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Challenges in predicting the impact of climate change on thermal building performance through simulation: A systematic review

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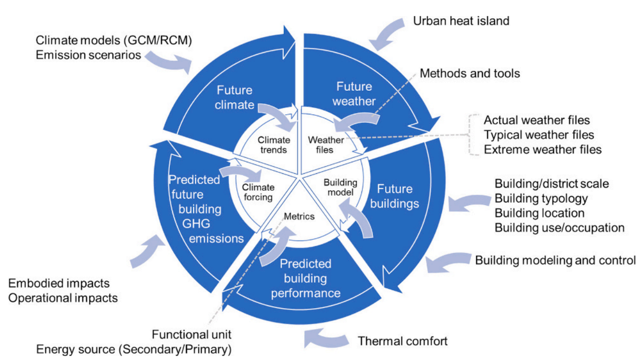
HIGHLIGHTS

- Identified the self-reinforcing loop between climate change and buildings.
- Inconsistencies in methods and geographical disparities.
- Scaling challenges from individual building to district-level predictions.
- Need robust and resilient design to address uncertainties, microclimate and extremes using the latest models and scenarios.

GRAPHICAL ABSTRACT



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ABSTRACT

The intricate relationship between climate change and the building sector is characterized by a self-reinforcing loop. Rising temperatures driven by global warming will inevitably impact heating and cooling energy, while buildings simultaneously contribute significantly to carbon emissions throughout their lifecycle, further exacerbating climate change. However, current knowledge regarding the interaction between climate change and the building sector remains fragmented, often limited to specific regions, climate zones, and mitigation strategies, lacking a holistic view. This systematic review analyzes 212 peer-reviewed articles to examine current approaches, challenges, and future directions in predicting building thermal performance under climate change. The analysis covers key aspects, including climate data, methods/tools for future weather file generation,

Abbreviations: GHG, Greenhouse Gas; IPCC, Intergovernmental Panel on Climate Change; AR, Assessment Report; CMIP, Coupled Model Intercomparison Project; HDD, Heating Degree Day; CDD, Cooling Degree Day; HDH, Heating Degree Hour; CDH, Cooling Degree Hour; ASHRAE, American Society of Heating, Refrigerating and Air-Conditioning Engineers; HVAC, Heating, Ventilation, and Air Conditioning; AC, Air conditioning; UHI, Urban Heat Island; SRES, Special Report on Emissions Scenarios; RCP, Representative Concentration Pathway; SSP, Shared Socioeconomic Pathway; GCM, General Circulation Model; RCM, Regional Climate Model; EPW, EnergyPlus Weather; IOcD, Indoor Overcooling Degree; IOhD, Indoor Overheating Degree; PV, Photovoltaic; IHG, Internal Heat Gain; TDY, Typical Downscaled Year; ECY, Extreme Cold Year; EWY, Extreme Warm Year; CDF, Cumulative Distribution Function; TMY, Typical Meteorological Year; TRY, Test Reference Year; DRY, Design Reference Year; DOE, Department of Energy; ANN, Artificial Neural Network; AI, Artificial Intelligence; ML, Machine Learning; XAI, Explainable Artificial Intelligence; GA, Genetic Algorithm; MAE, Mean Absolute Error; RMSE, Root Mean Squared Error; LCA, Life Cycle Assessment.

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computational methods and performance metrics. The reliance on outdated climate scenarios and models undermines the accuracy and applicability of predictions. Despite a general rise in cooling and decline in heating, considerable variances occur among geographies, climate data, and carbon emissions. This review highlights several important gaps, including 1) inconsistencies in geographical disparities and data quality; 2) challenges in scaling from individual buildings to district-level predictions; 3) the need for more advanced control and modeling capabilities in simulation; and 4) insufficient consideration of robust, resilient design strategies to address uncertainties posed by climate change, localized microclimate, and extremes. In addition, significant methodological inconsistencies across studies hinder reliable comparisons and potentially undermine prediction accuracy. The review proposes the development of a standardized protocol to guide researchers while preserving context-specific investigations. This aims to incorporate updated climate scenarios, high-resolution data, and robust modeling techniques to enhance prediction accuracy under a changing climate. Breaking this vicious cycle requires an integrated approach combining building science, climate science, and urban planning.

1. Introduction

Since the pre-industrial era, human activities have increased the concentration of greenhouse gas (GHG) in the atmosphere and global warming. The global average temperature in 2010–2019 was 0.8–1.3 °C higher than that of 1850–1900 [1]. Furthermore, in the long term (2080–2100), the global average temperature is likely to rise by a further 1.4–4.4 °C. In response to this threat, the Paris Agreement has set the target of restricting global temperature rise to less than 1.5 °C to prevent serious health impacts from climate change [2].

The building industry is a major contributor to environmental impacts [3,4]. As stated in the Global Status Report by UN Environment [5], buildings accounted for 36 % of global energy consumption and 37 % of associated carbon emissions in 2020. Furthermore, residential, commercial and infrastructure development will inevitably lead to an increase in environmental impact as a result of population growth, urbanization and changes in household size [6]. However, the current progress made by the construction sector towards decarbonization falls far short of the necessary 2050 targets [5]. Thus, the significance of the building sector in addressing the pressing issues of global warming is highlighted.

Buildings that typically stand for 50 years or more will inevitably be affected by global warming. Although there is a large body of literature assessing the implications of global warming on buildings at diverse scales/regions, there remains a research gap in the form of a systematic review that synthesizes findings and impacts. Previous studies (Table 1) have primarily focused on specific elements, such as specific regions or countries [7–9], climate zones [10], future weather prediction methods [11], quantitative analysis [12], heating/cooling degree day (HDD/CDD) [13], and mitigation strategies [8,14,15]. For instance, Li et al. [7] explored building energy demand under global warming in different regions, including Europe, Asia, and the U.S. in 2012. Andrić et al. [14] focused on building renovations as a mitigation measure under global warming. Abolhassani et al. [10] explored future building thermal performance based on ASHRAE climatic zones.

While numerous studies have explored future building energy demands, this review presents the first comprehensive analysis specifically focused on the intersection of climate change projections and building energy simulations. The absence of such a comprehensive review not only impedes our understanding of this critical intersection but also jeopardizes building resilience to climate-induced challenges, potentially hindering efforts to mitigate effects of global warming on human health and productivity.

The primary contributions of this review are multifaceted and extend beyond previous studies in several key aspects: 1) It presents a comprehensive and updated analysis of literature published, encompassing a wide range of building types, climates, and geographical areas, thereby offering a global perspective on the challenges. This scope surpasses previous reviews that focused on specific regions or climate zones [7–9], or were conducted when the field was emerging [7,9,16]. 2) This review overcomes the limitations of previous studies that either lacked a systematic approach [10,11] or focused on specific methods such as degree day methods [13]. It provides a holistic global assessment of current predictive tools and methods for generating future weather files, including various downscaling techniques. It identifies their limitations and proposes enhancements to improve accuracy and reliability. 3) This review highlights the self-reinforcing loop between weather, building simulations, emissions, and environment, as well as challenges and sources of uncertainty inherent in current modeling practices. 4) This review identifies priority areas for future research based on recognized knowledge gaps to advance our understanding of future building energy performance, which have not been previously summarized in such a way. By addressing these key aspects, the review aims to provide valuable insights for engineers, policymakers, and researchers, informing decision-making processes related to building design and retrofitting in the face of a warming climate.

This review is structured as follows: Section 2 outlines the systematic review methodology. Section 3 examines the general information typically considered in climate change impact studies. These include future scenarios, weather file generation methods, and performance metrics. Section 4 scrutinizes key challenges, including data quality issues, urban heat island (UHI) effects, extreme weather modeling, scaling problems, and limitations in current building simulations. Section 5 highlights the self-reinforcing loop and inconsistencies in methodologies. Section 6 concludes the paper by synthesizing findings and proposing future research directions.

2. Materials and methods

This paper adopts a systematic review approach to collect and analyze the latest research on the effects of global warming on building thermal performance. A systematic literature review is considered a thorough, transparent, and reproducible method for identifying, compiling, selecting, and critically assessing relevant studies [17]. This is effective in reducing subjectivity and bias, thereby increasing the objectivity and reliability of the review process [18]. To ensure the inclusion of sufficient relevant studies, a meticulous screening process was conducted using Web of Science and Scopus.

The search engine was queried with four keywords: Keywords1 ("climate change" OR "global warming"), Keywords2 ("impact" OR "effect"), Keywords3 ("energy demand" OR "energy performance" OR "energy consumption" OR "energy use"), and Keywords4 ("building"). The search was conducted in July 2023 with 5745 returns from Web of Science and Scopus (Fig. 1). Inclusion criteria included peer-reviewed English journal articles, which must be available in full text and be relevant to the building thermal performance under global warming. After removing duplicates, a total of 2979 unique articles were found. The next step was to thoroughly screen the titles, abstracts, and keywords of these articles to exclude studies that were not relevant. For example, studies focusing only on global warming potential were

Table 1
Previous reviews on the impact of climate change on the building sector.

Year	Focus Area	Region/Climate	Systematic Review	Key Findings	Future Directions	Refs.
2012	Special issue summary	/	N	Growing research focuses on adaptation and resilience. Regulations based on historical weather data Need for caution in handling performance metrics	Flexible, robust and resilient building design Address the UHI effect and occupant behavior	[16]
2012	Building energy, adaptation and migration	U.S., Europe and Asia	N	The impacts vary by climate Shift towards electricity demand expected Modifying temperature setpoints and lighting can mitigate energy use	Dynamic building-system-environment interactions Adaptive thermal comfort in design energy codes Regular updating of climatic information for building design	[7]
2013	(Peak) Energy demand, comfort, and emissions	Commercial buildings in Tropic	N	Energy demand will increase in the tropics while decrease in temperate regions Climate variability strongly influences building energy demands	Limited regional studies in tropical countries Consider increasing cooling requirements, carbon emissions, and extreme weather events in future building designs	[9]
2019	Passive and active measures	Middle East region	Y	Middle East buildings face increasing cooling demands. Passive design, efficient AC, and renewables offer potential improvements.	Adopt clean energy and efficiency in hot-dry climates Building design measures efficiency under future climate conditions	[8]
2019	Building energy demand and systems Passive and active renovation measures	Developed and developing countries	Y	Building renovation shows great potential in mitigating urban-related emissions Green walls need further research, especially in hot climates.	Investigate building stock renovation Prioritize policy development for energy efficiency	[14]
2019	Future weather file creation, uncertainties	/	N	Climate models need downscaling for building simulations Methods for reflection, propagation and partitioning of major sources of uncertainty in weather files and buildings	Integrate climate models into building design	[11]
2020	Different model methods, degree days	/	N	Degree days studies neglected the impacts of relative humidity, solar radiation, population	Spatiotemporal variations Estimating urbanization impacts on HDDs, CDDs, and their sum at various scales	[13]
2022	Meta-Analysis	/	Y	Heating decreases while cooling increases Total energy use rises, varying by climate zone	Different methods to address uncertainties	[12]
2023	Building energy, future weather scenarios and methods	ASHRAE climate zones	N	Heating decreases while cooling increases Morphing method commonly used but not very accurate Need for enhanced downscaling methods	Follow standardized future energy prediction method	[10]
2024	Energy retrofit strategies	/	Y	Future climate favors overheating Passive strategies help, but active cooling remains necessary	Adapt climate resilience criteria to building renovation Establishing climate resilience benchmarks	[15]

excluded. During the full-text review process, an in-depth review was also conducted to exclude studies that did not consider both global warming and building energy. In the end, 188 papers met the specific criteria and were retained for the systematic review. Moreover, 24 additional papers were added through the snowballing method [19]. These papers were relevant to the research objectives but were not initially included in the search results. Thus, the review ultimately included a total of 212 articles.

