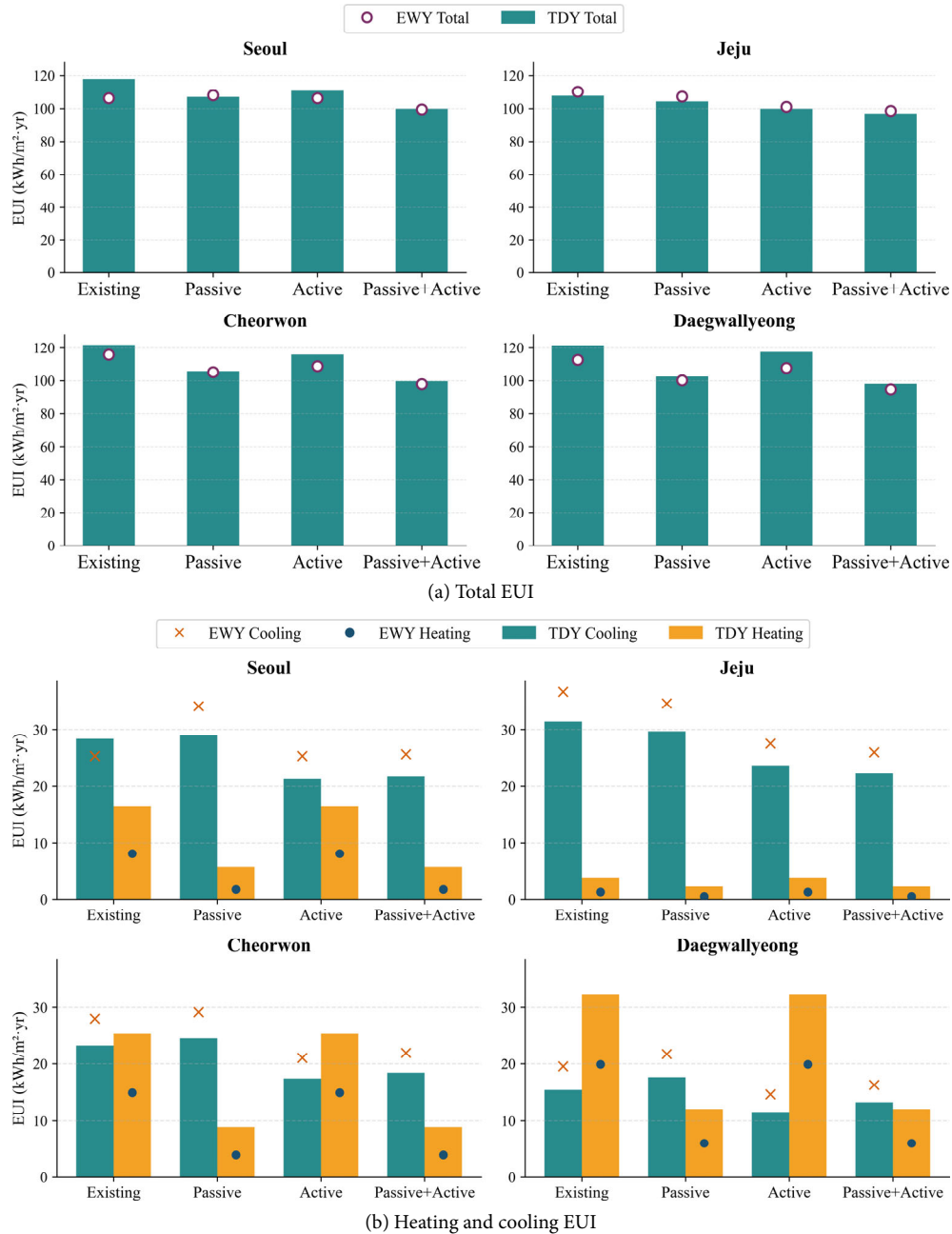


Fig. 9 Comparison of EUI before and after retrofits – medium office

Table 9 Annual cooling coil total and latent cooling energy and latent fraction for the Seoul and Jeju Combined medium office model under TDY/EWY weather files (Base year, 2050s, 2080s)

		TDY			EWY		
		Base year	2050s	2080s	Base year	2050s	2080s
Seoul	Cooling coil total energy (Wh)	66632.60	82879.50	97591.51	79797.66	97720.64	112746.74
	Cooling coil latent energy (Wh)	17987.32	19284.01	19928.53	19356.24	19908.99	20227.79
	Latent fraction (%)	27.0	23.3	20.4	24.3	20.4	17.9
Jeju	Cooling coil total energy (Wh)	65855.09	85694.41	101141.2	76510.21	99272.41	116004.6
	Cooling coil latent energy (Wh)	22035.65	25426.15	27311.07	24049.14	26948.44	28462.22
	Latent fraction (%)	33.5	29.7	27.0	31.4	27.1	24.5

