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Citation for the original published paper (version of record):
Manfren, M., James, P., Chater, M. et al (2026). A multi-dimensional approach to thermal resilience for UK schools: quantifying cognitive,
comfort and heat strain impacts due to overheating. Energy and Buildings, 358.
http://dx.doi.org/10.1016/j.enbuild.2026.117164

Energy & Buildings 358 (2026) 117164

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

A multi-dimensional approach to thermal resilience for UK schools: quantifying cognitive, comfort and heat strain impacts due to overheating ☆

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ARTICLE INFO

Keywords:
Overheating risk
School buildings
Climate change impacts
Cognitive performance
Thermal comfort
Interpretability
Thermal resilience

ABSTRACT

Overheating in school buildings poses a significant threat to pupils' learning attainment, comfort and health, a risk expected to intensify with climate change. This study conducted a regional, building stock-scale assessment for Hampshire, United Kingdom, encompassing over 500 maintained schools and nearly 9,000 classrooms. Representative schools (10 buildings, 60 classrooms) were selected from a high-resolution inventory and monitored from 2022 to 2023. Six heatwave events were recorded during monitoring, including record temperatures in 2022. Overheating risk was quantified in the buildings using three metrics: cognitive performance, adaptive comfort based on BB101 guidelines and heat strain based on Gagge's model. The risk criteria were then incorporated into an interpretable data-driven workflow using classroom data, building stock inventory data, and climate projections. This method is used to estimate classroom-level overheating risk and thermal resilience across Hampshire schools. A medium-to-high impact on cognitive function is projected in 66% of classrooms at present, rising to 92% (the large majority of classrooms without air conditioning) by 2050 without targeted interventions. By 2050, heat strain is expected to increase from 6% to 10% of classrooms and BB101 thermal comfort limits exceedance from 50% to 76%. Overheating risk is highest in lightweight, single-sided naturally ventilated classrooms like SCOLA with high glazing ratios and limited solar control. The transferable workflow developed can bridge strategic school-estate planning for local authorities and national overheating risk mitigation and adaptation policy.

1. Introduction

Climate change is driving increased heatwave frequency, intensity, and duration across the UK, with surface temperatures exceeding 39°C for the first time in July 2022, severely impacting the education sector. The Met Office's "State of the UK Climate in 2024" [1] reports steady warming since the 1980s, with daily temperature extremes doubling, trebling, and quadrupling for 5°C, 8°C, and 10°C anomalies respectively in 2015–2024 versus 1961–1990. School buildings are particularly vulnerable environments due to their high occupancy densities and the physiological susceptibility of children to heat stress. Children have reduced thermoregulatory capacity compared to adults, making them more exposed to heat-related issues [2]. The Department for Education (DfE) predicts that by 2100, extreme heat events will render teaching unreasonable for 8 days annually, with general warming causing 12 days of learning loss without adaptation [3].

☆ This article is part of a special issue entitled: 'Rethinking Resilience' published in Energy & Buildings.

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https://doi.org/10.1016/j.enbuild.2026.117164
Received 8 December 2025; Received in revised form 5 February 2026; Accepted 12 February 2026
Available online 15 February 2026

Furthermore, research consistently shows that cognitive performance deteriorates once indoor operative temperature surpasses certain thresholds [4], thereby impacting educational attainment. For these reasons, overheating is thus not merely a thermal comfort issue, but a critical matter of educational outcomes and health for the young population. Most UK classrooms are not designed and equipped with mechanical cooling, relying predominantly on passive measures to maintain safe, educationally conducive conditions in the summer and shoulder seasons. 81% of the school building stock in England was constructed prior to 1976 [5]. Current statutory guidance (BB101) [6] focuses on thermal comfort and energy performance but omits cognitive performance or health thresholds, lacking absolute maximum temperatures for learning safety. Therefore, schools may meet BB101 criteria while experiencing temperatures that reduce cognitive performance. The DfE Net-Zero Strategy similarly requires integration of overheating risk mitigation [7]. Overheating risk quantification requires multi-dimensional assessment across a heterogeneous UK school stock ranging from high-thermal-mass Victorian structures to modern lightweight buildings. Notably, a significant proportion of post-war schools used lightweight construction methods, making them particularly susceptible to overheating. The last system-build SCOLA-type schools were built in 1979. Regional assessment methodologies have often relied on archetypes or detailed, computationally intensive, simulations. These methods, however, present limitations when it comes to assessing each classroom individually and considering local microclimate effects. This reduces the ability to capture the full heterogeneity of conditions within building stocks and implement precise, informed actions.

This study addresses these critical knowledge and policy gaps by focusing on Hampshire County Council (HCC), England's largest Local Authority Responsible Body, which maintains over 500 schools across diverse contexts. HCC recognises overheating as a pressing issue and has encouraged the creation of an overheating risk assessment methodology that could be integrated into a long-term strategy for estate management and climate adaptation. To address these challenges, this study seeks to:

- Propose a transferable data-driven workflow for overheating risk assessment.
- Quantify current and future overheating risk across the Hampshire school stock.
- Identify the main determinants of overheating risk at the building and room level.
- Propose indications for further actions, in line with policy.

This study is framed around a series of explicit research questions: (RQ1) How can overheating risk in schools be quantified beyond thermal comfort limits to include cognitive performance and health impacts? (RQ2) What are the relationships between indoor temperatures, outdoor conditions, and building characteristics in free-running classrooms during heatwave events? (RQ3) How can data-driven methods calibrated against empirical monitoring data enable room-by-room risk assessment at regional scale based on similarity principle? (RQ4) How does a new weighted performance index (combining cognitive, comfort and health risk) perform compared to BB101 comfort assessment, under present and future climates?

These research questions guide the hypothesis that a physics-informed, data-driven workflow combining monitored data with building stock characteristics can identify classrooms at risk of cognitive, comfort, and health impacts. The identification of risk can then inform targeted intervention strategies, bridging strategic school-estate planning and national overheating risk mitigation and adaptation policy. Going forward, this approach will enable providers such as councils to undertake classroom level assessment of mitigation measures. The novelty of this work is twofold: (1) the integration of cognitive performance and health risk alongside thermal comfort in a unified weighted overheating risk index; and (2) an empirically grounded, data-driven workflow that delivers room-by-room assessment at regional scale under data scarcity constraints and without requiring full-building simulation for each classroom.

2. Background and literature review

This section critically analyses the existing knowledge base concerning overheating risk in school buildings, focusing on the crucial elements required to develop a comprehensive risk assessment framework. It examines the limitations of current thermal comfort guidelines (Section 2.1), the diverse nature of the UK school building stock, the necessity for granular, room-by-room assessments (Section 2.2), and, finally, the evolution of scalable, data-driven, and physics-informed modelling approaches for future risk projections (Section 2.3).

2.1. *Overheating risk assessment beyond thermal comfort limits*

Overheating in school buildings is an escalating concern, exacerbated by climate change, posing significant threats that extend beyond mere thermal comfort to impact pupil health, learning outcomes, and overall well-being. The UK Health Security Agency provides guidance to teachers and other educational professionals for looking after children during hot weather. This includes consideration of heat stress, heat exhaustion and heatstroke in both an outdoor and indoor environments [8]. The provision of a comprehensive overheating risk assessment in these environments necessitates a multi-dimensional approach, considering not only thermal comfort but also cognitive performance and direct health risks (heat strain).

2.1.1. *Cognitive performance and comfort in classrooms*

Ensuring thermal comfort [9,10] has a significant impact on children's performance and health, particularly for those aged 7–11 years old [11–13]. Current thermal comfort guidelines, such as the UK's Building Bulletin 101 (BB101), primarily assist school designers in evaluating whether a classroom is at risk of overheating, without detailing the percentage of students who may be affected. These guidelines, including BS EN 15251:2007 [14], are predominantly based on adult perceptions and preferences [13]. However, studies consistently demonstrate that children's threshold comfort temperatures are lower than adults', with children preferring temperatures up to 3 K cooler [13,15–18]. For example, studies suggest children's comfort temperatures (20.9°C non-heating, 20.2°C heating seasons) are 1.9–2.8 K cooler than BS EN 15251 predictions due to higher metabolic rates, different clothing, and limited adaptation. Consequently, designing solely to adult-based thresholds risks children's thermal discomfort and potential building underperformance. For instance, even when the indoor temperature aligns with the adult comfort temperature, a typical UK primary school classroom shows a 16% likelihood of children being overheated, significantly higher than the 7% for adults in a comparable office setting [13]. Overall, approximately 15% of children in primary schools were found to be overheated during both non-heating and heating seasons [18].