The review highlights a consistent upward trend in research output over the years, indicating a growing academic interest in this field. The earliest research, performed by Scott et al. [20], estimated the effect of global warming on three-storey office buildings in the states. The limited publications in the early years resulted from a lack of future weather files for analysis. A significant breakthrough occurred in 2005 when the morphing method was proposed for generating future weather files [21]. Post-2008, there was a discernible upward trend in the number of published studies. In 2013, Jentsch et al. [22] contributed to the field by developing an Excel-based tool capable of generating future weather data using the morphing method, significantly facilitating research on this topic globally. The substantial output in the last five years indicates a sustained academic focus on discussing the nexus between global warming and building energy, integrating aspects such as UHI, extreme weather conditions, and GHG emissions. Future research on this topic is expected to continue growing, as the building industry has yet to align with the climate goals.

3. State-of-the-art on buildings and climate change

3.1. Future scenarios considered

The IPCC has developed a set of scenarios (Table 2) that project future GHG emissions based on socio-economic storylines [23]. To generate climate projections, the general circulation models (GCMs) or regional climate models (RCMs) are used as inputs. These models reflect the Special Report on Emissions Scenarios (SRES) of the third and fourth Assessment Report (AR), the Representative Concentration Pathways (RCPs) of the AR 5, and Shared Socioeconomic Pathways (SSPs) from the AR 6. In the review (Fig. 2), more than half of the publications (116 studies) employed the SRES scenarios. The RCP scenarios were used in 36 % of the studies (77 papers), while only a small fraction (6 %) of the studies (13 studies) considered the latest SSP scenarios. A total of 107 studies focused on individual scenarios. Of these, the A2 scenario was applied in 61 cases, which is attributed to the widespread use of the CCWorldWeatherGen tool. In addition, 89 studies considered two or more scenarios to address scenario uncertainty, with the combination of RCP 4.5 and 8.5 being the most widely adopted (20 studies). It was found that 16 studies either did not provide or used alternative scenarios, such as a fixed temperature increase.

The SRES defined four storylines (A1, A2, B1, and B2), comprised of six scenarios. According to Fig. 2, the A2 scenario was the most frequently utilized SRES scenario (83 studies), and it remained the

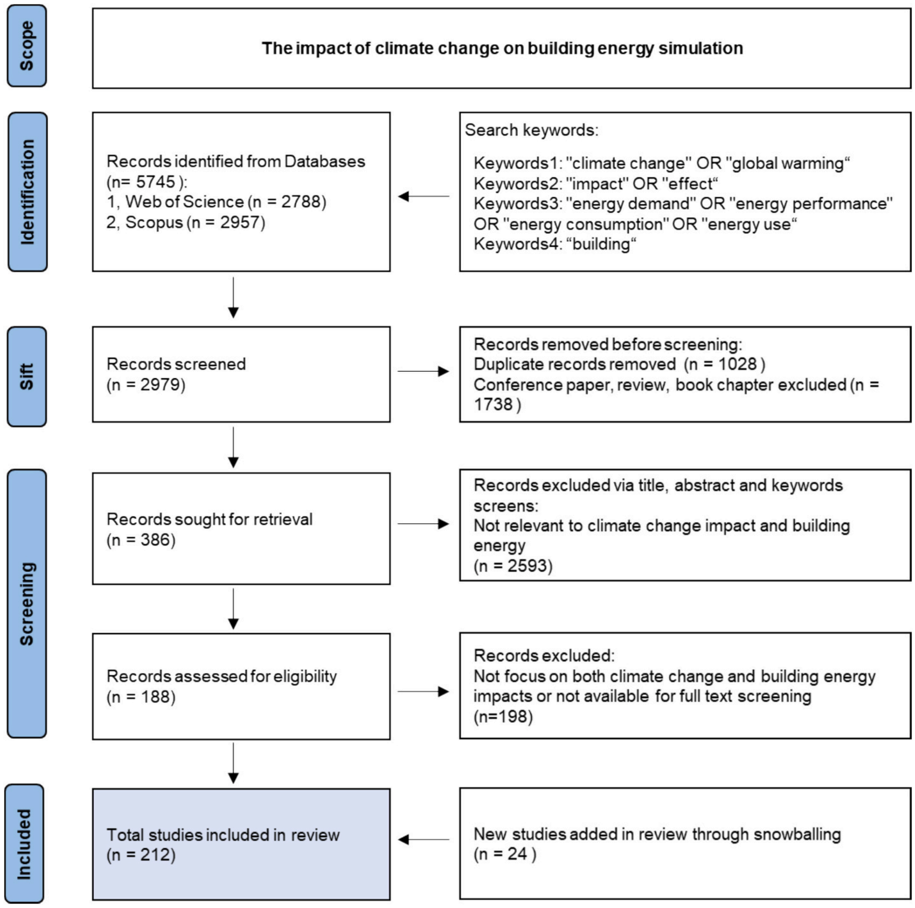

Fig. 1. Flow diagram for the selection procedure for the review.

largest even when considering all scenarios. A1B was the second most utilized SRES scenario (31 studies), followed by B1 (25 studies), A1FI (17 studies), and B2 (7 studies). There were no studies in this review related to the A1T scenario. Videras Rodríguez et al. [24] compared four SRES emissions scenarios for four time slices. RCPs incorporate more uniform depictions of short-lived gases and alterations in land use, distinct from the SRES scenarios [25]. Among RCP scenarios, RCP8.5 was frequently studied, featuring 65 cases. RCP2.6, RCP4.5, and RCP6.0 represented 21, 48 and 8 papers, respectively. Liu et al. [26] employed a pair of scenarios: the RCP8.5, which aligned most closely with Hong Kong's current trajectory within the framework of medium and high emission possibilities, and the RCP4.5, identified as the most probable scenario by researchers. For this review, SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5 scenarios featured 7, 12, 10 and 12 papers, respectively. For instance, SSP2–4.5 was considered a potential future scenario for Singapore in [27].

The selection of future climate scenarios for building performance studies requires careful consideration of multiple factors. It is recommended prioritizing the most recent scenarios, currently the SSPs, which incorporate updated climate data and socioeconomic pathways. To account for uncertainties in future emissions trajectories, researchers should consider multiple scenarios, typically including both moderate (SSP2–4.5) and high-emission (SSP5–8.5) scenarios. The chosen scenarios should also correspond to the study time horizon, as near-term projections may exhibit less variation between scenarios compared to long-term projections. For studies focusing on specific locations, selecting scenarios representing pathways relevant to the studied location context is advisable. Validation against recent climate observations can enhance the robustness of the selected scenarios.

3.2. Future weather files

Understanding future weather conditions is important for predicting building energy performance under climate change. This section explores climate data and methods used to facilitate the intricate process of generating future weather datasets.

3.2.1. Climate data

The generation of future weather files relies heavily on climate data derived from advanced climate modeling techniques. Key considerations include the selection of weather files, appropriate models, and the application of bias correction to ensure reliability.

3.2.1.1. Weather files. Generating future weather data typically requires weather files but can also be generated without relying on historical weather files. Weather files include different types, such as actual, typical, and extreme weather files, each serving a distinct purpose in building energy simulations. Actual weather files represent observed meteorological conditions for specific locations and time periods, providing high-resolution temporal data essential for model calibration and validation. Typical weather files, such as typical meteorological year (TMY), test reference year (TRY), and design reference year (DRY), are synthetic compilations reflecting long-term average conditions [28]. These files are commonly used in standard energy simulations but often fail to account for the impact of climate extremes, which are captured in extreme weather files. Historical EnergyPlus weather (EPW) files can be downloaded freely from Ladybug (https://www.ladybug.tools/epwmap/), EnergyPlus websites (https://energyplus.net/weather), and Climate.OneBuilding.Org websites. These historical files can have significant impacts depending on the years they

Table 2
Detailed classification of climate change scenarios.

IPCC Assessment Report (Year)	Scenario Type	Scenario Name	Description
AR 3 (2001)	Special Report on Emissions Scenarios (SRES)	A1FI	Fast economic expansion, population peaking mid-century, fossil-intensive
		A1B	Fast economic expansion, population peaking mid-century, balanced energy sources
		A1T	Fast economic expansion, population peaking mid-century, non-fossil energy sources
		A2	Heterogeneous world, steadily growing population, regionally focused economic expansion
		B1	Convergent world, same population as A1, shift towards service and information economy
		B2	Lower intermediate population and economic growth than A2, emphasis on environmental sustainability and social justice
AR 5 (2014)	Representative Concentration Pathway (RCP)	RCP 2.6	Stringent mitigation scenario, with radiative forcing peaking at ~3 W/m^2 before 2100, followed by a decline
		RCP 4.5	Intermediate scenario, radiative forcing stabilized at ~4.5 W/m^2 after 2100
		RCP 6.0	Intermediate scenario, radiative forcing stabilized at ~6 W/m^2 after 2100
		RCP 8.5	Very high GHG emissions, radiative forcing reaches >8.5 W/m^2 by 2100 and continues to rise
AR 6 (2021)	Shared Socioeconomic Pathway (SSP)	SSP1–1.9	Sustainability, very low GHG emissions
		SSP1–2.6	Middle of the road, low GHG emissions
		SSP2–4.5	Regional rivalry, intermediate GHG emissions
		SSP3–7.0	Inequality, high GHG emissions
		SSP5–8.5	Fossil-fueled intensive development, very high GHG emissions

Note: SSPx-y, where x indicates the shared socio-economic pathway, and y represents the estimated radiative forcing level (W/m^2) projected for the year 2100. SRES were also continuously used in AR 4 (2007).

represent. Recent research by Parker et al. [29] demonstrates that newer TMY2021 files (2007–2021) show significant changes in average temperature and solar irradiance compared to older TMY3 files (ending 2005). This highlights the importance of using up-to-date climate data for accurate building simulations and future energy predictions.