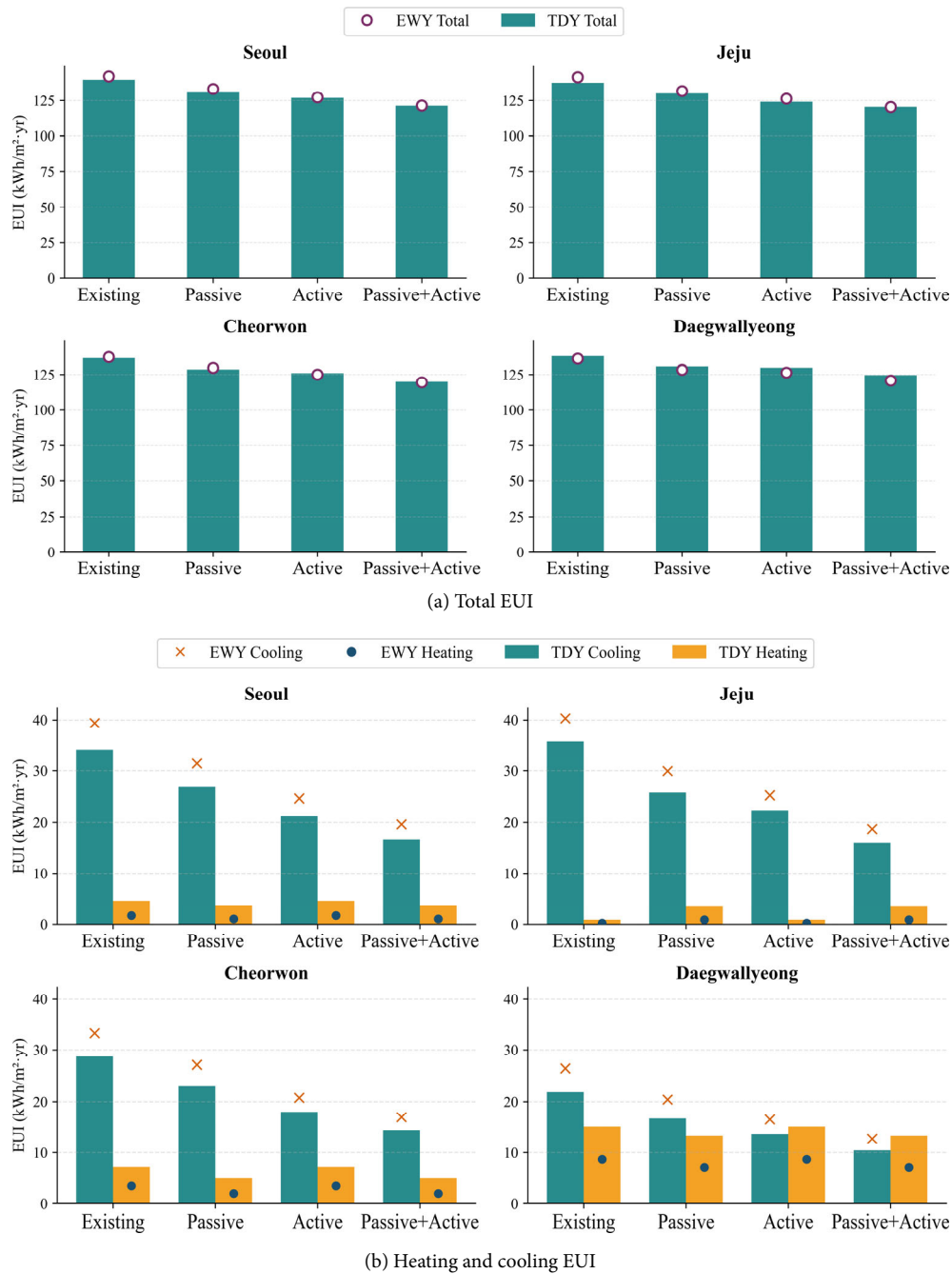


Fig. 10 Comparison of EUI before and after retrofits – high-rise apartment buildings

coil energy of the Seoul and Jeju medium office into total and latent components. Across both regions, total and latent cooling energies increased from the base year to the 2050s and 2080s under both TDY and EWY, and EWY consistently remained higher than TDY for the same period. Meanwhile, the latent fraction decreased toward future periods and from TDY to EWY in both regions, indicating that the increase in total cooling is larger than the increase in latent cooling. This trend is consistent across both regions, further indicating that sensible cooling accounts for an increasing

share of total cooling demand under future and extreme warm conditions.

Figure 11 illustrates changes in heating and cooling energy performance for buildings with the applied mitigation measures. Results for the high-rise apartment and for other regions are provided in Appendix B.2.