High temperatures directly impair cognitive performance and learning outcomes [4], with measurable decline above 25°C [19] manifesting as reduced reaction time, processing speed, and accuracy. Temperature reductions from 25°C to 20°C improve task speed by 2% per 1°C [12] and academic performance by 2–4% per 1°C [20]. Inadequate ventilation, indicated by elevated CO_2, impairs cognitive functions [21], with low ventilation reducing attention, vigilance, memory, and concentration [21,22]. Classroom CO_2 often exceeds 3000 ppm [23], with evidence of impaired decision-making above 2500 ppm [24].

2.1.2. *Upper thermal comfort limits and heat strain*

Extreme heat introduces direct physiological health risk through heat strain [25], with children particularly vulnerable due to reduced thermoregulatory capacity, higher surface-area-to-mass ratio, elevated metabolic rates, and lower sweating rates. For healthy adults, a 35°C wet-bulb temperature is considered an upper limit of acceptability, a condition that can be exacerbated by high relative humidity. Experimental exposures to 35°C have been shown to significantly increase core temperature, heart rate, and sweat rate in subjects, leading to uncomfortable warmth, diminished perceived air quality perception, increased sleepiness, and acute symptoms such as dry eyes, fatigue, and dizziness [2]. These physiological changes indicate elevated stress, and while such conditions are typically not considered a "risk to life" for healthy adults, they pose a notable risk factor for vulnerable populations. Heat strain calculations are reported in ISO 7933:2023 [26], discussed in recent research [25] and implemented in calculation tools [27].

2.1.3. Thermal comfort indicators used in BB101 guidelines

BB101 guidelines [6], despite incorporating adaptive comfort models, omit cognitive performance degradation and health outcomes, indicating a policy gap. The BB101 (2018 edition) employs an adaptive thermal comfort methodology, derived from BS EN 15251:2007 [14], for assessing overheating risk in "free-running" buildings (those without active heating or cooling). This assessment typically applies to the period from 1st May to 30th September, between 09:00 and 16:00, Monday to Friday, assuming full occupancy even during holidays for future-proofing against climate change. The three comfort indicators used to evaluate overheating risk within BB101 are:

1. **Hours of Exceedance (H_e):** Occupied hours with operative temperature (T_{op}) $\geq$ 1 K above maximum acceptable limit (T_{max}), which should not exceed **40 h.**
2. **Daily Weighted Exceedance (W_e):** Daily weighted exceedance (W_e), which should be less than or equal to **6** in any one day. The weighting factor (w_f) is equal to the temperature difference ($\Delta T = T_{op} - T_{max}$) if $\Delta T > 0$, increasing with the degree of exceedance.
3. **Upper Limit Temperature (T_{upp}):** Absolute maximum value for the indoor operative temperature, stating that the difference (ΔT) between the operative temperature (T_{op}) and the limiting maximum acceptable temperature (T_{max}) shall **not exceed 4 K**.

T_{max} derives from comfort temperature ($T_{comf} = 0.33\ T_{rm} + 18.8$°C, where T_{rm} is the exponentially weighted running mean outdoor temperature) plus acceptable range (e.g., +3°C for Category II: $T_{max} = 0.33\ T_{rm} + 21.8$°C). BS EN 16798–1:2019 [28] supersedes BS EN 15251:2007 [14], retaining the same comfort formulation and category structure with minor changes: 1 K lower comfort boundary and extended outdoor temperature range (from 10°C). As this study focuses on overheating criteria that are governed by the upper comfort boundary and BB101′s three-part test, the practical effect of this transition on the reported exceedance results is limited; nevertheless, EN 16798–1 is referenced in the methodology to align the modelling with current standardisation while maintaining BB101 comparability.

2.2. UK school stock performance characterisation and the need for granular assessment

The UK's Net Zero 2050 [29] commitment requires addressing schools, which account for 2% of national energy consumption [30] and 15% of public sector emissions [31]. The Department for Education (DfE) is actively supporting this transition and there is a large potential for emissions reduction, particularly by transitioning from gas to electric heating, driven by projected reductions in grid carbon intensity and the higher efficiency of heat pumps. Net-zero conversion requires an estimated £14 billion plus maintenance costs [32]. The UK's school building stock is highly heterogeneous, reflecting successive construction waves and varied designs, which further complicates performance assessment and retrofit strategies. An analysis of 150 energy audits [33] reveals dominant thermal archetypes: Pre-1945 heavyweight masonry schools with higher ceilings show lower peak temperatures (varying with refurbishment); post-war system-builds (SCOLA/CLASP) are lightweight with high glazing and limited solar control, exhibiting greater overheating risk; recent buildings show wider variability from differing ventilation strategies, layouts and retrofit solutions. [33] More recent buildings tend to consume less energy for heating but more electricity, possibly due to increased Information and Communication Technology (ICT) use. Also, an increase can be determined by mechanical ventilation systems but compensated by heat recovery [34].

Further, innovative wood-based constructions are increasingly viewed as ideal applications for schools due to their energy efficiency and short construction time [35], but the actual thermal inertia should be carefully considered. Importantly, maintenance and operational status (e.g., operable windows, functional shading, and ventilation pathways) can shift performance substantially within each archetype, motivating the room-level assessment adopted in this work.

To evaluate performance at scale, the Modelling Platform for Schools (MPS) [36] has been developed as an automated framework to generate one-by-one dynamic thermal models for school buildings in England. MPS integrates diverse national data sources, including Edubase, Property Data Survey Programme (PDSP), Ordnance Survey (OS) GIS data, and Display Energy Certificates (DEC), to create EnergyPlus simulation models. Initial evaluations showed MPS could automatically generate models for approximately 15,245 schools, with around 50% achieving high reliability and 64% exhibiting excellent geometric fidelity. However, MPS applicability is limited by data quality, with 25% of models showing low confidence [36]. Granular, room-by-room assessment remains critical as archetypal models fail to capture diversity within buildings and large-scale simulations are computationally intensive. Classroom-level variations (orientation, glazing, ventilation) create vastly different risks, requiring detailed analysis to identify vulnerabilities and prioritise interventions. Crucially, overheating risk must be a primary consideration in design and operation. Children are highly vulnerable to elevated indoor temperatures and air pollutants, which can negatively impact their cognitive performance and comfort, as discussed in Section 2.1. Improvements to building fabric airtightness and thermal insulation, while reducing heating demand, can paradoxically exacerbate indoor overheating. Post-1976 building archetypes, despite being better insulated, are more susceptible to overheating, illustrating the inherent conflict between energy efficiency and overheating prevention [7]. This constitutes a problem to be considered for the evolution of the built environment.

2.3. Interpretable and physics-informed data-driven methods for building performance characterisation

A combination of on-site measurements, simulation and qualitative methods (e.g., interviews and surveys) is often the more effective way to understand thermal resilience and adaptation issues [37]; overheating risk assessment methods need to be tailored for the specific use [38].

A growing body of literature in building science leverages regression models to evaluate the thermal response and energy performance of buildings as a function of external conditions and inherent building characteristics. This approach supports critical decisions in design and retrofit for improved energy efficiency and indoor comfort.

Dawkins et al. [39], use linear regression relating outdoor daily mean temperature to indoor daily maximum, creating vulnerability functions to assess risk and prioritise adaptation in distributed school assets. Ghiaus [40,41] investigated free-running temperature (indoor temperature without HVAC), expressed as a linear function of outdoor temperature and gains, characterizing thermal response to assess HVAC suitability [40] and free cooling potential [42]. Ventilative cooling effectiveness is measured via degree-hour distributions from free-running temperature, indicating energy savings. Artmann et al. [43] and Belleri et al. [44] evaluate climatic potential for night ventilation based on ambient-structure temperature differences. Their Ventilative Cooling (VC) tool [44] assumes variable temperature or single-zone models to estimate airflow rates and offsettable gains, useful for early design despite dynamic simplifications. The VC methodology is standardized in BS EN ISO 52016-1:2017 [45] and developed via CEN/TC 156/WG21, integrating BS EN 16798-1:2019 [28] adaptive comfort criteria, recalled in Section 2.1. This integration of physics-based principles and statistical modelling extends to multi-scale applications, as demonstrated by Tronchin et al. (2016) [46]. They employ regression models informed by lumped thermo-physical properties and energy balance principles to evaluate building performance from the component to the system level. Their work highlights how regression coefficients can gain physical meaning when models are appropriately formulated, enabling a more insightful analysis of building characteristics and performance benchmarks, while retaining model interpretability [47]. Similar principles have been used by Botti et al. [48], in the context of statistical surrogate modelling, and by Baasch et al. [49] and Liguori et al. [50], in the context of physics-informed machine learning. For large stocks, Pistore et al. [51] integrate clustering and regression to group similar buildings for targeted retrofit, enabling strategic decision-making at scale.