3.2.1.2. Climate model. Climate models serve as the foundation for future weather projections with GCMs and RCMs commonly utilized. GCMs employ mathematical equations to simulate earth's climate, encompassing atmospheric, oceanic, and biotic processes along with their interactions and feedbacks [30]. However, the coarse spatial resolution of GCMs, typically ranging from 100 to 300 km [31], poses significant limitations for localized climate projections essential for building energy simulations. RCMs address these limitations by refining GCM outputs through downscaling to spatial resolutions as fine as 2.5 km and temporal resolutions as detailed as 15 min [32]. RCMs enhance the representation of topographical features, land-use patterns, and mesoscale processes. This increased resolution contributes to more accurate and region-specific climate projections. However, their use is constrained by the computational intensity and substantial resources and expertise required, which can be a barrier for widespread adoption, particularly in developing regions.

For building simulations, these GCMs need to be downscaled to achieve higher resolutions. The resolution of climate data, both spatial and temporal, is important for the accuracy and reliability of future building energy simulations [32]. This level of detail is particularly important for urban areas, where the interplay between built environments and local climate can lead to significant deviations from broader climate patterns. Higher spatial resolution data, such as that provided by RCMs, allows for a more detailed representation of local climate conditions. Temporal resolution affects the granularity of simulations and the ability to capture dynamic interactions between climate variables and energy performance. Coarse resolution may fail to accurately capture daily weather patterns and extreme conditions. This can lead to inaccuracies in peak load estimations and diurnal temperature ranges, which are essential for building performance and mitigation strategies. However, the increased computational demands and data storage requirements associated with high-resolution data pose challenges for researchers. The resolution of climate data challenges the trade-off between accuracy and practicality in future building energy simulations.

3.2.1.3. Bias correction. The outputs from GCMs and RCMs exhibit specific biases unique to each model, often due to factors such as coarse spatial resolutions and limited available weather parameters [33,34]. GCM outputs fail to account for regional and local characteristics, including vegetation and topographical features. This limitation results in significant discrepancies between historical GCM model data and corresponding observations from local weather stations. These differences highlight the importance of downscaling and bias correction techniques when applying GCM data to local-scale analysis. Consequently, bias correction, which aims to adjust systematic errors in climate model outputs [35], is essential for creating accurate future climate files for building simulations. However, not all climate datasets undergo bias correction, and the absence of such adjustments can introduce uncertainties into simulation results, potentially compromising the reliability of predictions.

Bias correction techniques range from simple methods, such as delta approaches, to more advanced techniques like the quantile method [33]. For example, Arima et al. [34] applied correction formulas to temperature, humidity, and radiation data from projected climate models (GCMs and RCMs). Their results showed that the adjusted typical weather data closely matched observational datasets. The quantile delta mapping method is used to correct biases in downscaled hourly climate model outputs in [36]. Hosseini et al. [33] utilized the quantile-quantile method to correct bias and adapt climate models to a specific location. They corrected the future climate dataset using the cumulative distribution function (CDF). Specifically, they compared and quantified the discrepancies between CDFs of historical model and observation data, and then applied to the CDF of future model projections on a quantile-by-quantile basis.

3.2.2. Methodologies for generating future weather files

Herrera et al. [28] performed a comprehensive review of the methods for creating current and future weather data. Studies by Guan [37] and Belcher et al. [21] also briefly reviewed methodologies to construct future weather data. The review examines various downscaling approaches used to enhance the spatial or temporal resolution of large climate ensemble datasets for building simulation purposes. It highlights two primary approaches: statistical downscaling (including morphing and stochastic approaches) and dynamic downscaling.

3.2.2.1. Morphing. Morphing is a well-established statistical technique widely utilized for generating future weather files. Belcher et al. [21] introduced the method to adjust present weather data by the changes predicted by GCM and RCM in 2005, which encompasses three fundamental operations: 1) shifting, 2) stretching (scaling factor), and 3) a combination of shift and stretch. Different algorithms are employed based on the weather variable being considered [23].

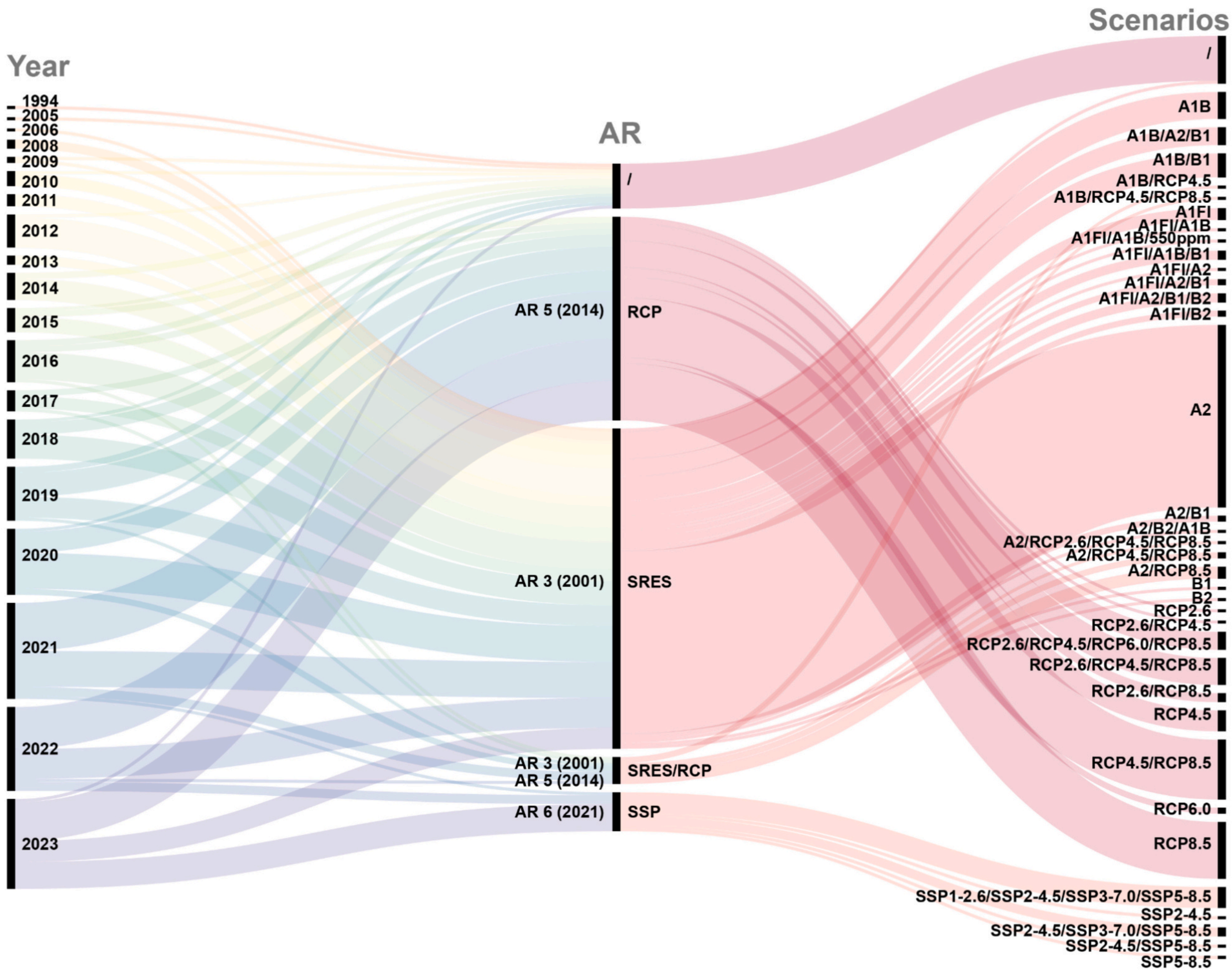

Fig. 2. Distribution of climate change scenarios used in building energy studies across IPCC assessment reports.

The morphing method successfully produces future weather files for HDD calculations, displaying agreement with the results derived directly from the climate models [21]. For all methods to generate future climate data, morphing is the most popular approach and was utilized in more than half of the studies (123 studies). For instance, Wang and Chen [38] adopted morphing to investigate the various types of buildings energy performance under global warming in 15 U.S. cities. Nonetheless, the morphing method retains the characteristics and variability of the current weather data and does not reflect fluctuations at various time scales (from seasonal to hourly [32]) and extreme events, such as the frequency of heatwaves [21,31].

3.2.2.2. Stochastic weather model. The stochastic weather model, a method for generating synthetic weather files, was developed by Van Paassen and Luo [39]. They revealed that all weather variables are influenced, to varying degrees, by solar radiation. Consequently, solar radiation can be considered the independent weather variable from which all other dependent variables can be derived. When the model is applied to a specific location, certain local statistical data, such as average temperature, wind speed, and humidity, are required to produce synthetic weather data for that site. If such statistics are not available, they can be estimated through interpolation from nearby weather stations. In Meteonorm software, the generation of typical years in minute and hourly resolutions is based on a stochastic approach and interpolation algorithms [40]. However, Guan [37] argued that this approach faces challenges in accurately modeling numerous climatic variables, and Belcher et al. [21] reported that the weather series it creates may not always exhibit meteorological consistency.

3.2.2.3. Dynamical downscaling. Dynamic downscaling employs a physical-based process, using RCMs to enhance the resolution of GCM outputs. This process involves running a high-resolution RCM over a limited area, using GCM outputs as boundary conditions [33]. RCMs offer the benefit of producing physically coherent datasets across various variables and provide a higher temporal and spatial resolution [41], as well as enhanced representation of topography and mesoscale processes for a more accurate representation of local climate [21]. Researchers are increasingly using dynamically downscaled climate datasets to generate future weather files, leveraging the improved spatial and temporal resolution offered by these datasets [31,32]. For instance, Nik [32] proposed a method to synthesize three weather datasets from RCM, namely (1) typical downscaled year (TDY), (2) extreme cold year (ECY), and (3) extreme warm year (EWY).

Each of these three widely used methods has its pros and cons, as detailed in Table 3. While statistical methods require minimal computation and capture variations in average weather patterns, they often fail to account for extremes. This limitation can lead to the underestimation of global warming effects and inadequate representation of extreme events. In contrast, the higher resolution of dynamical downscaling enables better simulation of local climate features and extreme events but demands greater computational resources and expertise.

Table 3
Pros and cons of the methods used for generating future weather files.

Methods	Advantages	Disadvantages
Morphing	• Simple [21] • Versatile for use with numerous worldwide weather files [22,23] • Minimum computation required and efficient [30] • Captures weather conditions specific to a particular location [21,23]	• Not reflect variations at diverse time scales (from seasonal to hourly [32]) • Lack of future extreme events, such as the frequency of heatwaves [21,31] • Constrained significantly by past climate observations [30] • Potential time difference between GCM data and the chosen present EPW file [22]
Stochastic	• Minimum computation required [21] • Typical years with stochastic generations can be calculated for any site [42]	• Difficulty in accurately modeling many climate variables [37] • Generated weather series may lack consistent meteorological patterns [21]
Dynamical downscaling	• Extreme event scenarios [30] • Not restrained by historical observation data [23,30]	• Large volume of data required [30] • High level of expertise [30] • Computationally intensive [30] • Only a few RCMs are available, and many parts of the world lack model results [30]

3.2.2.4. Others. The interpolation method involves interpolating the output from coarse-resolution climate models in both space and time. However, Belcher et al. [21] highlighted that the output of climate models was often biased, and even the current-day climate might exhibit bias. In Salata et al. [43], the grid temperature is processed using an interpolation technique known as "kriging" to quantify cooling degree hour (CDH).