For heating in Figure 11(a), passive measures most clearly improve the temperature-heating energy relationship under both TDY and EWY. Because no heating-system efficiency upgrades were applied in this study, the Active case for

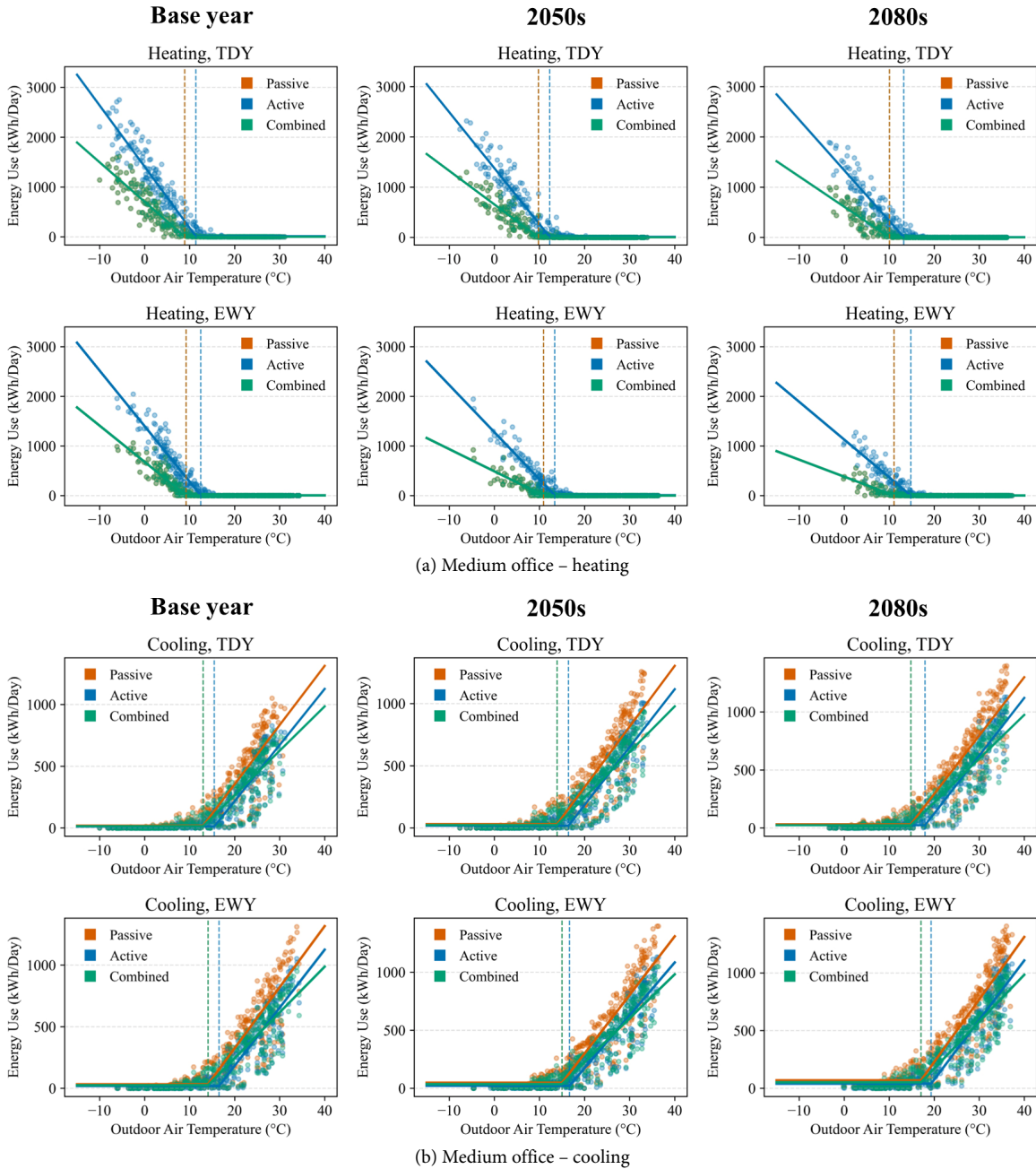


Fig. 11 Relationship between the outdoor temperature and daily energy use with 3P change-point model – medium office

heating shares the same configuration as the baseline. In the Passive and Combined cases, the change-point temperature is lower than in the Active case, and the absolute slope at low temperatures is less steep, leading to systematically lower energy use under the same temperature conditions. These results indicate that improvements to the envelope and windows shift heating response to lower outdoor temperatures and reduce heating sensitivity, as summarized in Table B.3.

In contrast, cooling in Figure 11(b) shows clearly differentiated temperature-energy response patterns by

mitigation measure. Under TDY, the Combined case maintained a consistently lower slope (β_2) in the future periods, indicating a more effective reduction in cooling sensitivity than either Passive-only or Active-only. Under TDY 2080s, the Combined β_2 is estimated at 37.7, lower than Passive 50.26 and Active 49.7 (Table B.4), indicating that the Combined strategy suppresses the increase in cooling demand associated with rising outdoor temperatures. This pattern suggests that cooling sensitivity is most effectively reduced when envelope improvements are coupled with high-efficiency equipment.

Under EWY, the regression terms provide a clearer separation between the temperature-driven cooling response (β_2) and the base load (β_3) cooling level in the 3P change-point model. In this context, the Combined strategy is most effective in reducing β_2 , whereas Active measures are more effective in constraining β_3 . This two-term interpretation supports cooling-oriented retrofit planning that jointly considers both temperature sensitivity and baseline cooling demand under extreme-year conditions.

To assess extreme weather impacts on peak demand,

we evaluated the baseline and the combined retrofit under 2080s TDY and 2080s EWY. In Figure 12, heating peaks decline across all locations and both building types, except for the high-rise apartment in Jeju. Under EWY, cooling peaks increase, and the cooling season extends from May to September. With the combined case, medium office cooling peaks fall by about 23%–28% under both TDY and EWY, and high-rise apartment cooling peaks fall by 38%–46%. Detailed monthly peak demand data are provided in Appendix C.2.