Further, the combination of clustering and regression techniques has been used also by Westermann et al. [52], to identify building characteristics at large scale. Overall, as discussed in recent papers dealing with best practice for simulation-based research [53] and use of AI/ML tools [54], it is important to clarify the frame of the study, its limitation and uncertainties, and document its logic. In this sense, the techniques presented earlier (i.e., regression to remove weather dependence and use of lumped physical quantities to obtain thermal response estimates) represent the foundation for a methodology meant to be applied for building stock analysis, tailored to free-running temperatures and free/ventilative cooling potential estimation. Therefore, the workflow proposed in this research shares similarities with prior overheating risk assessment approaches in terms of the use of data-driven techniques (statistical/ML) for analysis but differs with respect to the direct use of measured heatwave events data and the room-by-room assessment. A synthetic comparison is reported in Table 1.

Finally, the study discussed in this paper can be placed within the broader framework of methods for building performance assessment during heat waves [55] and thermal resilience [37]. Table 2 presents a synthetic comparison with the papers reviewed in the two aforementioned papers.

3. Methods and tools

The methods and tools developed in this research aim to address the issues discussed in Section 2. The definition of an overheating risk index that extends beyond pure comfort to encompass cognitive performance and health risk (heat strain), is presented in Section 3.1. The description of a monitoring programme capable of yielding field data regarding classroom behaviour throughout the summer season and heatwave events, along with data for the complete school stock, is addressed in Section 3.2. Finally, the development of a modelling workflow that employs the overheating risk index and the gathered data to assess overheating risk at the building stock level, is described in Section 3.3.

3.1. Overheating risk index definition and formulation

The overheating risk score introduced in this study relies on five performance indicators: one for cognitive performance [19], three for comfort (derived from BB101 [6]), and one for health risk associated with heat strain [25]. The indicators encompass the essential domains (cognitive, comfort, and health) outlined in Section 2.1 and summarised in Table 3; they are first computed individually and then converted into scores between 0 and 100. A value of 0 signifies negligible risk, whereas 100 denotes a high risk. The risk scores in the range 0–100 can be considered individually or aggregated with weights. Equal weighting has been implemented at this stage, but this may change depending on the choice of assigning relatively more importance to one indicator and its corresponding risk score.

For the sake of consistency, the indicators are calculated in accordance with BB101 guidelines for school hours, from 09:00 to 16:00 on weekdays (excluding weekends and holidays), from the 1st of May to the 30th of September.

3.1.1. Cognitive risk index formulation

This metric assesses temperature-related learning impairment using a 25°C operative temperature threshold for cognitive impact onset, acknowledging this may be prudential [19]; lower upper threshold temperature for optimal cognition [4] may be considered. A linear cognitive performance decrease (corresponding to a risk increase) was assumed up to the adaptive thermal comfort limit. Alternative decrease patterns [4] (e.g., Hancock and Vasmatzidis's inverted-U [56], extended-U models [57,58]) may be considered.

Finally, a fraction of sub-optimal hours considered as the upper limit needs to be established, in this case 10% of operating hours (0.10). A score of 0 (no risk) corresponds to 0% of hours above the threshold temperature, 100 would mean 10% or more of BB101 hours would have compromised cognitive learning. The cognitive performance risk score S_{cog} is computed as follows:

- **Temperature threshold:** Set upper limit for optimal learning at $T_{\text{cog,thresh}} = 25^{\circ}C$
- **Sub-optimal hours threshold:** Set maximum fraction of sub-optimal hours threshold $f_{\text{subopt,max}} = 0.1$.
- **Score calculation:** For each hour h where $T_{in,h} > T_{\text{cog,thresh}}$, a linear penalty is applied, such that a value of 0 implies all hours below threshold; the score linearly scales up to 100 when the temperature reaches the adaptive comfort upper limit used in BB101 Indicator 2, discussed in Section 3.1.2.
- **Averaging:** The hourly scores are averaged across the reference BB101 period.
- **Aggregation:** Final cognitive risk score is 0 for no sub-optimal hours, 100 if ≥ 10% of hours (0.10) exceed threshold.

$$S_{\text{cog}} = \begin{cases} 0 & \text{if } f_{\text{subopt}} = 0 \\ 100 \cdot \dfrac{f_{\text{subopt}}}{0.10} & \text{if } 0 < f_{\text{subopt}} < 0.10 \\ 100 & \text{if } f_{\text{subopt}} \geq 0.10 \end{cases}$$

Table 1
Overheating risk assessment approaches comparison.

Study	Target	Granularity/scale	Methods and tools	Outputs
Gul et al. (2012) [38]	Domestic & non-domestic buildings (design)	Zone/building	Simulation and regression-based climate response tool	Overheating risk indicators and probabilities
Botti et al. (2022) [48]	Domestic buildings (early stage design	Dwelling	Parametric simulations and statistical/ML meta-models.	Overheating metrics and predictors
Dawkins et al. (2024) [39]	Schools (risk assessment)	Classroom archetypes, national scale	Physics-based stock simulations to derive vulnerability and spatial climate projections.	Risk frequency and prioritisation maps
Present research	Schools (risk assessment)	Classrooms, regional scale	Measured data, regression and physics-informed similarity calculations	Cognitive, BB101 thermal comfort, heat strain, weighted aggregated risk

Table 2
Building typology, granularity, target population and methodology comparison with papers on thermal resilience and performance during heat waves.

Feature	Typical approaches	Present research approach
Building typology	Primarily **residential** and **offices**.	**Educational** (Schools/Classrooms).
Spatial granularity	Often **archetypal or building-level**; large-scale studies frequently lack disaggregated building-level analysis.	**Room-level (disaggregated):** Individual assessment of ~ 9,000 classrooms.
Target population	**Healthy adults**: Most comfort models used in literature still center on this demographic.	**Children**: Explicitly addresses reduced thermoregulatory capacity and cognitive vulnerability of students.
Methods and tools	Primarily **Building Performance Simulation (BPS)** or pure **climatological detection** using fixed/relative thresholds.	**Hybrid Physical-Statistical**: Combines monitoring, regression-based weather normalization, and K-Nearest Neighbour (KNN) for similarity-based interpolation.
Role of Monitoring	**Validation and testing**: Measurements are often used for post-occupancy evaluation or small case studies rather than as the primary engine for regional stock modelling.	**Empirical Foundation**: Monitoring data from 60 classrooms during record heatwaves (2022–2023) is used to calibrate the entire stock assessment.

Table 3
Indicators used for individual and weighted overheating risk index definition and score attribution.

N.	Domain	Indicator	Reference
1	Cognitive	Cognitive-performance reduction	Wargocki et al. [4]
2	Comfort	BB101 "Threshold hours violation"	BB101 [6]
3	Comfort	BB101 "Daily exceedance"	BB101 [6]
4	Comfort	BB101 "Upper absolute temperature limit"	BB101 [6]
5	Health	Heat-strain threshold	Gagge's model [25], CBE Comfort Tool [65]

where f_{subopt} = fraction of occupied hours > $T_{\text{cog,thresh}}$. As explained earlier, the number of sub-optimal hours is set to 10% (0.10), but this assumption may be revised based on additional evidence regarding cognitive performance loss.

3.1.2. Comfort risk index formulation

This metric aligns with the comfort requirements established in BB101 guidelines, which used a three-part test derived from CIBSE Guide A and BS EN 16798 [28] adaptive comfort model. The comfort requirements are summarised in Table 4 and related to the risk score attribution, explained more in detail later.

The BB101 comfort risk score 1 $S_{BB101,1}$ (upper comfort threshold violation hours) is computed as follows:

- **Definition:** Total hours exceeding H the adaptive comfort temperature ($T_{\text{ac,upp}}$), as per BB101.
- **Scoring:** 0 for 0 h of violation; 100 for ≥ 40 hours.

$$S_{\text{BB101,1}} = \begin{cases} 0 & \text{for } H \leq 0 \\ 100 \cdot \dfrac{H}{40} & \text{for } 0 < H \leq 40 \\ 100 & \text{for } H > 40 \end{cases}$$

where H = hours above $T_{\text{ac,upp}}$, set in BB101 to 40 h.

The BB101 comfort risk score 2 $S_{BB101,2}$ (degree-hours, daily max exceedance).

Table 4
Indicators used for the comfort definition according to BB101 guidelines.