Moazami et al. [23] indicated that UK Climate Projections 2009 (UKCP09) employed a hybrid downscaling methodology to alleviate the computational and storage burdens associated with dynamical downscaling. Within this hybrid method, the RCM data outputs are preserved at coarser spatial and temporal resolutions, subsequently undergoing additional statistical downscaling for refinement. UKCP09 amalgamates weather data into decade-long segments spanning from 2020 to 2080. In the review, 11 papers utilized future weather data from UKCIP02 (2 studies) and UKCP09 (9 studies). Two studies utilized the future weather files from Whitebox technology (commercial) for RCP scenarios [44,45], which used hybrid downscaling (dynamical and statistical). In addition, Hosseini et al. [33] employed a hybrid machine learning (ML) method to pair a weather classification model with the regression model to downscale GCM data for building simulation. Several investigations [20,46–51] employed a simplistic uniform temperature increase as the climate change weather files. For instance, Radhi [47] considered four temperature increase scenarios: 1.6, 2.3, 2.9 and 5.9 °C, reflecting the 2050 and 2100 climates.

The selection of methods for generating future weather files requires a nuanced approach that balances multiple factors. While recent advancements in weather file generation techniques offer potential improvements, the appropriateness of a method depends on specific research objectives, data availability, and computational resources. Statistical methods like morphing offer computational efficiency but may inadequately represent future climate variability and extreme events. Conversely, dynamical downscaling provides higher temporal and spatial resolution but demands significant computational power and expertise. Researchers should evaluate the trade-offs between accuracy, practicality, and the required temporal and spatial resolution for their building performance simulations. The chosen method should align with the scope of the study, such as capturing extreme weather events or assessing long-term trends. Importantly, researchers should transparently articulate their rationale for method selection and acknowledge associated limitations and uncertainties.

3.3. Future weather generator tools

Interest in the topic is on the rise; however, the availability of future weather files remains limited, and outdated climate data is being adopted across numerous regions. Researchers dedicate their efforts to developing personalized morphing solutions; however, such endeavors frequently demand programming expertise, engender time constraints, and pose challenges for researchers. Thereby, future weather file generation tools are widely used (Fig. 3). CCWorldWeatherGen, Weathershift, and Meteonorm were the top three widely used tools. Despite relying on outdated climate models and scenarios, these tools remain popular even in recent years. CCWorldWeatherGen and Weathershift employ a morphing approach to generate future climate data [23]. On the other hand, Meteonorm employs a stochastic generation method. The details of the merits and limitations of these tools can be found in [52]. In contrast, *Future Weather Generator* provides files using the latest SSP scenarios. In addition, Epwshiftr [53] is a free, open-source R package that also employs a downscaling morphing method using CMIP6 GCMs. Guarino et al. [54] proposed a simple, free and easy-to-use tool to examine the effect of global warming on the ASHRAE models for three time slices. However, this tool has not been published on an online webpage and is not accessible for use by others.

3.3.1. CCWorldWeatherGen

In 2008, Jentsch et al. [55] developed CCWeatherGen, a free and open-source software tool based on Microsoft Excel. They used morphing and implemented it at 14 CIBSE UK weather sites for three time slices and four emissions scenarios (B1, B2, A2 and A1Fl). In 2013, Jentsch et al. [22] extended this method to any location in the world and introduced the CCWorldWeatherGen tool, which can create future weather files for A2 emissions scenario based on the HadCM3 model. The HadCM3 A2 data simulated the baseline climate for the period from 1961 to 1990, and projected for three future slices (2020s/2050s/2080s) [22,23]. Jiang et al. [56] developed Weather Morph (http://139.62.210.131/weatherGen/), an online version of the CCWorldWeatherGen, which provides four emission scenarios: B1, B2, A2 and A1Fl.

The easy-to-use CCWorldWeatherGen tool has become the most popular choice for subsequent studies, though it uses outdated data. 53 papers employed the CCWorldWeatherGen for future weather scenarios (A2), even in 2023 [57]. For instance, Ciancio et al. [58] adopted this tool to comprehensively investigate future energy and the related carbon emissions for 19 European cities.

Jentsch et al. [22] also acknowledged certain limitations inherent in the specific methodology employed. Specifically, potential differences between HadCM3 and EPW data on the reference timeframe were identified. To address this, it is recommended that the EPW files be consistent with the period of HadCM3's reference timeframe (1961–1990). However, only a small subset of EPW datasets, like TMY2 for the U.S., meet this criterion. Therefore, using a different dataset or period, for example, the year 1999–2000 in [59], and then morphing it for future weather files may result in higher temperatures and an overestimation of the outcomes. The morphing process also carries the risk of generating unrealistic results, particularly concerning relative humidity values at some weather stations. The exclusive consideration of the A2 scenario is suboptimal, as it overlooks the uncertainty associated with climate scenarios. Furthermore, a significant limitation of CCWorldWeatherGen is its reliance on the coarse grid of the HadCM3 model. The global model is characterized by a spatial grid resolution of

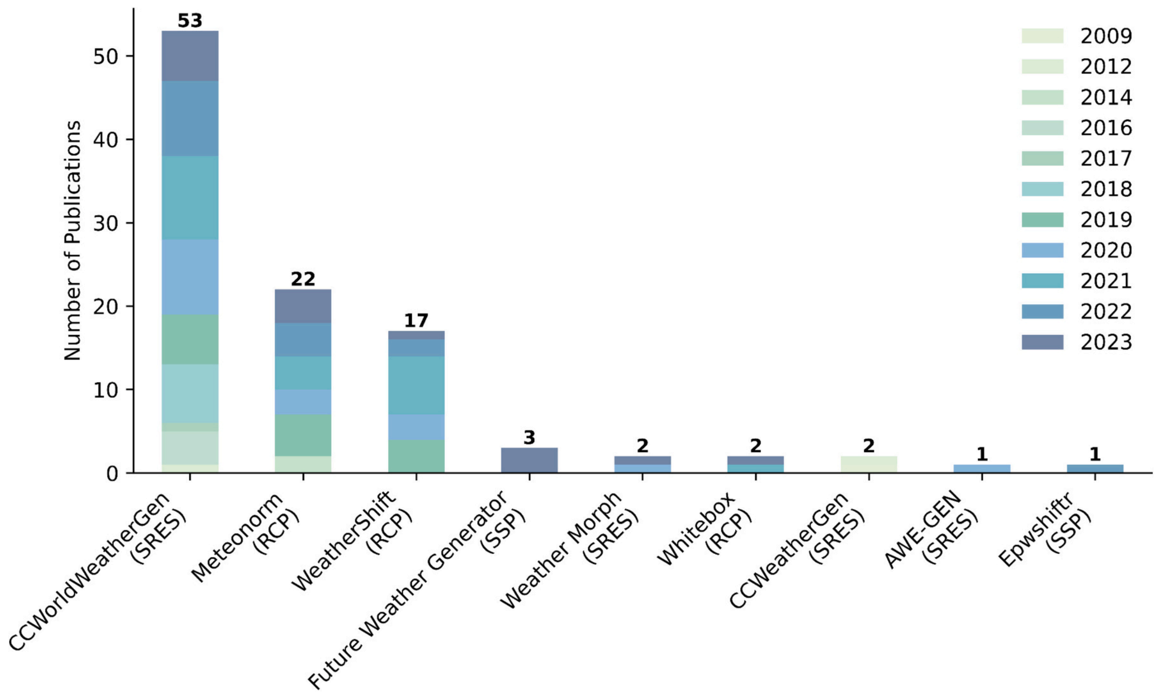

Fig. 3. Weather tools used to create future weather files.

Table 4
Comparative analysis of future weather file generation tools.

Tool	Strengths	Limitations
CCWorldWeatherGen	Free, open access and easy to use Any location in the world	Outdated HadCM3 model Limited to A2 scenario Coarse spatial resolution (2.5° × 3.75°) Less accurate in regions with complex topography Future timeframe already outdated (2020s) Limited extreme weather [52] No longer maintained Third-party commercial software Excel required Baseline does not accept latest meteorological data [52]
WeatherShift	Uses 14 GCMs from CMIP5 [60] Self-contained tool and easy to use [52]	Commercial tool Limited to 259 cities Outdated climate models Closed-source code Baseline does not accept latest meteorological data [52]
Meteonorm	10 global climate models Stochastic generation capability Multiple scenarios (RCP 2.6, 4.5 und 8.5)	Commercial tool Outdated climate models from CMIP5 Closed-source code
Future Weather Generator	Open-source, cross-platform, free, and customizable. latest EC-Earth3 model from CMIP6 Generates the typical, warmest, and coldest future years More weather variables considered like precipitation and snow depth Multiple latest SSP scenarios	Relatively new, less validated

approximately 2.5° × 3.75° [22], which is relatively coarse for local-scale applications. This limitation can lead to inaccuracies in regions with highly variable topography, where local climate conditions can change dramatically over short distances. In such areas, the tool may not capture important microclimatic effects, potentially leading to less accurate future weather projections. Relying on historical data from 1961 to 1990 and the outdated climate model may not be suitable for current studies, given its age, and it is recommended to use more recent data to improve the accuracy and relevance of the research.

3.3.2. WeatherShift

WeatherShift utilizes 14 GCMs for RCP4.5 and RCP8.5 scenarios [60]. 16 studies employed WeatherShift tools for weather generation. Employing the morphing approach, this tool generates three future periods: 2035 (2026–2045), 2065 (2056–2075), and 2090 (2081–2100), relative to a baseline period (1976–2005), for 259 cities worldwide [61]. However, the tool does not utilize a global grid similar to CCWorldWeatherGen. Instead, it is restricted to a dataset encompassing only 259 cities. A critical limitation is that WeatherShift is a web-based commercial service, which hampers its accessibility to researchers. Furthermore, concerns have also been raised about the code closedness of the tool [52].

3.3.3. Meteonorm

The Meteonorm software serves as a climate database and is capable of generating weather files for any location by employing stochastic generation and interpolation algorithms of typical years [42], which are utilized in 21 papers. In previous studies [23,62], Version 7 was utilized, which could generate B1, A1B, and A2 emissions weather files. The updated Version 8 is based on RCP 2.6, 4.5, and 8.5 scenarios, covering the period from 2020 to 2100 based on data from 10 GCMs [40].

3.3.4. Future weather generator

The above three tools are hampered by several limitations, including outdated climate model data, coarse spatial resolution, and a limited number of scenarios (Table 4). Moreover, these tools are commercially available or depend on third-party commercial software. The closed nature of the code restricts opportunities for corrections, enhancements, updates and transparency. Thereby, Rodrigues et al. [52] have formulated an open-source, cross-platform morphing tool: *Future Weather Generator* (https://adai.pt/future-weather-generator/). This tool is designed to create future weather data for SSP scenarios. It utilizes the latest climate data model (EC-Earth3) to enhance accuracy and grid resolution and incorporates a wider range of variables (liquid precipitation depth and snow depth). Fereidani et al. [63] used it to investigate the effectiveness of the building codes in energy saving in Iran for present and future weather conditions.