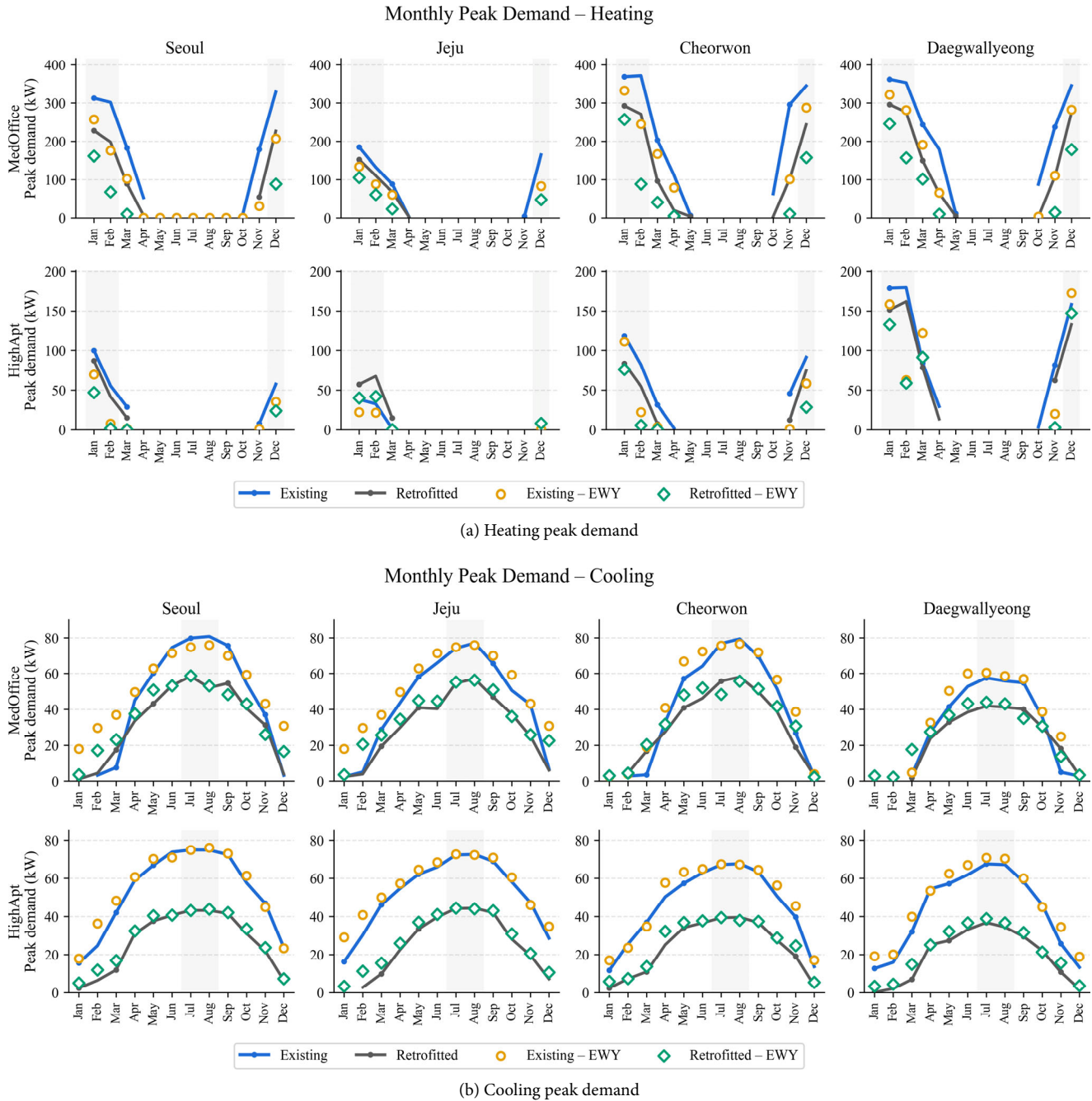


Fig. 12 Comparison of peak demand before and after retrofits

Overall, under 2080s conditions, the mitigation effects can be summarized in terms of total EUI reduction, differences in the dominant mitigation drivers for heating and cooling, and peak mitigation under extreme conditions. For both building types, the Combined strategy achieves the lowest total EUI under TDY and EWY, although the magnitude of savings tends to narrow under EWY. IMT analysis further shows that Passive measures dominate the improvements for heating, whereas for cooling the effects differ by measure, with sensitivity and base load improvements emerging through different strategies. Finally, although EWY increases cooling peaks and extends the cooling season, the Combined retrofit still delivers meaningful reductions in cooling peak demand for both building types.

4.3 Impacts of climate change on thermal comfort

Figures 13 and 14 compare PMV-based comfort before and after retrofit and SET-based heat stress outcomes under EWY.

For the medium office, Figure 13 shows that the share of occupied hours with $PMV > +0.5$ increases after retrofit in all regions except Daegwallyeong, and this holds under both TDY and EWY. Under TDY, Seoul and Cheorwon rise to 60.8% and 55.6%, respectively, which is an increase of about 7%–10% relative to the baseline. Jeju changes little.