N.	BB101 indicator	Risk score attribution
1	**Threshold hours**: total hours with $T_{\text{op}} > T_{\text{comf}}$.	0 if 0 h; 100 if > 40 h (linear in- between)
2	**Daily weighted exceedance**: maximum daily degree- hours above T_{comf}.	0 if 0 Kh; 100 if > 6 Kh (linear)
3	**Upper absolute limit**: $T_{\text{op}} > T_{\text{comf}} + 4$ K.	0 if 0 h; 100 immediately if > 0 h

- **Definition:** Maximum daily exceedance D over BB101 adaptive comfort limit, in degree-hours.
- **Scoring:** 0 for 0 degree-hours; 100 for > 6 degree-hours.

$$S_{\text{BB101,2}} = \begin{cases} 0 & \text{if } D = 0 \\ 100 \cdot \dfrac{D}{6} & \text{if } 0 < D \leq 6 \\ 100 & \text{if } D > 6 \end{cases}$$

where D = maximum daily degree-hours, set in BB101 to 6 degree-hours.

The BB101 comfort risk score 3 $S_{BB101,3}$ (upper temperature limit) is computed as follows:

- **Definition:** Hours (H) above a fixed upper threshold ($T_{\text{comf,neutral}} + 4\,K$)), using the adaptive comfort approach.
- **Scoring:** Binary—0 for 0 h; 100 for > 0 h.

$$S_{\text{BB101,3}} = \begin{cases} 0 & \text{if } H = 0 \\ 100 & \text{if } H > 0 \end{cases}$$

To assess the aggregate impact on comfort, the final comfort risk index is the weighted sum of the previously reported individual scores.

3.1.3. Heat strain risk index formulation

This metric captures dangerous heat exposure per BS EN ISO 7933:2023 [26], using CBE Comfort tool methods [27,59] and Gagge's model [25], tailorable for children despite adult-focused standards. The heat strain risk index is computed as follows:

- **Definition:** Hours (H_{HS}) in which physiological heat strain threshold (per adapted Gagge's model) is exceeded.
- **Scoring:** Binary—0 for 0 h; 100 for > 0 h.

The formula used is the following.

$$S_{\text{HS}} = \begin{cases} 0 & \text{if } H_{HS} = 0 \\ 100 & \text{if } H_{HS} > 0 \end{cases}$$

3.1.4. Risk scores weighting and classification

The final step, after the calculation of the individual risk scores illustrated earlier, is the aggregation and risk classification. The final overheating risk score (S_{total}) is calculated as the weighted sum of indicator scores ($n = 4$ in this case), with any fail-safe indicators (e.g., heat strain) enforcing an automatic maximum of risk:

$$S_{\text{total}} = \begin{cases} \dfrac{1}{n}\sum_{i=1}^{n} S_{\text{risk},i} & \text{if no fail-safe (heat-strain) breach} \\ 100 & \text{if fail-safe (heat-strain) indicator triggered} \end{cases}$$

The final risk classification (A–G) is determined by mapping S_{total} to pre-

Table 5
Overheating risk classification and interpretation.

Class	Score range	Interpretation
A	$0 \leq S_{total} \leq 20$	No risk/Negligible risk
B	$21 \leq S_{total} \leq 38$	Very low risk
C	$39 \leq S_{total} \leq 54$	Low-to-moderate risk
D	$55 \leq S_{total} \leq 69$	Moderate risk
E	$70 \leq S_{total} \leq 79$	Elevated risk
F	$80 \leq S_{total} \leq 89$	High risk
G	$90 \leq S_{total} \leq 100$	Very high/unacceptable risk

defined bands, reported in Table 5, to ease practical decision-making and interpretation of results.

3.2. Monitoring and data collection for overheating risk assessment

Monitoring was designed to collect classroom thermal data during summer and heatwaves alongside school inventory data. While room-by-room evaluation at scale requires simplifications (Section 2.2), empirical data capturing actual thermal response and occupant behaviour is essential.

3.2.1. Monitoring programme

The objective of the monitoring programme is capturing indoor environmental conditions during typical summer weather and documented heatwave events, providing a representative sample of classrooms for the calculation of the overheating risk indexes described in Section 3.1. Ten maintained schools (60 instrumented classrooms, 71 indoor spaces monitored) were chosen in consultation with Hampshire County Council (HCC) to cover the principal building archetypes found across the estate. Schools were also geographically distributed to reflect multiple locations within Hampshire. Each classroom used calibrated temperature/humidity loggers (Madgetech RHTemp101A, ±0.5 K accuracy) recording at 10-min intervals (April 2022–December 2023), positioned at mid-occupancy height (≈1.2–1.5 m) per BS EN ISO 7726. Hourly outdoor weather data were obtained from Visual Crossing API [60], referenced to nearest grid-points. Minor anomalies were removed. Six heatwave events were recorded in the monitoring period between 2022 and 2023.

3.2.2. Building stock data collection

A database covering 533 HCC schools (≈9,000 classrooms) compiled these variables:

- School location and type (infant, primary, secondary, all through).
- Site context (i.e., urban, rural, etc.).
- Construction type and year (i.e., masonry, steel-frame, SCOLA, timber-frame, Passivhaus, etc.).
- Orientation (azimuth of surface), floor level and window-to-wall ratio.
- Wall/roof/floor U-values (based on construction type and age).
- Glazing U and g-value (based on construction type and age), presence/type of shading.
- Ventilation (i.e., single-sided, cross-flow, etc.).
- Thermal-mass (based on construction type and age).

Parameters were extracted from HCC databases and manual floorplan/satellite imagery classification by university interns, supported by HCC. Additional information, such as the level of urbanisation of a location of a school, was obtained by matching to an external georeferenced database. The database enables: (i) simplified thermal modelling, (ii) generalization to unmonitored classrooms, and (iii) stock-scale scenarios evaluation. This, in turn, provides the opportunity for a council to assess risks and plan for interventions. Collectively, the building stock data and the monitoring data provide a robust empirical foundation for the overheating risk assessment presented in Sections 4 and 5. Classrooms with active cooling were excluded from the free-running overheating projections presented in Section 5, to keep the assessment consistent with BB101 criteria. In the HCC estate, this corresponds to approximately 86 classrooms, largely associated with modular portable cabins working as a temporary solution.

3.3. Modelling workflow for overheating risk assessment

The modelling workflow employs risk indices (Section 3.1), monitoring data (Section 3.2), and interpretable physics-informed methods (Section 2.3). The workflow is delineated in the following steps:

1. Regression-based weather normalisation of the thermal response of monitored classrooms to outdoor temperature.
2. Derivation of lumped physical parameters for each classroom, based on collected data (construction technology, age, etc.).
3. K-Nearest Neighbour (KNN) to match monitored classrooms with assessed classrooms (building stock data).
4. Calculation of projected thermal response (peak indoor temperatures) of the assessed classrooms in different weather reference climate scenarios (present and future).
5. Calculation of risk scores using the sigmoid function and aggregation of scores to attribute a risk class, as indicated in Section 3.1.4.

The details of each step are reported hereafter.

3.3.1. Regression modelling for peak indoor air temperature estimation

For each monitored classroom, daily peak indoor temperatures ($T_{peak,indoor}$) were regressed against daily mean outdoor temperature (Equation 7), following approaches in Section 2.3.

$$T^{(i)}_{\text{peak, indoor}} = a_i \cdot T^{(j)}_{\text{mean, outdoor}} + b_i$$

where *(i)* denotes the classroom and *(j)* the specific weather file or event.

UKCP18-derived CIBSE DSY1 probabilistic files (2020s, 2050s, 2080s RCP8.5, 50th percentile) and Swindon location were used for Hampshire projections. Additional climate change scenario percentiles have been considered in the sensitivity analysis.

3.3.2. Building stock data analysis and manipulation

Physical parameters influencing overheating were computed:

1. Surface-to-volume ratio (S/V), room compactness.
2. Thermal transmittance (U), envelope heat transfer.
3. Air change rate (ACH),ventilation capacity.
4. Thermal capacity and time constant (τ), thermal inertia.
5. Solar heat gain coefficient (g_{sol}), glazing- and orientation-weighted solar gains.
6. Roof solar gain factor ($f_{roof,sol}$), roof solar gains.

These enable similarity-based matching and strengthen empirical correlation reliability when scaling to unmonitored classrooms.

3.3.3. K-Nearest Neighbours interpolation of classroom response

KNN algorithm matches unmonitored classrooms to monitored ones via physical parameter proximity. Features from Section 3.3.2 form vector x_k.

$$x_k = \left[\frac{S}{V}, U, ACH, \tau, g_{\text{sol}}, f_{\text{roof, sol}}\right]_k$$

Euclidean distance identifies K-Nearest Neighbours (e.g., $k = 1$–3):

$$d_{kl} = \sqrt{\sum_p w_p (x_{k,p} - x_{l,p})^2}$$

where $x_{k,p}$ is parameter p of classroom k,l, and w_p are weights that can be customised.