While these tools offer varying degrees of accessibility and coverage, their accuracy can significantly impact simulation results. CCWorldWeatherGen, despite its popularity, may lead to inaccuracies in energy demand predictions due to its reliance on older climate data. WeatherShift's limited geographical coverage restricts its applicability. Meteonorm is a commercial tool with stochastic generation capability. The *Future Weather Generator* shows promise in terms of using up-to-date climate models, but its performance across different building types and climates requires further validation. This may necessitate comparing its results with alternative methods or tools. The previous three tools are either commercial or based on commercial software. Given its open-source nature, transparency, utilization of the latest model, and compatibility across different platforms, *Future Weather Generator* is recommended for researchers interested in long-term climate change impacts on buildings, especially in regions with limited research. Researchers should prioritize tools that generate future weather using the latest models and scenarios where possible. Moreover, these tools often struggle to capture microclimates and extreme events, which may be directions for future development.

3.4. Computational methods for assessing future building energy performance

This systematic review focuses primarily on the main approaches for assessing the impact of global warming on building energy: the degree day/degree hour method, building energy simulation, and artificial intelligence (AI) and machine learning (ML) methods. Hourly energy simulation involves modeling the building thermal performance and simulating its energy use based on weather data. The degree day method, on the other hand, uses HDD/CDD to estimate the energy requirements based on the difference between ambient and base temperatures. More advanced methods using AI/ML techniques are also discussed. Among the publications surveyed, 40 studies incorporate both the degree method and simulation. It was observed that the majority of these studies opt for hourly energy simulation (181 studies), constituting 85 % of the retrieved articles. Additionally, the degree day and degree hour methods were featured in 50 studies.

3.4.1. Degree day method

There is a lack of consistent detail regarding the calculation of HDD and CDD, with some studies even omitting the specification of the base temperature. Consequently, various methods and equations, leading to potentially disparate outputs, are employed for calculations, rendering the HDD and CDD metrics incomparable. Some [64–66] used the daily mean external temperature to compute HDD and CDD based on different standards and different base temperatures (see Supplementary Material). The Eurostat methodology calculates CDD and HDD based on the daily mean air temperature [67]. Jylhä et al. [68] considered internal heat gain (IHG) and implemented an effective indoor temperature set lower than the target temperature. To address temperature fluctuations and diurnal variations, studies [69–72] employed the weighted summation method with reference to the UK MET-Office or UKCP09 report [73]. Moreover, the differences between the reference and hourly external temperatures are divided by 24, and the resulting values are summed over the chosen period to capture the hourly variations within a day [38,44,74–76]. Heating/Cooling degree hours (HDH/CDH) are also employed in [43,67,72,77–83].

The simplicity, transparency, and repeatability of using HDD and CDD provide advantages over hourly energy simulations, which may not offer the same ease of use. Jylhä et al. [68] represented that the annual HDD had almost the same percentage change as the dynamic simulation results of the annual heating energy demand. This suggests that changes in heating energy are almost entirely due to temperature changes alone. However, the study also noted that degree days tend to underestimate the energy decline in September, primarily due to the rise in solar radiation during this period. Degree day method has several limitations that affect its accuracy and applicability, including:

(1) ignoring the influence of non-temperature factors like occupancy, behavior, radiation, and humidity [84]. Results from degree day method closely aligned with those of dynamic simulations in hot or cold climates [38]; however, a large discrepancy was observed in milder climates, such as San Francisco. Particularly in humid regions like Sydney and Brisbane [37], cooling demand is notably influenced by both sensible and latent heat.
(2) neglecting the variation of temperature within a day, which may introduce errors when the degree days are zero but the building still needs cooling or heating [85]. Cox et al. [84] identified a notable relative error in energy when the climate temperature approached the balance point.
(3) overlooking the nonlinear relationship between temperatures and building energy consumption due to factors such as heat pump performance, thermal mass and HVAC efficiency.
(4) assuming a fixed base temperature for all types of buildings and regions, regardless of their specific characteristics and preferences [37,86].

3.4.2. Hourly energy simulation

Building energy simulation tools are widely utilized to predict future building energy. EnergyPlus, a free software developed by the U.S. DOE, takes the lead with 88 studies. DesignBuilder (26 studies), Ladybug and Honeybee plugins of Grasshopper in Rhinoceros (7 studies), and NREL BEopt (1 study) are also based on the EnergyPlus simulation engine. TRNSYS (9 studies), IES VE (7 studies), and IDA ICE (6 studies) serve as alternative simulation tools to EnergyPlus. CitySim is used in [87–89] as an urban energy modeling tool.

With the development of coding and programming, researchers used programming languages to facilitate this process. For instance, Shen et al. [90] used SimBldPy, a self-developed Python building simulation tool, and random forest to examine the future energy of various energy saving measures. Silva et al. [91] used *Combined Energy Simulation and-Retrofit, in Python* to create building simulation models, which are also based on EnergyPlus. In addition, model calibration and verification are used between the model and real house units to check the accuracy of the simulation model with real performance, such as in Refs. [92–96].

3.4.3. Advanced computational methods

The increasing popularity of building retrofitting and optimization involves exploring large combinations of parameters to understand the interactions between variables and related parameters. Furthermore, adding another variable can cause simulations to grow exponentially [96]. This computational challenge has spurred the development of more efficient predictive methods. The application of AI and ML techniques to forecast future building energy consumption represents a significant advancement in the field [97]. These techniques excel in capturing complex, non-linear relationships between climate variables and building energy performance, potentially enhancing prediction accuracy while reducing computational demands. These methods include artificial neural networks (ANNs), explainable artificial intelligence (XAI), random forests, support vector machine and other deep learning approaches [98]. For instance, Zhang et al. [99] employed XAI method to analyze building energy and GHG emissions and considered effects of building geometry and urban morphology.

Several recent studies demonstrate the effectiveness of these approaches in climate change studies. Shi et al. [53] utilized the ANN model to calculate energy consumption to replace the EnergyPlus engine. Shen et al. [90] developed a predictive model using random forest algorithms to forecast future hourly energy. Chakraborty et al. [100] implemented an XAI model, combining XGBoost with SHapley Additive exPlanations (SHAP), to forecast cooling energy consumption. The XAI model demonstrated high accuracy, achieving R^2 values exceeding 0.9, which suggests robust performance in predicting cooling energy consumption patterns.

Luo and Oyedele [101] developed a hybrid GA-ANN model, leveraging historical weather data and existing energy profiles to forecast future building energy demands for two campus buildings in Bristol. The accuracy of the model was evaluated using metrics such as mean absolute error (MAE) and root mean squared error (RMSE). It demonstrated promising results, achieving R^2 values of 81.3–87.4 % for heating gas and 89.3–96.6 % for electricity predictions on the training data for two buildings. These error metrics suggest that the hybrid GA-ANN model predicted energy demand with reasonable accuracy, particularly for electricity consumption. However, the use of a coarse grid and the outdated HadCM3 climate model may have limited the accuracy of results.

While these AI and ML methods show great promise, they also face significant challenges. These data-driven methods are highly effective for predicting performance under conditions similar to those in the training data. However, their accuracy can diminish when applied to scenarios with varying features or conditions that are outside of their training range [102]. Models trained on historical weather data may struggle to generalize to new or extreme climate conditions. These conditions include prolonged heatwaves and snaps, and unprecedented fluctuations in humidity and solar radiation, which are increasingly frequent and intensive due to climate change. Another challenge is the dependence of data-driven methods on large, high-quality datasets [103]. In regions where such datasets are scarce, such as developing countries or extreme climatic zones, the performance of these models may degrade significantly. This raises concerns about equity and global applicability. The ‘black box’ nature of some AI models also poses a challenge for interpretability and trust in the predictions [98]. This issue is particularly important in decision-making processes for building design and retrofit under future climate scenarios, where transparent reasoning and interpretable predictive insights are essential.

3.5. Performance metrics

Performance metrics serve as key indicators for assessing building thermal performance, yet their variability across studies poses challenges for meaningful comparisons. Among the most employed metrics for future building energy assessments are kWh/m^2 or kWh/m^2/y. Typically, these two are used interchangeably, representing the annual energy evaluation. Additionally, kWh and kWh/y are used in 33 cases. Some studies use unique metrics, such as energy per building occupant (kWh/person) [104]. The U.S. study [105] adopted different units and standards for measuring energy density or consumption (kBtu/sq-ft). This emphasizes the need for standardization in reporting energy metrics to facilitate cross-study comparability. Additionally, some studies utilized larger metrics, such as GWh/km^2/y for district heating demand [106], and GWh/y for building stock [79].

The energy source may be another issue; while some studies focus on electricity and natural gas usage, others utilize primary energy as the indicator, thus making it hard to compare. The primary energy factor was used to convert the building energy use (typical electricity and natural gas) to primary energy to allow comparisons of different building systems by different energy sources [23,46,107]. The conversion factor for electricity/natural gas to primary energy was 2.97 /1.15 kWh_{PE}/kWh in Swiss, respectively [23,108]. Ascione et al. [109] utilized the conversion coefficient of 0.554 for electricity in Italy. Troup et al. [110] applied a factor of 1.092 for natural gas and 3.317 for electricity in the U.S. In Spain, Videras Rodríguez et al. [24] utilized a factor of 1.95 for electricity conversion to non-renewable primary energy. In Belgium, Amaripadath et al. [111] used 2.5 and 1 for electricity and natural gas conversion factors. Similar considerations apply to carbon emissions metrics, where differences in energy mix or GWP calculation method may create inconsistencies in results across studies. Even when using the same unit, comparisons between studies should be made with caution. This is because some studies use the gross floor area, while others use the net-conditioned floor area [111,112]. Such disparities may give rise to potential incompatibility. This highlights the importance of clearly defining and consistently applying performance metrics across studies. Furthermore, careful consideration is essential when comparing percentage changes between current and future scenarios, as these are highly dependent on the base value. The 27 % increase in large office buildings indicates an absolute change of 644.05 GJ, while the 90.6 % increase in small office buildings only reflects an increase of 19.1 GJ [113].

In addition, current building codes, policies, and performance metrics primarily focus on quantifying energy consumption and associated carbon emissions [114,115]. This focus overlooks indicators for analyzing building discomfort hours under future climate scenarios, especially in the absence of air conditioning (AC). Lizana et al. [114] emphasize that future building design could benefit from two heat-related indicators: energy consumption/carbon emissions with AC and passive survivability metrics without AC. These metrics include (dis) comfort hours [116,117], indoor overheating/overcooling degree [107], percentage of discomfort hours [118], and overheating escalation factor [119], which provide a more comprehensive assessment of climate change adaptation capacity. Integrating energy consumption, carbon emissions, and thermal metrics provides a comprehensive framework to evaluate the impact of climate change on building thermal performance.