Daegwallyeong is the only region with improved comfort, decreasing by about 7% under both TDY and EWY. The exceedance is concentrated in summer, as detailed in Appendix D, indicating that some post-retrofit indoor conditions may shift from neutral toward “warm.” These findings suggest that medium office retrofits are most effective when coupled with summer-focused operational measures.

For high-rise apartments, Figure 14 indicates a clear reduction in $PMV > +0.5$ after retrofit under both TDY and EWY. Post-retrofit percentages remain mostly below 2%–3%, and all regions remain below 5% even under EWY. Thus, for apartments, the proposed measures consistently improved thermal comfort outcomes.

For SET-based heat stress under EWY, Figure 15 shows cooling SET occupant-weighted degree-hours above 30 °C. The medium office shows heterogeneous responses: Seoul increases after retrofit, whereas Jeju, Cheorwon, and Daegwallyeong decrease substantially. The high-rise apartment approaches zero in all regions, indicating that occupants’ heat-stress exposure remains very limited across regions.

In summary, apartments can substantially reduce overheating risk through the proposed retrofit alone, while medium offices require additional summer measures centered on cooling, solar control, and dehumidification to achieve

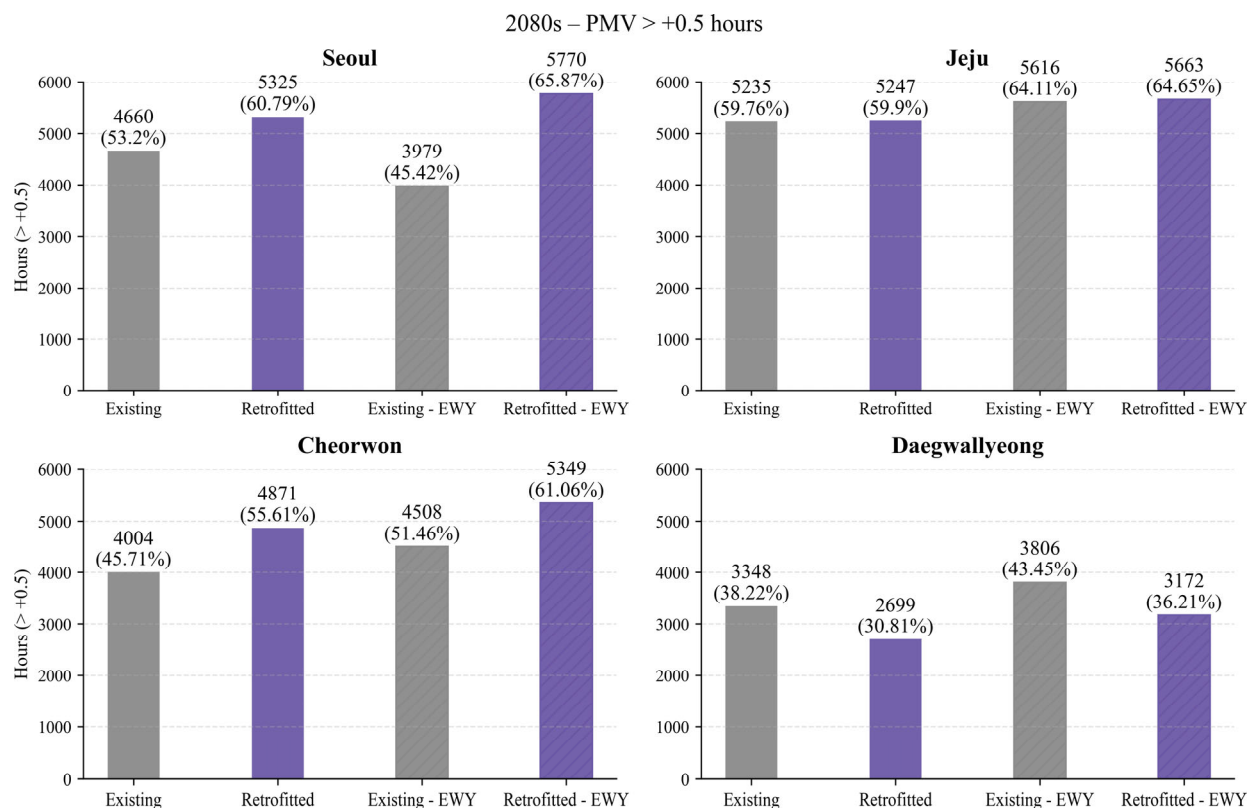


Fig. 13 Thermal comfort changes before and after retrofits in medium office buildings