Min-Max scaling (mapping values to the [0,1] range while preserving the original distribution shape) prevents parameter dominance in distance calculation. Default $k = 1$ identifies the most similar classroom; sensitivity to k and weighting schemes (inverse-quadratic, inverse-linear, unweighted) is reported in Appendix A. This physics-based similarity approach enables interpretable, scalable risk assessment.

3.3.4. Projected peak indoor air temperature and risk scoring computation

Matched classroom parameters (Section 3.3.3) and climate scenario temperatures (Section 3.3.1) are used to compute peak indoor temperature

$$T^{(m)}_{\text{peak, indoor}} = a_{nn} \cdot T^{(m)}_{\text{mean, outdoor}} + b_{nn}$$

where nn denotes the coefficient from KNN model, and superscript *(m)* denotes the specific climate data file.

3.3.5. Risk scoring with sigmoid function and aggregation of risk score

Predicted peak temperatures (Section 3.3.4) generate risk scores (standardized in the range 0–100, both continuous and discrete) via sigmoid function for each index (Section 3.1):

$$S_{\text{risk}}(x) = \frac{100}{1 + exp[-k \cdot (x - x_0)]}$$

where $S_{risk}(x)$ is the risk score (0–100), x is the input metric (e.g., hours > threshold, degree-hours, etc.), x_0 is the inflection (policy-based threshold), k sets the scale/steepness.

3.4. Model evaluation, sensitivity and uncertainty

The assumptions related to physical building properties used in KNN interpolation are based on data from literature reported in Section 2.2 and described in Section 3.2.2. The properties are attributed based on year of construction (and year of retrofit, for the retrofitted ones), building geometry, and construction technology.

This implies that the properties attributed to the measured buildings and to the entire stock are coherent and, since the overall modelling approach is based on similarity principle (i.e. similar buildings have a similar thermal response), a change in the underlying assumptions will reflect to the entire stock of similar buildings in a consistent manner.

Model evaluation follows two steps: (1) the sigmoid risk scoring approach (Section 3.3.5) is assessed via standard goodness-of-fit metrics (*RMSE* and R^2) for each index; (2) the full workflow is tested across monitored classrooms, to assess whether the approach generalises without evidence of overfitting to measured conditions.

Sensitivity analysis is then performed in Appendix A to quantify robustness to key modelling choices that are known to influence kNN interpolation in small datasets such as the number of neighbours k and the distance weighting function. Finally, given the intrinsic uncertainty in future climate projections, climate sensitivity analysis is reported separately in Appendix B, including alternative climate change scenarios.

4. Case study presentation

The climate characteristics of Hampshire are introduced in Section 4.1, while the characteristics of the building stock and its monitoring activity are reported in Section 4.2.

4.1. Hampshire's climate characteristics

HCC uses Swindon CIBSE weather files, more representative of Northern Hampshire than Southampton airport data (cooler, non-urban). This variation of temperatures within Hampshire is highlighted in Fig. 1 which shows the predicted percentage increase in the number of hot summer days (peak above 25°C) from the 2001–2020 median and the number of hot summer days at a 12x12km grid square resolution, using data from UKCP18 [61]. The greatest percentage increase in number of days from the baseline occurs on the Isle of Wight but the number of hot summer days is higher inland with the exception of Southampton itself due to it being an urban area. During the monitoring period, between 2022 and 2023, there were six heatwave events.

Fig. 1 shows that Hampshire's coastal-inland contexts present varying hot-day frequencies. Using a single DSY file ensures modelling consistency but may over/underestimate risk in coastal/urban areas respectively. Future work will incorporate location-specific weather files for better geographic differentiation.

4.2. Hampshire's school stock characteristics

The built typology of a school and the local climate conditions have a strong influence on its overheating risk. Victorian schools and schools built before the 2nd world war which generally have medium to high thermal mass, high ceilings and small levels of glazing represent a low risk built form in terms of overheating. In contrast, overglazed, lightweight structures such as SCOLA system school buildings, constructed between 1960 and 1980 pose a far greater risk of summer overheating.

School typology strongly influences overheating risk. Pre-WWII Victorian schools (high thermal mass, high ceilings, low glazing) show low risk, while 1960–1980 decades SCOLA buildings (lightweight, overglazed) show high risk. In previous monitoring activity [62], medium-weight building typology was cooler by an average of 2.7°C during occupied hours compared to lightweight one.

In principle, single sided ventilation classrooms, with no external shading in low thermal mass buildings can be considered as an example of classrooms that are at high risk of overheating. This risk may be exacerbated by local microclimate effects such as surrounding low albedo surfaces (e.g. flat roofs with dark surfaces, asphalt, etc.) and the

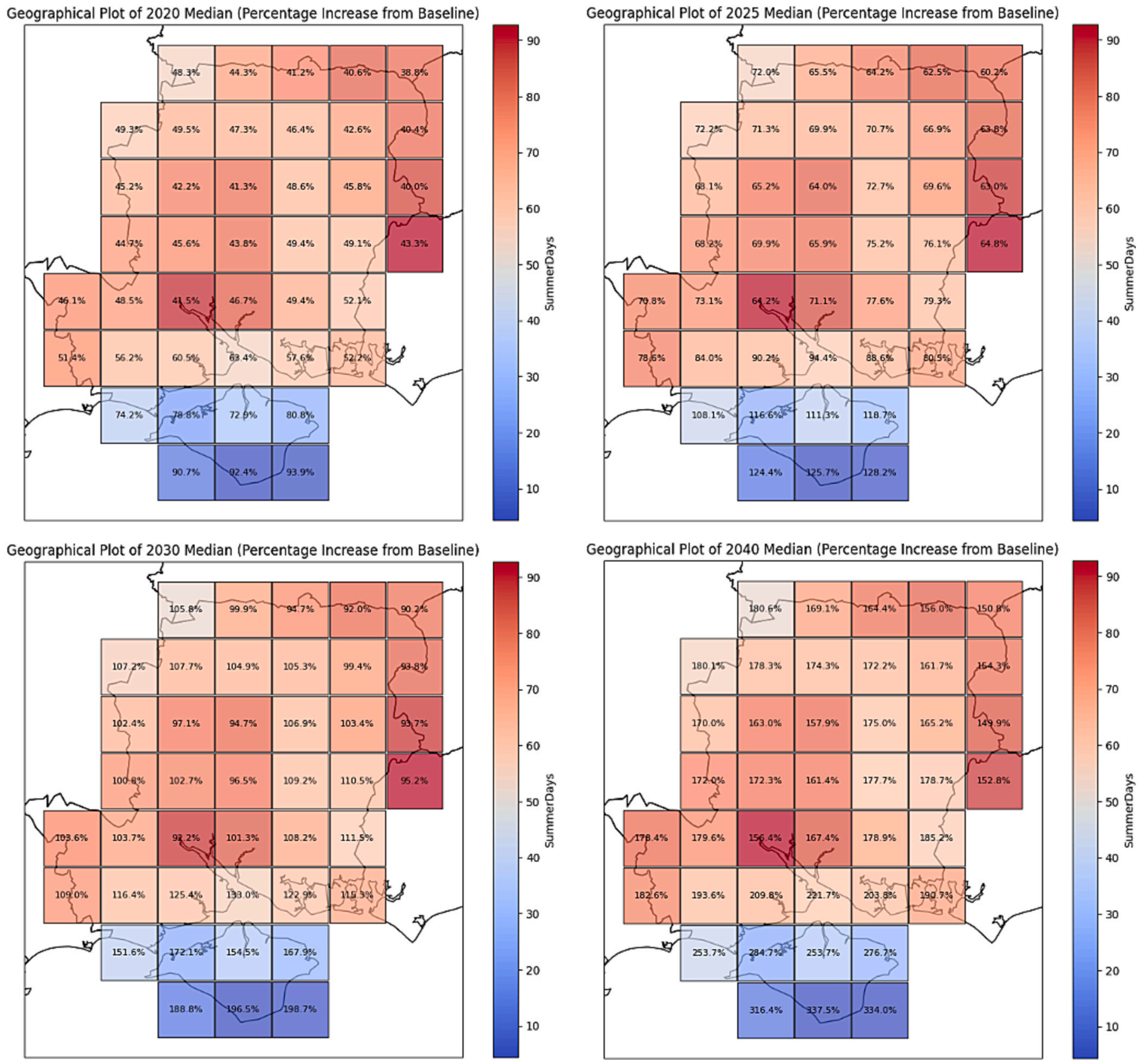

Fig. 1. Percentage increase in number of hot summer days (peak temperature > 25°C) from the baseline (2001–2020 median) in Hampshire at 12x12 km gridsquare resolution for 2020, 2025, 2030 and 2040 – Colour grid square represents the number of days above baseline.

requirement to close windows at night for security, which compromises the possibility to perform night passive cooling.