4. Challenges in predicting the impact of climate change on building performance

Section 4 examines key obstacles in predicting and mitigating the impact of climate change on buildings, including data quality and availability, the complexities of microclimates and extremes, scaling issues, limitations in current modeling techniques, thermal comfort considerations, and GHG emissions.

4.1. Inconsistencies in data quality and geographical disparities

The accuracy and reliability of predicting future thermal building performance are significantly undermined by challenges in data quality and availability. Building simulation files rely on different sources of climate data, such as GCMs and RCMs, which can lead to significant discrepancies. Studies have shown that the uncertainty introduced by different GCMs can exceed the variations between climate scenarios and time intervals [26,120]. This finding calls into question the reliability of current prediction methods for climate models selection and processing. While some researchers have proposed a data-fused approach to account for different GCMs to provide a robust new ‘data-fusion’ dataset to mitigate this issue [121], the efficacy remains to be fully validated.

Furthermore, inconsistencies between climate models and EPW data in terms of reference timeframes when morphing may result in an underestimation or overestimation of impacts. The limitations of current methods for generating future weather files add another layer of difficulty. Each method has its drawbacks. Statistical methods, while computationally efficient, fail to capture short-term extreme weather events [31], potentially leading to underestimation of cooling loads [62]. Conversely, dynamical downscaling, though more comprehensive, is prohibitively resource-intensive for many researchers [21,30], particularly in developing countries.

The rapid evolution of climate scenarios from SRES to RCP and now to SSP further exacerbates the problem. A significant challenge is that most tools used in building energy simulations such as CCWorldWeatherGen, WeatherShift, and Meteonorm are not updated to the latest IPCC models and scenarios. The use of outdated scenarios, particularly SRES, can lead to significantly biased results due to the deviation of actual global emissions from earlier projections. This discrepancy is evident in studies such as Yang et al. [31], where projected reductions in future heating demand under RCP scenarios were notably smaller than those predicted using SRES. This observation underscores the importance of continuous updating of climate data and scenarios in building performance simulations. The lag in adopting the most recent projections potentially compromises the accuracy, which may lead to inaccurate or inappropriate policy decisions.

Another significant concern lies in the notable geographical disparity in research focus and data availability. Fig. 4 reveals a concentration of studies in Europe, North America, and parts of Asia, indicating a substantial imbalance in global research efforts. The predominant focus of research persists in countries projected to overcome or be well-equipped to address climate change, such as those in Europe. However, limited research has been carried out in Africa, South America and the regions near the poles that are not only particularly vulnerable but also face significant challenges in adapting to these changes. This research gap is further exacerbated by disparities in the accessibility of future weather files. For instance, countries like the UK benefit from readily available future weather files for multiple locations [16,23], while many developing countries struggle with data scarcity. The implications of this data inequality are significant. Africa, in particular, is experiencing a rapid increase in energy consumption driven by population growth and urbanization, with a heavy dependence on fossil fuels for electricity. This geographical imbalance raises concerns about the equitable distribution of resources and efforts in achieving climate goals. The lack of region-specific research hinders the development of suitable adaptation measures and may lead to misguided policy decisions. Addressing this imbalance requires a concerted effort to expand research in underrepresented regions and promote cross-country collaborations.

4.2. Inadequate integration of UHI effects in building energy simulations

Data from weather files are commonly collected away from urban areas and omit the local microclimate and UHI effect [22]. This omission introduces a fundamental flaw in understanding urban building energy dynamics and overheating risks, particularly as cities continue to grow and densify. The UHI effect results from the interplay of built environment and the local climate, leading to elevated temperatures within urban settings than in the surrounding rural areas.

The challenge of integrating UHI effects into building simulations is threefold: quantifying the UHI intensity, understanding its temporal-spatial variations, and capturing its complex interactions with global warming. Studies by [76,118,122,123] highlight the significant combined impact of these phenomena. For instance, Salvati and Kolokotroni [118] reported that the culmination of UHI and climate change effects yielded a peak temperature increase of 3.4 °C in July for Cadiz, wherein global warming contributed a rise of 1.6 °C and UHI contributed 1.8 °C. This finding raises concerns about the relative importance of factors in urban temperature increases, be it global warming, microclimates or both.

The temporal and spatial variation of the UHI effect further complicates its integration into building energy models. Akkose et al. [122] projected that the UHI effect would vary seasonally in Ankara, increasing temperatures by 1.8 °C in January and 2.9 °C in June by 2060, with peak intensities occurring in early morning hours. Long-term projections by [94] indicate that microclimate conditions will consistently elevate average annual temperatures by 4–5 % above mesoclimate conditions across different time periods (2010–2039, 2040–2069, and 2070–2099).

The implications of microclimate on building energy requirements and overheating risk are substantial and multifaceted. Santamouris

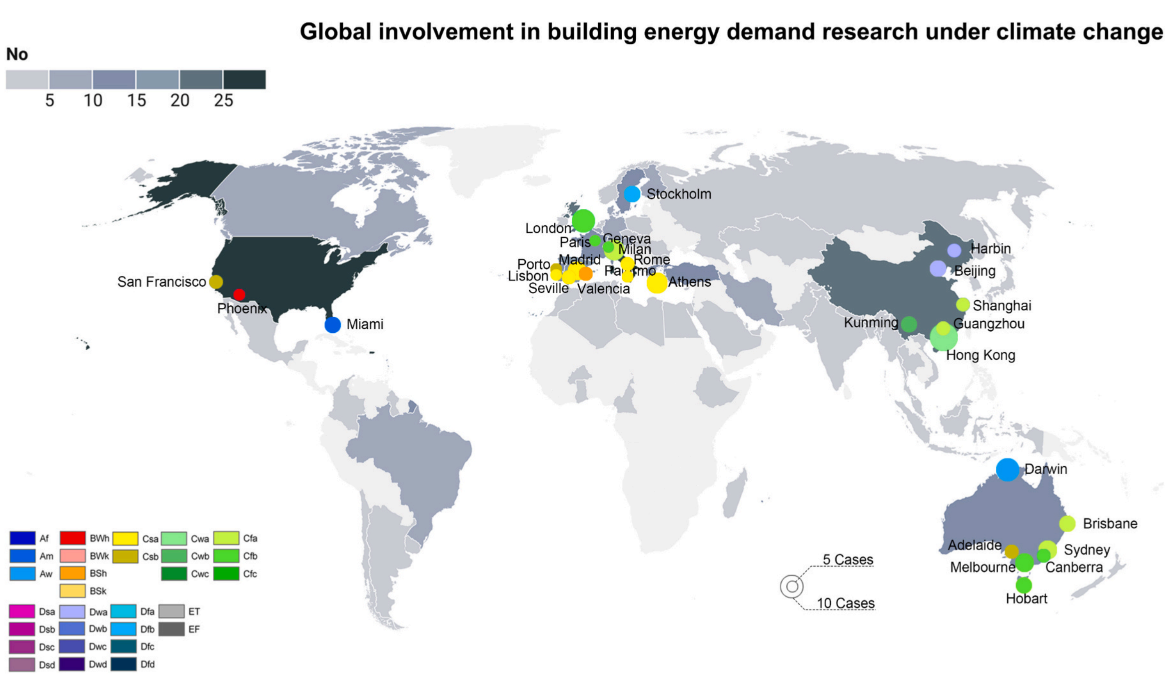

Fig. 4. Global involvement by cities (>5 investigations) and countries.

[124] showed that the building cooling demand in urban regions is, on average, 13 % greater than that in rural regions. More significantly, Tsoka et al. [123] revealed that neglecting UHI effects leads to a 21 % overestimation of heating and 22.4 % underestimation of cooling energy demand under future scenarios. The impact extends beyond energy consumption, as urban climate conditions can increase cooling energy demand by 19 % in air-conditioned buildings while raising indoor discomfort hours by 32 % in non-air-conditioned buildings [125]. Furthermore, microclimate can increase heating demand in dense urban areas due to reduced solar gains [88].

This persistent energy disparity between urban and rural buildings, combined with the increased risk of overheating in urban environments, reveals a fundamental limitation in current building thermal assessment methodologies. The challenge extends beyond mere temperature differences, encompassing complex interactions between urban morphology, building characteristics, and climate change effects. Future research must prioritize several key areas: developing integrated modeling approaches that capture UHI effects across different urban morphologies, creating standardized methods for incorporating microclimate data into building simulations, understanding the combined impacts of UHI and climate change on building performance, and establishing metrics that holistically assess both energy, carbon and overheating risks under future urban conditions. These advancements are essential for designing resilient and energy-efficient urban buildings that can effectively respond to the combined challenges of urbanization and climate change.

4.3. Beyond the average: Towards integrating extremes in energy simulations

Energy modeling weather data is typically based on 30 years of monthly average weather conditions. This practice, while providing a stable baseline, greatly underestimates the impact of extremes, including heatwaves and cold snaps [23,94]. This oversight is particularly concerning given the increased frequency and intensity of such events due to global warming.

The impact of extreme weather manifests in multiple, interconnected ways across the building energy system. Heatwaves create a dual challenge: they not only drive unprecedented peak cooling loads but simultaneously compromise power infrastructure by reducing transmission efficiency and generation capacity [126]. On the other hand, extreme cold events strain heating systems and electrical grids, a challenge that intensifies with the growing trend towards heating electrification [127].

Quantitative studies reveal the magnitude of this challenge: Hosseini et al. [94] found that during EWY in 2070–2099, cooling system operation hours increased dramatically from 530 h during typical days to 1860 h. Nik [32] found that using an ECY file increased heating demand by 29–40 % compared to a TDY file and by 42–54 % compared to average 30-year weather data. Similarly, Bell et al. [128] projected peak cooling demand increases of 24–35 % under extreme scenarios, while Zhai and Helman [129] forecast a 27 % rise in peak demand for U.S. campus buildings. Furthermore, there exists a significant discrepancy between modeled and actual building energy performance, with real-world commercial building consumption often exceeding predictions by 2–3 times [23,130]. These findings suggest that current design practices may severely underestimate future heating and cooling needs, potentially leading to widespread thermal discomfort and increased health risks during extreme events. The implications extend beyond individual buildings to energy power infrastructure. Tarroja et al. [127] demonstrated that future grid capacity needs may increase by up to 32 % due to heating electrification under climate change. The challenge is compounded during extreme cold events when heating demands peak precisely as renewable energy availability diminishes due to reduced solar resources. This temporal mismatch between peak demand and renewable energy availability presents a significant challenge for grid resilience and reliability.

These heatwaves and cold snaps pose a huge burden on the grid and could potentially lead to outages due to insufficient grid capacity. The integration of extreme weather considerations into building energy simulation is not merely a matter of improved accuracy for future-proof HVAC designs, but a crucial requirement for ensuring building resilience and occupant safety in a changing climate.