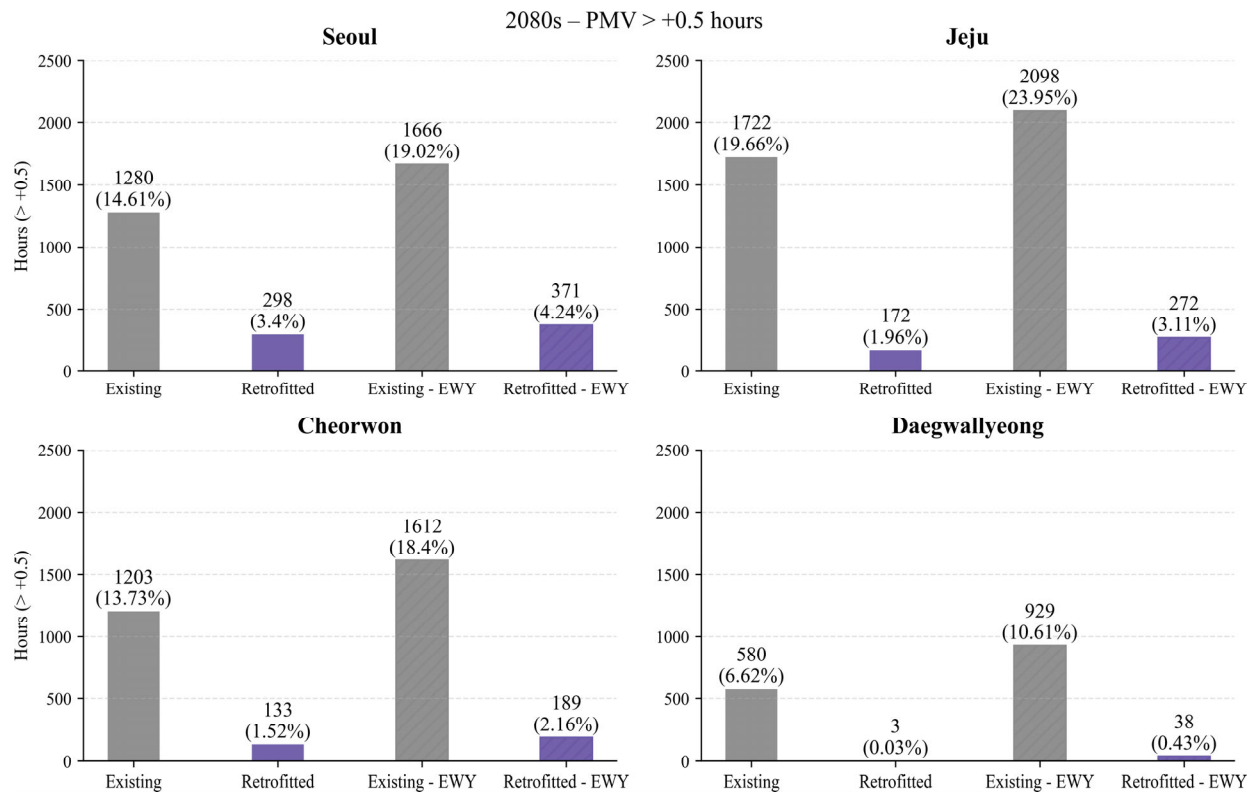


Fig. 14 Thermal comfort changes before and after retrofits in high-rise apartment buildings

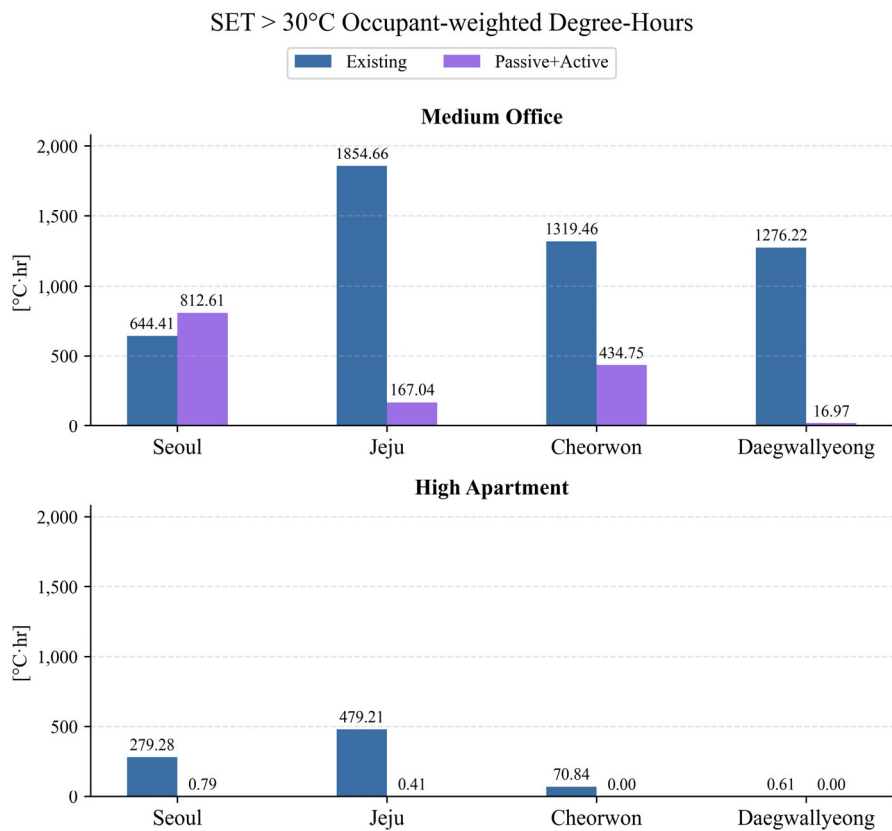


Fig. 15 Comparison of cooling SET occupant-weighted degree-hours above 30 °C under EWY conditions before and after retrofit for medium office and high-rise apartment buildings

comparable improvements in comfort. Detailed PMV- and SET-based thermal comfort results for all building types and regions are provided in Appendix D.

