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Building Energy Thermal Resilience under Compound Long-and-Short-Term Climate Disturbances: Impact Mechanisms, Quantitative Evaluation, and Energy Storage Enhancement

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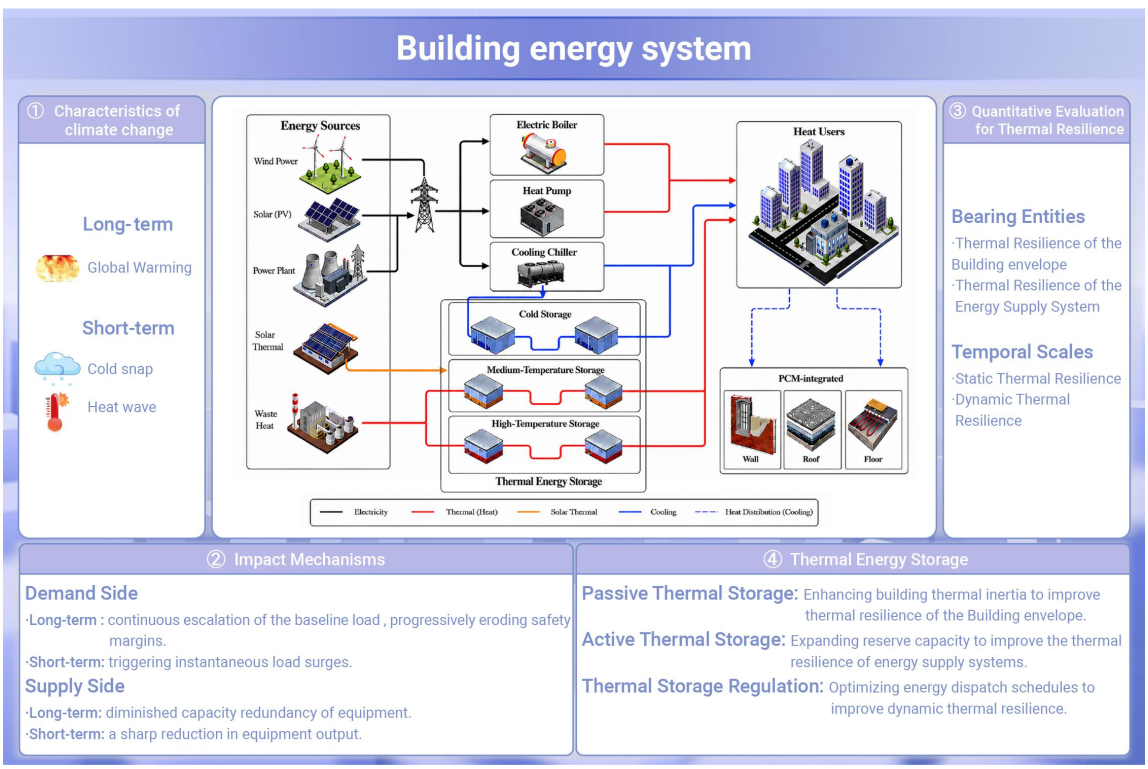
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Boosting buildings' energy thermal resilience amid compound climate change with gradual warming and frequent extreme weather.
- Hourly meteorological data reconstruction evolves from single climate feature extraction to coupled generation of long-term warming and short-term extreme signals.
- Compound climates exert cascading impacts: steady warming reduces safety margins, while sudden extremes cause sharp load spikes and equipment capacity limits.
- A multi-dimensional evaluation framework for thermal resilience is built, combining passive building design, active systems, static adaptability and dynamic emergency response.
- Hybrid thermal energy storage with coordinated control relieves long-term load drifts and short-term shocks; key research bottlenecks and future research paths are summarized.

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Climate change exhibits compound evolutionary characteristics where long-term gradual warming superimposes with short-term high-frequency extreme weather events. Building energy supply and demand, especially HVAC systems, are highly constrained by meteorological boundaries. Therefore, enhancing building energy thermal resilience for compound climate evolution is a core scientific issue needing urgent breakthrough, and this paper conducts a comprehensive systematic review. First, it summarizes future hourly meteorological data reconstruction methods targeting multi-scale climate disturbances, identifying the inevitable trend from extracting singular climate features toward the unified coupled generation of long- and short-term climate signals. Second, it reveals the cascading impact mechanisms on both the supply and demand sides under compound climate disturbances, indicating that long-term warming persistently erodes system safety margins while short-term extreme events instantaneously trigger load surges and equipment output constraints. Furthermore, it clarifies the scientific connotation of building energy thermal resilience and establishes a multi-dimensional quantitative evaluation framework that integrates passive building defense with active system provision and balances long-term static adaptability with short-term dynamic response. Subsequently, it explores the physical support role of thermal energy storage technologies in mitigating long-term load shifts and resisting short-term shocks, emphasizing the critical value of constructing diversified hybrid energy storage architectures and holistic coordinated control strategies to overcome the physical bottlenecks of singular technologies. Ultimately, this paper distills the core bottlenecks confronting current research across various stages and prospects future cutting-edge evolutionary directions, aiming to provide theoretical frameworks and engineering practice references for constructing highly resilient building energy systems.

INTRODUCTION

Climate change represents one of the most severe global challenges currently facing human society. Characterized primarily by global warming, the climate system is undergoing unprecedented and profound transformations. Its impacts extend far beyond mere temperature increases, widely triggering the extensive restructuring of precipitation patterns, continuous sea-level rise, accelerated retreat of the cryosphere, and significant increases in the frequency and intensity of extreme weather events.[1,2] Notably, climate change exhibits multi-scale coupled characteristics, where long-term gradual warming trends are superimposed with short-term, high-intensity extreme shocks. On the one hand, the continuous rise in global average temperatures is fundamentally reshaping regional energy consumption patterns and thermal environment baselines.[3] On the other hand, extreme weather events, typically heatwaves and cold spells, are becoming increasingly frequent and severe, posing a direct challenge to the disturbance resistance of built environment systems.[4] Building energy systems, as the core of the built environment, are deeply intertwined with climate change. Both the load fluctuations on the demand side and the operational efficiency on the supply side are highly dependent on external meteorological conditions. Therefore, there is an urgent need to systematically investigate the dynamic response and adaptability of building energy systems to climate change.

The capability of a system to withstand climate disturbances and maintain its core functions without failure is defined as climate resilience. In the energy sector, this concept originated from the disaster resistance and recovery capabilities of power systems in response to extreme events.[5] It was subsequently extended to the building scale, evolving into "building energy resilience," which aims to maintain a reliable supply of multiple energy vectors, including electricity, heating, and gas. In the face of both long- and short-term thermal disturbances induced by climate change, maintaining an appropriate indoor thermal environment is a core task for buildings to withstand such shocks. Consequently, the concept of Thermal Resilience in building energy systems has emerged. It specifically refers to the core capability of building heating and cooling systems to safeguard and restore the indoor thermal environment under meteorological disturbances. Although the realization of this capability heavily relies on the stable operation of electricity-driven equipment (e.g., heat pumps, fans), the ultimate benchmark for its evaluation remains the state of the indoor thermal environment. However, existing reviews on building resilience predominantly focus on the "passive survivability" of the building envelope under extreme conditions such as power outages. Systematic research dedicated specifically to the thermal resilience of building energy systems remains remarkably scarce.

Focusing on the thermal resilience of building energy systems, this paper provides a comprehensive review of three core aspects: the types of climate disturbances and their impact mechanisms, the scientific connotations and evaluation methods of thermal resilience, and the enhancement pathways enabled by thermal energy storage technologies. This review aims to provide a clear conceptual framework and evaluation paradigms for future research in this field.

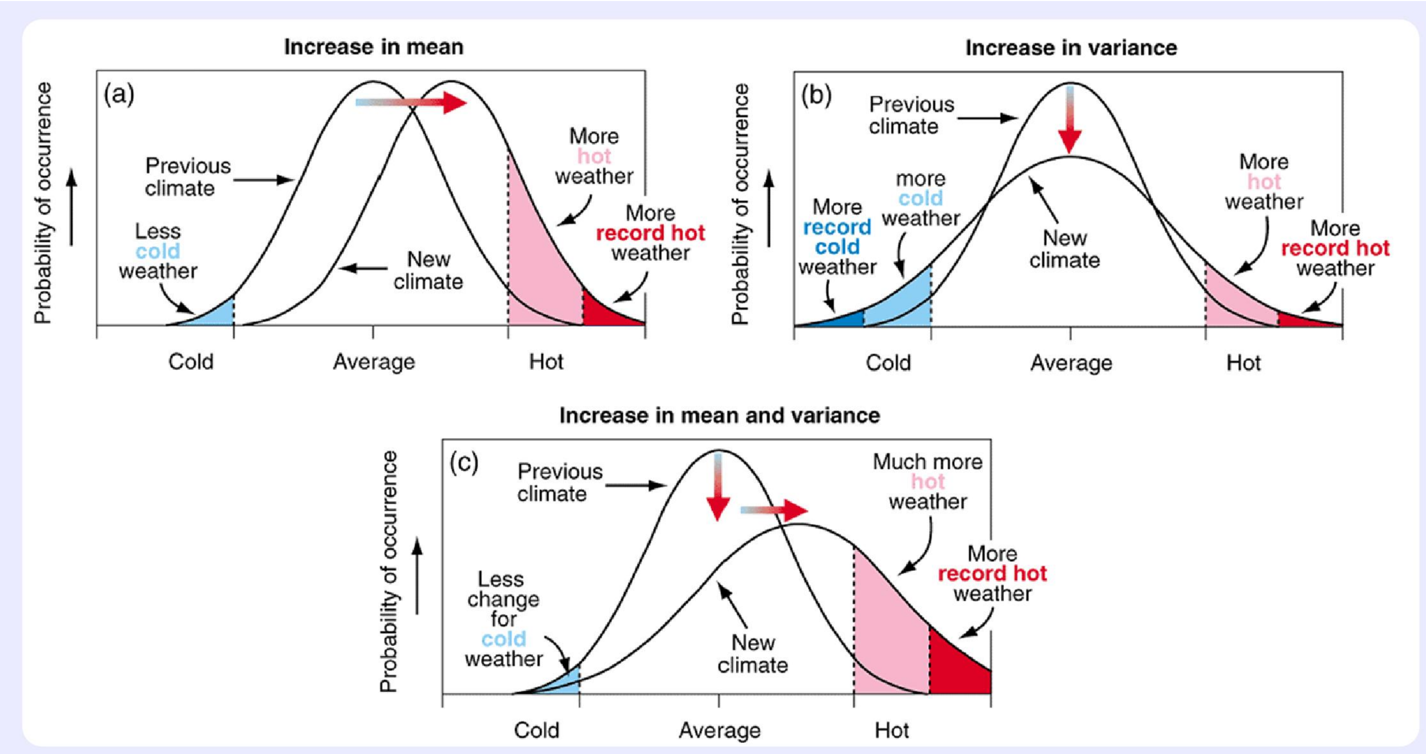

Figure 1. Schematic showing the effect on extreme temperatures when (A) the mean temperature increases, (B) the variance increases, and (C) when both the mean and variance increase for a normal distribution of temperature.[7]

MULTI-SCALE CLIMATE CHANGE AND BUILDING WEATHER DATA GENERATION

The impact of climate change on buildings propagates progressively along a cascading chain: "macro-scale climate models—micro-scale weather files—dynamic building responses (e.g., thermal environment and energy consumption fluctuations)".[6] As research scenarios extend into the future, the meteorological inputs required for building simulations have evolved from a single Typical Meteorological Year (TMY) into multi-scale data frameworks that must simultaneously characterize long-term trends, short-term extreme events, and microclimate effects. Therefore, accurately translating macro-scale climate signals into high-spatiotemporal-resolution meteorological boundary conditions directly applicable at the building scale—via techniques such as downscaling, bias correction, and stochastic reconstruction—has become the core foundation for scientifically evaluating and investigating the thermal resilience of building energy systems.

Characteristics and classification of climate change

Climate change is not a singular warming phenomenon, but a sustained alteration in the statistical state of the climate system over extended time scales. According to the general definition by the IPCC,[7] climate change refers to a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. This definition carries twofold implications: First, climate change is inherently a statistical shift, rather than the random fluctuations of isolated weather events. Second, the characteristics of climate change are not limited to changes in the mean state; they also encompass changes in the internal variability of the climate system, such as alterations in the frequency, intensity, and duration of extreme events, as well as multi-variable coupling relationships.

Oriented towards the impact assessment of building energy systems, climate change-related meteorological disturbances can be classified temporally into two categories: long-term gradual climate changes and short-term extreme weather events.[7] Long-term gradual climate change primarily occurs on interannual to decadal scales, manifesting as a continuous shift in the background climate state, with typical manifestations including global warming and its regionalized responses. Short-term extreme weather events predominantly occur on daily to weekly scales, characterized by the concentrated emergence of exceedance events, such as heatwaves and cold spells, within a short period. These two are not mutually exclusive phenomena; rather, they are manifestations of the same climate evolution process across different time scales. Long-term gradual change determines the background state, while short-term extreme events reflect the tail risks of the distribution. Because extreme events frequently occur superimposed on an already shifted background climate, they cannot be understood in isolation.[8]

Due to the interactions between changes in the mean and changes in variability, the evolution patterns of climate variability and extreme events are often difficult to characterize clearly,[9] Moreover, such interactions vary significantly depending on the statistical distribution forms of different climate variables. Therefore, relying solely on separate analyses of either the mean or the variance is insufficient to comprehensively describe the changing characteristics of the climate system. In this context, a theoretical framework capable of uniformly characterizing the evolutionary features of the full probability distribution of climate variables is required. The Probability Density Function (PDF) serves as an effective tool to describe the synergistic changes between long-term climate trends and short-term extreme weather events.[10] Taking temperature as an example, long-term climate warming can be manifested as an overall shift of the temperature distribution toward the higher-temperature end. Assuming the shape of the distribution remains basically unchanged, this mean shift renders events originally located in the high-temperature tail more frequent, while simultaneously shifting the common temperature range entirely toward higher temperatures (Figure 1A). Conversely, enhanced climate variability can manifest as increased distribution dispersion or thicker tails (heavier tails), simultaneously increasing the probability of tail events at both ends, thereby raising the frequency of both high- and low-temperature extreme events (Figure 1B). In actual climate change processes, mean shifts, variance changes, skewness changes, and tail thickening often co-occur. When an increased mean is superimposed on enhanced variability, the probability at the high-temperature tail increases significantly, making extreme and record-breaking heat events more prone to occur. Meanwhile, changes at the low-temperature end depend on the relative strength between the warming magnitude and the variability enhancement, which may manifest as a decrease, maintenance, or localized increase (Figure 1C). Therefore, understanding climate change from the perspective of probability distributions facilitates the simultaneous characterization of long-term background state migrations and short-term extreme risk variations.[7]

Weather data generation methods for long-term climate trends

One of the most commonly used historical meteorological data formats in Building Performance Simulation is the TMY. Its core objective is to encapsulate the mean climatic characteristics of multi-year observational data into a single representative year. However, as the issue of climate change is gradually incorporated into building energy system research, the research focus is no longer confined to building performance under historical average climate conditions. Instead, it has further expanded to encompass energy consumption variations, thermal comfort risks, and system adaptability under future climate scenarios. Consequently, meteorological data generation methods have progressively evolved from the traditional TMY toward future climate-oriented weather file generation techniques. Early methods for generating future weather data primarily retained TMY as the baseline data carrier, superimposing monthly-scale climate change signals onto the historical typical year, thereby formulating a classic framework represented by the *morphing* method.[11-13] By applying systematic perturbations to historical hourly weather sequences, such methods translate future warming signals provided by Global Climate Models (GCMs) into hourly meteorological input files directly applicable for building simulations, thereby achieving a preliminary coupling between climate change scenarios and Building Performance Simulation.