4.4. Scaling challenges: From building to district predictions

Climate change impacts manifest at both individual building and district scales, presenting a complex pattern of energy demand shifts. At the individual building level, representative buildings are designed to reflect the typical features and performance of larger building groups based on national surveys and databases. These prototype buildings include models from ASHRAE Standard [23,45,54,100,108,113,131–135] and other national templates [128,136,137], which are often employed in climate change studies. The response to climate change, however, varies significantly among different building types. Studies have revealed substantial disparities in energy changes under global warming, depending on building characteristics and thermal properties [131,132,138,139]. For instance, smaller buildings exhibit greater sensitivity due to their relatively higher proportion of envelope heat loss/gain compared to larger structures [132,140,141].

While building-level studies generally indicate a decrease in heating demand and an increase in cooling demand, the patterns become significantly more intricate when expanded to larger scales. At the neighborhood scale, studies like those by Moazami et al. [23] and Zhai and Helman [129] explored the complexity of district building energy performance. Unlike individual building simulations where data can be meticulously gathered and validated, district-wide assessments face significant challenges in data heterogeneity. This is due to the diversity of building types, vintages, use patterns, and thermal properties. These factors impose immense computational demands for accurate simulations at this scale.

City level analyses emphasize the difficulties of scaling up. These analyses may involve dynamic building stock models that account for factors such as demolition/renovation rate [142], as well as microclimate and interaction effects that current methods struggle to capture. For instance, trees and water features create interaction effects that can alter building energy performance.

National level analyses introduce additional layers of complexity, necessitating the consideration of broader socioeconomic and behavioral factors such as population growth, urbanization, lifestyle changes, the rebound effect and the increasing adoption of cooling equipment. These factors can substantially alter energy demand patterns, potentially leading to underestimation, amplification, or counterintuitive outcomes. For instance, anticipated heating savings from global warming might be significantly offset by population growth [74], challenging simplistic projections of future national energy demand.

The transition from individual buildings to district level thermal performance predictions under climate change introduces several formidable challenges. Addressing these requires advancements in data integration, computational methods, and interdisciplinary collaboration.

4.5. Oversimplification of building control systems and occupant behavior in simulations

Accurate building modeling and control systems are essential for addressing these challenges. Traditional building energy simulation tools often assume idealized control scenarios, such as perfectly tuned HVAC systems operating based on basic setpoint schedules. However, in practice, building controls can be poorly configured, override schedules may be used, and also the equipment performance can degrade over time [46]. For instance, Coefficient of Performance or Energy Efficiency

Ratio of cooling can decrease due to increased temperature as reinforced by [38,135,143]. These operational factors can significantly impact energy use in ways not captured by traditional simulations.

Occupant behavior observed in building performance simulation models is often characterized by a simplification of pre-defined static assumptions. However, this approach ignores the inherent stochastic and dynamic nature of occupant behavior [144]. The inefficient occupant behavior scenario led to a twofold rise in energy consumption relative to the standard scenario, while the most impactful climate change scenario resulted in a mere 15 % escalation in [145]. In addition, using fixed temperature setpoints in simulation may overlook occupant behavior, overestimate cooling needs, and underestimate people's ability to progressively adapt to global warming. There is considerable variability in both heating and cooling setpoints across different studies (Supplementary Material Table A.1). In the majority of studies utilizing the degree method, a base temperature of 18, 18.3 (65 °F), and 20 °C is commonly employed during the heating periods, while 18 and 26 °C are used during the cooling season. For simulation-based studies, setpoints of 20 and 26 °C are widely prevalent for heating and cooling, respectively, in [45,53,54,62,75,76,78,112,117,123,143,146–156]. There is no universal standard, and preferences may vary depending on factors such as locations [157,158], regulations [92], building type, room function [159], time [158,160], and occupant behavior.

In conclusion, the main issues in using simulation remain the consideration of the actual operation of building controls, the prediction of dynamic occupant behavior, possible control adaptations, and the incorporation of future intelligent control systems. Further research is needed to develop more robust control and modeling capabilities within building energy simulation tools.

4.6. Complexities in thermal comfort modeling under climate change scenarios

The assessment of thermal comfort under global warming presents significant challenges, as historical weather conditions fail to accurately represent the current and future risks of indoor overheating [161]. The reviewed literature (Supplementary Material Table A.2) examines both fixed and adaptive temperature thresholds used in evaluating thermal comfort and determining temperature setpoints. For example, Hao et al. [162] considered two methods for assessing indoor overheating levels: the fixed temperature based on CIBSE Guide A, and an adaptive thermal comfort model proposed in EN 15251. While fixed thresholds offer simplicity and standardization, they fail to capture the dynamic nature of human thermal adaptation such as clothing under global warming. Conversely, adaptive models, such as those proposed in EN 15251 and ASHRAE 55, attempt to account for this adaptability but introduce their own set of complexities and inconsistencies.

The quantification of thermal comfort through indicators such as discomfort hours, indoor overcooling degree (IOcD), and indoor overheating degree (IOhD) offers valuable insights but also reveals alarming trends. The projected increase in IOhD by 154–528 % by 2100, contrasted with a modest decrease in IOcD, suggests a significant shift towards overheating risks under climate change [107]. This imbalance raises questions about the adequacy of current building design and HVAC systems to maintain comfort in future climates. Moreover, the finding that the severity of overheating is more affected by climate change than its duration [161], challenges conventional approaches to thermal comfort management.

The lack of consistency in the approaches used to determine the mean or weighted outdoor air temperature (To) for acceptable comfort thresholds raises concerns about the comparability of the findings. While some studies utilize monthly mean temperatures [122,161,163–166], others consider temperatures from the previous three days [70], seven days [112,156], 7 to 30 days [50], or daily mean temperatures [167]. The reliance on various international standards, such as ASHRAE 55 [50,116,117,122,156,161,163–166,168–171], ISO 17772-1 [107], EN 16798–1 [62,112,118,172], EN 15251 [82,153,162,167,169,173,174], and CIBSE Guide A [61,162,175–178] for adaptive thermal comfort temperatures further complicates the issue. While these standards provide a common framework, they may overlook cultural, regional, seasonal, and building type variations, as well as occupant characteristics in thermal preferences.

The intersection between global warming and building thermal performance poses a formidable challenge to accurately predict and ensure occupant thermal comfort. Future research needs to take into account adaptive thermal comfort models, microclimates and climate extremes with global warming.

4.7. Variability in operational GHG emission trends due to regional energy mix

The operational carbon emissions from buildings under global warming present complex and often contradictory patterns. While a general trend of decreasing heating energy and increasing cooling energy is observed, the resulting operational GHG emissions vary significantly across regions, driven primarily by differences in energy sources, climate conditions, and the pace of transition to cleaner electricity generation.

The carbon intensity of energy sources emerges as a key factor shaping operational emissions patterns (Supplementary Material Table A.3). Natural gas, predominantly used for heating, shows a relatively consistent carbon intensity (~0.18 $kgCO_2/kWh$), while electricity exhibits a wide range (0.0013 to 1.39 $kgCO_2/kWh$). This disparity in carbon intensity creates distinct regional emission patterns that challenge predicting future building carbon emissions.

Analysis of the literature reveals three distinct emission trajectories: decreasing, increasing, and complex or consistent trends. In regions with increasingly clean electricity supplies or heating domains, emissions may show a decreasing trend. For example, in cold climates such as Copenhagen and Gothenburg, reduced heating demand favored carbon reduction [58]. Most notably, in regions where electricity is mainly generated from clean sources such as solar, wind and hydro, the increased cooling demand would have a small impact on GHG emissions [107,132,179]. This effect is exemplified in Canada, where Berardi and Jafarpur [132] found that reduced natural gas heating, rather than increased electrical cooling, drove emission reductions. This is owing to the difference between electricity (0.036 $kgCO_2/kWh$) and natural gas (0.180 $kgCO_2/kWh$) carbon intensities, setting it apart from findings in the UK [59] and China [180].

In contrast, regions with carbon-intensive electricity face increasing emission trajectories, particularly in areas with surging cooling demands [47,58,71,180–182]. This challenge is evident in the study [181] where winter heating savings (−12 % to −42 %) were overwhelmed by summer cooling increases (26 % to 70 %), resulting in net emission increases of 0.4 % to 18 %. Similarly, in developing countries like China [180,182], future projections indicate rising operational GHG emissions despite anticipated decreases in operational energy loads in certain cities [180].

The complexity of these patterns is further illustrated by regions showing non-linear trends. Ciancio et al. [58] identified cities like Cluj-Napoca and Prague experiencing initial emission decreases followed by post-2050 increases. Similarly, Kim et al. [183] found the total GHG emissions of the office building remained relatively consistent across all climate scenarios.

The effectiveness of emission reduction strategies, particularly heating electrification, varies significantly with regional electricity carbon intensity. Kolokotroni et al. [59] suggested that reducing cooling is more crucial for lowering GHG emissions in the UK, even in a heating-dominated climate, as electricity has a higher carbon intensity than natural gas. This may contrast with regions having cleaner electricity supplies, where increasing cooling has a negligible impact on carbon emissions. However, the potential rebound effect and peak demand

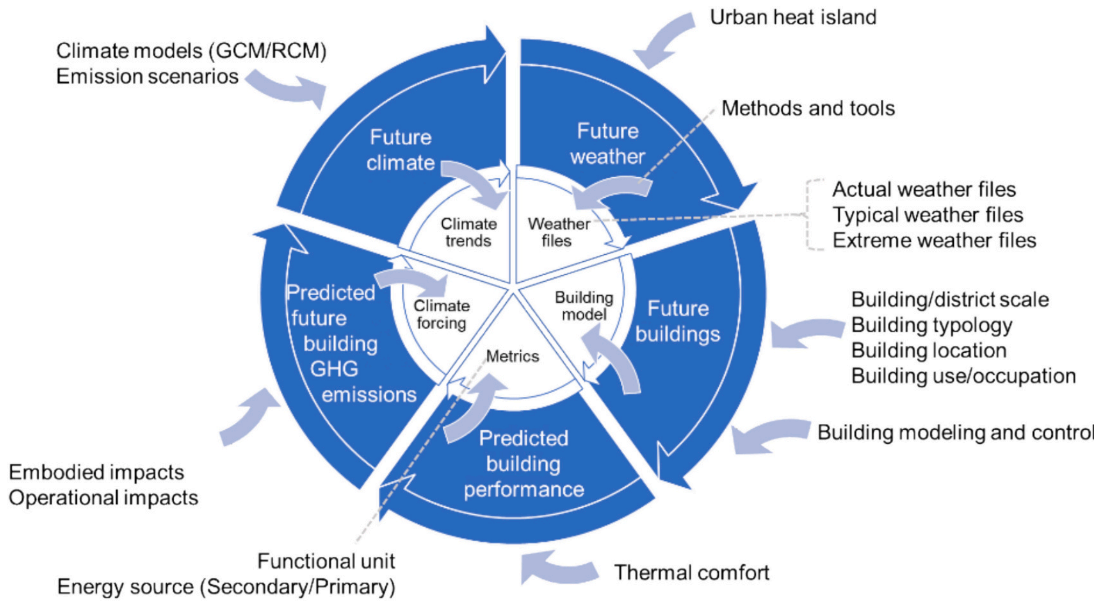

Fig. 5. Schematic overview of climate change and building interaction mechanisms and their abstraction in building science.

challenges warrant careful consideration in energy planning, even in regions with low-carbon electricity.