4.4 Discussion

The dual-year approach enables a more comprehensive assessment of future building performance under both typical and extreme warm conditions and helps derive policy implications for the current Korean Building Energy Codes (Ministry of Land, Infrastructure and Transport 2024). In the baseline models, heating decreases and cooling increases, with a structural shift in the temperature-energy relationship. For heating, the change point shifted upward and the absolute slope decreased, indicating weaker temperature sensitivity and a smaller heating-dominant regime. For cooling, the slope increased under TDY, whereas under EWY the base load component β_3 increased, suggesting a change in the composition of cooling demand under extreme heat. In the retrofitted models, dominant mitigation mechanisms differ between heating and cooling. Envelope and window upgrades drive heating reductions by moderating the change point and sensitivity. For cooling, the Combined strategy more effectively reduces sensitivity β_2 , while the Active strategy better constrains the base load component β_3 . Notably, the results indicate that the Passive-only strategy may be insufficient to restrain base load cooling energy use under extreme-year conditions. Overall, these results indicate that cooling-oriented retrofits benefit from integrated packages rather than single measures, because different measures primarily target different components of cooling energy use.

The results go beyond a general description of heating and cooling energy changes under warming by explaining shifts in load structure through concurrent changes in the change point, temperature sensitivity, and base load. For cooling in particular, the same increase in demand can reflect different underlying drivers under TDY and EWY,

implying that response priorities may differ by climate condition. This provides a basis for interpreting the mechanisms behind growing cooling demand in design and operation and for comparing the effects of measures on a consistent parameter scale.

Moreover, these differences highlight the complementary roles of TDY and EWY, showing that incorporating extreme climate conditions enables a more complete assessment of building energy performance, peak demand, and occupant thermal safety outcomes. Accordingly, building performance and comfort evaluations should extend beyond energy efficiency and carbon reduction to a multi-axis framework that also accounts for the cooling energy-temperature response, peak demand, and occupant thermal safety under extreme conditions across the design, operation, and evaluation stages.

Such an expanded evaluation framework can also inform directions for improving the current Korean Building Energy Codes. While the existing standards place relatively greater emphasis on passive measures, such as envelope performance, our results show that active measures play a critical role in limiting cooling energy use, underscoring the need for clearer and more robust requirements for high-efficiency cooling systems. In addition, retrofit strategies should be tailored to building type and climate zone, with integrated passive-active measures applied to maximize both energy performance and thermal comfort. Although this study focuses on the building scale, the quantified changes in thermal sensitivity under extreme heat provide critical inputs for modelling and mitigating urban overheating at the city scale.

To assess whether the main findings are sensitive to key modeling assumptions, a one-at-a-time sensitivity sweep was conducted for three high-impact inputs (infiltration, internal gains, and cooling setpoint) under the EWY 2080s scenario. The resulting changes in heating and cooling energy use and thermal discomfort hours (i.e., PMV > +0.5) are summarized in Table 10. Infiltration had a limited

Table 10 Results of the one-at-a-time sensitivity sweep for infiltration, internal heat gains from people, lights, electric equipment, and cooling setpoint under the EWY-2080s condition

	Baseline			Combined		
	Δ Cooling energy (%)	Δ Heating energy (%)	Δ Discomfort hours (%)	Δ Cooling energy (%)	Δ Heating energy (%)	Δ Discomfort hours (%)
Infiltration +20%	0.177	2.613	-0.101	0.117	8.819	-0.260
Infiltration -20%	-0.186	-2.592	-0.075	-0.116	-8.656	0.139
Internal gains +20%	9.643	-22.527	4.095	10.556	-44.194	3.570
Internal gains -20%	-9.029	27.289	-3.769	-10.12	70.247	-3.743
Cooling setpoint +1 °C	-8.327	-5.269	33.367	-8.021	-7.230	14.521
Cooling setpoint -1 °C	9.739	2.454	-41.608	8.403	10.430	-32.196

effect on cooling energy use, with changes within $\pm 0.2\%$ for the Baseline case and within $\pm 0.1\%$ for the Combined case. Its influence on heating energy use was limited for the Baseline case (within $\pm 2.6\%$), but more pronounced for the Combined case (up to $\pm 8.8\%$). Internal heat gains affected heating energy more strongly than cooling energy. A $\pm 20\%$ variation changed cooling energy by about $\pm 9\%$ – 11% , while heating energy changed by approximately 23% – 27% for the Baseline case and 44% – 70% for the Combined case. The cooling setpoint was the most influential factor for thermal discomfort, with a $\pm 1^\circ\text{C}$ shift changing discomfort hours by 33% – 42% for the Baseline case and 14% – 32% for the Combined case. Overall, the sensitivity sweep indicates that thermal discomfort outcomes are most responsive to cooling setpoint assumptions, while infiltration has a negligible effect. These results indicate that although absolute energy use varies with operational assumptions, the relative differences between TDY and EWY scenarios and the comparative performance of retrofit strategies remain consistent.