As research objectives gradually broaden from annual average building energy analysis to overheating risk assessment, peak load analysis, and long-term adaptive design, future typical years relying solely on uniform incremental adjustments have become inadequate to meet these demands. Consequently, studies have begun to construct weather files such as Future Probabilistic Design Years[14,15] and Design Reference Years (DRYs)[16] based on the statistical distributions of future climates. By redefining representative years using the probability distributions of future climate change signals, the representation of long-term global warming has advanced from simple mean shifts to the comprehensive characterization of future climatic probability distribution features.[17-19] Researchers have started to extract and reconstruct future TMYs directly from multi-year future climate sequences,[20] thereby enhancing the performance of weather files in terms of physical consistency, local adaptability, and temporal structural continuity. In recent years, the research focus on future meteorological data has further shifted from single-year representations to multi-year ensemble expressions. Stochastic Weather Generators (SWGs),[21] scenario-conditioned generation methods,[22] and multi-model ensemble techniques[23,24] have been widely adopted to simultaneously capture multiple characteristics, including long-term mean drifts, interannual variability, and future climate uncertainties.

Although future meteorological data generation methods have progressively evolved into multi-model, multi-year, and high-resolution ensemble frameworks, the morphing method continues to occupy a foundational position in long-term climate change impact assessments in engineering practice. This enduring relevance is attributed to its low computational cost, straightforward implementation pathways, minimal input data requirements, and seamless integration with mainstream building energy simulation software such as EnergyPlus and TRNSYS. In recent years, researchers have continuously expanded and refined the morphing method. For instance, recent studies have integrated support for CMIP6 multi-model datasets,[25,26] enabling the automated processing and batch conversion of standardized climate data formats such as NetCDF, thereby promoting the open-source development and engineering application of morphing tools. Furthermore, McCarty et al.[27] extended the temporal resolution of morphing statistical adjustments from the monthly to the daily scale, while simultaneously accounting for the impacts of regional and seasonal variations on climate perturbations.

From a mechanistic perspective, the core of the morphing method lies not in complex dynamical climate modeling, but rather in applying systematic statistical transformations to historical meteorological sequences. Its fundamental rationale can be categorized into three typical transformation operations: shifting, scaling, and a combination of shifting and scaling.[12] Shifting involves directly adding the absolute mean increment between the future and historical months to each hourly value within that month, causing the entire hourly sequence to shift upwards or downwards in tandem with the background mean. Scaling adjusts the deviation of each hourly value from the monthly mean based on the future climate change signal (fractional change), thereby reflecting changes in the diurnal range or fluctuation amplitude of future weather conditions. The combination of shifting and scaling is applied to variables that require simultaneous representation of both the shift in the monthly average level and the change in intra-monthly variance. By first scaling the hourly deviations from the monthly mean and subsequently shifting the overall monthly average up or down, this operation successfully maps macro-scale climate change signals onto hourly building meteorological boundary conditions (Figure 2).

However, the essence of the morphing method remains the application of statistical perturbations to historical meteorological sequences, and its representational capacity has clear boundaries. First, this method relies on historical hourly weather as its temporal framework. Since future meteorological sequences are essentially transformations of historical samples, the method struggles to generate novel weather evolution processes that transcend historical weather structures. Second, the traditional morphing method is primarily driven by monthly-scale climate change signals. While it adequately reflects long-term mean warming trends, it possesses limited capability in characterizing daily-scale extreme fluctuations, heatwave persistence, extreme event frequencies, and tail risks.[18] Consequently, future meteorological data generated via the morphing method may underestimate the impacts of climate change in extreme thermal risk assessments. Therefore, in studies of building thermal resilience and extreme climate adaptability, relying solely on future weather files modified by long-term mean adjustments remains insufficient. It is necessary to further integrate meteorological data generation methods capable of representing short-term extreme weather events.

Weather data generation methods for short-term extreme events

The generation of short-term extreme weather event data has evolved into three relatively distinct yet intersecting methodological approaches: the scenario extraction and concatenation method, the parametric generation method, and the Extreme Value Theory (EVT) approach. Their fundamental distinction lies in how extreme events themselves are defined and characterized. Specifically, the scenario extraction and concatenation method treats extreme weather as actual weather processes that can be directly extracted and recombined from historical observations or climate model sequences; the parametric generation method views extreme weather as stochastic outcomes generated through extensive sampling via statistical models; whereas the EVT approach regards extreme weather as tail distributions or persistent events that require explicit constraints and independent modeling (Figure 3). These three categories of methods each have specific emphases regarding data sources, modeling assumptions, output formats, and engineering applicability, collectively constituting the primary technical framework for the generation of short-term extreme weather data.

The scenario extraction and concatenation method. are a commonly utilized approach for reconstructing extreme weather in building simulations. Its fundamental concept involves extracting representative extreme months or complete events from multi-year hourly sequences of historical observations or climate model outputs, based on indicators such as temperature, solar radiation, and heatwave intensity or duration. These authentic weather fragments are then recombined into meteorological input files—such as Extreme Meteorological Years (XMYs) and Extreme Heatwave Years—that can be directly utilized for building simulations.

During this developmental process, the research focus has gradually expanded from the traditional TMY to a variety of extreme scenario files. Early studies incorporated high-temperature risks into the reference year framework by designing the Summer Year[28] and the Near-Extreme Summer Reference Year,[29] thereby redefining the representativeness of anomalously warm years using return periods and quantiles. Subsequently, concepts such as the Extreme Reference Year (ERY)[30] and the XMY[31] were proposed, shifting the logic of typical month selection from average representativeness to extreme deviation screening. In recent years, this approach has been further deeply integrated with Regional Climate Models (RCMs).[31] By identifying heatwave events through multi-threshold percentile rules and reconstructing

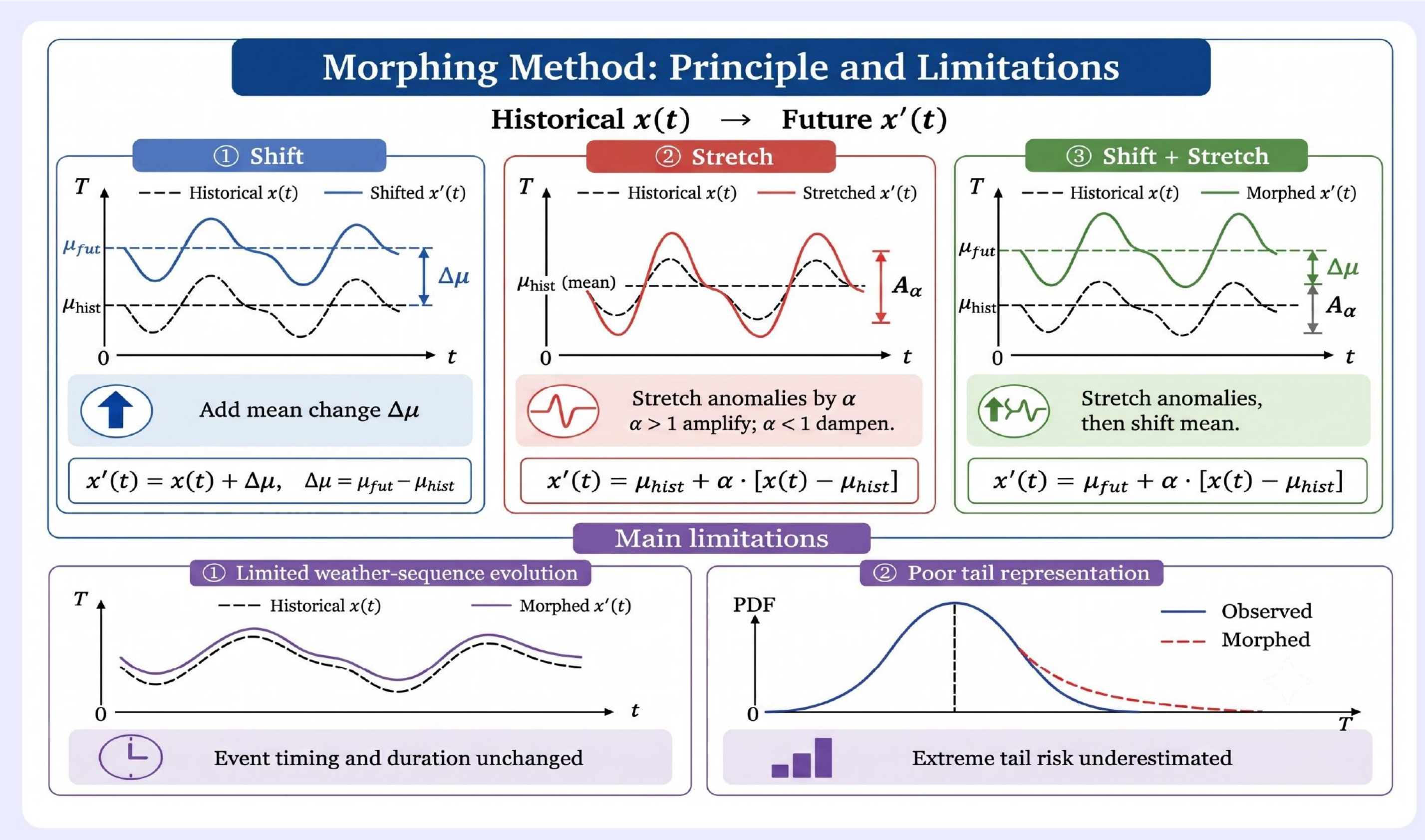

Figure 2. Schematic of the core operations and limitations of the morphing method.

files such as XMY and HWE (Heat Wave Event), this method generates input files directly applicable for building energy and thermal comfort simulations, while simultaneously preserving the duration, intensity, and realistic hourly fluctuation characteristics of future heatwaves.

The advantages of this method lie in its ability to effectively preserve the physical consistency and multivariate co-variation of the original weather processes. Furthermore, it possesses mature engineering interfaces and produces results that are highly interpretable for designers. However, its capability to control tail probabilities and return periods is relatively weak. The statistical significance of its extremity often relies on empirical month-selection rules rather than rigorous tail modeling. Moreover, cross-month concatenation can disrupt chronological continuity, making it challenging to comprehensively represent long-lasting heatwaves or cross-seasonal persistent anomalies.

The parametric generation method. Rather than directly extracting intact weather fragments from long sequences, the parametric generation method synthesizes a vast number of possible weather sequences through structures such as SWGs, seasonal non-stationary Vector Autoregressive (VAR) models, Markov chains, or multivariate statistical models. This approach effectively captures future climate uncertainties and the distribution of building responses. Early research primarily focused on the representation of future climate uncertainties. For instance, Williams et al.[21] utilized SWGs to generate extensive future hourly weather samples and evaluated building heating and cooling loads using sample ensembles rather than a single year, highlighting the advantages of parametric methods in the probabilistic representation of future risks. Subsequently, Lee et al.[32] modeled building meteorological boundaries as a VAR process exhibiting seasonal non-stationarity, thereby advancing the parametric method from univariate weather generation to comprehensive sequence construction tailored for full-year building simulations.

In recent years, the evolution of such methods has predominantly concentrated on two trajectories. The first is the enhancement of multivariate joint modeling capabilities. By employing Copula methods, researchers can preserve the dependence structures among variables such as temperature, humidity, and solar radiation, further extending this to spatiotemporal joint generation.[24,33] The second trajectory involves a transition from traditional parametric fitting to constrained stochastic reconstruction and temporal downscaling. Through stochastic resampling and daily-to-hourly scale conversions, this approach enhances the characterization of the persistence of future extreme events while maintaining physical consistency and short-term structural integrity.[34]

The core merit of this approach lies in its ability to transition from a single-scenario file to multi-year sample ensembles. This inherently facilitates a more natural representation of future uncertainties, event occurrence probabilities, and the distribution of building responses, making it highly suitable for probabilistic risk analysis and scenario ensemble simulations. However, since generic parametric models typically target the overall statistical characteristics of weather as their primary fitting objectives, their capability to reproduce temperature tails, heatwave durations, and multivariate extreme joint behaviors may remain inadequate. Consequently, the reconstruction of extreme weather utilizing this method often necessitates additional tail corrections or extreme value constraints.

The Extreme Value Theory (EVT) approach. primarily focuses on modeling the tails of meteorological variable distributions. Its fundamental rationale is that when quantifying the risk of extreme weather events, the tail should not be treated merely as an incidental by-product of general weather generation processes; instead, it must be explicitly identified, constrained, and modeled independently. Within this approach, research targeting extreme heatwave events occupies a dominant position.