Building emission patterns are influenced by factors beyond energy mix considerations. Additional drivers include embodied emissions in building materials, population growth, and increasing cooling adoption. These factors can potentially offset efficiency gains and complicate emission reduction efforts, especially at larger district scales. This multifaceted challenge necessitates comprehensive strategies that address both direct emissions and indirect factors while remaining adaptable to regional contexts and evolving energy systems.

5. Addressing the self-reinforcing loop and methodological inconsistencies

Rising temperatures, fluctuating humidity and radiation driven by global warming influence building energy demands, while buildings contribute significantly to GHG emissions through both material use and operational energy consumption, further exacerbating climate change. This systematic review identifies a complex self-reinforcing loop between climate change and building energy performance (Fig. 5). The diagram divides this intricate interaction into several key components: future climate (influenced by emission scenarios and climate models), future weather (incorporating typical weather, extremes and UHI), future buildings (considering scale, typology, location, and use/occupation), predicted building performance (affected by functional unit and thermal comfort considerations), and predicted future building GHG emissions (impacted by the embodied and operational impacts). At the core of the diagram, building science abstracts these components through weather files (representing future weather), building models (representing the built environment), performance metrics (capturing overall building performance), and climate forcing (linking climate trends to building impacts). This comprehensive visualization serves to illustrate the multifaceted challenges inherent in predicting and mitigating the impacts of global warming on building performance. To break this self-reinforcing cycle, effective mitigation and adaptation measures are needed. These include passive, active and renewable energy conservation measures under climate change, which have been extensively discussed in our previous work [184].

To address the limitations associated with outdated weather files and climate scenarios, this study proposes the following roadmap for transitioning to the latest climate models and enhancing predictive accuracy:

1. **Adoption of state-of-the-art scenarios:** Prioritize the use of latest climate scenarios in all new studies. Urgently develop and validate weather files based on these scenarios for diverse global locations. The newly developed *Future Weather Generator* tool, which provides SSP scenarios, requires rigorous validation by the building science community.
2. **Integration of advanced downscaling techniques:** Combine the latest climate models and scenarios with sophisticated downscaling methods. This integration should aim to enable more accurate capture of local climate variations and extreme weather events.
3. **Standardization of climate data sources:** Establish a centralized repository of future climate data, specifically formatted for building simulations. This initiative could be coordinated through international organizations such as the International Building Performance Simulation Association (IBPSA) to facilitate widespread adoption and standardization.
4. **Regular updates to simulation software and weather file platforms:** Major building simulation software providers should be encouraged to incorporate the latest climate weather data and develop user-friendly interfaces for importing and utilizing this data, such as in EnergyPlus weather websites and Ladybug tools.
5. **Enhanced training and knowledge dissemination:** Develop training programs and guidelines to educate researchers on the proper use of the latest climate scenarios in building simulations. Particularly, life cycle assessment (LCA) researchers should be educated on incorporating future climate weather files into dynamic LCA methodologies.

Furthermore, the methodological inconsistencies across studies hinder reliable comparisons and potentially undermine the accuracy of predicting future building energy [10]. These inconsistencies manifest in, but are not limited to, several key areas:

1. **Future weather generation:** variations in methods (e.g., morphing, stochastic models, dynamical downscaling) and tools, choice of original weather files, selection of GCM/RCM models, time periods considered, microclimates and extremes integrated, and climate scenarios chosen.

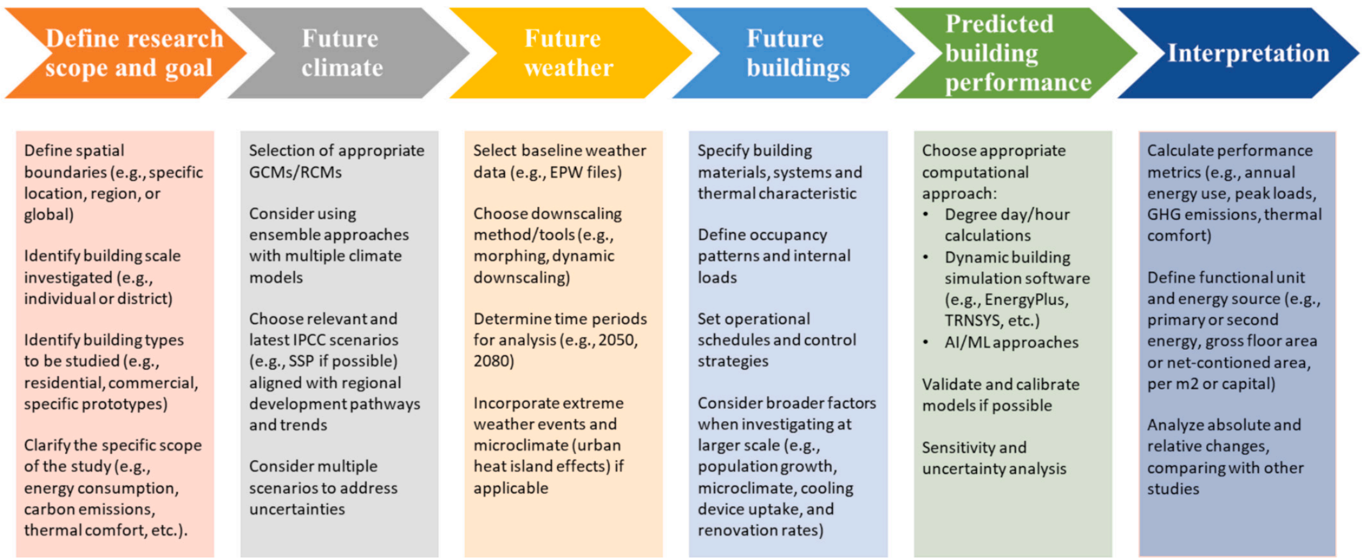

Fig. 6. Step-by-step procedure for investigating future building thermal performance.

2. **Building simulations:** discrepancies in simulation methods (e.g., degree day, hourly simulations, AI/ML-based approaches), modeling of occupant behavior dynamics, simulation timespan, building modeling and control, and HVAC efficiency.
3. **Results reporting:** lack of standardization in performance metrics and energy source considerations (secondary or primary energy).

Future research should prioritize addressing methodological inconsistencies and working towards the standardization of methods for guiding researchers to investigate the impact of climate change on building energy performance. The goal is to preserve the value of context-specific investigations while enhancing the reliability and comparability of studies. The protocol can be based on and developed further on Fig. 6, helping researchers to check or follow to ensure no critical aspects are overlooked in their methodologies. Thereby, ensuring future research encompasses a clear definition of the research scope and goal, detailed documentation of data sources, specifying methods/tools for generating future weather files, explicit description of simulation methods, standardized result reporting, and uncertainty analysis. When faced with data gaps or context-specific challenges, researchers can follow protocols or standardized approaches to fill these gaps.

6. Conclusion and outlook

This systematic review focuses on the impact of climate change on building energy simulation, analyzing 212 peer-reviewed articles comprehensively. The past two decades have witnessed a significant global rise in this area, with a continued surge over the last five years.

The current literature predominantly relies on the A2 scenario from the Third Assessment Report, with less emphasis on the latest SSP scenarios. This trend underscores the urgent need to adopt more up-to-date climate data and scenarios for building performance analysis. Morphing emerged as the most popular method, and CCWorldWeatherGen, Weathershift, and Meteonorm were the top three widely used tools. Notably, these tools that use outdated data are either commercial or based on third-party commercial software. As a response, a new morphing tool, the *Future Weather Generator* (https://adai.pt/future-weather-generator/), has been developed, utilizing more recent and finer grid resolution for the latest scenarios. However, further validation of its accuracy and reliability is needed.

The review identifies several key challenges and future research directions in predicting the impact of climate change on building energy performance.

1. **Addressing geographical research disparities and data quality:** Current research shows significant bias towards Europe, North America, and parts of Asia, neglecting vulnerable regions such as Africa, South America, and polar areas. Future research must address this geographical imbalance and ensure the use of up-to-date climate scenarios to improve global applicability and accuracy of findings.
2. **Urban heat island and extreme weather integration:** Current methods and tools often fail to adequately account for urban microclimates, particularly the urban heat island effect, and extreme weather events. This omission can result in a significant underestimation of energy demands and system stress. Future research should prioritize integrating microclimate effects and extreme weather scenarios into building energy simulations and HVAC system design.
3. **Scaling from building to district level:** A fundamental challenge lies in scaling predictions from individual buildings to district-level assessments due to data heterogeneity. Moreover, socioeconomic and behavioral factors, including population growth, urbanization, the rebound effect and the increasing adoption of cooling devices, become more prominent at larger scales. Future research must develop advanced methodologies capable of bridging this gap for district-level energy predictions.
4. **Enhancing building control systems and occupant behavior in modeling:** Current simulation tools often employ idealized assumptions that fail to capture real-world operational dynamics. In practice, building controls are frequently misconfigured, schedules are overridden, and equipment performance degrades over time. More advanced models that can forecast dynamic occupant behavior, potential control adaptations, and the integration of future intelligent control systems are needed.
5. **Interconnected challenges on thermal comfort and carbon emissions:** Thermal comfort assessment under global warming demands adaptive models that reflect evolving occupant expectations and behaviors. Simultaneously, the impact on building-related carbon emissions fluctuates widely due to regional energy mixes. This interplay creates a cascading effect where improperly managed pursuit of thermal comfort can strain energy systems, potentially exacerbating the very environmental impacts buildings aim to mitigate. Future research needs to address these interconnected aspects, balancing human well-being, energy efficiency, and environmental sustainability in the face of a warming climate.

In conclusion, this review underscores the existence of a self-reinforcing loop between climate change and the building sector. Increased energy consumption, if not met by clean energy sources, leads to higher carbon emissions, thereby worsening climate change. While significant progress has been made in understanding impacts, significant barriers remain. A critical barrier identified is the lack of standardization in methodologies, particularly in weather file generation, simulation, and results reporting. This inconsistency significantly hinders reliable comparisons across studies and regions. The proposed protocol aims to enhance the reliability and comparability of studies while allowing for necessary context-specific investigations. This looping process underscores the urgent need for an integrated approach and interdisciplinary collaboration combining building science, climate science, and urban planning to break this vicious cycle. Enhancing resilience requires the integration of energy-efficient design at both the building and district levels, the promotion of carbon-neutral energy sources, and the implementation of effective energy conservation measures.

CRediT authorship contribution statement

Zhuocheng Duan: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Pieter de Wilde:** Writing – review & editing, Visualization. **Shady Attia:** Writing – review & editing. **Jian Zuo:** Writing – review & editing, Supervision.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2025.125331.

Data availability

No data was used for the research described in the article.

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