Hampshire County Council (HCC), England's largest Responsible Body, educates 184,000 children across 500 diverse schools ranging from 400-year-old listed buildings to new urban schools and those in national parks. The most common building type (approximately 40% of the estate) are 'SCOLA' system buildings constructed between 1960 and 1980, particularly at risk of overheating. Hampshire has around 25% of the 'SCOLA' buildings constructed nationally. The overall condition liability that HCC is monitoring and managing across its maintained school estate is estimated from surveys to be circa £420 million. The age distribution of HCC classrooms by school type and by decade after 1900 is reported in Fig. 2, indicating the vast majority of the stock has been built between 1951 and 2020, with the largest value in the decades 1961–70 and 1971–1980. In this period a large part of the schools have been built using the SCOLA system, as indicated in Fig. 3.

71 internal building spaces have been monitored across 10 schools in Hampshire for temperature and relative humidity between 2022 and 2023, using then 60 classrooms (out of 71) for modelling purposes. During this period there were six heatwave events, which enable the overheating modelling across normal and peaking temperature conditions. In general, classrooms are observed to overheat during heatwaves, with those with inadequate ventilation, single-sided ventilation, overglazed facades and lightweight construction performing the worst. The schools were selected to be representative of the school building stock in terms of construction types, including brick, SCOLA, and SCOLA-reclad from post-war to present day (including newly built). Selection was conducted in such a way that their configurations represent multiple possible combinations of the building characteristics reported in Section 3.2.2. It can be seen in Fig. 3 that the proportion of classrooms chosen is well aligned with the most diffuse construction systems and age of the building

Fig. 4 illustrates that in Hampshire, most classrooms are situated in buildings within urban environments, while only a small fraction is

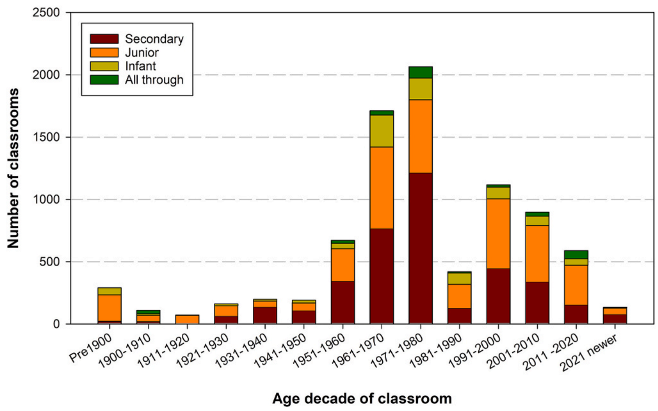

Fig. 2. Age distribution of HCC classrooms by school type (infant, junior, secondary, all through).

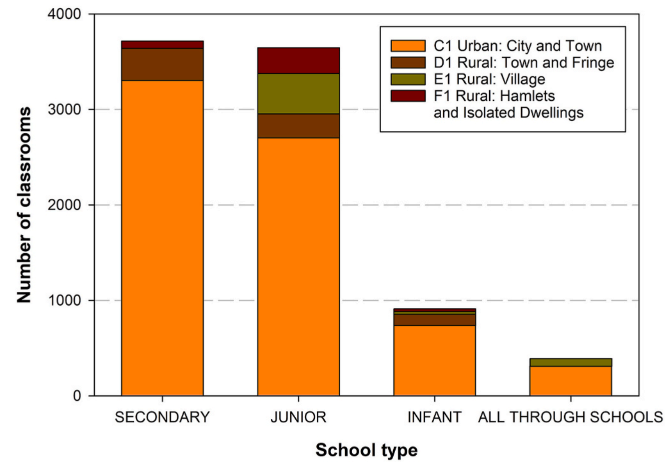

Fig. 4. *HCC classrooms by type (Secondary, Junior, Infant, All through) and urbanisation (Urban vs Rural).*

found in rural areas. This factor exposes the classrooms potentially to a higher risk of suffering from the urban heat island effect, but this needs to be addressed using more specific contextual information.

5. Results and discussion

The monitoring data are analysed using regression and time series techniques and discussed in Section 5.1. In Section 5.2 the results of overheating risk estimation are presented for the HCC regional school stock, following the methodological approach explained in Section 3.3. Limitations and further work are reported in Section 5.3, to indicate potential directions for future research development.

5.1. Overheating risk assessment for monitored schools/classrooms

Fig. 5 and Fig. 6 contrast good versus poor school performance during September 2023 heatwave, showing outdoor temperature, 7-day running mean, adaptive comfort temperature, Category II maximum [28], and heat strain limit. The brick school designed to Passivhaus principles in Fig. 5, exhibits an excellent thermal response with peak temperatures remaining under the maximum category II temperature throughout the heatwave. In contrast, the SCOLA school in Fig. 6 has classrooms that consistently breach the maximum category II temperature, with higher temperatures observed on the first floor of the building.

The two figures are meant to present the behaviour during a heat wave; however, the calculations of indicators for the monitored buildings have been conducted using the entire BB101 reference period, as explained in Section 3.1, and the computation of the overheating risk projections is the one presented in Section 3.3. The results in the latter case are reported in the next section.

5.2. Overheating risk assessment projections for Hampshire school stock

School stock overheating risk was estimated for present (CIBSE 2020 High 50th percentile DSY1, characterised by temperatures similar to those of the monitored period) and 2050s (CIBSE 2050 High 50th percentile DSY1) standard conditions.

Fig. 7 shows cognitive risk assessment: classrooms never exceeding 25°C score 0 (bin A), while those with $\geq$ 10% BB101 hours > 25°C score

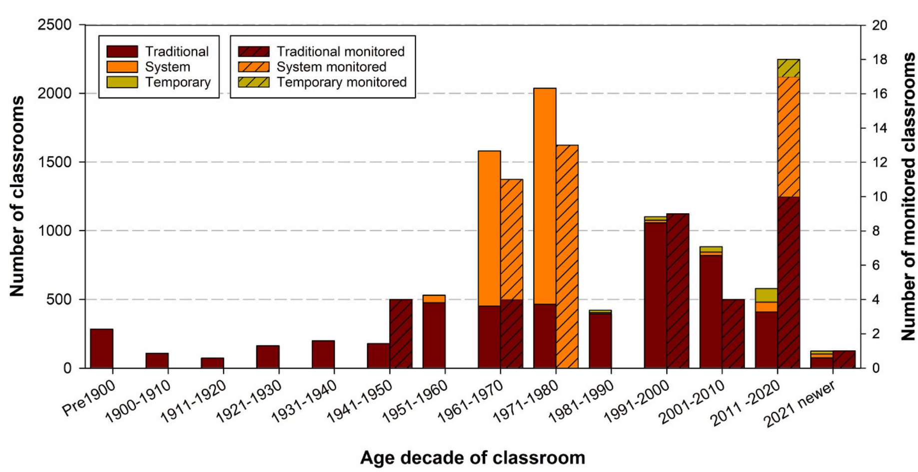

Fig. 3. Age distribution of HCC classrooms aggregated by construction system compared to monitored cases (hatched).

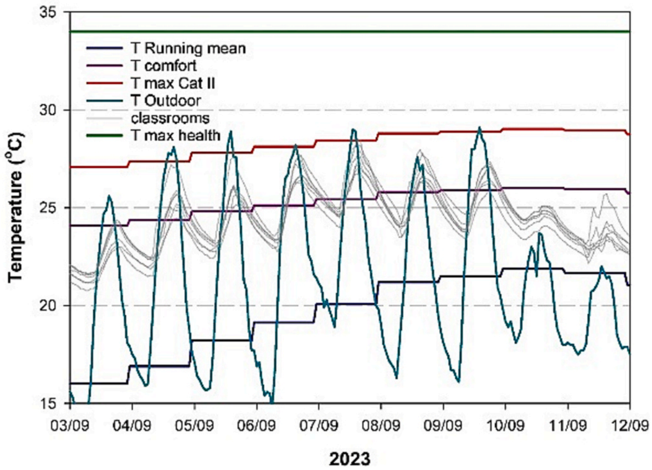

Fig. 5. Response of brick designed to Passivhaus principles, 2 storey school during September 2023 heatwave (school week: 04/09 Monday – 08/09 Friday).