Furrer et al.[35] decomposed heatwave events into multiple components—namely, occurrence frequency, duration, and intensity—and characterized them using the Poisson distribution, Geometric distribution, and Generalized Pareto Distribution (GPD), respectively, thereby reflecting the physical characteristics of heatwaves across multiple dimensions. Building upon this, Shaby et al.[36] further accounted for the temporal dependence of heatwaves. They described the occurrence and persistence of heatwave events through a two-state Markov chain framework, and combined it with the GPD to characterize tail intensity and inter-daily dependence. This effectively embedded the concept of "heatwaves as persistent tail events" into the model structure. In recent years, Di Credico et al.[37] further enhanced the characterization of the

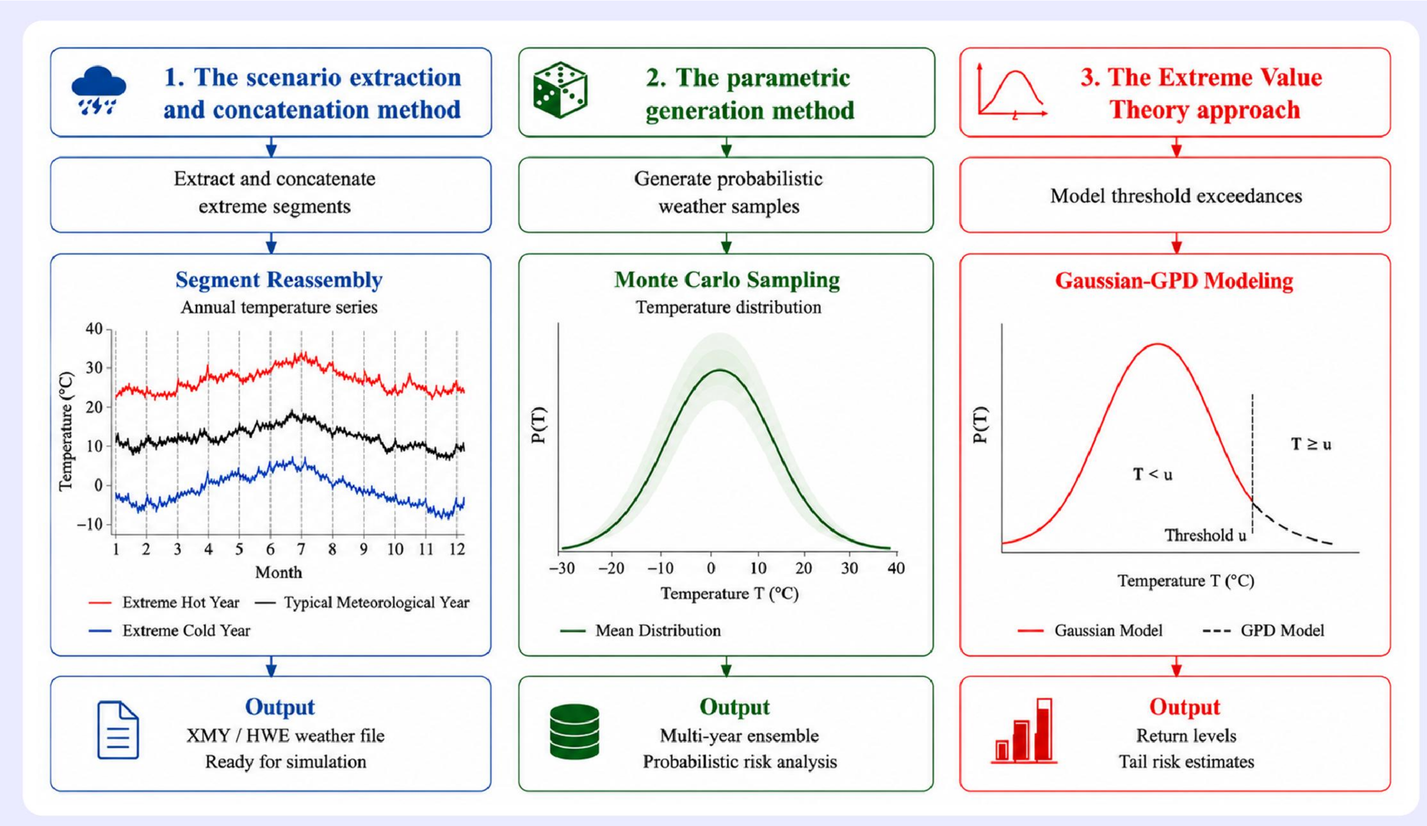

Figure 3. Schematic of the weather data generation method for short-term extreme weather events.

internal temporal structure of heatwave events. Their model better captures the attenuation of tail dependence, event persistence, and extreme cluster structures within multi-day continuous heatwaves, thereby facilitating the estimation of key risk metrics, such as the occurrence probability of long-lasting heatwaves.

Overall, the EVT approach typically targets exceedance samples (i.e., Peaks-Over-Threshold) or extreme weather event states as its analytical subjects. It employs methods such as the Generalized Extreme Value distribution, GPD, and Markov chains to rigorously characterize the frequency, duration, and intensity of extreme weather events. The distinct advantage of this approach lies in its strong statistical rigor in tail modeling and its outstanding capability in representing persistent extreme events, making it highly suitable for analyzing how extreme risks evolve under non-stationary climate contexts. However, this approach generally does not directly generate complete full-year hourly weather files. Consequently, it is more optimally utilized as a tail constraint layer, functioning in conjunction with the scenario extraction method or the parametric generation method.

Compare of three methods. In summary, the three categories of short-term extreme weather event data generation methods exhibit a distinct complementary relationship between engineering applicability and statistical rigor. The scenario extraction and concatenation method can rapidly generate standard meteorological files, making it highly suitable for direct application in building simulations; however, its capability to control the return periods, persistence, and tail probabilities of extreme events is limited. The parametric generation method can generate multi-year sample ensembles, excelling at representing future climate uncertainties and building response distributions; yet, its simulation of tail extremes and compound extreme events still requires enhancement. The Extreme Value Theory approach holds distinct advantages in modeling the intensity, frequency, and persistence of heatwaves, but it struggles to independently provide complete input files for full-year building simulations. Looking ahead, the development of short-term extreme weather data generation methods will progressively trend toward multi-method fusion. By coupling Regional Climate Models (RCMs), stochastic generation frameworks, and Extreme Value Theory, researchers can simultaneously preserve the full-year climate background, multivariate dependence structures, event persistence structures, and extreme tail characteristics within a unified data framework. Ultimately, this paradigm shift will facilitate the construction of high-fidelity future meteorological databases, which are more exquisitely tailored for the assessment of building thermal resilience.

Weather data generation methods for compound climate scenarios

In the actual climate system, long-term gradual changes and short-term extreme events exhibit synergistic co-evolution, meaning that traditional independent modeling approaches possess inherent limitations. Specifically, long-term methods, constrained by historical weather backbones, tend to underestimate extreme risks, whereas short-term methods extract extreme events in isolation, thereby detaching them from the macroscopic warming background. Such a fragmented approach is highly prone to inducing structural distortions in building meteorological boundary conditions. To address this issue, there is an urgent need to construct a unified coupled generation framework for both long- and short-term climate signals. Rather than a mere superposition of the two types of features, this framework must maintain the consistency of multi-scale physical laws within a unified data system. A comprehensive coupled model must simultaneously achieve five core objectives:[8,22,38] (1) characterizing long-term backgrounds, such as rising means and seasonal shifts; (2) reproducing extreme quantiles and tail probability distributions; (3) capturing extreme event frequencies and the persistence characteristics of continuous threshold exceedances; (4) preserving multivariate joint dependence structures among various meteorological variables; and (5) possessing the engineering applicability to directly output standard weather files, such as the EPW format.

In recent years, coupled generation technologies for long- and short-term climate features, tailored for the assessment of building energy systems, have evolved rapidly. This evolution has mainly formed four distinct technical pathways (Figure 4), which include the macro-signal constrained stochastic generation method, the combined modeling method of baseline climate and extreme events, the scenario-constrained resampling and multivariate joint generation method, and the generative AI and statistical downscaling method. The macro-signal constrained stochastic generation method repre-

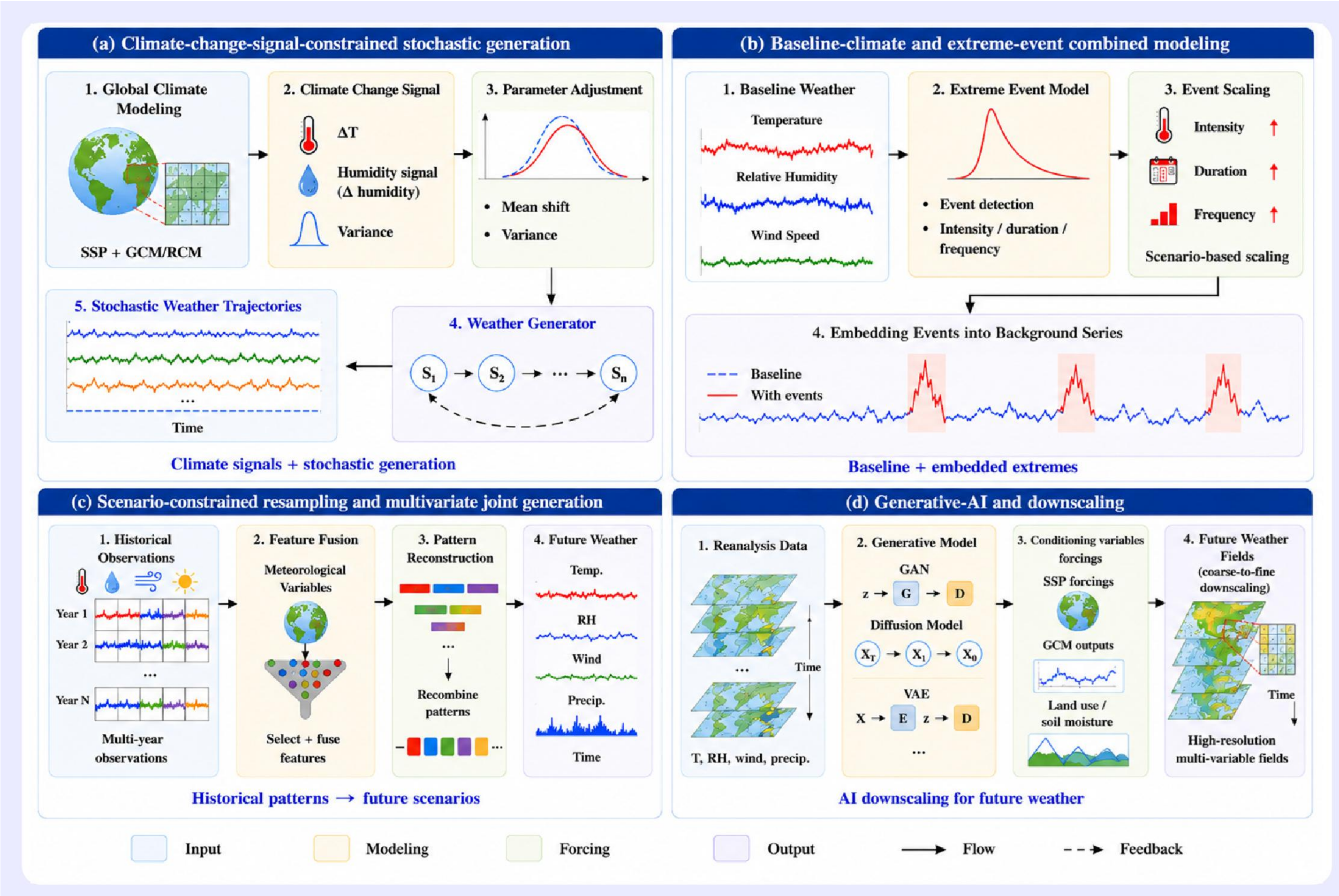

Figure 4. Schematic of the weather data generation method for compound climate change scenarios.

sents a profound extension of the traditional *morphing* concept. Its specific logic involves first extracting medium- to long-term future change signals from climate models and converting them into statistical constraints. Subsequently, these constraints are used to drive Stochastic Weather Generators (SWGs) to regenerate hourly meteorological data under the bounds of long-term scenarios.[23,39] This approach of "first setting the background, then recreating the fluctuations" endows future weather with entirely novel short-term fluctuation structures (see Figure 4A). The combined modeling method of baseline climate and extreme events[40,41] decouples long- and short-term features. It typically utilizes a Typical Meteorological Year (TMY) or future stationary weather as the long-term background baseline, while treating extreme weather as an independent stochastic process modeled separately. Its core mechanism lies in first estimating the parameters of extreme events based on historical data, then recalibrating their frequency, intensity, and duration according to future climate scenarios. Finally, the generated future extreme event sequences are directly embedded into or used to replace corresponding periods in the baseline weather (Figure 4B). The scenario-constrained resampling and multivariate joint generation method[22] owes not rely on purely parametric fitting; rather, it intelligently reconstitutes historical observations or reanalysis data based on future scenario constraints. Its significant advantage is the inherent maintenance of authentic physical consistency among multiple variables such as temperature, humidity, wind, and solar radiation. Existing research indicates that even if future daily extremes do not exceed historical records, this method can still synthesize longer-lasting extreme heatwave processes through the rational recombination of historical weather fragments, demonstrating immense application potential in building thermal resilience simulations (see Figure 4C). Within the generative AI and statistical downscaling method,[42,43] deep learning frameworks represented by Diffusion models and Generative Adversarial Networks (GANs) are being widely introduced into meteorological field reconstruction. Its major breakthrough lies in the capability to directly generate high-resolution weather data under the guidance of large-scale climate signals, progressively integrating extreme statistical features, multivariate physical coupling, and spatiotemporal consistency into a unified generation task (Figure 4D).