While the analysis provides consistent insights, several limitations remain. First, building geometries are based on DOE prototype buildings and are used as standardized archetypes; only selected key inputs were informed by Korean literature. As a result, the findings should be interpreted primarily in terms of comparative trends and mechanism-level shifts. Second, standardized reference archetype models cannot entirely represent real-building schedules, control logic, occupancy variability, urban heat island effects, or radiative environments. Third, EWY is constructed using dry-bulb temperature as the sole selection variable and therefore does not explicitly account for simultaneous extremes in solar radiation, wind speed, and humidity. Accordingly, the EWY is best interpreted as a temperature-driven extreme warm scenario. This means that the present approach is most directly suited to evaluating temperature-dominant cooling responses, whereas responses influenced by concurrent extremes in solar radiation, wind, or humidity should be interpreted with caution. In this sense, the EWY provides a useful basis for comparative assessment under extreme warm conditions, but it does not fully represent compound hot-weather extremes. Furthermore, the present approach does not directly address short-duration or disruption-related scenarios such as equipment faults or power outages, nor does it capture the cumulative effects of multi-day heat waves. Additional scenario-based analyses would be needed for such assessments. Fourth, although we discussed policy implications, a unified quantitative comparison of retrofit economics, life-cycle carbon, demand response, storage, and renewable integration was beyond the present scope.

Based on these limitations, future work should address

several gaps. Field-simulation cross-validation using measured data from real buildings is needed to confirm the estimated temperature-load sensitivities and to better constrain internal gains, schedules, and control logic. Model development should incorporate Korean archetypes and microclimate effects, urban heat island effects and radiation, so that efficiency, peak demand, and thermal safety can be evaluated together across more building types. Standardizing parallel TDY/EWY verification and specifying multi-axis performance targets would help translate results into region- and use-specific retrofit pathways for practice and policy. Finally, a multi-criteria optimization framework that treats retrofit, operations, demand response and storage, and renewable integration together—across performance, cost, carbon, and system value—would connect the present findings more directly to investment decisions.

5 Conclusions

This study evaluated climate-driven changes in building energy performance and thermal comfort in South Korea, with a focus on cooling behavior under extreme warm conditions. Building energy simulations were interpreted using a three-parameter change-point approach that represents cooling responses through the change-point temperature, temperature sensitivity, and the base load component. The impacts of passive, active, and combined retrofit strategies were also examined. The primary conclusions are as follows:

- (a) Under extreme warm-year conditions, the 2080s baseline showed a higher cooling base load component and an upward shift in the cooling change-point temperature relative to the base-year baseline. Using the Seoul medium office as a representative case, the base load component increased by 112.7% and the change-point temperature rose by 2.79°C , indicating that late-century extremes are associated with both persistent base load growth and a shifted cooling threshold, rather than being explained solely by temperature sensitivity.
- (b) Retrofit impacts were evaluated relative to the 2080s extreme warm-year baseline. Passive envelope retrofits increased the base load component by 30% , indicating a cooling base load penalty because cooling reductions in summer months were outweighed by increases across the remaining months. In contrast, active measures reduced temperature sensitivity by 25% , moderating the growth of cooling energy use with rising outdoor temperature. The combined strategy delivered the most moderated cooling energy–temperature response by improving multiple change-point regression parameters simultaneously, decreasing the change-point temperature by 2.3°C and reducing temperature sensitivity by 41% .

The combined strategy also reduced the base load component, although the magnitude was modest (2.4%), suggesting that additional measures may be needed to mitigate shoulder-season cooling drivers under extreme warming.

- (c) Peak cooling demand and thermal comfort outcomes were building-type dependent. Under the 2080s EWY conditions, cooling peak demand increased relative to TDY, while the combined retrofit consistently reduced monthly cooling peak demand by 23%–28% for medium offices and 38%–46% for high-rise apartments under both TDY and EWY. In terms of thermal comfort, medium offices showed limited or adverse changes in PMV-based discomfort after retrofit in most regions, whereas apartments maintained low PMV exceedance and near-zero SET-based heat-stress exposure under extreme warm years.

Overall, these findings show that operational resilience under extreme warm-year conditions is better assessed through complementary dimensions—cooling energy–temperature response, cooling peak demand, and occupant thermal safety—than through aggregate energy metrics alone. Change-point parameters further provide useful diagnostics for interpreting the energy–response dimension and its implications for performance-based retrofit planning under extreme heat.

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Data availability

The research data and code are available upon request.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

All authors contributed to the study conception and design. Conceptualization and writing of the original draft, as well as review and editing of the manuscript, were performed by Eunkyung Lim and Minjae Shin. Data curation, formal

analysis, and visualization were performed by Eunkyung Lim and Ahhun Song. Investigation and validation were carried out by Eunkyung Lim and Jisoo Lee. Methodology was developed by Eunkyung Lim. Funding acquisition and supervision were provided by Minjae Shin. All authors read and approved the final manuscript.

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