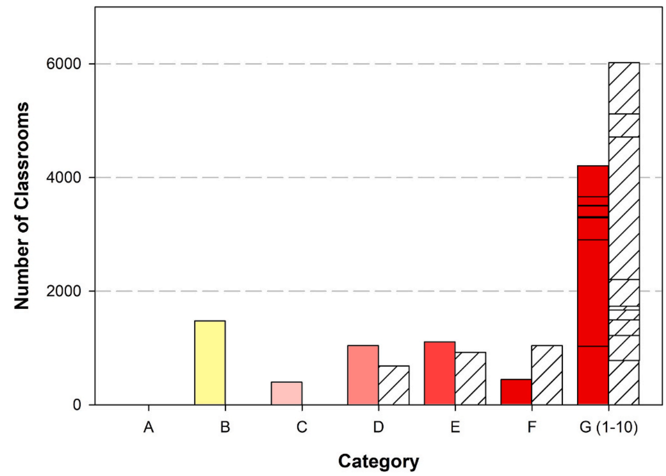

Fig. 7. Cognitive risk assessment for present state and 2050 future climate (hatched) all schools as location Swindon DSY1 50th percentile 2050. The G classification has 10 sub-bands which are stacked together (from G1 lowest to G10 most severe).

100 (bin G10), as explained in Section 3.1.1. Significant learning loss likely begins at bins D–E. Currently, 66% of classrooms are in E-G range (49% in G, red); by 2050, 92% are in E-G range (70% in G, hatched), with the most severe category (G10) rising from 6% to 10%. It should be noted that these estimates are based around the behaviour of the monitored classrooms, i.e., they represent a projection of the actual thermal response of the monitored building, extended to the other buildings using a similarity principle. The thermal response may vary based on intervention measures, which are not considered at this stage and discussed in Section 5.3.

Fig. 8 shows thermal comfort risk assessment. Currently, 50% of classrooms are in E-G range (10% in G, red); by 2050, 76% are in E-G range (50% in G, hatched), with the most severe category (G10) rising from 5% to 10%. A clear shift to the right is visible because the ‘A’ category practically disappears, and classrooms in the range A-C are spread across the range B-E by 2050.

Fig. 9 shows the health risk due to heat strain (i.e., number of classrooms that experience at least one hour in the heat strain range as defined in the CBE Comfort tool [27,59]), which increases from 6% to 10% by 2050.

Fig. 10 presents the overall weighted risk assessment with proportions similar to the ones identified for thermal comfort indexes presented in Fig. 8. Currently, 51% of classrooms are in E-G range (12% in G, red); by 2050, 79% are in E-G range (54% in G, hatched), with the most severe category (G10) rising from 6% to 10%. Also in this case, a clear shift to the right is identified, and the weighted approach is slightly more conservative compared to the one based on thermal comfort only, due to the more restrictive cognitive performance requirements in Fig. 7.

In summary, the results presented in the previous figures correspond to the application of the overheating risk assessment methodology presented in Section 3, considering first the individual areas of risk (cognitive, comfort, health) and then the weighted aggregation of the risk indexes. The results obtained for each risk class in percentage are reported in Table 6, considering the chosen reference scenarios. The classrooms which are at risk of having indoor temperatures in the heat strain range (bin G) will be prioritised for action to ensure the school stock can continue to be used.

The sensitivity analysis performed according to indications in Section 3.4 is reported in Appendices A and B, respectively focusing on modelling assumptions and climate uncertainty. Finally, an actionable checklist is reported in Appendix C.

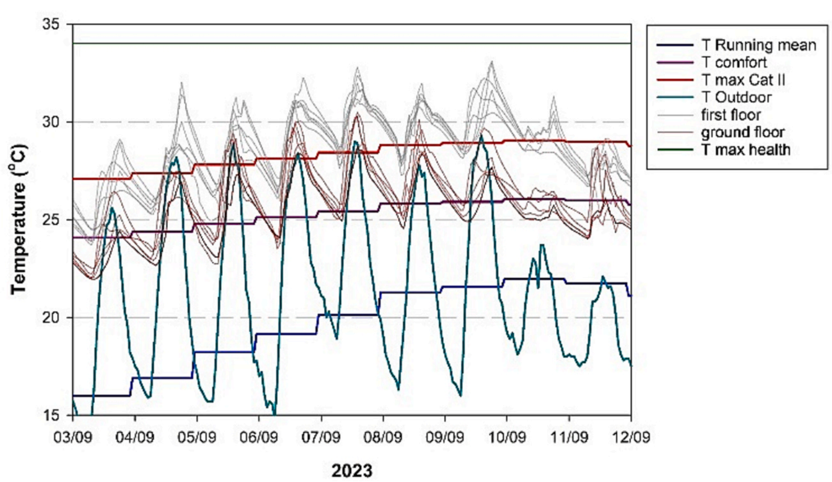

Fig. 6. Response of 2 storey SCOLA system school during September 2023 heatwave (school week: 04/09 Monday – 08/09 Friday).

5.3. Limitations and further work

In this research, the same standard weather files were used regardless of the school location in Hampshire. Such an approach will result in an overestimate of overheating risk for locations near the coast which are cooler, as shown in Fig. 1. The workflow uses simplifications necessary for regional scale application (around 9000 classrooms), with future refinement possible via additional evidence and more sophisticated algorithms in each step outlined in Section 3. Monitored schools were purposively selected to cover dominant systems and age bands (Fig. 3), introducing potential bias for rare typologies, though well-aligned with most diffuse building types. Estimates reflect 2022–2023 monitored behaviour, which can be changed via appropriate interventions (from low- to high-cost) reported in Appendix C. The use of low-cost intervention measures has been discussed in previous research [63], indicating a significant impact of behavioural interventions on pupils' actions in response to a hot day at school. Further, increased night ventilation and technology advances can help reduce internal gains (notably high-efficiency lighting and appliances) and temperatures. Finally, devices such as ceiling fans can shift thermal comfort boundaries. In the results presented, there is no externally driven adaptive behaviour considered (e.g., school policies to control temperatures, such as mandatory night cooling during certain months of the year or targeted heatwave education campaigns [64]. The monitoring activity does, of course, capture the naturally evolving conditions in the monitored classrooms during hot days, such as attempts to maximise ventilation during operating hours, which were observed when visiting schools. The workflow does not explicitly model behavioural variables at estate scale (e.g., window opening schedules, blind use, night purge policies), nor does it capture maintenance condition (e.g., inoperable windows, shading failures, restricted openings). Projections in Section 5.2 assume HCC buildings behave similarly to monitored samples (physics-informed similarity), as room-by-room monitoring at scale is infeasible. Further validation could be performed by applying the workflow to an independent monitored sample and comparing the predicted risk distributions against the one derived by measured data. Additionally, to address the problem of modelling interventions such as changes in occupants' behaviour and operation, as well as the introduction of new technologies such as ceiling fans or more radical refurbishment, it is necessary to use calibrated simulations (i.e., supported by experimental monitoring). Nonetheless, the physics-informed

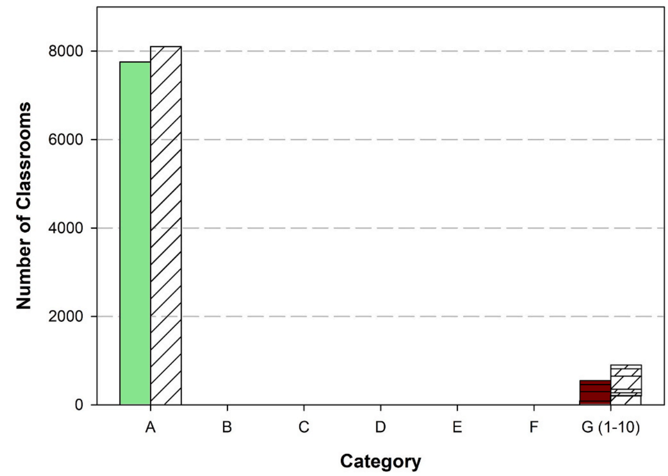

Fig. 9. Health risk assessment for present state and 2050 future climate (hatched) all schools as location Swindon DSY1 50th percentile 2050. The G classification has 10 sub-bands which are stacked together (from G1 lowest to G10 most severe).

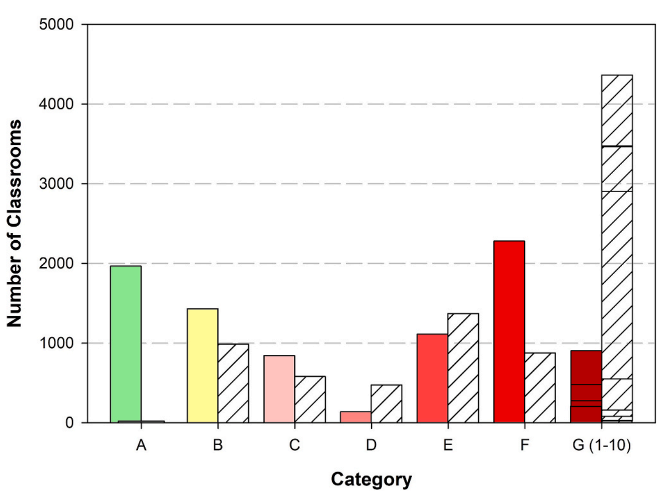

Fig. 8. Thermal comfort risk assessment for present state and 2050 future climate (hatched) all schools as location Swindon DSY1 50th percentile 2050. The G classification has 10 sub-bands which are stacked together (from G1 lowest to G10 most severe).