In summary, the construction of future meteorological boundary conditions for buildings is transitioning from independent long- and short-term modeling toward a coupled generation framework that accommodates both macroscopic trends and short-term extremes. Supported by technologies such as resampling, stochastic generation, and large AI models, meteorological data generation has transcended the limitations of simple mean shifting and is advancing toward a unified system that integrates tail risks, event persistence, and multivariate consistency. Nevertheless, current research remains constrained by two major bottlenecks. First, the capability to characterize the joint responses of multiple meteorological elements is weaker than that of univariate temperature models. Consequently, it struggles to meet the demands of building heating and cooling load assessments, which rely heavily on the compound interactions of variables such as temperature, humidity, wind speed, and solar radiation.[44,45] Second, a substantial application gap exists between statistical theories focused on controlling tail extremes and engineering tools geared toward outputting standard EPW files, making it difficult to simultaneously balance the accuracy of reproducing extreme characteristics with the convenience of simulation software interfaces.[46] Therefore, future climate data generation methods urgently need to seek an optimal balance among statistical rigor, physical consistency, and engineering applicability, thereby providing a solid data foundation for assessing the thermal resilience of building energy systems under the superimposed impacts of long- and short-term meteorological disasters.

Spatial downscaling methods for urban microclimates

Against the backdrop of global warming, extreme heatwave events have become increasingly frequent. Their impact on urban building energy systems stems not only from regional background warming but is also

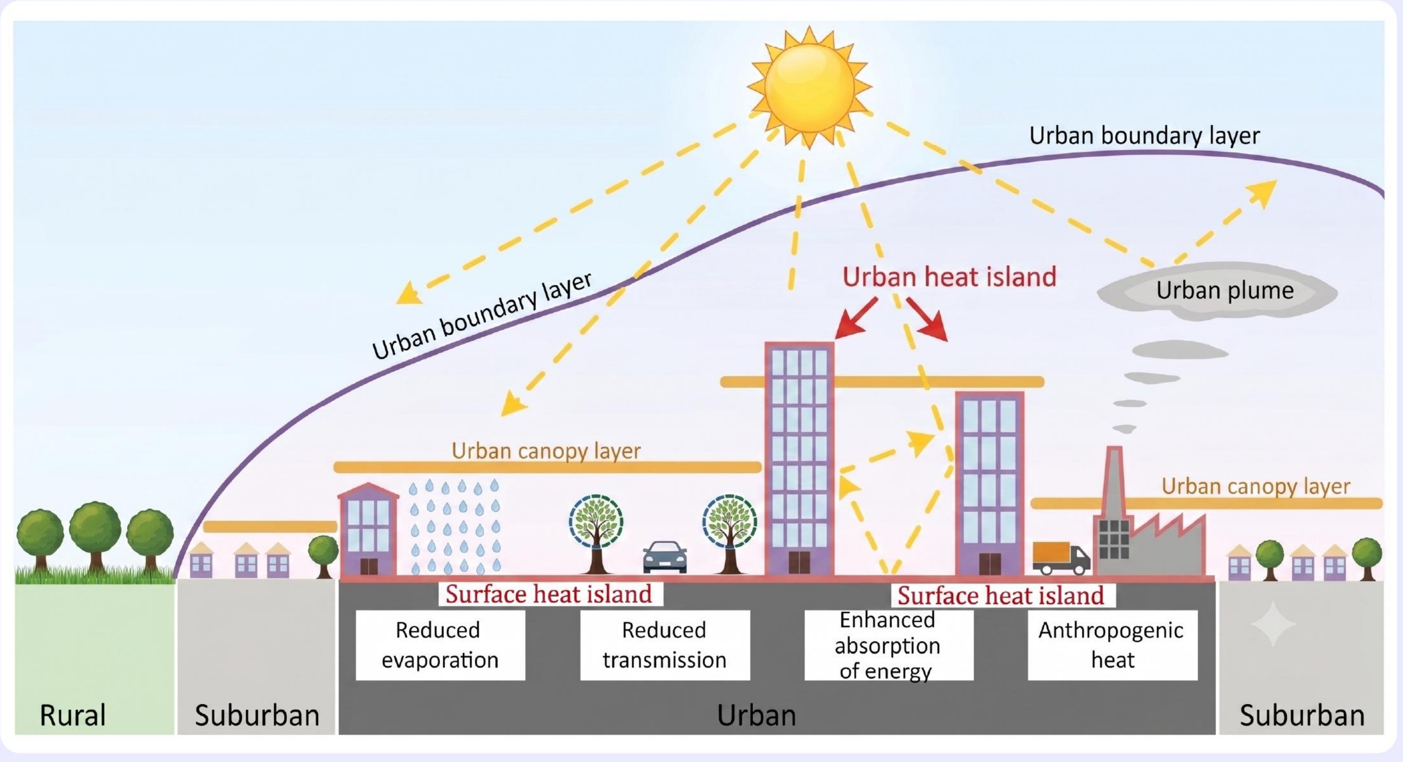

Figure 5. Urban heat island.[49]

closely associated with the synergistic amplification of the Urban Heat Island (UHI) effect during heatwaves. Studies indicate that heatwaves and the UHI effect are not merely a simple linear superposition; rather, they generate significant non-linear coupling effects under the dominance of stagnant high-pressure systems.[47,48] Specifically, clear-sky conditions under stagnant weather increase solar shortwave radiation input, while low wind speeds and weak turbulence impede the outward dispersion of heat from the near-surface layer. Compared to natural suburban surfaces, the high proportion of impervious surfaces in urban areas leads to weakened evapotranspiration. Consequently, large amounts of additional net radiation cannot be readily dissipated through latent heat release, and are predominantly converted into sensible heat and surface heat storage instead. During the daytime, building envelopes and pavements absorb and store massive amounts of heat; at night, this stored heat is slowly released, severely hindering urban cooling and resulting in continuous heat accumulation. Therefore, urban temperature elevation under heatwave conditions is not a simple uniform upward shift of regional air temperatures, but rather exhibits pronounced diurnal asymmetry, continuous heat storage accumulation, and extreme nighttime high temperatures (Figure 5).

For building energy systems, external thermal boundaries are not directly determined by regional weather station data; rather, they are shaped through multi-stage transmission and modulation from the regional climate, through the urban canopy layer, down to the building surfaces.[50,51] Influenced by factors such as urban morphology, underlying surface materials, and anthropogenic heat emissions, regional meteorological conditions are transformed into local microclimates in the vicinity of buildings that deviate significantly from station observations. Particularly during extreme heatwave periods, weakened heat dissipation caused by low wind speeds, the nighttime release of surface heat storage, and superimposed surging waste heat from air conditioning systems collectively forge a localized amplification effect, wherein heatwaves and the UHI mutually reinforce each other. However, current building simulations predominantly rely on airport or suburban weather station data that merely reflect background weather, making it difficult to authentically characterize the thermal environment within the urban canopy. Consequently, directly adopting conventional station data as meteorological boundary conditions makes studies highly prone to underestimating the actual thermal exposure intensity experienced by urban buildings under extreme climates.

To address the inadequacy of regional meteorological data in representing local urban thermal environments, spatial downscaling methods for urban microclimates have recently become a research focus, primarily comprising physics-based models and data-driven methods. Physics-based models typically employ multi-scale coupling frameworks. They utilize mesoscale models (e.g., WRF) combined with Urban Canopy Models (UCMs) to reconstruct the urban background thermal environment, subsequently coupling with CFD or Large Eddy Simulation (LES) tools to downscale meteorological data to the neighborhood or building-surface scale.[52-55] While these models offer strong mechanistic interpretability and high accuracy in simulating complex processes during heatwaves—such as enhanced radiation, urban heat storage, ventilation stagnation, and building heat-rejection feedback—they demand extensive boundary conditions, 3D geometric data, and computational resources. Furthermore, multi-scale nesting and two-way coupling hinder their application in large-scale, multi-scenario batch analyses. In contrast, data-driven methods based on GIS and machine learning offer higher computational efficiency and engineering deployment flexibility.[51,56] Utilizing spatial features like land use, Local Climate Zones (LCZs), building morphological parameters, and green space ratios, these methods rapidly map regional station data to local urban conditions via empirical formulas or machine learning algorithms. They are highly suitable for city-scale scheme screening, early planning assessments, and rapid integration with building energy simulation platforms. However, lacking comprehensive descriptions of the energy budget and fluid dynamics, data-driven models may struggle to accurately characterize key mechanisms—such as heat storage release, ventilation stagnation, and building heat-rejection feedback—under highly non-linear events like extreme heatwaves. Consequently, their cross-regional generalization capabilities and adaptability to extreme scenarios require further improvement.

In summary, the amplification of the UHI effect under heatwave conditions is not a simple elevation of regional temperatures, but a multi-scale localized thermal evolution driven by the combined effects of the regional climate background, urban surface heat storage, neighborhood ventilation conditions, and building heat-rejection feedback. The actual external thermal boundaries experienced by buildings are forged during the progressive transmission of regional meteorology through the urban canopy, into the neighborhood

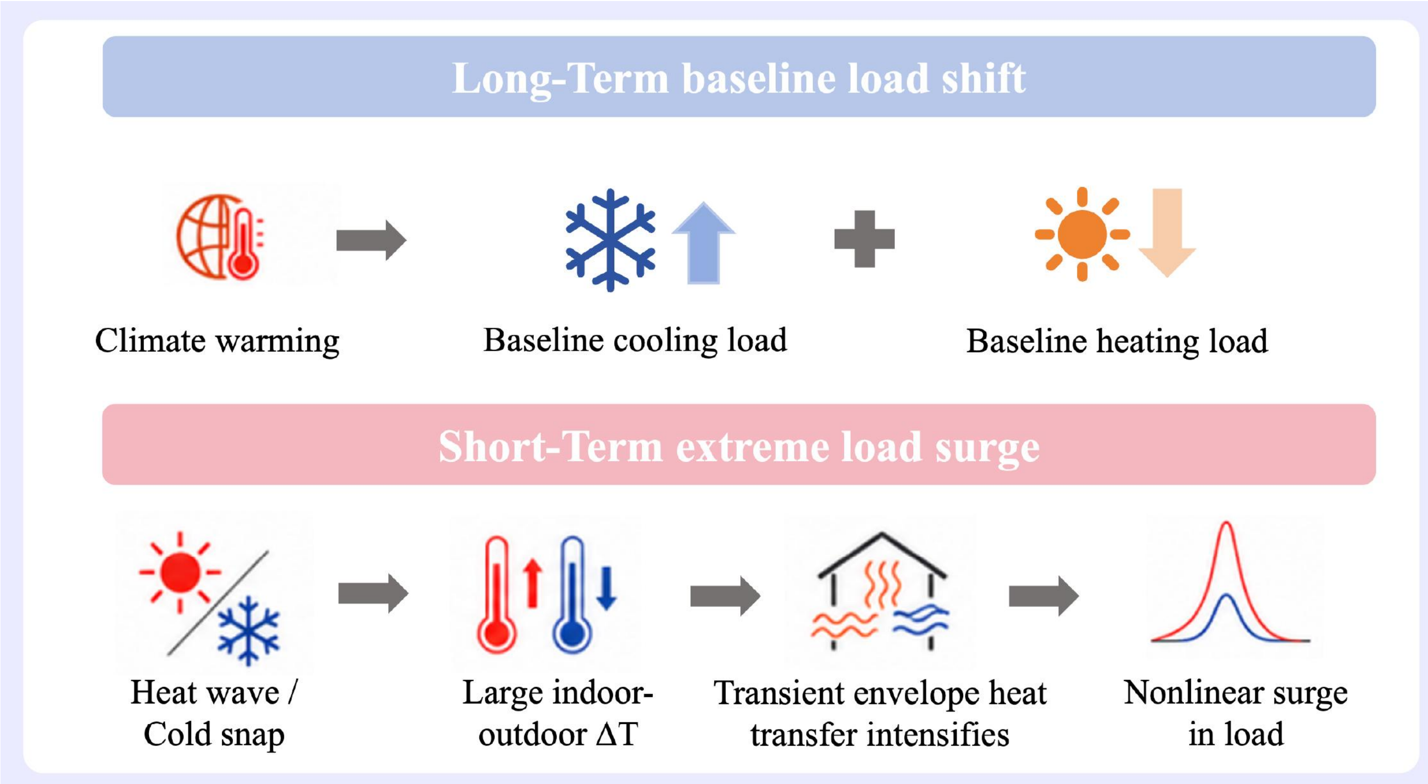

Figure 6. Schematic diagram of the demand-side influence mechanism.

space, and down to the building surfaces, necessitating reconstruction via spatial downscaling methods. Directly substituting local urban boundary conditions with airport or suburban weather station data can lead to a systematic underestimation of the impacts of extreme high temperatures on building energy load profiles, indoor overheating risks, and equipment operational stress, thereby undermining the reliability of future climate change assessment results.

IMPACT MECHANISMS OF CLIMATE CHANGE ON BUILDING ENERGY SYSTEMS

Demand-side impacts

The impacts of climate change on building energy demand exhibit distinct multi-timescale features, which can be encapsulated by a dual mechanism of long-term baseline shift and short-term load surge (Figure 6). Specifically, long-term gradual global warming drives a continuous baseline shift in annual heating and cooling loads, while frequent extreme weather events, such as heatwaves and cold spells, trigger short-term peak loads that far exceed normal levels.

On a long-term scale, existing studies consistently indicate that gradual warming is driving significant baseline shifts in building heating and cooling loads. Scenario-based projections show that building cooling energy consumption increases continuously across different building types and climate regions under multiple SSP pathways, with higher-emission scenarios leading to substantially greater increments and some residential categories exhibiting increases exceeding 100% by the end of the century.[57] In addition, existing studies further confirm that this warming-driven shift is generally characterized by a faster rise in cooling demand compared to the decline in heating demand.[58] Globally, based on degree-day analysis, Deroubaix et al.[3] pointed out that since 1990, climate-driven cooling demand has increased by over 10% worldwide, 20% in mid-latitudes, and over 60% in many parts of the Northern Hemisphere, with the surge in cooling demand generally outpacing the decline in heating demand. Global hourly load simulations by Staffell et al.[59] further confirmed that in certain regions, cooling demand has transitioned from a traditional seasonal requirement to a high-frequency, normalized necessity. At regional and urban scales, Berardi et al.[60] predicted that by 2070, heating energy intensity in Canadian buildings will decrease by 18%–33%, while cooling energy intensity could surge by up to 126%. Similarly, Yan and Ogata[61] found that under the SSP585-2080 scenario, residential heating demand in Japan drops by 31.7% on average, whereas cooling demand skyrockets by 135.6%. Focusing on highly insulated buildings in typical Chinese climate zones, Wang et al.[62] further demonstrated that by 2080, annual cooling energy consumption could increase by up to 22.1% for apartments and 5.0% for offices compared to the baseline climate, suggesting that current climate conditions significantly underestimate future indoor overheating risks. Overall, the aforementioned studies demonstrate that long-term warming causes actual building heating and cooling demands to deviate significantly from the initial design baselines of existing HVAC systems. This is primarily reflected in the prolonged high-load operation cycles during summer and the emergence of redundant equipment capacity during winter, ultimately leading to a chronic mismatch between the original installed capacity configurations and actual long-term demands.

Unlike long-term gradual effects, the impacts of extreme weather events on the demand side over short-term scales manifest more intensely as nonlinear surges in peak loads. Focusing on eastern Chinese cities, Yang et al.[63] pointed out that under the superimposed coupling of heatwaves and urban microclimates, the daily peak cooling load of buildings can increase by 21%–62%. High-spatiotemporal-resolution simulations by Hosseini et al.[64] demonstrated that, driven by the combined effects of extreme weather and microclimates, Cooling Degree Days (CDDs) during extreme warm months can surge by up to 500% compared to typical months, with extreme daily peak loads spiking by 25%. Furthermore, Meng et al.[65] found that during heatwaves, daily loads for residential and office buildings in the Beijing-Tianjin region of China increased by 10%–40% and 10%, respectively. Research by Amonkar et al.[66] on load fluctuations in the U.S. emphasized that annual peak loads exhibit profound instability under extreme events. Extreme high temperatures do not merely shift the load curve upwards uniformly; rather, through physical mechanisms such as persistent high temperatures, high humidity, and obstructed nighttime heat dissipation, they cause continuous heat accumulation in building envelopes and dramatically widen the indoor-outdoor temperature difference, thereby exerting an amplification effect on the hourly peak cooling loads. Such short-term, non-linear surges often instantaneously breach the rated design limits of existing HVAC systems.

In summary, the evolution of building energy demand under climate

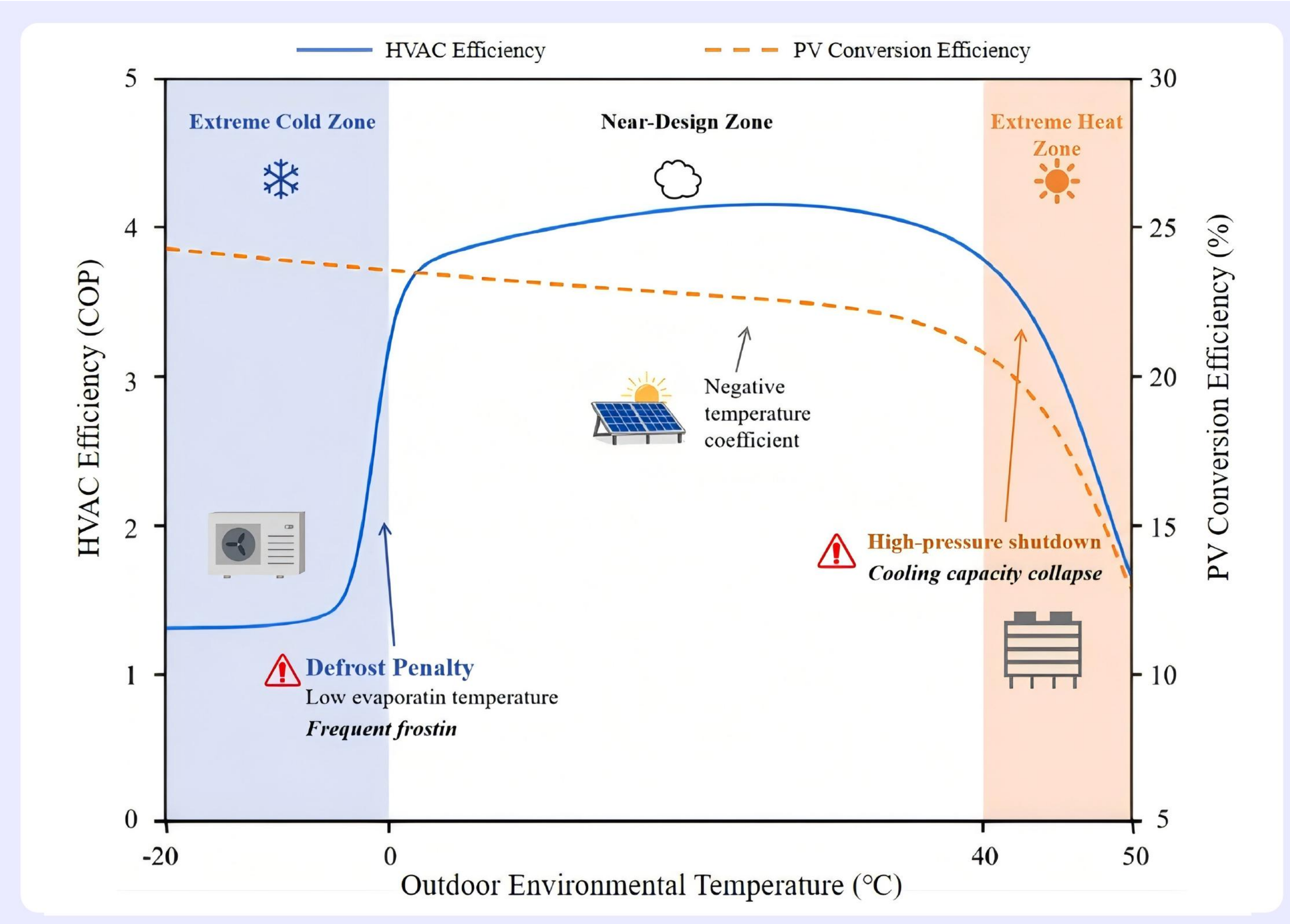

Figure 7. Schematic diagram of the mechanism of supply-side influence.

change is not a simple fluctuation in loads, but a complex process driven by the combined effects of long-term baseline shifts and short-term load surges. Long-term baseline shifts progressively erode the original safety margins of building energy systems, degrading their reliability in coping with extreme weather. Consequently, short-term extreme load surges act as a direct trigger, highly prone to inducing equipment overload under insufficient system redundancy, thereby threatening indoor thermal safety and causing operational interruptions.

Supply-side impacts

The impacts of climate change on the building supply side are prominently manifested as performance degradation and capacity derating of local energy equipment under off-design conditions, encompassing systems such as HVAC and photovoltaics (PV) (Figure 7). When external meteorological conditions deviate from the equipment's designated operational bounds, shifting towards extreme high or low-temperature zones, the energy conversion efficiencies of both HVAC and PV systems exhibit downward trends. Notably, HVAC equipment demonstrates far more pronounced and abrupt performance drops at both extreme temperature spectrums.

On a long-term scale, the continuous rise in average ambient temperatures is persistently degrading the long-term operational efficiency of HVAC systems. Research by Martins et al.[67] on office buildings in the Iberian Peninsula indicated that under future warming climates, hybrid heating and cooling schemes utilizing both air-source and ground-source heat pumps will face declines in the Cooling Coefficient of Performance (COP) alongside increases in total electricity consumption. Yu et al.[68] further confirmed that chiller operation is highly sensitive to external weather conditions. As air temperatures rise, particularly in air-cooled heat dissipation modes, the heat rejection capacity of the condenser decreases significantly, thereby curtailing the actual capacity and efficiency of the chillers. The elevation of outdoor air temperatures narrows the temperature difference for heat dissipation on the condensation side, forcing the equipment to operate at higher condensation temperatures and greater compression ratios. This constitutes the primary physical mechanism underlying the long-term decline in the seasonal performance of these systems.

On a short-term scale, extreme high-temperature events inflict a dual penalty on local building cooling and power supply capacities.[69] Regarding cooling equipment, venturing into extreme high-temperature zones precipitates a rapid plunge in the efficiency curve, accompanied by the risk of sudden cooling capacity plummeting. Hajidavalloo et al.[70] noted that under extreme heat, the temperature and pressure of air-cooled condensers rise significantly with ambient temperatures, resulting in elevated compressor pressure ratios and increased power consumption. Their research demonstrated that the efficiency of evaporative coolers was approximately 81.8% at 35°C, but plummeted to 68.0% at 49°C. Moreover, elevated system pressures under such extreme conditions may even trigger protection mechanisms, forcing equipment shutdowns. Wang et al.[71] corroborated that increases in air temperature, humidity, and heatwave frequency all substantially diminish the actual available capacity of chillers. Yang et al.[72] proposed a spray evaporative cooling strategy for high-temperature conditions, indicating that the unit COP could be enhanced by 4%–8% and system power savings could reach 2.37%–13.53%. This effectively corroborates, from a secondary perspective, that extreme thermal environments severely drive air-cooled equipment off its design conditions. In addition to cooling equipment, extreme heat simultaneously curtails the power generation capability of distributed photovoltaic (PV) systems. Bamisile et al.[73] pointed out that for

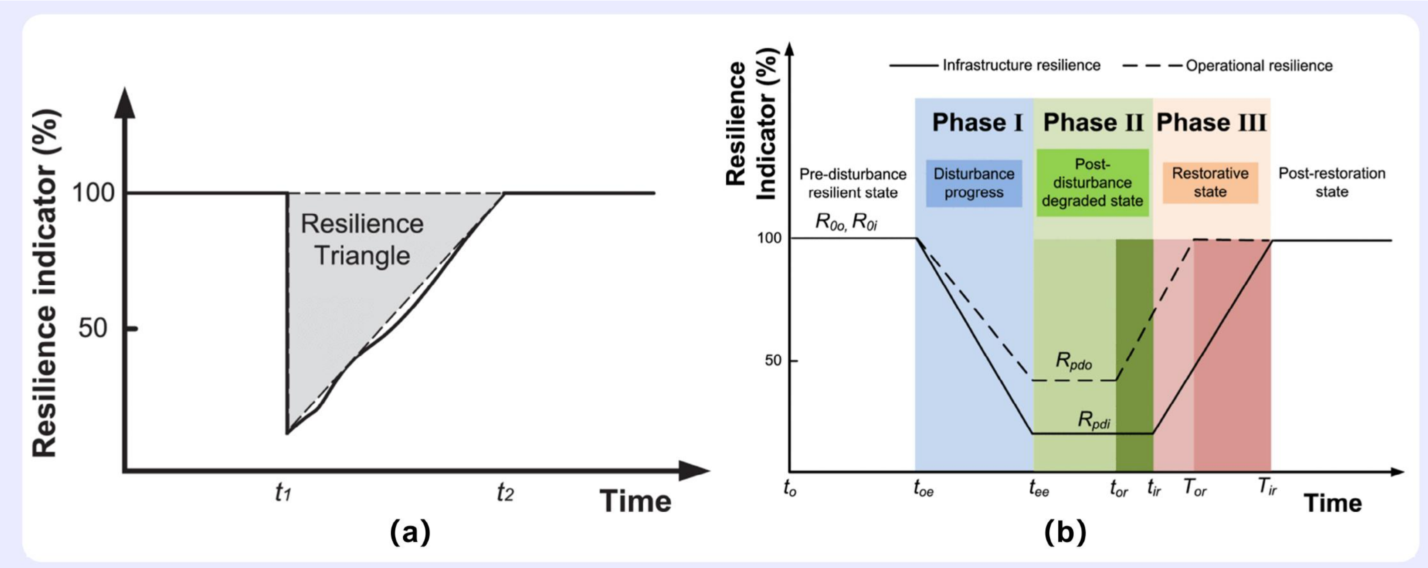

Figure 8. Resilience curves: (A) resilience triangle model;[92] (B) resilience trapezoid model.[93]

every 1°C increase in PV module temperature, its conversion efficiency typically decreases by 0.4%–0.5%. Wu et al.[74] further indicated that climate change will escalate the high-temperature risks of rooftop PVs by 29%–97%, consequently exacerbating associated performance degradation and cost pressures.

Corresponding to the suppressive effects of extreme heat, extreme severe cold weather profoundly compromises the heating performance and operational efficiency of Air-Source Heat Pumps. This degradation phenomenon primarily stems from frosting on the evaporation side and the frequent defrosting cycles required at low ambient temperatures. From a physical mechanism perspective, Ma et al.[75] corroborated that frost accumulation increases thermal resistance and obstructs airflow, thereby degrading the heat transfer efficiency of the outdoor heat exchanger and substantially escalating defrosting energy consumption. Quantitative analysis by Ikram et al.[76] further revealed that in actual operation, delayed responses from the defrosting control system can cause heating efficiency to plummet by 30% to 57%, and the system COP to plunge by up to 60%. Passarelli et al.,[77] through large-scale simulations of air-source heat pumps, found that neglecting the frosting process during the design phase leads to severe overestimation of equipment performance, resulting in actual total cost deviations of up to 70%.

Coupled impacts on supply and demand sides

The ultimate impact of climate change on building energy systems is fundamentally a coupled interaction between demand-side load increases and supply-side capacity degradation. As illustrated in Figure 8, these integrated supply-demand impacts exhibit distinct mechanisms across different time scales. Long-term climate change persistently erodes system capacity margins and operational redundancy by elevating life-cycle heating and cooling loads and diminishing the seasonal energy efficiency and effective capacity of energy equipment. Consequently, even prior to the onset of extreme events, building energy systems are already relegated to a vulnerable state characterized by higher base loads, reduced efficiencies, and compromised safety boundaries. Superimposed on this baseline vulnerability, short-term extreme climate events trigger acute surges in demand-side peak loads alongside rapid deterioration in supply-side equipment performance. In severe scenarios, this compound stress can precipitate protective equipment shutdowns and drastically widen energy supply deficits.