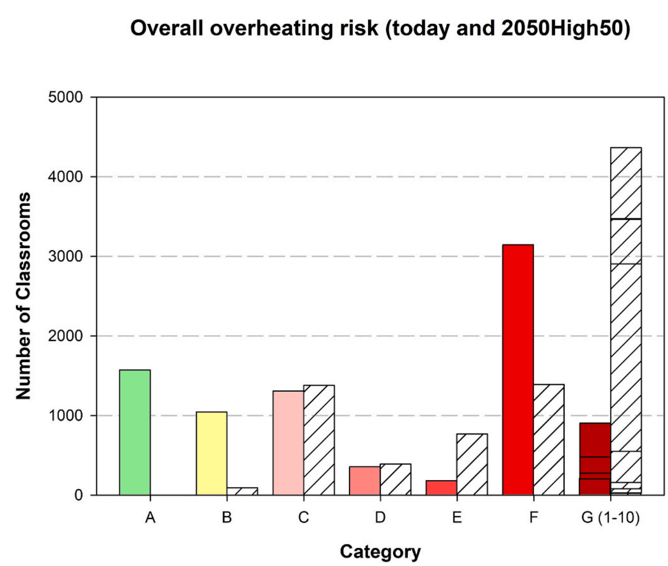

Fig. 10. Overall weighted overheating risk assessment for present state and 2050 future climate (hatched) all schools as location Swindon DSY1 50th percentile 2050. The G classification has 10 sub-bands which are stacked together (from G1 lowest to G10 most severe).

Table 6
Summary of overheating risk projections across different risk indexes, all schools as location Swindon DSY1 50th percentile 2020 and 2050.

Performance indexes	Climate projection			Classification						
	Year	Percentile	Scenario	A	B	C	D	E	F	G
		%	–	%	%	%	%	%	%	%
Cognitive risk	2020	50	High	0.0	17.0	4.5	12.0	12.8	5.1	48.6
	2050	50	High	0.0	0.0	0.0	7.8	10.6	12.0	69.6
Thermal comfort risk	2020	50	High	22.7	16.5	9.7	1.5	12.8	26.3	10.4
	2050	50	High	0.2	11.4	6.7	5.4	15.8	10.1	50.4
Heat strain risk	2020	50	High	93.7	0.0	0.0	0.0	0.0	0.0	6.3
	2050	50	High	89.6	0.0	0.0	0.0	0.0	0.0	10.4
Weighted overheating risk	2020	50	High	18.1	12.0	15.1	4.1	2.1	36.3	12.3
	2050	50	High	0.0	1.0	15.9	4.5	8.8	16.0	53.7

regression-based approach employed in this research can be used to support the calibration process (e.g., weather normalisation) and reduce the amount of simulations required. Finally, beyond coastal/inland temperature differences mentioned earlier, urban heat island effects and socio-economic constraints (e.g., budget limitations affecting maintenance and retrofit capacity) may influence both exposure and adaptive capacity. Future work could incorporate morphed/local weather files and link school locations to deprivation indices or condition-survey data to better capture these drivers.

6. Conclusions

This study assesses overheating risk in Hampshire schools under current and future climates, employing a hybrid physical-statistical workflow combining monitoring, stock modelling, climate projections, and multi-dimensional risk scoring (cognitive, comfort, health). Key contributions are: (i) multi-dimensional risk index complementing BB101 with cognitive and heat-strain indicators; (ii) empirically grounded, interpretable workflow scaling measured response to ~ 9000 rooms; (iii) estate-scale prioritization enabling actionable planning, complementing previous research on behavioural interventions.

The key findings are summarised hereafter:

- 66% of classrooms currently face cognitive performance degradation, rising to 92% (majority without cooling) by 2050 in the absence of interventions.
- Thermal comfort limits are exceeded by 50% of classrooms currently, increasing to 76% by 2050.
- Health risk (heat strain), which currently affects 6% of classrooms, is projected to impact 10% by 2050, nearly a two-fold increase in exposure to potentially dangerous thermal conditions during extreme heatwaves.
- Weighted overheating risk index indicates that the impact is substantial in the 51% of classrooms currently, increasing to 79% by 2050; the weighted index is more conservative compared to thermal comfort one, due to the more restrictive cognitive performance requirements.
- Building characteristics significantly influence vulnerability. Lightweight buildings with poor solar control and limited natural ventilation potential are the ones at higher risk. Conversely, well-designed modern schools demonstrate that comfortable conditions can be maintained also during heatwave events. This ability, however, will decrease in future climate scenarios. Older schools with high thermal mass and high ceilings perform well.

This study's methodology provides a scalable and transferable framework for assessing overheating risk, potentially applicable at a nationwide level. This approach integrates weather normalisation of the thermal response in monitored classrooms with the alignment of monitored and assessed classrooms based on physical characteristics, acting as an alternative to purely simulation-based models, thus providing a practical solution for local authorities aiming to enhance planning for their educational facilities. A "screening-to-action" checklist is provided in Appendix C. Based on these findings, several **policy implications and areas for future work** emerge:

- **Department for Education (DfE) guidance update**: Incorporate **cognitive and health thresholds** (maximum temperatures) alongside comfort limits to guide climate-adaptive design and operation.
- **Targeted interventions:** Prioritise high-risk buildings using low-to-medium cost measures (education, fans) through refurbishment. Ensure new builds address overheating in design. Embed risk scores in funding criteria.
- **National roll-out pathway:** The demonstrated workflow can be potentially scaled at the national level by incorporating additional building stock characteristics from other regions of England and can leverage simulated data from available platforms to provide a transparent overheating risk mapping across ~ 20,000 English schools.
- **Monitoring and contingency plans**: Schools should install simple temperature monitors and establish heatwave plans, including adjusting behaviour, operational schedules and utilising cooler spaces during extreme heatwave events.

The limitations of this research include the simplification of climate data analysis, the simplification of building stock modelling and the need to update the underlying model training data in the event of future building upgrades, changes in occupant behaviour, and different operational strategies (what-if analysis). To overcome these limitations, further research could concentrate on a better quantification of the local climate variations within the region, based on additional data acquisition, and on the integration of results from dynamic building simulations performed at the stock level, as well as considering other socio-economic factors influencing risk.

Further, additional monitoring activity is necessary to calibrate dynamic building performance simulations based on actual measured conditions and, therefore, improve the understanding of buildings and occupants' behaviours during heatwave events. Although detailed design of interventions is beyond the scope of the present assessment, the results indicate that solar control, ventilation effectiveness and thermal mass are critical levers for reducing overheating risk in both retrofit and new-build contexts.

Finally, exploring the relationships between the cognitive risk metrics suggested in studies and real student performance data, along with gathering information about heatwave-related incidents in schools, would significantly improve the understanding of these extra factors added to thermal comfort for measuring the risk of overheating.

Nevertheless, the results provided allow for planning future actions towards the prevention of the risk due to overheating in schools. The consequences of inaction will manifest as diminished educational achievements, increased health issues, and expensive emergency interventions. Proactive design and retrofitting procedures are essential to guarantee that school buildings remain safe, healthy, and conducive to learning in a changing climate. The developed tool provides an ability for a council to prioritise resource where it is needed most in the context of severe budget constraints.

Ethical approval

This project was approved by University of Southampton Ethical Committee with code ergo2.soton.ac.uk, 74198.

CRediT authorship contribution statement

Massimiliano Manfren: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Data curation, Conceptualization. **Patrick James:** Writing – review & editing, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization, Supervision. **Michael Chater:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization. **Colin Jackson:** Supervision, Project administration, Funding acquisition, Conceptualization. **Victoria Aragon:** Software, Investigation, Data curation. **Azadeh Montazami:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Stephanie Gauthier:** Methodology, Conceptualization. **Despoina Teli:** Writing – review & editing, Methodology, Conceptualization. **Beverly Quinn:** Supervision, Conceptualization. **Karam Kalsi:** Visualization, Software, Data curation. **Samuel Hough:** Data curation. **Carys Thomas:** Data curation. **James Partington:** Data curation. **Jay Jarrett:** Data curation.

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.

Acknowledgements

This study and project is financially supported by Hampshire County Council and the Department for Education (DfE), UK.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2026.117164.

Data availability

The monitoring dataset and the classroom-level stock database contain information that could enable identification of individual schools and are therefore subject to access restrictions. Access to disaggregated data may be considered subject to permission from Hampshire County Council and an appropriate data-sharing agreement.

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