Existing research evaluating the response capabilities of buildings to extreme events rarely integrates the impacts of long-term climate change into a unified analytical framework. Current studies typically assess emergency response capabilities using historical normal climates or singular typical scenarios as baselines,[78] inadequately addressing the degradation of initial capacity margins and operational health induced by long-term gradual climate shifts. In reality, this chronic erosion constitutes the very inception of the cascading failure chain across both the supply and demand sides. As future climates continue to warm, building cooling loads will persistently escalate,[79] while the operational efficiency and capacity boundaries of energy equipment, such as air conditioners and heat pumps, will be progressively compressed under higher ambient temperatures. Consequently, systems are relegated to significantly lower redundancy levels even before extreme events strike. A comprehensive energy system platform developed by Wu et al.[80] demonstrated that under climate change, cooling-dominated cities may face energy cost increases of up to 50% and electricity cost spikes of approximately 20%. This underscores that long-term warming not only heightens buildings' reliance on cooling and electricity but also undermines the systems' autonomy and redundancy capabilities prior to the onset of extreme events.

Superimposed on the degraded long-term capacity margins, short-term extreme climate events inflict a further concurrent impact on both the supply and demand sides of building energy systems. Following the onset of a heatwave or cold spell, the thermal storage (or cooling storage) capacity of the building envelope is progressively depleted, and indoor-outdoor heat transfer persistently intensifies, transforming the long-term baseline load shift into acute short-term peak surges. Research by Sengupta et al.[81] on nearly Zero Energy Buildings demonstrated that the impact of heatwaves on building overheating resilience is 20–93 times more severe than the most critical system failures. Moreover, if the system shock occurs at dawn, its severity is approximately 1.2 times greater than if it occurs at midday. Simultaneously with this rapid escalation in demand-side loads, the actual power output capacity of supply-side equipment is curtailed by environmental conditions. For instance, the temperature and pressure of air-cooled condensers rise significantly with elevated ambient temperatures, concomitantly increasing the compressor pressure ratio and power consumption. Under certain conditions, excessive pressures can even directly trigger protection mechanisms, causing compressor shutdowns. Such high-pressure shutdown risks have been experimentally observed at ambient temperatures up to approximately 49°C.[70] Consequently, when demand-side peak load surges coincide with supply-side capacity constraints, building energy systems transition from general performance deterioration to catastrophic functional loss.

The intricate coupling relationships among multiple subsystems within building Integrated Energy Systems (IES) further amplify localized faults, propelling their propagation along the energy chain. Within an IES, tight coupling exists among heating and cooling sources, power systems, energy storage devices, terminal units, and control systems. Performance degradation in any single component can disseminate to other subsystems via energy flows, power flows, or control logic. Previous studies have demonstrated that faults within building IES can propagate across subsystems.[82] This implies that equipment performance degradation and localized power failures under extreme weather are no longer isolated events; rather, they can evolve into a cascading process, progressively transmitting from demand-side load disturbances to supply-side equipment, microgrid operations, and ultimately to backup energy systems.

When building-level energy system failures superimpose with large-scale energy network disturbances, cascading failures further expand into cross-domain risk transmission. Research published by Xu et al.[83] highlighted that the impacts of extreme weather on renewable energy generation and transmission-distribution networks significantly exacerbate the risk of wide-area power outages. Translating this to building systems, Shi et al.,[84] pointed out that traditional methods predominantly focus on individual buildings, neglecting the impacts of urban scales and upstream infrastructure, thereby failing to capture authentic risk transmission pathways under compound heatwave and power outage events. Existing quantitative studies have also preliminarily elucidated the consequences of this failure chain. At the building envelope level, Sheng et al.[85] simulated two compound scenarios for assisted living facilities—a 6-day heatwave power outage and a 3-day cold spell power outage. The results indicated that without external power supply, buildings face significant thermal safety risks; moreover, even with energy-efficient retrofits, mitigating these risks requires scaling down backup power capacity by 19%. At the building distributed energy system level, Han et al.[86] discovered that under grid-connected modes, although the power supply reliability can be maintained at 100%, cooling supply reliability may still degrade by up to 5%. Conversely, under off-grid modes, the maximum cooling supply deficit in Chinese city case studies reached 20%. Furthermore, the longer the heatwave duration, the larger the cooling shortfall and the poorer the system reliability.

In summary, the impacts of climate change on building energy systems constitute a systemic cascading process driven collectively by long-term margin erosion, short-term extreme shocks, subsystem fault propagation, and external energy network disturbances. Consequently, continuing to employ single-scale, single-device, or single-scenario analytical methods will fail to accurately characterize authentic risks. Moving forward, it is imperative to introduce cross-scale, cross-system co-simulation frameworks to substantiate the quantitative assessment and enhancement strategies for building energy thermal resilience.

QUANTITATIVE EVALUATION FRAMEWORK FOR BUILDING ENERGY THERMAL RESILIENCE

Conceptual framework

The conceptual evolution of building thermal resilience has transitioned from singular perspectives toward systemic synergy. Initially, literature primarily defined thermal resilience from a passive defense perspective,[85] viewing it as the building envelope's ability to maintain a stable thermal environment without active energy inputs.[87] Subsequently, studies extended this concept to active provision, emphasizing the capacity of energy systems (e.g., HVAC) to sustain critical heating and cooling loads under disturbances[88] and recover rapidly.[89] Recently, recognizing the limitations of singular perspectives, academia has shifted thermal resilience assessments toward active-passive synergistic responses. For instance, by coupling phase change materials (PCMs) with heat pumps, research[90] confirmed that the synergy between passive thermal mass storage and active energy supply not only optimizes baseline energy efficiency but also substantially enhances the system's thermal resilience during extreme power outages.

However, existing studies have yet to establish a clear, unified definition of building energy thermal resilience, lacking a systematic theoretical classification framework. Synthesizing previous literature, this paper proposes that building energy thermal resilience is fundamentally a multi-dimensional composite concept, with the core objective of safeguarding indoor thermal stability under climate evolution. The realization of this capability is jointly determined by two major dimensions: resilience-bearing entities and the temporal characteristics of disturbances. Specifically, in the entity dimension, thermal resilience relies not only on the resistance and adaptability of the building envelope but also heavily on the regulation and capacity assurance of active systems. In the temporal dimension, given the multi-scale nature of climate features, thermal resilience can be bifurcated into static resistance against long-term gradual warming, and dynamic response against short-term extreme shocks. These two mutually orthogonal dimensions constitute a complete theoretical framework for thermal resilience analysis. Namely, only when both the building envelope and energy systems possess the comprehensive capacity for long-term static resistance and short-term dynamic response can the scientific connotation of building energy thermal resilience be fully articulated.

Quantitative evaluation methods

While the scientific connotation defines the core concept of building energy thermal resilience, translating it into measurable and comparable metrics to guide system design and operational optimization urgently demands robust quantitative assessment methods. In the power sector, resilience quantification primarily revolves around the curve integration approach. Its core lies in characterizing the temporal evolution trajectory of system performance under disturbances, utilizing the cumulative loss area under the curve as a comprehensive resilience metric.[91] Representative frameworks include the resilience triangle and trapezoid models (Figure 8). The former, pioneered by Tierney and Bruneau,[92] simplifies the performance loss from disturbance onset to full functional recovery into a triangular area. The latter, expanded by Panteli et al.,[93] further dissects the evolution into three phases—performance degradation, extreme state maintenance, and post-disaster recovery—forming the classic resilience trapezoid curve, whose integral area serves as the core metric for evaluating overall resilience.[94] Although these models lay the foundation for resilience quantification, their roots in power system operational logic present three levels of applicability limitations when transferred to the building energy domain. First, there is a structural deficiency regarding the temporal scales of disturbances. Traditional power system resilience assessments focus almost exclusively on short-term extreme events (e.g., instantaneous outages caused by equipment failures or natural disasters), anchoring their evaluation targets to power transmission continuity and load recovery ratios while overlooking the persistent impacts of long-term, gradual climate evolution. In contrast, the building energy thermal resilience defined herein encompasses both static and dynamic temporal dimensions. It must not only respond to the instantaneous shocks of short-term extreme weather but also evaluate the progressive impacts of long-term climate change on the systems' energy-efficient performance. Second, there are fundamental differences in physical degradation mechanisms. When traditional grid facilities sustain damage, the loss of topological connectivity often triggers an abrupt, cliff-like shutdown, with the performance curve plummeting from the rated state to near zero within an extremely short duration.[95] Conversely, in the built environment, the dynamic transfer of thermal energy is constrained by the thermal resistance and capacitance characteristics of the building envelope.[96] This inherent thermal inertia endows buildings with a pronounced lag effect. Consequently, when subjected to extreme climate assaults or internal energy supply interruptions, the degradation of the indoor thermal environment avoids instantaneous collapse, manifesting instead as a gradual decline curve with substantial time delays.[97] In summary, building energy thermal resilience is inherently more complex than power system resilience. This necessitates the development of differentiated quantitative assessment methods tailored to varying dimensions, constituting a core direction for future research in this field.

Quantitative metrics

Building upon the previously defined connotations of thermal resilience, this section systematically reviews existing quantitative metrics across three dimensions: building envelope thermal resilience, and the static and dynamic thermal resilience of energy supply systems. Specifically, building envelope metrics comprehensively reflect the passive resistance against both long- and short-term climate changes; static system metrics primarily gauge the energy supply system's static adaptability to long-term gradual climate shifts; while dynamic system metrics focus intently on the system's dynamic response level to short-term extreme weather shocks.

The building envelope thermal resilience. refers to its capacity to withstand climate disturbances relying solely on its passive design and thermal inertia. Depending on the investigated temporal scales and system operational conditions, existing evaluation frameworks have primarily evolved into two distinct quantitative pathways. The first pathway focuses on indoor thermal environmental characteristics, primarily quantifying the building's passive defense capability against short-term extreme events under conditions devoid of active energy supply, such as power outages. The second pathway centers on building energy characteristics, aiming to comprehen-

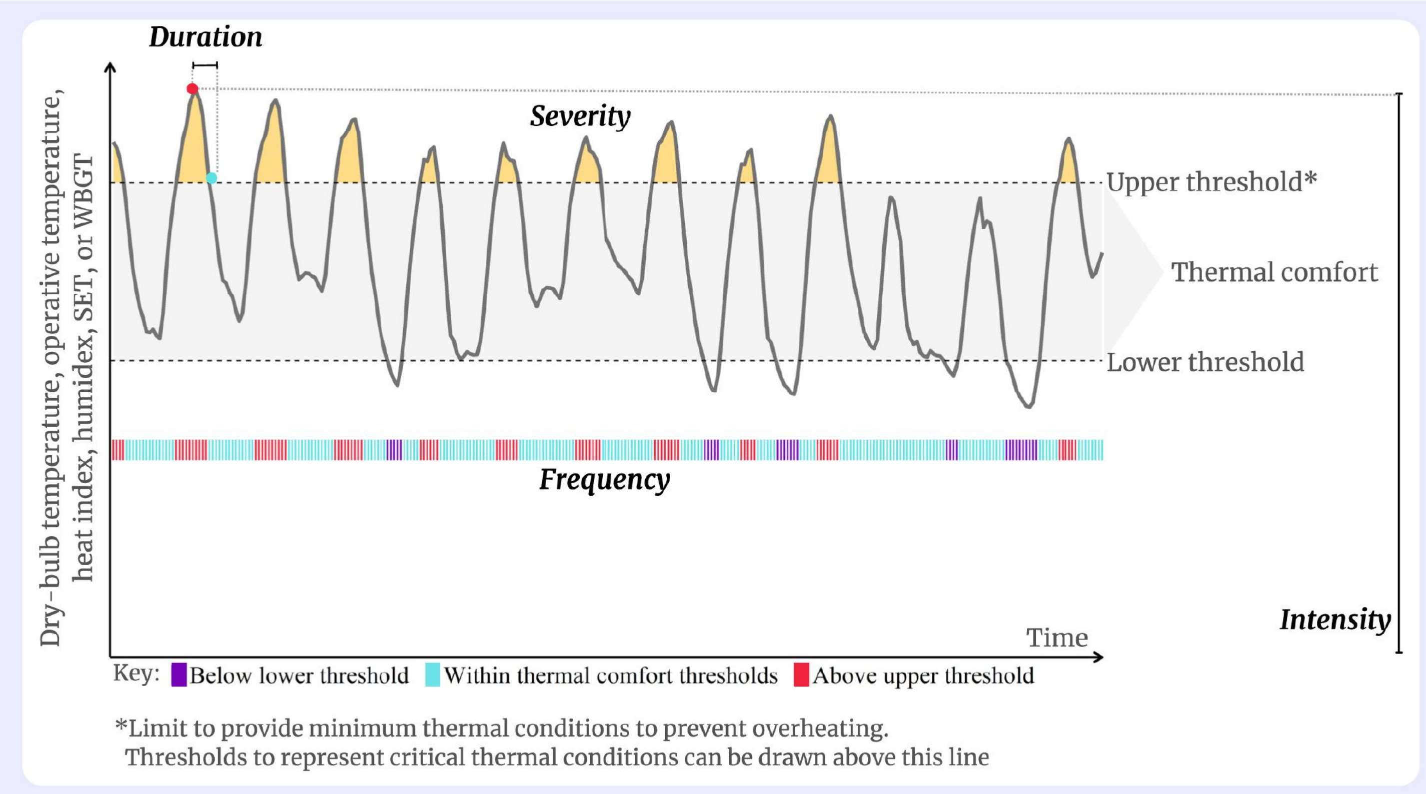

Figure 9. Core evaluation metrics of the indoor thermal environment.[78]

sively characterize the building's adaptability to long-term gradual climate warming as well as its load endurance against short-term extreme shocks.

Evaluation frameworks related to the indoor thermal environment are fundamentally based on core indices such as indoor air temperature, comprehensive thermal indices, or Standard Effective Temperature (SET).[78] The quantitative metrics of these frameworks typically encompass three dimensions: intensity, duration, and severity. Specifically, *intensity* reflects the extreme level reached by environmental parameters during the assessment period; *duration* denotes the continuous time length that the parameter exceeds a safety threshold; and *severity* comprehensively measures the cumulative disaster effect through the time integral of the exceedance beyond the threshold (see Figure 9 and Table S1). Establishing these evaluation thresholds is crucial, serving as the baseline for the quantitative framework. Lacking a unified paradigm, current academia predominantly sets these thresholds flexibly based on specific human health standards or building code tiers. For instance, some studies adopt the lower limit of the mild range for healthy populations for indoor air temperature,[98] the lower limit of the moderate level for operative temperature,[99] or the lower limit of the caution level for comprehensive thermal indices.[99,100] Meanwhile, other research directly benchmarks international assessment standards, such as adopting the habitable condition temperature ranges stipulated in LEED v4.1[85] or utilizing specific temperature limits corresponding to comfort, caution, and emergency states in ASHRAE 7.[94,100] Overall, the establishment of these thresholds exhibits pronounced diversity due to variations in evaluation objectives and reference standards.

Energy characteristic evaluation frameworks predominantly utilize core metrics such as long-term heating/cooling load variation rates and life-cycle energy deviation amounts.[101] This pathway aims to quantitatively assess the long-term mechanism by which the building envelope resists climate impacts through tracking the dynamic evolution of building loads. For example, Duan et al.[102] combined life-cycle energy consumption and carbon emission characteristics to conduct a sensitivity analysis of building load variations across multiple climate zones. Through this approach, they deeply evaluated the long-term resilience performance and adaptive efficacy of various passive energy-saving technologies under global warming scenarios.

The static thermal resilience of energy supply systems. aims to quantify the physical support capability of hardware configurations against climate disturbances. Based on the temporal scales of these disturbances, this capability confronts two core challenges. In the long-term dimension, it primarily faces the challenge of life-cycle adaptability regarding installed capacity. With the continuous shift in outdoor temperature baselines and the year-on-year escalation of cooling loads, original system design capacities are highly susceptible to chronic output deficits and energy efficiency degradation. In the short-term dimension, it confronts the dual stress on both supply and demand sides triggered by extreme events. Extreme climates drastically curtail equipment output while simultaneously inducing instantaneous surges in building loads, thereby tearing open a substantial supply deficit between the conventional installed capacity and the extreme peak load.

Synthesizing these dual challenges, the essence of thermal resilience metrics for energy supply systems lies in quantifying the physical bottom line of system hardware configurations. Current research primarily distills this into two core evaluation dimensions. The first encompasses adaptability metrics that gauge the level of long-term capacity matching, such as the equipment capacity degradation rate and life-cycle energy efficiency deviation. The second encompasses redundancy metrics that quantify the buffering capability against short-term supply deficits, such as the hardware oversizing ratio and supply reliability under extreme conditions (Table S2).

The dynamic thermal resilience of energy supply systems. aims to evaluate a system's capability to withstand short-term extreme shocks and rapidly restore core functions via active operational control strategies, such as multi-energy complementary scheduling and load curtailment. Distinct from static thermal resilience, which emphasizes hardware boundary configurations, dynamic thermal resilience introduces a temporal evolution dimension, underscoring the sequential response characteristics of system functions throughout the entire disturbance cycle. Current research has primarily evolved three categories of quantitative metrics: time-dimension metrics depicting the recovery rate, extent-dimension metrics measuring the recovery state, and global cumulative metrics quantifying the total performance loss over the full cycle. These three categories—addressing response speed, reconstruction level, and cumulative loss, respectively—constitute a complete closed-loop metric for the effectiveness of dynamic control strategies

(Table S3).

BUILDING THERMAL RESILIENCE ENHANCEMENT VIA THERMAL ENERGY STORAGE

Passive thermal energy storage technology

Passive thermal energy storage technologies enhance building envelope thermal resilience by fortifying thermal inertia. Their mechanisms primarily encompass two pathways namely sensible heat storage and latent heat storage as illustrated in Figure S1.[114,115] Sensible heat storage predominantly relies on the high thermal inertia of heavyweight envelopes such as masonry and concrete. It utilizes the intrinsic sensible heat absorption and release processes of these materials to dampen indoor temperature fluctuations, thereby achieving temporal shifts in heating and cooling loads.[116] Latent heat storage is primarily realized by integrating phase change materials. This pathway utilizes the high latent heat characteristics of materials during solid-liquid phase transitions within specific temperature ranges to conduct near-isothermal heat storage. As ambient temperatures alternate diurnally, phase change materials cyclically absorb and release substantial amounts of heat through state transitions.[117] This unique isothermal storage and release mechanism enables the materials to effectively shave peaks, fill valleys, and mitigate indoor overheating risks without significantly increasing the physical mass of the building.[118] However, the passive regulation efficacy of both sensible and latent heat storage is highly constrained by external temperature thresholds, diurnal temperature differences, and heat transfer gradients. Therefore, assessing the actual contribution of passive thermal energy storage to building thermal resilience necessitates comprehensively considering the heat transfer baseline shifts induced by long-term gradual climate changes and the acute thermal shock effects caused by short-term extreme weather.[119]

Long-term climate warming continually alters thermodynamic boundaries, substantially elevating building cooling loads and thermal environmental regulation pressures while progressively compressing the effective operational space of passive thermal energy storage technologies. Multiple model predictions indicate that under the influence of future cumulative thermal stress, residential cooling loads in multiple climate zones including warm regions of Japan,[61] subtropics,[120] and temperate regions of Central Europe[121] face non-linear surges, with energy consumption increases reaching up to 135.6% to 250%. Against this backdrop, passive thermal energy storage technologies can delay indoor temperature rises and shave partial cooling load peaks by enhancing envelope thermal inertia.[122] Studies demonstrate that under future climate scenarios, heavyweight envelopes can reduce summer overheating hours in typical cold climate residential buildings by up to 10%.[123] Serving as a crucial supplement for high-density energy storage, latent heat storage via phase change materials can drastically reduce cooling load surges without adding structural weight. Research indicates that composite walls integrating phase change materials can achieve annual energy savings of 17% to 23% when coping with high-frequency extreme high temperatures.[124] If the phase change temperature threshold is dynamically adjusted upwards under far-future 2095 subtropical scenarios, this energy-saving rate can even be maintained at 37%.[120] Nevertheless, persistent long-term temperature rises are severely eroding the regulation efficacy of both technologies at the underlying physical level regarding heat rejection conditions and temperature difference driving forces. For sensible heat storage, its temperature regulation highly depends on indoor-outdoor temperature gradients. As minimum nighttime temperatures continually rise, the natural nighttime heat rejection of heavyweight walls is obstructed, leading to vicious heat accumulation indoors. Quantitative evaluations reveal that by 2050 and 2080, the energy efficiency advantages of high thermal inertia envelopes will drastically degrade by 40% and 63% respectively.[125] Simultaneously, elevated nighttime minimum temperatures hinder effective heat rejection from high thermal inertia envelopes, potentially causing increases in cumulative summer peak cooling loads.[126] Similarly, the efficacy of latent heat storage is constrained by the complete melting and solidification phase change cycle. When nighttime outdoor temperatures linger persistently above the material solidification threshold, phase change materials fail to complete solidification and heat release, rendering the latent heat storage capacity completely ineffective for the following day. Predictions show that due to this obstructed nighttime solidification mechanism, the overall energy-saving performance and latent heat utilization rate of phase change materials in most global climate zones may drop by 10.2% to 18.5% by 2050.[127] In summary, although passive thermal energy storage technologies can exert a buffering role under long-term climate warming, their long-term applicability faces severe challenges. The core bottleneck lies in maintaining a dynamic match between material thermophysical properties including heat capacity and phase change thresholds and the progressively deteriorating diurnal temperature difference boundaries of the future.

Distinct from long-term gradual climate changes, short-term extreme weather primarily tests the instantaneous thermal buffering and passive survivability of passive thermal energy storage technologies through acute heating and cooling shocks. When confronting extreme conditions such as heatwaves or cold spells superimposed with power outages, both sensible and latent heat storage technologies demonstrate significant shock resistance efficacy. Regarding sensible heat storage, heavyweight envelopes can effectively smooth drastic indoor temperature variations relying on their high heat capacity. Experiments confirm that during heatwaves without active cooling, sensible heat storage can drop indoor peaks on extreme high-temperature days by 3.5°C to 3.7°C and shave equivalent thermal loads by 12.3% over a two-week event period.[119] Its supporting role is equally prominent under extreme cold spells superimposed with heating interruptions. When outdoor temperatures plummet to 0°C, buildings can sustain up to 168 hours of thermal-safe passive survivability relying solely on sensible heat release from the envelope.[127] By comparison, composite structures integrating phase change materials exhibit more potent precision peak shaving and thermal lag capabilities when tackling extreme heatwaves. Physical simulations indicate that by integrating composite phase change materials with a latent heat capacity of 180.4 J/g into traditional masonry envelopes, the materials can drastically reduce the absolute maximum indoor temperature by 6.0°C under extreme heatwave conditions with peak outdoor temperatures reaching 56.9°C. Relying on their phase change heat absorption mechanism within the 44°C to 48°C zone, they also lower the average indoor temperature peak by 3.8°C and achieve a daily peak cooling load reduction of approximately 1.38 kWh.[128] Furthermore, in simulated assessments of heatwaves superimposed with power outages, integrating phase change materials into envelopes can slash the proportion of time indoors exposed to severe thermal stress dangers by 65% provided peak temperatures reach 45.1°C and fundamental nighttime cooling mechanisms are maintained,[129] vastly alleviating thermal safety crises. However, similar to coping with long-term warming, the thermal resilience of energy storage technologies during short-term extreme events also exhibits strong boundary dependencies. Its most core physical constraint remains the scarcity of nighttime cooling energy. During compound heatwaves with sustained diurnal high temperatures, if outdoor nighttime temperatures fail to drop below the solidification threshold, phase change materials cannot complete the complete physical cycle of heat absorption and release. Their latent heat storage capabilities will rapidly degrade or completely vanish during continuous high temperatures. Empirical data warn that under such severe conditions lacking nighttime cooling supplementation, phase change materials can only reduce the maximum room temperature by 1.0°C and may even trigger a negative reverse regulation effect causing the minimum nighttime room temperature to inversely rise by 0.3°C.[127] Overall, passive thermal energy storage technologies still face significant bottlenecks and challenges in resisting extreme climates. The short-term thermal resilience contributions they provide possess a definitive upper limit. This limit is profoundly constrained by the dynamic interplay among factors including storage material thermophysical properties, structural thermal inertia, diurnal temperature difference amplitudes, and the duration of extreme events.

Active thermal energy storage technology

Active thermal energy storage (TES) refers to the technology that actively stores thermal energy using a storage medium and controls its release on demand. Based on the storage mechanism, it can be classified into three categories: sensible heat storage(e.g., hot water tanks,[130] solid sensible storage[131]), latent heat storage (e.g., phase change storage,[132] ice storage[133]), and thermochemical heat storage Distinct from passive TES, this technology features configurable capacities, dispatchable operations, and controllable release processes. Its core resilience value lies in mitigating supply-demand mismatches under normal operations through flexible thermal energy transfer, and providing physical redundancy and backup capacity for critical heating and cooling loads during external energy interruptions triggered by extreme events.

Facing load baseline shifts and peak elevations induced by long-term climate warming, existing HVAC equipment is highly susceptible to capacity mismatch dilemmas due to insufficient rated cooling capacities.[134] Active TES, leveraging its advantages in capacity expansion and cross-temporal dispatch, offers an effective pathway to resolve this long-term evolutionary risk. Wei et al.[135] showed that coordinated operation of interconnected energy stations and water/ice thermal storage could unlock an additional 16.2%–23.4% of effective cooling capacity, delaying capacity mismatch under SSP5-8.5 from 2028 to 2059–2068 without new infrastructure investment (Figure 10). Quantitative studies confirm that properly configuring active TES devices can equivalently release substantial capacity redundancy, reducing the installed capacity requirements of auxiliary energy equipment by up to 78.5%.[136] Coupled simulations by Wei et al.[135] on the Hengqin district cooling system in Zhuhai under CMIP6 climate scenarios further demonstrated that through multi-energy station interconnection and the collaborative dispatch of water/ice storage systems, the system can release an additional 16.2%–23.4% of effective cooling capacity. Under the SSP5-8.5 high-emission scenario, this capacity increment can defer the critical year of system capacity mismatch from 2028 to the 2059–2068 period, thereby significantly extending the adaptability of existing cooling systems to continuous warming without additional infrastructure investment. From the perspective of seasonal TES, Perera et al.[137] conducted stochastic optimization simulations for a distributed multi-energy system in a Chicago residential area from 2020 to 2080, based on the WRF climate model RCP8.5 scenario. The study found that under a long-term climate trend where Cooling Degree Days (CDDs) double and Heating Degree Days (HDDs) decrease by one-third, seasonal Aquifer Thermal Energy Storage (ATES) can improve the system's flexibility index against climate evolution and load uncertainties by approximately 33%. In summary, the core contribution of active TES under long-term warming transcends mere energy savings; its profound significance lies in fundamentally delaying and resolving the capacity mismatch risks of existing energy systems through capacity redundancy release, cross-temporal flexible dispatch, and operational strategy reconfiguration.

On the short-term extreme climate scale, events such as heatwaves and cold spells inflict sudden supply-demand imbalance shocks on building integrated energy systems, primarily by inducing demand-side load surges, source-side output degradation, and grid-side energy interruptions. Under such extreme conditions, active TES can rely on pre-stored thermal resources to maintain critical heating and cooling loads in islanded or emergency modes when external energy supplies are restricted. Gautier et al.[138] further demonstrated that active thermal storage could meet approximately 80% of peak cooling demand during heatwaves, even when chillers were shut down at peak periods (Figure S1). Simulation studies by Ren et al.[139] on the district integrated energy system in Shanghai confirmed that configuring backup TES significantly elevates the system's energy supply guarantee level. In equipment failure scenarios, this configuration reduced energy interruption frequencies in summer and winter by 68.1% and 81.8%, respectively. Under extreme conditions such as external power and gas outages, backup TES substantially reduced the system's emergency load shedding requirements, achieving 100% fulfillment of core heating and cooling loads throughout the events. A simulation assessment by Gautier et al.[138] on a geothermal-coupled district energy system during a heatwave period similarly validated the dynamic resilience value of active TES. The study showed that even when chillers were actively shut down during heatwave peaks, relying solely on active TES allowed the system to meet approximately 80% of peak cooling demands and maintain most areas within acceptable thermal comfort ranges. Concurrently, total system electricity consumption was reduced by over 60% compared to normal operations, offering a highly promising engineering solution to alleviate urban grid load pressures during extreme heatwaves. For severe winter power outage scenarios, emergency heat release mechanisms leveraging underlying thermal networks and TES equipment can independently support over 33.0% of emergency heating loads, effectively curbing the further expansion of unmet load areas.[140] The aforementioned quantitative studies fully demonstrate that under short-term extreme conditions, active TES can differentially undertake multiple functions—such as emergency heating, load substitution, and cross-source synergy—based on disturbance types. It serves as a crucial foundational support for enhancing the event response capabilities and operational resilience of building integrated energy systems.

Although active TES exhibits critical capabilities in providing capacity redundancy and thermal load support against long- and short-term climate shocks, building integrated energy systems often need to simultaneously achieve multiple rigorous objectives under complex extreme conditions. These include meeting prolonged heating and cooling supplies, maintaining short-term power balances, and achieving transient disturbance suppression. In such scenarios, a single-attribute storage medium, strictly constrained by its inherent physical properties, typically struggles to accommodate the compound regulation demands across diverse time scales and energy forms.[141] Specifically, active TES possesses technical advantages of lower unit capacity costs and strong long-duration storage capabilities, making it highly suitable for sustained thermal load support tasks. However, its relatively slow response speeds and energy conversion pathways are inadequate to meet the millisecond-level regulation requirements of transient electrical disturbances. Conversely, electrochemical energy storage boasts extremely fast dynamic response capabilities, enabling the rapid smoothing of instantaneous power-side fluctuations. Yet, when addressing long-duration and large-scale heating/cooling load guarantees, it faces multiple rigid constraints, including exorbitant costs, capacity limitations, and insufficient sustained supply capabilities.[142,143] Therefore, constructing a diversified hybrid energy storage system—deeply coupling thermal storage, electrical storage, and other forms—has emerged as a critical evolutionary direction to break through the physical bottlenecks of single-storage technologies and comprehensively elevate the overall resilience of building integrated energy systems. Research based on a multi-time-scale hybrid energy storage configuration framework has confirmed that a synergistic hybrid architecture can substantially slash external transient disturbance extremes by up to 96.65%, thereby fundamentally reshaping the system's underlying robustness against severe shocks.[144] Furthermore, research by Masrur et al.[145] on the optimal configuration and resilient operation of a multi-energy microgrid for a hospital in Okinawa, Japan, revealed the ultimate guarantee capability of this architecture. Calculations showed that under a 24-hour extreme power outage scenario covering summer, winter, and peak conditions with a 50% critical load ratio, a diversified scheme configuring both batteries and hot water storage could robustly support the synergistic supply of critical electrical and thermal loads, achieving a 100% survivability rate across cross-seasonal extreme outage conditions. This demonstrates that the synergistic configuration of electro-thermal storage not only significantly fortifies the system's rapid response capabilities under transient power disturbances but also substantially extends the sustained guarantee duration for critical thermal loads during outages.

In summary, by deeply integrating the complementary advantages of different storage media in terms of power response rates, energy density/capacity, and physical supply forms, the diversified hybrid energy storage architecture can simultaneously satisfy the dual extreme demands of short-term power disturbance suppression and long-term thermal load guarantees. This significantly expands the resilient operational boundaries of building integrated energy systems under extreme conditions. Compared to the singular deployment of active TES, a diversified energy storage system better aligns with the compound risk characteristics of long-term load shifts, short-term extreme shocks, and external energy interruptions superimposing under climate change. It provides a more holistic and systemic technical evolutionary pathway for comprehensively enhancing system energy thermal resilience.

System regulation technology considering multi-element energy storage

Hardware capacity configuration establishes the potential resilience ceiling for building Integrated Energy Systems (IES) against extreme disturbances, while operational control strategies dictate the efficiency of translat-

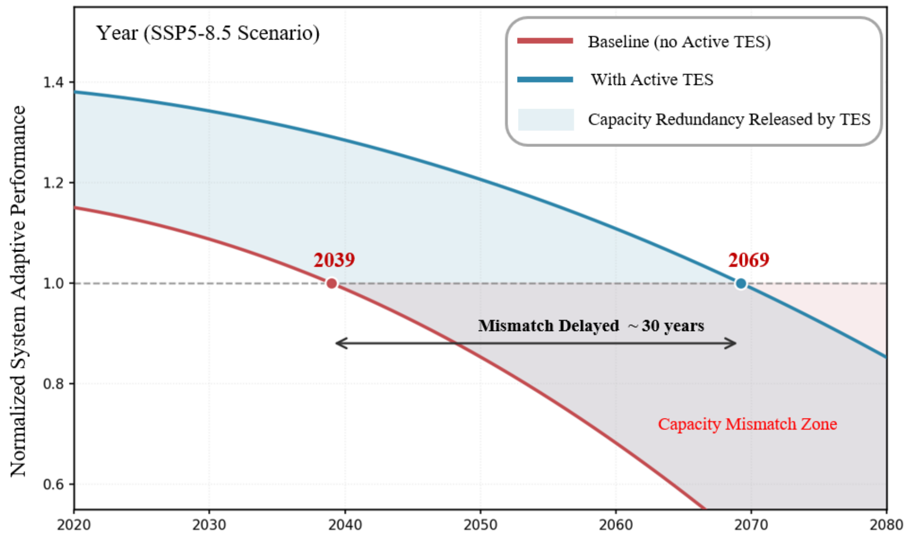

Figure 10. Long-term climate adaptability of active thermal energy storage.[135]

ing this potential into actual disaster-resistance performance. To address short-term extreme events, systems must not only rely on active storage for explicit backup capacity but also activate implicit thermal inertia resources within building envelopes and heating networks. Through optimizing charge/discharge sequences, multi-energy coordinated dispatch, and load priority management, systems can enhance energy supply guarantee capabilities across the entire lifecycle: pre-event prevention, mid-event response, and post-event recovery. Therefore, system control technologies incorporating diversified thermal energy storage (TES) are critical for unlocking storage resilience, mitigating load shedding risks, and enhancing system recovery capabilities.

During the pre-event warning phase, the primary task of system control is to accumulate available energy reserves before the shock arrives, shifting the operational paradigm from economy-first to safety-defense-first. On the one hand, systems can reserve emergency capacity for key nodes—such as batteries, active TES, gas tanks, and backup fuels—via pre-charging and resource pre-allocation mechanisms to address impending supply-demand imbalances (Figure S2).[88] A two-stage risk-averse stochastic programming model by Li et al.[142] for multi-energy distribution systems showed that pushing batteries and TES to a maximum initial state of charge and pre-allocating emergency fuel to generators beforehand can slash post-disaster operational costs by approximately 25.5% compared to no-warning schemes. Qi et al.[143] proposed a preventive dispatch mode for multi-area IES. Upon receiving warnings, areas collaboratively maximize storage across batteries, gas tanks, and TES. This mechanism ensures an absolute survival time of 5 hours with 100% zero-load-shedding continuous supply. On the other hand, systems can preemptively activate the inherent thermal inertia of building envelopes and thermal networks. Techniques like building pre-cooling/pre-heating and network water temperature pre-adjustment convert implicit thermal capacity into dispatchable Virtual TES (VTES) resources.[88] Simulations of the California heatwave by Zeng et al.[144] confirmed that pre-storing cooling energy in building thermal mass by lowering setpoints during off-peak hours can reduce the cumulative unmet degree-hours (temperatures exceeding comfort thresholds) by ~25.7%. Based on the 2020 California power outage and heatwave, Wang et al.[145] found that pre-cooling room temperatures from 24°C to 22°C following an early warning delay the time to reach the 28°C overheating threshold by ~1 hour, validating the VTES value of building thermal mass under compound extreme conditions. Chen et al.[146] demonstrated that actively regulating the mass flow of heating networks transforms pipeline thermal inertia into a physical resilience reserve; compared to traditional robust optimization, this preventive dispatch limits extreme fault load shedding to within 5.0 MWh while reducing comprehensive operational costs by 30.6%. In summary, the core of pre-event warning lies in the collaborative dispatch of active storage pre-charging and VTES activation to secure energy and thermal inertia in advance, thereby minimizing mid-event load shedding scales and post-event recovery costs.

Entering the mid-event response and post-event recovery phases, control objectives shift to reconstructing supply-demand balance under constrained resource boundaries and prioritizing continuous supply for critical loads. Extreme events may damage power, gas, and thermal infrastructures and trigger cascading faults across energy networks, significantly reducing available system resources. At this juncture, the instantaneous energy release of active TES and the delayed buffering of passive TES must be leveraged alongside multi-energy equipment—such as batteries, heat pumps, Combined Heat and Power (CHP) units, and electric boilers—to optimize emergency resource allocation. For mid-event dispatch in integrated power-gas-heat networks, Javadi et al.[147] proposed an active-passive collaborative TES control mechanism. Actively, TES charges/discharges instantaneously to compensate for thermal deficits; passively, network thermal inertia acts as distributed virtual thermal storage, cooperating with CHP and electric boilers for delayed heat flow redistribution. This strategy reduced mandatory load shedding by 30.66% and boosted the comprehensive dynamic resilience index by over 40%. For building-level multi-energy systems, Wang et al.[82] developed a collaborative dispatch framework involving batteries, stratified TES, and heat pump operations. During outages, the heat pump (acting as the electro-thermal hub) adjusts its state dynamically based on load shedding costs; when inactive, stratified TES releases heat to cover domestic hot water deficits, while batteries charge off-peak and discharge during heat pump activation to smooth power deficits, reducing daily costs by ~10.2%. Yang et al.[148] corroborated this with a distributed energy system framework for office buildings, treating building envelopes as VTES for load compensation. This active-passive synergy compressed the annual energy shortage duration to 26.90 hours, improving performance by 80.12%–88.18% over traditional methods treating buildings as purely passive loads. During post-event recovery, a distribution system recovery mechanism (Figure S3) by Li et al.[146] showed that when CHP units are forced offline, active TES releases heat to cover deficits, while pipeline storage formed by transmission delays is activated as passive TES to synergistically redistribute heat flows, effectively lowering economic costs. Ultimately, resilience control during response and recovery phases avoids isolated equipment operation. Instead, it relies on the instantaneous compensation of active TES, the delayed buffering of passive TES, and the synergistic optimization of multi-energy devices to prioritize critical loads under limited resources, minimize mandatory load shedding, and reduce overall system recovery costs.

CONCLUSION

Climate change, exhibiting multi-scale and multi-type evolutionary characteristics, has become the primary disturbance threatening the stable operation of building energy systems. While existing climate resilience research predominantly focuses on the narrow security resilience of macro power systems against paralysis, the core requirement of building energy systems lies in the broader concept of thermal resilience. This concept demands not only guaranteeing the basic operational safety of energy supply equipment under extreme conditions but also emphasizes the comprehensive capability to maintain indoor thermal stability and energy-efficient system operation under complex climate disturbances. Therefore, this study conducts a systematic review of meteorological data reconstruction, impact evolution mechanisms, quantitative assessment frameworks, and thermal energy storage enhancement technologies, distilling existing research bottlenecks and prospecting future evolutionary directions.

Accurate meteorological forecasting data is the prerequisite for building energy resilience analysis. Long-term gradual climate change dictates the background base state of building operations, whereas short-term extreme events reflect the tail risks of meteorological distributions. Because extreme events frequently superimpose on already shifted climate baselines, the two exhibit significant non-linear coupling effects. However, existing meteorological modeling methods are predominantly confined to the isolated analysis of singular climate features. Moving forward, it is imperative to break through the constraints of historical weather backbones and construct composite meteorological data generation systems that deeply integrate long-term warming trends with short-term extreme characteristics.

In-depth analysis of the impact mechanisms of climate change on building energy constitutes the theoretical foundation for resilience enhancement. These impacts exhibit pronounced concurrent characteristics on both the supply and demand sides. On the demand side, long-term warming causes seasonal shifts in baseline loads, while extreme weather triggers instantaneous peak surges. On the supply side, extreme environments not only lead to precipitous drops in equipment conversion efficiencies but also easily trigger cross-network cascading faults such as external power grid outages. Thus, the ultimate impact is not a simple superposition of unilateral factors, but rather a systemic disruption induced by demand surges coupled with supply constraints. Future research urgently needs to break the static and unilateral assessment perspective to establish co-simulation frameworks that incorporate supply-demand dynamic feedback and cascading failures.

Scientifically constructing quantitative evaluation frameworks is the critical standard for achieving thermal resilience optimization. Building energy thermal resilience is fundamentally a multi-dimensional composite concept, whose realization depends on two orthogonal dimensions namely resilience-bearing entities and temporal characteristics of disturbances. Specifically, both the building envelope acting as passive defense and the energy supply system acting as active provision must concurrently possess static adaptability to long-term gradual changes and dynamic response capabilities to short-term shocks. Given the current status of ambiguous concepts and singular evaluation systems, there is a pressing need to construct a standardized theoretical framework covering these entity and time dimensions and to develop multi-level comprehensive quantitative evaluation systems.

Thermal energy storage technologies serve as the core physical support for enhancing building energy system thermal resilience, yet face stringent boundary challenges in practical deployment. For passive thermal energy storage such as phase change envelopes, obstructed nighttime heat rejection under extreme high temperatures breaks the physical charge-discharge cycle of materials, not only constraining long-term performance but also exacerbating the difficulty of dynamically optimizing phase change temperature points. For active thermal energy storage, existing studies are mostly limited to capacity configurations for specific systems or singular extreme events, lacking a systematic planning method to address the compound risks of long-term gradual changes, short-term shocks, and external energy interruptions. Ultimately, resilience enhancement technologies must break through toward holistic synergy. On the one hand, this requires establishing robust capacity configuration methods for active storage that account for multi-scenario climate evolutions. On the other hand, it necessitates developing diversified hybrid energy storage coordinated control strategies that span the entire process of pre-event warning accumulation, mid-event emergency reconstruction, and post-event rapid recovery.

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The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Readers may contact the corresponding authors for data upon reasonable request.

SUPPLEMENTAL INFORMATION

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